Drought Monitoring Index for Texas

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EXECUTIVE SUMMARY

Drought is a pressing environmental issue that is of great importance to the State of Texas. The main objectives of this study were to 1) examine the current drought monitoring and drought prediction tools that are available, 2) evaluate the existing drought monitoring and prediction tools to determine which are the most appropriate for monitoring moisture conditions at the local level in the state of Texas, 3) develop operational definitions of meteorological and hydrological/water supply droughts so that the onset of duration of droughts events can be clearly identified, 4) develop guidelines for the reporting of moisture (drought) conditions at the local level in the state of Texas, and 5) make recommendations on how this information can be most effectively implemented by the end user.

A thorough review of the literature was conducted to identify existing drought monitoring tools (Task 1- Section 2). The most promising tools for monitoring meteorological and hydrological/water supply drought were evaluated using both a qualitative and quantitative approach (Task 2- Section 3). We recommend using the Standardized Precipitation Index (SPI), Percent Normal, and Deciles to monitor meteorological drought in Texas because these three indices are relatively easy to calculate and they are transparent and easy to understand. Soil moisture models, such as the Decision Support System for Agrotechnology Transfer (DSSAT), were also found to provide useful information that can augment the precipitation-based indices. Although these models require more input data, unlike the precipitation-based indices, they can simulate all aspects of the soil water budget including infiltration, runoff, evapotranspiration. Other indices such as the Palmer Drought Severity Index (PDSI),

Moisture Anomaly Index (Z-index), and Vegetation Condition Index (VCI) performed poorly.

We recommend using the Standardized Streamflow Index (SSFI), Reservoir Deficit Index (RDI), and 6-month, 9-month, and 12-month SPI to monitor hydrological/water supply drought in Texas. SSFI and RDI were specifically developed for this study and both demonstrate great promise for monitoring hydrological/water supply drought. SSFI is a standardized measure of streamflow that is similar in formulation to the SPI. RDI measures reservoir levels and utilizes the WRAP model to avoid the problems associated with changes in water usage over time. The analysis determined that the most appropriate timescale for monitoring hydrological/water supply drought varies by basin. Although the Palmer Hydrological Drought Index (PHDI) and Surface Water Supply Index (SWSI) have been commonly used, they have little utility in Texas.

Operational drought definitions were developed by fitting an appropriate distribution function to a drought index (Task 3- Section 4). Five drought thresholds (ranging from abnormally dry to exceptional drought) were defined based on the percentiles used by the United States Drought Monitor. Using an objective approach for determining drought definitions ensures that droughts are accurately and correctly identified at the local level. It is inappropriate to use a single set of drought definitions for an entire state (especially a state the size of Texas).

Overall, no single index can represent all aspects of meteorological or hydrological/water supply drought so it is best to use a multi-index approach for operational drought monitoring. Drought information should be collected and stored in

Texas at the finest spatial resolution practicable. The information should then be aggregated to appropriate physical and jurisdictional domains. For example, meteorological drought conditions should be reported at the county level and hydrological/water supply drought conditions should be reported using watershed boundaries. The Texas Drought Preparedness Council should establish a system for issuing drought watches and drought warnings based on current conditions and climate forecasts. Such warnings should be conveyed to the appropriate county judges and water supply agencies.

This study demonstrates that there is a serious need for developing a Texas Drought Monitoring System that utilizes the most appropriate meteorological and hydrological/water supply drought indices to provide decision makers with valuable data, at the local level, to facilitate the adoption of appropriate adaptation, mitigation, and avoidance strategies. We encourage the Texas Drought Preparedness Council in cooperation with the State of Texas to utilize the recommendations contained in this report as the basis for developing a Texas Drought Monitoring System.

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1. INTRODUCTION

1.1 Background

Drought is a naturally recurring climatic phenomenon that has a significant impact on both the environment and society (Stahle *et al.*, 1998; Stahle *et al.*, 2000; deMenocal, 2001). Although it has numerous definitions, drought originates from a deficiency of precipitation over an extended period of time, usually a season or more. Since drought is a temporary departure from normal (or expected) climate conditions, it can occur in any climate zone. Drought differs from aridity since aridity is restricted to low rainfall regions and is a permanent feature of climate.

There are two main types of drought definitions: conceptual and operational. Conceptual definitions are formulated in general terms and they are used to help people understand the concept of drought. Operational definitions are very specific and they are used to identify the beginning, end, and degree of severity of a drought (National Drought Mitigation Center, http://www.drought.unl.edu). Wilhite and Glantz (1985) identified more than 150 conceptual definitions of drought and classified these definitions into four categories: meteorological, agricultural, hydrological and socio-economic drought. Meteorological drought refers to a period of time where there is a significant negative departure from normal precipitation. Agricultural drought is a period of moisture deficiency that is sufficient to have a lasting adverse impact on plant growth or crop yield. Hydrological drought refers to an extended period of time (on the order of months or years) of below normal precipitation that results in deficiencies in streamflow, groundwater, and lake and reservoir levels (Keyantash and Dracup, 2002). Similarly, the American Meteorological Society defines hydrological drought as "*Prolonged period of below-normal precipitation, causing deficiencies in water supply, as measured by below-*

normal streamflow, lake and reservoir levels, groundwater levels, and depleted soil moisture content". In this study we will refer to this type of drought as hydrological/water supply drought since below-normal streamflow, groundwater, and lake and reservoir levels will have a negative impact on water supply. Operational definitions for meteorological and hydrological/water supply drought in Texas are discussed in section 4.

According to the Federal Emergency Management Agency (FEMA), the average annual cost of droughts in the United States is 6 to 8 billion dollars. Lott and Ross (2006) documented 11 billion-dollar heat waves/droughts between 1980 and 2005 that caused a total of 145 billion dollars in damages (all damages standardized and reported in 2002 dollars). This includes the widespread drought of 2002 that influenced portions of 30 states and caused an estimated 10 billion dollars in damages (Lott and Ross, 2006). The drought during the summer of 1998 drought caused approximately 7 to 10 billion dollars in damages, the majority of these losses were in Texas. The most severe drought in recent memory occurred in 1988. It affected much of the central and eastern U.S. and it is estimated to have caused 61 billion dollars in damages/losses, most of which occurred in the agricultural sector (Lott and Ross, 2006).

While the effects of droughts are well documented, a uniform method for monitoring drought conditions and quantifying the severity of drought does not exist. Drought is a complex phenomenon that is difficult to accurately describe because its definition is both spatially variant and context dependent. As a result, there are a large number of tools that have been developed to monitor moisture conditions. The most common tool for monitoring drought conditions is a drought index. A drought index can be used to quantify the moisture condition of a region and thereby to detect the onset and measure the severity of drought events. A drought index can also be used to quantify the spatial extent of a drought event, thereby allowing a comparison of moisture supply conditions between regions (Alley, 1984).

Drought indices can be useful tools for providing information to decision-makers in business, government and to public stakeholders. For example, drought indices can be used to provide an early drought warning system (Lohani and Loganathan, 1997; Lohani *et al.*, 1998), to calculate the probability of drought termination (Karl *et al.*, 1987), to determine drought assistance (Wilhite *et al.*, 1986), to assess forest fire hazard and dust storm frequency (Cohen *et al.*, 1992), to predict crop yield (Kumar and Panu, 1997), to examine the spatial and temporal characteristics of drought, the severity of drought, and to make comparisons between different regions (Alley, 1984, 1985; Soule, 1992; Kumar and Panu, 1997; Dai *et al.*, 1998; Nkemdirim and Weber, 1999).

A large number of drought indices exist, each having a variety of data input requirements and each providing a somewhat different measure of drought (Heim, 2002). Some of the indices that are used include the Palmer Drought Severity Index (PDSI) and the Moisture Anomaly Index (Z-index) (Palmer, 1965), the Standardized Precipitation Index (SPI) (McKee *et al.*, 1993), the Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982), Percent Normal, Deciles (Gibbs and Maher, 1967), and the Normalized Difference Vegetation Index-based Vegetation Condition Index (Kogan, 1995). Given the range in derivations and the different responses of these drought indices, not all are suitable for measuring meteorological or hydrological/water supply drought. Unfortunately, many drought indices have limited utility for state agencies, stakeholders, and decision makers because they are often difficult to interpret (e.g., the method used to calculate the indices and their meaning is often unclear to non-scientists), difficult to calculate, and they do not provide location-specific drought information (e.g., they are spatially coarse).

The most advanced ('state-of-the-art') national drought monitoring product currently available is the United States Drought Monitor (hereafter Drought Monitor) which was introduced in 1999 (Svoboba *et al.*, 2002). The Drought Monitor provides a subjective measure of drought conditions since it is based on a consensus of opinions and a blend of different drought and soil moisture indices. It is also a highly generalized product, spatially (since it is based on climate division data), temporally (since it is only updated on a weekly basis), and in its focus (since it attempts to account for all types of drought: meteorological, agricultural, and hydrological). Other drought monitoring products are also produced by the Climate Prediction Center (CPC) and the National Climatic Data Center (NCDC), and the National Drought Mitigation Center (NDMC). The majority of these monitoring products are updated on a weekly or monthly basis and they provide drought information at the climate division level. The size of each of these climate divisions is quite variable. For example, Texas is composed of 10 climate divisions that range in size from 7,870 to 100,880 km^2 and each contains between 3 and 44 counties. Climate division data is not appropriate for providing local-level drought information given that moisture (drought) conditions exhibit a great degree of spatial variability (e.g., they are spatially hetereogeneous). Most of this spatial variability is due to precipitation, which can vary greatly over short distances, especially during the growing season, as a result of convective activity. Therefore, most of the drought monitoring products that are currently available are too coarse, both spatially and temporally, for local-level monitoring and decision-support applications.

1.2 Scope of Work

The purpose of this research is to develop tools for monitoring meteorological and hydrological/water supply drought at the local level in the state of Texas. Specifically, the main objectives of this research are to 1) examine the current drought monitoring and drought prediction tools that are available, 2) evaluate the existing drought monitoring and prediction tools to determine which are the most appropriate for monitoring moisture conditions at the local level in the state of Texas, 3) develop operational definitions of meteorological and hydrological/water supply droughts so that the onset and duration of droughts events can be clearly identified, 4) develop guidelines for the reporting of moisture (drought) conditions at the local level, and 5) make recommendations on how this information can be most effectively implemented by the end user.

Task 1 provides a summary of the drought monitoring tools that are commonly being used within the United States. This section of the report is divided into five parts. The first section provides a list of the drought monitoring products that are currently available in the United States. The second section describes nine meteorological drought indices, including their purpose, data requirements, and how they are calculated. The third section describes four indices that are commonly used for monitoring hydrological/water supply droughts. In addition four new drought indices in the context of hydrological/water supply droughts are also proposed. This is followed by a discussion of a number of hybrid drought monitoring tools. Finally, the drought prediction tools that are currently available are introduced, although it is not currently possible to forecast drought in Texas with a useful level of accuracy in most circumstances.

Task 2 involved selecting the most appropriate indices for monitoring meteorological and hydrological/water supply drought at the local level. The evaluation was carried out in three stages. The first stage was to review the literature and identify the strengths and weaknesses of the meteorological and hydrological/water supply drought indices considered in this study. As implied by Tasks 2 and 3, drought is not a single phenomenon with a single index for measuring its severity. The review of drought monitoring tools revealed a broad array of indices that varied greatly in regards to their complexity and utility for monitoring moisture conditions at the local level. In the second stage the indices were evaluated using a modified version of the criteria developed by Keyantash and Dracup (2002). This qualitative evaluation is based on six criteria, namely robustness, tractability, transparency, sophistication, extendibility, and dimensionality. Finally, all of the indices were calculated for a variety of representative locations within Texas and compared using goodness-of-fit measures. The most appropriate indices for monitoring meteorological and hydrological/water supply drought were selected based on the results of the three stage evaluation process. Preference was given to those tools that are simple to calculate, easy to understand, and have gained scientific or community acceptance. It was demonstrated that each type of drought (meteorological, hydrological/water supply) requires its own set of drought indices to effectively monitor it.

Task 3 involved developing appropriate operational definitions (or thresholds) for meteorological and hydrological/water supply drought. Thirty-three State Drought Plans were reviewed to identify the operational drought definitions that are currently being used within Texas and across the United States. In most cases a single definition is used for the entire state and often these definitions are not based on drought impacts. Therefore a new method for developing appropriate drought thresholds for monitoring meteorological and hydrological/water supply drought at the local level in the state of Texas was introduced. The benefits of this method were illustrated using data from a number of representative stations from across Texas.

Task 4 involved developing guidelines for reporting moisture conditions at the local level. This section opens with a discussion of why drought conditions should be monitored and reported at the local level. This is followed by a discussion of various strategies that are being used for reporting drought information at the local level in other states. The third section investigates what spatial scale is most appropriate for monitoring drought at the local level and the fourth section details specific recommendations for developing a high-resolution drought information system. It is recommended that, to the extent possible and appropriate, drought and dryness indices should be computed at the resolution of the observations (e.g., station, pixel, grid cell). For reporting, planning, and response purposes, the dryness information should then be aggregated to the appropriate scale, such as county, watershed or water district, in order to provide the end users with information that is both precise and simple.

The final section of this report summarizes our recommendations for implementation. Recommendations are presented for each of the specific tasks and the report closes with some concluding remarks.

2.0 TASK 1: REVIEW OF EXISTING DROUGHT MONITORING AND DROUGHT PREDICTION TOOLS

2.1 Introduction

The objective of Task 1 is to examine the tools that are available for monitoring and predicting meteorological and hydrological/water supply droughts. Particular attention will be paid to those that are currently being used operationally within the United States (Table 1). This section will be divided into four parts. First the indices that are commonly used to measure meteorological drought will be reviewed. This will be followed by a review of four indices that are commonly used to measure hydrological/water supply droughts. In addition four new drought indices in the context of hydrological/water supply droughts are also proposed. The third section will discuss hybrid drought monitoring tools. These are indices/tools that are not specific to a single type of drought (e.g., meteorological or hydrological), they try to monitor multiple types of drought. Finally, there will be a brief discussion of the drought prediction tools that are currently available. The characteristics of the more common drought indices, such as the Palmer Drought Severity Index (PDSI), have been extensively analyzed and discussed elsewhere; in this study we will refer to but not duplicate that work. This information will be used to identify those tools that will most likely be appropriate for monitoring meteorological and hydrological/water supply droughts at the local level in the state of Texas. Task 2 will include a more detailed analysis of the strengths and weaknesses of the indices as part of the drought index evaluation.

Table 1. Selected drought monitoring products that are currently available in the United States (superscript numbers indicate that an example of this drought monitoring product is provided in Appendix A)

Source	URL	Indices/Data Available	Update Frequency	Spatial Coverage	Spatial Resolution
Climate Prediction Center	http://www.cpc.ncep.noaa.gov/	PDSI[1], PDSI Percentile	weekly	US	Climate Division
		Crop Moisture Index[2]	weekly	US	Climate Division
		Soil Moisture Anomaly[3]	daily, monthly, 12 month	US, global	½ degree
		Evaporation Anomaly[4]	daily, monthly, 12 month	US, global	½ degree
		Runoff Anomaly[5]	daily, monthly, 12 month	US, global	½ degree
		Precipitation Anomaly[6]	daily, monthly, 12 month	US, global	½ degree
		Experimental Drought Indicator Blends (Short[7] & Long[8])	weekly	US	Climate Division
		Topsoil Moisture[9]	weekly, 5 and 10 year means	US	State
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
National Climatic Data Center	http://www.ncdc.noaa.gov/climate/research/monitoring.html	PDI, PHDI[10], Z-index[11]	weekly, monthly	US	Climate Division
		Standardized Precipitation Index (1–24 months)[12]	monthly	US	Climate Division
		Precipitation Ranks[13]	monthly	US	State, Climate Division
		Percent of Long-term Precipitation (6, 12, 24, 36, 48, & 60 months)[14]	monthly	US, Mexico	Climate Division
		Percent of Pasture and Range Land in Poor Condition[15]	monthly	US	State

	http://www.ncdc.noaa.gov/oa/climate/research/cie/cmsi.html	Corn (Soybean) Moisture Stress Index[16]	annual	US	Climate Division
	http://www.ncdc.noaa.gov/oa/climate/research/snow/snow.html	Snow Monitoring[17]	1–7 day snowfall, monthly	National or State	Individual stations
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
Spatial Climate Analysis Service	http://www.ocs.orst.edu/prism/	Precipitation Anomaly[18]	monthly, monthly climatology (1971–2000)	US	2.5 arc-minute (~ 4 km)
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
Texas Water Development Board (Texas WaterInfo.net)	http://www.texaswaterinfo.net/	PDSI, PDSI Probability, Crop Moisture Index, Standardized Precipitation Index	monthly	Texas	Climate Division
	http://www.tceq.state.tx.us/permitting/water_supply/pdw/trot/location.html	Community Water Systems[19]	monthly	Texas	Individual communities
	http://www.twdb.state.tx.us/publications/reports/waterconditions/conservationstorage/conservation_storage.htm	Reservoir Storage[20]	monthly	Texas	Individual reservoirs
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
Texas Forest Service	http://www.tamu.edu/ticc/rgmap.jpg	Relative Greenness[21]	weekly	Texas	4 km
	http://webgis.tamu.edu/kbdi-map.aspx	Keetch-Byram Drought Index[22]	daily	Texas	4 km
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
NOAA Drought Information Center	http://www.drought.noaa.gov/	U.S. National Drought Overview	monthly	US	Climate Division
	http://www.orbit.nesdis.noaa.gov/smcd/emb/vci/index.html	Vegetation Health Index[23] & Fire Risk Index	weekly, annual	US, Global	1.1 km
	http://lwf.ncdc.noaa.gov/oa/climate/research/drought/drought.html	Drought Calculator	N/A	US	Climate Division

Source	URL	Indices/Data Available	Update Frequency	Spatial Coverage	Spatial Resolution
US Geological Survey	http://waterdata.usgs.gov/tx/nwis/rt	Streamflow Condition[24]	daily, 7-day, monthly	US, State	Individual stream gauges
	http://waterdata.usgs.gov/nwis/current/?type=gw	Groundwater Condition	daily	US	Individual gauges
	http://www.cpc.ncep.noaa.gov/products/predictions/experimental/edb/usdm-streamflows-overlay.gif	7-day Streamflow percentiles and Drought Monitor Overlay[25]	weekly	US	Individual stream gauges
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
Southeast Regional Climatic Center	http://www.sercc.com/climateinfo/drought.html	Percent Field Capacity[26]	weekly	Southeast US	Climate Division
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
National Drought Mitigation Center	http://www.drought.unl.edu/monitor/spi-dailygridded.html	Gridded Standardized Precipitation Index[27]	daily	US	½ degree
	http://droughtreporter.unl.edu/	Drought Impact Reporter	daily	US	County
	http://www.drought.unl.edu/dm/index.html	Drought Monitor[28]	weekly	US, North America	Climate Division
	http://drought.unl.edu/monitor/raindry/precipitationdays.html	Number of Rain days, Number of Dry Days, Number of days since last rain[29]	weekly	US	½ degree
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
Joint Agricultural Weather Facility	http://www.usda.gov/oce/waob/jawf/wwcb.html	Weekly Weather and Crop Bulletin (1971–present)	weekly	US, global	N/A
Source	**URL**	**Indices/Data Available**	**Update Frequency**	**Spatial Coverage**	**Spatial Resolution**
University of Washington Surface Water Monitor	http://www.hydro.washington.edu/forecast/monitor/index.shtml	Soil Moisture Percentile[30]	daily	US	½ degree

Source	URL	Indices/Data Available	Update Frequency	Spatial Coverage	Spatial Resolution
Wildfire Assessment System	http://www.fs.fed.us/land/wfas/	Keetch-Byram Drought Index[31]	daily	US	Interpolated from station data

2.2 Review of Meteorological Drought Indices

This section reviews the drought indices that are most commonly used for measuring meteorological drought. Meteorological drought is usually defined as a shortage of precipitation (or moisture supply) over some period of time (weekly, monthly, seasonal, or annual time scales). Definitions of meteorological drought, therefore, are location specific since the expected (normal) precipitation is a function of the climate. Some definitions of meteorological drought focus on the amount of time since the last significant precipitation (e.g., number of consecutive dry days), while others focus on the magnitude of the precipitation departure from normal. There are numerous meteorological drought indices. This section will describe some of the more common ones, including the Palmer Drought Severity Index (PDSI) and Moisture Anomaly Index (Z), Standardized Precipitation Index (SPI), Effective Drought Index (EDI), Vegetation Condition Index (VCI), Percent Normal, and Deciles.

This section also describes three different methods for modeling soil moisture. Soil moisture in the upper layers of the soil (top 5 or 10 cm) can also be used as a measure of meteorological drought since it accounts for the influence of all components of the hydrological cycle (infiltration, runoff, evaporation), not just precipitation (Ogelsby and Erickson, 1989; Quiring and Papakyriakou, 2003). Field measurement of soil moisture is time-consuming and expensive, and in some cases, it is impossible to measure at a regional scale. Therefore it is difficult to use observed soil moisture for drought monitoring activities (except in places where there is a relatively dense mesonet (e.g., Oklahoma). Therefore, most drought monitoring applications that utilize soil moisture information rely on modeled soil moisture. Many different soil moisture models have been developed and these models have different complexities and require different data inputs. In this study three different models of varying complexity are investigated, namely the Variable Infiltration Capacity (VIC) (Liang *et al.*, 1994), Decision Support System for Agrotechnology Transfer (DSSAT) (Ritchie and Otter, 1985) and Climatic Water Budget (CWB) (Thornthwaite, 1948; Thornthwaite and Mather, 1955).

2.2.1 Palmer Drought Severity Index (PDSI) and Moisture Anomaly Index (Z)

The PDSI and the Z-index were both developed by Palmer (1965) and have been widely used in the scientific literature (Alley, 1984; Karl *et al.*, 1987). The PDSI and Z-index are derived using a soil moisture/water balance algorithm that requires a time series of daily air temperature and precipitation data, and information on the available water content (AWC) of the soil. Soil moisture storage is handled by dividing the soil into two layers. The top layer has a field capacity of 25 mm, moisture is not transferred to the second layer until the top layer is saturated, and runoff does not occur until both soil layers are saturated. Potential evapotranspiration (PE) is calculated using the Thornthwaite (1948) method and water is extracted from the soil by evapotranspiration when PE > P (where P is the precipitation for the month). Evapotranspiration loss from the surface layer of the soil (L_s) always is assumed to take place at the potential rate. It is also assumed that the evapotranspiration loss from the underlying layer of the soil (L_u) depends on the initial moisture conditions in this layer, PE, and the combined available water content in both layers.

The Z-index is a measure of the monthly moisture anomaly and it reflects the departure of moisture conditions in a particular month from normal (or climatically appropriate) moisture conditions (Heim, 2002). The first step in calculating the monthly moisture status (Z-index) is to determine the expected evapotranspiration, runoff, soil moisture loss and recharge rates based on at least a 30-year time series. A water balance equation is subsequently applied to derive the expected or normal precipitation. The monthly departure from normal moisture, d, is determined by comparing the expected precipitation to the actual precipitation. The Z-index, Z_i, then is the product of d and a weighting factor K for the month i,

$$Z_i = d_i K_i \tag{1}$$

where K_i is a weighting factor that is initially determined using an empirically derived coefficient, K', and then adjusted by a regional correction factor that is used to account for the variation between locations. Monthly values of K_i are calculated using

$$K_i = \left(\frac{17.67}{\sum D_i K_i} \right) K' \tag{2}$$

where D is obtained during the calibration period by determining the mean of the absolute values of d for each month of the year. In (2), a revised regional correction factor of 14.2, established by Akinremi *et al.* (1996), has been substituted for Palmer's original value of 17.67 (Palmer, 1965). Akinremi *et al.* (1996) found Palmer’s original values artificially inflated the drought index values when applied to the Canadian prairie.

The PDSI, indicated by X_i, is a combination of Z_i, for the current month, and the PDSI value for the previous month,

$$X_i = \left(\frac{Z_i}{3} \right) + 0.897 X_{i-1} \quad . \tag{3}$$

While both the Z-index and the PDSI are derived using the same data, their monthly values are quite different. The Z-index is not affected by moisture conditions in the previous month, so Z-index values can vary dramatically from month to month. On the other hand, the PDSI varies more slowly because antecedent conditions account for two-thirds of its value. Although the PDSI was designed to measure meteorological drought (Table 2), it may be more appropriate as a measure of hydrological drought (Strommen and Motha, 1987; Akinremi *et al.*, 1996a) and, according to Karl (1986), the Z-index may be a better measure of meteorological or agricultural drought. It should be noted that although both the Z-index and PDSI are strongly weighted by both precipitation and temperature anomalies (Hu and Willson 2000), most other meteorological indices (e.g., SPI, EDI, percent normal, deciles) are calculated using only precipitation. Alley (1984), Karl (1986), and Guttman (1998) have completed detailed evaluations of the limitations of the PDSI and Z-index, their work, along with the work of other researchers, has been summarized by Heim (2002).

Table 2. PDSI classification (Palmer, 1965)

PDSI Value	Category
> 4.0	Extremely Wet
3.0 to 3.99	Very Wet
2.0 to 2.99	Moderately Wet
1.0 to 1.99	Slightly Wet
0.5 to 0.99	Incipient Wet Spell
0.49 to -0.49	Near Normal
-0.5 to -0.99	Incipient Dry Spell
-1.0 to -1.99	Mild Drought
-2.0 to -2.99	Moderate Drought
-3.0 to -3.99	Severe Drought
< -4.0	Extreme Drought

2.2.2 Standardized Precipitation Index (SPI)

The SPI was developed by McKee *et al.* (1993, 1995) to provide a moisture supply index that performed better than the PDSI. The SPI is based on statistical probability and was designed to be a spatially invariant indicator of drought (e.g., SPI is supposed to be spatially and temporally comparable). It is produced by standardizing the probability of observed precipitation for any duration. For example, durations of weeks or months can be used to apply this index for agricultural or meteorological purposes, and longer durations of years can be used to apply this index to water supply and water management purposes (Guttman, 1999). The SPI can be calculated for any location that has a long-term precipitation record. The precipitation record is fit with a probability density function and subsequently transformed using an inverse normal (Gaussian) function (Guttman, 1999). This insures that the mean SPI value for any given location (and duration) is zero and the variance is one. Positive values of the SPI indicate greater than median precipitation, while negative values indicate less than median precipitation (Table 3). An SPI value of less than -1 indicates that a drought event is taking place and drought intensity can be calculated by summing the SPI values for all months within a drought event (McKee *et al.*, 1993, 1995).

There are at least two different probability distributions (e.g., Pearson Type III or Gamma) that are used to calculate the SPI. This is important to note because using a different probability distribution will produce different SPI values, even with the same input data. Guttman (1999) experimented with different probability distributions and concluded that the Pearson Type III distribution provides the best model for calculating the SPI. However, this remains a matter for debate since other studies have identified different probability distributions as being the most appropriate for evaluating monthly precipitation probabilities (Legates, 1991; Husak *et al.*, in press). For example, the National Drought Mitigation Center (NDMC, drought.unl.edu) uses the 2-parameter gamma PDF to fit the frequency distribution of precipitation and calculate the SPI (Wu *et* *al.*, 2007). The 2-parameter gamma model has also been implemented in the SPI software distributed by the National Agricultural Decision Support System (NADSS, nadss.unl.edu). The calculation of all SPI values for this study will be carried out using Guttman's (1999) algorithm.

The Standardized Precipitation Index (SPI) is widely used in North America and around the world for research and operational applications because it standardizes precipitation for a specific location and time period of interest (Hayes *et al.*, 1999; Wu *et al.*, 2001; Wu *et al.*, 2005; Wu *et al.*, 2007). The standardization also provides a means for determining the rarity of the drought event (and the probability of receiving enough precipitation to end the drought) (Table 3). The SPI also provides the user with a great deal of flexibility since it can be calculated for any period of interest (e.g., weeks, months, seasons, years).

Table 3. SPI classification (McKee *et al.*, 1993)

SPI Value	Category	Probability
> 2.0	Extremely Wet	2.3%
1.5 to 1.99	Very Wet	4.4%
1.0 to 1.49	Moderately Wet	9.2%
-0.99 to 0.99	Near Normal	68.2%
-1.0 to -1.49	Moderately Dry	9.2%
-1.5 to -1.99	Very Dry	4.4%
< -2.0	Extremely Dry	2.3%

2.2.3 Effective Drought Index (EDI)

The EDI was designed to overcome the limitations that other drought indices have in identifying the start and end of a drought and calculating drought duration (Byun and Wilhite, 1999). The EDI is calculated on a daily time step and is a function of the precipitation needed to return to normal conditions (PRN) (Morid *et al.*, 2006):

$$EDI_j = \frac{PRN_j}{ST(PRN_j)} \tag{4}$$

where *j* is the actual duration (in days) and ST(PRN) is the standard deviation of each day's PRN. PRN is determined from

$$PRN_j = \frac{DEP_j}{\sum_{N=1}^{j}(1/N)} \tag{5}$$

where DEP is the deviation of effective precipitation (EP) for each day from the mean of that day’s EP (MEP)

$$DEP = EP - EMP \quad . \tag{6}$$

The effective precipitation (EP) for any day is a function of precipitation for the current day and precipitation from previous days, but with lower weights. The duration of the preceding period, over which the EP sum is calculated, can vary but for simplicity assume it is 365 days. Once the duration is set the daily effective precipitation (EP_i) is calculated as follows

$$EP_i = \sum_{n=1}^{i}[(\sum_{m=1}^{n} P_m)/n] \tag{7}$$

where *i* is the duration over which the sum is calculated and P_m is the precipitation m – 1 days before the current day. For example, if *i* equals 3 then daily EP is (P_1+(P_1+P_2)/2+(P_1+P_2+P_3)/3). More details on calculating the EDI are available from Byun and Wilhite (1999).

The EDI normally varies from –2.5 to 2.5 and EDI values are standardized so drought severity at different locations can be compared (Table 4). Drought (or dry) duration may now be defined similarly to the SPI, as a period where the index is consistently negative.

Table 4. EDI classification (Morid *et al.* 2006)

EDI Value	Category
> 2.5	Extremely Wet
1.5 to 2.49	Severely Wet
0.7 to 1.49	Moderately Wet
-0.69 to 0.69	Near Normal
-0.7 to -1.49	Moderate Drought
-1.5 to -2.49	Severe Drought
< -2.5	Extreme Drought

2.2.4 Vegetation Condition Index (VCI)

Drought/vegetation indices derived from satellite data have been used for drought studies since the beginning of the 1980s (Kogan, 1995). The use of satellites for drought monitoring provides several key advantages over other methods. Most drought indices rely on *in situ* data and therefore the spatial resolution of these indices depends on the density of the data collection network. It is often difficult to calculate station-based drought indices in a timely fashion because the required data is usually not available in real-time. Satellites, on the other hand, can provide near real-time data over large areas at a relatively high spatial resolution. For example, the NOAA series of Polar-orbiting Operational Environmental Satellites (POES) (known as the Advanced Tiros-N (ATN) series) cover an approximately 3000 km swath and have a relatively high spatial resolution (1.1 to 16 km^2 depending on the product). In addition, satellite-based drought/vegetation indices are calculated based on the health of the vegetation, rather than using meteorological (e.g., precipitation) and environmental variables (e.g., soil moisture). This means that satellite-based drought/vegetation indices may able to detect droughts earlier and more accurately than other methods (Kogan, 2001). Satellites have proven to be a useful means for detecting drought onset and measuring the intensity, duration, and impact of drought in regions around the world (Gutman, 1990; Nicholson and Farrar, 1994; Kogan, 1995; Unganai and Kogan, 1998; Seiler *et al.*, 2000; Anyamba *et al.*, 2001; Wang *et al.*, 2001; Ji and Peters, 2003).

The ATN series of satellites carries the Advanced Very High Resolution Radiometer (AVHRR). The AVHRR is a five channel passive scanning radiometer that is sensitive to light in the visible (channel 1 = 0.58-0.68 µm), near-infrared (channel 2 = 0.75-1.0 µm), mid-infrared (channel 3A = 1.58-1.64 µm, channel 3B = 3.55-3.93 µm), and thermal infrared (channel 4 = 10.3-11.3 µm, channel 5 = 11.5-12.5 µm) regions of the spectrum. The normalized difference vegetation index (NDVI) is a measure of the 'greenness', or vigour of vegetation. It is derived based on the known radiometric properties of plants, using channel 1 (visible (red)) and channel 2 (near-infrared radiation (NIR)) from AVHRR

$$NDVI = \frac{(CH1 - CH2)}{(CH1 + CH2)} \tag{8}$$

because when sunlight strikes a plant most of the red wavelengths in the visible portion of the spectrum (0.4-0.7 µm) are absorbed by chlorophyll in the leaves, while the cell structure of leaves reflects the majority of NIR (0.7-1.1 µm) (Weier and Herring, 2000). Healthy plants absorb much of the red light and reflect most NIR. In general, if there is more reflected radiation in the NIR wavelengths than in the visible wavelengths, the vegetation is likely to be healthy (dense). If there is very little difference between the amount of reflected radiation in the visible and infrared wavelengths, the vegetation is probably unhealthy (sparse) (Weier and Herring, 2000). NDVI values range from 0 to 1, with 0 indicating no green leaves and 1 indicating the highest possible density of vegetation. Areas of barren rock, sand, and snow produce NDVI values of <0.1, while shrub and grassland typically produces NDVI values of 0.2 to 0.3, and temperate and tropical rainforests produce values in the 0.6 to 0.8 range (Weier and Herring, 2000).

Daily NDVI images are routinely composited over seven days by saving those values that have the largest difference between radiance for the NIR and visible wavelengths during that period for each pixel (Kogan, 1995). This is done to minimize the effect of cloud contamination. Noise in the calibrated NDVI can also be caused by other sources such as changes in atmospheric composition and transparency, variations in the sun/target/sensor geometry, and satellite drift (Kogan, 1995). It is impossible to make physically-based corrections for all error sources, but temporal fluctuations in the weekly NDVI time-series can be removed by smoothing the time series using a compound median filter (Kogan, 1995). According to Kogan (1995), this method eliminates outliers while emphasizing the annual growth cycle and weather-related NDVI fluctuations.

Comparing the NDVI time series for a number of years at the same location provides information about the relative health of the vegetation in a given year. Interannual variations in the magnitude and evolution of the NDVI for a particular location are mainly governed by meteorological variables such as precipitation, temperature, and relative humidity. It can be inferred that low productivity (lack of 'greenness' or vigour) is caused, in part, by poor weather conditions, and that high productivity is due, in part, to favourable weather conditions. It should be noted that the interpretation of NDVI values is spatially dependent. This is because more productive ecosystems have different radiometric properties than less productive ones (due to differences in climate, soil, and topography).

Kogan (1990, 1995) developed the Vegetation Condition Index (VCI) to control for local differences in ecosystem productivity. The VCI is a pixel-wise normalization of NDVI that is useful for making relative assessments (e.g., pixel-specific) of changes in the NDVI signal by filtering out the contribution of local geographic resources to the spatial variability of NDVI. The VCI is computed as

$$VCI_i = 100 \cdot \frac{(NDVI_i - NDVI_{\min})}{(NDVI_{\max} - NDVI_{\min})} \tag{9}$$

where $NDVI_i$ is the smoothed weekly NDVI, and $NDVI_{max}$ and $NDVI_{min}$ are the absolute maximum and minimum NDVI, respectively, calculated for each pixel and week from the multi-year NDVI climatology (several years of data are necessary to accurately establish the maximum and minimum NDVI values for each location). Individual years can then be compared and assessed against the 'normal' conditions. The VCI smoothes out non-uniformity in the AVHRR data and it indicates how weather conditions have influenced the relative vigour of the vegetation with respect to the ecologically-defined limits.

2.2.5 Variable Infiltration Capacity (VIC) (Soil Moisture Model)

The Variable Infiltration Capacity (VIC) model was first developed as a single-layer land surface model by Wood *et al.* (1992) and was later expanded to a two-layer model by Liang *et al.* (1994). VIC is a semi-distributed hydrological model that is capable of representing subgrid-scale variations in vegetation, available water holding capacity, and infiltration capacity (Liang *et al.*, 1994; Liang *et al.*, 1996a; Liang *et al.*, 1996b). The influence of variations in soil properties, topography, and vegetation within each grid cell are accounted for statistically by using a spatially varying infiltration capacity. VIC utilizes a soil-vegetation-atmosphere transfer scheme that accounts for the influence of vegetation and soil moisture on land-atmosphere moisture and energy fluxes and these fluxes are balanced over each grid cell (Andreadis *et al.*, 2005). The model has been utilized in basin-scale hydrological and soil moisture modeling (Abdulla *et al.*, 1996; Nijssen *et al.*, 1997; Wood *et al.*, 1997; Cherkauer and Lettenmaier, 1999), continental-scale simulations associated with the North American Land Data Assimilation System (NLDAS) (Maurer *et al.*, 2002; Robock *et al.*, 2003), and global-scale applications (Nijssen *et al.*, 2001). A thorough evaluation of VIC was undertaken as part of NLDAS and the results indicated that soil moisture is generally well simulated by the VIC model (Robock *et al.*, 2003).

The VIC model was forced using station-based measurements of daily maximum and minimum temperatures and precipitation. Daily 10 m wind speeds from NCEP/NCAR reanalysis were also used. Additional meteorological and radiative forcings such as vapor pressure, shortwave radiation, and net longwave radiation were derived using established relationships with maximum and minimum temperatures, daily temperature range, and precipitation. Soil characteristics were extracted from the Natural Resource Conservation Service's State Soil Geographic Database (STATSGO). Land cover and vegetation parameters were derived using the global vegetation classification developed by Hansen et al. (2000). Soil moisture was simulated by VIC in three layers. The first soil layer was 10 cm deep, the depth of the second soil layer varied from 30 to 50 cm, and the depth of the third soil layer varied from 40 to 60 cm.

2.2.6 Decision Support System for Agrotechnology Transfer (DSSAT) (Soil Moisture Model)

The DSSAT soil water module was originally developed by Ritchie and Otter (1985) for use with the CERES-Wheat model and was subsequently modified and incorporated into all DSSAT crop models (Jones and Ritchie, 1991; Jones, 1993; Ritchie, 1998). The one-dimensional DSSAT soil water module computes daily changes in soil moisture (ΔS) based on infiltration from rainfall (or irrigation), vertical drainage, unsaturated flow, soil evaporation and root water uptake using

$$\Delta S = P + I - T - E - R - D \tag{10}$$

where P is precipitation, I is irrigation, T is plant transpiration, E is soil evaporation, R is root absorption, and D is drainage. The soil water content of an individual soil layer also increases/decreases through flow (either unsaturated flow or vertical drainage) to/from an adjacent layer.

The DSSAT soil water model requires knowledge of soil water content for the lower limit of plant water availability (e.g., the lowest volumetric water content after plants stop extracting water, which corresponds closely to the permanent wilting point), for the drainage upper limit (e.g., the highest field-measured water content of a soil after thorough wetting and draining, closely related to field capacity), and for field saturation (e.g., the volumetric water content of a soil when all pores of the soil is filled with water) to calculate processes such as root uptake, drainage, and soil evaporation. These parameters are necessary for all soil layers due to the heterogeneity of the subsurface. The layer depths for each layer are also needed. In general, the layer depths are approximately 20 cm for the top layers and approximately 30 cm for lower layers with a total of between 7 to10 layers. To promote appropriate comparison, it is also often useful to divide the soil profile based on measured data depths. Several of the soil inputs are not required for every layer; these include the soil surface albedo, the limit of first stage soil evaporation, the runoff curve number and the drainage coefficients. These variables will be used to calculate the various components of the water balance in equation (10)

(Ritchie, 1998). The daily runoff is computed in the DSSAT model using a modified USDA-Soil Conservation Service curve number method (Williams *et al.*, 1984). The method applies a SCS curve number that is used to partition the daily precipitation into runoff and infiltration based on the wetting or drying condition of the surface soil. Thus, DSSAT ignores rainfall intensity since the SCS procedure does not include time. When irrigation is applied, the amount of water applied is added to the amount of rainfall before calculating the partition of runoff and infiltration.

Drainage can only occur when the current volumetric water content is greater than the drained upper limit of volumetric soil water in the layer. The model uses a 'tipping bucket' approach to estimate the soil water drainage. A downward flux for each layer is first calculated based on infiltration. Then the amount of water that the layer can hold is calculated as the difference between the current volumetric water content and saturation. If the calculated downward flux is less than or equal to what the layer can hold, the soil water content of the layer is calculated and compared with the drained upper limit of soil water content to decide whether drainage will occur. The amount of drainage is calculated using the drainage coefficient, layer depth, the current volumetric water content, and the drainage upper limit of soil water content. Upward unsaturated flow is approximated using a normalized soil water diffusion equation operating on a daily time-step (Ritchie, 1998).

Evaporation from the soil surface, root water uptake, and plant transpiration are based on methods developed by Ritchie (1972). Four options for calculating potential evapotranspiration (PE) are included in the DSSAT soil water model. The default option is the Priestley-Taylor method (Priestley and Taylor, 1972). The Priestley-Taylor method is a simplified form of the Penman method (Penman, 1948) and it requires only daily values of net solar radiation and daytime air temperature. The Priestley-Taylor method (1972) can be defined as

$$c_t L_v \rho_w PE_s = \frac{1.26 \Delta R_n}{\Delta + \gamma} \tag{11}$$

where PE_s is the surface-dependent potential evaporation (mm d^{-1}), c_t is a conversion constant (0.01157 W m d MJ^{-1} mm^{-1}), L_v is the latent heat of vaporization (2448.0 MJ Mg^{-1}), R_n is the net radiation (W m^{-2}), γ is the psychrometer constant (0.067 kPa K^{-1}), ρ_w is the density of water (1 Mg m^{-3}), and Δ is the slope of the saturation vapor pressure versus air temperature curve (kPa K^{-1}). Daytime air temperature is approximated from daily maximum and minimum air temperatures and daily net solar radiation is computed by adjusting total solar radiation to account for the combined albedo of the soil and plant canopy. The model determines soil albedo using the specified soil color. Plant canopy albedo is a function of the leaf area index (LAI) of the crop (a parameter calculated by the model). The slope of the saturation vapor pressure versus air temperature curve, Δ, is calculated using

$$\Delta = \frac{4098\left[0.6108 \cdot \exp\left(\frac{17.27 \cdot T}{T + 237.3}\right)\right]}{(T + 237.3)^2} \quad . \tag{12}$$

More details on how the Priestley-Taylor method was implemented in the DSSAT soil moisture model can be found in Ritchie (1972) and Jones and Ritchie (1991).

Once PE has been calculated, it is partitioned into potential soil evaporation and potential plant transpiration based on the fraction of solar energy reaching the soil surface and the LAI (Jones *et al.*, 2003). Calculation of actual soil evaporation is based on a two-stage process: free soil evaporation and soil-limiting evaporation stages. The actual soil evaporation is the minimum of the potential soil evaporation and soil-limiting evaporation on a daily basis. The actual plant transpiration is considered to be the minimum of the potential plant transpiration and potential root water uptake. The potential root water uptake is estimated by calculating a maximum water flow to roots in each layer and summing these values.

2.2.7 Climatic Water Budget (CWB) (Soil Moisture Model)

A modified version of the CWB can also be used to simulate soil moisture. The CWB is a one dimensional model that calculates the daily or monthly change in soil moisture storage due to evaporation, precipitation, infiltration, and runoff assuming that the subsurface is a single soil layer (Thornthwaite, 1948; Thornthwaite and Mather, 1955; Mather, 1979). Soil moisture storage will increase whenever precipitation exceeds climate demand for water. When the climate demand (e.g., PET) is greater than precipitation, then soil moisture storage will be depleted. By comparing precipitation and potential evapotranspiration, it is possible to estimate the soil moisture change for a specific period of time. The CWB model is calculated using precipitation, temperature and soils data. The available water capacity data (AWC) of the soil (the difference between field capacity (FC) and permanent wilting point (PWP)) is a key component in calculating soil moisture since it represents the maximum water that could be held in the soil by capillary forces after runoff, percolation and evapotranspiration have occurred. Potential evapotranspiration (PE) is calculated using the Thornthwaite method which accounts for the influence of temperature, and the number of hours of daylight (Thornthwaite, 1948). If potential evapotranspiration exceeds precipitation a soil moisture loss function developed by Willmott *et al.* (1985) is applied to calculate the current soil moisture. When calculated soil moisture is greater than FC, surplus water (S) is calculated as the difference of soil moisture and FC. This model assumes that half of the surplus for a give time step is converted to runoff (streamflow) and the other half is held over to the next time step where it is added to the surplus for that period of time.

2.2.8 Percent Normal

Percent normal is a simple method for comparing observed precipitation to normal precipitation for a particular location and time period. Observed precipitation is divided by normal (mean) precipitation (usually based on 30 years of data) and the result is expressed as a percentage. It can be calculated for any time scale of interest (e.g., day, week, month, season, year).

2.2.9 Deciles

Deciles are used to give an element a ranking by arranging the data in order from lowest to highest and then splitting into ten equal groups (or deciles). For example, with 40 precipitation observations, the first decile would contain the four lowest precipitation totals, that is, the lowest 10%. Reporting decile values of observed precipitation for drought monitoring was first suggested by Gibbs and Maher (1967). Deciles are simple to calculate, but they require a relatively long record of precipitation.

2.3 Review of Hydrological/Water Supply Drought Indices

Hydrological droughts are associated with the impact of prolonged precipitation deficiencies on water supply from surface or subsurface sources such as rivers, reservoirs and groundwater (Keyantash and Dracup, 2002). Similarly, the American Meteorological Society defines hydrological drought as "*Prolonged period of below-*

normal precipitation, causing deficiencies in water supply, as measured by below-normal streamflow, lake and reservoir levels, groundwater levels, and depleted soil moisture content". In this study we will refer to this type of drought as hydrological/water supply drought since below-normal streamflow, groundwater, and lake and reservoir levels will have a negative impact on water supply. The drought indices reviewed in this section can be used to represent hydrological/water supply droughts.

There is an inherent time-lag between meteorological drought and hydrological/water supply drought because it takes longer for the precipitation deficiency to be reflected in streamflow and reservoir levels. This is especially important in places where groundwater is a major contributor to the streamflow and reservoirs. After a hydrological drought becomes established, even if the precipitation level returns to normal, it takes time for the hydrological drought to end. The time-lag will be small in areas with high precipitation and small reservoirs such as Trinity River basin, because storm flows usually fill up the reservoirs to pre-drought levels. The time-lag will be large in areas of low precipitation and where spring discharge (from snowmelt) accounts for a significant amount of the total annual flow (e.g., Colorado River basin).

Drought indices such as Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982) and Palmer Hydrological Drought Index (PHDI) (Karl, 1986) are commonly used by various states to monitor hydrological/water supply drought. In addition, the TWDB also uses Percent of Reservoir Conservation Storage Capacity and Streamflow Percent Exceedance as indicators of hydrological/water supply drought. Four new indices for monitoring hydrological/water supply drought were developed as a part of this study. They are the Standardized Streamflow Index (SSFI), Streamflow

Deficit Index (SDI), Standardized Reservoir Index (SRI), and the Reservoir Deficit Index (RDI). These four indices are based directly on the reservoir and streamflow data that is already being used by the TWDB, but these indices use a different standardizing procedure.

2.3.1 Palmer Hydrological Drought Index (PHDI)

The Palmer Drought Severity Index (PDSI) (Palmer, 1965) is a meteorological drought index used to classify wet and dry spells. The PDSI is a retrospective index because its values are back calculated and adjusted after the establishment of a dry or wet spell. Hence, the current value of the index might change if a drought becomes established 2 or 3 months from now. However, when computed in near real-time the PDSI is more appropriately termed the Palmer Hydrological Drought Index (PHDI) (Karl, 1986) because it does not take into account future dry or wet weather that impacts the meteorological drought. PDSI and PHDI values are identical during an established spell and only differ during the onset and ending of a spell. According to Heim (2002), the PDSI considers a drought ended when the moisture conditions begin to recover continuously to erase the water deficit, however, PHDI considers a drought ended only when the water deficit actually vanishes. Therefore, the PHDI is a slow-varying version of the PDSI. The lagged response to variations in precipitation makes the PHDI a suitable index for monitoring hydrological/water supply droughts (Keyantash and Dracup, 2002). The PHDI is calculated using the same code and input data as the PDSI (described in Section 2.2.1).

2.3.2 Surface Water Supply Index (SWSI)

The SWSI is a hydrological drought index that was developed to replace the PDSI in areas where local precipitation is not the sole (or primary) source of streamflow (Shafer and Dezman, 1982). SWSI was designed for mountainous locations with significant snowfall because of the delayed contribution of snowmelt runoff to surface water supplies. The SWSI is calculated based on the monthly non-exceedance probability which is determined using available historical records of reservoir storage, streamflow, precipitation, and snowpack. Using a basin-calibrated SWSI algorithm, weights are assigned to each hydrological component based on its typical contribution to the water supply (Garen, 1992). Then SWSI is calculated as a sum of the products of the probability of each the hydrological components and their respective weights:

$$SWSI = \frac{[(aP_{resv} + bP_{strm} + cP_{prec} + dP_{snow}) - 50]}{12} \tag{13}$$

where *a*, *b*, *c*, and *d* are the weighting coefficients representing approximate contribution of each component to surface water supplies and *P* represents the non-exceedance probability (%) based on historical records for reservoir storage (resv), streamflow (strm), snowpack (snow), and precipitation (prec). Because it is dependent on the season, the SWSI is calculated using only reservoir storage, snowpack, and precipitation during the winter (December through May). During the rest of the year (June to November) streamflow replaces snowpack in the SWSI equation. Calculations are performed on a monthly time step. Monthly data are collected and summed for all locations where reservoir storage, streamflow, precipitation, and snowpack are measured in the basin. Each component is normalized using the historical data. The probability of non-exceedance (e.g., the probability that subsequent values of that component will not exceed the current value) is determined for each component using frequency analysis. Converting all of the components to a non-exceedance probability allows their values to be compared to each other. The SWSI, similar to PDSI, has an arbitrary scale that is centered on zero and ranges from –4.2 to +4.2.

SWSI is a particularly good measure of surface water supply conditions in the Western United States because it accounts for the major hydrological variables that contribute to surface water supply there. Keyantash and Dracup (2002) compared SWSI and PHDI for the Willamette Valley and North Central Oregon climate divisions and found that they are similar (correlation coefficients of 0.70 and 0.78, respectively) even though they take a different approach for determining water shortages. The similarity of the two indices suggests that precipitation is the most important factor in both SWSI and PHDI. SWSI is routinely calculated by Natural Resources Conservation Service (NRCS) for Colorado, Idaho, Montana, New Mexico, Oregon, Utah, and Wyoming because snowpack makes a significant contribution to surface water supplies in these states. However, it is not routinely calculated for states such as Texas where snowpack is not a major contributor to surface water supply.

2.3.3 Percent of Reservoir Storage Capacity

Percent of Reservoir Storage Capacity is a straightforward measure of hydrological/water supply drought. It is calculated by dividing the current volume of water in the reservoir by the volume at conservation pool elevation. The TWDB defines conservation storage as the volume of water stored in the reservoir between the conservation pool elevation and the lowest intake in the reservoir. This water is available for municipal water supply, power, and irrigation. Table 5 shows the thresholds currently used by the Texas Drought Preparedness Council (TDPC) for assigning drought severity based on reservoir level and streamflow.

Table 5. Water availability assessment values currently used by Texas Drought Preparedness Council (TDPC, 2005)

DROUGHT SEVERITY CLASSIFICATION		RANGES		
DCP STAGE	DESCRIPTION	POSSIBLE IMPACTS	PERCENT OF RESERVOIR CONSERVATION STORAGE CAPACITY WITHIN REGION	STREAMFLOW PERCENT EXCEEDANCE WITHIN REGION
Advisory	Abnormally Dry	Going into drought: short-term dryness slowing planting and growing crops or pastures; fire risk above average. Coming out of drought: lingering water deficits; pastures or crops not fully recovered.	<70	70-79
Watch	First-Stage Drought	Damage to crops, pastures; fire risk high; streams, reservoirs, or wells low, water shortages developing or imminent, voluntary water use restrictions requested	<60	80-89
Warning	Severe Drought	Crop or pasture losses likely; fire risk very high; water shortages common; water restrictions imposed	<40	90-94
Emergency	Extreme Drought	Major crop/pasture losses; extreme fire danger; widespread water shortages or restrictions	<20	95-98
Disaster	Exceptional Drought	Exceptional and widespread crop/pasture losses; exceptional fire risk; shortages of water in reservoirs, streams, and wells, creating water emergencies	<10	99-100

2.3.4 Streamflow Percent Exceedance

TWDB currently computes Streamflow Percent Exceedance by comparing the 30-day mean flow to historical streamflow records. Currently there are 29 streamflow stations used to calculate this index.

2.3.5 Standardized Streamflow Index (SSFI)

McKee *et al.* (1993) developed a standardizing procedure for evaluating precipitation departures (e.g., SPI) using a PDF. A similar approach was used to develop the Standardized Streamflow Index (SSFI). Rather than computing SSFI on a monthly time step, it is computed on a daily time step using rolling cumulative flows for a variety of time scales. The computation of SSFI consists of following steps:

1. Compute rolling cumulative stream flow for 10, 30, 90, 180, 360, 720, and 1440 day time scales for the 30-year based period of record (1971–2000).

2. Convert the cumulative stream flow rate into flow depth by dividing the flow rate by the contributing drainage area.
3. For each time scale, for each day of the year, based on the 30-year record, fit a Box-Cox transformation to convert the data into normal distribution (365 Box-Cox transformations). A Box-Cox transformation was used because the data failed to fit any particular distribution. Even after applying the Box-Cox transformation there were still days for which the data did not fit the normal distribution. However, for the sake of consistency we assumed that the transformed data fit the normal distribution.
4. Compute the mean and standard deviation of the transformed data.
5. Use the Box-Cox transformation coefficient to transfer the current cumulative stream flow measurement (X).
6. Using the mean and standard deviation from historical records, compute the Z values in a standard normal distribution (i.e., Z = (X – Mean)/Standard Deviation), which is SSFI.

SSFI is very similar to the percent exceedance of streamflow currently used by TWDB. The percent exceedance of 30-day mean flow would be equivalent to the SSFI30 calculated using 30-day cumulative stream flow.

2.3.6 Streamflow Deficit Index (SDI)

Another standardizing approach, the Streamflow Deficit Index (SDI), was developed to overcome the problem of fitting a statistical distribution to the cumulative streamflow data as described previously in SSFI. The SDI is calculated by scaling cumulative streamflow values using the median, maximum, and minimum cumulative values:

$$SDI_{i,j} = \frac{SW_{i,j} - MSW_j}{MSW_j - \min SW_j} \times 100 \qquad \text{if } SW_{i,j} \leq MSW_j \qquad (14)$$

$$SDI_{i,j} = \frac{SW_{i,j} - MSW_j}{\max SW_j - MSW_j} \times 100 \qquad \text{if } SW_{i,j} > MSW_j \qquad (15)$$

where *i* is the years, *j* is the day of the year (1 to 365), $SDI_{i,j}$ is the Streamflow Deficit Index (%), $SW_{i,j}$ is the cumulative streamflow for period of interest (mm), MSW_j is the long-term median cumulative streamflow for period of interest (mm), max.SW_j is the long-term maximum cumulative streamflow for period of interest (mm), and min.SW_j is the long-term minimum cumulative streamflow for period of interest (mm). These equations were used for scaling because they create an index that has a lower bound of -100 and an upper bound of +100.

2.3.7 Standardized Reservoir Index (SRI)

As discussed in relation to the SWSI, reservoir levels are strongly influenced by human decisions such as the magnitude, duration and frequency of releases. The amount of water that is annually released or pumped from a reservoir may have increased over time due to increases in population or water demand around the reservoir. Hence, using historical reservoir levels to compute non-exceedance probability may lead to errors in the calculation of the drought index. Further, for some reservoirs there may not be adequate length of measurement record to compute non-exceedance probability. The Water Rights Analysis Package (WRAP), available within the Water Availability Modeling (WAM) system, was used to avoid this problem. “WRAP simulates management of water resources of river basins or multiple-basin region, under a priority-based water allocation system, such as Texas Water Rights system" (Wurbs, 2001). Based on historical weather data and naturalized streamflow data, WRAP estimates the availability of water in streams and reservoir based on existing water rights. WRAP operates on a monthly time step.

The Texas Commission on Environmental Quality (TCEQ) developed WAM for predicting the amount of water that would be available in a river or stream under a specified set of existing water rights conditions and for determining the availability of water for new water rights. TCEQ has developed input files with existing withdrawals, inter-basin transfers and other complex water allocation systems that are in used in Texas River Basins. These input files were used to simulate the reservoir levels for a 57-year period (1941–1996) using the existing water rights conditions. This long-term simulated reservoir level data was used rather than the observed reservoir level data to calculate the Standardized Reservoir Index (SRI). The SRI was calculated using the following steps:

1. Use WRAP to simulate historical reservoir water levels on a monthly time scale.
2. Use the current daily reservoir water level data to calculate the percent of non-exceedance (cumulative probability) based on the simulated reservoir level data for that month. The cumulative probability based on empirical distribution approach was used because it was difficult to fit a statistical distribution for the data, even after Box-Cox transformation.
3. Use the cumulative probability to calculate the Z value for the current reservoir level (based on the standard normal distribution).
4. This Z value is the Standardized Reservoir Index (SRI).

2.3.8 Reservoir Deficit Index (RDI)

The Reservoir Deficit Index (RDI) was developed to overcome the problem of fitting a statistical distribution to the SRI. The RDI is calculated as a ratio of the difference of the current reservoir level and the median reservoir level:

$$RDI = \frac{(wl - Mwl)*100}{Mwl} \qquad (16)$$

where *wl* is current reservoir water level and *Mwl* is the long-term monthly median water level from WRAP simulation. The RDI is calculated (and interpreted) in a similar manner to Percent Normal.

2.4 Hybrid Drought Monitoring Tools

2.4.1 Experimental Blends of Drought Indicators

In addition to the drought indices that are described above, new drought monitoring products have been developed that blend a number of these drought indices. The CPC developed two drought blends that objectively combine a number of commonly used drought indices, a short-term blend and a long-term blend[1]. The short-term blend is designed to represent moisture conditions on time scales ranging from days to a few months. It is calculated using Palmer's Z-index, 1-month precipitation, 3-month precipitation, Palmer's Drought Severity Index, and the CPC Soil Moisture model (Table 6). According to the CPC, the short-term blend should be relevant for non-irrigated agriculture, topsoil soil moisture, wildfire danger, rangeland and pasture conditions, and unregulated streams. The short-term blend is best described as a measure of agricultural and/or meteorological drought. The long-term blend is designed to represent moisture conditions on time scales ranging from several months to several years. There are two

[1] Short-term and long-term drought blends are available at:
http://www.cpc.ncep.noaa.gov/products/predictions/experimental/edb/droughtblend-access-page.html

different methods for calculating the long-term blend, but both utilize the Palmer Hydrological Drought Index, 12-month precipitation, 24-month precipitation, 60-month precipitation, and the CPC Soil Moisture model (Tables 7 and 8). According to the CPC, the long-term blend should be related to reservoir storage, irrigated agriculture, groundwater levels, and well water depth. Therefore the long-term blend can be described as a measure of hydrological/water supply drought. However, the CPC notes "the relationship between indicators and impacts varies, sometimes markedly, with location and season. This is particularly true of water supplies, which are additionally dependent on the source (or sources) tapped, management practices, and legal mandates" (CPC, 2006). Both of these blends, although they are labelled as "experimental", have been routinely produced on a weekly basis since 2003. They are calculated and reported at the climate division level. In order to calculate the short-term and long-term drought blends all of the indices (Tables 6, 7, and 8) are converted into percentiles using the 1932–2000 data. Then a weighted average percentile is calculated and is fit against the historical percentiles for all prior months to assign the blended percentile for each climate division.

Table 6. Short-term drought blend

Index	Weight
Palmer's Z-index	35%
3-Month Precipitation	25%
1-Month Precipitation	20%
CPC Soil Moisture Model	13%
Palmer (Modified) Drought Index	7%

Table 7. Long-term drought blend (Eastern U.S.)

Index	Weight
Palmer Hydrological Drought Index	25%
24-Month Precipitation	20%
12-Month Precipitation	20%
6-Month Precipitation	15%
60-Month Precipitation	10%
CPC Soil Moisture Model	10%

Table 8. Long-term drought blend (Western U.S.)

Index	Weight
Palmer Hydrological Drought Index	30%
60-Month Average Z-index	30%
60-Month Precipitation	10%
24-Month Precipitation	10%
12-Month Precipitation	10%
CPC Soil Moisture Model	10%

2.4.2 Drought Monitor

The most advanced ('state-of-the-art') national drought monitoring product currently available is the United States Drought Monitor (hereafter Drought Monitor) which was introduced in 1999 (Svoboba et al., 2002). The Drought Monitor provides a subjective measure of drought conditions since it is based on numerous drought and soil moisture indices and the consensus of opinions from a variety of experts. The main contributors to the Drought Monitor are scientists from the Joint Agricultural Weather Facility, National Weather Service, National Climatic Data Center, National Drought Mitigation Center, Regional Climate Centers, State Climate Offices, U.S. Geological Survey, and a variety of university researchers. Since no single drought index works well under all circumstances (and for all types of drought), the Drought Monitor is constructed using data from a large number of disparate sources. This includes many of the drought indices described above (including the short-term and long-term drought blends) as well as crop reports, local input, outlooks, and news stories about drought impacts. The

Drought Monitor is a highly generalized product, spatially (since it is intended to represent drought on the climate division scale), temporally (since it is only updated on a weekly basis), and in its focus (since it attempts to account for all types of drought: meteorological, agricultural, and hydrological). It is designed to serve the needs of decision-makers at the federal, state, and local levels. The Drought Monitor classifies drought into four categories based on severity (Table 9). The Drought Monitor also indicates whether drought impacts are primarily affecting agriculture (A) or streamflow/water supply/hydrology (H).

Table 9. Drought Monitor Classification

Category	Description	Percentile
D0	Abnormally dry	21-30%
D1	Moderate drought	11-20%
D2	Severe drought	6-10%
D3	Extreme drought	3-5%
D4	Exceptional drought	<2%

2.5 Drought Prediction Tools

A variety of statistical and dynamical models are used to produce monthly-to-seasonal forecasts. These forecasts often rely upon known associations between teleconnections such as the phase of El Niño/Southern Oscillation (ENSO) and climatic conditions in various regions around the world. These long-range forecasts can be relatively accurate during strong ENSO events, but most seasonal forecasting skill lies in the tropics and subtropics, and forecasts are less skillful at higher latitudes in the Northern Hemisphere. Nonetheless, operational seasonal forecasts are produced by a number of centers, including the Hadley Center, Climate Prediction Center, European Center for Medium-Range Weather Forecasts (ECMWF), and International Research Institute for Climate Prediction (IRI) (Table 10). However, many of their products are still considered experimental because their forecasts lack demonstrated skill, particularly in terms of forecasting growing-season precipitation in the mid-latitudes. While these seasonal-forecast models are continually improved, much work remains before they can be considered generally useful for forecasting droughts.

Table 10. Selected climate and drought forecasting products that are currently available in the United States (superscript numbers indicate that an example of this product is provided in Appendix B)

Source	**URL**	**Product Description**
Climate Prediction Center (CPC)	http://www.cpc.ncep.noaa.gov/products/forecasting/	6-10 day temperature and precipitation forecasts
		8-14 day temperature and precipitation forecasts
		Monthly temperature and precipitation forecasts
		Seasonal temperature and precipitation outlooks (up to 1 year in advance)[1]
	http://www.cpc.ncep.noaa.gov/soilmst/forecasts.shtml	Soil moisture forecasts
	http://www.cpc.ncep.noaa.gov/products/expert_assessment/seasonal_drought.html	Seasonal drought outlook[2]
Source	**URL**	**Indices/Data Available**
Center for Ocean-Land-Atmosphere Studies (COLA)	http://wxmaps.org/pix/soil1.html	Short-term climate outlooks for temperature, precipitation, and soil moisture[3] (0-7 days and 7-14 days)
International Research Institute for Climate Prediction (IRI)	http://iri.columbia.edu/climate/forecast/net_asmt/	Seasonal climate forecasts of temperature and precipitation (up to 2 seasons in advance)[4]

3.0 TASK 2: EVALUATION OF THE EXISTING DROUGHT MONITORING AND PREDICTION TOOLS TO DETERMINE WHICH ARE THE MOST APPROPRIATE FOR MONITORING MOISTURE CONDITIONS AT THE LOCAL LEVEL IN THE STATE OF TEXAS

3.1 Introduction

This objective of this task is to analyze the drought indices that were introduced in Task 1 and a number of new indices that were specifically developed during this project to determine which are most appropriate for monitoring meteorological and hydrological/water supply droughts at the local level in the state of Texas. These two types of drought are considered separately since each has a unique time scale and is associated with different impacts. Since the objective of this study is to make practical suggestions for developing a state-wide drought monitoring system at the local level the analysis was preformed using pragmatic (e.g., data availability, complexity) as well as scientific criteria. The selection of the most appropriate meteorological and hydrological/water supply drought indices was carried out in three stages. The first stage was to review the literature and compile a list of the known strengths and weaknesses of each of the drought indices. Then the indices were evaluated qualitatively using a modified version of the criteria developed by Keyantash and Dracup (2002). Finally, all of the indices were calculated for a variety of representative locations within Texas and compared using goodness-of-fit measures. The most appropriate indices for monitoring meteorological and hydrological/water supply drought were selected based on the results of the three-stage evaluation process.

All of the meteorological drought indices (including those derived from station data, satellite data, and soil moisture models) were calculated at a number of scales over Texas ranging from individual stations and grid cells (resolution of 4 km^2) to the county, watershed, and climate division levels. The spatial resolution that was used was determined by data availability and the type of drought index. All of the hydrological/water supply indices were evaluated using data from six watersheds from across Texas: Red River, Upper Trinity, Lower Trinity, Colorado, Guadalupe, and San Antonio. These watersheds were chosen because they encompass a wide range of climate, vegetation, soil, and hydrologic conditions that are representative of Texas and because good drought verification data was available within them.

3.2 Review of Drought Index Strengths and Weaknesses

The first step in determining which meteorological and hydrological/water supply drought indices are the most appropriate for monitoring drought conditions at the local level was to review the scientific literature and compile a list of the strengths and weaknesses of each index. In this section the data requirements of each drought index will also be described since the purpose of this study is to identify drought indices that can be calculated operationally. Therefore the "best" drought indices are those that can be calculated using readily available data. Only those indices that are critiqued in the literature have been included in this section.

3.2.1 PDSI, PHDI, Z-index

The PDSI, PHDI, and Z-index are all calculated using the algorithm that was developed by Palmer (1965) and therefore these indices will be discussed together. For simplicity, all of the discussion will use the term PDSI to refer to all three of these indices.

The PDSI is calculated using temperature and precipitation data. The daily temperature and precipitation data are aggregated to weeks or months, depending on the time-scale of interest. The PDSI also needs information on the available water holding capacity of the soil. These data can be extracted from the NRCS STATSGO soil database.

Since the PDSI uses the Thornthwaite (1948) method for estimating PET, the latitude of the location also needs to be provided.

The PDSI was the first comprehensive drought index developed in the U.S. and it is widely used for drought monitoring and within state drought plans (Heim, 2002). Despite its widespread use, the PDSI has many limitations. One of the limitations of the PDSI is that PET is estimated using Thornthwaite's method (which only considers monthly temperatures to estimate PET) (Narasimhan and Srinivasan, 2005). More realistic estimates of PET can be generated by using a physically-based method such as the FAO Penman-Montieth equation (Allen *et al.*, 1998). However, it should be noted that a recent study (Mavromatis, unpublished) determined that calculating the PDSI with a more physically-based method of calculating ET did not improve the correlation between the PDSI and soil moisture at the study sites in Greece.

Another limitation of the PDSI is that it uses a two layer soil model with just a single parameter for the available water holding capacity of the soil. This may be reasonable when calculating the PDSI for a single location (e.g., station), but it is inappropriate for calculating the PDSI for regions, such as climate divisions within which the soil is highly spatially heterogeneous (Narasimhan and Srinivasan, 2005). In Texas climate divisions range in size from from 7,870 to 100,880 km^2 and so each encompasses a wide range of soil types. There is no way to represent the horizontal and vertical heteorogeneity of soil properties in the PDSI water balance. It is important to use an appropriate value for the available water holding capacity of the soil because it has been demonstrated that the PDSI is sensitive to changes in this parameter (Karl, 1983).

The PDSI also assumes that runoff only occurs when the two soil layers are both completely saturated. In reality runoff varies due to differences in slope, soil type, land use, land cover, and land management practices (Narasimhan and Srinivasan, 2005). None of these factors are accounted for in the PDSI. Alley (1984) noted that there are also problems with how runoff is generated because the model does not account for the distribution (or intensity) of precipitation within the week or month. The PDSI also does not account for the seasonal changes in vegetation growth and root development and it is not designed to deal with a snowpack or frozen soil (Alley, 1984; Karl, 1986; Karl *et al.*, 1987).

PDSI is highly dependent on the weighting factor used to make it comparable between different regions (and months) (Heim, 2002). Palmer (1965) calculated the regional correction factor (K) based on data from only nine locations in seven states (Wells *et al.*, 2004). Akinremi *et al.* (1996) found Palmer's original value of 17.67 artificially inflated the drought index values when applied to the Canadian prairie and used a revised regional correction factor of 14.2. Palmer (1965) calculated the duration factors 0.897 and 1/3 based on data from western Kansas and central Iowa and they affect the sensitivity of the index to precipitation events (Wells *et al.*, 2004). An improvement proposed by Wells *et al.* (2004) is meant to correct the lack of spatial comparability by dynamically calculating the regional correction factor (K) and the duration factors using historical climate data from each location. This revised PDSI is called the self-calibration PDSI (SC-PDSI). The original formulation of the PDSI is known to be spatially and temporally variant and therefore it cannot be compared across the U.S. or between months (Alley, 1984; Guttman *et al.*, 1992; Guttman, 1998; Heim, 2002). This means that severe and extreme droughts as defined by the PDSI occur more often in some parts of the country than others (Wells *et al.*, 2004). The SC-PDSI is supposed to correct these problems by dynamically calculating all of the empirical constants (e.g., regional correction factor). However, the length of the calibration period (historical record) will have an influence on the stability of the estimated parameters. Longer calibration periods tend to provide more consistent PDSI values (Karl, 1986). For comparison purposes, the same calibration period should be used for all locations.

Interpreting the PDSI can also be a challenge since it is a function of both temperature and precipitation data (Hu and Willson 2000). It has been demonstrated that the PDSI responds in a non-linear fashion to changes in precipitation (Hu and Willson 2000). Although the PDSI is often defined as a meteorological drought index the PDSI responds rather slowly to changes in moisture conditions. According to Guttman (1998), the PDSI has a 'memory' (its spectrum conforms to that of an autoregressive process) and it is highly correlated with the 12-month SPI (Heim, 2002). This means that both the PDSI and PHDI are more appropriate for measuring hydrological/water supply droughts. The Z-index can be used for measuring agricultural and meteorological drought since it only accounts for the moisture conditions during the current week or month (Quiring and Papakyriakou, 2003).

The drought classification that was proposed by Palmer (1965) (Table 2) was arbitrarily determined, so those thresholds are not appropriate for making water management decisions or triggering drought response programs or declarations of drought emergency unless they have been confirmed by an independent local assessment (Alley, 1984). It has also been demonstrated that the calculation procedure for transitioning between wet and dry spells tends to produce an asymmetrical and bimodal distribution of PDSI values (Alley, 1984; Heim, 2002). Therefore, the PDSI is not normally distributed and can not be interpreted in the same way as other indices, such as the SPI.

In addition, it is difficult to interpret or visualize the PHDI in terms of actual deficit in observed streamflow or reservoir level because the index only quantifies soil moisture balance and does not look specifically at streamflow which is most often the major source of water supply to reservoirs.

3.2.2. SPI

The SPI is a popular drought index because of its simplicity and versatility. To calculate the SPI one only needs weekly or monthly precipitation data (depending on the time scale on the intended application). The SPI can be calculated for any time period of interest. It is commonly calculated using 1-month, 3-month, 6-month, 9-month, 12-month, and 24-month intervals. These time-scales are appropriate for monitoring different types of drought and correspond to different drought impacts. Unlike the PDSI, the SPI is spatially invariant (Guttman, 1998; Heim, 2002; Wu *et al.*, 2007) and so values of the SPI can readily be compared across time and space. Although the SPI can be calculated in all climatic regions (Heim, 2002), it is important to note that arid regions, those that experience many months with zero precipitation, may be problematic for the SPI depending on which PDF is used to normalize precipitation (Wu *et al.*, 2007). The SPI is also easier to understand and interpret than the PDSI since its value is only based on precipitation and since it is reported in standard deviations away from the mean.

However, there are some limitations associated with the SPI. Like the PDSI, it is computationally complex (it cannot be calculated by hand or with a spreadsheet) and it requires specialized code. The SPI also requires a long (and complete) precipitation record. It has been demonstrated that the SPI is strongly influenced by record length (Wu *et al.*, 2005). Therefore when comparing stations to each other, it is best if they have the same length of precipitation record. The minimum precipitation record for calculating the SPI is 30 years, but it is recommended to use 50+ years of data (and the extreme values of the SPI may only be accurate when even longer precipitation records are used (80+ years)) (Wu *et al.*, 2005).

The SPI is also influenced by normalization procedure (e.g., PDF selection) that is used. The National Drought Mitigation Center (NDMC), Western Regional Climate Center (WRCC), and National Agricultural Decision Support System (NADSS) all use the two-parameter gamma PDF to calculate SPI. However, there is little consensus about what normalization procedure is best. Guttman (1999) analyzed six different PDFs (including: the two-parameter gamma; the two-parameter gamma, for which the parameters are estimated by the maximum likelihood method; the three-parameter Pearson Type III; the three-parameter generalized extreme value; the four-parameter kappa; and the five-parameter Wakeby) and determined that the Pearson Type III was the most appropriate PDF for calculating SPI. Using a different PDF will generate different SPI values.

Although it has not been reported in the literature, it can also be demonstrated that the SPI will be strongly influenced by the presence of missing data (and the interpolation/replacement of missing data). This analysis demonstrates that decisions that are made about how missing data is handled will have a direct impact on the magnitude of precipitation-based drought indices such as the SPI.

The SPI requires accurate precipitation data. Although collecting accurate precipitation data is important for all of the precipitation-based drought indices, it is particularly important for the SPI because it is extremely sensitive to precipitation events in both tails of the distribution. Because precipitation is highly spatially heterogeneous and the density of precipitation gages in Texas is relatively low, this means that individual gages may miss some heavy (convective) precipitation events. It also means that care should be taken when aggregating precipitation records to determine mean county (or climate division) precipitation. Averaging precipitation over space (and time) will tend to smooth the data and distort the true distribution of precipitation. This has implications for how precipitation data should be handled and aggregated prior to calculating the SPI.

3.2.3 EDI

The EDI is calculated using daily precipitation data and it was designed for detecting the onset and termination of drought events. The EDI was also designed to use a time dependent weighting function that places more emphasis on recent precipitation surpluses or deficits and less emphasis on conditions a number of months in the past (Byun and Wilhite, 1999).

One of the major weaknesses of the EDI is that it is relatively unknown so its ability to accurately monitor drought conditions remains largely untested (Morid *et al.*, 2006). In addition, the methodology for calculating the EDI is not straightforward. Even though both the SPI and EDI only use precipitation data, the EDI is almost uncorrelated with the SPI. Therefore, the EDI cannot be easily interpreted. The EDI is also difficult to use because code for calculating it is not readily available. Those interested in calculating the EDI must write their own code. Another major disadvantage to using the EDI is that it lacks the nice statistical properties of some of the other precipitation-based indices (SPI, deciles, etc.). For example, Morid *et al.* (2006) demonstrated that the EDI is not normally distributed.

3.2.4 VCI

The VCI is calculated using AVHRR-based NDVI data. One of the main advantages of the VCI is that, because it is a satellite-based drought product, it can provide near real-time data over the globe at a relatively high spatial resolution. The spatial resolution of the VCI greatly exceeds that of all of the other drought indices that have been evaluated. In addition, the VCI uses a completely independent methodology for monitoring drought, while all of the other meteorological indices rely, to some extent, on station-based meteorological data. Although the station-based indices may provide accurate point estimates of drought conditions, they cannot provide the same spatial resolution as the VCI because of the relatively sparse station network (particularly if when considering only those meteorological stations that have at least 30+ years of continuous data). There have also been a number of studies that have evaluated the ability of the VCI to monitor drought in a variety of regions around the world (Gutman, 1990; Nicholson and Farrar, 1994; Kogan, 1995; Unganai and Kogan, 1998; Seiler *et al.*, 2000; Anyamba *et al.*, 2001; Wang *et al.*, 2001; Ji and Peters, 2003).

One of the main limitations of the VCI is that it requires specialized software to calculate. In addition, because the VCI is calculated using the entire time series of AVHRR data, calculating the VCI involves managing relatively large data volumes.

The VCI is most useful during the growing season because it is a measure of vegetation vigor, when the vegetation is dormant (or there is snow cover) the VCI cannot be used to measure moisture stress or drought. Interpretation of the VCI may be more complicated than other drought indices because the satellite is providing an indirect measure of moisture (drought) conditions. Anything that stresses the vegetation including insects, disease, and lack of nutrients will result in decreases in plant growth and therefore lower VCI values. Also, areas that have significant irrigation may not respond to precipitation deficiencies.

In addition, there are some challenges to using satellite data for monitoring drought because there have been changes in satellites and sensor and sensor degradation can bias the AVHRR data. There is also contamination of the vegetation response signal by clouds. The compositing procedure is meant to reduce the influence of clouds, but in some locations and seasons cloud contamination may still be an issue. In addition there are numerous other sources of atmospheric attenuation and the atmospheric correction, smoothing, and compositing procedures will not account remove all of these influences.

The VCI is most appropriate for monitoring meteorological and agricultural drought. It has not been demonstrated that the VCI can be used to monitor hydrological/water supply droughts. The VCI is not suitable for comparing current drought conditions with historical droughts because AVHRR data is only available since 1981. It is also difficult to compare droughts that occur in different locations because the response of VCI is ecosystem dependent. Thus, VCI only provides a relative measure of drought conditions and because different locations may have experienced different drought severity since 1981.

3.2.5 Soil Moisture Models (VIC, DSSAT, CWB)

The strengths and weaknesses of the three soil moisture models will be considered together since it is unlikely that there would be a need for using more than one soil moisture model for monitoring drought. The data requirements for VIC, DSSAT, and CWB have been already described in sections 2.2.5, 2.2.6, and 2.2.7, respectively.   This section describes the general strengths and weaknesses of using soil moisture models, and section 3.4.1 shows the results of a model evaluation that was performed to determine which of these three soil moisture models are most appropriate for simulating soil moisture in Texas.

