Estimation of Long-Term Soil Moisture Using a Distributed Parameter Hydrologic Model and Verification Using Remotely Sensed Data

B. Narasimhan, R. Srinivasan, J. G. Arnold, M. Di Luzio

Abstract. *Soil moisture is an important hydrologic variable that controls various land surface processes. In spite of its importance to agriculture and drought monitoring, soil moisture information is not widely available on a regional scale. However, long-term soil moisture information is essential for agricultural drought monitoring and crop yield prediction. The hydrologic model Soil and Water Assessment Tool (SWAT) was used to develop a long-term record of soil water at a fine spatial (16 km*^{2}*) and temporal (weekly) resolution from historical weather data. The model was calibrated and validated using stream flow data. However, stream flow accounts for only a small fraction of the hydrologic water balance. Due to the lack of measured evapotranspiration or soil moisture data, the simulated soil water was evaluated in terms of vegetation response, using 16 years of normalized difference vegetation index (NDVI) derived from NOAA-AVHRR satellite data. The simulated soil water was well-correlated with NDVI (r as high as 0.8 during certain years) for agriculture and pasture land use types, during the active growing season April-September, indicating that the model performed well in simulating the soil water. The study provides a framework for using remotely sensed NDVI to verify the soil moisture simulated by hydrologic models in the absence of auxiliary measured data on ET and soil moisture, as opposed to just the traditional stream flow calibration and validation.*

Keywords. *Drought, Evapotranspiration, NDVI, Soil moisture, SWAT, Texas.*

Soil moisture is an important hydrologic variable that controls various land surface processes. The term "soil moisture" generally refers to the temporary storage of precipitation in the top 1 to 2 m of soil horizon. Although only a small percentage of total precipitation is stored in the soil after accounting for evapotranspiration (ET), surface runoff, and deep percolation, soil moisture reserve is critical for sustaining agriculture, pasture, and forestlands. Given the fact that precipitation is a random event, soil moisture reserve is essential for regulating the water supply for crops between precipitation events. Soil moisture is an integrated measure of several state variables of climate and physical properties of land use and soil. Hence, it is a good measure for scheduling various agricultural operations, crop monitoring, yield forecasting, and drought monitoring.

In spite of its importance to agriculture and drought monitoring, soil moisture information is not widely available on a regional scale. This is partly because soil moisture is highly variable both spatially and temporally and is therefore difficult to measure on a large scale. The spatial and temporal variability of soil moisture is due to heterogeneity in soil properties, land cover, topography, and non-uniform distribution of precipitation and ET.

On a local scale, soil moisture is measured using various instruments, such as tensiometers, TDR (time domain reflectometry) probes, neutron probes, gypsum blocks, and capacitance sensors. The field measurements are often widely spaced, and the averages of these point measurements seldom yield soil moisture information on a watershed scale or regional scale due to the heterogeneity involved.

In this regard, microwave remote sensing is emerging as a better alternative for getting a reliable estimate of soil moisture on a regional scale. With current microwave technology, it is possible to estimate soil moisture accurately only in the top 5 cm of the soil (Engman, 1991). However, the root systems of most agricultural crops extract soil moisture from 20 to 50 cm at the initial growth stages and extend deeper as the growth progresses. Further, the vegetative characteristics, soil texture, and surface roughness strongly influence the microwave signals and introduce uncertainty in the soil moisture estimates (Jackson et al., 1996).

Field-scale data and remotely sensed soil moisture data are available for only a few locations and are lacking for large areas and for multiyear periods. However, long-term soil moisture information is essential for agricultural drought monitoring and crop yield prediction (Narasimhan, 2004). Keyantash and Dracup (2002) also noted the lack of a national soil moisture monitoring network in spite of its usefulness for agricultural drought monitoring.

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Long-Term Soil Moisture Modeling

A possible alternative for obtaining long-term soil moisture information is to use historical weather data. Long-term weather data, such as precipitation and temperature, are widely available and can be used with spatially distributed hydrologic models to simulate soil moisture. Very few modeling studies conducted in the past were aimed at using hydrologic models for the purpose of monitoring soil moisture and drought.

Palmer (1965) used a simple two-layer lumped parameter water balance model to develop the Palmer Drought Severity Index (PDSI). The model is based on monthly time step and uses monthly precipitation and temperature as weather inputs and average water holding capacity for the entire climatic division (7000 to 100,000 km^2). From these inputs, a simple lumped parameter water balance model is used to calculate various water balance components including ET, soil recharge, runoff, and moisture loss from the surface layer. Akinremi and McGinn (1996) found that the water balance model used by Palmer (1965) did not account for snowmelt, which is significant in Canadian climatic conditions. In order to overcome this limitation, Akinremi and McGinn (1996) used the modified Versatile Soil Moisture Budget (VB), developed by Akinremi et al. (1996). Huang et al. (1996) developed a one-layer soil moisture model to derive a historical record of monthly soil moisture over the entire U.S. for applications of long-range temperature forecasts. The model uses monthly temperature and monthly precipitation as inputs, calculates surface runoff as a simple function of antecedent soil moisture and precipitation, and estimates ET using the Thornthwaite method.

In all of the aforementioned studies for determining soil moisture, the weather data are used at a coarse temporal (monthly) and spatial (several thousand km^2) resolution. However, precipitation has high spatial and temporal variability; hence, it is not realistic to assume a uniform distribution of precipitation over the entire climatic division. Further, physical properties of soil, land use, and topography are highly heterogeneous and govern the hydrologic response on a local scale. In addition, soil moisture stress can develop rapidly over a short period of time, and moisture stress during critical stages of crop growth can significantly affect the crop yield. For example, a 10% water deficit during the tasseling-pollination stage of corn could reduce the yield as much as 25% (Hane and Pumphrey, 1984).

There are other classes of models similar to the Simple Biosphere Model (SiB) (Sellers et al., 1986) that simulate land surface fluxes (radiation, heat, moisture) for use within the General Circulation Model (GCM), which handles large-scale climate change studies and climate forecasts over a long period of time. However, these models were developed for a different purpose, i.e., climate forecasting on a larger scale, and are data intensive. They cannot be applied on a catchment scale due to the lack of model parameters and sub-hourly input data, primarily radiation.

Many comprehensive spatially distributed hydrologic models have been developed in the past decade due to advances in hydrologic sciences, Geographical Information System (GIS), and remote sensing. A good compromise would be to select a hydrologic model that (1) takes into account the major land surface processes and climatic variables, (2) gives proper consideration to spatial variability of soil and land use properties, (3) models crop growth and root development, and (4) uses readily available data inputs. Such a model will certainly improve our ability to monitor soil moisture at a higher spatial and temporal resolution (Narasimhan, 2004).

Among the many hydrologic models developed in the past decade, the Soil and Water Assessment Tool (SWAT), developed by Arnold et al. (1998), has been used extensively by researchers. This is because SWAT (1) uses readily available inputs for weather, soil, land, and topography, (2) allows considerable spatial detail for basin-scale modeling, and (3) is capable of simulating crop growth and land management scenarios. SWAT has been integrated with GRASS GIS (Srinivasan et al., 1998b) and with ArcView GIS (Di Luzio et al., 2002b). SWAT was applied to design the Hydrologic Unit Model of the United States (HUMUS) to improve water resources management at local and regional levels (Srinivasan et al., 1998a). SWAT is recognized by the U.S. Environmental Protection Agency (EPA) and has been incorporated into the EPA's BASINS (Better Assessment Science Integrating Point and Non-point Sources) (Di Luzio et al., 2002a). (BASINS is a multipurpose environmental analysis software system developed by the EPA for performing watershed and water quality studies on various regional and local scales.) In order to optimally calibrate the model parameters, especially for large-scale modeling, an auto-calibration routine has been added to SWAT (Eckhardt and Arnold, 2001; Van Griensven and Bauwens, 2001). Hence, SWAT was used in this study.

