This is an Accepted Manuscript of an article published in the Journal of Hydrology in 2011, available online: doi:10.1016/j.jhydrol.2011.08.045

Annual and interannual variations in terrestrial water storage during and following a period of drought in South Carolina, USA

Mirza M. Billah[a], Jonathan L. Goodall[a]

[a]*Department of Civil and Environmental Engineering, University of South Carolina, 300 Main Street, Columbia, SC 29208 USA*

Abstract

The goal of this research is to quantify variations in both space and time of water stored in the terrestrial environment within South Carolina during and following a period of drought. We use a water balance approach that synthesizes observed and modeled hydrologic fluxes for sub-watersheds defined by the drainage area between streamflow gaging stations. We apply the approach for the period 1998-2007 to study the impact of a drought that occurred during the early part of this time period on terrestrial water storage within the state. Results from the analysis provide evidence of distinct annual and interannual variation in water storage for different regions of the state, with the fall season having a water surplus and spring season exhibiting a water deficit. The impact of the drought varied for different regions of the state depending in part on hydrogeological conditions including soil type and depth to the groundwater level. Comparing estimates of rate of change in terrestrial water storage with observed groundwater levels, as an independent validation of the terrestrial water storage estimations, shows that many of the sub-watersheds within the state exhibited similar patterns between vari-

ation of rate of change in terrestrial water storage estimates and observed groundwater levels during the period of analysis, as expected. However, some sub-watersheds did not follow general annual and interannual variations in groundwater level or in estimated rate of change in terrestrial water storage relative to neighboring sub-watersheds. We speculate that these abnormalities may be related to human influences that alter local water storage trends within specific sub-watersheds of the state, however future work is needed to further investigate this possible explanation. We conclude through this study that the water balance approach presented is a simple yet valuable means for estimating variations in water availability at a regional spatial scale by synthesizing existing observations and model output data within a geospatially-explicit context.

Keywords: Regional-scale water resources, drought, water availability, water balance

Introduction

South Carolina experienced a severe drought between 1998 and 2002. During this time, precipitation decreased by 10-30% from normal levels resulting in reduced streamflows and groundwater levels throughout the state (Badr et al., 2004; Gellici et al., 2004). The drought presented challenges to the state such as meeting water supply needs for human and industrial purposes, salt water intrusion in the coastal region of the state, and decreased water levels in lakes and groundwater aquifers. The drought intensified water rights issues in the state as well because South Carolina shares two of its major river basins with neighboring states: the Savannah River with Georgia and the Catawba River with North Carolina. Growing water demands and increased hydrologic variability due to global climate change (Oki and Kanae, 2006) will likely intensify the challenges faced by the state during future droughts. Other regions of the world facing similar challenges also require techniques for understanding regional water resources under a variety of demands and stresses. We present research that investigates an approach for quantifying regional scale water balances through an application case study for river basins whose rivers flow through South Carolina.

Hydrologic modeling and analysis can aid in this problem by providing estimates of future water availability under changing conditions such as climate change, land use change, and increasing water demands (e.g., Lettenmaier et al., 1999; Rossi et al., 2008; Tung and Haith, 1995; Legesse et al., 2003; Wurbs et al., 2005). Detailed, physically-based models of regional-scale hydrologic systems used to address such questions can be problematic for reasons that have been well described in the literature (e.g., Grayson et al., 1992; Jakeman and Hornberger, 1993; Beven, 2002; McDonnell et al., 2007). Part of the problem has been that, at the river-basin-scale, hydrology is subject to complex interactions between physical, biological, and social systems, and no model is capable of addressing all of the interactions at play in watershed systems. Furthermore, those models that do attempt to simulate such interactions are difficult to parameterize and calibrate at a regional scale due in part to a lack of data describing system parameters, initial conditions, and boundary conditions. This leads to the need for uncertainty analysis both in terms of process representations, system parameters, and forcing data (Minville et al., 2008; Yang et al., 2008; Fekete et al., 2004; Christensen and

Lettenmaier, 2007).

Alternative approaches have been proposed for estimating basin-scale water resources that include developing statistical tools for time series records (e.g., Novotny and Stefan, 2007), analyzing of components of the hydrologic cycle (e.g., baseflow recession as in Wang and Cai, 2009), or using semiemperical relationships for coupled water-energy balances such as the Budyko hypothesis (Wang et al., 2009; Yang et al., 2007). One such approach, developed and applied primarily in the climate science community for quantifying changes in basin-scale water resources, is the so called Moisture Convergence minus Runoff (MCR) approach (Rasmusson, 1967; Seneviratne et al., 2004; Yeh et al., 1998). In this approach, water balance equations for the terrestrial and atmospheric portions of the hydrologic cycle are equated to estimate the rate of change in terrestrial water storage (TWS). TWS is a term that includes all stores of water within the terrestrial environment including soil moisture, snow, groundwater, and surface water. The MCR approach has been applied to river basins within Europe, Asia, North America, and Australia (Hirschi et al., 2006, 2007), demonstrating that the MCR approach can successfully estimate TWS on a monthly time step after comparing estimates with independent measures of TWS including soil moisture, groundwater levels, and snow depths. More recent work by Zeng et al. (2008) proposed a modification to the MCR approach where, instead of equating water balance equations for the surface and atmospheric systems, the surface water balance equation is solved directly by using observations of precipitation and stream discharge along with estimates of evaporation derived from climate reanalysis to quantify changes in TWS. This approach, termed the Precipitation, Evapotranspiration, and Runoff (PER) method, was shown to be more robust in estimating TWS for the Amazon Basin and the Mississippi Basin when compared to the MCR approach and validated against independent estimations of TWS components (Zeng et al., 2008). Details of the PER method and how it compares to the more commonly used MCR method are provided in the Methodology Section of this paper.

One of the major challenges in applying a water balance method is quantifying evapotranspiration at a regional spatial scale. The North American Regional Reanalysis (NARR) product is considered to be best of the renalysis datasets, in part because it has an improved land surface model (Ek et al., 2003; Ruiz-Barradas and Nigam, 2006). Another possible means for quantifying evapotranspiration is using remote sensing products. This approach is promising, although it requires calibrate of the remote sensing evaportranspiration estimates based on local conditions (Ferguson et al., 2010), and it is uncertain if remote sensing observations of evaporation will be effective at closing the water balance (Sheffield et al., 2009). Future research would be required to address the benefit of remote sensing derived evapotranspiration estimates compared to NARR evaporation estimates. Despite the uncertainty of evapotranspiration estimates, a comparative analysis of the estimated evapotranspiration from different climate model and reanalysis datasets (ERA40, NCEP2, NARR, and SLand) in the PER model suggested that evapotranspiration estimates have a small variation relative to difference between observed precipitation and streamflow, therefore capturing variation in precipitation and streamflow is most important for estimating the rate of change in TWS (Zeng et al., 2008).

In this paper we use the PER method with NARR estimates of evapotranspiration to understand how water resources within South Carolina responded during and following the 1998-2002 period of drought. Using observational data from streamflow and precipitation monitoring networks along with estimations of evaporation from climate model reanalysis products, we estimated rate of change in TWS on a monthly time step for 54 sub-watersheds where stream inflow and outflow were monitored for the period 1998-2007. The sub-watersheds were defined using geospatial data describing the terrain, hydrography, and streamflow gaging network and account for 60% of the surface area within the state. We then compared estimates of rate of change in TWS obtained using the PER method with groundwater levels in the state to determine how both measures of water storage varied during and following the period of drought.

The change in TWS measured from GRACE observations, while being a good source for independent validation of the estimated change in terrestrial water storage derived from various land surface hydrologic models (Wahr et al., 2004), is not appropriate for this study do to the scale of the sub-watersheds used. Swenson et al. (2003) showed that the accuracies of measuring monthly change in TWS from GRACE are better than 1 cm of equivalent water thickness with spatial extent of 4.0×10^5 km^2 or larger, and these accuracies increase with the increase in the spatial extent. Given that the total area of South Carolina is one-fourth the recommended area for application of GRACE data, we could not justify the use of GRACE as a means for validating our analysis estimates of change in TWS.

Following a brief description of the study area, we next describe our methodology for the study including a more detailed description of (1) the water balance method on which this analysis is based, focusing in particular on how the PER method compares to the more common MCR method for estimating rate of change in TWS and (2) the datasets and data preparation steps carried out as a part of the analysis. We next discuss the resulting estimates of the rate of change in TWS for the state summarized in space and time, including a comparison between rate of change in TWS estimates and observed groundwater levels. Finally we conclude with a discussion of the benefits and weaknesses of the PER approach for estimating rate of change in TWS, and suggest future directions needed to improve the approach as a tool for regional-scale water resources management.

