Improving Groundwater Predictions Utilizing Seasonal Precipitation Forecasts from General Circulation Models Forced with Sea Surface Temperature Forecasts

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Abstract: Recent studies have found a significant association between climatic variability and basin hydroclimatology, particularly groundwater levels, over the southeast United States. The research reported in this paper evaluates the potential in developing 6-month-ahead groundwater-level forecasts based on the precipitation forecasts from *ECHAM 4.5* General Circulation Model Forced with Sea Surface Temperature forecasts. Ten groundwater wells and nine streamgauges from the USGS Groundwater Climate Response Network and Hydro-Climatic Data Network were selected to represent groundwater and surface water flows, respectively, having minimal anthropogenic influences within the Flint River Basin in Georgia, United States. The writers employ two low-dimensional models [principle component regression (PCR) and canonical correlation analysis (CCA)] for predicting groundwater and streamflow at both seasonal and monthly timescales. Three modeling schemes are considered at the beginning of January to predict winter (January, February, and March) and spring (April, May, and June) streamflow and groundwater for the selected sites within the Flint River Basin. The first scheme (model 1) is a null model and is developed using PCR for every streamflow and groundwater site using previous 3-month observations (October, November, and December) available at that particular site as predictors. Modeling schemes 2 and 3 are developed using PCR and CCA, respectively, to evaluate the role of precipitation forecasts in improving monthly and seasonal groundwater predictions. Modeling scheme 3, which employs a CCA approach, is developed for each site by considering observed groundwater levels from nearby sites as predictands. The performance of these three schemes is evaluated using two metrics (correlation coefficient and relative RMS error) by developing groundwater-level forecasts based on leave-five-out cross-validation. Results from the research reported in this paper show that using precipitation forecasts in climate models improves the ability to predict the interannual variability of winter and spring streamflow and groundwater levels over the basin. However, significant conditional bias exists in all the three modeling schemes, which indicates the need to consider improved modeling schemes as well as the availability of longer time-series of observed hydroclimatic information over the basin. **DOI: 10.1061/(ASCE)HE.1943-5584.0000776.** *© 2014 American Society of Civil Engineers.*

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Introduction

It is well-known that climatic variability can affect both water quantity (Ropelewski and Halpert 1987; Hanson and Dettinger 2005; Sankarasubramanian et al. 2008) and quality (Oh and Sankarasubramanian 2012) at regional and continental scales. Hence, incorporation of climatic information into hydrologic models could provide useful information to quantify and manage surface water and groundwater resources over the watershed. Most of the studies that have linked climate variability to basin hydrology primarily focused on precipitation (Ropelewski and Halpert 1987; Devineni and Sankarasubramanian 2010) and streamflow (Tootle and Piechota 2006; Devineni et al. 2008). Nevertheless, the effect of climate variability on groundwater quantity and quality remains poorly understood (Green et al. 2007), particularly in comparison to other components of the water budget.

Understanding the role of climate in influencing streamflow-groundwater interactions has significant implications for conjunctive management of both surface water and groundwater, particularly during multiyear droughts (Hanson and Dettinger 2005). Recent studies have also found a significant association between climatic variability and groundwater resource-variability at regional scales (Hanson et al. 2009; Almanaseer and Sankarasubramanian 2012). The impact of climate variability on groundwater is more complex than for surface water (Holman 2006) since the availability of groundwater is more difficult to quantify (Alley et al. 2002). The research reported in this paper is motivated by the importance of groundwater resources over the southeast United States for water supply and baseflow to streams, and also based on the relatively good skill in predicting winter precipitation (Devineni and Sankarasubramanian 2010) that potentially control groundwater resource-availability (Almanaseer and Sankarasubramanian 2012) over the region.

The writers' primary intent is to evaluate the potential in developing groundwater-level forecasts utilizing the season-ahead precipitation forecasts from climate models forced with sea-surface temperature (SST) forecasts (Li and Goddard 2005). Both statistically based (Maurer and Lettenmaier 2004; Devineni et al. 2008)

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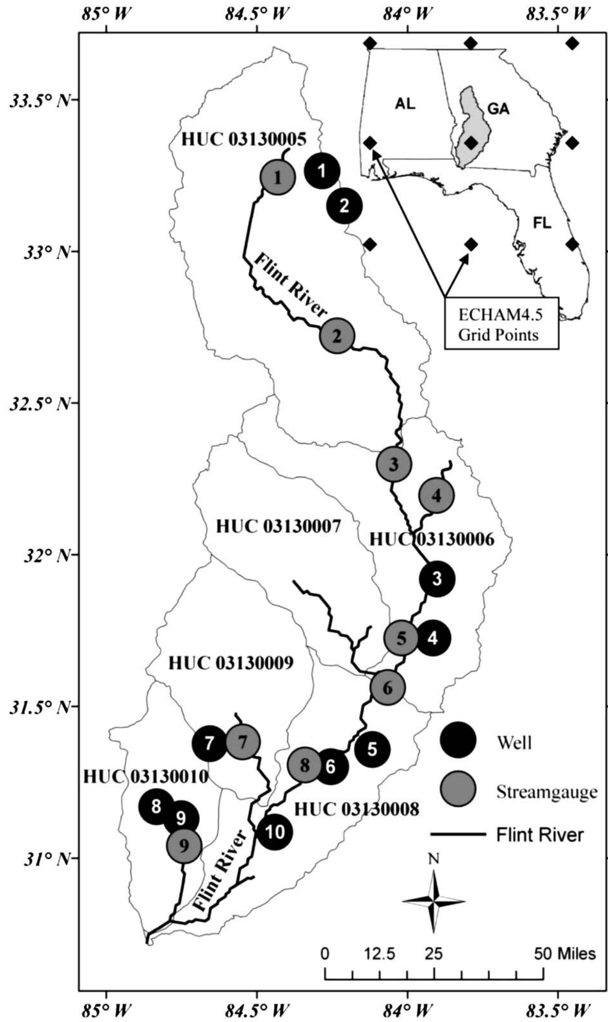

Fig. 1. Location map for the selected streamgauges and groundwater wells in Flint River Basin (FRB); Tables 1 and 2 provide index numbers for streamgauges and groundwater wells

and physically based (Wood et al. 2002; Luo et al. 2007) techniques are commonly used to develop hydrologic forecasts based on climate forecasts issued from general circulation models (GCMs). Developing hydrologic forecasts using physically based watershed models first require spatial downscaling of climate forecasts (primarily precipitation and temperature) to subgrid scale (Wood et al. 2002). Furthermore, the downscaled climate forecasts need to be disaggregated to a daily time-step using either parametric (Stedinger and Vogel 1984) or nonparametric (Kumar et al. 2000) techniques. Apart from the errors that could arise from spatial downscaling, effective coupling of surface water and groundwater components have always been challenging (Sophocleous et al. 1999). Consequently, this paper employs two statistical techniques, (1) principal component regression (PCR), and (2) canonical correlation analysis (CCA), to develop seasonal (winter and spring) and monthly (January–June) groundwater-level prediction models, using precipitation forecasts from the *ECHAM 4.5* GCM (Roeckener 1996) along with observed streamflow and groundwater in October.

The subsequent sections of this paper are as described next. The writers first provide details on the study area and database used in the modeling. The next section describes the dependency analysis performed to develop a preliminary understanding of the interrelationships among the hydroclimatic variables for identifying relevant predictors. The next section presents the low-dimensional models and skill metrics. The next section discusses the skill of the developed seasonal and monthly groundwater-level forecasts. The final section summarizes the findings and salient conclusions arising from the research reported in this paper.

