



Development of a large-sample watershed-scale hydrometeorological dataset for the contiguous USA: dataset characteristics and assessment of regional variability in hydrologic model performance

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Abstract

We present a community dataset of daily forcing and hydrologic response data for 671 small- to medium-sized basins across the contiguous United States (median basin size of 336 km²) that spans a very wide range of hydroclimatic conditions. Areal averaged forcing data for the period 1980–2010 was generated for three basin delineations – basin mean, Hydrologic Response Units (HRUs) and elevation bands – by mapping the daily, 1 km gridded Daymet meteorological dataset to the sub-basin and basin polygons. Daily streamflow data was compiled from the United States Geological Survey National Water Information System. The focus of this paper is to (1) present the dataset for community use; and (2) provide a model performance benchmark using the coupled Snow-17 snow model and the Sacramento Soil Moisture Accounting conceptual hydrologic model, calibrated using the Shuffled Complex Evolution global optimization routine. After optimization minimizing daily root mean squared error, 90 % of the basins have Nash–Sutcliffe Efficiency scores > 0.55 for the calibration period. This benchmark provides a reference level of hydrologic model performance for a commonly used model and calibration system, and highlights some regional variations in model performance. For example, basins with a more pronounced seasonal cycle generally have a negative low flow bias, while basins with a smaller seasonal cycle have a positive low flow bias. Finally, we find that data points with extreme error (defined as individual days with a high fraction of total error) are more common in arid basins with limited snow, and, for a given aridity, fewer extreme error days are present as basin snow water equivalent increases.

1 Introduction

With the increasing availability of gridded meteorological datasets, streamflow records and computing resources, large sample hydrology studies have become more common in the last decade or more (e.g. Maurer et al., 2002; Merz and Blöschl, 2004;

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Andreassian et al., 2004; Lohmann et al., 2004; Oudin et al., 2006, 2010; Samaniego et al., 2010; Nester et al., 2011, 2012; Livneh and Lettenmaier, 2012, 2013; Kumar et al., 2013; Oubeidillah et al., 2013). Gupta et al. (2014) emphasize that more large-sample hydrologic studies are needed to “balance depth with breadth” – to wit, most hydrologic studies have traditionally focused on one or a small number of basins (depth), which hinders the ability to establish general hydrologic concepts applicable across regions (breadth) (Gupta et al., 2014). Gupta et al. (2014) go on to discuss practical considerations for large sample hydrology studies, noting first and foremost that large datasets of quality basin data need to be available and shared in the community.

In support of this philosophy, we present a large-sample hydrometeorological dataset and modeling tools to understand regional variability in hydrologic model performance across the contiguous USA. The development of the basin dataset presented herein takes advantage of high quality freely-available data from various US government agencies and research laboratories. It includes (1) daily forcing data for 671 basins for multiple delineations over the 1980–2010 time period; (2) daily streamflow data; (3) basic metadata (e.g. location, elevation, size, and basin delineation shapefiles) and (4) benchmark model performance which contains the final calibrated model parameter sets, model output timeseries for all basins as well as summary graphics for each basin. This dataset and benchmark application is intended for the community to use as a test-bed to facilitate the evaluation of hydrologic modeling and prediction questions. To this end, the benchmark consists of the calibrated, coupled Snow-17 snow model and the Sacramento Soil Moisture Accounting conceptual hydrologic model for all 671 basins using the Shuffled Complex Evolution global optimization routine. We provide some basic analysis on how this choice of hydrologic modeling method impacts regional variability in model performance.

The next section describes the development of the basin dataset from basin selection through forcing data generation. It then briefly describes the modeling system and calibration routine. Next, example results using the basin dataset and modeling platform are presented. Finally, concluding thoughts and next steps are discussed.

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2 Basin dataset

The development of a freely available large sample basin dataset requires several choices and subsequent data acquisition. Three major decisions were made and are discussed in this section: (1) the selection process for the basins, (2) the various basin delineations to be developed, and (3) selection of underlying forcing dataset used to develop forcing data timeseries. Additionally, aggregation of the necessary streamflow data is described.

2.1 Basin selection

The United States Geological Survey (USGS) developed an updated version of their Geospatial Attributes of Gages for Evaluating Streamflow (GAGES-II) in 2011 (Falcone et al., 2010; Falcone, 2011). This database contains geospatial information for over 9000 stream gages maintained by the USGS. As a subset of the GAGES-II database, a portion of the basins with minimal human disturbance (i.e. minimal land use changes or disturbances, minimal human water withdrawals) are noted as “reference” gages. A further sub-setting of the reference gages were made as a follow-on to the Hydro-Climatic Data Network (HCDN) 1988 dataset (Slack and Landwehr, 1992). These gages, marked HCDN-2009 (Lins, 2012), meet the following criteria: (1) have at least 20 years of complete flow data between 1990–2009 and were active as of 2009, (2) are a GAGES-II reference gage, (c) have less than 5 % imperviousness as measured by the National Land Cover Database (NLCD-2006), and (d) passed a manual survey of human impacts in the basin by local Water Science Center evaluators (Falcone et al., 2010). There are 704 gages in the GAGES-II database that are considered HCDN-2009 across CONUS. This study uses that portion of the HCDN-2009 basin set as the starting point since they should best represent natural flow conditions. After initial processing and data availability requirements, 671 basins are used for analysis in this study. Because these basins have minimal human influence they are almost exclusively smaller, headwater-type basins.