Study Area

South Carolina is located in the Southeastern United States and has an area of 82,930 km^2 (32,020 mi^2) from latitude $32°02'N$ to $35°13'N$ and longitude $78°32'W$ to $83°21'W$ (Figure 1). South Carolina receives on average 1220 mm (48 in) of precipitation annually, mostly in the form of rainfall. Precipitation over the state is fairly consistent for different seasons, although the coastal plain region of the state does receive more precipitation in the summer relative to other seasons, while the remaining parts of the state generally receive more precipitation in the spring months. South Carolina has hot and humid summer months with daytime temperatures averaging between 30-34 °C (86-93 °F) for most of the state. In winter months, daytime temperatures in the coastal plain average 16 °C (60 °F) and decrease as one travels inland. The Savannah, Pee Dee, Santee, and Edisto Rivers are the largest rivers within the state, and each of these rivers plays a major role in agricultural and industrial practices. All but one of the rivers in South Carolina are shared with neighboring states. The exception is the Edisto River whose entire watershed is within the state boundaries (Badr et al., 2004).

South Carolina has three distinct aquifer systems (Figure 1): the Piedmont and Blue Ridge crystalline rock aquifers in the northwestern portion of the state, the Southeastern Coastal Plain aquifer system in the central part of the state, and the Surficial aquifer system in the coastal region of the state (Miller, 1990). The Piedmont and Blue Ridge crystalline rock aquifers consist of bedrock overlain by unconsolidated material. While the overall hydraulic characteristics of the aquifer are similar, there is considerable local variability due to heterogeneous rock types in the region. Groundwater obtained from the aquifer is used for public supply, commercial uses, and agricultural purposes within the upper region of the state (Kenny et al., 2009). The Southeastern Coastal Plain aquifers in South Carolina consist of sand or highly permeable limestone as well as confining layers composed of clay, silt or low permeable limestone that slow the infiltration of water to the aquifer system. The aquifers are primarily recharged by diffuse deep drainage and discharge into the upper or lower coastal plain rivers (Aucott and Speiran, 1985).The Surficial aquifer system is unconfined and water entering the aquifer system is discharged quickly as baseflow to streams. This aquifer in particular is prone to saltwater intrusion during periods of drought because it extends seaward under the Atlantic Ocean. It is important to note that, although South Carolina has groundwater resources, 95% of the freshwater used in the state comes from surface water rather than groundwater resources (Kenny et al., 2009).

Methodology

Model Description

Terrestrial Water Storage (TWS) can be expressed by a water balance equation for the terrestrial portion of the hydrologic cycle

$$\frac{\partial TWS}{\partial t} = P - E + R_{in} - R_{out} \tag{1}$$

where TWS represents Terrestrial Water Storage, P is precipitation, E is evapotranspiration, and R_{in} is streamflow entering a sub-watershed and R_{out} is streamflow exiting that same sub-watershed. The more traditional Moisture Convergence minus Runoff (MCR) approach used within the climate science community for solving Equation 1 uses a second water balance equation for the atmospheric portion of the hydrologic cycle

$$\frac{\partial W}{\partial t} = -\nabla_H \cdot Q - (P - E) \tag{2}$$

where W is storage of water as vapor within the column of air above the watershed, ∇_H is the horizontal divergence operator, and Q is the integration of the water vapor flux over the column (Seneviratne et al., 2004). The method assumes that the rate of change in liquid and solid water in the air column, as well as the horizontal transport of liquid and solid water, can be neglected. Terrestrial water storage is estimated by equating Equation 1 and Equation 2 and averaging over space and time, which results in the elimination of the $P - E$ term and gives

$$\left\{ \frac{\overline{\partial TWS}}{\partial t} \right\} = -\{\overline{\nabla_H \cdot Q}\} - \left\{ \frac{\overline{\partial W}}{\partial t} \right\} - \{\overline{R}\} \tag{3}$$

where brackets around the term signifies that it is averaged temporally and a bar over the term signifies that it is averaged spatially. One disadvantage of the MCR approach is that it is limited to very large river basins with areas of at least 10^5 km^2 because the estimation can become unreliable for smaller units due to inaccurate estimates of evaporation (Yeh et al., 1998).

In contrast to the MCR method, in the PER method P and R are observed and E is estimated using a land surface model so that Equation 1 becomes

$$\frac{\partial TWS}{\partial t} = P_{obs} - E_{est} - R_{obs} \tag{4}$$

where the subscript "obs" signifies that the term is taken from observational records and "est" signifies that the term is estimated using a model. The terms in Equation 4 can be spatially and temporally averaged in a manner similar to Equation 3 to yield Equation 5.

$$\left\{ \frac{\overline{\partial TWS}}{\partial t} \right\} = \{\overline{P_{obs}}\} - \{\overline{E_{est}}\} - \{\overline{R_{obs}}\} \tag{5}$$

One disadvantage of the PER method is that it requires streamflow observations, which are only available for select locations. Furthermore, the method requires both stream inflow and outflow observations for sub-watersheds, and large gaps in monitoring of either of these flows means that PER approach cannot be applied.

Previous work applying both the MCR and PER methods for water balance calculations has noted a systematic bias in E estimated from reanalysis products when compared to $P - R$ calculated from observed data (see Zeng et al., 2008 for a complete discussion). Zeng et al. (2008) used a correction factor to adjust the estimated E values so that the long term average of $P - E^* - R$ equals zero over the entire study region, where E^* is a corrected evapotranspiration term such that $E^* = E + c$ where c is the correction factor. We determined the value of c for this study by setting the overall change in water storage for all 54 sub-watersheds and all 120 months during the study period to zero

$$\sum_{i=1}^{54}\sum_{j=1}^{120}\{\overline{P_{obs\ i,j}}\} - \left(\{\overline{E_{est\ i,j}}\} + c\right) - \{\overline{R_{obs\ i,j}}\} = 0 \tag{6}$$

where i is a sub-watershed and j is a month during the study period. Equation 6 was solved for c which was then used to calculate a corrected evapotranspiration rate E^*_{est}. This corrected evapotranspiration estimate was then used in Equation 7 to estimate rate of change in TWS with respect to time.

$$\left\{\frac{\overline{\partial TWS}}{\partial t}\right\} = \{\overline{P_{obs}}\} - \{\overline{E^*_{est}}\} - \{\overline{R_{obs}}\} \tag{7}$$

The assumption of no change in water storage over the ten year period is difficult to validate and may not be correct if portions of the study area experienced significant groundwater pumping over the period of analysis. The results of this analysis should be interpreted in light of this simplifying assumption.

We solved a discrete approximation of Equation 7 on a monthly time step for each sub-watershed identified in the state where there was a record of stream inflow and outflow. The procedure used to construct these sub-watersheds and the data used to quantify $\{\overline{P_{obs}}\}$, $\{\overline{E_{est}}\}$, and $\{\overline{R_{obs}}\}$, are described in the following section.

Data Preparation

The National Hydrography Dataset (NHD) provides a geographic representation of hydrologic features on the land surface in the United States (USEPA and USGS, 2005) (Table 1a). The NHD includes feature classes describing the location of streams, lakes, reservoirs, and other surface water bodies. An extension to the NHD named the NHDPlus adds catchment features for each river reach to the 1:100,000 scale version of the NHD. The catchments are generated using the National Elevation Dataset (NED) and terrain processing algorithms to estimate the drainage area for each NHD Flowline feature (Johnston et al., 2009). The NHD also includes information regarding the connectivity of river features that enables network-based flow tracing in upstream and downstream directions.

The procedure used to calculate the sub-watersheds in our analysis (Figure 1) was to first use linear referencing to locate active streamflow monitoring stations during the study period along the NHD stream network. We then wrote an algorithm that begins at the most downstream reach in the NHD Flowline feature class for each river basin in the state and "climbs" the network in the upstream direction in order to identify the next downstream monitoring station for each reach within the study area. With this information, and because there is a 1-1 relationship between reaches and catchments in the NHDPlus dataset, we were able to identify and then dissolve catchments within the study region that had the same downstream monitoring station. This data processing resulted in 54 sub-watersheds ranging in size from 1.20 to 3,350 km^2 for which stream inflow and outflow have been observed for the period 1998-2007.

