Texas Water Resources Institute
Annual Technical Report
FY 2012

Introduction

The Texas Water Resources Institute (TWRI), a unit of Texas A&M AgriLife Research, Texas A&M AgriLife Extension Service and the College of Agriculture and Life Sciences at Texas A&M University, and a member of the National Institutes for Water Resources, provides leadership in working to stimulate priority research and Extension educational programs in water resources. Texas A&M AgriLife Research and the Texas A&M AgriLife Extension Service provide administrative support for TWRI and the Institute is housed on the campus of Texas A&M University.

TWRI thrives on collaborations and partnerships and in fiscal year 2012 managed 26 active projects with $12,052,909 in funds. Those projects involved more than 100 Texas A&M University System faculty members and graduate students as well as faculty from other universities across the state. The Institute maintained joint projects with both Texas universities and out-of-state universities; federal, state and local governmental organizations; consulting engineering firms, commodity groups and environmental organizations; and numerous others. In 2012 the Institute was awarded 14 new TWRI-lead projects with direct funding of $2,303,509.

TWRI works closely with agencies and stakeholders to provide research-derived, science-based information to help answer diverse water questions and also to produce communications to convey critical information and to gain visibility for its cooperative programs. Looking to the future, TWRI now awards a Water Assistantship to graduate students at Texas A&M University through funding provided by the W.G. Mills Endowment and the U.S. Geological Survey.

Research Program Introduction

Through the funds provided by the U.S. Geological Survey, TWRI funded one Water Assistantship research project in 2012-13 conducted by a graduate student at Texas A&M University. Additionally, through funds provided by the U.S. Geological Survey, TWRI facilitated the continuation and completion of three competitive research programs at Texas A&M University, another at Texas State University, and a multi-state, international project.

Elizabeth Edgerton, of Texas A&M University, studied invasive aquatic species in Texas.

Dr. Benjamin F. Schwartz, of the department of biology at Texas State University, continued examining the role of epikarst in controlling recharge, water quality and biodiversity in karst aquifers comparing Virginia and Texas.

Dr. Ron Griffin, of the Department of Agricultural Economics at Texas A&M University, continued researching institutional mechanisms for accessing irrigation district water.

Finally, the other competitive research grant is a multi-state, international effort that involves the collection and evaluation of new and existing data to develop groundwater quantity and quality information for binational aquifers between Arizona, New Mexico, Texas and Mexico. The United States-Mexico Transboundary Aquifer Assessment Program completed the first year of the five-year program; however, no second- or third-year funding was allocated.

Hydrological Drought Characterization for Texas under Climate Change, with Implications for Water Resources Planning and Management

Basic Information

Title:	Hydrological Drought Characterization for Texas under Climate Change, with Implications for Water Resources Planning and Management
Project Number:	2009TX334G
Start Date:	9/1/2009
End Date:	8/31/2012
Funding Source:	104G
Congressional District:	17th, TX
Research Category:	Climate and Hydrologic Processes
Focus Category:	Drought, Surface Water, Climatological Processes
Descriptors:	None
Principal Investigators:	Vijay P Singh, Ashok Kumar Mishra

Publications

1. Singh, V. P., 2010, Entropy theory for derivation of infiltration equations, Water Resources Reseach, 46, W03527, doi:10.1029/2009WR008193.
2. Singh, V. P., 2010, Entropy theory for movement of moisture in soils, Water Resources Research, 46, W03516, doi:10.1029/2009WR008288.
3. Mishra, A. K., and V. P., Singh, 2010, Changes in extreme precipitations in Texas, J. Geophysical Research, American Geophysical Union, (In Press). Manuscript no: 2009JD013398.
4. Mishra, A. K., M., Özger, and V. P., Singh, 2010, Association between uncertainty in meteorological variables and water resources planning for Texas, Journal of Hydrologic Engineering, ASCE, (in press).
5. Ozger, M., A. K., Mishra, and V. P., Singh, 2010, Scaling characteristics of wet and dry spells of precipitation data, Journal of Hydrologic Engineering, ASCE, (In press).
6. Ozger, M., A. K., Mishra, and V. P., Singh, 2010, Long lead time drought forecasting using a wavelet and fuzzy logic combination model, Water Resources Research (Submitted after first review), American Geophysical Union, Manuscript no:2009WR008794.
7. Mishra, A. K., and V. P., Singh, 2010, A review on drought concepts, Journal of Hydrology, (Submitted after first review), Manuscript no: HYDROL 8529.
8. Mishra, A. K., and V. P., Singh, 2010, Drought modeling: A review, Reviews of Geophysics, (Submitted).
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Hydrological drought characterization for Texas under climate change, with implications for water resources planning

Project number: 2009TX334G

Progress report (Sep 2011 to May 2012)

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5. References

Hydrological drought characterization for Texas under climate change, with implications for water resources planning

1. Basic information

Title:	Hydrological drought characterization for Texas under climate change, with implications for water resources planning
Project number:	2009TX334G
Start Date:	September 1, 2009
End Date:	August 31, 2012
Funding source:	104G
Congressional District:	17th TX
Research Category:	Climate and Hydrologic Processes.
Focus Categories:	Drought (DROU), Surface water (SW), Climatological processes (CP)
Descriptors:	Hydrological drought, Climate change, Critical basin, Teleconnection.
Principal investigator(s):	Vijay P. Singh and Ashok K. Mishra

2. Publications

Long, D., Singh, V.P. and Li, Z.- L.2011. How sensitive is SEBAL to changes in input variables, domain size and satellite sensor? Journal of Geophysical Research, Vol. 116, D21107, doi: 10.1029/2011JD016542.

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3. Problem and Research objectives

Droughts in the United States result in an estimated average annual damage of $6 to 8 billion (Wilhite, 2000). The estimated loss from the 1988 drought was $40 billion (American Meteorological Society, 1997) and the estimated loss for the state of Texas alone from the 1996 drought was $6 billion (Wilhite, 2000). Like other western states, Texas is a water deficient state and is highly vulnerable to droughts, and its vulnerability is being compounded by rapidly growing population. According to the Water Plan (*Water for Texas 2007*) developed by Texas Water development Board, water shortages during droughts could cost businesses and workers in the state about $98.4 billion by 2060 and about 85 percent of the state's projected population would not have enough water by 2060 in drought conditions), if an additional 8.8 million acre-feet of water supplies are not developed. Further complicating the Texas water shortage is climate change, which is being much debated these days. The major concern arising from climate change is its effect on water resources in terms of droughts and the resultant impact on different sectors. The objective of the project is therefore threefold:

(i) Analysis of multivariate hydrologic droughts: Drought is characterized by severity, areal extent, and duration. Multivariate distributions of these characteristics are needed and they will be derived using copulas. Then, droughts will be characterized by constructing: (a) Severity – Duration – Frequency curves (SDF), (b) Severity – Area – Frequency (SAF) curves, and (c) Severity-Interarrival time Frequency (SIF) curves. These curves are important for water resources planning.

(ii) Assessment of drought risk under climate change: Climate change impact studies have been conducted using a top-down approach. First, outputs from Global Circulation Models (GCMs) are considered which are downscaled in a second step to the river basin scale using either a statistical/empirical or a dynamic approach. The local weather scenarios are then statistically linked to possible large-scale climate conditions that are available from GCMs. Finally the downscaled meteorological variables are used as input to a macro scale land surface hydrologic model (i.e., VIC model) for investigating future hydrological drought scenarios. Several questions will be addressed: (a) How much percentage of a basin will undergo a drought in year 2050? (b) What will be the severity of the 2050 drought? (c) Will the drought of 2050 be more severe than the 2020 or 2080 drought? (d) What will be the duration of the drought in 2050 or 2080? (e) How much will be the water deficit in a river in 2050, considering it as a hydrological drought? (f) How will drought properties vary, when compared to the past 50 years? This objective will also attempt to quantify uncertainties in drought characterization, considering primarily climate change and different water management strategies.

(iii) Understanding of low frequency climate variations in association with Southern Oscillation Index (SOI) and Nino indexes: These variations affect Texas and their understanding will help provide improved streamflow forecasting needed for reservoir operations and will aid water management decisions. The lead-time of forecasting will be annual.

4. Principal findings and significance

The research findings are highlighted with three broad objectives: (a) entropy based regionalization of Texas based on drought severity and duration, (b) drought atlas for the state of Texas for different severities, durations and recurrence intervals, (c) simulating hydrological drought properties at different spatial units based on wavelet-Bayesian regression approach, and (d) research on evaporation

4 (a) Entropy based regionalization of Texas based on drought characteristics

Introduction: A homogenous region can be defined as a group of stations with similar probability distribution functions of drought properties (Mirakbari et al., 2010). The common concept used in regional analysis of droughts is to classify weather stations that exhibit similarities in a statistical sense. There are several methods for performing regionalization. Selection of a suitable similarity measure is important in clustering. Mostly, clustering techniques use a simple linear measure like Pearson correlation as a similarity measure for grouping. In this study, we explore the possibility of using a mutual information based index known as Directional Information Transfer (DIT) for identification of homogenous regions. This measure is not only sensitive to non-linear dependencies, but it is also unique due to its information theory background (Kraskov, 2009). It has a three-fold advantage over other dependence measures in that it gives an idea about: (1) information content at a station, (2) amount of information transferred between stations and the amount lost, and (3) relationships among stations based on information transmission characteristics (Yang and Burn, 1994).
The study basically focuses on understanding the spatial distribution of drought characteristics. An areal zoning of the study region based on various drought properties was conducted using a methodology based on entropy theory for Texas. The methodology is based on an index developed by Yang and Burn (1994) for design of data collection network. The same principle has been extended for grouping of stations. The application of this method is not explored till now in the context of regionalization.

Model and data used: A land surface model called Variable Infiltration Capacity (VIC) model (Liang et al., 1996) , was used to simulate stream flow for a period of 1950-2000. This particular model was chosen, since it focuses on simulating hydrological processes relevant to the water and energy balance over the land surface for studying the effects of climate changes on stream flow generation. Distinguishing characteristics of the model include the sub-grid variability in land surface vegetation classes, sub-grid variability in the soil moisture storage capacity, and drainage from the lower soil moisture zone (base flow) as a nonlinear recession. The variable infiltration capacity (VIC) model has been well calibrated and applied in a number of large river basins over the continental US and the globe, and has participated in the World Climate Research Program (WCRP) Intercomparison of Land Surface Parameterization Schemes (PILPS) project and the North American Land Data Assimilation System (NLDAS), where it has performed well relative to other schemes and to available observations (Bowling et al. 2003a, 2003b, Lohmann et al., 1998). The VIC-3L is a large scale land surface model and is used for simulating land-atmosphere fluxes by solving water and energy balance at a daily or sub-daily temporal scale (Liang et al., 1994). The land surface is essentially divided into grids of specified resolution. Each of these cells will be simulated independent of each other. Land surface is divided into different vegetation covers in such a way that multiple vegetation classes can exist within a cell. The soil moisture distribution, infiltration, drainage between soil layers, surface runoff, and subsurface runoff are all calculated for each land cover tile at each time step. Then, for each grid cell the total heat fluxes (latent heat, sensible heat, and ground heat), effective surface temperature, and the total surface and subsurface runoff are obtained by summing over all the land cover tiles weighted by fractional coverage.

For this study, the VIC model for stream flow simulation was run at $1/8^{th}$ degree resolution and hence all input files, including forcing files, soil and vegetation parameters have this resolution. This resolution was chosen by also taking into consideration the availability of gridded daily forcing data of precipitation (mm), maximum and minimum temperature (^{o}C) and wind speed (m/s) which is needed to drive the model, at $1/8^{th}$ resolution from Maurer et al. (2002) who has provided a data base for 15 delineated basins in the United States, Canada and Mexico. The time period of data used was the latter half of the 20^{th} century: 1949-2000. The year 1949-1950 was considered as the spin up year for the model. Apart from forcing data, soil and land cover data is also required by the VIC model. The soil characteristics which will not be considered for calibration were taken from gridded 1/8 degree datasets developed as part of the Land Data Assimilation System (LDAS) project (Mitchell et al. 1999). Vegetation parameters needed were also obtained from LDAS. Land cover characterization was based on the University of Maryland global vegetation classifications described by Hansen et al. (2000), which has a spatial resolution of 1 km, and a total of 14 different land cover classes. From these global data we identified the land cover types present in each 1/8 grid cell in the model domain and the proportion of the grid cell occupied by each, as described by Maurer et al. (2001). The leaf area index (LAI) needed was derived from the gridded (1/4 degree) monthly global LAI database of Myneni et al. (1997), which is inverted using the Hansen et al. (2000) land cover classification to derive monthly mean LAIs for each vegetation class for each grid cell. The data needed for the routing scheme includes a fraction file, flow direction file, Xmask file, flow velocity and diffusion files, and unit hydrograph file. ArcMap was used for the preparation of files, and the DEM files needed for creating the required files were obtained from the USGS hydro 1k datasets.

Methodology:

Step 1: Drought classification using standardized streamflow index (SSFI)

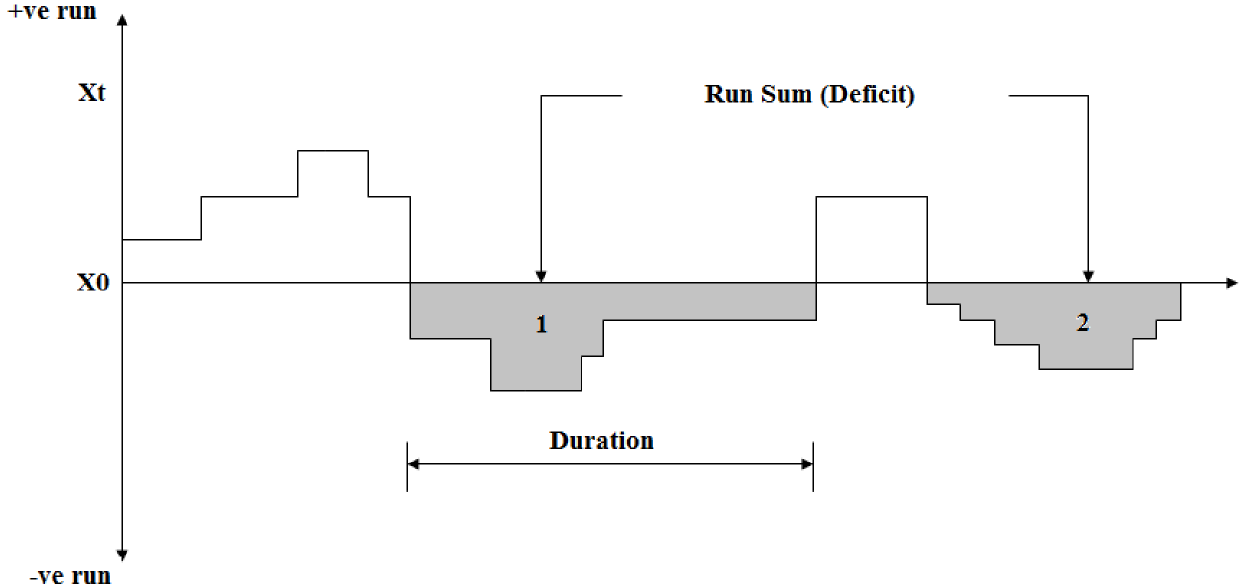


Figure 1. Drought Characteristics using the theory of runs

Figure 1 describes drought characteristics for a drought event using the theory of runs. A drought event is characterized by severity, duration and magnitude (Mishra and Singh, 2010). For any drought event, the cumulative deficit of the variable of interest during the drought event is defined as drought severity. Drought duration is the time between the onset and the end of a drought event. Drought magnitude is the average deficit per unit duration. In this study, drought duration and severity were considered.

The theory of runs was used for deriving drought characteristics from the stream flow time series. This method has been widely used in the field of hydrology. Yevjevich et al. (1967), Rodriguez-Iturbe (1969), Saldarriaga and Yevjevich (1970), Millan and Yevjevich (1971), Guerrero-Salazar and Yevjevich (1975), and Sen (1976, 1977) are among the first few who applied the run theory in hydrology. A run is defined as a portion of time series of drought variable X_t in which all values are either above or below a threshold level X_0. Accordingly, it can be called a positive or a negative run. The threshold level may be constant or it may vary with time. Thus, the drought characteristics essentially depend upon the threshold chosen (Mishra and Singh, 2010). In this study, the drought variable chosen was standardized stream flow index (SSFI). The concept of SSFI is statistically similar to that of standardized precipitation index (SPI) introduced by McKee (1993) and has been applied by Modarres (2007). Shukla and Wood (2008) used a standardized runoff index (SRI) as a complement to the SPI to assess hydrological aspects of a drought. Table 1 gives the classification of events based on the SSFI values (Modarres, 2007).

Table 1. SSFI Classification

SSFI value	Classification
2.0 or more	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2.0 or less	Extremely dry

Following this classification, a threshold value of -0.99 was chosen, since any value below that indicates the onset of a dry event.

The calculation of SSFI involves the following steps: (1) A suitable probability distribution is fitted to the monthly stream flow time series for the time period 1950-2000. (2) From the fitted frequency distribution, the cumulative probability distribution of stream flow is obtained. (3) Cumulative probability is transformed to a standard normal variate of zero mean and unit standard deviation. This will be calculated from a numerical approximation to the normal cumulative distribution function (CDF). The approximation given by Abramowitz and Stegun (1964) was used to obtain the standard normal probability distribution function (PDF). The approximation for $\phi(x)$ for $x>0$ is given by:

$$\phi(x) = 1 - \varphi(x)(b_1 t + b_2 t^2 + b_3 t^3 + b_4 t^4 + b_5 t^5) + \varepsilon(x), \quad t = \frac{1}{1 + b_0 x} \tag{1}$$

where $\varphi(x)$ is the standard normal PDF, b_0=0.2316419, b_1=0.319381530, b_2=-0.356563782, b_3=1.781477937, b_4=-1.821255978, b_5=1.330274429. This is the z-score and conceptually it represents the number of standard deviations above or below that an event is from the mean (McKee, 1993). Thus, essentially SSFI for a given series is given as:

$$SSFI = \frac{F_i - \bar{F}}{\sigma} \tag{2}$$

where F_i is the flow rate in time interval i, $\bar{F}$ is the mean of the series, and σ is the standard deviation of the series.

In this study, for each of the five climatic regions, considering a number of previous studies, like Zaidman et al. (2001), Kroll and Vogel (2002), McMahon et al. (2007), Shukla and Wood (2008) and Nalbantis and Tsakiris (2009), the log-normal distribution was selected for fitting monthly stream flow data. The two parameter log normal distribution was found to fit well for all the stations considered. The quantile plots and Kolmogorov-Smirnov (K-S) test were considered for assessing the goodness of fit. Table 2 gives the list of USGS stations considered for validation of the VIC model results. Table 3 gives the results of the K-S test for the goodness of fit at the 5%

significance level. The quantile – quantile plot for two parameter log normal distribution used to fit stream flow at the selected stations (Figure 2).

Table 2. Information on validation stations within Texas

Station Name	Station ID	Latitude	Longitude	Validation Period	Climate Zone
Pecos Rv at Pecos	8420500	31.436	-103.467	1951-1952	Arid
Canadian Rv Nr Amarillo	7227500	35.471	-101.88	1981-1982	Continental
Pr Dog Twn Fk Red Rv nr Wayside	7297910	34.837	-101.414	1968-1969	Continental
Canadian Rv Nr Canadian	7228000	35.935	-100.371	1965-1966	Continental
Independence Ck Nr Sheffield	8447020	30.452	-101.733	1975-1976	Semiarid
Nueces Rv Nr Asherton	8193000	28.5	-99.682	1959-1960	Semiarid
Colorado Rv Nr Gail	8117995	32.628	-101.285	1989-1990	Subtropical Semi humid
Colorado Rv Nr Stacy	8136700	31.494	-99.574	1969-1970	Subtropical Semi humid
Millers Ck Nr Munday	8082700	33.329	-99.465	1972-1973	Subtropical Semi humid
Medina Rv Nr Macdona	8180700	29.335	-98.689	1982-1983	Subtropical Semi humid
Cowhouse Ck at Pidcoke	8101000	31.285	-97.885	1955-1956	Subtropical Semi humid
Perdido Ck at M 622 Nr Fannin	8177300	28.752	-97.317	1979-1980	Subtropical Semi humid
Los Olmos Ck Nr Falfurrias	8212400	27.2645	-98.136	1967-1968	Subtropical Semi humid
Lake Fk Ck Nr Quitman	8019000	32.763	-95.463	1982-1983	Subtropical humid
Kickapoo Ck Nr Onalaska	8066170	30.907	-95.088	1991-1992	Subtropical humid
Vince Bayou at Pasadena	8075730	29.6947	-95.216	1973-1974	Subtropical humid

Table 3. Values of the Kolmogorov-Smirnov test at 5 percent significance level for two parameter log-normal distribution at selected stations

Station	Climate zone	p-value	k-s stat
ID 08101000	Subtropical Semi humid	0.0735	0.1280
ID 07227500	Continental	0.0684	0.2629
ID 08193000	Semiarid	0.0738	0.2546
ID 08420500	Arid	0.5500	0.1267
ID 08019000	Subtropical humid	0.4597	0.1689

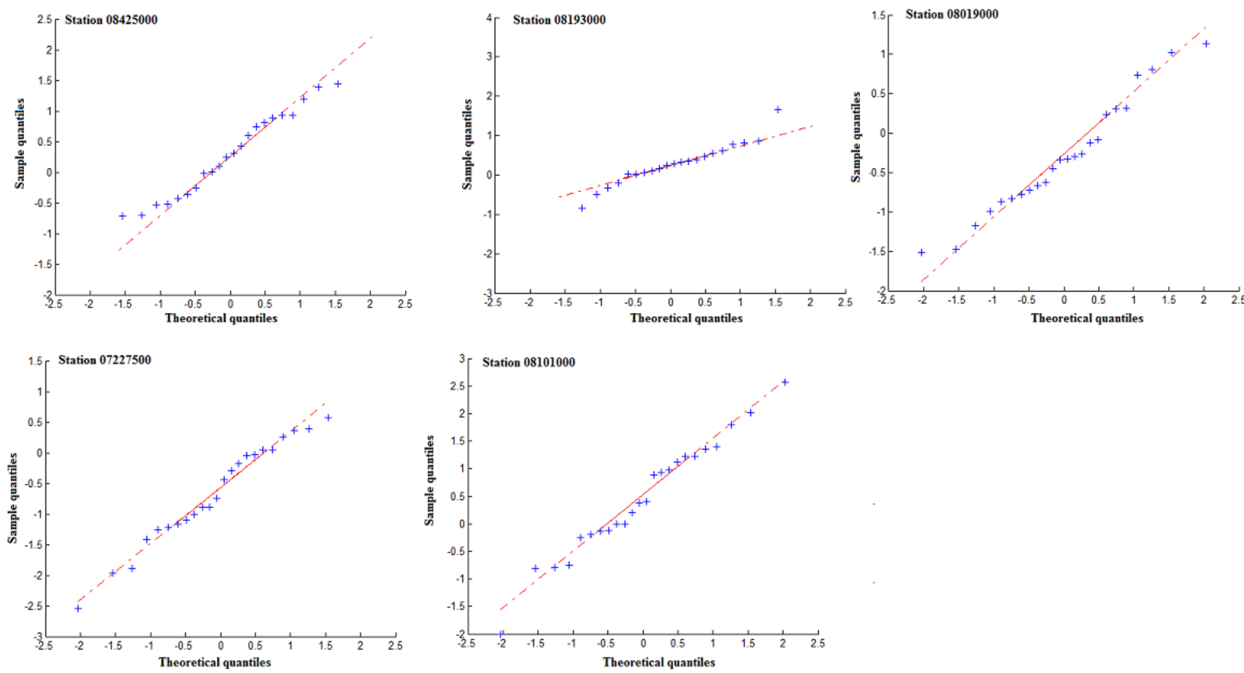


Figure 2. QQ plots for two parameter log normal distribution used to fit stream flow at selected stations

Step 2. Regionalization based on directional information transfer (DIT)

Regionalization is the process of identifying homogenous regions. In this context, a homogenous region comprises an area which has similar hydrologic response. This is generally done by grouping similar objects. In this study, an entropy based index, known as directional information transfer (DIT), was used for the grouping of grids into homogenous regions. This index is based on mutual information which measures information transfer among the stations. Entropy can be used to measure the information content of observations and mutual information can be used to measure the information transfer. Thus entropy and mutual information provide a threefold measure of information at a station, information transfer and loss of information between stations, and description of relationships among stations according to the information transfer between them (Yang and Burn, 1994).

Entropy concepts

Entropy, first introduced in the field of information theory by Shannon (1948), is defined for a random variable X as (Lathi,1968):

$$H(X) = \sum_{i=1}^{k} P(x_i) \log_2 P(x_i) \tag{3}$$

where *P(x*$P(x_i)$'s are the probabilities associated with the events X=x_i, and k denotes the total number of class intervals or bins. $H(X)$ is the marginal entropy of X, which means the measure of information contained in X. If two random variables (X,Y) are considered, the mutual information or the measure of information transfer between them can be computed as (Lathi, 1968):

$$T(X,Y) = H(X) - H(X \mid Y) \tag{4}$$

where $H(X|Y)$ represents the information lost during transmission which can be estimated as:

$$H(X \mid Y) = \sum_{i,j} P(X_i, Y_j) \log_2 \frac{P(X_i, Y_j)}{P(Y_j)} \tag{5}$$

where $P(X_i, Y_j)$ is the joint probability distribution and $P(Y_j)$ is the marginal distribution of random variable Y, i and j denotes the class intervals corresponding to X and Y, respectively.

When comparing objects with different marginal or joint pieces of information, one should preferably use a relative measure rather than an absolute one, so as to minimize the dependence on total information (Kraskov et al., 2005). Hence, mutual information should be standardized to form an index known as directional information transfer (DIT). Directional information transfer is the fraction of the information transferred from one site to another. It is a normalized version of mutual information between two gauges to obtain the fraction of information transferred from one site to another as a value between 0 and 1. DIT is a much better index than mutual information because the upper bound of mutual information can vary from site to site, depending on the marginal entropy value at the respective station which makes the mutual information a not so good index of dependence. DIT can thus be expressed as:

$$DIT_{xy} = \frac{T(X,Y)}{H(X)}; \; DIT_{yx} = \frac{T(X,Y)}{H(Y)} \tag{6}$$

where DIT_{xy} describes the fractional information inferred by station X about Y, and DIT_{yx} is the fractional information inferred by station Y about X ; $T(X,Y)$ is the mutual information between X and Y; and $H(X)$ and $H(Y)$ are the marginal entropy values for X and Y, respectively. Since $H(X|Y)$ is equivalent to the loss of information H_{lost}, the DIT can be rewritten as:

$$DIT = (H - H_{lost}) / H = 1 - (H_{lost} \mid H) \tag{7}$$

It should also be noted that while the mutual information term is symmetric, DIT is no longer symmetric.

Regionalization using DIT

While using DIT for regionalization, those stations for which both DIT_{xy} and DIT_{yx} are high can be considered to be strongly dependent, since information can be mutually inferred between them. If neither DIT is high, then the two stations should remain in separate groups. If only one DIT is high, say DIT_{xy}, then station Y, whose information can be predicted by X, can join station X if station Y does not belong to any other group; otherwise it stays in its own group. But, by no means can X enter station Y's group (Yang and Burn, 1994). The number of groups formed is controlled by the threshold value of DIT. A higher threshold value will lead to a larger number of groups. However, the size of each group will be small. A lower threshold value will result in the formation of a small number of groups, but the size of each group will be larger. There is no rule based on which the threshold of DIT can be fixed, and hence is case specific.
There were a total of 4174 grids of 1/8 degree size, which covers the state of Texas. The number of regions formed depends upon the threshold value of DIT. Table 4 shows the number of groups formed, while the threshold value of DIT was varied for drought severity and duration.

