

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

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Abstract

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

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

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

29 **Introduction**

30 South Carolina experienced a severe drought between 1998 and 2002.
31 During this time, precipitation decreased by 10-30% from normal levels re-
32 sulting in reduced streamflows and groundwater levels throughout the state
33 (Badr et al., 2004; Gellici et al., 2004). The drought presented challenges to
34 the state such as meeting water supply needs for human and industrial pur-
35 poses, salt water intrusion in the coastal region of the state, and decreased
36 water levels in lakes and groundwater aquifers. The drought intensified wa-
37 ter rights issues in the state as well because South Carolina shares two of its
38 major river basins with neighboring states: the Savannah River with Geor-

39 gia and the Catawba River with North Carolina. Growing water demands
40 and increased hydrologic variability due to global climate change (Oki and
41 Kanae, 2006) will likely intensify the challenges faced by the state during
42 future droughts. Other regions of the world facing similar challenges also re-
43 quire techniques for understanding regional water resources under a variety of
44 demands and stresses. We present research that investigates an approach for
45 quantifying regional scale water balances through an application case study
46 for river basins whose rivers flow through South Carolina.

47 Hydrologic modeling and analysis can aid in this problem by providing
48 estimates of future water availability under changing conditions such as cli-
49 mate change, land use change, and increasing water demands (e.g., Letten-
50 maier et al., 1999; Rossi et al., 2008; Tung and Haith, 1995; Legesse et al.,
51 2003; Wurbs et al., 2005). Detailed, physically-based models of regional-scale
52 hydrologic systems used to address such questions can be problematic for rea-
53 sons that have been well described in the literature (e.g., Grayson et al., 1992;
54 Jakeman and Hornberger, 1993; Beven, 2002; McDonnell et al., 2007). Part
55 of the problem has been that, at the river-basin-scale, hydrology is subject
56 to complex interactions between physical, biological, and social systems, and
57 no model is capable of addressing all of the interactions at play in watershed
58 systems. Furthermore, those models that do attempt to simulate such inter-
59 actions are difficult to parameterize and calibrate at a regional scale due in
60 part to a lack of data describing system parameters, initial conditions, and
61 boundary conditions. This leads to the need for uncertainty analysis both
62 in terms of process representations, system parameters, and forcing data
63 (Minville et al., 2008; Yang et al., 2008; Fekete et al., 2004; Christensen and

64 Lettenmaier, 2007).

65 Alternative approaches have been proposed for estimating basin-scale wa-
66 ter resources that include developing statistical tools for time series records
67 (e.g., Novotny and Stefan, 2007), analyzing of components of the hydrologic
68 cycle (e.g., baseflow recession as in Wang and Cai, 2009), or using semiem-
69 perical relationships for coupled water-energy balances such as the Budyko
70 hypothesis (Wang et al., 2009; Yang et al., 2007). One such approach, devel-
71 oped and applied primarily in the climate science community for quantifying
72 changes in basin-scale water resources, is the so called Moisture Convergence
73 minus Runoff (MCR) approach (Rasmusson, 1967; Seneviratne et al., 2004;
74 Yeh et al., 1998). In this approach, water balance equations for the terres-
75 trial and atmospheric portions of the hydrologic cycle are equated to estimate
76 the rate of change in terrestrial water storage (TWS). TWS is a term that
77 includes all stores of water within the terrestrial environment including soil
78 moisture, snow, groundwater, and surface water. The MCR approach has
79 been applied to river basins within Europe, Asia, North America, and Aus-
80 tralia (Hirschi et al., 2006, 2007), demonstrating that the MCR approach can
81 successfully estimate TWS on a monthly time step after comparing estimates
82 with independent measures of TWS including soil moisture, groundwater lev-
83 els, and snow depths. More recent work by Zeng et al. (2008) proposed a
84 modification to the MCR approach where, instead of equating water balance
85 equations for the surface and atmospheric systems, the surface water balance
86 equation is solved directly by using observations of precipitation and stream
87 discharge along with estimates of evaporation derived from climate reanalysis
88 to quantify changes in TWS. This approach, termed the Precipitation, Evap-

89 ottranspiration, and Runoff (PER) method, was shown to be more robust in
90 estimating TWS for the Amazon Basin and the Mississippi Basin when com-
91 pared to the MCR approach and validated against independent estimations
92 of TWS components (Zeng et al., 2008). Details of the PER method and
93 how it compares to the more commonly used MCR method are provided in
94 the Methodology Section of this paper.

95 One of the major challenges in applying a water balance method is quan-
96 tifying evapotranspiration at a regional spatial scale. The North American
97 Regional Reanalysis (NARR) product is considered to be best of the reanalysis
98 datasets, in part because it has an improved land surface model (Ek et al.,
99 2003; Ruiz-Barradas and Nigam, 2006). Another possible means for quanti-
100 fying evapotranspiration is using remote sensing products. This approach is
101 promising, although it requires calibrate of the remote sensing evapotran-
102 spiration estimates based on local conditions (Ferguson et al., 2010), and it
103 is uncertain if remote sensing observations of evaporation will be effective
104 at closing the water balance (Sheffield et al., 2009). Future research would
105 be required to address the benefit of remote sensing derived evapotranspi-
106 ration estimates compared to NARR evaporation estimates. Despite the
107 uncertainty of evapotranspiration estimates, a comparative analysis of the
108 estimated evapotranspiration from different climate model and reanalysis
109 datasets (ERA40, NCEP2, NARR, and SLand) in the PER model suggested
110 that evapotranspiration estimates have a small variation relative to difference
111 between observed precipitation and streamflow, therefore capturing variation
112 in precipitation and streamflow is most important for estimating the rate of
113 change in TWS (Zeng et al., 2008).