The objective of this study is to develop long-term soil moisture information, at 4 × 4 km spatial resolution and weekly temporal resolution, for selected watersheds in Texas, using the spatially distributed hydrologic model SWAT and verify the model predictions using remotely sensed data.

Methodology

Soil and Water Assessment Tool (SWAT)

SWAT is a physically based basin-scale, continuous time, distributed parameter hydrologic model that uses spatially distributed data on soil, land use, Digital Elevation Model (DEM), and weather data for hydrologic modeling and operates on a daily time step. Major model components include weather, hydrology, soil temperature, plant growth, nutrients, pesticides, and land management. A complete description of the SWAT model components (version 2000) is found in Arnold et al. (1998) and Neitsch et al. (2002). A brief description of the SWAT hydrologic component is given here.

For spatially explicit parameterization, SWAT subdivides watersheds into sub-basins based on topography, which are further subdivided into hydrologic response units (HRU) based on unique soil and land use characteristics. Four storage volumes represent the water balance in each HRU in the watershed: snow, soil profile (0 to 2 m), shallow aquifer (2 to 20 m), and deep aquifer (>20 m). The soil profile can be subdivided into multiple layers. Soil water processes include surface runoff, infiltration, evaporation, plant water uptake, inter (lateral) flow, and percolation to shallow and deep aquifers.

SWAT can simulate surface runoff using either the modified SCS curve number (CN) method (USDA-SCS, 1972) or the Green and Ampt infiltration model based on an infiltration excess approach (Green and Ampt, 1911) depending on the availability of daily or hourly precipitation data, respectively. The SCS curve number method was used in this study with daily precipitation data. Based on the soil hydrologic group, vegetation type, and land management practice, initial CN values are assigned from the SCS hydrology handbook (USDA-SCS, 1972). SWAT updates the CN values daily based on changes in soil moisture.

The excess water available after accounting for initial abstractions and surface runoff, using the SCS curve number method, infiltrates into the soil. A storage routing technique is used to simulate the flow through each soil layer. SWAT directly simulates saturated flow only and assumes that water is uniformly distributed within a given layer. Unsaturated flow between layers is indirectly modeled using depth distribution functions for plant water uptake and soil water evaporation. Downward flow occurs when the soil water in the layer exceeds field capacity and the layer below is not saturated. The rate of downward flow is governed by the saturated hydraulic conductivity. Lateral flow in the soil profile is simulated using a kinematic storage routing technique that is based on slope, slope length, and saturated conductivity. Upward flow from a lower layer to the upper layer is regulated by the soil water to field capacity ratios of the two layers. Percolation from the bottom of the root zone is recharged to the shallow aquifer.

SWAT has three options for estimating potential ET: Hargreaves, Priestley-Taylor, and Penman-Monteith. The Penman-Monteith method (Monteith, 1965) was used in this study. SWAT computes evaporation from soils and plants separately, as described in Ritchie (1972). Soil water evaporation is estimated as an exponential function of soil depth and water content based on potential ET and a soil cover index based on aboveground biomass. Plant water evaporation is simulated as a linear function of potential ET, leaf area index (LAI), root depth (from crop growth model), and soil water content.

The crop growth model used in SWAT is a simplification of the EPIC crop model (Williams et al., 1984). A single model is used for simulating both annual and perennial plants. Phenological crop growth from planting is based on daily-accumulated heat units above a specified optimal base temperature for each crop, and the crop biomass is accumulated each day based on the intercepted solar radiation until harvest. The canopy cover, or LAI, and the root development are simulated as a function of heat units and crop biomass.

Study Area

Six watersheds located in major river basins across Texas were selected for this study (fig. 1). These watersheds were selected to simulate hydrology under diverse vegetation, topography, soil, and climatic conditions. The watershed characteristics and the land use distribution of each watershed are given in table 1 and table 2, respectively. Pasture is the dominant land use in all of the watersheds except the Red River and Colorado watersheds. In the Red River and Colorado watersheds, agriculture and rangeland are the respective dominant land uses. A significant portion of the Guadalupe and San Antonio watersheds is forestland. The elevation difference between the upstream and downstream ends of all the watersheds is greater than 400 m, except for Lower Trinity, which is 180 m. Mean annual precipitation varies considerably among the different watersheds and within each watershed (table 1), which represents a wide spectrum of precipitation regimes in Texas.

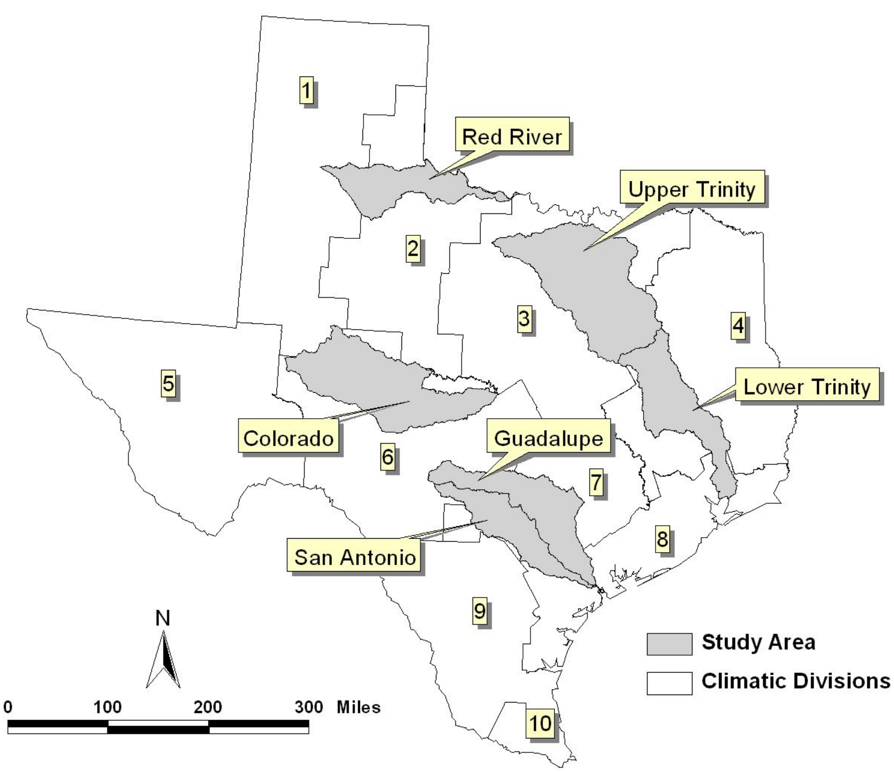


Figure 1. Texas climatic divisions and locations of six watersheds.

Table 1. Watershed characteristics.

