Predictability of Seasonal Streamflow and Soil Moisture in National Water Model and a Humid Alabama–Coosa–Tallapoosa River Basin[✉]

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ABSTRACT

This study investigates the potential predictability of streamflow and soil moisture in the Alabama–Coosa–Tallapoosa (ACT) river basin in the southeastern United States. The study employs the state-of-the-art National Water Model (NWM) and compares the effects of initial soil moisture condition with those of seasonal climate anomalies on streamflow and soil moisture forecast skills. We have designed and implemented seasonal streamflow forecast ensemble experiments following the methodology suggested by Dirmeyer et al. The study also compares the soil moisture variability in the NWM with in situ measurements and remote sensing data from the Soil Moisture Active and Passive (SMAP) satellite. The NWM skillfully simulates the observed streamflow in the ACT basin. The soil moisture variability is 46% smaller in the NWM compared with the SMAP data, mainly due to a weaker amplitude of the seasonal cycle. This study finds that initial soil moisture condition is a major source of predictability for the seasonal streamflow forecast. The contribution of the initial soil moisture condition is comparable or even higher than that of seasonal climate anomaly effects in dry seasons. In the boreal summer season, the initial soil moisture condition contributes to 65% and 48% improvements in the seasonal streamflow and soil moisture forecast skills, respectively. This study attributes a greater improvement in the streamflow forecast skill to the lag effects between the soil moisture and streamflow anomalies. The results of this study can inform the development and improvement of the operational streamflow forecasting system.

1. Introduction

This study investigates potentially useful skills in seasonal streamflow forecasts that can be helpful for water resource planning and management, including mitigation planning for drought impacts. The streamflow represents an integrated response of the climate, land use, topography, soil type, groundwater interactions, and human intervention in the hydrologic system (Gochis et al. 2018; Kam and Sheffield 2016; Kumar et al. 2009, 2016; Milly et al. 2018; Niu et al. 2005; Schilling 2016; Xiao et al. 2018; Zhang and Schilling 2006). Precipitation is one of the major factors contributing to streamflow. Other factors that contribute to streamflow include groundwater contribution to

the base flow in the streams (Larocque et al. 2010; Priest 2004), soil moisture memory (Koster et al. 2010; Mahanama et al. 2012), and snow storage and melt (Berghuijs et al. 2014; Li et al. 2019). Precipitation has a short memory that ranges from a few days to less than 4 weeks (Chow et al. 1988). Soil moisture memory ranges from several months to a year or even longer (Amenu et al. 2005; Dirmeyer et al. 2016; Entin et al. 2000; Nicolai-Shaw et al. 2016; Orth and Seneviratne 2012; Vinnikov et al. 1996; Wu et al. 2002) and can potentially contribute to improving streamflow forecast skill on seasonal to interannual time scale (Kumar et al. 2019). Thus, initial soil moisture state (ISMS) is one of the main contributors to the seasonal streamflow forecast skill (Mahanama et al. 2008). Greuell et al. (2019) found that ISMS contributed to improved skill in 0–2 months of lead streamflow forecast in Europe.

Studies have investigated the relative importance of snow and soil moisture initial conditions on streamflow forecast skill, especially in the snow-dominated regions

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of the United States and Europe (Koster et al. 2010; Orth and Seneviratne 2013a). Koster et al. (2010) found that the early-season snow water storage (snow initialization) contributes most to streamflow forecast skill in the mountain area basins in the northwest United States. For example, snow water storage is the dominant source of predictability in the Columbia River basin (Mahanama et al. 2012). Similarly, Orth and Seneviratne (2013a) found that the initial snow condition is a major contributor to streamflow forecast skill in high-altitude catchment (>2000-m elevation) in Switzerland. However, there are a limited number of studies that have investigated streamflow predictability in the humid U.S. Southeast, which is a rain-dominated region that may have smaller predictability than snow-dominated regions.

Seasonal streamflow predictability has been investigated using idealized experiments (Mahanama et al. 2012; Shukla et al. 2013; Wood and Lettenmaier 2008). The ensemble streamflow prediction (ESP) that generates streamflow forecast using observed initial conditions and climatological or randomized climate forcing, and vice versa (Rev-ESP), have been used to assess the role of initial hydrologic conditions on streamflow forecast skill (Wood and Lettenmaier 2008; Wood et al. 2016). Li et al. (2009) applied the ESP and Rev-ESP method to investigate streamflow predictability in the Ohio River basin and found that observed initial conditions improved forecast skill at short lead time up to 1 month. Shukla et al. (2013) applied the ESP and Rev-ESP methods globally and found that ISMS influenced 1-month lead forecasts, especially in the dry season. They also found that climate forcing dominated the predictability in the wet equatorial regions.

A knowledge gap exists in the area of assessing skills in the operational streamflow forecasting system and assessing the fidelity of the initial hydrologic condition using observations (Wanders et al. 2019). Particularly, the incorporation of human water management processes such as dams and reservoir operations are challenging. Further, real-time availability of the remotely sensed soil moisture observations, also called the SMAP (Soil Moisture Active and Passive; Entekhabi et al. 2014), makes it possible to evaluate model-simulated soil moisture within a large domain.

We investigate streamflow predictability using a state-of-the-art National Water Model's (NWM) streamflow forecasting system that has become operational in 2016 (<https://water.noaa.gov/about/nwm>). The NWM is an unprecedented effort by the National Oceanic and Atmospheric Administration (NOAA) to

provide high-resolution soil moisture (1 km) and streamflow forecasts for 2.7 million streams in the continental United States. The NWM is composed of the Noah multiparameterization land surface model (Noah-MP LSM), subsurface and terrain routing module, gridded diffusive wave channel, and reservoir routing modules (Gochis et al. 2018; Hooper et al. 2017). A simple parameterization of dam and reservoir operations is also available in the NWM (Gochis et al. 2018).

