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VULNERABILITY OF COASTAL WATERSHEDS TO CLIMATE CHANGE AND VARIABILITY

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ABSTRACT

We investigate the role of climatic variability on interannual groundwater and streamflow variability in the Southeast U.S. For this purpose, streamflow and associated groundwater levels are analyzed for 20 basins that are minimally affected by reservoirs and groundwater pumping. Using the spatially-averaged monthly precipitation time series obtained from the Precipitation Regressions on Independent Slope Model (PRISM), we identify the recharge and discharge periods that influence the groundwater levels during the winter (January-February-March, JFM) and summer (July-August-September, JAS) seasons. Recharge-discharge dependency analyses indicate that precipitation during the previous three months influences the groundwater level in a given month. Streamflow in any given month depends on the groundwater level during the previous three months. Principal component analysis (PCA) on the precipitation, temperature, streamflow and groundwater data indicate that groundwater levels and streamflow are the two dominant variables influencing the basin hydroclimatology. Further, relating the percentage variance explained from the PCA to baseflow index (BFI) clearly shows that basins with high BFI have higher eigenvalues, indicating that groundwater is a spatial integrator of hydroclimatic processes. Relating the groundwater levels with El Nino Southern Oscillation (ENSO) index, Nino3.4, shows that interannual variability in JFM groundwater levels could be partially explained by the ENSO conditions, but the relation between JAS groundwater levels and JAS Nino3.4 is not statistically significant. Precipitation forecasts from ECHAM4.5 General Circulation Model indicate that it is possible to quantify groundwater availability during the winter season based on the forecasted precipitation and ENSO conditions.

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1. Introduction

Climate variability, primarily resulting from Sea Surface Temperature (SST) variability, plays an important role in basin hydroclimatology, including precipitation, temperature and streamflow. Considerable research now exists on the association between low frequency climatic variability (e.g., El Nino Southern Oscillation (ENSO) conditions) and its impact on local/regional precipitation, temperature and streamflow (Ropelewski and Halpert, 1987; Dettinger and Diaz, 2000; Devineni and Sankarasubramanian, 2010 and references therein). It is well known that soil moisture holding capacity (Koster and Suarez, 2001; Sankarasubramanian and Vogel, 2002) and aquifer storage (Shun and Duffy, 1999) influence the interannual variability in streamflow and the associated baseflow. In comparison, however, the teleconnection between various sources of climatic variability and groundwater variability has received relatively less attention. Shun and Duffy (1999) showed that basins experiencing weak climate signal, but with relatively high baseflow discharge, could exhibit significant low frequency variability in streamflow induced by changes in groundwater storage. Hansen et al. (2004) investigated the quasi-periodic oscillations among groundwater levels, streamflow, precipitation and tree-ring indices in four basins from the Southwest U.S, and found that the reconstructed components exhibited ENSO and Pacific Decadal Oscillation (PDO) signals. Scanlon et al. (2006) found that groundwater recharge during El Nino was three times higher than the recharge during La Nina conditions over the Southwest U.S. Anderson and Emanuel (2008) associated ENSO conditions with baseflow records in eastern North Carolina and concluded that baseflow from coastal aquifers exhibited significant correlation with ENSO.

As in most regions of the world, groundwater in the Southeast U.S. (SEUS) is important for water supply, irrigation, and maintenance of baseflow. Given the significant association between low-frequency climate variability and streamflow (Schmidt et al. 2001; Lecce, 2000; Hansen et al. 1998; Zorn and Waylen, 1997), we present results from a systematic investigation of surface water and groundwater interaction in the SEUS and demonstrate their interdependence with exogenous climatic variability. For this purpose, we have assembled groundwater and surface water data along with spatial estimates of precipitation and temperature for 20 relatively undeveloped basins in the SEUS. Initially, we proposed to focus both on climate change and variability. However, due to large uncertainty in climate change projections (Moreau, 2006) over the Southeast US, we have decided to focus only on the role of climate variability in influencing groundwater-surface water interaction over the coastal watersheds in the Southeast US.

2. Data Description and Seasonality of Groundwater

Surface-water and groundwater data were carefully selected from twenty sites that are minimally affected by anthropogenic influences such as reservoir storage and groundwater pumping (Table 1). Streamflow and groundwater stations were selected based on the following criteria:

a) Streamflow data were selected from the USGS Hydroclimatic Data Network (HCDN) database (Slack et al. 1993) and groundwater records were selected from the USGS Climate-Groundwater Response Network (http://pubs.usgs.gov/fs/2007/3003/) database. Both networks consist of stations having natural basin response with minimal impacts due to surface-water storage, diversions, and groundwater pumping.

b) Groundwater wells were screened in the surficial, unconfined aquifer or in a near-surface confined aquifer so that the data could be used to account for the interaction between streamflow and groundwater.
c) Groundwater wells were selected such that the distance between the stream gauge and the well is minimal. The majority of the selected wells are within 9 miles of the corresponding streamflow gauges.
d) Sites were geographically well distributed (Figure 1) to represent a wide range of basin characteristics in the SEUS.

We briefly discuss the sources and the spatio-temporal coverage of the various databases employed in the study.

Table 1: Stream gauges and associated groundwater wells used in data analysis

Site index	Surface water station		Drainage area (square miles)	Groundwater well number	Period of groundwater records (years)
	Stream gauge no.	Stream gauge name			
1	02342500	Uchee Creek near Fort Mitchell, AL	322	322036084590301	1980-2006
2	02240000	Ocklawaha River near Conner, FL	1196	291115081592501	1980-2002
3	02353500	Ichawaynochaway Creek at Milford, GA	620	312232084391701	1980-2007
4	02392000	Etowah River at Canton, GA	613	342125084083301	1990-2007
5	02344500	Flint River near Griffin, GA	272	331507084171801	1980-2007
6	02226000	Altamaha River at Doctortown, GA	13600	313253081433504	1983-2007
7	02202500	Ogeechee River near Eden, GA	2650	321240081411501	1983-2006
8	02314500	Suwannee River at US 441, at Fargo, GA	1260	304942082213801	1980-2007
9	02084160	Chicod Cr at Sr1760 Near Simpson, NC	45	353219077153801	1980-2007
10	02092500	Trent River near Trenton, NC	168	345809077301408	1987-2007
11	02111000	Yadkin River at Patterson, NC	2280	355359080331701	1982-2006
12	02131000	Pee Dee River at Pee Dee, SC	8830	341144079345001	1982-2005
13	02132000	Lynches River at Effingham, SC	1030	340806079563100	1981-2005
14	02176500	Coosawhatchie River Near Hampton SC	203	324143080505900	1980-2007
15	02353000	Flint River at Newton, GA	5740	311802084192302	1981-2007
16	02350512	Flint River at GA 32, near Oakfield, GA	3880	314330084005402	1987-2007
17	02357000	Spring Creek near Iron City, GA	485	311009084495503	1982-2006
18	03443000	French Broad River at Blantyre, NC	296	351808082374302	1982-2007
19	02335700	Big Creek near Alpharetta, GA	72	335517084164001	1982-2007
20	02313100	Rainbow Springs near Dunnellon, FL	1960	290514082270701	1982-2005

Hydroclimatic Data

Monthly time series of streamflow were obtained for each station (Table 1) from the HCDN database (Slack et al. 1993) and from the USGS National Water Information System (http://waterdata.usgs.gov/nwis). We also assembled spatially averaged monthly time series of precipitation and temperature over the watershed from the HCDN hydroclimatic database (Vogel and Sankarasubramanian, 2005) and from the PRISM (Precipitation Regressions on Independent Slope Model, Daly et al., 1994) database. Because of the limited length of groundwater records, streamflow and hydroclimatic records available over the period 1980-2007 were used in the analysis.

