

Sensitivity of Hydrological Simulations of Southeastern United States Watersheds to Temporal Aggregation of Rainfall

SATISH BASTOLA

Center for Ocean–Atmospheric Prediction Studies, The Florida State University, Tallahassee, Florida

VASUBANDHU MISRA

Department of Earth, Ocean and Atmospheric Sciences, and Center for Ocean–Atmospheric Prediction Studies, The Florida State University, Tallahassee, Florida

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ABSTRACT

This study investigates the sensitivity of the performance of hydrological models to certain temporal variations of precipitation over the southeastern United States (SEUS). Because of observational uncertainty in the estimates of rainfall variability at subdaily scales, the analysis is conducted with two independent rainfall datasets that resolve the diurnal variations. In addition, three hydrological models are used to account for model uncertainty. Results show that the temporal aggregation of subdaily rainfall can translate into a markedly higher volume error in flow simulated by the hydrological models. For the selected watersheds in the SEUS, the volume error is found to be high (~35%) for a 30-day aggregation in some of the selected watersheds. Hydrological models tend to underestimate flow in these watersheds with a decrease in temporal variability in precipitation. Furthermore, diminishing diurnal amplitude by removing subdaily rainfall corresponding to times of climatological daily maximum and minimum has a detrimental effect on the hydrological simulation. This theoretical experiment resulted in the underestimation of flow, with a disproportionate volume error (of as high as 77% in some watersheds). Observations indicate that over the SEUS variations of diurnal variability of rainfall explain a significant fraction of the seasonal variance throughout the year, with especially strong fractional variance explained in the boreal summer season. The results suggest that, should diurnal variations of precipitation get modulated either from anthropogenic or natural causes in the SEUS, there will be a significant impact on the streamflow in the watersheds. These conclusions are quite robust since both observational and model uncertainties have been considered in the analysis.

1. Introduction

The impact of spatial and temporal variability of rainfall on the water cycle has long been identified as an important issue in simulating hydrological responses of river basins. A number of studies in the past have looked into the influence of these rainfall characteristics in simulating hydrological response (e.g., Krajewski et al. 1991; Finnerty et al. 1997; Littlewood and Croke 2008; Wang et al. 2009; Bastola and Murphy 2013). Krajewski et al. (1991) observed that the temporal

aggregation of rainfall data has a profound effect on hydrological response, especially on the timing and the magnitude of peak flow, as compared to the spatial resolution of the data. Michaud and Sorooshian (1994) found that aggregating the rainfall data from 4 min to 1 h could lead to a bias (underestimation) of nearly 80% in the simulation of a peak flow event. This study investigates the sensitivity of the hydrological response to some well-known temporal variation of precipitation in the southeastern United States (SEUS).

Several authors in the past (e.g., Giambelluca and Oki 1987; Alley 1984) have noted that using a monthly interval of rainfall as input to hydrological models tends to result in overestimation of actual evapotranspiration and underestimation of groundwater recharge. Furthermore, bias may also result from sensitivity of hydrological model parameters to model time step.

Corresponding author address: Vasubandhu Misra, Department of Earth, Ocean and Atmospheric Sciences, Florida State University, 1017 Academic Way, 404 Love Building, Tallahassee, FL 32306-4520.
E-mail: vmisra@fsu.edu

TABLE 1. Brief details of the observed rainfall datasets.

Dataset	Reference	Period available	Spatial resolution	Temporal resolution	Domain available
CMORPH	Joyce et al. (2004)	2003–11	0.25°	3-hourly	Global
NCEP Stage IV	Lin and Mitchell (2005)	2003–11	4 km	1-hourly	Continental United States

O’Loughlin et al. (2013) and Cullmann et al. (2006) provide empirical evidence that the dependency of model parameters on time step may introduce biases in prediction if the model is calibrated with a different time step than that used for simulating flow.

The variability in precipitation propagates through hydrological models. However, the variability in streamflow may diffuse, depending upon the watershed characteristics and the size of the watershed. This is because hydrological processes occur at a wide range of scales (e.g., unsaturated flow, flash floods; Blöschl and Sivapalan 1995). Runoff diffusion is likely to be less in watersheds where the gradient is steep and more in relatively large watersheds.

The current generation of global climate models (GCMs) have deficiencies in simulating the rainfall variability with a fidelity that can yield useful hydrological simulation (e.g., Christensen and Christensen 2003; Meehl et al. 2007; Maraun et al. 2010). More recently, dynamically downscaled datasets from global reanalysis have shown some skill in reproducing the observed diurnal variability of meteorological variables such as rainfall and surface winds over the SEUS (Stefanova et al. 2012; Misra et al. 2011).

The sensitivity of the response of the hydrological models to various modes of rainfall variability is investigated by using aggregated observed rainfall at different time intervals. The specific time scales of precipitation targeted in this study are diurnal scales, mesoscales, synoptic scales, and intraseasonal scales. Through specially designed numerical sensitivity experiments, we examine the importance of these temporal scales to the fidelity of hydrological simulations in 28 watersheds of the SEUS.

2. Methodology

Averaging of the model forcing, for example, aggregation of rainfall in time, impacts hydrological simulation mainly through the loss of information of the hydrological system’s process dynamics. The aggregation of precipitation data causes a gradual loss of temporal information while conserving the total volume, that is, the rainfall intensity is uniformly distributed over each sampling period.

a. Rainfall datasets

Where there is lack of reliable subdaily precipitation data, the examination of the diurnal cycle of precipitation

is hindered. The observation network of automatic rain gauge sensors offers the most feasible way to collect hourly precipitation data covering the spatial domain of interest. However, datasets with both a sufficiently long time span and a high spatial density are limited. In this study we use two datasets of observed rainfall (Table 1) that resolve the diurnal variations of rainfall over the SEUS. The two datasets cover a relatively short span of time (2003–11), but they are available for an overlapping period and they are independent, which gives an opportunity to ascertain any associated observational uncertainty.