One of the main advantages of using soil moisture models for monitoring drought are that they integrate the effects of temperature, precipitation, solar radiation, wind speed, and other meteorological variables. The influence of these variables is accounted for either explicitly or implicitly, depending on the model, so soil moisture should be more directly linked to impacts (reservoir storage, groundwater recharge, streamflow, agriculture, etc.) than indices that are only based on precipitation.

Soil moisture models provide a variety of parameters that can be analyzed. For users interested in meteorological drought, the soil moisture anomalies in the upper 5 or 10 cm of the soil are highly correlated with other measures of meteorological drought. Users who are interested in hydrological/water supply drought can analyze the soil moisture in the lower layers of the soil since these will be strongly related to base flow, groundwater recharge, and reservoir levels. Root zone soil moisture is highly correlated with yield and agricultural drought. Another advantage of soil moisture models is that they provide high resolution (both spatially and temporally) drought monitoring data since they calculate soil moisture at a daily time-step and for a specific location.

There are also some drawbacks to using soil moisture for drought monitoring applications. Since observed soil moisture data is not commonly available, soil moisture must be estimated with a model. Although these models can successfully simulate soil moisture they may require extensive calibration and validation. Soil moisture models also require more input data than precipitation-based indices and they are more complicated to calculate and run than many of the other drought indices that are considered in this study.

Soil moisture models are particularly sensitive to the soil parameters that are used. Since it is not practical to collect field data for every location in Texas for which soil moisture will be simulated, it is necessary to use existing soil databases to extract the required soil variables. These databases tend to have a relatively coarse spatial resolution so they may not be appropriate for simulating soil conditions for a specific location. It should also be noted that soil parameters and precipitation are both highly spatially heterogeneous. In addition, other factors such as the distribution of vegetation, plant rooting depths, slope, and cracks in the soil can have a significant influence on the spatial and temporal distribution of soil moisture. Therefore soil moisture is known to vary greatly over short distances (for example within a single agricultural field). Therefore, it is important to note that there are some fundamental scale issues that need to be addressed when using soil moisture models to monitor drought at the local and regional level.

The three models that were considered in this study also have there own specific strengths and weaknesses and they all differ in regards to how they attempt to calculate soil moisture. In regards to modeling soil moisture, DSSAT can divide the soil into up to 10 layers, VIC divides the soil into 3 unequal layers, and CWB only uses a single layer to simulate soil moisture. Therefore, VIC and DSSAT are designed to more accurately account for heterogeneity within the soil profile. Both VIC and DSSAT are also more sophisticated in their treatment of ET. VIC calculates ET from three separate components, the evaporation from the soil, evaporation water intercepted by the plant, and transpiration from the plant leaves. DSSAT first calculates potential evapotranspiration (PET) and then partitions it into potential evaporation and potential transpiration based on the leaf area index. CWB uses the Thornthwaite method to estimate PET (where PET is a function of the mean temperature and the number of hours of daylight). Therefore, CWB is not sensitive to vegetation types and it excludes root water extraction in the subsurface. Both VIC and DSSAT models include root water extraction and root water uptake changes with time.

3.2.6 Percent Normal and Deciles

Due to the similarity of Percent Normal and Deciles, and the lack of published literature that critiques these two methods, they will be treated together. Both of these simple indices only require precipitation data. Percent Normal and Deciles are both easy to calculate (e.g., they do not require any specialized software) and interpret. Both indices provide an accurate, statistical measurement of precipitation, and both can be calculated for any period of interest. Deciles also provide an estimate of how rare a particular precipitation event is in relation to the historical record.

The main limitations of these two indices are that, like the SPI, they require long data records. For percent normal, the previous three complete decades are normally used, but some applications use the period of record. For deciles, more than three decades are desirable, the longer the better. Percent Normal is based on the statistical concept of "normal" (mean) which may not have much meaning in regards to drought impacts. The idea of normal is not always well understood by the general public since it does not necessarily correspond with what we expect the weather to be. Percent Normal also does not account for precipitation variability (standard deviation) since it is only based on the first moment. It is also inappropriate to compare Percent Normal between locations, since 30% of normal in west Texas will refer to a much different precipitation deficit than 30% of normal in east Texas and may be associated with very different impacts.

3.2.7 SWSI

SWSI is calculated using monthly precipitation (both snow and rain), streamflow, and reservoir storage levels. SWSI is particularly useful in the western U.S. where snowpack makes a major contribution to streamflow (Garen, 1993). One of the major advantages of using the SWSI to monitor hydrological/water supply drought is that it incorporates snowpack, reservoir storage, and precipitation at high elevations (Shafer and Dezman, 1982; Garen, 1993). Rather than using model estimates of hydrological variables as in PHDI, SWSI explicitly looks at measured hydrological variables in the calculation of the index. Hence the interpretation of SWSI is easier than PHDI. SWSI is also useful because it is designed to represent the water supply conditions unique to each basin. However this is also one of the drawbacks of the index because the SWSI must be calibrated for each basin and the factor weights vary from state to state and month to month (Doesken and Garen, 1991; Doesken *et al.*, 1991). Therefore the SWSI for each basin has different statistical properties and the meaning of SWSI is spatially and temporally variant (Doesken and Garen, 1991; Doesken *et al.*, 1991).

Another limitation of the SWSI is that it was designed for mountainous basins that are dependent on snow melt so it is not appropriate for the eastern or southern U.S.. The weighting factors also need to be recalculated anytime there is a change in station locations, the number of stations being used to calculate the average basin conditions, or water management strategies. There is also a lack of consensus over the definition of surface water supply and this influences how the index is calculated (Doesken and Garen, 1991; Doesken *et al.*, 1991). The index is also heavily reliant on good historical records of reservoir levels and stream flow in addition to precipitation. Although a good historical record of precipitation are available for many regions, it is difficult to find stations with continuous records of reservoir levels and virgin stream flow measurements that are unaffected by upstream reservoirs or diversions. Reservoir levels are also severely affected by human decisions in terms of magnitude, duration and frequency of releases or pumping for public water supply. The amount of water released or pumped would have continually increased since reservoir construction due to the population/community growth in and around the reservoir. Hence, using historical reservoir levels to compute non-exceedance probability could lead to errors in the calculation of relative drought severity.

3.2.8 Percent of Reservoir Storage Capacity

Percent of reservoir storage capacity is a relatively simple measure of hydrological/water supply drought that is very easy to compute and interpret since it is a simple ratio of volumes. Another advantage of this index is that it is dimensionless and so it can be compared across regions.

One of the weaknesses of this index is that it is a simple measure of reservoir volume during a particular time step and not a measure of drought. From the value it would be difficult to say if we are in drought because reservoir storage naturally varies throughout the year as a function of normal changes in supply and demand. For example, a value of 60% can have totally different meaning in summer versus winter. Therefore, a better measure of drought would place the current value into historical perspective based on the time of year.

3.2.9 Streamflow Percent Exceedance

Streamflow Percent Exceedance is simple to interpret and more robust than other measures of the hydrological/water supply drought (e.g., PHDI) because it is based on a statistical measure of an important hydrologic variable. Also, because this index is dimensionless, the current value can be compared across regions and the current values can be viewed in terms of historical perspective as opposed to the percent of reservoir conservation storage capacity.

One of the main weaknesses of the Streamflow Percent Exceedance is that measurements are usually only available for major tributaries where the flows are strongly affected by large reservoirs upstream. Such stations should not be used since they are not necessarily representative of climate conditions. Unfortunately, there are only a limited number of stations that are unaffected by upstream reservoirs and have long records for statistical analysis. Also, many Texas rivers, especially in west Texas, can be dry during many seasons, making it impossible to calculate the percent exceedance during those periods.

3.2.10 SSFI

One of the main advantages of the SSFI is that is can be calculated for a wide range of time scales and it can be updated on a daily rather than monthly basis. Therefore it can be used to monitor short, medium, or long-term hydrological/water supply drought in near-real time. The index is a standardized measure of streamflow based on a statistical measure and so it is more robust that just using streamflow departures. Interpretation of SSFI is straightforward, negative values indicate below normal streamflow and positive values indicate above normal streamflow. For example, a value of -1.0 indicates that, based on standard normal distribution, the current streamflow is only greater than 15.87% of the streamflow from historical records. Since the index is standardized, it can be compared across space and time. The statistical parameters can also be interpolated across a region, enabling the use of short term record available from recently installed stream gages in the calculation of the index.

One of the main weaknesses of the SSFI is that it is very difficult to fit a statistical distribution to the raw cumulative streamflow data, hence the data has to be transformed using procedures such as Box-Cox transformations. Even after being transformed, especially during low-flow periods and for short-accumulation time scales, the data did not fit a normal distribution. This could potentially introduce errors in the calculation of the index. Also it is difficult to find gage records that are appropriate for calculating the SSFI since there are a limited number of long streamflow records for gages unaffected by upstream reservoirs.

3.2.11 SDI

Although the SDI is very similar to the Streamflow Percent Exceedance currently used by TWDB, it is a more flexible drought index because rather than using only 30-day mean value on a monthly basis, a wide range of time scales can be used (for short, medium, and long-term drought) and the index can be updated on a daily basis . The interpretation of the SDI is relatively straightforward. Large positive (negative) values indicate above normal (below normal) streamflow conditions. The statistical parameters (e.g., median, minimum and maximum) are measured as the cumulative discharge per unit area, so they can be interpolated across Texas. This provides the opportunity to calculate the SDI at locations that only have a short record.

A weakness of the SDI is it is calculated using a linear scale that is based on the median, maximum, and minimum values. However, the actual drought response could be highly non-linear. Another weakness of the SDI is that although a value of 0, 100 or -100 is easy to interpret, the intermediate values are not easy to interpret. For example, an SDI of -50% would mean that the numerator is 50% of the denominator, it does not mean that the measured cumulative value is 50% higher than the minimum value or 50% less than the median value. Like the SSFI it is also requires long streamflow records for gages unaffected by upstream reservoirs.

3.2.12 SRI

Using WRAP instead of historical reservoir level data avoids the problems associated with changes in water usage over time. This procedure also provides a framework to monitor drought for new reservoirs or reservoirs with short reservoir level records. SRI is a statistically-based index that has a straightforward interpretation with negative values indicating dry conditions and positive values indicating wet conditions. For example, a value of -1.0 would mean that the current reservoir level is only greater than 15.87% of the monthly simulated reservoir levels based on standard normal distribution. Another advantage of the SRI is that since it is a standardized index, it can be compared across space and time.

A weakness of the SRI is that it is very difficult to fit a statistical distribution that fits the simulated reservoir data. Hence percent non-exceedance was calculated by comparing measured data directly with simulated historical records without fitting any distribution. Therefore, the values of SRI are limited by the amount of historical data available from simulation. For most river basins there are only 57 years of monthly simulated reservoir level data, therefore the lowest (highest) SRI would correspond to a cumulative probability of 1/57 (56/57) or 0.0175 (0.9825) which corresponds to -2.1 (2.1) in the standard normal distribution.

3.2.13 RDI

Like the SRI, the RDI is based on using WRAP and so it avoids the problems associated with changes in water usage over time. This procedure also provides a framework to monitor drought for new reservoirs or reservoirs with short reservoir level records. RDI is a statistically-based index that has a straightforward interpretation with negative values indicating dry conditions and positive values indicating wet conditions. For example, a value of 0 would indicate that the current water level is in the same level as that of the long-term median and values less (greater) than zero of indicate that the current reservoir level below (above) the median level for that month.

3.3 Qualitative Drought Index Evaluation

The second step in determining which drought indices meteorological and hydrological/water supply indices are the most appropriate for monitoring drought conditions at the local level was to evaluate all of the candidate drought indices using a modified version of the criteria developed by Keyantash and Dracup (2002). This methodology was originally developed to select the most appropriate agricultural, meteorological, and hydrological drought indices for monitoring drought in Oregon. A revised version of their evaluation criteria have been adopted in this study to select the most appropriate meteorological and hydrological/water supply indices for monitoring drought at the local level in Texas. To judge the overall utility of each of the candidate drought indices six criteria were identified based on the ideal characteristics of a drought index (Keyantash and Dracup, 2002; Narasimhan and Srinivasan, 2005). These six criteria are robustness, tractability, transparency, sophistication, extendability, and dimensionality. Each of the candidate drought indices were evaluated using these six criteria and were assigned values ranging from 1 (lowest) to 5 (highest). The rankings for each drought index were tabulated using a weighting system (Table 11).

Robustness (30%)

Robustness refers to the ability of an index to measure drought over a wide range of climatic conditions (Keyantash and Dracup, 2002). It also refers to the ability of the index to be spatially and temporally comparable (Narasimhan and Srinivasan, 2005). That is, can a particular index calculated in one part of Texas be directly compared with an index calculated in another part of Texas (do the index values mean the same thing at different locations). A robust drought index is also one that whose values are independent of the seasonal cycle (can index values from summer months be directly compared to index values from winter months). A robust drought index should be correlated with (and sensitive to) drought impacts and it should be able to discriminate amongst drought impacts. Obviously, robustness is a very important criterion for a drought index, but tractability is given nearly equal importance in the weighting scheme because a robust index may not be the most appropriate to use if it can not be calculated using readily available data.

Tractability (25%)

Tractability is the term chosen to represent the practical aspects of calculating drought indices (Keyantash and Dracup, 2002). Since the purpose of this study is to develop a strategy for monitoring drought at the local level in Texas, it is extremely important that the recommended indices be ones that are easy to calculate at the local level using readily available data. There are three main questions that need to be answered to determine whether a given drought index is tractable. Is the drought index easy to calculate? Is the data required to calculate the drought index readily available? Is the drought index useful at the local level in Texas? Affirmative answers to these three questions indicate that an index is tractable.

Transparency (15%)

Transparency is used to evaluate whether an index is clear, rational, and easy to understand (Keyantash and Dracup, 2002). A good drought index is one that is readily understandable to decision-makers and the user-community. Transparency and tractability are the two most important criteria because the purpose of performing this analysis is to identify drought indices that can be used for operational drought monitoring in Texas. Therefore, the chosen indices need to be both scientifically defensible and useful (and therefore understandable) to the public. Transparency represents the general utility of a drought index (Keyantash and Dracup, 2002).

Sophistication (10%)

Although sophistication is somewhat counter to transparency, it is nonetheless an important characteristic of a good drought index (Keyantash and Dracup, 2002). A sophisticated drought index is one that has conceptual (scientific) merit. Therefore, even if a drought index is not easy to understand, it may be valuable if it accurately represents some important physical aspect of drought. Of course, one of the drawbacks with sophisticated approaches to measuring drought is that they typically require more data (and higher quality data) and this means that they are not only less transparent, but also less tractable. Since the purpose of this evaluation is to identify indices that can be used in an operational context for monitoring drought at the local level in the Texas, the weighting system will give more credit to an index that is easy to use and easy to understand, than to an index that is sophisticated, but difficult to calculate.

Extendability (10%)

Extendability refers to whether an index can be extended back in time. For example, an index that only uses precipitation data can be used to measure drought all the way back to the start of the instrumental record (100+ years), while an index that utilizes satellite or radar data is limited to the last few decades (Keyantash and Dracup, 2002). An index that is extendable is of value because it can be used to place current (and future) droughts into historical context. This is of particular importance to decision makers who have designed drought response plans based on past droughts. Extendability is not as important as the other criteria and therefore it has a lower weight.

Dimensionality (10%)

Dimensionality refers to the connection between the drought index and the physical world (Keyantash and Dracup, 2002). It is ideal if a drought index has a unit that has physical meaning (e.g., mm of soil water, percent of normal precipitation), rather than a strictly dimensionless unit. There should be a clear connection between the drought index and the physical world. It is also desirable if a drought index uses simple units.

Table 11. Drought index evaluation criteria and their relative importance

Criterion	Relative Importance
Robustness	30%
Tractability	25%
Transparency	15%
Sophistication	10%
Extendability	10%
Dimensionality	10%

3.3.1 Meteorological Drought Indices

The results of the qualitative evaluation of meteorological indices indicates that SPI, Percent Normal, and Deciles were the most highly ranked (Table 12). The results of this study are supported by the work of Keyantash and Dracup (2002) who determined that SPI and Deciles were the two indices most appropriate for monitoring meteorological drought in Oregon. SPI was also one of the drought indices most appropriate for monitoring meteorological drought in Iran (Morid *et al.*, 2006).

SPI, Percent Normal, and Deciles are relatively easy to calculate because they only use precipitation data. Therefore these indices can be readily calculated for all stations in the Texas that have a long record of precipitation. As previously mentioned, one of the main limitations of the SPI is that it requires a relatively long (and continous) precipitation record to be accurate (50+ years of data is ideal) (Wu *et al.*, 2005). Percent normal and deciles also require long precipitation records, but they can be calculated with 30+ years of precipitation data. These three indices are also transparent and easy to understand. All of these indices are reported in units that can easily be converted into precipitation values and they can all be extended back in time (based on the availability of precipitation data). This allows current droughts to be placed in proper historical context. All of these indices are flexible and can be calculated for any period of interest (week, month, season, year). The main drawback of these indices is that they only consider precipitation (atmospheric moisture supply) and not evapotranspiration (atmospheric moisture demand).

After the SPI, percent normal, and deciles, the VIC and DSSAT soil moisture models received the next highest ranking. VIC and DSSAT are two different models that are used for simulating soil moisture. One of the advantages of using this approach is that it provides a more sophisticated (and potentially realistic) simulations of soil water budget including infiltration, runoff, evapotranspiration. However, they require more input data (at a minimum daily temperature and precipitation and soils data) which may limit their utility in certain locations. Another advantage of using these soil moisture models is that they reported conditions using a unit that has physical meaning (e.g., mm of soil water or fraction of field capacity). Although these models are relatively complex, they can still be calculated at the local level in Texas. They provide very different information than the rainfall indices.

Even though the PDSI and Z-index are commonly used for drought monitoring, they were not highly ranked using this method of qualitative evaluation. This is because these indices are complicated to calculate, require more detailed information than the precipitation indices, and report drought conditions using a dimension-less index. In addition, it has been demonstrated that the PDSI, as originally formulated by Palmer (1965) is spatially variant. Therefore it is not appropriate to compare PDSI values from different locations (particularly in a large state like Texas that encompasses a broad range of climate regions).

Table 12. Meteorological drought index evaluation criteria and their relative importance

Index	Robustness	Tractability	Transparency	Sophistication	Extendability	Dimensionality	Weighted Total
PDSI	2	3	1	4	4	1	2.4
Z index	2	3	1	4	4	1	2.4
SPI	5	4	4	4	5	4	4.4
EDI	1	4	1	3	5	1	2.4
VCI	2	1	1	4	1	1	1.6
CWB	3	3	4	4	3	5	3.5
DSSAT	4	3	4	5	3	5	3.9
VIC	4	3	4	5	3	5	3.9
Percent Normal	4	5	5	2	5	5	4.4
Deciles	4	5	5	2	5	4	4.3

3.3.2 Hydrological/Water Supply Drought Indices

The results of the qualitative evaluation of hydrological/water supply indices indicate that SPI, SSFI, and RDI were the most highly ranked (Table 13). Although the SPI is traditionaly considered a measure of meteorological drought, it can be used to indicate hydrological/water supply drought if the SPI is calculated for timescales that are more representative (e.g, 3-months, 6-months, 9-months, or longer). The SSFI is a new index that was developed specifically for this study. The SSFI is a standardized measure of streamflow. Like the SPI, the SSFI is simple to calculate because it only utilizes streamflow data. The RDI is also a new index that was specifically developed for this study to measure reservoir levels. The main advantage of the RDI is that it utilizes the WRAP model so it avoids the problems associated with changes in water usage over time. The RDI only requires reservoir data to be calculated and like thte SSFI it can be updated on a daily basis. Unlike the SWSI and PHDI, these three indices are transparent and easy to understand. SPI, SSFI, and RDI are all reported in units that can be directly related to precipitation, streamflow, and reservoir levels, resepectively. They can all be used to place current droughts in proper historical context. All of these indices are flexible and can be calculated for any period of interest (week, month, season, year). This is important because, as will be shown in the quantitative evaluation, the most appropriate timescale for monitoring hydrological/water supply drought varies by basin.

The qualitative analysis also showed that Percent of Reservoir Storage Capacity and Percent Streamflow Exceedance are useful for monitoring hydrological/water supply drought. Like the SSFI and RDI, both of these measures are simple to calculate and use readily available data. However, one of the major drawbacks of Percent of Reservoir Storage Capacity is that reservoir storage naturally varies throughout the year as a function of normal changes in supply and demand. For example, a value of 60% can have totally different meaning in summer versus winter. This accounted for in RDI but not in Percent of Reservoir Storage Capacity. RDI was also ranked higher because it is more sophisticated since it uses the WRAP model to avoid the problems associated with changes in water usage over time. One of the main advantages of the SSFI over the Percent Streamflow Exceedance is that it can be calculated for a wide range of time scales and it can be updated on a daily rather than monthly basis. Therefore it can be used to monitor short, medium, or long-term hydrological/water supply drought in near-real time.

Even though the PHDI and SWSI are commonly used for monitoring hydrological/water supply, they were not highly ranked using this method of qualitative evaluation. This is because these indices are complicated to calculate, require more detailed information, and report drought conditions using a dimension-less index. In addition, the PHDI is not highly correlated with streamflow (or streamflow indices). SWSI is more appropriate for mountanous basins and basins in which snowpack significantly affects that timing of magnitude of streamflow. SWSI also cannot be compared spatially or temporally.

Table 13. Hydrological/water supply drought index evaluation criteria and their relative importance

Index	Robustness	Tractability	Transparency	Sophistication	Extendability	Dimensionality	Weighted Total
PHDI	2	2	1	4	4	1	2.2
SWSI	2	2	2	4	2	1	2.1
SPI	5	4	4	4	5	3	4.3
Percent of Reservoir Storage Capacity	3	4	5	2	3	4	3.6
Streamflow Percent Exceedance	4	4	4	3	3	4	3.8
SSFI	5	4	4	4	3	4	4.2
SDI	3	2	2	4	3	2	2.6
SRI	3	2	2	4	3	2	2.6
RDI	5	4	4	4	3	4	4.2

3.3.3 Recommendations Based on the Qualitative Drought Index Evaluation

Based on the results of the qualitative drought index evaluation, the best indices for monitoring meteorological drought at the local level in Texas are SPI, Percent Normal, and Deciles. These indices are easy to calculate because they only use precipitation data and they are transparent and easy to understand. All of these indices are reported in units that can easily be converted into precipitation values and they can all be extended back in time (based on the availability of precipitation data). This allows current droughts to be placed in proper historical context.most highly ranked.

The results of the qualitative evaluation of indices indicate that SPI, SSFI, and RDI are the most appropriate for monitoring hydrological/water supply drought at the local level in Texas. These indices are simple to calculate and they are transparent and easy to understand. SPI, SSFI, and RDI are all reported in units that can be directly related to precipitation, streamflow, and reservoir levels, resepectively and they can be used to place current droughts in proper historical context. All of these indices are flexible and can be calculated for any period of interest (week, month, season, year).

3.4 Quantitative Drought Index Evaluation

This section provides the results of the quantitative drought index evaluations. The first section describes the soil moisture model comparison. The second section describes the evaluation of the meteorological drought indices and the final section describes the evaluation of the hydrological/water supply indices.

3.4.1 Soil Moisture Models

Three different soil moisture models were evaluated to determine the most appropriate model for simulating soil moisture in Texas. VIC is a hydrology model that can handle complex vegetation interactions with the soil column and atmosphere. DSSAT is a crop model that was designed to accurately simulate the influence of water stress (soil moisture deficiencies) on crop production. CWB is a simple water balance model that calculates changes in soil moisture based on changes in supply (precipitation) and demand (ET, drainage, and surface runoff) and it has been shown to accurately simulate stream flow at regional scales (Hawkins and Ellis, 2006, unpublished). The ability of these three models to accurately simulate soil moisture was evaluated using observed soil moisture data from the Soil Climate Analysis Network (SCAN) site in Bushland, TX (Figure 1). The Bushland site is a native, undisturbed rangeland that is dominated by blue grama and buffalograss[2] (Figure 2).

Hourly soil moisture data is collected at the SCAN site and these data were converted to mean daily (for comparison to VIC and DSSAT) or mean monthly (for comparison to

[2]detailed information is available at: http://www.wcc.nrcs.usda.gov/scan/site.pl?sitenum=2006&state=tx

CWB) values. Volumetric soil moisture data is collected at 5 cm (2 in.), 10 cm (4 in.), 20 cm (8 in.), 50 cm (20 in.), and 100 cm (40 in.). These point measurements of volumetric soil moisture were combined to make them comparable with the layers used in the soil moisture models. Since the CWB is a one-layer model, an average soil moisture value was calculated using all five of the SCAN measurements. DSSAT was run using a seven layer soil profile that is comparable to the measured SCAN data (Table 14). VIC was run using a three layer soil profile and the observed data from a number of depths were averaged before comparison with the model (Table 15). The soil moisture models were run using meteorological data extracted from the closest COOP site (Figure 1).

Figure 1 Location of the Bushland, TX (red triangle) SCAN site and the closest COOP weather stations (black circles).

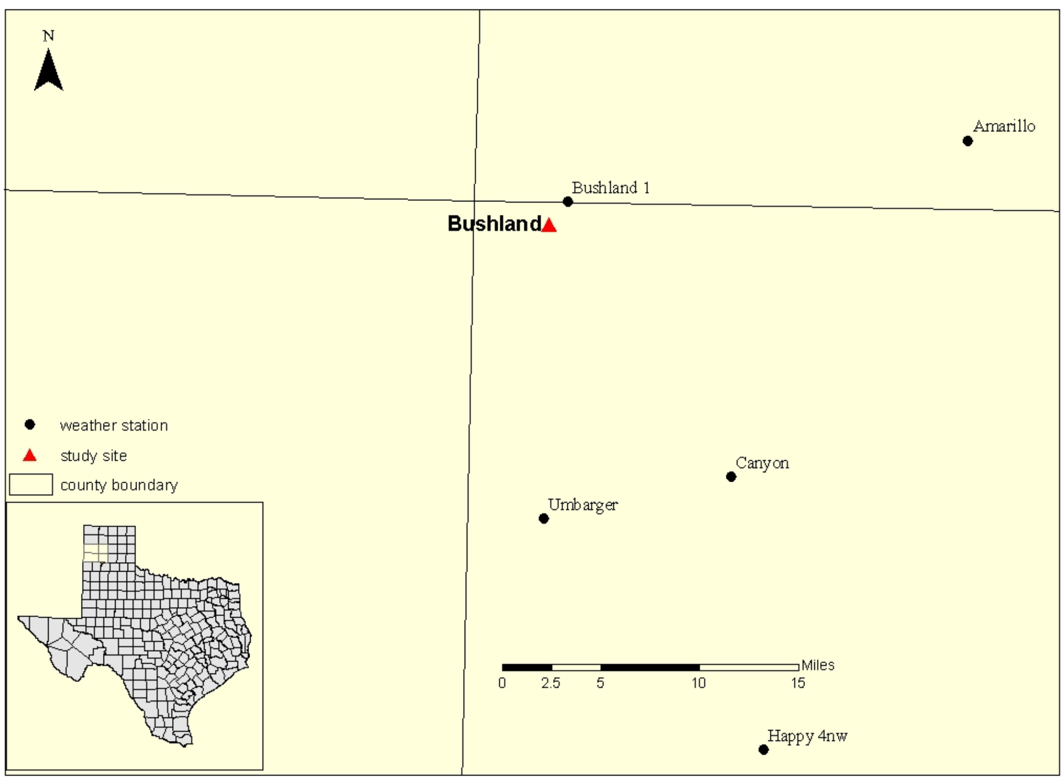


Figure 2 Photograph of the Bushland, TX SCAN site (NRCS, 2006).

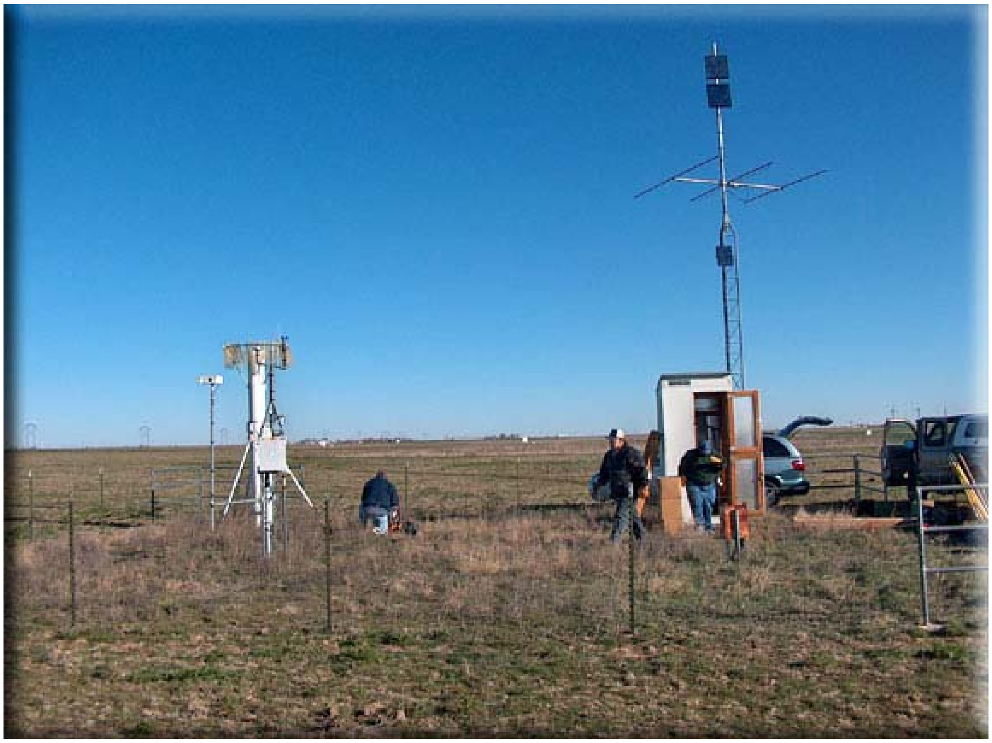


Table 14. Relationship between soil moisture measurements and DSSAT soil layers

Measured Soil Moisture	DSSAT
5 cm	0-5 cm
10 cm	5-15 cm
20 cm	15-30 cm
100 cm	90-120 cm

Table 15. Relationship between soil moisture measurements and VIC soil layers

Measured Soil Moisture	VIC
5 + 10 cm	0-10 cm
20 + 40 cm	10-50 cm
100 cm	50-150 cm

The degree of fit between the observed and modeled soil moisture was evaluated using the root mean square error (RMSE), mean absolute error (MAE), Pearson's correlation coefficient (*r*), and the coefficient of efficiency (E) (Legates and McCabe, 1999). The coefficient of efficiency (E) represents the difference in magnitude between modeled and observed soil moisture. It ranges from -∞ to 1.0, with higher values indicating better agreement. For the CWB model, the goodness-of-fit statistics are based on eleven years of monthly soil moisture data (1995–2005). The goodness-of-fit statistics for VIC and DSSAT are based on daily soil moisture data from 2004 and 2005 data.

Results

DSSAT provides the most accurate simulation of soil moisture at all depths. DSSAT has the highest correlation coefficient and coefficient of efficiency in all soil layers (Table 16). DSSAT performs best in the upper 30 cm of the soil. Although the correlation coefficient is higher in the lowest layer soil layer, the coefficient of efficiency, RMSE, and MAE are worse. This indicates that DSSAT is able to correctly simulate the wetting and drying of the soil, but is not able to correctly simulate the actual volume of soil moisture in the deepest soil layers. These findings agree with other studies that have demonstrated that DSSAT accurately simulates soil moisture in the upper soil layers (Quiring, 2004; Popova and Kercheva, 2005).

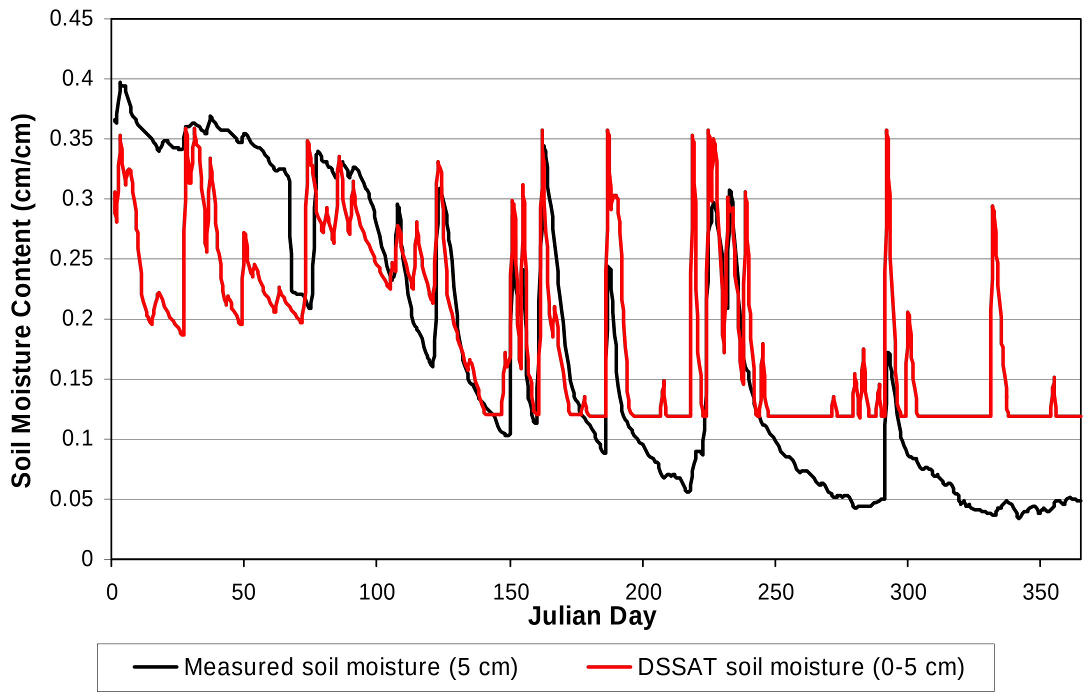
Table 16. Summary of model performance for the CWB (n=132), DSSAT (n=365) and VIC (n=365) soil moisture at Bushland, TX in 2005

Model Performance Statistics	CWB	DSSAT				VIC		
		0-5 cm	5-15 cm	15-30 cm	90-120 cm	0-10 cm	10-50 cm	50-150 cm
RMSE (cm cm^{-1})	0.12	0.08	0.04	0.04	0.09	0.15	0.05	0.08
MAE (cm cm^{-1})	0.10	0.06	0.04	0.04	0.09	0.12	0.04	0.08
Correlation (r)	0.49	0.75	0.92	0.94	0.97	0.59	0.78	0.94
Coefficient of Efficiency (E)	-0.81	0.54	0.76	0.43	-2.90	-1.04	0.10	-2.50

In the top layer of the soil, DSSAT starts out too dry and it takes about 70 days to achieve good agreement between the observed and simulated soil moisture data (Figure 3).

DSSAT also ends the year much wetter than the observed data. This accounts for the relatively large RMSE (0.08 cm cm^{-1}) in this layer and the lower coefficient of efficiency (0.54). The model appears to be very sensitive to the precipitation and even small precipitation events cause dramatic spikes in soil moisture (precipitation data not shown). The observed soil moisture shows a much more muted response to small precipitation events. The difference between the model and observed soil moisture is likely due to the inability of the model to accurately parameterize infiltration. It is likely that most of the water from small precipitation events will evaporate before it has a chance to infiltrate the soil.

Figure 3 Daily soil moisture (cm/cm) in Bushland, TX (2005): measured (5 cm) vs. DSSAT (0-5 cm).



Soil moisture is most accurately simulated by DSSAT in the second and third soil layers (Figures 4 and 5). These layers have the lowest errors and highest degree of agreement between the observed and modeled data. Soil moisture is not well simulated in the lowest soil layer (Figure 6). The model systematically underpredicts the amount of soil moisture. It may be possible to remove this systematic bias by tuning the soil parameters in the model since no tuning was done for this model evaluation. Some of the error is also due to the scale mismatch (comparing a point measurement to a layer that is 30 cm thick).

Figure 4 Daily soil moisture (cm/cm) in Bushland, TX (2005): measured (10 cm) vs. DSSAT (10-15 cm).

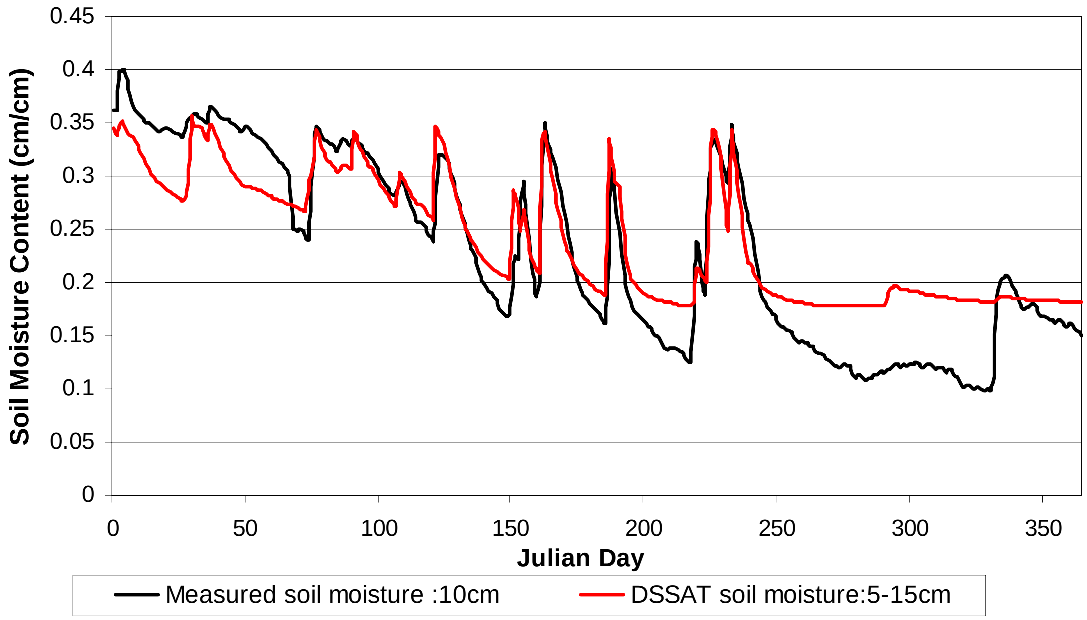


Figure 5 Daily soil moisture (cm/cm) in Bushland, TX (2005): measured (20 cm) vs. DSSAT (15-30 cm).

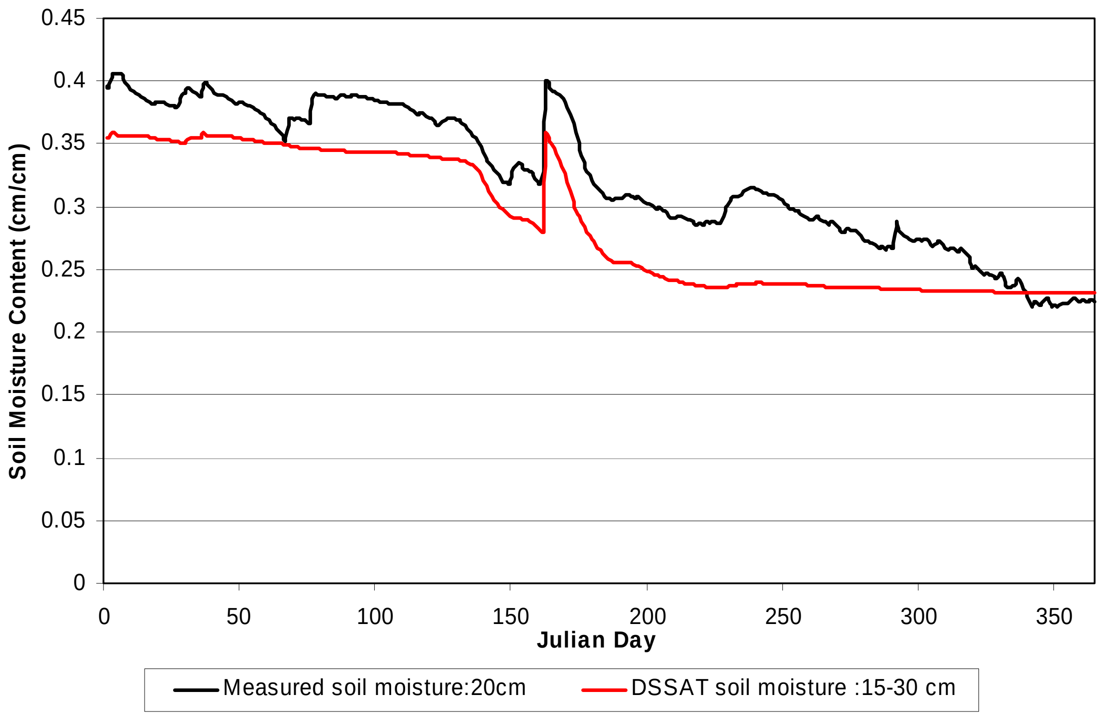
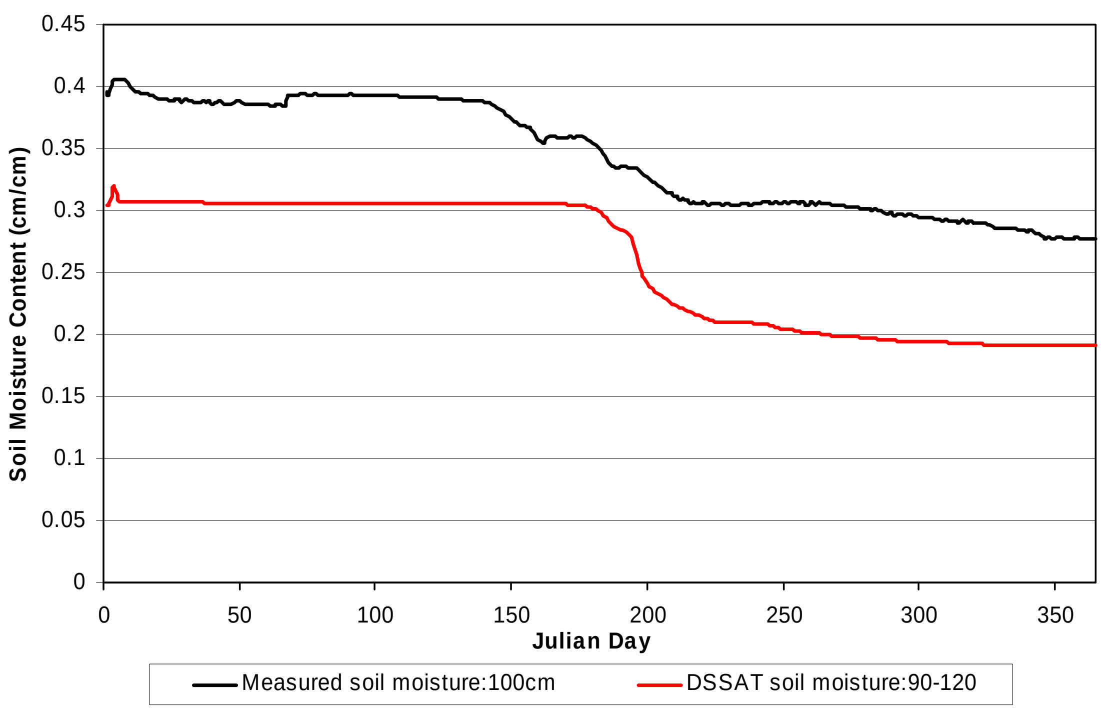


Figure 6 Daily soil moisture (cm/cm) in Bushland, TX (2005): measured (100 cm) vs. DSSAT (90-120 cm).



VIC did a reasonable of simulating the patterns of soil wetting and drying. This is demonstrated by the correlation coefficients (which ranged from 0.59 (top layer) to 0.94 (lowest layer)). However, VIC was not able to provide accurate estimates of the amount of soil water in each layer. VIC had high RMSE values (which ranged from 0.05 to 0.15 cm cm^{-1}) and the low coefficient of efficiency values (which ranged from 0.10 to -2.50) for all three layers. Soil moisture variation and the amount of soil water were accurately simulated in the top layer of the soil at the beginning of 2005 (Figure 7). However after a couple of months the observed soil moisture began to significantly deviate from the VIC-simulated soil moisture. The reasons for these deviations are not clear, but VIC soil moisture was much wetter than the observed soil moisture for the remainder of 2005. VIC did a better job of simulating soil moisture in the second layer of the soil (Figure 8), but there were still some large differences between the observed and simulated soil moisture at certain times of the year. The third layer of the VIC model accurately captured the trend in soil moisture over the year, but it systematically underestimated the amount of soil water (Figure 9). VIC was also evaluated using observed soil moisture data from 2004 and the simulation yielded nearly identical results to 2005 (results not shown).

Figure 7 Daily soil moisture (cm/cm) in Bushland, TX (2005): measured (mean of 5 & 10 cm) vs. VIC (0-10 cm).

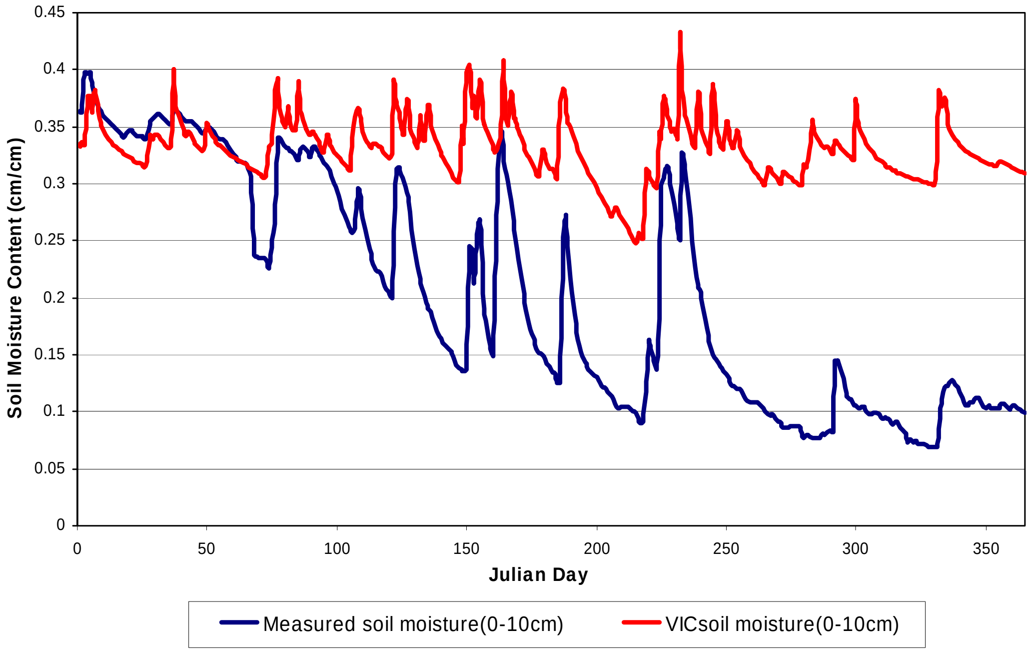


Figure 8 Daily soil moisture (cm/cm) in Bushland, TX (2005): measured (mean of 20 & 40 cm) vs. VIC (10-50 cm).

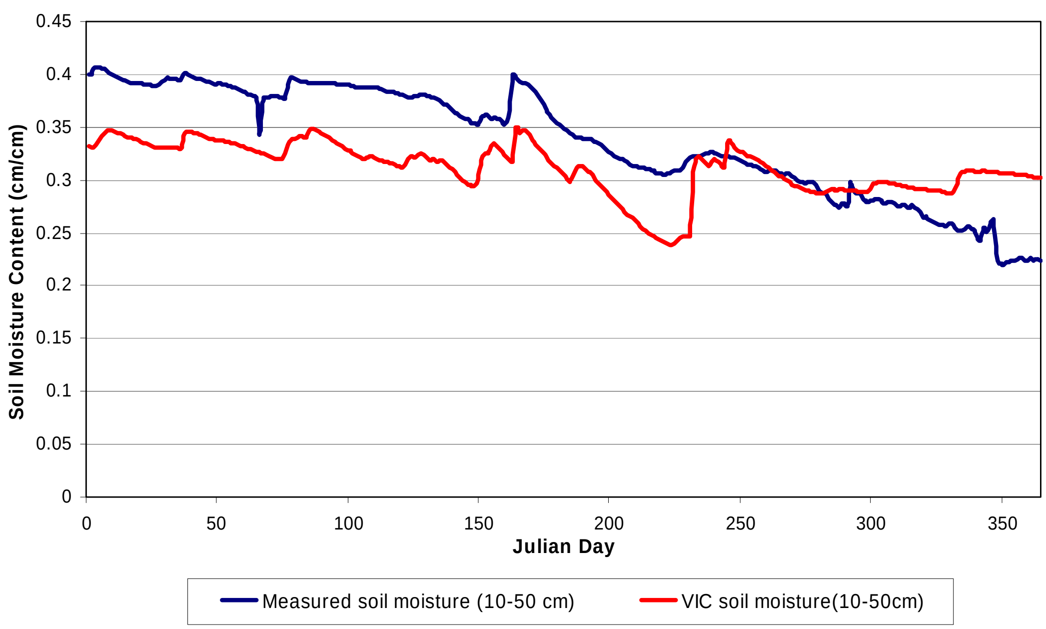
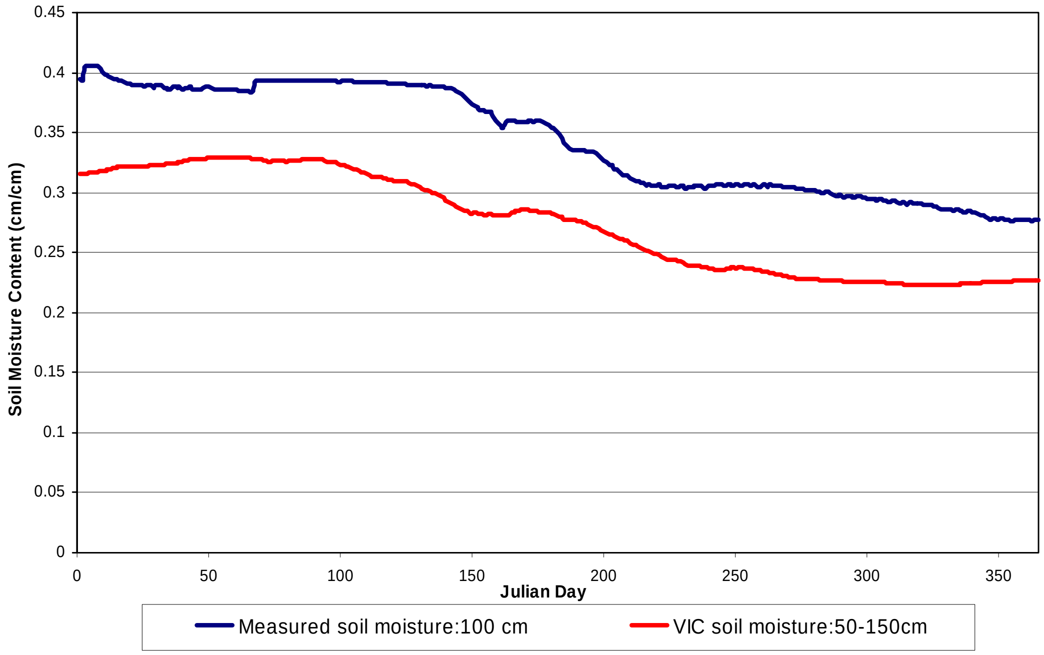
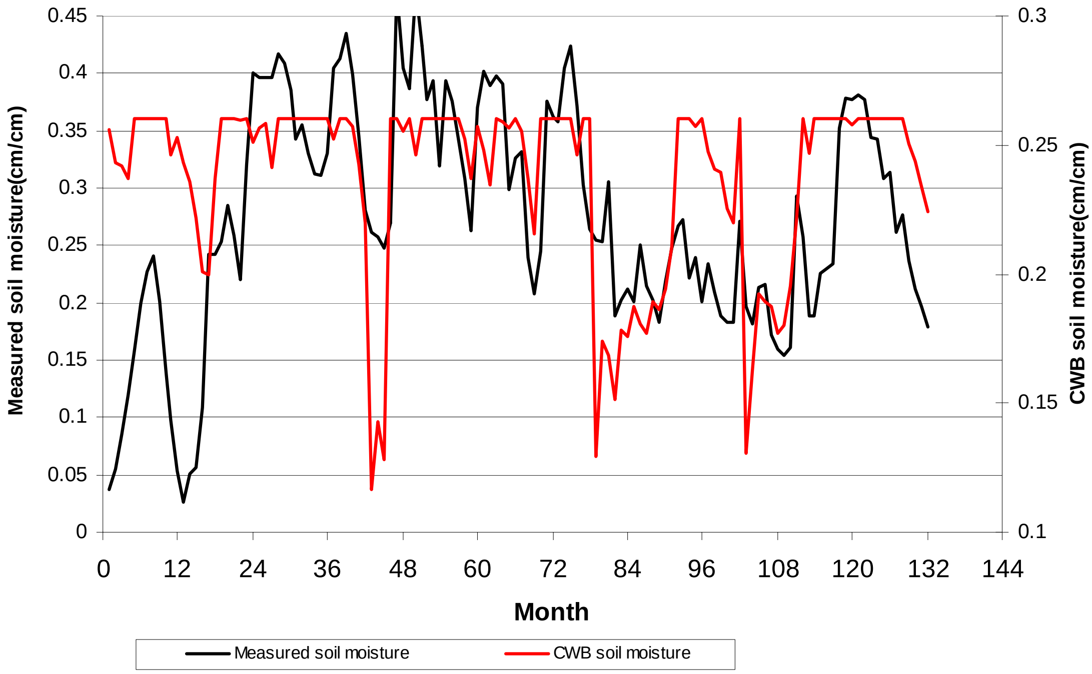


Figure 9 Daily soil moisture (cm/cm) in Bushland, TX (2005): measured (100 cm) vs. VIC (50-150 cm).



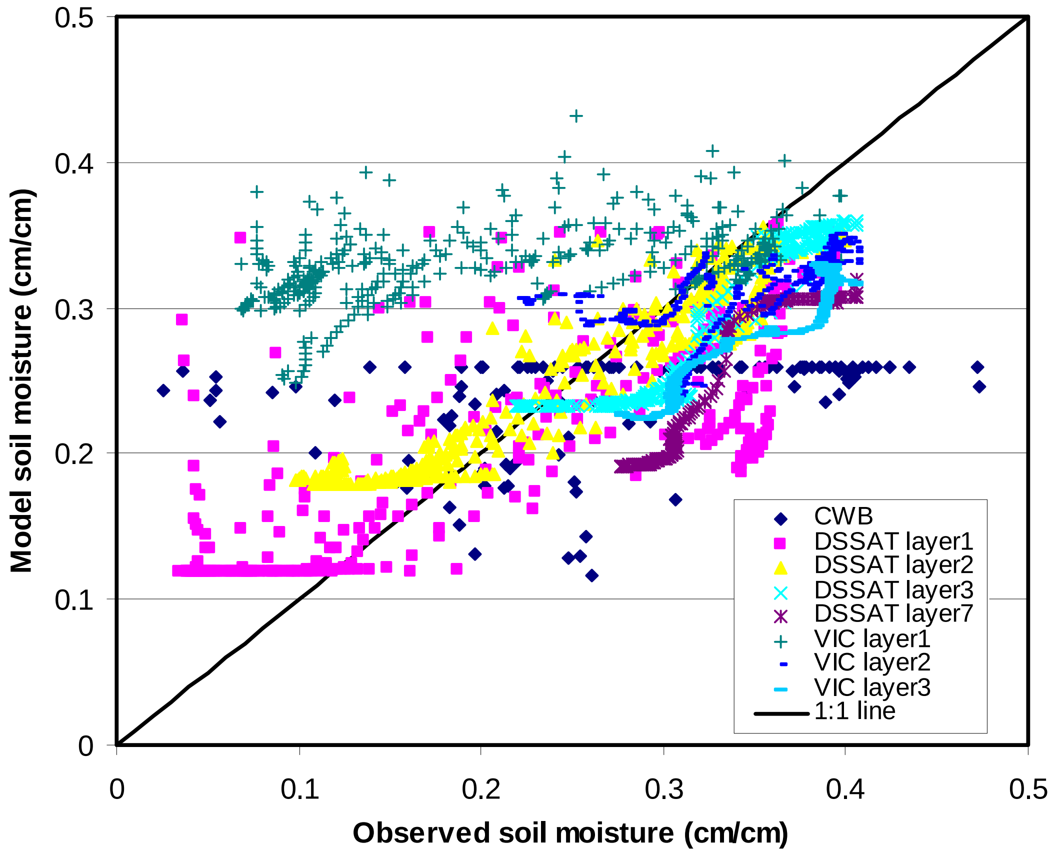
Soil moisture was poorly simulated by CWB. The CWB model is a simple one-layer soil model that simulates soil moisture and the water balance monthly on a monthly basis. Although the annual cycle of soil moisture can be predicted in most cases by the CWB model (Figure 10), the CWB had a higher RMSE and lower correlation coefficient than the other two models. It is evident from Figure 10 that CWB is unable to capture the full range of soil moisture values since it underestimates the soil moisture content during the wettest months. Changing the field capacity (upper limit of soil moisture) might allow the model to more closely replicate actual soil moisture conditions. Because of the poor performance of the CWB model, it was also tested at another SCAN site (Prairie View, TX). Although the model performed slightly better at Prairie View, it still was not as accurate as DSSAT or VIC. This suggests that CWB is too simplistic to accurately simulate soil moisture.

Figure 10 Monthly soil moisture (cm/cm) in Bushland, TX (1995–2005): measured (averaged over all depths) vs. CWB.



The results from all three models are shown in Figure 11. The scatter plot shows that the DSSAT is the most appropriate model for simulating soil moisture in Texas. The DSSAT model was able to simulate soil moisture with a relatively high degree of accuracy (particularly in Layer 2). The VIC model also was relatively accurate in layer 2, but has significant systematic biases in layer 1 and layer 3. CWB is too simplistic and was not able to accurately simulate soil moisture at this location.

Figure 11 Scatter plot of observed versus modeled soil moisture for the CWB (1995–2005), DSSAT (2005) and VIC (2005). The black line represents the perfect prediction line.



3.4.2 Meteorological Drought Indices

Seven different meteorological drought indices (PDSI, Z, SPI, Percent Normal, Deciles, EDI, and VCI) were evaluated at stations located in six Texas watersheds (Figure 12). These meteorological drought indices (all except the VCI) were calculated and compared using data from six stations from the Historical Climate Network (HCN). These are stations that have long and relatively complete records (~100+ years). One station was selected from each of the watersheds evaluated in section 3.4.3 (e.g., Red River, Upper Trinity, Lower Trinity, Colorado, Guadalupe, and San Antonio). A number of these indices (PDSI, Z, SPI, Percent Normal, and Deciles) are commonly used for monitoring meteorological drought across the U.S. and, in some cases, around the world. The EDI is a relatively new drought index that has not been extensively tested or evaluated and the VCI is a satellite-based drought index used for monitoring vegetation health. Evaluation of the VCI was carried out by aggregating the VCI data at the county level and on a monthly time step. A correlation matrix was used to compare all of the drought indices. A high correlation between two indices was interpreted to mean that those two indices behave similarly.

Evaluation of VCI

The VCI was compared against a selection of meteorological drought indices, specifically: PDSI, Z, SPI (1-, 2-, 3-, 6-, 9-, 12-, and 24-month), Percent Normal, and Deciles. Each of these indices were calculated on a monthly time step using monthly temperature and precipitation from PRISM (http://www.ocs.oregonstate.edu/prism/). These data, which are available at 4 km resolution, were aggregated to counties for comparison with the VCI. The Available Water Content (AWC) was obtained from the website maintained by the National Resources Conservation Service (NRCS) in a raster format. Using this, AWC values were computed for each county of Texas. The latitude of each Texas county was calculated by determining the centroid of each county's polygon. These data were used to calculate each of the meteorological drought indices from 1895–2005. However the comparison with the VCI was only done using data from 1982–1999 do to the availability of the satellite data.

The VCI is calculated using NDVI data. The data used in this analysis was the 10-day NDVI composites that were provided at 8-km spatial resolution. These data were obtained from the Goddard Earth Sciences, Distributed Active Archive Center (GES-DAAC) (http://daac.gsfc.nasa.gov/). After determining the maximum and minimum values of the NDVI for each 10-day composite, the VCI was calculated for the period of study (1982–

1999). These 10-day VCI values were averaged spatially (e.g., to the county level) and temporally (e.g., to create monthly values) for comparison to the meteorological drought indices. Because the VCI measures vegetation health (or vigor), it is most appropriate for detecting growing-season drought. Therefore, the comparison with the meteorological drought indices was based on the months of March to August (selecting other months to represent the growing-season has a relatively minor impact on the results of the analysis (results not shown)). The VCI was evaluated against each of the traditional meteorological drought indices for each county in Texas using the coefficient of determination (R^2). The overall performance of the VCI against each of the traditional meteorological drought indices was computed by taking the average R^2 of all the counties.

Results

The coefficient of determination (R^2) describes the fraction of the total variation in the observed data that is explained by the model. It ranges from 0 to 1 with higher values indicating that a greater amount of the variance is "explained" by the predictor(s). However, the coefficient of determination (R^2) has a number of limitations that have been summarized by Legates and McCabe (1999) (e.g., assumption of a linear relationship between the variables, extreme sensitivity to outliers). Ideally these drought indices should be evaluated using data on meteorological drought impacts. Since such a dataset is not available for Texas, this method of evaluation was used instead. The results of this evaluation will not necessarily show which meteorological drought index is the most appropriate, but it will show which drought indices are highly correlated with the VCI. If the information provided by the VCI is already provided by another drought index, then it may be considered as having limited utility. However, if the VCI has a relatively low correlation with the other meteorological drought indices, then this might suggest that it is providing a unique perspective for characterizing drought.

The mean relationship (for all 254 counties) between the VCI and meteorological drought indices are summarized in Table 17. Overall, none of the meteorological drought indices is strongly correlated with the VCI. The 6-month SPI ($R^2 = 0.287$) has the highest correlation, followed by the PDSI ($R^2 = 0.256$), and the 9-month SPI ($R^2 = 0.255$). The Z-index, Percent Normal, and Deciles model show almost no correlation with the VCI. However, there is significant spatial variability in these relationships. This is not illustrated by looking at the mean coefficient of determination.

Table 17 Mean relationship between VCI and meteorological drought indices (n = 254)

Drought Index	R^2
Z-index	0.110
PDSI	0.256
1-month SPI	0.042
2-month SPI	0.150
3-month SPI	0.202
6-month SPI	0.287
9-month SPI	0.255
12-month SPI	0.200
24-month SPI	0.124
Percent Normal	0.033
Deciles	0.048

Figure 12 shows that there is a great deal of spatial variability in the relationship between the VCI and the 6-month SPI. Generally, the counties in north-western and south-western Texas have much higher correlations than counties in eastern Texas or counties along the Gulf Coast. For example, Brazoria, Montgomery, and Harding counties (south-east Texas) have coefficients of determination near zero, while Maverick, Borden, and McMullen (west-central, south-west Texas) have coefficients of determination that exceed 0.6. This means that in the counties with the highest coefficients of determination, the 6-month SPI “explains” more than 60% of the variance in the VCI. A similar spatial pattern in the variability of the coefficient of determination is also shown for the VCI and PDSI (Figure 36). Figure 13 shows a stronger and more east to west gradient in the coefficient of determination. Brazoria County has the lowest R^2 and Upton, Reeves and Pecos (western Texas) have the highest R^2. Figure 14 also has a similar spatial pattern to Figure 36, with Harding County (south-east Texas) having the lowest R^2 while Upton, Reagan and Pecos counties (western Texas) have the highest R^2. This spatial pattern is evident for all of the meteorological drought indices that were evaluated, even those that had a mean coefficient of determination near zero (such as the Z-index) (Figure 15). Although the overall magnitude of the coefficient of determination is lower, there are still a number of counties in western and south-western Texas where the coefficient of determination exceeds 0.2. This suggests that there are some spatially-varying factors that control the strength of the relationship between the VCI and the meteorological drought indices. An investigation of these factors is beyond the scope of this study, but it is likely that they include things like climate (mean annual precipitation), soil type, vegetation type, land-use/land-cover, groundwater levels, soil fertility, soil salinity, and other factors that influence the vegetation resilience to drought and overall vegetation health.

Figure 12 Spatial variation of the Coefficient of Determination (VCI and 6-month SPI) over Texas

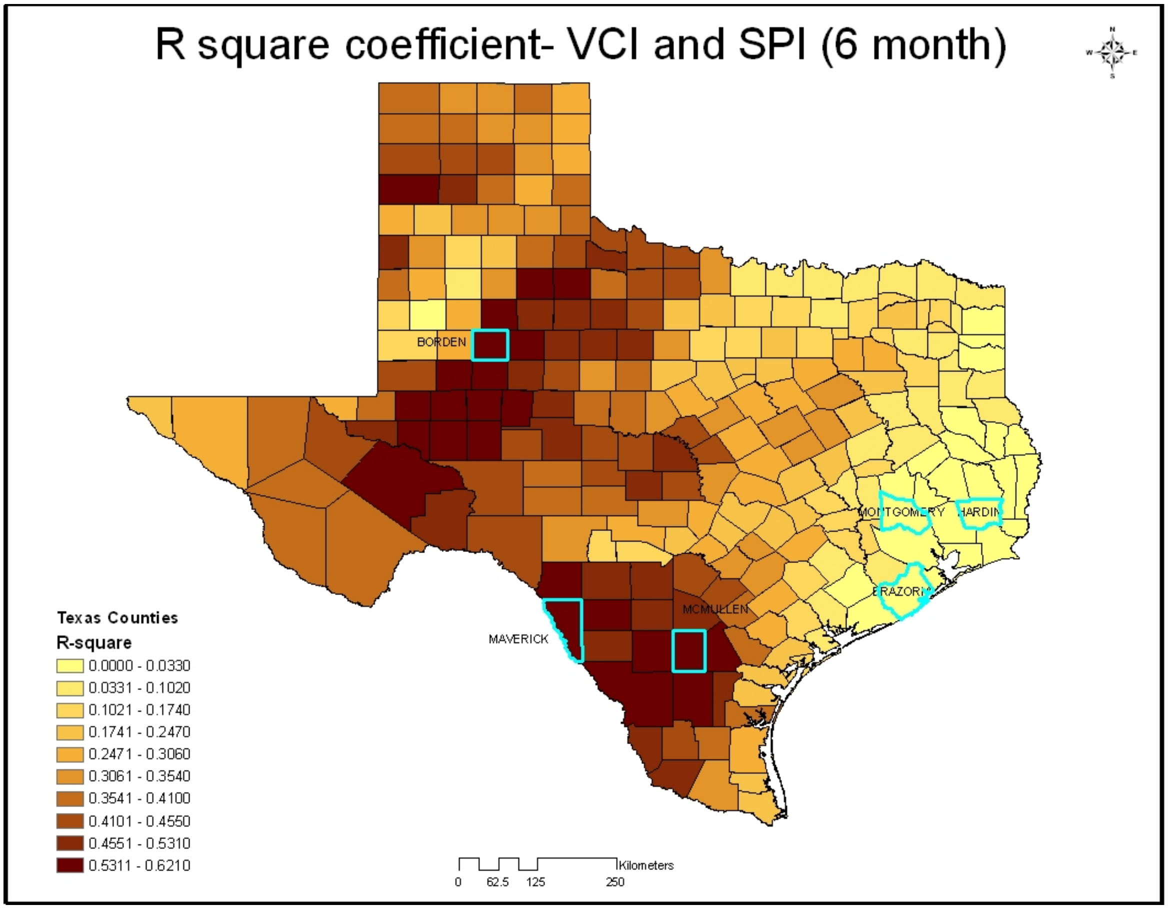


Figure 13 Spatial variation of the Coefficient of Determination (VCI and PDSI) over Texas

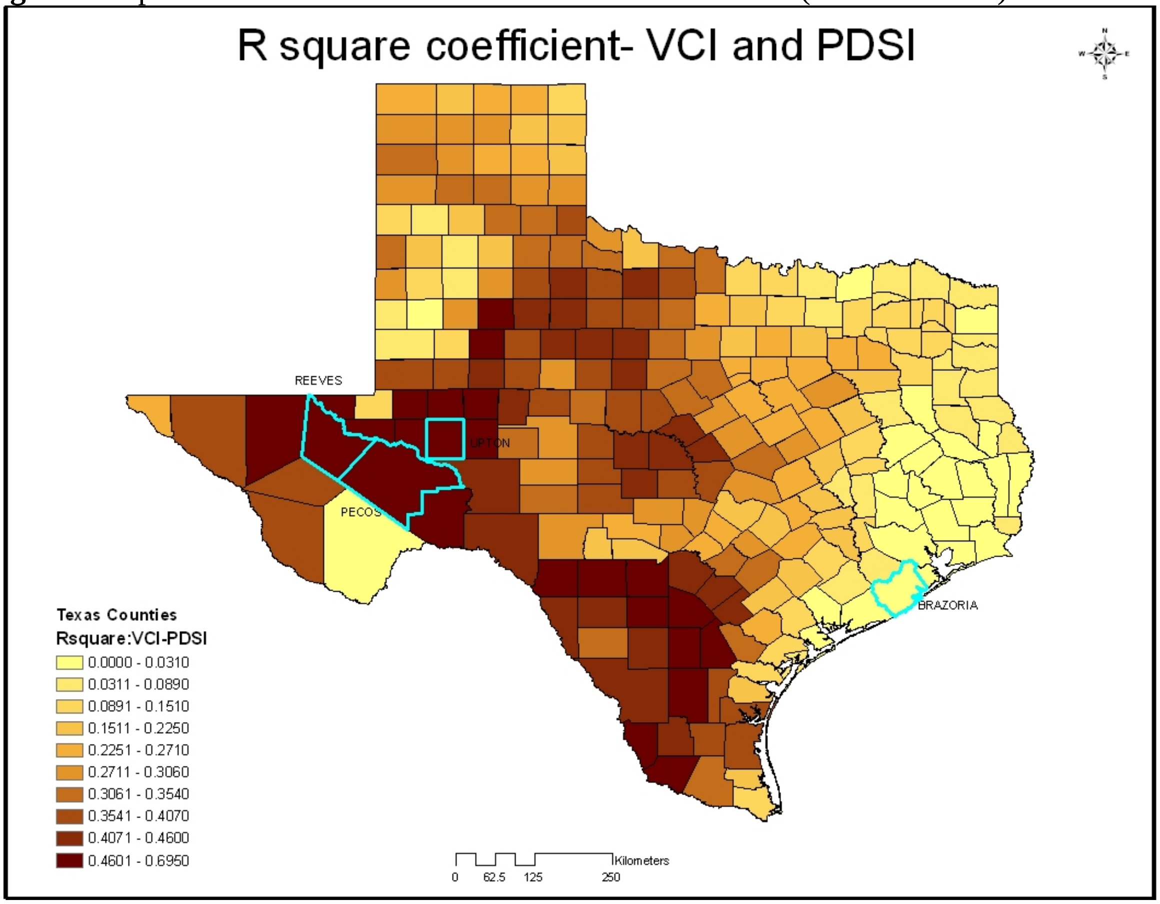


Figure 14 Spatial variation of the Coefficient of Determination (VCI and 9-month SPI) over Texas

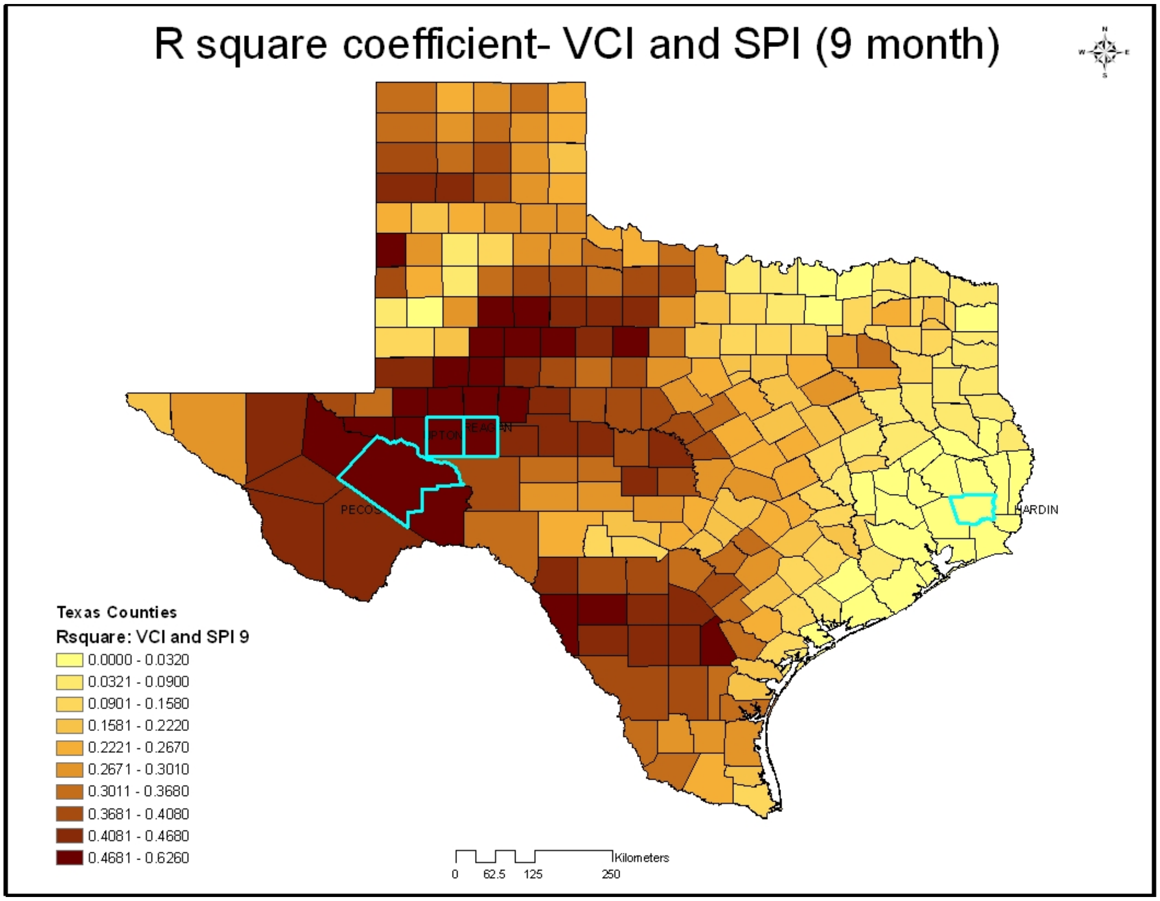
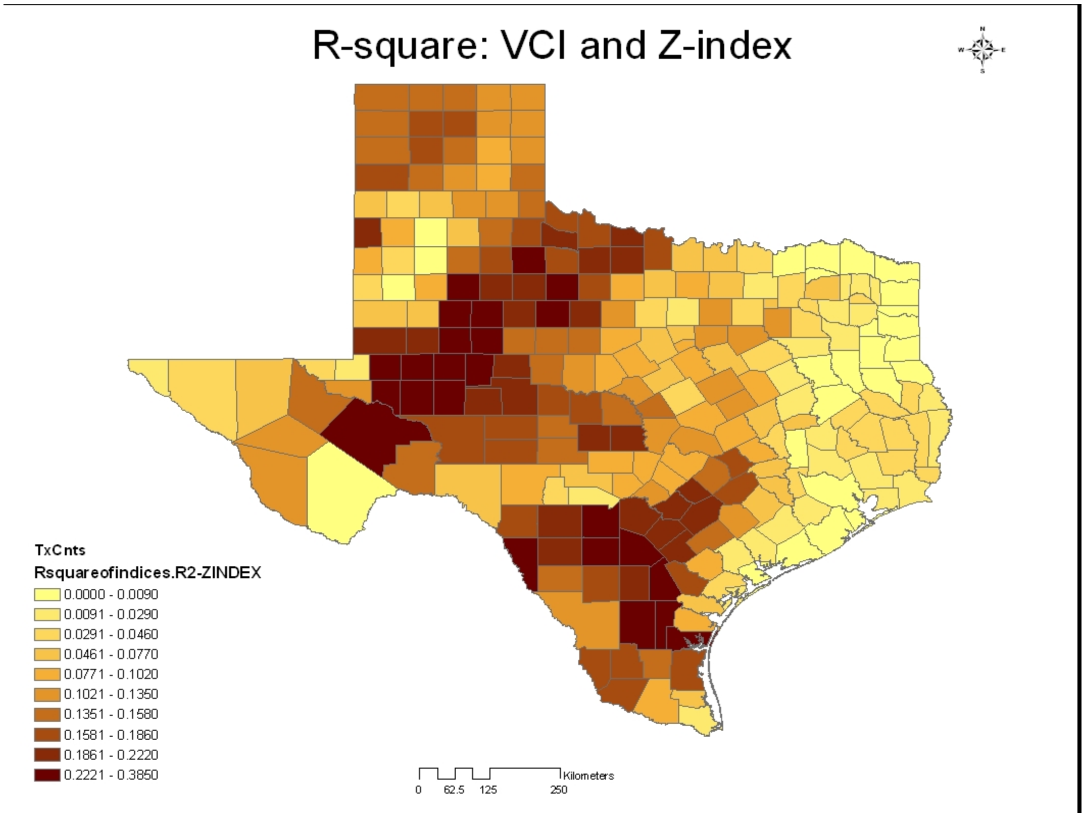


Figure 15 Spatial variation of the Coefficient of Determination (VCI and Z-index) over Texas



Conclusions

Overall the VCI is most strongly correlated with the 6-month SPI, PDSI, and 9-month SPI. This is somewhat surprising given that the VCI measures vegetation health. Studies that have examined agricultural drought have found that drought indices with a short time scale (a month or less) are usually most highly correlated with crop growth (Quiring and Papakyriakou, 2003). Therefore, it is surprising that the 1-month SPI, Z-index, and Percent Normal are not more highly correlated with the VCI. PDSI is heavily influenced by antecedent moisture conditions and has been shown to have a memory of at least 9 months. Therefore it is not surprising that the PDSI and 6- and 9-month SPI are all highly correlated with the VCI since they are highly correlated with each other. This indicates that, at least over Texas, the VCI shows the strongest response to prolonged precipitation deficiencies and it appears to be less sensitive to short-term precipitation deficiencies. This finding does not agree with what has been reported in the literature and therefore merits further study (Kogan, 1995, 1997; Kogan and Unganai, 1998; Kogan, 2001; Kogan, 2002). This might be due to the type of vegetation that is present. These spatial variations in vegetation, in turn, might account for the spatial patterns that are evident across Texas. Generally one would expect that vegetation that has deeper roots would be less susceptible to drought since it has greater access to soil moisture. This deeper rooting system helps to buffer the vegetation from short-term stress. Alternatively, it may be that the spatial pattern is due to climatic factors, since it appears to partly resemble the east-west precipitation gradient.