Study Area and Database

The 21,900 km^2 Flint River Basin (FRB) in Georgia is part of the Apalachicola-Chattahoochee-Flint (ACF) River Basin in Georgia, Alabama and Florida, United States (Fig. 1). It is composed of six hydrologic units [hydrologic unit code 8 (HUC-8)] and contains multiple streamflow and groundwater-level data-recording stations with relatively long periods of record (1980–2010). In addition to data availability, the FRB exhibits significant interactions between surface water and groundwater, which are conditioned on climatic variability (Almanaseer and Sankarasubramanian 2012). In many streams within the basin, a substantial portion of the baseflow consists of groundwater discharge (USGS 2007). The FRB is located within two physiographic provinces, as follows: (1) the Piedmont physiographic province in the upper basin, and (2) the Coastal Plain physiographic province in the majority of the basin. The Piedmont physiographic province is underlain by local, crystalline-rock aquifers. In the Coastal Plain physiographic province, large regional porous-media aquifers are present in order of descending stratigraphy and increasing age, i.e., the Floridan Aquifer System, Claiborne Aquifer, Clayton Aquifer, and Providence Aquifer System (Torak et al. 2010). Generally, the regional groundwater flow-direction in the Coastal Plain is from north to south, but local flow directions vary, especially in the vicinity of streams and within heterogeneous crystalline-rock and carbonate aquifers. In addition, strong stream-aquifer interaction between the Floridan aquifer system and Flint River results in significant groundwater contributions to baseflow (Table 1). Base flow index (BFI) was computed as part

Table 1. List of the Selected Streamgauges in the Flint River Basin

Index number	USGS streamgauge number, upstream to downstream	Hydrologic unit, HUC-8	Altitude [m (ft) above NGVD29]	Drainage area [km^2 (mi^2)]	Baseflow index
1	02344500	03130005	216.8 (711.4)	704.5 (272)	0.58
2	02347500	03130005	102.0 (334.5)	4791.5 (1,850)	0.65
3	02349500	03130006	78.0 (255.8)	7511.0 (2,900)	0.71
4	02349900	03130006	87.2 (286)	116.5 (45)	0.61
5	02350512	03130006	56.7 (185.9)	10049.2 (3,880)	0.67
6	02352500	03130008	45.7 (150.03)	13752.8 (5,310)	0.68
7	02353500	03130009	45.8 (150.30)	1605.8 (620)	0.76
8	02353000	03130008	33.6 (110.2)	14866.5 (5,740)	0.71
9	02357000	03130010	26.1 (85.7)	1364.9 (527)	0.73

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Table 2. List of the Selected Groundwater Wells in the Flint River Basin

Index number	USGS well number	Hydrologic unit, HUC-8	Altitude [m (ft) above NGVD29]	Aquifer	Well depth [m (ft)]
1	11AA01	03130005	289.6 (950)	Surficial	9.1 (30)
2	12Z001	03130005	259.7 (852)	Surficial	9.4 (31)
3	13M006	03130006	72.5 (238)	Floridan	37.5 (123)
4	13M007	03130006	72.5 (238)	Surficial	7.6 (25)
5	13J004	03130008	59.1 (194)	Floridan	63.4 (208)
6	11J012	03130008	50.3 (165)	Floridan	68.6 (225)
7	08K001	03130009	70.1 (230)	Floridan	38.1 (125)
8	07H002	03130010	50.9 (167)	Floridan	22.9 (75)
9	07H003	03130010	50.9 (167)	Surficial	12.2 (40)
10	10G-313	03130008	44.2 (145)	Floridan	62.8 (206)

of the research reported in this paper using the automated Web GIS-based Hydrograph Analysis Tool [*WHAT* (Lim et al. 2005)]. The relatively high BFIs computed for the nine streamgauges (Table 1) indicates the significant role of groundwater in controlling streamflow discharge within the basin.

The selection of the sites was made to ensure natural groundwater and streamflow records with minimal to no anthropogenic influences such as upstream storage and groundwater pumping, thereby representing adequate hydrologic responses. Fig. 1 shows locations from which hydroclimatic data were used. Tables 1 and 2 list the selected streamgauges and groundwater wells in addition to relevant information. The index numbers (Tables 1 and 2) are used in the location map to identify the sites.

Observed Precipitation

Total monthly precipitation from the gridded precipitation data supported by the Precipitation Regressions on Independent Slope Model (PRISM; Daly et al. 1994) is considered for the research reported in this paper. Monthly precipitation during the period 1980–2010 for each HUC was computed from this gridded data as a spatial average over that HUC using a statistical-zoning function in *ArcGIS 9.1*. Time-series monthly precipitation data were computed and used to represent monthly observed precipitation over the six HUCs in the FRB (Fig. 1).

Streamflow and Groundwater

Monthly mean time-series of streamflow and groundwater level at sites with limited to no anthropogenic influences were obtained for 10 groundwater wells and nine streamgauges during the period 1980–2010 (Table 1). The writers selected streamgauges and groundwater wells primarily from the Hydro-Climatic Data Network (HCDN; Slack et al. 1993; Sankarasubramanian and Vogel 2002; Vogel and Sankarasubramanian 2005) and the Climate Groundwater Response Network (CGRN; USGS 2007), respectively. All groundwater wells were screened in unconfined aquifers, with a relatively shallow phreatic water table mainly in the Floridian Aquifer in the southern FRB and in the surficial aquifer. Two streamflow-gauges (02344500 and 02350512) are not HCDN sites and three groundwater wells (13M006, 11J012, and 08K001) are not in the CGRN.

Precipitation Forecasts

The retrospective winter [January, February, and March (JFM)] and spring [April, May, and June (AMJ)] precipitation forecasts from *ECHAM 4.5* is available from the International Research Institute (IRI) for Climate and Society data library (Li and Goddard 2005). To force *ECHAM 4.5* 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 *ECHAM 4.5* using constructed analogue SST forecasts, see Li and Goddard (2005).

In this paper, the writers utilize the forecasted monthly precipitation, which is obtained by computing the average over 24 *ECHAM 4.5* ensembles for JFM and AMJ issued at the beginning of January. Time series of JFM-observed and AMJ-observed precipitation for 1980–2010 over the six HUCs are correlated to JFM and AMJ precipitation-forecasts obtained for 25 *ECHAM 4.5* grid points with spacing of $2.5 \times 2.5°$. Among the 25 *ECHAM 4.5* grid points over FRB and the nearby regions, nine were used for the research reported in this paper (Fig. 1, inset) since these grid points exhibited significant correlation between the observed and predicted precipitation.

To recapitulate, the hydroclimatic variables considered for seasonal and monthly groundwater predictions include precipitation forecasts from nine *ECHAM 4.5* grid points, observed monthly total precipitation computed over six HUCs, monthly mean streamflow observed at nine streamgauges, and monthly mean groundwater level (depth from land surface) measured at 10 groundwater wells. Understanding the dependency among these hydroclimatic variables at different time lags could help identify potential predictors that influence the streamflow and groundwater potential during the winter and spring seasons.

Dependency Analysis

Spearman rank-correlation is used to quantify the dependency among precipitation P, streamflow Q, and depth to groundwater G observed during the period 1980–2010. Correlation analysis was also performed between the observed hydroclimatic variables and precipitation forecasts. Both concurrent and lag correlations were also performed between P, Q, and G. The analysis shows that for a given groundwater well, the observed G at a given month is significantly correlated to the observed G during the previous 3 months. Similarly, the observed Q at a given month is significantly correlated with Q for the previous 3 months. These findings are in line with the dependency analyses reported in Almanaseer and Sankarasubramanian (2012). Furthermore, correlation between the concurrent G observed at 10 groundwater wells also indicate significant similarity in groundwater-level patterns over FRB for the period of record analyzed. In conclusion, October, November, and December (OND) observations can be used to predict at a specific site since they provide information on the baseflow as part of JFM streamflow and also about the potential JFM groundwater-levels. Spatial correlations between streamflow and groundwater also indicate that historic information from nearby wells and gauges can also be used to develop low-dimensional models (Sankarasubramanian et al. 2009) for predicting streamflow and groundwater.

