Final Report No. ST-2019-178-01

Better Representation of Low Elevation Snowpack to Improve Operational Forecasts

Science and Technology Program
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14. ABSTRACT This study brought together a range of new snow datasets for watershed applications, including watershed model validation, to assess different strategies for watershed modeling to shed insight on how model representations of watershed heterogeneity impact snow accumulation and melt, and runoff generation. The work created a new snow data processing and analysis tool called SHREAD and developed new capabilities for model implementation and discretization, including additional scripts and insights for configuring the Structure for Unifying Multiple Modeling Alternatives (SUMMA) and mizuRoute models. Eight configurations of SUMMA with varying levels of spatial complexity were generated and tested for the drainage basin of Buffalo Bill Reservoir, on the Shoshone River, Wyoming. These models were assessed with *a priori* parameters and after calibration. A key finding is that, before calibration, more complex models that recognize differences in radiation exposure in subelements of the model simulation perform markedly better than those that do not, whereas all models perform similarly after calibration. Given the influence of solar radiation on snowmelt in the Western United States, this finding may guide more judicious implementation of watershed models not only for forecasting (for which operational models recognize mainly elevation aspects of watersheds) but also climate impact analyses.						
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The U.S. Department of the Interior protects and manages the Nation's natural resources and cultural heritage; provides scientific and other information about those resources; honors its trust responsibilities or special commitments to American Indians, Alaska Natives, and affiliated Island Communities.

The mission of the Bureau of Reclamation is to manage, develop, and protect water and related resources in an environmentally and economically sound manner in the interest of the American public.

Cover Photo – Wind River Range, Wyoming (Daniel Broman).

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Acronyms and Abbreviations

ASO	Airborne Snow Observatory
CoCoRaHS	Collaborative Rain Hail and Snow
CONUS	contiguous United States
COOP	Cooperative Observer Network
DDS	dynamically dimensioned search
fSCA	fractional snow-covered area
ft	foot/feet
ft^3/s	cubic feet per second
GMET	Gridded Meteorological Ensemble Tool
GRU	grouped response unit
HUC	hydrologic unit code
HRU	hydrologic response unit
IGBP	International Geosphere-Biosphere Programme
iSnobal	Image snowcover energy and mass balance
JPL	National Aeronautics and Space Administration's Jet Propulsion Laboratory
KAF	thousand acre-feet
KGE	Kling-Gupta Efficiency
km	kilometer(s)
m	meter/meters
MBRFC	National Oceanic and Atmospheric Administration's Missouri Basin River Forecast Center
MERIT	Multi-Error-Removed Improved-Terrain
mizuRoute	a tool that post-processes runoff outputs from any distributed hydrologic model or land surface model to produce spatially distributed streamflow at various spatial scales
MODDRFS	Moderate Resolution Imaging Spectroradiometer Dust Radiative Forcing in Snow model
MODIS	Moderate Resolution Imaging Spectroradiometer
MODSCAG	Moderate Resolution Imaging Spectroradiometer snow-covered area and grain size
MTCLIM	Mountain Microclimate Simulation Model

n/a	not applicable
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
NOHRSC	National Oceanic and Atmospheric Administration's National Operational Hydrologic Remote Sensing Center
NRCS	Natural Resources Conservation Service
PSMBP	Pick-Sloan Missouri Basin Program
RMSE	root-mean squared error
RPSS	ranked probability skill score
Sac-SMA	Sacramento-Soil Moisture Accounting
SHREAD	Snow-Hydrology Repo for Evaluation, Analysis, and Decision-making
SNODAS	Snow Data Assimilation System
SNOTEL	SNOw TELemetry
SUMMA	Structure for Unifying Multiple Modeling Alternatives
SWANN	Snow Water Artificial Neural Network Modeling
SWE	snow water equivalent
UA	University of Arizona
USGS	U.S. Geological Survey

Symbols

>	greater than
<	less than
%	percent

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Executive Summary

The Wind River and Bighorn River in Wyoming and Montana includes several Bureau of Reclamation facilities, including Bull Lake, Buffalo Bill Reservoir, Boysen Reservoir, and Bighorn Lake. Operation of these facilities requires knowledge of the timing and volume of snowpack-driven runoff during the spring runoff season. Water managers are challenged by two related issues – a lack of skill in seasonal water supply forecasts and a lack of skill in short- to mid-term streamflow forecasts. The latter lack of skill may come in part from the watershed forecast model's inability to capture snowmelt events from low-elevation snowpack. The terrain of the Wind and Bighorn River Basins is mostly made up of high plains – low elevation relative to the surrounding mountains – which often see snow events that accumulate shallow, ephemeral snowpack across a broad area. Limited snow observation stations at lower elevations exist, and consequently, snow information used to set initial model states when developing streamflow forecasts may overlook this low elevation snowpack, leaving water managers unaware of the inflow produced when this snowpack melts.

These two related forecasting challenges in the Wind and Bighorn River Basins motivated this research project to examine how more skillful forecasts may be developed by better representing snow processes within physically based hydrology models, and by identifying potentially useful snow and snow-related datasets and incorporating them into hydrology models.

A literature review was conducted (section 1.3) of available snow products and select candidate products for use in hydrology modeling. Based on this review, five data products of snow variables, such as snow water equivalent (SWE) and fractional snow-covered area (fSCA) were selected for further study in this project (Table ES-**1**).

Table ES-1.—Summary of selected snow data products

Product	Source	Variable(s)
Snow Data Assimilation System (SNODAS)	NOAA[2] / NOHRSC[3]	SWE and fSCA
MODIS[1] Snow Covered Area and Grain-size (MODSCAG)	NASA[4] JPL[5]	fSCA
MODIS[1] Dust Radiative Forcing in Snow (MODDRFS)	NASA[4] JPL[5]	Albedo
MODIS[1] Normalized Difference Snow Index (NDSI)	NASA[4]	fSCA
Snow Water Artificial Neural Network Modeling (SWANN)	University of Arizona	Snow Depth and SWE

1. Moderate Resolution Imaging Spectroradiometer.
2. National Oceanic and Atmospheric Administration (NOAA).
3. National Operational Hydrologic Remote Sensing Center (NOHRSC).
4. National Aeronautics and Space Administration.
5. Jet Propulsion Laboratory.

A snow data processing tool – the Snow-Hydrology Repo for Evaluation, Analysis, and Decision-making (SHREAD) – was developed to retrieve snow product data and format it for use in subsequent analyses (section 2.1). SHREAD provides functionality for downloading online snow datasets and processing them to match a user-specified spatiotemporal format, ideally to facilitate comparison to model outputs or input for model data assimilation.

An assessment of existing forecast skill was conducted to examine the skill of existing seasonal water supply forecasts developed by the Natural Resources Conservation Service, and a brief review of the operational forecast models run by the National Oceanic and Atmospheric Administration's Missouri Basin River Forecast Center (MBRFC) and their initial snow states was conducted (section 3.1). Because the MBRFC does not maintain a sufficient hindcast archive, verification was only possible for the Natural Resources Conservation Service forecasts. An assessment of the January and April forecasts for spring water supply showed a correlation skill (r^2) reaching 0.82 for the Shoshone River below Buffalo Bill Dam.

To assess the question of how model structural complexity relates to the ability of a model to simulate runoff, the Structure for Unifying Multiple Modeling Alternatives (SUMMA) and mizuRoute models were implemented on eight different configurations for the Buffalo Bill drainage area. Each configuration utilized different discretizations and permutations of key factors influencing snow accumulation, melt, and runoff: elevation, solar radiation exposure, and presence of canopy cover. For comparison, National Weather Service watershed models used in forecasting account only for elevation. A new public repository of the python-based geospatial analysis code (Github 'watershed_tools') was created to apply the analysis more broadly within the research and applications community. The SUMMA model was also upgraded to apply slope and aspect factors to the calculation of radiation inputs for different watershed areas, and workflows were created to set up and run SUMMA models with specialized discretizations. The analysis showed that among the three factors, accounting for radiation exposure had the most impact toward improving the skill of a watershed model before calibration. After calibration, however, all of the discretized models performed similarly, but their snow states during the melt period were notably different, with several of the discretized models appearing to be more realistic.

The project builds on several years of prior development aimed at providing a new process-oriented watershed modeling framework for watershed studies and applications including long-range climate impact studies and forecasting. The effort led to the generation of Bureau of Reclamation-wide datasets and SUMMA models at a lumped, intermediate scale (HUC12). The new discretization capabilities developed in this project set the stage for a new phase of this modeling and applications that incorporate and additional level of physical realism and fidelity to real-world hydroclimate processes. The SHREAD tool complements this development by streamlining access and processing of snow datasets in model evaluation and assimilation.

1.0 Background

The Wind River and Bighorn River in Wyoming and Montana includes several Bureau of Reclamation (Reclamation) facilities, including Bull Lake, Buffalo Bill Reservoir, Boysen Reservoir, and Bighorn Lake. Operation of these facilities requires knowledge of the timing and volume of snowpack-driven runoff during the spring runoff season. Water managers are challenged by two related issues – a lack of skill in seasonal water supply forecasts and a lack of skill in short- to mid-term streamflow forecasts. The latter lack of skill is hypothesized to be impacted, to an extent, by the forecast model's inability to capture snowmelt events from low-elevation snowpack. The Wind and Bighorn River Basins are comprised of a large percentage of high plains – low elevation relative to the surrounding mountains – which often see snow events that accumulate shallow snowpack, but across a broad area. Limited snow observation stations at lower elevations exist, and consequently, snow information used to set initial model states when developing streamflow forecasts may miss this low elevation snowpack, leaving water managers unaware of the inflow produced when this snowpack melts. These two related forecasting challenges in the Wind and Bighorn River Basins motivated this research project to examine how more skillful forecasts may be developed by better representing snow processes within physically based hydrology models, and by identifying potentially useful snow and snow-related datasets and incorporating them into hydrology models. A literature review was conducted to review available snow products and select products for use in hydrology modeling. This review is presented in section 1.3. A tool was developed to retrieve snow product data and format it for use in subsequent analyses. The development process for this tool and details about its functions are presented in section 2.1. An assessment of forecast skill was conducted to examine existing seasonal water supply forecasts developed by the Natural Resources Conservation Service (NRCS) and the operational forecast models run by the National Oceanic and Atmospheric Administration's (NOAA) Missouri Basin River Forecast Center (MBRFC), as presented in section 3.1. Finally, new physically based hydrology models were developed with different configurations to assess how the structure impacts their representation of snowpack and overall skill in simulating streamflow. These results are presented in section 3.0, with a discussion of overall project findings in section 4.0.

1.1 Nomenclature

The Wind River and Bighorn River are names given to the same river, with "Wind River" used for the upper portion and "Bighorn River" used for the lower portion. The names change at the "Wedding of the Waters," a location at the north end of the Wind River Canyon (Figure 1). Throughout this report, either Wind River or Bighorn River are used following this convention, with the overall basin referred to as the Wind and Bighorn River Basins. "Bighorn" has been written variously as "Bighorn" or "Big Horn" when referring to the River, Lake, Canyon, or other related feature. For consistency, this report uses "Bighorn" in all instances.

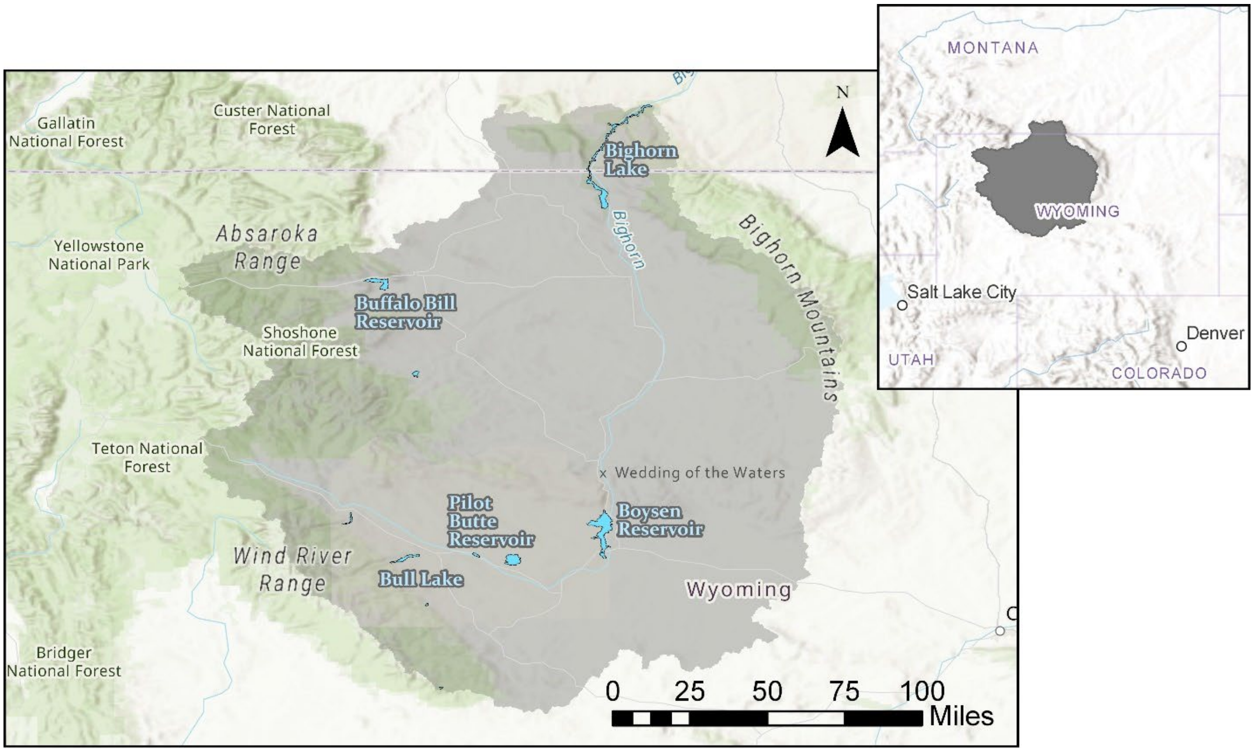

Figure 1.—Location map of Wind and Bighorn River Basins.