Subdaily time series of precipitation from two high-resolution precipitation products, the Climate Prediction Center’s morphing method (CMORPH) and the National Centers for Environmental Prediction (NCEP) Stage IV, are selected. CMORPH (Joyce et al. 2004) combines estimates from low-orbiter satellite microwave observations with geostationary infrared data to produce global precipitation analyses at 3-hourly intervals and at 0.25° horizontal-grid resolution. CMORPH data are available over the domain of 60°S–60°N. Similarly, hourly data from NCEP Stage IV, produced by the National Weather Service River Forecast Centers (RFCs) (Lin and Mitchell 2005), are used in this study. NCEP Stage IV is a multisensor (radar and rain gauge) precipitation estimate. Hourly precipitation estimates from radars (WSR-88D) are compared to gauge values, and a bias is calculated and applied to the radar field. In NCEP Stage IV, 1-h precipitation from the regional multisensor and 6-h analysis from 12 RFCs are mosaicked. The radar and gauge fields are combined and quality controlled on a 6-hourly basis, which is done manually at the RFCs. NCEP Stage IV data have been used widely as a reference dataset for verification of model output (e.g., Misra et al. 2011; Clark et al. 2007). Besides serving as an alternative to NCEP Stage IV rainfall datasets, CMORPH is also selected because it shows high correspondence with the data from the WSR-88D radars, especially over the SEUS, thereby showing the ability to represent the diurnal cycle of precipitation over the SEUS (e.g., Janowiak et al. 2005). These two datasets serve as our reference datasets.

b. Study region

For the hydrological simulations, we select 28 watersheds (Table 2) in the SEUS from the Model Parameter

TABLE 2. Brief details of the selected watersheds in SEUS.

Serial no.	Basin (USGS ID)	State	Lon	Lat	Elevation (ft)	Area (sq. miles)	River system
1	2456500	AL	-86.98	33.71	258	885	Locust Fork at Sayre, AL
2	3574500	AL	-86.31	34.62	570	320	Paint Rock River near Woodville, AL
3	2414500	AL	-85.56	33.12	599	1675	Tallapoosa River at Wadley, AL
4	2296750	FL	-81.88	27.22	6	1367	Peace River at Arcadia, FL
5	2329000	FL	-84.38	30.55	59	1140	Ochlockonee River near Havana, FL
6	2365500	FL	-85.83	30.78	39	3499	Choctawhatchee River at Caryville, FL
7	2375500	FL	-87.23	30.97	28	3817	Escambia River near Century, FL
8	2236000	FL	-81.38	29.01	0	3066	St. Johns River near Deland, FL
9	2192000	GA	-82.77	33.97	356	1430	Broad River near Bell, GA
10	2202500	GA	-81.42	32.19	17	2650	Ogeechee River near Eden, GA
11	2217500	GA	-83.42	33.95	555	392	Middle Oconee River near Athens, GA
12	2347500	GA	-84.23	32.72	334	1850	Flint River near Culloden, GA
13	2383500	GA	-84.83	34.56	616	831	Coosawattee River near Pine Chapel, GA
14	2339500	GA	-85.18	32.89	551	3550	Chattahoochee River at West Point, GA
15	2387000	GA	-84.93	34.67	622	687	Conasauga River at Tilton, GA
16	2387500	GA	-84.94	34.58	604	1602	Oostanaula River at Resaca, GA
17	2102000	NC	-79.12	35.63	185	1434	Deep River at Moncure, NC
18	2118000	NC	-80.66	35.85	663	306	South Yadkin River near Mocksville, NC
19	2126000	NC	-80.18	35.15	212	1372	Rocky River near Norwood, NC
20	2138500	NC	-81.89	35.79	1203	67	Jinville River near Nebo, NC
21	3443000	NC	-82.62	35.30	2060	296	French Broad River at Blantyre, NC
22	3451500	NC	-82.58	35.61	1950	945	French Broad River at Asheville, NC
23	3504000	NC	-83.62	35.13	3072	52	Nantahala River near Rainbow Springs, NC
24	3512000	NC	-83.35	35.46	1843	184	Oconaluftee River at Birdtown, NC
25	3550000	NC	-83.98	35.14	1556	104	Valley River at Tomotla, NC
26	2156500	SC	-81.42	34.60	290	2790	Broad River near Carlisle, SC
27	2165000	SC	-82.18	34.44	451	236	Reedy River near Ware Shoals, SC
28	3465000	TN	-83.16	35.98	1011	1858	French Broad River near Newport, TN

Estimation Experiment (MOPEX) (Schaake et al. 2006) dataset that are stated to be free of or minimally affected by water management (Schaake et al. 2006). The daily potential evapotranspiration data for the selected watersheds are also obtained from MOPEX.