Relevant *ECHAM 4.5* grid points that influence the hydroclimatology of the basin during winter (JFM) and spring (AMJ) are identified by computing Spearman rank-correlation coefficients between the hydroclimatic variables (P, Q, and G) and precipitation forecasts obtained from 25 *ECHAM 4.5* grid points covering large area over the southeast United States during the period 1980–2010. The analysis identified nine grid points (Fig. 1) that are significantly correlated with the observed P, Q, and G over the FRB. In addition, precipitation forecasts from these nine grid points are

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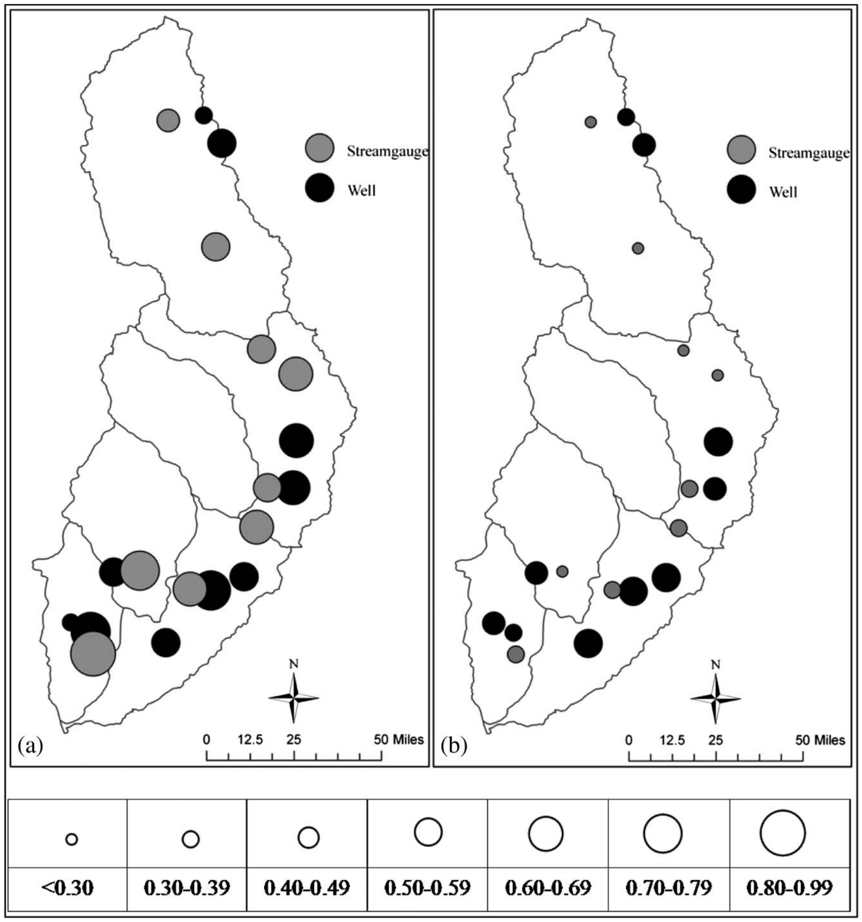

Fig. 2. Correlation coefficients between the first principal component (PC1) obtained from nine *ECHAM 4.5* grid points and seasonal streamflow and depth to groundwater: (a) January–March (JFM); (b) April–June (AMJ); the correlation 0.3 is statistically significant at a 95% confidence interval

highly correlated among themselves, indicating a strong spatial correlation. Hence, principal component analysis (PCA) on JFM and AMJ precipitation-forecasts was performed to reduce the dimensionality of the forecasts over the period 1980–2010. Principal component analysis basically rotates the correlated time-series into orthogonal principal components, which are basically determined by the loadings associated with the original time-series. The first principal component (PC1) of the precipitation forecasts for JFM explains 92% of the variability among the nine grid points, whereas PC1 for AMJ explains 86% of the variability. The loadings for PC1 for the nine grid points indicate that all grid points play a nearly equal role in determining PC1 (data not shown).

Correlation analysis between PC1 and the observed Q and G, respectively, during JFM and AMJ [Figs. 2(a and b), respectively] indicates that precipitation forecasts (issued in January) for the winter are significantly correlated ($\rho \geq 0.3$) with G at all wells during JFM ($0.35 \leq \rho \leq 0.71$). Similarly, the correlation ($0.33 \leq \rho \leq 0.59$) between PC1 for AMJ and the observed G are statistically significant at all wells during AMJ. However, the observed Q shows a significant correlation with PC1 during JFM ($0.46 \leq \rho \leq 0.68$) and a statistically insignificant correlation with PC1 during AMJ ($0.18 \leq \rho \leq 0.33$). Thus, the JFM precipitation-forecasts issued at the beginning of January show better skill in predicting JFM P, Q, and G, whereas AMJ precipitation-forecasts issued at the beginning of January show relatively lower skill in predicting AMJ P, Q, and G, which is partly due to potential changes in the climate over the 6-month period. The correlation coefficients also tend to increase towards downstream, indicating the role of storage in increasing the correlation between precipitation and the hydrogeologic attributes.

In summary, the dependency analysis at different lags suggests that G and Q could be predicted at a given site using records from previous months. The significant correlation between P, Q, and G with precipitation forecasts, especially during JFM, suggests that precipitation forecasts could be used as an additional predictor in the development of the groundwater-level prediction models. Moreover, the groundwater levels and streamflow observed over the basin are also significantly correlated among each other. Hence, predictions at a given site also could be improved by incorporating information from adjacent sites for model development.

Development of Low-Dimensional Models

The main purpose of the modeling effort described in this paper is to evaluate the utility of precipitation forecasts for improving seasonal and monthly groundwater-level predictions. For this purpose, the writers consider two low-dimensional models, as follows: (1) PCR, and (2) CCA (Oh and Sankarasubramanian 2012). Low-dimensional models reduce the correlated predictors (e.g., precipitation forecasts) and predictands (e.g., groundwater levels) so that a subspace of uncorrelated predictors and predictands could be used for regression model development (Tippett et al. 2003; Sankarasubramanian et al. 2008). Furthermore, these low-dimensional models also recalibrate the GCM forecasts so that any marginal bias in predicting the observed precipitation could be adjusted based on the regression model (Landman and Goddard 2003). A brief description of the low-dimensional models is provided next.

Principal Component Regression

Principal component regression, which is otherwise known as model-output statistics (MOS; Wilks 1995), eliminates systematic errors and biases in GCM fields and also recalibrates the principal components (PCs) of GCM fields to predict the hydroclimatic variable of interest using regression analyses. The predictand could be streamflow Q_t or groundwater levels G_t over a watershed. Since the gridded precipitation forecasts over a given region are spatially correlated, employing precipitation forecasts from multiple grid points as predictors would raise multicollinearity issues in developing the regression. To avoid this, the writers employ PCR based on Eq. (1)

$$\ln(G_t) = \hat{\beta}_0 + \sum_{k=1}^{K} \hat{\beta}_j \times PC_t^k + \hat{\varepsilon}_t \tag{1}$$

where G_t = monthly mean of groundwater levels during a given month/season in year t; PC_t^k denotes the kth PCs from the retained K PCs of the predictors; and $\hat{\beta}$ denotes the regression coefficients, the estimates of which are obtained by minimizing the sum of squares of error. The writers employ stepwise regression to select K PCs out of the selected predictors for developing the PCR model.