114 In this paper we use the PER method with NARR estimates of evap-
115 otranspiration to understand how water resources within South Carolina
116 responded during and following the 1998-2002 period of drought. Using
117 observational data from streamflow and precipitation monitoring networks
118 along with estimations of evaporation from climate model reanalysis prod-
119 ucts, we estimated rate of change in TWS on a monthly time step for 54 sub-
120 watersheds where stream inflow and outflow were monitored for the period
121 1998-2007. The sub-watersheds were defined using geospatial data describ-
122 ing the terrain, hydrography, and streamflow gaging network and account
123 for 60% of the surface area within the state. We then compared estimates of
124 rate of change in TWS obtained using the PER method with groundwater
125 levels in the state to determine how both measures of water storage varied
126 during and following the period of drought.

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

138 Following a brief description of the study area, we next describe our

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

150 **Study Area**

151 South Carolina is located in the Southeastern United States and has
152 an area of 82,930 km² (32,020 mi²) from latitude 32°02'*N* to 35°13'*N* and
153 longitude 78°32'*W* to 83°21'*W* (Figure 1). South Carolina receives on average
154 1220 mm (48 in) of precipitation annually, mostly in the form of rainfall.
155 Precipitation over the state is fairly consistent for different seasons, although
156 the coastal plain region of the state does receive more precipitation in the
157 summer relative to other seasons, while the remaining parts of the state
158 generally receive more precipitation in the spring months. South Carolina
159 has hot and humid summer months with daytime temperatures averaging
160 between 30-34 °C (86-93 °F) for most of the state. In winter months, daytime
161 temperatures in the coastal plain average 16 °C (60 °F) and decrease as one
162 travels inland. The Savannah, Pee Dee, Santee, and Edisto Rivers are the

163 largest rivers within the state, and each of these rivers plays a major role
164 in agricultural and industrial practices. All but one of the rivers in South
165 Carolina are shared with neighboring states. The exception is the Edisto
166 River whose entire watershed is within the state boundaries (Badr et al.,
167 2004).

168 South Carolina has three distinct aquifer systems (Figure 1): the Pied-
169 mont and Blue Ridge crystalline rock aquifers in the northwestern portion
170 of the state, the Southeastern Coastal Plain aquifer system in the central
171 part of the state, and the Surficial aquifer system in the coastal region of the
172 state (Miller, 1990). The Piedmont and Blue Ridge crystalline rock aquifers
173 consist of bedrock overlain by unconsolidated material. While the overall
174 hydraulic characteristics of the aquifer are similar, there is considerable lo-
175 cal variability due to heterogeneous rock types in the region. Groundwater
176 obtained from the aquifer is used for public supply, commercial uses, and
177 agricultural purposes within the upper region of the state (Kenny et al.,
178 2009). The Southeastern Coastal Plain aquifers in South Carolina consist
179 of sand or highly permeable limestone as well as confining layers composed
180 of clay, silt or low permeable limestone that slow the infiltration of water
181 to the aquifer system. The aquifers are primarily recharged by diffuse deep
182 drainage and discharge into the upper or lower coastal plain rivers (Aucott
183 and Speiran, 1985). The Surficial aquifer system is unconfined and water en-
184 tering the aquifer system is discharged quickly as baseflow to streams. This
185 aquifer in particular is prone to saltwater intrusion during periods of drought
186 because it extends seaward under the Atlantic Ocean. It is important to note
187 that, although South Carolina has groundwater resources, 95% of the fresh-

188 water used in the state comes from surface water rather than groundwater
 189 resources (Kenny et al., 2009).

190 **Methodology**

191 *Model Description*

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

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

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

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

200 where W is storage of water as vapor within the column of air above the
 201 watershed, ∇_H is the horizontal divergence operator, and Q is the integration
 202 of the water vapor flux over the column (Seneviratne et al., 2004). The
 203 method assumes that the rate of change in liquid and solid water in the air
 204 column, as well as the horizontal transport of liquid and solid water, can
 205 be neglected. Terrestrial water storage is estimated by equating Equation
 206 1 and Equation 2 and averaging over space and time, which results in the
 207 elimination of the $P - E$ term and gives

$$\left\{ \frac{\partial \overline{TW S}}{\partial t} \right\} = -\{\overline{\nabla_H \cdot Q}\} - \left\{ \frac{\partial \overline{W}}{\partial t} \right\} - \{\overline{R}\} \quad (3)$$

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

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

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.

$$\left\{ \frac{\partial \overline{TW S}}{\partial t} \right\} = \{\overline{P_{obs}}\} - \{\overline{E_{est}}\} - \{\overline{R_{obs}}\} \quad (5)$$

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

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

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.

$$\left\{ \frac{\partial TWS}{\partial t} \right\} = \{\overline{P_{obs}}\} - \{\overline{E_{est}^*}\} - \{\overline{R_{obs}}\} \quad (7)$$

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.