Watershed	USGS 6-digit Hydrologic Cataloging Unit Number	Area (km^2)	Number of 4 × 4 km Sub-basins	Elevation[a] (m)	Mean Annual Precipitation[b] (mm)
Upper Trinity	120301	29664	1854	78 - 408	729 - 1084
Lower Trinity	120302	15200	950	0 - 180	978 - 1368
Red River	111301	11632	727	295 - 1064	488 - 748
Guadalupe	121002	14736	921	6 - 728	712 - 990
San Antonio	121003	10320	645	7 - 688	693 - 976
Colorado	120901	25656	1541	400 - 886	365 - 708

[a] USGS 7.5 min DEM (USGS, 1993).
[b] NRCS PRISM annual precipitation data (Daly et al., 1994).

Table 2. Land use distribution in watersheds obtained from the USGS 1992 National Land Cover Data (NLCD, 1992).

Watershed	Land Use (%)						
	Agriculture	Urban	Forest	Pasture	Rangeland	Wetland	Water
Upper Trinity	5.1	8.8	1.6	79.9	0	0.4	4.2
Lower Trinity	1.5	0.8	34.2	54.2	0	6.2	3.1
Red River	49.9	0.1	0	34	16	0	0
Guadalupe	1.8	1.1	30.4	59.1	6.2	1.1	0.3
San Antonio	4.3	8.5	32.9	47	6.4	0.6	0.3
Colorado	10.3	0.5	1.1	4.9	82.9	0	0.3

Model Inputs

Weather inputs needed by SWAT are precipitation, maximum and minimum air temperatures, wind velocity, relative humidity, and solar radiation. Except daily air temperature and precipitation, daily values of weather parameters were generated from average monthly values using the weather generator WXGEN (Sharpley and Williams, 1990) within SWAT. For this study, daily precipitation measured at 903 weather stations and maximum and minimum air temperatures measured at 492 weather stations across Texas were obtained from the National Climatic Data Center (NCDC) (fig. 2). The data were obtained for the past 102 years (1901-2002) for the purpose of simulating a historical record of soil moisture for the watersheds. Missing precipitation and temperature records of individual stations were filled from the nearest stations where data were available.

The USDA-NRCS State Soil Geographic Database (STATSGO; USDA-SCS, 1992) soil association map (1:250,000 scale) and datasets were used for obtaining soil attributes. The physical soil properties needed by SWAT are texture, bulk density, available water capacity, saturated hydraulic conductivity, and soil albedo for up to ten soil layers. The land use/land cover data are the 1992 National Land Cover Data (NLCD) at 30 m resolution, obtained from the USGS. The elevation data are the 7.5 min Digital Elevation Model (DEM) obtained at 30 m resolution from the USGS.

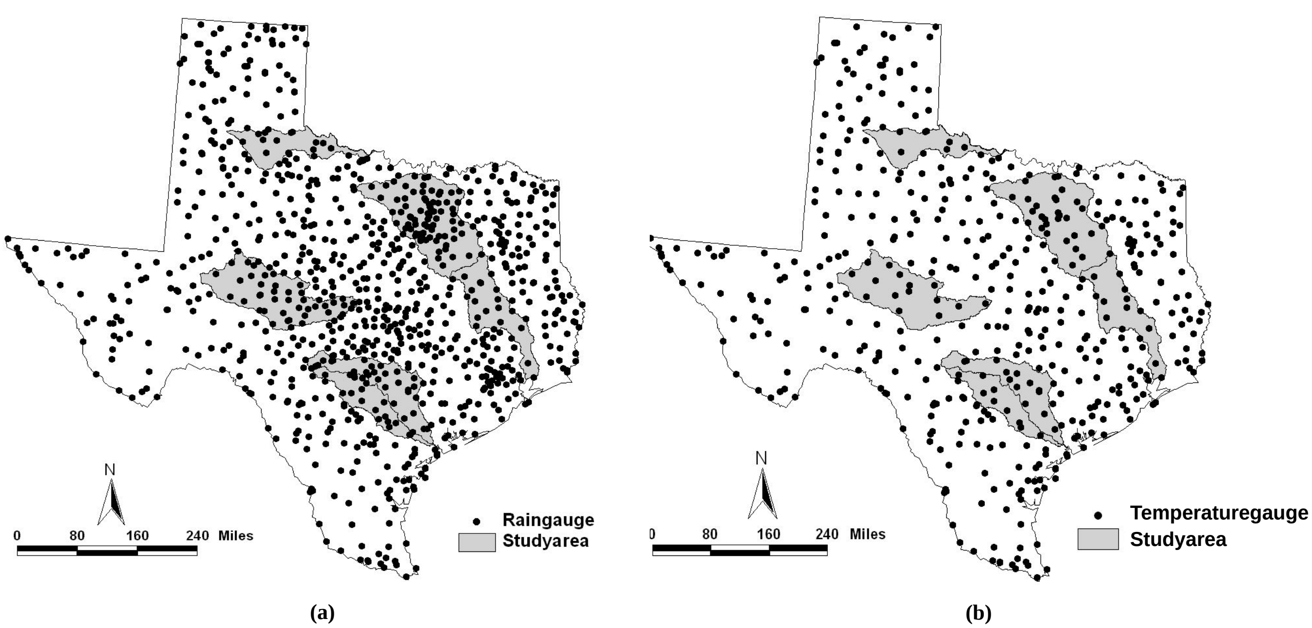


Figure 2. NCDC weather stations that measure (a) precipitation (b) temperature.

Model Setup

For this study, a spatial resolution of 4 × 4 km was chosen to capture adequate spatial variability over a large watershed and for future integration studies with NEXRAD radar precipitation that has a similar spatial resolution. The ArcView interface for the model (Di Luzio et al., 2002b) was used to extract model parameters from the GIS layers with minor modifications to delineate sub-basins at 4 × 4 km resolution. Each watershed was divided into several sub-basins (grids) at 4 × 4 km resolution, using a DEM resampled to the same resolution (e.g., Upper Trinity was divided into 1854 sub-basins, each 4 × 4 km). Topographic parameters and stream channel parameters were estimated from the DEM. A dominant soil and land use type within each sub-basin was used to develop soil and plant inputs to the model. Initial curve number values were assigned based on the soil hydrologic group and vegetation type for an average antecedent moisture condition (USDA-SCS, 1972). Based on the land use assigned for each grid, plant growth parameters like maximum leaf area index, maximum rooting depth, maximum canopy height, and optimum and base temperatures, were obtained from a crop database within SWAT. Corn was assumed to be the crop grown in all agricultural land. The planting and harvest dates of crops and active growing period of perennials were scheduled using a heat unit scheduling algorithm (Arnold et al., 1998). The weather data for each sub-basin was assigned from the closest weather station. In order to simulate the natural hydrology and long-term soil moisture balance, all the crops in the watershed were assumed to be rainfed, and hence irrigation was not considered in this study.

Calibration and Validation of Stream Flow

Stream flow, measured at 24 USGS stream gauges located in six watersheds, was used for calibrating and validating the model. Only those stream gauges that are not affected by reservoirs, diversions, or return flows were selected for model calibration and validation. Five years of measured stream flow data were used for model calibration. The calibration period for each USGS station was selected after careful analysis of the stream flow time series. The five contiguous years of stream flow that had fair distribution of high and low flows were selected for model calibration. This was done to obtain optimal parameters that improve the model simulation in both wet and dry years.

