ABSTRACT

ALMANASEER, NASER MOHAMMAD ABDALLAH. Role of Climate Variability in Groundwater-Surface Water Interactions over the Southeast United States. (Under the direction of Dr. Sankar Arumugam.)

Groundwater-surface water interaction is a complex process that is controlled by several hydroclimatic attributes and basin characteristics. The complexity of this interaction originates from the temporal and spatial variability of hydrogeologic system and from the external forces such as climatic variations. This research seeks to understand the role of climate in modulating groundwater-surface water interactions and to better utilize this relationship in predicting seasonal to interannual streamflow and groundwater availability.

To investigate this, we selected 20 basins with limited anthropogenic influences within the Southeast United States to represent the broad climate, surface and subsurface hydroclimatic over the selected region.

The study performs a detailed dependency analysis among basin-level precipitation, temperature, streamflow and groundwater to identify recharge and discharge periods that influence the seasonal streamflow and groundwater interaction. Based on this analysis, the most dominant variable for each season is identified using singular spectrum analysis (SSA) on the recharging months of precipitation, and discharging months of streamflow along with groundwater and temperature. Findings from SSA clearly indicate that groundwater and streamflow are the two critical variables influencing the basin hydroclimatic variability in comparison to precipitation and temperature. Relating the eigenvalues with baseflow index shows that significant groundwater discharges are associated with larger eigenvalues which
indicate the role of groundwater as a spatial integrator of hydroclimatic process. Further, basins with higher Baseflow Index (BFI) show higher eigenvalues, which indicate that groundwater is a spatial integrator of hydroclimatic processes. On the other hand, relating groundwater levels to El Nino Southern Oscillation (ENSO) index, Nino3.4, shows that the interannual variability in winter groundwater levels can be partially explained by the ENSO conditions. Associating precipitation forecasts from ECHAM4.5 General Circulation Model with winter groundwater levels indicates that forecasted precipitation and ENSO conditions can be used to quantify groundwater availability during the winter season over the Southeast U.S.

To evaluate the potential in predicting groundwater and streamflow using precipitation forecast at seasonal and monthly time scales, we consider Flint River Basin, Georgia. For this purpose, we developed statistical and physical prediction models to examine the potential in using precipitation forecasts as a primary predictor in predicting streamflow and groundwater. Results show that incorporating precipitation forecasts can significantly improve the skill of the developed prediction models at seasonal and monthly time scales. Collectively, this research summarizes the relationship between climate and groundwater over the Southeast U.S. and demonstrates the utilization of precipitation forecasts in predicting seasonal groundwater.
Role of Climate Variability in Groundwater-Surface Water Interactions over the Southeast United States

by
Naser Mohammad Abdallah Almanaseer

A dissertation submitted to the Graduate Faculty of North Carolina State University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

Civil Engineering

Raleigh, North Carolina

2011

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DEDICATION

This work is dedicated to my late father, my mother, brothers and sisters.

I thank you all for your continuous love, support, and sacrifices throughout my life.
Naser Almanaseer was born in Sbihi, a small village in Jordan, and was graduated from Salt High School in Jordan in 1988. In 1993, he was graduated from Mansoura State University in Egypt with a Bachelor of Science in Geology. He started his career in 1993 as a hydrogeologist with the United Nations Development Program (UNDP) in Jordan and his second job was for the Water Resources and Environmental Research Center in the University of Jordan. He was awarded a full scholarship by the Netherlands Fellowship Program (NFP) to study a master of engineering in hydrology at the UNESCO-IHE, Delft in The Netherlands and he was graduated on October 2001. In 2002, he came to Jordan to work as a Hydrogeologist for the United States Geological Survey. Two years later, he accepted a teaching job with the Department of Water Resources and Environmental Management at Al-Balqa Applied University (BAU) in Jordan. In October 2006 he was awarded a scholarship by BAU to pursue his PhD in Civil Engineering at North Carolina State University in Raleigh. During his study, he worked as a hydrologist for the United States Geological Survey in North Carolina. In June 2011, he was graduated with a PhD in Civil Engineering – Water Resources and he is planning to join Al-Balqa Applied University as a professor at the Department of Water Resources and Environmental Management starting September 2011.
ACKNOWLEDGMENTS

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1. INTRODUCTION

1.1. Motivation

Groundwater is estimated to exceed ninety five percent of the global, unfrozen freshwater reserves. Considering its vast reserves, broad geographical occurrence and limited vulnerability to contamination and seasonal fluctuations, renewable groundwater remains the primary source of water supply in many places around the Globe. Groundwater resources assessment is necessary to evaluate and quantify groundwater availability at various time scales in most watersheds especially in areas where groundwater is the sole or the major water source. Renewable groundwater resources from shallower unconfined aquifers are affected by climatic and surface water variations. This interaction between surface and subsurface water components can be very complex and it depends on the spatial and temporal scale of the problem. However, understanding the interaction process is essential for comprehensive water resources assessment and management plans. To simplify this complex relationship, it is necessary to identify the major source of variability within the hydroclimatic system and to define the proper time scale of the research problem. For example, groundwater variability in most regions is significant at seasonal to interannual rather than at hourly to weekly time scales.

Temporal and spatial variation in groundwater storage is critical components of the water balance at regional and local scales especially for basins with shallow groundwater tables. This variability is essentially controlled by surface and subsurface physical characteristics of
the basin. For example, basins with higher slopes and impervious surfaces have the ability to generate more runoff and therefore less groundwater recharge. In addition to basin characteristics, climate also play significant role in driving the relationship between surface and subsurface water components. However, groundwater can be a dominant factor, in the form of baseflow, in maintaining surface water in streams during periods between precipitation events and especially in basins with high permeable aquifers such as the Upper Floridan Aquifer in the Southeast United States.

Sea surface temperature (SST) plays an important role in influencing temporal and special variability of land temperature (T) and precipitation (P). Apart from P and T, catchment characteristics and the initial land surface conditions such as soil moisture control the variability in streamflow (Q). Therefore, relation between depth to groundwater (h) and Q in the form of recharge-discharge interaction can be broadly understood based on hydroclimatic variables considering catchment and aquifer characteristics. However, defining the appropriate time and spatial scales to reasonably understand the interaction between groundwater and surface water is critical and depends on the scale of the problem. Given the role of climate, typically at larger special and time scales, we choose the entire Southeast U.S. and seasonal time scale as the basis for the analysis.

Several hydrologic modeling techniques can be used to provide hydrologic representations and future predictions including statistical or physical models depending on the model purpose(s) and data availability. Occasionally, the applications of prediction models involve
the use of climate data, mainly precipitation forecasts, from General Circulation Models (GCMs) such as ECHAM 4.5. Precipitation forecasts are available for six months ahead, and it is so clear that the skill of any GCM is not reliable after three months ahead. Also, precipitation forecasts are normally provided in the form of gridded data with a relatively coarse scale (2.5 x 2.5 degree) which negatively affect the outcome of any research at a smaller spatial scale because downscaling climate data decreases its accuracy. In addition to climate information, groundwater records and streamflow discharges observed at adjacent sites can be used as additional predictors to improve groundwater and streamflow predictions at a given site. However, and since shallower groundwater systems are connected to surface water systems in most hydrologic systems, modeling these two water resources individually should be avoided to better represent the hydrologic system and to improve future predictions.

Finally, this research focuses on providing better understanding of the climate variability role in controlling groundwater and streamflow variation at larger scales with the emphasis on groundwater component. Also, the research examines the possibility of improving seasonal and monthly streamflow and groundwater predictions with climate information based precipitation forecasts.

1.2. Background and Literature Review

Groundwater is generally considered the most difficult component of the water budget to quantify (Randall et. al. 1999). Hence, the importance of considering groundwater and
surface water as a single resource has become increasingly evident (Winter et al. 1998). On the other hand, climate variability, primarily resulting from SST variability, plays an important role in influencing basin hydroclimatology that includes P, T and Q. 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). Similarly, 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 teleconnections between various sources of climatic variability and groundwater variability has received relatively less attention. Shun and Duffy (1999) also 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.