Canonical Correlation Analysis

In PCR, the writers develop separate regression models for each groundwater well or a given streamgauge. Given that the predictands across the FRB (groundwater levels) are also spatially correlated, one could utilize that information to develop a reduced set of regression models. This could help in utilizing the intersite correlations to develop multiple (multiple low-dimensional components of predictands with the multiple low-dimensional components of predictors) regression relationships. Consider the logarithm of the winter groundwater levels available from m sites represented by $\mathbf{LG^T} = [\ln(G_1), \ln(G_2), \ldots, \ln(G_m)]$ (dimensions $= n \times m$), where the corresponding p predictors (includes precipitation forecasts and OND groundwater-levels, $p > m$) are represented as $\mathbf{X^T} = (X_1, X_2, \ldots, X_p)$ (dimensions $= n \times p$); canonical correlation analysis finds a linear combination of the p predictors $\mathbf{Y}^* = \mathbf{b^T Y}$ that maximally correlates with the linear combination of m predictands $\mathbf{X}^* = \mathbf{a^T X}$. Mathematically, the canonical correlation is obtained by choosing the vectors $\mathbf{a}$ and $\mathbf{b}$ that maximizes the relationship $(\mathbf{a^T} \sum_{\mathbf{xy}} \mathbf{b})/[(\mathbf{a^T} \sum_{\mathbf{xx}} \mathbf{a})(\mathbf{b^T} \sum_{\mathbf{yy}} \mathbf{b})]^{1/2}$ where $\sum$ denotes the variance-covariance matrix between the two variables in the subscript. For a detailed mathematical treatment of CCA, see Wilks (1995). The number of components from m predictands and p predictors to be retained for the regression is decided based on stepwise regression. Squared values of canonical correlation represent the percentage of variance explained in each predictand by the predictors under that dimension. Thus, the skill in predicting the groundwater levels for each site could be obtained based on the precipitation forecasts by developing a reduced set of models in the FRB study area.

Model Validation

Both the low-dimensional models are validated using leave-five-out cross validation (Stone 1974). Leave-K-out cross validation is a rigorous model-validation procedure that is usually carried out by leaving out K predictand and predictors (including the groundwater and principal components for the validating year) from the observed data set (G_t, X_t, $t = 1, 2, \ldots, n$) and the parameters of the PCR model are estimated using the remaining $n - k$ observations, where n is the total length of observed records in a given site. Using the PCR/CCA developed with $n - k$ observations, the ability of the model to predict the groundwater levels/streamflow is evaluated using the state of the predictor at the validating year. Thus, if the writers have n years of data, then a total of n different regression relationships were developed by leaving out K predictors and predictands to develop predicted values for each year.

Performance Measures

The performance of both low-dimensional models is evaluated using Spearman rank-correlation coefficient (ρ) and relative RMSE (RRMSE). Both these measures are computed based on the observed and predicted values of groundwater level or streamflow obtained from leave-five-out cross validation. Relative RMSE is simply the RMSE computed by normalizing the error by the observed values in a given time step based on Eq. (2)

$$R - \text{RMSE} = n^{-1}\sqrt{[(1 - \hat{G}_{-t})/G_t]^2} \tag{2}$$

where G_t and $\hat{G}_{-t}$ = observed and predicted groundwater-levels, respectively, and $-t$ denotes the values being obtained from leave-five-out cross validation. Because the groundwater levels in the wells used in the research reported in this paper have different magnitudes of seasonal and monthly groundwater-level fluctuation, RRMSE is more appropriate because it allows the writers to compare the performance of the prediction models developed across the wells.

Low-Dimensional Model Schemes: Overview

Both the low-dimensional models (PCR and CCA) were developed for 10 groundwater wells (Table 2). The writers also present the skill, rank correlation, and RRMSE in predicting the observed streamflow for nine streamgauge sites (Table 1). To develop streamflow forecasts, the predictands were simply replaced with observed monthly/seasonal streamflow. The skill in predicting both streamflow and groundwater were evaluated based on leave-five-out cross

Table 3. List of Predictors and Predicands Considered for the Three Modeling Schemes at Monthly and Seasonal Time-Scales

Modeling scheme	Method	Predictors	Predictands, seasonal	Predictands, monthly
Q-1/G-1	Regression	OND, Q/G	JFM, Q/G	January–June, Q/G
Q-1/G-1	Regression	OND, Q/G	AMJ, Q/G	January–June, Q/G
Q-2/G-2	PCR	OND, Q/G; JFM, P	JFM, Q/G	January–March, Q/G
Q-2/G-2	PCR	OND, Q/G; JFM, P; AMJ, P	AMJ, Q/G	April–June, Q/G
Q-3/G-3	CCA	OND, Q/G; JFM, P	JFM, Q/G	January–March, Q/G
Q-3/G-3	CCA	OND, Q/G; JFM, P; AMJ, P	AMJ, Q/G	April–June, Q/G

Note: Models predicting groundwater levels or streamflow used the corresponding monthly and seasonal groundwater levels (or streamflow and precipitation forecasts) for developing forecasts.

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validation. To quantify the role of precipitation forecasts and the importance of using spatial correlations between the observed hydroclimatic variables, the writers consider three low-dimensional schemes, which are detailed next. Table 3 provides a detailed overview of the set of predictors and predictands for each modeling scheme.

Low-Dimensional Model Schemes: Model 1, Q-1/G-1

Model 1 is the null model that does not include precipitation forecasts as predictors, but simply previously recorded groundwater-levels and streamflow used to predict future groundwater-levels and streamflow, respectively. The null model is developed using regression to predict seasonal and monthly streamflow in addition to groundwater levels independently based on previous monthly (OND) observations of Q or G for a given site without using climate information. Seasonal predictions for JFM and AMJ are based on OND seasonal mean values. Monthly predictions for January–June are also based on OND mean values. Similarly, model predictands are groundwater level and discharge for JFM and AMJ for the seasonal model, and monthly mean values during January–June are employed as predictands for developing monthly streamflow and groundwater forecasts.

Low-Dimensional Model Schemes: Model 2, Q-2/G-2

Model 2 is developed using PCR with OND streamflow and groundwater-level values, but the model uses the precipitation forecasts issued in January for nine *ECHAM 4.5* grid points as additional predictors. For seasonal predictions, the model uses OND seasonal mean observed values and mean JFM precipitation forecasts from the nine *ECHAM 4.5* grid points as predictors (Table 3, 10 predictors total) to predict seasonal groundwater-level and streamflow. For AMJ predictions, model 2 uses seasonal mean OND observed values in addition to JFM and AMJ mean precipitation forecasts as predictors (19 predictors total) to predict AMJ