The model was calibrated using the VAO5A Harwell library subroutine (Harwell, 1974), a non-linear auto-calibration algorithm. VAO5A uses a non-linear estimation technique known as the Gauss-Marquardt-Levenberg method to estimate optimal model parameters. The objective function is to minimize the mean squared error in the measured versus simulated stream flow. The strength of this method lies in the fact that it can generally estimate parameters using fewer model runs than other estimation methods (Demarée, 1982). The model parameters selected for auto-calibration using the VAO5A algorithm are listed in table 3. These model parameters were selected because of the sensitivity of surface runoff to them, as reported in several studies (Arnold et al., 2000; Lenhart et al., 2002; Santhi et al., 2001; Texas Agricultural Experiment Station, 2000). In order to prevent the algorithm from choosing extreme parameter values, the model parameters were allowed to change only within reasonable limits (table 3).

After optimal calibration of parameters was achieved, the model was validated at each of the 24 USGS calibration stations using 10 to 30 years of observed stream flow data, based on data availability. As the objective of this study was to develop the soil moisture data on a weekly time step, the measured and simulated stream flow was also averaged over a weekly period for statistical comparison. The coefficient of determination (R^2) and the coefficient of efficiency (E) (Nash and Sutcliffe, 1970) were the statistics used to evaluate the calibration and validation results. The R^2 and E values are calculated as follows:

$$R^2 = \left(\frac{\sum_{i=1}^{N} \left(O_i - \overline{O}\right)\left(P_i - \overline{P}\right)}{\sqrt{\sum_{i=1}^{N} \left(O_i - \overline{O}\right)^2} \sqrt{\sum_{i=1}^{N} \left(P_i - \overline{P}\right)^2}} \right)^2 \qquad (1)$$

$$E = 1.0 - \frac{\sum_{i=1}^{N} \left(O_i - P_i\right)^2}{\sum_{i=1}^{N} \left(O_i - \overline{O}\right)^2} \qquad (2)$$

where

O_i = observed stream flow at time i
P_i = predicted stream flow at time i
$\overline{O}$ = mean of the observed stream flow
$\overline{P}$ = mean of the predicted stream flow
N = number of observed/simulated values.

Table 3. Parameters used in model calibration.

Parameter	Description	Calibration Range
CN2	Moisture condition II curve number	±20%
SOL_AWC	Available water capacity	±20%
SOL_K	Saturated hydraulic conductivity	±20%
ESCO	Soil evaporation compensation coefficient	0.10 to 0.95
CANMX[a]	Maximum canopy storage	0 to 20 mm
GW_REVAP	Groundwater revap coefficient	0.05 to 0.40
RCHRG_DP	Deep aquifer percolation coefficient	0.05 to 0.95
GWQMN	Threshold water level in shallow aquifer for base flow	0 to 100 mm
REVAPMN	Threshold water level in shallow aquifer for revap or percolation to deep aquifer	0 to 100 mm
CH_K(2)	Effective hydraulic conductivity of main channel	0 to 50 mm h^{-1}

[a] Maximum canopy storage is calibrated only for forest and heavy brush infested rangeland. For other land cover types, CANMX is 0 mm.

The value of R^2 ranges from 0 to 1, with higher values indicating better agreement between predicted and observed stream flow. The value of E ranges from $-\infty$ to 1, with E values greater than zero indicating that the model is a good predictor. R^2 evaluates only linear relationships between variables; thus, it is insensitive to additive and proportional differences between model simulations and observations (Willmott, 1984). However, E is sensitive to differences in the means and variances of observed and simulated data and hence is a better measure to evaluate model simulations (Legates and McCabe, 1999).

Soil Moisture and Vegetation Index

Stream flow is often the only component of the water balance that is regionally observed and, hence, widely used for calibrating hydrologic models. However, stream flow accounts for a smaller fraction of the hydrologic component than ET and soil moisture. In the current study, soil water is the hydrologic component of interest, and it would be ideal to use soil moisture and/or ET for calibration if the measured data were available at the study area in a natural hydrologic setting (without irrigation). Due to a lack of measured soil moisture and ET data, a pseudo indicator of soil moisture condition, the normalized difference vegetation index (NDVI), was used to analyze the model's predicted soil moisture.

NDVI is a vegetation index obtained from red and infrared reflectance measured by satellite. It is an indicator of photosynthetic activity, greenness, and health of vegetation (DeFries et al., 1995). Among various stress factors that affect vegetation, water stress is an important factor that affects photosynthetic activity and greenness of the vegetation. Farrar et al. (1994) found that NDVI and soil moisture are well correlated in the concurrent month of the growing season. Hence, NDVI can be a useful indicator to analyze the simulated soil moisture during the active growing season of the crop and to determine the usefulness of soil moisture for drought monitoring.

Ten-day NDVI composite data measured by NOAA-AVHRR satellite from 1982 to 1998 at a spatial resolution of 8 × 8 km was used for this study. The satellite data was resampled to 4 × 4 km to match the sub-basin resolution used in this study and was linearly interpolated between two 10-day composites to get weekly NDVI data. The weekly NDVI data were correlated with weekly simulated soil moisture to evaluate the soil moisture predictions of the hydrologic model.

Results and Discussion

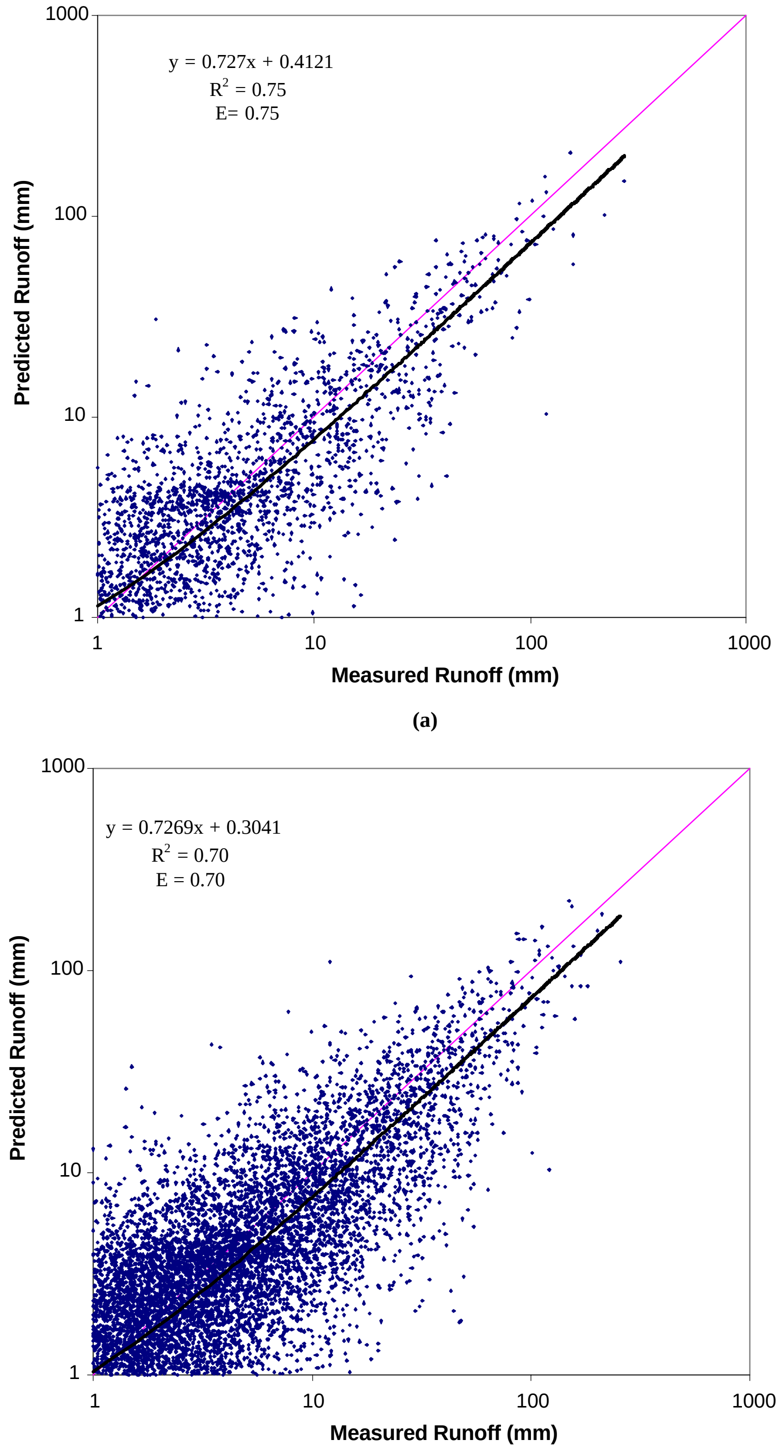
Calibration and Validation of Stream Flow