249 *Data Preparation*

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

261 The procedure used to calculate the sub-watersheds in our analysis (Fig-
262 ure 1) was to first use linear referencing to locate active streamflow moni-
263 toring stations during the study period along the NHD stream network. We
264 then wrote an algorithm that begins at the most downstream reach in the
265 NHD Flowline feature class for each river basin in the state and “climbs” the
266 network in the upstream direction in order to identify the next downstream
267 monitoring station for each reach within the study area. With this informa-
268 tion, and because there is a 1-1 relationship between reaches and catchments
269 in the NHDPlus dataset, we were able to identify and then dissolve catch-
270 ments within the study region that had the same downstream monitoring
271 station. This data processing resulted in 54 sub-watersheds ranging in size
272 from 1.20 to 3,350 km² for which stream inflow and outflow have been ob-
273 served 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 Geological 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

299 show the distribution of precipitation, evapotranspiration, and streamflow
 300 values for the study period when viewed on both an annual scale (Figure 2)
 301 and on a seasonal scale (Figure 3). In the plots, the box represents the 25th,
 302 50th and 75th percentiles of the distribution while the whiskers represent the
 303 minimum and maximum values. Outliers identified as data values more than
 304 1.5 times larger or smaller of the Interquartile Range (IQR) are represented
 305 in the plots as “+” marks. Seasonal variability of streamflow in particular
 306 provides clear evidence of the 1998-2002 drought in spring, summer, and fall
 307 months. During these periods, the entire distribution of streamflow values
 308 was lower compared to the distribution of streamflow values during the years
 309 following the drought.

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

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

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

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

330 **Results and Discussion**

331 *Annual Variations of Rate of Change in TWS*

332 Box and whisker plots of average monthly rate of change in TWS show
333 the distribution of these values for the study period on an annual scale (Table
334 2, Figure 2). Figure 2 shows that the median rate of change for most of the
335 years in the analysis was negative. Stated differently, this means that sub-
336 watersheds in the state tended to lose water during the majority of the years
337 of the study period, but gained water at a high rate during a few wet years.
338 Figure 2 also shows that the median rate of change in TWS increased for each
339 of the drought years. That said, the rate remained negative during the early
340 period of the drought meaning that the region was still losing water during
341 this period of time, but doing so less rapidly until the end of the drought
342 (2001 and 2002) when the sub-watersheds actually began to gain water.

343 This result of a positive rate of change in TWS for the last two years of
344 the drought was somewhat surprising, but could possibly be explained by a
345 reduction of in stream discharge due to the drought. Because net streamflow
346 decreased during the drought years ($R \downarrow$), $P - E$ became more significant

347 in estimating the rate of change in TWS. From a mechanistic perspective, a
 348 possible explanation for this result is a decrease in the soil moisture caused
 349 by the drought. Because of this decrease in soil moisture, a greater portion of
 350 $P - E$ infiltrated and recharged groundwater resources and therefore did not
 351 result in runoff and increased stream discharge rates. Therefore, during this
 352 period $\Delta TWS/\Delta t$ actually increased because of an increase in the portion of
 353 $P - E$ that contributed to recharge rather than runoff. In the years following
 354 the drought (2003-2007), the sub-watersheds were wetter, in general, so a
 355 greater portion of $P - E$ became runoff and did not contribute to increasing
 356 the TWS.

357 *Seasonal Variations of Rate of Change in TWS*

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

368 The rate of change in TWS for drought years compared to the non-
 369 drought years showed different patterns relative to one another. One common
 370 trait was an increase in $\Delta TWS/\Delta t$ for each year of the drought. For the
 371 spring and summer months, although the rate of change in $\Delta TWS/\Delta t$ in-

creased, 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 precipi-
 tation 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 75th percentile for precipitation in the winter months was inline
 with that of months following the period of drought, and the 75th 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 terres-
 trial 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 Pied-
 mont and Blue Ridge aquifers and the Southeastern Coastal Plain aquifers.
 Sub-watersheds above the surficial aquifers in general showed a negative an-

397 nual rate change in TWS. This pattern was expected because $P - E$ will con-
 398 tribute more to recharge aquifers in the inland portion of the state relative
 399 to stream discharge. In contrast, groundwater will be a larger contributor to
 400 streamflow in the coastal region of the state, meaning stream discharge will
 401 be larger than $P - E$ and, as a result, $\Delta TWS/\Delta t$ will tend to be positive.
 402 For sub-watersheds in Blue Ridge and Piedmont region, as well as the South-
 403 eastern Coastal Plain regions, as expected, the fall months showed a positive
 404 rate of change in terrestrial water storage for most of the sub-watersheds,
 405 while spring months showed a deficit for most of the sub-watersheds.