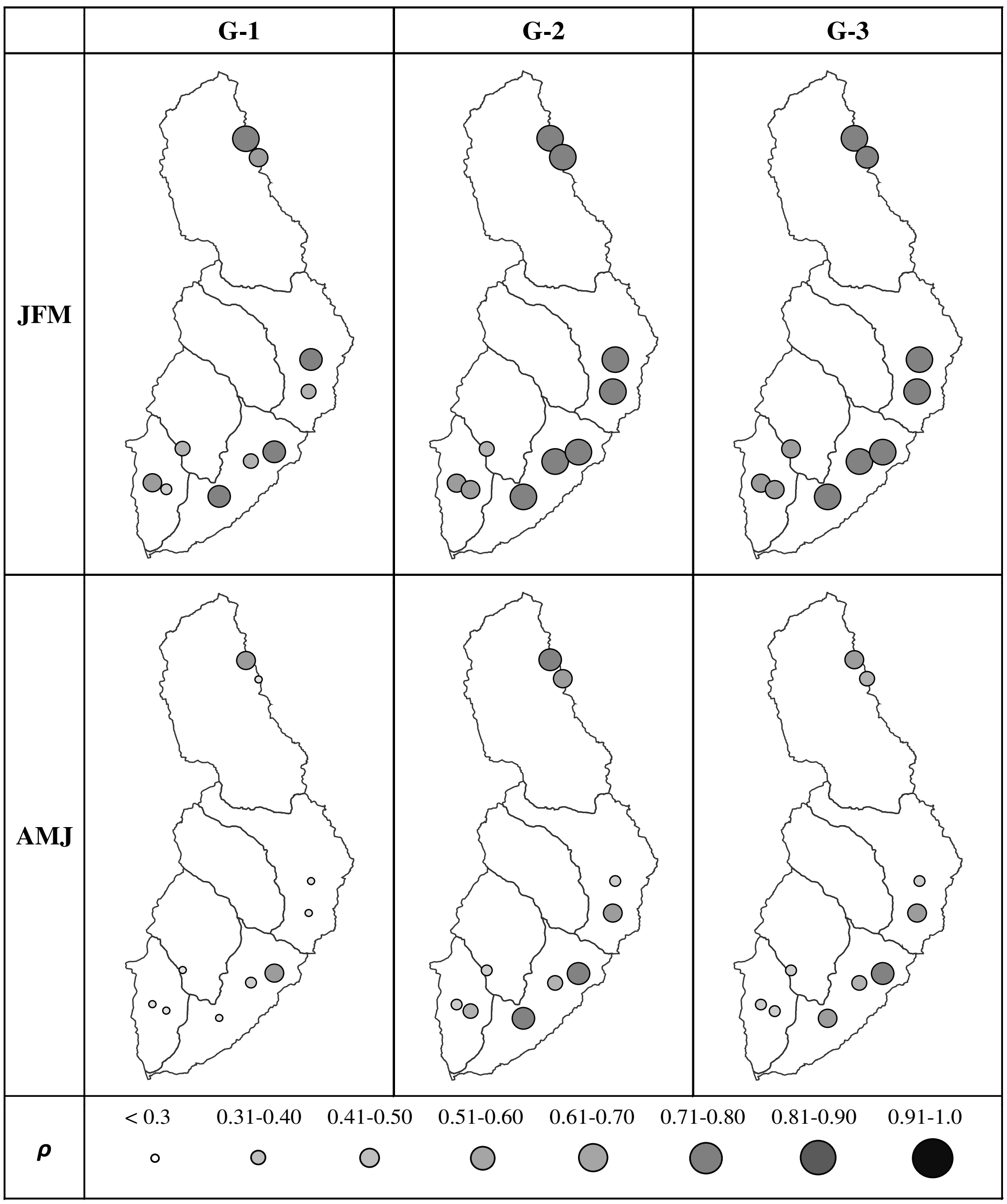

Fig. 3. Correlation between observed and predicted JFM and AMJ depth to groundwater for 10 groundwater wells under three models (G-1, G-2, and G-3) during the period 1980–2010; the correlation 0.3 is statistically significant at a 95% confidence interval

groundwater-level and streamflow. The same set of seasonal predictors was employed for monthly predictions but the predictands are replaced with observed monthly mean values of streamflow/groundwater. For instance, for predicting February monthly mean groundwater-level, the model uses observed mean groundwater-levels during OND and JFM precipitation forecasts. Comparisons between models 1 and 2 help evaluate the role of climate information in improving streamflow and groundwater level predictions with the addition of precipitation forecasts in model 2.

Low-Dimensional Model Schemes: Model-3, Q-3/G-3

Model 3 is developed using CCA with the aim of utilizing the spatial correlation between the predictands and predictors from adjacent subbasins (HUC units) to improve the prediction at a given station. Apart from using precipitation forecasts from the relevant grid points as predictors, model 3 considers observed groundwater from nine other wells in the case of groundwater-level predictions (of the 10 wells selected for the research reported in this paper) and observed streamflow from eight streamgauges in the case of streamflow prediction (of the nine streamgages selected for the research reported in this paper). In the case of seasonal (monthly) models, observed OND (monthly mean during October–December) information from nearby sites are added as predictors and the observed JFM (monthly mean of the respective months during January–March) and AMJ (monthly mean of the respective months during April–June) information from nearby sites are added as predictands (Table 3). Thus, CCA model develops regression models for the entire basin by considering the reduced components of predictors and predictands. Although model 3 uses information from adjacent sites for predicting streamflow and groundwater levels in a given year, it leaves out five observations over the entire basin, including the year for which the forecasts were developed.

Thus, for each groundwater well and streamgauge site, the three low-dimensional schemes are indicated as G-1 (model 1), G-2 (model 2), and G-3 (model 3), whereas streamflow prediction models are indicated as Q-1 (model 1), Q-2 (model 2), and Q-3 (model 3). All the three schemes have the same period of analysis 2010–1980)) and develops forecasts of seasonal (JFM and AMJ) and monthly (January–June) groundwater levels and streamflow.

Seasonal and Monthly Groundwater-Level Forecasts: Overview

This section presents the skill in developing seasonal and monthly groundwater-level forecasts for each well within FRB used for the research reported in this paper.

Seasonal Groundwater Forecasts

Figs. 3 and 4 show the correlation coefficients ρ and RRMSE between the observed and predicted JFM and AMJ depth to groundwater for 10 groundwater wells using models G-1, G-2, and G-3 during the period 1980–2010. For comparison (Table 4), the writers also present the correlation in predicting the JFM-observed and AMJ-observed streamflow for nine streamgauges under three models (Q-1, Q-2, and Q-3) based on leave-five-out cross validation over the same period. The analysis indicates that G-2 and G-3 show significant improvements relative to G-1 in predicting groundwater levels at most of the 10 wells during JFM and AMJ. For instance, the improvement in correlation during JFM is only modest for models G-2 and G-3, but the RRMSE showed significant reduction for at least seven wells out of 10. Three wells (well indices 7, 8, and 9; Fig. 1) for which the RRMSE of G-1 is lower during the JFM

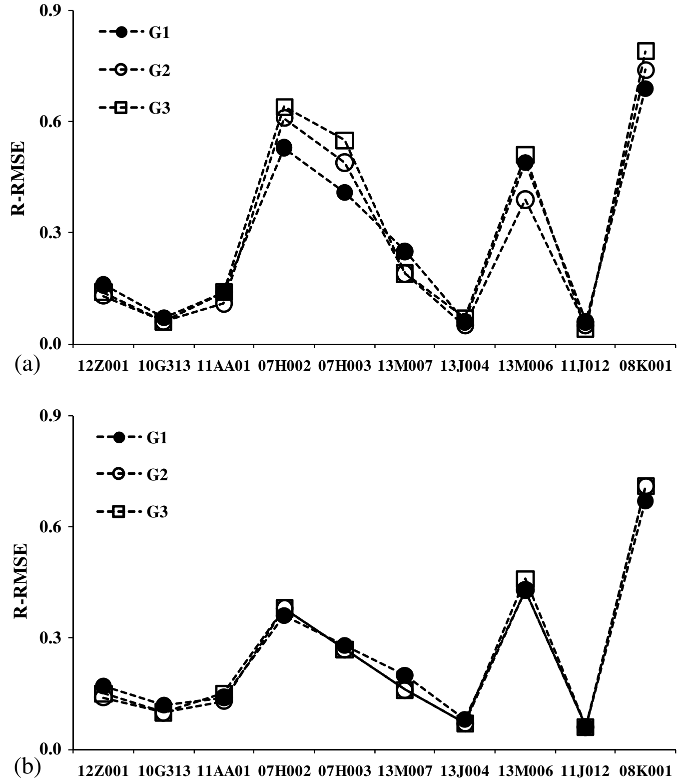

Fig. 4. Relative RMSE between observed and predicted depth to groundwater at 10 groundwater wells under three models (G-1, G-2, and G-3) during the period 1980–2010: (a) JFM; (b) AMJ

season are primarily in the subbasins over the two smaller HUCs. However, models G-2 and G-3 showed significant improvements in correlation during the spring season, but the RRMSE of G-2 and G-3 did not differ much from the RRMSE of G-1. This is expected since the groundwater levels between two seasons have significant temporal correlation, resulting in only limited improvements in correlation from the G-1 model, which uses only OND mean values (not precipitation forecasts) to predict the groundwater levels. However, the addition of precipitation forecasts in models G-2 and G-3 results in improved prediction of groundwater levels since the forecasts account for the potential recharge during the JFM season. Since the groundwater levels during the AMJ season have lesser dependence on the OND season, adding precipitation forecasts during the JFM and AMJ seasons results in improved correlation (i.e., variability) under G-2 and G-3 for the AMJ season. However, the forecasts ability to predict the total precipitation over

Table 4. Correlation between Observed and Predicted JFM and AMJ Streamflow for Nine Streamgauges under Three Models (Q-1, Q-2, and Q-3) during the Period 1980–2010

Modeling scheme	Season	USGS streamgauge index number								
		1	2	3	4	5	6	7	8	9
Q1	JFM	0.53	0.53	0.62	0.61	0.61	0.67	0.47	0.68	0.41
	AMJ	0.17	0.09	0.11	0.21	0.31	0.14	0.21	0.21	0.08
Q2	JFM	0.62	0.61	0.72	0.82	0.64	0.85	0.81	0.86	0.81
	AMJ	0.22	0.21	0.21	0.22	0.41	0.31	0.21	0.32	0.22
Q3	JFM	0.63	0.64	0.74	0.83	0.61	0.85	0.81	0.86	0.82
	AMJ	0.23	0.21	0.25	0.22	0.32	0.32	0.26	0.33	0.21

Note: A correlation greater than 0.3 is statistically significant at a 95% confidence interval.