Precipitation was estimated by using the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset (Gibson et al., 2002) (Table 1b). The precipitation data used in this analysis have a spatial resolution of approximately 4 km (2.5′) and a temporal resolution of one month. The term precipitation in context of the PRISM dataset means all forms of water that reach the earth from the atmosphere (i.e., rainfall, snow, freezing rain, hail, frost, or dew). Of these, rainfall contributes the majority of water in South Carolina, although it is not uncommon for northern parts of the state to experience snow or freezing rain. Evapotranspiration rates were estimated by using data from the North American Regional Reanalysis (NARR) program (Mesinger et al., 2006). The evaporation data from NARR have a spatial resolution of 32.5 km (20′) and have a temporal resolution of one month. The reanalysis data products are produced by running a state-of-the-art climate model and assimilating historical weather observational data to estimate historical weather and hydrologic conditions.

Streamflow data within the state are collected by the United States Geologic Survey (USGS) at more than 170 monitoring stations. We identified 152 USGS monitoring stations with an adequate daily streamflow record during the period of analysis (1998-2007). The streamflow data were downloaded using tools from the Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI) Hydrologic Information System (HIS) (Maidment, 2008; Goodall et al., 2008; Horsburgh et al., 2009). Groundwater level data from USGS wells were assembled also using the CUAHSI HIS for comparison purposes, as described in the discussion section of this paper.

Box and whisker plots of average monthly conditions for all sub-watersheds show the distribution of precipitation, evapotranspiration, and streamflow values for the study period when viewed on both an annual scale (Figure 2) and on a seasonal scale (Figure 3). In the plots, the box represents the 25^{th}, 50^{th} and 75^{th} percentiles of the distribution while the whiskers represent the minimum and maximum values. Outliers identified as data values more than 1.5 times larger or smaller of the Interquartile Range (IQR) are represented in the plots as "+" marks. Seasonal variability of streamflow in particular provides clear evidence of the 1998-2002 drought in spring, summer, and fall months. During these periods, the entire distribution of streamflow values was lower compared to the distribution of streamflow values during the years following the drought.

We organized the geospatial and temporal data used in the analysis into the spatio-temporal data model described in Goodall and Maidment (2009). In this data model, the landscape is represented as a set of control volumes (sub-watersheds in this case) and geospatially-referenced hydrologic time series (streamflow time series and interpolated surfaces of precipitation and evapotranspiration in this case). Each control volume is related to one or more time series that describe either an inflow or outflow for that control volume through time. Because control volumes and time series are georeferenced, it is possible to determine the mass flux into and out of each control volume through time. For example, the precipitation and evaporation fields were averaged over watersheds areas as

$$\{P, E\} = \frac{1}{T} \int \{p, e\} dA \tag{8}$$

where P is the precipitation into a watershed and E is the evapotranspiration exiting a watershed and both are expressed in flow rate dimensions [$\mathrm{m}^3\ \mathrm{s}^{-1}$],

A is the area of a given watershed [m^2], p is monthly precipitation and e is the monthly evapotranspiration for the sub-watershed accumulated over the time period T [s] and expressed in length dimensions [m]. The organization of the data within the data model facilitated our ability to write code to estimate rate of change in TWS on a monthly time step using a discrete approximation of Equation 7 to estimate changes in TWS for all sub-watersheds identified in the study region.

Results and Discussion

Annual Variations of Rate of Change in TWS

Box and whisker plots of average monthly rate of change in TWS show the distribution of these values for the study period on an annual scale (Table 2, Figure 2). Figure 2 shows that the median rate of change for most of the years in the analysis was negative. Stated differently, this means that sub-watersheds in the state tended to lose water during the majority of the years of the study period, but gained water at a high rate during a few wet years. Figure 2 also shows that the median rate of change in TWS increased for each of the drought years. That said, the rate remained negative during the early period of the drought meaning that the region was still losing water during this period of time, but doing so less rapidly until the end of the drought (2001 and 2002) when the sub-watersheds actually began to gain water.

This result of a positive rate of change in TWS for the last two years of the drought was somewhat surprising, but could possibly be explained by a reduction of in stream discharge due to the drought. Because net streamflow decreased during the drought years ($R \downarrow$), $P - E$ became more significant in estimating the rate of change in TWS. From a mechanistic perspective, a possible explanation for this result is a decrease in the soil moisture caused by the drought. Because of this decrease in soil moisture, a greater portion of $P - E$ infiltrated and recharged groundwater resources and therefore did not result in runoff and increased stream discharge rates. Therefore, during this period $\Delta TWS/\Delta t$ actually increased because of an increase in the portion of $P - E$ that contributed to recharge rather than runoff. In the years following the drought (2003-2007), the sub-watersheds were wetter, in general, so a greater portion of $P - E$ became runoff and did not contribute to increasing the TWS.

Seasonal Variations of Rate of Change in TWS

Box and whisker plots of average monthly rate of change in TWS show the seasonal distribution of these values for the study period on an annual time scale (Table 3; Figure 3). While the winter and summer seasons showed more variability between different years of the study period, the fall season was in general a period of positive $\Delta TWS/\Delta t$ and spring was a period of negative $\Delta TWS/\Delta t$. This result was expected because fall months tend to be a period of aquifer recharge in the state (measured by increases in groundwater levels, as shown later in this section), whereas spring months tend to be, in general, a period when groundwater levels decrease in large part to higher evapotranspiration rates.

The rate of change in TWS for drought years compared to the non-drought years showed different patterns relative to one another. One common trait was an increase in $\Delta TWS/\Delta t$ for each year of the drought. For the spring and summer months, although the rate of change in $\Delta TWS/\Delta t$ increased, it remained negative or close to zero. We suspect that this is a result of a loss of TWS during the drought so that in later years of the drought, TWS was low so $\Delta TWS/\Delta t$ approached zero. In the fall months, there is no clear pattern in $\Delta TWS/\Delta t$ between drought and non-drought years. This is likely due to the fact that fall months experienced near normal precipitation rates. In the winter months during the drought years, there was a large variation in the rate of change in TWS compared to the non-drought years. The winter period of the drought years also had a large variation in precipitation, which would explain the large variation in TWS change rates. However, the 75^{th} percentile for precipitation in the winter months was inline with that of months following the period of drought, and the 75^{th} percentile for $\Delta TWS/\Delta t$ during the winter months of the drought years was lower compared to non-drought years. A possible explanation for this result is a higher antecedent soil moisture condition in the winter months, due to the proceeding fall season that was found to be the primary period of increases in TWS.

Spatial Variations in Annual and Seasonal Rate of Change in TWS

The spatial distribution of annual and seasonal rate of change in terrestrial water storage in the sub-watersheds is shown in Figure 4. For the annual plot, the monthly $\Delta TWS/\Delta t$ estimates were averaged for all 12 months, and for the seasonal plots, the monthly $\Delta TWS/\Delta t$ estimates were averaged for the three months within each season. The annual estimation showed both general patterns of rate change in TWS for sub-watersheds above the Piedmont and Blue Ridge aquifers and the Southeastern Coastal Plain aquifers. Sub-watersheds above the surficial aquifers in general showed a negative annual rate change in TWS. This pattern was expected because $P-E$ will contribute more to recharge aquifers in the inland portion of the state relative to stream discharge. In contrast, groundwater will be a larger contributor to streamflow in the coastal region of the state, meaning stream discharge will be larger than $P-E$ and, as a result, $\Delta TWS/\Delta t$ will tend to be positive. For sub-watersheds in Blue Ridge and Piedmont region, as well as the Southeastern Coastal Plain regions, as expected, the fall months showed a positive rate of change in terrestrial water storage for most of the sub-watersheds, while spring months showed a deficit for most of the sub-watersheds.

Within these general trends there was some variability. For example, one sub-watershed near the coast gained water consistently throughout the year at a rate that exceeded 25 m^3 s^{-1}. Four sub-watersheds distributed throughout the study region lost water during all four seasons, two at a rate that exceeded 100 m^3 s^{-1}. There are many possible reasons for these sub-watersheds having abnormal TWS change rates. One possible explanation is that the sub-watersheds have internal surface water storage (i.e., a reservoir) that alters its $\Delta TWS/\Delta t$ from neighboring sub-watersheds. For example sub-watersheds with reservoirs may have $\Delta TWS/\Delta t < 0$ because they released water during drought years that was stored prior to the drought. If a reservoir stores water, the $\Delta TWS/\Delta t$ increases because $Q_{in} > Q_{out}$ and therefore $R < 0$. When the reservoir later releases water, the $\Delta TWS/\Delta t$ decreases because $Q_{out} > Q_{in}$, and therefore $R > 0$. For sub-watersheds where reservoirs must be accounted for rate of change in TWS, information is needed about reservoir volume through time and how the reservoir released water through time. Three of the sub-watersheds with negative annual rate of change in TWS for the study period are near cities in the study region: Charlotte, North Carolina; Charleston, South Carolina; and Augusta, Georgia. Another possible explanation, therefore, is that there is significant surface water diversion for public or industrial water use in these regions of the state. Both of these examples suggest that human influences could be responsible for abnormal rate of change in TWS rates for the study region. Future work that includes other datasets related to water use for human and industrial purposes is needed to test this hypothesis.