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2.2 Forcing and streamflow data

The Daymet dataset was selected to derive forcing data for our streamflow simulations (Thornton et al., 2012). Daymet was chosen because of its high spatial resolution, a necessary requirement to more fully estimate spatial heterogeneity for basins in complex topography. Daymet is a daily, gridded (1 km × 1 km) dataset over the CONUS and southern Canada and is available from 1980 to present. It is derived solely from daily observations of temperature and precipitation. The Daymet variables used here are daily maximum and minimum temperature, precipitation, shortwave downward radiation, day length, and humidity; additionally snow water equivalent is included (not used in this work). These daily values are estimated through the use of an iterative method dependent on local station density and the spatial convolution of a truncated Gaussian filter for station interpolation, and MT-CLIM to estimate shortwave radiation and humidity (Thornton et al., 1997, 2000; Thornton and Running, 1999). Daymet does not include estimates of potential evapotranspiration (PET), a commonly needed input for conceptual hydrologic models or wind speed and direction. Therefore, PET was estimated using the Priestly–Taylor method (Priestly and Taylor, 1972) and is discussed further in Sect. 3.

Hydrologic models are run with a variety of spatial configurations, including entire watersheds (lumped), elevation bands, hydrologic response units (HRUs), or grids. For this dataset, forcing data were calculated (via areal averaging) for watershed, HRU and elevation band delineations. The basin delineations were created from the base national geospatial fabric for hydrologic modeling developed by the USGS Modeling of Watershed Systems (MoWS) group. The geospatial fabric is a watershed-oriented analysis of the National Hydrography Dataset that contains points of interest (e.g. USGS streamflow gauges), hydrologic response unit boundaries and simplified stream segments (not used in this study). This geospatial fabric contains points of interest that include USGS streamflow gauges and allowed for the determination of upstream total basin area and basin HRUs. A digital elevation model (DEM) was applied to the

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geospatial fabric dataset to create elevation contour polygon shapefiles for each basin. The USGS Geo Data Portal (GDP) developed by the USGS Center for Integrated Data Analytics (CIDA) (Blodgett et al., 2011) was leveraged to produce areally-weighted forcing data for the various basin delineations over our time period. The GDP performs all necessary spatial subsetting and weighting calculations and returns the areally weighted timeseries for the specified inputs.

Daily streamflow data for the HCDN-2009 gages were obtained from the USGS National Water Information System server (<http://waterdata.usgs.gov/usa/nwis/sw>) over the same forcing data time period, 1980–2010. While the period 1980–1990 is not covered by the HCDN-2009 review, it was assumed that these basins would have minimal human disturbances in this time period as well. For the portion of the basins that do not have streamflow records back to 1980, analysis is restricted to the available data records.

3 Hydrologic modeling benchmark

As stated in the introduction, the intended purpose of this dataset is a test-bed to facilitate assessment of hydrologic modeling and prediction questions across broad hydroclimatic variations, and we focus here on providing a benchmark performance assessment for a widely used calibrated, conceptual hydrologic modeling system. This type of dataset can be used for many applications including evaluation of new modeling systems against a well know benchmark system over wide ranging conditions, or as a base for comprehensive predictability experiments exploring importance of meteorology or basin initial conditions (e.g. Wood et al., 2014). To this end, we have implemented and tested an initial model and calibration system described below, using the primary models and objective calibration approach that have been used by the US National Weather Service River Forecast Centers (NWSRFCs) in service of operational short-term and seasonal streamflow forecasting.

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3.1 Models

The HCDN-2009 basins include those with substantial seasonal snow cover (Fig. 1), necessitating a snow model is required in addition to a hydrologic model. Within the NWSRFCs, the coupled Snow-17, Sacramento Soil Moisture Accounting Model (Snow-17 and SAC-SMA) system is used. Snow-17 is a conceptual air temperature index based snow accumulation and ablation model (Anderson, 1973). It uses near surface air temperature to determine the energy exchange at the snow–air interface and the only time-varying inputs are typically air temperature and precipitation (Anderson, 1973, 2002). The SAC-SMA model is a conceptual hydrologic model that includes representation of physical processes such as evapotranspiration, percolation, surface flow, sub-surface lateral flow. Required inputs to SAC-SMA are potential evapotranspiration and water input to the soil surface (Burnash et al., 1973; Burnash, 1995). Snow-17 runs first and determines the partition of precipitation into rain and snow and the evolution of the snowpack. Any rain, snowmelt or rain passing unfrozen through the snowpack for a given timestep becomes direct input to the SAC-SMA model. Finally, streamflow routing is accomplished through the use of a simple two-parameter, Nash-type instantaneous unit-hydrograph model (Nash, 1957).

3.2 Calibration

We employed a split-sample calibration approach, assigning the first 15 years of available streamflow data for calibration and the remainder for validation; thus, approximately 5500 daily streamflow observations were used for calibration. To initialize the model calibration moisture states on 1 October, we specified an initial wet SAC-SMA soil moisture state that was allowed to spin down to equilibrium for a given basin by running the first year of the calibration period repeatedly and assume no snow pack. This was done until all SAC-SMA state variables had minimal year over year variations, which is a spin-up approach used by the Project for Intercomparison of Land-Surface Process Schemes (e.g. Schlosser et al., 2000). Determination of optimal calibration

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sampling and spin-up procedures is an area of active research. Spin-up was performed for every parameter set specified by the optimization algorithm, then the model was integrated for the calibration period and the RMSE for that parameter set was calculated.

Objective calibration was done by minimizing the root mean squared error (RMSE) of daily modeled runoff vs. observed streamflow using the Shuffled Complex Evolution (SCE) global search algorithm of Duan et al. (1992, 1993). The SCE algorithm uses a combination of probabilistic and deterministic optimization approaches that systematically spans the allowed parameter search space and also includes competitive evolution of the parameter sets (Duan et al., 1993). Prior applications to the SAC-SMA model have shown good results (Sorooshian et al., 1993; Duan et al., 1994). In the coupled Snow-17 & SAC-SMA modeling system, 35 potential parameters are available for calibration, of which we calibrated 20 parameters having either a priori estimates (Koren et al., 2000) or those found to be most sensitive following Anderson (2002) (Table 1). The SCE algorithm was run using 10 different random seed starts for the initial parameter sets for each basin, in part to evaluate the robustness of the optimum in each case, and the optimized parameter set with the minimum RMSE from the ten different optimization runs was chosen for evaluation.

