EXPERIMENTAL RESERVOIR STORAGE FORECASTS UTILIZING CLIMATE-INFORMATION BASED STREAMFLOW FORECASTS

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Final Report

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Abstract:

Seasonal streamflow forecasts, contingent on climate information, can be utilized to ensure water supply for multiple uses including municipal demands, hydroelectric power generation, and for planning agricultural operations. However, uncertainties in the streamflow forecasts pose significant challenges in their utilization in real time operations. In this study, we systematically decompose various sources of errors in developing seasonal streamflow forecasts from multiple Land Surface Models (LSMs), which are forced with downscaled and disaggregated climate forecasts. In particular, the study quantifies the relative contributions of the sources of errors from LSMs, climate forecasts, and downscaling/disaggregation techniques in developing seasonal streamflow forecast.

For this purpose, three-month ahead seasonal precipitation forecasts from the ECHAM4.5 General Circulation Model (GCM) were statistically downscaled from 2.8° to 1/8° spatial resolution using Principal Component Regression (PCR) and then temporally disaggregated from monthly to daily time step using K-Nearest-Neighbor (K-NN) approach. For other climatic forcings, excluding precipitation, we considered NLDAS2 hourly climatology over the 1979 to 2010. Then the selected LSMs were forced with precipitation forecasts and NLDAS2 hourly climatology to develop retrospective seasonal streamflow forecasts over a period of 20 years (1991-2010). Finally, the performance of different LSMs in forecasting streamflow under different schemes were analyzed to quantify the relative contribution of various sources of errors in developing seasonal streamflow forecast. Our results indicate that the most dominant source of errors during winter and fall seasons is the errors due to ECHAM4.5 precipitation forecasts while temporal disaggregation scheme contributes to maximum errors during summer season.

The project objectives also include developing experimental reservoir storage forecasts utilizing the monthly/seasonal streamflow forecasts obtained from climate forecasts. This includes: (a) automating the experimental inflow forecasts portal for issuing and updating real-time monthly and seasonal streamflow forecasts for water supply systems in NC and (b) developing reservoir simulation module and link it to the automated inflow forecasting portal for issuing experimental storage forecasts for the selected systems.
1.0 Introduction

Seasonal streamflow forecasts, contingent on climate information, can effectively be utilized to ensuring water supply for multiple uses including municipal demands, hydroelectric power generation, and for planning agricultural operations. In this regard, considerable progress has been made in reducing the uncertainty in seasonal streamflow forecasts via improved understanding of climatic variability (e.g., El Nino Southern Oscillation–ENSO) as well as utilizing process based Land Surface Models (LSMs) that capture land-atmosphere interactions (Betts et al., 1997; Hamlet et al., 2002; Koster and Suarez, 1995; Mahanama et al., 2012; Maurer et al., 2002). However, errors introduced during different stages of developing seasonal streamflow forecasts limit the application of those forecasts in real time water management operations (Sinha et al., 2014; Hartmann et al., 2002). In other words, apart from the errors in climate forecasts, errors due to spatio-temporal downscaling and errors arising from LSMs also contribute to in accuracy in streamflow forecasts. Such errors and their relative contributions from different sources could vary over different regions and seasons.

One of the major challenges in developing streamflow forecasts is the spatio-temporal scale mismatch between climate models and LSMs (Luo and Wood, 2008; Yuan et al., 2011; Wood et al., 2002; Wood and Lettenmaier, 2006). Climate forecasts from General Circulation Models (GCM) are typically available on a monthly basis at relatively coarser spatial and temporal scales (e.g. monthly scales) in comparison to the scales at which LSMs are implemented for developing streamflow forecasts. To address these scaling issues, studies have employed both statistical (Wood et al., 2004; Maurer and Hidalgo, 2008) and dynamical downscaling techniques. Under dynamical downscaling, Regional Climate Model (RCM) forecasts are used to run LSMs for predicting streamflow (Leung et al., 2004; Wood et al., 2004; Wilby et al., 2000; Wood et al., 2002). But few studies suggest both GCM and RCM exhibit similar skill in climatic variables after downscaling (Wilby et al., 2000; Caldwell, 2010). Particularly, RCMs do not exhibit better correlations than their corresponding GCMs in predicting extreme precipitation (Di Luca et al., 2012; Halmstad et al., 2013). In addition, RCMs based retrospective climate forecasts from multiple models are not readily available at a daily time scale due to high computational requirements. This limits their application with LSMs in developing streamflow forecasts. Therefore, in this study, a statistical downscaling is employed by downscaling the ECHAM4.5 GCM monthly precipitation forecasts available at 2.8° to obtain monthly precipitation forcings at LSMs spatial scale. These spatially downscaled ECHAM4.5 precipitation forecasts are then temporally disaggregated to reproduce a daily time series from the monthly time step. Both spatial downscaling and temporal disaggregation techniques introduce errors in precipitation forcings, which are further propagated into the developed streamflow forecasts (Hayhoe et al., 2004; Prairie et al., 2007).