Comparison of Cumulative Rate of Change in TWS Estimates with Observed Groundwater Levels

The relationship between cumulative $\Delta TWS/\Delta t$ and the groundwater level (GWL) provides a means for validating the PER method for calculating rate of change in TWS for sub-watersheds where groundwater is a significant portion of the TWS and there is no substantial groundwater pumping. We compared the estimates of cumulative $\Delta TWS/\Delta t$ with GWL for eight sub-watersheds within the state where a groundwater monitoring station was in proximity to the sub-watershed (Figure 5). Because TWS is a collective term that includes groundwater storage in addition to the surface storage and soil moisture storage, we expected $\Delta TWS/\Delta t$ to be correlated with GWL. However, other factors such as groundwater pumping, surface water storage (reservoirs), surface water diversions for public water supply or industrial water use, or simply a disconnect between surface water and groundwater resources could impact the two variables and remove any correlation between them. Therefore, we expected some sub-watersheds to show clear correlation between $\Delta TWS/\Delta t$ and GWL, while at the same time we expected other sub-watersheds to show no correlation. In some ways, this analysis is most helpful in identifying sub-watersheds where GWL and cumulative $\Delta TWS/\Delta t$ do not match because it suggests some other factor, possibly anthropogenic, may be altering the local water budget for that particular sub-watershed.

Comparison between cumulative $\Delta TWS/\Delta t$ and GWL for eight sample sub-watersheds (Figure 6) showed that sub-watersheds A, C, D and F, located above the surficial aquifers showed a clear correlation between cumulative $\Delta TWS/\Delta t$ and GWL. On the other hand, sub-watersheds B, E, G and H did not show a clear correlation. In some cases, this lack of correlation appeared to be due to a phase shift between cumulative $\Delta TWS/\Delta t$ and GWL. This phase shift may be related to the travel time through the soil to the aquifer including parameters such as the depth from the land surface to the saturated soil and the characteristics of the soil column (hydraulic conductivity, antecedent soil moisture, etc.). Sub-watershed B's groundwater level pattern appeared to be influenced by pumping, and there is some documentation on pumping in this sub-watershed (USDI and USGS, 2009). It is possible that this pumping affected the correlation between GWL and cumulative $\Delta TWS/\Delta t$. In other cases, in particular for sub-watersheds E, G, and H, $\Delta TWS/\Delta t$ showed an increase during fall months that was not present in the GWL observations. Again, further work is needed to understand the specific characteristics and factors present in these sub-watersheds in order to explain divergence between $\Delta TWS/\Delta t$ and GWL. The seasonal variations were also visible in this analysis with the tendency of the groundwater level to rise in the fall and winter months and to decrease in spring and summer months, as expected.

When viewed as a time series with rate of changes in TWS accumulated during the year (Figure 7), it is possible to visualize the increase or decrease in $\Delta TWS/\Delta t$ during each year of the period of analysis. Sub-watersheds C, D, and G included data for the entire study period, while the other sub-watersheds included data for at least two years of the study period. Sub-watershed C showed evidence of the drought in 1998, but also signs of a drought in 2003. The other years of record show a general decrease in water storage during the year, but not at the rate experienced during the years 1998 and 2003. Sub-watershed D showed evidence of the drought primarily in 1998, but also in 1999 and 2003. The other years showed less of a decline in cumulative $\Delta TWS/\Delta t$ and in 2002 the analysis estimated that $\Delta TWS/\Delta t$ increased within the sub-watershed. Sub-watershed G showed an increasing $\Delta TWS/\Delta t$ for most years in the study period, but also showed evidence of the drought in 1998 and 2003 because there was little or no increase in $\Delta TWS/\Delta t$ during these years, whereas other years in the study period showed an increase in $\Delta TWS/\Delta t$ throughout the year. One pattern of interest is the increase in $\Delta TWS/\Delta t$ that occurred directly following the drought in 2002. This increase in $\Delta TWS/\Delta t$ is evident from the time series plots for sub-watersheds B, E, G, and H and match increases in the groundwater level that also occurred during this time period. What is also clear from this plot is the marked difference in how each sub-watershed responded during and following the period of drought. Some sub-watersheds gained $\Delta TWS/\Delta t$ during drought years, others lost water. Some sub-watersheds gained $\Delta TWS/\Delta t$ in years following the drought, others lost water. This provides evidence of the variability of hydrologic systems that are under influences from geologic, climate, human, and other dimensions.

Conclusion

The PER water balance approach presented by Zeng et al. (2008) was used to synthesize existing hydrologic and geographic datasets in our study in order to estimate rate of change in terrestrial water storage (TWS) for sub-watersheds within South Carolina. Estimates of changes in TWS through time derived using the PER method show evidence of the drought in South Carolina and how the drought impacted different regions of the state. Comparison of estimated rates of TWS change with observed groundwater level changes in the region over the same period of time provided confidence in the PER method because the rate of change in TWS estimates follow seasonal and annual variations in groundwater levels for many of the sub-watersheds considered in this work. Although systematic biases in evapotranspiration rates noted in Zeng et al. (2008) limit the approach to quantifying relative rate of changes in TWS, the results from the PER method can be analyzed to identify how different regions of the state responded during and following the period of drought, information that may prove useful in managing the state's water resources.

We found that the method was most valuable in its ability to identify sub-watersheds in the state that do not follow general spatial and temporal variations. There could be many factors at play that result in these abnormalities. In some cases, there could be an internal storage (e.g., reservoir) that is altering storage rates relative to neighboring sub-watersheds. In other cases, there could be an unaccounted source or sink for water within the sub-watershed. For example, there may be an inter-watershed transfer of water or a diversion of surface water for public industrial water use purposes. These abnormalities, therefore, suggest that there is a human dimension to the water balance for that particular sub-watershed. Future work should further investigate this finding by gathering other water use data in an attempt to close the water balance for these sub-watersheds.

It should be noted that the hydrological data inputs used in the study have different levels of uncertainty, and this uncertainty impacted the results of this analysis. The most uncertain flux in the water balance is almost certainly evapotranspiration. Although the correction of evaporation is incorporated, the evaporation estimates in particular, being generated by a continental scale weather model may not capture true evaporation rates during the study period. However, evaporation is one of the most difficult hydrologic fluxes to quantify at the river basin scale as its rate depends on quantifying soil moisture through time (Lu et al., 2003; Rodell et al., 2004). Future work should be directed at better quantifying evaporation during this time period by using a regional hydrologic model capable of simulating soil moisture on a daily or sub-daily time scale and remote sensing of evapotranspiration. For example, an improvement over this work would be to use groundwater levels to estimate recharge rates (Healy and Cook, 2002) that then can be incorporated directly into the water balance to estimate water storage in the unsaturated and surface environments. Another potential means for improving this work would be to use remote sensing derived estimates of evapotranspiration to quantify this flux in place of, or in addition to, model derived estimates for the water balance calculations (Swenson et al., 2003).

References

Aucott, W. R., Speiran, G. K., 1985. Ground-Water flow in the coastal plain aquifers of South Carolina. Ground Water 23 (6), 736–745.

Badr, A. W., Wachob, A., Gellici, J. A., 2004. South Carolina water plan. Second Edition. South Carolina Department of Natural Resources. Land, Water and Conservation Division, Columbia, SC.

Beven, K. J., 2002. Towards an alternative blueprint for a physically-based digitally simulated hydrologic response modelling system. Hydrological Processes 16 (2), 189–206.

Christensen, N. S., Lettenmaier, D. P., 2007. A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado river basin. Hydrology and Earth System Sciences 11 (4), 1417–1434.

Ek, M., Mitchell, K., Lin, Y., Rogers, E., Grunmann, P., Koren, V., Gayno, G., Tarpley, J., 2003. Implementation of noah land surface model advances in the national centers for environmental prediction operational mesoscale eta model. J. Geophys. Res 108 (D22), 8851.

Fekete, B. M., Vorosmarty, C. J., Roads, J. O., Willmott, C. J., 2004. Uncertainties in precipitation and their impacts on runoff estimates. Journal of Climate 17 (2), 294–304.

Ferguson, C., Sheffield, J., Wood, E., Gao, H., 2010. Quantifying uncertainty in a remote sensing-based estimate of evapotranspiration over continental usa. International Journal of Remote Sensing 31 (14), 3821–3865.