406 Within these general trends there was some variability. For example,
 407 one sub-watershed near the coast gained water consistently throughout the
 408 year at a rate that exceeded $25 \text{ m}^3 \text{ s}^{-1}$. Four sub-watersheds distributed
 409 throughout the study region lost water during all four seasons, two at a rate
 410 that exceeded $100 \text{ m}^3 \text{ s}^{-1}$. There are many possible reasons for these sub-
 411 watersheds having abnormal TWS change rates. One possible explanation is
 412 that the sub-watersheds have internal surface water storage (i.e., a reservoir)
 413 that alters its $\Delta TWS/\Delta t$ from neighboring sub-watersheds. For example
 414 sub-watersheds with reservoirs may have $\Delta TWS/\Delta t < 0$ because they re-
 415 leased water during drought years that was stored prior to the drought. If
 416 a reservoir stores water, the $\Delta TWS/\Delta t$ increases because $Q_{in} > Q_{out}$ and
 417 therefore $R < 0$. When the reservoir later releases water, the $\Delta TWS/\Delta t$
 418 decreases because $Q_{out} > Q_{in}$, and therefore $R > 0$. For sub-watersheds
 419 where reservoirs must be accounted for rate of change in TWS, informa-
 420 tion is needed about reservoir volume through time and how the reservoir
 421 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

447 sub-watersheds to show no correlation. In some ways, this analysis is most
448 helpful in identifying sub-watersheds where GWL and cumulative $\Delta TWS/\Delta t$
449 do not match because it suggests some other factor, possibly anthropogenic,
450 may be altering the local water budget for that particular sub-watershed.

451 Comparison between cumulative $\Delta TWS/\Delta t$ and GWL for eight sam-
452 ple sub-watersheds (Figure 6) showed that sub-watersheds A, C, D and F,
453 located above the surficial aquifers showed a clear correlation between cu-
454 mulative $\Delta TWS/\Delta t$ and GWL. On the other hand, sub-watersheds B, E, G
455 and H did not show a clear correlation. In some cases, this lack of correla-
456 tion appeared to be due to a phase shift between cumulative $\Delta TWS/\Delta t$ and
457 GWL. This phase shift may be related to the travel time through the soil
458 to the aquifer including parameters such as the depth from the land surface
459 to the saturated soil and the characteristics of the soil column (hydraulic
460 conductivity, antecedent soil moisture, etc.). Sub-watershed B's groundwa-
461 ter level pattern appeared to be influenced by pumping, and there is some
462 documentation on pumping in this sub-watershed (USDI and USGS, 2009).
463 It is possible that this pumping affected the correlation between GWL and
464 cumulative $\Delta TWS/\Delta t$. In other cases, in particular for sub-watersheds E,
465 G, and H, $\Delta TWS/\Delta t$ showed an increase during fall months that was not
466 present in the GWL observations. Again, further work is needed to under-
467 stand the specific characteristics and factors present in these sub-watersheds
468 in order to explain divergence between $\Delta TWS/\Delta t$ and GWL. The seasonal
469 variations were also visible in this analysis with the tendency of the ground-
470 water level to rise in the fall and winter months and to decrease in spring
471 and summer months, as expected.

472 When viewed as a time series with rate of changes in TWS accumu-
473 lated during the year (Figure 7), it is possible to visualize the increase or
474 decrease in $\Delta TWS/\Delta t$ during each year of the period of analysis. Sub-
475 watersheds C, D, and G included data for the entire study period, while the
476 other sub-watersheds included data for at least two years of the study period.
477 Sub-watershed C showed evidence of the drought in 1998, but also signs of
478 a drought in 2003. The other years of record show a general decrease in
479 water storage during the year, but not at the rate experienced during the
480 years 1998 and 2003. Sub-watershed D showed evidence of the drought pri-
481 marily in 1998, but also in 1999 and 2003. The other years showed less of
482 a decline in cumulative $\Delta TWS/\Delta t$ and in 2002 the analysis estimated that
483 $\Delta TWS/\Delta t$ increased within the sub-watershed. Sub-watershed G showed an
484 increasing $\Delta TWS/\Delta t$ for most years in the study period, but also showed
485 evidence of the drought in 1998 and 2003 because there was little or no in-
486 crease in $\Delta TWS/\Delta t$ during these years, whereas other years in the study
487 period showed an increase in $\Delta TWS/\Delta t$ throughout the year. One pattern
488 of interest is the increase in $\Delta TWS/\Delta t$ that occurred directly following the
489 drought in 2002. This increase in $\Delta TWS/\Delta t$ is evident from the time series
490 plots for sub-watersheds B, E, G, and H and match increases in the ground-
491 water level that also occurred during this time period. What is also clear
492 from this plot is the marked difference in how each sub-watershed responded
493 during and following the period of drought. Some sub-watersheds gained
494 $\Delta TWS/\Delta t$ during drought years, others lost water. Some sub-watersheds
495 gained $\Delta TWS/\Delta t$ in years following the drought, others lost water. This
496 provides evidence of the variability of hydrologic systems that are under in-

497 fluences from geologic, climate, human, and other dimensions.

498 **Conclusion**

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

515 We found that the method was most valuable in its ability to identify
516 sub-watersheds in the state that do not follow general spatial and temporal
517 variations. There could be many factors at play that result in these abnor-
518 malities. In some cases, there could be an internal storage (e.g., reservoir)
519 that is altering storage rates relative to neighboring sub-watersheds. In other
520 cases, there could be an unaccounted source or sink for water within the sub-

521 watershed. For example, there may be an inter-watershed transfer of water
522 or a diversion of surface water for public industrial water use purposes. These
523 abnormalities, therefore, suggest that there is a human dimension to the wa-
524 ter balance for that particular sub-watershed. Future work should further
525 investigate this finding by gathering other water use data in an attempt to
526 close the water balance for these sub-watersheds.