SMAP provides spatially continuous surface soil moisture (top 5 cm) estimates from the National Aeronautics and Space Administration (NASA) satellite observations since 2015 (Entekhabi et al. 2014). Zhang et al. (2017) evaluated SMAP soil moisture estimates with in situ measurements and found that SMAP soil moisture captured the spatial distribution of surface soil moisture in the contiguous United States. Chan et al. (2016) and Colliander et al. (2017) found that accuracy of the SMAP soil moisture estimates averaged over the core validation sites was $0.038 \text{ m}^3 \text{ m}^{-3}$ unbiased root-mean-square difference (RMSD), that is, within the acceptable range of the SMAP mission ($0.040 \text{ m}^3 \text{ m}^{-3}$). Pan et al. (2016) found that SMAP soil moisture performed better than the land surface model products driven by observed meteorological forcing. SMAP time series correlated well with in situ measurements from the Soil Climate Analysis Network (SCAN), and U.S. Climate Reference Network (CRN) with the network average temporal correlation of 0.64 for SCAN and 0.65 for CRN (Pan et al. 2016). Reichle et al. (2017) found acceptable accuracy in 9-km resolution SMAP soil moisture data products. Hence, SMAP data can be used to assess initial hydrologic conditions in the NWM.

The southeastern United States is a hotspot of climate variability, land-use change, and irrigation expansion, especially in recent decades. The Southeast has shown an anomalous longer temperature trend than the rest of the globe (Kumar et al. 2013; Meehl et al. 2015; Pan et al. 2013). From 1973 to 2011, the southeastern plains had one of the highest rates of land use and land cover change of any ecoregion nationally (Napton et al. 2009). There is renewed pressure to increase production of the warm weather crops in the Southeast due to long-term drought in the west (Alston et al. 2010; McNider and Christy 2007).

The overarching goal of this study is to assess skills in the seasonal streamflow forecast in the southeastern United States. We answer the following scientific questions:

- 1) Are there potentially useful forecast skill available on the seasonal time scale for streamflow forecasting?

FIG. 1. (a) The ACT basin topography, (b) land use reclassified from NLCD 2011 land cover data, (c) surface soil texture categories, and (d) 30 years of normal precipitation and temperature. Panel (a) also shows 15 subwatersheds, 15 USGS gauges, and 7 SCAN and CRN soil moisture gauges in the ACT basins.

FIG. 2. A text schematic of the WRF-Hydro model, and coupling among its components. Compared to the traditional land surface model, the WRF-Hydro model has added strengths in the high-resolution (10 times) terrain routing module and channel routine module. Hence, the WRF-Hydro model is more suitable for simulating daily streamflow in operational conditions.

This is an important question because, in the NWM, the forecast is limited to one month only.

- 2) What is the accuracy of initial soil moisture conditions in the NWM? We compare NWM soil moisture with the in situ measurements and SMAP data.
- 3) Is streamflow more predictable than soil moisture? If so, why? We employ WRF-Hydro model version 5, which is the research version of the NWM (Gochis et al. 2018). We investigated the streamflow and soil moisture predictability using observed and random climate forcing experiments.

Section 2 gives the description of the data, WRF-Hydro model configuration, and its parameterization, and predictability experiment design. Section 2 also describes the model calibration and validation results. Section 3 presents the findings of this study. Summary and discussions are presented in section 4.

2. Data and methods

a. Study area

The Alabama–Coosa–Tallapoosa (ACT) river basin is located in the states of Georgia and Alabama in the U.S. Southeast (Fig. 1a), and the basin is characterized by a humid subtropical climate (Peel et al. 2007). The average slope of the basin is 5% (not shown). There are 15 active U.S. Geological Survey (USGS) streamflow gauges in the basin (Table S1 in the online supplemental material). These gauges were used as the subwatershed outlets for the watershed

delineation. The observed streamflow at the watershed outlet, Alabama River at Claiborne Lock and Dam near Monroeville (USGS gauge 02428400), is used for model calibration and validation. Besides, 15 reservoirs are treated as one-orifice weir reservoirs for the model setup.

The majority of land cover type is forest (57%), followed by grassland/shrub (24%) and urban area (9%). Agriculture only occupies 3% (Fig. 1b). Two main surface soil categories are silt loam and sandy loam (Fig. 1c). The annual average temperature decreases from south to north (Fig. 1d), but the temperature remains well above the freezing point for the majority of the year, and snow is not a major factor in the ACT basin. The mountainous range in the northeast corner receives the highest precipitation ($>1500 \text{ mm yr}^{-1}$). The annual precipitation decreases toward the center of the basin to $\sim 1300 \text{ mm yr}^{-1}$ and then increases again to the 1500 mm yr^{-1} toward the Gulf Coast (Fig. 1d).

b. Model and data

The National Center for Atmospheric Research (NCAR) has developed the WRF-Hydro modeling system (Gochis et al. 2018), which is the core of the NWM. The three main components of the WRF-Hydro model are the Noah-MP LSM, subsurface and terrain routing module, and gridded diffusive wave channel and reservoir routing modules (Gochis et al. 2018) (Fig. 2). We employed the following modeling tools: WRF-Hydro v5, WRF-Hydro ARC-GIS tools, create_wrfinput tool, and NLDAS regridding tool,

TABLE 1. List of model input data, and their sources.

Data name	Source	Reference/remarks
Digital elevation model	National Elevation Dataset at 30-m resolution	Gesch et al. (2012)
Soil texture	WPS v4 geographical static data	https://www2.mmm.ucar.edu/wrf/users/download/get_sources_wps_geog.html
Land use	USGS land cover classification	McKay et al. (2012)
Watershed boundary, water body, river network	National Hydrography Dataset Plus	
Reservoir information like broad-crested weir length	U.S. Army Corps of Engineers	U.S. Army Corps of Engineers (2014)
Meteorological forcing	North American Land Data Assimilation version 2 (NLDAS2)	Xia et al. (2012) ; interpolation to WRF-Hydro grid
Streamflow	United States Geological Survey	Fifteen USGS gauges listed in Table S1, used for model calibration and validation
Soil moisture (in situ)	Soil Climate Analysis Network (SCAN) and Climate Reference Network (CRN)	Schaefer et al. (2007) and Bell et al. (2013) used for model evaluations
Soil moisture (remote sensing)	Soil Moisture Active and Passive (SMAP) L4 Global 3-hourly 9-km EASE-Grid Surface Soil Moisture Geophysical Data V004	Reichle et al. (2014) used for model evaluations

WRF Preprocessing System (WPS) to develop NWM configuration for the study area. The WRF-Hydro model for the study area is configured using two meshes: the coarse mesh of $13\,667\text{ m} \times 13\,667\text{ m}$ ($1/8^\circ$ latitude $\times$ $1/8^\circ$ longitude) for the land surface model grid, and fine mesh of $1367\text{ m} \times 1367\text{ m}$ ($1/80^\circ$ latitude $\times$ $1/80^\circ$ longitude) for the terrain routing module. The model time step is 90 s to avoid numerical instability.