It is clear from this analysis that the VCI measures drought in a way that is quite different from traditional meteorological drought indices. This is both an advantage and a disadvantage. One of the major benefits of the VCI is that is provides continuous spatial coverage and it attempts to directly measure vegetation health. The disadvantage of this approach is that it appears to provide very different information than the traditional meteorological drought indices. The VCI should be employed with caution until it can be more fully evaluated (e.g., the reasons for the spatial and temporal variability in its relationship with other drought indices can be explained) and its relationship to drought impacts is better understood.

Evaluation of Meteorological Drought Indices

San Antonio Basin

The drought index comparison for the San Antonio Basin was carried out using data from 1904–2001 (station 410902). The correlation matrix for this station (Table 18) shows that the 1-month SPI (SPI1) is highly correlated with both Percent Normal (PN) and Deciles.

Together with the 2-month SPI (SPI2), these indices can collectively be referred to as short-term precipitation indices. It is also clear that the 3- and 6-month SPI (SPI3, SPI6) is highly correlated with Effective Drought Index (EDI). These indices collectively characterize precipitation on medium timescales. It should also be noted that the EDI has moderate correlations with many of the other SPI timescales and with the PDSI, PHDI, and Percent Normal. It appears that EDI is an integrative index that combines features of many of the other drought indices. The drought indices were also analyzed using Principal Component Analysis to identify the main modes of variability in the data. It is evident from the results that many of these indices are providing the same type of information (Tables 19 and 20). Only three significant PCs were extracted. The first PC explains nearly 60% of the variance in the drought index data. PC1 can be described as a general precipitation component since most of the drought indices load highly on this component. The EDI has the largest loading on PC1, this is not surprising given that, as previously mentioned, EDI appears to integrate features of many of the other drought indices. PC2 accounts for approximately 16% of the variance and it loads highly on a number of the short-term precipitation indices (e.g., 1-month SPI and deciles). PC3 only accounts for 10% of the variance and it loads highly on the Z-index. The PDSI and PHDI are also related to this component. Therefore, PC3 can be described as the Palmer component. The three Palmer indices are the only ones that include temperature in their calculation and they are all based on a simple water balance so it is not surprising that they are highly correlated and respond it a different fashion than the indices that are only based on precipitation.

Table 18 Correlation matrix for meteorological indices in the San Antonio Basin

Correlation Matrix

		zindex	pdsi	phdi	EDI	PN	decile	SPI1	SPI2	SPI3	SPI6	SPI9	SPI12	SPI24
Correlation	zindex	1.000	.640	.513	.169	.170	.138	.172	.155	.153	.150	.136	.130	.072
	pdsi	.640	1.000	.879	.737	.489	.433	.473	.569	.628	.677	.663	.622	.439
	phdi	.513	.879	1.000	.838	.469	.408	.444	.582	.666	.783	.801	.781	.605
	EDI	.169	.737	.838	1.000	.670	.579	.624	.758	.834	.883	.848	.785	.543
	PN	.170	.489	.469	.670	1.000	.843	.909	.704	.595	.442	.366	.317	.209
	decile	.138	.433	.408	.579	.843	1.000	.922	.689	.568	.407	.335	.275	.188
	SPI1	.172	.473	.444	.624	.909	.922	1.000	.742	.608	.442	.359	.297	.191
	SPI2	.155	.569	.582	.758	.704	.689	.742	1.000	.840	.625	.512	.436	.287
	SPI3	.153	.628	.666	.834	.595	.568	.608	.840	1.000	.755	.626	.544	.363
	SPI6	.150	.677	.783	.883	.442	.407	.442	.625	.755	1.000	.858	.760	.519
	SPI9	.136	.663	.801	.848	.366	.335	.359	.512	.626	.858	1.000	.905	.634
	SPI12	.130	.622	.781	.785	.317	.275	.297	.436	.544	.760	.905	1.000	.737
	SPI24	.072	.439	.605	.543	.209	.188	.191	.287	.363	.519	.634	.737	1.000

Table 19 Results of the unrotated Principal Components Analysis (San Antonio Basin)

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.741	59.545	59.545	7.741	59.545	59.545
2	2.099	16.145	75.690	2.099	16.145	75.690
3	1.294	9.958	85.648	1.294	9.958	85.648
4	.655	5.038	90.686			
5	.371	2.856	93.541			
6	.176	1.358	94.899			
7	.169	1.296	96.195			
8	.130	1.002	97.197			
9	.121	.927	98.125			
10	.085	.657	98.782			
11	.066	.510	99.292			
12	.057	.437	99.729			
13	.035	.271	100.000			

Extraction Method: Principal Component Analysis.

Table 20 PCA component matrix (San Antonio Basin)

Component Matrix[a]

	Component		
	1	2	3
zindex	.315	-.079	.922
pdsi	.823	-.159	.456
phdi	.885	-.297	.253
EDI	.957	-.061	-.137
PN	.722	.584	-.014
decile	.680	.629	-.041
SPI1	.720	.633	-.017
SPI2	.809	.350	-.084
SPI3	.845	.127	-.112
SPI6	.862	-.246	-.151
SPI9	.834	-.412	-.178
SPI12	.783	-.487	-.184
SPI24	.586	-.481	-.208

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Upper Trinity Basin

Evaluation of the meteorological drought indices for the Upper Trinity Basin was carried out using data from 1902–2001 (station 412019). The results are similar to those in the San Antonio Basin. The correlation matrix for this station (Table 21) shows that the 1-month SPI (SPI1) is highly correlated with both Percent Normal (PN) and Deciles. The 3- and 6-month SPI (SPI3, SPI6) are highly correlated with Effective Drought Index (EDI). The drought indices were also analyzed using Principal Component Analysis to identify the main modes of variability in the data. It is evident from the results that many of these indices are providing the same type of information (Tables 22 and 23). Only three significant PCs were extracted. The first PC explains nearly 55% of the variance in the drought indices. Similar to the San Antonio basin, PC1 can be described as a general precipitation component since most of the drought indices load highly on it. The EDI has the largest loading on PC1

(0.954). PC2 accounts for approximately 17% of the variance and it loads highly on a number of the long-term precipitation indices (e.g., 9-, 12-, and 24-month SPI). The PDSI also has positive loadings, while a number of the short-term precipitation indices (e.g., Percent Normal, Deciles, 1-month SPI) have negative loadings. This suggests that PC2 is characterizing the long-term precipitation variability. PC3 only accounts for 12% of the variance and it loads highly on the Z-index (and the other Palmer indices). Therefore, PC3 can again be described as the Palmer component.

Table 21 Correlation matrix for meteorological indices in the Upper Trinity Basin

Correlation Matrix

		zindex	pdsi	phdi	EDI	PN	decile	SPI1	SPI2	SPI3	SPI6	SPI9	SPI12	SPI24
Correlation	zindex	1.000	.644	.522	.109	.109	.099	.095	.099	.068	.089	.121	.093	.098
	pdsi	.644	1.000	.908	.496	.293	.282	.282	.361	.393	.462	.511	.494	.427
	phdi	.522	.908	1.000	.599	.347	.339	.336	.432	.483	.554	.603	.600	.540
	EDI	.109	.496	.599	1.000	.664	.611	.651	.788	.850	.888	.835	.768	.548
	PN	.109	.293	.347	.664	1.000	.872	.936	.706	.582	.413	.336	.305	.226
	decile	.099	.282	.339	.611	.872	1.000	.920	.684	.564	.393	.327	.297	.225
	SPI1	.095	.282	.336	.651	.936	.920	1.000	.728	.597	.414	.338	.310	.226
	SPI2	.099	.361	.432	.788	.706	.684	.728	1.000	.836	.596	.475	.433	.321
	SPI3	.068	.393	.483	.850	.582	.564	.597	.836	1.000	.731	.582	.526	.384
	SPI6	.089	.462	.554	.888	.413	.393	.414	.596	.731	1.000	.836	.730	.533
	SPI9	.121	.511	.603	.835	.336	.327	.338	.475	.582	.836	1.000	.888	.645
	SPI12	.093	.494	.600	.768	.305	.297	.310	.433	.526	.730	.888	1.000	.744
	SPI24	.098	.427	.540	.548	.226	.225	.226	.321	.384	.533	.645	.744	1.000

Table 22 Results of the unrotated Principal Components Analysis (Upper Trinity Basin)

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.144	54.957	54.957	7.144	54.957	54.957
2	2.213	17.025	71.982	2.213	17.025	71.982
3	1.553	11.948	83.930	1.553	11.948	83.930
4	.672	5.170	89.100			
5	.402	3.090	92.190			
6	.334	2.570	94.760			
7	.192	1.477	96.237			
8	.135	1.038	97.275			
9	.124	.957	98.232			
10	.078	.598	98.829			
11	.074	.567	99.397			
12	.052	.401	99.798			
13	.026	.202	100.000			

Extraction Method: Principal Component Analysis.

Table 23 PCA component matrix (Upper Trinity Basin)

Component Matrix[a]

	Component		
	1	2	3
zindex	.254	.359	.791
pdsi	.648	.461	.523
phdi	.736	.439	.374
EDI	.954	-.027	-.196
PN	.723	-.577	.185
decile	.703	-.578	.188
SPI1	.728	-.601	.175
SPI2	.806	-.356	-.002
SPI3	.828	-.176	-.137
SPI6	.831	.182	-.299
SPI9	.808	.359	-.312
SPI12	.772	.398	-.326
SPI24	.622	.413	-.248

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Red River Basin

Evaluation of the meteorological drought indices for the Red River Basin was carried out using data from 1902–2001 (station 412121). The correlation matrix for this station (Table 24) is similar to those of the other two basins. The drought indices were also analyzed using Principal Component Analysis to identify the main modes of variability in the data. It is evident from the results that many of these indices are providing the same type of information (Tables 25 and 26). Once again three significant PCs were extracted. The first PC explains nearly 55% of the variance in the drought indices. Similar to the other basins, EDI has the largest loading on PC1 (0.946) and it can be described as describing the general precipitation. PC2 accounts for approximately 17% of the variance and, like the San Antonio basin, it loads highly on a number of the short-term precipitation indices. PC3 only accounts for 10% of the variance and it loads highly on the Z-index (and the other Palmer indices).

Table 24 Correlation matrix for meteorological indices in the Red River Basin

Correlation Matrix

		zindex	pdsi	phdi	EDI	PN	decile	SPI1	SPI2	SPI3	SPI6	SPI9	SPI12	SPI24
Correlation	zindex	1.000	.664	.539	.226	.128	.109	.132	.165	.166	.200	.219	.179	.103
	pdsi	.664	1.000	.894	.627	.315	.258	.314	.413	.465	.552	.590	.564	.436
	phdi	.539	.894	1.000	.714	.338	.274	.330	.439	.509	.649	.725	.729	.602
	EDI	.226	.627	.714	1.000	.614	.501	.615	.734	.795	.849	.830	.778	.520
	PN	.128	.315	.338	.614	1.000	.773	.940	.684	.569	.380	.333	.305	.176
	decile	.109	.258	.274	.501	.773	1.000	.830	.579	.480	.324	.285	.245	.140
	SPI1	.132	.314	.330	.615	.940	.830	1.000	.710	.588	.396	.345	.305	.183
	SPI2	.165	.413	.439	.734	.684	.579	.710	1.000	.821	.556	.480	.428	.265
	SPI3	.166	.465	.509	.795	.569	.480	.588	.821	1.000	.690	.582	.523	.330
	SPI6	.200	.552	.649	.849	.380	.324	.396	.556	.690	1.000	.808	.726	.475
	SPI9	.219	.590	.725	.830	.333	.285	.345	.480	.582	.808	1.000	.876	.588
	SPI12	.179	.564	.729	.778	.305	.245	.305	.428	.523	.726	.876	1.000	.691
	SPI24	.103	.436	.602	.520	.176	.140	.183	.265	.330	.475	.588	.691	1.000

Table 25 Results of the unrotated Principal Components Analysis (Red River Basin)

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.115	54.732	54.732	7.115	54.732	54.732
2	2.255	17.344	72.076	2.255	17.344	72.076
3	1.301	10.004	82.080	1.301	10.004	82.080
4	.715	5.498	87.578			
5	.442	3.403	90.981			
6	.264	2.030	93.012			
7	.247	1.901	94.913			
8	.217	1.666	96.579			
9	.145	1.115	97.694			
10	.103	.790	98.484			
11	.078	.602	99.086			
12	.069	.530	99.616			
13	.050	.384	100.000			

Extraction Method: Principal Component Analysis.

Table 26 PCA component matrix (Red River Basin)

Component Matrix[a]

	Component		
	1	2	3
zindex	.359	-.291	.820
pdsi	.733	-.369	.471
phdi	.812	-.418	.248
EDI	.946	-.012	-.152
PN	.682	.629	.100
decile	.596	.625	.113
SPI1	.695	.648	.097
SPI2	.774	.383	-.028
SPI3	.808	.197	-.120
SPI6	.825	-.193	-.228
SPI9	.829	-.334	-.244
SPI12	.794	-.384	-.286
SPI24	.584	-.413	-.283

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Lower Trinity Basin

Evaluation of the meteorological drought indices for the Lower Trinity Basin was carried out using data from 1906–2001 (station 415196). The correlation matrix for this station (Table 27) is similar to the other basins. The drought indices were also analyzed using Principal Component Analysis (Tables 28 and 29). Once again three significant PCs were extracted. The first PC explains nearly 52% of the variance in the drought indices. Similar to the other basins, EDI has the largest loading on PC1 (0.957) and it can be described as describing the general precipitation. PC2 accounts for approximately 17% of the variance and, like the San Antonio basin, it loads highly on the Z-index (and the other Palmer indices) and it loads negatively on the short-term precipitation indices. PC3 accounts for 14% of the variance and it is difficult to interpret since it has moderate positive/negative loadings on most of the drought indices. This is the only basin and PC that is not easy to interpret.

Table 27 Correlation matrix for meteorological indices in the Lower Trinity Basin

Correlation Matrix

		zindex	pdsi	phdi	EDI	PN	decile	SPI1	SPI2	SPI3	SPI6	SPI9	SPI12	SPI24
Correlation	zindex	1.000	.637	.514	.074	.081	.062	.069	.070	.069	.064	.054	.037	.061
	pdsi	.637	1.000	.884	.275	.174	.168	.174	.221	.252	.281	.255	.227	.199
	phdi	.514	.884	1.000	.389	.215	.199	.213	.278	.315	.386	.385	.362	.328
	EDI	.074	.275	.389	1.000	.685	.618	.636	.772	.839	.877	.844	.783	.567
	PN	.081	.174	.215	.685	1.000	.882	.921	.682	.594	.426	.369	.322	.228
	decile	.062	.168	.199	.618	.882	1.000	.944	.668	.576	.412	.353	.307	.213
	SPI1	.069	.174	.213	.636	.921	.944	1.000	.698	.596	.425	.363	.316	.218
	SPI2	.070	.221	.278	.772	.682	.668	.698	1.000	.825	.599	.504	.448	.297
	SPI3	.069	.252	.315	.839	.594	.576	.596	.825	1.000	.727	.610	.550	.369
	SPI6	.064	.281	.386	.877	.426	.412	.425	.599	.727	1.000	.844	.758	.532
	SPI9	.054	.255	.385	.844	.369	.353	.363	.504	.610	.844	1.000	.898	.655
	SPI12	.037	.227	.362	.783	.322	.307	.316	.448	.550	.758	.898	1.000	.758
	SPI24	.061	.199	.328	.567	.228	.213	.218	.297	.369	.532	.655	.758	1.000

Table 28 Results of the unrotated Principal Components Analysis (Lower Trinity Basin)

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.704	51.571	51.571	6.704	51.571	51.571
2	2.198	16.906	68.477	2.198	16.906	68.477
3	1.870	14.385	82.862	1.870	14.385	82.862
4	.677	5.207	88.069			
5	.473	3.642	91.711			
6	.370	2.846	94.557			
7	.181	1.393	95.950			
8	.140	1.073	97.023			
9	.136	1.049	98.072			
10	.094	.721	98.792			
11	.077	.596	99.388			
12	.054	.415	99.803			
13	.026	.197	100.000			

Extraction Method: Principal Component Analysis.

Table 29 PCA component matrix (Lower Trinity Basin)

Component Matrix[a]

	Component		
	1	2	3
zindex	.180	.610	.532
pdsi	.410	.716	.475
phdi	.507	.692	.332
EDI	.957	-.046	-.164
PN	.750	-.426	.376
decile	.730	-.445	.391
SPI1	.749	-.446	.398
SPI2	.812	-.253	.145
SPI3	.843	-.132	-.012
SPI6	.838	.116	-.313
SPI9	.812	.194	-.442
SPI12	.767	.221	-.499
SPI24	.596	.270	-.456

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Colorado Basin

The meteorological drought indices were evaluated for the Colorado Basin using data from 1902–2001 (station 415272). The correlation matrix for this station (Table 30) is similar to the other basins. The drought indices were also analyzed using Principal Component Analysis (Tables 31 and 32). There were only two significant PCs extracted. The first PC explains nearly 66% of the variance in the drought indices. Similar to the other basins, EDI has the largest loading on PC1 (0.957) and it can be described as describing the general precipitation. PC2 accounts for approximately 18% of the variance and, it has positive loadings on the short-term precipitation indices and negative loadings on the long-term precipitation indices.

Table 30 Correlation matrix for meteorological indices in the Colorado Basin

Correlation Matrix

		zindex	pdsi	phdi	decile	EDI	PN	SPI1	SPI2	SPI3	SPI6	SPI9	SPI12	SPI24
Correlation	zindex	1.000	.650	.518	.773	.722	.911	.870	.712	.637	.517	.448	.374	.256
	pdsi	.650	1.000	.889	.481	.852	.531	.533	.654	.717	.795	.790	.755	.592
	phdi	.518	.889	1.000	.351	.838	.406	.396	.545	.641	.812	.872	.861	.697
	decile	.773	.481	.351	1.000	.586	.832	.908	.652	.545	.419	.351	.286	.219
	EDI	.722	.852	.838	.586	1.000	.680	.654	.785	.845	.894	.856	.772	.555
	PN	.911	.531	.406	.832	.680	1.000	.930	.693	.599	.458	.381	.317	.236
	SPI1	.870	.533	.396	.908	.654	.930	1.000	.726	.614	.477	.393	.324	.247
	SPI2	.712	.654	.545	.652	.785	.693	.726	1.000	.840	.651	.541	.456	.335
	SPI3	.637	.717	.641	.545	.845	.599	.614	.840	1.000	.767	.645	.547	.398
	SPI6	.517	.795	.812	.419	.894	.458	.477	.651	.767	1.000	.872	.768	.551
	SPI9	.448	.790	.872	.351	.856	.381	.393	.541	.645	.872	1.000	.908	.663
	SPI12	.374	.755	.861	.286	.772	.317	.324	.456	.547	.768	.908	1.000	.754
	SPI24	.256	.592	.697	.219	.555	.236	.247	.335	.398	.551	.663	.754	1.000

Table 31 Results of the unrotated Principal Components Analysis (Colorado Basin)

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.524	65.567	65.567	8.524	65.567	65.567
2	2.331	17.929	83.495	2.331	17.929	83.495
3	.667	5.130	88.626			
4	.392	3.019	91.645			
5	.303	2.332	93.977			
6	.203	1.562	95.539			
7	.163	1.253	96.792			
8	.121	.929	97.721			
9	.079	.604	98.326			
10	.070	.539	98.865			
11	.060	.460	99.325			
12	.058	.446	99.771			
13	.030	.229	100.000			

Extraction Method: Principal Component Analysis.

Table 32 PCA component matrix (Colorado Basin)

Component Matrix[a]

	Component	
	1	2
zindex	.796	.481
pdsi	.887	-.204
phdi	.848	-.417
decile	.695	.578
EDI	.964	-.082
PN	.753	.579
SPI1	.761	.588
SPI2	.822	.262
SPI3	.846	.062
SPI6	.866	-.283
SPI9	.839	-.443
SPI12	.778	-.521
SPI24	.612	-.492

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Guadalupe Basin

The meteorological drought indices were also evaluated for the Guadalupe Basin using data from 1903–2001 (station 415429). The correlation matrix for this station (Table 33) is similar to the other basins. The drought indices were also analyzed using Principal Component Analysis (Tables 34 and 35). There were three significant PCs extracted. The first PC explains nearly 48% of the variance in the drought indices. Similar to the other basins, EDI has the largest loading on PC1 (0.961) and it can be described as describing the general precipitation. PC2 accounts for approximately 18% of the variance and, a number of other basins, it loads highly on the Z-index (and the other Palmer indices). PC3 accounts for 15% of the variance and it has negative loadings on the short-term precipitation indices and positive loadings on the long-term precipitation indices. This suggests that PC3 represents variance in the long-term precipitation indices.

Table 33 Correlation matrix for meteorological indices in the Guadalupe Basin

Correlation Matrix

		zindex	pdsi	phdi	EDI	PN	decile	SPI1	SPI2	SPI3	SPI6	SPI9	SPI12	SPI24
Correlation	zindex	1.000	.655	.521	-.026	.025	.034	.028	.020	-.013	-.043	-.044	-.042	-.066
	pdsi	.655	1.000	.883	.100	.114	.094	.106	.124	.107	.070	.059	.052	-.034
	phdi	.521	.883	1.000	.238	.177	.158	.173	.224	.229	.212	.184	.164	.052
	EDI	-.026	.100	.238	1.000	.652	.582	.623	.763	.835	.891	.848	.776	.490
	PN	.025	.114	.177	.652	1.000	.854	.921	.672	.567	.416	.330	.285	.163
	decile	.034	.094	.158	.582	.854	1.000	.923	.658	.546	.395	.311	.265	.145
	SPI1	.028	.106	.173	.623	.921	.923	1.000	.702	.585	.424	.332	.282	.155
	SPI2	.020	.124	.224	.763	.672	.658	.702	1.000	.820	.600	.475	.415	.231
	SPI3	-.013	.107	.229	.835	.567	.546	.585	.820	1.000	.730	.596	.522	.303
	SPI6	-.043	.070	.212	.891	.416	.395	.424	.600	.730	1.000	.852	.748	.457
	SPI9	-.044	.059	.184	.848	.330	.311	.332	.475	.596	.852	1.000	.893	.572
	SPI12	-.042	.052	.164	.776	.285	.265	.282	.415	.522	.748	.893	1.000	.683
	SPI24	-.066	-.034	.052	.490	.163	.145	.155	.231	.303	.457	.572	.683	1.000

Table 34 Results of the unrotated Principal Components Analysis (Guadalupe Basin)

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.263	48.174	48.174	6.263	48.174	48.174
2	2.378	18.296	66.470	2.378	18.296	66.470
3	1.989	15.301	81.770	1.989	15.301	81.770
4	.724	5.569	87.340			
5	.482	3.707	91.046			
6	.427	3.284	94.330			
7	.188	1.447	95.777			
8	.155	1.189	96.966			
9	.141	1.083	98.048			
10	.092	.705	98.754			
11	.076	.581	99.335			
12	.059	.455	99.790			
13	.027	.210	100.000			

Extraction Method: Principal Component Analysis.

Table 35 PCA component matrix (Guadalupe Basin)

Component Matrix[a]

	Component		
	1	2	3
zindex	.036	.775	.232
pdsi	.180	.890	.304
phdi	.311	.801	.326
EDI	.961	-.116	.114
PN	.754	.146	-.530
decile	.727	.147	-.556
SPI1	.764	.150	-.559
SPI2	.825	.068	-.250
SPI3	.848	-.022	-.051
SPI6	.841	-.179	.293
SPI9	.792	-.245	.451
SPI12	.739	-.267	.504
SPI24	.497	-.308	.461

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

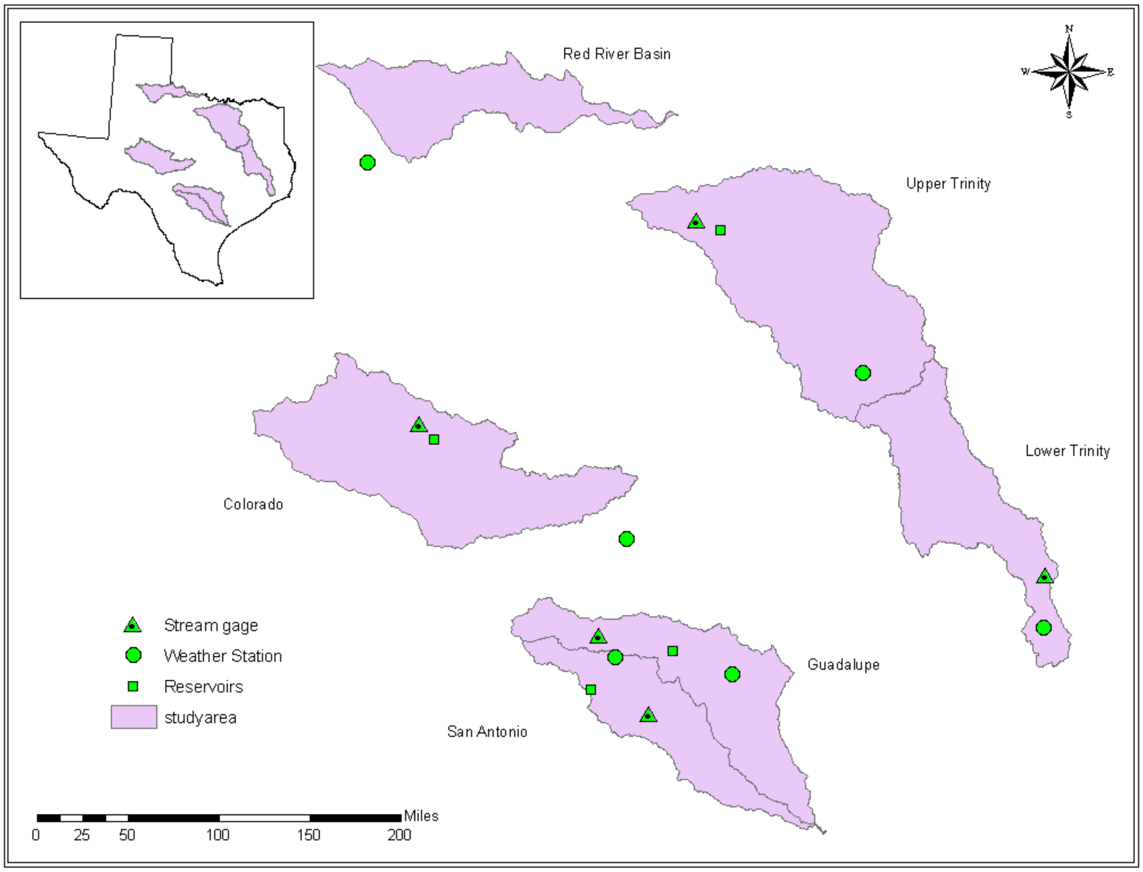
3.4.3 Hydrological/Water Supply Drought Indices

Nine different indices of hydrological/water supply drought indices were evaluated in six Texas watersheds. Three of these indices (SPI, PDSI, and PHDI) are frequently used to monitor hydrological/water supply drought across the U.S. and, in some cases, around the world. Two of the indices, Percent of Reservoir Conservation Storage Capacity and Streamflow Percent Exceedance, are currently used by the TWDB. Four of these indices, Standardized Streamflow Index (SSFI), Streamflow Deficit Index (SDI), Standardized Reservoir Index (SRI), and Reservoir Deficit Index (RDI), are new indices that were specifically developed for this study. The streamflow indices are evaluated first and this is followed by the evaluation of the reservoir indices.

Evaluation of Streamflow-based Indices

The two new streamflow-based drought indices proposed in this study (Standardized Streamflow Index (SSFI) and Streamflow Deficit Index (SDI)) were evaluated against a number of existing drought indices (PDSI, PHDI, and SPI). Although not explicitly hydrological drought indices, PDSI and SPI were used in the assessment because a major drought event will first affect precipitation and then, with some time lag, it will subsequently affect streamflow. SPI calculated at 1-, 2-, 3-, 6-, 9-, 12- and 24-month time scales were used for comparison with SSFI and SDI. SSFI and SDI were calculated at 30-, 60-, 90-, 180-, 360- and 720-day time scales using a daily rather than monthly time step. Hence, only the SSFI and SDI calculated during the last day of the month was used for comparison with the PHDI and SPI. A correlation matrix was used to compare all of the drought indices. A high correlation between two indices was interpreted to mean that those two indices behave similarly. In addition, graphical plots were used to visually compare the behavior of all of the indices during the 1990s drought. All of the indices were evaluated in six representative basins in Texas. The stream gages and the weather stations used for computing the indices are shown in Figure 16.

Figure 16 Stream gages, reservoirs and weather stations used for calculating the hydrological/water supply drought indices.



Upper Trinity Basin

The correlation matrix for Upper Trinity (Table 36) shows that both PDSI and PHDI are poorly correlated with SPI, although PHDI has a slightly better correlation. Among the all SPI time scales, SPI-9 has the highest correlation (0.447) with PHDI indicating a 9-month time scale inherent in PHDI. SSFI and SDI have a stronger correlation with the SPI than with PDSI or PHDI. SSFI and SDI are direct measures of hydrological conditions since they are derived from streamflow. Therefore, the poor correlation between the SSFI and PHDI demonstrates that PDSI has limited value for monitoring hydrological/water supply drought, but the SPI may have some value. There appears to be lag in correlation between SSFI/SDI and the SPI. For example, SSFI90 and SDI90 have a stronger correlation with the 6-month

SPI than they do with the 3-month SPI. This demonstrates that hydrological/water supply drought on the 3-month time scale is a function of precipitation over the last 6 months. As expected, SSFI and SDI are highly correlated with each other, because both are calculated from the same streamflow data, but with a different standardizing procedure.

Figure 17 shows that the Palmer indices and the SPI were able to capture the 1996–2000 drought. However, a short-term drought (6 months) during the summer of 1998 that was measured by the SPI was not captured by the Palmer indices. Figure 18 shows that SSFI captured all the major drought events, including the short-term droughts during autumn 1998 (the same drought event indicated by SPI during summer 1998). This suggests that the SPI could be used as a leading indicator of upcoming hydrologic drought events. Although SSFI and SDI seem to have the same temporal pattern (Figures 18 and 19), SDI seems to reach extreme dryness values much more frequently than the SSFI. This could be due to the linear scaling that is used to calculate the SDI. Although it is difficult to fit a statistical distribution to cumulative streamflow, SSFI seems to provide a more realistic indication of the drought magnitude than the SDI. Hence, SSFI is a better indicator of hydrological/water supply drought than SDI.

Table 36 Correlation matrix for hydrological/water supply indices in the Upper Trinity Basin

	pdsi	*phdi*	*SPI-1*	*SPI-2*	*SPI-3*	*SPI-6*	*SPI-9*	*SPI-12*	*SPI-24*	*SSFI30*	*SSFI60*	*SSFI90*	*SSFI180*	*SSFI270*	*SSFI360*	*SSFI720*	*SDI30*	*SDI60*	*SDI90*	*SDI180*	*SDI270*	*SDI360*	*SDI720*
pdsi	1.000																						
phdi	0.842	1.000																					
SPI-1	0.205	0.300	1.000																				
SPI-2	0.228	0.357	0.757	1.000																			
SPI-3	0.216	0.370	0.615	0.857	1.000																		
SPI-6	0.203	0.407	0.339	0.529	0.678	1.000																	
SPI-9	**0.235**	**0.447**	0.269	0.393	0.491	0.774	1.000																
SPI-12	0.182	0.411	0.266	0.382	0.472	0.638	0.825	1.000															
SPI-24	0.158	0.372	0.172	0.268	0.330	0.443	0.523	0.634	1.000														
SSFI30	0.163	0.294	**0.389**	**0.494**	0.465	0.445	0.391	0.350	0.173	1.000													
SSFI60	0.137	0.265	0.298	0.472	**0.508**	0.500	0.444	0.391	0.192	0.853	1.000												
SSFI90	0.119	0.232	0.216	0.384	0.488	**0.528**	0.485	0.430	0.208	0.766	0.894	1.000											
SSFI180	0.119	0.166	0.035	0.111	0.188	0.434	**0.509**	0.467	0.198	0.533	0.652	0.770	1.000										
SSFI270	0.127	0.180	0.057	0.090	0.119	0.250	0.443	**0.490**	0.262	0.431	0.516	0.597	0.833	1.000									
SSFI360	0.120	0.178	0.078	0.142	0.175	0.250	0.361	0.490	**0.377**	0.361	0.435	0.512	0.705	0.871	1.000								
SSFI720	0.135	0.187	0.092	0.148	0.170	0.211	0.263	0.299	0.368	0.252	0.286	0.313	0.429	0.523	0.604	1.000							
SDI30	0.137	0.255	**0.381**	0.464	0.432	0.406	0.357	0.317	0.144	**0.941**	0.790	0.708	0.474	0.374	0.320	0.207	1.000						
SDI60	0.129	0.253	0.330	**0.483**	**0.493**	0.479	0.428	0.360	0.189	0.808	**0.945**	0.834	0.606	0.483	0.400	0.212	0.793	1.000					
SDI90	0.113	0.219	0.235	0.404	0.487	**0.492**	0.460	0.389	0.195	0.716	0.842	**0.943**	0.726	0.567	0.483	0.261	0.689	0.851	1.000				
SDI180	0.120	0.186	0.047	0.127	0.203	0.441	**0.517**	0.458	0.208	0.502	0.620	0.737	**0.956**	0.808	0.685	0.395	0.448	0.596	0.736	1.000			
SDI270	0.129	0.198	0.057	0.086	0.121	0.274	0.466	**0.506**	0.283	0.428	0.513	0.596	0.824	**0.971**	0.860	0.516	0.374	0.487	0.579	0.832	1.000		
SDI360	0.126	0.192	0.082	0.135	0.160	0.240	0.363	0.486	0.392	0.364	0.438	0.510	0.702	0.861	**0.975**	0.597	0.325	0.408	0.495	0.697	0.873	1.000	
SDI720	0.162	0.230	0.074	0.119	0.140	0.207	0.292	0.367	**0.444**	0.278	0.314	0.342	0.466	0.595	0.717	**0.830**	0.237	0.269	0.313	0.453	0.594	0.722	1.000

Figure 17 Comparison of PHDI, PDSI, and 3-, 6-, and 9-month SPI for the Upper Trinity basin (1991–2001).

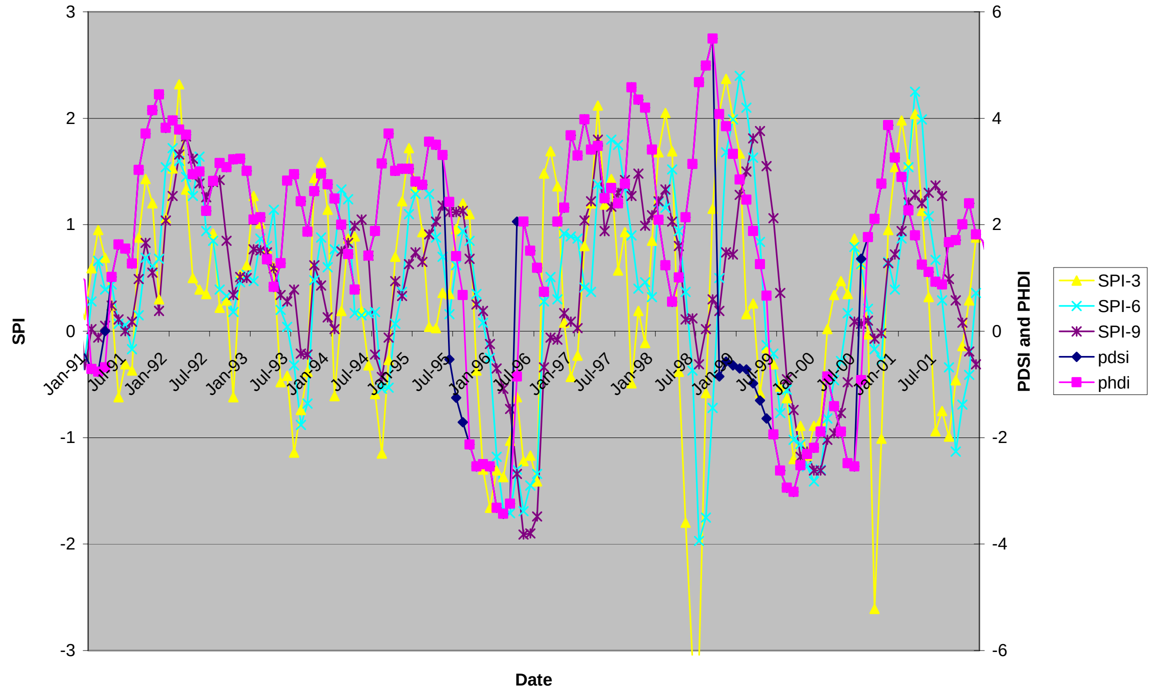


Figure 18 Comparison of SSFI with PDSI and PHDI for the Upper Trinity basin (1991–2001).

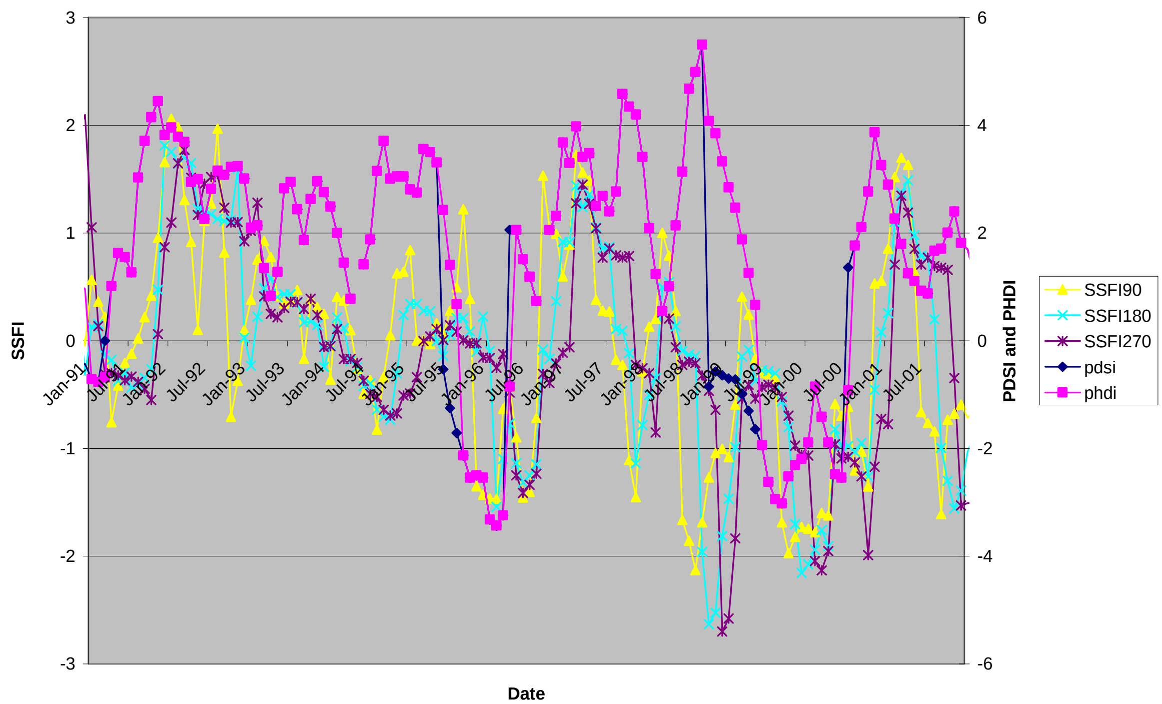
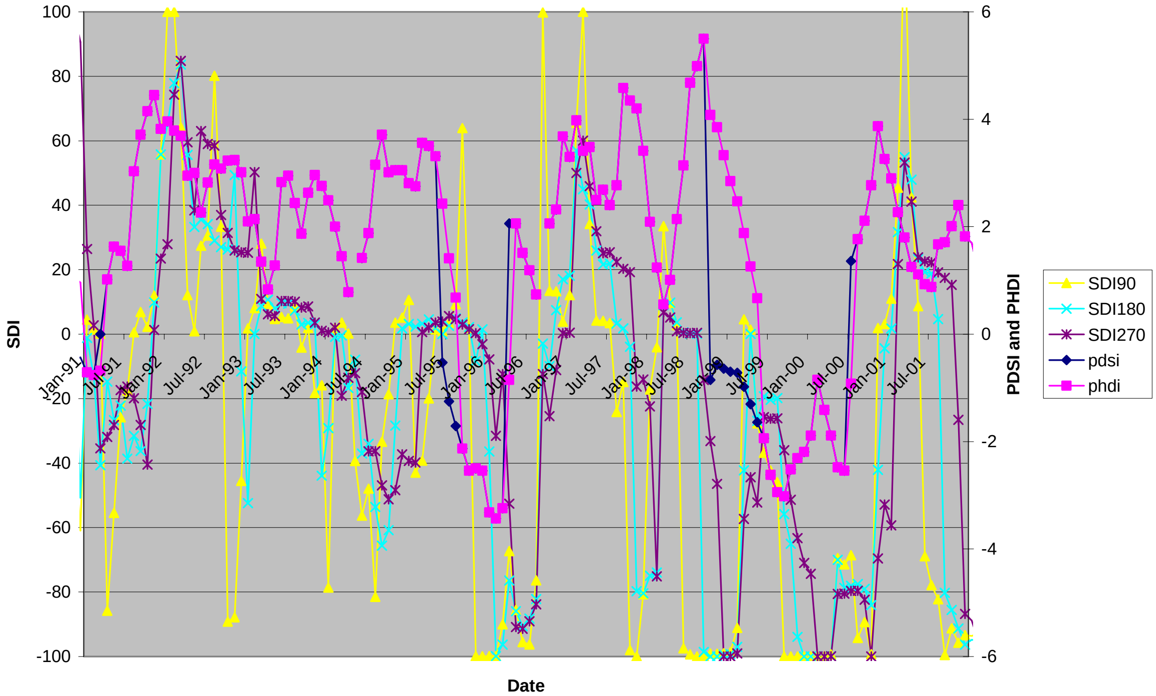


Figure 19 Comparison of SDI with PDSI and PHDI for the Upper Trinity basin (1991–2001).



Lower Trinity Basin

The correlation matrix for Lower Trinity (Table 37) shows that both PDSI and PHDI are poorly correlated with SPI, much lower than the correlations observed in Upper Trinity. However, SPI has a much stronger correlation with SSFI and SDI than in Upper Trinity. Further, there does not seem to be the same time-lag in correlation between SSFI and SPI that was observed in Upper Trinity. The reason could be that Lower Trinity basin is located in a wetter region than the Upper Trinity and so streamflow responds more synchronously with rainfall.

Analysis of Figures 20, 21 and 22 demonstrates that the minor drought event of 1996 and the major multi-year drought of 2000–2001 (as represented by SPI) are captured well by SSFI. The amount of time that it took for the streamflow to recover after these drought events indicates that SSFI is satisfactorily capturing the duration of the drought. As observed previously in Upper Trinity, SDI seems to reach extreme values much more frequently than SSFI (Figure 22).

Table 37 Correlation matrix for hydrological/water supply indices in the Lower Trinity Basin

	pdsi	*phdi*	*SPI-1*	*SPI-2*	*SPI-3*	*SPI-6*	*SPI-9*	*SPI-12*	*SPI-24*	*SSFI30*	*SSFI60*	*SSFI90*	*SSFI180*	*SSFI270*	*SSFI360*	*SSFI720*	*SDI30*	*SDI60*	*SDI90*	*SDI180*	*SDI270*	*SDI360*	*SDI720*
pdsi	1.000																						
phdi	0.785	1.000																					
SPI-1	0.077	0.121	1.000																				
SPI-2	0.089	0.163	0.748	1.000																			
SPI-3	0.087	0.162	0.619	0.842	1.000																		
SPI-6	0.051	0.158	0.382	0.541	0.690	1.000																	
SPI-9	-0.030	0.086	0.321	0.432	0.528	0.788	1.000																
SPI-12	-0.049	0.062	0.278	0.388	0.486	0.662	0.845	1.000															
SPI-24	0.004	0.124	0.209	0.245	0.305	0.422	0.508	0.618	1.000														
SSFI30	0.072	0.119	**0.550**	**0.625**	0.610	0.539	0.488	0.482	0.387	1.000													
SSFI60	0.071	0.133	0.397	0.606	**0.650**	0.608	0.542	0.527	0.413	0.884	1.000												
SSFI90	0.054	0.131	0.337	0.502	0.645	0.667	0.579	0.555	0.438	0.797	0.925	1.000											
SSFI180	0.013	0.091	0.205	0.321	0.434	**0.703**	0.675	0.614	0.493	0.630	0.735	0.825	1.000										
SSFI270	-0.052	0.019	0.141	0.216	0.304	0.535	**0.707**	0.687	0.565	0.539	0.618	0.683	0.865	1.000									
SSFI360	-0.077	-0.018	0.106	0.155	0.227	0.407	0.572	**0.697**	0.612	0.506	0.570	0.618	0.758	0.912	1.000								
SSFI720	-0.089	-0.064	-0.007	-0.015	0.013	0.093	0.155	0.249	**0.664**	0.255	0.288	0.325	0.431	0.558	0.690	1.000							
SDI30	0.074	0.125	**0.561**	**0.616**	0.606	0.541	0.489	0.478	0.378	**0.970**	0.865	0.778	0.621	0.529	0.496	0.241	1.000						
SDI60	0.057	0.134	0.389	0.586	0.623	0.600	0.533	0.516	0.394	0.856	**0.977**	0.908	0.731	0.614	0.566	0.282	0.853	1.000					
SDI90	0.043	0.131	0.328	0.482	**0.627**	0.661	0.567	0.547	0.429	0.779	0.907	**0.987**	0.821	0.676	0.614	0.328	0.768	0.909	1.000				
SDI180	0.012	0.095	0.204	0.314	0.422	**0.694**	0.659	0.597	0.497	0.620	0.729	0.819	**0.994**	0.855	0.750	0.440	0.610	0.724	0.816	1.000			
SDI270	-0.054	0.020	0.142	0.219	0.303	0.531	**0.704**	0.681	0.570	0.534	0.613	0.678	0.860	**0.994**	0.908	0.566	0.522	0.609	0.671	0.852	1.000		
SDI360	-0.072	-0.013	0.100	0.146	0.217	0.397	0.565	**0.690**	0.605	0.500	0.562	0.613	0.753	0.908	**0.993**	0.688	0.491	0.564	0.611	0.744	0.905	1.000	
SDI720	-0.082	-0.062	-0.001	-0.002	0.023	0.092	0.153	0.250	**0.663**	0.253	0.286	0.321	0.424	0.549	0.682	**0.991**	0.234	0.277	0.323	0.435	0.557	0.678	1.000

Figure 20 Comparison of PHDI, PDSI, and 3-, 6-, and 9-month SPI for the Lower Trinity basin (1991–2001).

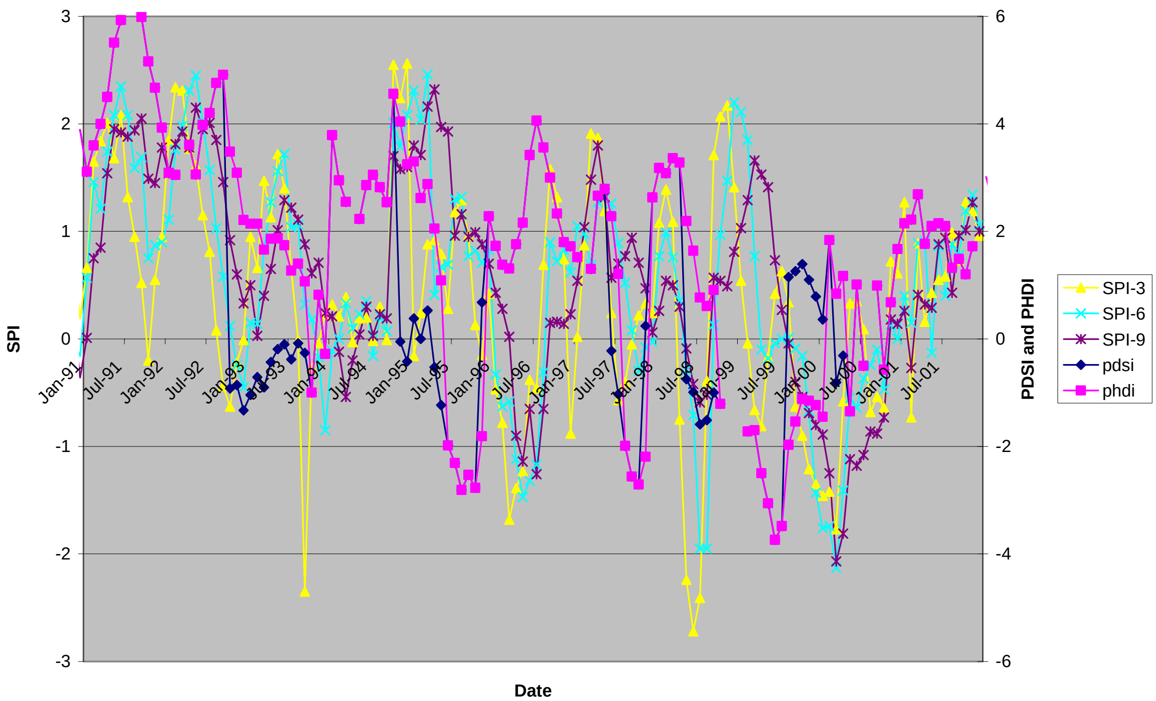


Figure 21 Comparison of SSFI with PDSI and PHDI for the Lower Trinity basin (1991–2001).

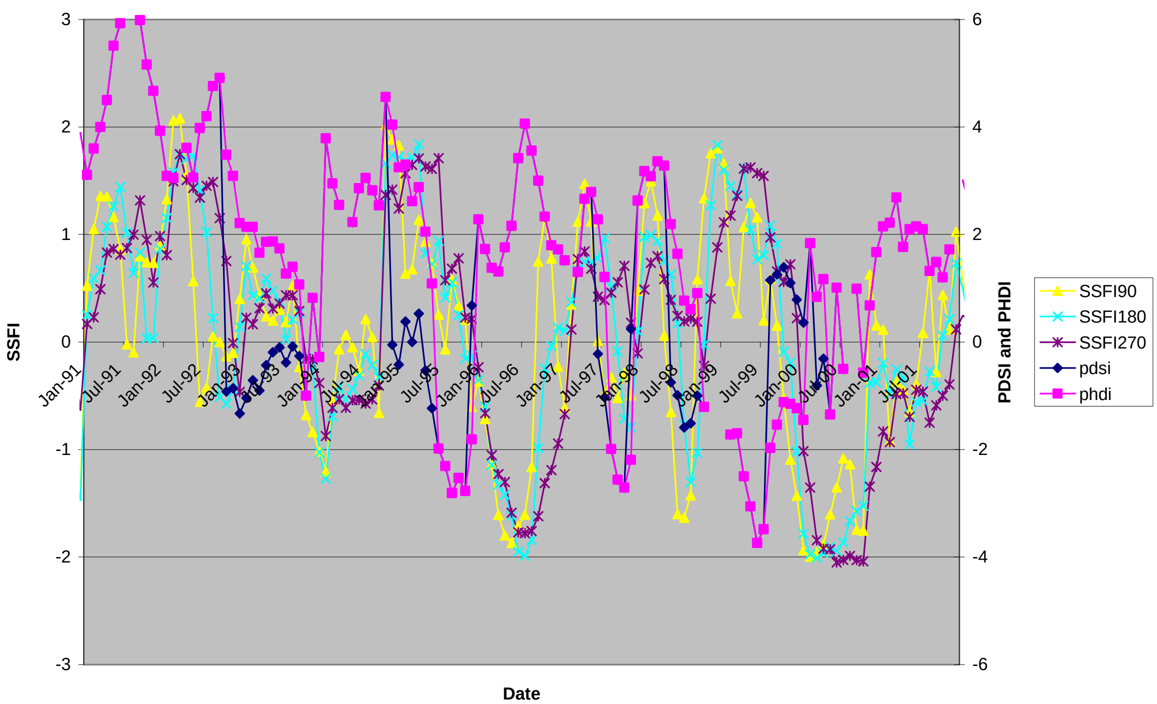
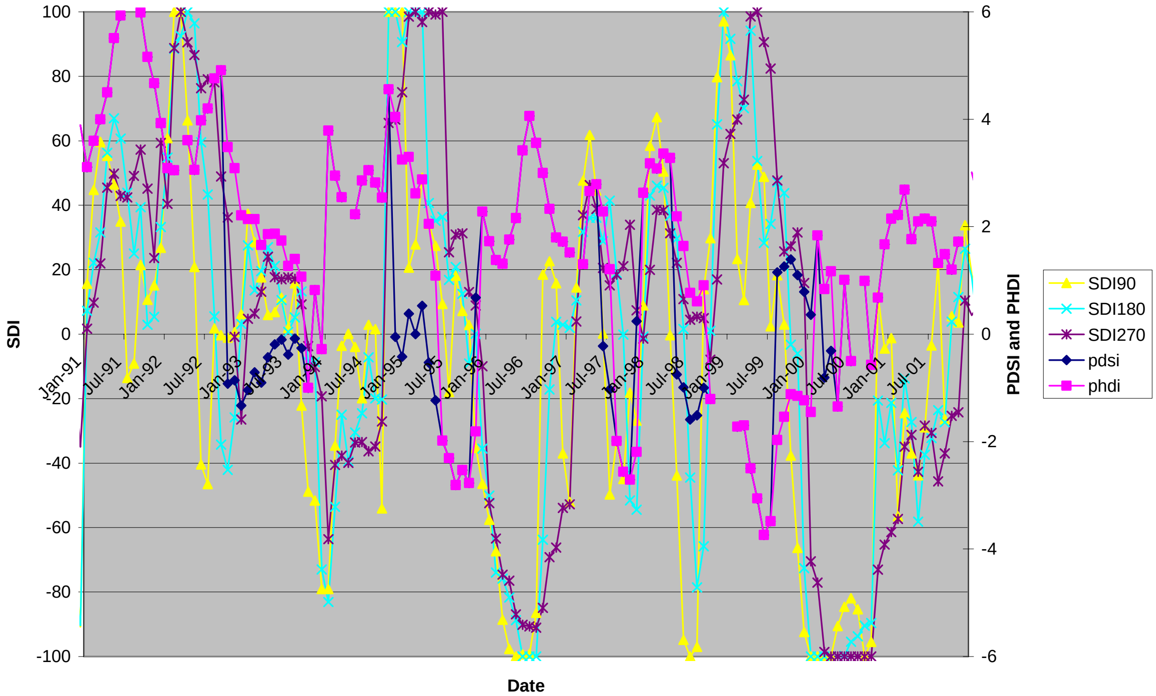


Figure 22 Comparison of SDI with PDSI and PHDI for the Lower Trinity basin (1991–2001).



Colorado Basin

The correlation matrix for Colorado Basin (Table 38) shows that both PDSI and PHDI are highly correlated with SPI. This basin has the highest correlation between the Palmer indices and SPI of the six basins studied in this project. However, the correlation between SPI and SSFI is among the lowest observed among the basins. The reason could be that groundwater may be contributing water to the streamflow and hence streamflow (SSFI) is not correlated well with rainfall (SPI). The Colorado basin is known to have many active springs that discharge continuously to the streams.

As observed in Table 38, the time series plot of PDSI and PHDI during the 1990's (Figure 23) also shows a good match of the indices with SPI. The moderate meteorological drought events indicated by SPI in 1996, 2000 and summer 2001 seem to have had a much stronger influence on the streamflow (Figure 24) with SSFI showing a drought of higher magnitude and duration than the SPI. This could be due to the time-lag between meteorological and hydrological drought in addition to the effect of temperature. As observed in other basins, the SDI (Figure 25) reach extreme dryness values much more frequently than the SSFI.

Table 38 Correlation matrix for hydrological/water supply indices in the Colorado Basin

	pdsi	*phdi*	*SPI-1*	*SPI-2*	*SPI-3*	*SPI-6*	*SPI-9*	*SPI-12*	*SPI-24*	*SSFI30*	*SSFI60*	*SSFI90*	*SSFI180*	*SSFI270*	*SSFI360*	*SSFI720*	*SDI30*	*SDI60*	*SDI90*	*SDI180*	*SDI270*	*SDI360*	*SDI720*
pdsi	1.000																						
phdi	0.858	1.000																					
SPI-1	0.530	0.326	1.000																				
SPI-2	0.653	0.474	0.694	1.000																			
SPI-3	0.696	0.565	0.576	0.820	1.000																		
SPI-6	**0.745**	0.744	0.372	0.556	0.695	1.000																	
SPI-9	0.712	**0.824**	0.290	0.435	0.534	0.808	1.000																
SPI-12	0.669	0.820	0.243	0.364	0.457	0.686	0.855	1.000															
SPI-24	0.452	0.584	0.195	0.242	0.271	0.353	0.427	0.550	1.000														
SSFI30	0.197	0.209	**0.252**	**0.329**	**0.371**	0.395	0.329	0.304	0.347	1.000													
SSFI60	0.185	0.197	0.202	0.314	0.369	0.395	0.310	0.280	0.327	0.884	1.000												
SSFI90	0.158	0.182	0.163	0.251	0.343	0.397	0.318	0.268	0.299	0.784	0.911	1.000											
SSFI180	0.169	0.207	0.129	0.216	0.289	**0.416**	0.368	0.291	0.291	0.629	0.726	0.798	1.000										
SSFI270	0.166	0.226	0.133	0.206	0.266	0.393	0.426	0.353	0.283	0.547	0.609	0.670	0.864	1.000									
SSFI360	0.184	0.246	0.150	0.217	0.282	0.399	**0.444**	**0.424**	0.300	0.532	0.568	0.617	0.774	0.907	1.000								
SSFI720	0.115	0.206	0.101	0.140	0.173	0.252	0.305	0.360	**0.495**	0.450	0.461	0.480	0.566	0.644	0.730	1.000							
SDI30	0.222	0.223	**0.276**	**0.347**	0.362	0.359	0.317	0.297	0.337	**0.815**	0.710	0.615	0.508	0.453	0.427	0.344	1.000						
SDI60	0.151	0.196	0.201	0.318	**0.372**	0.366	0.299	0.267	0.309	0.789	**0.909**	0.806	0.647	0.559	0.517	0.420	0.673	1.000					
SDI90	0.149	0.186	0.168	0.263	0.353	0.373	0.311	0.262	0.284	0.723	0.836	**0.924**	0.733	0.622	0.577	0.445	0.604	0.799	1.000				
SDI180	0.172	0.210	0.125	0.210	0.278	**0.414**	0.361	0.281	0.274	0.603	0.695	0.764	**0.962**	0.824	0.734	0.540	0.494	0.637	0.733	1.000			
SDI270	0.148	0.211	0.105	0.183	0.233	0.361	**0.409**	0.340	0.273	0.524	0.578	0.633	0.830	**0.966**	0.863	0.621	0.436	0.533	0.597	0.824	1.000		
SDI360	0.154	0.219	0.120	0.177	0.232	0.352	0.407	**0.403**	0.292	0.517	0.538	0.579	0.730	0.861	**0.965**	0.719	0.421	0.499	0.554	0.714	0.866	1.000	
SDI720	0.115	0.205	0.092	0.128	0.161	0.237	0.293	0.341	**0.489**	0.436	0.447	0.467	0.548	0.620	0.700	**0.985**	0.333	0.407	0.432	0.528	0.607	0.700	1.000

Figure 23 Comparison of PHDI, PDSI, and 3-, 6-, and 9-month SPI for the Colorado basin (1991–2001).

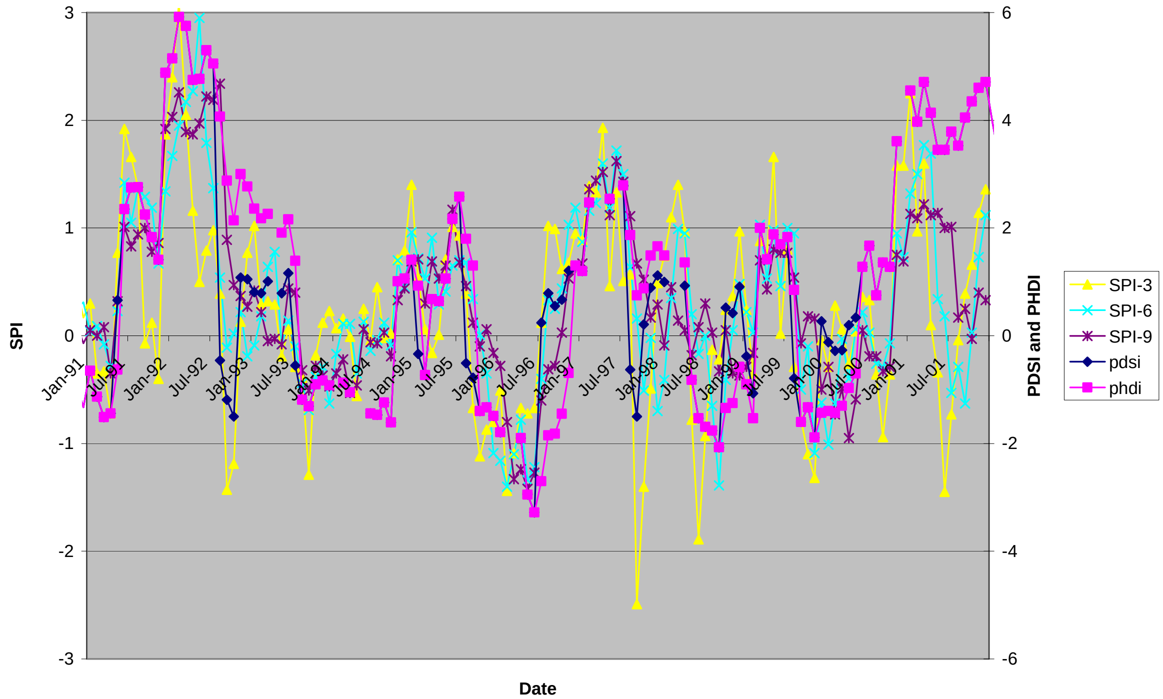


Figure 24 Comparison of SSFI with PDSI and PHDI for the Colorado basin (1991–2001).

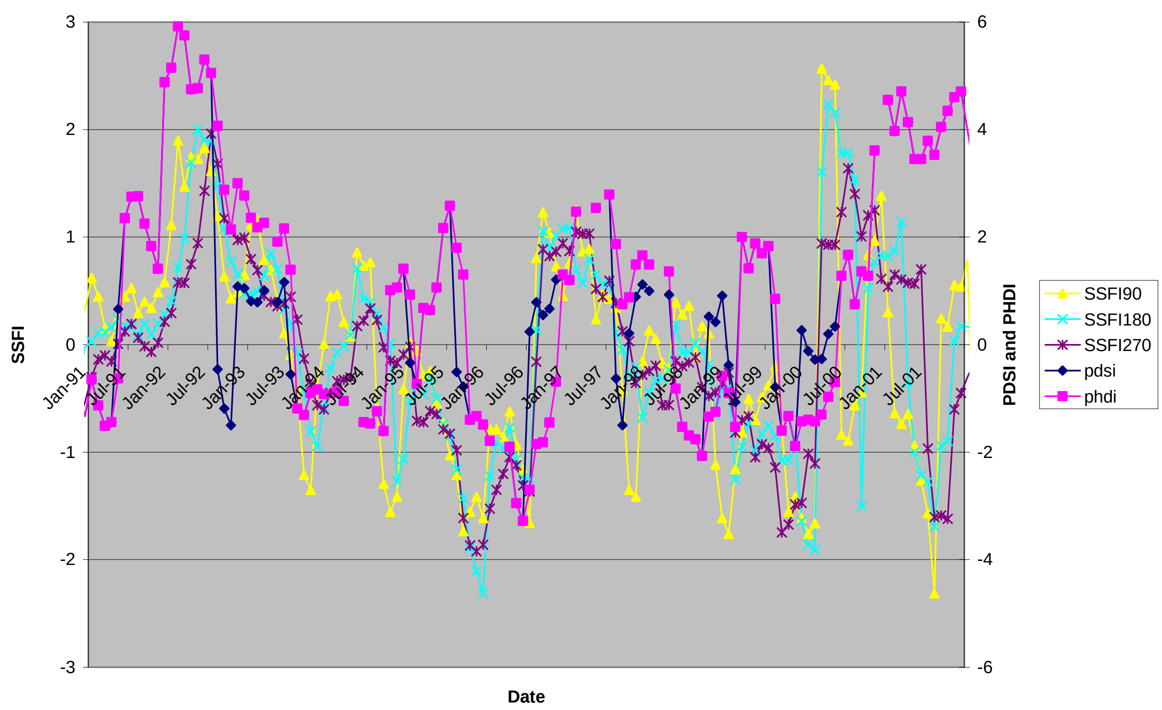
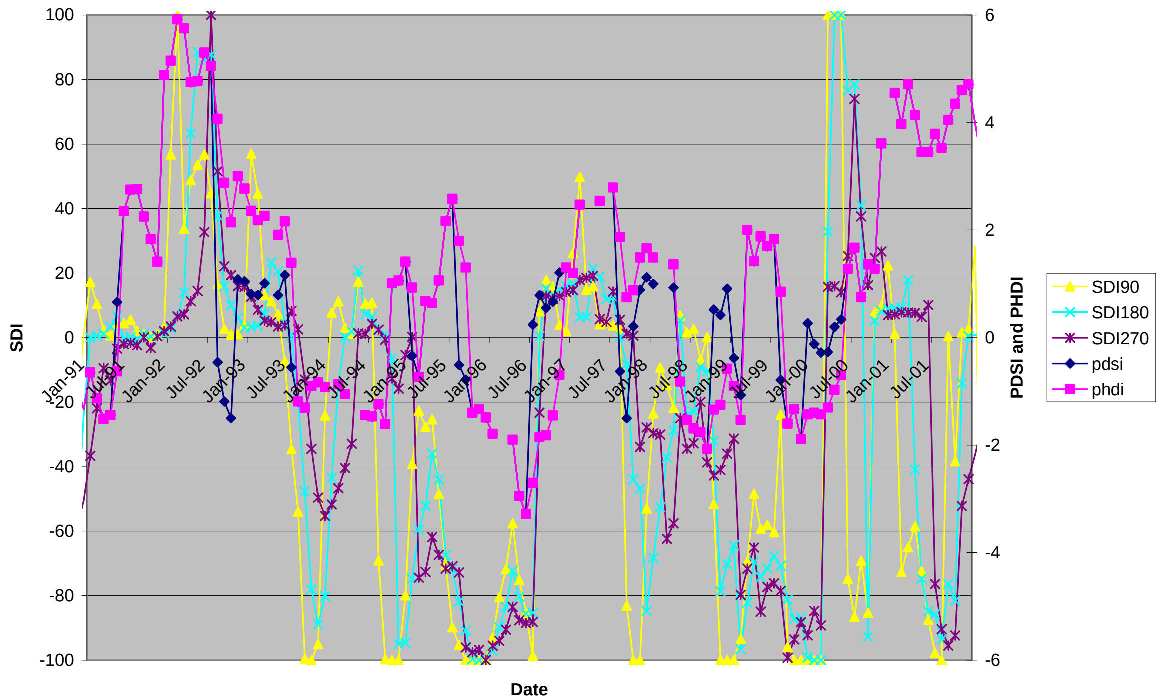


Figure 25 Comparison of SDI with PDSI and PHDI for the Colorado basin (1991–2001).



Guadalupe Basin

The correlation matrix for Guadalupe basin (Table 39) illustrates that both PDSI and PHDI are poorly correlated with SPI. However, as in other basins, the SSFI were correlated better with SPI. Although the correlation matrix shows a slight time-lag between SPI and SSFI, the streamflow seems to respond synchronously to rainfall. While SPI indicates severe drought during 1996 and 2000 (Figure 26), the SSFI only indicates a moderate drought during both of these periods (Figure 27). This suggests a complex interplay between temperature (evapotranspiration), soil moisture and runoff that may have moderated the effect that the rainfall deficit had on streamflow. As observed in other basins, the SDI (Figure 28) reaches extreme dryness values much more frequently than the SSFI.

Table 39 Correlation matrix for hydrological/water supply indices in the Guadalupe Basin

	pdsi	*phdi*	*SPI-1*	*SPI-2*	*SPI-3*	*SPI-6*	*SPI-9*	*SPI-12*	*SPI-24*	*SSFI30*	*SSFI60*	*SSFI90*	*SSFI180*	*SSFI270*	*SSFI360*	*SSFI720*	*SDI30*	*SDI60*	*SDI90*	*SDI180*	*SDI270*	*SDI360*	*SDI720*
pdsi	1.000																						
phdi	0.888	1.000																					
SPI-1	0.128	0.225	1.000																				
SPI-2	0.129	0.262	0.718	1.000																			
SPI-3	0.092	0.250	0.592	0.830	1.000																		
SPI-6	0.056	0.210	0.421	0.585	0.724	1.000																	
SPI-9	0.097	0.206	0.329	0.469	0.585	0.844	1.000																
SPI-12	0.110	0.203	0.306	0.427	0.527	0.742	0.887	1.000															
SPI-24	0.087	0.194	0.167	0.247	0.318	0.474	0.566	0.674	1.000														
SSFI30	-0.005	0.127	**0.378**	**0.506**	**0.550**	0.594	0.565	0.521	0.321	1.000													
SSFI60	-0.017	0.108	0.297	0.460	0.536	**0.602**	0.575	0.526	0.314	0.950	1.000												
SSFI90	-0.024	0.094	0.244	0.382	0.492	0.599	**0.585**	0.536	0.313	0.908	0.966	1.000											
SSFI180	-0.036	0.055	0.167	0.256	0.336	0.539	**0.585**	0.558	0.320	0.790	0.847	0.898	1.000										
SSFI270	-0.032	0.040	0.141	0.216	0.277	0.429	0.555	**0.571**	0.366	0.700	0.745	0.792	0.926	1.000									
SSFI360	-0.017	0.048	0.109	0.173	0.234	0.365	0.470	0.556	0.427	0.615	0.656	0.704	0.837	0.944	1.000								
SSFI720	-0.077	0.013	0.032	0.063	0.097	0.189	0.252	0.320	**0.504**	0.396	0.415	0.440	0.538	0.638	0.734	1.000							
SDI30	0.003	0.120	**0.395**	**0.515**	**0.543**	0.592	0.567	0.539	0.335	**0.942**	0.888	0.854	0.741	0.654	0.576	0.377	1.000						
SDI60	-0.021	0.095	0.303	0.467	0.540	**0.600**	**0.586**	0.559	0.334	0.918	**0.969**	0.935	0.829	0.733	0.652	0.417	0.906	1.000					
SDI90	-0.030	0.085	0.245	0.387	0.498	0.589	0.583	0.551	0.322	0.878	0.937	**0.973**	0.879	0.777	0.698	0.440	0.852	0.950	1.000				
SDI180	-0.042	0.056	0.175	0.264	0.347	0.545	0.584	0.558	0.327	0.775	0.825	0.875	**0.977**	0.907	0.825	0.535	0.730	0.815	0.874	1.000			
SDI270	-0.026	0.051	0.147	0.216	0.280	0.437	0.561	**0.573**	0.375	0.688	0.729	0.775	0.906	**0.984**	0.929	0.634	0.638	0.712	0.757	0.904	1.000		
SDI360	-0.013	0.053	0.116	0.182	0.243	0.375	0.477	0.567	0.438	0.608	0.649	0.694	0.821	0.932	**0.990**	0.732	0.566	0.642	0.686	0.811	0.932	1.000	
SDI720	-0.079	0.011	0.039	0.069	0.100	0.187	0.244	0.315	**0.511**	0.385	0.402	0.425	0.522	0.624	0.724	**0.995**	0.365	0.404	0.426	0.526	0.627	0.727	1.000

Figure 26 Comparison of PHDI, PDSI, and 3-, 6-, and 9-month SPI for the Guadalupe basin (1991–2001).

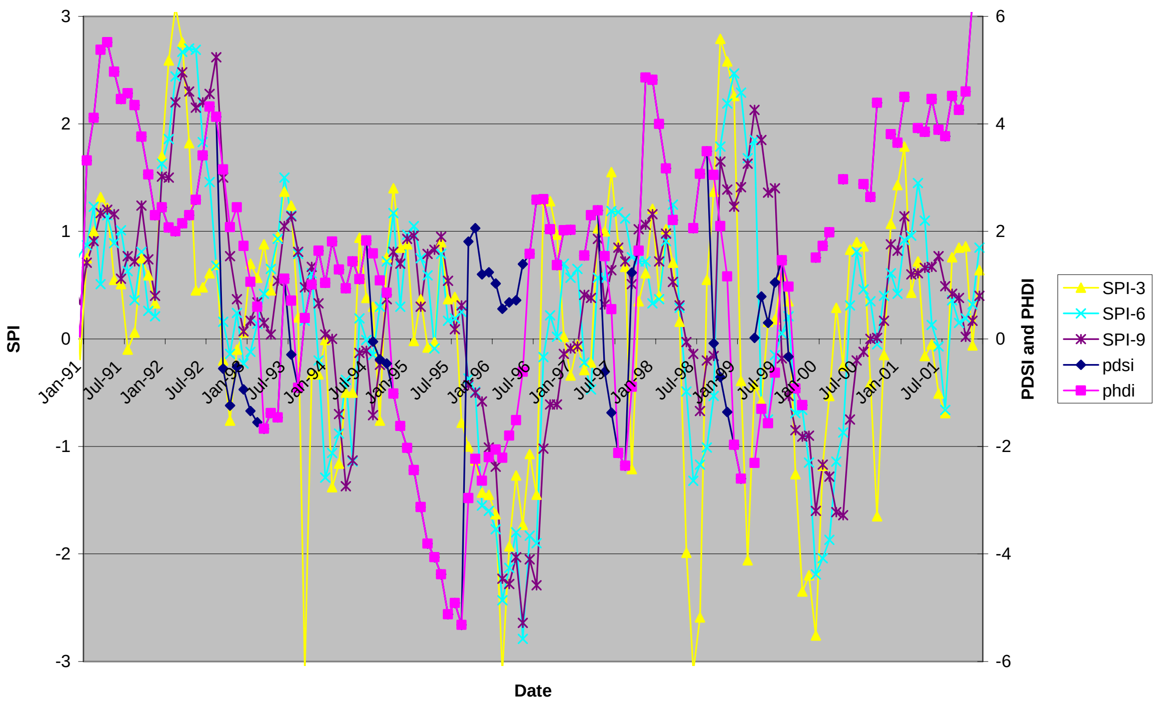


Figure 27 Comparison of SSFI with PDSI and PHDI for the Guadalupe basin (1991–2001).

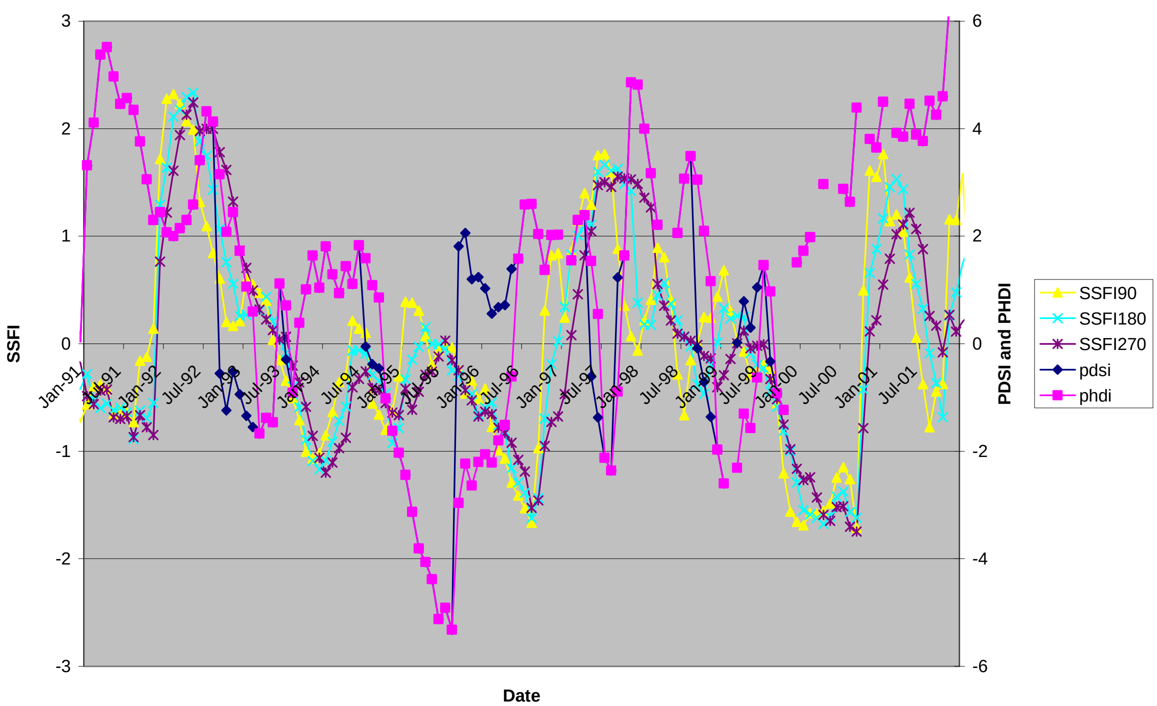
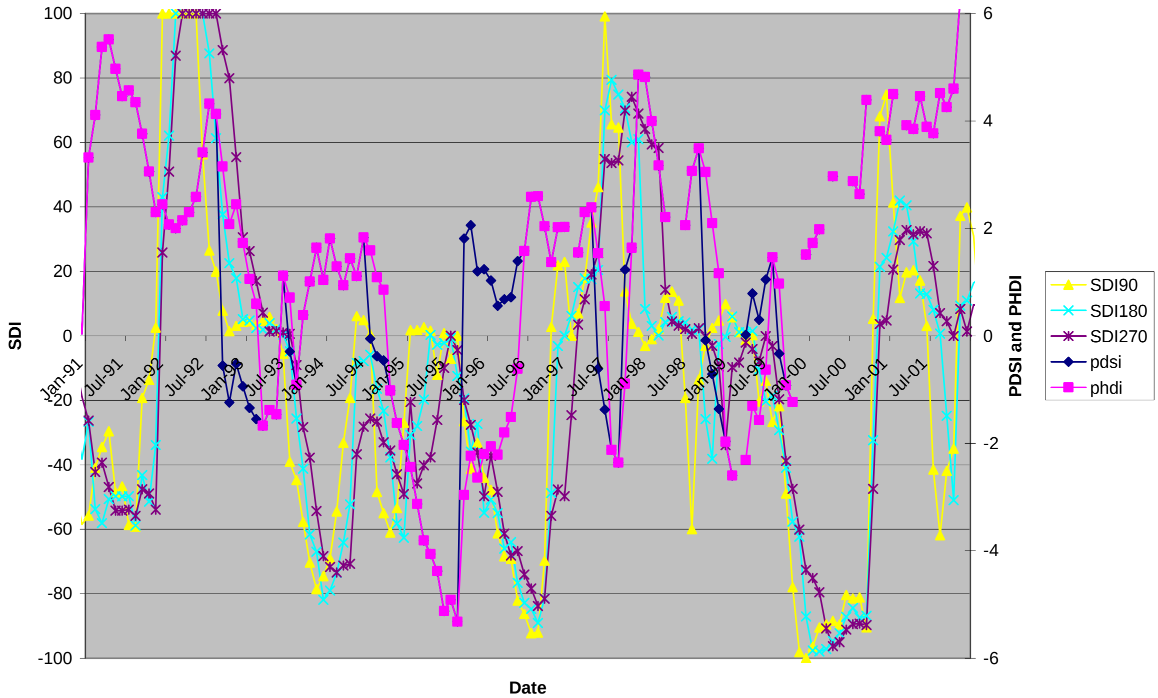


Figure 28 Comparison of SDI with PDSI and PHDI for the Guadalupe basin (1991–2001).



