Nevada Irrigation District

Plan for Water

Plan for Water

FINAL TECHNICAL MEMORANDUM

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NID

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Nevada Irrigation District *Plan for Water*

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Abbreviations

AF	acre-feet
ATI	antecedent temperature index
BOD	Board of Directors
CDEC	California Data Exchange Center
CFS	cubic feet per second
CIMIS	California Irrigation Management Information System
CMIP	Coupled Model Intercomparison Project
COA	Coordinated Operating Agreement
CSL	Central Sierra Snow Lab
CWC	California Water Commission
DEM	Digital Elevation Model
DSS	Data Storage System
DWR	Department of Water Resources
EM	Engineering Manual
FAO	Food and Agriculture Organization
FERC	Federal Energy Regulatory Commission
GCM	Global Climate Model
GIS	Geographic Information System
gSSURGO	Gridded Soil Survey Geographic Database
HEC	Hydrologic Engineering Center
HMS	Hydrologic Modeling System
HUC	Hydrologic Unit Code
IPCC	Intergovernmental Panel on Climate Change
ITRC	Irrigation Training and Research Center
IWFM	Integrated Water Flow Model

LOCA	Localized Constructed Analogs
MAD	management allowable depletion
MMC	Modeling, Mapping and Consequences
NAD 83	North American Datum of 1983
NAVD 88	North American Vertical Datum of 1988
NCAR	National Center for Atmospheric Research
NCSS	National Cooperative Soil Survey
NED	National Elevation Dataset
NID	Nevada Irrigation District
NLCD	National Land Cover Database
NOAA	National Oceanic and Atmospheric Administration
NRCS	Natural Resources Conservation Service
NSE	Nash-Sutcliffe Efficiency
NWIS	National Water Information System
NWS	National Weather Service
PBIAS	Percent Bias
PCWA	Placer County Water Agency
PFW	Plan for Water
PG&E	Pacific Gas & Electric
PRISM	Parameter-Elevation Regressions on Independent Slopes Model
RAS	River Analysis System
ResSim	Reservoir System Simulation
RMSE	Root Mean Square Error
RSR	Ratio of the Root Mean Square Error to the Standard Deviation
RWMP	Raw Water Master Plan
SCS	Soil Conservation Service

SHG	Standard Hydrologic Grid
SNODAS	Snow Data Assimilation System
SNOTEL	Snow Telemetry
SSURGO	Soil Survey Geographic Database
SWE	Snow Water Equivalent
SWRCB	State Water Resources Control Board
TAF	thousand acre-feet
UH	unit hydrograph
UNEP	United Nations Environment Programme
USACE	U.S. Army Corps of Engineers
USGS	U.S. Geological Survey
WMO	World Meteorological Organization
WPLM	Weighted Palmer Drought Severity Index
WRCC	Western Regional Climate Center
WRF	Weather Research and Forecasting
WY	water year

Executive Summary

The Nevada Irrigation District (NID) is committed to meeting the community's demand for water over the coming decades. To achieve this goal, NID is currently implementing the Plan for Water (PFW), a collaborative process to review NID's historical and projected available water supply and demands. The PFW will support NID's decisions about future investments and changes in water management practices to ensure the community enjoys the same high-quality water and reliable water system it has now and for the coming years. For more information on PFW follow the link: https://www.nidwater.com/plan-for-water#page-content.

Three numerical models were developed to collectively represent how NID's water delivery system works: a hydrology model to represent watershed performance, a demand model to estimate how much water is required to meet customer and regulatory needs, and an operations model to simulate the functions of NID's system of water storage and conveyance. Together, the models were used to evaluate a range of alternative operating strategies and their ability to meet the future needs of NID customers.

Hydrological Model Development

A physically based hydrological model (Chapter 2) was developed to best represent runoff conditions in NID watershed. Runoff scenarios were developed using the hydrological model with precipitation and temperature projections as input. Projections were generated based on global climate models known to best represent California's climate. (Chapter 3) From these projections, three scenarios were chosen for further analysis: bookend projections that represent the plausible extreme dry and wet climate conditions, plus a median condition.

Demand Model Development

"Demand" refers to the total volume of water required to meet NID's water users' needs. A well-known demand model (Chapter 4) was configured and applied to estimate projected demands for a 50-year horizon. The demand model provides a means of estimating NID customer demand under different potential future scenarios by physically simulating the processes that drive water use. The demand model leverages available local data, standard technical approaches, and best practices to account for the relative effects of estimated future changes in climate, land use, irrigation practices, soil properties, and other factors that impact demand. Results of the demand model were used to estimate the outflows required from NID's reservoirs to meet potential demands over the next 50 years.

Operations Model Development

A reservoir operations model (Chapter 5) was developed that simulates how NID operates its current storage, conveyance, and delivery system. The operations model used inflows from the hydrology model, current operating rules, and regulations to assess how well customer demands are met.

NID operations were simulated using a wide range of conditions, including historical conditions, current baseline operations, demands (low, median, and high), and climate (dry, median, and wet). Three future scenarios were selected for evaluation of potential PFW strategies.

- Dry Future Climate with High Demands
- Median Future Climate with Baseline Demands
- Wet Future Climate with Low Demands

These scenarios provide dry and wet bookends with a median climate scenario to represent a plausible mid-point. Use of these scenarios provides a wide range of hydrologic conditions and consumptive demands; the scenarios are suitable for testing the strategic alternatives.

Strategic Alternatives

Seven strategic alternatives (Chapter 6) were investigated to assess their potential to improve water security under projected climate conditions estimated by the Plan for Water HEC-ResSim model. These alternatives included:

- An extended irrigation season, assuming two additional weeks in October.
- A Rollins Reservoir storage increase of 10,000 acre-feet (AF), equivalent to an increase of 18 percent of existing storage capacity.
- A Rollins Reservoir storage increase of 50,000 AF, equivalent to an increase of 91 percent of existing storage capacity.
- The addition of Centennial Reservoir, a new reservoir on the Bear River downstream of Rollins Reservoir with a storage capacity of 96,660 AF
- A reduction in reservoir carryover storage targets in NID reservoirs at the end of the irrigation season totaling 50,000 ac-ft, equivalent to 38% of the current carryover storage target.
- Additional water purchases from PG&E based on the existing 2018 Coordinated operating Agreement (COA) between NID and PG&E.
- A combination of revised carryover storage targets (50,000 ac-ft) plus additional water purchases from PG&E based on the existing 2018 COA.

These seven alternatives were individually simulated by the HEC-ResSim operations model. Results of each strategic alternative simulation were compared against the baseline climate change scenario. Changes in average annual delivery, average annual unmet demand, and average annual carryover storage were calculated relative to the baseline to assess the relative benefit of each strategic alternative. This analysis was performed for all three climate change baseline scenarios: Dry Climate with High Demands, Median Climate with Baseline Demands, and Wet Climate with Low Demands.

The relative increase in average annual water delivery for each climate scenario is summarized in Figure 1 and annual average unmet demand (ac-ft) is shown in Table 1. Across all three climate scenarios, the Rollins Reservoir 50,000 AF storage increase alternative resulted in the largest relative increase in average annual deliveries, with similar reductions in average annual unmet demand. The Centennial Reservoir scenario and the Revised Carryover Targets + Water Purchase from PG&E scenario also produced relatively high relative increases in average annual deliveries. Despite the larger storage capacity increase for the Centennial Reservoir (96,000 ac-ft) alternative versus Rollins Reservoir (50,000 ac-ft) alternative, the lower elevation location of Centennial Reservoir limits its potential benefit to the NID water delivery system. An increase in storage capacity at Rollins has much greater potential benefit because it can be used to supply water to a much larger percentage of NID customers. Revised Carryover storage targets produced the least beneficial increase in average annual water delivery.

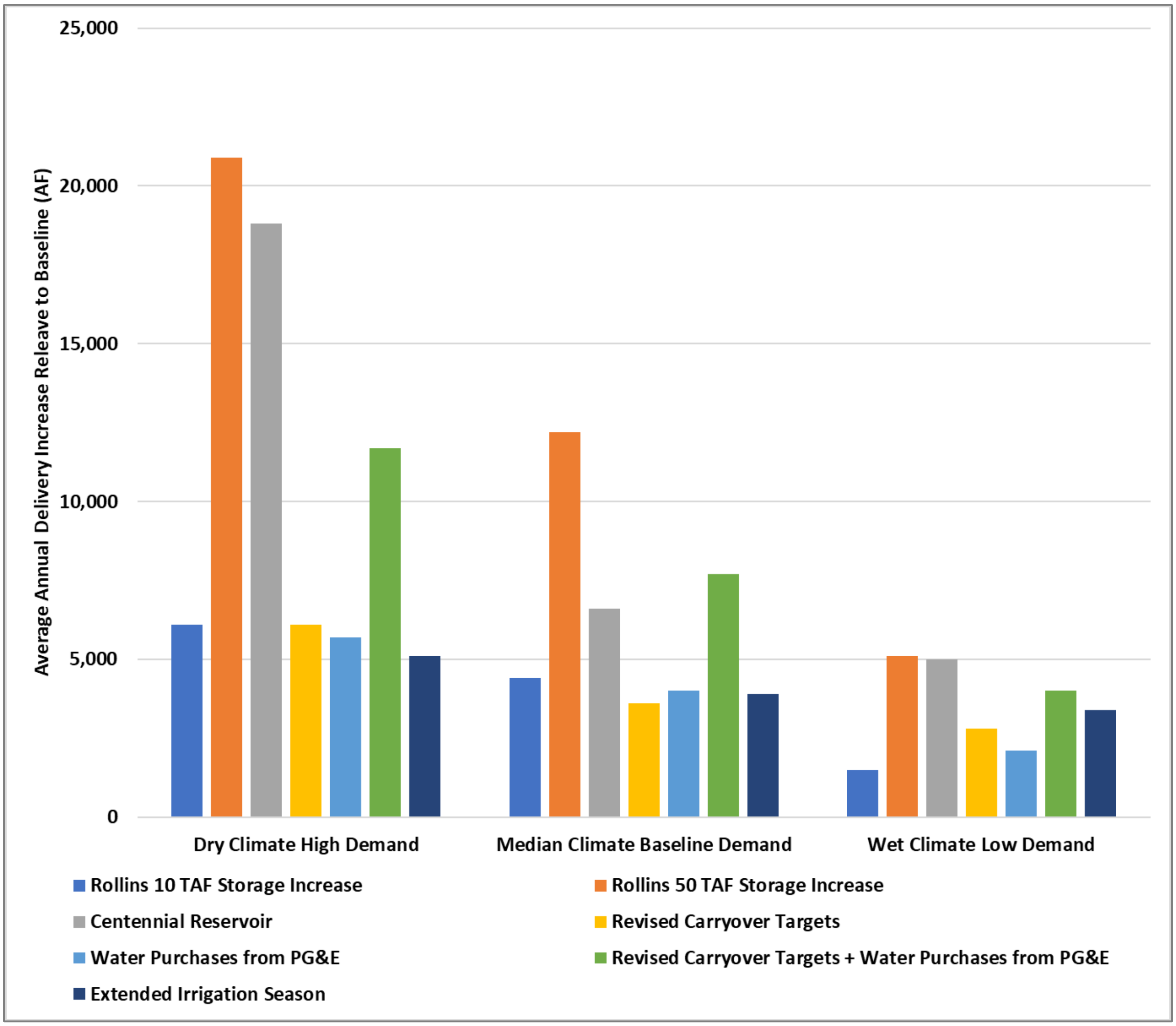

Figure 1. Relative Increase in Average Annual Water Delivery

Table 1. Annual Average Unmet Demand, Acre-Feet

Scenario	Dry Climate High Demand	Median Climate Baseline Demand	Wet Climate Low Demand
Baseline	35,000	13,900	5,900
Rollins 10 TAF Increase	28,900	9,500	4,400
Rollins 50 TAF Increase	14,100	1,700	800
Centennial Reservoir	16,200	7,300	900
Revised Carryover	28,900	10,300	3,100
Water Purchase	29,300	9,900	3,800
Revised Carryover + Water Purchase	23,300	6,200	1,900
Extended Irrigation Season	36,200	15,400	6,300

The relative change in average annual carryover storage for each climate scenario is summarized in Figure 2. Scenarios that added storage to the system, the two Rollins storage increase scenarios and the Centennial Reservoir scenario, increased the average annual carryover storage. The water purchases from PG&E scenario were relatively neutral, and the other scenarios result in a decrease in average annual carryover storage. Increased carryover storage provides additional protection against multi-year droughts. A decrease in carryover storage indicates a reduction in available NID water supply which increases risk.

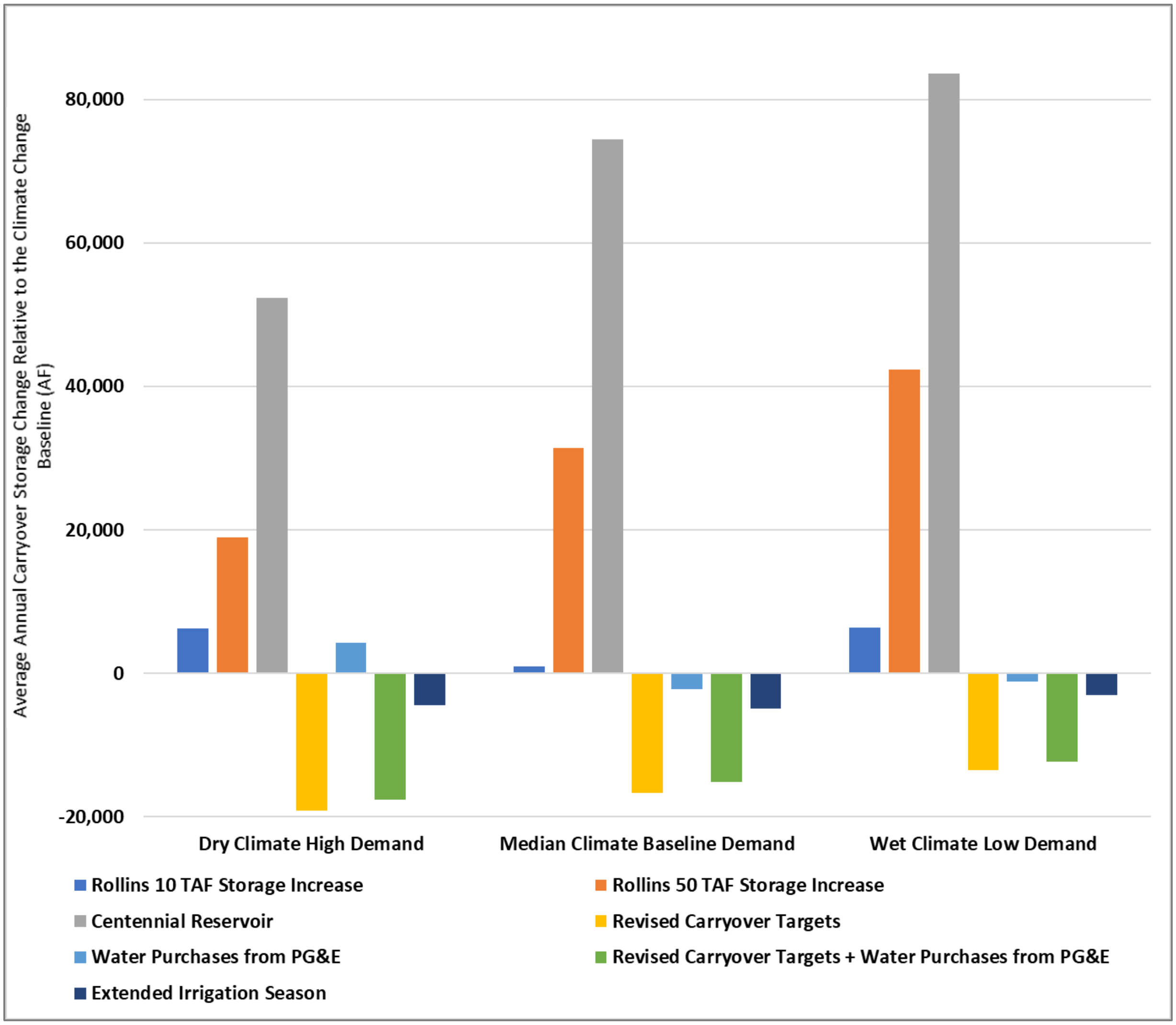

Figure 2. Relative Change in Average Annual Carryover Storage

Each of the strategic alternatives included in this analysis resulted in a net increase in water deliveries to NID customers under various projections of climate change. For some of these alternatives, the increase in deliveries comes with a negative impact on system storage, as measured by average annual carryover storage. Carryover storage is one of NID’s four primary sources of water supply, which also includes natural runoff, contract water purchases, and recycled water. Alternatives that increase both water deliveries and carryover storage are much more valuable than those that increase water deliveries alone.

Chapter 1. Introduction

1.1. The Nevada Irrigation District

The Nevada Irrigation District (NID) is an independent public agency governed by a 5-member elected Board of Directors (BOD) and employs about 200 full- and part-time employees. NID supplies water to 25,000 homes, farms, and businesses in portions of Nevada, Placer, and Yuba Counties in the foothills of Northern California's Sierra Nevada Mountains. Water is collected from mountain watersheds and stored in a system of reservoirs. As water flows to NID customers, it generates more than 354 gigawatts of clean, hydroelectric energy per year while supporting environmental flows and serving public recreation. NID supplies both treated drinking water and crop irrigation water. Approximately 90% of NID's annual demand is for raw water/agricultural water during the irrigation season, April 15 to October 15.

In any given year, four primary sources supply NID's water:

1. Reservoir storage carried over from the previous year,
2. Natural runoff (including snowmelt) from the contributing watershed areas,
3. Contract water purchases, and
4. Recycled water.

NID regularly evaluates and updates its water supply availability projections. In the past, this was completed through the Raw Water Master Plan (RWMP), originally developed in 1985. The RWMP assessed the adequacy of the existing water storage and conveyance system to accommodate current and future water demand. Since 1985, the RWMP was updated in two phases: first in 2005 (Kleinschmidt et al. 2005), and then again in 2011 (Kleinschmidt Associates 2011).

Currently, NID's is evaluating and updating its water supply availability projects through the Plan for Water (PFW).

1.2. NID's Water Supply Network

NID's water supply system is a store-and-release system. Reservoirs store snowmelt and seasonal runoff for release during the typically dry summers. Water is delivered to customers via a network of channels, canals, flumes, and pipes. While there is natural runoff during the summer months, this water is generally used to meet regulatory requirements for environmental flows in the rivers. Irrigation demand is met primarily with withdrawals from storage reservoirs. Careful management and operation of storage reservoirs is essential to capture the maximum amount of runoff captured, minimize spillage from reservoirs, and ensure there is sufficient volume available in reservoirs to accommodate runoff during the spring snowmelt and storm events.

Water is stored and released from the high-elevation reservoirs based on NID's consumptive needs and reservoir carryover storage targets. Discretionary releases for water supply are made from Jackson Meadows Reservoir and Jackson, French, Faucherie, and Sawmill reservoirs during the spring runoff season through late fall. Releases from Jackson Meadows Reservoir are conveyed to Bowman Lake via the Milton-Bowman Tunnel. Releases from Jackson, French, Faucherie, and Sawmill lakes are stored and released by Bowman Dam through Bowman Powerhouse into the Bowman-Spaulding Conduit Diversion

Impoundment. Five small diversions along creeks that run perpendicular to the Bowman-Spaulding Conduit augment flows in the conduit up to its capacity and spill the remainder into their respective natural drainages downstream of the conduit.

Flows from the Bowman-Spaulding Conduit pass through PG&E's Lake Spaulding into PG&E's Drum Canal and the South Yuba Canal. Water transported into the South Yuba Canal is diverted into South Fork Deer Creek to supply NID customers in the Nevada City-Grass Valley area. This water is largely diverted at the Cascade Canal Diversion Dam located immediately downstream but is also used to manage Scotts Flat Reservoir storage. Releases from Scotts Flat Reservoir provide water to four other downstream diversions downstream along Deer Creek.

Water transported into the Drum Canal is passed through PG&E's Drum Forebay into the Bear River at PG&E's Drum Afterbay. Water is diverted and returned several times along the Bear River reach upstream of Rollins Reservoir by NID and PG&E for power generation. Daily volumes are scheduled by NID and PG&E for downstream consumptive demand.

Rollins Reservoir is NID's major low-elevation storage reservoir on the Bear River. Rollins Reservoir is a multipurpose facility that meets municipal, irrigation, domestic water supply, recreation, and power generation needs. From Rollins, water supplies NID customers in southern Nevada County and Placer County.

1.3. The Plan for Water

The PFW is a long-range decision tool to guide NID's future water management. The PFW process is an open and comprehensive look at available water resources affected by new regulations, changes in land use, varying climate, and community aspirations. The PFW offers a range of potential scenarios for NID's BOD to consider when assessing ways to best meet customer demands for water over the next 50 years. While 50 years is a sufficient time horizon for major water infrastructure planning, shorter term changes in water supply, water demand, regulation, and technology dictate the need for PFW updates every five years. The NID board members approved a resolution to update the plan every 5 years (NID 2023).

NID's PFW contains 11 stages, the first 6 stages are predominantly planning stages while the last 5 stages are the active modeling and evaluating stages, the latter of which will be discussed further in the next section.

1. System Overview
2. Water Rights Overview
3. Watersheds
4. Risk
5. Strategic Planning
6. Basis for Plan Water
7. Hydrology and Hydrography
8. Demand

9. Supply Needs
10. Strategy Options
11. Evaluate Strategies

More information regarding these specific stages can be found on NID's website at: https://www.nidwater.com/the-11-stages-of-plan-for-water.

1.4. General Approach

As briefly discussed above, watershed, supply and demand, and operation modeling was conducted during Stages 7 through 10 of the PFW. The various models are heavily informed by each other, as shown in Figure 1-1.

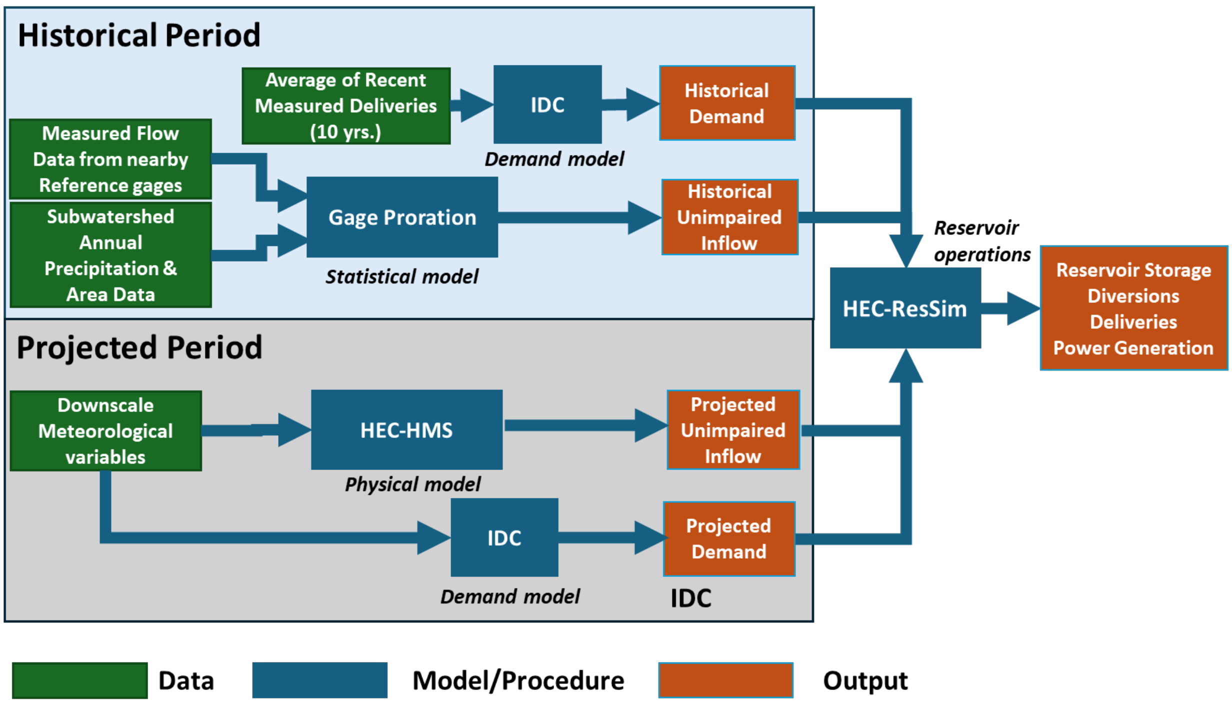

Figure 1-1. Modeling Schematic Demonstrating How Each Model Informs the Next

In the schematic in Figure 1-1, two modeling periods are highlighted: (1) historical and (2) projected. NID's snowpack-based supply and delivery strategy is affected by changing temperatures and precipitation associated with a warming climate. The PFW investigated potential impacts on supplies as temperature and precipitation patterns change. The analysis included projecting future temperatures and precipitation and their potential effect on watershed runoff and demand.

Historical and projected demands were estimated based on the California Department of Water Resources' Integrated Water Flow Model Demand Calculator (IDC model) built for NID's service area. Later chapters will describe the IDC model used for the PFW.

Unimpaired inflows were estimated based on two different methodologies for historical and projected data. For the historical period, the gage proration statistical method was used to estimate historical unimpaired inflow based on measured flow data from nearby reference gages, annual precipitation, and watershed drainage area.

For the projected period, the PFW incorporates hydrologic data representative of projected climate conditions for the next 50 years. Projected climate data cover a range of plausible outcomes based on different scenarios of greenhouse gas emissions. Since observed data are not available for the projected period, a physically based hydrological is required to estimate projected unimpaired flows based on projected precipitation and temperature. The U.S. Army Corps of Engineers' Hydrologic Engineering Center (HEC) – Hydrologic Modeling System (HMS) was used to simulate projected unimpaired flows. Historical flow data were used to calibrate HEC-HMS. Recent studies have shown that HMS is technically and scientifically defensible as it can adequately simulate streamflow from precipitation, temperature and other hydrometeorological data (Li et al. 2022, Mahato et al. 2022, Moothedan et al. 2022). Later chapters will describe the HMS model development, calibration, and validation for the PFW.

Unimpaired inflows need to be converted into impaired flows based in the influence of reservoirs and other manmade hydraulic structures. The flow impairments that are modeled for the PFW include how the various reservoirs in the watershed hold or divert the unimpaired flows and consumptive, hydroelectric, environmental, and other state-mandated demands. The effects of flow impairments are added using the HEC – Reservoir System Simulation (ResSim) model.

HEC-ResSim is widely used for water supply and flood management in planning studies. The model features rule-based operations that attempts to reproduce the decision-making process that reservoir operators use in reservoir management. The software is Java-based and has the ability for the user to write scripts in Jython, an implementation of the python programming language in Java, which augments the model's flexible rule structures. The HEC-ResSim modeling software is widely used throughout California to model hydropower and water supply projects. The software has all the features needed to model NID's system and previous models of NID's system have been built on HEC-ResSim making it easier to incorporate previous work done to refine the modeling of NID's system. Later chapters will describe the HEC-ResSim model development, calibration, and validation for the PFW.

The combinations of models and methods implemented for the PFW allow for large flexibility on updating the results of this project as situations change (e.g., additional storage or modified regulations) and more information (e.g., updated climate projections) becomes available.

1.5. Stakeholder Participation

Community stakeholders and the public have been involved in numerous workshops covering the 11 stages mentioned earlier in this chapter. NID asserts that the PFW benefits greatly from public outreach that increases the organization and the public's understanding of water resource challenges. It is integral that NID and the community's long-term plans and priorities align with each other.

From the onset of the PFW, NID has promised the community to: assess our water situation together; develop a deeper understanding of subsequent impacts to community interests and the community's future; provide a forum for community members to offer their input, as opposed to a closed process consisting only of technical experts; focus on overarching strategic policies and not on specific projects; understand what is really important to the community; and pursue community solutions within NID's legal responsibilities to its process customers and landowners within its service area.

Examples of stakeholder organizations that were prioritized and engaged throughout this process include: California Department of Fish & Wildlife, South Yuba River Citizens League, Nevada County Contractors' Association, Foothills Water Network, California Sporting Protection Alliance, and community members.

Chapter 2. Hydrological Model

2.1. Watershed Description Development

The NID watersheds, draining 448 sq. mi., are located on the western slope of the Sierra Nevada Mountains and cover portions of three counties: Nevada, Placer, and Yuba (Figure 2-1). The NID watersheds include the upper reaches of the Yuba River, Bear River, and Deer Creek. The highest peak in the NID watershed is the 8,373-ft English Mountain. NID transports water from high elevation mountain reservoirs to the lower elevation foothills and into portions of the northern Sacramento Valley near the City of Lincoln. Summers are dry with mild to hot temperatures. Winters are wet, especially in the upper elevations around Nevada City and Grass Valley. Snow levels are usually around 3,500 ft, but occasionally drop as low as 1,000 ft. Based on the historical data obtained from the California Irrigation Management Information System (CIMIS) and the Western Regional Climate Center (WRCC), the NID service area experiences average monthly temperatures ranging from 26 to 92 ˚F.

Throughout the NID watershed, several water management projects have been built to serve multiple purposes including flood control, water supply, irrigation, and recreation. These projects include dams/reservoirs, local flood reduction systems, and diversions, among others. The major dams and reservoirs located in the NID watershed are listed within Table 2-1. Figure 2-2 shows the locations of the various major water management projects throughout the NID watershed.

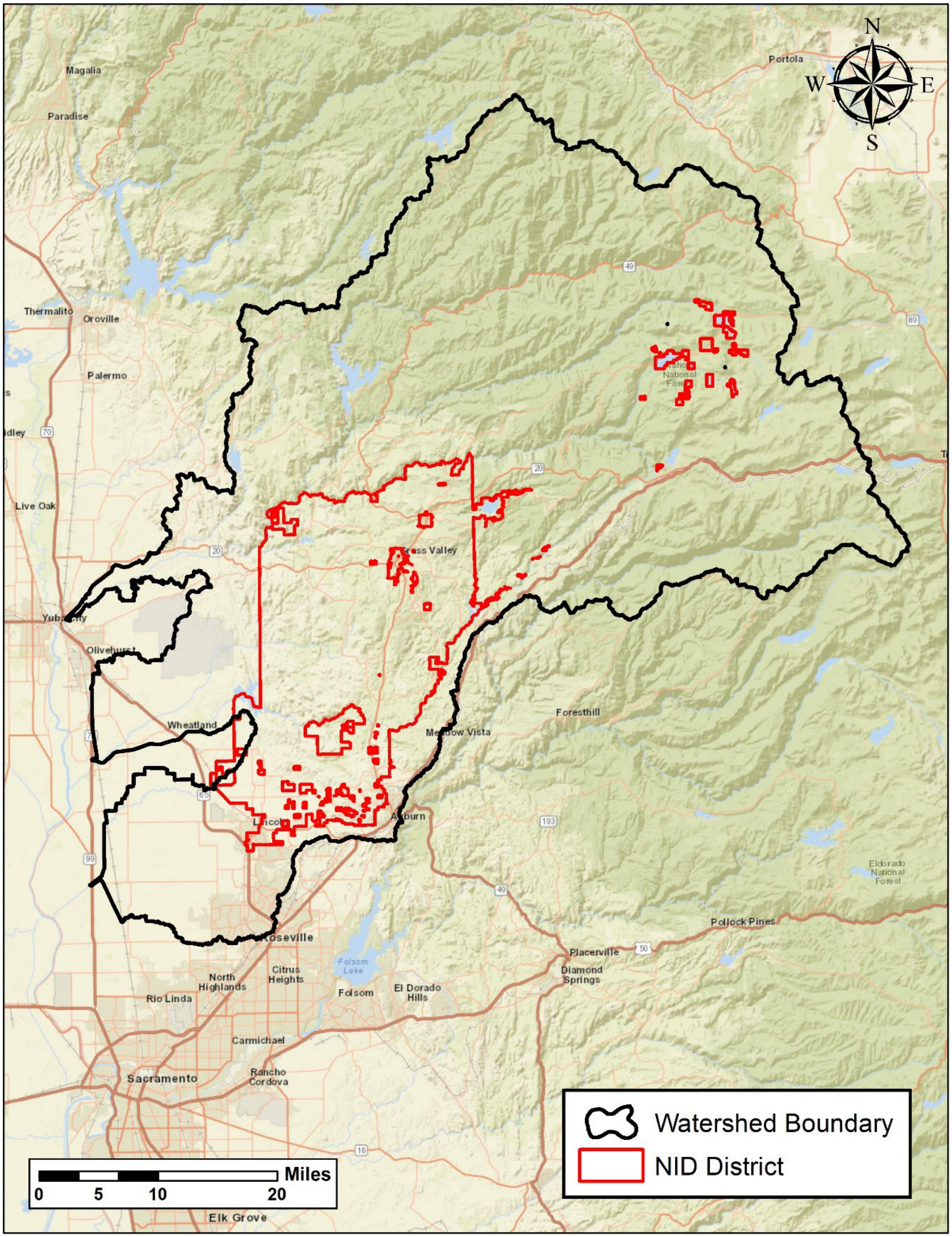

Figure 2-1. Nevada Irrigation District Map

Table 2-1. Major Dams and/or Reservoirs

Owner/Operating Agency	Dams and/or Reservoirs
Pacific Gas and Electric (PG&E)	Blue Lake Carr Lake Drum Afterbay Feeley Lake Fordyce Lake Fuller Lake Halsey Afterbay Kidd Lake Kelly Lake Lake Spaulding Lower Cascade Lake Lindsey Lakes Lake Valley Reservoir Lake Sterling Meadow Lake Rucker Lake Rock Creek Lake Upper Cascade Lake Upper Rock Lake White Rock Lake
USACE	Englebright Lake
PG&E and NID	Dutch Flat Afterbay
Camp Far West Irrigation District	Camp Far West Lake
South Feather Water and Power Agency	Slate Creek Reservoir
NID	Bowman Lake French Lake Faucherie Lake Jackson Meadow Reservoir Jackson Lake Milton Reservoir Lake Combie Sawmill Lake Scotts Flat Reservoir Rollins Reservoir
Placer County Water Agency	Lake Arthur Lake Theodore
Browns Valley Irrigation District	Collins Lake
Yuba Water Agency	New Bullards Bar Reservoir

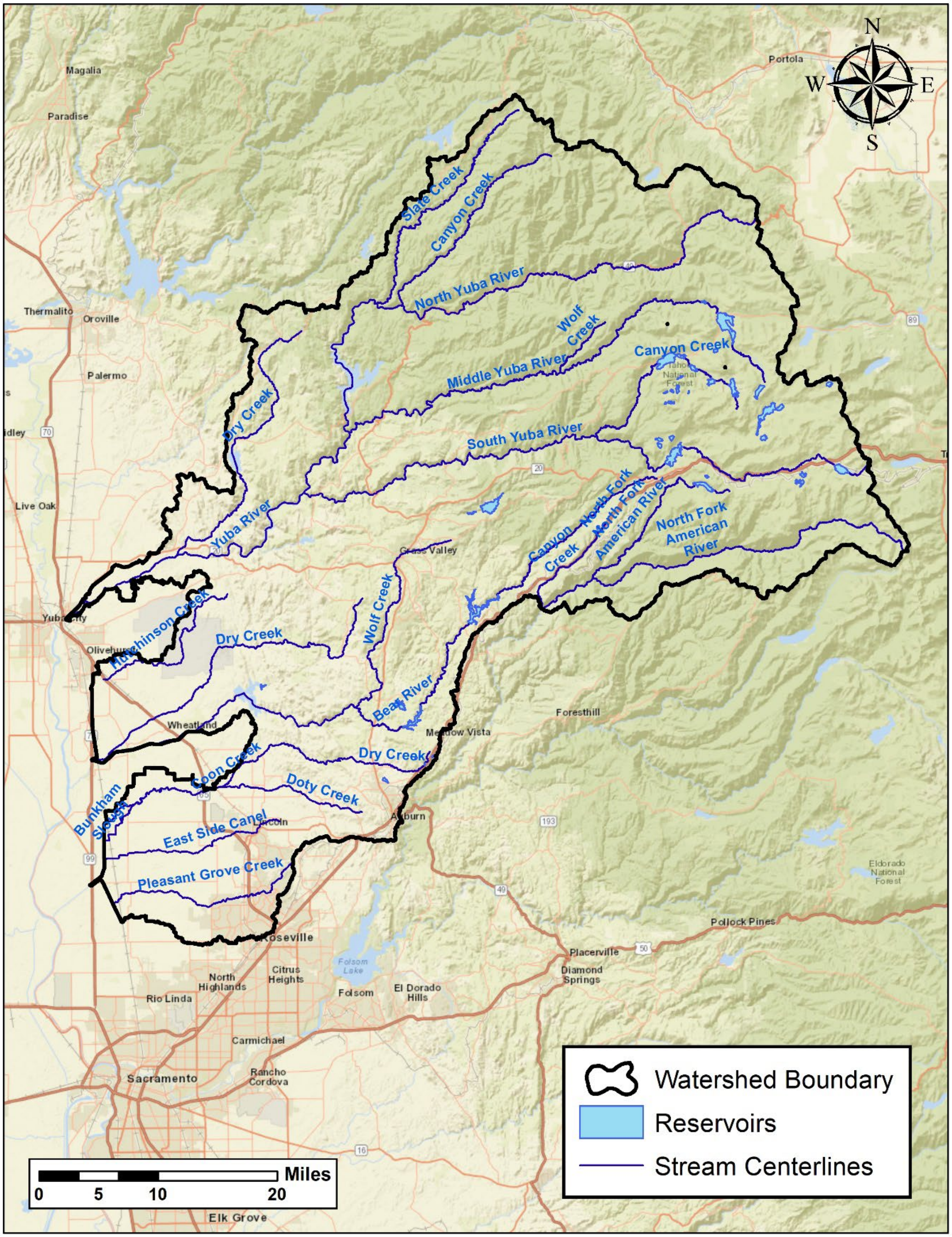

Figure 2-2. Major Tributaries and Reservoirs Within NID watersheds

2.2. Software

Table 2-2 provides a summary of the computer programs and their respective versions employed in development of the HEC-HMS model.

Table 2-2. Computer Programs Used

Program	Version	Capability	Developer
ArcGIS	10.7	Geographical Information System	ESRI
HEC-DSSVue	3.2.3	Plot, tabulate, edit, and manipulate data in HEC-DSS files	HEC
HEC-HMS	4.10	Catchment delineation and rainfall-runoff simulation	HEC
Vortex	0.10.20	Data Processing Utilities	HEC

2.3. Data Collection

The following sections discuss the data and tools used in the development of the HEC-HMS hydrologic model, which simulates NID's unimpaired hydrology.

2.3.1. Spatial Tools and Reference

To process and analyze the data necessary for hydrologic modeling and to generate the subbasin boundaries, ArcGIS and the HEC-HMS Geographic Information System (GIS) delineation tool were used.

The standard USGS map and projection parameters used for this study were:

- Horizontal Datum: North American Datum 1983 (NAD 83)- California State Plane Zone 2
- Projection: United States Contiguous Albers Equal Area Conic U.S. Geological Survey (USGS) version
- Vertical Datum: North American Vertical Datum, 1988 (NAVD 88)
- Linear units: U.S. ft.

2.3.2. GIS Data

The team used USGS web mapping services (USGS 2023) to download the Hydrologic Unit Code (HUC, a system used by USGS and other agencies to divide watersheds into smaller, more manageable units for hydrologic analysis and water resource management), soils, land cover, Federal agency gages, National Inventory of Dams locations, as well as the general base map layers. Additional GIS data were obtained from the ESRI database and used in figures prepared in this report.

2.3.3. Digital Elevation Model

The 10-m USGS National Elevation Dataset (NED, Gesch et al. 2002) was downloaded and merged to create a continuous Digital Elevation Model (DEM) that covers NID area of interest. That DEM was then used to delineate individual subbasins. (See Section 2.4.1).

2.3.4. Land Cover

Land cover data were obtained from the National Land Cover Database (NLCD 2019). The NLCD provides nationwide data on land cover and land cover change at a 30-m resolution with a 16-class legend based on a modified Anderson Level II classification system (Anderson 1976). NLCD 2019 is the latest evolution of NLCD land cover products focused on providing land cover and land cover change data for the United States. These datasets were used to estimate the subbasin-average percent impervious cover within the NID drainage basin. More discussion of land cover data and processing is provided in Section 2.4.2.

2.3.5. Soil Data

The USGS Gridded Soil Survey Geographic (gSSURGO, Soil Survey Staff 2022) for the NID basin were obtained from the Natural Resources Conservation Service (NRCS) for the State of California . The soil data were formatted and processed following instructions available in HEC-HMS Tutorials and Guides (USACE 2022a) to assign surface soil textures throughout the modeling domain and estimate initial soil loss parameters. The gSSURGO soils database includes information related to the available water storage depth as well as the hydrologic soil group classification. These datasets help estimate the initial values for the maximum soil moisture deficit and the initial values for the infiltration rates. More discussion about soils data is provided in Section 2.4.2.

2.3.6. Precipitation Data

Precipitation data used for the modeling effort were generated from Livneh Unsplit (Pierce et al. 2021) and Parameter-elevation Regressions on Independent Slopes Model (PRISM, PRISM Climate Group 2014). The continental-scale 4-km grid dataset was reprojected to the previously mentioned projection. Subsequently, the precipitation grids were delineated to the modeling domain’s boundary and transformed into gridded data storage system (DSS) format using HEC-Vortex V0.10.20, accessible at (https://github.com/HydrologicEngineeringCenter/Vortex/releases/tag/v0.10.20). Since HEC-HMS 4.10 is unable to manage gridded DSS V7 produced by HEC-Vortex, the DSS Version 7 was converted to V6 using HEC-DSSVue 3.2.3.

2.3.7. Temperature Data

Temperature data used for the modeling effort were generated from Livneh Unsplit and PRISM dataset. The continental-scale 4-km gridded dataset was reprojected to the previously mentioned projection. Subsequently, the temperature grids were delineated to the modeling domain’s boundary and transformed into gridded DSS format using HEC-Vortex V0.10.20. Given that HEC-HMS 4.10 is unable to manage gridded DSS V7 from HEC-Vortex, DSS V7 was converted to V6 using HEC-DSSVue 3.2.3.

2.3.8. Evapotranspiration

The Hamon Method (Hamon 1961) was used to simulate evapotranspiration (ET) losses throughout the modeling domain. Within the Hamon Method, ET losses are directly proportional to the daily average temperature and related to the location of interest and time of year. A modified, gridded version of the Hamon Method estimates potential ET losses using the daily average Livneh temperatures and a coefficient (Harwell 2012). The coefficient for NID watersheds was estimated as 0.0065.

2.3.9. Snow Data

Snow data are required to estimate the model parameters that control snow accumulation and melt. Snow data were obtained from the California Data Exchange Center (CDEC) managed by the Department of Water Resources (https://cdec.water.ca.gov/). The data available in CDEC are from the U.S. Department of Agriculture (USDA)-NRCS Snow Telemetry (SNOTEL) network and the California Cooperator Snow Sensors (https://www.wcc.nrcs.usda.gov/snow/). After analyzing the available data, four snow stations were chosen based on their diverse snowpack characteristics at elevations exceeding 5,000 ft and their data availability in time. The selected stations reflect different conditions present throughout the NID area of interest. The selected stations record key meteorological parameters, including precipitation, temperature, snow depth, and snow water equivalent (SWE). Table 2-3 identifies the snow stations and Figure 2-3 shows their locations within the NID basin.

Table 2-3. Snow Stations Used for Temperature Index Calibration

Source	Identifier	State	Site Name	Elevation (ft)	Latitude	Longitude
Cooperator Snow Sensors	BLC	CA	Blue Canyon	5,280	39.28	-120.71
	HYS	CA	Huysink	6,600	39.28	-120.53
	RCC	CA	Robinson Cow Camp	6,480	39.62	- 120.68
SNOTEL	CSS Lab (428)	CA	Central Sierra Snow Lab	6,894	39.33	-120.37

2.3.10. Streamflow and Reservoir Data

Daily average streamflow and reservoir data were obtained from the USGS National Water Information System (NWIS) (https://waterdata.usgs.gov/nwis) to support HEC-HMS model calibration. The stream flow and reservoir data observation sites are detailed in Table 2-4 and visualized in Figure 2-4.

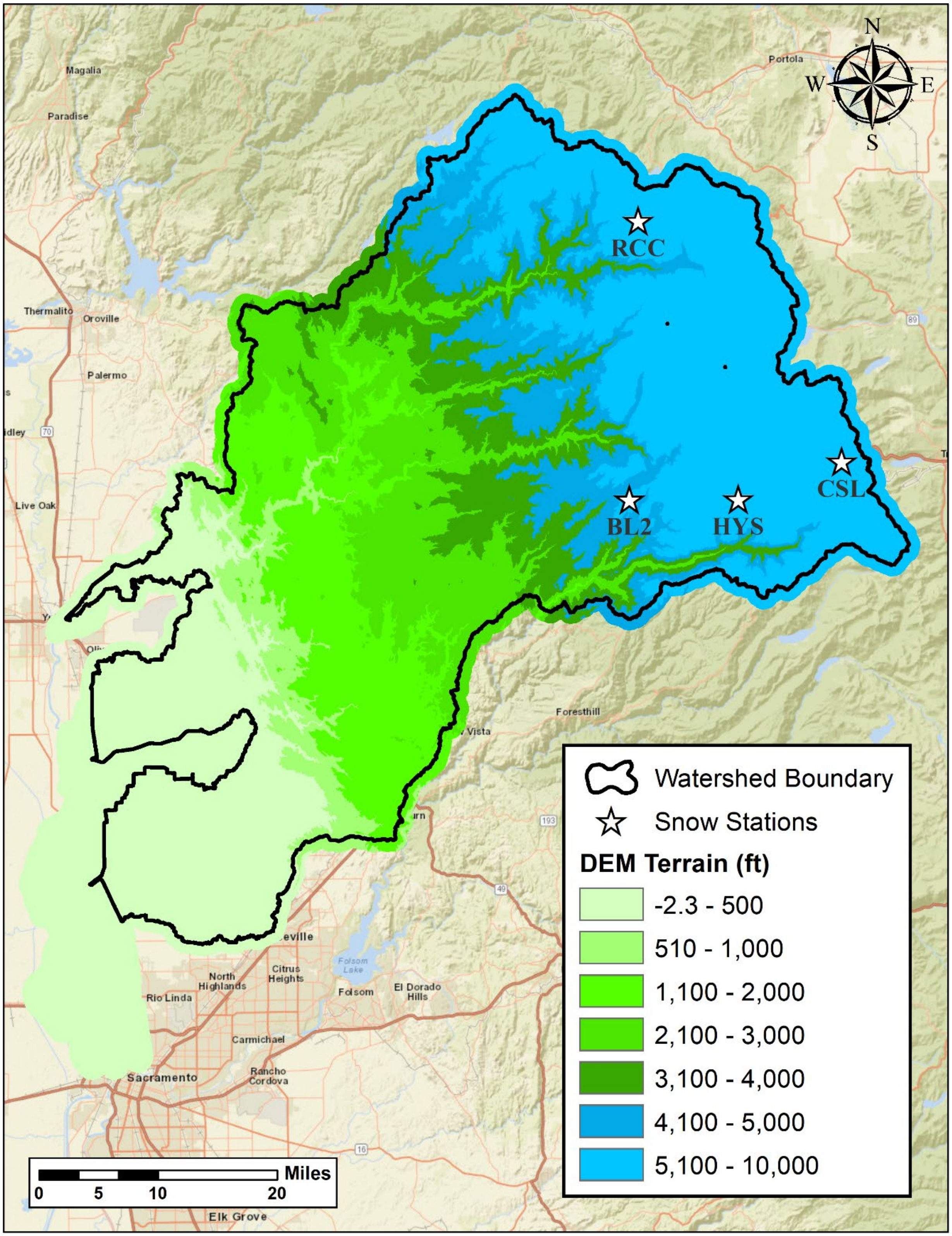

Figure 2-3. Snow Stations Used for Temperature Index Calibration

Table 2-4. Streamflow Gages for Model Calibration

Gage ID	Station Name	Latitude	Longitude
11408000	MILTON-BOWMAN TUNNEL OUTLET NR GRANITEVILLE CA	-120.611	39.46018
11408550	M YUBA R BL MILTON DAM CA	-120.584	39.52185
11408870	LOHMAN RIDGE TU A IT NR CAMPTONVILLE CA	-120.996	39.41239
11408880	M YUBA R BL OUR HOUSE DAM CA	-120.998	39.41156
11409350	CAMPTONVILLE TU A IT NR CAMPTONVILLE CA	-121.059	39.44017
11409400	OREGON C BL LOG CABIN DAM NR CAMPTONVILLE CA	-121.059	39.43934
11413000	N YUBA R BL GOODYEARS BAR CA	-120.938	39.52489
11413510	NEW COLGATE PH NR FRENCH CORRAL CA	-121.191	39.33073
11414100	FORDYCE C BL FORDYCE DAM NR CISCO CA	-120.499	39.3799
11414170	DRUM CN A TUNNEL OUTLET NR EMIGRANT GAP CA	-120.653	39.3174
11414194	DRUM NO 1 PH NR BLUE CYN CA	-120.766	39.25694
11414195	DRUM NO 2 PH NR BLUE CANYON CA	-120.767	39.25712
11414200	S YUBA CN NR EMIGRANT GAP CA	-120.663	39.31351
11414205	DEER C PH NR WASHINGTON CA	-120.844	39.29795
11414250	S YUBA R A LANGS CROSSING NR EMIGRANT GAP CA	-120.658	39.31851
11416000	BOWMAN-SPAULDING CN INTAKE NR GRANITEVILLE CA	-120.659	39.44046
11416100	BOWMAN-SPAULDING CN A JORDAN C SIPHON CA	-120.642	39.34212
11416500	CANYON C BL BOWMAN LK CA	-120.661	39.43962
11417500	S YUBA R A JONES BAR NR GRASS VALLEY CA	-121.105	39.29212
11418000	YUBA R BL ENGLEBRIGHT DAM NR SMARTSVILLE CA	-121.274	39.23517
11418500	DEER C NR SMARTSVILLE CA	-121.269	39.22434
11420750	BROWNS VALLEY IRR DITCH NR BROWNS VALLEY CA	-121.431	39.21711
11420760	BROPHY S YUBA CANAL NR MARYSVILLE CA	-121.45	39.16684
11420770	HALLWOOD-CORDUA ID CN NR MARYSVILLE CA	-121.458	39.20906
11421000	YUBA R NR MARYSVILLE CA	-121.525	39.17573
11421750	DUTCH FLAT NO 1 PH NR DUTCH FLAT CA	-120.835	39.21712
11421760	DUTCH FLAT NO 2 FLUME NR BLUE CANYON CA	-120.775	39.25434
11421770	BEAR R BL DRUM AFTERBAY NR BLUE CANYON CA	-120.775	39.25434
11421780	CHICAGO PARK FLUME NR DUTCH FLAT CA	-120.841	39.21518
11421790	BEAR R BL DUTCH FLAT AFTERBAY NR DUTCH FLAT CA	-120.845	39.21351
11422000	BEAR R CN NR COLFAX CA	-120.954	39.13267
11422500	BEAR R BL ROLLINS DAM NR COLFAX CA	-120.959	39.13129

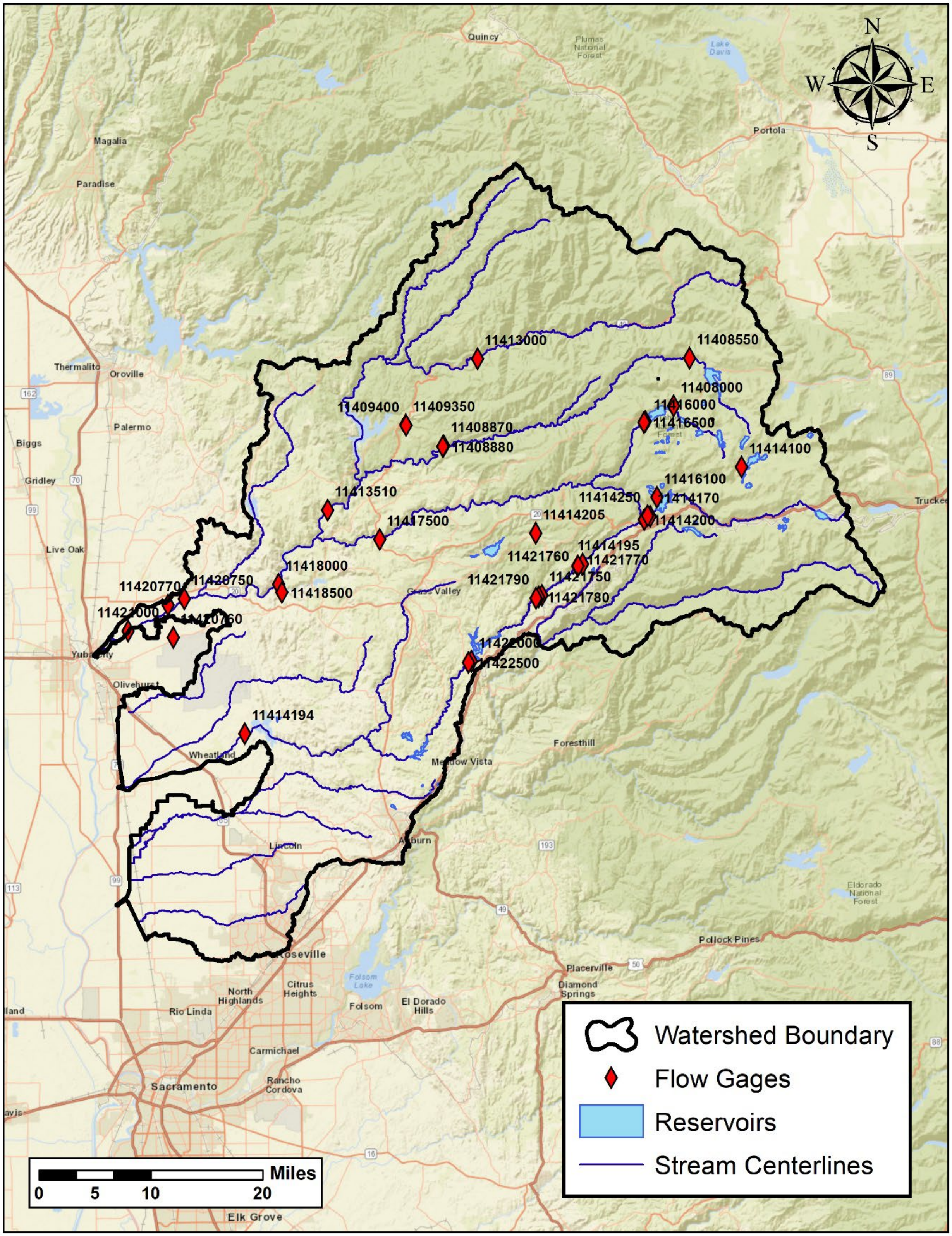

Figure 2-4. Streamflow Gages Used During Model Calibration

2.4. HEC-HMS Model Development

HEC-HMS is a hydrological model that simulates the physical processes that convert precipitation to runoff. An HEC-HMS model has three main components: a basin model, a meteorologic model, and control specifications. The basin model is the physical representation of the watershed. The meteorologic model describes watershed meteorological conditions that “drive” the basin model (i.e., the precipitation, evapotranspiration, and snowmelt data inputs). The control specifications define the length of the simulation period (e.g., years) and the temporal resolution of the simulated streamflow or reservoir storage (e.g., hours, days). HEC-HMS model development followed these steps:

- Collect relevant geographic, climatic, terrain, and time series data.
- Delineate the stream network and subbasins using the ArcGIS and HEC-HMS GIS processor.
- Develop the HEC-HMS basin model using the HEC-HMS GIS tools.
- Develop meteorological models for the calibration events.
- Select the physical models that best represent the dominant processes that control runoff generation in the area of interest. The selected physical models include, but are not limited to, snow, infiltration, baseflow, and routing models.
- Decide on the initial values for the hydrologic parameters required by the physical models chosen.
- Set the computational time step and simulation period in the HEC-HMS control specifications for each calibration event.