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the AMJ season is limited, resulting in smaller improvements in RRMSE under G-2 and G-3.

In contrast, comparing the correlations in Fig. 3 with Table 4, the writers infer that adding precipitation forecasts results in improved skill under Q-2 and Q-3 during the JFM season, but only a marginal improvement in correlation during the AMJ season for models Q-2 and Q-3. Given that streamflow is primarily a response to precipitation during the winter season and the increased skill of winter precipitation forecasts, the writers observe increased skill in predicting winter streamflow under models Q-2 and Q-3. However, in the spring season, since the runoff is also controlled by evaporation due to increased temperature and also the skill of precipitation forecasts drops appreciably over 6 months, models Q-2 and Q-3 did not improve the skill in predicting streamflow during AMJ. In contrast, groundwater-level forecasts show improved correlations during the AMJ season since groundwater being a storage system responds slowly to potential recharge during the JFM and AMJ seasons. The writers also infer from Fig. 4 that the performance of models G-2 and G-3 are very similar for the seven wells in which both models perform better than G-1.

Different wells also show different magnitudes of RRMSE (Fig. 4). The writers also infer that the RRMSE of streamflow decreases from a smaller drainage area to a larger area [left to right in Fig. 4(b)]. However, the differences in RRMSE across the three modeling schemes are very small for both streamflow and groundwater. The increased variability in RRMSE for groundwater is likely due to the spatial variations in the hydrogeological characteristics. Although 10 wells is not sufficient to draw clear conclusions, it seems that groundwater wells close to the main course of the Flint River (Fig. 1) exhibit higher correlation coefficients between the observed and predicted depth to groundwater levels. This indicates the role of drainage area in influencing groundwater-streamflow interactions over the basin.

Monthly Groundwater-Level Forecasts

Given that the month-to-month variations in groundwater levels are smaller within the season, the writers investigated the ability of seasonal precipitation forecasts in predicting monthly groundwater levels during the winter and spring seasons. Figs. 5 and 6 show the correlation and RRMSE between observed and predicted monthly mean streamflow for 10 wells based on models G-1, G-2, and G-3. For comparison, the writers also present the correlation (Table 5) between the observed and predicted streamflow for nine streamgauges based on models Q-1, Q-2, and Q-3. For developing monthly groundwater-level forecasts (G-2/Q-2 and G-3/Q-3) under leave-five-out cross validation, the writers employed seasonal-precipitation forecasts as a predictor along with the OND groundwater/streamflow information.

From Figs. 5 and 6, adding precipitation forecasts in models G-2 and G-3 result in improved correlation relative to G-1 for at least five groundwater wells (12Z001, 13M007, 11J012, 10G313, and

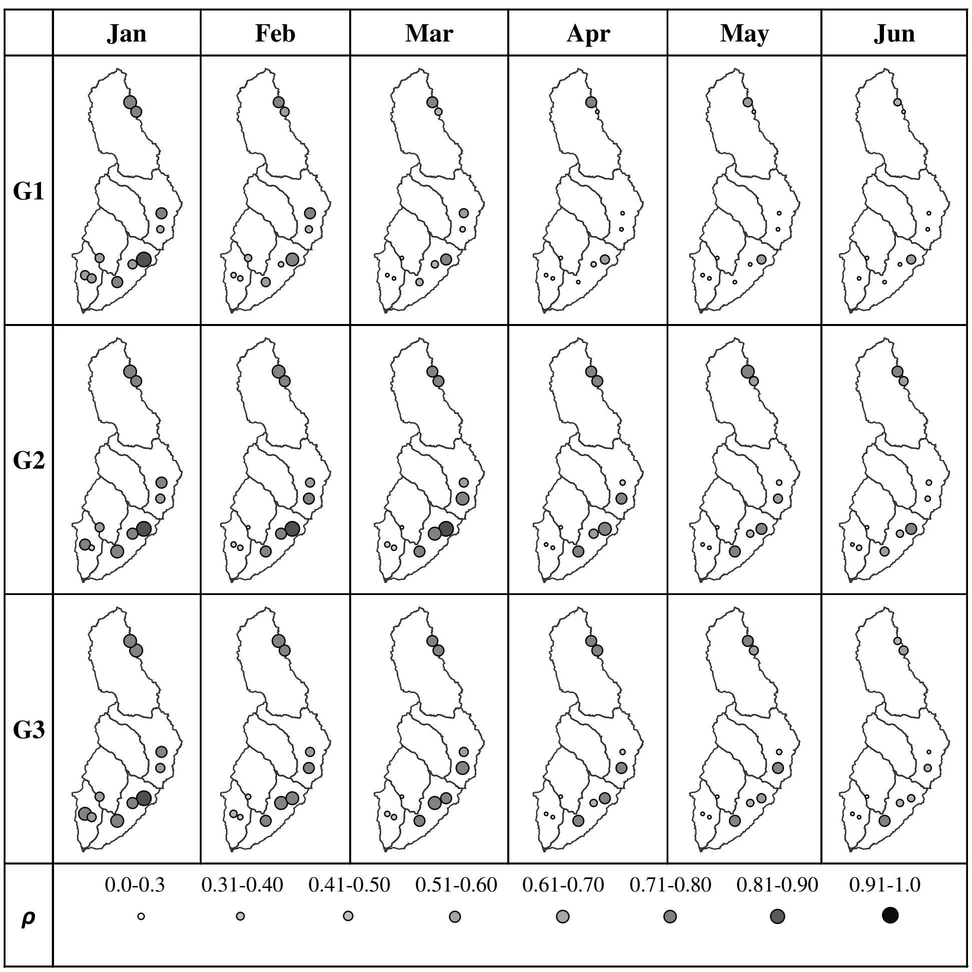

Fig. 5. Correlation between observed and predicted monthly depth to groundwater level for 10 groundwater wells under three models (G-1, G-2, and G-3) during the period 1980–2010; the correlation 0.3 is statistically significant at a 95% confidence interval