Model data and their sources are listed in [Table 1](#). We obtained the reservoirs' information, like broad-crested weir length from the water control manuals ([U.S. Army Corps of Engineers 2014](#)). The meteorological forcing data are from the North American Land Data Assimilation version 2 (NLDAS2; [Xia et al. 2012](#)). In situ soil moisture measurements and remote sensing data were used for evaluating initial hydrologic conditions in the model.

c. Model physics

The Noah-MP LSM runs at coarse grid resolution, and it has four vertical soil layers with thicknesses of 0.1, 0.3, 0.6, and 1.0 m from the surface to the bottom where it is connected to an unconfined aquifer. The Noah-MP model uses a two-stream radiative transfer scheme, a vegetation canopy layer, a Ball–Berry type stomatal resistance scheme, a TOPMODEL-based runoff scheme, a three-layer snow model, a frozen soil scheme, and a simple groundwater model ([Niu et al. 2011](#)). The incident energy at the surface is balanced by the net longwave radiation, latent and sensible heat fluxes, and the surface heating by iteratively solving the energy balance equation for the ground

temperature. The Noah-MP model uses the majority vegetation type to differentiate between vegetated fraction and bare ground fraction in the grid cell using the “semi-tile” approach ([Niu et al. 2011](#)).

The Penman–Monteith equation is used to compute latent heat flux or evapotranspiration, which is connecting the link between water and energy balance equations ([Cai et al. 2014](#); [Kumar and Merwade 2011](#)). Water flow in four soil layers is modeled using the diffusive form of Richard's equation, which includes soil water potential driven diffusive flow, gravity-driven flow, and the sink terms due to ET, and the drainage from the bottom soil layer ([Zheng et al. 2015](#)). Thus, compared to the traditional hydrological models which only solve the water balance equations, e.g., Soil and Water Assessment Tool (SWAT), the National Water Model solves full sets of water and energy balance equations, hence provides better constrain on water predictions. Infiltration excess, ponded water depths, and soil moisture are disaggregated to a finer resolution for the subsurface and terrain routing module using two-way couplings.

The terrain and subsurface routing model operates at a finer spatial resolution. Fully saturated grid cells generate lateral subsurface flow, which is added to the infiltration excess from the LSM ([Gochis et al. 2018](#)). Next, the model determines the water table depths, which are the depths to the topmost saturated layer and a key parameter in infiltration and saturation excess calculation ([Niu et al. 2005](#)). The baseflow contribution to the streams is modeled using the conceptual catchment storage–discharge bucket model ([Gochis et al. 2018](#)). The Bucket model calculates

FIG. 3. (a) The calibrated model monthly streamflow performance during the validation period (1990–99). (b) The frequency of the flow exceedance. Improved model performance, particularly for the low flows, can be seen in the flow exceedance curve. For comparison purposes, the figure also shows the uncalibrated model performance.

baseflow into streams using an empirically derived model as a function of the water depths in the bucket or overflow when it exceeds maximum bucket depth. Once water is discharged into the streams, the soil moisture states are updated and aggregated back to the coarse resolution for the LSM calculation in the next time step. Thus, the WRF-Hydro model enables two-way coupling between the LSM and the terrain and subsurface routing module (Fig. 2).

There is the one-way coupling between the terrain routing module and the channel and reservoir routing module, i.e., water cannot move from the channel to the land. The overland flow is routed through the channel using fully unsteady, spatially explicit, diffusive wave formulation and Manning's roughness coefficients that are the functions of land cover types (Gochis et al. 2018). Water passing into/through lakes and reservoirs is routed using a simple level pool routing scheme. This final section generates streamflow that has been compared against USGS observations in this study. Overall, the NWM combines a fully physics-based approach (solving water and energy balance equations) with the hydrology and hydraulics

characteristics of the terrain and the channel to generate streamflow forecast.

d. Model calibration

We performed manual calibration using sensitive parameter lists from the literature (Givati et al. 2016; Kerandi et al. 2018; Naabil et al. 2017; Senatore et al. 2015; Yucel et al. 2015). The baseflow and total flow volume are sensitive to saturated soil conductivity (SATDK). We also adjusted the parameter of the groundwater bucket model to increase the baseflow. Other sensitive parameters include saturated hydraulic conductivity parameter (REFDK) and saturated hydraulic infiltration parameter (REFKDT). A final set of calibrated parameters are given in Table S2. The calibration period was from 1980 to 1990, and validation was from 1990 to 2000. The model performance was evaluated using Nash–Sutcliffe efficiency (NSE) coefficient (Moriassi et al. 2007).

The calibrated model improved the streamflow simulation performance, especially for the low-flow conditions that can be seen in the flow exceedance probability curve shown in Fig. 3b. The NSE for monthly streamflow

FIG. 4. The seasonal streamflow forecast experiment design: the initialization process for the ensemble simulations with (a) realistic ISMS taken from the last 7 days and (b) randomized ISMS for the same date but from different years. The bottom-left panel x -axis labels are the last two digits of the year included in 2006, they represent five El Niño, five La Niña years, and five normal conditions; 1 Apr 2006 is an example. Control runs (CTRL) in (a) and (b) are the same.

improved from 0.64 for the uncalibrated model to 0.69 for the calibrated model during the validation period. Since NSE is more sensitive to high flows, the NSE improvement is small (Kumar and Merwade 2009). The calibrated model daily streamflow NSE is 0.55 (Fig. S1). We performed the predictability experiments (described next) using the calibrated model and from 1990 to 2016.

e. Seasonal streamflow predictability experiment design

We followed the seasonal climate predictability experiment design suggested by Dirmeyer et al. (2013). Here, we briefly describe the experiment design: a long control simulation from the year 1990 to 2016 treated as the synthetic observations or control run (27-yr CTRL) for forecast evaluations. The model is spun up by repeating the simulations from the year 1980 to 1989 three times and using the restart file generated at the end of the simulation in the subsequent run, thereby equilibrating the model's dynamical state as the warm start for the 27-yr CTRL simulation (Rodell et al. 2005). All experiments are driven by the synchronous

and random reanalysis climate forcing (NLDAS2) and are initialized by the ensemble of realistic and random ISMS (discussed below). A noteworthy difference from the Dirmeyer et al. (2013) study is that meteorological forcing is not interactive with soil moisture states in the model.

