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Improving Runoff Simulation in the Western United States with Noah-MP and VIC

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Abstract

Streamflow forecasts are critical for water and environmental management, especially in the water-short Western U.S.. Land Surface Models (LSMs), such as the Variable Infiltration Capacity (VIC) model and the Noah-Multiparameterization (Noah-MP) play an essential role in providing comprehensive runoff forecasts across the region. Virtually all LSMs require parameter estimation to optimize their predictive capabilities. We describe a systematic calibration of parameters for VIC and Noah-MP over 263 river basins in the Western U.S., and distribution of the calibrated parameters over the entire region. Post-calibration results showed a notable improvement in model accuracy in the calibration basins: the median daily streamflow Kling-Gupta Efficiency (KGE) for VIC rose from 0.37 to 0.70, and for Noah-MP, from 0.22 to 0.54. Employing the donor-basin regionalization method, we developed transfer relationships to hydrologically similar basins and extended the calibrated parameters to ungauged basins and the entire region. We assessed factors that influence calibration efficiency and model performance using regional parameter estimates. We evaluated high and low flow simulation capabilities of the two models

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and observed marked improvements after calibration and regionalization. We also generated gridded parameter sets for both models across all 4816 HUC-10 basins in the Western U.S., a data set that is intended to support regional hydrologic studies and hydrologic climate change assessments.

1. Introduction

Streamflow forecasts play a key role in various aspects of water and environmental management, especially in the Western U.S. (WUS). In the short term, these forecasts provide early warnings for impending flood events, thereby enabling timely preparation and response to mitigate immediate flood risk and damages (Maidment, 2017). They also serve as crucial input for managing reservoirs effectively for water supply (Raff et al., 2013), hydroelectric power generation (Boucher & Ramos, 2018), and river navigation (by providing a basis for predicting water levels) (Federal Institute of Hydrology, 2020). In the longer term, streamflow forecasts enable water utilities and agencies to plan water distribution within and across multiple uses—urban, agricultural, and industrial—which is especially vital during drought conditions when efficient water use becomes a necessity (Anghileri et al., 2016;). Streamflow forecasts also aid in understanding and predicting the impacts of climate change on water systems, thereby informing adaptive strategies for water resource management. Thus, in both short and longer-term contexts, streamflow forecasts are an important tool for promoting sustainable water practices and resilience to water-related challenges.

Streamflow forecasts are derived via a synthesis of hydrometeorological data, statistical methodologies, and computational modeling. Direct measurement of runoff is an important element of streamflow forecasts, however it is only possible in river basins with well-developed observational infrastructure (Sharma and Machiwal,

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2021). This limitation leaves vast areas, often critical to water resource management and climatology, without direct runoff observations on which to base streamflow forecasts. As an alternative, Land Surface Models (LSMs) can be used to simulate streamflow. LSMs typically are forced with air temperature, precipitation and other meteorological forcings. By integrating climatic, topographic, and land-use information, they can fill streamflow observation gaps and provide comprehensive, spatially distributed runoff forecasts (Fisher and Koven, 2020). The capabilities of LSMs equip us with the necessary tools to produce streamflow forecasts that can be used to prepare for severe weather conditions, form the basis for water resource management, and inform water management associated with our evolving climate. These benefits hold true irrespective of the limitations associated with direct streamflow observations. Through off-line simulations and reconstructions, LSMs enable us to gain insights into land surface hydrology at various scales - regional, continental, and global.

The parameterization of the underlying hydrological processes varies across different LSMs, but virtually all models require some level of parameter estimation based on historical observed streamflow data at forecast point, to ensure trustworthy predictions throughout the region (Beven,1989; Troy et al., 2008; Gong et al., 2015). In cases where observations don't exist, parameters can be transferred from river basins where they do (Arsenault and Brissette (2014)). In cases where observations do exist but aren't current, we can use a shorter span of historical streamflow data for model calibration and subsequently produce streamflow forecasts using meteorological forcings when observed streamflow data aren't available.

The process of calibration can be computationally demanding, and prior research typically has focused on obtaining parameters appropriate to facilitating model simulations that match observations as closely as possible at the observation point

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(Duan et al,1992; Tolson and Shoemaker, 2007). Most previous studies have concentrated on a limited number of basins and a single model (e.g. Mascaro et al., 2023; Sofokleous et al., 2023; and Gou et al., 2020). Here, we aim to establish parameterizations for two LSMs -- the Variable Infiltration Capacity (VIC) model and the Noah-Multiparameterization (Noah-MP) LSM across the WUS. Both models have found extensive application both within the U.S. and internationally (Mendoza et al.,2015; Tangdamrongsub, 2023). The approach we use involves the application of globally optimized calibration methods and regionalization, with the objective of facilitating these models to provide reliable runoff simulations.

In particular, we explore and elucidate (i) the choice of physical parameterizations and calibration of land surface parameters, (ii) extension of these calibrated parameters to areas without gauges, and (iii) factors that influence calibration efficiency and LSM performance using regional parameter estimates. In the case of Noah-MP, which offers multiple runoff generation (physics) options, our initial step involves choosing the most effective runoff parameterization option. Following this, we perform the calibration of land surface parameters. In the case of the VIC model, the runoff parameterization scheme is predetermined, so we commence immediately with calibration. We implemented calibration in 263 basins across the WUS where streamflow observations were available (see section 2.1 for details) and compared simulated and observed streamflow as the model predictions were affected by soil and other land surface properties. Our second step extended the initial calibrated land surface parameters to ungauged basins. We then explored the variables that most impact the calibration proficiency of Noah-MP and VIC across the WUS. In section 4, we employ a regionalization technique known as the donor basin method, as implemented by Bass et al. (2023). Finally, we evaluate both flood and low flow simulation skills for the baseline, and after calibration and regionalization.

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2. Study basins, land surface models and forcing dataset overview

2.1 Study Basins

We selected 263 river basins distributed across the WUS. Most of the basins were from USGS Gages II reference basins (Falcone 2011) which have minimum upstream anthropogenic effects such as dams and diversions. Among these basins, our selection criteria included having at least 20 years of record, and a minimum drainage area of 144 square kilometers, which is the size of four model grid cells. In addition to 250 Gages II reference stations, we included 13 basins located in California's Sierra Nevada for which natural flows are available from the California Department of Water Resources (2021). The geographical distribution of the 263 basins is shown in Figure 1. We focused on the hydrological models' calibration to full natural flow (the same as observed streamflow for GAGES II stations; estimated by DWR for the 13 Sierra Nevada sites), which indicates water flow conditions devoid of human interventions like reservoirs or diversions. Each basin was calibrated using the most recent 20-year period when the observation is available.