Table 4. Number of regions formed by varying thresholds

Drought Severity		**Drought Duration**	
Threshold DIT	**Number of Regions**	**Threshold DIT**	**Number of Regions**
0.2	4	0.15	3
0.25	5	0.3	5
0.35	7	0.45	6
0.5	8	0.55	9

Since a DIT value higher than 0.5 ensures a good information connection between two grids and higher values yield a large number of groups, eight regions based on drought severity, and nine regions based on drought duration were chosen. The corresponding threshold value of DIT was 0.5 for regions based on severity and 0.55 for regions based on duration.

Step 3. Regional homogeneity test

To check the heterogeneity of the regions obtained, the test suggested by Hosking and Wallis (1993, 1997) was performed. This test aims at estimating the degree of heterogeneity among the grouped sites and then assessing whether it is reasonable to treat it as a homogenous region or not. Three heterogeneity measures (HM) were devised and the values of HM should ideally be less than 1 for the regions to be considered as acceptably homogenous, and between 1 and 2 to be considered as possibly homogenous. If the value of HM is greater than or equal to 2, the region is definitely heterogeneous. The first HM, H_1, is based on the L-coefficient of variation (L-CV), the second HM, H_2, is based on L-CV and L-skewness and the third measure H_3 is based on L-skewness and L-kurtosis and they are given as:

$$H_1 = \frac{(V - \mu_{V_1})}{\sigma_{V_1}} \qquad H_2 = \frac{(V_2 - \mu_{V_2})}{\sigma_{V_2}} \qquad H_3 = \frac{(V_3 - \mu_{V_3})}{\sigma_{V_3}} \tag{8}$$

where

$$V = \left(\frac{\sum_{i=1}^{N} n_i (t_i - t_R)^2}{\sum_{i=1}^{N} n_i} \right)^{1/2} \quad (9)$$

$$V_1 = \left(\frac{\sum_{i=1}^{N} n_i \left\{ (t_i - t_R)^2 + (t_{3i} - t_{3R})^2 \right\}^{1/2}}{\sum_{i=1}^{N} n_i} \right) \quad (10)$$

$$V_2 = \left(\frac{\sum_{i=1}^{N} n_i \left\{ (t_{3i} - t_{3R})^2 + (t_{4i} - t_{4R})^2 \right\}^{1/2}}{\sum_{i=1}^{N} n_i} \right) \quad (11)$$

where n_i is the record length at the i^{th} grid considered out of a total of N grids, and t_i, t_{3i} and t_{4i} are the L-CV, L-skewness and L-kurtosis at the respective grid, whereas t_R, t_{3R}, and t_{4R} stand for the weighted average of L-CV, L-skewness and L-kurtosis, respectively, for the entire region under consideration. Here V, V_1 and V_2 are the statistics for the 'real' region, V is the weighted standard deviation of L-CVs at the site, V_1 is the weighted average distance from the site to the group weighted mean in a two-dimensional space of L-CV and L-skewness, and V_2 is the weighted average distance from the site to the group weighted mean in a two-dimensional space of L-skewness and L-kurtosis (Srinivas et al., 2008). the region is considered to be acceptably homogeneous if H_1<1, possibly homogeneous if H_1 is between 1 and 2, and definitely heterogeneous if H_1 is greater than or equal to 2 (Hosking and Wallis, 1997).

Following the procedure mentioned in the second step, once the regions were formed based on the chosen threshold, the next step was to check for their meaningfulness. The L-moments based the heterogeneity test by Hosking and Wallis (1997) was used for this purpose. To improve the homogeneity of a region, the discordant sites within each region were identified by computing a discordance measure. Any station which had a discordant measure value more than 3 was shifted to another region, provided the other region remained homogeneous even after the transfer. If the aforementioned condition was not satisfied, a site cannot be allocated to any other region, and hence it would be eliminated. Tables 5 and 6 give details of the discordant sites within the regions formed based on DIT for drought severity and duration, respectively. Tables 7 and 8 show the heterogeneity measures for the regions after elimination or shifting of discordant sites.

Table 5. Discordant sites in the regions formed based on drought severity

Region	Number of discordant sites	Adjustments
Region 1	8	4 deleted 4 moved to Region 4
Region 2	7	3 deleted 4 moved to Region 3
Region 4	0	-
Region 5	0	-
Region 6	9	2 moved to Region 4 1 moved to Region 5 6 moved to Region 7
Region 7	12	4 deleted 4 moved to Region 4 1 moved to Region 6 3 moved to Region 8
Region 8	8	4 deleted 2 moved to Region 5 2 moved to Region 6

Table 6. Discordant sites in the regions formed based on drought duration

Region	Number of discordant sites	Adjustments
Region 1	9	5 deleted 1 moved to Region 2 1 moved to Region 3 2 moved to Region 5
Region 2	4	4 deleted
Region 3	0	-
Region 4	13	7 deleted 1 moved to Region 3 3 moved to Region 5 2 moved to Region 8
Region 5	5	3 deleted 2 moved to Region 1
Region 6	5	2 deleted 1 moved to Region 5 2 moved to Region 8
Region 7	6	2 deleted 2 moved to Region 8 2 moved to Region 9
Region 8	4	2 deleted 2 moved to Region 6
Region 9	0	-

Table 7. Heterogeneity measures for the regions based on drought severity

Region	H_1	H_2	H_3	Conclusion
Region 1	-1.03	-1.68	0.352	Acceptably homogeneous
Region 2	-1.299	-3.09	1.14	Possibly homogeneous
Region 3	-1.332	0.376	0.241	Acceptably homogeneous
Region 4	-1.325	-1.698	0.189	Acceptably homogeneous
Region 5	-1.670	-8.703	-1.658	Acceptably homogeneous
Region 6	-2.176	-7.469	0.924	Acceptably homogeneous
Region 7	-1.481	-1.125	-1.636	Acceptably homogeneous
Region 8	-1.346	-1.008	-1.475	Acceptably homogeneous

Table 8. Heterogeneity measures for the regions based on drought duration

Region	H_1	H_2	H_3	Conclusion
Region 1	-2.514	0.894	0.722	Acceptably homogeneous
Region 2	-2.159	0.935	0.639	Acceptably homogeneous
Region 3	-2.682	0.946	0.644	Acceptably homogeneous
Region 4	-3.034	0.575	0.477	Acceptably homogeneous
Region 5	-2.477	-3.520	-2.205	Acceptably homogeneous
Region 6	-2.176	-7.469	0.924	Acceptably homogeneous
Region 7	-1.481	-1.125	-1.636	Acceptably homogeneous
Region 8	-1.162	-5.728	-4.716	Acceptably homogeneous
Region 9	-2.265	0.355	0.983	Acceptably homogeneous

Figures 3 and 4 show the homogenous regions formed based on the drought severity and drought duration, respectively.

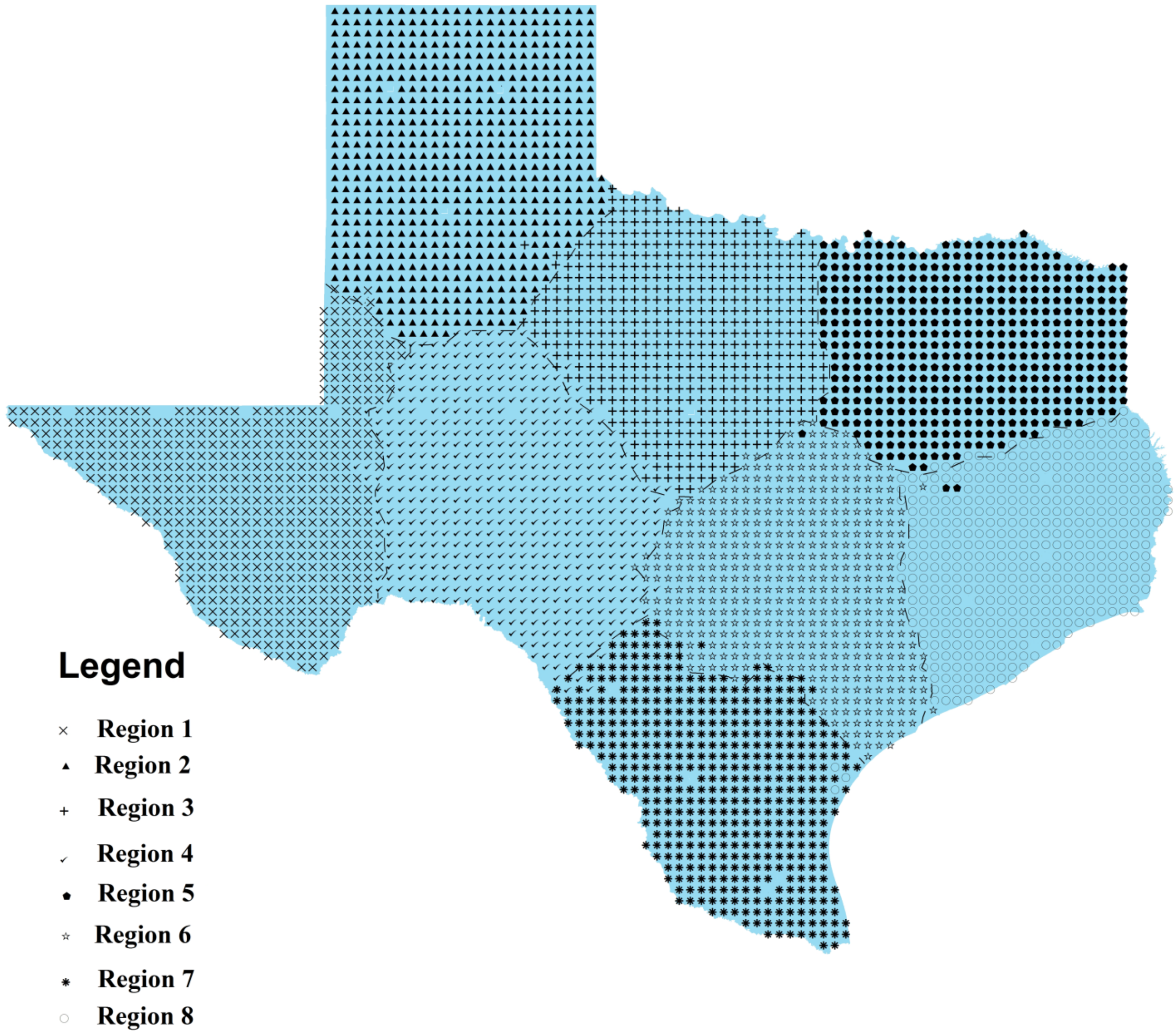


Figure 3. Homogenous regions formed using DIT based on drought severity

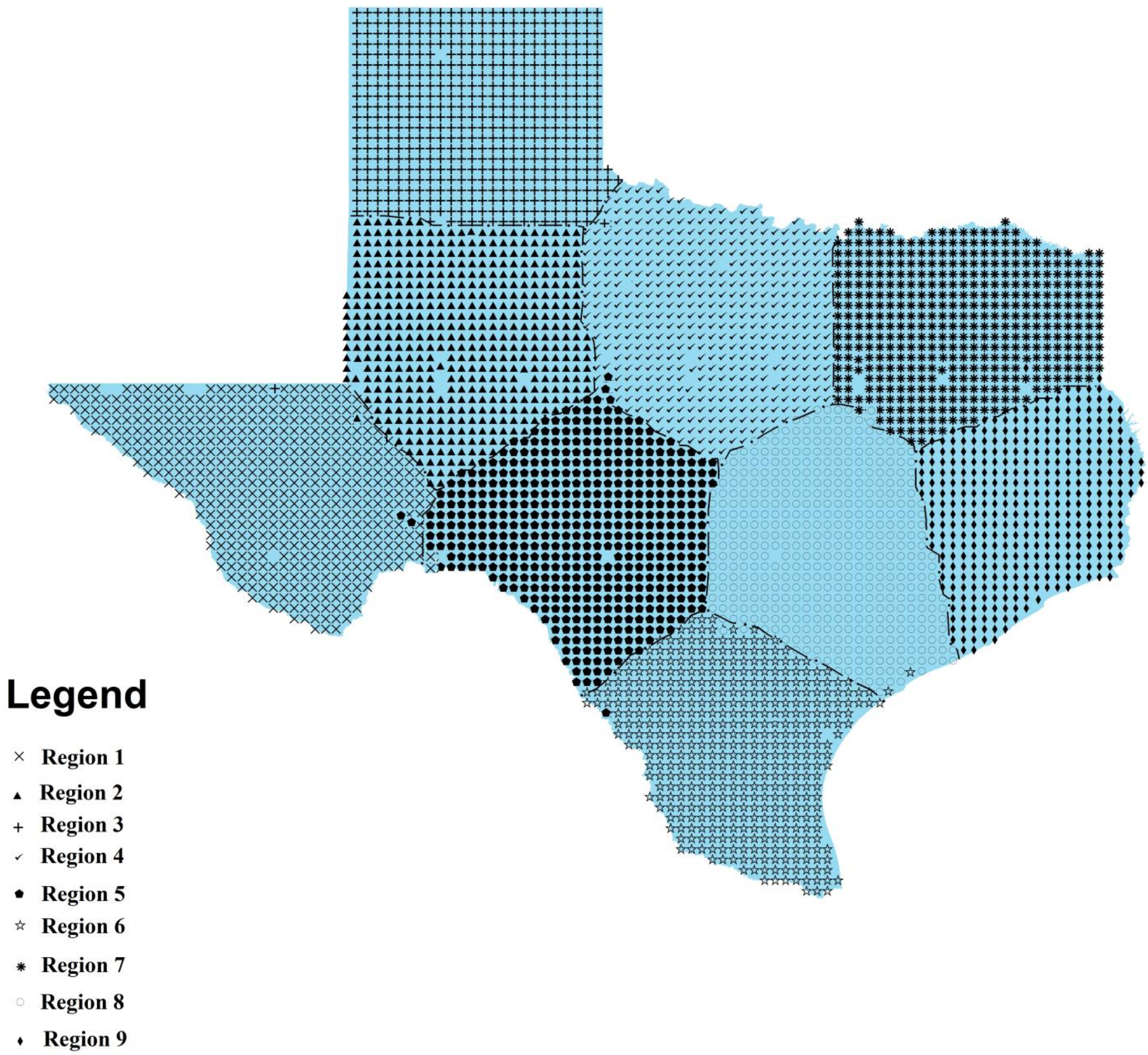


Figure 4. Homogeneous regions formed based on drought duration

Tables 9 and 10 give details of the regions based on severity and duration, respectively.

Table 9. Details of the regions formed based on drought severity

Region	Number of grids	Percentage Area covered	Annual average severity
1	478	11.495	7.65
2	489	11.761	7.219
3	658	15.824	6.294
4	574	13.804	6.632
5	550	13.227	7.074
6	483	11.616	5.435
7	453	10.895	5.346
8	473	11.375	4.898

Table 10. Details of homogenous regions formed based on drought duration

Region	Number of grids	Percentage Area covered	Average drought duration in months
1	499	11.11	73
2	462	10.52	64
3	498	12.02	58
4	485	9.13	47
5	484	10.51	77
6	436	11.69	91
7	437	11.37	33
8	473	12.01	42
9	379	11.66	27

The study can be extended to the bivariate case too, where both the drought severity and duration will be considered simultaneously for regionalization. The procedure followed for the bivariate case will be similar to the univariate case. However, the calculation of joint probabilities will be more complicated, since a four dimensional contingency table would be required for the same. The threshold value considered was 0.4, corresponding to which a total of five homogeneous regions were formed for the bivariate case. Table 11 gives the details of the heterogeneity measures for the five regions formed for the bivariate case. Figure 5 shows the homogeneous regions formed for the bivariate case. The details of each of the region are given in Table 12.

Table 11. Heterogeneity measures for the regions formed in the bivariate case

Region	H_1	H_2	H_3	Conclusion
Region 1	0.839	1.023	0.764	Possibly homogeneous
Region 2	-1.173	0.927	0.873	Acceptably homogeneous
Region 3	0.026	0.583	0.698	Acceptably homogeneous
Region 4	0.905	0.884	0.329	Acceptably homogeneous
Region 5	0.926	1.183	0.547	Possibly homogeneous

Table 12. Details of homogenous regions formed based on drought severity and duration

Region	Number of grids	Percentage Area covered	Annual average severity	Average drought duration in months
1	759	18.45	6.714	87
2	790	19.20	7.937	75
3	694	16.87	6.717	51
4	874	21.24	7.169	54
5	997	24.23	4.814	30

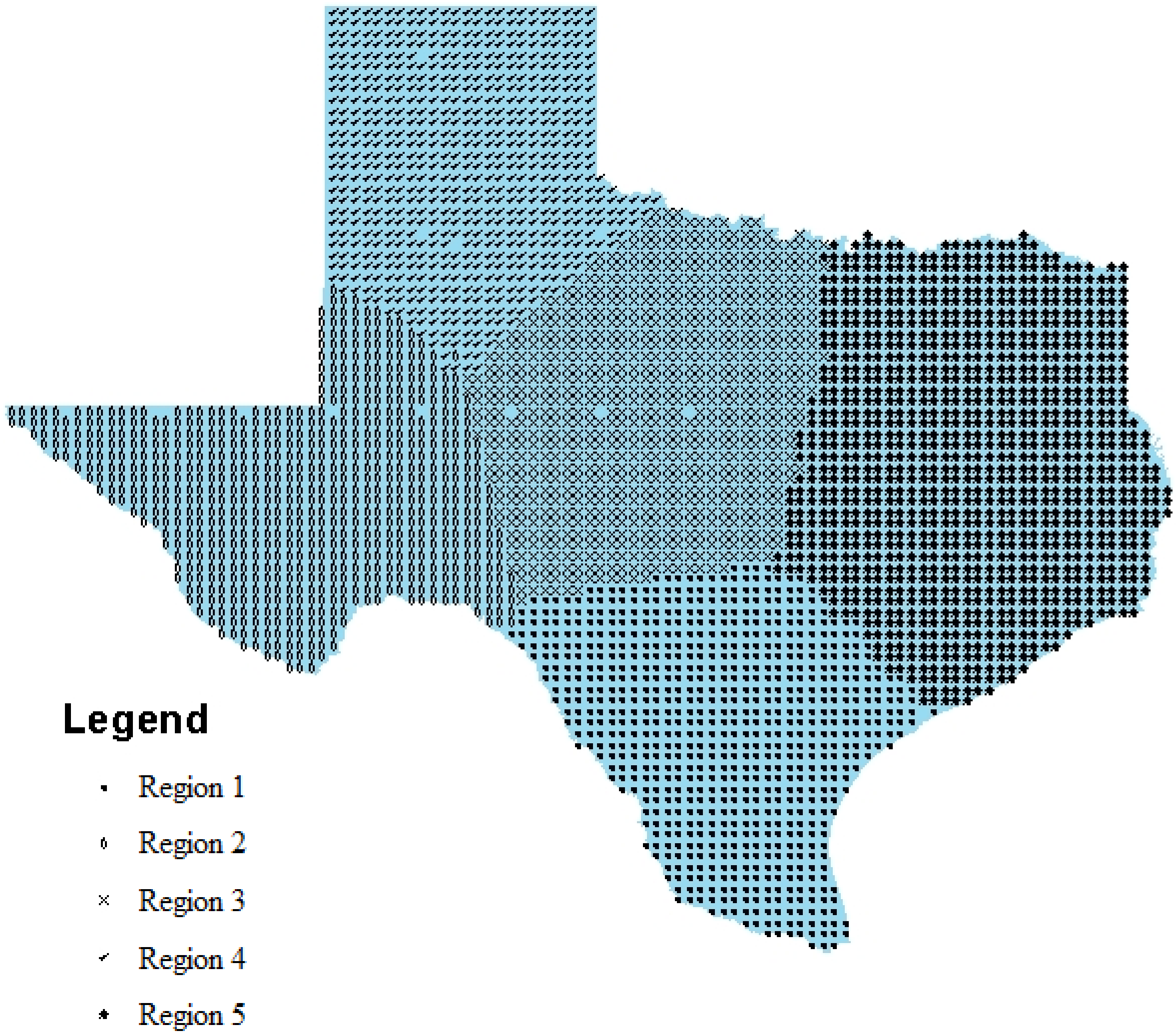


Figure 5. Homogeneous Regions formed in the bivariate case

Conclusions derived:

An entropy based similarity measure known as directional information transfer (DIT) is used to regionalize the state of Texas based on drought severity and duration. This measure, being more sensitive to nonlinear dependencies, is a better similarity measure than the commonly used linear dependence measures. By making use of the non-symmetric property of the index, if there is a great difference between the DIT_{xy} and DIT_{yx} values of a station pair, it can imply that given the observations at one station, the response at the other station is ambiguous. This can be due to greater loss during information transfer. It should however be noted that no strict guidelines are available for fixing a threshold value for the DIT. This is expected, since regionalization is essentially a subjective process, and hence, in any case the threshold will be user defined provided that the value is not too high (which may lead to strong dependence between stations belonging to different regions) or too low (which may lead to low dependence between stations within the same region). Finer adjustments can be made to the threshold value by observing how a change in its value affects the number and size of the regions formed. The following conclusions are drawn from the study:

1. DIT can satisfactorily identify homogeneous regions based on drought severity and duration, thus leading to the classification of Texas into zones based on stream flow drought properties.
2. Identification of critical regions in a drought prone state like Texas is done by assessing drought properties within each region formed. Region 1 lying within the Trans Pecos zone in the west Texas is the most critical region in terms of severity. Region 8 which lies in the eastern part of Texas has the lowest severity. The pattern is consistent with the precipitation pattern in Texas. As far as drought duration is concerned, region 6 which lies in south Texas, south central Texas and Lower Valley has the longest drought duration. Region 9 which lies in the eastern Texas has the lowest drought duration.
3. Parts of High Plains, Upper Coast, central and western Texas are affected by moderately dry droughts. However, severely dry and extremely dry droughts are mainly restricted to western, central and south Texas.

The study can be extended to bivariate case too. The stream flows at the USGS gauges are controlled/observed flow. The model has been calibrated and validated on the basis of the original controlled/observed flow instead of naturalized flow. This might have an impact on the runoff simulations obtained from the model. It might not be possible for any model to accurately reproduce the real world scenario for the runoff production process. However, it should be noted that the model simulations does show a satisfactory correlation with the original stream flow, and that the model in general underpredicts stream flow values in comparison to the original values. As an extension to the present work, it would be interesting to analyze how well the model simulations match if naturalized stream flow values were used instead of controlled flows.

Having obtained the homogeneous zones for stream flow drought, with the knowledge of variation of drought properties within each of these regions, a mitigation plan specific to that region can be developed. This will help water resources planners overcome the gravity of water crisis in coming years.

4(b) Drought atlas for the state of Texas

Purpose and scope: The purpose of this objective is to develop drought severity-duration – frequency maps for Texas. In addition to this, maps for average annual severity, decadal variation of drought severity, and drought duration have also been prepared. This helps in visualizing the spatial variation of drought characteristics within the state of Texas.

Mean drought severity map:

Step 1: Streamflow simulations at $1/8^{th}$ degree resolution for Texas

Land surface model named VIC, which has been explained in section 2 of the first objective, will be used for obtaining daily streamflow simulations over grids of $1/8^{th}$ degree resolution over Texas. The time period of simulation is 1949-2000.

Step 2 : Classification of drought variables from the streamflow time series for each grid

Theory of runs will be used for the classification of streamflow time series into drought variables: severity and duration. The details regarding the methodology are already given in step 1 under methodology section for the first objective.

Step 3: Plotting the contour lines for annual average drought severity

From the streamflow time series for each grid, the average of annual drought severities for the years 1949-2000 was calculated for each grid. Contours were plotted based on this raster data using arcGIS. Figure 6 shows the contour map of average annual drought severity for Texas.

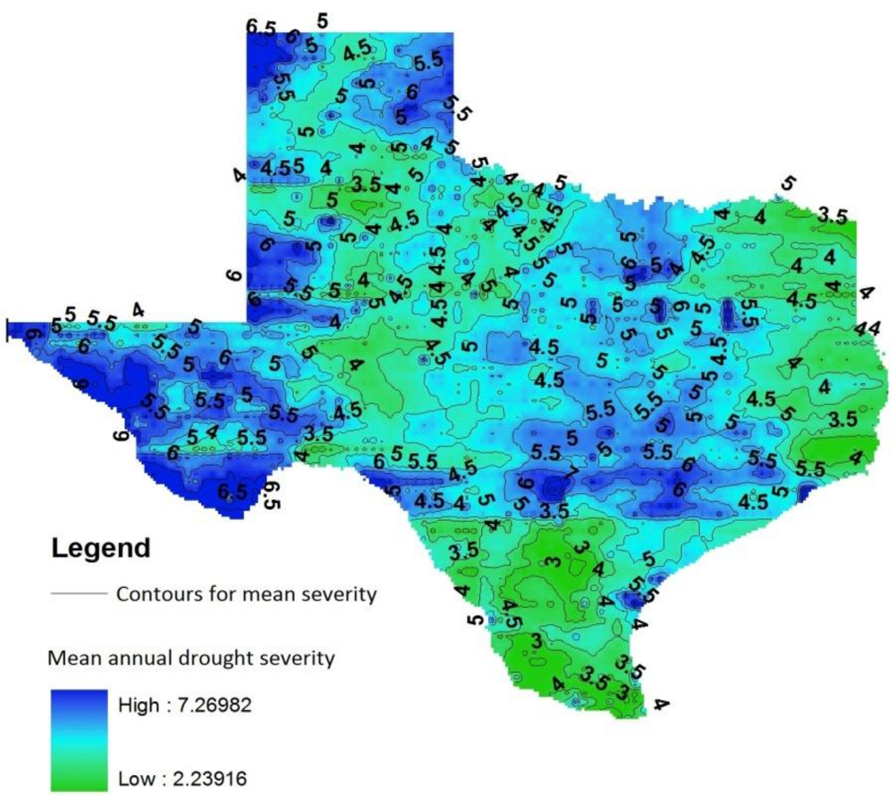


Figure 6. Contour map for average annual drought severity for Texas (1949-2000)

Observations from the map: It can be seen from the map that on an average, the severity levels were higher on the western and south eastern parts of Texas, with values ranging between 5.0-7.0. The lowest severity levels were observed over the southern and eastern parts of Texas, with values ranging between 2.0-4.0. The pattern is consistent with the precipitation pattern observed over Texas, which has a decreasing gradient from east to west.

Decadal means map for the drought severity

Following the same procedure for the mean annual drought severity map, to analyze the decadal variation of drought severity, contour maps for each decade: 1950-1959, 1960-1969, 1970-1979, 1980-1989, 1990-2000 were prepared using the annual average drought severities. Figure 7 shows decadal maps for drought severity.