Gellici, J. A., Harwell, S. L., Badr, A. W., Kiuchi, M., 2004. Hydrologic effects of the june 1998 - august 2002 drought in south carolina. Water Resources 34, South Carolins Department of Natural Resources.

Gibson, W. P., Daly, C., Kittel, T., Nychka, D., Johns, C., Rosenbloom, N., McNab, A., Taylor, G., 2002. Development of a 103-year high-resolution climate data set for the conterminous United States. In: 13th AMS Conf. on Applied Climatology. Amer. Meteorological Soc., Portland, OR, pp. 181–183.

Goodall, J., Horsburgh, J., Whiteaker, T., Maidment, D., Zaslavsky, I., 2008. A first approach to web services for the national water information system. Environmental Modelling & Software 23 (4), 404–411.

Goodall, J. L., Maidment, D. R., 2009. A spatiotemporal data model for river basin-scale hydrologic systems. International Journal of Geographical Information Science 23 (2), 233–247.

Grayson, R. B., Moore, I. D., McMahon, T. A., 1992. Physically based hydrologic modeling: 2. Is the concept realistic? Water Resources Research 28 (10), 26–59.

Healy, R. W., Cook, P. G., 2002. Using groundwater levels to estimate recharge. Hydrogeology Journal 10 (1), 91–109.

Hirschi, M., Seneviratne, S. I., Hagemann, S., Schr, C., 2007. Analysis of seasonal terrestrial water storage variations in regional climate simulations over europe. Journal of Geophysical Research 112 (D22).

Hirschi, M., Seneviratne, S. I., Schr, C., 2006. Seasonal variations in terrestrial water storage for major midlatitude river basins. Journal of Hydrometeorology 7, 39–60.

Horsburgh, J. S., Tarboton, D. G., Piasecki, M., Maidment, D. R., Zaslavsky, I., Valentine, D., Whitenack, T., 2009. An integrated system for publishing environmental observations data. Environmental Modelling & Software 24 (8), 879–888.

Jakeman, A. J., Hornberger, G. M., 1993. How much complexity is warranted in a rainfall-runoff model? Water Resources Research 29 (8), 26–37.

Johnston, C. M., Dewald, T. G., Bondelid, T. R., Worstell, B. B., McKay, L. D., Rea, A., Moore, R. B., Goodall, J. L., 2009. Evaluation of catchment delineation methods for the Medium-Resolution national hydrography dataset. U.S. Geological Survey Scientific Investigations Report 5233, 88 p.

Kenny, J. F., Barber, N. L., Hutson, S. S., Linsey, K. S., Lovelace, J. K., Maupin, M., 2009. Estimated use of water in the United States in 2005. U.S. Geological Survey Circular 1344, 52 p.

Legesse, D., Vallet-Coulomb, C., Gasse, F., 2003. Hydrological response of a catchment to climate and land use changes in Tropical Africa: case study South Central Ethiopia. Journal of Hydrology 275 (1-2), 67–85.

Lettenmaier, D. P., Wood, A. W., Palmer, R. N., Wood, E. F., Stakhiv, E. Z., 1999. Water resources implications of global warming: A US regional perspective. Climatic Change 43 (3), 537–579.

Lu, J. B., Sun, G., McNulty, S. G., Amatya, D. M., 2003. Modeling actual evapotranspiration from forested watersheds across the southeastern United States. Journal of the American Water Resources Association 39 (4), 887–896.

Maidment, D. R., 2008. Bringing water data together. Journal of Water Resources Planning and Management 134 (2), 95.

McDonnell, J. J., Sivapalan, M., Vache, K., Dunn, S., Grant, G., Haggerty, R., Hinz, C., Hooper, R., Kirchner, J., Roderick, M. L., Selker, J., Weiler, M., 2007. Moving beyond heterogeneity and process complexity: A new vision for watershed hydrology. Water Resources Research 43 (W07301).

Mesinger, F., DiMego, G., Kalnay, E., Mitchell, K., Shafran, P. C., Ebisuzaki, W., Jovic', D., Woollen, J., Rogers, E., Berbery, E. H., Ek, M. B., Fan, Y., Grumbine, R., Higgins, W., Li, H., Lin, Y., Manikin, G., Parrish, D., Shi, W., 2006. North American regional reanalysis. Bulletin of the American Meteorological Society 87 (3), 343–360.

Miller, J. A., 1990. Ground Water Atlas of The United States : Alabama, Florida, and South Carolina. U.S. Geological Survey.

Minville, M., Brissette, F., Leconte, R., 2008. Uncertainty of the impact of climate change on the hydrology of a nordic watershed. Journal of Hydrology 358 (1-2), 70–83.

Novotny, E. V., Stefan, H. G., 2007. Stream flow in Minnesota: Indicator of climate change. Journal of Hydrology 334 (3-4), 319–333.

Oki, T., Kanae, S., 2006. Global hydrological cycles and world water resources. Science 313 (5790), 1068–1072.

Rasmusson, E. M., 1967. Atmospheric water vapor transport and the water balance of North America: Part I. characteristics of the water vapor flux field. Monthly Weather Review 95 (7), 403–426.

Rodell, M., Famiglietti, J., Chen, J., Seneviratne, S., Viterbo, P., Holl, S., Wilson, C., 2004. Basin scale estimates of evapotranspiration using GRACE and other observations. Geophysical Research Letters 31 (20).

Rossi, C., Dybala, T., Arnold, J., Amonett, C., Marek, T., 2008. Hydrologic calibration and validation of the soil and water assessment tool for the leon river watershed. Journal of Soil and Water Conservation 63 (6), 533–541.

Ruiz-Barradas, A., Nigam, S., 2006. Great plains hydroclimate variability: The view from north american regional reanalysis. Journal of climate 19 (12), 3004–3010.

Seneviratne, S. I., Viterbo, P., Lthi, D., Schr, C., 2004. Inferring changes in terrestrial water storage using ERA-40 reanalysis data: The Mississippi river basin. Journal of Climate 17 (11), 2039–2057.

Sheffield, J., Ferguson, C., Troy, T., Wood, E., McCabe, M., 2009. Closing the terrestrial water budget from satellite remote sensing. Geophysical Research Letters 36 (7), L07403.

Swenson, S., Wahr, J., Milly, P., 2003. Estimated accuracies of regional water storage variations inferred from the gravity recovery and climate experiment (grace). Water Resour. Res 39 (8), 1223.

Tung, C. P., Haith, D. A., 1995. Global-warming effects on New York streamflows. Journal of Water Resources Planning and Management-ASCE 121 (2), 216–225.

USDI, USGS, 2009. Water-Data report 2009. <http://wdr.water.usgs.gov/wy2009/pdfs/340806079563100.2009.pdf> (verified 14.04.2011).

USEPA, USGS, 2005. National Hydrography Dataset Plus - NHDPlus. <ftp://ftp.horizon-systems.com/NHDPlus/documentation/metadata.pdf> (verified 09.08.2010).

Wahr, J., Swenson, S., Zlotnicki, V., Velicogna, I., 2004. Time-variable gravity from grace: First results. Geophys. Res. Lett 31 (11), L11501.

Wang, D., Cai, X., 2009. Detecting human interferences to low flows through base flow recession analysis. Water Resources Research 45 (7).

Wang, T., Istanbulluoglu, E., Lenters, J., Scott, D., 2009. On the role of groundwater and soil texture in the regional water balance: An investigation of the Nebraska Sand Hills, USA. Water Resources Research 45 (10).

Wurbs, R. A., Muttiah, R. S., Felden, F., 2005. Incorporation of climate change in water availability modeling. Journal of Hydrologic Engineering 10 (5), 375–385.

Yang, D., Sun, F., Liu, Z., Cong, Z., Ni, G., Lei, Z., 2007. Analyzing spatial and temporal variability of annual water-energy balance in nonhumid regions of china using the Budyko hypothesis. Water Resources Research 43 (4).

Yang, J., Reichert, P., Abbaspour, K. C., Xia, J., Yang, H., 2008. Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. Journal of Hydrology 358 (1-2), 1–23.

Yeh, P., Irizarry, M., Eltahir, E., 1998. Hydroclimatology of Illinois: A comparison of monthly evaporation estimates based on atmospheric water balance and soil water balance. Journal of Geophysical Research-Atmospheres 103 (D16), 19823–19837.

Zeng, N., Yoon, J. H., Mariotti, A., Swenson, S., 2008. Variability of Basin-Scale terrestrial water storage from a PER Water Budget Method: The Amazon and the Mississippi. Journal of Climate 21 (2), 248–265.

Table 1: Summary of geospatial and hydrologic time series data used in the study.