3. Experiment design

In this study, a number of forcing (test) datasets are constructed for the hydrological models. The NCEP Stage IV-based test dataset is created by removing separately the variability at different scales (i.e., aggregating data at 3-h and 1-, 2-, 5-, 15-, and 30-day intervals). For CMORPH data, which are available at 3-h intervals, it is aggregated at 1-, 2-, 5-, 15-, and 30-day intervals. Another two sets of daily rainfall dataset are constructed from both CMORPH and NCEP Stage IV by aggregating subdaily rainfall: one is constructed by aggregating subdaily rainfall to daily totals (which is identical to 1-day aggregated data), and the other is created by removing all rainfall events that occurred at the time of daily climatological maximum and minimum. The time of maximum and minimum daily rainfall for each Julian day of the year is determined uniquely for each grid point to compute the climatology. Any form of aggregation will carry a significant residual of

diurnal variation. However, creating the daily data by eliminating rainfall observed at the diurnal zenith and nadir will ensure the most significant diminishment of the diurnal signal, which will offer the cleanest way to assess the impact of diurnal variation of rainfall on the hydrology. The latter dataset is designed as a theoretical experiment to deliberately eliminate a larger fraction of the diurnal variations to understand their true impact on the hydrological simulation. As will be shown later, diurnal variations are significant components of the SEUS. The sensitivity of the hydrological model performance is evaluated by analyzing the discrepancies between the outputs of the hydrological models forced with the test data and with the control data. The flow simulated with the original NCEP Stage IV and CMORPH data is regarded as control data. The subdaily rainfall data (see Table 1) constitute the control input data, and the flow simulated with the control input data constitutes the control output data. The schematic of the experimental design is shown in Fig. 1.

4. The hydrological models

Because of the spatial and temporal aggregation of the hydrological process inherent in a typical hydrological model, the parameters of hydrological models

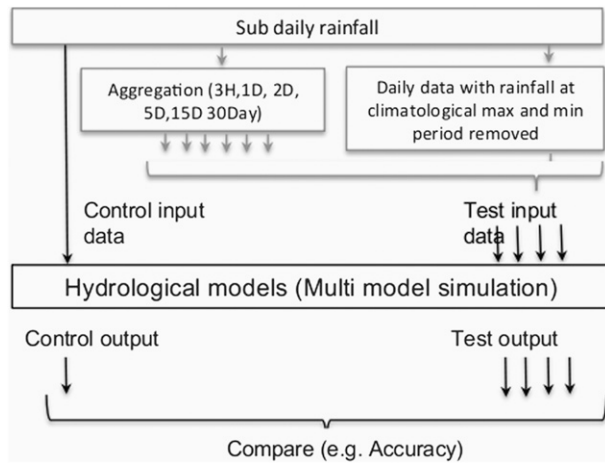


FIG. 1. Schematic of the experiment design.

are uncertain (e.g., Beven and Binley 1992). Consequently, the inferences based on hydrological models are conditional upon the choice of hydrological model structure and parameterization. To account for such uncertainty, we have used Generalized Likelihood Uncertainty Estimation (GLUE) framework (Beven and Binley 1992). GLUE method (Beven and Binley 1992) has been widely used to quantify the uncertainties in hydrological models. The GLUE method is based on the premise that for hydrological models, a larger combination of model parameters can produce equally an acceptable simulation. From the large number of conceptual hydrological models available for modeling flow in catchments, we select three conceptual rainfall runoff models: the Hydrological Model (HyMOD; Boyle 2001), the Nedbør–Afstørnings Model (NAM; Madsen 2000), and the Tank model (TANK; Sugawara 1995). Each model varies in its conceptualization of key hydrological processes and model complexity, mainly related to the number of parameters requiring calibration. NAM and TANK describe the behavior of each component of the hydrological cycle at the catchment level

by using a group of conceptual stores, whereas HyMOD is a variable contributing area model. In HyMOD spatial variability in soil moisture is modeled using a probability distribution function. A detailed explanation of the models and their frameworks can be found in Bastola et al. (2011a). The calibrated parameters, that is, the behavioral basin simulators, for all the models and catchments (i.e., 28 watersheds of the SEUS) are taken from a study by Bastola and Misra (2013).

5. Results

a. Rainfall datasets

The aggregation of data at 3-h (for NCEP Stage IV only) and 1-, 2-, 5-, 15-, and 30-day intervals in both CMORPH and NCEP Stage IV results in a progressive decrease in rainfall variability for all seasons. Figure 2 indicates that rainfall variability reduces as the scale of aggregation increases. For the study domain, the decrease in variability when moving from aggregation levels of 3 h to 1 day is the highest. This implies the significant contribution of the diurnal variations to the SEUS seasonal rainfall variability. Figures 3 and 4 show the fraction of diurnal variance (f) that explains the total seasonal variance from NCEP Stage IV and CMORPH, respectively.

This fraction (f) is computed as the ratio of variances

$$f = \frac{(IMF_d)^2}{(IMF_t)^2}, \tag{1}$$

where IMF_d is the intrinsic mode function (IMF) isolated for diurnal variability and IMF_t is the intrinsic mode function of the rest of the modes that comprise the season. These IMFs are computed from ensemble empirical mode decomposition (EEMD) analysis following Wu and Huang (2009) and Wu et al. (2011). It is clear from Figs. 3 and 4 that the diurnal variability of rainfall

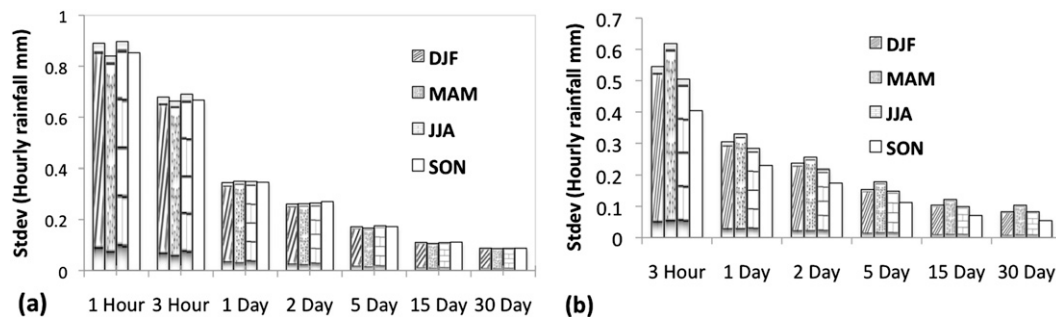


FIG. 2. Variation in standard deviation of rainfall data (aggregated across 28 watersheds) with level of aggregation of data (e.g., 3-h and 1-, 2-, 5-, 15-, and 30-day intervals) for (a) NCEP Stage IV and (b) CMORPH.