Besides the errors due to climate forcings, the LSM itself can add another source of uncertainty in the developed streamflow forecasts. Such errors in the forecasted streamflow can be reduced by multimodel combinations (Li and Sankarasubramanian, 2012; Devinini et al., 2008) or by implementing LSMs with continuously updated initial hydrologic conditions (IHCs) (Sankarasubramanian et al., 2008; Sinha and Sankarasubramanian, 2013). Therefore, we employed two LSMs (Noah (version 3.2) (Chen et al., 1996; Ek et al., 2003) and CLM (version 2.0) (Bonan et al., 2002; Hoffman et al., 2005)) in this study to develop seasonal streamflow forecasts by forcing them with continuously updated three-month ahead seasonal ECHAM4.5 precipitation forecasts issued at the beginning of January, April, July, and October.
Most studies have investigated the role of climatological forcings and initial conditions in snow-dominated basins (Maurer et al., 2004; Shukla and Lettenmaier, 2011; Mahanama et al., 2012; Mahanama and Koster, 2003), where initial conditions are dominant over climate forcings in determining the forecasting skill. For instance, Snow Water Equivalent (SWE) contribution on streamflow predictability is relatively higher than early-season soil moisture in snow dominated regions (Koster et al., 2010). However, in the Southeast, contribution of initial soil moisture is high during fall and winter for up to 5 or 6 months (Mahanama and Koster, 2003). Fewer studies have exclusively focused on developing streamflow forecasts using climate forecasts in the rainfall-runoff regimes, where precipitation forcings are more critical (Shukla and Lettenmaier, 2011; Maurer et al., 2004; Maurer and Lettenmaier, 2003). But such studies only focused on seasonal streamflow forecasting skill in a particular season (Li et al., 2009; Luo et al., 2007). In this study, we consider streamflow forecasting over all four seasons over the US Sunbelt which constitutes river basins dominated by both rainfall-runoff and snowmelt dominated regimes.

The intent of this study is to quantify different sources of errors in developing seasonal streamflow forecasts, such as spatial downscaling, temporal disaggregation, imprecise GCM climate forecasts, and imprecise climatological forcings during different seasons over the US Sunbelt. This study builds on the work of Sinha et al. (2014), which provided a systematic approach to decompose various sources of errors that arise in developing monthly streamflow forecasts using Variable Infiltration Capacity (VIC) model for a rainfall-runoff dominated basin from the Southeast US. In this study, we extend the analysis by considering two different LSMs to account model errors as well as by covering the analyses for four different seasons over the US Sunbelt region. For this purpose, we considered NASA’s Land Information System (LIS) (Kumar et al., 2006), which provides a flexible framework for running multiple LSMs under a single platform. Here, we prescribe a unique decomposition procedure for quantifying different sources of errors in developed forecasts and how those errors vary across the US Sunbelt during different seasons. We also compare the performance of two LSMs in forecasting streamflow with the observed streamflow over selected four river basins located in different hydroclimatic conditions across the US Sunbelt. Thus, the objectives of this study are: 1) Quantify various sources of errors arising due to different LSMs, climate forecasts, and downscaling/disaggregation techniques employed for developing streamflow forecasts, and 2) Compare the performance and the skill of different LSMs in streamflow forecasting over selected target basins in the study area.

The manuscript is organized as follows: Section 2 details study area and data set and Section 3 describes experimental design and error decomposition metrics. Section 4 presents the results and analysis of this study and finally, Section 5 describes overall conclusions.

2.0 Background and Hydroclimatic Data

This section describes the study area, modeling framework and hydroclimatic data used in decomposition of sources of errors in seasonal streamflow forecasting.

2.1 Study area

In this study, our analysis is focused on the Sunbelt of the United States, which we define as a region south of the 37° N latitude in the US (Figure 1) and includes 14 states. In order to evaluate the streamflow forecasting skill with respect to observed streamflow, we selected four
watersheds, which are located under different hydroclimatic regimes across the Sunbelt. These watersheds are selected since they have at least one stream gauging station that is minimally impacted by reservoir operations and listed under the Hydro-climatic Data Network (HCDN) (Slack et al., 1993)(Figure 1).

a) Verde River: It is located in desert climate with hot summers and mild winters. The Verde River is about 225 km long and the basin drains about 17,160 km² area in the north-central Arizona.
b) Guadalupe River Basin: It flows through Texas and drains about 3,367 km² area. It is located in a region which is classified as semiarid and sub-humid.
c) Apalachicola-Chattahoochee-Flint Basin (ACF): It is the largest basin among the selected basins, which has drainage area of 44,500 km². It drains through eastern Alabama, northwestern Florida, and western Georgia. ACF is listed as a humid basin which receives a uniform amount of precipitation throughout the year.
d) Tar River Basin: It is located in North Carolina with humid subtropical climate and drains around 5,700 km² area.

2.2 Land Surface Modeling

For developing streamflow forecasts, we used Land Information System (LIS), which is a flexible and powerful framework for land surface modeling and land data assimilation studies (Kumar et al., 2006). The LIS has been developed at National Aeronautical Space Agency’s (NASA) Goddard Space Flight Center (GSFC) with the goal of integrating advanced land surface models to the satellite and ground-based observational data in order to improve estimation of land surface states and fluxes. In this study, we considered two LSMs included in the LIS framework: 1) Noah3.2 and 2) CLM2 to develop gridded streamflow forecasts, which are described next.

Noah model was developed through multi-institutional cooperation in 1993 and since then it has been undergoing constant developments and has been widely used in operational weather and climate predictions (Chen et al., 1996; Niu et al., 2011). Noah is a 1-D column hydrological model which can be executed in either coupled or uncoupled mode. Version 3.2 of Noah used in this study requires near-surface atmospheric forcings as inputs and computes surface energy and water balance variables. The output of the Noah LSM includes soil moisture, soil temperature, snowpack depth, snowpack water equivalent, canopy water content, and the energy flux and water flux terms. See (Ek et al., 2003) for further details.

The Community Land Model (CLM) is a 1-D columnar (snow-soil-vegetation) model of the land surface and is the land component of the Community Earth System Model (CSM) (Bonan et al., 2002; Hoffman et al., 2005). Therefore, it represents exchange of mass, energy, and momentum over the land surface with the atmosphere. CLM2 can quantify physical states and land-surface fluxes over 10 layers for soil and up to 5 layers for snow. The unique feature of CLM2 is its utilization of more developed biophysics, carbon cycle, and vegetation dynamics. Given that we are interested in decomposing sources of errors in streamflow forecasts, the CLM2 version of the model is deemed to be adequate for this study.