San Antonio Basin

As observed in the Colorado Basin, the correlation matrix for San Antonio Basin (Table 40) shows that both PDSI and PHDI are highly correlated with SPI. Unlike other basins, the Palmer indices were also strongly correlated with SSFI and SDI. Further, the SPI is also strongly correlated with SSFI and SDI. Overall, the correlations among all the indices were quite strong for this basin. As observed in Lower Trinity and Colorado Basins, the drought events of the 1996 and 2000–2001 (Figure 29) seem to have had a much stronger influence on the streamflow (as shown by the SSFI) (Figure 30) than on precipitation (as shown by the SPI). This could be due to the time-lag between meteorological and hydrological drought in addition to the influence of temperature. As observed in other basins, the SDI (Figure 31) reached extremely dry values much more frequently than the SSFI.

Table 40 Correlation matrix for hydrological/water supply indices in the San Antonio Basin

	pdsi	*phdi*	*SPI-1*	*SPI-2*	*SPI-3*	*SPI-6*	*SPI-9*	*SPI-12*	*SPI-24*	*SSFI30*	*SSFI60*	*SSFI90*	*SSFI180*	*SSFI270*	*SSFI360*	*SSFI720*	*SDI30*	*SDI60*	*SDI90*	*SDI180*	*SDI270*	*SDI360*	*SDI720*
pdsi	1.000																						
phdi	0.887	1.000																					
SPI-1	0.479	0.435	1.000																				
SPI-2	0.582	0.569	0.749	1.000																			
SPI-3	0.649	0.661	0.626	0.849	1.000																		
SPI-6	**0.699**	0.783	0.458	0.634	0.755	1.000																	
SPI-9	0.678	**0.793**	0.362	0.502	0.607	0.849	1.000																
SPI-12	0.609	0.765	0.294	0.421	0.526	0.746	0.897	1.000															
SPI-24	0.377	0.535	0.166	0.242	0.302	0.425	0.522	0.640	1.000														
SSFI30	0.460	0.542	**0.569**	0.605	0.593	0.562	0.564	0.541	0.451	1.000													
SSFI60	0.504	0.606	0.386	**0.616**	**0.653**	0.614	0.619	0.608	0.507	0.848	1.000												
SSFI90	**0.507**	**0.629**	0.322	0.504	**0.653**	0.648	0.654	0.665	0.555	0.773	0.914	1.000											
SSFI180	0.435	0.600	0.166	0.298	0.411	**0.659**	**0.697**	**0.729**	0.670	0.627	0.732	0.828	1.000										
SSFI270	0.363	0.544	0.109	0.195	0.278	0.481	0.655	0.716	0.743	0.544	0.630	0.709	0.893	1.000									
SSFI360	0.277	0.465	0.071	0.146	0.225	0.376	0.519	0.670	**0.782**	0.488	0.564	0.636	0.800	0.923	1.000								
SSFI720	0.021	0.178	-0.043	-0.020	0.010	0.061	0.121	0.216	0.681	0.269	0.319	0.372	0.517	0.638	0.737	1.000							
SDI30	0.397	0.490	**0.558**	0.583	0.577	0.555	0.561	0.538	0.446	**0.929**	0.767	0.703	0.576	0.504	0.452	0.256	1.000						
SDI60	0.490	0.586	0.375	**0.595**	**0.628**	0.615	0.619	0.607	0.508	0.790	**0.961**	0.868	0.710	0.608	0.541	0.313	0.737	1.000					
SDI90	**0.504**	0.619	0.301	0.487	0.626	**0.647**	0.653	0.667	0.559	0.740	0.887	**0.965**	0.810	0.692	0.619	0.367	0.685	0.893	1.000				
SDI180	0.412	**0.578**	0.147	0.279	0.394	0.631	**0.681**	**0.721**	0.657	0.611	0.716	0.812	**0.984**	0.881	0.791	0.509	0.558	0.694	0.802	1.000			
SDI270	0.350	0.531	0.106	0.186	0.267	0.469	0.641	0.709	0.738	0.533	0.614	0.693	0.881	**0.989**	0.913	0.624	0.490	0.589	0.671	0.881	1.000		
SDI360	0.279	0.460	0.078	0.152	0.230	0.377	0.517	0.666	**0.784**	0.478	0.554	0.628	0.791	0.917	**0.994**	0.729	0.439	0.532	0.613	0.784	0.914	1.000	
SDI720	0.015	0.164	-0.050	-0.032	-0.005	0.047	0.109	0.207	0.677	0.257	0.306	0.359	0.508	0.629	0.725	**0.991**	0.243	0.296	0.345	0.500	0.617	0.715	1.000

Figure 29 Comparison of PHDI, PDSI, and 3-, 6-, and 9-month SPI for the San Antonio basin (1991–2001).

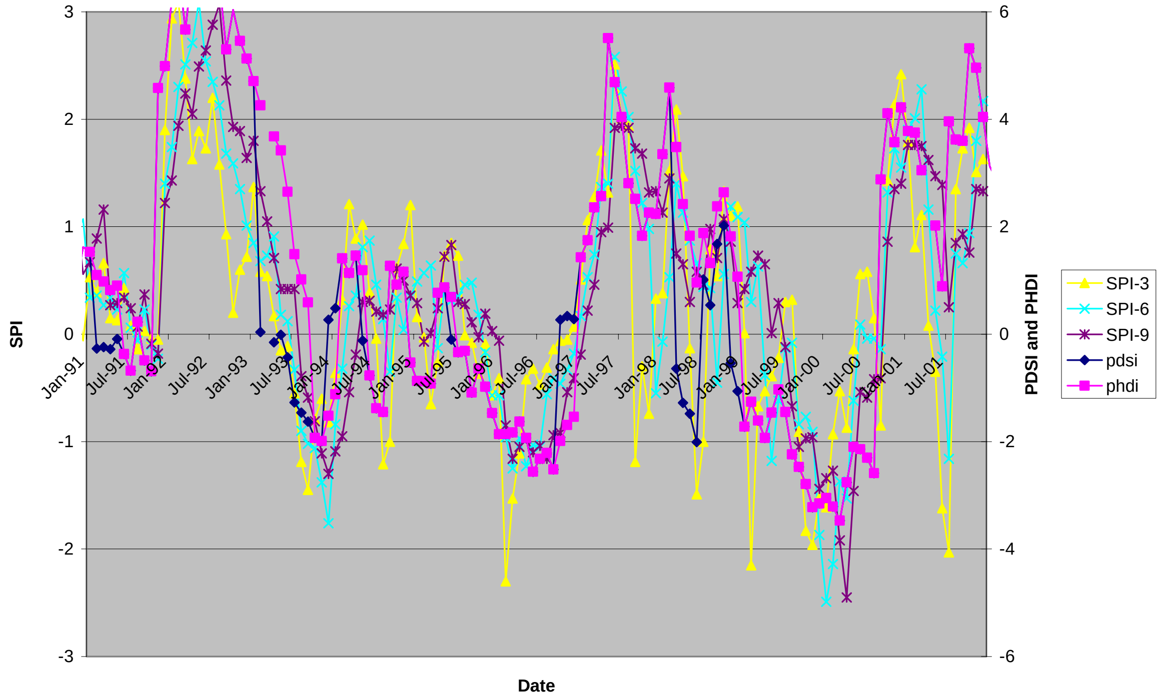


Figure 30 Comparison of SSFI with PDSI and PHDI for the San Antonio basin (1991–2001).

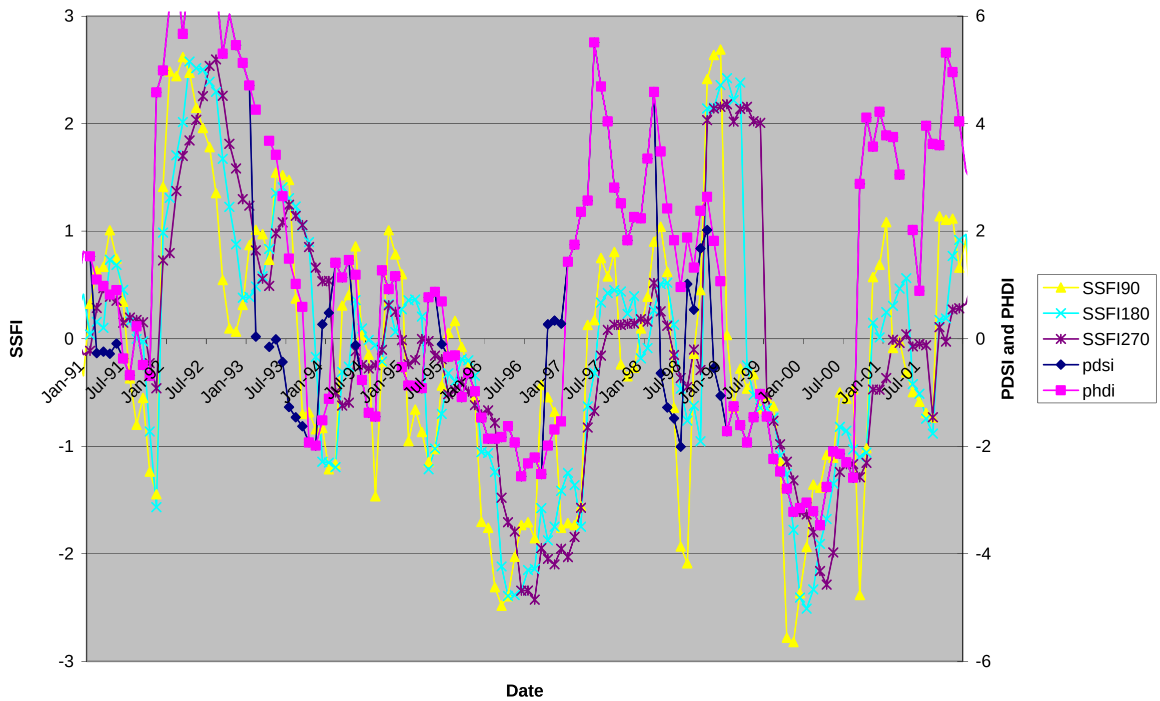
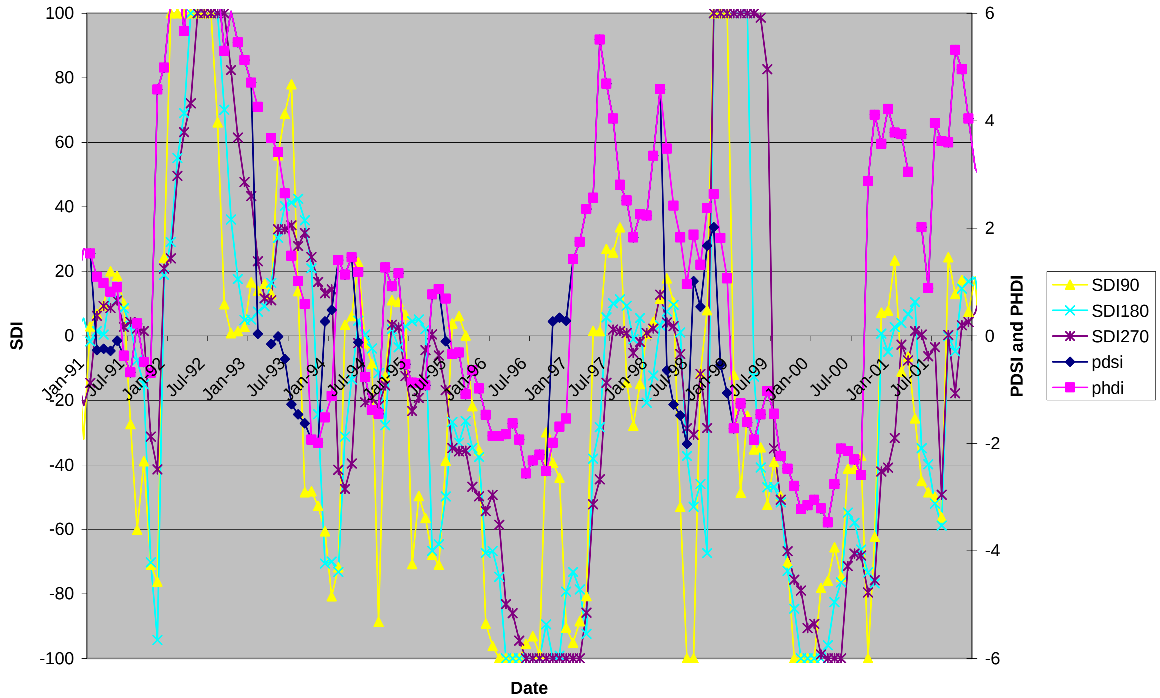


Figure 31 Comparison of SDI with PDSI and PHDI for the San Antonio basin (1991–2001)



Evaluation of Reservoir-based Indices

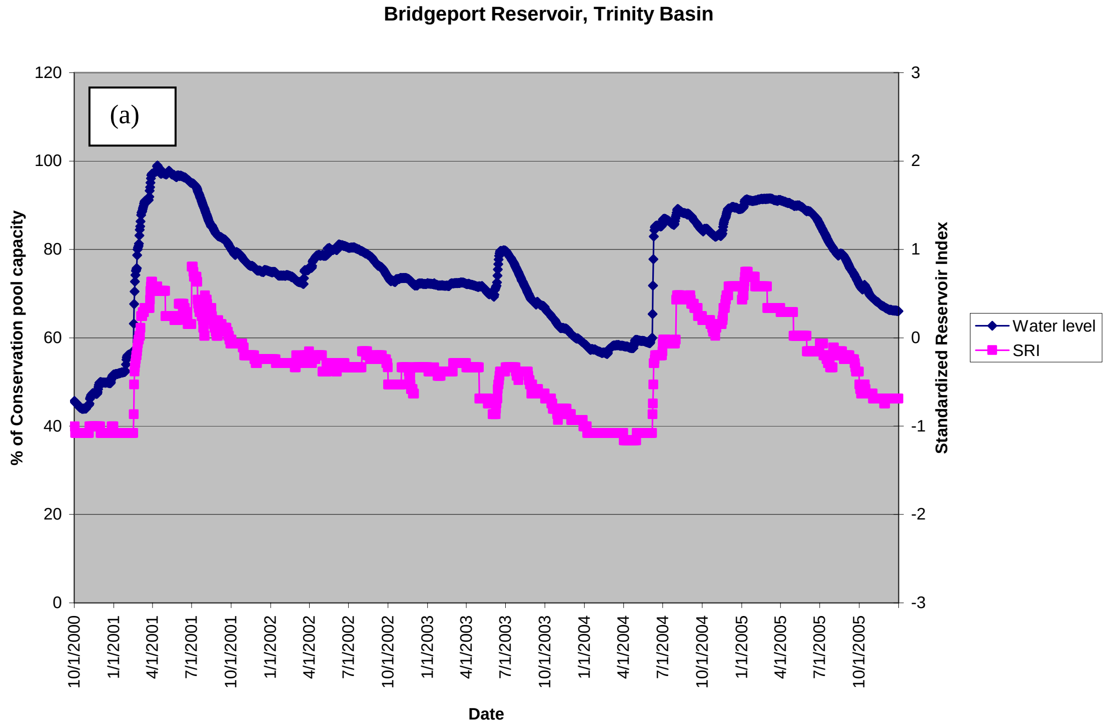
The two new reservoir-based indices that were developed for this study, namely the Standardized Reservoir Index (SRI) and the Reservoir Deficit Index (RDI), were evaluated against the Percent of Reservoir Conservation Storage Capacity at seven different reservoirs from across Texas. The water level data for most of the reservoirs were only available starting in October 2000 from the USGS. For some of the reservoirs only the water level elevation (ft) was reported as opposed to storage volume (ac-ft) and so the elevation-area-capacity curve available from the TWDB was used to convert the elevation reading into volume measurement.

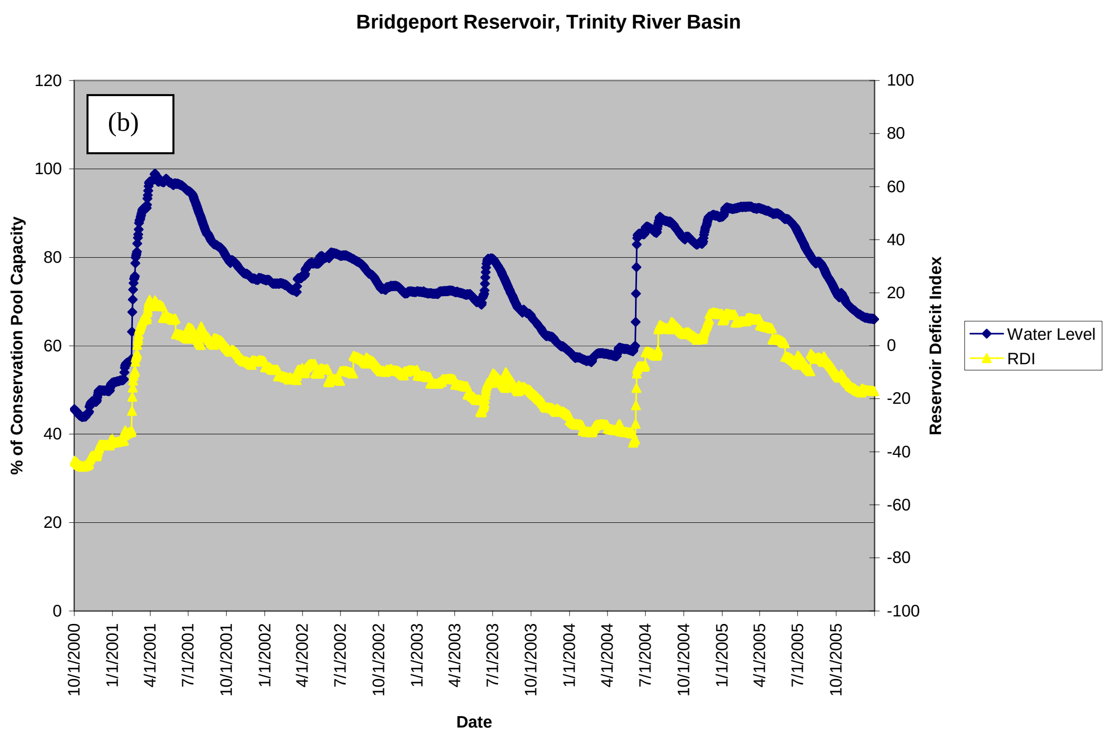
Bridgeport Reservoir, Trinity Basin

Bridgeport reservoir is one of the major water supply reservoirs in the Trinity River basin. SRI and RDI for Bridgeport Reservoir (Figure 32) show that it closely follows the water level data. This is because the long-term monthly median storage level obtained from

WRAP simulations does not vary too much between months. The information is, nevertheless, useful because it gives an estimate of percentage below the long-term normal reservoir storage level for each month. Figure 32b shows that except for a short time period during winter 2001, the reservoir was experiencing a dry spell until autumn 2004. The SRI plot (Figure 32a) shows more of a jig-saw pattern as compared to the smooth plot of RDI. This is because a continuous probability distribution was not fitted to the long-term data; rather the current storage volume is assigned a rank in comparison to long-term simulated storage volumes, which was then converted to cumulative probability and subsequently used to obtain the standard normal value for SRI.

Figure 32 a) Standardized Reservoir Index (SRI) b) Reservoir Deficit Index (RDI) for Bridgeport Reservoir, Trinity basin (2000–2005)

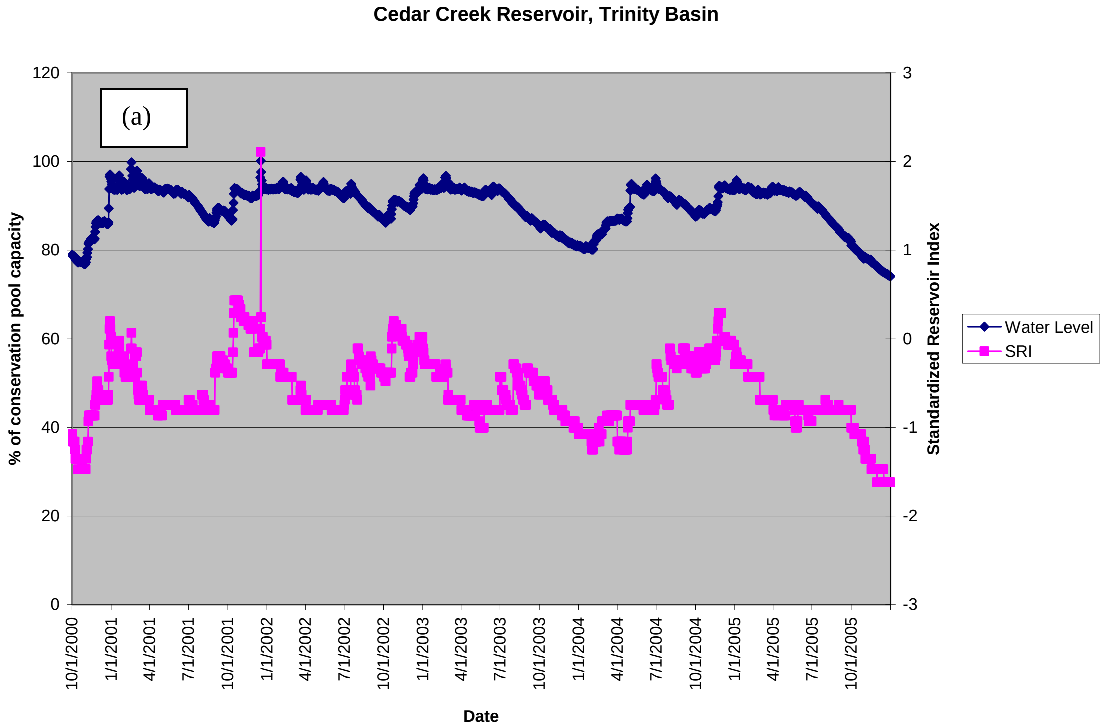


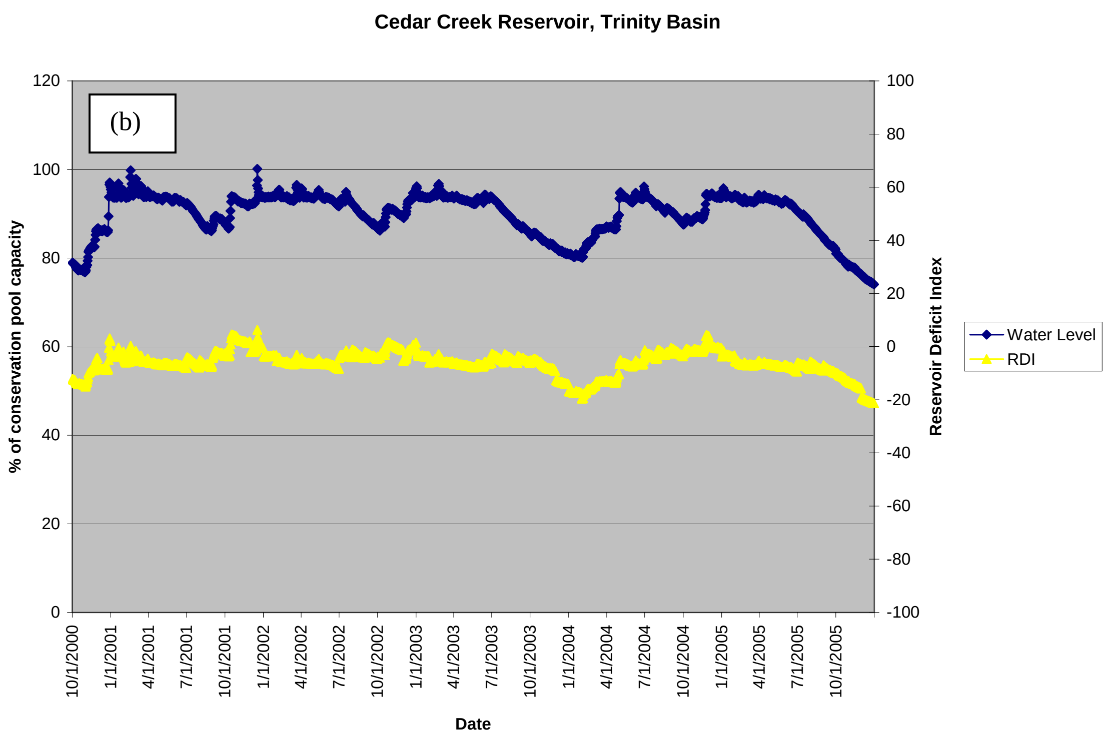


Cedar Creek Reservoir, Trinity Basin

Figure 33b shows the RDI for the past five years for the Cedar Creek reservoir. This reservoir has been 10 to 20% below normal continuously during this period. In contrast to Bridgeport, the RDI plot does not exactly follow the water level because, based on WRAP simulations, the monthly long-term median reservoir levels for each month were quite different from each other. The SRI plot (Figure 33a) shows much more variation than the RDI and also display a jagged pattern for the same reasons described previously.

Figure 33 a) Standardized Reservoir Index (SRI) b) Reservoir Deficit Index (RDI) for Cedar Creek Reservoir, Trinity basin (2000–2005)

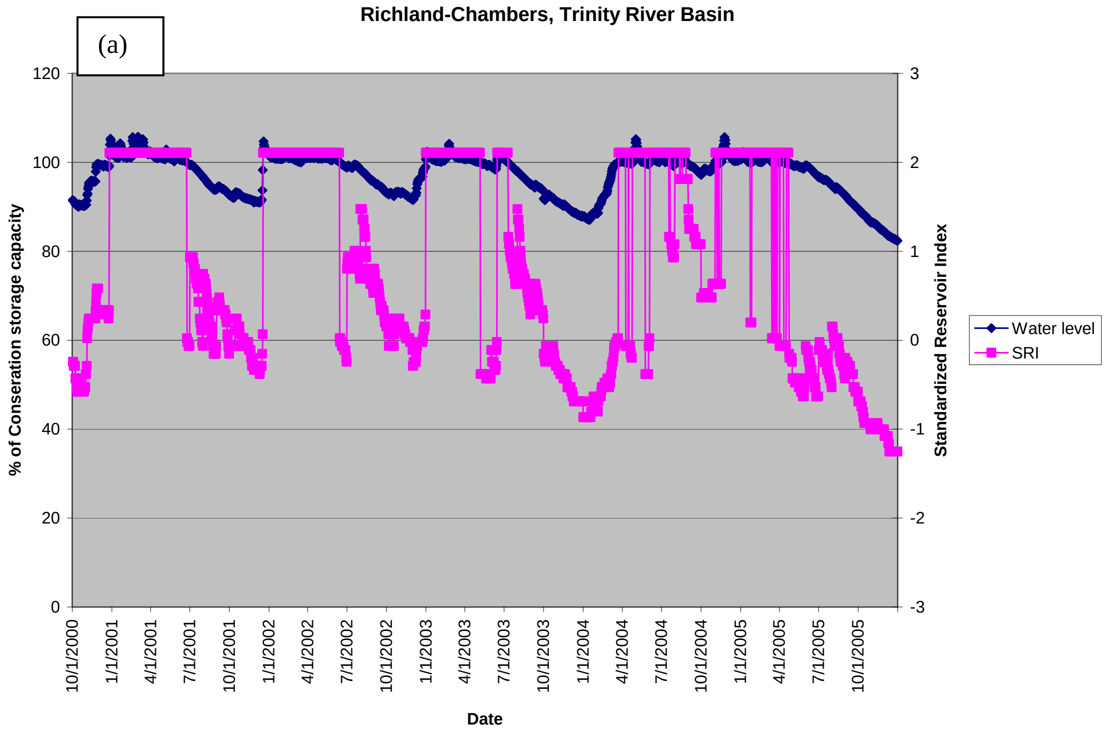


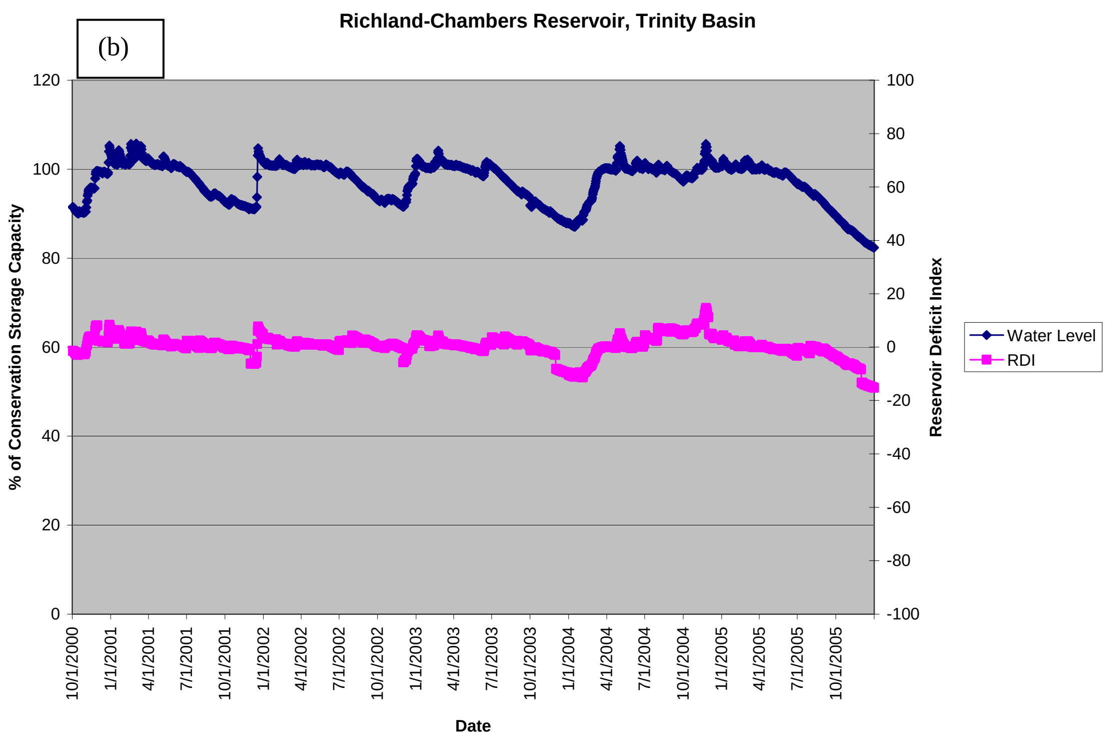


Richland-Chambers Reservoir, Trinity Basin

The RDI plot for Richland-Chambers reservoir (Figure 34b) shows that the reservoir level has been close to normal during most of the past six years. The water level was also never below 80% of the conservation storage capacity. However, the SRI plot (Figure 34a) shows more drastic variation, as compared to RDI, for the same reasons described previously.

Figure 34 a) Standardized Reservoir Index (SRI) b) Reservoir Deficit Index (RDI) for Richland-Chambers Reservoir, Trinity basin (2000–2005)

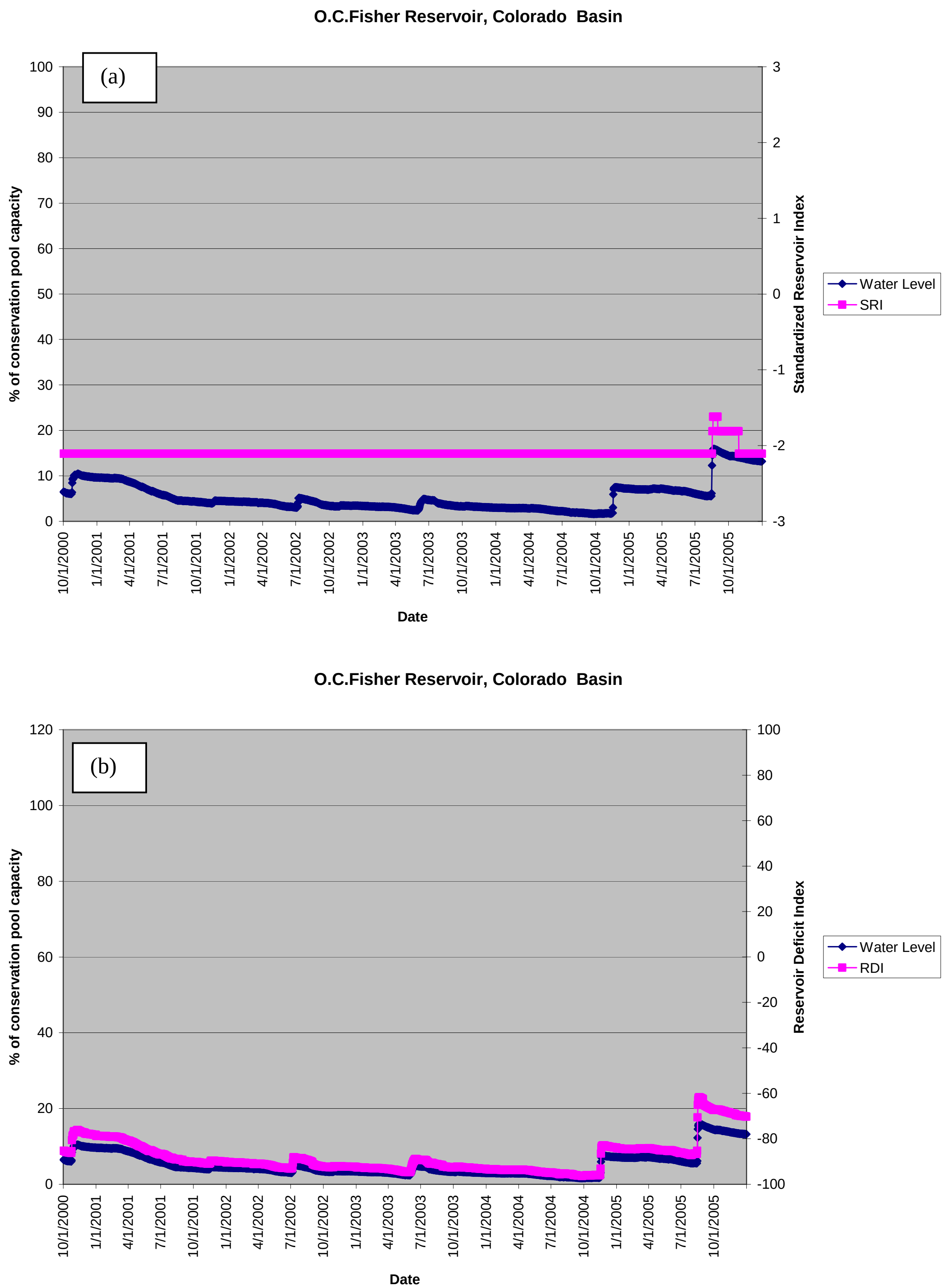




O.C. Fisher Reservoir, Colorado Basin:

The RDI plot for O.C. Fisher Reservoir (Figure 35b) shows that the reservoir has been under severe drought since 2000, and the water level has still not recovered. The water level has been 10% below conservation storage capacity consistently for the past six years. The RDI also shows that the reservoir has been below 80% of normal water level. The SRI plot (Figure 35a) shows almost a constant value, this is because the current water level is less than the water level simulated by WRAP model using weather and hydrology data from 1940 to 1996.

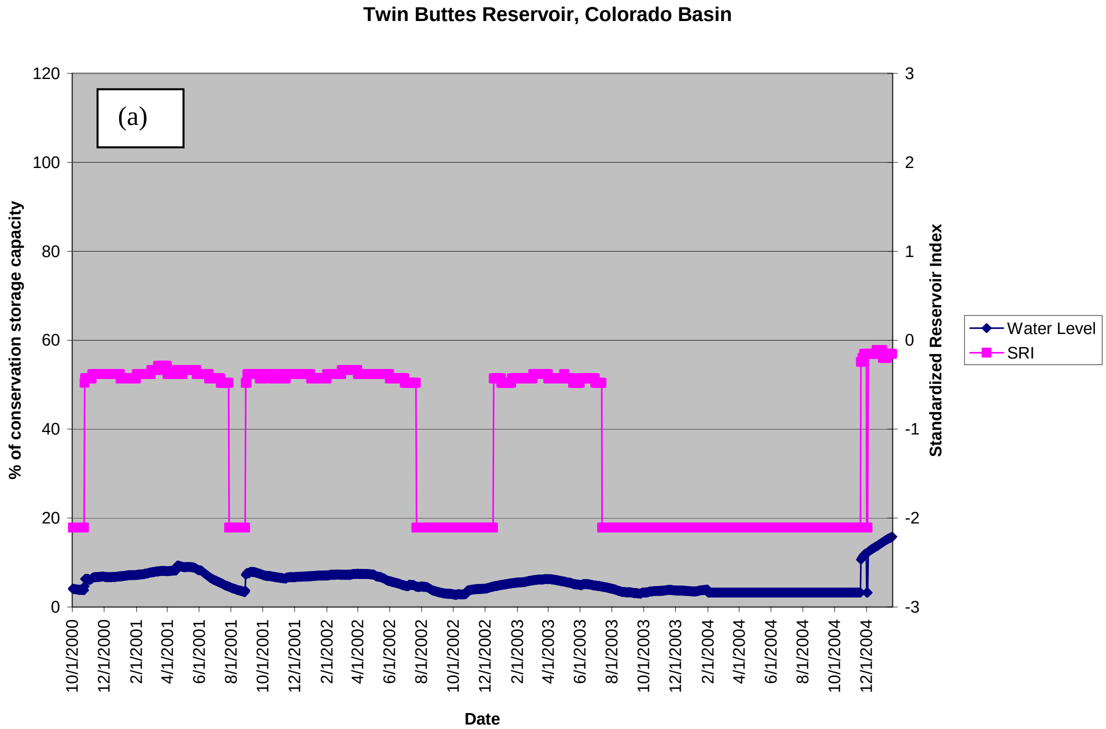
Figure 35 a) Standardized Reservoir Index (SRI) b) Reservoir Deficit Index (RDI) for O.C. Fisher Reservoir, Colorado basin (2000–2005)

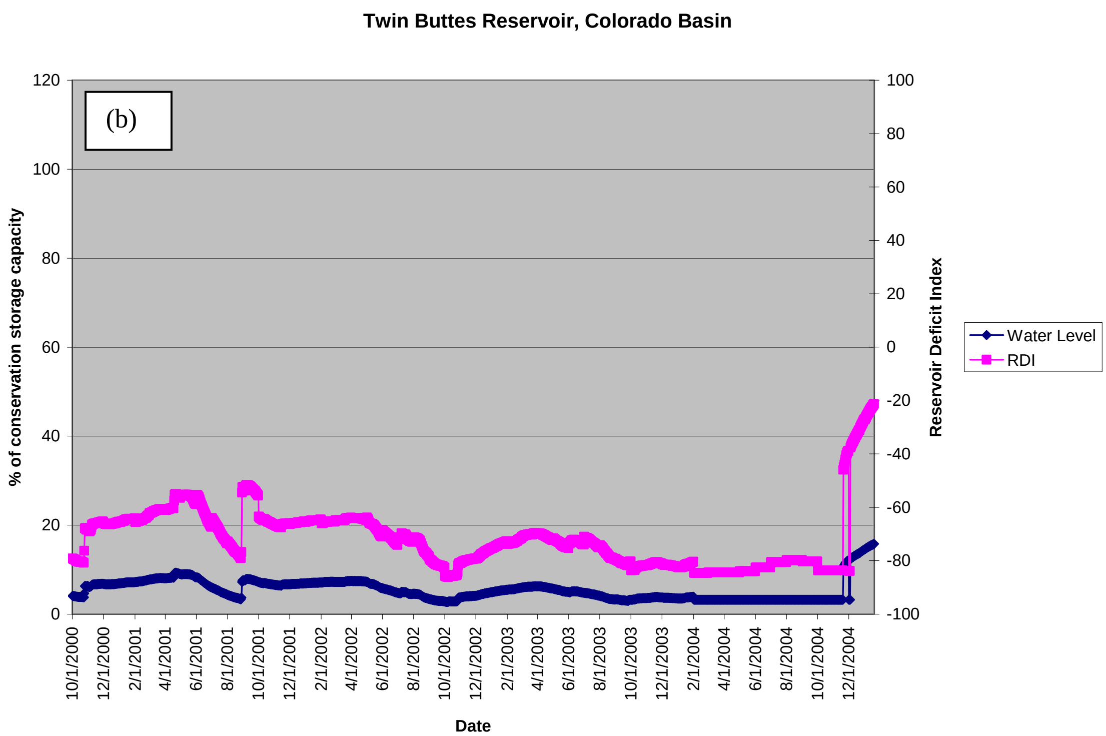


Twin Buttes Reservoir, Colorado Basin

The RDI plot for Twin Buttes reservoir shows that, similar to the O.C. Fisher Reservoir, this reservoir has been affected by a severe drought since 2000 (Figure 36b). The water level was also about 10% of conservation storage capacity for the past six years. The jagged response of SRI (Figure 36a) is due to the lack of proper probability distribution fit to the long-term water level data.

Figure 36 a) Standardized Reservoir Index (SRI) b) Reservoir Deficit Index (RDI) for Twin Buttes Reservoir, Colorado basin (2000–2005)

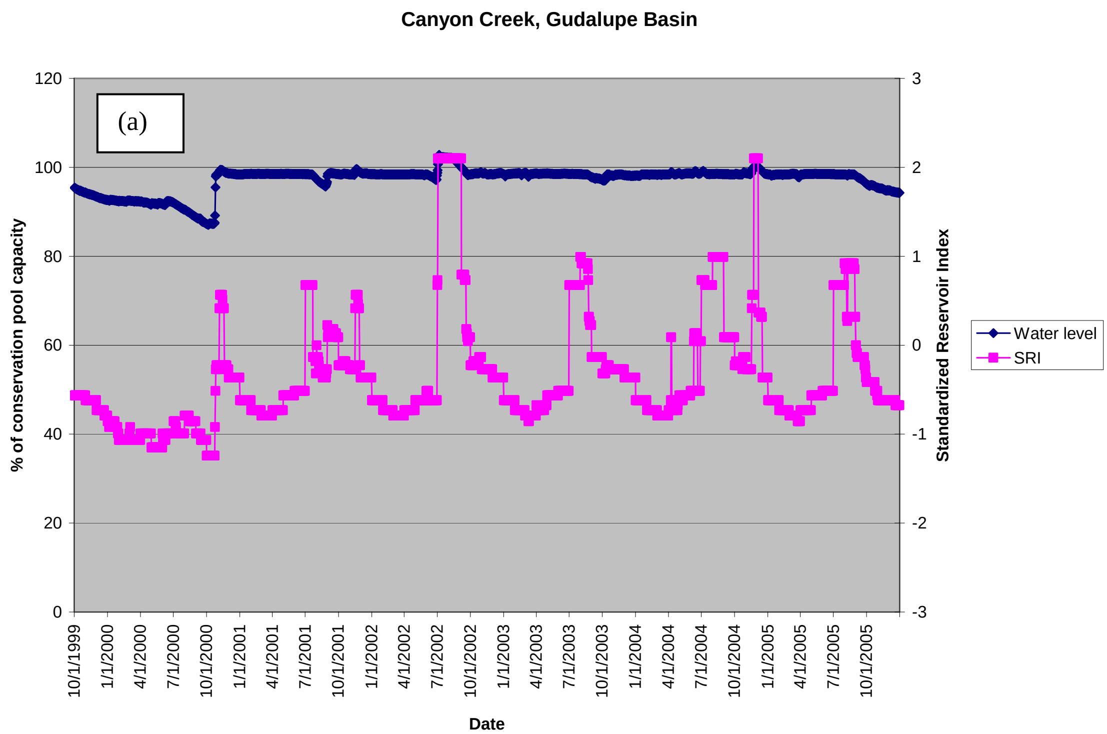


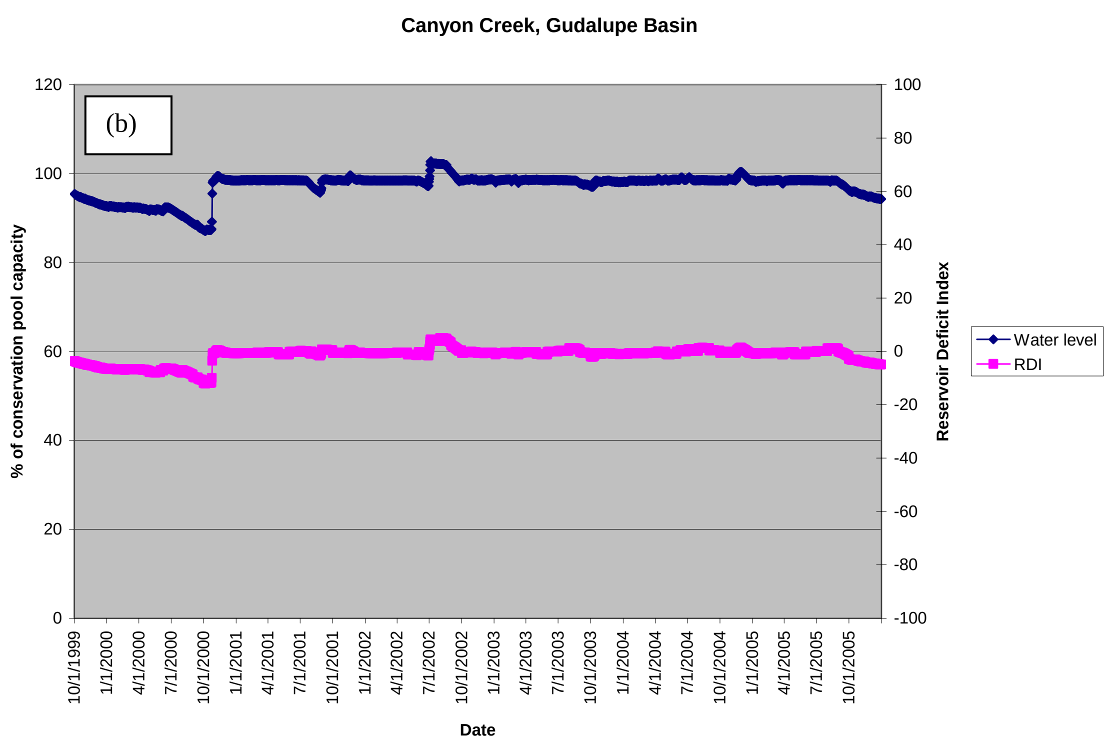


Canyon Lake, Guadalupe Basin

The RDI plot for Canyon Lake (Figure 37b) shows that the reservoir has been maintaining a normal water level since 2000. A closer examination of the WRAP simulation results and the current water level data show that either the reservoir water is not being used heavily or it is being recharged constantly by streamflow. The reservoir consistently maintained a water level of over 90% of conservation storage capacity. The jagged response of SRI (Figure 37a) is due to the lack of proper probability distribution fit to the long-term water level data.

Figure 37 a) Standardized Reservoir Index (SRI) b) Reservoir Deficit Index (RDI) for Canyon Lake Reservoir, Guadalupe basin (2000–2005)

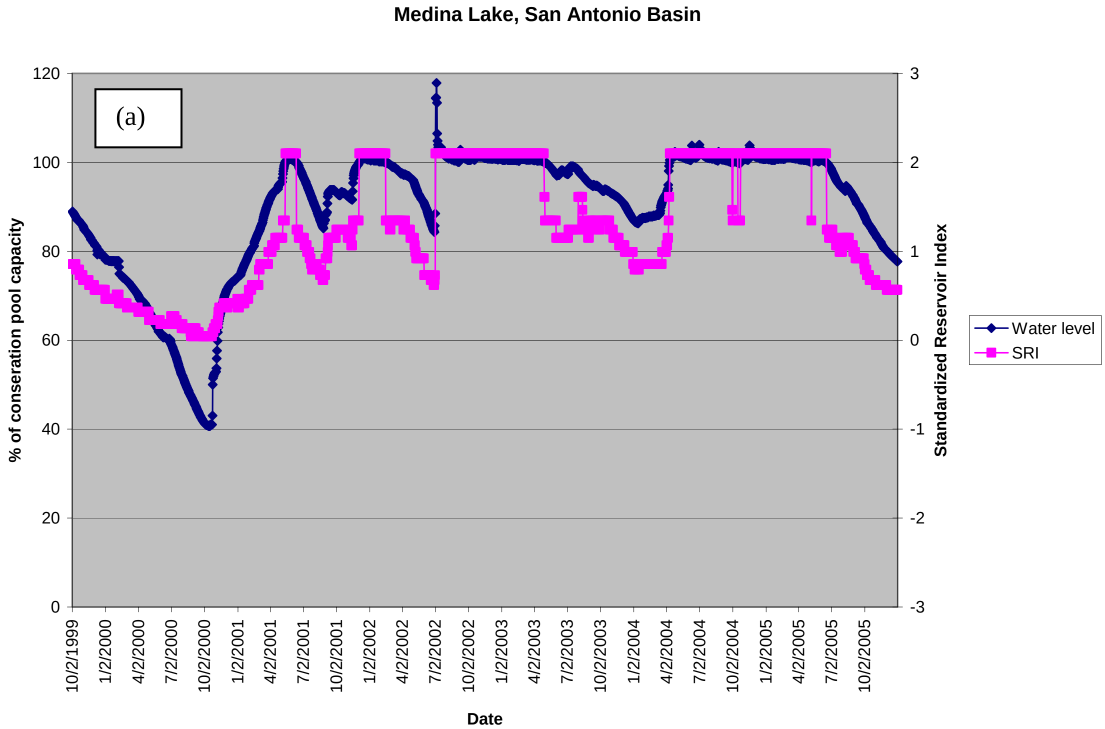


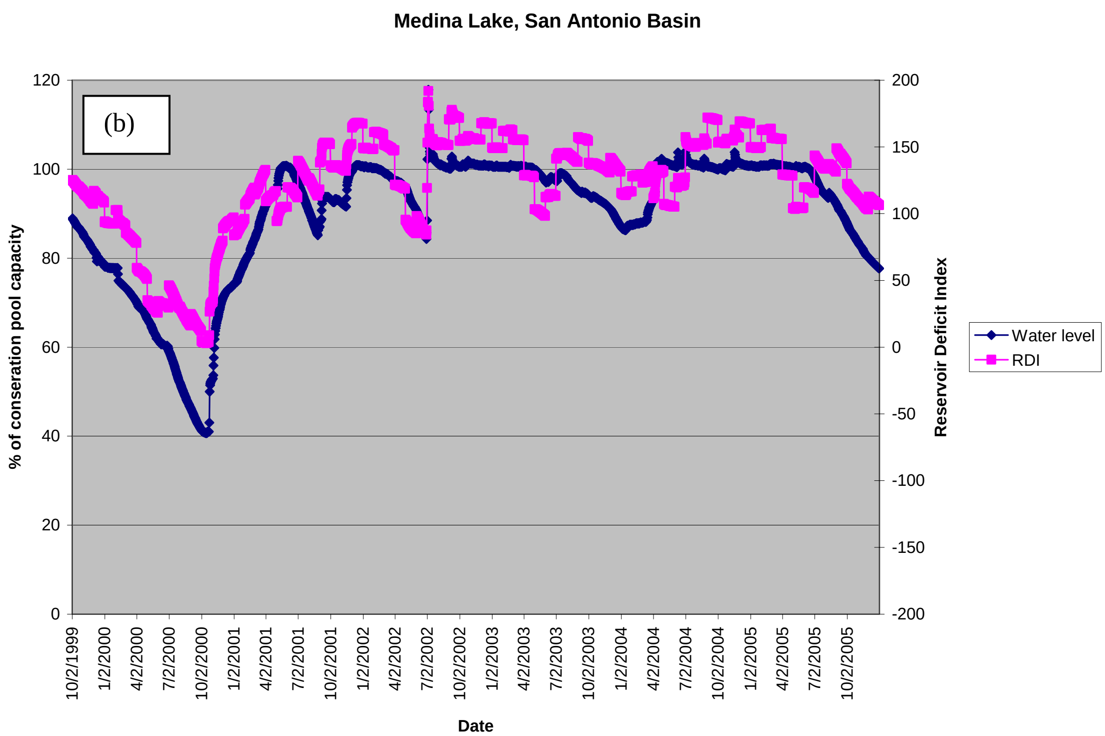


Medina Lake, San Antonio Basin

The RDI plot for Medina lake (Figure 38b) shows that this is the only reservoir to not to have even a single day below long-term normal water levels. Notice that although the water level dipped to 40% of conservation storage capacity during October 2000, that water level was still above the normal water level (indicated by positive values of RDI) expected for that time of the year based on WRAP simulations. Using "percentage of conservation storage capacity" as the only measure of drought would have classified this as a drought, even though reservoir usage was close to normal. After October 2000, the reservoir has consistently had more water, either due to changes in water usage from the reservoir or increased inflows to the reservoir. The jagged response of SRI (Figure 38a) is due to the lack of proper probability distribution fit to the long-term water level data.

Figure 38 a) Standardized Reservoir Index (SRI) b) Reservoir Deficit Index (RDI) for Medina Lake Reservoir, San Antonio basin (2000–2005)





3.4.4 Recommendations Based on the Quantitative Drought Index Evaluation

It is apparent that many of the meteorological drought indices that were evaluated provide similar (overlapping) information. Most of the meteorological drought indices that were evaluated are highly correlated with each other and these correlations are relatively spatially invariant. Therefore, it would be useful to select one short-term index, one medium term index and one long term index for monitoring meteorological drought. If these selections are made based on the qualitative drought index evaluation described in section 3.3.1, either Percent Normal, Deciles, or 1-month SPI should be selected for measuring short-term meteorological drought in Texas. The 6-month SPI is the most appropriate index for measuring medium-term drought, and 12-month SPI is the best index for measuring long-term drought. Although the Palmer indices provide some different information than the precipitation-based indices, their calculation and interpretation is problematic. Therefore, the Palmer indices are not recommended for operational drought monitoring in Texas. The EDI is also not recommended for monitoring meteorological drought because it is not clear on which timescale (e.g., 1 month, 6 months, or 12 months) it is providing information. In addition, the EDI is difficult to calculate and interpret.

Developing indices to measure (and monitor) hydrological/water supply conditions is a challenging task because of the complex interaction of weather, land cover, topography, and geology. Assessing hydrological/water supply drought is further complicated by human activities (and their impact on water supply and demand) and the multitude of competing demands for water. In this study a number widely used hydrological/water supply indices (e.g., PHDI, PDSI, and SPI) were evaluated in Texas. Four new drought indices based on measured cumulative streamflow at set time intervals (SSFI and SDI) and measured reservoir levels (SRI and RDI) were also developed and evaluated.

Based on the qualitative and quantitative analyses that were conducted, SSFI, RDI, and the 3-month, 6-month, and 9-month SPI are the most appropriate indices for monitoring hydrological/water supply drought in Texas. On the other hand, PHDI and SWSI are not recommended for monitoring hydrological/water supply drought in Texas. The newly developed Standardized Stream Flow Index (SSFI) seems to be a versatile index for monitoring hydrological/water supply drought. Comparison of the SPI and SSFI generally showed good agreement during major drought events, although the SSFI tends to record droughts of a higher magnitude and longer duration than the SPI. This is due to the natural time-lag between meteorological and hydrological drought. Since SSFI is calculated using a similar scale and it is based on the same assumptions as the SPI, the trigger levels currently used for SPI could also be used for monitoring hydrological/water supply drought. The other new streamflow-related index that was developed, the SDI, is not that useful since it frequently reaches extreme values.

In terms of water supply, the SRI is not recommended for monitoring water supply drought because of the problems with finding a PDF that fits the long-term water level data. The Reservoir Deficit Index (RDI) is the best index for monitoring water supply drought because it is calculated using a simple and robust method. Since the RDI is based on the simulated long-term monthly reservoir water levels from the WRAP model, it controls for changes in reservoir operation or water demand over time. This procedure also provides a framework to monitor drought for new reservoirs or reservoirs with short reservoir level records. The RDI can be used to complement the Percentage of Conservation Storage

Capacity currently used by TWDB. More detailed analysis would be needed at several other major reservoirs to determine what trigger levels should be used for droughts. However, as a starting point, RDI values of -30, -40, -60, -80 and -90 (consistent with the trigger levels currently used by TWDB (Table 5)) could be used to classify drought severity.

4.0 TASK 3: DEVELOPING OPERATIONAL DEFINITIONS FOR METEOROLOGICAL AND HYDROLOGICAL/WATER SUPPLY DROUGHTS

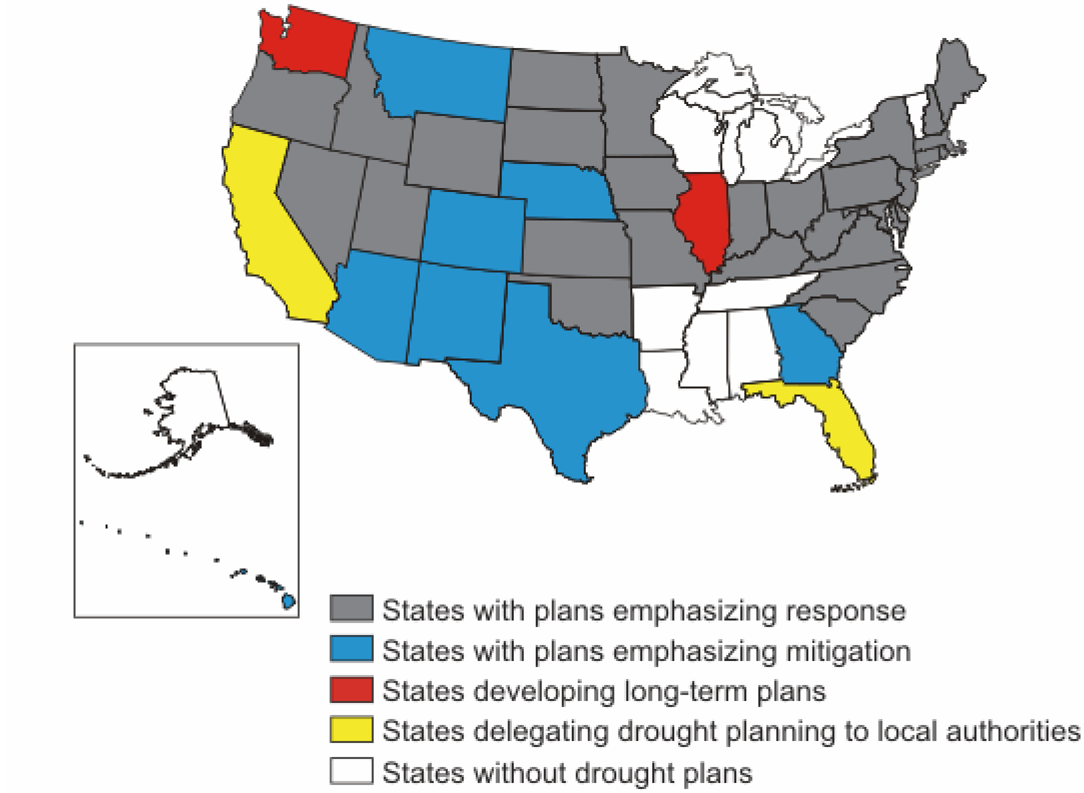
4.1 Introduction

This objective of this task is to develop a methodology for determining the appropriate operational definitions (or thresholds) for meteorological and hydrological/water supply drought. Approximately thirty-three State Drought Plans were reviewed to identify the operational drought definitions that are currently being across the United States. In most cases a single definition is used for the entire state and often these definitions have been developed using subjective criteria. Therefore a new method for developing appropriate drought thresholds for monitoring meteorological and hydrological/water supply drought at the local level in the state of Texas is introduced. The benefits of this method are illustrated using data from a number of representative stations from across Texas.

4.2 Description of Existing Operational Drought Definitions

Since there is no federal policy to address local water deficiencies (drought) within the United States, many individual states have developed their own methods for monitoring and responding to drought. There are currently 39 states that have some type of drought plan and two additional states (California and Florida) have delegated drought planning activities to local authorities (Figure 39). According to the National Drought Mitigation Center (NDMC), there are only nine states that still lack a drought plan (Alabama, Alaska, Arkansas, Louisiana, Michigan, Mississippi, Tennessee, Vermont, and Wisconsin).

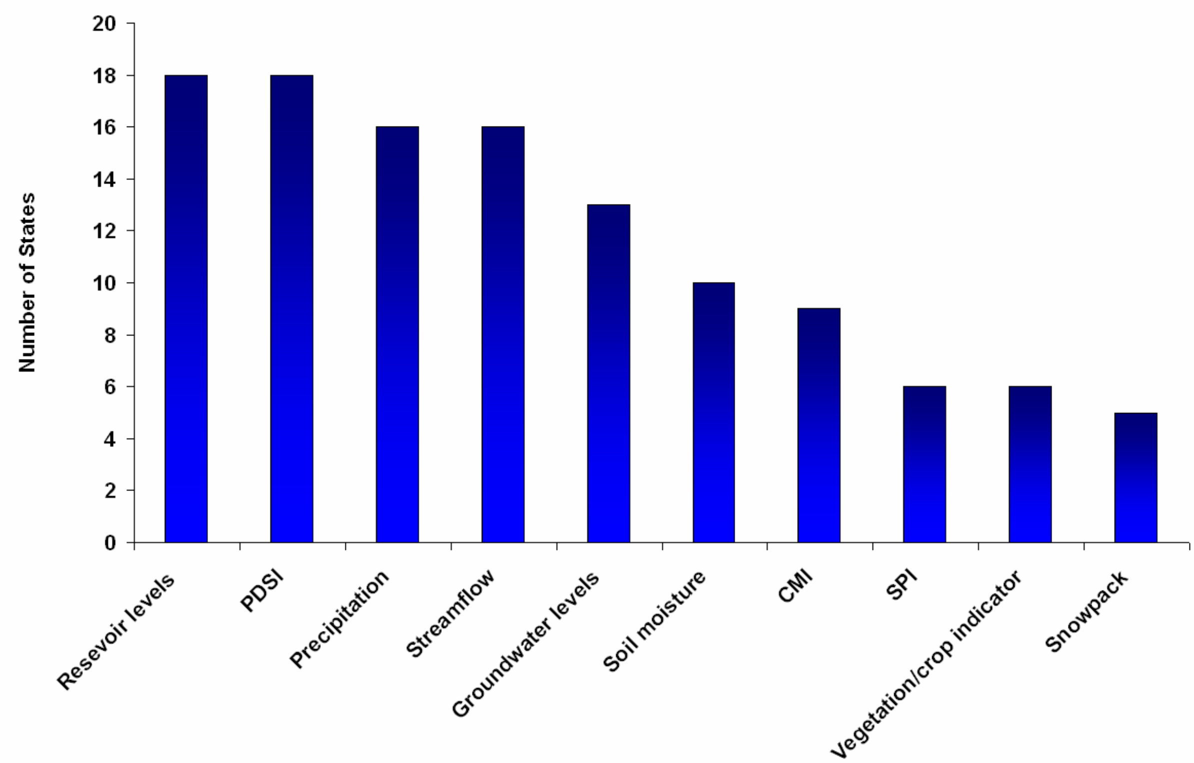
Figure 39 Status of state drought planning activities as of October 2006 (NDMC, 2007)



All of the state drought plans that were available in a digital format (33 in total) were reviewed to determine how each state established operational definitions of drought (drought thresholds). The drought plans were reviewed to identify which drought indices are most commonly used for monitoring drought and to determine what drought definitions (thresholds) are used for triggering state response. Given the wide range of detail provided in the state drought plans, it was not always possible to determine what drought indices and drought definitions are used in each state.

The most commonly used drought indices are shown in Figure 40. It is clear that most states are primarily interested in monitoring meteorological and hydrological/water supply drought since the most commonly used drought monitoring indices/tools are reservoir levels, PDSI, precipitation, and streamflow. There appears to be fairly good agreement in regards to what data are most important for drought monitoring since these indices were specifically mentioned in the majority of the state drought plans that were reviewed. Some state drought plans also utilized indicators of agricultural drought such as soil moisture levels, Crop Moisture Index (CMI), and a variety of vegetation/crop indicators.

Figure 40 Indices most commonly used for monitoring drought in state drought plans (based on 33 state drought plans)



There is less information in the state drought plans about the particular drought definitions (drought thresholds) that are being used to trigger drought response. Specific drought thresholds were listed in only 13 of the 33 state drought plans that were reviewed. The number of states decreases further when considering a specific drought index such as the PDSI or SPI. Drought definitions based on the PDSI are reported in Table 40. It should be noted that the drought categories listed in Table 40 may not correspond with the drought categories that are used in all of the state drought plans. Most states (24 out of 33) use three to five categories for classifying drought severity. This table was compiled by first comparing the drought definitions (thresholds) used for the most extreme drought category (labeled drought disaster in Table 40). Then the second most severe drought thresholds were compared, followed by the third, etc. So even though the states listed in Table 40 have a different number of categories they can be compared (at least for the most extreme drought categories). Generally, there is a good deal of agreement between in regards to the drought definitions that are used. This is somewhat surprising given that these states are located in very different climatic regions (Table 40 includes states from the northeastern, central, southern, and Gulf Coast regions of the U.S.). If the PDSI were a spatially invariant indicator of drought (e.g., if it could be interpreted the same way in all locations), this would not be a serious problem. However, since the PDSI is known to be a spatially variant indicator of drought and since the probability of getting a particular PDSI value is a function of the climate, this means that it is impossible for these drought definitions to be appropriate for all (or perhaps any) of the states listed. It appears that these definitions have been taken, almost without modification, from the thresholds defined by Palmer (1965) (Table 41). According to Palmer's classification, a PDSI of < -4.0 is used to indicate the most extreme category of drought. This threshold is also what is being used by the majority of states listed in Table 40. It is worthwhile noting once again (as mentioned in section 3.2.1) that the thresholds were arbitrarily (subjectively) developed by Palmer and are not necessarily well-correlated with drought impacts (Alley, 1984). There is no scientific basis for using Palmer's thresholds to trigger different levels of drought response.

Table 40 Drought definitions based on the PDSI as described in selected state drought plans

Category	AL	CT	CO	IN	MA	NM*	OH	TX**	UT	VT
1) disaster (most severe)	< -4	< -4	< -4	< -4	< -4	< -4	< -4	< -5	Governor's decision	< -3.0
2) emergency	-3 to -3.99	< -4	-3 to -3.99	-3 to -3.99	< -4	< -3	-2 to -4	-4 to -4.9	< -2	-2 to -3
3) warning	-2 to -2.99	-3 to -3.99	-2 to -2.99	-2 to -2.99	-3 to -3.99	-2 to -2.99	-1 to -2	-3 to -3.9	-1 to -2	.
4) watch	-0.9 to -1.9	-2 to -2.99	-0.9 to -1.9	.	-2 to -2.99	-1 to -1.99	.	-2 to -2.9	0 to -1	.
5) advisory (least severe)	.	.	.	.	-1 to -1.99	>-0.9	.	-1 to -1.9	.	.

* New Mexico = these are the thresholds for the 1-month PDSI, other thresholds have also been established
** Texas = these thresholds are only mean to be instructive, unlike other state drought where the thresholds automatically trigger particular actions

Table 41 PDSI drought classification (Palmer, 1965)

PDSI Value	Category
< -4.0	Extreme Drought
-3.0 to -3.99	Severe Drought
-2.0 to -2.99	Moderate Drought
-1.0 to -1.99	Mild Drought
-0.5 to -0.99	Incipient Dry Spell

Drought definitions based on the SPI are reported in Table 42. Although there are only 4 states listed in Table 42, it is apparent that there are similarities in the drought thresholds that are used. The drought thresholds that are being used are similar to those proposed by McKee *et al.* (1993) (Table 43). Although this is less problematic than for the PDSI, since the SPI is a standardized drought index that is more spatially invariant (consistent) than the PDSI, it can still create problems for some climates. For example, arid regions that experience many months with zero precipitation, may be have difficultly standardizing the SPI depending on which PDF is used to normalize precipitation (Wu *et al.*, 2007). SPI is also influenced by the length of the precipitation record and by the PDF that is being used to standardize the precipitation. Therefore, even though SPI thresholds are based on event probability and therefore have some scientific (and practical) merit, they also should be selected with care to make sure that they are appropriate for classifying drought in the region of interest.

Table 42 Drought definitions based on the SPI as described in selected state drought plans

Category	CO	HI	NM*	TX**
1) disaster (most severe)	< -1.99	< -2.0	< -1.7	< -2
2) emergency	< -1.0	-1.5 to -1.99	< -1.25	< -2
3) warning	-0.6 to -1.0	-1 to -1.49	< -0.5	-1.5 to -1.99
4) watch	> -0.6	.	< -0.25	-1 to -1.49
5) advisory (least severe)	.	.	> -0.25	0 to -0.99

* New Mexico = the thresholds differ depending on the time period of interest
** Texas = these thresholds are only mean to be instructive, unlike other state drought where the thresholds automatically trigger particular actions

Table 43 SPI classification (McKee *et al.*, 1993)

SPI Value	Category	Probability
< -2.0	Extremely Dry	2.3%
-1.5 to -1.99	Very Dry	4.4%
-1.0 to -1.49	Moderately Dry	9.2%
-0.99 to 0.99	Near Normal	68.2%

As far as we could tell, none of the state drought plans that were reviewed utilized an objective methodology for selecting operational drought definitions for each drought index. It appears that, at least for the PDSI and SPI, most states have either adopted the thresholds described in the literature or used other subjective means to establish drought thresholds.

4.3 Description of an Objective Method for Determining Operational Drought Definitions

Developing an appropriate method for determining operational drought definitions is extremely difficult since drought, unlike other natural hazards, has no definitive onset/end, is slow to evolve, and is regionally relative (Goodrich and Ellis, 2006). However, the science behind defining and monitoring drought is at the center of the communication between stakeholders and policymakers. Failure to adequately define and monitor drought can have a significant negative impact, particularly if it fails to trigger a response (e.g., limiting water use) when one is sorely needed, or if it triggers a response when one is not required. There is very little discussion in the scientific literature regarding how drought indices should be used from an application standpoint to monitor drought and to trigger drought response (Goodrich and Ellis, 2006). Because drought indices will be used by policymakers with little understanding of the mechanisms and flaws of each index, a certain level of standardization must be applied in order to limit the misleading or confusing message they may communicate to novice stakeholders. Goodrich and Ellis (2006) proposed an objective methodology for developing operation drought definitions for any drought index. They recommend fitting a parametric statistical distribution model, also referred to as a probability density function (PDF), to the drought index data and then using pre-selected percentiles to determine the drought thresholds. Goodrich and Ellis (2006) used the five percentile categories from the Drought Monitor to classify drought (Table 44).

Table 44 Drought Monitor Classification

Category	Description	Percentile
D0	Abnormally dry	21-30%
D1	Moderate drought	11-20%
D2	Severe drought	6-10%
D3	Extreme drought	3-5%
D4	Exceptional drought	<2%

Fitting a PDF to the drought index data provides a method for estimating the relative frequency (rarity) of an event of a given magnitude based on the observed data (Husak *et al.*, in press). There are many PDFs that have been fit to precipitation/drought data since precipitation is not normally distributed, having a lower bound (Wu *et al.*, 2007). This produces a distribution that is positively skewed. There are a variety of distributions that have been recommended for fitting precipitation (drought) data, including gamma, lognormal, Pearson Type III, and Box-Cox (Legates, 1991; Guttman, 1999; Wu *et al.*, 2007; Husak *et al.*, in press). The gamma distribution is frequently used to represent precipitation because it can represent a variety of distribution shapes using only two parameters, the shape and the scale (Husak *et al.*, in press). One of the advantages of using the gamma distribution to represent precipitation is that it is bounded on the left by zero. This is important since negative precipitation is impossible. The gamma distribution is also positively skewed, so this matches precipitation. Finally, it is a very flexible distribution that can represent a variety of distribution shapes ranging from exponential decay (when shape ~ 1) to nearly normal forms (when shape ~ 20) (Husak *et al.*, in press).

Once a distribution is selected and the parameters are estimated, the ability of the distribution to approximate precipitation (drought) can be tested by comparing the fitted distribution (e.g., gamma) with the empirical distribution using the Kolmogorov-Smirnov (KS) goodness-of-fit test. When the values being tested are the same as the values that were used to determine the distribution parameters, the test is known as the KS Lilliefors test (Husak *et al.*, in press). This test compares the cumulative distribution functions of the theoretical distribution (e.g., gamma), with the observed values and returns the maximum difference between the two cumulative distributions. If the maximum difference is large, then it means that the theoretical distribution is not adequately representing the observed precipitation (drought) at this location. The acceptable value for the KS statistic varies depending on the sample size and the rejection level chosen.

4.4 An Example of Determining Operational Drought Definitions for Percent Normal, SPI, and PDSI for Selected Stations in Texas

The methodology described in section 4.3 was used to determine drought thresholds for the SPI, PDSI, and Percent Normal at a number of representative stations in Texas. These thresholds were then mapped to illustrate the spatial variability in drought thresholds. All three of these drought indices were calculated for six stations from the Historical Climate Network (HCN). All of these stations have long (> 80 years of data) and relatively complete precipitation records (> 95% complete). Most of these stations began reporting data in the late 1890s and are continuing through the present.

Percent Normal

Percent Normal data for six stations in Texas were fit using the normal, gamma, lognormal, and exponential distributions (Figure 41). The KS Lilliefors test was applied to test how well these distributions fit the Percent Normal data (Table 45). Based on the results from these six stations, it appears that the exponential distribution fits the data best. The fitted exponential distribution was used to calculate the drought thresholds for the five drought classes used by the US Drought Monitor (Table 46). The drought thresholds are relatively consistent across all six stations and therefore were not mapped. This is somewhat surprising given that Texas is a large state and that it has a strong east-west precipitation gradient. Based on the objective drought thresholds, moderate drought (D1) is associated with ~22% of normal precipitation, extreme drought (D3) is associated with ~5% of normal precipitation, and exceptional drought (D4) occurs when precipitation is less than ~2% of normal. Of course these thresholds are only appropriate when dealing with 1 month precipitation totals and they would change if a different accumulating time period was used.

Table 45 KS statistic for Percent Normal after being fit using normal, gamma, lognormal, and exponential PDFs

Station	Gamma	Normal	Lognormal	Exponential
410902	0.06	0.11	0.27	0.02
412019	0.12	0.04	0.30	0.05
412121	0.03	0.14	0.26	0.02
415196	0.13	0.06	0.30	0.05
415272	0.05	0.11	0.27	0.03
415429	0.10	0.07	0.28	0.03

Figure 41 Cumulative probability distribution for Percent Normal (station 410902) showing the empirical distribution (EDF) and normal, gamma, lognormal, and exponential distributions that were fit to the data

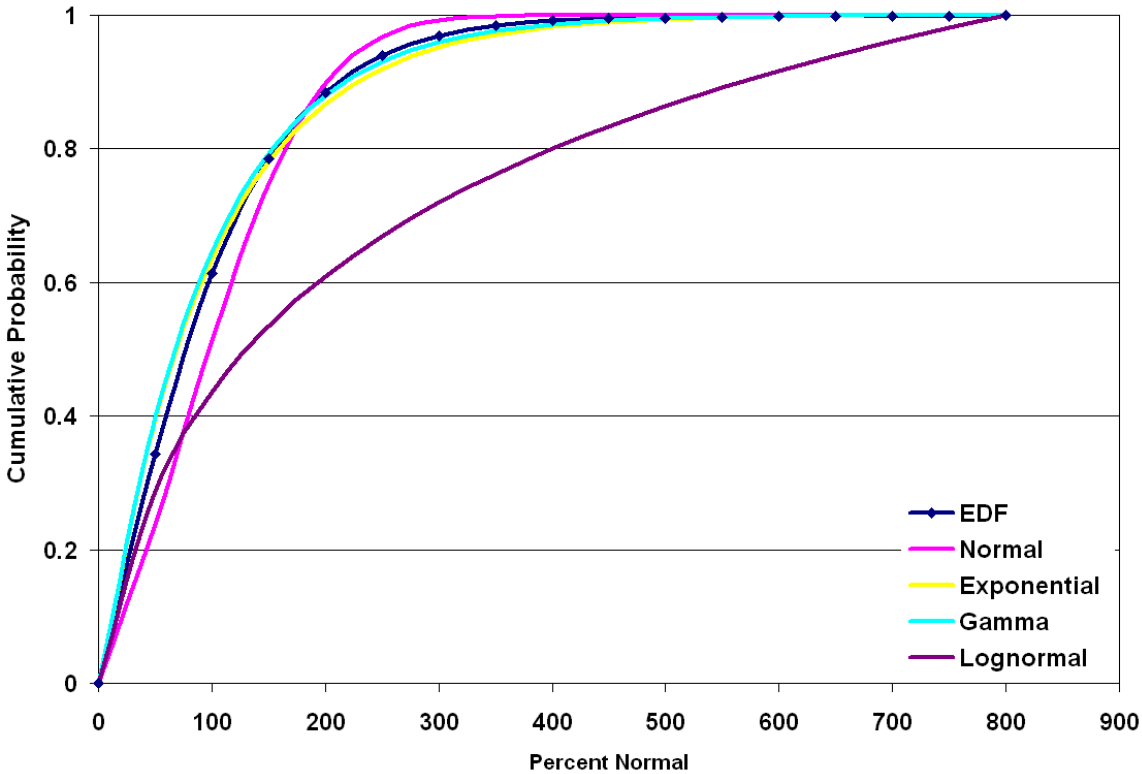


Table 46 Drought thresholds for Percent Normal calculated using the exponential distribution

Station	D0	D1	D2	D3	D4
410902	35.34	22.12	10.44	5.10	2.02
412019	35.76	22.38	10.58	5.16	2.04
412121	35.36	22.12	10.46	5.10	2.02
415196	35.94	22.50	10.62	5.18	2.04
415272	36.02	22.54	10.64	5.18	2.04
415429	35.50	22.20	10.50	5.12	2.02

PDSI

PDSI data for these six stations were fit using the normal, gamma, lognormal, and exponential distributions (Figure 42). The KS Lilliefors test was applied to test how well these distributions fit the PDSI data (Table 47). Based on the results from these six stations, it appears that the normal distribution fits the PDSI data reasonably well. Therefore, the fitted normal distribution was used to determine the drought thresholds for the five US Drought Monitor drought classes (Table 48). It is evident that the drought thresholds are not consistent across these stations. The thresholds for abnormally dry conditions (D0) vary from -1.30 to -1.7, the thresholds for moderate drought (D1) vary from -1.9 to -2.5, the thresholds for severe drought (D2) vary from -2.9 to -3.5, the thresholds for extreme drought vary from -3.7 to -4.3, and the thresholds for extreme drought vary from -4.5 to -5.1 (Figures 43, 44, 45, 46, and 47). In contrast, the threshold for moderate drought according to Palmer's scheme (and the criteria used in most state drought plans) is -2. This would suggest that if Palmer's criteria were utilized in Texas, moderate droughts would be slightly over-reported. The objective threshold for severe droughts varies from -2.9 to -3.5, this is also quite different (at some locations) that the criteria for severe droughts proposed by Palmer (e.g., -3). For all drought levels there is significant variation in PDSI thresholds in Texas. This suggests that using a single drought threshold for the state is inappropriate. It appears that the highest drought thresholds (the least negative) are found at the wettest stations (climatically). This underscores the fact that the PDSI is not a spatially invariant method for measuring drought conditions.