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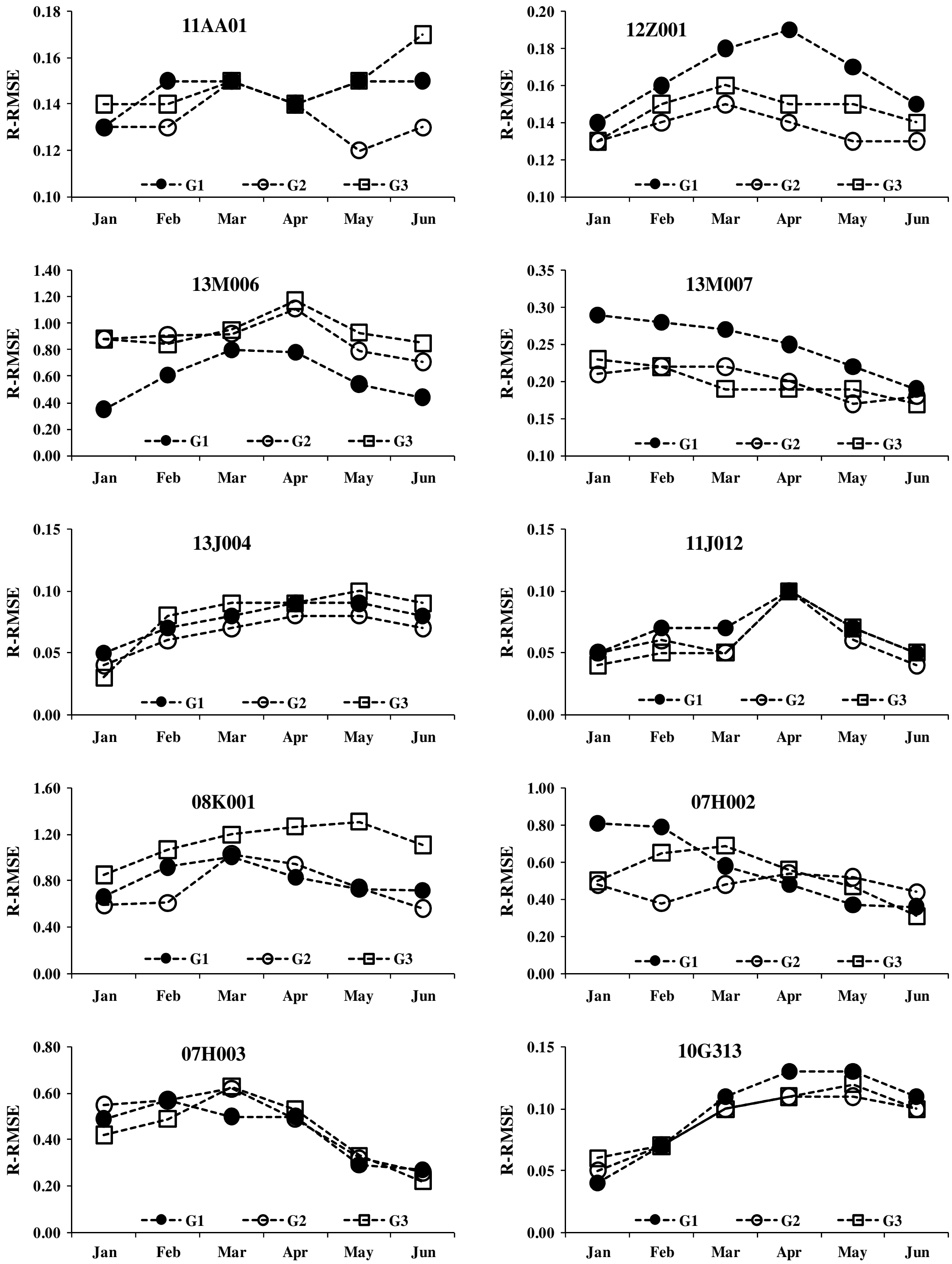

Fig. 6. Relative RMSE between observed and predicted monthly depth to groundwater level for 10 groundwater wells under three models (G-1, G-2, and G-3) during the period 1980–2010

Table 5. Relative RMSE of Seasonal-Streamflow Forecasts for Nine Streamgauge Stations over the Flint River Basin

Model	Season	02357000	02349900	02344500	02353500	02347500	02349500	02350512	02352500	02353000
Q-1	JFM	0.54	0.52	0.34	0.38	0.32	0.28	0.30	0.31	0.30
Q-1	AMJ	0.69	0.67	0.59	0.53	0.58	0.54	0.54	0.50	0.47
Q-2	JFM	0.62	0.50	0.32	0.25	0.31	0.26	0.36	0.24	0.23
Q-2	AMJ	0.70	0.67	0.60	0.63	0.57	0.55	0.54	0.48	0.46
Q-3	JFM	0.60	0.43	0.35	0.30	0.30	0.25	0.36	0.23	0.23
Q-3	AMJ	0.68	0.67	0.60	0.52	0.54	0.51	0.55	0.47	0.45

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13J004). However, adding precipitation forecasts in models G-2 and G-3 consistently resulted in improved RRMSE for only a few groundwater wells (12Z001 and 13M007) over the two seasons. Two wells (13M006 and 13M007) are very close to each other yet behave completely differently in terms of RRMSE under the three considered models. Well 13M007 is a surficial aquifer system and responds to climatic signals. The G-2 and G-3 models perform better than G-1. Well 13M006 is Floridan, a deep aquifer confined system, and does not respond to climatic signals. However, at seasonal time-scales, there seems to be some influence of climatic signals in improving groundwater predictions (Fig. 4). Considering the fact that all 10 wells are located within similar climatic conditions, all wells do not exhibit similar skill, which indicates the role of local hydrogeological characteristics influencing the recharge and discharge over the basin. Another reason for relatively marginal improvements in developing monthly groundwater-level forecasts under models G-2 and G-3 is primarily due to smaller variations in groundwater levels between months. Thus, adding precipitation forecasts in models G-2 and G-3 result in improved correlation only for the spring season (Fig. 5). Furthermore, the improved correlation is exhibited only along the main course of Flint River in groundwater discharge areas, whereas the wells (numbers 08K001, 07H002, and 07H003) in the subbasins did not result in improved skill by adding precipitation forecasts (Fig. 5). However, in estimating the observed monthly groundwater-level, the RRMSE (Fig. 6) is consistently lower for models G-2 and G-3 only in two wells (12Z001 and 13M007) for the entire 6 months of the forecasting period.

Comparing the performance of monthly groundwater level forecasts with monthly streamflow forecasts (Table 6), the writers infer that models Q-2 and Q-3 result in improved correlation relative to Q-1 in all the streamgauges. Table 6 clearly shows how the correlation improved for streamgauges downstream during the winter season. This is primarily due to two reasons, as follows: (1) increased climatic signals over a larger area due to winter frontal events, and (2) streamflow being a spatial integrator of precipitation associates better with the drainage from a larger area. However, both models Q-2 and Q-3 showed only marginal skill (correlation 0.31–0.40) for almost all the basins during the spring season. This is primarily due to the limited skill of precipitation forecasts in predicting observed precipitation over 6 months of lead time. However, there is a much higher skill in predicting observed monthly groundwater levels for wells in the main course of the Flint River (Fig. 6). This increased skill primarily results from the ability of the groundwater system to respond slowly to the recharge occurring during the winter and spring seasons.

Comparing the RRMSE of monthly streamflow and groundwater forecasts (Fig. 7) show that the RRMSE of monthly streamflow forecasts obtained from CCA (Q-3) is much lower than that of the RRMSE of Q-2. However, such a reduction in RRMSE between G-2 and G-3 is not clear. One possible reason for improved performance under Q-3 is due to increased spatial variability in monthly streamflow across the basin, which is better captured by the Q-3 model. Given that the monthly groundwater-levels are strongly correlated across the FRB, resulting in reduced spatial variability at the basin scale, the CCA approach does not improve the predictions by gaining information from across the sites. Employing CCA is attractive since the developed multivariate regression models consider the low-dimensional components of both predictors and predictands. Thus, CCA eliminates the need to develop individual PCR model for each site.