Under both LSMs, we used the gridded runoff as an analog to streamflow and no separate routing model is used. But we spatially aggregated the total runoff from all the contributing grids within the selected watersheds, described in Section 2.1, to make comparisons to observed streamflow.
2.3 Hydroclimatic Data

2.3.1 Streamflow Data: The Observed monthly streamflow data are obtained from the US Geological Survey (USGS) gauge sites shown in Figure 1 during the period from 1981 to 2010 for the four selected basins described above. These sites are minimally impacted by the reservoir management since they are included in the Hydro-climatic Data Network (HCDN) database (Slack et al., 1993). The streamflow data from 1981-1990 are used to estimate monthly percentage biases in simulating streamflow for both the LSMs when comparisons are made to observed streamflow for selected basins.

2.3.2 Meteorological Forcings Data: The Meteorological forcings data for LSM implementations are obtained from the North American Land Data Assimilation System version 2 (NLDAS-2) (Mitchell et al., 2004). These data are available at 1/8° spatial resolution at an hourly temporal resolution from 01 Jan 1979 to present. Land surface forcings, excluding precipitation, in the NLDAS-2 dataset are derived from the Reanalysis fields of the National Centers of Environmental Predictions (NCEP) North American Regional Reanalysis (NARR), which are originally estimated based on multiple land surface models (e.g., SAC, Mosaic, Noah, and VIC) (Mitchell et al., 2004). We also computed the mean hourly forcings of all the variables based on the NLDAS-2 hourly forcings over the 31 years period (from 1979 to 2010) to implement the two LSMs under climatological forcings. Observed precipitation data over the period of 1957 to 2010 were obtained from Maurer et al. (2002), which are available at 1/8° spatial resolution on a daily temporal scale for the conterminous US. Maurer et al. (2002) used interpolation between observations from weather gauges across the country to develop a gridded observed precipitation dataset. The errors due to interpolation are typically smaller, but can become significantly large under complex topographies, seasonality, and non-uniform gauge densities across the study region. However, we did not account for such errors since our focus is on the forecasted streamflow errors based on the LSM simulated flows as the reference.

2.3.3 Climate Forecasts: We obtained monthly updated precipitation forecasts from the ECHAM4.5 GCM from the International Research Institute of Climate and Society (IRI) Climate Data Library (Li and Goddard, 2005). These updated monthly precipitation forecasts are available from January 1957 up to present at 2.8° spatial scale for up to a 7-month lead time and consist of 24 ensemble members. To develop seasonal streamflow forecasts, we used the ensemble average of monthly updated precipitation forecasts issued at the beginning of each season. For instance, we obtained precipitation forecasts of January, February, and March (JFM) issued at the beginning of January for developing JFM streamflow forecasts. Thus, we utilized seasonal climate forecasts issued at the beginning of January, April, July, and October during the period from 1991 to 2010 in order to develop seasonal streamflow forecasts for winter (JFM), spring (AMJ), summer (JAS), and fall (OND) seasons, respectively.

3.0 Experimental Design and Error Decomposition Metrics

All streamflow simulations/forecasts by the two LSMs (Noah3.2 and CLM2) are developed at 1/4° × 1/4° spatial resolution and at a daily temporal step for the 20 years period (from 1991 to 2010) over the study area. These streamflow products were then aggregated to seasonal time steps for the analyses and finally, we performed a detailed analysis on the seasonal streamflow forecasting skill over the US Sunbelt as well as the four selected watersheds within the study domain.

3.1 Simulation Schemes
In this study, a combination of different precipitation forcings as well as other forcings variables, either from NLDAS-2 or its climatology, are used to drive the LSMs (Figure 2). All the forcings variables are available at an hourly time step, except the precipitation forecasts, which are generated at a daily time step in our experiments at 1/8° spatial scale. Each of these streamflow schemes are designed in such a way that they carry errors due to specific sources of uncertainty. Thus, we decompose and quantify the sources of errors as described below:

1. **Reference Streamflow (Q\text{ref}):** The reference streamflow is simulated by using all the hourly NLDAS-2 observed forcings as well as observed daily precipitation at 1/8° resolution (Maurer et al., 2002). Using these forcings, a continuous simulation for each LSM is conducted from 1988 to 2010. We discarded the first three years of simulations, which served as the spin up period to reach equilibrium conditions for each LSM. The reference simulation also served as the basis to update the initial hydrological conditions at the beginning of each season in the rest of the streamflow simulation/forecast schemes, which are described in the next section. This scheme is considered as the reference scheme to compare other schemes and we ignore the errors due to LSMs. An analysis of the errors due to LSMs is discussed in section 4.5, where we focus on the selected target basins to compare simulated flows to the streamflow observations.

2. **Temporally Disaggregated Scheme (Q\text{dis}):** Under this scheme, the daily observed precipitation at 1/8° resolution (Maurer et al., 2002) is aggregated to monthly time step and then statistically disaggregated to a daily time scale using the Kernel Nearest Neighbor approach (K-NN) (Prairie et al., 2007). For a given monthly precipitation, the K-NN approach identifies K nearest neighbors for that specific month based on its minimum distance to the historical monthly observations from 1961 to 2010 by leaving out the year in which the monthly precipitation is given. Finally, the daily time series of identified neighbors are resampled based on the Lall and Sharma kernel (Lall and Sharma, 1996) to obtain the temporally disaggregated daily time series of precipitation. Other forcing variables, excluding precipitation, are obtained from the NLDAS-2 forcings at an hourly time step. Thus, the LSMs are fed with temporally disaggregated observed precipitation as well as NLDAS-2 forcings, excluding precipitation. Therefore, this developed streamflow scheme contains error only due to the disaggregation procedure.