1.3. Dissertation Outline

The dissertation is presented over five chapters; Chapter 1 presents brief introduction and literature review along with a dissertation outline. Chapter 2 lists and describes all hydroclimatic data including precipitation, streamflow and groundwater data used for the analysis during the course of this research along with details on the basin selection criteria and the methodologies employed for developing the data base. Chapter 3 presents the first research topic entitled “Role of climate variability in modulating surface water and groundwater interaction over the southeast United States”. It focuses on understanding the role of climate variability in controlling groundwater level at various locations (20 sites) in the Southeast U.S. Chapter 4 focuses on developing seasonal streamflow and groundwater forecasts for various locations within Flint River Basin in Georgia using conceptual and statistical modeling techniques. Finally, Chapter 5 presents the main conclusions and findings from this dissertation research and suggests possible future work to improve groundwater and streamflow predictions.
2. HYDROCLIMATIC DATABASES

2.1. Introduction

Temporal and spatial scales of hydroclimatic data as well as the geographic location are normally decided based on the purpose and the scale of any hydrologic research problem. For example, monthly time scale is sufficient to study the role of climate variability in modulating streamflow and groundwater inter-relationships at a relatively large spatial scale and to capture the natural variability among hydroclimatic variables at basin level. It is also sufficient to examine the possibility of improving streamflow and groundwater predictions. On the other hand, and to adequately represent the hydrologic responses, natural groundwater and streamflow records with no to minimal anthropogenic influences are required. In addition, and to represent the role of climate variability, it is necessary to conduct the research in basins where groundwater flow systems is unconfined with clearly identified phreatic water tables. For this purpose, we develop a selection criteria considering the purpose of the study and taking into account data availability, geographic distribution, period of records, and several other factors. Based on the developed selection criteria and other factors we considered 20 basins (sites) for the study. The selected sites are composed of one groundwater well nearby one stream gauge.

Following is a brief description of this selection criteria followed by a list of the selected basins, streamflow stations and groundwater wells (Table 2.1), location map of the selected sites (Figure 2.1) and detailed description of their data availability.
2.2. Selection Criteria

The Southeast United States (SEUS) region is considered because it covers various climatic divisions ranging from the Atlantic Ocean in the southeast to the highly elevated mountainous in the northwest areas. This wide range of climatic conditions helps apply and understand the role of climate variability at various hydrologic basin characteristics.

Basins (sites) are selected to represent wide range of catchment sizes to help quantify the role of catchment characteristics in controlling streamflow variability and they also selected to cover various types of unconfined aquifers to help evaluate the various hydrologic responses to climate variability across the different unconfined aquifers.

One stream gauge and one groundwater well with at least 20 years of monthly records are selected within each basin to represent natural surface and groundwater flows. For this purpose, streamflow gauges and groundwater wells are mainly selected from the USGS Hydroclimatic Data Network (HCDN) database (Slack et al. 1993) and the USGS Climate-Groundwater Response Network respectively. Both Networks represent natural flows with no anthropogenic influences such as dams, reservoirs and other forms of flow regulation measures.

Every groundwater well is selected to be upstream and as close as possible to the stream gauge. The majority of the selected wells are within 9 miles of the corresponding streamflow gauges.
Groundwater data availability is the main-uncontrolled criteria, which results in only 20 candidate basins (sites) over the SEUS. However, and considering the purpose of this research, this number of sites is adequate.

Table 2.1: Selected streamgages and associated groundwater wells over the southeast U.S.

<table>
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<tr>
<th>Site index</th>
<th>Hydrologic Unit (HUC-8)</th>
<th>Streamgauge number</th>
<th>Drainage area (mile²)</th>
<th>Groundwater well number</th>
<th>Period of groundwater records (years)</th>
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<td>1960</td>
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</table>
Figure 2.1: Location of selected streamgauges and associated groundwater wells over the southeast U.S along with the grid points of ECHAM4.5 precipitation forecasts.

2.3. Databases

This section provides general overview of the sources and the spatio-temporal coverage of the various databases employed in the study including monthly and seasonal streamflow, groundwater, precipitation, precipitation forecasts and Nino 3.4 – ENSO – Index. Also, it
presents preliminary evaluation of the datasets especially groundwater and precipitation forecasts. However, hydroclimatic data obtained for additional sites for the purpose of groundwater and streamflow predictions is presented in chapters 4.

2.3.1. Streamflow and Groundwater

Monthly time series of streamflow were obtained for each station (Table 2.1) from the HCDN database (Slack et al. 1993) and from the USGS National Water Information System (http://waterdata.usgs.gov/nwis). On the other hand, and of the twenty selected wells, groundwater level data for seven 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 thirteen 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. Depths of groundwater wells range from 12 to 804 feet (Figure 2.2). Figure 2.2 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 2.2).

![Groundwater well](image)

Figure 2.2: 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.

The selected twenty 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 of eight different aquifer types (Miller, 1999). The selected wells are predominantly surficial aquifers (all along the Atlantic Coast), Floridian aquifers (2 wells in peninsular 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. Details of the hydrogeology of the SEUS are provided by Miller (1999).

2.3.2. Precipitation

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. Spatially averaged monthly time series of precipitation over each watershed are assembled from the HCDN hydroclimatic database (Vogel and Sankarasubramanian, 2005) and from the PRISM (Precipitation Regressions on Independent Slope Model, Daly et al., 1994) database.
2.3.3. Precipitation Forecasts

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/.ensemble 24/.MONTHLY/.prec/) obtained from International Research Institute of Climate and Society (IRI) data library) forced with constructed analogue SSTs (Li and Goddard, 2005). Grid-point indices over which the ECHAM4.5 forecasts are available are shown in Figure 2.1 and described in Table 2.2. 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.

2.3.4. 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/).
To sum up, records of all hydroclimatic variables observed at all selected sites are gathered from their reliable sources, tabulated, evaluated and used for the analysis. The availability of groundwater and the regulated streamflow are the major factors in the selection of groundwater and stream gauges respectively. The common period of record for the selected sites is 1980 to 2007 and it varies from site to site. Finally, additional data that is related to streamflow and groundwater prediction study is introduced and described in chapter 4.
Table 2.2: Precipitation forecasts that are significantly correlated to observed precipitation.

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<th>Site Index</th>
<th>streamgauge</th>
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<th>% variance of PC1</th>
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* See figure 2.1 for the numbers and locations of Echam4.5 grid points
3. ROLE OF CLIMATE VARIABILITY IN MODULATING SURFACE WATER-GROUNDWATER INTERACTION OVER THE SOUTHEAST U.S.

3.1 Introduction

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 twenty 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. Singular spectrum analysis (SSA) 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 SSA 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.

3.2. Data Analysis

3.2.1. Seasonality Analyses

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.

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 streamflow 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 3.1), indicating the role of storage in distributing the groundwater 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 3.1) 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.

3.2.2. Dependency Analyses

In this section, we 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. In this study, 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 were considered for understanding the recharge. Similarly, the period during which groundwater level in a given month influences streamflow in subsequent months is identified based on lead-correlation.

Figure 3.1: Seasonality Index and month of maximum groundwater levels for the study sites.

In addition, Figure 3.2 shows box-plots of lag (lead) correlations between groundwater and precipitation (streamflow) for winter (Figure 3.2a) and summer (Figure 3.2b) seasons.
Correlations are statistically significant at 5 % significant level (± 1.96/√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.

Figure 3.2 show 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 3.2a and Figure 3.2b), 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.
Figure 3.2: 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 twenty study basins.
3.2.3. Role of Climate Variability

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, 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.

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) months 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 3.3 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 3.3). The proportional variance explained by the first component in the winter season is higher than proportional variance explained in the summer season (Figures 3.3 and 3.4). 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 3.4 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 3.4), indicating the correlation of groundwater to precipitation (as recharge) and streamflow (as discharge) through the aquifer storage.
Figure 3.3: Proportional variance explained by the first component of 18 variables from SSA for (a) winter and (b) summer seasons.
Figure 3.4: 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 3.5). 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 3.6a, which indicates the dominant eigenvector for each station for JFM.
Figure 3.5: Box-plot of eigenvectors (loadings) from SSA for (a) winter and (b) summer seasons.
Figure 3.6: Maps of the dominant eigenvectors (loadings) from the 1st component of SSA for the (a) winter and (b) summer seasons.
The most important information from Figures 3.5a and 3.6a 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 3.5b and 3.6b) 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 3.7 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 is weak (Ropelewski and Halpert, 1987; Devineni et al. 2008).

Figure 3.7: Rank correlation between the scores of the first component and JFM Nino3.4 for the 20 selected stations.

Analysis presented in Figure 3.7 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 3.7 is statistically significant at all the stations except at the station on the eastern
border of Alabama and Georgia (Site 8, Figure 2.1). 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.

3.2.4. Role of ENSO Conditions

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 3.8a) in the winter, and at two stations in the summer (Figure 3.8b). 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. 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.

3.3. Predicting Winter Groundwater Levels using Precipitation Forecasts

In this section, 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.

Figure 3.8: 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.
To obtain the principal components of the precipitation forecasts, we identify the relevant grid points that exhibit statistically significant correlation between the ensemble mean of the precipitation forecasts and the observed precipitation over the selected basin. Table 2 provides the selected grid points (shown in Figure 2.1) 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 3.9 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 3.9 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 (Figure 3.8a).

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 3.9: 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.

