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Research papers

Conus-wide model calibration and validation for CRESTv3.0 – An improved Coupled Routing and Excess STorage distributed hydrological model

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ABSTRACT

The Coupled Routing and Excess Storage (CREST) is a flood-centric distributed hydrological model that has been widely used by researchers, educators, and decision-makers around the world since 2011. With growing public concern about the impact of climate change on water security, hydrological models such as CREST need to continue improving to provide more accurate simulations, more output products, and reduced application difficulties for users. In this study, an improved version of the CREST model (version 3.0) was proposed to consider the groundwater component of the hydrological cycle. A CONUS-wide CREST model calibration was conducted to provide usable model parameters for CREST users worldwide. The calibration improved the overall NSCE score from −0.97 to 0.11 over 3206 gauge points in CONUS. The validation results indicated that the CREST model performed well in the eastern CONUS but not in the Rocky Mountains and the Mountain West. The newly added groundwater module reduced the overestimation and the steepness of the falling limb during flood events in the eastern CONUS but drastically reduced the simulated water quantities in the mountainous regions.

1. Introduction

Water is one of the most essential resources in the world, and its proper management is crucial for the sustainable development of our society. Hydrological models are powerful tools used to understand, simulate, and predict the behavior of water systems, which play a fundamental role in many fields, such as water resources management, agriculture, energy, and environmental studies (Wood et al., 2011). The hydrological cycle is complex, and accurate hydrological models can help us to better understand the hydrological cycle and to make informed decisions regarding water management. Two extremes in the hydrological cycle, flood, and drought, can negatively impact ecosystems, economies, and human health (Ashley and Ashley, 2008; Chen et al., 2021; Liu et al., 2012; Riebsame et al., 1991; Wang et al., 2003). The need for hydrological modeling for both drought and flood has grown in recent years due to increasing concerns related to climate change and its potential impacts on water resources (Gobiet et al., 2014; USGCRP, 2017). Climate change is expected to increase the frequency and severity of extreme weather events, which will likely lead to more floods and droughts (Brauer et al., 2020; Meehl et al., 2000; van Oldenborgh et al., 2018).

The Coupled Routing and Excess STorage (CREST) model is a conceptually-based distributed hydrological model, that each grid cell that represents a fill and spill bucket to describe water storage and movement, and was developed by the University of Oklahoma (OU) and National Aeronautics and Space Administration (NASA), which was first published in 2011 (Wang et al., 2011). The basic building blocks of CRESTv1.x were distributed rain-runoff generation process and cell-to-

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cell routing, coupled routing and runoff generation mechanisms, and sub-grid variability of soil moisture capacity. The most significant improved and widely used version, CRESTv2.1 had multiple advancements including (a) implementation of distributed parameters, (b) replacement of three soil layers to one layer to reduce parameter requirements, (c) including impervious area ratio, (d) including a rainfall multiplier parameter to mitigate the precipitation forcing bias, e) auto-calibration, etc. (Shen et al., 2017; Xue et al., 2013, 2016). CRESTv2.1 was then adopted into the EF5 framework by the joint effort by OU and NOAA/National Severe Storms Laboratory (NSSL) to provide real-time flash flooding monitoring at every location in the USA, and became an operational system in the National Weather Services (NWS) and used by local NWS forecast offices as one of the tools used to issue flood warnings (Clark et al., 2017; Flamig et al., 2020; Gourley et al., 2017). The EF5 framework includes two important improvements: (a) the snow accumulation and ablation model (SNOW-17, Anderson, 2006) to simulate the process of accumulation of solid precipitation and its melting, and (b) the 1D kinematic wave model to describe the horizontal surface water movement over lands and river channels (Vergara et al., 2016). With the capacity for real-time hydrological simulation at a continental scale, the CREST model has been applied to many different regions of the world including East Africa under the NASA SERVIR program (Clark et al., 2017) and Peru under the OU-UNSA project (Chen et al., 2022).

The CREST model has been proven to be efficient and effective in monitoring floods, however, there is a list of limitations that need to be addressed to further improve to properly simulate both sides of the hydrological extremes. For example, the CREST model appeared to have much steeper falling limbs on the hydrograph compared to the observation data (Chen et al., 2020), the single soil layer structure could cause errors in soil moisture estimations, and the lack of groundwater storage and routing simulation could underestimation the water quantity in long-term hydrological simulations (Kan et al., 2017). Furthermore, when considering water management to achieve sustainability, especially in regions with temporally fluctuating precipitation, groundwater modeling is no longer a negligible component (Asrie and Sebhat, 2016; Massuel et al., 2017). Khadim et al. (2020) attempted to couple the MODular 3-D finite-difference (MODFLOW) model with the CREST model to provide water management insight for the upper Blue Nile River basin. Kan et al. (2017) added two more soil layers to the CREST model and the corresponding 15 parameters and tested in the Ganjiang River basin, China, to prove that the three soil layers could increase the model performance in streamflow simulation, reduce bias, and reduce overestimation of soil moisture. However, both utilizing a 3D finite-difference model and adding 15 more parameters would sacrifice the computational efficiency and ease of data preparation of the CREST model. Therefore, in this study, we explored an alternative approach to improve the CREST model while maintaining the effectiveness and efficiency of the model.

Ever since the first time the CREST model was applied at the Continental U.S. (CONUS), there has not been a systematically calibrated parameter dataset provided for the model user. Users are forced to calibrate the model basin by basin for their study areas, which limits the model applications to the larger regions. In this study, an improvement is made to add a conceptual groundwater simulating module (CRESTv3.0), and a CONUS-wide model calibration is conducted to provide a usable parameter set for the global CREST users. The calibration results are then validated against the U.S. Geological Survey (USGS) stream gauge observation data. The impact of the groundwater module is tested by comparing the CRESTv3.0 with and without (CRESTv2.1) groundwater module using the calibrated parameters. The rest of this paper is organized as follows. Section 2 describes the study area, the datasets, the description of the groundwater module, the calibration method, and the statistical methods used in this study. Section 3 describes the findings of the analysis. Section 4 gives a discussion of some findings, and Section 5 concludes and summarizes this study and proposes future studies.

2. Methodology

2.1. Study area and datasets (Table 1)

The calibration was conducted throughout the CONUS (Fig. 1), which includes 18 Hydrologic Unit Maps (*HUC 2*, Seaber et al., 1987) basins and 15 out of 30 climate zones according to the Köppen-Geiger-Pohl climate classification (Peel et al., 2007). The 1 km current climate classification data was obtained from Nature Scientific Data (Beck et al., 2018). The global climate classification map was then clipped within the study area and presented in Fig. 1. The HUC 2 data (GAGES-II, 2011) was obtained from the USGS National Hydrography Dataset (https://www.usgs.gov/national-hydrography/access-national-hydrography-products). The USGS stream gauge map data and attribute information data were obtained from GAGES-II: Geospatial Attributes of Gages for Evaluating Streamflow (https://water.usgs.gov/lookup/getspatial?gagesII_Sept2011). 6,036 USGS stream gauge flowrate data (U. S. Geological Survey, 1994) from 2018 to 2019 was obtained from the USGS Representational State Transfer (REST) web service through the Instantaneous Values (IV) IO package with Python (https://waterservices.usgs.gov/rest/IV-Service.html). All streamflow data were converted from cubic feet per second to cubic meters per second during the data downloading. The 2018–2019 Multi-Radar-Multi-Sensor (*MRMS,* Qi et al., 2016; Smith et al., 2016; Zhang et al., 2016) 1-hour gauge corrected Quantitative Precipitation Estimates (QPEs) data was obtained from the Iowa State University, Iowa Environmental Mesonet (IEM) data archive (https://mtarchive.geol.iastate.edu/). The MRMS QPEs dataset was proven to have higher accuracy in multiple studies (Chen et al., 2020; Li et al., 2020; Moazami and Najafi, 2021; Sadeghi et al., 2019), and it has been implemented in the FLASH project as the primary forcing (Gourley et al., 2017), which was used as the forcing data to drive the CRESTv3.0 model for consistency and accuracy purposes.