The following sections review the model-specific processes used in the NID HEC-HMS model.

2.4.1. Watershed Delineation

ESRI ArcGIS and the HEC-HMS GIS processor managed and analyzed spatial data such as topography and land cover for hydrologic modeling and to define subbasin boundaries. Shapefiles at the HUC-8 and HUC-12 levels were downloaded and reprojected for the delineation of the NID watershed boundary. Three HUC-8 and nine HUC-12 subbasins within the NID watershed are listed in Table 2-5 and shown in Figure 2-5. These selected subbasins were merged, and then buffered by 2 miles to create the watershed boundary. When individual subbasins are merged with the GIS tools, the boundaries might not match exactly, leaving small gaps with no elevation data along interior seams. Buffering mitigates edge effects and helps create a seamless terrain raster with no missing elevation data. The resulting rasters were thoroughly examined to ensure that the GIS tools could correctly process the files.

The resulting terrain raster was imported into a new HEC-HMS project and assigned to a basin model for subbasin delineation. The basin was delineated using the HEC-HMS GIS tool and the methods recommended in HEC-HMS Tutorials and Guides (USACE 2022a). Subbasins were sub-divided based on the inflow points of interest, which correspond to USGS gage and reservoir locations or locations with important hydraulic structures (diversions). The final HEC-HMS model has 146 subbasins encompassing approximately 2,329 sq. mi.

Table 2-5. HUC-8 and HUC-12 subbasins

HUC Level	Subbasin Name
HUC-8	Upper Yuba
	Upper Bear
	Upper Coon-Upper Auburn
HUC-12	Wabena Creek-North Fork American River (NFAR)
	Big Granite Creek
	Big Valley Canyon- NFAR
	East Fork North Fork- NFAR
	North Fork of NFAR
	Humbug Creek- NFAR
	Indian Creek- NFAR
	Upper Shirttail Canyon
	Lower Shirttail Canyon

Each model element—whether a subbasin, reach, or junction—was assigned a unique name. The first two letters of the element name represent an abbreviation for the major river associated with the element, followed by any pertinent secondary river name. The element name concludes with the symbol showing its type, “S” for subbasin, “R” for reach, or “J” for junction, followed by a unique identifying number. The identifying numbers were assigned in increments of 10, systematically increasing in the downstream direction. If an element linked to the main river did not have a secondary river, the secondary river name was designated as the same as the main river. In cases where more than one branch conveys flow into the main river, the element numbers (e.g., S10, S20) along one branch were labeled first. Then, succeeding element numbers (e.g., S30, S40) along the next branch were assigned, with the element numbering continuing after the confluence of the two branches (e.g., S50, S60). The major and secondary river names were determined using the National Hydrography Dataset (USGS 2016) flowlines. The final subbasin delineation is presented in Figure 2-6, and subbasin names, along with their respective drainage areas, are detailed in Appendix A.

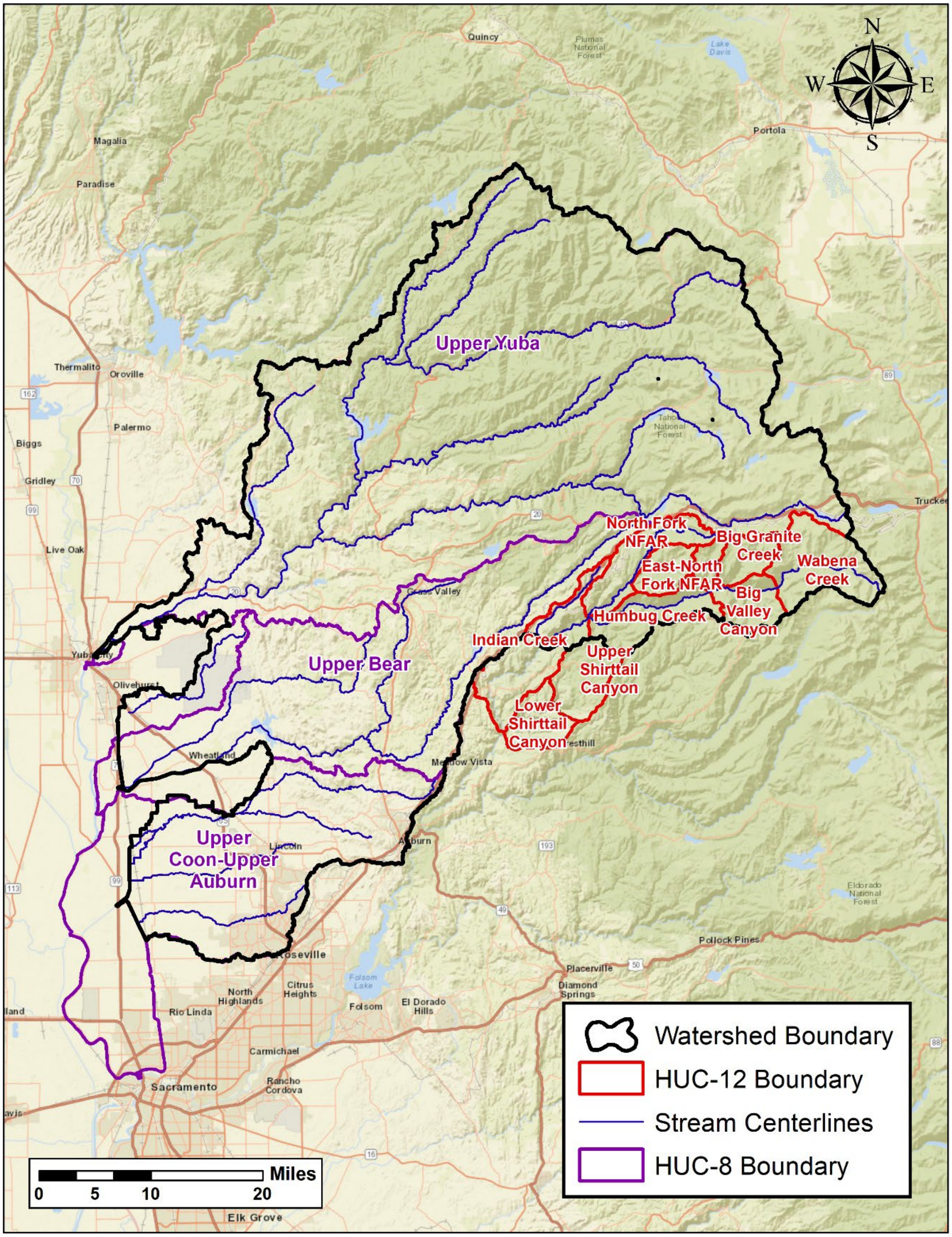

Figure 2-5. NID Watershed Delineation

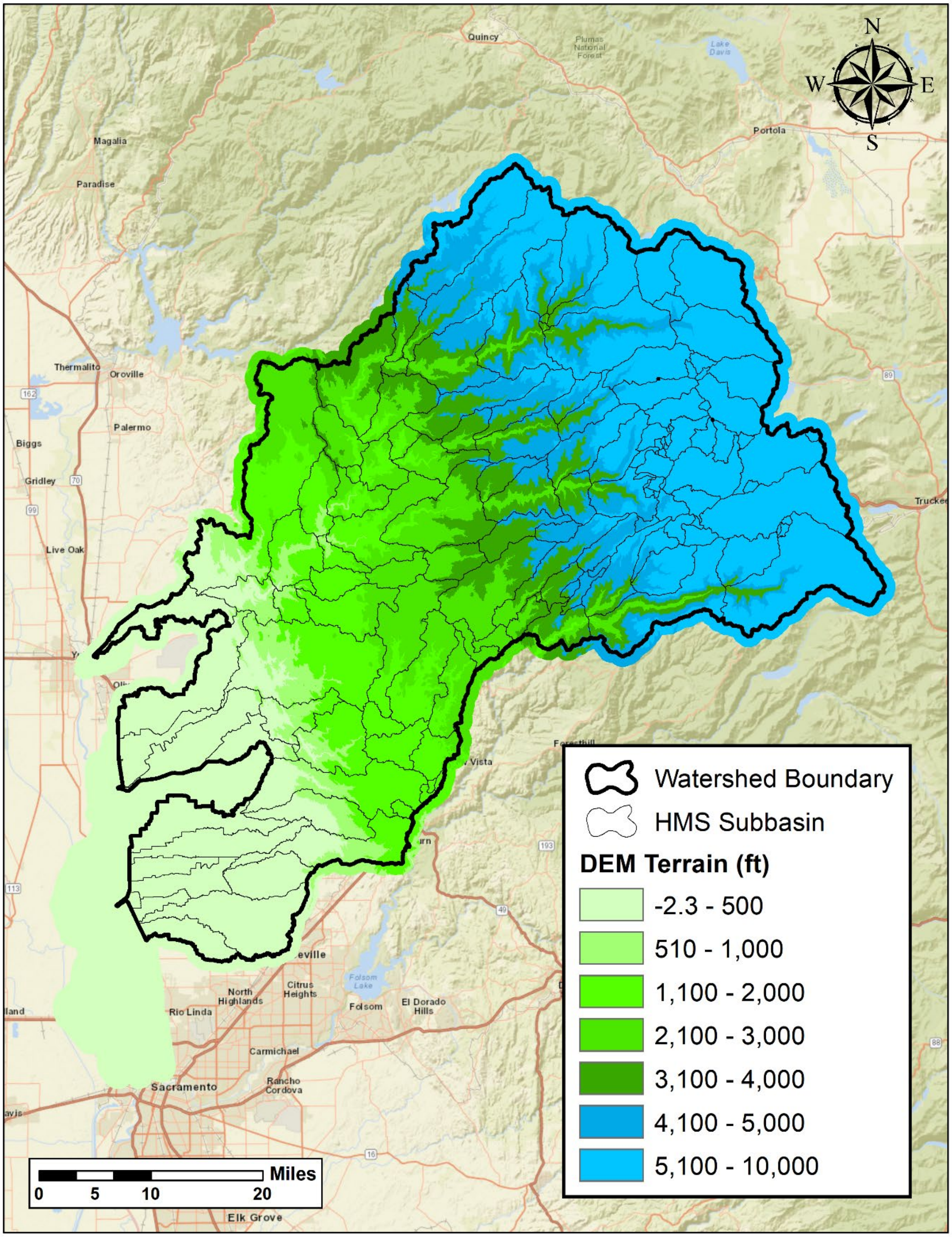

Figure 2-6. HEC-HMS Subbasins Delineation

2.4.2. Infiltration

Infiltration was estimated with the Deficit and Constant Loss Method. Required inputs for this method include initial soil moisture deficit, maximum soil moisture deficit, constant infiltration rate, and percent of directly connected impervious area. The first estimates for initial deficit, maximum deficit, and constant loss rate were based on surficial soil texture estimates. The soil texture was obtained from the NRCS gSSURGO soil coverages. Based on the soil gSSURGO datasets, the five dominant soil textures for the watershed were bedrock, sandy loam, loam, clay loam, and sandy clay loam.

Table 2-6, as listed in the Engineering Manual (EM) 1110-2-1417-Flood-Runoff Analysis (USACE 1994) and the HEC-HMS Technical Reference Manual (USACE 2022b), guided estimates of initial infiltration parameters. These parameters were based on effective porosity, wetting front suction head, saturated hydraulic conductivity, and wilting point. 'Note that the computed values are initial estimates subject to adjustment during model calibration.

The initial deficit parameter represents the initial soil moisture conditions for the soil layer. An initial deficit equal to zero indicates that the layer is fully saturated and that any precipitation falling at a rate exceeding the constant infiltration rate is transformed to runoff. The value used for the initial deficit was set to zero for all subbasins.

Table 2-6. Soil Textures and Effective Porosity, Wetting Front Suction Head, Saturated Hydraulic Conductivity, and Wilting Point (USACE 1994)

Soil Texture	Saturated Hydraulic Conductivity (in./hr)	Wetting Front Suction Head (in.)	Effective Porosity	Wilting Point
Clay	0.01	12.5	0.39	0.27
Clay Loam	0.04	8.2	0.31	0.2
Loam	0.1	3.5	0.43	0.12
Loamy Sand	1.2	2.4	0.4	0.06
Sand	4.6	1.9	0.42	0.03
Sandy Clay	0.02	9.4	0.32	0.2
Sandy Clay Loam	0.06	8.6	0.33	0.15
Sandy Loam	0.4	4.3	0.41	0.1
Silt Loam	0.3	6.6	0.49	0.13
Silty Clay	0.02	11.5	0.42	0.25
Silty Clay Loam	0.04	10.7	0.43	0.21
Bedrock	0	0	0	0

The maximum deficit parameter specifies the maximum depth of water held within the soil layer. This parameter is typically estimated as the difference between the saturation storage of the soil and the wilting point storage over an assumed active soil layer depth. In this study, an active soil layer depth of 24 in. was assumed. Therefore, based on the soil texture, the average (i.e., representative) maximum deficit for the study area was estimated to be 2 in. over the active soil layer depth.

The constant loss rate parameter defines the rate at which water is percolated out of the soil layer. Typically, this parameter is equated with the saturated hydraulic conductivity of the soil, which is defined as the rate at which water moves through a unit area of saturated soil in a unit time under a unit hydraulic gradient. Based on the study area soil texture, the initial value used for constant loss was set to 0.1 in./hr for all subbasins.

Directly connected impervious area estimates for each subbasin were assigned using the NLCD 2019 coverage. Figure 2-7 displays the 2019 NLCD Land Cover Classifications for the study area. The percent impervious parameter denotes the percentage of impervious area within each subbasin that is directly hydraulically connected to the conveyance network. It is assumed that no infiltration occurs within directly connected impervious areas, and all rainfall in such areas becomes direct runoff. Table 2-7 outlines the percent impervious cover defined per land cover type (USACE 2022a) that was used in this study.

Table 2-7. Impervious Values Defined Per Land Cover Category (USACE 2022)

Land Cover Type	Percent Impervious
Open Water	100
Perennial Snow/Ice	100
Developed, Low Intensity	20
Developed, Medium Intensity	40
Developed, High Intensity	60
Woody Wetlands	50
Emergent Herbaceous Wetlands	75
Barren Land	0
Deciduous Forest	0
Evergreen Forest	0
Mixed Forest	0
Shrub/Scrub	0
Herbaceous	0
Hay/Pasture	0
Cultivated Crops	0
Developed, Open Space	0

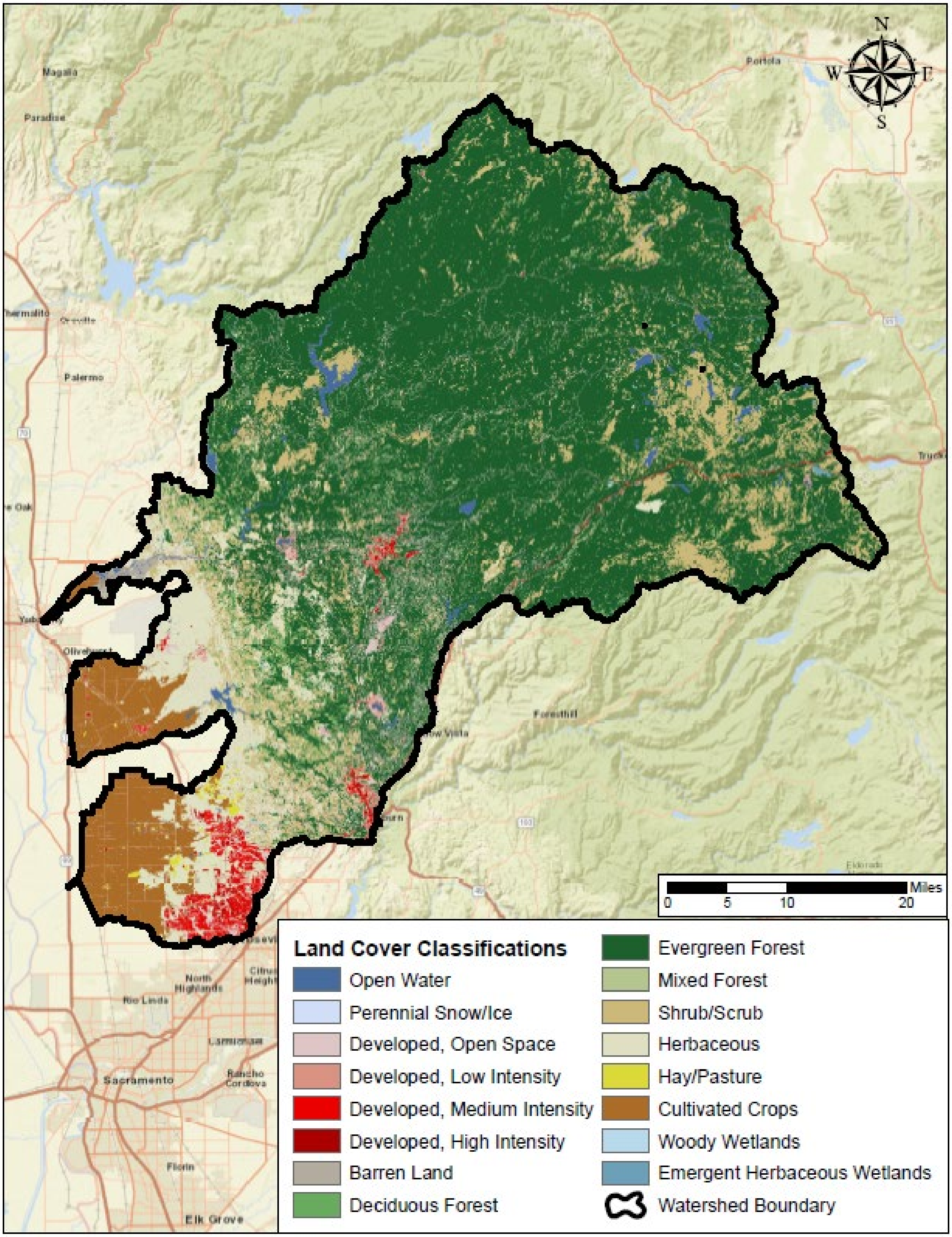

Figure 2-7. 2019 NLCD Land Cover Classifications for NID Basin

2.4.3. Canopy Losses

Canopy losses for this project were computed based on the simple canopy method, which requires five inputs: 1) initial storage percentage, 2) maximum storage, 3) crop coefficient, 4) evapotranspiration timing, and 5) uptake method.

The initial storage percentage was first set equal to 0, indicating a completely empty canopy, subject to adjustment during the calibration. Canopy storage depth depends on vegetation type or land cover. The 2019 NLCD land cover classification, shown in Figure 2-7, was applied to estimate the maximum canopy storage depths.

Canopy storage depths for each of the NLCD classes were recommended based on EM 1110-2-1417 (USACE 1994), HEC training materials, and engineering judgment. Table 2-8 lists the canopy storage values used for each NLCD land cover category.

The crop coefficient, used to adjust potential evapotranspiration, was set to 1.0 for all simulations. In HEC-HMS, evapotranspiration is set to take place either during periods without precipitation or throughout the entire simulation, regardless of whether precipitation is occurring. For this study, evapotranspiration is set to occur only during periods without precipitation ("Dry Periods"). Finally, the soil uptake method is defined as either simple or tension reduction. The tension reduction method only works when the soil moisture accounting method is selected as the soil infiltration loss method; therefore, the simple soil uptake method is used.

Table 2-8. Canopy Storage Depths for NLCD Land Cover Classifications (USACE 2022)

NLCD Code	NLCD Land Cover Classification	Canopy Storage (in)
11	Open Water	0.00
12	Perennial Snow/Ice	0.01
21	Developed, Open Space	0.05
22	Developed, Low Intensity	0.04
23	Developed, Medium Intensity	0.03
24	Developed, High Intensity	0.02
31	Barren Land	0.05
41	Deciduous Forest	0.08
42	Evergreen Forest	0.10
43	Mixed Forest	0.09
52	Shrub/Scrub	0.08
71	Grassland/Herbaceous	0.08
81	Hay/Pasture	0.08
82	Cultivated Crops	0.11
90	Woody Wetlands	0.10
95	Emergent Herbaceous Wetlands	0.09

2.4.4. Unit Hydrograph Transform

HEC-HMS offers a selection of eight transformation methods for modeling hydrologic processes. The ModClark unit hydrograph (UH) transform was used to route excess precipitation to the subbasin outlet within each subbasin. This linear, quasi-distributed transform method uses a grid of cells to depict travel times within a subbasin to the outlet point. It explicitly incorporates variations in travel time from all areas within a subbasin by employing a time travel index for each grid cell. These grid cells were laid out using the Standard Hydrologic Grid (SHG) system with a 2- x 2-km resolution (SHG 2000) and positioned across the modeling domain using tools provided within HEC-HMS.

Two essential parameters are needed for the ModClark method: the time of concentration for the basin, and the basin storage coefficient. USACE (2022a) suggests the following equations to estimate initial values of time of concentration and the basin storage coefficient:

$$T_c = 2.2\,(\frac{L *\ L_c}{\sqrt{S}})^{0.3}$$

$$\frac{R}{T_c + R} = 0.65$$

Where Tc is Time of concentration (hr), R is storage coefficient (hr), L is longest flow path length (miles), L_c is centroidal flow path length in miles, and S is 10-85 slope (ft/mi). The estimated T_c and R values were adjusted, as necessary, during calibration . Those equations were applied in this project to obtain initial parameters for the ModClark method.

2.4.5. Baseflow

The Linear Reservoir method was used to transform infiltrated water into interflow and baseflow. This helps simulate the movement of water within the soil. In this project, the storage and movement of infiltrated water is simulated using two layers. Linear reservoirs are used because, for every time step, the outflow is modeled as a linear function of the average storage within that specific time step. As a result of employing the Deficit and Constant Loss Method, the infiltrated water volume is evenly distributed between the two layers. The resulting outflow from both layers is combined to compute the total baseflow for each subbasin. The conceptualization of the two baseflow layers helps distinguish between short and long baseflow responses. The upper layer is set to respond faster than the lower layer.

Each calibration simulation starts on October 1st, after the summer months, and before the rainy season; therefore, the basin is usually quite dry. Because of that, all initial baseflow was set to originate from the slower draining groundwater storage (the Groundwater (GW) 2 layer).

Since processes that affect storage, attenuation, and timing of surface water also impact the response of interflow and baseflow, a ratio of ModClark storage coefficient was used for the groundwater storage coefficients in both layers. This approach ensures a consistent representation of these hydrological factors across the entire modeling framework. Initially, the GW 1 storage coefficient was set at 1.5 times the subbasin ModClark storage coefficient, while the GW 2 coefficient was set at 50 times the subbasin ModClark storage coefficient. Also, GW fractions in both layers are initially set to 0.5. These values are adjusted during model calibration, as necessary.

2.4.6. Streamflow Routing

Six different options are available in HEC-HMS to route flow through channels. For the routing of reaches across the modeling domain, the Muskingum-Cunge routing method was selected. This choice was made due to its ability to closely mimic more detailed hydraulic routing. The Muskingum-Cunge method uses physically based reach characteristics to compute flow attenuation and timing through the reach. Input parameters for this method are based on measurable physical parameters, which helps to increase the confidence in the routing calculations for ungaged watersheds. These physical parameters are often developed using existing hydraulic models and/or detailed topographic and hydrographic data.

To estimate the necessary depth-discharge, depth-area, and depth-top width relationships for all routing reaches, eight-point cross sections were used. While hydraulic models for rivers within the NID drainage basin were not readily available, cross-sectional data for certain reaches had been obtained during a recent relicensing study (Technical Memorandum 3-2, Instream Flow - October 2011). For the remaining reaches not covered in the study), the 1-m USGS NED was used to generate the cross-sectional data. This approach allowed for a comprehensive representation of the hydraulic characteristics across the modeling domain.

Initial estimates of channel roughness were 0.035 and 0.07 for the main channel and left/right overbank areas, respectively. These estimates were based on channel characteristics and engineering judgment. The length and average slope of each routing reach were determined within HMS GIS tool. For the celerity index method, an index celerity of 5 ft/second, and automatic optimization of space and time steps were used for all routing reaches.

2.4.7. Reservoir Routing

In the HEC-HMS model, dams and reservoirs were incorporated after a thorough screening process. The selection criteria for inclusion involved multiple factors, such as the available storage capacity, the intended purposes of the dam and reservoir, and the upstream drainage area. This approach ensured that major dams and reservoirs were correctly accounted for in the model. Elevation-area-discharge and elevation-storage relationships for the reservoirs were available from previous studies (NID, 2020). All reservoirs with observed discharge data were set to use the specified release method within HEC-HMS. In that method, HEC-HMS uses the observed outflow from a reservoir as input to the next sub-watershed. The observed outflow is a time series that combines all the reservoir’s outflow that are measured by gages, including diversions to other reservoirs, diversions to powerhouses, low flow outlet, spillway outlet, etc. If observed outflow discharge data were not available at a reservoir or for a specific year, the model uses the outflow curve method, which estimates reservoir outflow based on the relationship between storage and reservoir outflow discharge. Table 2-9 presents the list of reservoirs in the HEC-HMS model along with the corresponding routing methods.

Table 2-9. Inventory of Reservoirs in the Model and the Corresponding Routing Methods

Reservoirs	Routing Method		Reservoirs	Routing Method
JACKSON MEADOW RESERVOIR	Outflow Curve		SAWMILL LAKE	Outflow Curve
UPPER CASCADE LAKES	Outflow Curve		JACKSON LAKE	Outflow Curve
LOWER CASCADE LAKES	Outflow Curve		LAKE COMBIE	Outflow Curve
KIDD LAKE	Outflow Curve		ROCK CREEK LAKE	Outflow Curve
MEADOW LAKE	Outflow Curve		LAKE VALLEY RESERVOIR	Outflow Curve
WHITE ROCK LAKE	Outflow Curve		KELLY LAKE	Outflow Curve
LAKE STERLING	Outflow Curve		NEW BULLARDS BAR RESERVOIR	Specified Release
FULLER LAKE	Outflow Curve		MILTON RESERVOIR	Specified Release
BLUE LAKE	Outflow Curve		OUR HOUSE DAM	Specified Release
RUCKER LAKE	Outflow Curve		LOG CABIN DAM	Specified Release
UPPER LINDSEY LAKES	Outflow Curve		LAKE SPAULDING	Specified Release
LOWER LINDSEY LAKES	Outflow Curve		BOWMAN LAKE	Specified Release
CULBERTSON LAKE	Outflow Curve		ENGLEBRIGHT LAKE	Specified Release
UPPER ROCK LAKE	Outflow Curve		SCOTTS FLAT RESERVOIR	Specified Release
LOWER ROCK LAKE	Outflow Curve		DUTCH FLAT AFTERBAY	Specified Release
FEELEY LAKE	Outflow Curve		ROLLINS RESERVOIR	Specified Release
CARR LAKE	Outflow Curve		CAMP FAR WEST LAKE	Specified Release
FRENCH LAKE	Outflow Curve		FORDYCE LAKE	Specified Release (Outflow Curve for 1997)
FAUCHERIE LAKE	Outflow Curve			

2.4.8. Snowmelt

In this study, the gridded temperature index method was used for snowmelt modeling. The gridded temperature index method uses temperature and precipitation data to estimate snowpack melting and accumulation. When computing snowmelt runoff using the gridded temperature index method, multiple factors are considered, including the initial SWE, precipitation, air temperature, the form of precipitation (rain or snow), snowpack temperature, snowpack liquid water content, time of year, and the cumulative thawing degree-days. This comprehensive set of parameters supports a detailed and accurate representation of complex snow processes. The main assumption underlying this method is that the difference between air temperature and base temperature is directly proportional to the snowpack melt rate (USACE 1956). This implies that temperature, along with a melt rate coefficient, serves as the key factor in simulating snowmelt (USACE 1998). The gridded temperature index method requires 12 different parameters as inputs:

- **PX Temperature:** Distinguishes between precipitation falling as rain or snow.
- **Base Temperature:** Specifies the temperature at which snow melts.
- **Wet Melt Rate:** Defines the snow melt rate when rain is falling on the snowpack.
- **Rain Rate Limit:** Determines the difference between wet and dry melt rate.
- **ATI-Melt Rate Coefficient:** Adjusts the melt rate antecedent temperature index (ATI) calculated during the previous time step.
- **ATI-Melt Rate Function:** Allows the melt rate to change as the snowpack ages and the melting season progresses.
- **Cold Limit Rate:** Specifies the amount of snow that is required to accumulate before the snowpack temperature is reset to the base temperature.
- **ATI-Cold Rate Coefficient:** Adjusts the cold content of the snowpack based on the influence of the air temperature on the internal snowpack temperature.
- **ATI-Cold Rate Function:** Selects the cold rate based on the ATI for cold content.
- **Water Capacity:** Defines the maximum amount of melted water that can be held in the snowpack before the liquid water seeps into the soil or exits the snowpack as runoff.
- **Ground Melt Rate:** Specifies the rate at which the ground transfers heat to the snowpack, causing the snowpack to melt.

The parameters of the snowmelt meteorologic model were calibrated independently of the basin model by performing a multiyear daily simulation of SWE values. The calibration used observed SWE data from four stations located within the watershed boundary. A detailed discussion of the multiyear daily simulation calibration effort is presented in Section 2.5

2.5. Calibration of Snow Processes

Snow accumulation and melt depths are sensitive to topographical factors such as elevation and aspect. These factors influence the depth of snowfall and the extent of melting. The calibration efforts were concentrated on snow stations situated in higher elevation mountainous areas. Snow accumulation and melting at elevated locations tend to be more substantial compared to lower elevations. The following sections provide an overview of the calibration process, evaluate model performance, and presents results from multi-year snowmelt model calibration.

2.5.1. Approach

To accurately estimate flow rates when calibrating the HEC-HMS model, it is essential to initially calibrate the temperature index snowmelt and accumulation processes and parameters. The parameters calibrated are then used as the initial input to the HEC-HMS model. Parameters are further refined during calibration of the overall gridded HEC-HMS model. The methodology used to calibrate temperature index method parameters follows guidance in the USACE Modeling, Mapping and Consequences (MMC) Technical Manual for CWMS (USACE, 2016). The calibration steps include:

1. Perform data analysis on four SNOTEL and Cooperator Snow Sensors stations in the NID watershed, as previously illustrated in Figure 2-3 and listed in Table 2-3.
2. Create subbasins for each station, incorporating observed temperature, precipitation, and SWE data. The drainage area for each subbasin was set at 1 sq. mi. All the basin modeling methods are specified as “None” except for snow method. “Temperature Index” snow method was chosen for each subbasin, and a specific elevation band was assigned to each subbasin based on the elevation corresponding snow station. Table 2-10 lists the parameters that were used in the elevation band component for all the subbasin.

Table 2-10. Elevation Band Parameters

Elevation Band Parameter	Units	Value
Percent	%	100
Elevation	ft	Snow Station Elevation
Initial SWE	in.	0
Initial Cold Content	in.	0
Initial Liquid Water	in.	0
Initial Cold Content ATI	˚F	32
Initial Melt ATI	˚F-day	0

3. Set initial values for the parameters of the snow method (temperature index) for all subbasins (Table 2-11)

Table 2-11. Initial Temperature Index Method Parameters

Meteorologic Parameter	Units	Value
PX Temperature	˚F	34.5
Base Temperature	˚F	32
Wet Melt Rate	in./˚F-day	0.12
Rain Rate Limit	in./day	0.2
ATI-Melt Rate Coefficient	-	0.98
Cold Limit	in./day	0.8
ATI-Cold Rate Coefficient	-	0.84
Water Capacity	%	5
Ground Melt	in./day	0

4. Incorporate time series of observed precipitation, temperature, and SWE gages in the model.
5. Link the observed SWE at each snow station to the corresponding subbasins as observed SWE data.
6. Develop a meteorologic model using the specified hyetograph and thermograph methods for the observed precipitation and temperature components, respectively.

7. Assign precipitation and temperature gages to their corresponding subbasins in the meteorologic model.
8. Create paired data for ATI-Melt Rate Functions and ATI-Cold Rate Functions for all subbasins/stations and assign them to their respective subbasins/stations. The initial functions are in Table 2-12 and Table 2-13.

Table 2-12. Initial ATI-Melt Rate Function

ATI (˚F-day)	Melt Rate (in./˚F-day)
0.0	0.000
30.0	0.011
55.0	0.055
120.0	0.077
150.0	0.088
200.0	0.099
1000.0	0.110

Table 2-13. Initial ATI-Cold Rate Function

ATI (˚F-day)	Melt Rate (in./˚F-day)
-100.0	-2.00
-10.0	-0.20
-1.0	-0.02
1.0	0.02
10.0	0.20
100.0	2.00
1000.0	20.00

9. Create control specification using a daily time interval, spanning from January 1, 2017, to December 01, 2021. This 5-year time period was selected due to the availability of snow data for all four snow stations.
10. Create optimization trials and simulation runs to compare simulated and observed SWE at each snow station.
11. Conduct both automatic and manual calibration processes to find parameters that yield the best match to the observed SWE values at each station.

2.5.2. Performance

Model performance is measured using Nash-Sutcliffe Efficiency (NSE), the Ratio of the Root Mean Square Error (RMSE) to the Standard Deviation Ratio (RSR), and Percent Bias (PBIAS). Comparisons are also made for peak SWE, as well as the date of peak SWE.

NSE measures the relative magnitude of the residual variance compared to the measured data variance. NSE ranges between -∞ and 1, where NSE = 1 is optimal. A value of NSE ≤ 0 indicates the mean observed value is a better predictor than the simulated value. NSE is computed using the following equation:

$$NSE = 1 - \left[\frac{\Sigma_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\Sigma_{i=1}^{n}(Y_i^{obs} - \bar{Y}^{obs})^2}\right]$$

where n = number of observed values compared to computed over the duration of the simulation, Y_i^{obs} = observed values, Y_i^{sim} = computed values, $\bar{Y}^{obs}$ = average of observed values.

RSR normalizes the RMSE by using the standard deviation of the observations. By normalizing RMSE, that statistic can be directly compared among different stations. A lower RMSE-to-SDR ratio indicates that the model's predictions are relatively accurate compared to the variability in the observed data, which is desirable. Conversely, a higher RMSE-to-SDR ratio suggests that the model's predictions have lower accuracy relative to the variability in the observed data, which may indicate poor model performance. RSR is computed using the following equation:

$$RSR = \frac{RSME}{STDEV_{obs}} = \frac{\left[\sqrt{\Sigma_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}\right]}{\left[\sqrt{\Sigma_{i=1}^{n}(Y_i^{obs} - \bar{Y}_i^{sim})^2}\right]}$$

where RMSE = root mean square error, STDEVobs = standard deviation of the observations, and $\bar{Y}_i^{sim}$ = average of simulated values.

PBIAS measures the average tendency of the simulated data to be larger or smaller than the observed data. The optimal value for PBIAS is 0.0, with low absolute PBIAS indicating accurate model simulation. A negative PBIAS means the computed volume is low and a positive PBIAS means the computed volume is high, when compared to observed data. PBIAS is computed using the following equation:

$$PBIAS = \left[\frac{\Sigma_{i=1}^{n}(Y_i^{obs} - Y_i^{sim}) \times 100}{\Sigma_{i=1}^{n}(Y_i^{obs})}\right]$$

Summary statistic performance ratings are presented in Table 2-14. The ranges shown for each of the performance ratings are based on values found in the literature. An NSE of "Very Good" or "Good" might indicate an adequate fit to the magnitude and timing of the snowmelt; however, the simulated and observed hydrographs should be evaluated along with other metrics for a more complete picture of model performance.

Table 2-14. HEC-HMS Performance Ratings for Summary Statistics

Performance Rating	NSE	RSR	PBIAS
Very Good	$0.65<NSE\leq1.00$	$0.00<RSR\leq0.60$	$PBIAS< \pm10$
Good	$0.55<NSE\leq0.65$	$0.60<RSR\leq0.70$	$\pm10\leq PBIAS<\pm35$
Satisfactory	$0.40<NSE\leq0.55$	$0.70<RSR\leq0.80$	$\pm35\leq PBIAS<\pm50$
Unsatisfactory	$NSE\leq0.40$	$RSR>0.80$	$PBIAS\geq\pm50$

2.5.3. Results

A sensitivity analysis assessed how variations in the snow parameters influence the model's output. The analysis helped to identify which parameters have a significant impact on the model results. Based on the sensitivity analysis, snow melt and accumulation are extremely sensitive to the PX temperature, base temperature, and ATI-melt rate coefficient. Results were less sensitive to wet melt rate, rain rate limit, ATI-melt and cold rate functions, cold melt rate, ATI-cold rate coefficient, water capacity, and ground melt rate. Therefore, during calibration, attention was focused on the more sensitive parameters.

Figure 2-8 through Figure 2-11 show the precipitation, temperature, and simulated SWE versus observed SWE time series at the selected snow stations. Table 2-15 summarizes the performance statistics. The overall performance rating for all stations varies from Good to Very Good.

Table 2-15. Snow Model Calibration Results from January 1, 2017, through December 1, 2021

Stations	Peak SWE (in.)		NSE	RSR	PBIAS	Overall Performance Rating
	Model	Obs.				
BLC	26.00	31.08	0.91	0.3	-15.29	Good to Very Good
HYS	50.10	53.64	0.87	0.36	0.15	Very Good
RCC	71.06	77.32	0.92	0.28	-19.26	Good to Very Good
CSL	49.97	72.90	0.70	0.55	-29.20	Good to Very Good

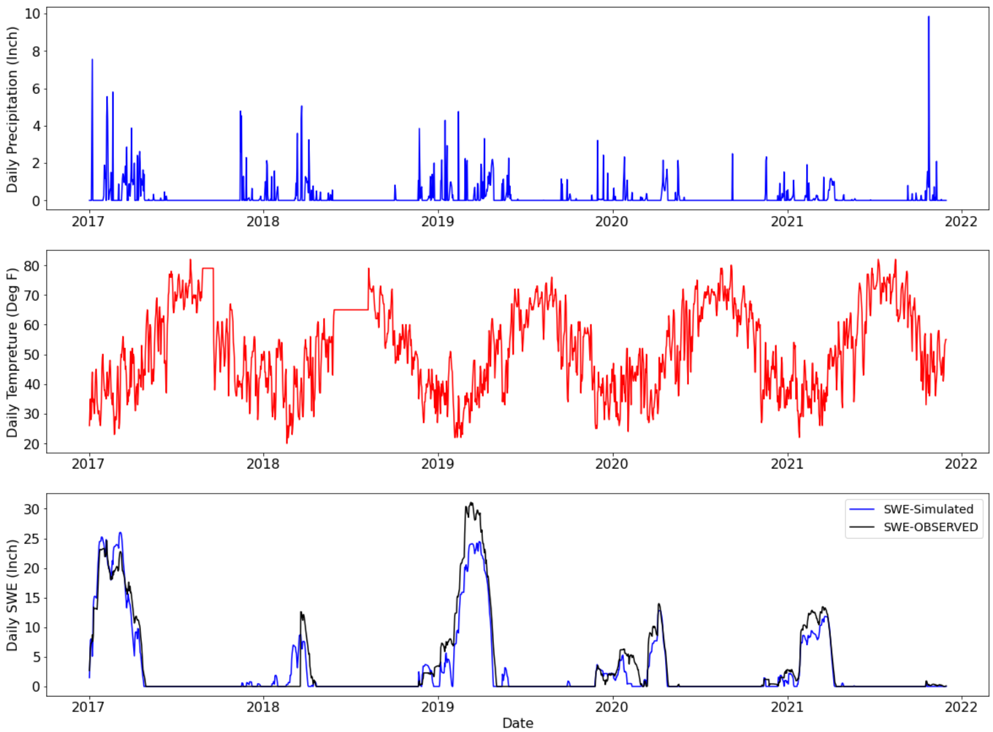

Figure 2-8. Precipitation, Temperature, and Modeled Versus Observed SWE Comparison at Blue Canyon Station (BLC)

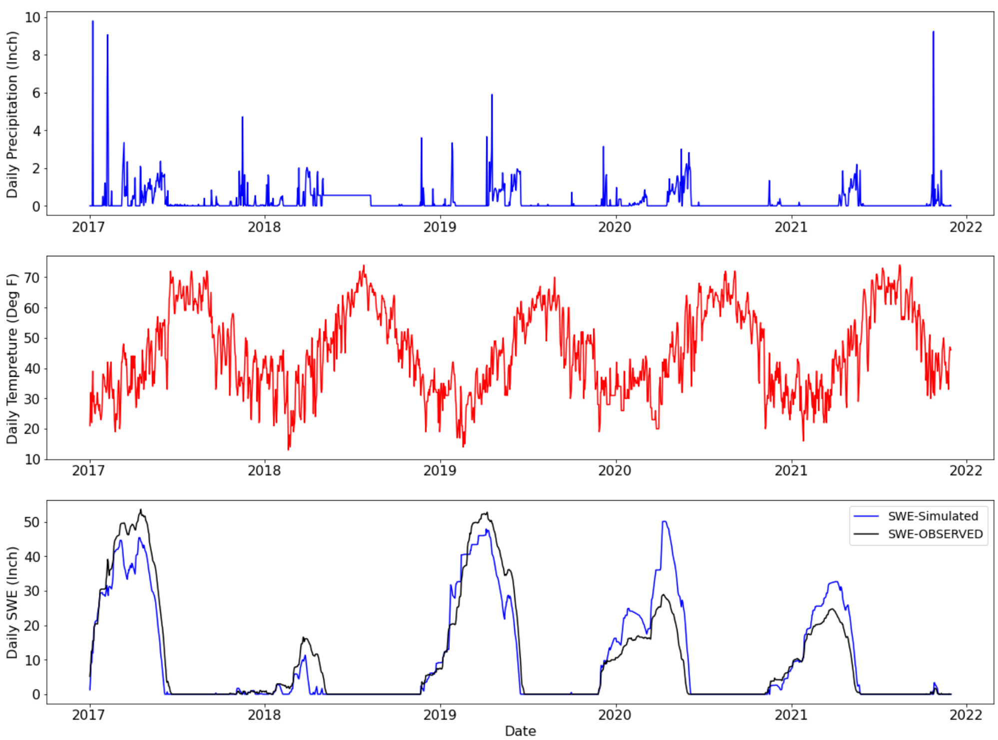

Figure 2-9. Precipitation, Temperature, and Modeled Versus Observed SWE Comparison at Huysink Station (HYS)

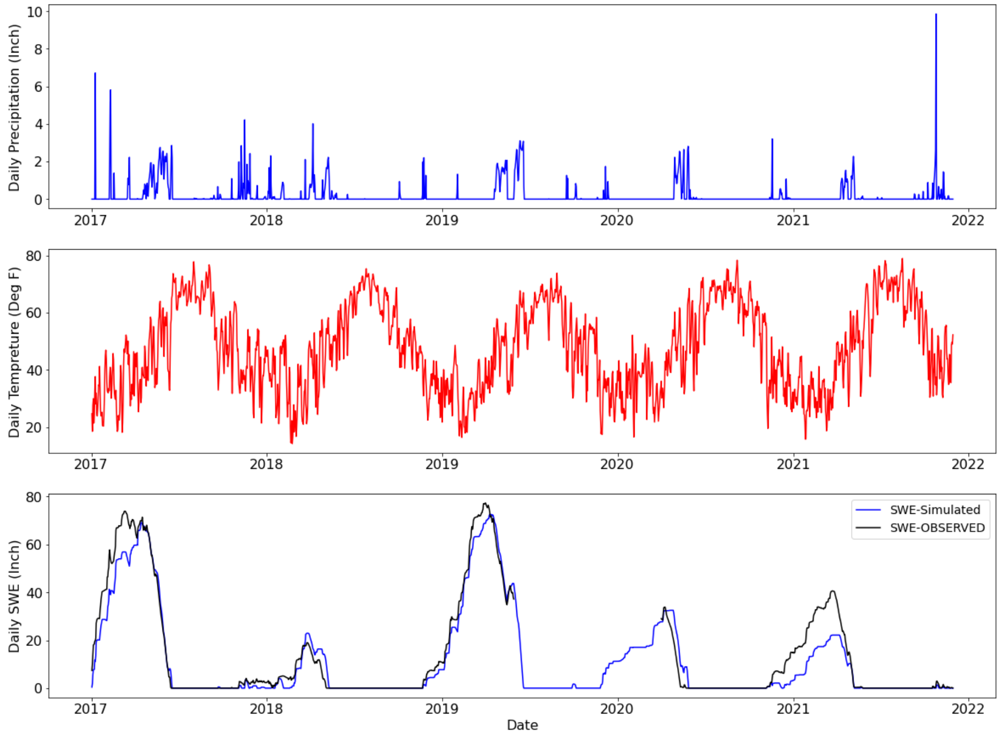

Figure 2-10. Precipitation, Temperature, and Modeled Versus Observed SWE Comparison at Robinson Cow Camp Station (RCC)

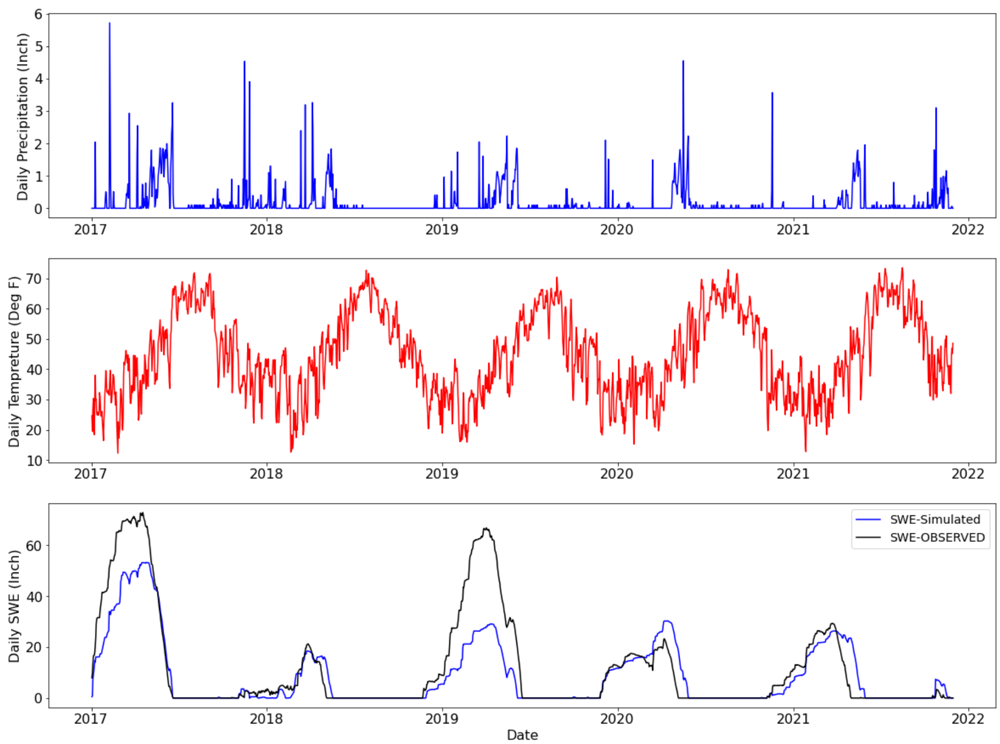

Figure 2-11. Precipitation, Temperature, and Modeled Versus Observed SWE Comparison at Central Sierra Snow Lab Station (CSL)

The calibrated snow parameters and ATI-melt and cold rate functions for each station are presented in Table 2-16 to Table 2-18. These parameters were used to define the initial parameters in the HEC-HMS model for the whole area of interest. Each subbasin in the model was assigned a specific set of snow parameters. The determination of these parameters for each subbasin was based on the nearest snow station in terms of elevation. Subbasin parameters were fine-tuned during HEC-HMS calibration as discussed in Section 2.6.

Table 2-16. Calibrated Temperature Index Parameters

Parameter	Unit	BLC	HYS	RCC	CSL
PX Temperature	°F	35	33.9	34.5	34.5
Base Temperature	°F	33	32.1	33.6	34.5
ATI - Meltrate Coefficient	-	0.8	0.98	0.94	0.9
Wet Meltrate	in./°F-day	0.13	0.099	0.11	0.17
Rain Rate Limit	in./day	0.1	0.1	0.1	0.5
Cold Limit (in./day)	in./day	0.1	0.1	0.1	0.1
ATI - Coldrate Coefficient	-	0.98	0.99	0.98	0.99
Water Capacity (%)	-	3	3	3	3
Groundmelt	in./day	0	0	0	0

Table 2-17. ATI-Meltrate Function

ATI (˚F-day)	BLC	HYS	RCC	CSL
0	0.000	0.0000	0.000	0.000
30	0.011	0.0075	0.010	0.012
55	0.055	0.0375	0.048	0.060
120	0.077	0.0525	0.067	0.084
150	0.088	0.0600	0.076	0.096
200	0.099	0.0675	0.086	0.108
1000	0.110	0.0750	0.095	0.120
2000	0.132	0.0900	0.105	0.132

Table 2-18. ATI-Coldrate Function

ATI (˚F – Day)	BLC	HYS	RCC	CSL
-100.0	-2.00	-1.800	-2.00	-2.00
-10.0	-0.20	-0.180	-0.20	-0.20
-1.0	-0.02	-0.018	-0.02	-0.02
1.0	0.02	0.018	0.02	0.02
10.0	0.20	0.180	0.20	0.20
100.0	2.00	1.800	2.00	2.00
1000.0	20.00	18.000	20.00	20.00

2.6. HEC-HMS Model Calibration

The previous section described the calibration of the snow model using observed SWE as reference. This section discusses the calibration of other important processes in HEC-HMS, including runoff generation, infiltration, and recharge. The calibration described in this section uses observed streamflow or reservoir inflow as reference.

The calibration procedure consists of adjusting several parameters to guarantee that the model accurately represents hydrological processes and outputs for selected historical events.

The following sections provide an overview of the HEC-HMS model calibration process and results.

2.6.1. Calibration Parameters and Approach

Like the calibration process for snow, the evaluation of model performance involved comparing computed results with observed results across the entire modeling domain. Model parameters were altered to minimize the differences between simulated and observed discharge volume and hydrograph shape at locations where they are available (Table 2-20). Since the focus on the hydrological model for this project is to simulate annual water availability, the calibration process was focused toward ensuring minimal bias in the model. Therefore, model performance evaluation was centered on PBIAS. For detailed explanation of PBIAS, Refer to Section 2.5.2. A second priority was the ability of the model to predict streamflow peak, since a large peak may result in water loss through the reservoir spillways. Differences less than or equal to 15% between computed and observed peak flow rates and flow volumes were desired.