3.4. Summary and Conclusions

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. This is primarily due to the increased role of temperature during the summer months. Associating the eigenvalues during these two seasons clearly show that basins with larger BFI values having higher eigenvalues (Figure 3.4) 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 3.5 and 3.6). 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 3.7) clearly show that streamflow and groundwater in March control the basin hydroclimatic covariability during the winter months. Further, associating the JFM eigenvalues (Figure 3.3a) with the ENSO-scores correlations in Figure 3.7 show that basins with larger eigenvalues have smaller correlations with Nino3.4 (e.g., two basins in peninsular Florida). This indicates that basins having strong hydroclimatic covariability are less susceptible to ENSO-related climatic fluctuations. This is primarily due to the ability of groundwater which acts as reservoir in reducing the interannual variability in hydroclimatic fluxes as well as being less susceptible to climatic variability/oscillations. Preliminary analysis in relating the retrospective climate forecasts from ECHAM4.5 with groundwater levels 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.

To sum up, 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.
4. IMPROVING STREAMFLOW AND GROUNDWATER PREDICTIONS USING SEASONAL PRECIPITATION FORECASTS

4.1. Introduction

Generally, the quantity and quality of various components in the global hydrologic cycle are affected by climate variability (Loáiciga et al., 1996; Sherif and Singh, 1999; Milly et al., 2005). For example, the availability and sustainability of surface water and groundwater is affected by climatic stresses (Brekke et al., 2009; Alley et al., 2002). Also, climate variability on interannual to multidecadal time scales has significant implications for groundwater resource management (Hanson et al., 2004, 2006, 2009; Hanson and Dettinger, 2005; Gurdak et al., 2007) particularly during multi-year droughts. Therefore, climatic information could be used to help quantify and manage surface water and groundwater resources at various spatial and time scales.

In recent decades, scientific research focused on the effects of climate variability on surface water due to the visibility, accessibility, and more obvious recognition of climate effects on surface water other than groundwater (U.S. Geological Survey 2009). Further, the relatively longer residence times of groundwater make it difficult to detect responses of groundwater to climate variability (Chen et al., 2004). Hence, understanding the potential effects of climate variability on groundwater is more complex than with surface water (Holman, 2006) and the effect of climate variability on groundwater quantity and quality remain poorly understood (Green, Bates, and others, 2007; Green, Taniguchi, and Kooi, 2007).
Tolerable predictions of surface water and groundwater availability could be a key factor toward successful water resources management plans and strategies. It normally provides adequate representation of the hydrologic system at present time as well as helps develop future scenarios. However, the skill of the prediction efforts is primarily depending on the relevance of the selected predictors. Traditionally, observed precipitation, streamflow and groundwater levels at a given site are used to predict streamflow and groundwater availability using linear and non-linear time series models. Thus, incorporating forecasted precipitation explicitly in conceptual water balance models or statistical models could improve streamflow and groundwater predictions. In this study, we focus on predicting seasonal groundwater variability purely based on forecasted climatic variability and using surrogate estimates of antecedent storage conditions for various locations in the FRB.

This research examines the possibility of improving seasonal and monthly streamflow and groundwater predictions using climate information, mainly precipitation forecasts as additional predictors. For this purpose, we developed multiple statistical models using principle component regression (PCR) and canonical correlation analysis (CCA) to evaluate the utility of precipitation forecasts in improving the prediction of streamflow and groundwater availability at ten selected groundwater wells and six streamgauges in Flint River Basin (FRB) during the period 1980-2010. In addition, we developed physically-based
water balance models for six sites using the “abcd” Model (Thomas et al., 1981; Thomas et al., 1983).

To assess the value of precipitation forecasts, null models (Model-1) that uses previous records of groundwater or streamflow is developed for each site. Afterward, Model-2 that uses precipitation forecasts from ECHAM 4.5 as additional predictors is developed and compared to Model-1. For further assessment, Model-3 that uses previous records and precipitation forecasts as well as preceding records from nearby stations is developed using CCA and compared to Model-1 and Model-2. While groundwater and streamflow predictions made with the absence of precipitation forecasts show limited skill for up to 3-months ahead, the utilize of precipitation forecasts as additional predictors result in improved prediction skill and in extended prediction period at most of the selected sites in FRB. Also, the integration of additional information from adjacent stations results in a slightly improved prediction skill.

4.2. Study Area and Data Description

FRB is part of the Apalachicola-Chattahoochee-Flint (ACF) River Basin in Georgia, U.S. (Figure 4.1). It is composed of six hydrologic Units (HUC-8) and contains multiple streamflow and groundwater stations with long records (more than 30 years). In addition to data availability, we select FRB for this study based on the interactions between surface water and groundwater resources conditioned on climatic variability (Chapter 3). FRB also reflects a geologic history of mountain building in the Appalachian Mountains and long
periods of repeated land submergence in the Coastal Plain Province. The northern part contains both the Piedmont and Coastal Plain Provinces while the remaining parts lie entirely within the Coastal Plain. FRB is a dynamic hydrological system with significant groundwater-surface water interaction where several streams within the basin receive a substantial contribution of water from baseflow during dry periods (U.S. Geological Survey, 2008). In order of descending stratigraphy and increasing age, the five major aquifers underlie the FRB are the Floridan Aquifer System, the Claiborne Aquifer, the Clayton Aquifer, the Providence Aquifer System and the Piedmont Province. Generally, the regional groundwater flow direction is from north to south, however, local flow directions vary, especially in the vicinity of streams. In addition, strata associated with the Floridan aquifer system are exposed along sections of the Flint River and streams in the Coastal Plain Province commonly are deeply incised into underlying aquifers and receive substantial amounts of groundwater discharge in the form of baseflow. Strong hydraulic connection between the Floridan aquifer system and the Flint River result in a significant groundwater contributions to baseflow in the Flint River.

Considering the purpose of the study, time series of monthly records of precipitation forecasts, observed precipitation, streamflow and groundwater levels during the period 1980 - 2010 is considered for the analysis. Finally, while precipitation forecasts and observed precipitation data is represented as spatial averages, streamflow and groundwater data on the other hand is observed at specific sites. The selected streamflow and groundwater stations are
listed in Tables 4.1 and 4.2 and shown in Figure 4.2. Following is a brief description of the data sources, locations, and period of availability.

Figure 4.1: Location map for Flint River Basin

**Precipitation Forecasts**

We utilize the retrospective winter (January, February, and March, or JFM) and spring (April, May and June, or AMJ) precipitation forecasts available from ECHAM4.5, developed
by Max Planck Institute in Germany, and available from the International Research Institute of Climate and Society (IRI) data library forced with constructed analogue SSTs (Li and Goddard, 2005). Retrospective precipitation forecasts from ECHAM4.5 are obtained for 6 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 precipitation, which is obtained by computing the average over 24 ensembles, for JFM and AMJ issued in the beginning of January. The observed precipitation and the ensemble mean of ECHAM 4.5 precipitation forecasts are correlated for each month to identify nine relevant ECHAM4.5 grid points covering the FRB (Grid points 7, 8, 9, 13, 14, 15, 19, 20, and 21 in Figure 2.1). Finally, since precipitation forecasts has a limited skill over finer time scales especially in summer months, we only consider precipitation forecasts from nine grid points for JFM and AMJ issued at the beginning of January during the period 1980 – 2010.

**Observed Precipitation**

We obtained total monthly precipitation from the gridded precipitation data supported by PRISM (Precipitation Regressions on Independent Slope Model, Daly et al., 1994) and maintained by Oregon State University http://www.prism.oregonstate.edu/. From this
gridded data, and using a statistical zoning function in ArcGIS, we compute the spatial average precipitation over each individual HUC as a time series for the period Jan 1980 through Dec 2010. The statistics of the monthly precipitation indicates similarity in precipitation pattern over the six HUCs.

**Streamflow and Groundwater**

Monthly time series of streamflow and groundwater with limited anthropogenic influences are obtained for 10 groundwater wells and 10 stream gauges during the period 1980 to 2010. To ensure limited anthropogenic influence over the obtained hydrologic data, we carefully selected streamflow gauges and groundwater wells from the Hydro-Climatic Data Network (HCDN) and the Climate Groundwater Response Network (CGRN) respectively. However, among the selected sites, two streamflow gauges (02344500 and 02350512) are not HCDN and three groundwater wells (13M006, 11J012 and 08K001) are not CGRN. Correlation analysis with other HCDN and CGRN stations within FRB indicate limited anthropogenic influences over these five stations.
Table 4.1: List of the selected streamgauges in Flint River Basin

<table>
<thead>
<tr>
<th>Streamgauge ID</th>
<th>Streamgauge Name</th>
<th>Hydrologic Unit (HUC-8)</th>
<th>Altitude (feet above NGVD29)</th>
<th>Drainage area (mile²)</th>
<th>Baseflow Index (BFI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>02344500</td>
<td>Flint River near Griffin</td>
<td>03130005</td>
<td>711.4</td>
<td>272</td>
<td>0.58</td>
</tr>
<tr>
<td>02347500</td>
<td>Flint River near Carsonville</td>
<td>03130005</td>
<td>334.5</td>
<td>1850</td>
<td>0.65</td>
</tr>
<tr>
<td>02349500</td>
<td>Flint River at Montezuma</td>
<td>03130006</td>
<td>255.8</td>
<td>2900</td>
<td>0.71</td>
</tr>
<tr>
<td>02350512</td>
<td>Flint River near Oakfield</td>
<td>03130006</td>
<td>185.9</td>
<td>3880</td>
<td>0.67</td>
</tr>
<tr>
<td>02352500</td>
<td>Flint River at Albany</td>
<td>03130008</td>
<td>130.03</td>
<td>5310</td>
<td>0.68</td>
</tr>
<tr>
<td>02353000</td>
<td>Flint River at Newton</td>
<td>03130008</td>
<td>110.2</td>
<td>5740</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Table 4.2: List of the selected groundwater wells in Flint River Basin