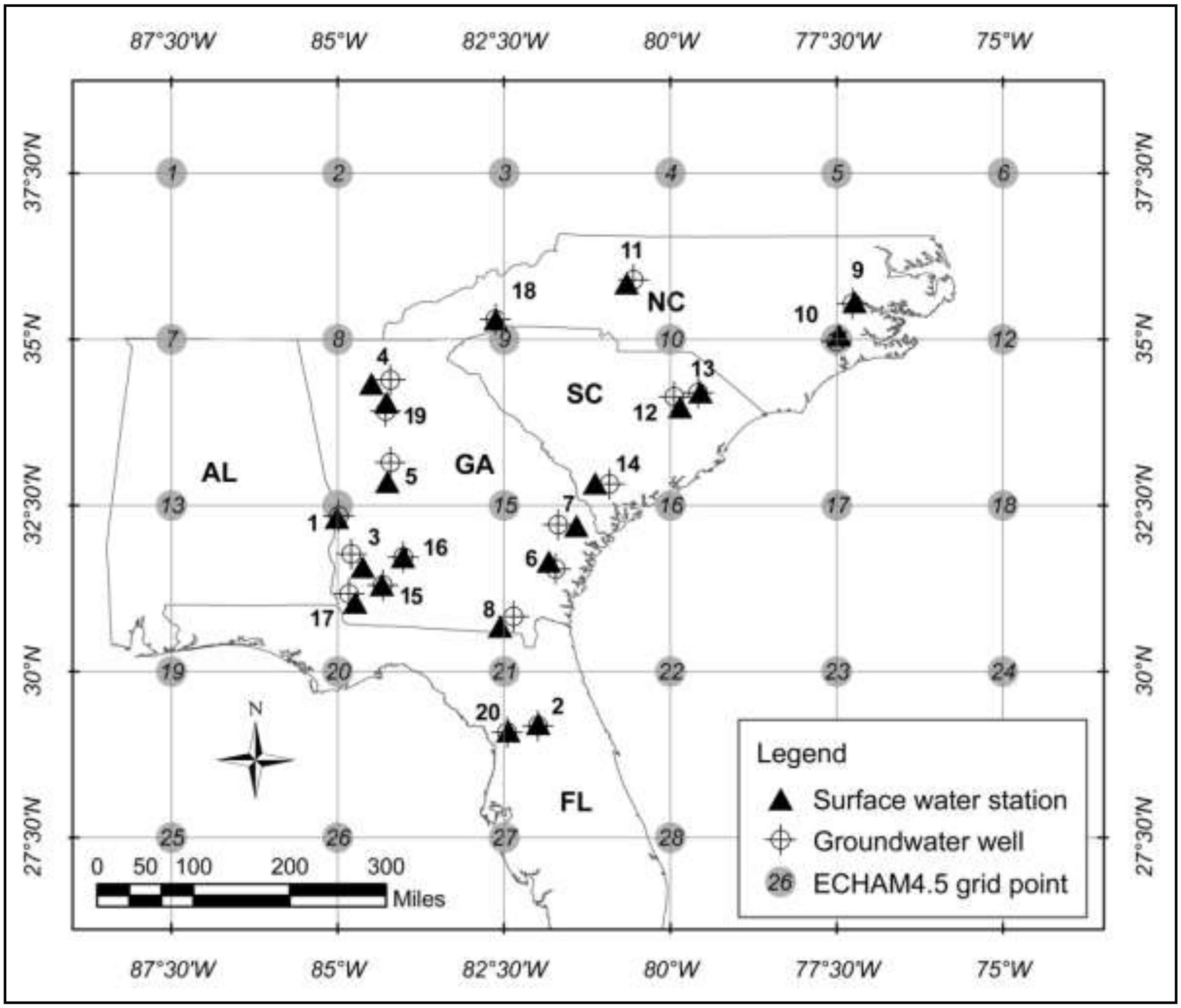

Figure 1: Location of twenty stream gauges and associated groundwater wells in the Southeast US along with the grid points having ECHAM4.5 precipitation forecasts.

Groundwater Data

Of the 20 selected wells, groundwater level data for 7 wells were obtained from the USGS Climate-Groundwater Response Network. USGS maintains this network of wells to monitor the effects of climate variability on groundwater levels in unconfined aquifers or near-surface confined aquifers that are minimally affected by pumping or other anthropogenic stresses (USGS, 2008). For the other 13 wells, we carefully reviewed the annual well reports to ensure that the groundwater levels were not influenced by pumping. Groundwater data were represented as mean monthly depth (in feet) from land surface to groundwater level.

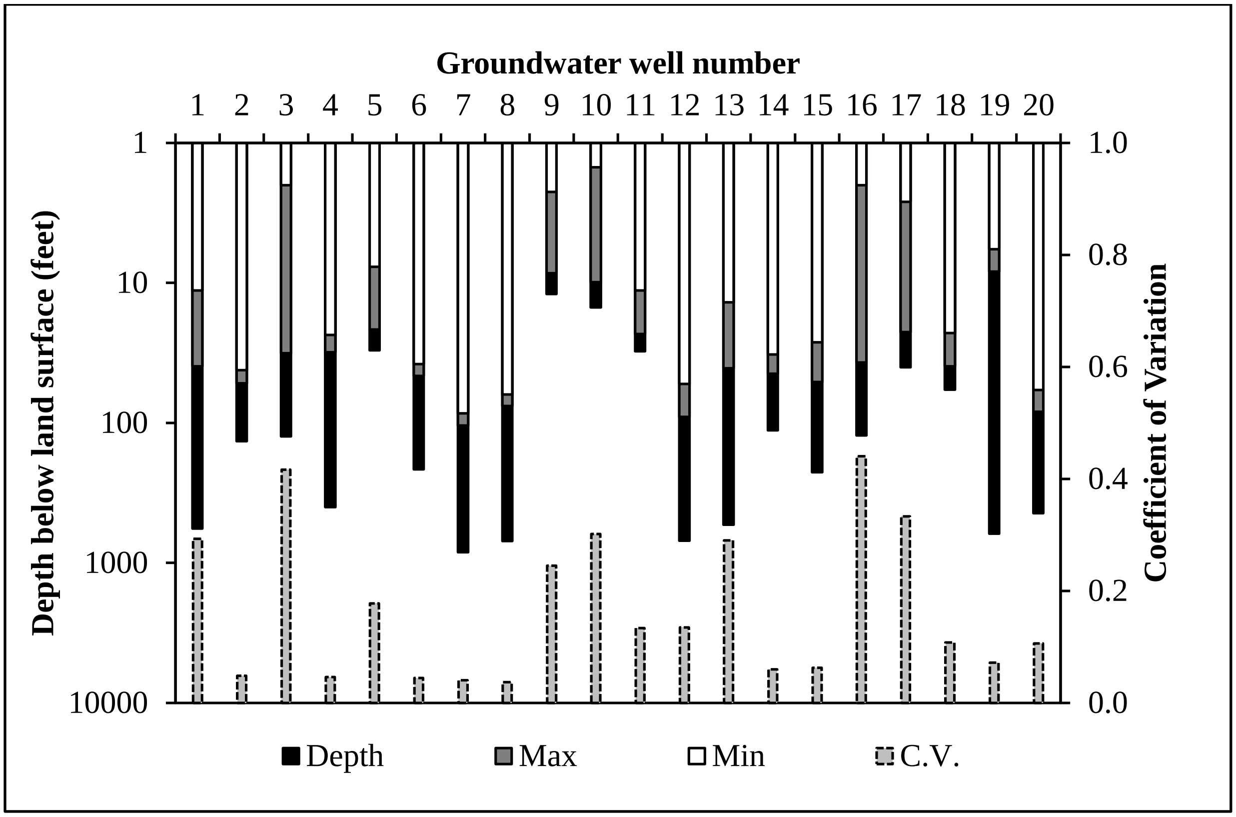

Figure 2: Total depth of the groundwater well along with monthly minimum (Min), maximum (Max) and coefficient of variation (CV) of observed depth to groundwater levels for the 20 selected sites.

Depths of groundwater wells range from 12 to 804 feet (Figure 2). Figure 2 also provides the coefficient of variation (CV) of monthly groundwater level indicating a small variability of groundwater at several sites. Although the interannual variability in groundwater level is relatively small, the effect of such small variation on interannual variability in baseflow and streamflow could be significant (Shun and Duffy, 1999; Anderson and Emanuel, 2008). Nevertheless, a small variation in groundwater level implies a significant variation in baseflow. Mean depth to groundwater ranged from 3.21 to 92.23 feet (Figure 2). Because the period of record of the hydroclimatic data exceeded that for groundwater data in most basins, the number of years considered for analysis generally was constrained by the groundwater period of record, with analysis periods ranging from 18 to 28 years.

The selected 20 wells span across five states – Alabama, Florida, Georgia, South Carolina and North Carolina – over the Southeast US comprising of 4 different aquifer types. The region overall comprises eight different aquifer types (Miller, 1999). The selected wells are predominantly surficial aquifers (all along the Atlantic Coast), the Floridan aquifer (2 wells in Florida), Piedmont and Blue Ridge Aquifers, and Southeast Coastal Plain Aquifers. The surficial aquifer system consists mostly of unconsolidated sand, but also contains a few beds of shell and limestone, whereas the Floridian aquifer system consists of limestone and dolomite, and is the most productive aquifer in terms of total water yield. The Southeastern Coastal Plain aquifer system is predominately sand, but also consists of some beds of gravel and limestone. Piedmont and Blue Ridge aquifers consist of indurated metamorphic rocks, such as gneiss and schist, and igneous rocks, such as granite, that underlie the hilly terrain of Piedmont and Blue Ridge area. Water is mostly present in these rocks in fractures, but locally a large volume of water is also stored in the regolith that overlies the rock. For additional details of the hydrogeology of the SEUS, see Miller (1999). Precipitation is the primary source of recharge into these aquifers with average annual precipitation ranging from 48 inches (in the plains) to 80 inches (mostly in the mountainous areas) per year. Several studies have shown the significant association between climatic variability and precipitation over the region (Ropelewski and Halpert, 1987; Devineni and Sankarasubramanian, 2010). Thus, understanding the linkages between climatic signals and groundwater levels will provide critical information on the source of interannual variability in groundwater potential over the region.

Precipitation Forecasts Database

To investigate the performance of precipitation forecasts to adequately represent the winter (January, February, and March, or JFM) streamflow and groundwater level in the study basins, we utilize the retrospective winter precipitation forecasts (PF) from ECHAM4.5 (http://iridl.ldeo.columbia.edu/SOURCES/.IRI/.FD/.ECHAM4p5/.Forecast/ca_sst/.ensemble24/.MONTHLY/.prec/) obtained from International Research Institute of Climate and Society (IRI) data library and forced with constructed analogue SSTs (Li and Goddard, 2005). Grid-point indices over which the ECHAM4.5 forecasts are available are shown in Figure 1 and described in Table 2. Retrospective precipitation forecasts from ECHAM4.5 are available for 5 months ahead for every month beginning from 1957. To force ECHAM4.5 with SST forecasts, retrospective monthly SST forecasts were developed from 1957 using the constructed analogue approach based on the observed SST conditions in that month. For additional details and documentation on forcing ECHAM4.5 using constructed analogue SST forecasts, see Li and Goddard (2005). For this study, we utilize the forecasted mean, which is obtained by computing the average over 24 ensembles, of JFM retrospective precipitation forecasts issued in the beginning of January.