Table 2-14 provides the summary statistic performance ratings for the NID HEC-HMS model calibration. Note that the PBIAS statistics at each location were mostly calculated using the complete water year for each calibration year. The exception was the USGS Station 11418500, between Scotts Flat Reservoir and USGS Station 11418500 on Deer Creek. Since the Deer Creek Diversion Dam is ungaged for flows moving down Deer Creek, the D-S Canal could not be incorporated into the unimpaired hydrology modeling efforts. The diversion predominantly affects the flow in Deer Creek from April through November. To mitigate these effects, the PBIAS statistics for USGS Station 11418500 were computed using the time series from

November through April. Schematics illustrating the complex systems of storage and diversions across the North, Middle, and South Yuba Rivers, along with the Bear River can be accessed on the USGS website and are included in Appendix A.

As described in more detail in the following sections, the calibration approach followed two main steps: (1) calibration based on 5 selected years with varying climatology, and (2) re-calibration based on extrapolation for the period of record.

2.6.1.1 Step 1: Calibration for Selected Years

Based on a first evaluation of the model results with initial model parameters (before calibration), it was concluded that the model captured streamflow peaks and timing reasonably well. For some of the events, disparities in the timing of snow accumulation and melting and in runoff volume were identified. The sensitivity analysis, calibration parameters, and general approach are summarized in Appendix A. To evaluate the model's performance under different hydrological conditions, including dry, normal, and wet conditions, five water years, spanning from October 1 to September 30, were chosen. The details of the calibration water years are provided in Table 2-19.

Table 2-19. Calibration Events

Wet Water-Year	Normal Water-Year	Dry Water-Year
Oct 1996–Sep 1997	Oct 2003–Sep 2004	Oct 2020–Sep 2021
Oct 2005–Sep 2006		Oct 2014–Sep 2015

2.6.1.2 Step 2: Re-Calibration Based on Extrapolation for Period of Record

Following model calibration for the five selected water years using the observed data, the next step was to use the same calibration parameters to simulate streamflow for other historical years (from 1975 to 2022 except WYs 1997, 2004, 2006, 2015, and 2021). A first step in this process was to develop a methodology for defining which of the five sets of calibrated parameters should be applied to simulate each historical year.

While evaluating the five sets of calibrated parameters for various climate conditions (dry, normal, and wet) within the NID basin, it was determined that the baseflow index is strongly correlated with watershed initial condition. Baseflow index in HEC-HMS represents the average percentage of water received as precipitation that is lost to recharge in each water year. In dry years, much of the received precipitation infiltrates in the dry soil and does not end up as runoff. For those years, the baseflow index is high. For years with high precipitation, the soil gets saturated, and a large percentage of the precipitation runs off to the river. Note that the baseflow recharge in HEC-HMS represents a percentage of total volume, not the actual recharge volume. In wet years, both recharge and runoff will present large volumes, with a smaller portion of the volume recharging the aquifer. The relationship between basin moisture condition and baseflow recharge was used to determine the most suitable set of parameters for each year in the historical period.

2.6.2. Results for Selected Water Years

Data for 16 locations for which streamflow data were available (USGS streamflow) or could be computed (reservoir inflow), were used for HEC-HMS model calibration. These locations are listed in Table 2-20 and shown in Figure 2-12. Data for Fordyce Lake were not fully available for the water year (WY) 1997. Therefore, the area delineated above Fordyce Lake for WY2004, WY2006, WY2015, and WY2021 is considered as part of the Lake Spaulding area for WY1997.

Table 2-20. Calibration Locations in NID Basin

River Basins	Number of Locations	Location Name/Stations
North Yuba River	2	USGS Gage 11413000; New Bullards Bar Reservoir
Middle Yuba River	3	Jackson Meadows and Milton Reservoirs jointly (Jackson Meadows-Milton); Our House Dam; Log Cabin Dam
South Yuba River	4	Fordyce Lake; Bowman Lake; Lake Spaulding; USGS Gage 11417500
Bear River	3	Dutch Flat Afterbay; Rollins Reservoir; Camp Far West Lake
Deer Creek	2	Scotts Flat Reservoir; USGS Gage 11418500
Yuba River (outlet)	2	Englebright Lake; USGS Gages 11421000, 11420750, 11420760, 11420770 jointly

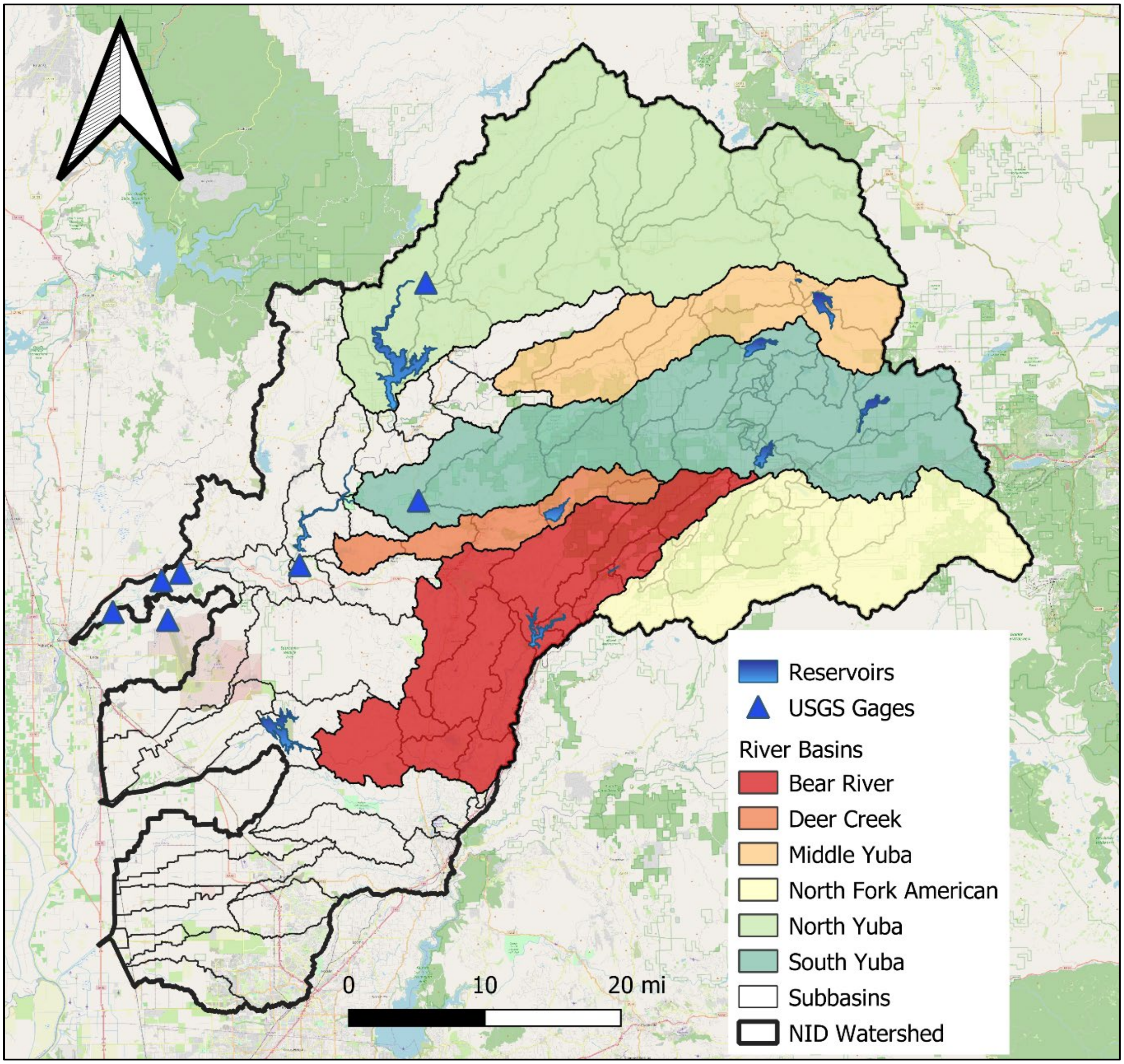

Figure 2-12. Calibration Locations for NID HEC-HMS Model (Described in Table 2-20)

The adjustments to the snowmelt parameters were made in the area upstream of Fordyce Lake, Bowman Lake, and Lake Spaulding. The Wet Meltrate and the ATI - Meltrate Function were adjusted for these subbasins by a factor of 1.1 to minimize differences in observed and simulated snowmelt. The adjusted parameters are listed in Table 2-21 and Table 2-22.

Table 2-21. Adjusted Calibrated Temperature Index Parameters

Parameter	Unit	BLC	HYS	RCC	CSL
Adjusted Wet Meltrate	in./°F-day	0.143	0.1089	0.121	0.187

Table 2-22. ATI-Meltrate Function

ATI (˚F-day)	BLC	HYS	RCC	CSL
0	0.0000	0.00000	0.0000	0.0000
30	0.0121	0.00825	0.0110	0.0132
55	0.0605	0.04125	0.0528	0.0660
120	0.0847	0.05775	0.0737	0.0924
150	0.0968	0.06600	0.0836	0.1056
200	0.1089	0.07425	0.0946	0.1188
1000	0.1210	0.08250	0.1045	0.1320
2000	0.1452	0.09900	0.1155	0.1452

The constant loss rate was first estimated to be 0.1 in./hr. Minor adjustments were made to ensure minimal to no excess precipitation was generated while maximizing runoff using the linear reservoir baseflow routine. The final values ranged between 0.06 and 0.13 in./hr.

Due to the high precipitation magnitudes necessary to generate excess precipitation runoff, most water was infiltrated and routed as baseflow. Therefore, adjustments to the baseflow recharge were implemented during the calibration process that provided the flexibility of varying the amount of water removed through the system based on deep groundwater recharging for different subbasins. To account for high positive/negative PBIAS across the NID watersheds, the fraction of GW 1 or GW 2 baseflow lost to aquifer recharge was adjusted iteratively to achieve Good to Very Good PBIAS.

2.6.2.1 Water Year 1997: Wet Year

This section describes the calibration results and statistics for WY1997. PBIAS statistics were calculated using the complete WY from 01 Oct 1996 through 30 Sep 1997 for all calibration locations except USGS Station 11418500, where the subsection of the WY from 01 Nov 1996 through 01 Apr 1997 was used. PBIAS maps and metrics are shown in Figure 2-13, comparing the computed results and observed time series of flow at each of the calibration locations. Tabular results summarizing the statistical metrics for the 15 previously mentioned calibration locations are shown in Table 2-23. Hydrographs comparing the computed and observed flow at the 15 calibration locations are shown in Appendix A.

Overall, calibration for this event was “Good” to “Very Good.” Unfortunately, the observed data at Fordyce Lake were not available for this WY. For WY1997, the observed runoff volume of the Yuba River at the Yuba River Outlet was approximately 3,475,200 AF.

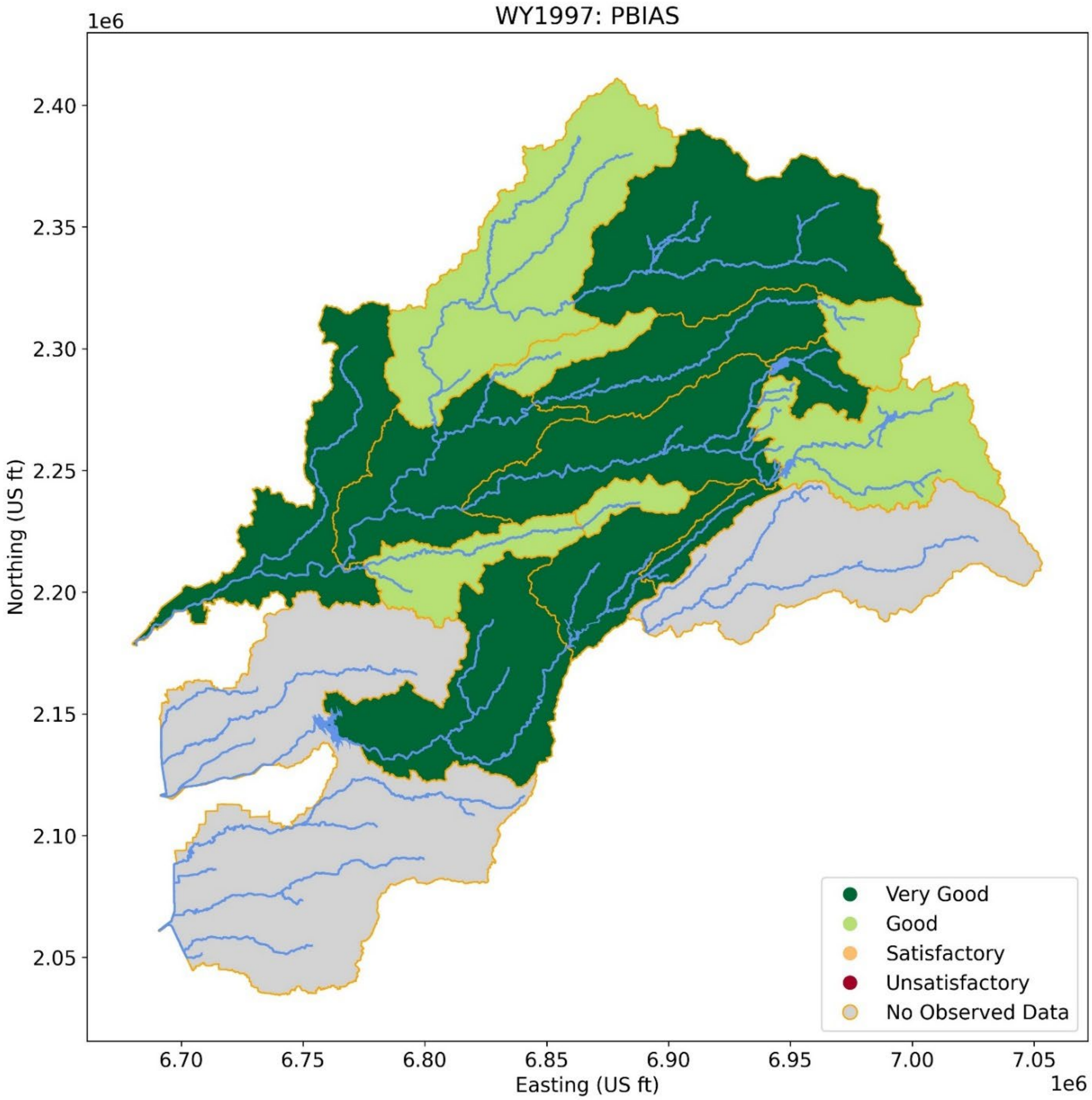

Figure 2-13. WY1997 PBIAS Results

Table 2-23. WY1997 Tabular Results for Primary Locations

Computation Point	PBIAS (%)	Volume Observed (TAF)	Volume Simulated (TAF)
USGS 11413000	-4.91	848.9	807.2
New Bullards Bar Reservoir	-19.55	1,834.6	1,476.0
Jackson Meadows – Milton Reservoirs	-19.71	137.5	110.4
Our House Dam	6.46	378.9	403.3
Log Cabin Dam	-21.25	170.2	134.0
Bowman Lake	-1.42	220.0	216.9
Lake Spaulding	11.26	694.0	772.1
USGS 11417500	9.15	676. 4	738.3
Scotts Flat Reservoir	26	108.2	136.3
USGS 11418500[1]	11.43	145.0	161.6
Englebright Lake	6.08	3,088.2	3,275.9
Yuba River Outlet	3.37	3,475.2	3,592.1
Dutch Flat Afterbay	-9.67	377.94	341.3
Rollins Reservoir	-2.85	709.4	689.2
Camp Far West Lake	-1.89	593.7	582.5

[1]Volume is considered only from 11/1/1996 to 4/1/1997.

2.6.2.2 Water Year 2004: Normal Year

This section describes the calibration results and statistics for WY2004. PBIAS statistics were calculated using the complete WY from 01 Oct 2003 through 30 Sep 2004 for all calibration locations except USGS Station 11418500, where the subsection of the WY from 01 Nov 2003 through 01 Apr 2004 was used. PBIAS maps and metrics are shown in Figure 2-14, comparing the computed results and observed time series of flow at each of the calibration locations. Tabular results summarizing the statistical metrics for the 16 previously mentioned calibration locations are shown in Table 2-24. Plots comparing the computed and observed flow at the 16 calibration locations are shown in Appendix A.

Overall, calibration for this event was “Good” to “Very Good.” For WY2004, the observed runoff volume of the Yuba River at the Yuba River Outlet was approximately 1,384,900 AF.

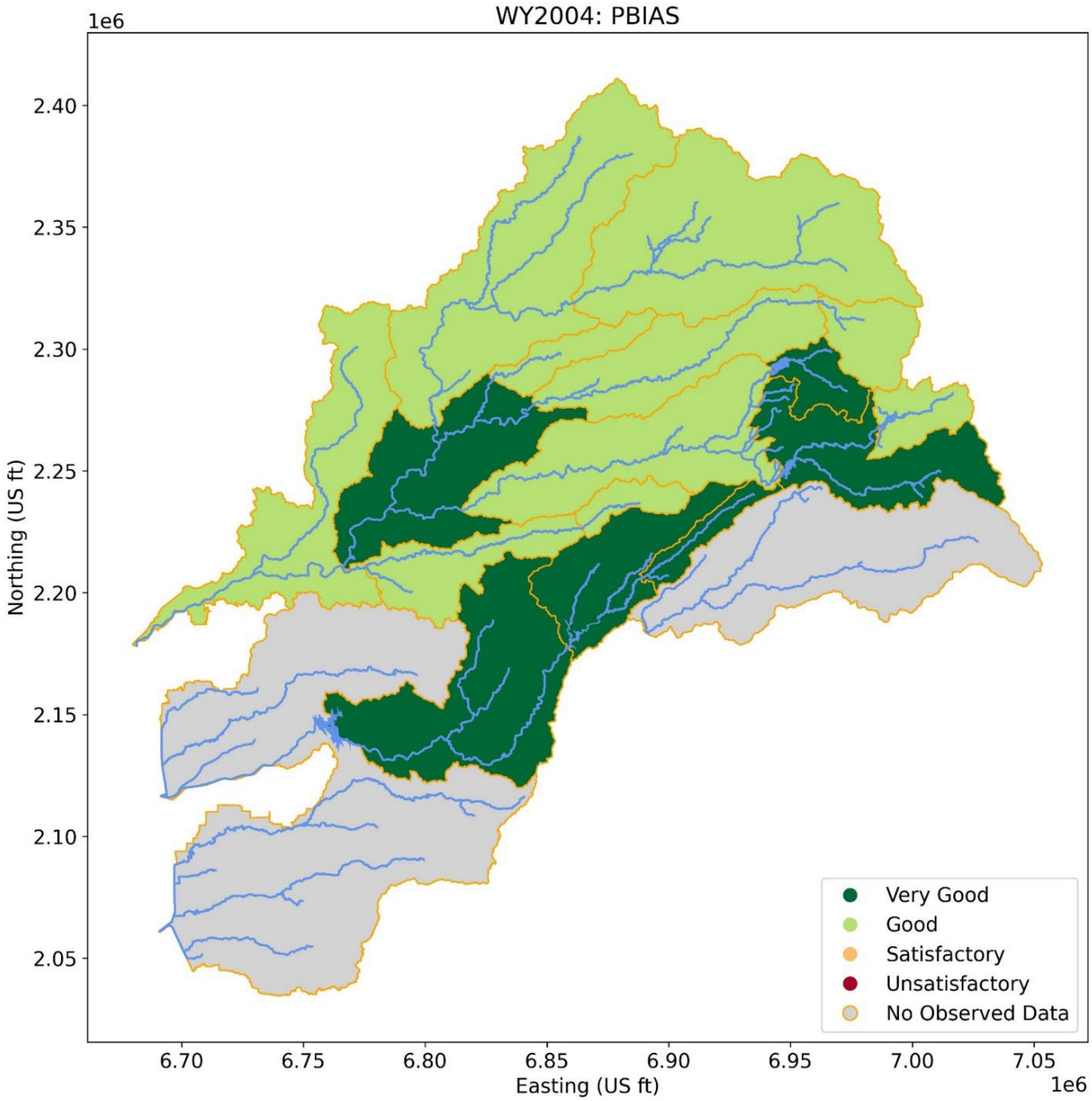

Figure 2-14. WY2004 PBIAS Results

Table 2-24. WY2004 Tabular Results for Primary Locations

Computation Point	PBIAS (%)	Volume Observed (TAF)	Volume Simulated (TAF)
USGS 11413000	-27.99	425.3	306.3
New Bullards Bar Reservoir	-28.29	861.8	617.9
Jackson Meadows – Milton Reservoirs	-23.00	66.5	51.2
Our House Dam	-19.87	141.7	113.5
Log Cabin Dam	-18.70	144.8	117.7
Fordyce Lake	-11.88	71.5	63.0
Bowman Lake	-0.40	128.6	128.1
Lake Spaulding	-2.60	425.1	414.0
USGS 11417500	-27.89	161.5	116.4
Scotts Flat Reservoir	11.99	53.9	60.4
USGS 11418500[1]	-26.39	41.5	30.5
Englebright Lake	-4.95	1,294.6	1,230.6
Yuba River Outlet	11.51	1,384.9	1,544.4
Dutch Flat Afterbay	-1.69	409.0	402.1
Rollins Reservoir	-9.64	510.6	461.4
Camp Far West Lake	0.44	273.6	274.8

[1]Volume is considered only from 11/1/2003 to 4/1/2004.

2.6.2.3 Water Year 2006: Wet Year

This section describes the calibration results and statistics for WY2006. PBIAS statistics were calculated using the complete WY from 01 Oct 2005 through 30 Sep 2006 for all calibration locations except USGS Station 11418500, where the subsection of the WY from 01 Nov 2005 through 01 Apr 2006 was used. PBIAS maps and metrics are shown in Figure 2-15, comparing the computed results and observed time series of flow at each of the calibration locations. Tabular results summarizing the statistical metrics for the 16 previously mentioned calibration locations are shown in Table 2-25. Plots comparing the computed and observed flow at the 16 calibration locations are shown in Appendix A.

Overall, calibration for this event was “Good” to “Very Good.” For WY2006, the observed runoff volume of the Yuba River at the Yuba River Outlet was approximately 4,161,200 AF.

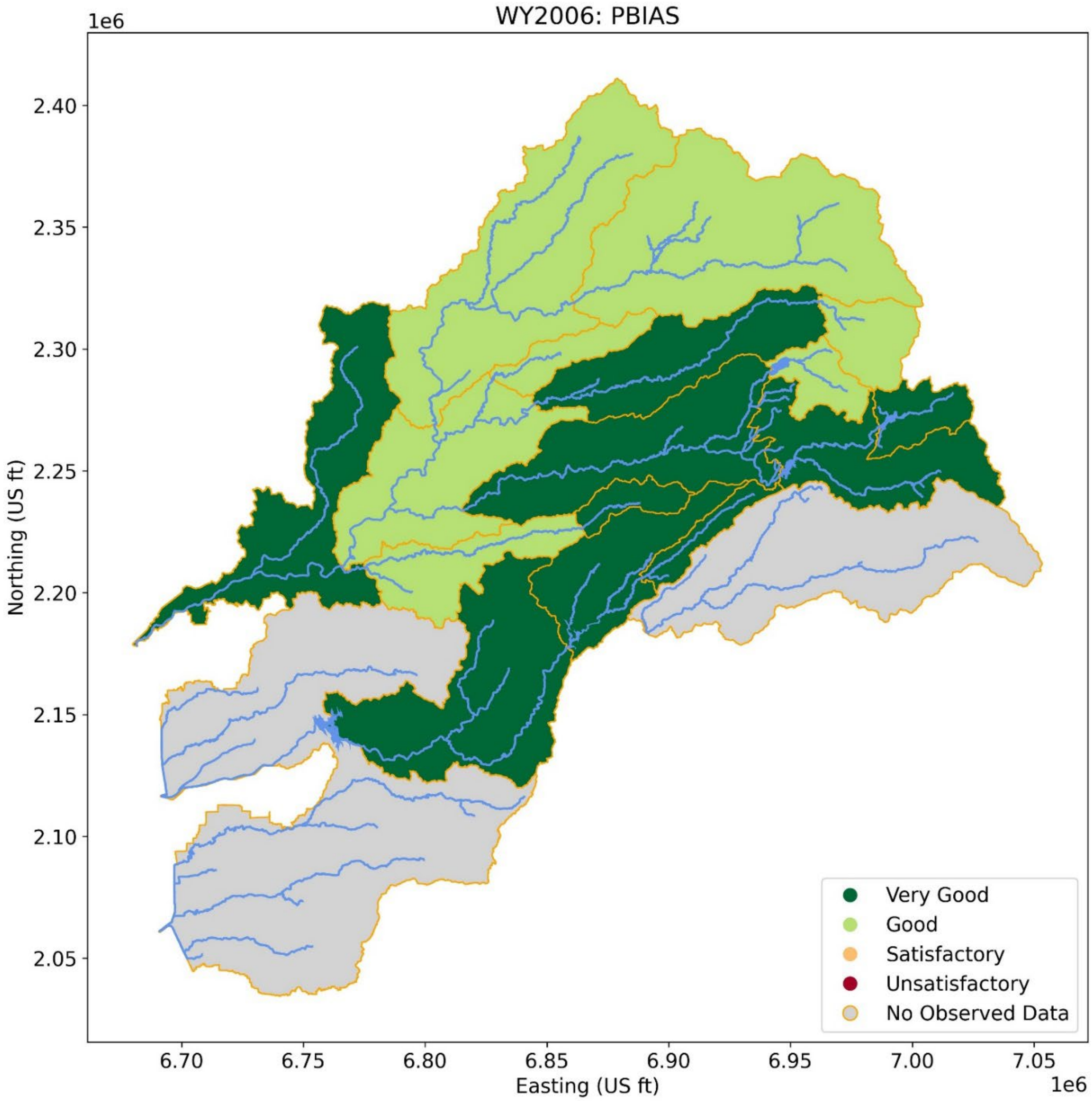

Figure 2-15. WY2006 PBIAS Results

Table 2-25. WY2006 Tabular Results for Primary Locations

Computation Point	PBIAS (%)	Volume Observed (TAF)	Volume Simulated (TAF)
USGS 11413000	-20.85	1,005.8	796.1
New Bullards Bar Reservoir	-23.39	2,152.6	1,649.1
Jackson Meadows – Milton Reservoirs	-19.07	149.2	120.8
Our House Dam	-0.92	510.3	505.7
Log Cabin Dam	-23.26	241.0	184.9
Fordyce Lake	-9.99	151.5	136.4
Bowman Lake	-10.3	239.3	214.6
Lake Spaulding	-4.06	780.8	749.1
USGS 11417500	8.83	788.0	857.6
Scotts Flat Reservoir	-8.85	104.5	95.2
USGS 11418500[1]	-14.61	121.4	103.6
Englebright Lake	13.75	3,340.9	3,800.3
Yuba River Outlet	-1.78	4,161.2	4,087.2
Dutch Flat Afterbay	-7.82	523.9	482.9
Rollins Reservoir	-6.28	864.0	809.7
Camp Far West Lake	-1.25	887.0	875.9

[1]Volume is considered only from 11/1/2005 to 4/1/2006.

2.6.2.4 Water Year 2015: Dry Year

This section describes the calibration results and statistics for WY2015. PBIAS statistics were calculated using the complete WY from 01 Oct 2014 through 30 Sep 2015 for all calibration locations except USGS Station 11418500, where the subsection of the WY from 01 Nov 2014 through 01 Apr 2015 was used. PBIAS maps and metrics are shown in Figure 2-16, comparing the computed results and observed time series of flow at each of the calibration locations. Tabular results summarizing the statistical metrics for the 16 previously mentioned calibration locations are shown in Table 2-26. Plots comparing the computed and observed flow at the 16 calibrations locations are shown in Appendix A.

Overall, calibration for this event was "Satisfactory" to "Very Good." PBIAS statistics for most locations were within the "Good" range that was previously described, with several basins in the "Very Good" range and a few basins in the "Satisfactory" range. It is unsurprising that a couple of basins fell in the "Satisfactory" range for WY2015. WY2015 is the first of two dry year examples, and hydrological processes during dry years are highly non-linear, and those non-linearities are not always captured by the model. However, since volumes are smaller during dry periods, a relatively higher PBIAS in comparison to wet years still represents a small volume of flow. For example, during WY1997, the total volume difference at Jackson Meadows-Milton reservoirs was approximately 27,100 AF and yielded a -19.71% PBIAS. During WY2015, the total volume difference at Jackson Meadows-Milton reservoirs was approximately 13,900 AF, nearly half of the volume difference from WY1997, and yielded a less desirable PBIAS of -39.07%. For WY2015, the observed runoff volume of the Yuba River at the Yuba River Outlet was approximately 633,800 AF.

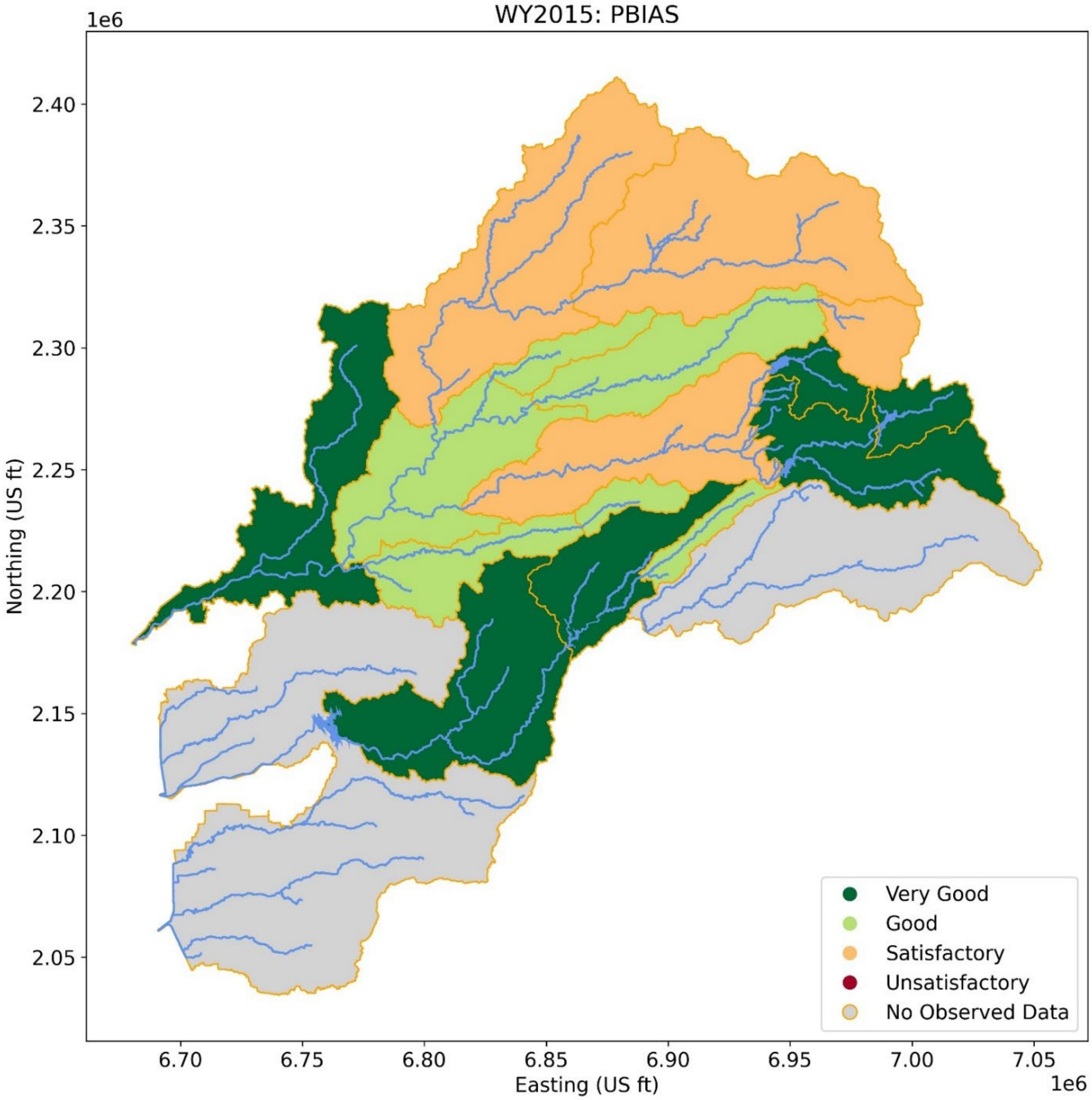

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Figure 2-16. WY2015 PBIAS Results

Table 2-26. WY2015 Tabular Results for Primary Locations

Computation Point	PBIAS (%)	Volume Observed (TAF)	Volume Simulated (TAF)
USGS 11413000	-49.63	202.4	102.0
New Bullards Bar Reservoir	-47.18	432.3	228.4
Jackson Meadows – Milton Reservoirs	-39.07	35.5	21.6
Our House Dam	-31.92	72.7	49.5
Log Cabin Dam	-23.14	63.1	48.5
Fordyce Lake	-3.86	44.5	42.7
Bowman Lake	-3.20	75.1	72.7
Lake Spaulding	-0.50	256.6	255.3
USGS 11417500	-43.74	83.3	46.9
Scotts Flat Reservoir	21.46	43.6	53.0
USGS 11418500[1]	-31.00	18.3	12.6
Englebright Lake	-10.26	596.7	535.5
Yuba River Outlet	9.84	633.8	696.2
Dutch Flat Afterbay	10.07	196.6	216.4
Rollins Reservoir	-4.14	236.6	226.8
Camp Far West Lake	-8.71	116.4	106.2

[1]Volume is considered only from 11/1/2014 to 4/1/2015.

2.6.2.5 Water Year 2021: Dry Year

This section describes the calibration results and statistics for WY2021. PBIAS statistics were calculated using the complete WY from 01 Oct 2020 through 30 Sep 2021 for all calibration locations except USGS Station 11418500, where the subsection of the WY from 01 Nov 2020 through 01 Apr 2021 was used. PBIAS maps and metrics are shown in Figure 2-17, comparing the computed results and observed time series of flow at each of the calibration locations. Tabular results summarizing the statistical metrics for the 16 previously mentioned calibration locations are shown in Table 2-27. Plots comparing the computed and observed flow at the 16 calibration locations are shown in Appendix A.

Overall, calibration for this event was “Satisfactory” to “Very Good.” PBIAS statistics for most of the locations were within the “Very Good” range that was previously described, with several basins in the “Good” range and a few basins in the “Satisfactory” range. As with WY2015, it is unsurprising that a couple of basins fall in the “Satisfactory” range for WY2021, as the water year was a significantly dry year with the same highly non-linear effects mentioned in Section 2.6.2.4. For WY2021, the observed runoff volume of the Yuba River at the Yuba River Outlet was approximately 630,500 AF.

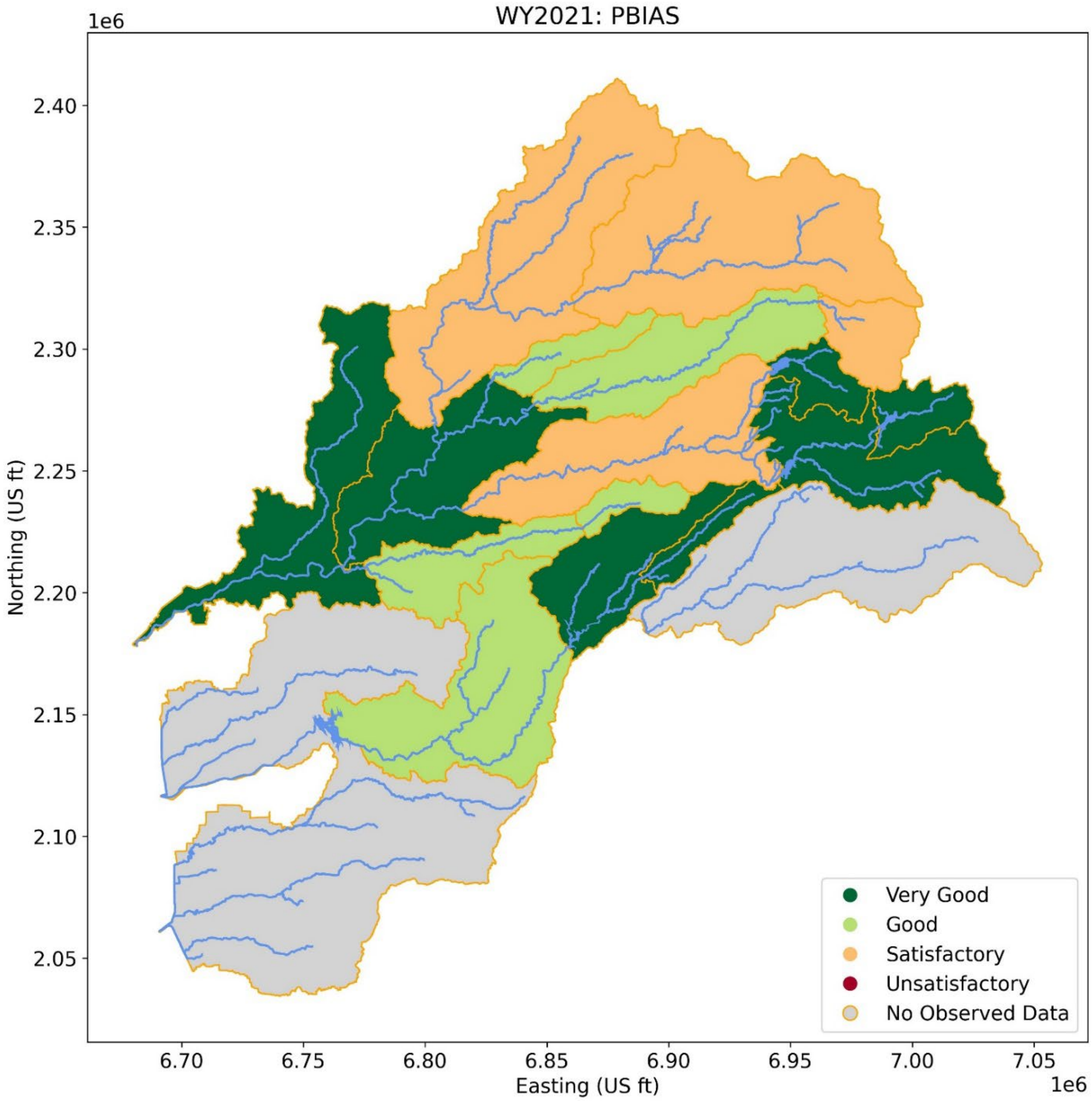


Figure 2-17. WY2021 PBIAS Results

Table 2-27. WY2021 Tabular Results for Primary Locations

Computation Point	PBIAS (%)	Volume Observed (TAF)	Volume Simulated (TAF)
USGS 11413000	-48.25	160.4	83.0
New Bullards Bar Reservoir	-42.13	317.0	183.4
Jackson Meadows – Milton Reservoirs	-37.78	25.1	15.6
Our House Dam	-32.81	51.7	34.7
Log Cabin Dam	-30.99	42.0	29.0
Fordyce Lake	-0.91	37.4	37.0
Bowman Lake	-1.31	65.1	64.3
Lake Spaulding	-0.40	275.7	274.6
USGS 11417500	-38.10	57.3	35.5
Scotts Flat Reservoir	21.75	42.8	52.1
USGS 11418500[1]	-13.64	7.4	6.4
Englebright Lake	-3.64	637.8	614.6
Yuba River Outlet	10.00	630.5	693.5
Dutch Flat Afterbay	4.29	182.6	190.4
Rollins Reservoir	-0.45	209.9	208.9
Camp Far West Lake	34.65	62.9	84.8

[1]Volume is considered only from 11/1/2020 to 4/1/2021.

2.6.3. Results for Other Water Years

The first step for simulating other water years was to identify an indicator that describes basin moisture condition. Multiple drought indicators were calculated for each river basin in the NID watershed (North Yuba River, Middle Yuba River, South Yuba River, Bear River, and Deer Creek) using a drought tool (Wells et al. 2004) developed by National Center for Atmospheric Research (NCAR). The input data for the tool include monthly basin-average temperature and precipitation data compiled from the daily Livneh dataset.

The correlation between multiple drought indicators and baseflow index were evaluated, and the indicator that presented the highest correlation was selected as a proxy to select the best parameter set. A different relationship was established for each region (North Yuba River, Middle Yuba River, South Yuba River, Bear River, and Deer Creek). Among all the relationships, it was observed that Weighted Palmer Drought Severity Index (WPLM) for July of each WY has the highest correlation with the weighted recharge for all the regions. The relationships for the multiple areas are shown in Figure 2-18.

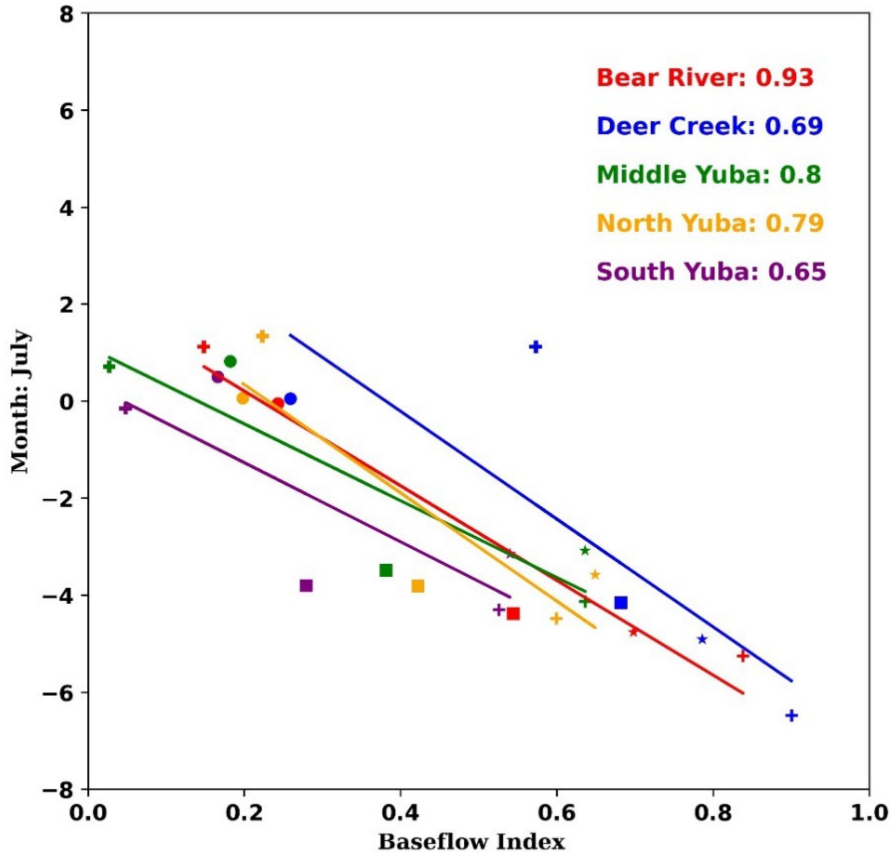


Figure 2-18. Scatter Plot of WPLM for July Versus Weighted Average Baseflow Index

The following procedure was used to define parameters for other water years for each river basin:

1. Identify the minimum monthly WPLM value within a WY.
2. Calculate the baseflow index value using the established relationship and the minimum WPLM value from Step 1.
3. Determine the closest weighted average recharge from the five calibrated parameter sets (WY1997, WY2004, WY2006, WY2015, and WY2021) to the one computed in Step 2. This identifies the calibrated parameter set suitable for that WY.
4. Adjust the GW 1 and GW 2 coefficients in the selected payment set (Step 3) to align with the weighted average recharge computed in Step 2. Other parameters remain unchanged.

The HEC-HMS model was run for the historical period using input daily precipitation and temperature data from the Livneh dataset (available from 1950 to 2018). The approach described above was used to define parameters for each water year. To evaluate the model, the cumulative simulated streamflow from 1975 to 2018 was compared with the one estimated based on the gage proration approach (HDR 2020) at various locations within the NID basin. The validation results revealed bias at six locations. Figure 2-19 presents the cumulative daily inflow (1975–2018) at Yuba at Smartsville (USGS gage 11419000) from the gage proration approach (red line) and HEC-HMS (blue line).

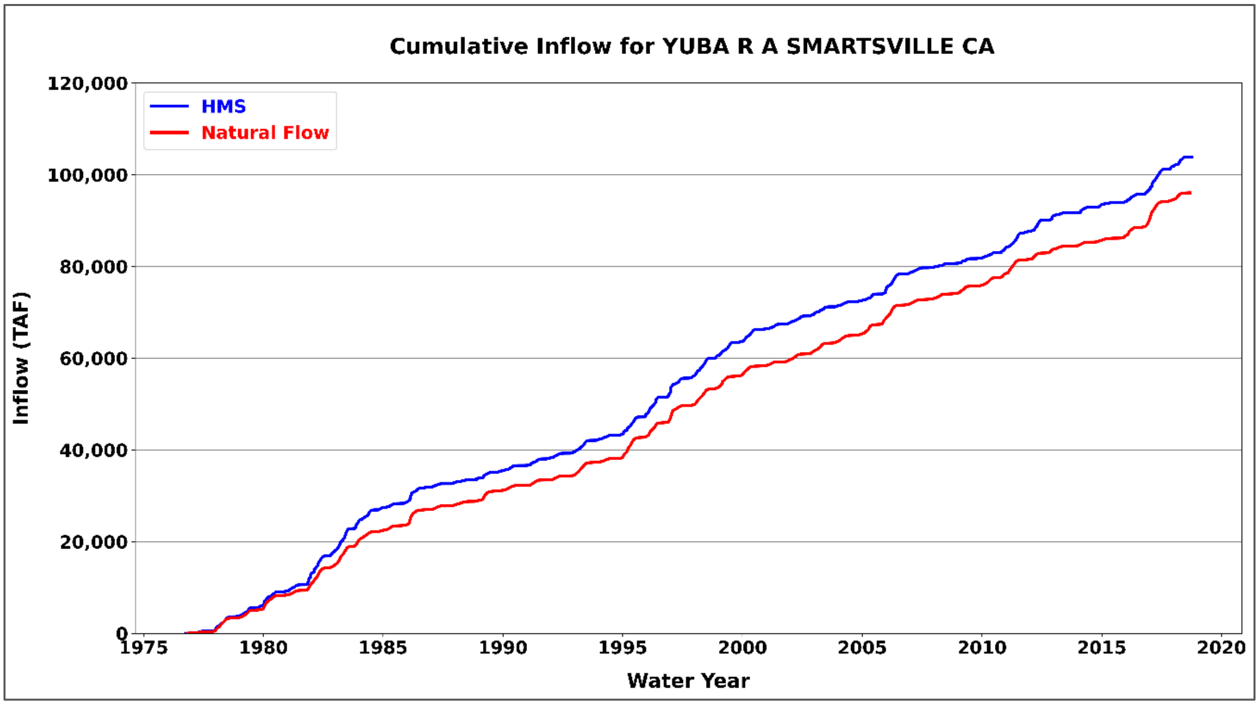


Figure 2-19. Cumulative Daily Inflow (1975–2018) for Yuba at Smartsville (USGS gage 11419000)—After Refinements

To address the bias in the model, calibration refinements were performed using gage proration flows as reference and accounting for all years between 1975 and 2018. In the refinement process, PX, base temperature, and baseflow recharge were adjusted to reduce the bias in the HEC-HMS model.

Figure 2-20 illustrates the cumulative daily inflow (1975–2018) at Yuba at Smartsville (USGS gage 11419000) using the gage proration approach (red line) and HEC-HMS (blue line) obtained after the calibration refinement procedure. Plots comparing the cumulative daily inflow using the gage proration approach and HEC-HMS for other locations are shown in Appendix A. The results for this location and others validate (the HEC-HMS model and demonstrate the mitigation of bias in the HEC-HMS model.

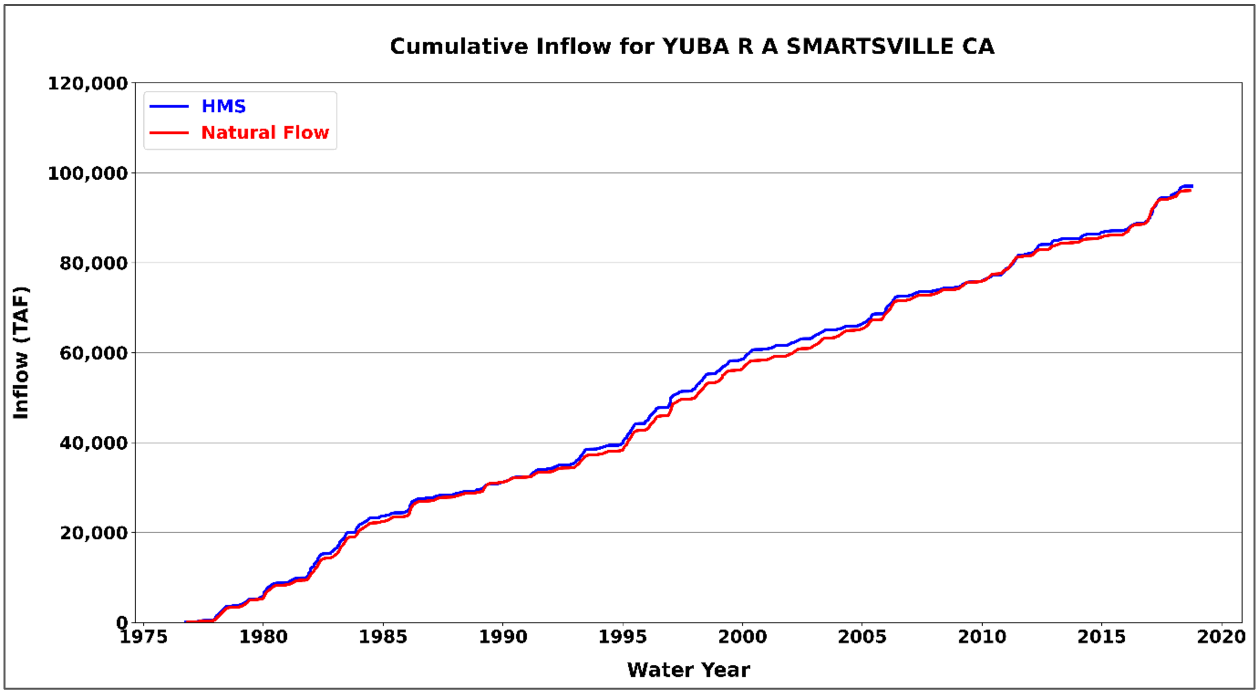


Figure 2-20. Cumulative Daily Inflow (1975–2018) for Yuba at Smartsville (USGS gage 11419000)—After Refinements

Chapter 3. Projected Hydrology

3.1. Introduction

This chapter discusses future unimpaired hydrology for the PFW. The goal of the unimpaired hydrology task is to update historical natural watershed runoff to the most recent available data as discussed in Chapter 2. This chapter discusses unimpaired hydrology anticipated under projected climate conditions. As shown in Figure 3-1, the generation of projected hydrology requires the development of three main datasets:

1. **Global Climate Model (GCM) Projections:** GCMs are mathematical representations of the Earth's climate system. GCMs are important tools for understanding the potential effects of climate variability and changes, providing climate projection data, including precipitation and temperature, at a resolution of 50–250 km for the period of 1950–2100. To understand the strengths and weaknesses of various GCMs, the Intergovernmental Panel on Climate Change (IPCC), established in 1988 by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP), manages the Coupled Model Intercomparison Project (CMIP). CMIP develops standards for model runs and collects, compares, analyzes, and shares the results of multiple GCMs from around the world. Because GCMs are constantly evolving and computational resources improving, model results and CMIP's protocols, standards, and data distribution mechanism are updated frequently. To reflect this, CMIP has been organized in different numbered phases (e.g., CMIP3, CMIP5, and CMIP6), with CMIP6 being the most recent phase to release its modeling output data.
2. **Downscaled Global Climate Model Projections:** The resolution of temperature and precipitation provided by current GCMs is too course for local and regional planning studies like the PFW. Data downscaling increases the resolution of GCM data to scales more appropriate for analyzing the hydrologic response of the complex terrain of NID watersheds, the variety of water demands across the NID service area, and the details of NID's water infrastructure.
3. **Reservoir Inflow Projections:** To obtain inflow to the reservoirs, hydrological or statistical methods are applied to convert meteorological forcing into projected inflows.