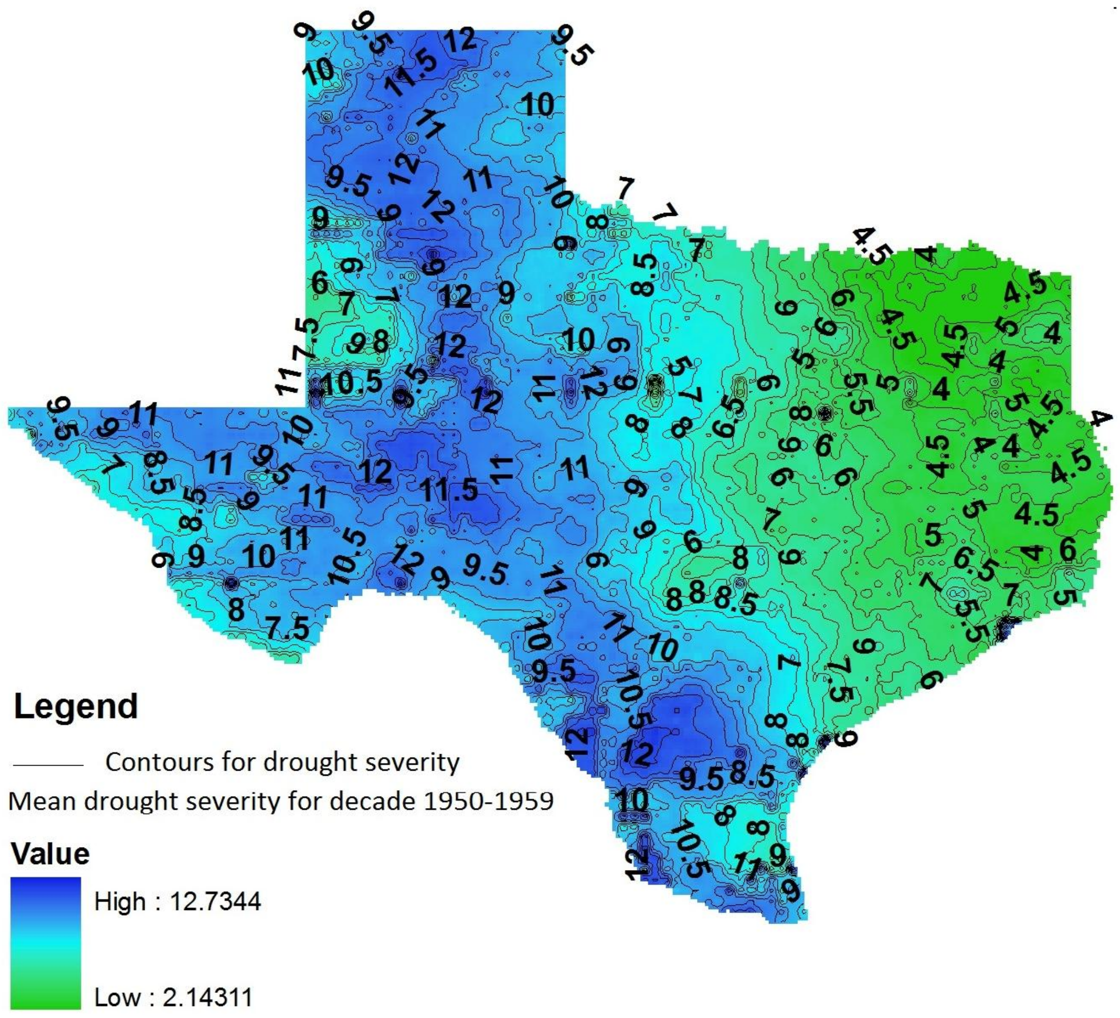


Figure 7a. Drought severity map for 1950-1959

Observations from the map: During the 1950s, the western parts of Texas showed higher severity levels in comparison to the eastern part. The 1950s show comparitively high severity levels, which might be attributed to the 1950s dust bowl.

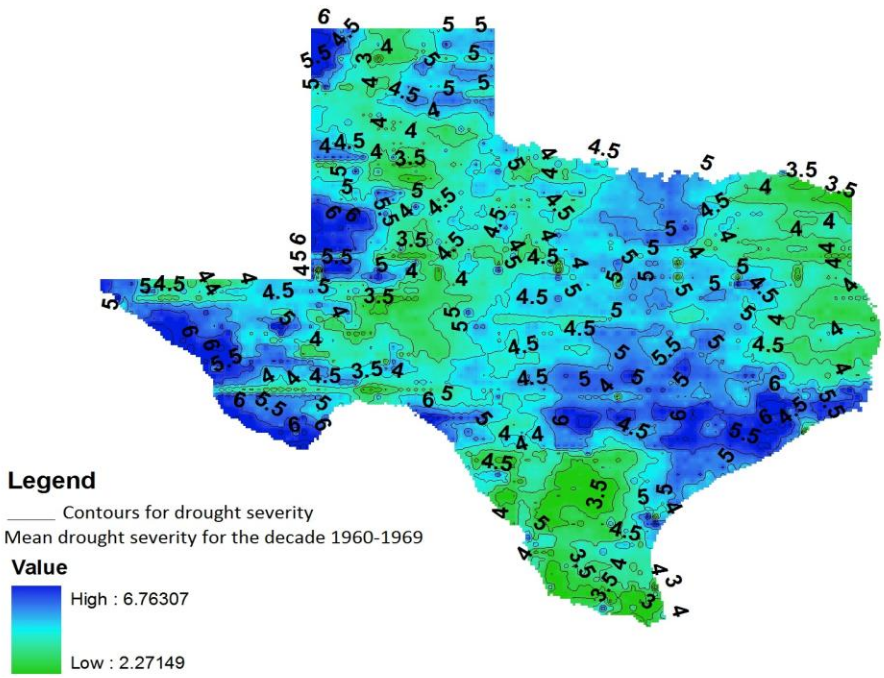


Figure 7b. Drought severity map for 1960-1969

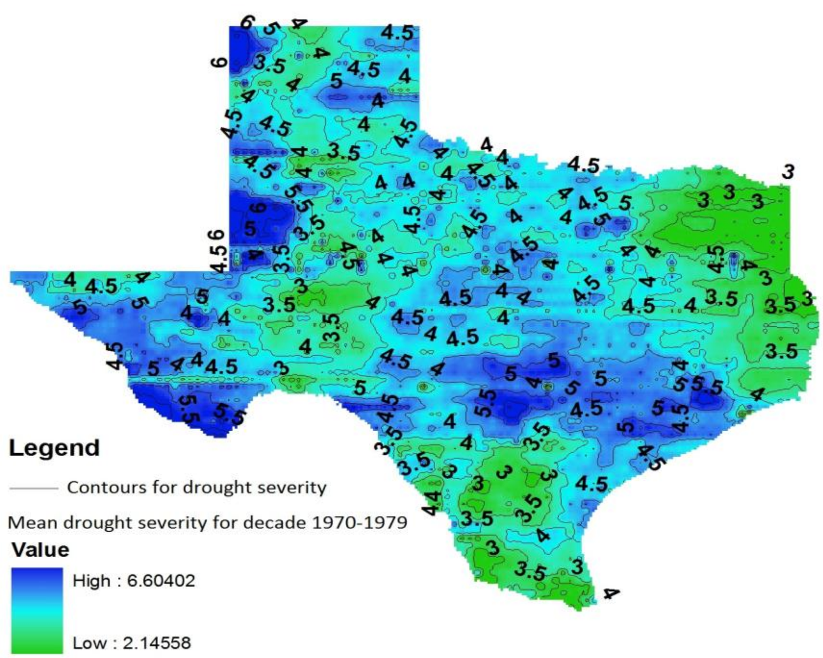


Figure 7c. Drought severity map for 1970-1979

Observations from the maps: The severity patterns were similar during the 1960s and 1970s. As compared to the 1950s, a shift in pattern can be seen wherein the severity levels have decreased along the northern, southern and central parts of Texas, and have increased towards the south eastern and eastern parts. The 1960s and 1970s have comparitively low severity levels than other decades (refer to figures below too).

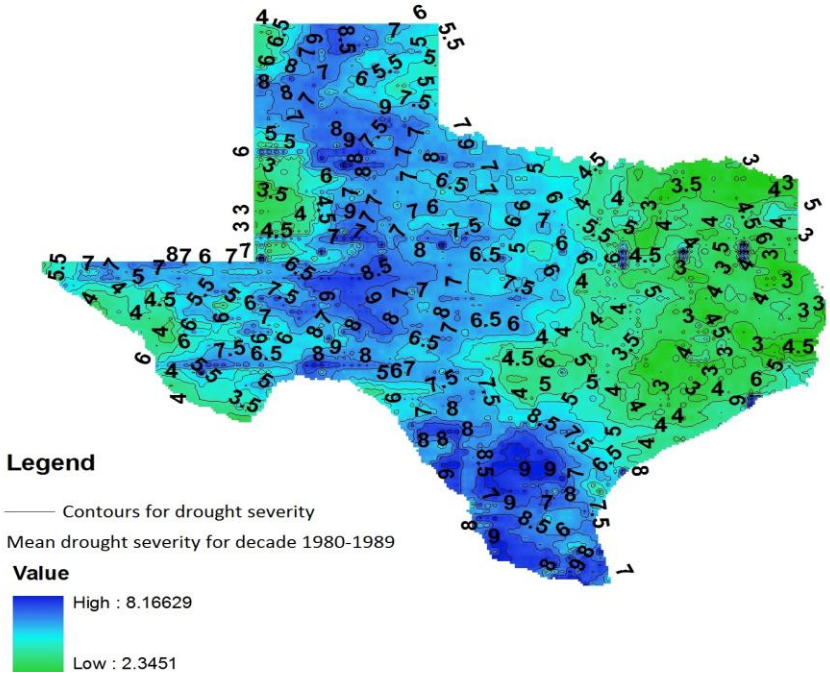


Figure 7d. Drought severity map for 1980-1989

Observations from the map: During the 1980s, the southern and central parts of Texas show an increase in severity level compared to the previous decades, whereas the southeastern parts show a decrease in severity levels. As compared to the previous decades, drought levels appear to be severe along southern Texas.

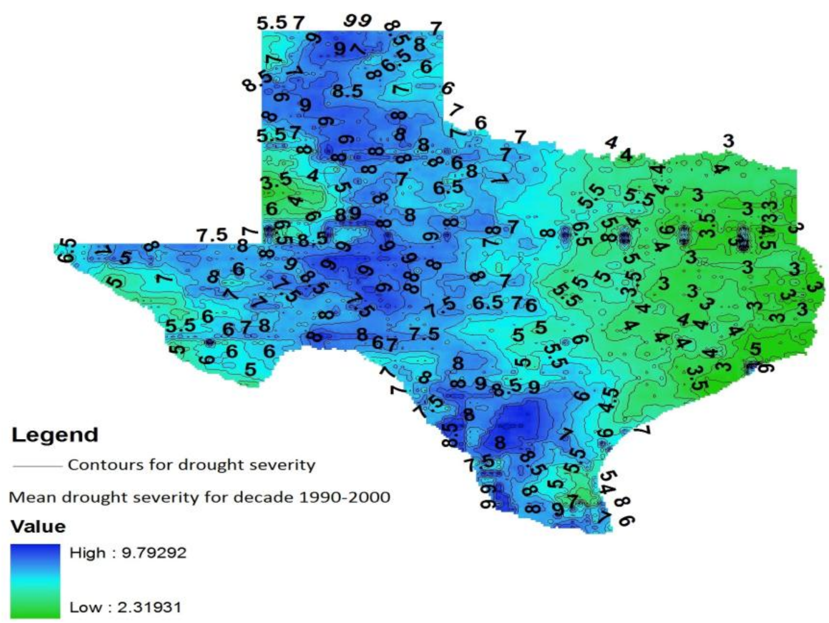


Figure 7e. Drought severity levels for 1990-2000

Observations from the map: During the 1990s, the pattern became similar to that during the 1950s, although the severity levels are not as high as the 1950s. The 1990s does show a higher severity level than the 1960s, 1970s and 1980s.

Contour maps for different drought classification:

It is shown in Table 1 that depending on the SSFI value, the events are classified as either wet or dry. If the index falls below -1.0, the event is considered to be dry, i.e. it indicates drought. Further, any drought event will fall under any of the following three types: moderately dry (If SSFI between -1.0 and -1.5), severely dry (If SSFI is between -1.5 and -2.0), and extremely dry (If SSFI is less than -2.0).
In this set of maps, the contour maps for moderately dry droughts, severely dry droughts and extremely dry droughts are considered on a case by case basis and plotted separately.

The steps for obtaining the drought characteristics were already explained in the beginning of the section.

Contour map for moderately dry droughts

In this case, while plotting contours, only the SSFI values that lie between -1.0 and -1.5 were considered, and the average of all such values for each grid was computed. Some of the grids might not have SSFI values lying within this specific range, and they correspond to the zero value grids in the map. Figure 8a shows the contour map for moderately dry droughts.

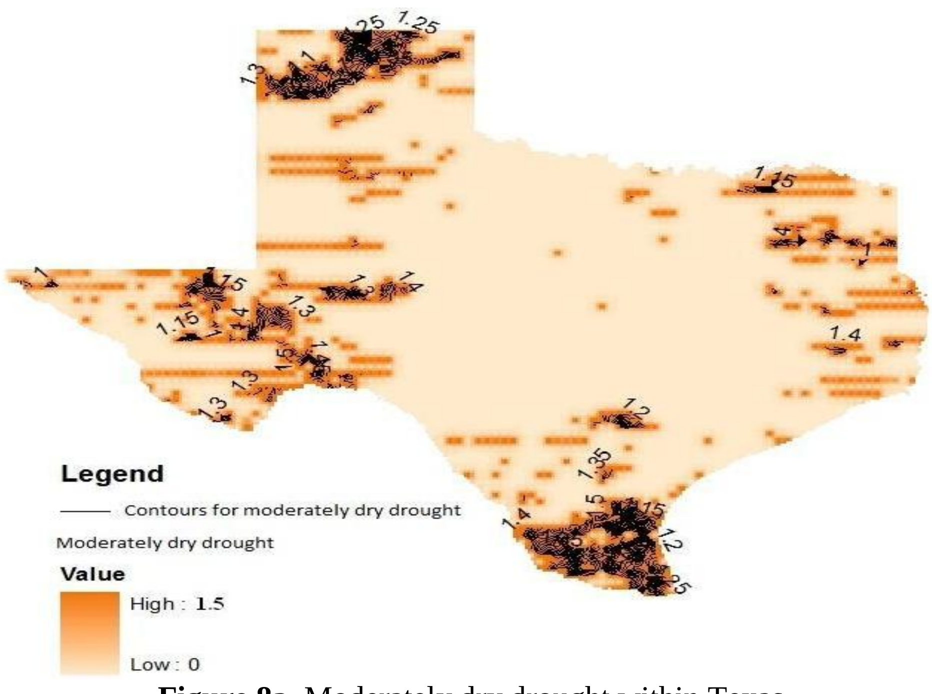


Figure 8a. Moderately dry drought within Texas

Contour map for severely dry droughts

In this case only the SSFI values lying between -1.5 and -2.0 was considered, and the rest of the values were neglected. Some grids might not have SSFI values within this specific range. Figure 8b shows the contour map for severely dry drought within Texas.

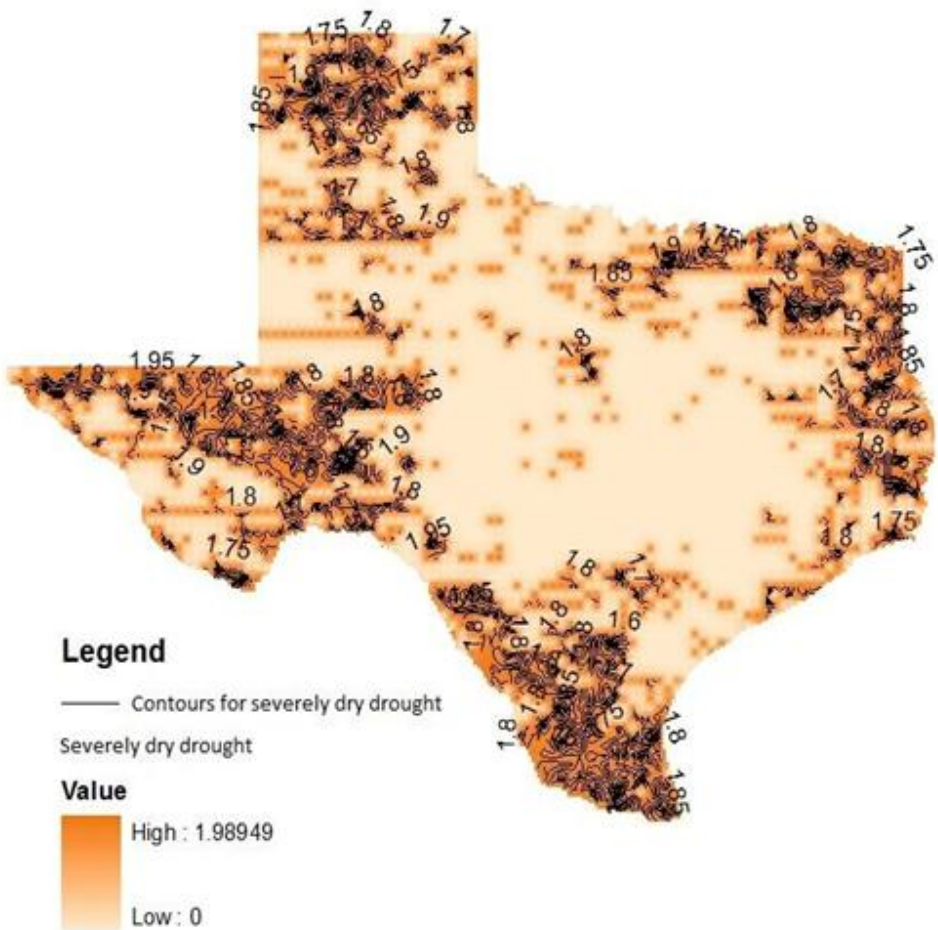


Figure 8b. Severely dry drought within Texas

Observations from the map: It can be seen that moderately dry and severely dry droughts are usually seen along the western, eastern, southern and northern tips, and not along the central parts of Texas.

Contour map for extremely dry drought

In this case, for calculating the drought severity, any SSFI value that falls below -2.0 will be considered. The annual average severity values thus calculated was used for plotting the contour map. Figure 8c shows the contour map for extremely dry drought.

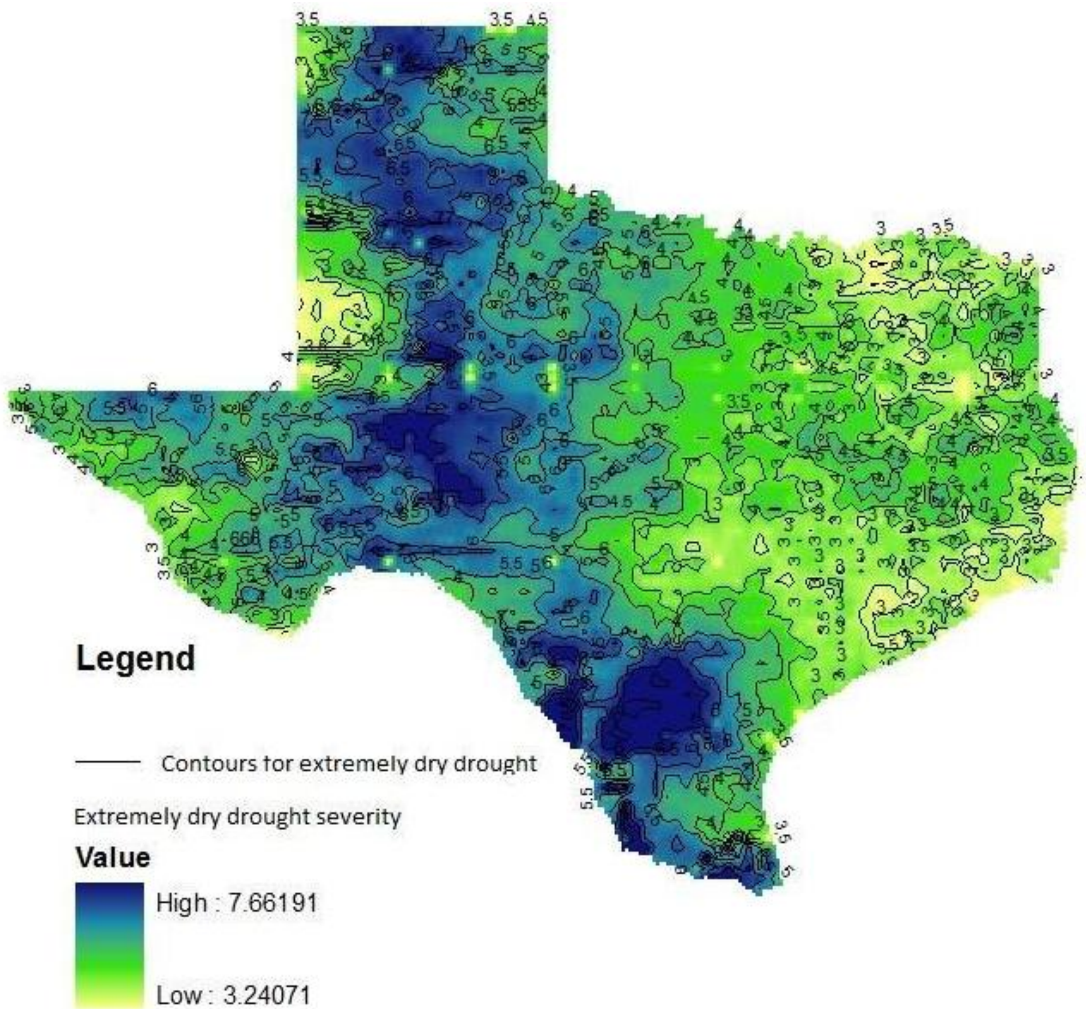


Figure 8c. Extremely dry droughts within Texas

Observations from the map: Extremely dry droughts were experienced throughout Texas during the past half century, with relatively higher levels along western, northern and southern tips.

Contours for mean duration in months for the time period 1950-2000

The drought duration represents the length of a negative run in months, i.e., it indicates how long the drought event lasts in months. Theory of runs explained in the methodology section of the first objective will be used for deriving drought durations from the VIC model streamflow simulations. Figure 9 represents the average duration of drought in months experienced by each grid over the time period 1950-2000.

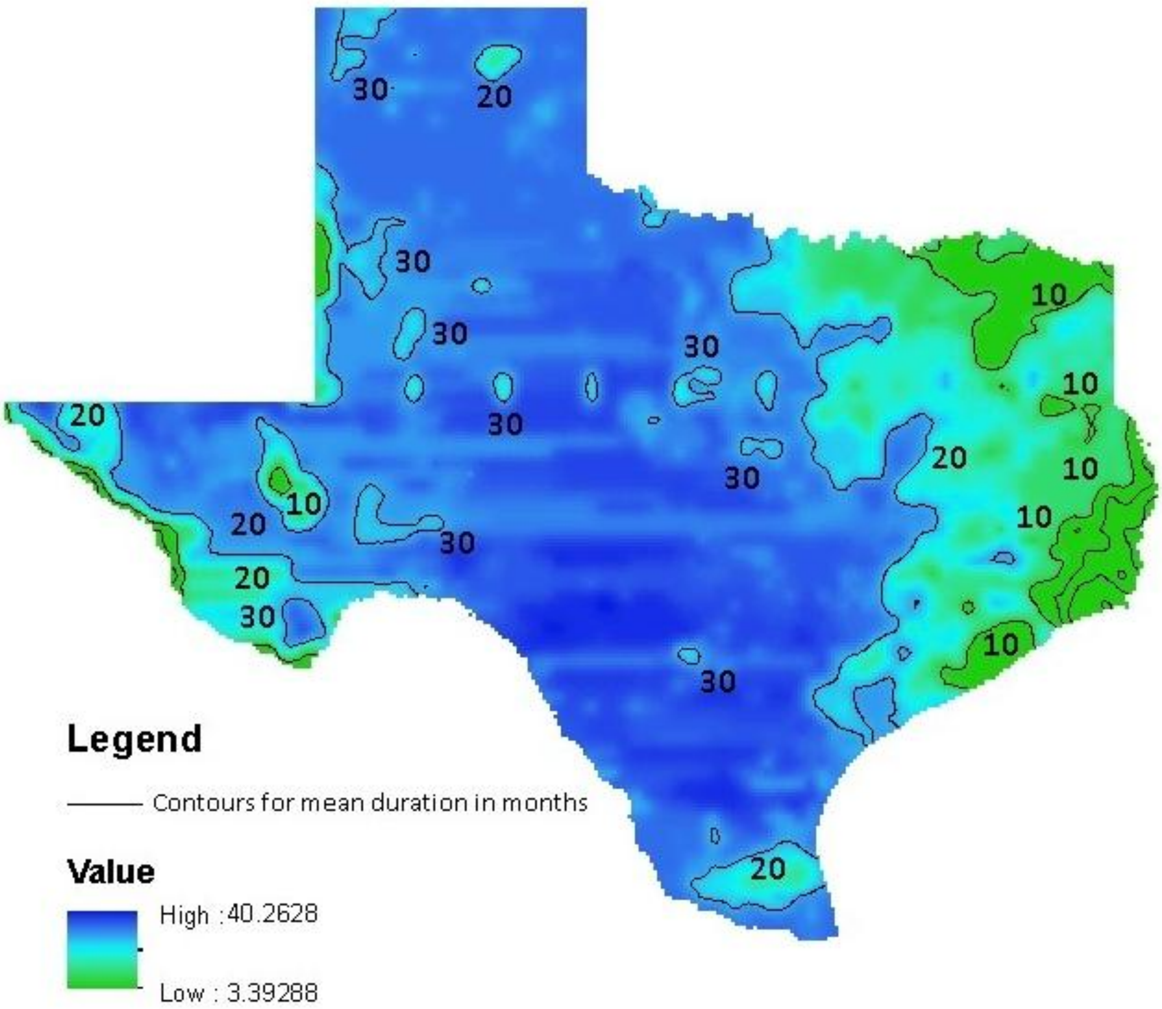


Figure 9. Average drought duration in months for each grid in Texas

Observations from the map: Relatively lower durations were seen on the western tip, and most of the eastern region. The central, western and southern parts of Texas in general show a higher incidence of drought events.

Drought severity-duration-frequency maps

Droughts are dynamic and are characterized by multiple attributes like severity, duration and magnitude (Mishra and Singh, 2010). Hence, a univariate analysis which considers each of these properties separately might not make sense. However, the derivation of bivariate distributions for drought characteristics poses problems since the marginal distributions used should belong to the same family, which might not be the case in reality since we use different distribution functions to fit different drought properties. The use of copulas to link marginal distributions to form a joint distribution was found to alleviate such problems and several studies focusing on the use of copulas in the context of drought analysis can be seen in the literature (Shiau, 2006, 2007, 2009; Kao & Govindaraju, 2010; Song & Singh, 2010a,b; Mirakbari et al.; 2010). Shiau et al. (2006, 2007, 2009) developed a methodology for drought frequency analysis and derivation of severity-duration-frequency curves using two-dimensional copulas, which will be followed to produce contour maps for drought severities for different durations and recurrence intervals.

The steps followed for preparing these maps are given below:

Step 1: Definition of drought events

For any drought event, the cumulative deficit of the variable of interest during the drought event is defined as drought severity. Drought duration is the time between the onset and the end of a drought event. The theory of runs was used for deriving drought characteristics from the stream flow time series. Details of the method are already mentioned in the report.

Step 2: Distributions of univariate drought variables

The second step will be the derivation of univariate distributions for each of the drought characteristics. Generally, drought duration is fitted as an exponential distribution (Zelenhastic and Salvai, 1987) if the drought duration is considered a continuous random variable. Gamma distribution is generally used to describe the drought severity (Zelenhastic and Salvai, 1987; Mathier *et al*., 1992; Shiau and Shen, 2001). The probability density functions of exponential distribution and gamma distribution are shown in Equations (12) and (13), respectively.

$$f_D(d) = \frac{1}{\lambda} e^{-d/\lambda} \tag{12}$$

$$f_S(s) = \frac{s^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} e^{-s/\beta} \tag{13}$$

where d>0 is the drought duration, and λ is the parameter, s>0 is the drought severity, and α, β are the shape and scale parameters, respectively. The exponential and gamma distribution parameters are derived first and separately. Given *n* independent paired observations (d_i , s_i), the log-likelihood functions for the drought duration and severity, ln $L_D(d;\ \lambda)$ and ln $L_S(s;\ \alpha,\ \beta)$, are maximized to derive the parameters.