1.2 Reclamation Operations

Reclamation owns five reservoirs within the Wind and Bighorn River Basins – Bull Lake, Pilot Butte Reservoir, Boysen Reservoir, Buffalo Bill Reservoir, and Bighorn Lake (see Figure 1). Two of these reservoirs are operated by Reclamation's Wyoming Area Office, Boysen Reservoir and Buffalo Bill Reservoir, and Bighorn Lake (Yellowtail Dam) is operated by Reclamation's Montana Area Office. Bull Lake and the off-stream Pilot Butte Reservoir are operated by the Midvale Irrigation District. Reservoir operations rely on a combination of internal and external forecasts to determine water user allocations and set releases, and to respond to short-term events. The Wyoming and Montana Area Offices develop in-house statistical water supply forecasts which estimate the volume of seasonal inflow between April and July. The NRCS also provides seasonal water supply forecasts for forecast points in the basin, including inflows into the three Reclamation-operated reservoirs – Boysen Reservoir, Buffalo Bill Reservoir, and Bighorn Lake. The MBRFC issues short- to mid-term daily forecasts of streamflow for periods around peak runoff in spring and early summer. These forecasts are used by water managers to adjust reservoir releases to mitigate the need for flood control operations, meet in-stream flow demands, ensure adequate irrigation season water supply, and support lake recreation. Lack of skill in seasonal water supply forecasts and unexpected inflow events not captured by the daily streamflow forecasts negatively impact reservoir operations. These impacts are discussed in more detail in the forecast evaluation section

(section 3.1). Below is a brief description of each reservoir and the basin upstream of the reservoir. These descriptions provide context for understanding forecasting challenges and decisions made in the new hydrology model configurations explored in sections 2.3 and 3.2.

1.2.1 Riverton Unit, Pick-Sloan Missouri Basin Program

The Riverton Unit of the Pick-Sloan Missouri Basin Program (PSMBP) is comprised of Bull Lake, impounded by Bull Lake Dam on Bull Lake Creek, and Pilot Butte Reservoir, which received water diverted from the Wind River by the Wind River Diversion Dam through the Wyoming Canal. The Riverton Unit is operated by Midvale Irrigation District and provides an irrigation water supply to 71,000 acres of farmland. Bull Lake is located at approximately 5,800 feet (ft) above sea level in a glaciated valley just east of the Wind River Range. Bull Lake Creek originates as a series of alpine lakes below the crest of the Wind River Range at elevation 12,000 ft and flows for approximately 30 miles before ending at Bull Lake. The drainage area is a mix of high alpine glacial moraine, and morainal deposits, with no to intermittent tree cover. Portions of the watershed contain denser subalpine conifer. The upper headwaters contain several small glaciers.

1.2.2 Boysen Unit, Pick-Sloan Missouri Basin Program

Boysen Reservoir, impounded by Boysen Dam on the Wind River, compromises the Boysen Unit of the PSMBP. It provides hydropower production, flood control, and sediment retention. Boysen Reservoir does not directly provide a water supply but instead provides water to downstream units of the PSMBP. It also allows for upstream irrigation by releasing water to satisfy downstream water users through an exchange program. Boysen Reservoir is operated by Reclamation’s Wyoming Area Office and is located at approximately elevation 4700 ft. The Wind River basin upstream of Boysen Dam includes the entire east side of the Wind River Range, which contains the highest peaks in Wyoming, reaching above elevation 13,000 ft. An extensive series of glaciers exist at higher elevations along the crest of the range. The Wind River also drains the south side of the Owl Creek Mountains, which reach elevations around 9000 ft. A small band of foothills buffer the mountains from the high plains and contain a mix of extensive glacial moraines, subalpine meadow, and subalpine conifer forest between the mountain crest and a transition to high plains between elevations 7000 and 8000 ft. The remainder of the basin is high plains with limited vegetation.

1.2.3 Shoshone Project

Buffalo Bill Reservoir, impounded by Buffalo Bill Dam on the Shoshone River, is the main storage reservoir on the Shoshone Project, which provides irrigation water supply to 93,000 acres of farmland. In addition, the dam provides a municipal water supply to the surrounding region, hydropower production, recreation, and incidental flood protection. Buffalo Bill Reservoir is operated by Reclamation’s Wyoming Area Office. The Shoshone River originates on the eastern slope of the Absaroka Range, reaching an elevation to 13,000 ft. Above Buffalo Bill Reservoir, located at approximately elevation 5300 ft, the North Fork Shoshone River flows through a steep-sided canyon through the foothills of the Absaroka Range containing denser stands of subalpine conifers on north-facing slopes and sparse vegetation on south-facing slopes. The South Fork Shoshone River flows through a valley for approximately 40 miles before reaching foothills similar to the North Fork. Both the North Fork and the South Fork contain small glaciers within their basins along the crest of the Absaroka Range.

1.2.4 Yellowtail Unit, Pick-Sloan Missouri Basin Program

Yellowtail Dam, which impounds Bighorn Lake on the Bighorn River on the border of Montana and Wyoming, is the main development of the Yellowtail Unit of the PSMBP. In addition to Yellowtail Dam, the unit contains the Yellowtail Power Plant and the Yellowtail Afterbay Dam just downstream of Yellowtail Dam.

1.3 Snow Product Review

Historically, Reclamation water managers have relied on data from the NRCS's SNOw TELemetry (SNOTEL) stations and snow courses, along with other external and internally collected snow course data. There has been limited use of other snow data products, including gridded products that could provide an assessment of snow conditions in areas without measurement sites and provide snow data to assimilate into hydrologic models. Seasonal water supply forecasts produced by the NRCS are developed using a principal component regression approach that uses snowpack data from SNOTEL sites (Garen, 1992). The NRCS is currently testing an updated forecasting methodology, the multi-model machine-learning metasystem (M^4; Fleming et al., 2019); however, forecasts from this new system have not yet been extensively tested by Reclamation. Water supply forecasting research has extensively tested additional data types, such as remotely sensed snow water equivalent (SWE), gridded precipitation datasets, seasonal-scale numerical climate model forecasts, and other products, but so far these experimental predictors have experienced limited uptake into operational forecasting systems in the Western United States. A literature review and data search were performed to identify other existing snow data products that could be used to support water management and improve forecasting. Highlighted below are the snow products identified as possible candidates.

NOAA's National Operational Hydrologic Remote Sensing Center (NOHRSC) produces the several gridded snow products from the Snow Data Assimilation System (SNODAS), including snow depth and SWE (Carroll et al., 2001; NOHRSC, 2004). SNODAS provides daily gridded estimates of snow depth and SWE at 06:00 Coordinated Universal Time, at a 1-kilometer (km) resolution, across the contiguous United States (CONUS). SNODAS uses a spatially distributed snow and energy balance model to produce snow products. This model assimilates snow observations and uses downscaled numerical weather prediction fields as forcings. Additional products available from SNODAS include snowmelt runoff at the base of the snowpack, sublimation of blowing snow, solid precipitation, liquid precipitation, and snowpack average temperature. SNODAS data are available from September 28, 2003, through the present.

The National Aeronautics and Space Administration's (NASA) Jet Propulsion Laboratory (JPL) produces several snow-related datasets using two different approaches. The Moderate Resolution Imaging Spectroradiometer (MODIS) snow-covered area and grain size (MODSCAG) algorithm provide fractional snow-covered area (fSCA) and snow grain size. The MODIS Dust Radiative Forcing in Snow (MODDRFS) model provides the radiative forcing caused by the presence of dust in the snowpack. Both approaches use remotely sensed data from the MODIS instruments on the Aqua and Terra satellites. MODSCAG (Painter et al., 2009) uses surface reflectance data from MODIS in a spectral mixture analysis to obtain fSCA and snow grain size. Heterogeneity across pixels due to differences in topographic shading is handled by using the relative shape of the reflectance data rather than absolute values where each pixel is processed independently. The two MODSCAG products are available daily from April 10, 2014, though the present at roughly 1-km resolution on the MODIS sinusoidal tile grid. The MODDRFS uses MODIS surface reflectance data to quantify the additional radiative forcing caused by light absorbing impurities like dust on the snowpack. MODDRFS data products are available daily from April 10, 2014, through the present at a roughly 1-km resolution on the MODIS sinusoidal tile grid.

The University of Arizona produces a 4-km gridded snow depth and SWE product using the Snow Water Artificial Neural Network Modeling System (SWANN) covering the CONUS for the period between October 1, 1981, and September 2020 (Broxton et al. 2016a, 2016b; Dawson et al., 2016, 2017, 2018; Zeng et al., 2018). SWANN generates its estimates using artificial neural networks that assimilate in a wide range of snow observations that include SNOTEL stations and NOAA's Cooperative Observer Network (COOP) stations. The University of Arizona also produces an equivalent product (Broxton et al., 2019) for the Salt River Project, who manage the Salt and Verde Rivers in Arizona. This product uses the same artificial neural networks as the CONUS product was trained using aerial lidar and field data collected over two field seasons. This product is provided to the Salt River Project by the University of Arizona and is not publicly available.

The NOHRSC operates the Operational Snow Survey Program (Carroll, 2001), which makes airborne snow SWE measurements from aircraft across 29 States and 7 Canadian provinces. SWE is derived from measurements of the attenuation of naturally emitted gamma radiation from the bare ground surface through the snowpack. This method estimates SWE across a roughly 2-square-mile area with a root-mean squared error (RMSE) of < 1/2 inch. This method is sensitive to soil moisture and atmospheric moisture.

The Airborne Snow Observatory (ASO), originally developed at JPL and now operated by ASO, Inc., makes airborne snow depth and SWE measurements from aircraft (Painter et al., 2016). Snow depth is calculated by taking the difference between a lidar-derived bare-earth ground surface and lidar-derived top of snowpack surface. If enough measurements are not available, snow density is estimated from mass spectrograph data and the image snowcover energy and mass balance model (iSnobal, Marks et al., 1999). Snow depth and snow density are then used to estimate SWE. Snow depth estimates are produced at a 3-meter (m) resolution, and SWE estimates are produced at a 50-m resolution. Data collection has been intermittent across the Western United States. As of 2020, flights cover river basins in the Sierra Nevada Mountains in California and river basins in the Rocky Mountains in Colorado.

NASA produces fSCA estimates from MODIS satellite data (using the MODIS instrument on the Aqua and Terra satellites) using an approach based on the Normalized Difference Snow Index (Salomonson and Appel, 2004; Riggs and Hall, 2016; Riggs et al, 2015). Data are available daily from April 10, 2014, through the present, at a roughly 500-m resolution on the MODIS sinusoidal tile grid.

The U.S. Geological Survey (USGS) produces fSCA estimates from Landsat satellite data (Selkowitz and Forster 2016; Selkowitz et al., 2017) on the 30-m Landsat grid. Data are produced from Landsat 4 and Landsat 5 TM data starting in March 1984, Landsat 7 ETM+ data starting in July 1999, and Landsat 8 OLI starting in April 2013.

The University of Colorado, Boulder, produces SWE estimates for the intermountain west, covering Colorado, Utah, and Wyoming, and estimates covering the Sierra Nevada. SWE estimates are produced at a 500-m resolution and developed using a regression-based approach (Schneider and Molotch, 2016), which takes in SWE measured by SNOTEL and Community Collaborative Rain Hail and Snow (CoCoRaHS) stations, MODSCAG fSCA, physiographic information, and historical daily SWE patterns using historical MODSCAG data and an energy-balance model (Guan et al., 2013).

2.0 Data and Methods

2.1 SHREAD

2.1.1 SHREAD Development

A deliverable of this project was to develop a snow tool to retrieve and process currently available snow products. This snow tool was envisioned to use the data processing and visualization capabilities of Google Earth Engine to provide water managers the ability to view current snow conditions and provide processed data to assimilate into hydrologic models. Because of U.S. Department of the Interior limitations on the use of Google Earth Engine, the snow tool instead was developed as a command-line tool in Python and focused just on data retrieval and processing. This tool, the Snow-Hydrology Repo for Evaluation, Analysis, and Decision-making (SHREAD), provides access to existing snow and snow-related datasets and provides results in a few standard formats.

2.1.2 SHREAD Background

SHREAD provides access to several snow and snow-related datasets identified in the literature review discussed in section 1.3. SHREAD was developed to be a stand-alone tool capable of retrieving and formatting snow data to meet the needs of this project. It was designed to be flexible enough to easily allow for changes to the output format of data and to easily add additional snow data products. It was also designed so that components of SHREAD, namely the data retrieval and data processing functions for each data product, could be easily repurposed into other production workflows (e.g., retrieving snow data and or saving to a database). The source code for SHREAD is available on GitHub at www.github.com/usbr/SHREAD.

The review presented in section 1.3 was used to identify products to include in SHREAD. All available point measurements of snow were included – this includes SNOTEL, State and local observing networks, and COOP snow observations. Gridded data products included in SHREAD were selected based on the following criteria:

- Products are available in near-real time
- Products have a reasonable historical record
- The temporal scale of a product is at least monthly
- The spatial scale of a product is at least 1 km

From this criteria, the following five data products were selected for inclusion:

Table 1.—Summary of selected snow data products

Product	Source	Variable(s)
Snow Data Assimilation System (SNODAS)	NOAA / NOHRSC	SWE and fSCA
MODIS Snow Covered Area and Grain-size (MODSCAG)	NASA JPL	fSCA
MODIS Dust Radiative Forcing in Snow (MODDRFS)	NASA JPL	Albedo
MODIS Normalized Difference Snow Index (NDSI)	NASA	fSCA
Snow Water Artificial Neural Network Modeling (SWANN)	University of Arizona	Snow depth and SWE

Several additional datasets were identified as good candidates but were not included because they did not meet the immediate needs of the project or had limitations that did not make them immediately useful. The USGS Landsat fSCA, for example, provides more spatially resolved fSCA data; however, the return period for spatial availability is 16 days.

SHREAD was designed to support processing of snow products for easy visualization and assimilation of that data into hydrologic and forecasting models. As a command-line based tool, it is lightweight and easily scriptable into existing workflows. A configuration file is used to set up remote data sources, login information, local data paths and other required configuration files.

SHREAD is provided with a list of the desired data products, and dates of desired data. Using a spatial boundary dataset, SHREAD retrieves each requested data product for each requested day, transforms the data into a standard raster format clipped to the spatial boundary dataset (if spatial data), calculates spatial statistics (mean, median, minimum, and maximum) for each polygon within the spatial boundary dataset, and extracts point measurements from the raster at specified point locations. These data are then written to standard comma-separated value files. With point measurement data (e.g., SNOTEL), the point dataset is clipped to the spatial boundary dataset, and the data are written to comma-separated files. SHREAD provides the option to specify output units as "English" or "Metric" and defaults to using inches for SWE and snow depth for English units and millimeters for Metric units. Additional information about SHREAD, including the tool itself, a readme file, relevant files, and examples can be found at the SHREAD GitHub repository.