Table 47 KS statistic for PDSI after being fit using normal, gamma, lognormal, and exponential PDFs

Station	Gamma	Normal	Lognormal	Exponential
410902	0.13	0.06	0.52	0.45
412019	0.12	0.05	0.44	0.39
412121	0.09	0.05	0.44	0.39
415196	0.11	0.04	0.48	0.41
415272	0.14	0.04	0.47	0.42
415429	0.13	0.03	0.45	0.39

Figure 42 Cumulative probability distribution for PDSI (station 410902) showing the empirical distribution (EDF) and normal, gamma, lognormal, and exponential distributions that were fit to the data

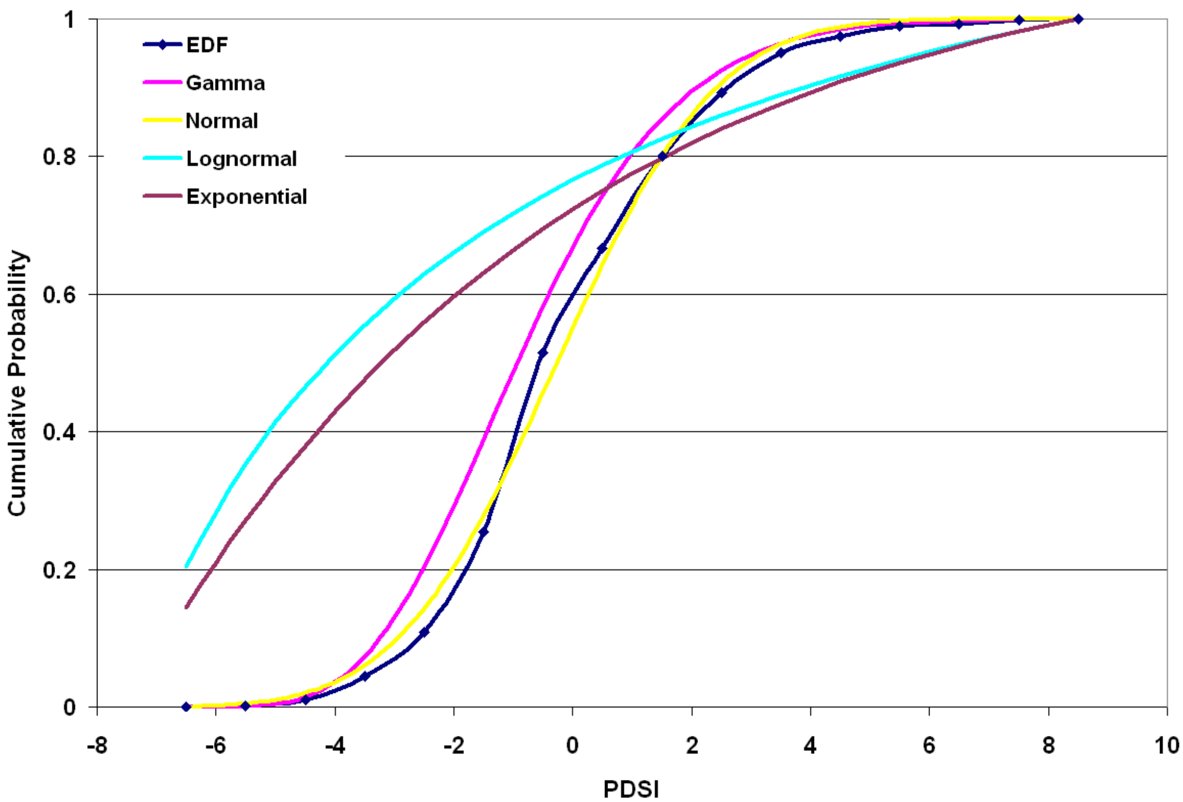


Table 48 Drought thresholds for PDSI calculated using the normal distribution

Station	D0	D1	D2	D3	D4
410902	-1.30	-1.90	-2.90	-3.70	-4.50
412019	-1.30	-2.10	-3.10	-4.10	-4.90
412121	-1.70	-2.50	-3.50	-4.30	-5.10
415196	-1.30	-2.10	-2.90	-3.70	-4.70
415272	-1.30	-2.10	-3.10	-3.90	-4.70
415429	-1.30	-2.10	-3.10	-3.90	-4.70

Figure 43 Thresholds for abnormally dry conditions (30th percentile) based on PDSI

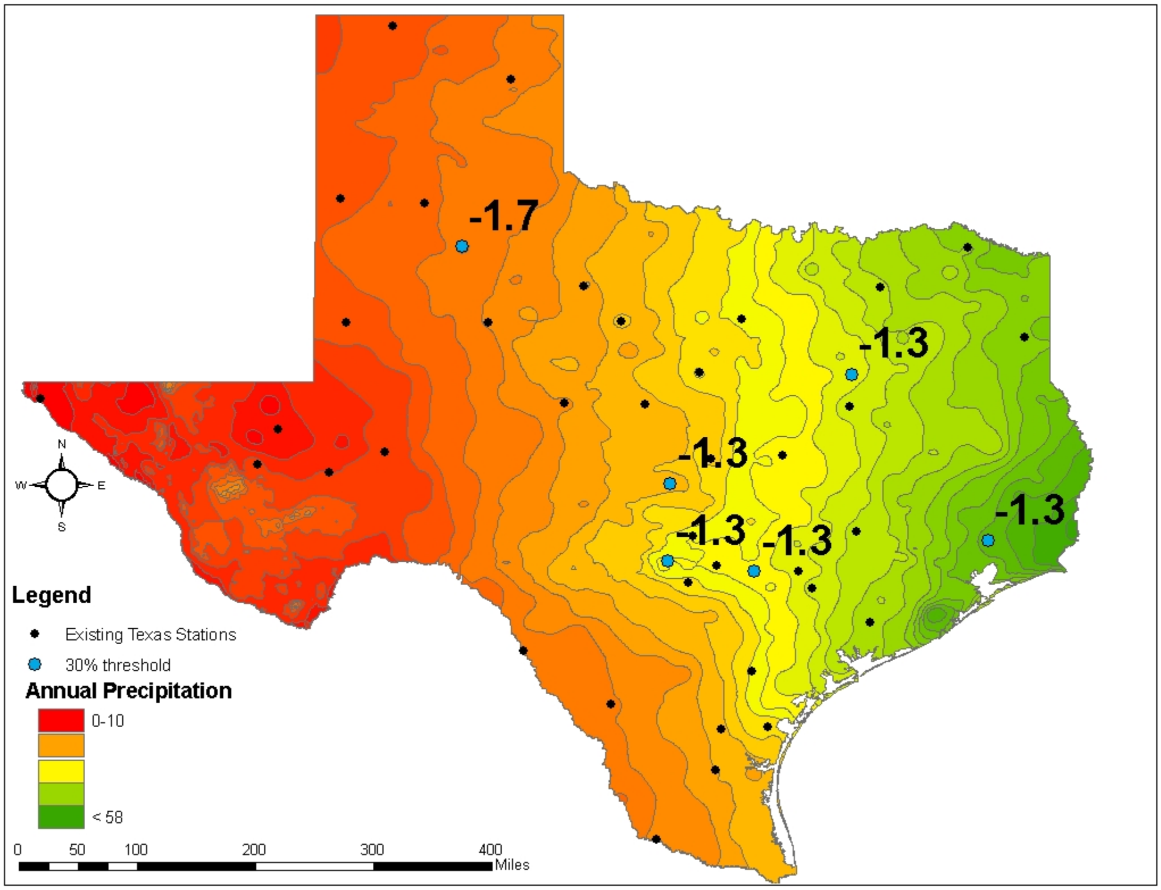


Figure 44 Thresholds for moderate drought (20th percentile) based on PDSI

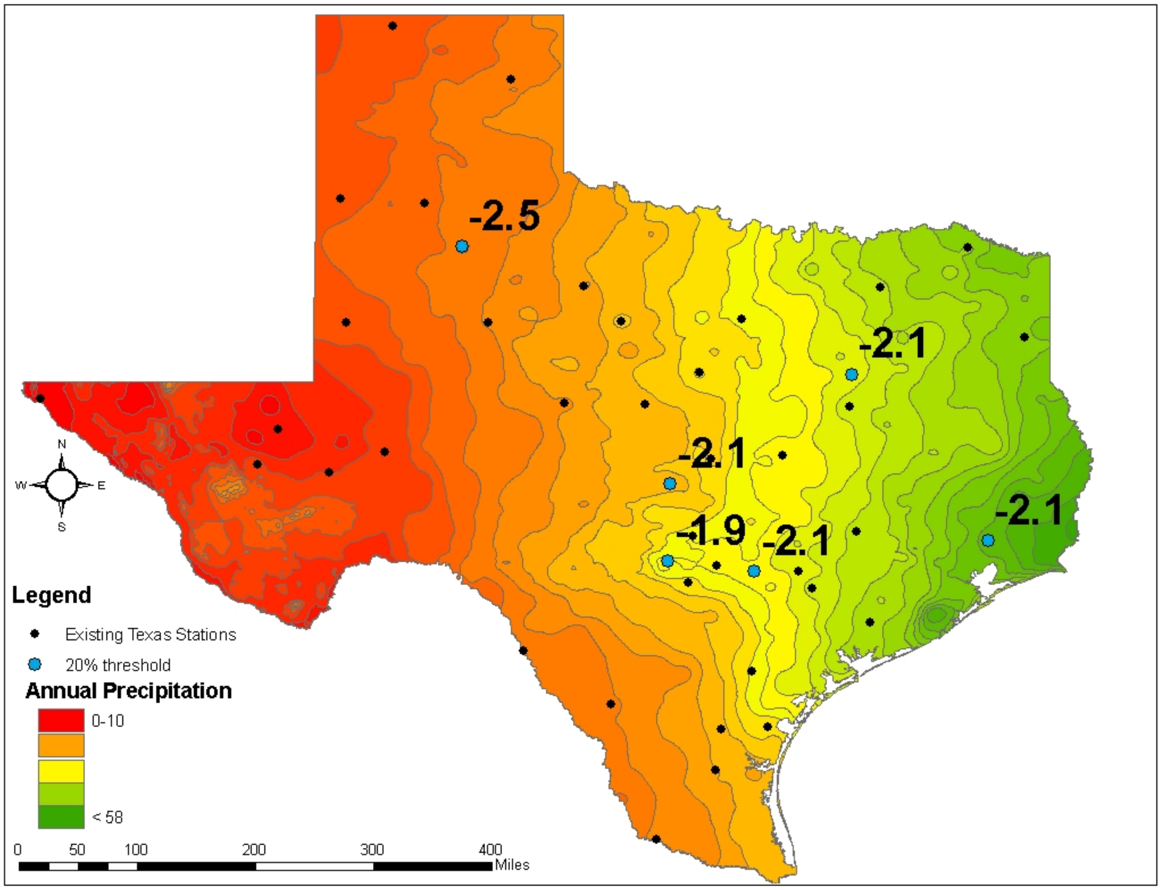


Figure 45 Thresholds for severe drought (10th percentile) based on PDSI

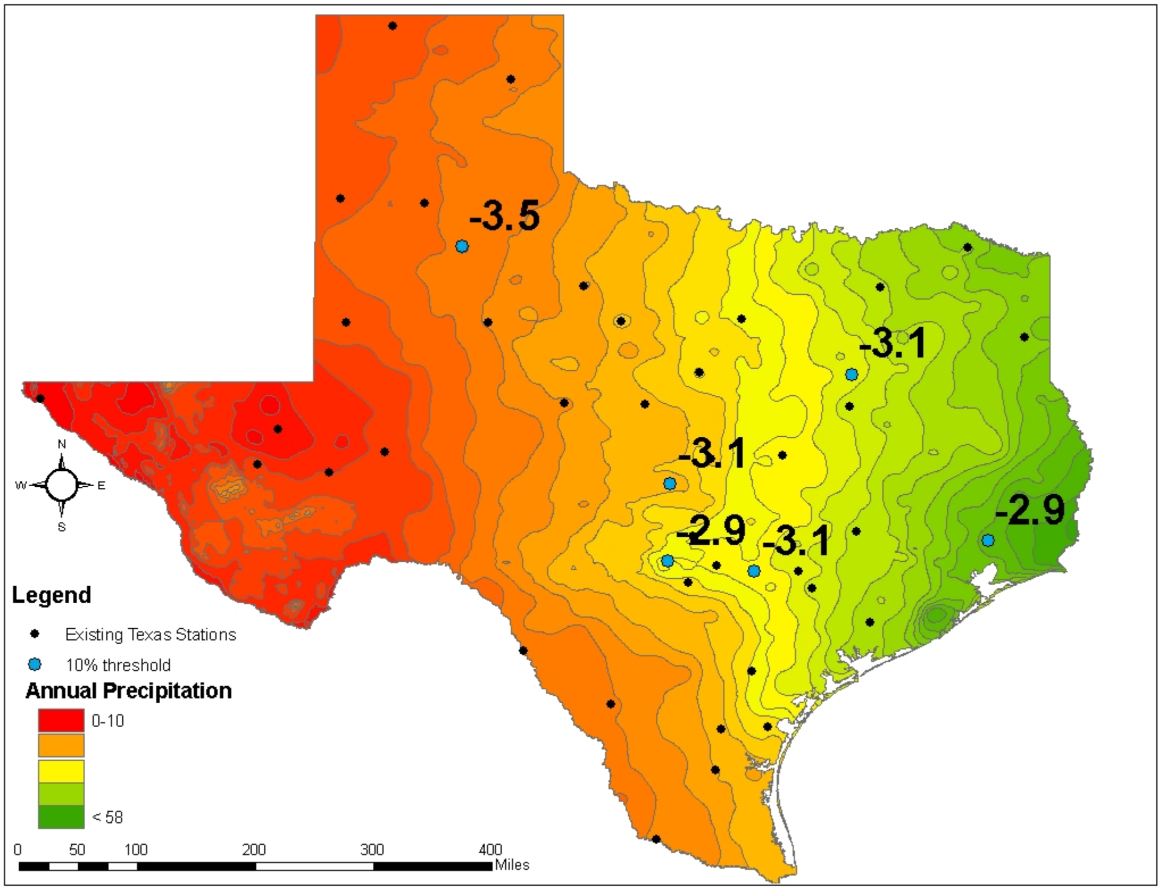


Figure 46 Thresholds for extreme drought (5th percentile) based on PDSI

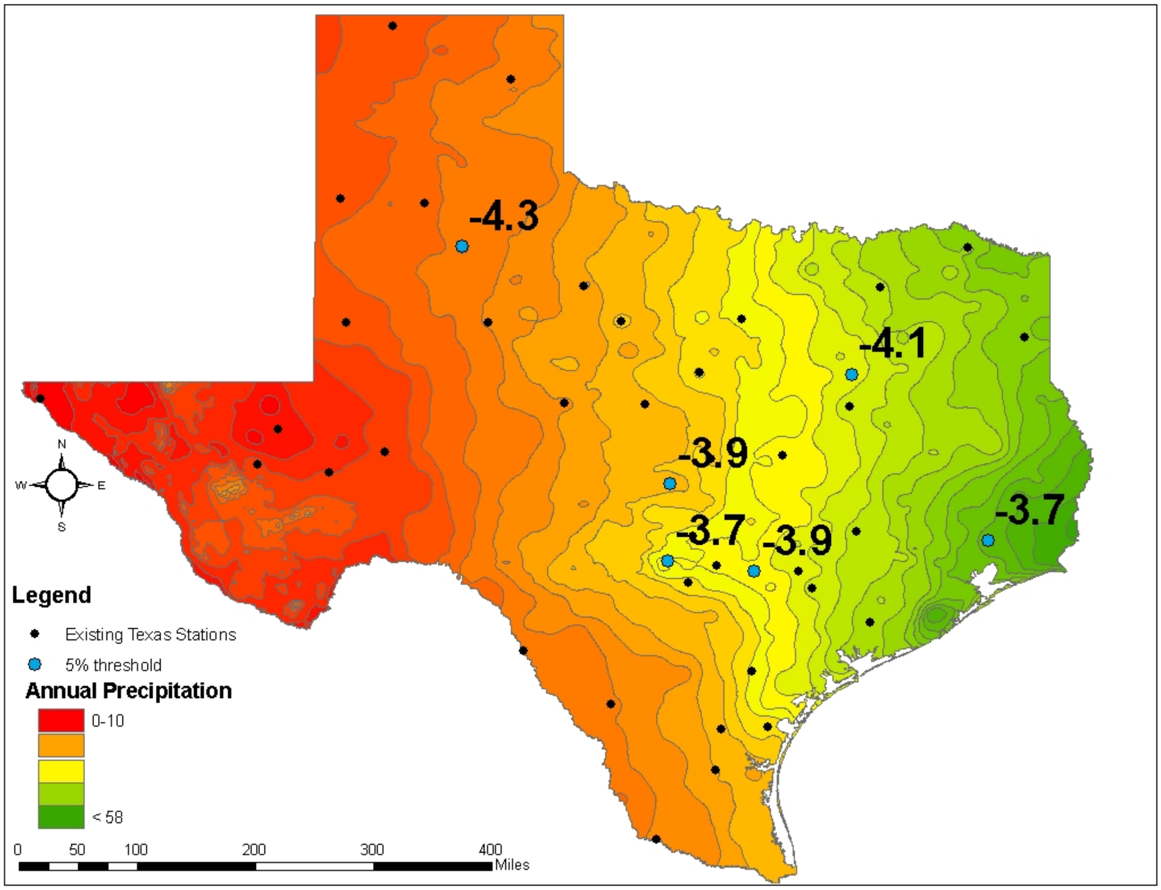
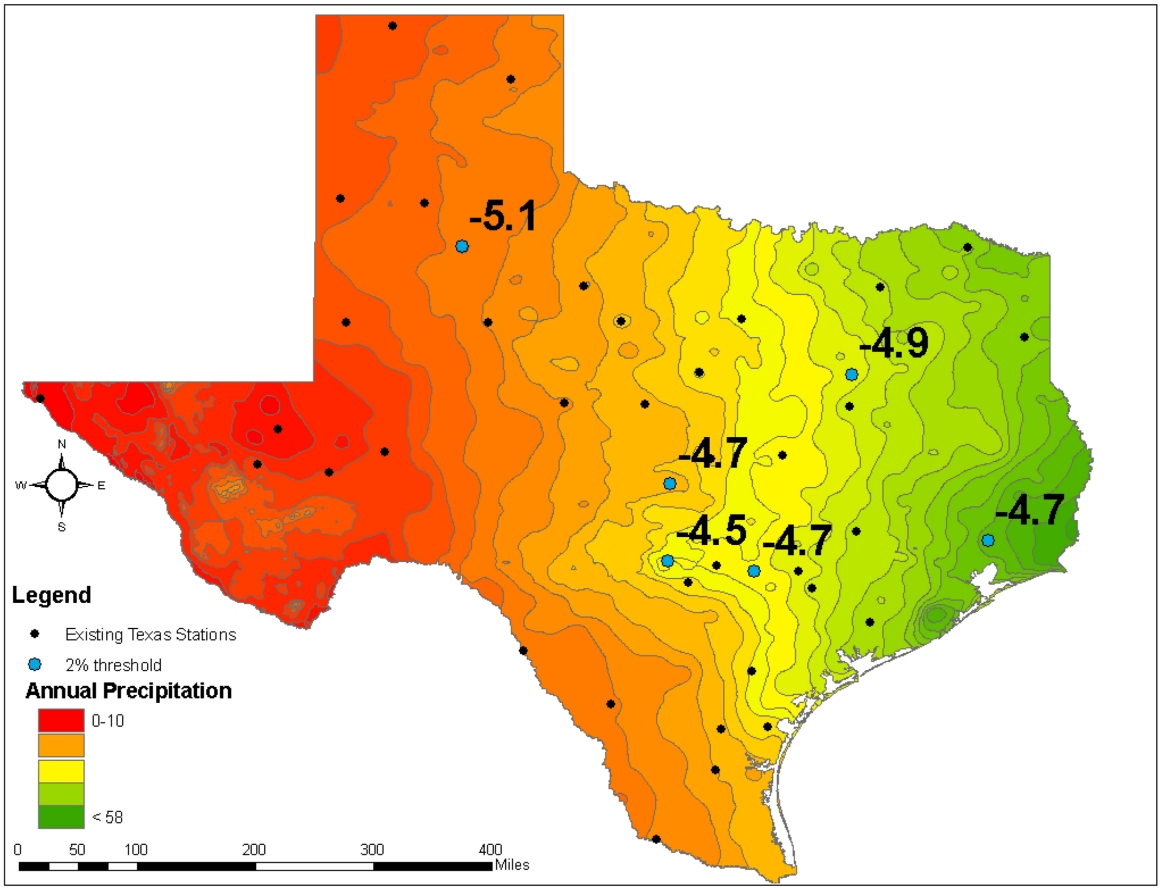


Figure 47 Thresholds for exceptional drought (2nd percentile) based on PDSI



SPI

SPI data for the six stations were also fit using the normal, gamma, lognormal, and exponential distributions (Figure 48). The KS Lilliefors test was applied to test how well these distributions fit the SPI data (Table 49). Based on the results from these six stations, it appears that the normal distribution fits the SPI data extremely well. This is not surprising given that the SPI is normalized as part of the calculation procedure. The fitted normal distribution was used to determine the drought thresholds for the five US Drought Monitor drought classes (Table 50). It is evident that there are some small variations in drought thresholds across these stations. The SPI drought thresholds are relatively consistent for moderate drought (they range from -0.75 to -0.80) (Figure 49). However, according to

McKee, and some of the state drought plans, the threshold for moderate drought is -1.0. For severe drought, the SPI thresholds vary between -1.15 (driest station) to -1.25 (wettest station) (Figure 50). Again, these thresholds are somewhat lower than those defined in the literature (-1.5). There is also some more variation in the thresholds for extreme drought (from -1.50 (driest station) to -1.60 (wettest station)) and again all of these thresholds (particularly at the driest station) are much less than those used in the literature (< -2.0) (Figure 51). Finally, there is the largest degree of difference between the stations for exceptional drought (from -1.85 (driest station) to -2.00 (wettest station)) (Figure 52). It is evident that, even though the SPI is a standardized index (and one that is normally distributed), the drought thresholds are not consistent across Texas, particularly for the extreme and exceptional drought. This suggests that no matter what drought index is used, it is necessary to develop appropriate thresholds using local data. Using a single drought threshold for the state is inappropriate.

Table 49 KS statistic for 1-month SPI after being fit using normal, gamma, lognormal, and exponential PDFs

Station	Gamma	Normal	Lognormal	Exponential
410902	0.103	0.017	0.582	0.450
412019	0.100	0.018	0.583	0.445
412121	0.077	0.030	0.648	0.475
415196	0.131	0.024	0.564	0.447
415272	0.086	0.021	0.611	0.454
415429	0.128	0.021	0.572	0.449

Figure 48 Cumulative probability distribution for 1-month SPI (station 410902) showing the empirical distribution (EDF) and normal, gamma, lognormal, and exponential distributions that were fit to the data

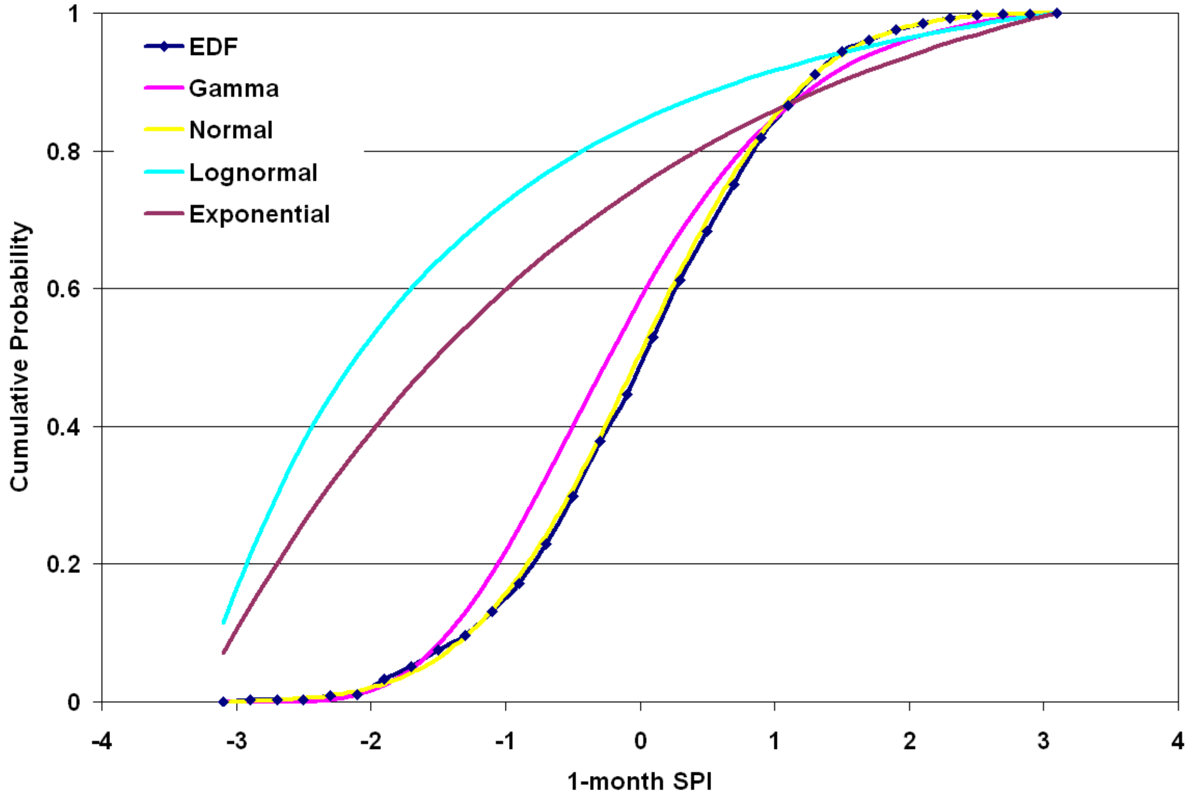


Table 50 Drought thresholds for 1-month SPI calculated using the normal distribution

Station	D0	D1	D2	D3	D4
410902	-0.50	-0.80	-1.25	-1.60	-2.00
412019	-0.50	-0.80	-1.20	-1.55	-1.95
412121	-0.45	-0.75	-1.15	-1.50	-1.85
415196	-0.50	-0.85	-1.25	-1.60	-2.00
415272	-0.45	-0.75	-1.20	-1.55	-1.90
415429	-0.50	-0.80	-1.25	-1.60	-2.00

Figure 49 Thresholds for moderate drought (20th percentile) based on SPI

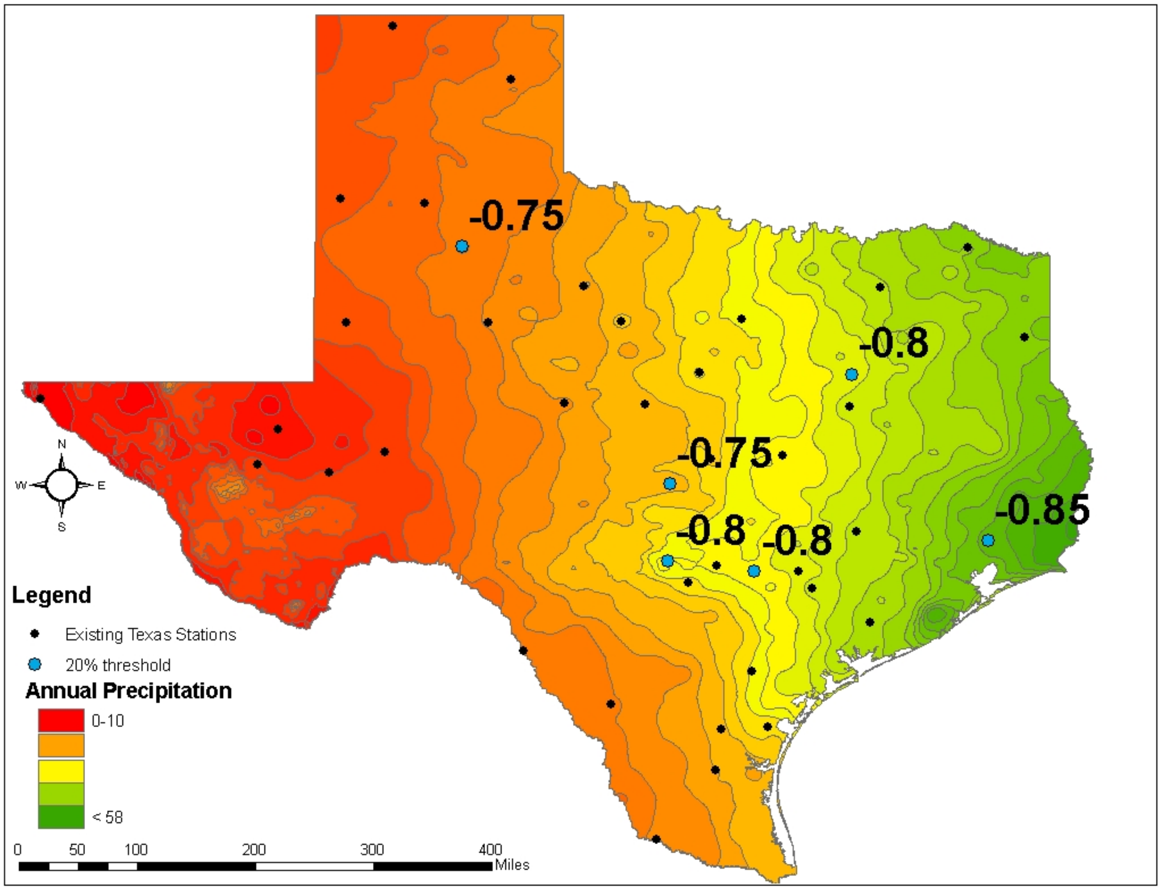


Figure 50 Thresholds for severe drought (10th percentile) based on SPI

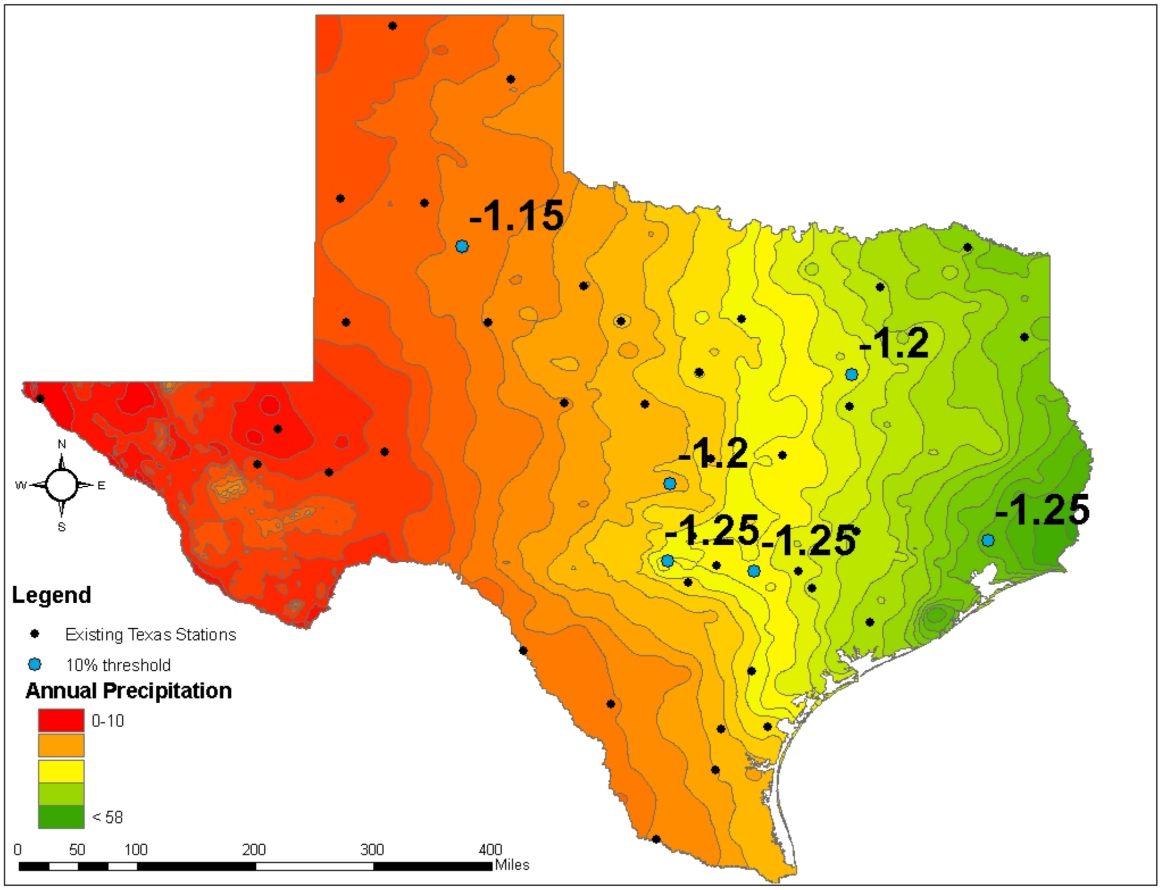


Figure 51 Thresholds for extreme drought (5th percentile) based on SPI

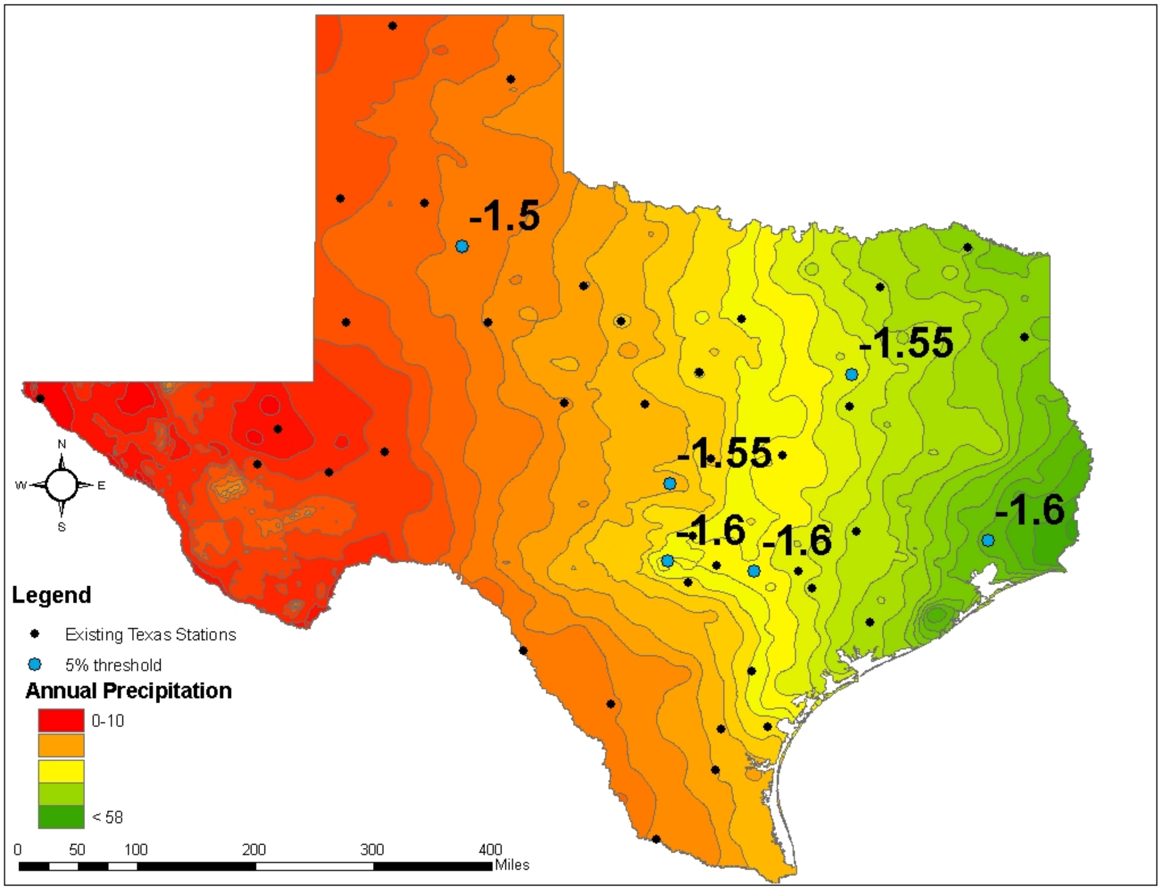
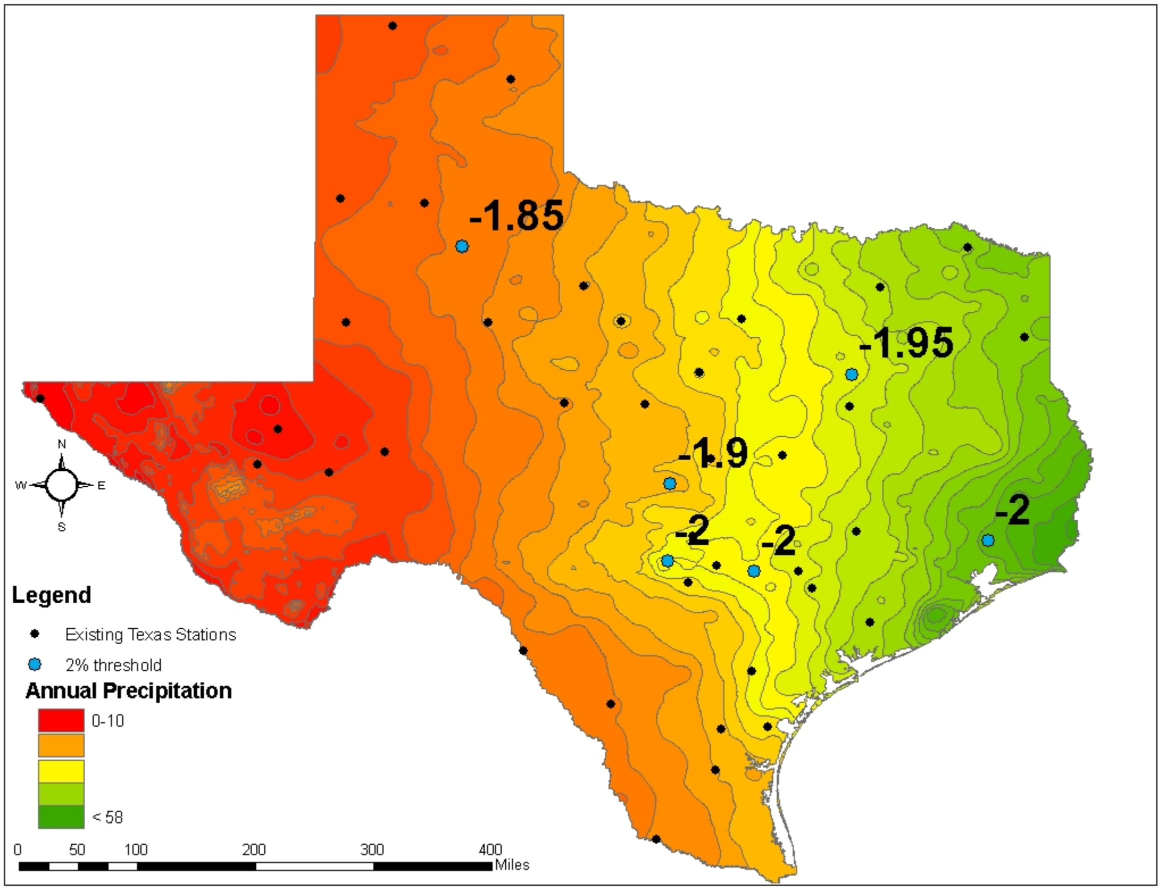


Figure 52 Thresholds for exceptional drought (2nd percentile) based on SPI



5.0 TASK 4: GUIDELINES FOR REPORTING MOISTURE (DROUGHT) CONDITIONS AT THE LOCAL LEVEL

5.1 Reasons for Local Reporting of Drought

Currently, drought events in Texas are reported as average conditions or a range of conditions within the ten NOAA climate divisions within Texas. Reporting of information on that spatial scale is compatible with most information on drought generated by NOAA, which developed the climate divisions specifically for the purpose of monitoring seasonal and inter-annual fluctuations in weather and climate conditions such as drought.

Variations of drought conditions within a climate division, though, can be considerable. The Texas climate divisions are among the largest in the United States, averaging 26,191 square miles in size (Figure 53). During summer 2006, the most severe drought was experienced in north-eastern Texas, which lies within the East Texas climate division. At the same time, the southern portion of the same climate division was experiencing abundant rainfall and was not in a drought situation at all. The nationally-developed indices depicted only weak to moderate drought for the East Texas climate division, an assessment that was not accurate for most sections of the climate division.

The US Drought Monitor, a multi-agency product that is effectively the official depiction of drought status in the United States, is designed to show variations on the climate division scale and larger. In Texas, allowance is made for the unusual size of the climate divisions by an attempt to show smaller-scale variations in drought conditions. Nonetheless, other federal agencies, such as the US Department of Agriculture, require county-level specificity of drought conditions. In their 2006 aid program, the USDA simply offered aid to those counties that happened to lie within the US Drought Monitor depiction of extreme drought, whether or not those counties actually experienced such conditions themselves, and ignored those counties that suffered through extreme drought but that were isolated and not part of the US Drought Monitor depiction.

Figure 53 Climate divisions in the United States.

Specificity finer than the climate-division scale is even more important at the state and local level. For the State of Texas to know which areas are suffering from the effects of drought rather than, say, poor water planning, it is necessary to know drought conditions within a specific water supply, river basin, or agricultural area. This information is needed for current and future drought conditions as well as past drought conditions, so that planners and other stakeholders can know how current situations compare to past extreme events and whether past extreme events were comparable in severity across broad areas.

Most drought actions are taken at the local level. Individual counties issue burn bans based on local drought index values. Water supplies implement water restrictions on the basis of water use within the district or water supply at the water source location(s). Farmers plant and harvest based on weather conditions specific to their location. For optimal use to be made of drought information, the information must be provided at the spatial scale of relevance to the decision-makers.

In the past, such an approach was not entirely practical. The primary source of drought data was NOAA's Cooperative Observer Program (COOP) network, consisting of about 8,000 stations across the United States. Any individual COOP observing station is not likely to representative of regional conditions, so the data from the several stations within a climate division were averaged together. This approach worked well in much of the country, but even so, places with larger-than-normal climate divisions such as Texas could have had climatic conditions reported at a finer regional scale.

Nowadays, tools such as radar and satellite allow drought information to be generated at a much finer local level. Technological challenges exist in combining data from different observing systems or relating observations from new systems to historical events, but it is clear that considerably more local-scale information is being lost now than in the past.

For these reasons, it is appropriate to reconsider the climate division as the standard spatial reporting unit for moisture and drought information.

5.2 Reporting of Drought Information

In Texas, the primary unit for reporting drought information is the climate division. The Texas Water Information Network web site, operated by the Texas Water Development Board, provides climate-division drought index data and other information gathered from national sources (Figure 54). The same web site also posts other locally-generated water information, such as reservoir storage, both in raw form and aggregated to the climate division scale (Figure 55).

One possible approach would be to retain the climate division framework, but utilize Texas-specific, smaller climate divisions. Rainfall and other drought information would still be computed by straight averages of observations within climate divisions, but the divisions themselves would be smaller and better represent local conditions.

Figure 54 Palmer Drought Severity Index values for climate divisions in Texas, as depicted by the Texas Water Development Board. Web site: http://www.txwin.net/Monitoring/Meteorological/Drought/pdsi.htm

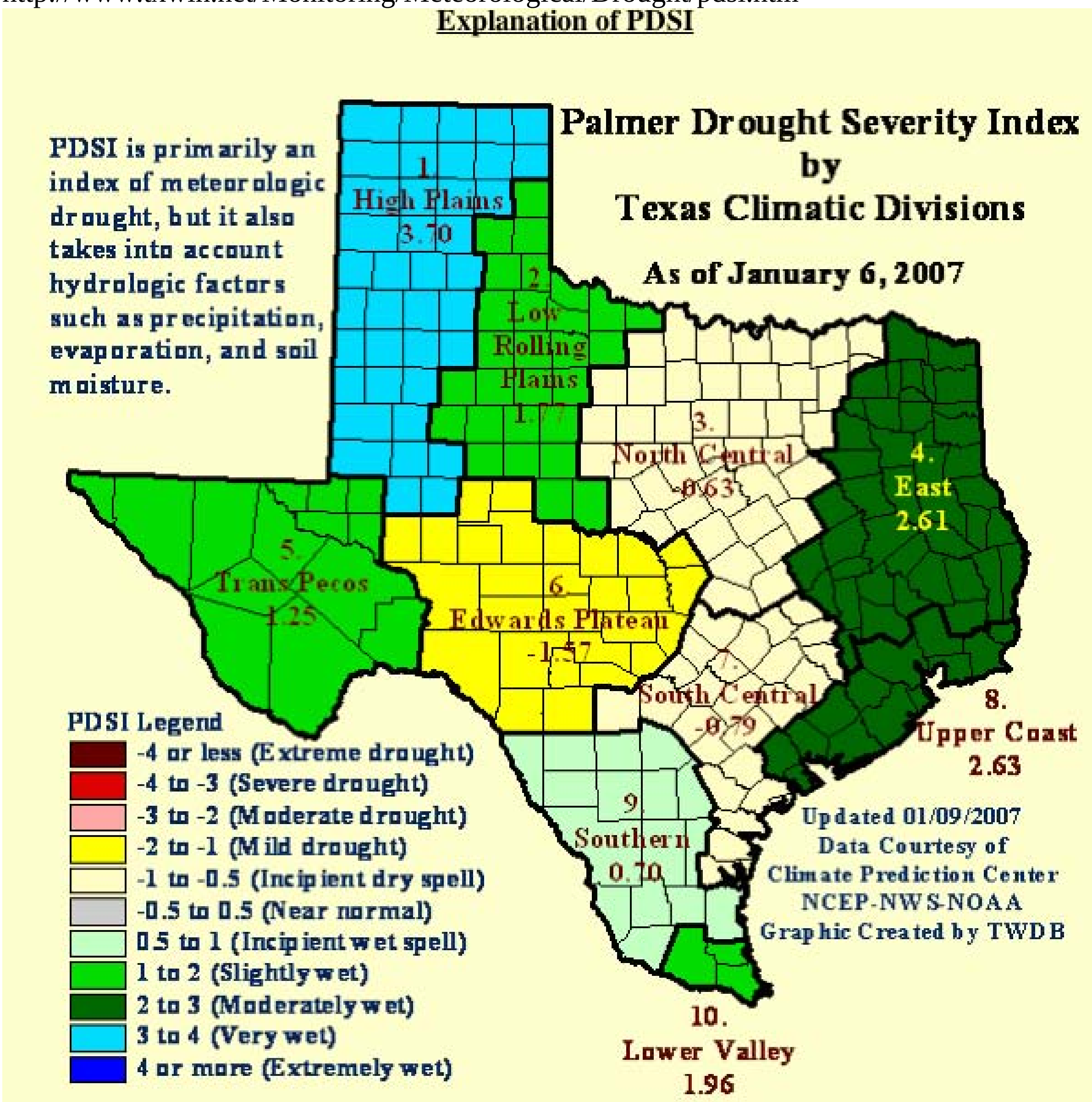
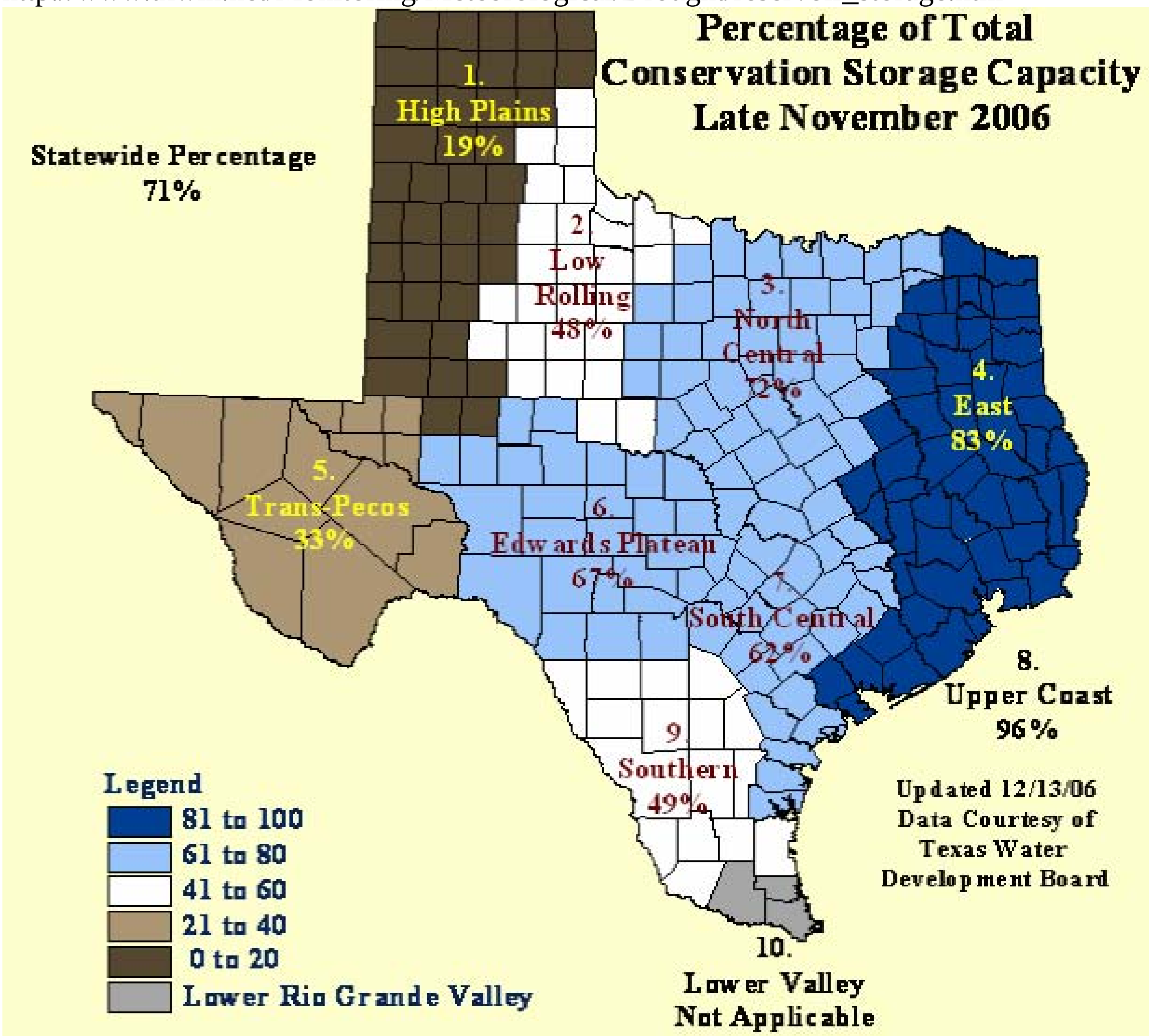
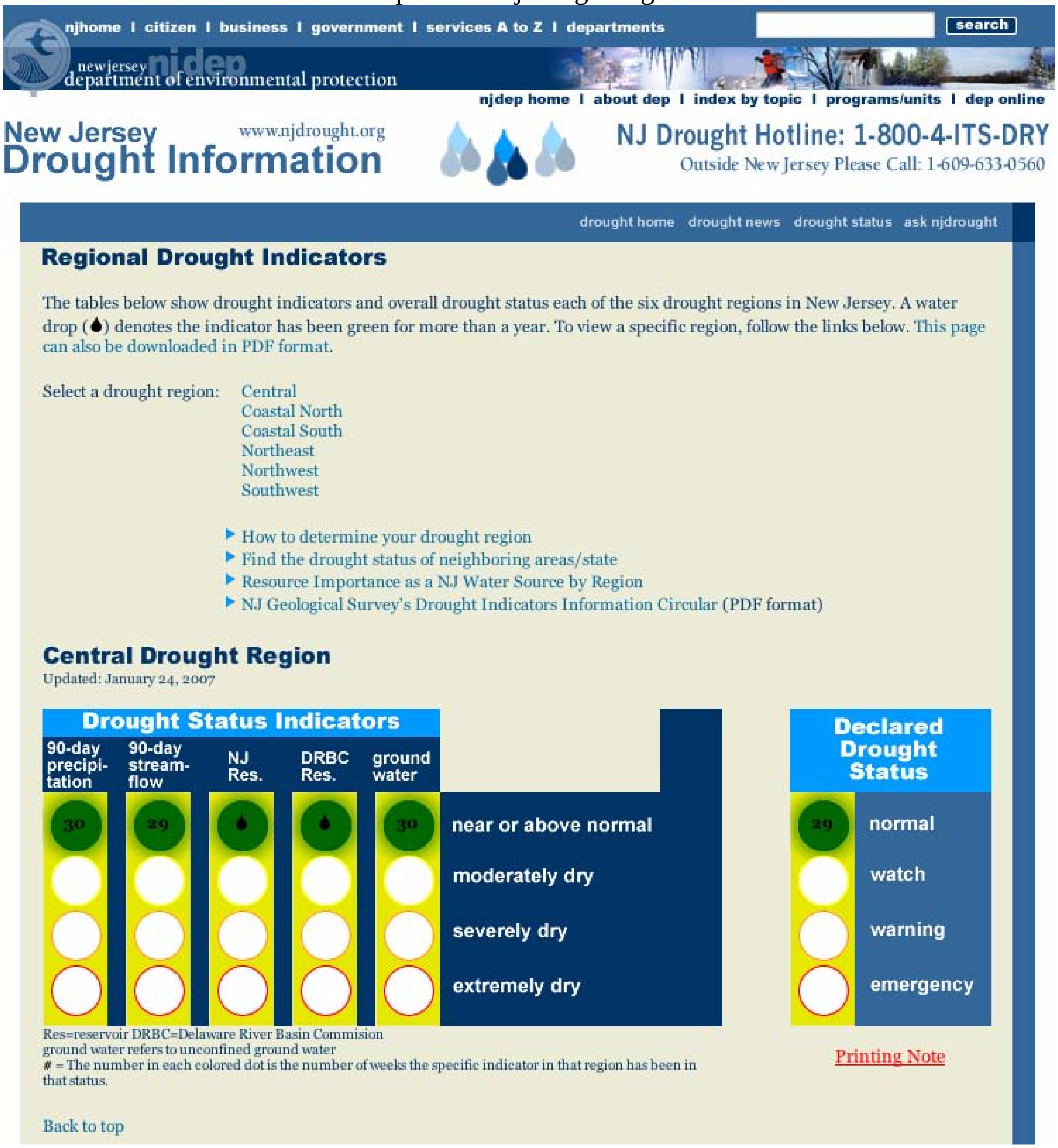


Figure 55 Reservoir storage values for climate divisions in Texas, as computed by the Texas Water Development Board. Web site: http://www.txwin.net/Monitoring/Meteorological/Drought/reservoir_storage.htm



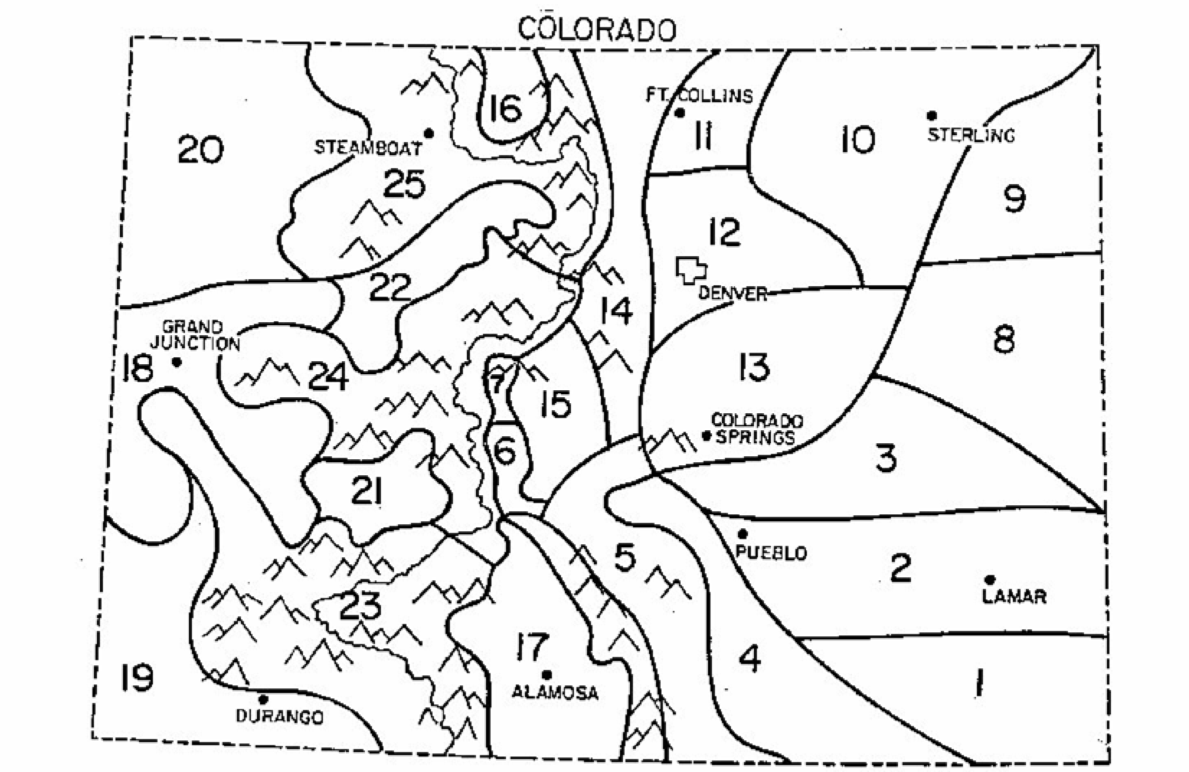
New Jersey has implemented one such modification of climate divisions. Their drought reporting regions are subdivisions of the existing climate divisions. Various drought indicators, both meteorological and hydrological, are computed and reported on a subdivision-wide basis (Figure 56).

Figure 56 A portion of New Jersey's drought information web site, reporting information by climate sub-division. Web site: http://www.njdrought.org/status.html



Colorado, whose climate divisions are on average even larger than those of Texas, has taken a different approach. They have developed a completely new set of finer-scale climate divisions. Ignoring the original climate divisions completely, they analyzed station data to determine which nearby stations tended to have similar temperature and precipitation anomalies from year to year. They ended up with 25 climate divisions, on a much finer scale than their original climate divisions. The new, smaller climate divisions are now the primary means for reporting drought indices in Colorado (Figure 57).

Figure 57 Locally-defined climate divisions in Colorado. Web site: http://ccc.atmos.colostate.edu/palmerindex.php



The approach taken by New Jersey has the advantage of allowing the revised data to be easily aggregated upward into the original climate divisions for comparison with other nationally-developed indices. Colorado's approach is more suited to a state such as Colorado in which there are rapid variations in climatic conditions caused by the local topography. The topographically-induced climatic variations in Texas are much smaller than those in Colorado, except in parts of West Texas, so there would be no need to abandon the existing climate division boundaries when creating subdivisions.

Subdivisions such as these, though, suffer from an important deficiency: they would not correspond to any particular user needs. No planning, water supply, or emergency relief decisions are presently made on a subdivision scale, so providing drought information for subdivisions would not be as useful as the selection of other finer-scale geographical divisions with more direct relevance to water decisions.

There are numerous other jurisdictional or political divisions within the State of Texas. Some such divisions, such as regional water planning districts and agricultural districts, are potentially more useful than simple climate district subdivisions. However, such divisions are generally application-specific and would not be especially useful for drought planners not specifically tied to that particular application.

The only small-scale political subdivision of relevance to a wide range of policy and decision makers in Texas is the county. Elsewhere in the United States, the county is being used as the basic geographical information for water usage. The NWS's Mid-Atlantic River Forecast Center reports county-wide values of accumulated precipitation and percentage of normal on a variety of time scales, both spatially (Figure 58) and in individual climate status reports (Figure 59). Pennsylvania uses this data to generate time series graphs that show the relevant precipitation deficiencies and the extent to which such precipitation deficiencies are unusual (Figure 60).

Figure 58 Precipitation reported on a county basis by the Mid-Atlantic River Forecast Center. Web site: http://www.erh.noaa.gov/er/marfc/Maps/precip.html

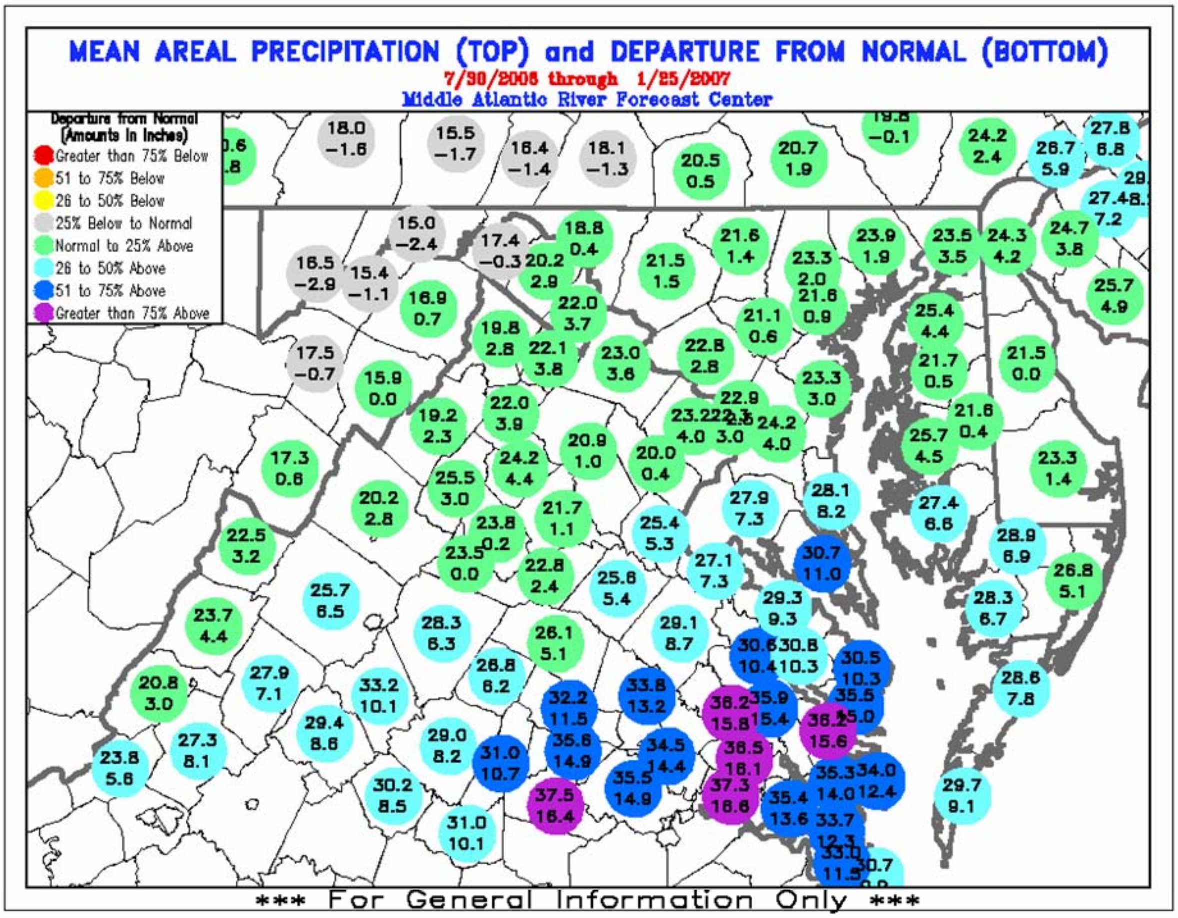
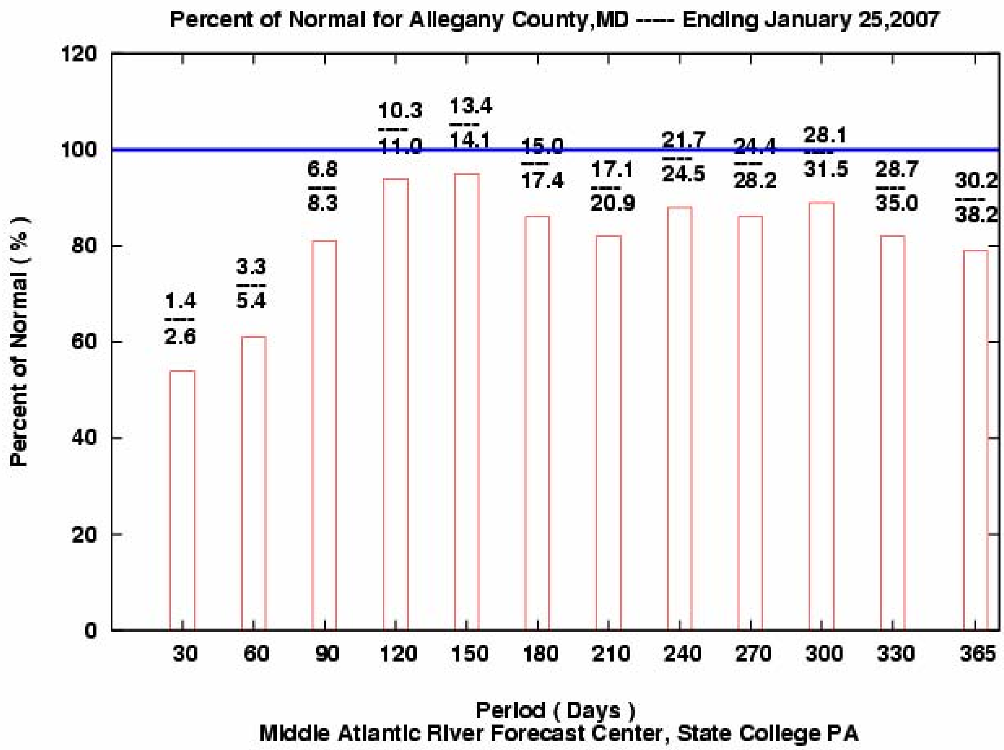


Figure 59 Recent precipitation history analysis on a county basis by the Mid-Atlantic River Forecast Center. Web site: http://www.erh.noaa.gov/marfc/Maps/barcharts/Allegany.MD.html

Percent of Normal Barchart for Allegany County, MD

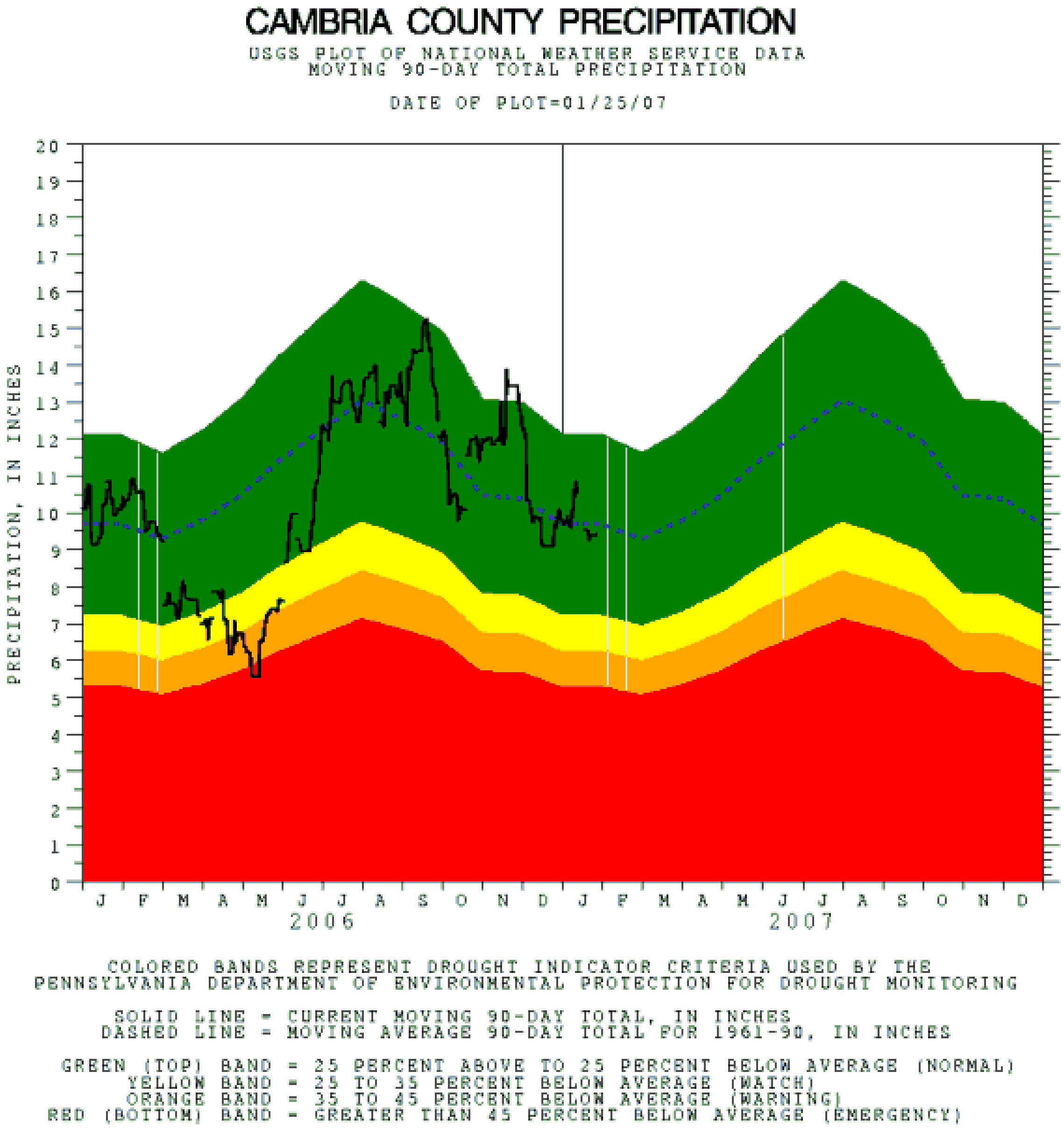
Key to this graph



Supporting data for barchart ... Allegany County, MD

Starting Date	Ending Date	# of Days	Actual Pcpn	Normal Pcpn	Surplus / Deficit	% of Normal
12/27/06	01/25/07	30	1.4	2.6	-1.2	54
11/27/06	01/25/07	60	3.3	5.4	-2.1	61
10/28/06	01/25/07	90	6.8	8.3	-1.5	81
09/28/06	01/25/07	120	10.3	11.0	-0.7	94
08/29/06	01/25/07	150	13.4	14.1	-0.7	95
07/30/06	01/25/07	180	15.0	17.4	-2.4	86
06/30/06	01/25/07	210	17.1	20.9	-3.8	82
05/31/06	01/25/07	240	21.7	24.5	-2.8	88
05/01/06	01/25/07	270	24.4	28.2	-3.8	86
04/01/06	01/25/07	300	28.1	31.5	-3.4	89
03/02/06	01/25/07	330	28.7	35.0	-6.2	82
01/26/06	01/25/07	365	30.2	38.2	-8.0	79

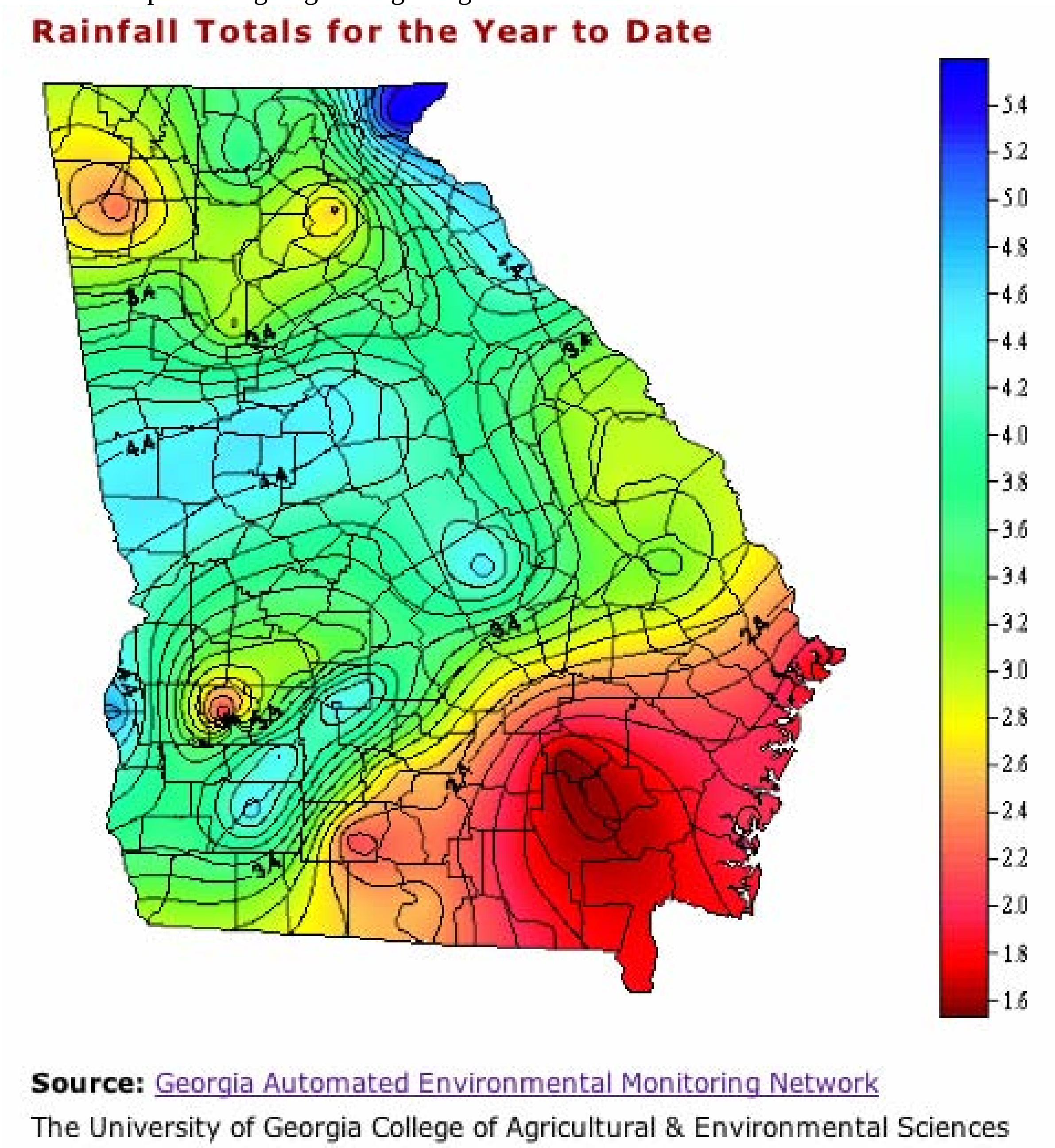
Figure 60 Time series analysis of precipitation record by county, by the United States Geological Survey in Pennsylvania. Web site: http://pa.water.usgs.gov/monitor/all_precip2.php



A different approach to the reporting of moisture and drought information is to create analyses and products that are essentially spatially continuous. This can be done from discrete, individual station-based observations through a process known as objective analysis. Some objective analysis techniques, such as Kriging, are constrained to agree exactly with observations at the observation locations. Other objective analysis techniques effectively use a weighted average of several observations throughout the analysis domain, thereby conveying the reliability benefits of regional station aggregation while allowing that aggregation to continuously change by location.

Georgia (Figure 61) performs spatial analysis of precipitation using conventional observations. The analysis is constrained to agree exactly with observations, and the observation locations are apparent in the figure. Because many portions of the state are sparsely observed, the rainfall pattern produced by the analysis is significantly influenced by the analysis scheme.

Figure 61 Georgia performs spatial analyses of precipitation over various time windows. Web site: http://www.georgiadrought.org/



Colorado also performs spatial analysis of precipitation, but here the analysis is not constrained to match observations so the analysis is smoother and more representative. Going beyond this, Colorado converts the continuous precipitation analysis into a continuous analysis of a precipitation-based drought index, the SPI, for a range of time intervals. Even more valuable is the regular calculation of likely future values of SPI, under the contingencies of low, middling, and high values of precipitation (Figure 62). The resulting plots show these SPI values with a continuous spatial distribution, just like the precipitation analyses from which they originated (Figure 63).