Step 3:Copula based joint CDF for drought severity and duration

Since drought severity and duration are modeled by different CDFs, copulas are used to link the fitted models and construct the JCDF of drought severity and duration. In this study, the Clayton copula is employed to model the dependence between drought severity and duration, since it is of simple form and is commonly used in hydrology. The copula-based JCDF of drought severity and duration, therefore, become:

$$C(F_S, F_D) = (F_S^{-\theta} + F_D^{-\theta} - 1)^{-\frac{1}{\theta}}, \theta \geq 0 \tag{14}$$

where F_S and F_D are the univariate CDFs for drought severity and duration, respectively; and θ is a parameter used to measure the degree of association between F_S and F_D. The parameter of Clayton copula is estimated by the method of Inference Function for Margins (IFM) (Joe, 1997). Substituting the values of θ in Eq. (19) will give the expression for the copula based JCDF of drought severity and duration.

Step 4: Copula based drought severity-duration-frequency relationship

The relationship among drought severity, duration and frequency in terms of recurrence interval for drought events can be represented by the conditional recurrence interval which is given by (Shiau, 2007):

$$T_{S|D}(s \mid d) = \frac{1}{\gamma(1 - F_{S|D}(s \mid d))} \tag{15}$$

where s and d denote the drought severity and duration, respectively; $F_{S|D}(s|d)$ is the conditional CDF of S, given D=d, $T_{S|D}(s|d)$ is the conditional recurrence interval of S given D = d; and γ is the arrival rate of drought events which need to be fitted from the observed data.

The conditional CDF is given as:

$$F_{S|D}(s \mid d) = \frac{\partial F_{S,D}(s,d)}{\partial F_D(d)} \tag{16}$$

where $F_D(d)$ is the CDF of drought duration, and $F_{S,D}$ (s,d) is the joint CDF of drought severity and duration which will be derived using copulas as explained in step 3. The conditional distribution in eq. (16) can be rewritten as:

$$F_{S|D}(s \mid d) = \frac{\partial F_{S,D}(s,d)}{\partial F_D(d)} = \frac{\partial C(F_S(s), F_D(d))}{\partial F_D(d)} = \mathrm{C}_{F_S|F_D}(F_S(s) \mid F_D(d)) \tag{17}$$

where C is the unique copula function that links $F_S(s)$ and $F_D(d)$ to form the joint CDF. The conditional copula in terms of $F_S(s)$ and $F_D(d)$ has the following form (Joe, 1997):

$$C_{F_S|F_D}(F_S(s) \mid F_D(d)) = \left\{1 + F_D(d)^{\theta}(F_S(s)^{-\theta} - 1)\right\}^{-\frac{1}{\theta}-1} \tag{18}$$

The copula based drought SDF curve is thus given by:

$$T_{S|D}(s \mid d) = \frac{1}{\gamma\left[1 - \left\{1 + F_D(d)^{\theta}\left(F_S(s)^{-\theta} - 1\right)\right\}^{-\frac{1}{\theta}-1}\right]} \tag{19}$$

This theoretical drought SDF relationship can be used to construct the dependence between drought severity, duration and the arrival rate of drought events.

Step 5: Plotting contour maps for drought severities corresponding to different durations and recurrence intervals

For selected recurrence intervals of 10, 25, 50 and 100 years, drought severity quantiles for specific drought durations can be obtained for each of the grids. This raster data will then be used for plotting the contour maps using arcGIS. Figures 10 (a to h) show the drought severity maps for drought durations of 6 and 12 months for recurrence intervals of 10, 25, 50 and 100 years.

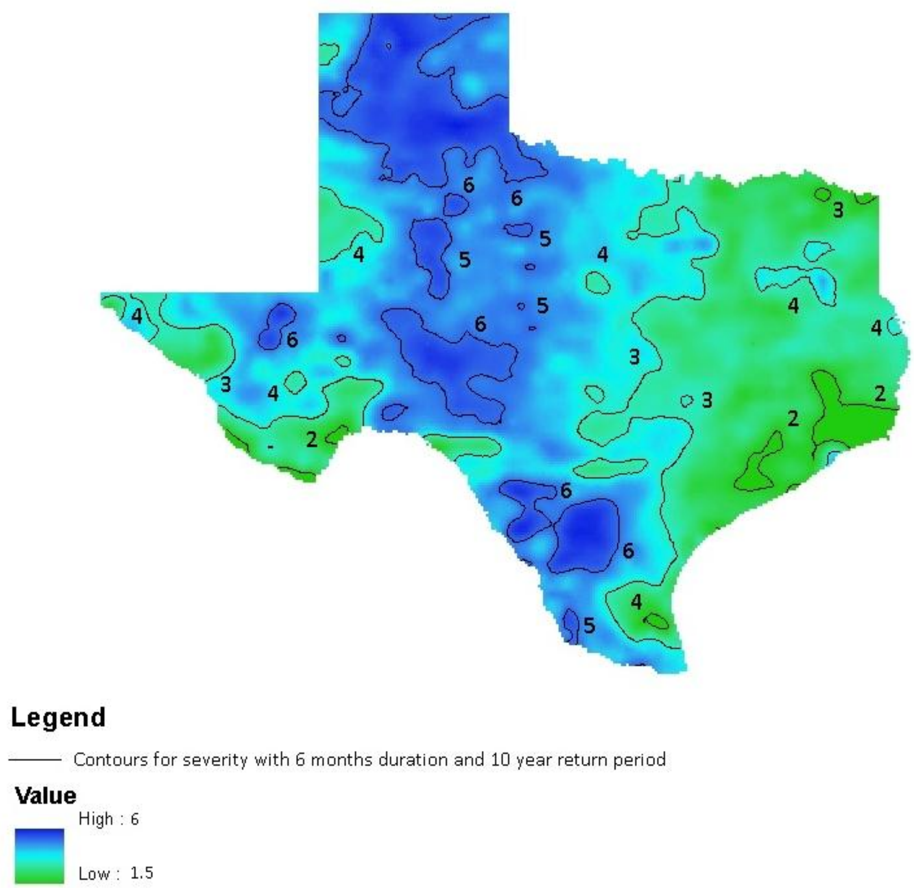


Figure 10a. Drought severity with 6 months duration and 10 year return period

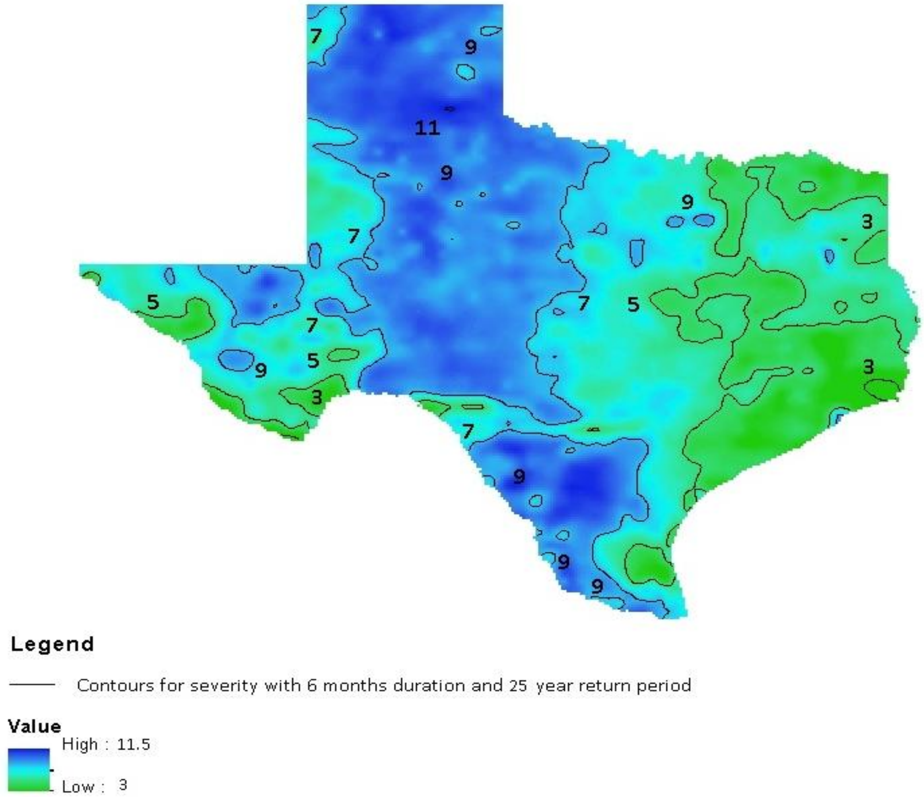


Figure 10b. Drought severity with 6 months duration and 25 year return period

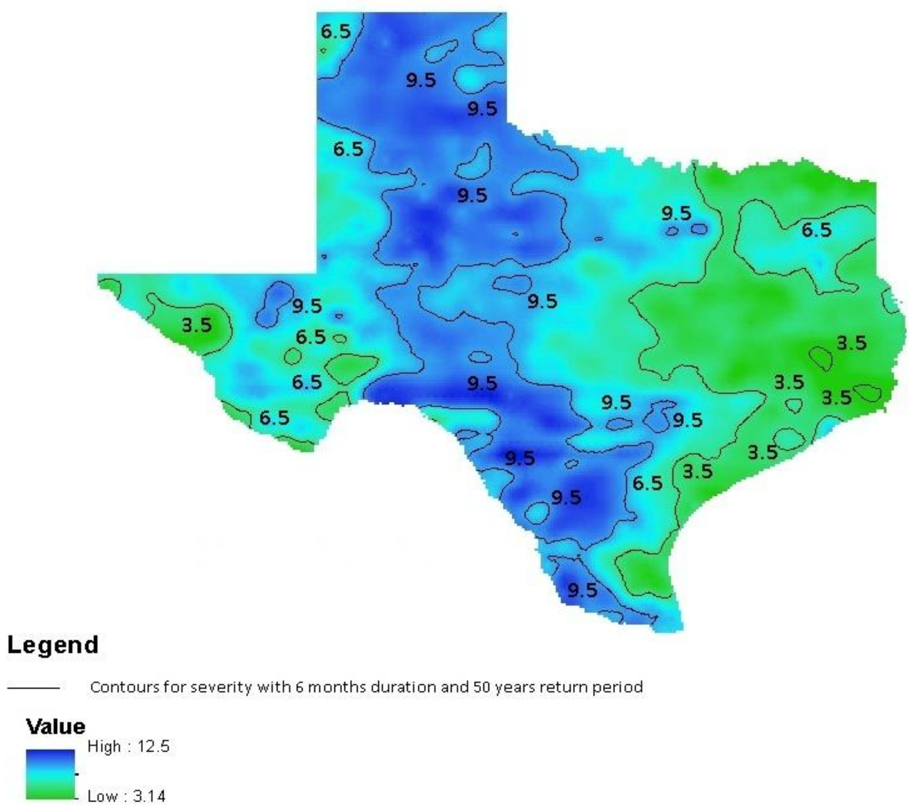


Figure 10c. Drought severity with 6 months duration and 50 years return period

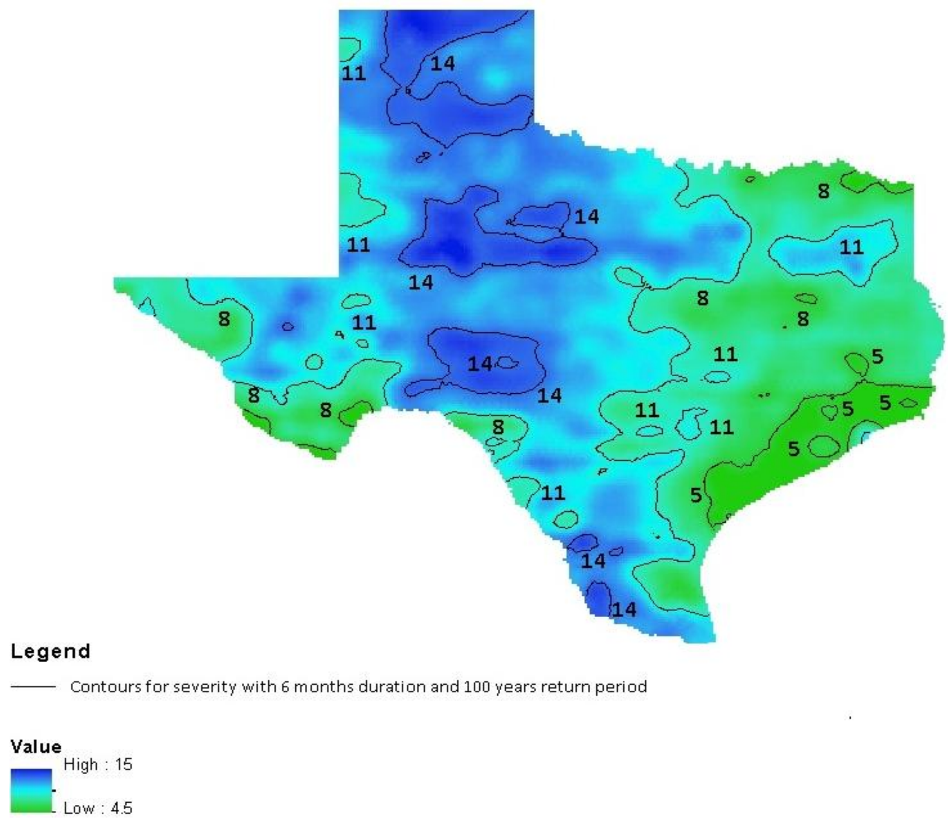


Figure 11d. Drought severity with 6 months duration and 100 years return period

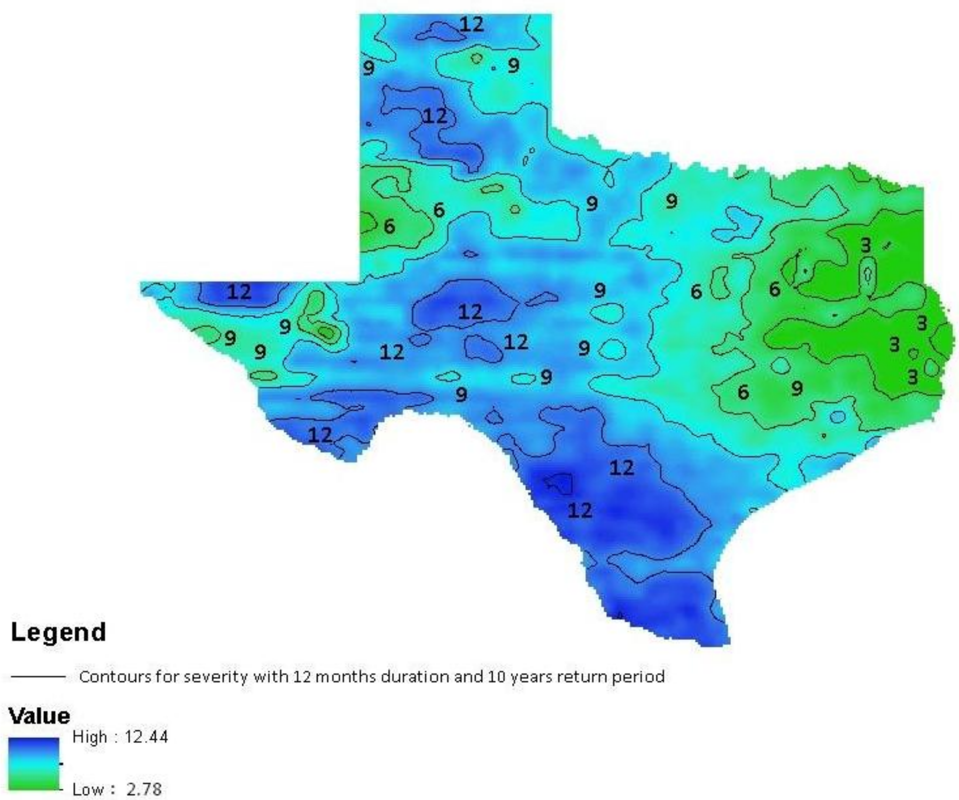


Figure 11e. Drought severity with 12 months duration and 10 years return period

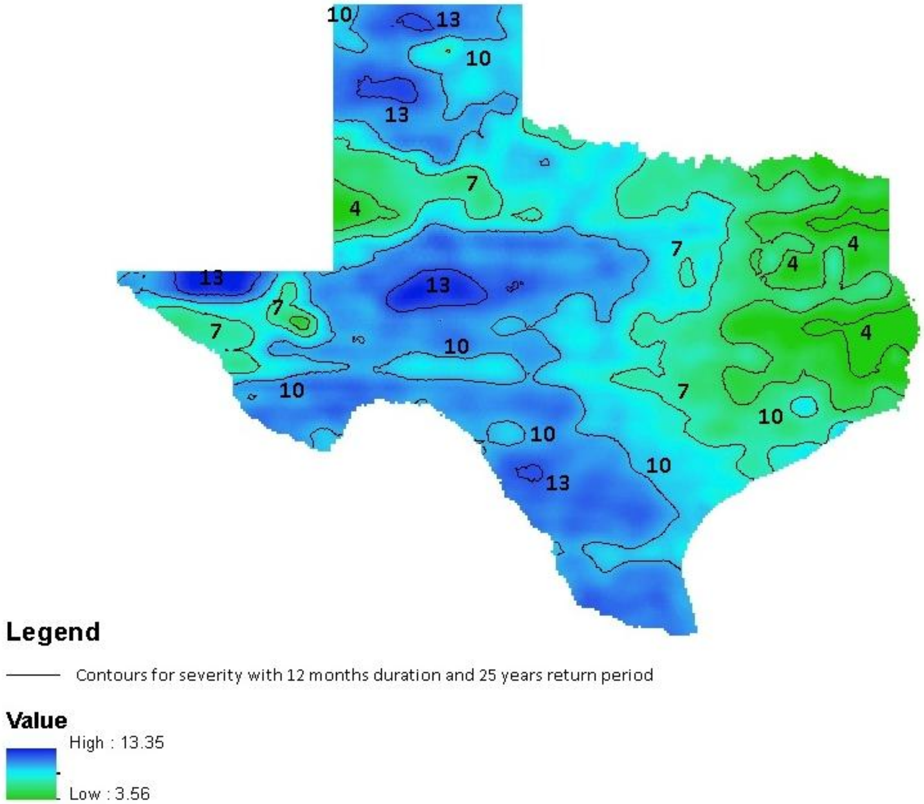


Figure 11f. Drought severity with 12 months duration and 25 years return period

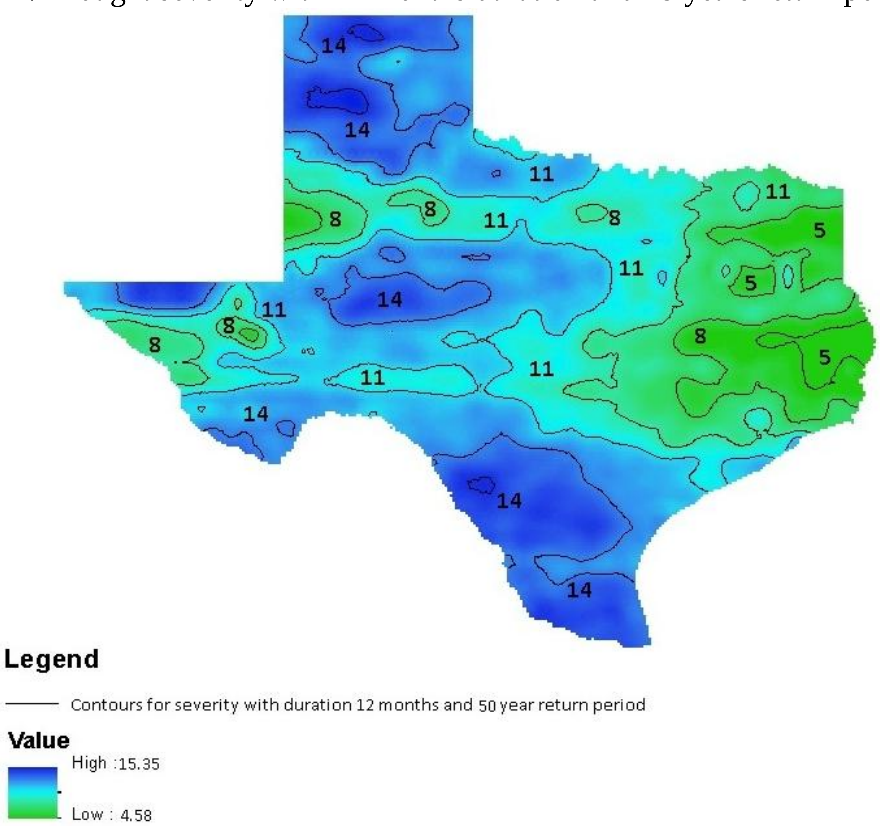


Figure 11g. Drought severity with 12 months duration and 50 years return period

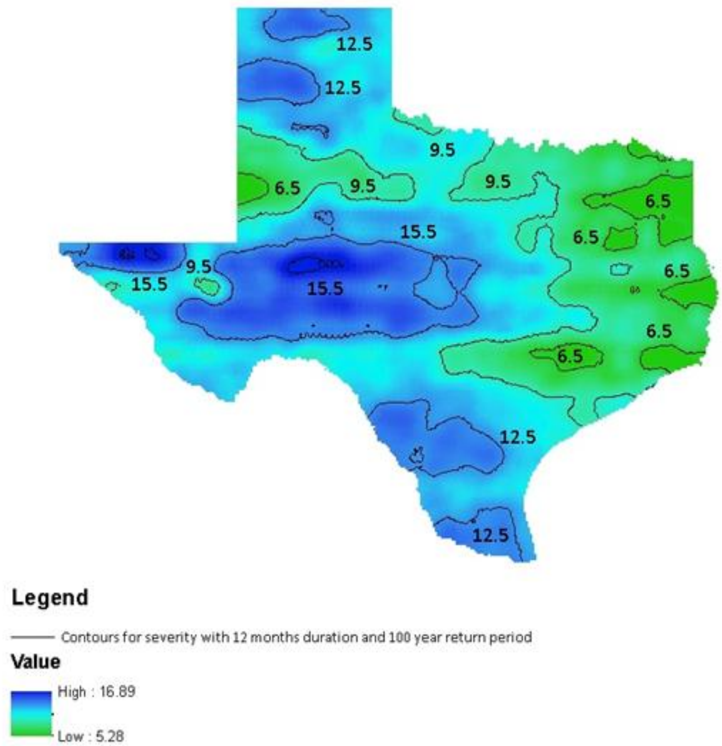


Figure 11h. Drought severity with 12 months duration and 100 year return period

Observations from the maps:

1. The drought severity varies systematically for different durations and return periods, with maximum severities along western, northern and south western Texas, which gradually decreases towards eastern Texas.
2. 6-month duration 10-year return period droughts have severities ranging from 1.5 along eastern Texas to 6 along western, northern and central Texas, whereas for 100 year return period droughts with 6 months duration, the severities range from 4.5 along eastern and south eastern Texas to 15 along the northern and south western parts.
3. 12-month duration 10-year return period droughts have severities ranging from 2.78 along eastern Texas to 12.44 along western and south western parts, whereas for 100 year return period droughts with 12 months duration, the severities range from 5.3 along eastern Texas to 16 along the central part.
4. In general, the severity-duration-frequency relationship shows a concave down pattern, i.e. the drought severity increases rapidly if the drought duration is short. As the drought duration increases, the drought severity also increases but the rate at which it severity increases will become lesser for longer drought durations.

4(c) Simulating hydrological drought properties at different spatial units based on wavelet-Bayesian regression approach

Methodology used in the study

Palmer Hydrological Drought Index (PHDI)

This is a hydrological drought index used to assess long-term moisture supply. The monthly time series generated indicates the severity of a wet or dry spell based on the balance between moisture supply and demand. The PHDI is suitable to quantify the hydrological impacts of droughts (e.g., reservoir levels, groundwater levels, etc.) which take longer to develop and it takes longer to recover from them (Palmer, 1965).

The PHDI generally ranges from - 6 to +6, with negative values denoting dry spells and positive values indicating wet spells. In the present study, we have taken different thresholds for identifying severity levels of different droughts, i.e., PHDI values less than 0 include all types of drought; PHDI less that -1 includes a range of drought from mild drought to extreme drought; PHDI values less than -2 includes moderate drought to extreme drought; PHDI values less than -3 represents severe drought and extreme droughts and PHDI less than -4 represents extreme droughts.

Bayesian linear regression

The description of the Bayesian regression model is summarized from Hoff (2009). Regression modeling describes the sampling distribution of dependent variable *y* varies with another variable or sets of independent variable $x = (x_1, \ldots, xp)$.

$$y_i = \beta^T x_i + \varepsilon_i, \quad \text{where } \varepsilon_i \sim i.i.d.\ normal\ (0, \sigma^2) \tag{20}$$

Where, β^T represents the vector of coefficients associated with a row vector of independent variables x_i and ε is *i.i.d* random normal term with mean zero and standard deviation σ.

Continuous wavelet transform

A continuous wavelet transform (CWT) decomposes a PHDI time series into wavelets and produces coefficients at a given scale. CWT's basis functions are scaled and shifted versions of the time-localized mother wavelet. A Morlet wavelet is one of the many wavelet functions which has a zero mean and is localized in both frequency and time. It provides a good balance between time and frequency localizations and is therefore preferred for application. It can be represented as (Grinsted et al., 2004):

$$\psi(\eta) = \pi^{-1/4} e^{i\omega\eta - 0.5\eta^2} \tag{21}$$

where ω is the dimensionless frequency, and η is the dimensionless time parameter. The wavelet is stretched in time (*t*) by varying its scale (*s*), so that $\eta = s/t$. When using wavelets for feature extraction purposes, the Morlet wavelet [with ω = 6] is a good choice, since it satisfies the admissibility condition (Farge, 1992; Torrence and Compo, 1998). For a given wavelet $\psi_0(\eta)$, it is assumed that X_j is a time series of length *N* [X_j, i=1, …, *N]* with equal time spacing δt. The continuous wavelet transform of a discrete sequence X_j is defined as convolution of X_j with the scaled and translated wavelet, $\psi_0(\eta)$:

$$W_n^X(s) = \sum_{j=1}^{N} X_j \psi^* \left[\frac{(j-n)\delta t}{s} \right] \tag{22}$$

CWT decomposes PHDI time series into time-frequency space, enabling the identification of both the dominant modes of variability and how those modes vary with time.

Goodness-of-fit test

To compare the observed and simulated drought time series, the goodness-of-fit was calculated based on correlation coefficient, root mean square error and mean bias error. If O_i and S_i represent observed and simulated drought time series, then:

Correlation coefficient (CC): $$\frac{n\sum O_i S_i - (\sum O_i)(\sum S_i)}{\sqrt{n(\sum O_i^2) - (\sum O_i)^2}\sqrt{n(\sum S_i^2) - (\sum S_i)^2}} \tag{24}$$

If $e_i = O_i - S_i$ denoted as individual model-prediction errors, then model performances are based on statistical summaries of e_i (*i=1, 2, 3,…,n*):

Root mean square error (RMSE): $$\left[\frac{1}{n} \sum_{i=1}^{n} |e_i|^2 \right]^{1/2} \tag{25}$$

Mean bias error (MBE): $$\frac{1}{n} \sum_{i=1}^{n} e_i \tag{26}$$

Study area and data used

Different spatial units were chosen to test the potential of precipitation and temperature to simulate hydrological drought using PHDI. The definition of spatial units used in this paper is based on the following notion: (a) climatic division is the smallest unit used in this study, (b) the state (say Texas) is combination of several climatic divisions (units), and (c) the regional unit is combination of several states. The spatial units include (see table 1 and figure 12): all climatic division (1 to 10) of the state of Texas, state of Texas, different regions of USA (Northeast, East North Central, Central, Southeast, West North Central, South, Southwest, Northwest and West regions). Monthly precipitation, temperature and PHDI values which are available from 1900 to 2000 were retrieved from National Climatic Data Center of National Oceanic and Atmospheric Administration (NOAA). For both precipitation and temperature, monthly averages within a climatic division have been calculated by giving equal weight to stations. To adjust the climatic division averages, the model described by Karl, et al. (1986) was used such that all stations end their climatological day at midnight; i.e., climatological day coincides with calendar day.