(a) Geospatial data

Description	Source	Data Type
Hydrography flow lines	National Hydrography Dataset	Vector (Polyline)
Flow line catchments	National Hydrography Dataset Plus	Vector (Polygon)
USGS streamflow gages	National Hydrography Dataset Plus	Vector (Point)

(b) Hydrologic time series data

Name	Source	Measurements Units	Data Type	Grid Size
Precipitation	PRISM Group Dataset	$m^3\ s^{-1}$	Raster	4km
Evaporation	North American Regional Reanalysis (NARR) program	$m^3\ s^{-1}$	Raster	32.5km
Streamflow	U. S. Geological Survey	$m^3\ s^{-1}$	Vector (Point)	-
Groundwater level	U. S. Geological Survey	m from surface	Vector (Point)	-

Table 2: Annual rate of change in terrestrial water storage ($m^3\ s^{-1}$) for all sub-watersheds

Year	Avg	STD	Min	25%	Med	75%	Max
1998	-26.9	25.0	-63.0	-48.9	-15.3	-10.7	8.8
1999	-6.5	13.9	-28.2	-12.9	-7.4	-1.3	24.0
2000	-4.4	17.9	-28.8	-22.4	-1.0	4.9	22.5
2001	-2.7	11.9	-33.2	-6.3	0.3	3.8	12.4
2002	7.0	12.8	-16.0	-0.3	10.2	15.6	23.8
2003	-16.2	18.8	-45.8	-30.7	-13.1	-0.4	8.7
2004	-4.0	15.5	-36.5	-10.2	-2.0	3.4	26.4
2005	-10.3	18.7	-52.7	-18.2	-9.9	6.1	13.6
2006	-0.9	20.3	-23.0	-17.7	-5.4	9.3	46.1
2007	-3.2	21.6	-29.0	-20.0	-3.1	6.8	43.1

Table 3: Seasonal rate of change in terrestrial water storage ($m^3\ s^{-1}$) for all sub-watersheds

	Spring (March to May)							Summer (June to August)						
Year	Avg	STD	Min	25%	Med	75%	Max	Avg	STD	Min	25%	Med	75%	Max
1998	-56.3	9.1	-63.0	-61.5	-60.0	-52.9	-45.9	-22.0	15.8	-40.2	-26.7	-13.3	-12.9	-12.6
1999	-17.3	9.4	-28.2	-20.2	-12.2	-11.9	-11.5	-8.8	6.1	-14.7	-12.0	-9.3	-5.9	-2.5
2000	-21.9	8.8	-28.8	-26.9	-25.0	-18.5	-11.9	0.0	2.1	-2.2	-1.0	0.2	1.1	2.0
2001	-11.8	22.9	-33.2	-23.8	-14.5	-1.0	12.4	-2.0	5.9	-8.4	-4.6	-0.8	1.2	3.2
2002	-5.0	13.1	-16.0	-12.3	-8.5	0.5	9.5	6.2	16.3	-8.3	-2.6	3.1	13.5	23.8
2003	-25.0	22.8	-45.8	-37.1	-28.4	-14.5	-0.6	-31.9	13.7	-41.9	-39.7	-37.5	-26.9	-16.2
2004	-14.4	5.6	-18.4	-17.6	-16.8	-12.4	-8.0	9.4	14.9	-1.6	0.9	3.4	14.9	26.4
2005	-26.4	23.2	-52.7	-35.2	-17.8	-13.3	-8.7	-14.1	5.6	-19.5	-17.0	-14.4	-11.4	-8.3
2006	-19.6	3.0	-23.0	-20.7	-18.4	-17.9	-17.5	2.0	19.9	-19.2	-7.0	5.2	12.7	20.1
2007	-24.5	7.2	-29.0	-28.6	-28.2	-22.2	-16.2	4.2	6.8	-3.2	1.2	5.7	7.9	10.1
	Fall (September to November)							**Winter (December to February)**						
Year	Avg	STD	Min	25%	Med	75%	Max	Avg	STD	Min	25%	Med	75%	Max
1998	-7.9	6.4	-15.3	-10.1	-4.8	-4.3	-3.7	-21.5	33.8	-57.9	-36.6	-15.3	-3.3	8.8
1999	4.6	16.8	-5.5	-5.0	-4.6	9.7	24.0	-4.7	16.9	-24.0	-10.9	2.2	5.0	7.7
2000	4.0	22.7	-21.8	-4.3	13.2	16.9	20.7	0.1	23.5	-24.3	-11.1	2.1	12.3	22.5
2001	0.3	5.5	-5.6	-2.2	1.3	3.3	5.3	2.5	3.8	0.2	0.3	0.4	3.6	6.8
2002	16.0	5.8	11.0	12.9	14.8	18.5	22.3	10.8	8.0	2.3	7.1	11.9	15.1	18.2
2003	-7.7	13.1	-19.5	-14.7	-9.9	-1.8	6.3	-0.3	9.2	-9.7	-4.7	0.2	4.4	8.7
2004	-11.8	21.6	-36.5	-19.4	-2.4	0.5	3.4	0.9	5.9	-3.7	-2.4	-1.1	3.2	7.5
2005	-1.1	23.1	-27.8	-8.4	10.9	12.3	13.6	0.4	10.1	-11.2	-2.6	5.9	6.3	6.6
2006	22.0	20.9	8.6	10.0	11.3	28.7	46.1	-8.1	4.9	-13.7	-10.0	-6.3	-5.4	-4.5
2007	6.4	15.0	-3.0	-2.3	-1.5	11.1	23.6	1.0	36.4	-20.2	-20.0	-19.9	11.6	43.1

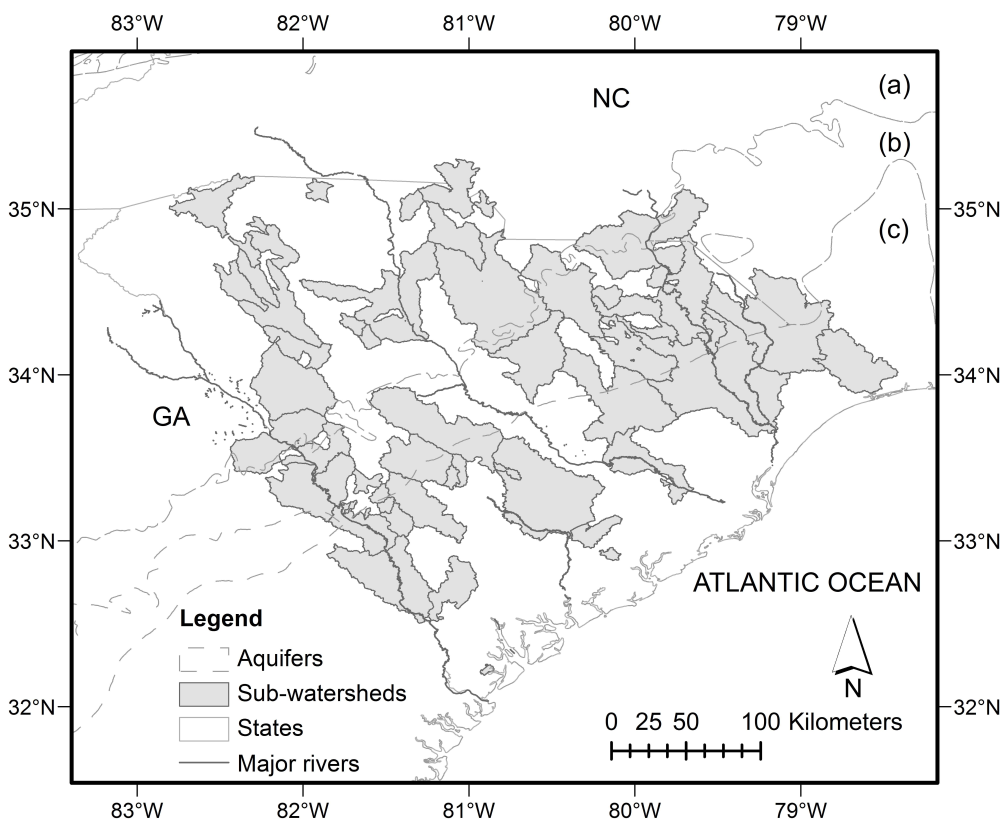

Figure 1: Map of the study area showing gaged sub-watersheds, aquifers (a) Piedmont and Blue Ridge aquifers (b) Southeastern Coastal Plain aquifers (c) Surficial aquifers