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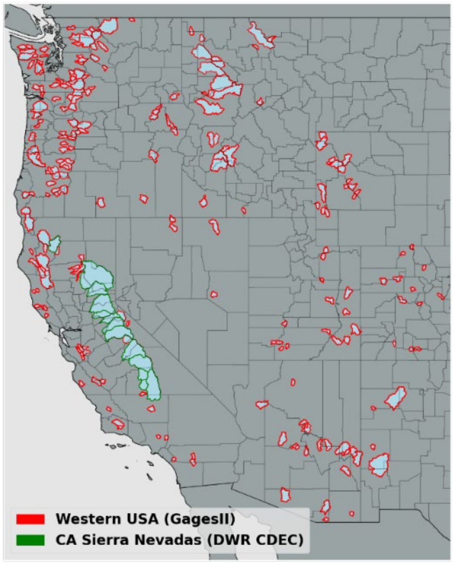

Figure. 1. 263 river basins for which calibration was performed. The Gages II reference basins are delineated with red boundaries and the CA Sierra Nevade basins with green boundaries.

2.2 Land Surface Models

We included two widely used hydrological models, VIC (Liang et al., 1994) and Noah-MP (Niu et al. 2011). This decision was informed by the varying levels of complexity these two models offer in conceptualizing the effects of vegetation, soil, and seasonal snowpack on the land surface energy and water balances (refer to Table 1 for more details). The two models also use different parameterizations for certain hydrological processes, including unique model equations for canopy water storage, base flow, and other processes. Both of these hydrological model structures have found extensive application both within the U.S. and internationally, as indicated by Mendoza et al. (2015) and Tangdamrongsub (2023).

To generate streamflow, the gridded runoff from Noah-MP and VIC was

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accumulated over each watershed. We didn't implement routing since its impact on daily streamflow simulations was small given the relatively small size of most of the basins. This aligns with earlier research (e.g., Li et al. 2019). However, in both the case of VIC and Noah-MP, the output of our simulations (runoff) could be used as input to routing models, such as those that are options in the implementation of both models.

2.2.1 VIC

VIC is a macroscale, semi-distributed hydrologic model (described in detail by Liang et al 1994) that determines land surface moisture and energy states and fluxes by solving the surface water and energy balances. VIC is a research model and in its various forms it has been employed to study many major river basins worldwide (e.g. Adam et al 2003 & 2006; Livneh et al 2013; Schaperow et al 2021). This model enjoys a broad user community — as per the citation index Web of Science, the initial VIC paper has been referenced more than 2600 times, with contributing authors spanning at least 56 different countries (Schaperow et al 2021). We obtained initial VIC model parameters from Livneh et al 2013, who validated model discharges over major CONUS river basins. The origins of the soil and land cover data are outlined in Table 1. The version of the VIC model implemented here is 4.1.2, and it operates in energy balance mode.

2.2.2 Noah-MP

Noah-MP is a state-of-the-art LSM originally designed as the land surface scheme for numerical weather prediction (NWP) models like the Weather Research and Forecasting (WRF) regional atmospheric model. Currently, it's being utilized for physically based, spatially-distributed hydrological simulations as a component of the

National Water Model (NWM) (NOAA, 2016). It enhances the functionalities of the Noah LSM (as per Chen et al., 1996 and Chen and Dudhia, 2001) previously used in NOAA's suite of numerical weather prediction models by offering multiple options for key processes that control land-atmosphere transfers of moisture and energy. These include surface water infiltration, runoff, evapotranspiration, groundwater movement, and channel routing (see Niu et al., 2007; 2011). The model has been widely used for forecasting seasonal climate, weather, droughts, and floods not only across the continental United States (CONUS) but also globally (Zheng et al., 2019).

2.3 Forcing Dataset

We ran both models at a 3-hour time step and at $1/16°$ latitude–longitude spatial resolution. The forcings were the gridded observation dataset developed by Livneh et al (2013) and extended to 2018 by Su et al (2021) (hereafter referred to as L13). This data set spans the period from 1915 to 2018. For the VIC model, the L13 dataset provided daily values of precipitation, maximum and minimum temperatures, and wind speed (additional variables used by VIC including downward solar and longwave radiation, and specific humidity, are computed internally using MTCLIM algorithms as described by Bohn et al. (2013)). The Noah-MP model, on the other hand, necessitated additional meteorological data such as specific humidity, surface pressure, and downward solar and longwave radiation, in addition to precipitation, wind speed, and air temperature. We used the MTCLIM algorithms, as detailed by Bohn et al. (2013), to calculate specific humidity and downward solar radiation. We employed the Prata (1996) algorithm to compute the downward longwave radiation. Additionally, we deduced surface air pressure by considering the grid cell elevation in conjunction with standard global pressure lapse rates. Following this, we transitioned the daily data to hourly metrics using a cubic spline to interpolate between Tmax and

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Tmin, and derived other variables using the methods explained by Bohn et al. (2013). Lastly, we distributed the daily precipitation evenly across three hourly intervals.

Table 1. Overview of hydrologic model components and parameter data sources.

MODEL	SNOW ACCUMULATION AND MELT	MOISTURE IN THE SOIL AND COLUMN/SURFACE RUNOFF	BASE FLOW	CANOPY STORAGE	VEGETATION DATA	SOIL DATA
VIC (V4.1.2)	Two-layer energy–mass balance model	Infiltration capacity function. Vertical movement of moisture through soil follows 1D Richards equation.	A function of the soil moisture in the third layer. Linear below a soil moisture threshold and becomes nonlinear above that threshold. [Liang et al., 1994]	Mosaic representation of different vegetation coverages at each cell.	University of Maryland 1-km Global Land Cover Classification (Hansen et al. 2000)	1-km STATSGO database (Miller and White 1998).
NOAH-MP (WRF-HYDRO 5.2.0)	Three-layer energy–mass balance model that represents percolation, retention, and refreezing of meltwater within the snowpack.	1. TOPMODEL-based runoff scheme	Simple groundwater (hereafter SIMGM) [Niu et al., 2007].	Semi-tile approach for computing longwave, latent heat, sensible heat and ground heat fluxes	MODIS 30-second Modified IGBP 20-category land cover product	1-km STATSGO database (Miller and White 1998).
		2. Simple TOPMODEL-based runoff scheme with an equilibrium water table (hereafter SIMTOP)	Similar to SIMGM, but with a sealed bottom of the soil column [Niu et al., 2005]			
		3. Infiltration-excess-based surface runoff scheme	Gravitational free-drainage subsurface runoff scheme [Schaake et al., 1996]			
		4. BATS runoff scheme, which parameterized surface runoff as a 4th power function of the top 2 m soil wetness (degree of saturation)	Gravitational free drainage [Dickinson et al.,1993]			