2.2. Groundwater module and CRESTv3.0

CRESTv1.0 model was first released in 2011 (Wang et al., 2011) and was then developed into the most widely implemented version CRESTv2.1 (Shen et al., 2017), which was later reprogrammed in C++ language and written into the EF5 framework in the FLASH project (Clark et al., 2017; Flamig et al., 2020; Gourley et al., 2017; Vergara et al., 2016). In CRESTv3.0, a conceptual bucket model was added to simulate the basic groundwater storage as one of the hydrologic cycle components. This classic fill-spill strategy is currently implemented in the US National Water Model (NWM) v2.1. The groundwater module follows a few simple governing equations:

$$Q_{ge,exc} = recharge + Z_{gw} - Z_{gw,max} - ET \tag{1}$$

$$Q_{gw,exp} = \left\{ \begin{array}{cc} 0 & Z_{gw} = 0 \\ C^{*}e^{\left(\left(\frac{Z_{gw}}{Z_{gw,max}}\right)-1\right)} & Z_{gw} > 0 \end{array} \right\} \tag{2}$$

$$GWflow = Q_{ge,exc} + Q_{gw,exp} \tag{3}$$

Where Z_{gw} is the conceptual groundwater depth at each pixel; $Z_{gw,max}$ is the conceptual maximum groundwater depth at each pixel; *recharge* is the water influx from the conceptual subsurface soil layer; $Q_{ge,exc}$ is the "spill" water from the groundwater 'bucket'; $Q_{gw,exp}$ is the release of groundwater when the 'bucket' is not full; C is an empirical factor to generate the $Q_{gw,exp}$ based on the Z_{gw} value; *ET* is the evapotranspiration process that takes water out of the groundwater 'bucket'. Since C ranges from 0.01 to 3 in this study, the $Q_{gw,exp}$ value is not large even when Z_{gw} is very small. The *GWflow* will be routed by a linear reservoir routing scheme to replenish the downstream channels. Fig. 2 demonstrates the theoretical concept of the bucket groundwater model. There are multiple disadvantages and advantages of such a method. First, groundwater

Table 1
Datasets used in the study.

Data name	Full Name	Reference	Sources
HUC2	Hydrologic Unit Maps	Seaber et al., 1987	USGS National Hydrography Dataset
Climate classification	Köppen-Geiger-Pohl climate classification	Peel et al., 2007,	Nature Scientific Data
USGS GAGES-II	Geospatial Attributes of Gages for Evaluating Streamflow	GAGES-II, 2011	USGS National Hydrography Dataset
Streamflow	USGS Streamflow observation data	U. S. Geological Survey, 1994	USGS Representational State Transfer (REST)
MRMS QPEs	Multi-Radar-Multi-Sensor Quantitative Precipitation Estimates	Qi et al., 2016; Smith et al., 2016; Zhang et al., 2016	Iowa Environmental Mesonet (IEM) data archive

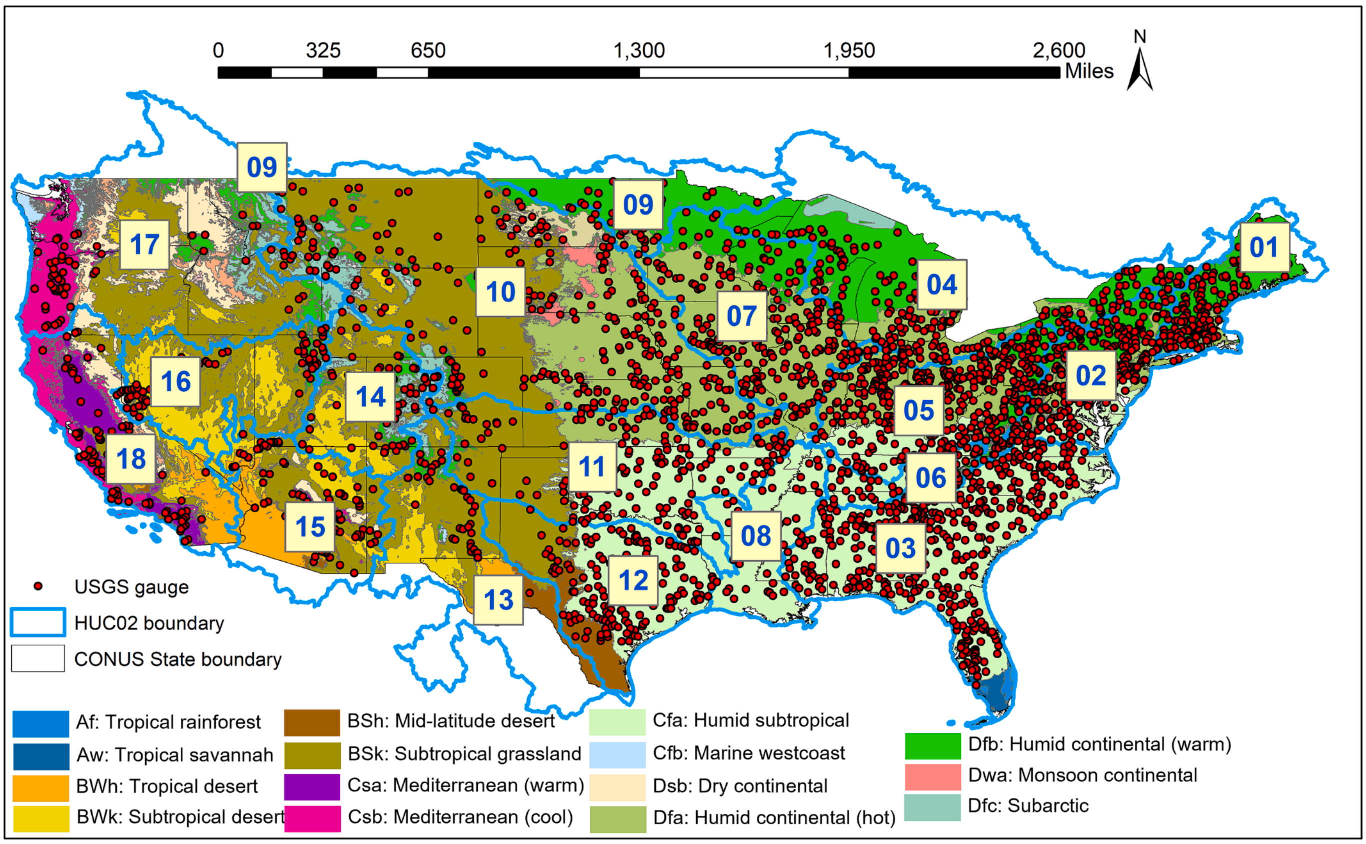

Fig. 1. The study area, HUC 2 maps, and the Köppen-Geiger-Pohl climate zones in the study area.

does not replenish the conceptual upper layer of soil through the capillary pressure, so groundwater level Z does not affect soil moisture. Second, the groundwater flow follows the linear reservoir routing scheme, which might not follow many underlying physical rules for groundwater flow, but it reduces the data requirement of the underground soil profile across the CONUS.