3. **Spatially Downscaled and Temporally Disaggregated Scheme (Q\text{down\_dis}):** The simulated streamflows under this scheme were produced by feeding LSMs with downscaled and disaggregated observed precipitation as well as NLDAS-2 forcings, excluding precipitation. The precipitation forcings under this scheme are obtained in three steps:

   (a) First, 1/8° observed daily precipitation are aggregated to monthly precipitation and then upscaled to 2.8° scale to be consistent with the spatial resolution of the ECHAM4.5 precipitation forecasts.

   (b) Then the monthly precipitation at 2.8° in (i) is spatially downscaled to 1/8° resolution using the Principal Component Regression (PCR) approach. For each 1/8° grid, 4 nearest 2.8° neighboring grids were selected as predictors given that the coarse scale gridded precipitation are correlated with each other while the observed precipitation at 1/8° grid is assigned as predicted. Then, a retroactive PCR model is developed for a given 1/8° grid for each month using the previous 25 years of data as training period prior to the forecasting year. For example, to obtain spatially downscaled value for a given 1/8° grid for January 1991, previous 25 years of January (i.e., from 1966 to 1990) served as the training period.
Finally, the temporal disaggregation procedure is performed using the same K-NN approach (Prairie et al., 2007) described above. Thus, spatially downscaled and temporally disaggregated precipitation at 1/8° is used as primary forcing, along with NLDAS-2 forcings excluding precipitation, to implement the LSMs.

Thus the seasonal streamflow developed in this case carries errors due to both spatial downscaling and temporal disaggregation procedures.

4. Precipitation Forecasts (Q^{ECHAM4.5}): In this scheme, the 2.8° monthly ECHAM4.5 precipitation forecasts are spatially downscaled and then temporally disaggregated using the similar approach described above to obtain daily precipitation forcings at 1/8° to implement LSMs. Other forcings, excluding precipitation, are obtained from NLDAS-2 dataset so the sources of errors in this scheme are the imprecise precipitation forecasts as well as downscaling and disaggregation procedures.

5. Climatological Forcings (Q^{clim}): In this scheme, all the climatological forcings obtained either from observed precipitation or NLDAS-2 dataset, are used to implement LSMs. These climatological forcings are computed directly from the observed forcings which are available at 1/8° spatial scale on daily or sub-daily basis. Therefore, this scheme does not have any errors due to spatial downscaling or temporal disaggregation in the developed streamflow.

6. Climatological Forcings Excluding Precipitation (Q^{clim_excl_prcp}): In this scheme, land surface models are fed with climatology of non-precipitation forcings accompanied by the observed precipitation. The goal is to decompose sources of errors due to climatological precipitation forcings alone and errors associated with climatology of forcings, excluding precipitation.

7. Operational Forecast (Q^{fcst}): Under the forecasting mode, we used the monthly updated spatially down-scaled and temporally disaggregated ECHAM4.5 precipitation forecasts as the precipitation forcing and the NLDAS-2 climatological forcings, excluding precipitation. Using these forcings as well as updated initial hydrological conditions based on reference simulation, the seasonal streamflow forecasts are developed for each 1/4° grid point during the period of 1991 to 2010 by each LSM.

3.2 Error Decomposition Metrics

All the streamflow estimates/forecasts are developed at a daily time step and at 1/4° spatial resolution covering the US Sunbelt. From these daily values, we computed seasonal mean streamflow for 20 years (from 1991 to 2010) for each grid point. Furthermore, all the decomposed errors in our study are computed in the form of Root Mean Square Error (RMSE), which are described next.

3.2.1 Errors due to Temporal Disaggregation

In order to quantify errors due to temporal disaggregation technique alone, we computed Root Mean Square Error (RMSE) between the reference streamflow (Q^{ref}) and simulated streamflow under the "Temporally disaggregated" scheme (Q^{dis}). Thus, based on the assumption in equation (1), errors due to disaggregation ($RMSE^{dis}_i$) can be quantified as equation (2).

\[ Q^{dis}_{i,s,m} = Q^{ref}_{i,s,m} + e^{dis}_{i,s,m} \]  

(1)
\[
RMSE_{s,m}^{dis} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Q_{t,s,m}^{ref} - Q_{t,s,m}^{dis})^2}
\]  

(2)

Where \(Q\) and \(\varepsilon\) represent the streamflow and the error respectively, \(t\) refers to a given year, \(s\) denotes each season, \(m\) is the land surface model, and \(n\) refers to the number of years used to compute RMSE, which is equal to 20 in this study.

3.2.2 Errors due to Spatial Downscaling

Based on the equation (3), we assume that the developed streamflow under "Spatially downscaled and temporally disaggregated" scheme (Q_{down\_dis}) contains errors due to both downscaling as well as disaggregation techniques. Thus, in equation (4), errors associated with spatial downscaling technique alone (RMSE_{down}^{dis}) are detected by comparing Q_{down\_dis} with streamflow values simulated in the "Temporally disaggregated" scheme (Q_{dis}).

\[
Q_{t,s,m}^{down\_dis} = Q_{t,s,m}^{ref} + \varepsilon_{t,s,m}^{down} + \varepsilon_{t,s,m}^{dis}
\]  

(3)

\[
RMSE_{s,m}^{down} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Q_{t,s,m}^{down\_dis} - Q_{t,s,m}^{dis})^2}
\]  

(4)