<table>
<thead>
<tr>
<th>Groundwater Well ID</th>
<th>Groundwater Well Name</th>
<th>Hydrologic Unit (HUC-8)</th>
<th>Altitude (feet above NGVD29)</th>
<th>Aquifer</th>
<th>Well depth (feet)</th>
</tr>
</thead>
<tbody>
<tr>
<td>310507084262201</td>
<td>10G313</td>
<td>03130008</td>
<td>145.0</td>
<td>Floridan</td>
<td>206.0</td>
</tr>
<tr>
<td>311009084495502</td>
<td>07H002</td>
<td>03130010</td>
<td>167.0</td>
<td>Floridan</td>
<td>75.0</td>
</tr>
<tr>
<td>311009084495503</td>
<td>07H003</td>
<td>03130010</td>
<td>167.0</td>
<td>Surficial</td>
<td>40.0</td>
</tr>
<tr>
<td>312127084065801</td>
<td>13J004</td>
<td>03130008</td>
<td>194.0</td>
<td>Floridan</td>
<td>208.0</td>
</tr>
<tr>
<td>311009084495503</td>
<td>13M007</td>
<td>03130006</td>
<td>238.0</td>
<td>Surficial</td>
<td>25.0</td>
</tr>
<tr>
<td>330858084122901</td>
<td>12Z001</td>
<td>03130005</td>
<td>852.0</td>
<td>Surficial</td>
<td>31.0</td>
</tr>
<tr>
<td>331507084171801</td>
<td>11AA01</td>
<td>03130005</td>
<td>950.0</td>
<td>Surficial</td>
<td>30.0</td>
</tr>
<tr>
<td>311802084192302</td>
<td>11J012</td>
<td>03130008</td>
<td>165.0</td>
<td>Floridan</td>
<td>225.0</td>
</tr>
<tr>
<td>312232084391701</td>
<td>08K001</td>
<td>03130009</td>
<td>230.0</td>
<td>Floridan</td>
<td>125.0</td>
</tr>
<tr>
<td>314330084005402</td>
<td>13M006</td>
<td>03130006</td>
<td>238.0</td>
<td>Floridan</td>
<td>123.0</td>
</tr>
</tbody>
</table>
Figure 4.2: Streamgauges and groundwater wells in Flint River Basin.
4.3. Dependency Analysis

In this section, we study the dependency among the various hydroclimatic variables as well as with the precipitation forecasts at various locations within FRB to identify suitable sets of predictors and predictands for predicting streamflow and groundwater over six months starting January using statistical and conceptual hydrologic models.

To begin with, we identify relevant ECHAM4.5 grid points that influence the hydroclimatology of the basin during winter (JFM) and Spring (AMJ). For this purpose, we obtain rank correlation coefficients between hydroclimatic variables (P, Q and G) and precipitation forecasts obtained from 25 ECHAM4.5 grid points covering large area over the Southeast U.S. during. Based on this, we identify precipitation forecasts from nine ECHAM 4.5 grid points as potential predictors. Since the precipitation forecasts from the selected nine grid points are strongly correlated, we perform a principal component analysis (PCA) on JFM and AMJ precipitation forecasts records during the period 1957 - 2010. The first component (PC1) for JFM and AMJ explains 90% and 86% of variability among these nine grid points. The loadings for PC1 indicate that all grid points play equal role in determining PC1 (Figure 4.3). A correlation analysis between PC1 and observed Q and G during JFM and AMJ (Figure 4.4) indicates that precipitation forecasts are significantly (ρ>0.3) correlated with the groundwater level observed at all wells during JFM (0.35 ≤ ρ ≤ 0.71) and AMJ (0.33 ≤ ρ ≤ 0.59). On the other hand, observed Q at six stream gauges show significant correlation with PC1 during JFM (0.46 ≤ ρ ≤ 0.68) and relatively less correlation coefficients during AMJ (0.18 ≤ ρ ≤ 0.33). Further, it is noticeable that the correlation coefficients tend to
increase towards downstream indicating the role of storage in increasing the correlation between precipitation and hydrogeologic attributes.

Given the dependency between PC1 and the hydrologic variables, we perform principle component regression (PCR) under leave-one-out cross validation to spatially downscale precipitation forecasts to basin precipitation during the period 1980 - 2010. We consider JFM precipitation forecasts from nine ECHAM4.5 grid points as nine predictors and JFM observed precipitation over six HUCs as six predictands. The skill of the downscaling schemes is evaluated using multiple evaluation criteria including correlation coefficients ($\rho$), root mean square error (RMSE) and mean absolute error (MAE) computed based on the observed monthly precipitation and downscaled precipitation. Comparisons between the downscaled precipitation and the observed average precipitation over the six HUCs during JFM (Figures not shown) indicate that the downscaling scheme works better for JFM in comparison to AMJ. This observation coincides with the fact that precipitation forecasts tend to have poor skill beyond three months. On the other hand, the analysis indicates that precipitation is consistently correlated with precipitation forecasts over the six HUCs ($\rho>0.6$) during winter season (JFM) while the correlation between Q and G with precipitation forecasts vary from site to site depending on the hydroclimatic and physical characteristics of the basin.
Figure 4.3: Proportional variance (A) and loadings (B) of nine ECHAM 4.5 grid points.
Figure 4.4: Rank correlation coefficients between the first principal component (PC1) of nine ECHAM 4.5 grid points and streamflow (Q) and groundwater (G) during JFM (A) and AMJ (B). Correlation above 0.3 is statistically significant at 95% confidence interval.

Based on the dependency analysis, PCA and PCR analysis suggest that G and Q can be predicted at a given site using records of previous months. Further, groundwater levels observed at wells within FRB are also significantly correlated among each other, and therefore, groundwater prediction at a given well can be improved by incorporating
information form adjacent wells. Finally, the significant correlation between P, Q and G with precipitation forecasts suggests that precipitation forecasts can be considered as an additional predictor in the development of prediction models.

4.4. Model Selection

We select two different types of models to predict groundwater and/or streamflow in FRB. One is conceptual water balance model that accounts for the mass balance by considering various hydrologic components within the basin. Other set of models employ a purely statistical approach. Following is a brief description of the selected models.

Conceptual Water Balance Model - The “abcd” Model

Water balance models can be effective tools in representing and predicting streamflow while a proper representation of groundwater is more complex. The ‘abcd’ model is a nonlinear hydrologic model which uses precipitation and potential evaporation as input to produce streamflow.

The model was originally introduced by Thomas (1981) at an annual time step and was later compared with numerous monthly water balance models leading to its recommendation by Alley (1984). Unlike statistically-based models, the ‘abcd’ model has four parameters $a$, $b$, $c$ and $d$ that have some physical interpretation. Parameter $a$ ($0 \leq a \leq 1$) reflects the "propensity of runoff to occur before the soil is fully saturated" (Thomas et al., 1981), parameter $b$ is an upper limit on the sum of evaporation and soil moisture storage, parameter $c$ ($0 \leq c \leq 1$) is
equal to the fraction of streamflow which arises from groundwater, so that it is equivalent to
the baseflow index discussed in textbooks, and finally the reciprocal of the parameter \( d \)
\((0 \leq d \leq 1)\) is equal to the groundwater residence time.

Basically, we select this model to predict monthly streamflow at selected sites in FRB. The
Model parameters can be calibrated for streamflow using a single-objective optimization
calibration technique to predict monthly streamflow at a given site. The model requires
sufficient records for calibration and validation periods. On the other hand, the groundwater
component produced by the model for each time step represents the groundwater contribution
to the stream, and therefore, the model cannot be used directly to predict groundwater level
unless it is calibrated for both streamflow and groundwater using a multi-objective
calibration technique.