Figure 62 An example of Colorado's spatially-continuous projected value of SPI. Web site: http://ccc.atmos.colostate.edu/spi/current/spi_24mon_12_0.2.gif

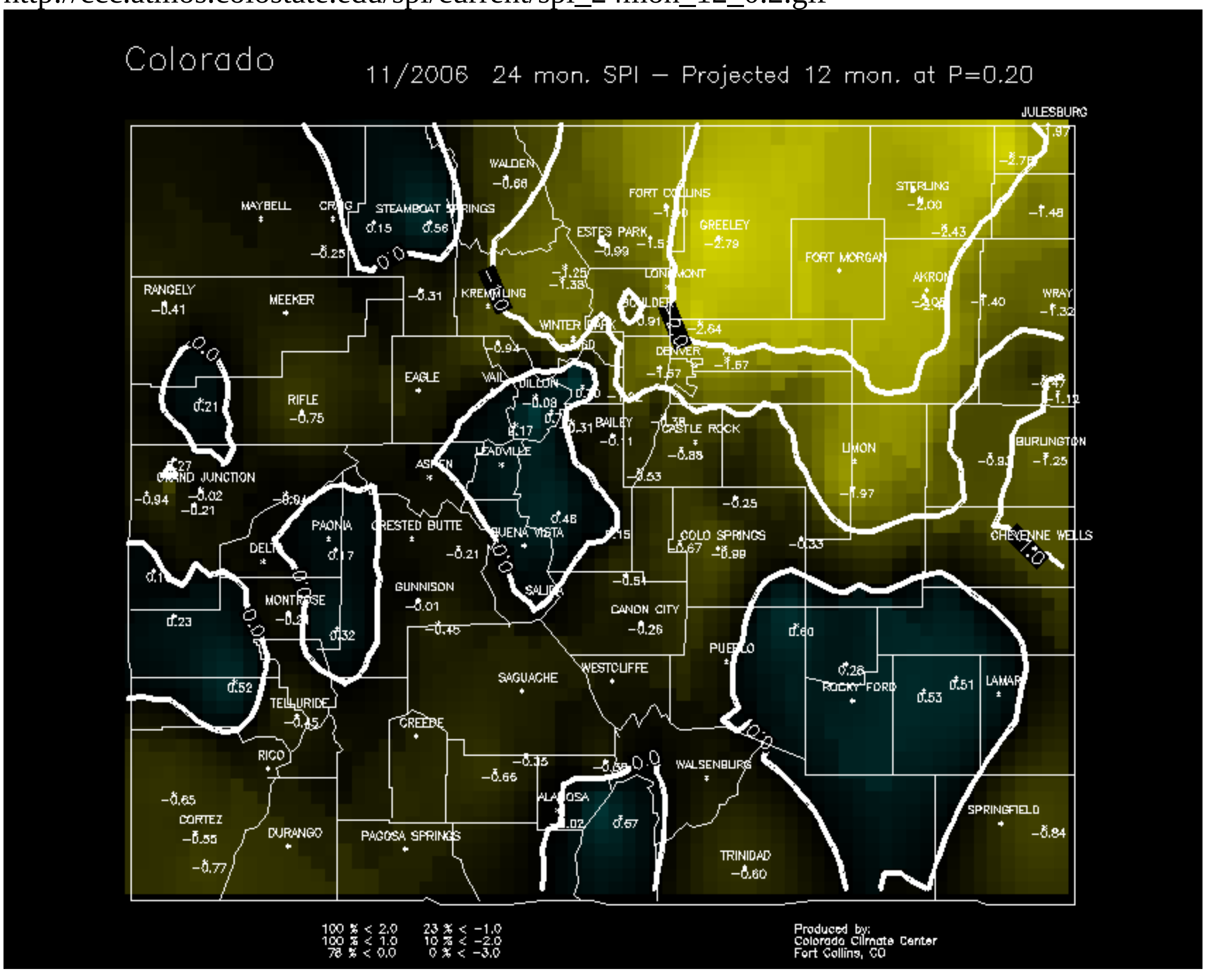


Figure 63 Colorado's SPI monitoring web site, using spatially continuous precipitation analyses. Web site: http://ccc.atmos.colostate.edu/standardizedprecipitation.php

Standardized Precipitation Maps

Introduction

The Standardized Precipitation Index (SPI) was developed for the purpose of defining and monitoring drought. Among others, the Colorado Climate Center, the Western Regional Climate Center, and the National Drought Mitigation Center use the SPI to monitor current states of drought in the United States.

For more information on the methodology behind SPI, click on either a PostScript version or an Adobe PDF version of Chapter 3 of Dan Edwards' Masters Thesis. This document details the mathematics used in SPI calculation.

For source code for a simple SPI program, click here for Unix tar format or zip format.

SPI Archive

2002	2003	2004	2005	2006
January	January	January	January	January
February	February	February	February	February
March	March	March	March	March
April	April	April	April	April
May	May	May	May	May
June	June	June	June	June
July	July	July	July	July
August	August	August	August	August
September	September	September	September	September
October	October	October	October	October
November	November	November	November	November
December	December	December	December	

Latest Conditions

- 3 month SPI
- 6 month SPI
- 12 month SPI
- 24 month SPI
- 48 month SPI

Projected Conditions at 0.2 Probability Level

- 3 month SPI projected 1 month
- 6 month SPI projected 2 months
- 12 month SPI projected 4 months
- 12 month SPI projected 6 months
- 24 month SPI projected 6 months
- 24 month SPI projected 12 months
- 48 month SPI projected 6 months
- 48 month SPI projected 12 months

Projected Conditions at 0.5 Probability Level

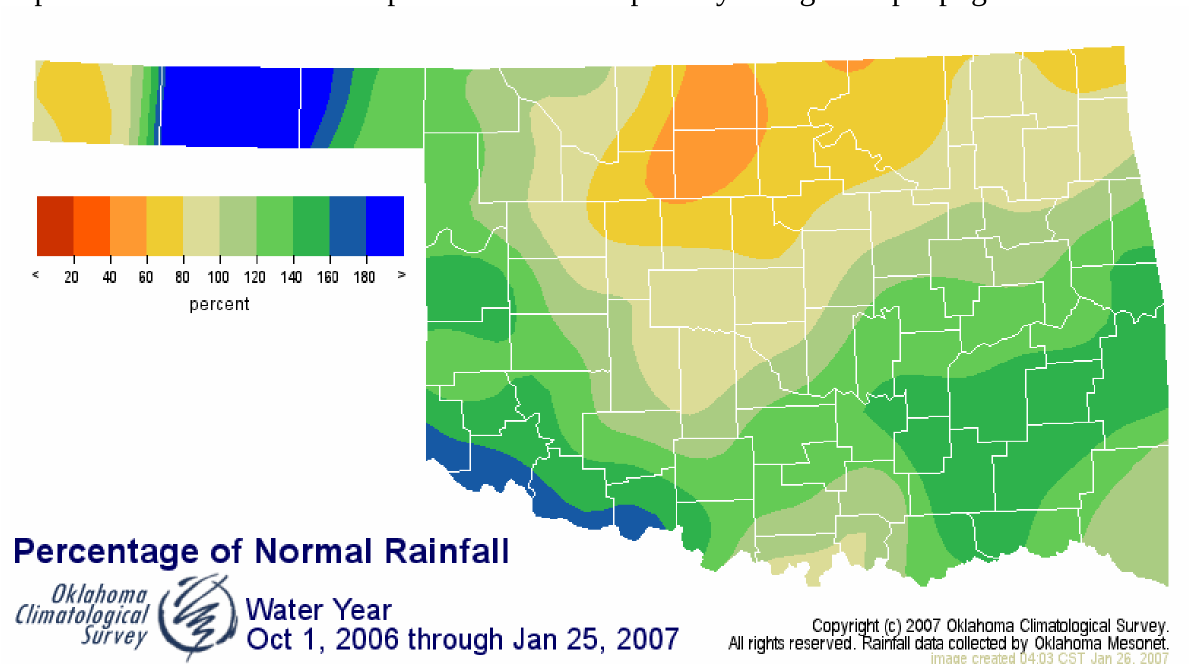
- 3 month SPI projected 1 month
- 6 month SPI projected 2 months
- 12 month SPI projected 4 months
- 12 month SPI projected 6 months
- 24 month SPI projected 6 months
- 24 month SPI projected 12 months
- 48 month SPI projected 6 months
- 48 month SPI projected 12 months

Projected Conditions at 0.8 Probability Level

- 3 month SPI projected 1 month
- 6 month SPI projected 2 months
- 12 month SPI projected 4 months
- 12 month SPI projected 6 months
- 24 month SPI projected 6 months
- 24 month SPI projected 12 months
- 48 month SPI projected 6 months
- 48 month SPI projected 12 months

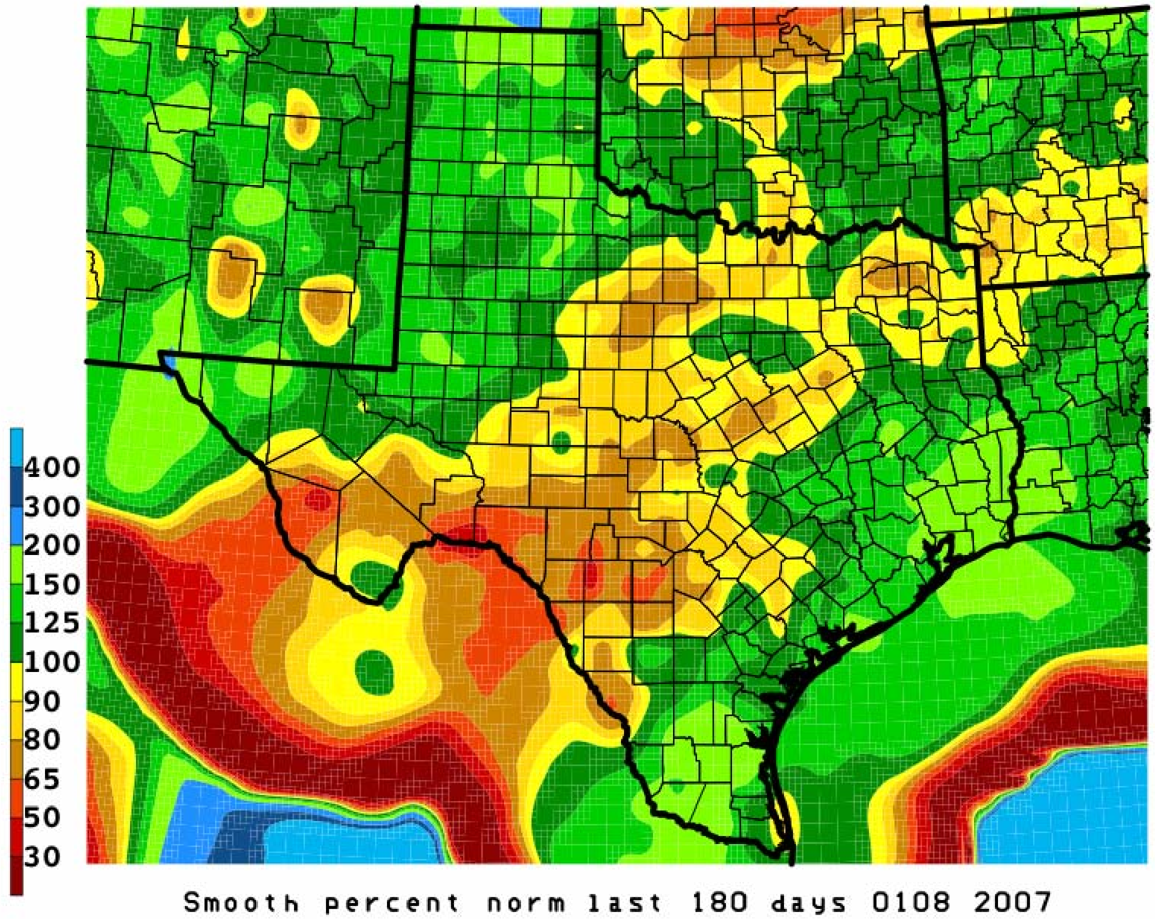
With its statewide mesonet, Oklahoma can produce fairly detailed observation-based continuous analyses of precipitation. Oklahoma has at least one mesonet rain gauge per county, but rather than assume that an individual gauge observation represents conditions across an entire county, an objective analysis is performed to produce a continuous rainfall field. Simple derived products are available as well, such as percent of normal precipitation (Figure 64).

Figure 64 Analysis of percent of normal precipitation in Oklahoma. Web site: http://climate.ocs.ou.edu/data/public/mesonet/maps/daily/drought/wtrpct.png



Similar products are produced by the Texas State Climatologist for the Texas Drought Preparedness Council. Daily precipitation analyses are obtained from the Climate Prediction Center and remapped to depict Texas conditions. Derived products are also available, such as a smoothed percent of normal map that weights recent rainfall more heavily (Figure 65).

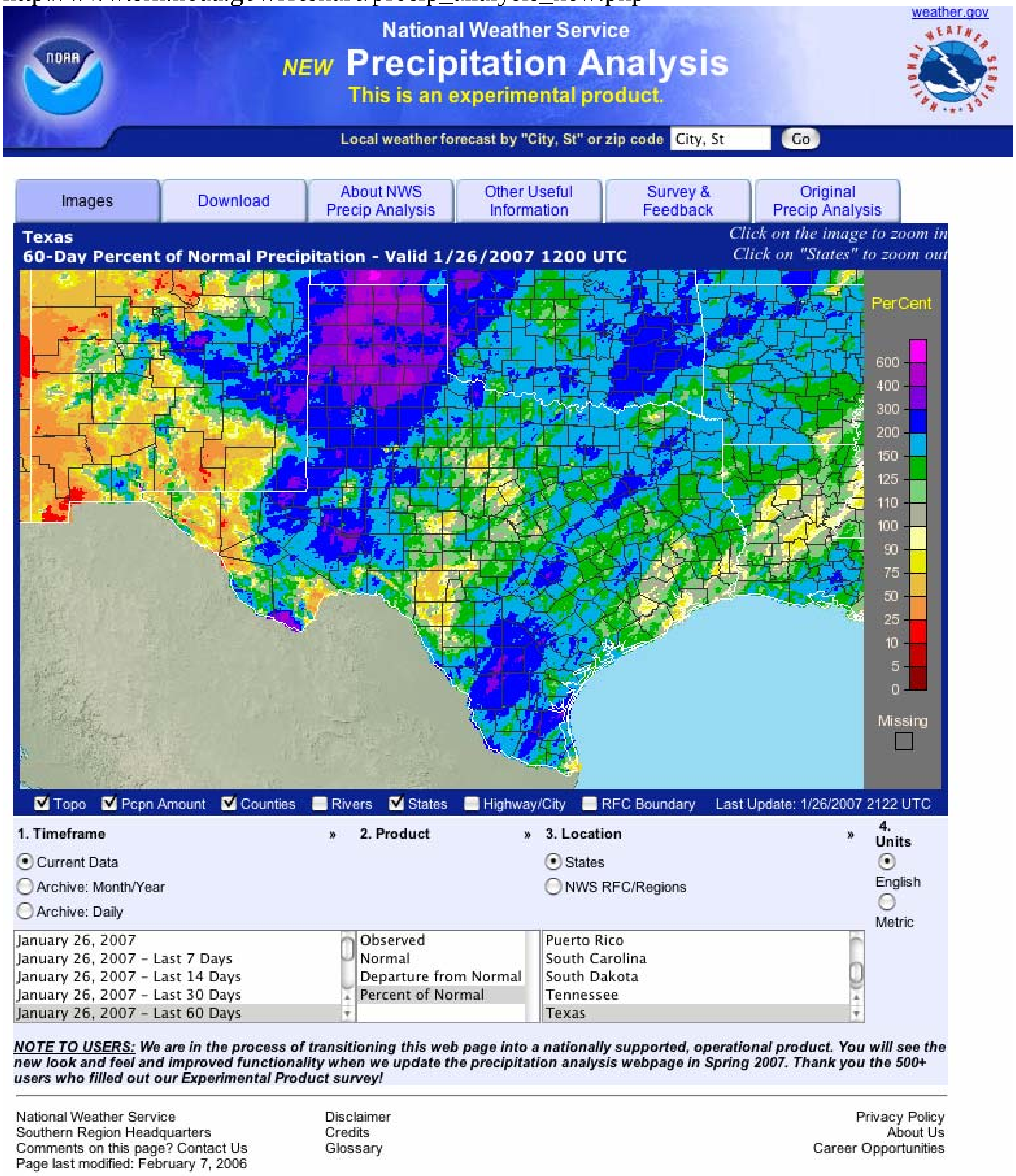
Figure 65 Analysis of smoothed percent of normal precipitation in Texas and surrounding states, produced by the Texas State Climatologist.



While all of these precipitation analyses are created from rain gauge data, the advent of the WSR-88D radar network makes precipitation analyses at finer scales possible. Radars detect aspects of precipitation related to precipitation intensity, and the resulting precipitation estimates are reported on a 4 km grid across the United States. The amount of detail available is far superior to that of most existing rain gauge networks.

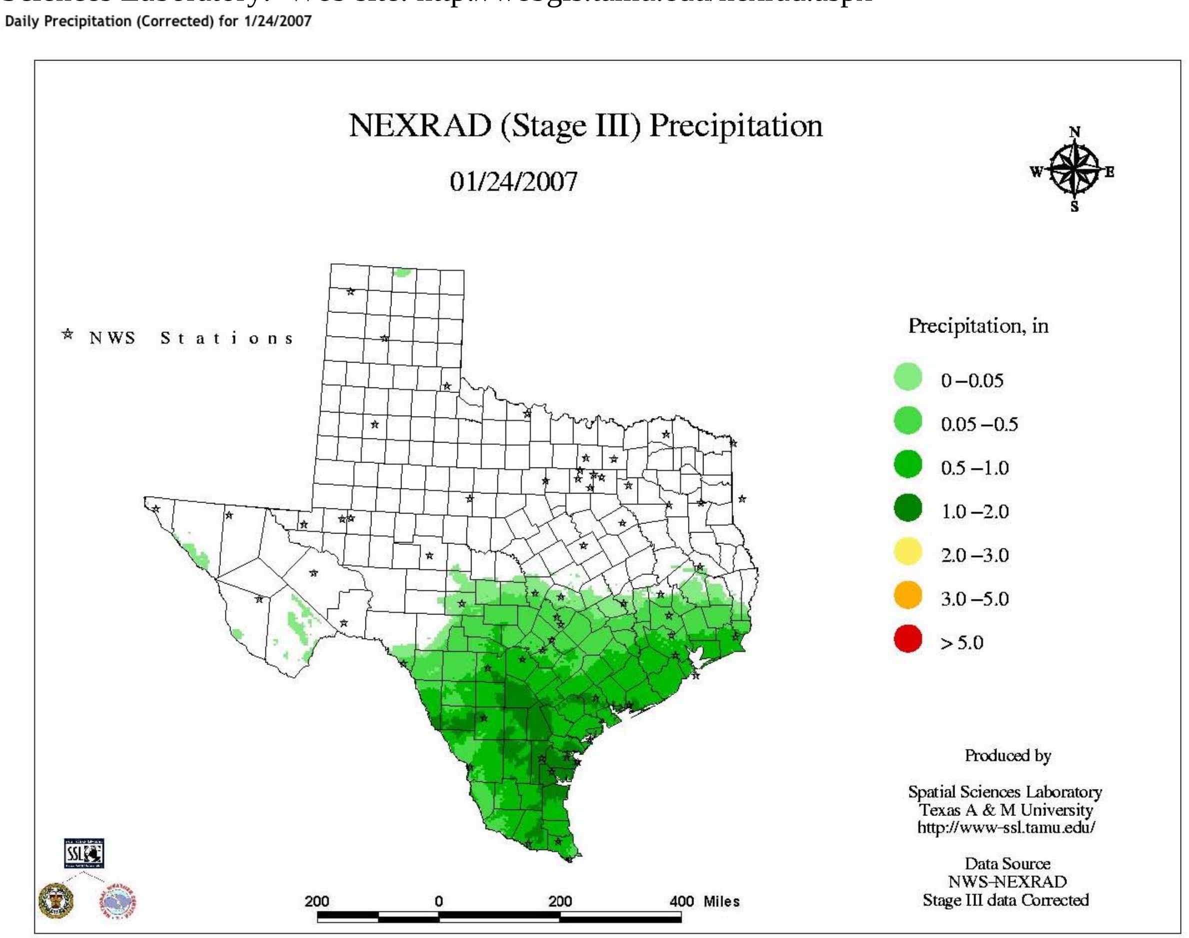
The radar estimates are subject to large biases that are storm-dependent or caused by imperfect coverage of radar scans, so they are not usable directly as indicators of moisture or drought. To compensate for this shortcoming, the NWS applies a "bias correction" by comparing radar precipitation estimates to actual precipitation measurements. The resulting data is plotted and displayed on NWS web sites in the form of accumulated precipitation over a variety of durations and precipitation percentages of normal (Figure 66).

Figure 66 Radar-estimated precipitation web site at the NWS-Southern Region, showing 60-day percentage of normal precipitation for Texas and surrounding states. Web site: http://www.srh.noaa.gov/rfcshare/precip_analysis_new.php



Texas A&M's Spatial Sciences Laboratory (SSL) retrieves these precipitation estimates and provides a separate plotting and archival system. SSL also applies its own bias correction in an attempt to improve the agreement between radar estimates and gauge observations (Figure 67).

Figure 67 Radar-estimated precipitation (gauge-corrected) from the Texas A&M Spatial Sciences Laboratory. Web site: http://webgis.tamu.edu/nexrad.aspx



With the high-resolution precipitation estimates, it is possible to compute drought indices at high resolution as well. Thus far, only firefighting agencies have made significant use of such high-resolution information at the state level. Both Texas and Florida produce KBDI maps at the 4 km resolution provided by the radar-based precipitation estimates. The SSL generated the KBDI maps at full resolution (Figure 68), and also aggregates the KBDI information to the county scale (Figure 69), while Florida provides a zooming functionality for county-scale interpretation (Figure 70).

Figure 68 Keetch-Byram Drought Index, computed at 4 km resolution from gauge-corrected radar-based rainfall estimates, supplied by the Texas Forest Service and generated by the Texas A&M Spatial Sciences Laboratory. Web site: http://webgis.tamu.edu/kbdi.aspx

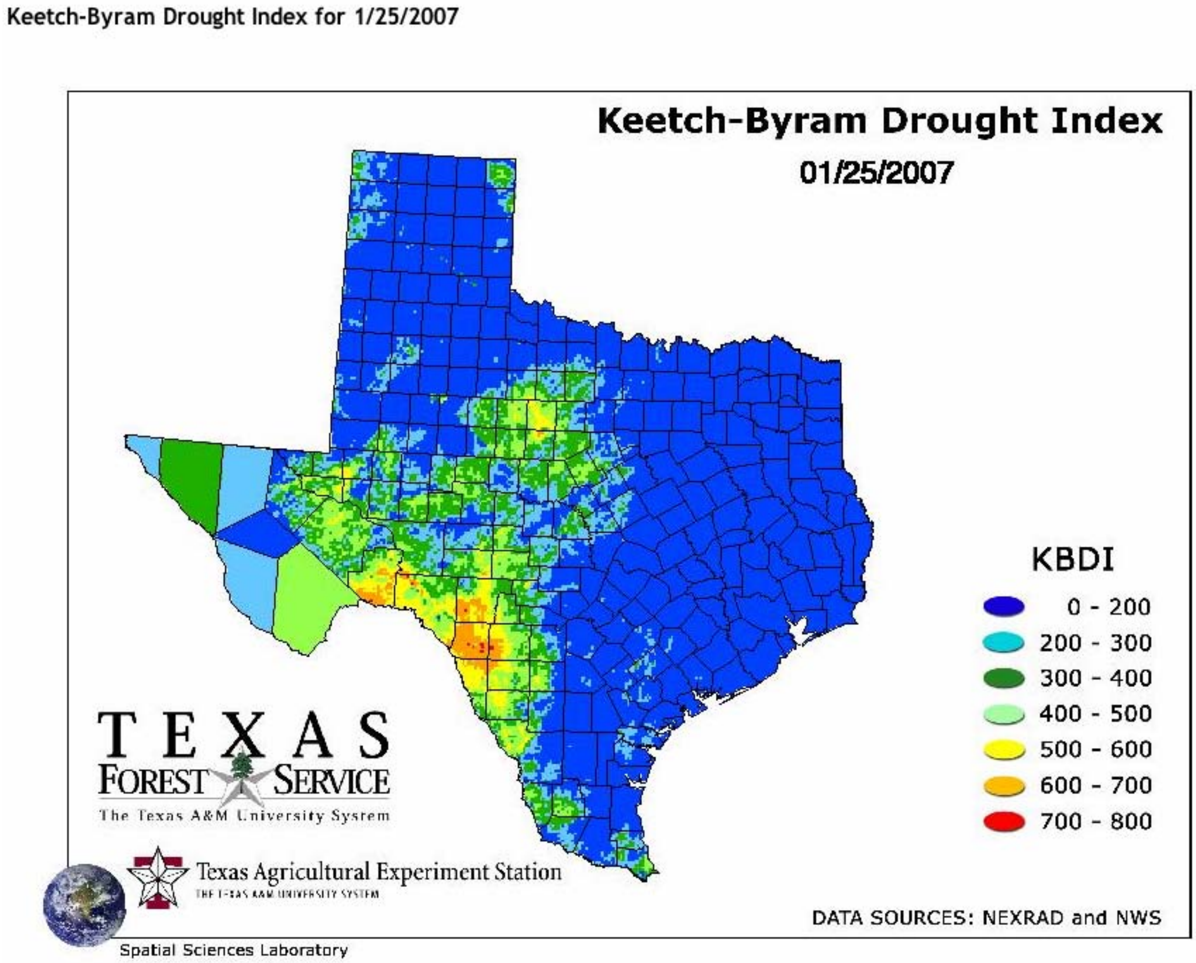


Figure 69 As in the previous figure, but aggregated to the county scale.

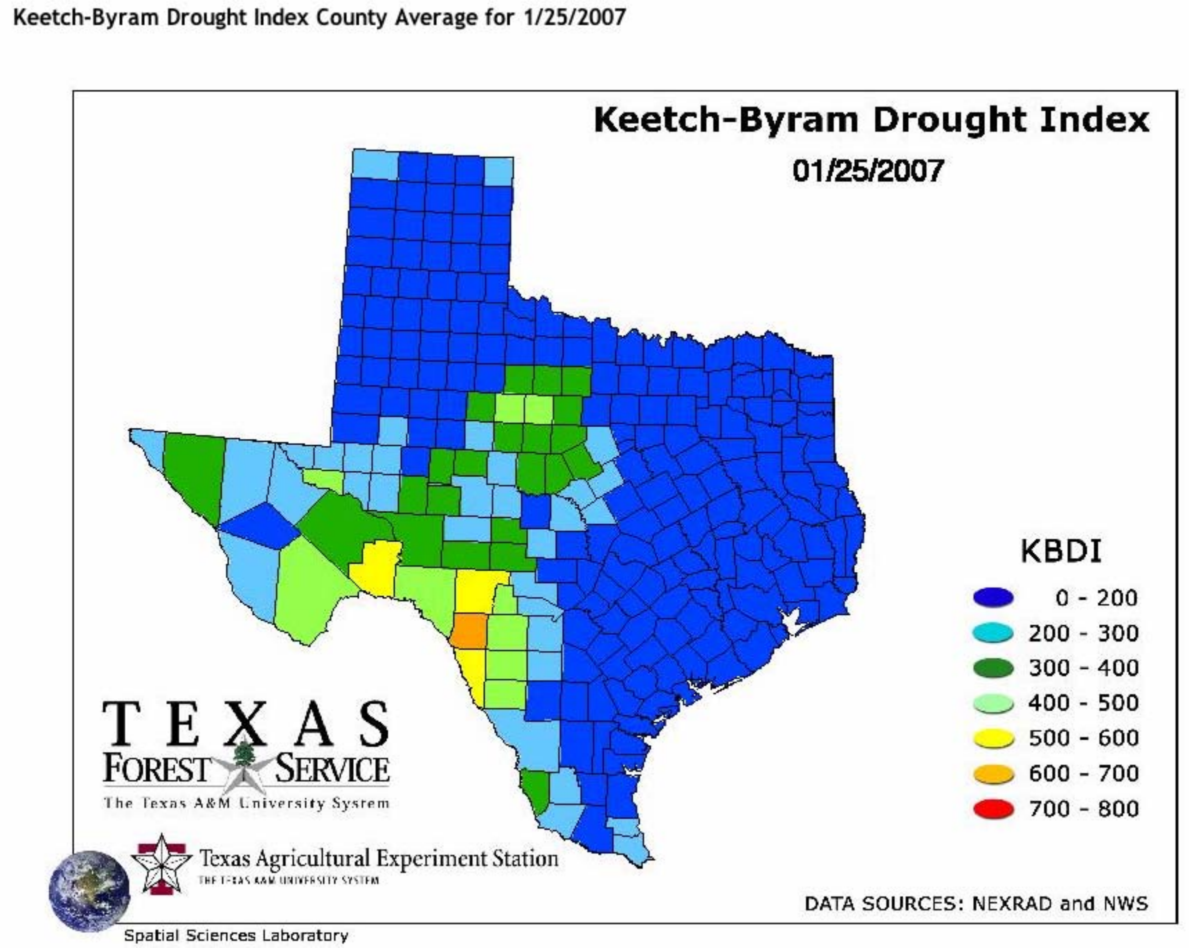
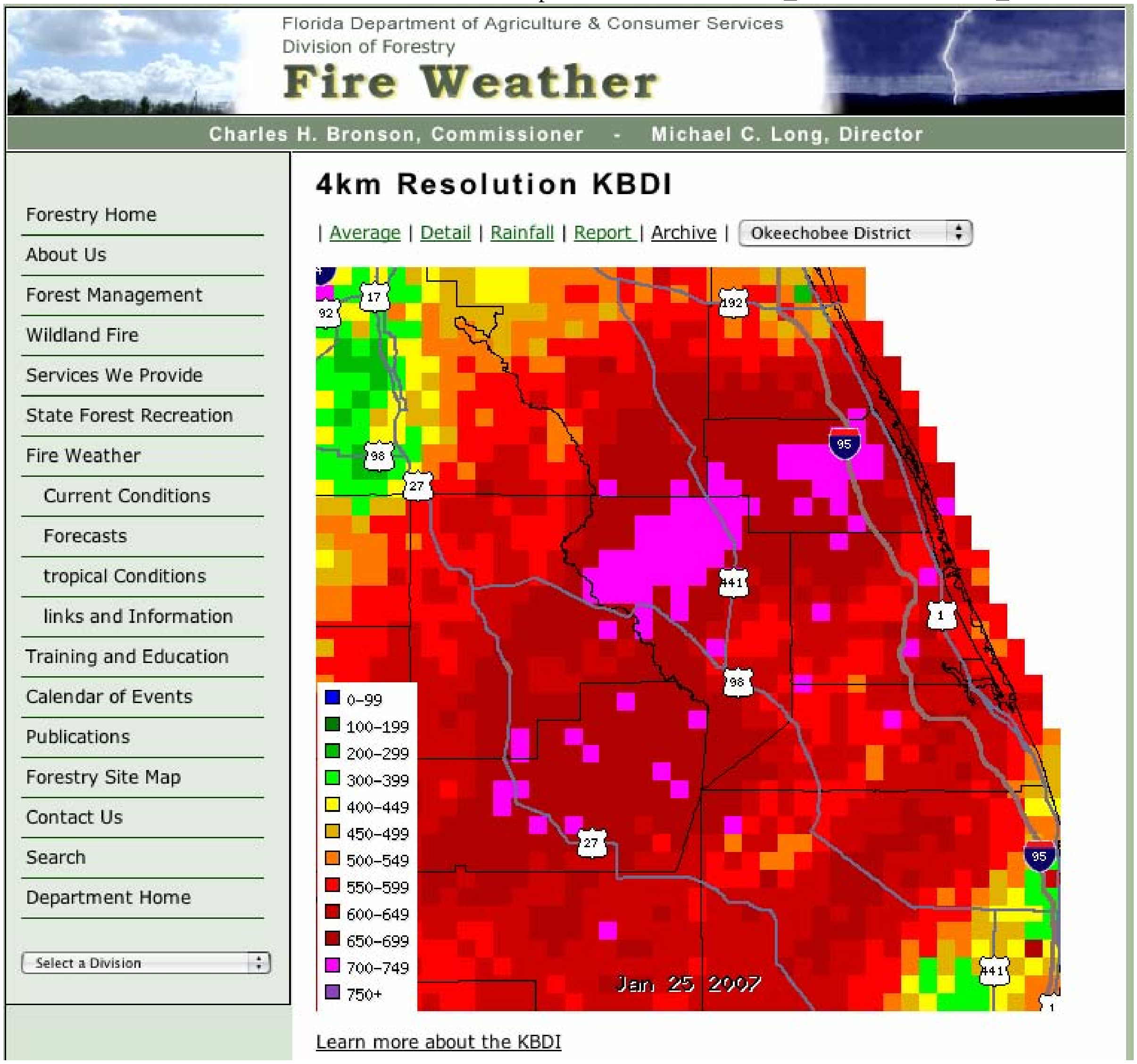


Figure 70 Keetch-Byram Drought Index, computed at 4 km resolution for Florida, here shown as a web-available zoom. Web site: http://flame.fl-dof.com/fire_weather/KBDI/4km_main.html



One final approach that deserves mention is that of Wyoming. Rather than develop a suite of products at a particular spatial scale, Wyoming simply utilizes all available information, at all available spatial scales. Their resource web site (Figure 71) is an excellent compendium of local, regional and national drought monitoring products.

Figure 71 Wyoming drought web site, listing internal and external resources at a variety of spatial scales. Web site: http://www.wrds.uwyo.edu/wrds/wsc/wy_drought_2001/wy_drought.html

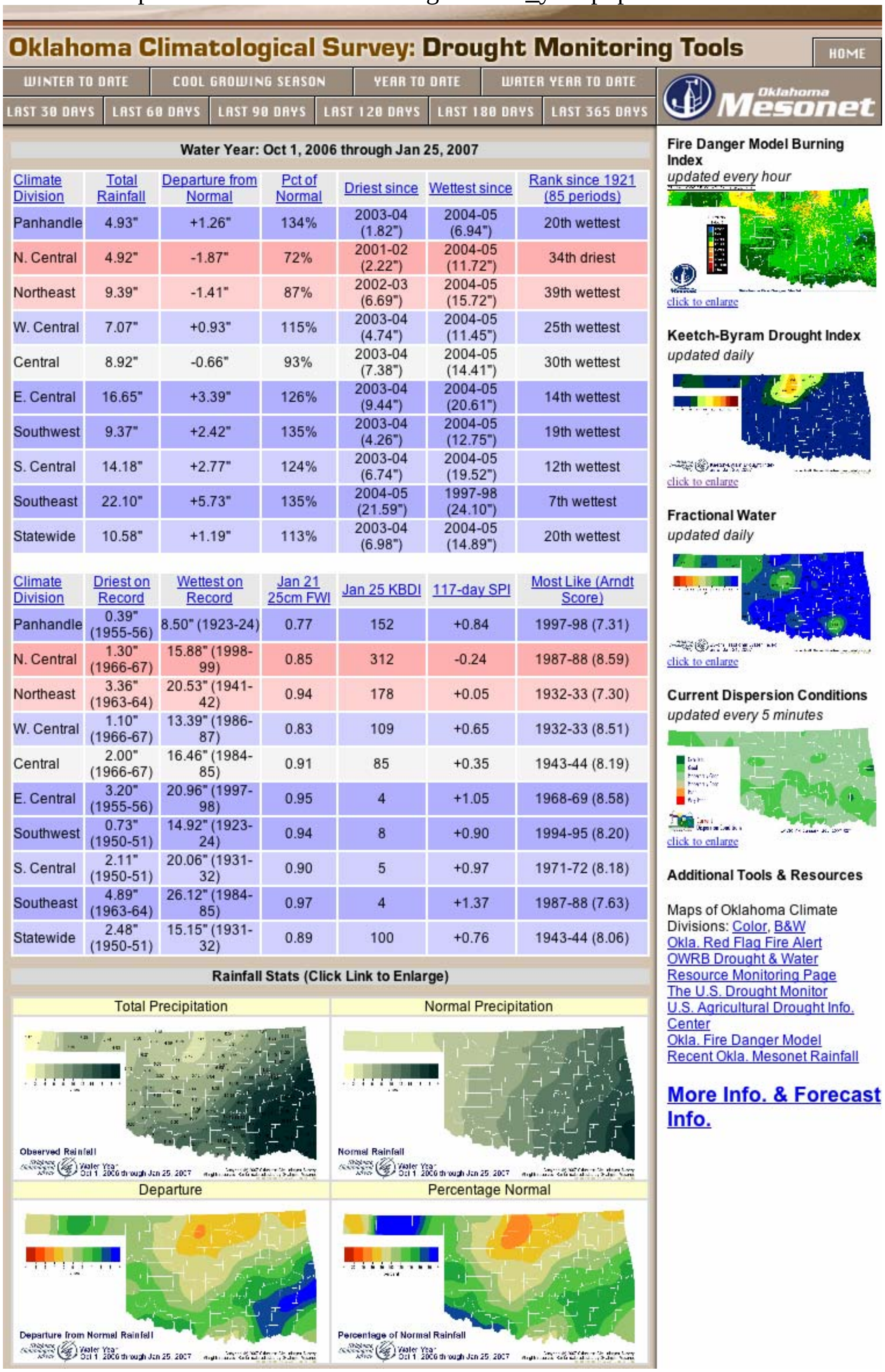
Wyoming Drought Monitoring Products

Drought Maps	
Link	**Frequency**
Current Climate Summary Maps	Daily
Interactive Snow Information	Hourly, Daily
Runoff Charts	As Required
Precipitation	Daily
Month to Date Radar Precip Est	Daily
Precipitation: Lander, Cheyenne, Casper, Sheridan	Daily (30 Days)
Precipitation: Lander, Cheyenne, Casper, Sheridan	Daily (90 Days)
Precipitation: Lander, Cheyenne, Casper, Sheridan	Daily (365 Days)
Precipitation: 40N-45N, 105W-110W 90 Days	Daily (30 Days)
Recent Snowfall, Precipitation	Daily
Torrington Soil Moisture	2005, 2004, 2003, 2002, 2001
Top Soil	Weekly
Afton AG Weather	Hourly, Daily
Daily and Monthly Soil Moisture	Daily
Objective Drought Blend	Daily
Climate Retrospective	Weekly, Monthly
Assessment Products (Archived)	Daily
Basin Precipitation	4 times Daily
Daily Solar Insolation"	Daily
Greenness Departures	March-October
Vegetation Health	Weekly, Archived
Keetch-Byram Index	Daily
Lightning Ignition Efficiency	Daily
Fire Danger	Daily, Tomorrow
Mountain Snow-Water Data	Daily
Snowpack Maps	Monthly (Jan-May)
Precipitation	Monthly & Seasonal
Regional Maps	Water Year
PDSI - Palmer Drought Severity Index Map	Updated Saturdays
Palmer Drought and Crop Moisture	Weekly
Precip Needed To End Drought Map	Updated Saturdays
SPI - Standardized Precipitation Index Maps (1-72 months)	Monthly
CMI - Crop Moisture Index Maps	Updated Saturdays
Daily & Month Soil Moisture	Daily
Drought Impacts Map & News	Monthly
Streamflow	Hourly
Streamflow - Wyoming, US	Daily, Weekly
Historic Flow	
Streamflow & Reservoir Levels, Missouri Tributary	Daily
Weekly Weather & Crop Bulletin	Wednesday 5PM Eastern
WY-Crop Weather	Updated Tuesdays
US AG Weather Highlights	Daily
Water Supply Outlook for the Western United States	Monthly
Reservoir Levels	Monthly
Daily Western WY Reservoirs	Daily, TEACUPS
Reservoirs North Platte and Bighorn	Monthly
North American Drought Monitor	Monthly

5.3 Drought Designation and Assessment

The issue of the appropriate scale at which to assess drought severity is closely linked to the scales at which drought information is available. Drought severity cannot be assessed at the county scale if reliable drought information is only available at the climate division scale. Taking advantage of the wealth of drought assessment tools available at the climate division scale, many states only assess drought severity at that scale. One such state is Oklahoma (Figure 72), despite the availability of a high-resolution observing network and various high-resolution drought index products.

Figure 72 Oklahoma drought monitoring resources, available on the climate division scale. Web site: http://climate.ocs.ou.edu/drought/water_year.php



Oklahoma Climatological Survey: Drought Monitoring Tools

HOME

WINTER TO DATE | COOL GROWING SEASON | YEAR TO DATE | WATER YEAR TO DATE

LAST 30 DAYS | LAST 60 DAYS | LAST 90 DAYS | LAST 120 DAYS | LAST 180 DAYS | LAST 365 DAYS

Oklahoma Mesonet

Water Year: Oct 1, 2006 through Jan 25, 2007

Climate Division	Total Rainfall	Departure from Normal	Pct of Normal	Driest since	Wettest since	Rank since 1921 (85 periods)
Panhandle	4.93"	+1.26"	134%	2003-04 (1.82")	2004-05 (6.94")	20th wettest
N. Central	4.92"	-1.87"	72%	2001-02 (2.22")	2004-05 (11.72")	34th driest
Northeast	9.39"	-1.41"	87%	2002-03 (6.69")	2004-05 (15.72")	39th wettest
W. Central	7.07"	+0.93"	115%	2003-04 (4.74")	2004-05 (11.45")	25th wettest
Central	8.92"	-0.66"	93%	2003-04 (7.38")	2004-05 (14.41")	30th wettest
E. Central	16.65"	+3.39"	126%	2003-04 (9.44")	2004-05 (20.61")	14th wettest
Southwest	9.37"	+2.42"	135%	2003-04 (4.26")	2004-05 (12.75")	19th wettest
S. Central	14.18"	+2.77"	124%	2003-04 (6.74")	2004-05 (19.52")	12th wettest
Southeast	22.10"	+5.73"	135%	2004-05 (21.59")	1997-98 (24.10")	7th wettest
Statewide	10.58"	+1.19"	113%	2003-04 (6.98")	2004-05 (14.89")	20th wettest

Climate Division	Driest on Record	Wettest on Record	Jan 21 25cm FWI	Jan 25 KBDI	117-day SPI	Most Like (Arndt Score)
Panhandle	0.39" (1955-56)	8.50" (1923-24)	0.77	152	+0.84	1997-98 (7.31)
N. Central	1.30" (1966-67)	15.88" (1998-99)	0.85	312	-0.24	1987-88 (8.59)
Northeast	3.36" (1963-64)	20.53" (1941-42)	0.94	178	+0.05	1932-33 (7.30)
W. Central	1.10" (1966-67)	13.39" (1986-87)	0.83	109	+0.65	1932-33 (8.51)
Central	2.00" (1966-67)	16.46" (1984-85)	0.91	85	+0.35	1943-44 (8.19)
E. Central	3.20" (1955-56)	20.96" (1997-98)	0.95	4	+1.05	1968-69 (8.58)
Southwest	0.73" (1950-51)	14.92" (1923-24)	0.94	8	+0.90	1994-95 (8.20)
S. Central	2.11" (1950-51)	20.06" (1931-32)	0.90	5	+0.97	1971-72 (8.18)
Southeast	4.89" (1963-64)	26.12" (1984-85)	0.97	4	+1.37	1987-88 (7.63)
Statewide	2.48" (1950-51)	15.15" (1931-32)	0.89	100	+0.76	1943-44 (8.06)

Rainfall Stats (Click Link to Enlarge)

Total Precipitation

Observed Rainfall

Normal Precipitation

Normal Rainfall

Departure

Departure from Normal Rainfall

Percentage Normal

Percentage of Normal Rainfall

Fire Danger Model Burning Index

updated every hour

click to enlarge

Keetch-Byram Drought Index

updated daily

click to enlarge

Fractional Water

updated daily

click to enlarge

Current Dispersion Conditions

updated every 5 minutes

click to enlarge

Additional Tools & Resources

Maps of Oklahoma Climate Divisions: Color, B&W

Okla. Red Flag Fire Alert

OWRB Drought & Water Resource Monitoring Page

The U.S. Drought Monitor

U.S. Agricultural Drought Info. Center

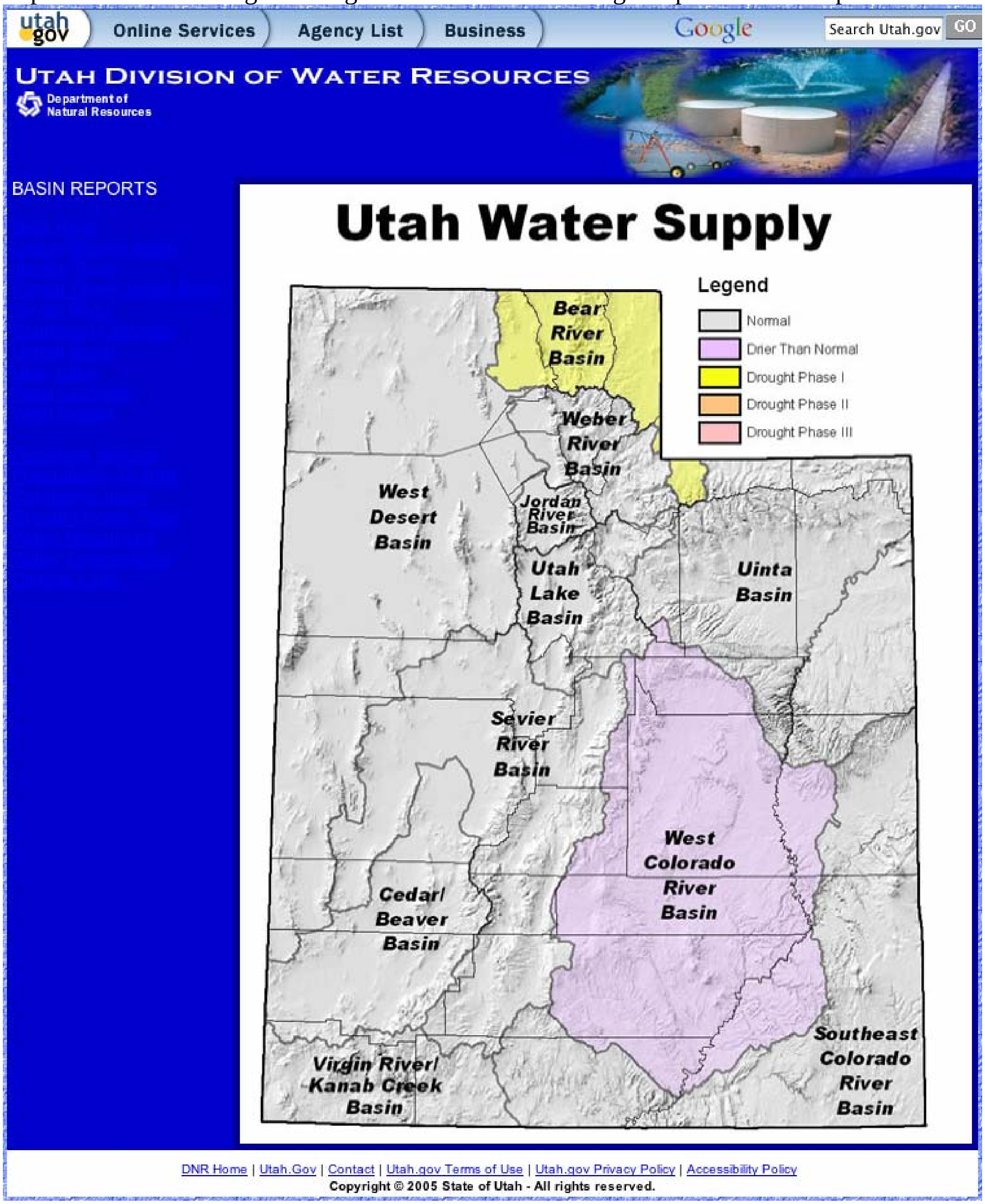
Okla. Fire Danger Model

Recent Okla. Mesonet Rainfall

More Info. & Forecast Info.

Other states use different regional aggregations by which to assess drought severity. New Jersey, as mentioned above, utilizes subdivisions of climate divisions for drought severity assessment. Utah, recognizing that the most important drought impacts in that state are felt on a river basin scale, reports drought severity by river basin (Figure 73).

Figure 73 Utah drought assessment is performed on a river basin scale. Web site: http://www.water.utah.gov/DroughtConditions/BasinDroughtReports/default.asp



Only a few states assess drought status on a county-by-county basis. Two such states are Montana (Figure 74) and Wyoming (Figure 75). Both of these states have unusually large counties, counties that are as large as the climate divisions of other, smaller states. The third state is Missouri (Figure 76). Missouri's counties are similar in size to those of Texas, so the comparison is apt. However, Missouri does not appear to do a county-by-county assessment. Rather, it appears from the smoothness of the drought severity designations that Missouri uses a continuous, large scale drought assessment tool such as the US Drought Monitor and simply reports the drought status on a county-by-county basis.

Figure 74 Montana drought assessment is performed on a county scale. Web site: http://nris.mt.gov/drought/status/Dec06/drtstatusbg.jpg

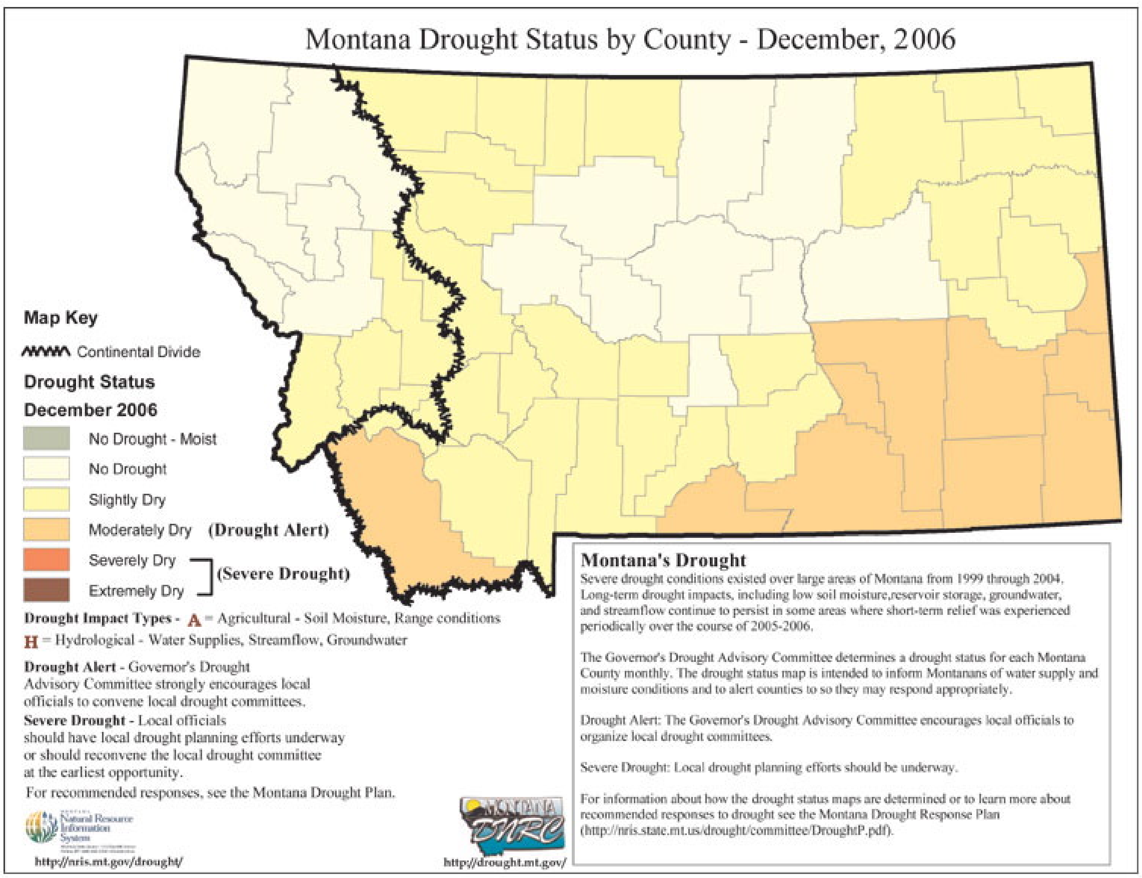


Figure 75 Wyoming drought assessment also is performed on a county scale. Web site: http://www.wrds.uwyo.edu/images/wrds/wsc/countystatus/countystatus.jpg

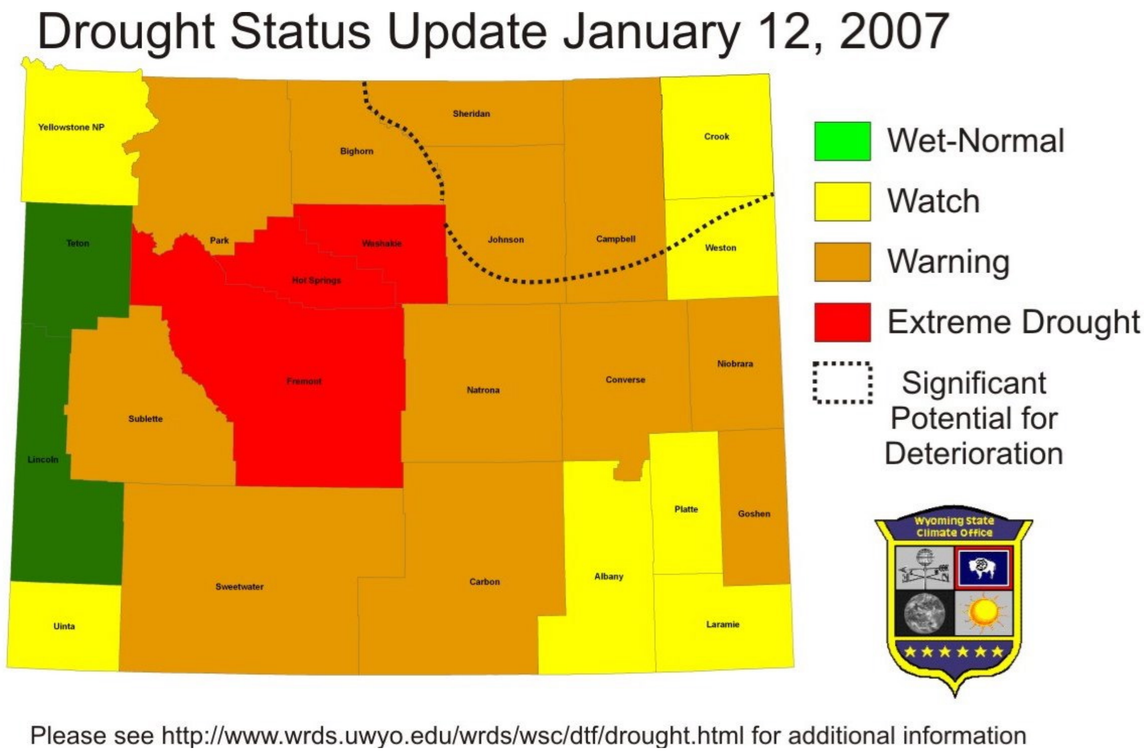
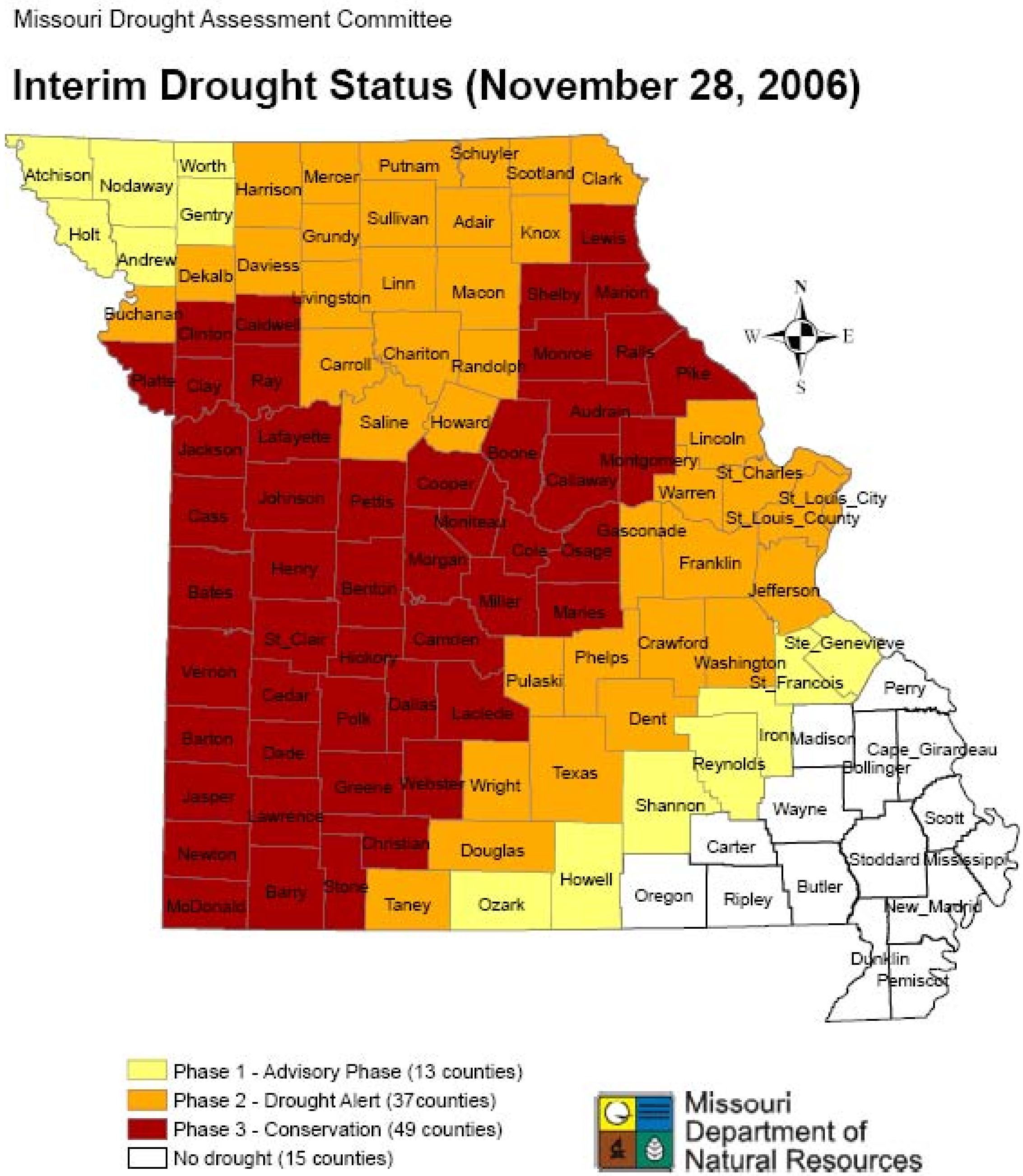
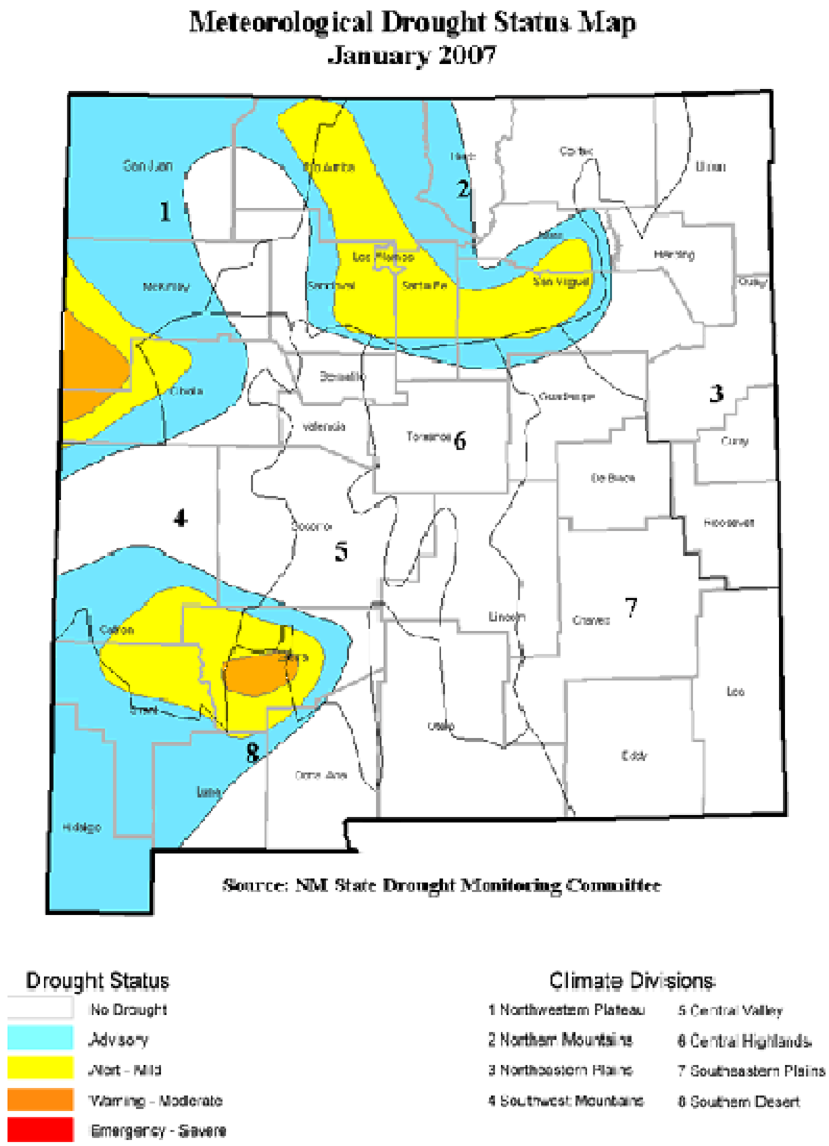


Figure 76 Missouri drought assessment is reported on a county scale. Web site: http://www.dnr.mo.gov/env/wrc/drought/MODroughtCond.htm



An alternative to using climate or political divisions for assessing drought status would be the generation of a spatially-continuous map of overall drought severity. Such an approach is followed in New Mexico (Figure 77). There, available tools are used to attempt to assess the true spatial distribution of drought severity. Judging from the details present on the map, an attempt is made to resolve drought status on a scale finer than New Mexico counties and probably comparable to Texas-sized counties.

Figure 77 New Mexico generates a continuous drought status map, effectively assessing drought status at each location in the state. Web site: http://www.nmdrought.state.nm.us/nmdmap.gif



With a range of possible scales for drought assessment in current use across the United States, and all of them to a greater or lesser extent supported by coarse and fine resolution drought monitoring information, it is important to consider the situation from the point of view of the potential or likely users of drought assessment information.

5.4 Creating a Fine-Scale Drought Information System

With a range of possible scales for drought assessment in current use across the United States, and all of them to a greater or lesser extent supported by coarse and fine resolution drought monitoring information, it is important to consider the situation from the point of view of the potential or likely users of drought assessment information.

For many applications, the county is the logical unit. Counties across Texas are nearly uniform in size, and the county is the standard unit of local government. Most disaster declarations are made on a county basis. Meteorological information is generally available on a county scale, but no smaller, except for radar-estimated precipitation. The county is probably the most appropriate scale on which to make subjective assessments of drought severity.

However, there are other jurisdictional units for which moisture and drought information are critical. For example, all individual water suppliers require information over the geographical area for which they supply water, to understand past, current, and future water demand. In addition, for surface water supplies and aquifer recharge, the water suppliers require information over the drainage that supplies their reservoir or the recharge area for their aquifer, to understand past, current, and future water supply. Finally, if other water suppliers make use of the same water supply and possess priority of water rights, the water supplier will require information about drought conditions in all other locations for which water from their source is used. For such users of drought information, any single geographical unit for drought information reporting will provide suboptimal or possibly useless information.

Recent years have seen the widespread adoption of GIS technologies and the availability of continuous or fine-scale meteorological and hydrological information. Consequently, it is no longer necessary to choose among several less-than-satisfactory options. Instead, we propose the following:

Drought information should be collected and processed as a continuous georeferenced data set with as fine a spatial resolution as observing technologies allow. The information should then be aggregated to appropriate physical and jurisdictional domains. On a statewide basis, standard aggregational units should include counties as well as river drainages relevant to surface water storage. In addition, the georeferenced information should be available for individual planners and users for user-specific extraction and aggregation.

Raw moisture and drought information already exists on a continuous or high-resolution georeferenced basis. As noted in Section 6.2, precipitation information is available in both quasi-continuous objective analysis form (from rain gauges) and high-resolution (4 km) rainfall estimates (from NWS radars). Other meteorological fields utilized by some drought indices are or can be analyzed in a spatially quasi-continuous manner as well. Some useful satellite products (such as normalized difference vegetation index, a measure of vegetation greenness) are also produced at a similar high spatial resolution.

In general, the raingauge objective analyses are bias-free, but the radar estimates provide considerably more spatial resolution. In some circumstances, the raingauge data may be best, in others, the radar-derived rainfall estimates. With the present state of rainfall estimation technology, it is probably best to retain both sources of data as complementary versions of the spatial distribution of rainfall.

Conversion of the raw information to drought indices will require considerable care. Some drought indices were designed for larger spatial units, such as a climate division, and would require adjustment before being applied to a finer scale. Other common drought indices assess drought severity with respect to the historical record, and no historical record exists at such fine resolution. For the latter problem, the historical probability distributions may be estimated from known probability distributions at the individual station or climate division scale.

Similarly, the aggregation of a climate index value is in general not the same as the climate index value computed from the aggregation of input data. For example, every single point within a given county may be experiencing moderate drought, but the fact that such drought is so widespread within the county may mean that for the county as a whole the drought is severe. Consequently, drought indices must be recomputed separately for each aggregation. Indices that are essentially linear, such as the KBDI, can be aggregated by simple averaging.

Some drought information, such as reservoir and streamflow levels, is inherently spatially discontinuous. This information may be available graphically at its georeferenced location, and naturally aggregated by drainage or river basin. In general, hydrological/water supply drought indices should also be reported on a drainage or river basin scale, as they are not continuous quantities and political boundaries (such as counties) have little relevance in this context.

In practice, the way this system might work is as follows: A web and GIS server serves as a central data and information source for users throughout the State. On this server, the necessary historical drought calculations have been performed for all geographical and jurisdictional boundaries likely to be of interest. Users can request raw data at full resolution or aggregated data and products for any requested region. An ideal system would also include options for time series analysis and cross-index comparisons for individual regions, as well as projections of future drought index values based upon high, medium, low, and historical worst case scenarios, with probabilities of each given by downscaled Climate Prediction Center medium and long range forecasts. This would allow water suppliers to more accurately project usage and implement water conservation strategies before the situations become critical.

5.5 Recommendations for Reporting Drought at the Local Level in Texas

Based on the results of this study, we make the following recommendations for monitoring and reporting drought at the local level in Texas:

1. All drought indices should compare current conditions to historic droughts. This should be done using percentiles estimated from probability distributions using the historical record (for meteorological drought) or model simulations using the historical record (for hydrological and water supply drought).

2. Drought information should be collected and stored in Texas at the finest spatial resolution practicable. At present, a spatial scale comparable to county scale is possible with the existing rain gauge network, and a 4 km scale is possible with experimental radar-based precipitation estimates. County-scale analyses should be used immediately, and radar-based analyses should be utilized in parallel on an experimental basis.

3. Meteorological drought should be identified using the Standardized Precipitation Index (SPI), Percent Normal, and Deciles. Initially, the conventional SPI should be used, but an experimental set of SPI products should also be developed that does not have a sudden onset time and weights recent precipitation more heavily than earlier precipitation.

4. The SPI values should be calculated at station locations (not using climate division or radar-derived precipitation data). The SPI values should then be aggregated to single-county values. The precipitation probability distributions for each station, needed for the SPI calculations, should be estimated using a spatially-coherent technique such as L-moments. Statistical tests should be performed to ensure that radar-estimated point values of precipitation have similar probability distributions as rain gauge values; if not, the appropriate probability distributions should be estimated.

5. Hydrological/water supply drought should be monitored using the Standarized Streamflow Index (SSFI), Reservoir Deficit Index (RDI), and SPI. The SPI is a useful index for monitoring both meteorological and hydrological drought, but for hydrological drought the longer time scales (6 to 9+ months) are most important, while for meteorological drought the shorter time scales (< 6 months) are most important. The SSFI should be calculated and supported at the watershed scale, while the RDI should be reported for individual reservoirs which can then be aggregated using the water supply district boundaries.

6. Meteorological and hydrological drought should be reported by the Texas Drought Preparedness Council using a rating system consistent with the US Drought Monitor (Table 44) that ranges from D0 (abnormally dry) to D4 (exceptional drought). The focus for these drought severity estimates should be the 1-month and 3-month SPI (meteorological drought as relevant to crops), 6-month and 9-month SPI (meteorological drought as relevant to

streamflow), 12-month and 24-month SPI (long-term drought), RDI (hydrological/water supply drought as measured by reservoirs), and SSFI (hydrological/water supply drought as measured by streamflow).

7. Projections of future drought conditions (assuming 20th percentile, 50th percentile, and 80th percentile rainfall) for the next 1 to 3 months should be made on the basis of historical climatology.

8. The Texas Drought Preparedness Council should develop guidelines for reporting the likelihood of future drought across the state using a consistent synthesis of indices and forecasts. For example, a drought watch might be declared if a county has a 20% chance of D2 or worse drought on any of the indices listed in (6), a drought alert might be declared if a county is already in D2 or has a 50% chance of developing D2, a drought warning might be declared if a county is already in D3 or has a 50% chance of developing D3, and a drought emergency might be declared if a county is already in D4 or has a 50% chance of developing D4. These levels of warning might be rescinded if a county has an 80% chance of leaving the corresponding drought level. Such warning messages should be conveyed to the appropriate county judges and water supply agencies.

9. The primary drought status product should be a color-coded map of Texas with the appropriate drought warning levels by county and more detailed drought information should be readily available on a web site for in-depth analysis of the situation.

6.0 TASK 5: RECOMMENDATIONS FOR IMPLEMENTATION

The final section of this report provides the TWDB with a series of recommendations that are based on our findings. These recommendations specifically relate to what we see as the logical next step for the TWDB and the State of Texas; developing a Texas Drought Monitoring System that provides the TWDB, Texas Drought Preparedness Council, and other decision-makers and stakeholders with a means of monitoring drought at a relatively high spatial and temporal resolution (near-real time). The Texas Drought Monitoring System will provide better information and will facilitate better decision making. Overall it is clear that drought information should be collected and processed as a continuous georeferenced data set with as fine a spatial resolution as observing technologies allow. The information should then be aggregated to appropriate physical and jurisdictional domains. On a statewide basis, standard aggregational units should include counties, river basins, and water supply districts. In addition, the georeferenced information should be available to individuals and organizations for user-specific extraction and aggregation.

6.1 Recommendations from Tasks 1 and 2

The purpose of Tasks 1 and 2 were to review and evaluate existing drought indices to determine which indices are the most appropriate for monitoring meteorological and hydrological/water supply drought at the local level in the state of Texas.

Meteorological Drought

Based on the qualitative and quantitative analyses that were conducted the SPI, Percent Normal, and Deciles were the most highly ranked. All three of these indices are relatively easy to calculate because they only require precipitation data. These three indices are also transparent and easy to understand. All of these indices are reported in units that can easily be converted into precipitation values and they can all be extended back in time (based on the availability of precipitation data). This allows current droughts to be placed in proper historical context. All of these indices are flexible and can be calculated for any period of interest (week, month, season, year). The main drawback of these indices is that they only consider precipitation and they require a relatively long precipitation record to be accurately calculated.

Soil moisture in the upper layers of the soil (top 5 or 10 cm) can also used as a measure of meteorological drought since it accounts for the influence of all components of the hydrological cycle (infiltration, runoff, evaporation) not just precipitation. Field measurement of soil moisture is time-consuming and expensive, and in some cases, it is impossible to measure at a regional scale. Therefore, most drought monitoring applications that utilize soil moisture information rely on modeled soil moisture. VIC and DSSAT are two different models that were used for simulating soil moisture. It was determined that both of these models provided reasonable simulations soil moisture in Texas, although the performance of DSSAT was slightly superior to that of VIC. One of the advantages of using this approach is that it provides a more sophisticated (and potentially realistic) simulations of soil water budget including infiltration, runoff, evapotranspiration. However, these models require more input data (at a minimum daily temperature and precipitation and soils data) which may limit their utility in certain locations. Although these models are relatively complex, they can still be calculated at the local level in Texas and they provide information that can augment what is provided by the precipitation-based indices.

Even though the PDSI and Z-index are commonly used for drought monitoring, they were not highly ranked by the qualitative evaluation. This is because these indices are complicated to calculate, require more detailed information than the precipitation indices, and report drought conditions using a dimension-less index. In addition, it has been demonstrated that the PDSI, as originally formulated by Palmer (1965), is spatially variant. Therefore it is not appropriate to compare PDSI values from different locations (particularly in a large state like Texas that encompasses a broad range of climate regions). The PDSI is not recommended for drought monitoring in Texas.

The satellite-based VCI was also evaluated against other meteorological indices. However, the results of the qualitative and quantitative evaluations suggest that, despite its advantages, the VCI may not be an appropraite index for monitoring meteorological drought in Texas because the utility of the VCI is limited to the growing-season and it is not clear how the VCI is related to meteorological drought impacts. The VCI is not recommended for drought monitoring in Texas.

No single index can represent all aspects of meteorological drought so it is best to use a multi-index approach for operational drought monitoring.

Hydrological/Water Supply Drought

Based on the qualitative and quantitative analyses that were conducted, the SSFI, RDI, and the SPI are the most appropriate indices for monitoring hydrological/water supply drought in Texas. It is recommended that the SSFI, RDI, and SPI be used for monitoring hydrological/water supply drought in Texas. On the other hand, PHDI and SWSI are of limited use for monitoring hydrological/water supply drought in Texas. The SSFI and RDI are both newly indices that demonstrate great promise for monitoring hydrological/water supply drought. The SSFI is a standardized measure of streamflow. Like the SPI, the SSFI is simple to calculate because it only utilizes streamflow data. The RDI was specifically developed for this study to measure reservoir levels and it utilizes the WRAP model so it avoids the problems associated with changes in water usage over time. All of these indices can be used to place current droughts in proper historical context and they can all be calculated for any period of interest (week, month, season, year). This flexibility is important because the most appropriate timescale for monitoring hydrological/water supply drought varies by basin.

No single index can represent all aspects of hydrological/water supply drought so it is best to use a multi-index approach for operational drought monitoring.

6.2 Recommendations from Task 3

The purpose of Task 3 was to identify the most appropriate method for determining drought definitions (thresholds). A review of state drought plans revealed that many states have adopted drought thresholds listed in the scientific literature without considering whether they are appropriate for their climate or whether the drought indices upon which they are spatially invariant. It is more appropriate to use an objective location-specific method for defining drought thresholds at the local level. Applying this method involves the following steps:

1. Utilize a relatively long (station-based) record to calculate the drought index of interest (e.g., SPI)
2. Apply an appropriate PDF to the drought index data; since some drought indices are not normally distributed it may not be appropriate to use a Gaussian (normal) distribution for all indices
3. Utilize the PDF to determine appropriate drought thresholds based on the percentiles used by the US Drought Monitor (moderate drought (11-20 percentile),

severe drought (6-10 percentile), extreme drought (3-5 percentile), exceptional drought (<2 percentile)).

This methodology should be applied to all drought indices, including those that are supposed to be spatially invariant (e.g., SPI). These definitions can be determined at the local (e.g., county) level by fitting a PDF to all of the available stations that have a long record and then interpolating the parameters of the PDF to determine what the thresholds should be in data sparse regions.

Using an objective approach for determining drought definitions ensures that droughts are accurately and correctly identified at the local level. It is inappropriate to use a single set of drought definitions for an entire state (especially a state the size of Texas). Ideally these objective drought thresholds should be validated using local drought impacts data.

6.3 Recommendations from Task 4

The purpose of Task 4 was to propose guidelines for reporting moisture (drought) conditions at the local level. These guidelines should be used to develop a Texas Drought Monitoring System that will provide the TWDB, TDPC, and other decision-makers and stakeholders with a means of monitoring drought at a relatively high spatial and temporal resolution (near-real time). The Texas Drought Monitoring System should be developed in accordance with the following recommendations:

1. All drought indices should compare current conditions to historic droughts. This should be done using percentiles estimated from probability distributions using the historical record (for meteorological drought) or model simulations using the historical record (for hydrological and water supply drought).

2. Drought information should be collected and stored in Texas at the finest spatial resolution practicable. At present, a spatial scale comparable to county scale is possible with the existing rain gauge network, and a 4 km scale is possible with experimental radar-based precipitation estimates. County-scale analyses should be used immediately, and radar-based analyses should be utilized in parallel on an experimental basis.

3. Meteorological drought should be identified using the Standardized Precipitation Index (SPI), Percent Normal, and Deciles. Initially, the conventional SPI should be used, but an experimental set of SPI products should also be developed that does not have a sudden onset time and weights recent precipitation more heavily than earlier precipitation.

4. The SPI values should be calculated at station locations (not using climate division or radar-derived precipitation data). The SPI values should then be aggregated to single-county values. The precipitation probability distributions for each station, needed for the SPI calculations, should be estimated using a spatially-coherent technique such as L-moments. Statistical tests should be performed to ensure that radar-estimated point values of precipitation have similar probability distributions as rain gauge values; if not, the appropriate probability distributions should be estimated.

5. Hydrological/water supply drought should be monitored using the Standarized Streamflow Index (SSFI), Reservoir Deficit Index (RDI), and SPI. The SPI is a useful index for monitoring both meteorological and hydrological drought, but for hydrological drought the longer time scales (6 to 9+ months) are most important,

while for meteorological drought the shorter time scales (< 6 months) are most important. The SSFI should be calculated and supported at the watershed scale, while the RDI should be reported for individual reservoirs which can then be aggregated using the water supply district boundaries.

6. Meteorological and hydrological drought should be reported by the Texas Drought Preparedness Council using a rating system consistent with the US Drought Monitor (Table 44) that ranges from D0 (abnormally dry) to D4 (exceptional drought). The focus for these drought severity estimates should be the 1-month and 3-month SPI (meteorological drought as relevant to crops), 6-month and 9-month SPI (meteorological drought as relevant to streamflow), 12-month and 24-month SPI (long-term drought), RDI (hydrological/water supply drought as measured by reservoirs), and SSFI (hydrological/water supply drought as measured by streamflow) (Table 51).

7. Projections of future drought conditions (assuming 20th percentile, 50th percentile, and 80th percentile rainfall) for the next 1 to 3 months should be made on the basis of historical climatology.

8. The Texas Drought Preparedness Council should develop guidelines for reporting the likelihood of future drought across the state using a consistent synthesis of indices and forecasts. For example, a drought watch might be declared if a county has a 20% chance of D2 or worse drought on any of the indices listed in (6), a drought alert might be declared if a county is already in D2 or has a 50% chance of developing D2, a drought warning might be declared if a county is already in D3 or has a 50% chance of developing D3, and a drought emergency might be declared if a county is already

in D4 or has a 50% chance of developing D4. These levels of warning might be rescinded if a county has an 80% chance of leaving the corresponding drought level. Such warning messages should be conveyed to the appropriate county judges and water supply agencies.

9. The primary drought status product should be a color-coded map of Texas with the appropriate drought warning levels by county and more detailed drought information should be readily available on a web site for in-depth analysis of the situation.

Table 51 Summary of recommendations for monitoring meteorological and hydrological/water supply drought.