Nino3.4 – ENSO Index

Nino3.4 is an index commonly used to denote the strength of ENSO conditions and represents average anomalous SST conditions over 5S-5N and 170W-120W in the tropical Pacific. The Nino3.4 indices were obtained from the Kaplan's SST database (Kaplan et al. 1998) IRI Data Library (http://iridl.ldeo.columbia.edu/).

3. Streamflow-Groundwater interaction in the SEUS

A simple way to quantify the seasonality of a hydroclimatic attribute is to plot their mean monthly values and quantify the individual season's total to the annual total. However, such an approach will be difficult to summarize over a region. To overcome this, Markham (1970) suggested quantitative expressions for seasonality by adding the mean monthly values vectorially. The resultant's magnitude and direction denote the degree of seasonality and the period of seasonal concentration. The ratio of the magnitude of the resultant to the mean annual values of the hydroclimatic attribute is expressed as Seasonality Index (SI). Large values of SI show significant contribution of the seasonal values to the annual total. For instance, if the SI is closer to 1, then it implies all the annual total comes from a single month. On the other hand, if the SI is closer to zero, then it indicates no seasonality in the monthly distribution of the hydroclimatic attribute. We consider a station to have significant seasonality if the SI of the hydroclimatic attribute is greater than 0.2.

Table 2: Grid points (shown in Figure 1) of ECHAM4.5 precipitation forecasts that are significantly correlated to observed precipitation

Site Index	USGS Station No.	Grid points index	Number of grid points	%variance of PC1
1	02342500	7-11, 13-17	10	0.92
2	02240000	15-17, 21-23, 27-29	9	0.98
3	02353500	8-10, 14-16, 20-22	9	0.89
4	02392000	2-4, 8-10	6	0.88
5	02344500	2-4, 8-10	6	0.88
6	02226000	9,10,15,16	4	0.91
7	02202500	9-11,15-17,21-23	9	0.91
8	02314500	15-17, 21-23	6	0.98
9	02084160	4,6,10,12	6	0.88
10	02092500	5,6,11,12	6	0.92
11	02111000	4,5,10,11	4	0.88
12	02131000	10,11,16,17	4	0.95
13	02132000	10,11,16,17	4	0.95
14	02176500	10,11,16,17	4	0.95
15	02353000	9,10,15,16,21,22	6	0.89
16	02350512	9,10,15,16	4	0.91
17	02357000	8-10, 14-16, 20-22	9	0.89
18	03443000	9,10	2	0.98
19	02335700	9,10	2	0.98
20	02313100	21,22,27,28	4	0.99

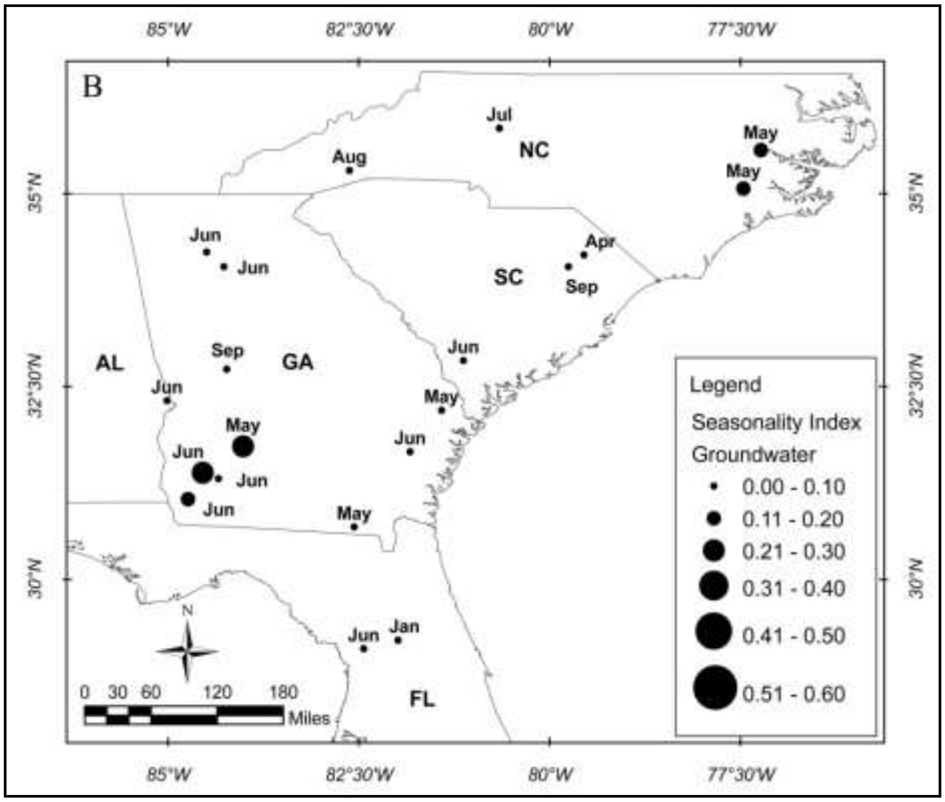

Figure 3: Seasonality Index and month of maximum groundwater levels for study sites.

The seasonality of precipitation in the SEUS is uniform (monthly percentage of annual total being between 0.1-0.2) indicating that monthly precipitation is almost equal in all the months (Markham 1970). The only exception is peninsular Florida, where the monthly peak precipitation is in July, with an index of 0.4 to 0.6. Monthly maximum temperatures, as expected, occur in July-August. Maximum streamflows occur during the winter, with the exception of Florida, where seasonal peaks are in July-August, consistent with maximum precipitation (Devineni and Sankarasubramanian, 2010). Streamflow seasonal indices range from 0.3 to 0.6**.** With the exception of few sites in southern Georgia, there is little seasonality in maximum groundwater levels (Figure 3), indicating the role of storage in distributing the groundwater is relatively uniform throughout the year. From a water management perspective, we consider winter months to be months during which most of the groundwater recharge occurs, although recharge generally appears to continue through May–June, when groundwater levels are at a maximum (Figure 3) at most sites. During summer months (July, August, and September, or JAS), groundwater level declines due to high evapotranspiration rates. Hence, for our study, we consider these two seasons, winter and summer, for understanding the role of climate variability in influencing surface water and groundwater interaction in the SEUS.

Precipitation-Groundwater-Streamflow Interactions: Dependency Analyses

To begin with, we first present dependency analyses among precipitation, groundwater and streamflow interaction in the SEUS. The purpose of this analysis is to identify the lag (lead) time in months between precipitation (streamflow) and groundwater levels in terms of recharge (discharge) months. The period over which interaction among these three hydroclimatic variables is significant was estimated using Spearman rank correlation analysis. We employ Spearman rank correlation because it better estimates the dependency between two variables, even if the variables are monotonically related. We consider precipitation to be the primary variable responsible for recharging the aquifer and a period of six months prior to a given month was considered for understanding the recharge. Thus, the period during which groundwater level in a given month influences streamflow in subsequent months is identified based on lead-correlation.

Figure 4 shows box-plots of lag (lead) correlations between groundwater and precipitation (streamflow) for winter (Figure 4a) and summer (Figure 4b) seasons. Correlations are statistically significant at 5 % significant level ($\pm$ 1.96/$\sqrt{n-3}$, where '*n*' denotes the number of data used for calculating the correlation). Each box-plot is obtained by pooling the lag (lead) correlation with precipitation (streamflow) for five months prior (subsequent) to the groundwater level in a given month over a particular season. From Figure 4, we conclude that recharge from precipitation for a given groundwater month is significant for lags of three months or less. Likewise, groundwater levels for a given month are correlated with discharge for no more than the subsequent three months. Comparing the box-plots for the winter and summer season (Figure 4a and Figure 4b), we also conclude that the groundwater level correlations with precipitation are similar during both winter and summer, which primarily is due to the relative uniformity of monthly precipitation during the year at most sites. On the other hand, the correlation between the groundwater level and streamflow is lower during the summer than in the winter, which is due to reduced groundwater storage during the summer months. Based on these analyses, we conclude that precipitation over the previous three months and streamflow for the subsequent three months capture the recharge and discharge dynamics of groundwater in any given month. Thus, we consider a total of 18 monthly time series of precipitation, temperature, streamflow and groundwater levels for analyzing the role of climate in influencing the basin hydroclimatology.