2.3. Parameter calibration and validation

A CONUS-wide, 1-km gridded CREST parameter set was prepared for the FLASH project (Gourley et al., 2017; Vergara et al., 2016) by estimation based on soil property data, landcover data, population data, and water channel data, however, the gridded parameter has not been calibrated (Flamig et al., 2020). By calibrating the parameters, the process will yield a multiplier to each of the gridded parameters at each gauge point and its contributing basin area. The calibration goal is to achieve a higher log-NSCE score, by utilizing the Differential Evolution Adaptive Metropolis (DREAM) algorithm (Vrugt et al., 2009a; Vrugt, 2016). The DREAM algorithm is an improved adaptation of the SCEM-UA global optimization algorithm that was built in CRESTv2.0 (Xue et al., 2016), and it is part of the Markov Chain Monte Carlo (MCMC) simulation, which simultaneously runs multiple chains for global sampling and tunes the orientation and scale of the proposal distribution automatically during evolution. This method has the advantage of maintaining details and ergodicity on complex, nonlinear, and multimodal target distributions (Vrugt et al., 2009b; Vrugt et al., 2008).

In this study, the calibration period was 2018/01/01 to 2018/12/31, and the sampling draws were limited to 5000 times for gauge drainage area less than 1000 km^2, 8000 times for gauge drainage area between 1000 km^2 to 10,000 km^2, and 12,000 times for gauge drainage area is larger than 10,000 km^2 to maintain reasonable computation time. The year 2018 and 2019 was selected for calibration since it was relatively recent so the calibrated parameters can be used for hydrological simulations for the most recent events, and both 2018 and 2019 generally have less extreme hydrological events than other years in 2010 s such as severe drought or historical flood in CONUS according to the USGA National Water Information System and National Flood Hazard Coordinator documentation. The less hydrologically extreme years were chosen to have a higher quality of the observation data as the cases of overbank flows and dry channels were less frequent. The CRESTv3.0

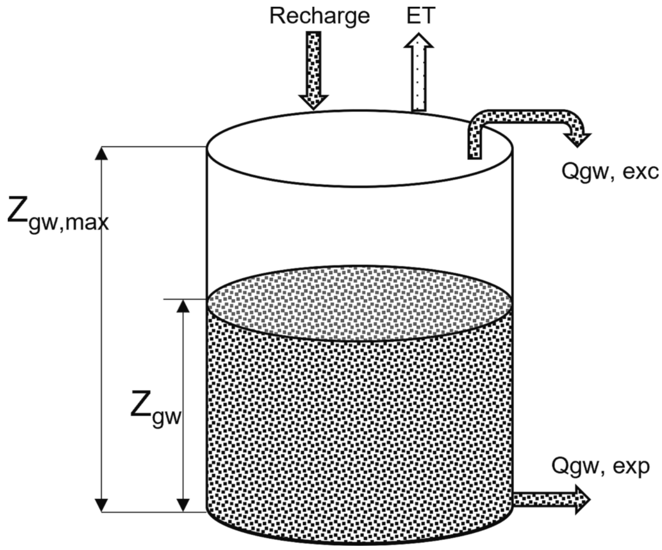

Fig. 2. The schematic diagram of the fill-spill bucket groundwater module.

model ran at 1-km and 1-hour resolution forced by MRMS 1-hr gauge corrected QPEs, and each time step took 0.004 to 0.05 s depending on the drainage area, and each gauge took from 20 h to over 120 h to complete the calibration. Due to the limitation of the sampling, some gauge points did not converge, and no reasonable parameter multipliers were yielded. The validation of the calibration was conducted for the following year from 2019/01/01 to 2019/12/31, with all calibrated gauge points, using MRMS 1-hr gauge corrected QPEs to run CRESTv3.0 model at 1 h and 1 km resolution. The benchmark for the validation was the same aforementioned simulation using the uncalibrated 1 km gridded parameter sets for EF5. The initial conditions for the validation runs are the last time step of 2018/01/01 to 2018/12/31 simulations using uncalibrated parameters for the benchmark and calibrated parameters for the calibrated simulation in 2019. Note that using only one year for calibration and one more for validation/benchmark is a step forward for CREST model implementation, but it is not conclusive nor definitive about the model performance.

2.4. *Statistic metrics and slope of the falling limb of the hydrograph*

To test if the calibration improves the model performance, both the calibrated simulation and the benchmark were compared to the USGS streamflow observation data using several statistical metrics listed below (Table 2).

The correlation coefficient (CC) represents the degree of agreement between the simulated streamflow and the stream gauge observation as the "ground truth." Three metrics were selected to discover the error and bias between the streamflow simulation and observations, which were the normalized bias (NB) and relative bias (RB) to describe the systematic bias as a ratio, as well as the root-mean-square error (RMSE) to measure the average error magnitude. The Nash–Sutcliffe coefficient of efficiency (NSCE) tests the hydrological model efficiency of simulating the streamflow, which is a widely used comprehensive performance metric for hydrological modeling studies.

To examine if the groundwater module would reduce the steepness of the falling limb in the hydrographs (Fig. 3), the slope of the falling limbs is calculated by a) identifying the falling limb using two or more consecutive time steps (2 + hours) having streamflow reduction of the half of its base flow value or more, b) fitting a linear regression over the falling limb, c) calculate the slope of the fitted linear line.

Table 2
The statistic metrics.

Statistic metrics	Equation	Value Range	Perfect value
Correlation coefficient (CC)	$CC = \frac{\sum_{n=1}^{N}(f_n-\bar{f})(r_n-\bar{r})}{\sqrt{\sum_{n=1}^{N}(f_n-\bar{f})^2}\sqrt{\sum_{n=1}^{N}(r_n-\bar{r})^2}}$	−1, 1	1
Normalized bias (NB)	$NB = \frac{1}{N}\sum_{n=1}^{N}\frac{f_n-r_n}{f_n+r_n}$	−1, 1	0
Relative bias (RB)	$NB = \frac{1}{N}\sum_{n=1}^{N}\frac{f_n-r_n}{r_n}$	−1, +∞	0
Root-mean-square error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(f_n-r_n)^2}$	0, +∞	0
Nash-Sutcliffe coefficient efficiency (NSCE)	$NSCE = 1-\frac{\sum_{n=1}^{N}(f_n-r_n)^2}{\sum_{n=1}^{N}(r_n-\bar{r})^2}$	-∞, 1	1

[a]Variables: n and N, sample index and a total number of samples, f represents the model simulated streamflow, r represents the USGS observation.