The model was calibrated using the non-linear auto-calibration algorithm VAO5A (Harwell, 1974), and selected model parameters were changed within reasonable limits, as indicated in table 3. The model was calibrated using five

Table 4. Calibration and validation statistics at 24 USGS stream gauges in six watersheds.

USGS Gauge No.	Calibration Years	Calibration No. of Years	Calibration R^2	Calibration E	Validation Years	Validation No. of Years	Validation R^2	Validation E
Upper Trinity								
08042800	1980 to 1985	6	0.91	0.90	1962 to 1997	36	0.83	0.81
08048800	1962 to 1967	6	0.72	0.66	1962 to 1972	11	0.70	0.59
08051500	1986 to 1990	5	0.90	0.87	1962 to 1997	36	0.80	0.80
08053500	1986 to 1990	5	0.82	0.80	1962 to 1997	36	0.70	0.68
08057450	1970 to 1974	5	0.70	0.68	1970 to 1978	9	0.68	0.67
08061540	1980 to 1985	6	0.80	0.77	1969 to 1997	29	0.70	0.69
08062900	1977 to 1982	6	0.73	0.69	1963 to 1986	24	0.71	0.68
08064100	1988 to 1993	6	0.76	0.74	1984 to 1997	14	0.70	0.66
Lower Trinity								
08065200	1967 to 1972	6	0.54	0.54	1963 to 1997	35	0.63	0.63
08065800	1979 to 1984	6	0.83	0.80	1968 to 1997	30	0.75	0.70
08066100	1976 to 1981	6	0.68	0.68	1975 to 1984	10	0.67	0.66
08066200	1989 to 1994	6	0.70	0.68	1975 to 1995	21	0.64	0.62
08064100	1988 to 1993	6	0.76	0.74	1984 to 1997	14	0.70	0.66
Red River								
07307800	1978 to 1981	4	0.56	0.52	1975 to 1992	18	0.65	0.55
07308200	1976 to 1981	6	0.85	0.85	1962 to 1982	21	0.67	0.60
Guadalupe								
08167000	1986 to 1990	5	0.82	0.75	1962 to 1992	31	0.68	0.66
08171000	1985 to 1990	6	0.87	0.85	1962 to 1992	31	0.78	0.76
08173000	1985 to 1990	6	0.90	0.90	1962 to 1992	31	0.76	0.73
San Antonio								
08178800	1972 to 1977	6	0.87	0.85	1965 to 1978	14	0.81	0.80
08179000	1972 to 1977	6	0.66	0.57	1965 to 1977	12	0.70	0.68
Colorado								
08128000	1938	1	0.92	0.92	1959	1	1.00	0.97
08128400	1974	1	0.99	0.99	1986	1	0.98	0.85
08136500	1956 to 1961	6	0.87	0.78	1940 to 1961	22	0.78	0.74
08144500	1935 to 1938	4	0.91	0.88	1974 to 1975	2	0.92	0.90

years of measured stream flow data and validated using a long record (>5 years) of measured stream flow data whenever available. Measured stream flow data from 24 USGS stream gauge stations was used, with about 125 and 490 combined station years of stream flow data for model calibration and validation, respectively. Weekly stream flow statistics during the calibration and validation periods at the 24 USGS stream gauges in the six watersheds are given in table 4. In general, the simulated stream flow compared well with the measured stream flow, with R^2 values greater than 0.7 and E values greater than 0.65 for most of the stream gauges. The log-log scatter plots of measured and simulated stream flows at all 24 USGS stream gauges during the calibration and validation period are shown in figure 3. The overall R^2 and E values were 0.75 for the calibration period and 0.70 for the validation period.



(a)

(b)

Figure 3. Weekly measured and predicted stream flows (log-log scale) at all 24 USGS stream gauges: (a) calibration (b) validation.

Analysis of time series plots for individual stream gauges showed that most of the differences between the observed and measured rainfall/stream flow data occurred due to non-availability of a rain gauge at the watershed or precipitation events that were not measured by a rain gauge nearest to the watershed. A few runoff peaks observed in each of the 24 USGS stream gauges either did not match with the measured precipitation data to the same intensity or the precipitation event was not at all captured by the rain gauge at or near the watershed. These missed precipitation events resulted in reduced R^2 and E statistics at a few USGS stream gauges. Using spatially distributed rainfall from NEXRAD radar could improve the model results. Overall, the model was well calibrated (R^2 = 0.75 and E = 0.7), and the simulated stream flow compared well with the observed stream flow under varying land use, hydrologic, and climatic conditions.