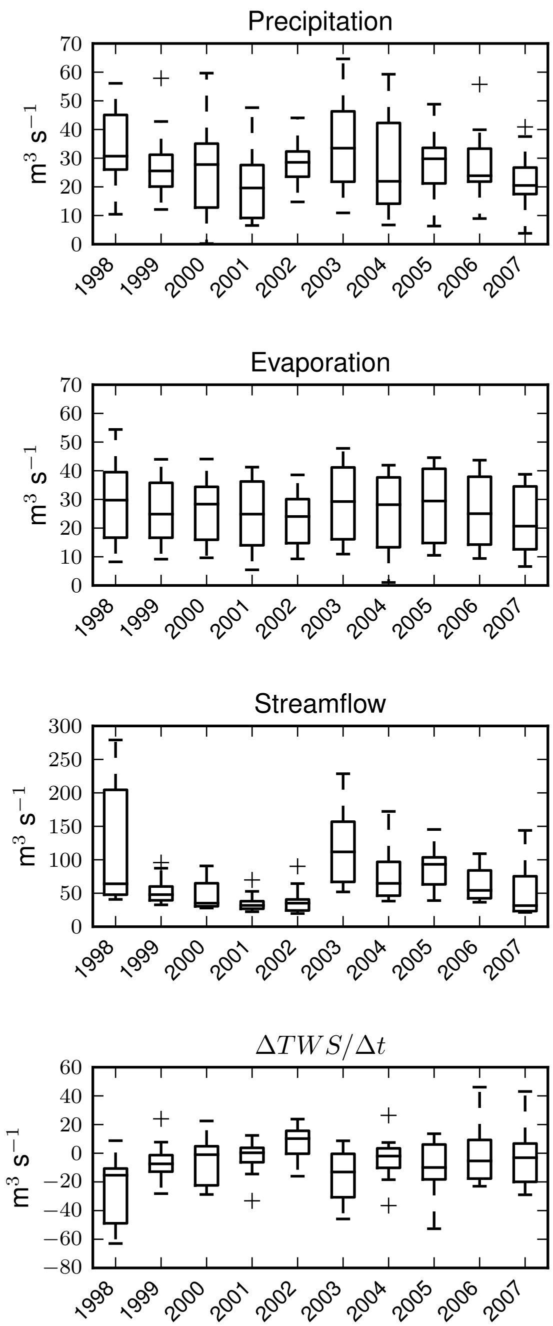

Figure 2: Annual variations (box with 25^{th}, 50^{th}, and 75^{th} percentiles, whiskers with minimum and maximum values, and outliers observations as "+" marks) of precipitation, evaporation, streamflow and $\Delta TWS/\Delta t$ in the sub-watersheds.

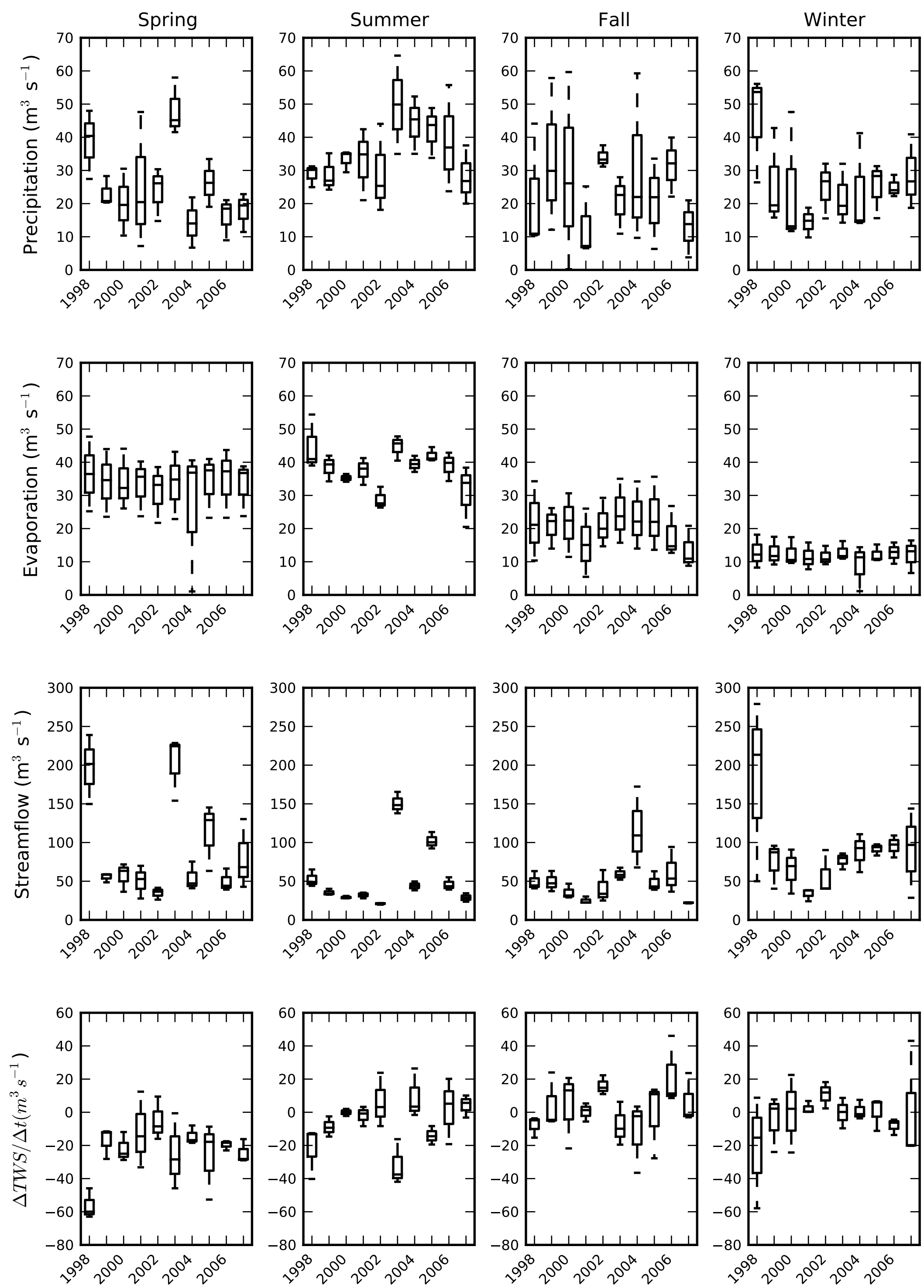

Figure 3: Seasonal variations (box with 25^{th}, 50^{th}, and 75^{th} percentiles, whiskers with minimum and maximum values) of precipitation, evaporation, streamflow and $\Delta TWS/\Delta t$ in the sub-watershedsn) of precipitation, evaporation, streamflow and $\Delta TWS/\Delta t$ in the sub-watersheds.

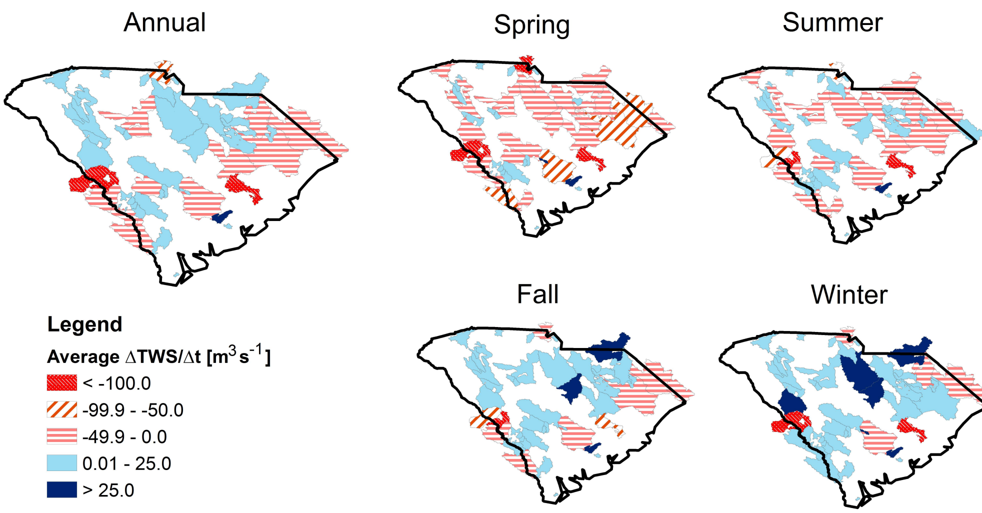

Figure 4: Spatial variation of rate of change in terrestrial water storage in the sub-watersheds.