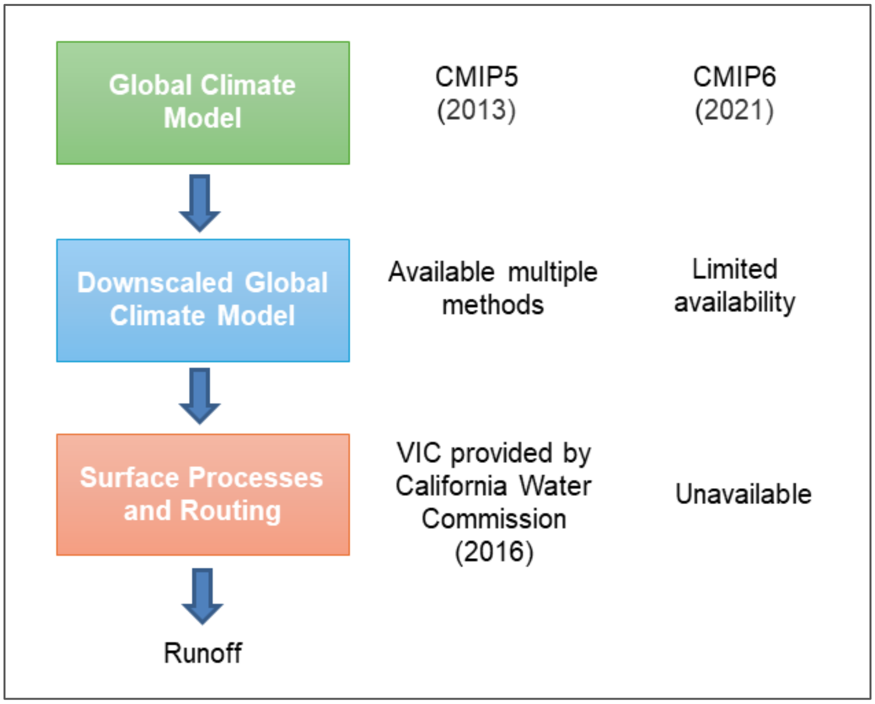


Figure 3-1. Required Datasets for the Generation of Projected Inflow and Their Current Availability for CMIP5 and CMIP6

The NID water plan developed in 2013 applied the projected hydrology the California Water Commission (CWC) developed and provided (2016). The CWC used CMIP5 and the Variable Infiltration Capacity hydrology model to generate projected inflow across multiple California regions. That information was used to generate local inflows to NID's service area. A full description of the hydrologic data and methods used to develop the 2070 projection of unimpaired hydrology are presented in the Hydrologic Analysis Technical Memorandum (HDR 2020).

3.1.1. Global Climate Model Projections

In 2021, a new, updated version of the GCM projections, CMIP6, was released (Li et al. 2021). CMIP6 continues the pattern of evolution and adaptation characteristics of previous CMIP phases, with the CMIP6 models generally having finer resolution with improved dynamical processes and emission scenarios based on the new Shared Socioeconomic Pathways (SSPs) for future climate change projections (Li et al. 2021, O'Neill et al. 2016). Therefore, CMIP6 data were selected for use in the PFW.

3.1.2. Downscaled Global Climate Model Projections

Since CMIP6 was only recently published, precipitation and temperature downscaled datasets were not widely available when the present project was being developed. Multiple groups were working to generate CMIP6 downscaled information using dynamical and statistical methods. In dynamical downscaling, the data from a GCM is used as input and boundary conditions for higher resolution Regional Climate Models. Statistical downscaling uses relationships between the large-scale climate patterns provided by GCMs and observed local climate responses. More details on these two methods are provided at this link.

A research group at the University of California, Los Angeles, is applying dynamical methods to downscale CMIP6 data. The researchers used the Weather Research and Forecasting (WRF) model to generate downscaled information for the period of 1980 through 2100 at a spatial resolution of 3 km and temporal resolution of 1 hr (Rahimi and Lei 2022). While publicly available, because the dataset was still under review, the UCLA researchers suggested not applying this dataset until the review process is complete (Rahimi 2022).

Krantz et al. (2021) is applying a combination of statistical and dynamical methods to downscale CMIP6 precipitation and temperature. The approach is new and combines physics-based simulations with an updated version of the Localized Constructed Analogs (LOCA) statistical downscaling method (Pierce et al. 2014). First, high-resolution physics-based simulations are applied to downscale a selection of GCMs. The simulations are then used to train a new version of LOCA based on statistics of the future climate. Finally, the method is applied to downscale a broader set of GCMs. The downscaled meteorological variables are publicly available and used in the PFW analysis to provide temperature and precipitation time series data at each location in the NID basin grid for 50 years of projected climate.

3.1.3. Reservoir Inflow Projections

The last step includes the application of downscaled temperature and precipitation to estimate runoff and inflow to the reservoirs.

Two types of approaches are commonly used to convert projected temperature and precipitation into inflows: 1) statistical methods (Freni et al. 2009, Xing et al. 2018, Yang and Yang 2011), and 2) hydrological models (Chiew et al. 2018, Islam et al. 2014, Shi et al. 2022). Statistical models are not recommended since they predict the future based on what has happened in the past. However, with climate change, that relationship might not be valid. Moreover, these types of models are usually inaccurate in predicting rare extreme dry or wet events. Hydrological models are preferable since they simulate the important physical processes affecting the rainfall-runoff conversion, including snow accumulation, snow melt, evapotranspiration, and soil dynamics including infiltration (Fowler et al. 2018, Li et al. 2022, Pechlivanidis et al. 2016, Shi et al. 2022). Recent studies (Li et al. 2022, Mahato et al. 2022, Moothedan et al. 2022) show that the HEC- HMS model can accurately simulate the range of inflow scenarios desired for the PFW. Therefore, the HEC-HMS model was selected for the PFW studies.

To obtain the projected inflows to the NID areas of interest, the downscaled precipitation and temperature data were used as inputs to the HEC-HMS hydrological model described in Chapter 2.

3.2. Climate Scenario Selection

To determine which GCMs perform better for the State of California climate, Krantz et al. (2021) evaluated the performance of CMIP5 and CMIP6 models. The results of the analysis are presented in Figure 3-2, reproduced from Krantz et al. (2021). The GCMs that perform best in California are shown in the green box. Additional well performing models are in the blue box. Seven downscaled climate models listed in Table 3-1 were chosen for the analysis from the red box in Figure 3-2.

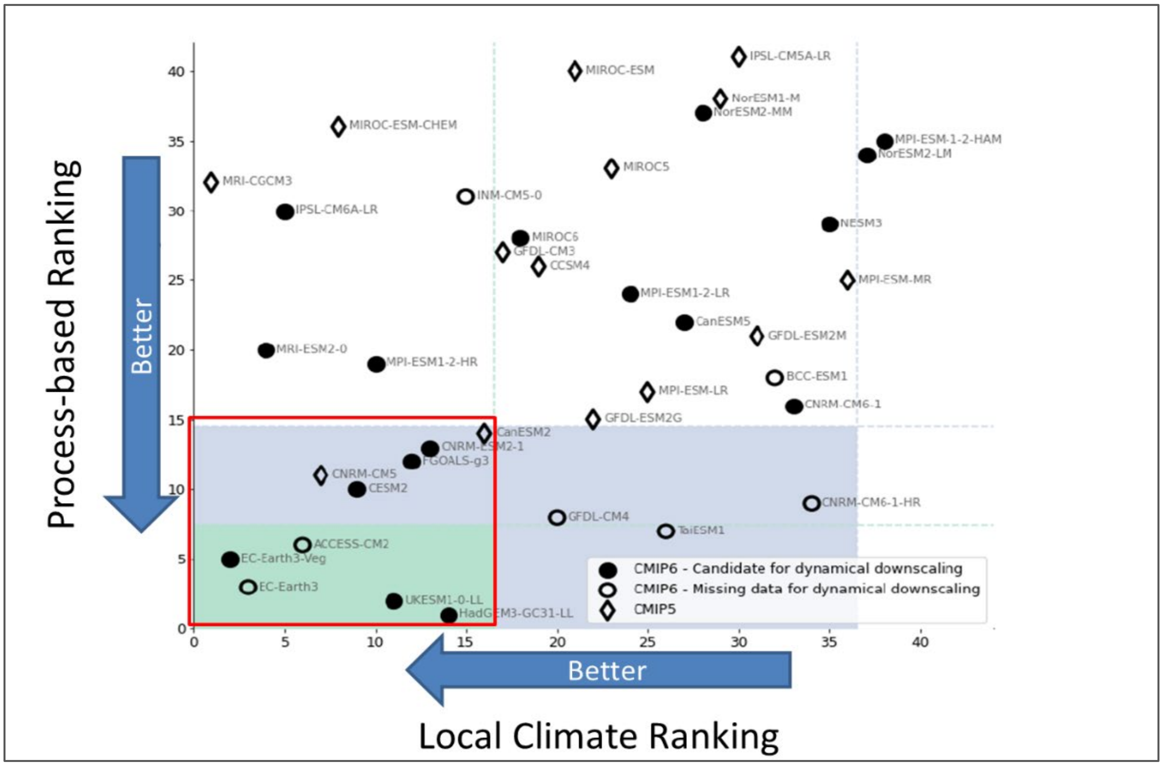


Figure 3-2. Comparison of the GCM Rankings by Local Climate Metric Performance and Process-Based Metric Performance (Source: Krantz et al. 2021).

GCMs use emission scenarios as input data to estimate the amount of CO_2 and other greenhouse gases launched to the atmosphere. Each GCM can use multiple emission scenarios to explore a range of potential future climate outcomes and their associated uncertainties. These scenarios, known as SSPs, outline various trajectories of energy production, land use, and greenhouse gas emissions implications. The SSPs are part of a new scenario framework established by the climate change research community to facilitate the integrated analysis of future climate impacts, vulnerabilities, adaptation, and mitigation. The SSPs do not predict the future, but rather provide a range of plausible scenarios that help researchers and policymakers explore the potential consequences of different pathways of human development. In this project, three SSPs were selected to represent endpoints and median scenarios for the analysis:

1. SSP245 (optimistic scenario): This scenario portrays a future characterized by relatively rapid and effective mitigation of environmental and societal challenges. This scenario envisions proactive efforts to address issues such as climate change, resource management, and social equity. Technological innovation, international cooperation, and sustainable development practices feature prominently in this optimistic narrative. Economic growth is balanced with environmental stewardship, leading to a world where human wellbeing is prioritized alongside ecological preservation.
2. SSP370 (median scenario expected to be exceeded): This scenario represents a middle-of-the-road projection in terms of societal and environmental trends. It anticipates moderate efforts to address global challenges, with progress occurring at a pace that may not be sufficient to prevent significant disruptions. While some measures are taken to address issues like climate change and

social inequality, they may fall short of what is necessary to avoid more severe consequences. This scenario reflects a world grappling with both opportunities and challenges, where progress is made but not at a pace that ensures long-term sustainability or resilience.

3. SSP585 (pessimistic scenario): This scenario presents a future marked by escalating environmental degradation, societal conflict, and economic inequality. In this pessimistic narrative, efforts to mitigate climate change and other global challenges are limited or ineffective. Technological progress may exacerbate rather than alleviate societal divisions and environmental pressures. Resource depletion, extreme weather events, and geopolitical tensions are prominent features of this scenario. It paints a picture of a world facing significant crises, with profound implications for human wellbeing, biodiversity, and the stability of global systems.

Table 3-1 shows the 7 selected downscaled GCMs with 3 emission scenarios (SSP245, SSP370, and SSP585) that were selected for this project. Out of the 21 climate scenarios (7 GCMs for each of 3 emissions scenarios), 18 scenarios with available downscaled temperature and precipitation (indicated with "√" in Table 3-1) were used for NID projected hydrology simulations.

Table 3-1. Climate Change Scenarios for HEC-HMS Simulations

GCMs	Emissions		
	SSP245	SSP370	SSP585
ACCESS-CM2	√	√	√
EC-Earth3	√	√	√
EC-Earth3-Veg	√	√	√
CNRM-ESM2-1	√	√	√
FGOALS-g3	√	√	√
HadGEM3-GC31-LL	√	-	√
CESM2-LENS	-	√	-

3.3. Historical Hydrology

Historical hydrology analysis was employed to assess the bias in both the calibrated NID HEC-HMS model (discussed in Chapter 2) and the selected climate models. Model bias refers to the presence of systematic errors in a model resulting in consistent deviations from observed or expected values, leading to inaccurate predictions. It indicates a tendency for the model to consistently overestimate or underestimate certain aspects of the system it is simulating. These errors can arise from many sources, among them, inaccuracies or limitations in the input datasets used for model calibration, the assumptions underlying the model's construction, and the algorithms employed in the modeling process. Climate models can also exhibit some systematic biases due to the limited spatial resolution, simplified physics and thermodynamic processes, numerical schemes, or incomplete knowledge of climate system processes.

To evaluate the bias in the calibrated NID' HEC-HMS model, a comparison was conducted for the average annual local inflow in the NID basin. This assessment focused on the historical period from 1976 to 2021 and involved three independent methods:

1. **Gage Proration:** The local inflows from the gage proration method from the unimpaired hydrology study by HDR (2020).
2. **Water Balance:** The average annual local inflow for the NID basin was estimated from the equation:

   Annual runoff = Streamflow at the basin outlet + Losses + Diversions

   Streamflow at the basin outlet = Sum (USGS gages at outlet)

Where:

USGS streamflow gages downstream at 11418000, 11424000, 11418500, and 11408880 were summed, and the streamflow at location 11413510 was subsequently subtracted.

The estimated annual losses and diversions (Western Hydrologics 2023):

- Evaporation: ~23,300 AF/year
- Diversions to the Bear River Canal: ~132,300 AF/year
- Diversions out of Lake Combie: ~62,000 AF/year
- Diversions: diversions off Deer Creek: ~53,000 AF/year

3. **HEC-HMS:** The calibrated NID HEC-HMS model using the Livneh precipitation and temperature data as input for simulating local inflows within the NID basin.

Figure 3-3 displays the average annual local inflows estimated from the three methods for the historical period (1976–2021), with the y-axis representing the average annual inflow in thousand acre-feet (TAF). Figure 3-3 shows that the three independent methods applied to estimate average annual inflow to the area of interest present very similar results, increasing confidence that the estimates are accurate (negligible bias). The annual average from the HEC-HMS model (1,547 TAF) closely aligns with the estimates from the gage proration method (1,509 TAF) and the water balance method (1,444 TAF).

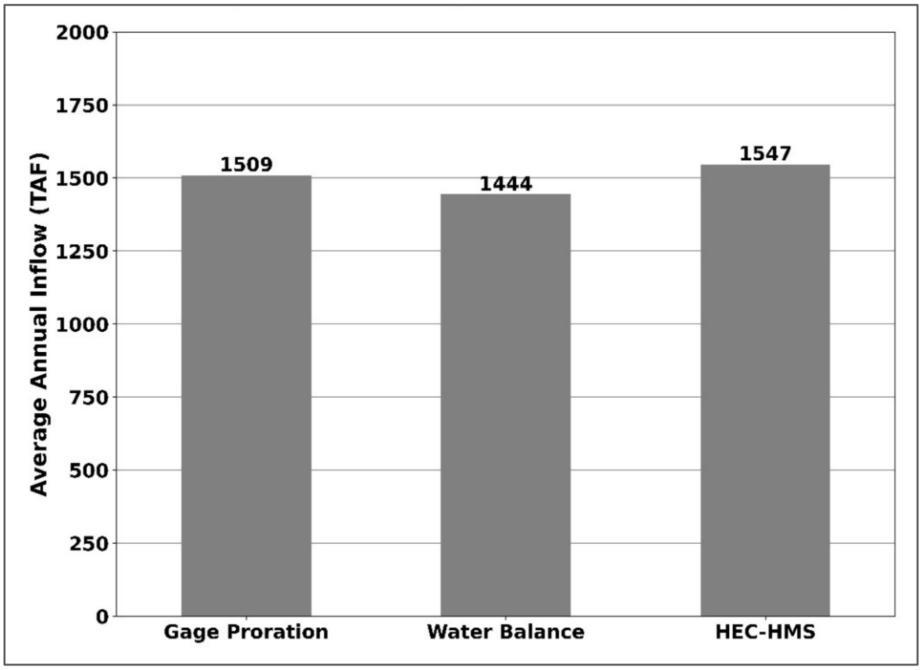


Figure 3-3. Comparison of Average Annual Inflow (1976–2021) for NID Basin

To assess bias in the climate models, the downscaled precipitation and temperature data from the selected climate models and scenarios (refer to Table 3-1) were used as inputs to the calibrated NID HEC-HMS model. This was done to generate local inflow simulations for the entire NID basin during the historical period 1976–2021.

Figure 3-4 visually presents a comparison between the average annual inflow for the NID basin from 1976–2021, as obtained from the HEC-HMS model using the climate model data as input. The average historical inflows derived from the gage proration method (indicated by the green dashed line) is used for validation. This graph contrasts the model's performance against historical inflow estimates, providing insights into any potential biases in the climate models. The x-axis of Figure 3-4 corresponds to a specific combination of a climate model and its associated emission scenario. For instance, the label "HadGEM3-GC31-LL_ssp585" signifies the HadGEM3-GC31-LL climate model paired with the SSP585 emission scenario. Some spread in the results is expected due to natural variability in climate, since the historical simulations represent just one realization of what could have happened in the past, and not exactly the observed historical climate for that period. Since the average annual inflow obtained from the climate models closely aligns with the average historical inflow, it indicates that the climate models are not biased, and are providing simulations that, on average, and considering the whole area of interest, are consistent with the historical data over the historical period.

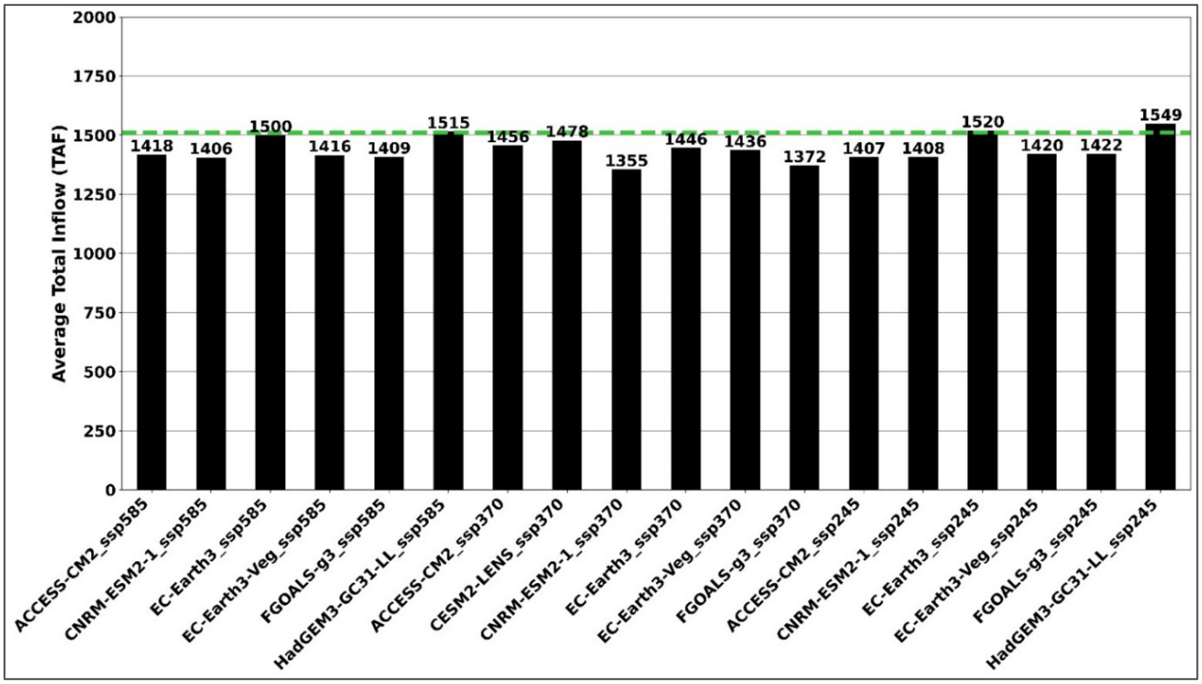


Figure 3-4. Comparison of Average Annual Inflow (1976–2021) for NID Basin

3.4. Projected Hydrology

The downscaled precipitation and temperature dataset from the selected climate models and scenarios (refer to Table 3-1) were used as inputs in the calibrated NID HEC-HMS model to obtain the local inflows for the entire NID basin for the projected period (2022–2071).

Figure 3-5 to Figure 3-7 illustrate the 50-year average total inflow for durations of 1, 5, and 10 years, while Figure 3-8 and Figure 3-9 depict the median of annual total inflow for the same durations using the 18 climate model scenarios. Based on the analysis, three representative hydrology scenarios were selected, and they are outlined as follows:

High Bookend (Wet) Scenario: This scenario implies conditions characterized by higher-than-average precipitation, increased temperature, and/or more frequent and intense rainfall events. The climate model EC-Earth3-Veg_ssp370 has been selected to represent the high bookend (wet) scenario. In this climate scenario, the 50-year average total inflow is highest for all durations along with the highest median annual inflow for 5- and 10-year durations. In Figure 3-5 through Figure 3-10, this scenario is visually presented by the blue bars, indicating a wet 50-year runoff pattern.

Median Scenario: This scenario typically reflects moderate changes or trends, neither excessively optimistic nor pessimistic. The climate model CNRM-ESM2-1_ssp245 has been chosen to represent the median scenario. In Figure 3-5 through Figure 3-10, this scenario is depicted by the green bar , indicating a median 50-year runoff pattern.

Low Bookend (Dry) Scenario: This scenario implies conditions characterized by lower-than-average precipitation, decreased humidity, and/or more prolonged periods of drought. The climate model CESM2-

LENS_ssp370 scenario has been chosen as the representative for low bookend (dry) scenario. In this climate scenario, the 50-year average total inflow is lowest for all durations. accompanied by a consistently low median annual inflow for all durations. This scenario is represented as the red bar in Figure 3-5 through Figure 3-10, indicating a dry 50-year runoff pattern.

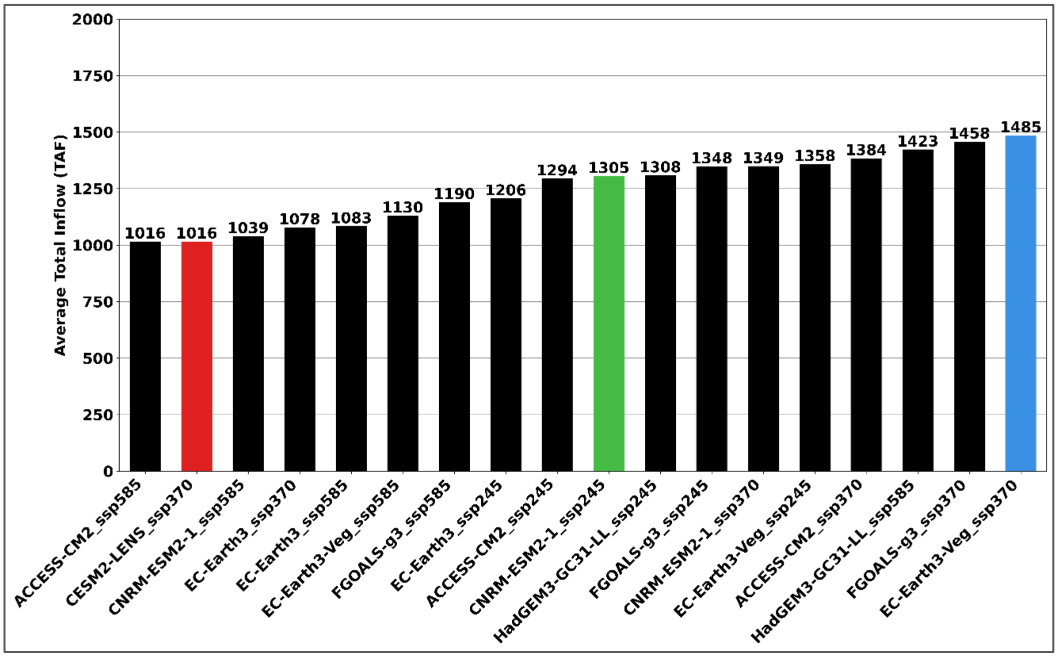


Figure 3-5. 50-Year Average Total Inflow for 1-Year Duration highlighting the dry (red), median (green) and wet (blue) scenarios

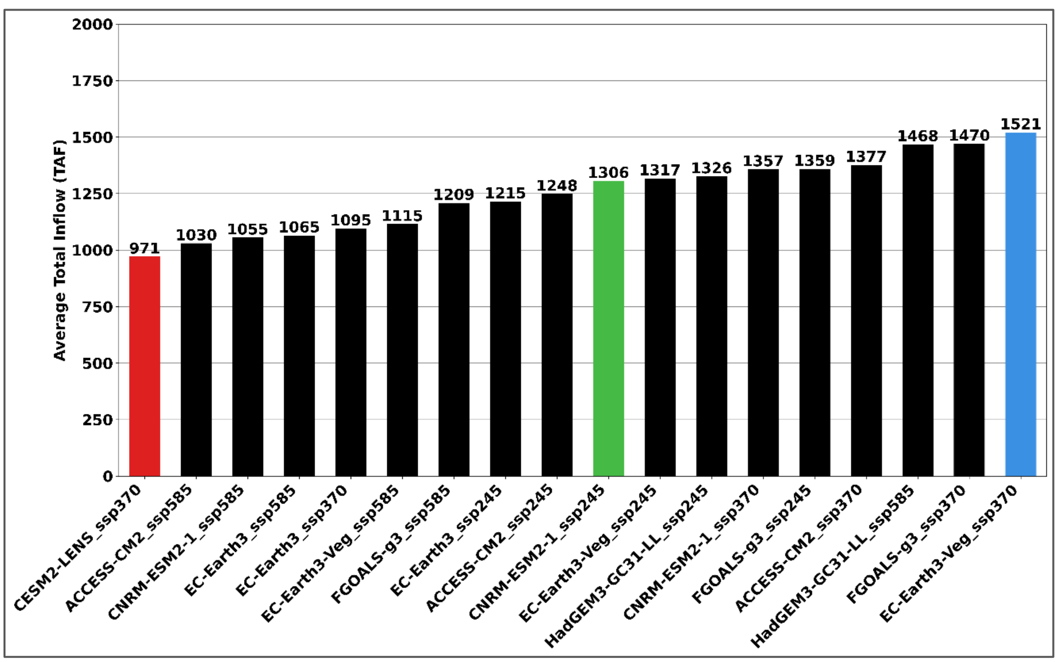


Figure 3-6. 50-Year Average Total Inflow for 5-Year Duration highlighting the dry (red), median (green) and wet (blue) scenarios

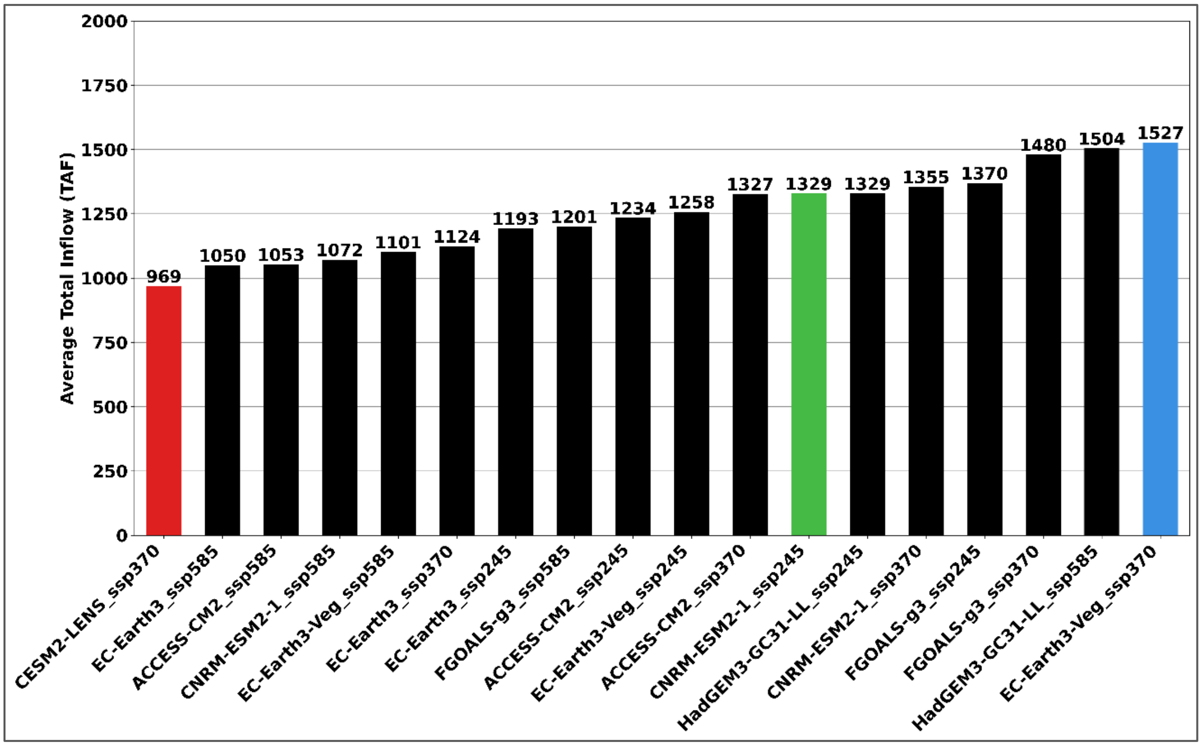


Figure 3-7. 50-Year Average Total Inflow for 10-Year Duration highlighting the dry (red), median (green) and wet (blue) scenarios

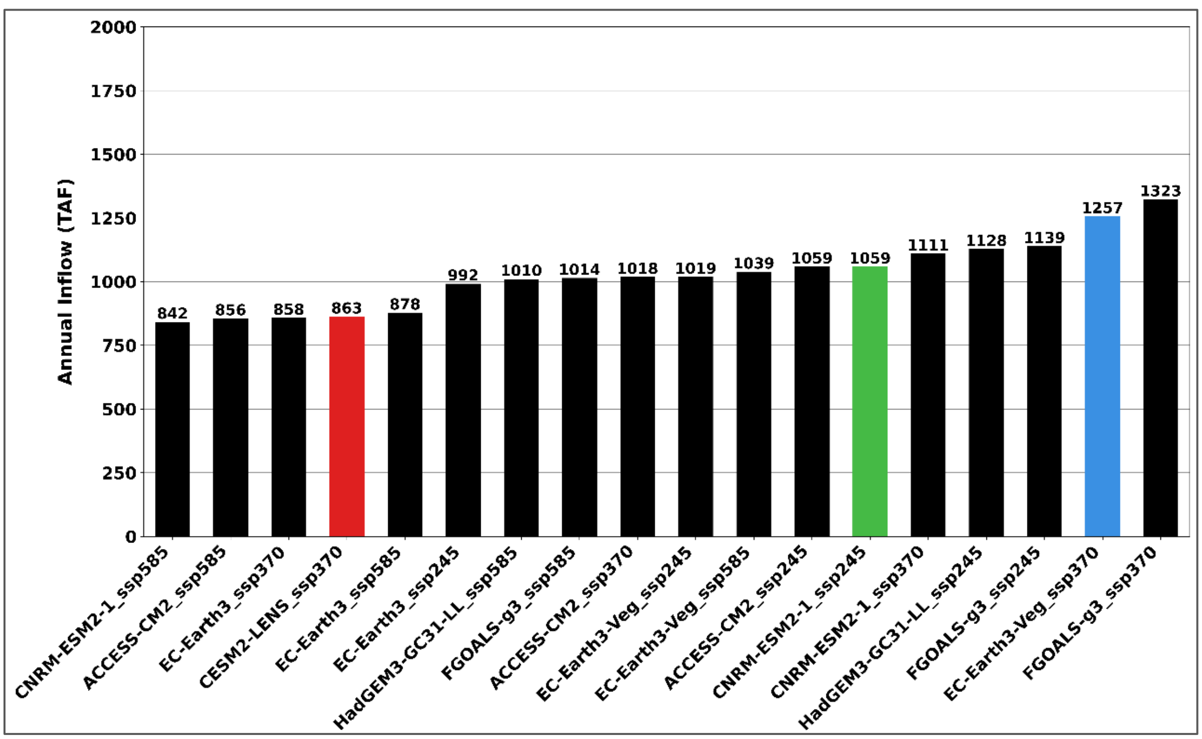


Figure 3-8. Median Annual Inflow for 1-Year Duration highlighting the dry (red), median (green) and wet (blue) scenarios

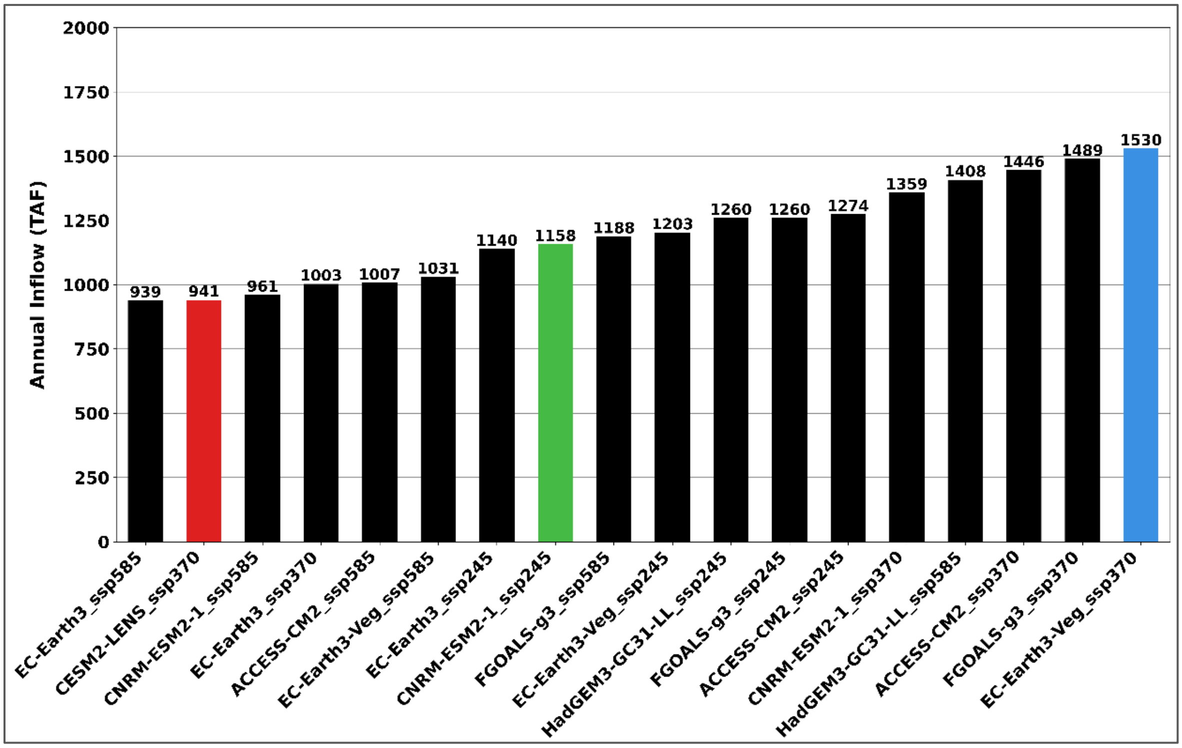


Figure 3-9. Median Annual Inflow for 5-Year Duration highlighting the dry (red), median (green) and wet (blue) scenarios

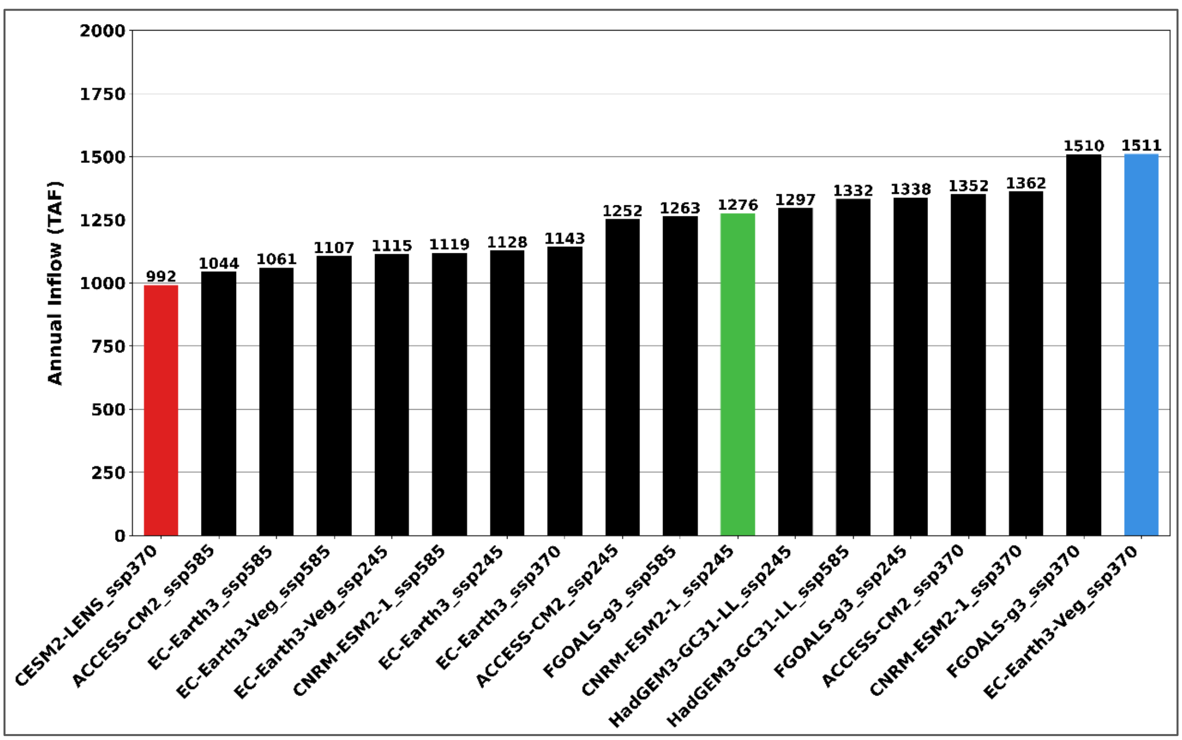


Figure 3-10. Median Annual Inflow for 10-Year Duration highlighting the dry (red), median (green) and wet (blue) scenarios

3.5. Representative Scenarios

Table 3-2 provides a summary of the three representative hydrologic scenarios. These scenarios encompass two extremes, serving as bookends, and a moderate, middle-of-the-road hydrologic scenario. The range of outcomes covered by these three scenarios reflects both low and high inflow possibilities. It is important to note that while the scenarios may not follow a normal distribution statistically, they are treated as having equal probabilities for analytical purposes. Actual future conditions inflow patterns are expected to be between the low and the high bookends, without preference for any scenario.

Table 3-2. Climate Change Scenarios for HEC-HMS Simulations

Scenarios	Models and Emissions
High Bookend (Wet)	EC-Earth3-Veg_ssp370
Median	CNRM-ESM2 1_ssp245
Low Bookend (Dry)	CESM2-LENS_ssp370

The total annual inflow simulated record from 2022–2071 for the entire NID basin for the three representative scenarios is illustrated in Figure 3-11. The wet bookend (blue line) has the greatest number of high inflow events, but also has occurrences of drought conditions. The dry bookend (red line) has the greatest number of drought conditions, but also has few occurrences of high inflow events. The median scenario (green line) has some high inflow events and some drought events, but not as significant as the bookends.

Figure 3-12 presents the 50 years (2022–2071) cumulative total annual inflow for the entire NID basin for the three representative scenarios. This graph demonstrates that over the 50-year projection of inflows, the cumulative values lie in the proper order. The wet has the highest cumulative total inflow for the 50-year projection, the dry has the lowest, and the median is in the middle. The black dashed line takes the average annual inflow value of 1,509 TAF from the historical dataset of 1976–2021 and creates a cumulative trend line using this average value. This line was included only for comparison. One takeaway is that the wet bookend has a very similar total inflow to historical values over the projected period.

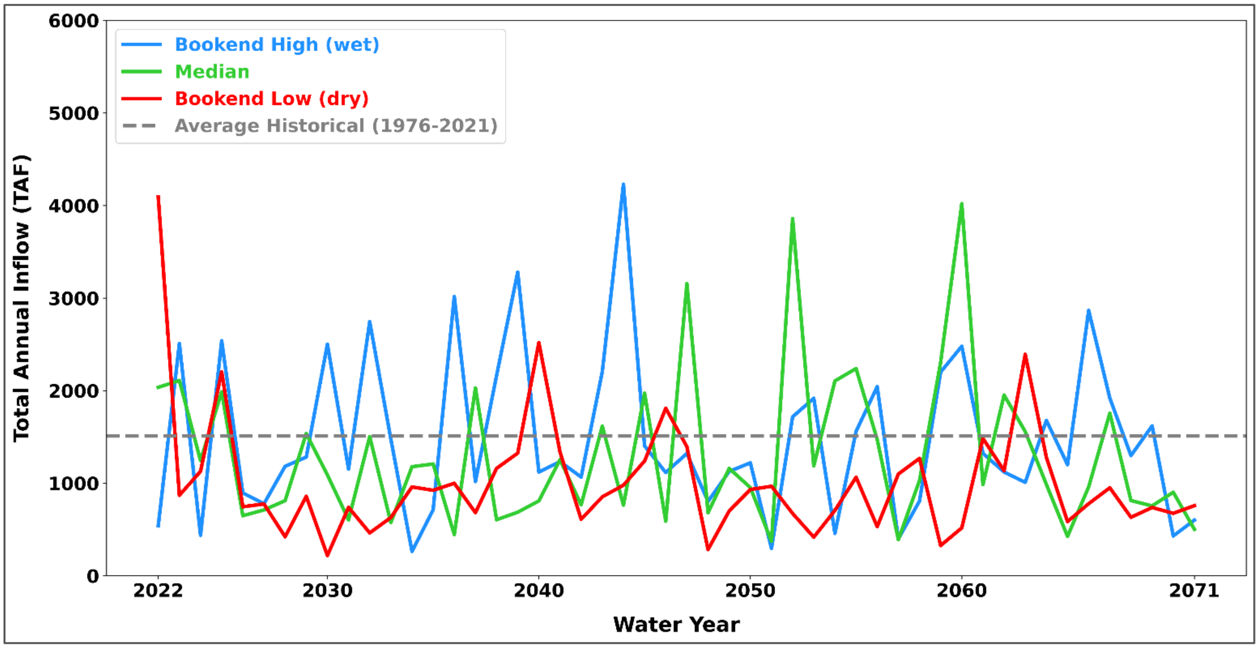


Figure 3-11. Total Annual Inflow Time Series for NID Basin, 2022–2071

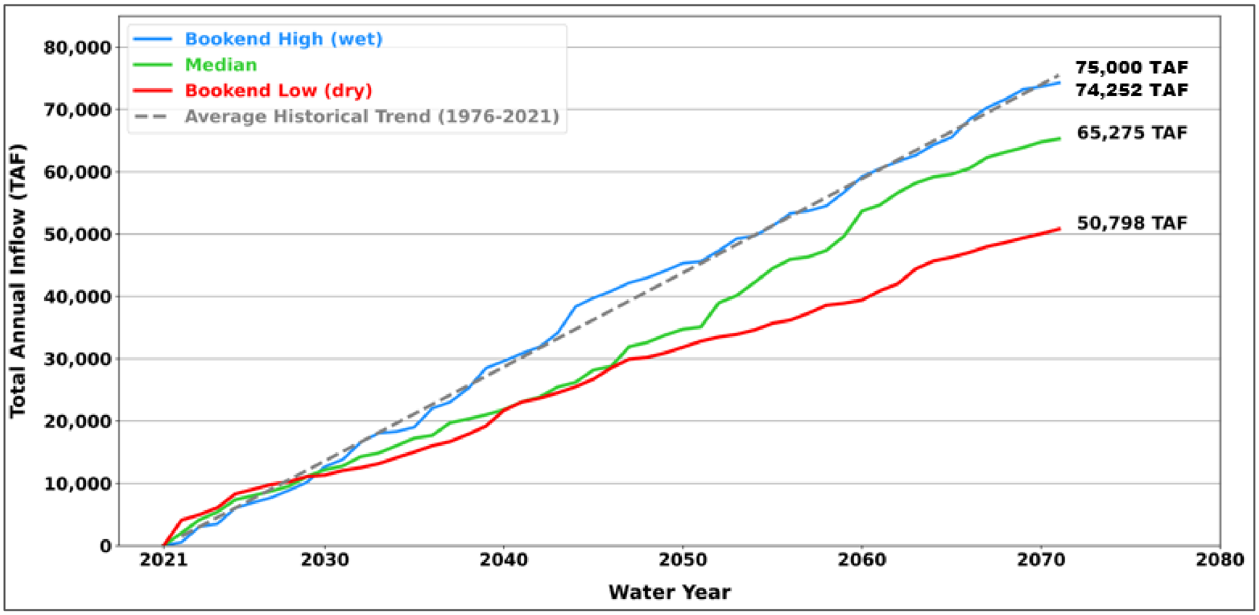


Figure 3-12. 50-Years Cumulative Total Annual Inflow for NID Basin

Chapter 4. Demand Model

4.1. Introduction

This section discusses the development and application of the demand model used to support the NID PFW process. In the context of the NID PFW process, demand generally refers to the total volume of water required to meet water users' needs. This includes water used by raw water customers, treated water customers, and municipal water suppliers that receive water from NID (collectively referred to as NID's customers), together with the system losses that occur delivering water to NID's customers and the regulatory-required environmental flows that NID provides.

The demand model discussed in this section was developed to estimate the demand, or outflows, from NID's reservoirs, required under various scenarios to supply the water needs of NID's customers, inclusive of system losses in NID's canals and distribution system downstream of NID's reservoirs. Regulatory-required environmental flows are included in the reservoir operations model discussed in Chapter 5.

The purpose of this demand model is to provide a means of estimating the demand of NID's customers under different potential projected (i.e., future) scenarios by physically simulating the processes that drive water use on the landscape under the effects of those scenarios. The demand model was thus developed to leverage available local data, standard technical approaches, and best practices to account for the relative effects of estimated future changes in climate, land use, irrigation practices, soil properties, and other factors that impact demand. Results of the demand model were then used to estimate the outflows required from NID's reservoirs to meet those demands, facilitating analyses of water supply versus demand and conditions of unmet demand under potential projected scenarios.

The subsections that follow describe in greater detail the structure and development of the demand model, the projected demand scenarios evaluated in the demand model, and the results of those scenarios.

4.2. Demand Model Development

4.2.1. Background and Major Drivers of Water Demand

Generally, the demand model was developed to create water budgets for the areas within NID where NID's customers receive and use water (e.g., parcels associated with raw and treated water customers). A water budget is a method of accounting for the water that flows into and out of, or is stored within, an area of interest (Healy et al. 2007). A water budget can be calculated for virtually any area of any size, ranging from local (e.g., particular parcels or canal reaches) to regional (e.g., NID service area or canal system) to global. Both the driving forces of water use and uncertainty around water use impact the estimates of water demand at each scale and influence the assumptions and decisions that are made for developing the water budget. The United Nations and other organizations recognize many important environmental, social, economic, and political factors that impact water demand at all scales, including land use change, population change, global climate change, and other technological and economic factors (United Nations 2018, Wada et al. 2016). While the net effects of each individual factor are difficult to quantify and carry significant uncertainty, the importance of considering these factors within the context of local and regional water planning is clear.

4.2.1.1 Major Drivers of Agricultural Water Demand

The majority of NID's raw water customers receive water deliveries from NID to support irrigation of agricultural lands. In general, agricultural water demand includes all water used to irrigate crops or otherwise meet agricultural production-related needs. Agricultural water demand can be divided into consumptive use and non-consumptive use:

- **Consumptive Use:** "That part of water withdrawn that is evaporated, transpired, incorporated into products or crops, consumed by humans or livestock, or otherwise removed from the immediate water environment" (ASCE-EWRI 2016). The vast majority of consumptive use occurs through evapotranspiration (ET) from plants and water surfaces. Consumptive use is often used interchangeably with ET (Allen et al. 1998).
- **Non-consumptive Use:** "That part of water withdrawn that is not evaporated, transpired, incorporated into products or crops, consumed by humans or livestock, or otherwise removed from the immediate water environment" (ASCE-EWRI 2016). Non-consumptive use encompasses other water uses that do not result in water being removed from the local environment, such as spillage, tailwater, and deep percolation of water into the groundwater system.

At the local level, cropping, soil management practices, land management practices, and irrigation practices all significantly impact both the consumptive and non-consumptive components of agricultural water demand and can also significantly affect water availability in surrounding landscapes (FAO 2011).

Consumptive use (primarily ET) is a major focus of long-term water management planning and irrigation demand projections. In total, projected ET is expected to be significantly impacted by future changes in land use and climate, the major parameters evaluated by the U.S. Bureau of Reclamation (USBR) when developing the irrigation demand projections as part of the "West-Wide Climate Risk Assessments: Irrigation Demand and Reservoir Evaporation Projections" (USBR 2015). Shifting land use toward or away from higher-demand crops and land uses will likewise shift agricultural water demand (Allen et al. 1998). Increasing temperatures in the future are also expected to increase ET demand across all land uses (USBR 2015). While non-consumptive use also impacts agricultural demand, there are opportunities for improving water use efficiency to reduce or strategically leverage those demands, for example through conservation, reuse, or conjunctive management efforts.

4.2.1.2 Major Drivers of Urban Water Demand

In addition to raw water customers, NID also supplies water to a substantial number of treated water customers and municipal water suppliers to support what may be referred to as urban water demand. In the context of water budget development for demand modeling, urban water demand typically includes water demand from municipal water suppliers, public water systems, and urban, commercial, industrial, or residential water users who either supply or directly use water to meet demands in urban or residential settings. Urban water demand can include water use for indoor uses (drinking, sanitation, etc.) and certain outdoor uses (household landscape irrigation, etc.). Like agricultural water demand, urban water demand can also be divided into consumptive use and non-consumptive use by the same definitions given above (ASCE-EWRI 2016).

Projected urban water demand is expected to be impacted by pressures associated with future changes in land use, climate, and population (USBR 2021). Pressures associated with land use change and climate change are similar to those anticipated for agricultural land use change (described above). In NID, pressures associated with population change are expected to include changes in the total population and changes in per capita water use of NID's treated water customer base and municipal suppliers served by NID. Because the net effect of these changes over the next 50 years is unknowable, a variety of potential projected demand scenarios were developed to evaluate possible future outcomes. However, it is worth noting that a retrospective analysis of total and per capita water use among multiple water suppliers in California between 2000–2015 found that shifts toward increased efficiency (i.e., lower per capita water use) were enough to offset increases in population and decrease the total urban water demand over the same period (Abraham et al. 2000).

4.2.2. Overview of the NID Demand Model Structure and Inputs

As described above, demand in the NID PFW process generally refers to the total volume of water required to meet water users' needs, including water used by NID's customers, the system losses that occur delivering water to customers, and the regulatory-required environmental flows that NID provides.

The demand model developed to support the NID PFW process was used to estimate the components of demand that are directly related to NID's operations to distribute water to NID's customers, including:

- Raw water demand
- Treated water demand
- Municipal water demand
- System losses (in NID's canals and distribution system downstream of NID's reservoirs)

Regulatory-required environmental flows are included in the reservoir operations model discussed in Chapter 5. An overview of the simulation approach for each demand component is shown in Table 4-1.

The demand model was developed to estimate these demands through two integrated model components:

- **Integrated Water Flow Model Demand Calculator (IDC) model**: The IDC model was used to estimate the raw water demand and treated water demand of NID's customers based on information about land use, irrigation practices, soil properties, population, per capita water use, and other factors that impact the water use of NID's customers. Results of the IDC model were linked to parcels within the NID service area to identify the location(s) in NID where demand occurs for raw water and treated water customers and to quantify the volume of demand in those locations (Table 4-1). The IDC model is discussed in detail later in this subsection.
- **Canal system balance model**: The canal system balance model was developed to link the results of the IDC model (by parcel) and the municipal water demand estimates to the conveyance system and canals that NID uses to distribute water to those customers. The canal system balance was then used to estimate the system losses and the inflows to those canal systems from NID's reservoirs that would occur to supply those demands (Table 4-1). The canal system balance model is also discussed in detail later in this subsection.

Table 4-1. Overview of Demand Component Simulation Approach

Demand Component	Model Component Where Demand is Simulated	Associated Section(s) Describing Model Component
Raw water demand	IDC model	Section 4.2.3
Treated water demand	IDC model	Section 4.2.3
Municipal water demand	Quantified outside IDC model, included in canal system balance model	Section 4.2.3
System losses	Canal system balance model	Section 4.2.4
Environmental flows	Reservoir operations model	Chapter 5
Total demand to supply the water needs of NID's customers. (excluding environmental flows)	Demand model	Chapter 5
Total demand (including environmental flows)	Reservoir operations model	Chapter 5

Various data sources and inputs were considered and incorporated into the demand model development, including (but not limited to) the following general information:

- GIS parcel information
- Land use
- Zoning
- Historical water delivery data
- Treatment plant data
- Canal flows
- Cropping and agricultural development
- Typical agricultural practices relating to water use and management
- Soil parameters
- Precipitation data
- Evaporative demand
- Population
- NID's service area, including existing customers
- Changes to NID's service area (e.g., soft service areas, "fill in" areas)
- Population changes stemming from COVID-19 and other factors

The data and assumptions used to develop the demand model and its inputs were documented and discussed through a stakeholder engagement process, leveraging information gained from available local data, technical standards, best practices, and outreach to local agencies, as needed. A comprehensive summary of the data sources, inputs, and assumptions used to develop the demand model is provided in Appendix B.1.