2.2 Watershed Modeling with SUMMA and mizuRoute

Clark et al. (2015) created a flexible modeling framework, namely the Structure for Unifying Multiple Modeling Alternatives (SUMMA), as a platform for testing and benchmarking different modeling approaches and parameterizations, different process representations across spatial scales, and different representations of spatial variability and hydrological connectivity. SUMMA's spatial organization has two levels with hydrologic response units (HRUs) that are nested within grouped response units (GRUs) to represent the modeling domain. The units can have any dimensionality, such as grid or polygon shapes. To achieve a balance in complexity that allowed the model to represent a useful degree of spatial heterogeneity without being prohibitively expensive (computationally) to run, the Bighorn River basin implementation used a single HRU per GRU and the distributed *a priori* parameters were estimated for HRUs and GRUs defined by the USGS hydrologic unit code (HUC) watershed boundary dataset over the Bighorn River basin at a HUC12 scale. The *a priori* SUMMA model was configured with three soil layers, one aquifer layer, and a maximum of five snow layers. The nominal depth of the soil layers was fixed at 2 m, which is consistent with other land models used in large domain applications. The heights of the snow layers vary. The model timestep was set at 3 hours; 1 hour or less is more common in process-oriented modeling, but also computationally demanding, which limits the number of runs possible. Sensitivity testing of these choices (e.g., three- versus eight-layer soil, different timesteps, different total soil depths) using a CAMELS SUMMA dataset (Wood et al, 2022) spanning 761 watersheds across the CONUS confirmed that these are efficient selections with an acceptable tradeoff between model agility and complexity.

The mizuRoute multi-method channel routing model (Mizukami et al, 2016) was implemented to route hydrologic total runoff (surface and subsurface) through a basin's stream channel network, calculating streamflows at every stream reach represented. The model network is defined by the reach-based global Multi-Error-Removed Improved-Terrain (MERIT) Hydro Flowlines network (Yamazaki et al, 2019), after extracting stream channel segments local to the drainage area and adding necessary routing parameters. The network resolves the stream reaches and key flow locations at an intermediate scale, somewhat finer than the HUC12 SUMMA model scale. A unit hydrograph routing method, termed "impulse response function" or IRF in mizuRoute, was applied. As noted earlier regarding SUMMA, the complexity (density) of this network and routing algorithm influences the agility, usability, and computational efficiency of the routing model solution. For purposes of bulk spring runoff prediction, this intermediate-scale, intermediate-complexity modeling approach was chosen to enhance the computational feasibility of running multiple sequences of ensemble predictions.

The SUMMA and mizuRoute combination was implemented for the Bighorn River drainage area upstream of the Bighorn River near Xavier, Montana (USGS Gage 06287000), an area that was represented by 458 subcatchments (GRUs) and 1,117 stream reaches (Figure 2). Model control points were identified for the locations listed in Table 2.

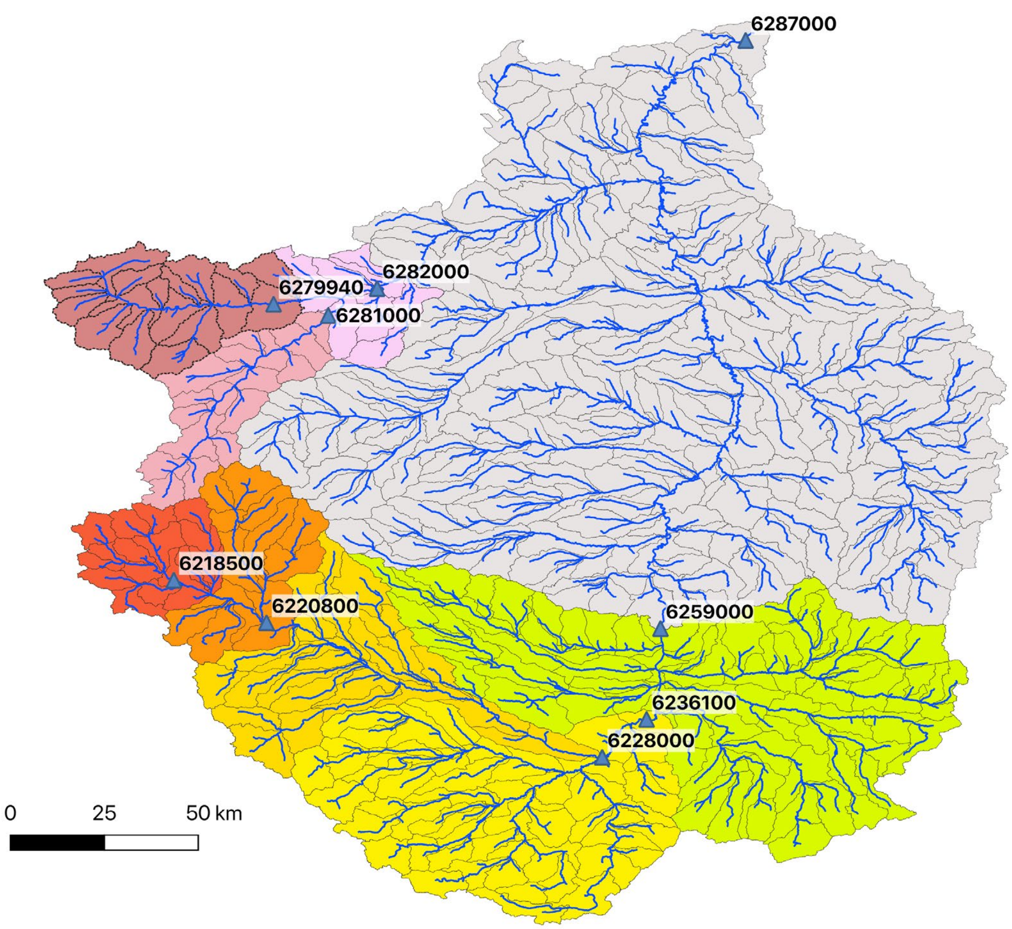

Figure 2.—Map of Bighorn Basin SUMMA model and feasible direct calibration points.

Table 2.—Model control points mapped to the SUMMA and mizuRoute HUC-based model implementation

USGS ID	reachID (mizuRoute)	SUMMA HRU (HUC12)	H5_ID (MBRFC)	Name
06279940	74016593	100800120304	NFSW4	North Fork Shoshone River above Buffalo Bill Reservoir, Wyoming
06281000	74016694	100800130302	BBRW4	South Fork Shoshone River above Buffalo Bill Reservoir, Wyoming
06218500	74018969	100800010212	DUBW4	Wind River near Dubois, Wyoming
06228000	74020462	100800011004	WDRW4	Wind River near Riverton, Wyoming
06259000	74018438	100800050607	SBDW4	Wind River below Boysen Reservoir, Wyoming
06287000	74011555	100800150302	BHRM8	Bighorn River near St. Xavier, Montana
06282000	74014171	100800140106	CDYW4	Shoshone River below Buffalo Bill Reservoir, Wyoming
06236100	74020458	100800011006	n/a[1]	Wind River above Boysen Reservoir near Shoshoni, Wyoming
06253000	74020952	100800050408	n/a	Fivemile Creek near Shoshoni, Wyoming
06280300	74016827	100800130106	VLYW4	South Fork Shoshone River near Valley, Wyoming
06225000	74020802	100800011002	n/a	Bull Lake Creek near Lenore, Wyoming
06220800	74020657	100800010501	WRCW4	Wind River above Red Creek near Dubois, Wyoming
06228000i	74020462	100800011004	n/a	Wind River near Riverton, Wyoming; incremental

[1] n/a = not applicable.

2.2.1 Meteorological Inputs

Meteorological input forcings for SUMMA were created using the Gridded Meteorological Ensemble Tool (GMET) methodology, which is based on multiple logistic and linear regression using static geophysical attributes to predict precipitation and temperature across a grid (Newman, 2015). The GMET has been recently updated to allow for the inclusion of dynamic gridded predictions from sources such as reanalysis products and numerical weather prediction (Bunn et al, 2021). Regression errors are used to condition spatially correlated Gaussian random fields for ensemble generation. The spatial regression approach for interpolating in situ meteorological observations uses spatially distributed information as predictor fields in an ordinary least squares linear regression to explain the spatial distribution of point in situ observations. In this project's application of the GMET, the spatial predictors are static geophysical attributes (slope, elevation, latitude, and longitude). The regression was applied to predict daily precipitation, mean temperature, and diurnal temperature range for each target grid cell, on each day, based on the current observed values of those variables within a sample from the 30 nearest meteorological stations and given their relationship to the local terrain features at the station locations. This strategy generates dynamic (time-varying) uncertainty estimates that were driven by daily observed meteorological conditions. Using the uncertain estimates coupled with spatially correlated random number fields (adopting spatial correlations from observations), a 36-member ensemble of daily meteorological inputs was generated.

In support of this study and related SUMMA modeling projects, the GMET was applied for the period 1970 to present at both 1/8th and 1/16th degree resolutions, yielding daily precipitation and temperature minima and maxima. The 16^{th} degree outputs were spatially remapped to the HUC12 modeling fabric and then disaggregated to 3-hourly time resolution and to a full set of meteorological fields (including radiation, pressure, humidity, wind variables) using MetSim (Bennett et al, 2019), a python-based wrapper for the mountain microclimate simulator (MT-CLIM) spatial meteorological extrapolation program (Running et al, 1987). This approach was applied to the entire Western United States, and the model forcing inputs for the Bighorn domain were extracted from the large Reclamation-domain forcing dataset. Although ensemble forcings have been used in other data assimilation or forecast studies (e.g., Huang et al, 2017) as a strategy for estimating model state uncertainty or initializing forecasts, here we use only the first ensemble member as a deterministic model forcing in calibration and simulation.

2.2.2 Model Calibration

Because SUMMA had not been applied for streamflow prediction in prior studies, significant effort was made to develop a model streamflow calibration strategy. Approximately 40 parameters were exposed for calibration and a one-at-a-time sensitivity analysis and model diagnosis was used to identify a smaller tractable set of parameters to enable SUMMA to be optimized to produce streamflow of acceptable quality (i.e., a Kling-Gupta Efficiency [KGE] value of > 0.7). This set of calibration parameters was chosen and refined over several months to impact key hydrologic processes, leading to the set of 13 parameters listed in Table 3. These parameters affect infiltration, evapotranspiration and interception, soil water storage and transmission, snow accumulation and melt, aquifer baseflow generation, and hillslope runoff timing. The selection of a small, but effective, set of calibration parameters is critical because optimization algorithms perform best within a small parameter search space.

Table 3.—List of SUMMA calibration parameters

Parameter name	Description	Distributed (D) or constant (C) and relevance
k_soil	Soil hydraulic conductivity	(D) Soil water transmission
theta_sat	Soil porosity	(D) Soil water storage
Fcapil	Capillary retention as a fraction of the total pore volume	(C) Snowmelt
aquiferBaseflowExp	Baseflow exponent	(C) Baseflow
aquiferBaseflowRate	Baseflow rate when aquifer storage = aquifer Scale Factor	(C) Baseflow
heightCanopyTop	Height of canopy top	(D) Snow accumulation and melt, evapotranspiration, interception
heightCanopyBottom	Height of canopy bottom	(D) Snow accumulation and melt, evapotranspiration, interception
frozenPrecipMultip	Frozen precipitation multiplier	(C) Snow accumulation
k_macropore	Saturated hydraulic conductivity for macropores	(C) Soil water transmission
qSurfScale	Scaling factor in the surface runoff parameterization	(C) Runoff
routingGammaScale	Scale parameter in gamma distribution used for subgrid routing	(C) Hillslope routing
routingGammaShape	Shape parameter in gamma distribution used for subgrid routing	(C) Hillslope routing
summerLAI	Maximum leaf area index at the peak of the growing season	(C) Evapotranspiration, interception

This project developed workflows for SUMMA calibration based on a multi-method general parameter optimization program called Ostrich (Matott et al., 2013). Ostrich has become an in-house capability being actively developed by Reclamation. In Ostrich, the dynamically dimensioned search (DDS) algorithm (Tolson and Shoemaker, 2007) was used to optimize model parameters to minimize errors in simulated daily flow with respect to observed flow. A shell script workflow for applying Ostrich-DDS was written to leverage high-performance computing on the National Center for Atmospheric Research (NCAR) system. The workflow sets initial parameter ranges based on the SUMMA local parameter range specifications, runs a split domain simulation in which parameter multipliers are calibrated, merges the GRU-level total runoff outputs, runs the mizuRoute model to produce streamflow, and assesses performance. A number of supporting scripts for generating initial parameter limit files, updating parameters in text and NetCDF input files, and assessing performance were written as part of the workflow.

2.3 Spatial Discretization Approach

Until this project, the spatial discretization of SUMMA implementations for streamflow simulation has always used the lowest level of heterogeneity possible, namely that each GRU has contained only one HRU. This approach performs satisfactorily over medium to large domain basins containing > 10 GRUs, but in smaller basins, such as for Taylor Park Reservoir (with 3 GRUs), the need to specify uniform characteristics across each catchment proves limiting, particularly for catchments with mixed canopy cover or mixed aspect. Thus, we sought to develop scientific rationale and implementation methodologies for creating sub-GRU HRU representations that efficiently represented the major factors controlling snow accumulation and melt, and runoff processes. We focus on representing elevation, vegetation (in the form of canopy or noncanopy land cover types), and solar radiation loading, which combines the terrain features of aspect and slope to depict their impact on direct incoming radiation, a strong driver of snowmelt.

2.3.1 Discretization Factor Inputs

The GRU shapefile is derived from the watershed boundary dataset for 12-digit hydrologic units (HUC12, USGS 2019). The elevation raster data is from the MERIT Digital Elevation Model (Yamazaki et al., 2017) at 3-second resolution (approximately 90 m at the equator). The land cover raster data is from the 17-category International Geosphere-Biosphere Programme (IGBP) land cover dataset at 1/160th degree resolution (IGBP, 1990) (http://www.eomf.ou.edu/static/IGBP.pdf). The radiation data are calculated from the elevation data based on the algorithm developed by Allen et al. (2006).

2.3.2 Method

In this study, HRUs are developed within each GRU independently, given analysis of fine resolution gridded elevation, land cover, and radiation data. The HRU discretization process includes three steps.

Step 1: Classify the continuous input and the fine category input (e.g., land cover) that are needed for HRU definition into a limited number of classes. This procedure simplifies input data and helps to reduce the number of the derived HRUs. In detail, the elevation data are classified into two types, high and low classes, by taking the median value of GRU elevation as the classification threshold. The elevation classification threshold varies by GRU. The land cover data are classified into two types, canopy and noncanopy, by taking all the forest and woody savanna lands as canopy and the others as noncanopy, as summarized in Table 4.

Step 2: An integrated analysis of the GRU, classified elevation, land cover, and radiation to get the HRU configuration. Each HRU is identified as a unique combination of GRU affiliation, elevation band, land cover class, and radiation class.

Step 3: The third step is to simplify the HRU configuration by merging some small HRUs with other HRUs. There are many merging methods available, such as merging small HRUs with the neighboring HRUs that have the largest area or the longest shared border, merging small HRUs with the neighboring HRUs that have the most similar attribute based on the modeler's definition of similarity, or merging small HRUs with the largest HRU within the same subbasin if they are adjacent or not. In addition, modelers can simplify the HRU configuration by merging the HRUs with a certain specified attribute. For example, merge all the HRUs with the land cover type of water within one subbasin into one HRU. In this study, we merged the HRUs that have areas smaller than 5% of the GRU area to which it is affiliated with their largest neighbors.