4. Climate Variability and Surface Water and Groundwater Interaction

To understand the role of climate in influencing surface water and groundwater interaction, we first identify the dominant hydroclimatic variable(s) that influence the recharge-discharge dynamics of groundwater during the winter and summer seasons. For this purpose, we employ singular spectrum analyses (SSA), which basically is principal component analysis (PCA) on lagged variables. SSA, when employed over multiple sites, is known as multichannel SSA and is the application of Karhunen-Loeve theorem on spatio-temporal data (Plaut and Vautard, 1994). Multichannel SSA employs orthogonal decomposition of a cross-covariance matrix, which is otherwise known as Toeplitz matrix. Shun and Duffy (1999) applied SSA to identify the low frequency variability among precipitation, temperature and streamflow at different elevations over a mountain front. Hanson et al. (2004) proposed SSA for understanding surface water and groundwater interaction and related the reduced components of SSA to climatic indices. Allen and Smith (1996) proposed Monte Carlo techniques to discriminate between potential oscillations and colored noise following first-order autoregressive analysis.

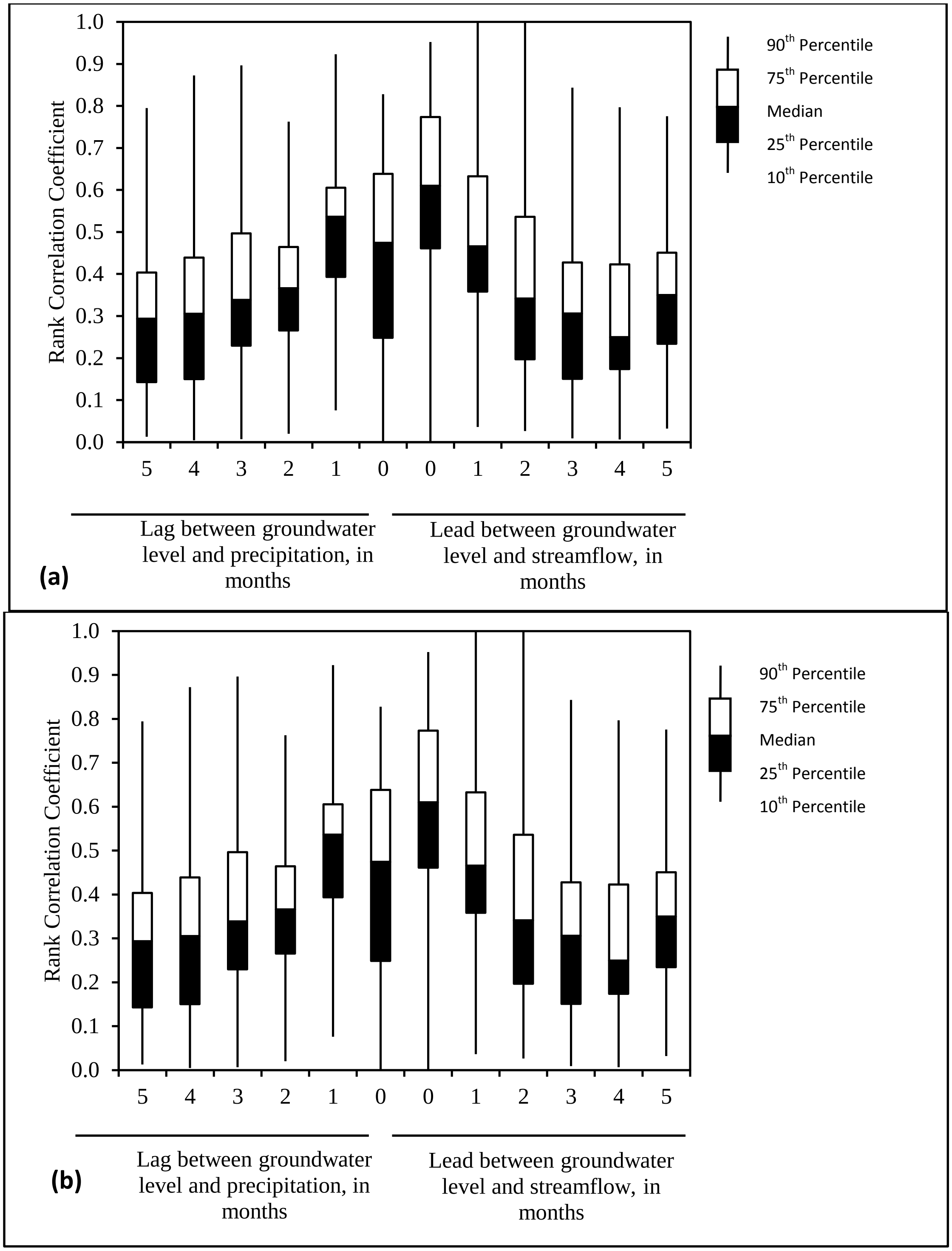

Figure 4: Box-plots of monthly rank correlation between groundwater level with previous (lag) five months of precipitation and the following (lead) five months of streamflow during winter (a) and summer (b) seasons for the 20 study basins.

SSA is used to reduce both spatial and temporal interdependences using PCA. SSA rotates the lagged time series into orthogonal components known as scores. Eigenvalues and eigenvectors for each component from SSA summarize the total variance explained and the dominant variable for that component. In this study, we perform only single channel SSA on the precipitation, temperature, streamflow and groundwater levels at the 20 study sites to understand the dominant modes and components of hydroclimatic variability and their association to climatic variability during winter and summer. Because the period of record for groundwater data is less than 30 years, we did not try to identify the underlying periodic components based on eigenvalues spectrum (Hanson et al., 2004), which requires a longer period of record. Essentially, this forces the SSA to be PCA on lagged precipitation, streamflow, groundwater and temperature at a given site.

Our pooled variables for SSA include a lag/lead window of three months for recharge (discharge), October-March (April-September), six months of precipitation, January-June (July-December), six months of streamflow, and three months of JFM (JAS) temperature and groundwater levels. This results in a set of 18 variables for a given season which were used in the SSA. Results from SSA are summarized as follows: Eigenvalues from the first component are presented and related to the baseflow index (BFI) to understand the role of groundwater in increasing the covariability among the 18 variables. Following that, eigenvectors for the first component are summarized and the dominant variable for first component is identified. Finally, we relate the scores of the first component from SSA to the climatic indices in order to quantify the role of climatic variability in influencing the hydroclimatic covariability over the basin.

Figure 5 shows the proportional variance explained by the first component for the winter and summer seasons. Proportional variance explained by each component was computed from the ratio of the eigenvalue of that component to the total variance of all 18 variables. Higher proportional variance for the first component indicates increased temporal covariability among the 18 variables. Overall, proportional variance explained by the first component is higher in Florida (higher precipitation seasonality) and Southern Georgia (higher groundwater seasonality; Figure 5). The proportional variance explained by the first component in the winter season is higher than proportional variance explained in the summer season (Figures 5 and 6). This is primarily due to higher temperatures and evapotranspiration in summer, which reduces the temporal correlation among the variables resulting in smaller summer eigenvalues. Figure 6 shows the relation of the proportional variance explained by the first component during the winter and summer season to respective season's baseflow index (BFI), which was computed using the observed daily flow values and the online BFI tool of Lim et al. (2005). The correlations between the proportional variance explained and the BFI for the winter and summer seasons are 0.60 and 0.66 respectively. Higher eigenvalues (increased temporal covariability) are associated with basins have higher BFI's (Figure 6), indicating the correlation of groundwater to precipitation (as recharge) and streamflow (as discharge) through the aquifer storage.