3. Results

3.1. *Conus-wide CRESTv3.0 calibration*

After the calibration, 3,206 out of 6,036 gauge-points converged and found 'optimal' parameter multipliers for CRESTv3.0 and were validated for the year 2019, and the remaining gauges were included in the validation. The overall statistical summary for the validation period before and after the calibration is listed in Table 3.

Compared to the baseline, where the parameters were not optimized, the most improved statistic metric was the CC, which means that the calibration helped improve the temporal agreement between the model simulation and the USGS gauge observation. The median values of CC among 3,206 gauge-points were 0 and 0.52 before and after the calibration, respectively. Other metrics had considerable improvements, there the median relative bias (RB) increased by 1 % from 17.37 % to 18.95 %, however, since the RB ranges from −1 to positive infinity and samples can be skewed by large positive values, the normalized bias (NB) provides more accurate insight for this aggregate score. The calibration reduced over 10 % of negative bias from NB of −27.9 % to −15.27 %, and it reduced about 10 m^3/s of absolute error from RMSE of 31.67 m^3/s to 21.23 m^3/s. A previous study (Flamig et al., 2020) examined the performance of EF5v1.2 (contains CRESTv2.1) from 2002 to 2011 across all USGS gauges smaller than 1,000 km^2 of basin area, and the study indicated that the median CC was 0.40, RB was 9 % and NSCE was −0.06, and the metrics listed in Table 1 surpassed all the scores. The near-optimal CC value was 0.97 and the NSCE value was 0.82 after calibration, which proved that the calibrated parameters could provide considerable accurate streamflow simulation at their best. In the USGS GAGES-II dataset, some gauges are categorized as "REF" gauges, which are defined as the streams that have minimal human interferences to their streamflow, such as dams, reservoirs, irrigations, etc.

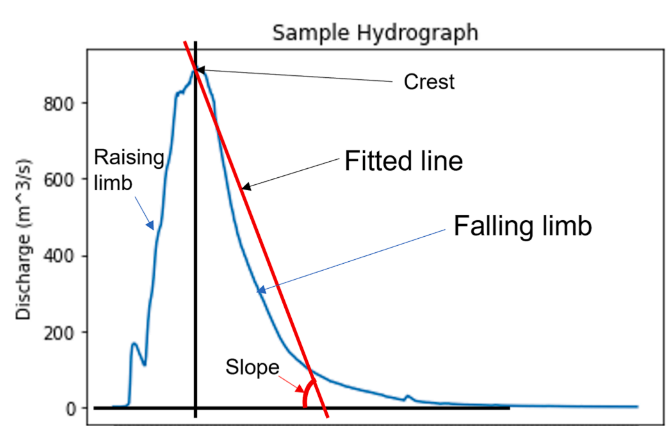

Fig. 3. An example of the falling limb of a hydrograph and its slope.

Table 3
The overall statistical results of CRESTv3.0 simulation over CONUS in 2019, over 3,206 gauge points.

Metrics	Baseline (median)	Calibrated (median)	Baseline (near optimal)	Calibrated (near optimal)	Calibrated results	
					USGS non-ref gauges	USGS ref gauges
CC	0.00	0.52	0.04	0.97	0.53	0.51
RB (%)	17.37	18.95	nan	nan	19.66	29.88
NB (%)	−27.90	−15.27	nan	nan	−13.70	−18.81
RMSE (m^3/s)	31.67	21.23	0.02	0.02	24.54	13.03
NSCE	−0.97	0.11	0.00	0.82	0.11	0.14

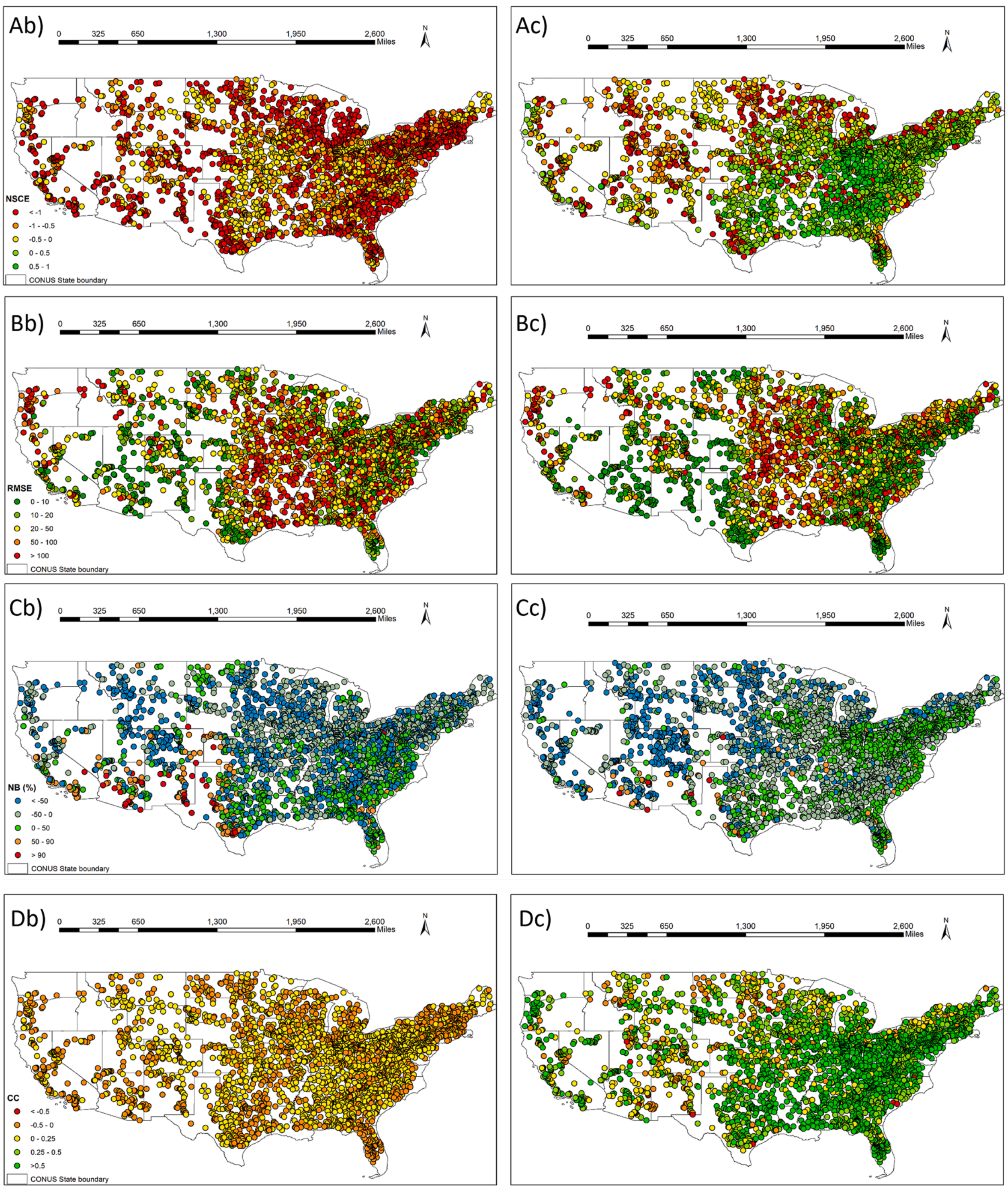

Fig. 4. The statistical results of A) NSCE, B) RMSE, C) NB, and D) CC at 3206 gauge-points for 2019 for baseline (b) and calibrated (c) CRESTv3.0 simulated streamflow.