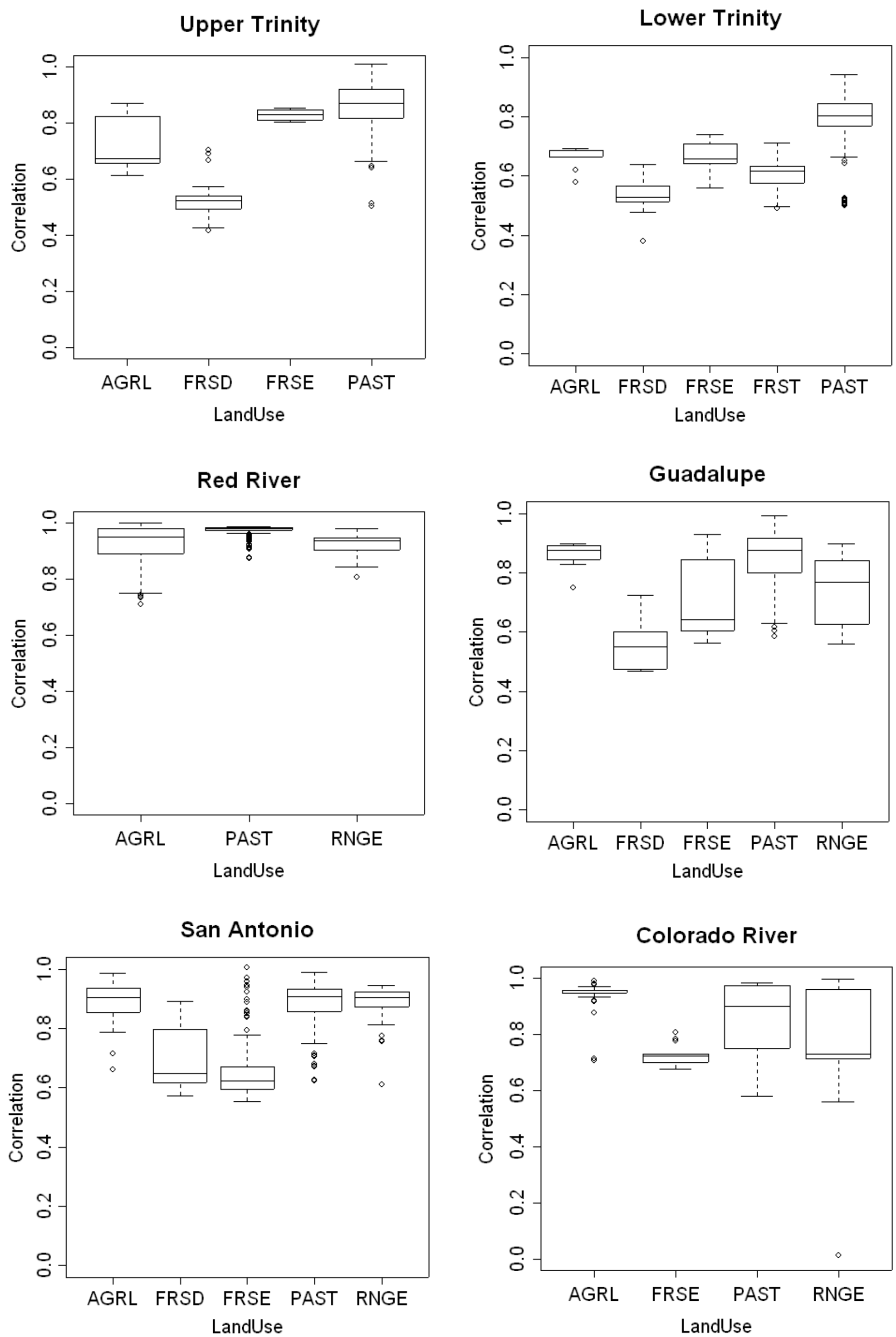


Figure 4. Ratio of growing season ET to growing season precipitation at the six watersheds (AGRL = agriculture, PAST = pasture, RNGE = rangeland, FRSE = evergreen = forest, FRSD = deciduous forest, and FRST - mixed forest).

EVAPOTRANSPIRATION

Analysis of the simulation results at each watershed showed that actual growing season ET (March through October) was about 45% to 90% of growing season precipitation (P) and varied with land use and the climatic zone of each watershed. The distributions of ET/P ratio among each land use for the six watersheds are shown using box-and-whisker plots in figure 4. Upper Trinity and Lower Trinity had low ET/P ratios compared to the other watersheds due to a high amount of precipitation in these watersheds. Red River had the highest ET/P ratio, with over 90% of precipitation returning as ET for all the land use classes in the watershed. Irrespective of the watershed, agriculture and pastureland had the highest ET/P ratio, with 70% to 90% of precipitation returning to the atmosphere as ET. This was because agriculture and pastureland were mainly located in soils with high available water capacity. Thus, more water was stored from precipitation and was available for ET when compared to soils of low water holding capacity. Dugas et al. (1999) measured ET by the Bowen ratio/energy balance method for Bermuda grass, native prairie, and sorghum at the Blackland Research Center in Temple, Texas, which has an average annual precipitation of about 880 mm. The measured ET reported by Dugas et al. (1999) during the growing season (March through October of 1993 and 1994) accounted for about 75% to 90% of the growing season precipitation. This matches well with the model results and indicates that the model was able to simulate the growing season ET of pasture and agriculture land within reasonable limits.

ANALYSIS OF SIMULATED SOIL WATER USING NDVI

Stream flow was the only water balance component that was widely available for the model calibration and validation. The ability of the model to simulate soil water could not be evaluated quantitatively due to a lack of measured data. Hence, simulated soil water was analyzed using NDVI measured by NOAA-AVHRR satellite. The weekly NDVI was compared with simulated average weekly soil water for each sub-basin during the active phase of the growing season (April to September) from 1982 to 1998 (except 1994). A lag analysis was performed with the current week's NDVI and the simulated soil water in the concurrent week and past four weeks. The lag analysis showed that NDVI lags behind simulated soil water by at least one week for most of the sub-basins. This was expected because it takes some time for the plants to respond to the water stress in the root zone. However, the lag between NDVI and soil water was not a constant and varied from year to year for the same land use and sub-basin. This could be due to the difference in the onset of seasonal precipitation from year to year and the quantity of precipitation. Nevertheless, for most of the sub-basins, the correlation between NDVI and soil water at zero lag was only slightly less than the maximum correlation obtained at a certain lag. The distributions of maximum correlation obtained from lag analysis between NDVI and soil water among each land use within a watershed is given as a box-and-whisker plot in figure 5. Except for Lower Trinity, in general, there is a good correlation between NDVI and simulated soil water for agriculture and pastureland cover types ($r \sim 0.6$).

The distributions of correlations between NDVI and soil water for agricultural sub-basins for each year at six watersheds are shown as box-and-whisker plots in figure 6. The correlations were as high as 0.8 during some years, yet low in other years. In general, Upper Trinity had better correlation between NDVI and soil water than the other watersheds. This is because there is less irrigation activity in this watershed and the crop growth depends mostly on soil water replenished by rainfall. In contrast, a large portion of agricultural lands in the Red River and Colorado River watersheds are under irrigation. Some agricultural lands in Red River grow winter wheat that has a different growing season than corn. It is a common agricultural practice to grow corn and wheat during alternate years in the same agricultural field. Hence, there was a wide distribution of correlation in the Red River watershed when compared to other watersheds. The lower correlation between NDVI and soil water for agricultural lands during certain years could be due to several reasons. For example, in Upper Trinity, the lower correlations during 1989 and 1992 were because of high precipitation during those years for which the NDVI response was much different from that of other years. Similarly, during 1996, much less precipitation was received during the growing season. Hence, the NDVI was much less, indicating no crop growth during that year. This was the same case for a lower correlation at the Guadalupe River watershed during 1996 and at the Colorado watershed during 1988 and 1989. In Lower Trinity, there were only a few agricultural lands and they were scattered adjacent to the wetlands close to Gulf of Mexico. These agricultural lands predominantly grow rice. Further, among the six study areas, Lower Trinity is located in a high rainfall zone. Because of the high annual rainfall, the NDVI did not fluctuate much with changes in soil water. Thus, the correlation between NDVI and SW was low at Lower Trinity.

The distributions of correlations between NDVI and soil water for pasture sub-basins for each year at six watersheds are shown as box-and-whisker plots in figure 7. In general, pasture had a wider spread of correlation distribution across sub-basins than agriculture. This could be because pasture is cut and grazed all summer during the growing season. Cutting and grazing of pasture could change the NDVI values sensed by satellite due to lesser leaf area. Hence, the NDVI fluxes were not purely due to natural soil moisture fluctuations alone. The correlation was generally less at Lower Trinity, except during some years. Analysis of precipitation data showed that the correlation between NDVI and soil water was markedly high at Lower Trinity during the dry years 1985 and 1988. This could be because Lower Trinity is wet during most parts of the year, with an annual precipitation of more than 1000 mm, and has a lesser evaporative fraction for all land use types when compared to the other watersheds (fig. 4). Hence, the fluctuations in soil moisture during normal or high precipitation years do not seem to affect the NDVI much, except during dry years when the available soil moisture becomes less at the root zone.