Table 4.—Land cover classification

IGBP land cover class	IGBP land cover class name	Class in this study
1	Evergreen needleleaf forests	Canopy
2	Evergreen broadleaf forests	Canopy
3	Deciduous needleleaf forests	Canopy
4	Deciduous broadleaf forests	Canopy
5	Mixed forests	Canopy
6	Closed shrublands	Noncanopy
7	Open shrublands	Noncanopy
8	Woody savannas	Canopy
9	Savannas	Noncanopy
10	Grasslands	Noncanopy
11	Permanent wetlands	Noncanopy
12	Croplands	Noncanopy
13	Urban and built-up lands	Noncanopy
14	Cropland/natural vegetation mosaics	Noncanopy
15	Snow and ice	Noncanopy
16	Barren	Noncanopy
17	Water bodies	Noncanopy

2.3.3 Experimental Design

To understand the influence of accounting for each of the runoff factors alone and in combination, we assessed eight different strategies for HRU discretization, summarized in Table 5. The level 0 variation corresponds to no discretization, and the three level 1 variations each discretize by an individual factor. The three level 2 variations each assess two factors (in level 2b, as an example, the input factor layers describing elevation and radiation are jointly assessed to assign all grid cells in the basin to one of four classes: low elevation and low radiation, low elevation and high radiation, high elevation and low radiation, high elevation and high radiation). The level 3 variation applies all three factors. A threshold can be set to merge GRU areas that are smaller than a specified percent of the GRU area (e.g., 5%), which results in efficiencies for the simulation. For instance, in the level 3 case, though the GRU is split into eight permutations of HRU type, the number of final HRUs only increases by a factor of 6.

Table 5.—Five levels of HRU discretization complexity

Level name	Input factor layers	Number of HRUs
0	None	43
1a	Elevation	86
1b	Canopy cover	81
1c	Radiation	86
2a	Elevation, canopy cover	141
2b	Elevation, radiation	172
2c	Canopy cover, radiation	147
3	Elevation, canopy cover, radiation	253

3.0 Results

3.1 Assessment of Existing Forecasts

3.1.1 NRCS Water Supply Forecasts

The NRCS currently produces water supply forecasts for 13 forecast points within the Wind and Bighorn basin upstream of Bighorn Lake in addition to the Bighorn River near St. Xavier, Montana. Three of these locations correspond to inflows into Reclamation reservoirs – Wind

River below Boysen Reservoir, Wyoming (USGS 06259000) for inflows into Boysen Reservoir, Shoshone River below Buffalo Bill Reservoir, Wyoming (USGS 06282000) for inflows into Buffalo Bill Reservoir, and Bighorn River near St. Xavier, Montana (USGS 06287000) for inflows into Bighorn Lake. The NRCS water supply forecasts provide estimates of total inflow for the April to July runoff season and are issued monthly on January 1, February 1, March 1, April 1, May 1, and June 1. The forecasts provide volume estimates at five percentiles – 10^{th}, 30^{th}, 50^{th}, 70^{th}, and 90^{th} – providing a probabilistic estimate of streamflow volumes and what can be viewed as an ensemble. Forecasts for the three reservoir inflow points were available for the years 2008 to 2020. Reservoir inflow data available through the Missouri Basin Region Hydromet (Reclamation, 2020) were used to evaluate the skill of the NRCS forecasts using three different metrics – coefficient of variation (R^2), RMSE, and ranked probability skill score (RPSS). R^2 and RMSE were computed using the 50^{th} percentile forecast. The RPSS (NCAR, 2015; Wilks, 2005) is a measure of the accuracy of probabilistic ensemble forecasts relative to a naïve climatological forecast (climatology). Water supply forecasts were categorized into three categories, "low" (below the 33^{rd} percentile of the long-term record), "average" (between the 33^{rd} and 66^{th} percentile of the long-term record inclusive), and "high" (above the 66^{th} percentile of the long-term record), and the percentage of estimates falling into each category were computed to develop probabilities. For example, if two out of the five forecast volumes were below the 33^{rd} percentile, the probability would be 2/5 or 0.4 for the low category. The naïve climatological forecast assumes an equal probability (0.33) for each category. The RPSS values range from negative infinity to 1, with values < 0 meaning the forecast accuracy is worse than climatology, 0 equal to climatology, and 1 perfect accuracy. To develop the 33^{rd} and 66^{th} percentile thresholds, the 30-year period between 1990 and 2009 was used as the long-term record (Table 6).

Table 6.—Seasonal April through July inflow volumes in thousand acre-feet for different percentiles over the 1990 to 2009 historical period

Forecast point	Reservoir	33% inflow	50% inflow	66% inflow
Wind River below Boysen Reservoir	Boysen Reservoir	586	743	827
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	306	663	806
Bighorn River near St. Xavier, Montana	Bighorn Lake	764	1188	1587

Table 7 contains the forecast skill metrics for the three reservoir inflow forecast points and shows metrics for forecasts issued on January 1 and April 1. Additional forecast dates are provided in appendix A. 50^{th} percentile forecasts exhibit moderately good coefficient of variation (R^2), with the observations for both forecast periods (0.537–0.820); however, there also exist large RMSEs. Forecasts for Buffalo Bill Reservoir show the best performance with the smallest RMSE relative to reservoir median inflow (47% for the January 1 forecast and 28% for the April 1 forecast). Forecasts for Bighorn Lake show the worst performance using this same metric. January 1 forecasts for Boysen Reservoir are slightly worse when looking at R^2 and RMSE relative to median inflow; however, the April 1 forecast for Bighorn Lake has a noticeably poorer skill metric.

Table 7.—NRCS forecast skill metrics for forecasts issued on January 1 and April 1

Forecast point	Reservoir	Issue date	R^2	RMSE[a]	RPSS
Wind River below Boysen Reservoir	Boysen Reservoir	January 1[b]	0.537	347 (47%)	0.385
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	January 1[b]	0.761	239 (36%)	0.481
Bighorn River near St. Xavier, Montana	Bighorn Lake	January 1[b]	0.676	547 (46%)	0.325
Wind River below Boysen Reservoir	Boysen Reservoir	April 1	0.735	256 (34%)	0.302
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	April 1	0.820	184 (28%)	0.723
Bighorn River near St. Xavier, Montana	Bighorn Lake	April 1	0.704	492 (41%)	0.435

Note: R^2 and RPSS are unitless; RMSE is in thousand acre-feet.
[a] Percentages next to RMSE values show percent of long-term median inflow.
[b] No January 1 forecasts were issued in 2019; these metrics are based on available years (2008–2018; 2020).

For Boysen Reservoir, RMSE for the January 1 forecast is 347 thousand acre-feet (KAF), approximately 47% of the long-term median inflow. RMSE for the April 1 forecast is reduced to 256 KAF, but such errors still pose challenges for water management. For Buffalo Bill Reservoir, RMSE for the January 1 forecast is 239 KAF, 36% of the long-term median inflow. RMSE for the April 1 forecast is reduced to 184 KAF.

The NRCS forecast ensemble exhibits only moderate skill in discerning the category of inflow year (low, average, or high), with the RPSS ranging around 0.4. The one exception is the April 1 forecast for Buffalo Bill Reservoir, where the RPSS is 0.723. Figure 3 shows computed reservoir inflows against the April 1 NRCS forecasts. There are numerous instances of the range of 10^{th} to 90^{th} percentile forecasts not containing the computed inflow, suggesting that the forecasts are not adequately capturing the true range of variability.

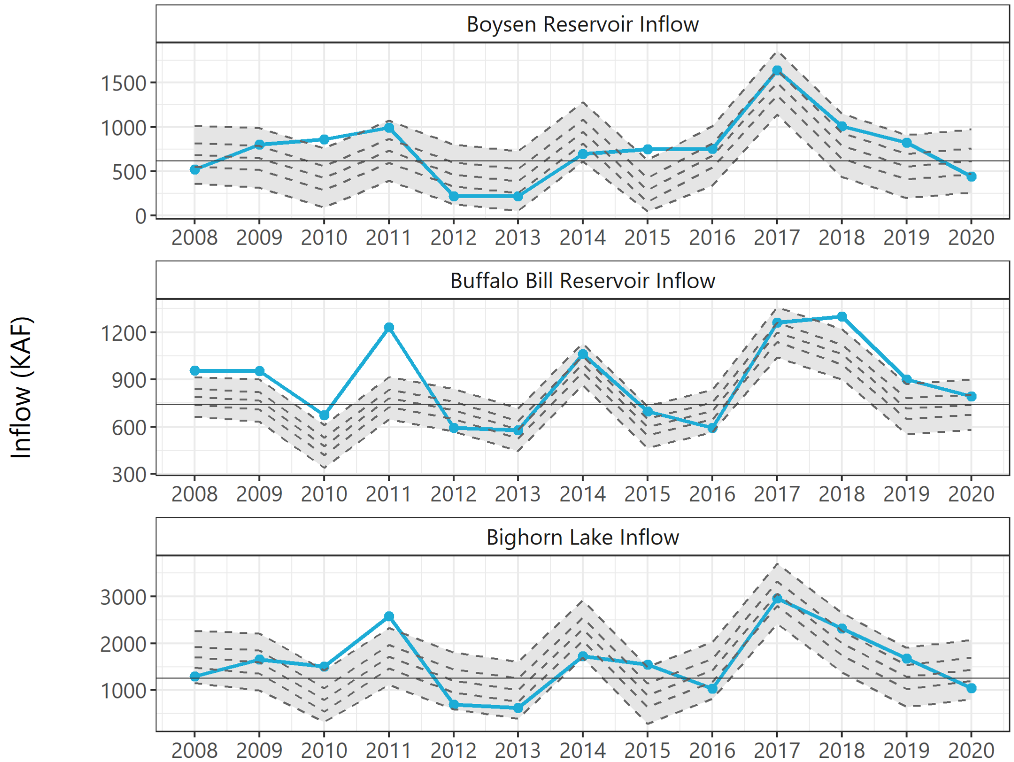

Figure 3.—Computed April to July reservoir inflow (blue) and NRCS April 1 forecasts (dashed showing different percentile forecasts).
Shaded region shows the range of the 10th to 90th percentile forecasts. Long-term median inflow is shown as the solid gray line.

3.1.2 MBRFC Streamflow Forecasts

The MBRFC issues deterministic streamflow forecasts with 5- or 10-day lead times for forecast points in the Wind and Bighorn River Basins only during the spring runoff season. The MBRFC uses the Sacramento-Soil Moisture Accounting (Sac-SMA) hydrology model, coupled to the SNOW17 temperature-index snow model, with additional routines to account for channel loss, river management, and known but unmodeled gains and losses. The Sac-SMA model is a semidistributed model simulating hydrologic components within defined subbasins. Basins can be subdivided into subbasins and further into "zones," typically by elevation, to account for differences across potentially large subbasins. The MBRFC has, over the past decade, continued to develop their models of these Basins to improve simulations of high-elevation zones (Figure 4). In 2012, all subbasins within the Wind and Bighorn River Basins contained one or two elevation zones. An updated model put into use in 2017 added a third elevation zone for subbasins covering the southern half of the Wind River Mountains. Further updates put into use in 2019 added a third elevation zone to the subbasins covering the remainder of the Wind River Mountains and other mountain ranges along the western edge of the Wind and Bighorn River Basins.

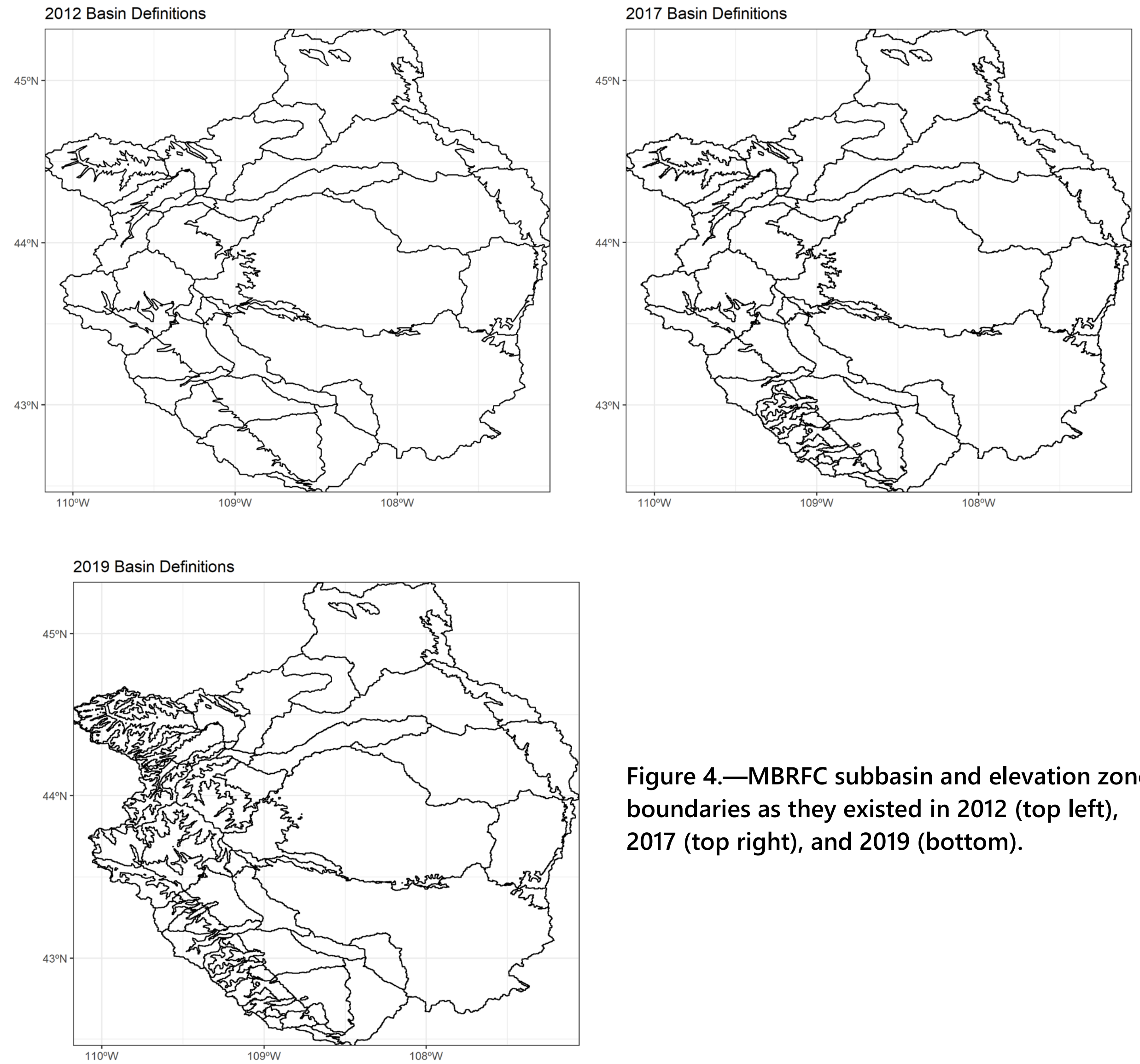

Figure 4.—MBRFC subbasin and elevation zone boundaries as they existed in 2012 (top left), 2017 (top right), and 2019 (bottom).