The Southeast winter precipitation anomalies are significantly correlated with the El Niño–Southern Oscillation (ENSO) index (Newman et al. 2016). Maleski and Martinez (2018) found that the El Niño (La Niña) events are associated with increased (decreased) precipitation at most stations in the ACT basin. Hence, we select 15 years for seasonal streamflow forecast experiments: five El Niño years (1991, 1992, 1997, 1998, 2015), five La Niña years (2000, 2007, 2008, 2010, 2012), and five normal years (1993, 1996, 2004, 2006, 2014). The seasonal streamflow forecast experiments are launched in each of the 15 selected years on 1 January, 1 April, 1 July, and 1 October, and the forecast simulations run for 91 days. Thus, we assess the streamflow forecast skills in four seasons: winter (1 January), spring (1 April), summer (1 July), and fall (1 October).

TABLE 2. List of perturbed soil moisture variables in the NWM for seasonal streamflow forecast experiments. Abbreviations correspond to WRF-Hydro FORTRAN scripts. For groundwater experiments (described later) only variables with star sign (*) are perturbed.

	Abbreviation	Note	Unit
LSM restart variables			
Volumetric soil moisture	SMC	4 layers soil moisture from 0.1 to 2.0 m	$\text{m}^3 \text{m}^{-3}$
Volumetric liquid soil moisture	SH2O	SH2O = SMC – SICE (soil ice)	$\text{m}^3 \text{m}^{-3}$
Volumetric soil moisture	SMOISEQ	Equilibrium soil water content	$\text{m}^3 \text{m}^{-3}$
Soil moisture below the bottom of the column (water table depth)	SMCWTDXY*	Below 4 layers (2 m)	$\text{m}^3 \text{m}^{-3}$
Soil moisture below the bottom of the column (deep reach)	DEEPRECHXY*	Below 4 layers (2 m)	$\text{m}^3 \text{m}^{-3}$
Water in aquifer relative to reference level	WA*	Below 4 layers (2 m)	kg m^{-2} (mm)
Water in the aquifer and saturated soil	WT*	Below 4 layers (2 m)	kg m^{-2} (mm)
Water table depth	ZWT*	Below 4 layers (2 m)	$\text{m}^3 \text{m}^{-3}$
HYDRO restart variables			
Total liq + ice soil moisture	Smc	4 layers	$\text{m}^3 \text{m}^{-3}$
Liquid soil moisture	sh2ox	4 layers	$\text{m}^3 \text{m}^{-3}$
Depth in groundwater bucket	z_gwsbbas*	Bucket model water depth	m

We assessed the role of initial hydrologic conditions on the streamflow forecast using ensemble forecast experiments with realistic and randomized ISMS (Fig. 4). On each forecast experiment start date, for example, 1 April 2006, we generate two sets of ensemble forecasts, each having a 14-member ensemble: the first set with realistic ISMS and the second set with unrealistic or random ISMS. Following Dirmeyer et al. (2013), we selected 14 realistic ISMS from the last 7 days by saving the HRLDAS and hydro restart file every 12 h. For the second set of the experiment, the random soil moisture states were selected from the same date but from the remaining 14 years, not including the year for which forecast is generated. For example, on 1 April 2006, in Fig. 4, the remaining 14 years of 1 April soil moisture states not including the 2006 state are the 14 random ISMS. Table 2 shows the list of the states we edited for the forecast experiment. The methodology produces significantly different initial hydrologic conditions between realistic and randomized ISMS experiments, as designed (Fig. S2). Each forecast experiment was integrated for 90 days.

We compared the effects of the initial hydrologic conditions on streamflow forecast to the impacts of the skill in seasonal climate forecast using the ensemble

forecast experiment with synchronous and randomized reanalysis climate forcing. The random climate forcing is the climate forcing from the same season but the remaining 14 years that do not correspond to the year for which streamflow forecasts are generated (e.g., 2006 in Fig. 4). We rearranged the ensemble accordingly (Dirmeyer et al. 2013). The actual seasonal climate forecast skill would be in between the best forecast (obs. CF) and the random climate forcing. Hence, we cover the range of the forecast skill that can be potentially derived using the operational forecast system (Wood et al. 2016). Table 3 lists all experiments with realistic and randomized ISMS and climate forcing permutations. Overall, we have generated 2 kinds of ISMS $\times$ 14 ensemble members for each kind $\times$ 15 years $\times$ 4 seasons = 1680 seasonal streamflow forecast experiments.

We have also differentiated the soil moisture contributions from the groundwater contributions by repeating our forecast experiments for groundwater perturbations only (Table 2).

f. Statistical methods

We assessed the improvement in the forecast due to realistic ISMS by comparing the RMSD [Eq. (1)] between realistic and random ISMS experiments:

TABLE 3. List of seasonal streamflow forecast experiments.

Expt No.	Experiment ID	ISMS	Climate forcing (CF)	Remarks
E1	Real ISMS + obs. CF	Realistic	Observed	Most predictable scenario
E2	Rand. ISMS + obs. CF	Random	Observed	Effects of ISMS under observed climate forcing (E1–E2)
E3	Real ISMS + rand. CF	Realistic	Random	Effect of CF only (E1–E3), effects of ISMS only (E3–E4)
E4	Rand. ISMS + rand. CF	Random	Random	Noise

FIG. 5. The soil moisture climatology and variability ($\text{m}^3 \text{m}^{-3}$) in the NWM and its comparison with the SMAP observations. (top) Daily soil moisture average and standard deviation for the March 2015–December 2018 period from SMAP data at its native resolution (9 km). (bottom) The same for the NWM model at its original resolution (13.7 km). The blank pixels are water bodies. Please note that SMAP data are available from March 2015 onward only. Triangles show ground truth observation sites from SCAN and CRN networks. SMAP is a 5-cm layer of soil moisture and NWM is 10-cm layer soil moisture.

$$\text{RMSD}_i = \sqrt{\frac{1}{N \times E} \left[\sum_{y=1}^N \sum_{e=1}^{14} (f_{y,e,i} - o_{y,i})^2 \right]}, \quad (1)$$

where $f_{y,e,i}$ is the e th member seasonal streamflow or soil moisture forecast in the year y for the given season and i th day forecast period, $o_{y,i}$ is the corresponding value in the synthetic observation (o_y is the same for all 14-member

ensemble forecasts). The total number of ensemble members is 14, N is 15 for all years, and $N = 5$ for El Niño only, La Nina only, or normal only years. The 95% uncertainty range is computed as 2 times the standard error of the RMSD across ensemble members and years. Two forecasts (realistic and random ISMS) are statistically indistinguishable if the 95% uncertainty range overlaps.