The NDVI responded well to changes in soil water for agriculture and pasturelands because they have shallow root systems that can extract water only from the root zone. However, the NDVI for brush species in rangeland and trees of forestland did not respond well to the simulated soil water. Hence, a lagged correlation analysis was conducted with current NDVI and cumulative precipitation of the past four, eight, and twelve weeks. The analysis (the results are not presented here) yielded similar or lesser correlations than that of soil water. Thus, with the current understanding of the

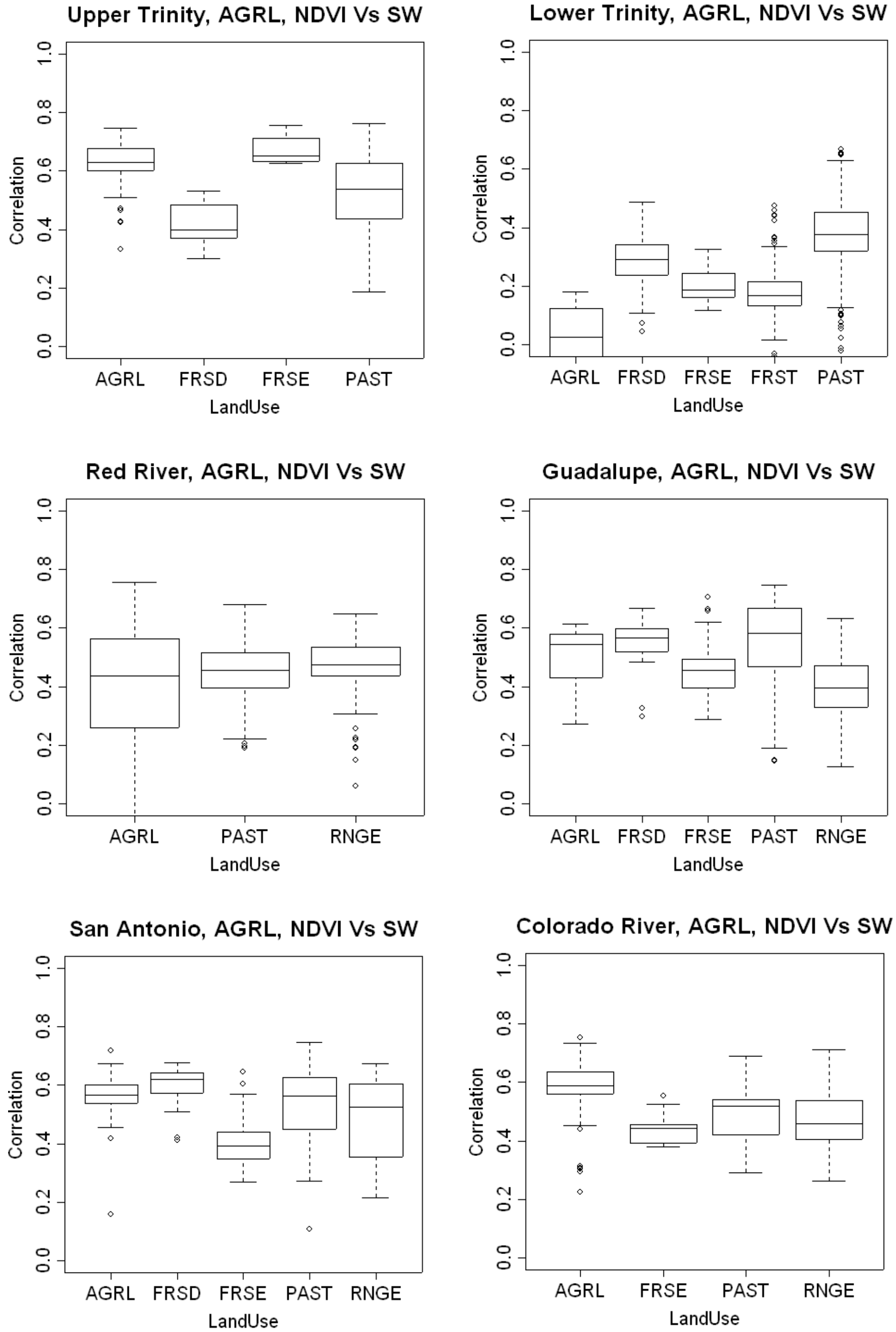


Figure 5. Correlations of weekly NDVI and simulated soil water during active growing period (April-September) of 1982-1998 for all sub-basins within each watershed (AGRL = agriculture, PAST = pasture, RNGE = rangeland, FRSE = evergreen forest, FRSD = deciduous forest, and FRST = mixed forest).

processes, it was difficult to explain the NDVI responses of rangeland and forestland in terms of soil water or precipitation alone, and this result needs further analysis.

Summary and Conclusions

The hydrologic model SWAT was used for developing a long-term soil moisture dataset at a spatial resolution of 4 × 4 km and at a weekly temporal resolution. The hydrologic model was calibrated for stream flow using an auto-calibration algorithm and validated over multiple years. The overall R^2 and E values on weekly stream flow were 0.75 for the calibration period and 0.70 for the validation period. Most of the differences between the measured and simulated stream flow occurred due to the lack of a rain gauge network in the watershed. This could be overcome by using spatially distributed RADAR rainfall data. Overall, the model was well calibrated, and the simulated stream flow compared well with the observed stream flow under varying land use, hydrologic, and climatic conditions.