Forecasts for 14 forecast points were available between 2008 and 2018 for review. These include forecasts for inflows into three Reclamation-operated reservoirs: Boysen Reservoir (ID SBDW4), Buffalo Bill Reservoir (ID CDYW4), and Bighorn Lake (ID BHRM8). A summary of forecasts for inflow into the Buffalo Bill Reservoir (ID BBRW4) are shown in Table 8.

Table 8.—Buffalo Bill Reservoir forecast summary for available water years between 2008 and 2018

Water year	Forecast start date	Forecast end date	Forecast period length (days)	Peak flow date	Peak flow (ft^3/s)[c]
2008	2008-05-17	2008-06-29	43	2008-06-27	3,360
2011	2011-06-24	2011-07-11	17	2011-06-30	6,520
2014	2014-05-27	2014-07-09	43	2014-05-30	3,540
2015	2015-05-16	2015-06-12	27	2015-06-11	4,390
2016[a]	2016-06-05	2016-06-07	2	2016-06-05	2,950
2017	2017-05-11	2017-06-23	43	2017-06-09	5,590
2018[b]	2018-05-19	2018-05-29	10	2018-06-18	3,750

[a] Few forecasts were issued in 2016.
[b] Forecasts missed streamflow peak.
[c] Peak flows reported in cubic feet per second (ft^3/s).

3.2 Spatial Discretizations

To troubleshoot and refine the discretization and model generation and calibration workflows, the project focused on the drainage area of the Shoshone River watershed above Buffalo Bill Reservoir rather than tackling larger or multiple Bighorn drainage areas. As described above, eight levels of complexity in GRU discretization were developed based on various permutations of elevation, canopy cover, and radiation. The factors were applied in binary fashion (high/low elevation, high/low radiation, canopy/noncanopy land cover), resulting in eight permutations. These classifications were applied within each GRU separately.

To this end, a workflow comprising eight python scripts was developed and archived in a new code repository, https://github.com/NCAR/watershed_tools/. It is written in python, using various python GIS libraries, and the effort to create, test, and refine it to be robust was significant. To handle the radiation estimation, a number of methods were investigated, ultimately leading to the adoption of code written by Genevieve Brown of the University of Waterloo (who agreed to be a co-author on the methods). Particular suboptimal characteristics of shapefile topologies and raster processing algorithms, such as aliasing and topology issues, led to a repeated need to diagnose arcane errors related to geostatistical data processing and methodological choices. Ultimately, these were resolved, and the resulting terrain decomposition approach (which is nontrivial), is expected to be a valuable resource for the modeling community.

The basin discretizations resulting from the application of the code are shown on Figure 5 through Figure 12. The workflow has since been applied to other Reclamation basins of interest, including the Tuolumne River Basin, Taylor Park Basin (which will become the test case in the repository), and the Big Thompson above Moraine Park.

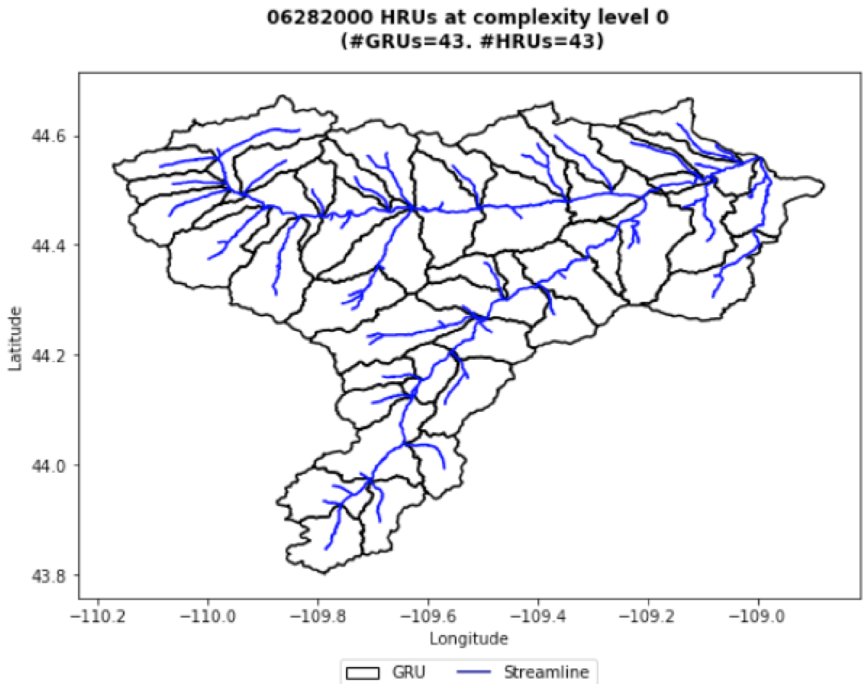

Figure 5.—Basin discretization for level 0 complexity (HRU = GRU).

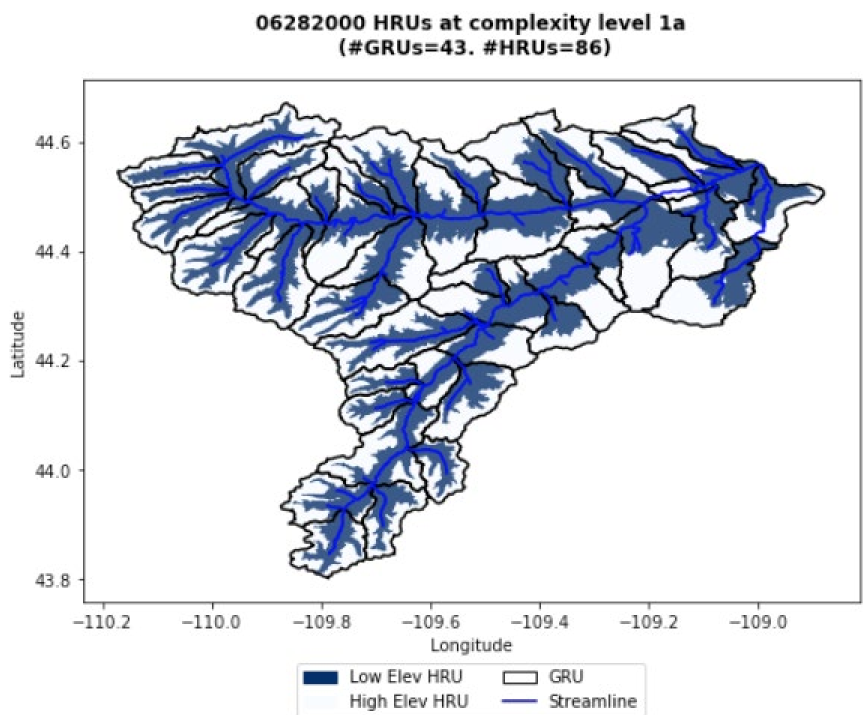

Figure 6.—Basin discretization for level 1a complexity.

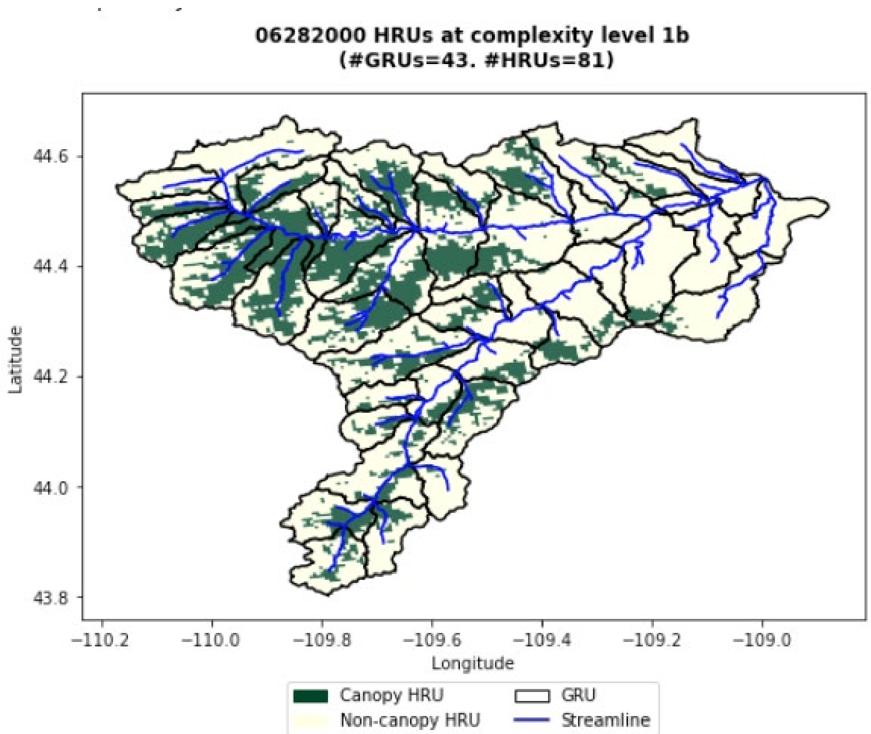

Figure 7.—Basin discretization for level 1b complexity.

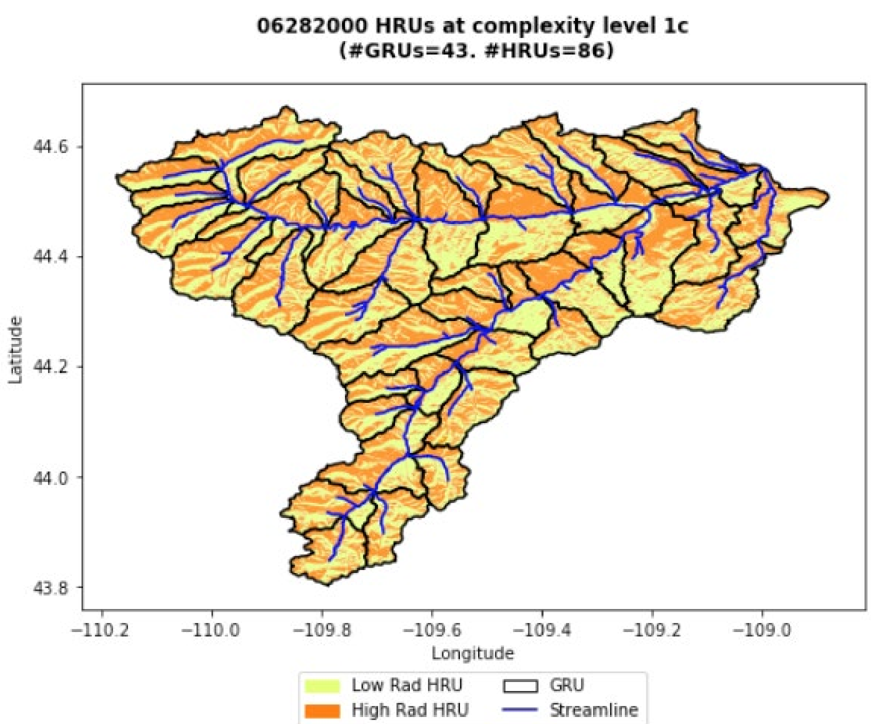

Figure 8.—Basin discretization for level 1c complexity.

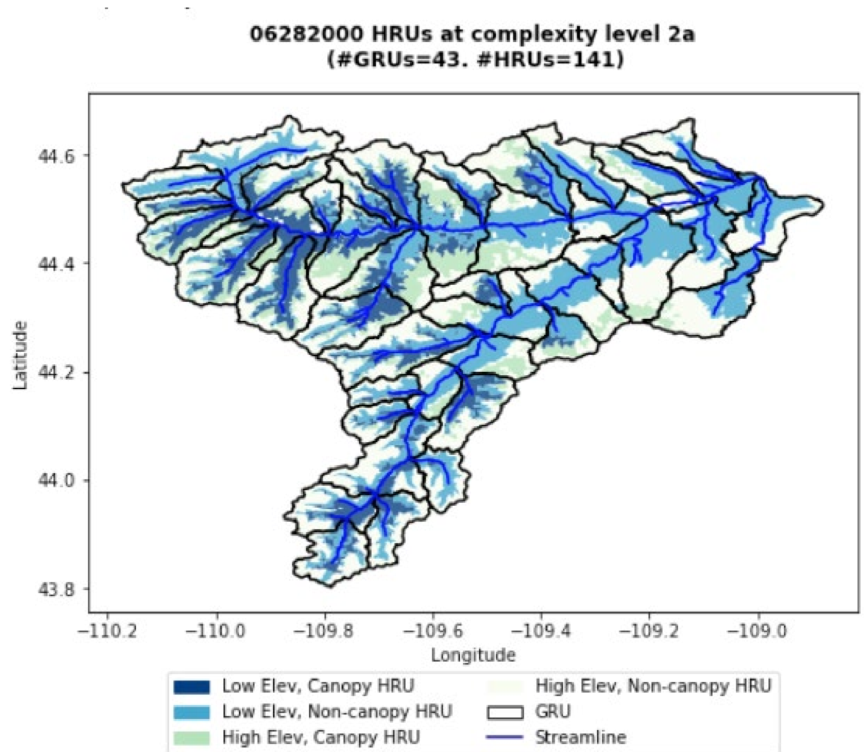

Figure 9.—Basin discretization for level 2a complexity.