The key data sources, inputs, and methods used to develop the IDC model and the canal system balance are described in the sections below.

4.2.3. IDC Model

The Integrated Water Flow Model Demand Calculator (IDC) model is a modeling tool developed, maintained, and supported by the California Department of Water Resources (DWR). As a tool, IDC is used for applications in estimating demand through simulation of the physical processes that occur on the land surface that drive demand. IDC is the demand-modeling module of DWR's broader Integrated Water Flow Model (IWFM), an integrated surface water-groundwater modeling platform that has been broadly used to support long-term strategic water planning in numerous Groundwater Sustainability Plans (GSPs), Agricultural Water Management Plans (AWMPs), and other long-term, often multi-decade planning documents developed by water managers throughout California. The IDC model used in the NID PFW process was built using DWR's IDC Version 2015.0.0140, the latest available as of early 2023 (DWR 2022a).

The IDC model uses data and information about climate, land use, soil properties, agricultural and irrigation practices, and urban and residential parameters to physically simulate inflows and outflows of water through the landscape over time (Figure 4-1). IDC estimates the amount of water required to meet the demands of water users under different conditions, whether for agricultural, urban, or residential use. The IDC model structure is designed to simulate these inflows and outflows through finite elements, or grids of simple three- or four-sided polygons. Functionally, IDC models (and IWFM models) are typically developed and operated with a relatively coarse grid, in which each element represents tens to hundreds of acres.

The IDC model used in the NID PFW process was developed as a unitized model (as compared to a spatial model) to simulate conditions for unique and representative combinations of land use, soil characteristics, and climate zones that are found throughout the NID service area within each finite element. In the unitized model structure, demand is simulated for each combination (i.e., each element) and represented on a unit basis (e.g., feet of water required per unit area, or AF/acre). Those unitized results are then linked directly to individual parcels matching one of the simulated land use/soil/climate combinations, permitting parcel-level spatial quantification of demand volumes outside the coarse grid and spatial constraints of a typical spatial IDC model (Figure 4-2).

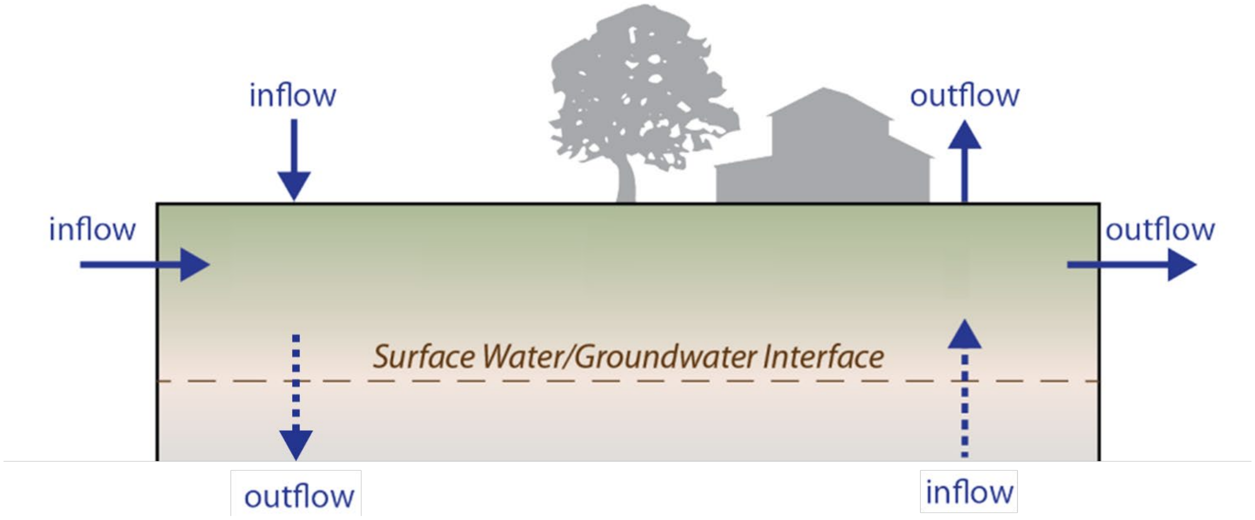


Figure 4-1. Conceptual Water Budget as Simulated in the IDC Model, Quantifying Inflows and Outflows of Water Through the Landscape (DWR 2016)

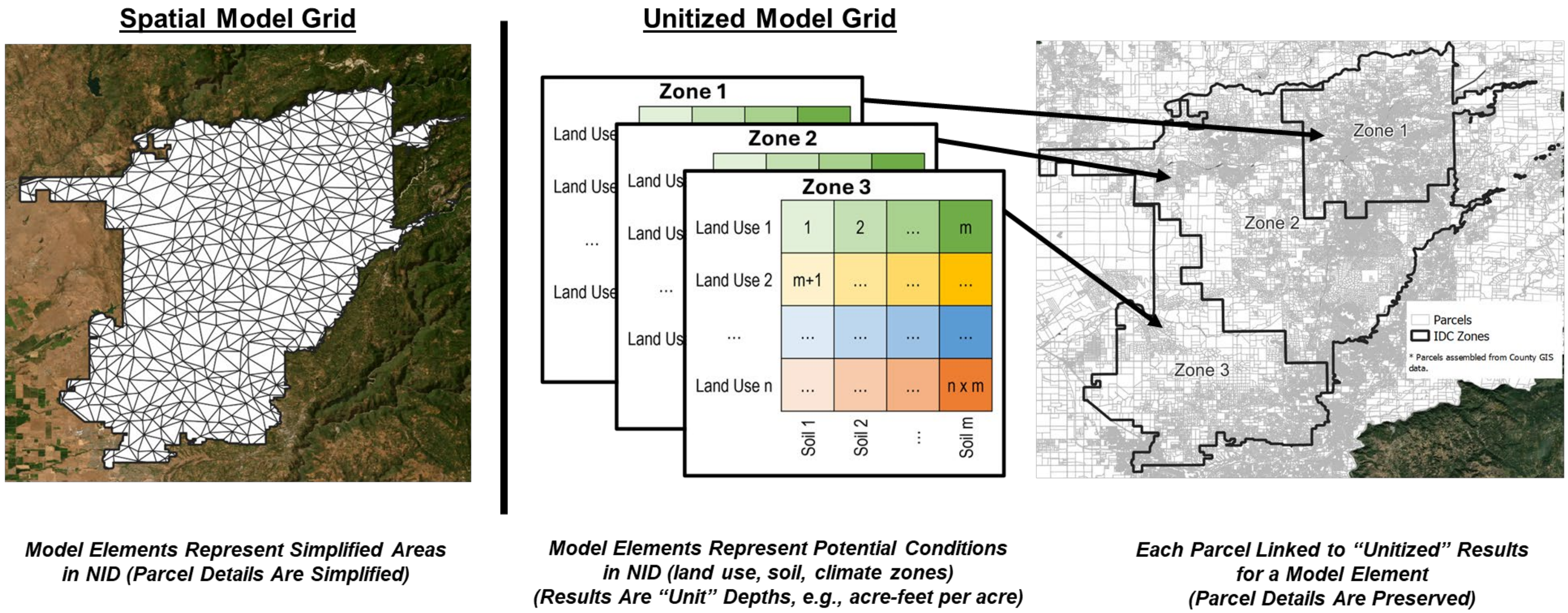


Figure 4-2. Overview of Structural Differences Between a Spatial IDC Model and a Unitized IDC Model

In total, 11 land use categories, 5 soil textures, and 3 climate zones were simulated in the IDC model used in the NID PFW process (Table 4-2). Altogether, these represent 165 unique combinations of land use, soil, and climate zones simulated within the NID service area. The land use categories and soil textures were developed through analyses described in Section 4.2.3.2. The representative climate zones were developed by assessing elevation profiles, precipitation, and reference evapotranspiration (ETo) within the NID service area (Section 4.2.3.1) to identify regions with similar climate characteristics.

Table 4-2. Combinations of Land Use Categories, Soil Textures, and Climate Zones Simulated in the IDC Model

Climate Zone	Soil Texture	Land Use Categories[1]
Zone 1 (Higher Elevation)	Clay Loam	Citrus and Subtropical
		Miscellaneous Deciduous
		Miscellaneous Truck and Nursery
		Pasture
		Vineyard
		Young Perennial
		Idle
		Native Vegetation
		Riparian Vegetation
		Water
		Urban and Residential
	Loam	*[All Land Use Categories Repeated]*
	Sandy Loam	*[All Land Use Categories Repeated]*
	Silt Loam	*[All Land Use Categories Repeated]*
	Sandy Clay Loam	*[All Land Use Categories Repeated]*
Zone 2 (Middle Elevation)	Clay Loam	*[All Land Use Categories Repeated]*
	Loam	*[All Land Use Categories Repeated]*
	Sandy Loam	*[All Land Use Categories Repeated]*
	Silt Loam	*[All Land Use Categories Repeated]*
	Sandy Clay Loam	*[All Land Use Categories Repeated]*
Zone 3 (Lower Elevation)	Clay Loam	*[All Land Use Categories Repeated]*
	Loam	*[All Land Use Categories Repeated]*
	Sandy Loam	*[All Land Use Categories Repeated]*
	Silt Loam	*[All Land Use Categories Repeated]*
	Sandy Clay Loam	*[All Land Use Categories Repeated]*

[1]Additional information about the land use categories is provided in Section 4.2.3.2.

In the NID PFW process, the IDC model was developed, refined, and operated to simulate NID customers' demand under different scenarios, in particular:

- Current demand scenario: developed to simulate recent historical demand in 2013–2021, for the purpose of serving as a baseline for comparison and interpretation of the projected demand scenarios.
- Projected demand scenarios: developed to simulate multiple baseline or bookend (low or high) scenarios in 2022–2071 under alternate future conditions with regard to climate, land use, agricultural and irrigation practices, population, and NID system operations.

This section summarizes the general data sources and inputs used to develop the IDC model.

The IDC model was developed using data sources and information that capture the unique, local conditions within the NID service area to the extent available. More details on the assumptions and results of the demand model scenarios—including the projected demand scenario assumptions and rationale—are described in Section 4.3.

4.2.3.1 Climate-Related Inputs

Climate-related inputs to the IDC model included ET and precipitation. Data sources used to develop these inputs are described below.

4.2.3.1.1. Evapotranspiration (ET)

ET, or consumptive water use, is the major driver of agricultural water use. Unlike recoverable water uses, such as surface runoff or infiltration of water into the groundwater system (whether through seepage, deep percolation, recharge, or other means), ET is water that cannot be recovered or directly reused in the NID service area. ET is impacted by: the types of crops or vegetation that are grown (reflecting the inherent differences in water needs of different crops and vegetation); the quality of crops, vegetation, or land use, including water availability, nutrient and pest management, and other factors; and environmental demand for evaporation related to weather and climate parameters, as a function of temperature, solar radiation, wind speed, and humidity. Each of these factors are accounted for in the methods used to quantify ET.

In the IDC model, ET time series information was quantified for different land uses and different climate zones in NID for each of the demand model scenarios using the best available local information and standard technical approaches (ASCE-EWRI 2016).

In the current demand scenario, ET was quantified based on an evaluation of satellite-based remote sensing analyses available from OpenET (described below):

- The ensemble mean ET from OpenET was used to quantify spatial ET on a monthly timestep from 2016 to 2022 for all areas within NID (with a spatial resolution of 30 m by 30 m, or approximately 0.22 acre/pixel).
- Spatial ET results were linked to land uses in NID based on parcel-level land use data (described in Section 4.2.3.2).
- Representative average ET curves (i.e., ET rates over time) were quantified from the spatial ET results for different land uses in the different climate zones within NID, generating monthly ET curves representing hundreds of parcels in NID over the period from 2016–2022. These monthly

ET curves were used to quantify ET for the corresponding land uses within the corresponding climate zones. Before the availability of OpenET data, ET was estimated for each land use based on the monthly ET curves for the same land use and climate zone in a hydrologically similar WY.

In the projected demand scenarios, ET was quantified following the standard crop coefficient approach described in the United Nations Food and Agriculture Organization (FAO) Irrigation and Drainage Paper 56 (Allen et al. 1998). In the crop coefficient approach, ET is calculated by multiplying a reference evapotranspiration (ETo) value by a crop coefficient (Kc) such that: ET = Kc × ETo. Reference evapotranspiration, crop coefficients, and the calculation of ET by this method are described below. Adjustments were made to these parameters, as appropriate, to reflect changes in climate and water needs for particular land uses over time following the assumptions of the projected demand scenarios (described in Section 4.3).

Data sources used to calculate ET, or the parameters comprising ET, are summarized in Table 4-3 and in the sections below.

Table 4-3. Evapotranspiration Data Sources

Parameter	Demand Scenario	Source	Description
ET	Current	OpenET	OpenET data used to generate representative average ET curves for different land uses in the different climate zones in NID
ET	Projected	Calculated	Based on ET = ETo x Kc
ETo	Projected	Calculated based on CMIP-6 results (hydrology scenarios)	Values calculated for the different climate zones in NID based on CMIP-6 results used in the hydrology scenarios (Chapter 3)
Kc	Projected	Calculated	Kc values estimated based on the ratio of recent historical ET (from OpenET) to recent historical ETo (from Spatial CIMIS) for different land uses in the different climate zones in NID

OpenET Data

OpenET is a multi-agency web-based geospatial utility that quantifies ET over time with a spatial resolution of 30 m x 30 m (approximately 0.22 acre). OpenET information is available in raster coverages of the NID service area on both a daily and monthly timestep from 2016 through present. While OpenET is a new utility, the underlying methodologies to quantify ET apply a variety of well-established modeling approaches that are widely used in local, state, and Federal Government and research applications. Additional information about the OpenET team, data sources, and methodologies is available at: https://openetdata.org/. For the NID demand model, OpenET data were used to observe recent historical ET trends and evaluate representative ET rates for land uses in NID (e.g., average ET and percentiles across tens to thousands of pixels in NID) (Figure 4-3). Importantly, OpenET data were not used to directly assign an ET value representing any single point within NID in the demand model.

The OpenET data in Figure 4-3 shows areas with generally higher ET in the upper elevation regions of the NID service area (e.g., climate zone 1) and areas with generally lower ET in the lower elevation regions of NID (e.g., climate zone 3). These differences are mainly attributed to water availability within the landscape and land use within NID. While NID supplies raw water for irrigation to approximately 30,000 acres, most land within the boundaries of NID is “native vegetation” (undeveloped natural vegetation, such as forest, meadows, and non-irrigated open spaces) that relies on precipitation, shallow groundwater, and other water supplies in the landscape. Greater water availability in the higher elevation regions of NID supports generally higher ET for native vegetation in those areas, while generally lower ET occurs in lower elevation regions where less water is available in the landscape. Open water surfaces, such as reservoirs, also show higher ET rates indicating evaporation that occurred.

For the current demand scenario, an analysis of OpenET data spatially across the land uses in NID was used to generate representative average ET curves (i.e., ET rates over time) for land uses in the different climate zones within NID (Figure 4-4). The ET curves from this analysis were compared to representative ET curves reported from other sources—including DWR’s Cal-SIMETAW (DWR 2022b) and the Irrigation Training and Research Center (ITRC) at California Polytechnic State University, San Luis Obispo (ITRC 2023)—to verify their general consistency with the ET trends for each crop reported in technical literature. In contrast with OpenET, many ET approaches do not account for crop stress, which is caused by a variety of factors, and if present, will reduce ET; thus, many ET approaches overestimate ET. One benefit of the approach used for quantifying ET in the demand model is that the variability of ET is evaluated within NID for each crop group, allowing for identification and use of a representative ET curve that captures local conditions and agronomic practices. The ET curves from other sources (e.g., Cal-SIMETAW, ITRC) tended to be higher than the OpenET results, especially in the mid to late summer period when evaporative demand is highest and when crop stress, if present, will be most noticeable. Differences observed between other sources and OpenET are influenced by these factors.

For the projected demand scenarios, OpenET ET data were used together with ETo information to calculate Kc curves that represent the unique, local water use characteristics of land uses within NID. This was intended to provide a more accurate understanding of local water demands directly in NID, rather than relying on Kc values from technical literature that were developed in other areas of California or the United States. The evaluation of ET data and development of Kc curves are discussed further in Appendix B.2.

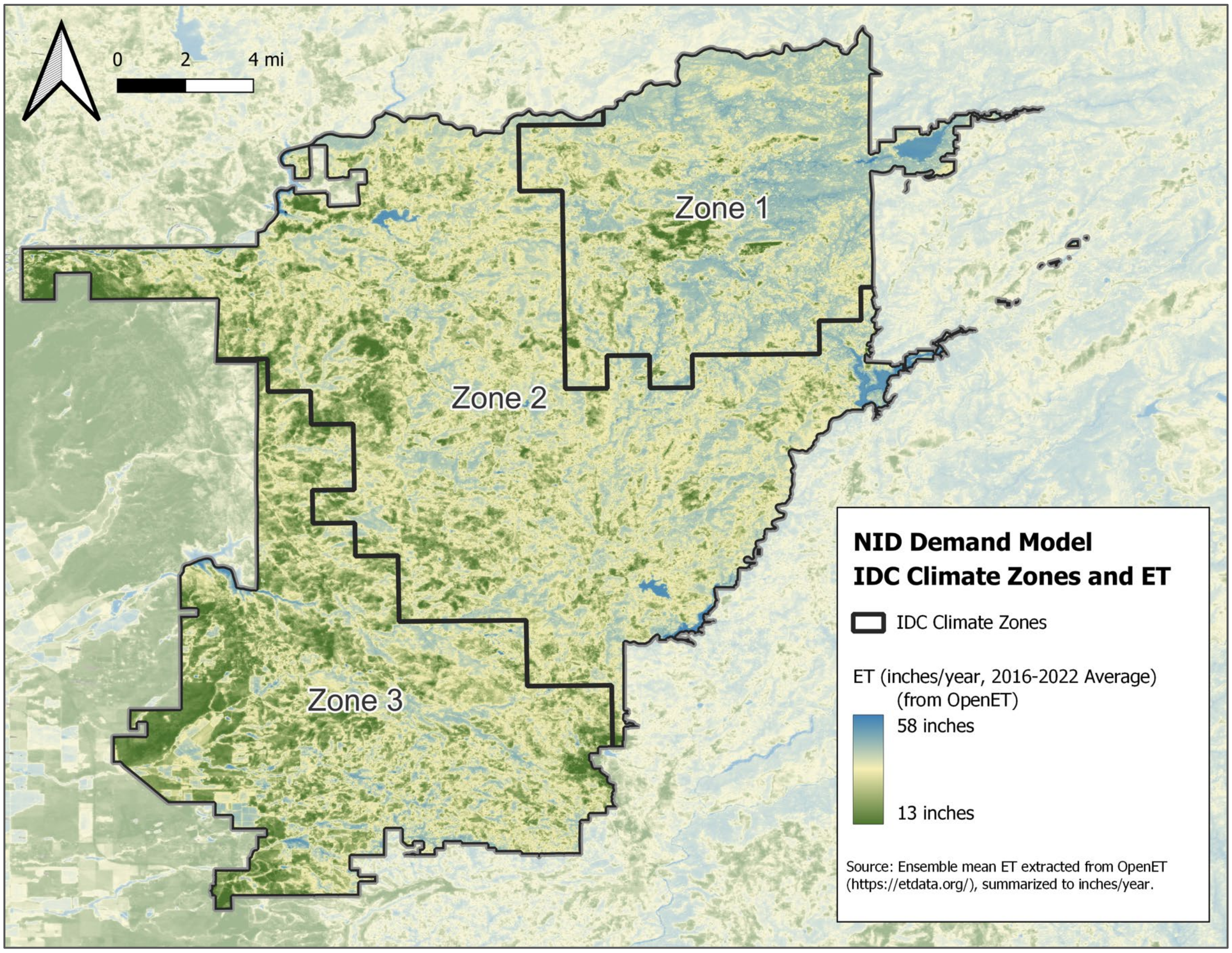


Figure 4-3. Average ET (2016–2022) from OpenET and Climate Zones

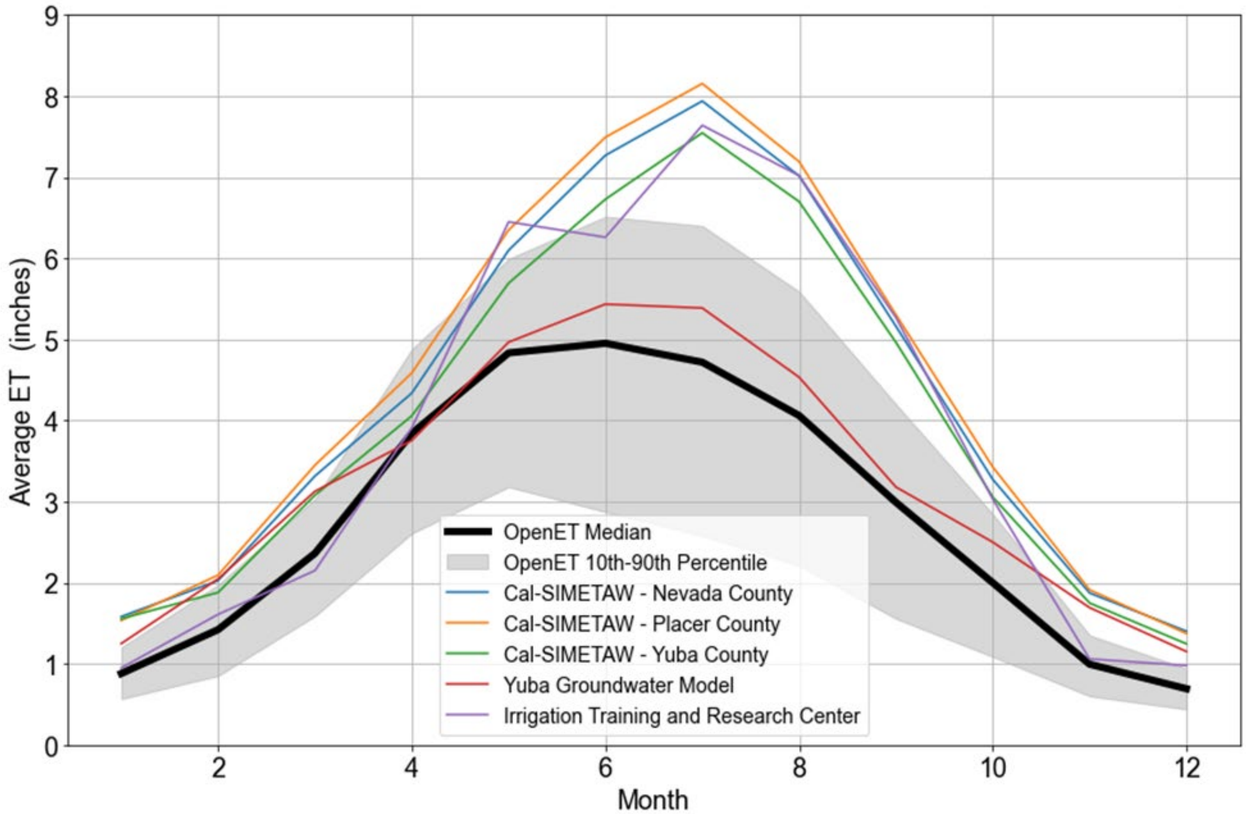


Figure 4-4. Sample ET Curve Summarized for all Parcels Categorized as Pasture in Climate Zone 3 (2021), with Comparisons to Other Representative ET Estimates for Pasture from Cal-SIMETAW (DWR 2022b), the Yuba Groundwater Model (YWA, 2019), and the Irrigation Training and Research Center ET Data for Water Budget Applications (ITRC 2023)

Reference Evapotranspiration (ETo)

Reference evapotranspiration represents the evapotranspiration rate from a reference surface. Throughout California, the standard reference surface used by the CIMIS is a well-watered, full-cover grass surface, commonly referred to as ETo (CIMIS 2023). ETo provides information about climatic parameters that affect ET and essentially quantifies the evaporative demand of the environment. Recent historical ETo estimates are available directly from CIMIS. Projected ETo can be calculated from projected climate parameters or can be scaled to reflect changes in climate parameters.

In the current demand scenario, ET was quantified primarily based on OpenET information (2016–2022), so ETo was not directly necessary for quantifying ET in those years. However, recent historical ETo was quantified to generate local Kc curves for different land uses in different climate zones of the NID service area that were then used to estimate ET in earlier years and projected ET in the future following the standard crop coefficient approach (Allen et al. 1998). The approach used to generate local Kc values is described below. Recent historical ETo used to generate local Kc values was summarized from spatial CIMIS data (Figure 4-5 and Figure 4-6). Spatial CIMIS data extracted for the NID service areas was calculated based on available quality controlled CIMIS station data and interpolation between stations with reference to topography and other factors that impact climate conditions. Additional information about the spatial CIMIS data sources and methodologies is available at: https://cimis.water.ca.gov/SpatialData.aspx.

In the projected demand scenarios, ETo was quantified following the standard Hargreaves-Samani approach (Hargreaves and Samani 1985, Allen et al. 1998). In contrast with other more complex methodologies for quantifying ETo, the Hargreaves-Samani approach simplifies the estimation of ETo based on data and assumptions pertaining to air temperature and extraterrestrial radiation. Average daily ETo for each climate zone within the NID service area was quantified based on spatial projected temperature information derived from the CMIP-6 analyses used in the hydrology scenarios, as described in Chapter 3 and assumptions regarding extraterrestrial radiation based on the geographic location of the NID service area and the day of the year. In this way, projected ETo was calculated and scaled to reflect changes in climate parameters over time and under different projected demand scenarios that will impact ET.

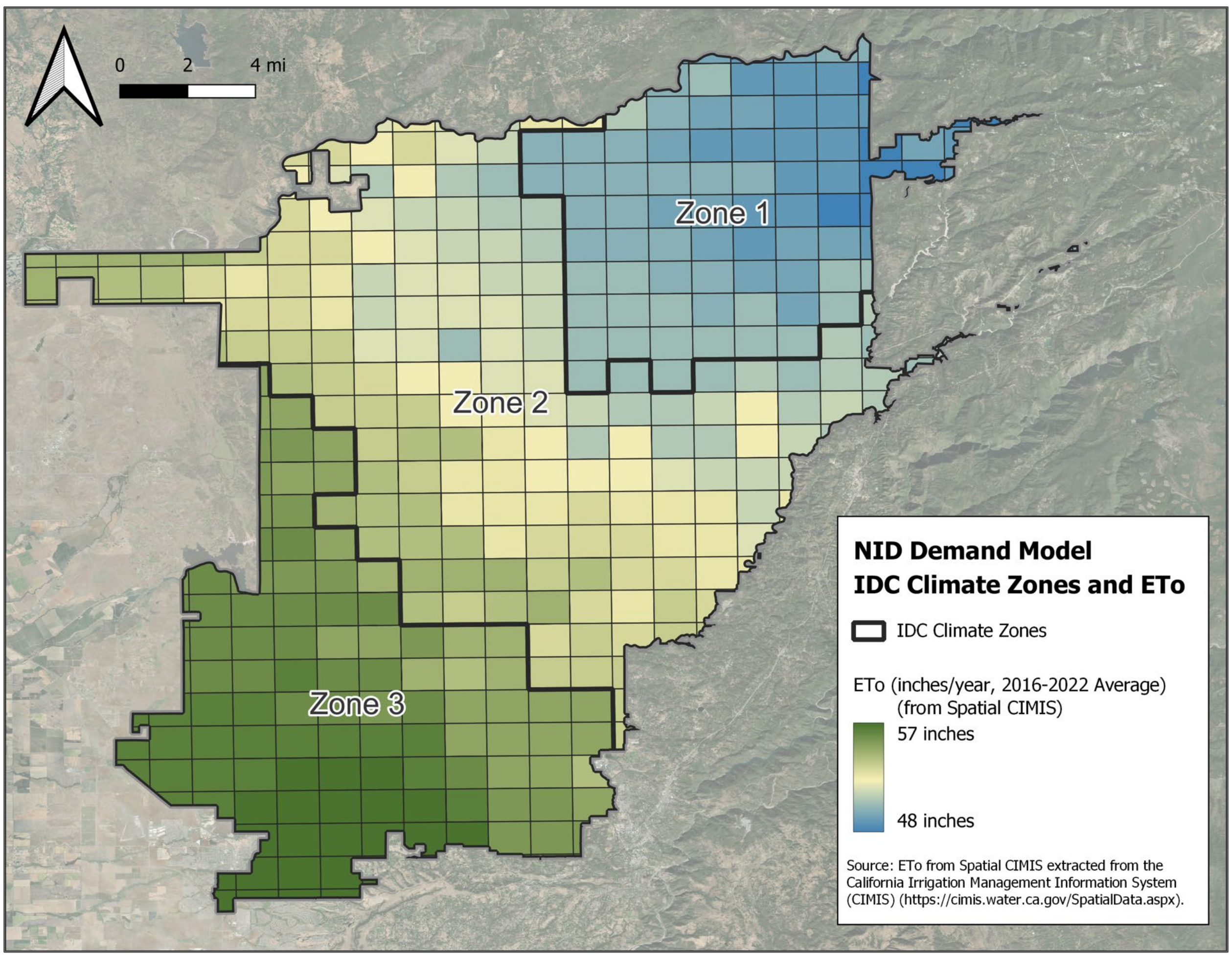


Figure 4-5. Average ETo (2016–2022) from Spatial CIMIS and Climate Zones

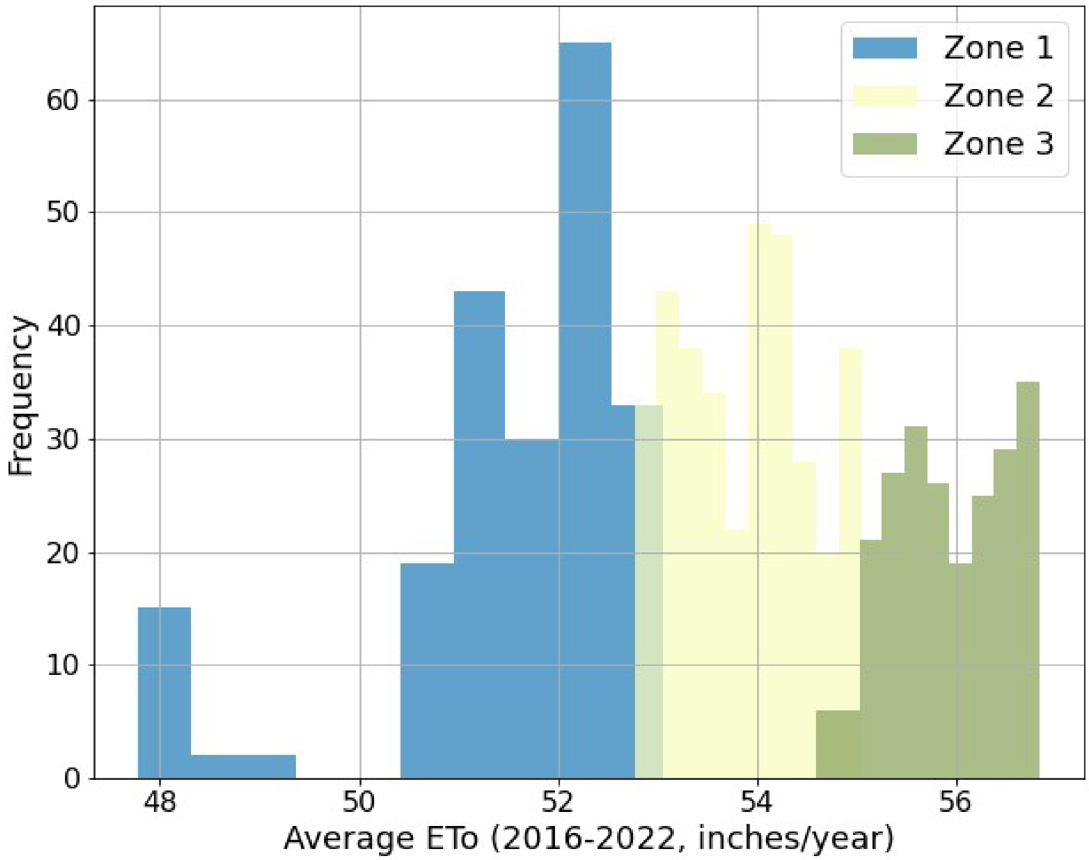


Figure 4-6. Distribution of ETo (2016–2022) from Spatial CIMIS Across the Climate Zones, Where Frequency Represents the Number of Pixels Within Each Zone

<u>Crop Coefficients (Kc)</u>

Kc is calculated based on the ratio of ET to ETo and represents the unique crop characteristics that distinguish a particular land use's water use needs from that of a reference grass surface. Different land uses and crops have different Kc values and curves, depending on their water use needs. In use, Kc is a scaling factor that adjusts the climate-related factors that affect ET (captured in ETo) to reflect the crop-related factors that affect ET as a land use or crop grows and matures.

Local Kc values were developed for land uses in the NID service area over the period from 2016–2022 based on the ratio of:

- ET values from OpenET, which were used to observe trends in consumptive water use and evaluate representative ET rates for specific land uses in NID.
- ETo values from spatial CIMIS, which were used to observe trends in climate and weather conditions that impact ET over the same time period.

Local Kc values were calculated through a geospatial analysis of ET (OpenET data at a 30 m x 30 m resolution) and ETo (spatial CIMIS data averaged over each of the three climate zones in NID, and then downscaled to the ET resolution) over time. From these two data sources, Kc values were calculated on a monthly timestep at a 30 m x 30 m resolution over the full spatial extent of the NID service area and were mapped to specific land uses in NID based on spatial land use information (described below). The end result was a distribution of monthly Kc curves from 2016–2022 that represent the water use needs of particular land uses in particular climate zones within NID calculated across tens to thousands of parcels in NID. Development of the Kc curves is discussed further in Appendix B.2. Evaluation of this range of Kc curves allowed simulation of a range of crop water use conditions across NID. The projected demand scenarios considered the 25th percentile, median, and 75th percentile Kc distribution (described in Section 4.3).

4.2.3.1.2. Precipitation

Precipitation is an important source of water on the landscape that is used to support ET and that results in runoff, percolation, and changes in soil moisture. For the IDC model, precipitation time series information was quantified for the different climate zones in NID for each of the demand model scenarios using the best available information (Table 4-4).

For the current demand scenario, spatial precipitation estimates were extracted from the PRISM developed by the PRISM Climate Group at Oregon State University (Figure 4-7). PRISM quantifies spatial precipitation estimates, among other climate parameters, based on available weather station data and modeled spatial relationships with topography and other factors influencing weather and climate. Additional information about the PRISM data and methodologies is available at: https://prism.oregonstate.edu. Monthly precipitation rasters were evaluated at a spatial resolution of 4 km x 4 km for the demand model.

For the projected demand scenarios, spatial projected precipitation estimates for each climate zone in the NID service area were summarized from the CMIP-6 analyses used in the hydrology scenarios, as described in Chapter 3. In each case, precipitation data were summarized into representative, average precipitation curves (i.e., precipitation rates over time) for the different climate zones within NID.

Table 4-4. Precipitation Data Sources

Scenario	Source	Description
Current	PRISM	PRISM data used to generate representative average precipitation curves for the different climate zones in NID.
Projected	CMIP-6 results (hydrology scenarios)	Values summarized for the different climate zones in NID based on CMIP-6 results used in the hydrology scenarios (Chapter 3)

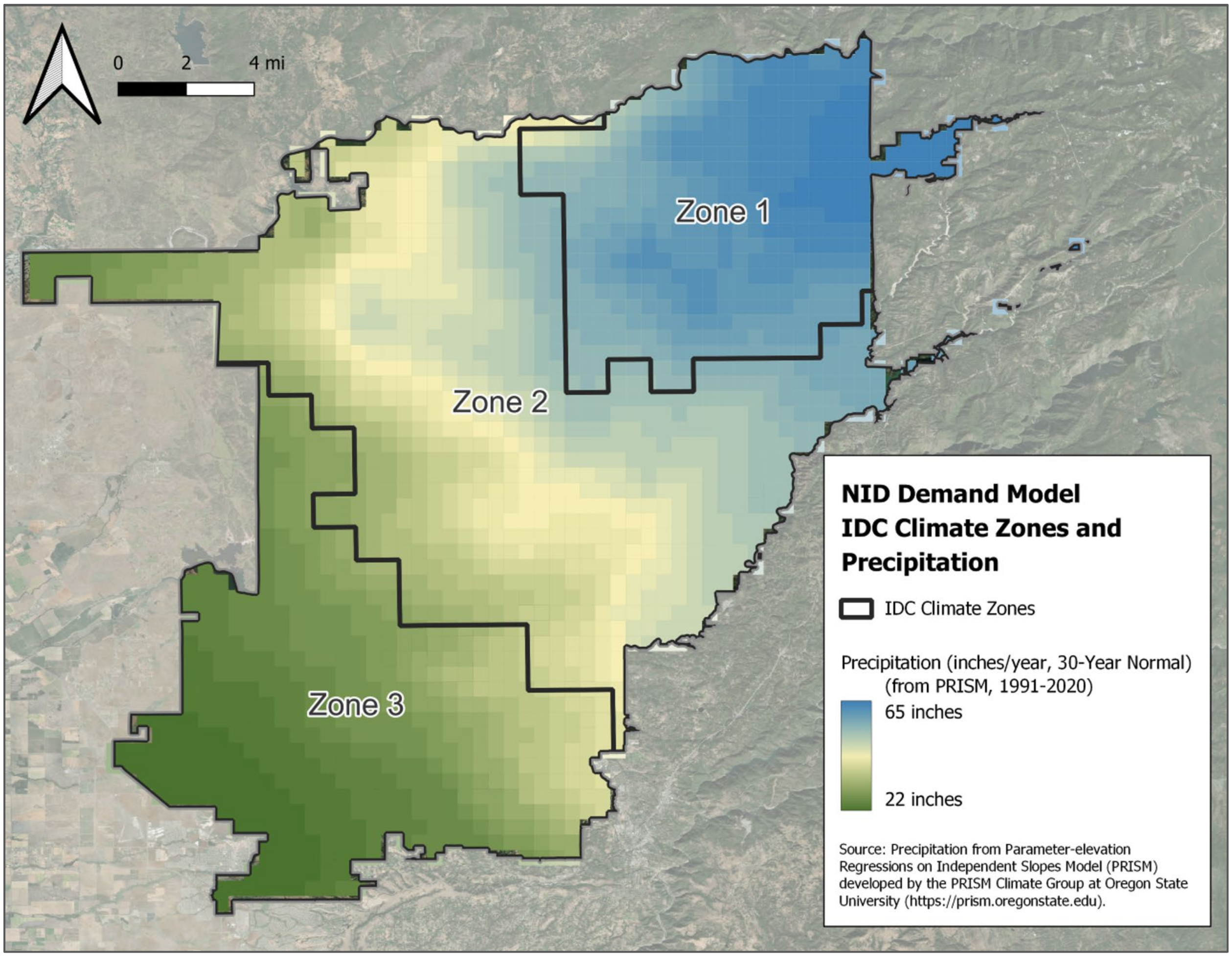


Figure 4-7. Average Precipitation from PRISM (30-Year Normal, 1991–2020) and IDC Climate Zones

4.2.3.2 Land Use and Soil-Related Inputs

Land use and soil-related inputs to the IDC model included parcel-level land use information, runoff characteristics, as well as soil textures and related parameters that influence soil moisture storage. Data sources used to develop these inputs are described below.

4.2.3.2.1. Land Use

Parcel-level land use data across the NID service area were identified using the most recent and reliable geospatial land use data for California, as well as available local information from Nevada, Placer, and Yuba Counties and their General Plans regarding zoning and anticipated land use changes over time. Land use and land cover (simplified to land use in this discussion) refers to both the vegetation and development of the landscape, ranging from developed urban or rural residential areas, to agricultural land, to undeveloped natural vegetation (referred to as native vegetation in the IDC model).

For the current demand scenario, spatial land use information was summarized through a land use analysis process based on:

1. Statewide land use mapping, available from the California DWR (DWR 2023).

2. CropScape Cropland Data Layer coverage, available from the USDA (USDA 2023).

To generate a complete land use map of the NID service area, land use data from these sources were compiled into 30 m x 30 m raster coverages of the NID service area for 2016–2022, according to the following order of preference:

- The statewide land use mapping from DWR was preferentially used to identify agricultural land (including irrigated and non-irrigated lands) and urban areas. These data include extensive ground-truthing and analytical review of results statewide and are considered the most accurate spatial land use data source available within the NID service area in recent years.
- The CropScape Cropland Data Layer coverage from the USDA was subsequently used to back-fill gaps of non-irrigated, idled, and non-developed (i.e., native vegetation) areas within the NID service area that were not captured in the DWR data.

The unique land uses within NID that were identified from these sources were then summarized and aggregated into predominant land use categories for simulation in the IDC model (Table 4-5 and Figure 4-8).

After generating a complete land use map of the NID service area, land use data were then linked to parcels within NID using parcel delineations gathered from Nevada, Placer, and Yuba County and parcel identification numbers from NID's customer and delivery records (described further in Section 4.2.3.5). This linkage allowed identification of the predominant land use that existed within each parcel in each year, and the fraction of the parcel area that was represented by that land use (based on an analysis of the 30 m x 30 m raster coverage within the parcel boundaries). Ultimately, the demand model was developed to estimate raw and treated water demand at the parcel level based on the developed area of each parcel—that is, the area of the parcel in which agricultural, urban, or residential water use occurs, excluding non-developed land (i.e., non-irrigated native vegetation, etc.). Thus, at this stage, the relative fraction of each parcel that was developed was also determined from the land use data based on the relative proportion of developed areas within that parcel. Results of this land use analysis process were then compared with NID crop report information to verify the general acreages and relative proportions of crops grown in NID. Additional discussion of the land use analysis process is available in Appendix B.3.

For the projected demand scenarios, the current demand scenario land use from 2022 was used as a baseline for land use changes over time, layering in information from the counties and their General Plans regarding parcel zoning, land use mapping, and areas where development may occur, as well as information from NID identifying NID's potential growth areas ("soft service areas"). This information was used to modify land use to reflect growth or contraction of customers in the NID service area over time following the assumptions of the projected demand scenarios (described in Section 4.3).

Table 4-5. Land Uses Simulated in the IDC Model

Land Use Sector	Land Use Category	Description
Agricultural	Citrus and Subtropical	Irrigated citrus and subtropical crops (e.g., citrus trees)
	Miscellaneous Deciduous	Irrigated orchard crops (e.g., fruit and nut orchard crops)
	Miscellaneous Truck and Nursery	Other miscellaneous irrigated truck and nursery crops (e.g., berries, tomatoes, cucurbits)
	Pasture	Irrigated pasture, turf, and alfalfa
	Vineyard	Irrigated vineyards and grapes
	Young Perennial	Irrigated young perennial crops (prior to maturation)
	Idle	Non-irrigated, non-cropped agricultural land
Urban	Urban and Residential	Land uses include urban and residential areas
Native and Riparian Vegetation	Native Vegetation	Undeveloped natural vegetation is referred to and simulated as native vegetation in the IDC model. While native vegetation is included in land use analyses and is simulated in the IDC model, demand from native vegetation is not included in the demand results.
	Riparian Vegetation	Undeveloped natural riparian vegetation is referred to and simulated as riparian vegetation in the IDC model. While riparian vegetation is included in land use analyses and is simulated in the IDC model, demand from riparian vegetation is not included in the demand results.
	Water	Reservoirs, ponds, waterways, and other water surfaces are simulated as water in the IDC model. While water is included in land use analyses and is simulated in the IDC model, demand from water is not included in the IDC results but would be included in the system losses.

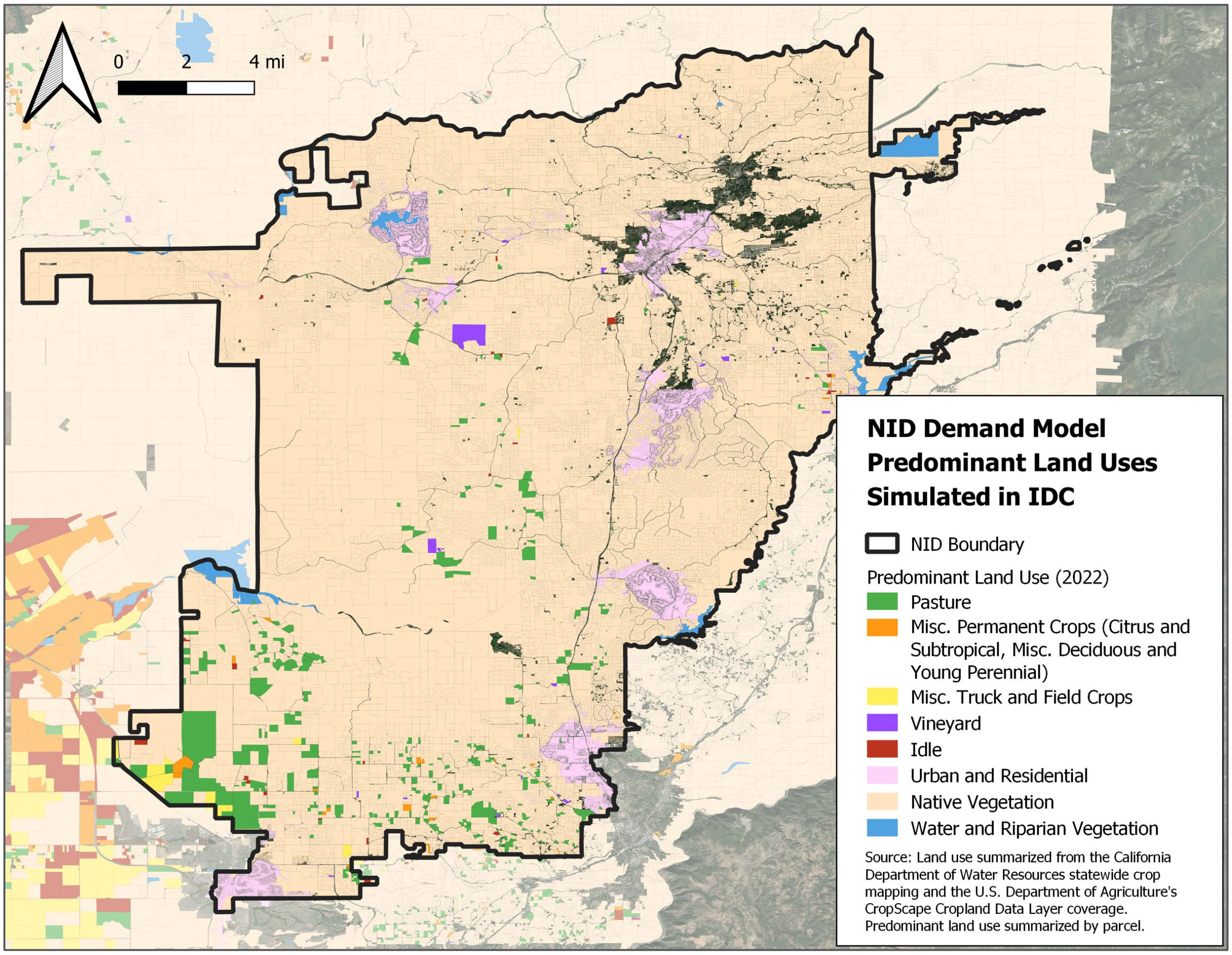


Figure 4-8. Land Uses Simulated in the IDC model, Summarized by Parcel (2022)

4.2.3.2.2. Soil Textures and Parameters

Soil textural classes and associated soil hydraulic parameters used in the IDC model were estimated from a compilation of the Soil Survey Geographic (SSURGO) and State Soil Geographic (STATSGO) datasets available from the California Soil Resource Lab at the University of California, Davis, and University of California – Agriculture and Natural Resources (UC-ANR) (Walkinshaw et al. 2022). The SSURGO and STATSGO datasets contain geospatial soil information collected by the National Cooperative Soil Survey (NCSS) regarding soil textures and soil properties in the United States. The USDA-NRCS organizes the NCSS and publishes soil surveys. The IDC model includes five soil textures representing the predominant soil texture classes found within the NID service area (Table 4-6 and Figure 4-9).

The following five soil parameters were provided as inputs to the IDC model and are summarized for each soil texture class in Table 4-6:

1. Permanent Wilting Point, dimensionless (ratio of volume/volume)
2. Field Capacity, dimensionless (ratio of volume/volume)
3. Total Porosity, dimensionless

4. Pore Size Distribution Index, dimensionless
5. Saturated Hydraulic Conductivity (K_{sat}), (ft/day)

An explanation of these soil parameters and their role in the IDC model is available from DWR in their IDC model documentation (DWR 2022a). Soil parameters were determined through a combination of area-weighted summaries of information in the SSURGO/STATSGO datasets, as well as a calibration process to refine the simulation of these soil parameters within the IDC model. For each soil texture class derived from SSURGO/STATSGO, initial soil parameters were estimated based on pedotransfer functions reported by Saxton and Rawls (2006) and refined to provide drainage from saturation to field capacity within a reasonable amount of time, as determined from the percentage of drainage after three days (generally exceeding 60–80%), and to predict minimal gravitational drainage once field capacity was reached.

Table 4-6. Predominant Soil Textures and Soil Parameters Simulated in the IDC Model

Soil Texture	Area (acres)	Field Capacity (-)	Wilting Point (-)	Total Porosity (-)	Pore Size Distribution Index (-)	Ksat (ft/d)
Clay Loam	100,175	0.31	0.17	0.42	0.150	1.200
Loam	107,757	0.28	0.15	0.40	0.173	1.625
Sandy Loam	45,051	0.19	0.09	0.38	0.322	8.350
Silt Loam	38,941	0.28	0.13	0.40	0.210	0.660
Sandy Clay Loam	11,833	0.24	0.14	0.39	0.195	5.800

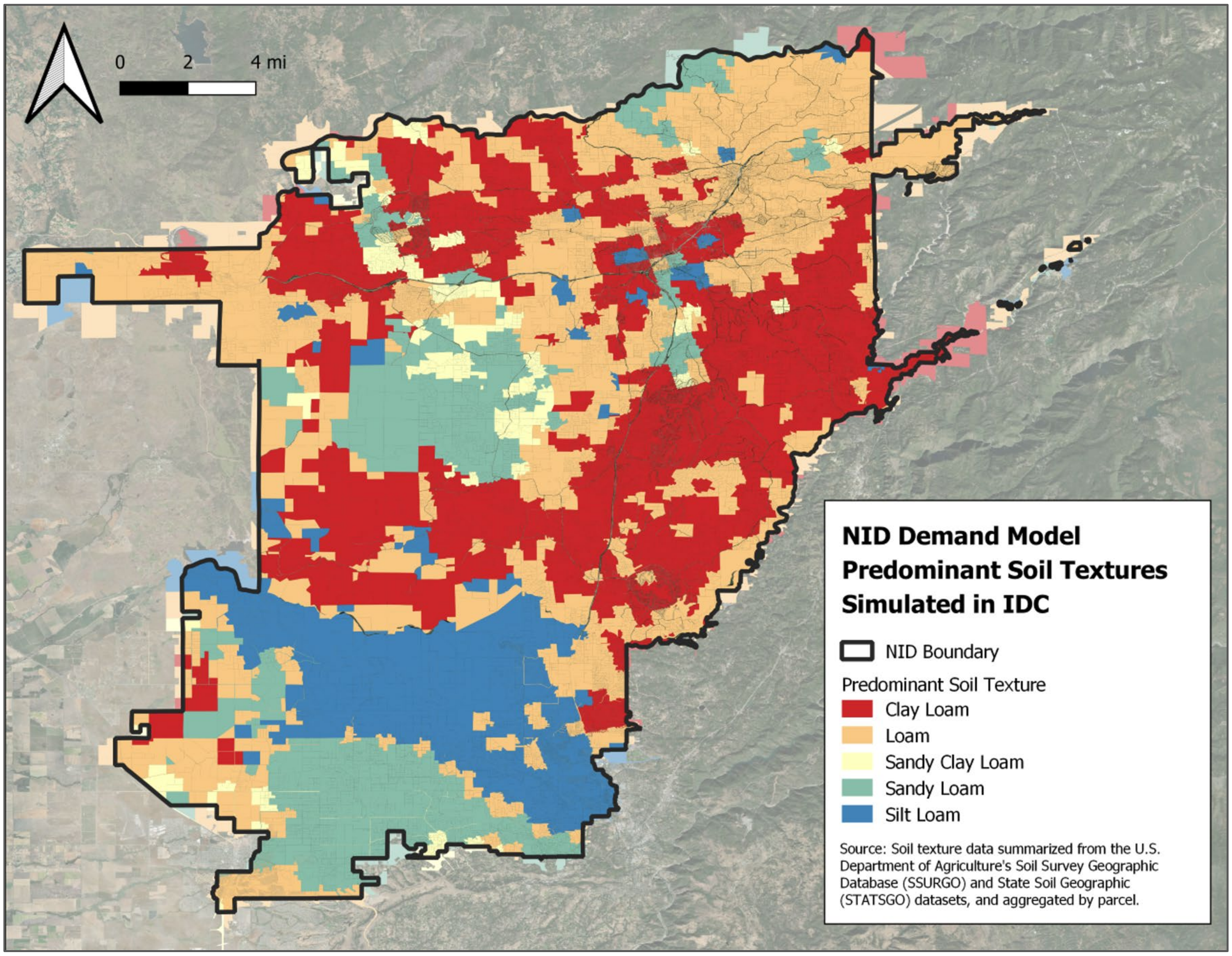


Figure 4-9. Predominant Soil Textures Simulated in the IDC Model

4.2.3.2.3. Runoff Curve Numbers

The IDC model uses a modified version of the SCS curve number (SCS-CN) method to compute runoff of precipitation, which uses curve numbers for each land use class and soil texture to simulate runoff. Curve numbers are used as described in the National Engineering Handbook Part 630 (USDA 2004, 2007) based on the land use or cover type, typical or representative treatment (straight rows, bare soil, etc.), hydrologic condition, and hydrologic soil group. An area-weighted average curve number for each land use-soil texture combination was calculated based on curve number values for each land use (SCS 1986) over the area in each hydrologic soil group, assuming generally good hydrologic conditions (Table 4-7).