3. Model calibration

3.1 Calibration methods

The initial step in our calibration effort was to optimize the land surface parameters of the two models for the 253 WUS basins. These parameters, primarily soil properties which can exhibit a substantial degree of uncertainty, were iteratively updated via hundreds of simulations to accurately reflect streamflow conditions in each basin. We calibrated six parameters for VIC and five for Noah-MP. This selection was guided by past research and the computational resources we had at our disposal (Mendoza et al. 2015; Hussein 2020; Shi et al. 2008; Holtzman et al., 2020; Bass et al., 2023; Schaperow et al., 2023). Each parameter underwent consideration across a physically viable range (refer to Table 2), drawing from values utilized in prior studies (Cai et al. 2014; Mendoza et al. 2015; Hussein 2020; Shi et al. 2008; Gochis et al., 2019; Holtzman et al., 2020; Lahmers et al. 2021; Bass et al., 2023; Schaperow et al., 2023). Through our iterative calibration method, each subsequent simulation learns from the previous ones using algorithms designed to reduce the discrepancy between the simulated and observed streamflow.

For VIC parameter estimation, we employed the Shuffled Complex Evolution algorithm developed at the University of Arizona (SCE-UA, Duan et al. 1992). This method is a global optimization method widely used in hydrology and environmental modeling, owing to its robustness and efficiency when addressing complex, non-linear, and multi-modal objective functions (Naeini et al., 2015).

For the Noah-MP model, which requires more computational core-hours per simulation, we used the Dynamically Dimensioned Search (DDS) algorithm of Tolson and Shoemaker (2007). This algorithm, specifically crafted for high-dimensional and computationally intensive problems, offers generally greater efficiency than SCE-UA. NOAA employs the DDS algorithm for their CONUS implementation of NWM, which is grounded in Noah-MP (Gochis et al. 2019). We evaluated both calibration methods (DDS and SCE-UA) for VIC for 20 randomly chosen basins, and obtained similar results. For VIC, we chose SCE-UA due to its inherent compatibility with the model and because the additional computation (relative to DDS) was less important given that the inherent computation required for VIC is considerably less than for Noah-MP.

In our application of SCE-UA, we performed a maximum of 3000 iterations for

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each basin, while the DDS method employed 250 iterations for each basin for Noah-MP. Each basin was calibrated using the most recent 20 years of streamflow data. For both models, our objective function was the Kling-Gupta Efficiency (KGE, Gupta et al., 2009) metric for daily streamflow. KGE is a widely used performance measure because of its advantages in orthogonally considering bias, correlation and variability (Knoben et al., 2019). KGE = 1 indicates perfect agreement between simulations and observations; KGE values greater than -0.41 indicate that a model improves upon the mean flow benchmark (Konben et al., 2019).

TABLE 2. Calibration methods, parameters and modifications to their initial default values evaluated in the calibration.

Model	**VIC**		**Noah-MP**	
Calibration Method	SCE-UA		DDS	
Iterations	3000		250	
Calibrated Parameter	Variable Infiltration Curve Parameter (INFILT)	0.001 – 0.4 (Shi et al.,2008)	Saturated Hydraulic Conductivity (Ksat)	$2 \times 10^{-9} to\ 0.07$(Cai et al.,2014)
	Baseflow parameter (Ds)	0.001 – 1.0 (Shi et al.,2008)	Saturation soil moisture content (MAXSMC)	0.1 to 0.71 (Cai et al.,2014)
	Thickness of Soil in Layer 1 (Depth_1)	0.01 – 0.2 (Shi et al.,2008)	Pore size distribution index (Bexp)	1.12 to 22 (Cai et al.,2014; Gochis et al.,2019)
	Total thickness of soil column (Depth_total)	0.6 – 3.5 (Shi et al.,2008)	Linear scaling of “openness” of bottom drainage boundary (Slope)	0.1-1 (Lahmers et al 2021)
	Max velocity parameter of baseflow (Dsmax)	0.001 – 30 (Schaperow et al.,2023)	Parameter in surface runoff (REFKDT)	0.1-10 (Lahmers et al 2021)
	Fraction of	0.001 – 1		

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	max soil moisture where nonlinear baseflow occurs (Ws)	(Shi et al.,2008)	

3.2 Noah-MP parameterization

As specified in Table 1, Noah-MP has four runoff and groundwater physics options (rnf). Initially, we adopted the options that are incorporated in the NWM, as elaborated in Gochis et al. (2020). Before we could proceed with calibrating Noah-MP for all the WUS basins, it was necessary to determine suitable rnfs. To streamline computational time, we initially selected 50 basins randomly from the total of 263 from which we created four experimental groups. Each group employed a different rnf option. We applied the DDS method to these groups and compared the cumulative distribution functions (CDF) of their baseline and calibrated KGEs (Figure 2). From this figure, it's apparent that the KGE improved post-calibration for all four rnfs. Notably, rnf3, also known as free drainage, exhibited the most substantial performance enhancement after calibration. As a result, we chose to continue using this option which is incorporated in the NWM. Nonetheless, it's worth noting that the use of different options for different basins—a feature currently not utilized in Noah-MP or WRF-Hydro—could potentially result in improved overall model performance.

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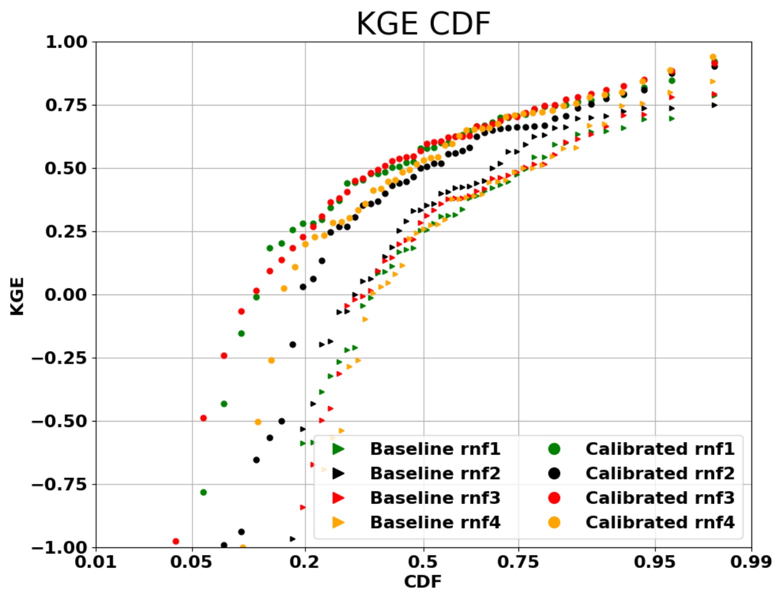

Figure 2. Streamflow performance (KGE of daily streamflow simulations) of different Noah-MP runoff generation options across 50 (of 263) randomly selected basins. The performances are shown for both baseline and calibrated simulations.