Statistical properties of precipitation across different spatial units are shown in Table 13. Precipitation in state of Texas is not evenly distributed and the mean annual precipitation distribution correlates roughly with longitude and varies little from north to south. The maximum mean annual precipitation was observed for climatic division 8 (121cm) and climatic division 4 (118cm) located in the far eastern part of Texas, whereas the minimum was observed in climatic division 5 (32 cm) located in the far western part of Texas. A higher amount of standard deviation was observed in the region witnessing a higher amount of precipitation, for example climatic divisions 8 and 7.

Based on the regional unit, the maximum mean annual precipitation was observed to be higher in southeast region (128cm) followed by the central region (108cm) and northeast region (104cm), whereas the minimum was observed in southwest region (34 cm) followed by west and west north central region (43cm). The standard deviation pattern witnesses higher values with higher mean annual precipitation, however the variation was noticed in lower amounts of annual precipitation. The west north central and west region observe the same amount of mean annual rainfall (42cm) considered to be among the lowest values, however they witness different standard deviations of 5.5 and 11 cm, respectively. Positive kurtosis and skewness are observed in the maximum number of selected spatial units.

Table 13. Spatial units and statistical properties of their annual precipitation for the period of 1900-2000.

Sl. No	Spatial location	Mean (cm)	Standard Deviation (cm)	Kurtosis	Skewness
1	Climatic division 1 (Texas)	47.92	10.63	5.88	0.71
2	Climatic division 2 (Texas)	59.85	13.53	4.32	0.45
3	Climatic division 3 (Texas)	87.23	17.58	2.58	-0.01
4	Climatic division 4 (Texas)	118.30	22.00	2.54	0.31
5	Climatic division 5 (Texas)	31.58	9.24	4.81	0.85
6	Climatic division 6 (Texas)	64.54	16.94	3.05	0.44
7	Climatic division 7 (Texas)	88.30	21.25	2.49	0.13
8	Climatic division 8 (Texas)	121.18	26.55	2.67	0.38
9	Climatic division 9 (Texas)	58.96	14.34	2.54	0.30
10	Climatic division 10 (Texas)	63.58	14.47	3.59	0.60
11	State of Texas	71.19	13.43	2.92	0.15
12	North east region (USA)	104.35	10.12	3.66	0.39
13	East north central region (USA)	75.63	8.56	2.91	-0.30
14	Central region (USA)	107.79	11.68	2.88	-0.09
15	South east region (USA)	127.71	13.56	2.45	0.07
16	West north central region (USA)	42.99	5.50	3.13	0.13
17	South region (USA)	90.02	12.41	2.91	-0.08
18	South west region (USA)	34.36	5.70	4.09	0.35
19	North west region (USA)	68.37	9.65	2.63	0.21
20	West region (USA)	42.82	10.95	3.69	0.87

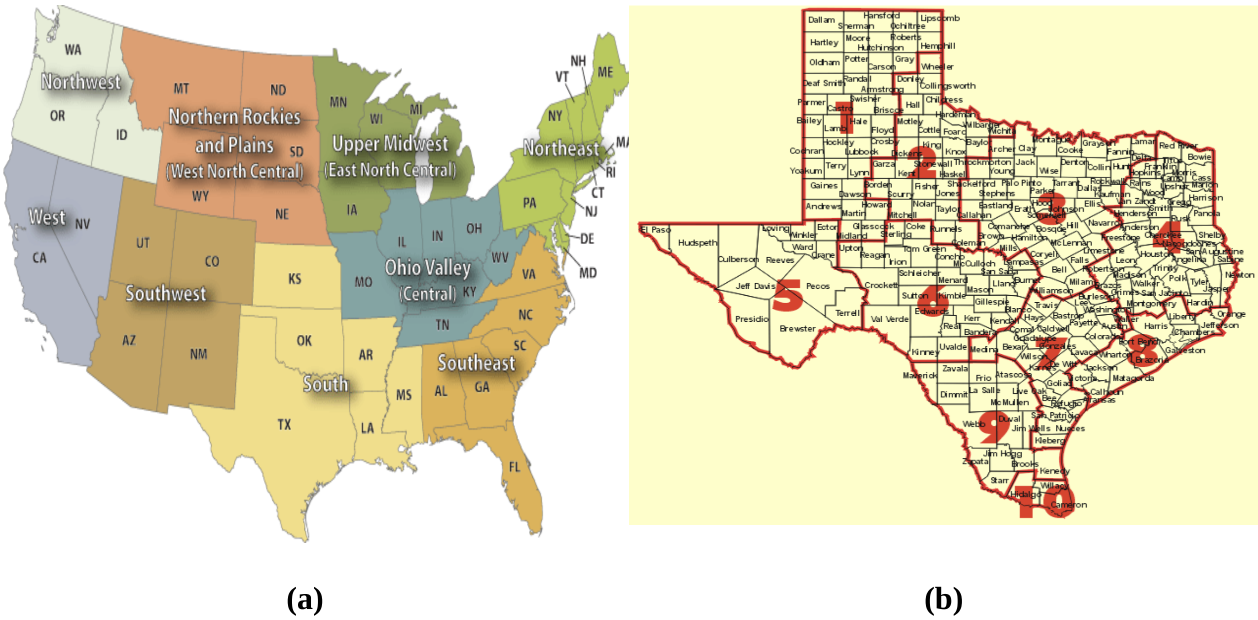


Figure 12. (a) Nine climatically consistent regions within the contiguous United States identified by National Climatic Data Center (Karl and Koss, 1984), (b) Ten climate division located within the state of Texas.

Results and Discussion

Comparison of drought properties among spatial units

Good correlation was observed among neighboring climatic divisions (Figure 13), for example the PHDI time series in climatic division 1 had a correlation strength of 0.84 (climatic division 2) and 0.71 (climatic division 5) which happen to be neighboring climatic divisions. This suggests that droughts are regional in nature for most parts of Texas. Therefore, the drought causing variables are likely to share similar association at a regional scale. The PHDI time series for the whole of Texas shares a stronger correlation coefficient (>0.74) with all climatic divisions except climate division 10 with a correlation coefficient of 0.6. The PHDI time series for larger spatial units beyond Texas, i.e., south region of USA which includes many states (TX, OK, KS, AR, LA and MS) shares a good correlation with climatic divisions of Texas except climatic divisions of 5, 9 and 10. It is worth noting that the correlation strength remains strong among climatic divisions, state and at region. However, no correlations were observed at higher spatial units which comprise multi states from different parts of the USA.

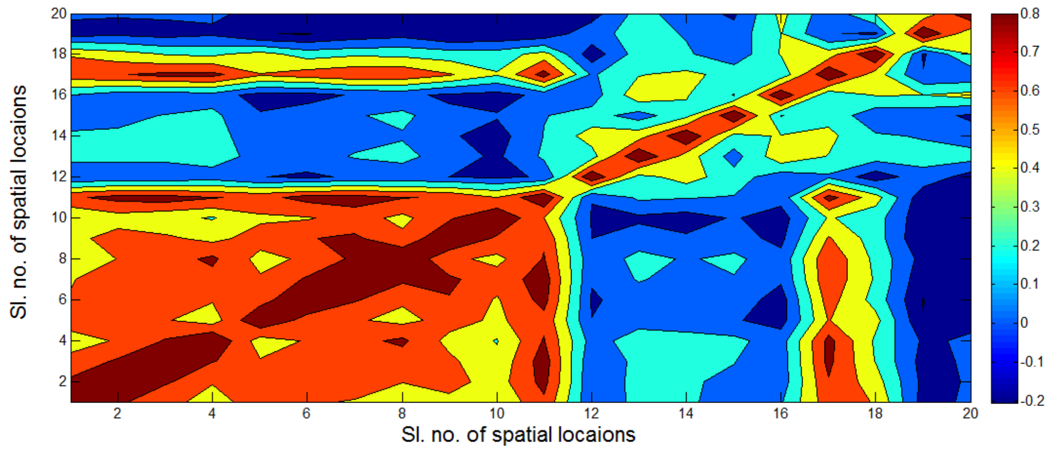


Figure 13. Linear correlation strength among spatial locations.

The number of droughts, maximum drought severity, and maximum drought duration were compared among spatial units. In this case all the droughts were considered for which the PHDI was consecutively less than -1. Based on this criterion the number of droughts that occurred among climate divisions of Texas included: climatic division 1 (61), climatic division 2 (58), climatic division 3 (49), climatic division 4 (65), climatic division 5 (60), climatic division 6 (51), climatic division 7 (50), climatic division 8 (60), climatic division 9 (65), climatic division 10 (58) and whole of Texas (45). Among the climatic divisions the number of droughts did not follow any pattern, as the maximum number occurred in all parts of Texas. The lowest number of droughts generally occurred in the sub-tropical semi-humid climate. Another interesting fact was found to be number of droughts based on the state of Texas was less in comparison to any climatic division within the state of Texas. The number of droughts at a regional unit found to be maximum in the regions located in Northeast, South east and Northwest region of the USA. The minimum number of droughts occurred in west north central region of the USA which happens to be the lowest among all the spatial selected regions.

After knowing the number of drought events, it will be good to look at the maximum drought duration and severity in different spatial units [Figure 14]. Based on number of drought events, maximum duration and maximum severity, different spatial units were compared. Important observations include: (a) the lowest number of drought events occurred in west north central region which happens to have witnessed the maximum drought severity and maximum drought duration (99 months). Therefore chances of getting longer duration drought are higher for this region. (b) The maximum number of drought events occurring in the regions (southeast and northwest regions) lies within the first five positions in terms of lowest drought duration or severity in comparison to all other spatial units. (c) The strong correlation coefficient was observed between maximum duration and maximum severity whereas the same is not true based on the number of events.

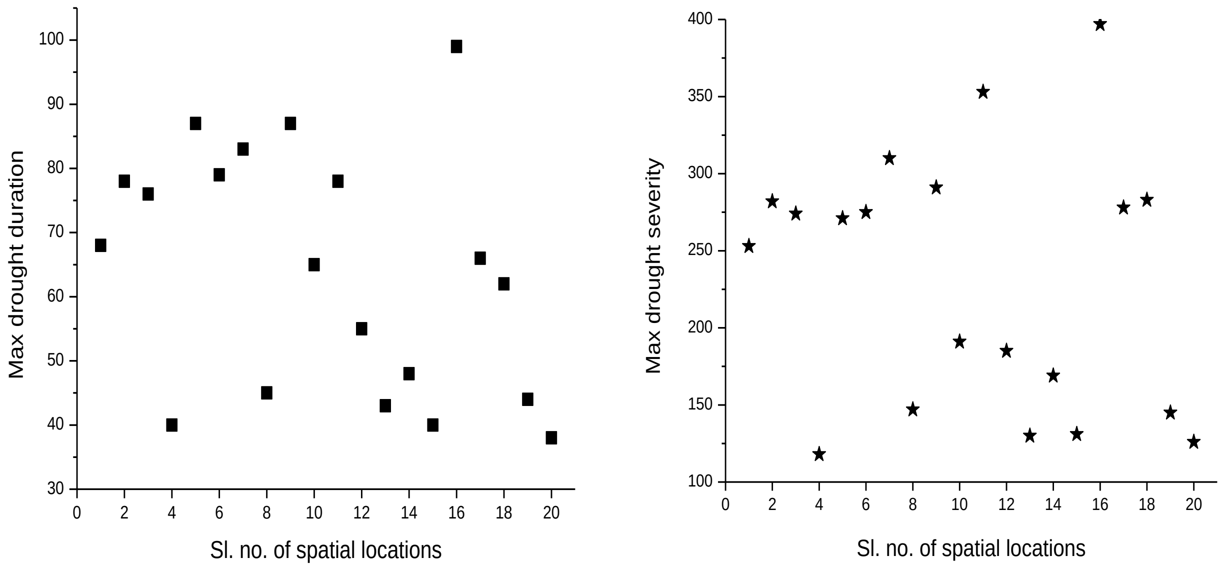


Figure 14. Plot of maximum duration and severity that occurred in the selected spatial units during the period of 1900 to 2000.

Comparison between wavelet Bayesian regression and Bayesian regression model

The wavelet Bayesian regression model depends on the decomposed PHDI time series and therefore the selection of number of bands which carry significant power is important for model setup. The spectral bands were obtained according to average wavelet spectra of PHDI. In the current discussion the PHDI time series for all spatial units can be separated into 6 significant bands so that the lower bands (first and second) show the noisy data, while the upper bands (fourth, fifth and sixth) stand for low frequency variation of PHDI. All the bands carry specific information related to original time series, for example, the higher level bands contain only information on long time cycles of the concerned variable and exclude other properties, such as noisy data, trends, whereas short times only accounts for noisy data. Therefore, predicting the homogenous (high and low frequency) time series obtained from wavelet decomposition is more stable which is its major advantage and enables the Bayesian regression models to simulate with more accuracy.

For comparison, the Bayesian regression and wavelet Bayesian regression models were applied to climatic division 1 located in Texas considering PHDI as the hydrological drought index and precipitation and temperature as meteorological variables. The length of burn-in period is 10,000 and the number of iteration was chosen as 50,000 during the sampling process of the Bayesian regression analysis. The simulation of PHDI was carried out considering 1900-1955 as training period and 1956-2000 as testing period (Figure 15).

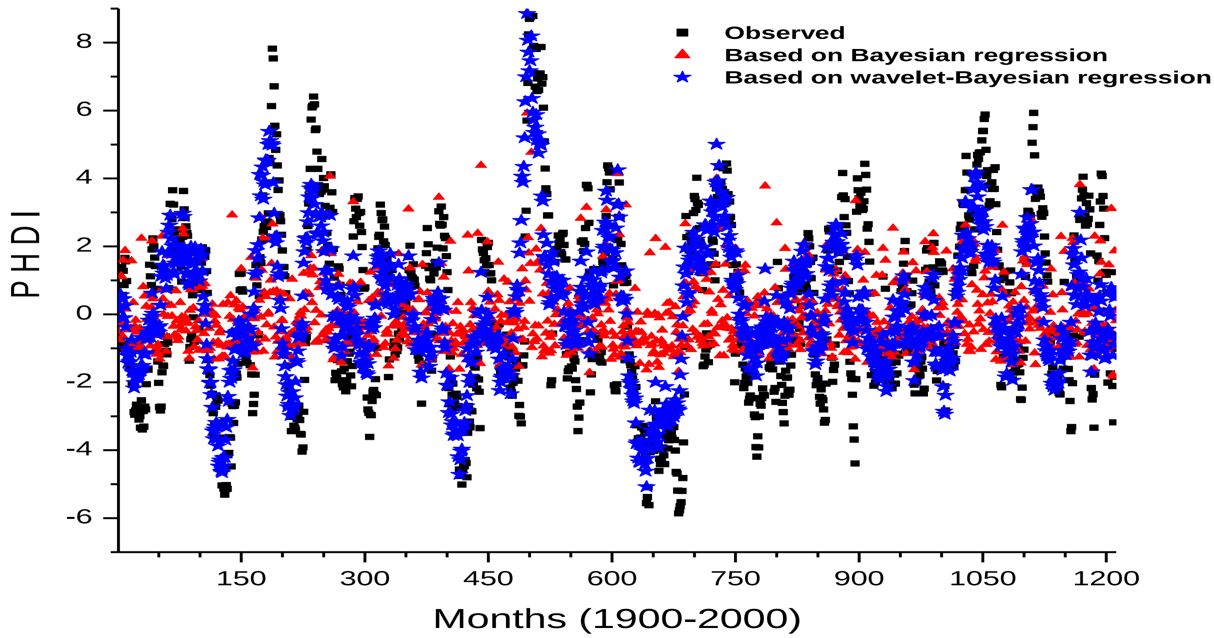


Figure 15. Training and testing of modeled PHDI time series based on Bayesian regression and a combination of wavelet Bayesian regression (Training set: 1900-1955, testing set: 1956-2000).

It was observed that the wavelet Bayesian regression approach was able to match the pattern and peaks better than the Bayesian regression approach. To further quantify the results obtained from training and testing periods, the goodness-of-fit was calculated using the correlation coefficient (CC), root mean square error (RMSE) and mean bias error (MBE). Based on CC it is 0.35 and 0.27 (Bayesian regression) and 0.78 and 0.65 (wavelet-Bayesian regression) during training and testing periods, respectively. For the Bayesian regression RMSE was 2.70 and 2.38, whereas for the wavelet-Bayesian regression it was 1.80 and 1.84 during training and testing period, respectively. Similarly, MBE was 0.07 and 0.34 for the Bayesian regression, whereas for the wavelet Bayesian regression it was -0.014 and 0.018 during training and testing periods, respectively. From these three goodness-of-fit tests it can be observed that the wavelet Bayesian regression performed better than did the Bayesian regression.

Application of wavelet Bayesian regression model to different spatial units

The Bayesian wavelet regression was applied to twenty selected spatial units and their goodness-of-fit values were calculated for comparison in terms of the predictability of hydrological droughts [Figure 16]. Hydrological droughts were simulated considering 1900-1955 as a training period and 1956-2000 as a testing period. The highest (rank 1st) CC for hydrologic drought simulation were observed with a CC value of 0.81 in Climatic division 5 (Texas) and with a CC value of 0.72 in northwest region (USA) during training and testing period respectively. However, based on the other two goodness-of-fit (RMSE and MBE), the northwest region (USA) ranked 3rd and 18th during testing period. Therefore, it is noted that all three goodness-of-fit tests rank differently in identifying the regions having better hydrological drought predictability. Based on CC the observation includes: (a) higher correlation coefficients (between 0.7 and 0.8) were observed for the climatic division in Texas for the training period, (b) during the testing period the performances were comparatively lower (CC values between 0.5 and 0.6) for climatic divisions in and including the state of Texas. The difference between the training and testing RMSE values was very small (0 to 0.04) for climatic division 1 in Texas, central region, south east and northwest regions of USA, and comparatively large (climatic division 5 and 9) in the south-western part of Texas. The variability in RMSE values did not follow a clear pattern.

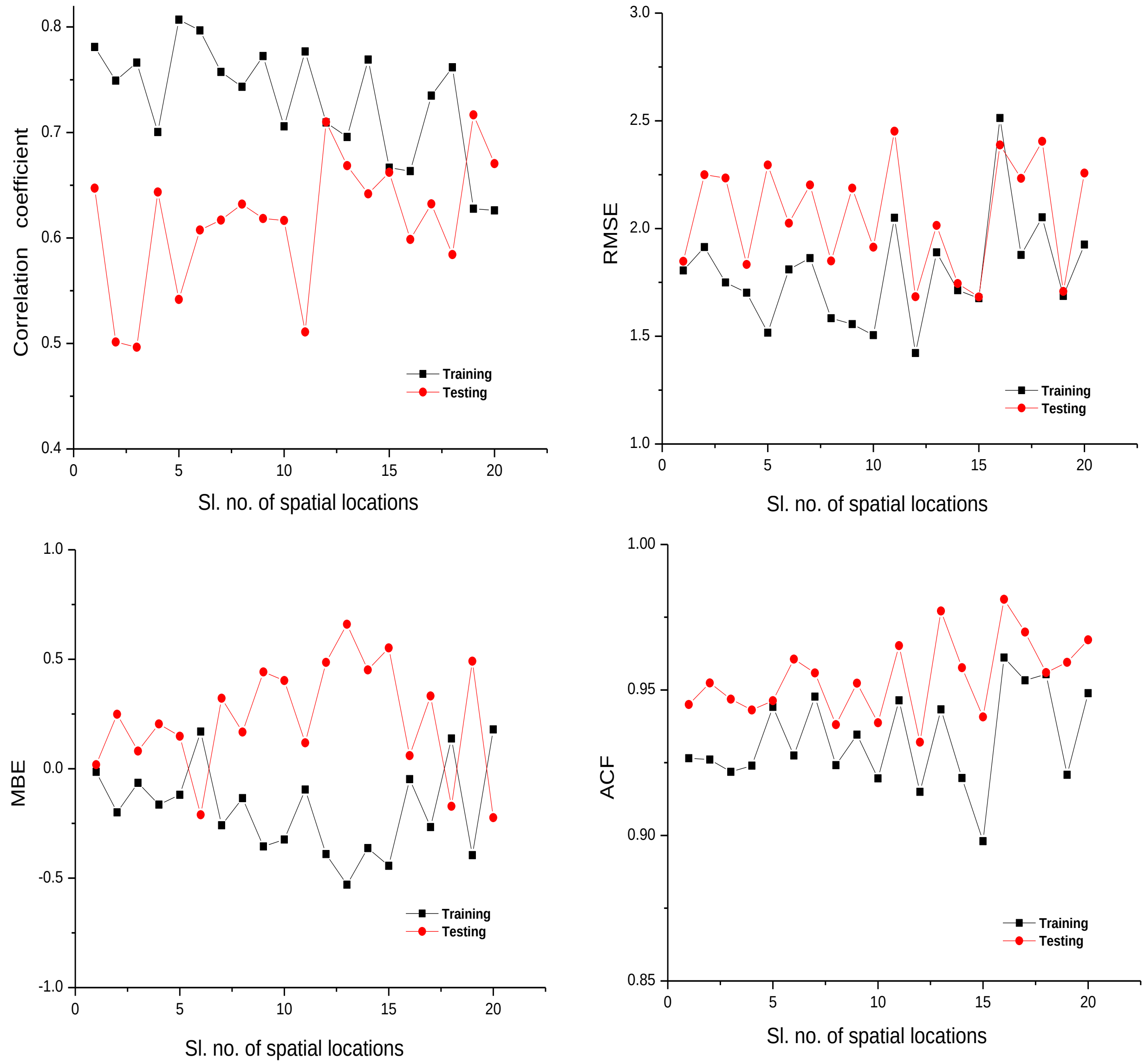


Figure 16. Comparison between training and testing PHDI time series obtained from wavelet Bayesian regression model in terms of (a) correlation coefficient, (b) root mean square error (RMSE), (C) mean bias error (MBE) and (d) lagged one autocorrelation coefficient for different spatial units.

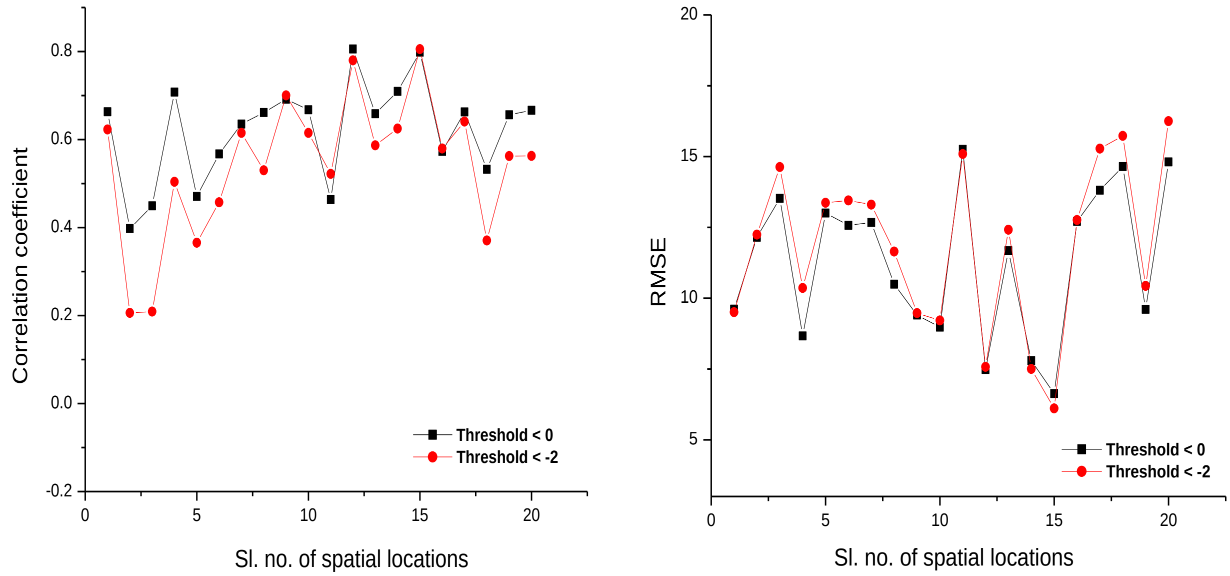
Based on MBE, a general pattern was observed in the predictability of hydrological drought using the wavelet Bayesian regression approach with a negative bias in the testing period except a few regions. Within the state of Texas, climatic divisions (9 and 10) had higher positive bias values (0.4 and 0.44), whereas at larger spatial units higher bias occurred in northeast region

(0.48), east north central region (0.66), central region (0.45), south east region (0.55) and northwest region (0.49) of USA.

The autocorrelation coefficient (ACF) which is the correlation with its own past values can be considered as a form of persistence. The ACF was calculated for actual, training and testing time series and based on observations: (a) the PHDI time series had stronger persistence with lag 1 ACF values varying between 0.87 and 0.97; (b) the lag 1 ACF obtained from the simulated time series was higher than that from the actual time series, leading to higher persistence in the time series.

After quantifying the simulated PHDI time series, it will be appropriate to compare the annual drought characteristics (severity and duration). As was observed in the previous section the wavelet Bayesian regression performed better in capturing peaks, therefore two thresholds (0 and -2) were chosen to further analyze the relationship between observed and simulated annual drought duration and severity. In general the performance for annual drought severity based on the zero thresholds was slightly higher than that with -2 threshold in most of the regions (Figure 17). Interesting patterns were observed based on the comparison of annual drought severity correlation coefficient: (a) the pattern for annual drought severity differed from that of PHDI time series; (b) based on the two threshold levels, lower performances were observed for climatic divisions 2, 3, and 5; (c) better performances were observed for climatic divisions 4 and 9 based on the zero threshold level, however the performance of climatic division 4 reduced significantly when threshold level increased to -2; (d) for the larger spatial units better performances were observed for northeast and south east regions and poor performance was observed for southwest region. The performance measured for simulated annual drought severity based on RMSE seemed to be poor when compared with the RMSE for the simulated PHDI time series.

Similarly, the performance based on MBE was poor for annual drought severity except for the spatial units of northeast, east north central, central, southeast and northwest regions. The positive biases were observed in most of the spatial units with maximum values in the southwest and west regions. This clearly explains that the positive bias values were due to the lower simulated values of annual drought severity with respect to the actual values. Based on the goodness-of-fit, comparison between observed and simulated annual drought durations at two threshold levels for selected spatial units are shown in Figure 18.