Type of Drought	Recommended Indices	Data Required	Reporting Unit
Meteorological	1-month SPI 3-month SPI Percent Normal Deciles	Station-based precipitation (from stations with a long, complete record)	County
Hydrological/ Water Supply	6-month SPI	Precipitation	County and watershed
	9-month SPI	Precipitation	County and watershed
	12-month SPI	Precipitation	County and watershed
	SSFI	Streamflow	Watershed
	RDI	Reservoir levels & WARP	Watershed and water supply district

6.4 Concluding Remarks

Most of the drought monitoring tools that are currently being used in Texas are too coarse, both spatially and temporally, for local-level monitoring and decision-support applications. In addition, it has been demonstrated that many of the tools that are currently being used for monitoring meteorological and hydrological/water supply drought are not the most appropriate. It has also been shown that using a single set of (subjective) drought thresholds is inappropriate for triggering responsive action at the local level. Therefore, this study demonstrates that there is a serious need for developing a Texas Drought Monitoring

System that utilizes the most appropriate meteorological and hydrological/water supply drought indices to provide decision makers with valuable data, at the local level, to facilitate the adoption of appropriate adaptation, mitigation, and avoidance strategies. Drought is a pressing environmental issue that is of great importance to the State of Texas (damages from the most recent drought in Texas were estimated to exceed 2 billion dollars). We encourage the Texas Drought Preparedness Council in cooperation with the State of Texas to utilize the recommendations contained in this report as the basis for developing a Texas Drought Monitoring System.

References

Abdulla FA, Lettenmaier DP, Wood EF, Smith JA. 1996. Application of a macroscale hydrologic model to estimate the water balance of the Akansas-Red river basin. *J. Geophys. Res.* **101:** 7449–7459.

Akinremi OO, McGinn SM, Barr AG. 1996a. Evaluation of the Palmer Drought Index on the Canadian prairies. *Journal of Climate* **9:** 897-905.

Allen RG, Pereira LS, Raes D, Smith M. 1998. *Crop evapotranspiration - Guidelines for computing crop water requirements*. FAO Irrigation and drainage paper 56, FAO - Food and Agriculture Organization of the United Nations: Rome.

Alley WM. 1984. The Palmer Drought Severity Index: Limitation and assumptions. *J. Clim. Appl. Meteorol.* **23:** 1100–1109.

Andreadis KM, Clark EA, Wood AW, Hamlet AF, Lettenmaier DP. 2005. Twentieth-century drought in the conterminous United States. *Journal of Hydrometeorology* **6:** 985–1001.

Anyamba A, Tucker CJ, Eastman JR. 2001. NDVI anomaly patterns over Africa during the 1997/98 ENSO warm event. *International Journal of Remote Sensing* **22:** 1847-1859.

Byun HR, Wilhite DA. 1999. Objective quantification of drought severity and duration. *Journal of Climate* **12:** 2747–2756.

Cherkauer KA, Lettenmaier DP. 1999. Hydrologic effects of frozen soils in the upper Mississippi River basin. *J. Geophys. Res.* **104:** 19,599–19,610.

Cohen S, Wheaton EE, Masterton J. 1992. *Impacts of Climatic Change Scenarios in the Prairie Provinces: A Case Study from Canada,* Canadian Climate Center: Downsview, ON.

deMenocal PB. 2001. Cultural responses to climate change during the late Holocene. *Science* **292:** 667-673.

Doesken NJ, Garen DC. 1991. Drought monitoring in the western United States using a Surface Water Supply Index. In: *Seventh Conference on Applied Climatology*, American Meteorological Society, Salt Lake City, UT; 266-269.

Doesken NJ, McKee TB, Kleist J. 1991. *Development of a Surface Water Supply Index for the western United States*, Colorado Climate Center, Department of Atmospheric Science, Colorado State University: Fort Collins, CO.

Garen DC. 1992. Revised Surface-Water Supply Index for the western United States. *Journal of Water Resources Planning and Management* **119:** 437-454.

Garen DC. 1993. Revised Surface-Water Supply Index for the western United States. *Journal of Water Resources Planning and Management* **119:** 437-454.

Gibbs WJ, Maher JV. 1967. *Rainfall Deciles as Drought Indicators*. Bureau of Meteorology Bulletin No. 48. Commenwealth of Australia: Melbourne.

Goodrich GB, Ellis AW. 2006. Climtological drought in Arizona: An analysis of indicators for guiding the Governor's Drought Task Force. *The Professional Geographer* **58:** 460-469.

Gutman GG. 1990. Towards monitoring drought from space. *Journal of Climate* **3:** 282-295.

Guttman NB. 1998. Comparing the Palmer Drought Index and the Standardized Precipitation Index. *Journal of the American Water Resources Association* **34:** 113-121.

Guttman NB. 1999. Accepting the Standardized Precipitation Index: A calculation algorithm. *Journal of the American Water Resources Association* **35:** 311-322.

Guttman NB, Wallis JR, Hosking JRM. 1992. Spatial comparability of the Palmer Drought Severity Index. *Water Resources Bulletin* **28:** 1111-1119.

Hansen MC, DeFries RS, Townshend JRG, Sohlberg R. 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. *International Journal of Remote Sensing* **21:** 1331–1364.

Hayes MJ, Svoboda MD, Wilhite DA, Vanyarkho OV. 1999. Monitoring the 1996 drought using the standardized precipitation index. *Bulletin of the American Meteorological Society* **80:** 429-438.

Heim RR, Jr. 2002. A review of twentieth century drought indices used in the United States. *Bulletin of the American Meteorological Society* **83:** 1149-1165.

Hu Q, Willson GD. 2000. Effects of temperature anomalies on the Palmer Drought Severity Index in the central United States. *International Journal of Climatology* **20:** 1899-1911.

Husak GJ, Michaelson J, Funk C. in press. Use of the gamma distribution to represent monthly rainfall in Africa for drought monitoring applications. *International Journal of Climatology*.

Ji L, Peters A. 2003. Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices. *Remote Sensing of Environment* **87:** 85-89.

Jones JW. 1993. Decision support systems for agricultural development. In: *Systems Approaches for Agricultural Development*, Penning de Vries F, Teng P,Metselaar K (eds). Kluwer: Boston; 459-471.

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT. 2003. The DSSAT cropping system model. *European Journal of Agronomy* **18:** 235-265.

Jones JW, Ritchie JT. 1991. Crop growth models. In: *Management of Farm Irrigation Systems*, Hoffman GJ, Howell TA,Solomon KH (eds). American Society for Agricultural Engineering; 63-89.

Karl T. 1986. The sensitivity of the Palmer Drought Severity Index and Palmer's Z-Index to their calibration coefficients including potential evapotranspiration. *Journal of Climate and Applied Meteorology* **25:** 77-86.

Karl T, Quinlan F, Ezell DS. 1987. Drought termination and amelioration: Its climatological probability. *Journal of Climate and Applied Meteorology* **26:** 1198-1209.

Karl TR. 1983. Some spatial characteristics of drought duration in the United States. *Journal of Climate and Applied Meteorology* **22**.

Keyantash J, Dracup JA. 2002. The quantification of drought: An evaluation of drought indices. *Bulletin of the American Meteorological Society* **83:** 1167-1180.

Kogan F. 2002. World droughts in the new millenium from AVHRR-based Vegetation Health Indices. *EOS* **83:** 557-563.

Kogan FN. 1995. Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. *Bulletin of the American Meteorological Society* **76:** 655-668.

Kogan FN. 1997. Global drought watch from space. *Bulletin of the American Meteorological Society* **78:** 621-636.

Kogan FN. 2001. Operational space technology for global vegetation assessment. *Bulletin of the American Meteorological Society* **82:** 1949-1964.

Kogan FN, Unganai LS. 1998. Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. *Remote Sensing of Environment* **63:** 219-232.

Kumar V, Panu U. 1997. Predictive assessment of severity of agricultural droughts based on agro-climatic factors. *Journal of the American Water Resources Association* **33:** 1255-1264.

Legates DR. 1991. An evaluation of procedures to estimate monthly precipitation probabilities. *Journal of Hydrology* **122:** 129-140.

Legates DR, McCabe GJ. 1999. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. *Water Resources Research* **35:** 233-241.

Liang X, Lettenmaier DP, Wood EF. 1996a. One-dimensional statistical dynamical representation of subgrid spatial variability of precipitation in the two-layer variable infiltration capacity model. *J. Geophys. Res.* **101:** 21,403–21,422.

Liang X, Lettenmaier DP, Wood EF, Burges SJ. 1994. A simple hydrologically based model of land surface water and energy fluxes for GCMs. *J. Geophys. Res.* **99:** 14,415–14,428.

Liang X, Wood EF, Lettenmaier DP. 1996b. Surface soil moisture parameterization of the VIC-2L model: Evaluation and modifications. *Global Planet. Change* **13:** 195–206.

Lohani VK, Loganathan GV. 1997. An early warning system for drought management using the Palmer Drought Index. *Journal of the American Water Resources Association* **33:** 1375-1386.

Lohani VK, Loganathan GV, Mostaghimi S. 1998. Long-term analysis and short-term forecasting of dry spells by Palmer Drought Severity Index. *Nordic Hydrology* **29:** 21-40.

Lott N, Ross T. 2006. Tracking and evaluating U.S. billion dollar weather disasters, 1980-2005. In: *Proceedings of the AMS Forum: Environmental Risk and Impacts on Society: Successes and Challenges*, American Meteorological Society, Atlanta, GA.

Mather JR. 1979. Use of the climatic water budget in select environmental water problems. *Publications in Climatology* **32**.

Maurer EP, Wood AW, Adam JC, Lettenmaier DP, Nijssen B. 2002. A long-term hydrologically-based data set of land surface fluxes and states from the conterminous United States. *J. Clim.* **15:** 3237–3251.

Mavromatis T. unpublished. Evaluation of drought indices as indicators of soil moisture in Greece.

McKee TB, Doesken NJ, Kleist J. 1993. The relationship of drought frequency and duration to time scales. In: *8th Conference on Applied Climatology*, AMS, Anaheim, CA; 179-184.

McKee TB, Doesken NJ, Kleist J. 1995. Drought monitoring with multiple time scales. In: *9th Conference on Applied Climatology*, AMS, Dallas, TX; 233-236.

Morid S, Smakhtin V, Moghaddasi M. 2006. Comparison of seven meteorological indices for drought monitoring in Iran. *International Journal of Climatology* **26:** 971-985.
Narasimhan B, Srinivasan R. 2005. Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. *Agricultural and Forest Meteorology* **133:** 69-88.
Nicholson SE, Farrar TJ. 1994. The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semaird Botswana: I. NDVI response to rainfall. *Remote Sensing of Environment* **50:** 107-120.
Nijssen B, Lettenmaier DP, Liang X, Wetzel SW, Wood EF. 1997. Streamflow simulation for continental-scale river basins. *Water Resources Research* **33:** 711–724.
Nijssen B, Schnur R, Lettenmaier DP. 2001. Global retrospective estimation of soil moisture using the variable infiltration capacity land surface model, 1980–93. *J. Clim.* **14:** 1790–1808.
Ogelsby RJ, Erickson DJ. 1989. Soil moisture and the persistence of North American drought. *Journal of Climate* **2**.
Palmer WC. 1965. *Meteorological drought*. Research Paper No. 45, U.S. Weather Bureau: Washington, D.C.
Penman HL. 1948. Natural evaporation from open water, bare soil, and grass. *Proceedings of the Royal Society of London A* **193:** 120-145.
Popova Z, Kercheva M. 2005. CERES model application for increasing preparedness to climate variability in agricultural planning - calibration and validation test. *Physics and Chemistry of the Earth* **30:** 125-133.
Priestley CHB, Taylor RJ. 1972. On the assessment of surface heat flux and evaporation on large-scale parameters. *Monthly Weather Review* **100:** 81-92.
Quiring SM. 2004. Developing a real-time agricultural drought monitoring system for Delaware. *Publications in Climatology* **LVII:** 1-104.
Quiring SM, Papakyriakou TN. 2003. An evaluation of agricultural drought indices for the Canadian prairies. *Ag. For. Meteorol.* **118:** 49–62.
Ritchie JT. 1972. Model for predicting evaporation from a row crop with incomplete cover. *Water Resources Research* **8:** 1204-1213.
Ritchie JT. 1998. Soil water balance and plant stress. In: *Understanding Options for Agricultural Production*, Tsuji GY, Hoogenboom G,Thornton PK (eds). Kluwer: Dordrecht, The Netherlands; 41-54.
Ritchie JT, Otter S. 1985. Description and performance of CERES-Wheat: a user-oriented wheat yield model. In: *ARS Wheat Yield Project*. National Technical Information Service: Springfield, MO; 159-175.
Robock A, Luo L, Wood EF, Wen F, Mitchell KE, Houser PR, Schaake JC, Lohmann D, Cosgrove B, Sheffield J, Duan W, Higgins RW, Pinker RT, Tarpley JD, Basara JB, Crawford KC. 2003. Evaluation of North American Land Data Assimilation System over the southern Great Plains during the warm season. *Journal of Geophysical Research* **108:** 8846, doi:10.1029/2002JD003245.
Seiler RA, Kogan F, Wei G. 2000. Monitoring weather impact and crop yield from NOAA AVHRR data in Argentina. *Advances in Space Research* **26:** 1177-1185.
Shafer BA, Dezman LE. 1982. Development of a Surface Water Supply Index (SWSI) to assess the severity of drought conditions in snowpack runoff areas. In: *Proceedings of the Western Snow Conference*, Fort Collins, CO; 164-175.
Stahle DW, Cleaveland MK, Blanton DB, Therrell MD, Gay DA. 1998. The Lost Colony and Jamestown droughts. *Science* **280:** 564-567.
Stahle DW, Cook ER, Cleaveland MK, Therrell MD, Meko DM, Grissino-Mayer HD, Watson E, Luckman BH. 2000. Tree-ring data document 16th century megadrought over North America. *EOS* **81:** 124-125.
Strommen ND, Motha RP. 1987. An operational early warning agricultural weather system. In: *Planning for drought: Toward a reduction of societal vulnerability*, Wilhite DA, Easterling WE,Wood DA (eds). Westview Press: Boulder, CO.
Svoboba M, LeComte D, Hayes M, Heim R, Gleason K, Angel J, Rippey B, Tinker R, Palecki M, Stooksbury D, Miskus D, Stephens S. 2002. The drought monitor. *Bulletin of the American Meteorological Society* **83:** 1181-1190.
Thornthwaite CW. 1948. An approach toward a rational classification of climates. *Geophysical Review* **38:** 55-94.
Thornthwaite CW, Mather JR. 1955. The Water Balance. *Publications in Climatology* **8**.
Unganai LS, Kogan FN. 1998. Southern Africa's recent droughts from space. *Advances in Space Research* **21:** 507-511.

Wang J, Price KP, Rich PM. 2001. Spatial patterns of NDVI in response to precipitation and temperature in the central Great Plains. *International Journal of Remote Sensing* **22:** 3827-3844.

Weier J, Herring D. 2000. Measuring Vegetation (NDVI & EVI). Earth Observatory, NASA. http://earthobservatory.nasa.gov/cgi-bin/printall?/Library/MeasuringVegetation/index.html [Sept. 27,2000].

Wells N, Goddard S, Hayes MJ. 2004. A Self-Calibrating Palmer Drought Severity Index. *Journal of Climate* **17:** 2335-2351.

Wilhite DA, Glantz MH. 1985. Understanding the drought phenomenon: The role of definitions. *Water International* **10:** 111-120.

Wilhite DA, Rosenberg NJ, Glantz MH. 1986. Improving federal reponse to drought. *Journal of Climate and Applied Meteorology* **25:** 332-342.

Williams JR, Jones CA, Dyke PT. 1984. A modeling approach to determining the relationships between erosion and soil productivity. *Transactions of the ASAE* **27:** 129-144.

Willmott CJ, Rowe CM, Mintz Y. 1985. Climatology of the terrestrial seasonal water cycle. *Journal of Climatology* **5:** 589-606.

Wood EF, Lettenmaier DP, Liang X, Nijssen B, Wetzel SW. 1997. Hydrological modeling of continental-scale basins. *Annual Review of Earth and Planetary Sciences* **25:** 279–300.

Wood EF, Zartarian V, Lettenmaier DP. 1992. A land-surface hydrology parameterization with subgrid variability for general circulation models. *Journal of Geophysical Research* **97:** 2717-2728.

Wu H, Hayes JT, Wilhite DA, Svoboda MD. 2005. The effect of the length of record on the Standardized Precipitation Index. *International Journal of Climatology* **25:** 505–520.

Wu H, Hayes MJ, Weiss A, Hu Q. 2001. An evaluation of the Standardized Precipitation Index, the China-Z Index, and the statistical Z-score. *International Journal of Climatology* **21:** 745-758.

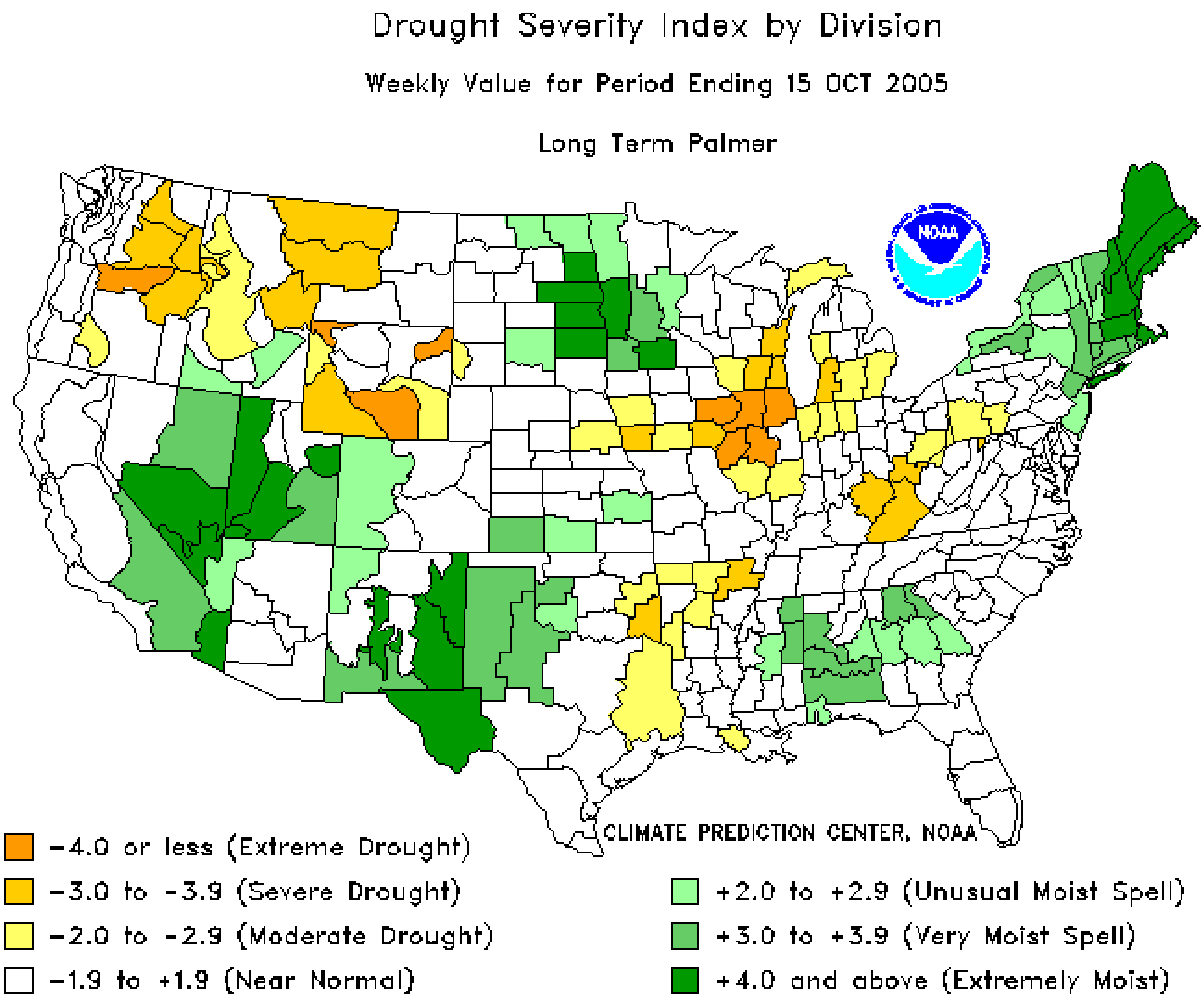
Wu H, Svoboda MD, Hayes MJ, Wilhite DA, Wen F. 2007. Appropriate application of the Standardized Precipitation Index in arid locations and dry seasons. *International Journal of Climatology* **27:** 65–79.

Wurbs RA. 2001. *Reference and Users Manual for the Water Rights Analysis Package (WRAP),* Texas Water Resources Institute: College Station, TX.

Appendix A

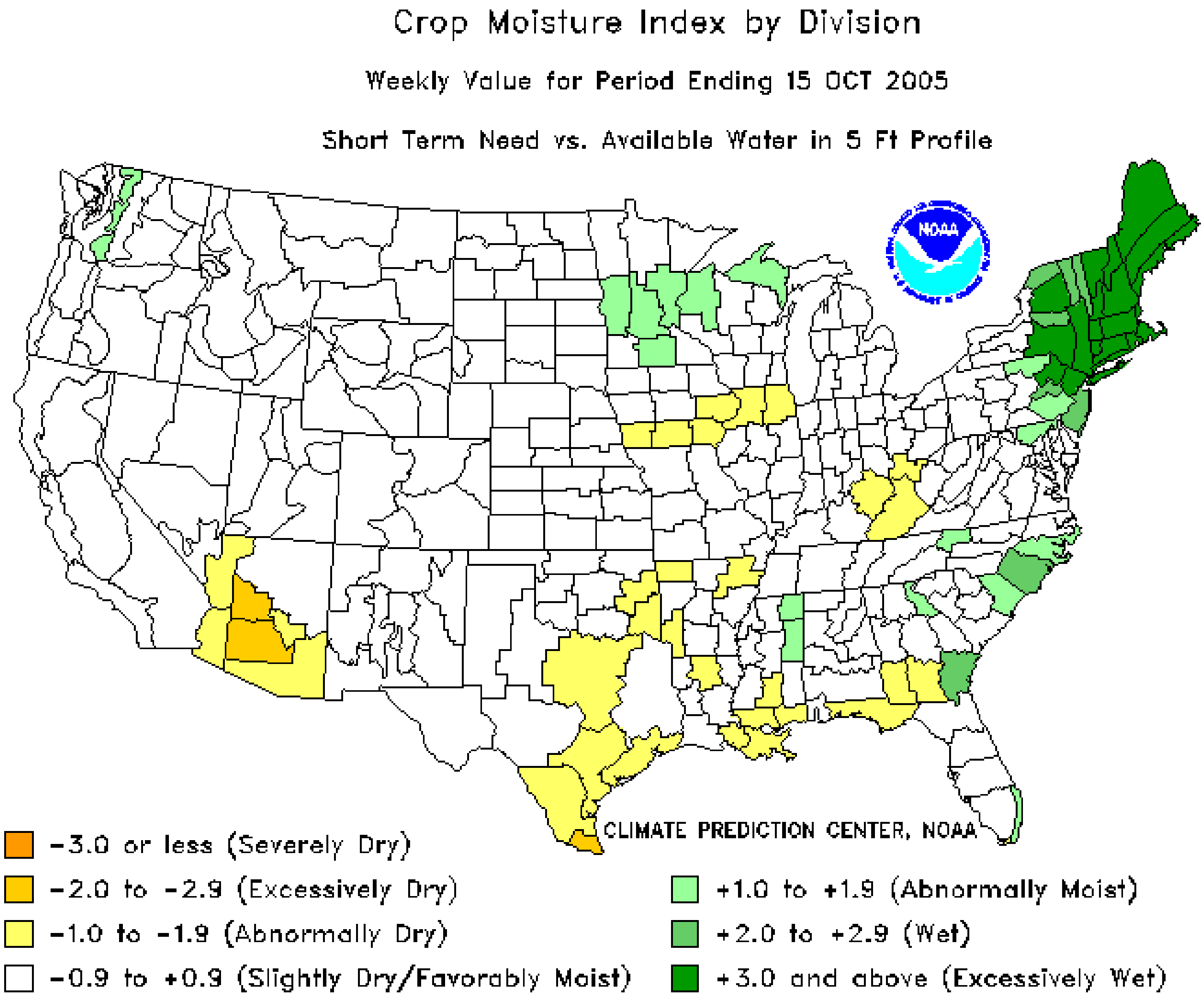
Selected Examples of Drought Monitoring Products (see Table 1)

A1



http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/palmer.gif

A2



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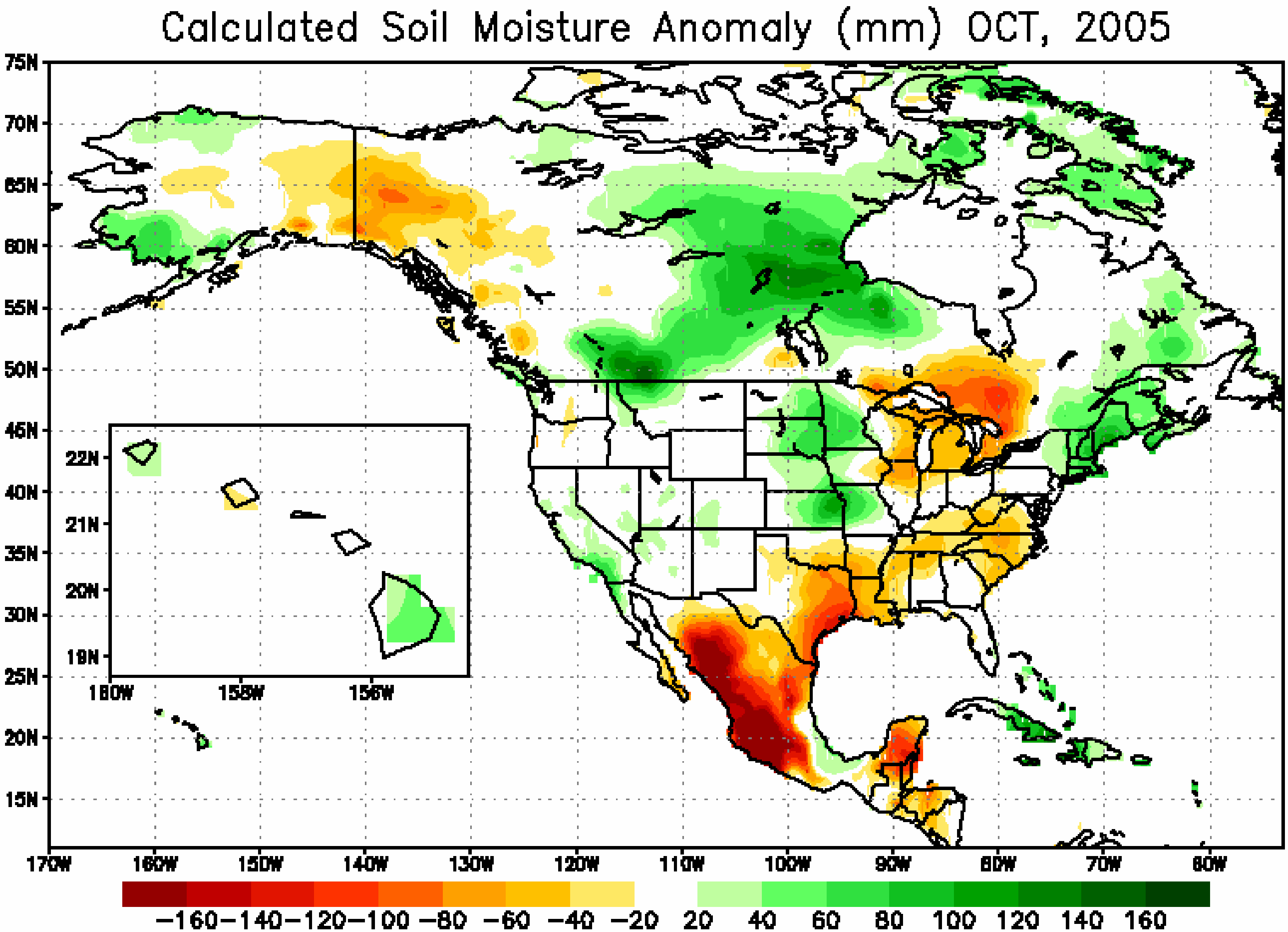
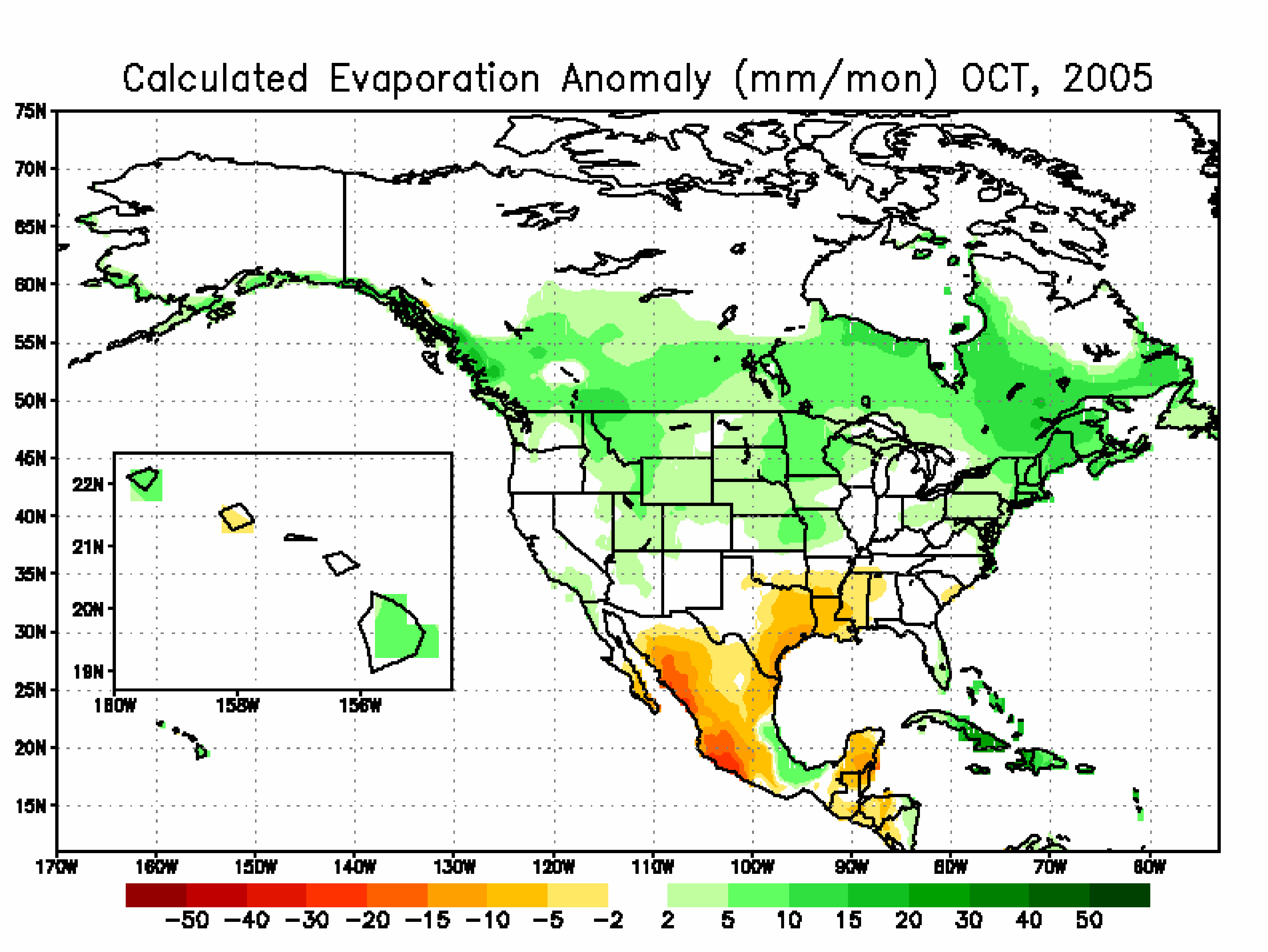
A3



http://www.cpc.ncep.noaa.gov/soilmst/na_wa.htm

A4



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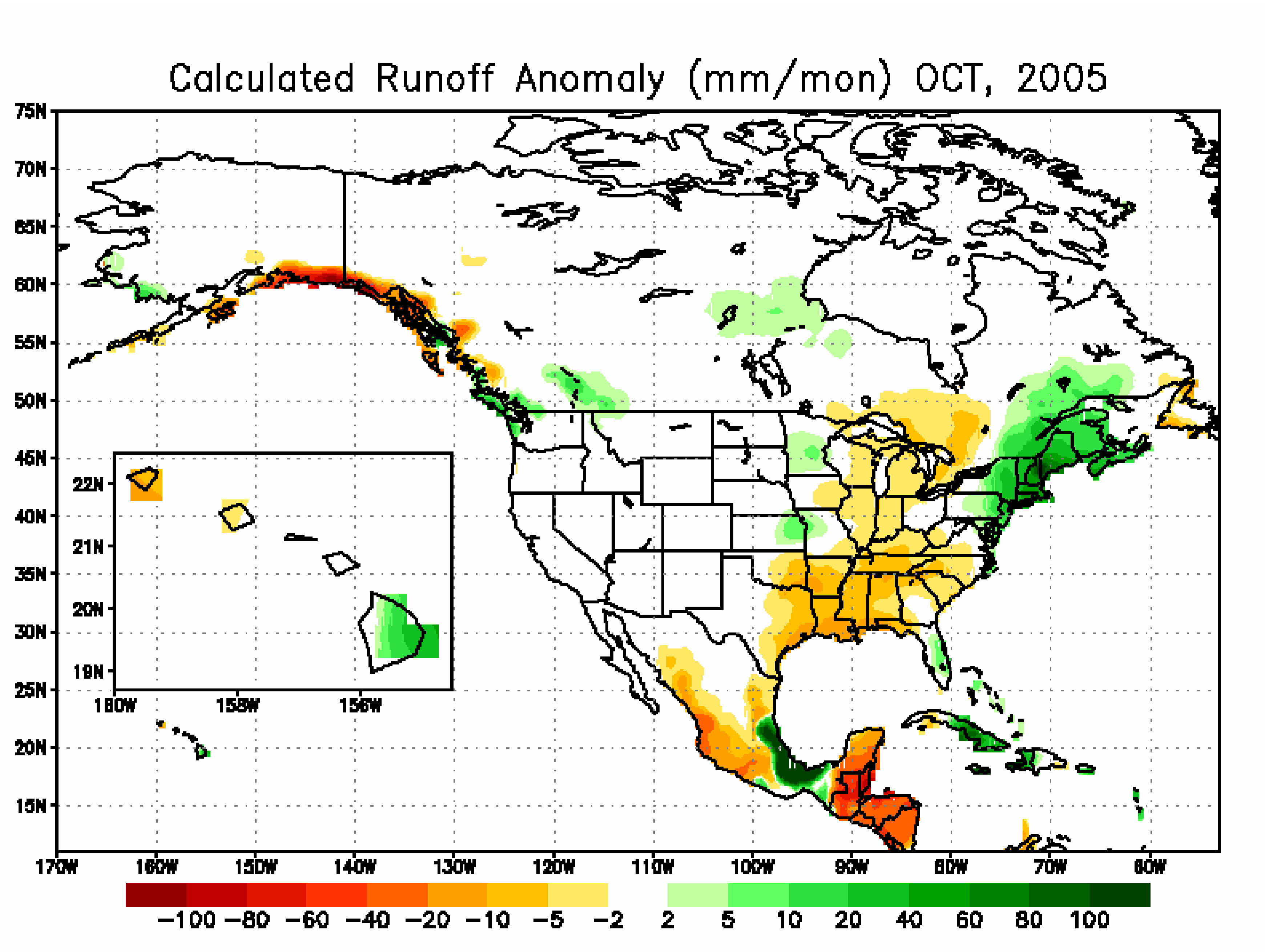
A5



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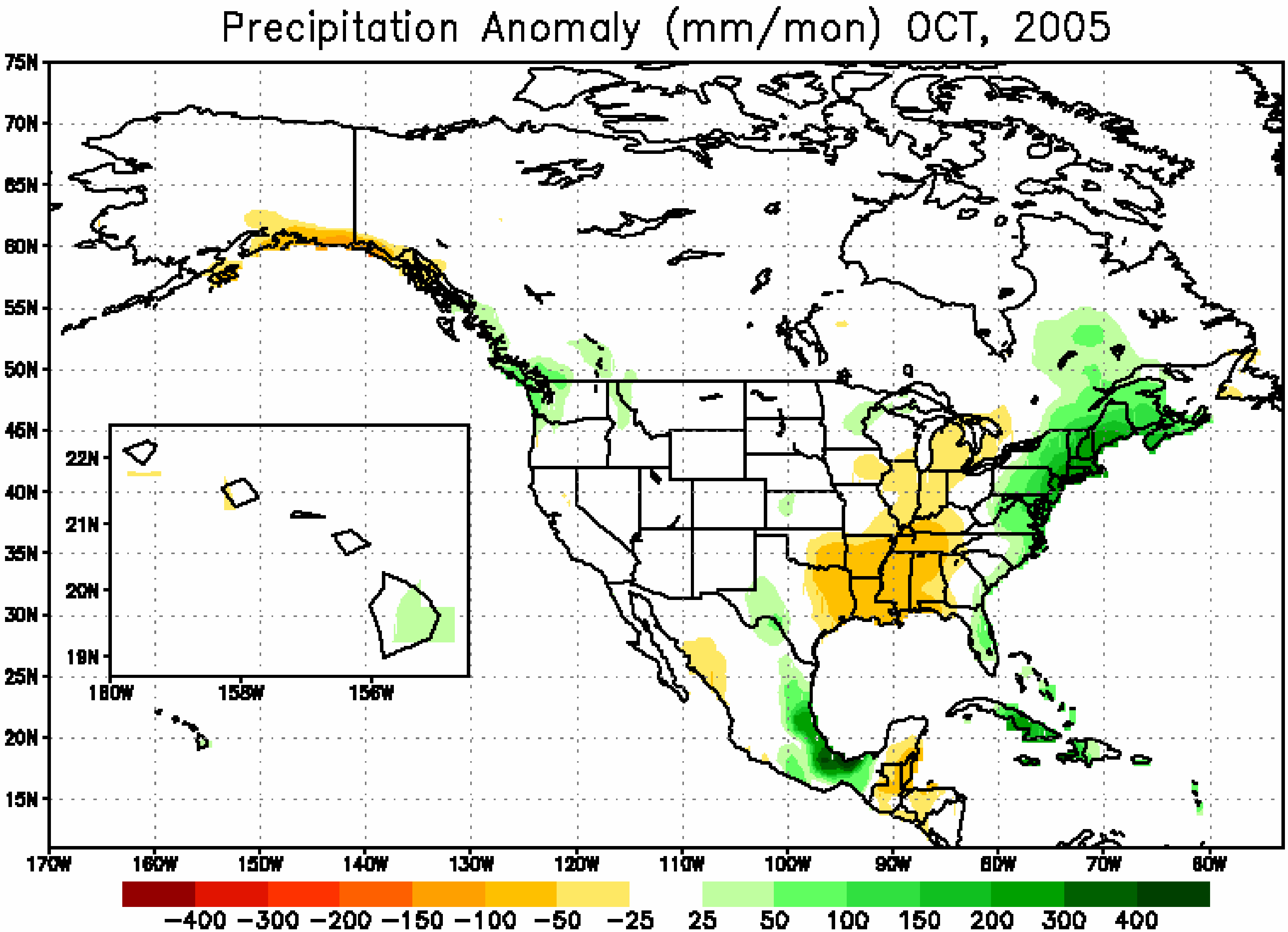
A6



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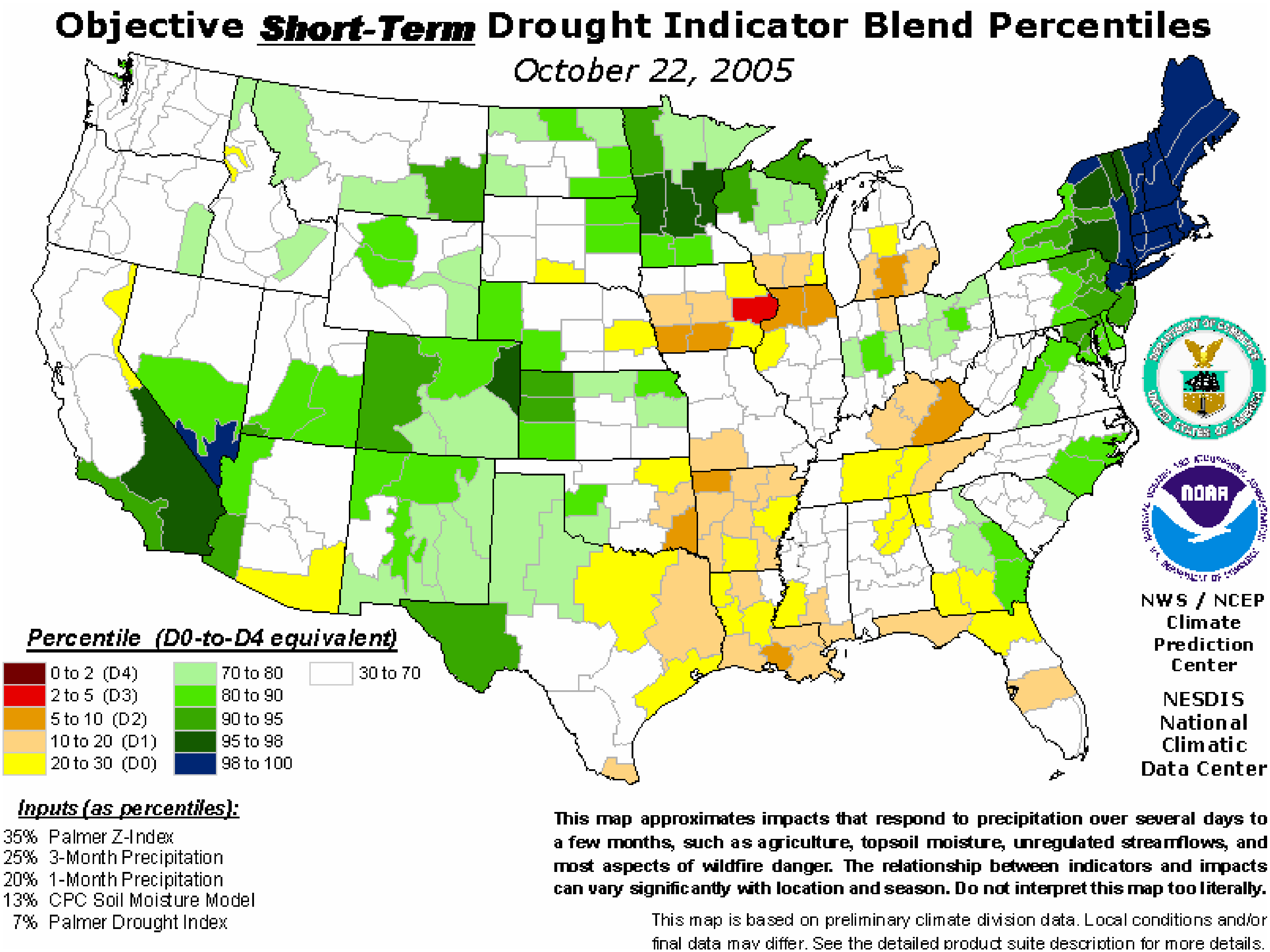
A7



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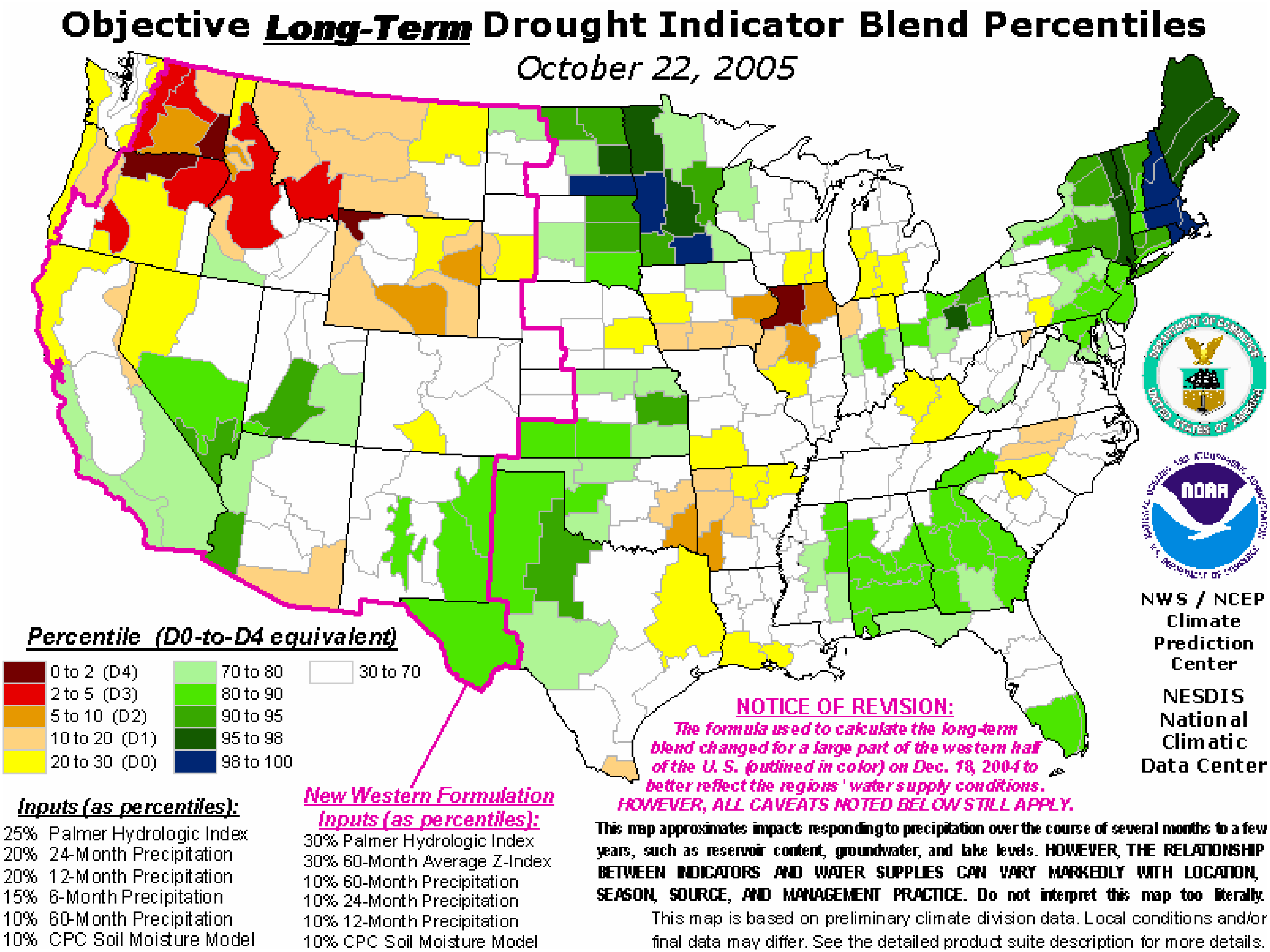
A8



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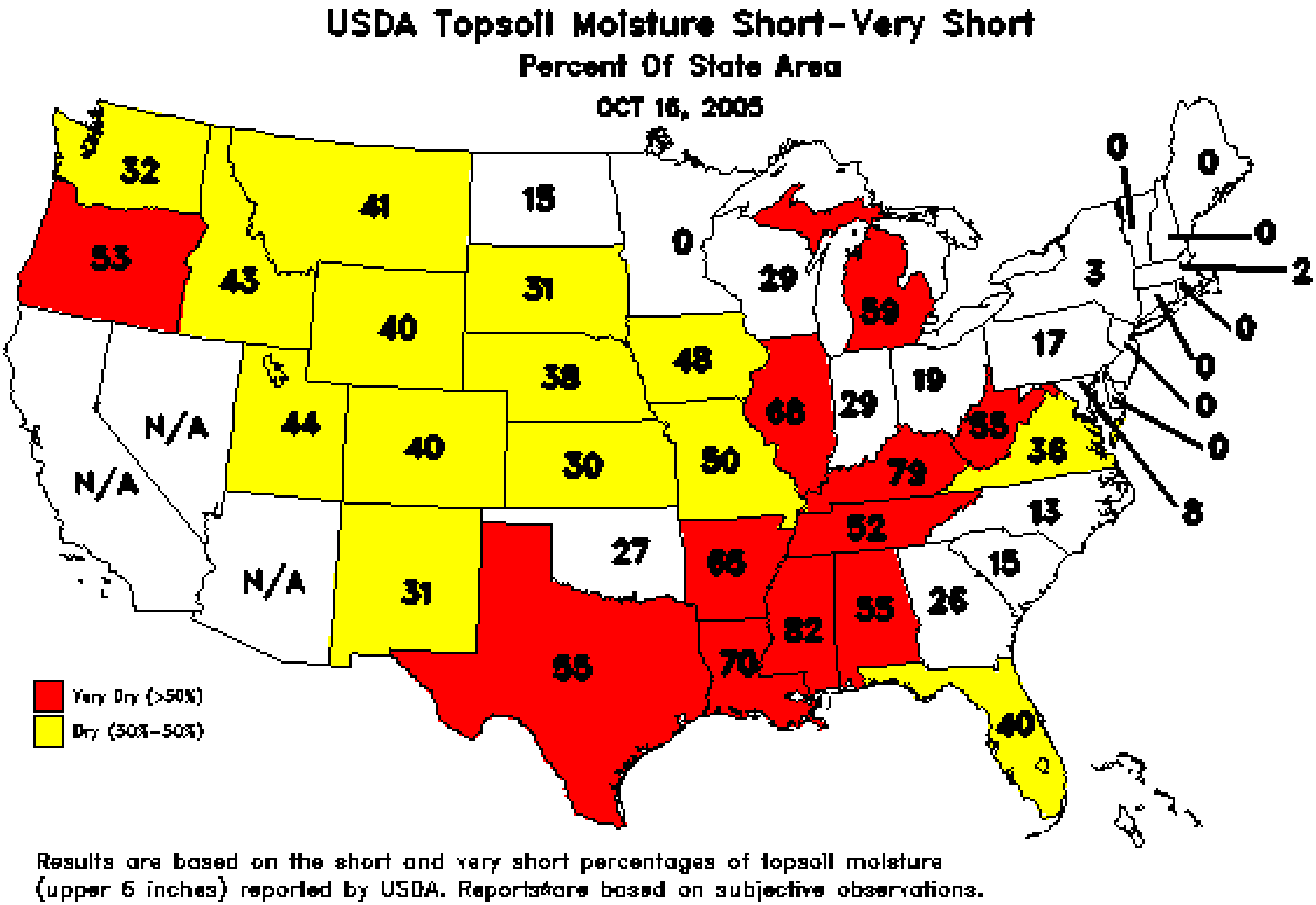
A9



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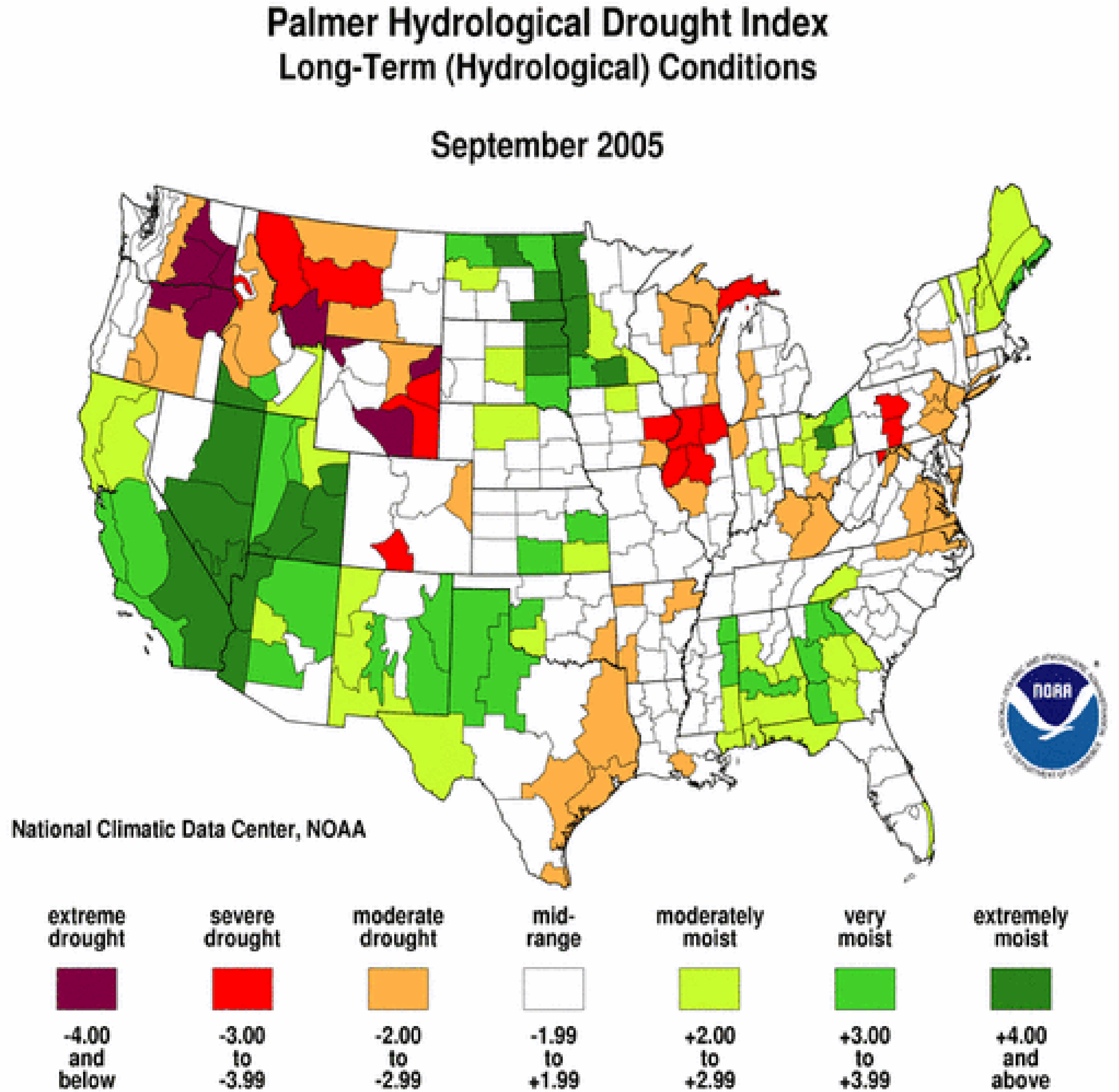
A10



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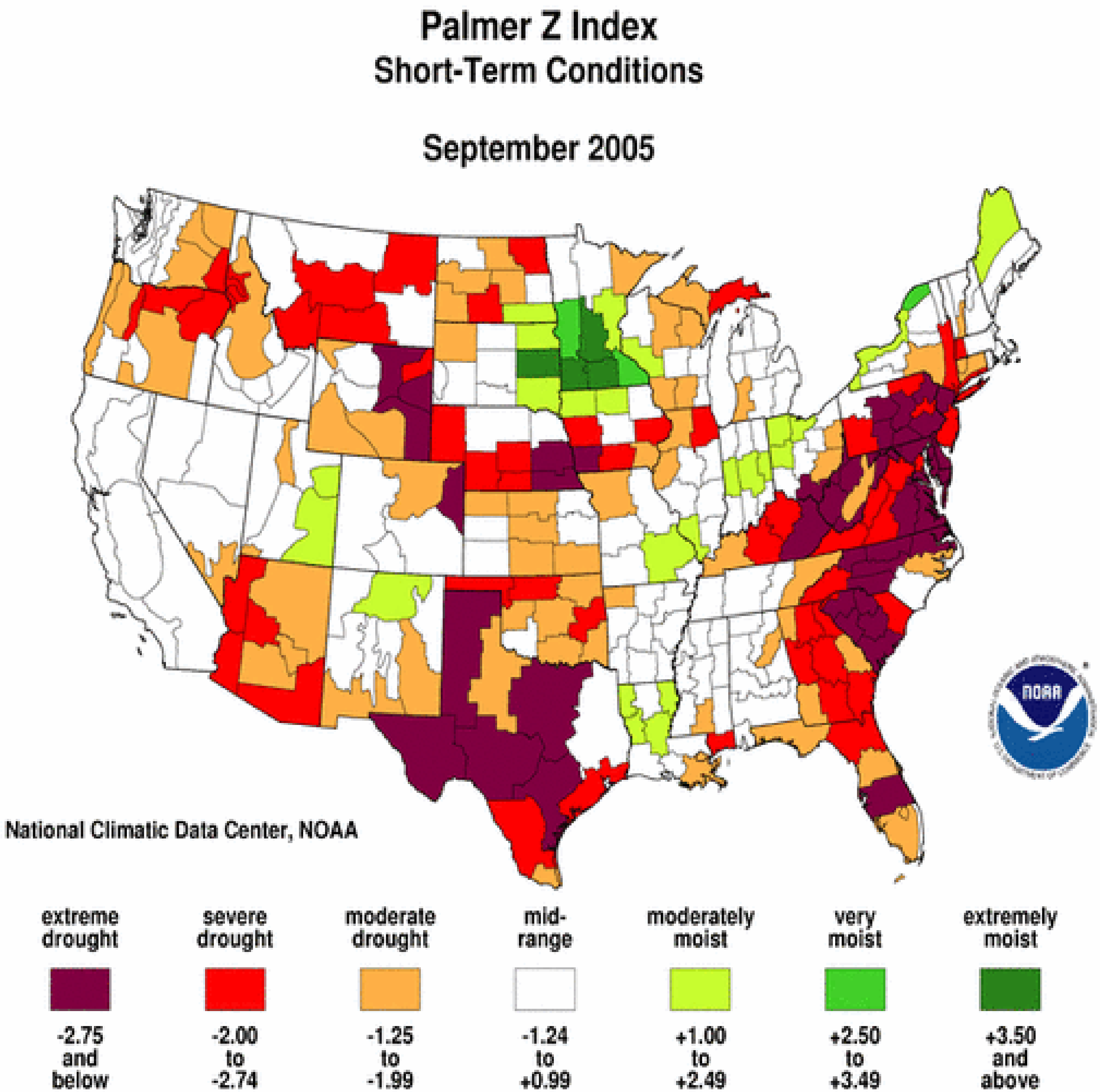
A11



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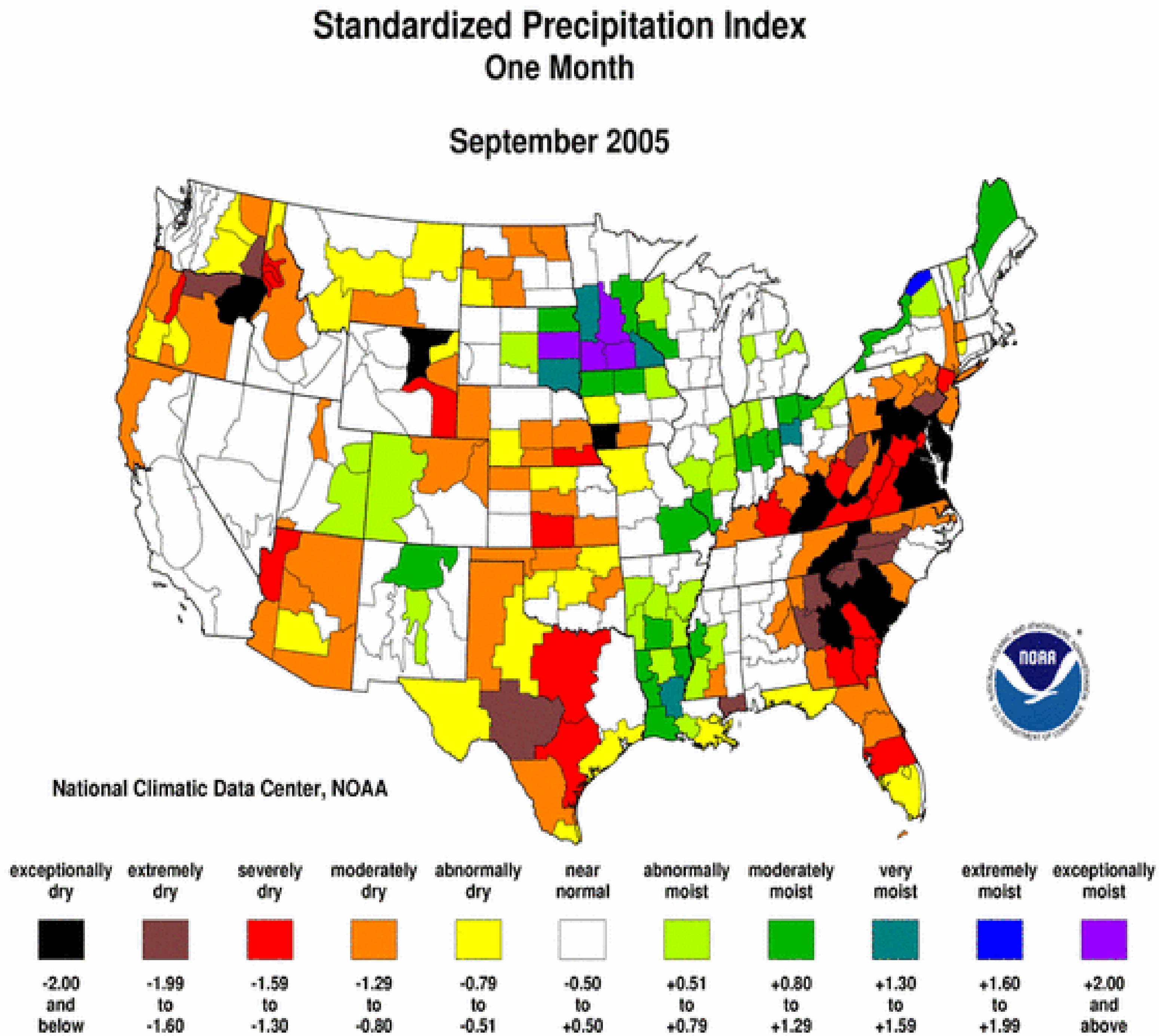
A12



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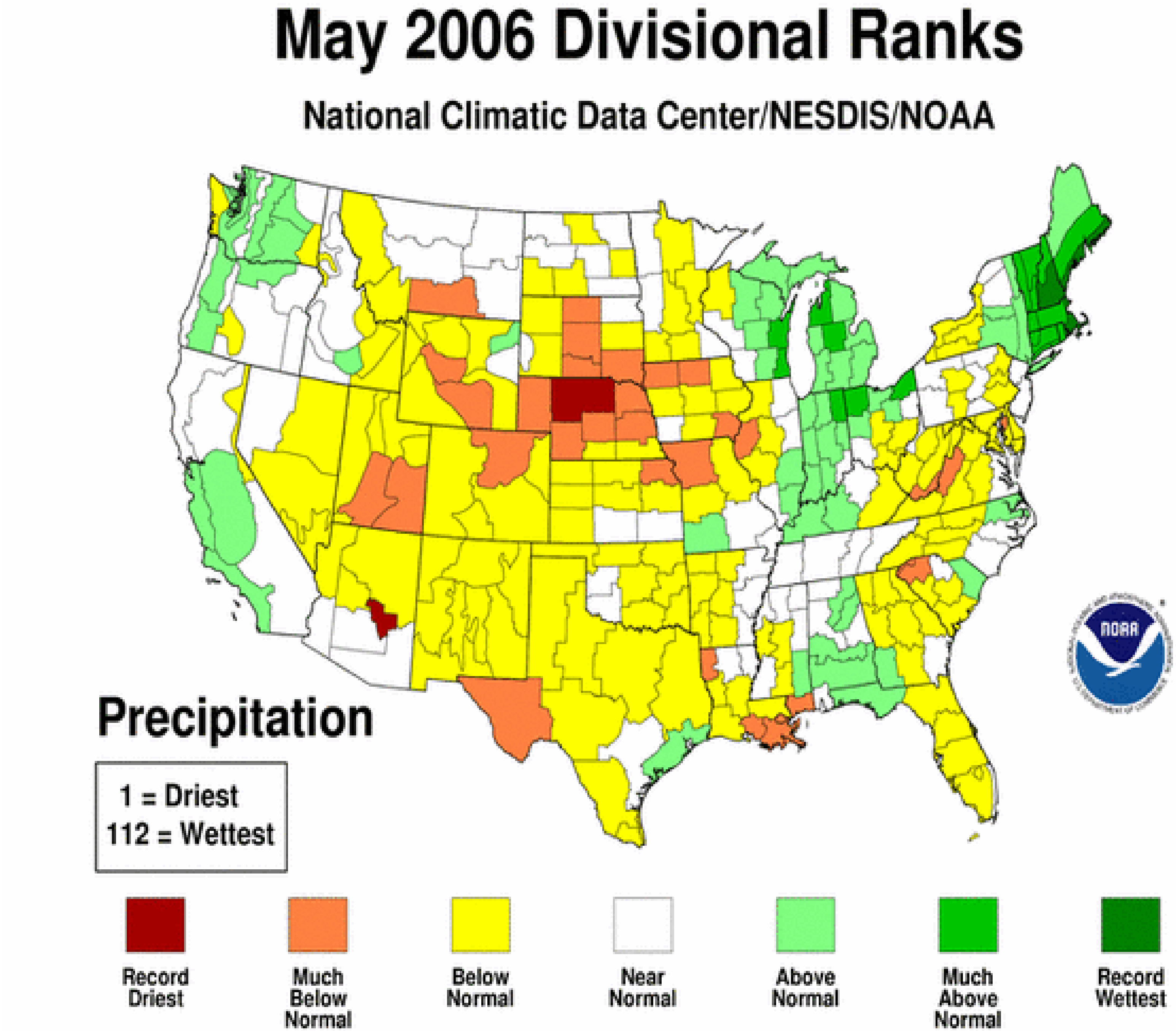
A13



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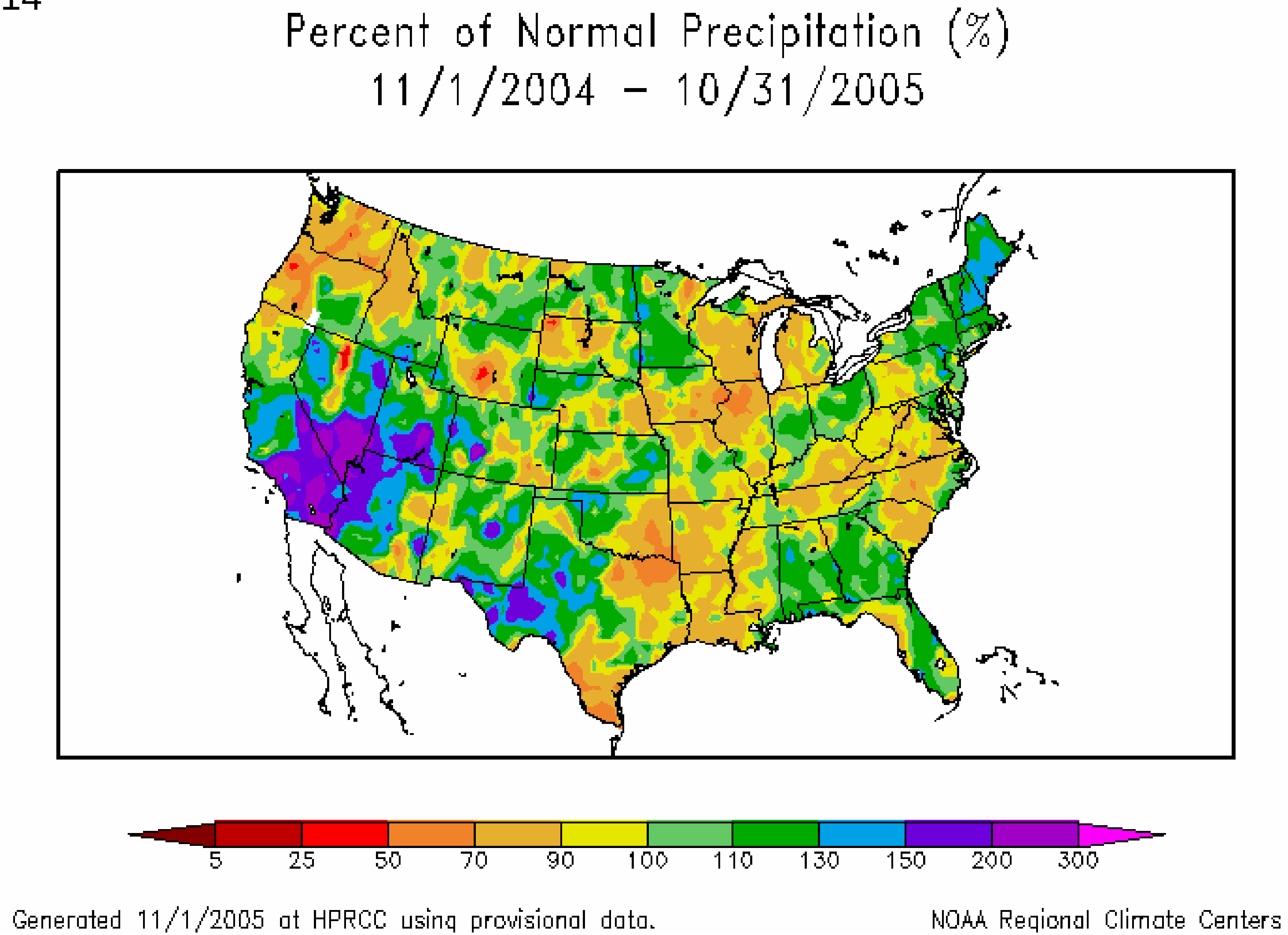
A14



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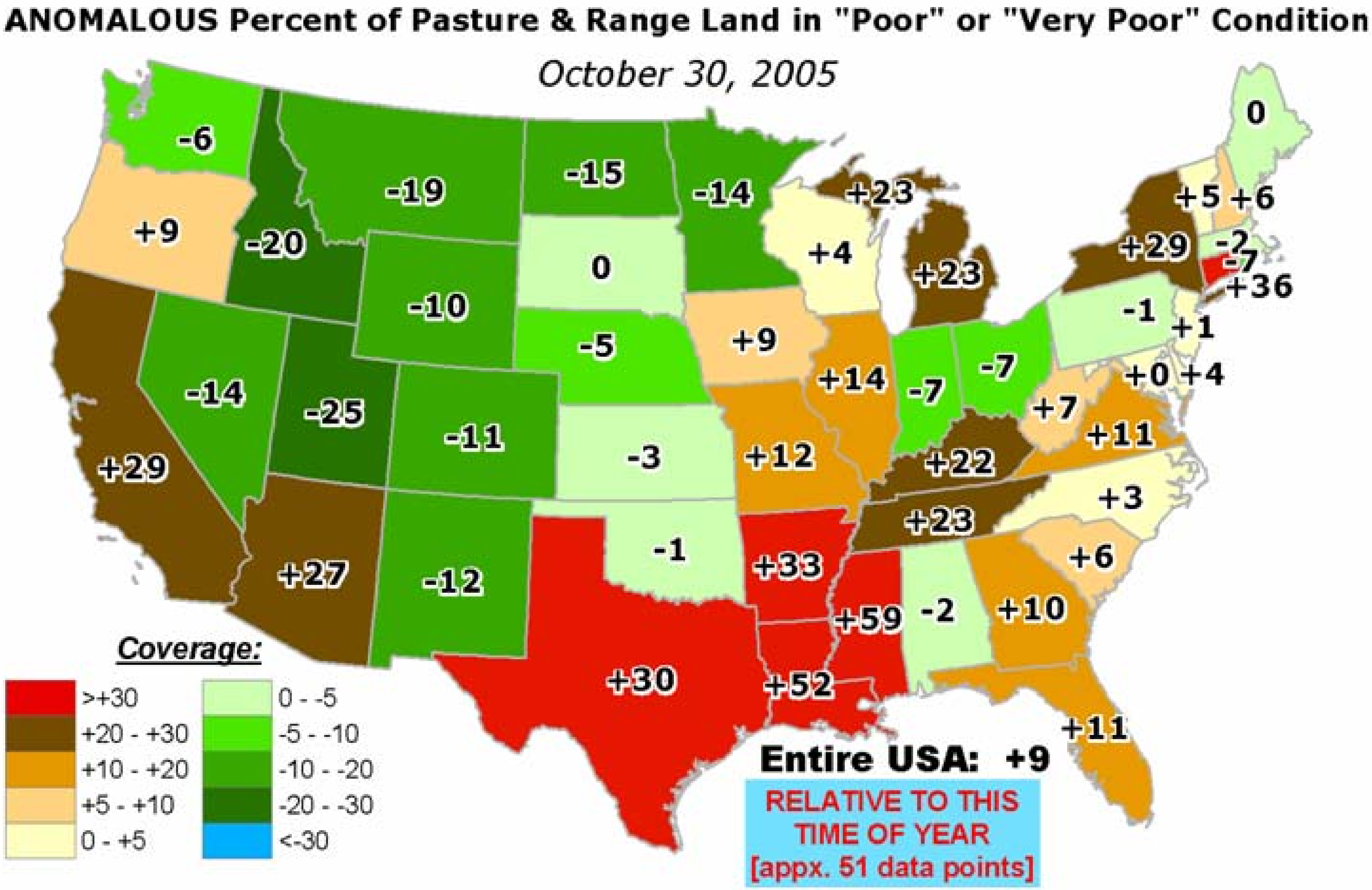
A15



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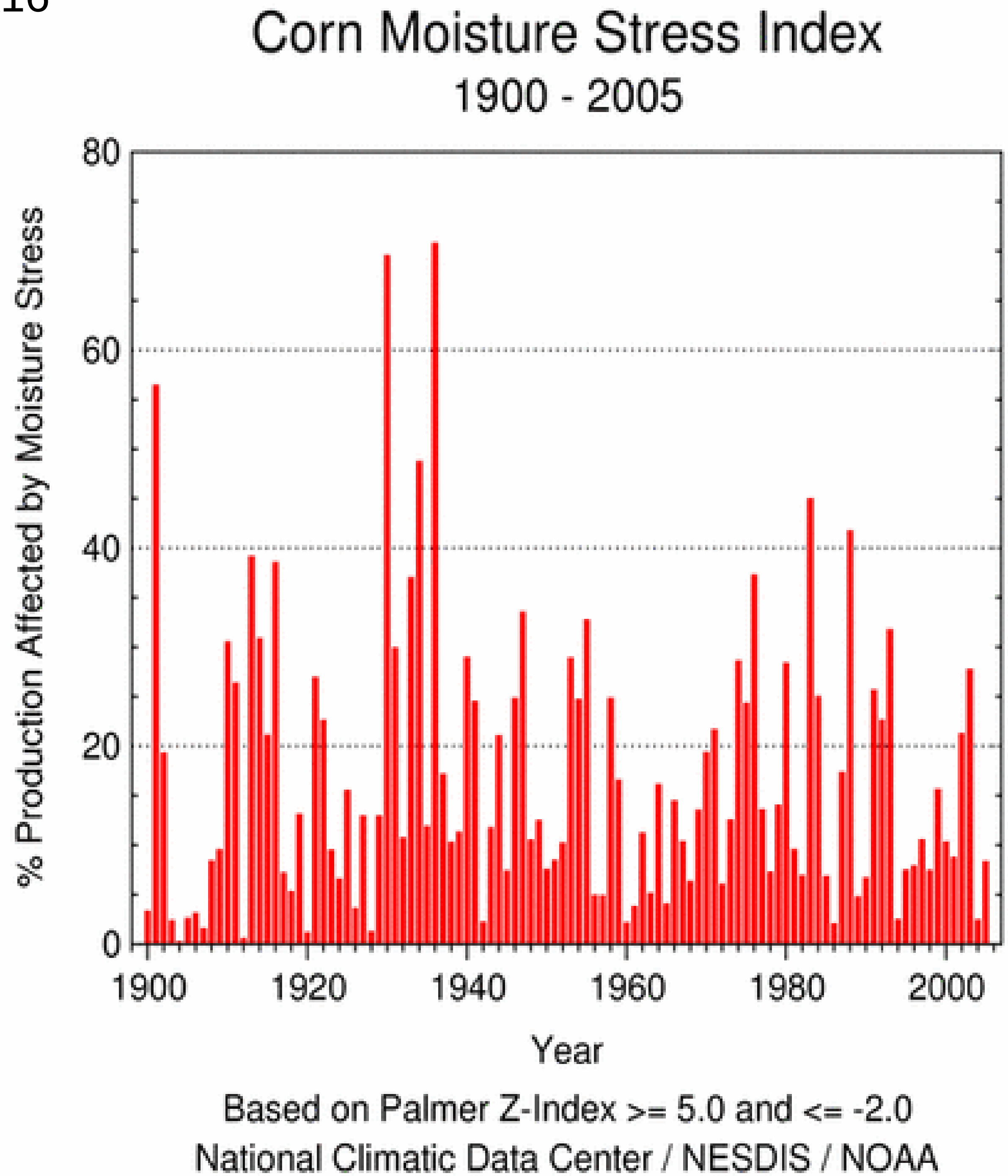
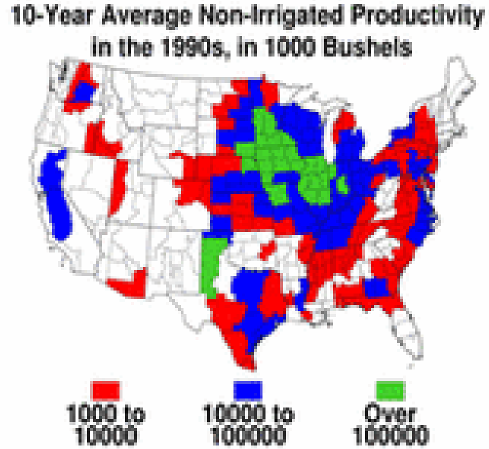
A16