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

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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	$\text{m}^3 \text{s}^{-1}$	Raster	4km
Evaporation	North American Regional Reanalysis (NARR) program	$\text{m}^3 \text{s}^{-1}$	Raster	32.5km
Streamflow	U. S. Geological Survey	$\text{m}^3 \text{s}^{-1}$	Vector (Point)	-
Groundwater level	U. S. Geological Survey	m from surface	Vector (Point)	-

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

Year	Spring (March to May)							Summer (June to August)						
	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

Year	Fall (September to November)							Winter (December to February)						
	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

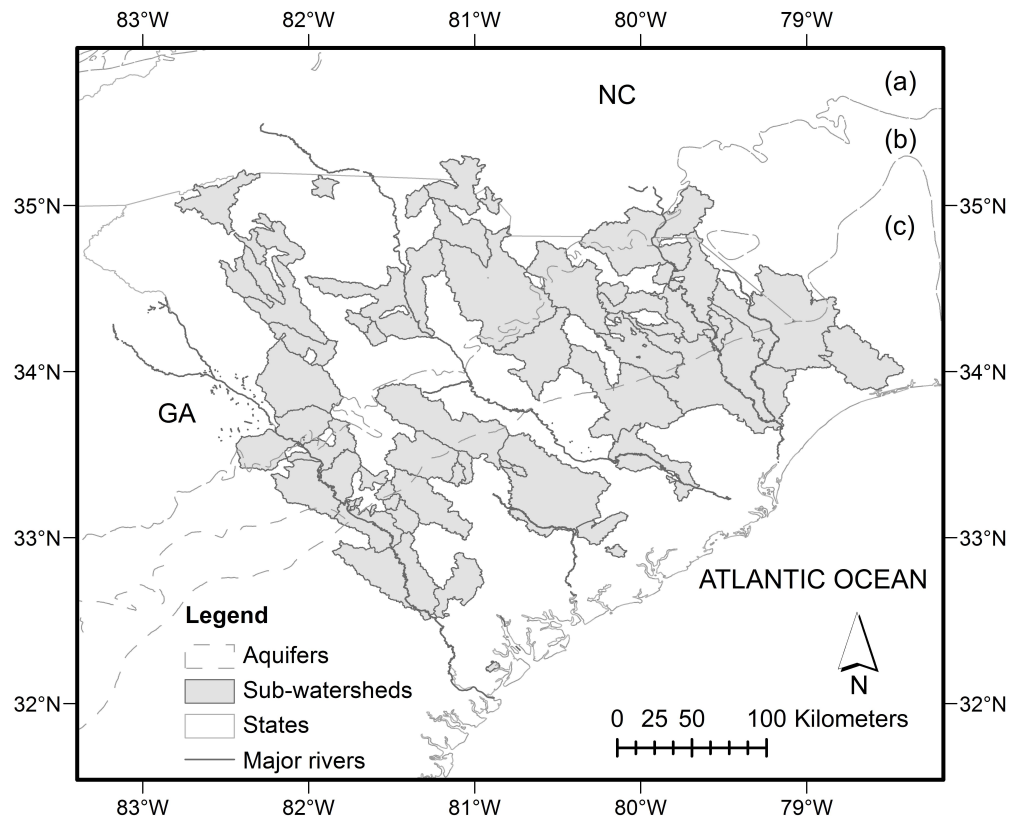


Figure 1: Map of the study area showing gaged sub-watersheds, aquifers (a) Piedmont and Blue Ridge aquifers (b) Southeastern Coastal Plain aquifers (c) Surficial aquifers