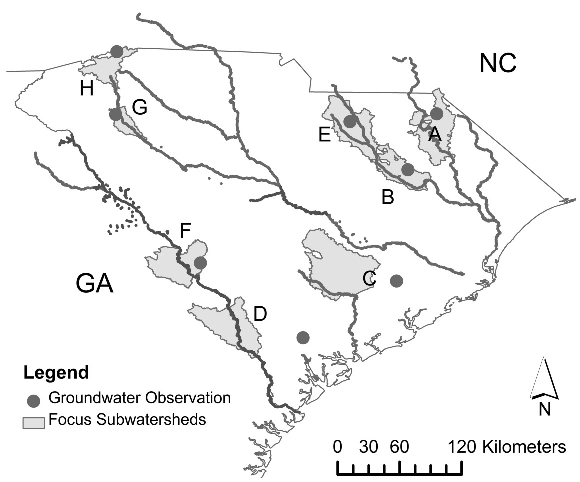

Figure 5: Location of the focus sub-watersheds in South Carolina.

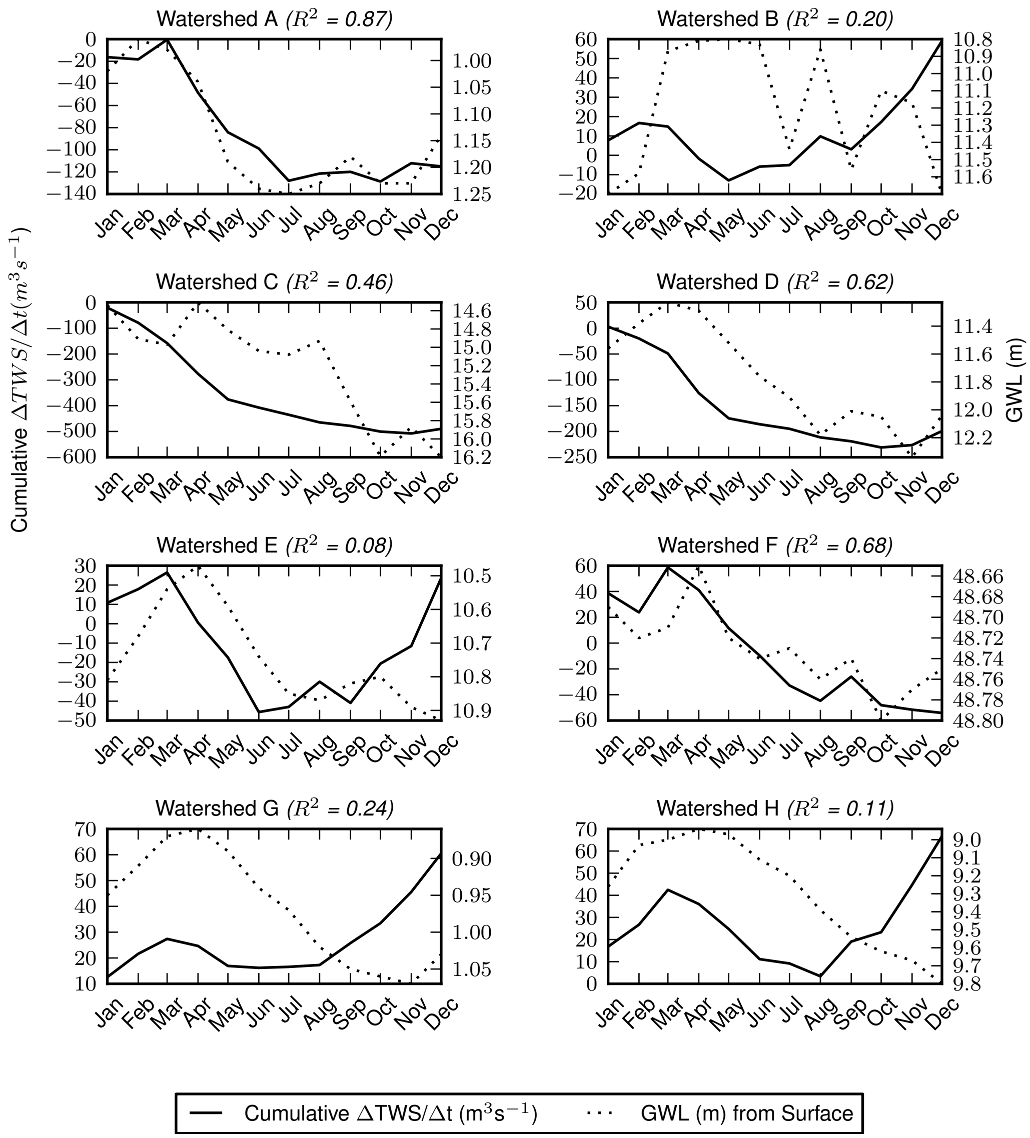

Figure 6: Relationship between cumulative rate of change in cumulative terrestrial water storage (averaged over same month from 1998-2007) and groundwater levels (1998-2007) in the sub-watersheds.

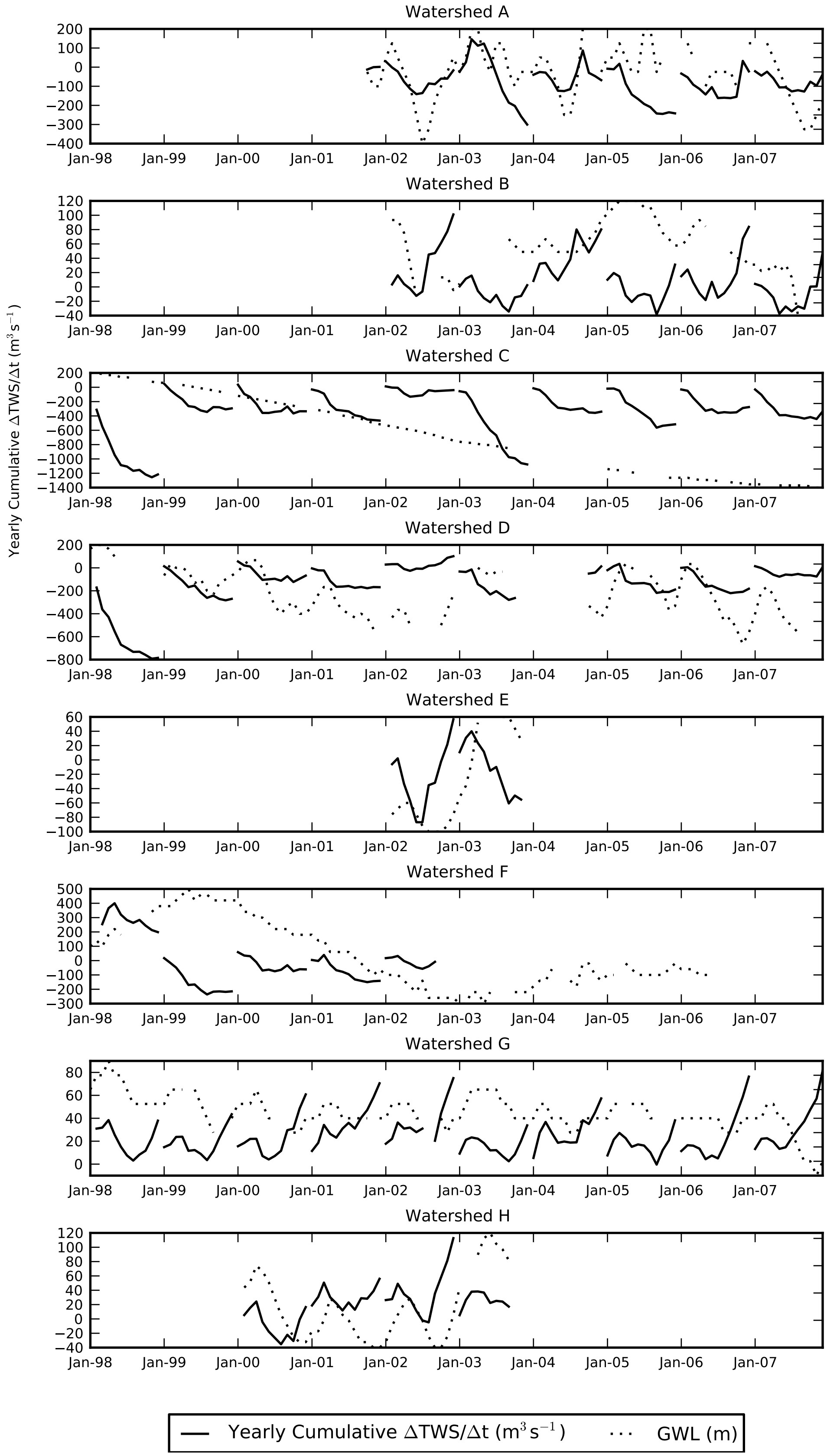

Figure 7: Long term relationship between the yearly cumulative rate of change in terrestrial water storage and groundwater levels in the sub-watersheds.