In Table 2, the REF gauges on average have lower RMSE (13.03 m3/s vs. 24.54 m3/s) and higher NSCE scores (0.14 vs. 0.11) compared to the NON-REF gauges. In this study, CREST v3.0 did not consider the human interferences to the streamflow, so the model produces better simulation results on the REF gauges (Table 3)

Fig. 4 demonstrates the model performance metric at each gauge point before and after the calibration. From the comparison between the baseline and the calibrated simulation, the most obvious improvement was the CC (Fig. 4 Db, Dc), where the majority of the gauge points on the eastern part of CONUS had a CC value greater than 0.5. However, the Rocky Mountains and northern plain regions remained at lower CC values with insignificant improvement. The high RMSE gauge points were mostly concentrated within the Mississippi River basin for both baseline and calibrated simulation (Fig. 4 Bb, Bc), which has a large baseflow rate due to its size and consequentially generated a larger error. The statistical results showed widespread underestimation of streamflow (Fig. 4Cb, Cc). After calibration, the eastern part of CONUS showed improvement, but the Rocky Mountains and the Mountain West appeared to have no significant improvement, which could be affected by the groundwater module. The impact of the groundwater module will be further explained in section 3.2. As a comprehensive performance metric for hydrological model simulation, NSCE (Fig. 4Ab, Ac) showed significant improvement in the eastern part of CONUS, but not the mountainous regions and the US west. Note that the northern plain showed low NSCE scores after the calibration, which could be caused by the uncalibrated SNOW-17 module parameters (Flamig et al., 2020; Gourley et al., 2017). Due to time constraints, there are 8 more parameters for the SNOW-17 module that were not calibrated in this current study effort. Therefore, the process of snow/ice melting was not properly modeled, hence the poor performance showed at the northern plain of the US, which is one of the multiple reasons for the poor modeling performance at the Rocky Mountains.

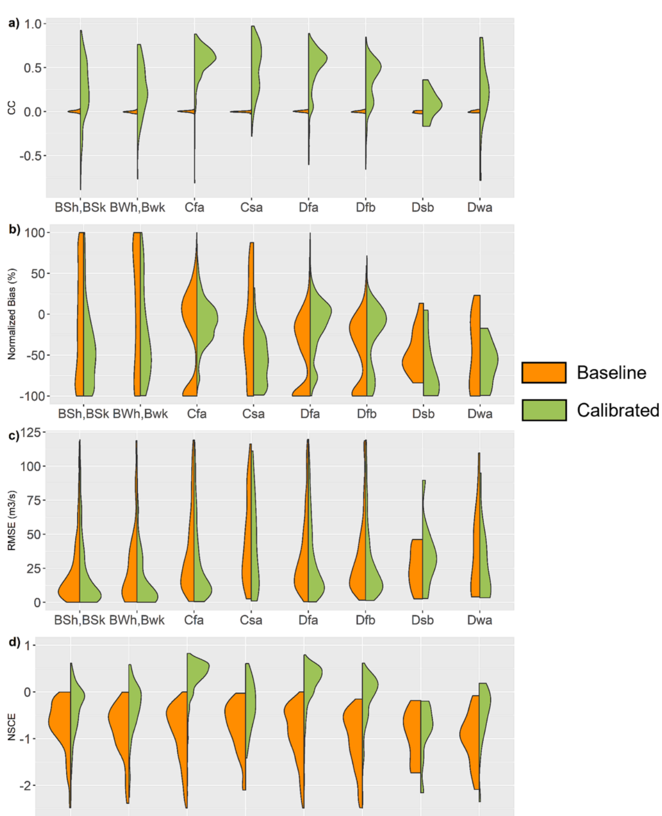

Fig. 5. The violin plot of statistical results before and after the calibration in 8 major climate zones in CONUS.

Fig. 5 displays the distribution of the statistical results of the baseline simulation and the calibrated simulation within 8 major climate zones in CONUS, compared against the USGS stream gauge observation. The most improved region by calibration was Cfa, a humid subtropical climate, which covers a large area in the southeast and southern plains of CONUS (Fig. 1). In this region, the calibration increased the median CC from 0.0 to 0.6, NSCE from −0.8 to 0.4, and reduced the RMSE from 41.6 m^3/s to 22.2 m^3/s. The second improved region was Dfa, a humid warm continental climate, which covers another large area north to Cfa climate including the majority of Northeast and Midwest regions of the USA. In this region, the calibration increased the median CC from 0.0 to 0.5, NSCE from −0.9 to 0.2, and reduced RMSE from 35.3 m^3/s to 26.3 m^3/s. These two regions include most of the area of the east part of CONUS including 32/50 states like AL, AR, CT, DE, DC, FL, GA, IL, IN, IA, KS, KY, LA, MD, a large portion of MA, MI, MS, MO, a large portion of NB, NH, NH, NY, NC, OH, OK, a portion of PA, RI, SC, TN, the eastern TX, VA, and WV. The results concluded that the calibration improved the CRESTv3.0 performance to be acceptable for 32 states on the east side of the CONUS. On the contrary, the region that was resistant to calibration was Dsb, dry continental climate, where the NSCE value changed from −0.88 to −0.86 after calibration. The Dsb climate scatters over the northern and western slopes of the Rocky Mountains and is located in California, Montana, Idaho, Oregon, and Washington. Multiple reasons could cause the poor performance of CRESTv3.0 including the groundwater module, the snowpack's impact on streamflow, and poor precipitation estimates in the mountains.

The other observation from Fig. 4 is that there was significant underestimation in desert/dry regions (BSh, BSk, BWh, BWk) and Mediterranean climate region (Csa), where the NB values were around −50 %, and the NSCE values were −0.39, −0.34, −0.35 respectively. The CREST hydrological model family was originally designed to model flood and flash flood events, and its capabilities to simulate the river flows in the dry regions needed to be specially calibrated or structurally improved in general.

The seasonal performance of calibrated CRESTv3.0 is worth exploring to provide the usefulness of the calibrated parameters. As the CC metric was the most improved score, Fig. 6 plots the median CC at each HUC2 zone in different seasons.

The ability to capture the flow variation using CRESTv3.0 hydrological simulation showed seasonal variability throughout the year 2019 (Fig. 6). One area that had a constant low score using calibrated parameters was HUC2 basin 13, Rio Grande region, which had the lowest score during the Winter season (median CC was −0.17, NB was −54 %, and NSCE was −2.22) when it was dry in the downstream and the precipitation in the upper stream was mostly snow. The other regions that had low scores throughout the year were HUC2 basins 14, 16, and 18, which are Upper Colorado, Great Basin, and California regions, where the median CC values were below 0.4 and the median NB values ranged from −54 % to −60 % and NSCE values ranged from −8.93 to −0.84. These lower score regions match the previous finding that the Rocky Mountains and the Mountain West were the poor performance regions for CRESTv3.0.