For Snow-17, six parameters were chosen for optimization (Table 1): the minimum and maximum melt factors (MFMIN, MFMAX), the wind adjustment for enhanced energy fluxes to the snow pack during rain on snow (UADJ), the rain/snow partition temperature, which may not be 0 °C (PXTEMP), the snow water equivalent for 100 % snow covered area (SI), and the gauge catch correction term for snowfall only (SCF). These parameters were chosen because MFMIN, MFMAX, UADJ, SCF, and SI are defined as major model parameters by Anderson (2002) with the addition of PXTEMP is shown by Mizukami et al. (2013). The areal depletion curve (ADC) is considered a major parameter in Snow-17. However, to avoid expanding the parameter space by the number of ordinates on the curve (typically 10), we manually specified the ADC according to regional variations in latitude, topographic characteristics (e.g. plains, hills or mountains) and typical air mass characteristics (e.g. maritime polar, continental polar)

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(as suggested in Anderson, 2002). The remaining Snow-17 parameters were set in the same manner. Following the availability of a priori parameter estimates for SAC-SMA from a variety of datasets and various calibration studies with SAC-SMA (Koren et al., 2000; Anderson et al., 2006; Pokhrel and Gupta, 2010; Zhang et al., 2012)

11 parameters from SAC-SMA are included for calibration (Table 1). We use an instantaneous unit hydrograph, represented as a two-parameter Gamma distribution for streamflow routing (Sherman, 1932; Clark, 1945; Nash, 1957; Dooge, 1959), the parameters of which were inferred as part of calibration.

Finally, the scaling parameter in the Priestly–Taylor PET estimate is also calibrated. The Priestly–Taylor (P-T) equation (Priestly and Taylor, 1972) can be written as:

$$\text{PET} = \frac{a}{\lambda} \cdot \frac{s \cdot (R_n - G)}{s + \gamma} \quad (1)$$

Where λ is the latent heat of vaporization, R_n is the net radiation estimated using day of year, all Daymet variables and equations to estimate the various radiation terms (Allen et al., 1998; Zotarelli et al., 2009), G is the soil heat flux (assumed to be zero in this case), s is the slope of the saturation vapor pressure–temperature relationship, γ is the psychrometric constant and a is the P-T coefficient. The P-T coefficient replaces the aerodynamic term in the Penman–Monteith equation and varies by the typical conditions of the area where the P-T equation is being applied with humid forested basins typically having smaller values and exposed arid basins having larger values (Shuttleworth and Calder, 1979; Morton, 1983; ASCE 1990). Thus the P-T coefficient was included in the calibration since it should vary from basin to basin.

4 Benchmark results

4.1 Assessment objectives and metrics

Assessment of the models will focus on overall performance across the basin set, regional variations, and error characteristics. Nash–Sutcliffe efficiency (NSE) (Nash

and Sutcliffe, 1970) and the decomposition components of NSE (Gupta et al., 2009) are the first metrics examined in two variations. Because NSE scores model performance relative to the observed climatological mean, regions in which the model can track a strong seasonal cycle (large flow autocorrelation) perform relatively better when measured by NSE, and this seasonal enhancement may be imparted when using NSE as the objective function for both the calibration and validation phases (e.g. Schaeffli et al., 2007). Additionally, basins with higher streamflow variance and frequent precipitation events have better model performance. Therefore, to give a more standardized picture of model performance across varying hydroclimatologies, the NSE was recomputed using the long-term monthly mean flow instead of mean flow (denoted MNSE hereafter), thus preventing climatological seasonality from inflating the NSE and more accurately ranking basins by the degree to which the model added value over climatology in response to weather events (Schaeffli et al., 2005). MNSE in this context is defined for each day of year (DOY) via a 31 day window centered on a given DOY. The long-term flow for that 31 day “month” is computed giving rise to a “monthly” mean flow. Using this type of climatology as the base for an NSE type analysis provides improved standardization in basins with large flow autocorrelations.

Also, several other advanced, more physically based, metrics of model performance are provided. First, three diagnostic signatures based on the flow duration curve (FDC) from Yilmaz et al. (2008) are computed: (1) the top 2 % flow bias, (2) the bottom 30 % flow bias and (3) the bias of the slope of the middle portion (20–70 percentile) of the FDC. Second, examination of the time series of squared error contribution to the RMSE statistic was performed to highlight events in which the model performs poorly following Clark et al. (2008). This analysis was performed to gauge the representativeness of performance metrics over the model record by using the sorted (highest to lowest) time series of squared error to identify the N number of the largest error days and determine their fractional error contribution to the total. Finally, we extend this analysis to introduce, a simple, normalized general error index for application and comparison across varying modeling and calibration studies. We coin the index, E50, the fraction

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of calibration points contributing 50 % of the error (Fig. 7c). This captures the number of points determining the majority of the error and thus the optimal parameter set.

4.2 Overall performance

The 671 basins span the entire CONUS and cover a wide range of hydro-climatic conditions. They range from wet, warm basins in the Southeast (SE) US to hot and dry basins in the Southwest (SW) US, to wet cool basins in the Northwest (NW) and dry cold basins in the intermountain western US (Fig. 1). This allows us to simulate a variety of energy and water limited basins with different snow storage, elevation, slope, and precipitation characteristics. There are many energy limited basins with dryness ratios as small as 0.2 and many water limited basins with dryness ratios as large as 4.5 (Fig. 1b). As noted in Sect. 2b, no additional quality control was performed on the candidate basins before calibration. For completeness and to highlight some of the tradeoffs made when performing large sample hydrologic studies, all basins are kept for analysis in this work.