3.2.3 Errors due to Imprecise Precipitation Forecasts

Given that the ECHAM4.5 precipitation forecasts are obtained over 2.8° spatial scale and at monthly time scales, both downscaling and disaggregation processes are used to implement LSMs with forecasted precipitation forcings. Therefore, developed streamflows under the "Precipitation Forecasts" scheme (Q_{ECHAM4.5}) include errors due to imprecise precipitation forecasts as well as due to downscaling and disaggregation procedures (equation 5). Thus, by removing the effect of disaggregation and downscaling errors, we can estimate errors just due to the ECHAM4.5 large scale precipitation forecasts (equation 6).

\[
Q_{t,s,m}^{ECHAM4.5} = Q_{t,s,m}^{ref} + \varepsilon_{t,s,m}^{ECHAM4.5} + \varepsilon_{t,s,m}^{down} + \varepsilon_{t,s,m}^{dis}
\]  

(5)

\[
RMSE_{s,m}^{ECHAM4.5} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Q_{t,s,m}^{ECHAM4.5} - Q_{t,s,m}^{down\_dis})^2}
\]  

(6)

3.2.4 Errors due to Climatological Forcings

In the "Climatological forcings" scheme (Q_{clim}) all forcings are obtained from NLDAS-2 climatology and precipitation climatology to implement LSMs. Therefore, by comparing developed streamflow under this scheme with the reference streamflow (Q_{ref}), we can estimate RMSE due to climatological forcings (RMSE_{clim}^{clim}) (equation 7). Note that in this scheme, there are no errors due to downscaling or disaggregation methods since we used climatological data at 1/8° spatial resolution on daily or sub-daily temporal scale to force the models.

\[
RMSE_{s,m}^{clim} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Q_{t,s,m}^{ref} - Q_{t,s,m}^{clim})^2}
\]  

(7)
On the other hand, we can assume that errors due to climatological forcings consist of two sources of errors: 1) errors due to just climatological precipitation forcings ($\epsilon_{\text{clim prcp}}$) and 2) errors due to climatological forcings excluding precipitation ($\epsilon_{\text{clim excl prcp}}$) as shown in equation (8).

$$Q_{t,s,m}^{\text{clim}} = Q_{t,s,m}^{\text{ref}} + \epsilon_{t,s,m}^{\text{clim prcp}} + \epsilon_{t,s,m}^{\text{clim excl prcp}} \quad (8)$$

Based on this assumption, we can use simulated streamflows under "Climatological forcings excluding precipitation" scheme ($Q_{\text{clim excl prcp}}$) to quantify each of these sources of errors shown in the following equations. $\text{RMSE}_{\text{clim prcp}}$ indicates the errors due to using climatological precipitation forcings and $\text{RMSE}_{\text{clim excl prcp}}$ indicates the errors due to using climatological forcings excluding precipitation in streamflow simulations.

$$Q_{t,s,m}^{\text{clim excl prcp}} = Q_{t,s,m}^{\text{ref}} + \epsilon_{t,s,m}^{\text{clim excl prcp}} \quad (9)$$

$$\text{RMSE}_{\text{clim excl prcp}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Q_{t,s,m}^{\text{ref}} - Q_{t,s,m}^{\text{clim excl prcp}})^2} \quad (10)$$

$$\text{RMSE}_{\text{clim prcp}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Q_{t,s,m}^{\text{clim}} - Q_{t,s,m}^{\text{clim excl prcp}})^2} \quad (11)$$

### 4.0 Results and Analyses

#### 4.1 Skill of the ECHAM4.5 Precipitation Forecasts

In order to evaluate the skill of the precipitation forecasts, we computed Spearman’s rank correlation between the spatially downscaled and temporally disaggregated forecasted precipitation issued at the beginning of each season and the observed precipitation for each season over the 1991-2010 time period (Figure 3a). This figure shows that the precipitation forecasts capture the observed variability in precipitation over the Southeast, Northeast, and the Southern coastal plains during winter and fall seasons. To better understand the skill of precipitation forecasts with reference to climatological precipitation, we plot the Mean Square Skill Score (MSSS) as shown in Figure 3b. The MSSS of the precipitation forecasts is computed based on the Mean Square Error (MSE) between the forecasted precipitation ($P_{\text{fcast}}$) and the observed precipitation ($P_{\text{obs}}$) for each season (equation 12).

$$\text{MSSS}_t = 1 - \frac{\text{MSE}(P_{t,s,fcast}, P_{t,s,obs})}{\text{MSE}(P_{t,s,obs}, P_{t,s,obs})} \quad (12)$$

Where $t$ refers to a given year from 1991 to 2010 and $s$ denotes the season. In fact, the MSSS represents the accuracy of the forecasted precipitation against climatological precipitation with respect to the observations. Thus, the positive MSSS values indicate that forecasted precipitation has higher skill (less error) than climatological precipitation. Figure 3b clearly demonstrates that the ECHAM4.5 precipitation forecasts offer added value over climatological precipitation during winter and fall seasons in most of the study area. However, improvement in skill of the precipitation forecasts against climatology is limited over spring and summer because of the smaller internal variability of precipitation during these seasons.
4.2 Decomposition of Sources of Errors in Seasonal Streamflow Forecasting

After obtaining all the streamflow simulations/forecasts based on different schemes described above (Figure 2), we decomposed sources of errors in the form of Root Mean Square Errors (RMSE) using the metrics defined in section 3.2. In order to analyze the results over the Sunbelt, we normalized RMSEs of each LSM based on its own mean seasonal reference streamflow ($Q_{\text{ref}}^{s}$) to obtain Relative Root Mean Square Error (R-RMSE) (equation 13).