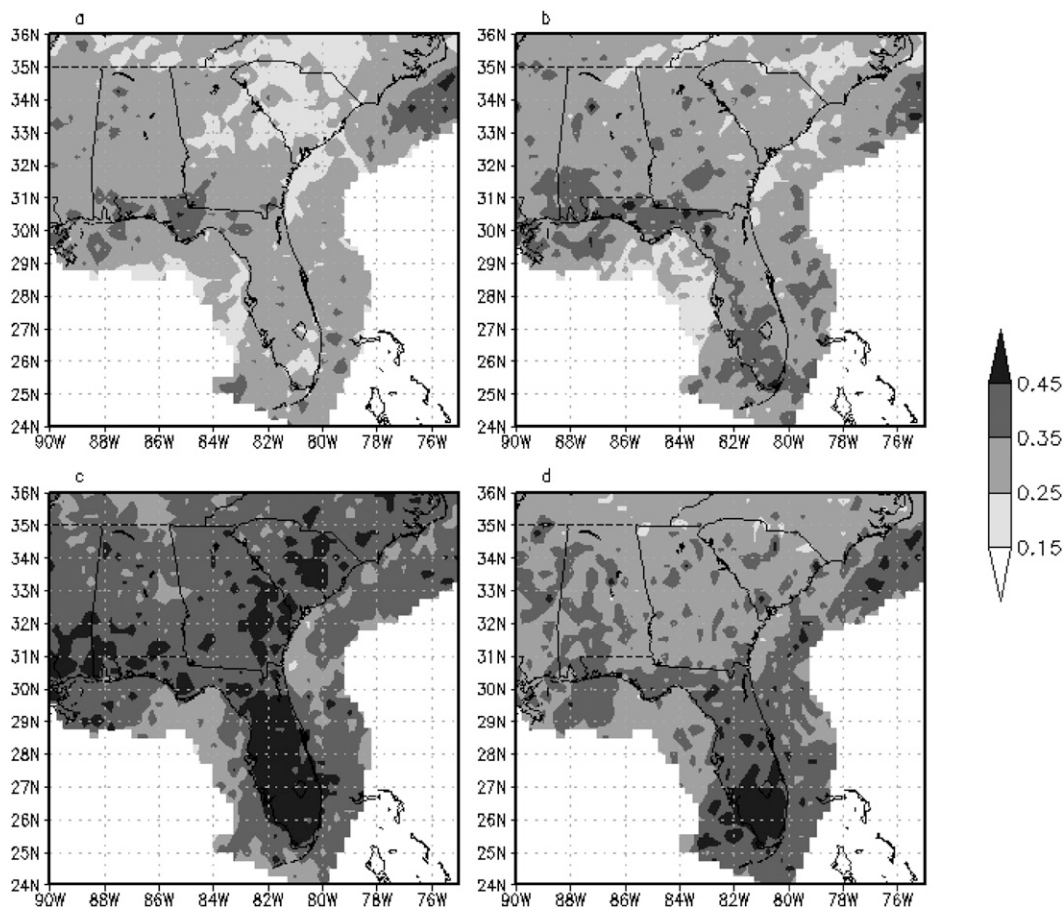


FIG. 3. The fraction of diurnal variability that explains the total seasonal variability in (a) December–February, (b) March–May, (c) June–August, and (d) September–November for NCEP Stage IV data.

explains a significant fraction of the summer seasonal rainfall variability and relatively less in the spring season. In the fall and winter seasons, the fractional variance explained by diurnal variability is comparatively low, but nonetheless significant, especially in the lower latitudes of the SEUS. Qualitatively, the two rainfall datasets in Figs. 3 and 4 suggest that diurnal variability of rainfall explains a significant fraction of the seasonal rainfall variation; however, they show considerable differences in their magnitude, which reflects the observational uncertainty of these rainfall estimates. Therefore, our analysis uses both datasets to account for this observational uncertainty.

b. Hydrological simulation

In comparison to the flow simulated with hourly data, the aggregated rain data result in loss of performance of the hydrological simulation (Fig. 5). From among the 28 selected watersheds, we only show the results from five watersheds [U.S. Geological Survey (USGS) identification numbers (IDs) 2296750, 2329000, 2202500, 2126000, and

3455000, shown in Table 2] having similar size but located at different latitudes for conciseness (Fig. 5). The loss, defined as the decrease in model performance measured with respect to the control simulation, associated with 3-hourly aggregation is negligible. However the loss associated with 1-day aggregation, especially in terms of Nash–Sutcliffe efficiency (NSE; Nash and Sutcliffe 1970), is significant. This loss in performance with 1-day aggregation indicates that diurnal scale variability has a marked impact on hydrological model performance in these SEUS watersheds. The loss in performance associated with 2- and 5-day aggregation levels is also predominately in terms of NSE. It should be mentioned that NSE is strongly impacted by any modulation to the peak events. Therefore, as we aggregate the rainfall to coarse time scales, the peak rain events are greatly reduced (smoothed out), as reflected in the significant decrease in NSE. This aggregation of rainfall translated into a volume error of +15% (overestimation flow) to –35% (underestimation of flow) in some of the watersheds in the SEUS.