For the calibration period, 90 % (604) of the basins produce a NSE greater than 0.55, while 72 % (484) of the basins had a validation period NSE > 0.55 (Fig. 2a). The decomposition of the NSE (Gupta et al., 2009) shows that nearly all basins have too little modeled variance (values less than one) for both the calibration and validation phases (Fig. 2b). The total volume biases are generally small with 94 % (79 %) of the basins having a calibration (validation) period total flow bias within 10 % of observed (Fig. 2c). These are expected results when using RMSE for the objective function (Gupta et al., 2009) and reaffirm that our implementation of SCE is calibrating the model properly.

The model under predicts high flow events in nearly all basins during calibration and slightly less so for the validation period (Fig. 3a). This is an expected result when using RMSE as the objective function because the optimal calibration underestimates flow variability (Gupta et al., 2009). Low flow periods are more evenly over and under predicted (Fig. 3b) for both the calibration and validation time frames with 58 % and

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61 % of basins having more modeled low flow. Finally, the bias in the slope of the FDC is generally under predicted with ~ 75 % of basins having a negative model bias (FDC slope is negative, thus a negative bias indicates the model slope is more positive and that the modeled flow variability is too compressed). The slope of the FDC indicates the variance of daily flows, which primarily relate to the seasonal cycle or the “flashiness” of a basin. Again this indicates model variability is less than observed, at both short and longer time scales. In aggregate, these results agree with Fig. 2 and are expected based on the analysis of Gupta et al. (2009). Optimization using RMSE or NSE as the objective function generally results in under prediction of flow variance and near zero total flow bias (Fig. 2). This manifests itself in the simulated hydrograph as under predicted high flows, generally over predicted low flows and a more positive slope to the middle portion of the FDC (Fig. 3). It is worth repeating that the goal of this initial application is to provide to community with a benchmark of model performance using well known models, calibration systems and widely used, simple objective functions, thus the use of RMSE.

4.3 Spatial variability

It is informative to examine spatial patterns of the aforementioned metrics to elucidate factors leading to weak (and strong) model performance. Poor performing basins are most common along the high plains and desert southwest (Fig. 4a, Sect. 3c). When examining MNSE (Fig. 4b), basins with high non-seasonal streamflow variance and frequent precipitation events (Gulf Coast and Pacific NW) have the highest model MNSE, while most of the snowmelt dominated basins see MNSE scores reduced relative to NSE, particularly in the validation phase (Figs. 2a and 4c). This indicates that RMSE as an objective function may not be well suited for model calibration in basins with high flow autocorrelation (Kavetski and Fenicia, 2011; Evin et al., 2014).

Areas with low validation NSE and MNSE scores have generally large biases when looking at FDC metrics as well (Fig. 5). Focusing on the high plains, high flow biases of ± 50 % are common. Extreme negative low flow biases are also present along the

high plains and desert SW along with a general model trend to have large negative FDC slope biases, consistent with a poorly calibrated model. For the 72 % of basins with validation NSE > 0.55 (basins with yellow-green to dark red colors in Fig. 5a), there is no noticeable spatial pattern across CONUS in regard to high flow periods.

However, basins with a more pronounced seasonal cycle (e.g. snowpack dominated watersheds, central California) generally have a negative low flow bias, while basins with a smaller seasonal cycle have a positive low flow bias. Correspondingly, basins with a pronounced seasonal cycle generally have a near zero or positive slope of the FDC bias, while basins with a smaller seasonal cycle have a negative slope bias.

4.4 Error characteristics

When examining fractional error statistics for the basin set, 15 basins have single days that contribute at least half the total squared error, whereas at the median, the largest error day contributes 8.3 % of the total squared error for the median basin (Fig. 6). The fractional error contribution for the 10, 100 and 1000 largest error days for the median basin are 33, 70 and 96 % of the total squared error respectively. This indicates that for nearly all basins, there are 100 or fewer points that drive the RMSE and therefore optimal model parameters. This type of analysis can be undertaken for any objective function to identify the most influential points and allow for more in-depth examination of forcing data, streamflow records, calibration strategies (i.e. Kavetski et al., 2006; Vrugt et al., 2008; Beven and Westerberg, 2011; Beven et al., 2011; Kauffeldt et al., 2013), or if different model physics are warranted.

The spatial distribution of fractional error contributions show that the issue of model performance being explained by a relatively small set of days is more prevalent in arid regions of CONUS (SW US and high plains) as well as basins slightly inland from the east coast of CONUS. (Fig. 7a and b). The arid basins are generally dry with sporadic high precipitation (and flow) events, while the Appalachian basins are wetter (Fig. 1) with extreme precipitation events interspersed throughout the record. Basins with significant snowpack tend to have lower error contributions from the largest error days

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(Fig. 7a and b). The E50 metric highlights mean peak snow water equivalent (SWE) and frequent precipitation basins as well. These regions contain and order of magnitude more days than the high plains and desert SW, giving insight into how representative of the entire streamflow timeseries the optimal model parameter set really is.