The regions that performed well throughout the year 2019 were HUC basins 2, 3, and 6, which are Mid-Atlantic, South Atlantic-Gulf, and Tennessee regions, where the median CC values ranged from 0.55 to 0.85, NB values ranged from −2.93 % to 9.90 %, and NSCE values ranged from 0.17 to 0.23. Considering Hurricane Dorian impacted the East Coast in late August and early September of 2019, including Florida, South Carolina, Delaware, and New Jersey, Fig. 6D showed high scores for all HUC 2 and 3 basins, which indicated that the parameters in these regions were well calibrated, and the extreme precipitation event did not introduce large error to the hydrological simulation. The HUC 8 basin, Lower Mississippi region, had high scores the most time of the year (median CC > 0.5), but not from October to December. It was reported that in the Spring and Summer of 2019, the Lower Mississippi River basin experienced high flow volume and flood. Given the averaged

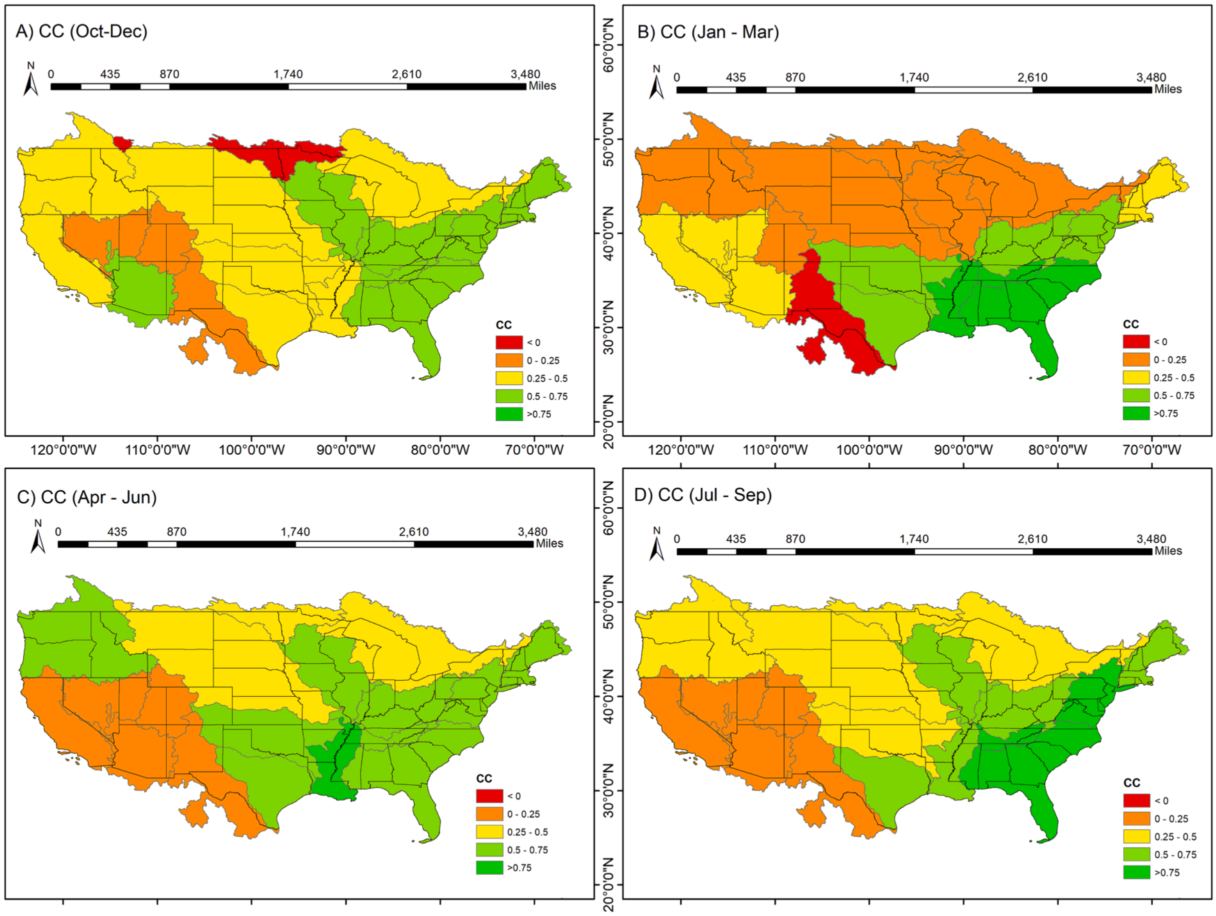

Fig. 6. The seasonal changes of median CC values in different HUC2 basins in water calendar years.

10 % positive bias from October to December 2019, it was possible that the CRESTv3.0 did not simulate the reduction of streamflow accurately after half of a year of high streamflow. In this seasonal analysis, the importance of the SNOW-17 module surfaced since Fig. 6B showed that the entire northern CONUS showed low scores during the winter season of 2019. The SNOW-17 module parameters (8 parameters) were not calibrated due to the time and computation limitations in this study.