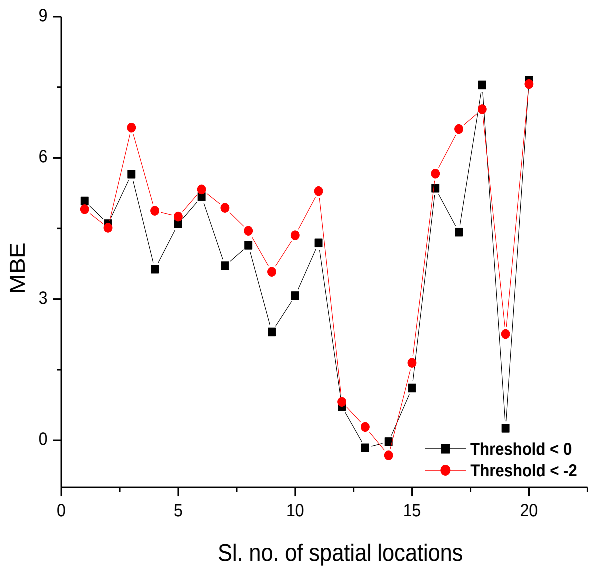
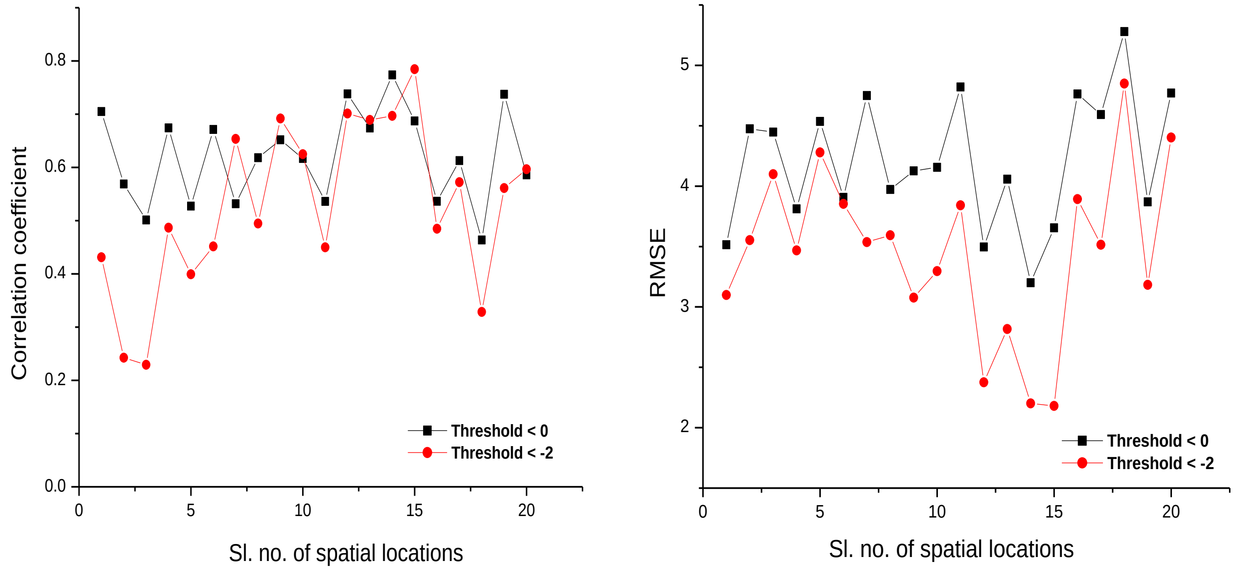


Figure 17. Comparison between observed and simulated annual drought severity at two threshold levels for selected spatial units (simulated period: 1956-2000).



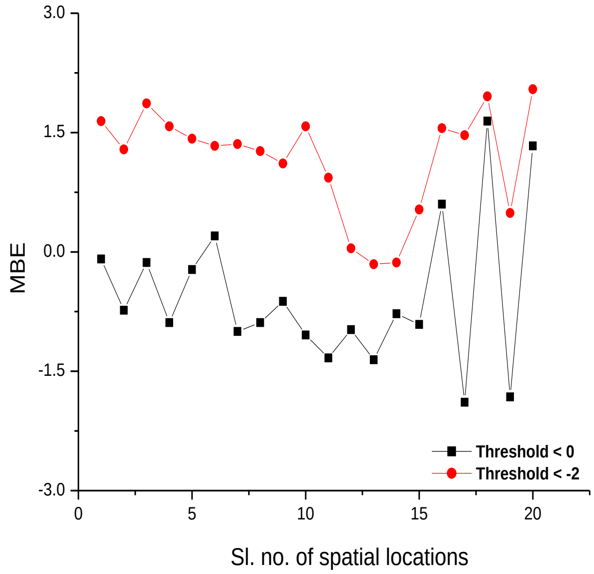


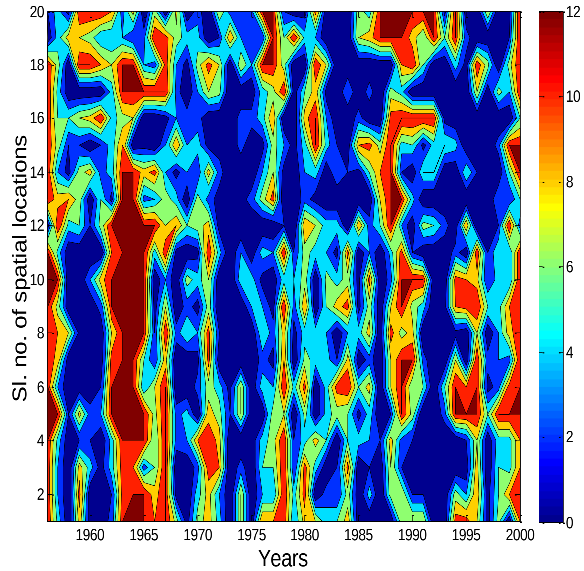
Figure 18. Comparison between observed and simulated annual drought duration at two threshold levels for selected spatial units (simulated period: 1956-2000).

The CC based on the zero threshold was higher than the minus two threshold level, with the higher difference observed for climatic divisions (1-5) located in Texas. The better performance during the testing period based on the CC values occurring in decreasing order up to first three regions included central region, northeast region, and northwest region. Higher CC values for these regions were supplemented by the lower RMSE values in most of the spatial units. An important observation was made based on MBE: (a) using the zero threshold the positive bias was noted among spatial units, (b) whereas using the minus two threshold level negative bias values were seen in 17 out of a total 20 spatial units, and (c) it is worth noting that bias varied with the type of drought time series used, with the highest values observed in annual drought severity followed by annual drought duration and the PHDI time series.

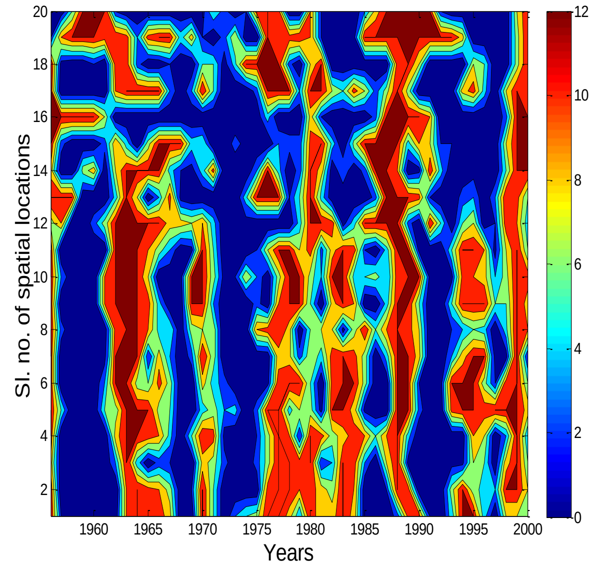
Spatio-temporal comparison based on annual drought severity and duration

The annual drought severities at two different thresholds (0 and -2) are plotted for selected spatial units as shown in Figure 19. It was observed that based on these comparison are: (a) the simulated annual drought severity could not capture the actual maximum annual drought severity, for example the maximum annual drought based on the observed PHDI time series reached about 70, whereas based on the simulated data it reached 55. (b) The simulated annual drought time series could capture the units of actual drought events, however the limitation included frequent indications of drought events in the simulated time series which did not occur in the observed time series. (c) Even though all spatial units are not affected by the drought in the observed time series, however the simulated time series indicated droughts in larger number of spatial units. (d) The performance improved when the threshold of both observed and simulated time series changed to -2, as the spatial and temporal units were more pronounced.

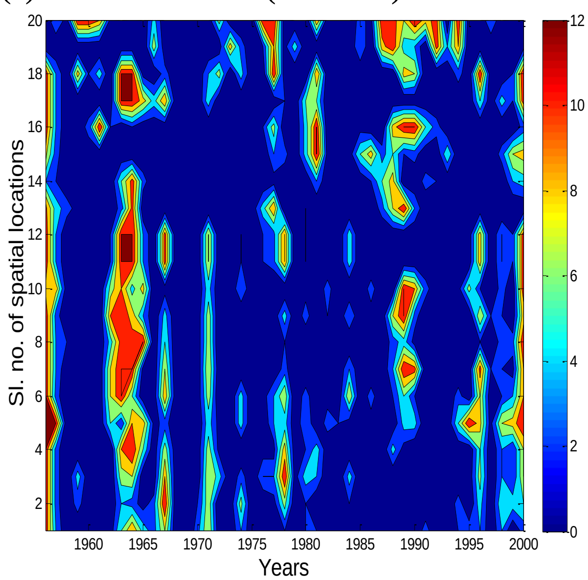
Comparison between observed and simulated annual drought durations for different spatio-temporal units is shown in Figure 20. Based on the observed PHDI time series at the zero threshold the maximum drought durations were observed for larger number of spatial units observed in six time periods (1950’s, 1965’s, 1990’s, 1995’s and in the year of 2000). However, based on the simulated time series the maximum annual drought durations for larger number of spatial units were observed more often, including the drought epochs observed from observed data. The accuracy of simulating maximum annual drought duration increased when the threshold level changed to -2 as it was able to replicate droughts during the 1965’s and the 1990’s as noticed in the observed time series.



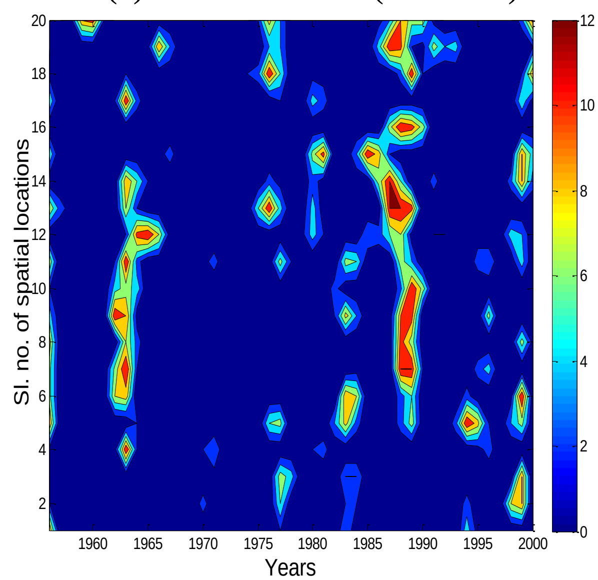
(a) threshold at zero (observed)



(b) threshold at zero (simulated)

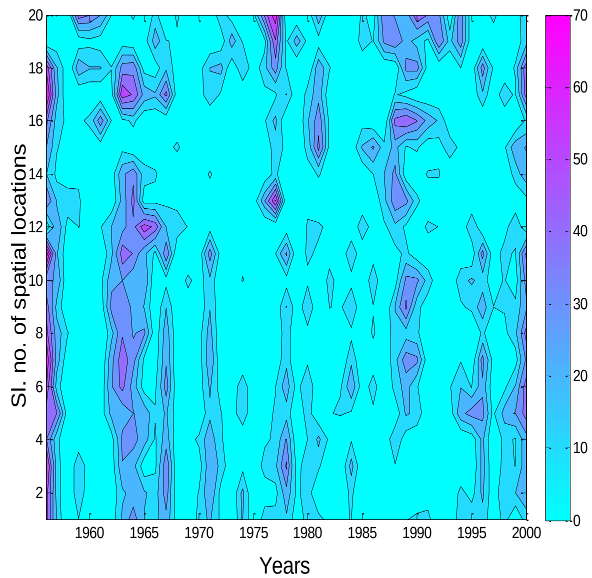


(c) threshold at minus two (observed)

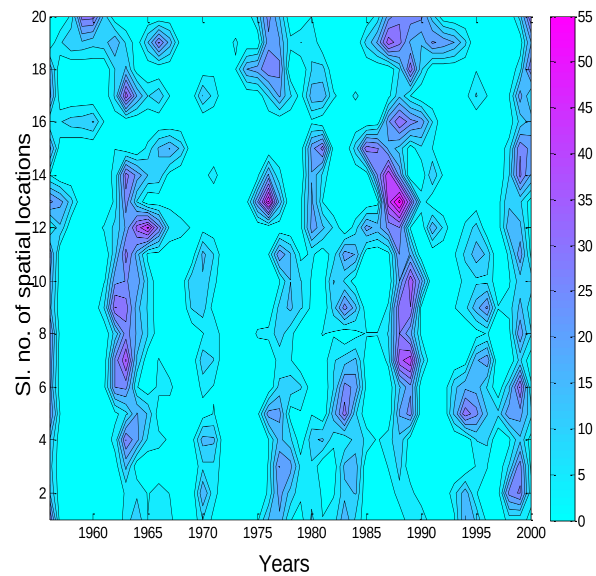


(d) threshold at minus two (simulated)

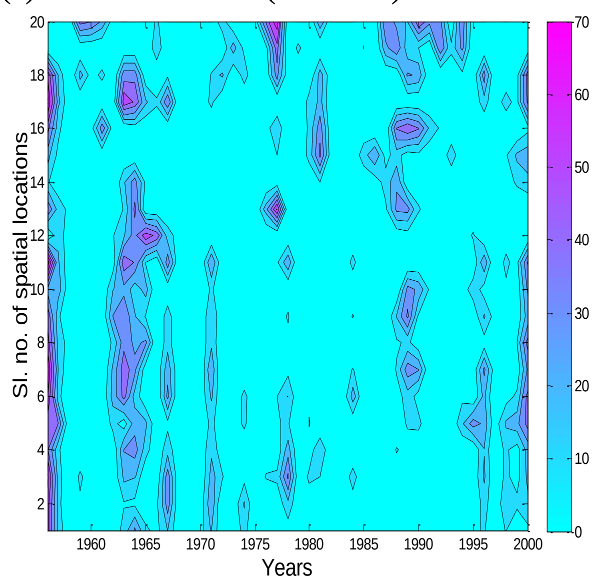
Figure 19. Comparison between observed and simulated annual drought durations on temporal scale for different spatial units.



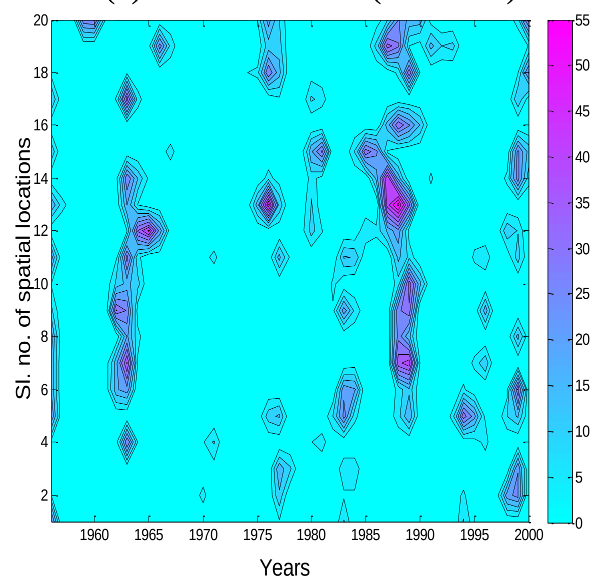
(a) threshold at zero (observed)



(b) threshold at zero (simulated)



(c) threshold at minus two (observed)



(d) threshold at minus two (simulated)

Figure 20. Comparison between observed and simulated annual drought durations on temporal scale for different spatial units.

Predictability of PHDI based on GCM outputs

This section discusses the predictability of PHDI using Global climate models output and observed precipitation and temperature during the period of 1950-2000. To test the predictability the available historical data for GCMs was divided into training set (1950-1985) and testing set (1986-2000). The projected meteorological variables rely on historical observations and thereby provide information for simulating the PHDI time series.

The chosen study area was climate division 1 located in Texas. The observed monthly temperature, precipitation and PHDI time series were collected from the National Climatic Data Center of National Oceanic and Atmospheric Administration. To test the predictability of PHDI time series, the climate projections for different models for A2 scenarios were obtained from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset. The details can be found in the National Laboratory (LLNL)–Reclamation–Santa Clara University (SCU) multimodal dataset, stored and served out of the LLNL Green Data Oasis (available online at http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/dcpInterface.html). Each WCRP CMIP3 climate projection was bias-corrected and spatially downscaled (Wood et al. 2004 and Maurer 2007) using a two-step procedure: (a) bias correction and, (b) spatial scale downscaling. The statistical properties of annual precipitation time series obtained from multiple GCMs are shown in Table 14 during the period of 1950-2000. The mean annual precipitation during the second half of the century did not vary much among GCMs and the values were lower with respect to the observed time series located in climatic division 1. Both higher and lower standard deviations, kurtosis and skewness were observed in GCMs precipitation output than in observed precipitation.

Table 14. Different GCMs and the statistical properties of their annual precipitation located in Climatic division 1 of Texas for A2 scenarios during the period of 1950-2000.

Sl. No	List of GCMs	Mean (cm)	Standard Deviation (cm)	Kurtosis	Skewness
1	Climatic division 1(Actual data)	47.63	9.07	2.94	-0.22
2	bccr_bcm2_0.1.sresb1	44.96	9.17	2.33	-0.06
3	cccma_cgcm3_1.1.sresb1	45.03	8.61	2.14	0.11
4	cccma_cgcm3_1.2.sresb1	44.86	9.35	2.55	0.13
5	cccma_cgcm3_1.3.sresb1	45.01	10.21	2.94	0.42
6	cccma_cgcm3_1.4.sresb1	45.16	9.86	2.42	0.00
7	cccma_cgcm3_1.5.sresb1	45.21	7.62	2.60	-0.07
8	cnrm_cm3.1.sresb1	45.01	8.97	2.91	-0.58
9	csiro_mk3_0.1.sresb1	45.34	11.48	3.41	0.46
10	gfdl_cm2_0.1.sresb1	44.91	12.78	2.27	0.07
11	gfdl_cm2_1.1.sresb1	45.39	10.36	2.86	-0.54
12	giss_model_e_r.1.sresb1	45.21	6.96	2.11	0.34
13	inmcm3_0.1.sresb1	44.98	9.04	3.44	0.70
14	ipsl_cm4.1.sresb1	44.88	8.59	2.17	-0.11
15	miroc3_2_medres.1.sresb1	45.31	8.36	2.30	0.02
16	miroc3_2_medres.2.sresb1	45.11	9.14	2.33	-0.34
17	miroc3_2_medres.3.sresb1	45.14	8.33	2.96	0.33
18	miub_echo_g.1.sresb1	45.06	7.98	2.93	-0.49
19	miub_echo_g.2.sresb1	44.96	7.57	5.00	1.37
20	miub_echo_g.3.sresb1	45.24	7.47	2.92	0.13
21	mpi_echam5.1.sresb1	45.16	11.05	3.45	0.52
22	mpi_echam5.2.sresb1	44.83	11.33	2.24	0.27
23	mpi_echam5.3.sresb1	44.98	9.83	2.45	-0.13
24	mri_cgcm2_3_2a.1.sresb1	45.19	8.38	2.90	0.15
25	mri_cgcm2_3_2a.2.sresb1	44.91	8.48	3.76	0.84
26	mri_cgcm2_3_2a.3.sresb1	45.09	10.92	2.53	0.11
27	mri_cgcm2_3_2a.4.sresb1	45.11	8.51	3.04	0.62
28	mri_cgcm2_3_2a.5.sresb1	44.88	9.04	2.30	0.31

29	ncar_ccsm3_0.1.sresb1	45.19	8.66	2.05	0.07
30	ncar_ccsm3_0.2.sresb1	45.06	9.37	2.55	0.55
31	ncar_ccsm3_0.3.sresb1	45.39	9.78	2.23	0.16
32	ncar_ccsm3_0.4.sresb1	45.21	10.08	1.99	0.06
33	ncar_ccsm3_0.7.sresb1	45.21	10.34	3.19	0.14
34	ncar_pcm1.2.sresb1	45.01	9.68	2.26	0.29
35	ncar_pcm1.3.sresb1	45.09	9.83	2.47	0.00
36	ukmo_hadcm3.1.sresb1	44.78	9.86	2.76	0.18

Before applying wavelet the Bayesian regression model the correlation coefficient plot was plotted between observed precipitation and temperature monthly time series obtained from (NCDC website, CHECK) and those obtained from GCM's output for the period 1950-2000 as shown in Figure 21. It is worth noting that the CC between observed and different GCM's monthly temperature was found to be consistent and had a value of 0.96, whereas based on the precipitation the CC values fluctuated between 0.35 and 0.5. This preliminary analysis demonstrated that the GCM's were capable of reproducing temperature well, whereas in the case of precipitation it was weak.

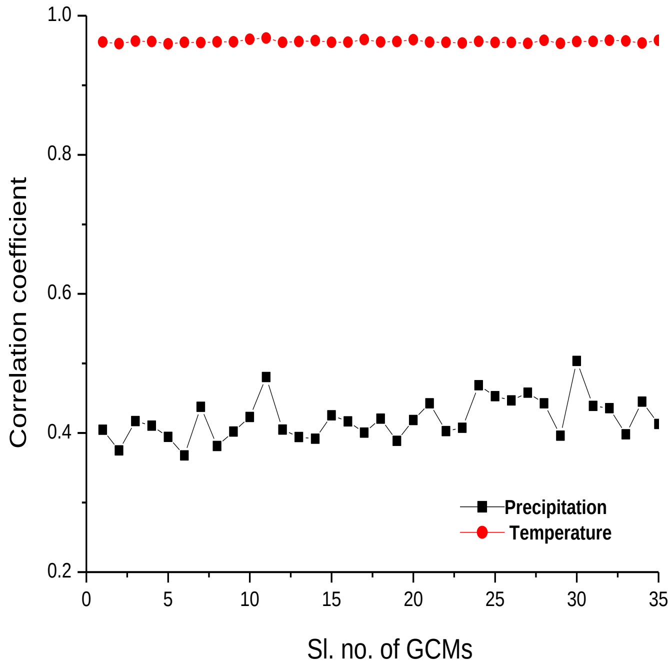
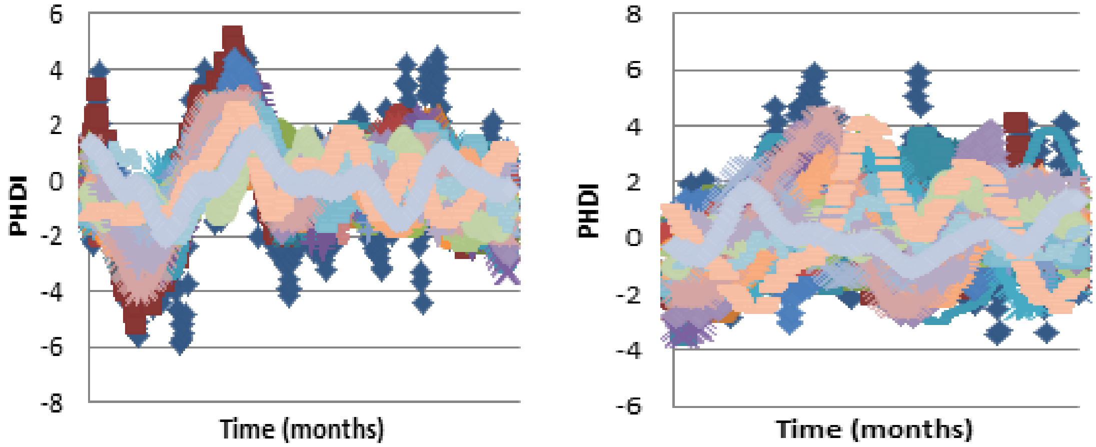


Figure 21. Correlation between observed precipitation and temperature located in climatic division 1 (Texas) with different GCMs (Time period: 1950-2000).

Since precipitation plays an important role in characterizing drought, including PHDI, it will be interesting to look at their predictability using precipitation and temperature obtained from GCMs output. The PHDI time series simulated using the selected GCMs for training (1950-1980) and testing (1981-2000), is shown in Figure 22. It can be observed from the figure that a pattern is noticed during the training period, however during the testing period the pattern is missing. This can be quantified using the CC plot during training and testing periods in simulating PHDI time series (Figure 23). The CC values during the training period vary between

0.4 and 0.7, whereas during the testing set the predictability performance was poor. Therefore it is worth noting that using the GCMs the PHDI time series were not able to simulated properly.



(a) (b)

Figure 22. Simulation of PHDI time series during (a) training period (1950-1980), (b) testing period (1981-2000) using selected GCMs.

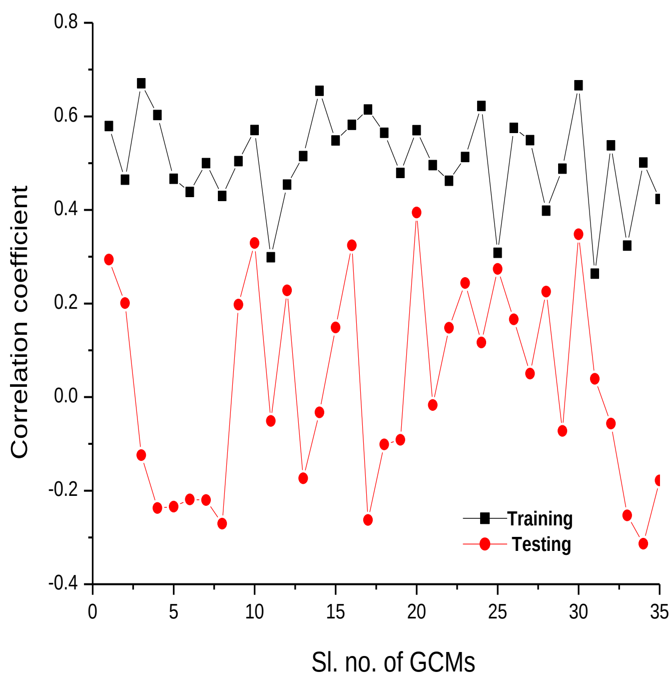


Figure 23. Correlation coefficient between observed and simulated PHDI located in climatic division 1 (Texas) based on wavelet Bayesian regression during training and testing periods for different GCMs.

Conclusion

The following conclusions are drawn from this study:

1. Common drought information is likely to be observed between neighboring climatic divisions, however with the increase in spatial units to a state or regional scale, the quality of information sharing reduces. The number of drought events at regional scale is found to be maximum in northeast, southeast and northwest regions and minimum in the west northcentral region of USA.

2. The wavelet Bayesian regression model performs better than the Bayesian regression model based on different goodness-of-fit results. This advantage results due to the decomposition of PHDI time series into high and low frequency individual time series to capture better information.

3. Using the wavelet Bayesian regression model the performance of precipitation and temperature for simulating PHDI time series at different spatial unit varies, as judged by the goodness-of-fit tests. The performance during the testing period is better at regional units based on the correlation coefficient and a clear pattern is not observed using the root mean square error measure. The bias in the simulation time series is observed to be negative during the training period and positive during the testing period at large number of spatial units. Higher persistence is observed in the simulated PHDI time series in comparison to observed time series.

4. The performance to evaluate annual drought characteristics (severity and duration) decreases in comparison to simulating only PHDI time series. Based on the threshold in selecting drought properties the performance is better at the zero threshold level than at the minus two threshold level. A higher bias is observed in simulating annual drought severity except for the spatial units in northeast, east north central, southeast and northwest region. The maximum positive bias for annual drought severity is observed in the southwest and west regions as the simulated values are lower than the observed values.

5. By changing the threshold levels in identifying the annual drought duration it affects the bias. Using the zero threshold the positive bias is noted in many spatial units, whereas using the minus two threshold negative bias is observed in most of the spatial units.

6. The output from GCMs is able to capture temperature well and it is not observed in the case of precipitation. Therefore, using these GCMs output in simulating PHDI time series does not perform well.