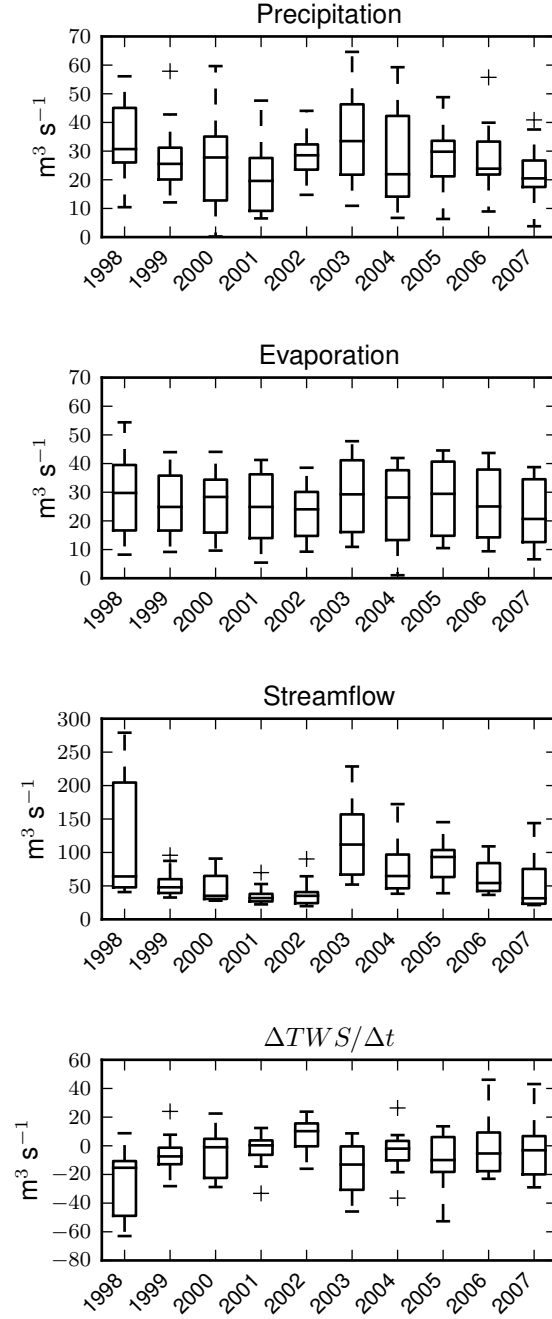


Figure 2: Annual variations (box with 25th, 50th, and 75th percentiles, whiskers with minimum and maximum values, and outliers observations as “+” marks) of precipitation, evaporation, streamflow and $\Delta TWS/\Delta t$ in the sub-watersheds.

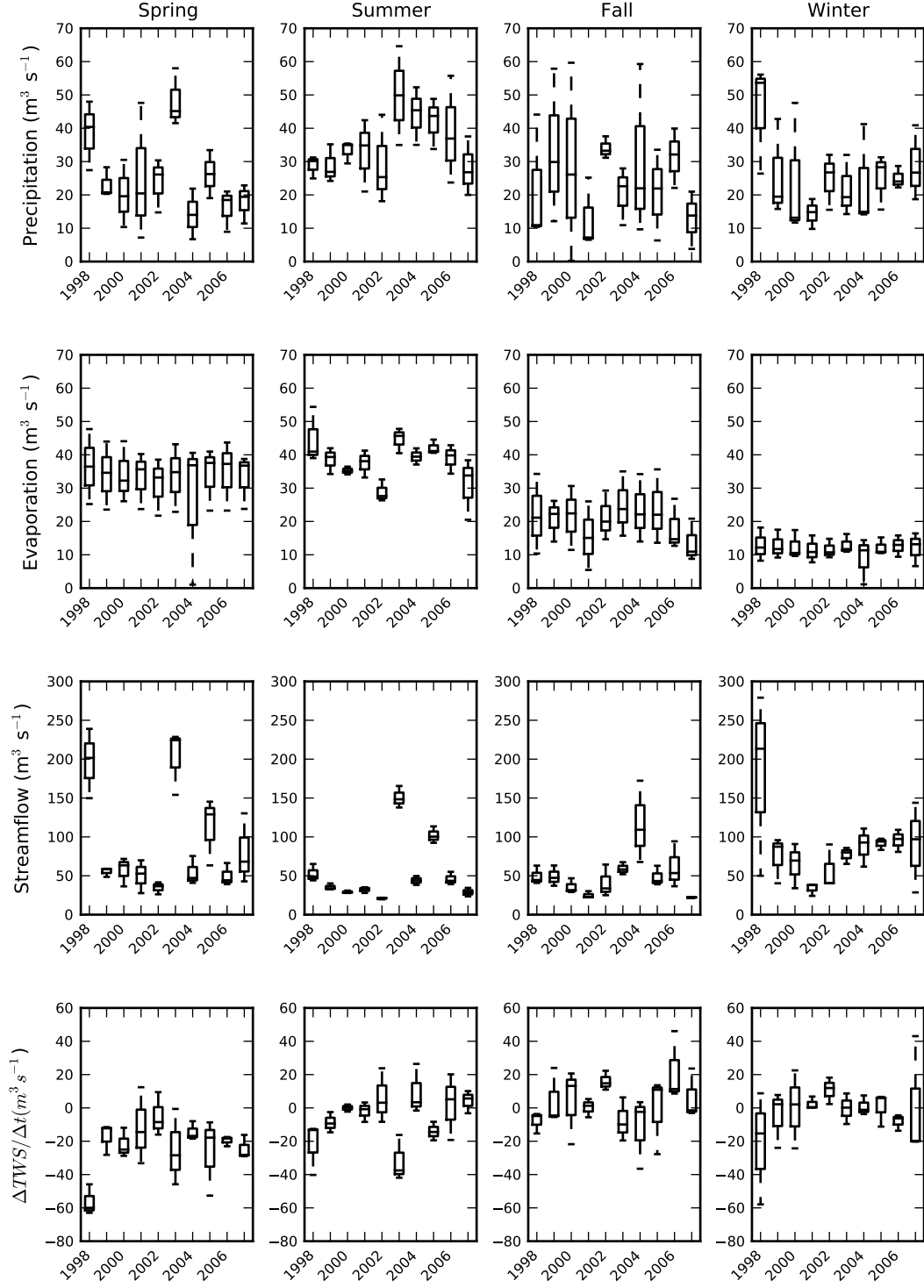


Figure 3: Seasonal variations (box with 25th, 50th, and 75th percentiles, whiskers with minimum and maximum values) of precipitation, evaporation, streamflow and $\Delta TWS/\Delta t$ in the sub-watersheds.