3.3 Calibration of gauged basins

Following the selection of the most effective set of runoff generation options across the domain, we estimated model parameters for all 263 basins. The comparative performance of the models, before and after calibration, is shown in Figure 3. It's apparent from the figure that both Noah-MP and VIC have significantly enhanced their daily streamflow simulation skills post-calibration. After calibration, the median KGE of Noah-MP improved from 0.22 to 0.54, and the VIC's median KGE increased from 0.37 to 0.70. When contrasting the two models, we observed that VIC outperformed Noah-MP both pre- and post-calibration. One possible explanation could be that the baseline VIC parameters were taken from Livneh et al. (2013), and these parameters had already been validated and adjusted for major U.S. basins

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(although not for our 263 basins specifically), while the Noah-MP parameters are default values from NWM. Another possibility is inherent differences in the physics of streamflow simulation between the two models (VIC primarily generates runoff via the saturation excess mechanism), although that isn't the main focus of our research.

Following the calibration with data from the past 20 years, we performed a test where we calibrated the streamflow using the first 10 years of data and validated with the subsequent 10 years of data. This test revealed that the KGE distribution from the 10-year calibration is similar to that from the 20-year data. The median KGE values for VIC and Noah-MP after calibration with 10 years of observations were 0.52 and 0.69, respectively. Correspondingly, the median KGEs during the validation period were 0.50 and 0.68, respectively, which are only slightly lower. These comparisons demonstrate general consistency over time in the performance of the calibrated parameters.

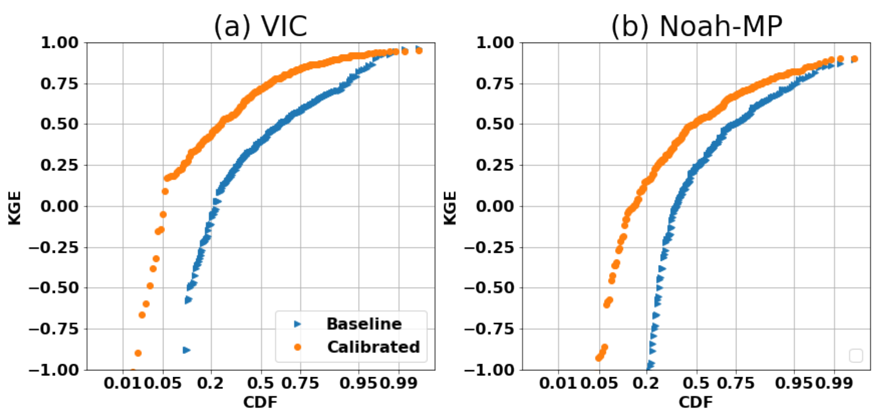

Figure 3. Cumulative Distribution Function (CDF) plot of the daily streamflow KGE for (a) VIC and (b) Noah-MP, comparing baseline and calibrated runs across all 263 basins.

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We examined the spatial variability of daily streamflow KGE for Noah-MP and VIC, both before and after the calibration (see Figure 4). The highest baseline KGEs are along the Pacific Coast, in central to northern CA for both models. VIC's baseline KGE generally is high in the Pacific Northwest. Post-calibration improvements occurred for both models in most areas, especially in regions where the baseline KGE was low, such as southern CA and the southeastern part of the study region. Median improvements after calibration were 0.27 for Noah-MP and 0.30 for VIC.

We observed that basins displaying higher KGE values typically were more humid than those with lower KGE. To further delve into the relationship between KGE and basin characteristics, we explored correlations between KGE and 21 different characteristics, including drainage area, elevation, seasonal/annual average temperature and precipitation, annual maximum precipitation, and seasonal/annual runoff ratio. Of these, 12 characteristics were statistically significantly correlated with the VIC KGE, including four seasonal and annual runoff ratios; mean precipitation in winter, spring, and fall; annual maximum precipitation; and minimum elevation. Figure 5 shows scatterplots of eight representative characteristics. Apart from minimum elevation and mean summer temperature, all other characteristics were positively correlated with KGE. Typically, spring runoff ratio, annual runoff ratio, mean annual max precipitation, and mean winter precipitation exhibited the highest correlations with KGE. This implies that basins with higher runoff ratios (particularly in spring), higher precipitation (especially maximum precipitation), lower summer temperature, and lower elevation are more likely to exhibit strong VIC performance. The same applies to Noah-MP, as indicated in Figure 6, although Noah-MP showed relatively weaker correlations. Correlations between mean summer temperature and mean fall precipitation and Noah-MP KGE weren't statistically significant.

The spatial distribution of the eight characteristics is qualitatively similar with

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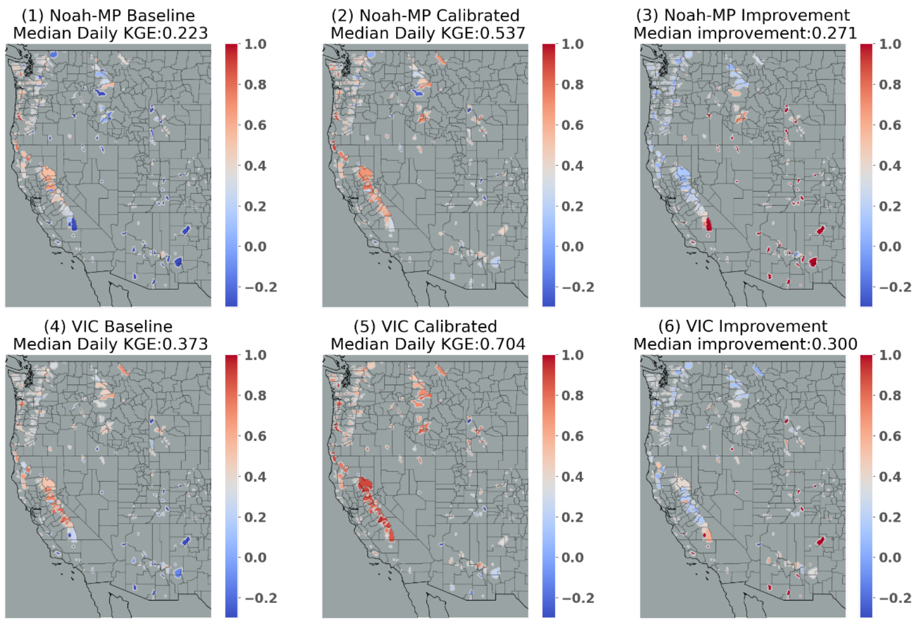
302 the KGE spatial distribution, as shown in Figure 7. Generally, basins with higher KGE

303 have higher characteristic values when the correlation is positive, and lower

304 characteristic values when the correlation is negative.