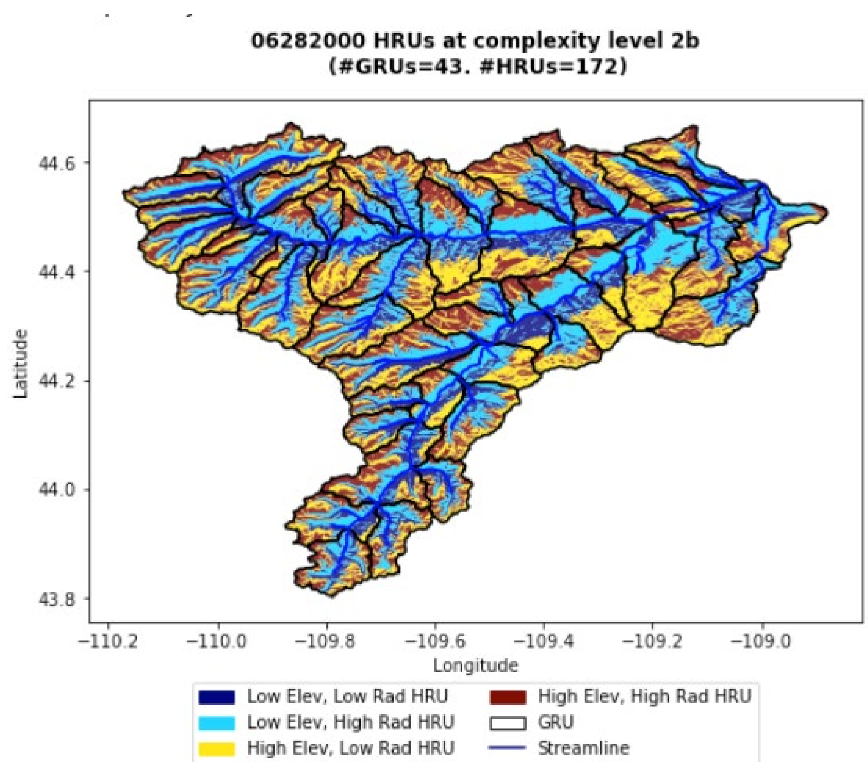

Figure 10.—Basin discretization for level 2b complexity.

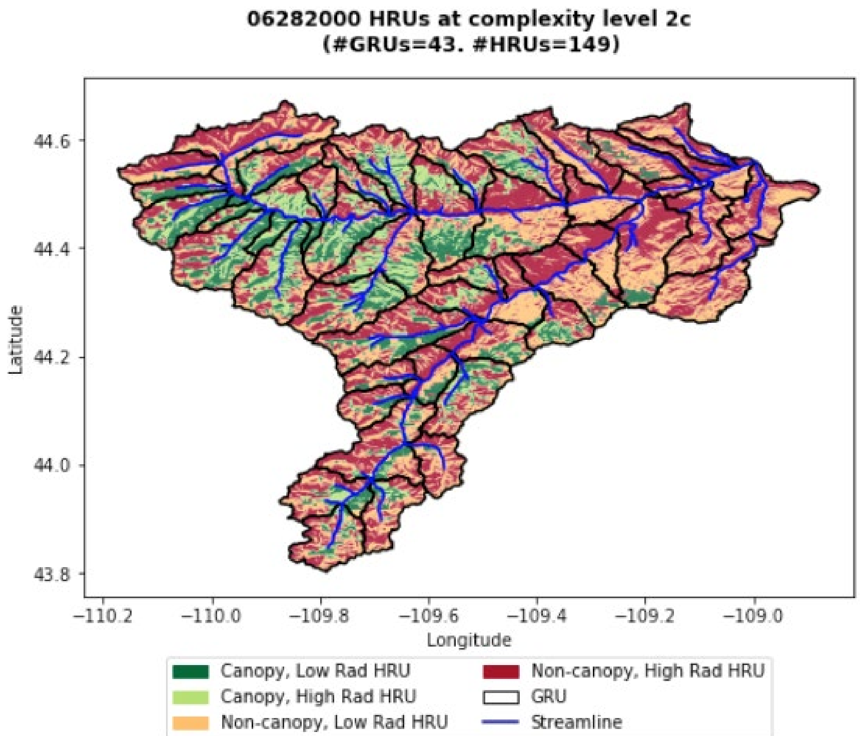

Figure 11.—Basin discretization for level 2c complexity.

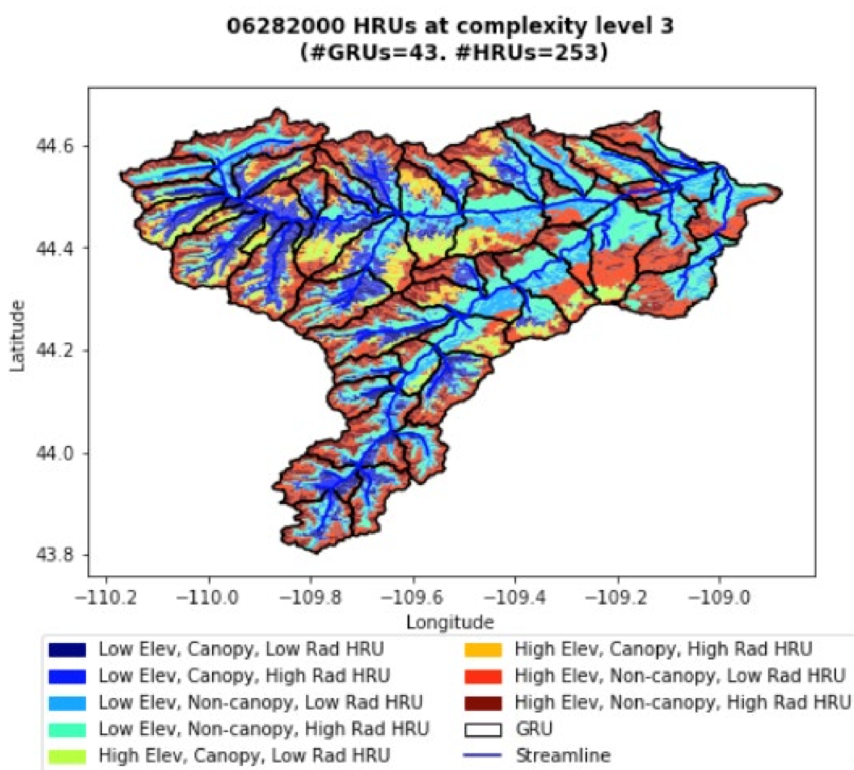

Figure 12.—Basin discretization for level 3 complexity.

3.3 Watershed Modeling and Calibration

It was unclear at the outset of the project whether the hierarchical multi-HRU implementations would work or what input protocols would be needed. This project helped us discover that several code alterations were necessary to run a multi-HRU simulation approach, to use radiation information correctly, and that there are several requirements for input formatting (regarding ordering of the HRU and GRU attribute and parameter files). During the project, bugs were discovered and corrected in SUMMA (such a double counting of basin runoff) and in the GMET (erroneous calculation of ensemble uncertainty, among other things), and at several stages, model simulations and inputs needed to be regenerated. An ID number scheme for the HRUs, which fit inside HUC12 GRUS was devised to allow for potential use in targeted calibration (e.g., the HRUs IDs are the GRU IDs with 2 digits appended to indicate the type of discretization units they are associated with). A split domain run strategy was devised, recognizing that all HRUs within a GRU must currently be run together so that their runoff can be combined into a common timestep output before routing (allowing for the possibility of structures that pass runoff from one HRU to another in a Topmodel type formulation).

Scripts were written and applied to remap parameters and attributes to the new HRU discretization models. In this first attempt to develop discretized multi-HRU SUMMA models, the forcings were spatially remapped as well, yielding forcings that were relatively uniform within each GRU. Due to upgrades in SUMMA, the radiation forcings will at least be conditioned on slope and aspect, which can now be input to SUMMA as an HRU attribute.

Model calibration was affected using the same Ostrich strategy used in other studies, albeit with a slightly refined parameter set. Parameter multipliers were calibrated and applied to the distributed *a priori* parameter fields to generate semidistributed optimized parameters. Calibrated model results are shown in appendix C, Figures C1–C8. Calibration scores are shown in Table 9.

Table 9.—Calibration skill metrics (KGE) before and after calibration

Complexity level	*a priori* KGE	KGE after calibration	Calibration iterations used
0	0.39	0.92	62
1a	0.39	0.90	40
1b	0.42	0.92	57
1c	0.72	0.87	85
2a	0.40	0.92	120
2b	0.74	0.86	57
2c	0.74	0.89	36
3	0.74	0.88	20

4.0 Discussion

This study sought to bring together a range of new snow datasets for watershed applications, including watershed model validation, and to assess different strategies for watershed modeling to shed insight on how model representations of watershed heterogeneity impact snow accumulation and melt, and runoff generation. Ultimately, this insight could inform our understanding of streamflow forecast errors and help the community build more accurate forecast models.

To this end, the study created a new snow data processing and analysis tool, SHREAD. It also developed new capabilities for model implementation and discretization (in the form of a new python workflow called watershed_tools) and additional scripts and insights for configuring the SUMMA and mizuRoute models. Previously, SUMMA had not been run in a multi-HRU fashion for streamflow simulation. The study led to a number of code enhancements and bug fixes in SUMMA. The workflows, once developed, debugged, and refined, were also applied to other basins in the Western United States.

Eight configurations of SUMMA with varying levels of spatial complexity were generated and tested for the drainage basin of Buffalo Bill Reservoir, on the Shoshone River, Wyoming. These models were assessed with *a priori* parameters and after calibration. A key finding is that before calibration, more complex models that recognize differences in radiation exposure in subelements of the model simulation perform markedly better than those that do not, whereas all models perform similarly after calibration. Given the influence of solar radiation on snowmelt in the Western United States, this finding may guide more judicious implementation of watershed models not only for forecasting (for which operational models recognize mainly elevation aspects of watersheds) but also climate impact analyses.

We note that there is more work to be done in the direction begun by the project, and indeed, due to the need to address challenges in model development as well as the discretization approach, parts of the planned scope were not accomplished. The work does, nonetheless, establish an important foundation for future modeling work not only involving SUMMA but any intermediate-scale (i.e., not hyperresolution) watershed model. Greater refinement of the model forcing strategy is needed to be more compatible with the model discretization work of this project. Many alternative approaches are possible, with a likely superior approach being to develop forcings either specifically for the HRU characteristics (e.g., elevation, aspect), or for a fine resolution grid that imposes terrain characteristics on the forcings, before remapping.

5.0 Data Availability

This project helped create standard workflows for SUMMA model discretization. These have become part of the SUMMA script ecosystem and can be used in multiple Science and Technology projects as well as by collaborators in other institutions. These workflows and scripts are housed in online code repositories, listed below. All data files from this project are archived in the form of tarred and gzipped files on a File Transfer Protocol site: ftp://ftp.rap.ucar.edu/pub/andywood/SnT/178/.

Related online repositories used in this work include:

- github.com/NCAR/watershed_tools (private)
- github.com/NCAR/summa (public)
- github.com/NCAR/mizuRoute (public)
- github.com/NCAR/GMET (public)
- https://github.com/NCAR/hydro_model_utils (private)

6.0 Publication

The SUMMA model discretization development work and SUMMA modeling using different levels of complexity for the Wind/Bighorn basin are being written up in a publication to be submitted to the Water Resources Research journal.

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Appendix A

Natural Resources Conservation Service (NRCS) Forecast Skill Metrics

Forecast point	Reservoir	Issue date	R^2	RMSE[a]	RPSS[b]
Wind River below Boysen Reservoir	Boysen Reservoir	January 1	0.537	347	0.385
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	January 1	0.761	239	0.481
Bighorn River near St. Xavier, Montana	Bighorn Lake	January 1	0.676	547	0.325
Wind River below Boysen Reservoir	Boysen Reservoir	February 1	0.575	345	0.324
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	February 1	0.796	230	0.506
Bighorn River near St. Xavier, Montana	Bighorn Lake	February 1	0.649	545	0.232
Wind River below Boysen Reservoir	Boysen Reservoir	March 1	0.590	313	0.238
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	March 1	0.778	198	0.610
Bighorn River near St. Xavier, Montana	Bighorn Lake	March 1	0.646	517	0.275
Wind River below Boysen Reservoir	Boysen Reservoir	April 1	0.735	256	0.302
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	April 1	0.820	184	0.723
Bighorn River near St. Xavier, Montana	Bighorn Lake	April 1	0.704	492	0.435
Wind River below Boysen Reservoir	Boysen Reservoir	May 1	0.853	223	0.409
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	May 1	0.923	176	0.628
Bighorn River near St. Xavier, Montana	Bighorn Lake	May 1	0.824	404	0.514
Wind River below Boysen Reservoir	Boysen Reservoir	June 1	0.881	290	0.310
Shoshone River below Buffalo Bill Reservoir	Buffalo Bill Reservoir	June 1	0.897	358	0.118
Bighorn River near St. Xavier, Montana	Bighorn Lake	June 1	0.867	562	0.156

[a] RMSE = root-mean squared error.
[b] RPSS = ranked probability skill score.

Appendix B

Draft Abstract: Assessing the Contribution of Hydrologic Spatial Heterogeneity to Runoff and Streamflow Variability in the Shoshone River Basin

A paper from this work is in preparation.

Assessing the contribution of hydrologic spatial heterogeneity to runoff and streamflow variability in the Shoshone River basin

Authors: H Liu, A.W. Wood, D. Broman, G. Brown, J. Lanini, and L. Bearup

Draft Abstract:

Throughout the Western United States, sparse observations and variable weather can make snowmelt runoff volume and timing difficult to predict. Errors in model-based streamflow forecasts can challenge water managers' ability to optimally manage reservoir systems, particularly in years with extreme or unusual snow conditions. During periods of snow accumulation and snowmelt when watershed temperature and radiation inputs straddle the range separating freezing from melting conditions, forecast models that do not represent spatial heterogeneity in factors controlling snow accumulation, melt, and related runoff generation may be unable to simulate streamflow variability. This study assesses whether resolving such heterogeneity in three factors – elevation, solar radiation exposure, and the presence of canopy – can improve the ability of a process-oriented model to represent runoff and streamflow in snowmelt-driven runoff events. We focus on the Shoshone River basin upstream of the Buffalo Bill Reservoir, in Wyoming, USA, using simulations from the Structure for Unifying Multiple Modeling Alternatives hydrologic modeling framework and the mizuRoute routing model. We describe new watershed-based configurations of these models and new strategies for model configuration, discretization, and calibration. We assess six different watershed discretization strategies and find that the models with higher complexity yield greater performance before calibration, but calibration brings all models to a similar skill level.