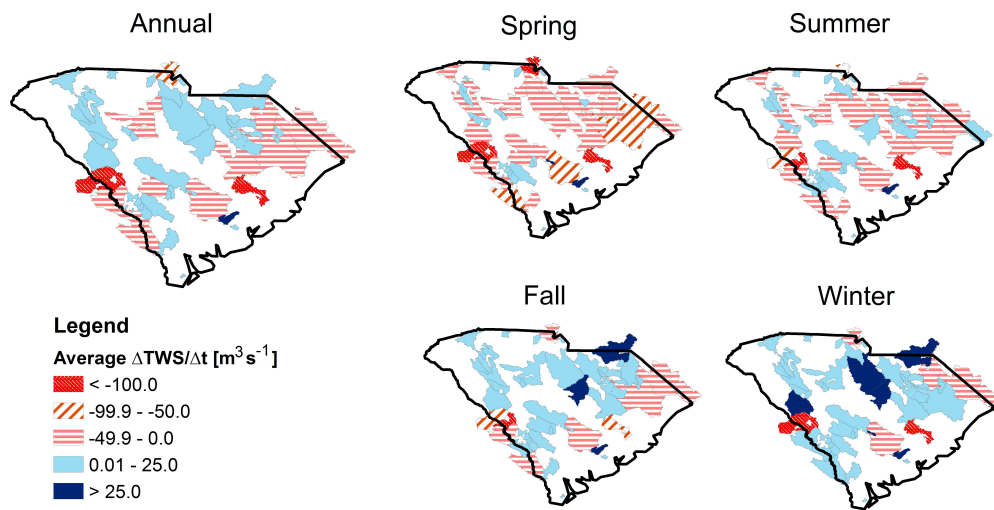


Figure 4: Spatial variation of rate of change in terrestrial water storage in the sub-watersheds.

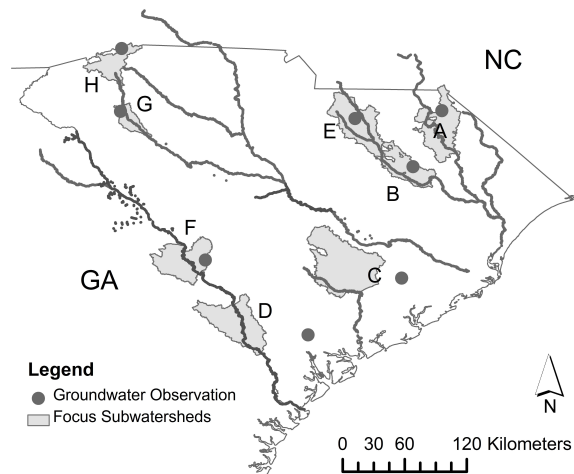


Figure 5: Location of the focus sub-watersheds in South Carolina.