To assess the improvements over the climatology forecast, we computed the NSE [Eq. (2)] of the average ensemble forecast in the given season and year, as defined below for the first 10 days of the forecast:

$$\text{NSE} = 1 - \frac{\sum_{i=2}^{11} \left(o_{y,i} - \frac{1}{14} \sum_{e=1}^{14} f_{y,e,i} \right)^2}{\sum_{i=2}^{11} (o_{y,i} - \bar{o})^2}, \quad (2)$$

where $\bar{o} = [1/(27 \times 10)] \sum_{y=1}^{27} \sum_{i=2}^{11} o_{y,i}$ is the climatology forecast for the given forecast period. Similarly, we computed NSE for every nine nonoverlapping forecast periods, each having 10 days (2–11, 12–21, 22–31, 32–41, 42–51, 52–61, 62–71, 72–81, and 82–91 days). The NSE can range from $-\infty$ to 1, where values greater than 0 mean useful forecast skill (better than climatology). We compared the NSE score between two experiments (realistic and random ISMS) using a Student's t test and 15 years of data for each forecast period. We assigned any negative NSE values to zero for the t -test calculations.

Finally, we compare the contribution of ISMS, and climate forcing using signal to noise ratio metric (Guo et al. 2011):

$$\text{SNR} = \frac{V_s}{V_n} = \frac{\frac{1}{N} \sum_n (f_n - f_{..})^2}{\frac{1}{NE} \sum_n \sum_e (f_{en} - f_n)^2}, \quad (3)$$

where $f_{..} = (1/NE) \sum_{e=1}^E \sum_{n=1}^N f_{e,n}$ and $f_n = (1/E) \sum_{e=1}^E f_{e,n}$. The term V_s represents variability of ensemble mean, or the signal, and V_n is variability about the ensemble mean or the noise term. The null hypothesis of no predictability can be rejected at 95% level if $\text{SNR} \geq F_{N-1, N(E-1)}^{0.05} \times N - 1/N(E-1)$, where $F_{N-1, N(E-1)}^{0.05}$ is upper 5% threshold for F distribution with N and $N(E-1)$ degrees of freedom. The signal-to-total ratio is defined by $\text{STR} = \text{SNR}/(\text{SNR} + 1)$ and varies between 0 and 1.

3. Results

We have first compared the soil moisture in the CTRL experiment and its extension until 2018 with the SCAN and SMAP data because SMAP data are only available from 2015 to the present. Effects of initial hydrologic conditions and climate forcing on streamflow and soil moisture predictability are evaluated in the 15 selected years, also separately for five El Niño, five La Niña, and five normal years. Finally,

FIG. 6. Comparison of the SMAP and the NWM soil moisture data with ground-truth observations from SCAN and CRN Network. (a) Seven sites average monthly soil moisture and standard deviation from April 2015 to December 2018, and (b) basin-average monthly climatology comparing SMAP and the NWM for the same period. The x axis represents months from January to December, and the y axis represents soil moisture ($\text{m}^3 \text{m}^{-3}$). Error bars represent ± 1 standard deviation calculated from daily values in the corresponding month. The solid line is the monthly mean. SMAP is a 5-cm layer of soil moisture and NWM is 10-cm layer soil moisture. In (a), SCAN/CRN is a 5-cm layer of soil moisture.

we compare the potential predictability of soil moisture to that of streamflow.

a. Comparison with the SMAP and SCAN/CRN soil moisture data

The NWM simulates soil moisture climatology (mean) well, but it underestimates the soil moisture variability. Figure 5 shows the average and standard deviations of the SMAP 0–5-cm soil moisture from April 2015 to December 2018 and compares them with 0–10-cm soil moisture from the NWM. The topmost soil layer in the model is 0–10 cm, which is a limitation of this study. Since the data availability is small, we averaged the data for the entire period. The agricultural

FIG. 7. Effects of ISMS on seasonal streamflow predictability with perfect (observed) climate forcing. (first row) The RMSD with realistic (blue) and randomized (red) ISMS in all 15 years, (second row) five El Niño years, (third row) five La Niña years, and (fourth row) five normal years. Simulation initialization dates are the first day of January, April, July, and October, then averaged over 14 ensemble members and 15 selected years as a function of simulation sustained time (1–91) days. The solid lines are the results of Eq. (1). Shaded regions show a 95% confidence interval uncertainty range. Forcing is observation-based reanalysis NLDAS data.

subwatersheds located toward the south show a higher soil moisture than forested subwatersheds that are generally located in the north. The NWM generally captures large-scale spatial variations in the study domain. It is worth noting the drier soil moisture condition in the southeast corner of the study domain in both NWM and the SMAP (Fig. 5). The NWM considerably underestimates the soil moisture variability in the study domain. The soil moisture variability ranges from 0.02 to $0.04 \text{ m}^3 \text{ m}^{-3}$ in the NWM compared with the SMAP's range: 0.06 – $0.08 \text{ m}^3 \text{ m}^{-3}$.

The amplitude of seasonal cycle variability is weak in the NWM. Figure 6a shows a comparison of the NWM and SMAP with the in situ observations at seven sites from the SCAN and CRN networks. Data from the nearest grid point and the concurrent period are used for the analysis. The NWM shows comparable soil moisture with the observations during winter and spring seasons, but the NWM overestimates the soil moisture in the summer and fall seasons. Also, the NWM underestimates the soil moisture variability generally for all seasons. A comparison at the individual sites shows that SMAP performs better than the NWM data (Table S3). The SMAP has a positive bias in the winter and spring seasons (Fig. 6a). The positive bias is generally reduced during the summer and fall seasons. The SMAP soil

moisture variability is generally higher than that of the NWM.