4 (d) Evaporation Research

Evapotraspiration is the primary source by which plants extract water from the soil. In the event of a drought, the role of evapotranspiration becomes even more crucial, because it aggravates the water deficiency. Problems about evapotranspiration (ET) estimation at varying spatial and temporal scales that were addressed included: (1) comparison and contrasting strengths and shortcomings of a series of satellite-based ET estimation models at watershed scales, and evaluating their accuracy based on hydrologic methodologies; (2) improvement of the accuracy of critical inputs for all satellite-based ET estimation models, the instantaneous and daily net radiation, by comprehensively accommodating the effects of terrain on the energy availability for improving the spatial representation and reliability of ET estimates; (3) extension of satellite snapshot latent fluxes to cloudy days and days without good-quality imageries by integration of SEBAL with the GG model; (4) development of a robust entropy-based multi-spectral imagery classification framework to derive land cover maps, providing input for land surface models and ET estimation; (5) quantification of the sensitivity of SEBAL to inputs and investigation of its domain and resolution scale effects. The details of these objectives can be found in the list of publications.

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The Role of Epikarst in Controlling Recharge, Water Quality and Biodiversity in Karst Aquifers: A Comparative Study between Virginia and Texas

Basic Information

Title:	The Role of Epikarst in Controlling Recharge, Water Quality and Biodiversity in Karst Aquifers: A Comparative Study between Virginia and Texas
Project Number:	2009TX335G
Start Date:	8/1/2009
End Date:	7/31/2012
Funding Source:	104G
Congressional District:	Texas District 25
Research Category:	Ground-water Flow and Transport
Focus Category:	Groundwater, Water Quantity, Hydrogeochemistry
Descriptors:	
Principal Investigators:	Benjamin F Schwartz

Publications

1. Goodsheller, Kelly R., 2011, Differentiation of water use for three dominant species on the Edwards Plateau, MS Thesis, Department of Biology, Texas State University, San Marcos, TX.
2. Dammeyer, Heather Cardella, 2011, Short-term responses of clear-cutting on the water supplies, water status and growth of remaining vegetation: which species have the most to gain? MS Thesis, Department of Biology, Texas State University, San Marcos, TX.
3. Gerst, Jonathan, 2010, Epikarst control on flow and storage at James Cave, VA: An analog for water resource characterization in Shenandoah Valley karst, MS Thesis, Department of Geosciences, Virginia Tech, Blacksburg, VA.
4. Stinson, C. L, B. F. Schwartz, B. W. Tobin, B. R. Gerard, P. Ramirez, G. Timmins, B. Hutchins, and S. Schwinning, 2012, Trinity Aquifer Epikarst Study Using 18O and 2D Stable Isotope Analysis, Cave Without A Name, South-Central Texas (Abstract), Geological Society of America, South-Central Section Annual Meeting, Alpine, TX, March 8-9, 2012.
5. Tobin, B. W., B. F. Schwartz, B. R. Gerard, P. Ramirez, G. Timmins, B. Hutchins, C. L. Stinson, and S. Schwinning, 2012, Autogenic vs. Allogenic Recharge: Searching for the Source of the Stream in Cave Without A Name, Boerne, TX (Abstract), Geological Society of America, South-Central Section Annual Meeting, Alpine, TX, March 8-9, 2012.
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9. Schwartz, B. F., B. R. Gerard, B. W. Tobin, P. Ramirez, B. Hutchins, S. Schwinning, and M. E. Schreiber, 2011, Hydrogeochemical Responses at in-Cave Sites as Indicators of Epikarst Processes: Cave Without A Name, Central Texas, USA (Abstract), Geological Society of America Annual Meeting, Minneapolis, MN, October 8 – 13, 2011.
10. Scott, Heather, M. E. Schreiber, B. F. Schwartz, and W. D. Orndorff, 2011, Spatial and Temporal Patterns of Temperature at James Cave, Virginia (Abstract). Paper No. 6-8. Geological Society of America – Southeastern Section Meeting, Wilmington, NC, March 23-25, 2011.
11. Schwinning, S., K. R. Goodsheller, and B. F. Schwartz, 2010, Fractured Epikarst Bedrock as Water Source for Woody Plants in Savanna (Abstract H11H-0925), AGU Fall Meeting, San Francisco, CA, December 13-17, 2010.
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22. Schreiber, M. E., B. F. Schwartz, W. D. Orndorff, J. Gerst, and H. Scott, 2011, Epikarst Control on Quantity and Quality of Recharge to Karst Aquifers: Current Results from Long-Term Monitoring Within James Cave, Virginia (Abstract), Geological Society of America Annual Meeting, Minneapolis, MN, October 8-13, 2011.

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31. Schwartz, B. F., S. Schwinning, B. Gerard, K. R. Kukowski, C. L. Stinson, and H. C. Dammeyer, 2013, Using Hydrogeochemical and Ecohydrological Responses to Understand Epikarst Processes in Semi-Arid Systems, Edwards Plateau, Texas, USA, Acta Carsologica, Accepted pending minor revisions.
32. Kukowski, K. R., S. Schwinning, and B. F. Schwartz, 2013, Hydraulic responses to extreme drought conditions in three co-dominant tree species in shallow soil over bedrock, Oecologia, V 171, p 819-830.
33. Eagle, S.D., W. Orndorff, J.D. Gerst, H. Scott, W. Orndorff, B.F. Schwartz, M.E. Schreiber, (In prep), Analysis of Hydrologic and Geochemical Time Series Data at James Cave, Virginia: Implications for Epikarst Influence on Recharge, for submission to Journal of Hydrology.
34. Eagle, Sarah D., 2013. Analysis of Hydrologic and Geochemical Time Series Data at James Cave, Virginia: Implications for Epikarst Influence on Recharge. MS Thesis, Department of Geosciences, Virginia Tech, Blacksburg VA.
35. Gerard, Brett R., 2012, Effects of Environmental Parameters and Precipitation Dynamics on Infiltration and Recharge into the Trinity Aquifer of Central Texas. MS Thesis, Department of Biology, Texas State University, San Marcos, TX.
36. Schwartz, B. F., and B. R. Gerard, Fine-scale Hydrologic and Geochemical Responses in Continuous Data Provide Clues to Understanding Epikarst Structure and Hydrogeology in the Edwards Plateau, Texas, USA, Geological Society of America, South-Central Section Annual Meeting, Austin, TX, April 5-6, 2013.
37. Schwartz, B. F., S. Schwinning, B. Gerard, K. R. Kukowski, C.L. Stinson, and H.C. Dammeyer, 2013, Using Hydrogeochemical and Ecohydrological Responses to Understand Epikarst Processes in Semi-Arid Systems, Edwards Plateau, Texas, USA, Karst Waters Institute Conference – Carbon and Boundaries, Carlsbad, New Mexico, January 7-11, 2013.

38. Schwinning, S., K. Kukowski, and B.F. Schwartz, Which traits are correlated with high drought mortality in trees? A case study from the Edwards Plateau, Texas, USA, Annual Conference of the British Ecological Society, Birmingham, UK, December 17-20, 2012.
39. Eagle, S., M.E. Schreiber, W. Orndorff, B. F. Schwartz, J. D. Gerst, and H. Scott, 2012, Statistical analysis of geochemical data to characterize the role of the epikarst in controlling the quantity and quality of recharge to a telogenetic karst aquifer, Geological Society of America Annual Meeting, Charlotte, NC, Nov 4-7, 2012.

Final Report: April 30, 2013

Title: The Role of Epikarst in Controlling Recharge, Water Quality and Biodiversity in Karst Aquifers: A Comparative Study between Virginia and Texas

Project Number: 2009TX335G

Start Date: 8/1/2009

End Date: 7-31-2012

Funding Source: 104g

Congressional District: 25

Focus Category: Groundwater, Water Quantity, Hydrogeochemistry

Descriptors: Epikarst, Karst, Recharge, Water Quality, Biodiversity

Principle Investigator: Benjamin F. Schwartz, Texas State University

Co-PI: Madeline E. Schreiber, Virginia Polytechnic Institute and State University.

Abstract:

The epikarst, often called the “skin” of karst aquifers, is a critical zone that significantly influences hydrology, water quality, and ecosystems in karst aquifer systems. The epikarst regulates both the quantity and quality of autogenic recharge to karst aquifers and, as a result, may be the most important component of the system. However, due to its extreme heterogeneity, the epikarst is notoriously difficult to characterize. Our primary research objective was to use interdisciplinary methods in a ‘holistic’ approach to studying the epikarst at different scales in diverse geologic and climatic settings. We utilized this dataset to address questions about the mechanisms and processes controlling movement and quality of water between the surface and karstic aquifers that are otherwise difficult to answer.

To accomplish this, we installed instrumentation at four research sites in the shallow Virginia James Cave (beginning in late 2007) and at 8 research sites in two different shallow Texas caves (beginning in late 2008), and collected continuous and periodic hydrologic, geochemical and biologic data. Each station is instrumented to allow continuous measurements and periodic sampling of hydrologic (precipitation and drip rates), geochemical (pH, temperature, redox potential, specific conductance, dissolved oxygen, major ions) and biological (Virginia only:

copepods and other invertebrates) parameters. In-cave drip sites have been chosen where cave ceilings are within 15 m of the surface to ensure proximity to the hydrogeologically complex epikarst zone. This is within the generally accepted vertical limit of the epikarst (15m) in most regions. In Virginia, James Cave is located in a low-relief, autogenically recharged karst region in Pulaski County; representative of much of the Shenandoah Valley and other karst regions in Virginia. In Texas, the two caves (Cave Without A Name (CWAN) and McCarty Cave) are located on the eastern edge of the Edwards Plateau between Austin and San Antonio in autogenic portions of the sensitive recharge and contributing zones for the Edwards Aquifer. Our data show that we are able to detect changes in epikarst parameters that are related to local climatic and geologic conditions.

For this study, we extended data collection by 2 additional years for drip rate, continuous geochemical parameters, water chemistry, and invertebrate biology in the James Cave system, and to expand the scope and scale of the project to monitor chemistry and discharge at the cave stream. To our knowledge, this study marks the first time that biology has been used in conjunction with continuous hydrologic and geochemical monitoring, which we believe will allow epikarstic fauna to be used as a proxy for hydrogeochemical conditions in, and structure of, the epikarst. We also expanded on the study in both states by analyzing water from drips, soil water, precipitation, and ground water sources for: major ions, inorganic and organic carbon, water stable isotopes ($^{18}O/^{16}O$, $^{2}H/^{1}H$), and $^{13}C/^{12}C$ of inorganic and organic carbon species.

Results of our collaborative project can be used to support the design and implementation of studies at larger scales, with the ultimate goal of characterizing the small scale processes in the epikarst that influence the quantity and quality of water in a larger karst aquifer system.

<u>Problems and Research Objectives:</u>

Karst aquifers are unique groundwater reservoirs that provide significant amounts of water. It is estimated that karst aquifers supply the United States with 40% of its drinking water, and that more than 25% of the world's population lives on or obtains its water from karst aquifers (KWI 2003). Although karst aquifers host significant water supplies, they are easily contaminated because the predominant recharge mechanism to the aquifer is fast flow through open conduits and fractures (sometimes to great depths) that have been enlarged by chemical dissolution. Population growth, urban development, and agriculture are increasing demands while also increasing contamination of these sensitive water resources. Due to the importance of these water resources, it is critical that we improve our understanding of recharge mechanisms for karst aquifers.

The epikarst, or the "skin" of karst aquifers (Bakalowicz 2004), serves as the interface between surface environmental conditions and karst aquifer functioning. Deemed a "critical zone" (Mangin 1975), the epikarst regulates water quantity, water quality, and ecosystems in karst aquifer systems. The epikarst, which is also called the subcutaneous zone, is the region of vegetation, soil, and weathered bedrock at the top of the vadose zone in karst aquifers. Due to its extreme heterogeneity, recharge and storage in the epikarst are notoriously difficult to characterize. However, much research has been conducted to characterize epikarst controls on recharge to karst aquifers (White 2003; Bakalowicz 2004; Klimchouk 2004). Results of these studies have shown that not only does the epikarst determine how much, how fast, and at what time of year rainwater recharges an underlying karst aquifer, but is also linked with if, how, where, and when contaminants are transported from the surface to the aquifer.

Results from the above studies on epikarst flow show that high heterogeneity and scaling issues (e.g., local, regional, global) make it difficult to generalize epikarst's control on aquifer recharge. However, the need to understand these high yield water resources is paramount for managing increasing demands. The objective of this project was to develop a comprehensive model of epikarst hydrodynamics as water progresses through the epikarst using intensive field techniques. To accomplish this objective, long-term (4-6 years) continuous hydrology measurements were collected from James Cave (Pulaski Co, VA) and two caves in Texas. More details on each of the sites are presented below.

The primary objectives of this research were to answer the following questions:

1) What factors determine thresholds of water excess (precipitation-evapotranspiration) that must be crossed in order to generate cave drips, and thus recharge, to karst aquifers?

2) Does the epikarst's influence on recharge vary seasonally?

3) How does water quality vary under different conditions of recharge?

Materials and Methodology:

All of our field sites, including Cave Without A Name and McCarty Cave in Texas and James Cave in Virginia are instrumented with equipment that allows continuous monitoring of precipitation, air temperature, and other weather data, cave drip rate, groundwater level, and/or stream discharge (note that instrumentation varies, depending on site characteristics).

For the James Cave (Virginia) site, field activities supported by the USGS funding were completed in July 2012. During the period of USGS funding, the instrumentation and sampling at James Cave was streamlined to allow for more efficient use of limited time by volunteer staff. At the Virginia site, drips and the cave stream are also monitored continuously for specific conductance and water temperature. At all sites, composite water samples were collected and analyzed for geochemical (major ions, DOC) and stable isotopes (water, carbon).

For the Texas sites, the time period for field research supported by the USGS funding was completed in April, 2012. Data collection continued through one of the most severe one-year droughts the region has ever experienced during most of 2011, followed by a period of several months with average rainfall during late 2011 and early 2012. This allowed us to collect data from two drought periods and two wet periods, and to begin understanding how the system responds under these very different hydrologic conditions.

Since the completion of field activities, our research groups have been working on analyzing data and submitting manuscripts for publication. We applied for and received a one-year no-cost extension for the project. Because the transfer of funds was significantly delayed beyond the original start-date, this allowed our project completion date to be 7-31-2012 rather than 7-31-2011, which meant that we had enough data for meaningful analyses before completion of a final report.

Principal Findings:

What follows is a summary of our principal findings from data collected using USGS funding.

Texas

Because we have recently experienced a change from drought conditions to slightly wetter, and now back into drought conditions, we are collecting information that is finally allowing us to better understand the dynamics of infiltration, flow, and recharge into and through the epikarst.

In Headquarters Cave, McCarty Cave, and Cave Without A Name (CWAN), drip rates slowed or nearly stopped during 2009, recovered after the rains in the fall season of 2009, and steadily declined when rainfall was ~30% of average between September 2010 through October 2011. After a brief period of average precipitation from October 2010 to March 2011, we are again in a serious hydrologic drought in TX, and geochemical and drip data are revealing how the epikarst responds to the second extended period of depletion by drainage and ET on the surface.

Preliminary analysis of the time-series drip rate data has resulted in several interesting findings. These can be summarized as follows:

1) Baseflow drip rates are primarliy controlled by variable amounts of storage in bedrock matrix and secondary porosity (e.g., fractures), as well as some rapid flow during wet periods, which is allowing us to investigate what we believe to be a representative range of the flow systems in the epikarst. For example, some sites respond only briefly to large rain events and completely dry up, while others drip continuously and appear to have very slight responses to large rain events, but with a ~4-month lag time. A graduate student (Brett Gerard) completed a model which can be used to predict if and how much a drip site will respond to a rain event. This is important, because a drip response indicates that recharge is occurring, which implies that this model is useful for modeling the amount and timing of recharge in the region.

2) Recharge rates were estimated using a Chloride Mass Balance method, and average recharge rates of between 4.3 and 9.6% of annual precipitation (depending on the individual site monitored) are similar to other recharge estimates for the region. The recharge rate also allowed us to calculate an approximate groundwater basin area of 27 km^2 for the CWAN site, though this does not delineate the boundaries of the basin.

3) At all sites in TX and some in VA, close investigation of ‘noise’ in drip rates has revealed that the drip rate responds inversely to changes in barometric pressure. Work to understand and model these responses is in intermediate stages and we anticipate that the

results can be used to estimate epikarst hydraulic properties such as storage and hydraulic conductivity, as well as to improve our understanding of rates of epikarst evolution and dissolution of bedrock.

4) Long term drip records at some of the TX sites show that there is a perched aquifer system which drains through fractures leading to the monitoring sites. The perched aquifer has different storage and hydraulic conductivity properties. Once depleted, drip discharge drops sharply to a new baseflow level (White Grapes site, Figure 1). A certain amount of precipitation is then required to reach a recharge/infiltration threshold where drainage from the perched aquifer is re-activated. This site has also provided data which indicates that the effects of a drought on epikarst storage take more than a short re-wetting period to fully recover.

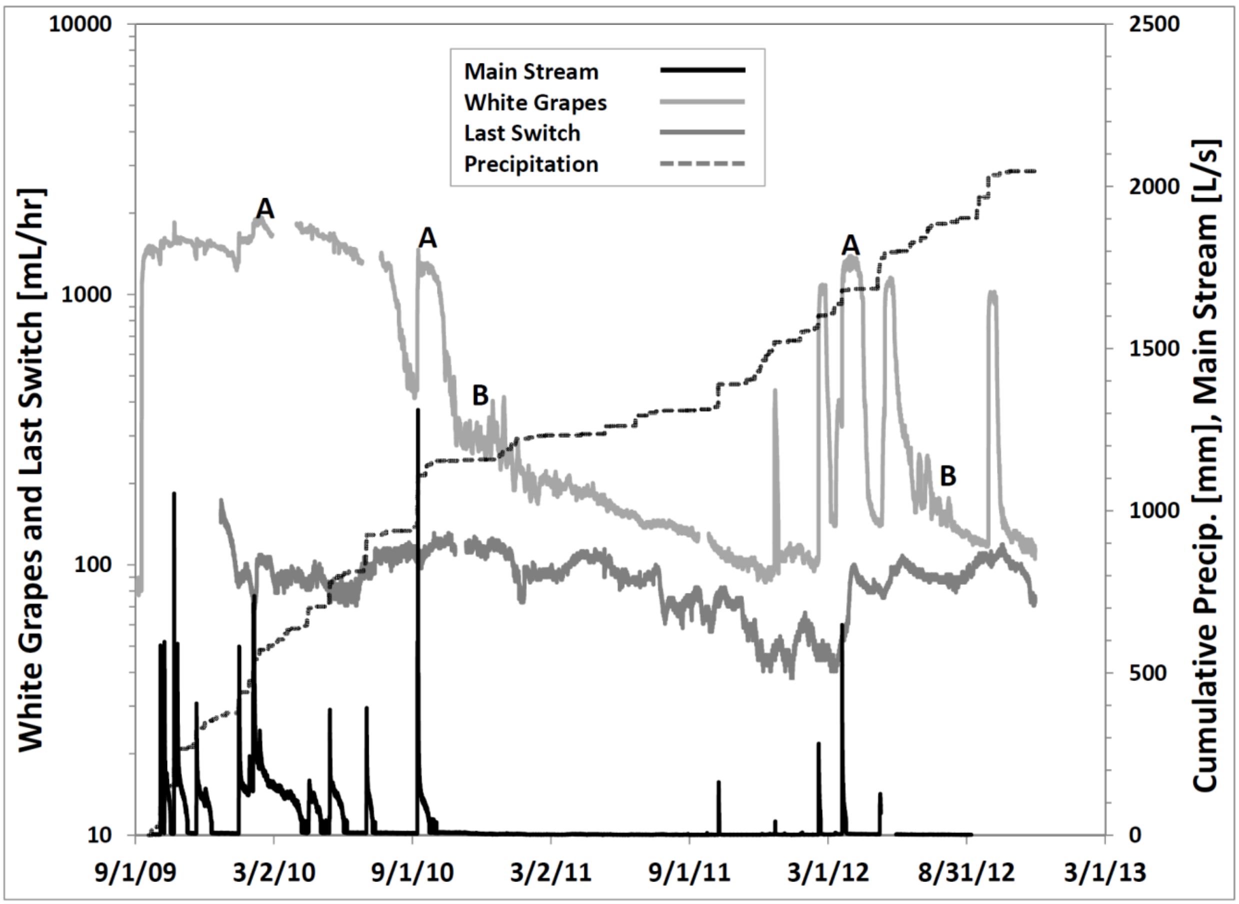


Figure 1. Hydrographs for the White Grapes and Last Switch drip sites, and the Main Stream discharge site, in CWAN over a three year period, and cumulative precipitation above the cave. Regions marked with 'A' illustrate a plateau in drip rates that is maintained at >1000 mL/hr at the White Grapes Site prior to behavior attributed to the drainage of a perched aquifer (sudden declines in drip rate after 'plateaus' marked A). Large scale 'noise' in regions marked 'B' is

attributed to barometric pressure effects on drip rates from variably saturated fracture/matrix. The Last Switch data represent drip flow dominated by matrix flow, Main Stream represents both base flow and direct recharge via conduits, and White Grapes represents a mixture of rapid direct recharge, perched aquifer drainage, and drainage from matrix and fracture storage. Gaps represent missing data due to instrument or logger failure.

At the TX sites, storage in the matrix supports baseflows at drip sites for long periods of time and (for some sites) attenuates signals from precipitation events. In contrast, bedrock matrix storage appears to be much less important at the Virginia site and precipitation signals at drip sites are dominated by seasonality of ET.

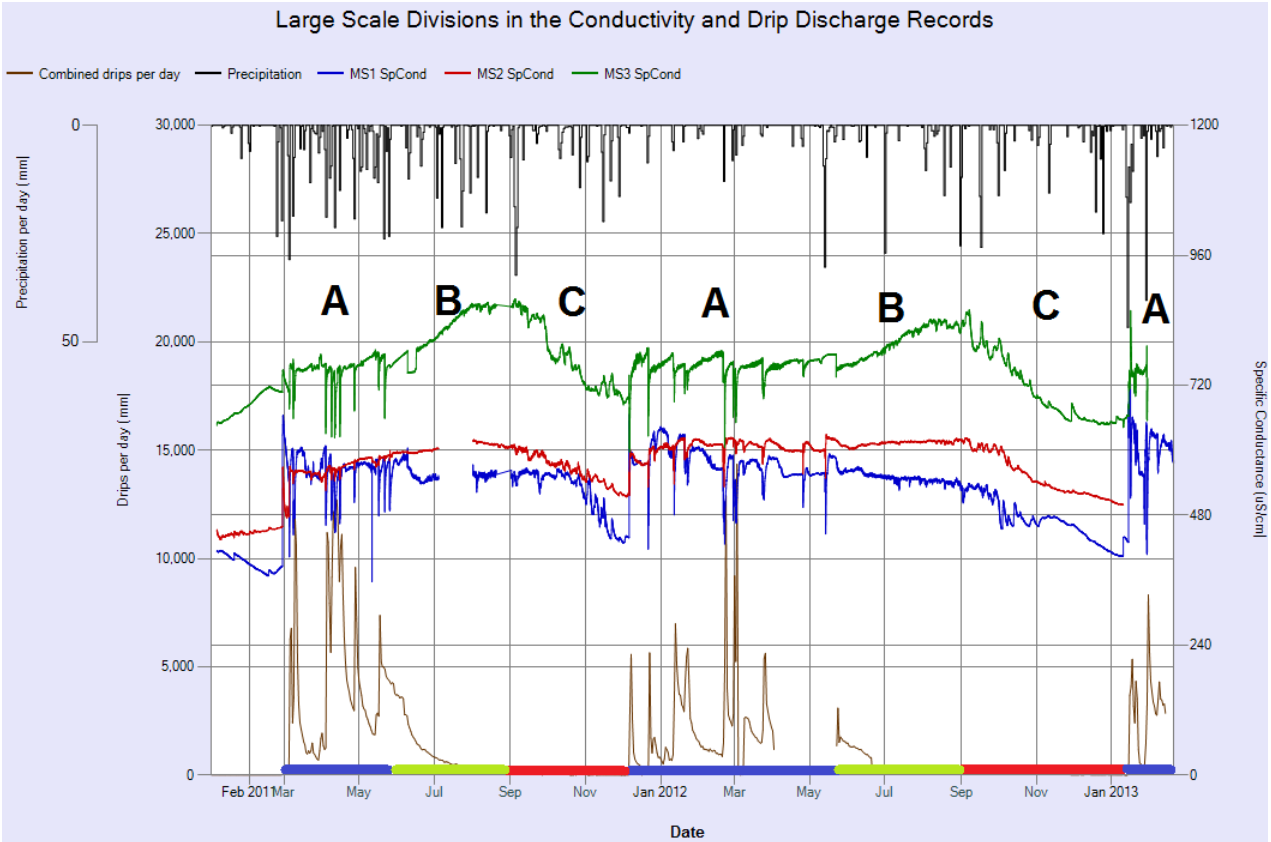
<u>Virginia</u>

With this funding, we extended our collection of long term records of hydrologic and geochemical data in James Cave and continue to examine the role of epikarst in controlling the quantity and geochemical evolution of recharge water as it passes through the epikarst.

Principal findings from James Cave are as follows:

1) Rates of effective recharge, reported in Gerst (2010) show that from 10/07 to 10/09, effective recharge was estimated to be between 23% and 34% of total precipitation received during that season. These values correspond well with 28% annual ER as predicted for the region with Thornthwaite's Method by the University of Virginia Climatology Office (2010). It also corresponds with another measurement of ER (30%) through mantled sinkholes from the nearby Kentland Farms site (Schwartz and Schreiber 2009).
2) Calculation of lag times, or the difference in time between peak precipitation rate and peak drip rate, indicate that after significant seasonal recharge, drips occur two to five hours after initiation of a rain event (Gerst, 2010). During the growing season, however, precipitation often does not trigger drips because most, if not all, infiltrating water is removed by evapotranspiration. Drips are re-initiated only after there has been enough precipitation to reactivate hydraulic pathways in the epikarst, a process that can take up to several months. Variations in lag time throughout the recharge season show that sustained recharge results in progressively shorter lag times between rain events and drip events.
3) Hydrograph recession analysis was also used to estimate the dynamic baseflow and floodwater (quickflow) volumes for individual hydrographs. Results suggest that in response to seasonal recharge, the epikarst at James Cave may be able to store more than 50% of recharge as baseflow. (Gerst 2010)

4) The combination of the long term continuous hydrologic and geochemical datasets, shown in Figure 2 for 2011-2013 were used to support development of a conceptual model of the epikarst (Eagle 2013).



<u>Figure 2.</u> *Large scale divisions in the conductivity and drip discharge records at James Cave indicated by color coding on the x-axis. Colors indicate the division in the time series record: 1) blue indicates the hydrologic recharge season and the conductivity period A (period of variable conductivity); 2) green indicates the hydrologic recession period and the conductivity period B (period of increasing conductivity); and 3) red indicates the hydrologic low flow period and conductivity period C (period of increasing conductivity). From Eagle, S (2013).*

The conceptual model of the epikarst includes the following three periods:

Recharge (winter-spring): During this period significant recharge to the underlying karst aquifer occurs and there is consistency of P_{CO2} throughout the system due to the lack of opportunity for gaseous diffusion. The initial flush of drip water has high specific conductance due to interaction of epikarst water with rock during the baseflow (epikarst filling) season. However, as discharge continues, fully saturated macropores in the soil and fractures in the epikarst allow dilute precipitation to bypass storage and flow directly through the epikarst and into the cave. As a result, after the first flush, subsequent drip water has lower conductance due to mixing of precipitation with epikarst water.