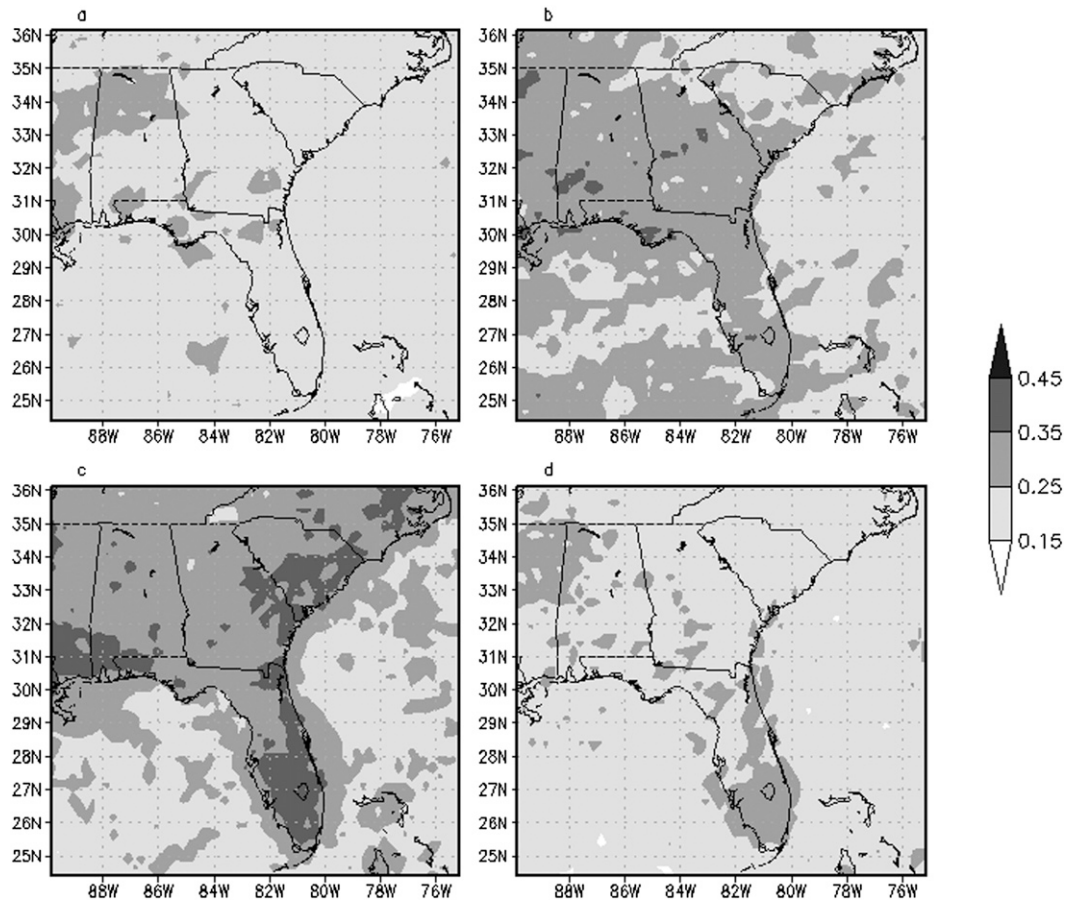


FIG. 4. As in Fig. 3, but for CMORPH.

Averaged over all 28 watersheds, the volume error for CMORPH (NCEP Stage IV) in runoff estimation is -11% (-7%) and -16% (-13%) for 15- and 30-day aggregations. The volume error associated with 1-, 2-, and 5-day aggregations is not shown, as they are not significant. The progressive increase in volume error of runoff estimation with larger temporal aggregation can

be attributed to change in the actual evapotranspiration (e.g., Giambelluca and Oki 1987; Alley 1984). Figure 6 shows the estimated evapotranspiration, a primary hydrological abstraction, for four different aggregation levels for NCEP Stage IV data (results for CMORPH are not shown as the effects are similar). Hydrological models used in this study showed the tendency to

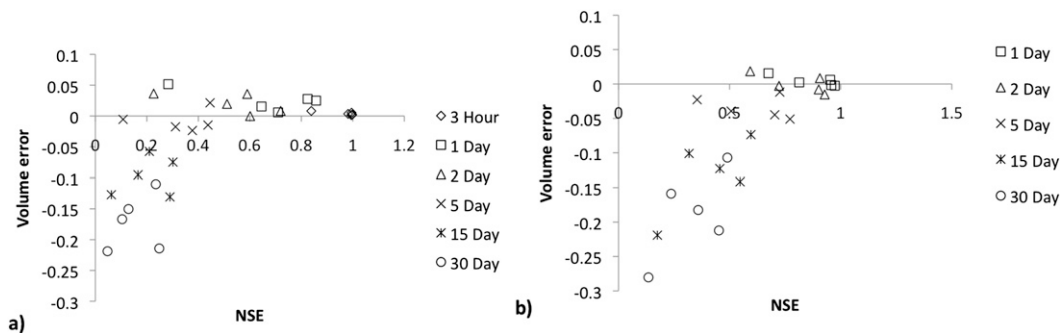


FIG. 5. The volume error and NSE for five selected watersheds (USGS IDs 2296750, 2329000, 2202500, 2126000, 3455000) from temporal aggregation of (a) NCEP Stage IV and (b) CMORPH.