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306 Figure 4. Spatial distribution of daily streamflow KGE for Noah-MP baseline

307 (1); calibrated Noah-MP (2); difference between calibrated and baseline Noah-MP;

308 VIC baseline (4); calibrated VIC (5); difference between calibrated and baseline VIC.

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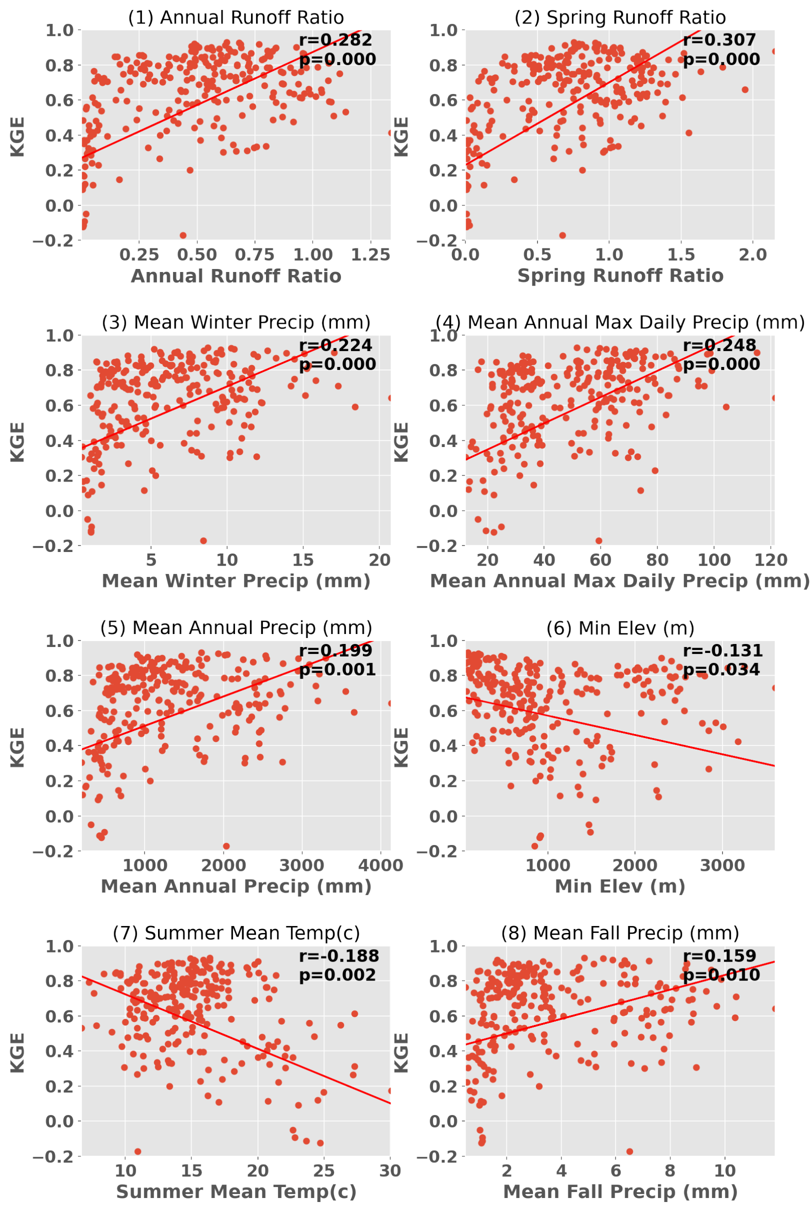

Figure 5. Scatterplots of VIC KGE in relation to significantly correlated characteristics. Each subplot indicates the corresponding Pearson correlation coefficients and the P-value.

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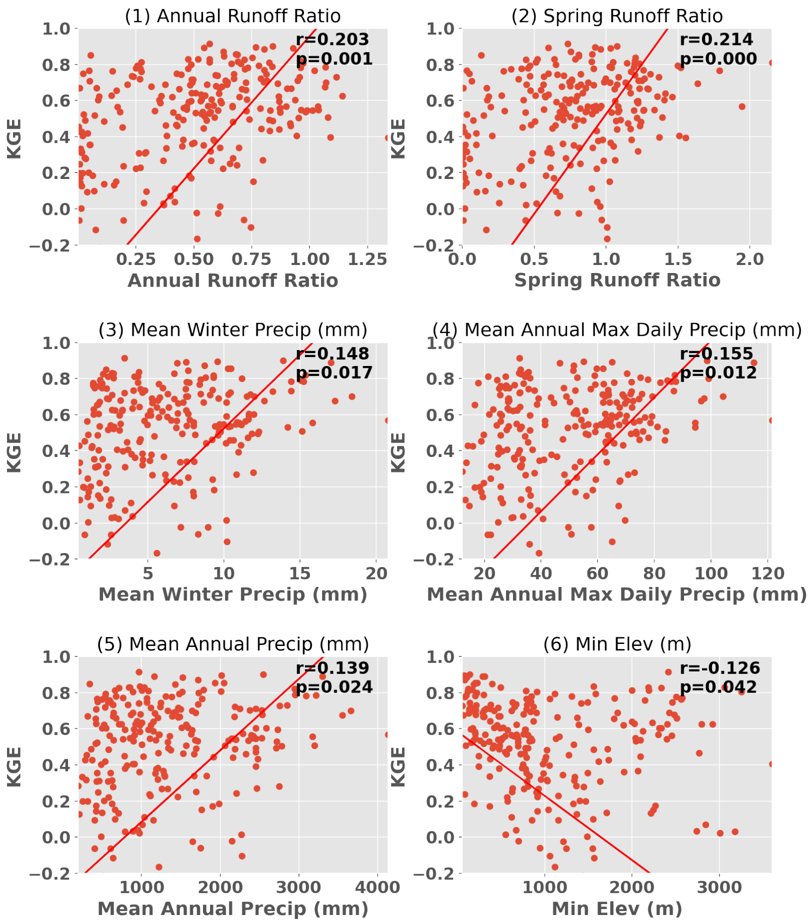

Figure 6. Scatterplot of Noah-MP KGE in relation to significantly correlated characteristics. Each subplot indicates the corresponding Pearson correlation coefficients and the P-value.