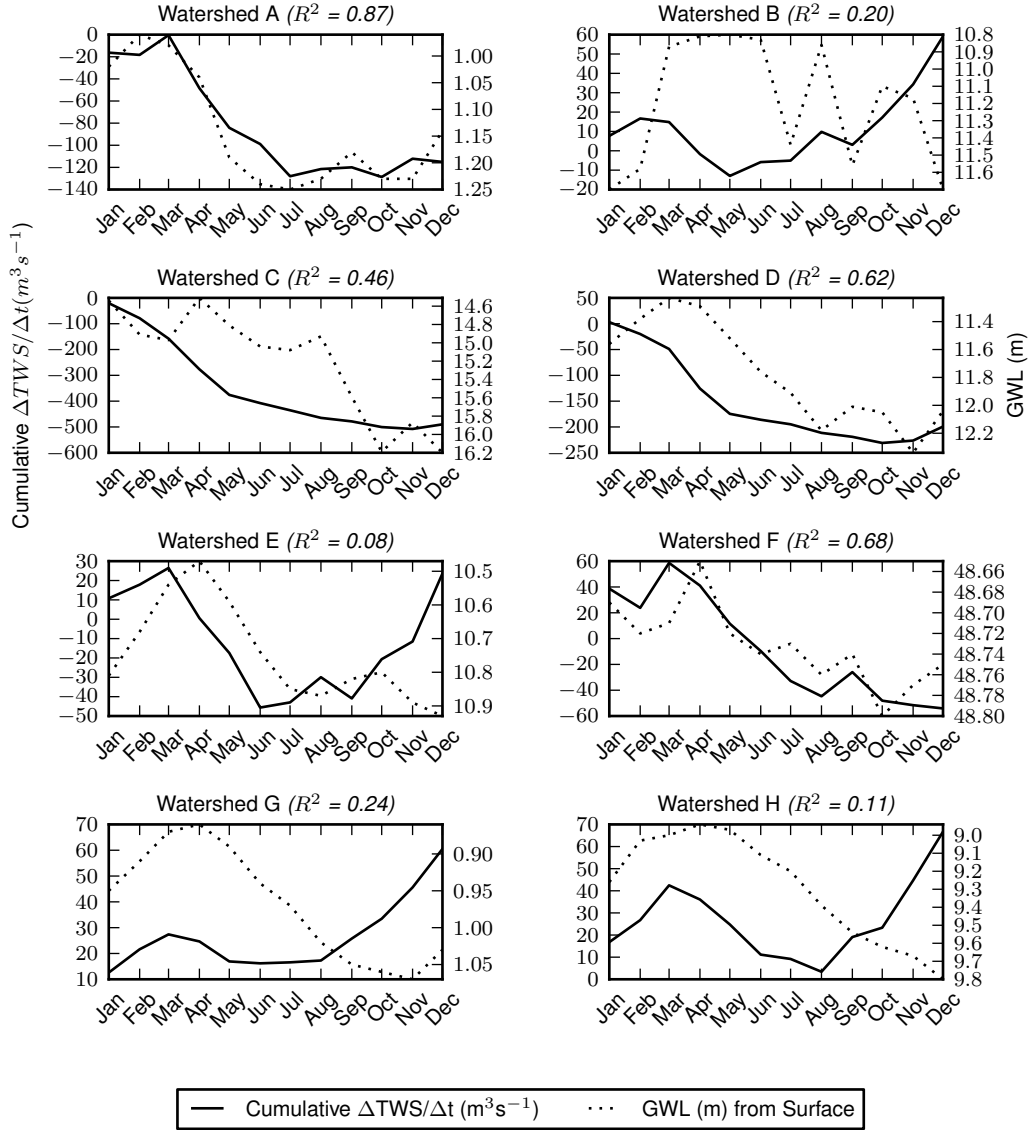


Figure 6: Relationship between cumulative rate of change in cumulative terrestrial water storage (averaged over same month from 1998-2007) and groundwater levels (1998-2007) in the sub-watersheds.

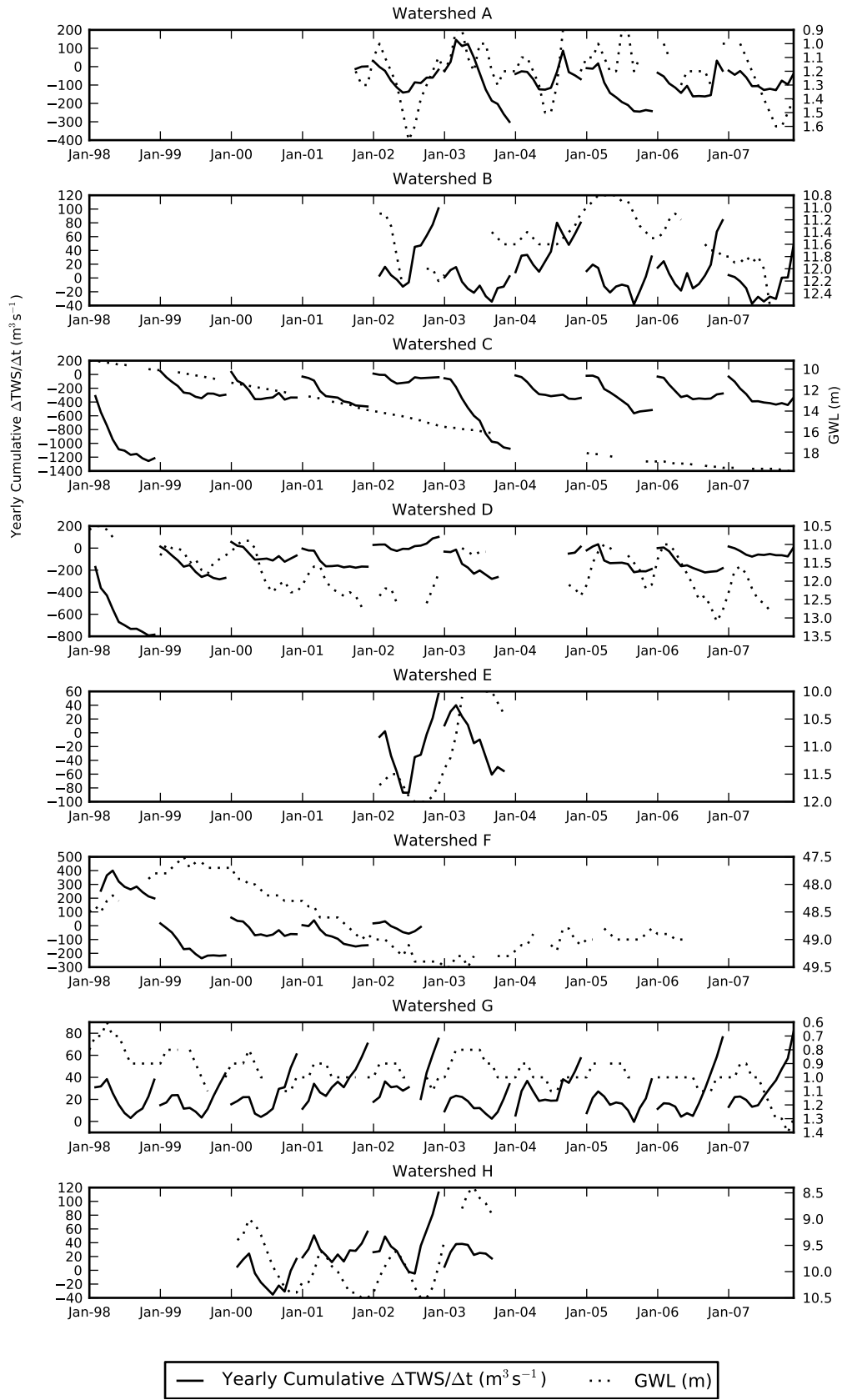


Figure 7: Long term relationship between the yearly cumulative rate of change in terrestrial water storage and groundwater levels in the sub-watersheds.