**Statistical Models**

We consider principle component regression (PCR) and canonical correlation analysis (CCA)
as statistical models for predicting streamflow and groundwater within FRB. We utilize
Climate Predictability Tool (CPT), supported by The International Research Institute of
Climate and Society (IRI) to construct seasonal and monthly regression models and we
evaluate the developed models using leave-one-out cross-validation approach. While PCR
consider single predictand at a time, CCA develop best regression models from multiple
predictands. We consider three statistical models (Model-1, Model-2 and Model-3) to predict
streamflow and groundwater. The three models implemented for groundwater predictions are
indicated as G-1, G-2, and G-3. Similarly, streamflow prediction models are indicated as Q-1, Q-2 and Q-3. All models have the same period (1980-2010) and aim to predict seasonal (JFM and AMJ) and monthly (Jan. through Jun.) streamflow and groundwater. All models are evaluated using leave-one out cross validation approach. Following is a brief description of the three models:

**Model-1:** Model-1 is the null model that does not consider precipitation forecasts from ECHAM 4.5. Model-1 is developed using Principal Component Regression (PCR) to predict seasonal and monthly Q and G independently based on previous observations of Q or G for a given site without using climate information. For seasonal predictions, the model uses observed records of OND as a predictor to predict JFM and AMJ. For monthly, the model uses Oct, Nov and Dec monthly records as three predictors to predict 6-months ahead (Jan through Jun).

**Model-2:** Model-2 is also developed using Principal Component Regression (PCR), but uses climate forecasts from nine ECHAM 4.5 grid points issued at January as additional predictors. Comparisons between Model-1 and Model-2 for individual sites help evaluate the role of using climate information in improving Q and G predictions.

**Model-3:** This model is developed using Canonical Correlation Analysis (CCA) and aims to integrate additional information on the predictands (i.e., groundwater) from adjacent basins
to improve the prediction. Model-3 is designed to evaluate the role of climate versus the role of groundwater and surface water flows in the selected basins.

The performance of all models is evaluated using correlation coefficients (\(\rho\)) root mean square error (RMSE) and relative root mean square error (R-RMSE) as primary skill metrics. Table 4.3 presents a list of these three models and Figure 4.5 provides pictorial representation of the statistical model design.
Table 4.3: List of statistical models and their description.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model</th>
<th>Method</th>
<th>Predictors</th>
<th>Predictand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Groundwater</td>
<td>G-1</td>
<td>PCA</td>
<td>OND</td>
<td></td>
</tr>
<tr>
<td>(G)</td>
<td>G-2</td>
<td></td>
<td>OND</td>
<td>JFM AMJ Jan - Sep</td>
</tr>
<tr>
<td></td>
<td>G-3</td>
<td>CCA</td>
<td>OND</td>
<td></td>
</tr>
<tr>
<td>Streamflow</td>
<td>Q-1</td>
<td>PCA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Q)</td>
<td>Q-2</td>
<td></td>
<td></td>
<td>JFM AMJ Jan - Sep</td>
</tr>
<tr>
<td></td>
<td>Q-3</td>
<td>CCA</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 4.5: Statistical model design.
4.5. Model Development and Predictions

In this section, we develop streamflow and groundwater predictions at seasonal and monthly time scales using conceptual and statistical models.

4.5.1. The “abcd” Model

The “abcd” Model is a physically-based water balance model that normally calibrated uses with a single-objective calibration approach to provide streamflow predictions at monthly time scale. We modify and use this conceptual model to predict seasonal and monthly streamflow time scales for six stream gauges during in FRB during the period 1951-2010. Since the model produces groundwater component that is basically a baseflow, we correlate groundwater records from nearby unconfined wells with the simulated groundwater component produced by the “abcd” Model to evaluate the ability of the in simulating groundwater.

Model Development

Because the “abcd” models developed based on observed precipitation provide the upper bond of the model in predicting streamflow, we develop and compare two sets of models; one based on observed precipitation and another based on precipitation forecasts. To develop conceptual models based on monthly observed precipitation, we compute the total monthly precipitation (P) and potential evapotranspiration (PET) as a spatial average over each HUC-8 in FRB. We use the computed monthly P and PET time series for a specific HUC as model inputs to develop prediction model for streamflow gauge(s) located within the same HUC-8.
The available period of records (1951-2010) is divided into two periods; 1951-1980 for calibration and 1981-2010 for validation. To evaluate the performance of the models during the validation period (1981-2010), we use long-term streamflow records observed at the six selected streamflow gauges (Tables 4.1 and 4.2 and Figure 4.2). Table 4.4 presents calibrated model parameters and RMSE obtained for the six stream gauges using monthly P and PET for the calibration and validation periods.

Table 4.4: Model parameters and skills computed for all months (Jan through Dec) using observed precipitation for six stream gauges in Flint River Basin.

<table>
<thead>
<tr>
<th>Stream Gauge Number</th>
<th>Drainage Area (Mile²)</th>
<th>Base Flow Index (BFI)</th>
<th>Model Parameters</th>
<th>RMSE (mm/month)</th>
</tr>
</thead>
<tbody>
<tr>
<td>USGS 02344500</td>
<td>272</td>
<td>0.58</td>
<td>0.89</td>
<td>286.0</td>
</tr>
<tr>
<td>USGS 02347500</td>
<td>1850</td>
<td>0.65</td>
<td>0.91</td>
<td>286.0</td>
</tr>
<tr>
<td>USGS 02349500</td>
<td>2900</td>
<td>0.71</td>
<td>0.87</td>
<td>286.0</td>
</tr>
<tr>
<td>USGS 02350512</td>
<td>3880</td>
<td>0.67</td>
<td>0.93</td>
<td>286.0</td>
</tr>
<tr>
<td>USGS 02352500</td>
<td>5310</td>
<td>0.68</td>
<td>0.94</td>
<td>286.0</td>
</tr>
<tr>
<td>USGS 02353000</td>
<td>5740</td>
<td>0.71</td>
<td>0.94</td>
<td>286.0</td>
</tr>
</tbody>
</table>

We also develop seasonal streamflow prediction models based on observed precipitation. To achieve this, we simply aggregate monthly precipitation, potential evapotranspiration as well as streamflow discharges and use the aggregated data to develop seasonal models. For
example, winter (JFM) is represented as the total of Jan, Feb and Mar while spring (AMJ) is represented as the total of Apr, May and Jun. Similarly, we represent JAS and OND.

**Model Evaluation**

Since our goal is to predict streamflow during winter and spring months (Jan through Jun), we focus on the performance of the conceptual model during this period. For this purpose, we consider multiple evaluation criteria for evaluating the modeling approach. Table 4.5 present root mean square error (RMSE), mean absolute error (MAE), relative root mean square error (R-RMSE) and correlation coefficients (ρ) for monthly (Jan through Jun) and seasonal (JFM and AMJ) computed for six stream gauges between observed and predicted streamflow during the validation period (1981-2010). The analysis shows significant skill in terms of correlation coefficients, RMSE and R-RMSE. Figure 4.6 obtained from Jan-Jun correlation coefficients, RMSE and R-RMSE for 6 stations (36 points). It shows that RMSE and R-RMSE decrease with the increase of the correlation coefficients.
In addition, Figure 4.7 shows the observed versus predicted streamflow, in mm/month, for six stream gauges during the validation period (1980-2010). Also, Figures 4.8 through 4.10 show observed versus predicted seasonal (JFM and AMJ) and monthly (Jan through Jun) for the stream gauges number 02344500. The performance of the model is similar in the other station (Figures not shown).
Table 4.5: Model evaluation for winter (Jan, Feb, Mar and JFM) and spring (Apr, May, Jun and AMJ) months during the validation period (1981-2010).

<table>
<thead>
<tr>
<th>USGS Station</th>
<th>Evaluation</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>JFM</th>
<th>AMJ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>13.30</td>
<td>16.37</td>
<td>15.15</td>
<td>9.69</td>
<td>8.38</td>
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Figure 4.7: Observed versus predicted streamflow, in mm/month, for six stream gauges.
Figure 4.8: Comparison between observed and predicted seasonal streamflow for the USGS station number 02344500 during JFM (A) and AMJ (B).
Figure 4.9: Predicted versus observed monthly streamflow for the station number 02344500 during Jan (A), Feb (B) and Mar (C).
Figure 4.10: Predicted versus observed monthly streamflow for the station number 02344500 during Apr (A), May (B) and Jun (C).
Groundwater Predictions using Observed Precipitation

In addition to streamflow, the “abcd” Model can simulate groundwater availability, which represents different groundwater component other than groundwater elevation or depth to groundwater. Hence, we relate the predicted groundwater availability from the model with the observed groundwater level. The model shows significant correlation between the simulated groundwater availability and the observed depth to groundwater level nearby the station (Figure 4.11). These preliminary modeling efforts indicate that the proposed conceptual model can be used to develop seasonal and monthly streamflow prediction models in FRB. Following this, we utilize this conceptual model with precipitation forecasts towards improving streamflow predictions within the basin.
Figure 4.11: Monthly observed groundwater level versus simulated groundwater availability in 12Z012 (A), 13M007 (B) and 11J012 (C).
Model Parameters versus Basin Characteristics

One of the commonly used basin parameters is the baseflow index (BFI) which quantifies the ratio of streamflow that comes as baseflow. Lim et al., 2005 provided Automated Web GIS Based Hydrograph Analysis Tool (WHAT) that is widely used to compute the BFI from daily streamflow. To comment on the performance of the “abcd” Model, we compare the calibrated parameters, mainly Parameter “c”, to the base flow index (BFI). The model optimizes for “c” and uses it to express the role of baseflow. Figure 4.12 shows a plot of BFI and “c” versus the drainage area. Also, we compute $\rho(BFI, c)$ as 0.80. Data can be found in Table 4.4.