Table 4-7. Curve Number Used to Represent Runoff Conditions in the IDC Model

Land Use Category	Soil Texture (Hydrologic Soil Group[1])				
	Clay Loam (D)	Loam (B)	Sandy Loam (A)	Silt Loam (B)	Sandy Clay Loam (C)
Citrus and Subtropical	82	65	44	65	77
Miscellaneous Deciduous	82	65	44	65	77
Miscellaneous Truck and Nursery	89	78	67	78	85
Pasture	78	58	30	58	71
Vineyard	82	65	44	65	77
Young Perennial	82	65	44	65	77
Idle	93	85	76	85	90
Urban and Residential	60	60	60	60	60
Native Vegetation	79	60	36	60	73
Riparian Vegetation	77	56	35	56	70
Water	100	100	100	100	100

[1]Hydrologic soil groups and curve numbers summarized from Appendix B.1 of the SCS Report "Urban Hydrology for Small Watersheds" (TR-55) (SCS 1986).

4.2.3.3 Agriculture and Irrigation Water Use Inputs

Other inputs to the IDC model pertaining to agricultural water use, irrigation, and operational practices are described below.

4.2.3.3.1. Root Depth

Root depths simulated in the IDC model for each of the agricultural land use categories were estimated primarily from ASCE-EWRI (2016) and Keller and Bliesner (1990) (Table 4-8).

Table 4-8. Root Depths Simulated in the IDC Model by Agricultural Land Use Category

Agricultural Land Use Category	Root Depth (ft)
Citrus and Subtropical	4.0
Miscellaneous Deciduous	4.0
Miscellaneous Truck and Nursery	2.5
Pasture	3.0
Vineyard	4.0
Idle	3.0

4.2.3.3.2. Irrigation Period

In the IDC model, the irrigation period determines the periods when each agricultural land use is irrigated. In the IDC model, the irrigation period was enabled, and demand was summarized between March and October for all irrigated agricultural land uses, roughly corresponding with the irrigation season in NID. For idle land uses (and other non-irrigated, non-agricultural land uses), the irrigation period was disabled in all months.

4.2.3.3.3. Tailwater

In the IDC model, tailwater is simulated as a fraction of the total applied irrigation water that results in runoff. In the IDC model, tailwater for all irrigated agricultural land uses was estimated to be approximately 5% of applied water on average, recognizing that a small amount of runoff typically occurs even with high-efficiency irrigation methods. Apart from tailwater, the IDC model assumed that all water supplied to parcels for irrigation of agricultural land uses was available or used for irrigation.

4.2.3.3.4. Soil Moisture Parameters

The minimum soil moisture value for each agricultural land use corresponds to the moisture content at the management allowable depletion (MAD) specified for that land use, which is the desired soil water deficit at the time of irrigation and can vary with growth stage (ASABE 2007). During irrigation, the minimum soil moisture is often restricted to the percent of total available moisture that a crop can withstand without suffering stress or yield loss. Water stress is estimated within the IDC model when the percentage of total available moisture exceeds 50%. Thus, values for the minimum soil moisture were set to 50% for all irrigated land uses to prevent additional stress from occurring in the simulation. However, it is important to note that the ET and Kc values, as described previously, were developed using satellite-based remote sensing analyses of actual ET occurring on the landscape. Thus, in the current demand scenario the ET estimates already included observed ET reductions that may have occurred due to water stress or other factors. In the projected demand scenarios, ET reductions due to water stress were simulated by proxy through other assumptions (described Section 4.3).

The target soil moisture fraction corresponds to the fraction of available soil moisture that irrigation provides. In the IDC model, target soil moisture fractions were estimated between approximately 0.80–1.05 for all land use classes based on common irrigation methods and scheduling practices in which irrigators typically irrigate near field capacity.

4.2.3.4 Urban and Residential Water Use Inputs

In the IDC model, urban and residential water use was simulated based on population data, per capita water use requirements, typical fractions of indoor versus outdoor water use, and parameters used to estimate outdoor water use (ET, curve numbers, etc. described above). Urban and residential water use inputs were simulated for different urban regions within NID to facilitate refinement of IDC inputs to represent population, per capita water use, and other conditions in different areas (Table 4-9). In the IDC model, these urban regions were used primarily to estimate the treated water demand of NID customers located within those regions. The data and information sources used to estimate population and treated water use are described below.

Table 4-9. Urban Regions Simulated in the IDC Model, With Average Per Capita Water Use

Urban Region	Simulated in Climate Zone(s)	Average Per Capita Water Use 2014–2021 (Gallons Per Person Per Day)
City of Grass Valley	Zone 1	150
City of Nevada City	Zone 1	150
City of Lincoln	Zone 3	130
Other Urban Areas (Rural Communities and Residential Areas, Unincorporated Areas, etc.)	Zone 1-3	150–180
Urban Soft Service Areas	Zone 1-3	150

4.2.3.4.1. Population

For the IDC model, annual population information was quantified for the different urban regions within NID for each of the demand model scenarios using the best available information. For the current demand scenario, annual population data were obtained from the California Department of Finance and from the United States Census Bureau American Community Survey for cities, census designated places, and unincorporated areas in Nevada, Placer, and Yuba Counties. Available population data were summarized for simulated urban and residential areas within the NID service area as unitized IDC inputs (i.e., average population per unit area). For the projected demand scenarios, population changes in NID's service area and customer base were evaluated based on analyses of population projections from the California Department of Finance and from Nevada, Placer, and Yuba County General Plan information (summarized in Section 4.3).

4.2.3.4.2. Treated Water Use

Monthly per capita water use and other parameters used to simulate indoor and outdoor water use were also quantified for the different urban regions within NID for each of the demand model scenarios using the best available information.

Per capita water use (as a volume per capita) is used in the IDC model to simulate the amount of treated water that is used within each urban and residential area, on average, across the population. In the current demand scenario, average monthly per capita water use rates were quantified from available historical water production data in 2014–2021 extracted from the California State Water Resources Control Board (SWRCB) and from NID water treatment plant data, with reference to population information available in the SWRCB records and population estimates quantified independently for the IDC model (above). The average daily per capita water use in each urban demand region is summarized in Table 4-9. In the projected demand scenarios, per capita water use in all years was estimated to be similar to the per capita water use in 2022 across all simulations, as changes to treated water demand were simulated through changes to population and other inputs (see Section 4.3). In all scenarios, the fraction of water used indoors versus outdoors was estimated based on the average monthly distribution of per capita water use from available data in 2014–2021, estimating that the water use in February (typically the minimum monthly use) is used primarily for indoor uses. The IDC model simulated all indoor use based on per capita water use requirements, while outdoor use was also simulated with respect to ET demands and available precipitation, similar to irrigated land uses (described above).

4.2.3.4.3. Municipal Water Use (Raw Water)

In addition to serving raw and treated water customers, NID also supplies raw water to municipal water suppliers. NID's municipal water supplies ("municipal water use") are not directly simulated in the IDC model, which simulates direct water use on the landscape for irrigation and urban or residential use. However, municipal water use is quantified outside the IDC model using the best available information. Municipal water use is incorporated into the demand estimates in the canal system balance and is included in the overall results of the demand model.

In the current demand scenario, municipal water use was quantified directly from NID's records of raw water deliveries to municipal water customers in 2013–2022. In the projected demand scenarios, changes to municipal water use were estimated based on five-year projected changes to municipal water use (2020–2040) from NID's Urban Water Management Plan, with interpolation or extrapolation in the intervening and following years through the end of the projected period.

4.2.3.5 Parcel Linkages to IDC and the Canal System Balance

Alongside development of the IDC model, geospatial parcel information was evaluated and summarized for all parcels within the NID service area. Historical parcel maps, parcel areas, and identifying information were gathered from Nevada, Placer, and Yuba Counties. Parcel data were then linked to other geospatial data and summarized to determine the predominant characteristics of each parcel (by area), including:

- Predominant land use within the parcel, based on the land use analysis described in Section 4.2.3.2.1.
- Predominant soil texture within the parcel, based on the soil analysis described in Section 4.2.3.2.2.
- Representative climate zone, based on delineations of climate zones through an assessment of elevation profiles, precipitation (Section 4.2.3.1.2), and ETo (Section 4.2.3.1.1).

The parcel linkages to a predominant land use, soil texture, and climate zone allowed the unitized IDC model results (e.g., AF/acre) to be linked directly to parcels matching the same combination of primary characteristics, with an associated area over which those IDC results are applied (e.g., acre). The IDC-parcel linkages thus permitted spatial representation of demand volumes (AF) across the NID service area over time under the different scenarios.

Parcels were also linked to information about the NID service area and NID customer base, identifying existing NID customers and providing the ability to add or remove NID customers spatially over time in the projected demand scenarios depending on their location within the NID soft service areas and proximity to NID canals. Additionally, parcels were linked to information from the Nevada, Placer, and Yuba County General Plans related to parcel zoning, land use mapping, and planning to identify areas where development may occur over the next 50 years.

In combination, these parcel linkages allowed for:

- Quantification of demand volumes from the IDC model, and connection of those demand volumes spatially within the NID service area and canal system through the canal system balance (Section 4.2.4).
- Verification of the historical demand model results compared to historical NID delivery records (Appendix B.4).
- Simulation of future changes to NID's customers and service area at the parcel-level in the projected demand scenarios (scenarios described in Section 4.3).

4.2.4. Canal System Balance

The canal system balance component of the demand model takes the results of the IDC model that are linked to parcels in NID and connects those results to specific NID reservoirs, incorporating estimates of the canal system losses incurred in the process of delivering water from the reservoirs to NID's customers. The canal system balance thus quantifies the demand, or outflows from NID's reservoirs, which would be required to supply the water needs of NID's customers, inclusive of system losses in NID's canals and distribution system downstream of NID's reservoirs. These demand volumes are incorporated and simulated within the reservoir operations model (Chapter 5. Operations Model), along with regulatory-required environmental flows. This section briefly describes the process and assumptions of the canal system balance.

4.2.4.1 Demand Zones

Parcels and municipal water suppliers within the NID service areas were associated with specific demand zones that identify the specific NID reservoir ("demand node") from which NID's customers receive water deliveries. Through development of the demand zones, linkages were made between:

- Parcels representing raw and treated water customers served by NID, either currently or in projected demand scenarios and the canals that deliver—or would deliver—water to those parcels.
- Municipal water suppliers that receive raw water from NID and the canals that deliver water to those suppliers.
- Canals within the overarching NID canal system and the upstream NID reservoir that supplies water to those canals within the canal system.

A map of NID's service area, the delineation of demand zones, and connection of demand zones to particular NID reservoirs (i.e., demand nodes) is shown in Figure 4-10. Demands within each demand zone are aggregated to the demand node and represent the outflows from the NID reservoir supplying water to that demand zone.

4.2.4.2 System Losses

As water is released from NID's reservoirs into the canal system, some water is lost to seepage, evaporation, and other downstream outflows. In the canal system balance, system losses were estimated to be approximately 15% of the canal inflows, based on findings from NID's RWMP and associated analyses by NID of water that is released into NID canals that is not delivered to NID customers. Opportunities exist for further refinement of these system loss estimates through further data collection and analysis. The system loss estimate is understood to include seepage (i.e., infiltration of water into the groundwater system) from the canal system, evaporation from open water surfaces, and downstream outflows not delivered to NID customers. The system loss estimate does not include losses from NID reservoirs simulated in the reservoir operations model or other upper system losses above those reservoirs. Losses from NID's reservoirs are accounted for in the reservoir operations model.

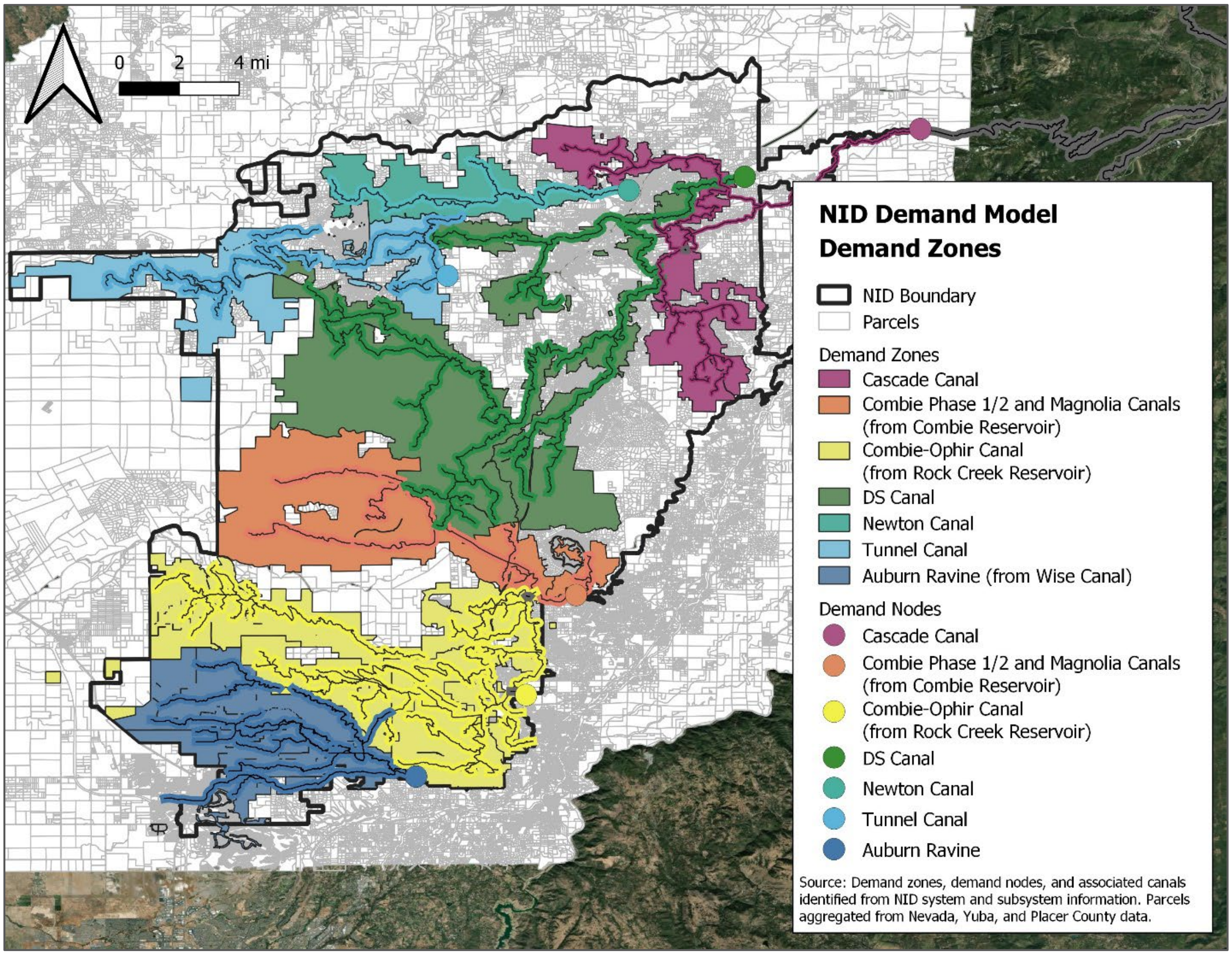


Figure 4-10. Demand Zones and Demand Nodes Simulated in the Demand Model

4.2.5. Demands from NID Reservoirs

As described previously, the demand (or outflows) from each of NID's reservoirs are summarized from the aggregated demands of NID's raw water customers, NID's treated water customers, municipal water customers, and system losses in the demand zones that are supplied from each respective NID reservoir (i.e., demand nodes).

The demand requirements at each demand node include the sum of:

- Demand results from the IDC model, representing the demand of NID's raw and treated water customers. Results are summarized for parcels within the demand zones supplied from the demand node.

- Municipal water use estimates, representing the demand of municipal water suppliers that receive raw water from NID.
- System losses, representing the loss of water from NID's canals downstream of NID's reservoirs that is not supplied to NID customers.

Regulatory-required environmental flows are not included in these demand model results but are included in the reservoir operations model.

The demand requirements from each of NID's reservoir (i.e., from each demand node) serve as an input and the primary point of connection between the reservoir operations model and the demand model. Additional information about how demands are incorporated into the reservoir operations model are described in Chapter 5. Operations Model.

4.3. Demand Model Scenarios

4.3.1. Summary of Scenarios

The demand model was developed and used to estimate demands for a total of 11 scenarios:

- One current demand scenario representing recent historical demand conditions in 2013–2021, as a baseline for comparison and interpretation of the projected demand scenarios.
- Ten projected demand scenarios, representing a range of potential future demand conditions in 2022–2071, including:
    - Nine scenarios representing the combinations of three potential demand scenarios and three potential climate scenarios.
    - One current demand constant baseline scenario, considering current demand (2022) and median hydrologic conditions for 2022–2071.

Assumptions and information used to develop the scenarios are summarized in Table 4-10.

The current demand scenario was developed using recent historical data for the NID service area based on the data sources and methodologies described in Section 4.2. The projected demand scenarios were developed based on the assumptions described in Section 4.3.2. Average results of the current and projected demand scenarios are summarized in Section 4.4.

Table 4-10. Summary of Demand Model Scenarios with Information about Underlying Assumptions and Data Sources

Demand Model Scenario			Climate-Related Conditions		Demand-Related Conditions		
Period	Demand Scenario	Hydrology Scenario (CMIP-6)	Precipitation	Evapotranspiration	Raw Water Demand	Treated Water Demand	System Losses
Current (2013–2021)	Recent historical	N/A	Recent historical data (Section 4.2.3.1)	Recent historical data (Section 4.2.3.1)	Recent historical customers and demand conditions (Sections 4.2.3 and 4.2.4)	Recent historical customers and demand conditions (Sections 4.2.3 and 4.2.4)	Historical canal losses (15%, from NID RWMP, Section 4.2.4)
Projected (2022–2071)	Low	**Dry** (CESM2-LENS_ssp370)	Climate change analysis (Dry hydrology scenario)	Calculated based on temperature-adjusted ETo (Dry hydrology scenario) and 25th percentile Kc curve (by land use, from 2022)	20% demand reduction from baseline	Population decline to lowest since 2000	10%
	Low	**Median** (CNRM-ESM2 1_ssp245)	Climate change analysis (Median hydrology scenario)	Calculated based on temperature-adjusted ETo (Median hydrology scenario) and 25th percentile Kc curve (by land use, from 2022)	20% demand reduction from baseline	Population decline to lowest since 2000	10%
	Low	**Wet** (EC-Earth3-Veg_ssp370)	Climate change analysis (Wet hydrology scenario)	Calculated based on temperature-adjusted ETo (Wet hydrology scenario) and 25th percentile Kc curve (by land use, from 2022)	20% demand reduction from baseline	Population decline to lowest since 2000	10%

Demand Model Scenario			Climate-Related Conditions		Demand-Related Conditions		
Period	Demand Scenario	Hydrology Scenario (CMIP-6)	Precipitation	Evapotranspiration	Raw Water Demand	Treated Water Demand	System Losses
Projected (2022–2071)	Baseline	Dry (CESM2-LENS_ssp370)	Climate change analysis (Dry hydrology scenario)	Calculated based on temperature-adjusted ETo (Dry hydrology scenario) and 50th percentile Kc curve (by land use, from 2022)	Expansion to soft service areas similar to historical rate (~20 acres/year developed land)	Expansion to soft service areas similar to historical rate (~50 customers/year)	15%
	Baseline	Median (CNRM-ESM2 1_ssp245)	Climate change analysis (Median hydrology scenario)	Calculated based on temperature-adjusted ETo (Median hydrology scenario) and 50th percentile Kc curve (by land use, from 2022)	Expansion to soft service areas similar to historical rate (~20 acres/year developed land)	Expansion to soft service areas similar to historical rate (~50 customers/year)	15%
	Baseline	Wet (EC-Earth3-Veg_ssp370)	Climate change analysis (Wet hydrology scenario)	Calculated based on temperature-adjusted ETo (Wet hydrology scenario) and 50th percentile Kc curve (by land use, from 2022)	Expansion to soft service areas similar to historical rate (~20 acres/year developed land)	Expansion to soft service areas similar to historical rate (~50 customers/year)	15%

Demand Model Scenario			Climate-Related Conditions		Demand-Related Conditions		
Period	Demand Scenario	Hydrology Scenario (CMIP-6)	Precipitation	Evapotranspiration	Raw Water Demand	Treated Water Demand	System Losses
Projected (2022–2071)	High	Dry (CESM2-LENS_ssp370)	Climate change analysis (Dry hydrology scenario)	Calculated based on temperature-adjusted ETo (Dry hydrology scenario) and 75th percentile Kc curve (by land use, from 2022)	Greater expansion to soft service areas at 150% baseline rate (~30 acres/year developed land)	Greater expansion to soft service areas at 150% baseline rate (~75 customers/year)	20%
	High	Median (CNRM-ESM2 1_ssp245)	Climate change analysis (Median hydrology scenario)	Calculated based on temperature-adjusted ETo (Median hydrology scenario) and 75th percentile Kc curve (by land use, from 2022)	Greater expansion to soft service areas at 150% baseline rate (~30 acres/year developed land)	Greater expansion to soft service areas at 150% baseline rate (~75 customers/year)	20%
	High	Wet (EC-Earth3-Veg_ssp370)	Climate change analysis (Wet hydrology scenario)	Calculated based on temperature-adjusted ETo (Wet hydrology scenario) and 75th percentile Kc curve (by land use, from 2022)	Greater expansion to soft service areas at 150% baseline rate (~30 acres/year developed land)	Greater expansion to soft service areas at 150% baseline rate (~75 customers/year)	20%
Current Demand Constant Baseline (2022–2071)	Recent historical (2022)	Median (CNRM-ESM2 1_ssp245)	Climate change analysis (Median hydrology scenario)	Calculated based on temperature-adjusted ETo (Median hydrology scenario) and 50th percentile Kc curve (by land use, from 2022)	Recent historical customers and demand conditions (2022)	Recent historical customers and demand conditions (2022)	Historical canal losses (15%, from NID RWMP, Section 4.2.4)

4.3.2. Projected Demand Scenario Assumptions

The 10 projected demand scenarios were developed using available estimates of future climate conditions from the projected hydrology scenarios, as well as assumptions about future changes to NID's raw water and treated water customer base over a range of potential system losses. The purpose of these projected demand scenarios was to develop a range of potential future demand conditions that could occur—as baseline or bookend conditions—from 2022 through 2071.

The primary data sources and assumptions used to develop the 10 projected demand scenarios are summarized in Table 4-10. Nine of the projected demand scenarios were developed as the combinations of:

- Three potential demand scenarios, corresponding to baseline or bookend (low or high) demand-related conditions with respect to raw water customer demand, treated water customer demand, and system losses.
- Three potential climate scenarios, corresponding to the climate change analyses (CMIP-6 results) used in the three projected hydrology scenarios (wet, median, and dry hydrologic conditions). The climate-related conditions were factored into estimates of precipitation and crop water use, as manifested through temperature-related impacts on ET. Precipitation and temperature information from the corresponding projected hydrology scenario were summarized for each of the IDC climate zones before their inclusion in the demand model.

Through these combinations, these nine projected demand scenarios resulted in:

- Three baseline demand scenarios, representing a baseline projection of demand conditions in 2022–2071 that follows the current trajectory and/or best information about expected projected changes to NID's customers and their demands. One scenario each accounted for wet, median, and dry hydrologic conditions.
- Three low demand scenarios, representing a lower bookend of low demand conditions in 2022–2071. These demand scenarios represented the lowest simulated projection of demand conditions, based on assumptions of potential raw water demand reductions, potential population decline, and potential reductions in system loss. One scenario each accounted for wet, median, and dry hydrologic conditions.
- Three high demand scenarios, representing an upper bookend of high demand conditions in 2022–2071. These demand scenarios represented the highest simulated projection of demand conditions, based on assumptions of potential raw water and treated water demand increases, associated with potential expansions of the NID service area, and potential increases in system loss. One scenario each accounted for wet, median, and dry hydrologic conditions.

The 10th projected demand scenario was developed to simulate a current demand constant baseline, considering current demand conditions in 2022 and median hydrologic conditions in 2022–2071. Current demand conditions were summarized from recent historical data for the NID service area based on the data sources and methodologies in Section 4.2. Median hydrologic conditions were summarized using the same data sources and methodologies used for summarizing the climate-related conditions in the other projected demand scenarios, described below.

The parameters and assumptions used to develop the projected demand scenarios are summarized below.

4.3.2.1 Climate-Related Conditions

Climate-related conditions that were considered in the projected demand scenarios include precipitation and evapotranspiration (also described in Section 4.2.3.1).

Precipitation was summarized directly from results of the climate change analyses (CMIP-6 results) used in the three projected hydrology scenarios (wet, median, and dry hydrologic conditions). Average precipitation from the corresponding projected hydrology scenario was summarized across each of the IDC climate zones and was then included in the IDC model component of the demand model. Additional information is provided in Section 4.2.3.1.2.

Evapotranspiration was calculated following the standard crop coefficient approach described in FAO Irrigation and Drainage Paper 56 (Allen et al. 1998), based on:

- Temperature-adjusted ETo, quantified following the standard Hargreaves-Samani approach using temperature information from the climate change analyses (CMIP-6 results) used in the three projected hydrology scenarios (wet, median, and dry hydrologic conditions). Average temperature from the corresponding projected hydrology scenario was summarized across each of the IDC climate zones.
- Kc curves for each land use, representing either the:
    - 25th percentile Kc curve (for the low demand scenario),
    - Median (50th percentile) Kc curve (for the baseline demand scenario), or the
    - 75th percentile Kc curve (for the high demand scenario).

Additional information is provided in Section 4.2.3.1.1 and Appendix B.2. The selection of the 25th percentile and 75th percentile Kc curve for the low and high demand scenarios was informed by comparison of ET differences from the baseline demand scenario to typical differences in ET under reasonable changes in cultivation and irrigation practices where ET is reduced (in the low bookend scenario) or ET is increased (in the high bookend scenario). Typical ranges of ET variability are +/-15% or more, depending on conditions, and are consistent with the ET variability from the baseline scenarios resulting from the 25th and 75th percentile Kc curves (Appendix B.2).

4.3.2.2 Demand-Related Conditions

Demand-related conditions considered in the projected demand scenarios include raw water demand, treated water demand, and system losses (described in Section 4.2.3.1).

Raw water demand was estimated for each of the projected demand scenarios as follows:

- For the low demand scenario: A 20% reduction in raw water demand from baseline conditions. These potential demand reductions are not explicitly tied to any specific future conditions within the NID service area but are considered to be within the range of potential changes due to agronomic practices, future impacts due to regulatory constraints, land use changes, or other constraints.

- For the baseline demand scenario: Expansion of NID's customer base into soft service areas at an average rate similar to the historical average growth of NID's raw water customers (approximately 20 acre/year of developed land). The historical average growth of NID's raw water customers was determined based on an analysis of NID delivery records from 2013–2022, in relation to the total areas (and developed areas) of parcels that received raw water deliveries from NID over time.
- For the high demand scenario: Expansion of NID's customer base into soft service areas at an average rate that is approximately 150% (1.5X) of the historical average growth of NID's raw water customers (approximately 30 acre/year of developed land). This potential growth of NID's raw water customer base was determined to be a high estimate, considering the total area of parcels potentially suitable for raw water customers within the soft service areas (based primarily on land use analyses).

Treated water demand was estimated for each of the projected demand scenarios as follows:

- For the low demand scenario: Estimated based on population decline to the lowest population identified in the NID service area since 2000, based on evaluation of available historical population data (Section 4.2.3.4.1). The potential population decline is not explicitly tied to any specific future conditions within the NID service area but is considered to be within the range of potential changes over the next 50 years.
- For the baseline demand scenario: Expansion of NID's customer base into soft service areas at an average rate similar to the historical average growth of NID's treated water customers (approximately 50 customers/year). The historical average growth of NID's treated water customers was determined based on an analysis of NID delivery records from 2013–2022.
- For the high demand scenario: Expansion of NID's customer base into soft service areas at an average rate that is approximately 150% (1.5X) of the historical average growth of NID's treated water customers (approximately 75 customers/year). This potential growth of NID's treated water customers was determined considering the parcels potentially suitable for treated water customers within the soft service areas (based primarily on land use analyses).

System losses in NID's canals and distribution system downstream of NID's reservoirs were estimated for each projected demand scenario as either:

- 10% of canal inflows (for the low demand scenario),
- 15% of canal inflows (for the baseline demand scenario), or
- 20% of canal inflows (for the high demand scenario).

The baseline demand scenario system losses were estimated as equal to historical canal losses, based on findings from NID's RWMP and associated analyses by NID of water that is released into NID canals that is not delivered to NID customers (Section 4.2.4.2). The low and high demand scenario system losses were estimated as a +/- 5% range around the baseline demand scenario system losses and are considered within the range of typical losses of canal systems in California.

4.4. Results

Average annual results of the current and projected demand scenarios are summarized in Table 4-11. Results of the projected scenarios are also shown in Figure 4-11 through Figure 4-14. The average annual demand estimates in the baseline demand scenarios were approximately 2,500 to 5,300 AF/year greater than the current demand scenario (2–3% greater), with higher demands experienced in the median and wet hydrology scenarios. In contrast, the average annual demand estimates in the low demand scenarios were approximately 39,000 to 41,000 AF/year lower (26–27% lower) than the current demand scenario, while the high demand scenarios were approximately 35,000 to 39,000 AF/year higher (23–25% higher) than the current demand scenario. Some variability was observed between the hydrology scenarios, although that was less than the differences between demand scenarios. The current demand constant baseline scenario resulted in approximately 156,000 AF/year of total demand.

Overall, the demand scenarios resulted in greater changes in total demand estimates versus the hydrology scenarios, pointing toward greater impacts between scenarios due to demand-related conditions rather than climate-related conditions. In total, average annual demand for the high and low demand scenarios ranged approximately +/- 40,000 AF/year around the current demand scenario, and with a similar range around the current demand constant baseline scenario. The wide range of potential demand conditions is reflective of the bookend nature of the high and low demand scenarios; although neither scenario is anticipated to occur with a high degree of certainty, these scenarios do provide useful bounds on the extremes that could strain NID's operations in the future. In reality, changes in demand conditions (either decreases or increases) would be expected to be less pronounced than those presented in the bookend scenarios.

Although climate-related conditions did result in some differences between scenarios—as observed in Table 4-11 and Figure 4-11 through Figure 4-14—the changes between scenarios resulted in less extreme changes. It is noted that the hydrology scenarios (dry, median, and wet) were developed and defined to be reflective of unimpaired inflows to NID's reservoirs, on average, over the projected period. The hydrology scenario naming conventions are not strictly indicative of hydrologic conditions with respect to average precipitation and temperature within the NID service area. For instance, higher average annual ETo is experienced in both the dry and wet hydrology scenarios, as compared to the median scenario, and is tied to higher temperatures in both the dry and wet scenarios. Additionally, while the wet hydrology scenario features the highest average annual precipitation of all scenarios, the timing of that precipitation occurs more during the winter months, whereas the highest precipitation during the irrigation season months occurs in the dry hydrology scenario. Nevertheless, demand estimates for all combinations of climate-related and demand-related conditions are useful for simulating potential future baseline and bookend conditions in the reservoir operations model to analyze water supply versus demand and conditions of unmet demand.

Table 4-11. Average Annual Results of the Current and Projected Demand Scenarios

Scenario			Years in Demand Model	Average Annual Demand (AF/year)	Difference from Current (AF/year)	Difference from Current (%)	Difference from Baseline Median (AF/year)	Difference from Baseline Median (%)
Period	Demand	Hydrology						
Current			2013-2021	153,000	0	0%	-4,000	-3%
Projected	Low	Dry	2022-2071	111,000	-42,000	-27%	-46,000	-29%
	Low	Median	2022-2071	113,000	-40,000	-26%	-44,000	-28%
	Low	Wet	2022-2071	113,000	-40,000	-26%	-44,000	-28%
	Baseline	Dry	2022-2071	155,000	2,000	1%	-2,000	-1%
	Baseline	Median	2022-2071	157,000	4,000	3%	0	0%
	Baseline	Wet	2022-2071	158,000	5,000	3%	1,000	1%
	High	Dry	2022-2071	188,000	35,000	23%	31,000	20%
	High	Median	2022-2071	190,000	37,000	24%	33,000	21%
	High	Wet	2022-2071	191,000	38,000	25%	34,000	22%
Current Demand Constant Baseline	Recent historical (2022)	Median	2022-2071	156,000	3,000	2%	-1,000	-1%

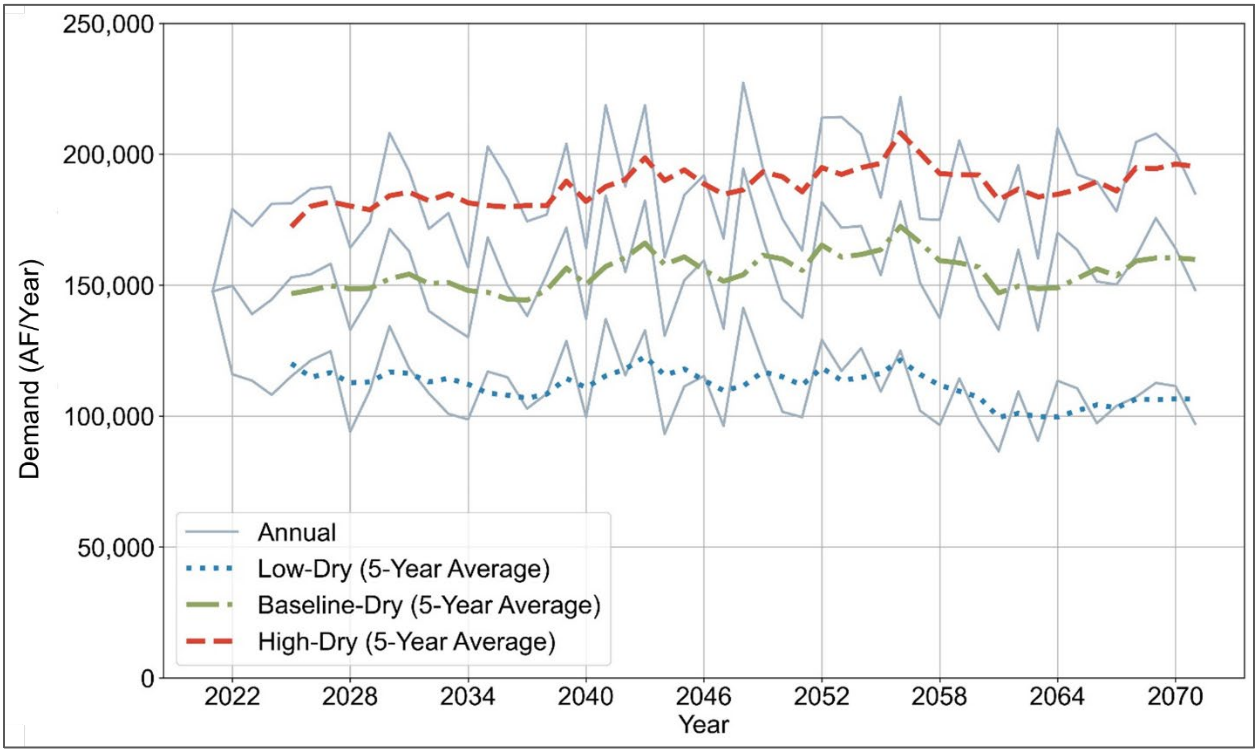


Figure 4-11. Annual Results of the Low, Baseline, and High Demand Scenarios, for Dry Hydrologic Conditions (2022–2071)

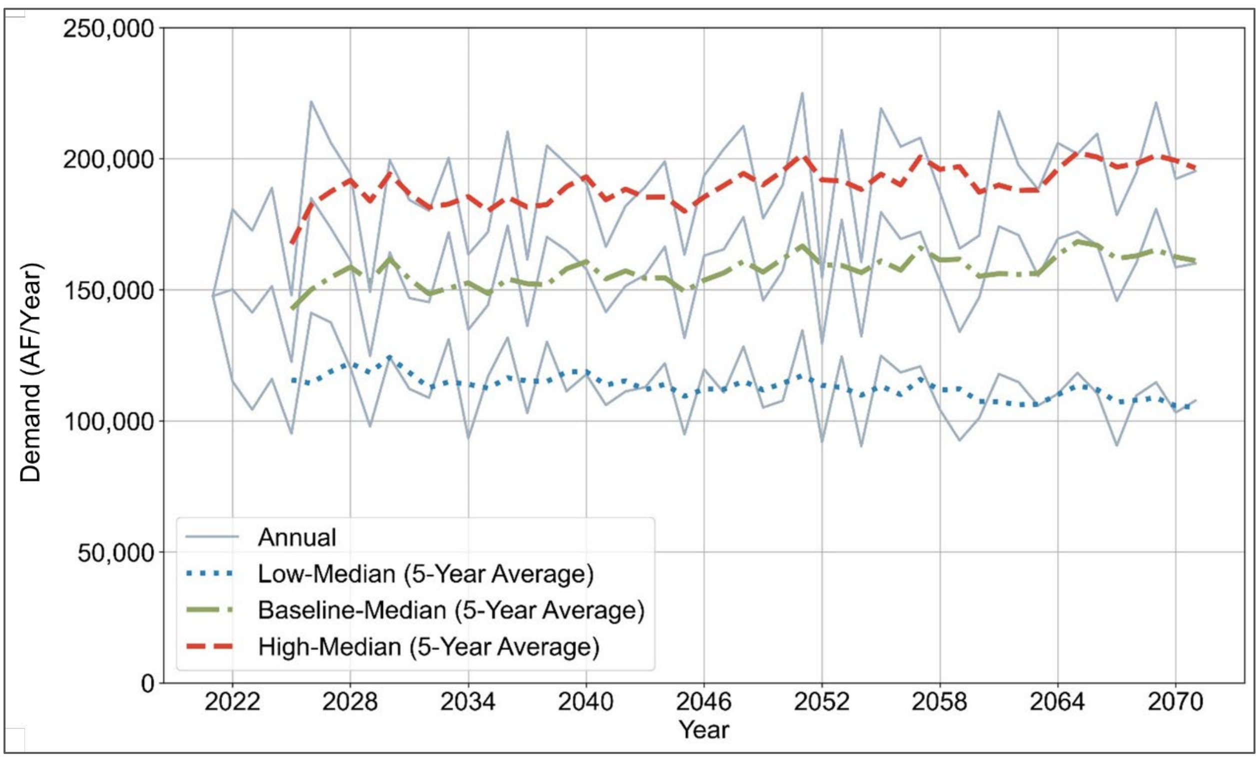


Figure 4-12. Annual Results of the Low, Baseline, and High Demand Scenarios, for Median Hydrologic Conditions (2022–2071)

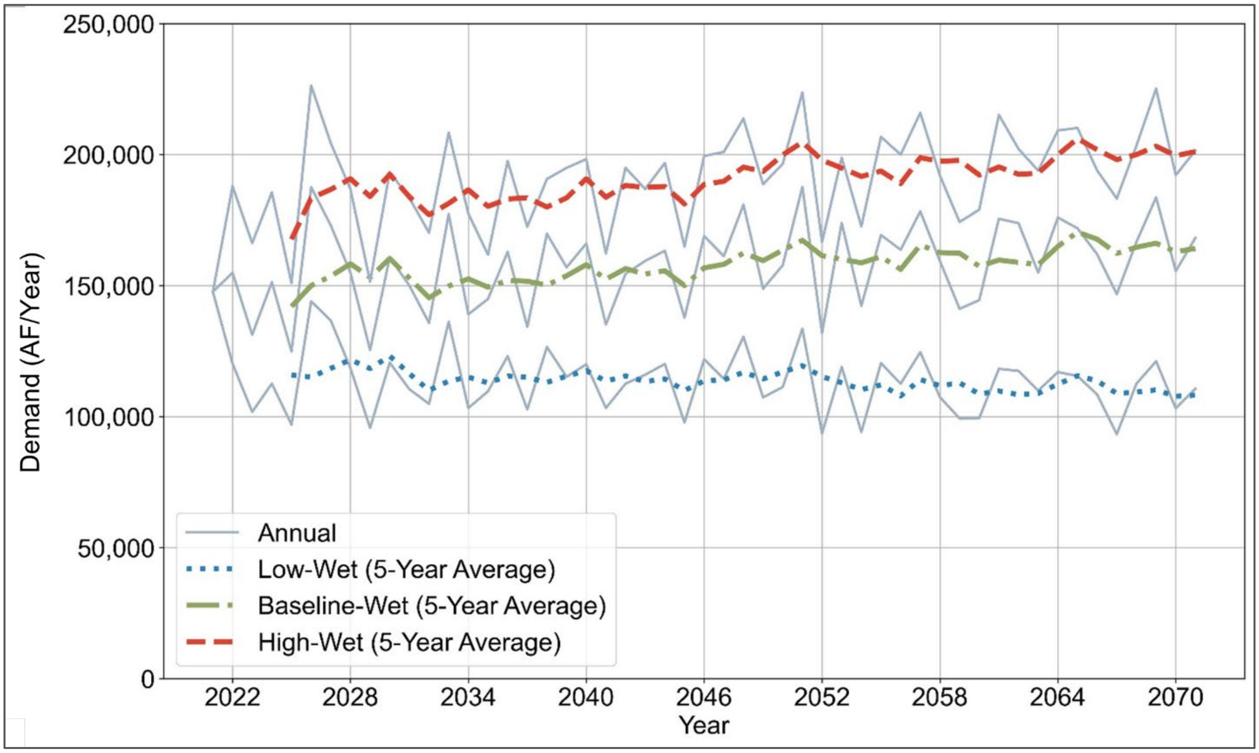


Figure 4-13. Annual Results of the Low, Baseline, and High Demand Scenarios, for Wet Hydrologic Conditions (2022–2071)

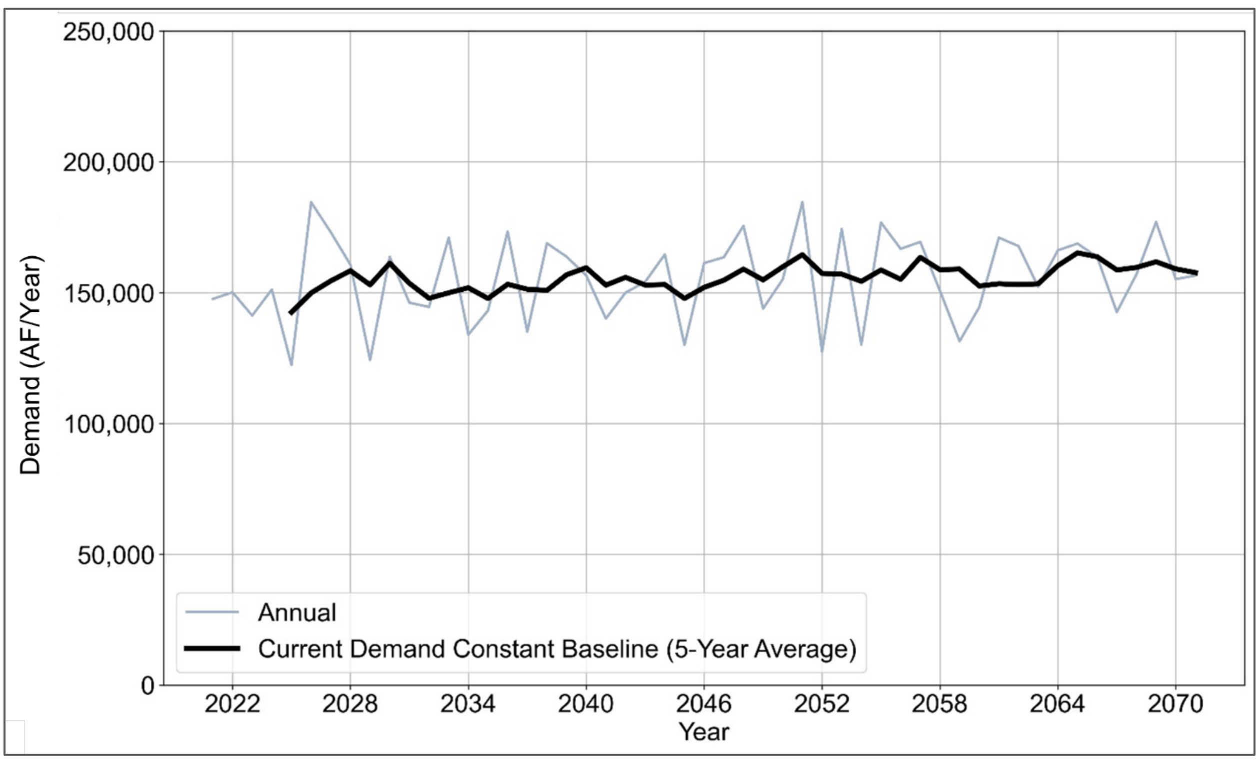


Figure 4-14. Annual Results of the Current Demand Constant Baseline Scenario (2022–2071)

Chapter 5. Operations Model

A reservoir operations model was developed that simulates how NID operates its current storage, conveyance, and delivery system. The operations model uses inflows from the hydrology model, current operating rules, and regulations to assess how well customer demands are met.

NID operations were simulated using a wide range of conditions, including historical conditions, current baseline operations, demands (low, median, and high), and climate (dry, median, and wet). Three future scenarios were selected for evaluation of potential PFW strategies.

- Dry Future Climate with High Demands
- Median Future Climate with Baseline Demands
- Wet Future Climate with Low Demands

These scenarios provide dry and wet bookends with a median climate scenario to represent a plausible mid-point. Use of these scenarios provides a wide range of hydrologic conditions and consumptive demands; the scenarios are suitable for testing the strategic alternatives.

5.1. Historical Inflow Hydrology

Historical inflow hydrology is needed for the calibration of the reservoir operations model and for the development of modeling studies that simulate current facilities and operations over historical inflow hydrology. No facilities in the project area have directly gaged inflows, so inflows need to be calculated or estimated using established hydrologic methods.

5.1.1. Methods

Most reservoirs in the project area do not have sufficient gaging to perform a mass balance calculation to determine inflows. Historical watershed inflows in the project area are estimated using a paired-basin approach, and these estimated inflows are compared to mass balance calculations where available to validate the paired-basin method.

The paired-basin approach used for these historical inflows is the same as that developed for the Yuba-Bear Drum-Spaulding Federal Energy Regulatory Commission (FERC) relicensing process and further refined for additional efforts since the relicensing. The approach is described in detail in NID's 2020 Raw Water Master Plan Hydrological Analysis Technical Memorandum, Appendix B (NID 2020).

5.1.2. Validation

The estimated historical inflow hydrology developed with the paired-basin approach is compared to mass balance calculations for reservoirs where sufficient data exist over a time when gage periods of record overlap. Average annual unimpaired flow is shown in Table 5-1. The comparison for Jackson Meadows Reservoir is shown in Figure 5-1. The comparison for Bowman Reservoir is shown in Figure 5-2. The comparison for Lake Spaulding is shown in Figure 5-3. The comparison for Scotts Flat Reservoir is shown in Figure 5-4.