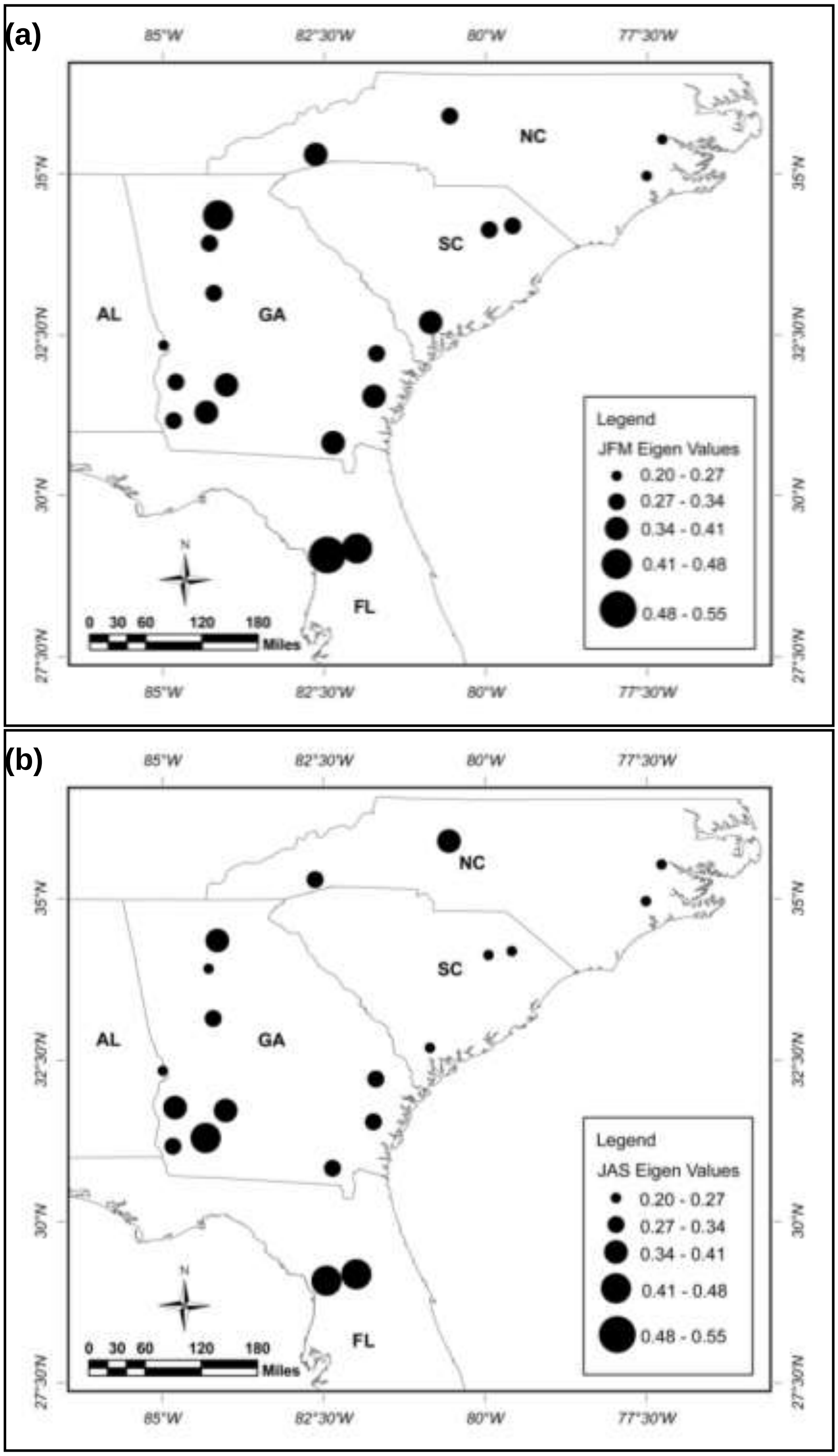

Figure 5: Proportional variance explained by the first component of 18 variables from SSA for (a) winter and (b) summer seasons.

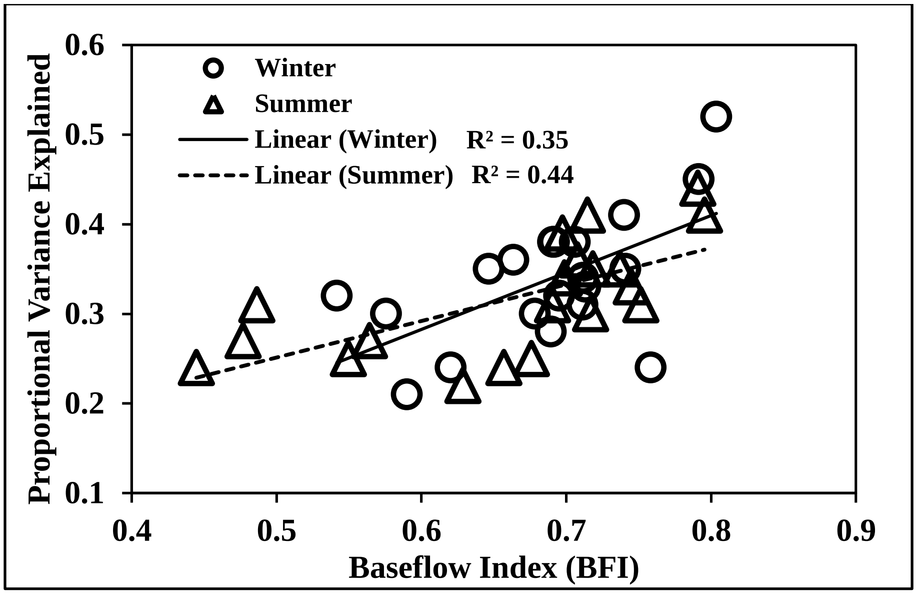

Figure 6: Relation between the proportional variance explained by the first component of 18 variables (winter and summer) from SSA with Baseflow Index for the 20 study basins.

To understand the source of variability related to the first component, we show the box-plot of eigenvectors related to the first component from SSA from 20 sites for both winter and summer (Figure 7). Groundwater level and streamflow in March have high eigenvectors indicating that these variables are the dominant source of variability in determining the first component for the winter season. This is also shown in Figure 8a, which indicates the dominant eigenvector for each station for JFM. The most important information from Figures 7 and 8a is that the precipitation is not the dominant source of variability in influencing the covariability among the hydroclimatic variables during winter in SEUS, which is in contrast to previous findings (Syed et al., 2004), which were based on analysis that did not include groundwater level in the PCA. On the other hand, precipitation in July, streamflow in July and August and groundwater in JAS have high eigenvectors (Figures 7b and 8b) during the summer. Precipitation in July is dominant primarily in some of the coastal and mountainous basins. Further, the eigenvectors for temperature are higher during the summer than the winter indicating their increased role in affecting covariability during summer.

Previous studies have shown that ENSO conditions significantly influence the winter precipitation and temperature over the SEUS with El-Nino over the tropical Pacific resulting in above-normal precipitation and below-normal temperature during the winter (Hansen et al., 1998; Devineni and Sankarasubramanian, 2010). Eigenvalues and eigenvectors obtained from the orthogonal decomposition of hydroclimatic covariability in the SEUS indicate that groundwater and streamflow in March are the dominant variables influencing the temporal covariance among other hydroclimatic variables in the winter. Based on these findings, we extend our analyses by relating the scores of the first component from SSA to JFM ENSO conditions to understand the role of climatic variability in influencing hydroclimatic covariability over the SEUS.

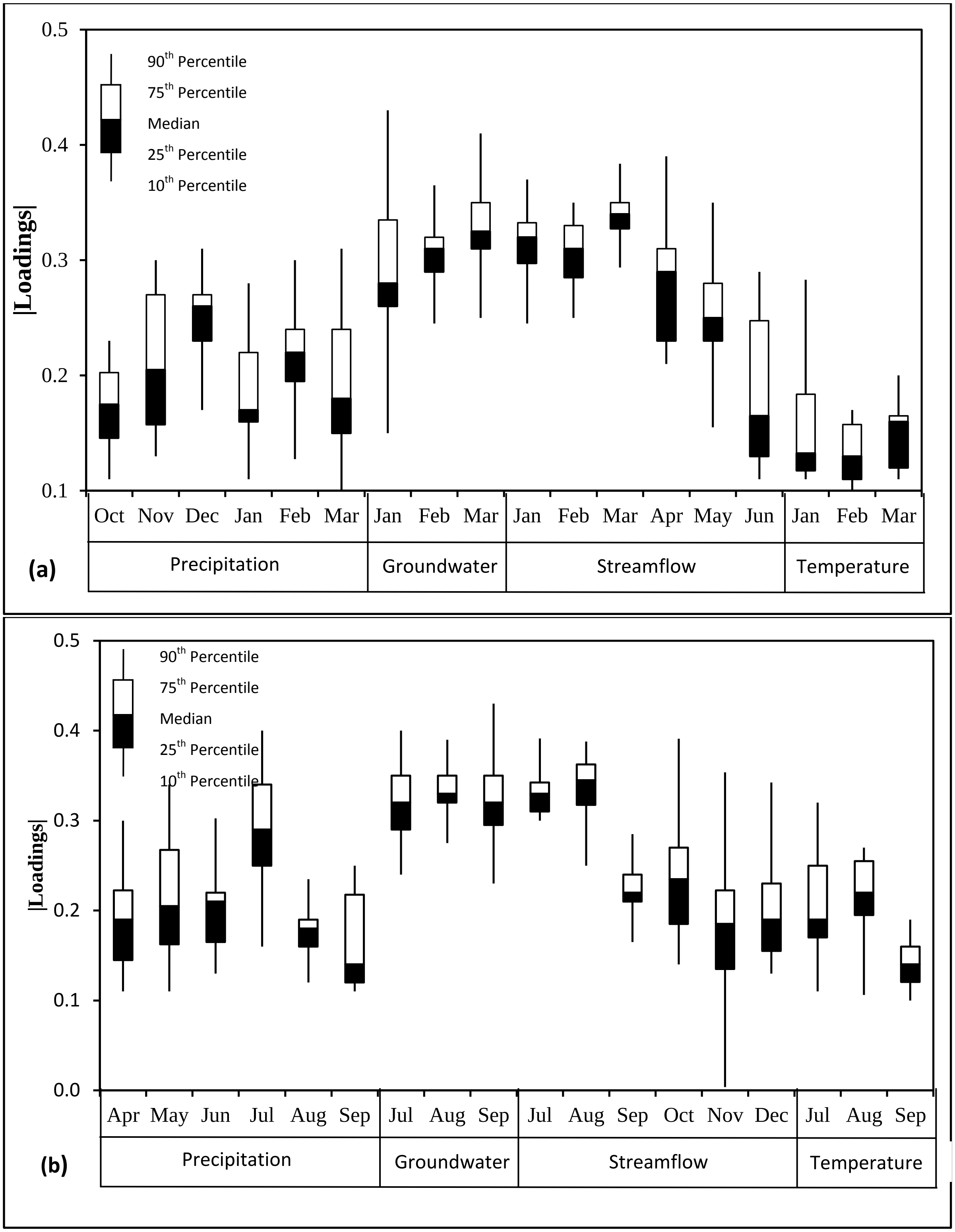

Figure 7: Box-plot of eigenvectors (loadings) from SSA for (a) winter and (b) summer seasons.