$$R - \text{RMSE}_{s,m} = \frac{\text{RMSE}_{s,m}}{Q_{\text{ref}}^{s}}$$

4.2.1 Error due to Disaggregation and Downscaling

Figures 4a and 4b show R-RMSE associated with spatial downscaling and temporal disaggregation for each LSM, which are obtained based on the equations (4) and (2), respectively. Comparing between these figures, we see that the errors due to temporal disaggregation are higher than the errors due to spatial downscaling scheme. Further, we see the errors increase from winter to summer and then decrease in the fall. Figure 4b shows that the highest error due to temporal disaggregation occurs in the summer for both LSMs. The reason is that the disaggregation procedure dampens the peak rainfall events during summer convective storms and spread them over larger number of days, resulting in higher errors in precipitation forcings, which are subsequently propagated to streamflow simulations. Particularly, high magnitude of errors can be found over the semiarid and the desert regions such as Texas and New Mexico, where higher variability in summer precipitation exists. In these regions, it is common to receive extreme precipitation events such as heavy downpours due to local convections, and such events are not well-captured in the temporal disaggregation scheme. Given that the R-RMSE uses different seasonal reference streamflow for the two LSMs considered in this study, it is not appropriate to make performance comparisons across the two LSMs. Next, we evaluate how the relative magnitude of climatological forcings compare to errors due to disaggregation and downscaling.

4.2.2 Errors due to Climatological Forcings

Figure 4c shows R-RMSE of forecasted streamflows when the LSMs are implemented with all climatological forcings. As expected, the errors are high in most of the study region during all seasons. Surprisingly, during the spring and summer seasons we see low errors over the West, indicating that the skill in snow dominated basins arises from the updated initial hydrological conditions. This is in contrast to the study of Koster et al. (2010) who concluded that the contribution of early-season soil moisture in streamflow predictability is relatively small in the West while SWE dominated streamflow predictability.

As discussed in section 3.2.4, we assumed that the errors due to all climatological forcings consist of two different sources: 1) errors due to climatological precipitation forcings alone, and 2) errors due to climatological forcings excluding precipitation (Figure 4d), which means that errors are caused due to all other climatological forcings, excluding precipitation. Comparing between figures 4c and 4d, we see that using climatological precipitation forcings adds significant errors in the simulated streamflow in comparison to the streamflow simulated by using observed precipitation since the precipitation is the primary driver of the streamflow. On the other hand, by comparing between figure 4d with figures 4a and 4b we notice that the errors introduced to streamflow by using climatological forcings, excluding precipitation, are less than errors due to downscaling and disaggregation.
4.2.3 Errors due to the Large-Scale Precipitation Forecasts

Figure 5 illustrates the errors due to the large-scale monthly ECHAM4.5 precipitation forecasts alone obtained by eliminating the role of spatial downscaling and temporal disaggregation based on equation (6). Note that we cannot directly compare the results in figure 5 with the skill of precipitation forecasts (Figure 3) since the streamflow forecasts also derive their skill from updated initial hydrological conditions besides precipitation forecasts.

We infer from figure 5 that during the winter season, both LSMs show better skill (lower R-RMSE) over the East in comparison to the West. Basically it is due to high skill in precipitation forecasts over the East which is derived due to the ENSO conditions. This is in agreement to the studies of Devineni and Sankarasubramanian (2010) and Sinha and Sankarasubramanian (2013). We also see poor performance of LSMs during the fall season over the East even though we have reliable skill in precipitation forecasts. Recent studies have shown that LSMs exhibit high bias during the fall season and moreover, initial conditions exhibit limited role in forecasting the flows during that time (Sinha et al., 2014).

4.3 Skill of Streamflow Forecasts

As described earlier, seasonal streamflow forecasts are developed by implementing LSMs with climatological forcings, excluding precipitation, as well as under downscal and disaggregated ECHAM4.5 precipitation forecasts. In order to estimate the skill of forecasted streamflows on each 1/4° grid point, Mean Square Skill Score (MSSS) are computed based on the Mean Square Error (MSE) between the forecasted streamflow \(Q_{\text{fcst}}\) and the reference streamflow \(Q_{\text{ref}}\) against the climatological streamflow \(Q_{\text{clim}}\) over 20 years (equation 14).

\[
MSSS_{s,m} = 1 - \frac{MSE(Q_{s,m}^{\text{fcst}}, Q_{s,m}^{\text{ref}})}{MSE(Q_{s,m}^{\text{clim}}, Q_{s,m}^{\text{ref}})}
\]  

(14)

Figure 6 indicates streamflow forecasts during winter are more skillful than the other seasons in both LSMs. During this season, the skill over the Southeast and central US are relatively higher than the skill over the West. However, the western US exhibit better skill during the spring and summer seasons. This strength of forecasting skill might be due to the dominant role of initial hydrological conditions such as snow storage over this region since most of the basins in the West are snow-melt dominated basins. This is consistent to the findings of Koster et al. (2010). Furthermore, the role of initial conditions decreases during fall season, resulting in relatively lower skill than other seasons in this region. Figure 6 is consistent with figure 5 which shows the errors due to ECHAM4.5 precipitation forecasts alone. We see that in most regions where there are low errors due to precipitation forecasts, streamflow forecasts are skillful. This implies that the ECHAM4.5 precipitation forecasts plays a significant role of in determining the skill of streamflow forecasts. The analysis so far did not include the model errors. But in order to incorporate model errors, we performed skill evaluation for four selected basins across the US Sunbelt, which is described in section 4.5.