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**Figure 4.12:** Base flow index (BFI) and Parameter “c” versus the drainage area
Predictions using Precipitation Forecasts

In this section, we use precipitation forecasts to develop and calibrate six conceptual models in attempt to predict seasonal and monthly streamflow for the selected stream gauges in FRB. Precipitation forecasts are available in gridded form over larger areas, and hence, a downscaling effort is necessary to downscale the gridded precipitation forecasts to basin (point) precipitation. For this purpose, we use principle component regression (PCR) to spatially downscale seasonal (JFM and AMJ) precipitation forecasts available from nine ECHAM 4.5 grid points to JFM and AMJ basin (HUC-8) precipitation.

Since we are interested in JFM and AMJ seasons and months, and considering the fact that precipitation forecasts issued at the beginning of Jan is not available beyond six months, we simply join the downscaled precipitation during JFM and AMJ and the observed precipitation during JAS and OND for every year to construct a seasonal time series for each HUC-8 and use it to run the model. The analysis indicates that JFM precipitation forecasts can be used to predict JFM streamflow in FRB while the model performs poorly in predicting AMJ streamflow due to the poor skill of AMJ precipitation forecasts.

To sum up, conceptual models developed based on observed precipitation are capable of predicting monthly streamflow over FRB and can be used as a baseline to evaluate the conceptual models developed based on precipitation forecasts. Similarly, the downscaled precipitation forecasts can be used to predict streamflow over FRB. However, these models appear to have few, but serious, limitations. In addition to the model uncertainty related to
the skill of the precipitation forecasts itself, the simplified downscaling scheme implemented through the study reduce the skill of the prediction models. Moreover, the ‘abcd’ model is not calibrated for groundwater and therefore, part of the skill in the predicted streamflow may come on the expense of groundwater misrepresentation. For these reasons, we focus on using statistical approach to predict streamflow and groundwater at monthly and seasonal time scales.

4.5.2. Statistical Models

To evaluate the possible utility of precipitation forecasts in improving streamflow and groundwater predictions, we predict seasonal (JFM and AMJ) and monthly (January through June) streamflow using three statistical models (Q-1, Q-2 and Q-3) for six stream gauges in FRB. Similarly, we develop three models (G-1, G-2 and G-3) to predict seasonal and monthly groundwater levels for ten wells in FRB. Q and G models are described in Section 4.4.2 and a list of stream gauges and groundwater wells is presented in Tables 4.1 and 4.2 as well as in Figure 4.2.

4.5.2.1. Streamflow Predictions

We develop and evaluate streamflow predictions models at seasonal time sale (JFM and AMJ) for the selected streamflow gauges. We start with Q-1, which uses OND streamflow observed at a given stream gauge as a predictor to predict JFM and AMJ streamflow for the same station. We develop this model for six stream gauges in FRB. The model skills expressed based on correlation coefficients and root mean square error (RMSE). The
comparisons between observed and predicted seasonal streamflow shows that Q-1 predicts streamflow during JFM with better skill in comparison to streamflow during AMJ over the six sites. On the other hand, Q-2 and Q-3 appear to have nearly the same skill and they both show better skill and are more successful in predicting JFM and AMJ streamflow (Figures 4.13, 4.14 and 4.15). Further, the analysis clearly demonstrates that the performance of the three models, developed for all the stations improves as we approach downstream.

Similar to seasonal streamflow predictions, we develop three statistical models (Q-1, Q-2 and Q-3) to evaluate the potential in improving streamflow predictions with precipitation forecasts at monthly time scale. The three models are developed for the selected six stream gauges located over FRB (Figure 4.1). The correlation between observed and predicted monthly streamflow during the period 1980-2010 indicates that Q-1 fails to predict streamflow beyond three months for all the investigated sites (Figure 4.16). However, Q-2 and Q-3 show significant improvement in streamflow prediction even beyond three months. In addition, Further, Figure 4.16 clearly shows the role of drainage area in improving the correlation coefficients between observed and predicted monthly streamflow as we progress from upstream to downstream.

To summarize, the analysis clearly demonstrates that incorporating precipitation forecasts result in improved skill in predicting seasonal and monthly streamflow and can extend the streamflow prediction period up to two seasons (JFM and AMJ). Since this significant improvement is mainly explained by the strong relationship between Q and P during winter...
months where surface water – groundwater interaction is dominant, we extend the same statistical modeling techniques to predict seasonal and monthly groundwater availability at selected wells in the basin.
Figure 4.13: Correlation coefficients between observed and predicted JFM (A) and AMJ (B) streamflow obtained by three statistical models (Q-1, Q-2 and Q-3) for six streamgauges in FRB. Correlation above 0.3 is statistically significant at 95% confidence interval.
Figure 4.14: Root mean square error (RMSE) between observed and predicted JFM (A) and AMJ (B) streamflow obtained by three statistical models (Q-1, Q-2 and Q-3) for six streamgauges in FRB.
Figure 4.15: Relative root mean square error (R-RMSE) between observed and predicted JFM (A) and AMJ (B) streamflow obtained by three statistical models (Q-1, Q-2 and Q-3) for six streamgauges in FRB.
Figure 4.16: Correlation coefficients between observed (Q obs) and predicted (Q pre) monthly streamflow obtained by three statistical models (Q-1, Q-2 and Q-3) for six streamgauges in FRB. Correlation above 0.3 is statistically significant at 95% confidence interval.
4.5.2.2. Groundwater Predictions

In this section, we investigate the possibility of predicting seasonal and monthly groundwater levels using precipitation forecasts over FRB. For this purpose, we choose ten groundwater wells (Figure 4.2) and we develop three statistical models (G-1, G-2 and G-3), as described in Section 4.4.2. Considering the significant correlation between groundwater levels observed in different wells within FRB, we conclude that there is similarity in groundwater flow patterns due to similarity in aquifer response to recharge and discharge processes in the basin. Therefore, we investigate the possibility of using groundwater levels, observed in adjacent wells, as additional predictors to improve groundwater predictions at a given well. Moreover, we correlate observed and predicted groundwater levels over the selected wells and we use these correlations to understand the role of climate variability in modulating groundwater levels. Precipitation forecasts obtained from the nine grid points over FRB show better skill in predicting basin precipitation at seasonal time scale in comparison to the monthly time scale. Further, seasonal precipitation forecasts are significantly correlated to seasonal groundwater levels in all selected wells. Hence, we use seasonal precipitation forecasts (JFM, and AMJ) issued at the beginning of Jan (Table 4.3). Since we are interested in predicting 2-seasons ahead (JFM and JAS) as well as 6-months ahead (Jan through Jun) groundwater levels, we include July, Aug and Sep as well as summer (JAS) to demonstrate the difficulty in predicting groundwater for extended periods (more than 6-months ahead).

We consider the period of 1980-2010 for the analysis and we start the analysis by developing G-1 models for all wells using OND groundwater levels to predict JFM, AMJ and Jan
through Sep groundwater levels. To develop G-2 models, and in addition to OND, we include JFM precipitation forecasts to predict Jan, Feb and Mar as well as JFM groundwater levels for each well. Similarly, we include AMJ precipitation forecasts to predict Apr, May and Jun as well as AMJ. Finally, we develop G-3 models for each well by including OND from all ten wells as well as precipitation forecasts using a regression modeling technique with canonical correlation. Figures 4.17 shows the correlation coefficients between observed and predicted seasonal (JFM, AMJ and JAS) groundwater levels in ten wells and Figure 4.18 shows spatial view of the correlation coefficients. Since precipitation forecasts show significant importance in improving groundwater at seasonal level, we investigate the possibility of similar role in predicting monthly groundwater levels. To achieve this goal, we develop G-1, G-2 and G-3 for each well to predict Jan through Sep groundwater levels.