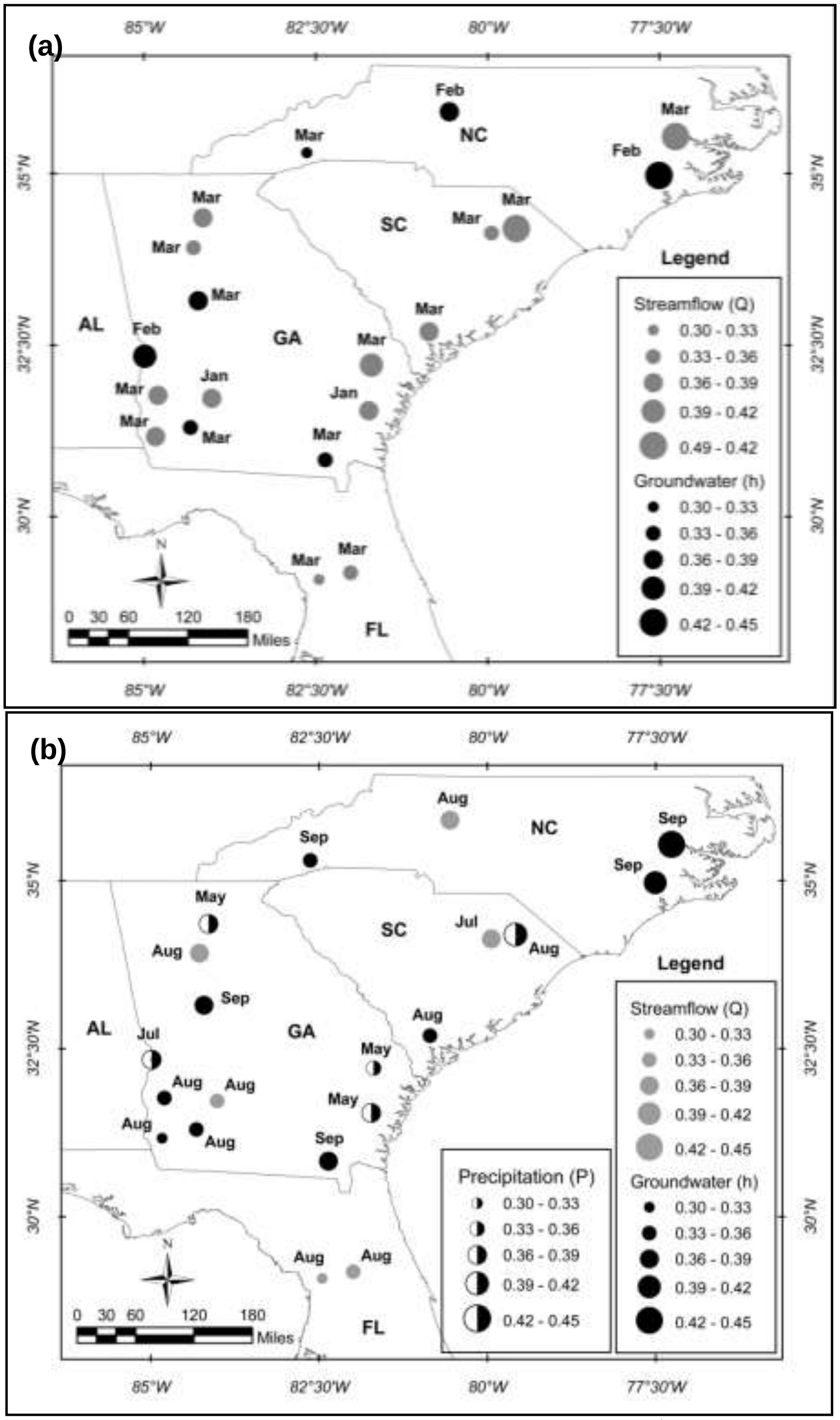

Figure 8: Maps of the dominant eigenvectors (loadings) from the 1st component of SSA for the (a) winter and (b) summer seasons.

Figure 9 shows the rank correlation between the scores of the first component for the winter and JFM Nino3.4 for each of the 20 selected basins. The correlation between the scores of the first component with JAS Nino3.4 did not result in statistically significant correlations. It is well known that association between ENSO conditions and summer climate over the SEUS is generally weak (Ropelewski and Halpert, 1987; Devineni et al. 2008). Analysis presented in Figure 9 clearly shows that ENSO is the exogenous climatic variable that controls basin hydroclimatic covariability over the SEUS. It is important to note that the scores are obtained from the eigenvectors of all the 18 variables. The correlation shown in Figure 9 is statistically significant at all the stations except at the station on the eastern border of Alabama and Georgia (Site 8, Figure 1). To further understand how the correlation between the scores and Nino3.4 depends on two dominant variables – streamflow and groundwater in March – during the winter, we compared the eigenvectors of streamflow and groundwater in March with the correlation between the scores of the first component and Nino3.4. Analyses showed that 24% (16%) of the variance in correlation could be explained by the eigenvectors of groundwater (streamflow) in March (figures not shown). To summarize the analyses on SSA, we understand that scores from the first component of 20 basins is significantly correlated to the JFM conditions. Because the scores for the first component are obtained from all the 18 variables, we exclusively analyze the relation between JFM Nino3.4 and average groundwater level in the winter season as well as the potential skill in predicting the groundwater level using ECHAM4.5 precipitation forecasts.

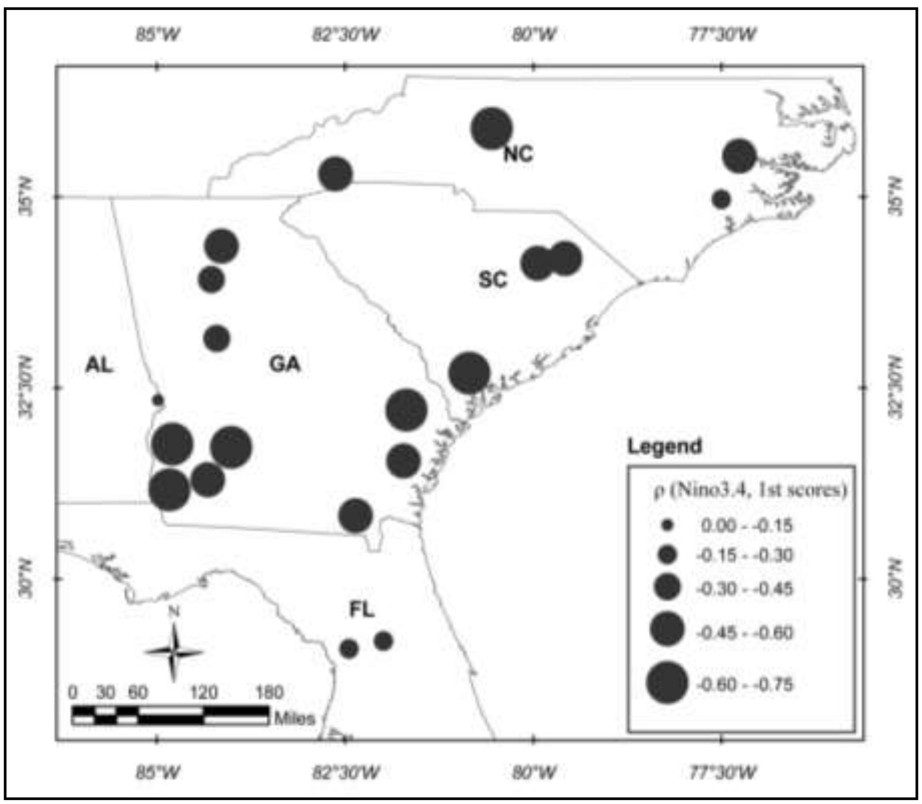

Figure 9: Rank correlation between the scores of the first component and JFM Nino3.4 for the 20 selected stations.

Role of ENSO conditions in influencing interannual groundwater variability

As previously noted, the main intent of this paper is to understand and describe the relation between climatic variability and groundwater variability during winter and summer. Therefore, we correlate the JFM (JAS) Nino3.4 and JFM (JAS) groundwater levels to identify the effect of ENSO conditions on groundwater variability in the SEUS. For comparison, we also compute the correlation between precipitation and streamflow with Nino3.4 for both seasons. Most of the studies focusing on climatic variability over the SEUS have shown that warm tropical Pacific conditions during October-December lead to above-normal precipitation during winter and below-normal precipitation during summer if ENSO conditions prevail during the spring (Schmidt et al., 2001; Lecce, 2000; Hansen et al., 1998; Zorn and Waylen, 1997). Teleconnections between ENSO and precipitation and temperature over North Carolina during the winter season also have been demonstrated (Roswintiarti et al., 1998; Rhome et al., 2000).

The relation between ENSO conditions and groundwater levels is significant (95 percent confidence level, correlation coefficient greater than 0.27) at six stations (Figure 10a) in the winter, and at two stations in the summer (Figure 10b). On the other hand, both precipitation and streamflow exhibit significant correlation with Nino3.4 at 14 and 18 stations, respectively. This implies that groundwater variability is less modulated by short-term climatic variability, in contrast to the effect of ENSO on precipitation and streamflow. This is to be expected because the storage of the aquifer dampens the interannual variability in the precipitation and temperature.