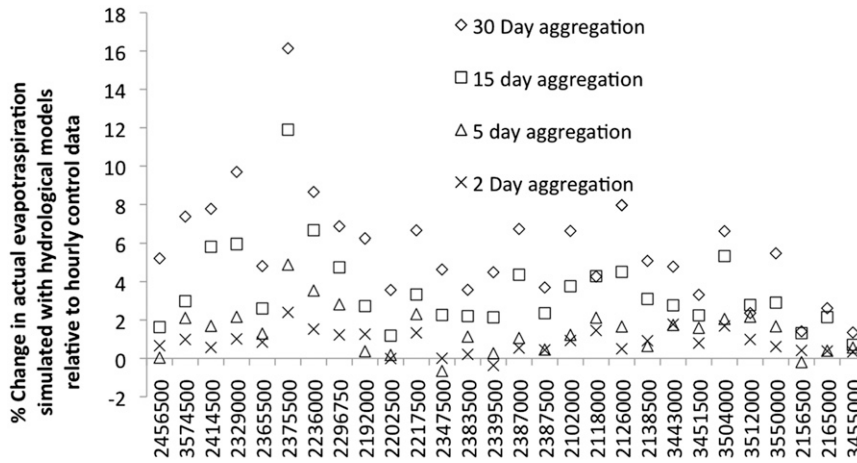


FIG. 6. The actual evapotranspiration estimated with rainfall runoff models forced with rainfall data aggregated at 30-, 15-, 5-, and 2-day time steps.

overestimate actual evapotranspiration, with respect to simulation conducted with an hourly time step (control simulation), by nearly 6%, 3%, 1%, and 0.5% for the 30-, 15-, 5-, and 2-day aggregations, respectively. Simulation of higher values of evapotranspiration (i.e., water abstraction) is responsible for underestimation of flow when the rainfall aggregation level is increased from hourly to monthly. Figure 7 shows the average (across watersheds) increase in actual evapotranspiration for the three models used in this model. This increase in actual evapotranspiration with aggregation level is generic among models used in this study; however, they vary in magnitude. Furthermore, the loss in the performances of the hydrological model and volume error also can be partly attributed to the scale dependencies of important hydrologic parameters (Littlewood and Croke 2008).

The progressive degradation of model performance with aggregation from an ideal point indicates the importance of the rainfall variability in simulating hydrological response. The ideal point in model performance space is defined as a point having NSE equal to one and volume error equal to zero. The performance is measured in terms of Euclidian distance from this ideal point, for example, the smaller the value, the closer it is to the ideal point and vice versa. However, as the watersheds included in this study are relatively large, the temporal aggregations at short intervals do not seem to affect the streamflow as much (Fig. 8). This feature of the watersheds in the SEUS could be especially beneficial in terms of seasonal predictability in summer and fall seasons when the frequency of spatially small and temporally short mesoscale events of rainfall is high and is harder to simulate by climate models (Stefanova et al. 2012). In winter and spring seasons, the SEUS typically

experiences synoptic scale weather events (3–5-day time scales), which, when aggregated, has a significant impact on the hydrology of the SEUS (Fig. 8).

Figure 8 summarizes the seasonal loss in performance with temporal aggregation of data. The loss in performances (across watersheds) increases with the level of aggregation. Moreover, this holds true for each of the four seasons. The size of the catchment and the temporal scale preferred for hydrological models are closely related (e.g., Blöschl and Sivapalan 1995). This is reflected in terms of the volume error, which tends to decrease with the increase in catchment size and level of aggregation. Similarly, for the structure of the hydrological models and catchments included in this study, the volume error tends to increase with increase in variability in input data. However, because of the limited sample of

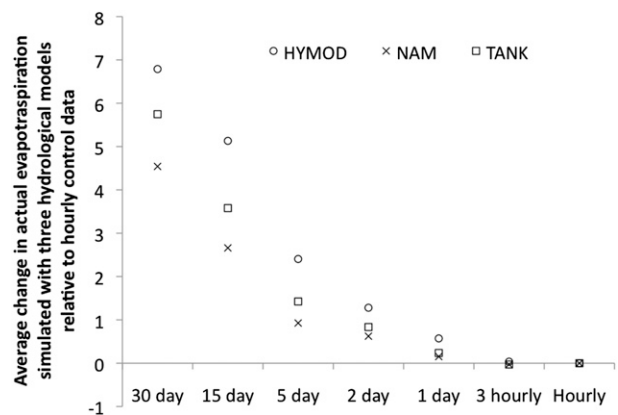


FIG. 7. The actual evapotranspiration estimated with three rainfall runoff models, namely, HyMOD, NAM, and TANK forced with rainfall data aggregated at 30-, 15-, 5-, 2-, and 1-day and 3-h time steps.

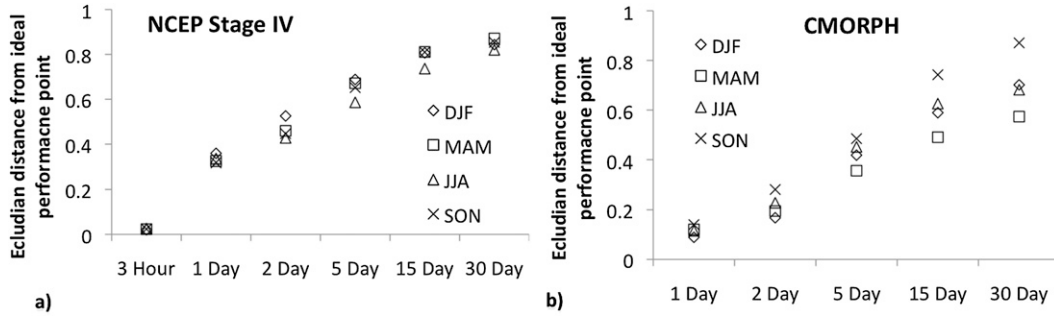


FIG. 8. Loss in model performance, measured in terms of Euclidian distance, with level of aggregation. The Euclidian distance is the average distance from models' ideal performance (i.e., NSE = 1 and volume error = 0) for (a) NCEP Stage IV and (b) CMORPH.

catchments, the correlations are not significant for all levels of aggregation.