Appendix C

Structure for Unifying Multiple Modeling Alternatives (SUMMA)/
mizuRoute Model Calibration Visualizations

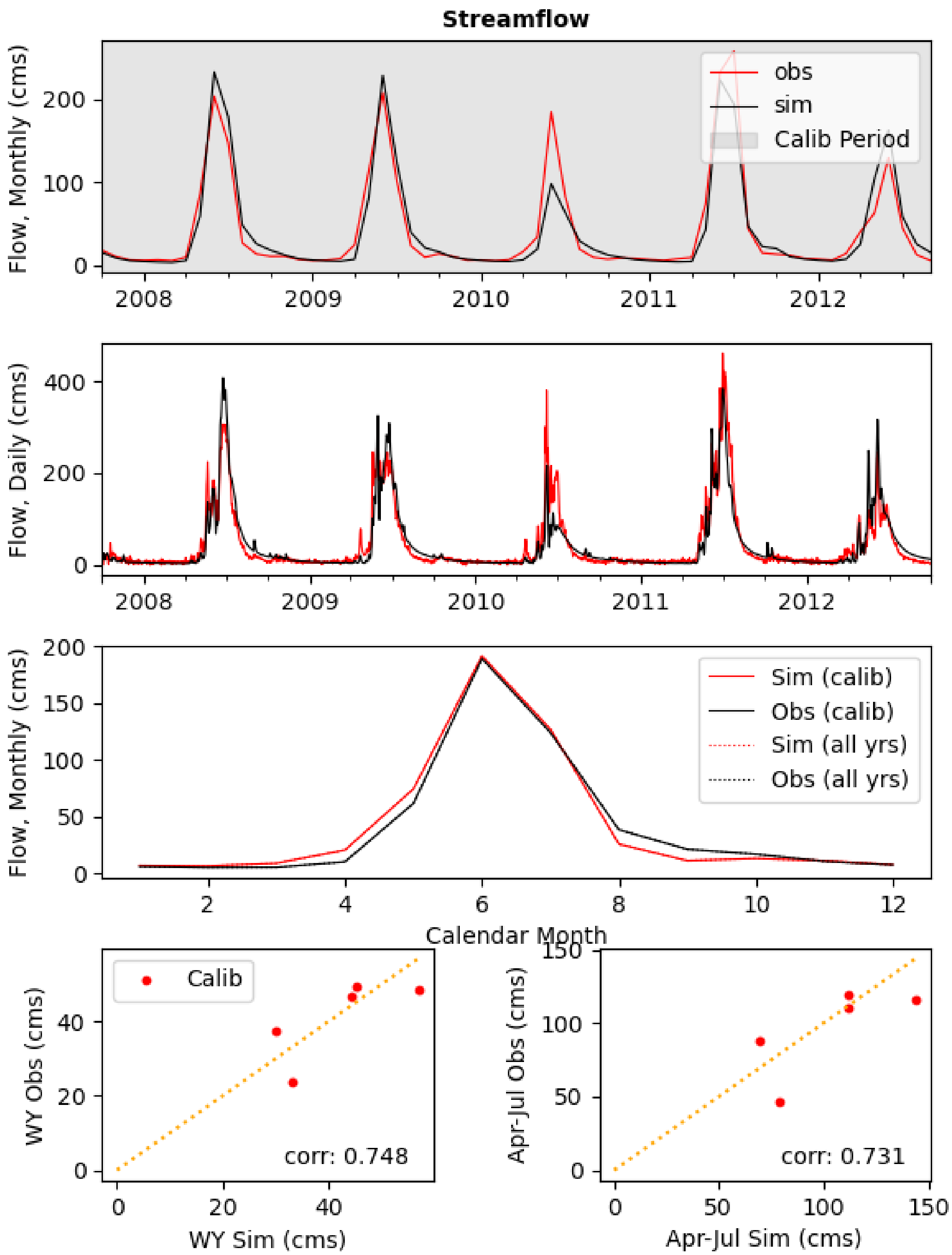

Figure C1.—Model calibration visualization for complexity level 0.

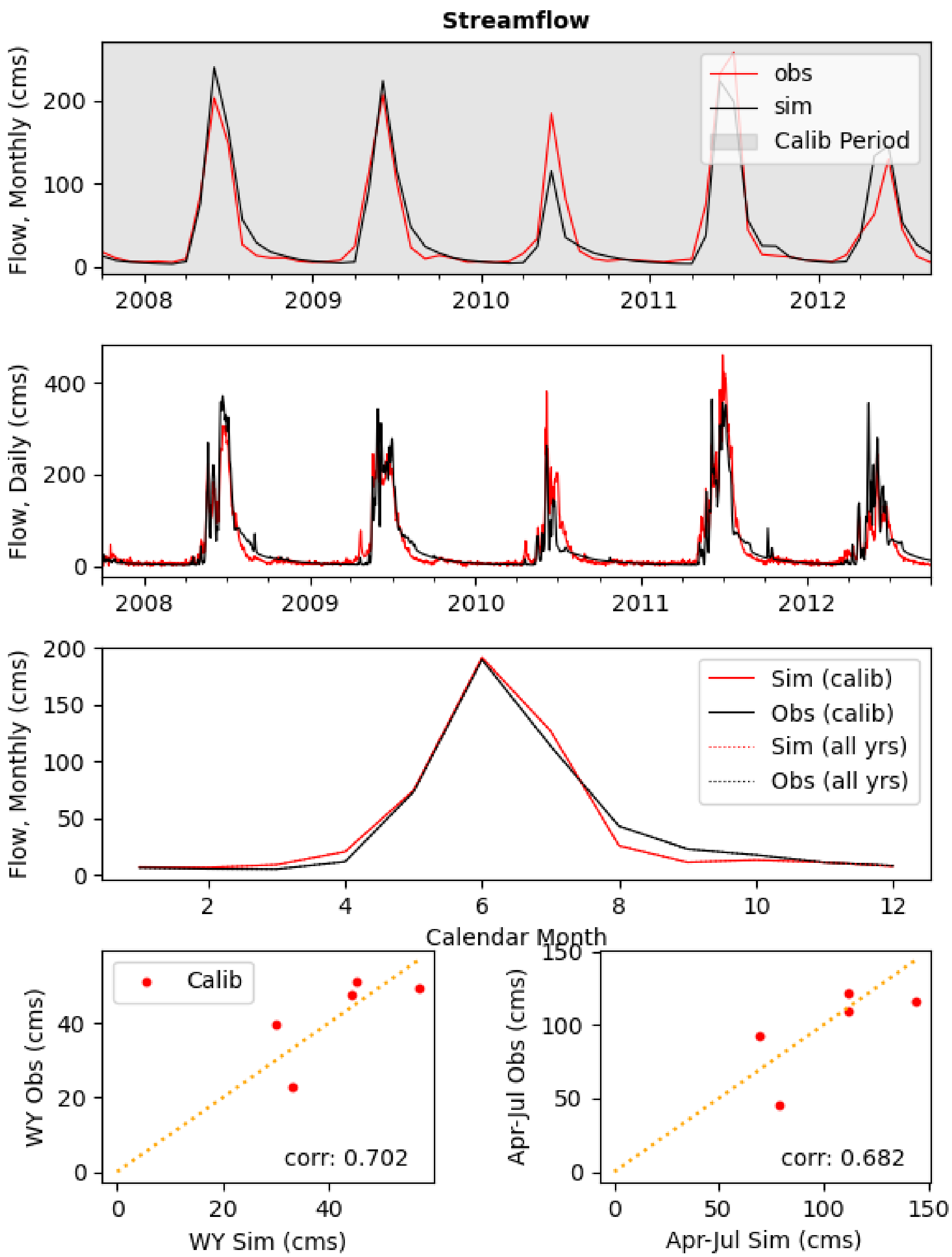

Figure C2.—Model calibration visualization for complexity level 1a.

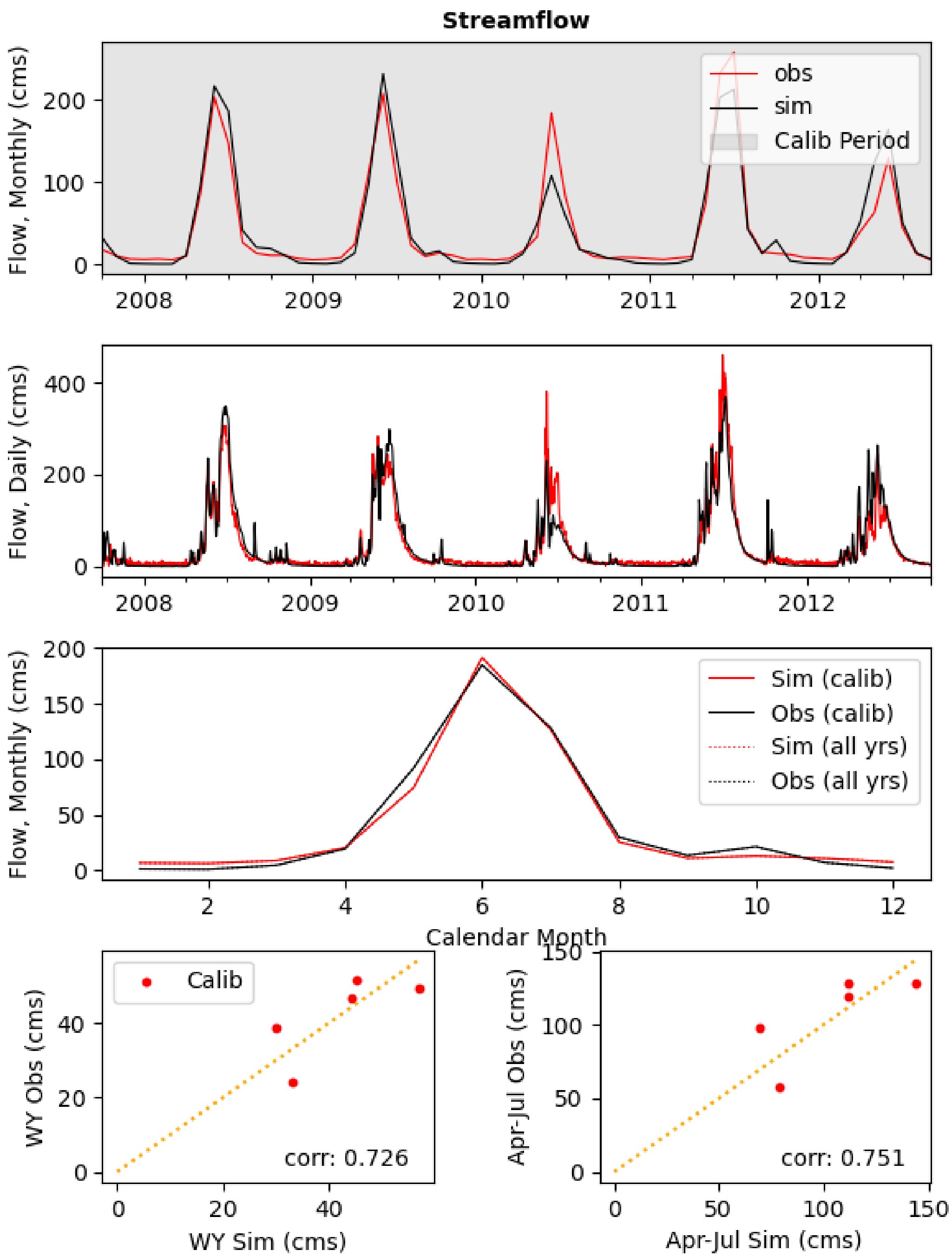

Figure C3.—Model calibration visualization for complexity level 1b.

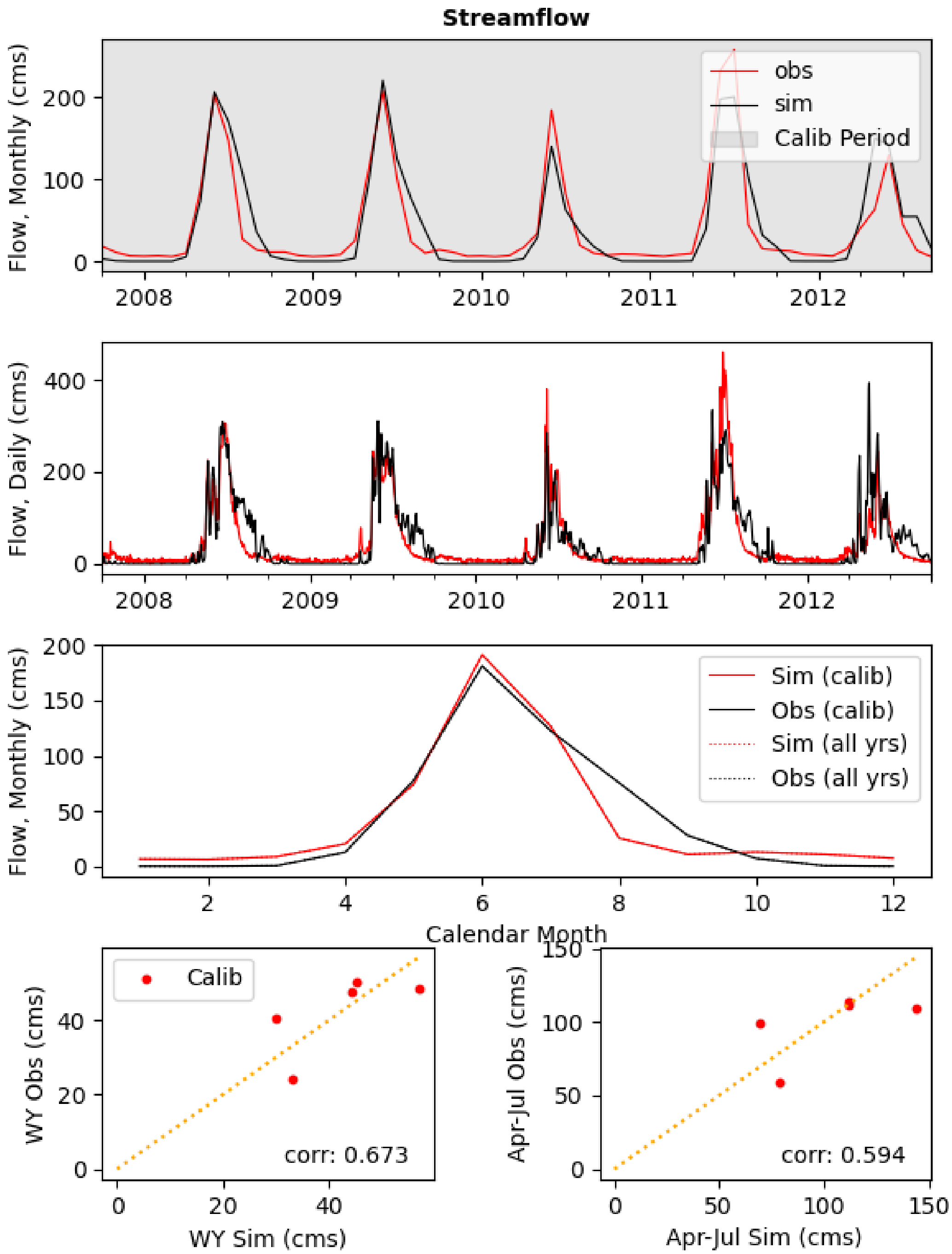

Figure C4.—Model calibration visualization for complexity level 1c.