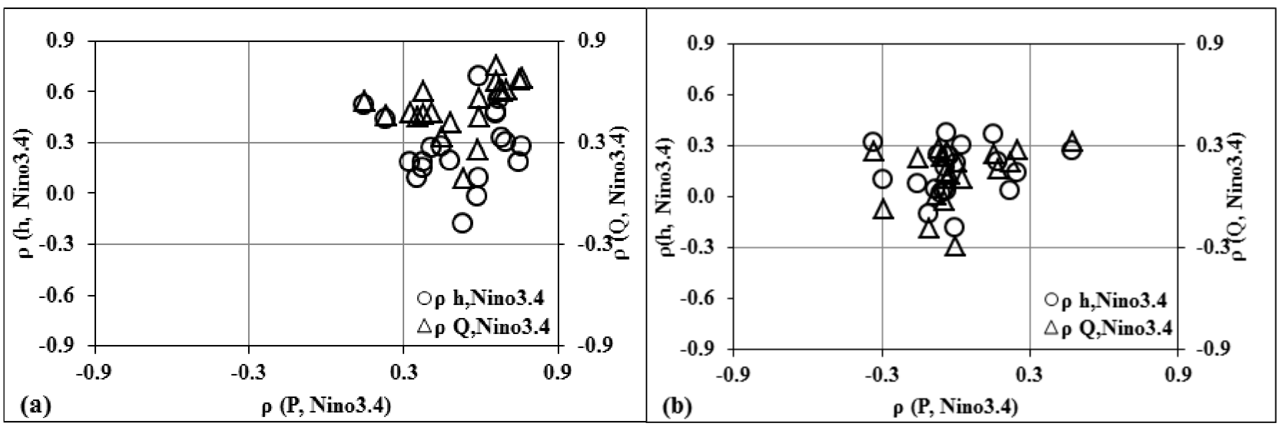

Figure 10: Concurrent rank correlation between groundwater levels and Nino3.4 expressed as function of concurrent correlation between precipitation and Nino3.4 for the (a) winter and (b) summer seasons. The secondary Y-axis in both figures shows the concurrent correlation between streamflow and Nino3.4 for the respective seasons.

Given that only six basins exhibit significant correlation between JFM Nino3.4 and JFM groundwater levels, we extend the analysis by associating groundwater levels with 3-month ahead retrospective precipitation forecasts to determine the utility of climate forecasts in explaining the variability of streamflow and groundwater levels. Because the precipitation forecasts from GCMs are obtained from forecasted SSTs and because of the uncertainty in initial atmospheric conditions, we expect the precipitation forecasts from GCMs could associate with groundwater levels better than did Nino3.4.

Predicting winter groundwater levels using forecasted precipitation

Finally, we explore the utility of using retrospective JFM precipitation forecasts (http://iridl.ldeo.columbia.edu/SOURCES/.IRI/.FD/.ECHAM4p5/.Forecast/.ca_sst/) from ECHAM4.5 General Circulation Model forced with constructed analogue SSTs for predicting the groundwater levels in the selected basins. For this purpose, we first obtain the principal components of the precipitation forecasts and then relate them with the JFM streamflow and groundwater levels. To obtain the principal components of the precipitation forecasts, we identify the relevant grid points that exhibit statistically significant correlation between ensemble mean of the precipitation forecasts and the observed precipitation over the selected basin. Table 2 provides the selected grid points (shown in Figure 1) for PCA for each station and the percentage variance explained by the first component. The first component of the precipitation forecasts explains about 85-99% of the variance in the forecasted precipitation fields, indicating strong correlation among the gridded precipitation forecasts.

Figure 11 shows the correlation between the first principal component of the forecasted precipitation and the respective observed variables (X-axis: precipitation, primary Y-axis: streamflow, secondary Y-axis: groundwater). Results shown in Figure 11 clearly indicate that if the forecasted precipitation is significantly correlated with observed precipitation, then the forecasted precipitation also is significantly correlated with streamflow and groundwater. Moreover, 11 stations exhibit significant correlation between groundwater levels and the forecasted precipitation, which is clearly more than the number of groundwater wells exhibiting statistically significant correlation with Nino3.4 alone (see Figure 10a). As a result, we conclude that nearby precipitation forecasts provides better season-ahead predictions of basin groundwater levels and streamflow than do ENSO conditions. Further, the association between climate and basin precipitation/streamflow also is evident in basin groundwater levels, thereby providing the scope for developing groundwater availability forecasts contingent on climate information.

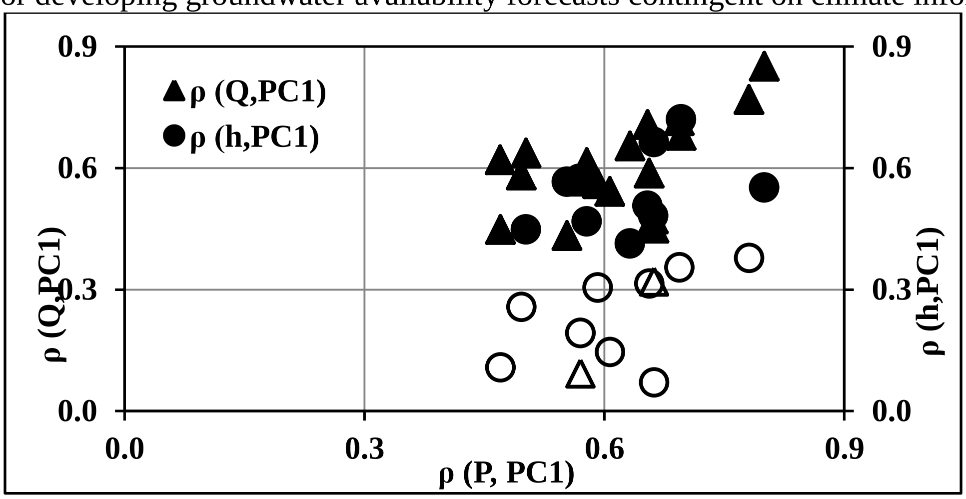

Figure 11: Plot of correlation between groundwater level (secondary Y-axis) and the first component of ECHAM4.5 precipitation forecasts and correlation between precipitation and the first component of ECHAM4.5 precipitation forecasts for the winter season. The primarily Y-axis shows the correlation between streamflow and the first component of ECHAM4.5 precipitation forecasts during both seasons. Hollow circles represent correlation that is not statistically significant.

5. Discussion

This study systematically investigated the dependency between precipitation, streamflow and groundwater to ENSO-related climatic variability during winter and summer months over the SEUS. Findings from SSA clearly show that hydroclimatic (precipitation, temperature, streamflow and groundwater) covariability is stronger during winter months compared to the summer months, which is indicated by the higher eigenvalues of the first component during winter (Figure 5). The reduced covariability during summer is primarily due to the increased role of temperature. Associating the eigenvalues during these two seasons with groundwater potential clearly show that basins with larger BFI values having higher eigenvalues (Figure 6) indicating the role of groundwater in controlling the hydroclimatic covariability within the basin. Box-plots of eigenvectors also substantiate this with the variability of the first component (i.e., 1st eigenvalues) being primarily contributed from the eigenvectors associated with groundwater (Figures 7-8). Further, we did not find any relationship between eigenvalues/eigenvectors of SSA with other basin characteristics (e.g., drainage area, permeability).

Relating the scores of the first components with JFM Nino3.4 (Figure 9) clearly show that streamflow and groundwater in March control the basin hydroclimatic covariability during the winter months. Further, associating the JFM eigenvalues (Figure 5a) with the Nino3.4-scores correlations (in Figure 9) show that basins with larger eigenvalues have higher correlations with Nino3.4 (Figure 12). This is true for all the selected stations except the two wells in in peninsular Florida (Stations 2 and 20 in Figure 1). The correlation between the JFM eigenvalues (in Figure 5a) and Nino3.4-score correlations (in Figure 9a) for the rest of the 18 stations is -0.64. This indicates that basins with strong hydroclimatic covariability (indicated by higher eigenvalues of PC1), which is primarily influenced by groundwater (i.e., basins with high BFI values), have significant association with ENSO conditions. This primarily implies that groundwater serves as a basin integrator resulting in significant association between basin-level hydroclimatic covariability and ENSO variability. Preliminary analysis in relating the retrospective climate forecasts from ECHAM4.5 with groundwater levels also show that there is scope in utilizing climate forecasts for predicting groundwater availability over the SEUS. Our future investigation will systematically evaluate the ability of climate forecasts in predicting groundwater over various target basins using both physical and statistical models.

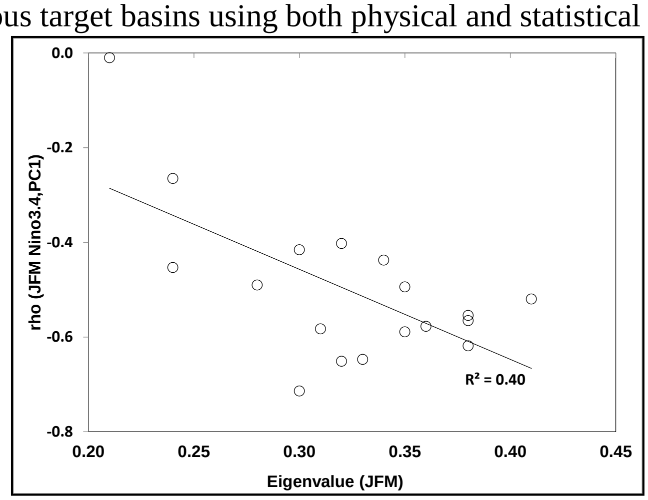

Figure 12: Association between JFM eigenvalues and the correlation between JFM Nino3.4 and the scores of the first component.