Overall, the calibration of CRESTv3.0 provided a useful set of

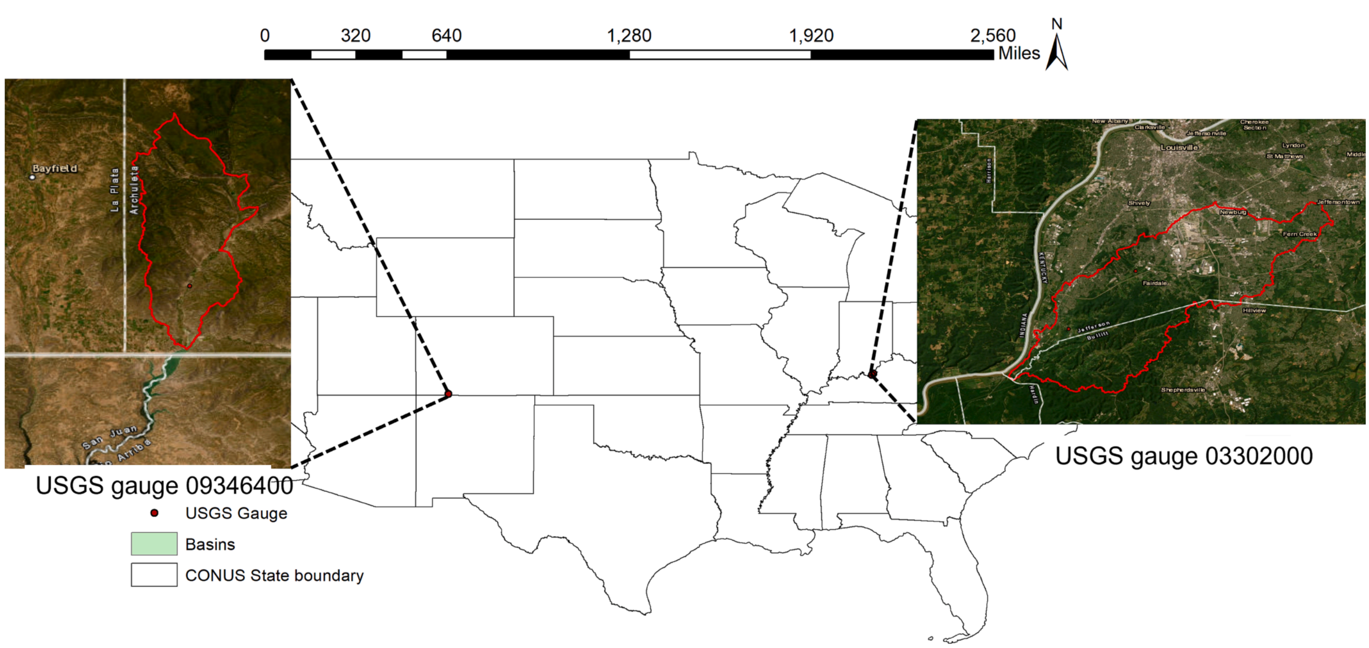

Fig. 7. Selected basins from the well and poorly performed regions to test the impact of the groundwater module.

parameters to support acceptable hydrological simulation in the Eastern side of CONUS, especially the southeast regions. The uncalibrated SNOW-17 module impacted the model performance in the northern CONUS and Rocky Mountain regions. The calibrated CRESTv3.0 generally has poor performance in the drier regions (desert, grassland, Mediterranean, dry continental climates), which are mostly located in mountain west regions.

3.2. The impact of the groundwater module

The conceptual groundwater module was expected to reduce the conceptual soil water content and consequentially decrease the slope of the falling limb of the hydrograph. In this section, a basin in the Mid-Atlantic region and one basin in the Mountains West region were selected to examine the impact of the groundwater module (Fig. 7). In this section, the streamflow and soil moisture were simulated with and without the groundwater module, and the difference in streamflow was demonstrated in Fig. 8.

Two basins were selected from HUC2 Region 5 Ohio river basin, and Region 14 upper Colorado river basin, which had high and low CC scores in 2019, respectively, based on the results shown in Fig. 6. The USGS gauge 03,302,000 is at the Pond Creek basin, near Louisville, KY, which is a tributary of the Ohio River. The Pond Creek basin covers a large Louisville metropolitan area, which is heavily developed and has a high percentage of impervious areas. The USGS gauge 09,346,400 is at the upper stream of the San Juan River before entering the Navajo Reservoir.

The USGS gauge 03,302,000 at Pond Creek is located at a region where CRESTv3.0 performed well after calibration, and the hydrograph (Fig. 8A) showed that the simulated streamflow caught all the flood peaks in 2019 and the overall NSCE score was 0.82 and RMSE was 3.38 m^3/s. One significant impact of the groundwater module after comparing the red (groundwater module turned on) and blue (groundwater module turned off) hydrograph, the groundwater module reduced the overestimations at the flood peak so the simulated streamflow during the flood was closer to the stream gauge observation (gray). For example, in the April 20th flood at Pond Creek, the observed peak streamflow was 65.66 m^3/s, and the simulated peak streamflow was 60.95 m^3/s with the groundwater module turned on, 131.87 m^3/s with the groundwater module turned off. The groundwater module reduced much overestimation, so the CRESTv3.0 can simulate a more realistic flood event. The expectation of reducing the slope of the falling limb of each high-flow event was not visible in Fig. 8A. After calculating the averaged slope of falling limbs through the year of 2019 for simulated and observed hydrographs, the groundwater module helped to reduce the steepness of falling limb slope from −1.43 (groundwater module turned off) to −0.86 (groundwater module turned on), yet much steeper than the USGS streamflow observation with the averaged falling limb slope of −0.43.

On the other hand, in the dry and mountainous regions like the upper stream of the San Juan River basin (Fig. 8B), the CRESTv3.0 simulation drastically underestimated the streamflow without the groundwater module turned on (blue). When the groundwater module turned on (red), the conceptual groundwater tank further drained surface runoff and caused a much lower simulated flowrate and the annual average NB was −95.31 %. The results showed that CRESTv3.0 needed more improvements and overcame obstacles (e.g. snow, mountain lakes, glacier melts) to provide more accurate simulation in the dry and mountainous regions.

The groundwater module had a positive impact in the CRESTv3.0 well-performed regions (eastern CONUS) by reducing overestimation during flooding events but had a negative impact in the poorly performed regions (mountain west of CONUS) by depleting the streamflow. The use of the groundwater module should be done after

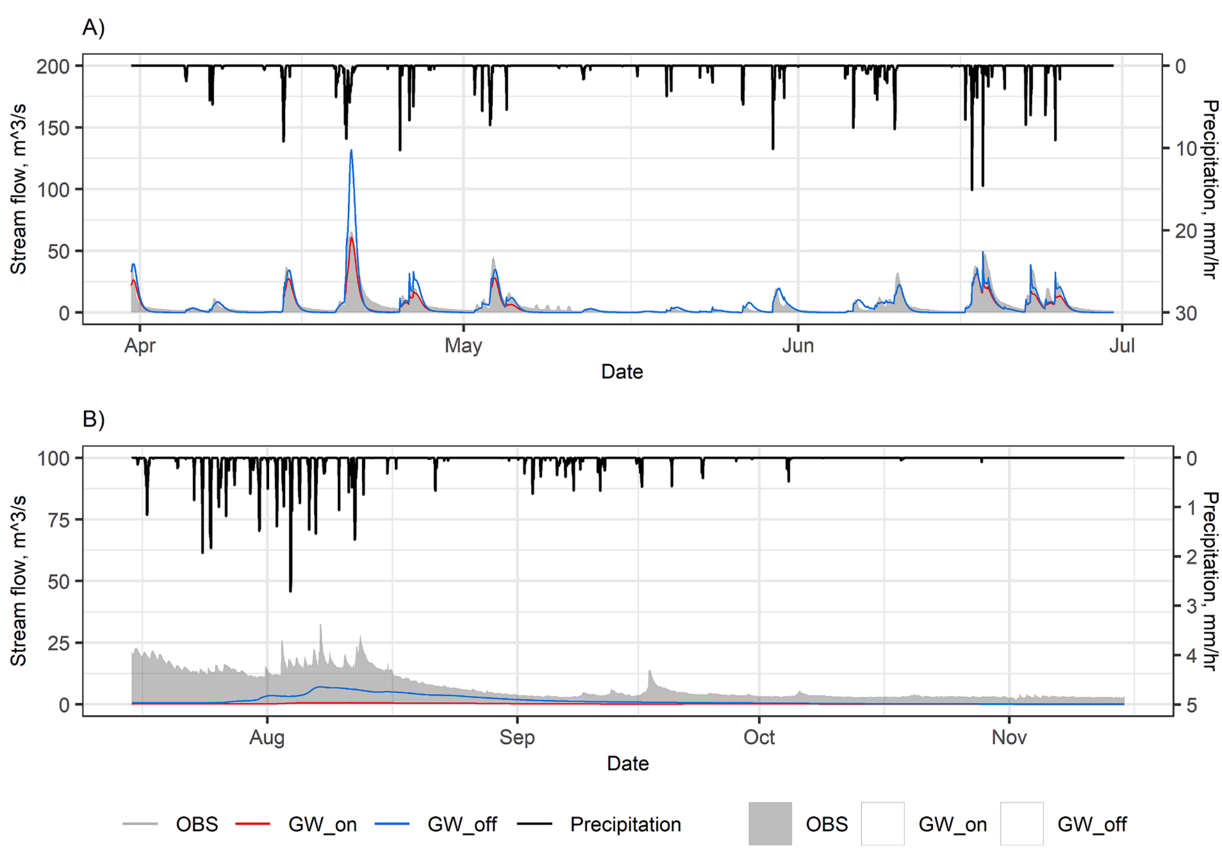

Fig. 8. The CRESTv3.0 simulated hydrograph of selected basin A) USGS gauge 03,302,000 and B) USGS gauge 09346400, with the groundwater module turned on (red) and off (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