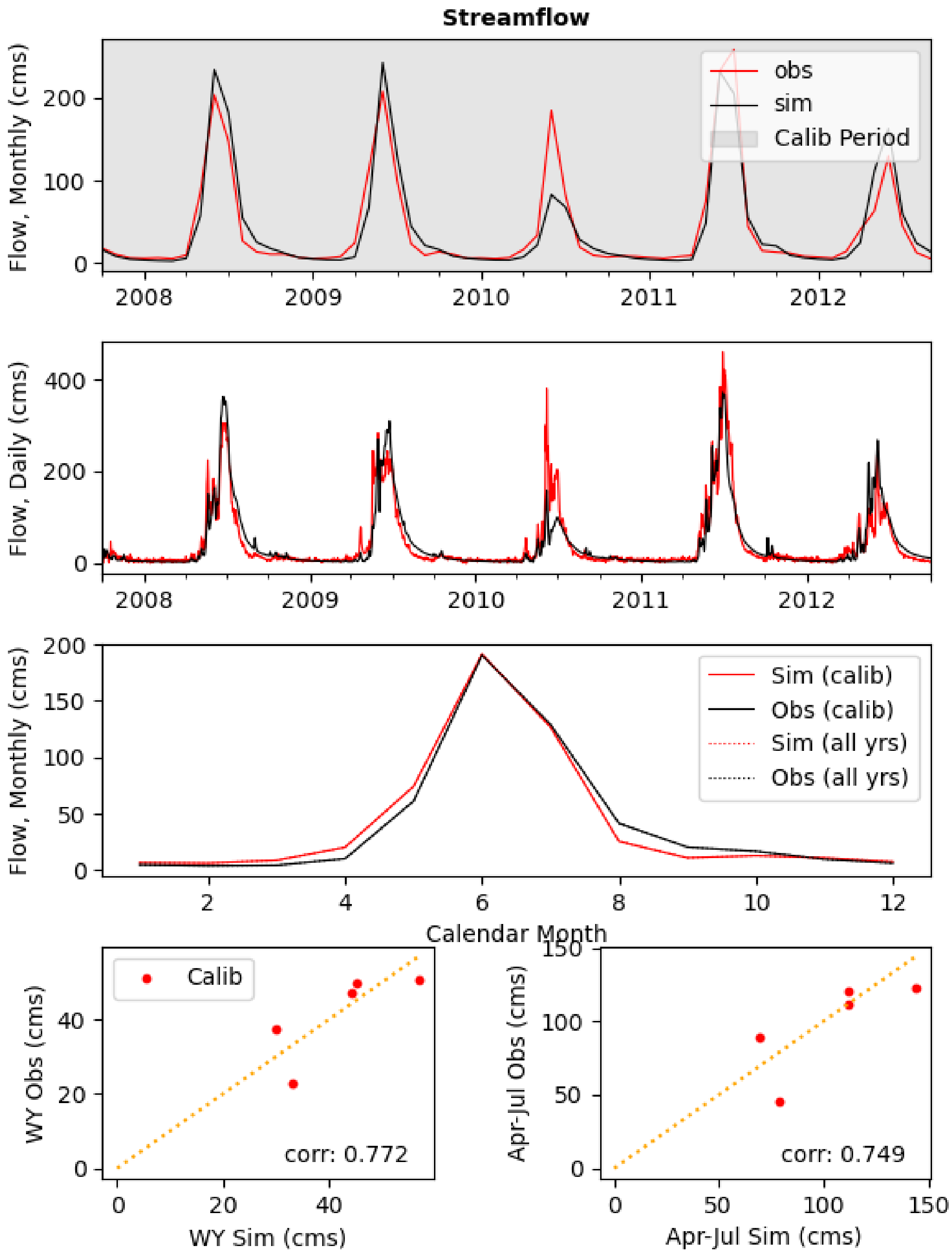

Figure C5.—Model calibration visualization for complexity level 2a.

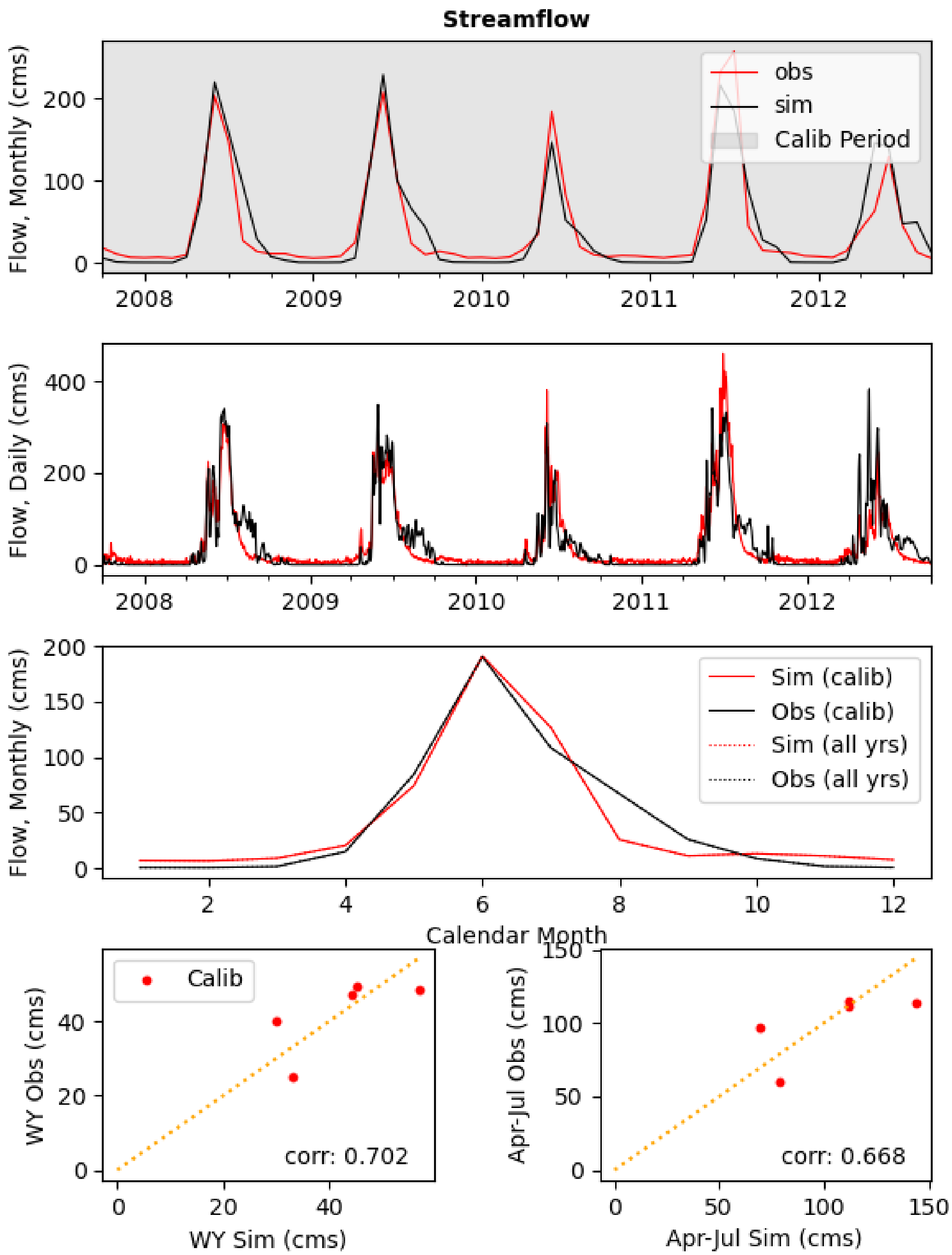

Figure C6.—Model calibration visualization for complexity level 2b.

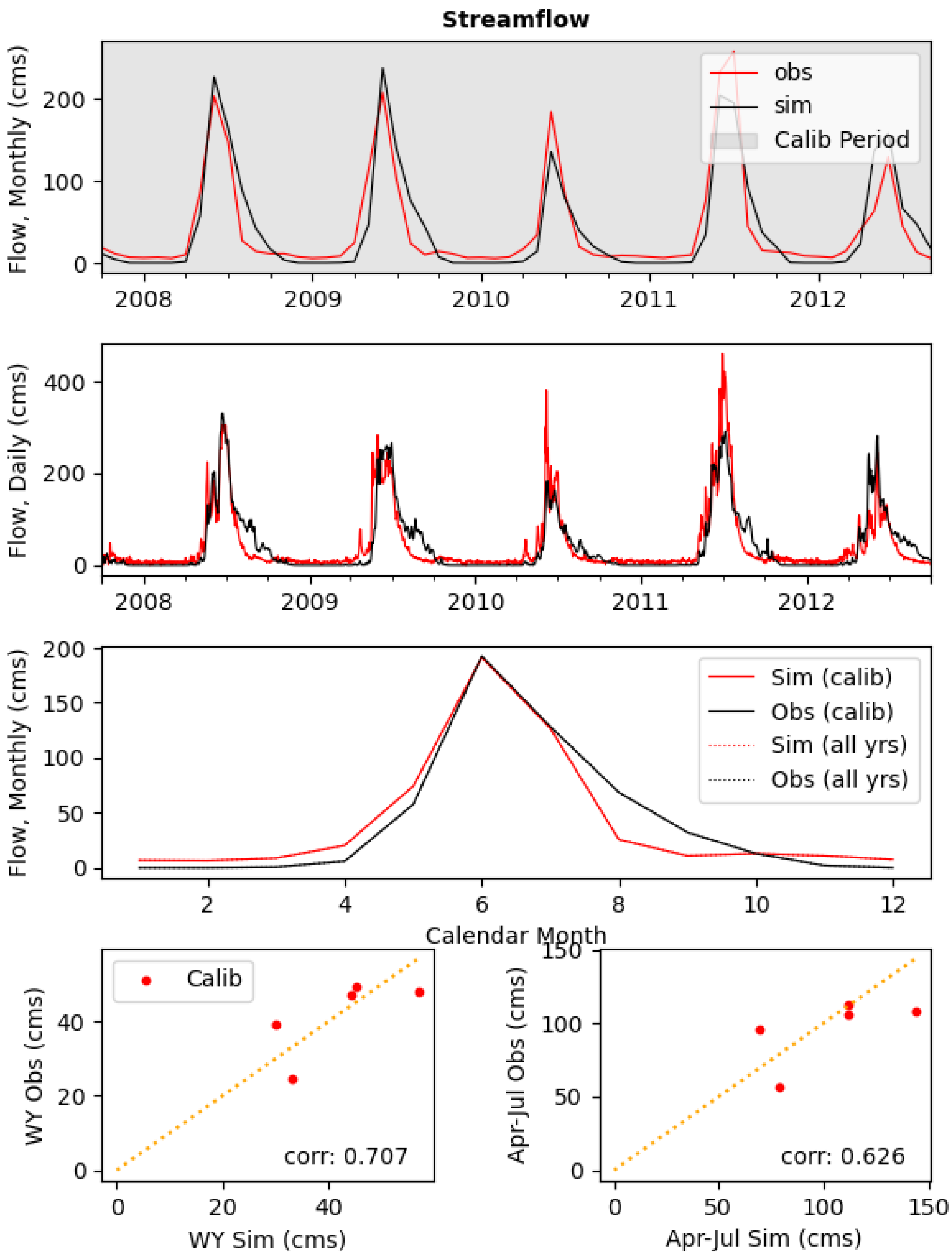

Figure C7.—Model calibration visualization for complexity level 2c.

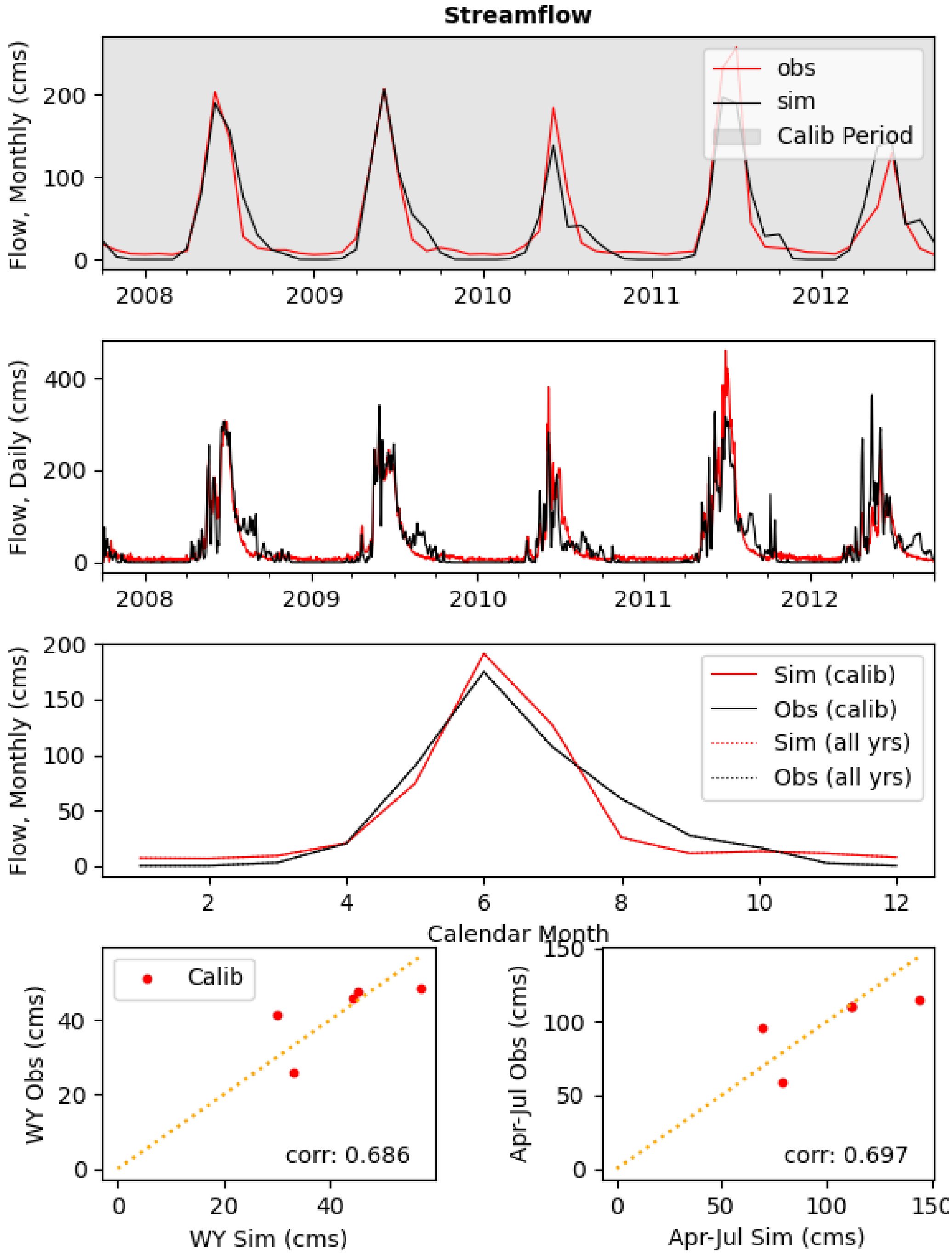

Figure C8.—Model calibration visualization for complexity level 3.