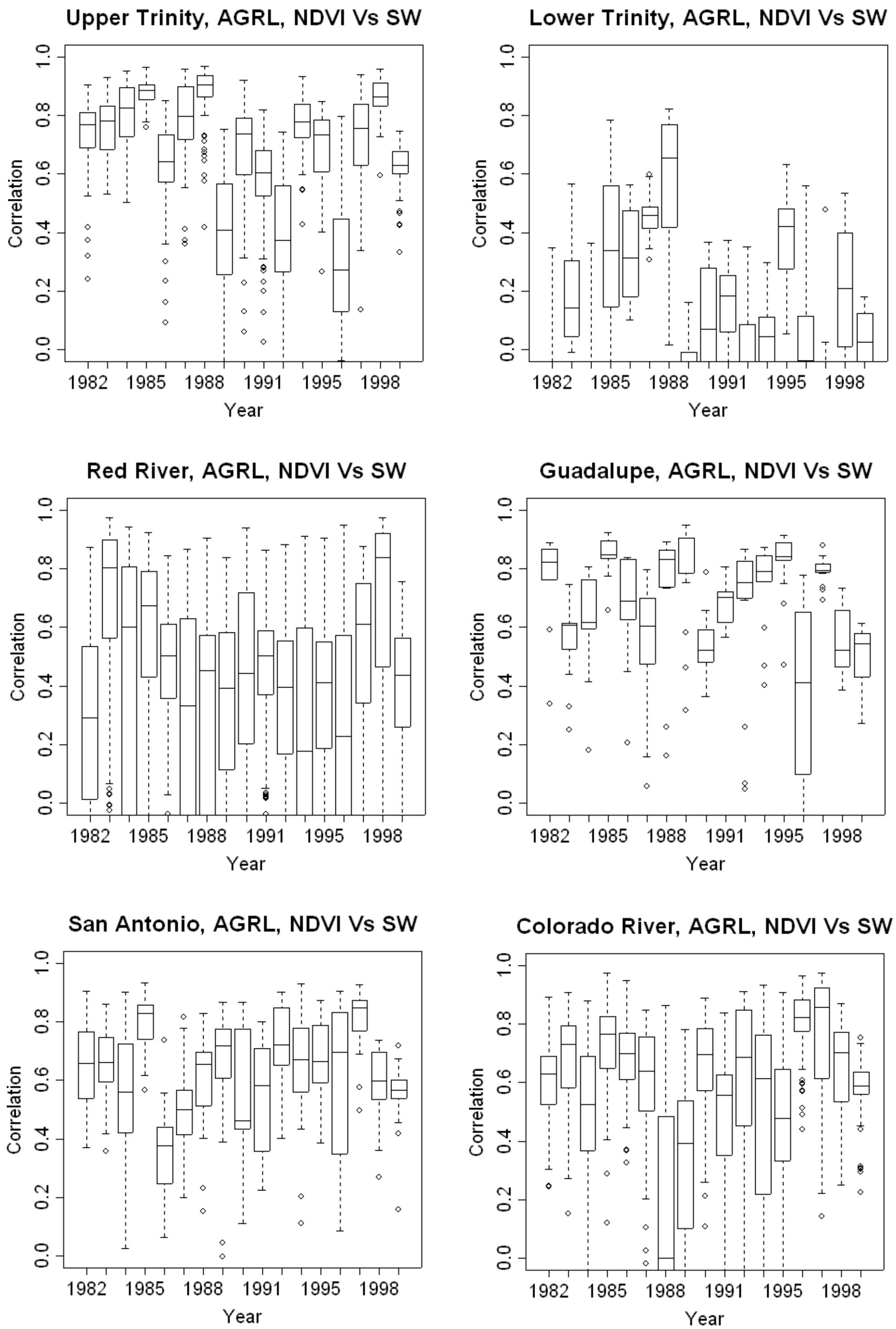


Figure 6. Correlations of weekly NDVI and simulated soil water during active growing period (April-September) for agriculture land use within each watershed.

Due to a lack of measured evapotranspiration or soil moisture data, simulated soil moisture was analyzed using 16 years of NDVI data. Analysis showed that the simulated soil moisture was well correlated with NDVI for agriculture and pastureland use types (r ~ 0.6). The correlations were as high as 0.8 during certain years, indicating that the model performed well in simulating the soil moisture. There was a lag of at least one week between the simulated soil moisture and NDVI because it takes some time for the plant to respond to the water stress in the root zone. In high-precipitation zones like Lower Trinity, NDVI was well correlated only during the dry years because NDVI does not fluctuate much during normal or wet years due to high available soil moisture. With the current understanding of the processes, it was difficult to explain the NDVI responses of rangeland and forestland in terms of soil water or precipitation alone, and this result needs further analysis.

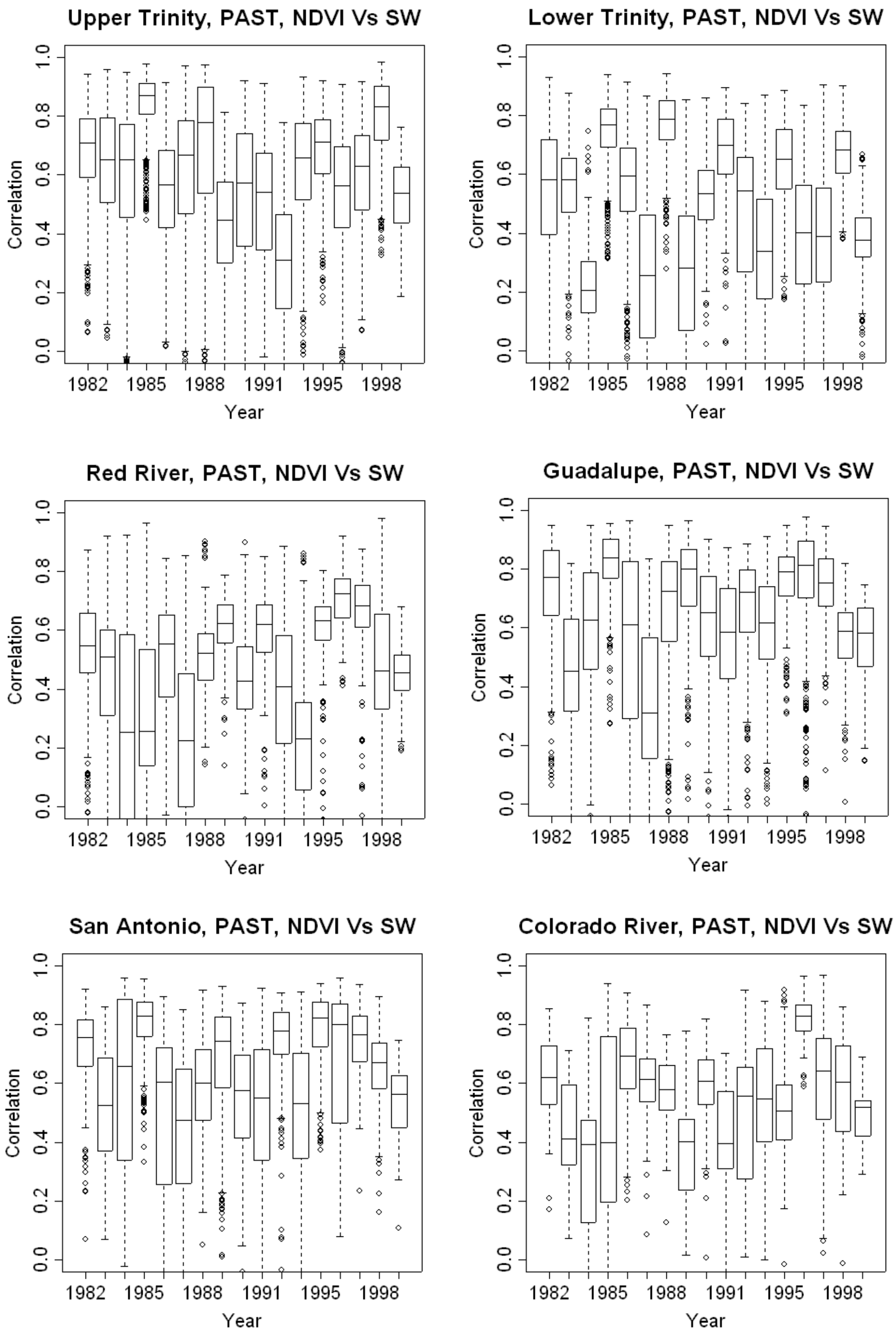


Figure 7. Correlations of NDVI and simulated soil water during active growing period (April-September) for pasture land use within each watershed.

The current study showed that NDVI could be used as a good indicator to evaluate the hydrologic model in terms of soil water prediction when measured soil moisture or evapotranspiration data are not available. Further, as NDVI responds well to soil water, it demonstrates that soil water can be a good indicator of crop stress and onset of agricultural drought under rainfed (non-irrigated) conditions in semi-arid climates. However, further research is needed to study the behavior of NDVI responses to soil moisture in high-precipitation zones (e.g., Lower Trinity) of humid and sub-humid climates. The simulated soil moisture data can be used in subsequent studies to develop a drought indicator for agricultural drought monitoring.

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