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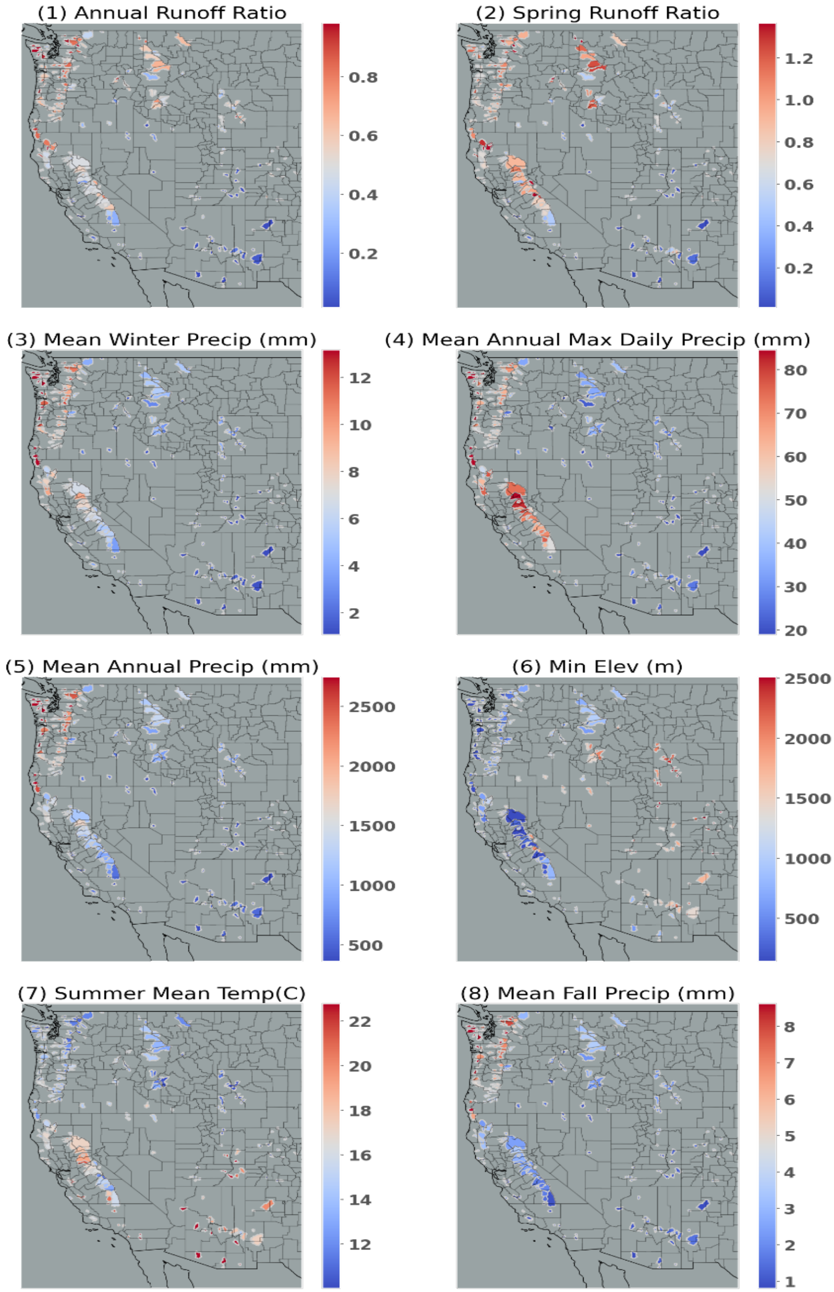

Figure 7. Spatial distribution of characteristics that are statistically significantly correlated with KGE. Note that all characteristics are significantly correlated with VIC KGE whereas only (1)-(6) are significantly correlated with Noah-MP KGE.

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4. Regionalization

Following the calibration process, we regionalized the parameters from gauged to ungauged basins based on a mathematical assessment of the spatial and physical proximity between the gauged and ungauged basins, following previous studies by Arsenault and Brissette (2014), and Razavi and Coulibaly (2017). We opted for this method over an alternate approach that first regionalizes the streamflow attributes (such as runoff depth, high flow indicators) and then standardizes the model throughout (as proposed by Castiglioni et al., 2010; Oubeidillah et al., 2014; and Yang et al 2017). The reason for our choice is our interest in actual streamflow time series rather than metrics. We carried out the regionalization after calibrating to specific streamflow gauges, ensuring high precision for these gauged basins and facilitating high-quality regionalization in ungauged basins. Specifically, we employed a donor-basin approach where an ungauged basin adopts calibrated parameters from its most similar gauged basin(s). This method has been applied in many studies including Arsenault and Brissette (2014); Poissant et al. (2017); Razavi and Coulibaly (2017); Gochis et al. 2019; Qi et al. (2021); and Bass et al (2023).

In the donor-basin method, an ungauged basin inherits its land surface parameters from the most similar gauged basin(s) (or the top 'x' most similar gauged basins). Here, we evaluated the similarity or proximity between gauged and ungauged basins based on the similarity index SI as defined and used by Burn and Boorman (1993) and Poissant et al. (2017):

$$SI = \sum_{i=1}^{k} \frac{|X_i^G - X_i^U|}{\Delta X_i} \qquad (1)$$

In this formula, k stands for the total number of features considered, X_i^G represents the ith feature of the gauged basin G, X_i^U is the ith feature of a specific ungauged basin, and ΔX_i is the range of potential values for the ith feature, grounded in the data from

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the gauged basins. This yields a unique value of SI for each gauged basin, contingent on the specific ungauged basin it is compared with. Typically, gauged basins that exhibit greater resemblance to the ungauged basin will have a smaller SI.

We assessed the donor-basin method's efficacy using a cross-validation approach, where each gauged basin was treated as ungauged one at a time. The pseudo-ungauged basin inherits its hydrological parameters from its three most similar gauged basins, determined by SI. The parameters inherited are a weighted average from the three donor basins. After testing one to five donor basins, we found that using three donors yielded the best results. Thus, every basin inherits parameters from the three most similar gauged basins in each simulation, offering a concise evaluation of the donor-basin method's regionalization performance.

We used 18 basin-specific features in the donor basin method, detailed in Table S1, calculated based on the forcings and parameters used in the study. For feature selection in the donor-basin method, we adopted an iterative approach. Each iteration added a single feature to the index, with the most beneficial feature (based on median KGE improvement) retained. This process was repeated until the median KGE no longer improved. Only basins with a KGE exceeding 0.3 were considered, following previous studies suggesting that inclusion of poorly performing basins can lower regionalization performance. We found that a KGE threshold of 0.3 resulted in a median performance improvement of 0.08 larger than did a KGE threshold of 0, hence it was chosen. After screening, 223 basins were utilized in VIC regionalization and 194 in Noah-MP regionalization.