Additionally, ranking the basins using their fractional error characteristics provides a similar insight. As the aridity index increases, the fractional error contribution increases for basins with little to no mean peak SWE. For basins with significant SWE, the fractional error contribution decreases with increasing aridity (Fig. 8). Alternatively, for a given aridity index the fractional error contribution for N days will decrease with increasing SWE. This dynamic arises because more arid basins with SWE produce a relatively greater proportion of their runoff from snowmelt, without intervening rainfall. This implies that the optimized model produces a more uniform error distribution with less heteroscedasticity in basins with more SWE. Moreover, as the fractional error contribution for the 10 largest error days increases, model NSE generally decreases in the validation phase (Fig. 9). This indicates fractional error metrics are related to overall model performance and that calibration methods to reduce extreme error days should improve model performance. This is not unexpected due to the fact that the residuals from an RMSE type calibration are heteroscedastic. Arid basins typically have few high flow events, which are generally subject to larger errors when minimizing RMSE. Using advanced calibration methodologies that account for heteroscedasticity (Kavetski and Fenicia, 2011; Evin et al., 2014) may produce improved calibrations for arid basins in this basin set and provide different insights into model behavior using this type of analysis.

4.5 Limitations and uncertainties

One interesting example of the usefulness (and a potential limitation) of large sample hydrology stemming from this work lies in the identification of issues with forcing datasets. When examining calibrated model performance in the Pacific Northwest, it

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is seen that several basins along the Olympic Peninsula have low outlier NSE scores. Tracing this unexpected result, we find the Daymet forcing data available for those basins has a negative temperature bias, preventing mid-winter rain and melt episodes in the modeling system, identifying scope to improve the Daymet forcing. Moreover, winter periods of observed precipitation and streamflow rises coincide with subzero $T_{\max}$ in the Daymet dataset, also suggesting areas to improve the Daymet forcing.

This limits interpretation of these results and other large sample hydrologic studies. As noted by Gupta et al. (2014), large sample hydrology requires a tradeoff between breadth and depth. The lack of depth inhibits discovery of data quality issues and introduces outliers in any analysis (e.g. Fig. 9). Explanation of these outliers is sometimes difficult due to the lack of familiarity with those specific basins and any forcing or validation data peculiarities.

5 Summary and discussion

Most hydrologic studies focus in detail on a small number of watersheds, providing comprehensive but highly local insights, and may be limited in their ability to inform general hydrologic concepts applicable across regions (Gupta et al., 2014). To facilitate large-sample hydrologic studies, large-sample basin datasets and corresponding benchmarks of model performance using standard methodology across all basins need to be freely available to the community. To that end, we have compiled a community dataset of daily forcing and streamflow data for 671 basins and provide a benchmark of performance using a widely used conceptual a hydrologic modeling and calibration scheme over a wide range of conditions.

Overall, application of the basin set to assessing an objectively calibrated conceptual hydrologic model representation of the 671 watersheds yielded Nash–Sutcliffe Efficiency (NSE) scores of > 0.55 for 90 % of the basins. Performance of the models varied regionally, and the main factors influencing this variation were found to be aridity and precipitation intermittency, contribution of snowmelt, and runoff seasonality. Analysis

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of the cumulative fractional error contributions from the largest error days showed that the presence of significant snow water equivalent (SWE) offset the negative impact of increasing aridity on simulation performance. Although this modeling application utilized low-order hydrologic models with a single-objective calibration strategy, the findings provide a baseline for assessing more complex strategies in each area, including multi-objective calibration of more highly distributed hydrologic models (e.g., in Shi et al., 2008). The dataset and model demonstration also provides a starting point for hydrologic prediction experiments (e.g. Wood et al. (2014), which utilized 425 of the models to investigate the sources of seasonal streamflow prediction skill). The unusually broad variation of hydroclimatologies represented by the dataset, which contains forcings and streamflow obtained by consistent methodology, makes it a notable resource for these and other future large-sample watershed-scale hydrologic analysis efforts.

This dataset and applications presented are made available to the community (see <http://ral.ucar.edu/projects/hap/flowpredict/subpages/modelvar.php>).

Acknowledgements. This work is funded by the United States Army Corps of Engineers and the Bureau of Reclamation. The authors would like to thank the USGS Modeling of Watershed Systems (MoWS) group, specifically for providing technical support and the national geospatial fabric data to generate all the basin delineations. We would also like to thank Jordan Read and Tom Kunicki of the USGS Center for Integrated Data Analytics for their help with the USGS Geodata Portal.

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Table 1. Table describing all parameters calibrated and their bounds for calibration.

Parameter	Description	Units	Calibration Range
Snow-17			
MFMAX	Maximum melt factor	mm °C ⁻¹ 6 h ⁻¹	0.8–3.0
MFMIN	Minimum melt factor	mm °C ⁻¹ 6 h ⁻¹	0.01–0.79
UADJ	Wind adjustment for enhanced flux during rain on snow	km 6 h ⁻¹	0.01–0.40
SI	SWE for 100 % snow covered area	mm	1.0–3500.0
SCF	Snow gauge undercatch correction factor	–	0.1–5.0
PXTEMP	Temperature of rain/snow transition	°C	–1.0–3.0
SAC-SMA			
UZTWM	Upper zone tension water maximum storage	mm	1.0–800.0
UZFWM	Upper zone free water maximum storage	mm	1.0–800.0
LZTWM	Lower zone tension water maximum storage	mm	1.0–800.0
LZFFM	Lower zone free water primary maximum storage	mm	1.0–1000.0
LZFSM	Lower zone free water secondary maximum storage	mm	1.0–1000.0
UZK	Upper zone free water lateral depletion rate	day ⁻¹	0.1–0.7
LZPK	Lower zone primary free water depletion rate	day ⁻¹	0.00001–0.025
LZSK	Lower zone secondary free water depletion rate	day ⁻¹	0.001–0.25
ZPERC	Maximum percolation rate	–	1.0–250.0
REXP	Exponent of the percolation equation	–	0.0–6.0
PFREE	Fraction percolating from upper to lower zone free water storage	–	0.0–1.0
Others			
USHAPE	Shape of unit hydrograph	–	1.0–5.0
USCALE	Scale of unit hydrograph	–	0.001–150.0
PT	Priestly–Taylor coefficient	–	1.26–1.74