In a follow-up experiment, two new daily rainfall datasets are constructed from NCEP Stage IV and

CMORPH. The new dataset is constructed at daily intervals by aggregating the 3-hourly rainfall. However, for one set the rainfall at the climatological time of diurnal zenith [climatological maximum (CLMA)] and

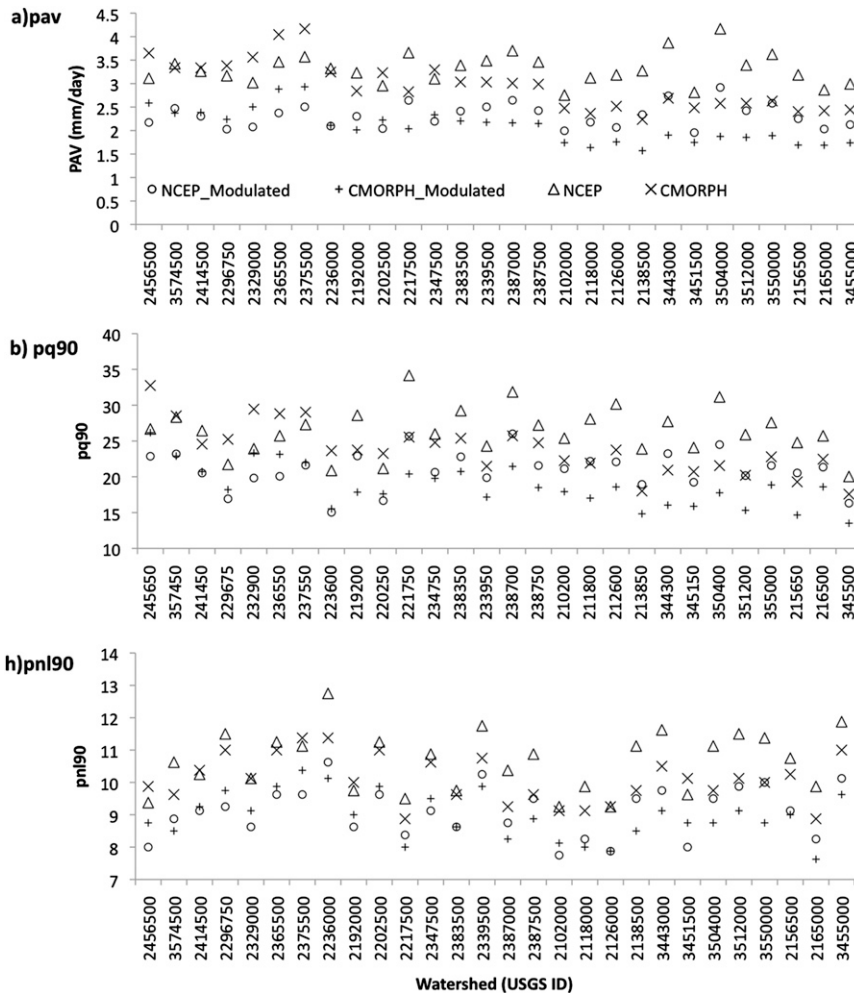


FIG. 9. Comparison of unmodified and modified NCEP Stage IV and CMORPH rainfall data using indices from STARDEX: (a) mean climatological precipitation (mm day^{-1}) (pav), (b) 90th percentile of rain day amounts (mm day^{-1}) (pq90), and (c) number of events greater than long-term 90th percentile of rain days (pnI90).

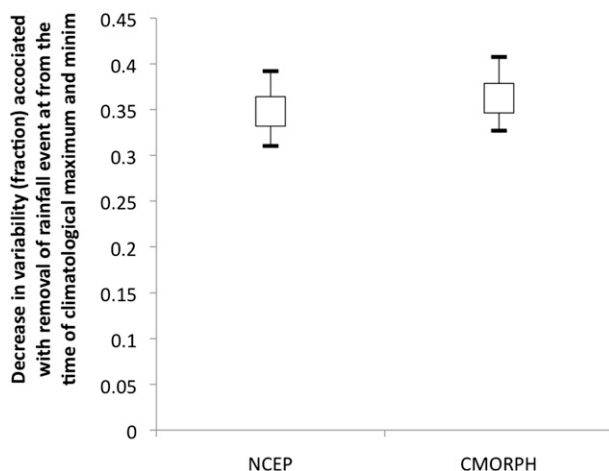


FIG. 10. Change in temporal variability (fraction) in rainfall for NCEP Stage IV and CMORPH when constructing daily rainfall by removing rainfall corresponding to times of daily climatological maximum and minimum.