Table 5-1. Average Annual Unimpaired Flow Comparisons for Historical Hydrology

Watershed	Paired-Basin Estimate (AF)	Mass Balance Calculation (AF)
Jackson Meadows Reservoir	78,477	78,847
Bowman Reservoir	84,705	90,827
Lake Spaulding	340,966	316,177
Scotts Flat Reservoir	19,394	20,537

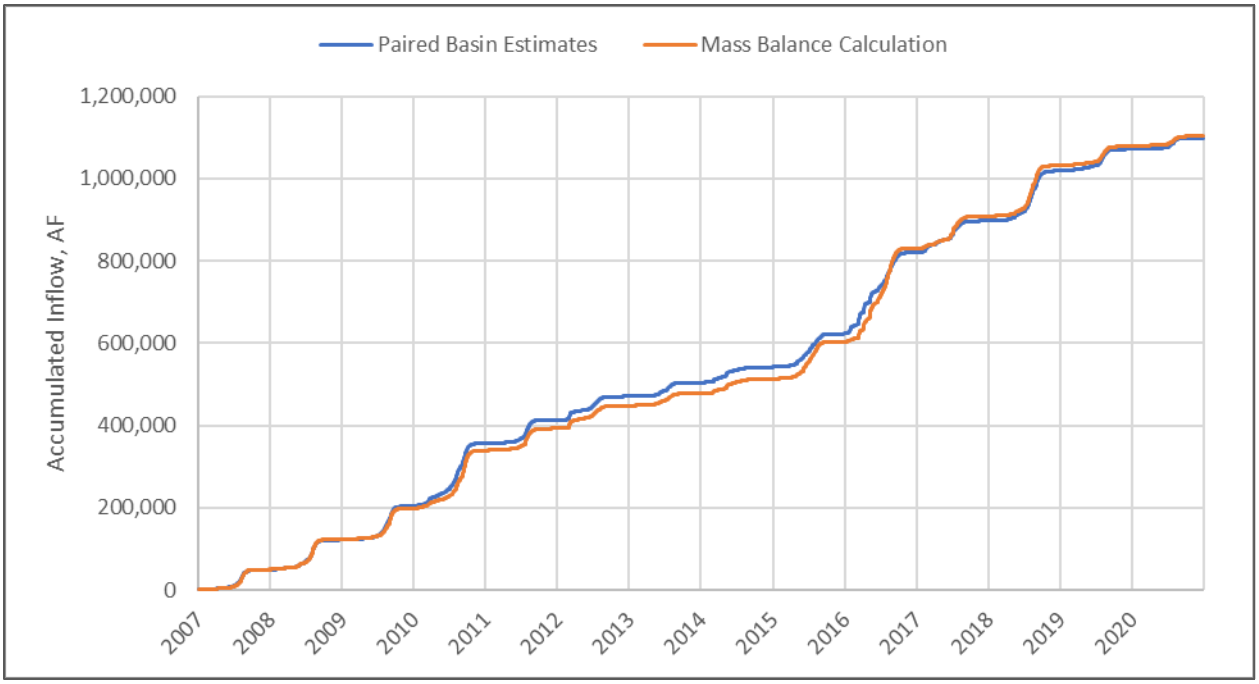


Figure 5-1. Accumulated Inflow Calculations, Jackson Meadows Reservoir, WYs 2008–2021

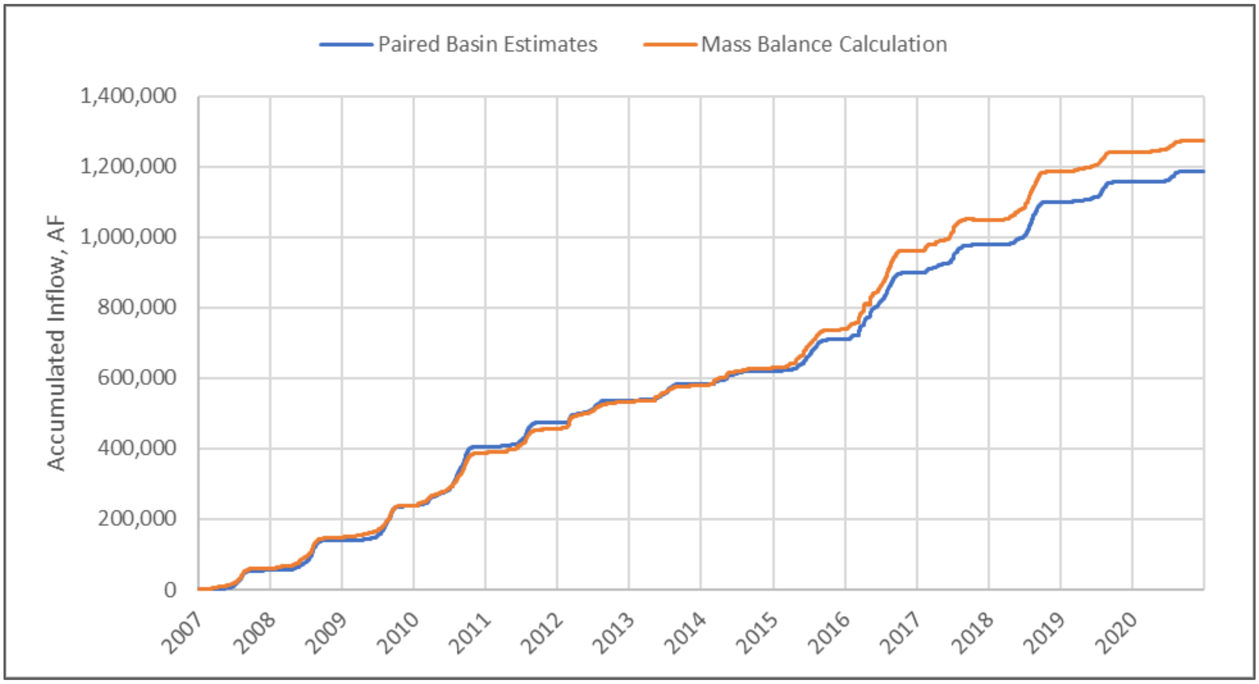


Figure 5-2. Accumulated Inflow Calculations, Bowman Reservoir, Water Years 2008–2021

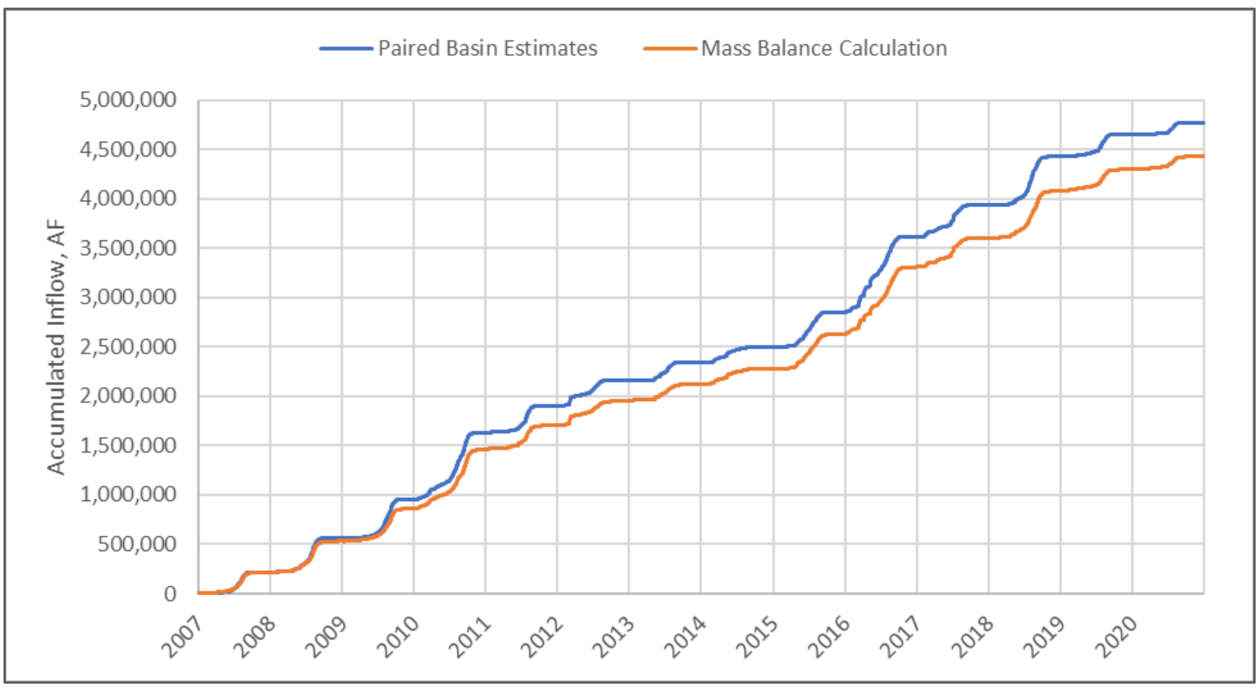


Figure 5-3. Accumulated Inflow Calculations, Lake Spaulding, Water Years 2008–2021

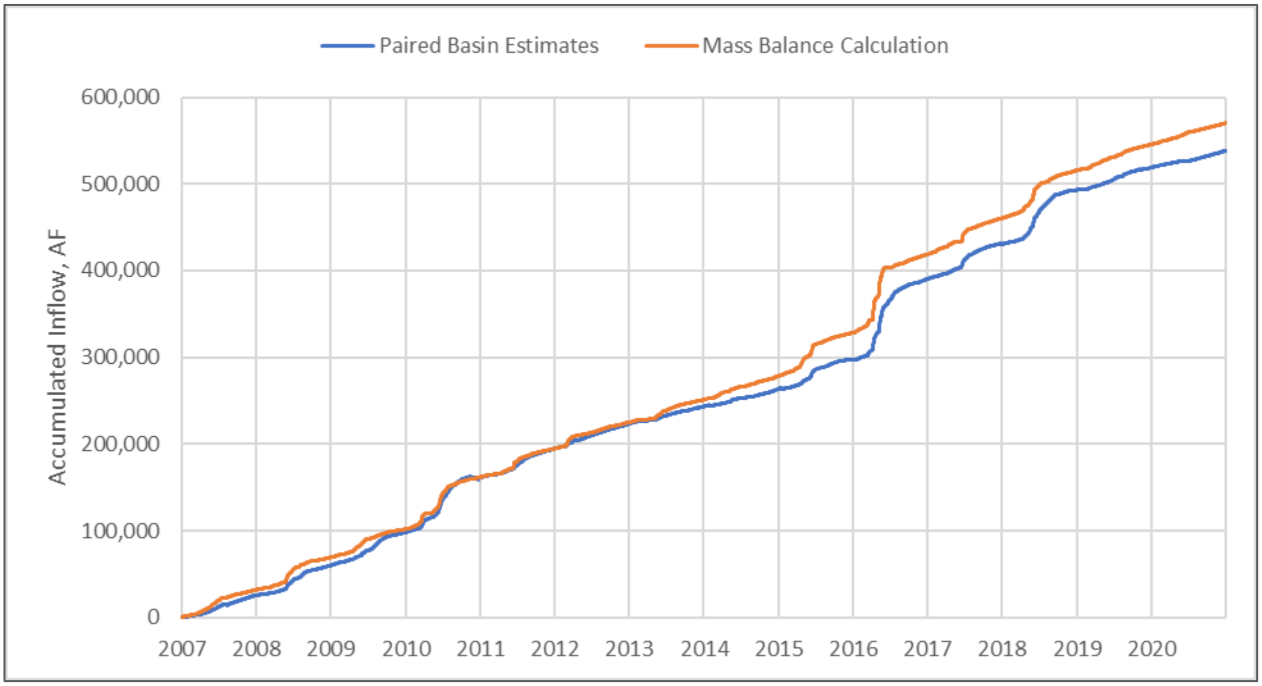


Figure 5-4. Accumulated Inflow Calculations, Scotts Flat Reservoir, Water Years 2008–2021

5.2. Recent Historical Deliveries

Recent historical deliveries were developed for model calibration and for modeling Placer County Water Agency (PCWA) demands[1]. To develop recent historical demand sets, the daily average delivery was calculated at each demand node. The gages used for each demand node are listed in Table 5-2. An example of the average delivery calculation for PCWA's Boardman canal is shown in Figure 5-5, and an example of the average delivery calculation for NID's delivery from Lake Combie is shown in Figure 5-6.

Table 5-2. Gages Used in Calculating Historical Deliveries

Model Demand Node	Diversion Location	Gages Used for Calculation*
NID-1	Rock Creek Reservoir	YB-64 + YB-86 + YB-108 + YB-255
NID-2	Auburn Ravine	YB-132 + YB-136 + YB-259
NID-3	Lake Combie	BR-301 + BR-311
NID-4	Cascade Canal	DC-102
NID-5a	DS Canal	DC-145
NID-5b	Newtown Canal	DC-131
NID-5c	Tunnel Canal	DC-140
PCWA-1	Lake Arthur	YB-184 + YB-95 – YB-288
PCWA-2	Halsey Forebay	YB-56 + YB-87 + YB-288
PCWA-3	Rock Creek Reservoir	YB-69
PCWA-4	Wise Forebay	YB-73

[1] Data received by email correspondence: from Chirs Sanderson, Hydrographer at PG&E, on 9/6/2022 and 9/8/2022.

PCWA-5	Auburn Ravine	YB-75 + YB-76 + YB-78 + YB-91 + YB-278

* Note: gage codes follow NID, PG&E and PCWA gage codes. These agencies group their gages by projects (YB=Yuba Bear System, DC=Deer Creek System, BR = Bear River)

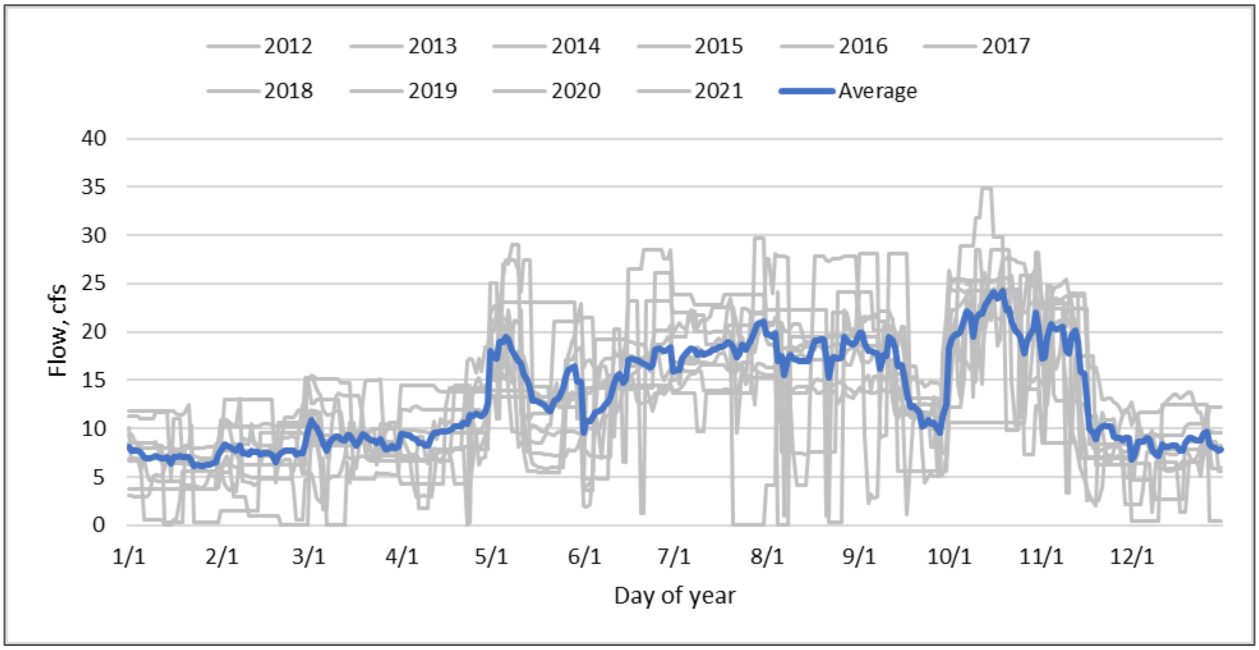


Figure 5-5. Historical Deliveries in Boardman Canal

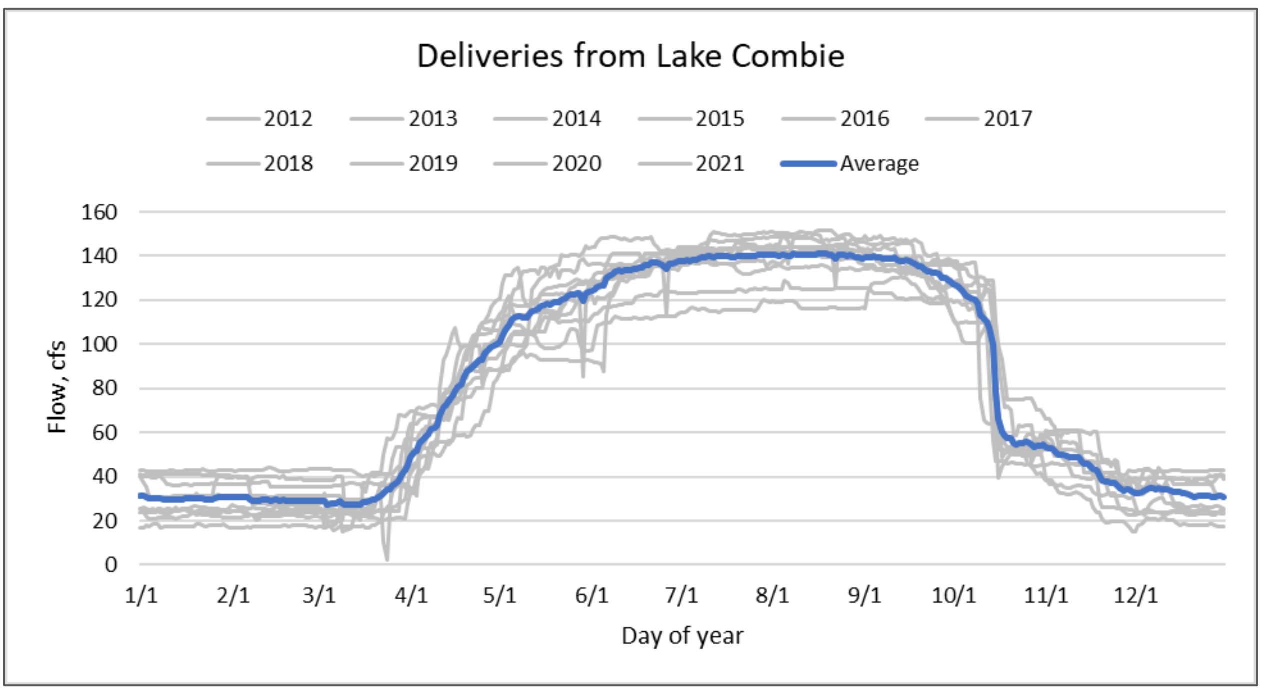


Figure 5-6. Historical Deliveries from Lake Combie

5.3. USACE Hydrologic Engineering Center ResSim Model

5.3.1. Description of the Software Package

The HEC-ResSim software is developed by the USACE HEC and is used to model reservoir operations for reservoir systems. The software is widely used for water supply and flood management in planning studies. The model features rule-based operations that attempts to reproduce the decision-making process that reservoir operators use in reservoir management. The software is Java-based and allows the user to write scripts in Jython, an implementation of the python programming language in Java, which augments the model's flexible rule structures.

5.3.2. Selection Rationale

The HEC-ResSim modeling software is widely used throughout California to model hydropower and water supply projects. The software has all the features needed to model NID's system; previous models of NID's system have been built on HEC-ResSim, making it easier to incorporate previous work done to refine the modeling of NID's system.

5.4. Model Development

5.4.1. Rebuild in Current ResSim Software Version

The latest version of HEC-ResSim is version 3.3, released in 2021, and the NID FERC relicensing model was built in HEC-ResSim version 3.0, released in 2007. Models built in version 3.0 cannot run using the latest ResSim software. Given the software incompatibility issue, the model had to be rebuilt in the current software version. Rules and facility information from the previous model were imported into the new model version, and Jython scripts were written to automate some input and output processing that was previously done in spreadsheets before and after a modeling study was run.

5.4.2. Model Facilities

Reservoirs that are modeled with usable storage are listed in Table 5-3. Additional reservoirs are included in the model that do not have usable storage, such as diversion dams, forebays, and afterbays, which are modeled as nodes or modeled as full at all times.

5.4.2.1 Reservoirs Modeled

Table 5-3. Reservoirs Modeled in the Reservoir Operations Model

Reservoir	Modeled Storage Capacity (AF[1])
Jackson Meadows Reservoir	67,435
French Lake	13,940
Faucherie Lake	3,740
Sawmill Lake	3,030
Jackson Lake	1,330
Bowman Reservoir	66,722
Upper Rock Lake	207

Lower Rock Lake	48
Culbertson Lake	953
Upper Lindsey Lake	17
Middle Lindsey Lake	110
Lower Lindsey Lake	289
Feely Lake	739
Carr Lake	150
Blue Lake	1,186
Rucker Lake	648
Kidd Lake	1,505
Upper Peak Lake	1,697
Lower Peak Lake	484
White Rock Lake	570
Meadow Lake	4,841
Lake Sterling	1,824
Fordyce Lake	49,426
Lake Spaulding	74,890
Kelly Lake	334
Lake Valley Reservoir	7,902
Rollins Reservoir	55,140
Lake Combie	2,790
Rock Creek Reservoir	319
Scotts Flat Reservoir	43,143

[1]Storage Capacity includes normal operating capacity with spill gates closed or flashboards in place and does not include additional reservoir space above spillway in which the reservoir may surcharge during times of high inflow.

5.4.2.2 Demand Nodes

The model has diversions for consumptive demands at seven locations for NID and five locations for PCWA, shown in Table 5-4.

Table 5-4. Model Consumptive Demand Nodes

Model ID	Diversion	Diversion Location
NID-1	North Auburn WTP and Combie-Ophir Canal	Rock Creek Reservoir
NID-2	Auburn Ravine	Auburn Ravine
NID-3	Combie Phase I and Magnolia Canals	Lake Combie
NID-4	Cascade Canal	Deer Creek
NID-5a	DS Canal	Deer Creek
NID-5b	Newtown Canal	Deer Creek
NID-5c	Tunnel Canal	Deer Creek
PCWA-1	Boardman Canal	Lake Arthur
PCWA-2	Ragsdale and Bowman Canals	Halsey Forebay
PCWA-3	Middle Fiddler Green Canal	Rock Creek Reservoir
PCWA-4	Lower Fiddler Green Canal	Wise Forebay
PCWA-5	Auburn Ravine and Dutch Ravine	Auburn Ravine

5.4.2.3 Conduit Capacities

Table 5-5 lists the canals and conduits that are explicitly modeled in the reservoir operations model.

Table 5-5. Conduit Capacities and Loss Rates

Conduit	Capacity (cfs)	Modeled Loss Rate
Milton-Bowman Conduit	425	0
Bowman-Spaulding Conduit		
At Bowman Reservoir	300	0
–Below Texas Creek Div Dam	300	0
–Below Clear Creek Div Dam	310	0
–Below Fall Creek Div Dam	320	0
–Below Trap Creek Div Dam	325	0
–Below Rucker Creek Div Dam	325	0
Spaulding Powerhouse No 1	645	0
Spaulding Powerhouse No 2	200	0
Spaulding Powerhouse No 3	334	0
Drum Canal	840	7.8%
Bear River Canal	470	6.9%
Wise Canal	488	0
South Canal	395	0
South Yuba Canal	90	14.3%
Chalk Bluff Canal	85	0[1]
Deer Creek Powerhouse	110	0
Towle Canal	42	12%
Pulp Mill Canal	25	0
Boardman Canal	58	0
Lake Valley Canal	24	0

[1]14.3% loss rate modeled in the South Yuba Canal is the combined loss for South Yuba Canal and Chalk Bluff Canal.

5.4.3. Significant Changes from the Previous NID ResSim Model

5.4.3.1 Lake Valley Canal Capacity

The Lake Valley Canal was piped in 2014, resulting in less capacity to move water to the Drum Canal. The model was updated to reflect this lowered capacity. The updated model uses a capacity of 26 cfs, while previous models have used a capacity of 36 cfs. Average daily flow in the Lake Valley Canal over three time periods is shown in Figure 5-7. An ensemble of daily flow rates in the Lake Valley Canal for 2016–2021 is shown in Figure 5-8, demonstrating that flow rates rarely exceed 26 cfs.

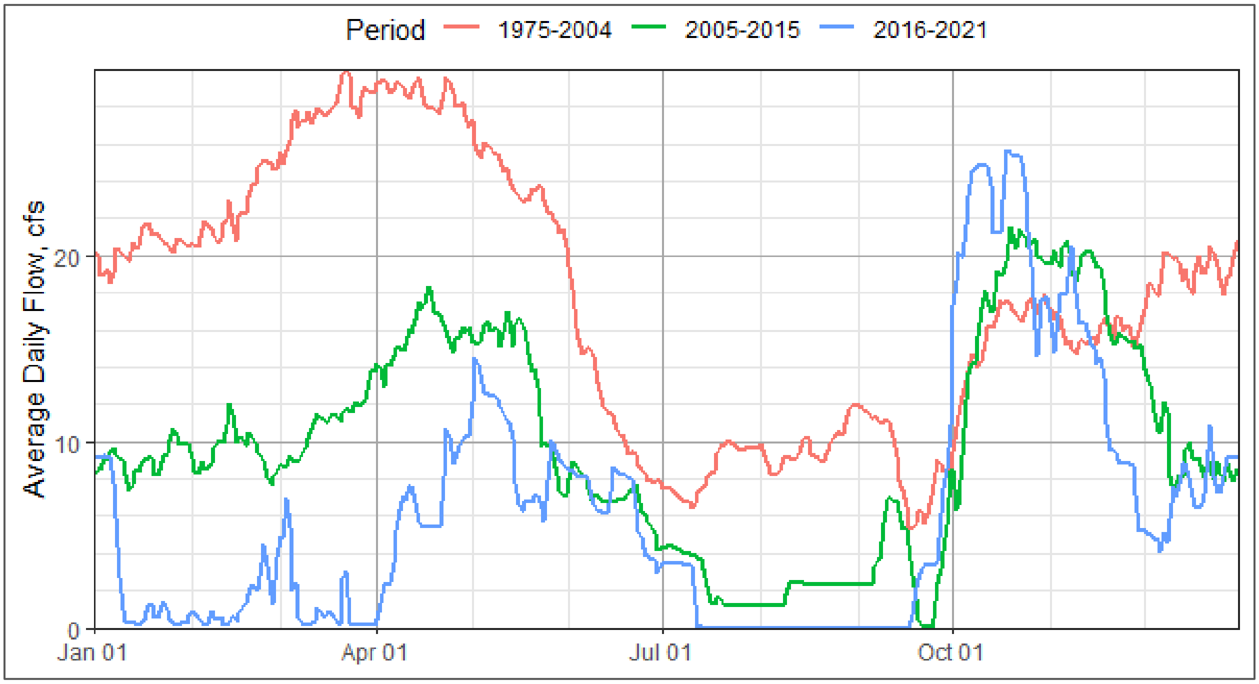


Figure 5-7. Lake Valley Canal Historic Daily Average Flow

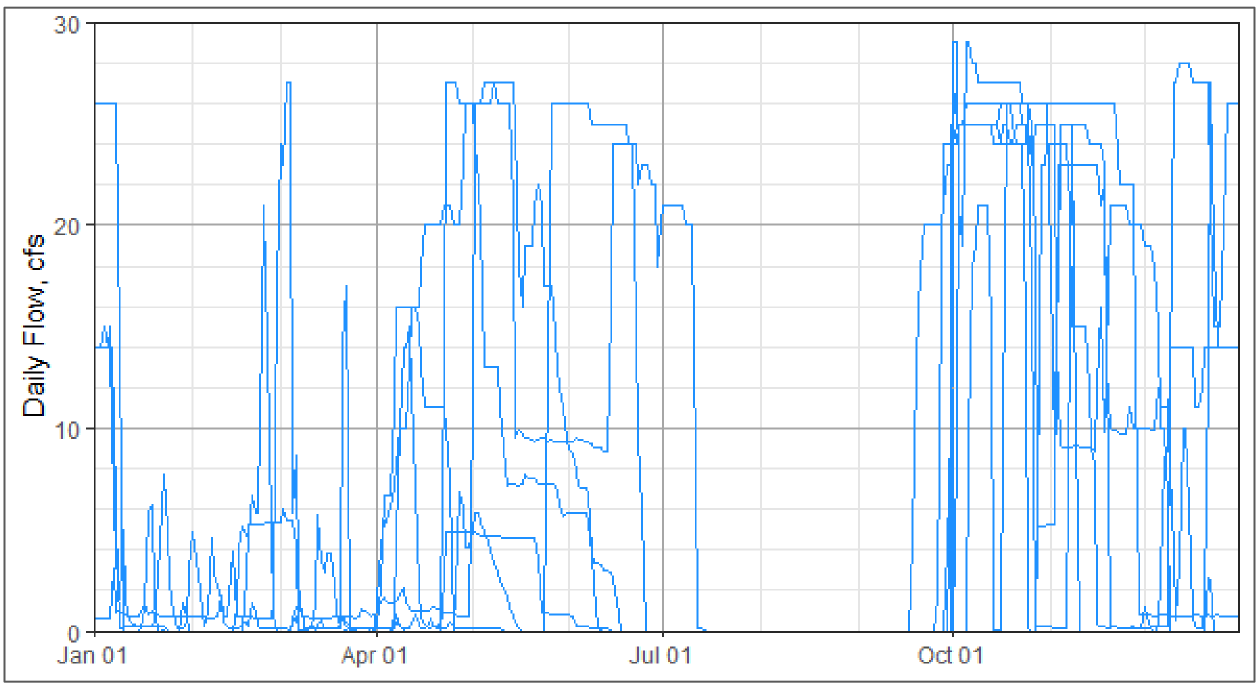


Figure 5-8. Lake Valley Canal Flow Ensemble, 2016–2021

5.4.3.2 Fordyce Lake Seepage (Increase in Seepage Estimate from 2020 SWRCB Document)

Previous modeling had seepage from Fordyce Lake up to a maximum of 24 cfs at full pool. In their Fordyce Lake Seepage Mitigation Project, Pacific Gas & Electric (PG&E) has estimated that Fordyce Lake seepage ranges from 24 to 60 cfs (SWRCB 2020). Historic data were analyzed to estimate the relationship between seepage and reservoir water surface elevation. The resulting relationship is shown in Figure 5-9 which shows that flow below Fordyce Dam increases with increasing water surface elevation above water surface elevations of around 6310 feet. Since minimum flow requirements and discretionary releases are not based on water surface elevations, this near-linear increase in flow below Fordyce Dam is likely due to increased seepage as reservoir head increases.

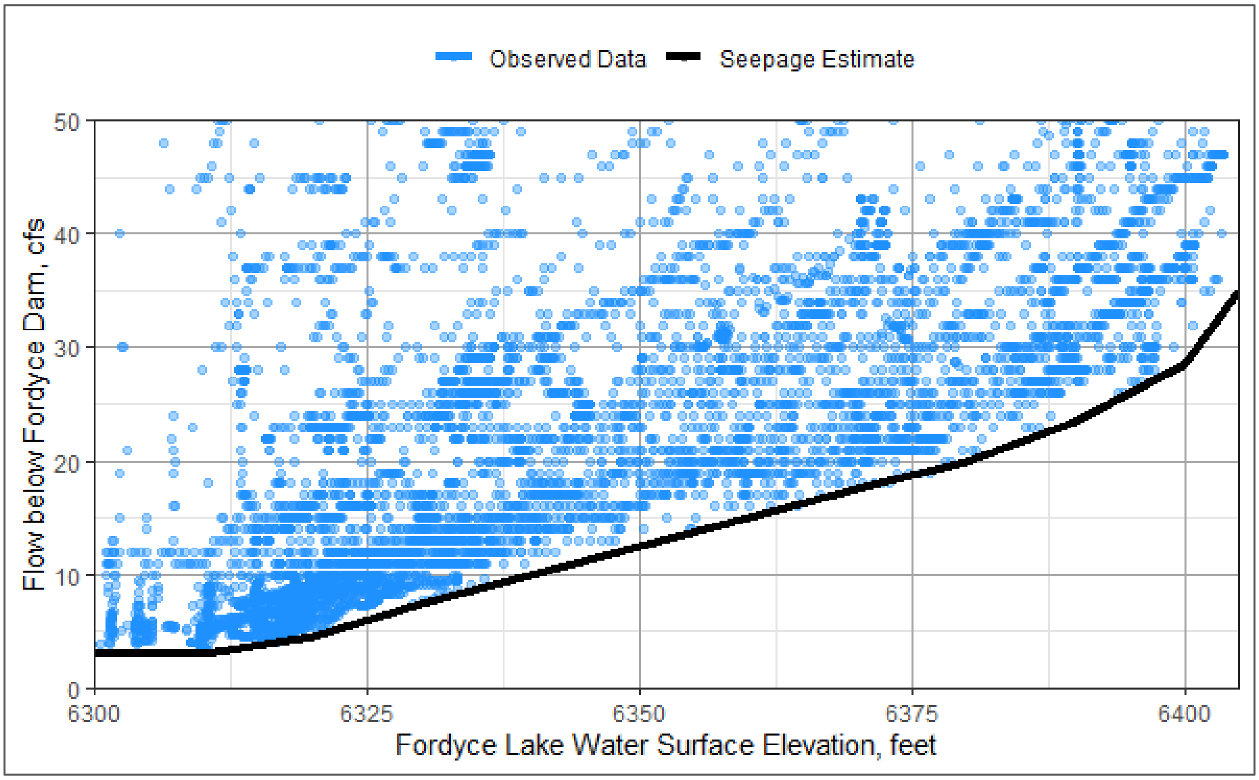


Figure 5-9. Fordyce Dam Seepage Estimate

5.4.4. Implementation of the Integrated Red-Blue Model

The model simulates the integrated operations of NID's Yuba-Bear Project, PG&E's Drum-Spaulding Project, PG&E's Deer Creek Project, and some non-FERC facilities that receive water from FERC projects. A system of tracking the ownership of NID and PG&E water throughout the projects is needed to properly process results. In the FERC relicensing process, this tracking was implemented in a post-processing spreadsheet named the "YB and DS Water Allocation Module" (Red-Blue Spreadsheet), which instituted a "water coloring" scheme where NID water is blue and PG&E water is red. This spreadsheet necessitated a workflow in which the ResSim model results do not correctly track water ownership and the true ownership was calculated in the Red-Blue Spreadsheet. Because the model did not have access to the ownership calculations, it could not implement restrictions on diversions based on ownership.

The updated model integrates ownership calculations into the model code. This allows for the model to make decisions based on ownership during runtime. The model assigns the ownership of water using the definitions contained in the COA between NID and PG&E (NID 2018). The model tracks ownership of water at the following locations:

- **Inflow to Lake Spaulding:** NID owns all water diverted into the Bowman-Spaulding Conduit at the Bowman Diversion Dam. PG&E owns Texas-Fall Creek Water diverted into Lake Spaulding between July 1 and November 30, up to 30 cfs and up to 3,500 AF/year. NID owns the remaining Texas-Fall Creek Water diverted into Lake Spaulding.
- **Head of South Yuba Canal:** All water in the South Yuba Canal that flows past the South Yuba Waste Gate is NID water.
- **Head of Drum Canal:** NID water in the Drum Canal is equal to NID inflows to Lake Spaulding minus NID flow in the South Yuba Canal. The remaining flow in the Drum Canal is PG&E water.
- **Inflow to Rollins Reservoir:** NID imports to Rollins Reservoir are equal to NID water in the Drum Canal minus a 7.8% canal loss. PG&E imports to Rollins Reservoir are equal to PG&E water in the Drum Canal plus diversions into the Lake Valley Canal minus a 7.8% canal loss, minus water diverted from Drum Forebay into Canyon Creek. PG&E diversions through the South Yuba Waste Gate or the Drum Canal Waste Gate are considered additional PG&E imports to Rollins Reservoir. PG&E natural flow into Rollins Reservoir is equal to the first 350 cfs of Bear River runoff into Rollins Reservoir. NID natural flow into Rollins Reservoir is any Bear River runoff into Rollins Reservoir in excess of 350 cfs.
- **Outflow from Rollins Reservoir:** Diversions from Rollins Reservoir into the Bear River Canal are determined from PG&E and NID demands along the canal. Releases from Rollins Reservoir that flow past the Bear River Diversion Dam are considered NID water.
- **Storage in Rollins Reservoir:** Change in storage in Rollins Reservoir for each storage account is calculated as Inflow minus outflow minus a fraction of evaporation equal to the fraction of each account's storage to the total storage volume.
- **Bear River Canal:** NID delivers any NID water diverted into the Bear River Canal minus a 6.9% canal loss. Remaining water in the Bear River Canal is PG&E water. Any minimum flow releases out of the Bear River Canal at Rock Creek or Dry Creek are from PG&E.

The model enforces the following restrictions based on ownership of water:

- NID diversions to the South Yuba Canal must be less than or equal to NID inflows to Lake Spaulding. As outlined in the COA, there is an exception to this restriction during the Bowman-Spaulding Conduit outage period.
- NID diversions to the Bear River Canal must be less than or equal to NID inflow to Rollins Reservoir plus NID storage in Rollins Reservoir minus minimum flow requirements below the Bear River diversion Dam.
- PG&E diversions to the Bear River Canal must be less than or equal to PG&E inflow to Rollins Reservoir plus PG&E storage in Rollins Reservoir.

5.4.5. Historical Conditions Model

The model was used to develop a simulation using historical inflow hydrology, recent historical consumptive demands, and regulatory requirements from the existing FERC licenses over a historical period of record covering water years 1976–2021. These modeling studies were calibrated to the last 10 years of record, water years 2012–2021.

5.4.6. Model Calibration and Validation

A model that is built with existing facility characteristics, historical hydrology, historic deliveries, and historic regulatory requirements should match historic observed data. Errors in historical hydrology estimation, differences between estimated evaporation and historic evaporation, anomalies in historic deliveries that are not modeled (canal collapse, etc.), anomalies in the meeting of regulatory requirements that are not modeled (variances obtained from FERC, accidental non-compliance, etc.), and errors or low precision in observed gage data will all cause the model to deviate from historic observed data. The process of calibrating a reservoir operations model is to find deviations from observed data and identify the cause to verify that the model is working correctly but is not meant to model the errors or anomalies that contribute to the deviation from observed data.

Additionally, at some reservoirs, releases are made to provide discretionary generation, or generation releases that are not required but made strictly for power generation revenue. This can be summer and fall generation in which the discretionary generation is used to generate during times of high prices, or winter and spring generation, in which the discretionary generation is made to make some revenue instead of reservoir spills. Discretionary generation is often scheduled in near real-time using estimates available in the moment that have a degree of uncertainty (weather forecasts, inflow forecasts, power price forecasts) and those decisions are difficult to reconstruct when building a planning model. Calibrating a model to these discretionary generation releases is generally a process of taking an average over a few variables (by month, by water year type, by reservoir elevation) and making a generalized rule that fits some years' observed data better than others.

Most reservoirs in the model match observed data well. An example of one of these reservoirs is shown in Figure 5-10 for Jackson Meadows Reservoir.

A few of the reservoirs on the Texas-Fall Creek system do not match observed data very well. While there are limited observed data at most of these reservoirs, it is likely that the deviations from observed data are due to the difficulty of creating estimated historical hydrology for these very small watersheds. An example of one of the Texas-Fall Creek reservoirs that do not match historical data is shown in Figure 5-11 for Culbertson Lake.

The large reservoirs that do not match observed data very well are Bowman Reservoir and Lake Spaulding. At both reservoirs this is mostly due to a wide variation in the carryover level in the observed data. The model has a simple rule for carryover level at Bowman Reservoir that does not have as wide a range as observed data. Bowman Reservoir storage calibration is shown in Figure 5-12. The carryover level at Lake Spaulding is mostly driven by discretionary generation, which historically varies year to year based on a variety of factors that are not modeled. One example is that in 2015, Lake Spaulding closed the spill gates in early February, which is much earlier than normal, whereas the model closes the spill gates on April 1 every year. This created a deviation in storage through the end of 2015. Lake Spaulding storage validation is shown in Figure 5-13.

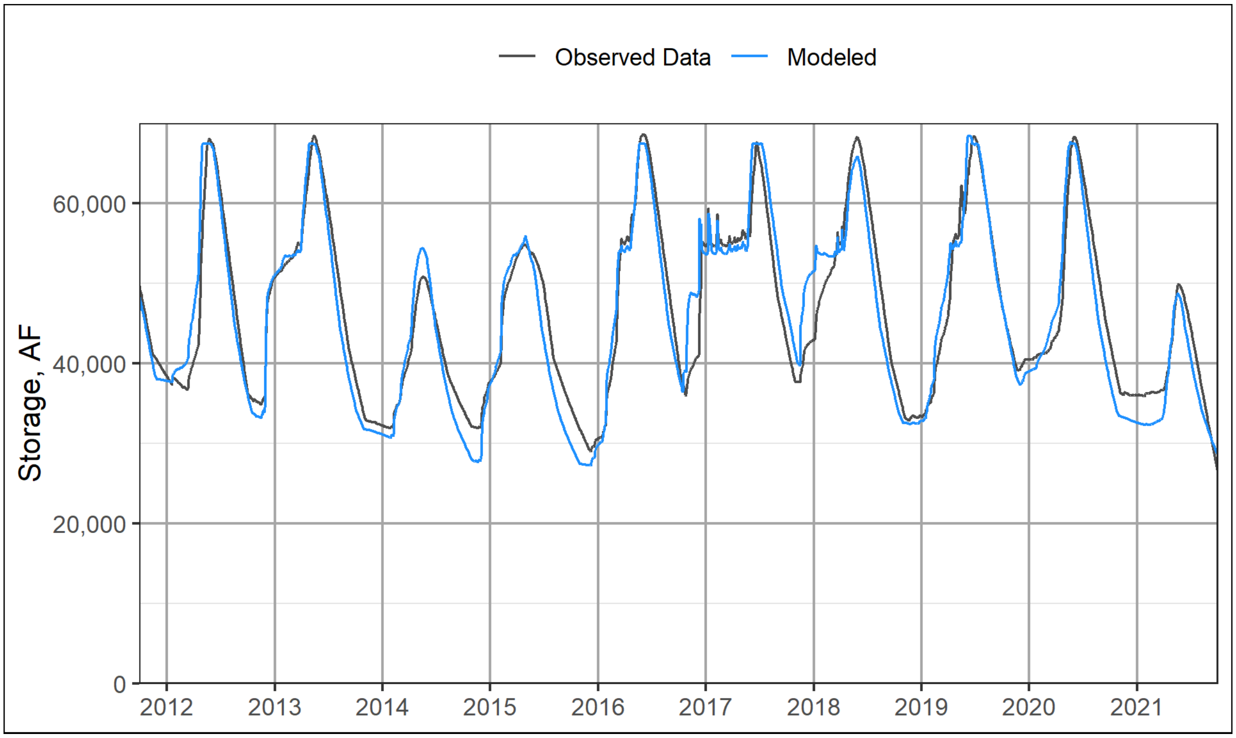


Figure 5-10. Jackson Meadows Reservoir Storage, Water Years 2012–2021

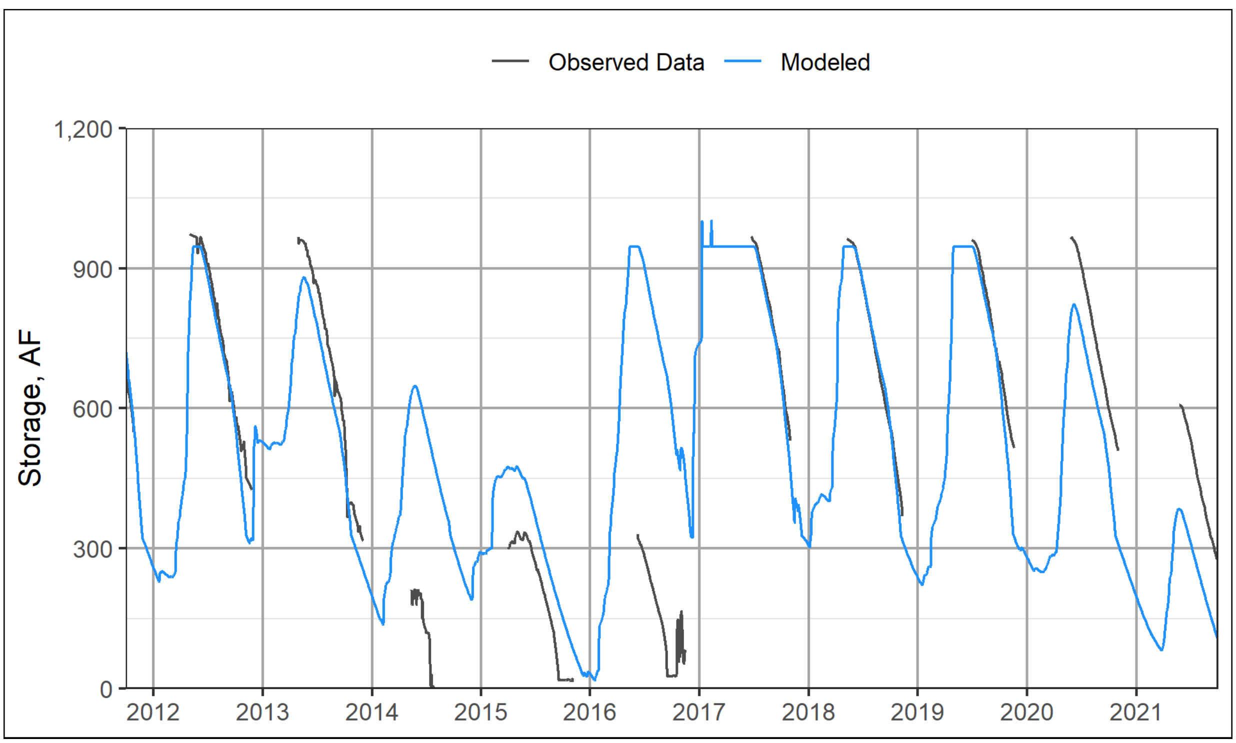


Figure 5-11. Culbertson Lake Storage, Water Years 2012–2021

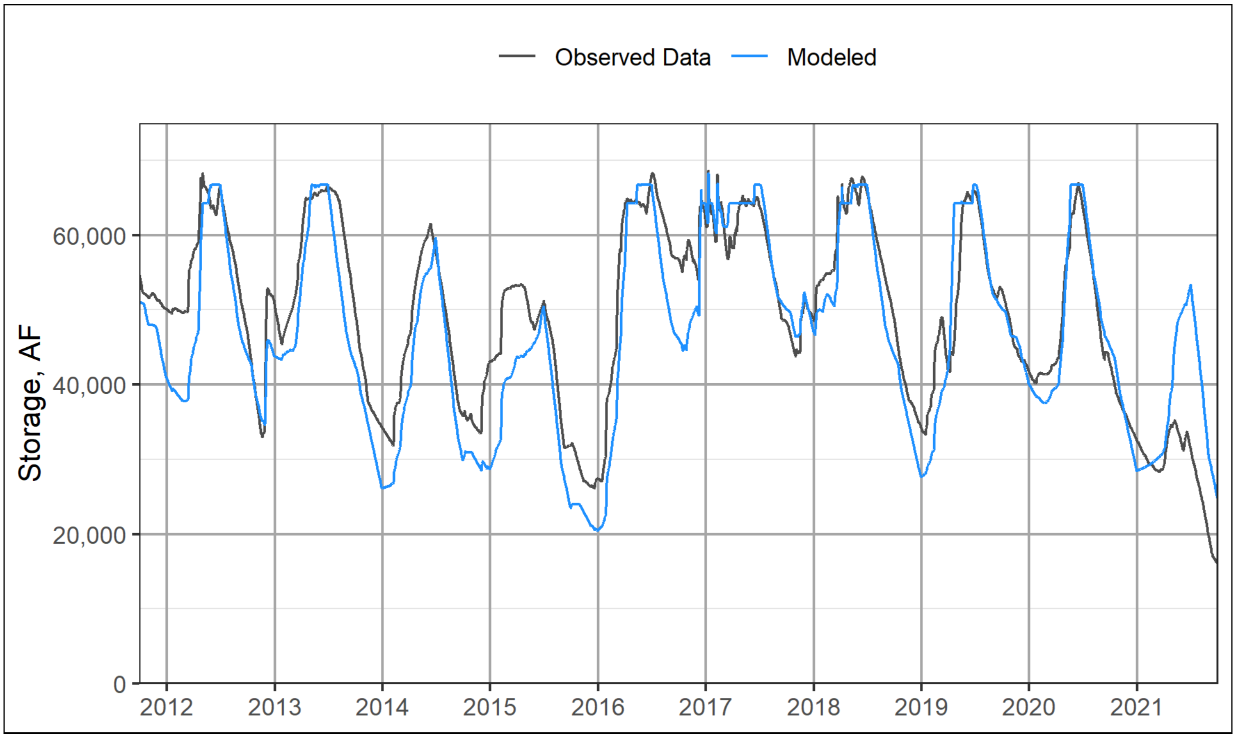


Figure 5-12. Bowman Reservoir Storage, Water Years 2012–2021

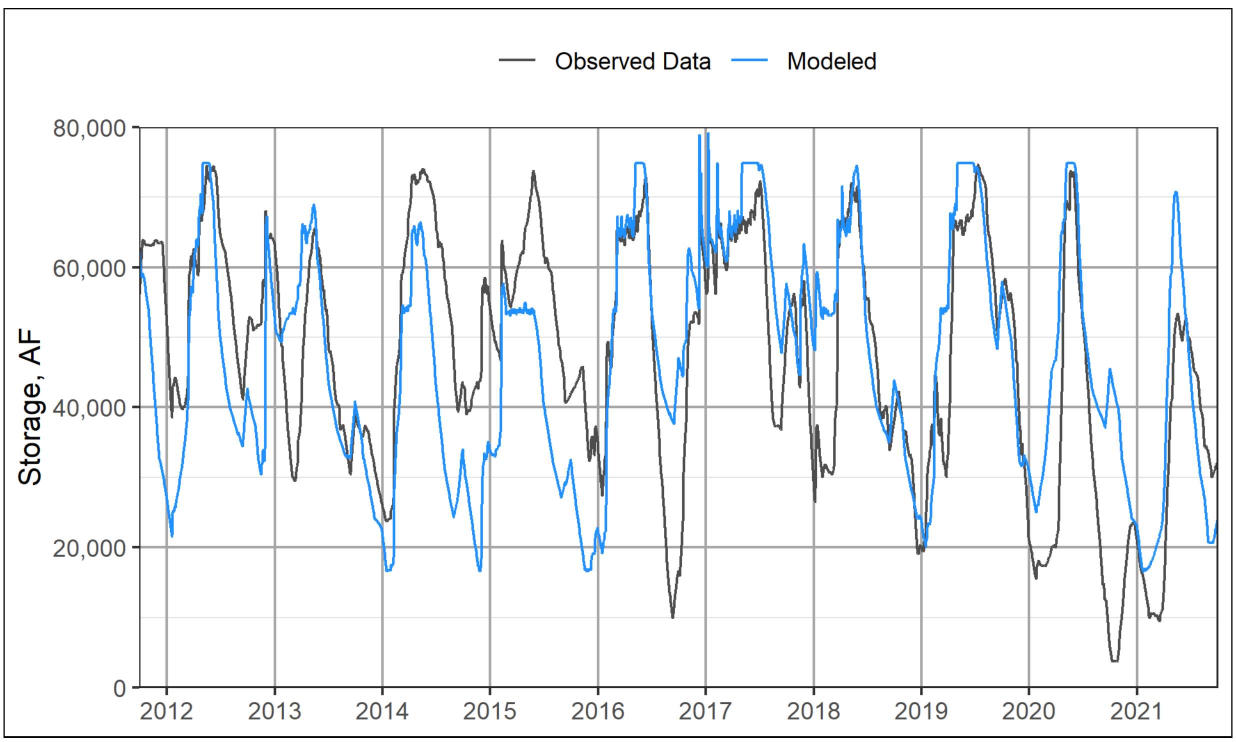


Figure 5-13. Lake Spaulding Storage, Water Years 2012–2021

5.5. Projection Inputs

5.5.1. Integrated Water Flow Model Demand Calculator (IDC) Demands

The model uses demands developed using the DWR's IDC built for NID's service area (NID PFW Demand Model), described in Chapter 4. The NID PFW Demand Model was used to develop 10 demand sets for use in the ResSim model. Annual Demands for these demand sets are summarized in Table 5-6. Annual Demands for each NID demand location in the ResSim model are summarized in Table 5-7.

Table 5-6. Annual Demands from IDC Model

	Dry Climate Bookend	Median Climate Scenario	Wet Climate Bookend
Low Demand	107,657	109,088	109,705
Baseline Demand	149,654	151,806	152,238
High Demand	181,616	183,483	184,638
2022 Demand	N/A	150,100	N/A

Table 5-7. Annual Demands at Each NID Demand Node

Demand Level		Low			Baseline			High		
Climate Bookend		Dry	Med	Wet	Dry	Med	Wet	Dry	Med	Wet
ID	Location	Demands (AF)								
1	Rock Creek Reservoir	3,954	4,018	4,045	6,027	6,135	6,152	7,539	7,664	7,694
2	Auburn Ravine	21,362	21,716	21,900	32,786	33,384	33,526	41,805	42,336	42,653
3	Lake Combie	41,437	42,073	42,379	59,316	60,484	60,567	72,490	73,558	74,033
4	Cascade Canal	15,090	15,120	15,143	17,218	17,210	17,261	18,923	18,887	18,965
5A	DS Canal	14,591	14,910	14,983	21,718	21,981	22,106	27,235	27,424	27,639
5B	Newtown Canal	4,943	4,952	4,951	5,189	5,187	5,194	5,370	5,366	5,377
5C	Tunnel Canal	6,280	6,298	6,303	7,400	7,424	7,433	8,255	8,247	8,277

5.5.2. HEC-HMS Climate Change Hydrology

The HEC-HMS Climate Change Hydrology Model, described in Chapter 2. Hydrological Model, developed three input datasets for the reservoir operations model: (1) a dry bookend scenario, (2) a wet bookend scenario, and (3) a median scenario. These projected hydrology datasets were generated for a 50-year projected period for WYs 2022–2073. The datasets do not predict what will happen, but rather represent what could happen under various climate scenarios. Average annual unimpaired flows in major NID watersheds are summarized for the climate change scenarios in Table 5-8. Average annual unimpaired inflow to all NID reservoirs is shown graphically in Figure 5-14. Daily average unimpaired flow to all NID reservoirs is shown in Figure 5-15 through Figure 5-17.