We found five features generated the best regionalization performance for VIC (longitude centroid, latitude centroid, maximum elevation, fall mean precipitation, and fall mean temperature) and three features were best for Noah-MP (latitude centroid, longitude centroid, and drainage area) (see Figure 8). Among them, latitude and longitude are the common features that contribute the most to regionalization when using the similarity index method. This suggests that geographical similarities are the most important factor in parameter information transfer from gauged to ungauged basins.

Upon evaluating the performance of baseline, calibrated, and regionalized simulations, the respective median daily KGEs for the VIC model were found to be 0.41, 0.71, and 0.49. For the Noah-MP, these values were 0.38, 0.60, and 0.49 (refer to Figures 8 & 9). These metrics are for basins that have a calibrated KGE greater than 0.3 only, resulting in higher median KGEs than for all 263 basins (See Figure 3). The KGE distribution also improved overall. It's noteworthy that the regionalization improvement relative to baseline is higher for Noah-MP than for VIC. While VIC's baseline and calibrated KGE skill distribution outperforms Noah-MP's, the regionalized skills of Noah-MP and VIC are quite comparable. This observation might be attributable to the constraints of the regionalization setup and could warrant future investigation.

After optimizing the features and specific design of the donor-basin method, parameters were regionalized to 4816 ungauged USGS Hydrologic Unit Code (HUC) -10 basins across the WUS. HUCs are delineated and quality controlled by USGS using high-resolution DEMs. The final hydrologic parameters for both VIC and Noah-MP for all WUS HUC-10 basins are shown in Figures S1&2. The baseline HUC-10 parameters are shown in Figures S3&4.

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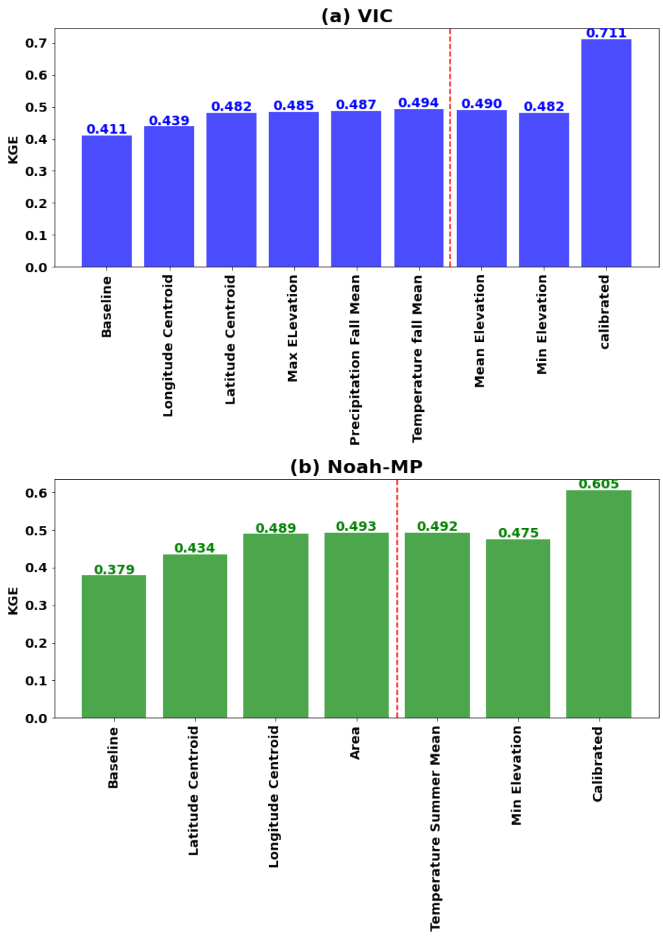

Figure 8. Best regionalization features for (a) VIC and (b) Noah-MP. The final regionalization to ungauged basins of the WUS incorporated all features up to the point marked by the red line since the addition of further features doesn't improve KGE.

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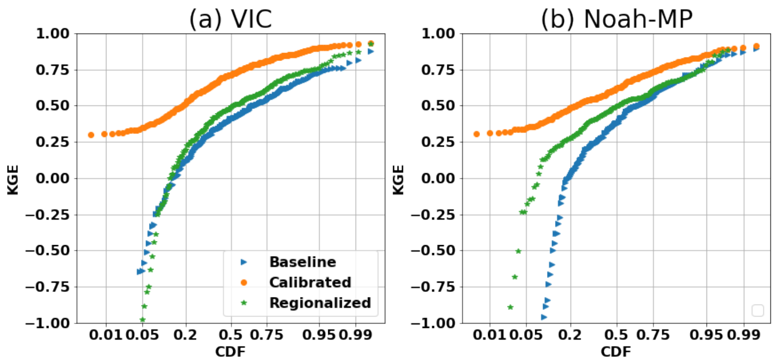

Figure 9. CDF of daily KGE for (a) VIC and (b) Noah-MP, comparing baseline and calibrated runs across selected regionalized basins within the WUS.

5. Evaluation of high and low flow simulation skill

To understand the capabilities of the two models in reconstructing high and low streamflow, we assessed their performance across baseline, calibrated, and regionalized settings.

(a) Evaluation of high flow performance

We used the peaks-over-threshold (POT) method (Lang et al. 1999) to identify extreme streamflow events as in Su et al (2023) and Cao et al. (2019, 2020). We first applied the event independence criteria from USWRC (1982) to daily streamflow data to identify independent events. We set thresholds at each basin that resulted in 3 extreme events per year on average. After selecting the flood events over the study period based on the observation, we sorted the floods based on the return period and then calculated the KGE of baseline, calibrated and regionalized floods. Figure 10 displays the associated CDF plots. The median KGE for baseline floods in Noah-MP was 0.14, which rose to 0.37 post-calibration, and receded to 0.22 after regionalization. For VIC, the flood KGE started at 0.11, increased to 0.41 after calibration, and declined to 0.20 post-regionalization. As anticipated, these numbers

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are lower than (all) daily streamflow skill due to our calibration target being daily streamflow. Still, flood competencies experienced considerable enhancement, surpassing the Noah-MP KGE benchmark of -0.41 found by Knoben et al. (2019).

(b) Evaluation of low flow performance

To assess low flow performance, we utilized the 7q10 metric. This hydrological statistic, commonly adopted in water resources management and environmental engineering, is the lowest 7-day average flow that occurs (on average) once every 10 years (EPA,2018). Scatterplots of 7q10 (Figure 11) showed high correlation between our model's simulated low flows and the observed data. Post-calibration, this alignment intensified. The VIC model tended to underestimate the low flows. After calibration, the median bias improved from -23.6% to -9.9%, and with regionalization, it was -11.7%. In contrast, Noah-MP began with an 11.20% overestimation in the baseline, improved to 0.61% post-calibration, and was -9.5% after regionalization. The outcomes underline the proficiency of both models for low flow prediction, exhibiting enhanced competencies post-calibration and commendable performance after regionalization.