Discussion

The writers identified 10 groundwater wells and nine streamgauges within a confined region (the drainage area of the FRB is 21,900 km^2) having little human influence and which (in the writers' opinion) adequately represent the interactions among the various hydroclimatic variables over FRB. The writers understand analyzing the skill in predicting over a large region (e.g., the southeast United States) will provide a better assessment of researchers' ability to develop groundwater-level forecasts. Given the study of Almanaseer and Sankarasubramanian (2012) provided the potential in predicting groundwater levels using precipitation forecasts, the writers focused in evaluating the skill in predicting the groundwater and streamflow within the FRB over periods of 6 months from 1980–2010. The limited spatial variability in climatic conditions within FRB provides researchers an opportunity

Table 6. Correlation between Observed and Predicted Monthly Streamflow for Nine Streamgauges under Three Models (Q-1, Q-2, and Q-3) during the Period 1980–2010

		USGS streamgauge index number								
Modeling scheme	Month	1	2	3	4	5	6	7	8	9
Q1	January	0.53	0.61	0.71	0.51	0.75	0.74	0.53	0.73	0.52
	February	0.32	0.32	0.41	0.31	0.57	0.52	0.31	0.57	0.15
	March	0.43	0.32	0.39	0.33	0.35	0.38	0.14	0.41	0.11
	April	0.09	0.17	0.21	0.08	0.26	0.22	0.21	0.27	0.08
	May	0.20	0.15	0.20	0.30	0.26	0.22	0.26	0.21	0.08
	June	0.07	0.09	0.07	0.08	0.21	0.08	0.11	0.11	0.08
Q2	January	0.41	0.63	0.71	0.56	0.74	0.75	0.57	0.75	0.63
	February	0.33	0.31	0.32	0.69	0.61	0.61	0.47	0.71	0.57
	March	0.31	0.37	0.46	0.41	0.49	0.45	0.65	0.65	0.48
	April	0.21	0.11	0.22	0.24	0.42	0.38	0.22	0.54	0.11
	May	0.09	0.21	0.36	0.27	0.36	0.43	0.33	0.36	0.08
	June	0.09	0.02	0.18	0.21	0.32	0.13	0.11	0.17	0.08
Q3	January	0.44	0.64	0.73	0.71	0.78	0.77	0.71	0.81	0.69
	February	0.41	0.51	0.56	0.57	0.61	0.71	0.61	0.72	0.58
	March	0.50	0.49	0.56	0.57	0.48	0.67	0.61	0.68	0.51
	April	0.43	0.23	0.22	0.37	0.43	0.31	0.31	0.45	0.07
	May	0.11	0.18	0.34	0.32	0.35	0.31	0.37	0.32	0.08
	June	0.08	0.14	0.31	0.08	0.42	0.31	0.08	0.21	0.08

Note: A correlation greater than 0.3 is statistically significant at a 95% confidence interval.

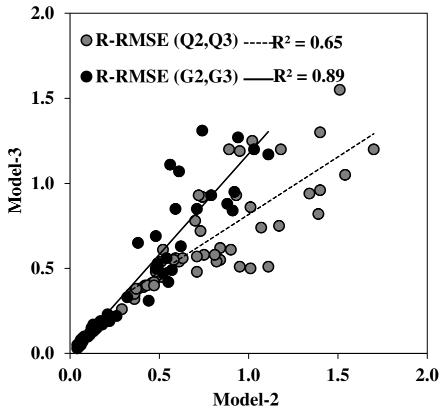

Fig. 7. Comparison between RRMSE obtained by modeling schemes [model 2 (G-2 and Q-2) and model 3 (Q-3 and G-3)] for monthly streamflow (January–June for nine streamgauges, 54 data points) and monthly groundwater (January–June for 10 groundwater wells, 60 data points)

to understand the role of aquifer types (e.g., shallow unconfined surficial versus deeper confined Floridan aquifers) and basin characteristics (e.g., drainage area) in influencing the skill in forecasting groundwater-levels. To ensure the nonlinear relationship between the predictors (i.e., precipitation forecasts and OND groundwater levels) and the forecasting period's groundwater-level, low-dimensional models were developed with the logarithm of the groundwater levels [Eq. (1)]. One could also consider other transformation, such as power transformation and Box-Cox transformation (Box and Cox 1964), for reducing the skewness of the predictand to be closer to zero. Skillful groundwater-level forecasts could be developed at monthly and seasonal time-scales by using both the previous season's groundwater level and the forecasting period's *ECHAM 4.5* precipitation forecasts.

The developed seasonal and monthly groundwater-forecasts show a significant correlation in predicting the observed groundwater levels within FRB. However, the RRMSE of models G-2 and G-3 did not reduce much from G-1, indicating the presence of similar forecast errors (i.e., conditional bias) in predicting groundwater levels. One could also improve the RRMSE of monthly and seasonal groundwater level forecasts by utilizing the monthly updated climate forecasts. Studies have shown that utilizing monthly updated precipitation forecasts reduces the intraseasonal variability in streamflow forecasts (Sankarasubramanian et al. 2008). This is left as a future study in this paper. Similarly, relatively short periods of groundwater records (1980–2010) forced the writers to adopt a leave-five-out cross validation technique. Although this approach, in this case, is rigorous and produces statistically significant streamflow and groundwater-level predictions over FRB, longer data periods would have helped the writers to evaluate the models under split-sample validation.

To apply the approach reported in this paper for basins with significant anthropogenic influences, it would be vital to identify the sources/causes of these influences in terms of their spatial and temporal scales, and to adjust the observed information by accounting influences such as groundwater abstraction or streamflow regulations. For example, periods of records prior to any significant anthropogenic influences might be used in conjunction with changes in groundwater storage to obtain naturalized streamflow. Another approach is to calibrate a coupled groundwater-surface water model (e.g., Sophocleous et al. 1999) and estimate naturalized flows and groundwater levels for a longer period of time, so that the naturalized groundwater levels could be utilized for forecast development. This remains an area of potentially fruitful research, as there are few areas that are not subjected to anthropogenic influences.

Summary and Conclusions

This paper documents the utility of precipitation forecasts in improving seasonal and monthly groundwater-level predictions over selected groundwater wells for the Flint River Basin study area in the state of Georgia. Hydroclimatic data was obtained from streamgauges and groundwater wells with minimal anthropogenic influences to better represent the climatic response for groundwater levels and streamflow. Principal component regression and canonical correlation analysis with a leave-five-out cross validation approach was used to develop three prediction models for each of the nine selected streamgauges and for each of the 10 selected wells. These two techniques were employed for developing monthly and seasonal streamflow and groundwater forecasts over the basin using 6-month-ahead precipitation forecasts from the *ECHAM 4.5* GCM. The performance of these two models was compared against a null model that estimated groundwater/streamflow purely based on the previous monthly/seasonal values without using precipitation forecasts. To summarize, incorporating seasonal precipitation forecasts resulted in improved skill over at least seven wells that lie primarily along the main course of the Flint River. The following are the main conclusions of this paper:

- Dependency analysis shows significant interaction between streamflow and groundwater, and indicates the role of climate variability in influencing the interaction over the study area at both seasonal and monthly time-scales. The analysis also indicates significant correlation between precipitation forecasts and streamflow, groundwater level, and observed precipitation over the FRB, especially during winter months. The relatively high BFIs computed for the nine streamgauges (Table 1) indicates the significant role of groundwater in controlling the hydroclimatic covariability within the basin.
- The research reported in this paper demonstrates that using precipitation forecasts could result in improved groundwater-predictions at seasonal (Figs. 3 and 4) and monthly (Figs. 5 and 6) time-scales. Comparing the skill in predicting groundwater (Figs. 3 and 5) with the skill in predicting streamflow (Tables 4 and 5), the writers infer clearly that the groundwater forecasts developed using precipitation forecasts exhibit higher prediction skill relative to the skill of streamflow forecasts. This is primarily due to the lower variability of the groundwater levels arising from the storage aquifers. Further, integrating information from nearby sites based on CCA results (G-3) show almost similar skill as that of PCR model (G-2) at both monthly and seasonal time-scales.
- The skill in predicting streamflow is primarily good only up to 3 months but the skill in predicting groundwater level is statistically significant up to 6 months since the recharge during the JFM season also influences the skill in predicting groundwater levels during the AMJ season.
- Incorporating precipitation forecasts results in improved correlation coefficients, but it did not result in substantial improvements in reducing the RRMSE in predicting both streamflow and groundwater. In other words, precipitation forecasts are helpful in capturing the interannual variability but it is not very useful in reducing the forecast errors or conditional bias in prediction.

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