6. Summary and Conclusions

This study documented the role of climatic variability in influencing interannual groundwater variability over the Southeast U.S. The analysis was based on monthly streamflow and groundwater level data from 20 Southeast U.S. basins which are unaffected by surface-water storage and groundwater withdrawals. We also obtained monthly time series of precipitation for each basin by spatially averaging the gridded precipitation obtained from the Precipitation Regressions on Independent Slope Model (PRISM). To understand the recharge-discharge dynamics among precipitation, streamflow and groundwater levels, we correlated the observed groundwater levels during the winter (January, February, March) and summer (July, August, September) seasons with the previous six months of precipitation and the following six months of streamflow. Analyses on the recharge-discharge dependency show that precipitation over the previous three months influence the groundwater level in a given month and streamflow in any given month depends on the groundwater level during the previous three months.

Using the identified time window of three months for understanding recharge-discharge dynamics, we performed singular spectrum analysis (SSA) on precipitation, temperature, streamflow and groundwater level records. SSA clearly shows that groundwater levels and streamflow are the two dominant variables influencing the hydroclimatic covariability within the basin. Further, basins with high baseflow indices (BFI) have high higher eigenvalues, indicating that groundwater is a spatial integrator of hydroclimatic processes. We also show that the eigenvalues of the first component during the summer season is lower than the eigenvalues of the first component during the winter season, which indicates the role of higher summer temperature in reducing runoff and recharge into the aquifer. The scores of the first component from SSA are correlated to JFM ENSO conditions, Nino3.4, which indicates that climatic variability plays an important role in influencing hydroclimatic covariability of the basin over the SEUS. Interannual variability in winter groundwater levels could partially be explained by the ENSO conditions, but the relationship between JAS groundwater levels and JAS Nino3.4 is not statistically significant. Finally, precipitation forecasts from ECHAM4.5 General Circulation Model, along with ENSO conditions, have the potential to forecast groundwater availability during the winter in the Southeast U.S.

References

Allen, M. R., and L. A. Smith (1996). “Monte Carlo SSA: Detecting irregular oscillations in the presence of colored noise.” Journal of Climate, 9, 3373-3404.

Anderson, W. P. and R. E. Emanuel (2008). "Effect of interannual and interdecadal climate oscillations on groundwater in North Carolina." Geophysical Research Letters 35(23).

Daly, C., R. P. Neilson, et al. (1994). "A Statistical Topographic Model for Mapping Climatological Precipitation over Mountainous Terrain." Journal of Applied Meteorology 33(2): 140-158.

Dettinger, M. D. and H. F. Diaz (2000). "Global characteristics of stream flow seasonality and variability." Journal of Hydrometeorology 1(4): 289-310.

Devineni, N., A. Sankarasubramanian, and S. Ghosh (2008). “Multi-model Ensembling of Probabilistic Streamflow Forecasts: Role of Predictor State Space in Skill Evaluation.” Water Resources Research, 44, W09404, doi:10.1029/2006WR005855.

Devineni, N. and A. Sankarasubramanian (2010). "Improving the Prediction of Winter Precipitation and Temperature over the Continental United States: Role of the ENSO State in Developing Multimodel Combinations." Monthly Weather Review 138(6): 2447-2468.

Hansen, J. W., and A. W. Hodges (1998). "ENSO influences on agriculture in the southeastern United States." Journal of Climate 11(3): 404-411.

Hanson, R. T., and M. W. Newhouse (2004). "A methodology to asess relations between climatic variability and variations in hydrologic time series in the southwestern United States." Journal of Hydrology 287(1-4): 252-269.

Kaplan, A., and M. A. Cane (1998). "Analyses of global sea surface temperature 1856-1991." Journal of Geophysical Research-Oceans 103(C9): 18567-18589.

Koster, R. D. and M. J. Suarez (2001). "Soil moisture memory in climate models." Journal of Hydrometeorology 2(6): 558-570.

Lecce, S. A. (2000). "Spatial variations in the timing of annual floods in the southeastern United States." Journal of Hydrology 235(3-4): 151-169.

Li, S., and L. Goddard, Retrospective Forecasts with the ECHAM4.5 AGCM, *IRI Technical Report* 2005, 05-02.

Lim, K. J., B. A. Engel, Z.Tang, J. Choi, K.Kim, S.Muthukrishnan, and D.Tripathy (2005). Automated Web GIS Based Hydrograph Analysis Tool, WHAT. Journal of the American Water Resources Association 41(6):1407-1416.

Lipp, E. K., and N. Schmidt (2001). "Determining the effects of El Nino - Southern Oscillation events on coastal water quality." Estuaries 24(4): 491-497.

Markham, C. G. (1970). "Seasonality of Precipitation in United-States." Annals of the Association of American Geographers 60(3): 593-597.

Miller, J.A., (1999). “Ground water atlas of the United States, introduction and national summary: U.S. Geological Survey Hydrologic Atlas”. 730–A, 15 p.

Plaut, G. and R. Vautard (1994). "Spells of Low-Frequency Oscillations and Weather Regimes in the Northern-Hemisphere." Journal of the Atmospheric Sciences 51(2): 210-236.

Rhome, J. R., and D. S. Niyogi (2000). "Mesoclimatic analysis of severe weather and ENSO interactions in North Carolina." Geophysical Research Letters 27(15): 2269-2272.

Ropelewski, C. F. and M. S. Halpert (1987). "Global and Regional Scale Precipitation Patterns Associated with the El-Nino Southern Oscillation." Monthly Weather Review 115(8): 1606-1626.

Roswintiarti, O., and D. S. Niyogi, (1998). "Teleconnections between tropical Pacific sea surface temperature anomalies and North Carolina precipitation anomalies during El Nino events." Geophysical Research Letters 25(22): 4201-4204.

Sankarasubramanian, A., and R.M. Vogel (2002). "Comment on the paper: "Basin hydrologic response relations to distributed physiographic descriptors and climate" by Karen Plaut Berger, Dara Entekhabi, 2001. Journal of Hydrology 247, 169-182", Journal of Hydrology, 263, 257-261.

Scanlon, B. R., and K. E. Keese (2006). "Global synthesis of groundwater recharge in semiarid and arid regions." Hydrological Processes 20(15): 3335-3370.

Schmidt, N., and E. K. Lipp (2001). "ENSO influences on seasonal rainfall and river discharge in Florida." Journal of Climate 14(4): 615-628.

Shun, T. and C. J. Duffy (1999). "Low-frequency oscillations in precipitation, temperature, and runoff on a west facing mountain front: A hydrogeologic interpretation." Water Resources Research 35(1): 191-201.

Slack, J. R., A. M. Lumb, and J. M. Landwehr (1993), Hydroclimatic data network (HCDN): A U.S. Geological Survey streamflow data set for the United States for the study of climate variation, 1874–1988, Water Resour. Invest. Rep., 93-4076.

Syed, T. H., and J. S. Famiglietti, (2005). "Total basin discharge for the Amazon and Mississippi River basins from GRACE and a land-atmosphere water balance." Geophysical Research Letters 32(24).

USGS (2008). "U.S. Geological Survey Ground-Water Climate Response Network" Fact Sheet 2007–3003, February 2007.

Vogel, R. M., and A.Sankarasubramanian (2005), USGS Hydro-Climatic Data Network (HCDN): Monthly Climate Database, 1951-1990. Data set available on-line from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, U.S.A.

Zorn, M. R. and P. R. Waylen (1997). "Seasonal response of mean monthly streamflow to ElNino/Southern Oscillation in north central Florida." Professional Geographer 49(1): 51-62.

Appendix I: Alphabetical list of abbreviations and symbols

All are defined within the text.

Appendix II: Presentations and Publications from the Project

One graduate student, Naser Almanaseer, and one undergraduate student, Harminder Singh, were supported from this study.

Dissertation (expected June 23, 2011):

Almanaseer, N., Role of Climate Variability in Surface water-Groundwater interaction, NC state University, 2011

Journal Publications:

1. Almanaseer, N., A. Sankarasubramanian and J. Bales, Role of Climatic Variability in Influencing Interannual Groundwater Variability over Southeast US, *Journal of Hydrologic Engineering*, 2011, under revision.
2. Almanaseer, N., A. Sankarasubramanian and J. Bales, Developing seasonal groundwater forecasts using seasonal to interannual climate forecasts, Journal of Hydrologic Engineering, 2011, under preparation.

Conference Publications:

1. Almanaseer, N., and A. Sankarasubramanian, Climate, Streamflow and Groundwater Interaction over the Southeastern US, *Proceedings of the EWRI- ASCE Conference*, Providence, May 12-22, 2010.
2. Almanaseer, N., S. Arumugam and J. Bales, Role of Climate Variability in Modulating Surface Water and Groundwater Interaction over the Southeast United States, American Geophysical Union, Fall Conference, San Francisco, 2010.
3. Almanaseer, N., and A. Sankarasubramanian, Improving surface water and groundwater predictions using precipitation forecasts, Annual WRRI Conference, Raleigh, March 22-23, 2011.