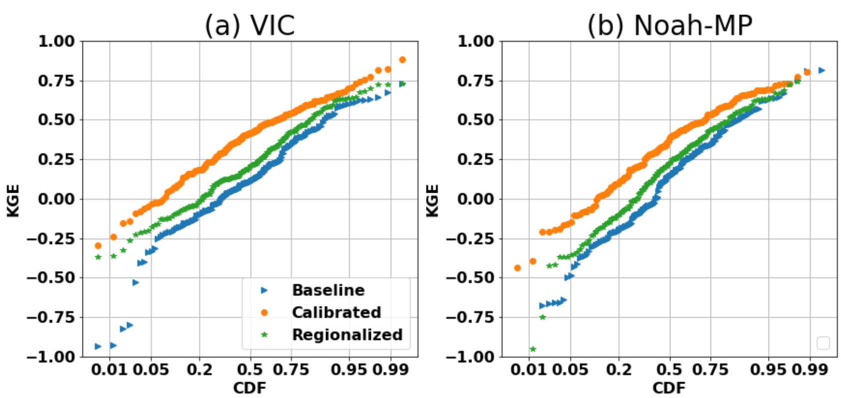

Figure 10. CDF of high flow KGE for (a) VIC and (b) Noah-MP, comparing baseline and calibrated runs across selected regionalized basins within the WUS.

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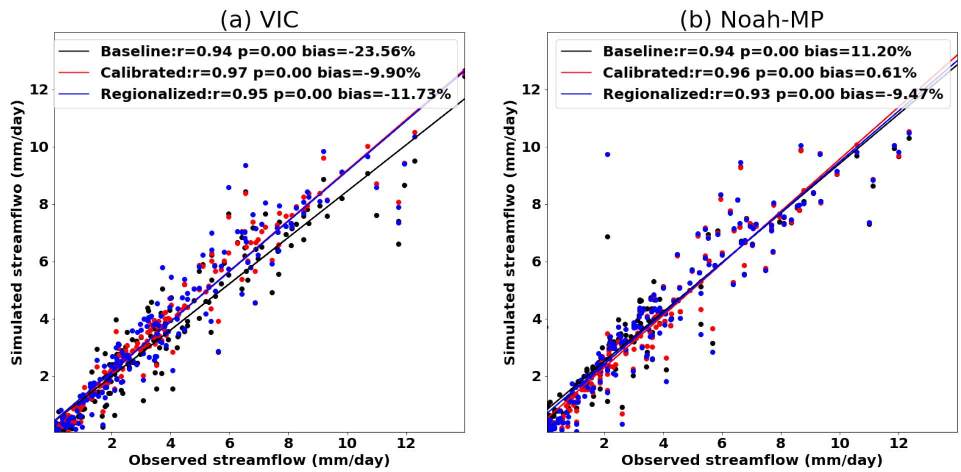

Figure 11. Scatterplot of 7q10 low flows (the lowest 7-day average flow that occurs (on average) once every 10 years) for the baseline and calibrated and regionalized runs for (a) VIC model and (b) Noah-MP. The correlation coefficients, P-values and percentage bias are denoted in the upper section of the figures. The x axis is observed low flow and the y axis is simulated low flow.

6. Summary

Our objective was to produce parameter sets for VIC and Noah-MP over WUS that could be used in regional studies, and would result in better model performance than default or other "off the shelf" parameters. We identified preferred runoff generation options for Noah-MP (physics options are fixed in VIC) using a subset of our WUS basins (50 in total) for which we evaluated all four Noah-MP runoff generation options. Once we identified the optimal runoff generation options for Noah-MP, we identified (calibrated) parameters for both Noah-MP and VIC for each of our 263 basins across WUS using the most recently available 20-years of streamflow observations. Following calibration, the Noah-MP median KGE increased from 0.22 to 0.54, while the median VIC KGE rose from 0.37 to 0.70. VIC KGEs

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were higher than Noah-MP's both before and after calibration across the 263 basins, possibly because the initial VIC parameters had the benefit of some previous calibration, albeit for much larger river basins across WUS (in the case of post-calibration KGE, it's unclear whether and how they might have been affected by the choice of initial parameters). Other possible cause of the differences could be inherent differences in streamflow simulation physics between the two models. We also conducted a test using the initial 10 years of data for calibration and the following 10 years for validation, and found results that were consistent with those we obtained using the entire 20 years for calibration.

Upon the selection of suitable parameterizations for Noah-MP and calibration of gauged basins for both VIC and Noah-MP, we extended the use of the calibrated parameters to ungauged basins across the WUS for both models. This extension was achieved through the donor-basin regionalization method, which allows ungauged basins to inherit parameters from gauged basins with similar hydroclimatic properties. We discovered that using a weighted combination of three similar basins yielded better regionalization results (in terms of KGE) compared to using the single most similar donor basin, as determined by a similarity index. Following regionalization, the median KGE for VIC rose from 0.41 to 0.49, and for Noah-MP it increased from 0.38 to 0.49 over the selected basins. Interestingly, even though the pre-regionalization KGE for VIC was considerably higher than for Noah-MP, the post-regionalization values for the two models were nearly identical. Stated otherwise, the regionalization enhancement was considerably greater for Noah-MP than for VIC. We further evaluated high and low flow simulation skills and found the skill significantly improved after calibration for both VIC and Noah-MP and improvements remained after regionalization. Following calibration and regionalization, we developed gridded parameter sets for both models at 1/16° latitude-longitude

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resolution for all 4816 HUC-10 basins across the WUS. These parameter sets should be useful for regional hydrologic and river hydrodynamic modeling studies over all or parts of the WUS domain. Improving the accuracy of the models' predictions should have benefits for water management across the region, and more and more generally for understanding the potential impacts of climate change across the region. Moreover, the methods and procedures we utilized are not restricted to our current research domain; they could be transferred readily to other geographic regions. In effect, our research contributes to both local and global efforts to understand and manage our critical hydrological systems better, demonstrating its broader relevance and utility.

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Data Availability statement

The Livneh (2013) forcings are available at http://livnehpublicstorage.colorado.edu:81/Livneh.2013.CONUS.Dataset/. The extended forcings used in this study are available at ftp://livnehpublicstorage. colorado.edu/public/sulu. The results are available online at https://figshare.com/s/66fe8305bff516e80f6f .

Competing interests. The contact author has declared that none of the authors has any competing interests.

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