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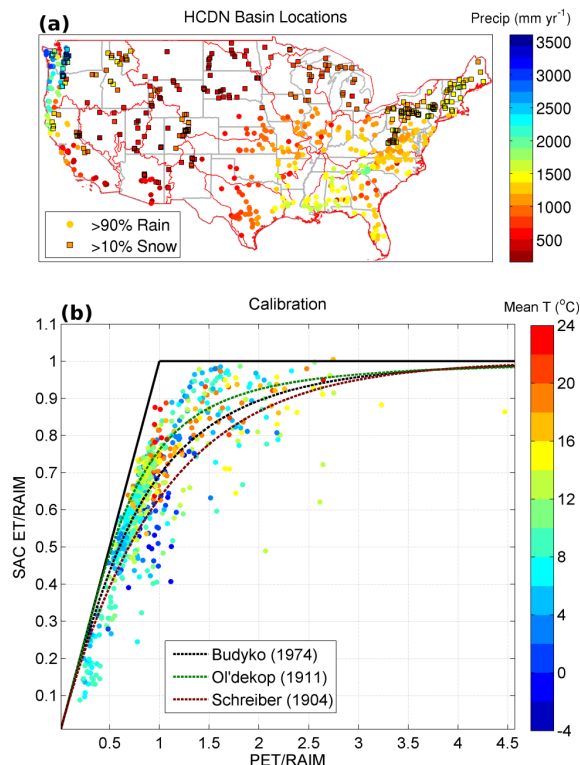


Figure 1. (a) Location of the 671 HCDN-2009 basins across the contiguous United States used in the basin dataset with precipitation shaded. Circles denote basins with > 90 % of their precipitation falling as rain, squares with black outlines denote basins with > 10 % of their precipitation falling as snow as determined by using a 0 °C daily mean Daymet temperature threshold. State outlines are in thin gray and hydrologic regions in thin red. (b) Model derived Budyko analysis for the 671 basins with basin mean temperature shaded (colored dots) and three derivations of the Budyko curve (dashed lines).

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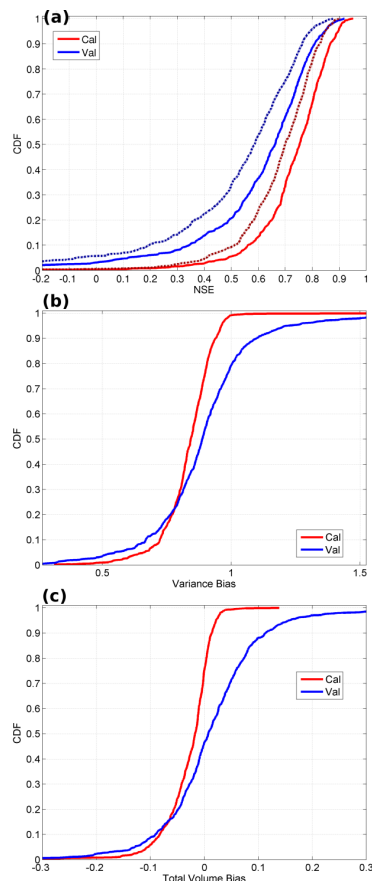
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Figure 2. (a) Cumulative density functions (CDFs) for model Nash–Sutcliffe efficiency (NSE) (solid) for the calibration (red) and validation periods (blue) and NSE using the long-term monthly mean flows (MNSE, dark shaded and dashed), (b) CDFs for the variance bias in the decomposition of the NSE, (c) total volume bias in the decomposition of the NSE.

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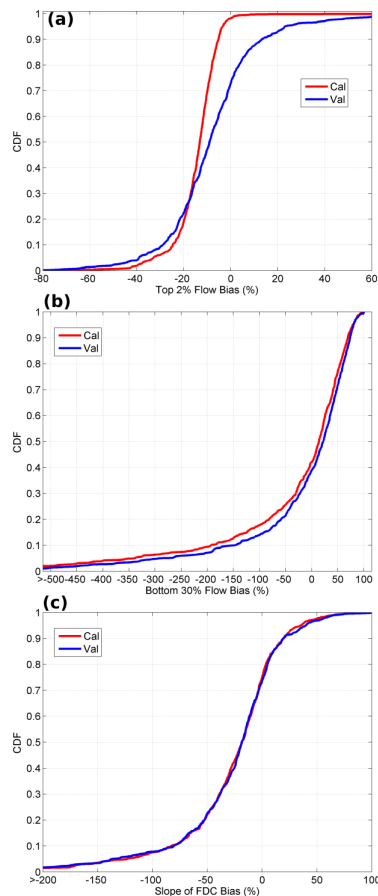


Figure 3. (a) Cumulative density functions (CDFs) for model high flow bias for the calibration (red) and validation periods (blue), (b) model low flow bias, (c) model flow duration curve slope bias.