Recession (summer). During hydrologic recession, there is reduced input (ET exceeds precipitation). Near surface moisture is lost and deep soil moisture continues to enter the epikarst while the declining pressure head leads to progressively lower drip rates. Gas exchange is limited to the deep soil zone and therefore P_{CO2} is expected to increase, along with calcite dissolution and as a result, specific conductance of drip water also increases.

Baseflow (fall). In the fall, epikarst continues to drain, reflected by low to negligible drip discharge. This draining results in the drying of the upper epikarst, which increases permeability for gas flow and allows for degassing of CO_2. Loss of CO_2 results in calcite precipitation in the epikarst, which is reflected in the decreased Ca concentrations, increased Sr/Ca ratios, and decreased specific conductance in drips. However, as evapotranspiration tapers off during the fall, precipitation infiltrates into soils and this water eventually fills the epikarst. The duration of this season depends on the quantity of precipitation received after precipitation exceeds PET. Once the epikarst is filled, the recharge period begins.

By assessing the timing and quality of recharge, both during base flow conditions and in response to multiple recharge events of varying magnitudes, we are able to use the results from James Cave as an analog for watersheds in the greater Shenandoah Valley region. This was one of our primary objectives of the research, and it allows managers to better understand and characterize the role of epikarst in controlling recharge and water quality in similar karst aquifers.

<u>Significance:</u>

Between the funding provided through the NIWR and two other earlier grants, we now have enough data from several different sites in two different climatic regions that we can begin to understand the how the shallow epikarst functions over a variety of spatial scales and over multiple years. This is important, especially in TX because of multi-year cycles of drought and rain, as opposed to the more seasonal cycles experienced in the Virginia site.

<u>Student involvement:</u>

Student involvement has been a critical component of research at both sites and has included many students at all levels of involvement ranging from occasionally assisting a graduate student on a volunteer basis, to being paid on an hourly basis, to being funded to perform graduate research. All students and P.I.s have benefited tremendously from these opportunities.

Six graduate students and four undergraduate students are or have been intimately involved with various aspects of the TX portion of this research, including thesis research performed by three of the graduate students (K. Kukowski, H. Dammeyer, and B. Gerard). An additional graduate student began thesis work on the project in Fall 2011 (C. Stinson).

In Virginia, two graduate students (J. Gerst and S. Eagle) have completed M.S. theses on the hydrology and geochemistry of cave drips at James Cave. One other graduate student (O. Oyewumi) was partially support to provide laboratory assistance for the project. Five undergraduates have completed research projects in the cave (S. Morgan, A. Brown, M. Kadilak, H. Scott, M. Blower) and scores of other students have helped as field assistants.

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Institutional Mechanisms for Accessing Irrigation District Water

Basic Information

Title:	Institutional Mechanisms for Accessing Irrigation District Water
Project Number:	2010TX375G
Start Date:	9/1/2010
End Date:	8/31/2012
Funding Source:	104G
Congressional District:	17
Research Category:	Social Sciences
Focus Category:	Law, Institutions, and Policy, Economics, Water Supply
Descriptors:	
Principal Investigators:	Ron Griffin

Publications

1. Griffin, Ronald C., 2012, Engaging Irrigation Organizations in Water Reallocation, Natural Resources Journal, forthcoming 2012.
2. Griffin, Ronald C., 2012, The Origins and Ideals of Water Resource Economics in the U.S., Annual Review of Resource Economics 4, forthcoming 2012.
3. Ghimire, Narishwar, 2012, Engaging Irrigation Organizations in Water Reallocation, Natural Resources Journal, in-progress.
4. Griffin, Ron, and Mary Kelly, 2012, The Future of Irrigation Organizations in the Colorado River Basin, The Water Report 95 (January 15, 2012, www.thewaterreport.com): 18-22.
5. Griffin, Ronald C., 2012, Engaging Irrigation Organizations in Water Reallocation, Natural Resources Journal, 52 (Fall 2012): 277-313.
6. Griffin, Ronald C., 2012, The Origins and Ideals of Water Resource Economics in the U.S., Annual Review of Resource Economics, 4 (2012), 353-77.
7. Ghimire, Narishwar, 2012, Engaging Irrigation Organizations in Water Reallocation, Natural Resources Journal, in-progress.
8. Griffin, Ron, and Mary Kelly, 2012, The Future of Irrigation Organizations in the Colorado River Basin, The Water Report 95 (January 15, 2012, www.thewaterreport.com): 18-22.
9. Ghimire, Narishwar, 2013, Evaluating Water Transfers In Irrigation Districts, Dissertation, Texas A&M University, College Station, TX.
10. Ghimire, Narishwar and Ronald C. Griffin, "Evaluating Water Transfers In and Out of Irrigation Districts," American Journal of Agricultural Economics, under review.
11. Ghimire, Narishwar and Ronald C. Griffin, 2013, Variable Irrigation District Action in Reallocation, Journal of the American Water Resources Association, working paper under preparation for submission.

Project Completion Report

Title: Institutional Mechanisms for Accessing Irrigation District Water

Award Number: G10AP00138

PI: Ronald C. Griffin

The prepared outputs of this project are 1 dissertation and 5 articles. One of the completed articles was published in a trade/professional outlet (*The Water Report*). Two of the articles have been published in academic journals. The 4th article is under review by a journal, and the final article is nearing submission to a journal.

The five articles are viewable at http://ron-griffin.tamu.edu/page2/page2.html

Citations for these six products and their abstracts are provided below.

Dissertation

Ghimire, Narishwar. "Evaluating Water Transfers In Irrigation Districts." TAMU, completed Spring 2013.

The participation of irrigation districts (IDs) in surface water transfers from agriculture-to-municipal uses is studied by examining IDs' economic and political behavior, comparing their performance with non-districts (non-IDs), and analyzing the role of economic and demographic heterogeneities in water transfers. Economic modeling, econometric, and analytical techniques are used to investigate these issues.

An economic model is developed to investigate how the collective-type institutional structure of IDs in the presence of local interdependencies (between internal water delivery and external water transfers) and increasing returns to scale in the internal water delivery causes reduction in marginal benefit of water transfers and the optimal transfers. The model is also used to investigate how the involvement of the U.S. Bureau of Reclamation in IDs causes more water uses in agriculture availing less for external transfers. The conjunction of multiple uses and exclusion rights without ownership rights in IDs' water and vote-maximizing political structure of IDs are found to create disincentive for water conservation and transfers.

Water transfer responses of IDs and non-IDs are empirically investigated by using a Quasi Maximum Likelihood Estimation (QMLE) technique. Based on the analysis of 38 years of time series water transfer data, IDs are found to be less responsive in water transfers relative to non-IDs in terms of water right-weighted transfers. It is found that water scarcity, private housing permits, and nonfarm establishments are positively associated with water transfers. The marginal effect of water scarcity on water transfer is stronger for non-IDs than for IDs.

Impacts of economic and demographic heterogeneities on water transfer behavior of IDs are investigated using unbalanced panel data econometric techniques. Water right holdings and population in nearby cities of IDs are found to be significantly correlated with water transfer behaviors of IDs. Larger IDs with higher water right holdings and higher population centers in nearby cities are found to be more responsive to water transfers.

The findings complement previous studies that commend public attention for policy redesign including institutional changes to motivate IDs to increase their water transfer activity.

Articles

Griffin, Ron and Mary Kelly. "The Future of Irrigation Organizations in the Colorado River Basin." *The Water Report* 95 (January 15 2012; www.thewaterreport.com): 18-22.

This article explores key changes affecting water scarcity within the Colorado River basin of the western U.S. and what these pressures might mean for the future of irrigation organizations in the region. It also discusses how irrigation organizations might prepare for the future in ways that will accommodate changing water demand and supply patterns while either sustaining or transforming local agricultural economies.

Griffin, Ronald C. "Engaging Irrigation Organizations in Water Reallocation." *Natural Resources Journal* 52 (Fall 2012): 277-313.

Rising water scarcity in the Western United States cannot be well addressed without strong reallocation of agriculturally assigned water rights. Irrigation organizations are necessary participants in this process. This article examines the special conditions and problems of improving the reallocative activities of these agencies and reviews historical background and challenges. Policy options are inventoried.

Griffin, Ronald C. "The Origins and Ideals of Water Resource Economics in the U.S." *Annual Reviews of Resource Economics* 4 (2012): 353-77.

An abbreviated history of water resource economics is reported within the context of coevolving water issues and the emerging institutions of the United States' past two centuries. Notable principles of water economics and their US origins are discussed. Some of the long-standing wisdom of the field is recalled. Landmarks for the founding doctrines of water marketing and efficient water pricing are identified.

Ghimire, Narishwar and Ronald C. Griffin. "Evaluating Water Transfers In and Out of Irrigation Districts." Under review by the *American Journal of Agricultural Economics*.

Irrigation districts (IDs) use a large portion of the surface water rights present in the American west. Microeconomic analysis of water use conditions within IDs indicates that it can be economically optimal for IDs to engage in less reallocative activities as compared to private water right holders. Institutional insights combine to show that the political orientation of IDs favors irrigation over irrigators in the sense that the rewards of water marketing tend to be incompletely captured. Based on an analysis of 38 years of time series water transfer data, it is found that IDs underparticipate in agricultural-to-municipal water transfers relative to nonirrigation districts in terms of water right-weighted transfers. The results support further policy redesign if reallocation is to be viewed as a scarcity-solving strategy in ID-dominated regions.

Ghimire, Narishwar and Ronald C. Griffin. "Variable Irrigation District Action in Reallocation." April 2013 working paper under preparation for submission to the *Journal of the American Water Resources Association*.

Irrigation districts (IDs) in the American west are highly diverse in terms of economic and demographic attributes. This diversity may affect reallocative activities as water scarcity rises. An econometric analysis of multiple decades of ID water transfer activities in the Lower Rio Grande Valley of Texas finds that IDs with larger initial water right holdings and higher population in nearby cities are more likely to participate in agricultural-to-municipal water transfer activities. The findings suggest that consolidation of smaller water right holding IDs may be an avenue for quickening the pace of reallocation, especially in more populated areas.

Evaluation of invasive aquatic species in Texas

Basic Information

Title:	Evaluation of invasive aquatic species in Texas
Project Number:	2012TX458B
Start Date:	6/1/2012
End Date:	2/28/2013
Funding Source:	104B
Congressional District:	17 & statewide
Research Category:	Biological Sciences
Focus Category:	Invasive Species, Management and Planning, Ecology
Descriptors:	None
Principal Investigators:	Michael Masser, Elizabeth Edgerton, Lucas Gregory, Allen E. Knutson

Publications

1. Edgerton, Elizabeth; Michael, Masser; Lucas, Gregory, 2012, Developing a Risk Assessment Model for Identifying Potential Aquatic Invasive Weeds in Texas, Poster,
2. Edgerton, Elizabeth; Masser, Michael; Gregory, Lucas; Grant, William; Knutson, Allen. 2013. Developing a Risk Assessment Tool for Identifying Potential Aquatic Invasive Plants in Texas. Poster.
3. Edgerton, Elizabeth; Michael, Masser,; Lucas, Gregory; William; Allen Knutson, 2013, Developing a Risk Assessment Tool for Identifying Potential Aquatic Invasive Plants in Texas in 18th International Conference on Aquatic Invasive Species Abstracts Review, Ontario, Canada, Page 79.

Title: Evaluation of invasive aquatic species in Texas

Project Number: 2012TX458B

Primary PI: Elizabeth Edgerton

Other PIs : Lucas Gregory, Michael Masser, William Grant, Allen Knutson

Abstract

Research on invasive aquatic species in Texas, funded through the USGS and the W.G. Mills Memorial Endowment, began last year and is currently ongoing. The time frame for this report is June 1, 2012 through February 28, 2013. The focus of this research is to evaluate aquatic invasive species in the state of Texas. Upon speaking with representatives from the Texas Parks and Wildlife Department and the Lady Bird Johnson Wildflower Center, it was determined that a risk assessment tool for aquatic invasive plants that is tailored to the state of Texas would be beneficial. The risk assessment will serve as a useful predictor of future potential invasive plant species, as well as prioritize existing invasive aquatic plants for management purposes, and will therefore be applicable to policy makers in determining which species to prohibit, as well as for managers deciding which species deserve the highest priority in management and control efforts.

Problem and Research Objectives

Determining which non-native aquatic plants have the greatest potential to invade a new area, and prohibiting those species prior to their introduction, is the key to preventing future serious infestations. The vast majority of non-native plants, either aquatic or terrestrial, are intentionally introduced to an area for purposes such as food crops, ornamental gardening, or as novelties. Once established in captivity, many plants are accidentally or intentionally released into the environment. The majority do not pose a serious threat of infestation, however a select number can quickly become well established and cause severe damage to both the ecosystem and the economy. Each year, millions of dollars are spent in an attempt to control these invaders in the United States. Additionally, invasive plants cause a multitude of negative impacts, such as reduced biodiversity, increased transportation costs, changes water chemistry, and decreased land values. Weed Risk Assessments, tools for determining the invasive potential of a plant species, have been developed and are currently being used around the world to screen non-native plant species and identify those which are likely to be invasive and should be excluded. Most notably, a risk assessment was developed for Australia in 1999 as a biosecurity tool, which is referred to as the Weed Risk Assessment or WRA. The Australian system is regarded as a highly accurate tool for screening non-native terrestrial plants prior to their introduction. This model has been widely adapted to screen for both terrestrial and aquatic plants in a number of other countries including New Zealand, Chile, and the United States, as well as individual states in the US such as California and Hawaii.

A tool specifically tailored to the unique ecosystems of Texas has not yet been developed, however. Texas is a major hub in the aquatic plants trade and has conditions, like a temperate climate, which are favorable for plant invasions. In fact, one of the most common sources of aquatic ornamental plants is internet sale, and Texas is home to some of the largest retailers in the country. So, developing and implementing an effective risk assessment tool is imperative to reducing future invasions. This study will review the models that are currently available, the New Zealand and United States models in particular, and adapt them to develop a tool that will accurately identify those aquatic species which should be prohibited from entering the state of Texas, while recognizing those which should be safe to import. The new tool will be referred to as the Texas Aquatic Plant Risk Assessment, or TX APRA, and will be comprised of two models: a questionnaire-style risk assessment which will give each plant an invasiveness score, and a stochastic model which will show potential plant growth and spread of over time.

Materials/Methodology

The research began with assessing existing risk assessments models that have been developed and are currently in use, specifically the New Zealand Weed Risk Model and the United States Weed Risk Assessment. The models are questionnaire-style assessments with a number of weighted questions which address various aspects of plant ecology, reproductive abilities, potential environmental and economic impacts, and history of invasion in other areas, among others. Questions include temperature tolerance, resistance to management, and aesthetic value. Upon completion of the questionnaire, each plant is given a score of invasiveness potential; the higher the score, the more likely the plant is to become invasive.

The risk assessment currently being developed for Texas, part one of the Texas Aquatic Plant Risk Assessment or TX APRA, will be similar to these previous models, however changes will be made so that the parameters accurately reflect conditions in Texas. The TX APRA will also likely be divided into regions, based on the USDA Plant Hardiness Zones Map. Each region will reflect environmental conditions in that area thus providing a more accurate predictor of aquatic plant invasive potential. To test for model accuracy, a number of plants which are known to have been previously introduced into Texas ranging from highly invasive, to slightly invasive, to exotic but not invasive will be scored to ensure that the model can correctly distinguish between the three categories.

Part two of the TX APRA will be a stochastic model which will show predicted rates of growth and spread of non-native plants over time. Both existing invasive plants and those which have not yet been introduced to Texas could be modeled. Annual extreme temperatures, water depth, and the plant's invasiveness score from part one of the tool are all components that will likely be included. Once the model is developed and validated, management techniques like manual removal, herbicide application, bio-control, or a combination of techniques could also be incorporated and the control technique's effectiveness could be predicted. A stochastic model of predicted growth and spread of aquatic plants has not been developed in any of the previous risk assessments and will be highly useful in aiding managers when deciding the best plan of action for controlling existing aquatic invasive plants.

Principal Findings

The TX APRA is still in the developmental stages, so testing and model validation has not yet been performed. Existing risk assessments in New Zealand and the United States have been tested, and both report a high level of accuracy in correctly distinguishing between plant species which are highly invasive, moderately invasive, or exotic but not invasive. We expect the

TX APRA to be at least as accurate as its predecessors, thus providing a highly beneficial tool in the fight against invasive species in Texas.

Significance

Implementing an accurate risk assessment tool in the state of Texas will be highly useful to policy makers. Prevention through prohibition is the most effective way of ensuring that new, potentially devastating invasive species do not enter our state's waters. With this tool, policy makers will be able to accurately determine those species which have a potential to be highly invasive and should be prohibited, while still allowing entrance of species which do not pose a serious threat.

The TX APRA will also benefit managers and those working to control and manage existing invasive species. The stochastic model of plant growth and spread will allow managers to model various control techniques and determine what the most effective course of action will be. Modeling control efforts prior to testing them in the field could prove very cost effective, as time spent in the field and money spent on control efforts could be saved by narrowing down the best plan of action.

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Information Transfer Program Introduction

In 2012, the Texas Water Resources Institute continued its outstanding communication efforts to produce university-based water resources research and education outreach programs in Texas.

The Institute publishes a monthly email newsletter, a periodic email newsletter specific to the drought in Texas and an institute magazine published three times a year. The Institute also publishes an online peer-reviewed journal in conjunction with a nonprofit organization and uses social media to publicize information.

Conservation Matters, an email newsletter, publishes timely information about natural and water resources news, results of projects and programs, and new natural resources and water-related research projects, publications and faculty at Texas universities. As of February 28, 2013, the newsletter has a subscription of 2,381.

Since August 2011, TWRI's communications team has periodically published a email newsletter dedicated to drought issues, Drought in Texas. The newsletter has covered such topics as predicted water policy changes because of the drought to interviews with the Texas state climatologist to reprints of AgriLife Extension articles on coping with the drought. As of February 28, 2012, Drought in Texas has about 2,500 subscribers.

txH2O, a 30-page glossy magazine, is published three times a year and contains in-depth articles that spotlight major water resources issues in Texas, ranging from agricultural nonpoint source pollution to landscaping for water conservation. Subscribers are at 2,632 for hard copies and 568 for email copies and approximately 1,000 more magazines are distributed.

The Texas Water Journal is an online, peer-reviewed journal devoted to the timely consideration of Texas water resources management and policy issues from a multidisciplinary perspective that integrates science, engineering, law, planning and other disciplines. The journal has published four issues. It currently has 410 enrolled users, although registration is not required to view the journal.

The Institute has a Twitter account to promote the institute and water resources news and education throughout the state. The Institute currently has 780 Twitter followers and engagement levels have steadily increased. It also has a project-specific blog and two project-specific Facebook pages.

Working to reach the public and expand its audience, the Institute generates news releases and cooperates with Texas A&M AgriLife Communications writers for them to produce news releases about projects as well. The Institute prepared numerous informational packets for meetings. TWRI projects or participating researcher efforts had at least 87 mentions in the media.

For each of the institute's projects, TWRI published a one-page fact sheet that explains the purpose, background, objectives, and, if applicable, accomplishments of the program.

In cooperation with research scientists and Extension education professionals, the institute published 32 technical reports and four educational materials publications, which provide in-depth details of water resource issues from various locations within the state.

Information Transfer

Basic Information

Title:	Information Transfer
Project Number:	2012TX423B
Start Date:	3/1/2012
End Date:	2/28/2013
Funding Source:	104B
Congressional District:	17
Research Category:	Not Applicable
Focus Category:	None, None, None
Descriptors:	None
Principal Investigators:	Neal Wilkins, Danielle Kalisek, Leslie H Lee, Courtney Smith, Jaclyn Tech, Kevin Wagner, Ralph Wurbs, Kathy Wythe

Publications

1. Berthold, Allen, 2012, Arroyo Colorado Agricultural Nonpoint Source Assessment Final Report, (TR-429), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 184 pages.
2. Berthold, A., Moench, E., Paschal, J., Wagner, K.,, 2012, Education Program for Improved Water Quality in Copano Bay Final Report, (TR-422), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 23 pages.
3. Bonaiti, Gabriele, Fipps, Guy, 2012, Use of GIS as a real time decision support system for irrigation districts, (TR-435), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 29 pages.
4. Enciso, Juan, 2012, Evaluation of BMPs to Reduce NPS Pollution at the Farm Level, (TR-423), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 59 pages.
5. Fipps, Guy, Swanson, Charles, 2012, Evaluation of Smart Irrigation controllers: Year 2011 Results, (TR-428), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 33 pages.
6. Gregory, Lucas, Smith, Courtney, Wagner, Kevin, Warrick, Loren, 2012, 2012 Bacterial Source Tracking - State of the Science Conference Conference Proceedings, (TW-427), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 292 pages.
7. Hoffpauir, Richard, Schnier, S.T., Wurbs, Ralph, 2012, Applications of Expanded WRAP Modeling Capabilities to the Brazos WAM 2nd ed., (TR-389), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 359 pages.
8. Hoffpauir, Richard, Wurbs, Ralph, 2012, Water Rights Analysis Package (WRAP) Daily Modeling System, (TR-430), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 277 pages.
9. Hoffpauir, Richard, Wurbs, Ralph, 2012, Water Rights Analysis Package (WRAP) Modeling System Programming Manual 2nd ed, (TR-388), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 195 pages.
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21. Berthold, A., 2012, Approaches to Watershed Planning in Texas, (EM-112), Texas Water Resources Institute, Texas A&M System, College Station, Texas, 2 pages.
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Texas Water Resources Institute
Information Transfer Activities
March 1, 2012 – February 28, 2013

In 2012, the Texas Water Resources Institute continued its outstanding communication efforts to produce university-based water resources research and education outreach programs in Texas.

The Institute publishes a monthly email newsletter, a periodic email newsletter specific to the drought in Texas and an institute magazine published three times a year. The Institute also publishes an online peer-reviewed journal in conjunction with a nonprofit organization and uses social media to publicize information.

Conservation Matters, an email newsletter, publishes timely information about natural and water resources news, results of projects and programs, and new natural resources and water-related research projects, publications and faculty at Texas universities. As of February 28, 2013, the newsletter has a subscription of 2,381.

Since August 2011, TWRI's communications team has periodically published a email newsletter dedicated to drought issues, *Drought in Texas*. The newsletter has covered such topics as predicted water policy changes because of the drought to interviews with the Texas state climatologist to reprints of AgriLife Extension articles on coping with the drought. As of February 28, 2012, *Drought in Texas* has about 2,500 subscribers.

txH$_2$*O*, a 30-page glossy magazine, is published three times a year and contains in-depth articles that spotlight major water resources issues in Texas, ranging from agricultural nonpoint source pollution to landscaping for water conservation. Subscribers are at 2,632 for hard copies and 568 for email copies and approximately 1,000 more magazines are distributed.

The Texas Water Journal is an online, peer-reviewed journal devoted to the timely consideration of Texas water resources management and policy issues from a multidisciplinary perspective that integrates science, engineering, law, planning and other disciplines. The journal has published four issues. It currently has 410 enrolled users, although registration is not required to view the journal.

The Institute has a Twitter account to promote the institute and water resources news and education throughout the state. The Institute currently has 780 Twitter followers and engagement levels have steadily increased. It also has a project-specific blog and two project-specific Facebook pages.

Working to reach the public and expand its audience, the Institute generates news releases and cooperates with Texas A&M AgriLife Communications writers for them to produce news releases about projects as well. The Institute prepared numerous informational packets for meetings. TWRI projects or participating researcher efforts had at least 87 mentions in the media.

For each of the institute's projects, TWRI published a one-page fact sheet that explains the purpose, background, objectives, and, if applicable, accomplishments of the program.

In cooperation with research scientists and Extension education professionals, the institute published 32 technical reports and four educational materials publications, which provide in-depth details of water resource issues from various locations within the state.

TWRI continues to enhance its web presence by posting new project-specific Web sites and continually updating the information contained within the websites. The institute currently maintains 36 websites.

TWRI Program Sites:

Arroyo Colorado	arroyocolorado.org
Attoyac Bayou Watershed Protection Plan Development	attoyac.tamu.edu
Bacteria Fate and Transport	bft.tamu.edu
Big Cypress Creek Modeling and BST	bcc.tamu.edu
Buck Creek Watershed Protection Plan Development	buckcreek.tamu.edu
Caddo Lake Data	caddolakedata.us
Carters and Burton Creeks Water Quality	cartersandburton.tamu.edu
Center for Invasive Species Eradication	cise.tamu.edu
Consortium for Irrigation Research and Education	cire.tamu.edu
Copano Bay Water Quality Education	copanobay-wq.tamu.edu
Efficient Nitrogen Fertilization	n-fertilization.tamu.edu
Environmental Effects of In-House Windrow Composting of Poultry Litter	windrowlitter.tamu.edu
Evaluating BMPs to Reduce Poultry Odors	poultrybmps.tamu.edu
Fort Hood Range Revegetation	forthoodreveg.tamu.edu
Groundwater / Surface Water Interactions	waterinteractions.tamu.edu
Groundwater Nitrogen Source Identification and Remediation	groundwatern.tamu.edu
Lake Granbury Water Quality	lakegranbury.tamu.edu
Leon/Lampasas BST	leon-lampasasBST.tamu.edu
Little Brazos River Bacteria Assessment	lbr.tamu.edu
Lone Star Healthy Streams	lshs.tamu.edu
North Central Texas Water Quality	nctx-water.tamu.edu
Pecos River WPP Implementation Program	pecosbasin.tamu.edu
Rio Grande Basin Initiative	riogrande.tamu.edu
Rio Grande Basin Initiative Conference	riogrande-conference.tamu.edu
State BST Infrastructure Support	texasbst.tamu.edu
Texas Water Resources Institute	twri.tamu.edu
Texas Watershed Planning	watershedplanning.tamu.edu
Texas Well Owner Network	twon.tamu.edu
Water Resources Training Program	watereducation.tamu.edu

Completed Program Sites:

Dairy Compost Utilization	compost.tamu.edu
Environmental Infrastructures	bosque-river.tamu.edu
Improving Water Quality of Grazing Lands	grazinglands-wq.tamu.edu
Irrigation Training Program	irrigationtraining.tamu.edu

Other Sites:

Save Texas Water	savetexaswater.tamu.edu
Texas Water Journal	journals.tdl.org/twj
WATER Scholars Program	waterscholars.tamu.edu

USGS Summer Intern Program

None.

Student Support					
Category	**Section 104 Base Grant**	**Section 104 NCGP Award**	**NIWR-USGS Internship**	**Supplemental Awards**	**Total**
Undergraduate	1	0	0	0	1
Masters	0	0	0	6	6
Ph.D.	0	0	0	0	0
Post-Doc.	0	0	0	0	0
Total	1	0	0	6	7

Notable Awards and Achievements

Edgerton, Elizabeth. 2nd Place; Student Poster Competition at the Texas Aquatic Plant Management Society's Annual Conference. Awarded October 23, 2012.

Publications from Prior Years

1. 2008TX353S ("Award No. 08HQAG0118 Transboundary Aquifer Assessment Program") - Other Publications - Michelsen, A., B. Alley, Z. Sheng, P. King, M. Darr, S. Megdal, and F. Cafaggi Felix, 2011, Transboundary aquifer assessment program [Abstract], Panel at AWRA 2011 Annual Water Resources Conference, Albuquerque, New Mexico, November 7-10.
2. 2008TX335S ("UNITED STATES – MEXICO TRANSBOUNDARY AQUIFER") - Conference Proceedings - Sheng, Z., J.P. King, and J. Gastelum, 2011, Effects of Groundwater Pumping on the Stream Flow and Aquifer Storage in Mesilla Basin [Abstract], Proc. Of World Environmental and Water Resources Conference, ASCE, Palm Springs, CA, May 21-26, 2011.