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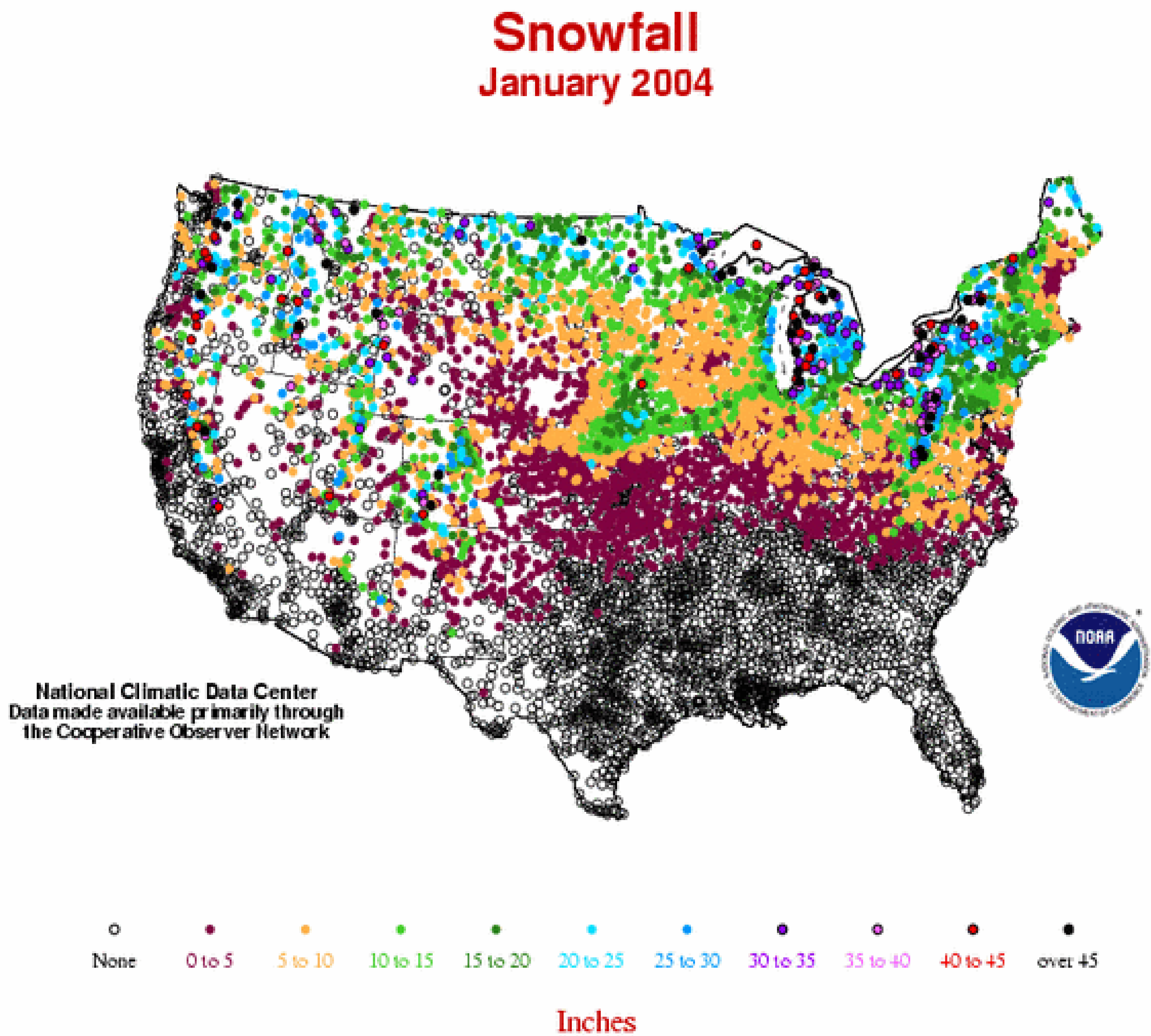
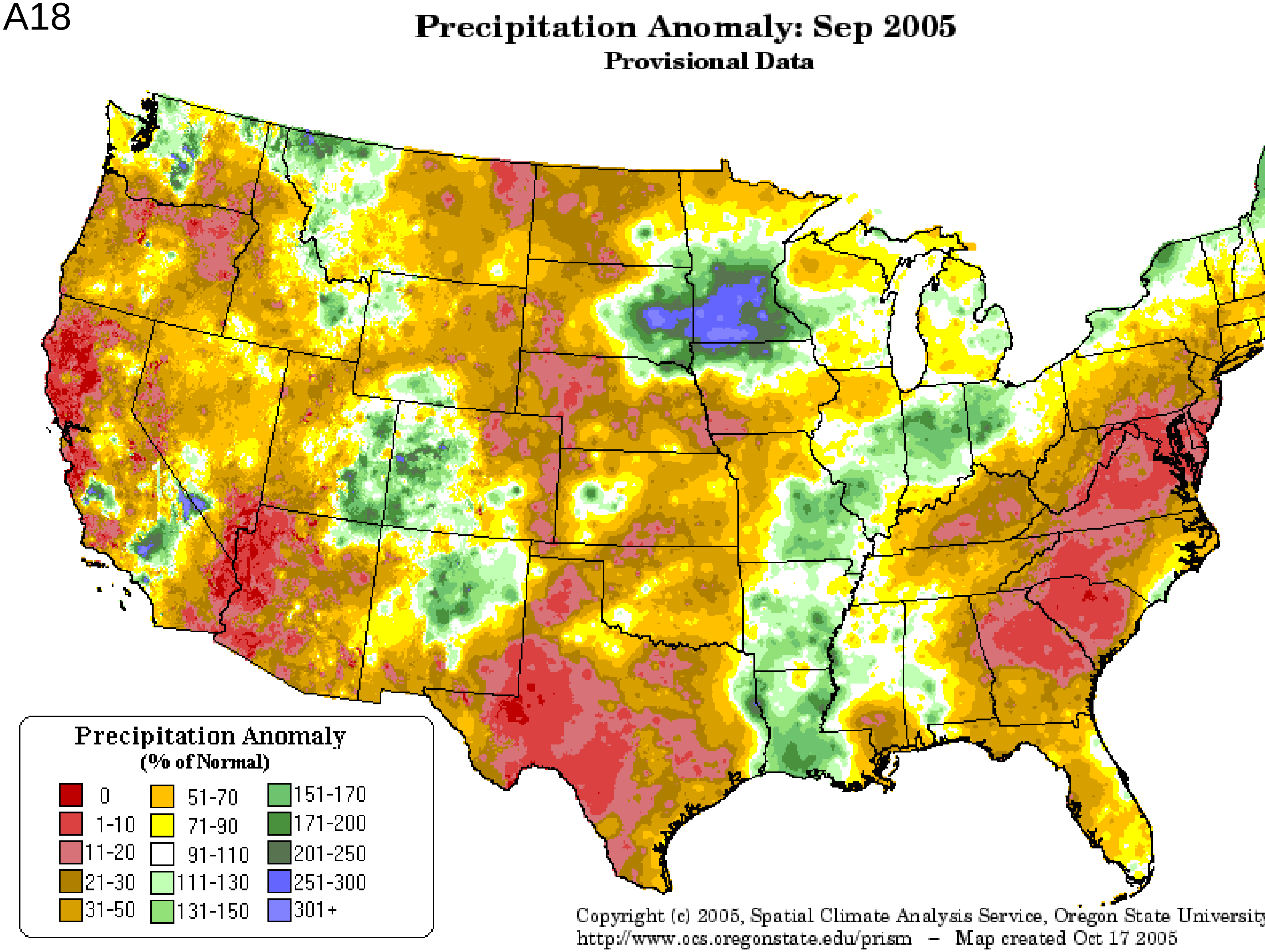
A17



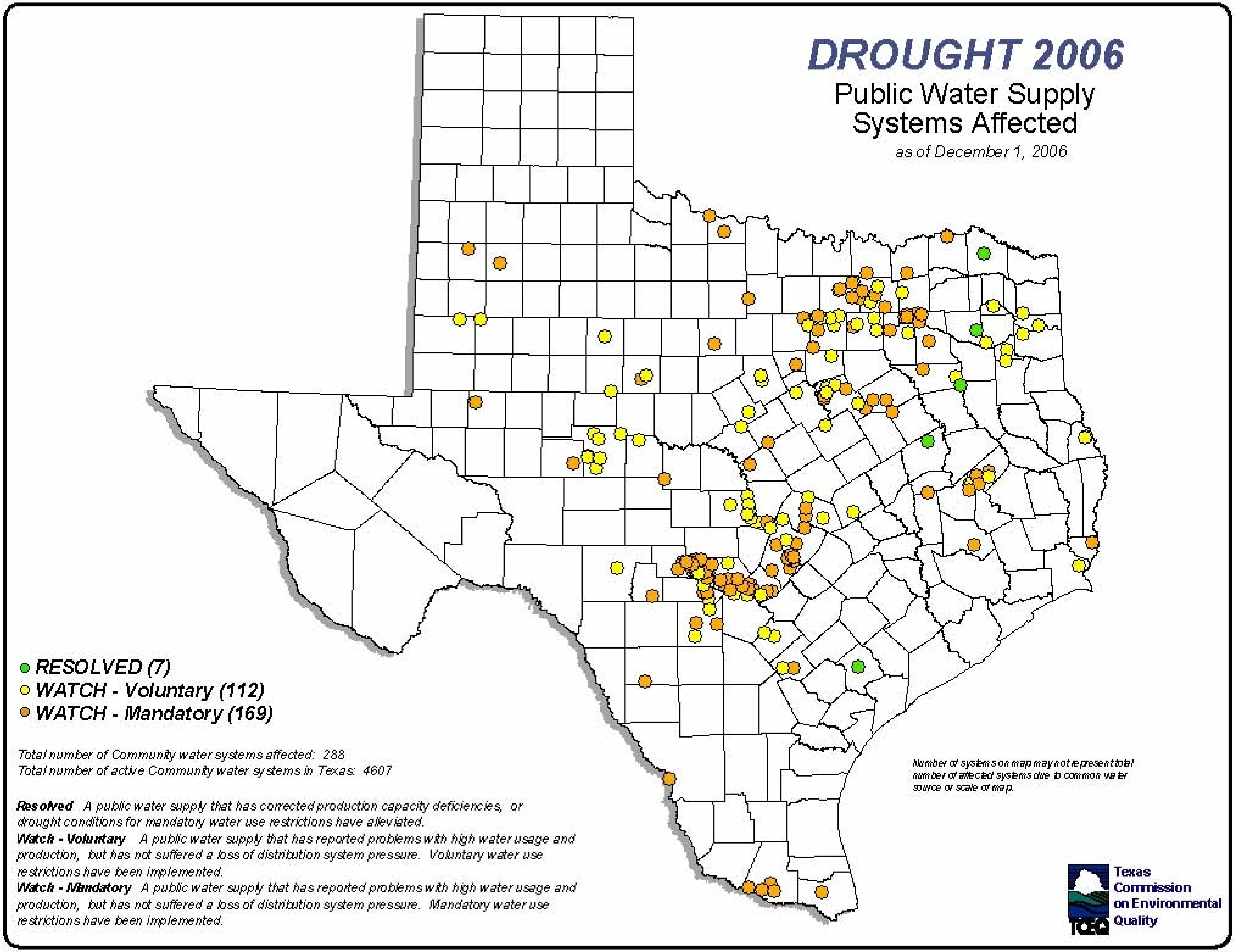
http://www.ncdc.noaa.gov/img/climate/snow/snow.html

A18



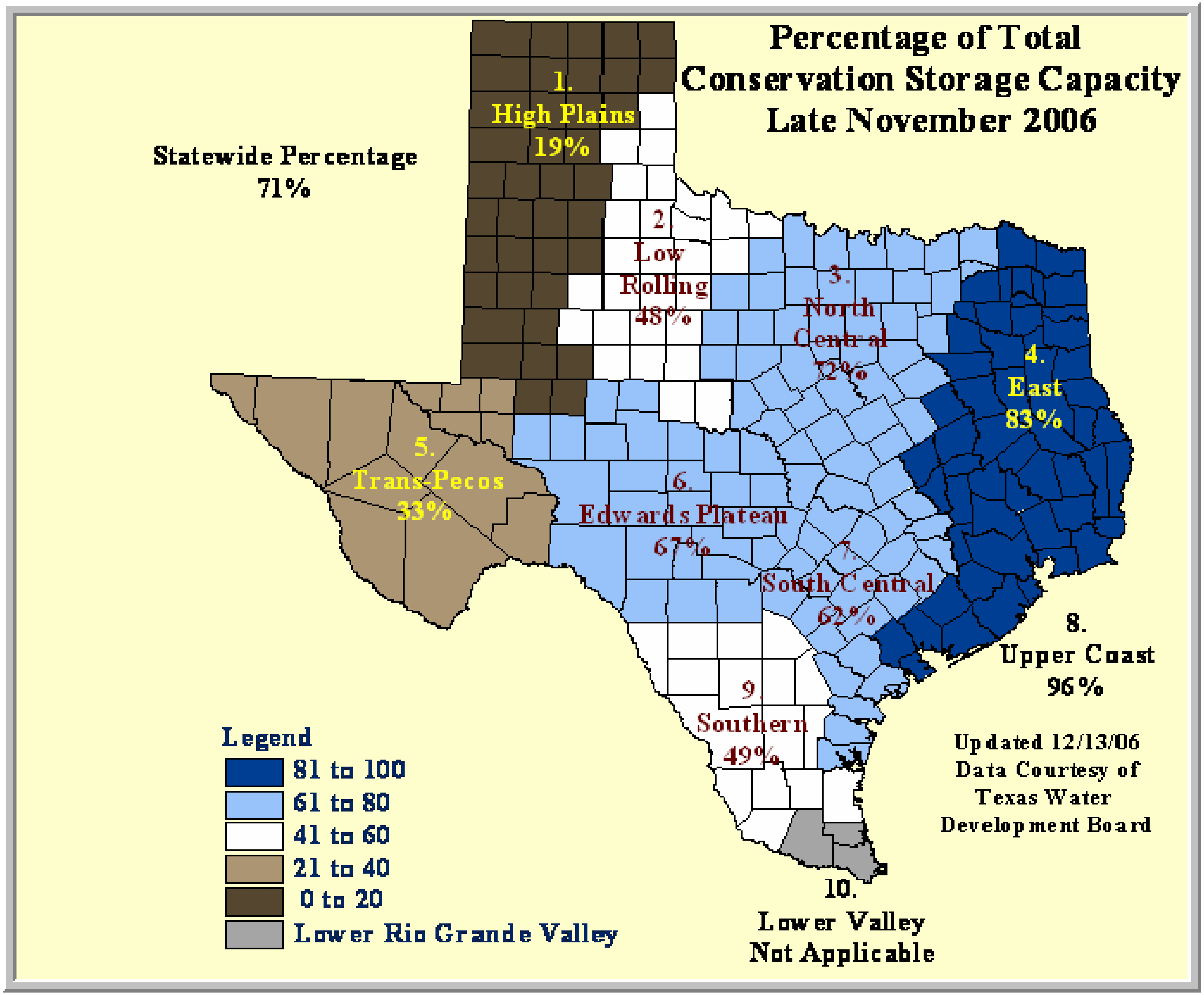
http://www.ocs.oregonstate.edu/prism/index.phtml

A19



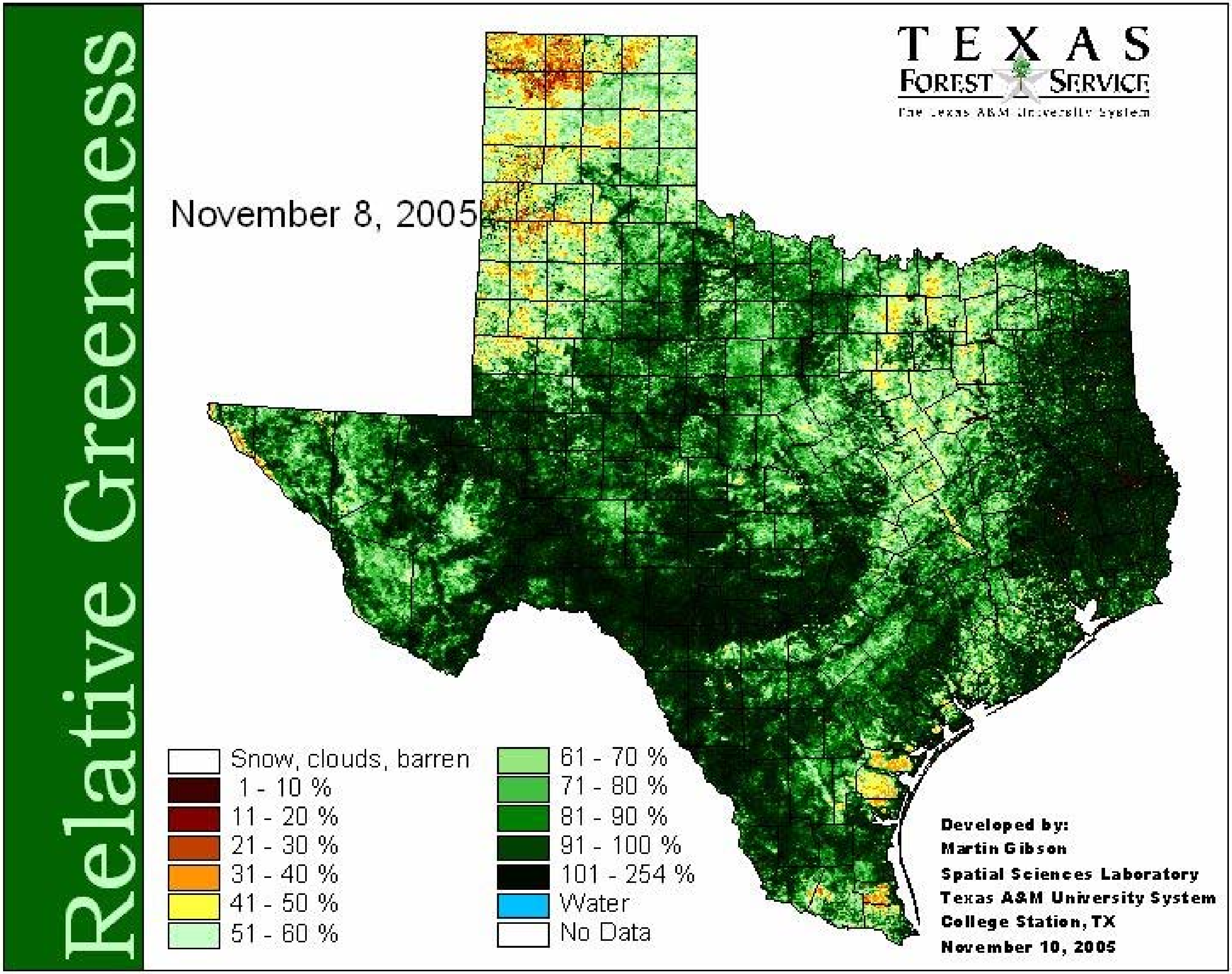
http://www.tceq.state.tx.us/permitting/water_supply/pdw/trot/location.html

A20



http://www.texaswaterinfo.net/Monitoring/Meteorological/Drought/reservoir_storage.htm

A21



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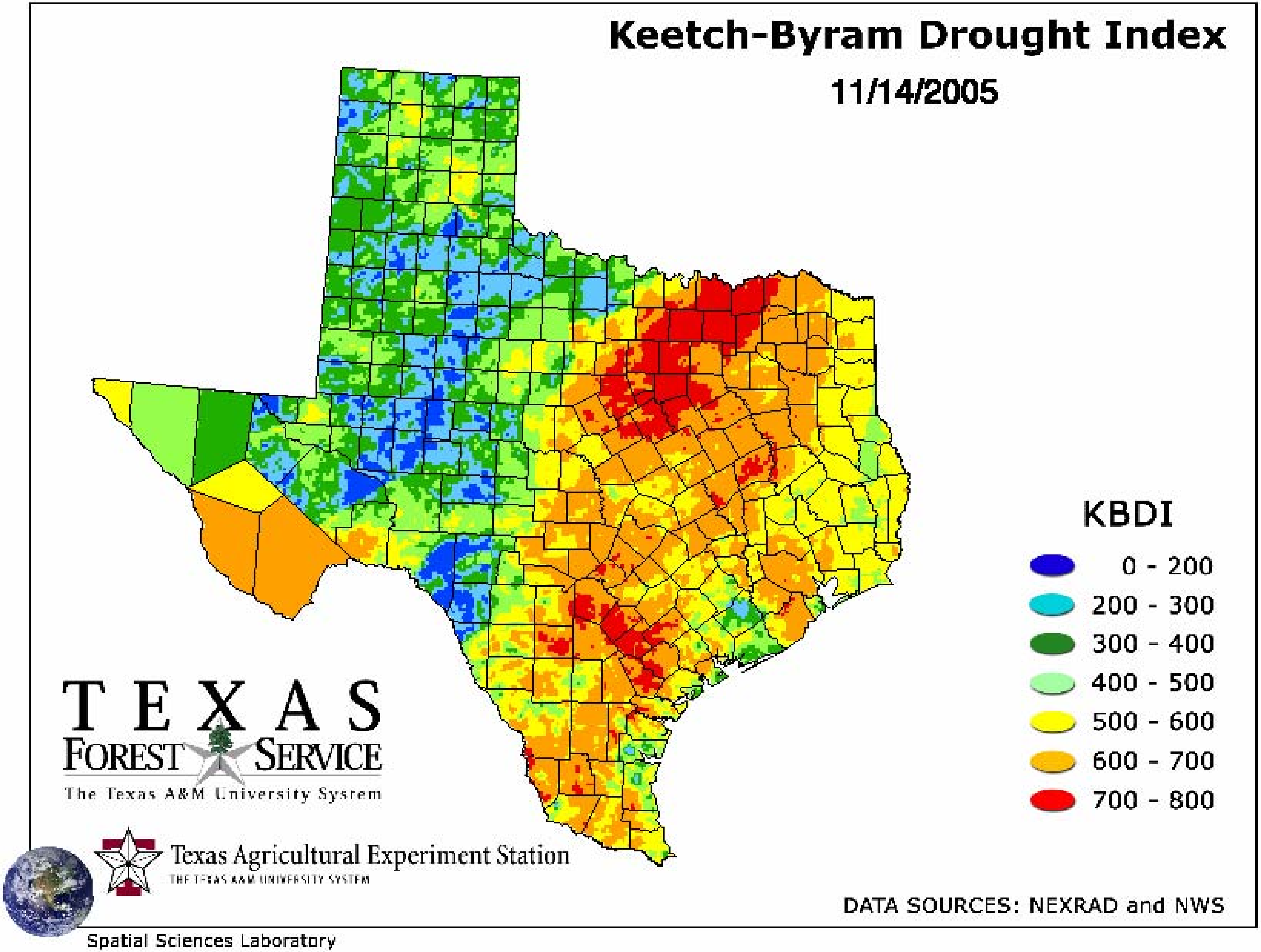
A22



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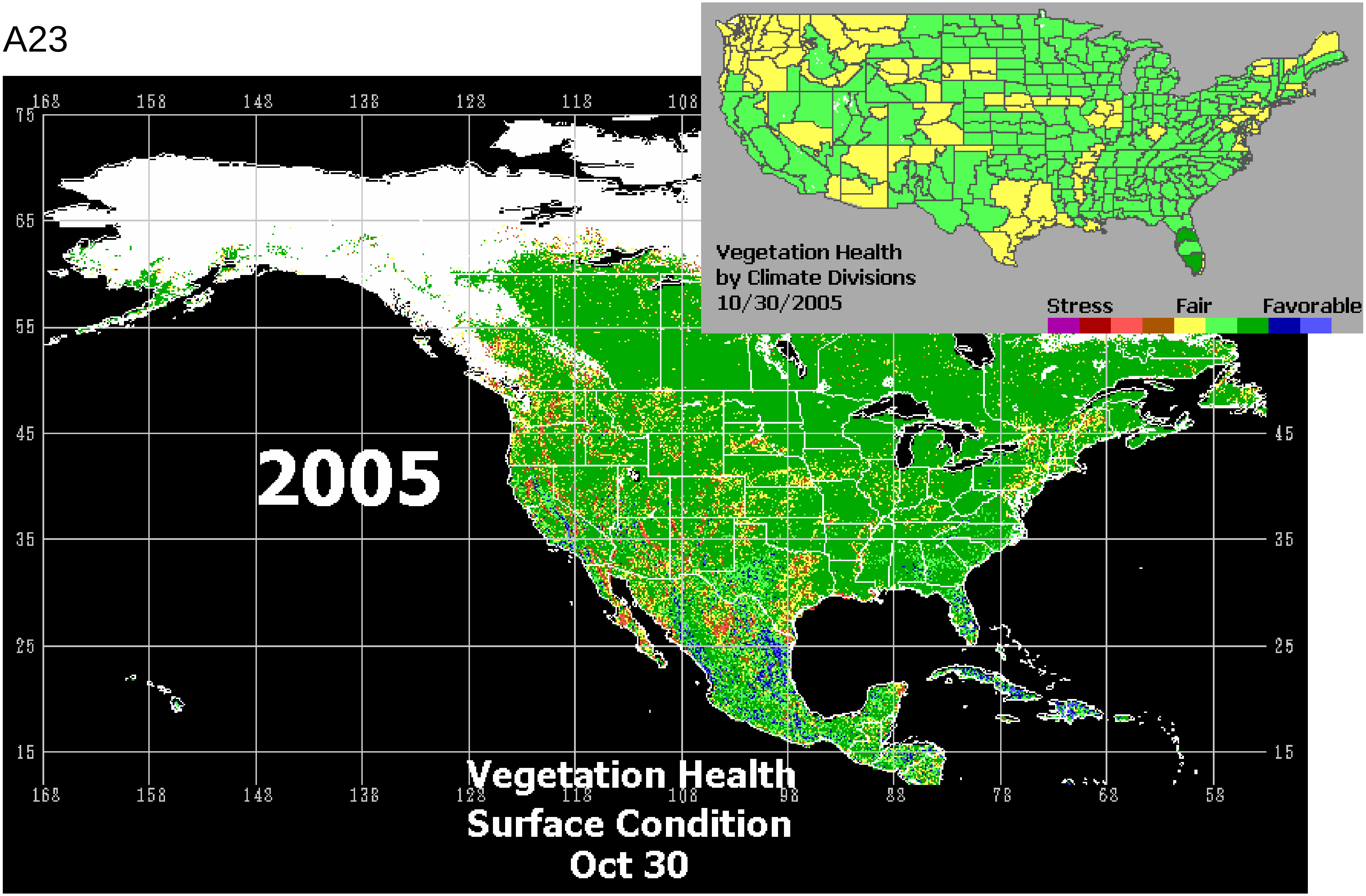
A23

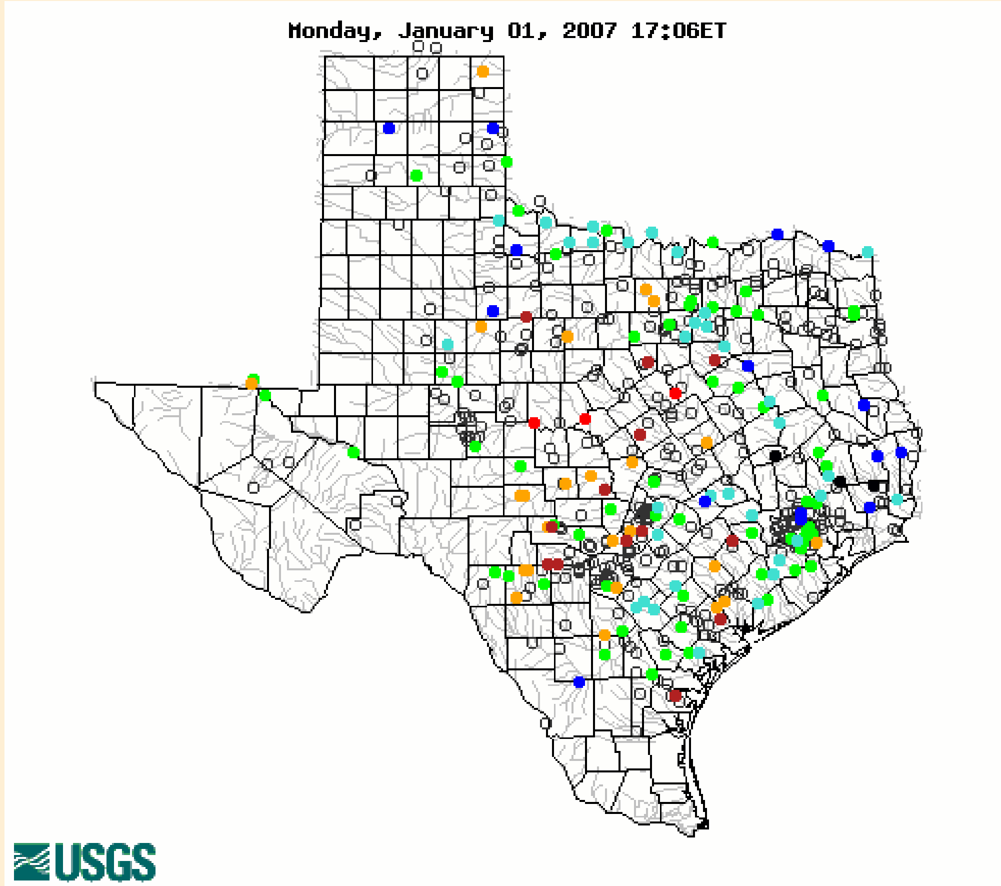


http://www.orbit.nesdis.noaa.gov/smcd/emb/vci/VH/index.html

A24

Daily Streamflow Conditions

Select a site to retrieve data and station information.



Explanation

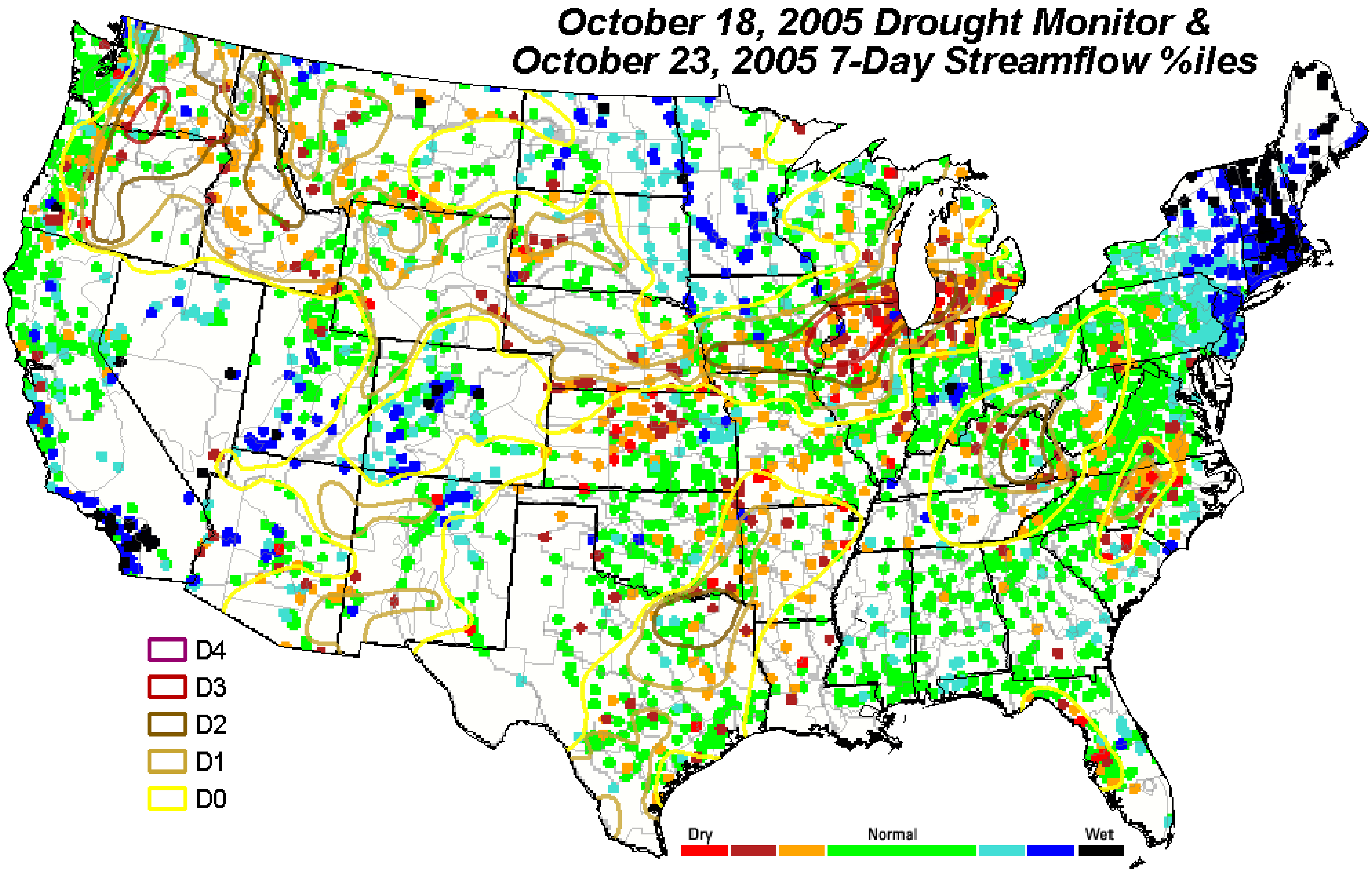
- High
- ≥ 90th percentile
- 75th - 89th percentile
- 25th - 74th percentile
- 10th - 24th percentile
- < 10th percentile
- Low
- Not ranked

The colored dots on this map depict streamflow conditions as a percentile, which is computed from the period of record for the current day of the year. Only stations with at least 30 years of record are used.

The **gray circles** indicate other stations that were not ranked in percentiles either because they have fewer than 30 years of record or because they report parameters other than streamflow. Some stations, for example, measure stage only.

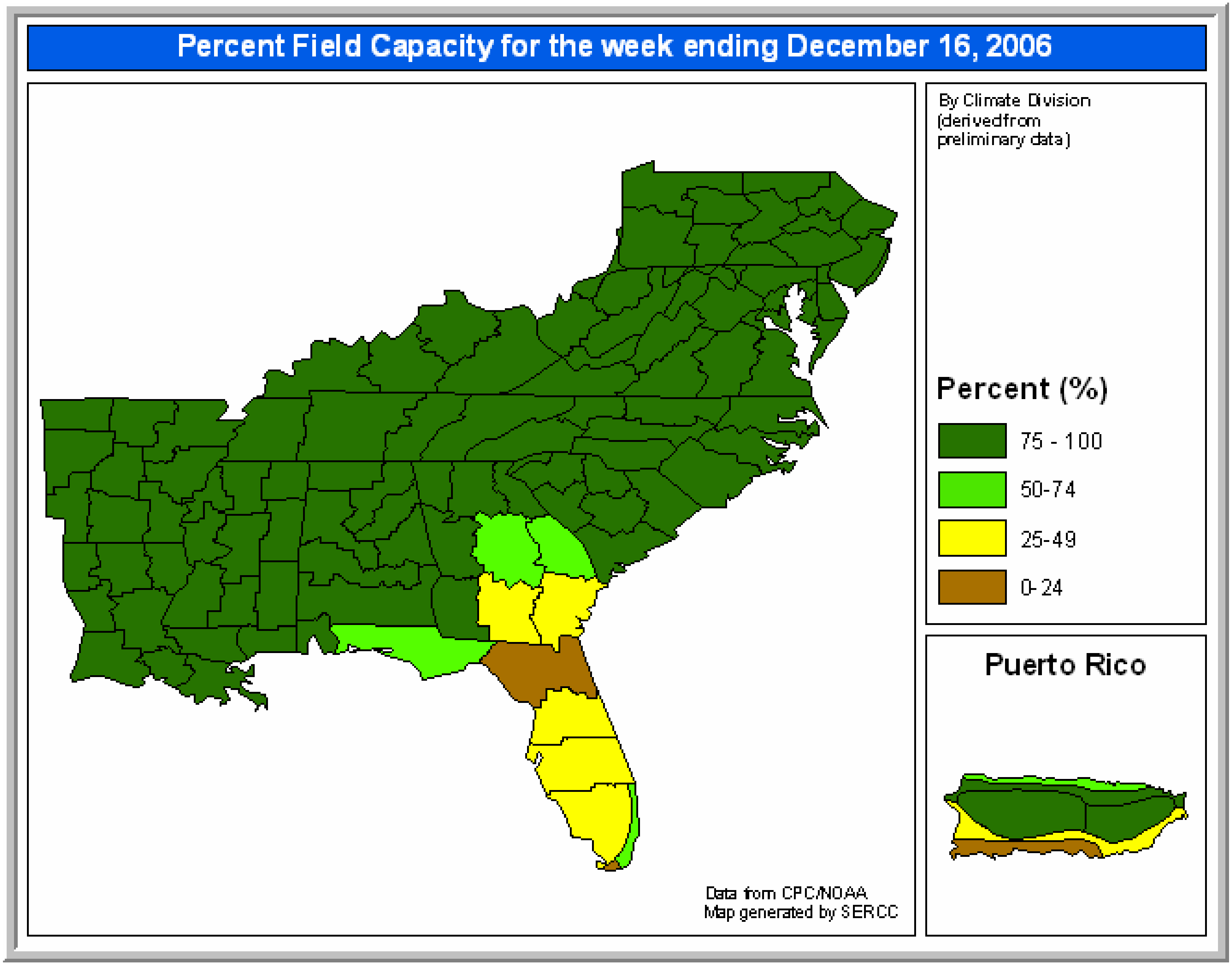
http://waterdata.usgs.gov/tx/nwis/rt

A25



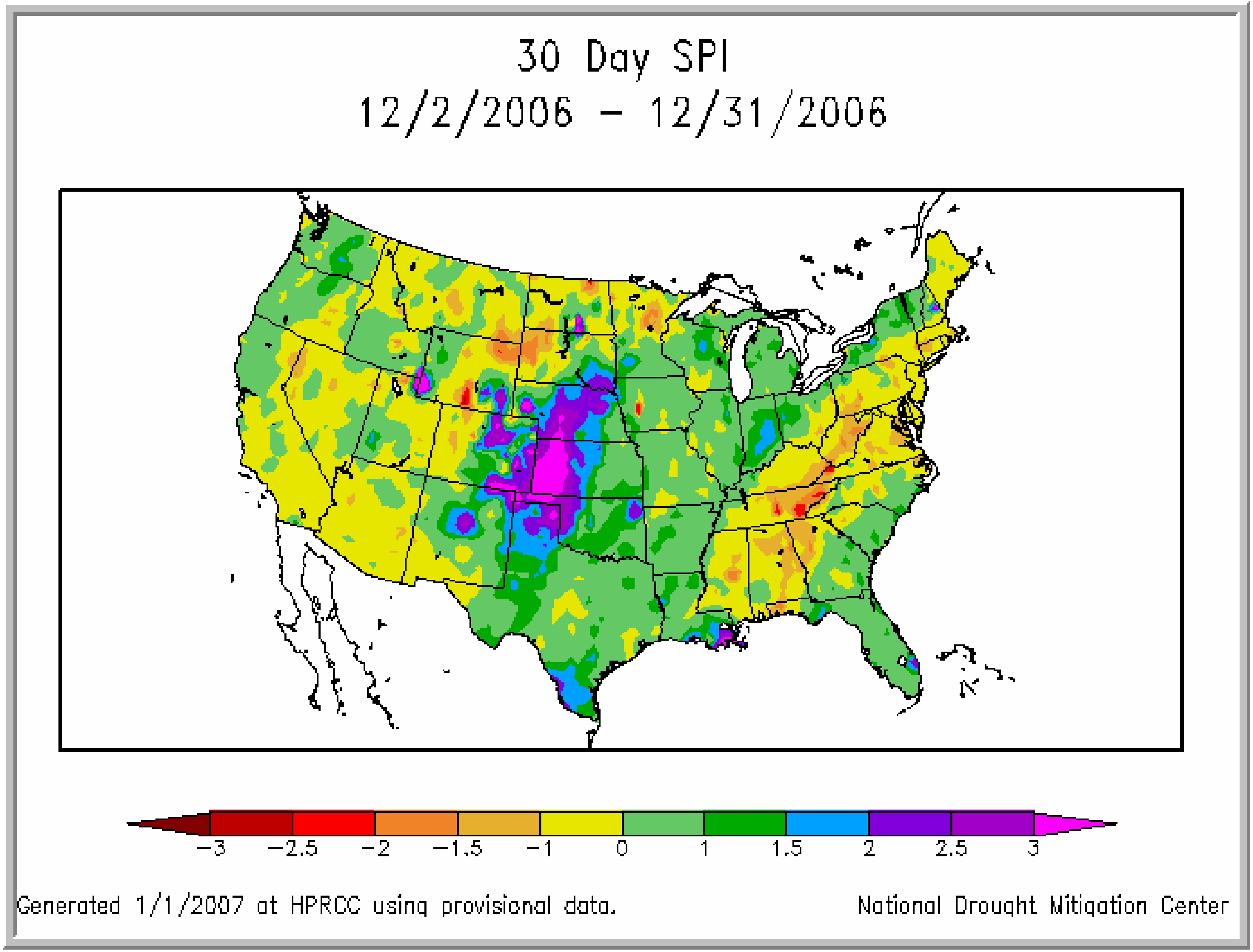
http://www.cpc.ncep.noaa.gov/products/predictions/experimental/edb/usdm-streamflows-overlay.gif

A26



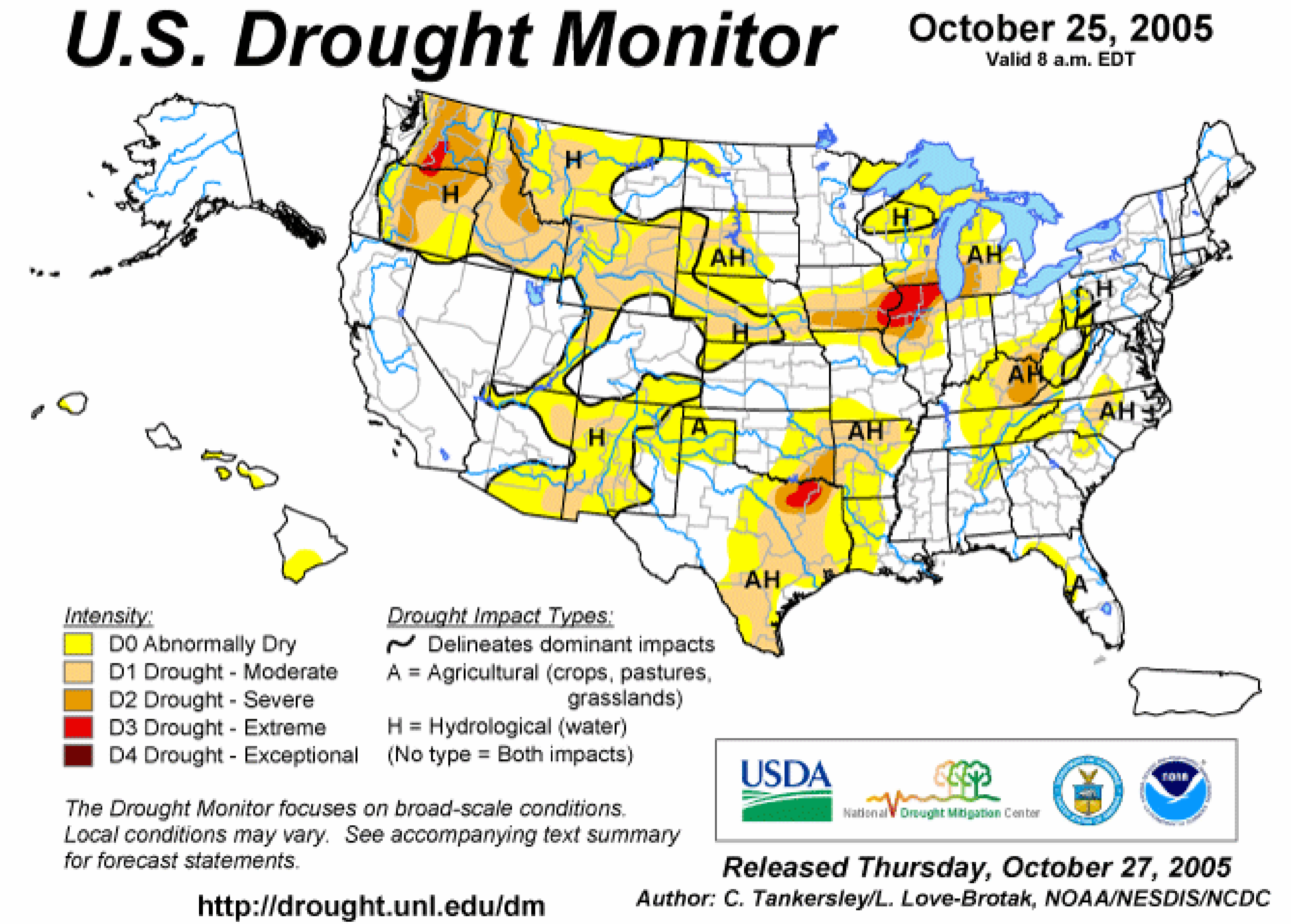
http://www.sercc.com/climateinfo/field_capacity/field_current.png

A27

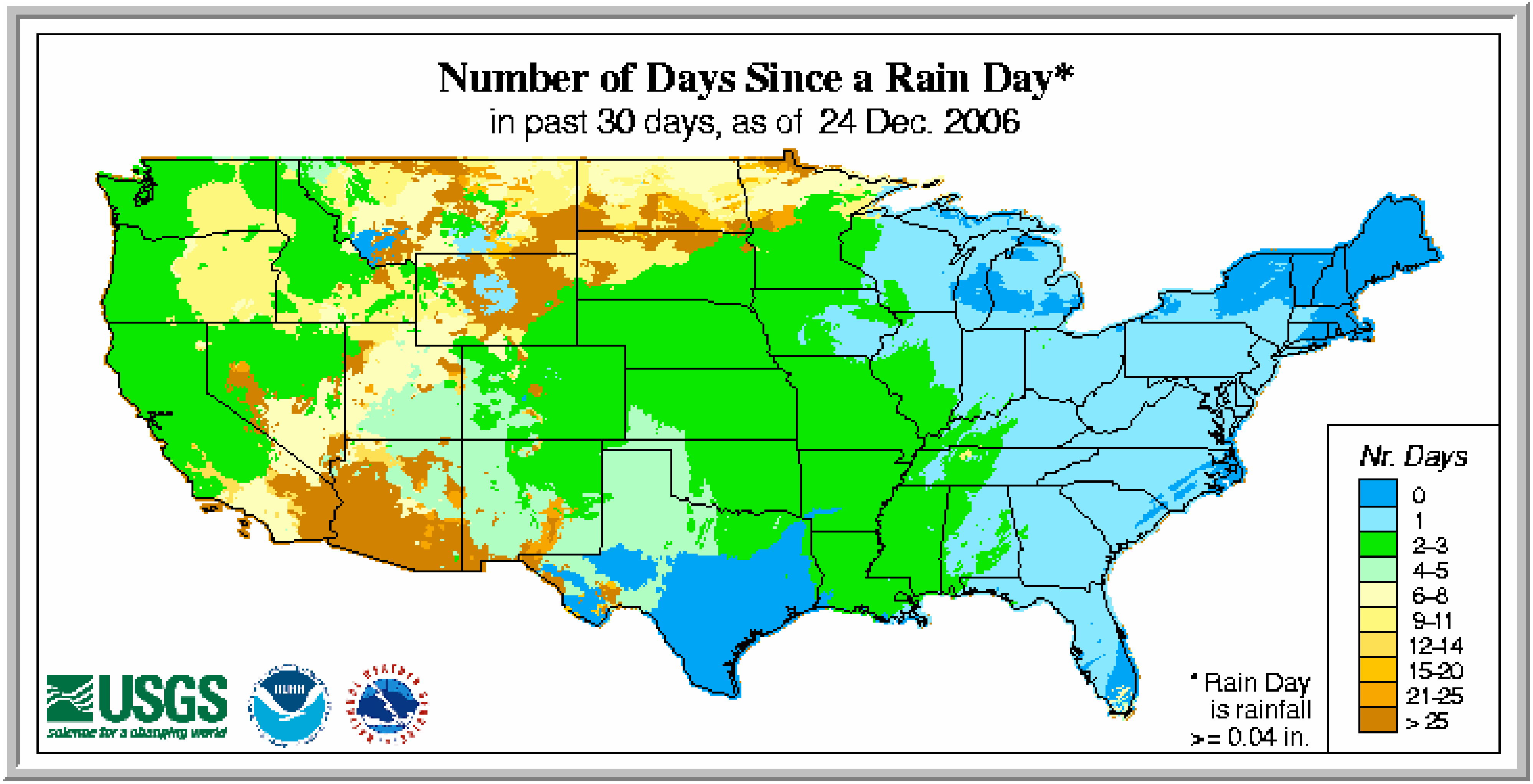


http://drought.unl.edu/monitor/spi-dailygridded.html

A28

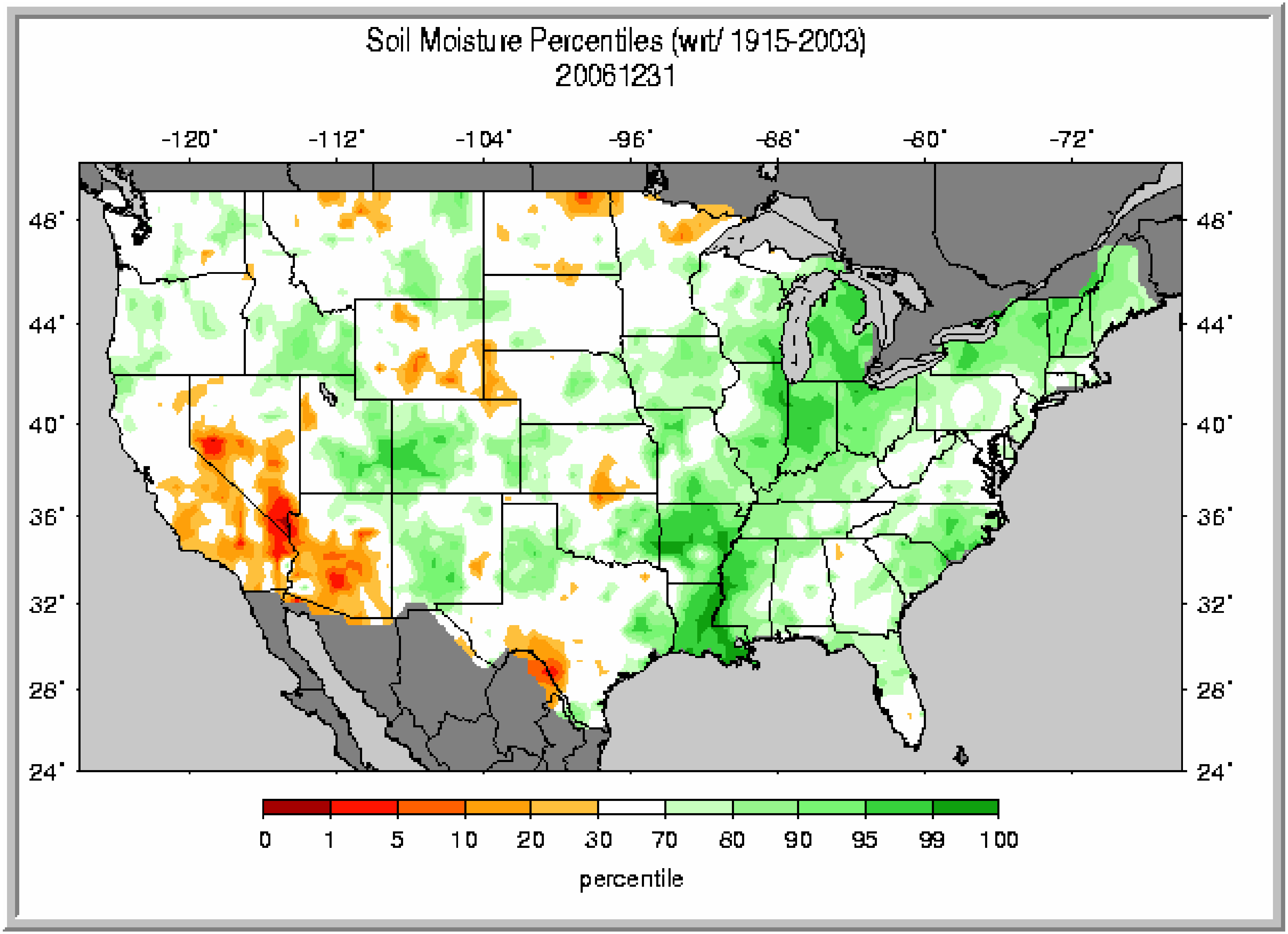

U.S. Drought Monitor
October 25, 2005
Valid 8 a.m. EDT
Intensity:
D0 Abnormally Dry
D1 Drought - Moderate
D2 Drought - Severe
D3 Drought - Extreme
D4 Drought - Exceptional
Drought Impact Types:
Delineates dominant impacts
A = Agricultural (crops, pastures, grasslands)
H = Hydrological (water)
(No type = Both impacts)
The Drought Monitor focuses on broad-scale conditions. Local conditions may vary. See accompanying text summary for forecast statements.
USDA
National Drought Mitigation Center
Released Thursday, October 27, 2005
Author: C. Tankersley/L. Love-Brotak, NOAA/NESDIS/NCDC
http://drought.unl.edu/dm

A29



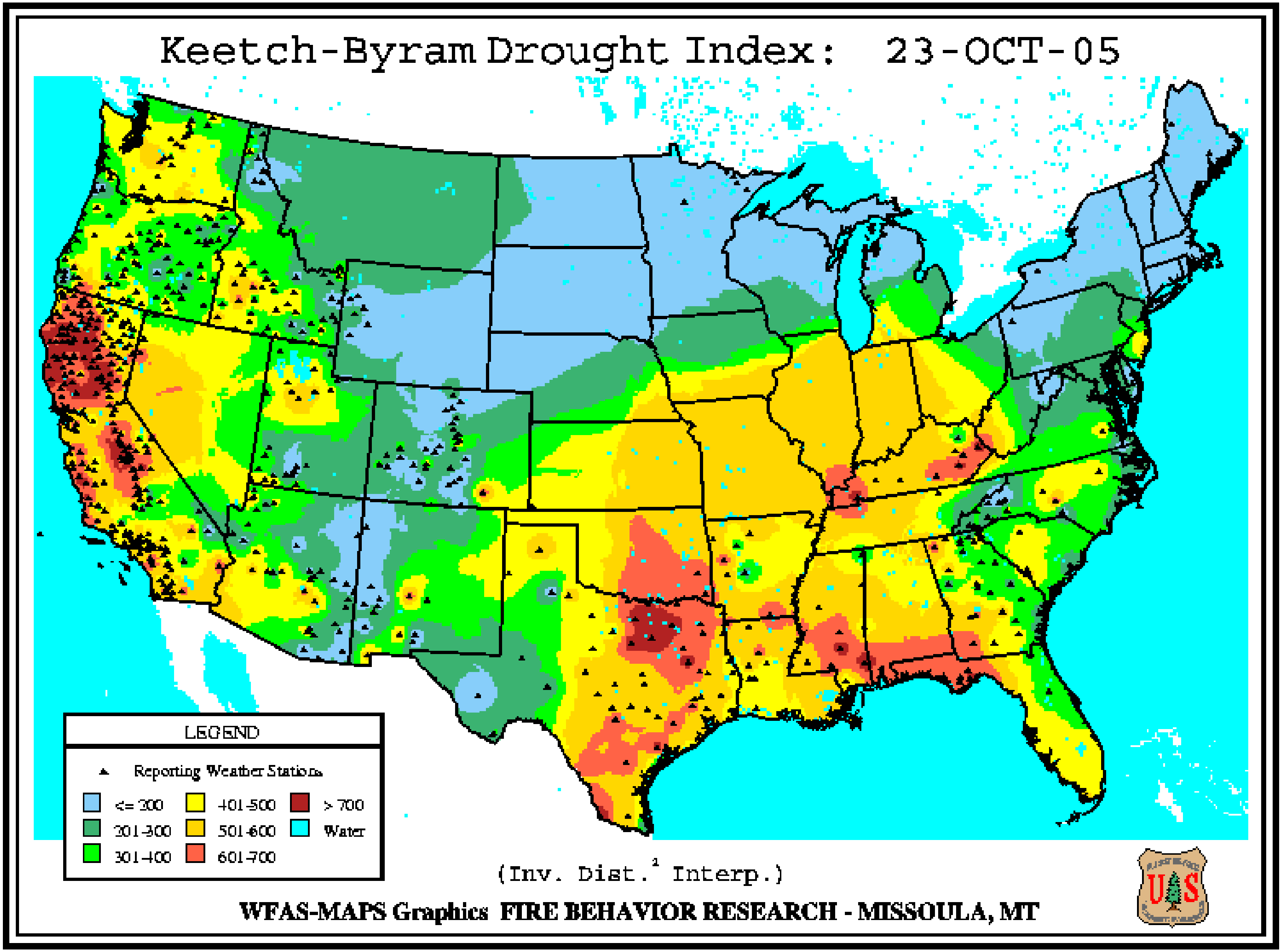
http://drought.unl.edu/monitor/raindry/precipitationdays.html

A30



http://www.hydro.washington.edu/forecast/monitor/index.shtml

A31



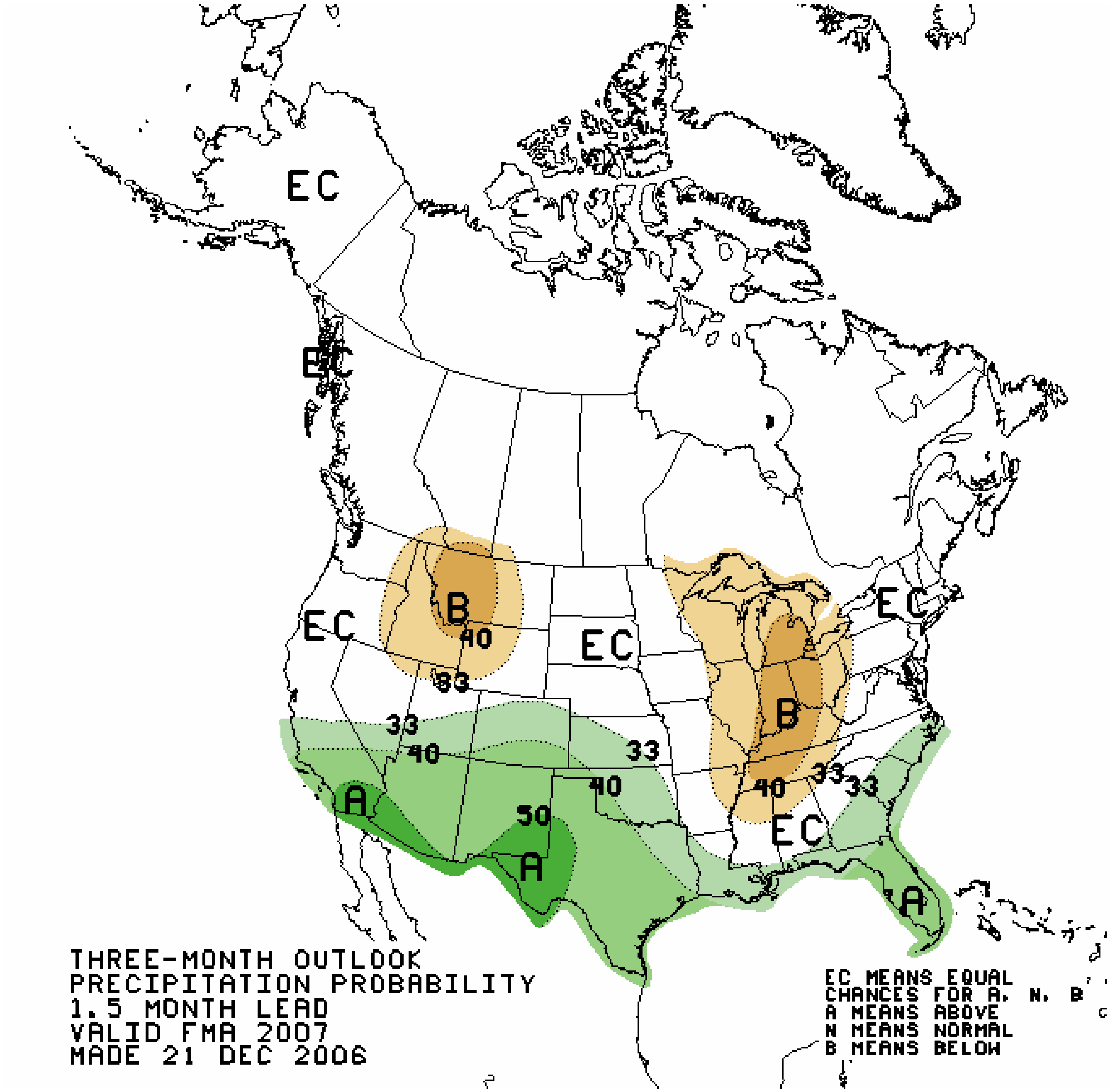
http://www.fs.fed.us/land/wfas/kbdi.gif

Appendix B

Selected Examples of Climate and Drought Forecasting Products

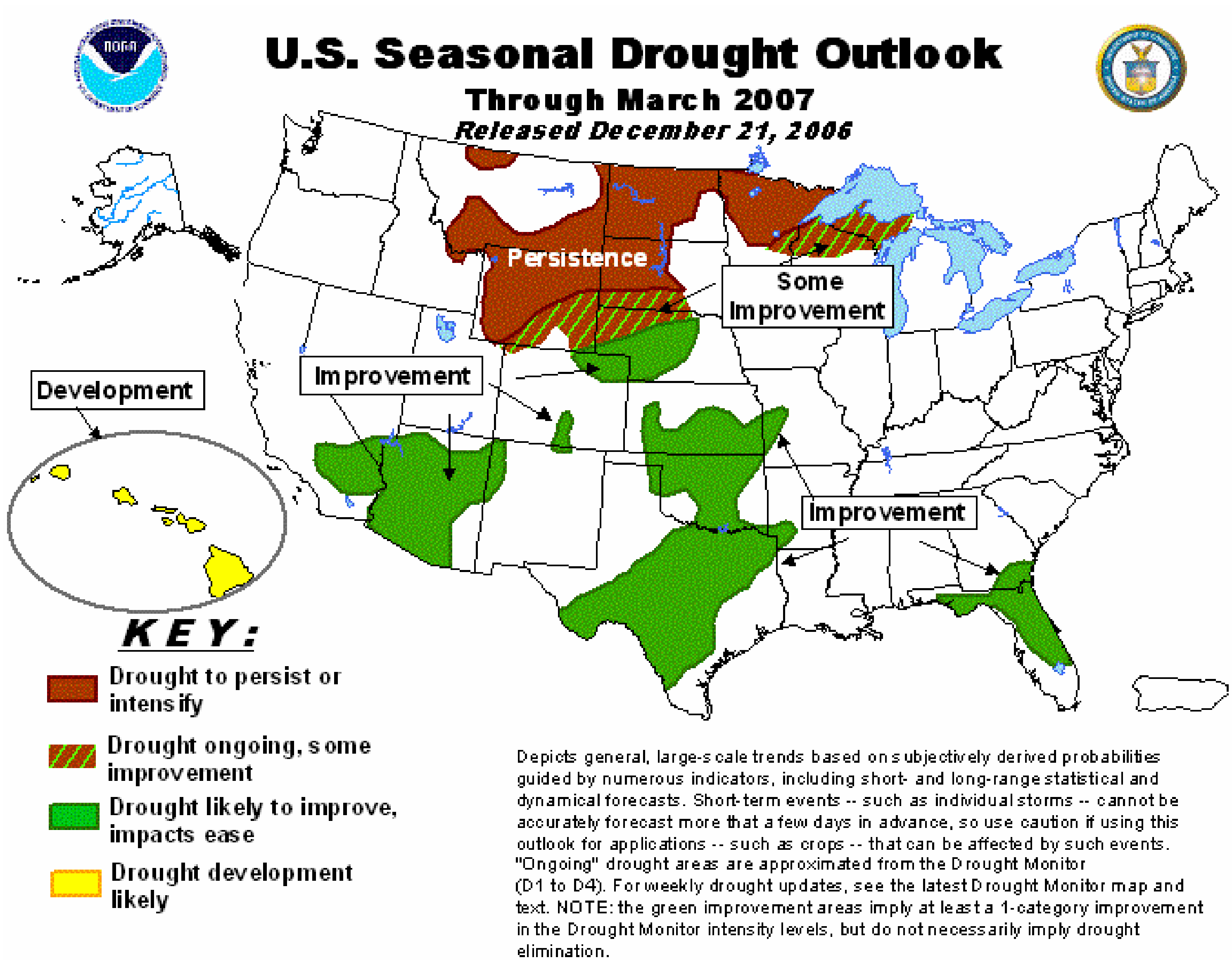
(see Table 10)

B1



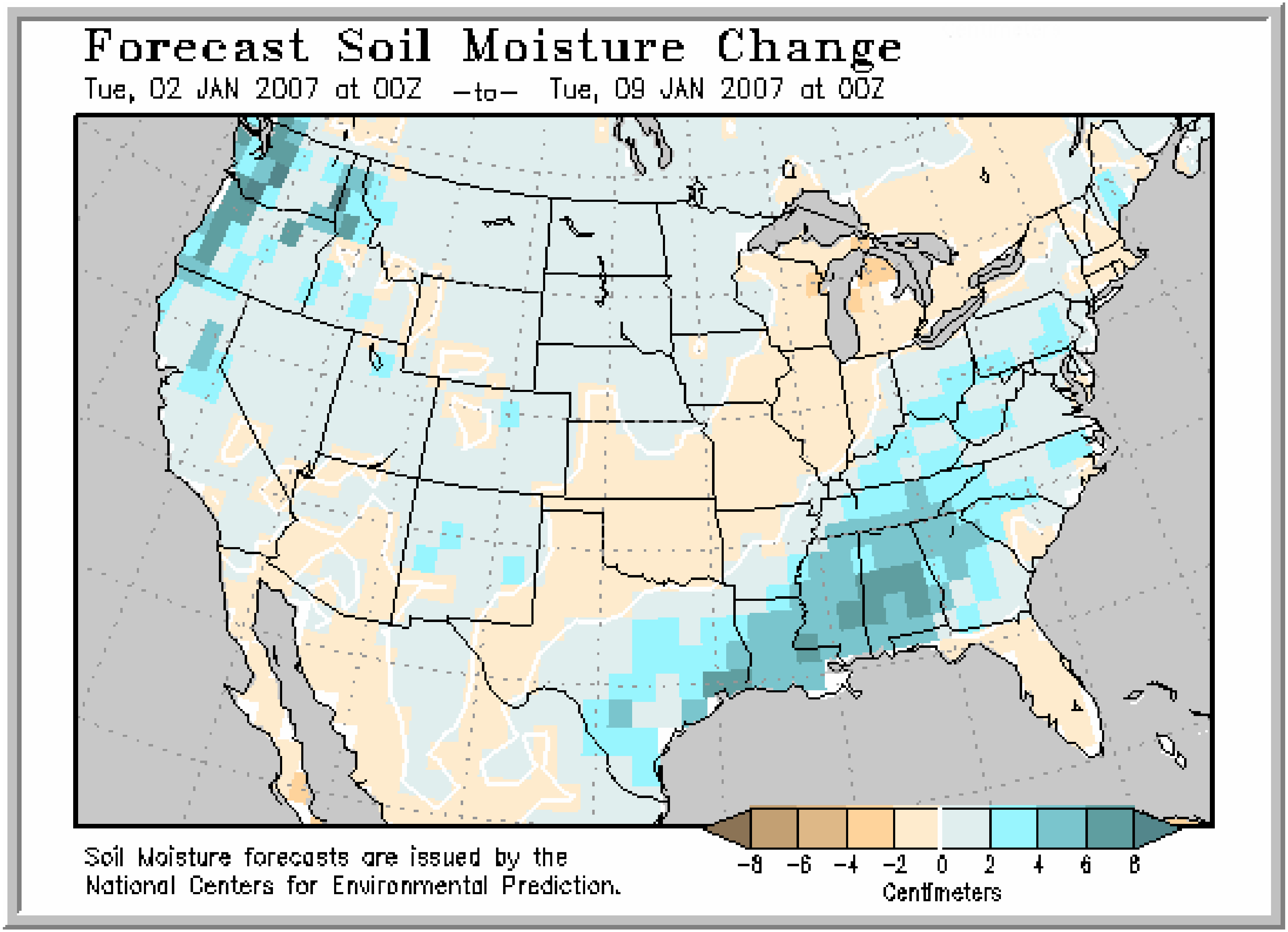
http://www.cpc.ncep.noaa.gov/products/predictions/long_range/lead02/off_index.html

B2



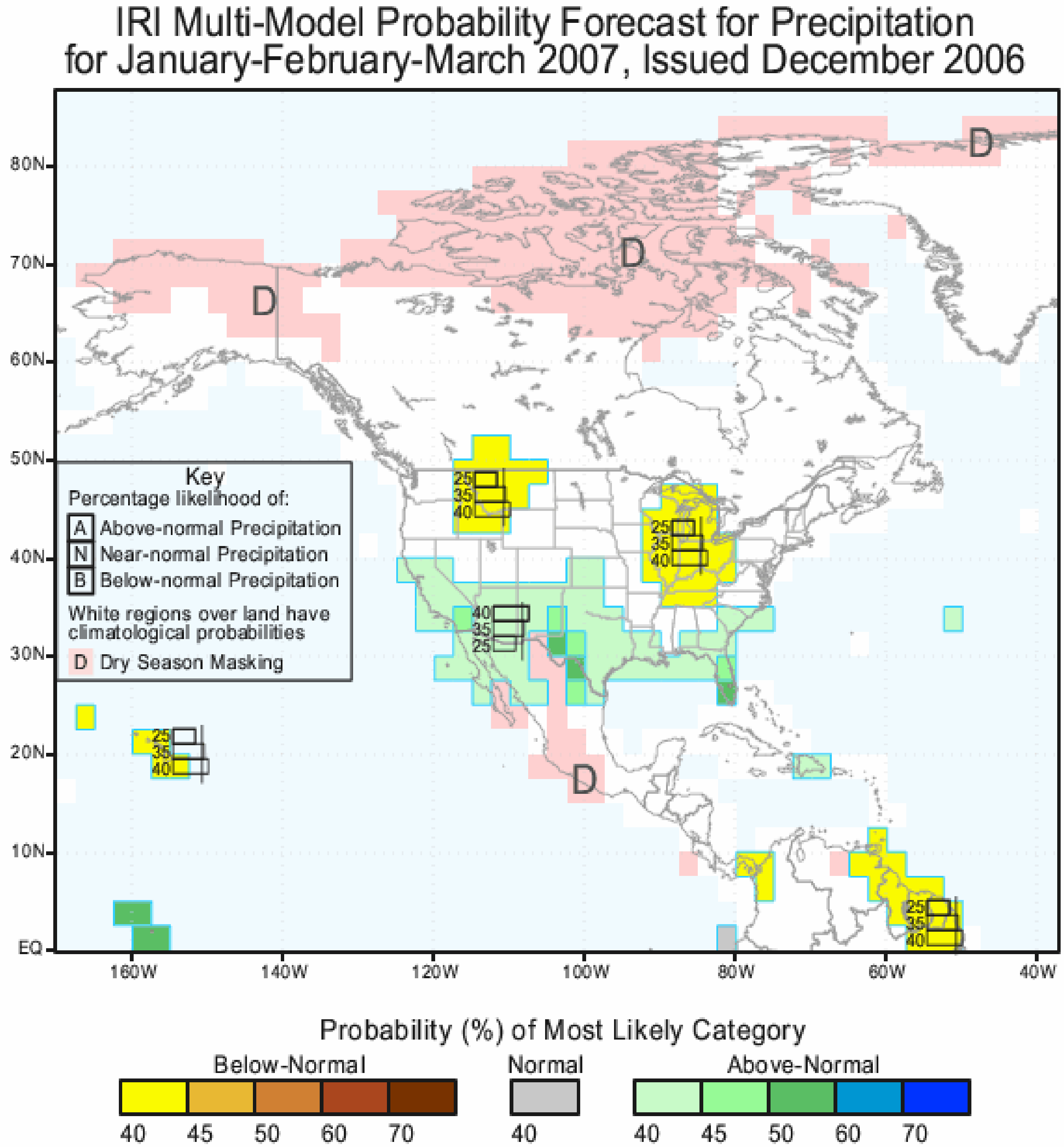
http://www.cpc.ncep.noaa.gov/products/expert_assessment/seasonal_drought.html

B3



http://wxmaps.org/pix/soil1.html

B4



http://iri.columbia.edu/climate/forecast/net_asmt/

APPENDIX C

"Drought Monitoring Index for Texas"
Contract No. 2005483028
Draft Report Review Comments

TWDB comments on draft final report are shown in black.
Responses to TWDB comments are shown in blue.

Executive Summary, Please provide a more robust executive summary to describe the recommendations you have reached in the study. The format of the report by task will be confusing unless the format is described and summarized in the executive summary.
Done.

Please provide drought definitions for the types of drought you are discussing.
Conceptual drought definitions were added to section 1.1.

Good summary information on the drought indices presented, including qualitative and quantitative evaluation of the indices.

Task 1.

The research focused on United States based methods; the scope clearly states that the study will incorporate methods used elsewhere in the world. The cumulative sum control chart (CUSUM) method as outlined in the scope of work is not included or discussed.
We completed a thorough search of the peer-reviewed literature, including many international journals, to identify all potentially relevant drought monitoring tools. To the best of our knowledge this report includes all the drought monitoring tools that are commonly used and highly regarded (both in the United States and around the world).

The cumulative sum control chart (CUSUM) is a statistical procedure that is used to detect a change point in a time series. It is not a method for monitoring or detecting drought. CUSUM requires that the data be independent and identically distributed and since monthly drought data are serially autocorrelated they violate this assumption. CUSUM was found to not be an appropriate operational drought monitoring tool.

In addition, page 39 table 5 lists the TWDB in the Table title. It should be the Texas Drought Preparedness Council only; they are the owners of this assessment.
This has been corrected.

Task 2.

This task is to evaluate existing tools that are most appropriate for Texas at the local level. Please provide a final statement for this task that recommends those indices most appropriate for Texas.
A summary of our recommendations was added (section 3.4.4).

Tables 12 and 13 (page 70) discuss the results, but never conclude which one is best for Texas at the local level.
A summary of our recommendations based on the qualitative evaluation was added (section 3.3.3).

Task 3.

Need definite definitions for drought. There is no clear definition of terms such as meteorological drought, threshold, hydrological drought, and water supply drought. Also, make clear the difference in the hydrological drought and water supply drought unless the authors are equating the two terms. Please clarify this issue.
Conceptual drought definitions were added to section 1.1 and the hydrological/water supply drought issue was discussed.

Part of this task is to develop operational definitions of meteorological, hydrological, and water supply drought. Please provide a clear summary for this task or and a list of thresholds to be met to indicate dry periods or drought conditions.
Operational drought definitions for Percent Normal, PDSI, and SPI are reported in section 4.4. These drought definitions are for specific stations and can not be applied to the whole state. Operational drought definitions for RDI are reported in section 3.4.4.

The drought evaluation tools on pages 66-70 are excellent.

Task 4.

Provide guidelines for taking action based on current drought conditions and future conditions.
This was not part of Task 4 as originally proposed in our Statement of Qualifications. This study provides recommendations on how drought monitoring and reporting should be carried out in Texas. It does not attempt to define appropriate drought responses since the PIs feel that these are largely matters of policy and politics. However, section 5.5 does discuss how future drought conditions should be predicted. These probabilistic predictions of future drought conditions will provide the Texas Drought Preparedness Council, politicians, and policy makers with useful information to assist them in deciding how they should respond to a drought.

This report provides good summary information on many drought indices, qualitative and quantitative evaluation of those indices, and good recommendations on future endeavors. However, an unambiguous recommendation on which indices (either existing or new), methods, and procedures to use should be included to aid the Texas Drought Preparedness Council.
Recommendations for how the TDPC should monitor and report drought conditions were added to Task 4 (section 5.5).

Task 5.

Provide specific recommendations on the reporting units for drought information, perhaps a table listing what type of index and the recommended reporting unit would clarify this issue.
Summary table was added to section 6.3.

General comments.

PHDI index is listed as a stream evaluation tool. However, the Palmer index methodology is composed of three indices to look at meteorological drought and not hydrologic drought.

The PDSI is a retrospective index because its values are back calculated and adjusted after the establishment of a dry or wet spell. Hence, the current value of the index might change if a drought becomes established 2 or 3 months from now. However, when computed in near real-time the PDSI is more appropriately termed the Palmer Hydrological Drought Index (PHDI) (Karl, 1986) because it does not take into account future dry or wet weather that impacts the meteorological drought. PDSI and PHDI values are identical during an established spell and only differ during the onset and ending of a spell. According to Heim (2002), the PDSI considers a drought ended when the moisture conditions begin to recover continuously to erase the water deficit, however, PHDI considers a drought ended only when the water deficit actually vanishes. Therefore, the PHDI is a slow-varying version of the PDSI. Although the PDSI and PHDI are often defined as a meteorological drought indices they respond slowly to changes in moisture conditions. According to Guttman (1998), the PDSI has a 'memory' (its spectrum conforms to that of an autoregressive process) and it is highly correlated with the 12-month SPI (Heim, 2002). Because of this long memory, the PDSI and PHDI are often out of phase with contemporary precipitation anomalies. This means that both the PDSI and PHDI are more appropriate for measuring hydrological/water supply droughts. The Z-index (the third Palmer index) can be used for measuring agricultural and meteorological drought since it only accounts for the moisture conditions during the current month (Quiring and Papakyriakou, 2003).

Comparing methodologies is good, but there is no baseline variable presented to measure deviation of the indices from each other (page 90) or the "true" condition.

We agree. Ideally all of the drought indices should have been evaluated using data on drought impacts. Since such data do not exist for Texas, we employed a qualitative and quantitative evaluation methodology instead. The National Drought Mitigation Center (NDMC) has recently begun collecting and archiving drought impacts data (http://droughtreporter.unl.edu/). According to NDMC, they "developed the Drought Impact Reporter in response to the need for a national drought impact database for the United States. Drought impacts are inherently hard to quantify, therefore there has not been a comprehensive and consistent methodology for quantifying drought impacts and economic losses in the United States. The Drought Impact Reporter is intended to be the initial step in creating a comprehensive database. The principal goal of the Drought

Impact Reporter is to collect, quantify, and map reported drought impacts for the United States and provide access to the reports through interactive search tools. The need for the Drought Impact Reporter and its comprehensive database becomes clear when one considers that drought is a normal part of the climate for virtually all portions of the United States. In addition, all evidence suggests that the impacts of drought are increasing in magnitude and complexity. A risk management approach to drought management, which strongly emphasizes improved monitoring and preparedness, requires more timely information on the severity and spatial extent of drought and its associated impacts. Improved information on drought impacts will help policy and decision makers identify what types of impacts are occurring and where. In addition, the Drought Impact Reporter will aid them in understanding the magnitude of the impacts by providing access to reported drought impacts. More precise estimates of drought impacts will aid the government in instituting programs before drought occurs, as opposed to incurring high expenditures on post-drought relief." This information is important for validating and improving drought monitoring and drought mitigation strategies, therefore it is recommend that the TWDB and TDPC should begin to actively collect and archive impacts data (either using the existing "Drought Impact Reporter" developed by the NDMC or using a separate database to be developed and maintained by the TWDB). It is further recommended that the TWDB work with other state and federal agencies to collect drought impact data for Texas from a variety of sectors (water resources, environment, socioeconomic, agriculture, fire, etc.).