comprehensively considering the geological and climatic properties of the study area.

4. Discussion

Multiple reasons could cause the poor performance of CRESTv3.0 in the mountain west regions of CONUS. One of the reasons is the precipitation forcing data quality. Since MRMS is a radar-based QPE, the density of radar networks and blockage by objectives can affect the accuracy of MRMS QPE. A 2015 NOAA report (Grim et al., 2015) and a 2021 study (Bagaglini et al., 2021) both analyzed the radar quality index (RQI) of MRMS products and the results indicated that the RQI was scattered low scores across the Rocky Mountains and mountain west. The location of the upper stream San Juan River basin (USGS gauge 09346400) had a very low MRMS RQI score, which was less than 0.1. Therefore, the bias of the QPE propagated through the hydrological model and caused errors in simulated streamflow (Hong et al., 2006). The second reason could be the uncalibrated SNOW-17 module that caused errors in water balance calculations that generated less surface runoff than needed for the Rocky Mountains regions. Since there were 8 more parameters from the SNOW-17 module, they were not calibrated to save computation time in this study. However, the glacier melting process and snow precipitation are important for generating surface runoffs in mountainous regions, therefore, to apply CRESTv3.0 to mountainous regions or northern CONUS, calibrating SNOW-17 module parameters is an essential procedure. The third reason could be the lack of capability to model the lake and reservoir in CRESTv3.0. In a recent study (Leach and Laudon, 2019), the authors indicated that even small headwater lakes (area < 1 km^2) could influence the baseflow quantity of their downstream river reaches. Especially in the mountainous regions, lakes and reservoirs can store surface runoff from glacier melt, snow melt, and precipitation, and they supply consistent waterflow to its downstream when precipitation does not occur, attenuate peakflows when mountain flood occurs (Dorava and Milner, 2000; Jones et al., 2014). In mountain west regions, the CREST-VEC model (Li et al., 2022) could be a more suitable option, since this model can simulate the natural lakes and engineered reservoirs when lake information and reservoir operation data are available. The fourth reason could be the current groundwater module is not suitable for mountainous regions. From section 3.2, the analysis indicated that the groundwater module benefits the hydrological simulation in the eastern CONUS by reducing the overestimations at peakflows during flood events, and the steepness of falling limbs, which made the simulation more realistic as the observation data. However, the current groundwater module technically takes water at a rate (m^3/s) from the surface runoff when precipitation and excessive rainfall occur, which heavily reduces the amount of water that remains on the surface and channels when the area is dry. As the current groundwater module sacrifices a degree of the physical aspect of groundwater movement and soil–water relationship to gain simplicity and computation efficiency, the CRESTv3.0 module should not be turned on when the study area is dry and lacks precipitation.

In the CRESTv3.0 setup, the groundwater module and infiltration module that produce soil moisture outputs are operating independently. There is no formula to describe the water interaction between the conceptual water 'bucket' and the conceptual soil layer, therefore the groundwater bucket cannot drain the water from the soil layer nor impact the soil moisture. The soil moisture outputs of the CRESTv3.0 gave 0 difference in 2019 between the groundwater module turned on and off, which exposed the flaw of the current groundwater module design. Darcy's law (Buckingham, 1907) and Richard equation (Richards, 1931) can address the capillary flow between soil and groundwater, however, a fully solved 3D Darcy's law (e.g. MODFLOW) would not be adequate for the CREST model, which would sacrifice its computational efficiency. Therefore, the next step to improve the CRESTv3.0 model is to use a simplified 1D equation to model the water flux with the addition of 1 or 2 more parameters.

5. Conclusions

This study provided an improvement to CRESTv2.x distributed hydrological model proposed a new version, CRESTv3.0, and provided a whole CONUS parameter calibration. With the calibration using the DREAM algorithm, the median NSCE value of all 3,206 gauge-points increased from −0.97 to 0.11 and the addition of the groundwater module helped to eliminate the overestimations at the flood peaks during flood events. Furthermore, the following conclusions are made here:

(1) CRESTv3.0 performed well and provided accurate flowrate simulation in the eastern CONUS but not in the Rocky Mountains and Mountain West regions. The best-performed regions were Southeast, Tennessee, and Mid-Atlantic, and the worst-performed regions were Upper Colorado, Rio Grande, Great Basin (Salt Lake), and California regions.
(2) The uncalibrated SNOW-17 module had an impact on the performance of CRESTv3.0 in Northern CONUS and mostly the Rocky Mountains region where the mountain glaciers melting was a major source of river flow.
(3) When working with CRESTv3.0 in mountainous and dry regions, the model needs to be operated with extra care to consider snow/ice melt, lake routing, groundwater module turned off, and precipitation forcing quality.
(4) Considering the heterogeneity of topography, climate, soil property, and land cover in a large country like the USA, the compartmentalization idea of the CREST model application should be promoted in the future to provide the best simulation results in every part of a large region.

The newly added groundwater module is yet to be perfect, but it showed its benefit in improving the streamflow simulation during flood events in the eastern CONUS and reducing the steepness of the falling limb of the hydrograph compared to the simulation without the groundwater module. The groundwater module will be improved in future studies to simulate the water flux interaction between the soil layer and the groundwater bucket. This study is the first attempt to calibrate the CRESTv3.0 model parameters for the whole CONUS, and calibrated parameters that can yield accurate simulation could be used for parameter transformations to other parts of the world, such as South America, Asia, etc.

CRediT authorship contribution statement

Mengye Chen: Conceptualization, Methodology, Software, Visualization. **Zhi Li:** Software. **Humberto J. Vergara:** Conceptualization, Writing – review & editing. **Jonathan J. Gourley:** Writing – review & editing. **Ming Xue:** Supervision, Writing – review & editing. **Yang Hong:** Conceptualization, Supervision. **Xiao-Ming Hu:** Writing – review & editing. **Hector Mayol Novoa:** Supervision. **Elinor R. Martin:** Supervision. **Renee A. McPherson:** Supervision. **Shang Gao:** Writing – review & editing. **Andres Vitaliano Perez:** . **Isaac Yanqui Morales:** .

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have share the link and step to my data at Attach File step

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