4.4 Identifying the Dominant Error Source

To further understand the relative magnitude of dominant source of errors, we plotted maximum RMSE among all other sources with respect to the total errors (sum of RMSEs) in the
developed seasonal streamflow forecasts (Figure 7). Primarily, we considered the following four sources of errors due to: temporal disaggregation, spatial downscaling, climatological forcings excluding precipitation, and the large scale ECHAM4.5 precipitation forecasts. If all of these four sources had fairly equal RMSEs, then the computed Relative Dominancy would approach 0.25, which is the lower limit for this variable indicating no dominancy. From figure 7, we infer that the most dominant sources of errors during different seasons are the ECHAM4.5 precipitation forecasts and temporal disaggregation procedure over most of the study area and there is relatively smaller contribution of errors due to spatial downscaling and climatological forcings excluding precipitation in the developed streamflow forecasts. During the winter and fall seasons, the dominant source of error is the imprecise ECHAM4.5 precipitation forecasts. This shows that in order to improve streamflow forecasting skills during winter and fall, emphasis should be given to improve climate forecasts from GCMs. On the other hand, during the summer season, we see temporal disaggregation as the dominant source of uncertainty in most of the regions. In dry seasons, the inability of the disaggregation model to reproduce the peak rainfall, flatten the variability of precipitation, thus results in higher errors. Consequently, improving the disaggregation technique is needed to improve the skill of streamflow forecasting in dry seasons.

4.5 River Basin Analyses

We developed retrospective streamflow forecasts (Qfcst) for the four selected basins described in section 2.2 and evaluated the forecasting skill by considering the observed streamflow records as the reference flows. First, we estimated monthly % bias for each LSM by comparing the reference streamflow (Qref) with the observed streamflows over the 10 years period prior to the forecasting period (from 1980 to 1991) for each month. These monthly % bias corrections were subsequently applied to the streamflow forecasts (Qfcst) over the analysis period from 1991 to 2010 to compensate for the systematic biases of each LSM.

Figure 8 indicates the Spearman’s rank correlation and Mean Square Skill Score (MSSS) between the bias-corrected seasonal streamflow forecasts and the seasonal observed streamflows over the period of 20 years (from 1991 to 2010). The black line in the Figure 8 represents the significant correlation corresponding to 95% confidence level. From this figure, we can infer that most of the correlation values are statistically significant, indicating that the forecasted streamflows explain the interannual variability of the observed streamflows. The MSSS shown in this figure is computed based on the equation (15) in order to evaluate the accuracy of streamflow forecasts by each LSM.

\[
MSSS_{s,m} = 1 - \frac{MSE(Q_{fcst,s,m}, Q_{obs,s,m})}{MSE(Q_{obs,s,m}, Q_{obs,s,m})}
\]

(15)

Figure 8 shows that seasonal streamflow forecasts have the highest skill during the winter season while the summer season exhibits the lowest skill. This is due to the strong ENSO signals during October to March, which adds better predictability (skill) to the ECHAM4.5 precipitation forecasts (Figure 3). This is consistent to other studies such as Sinha and Sankarasubramanian (2013). As expected, skill is lowest in the Verde River basin, which is the driest basin among all the basins considered in this study whereas the ACF basin shows the highest skill, which has the largest drainage area and located in a humid region.

5.0 Summary and Conclusions
By using spatially downscaled and temporally disaggregated precipitation forecasts from the ECHAM4.5 GCM along with the climatological forcings from the NLDAS-2 dataset, this study developed retrospective seasonal streamflows for the period of 20 years (from 1991 to 2010) over the US Sunbelt based on two LSMs - Noah3.2 and CLM2. We then performed a quantitative assessment of the different sources of errors in developed seasonal streamflow forecasts. To quantify these errors, our study employed Root Mean Square Error (RMSE) to compare the relative magnitudes of errors resulting from temporal disaggregation, spatial downscaling, large-scale ECHAM4.5 precipitation forecasts, and climatological forcings, excluding precipitation. Our analysis based on the decomposition metrics described in section 3.2 shows that disaggregation scheme introduces more errors in streamflow forecasting in comparison to spatial downscaling approach. The maximum and minimum errors due to downscaling and disaggregation procedures are found during the summer and the winter, respectively. The errors due to the disaggregation approach alone was dominant during dry seasons as well as in dry regions (i.e., semiarid and desert regions). This is due to the poor performance of the disaggregation method in reproducing peak rainfall events that are frequently observed during convective storms in arid regions. Analysis on errors arising from climatological forcings in streamflow simulations reveals that a significant portion of the errors are due to using climatological precipitation forcings in comparison to the errors arising from the climatological forcings excluding precipitation. In addition, we realized that some regions (e.g., the West) provide reliable skill in streamflow forecasting primarily due to the updated initial hydrological conditions (IHCs), even when the models are forced with climatological forcings. This is in agreement to other studies such as Shukla and Lettenmaier (2011), Sinha and Sankarasubramanian (2013), and Koster et al. (2010). Errors arising from the large-scale precipitation forecasts provide information on skill in streamflow forecasting in a given season over a region. During the winter season, since skill in precipitation forecasts is high due to ENSO conditions, we see good skill in streamflow forecasting as well over the most of the study area.

This study provides useful information on key sources of errors in streamflow forecasts in different hydro-climatic regions over the US Sunbelt and how those errors vary across different seasons. But this study only uses precipitation forecasts from a single GCM - ECHAM4.5. Combining climate forecasts from multiple GCMs can further reduce uncertainty in developed streamflow forecasts (Devineni et al., 2008; Singh and Sankarasubramanian, 2014). Data assimilation techniques could also be employed to reduce uncertainties due to initial hydrologic conditions. We intend to address these limitations as a part of our future research.

6.0 Experimental Storage and Inflow Forecasts Development

The project objectives also include developing experimental reservoir storage forecasts utilizing the monthly/seasonal streamflow forecasts obtained from climate forecasts. This includes: (a) automating the experimental inflow forecasts portal for issuing and updating real-time monthly and seasonal streamflow forecasts for water supply systems in NC and (b) developing reservoir simulation module and link it to the automated inflow forecasting portal for issuing experimental storage forecasts for the selected systems.