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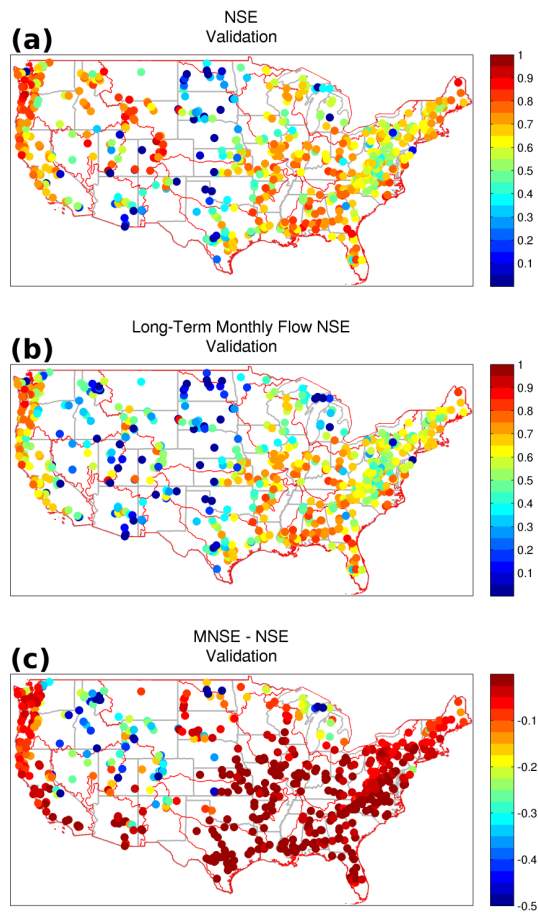



Figure 4. (a) Spatial distribution of Nash–Sutcliffe efficiency (NSE), (b) Nash–Sutcliffe efficiency using long-term monthly mean flows (MNSE) rather than the long-term mean flow, (c) MNSE–NSE for the validation period.

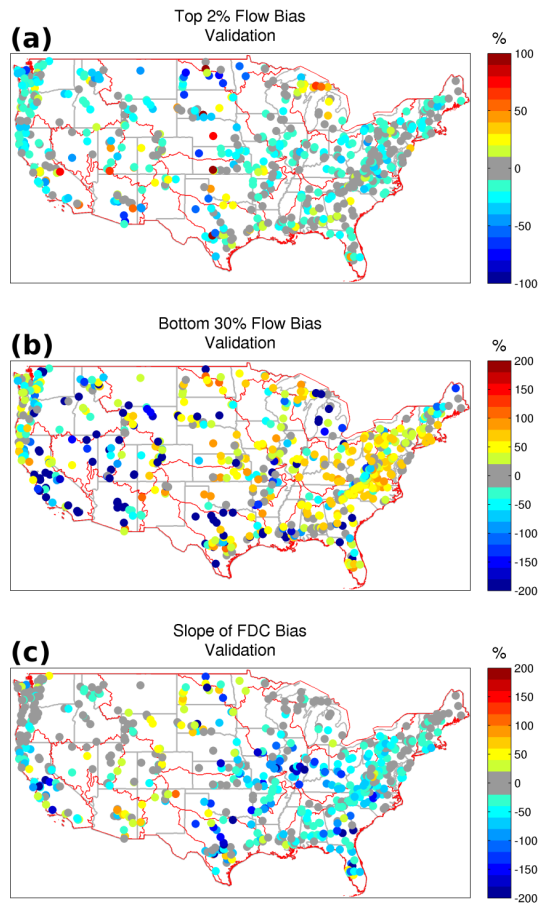


Figure 5. (a) Spatial distribution of the high flow bias, (b) low flow bias, (c) flow duration curve bias for the validation period.

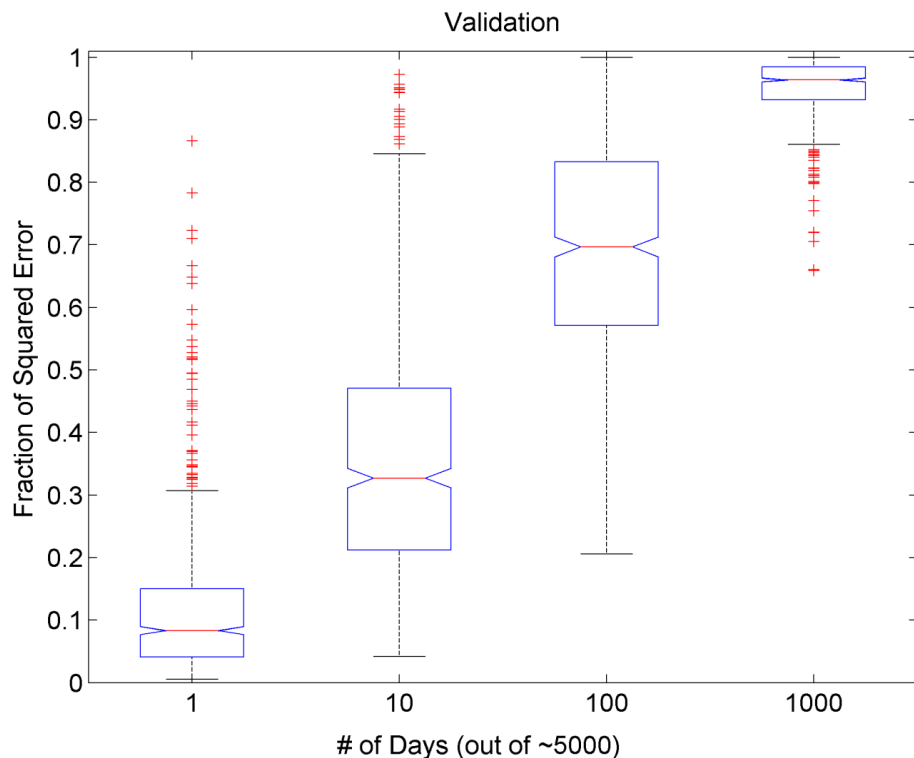


Figure 6. Fractional contribution of the total squared error for the 1, 10, 100, 1000 largest error days. The box plots represent the 671 basins with the blue area defining the interquartile range, the whiskers representing reasonable values and the red crosses denoting outliers. The median is given by the red horizontal line with the notch in the box denoting the 95 % confidence interval of the median value.