nadir [climatological minimum (CLMI)] is excluded in computing the daily aggregation, and for the other the entire event is included. The new dataset is then propagated through the hydrological models, and the simulated flow is compared with the flows simulated with NCEP Stage IV and CMORPH that were constructed without excluding CLMA and CLMI events (control simulations). The removal of CLMA and CLMI rainfall prior to construction of daily data allows an alternative way of understanding the impact of modulation of diurnal variability in daily rainfall and the subsequent impact on hydrological flux. In the tropical and subtropical latitudes of the SEUS diurnal variability is a significant component at the subdaily time scales. Any form of temporal aggregation will have substantial residual impact on diurnal variation. In computing daily mean precipitation by ignoring observations at climatological diurnal zenith and nadir, we ensure a significant and straightforward way to diminish the diurnal variation of rainfall in the SEUS. It is important to ignore the observations at diurnal zenith as well in order to avoid unfairly biasing the computed daily rainfall toward a lower value. Figure 9 shows the diagnostic indices [from the Statistical and Regional Dynamical Downscaling of Extremes for European Regions (STARDEX) project] (STARDEX 2004) for the modified and the unmodified NCEP Stage IV and CMORPH precipitation. A tool to calculate these indices was downloaded from <http://www.cru.uea.ac.uk/cru/projects/stardex/>. STARDEX provides a set of indices for the characterization of meteorological time series. A small change in the magnitude and number of peak rainfall events, a primary input to the hydrological model, could result in large changes in the magnitude

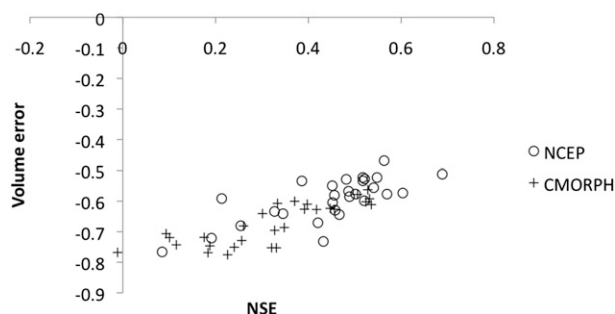


FIG. 11. Models' performance space (NSE and volume error) for two rainfall datasets derived from NCEP Stage IV and CMORPH.

of hydrological response depending on catchment characteristics. Therefore, only the three STARDEX indices, namely, the average (climatological) rainfall (pav), the 90th percentile rainfall day amount in millimeters per day (pq90), and the number of rainfall events in a year exceeding the 90th percentile event (pnl90) for unmodulated and modulated NCEP Stage IV and CMORPH data, are shown in Fig. 9. It may be noted that the modulation of rainfall with exclusion of CLMA and CLMI did not significantly affect other STARDEX indices such as wet day persistence, dry day persistence, and maximum number of consecutive dry days (not shown). In comparison to CMORPH, NCEP Stage IV is associated with larger rainfall events with relatively weaker dry day persistence (not shown). Figure 10 shows the decrease in variability (fraction) of rainfall for all the 28 watersheds for both CMORPH and NCEP Stage IV. In other words, with the removal of CLMA and CLMI, the variability in data reduces appreciably and the decrease in variability for CMORPH is more than that for NCEP Stage IV (Fig. 10).

The hydrological simulation results (Fig. 11) show that for both datasets the removal of CLMA and CLMI from subdaily precipitation has a detrimental effect on model performance, with volume error ranging from 45% to 78% (underestimation) among the watersheds. Moreover, the loss in the accuracy of simulation measured in terms of NSE for all the watersheds is higher for CMORPH data than for NCEP data. As expected, modulation of diurnal variability in this manner leads to a highly degraded simulation compared to temporal aggregation, where total volume is conserved. However degradation varies among the watersheds. The degradation of performance in terms of volume error can be attributed to reduction in volume of rainfall by nearly 29% (calculated from Fig. 11). Moreover, the loss in performance can also be partly attributed to the difference in climate condition used for model parameter calibration (e.g., Bastola et al. 2011b; Wagener 2007; Klemes 1986).

6. Conclusions

Improvement in the representation of variability of rainfall at different temporal scales in coupled atmospheric–hydrologic models is of critical importance in advancing our ability to predict variations in weather and climate and in subsequently using them for hydrological application. This study investigates to what degree the representation of temporal variability of rainfall is important in hydrological application over the SEUS.

We use two datasets (CMORPH and NCEP Stage IV) of observed rainfall that resolve the diurnal variations of rainfall over the SEUS. Compared to CMORPH, NCEP Stage IV is associated with larger rainfall events with relatively weaker dry day persistence. At 3-h intervals, the variability in NCEP Stage IV data is greater than the variability in CMORPH data; however, for both datasets, the decrease in variability when moving from aggregation levels of 3 h to 1 day is the highest.

For the hydrological simulation, it is observed that the temporal aggregation of subdaily rainfall can translate into a markedly higher volume error. For the watersheds used in this study, the volume error is as high as 30% in some watersheds for 30-day aggregation for NCEP Stage IV data and 35% in some watersheds for CMORPH data. This can be attributed partly to an increase in actual evapotranspiration, which tends to increase with the level of aggregation of rainfall. On average, the volume error associated with 15- and 30-day aggregation levels is greater for CMORPH (−11% and −16%) data than that for NCEP Stage IV (−7 and −13%) data.

Furthermore, with the modulation of diurnal variability resulting from the removal of subdaily rainfall corresponding to climatological maximum and minimum, the variability in both CMORPH and NCEP Stage IV decreases. However, the decrease in variability for CMORPH is more than that for NCEP Stage IV. The result shows that such modulation can result in volume error as high as 77% (76%) in selected watersheds for CMORPH (NCEP Stage IV). From this study, it can be concluded that, in the targeted region, diurnal scale variability has a marked impact on hydrological model performance. The reproduction of such variability in climate models is essential for hydrological application.

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