### 4.5.2.3. Model Evaluation

To evaluate the models, we use correlation coefficients ($\rho$) and root mean square error (RMSE). $\rho$ is one of the widely used performance measures and it is basically used to determine the strength of the linear relationship between observed and predicted values (Moriasi et al., 2007). On the other hand, RMSE is the most commonly used error indices in model evaluation because it has the same unit as the observed and simulated values which qualified this index to properly comment on the analysis. Since the investigated wells have different magnitudes of water levels, we extend the model evaluation criteria to include the relative root mean square error (R-RMSE). R-RMSE is very helpful in this case because it allow us to compare the performance of the prediction models across the basin (among the
ten wells). The analysis indicates that improved correlation coefficients are associated with neither improved RMSE nor R-RMSE. However, R-RMSE values for the ten wells clearly indicate that groundwater prediction skill vary from well to well. To demonstrate these results, we show the correlation coefficients and RMSE in Figures 4.19 and 4.20 respectively. Figures 4.21 through 4.23 show plots of correlation coefficients between observed and predicted monthly (Jan through Sep) groundwater levels in FRB. From these figures, we clearly see that there is skill in predicting monthly groundwater levels during JFM and AMJ. However, the skill of monthly models is lower compared to seasonal models.
Figure 4.17: Correlation coefficients between observed (G obs) and predicted (G pre) JFM (A) and AMJ (B) groundwater levels obtained by three statistical models (G-1, G-2 and G-3) for ten groundwater wells in FRB. Correlation above 0.3 is statistically significant at 95% confidence interval.
Figure 4.18: Comparison between observed and predicted JFM, AMJ and JAS groundwater level for ten wells under three different models during the period 1980 to 2010.
Figure 4.19: Correlation coefficients between observed (G obs) and predicted (G pre) monthly (Jan through Jun) groundwater levels obtained by three statistical models (G-1, G-2 and G-3) for ten groundwater wells in FRB. Correlation above 0.3 is statistically significant at 95% confidence interval.
Figure 4.20: Root Mean Square Error (RMSE), in feet, between observed and predicted monthly groundwater levels for ten wells under three different models during 1980-2020.
Figure 4.21: Comparison between observed and predicted Jan, Feb and Mar groundwater levels for ten wells using three different models during the period 1980 to 2010.
Figure 4.22: Comparison between observed and predicted Apr, May and Jun groundwater levels for ten wells using three different models during the period 1980 to 2010.
Figure 4.23: Comparison between observed and predicted Jul, Aug and Sep groundwater levels for ten wells using three different models during the period 1980 to 2010.
4.4. Conclusions

1. Conceptual models developed based on observed precipitation for multiple streamflow sites in FRB are more successful in predicting seasonal and monthly streamflow in comparison to conceptual models developed based on precipitation forecasts. However, the conceptual models are not capable of predicting groundwater levels and therefore statistical modeling techniques are developed for this purpose.

2. The skill of precipitation forecasts is a key factor in the predicting streamflow and groundwater. Overall, seasonal precipitation forecasts have better skill in comparison to monthly precipitation forecasts especially during winter months. Hence, we conclude that adopting seasonal precipitation forecasts result in better streamflow and groundwater predictions at seasonal and monthly time scales.

3. The statistical Model G-1, which uses only OND groundwater level as a predictor is capable of predicting season groundwater levels during JFM while the predictability of the model tend to decrease during spring (AMJ) and summer (JAS) seasons.

4. Model G-2, which is another statistical model that uses precipitation forecasts as additional predictor, shows a better skill in predicting groundwater during JFM. Also, it extends the period of groundwater predictions by showing acceptable skill in predicting AMJ for all wells and in predicting JAS for few wells. The third statistical model (Model G-3), which
uses additional information from adjacent wells in CCA scheme also show better skill in few wells.

5. Generally, G-1 is not capable of predicting monthly groundwater levels beyond three months. However, there are few cases such as 11A001 and 13J004 where G-1 models show good skill in predicting groundwater levels for up to 6 months. This indicates that groundwater levels in these two wells are controlled by local groundwater flow rather than climate variations.

6. Models G-2, and G-3 show nearly equal skills in predicting groundwater levels except for 07H003 and 08K001 where G-3 models show better skill indicating that groundwater levels of these two wells are highly correlated with groundwater levels in adjacent wells.

7. Groundwater predictions are significantly improved for most wells and this improvement varies from well to well and from model to model. The only exception is well 13M006 where no significant prediction is possible beyond three months.

8. All the computed correlation coefficients clearly demonstrate improved groundwater prediction with precipitation forecasts (Models G-2 and G-3). Further, the analysis also shows that the root mean square error (RMSE) computed between observed and predicted Jan through Sep groundwater levels for all the wells under the three models is only improved in few wells such as 12Z001, 10G313 and 13M007. This explains the importance of
precipitation forecasts is more successful in predicting the variability in groundwater levels but less skilful in reducing the bias.

9. Precipitation forecasts could be used as an additional predictor to improve streamflow and groundwater predictions at seasonal and monthly time scales using conceptual and statistical modeling techniques.

10. Finally, as a future study, developing and calibrating predictions model for streamflow and groundwater in a multi-objective calibration technique may help improve the predictions especially in basins where groundwater-surface water interaction process is dominant.
5. SUMMARY AND CONCLUSIONS

5.1. Summary

The primary motivations of this research can be summarized in the following two main points:

a. Surface water-groundwater interaction has been the focus of many researchers for long time but few studies have focused on understanding the interrelationships between these two primary water resources over larger areas.

b. While the role of climate variability in affecting the availability and sustainability of water resources has become the focus of research in the last few decades, the effect of climate variability on groundwater has received less attention due to limited groundwater data availability.

This dissertation provides better understanding of the interaction between atmospheric, surface and subsurface attributes of the hydroclimatic system over the southeast U.S. and suggests quantitative framework to improve streamflow and groundwater predictions using climate information. During the course of this research, the intent is to focus on the effect of climate variability on groundwater at seasonal and interannual time scales in basins with natural groundwater and stream flows. Hence, streamflow and groundwater observation stations are carefully selected from basins with limited anthropogenic influences. The choice
of southeast U.S. is made based on the importance of groundwater as well as the significant role of climate.

Considering the research objectives, methods and tools are carefully selected based on the nature and scale of the problem. Data analysis methods, discussed in Chapter 3, include seasonality analysis, dependency analysis, principle component analysis (PCA), and singular spectrum analysis (SSA). We also employ conceptual water balance model statistical models to evaluate the utility of precipitation forecasts in improving the predictions of streamflow and groundwater availability. Overall, and considering the research motivations, objectives, tools and methods, we conduct and organize this research to cover two main related topics. Following is a brief description of the two research topics:

First, the role of climate variability in modulating surface water and groundwater interaction over the southeast U.S: This topic is mainly presented in Chapter 3 and it focuses on understanding the role of climatic variability on interannual groundwater and streamflow variability over the Southeast U.S. For this purpose, streamflow and associated groundwater levels are analyzed for twenty basins. The study related basin hydroclimatic variables to ENSO Conditions and to precipitation forecasts during winter months. The significant role of groundwater and its dependency on climate variability motivate us to extend this work to include streamflow and groundwater predictions using precipitation forecasts.
Second, improving streamflow and groundwater predictions using seasonal precipitation forecasts: This part of the dissertation is discussed in Chapter 4 and it aims to examine the ability of climate information, mainly precipitation forecasts from GCMs, in predicting streamflow and groundwater at seasonal and monthly time scales. Hence, we consider multiple streamflow and groundwater sites in Flint River Basin and employ conceptual and statistical modeling techniques to predict streamflow and groundwater. The basic approach is to develop models based on previous records of groundwater or streamflow and compare them to another set of models that use precipitation forecasts as an additional predictor. The analysis clearly demonstrates the potential in incorporating climate information for predicting streamflow and groundwater over the basin.

5.2. Conclusions

Detailed conclusions and discussions are presented in Chapters 3 and 4. The main findings from the study are summarized in the following points:

i. The dependency analyses among the hydroclimatic variables show significant interaction between surface water and groundwater over the study area at seasonal time scale and indicate the role of climate variability in influencing the interaction is also statistically significant. For instance, precipitation over the previous three months influences the groundwater level in a given month while streamflow in any given month depends on the groundwater level during the previous three months.
ii. Findings from SSA clearly show that the hydroclimatic covariability among precipitation, temperature, streamflow and groundwater is stronger during winter months in comparison to summer months which indicate the increased role of temperature during summer.

iii. Groundwater appears to have significant role in controlling the hydroclimatic covariability within the basin. For example, the proportional variance during winter and summer seasons show that basins with larger base flow index (BFI) values have higher eigenvalues.

iv. Preliminary analysis on relating the retrospective climate forecasts from ECHAM4.5 with groundwater levels show that there is scope in utilizing climate forecasts for predicting groundwater availability over the region.

v. Correlation analysis for six streamflow stations and ten groundwater wells in Flint River Basin (FRB) show that there is a high inter-site correlation between the observed streamflow and groundwater levels over the basin.

vi. Using precipitation forecasts from ECHAM 4.5 as additional predictor result in significant improvement in predicting seasonal and monthly groundwater and streamflow over FRB. The improvement achieved includes better skill and longer lead time in predicting groundwater and streamflow.
vii. Though the suggested multisite multivariate modeling framework is site-specific, incorporating streamflow and groundwater information from adjacent sites using canonical correlation techniques result in improved predictions.