Figure 6b shows a comparison of the seasonal cycle of basin average soil moisture between SMAP and the NWM. The lack of soil moisture variability in the NWM mainly stems from considerably smaller inter-seasonal soil moisture variability. The NWM shows a generally drier soil moisture condition in the winter and spring and a wetter condition in the summer and fall, compared with the SMAP soil moisture seasonal cycle.

b. Effects of ISMS on streamflow predictability with the perfect (observed) climate forcing

Figure 7 shows improvements in the streamflow forecast due to realistic ISMS effects under the observed climate forcing scenario. We compare the forecast error [RMSD, Eq. (1)] between E1 and E2 experiments (Table 2). The difference between these two experiments can be attributed to the ISMS effects under the observed climate forcing. A smaller value of the RMSD suggests a reduced forecast error and, thereby, improvement in the forecast. Results shown are for all 15 years together, five El Niño years, five La Niña years, and five normal years. The shaded region shows a 95% uncertainty range in the mean RMSD estimate and the respective experiments.

FIG. 8. Streamflow in all 15 years' NSE for every 10 days [see Eq. (2)]. The x axis is each of the 10 days, and the y axis is NSE. Blue is realistic ISMS; red is random ISMS. NSE values less than zero are replaced with zero. When the two distributions are significantly different using the t test with a 95% confidence level, their average values are marked with a solid star.

The realistic ISMS brings significant improvement in the forecasts, as seen by a significantly smaller RMSD in the realistic ISMS experiments compared with the random ISMS effects. The improvement in forecast is found for almost all 90 days for the summer and fall seasons. This result suggests that ISMS can improve forecast skill at a seasonal time scale. A closer look at the RMSD growth trajectory shows that the RMSD grows at a faster rate in the first 10 days of the forecast but then the RMSD declines during the winter and spring seasons (first two columns of Fig. 7). Initial growth in the RMSD can be related to the lag effect between the soil moisture and streamflow (discussed later). The difference between the realistic and random ISMS experiments also grows initially, but then declines as the forecast lead increases during the winter and the spring seasons, i.e., the climate forcing effects to become dominant with the increasing forecast lead time.

In the summer and fall seasons, ISMS plays a larger role in predicting the streamflow than the climate forcing. This can be seen from the RMSD growth as the difference between the E1 and the E2 experiments' RMSDs do not decline after the initial growth period. We also found that dry years have a higher predictability than wet years by segregating the

streamflow predictability in El Niño (wet), La Niña (dry), and normal years shown in rows 2–4 in Fig. 7. The RMSD differences between the E1 and the E2 experiments are larger for the dry years particularly in the winter and spring seasons. We found similar results by grouping the forecasts in wet, dry, and normal years (Fig. S3). We investigated the effects of the seasonal cycle, e.g., peak streamflow in the spring and low streamflow in the fall on the forecast skill using a normalized metric, the anomaly correlation (Murphy and Epstein 1989). We found that the anomaly correlations remain significantly higher in the E1 experiment compared with the E2 experiments in the fall season for all through the 90-day forecast, but they become similar after the first 40 days in the spring (Fig. S4).

Reduction in the RMSD due to ISMS effects brings in significant improvements in the NSE for seasonal streamflow forecast. We assessed the NSE metric using average ensemble results for the nine 10-day forecast periods [Eq. (2) and Fig. 8]. We adopted the 10-day forecast window period from the NWM medium forecast range. The realistic ISMS brings statistically significant improvements in NSE for all 90 days forecasts in the summer and fall seasons. The NSE score is close to one with the minimal spread in the realistic ISMS

FIG. 9. Effects of ISMS only on the seasonal streamflow predictability. Forcing is random climate forcing. (first row) The RMSD with realistic and randomized ISMS in all 15 years, (second row) five El Niño years, (third row) five La Niña years, and (fourth row) five normal years. Simulation initialization dates are the first day of January, April, July, and October, then averaged over 14 ensemble members and 15 selected years as a function of simulation sustained time (1–91 days). The dashed lines are the results of Eq. (1). Shaded regions show a 95% confidence interval uncertainty range.

experiments, whereas the mean NSE score drops to 0.9 or less in the summer and 0.8 or less for the fall season (rand. ISMS + obs. CF). The significant improvement in the NSE is limited to the first 30 days in the winter.

c. Effects of ISMS on streamflow predictability with random climate forcing

The initial hydrologic conditions can bring in significant improvement in the streamflow forecast even with random climate forcing. Figure 9 compares the forecast error between E3 and E4 experiments uses randomized climate forcing, i.e., the difference is attributable to ISMS only (Table 3). The RMSD of the realistic ISMS experiment remains significantly smaller than the random ISMS experiment for several days in the initial forecast period and then becomes similar to the random ISMS experiment at the longer lead. We define the ISMS predictability time scale as the first lead days when the signal becomes statistically indistinguishable, i.e., their 95% uncertainty range as shown by blue and red shaded regions overlap (Fig. 9). The predictability due to ISMS persists for ~60 days in the summer and ~20 days in the spring. In the winter, the predictability time scale is approximately 30 days. By comparing rows 2 and 3 in Fig. 9, we find that the predictability time scale is longer in La Niña

(dry) years than El Niño (wet) years for all four seasons. This result implies that realistic ISMS can improve the streamflow forecast skill despite limited skill in the climate forecast.

d. Role of the groundwater in streamflow predictability in the NWM model

We assessed the role of groundwater (GW) by randomizing the soil moisture state variables below 2 m (Table 2) and comparing it with the realistic ISMS effects under the observed climate forcing. Since the realistic ISMS experiments also included realistic GW states, and so the difference between the realistic ISMS experiment and randomized GW experiments can be attributed to the effects of the ISMS condition from surface to 2-m depth. When the RMSD of the randomized GW experiment becomes equal to or less than the realistic ISMS forecast experiment, then we call it a loss of predictability due to GW.