Substantial progress has been made on both objectives. Currently, both inflow forecasting model and reservoir simulation model have been fully automated (http://www.nc-climate.ncsu.edu/inflowforecast) for both Lake Jordan and Falls Lake systems. Reservoir inflows are automatically updated every month during 15th-20th of every month for up to three months into the inflow forecasts database. Figure 9 and Table 1 display the results for the seasonal
forecasts for January-March (JFM) 2014 for the Jordan Lake issued in the middle of January. As part of the proposal, we proposed to include both Kerr-Scott Lake and Philpott Lake in the portal. But, the skill of the streamflow forecasts from the statistical model was not good enough to link it with the portal. The primary reason for the poor skill of the statistical models was due to the limited drainage area upstream of both lakes. In the case of Kerr-Scott (Philpott), the upstream area is around 367 (212) miles$^2$. Hence, the skill of streamflow forecast was not statistically significant. We intend to address this issue by developing streamflow forecasts using the NASA’s Land Information System (LIS) as part of the ongoing Integrated Drought Management portal (http://climate.ncsu.edu/water/map/) project.

The reservoir simulation model for Falls Lake and Jordan Lake could be run in two different ways: a) User-specified releases and (b) observed releases (applicable only in the past context). For a total release of 750 cfs, we have obtained the storage distribution (Figure 10 and Table 2) for Jordan Lake showing its ability in meeting the target storage at 216 MSL for Jordan Lake.

7.0 Overview Presentation and Demonstration Video
We have also developed an overview presentation (http://www.youtube.com/watch?v=wVjiOBTQQ9w) and a demonstration video of the inflow forecast portal (http://www.youtube.com/watch?v=tqajlw_oWx4). This should help the potential users to understand the utility of forecasts and how it could be managed for the two systems.

8.0 Student Training
We had one student, Amirhossein Mazoorei, working full time on this project. A manuscript based on quantifying the sources of errors in developing seasonal streamflow forecasts is submitted to the Journal of Geophysical Research. Amir defended his Master’s thesis in this semester and is continuing for PhD. Amir also received USGS Science center fellow for the year 2015-2016.

Another one student, Harminder Singh, was involved in developing the inflow and storage forecasting portal. Harminder completed his Masters at NC State and is currently working at Withers and Ravnel in Cary, NC.
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Figure 1: Location of the selected river basins across the Sunbelt of the US (dark area) and the considered USGS gauging stations.

Verde River basin, AZ
USGS# 09506000

ACF River basin, USGS# 02358000

Guadalupe River basin, TX
USGS# 08167500

Tar River basin, NC
USGS# 02083500
Figure 2: Total experimental design for quantifying different sources of errors in developing seasonal streamflow forecasts.
Figure 3: Evaluation of ECHAM4.5 precipitation forecasts with respect to the observed precipitation by a) Spearman Rank Correlation and b) Mean Square Skill Score. Gray values in figure (a) indicate insignificant correlation (<0.48) at 5% significance level and in figure (b) denote unskillful forecasts in comparison to climatology.
Figure 4: R-RMSE in streamflow simulations due to a) Downscaling, b) Disaggregation, c) using climatology of all the forcings and d) using climatology of all the forcings excluding precipitation (observed precipitation is used) by Noah3.2 and CLM2 land surface models.
Figure 5: R-RMSE in streamflow simulations due to large-scale monthly ECHAM4.5 precipitation forecasts by Noah3.2 and CLM2 land surface models.
Figure 6: MSSS of seasonal streamflow forecasts ($Q^{\text{test}}$) with respect to the reference streamflow ($Q^{\text{ref}}$) by Noah3.2 and CLM2 land surface models (equation 14).
Figure 7: Relative magnitude of dominant source of errors with respect to the total errors in seasonal streamflow forecasts (equation 15) over different seasons (rows) by Noah3.2 and CLM2 LSMs (columns). Darkness of each color denotes the magnitude of dominancy of the source of uncertainty among other sources (gray color infers no dominancy ($\eta = 0.25$) means that all the four sources of errors have equal contributions in total uncertainty of streamflow forecasts).
Figure 8: Evaluation of seasonal streamflow forecasts with respect to the observed streamflow over four selected basins by Spearman Rank Correlation and Mean Square Skill Score.
Figure 9: Seasonal Inflow Forecasts for JFM 2014 for Jordan Lake.
Figure 10: Probability of meeting the target storage at 216 MSL by April 30, 2014 using the seasonal forecasts issued in February based on the assumed release of 750 cfs.
Table 1: Categorical Forecasts for Jordan Lake (JFM 2014).

<table>
<thead>
<tr>
<th>Climatological Percentile</th>
<th>Percentile Values (CFS)</th>
<th>Model Probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;33%</td>
<td>&lt; 1830</td>
<td>0.286</td>
</tr>
<tr>
<td>33-67%</td>
<td>1830 - 3354</td>
<td>0.416</td>
</tr>
<tr>
<td>&gt;67%</td>
<td>&gt; 3354</td>
<td>0.298</td>
</tr>
</tbody>
</table>

Table 2: Probability of April 2014 storage being in different pools using the seasonal forecasts issued in February based on the assumed release of 750 cfs.

<table>
<thead>
<tr>
<th>Stage Level (ft above MSL)</th>
<th>Model Percentiles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below conservation pool:</td>
<td>&lt;202</td>
</tr>
<tr>
<td>Within limits of conservation pool:</td>
<td>202 - 216</td>
</tr>
<tr>
<td>Within limits of flood control pool:</td>
<td>216 - 240</td>
</tr>
<tr>
<td>Above flood control pool:</td>
<td>&gt;240</td>
</tr>
</tbody>
</table>