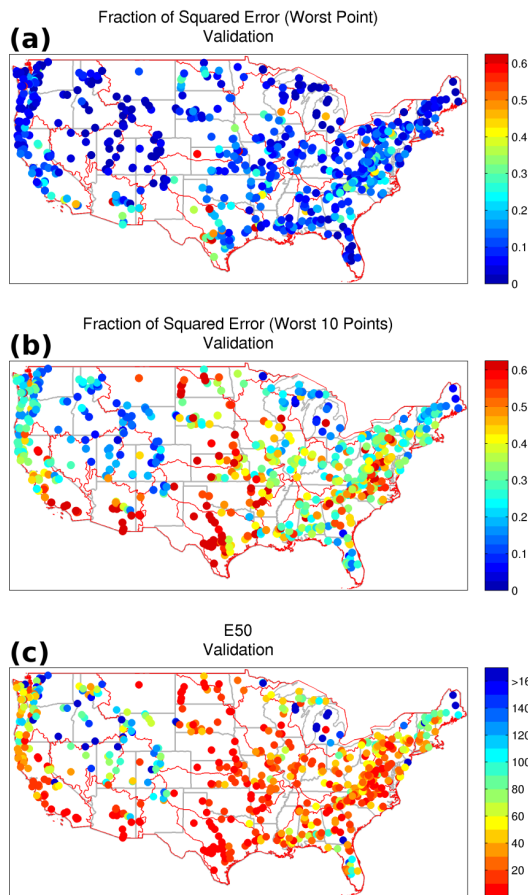


Figure 7. (a) Spatial distribution of the fractional contribution of total squared error for the largest day during the validation period, (b) 10 largest error days, (c) the number of days contributing 50 % of the total objective function error, E50.

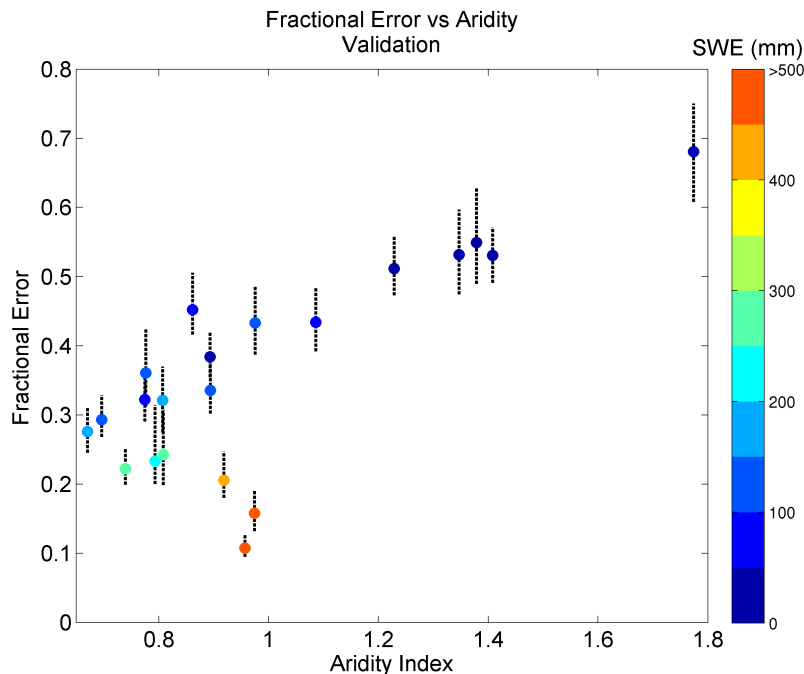


Figure 8. Ranked fractional squared error contribution for the 100 largest error days for the 671 basins vs. the aridity index with mean maximum snow water equivalent (SWE) shaded. Each dot represents a ~32 basin bin defined by the rank of the fractional error contribution for the 100-largest error days for all basins. The dashed vertical black lines denote the 95 % confidence interval for the mean of the fractional error contribution for a given bin.

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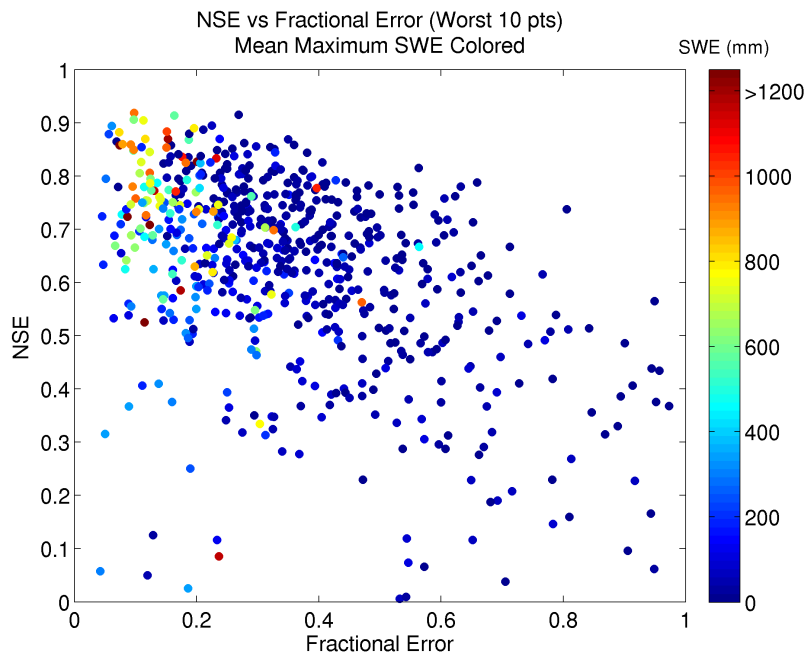


Figure 9. Nash–Sutcliffe efficiency vs. the fractional error of the 10 largest error days for the validation period for all basins with basin mean peak snow water equivalent (mm) colored.