The GW contribution to the streamflow predictability is generally smaller than the full field ISMS contributions (Fig. 10). This can be seen by comparing the area between the blue and yellow curves with the area between blue and red curves in the figure. The summer and fall seasons show maximum groundwater contribution that is limited to the 0–40-days forecast

FIG. 10. Comparing the GW contribution to that of ISMS experiments, effects of ISMS on seasonal streamflow predictability with perfect (observed) climate forcing. As in Fig. 7, but with added data from randomized GW experiments (green) with observed climate forcing. Forcing is observation-based reanalysis NLDAS data. (first row) The RMSD with realistic and randomized ISMS in all 15 years, (second row) five El Niño years, (third row) five La Niña years, and (fourth row) five normal years. Simulation initialization dates are the first day of January, April, July, and October, then averaged over 14 ensemble members and 15 selected years as a function of simulation sustained time (1–91 days). The solid lines are the results of Eq. (1). Shaded regions show a 95% confidence interval uncertainty range.

period. Compared to the realistic ISMS experiment, a smaller RMSD in the randomized GW experiment suggests that even a small error in the 0–2-m soil moisture state can produce a larger error in the streamflow forecast than the randomized GW states (see the 40–90-days forecast in the fall). In the summer, the GW contribution is higher in the El Niño and normal years than La Niña years. The GW contribution is minimal in the winter and spring season. Considering the simplistic representation of the GW in the NWM, the GW results may not be robust here because groundwater was expected to have a longer predictability time scale (Sutton 2019).

e. Effects of ISMS on soil moisture predictability using perfect climate (observed) and random forcing

We investigated the effects of ISMS on the soil moisture predictability itself by comparing the 0–2-m soil moisture RMSD between the E1 and E2 experiments (Table 3, and Fig. 11). As shown in the last section, 0–2-m soil moisture condition contributes most to the streamflow predictability; and hence, the 0–2-m choice is justified for water resource application. We computed the basin average soil moisture RMSD using the LSM

gridded data (13.6 km). The realistic ISMS experiments have significantly smaller RMSD than the randomized ISMS experiments for all through the 90 days and in all four seasons; i.e., ISMS can bring in significant improvements in seasonal soil moisture forecasts in the ACT basin (first row in Fig. 11). Comparison of the second and third rows show that the soil moisture predictability is higher during La Niña (dry) years than El Niño (wet) years and the wet season (JFM and AMJ). During the dry seasons (JAS and OND), the differences between El Niño and La Niña years are minimal or slightly higher for the El Niño and in the fall season. In fact, normal years (fourth row) show a higher difference between E1 and E2 experiments than both El Niño and La Niña years in the fall season.

The characteristics of the soil moisture predictability are considerably different from that of streamflow predictability (Figs. 11 and 7). A major difference is that the RMSD of the soil moisture forecast is highest at the start of the forecast and then continuously declines for all through the 90 days of the forecast. This means that the effects of the ISMS perturbations are highest at the 0th day and then decreases as both the experiments receive the same climate forcing. To explain the characteristic

FIG. 11. Effects of ISMS soil moisture predictability using perfect (observed) climate forcing. It is 0–2-m soil moisture averaged over the basin. Forcing is observation-based reanalysis NLDAS data. (first row) The RMSD with realistic and randomized ISMS in all 15 years, (second row) five El Niño years, (third row) five La Niña years, and (fourth row) five normal years. Simulation initialization dates are the first day of January, April, July, and October, then averaged over 14 ensemble members and 15 selected years as a function of simulation sustained time (1–91) days. The solid lines are the results of Eq. (1). Shaded regions show a 95% confidence interval uncertainty range.

difference between the soil moisture and streamflow predictability, we performed lag-correlation analysis between soil moisture and soil moisture (autocorrelation) and soil moisture and streamflow (cross-correlation) in the CTRL experiment.

The soil moisture lag-autocorrelation decays with time consistent with the previous study (Kumar et al. 2019), but the soil moisture–streamflow lag correlation first increases to reach a peak value several days after the soil moisture anomalies put into the system and then decays (Fig. 12). This result makes physical sense because there can be several days of lag effects for initial soil moisture perturbations to propagate through the soil system, update the water table, and drive surface and subsurface runoff to the streams. The cross correlation between the soil moisture and the streamflow increases in the first several days, e.g., 10 days for the summer, then either remain high in the summer and fall seasons or decreases in the winter and spring seasons. The RMSD growth and decay in Figs. 7 and 11 generally follow the corresponding lag correlation structure shown in Fig. 12. We limited our lag correlation to 20 day because longer lags will have significant overlaps from one season to the next season.

The effects of the ISMS on the soil moisture forecast are generally smaller under the randomized climate

forcing (Fig. 13). However, when it matters most, i.e., during dry years and a dry season, the ISMS can bring in statistically significant improvement in the soil moisture forecast skill despite limited skill or no skill in the climate forecast (see La Niña years and summer and fall RMSD difference in Fig. 13). By comparing Figs. 13 and 9, we hypothesize that the climate forcing plays a greater role in improving the soil moisture forecast skill than that of streamflow, whereas ISMS conditions play a greater role for the streamflow forecast. We make a quantitative assessment of this hypothesis in the next subsection.

f. Relative importance of factors contributing to streamflow and soil moisture predictability

The ISMS plays a larger role in improving seasonal streamflow forecast than the soil moisture forecast. Figure 14 compares relative importance of the four sources of predictability: 1) effects of the ISMS conditions only, 2) effects of ISMS with observed climate forcing, 3) effects of the climate-forcing anomaly only, and 4) effects of climate forcing anomaly with realistic ISMS using signal to total ratio metric as discussed in the method section. For quantitative assessment, we aggregated the results for 0–90 days as the

FIG. 12. Pearson sample linear cross correlations between soil moisture (0–2 m) and streamflow with soil moisture as the lead (blue dotted lines), and the autocorrelation for the soil moisture (green dotted lines). We computed the correlation using CTRL experiment data from 1980 to 2016. The x axis is lag days from 0 to 20. Soil moisture is basin area average. Streamflow is at watershed outlet streamflow.

fraction of total area (1×90) contributed by each source of the predictability, as shown in Table 4. The figure left column is for the streamflow forecast at the watershed outlet, and the right column is for basin-average 0–2-m soil moisture.

ISMS contributes significantly to the seasonal streamflow forecast. During the summer and fall seasons, ISMS contributes to the majority of the seasonal streamflow forecast skill (Fig. 14 and Table 4). For example, the ISMS contributes 65% of the forecast skill compared with the 30% contribution by the climate forcing in JAS season (Table 4). Contributions of the ISMS only effects are also generally higher than that of ISMS with CF in the JAS season. Hence, we conclude that ISMS is a major source of seasonal streamflow forecast skill in the NWM, and the contribution of the ISMS generally comparable or even higher than that of climate forcing at seasonal time scale.