5.3. Limitations

Basically, efforts aim to represent and model surface water-groundwater interaction are subject to spatial and temporal variability. In this section, we discuss some of the limitations we encountered in this research especially limitations related to methodologies, data availability and scales.

i. Although we strive to choose streamflow and groundwater sites with minimum anthropogenic influences, we still believe that there is a good chance that both surface water and groundwater could be influenced by development and urbanization. In addition, it is difficult, in most cases, to distinguish between hydrologic responses due to human activity (e.g., pumping) from responses caused by natural variability.

ii. The absence of long-term and reliable records, especially groundwater levels, challenges the accuracy of time series analysis and results in poor calibration and validation efforts. Despite the fact that we managed to study twenty sites, which, in our view, adequately represents the interactions among the various hydroclimatic variables over the SEUS, we still convinced that a larger number of sites could help provide better hydrologic representation and evaluation.
iii. The relatively limited spatial variability in climatic information and aquifer characteristics over the SEUS results in similar hydrologic responses. This could be better analyzed by including larger regions, probably the entire U.S., with multiple principle aquifers and diverse river basins.

iv. Unlike seasonal precipitation forecasts, the skill of the monthly precipitation forecasts is very poor especially during summer months. Therefore, the relatively poor precipitation forecasts negatively impacted the outcome of the study, especially for monthly streamflow and groundwater predictions.

v. The relatively short periods of groundwater records (1980-2010) force us to adopt a leave-one-out cross validation technique. Although this approach, in this case, is successful and produces statistically significant streamflow and groundwater predictions over FRB, we have no doubt that longer data periods would have helped us to evaluate the models more rigorously.

vi. We calibrated the conceptual model (The “abcd” Model) for streamflow using single-objective calibration approach. This approach results in poor prediction of other state variables such as groundwater availability and evapotranspiration. We believe that it is better to explore multi-objective calibration techniques by forcing the watershed models to predict not only streamflow but also other hydroclimatic variables in the basin. However, to develop
a model with streamflow and groundwater representation and future simulations capabilities is a “research problem” itself.

5.4. Scope for Future Work

Adequate hydrologic system representation and proper methodologies are vital to better understand the effect of climate variability on streamflow and groundwater availability. In this section, we discuss few options that we think it may help extend this study to cover the role of climate variability in influencing basin hydroclimatic variables.

I. Data availability

Basically, more observation points over diverse regions with longer periods of records are required for a comprehensive understanding of the role of climate variability in influencing streamflow and groundwater availability. For example, the USGS Climate-Groundwater Response Network (CGRN) is probably the best database to start with. Among the 580 CGRN wells located across the United States, 88 wells have at least 20 years of mean monthly groundwater records.

The 88 wells cover a wide range of climatic divisions and aquifer systems. For example, the 88 wells cover 18 different regional aquifers and represent 50 different local aquifers in the United States with altitude ranges from 10 to 6037 feet above sea level. In addition, depths of these wells range from 10 to 620 feet below land surface. Also, the 88 wells represent 65 different USGS Hydrologic Units Code – 8 (HUC-8) in 15 States. This diversity in the
hydrogeologic system helps evaluate the effect of climate variability on groundwater over the United States.

ii. Groundwater withdrawals

Basically, groundwater variability is affected by climatic stresses such as precipitation and temperature. It is also affected by human activities, mainly pumping and return flow from agricultural activities. To study basins with significant groundwater abstractions, it is important to quantify the percentage of groundwater variability caused by groundwater utilization first. Generally, groundwater aquifers are connected through their lateral, upper and lower boundaries which result in upward, downward and lateral flows. For example, groundwater abstraction from deeper confined aquifers may result in significant downward leakage and consequently noticeable decline in shallower groundwater table.

On the other hand, and while it is possible to observe and predict the variability in groundwater level at a given site, it is, in most cases, difficult to identify the exact cause(s) or source(s) of that variability. However, a thorough understating of the groundwater flow system and the existence of reliable data, mainly pumping rates and schedule, could be used to make that distinction between variability due to human activities and variability due to natural hydroclimatic processes. To achieve this goal, it is more effective and productive to employ data-mining techniques. Recently, Murray (2010) employed multivariate regression analysis several anthropogenic and climatic stressors and groundwater levels observed in two groundwater wells in Florida, one in the Surficial Aquifer and the other is in the Floridian
Aquifer. Abstraction rates from nearby well-field are among the anthropogenic stressors while precipitation and evapotranspiration are two examples of the climatic stressors used in the study. The analysis uses different sets of predictors to develop multiple models and then define the role of anthropogenic versus climatic based on the skill in the predicted values.

iii. Anthropogenic influences

Essentially, water resources management aims to resolve water conflicts and stresses in developed areas that are already under anthropogenic effects caused by urbanization spread and agriculture expansion. On the other hand, remote basins with minimal human agricultural and industrial activities lack long-term historic hydroclimatic records due to insufficient monitoring network. Therefore, it is vital to develop methodologies and techniques that can transform the hydrologic information affected by anthropogenic disturbances into naturalized inflows and groundwater levels over the basin. Though this study has focused primarily on virgin basins having limited anthropogenic influence, findings from this study could be translated to basins that are subjected to land-use changes, pumping and man-made storages. In addition to the suggestion made to work on basins with groundwater abstractions (see above), we offer the following suggestions on how our analyses could be carried out for basins with significant anthropogenic influence.

To apply this research on basins with significant anthropogenic influences, it is important to adjust the model inputs. The first step to achieve this goal is to properly identify the sources or causes and the importance of these influences in terms of their spatial and temporal scales,
as well as their impact on water quantity and quality. This can be achieved using the available information within the basin as well as by integrating more information from adjacent basins with similar hydrologic and climatic setting. Alternatively, periods of records prior to the anthropogenic activities may be used to develop and calibrate models to represent natural flows. Also, changes in storage and surface water release from reservoirs could be used to naturalize the flow downstream and therefore could be used to quantify the percentage of variability in surface water and groundwater that comes as a direct result to the exiting anthropogenic influences. Similarly, groundwater withdrawals could be used to establish natural groundwater levels especially in aquifers with high storativity and hydraulic conductivities where the recovery time is relatively short (several hours to few days). In other words, and depending on the recovery time, groundwater levels observed during days or periods with no pumping activities could be used to represent natural variability due to climatic variations in opposite to periods with pumping activities. Further, historic streamflow records, prior to significant urbanization, could be used to quantify anthropogenic influences due to the changes in land-use such as impervious surfaces and deforestation. Finally, there is considerable research on detecting trends in the observed hydrologic data. For example, Burn et al., 2002 employed several techniques including Mann-kendall non-parametric test to examine the dependency between 18 selected climatic and hydrologic variables at 248 watersheds in Canada. The study relates the trends and patterns in hydrologic variables to trends and patterns in climatic variables. Overall, the similarity in trends and patterns over watersheds prior to major development could be useful to fine-tune the hydrologic variables during the periods with significant anthropogenic influences.
Moreover, trends and patterns between climatic and hydrologic variables from nearby undeveloped watersheds could also be used to extend the observation at streamgauges and/or groundwater wells where you have longer record that are subjected to anthropogenic influences.

**iv. Regions with different climatic and hydrologic characteristics**

The study involves analysis of climate, surface water and groundwater variables over the southeast U.S. However findings from this study could be relevant to basins that are significantly impacted by ENSO during the winter season. ENSO is a coupled ocean-atmospheric phenomenon that has interannual variability with irregular 2- to 6-year cycles between the positive (El Niño) and negative (La Niña) phases (Wolter et al., 1998). Based on Devineni and Sankarasubramanian (2010), we know that ENSO has significant influence over the entire southern US (from Florida to Southern California) and over Northwest. Rest of the continent is not significantly affected by ENSO, and hence we expect the findings could be similar for these regions. However, local climatic and hydrogeologic characteristics could influence the actual predictability in a given region and therefore, detailed analyses may be necessary to validate the findings. Further, the skill of precipitation forecasts varies from region to another. For example, ECHAM 4.5 shows better skill over the southeast U.S. in comparison to the southwest U.S. Therefore, preliminary analysis on the association between precipitation forecasts and basin precipitation is required. Moreover, it is important to study the dimensions and the characteristics of the aquifer system(s) within the investigated region(s) to ensure surface water-groundwater interaction at the desired time.
scale, to choose the right set of predictors, and to make proper interpretations. For example, it is difficult to study the role of climate in modulating groundwater in regions with confined aquifer systems or even shallow unconfined aquifers with secondary porosity such as karst lime stone and fractured igneous rocks.

Finally, in addition to adequate surface water and groundwater resources assessment, which normally provide reasonable estimates of the water available at various time scales, comprehensive water resources management plans and strategies at regional or local scales requires full understanding of the interaction between atmospheric, surface and subsurface attributes of the hydroclimatic system. This understanding could provide answers related to the quantity and quality of the available water resources at a given time and therefore result in a better water resources management. While climate variability is considered to be a key factor in modulating temperature, precipitation and streamflow over land surface, this dissertation came to emphasize on these facts but to demonstrate the role of groundwater as well. This dissertation shows that unconfined groundwater flow systems could be linked to climate variability and hence, could play a major role in modulating surface water especially during spring and summer seasons. Therefore, considering groundwater component, especially where groundwater is significantly connected to climate, is vital to any comprehensive water resources management plan.
5.5. Journal Publications from the Research


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