The climate forcing plays an equally important role in the soil moisture forecast as the ISMS (Fig. 14 and Table 4). For example, the ISMS contributes 48% of the forecast skill, and climate forcing contributes to 49% in the summer season (JAS). It is worth noting that the ACT is a wet basin, and contributions of the ISMS can be higher in dry basins.

4. Summary and discussions

This study finds that ISMS has a greater impact on streamflow predictability than soil moisture predictability at the seasonal time scale. The effects of ISMS are comparable or even greater than that of CF for seasonal streamflow forecast in dry seasons. This is a new result compared with a previous study where authors conducted subseasonal streamflow and soil moisture forecast experiments using a simple water balance model and for 22 catchments in Switzerland (Orth and Seneviratne 2013b). They found that ISMS has a greater impact on soil moisture predictability than on streamflow predictability. Our study uses the coupled hydrological model that included two-way coupling between a physically based water and energy balance model (Noah-MP) and hydrology model for overland and subsurface flow, and an additional stream/lake model for flow routing in the streams. A bigger improvement in the streamflow forecast skill can be attributable to the complex model structure that allows realistic streamflow simulations.

This study also provides a physically plausible explanation of greater improvement in the streamflow forecast than soil moisture forecast. The explanation

FIG. 13. Effects of ISMS only on soil moisture predictability using random forcing. It is 0–2-m soil moisture averaged over the basin. (first row) The RMSD with realistic and randomized ISMS in all 15 years, (second row) five El Niño years, (third row) five La Niña years, and (fourth row) five normal years. Simulation initialization dates are the first day of January, April, July, and October, then averaged over 14 ensemble members and 15 selected years as a function of simulation sustained time (1–91 days). The dashed lines are the results of Eq. (1). Shaded regions show a 95% confidence interval uncertainty range.

is based on lag effects between soil moisture and streamflow anomalies (Fig. 12). A longer lag time to reach peak correlation between soil moisture anomalies and streamflow anomalies and a slower decay of the cross correlation lead to a higher impact on streamflow predictability, e.g., winter versus summer in Fig. 12. Hence, we hypothesize that streamflow forecast skill can be significantly improved beyond the skill in the seasonal climate forecast from two additional sources: 1) soil moisture memory effects (Kumar et al. 2019) and 2) lag effect between soil moisture and streamflow anomalies.

The seasonal cycle of soil moisture variability is muted in the NWM model compared with the SMAP data. This result is consistent with a previous study where authors have compared soil moisture variability simulated by the Noah land surface model with the SCAN sites in Alabama (see Fig. 7 in Xia et al. 2015). Dirmeyer et al. (2016) also found that the Noah land surface model generally underestimate the soil moisture variability. In Alabama, the problem of underestimated soil moisture variability can be larger due to the presence of karst geologic feature that allows rapid drainage of soil water from the bottom of the soil column and is not parameterized in Noah land surface model (Kuniansky et al. 2016; Norton 2018). The underestimated soil moisture variability can lengthen the

soil moisture memory time scale, and thereby can affect streamflow predictability (Dirmeyer et al. 2016; Orth and Seneviratne 2013b). Therefore, it is likely that our predictability estimate is somewhat positively biased. Model parameterization improvements can bring in further refinements in our predictability estimates.

Our result can be applied to other basins in the southeastern United States. For example, Yossef et al. (2013) used a different model, the PC Raster Global Water Balance model, to assess the forecast skill and found that initial hydrologic conditions can improve the forecast skill up to 1–2-months lead time in the Mississippi, Missouri, and Arkansas River basins. Shukla and Lettenmaier (2011) used the Variable Infiltration Capacity model and found that seasonal climate forecast dominates skill beyond 1-month lead time in the southeastern United States Wood et al. (2016) used the Sacramento Soil Moisture Accounting and SNOW-17 watershed models and found relatively higher impacts of climate forcing than initial hydrologic conditions on seasonal streamflow forecast. Thus, results presented in the study can be sensitive to the WRF-Hydro model, and intermodel spread or uncertainty in the streamflow predictability can be explored further.

FIG. 14. (left) Signal-to-total ratio of streamflow and (right) 0–2-m soil moisture forecasts in the NWM seasonal forecast experiments. The solid and dotted blue lines represent realistic ISMS with the observed and random climate forcing, respectively (E1 and E3, Table 2). The solid and dotted red lines represent random ISMS with the observed and random climate forcing, respectively (E2, and E4). Green regions: A represents the effect of ISMS only (with random climate forcing), and B is the effect ISMS under observed climate forcing. Blue regions: C represents the effect of climate forcing only (with random ISMS), and D is the effect of climate forcing with realistic ISMS. The dashed purple line is threshold with 0.05 significant level. See the text for details.

The forecast error (RMSD) increases with increasing lead time in the fully coupled climate model seasonal forecast experiment (Dirmeyer et al. 2013; Kumar et al. 2014). In this study, we used the observed climate forcing to drive land surface and hydrology model, and hence the forecast error decreased with the increasing lead time, particularly in the winter and spring when

climate forcing has a greater effect (Fig. 7 and Table 4). The streamflow predictability in the fully coupled system can be further investigated.

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TABLE 4. Fraction of total seasonal forecast skill contributed by the ISMS and CF effects. These two sources are further subdivided into ISMS only, ISMS with observed CF, CF only, and CF with realistic ISMS conditions.

Season	ISMS (ISMS only/ISMS with obs CF)	Climate forcing (CF) (CF only/CF with realistic ISMS)
Seasonal streamflow forecast		
JFM	30 (13/17)	66 (51/15)
AMJ	19 (07/12)	76 (67/09)
JAS	65 (36/29)	30 (15/14)
OND	53 (27/26)	40 (29/11)
AVG	41.75 (20.75/21)	53 (40.5/12.25)
Seasonal soil moisture (0–2.0 m) forecast		
JFM	27 (10/17)	71 (53/18)
AMJ	14 (03/11)	83 (75/08)
JAS	48 (21/27)	49 (26/23)
OND	39 (16/23)	58 (39/19)
AVG	32 (12.5/19.5)	65.25 (48.25/17)

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