Table 5-8. Average Annual Unimpaired Flow in NID Watersheds

Unimpaired Flow Location	Average Annual Unimpaired Flow Volume (AF)			
	Historic Hydrology	Dry Climate Scenario	Median Climate Scenario	Wet Climate Scenario
Middle Yuba River at Milton	87,357	67,699	79,470	90,726
Canyon Creek at Bowman	88,811	68,749	82,023	85,097
Deer Creek at Scotts Flat	36,415	14,310	20,822	25,298
Bear River at Lake Combie	171,183	107,410	159,730	193,843
Total Unimpaired Inflow to all NID Reservoirs	383,766	258,168	342,046	394,964

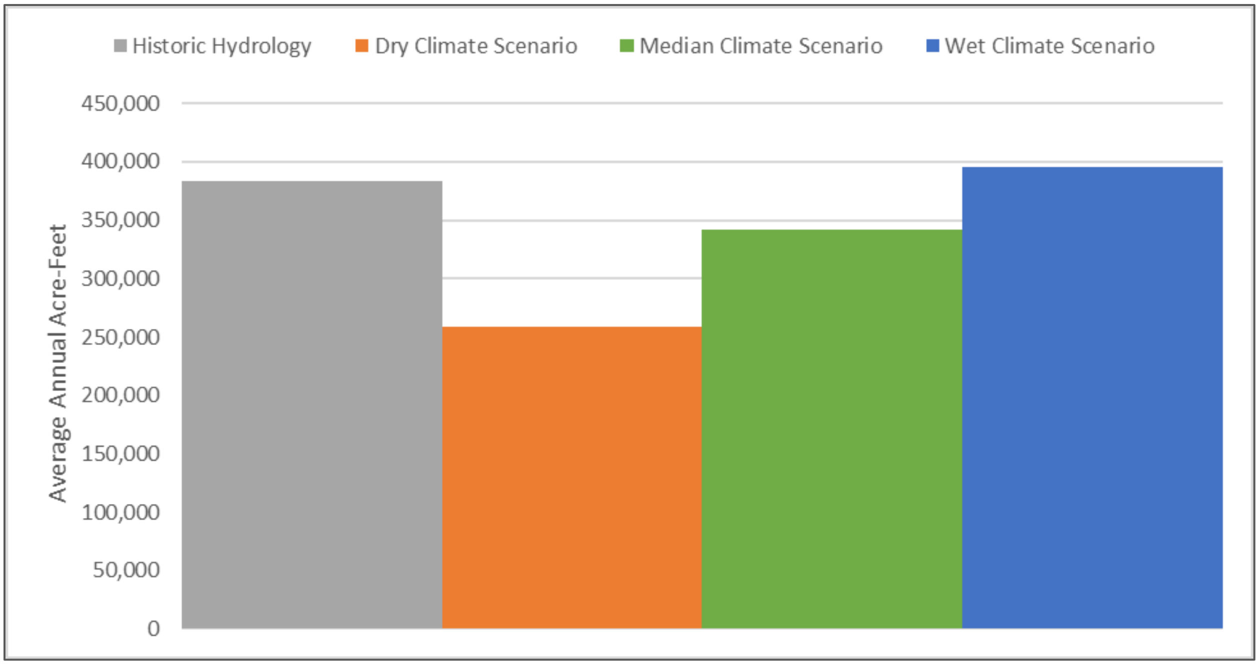


Figure 5-14. Average Annual Unimpaired Inflow to NID Reservoirs in Climate Change Hydrology

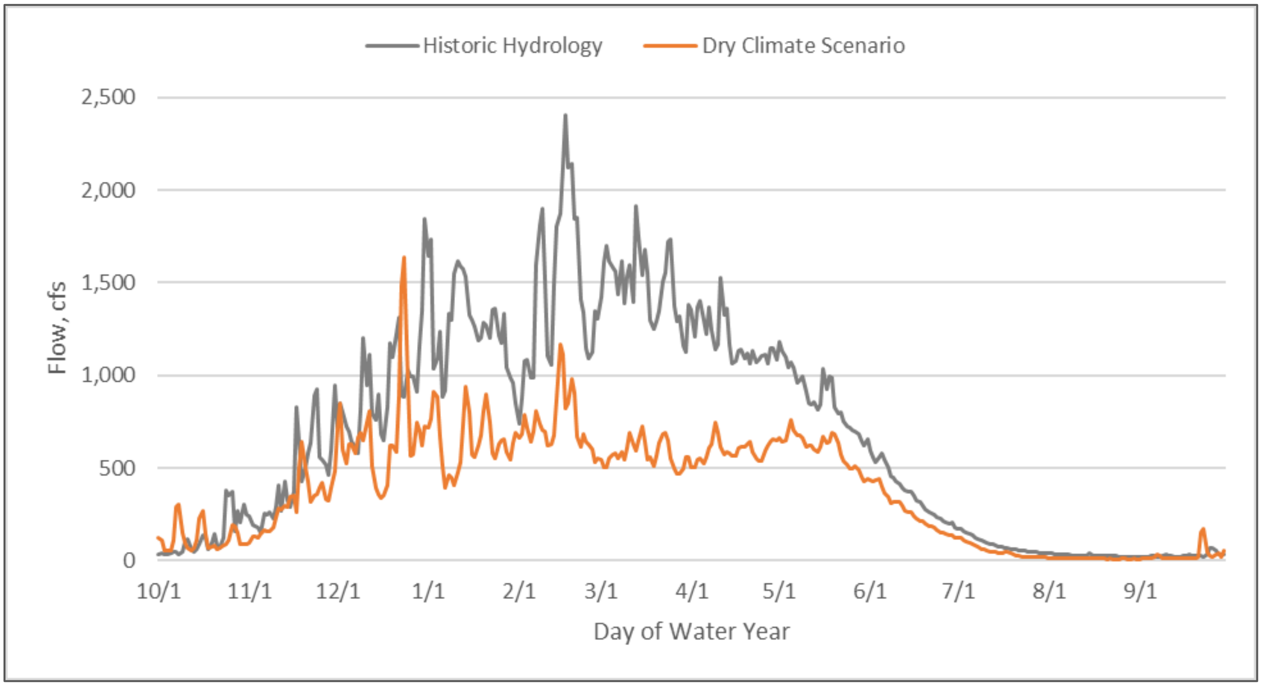


Figure 5-15. Daily Average Unimpaired Inflow to NID Reservoirs in Dry Climate Change Hydrology

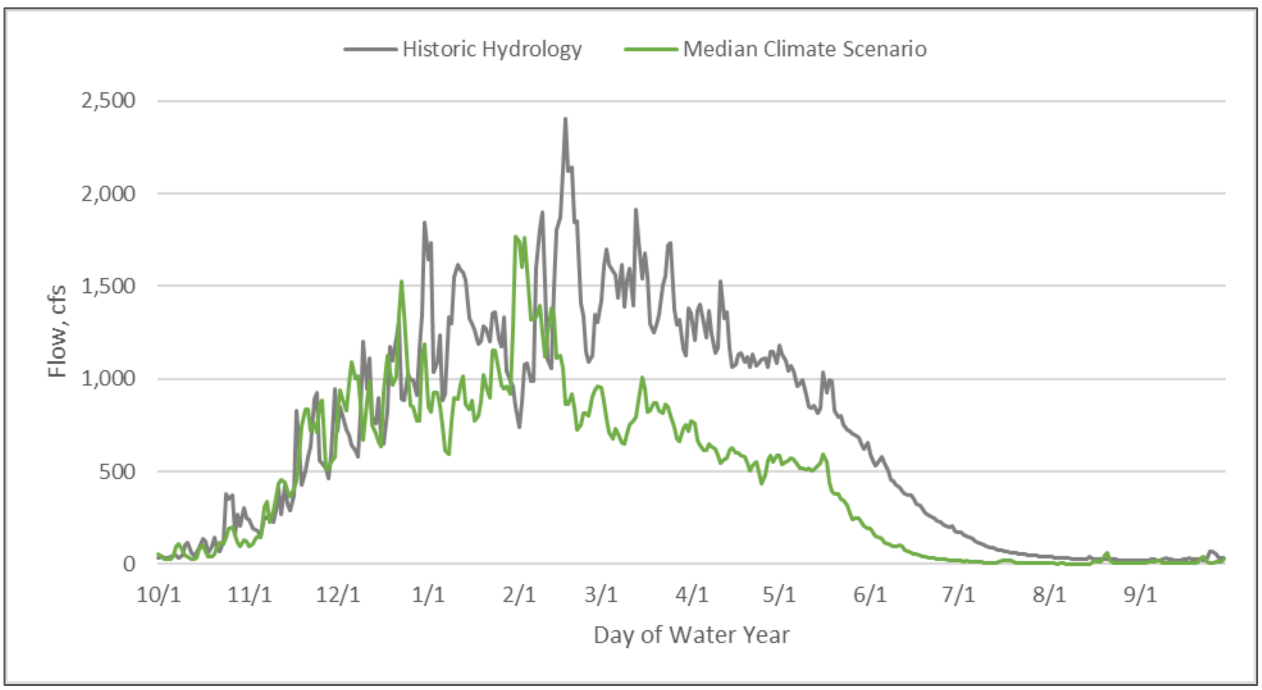


Figure 5-16. Daily Average Unimpaired Inflow to NID Reservoirs in Median Climate Change Hydrology

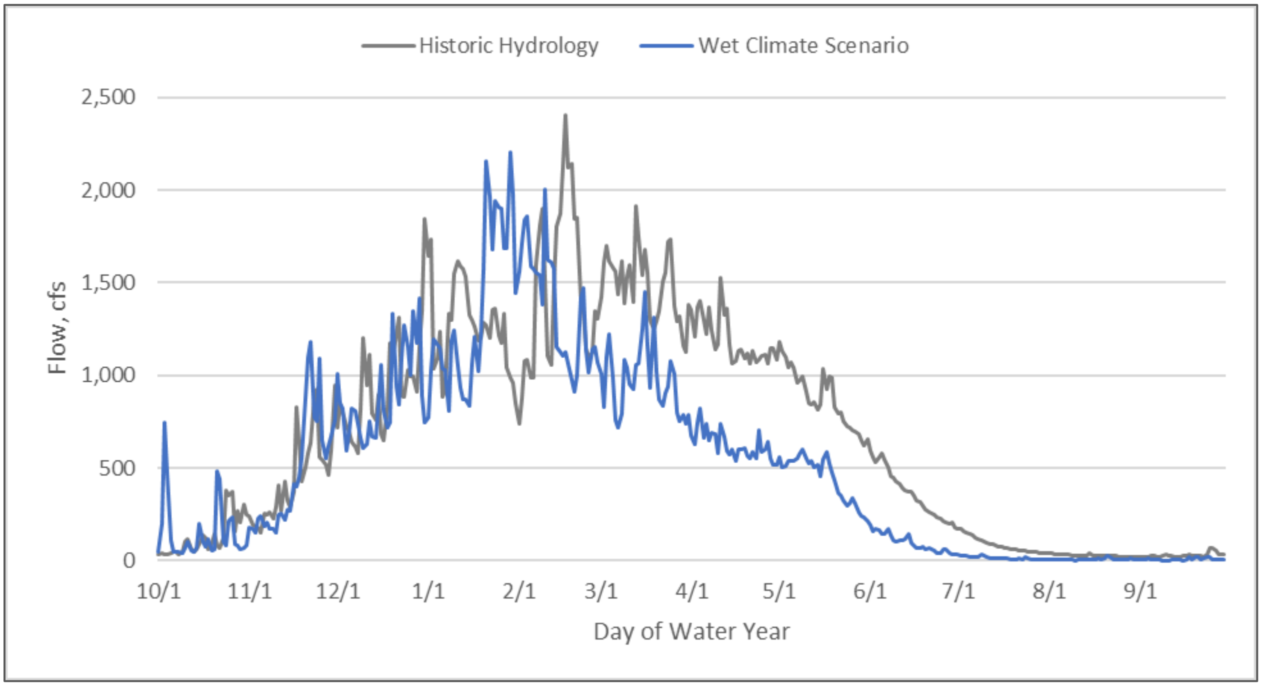


Figure 5-17. Daily Average Unimpaired Inflow to NID Reservoirs in Wet Climate Change Hydrology

5.6. Simulation Results Based on Existing Operations

5.6.1. Assumptions

Existing Operations scenarios were developed that simulate existing operations using each of the projection inputs discussed in Section 5.5. The use of these projection inputs is shown in Table 5-9. The Existing Operations scenarios each contain:

- Future FERC requirements for the Yuba-Bear, Upper Drum-Spaulding, Lower Drum-Spaulding, and Deer Creek Hydroelectric Projects from the 2014 Final Environmental Impact Statement for these projects (FERC 2014).
- 2018 COA accounting mechanisms.
- Existing facilities.
- The current Drought Contingency Plans for both NID deliveries and PG&E deliveries to PCWA.
- Recent historical deliveries are used to estimate PCWA demands.

Table 5-9. Existing Operations Scenario numbering.

	Low Demands	Baseline Demands	High Demands
Dry Climate	1	2	3
Median Climate	4	5	6
Wet Climate	7	8	9

5.6.2. Comparison to Historical Conditions

A modeling study was created to form a basis of comparison for the Existing Operations studies. This modeling study has the following assumptions:

- Historical inflow hydrology discussed in Section 5.1.
- Future FERC requirements for the Yuba-Bear, Upper Drum-Spaulding, Lower Drum-Spaulding, and Deer Creek Hydroelectric Projects from the 2014 Final Environmental Impact Statement for these projects (FERC 2014).
- 2018 COA accounting mechanisms.
- Existing Facilities.
- The current Drought Contingency Plans for both NID deliveries and PG&E deliveries to PCWA.
- Recent historical deliveries are used to estimate NID and PCWA demands.

Direct comparisons of the Existing Operations studies to the historical conditions are not possible due to the different periods of record of the hydrology inputs. Historical hydrology is derived from gage data for the 1976–2021 period. Climate hydrology projection scenarios represent the 2022–2073 period. Comparisons can be made by first calculating daily or annual averages over the respective periods of record. Sections 5.6.2.1 through 5.6.2.4 provide comparisons of selected storage, flows, deliveries, and generation under historic conditions to the climate scenarios using this approach.

5.6.2.1 Reservoir Storage Results

Figure 5-18 shows historic (1976–2021) and projected (2022–2073) average storage for Jackson Meadows as a function of the day of the year under Existing Operations. On average, under climate change, reservoir storage peaks earlier in the season, which is a common feature for all reservoirs due to earlier snow melting. This feature is observed in Figure 5-19 for Bowman Reservoir, Figure 5-20 for Rollins Reservoir, and Figure 5-21 for Scott Flats Reservoir.

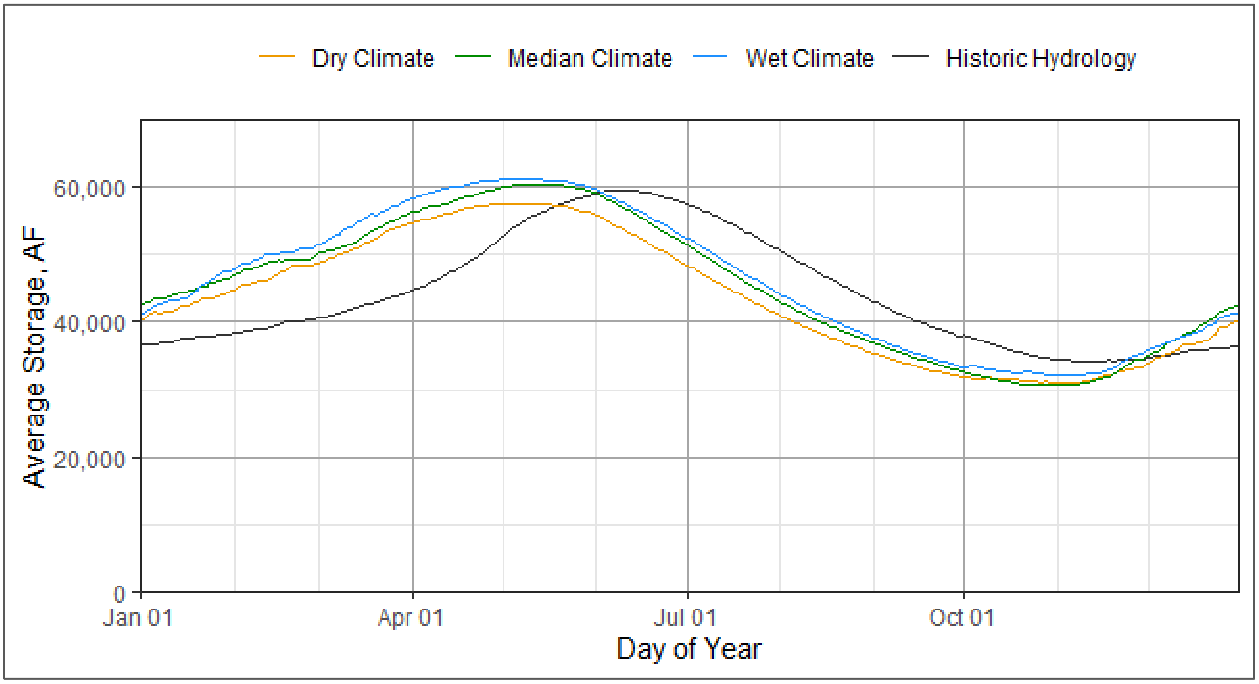


Figure 5-18. Jackson Meadows Reservoir Average Daily Storage, Existing Operations Simulation Results

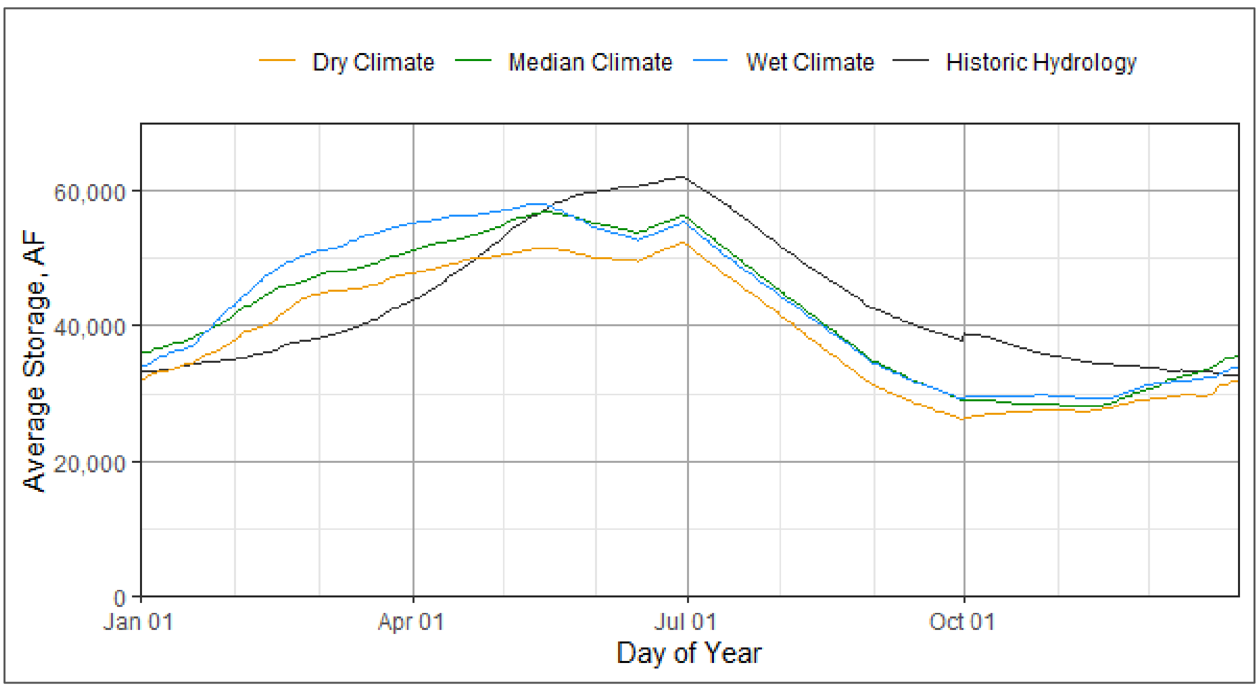


Figure 5-19. Bowman Reservoir Average Daily Storage, Existing Operations Simulation Results

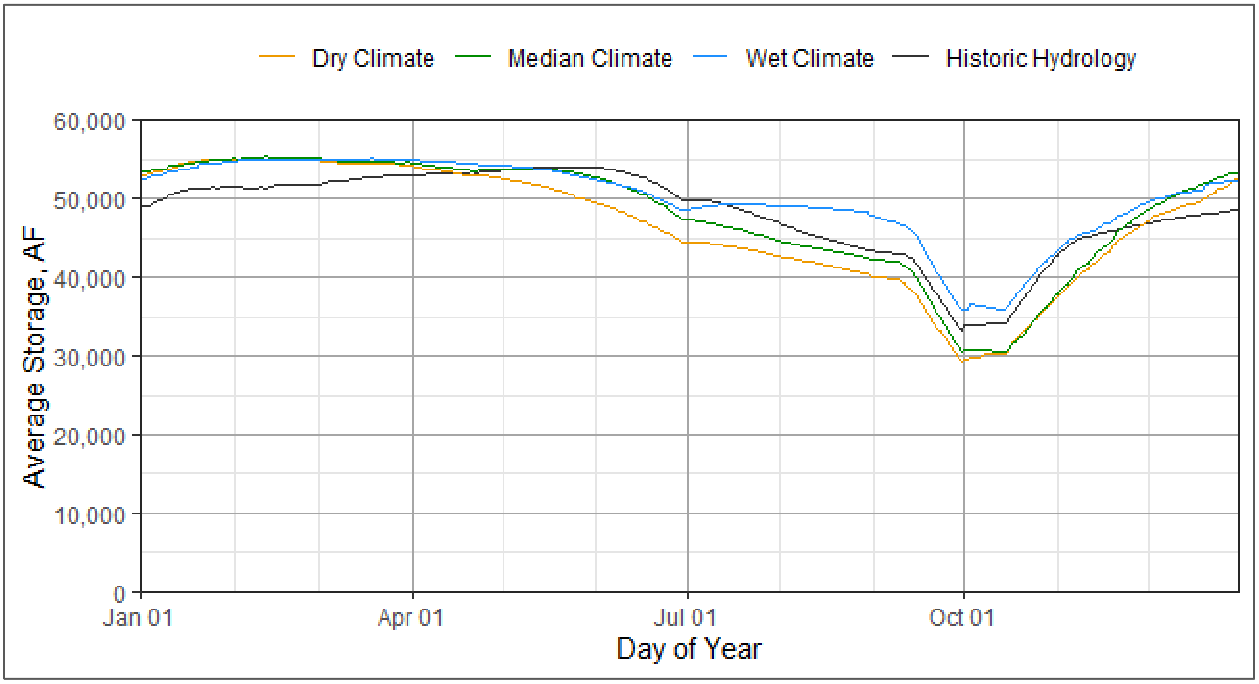


Figure 5-20. Rollins Reservoir Average Daily Storage, Existing Operations Simulation Results

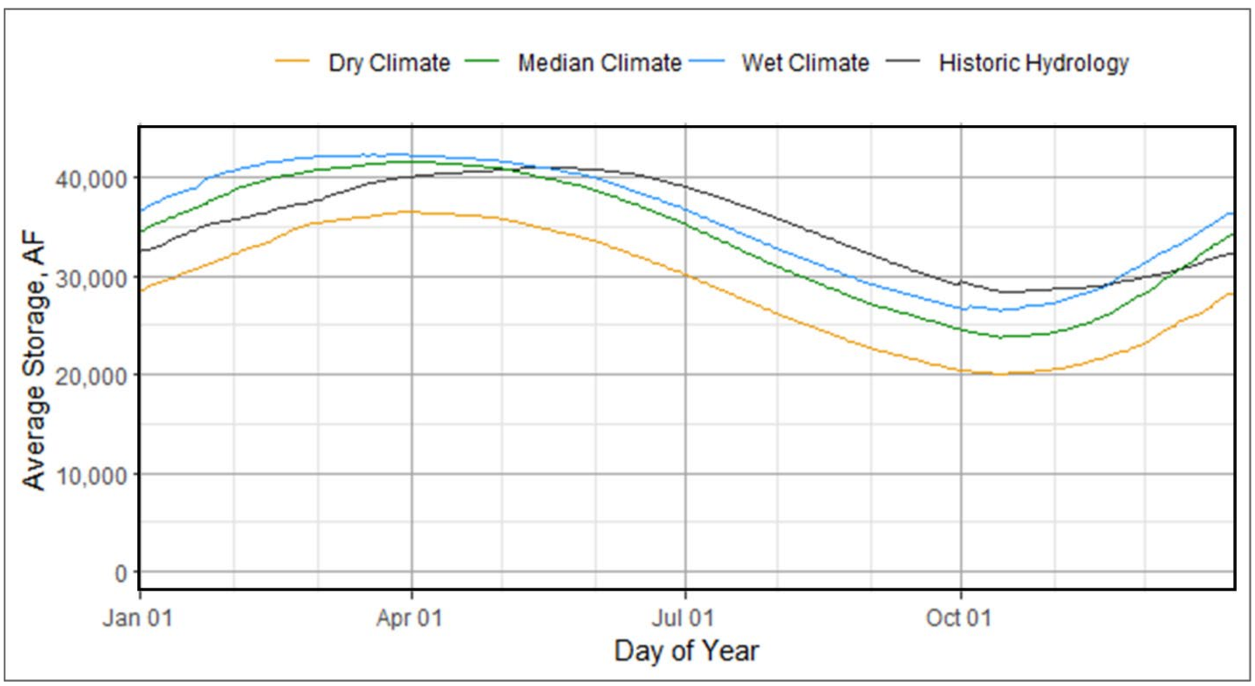


Figure 5-21. Scotts Flat Reservoir Average Daily Storage, Existing Operations Simulation Results

Table 5-10. Average Carryover Storage, Baseline Demands

Reservoir	Carryover Storage with Baseline Demands (AF)			
	Historic Hydrology	Dry Climate	Median Climate	Wet Climate
Jackson Meadows Reservoir	34,366	31,024	30,703	31,934
Bowman Reservoir	35,228	27,600	27,404	31,887
Sawmill Lake	1,670	1,625	1,561	1,548
French Lake	8,503	8,726	8,602	8,650
Faucherie Lake	2,109	2,170	2,144	2,167
Jackson Lake	994	962	891	874
Rollins Reservoir	42,051	36,981	37,339	36,907
Scotts Flat Reservoir	28,525	20,323	24,200	27,124
Lake Combie	1,126	1,857	1,972	2,097
Total	**142,818**	**120,524**	**124,440**	**131,774**

5.6.2.2 Flow Results

Average annual flows through selected conveyance structures are shown in Table 5-11. Figure 5-22 shows the average diversions from the Middle Yuba River to the Milton-Bowman Conduit as a function of day of year. The earlier runoff in the climate change hydrology causes reservoirs to make spill avoidance releases earlier in the year. This pattern is consistent across all major diversions in the system and can be observed for diversions into the Bowman-Spaulding Conduit in Figure 5-23, diversions from the South Yuba River into the Deer Creek Powerhouse in Figure 5-24, diversions from the South Yuba River into the Drum Canal in Figure 5-25, diversions from Rollins Reservoir into the Bear River Canal in Figure 5-26, diversions from Deer Creek into NID's Cascade Canal, DS Canal, Newtown Canal, and Tunnel Canal in Figure 5-27, and diversions from Lake Combie in Figure 5-28.

Table 5-11. Average Annual Diversions into Canals, Baseline Demands, AF

	Historical Hydrology	Dry Climate	Median Climate	Wet Climate
Diversions into Milton-Bowman Conduit	51,018	41,646	48,721	49,751
Diversions into Bowman-Spaulding Conduit	88,236	81,473	89,631	93,029
Diversions through Deer Creek Powerhouse	35,010	40,745	43,225	45,735
NID Diversions into Drum Canal	68,007	50,902	56,222	58,841
NID Diversions into Bear River Canal	38,494	28,969	33,166	31,650

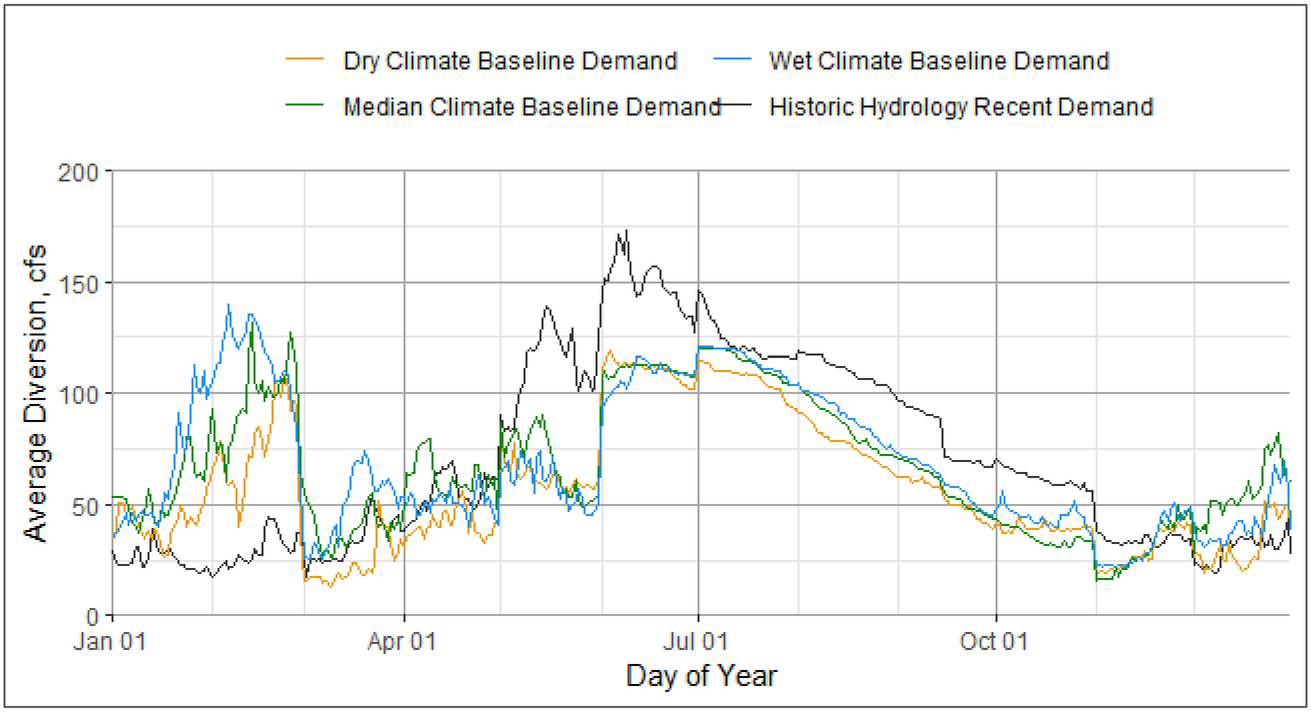


Figure 5-22. Average Daily Flow in Milton-Bowman Conduit, Existing Operations Simulation Results

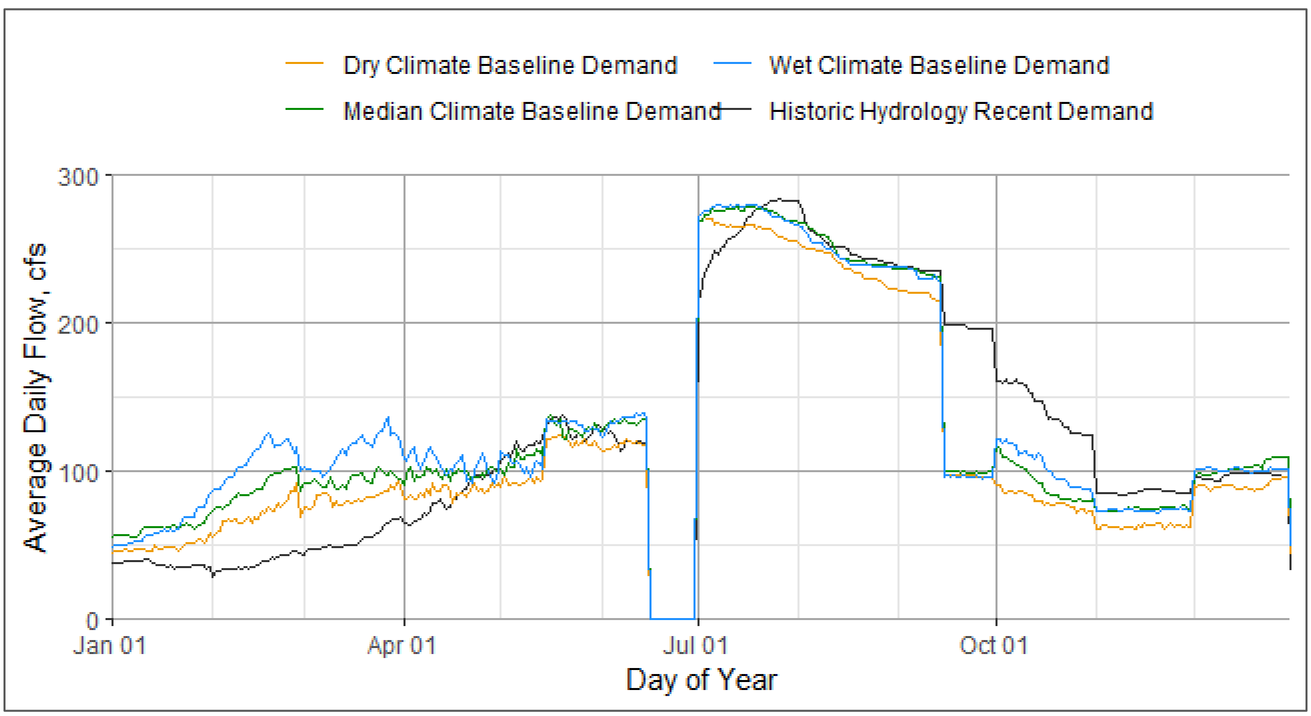


Figure 5-23. Average Daily Flow in Bowman-Spaulding Conduit at Bowman Reservoir, Existing Operations Simulation Results

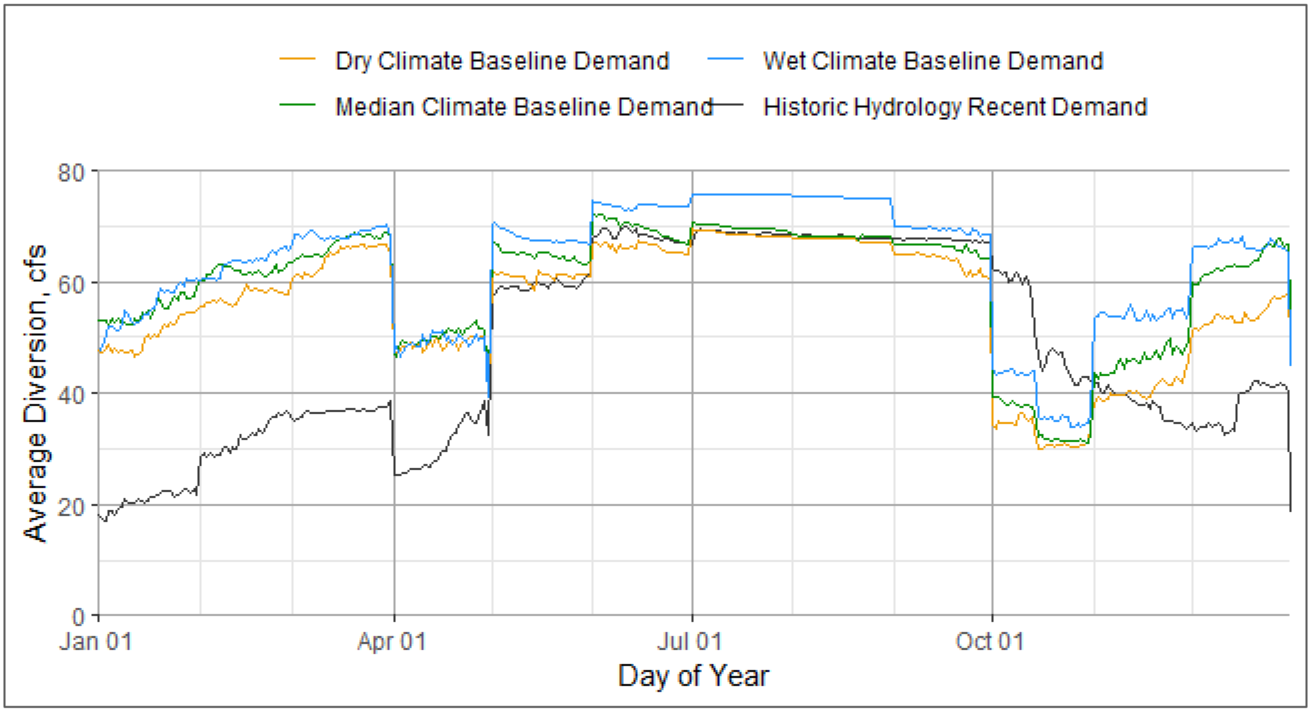


Figure 5-24. Average Daily Flow in Deer Creek Powerhouse, Existing Operations Simulation Results

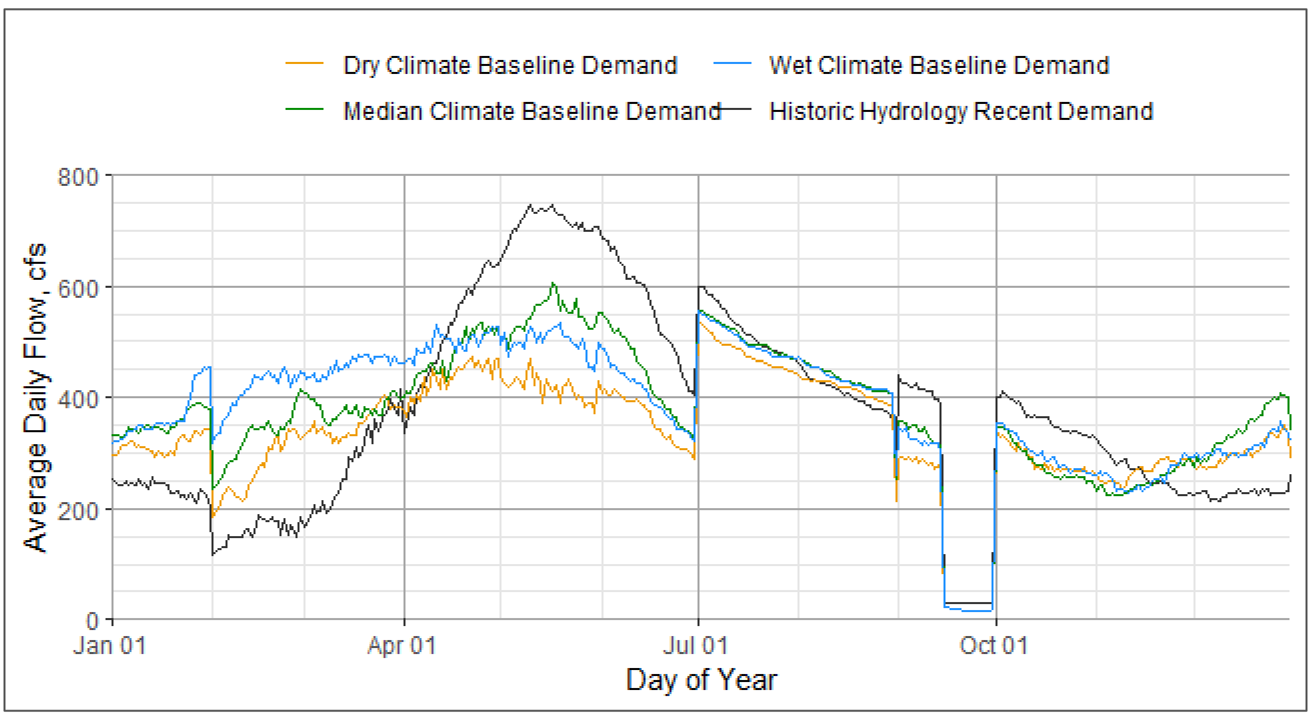


Figure 5-25. Average Daily Flow in Drum Canal below Spaulding Powerhouse No. 1, Existing Operations Simulation Results

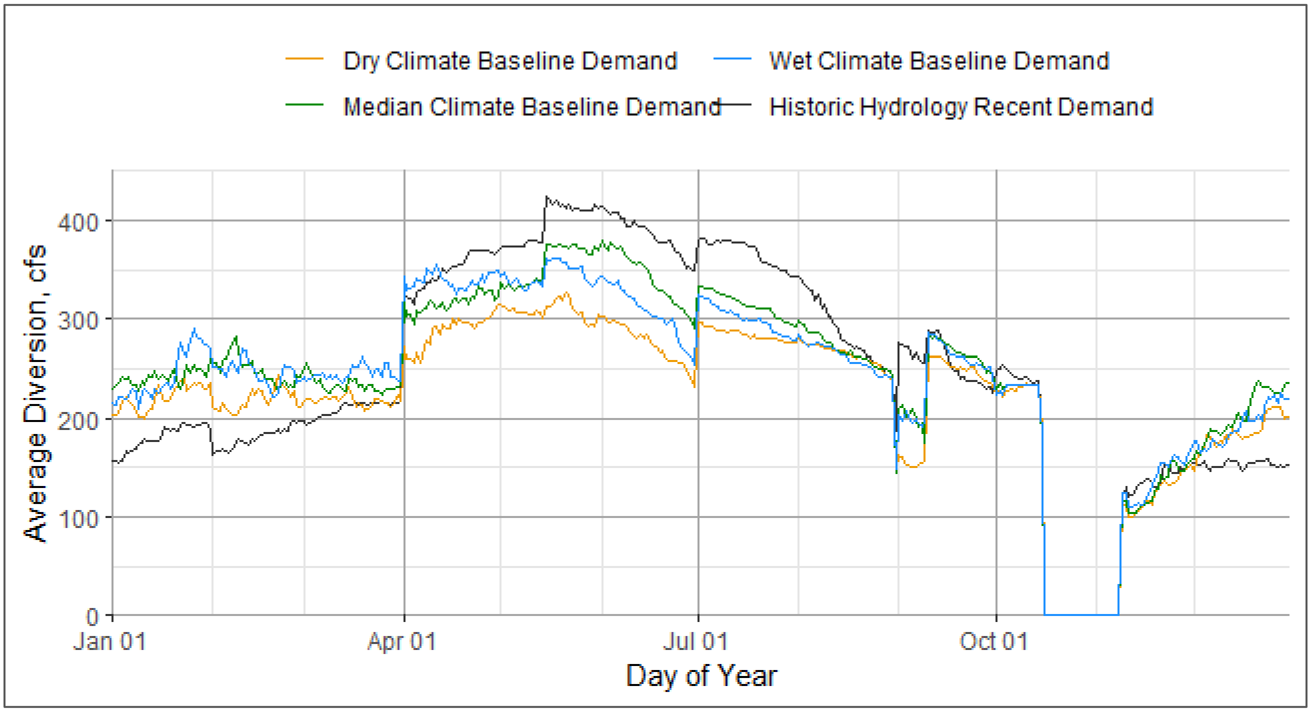


Figure 5-26. Average Daily Flow in Bear River Canal, Existing Operations Simulation Results

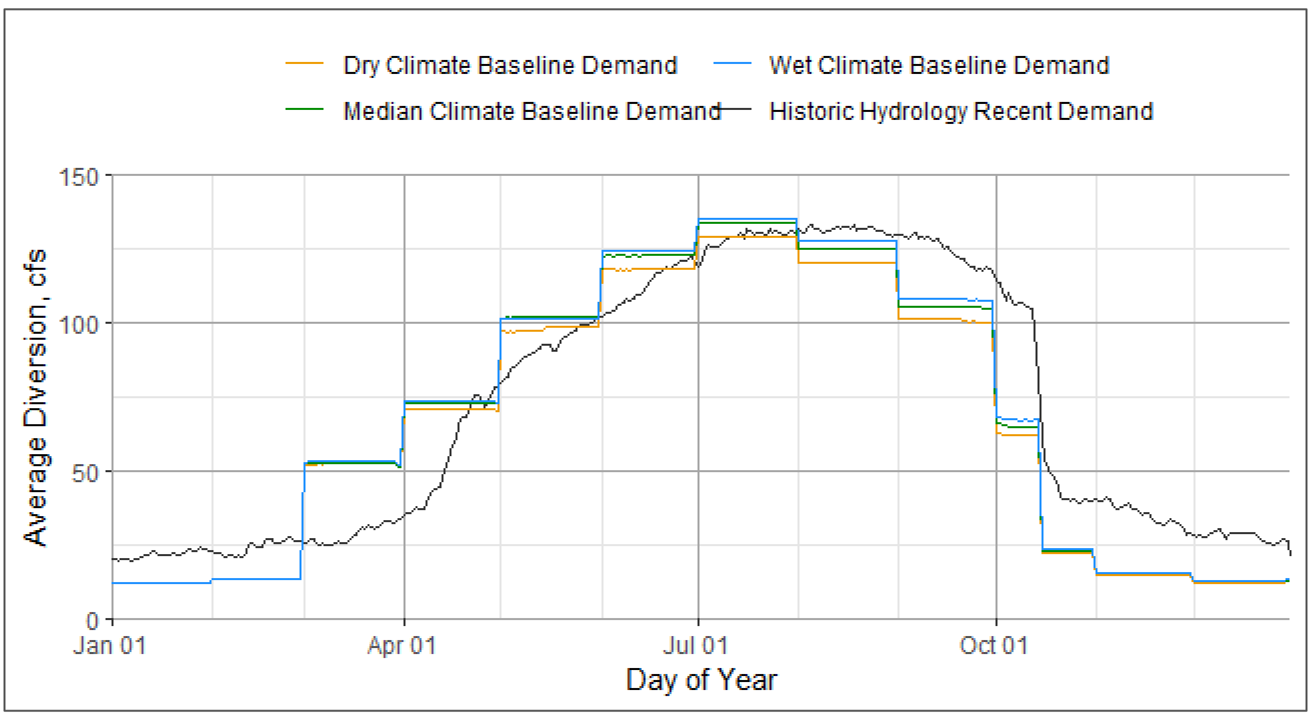


Figure 5-27. Average Daily Diversion from Deer Creek, Existing Operations Simulation Results

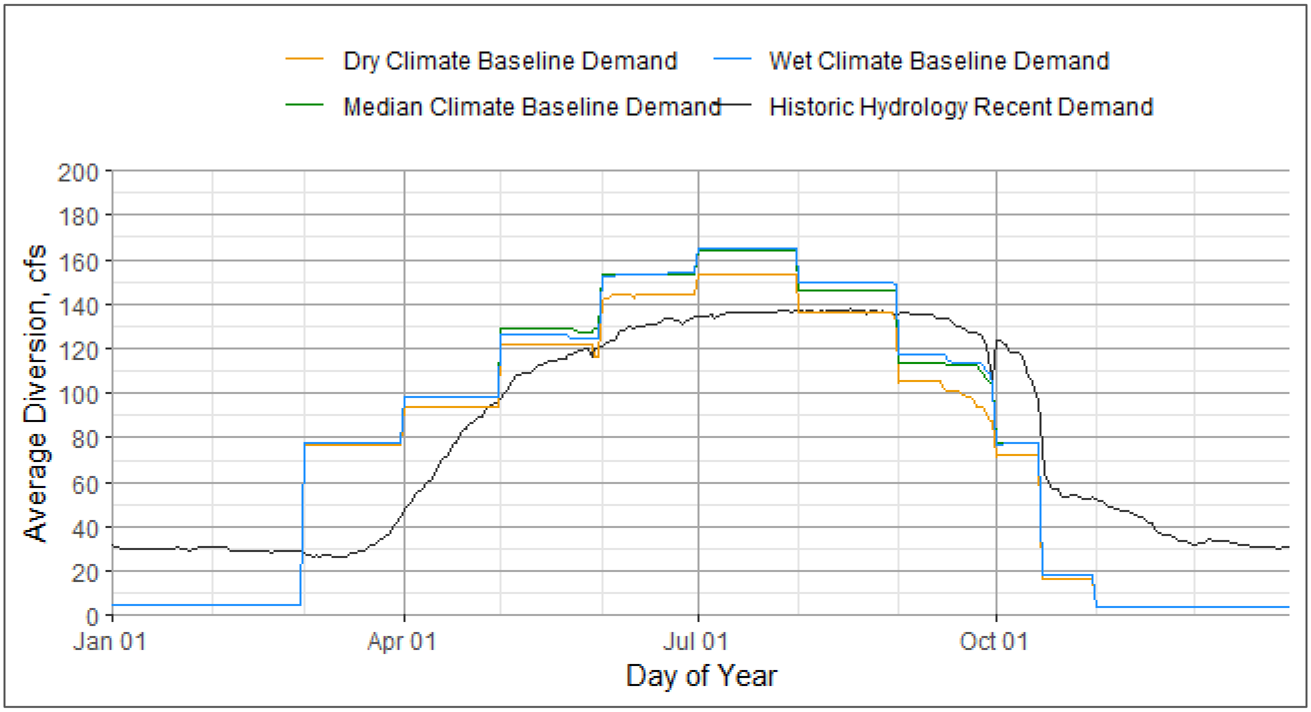


Figure 5-28. Average Daily Diversion from Lake Combie, Existing Operations Simulation Results

5.6.2.3 Deliveries

Average annual deliveries are shown in Table 5-12.

Table 5-12. Average Annual Deliveries in Existing Operations Studies, AF

	Dry Climate	Median Climate	Wet Climate
Low Demand	98,643	103,348	103,942
Baseline Demand	128,991	137,706	137,555
High Demand	146,458	159,371	161,611

Exceedance charts of annual deliveries, separated by demand level, are shown in Figure 5-29 through Figure 5-31. Figure 5-29 shows the low demand simulations, which have lower deliveries than the historic simulation due to the lower total demands. Figure 5-30 shows the baseline demand simulations, which generally have slightly lower deliveries than the historic simulation. Figure 5-31 shows the high demand simulations, which have higher deliveries in wet years due to the higher demands and lower deliveries in dry years than the historic simulation.

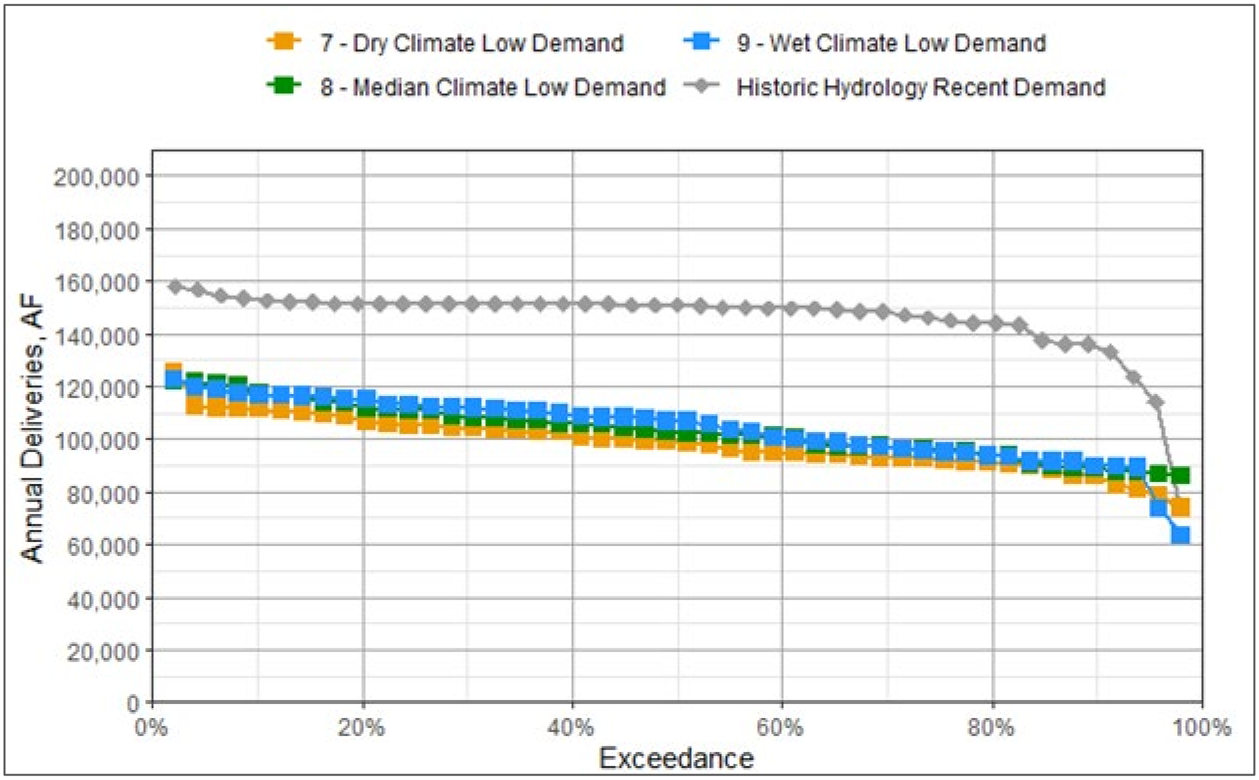


Figure 5-29. Annual Delivery Exceedance, Low Demand Existing Operations Studies

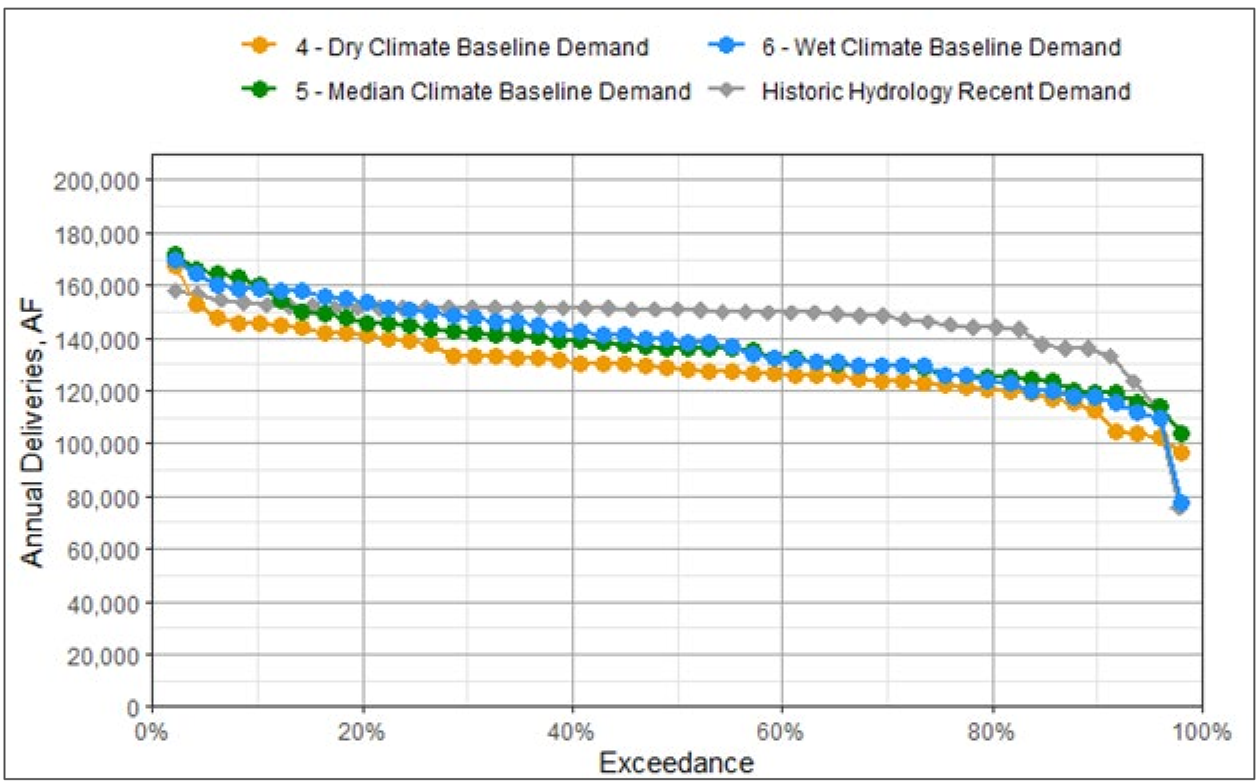


Figure 5-30. Annual Delivery Exceedance, Baseline Demand Existing Operations Studies

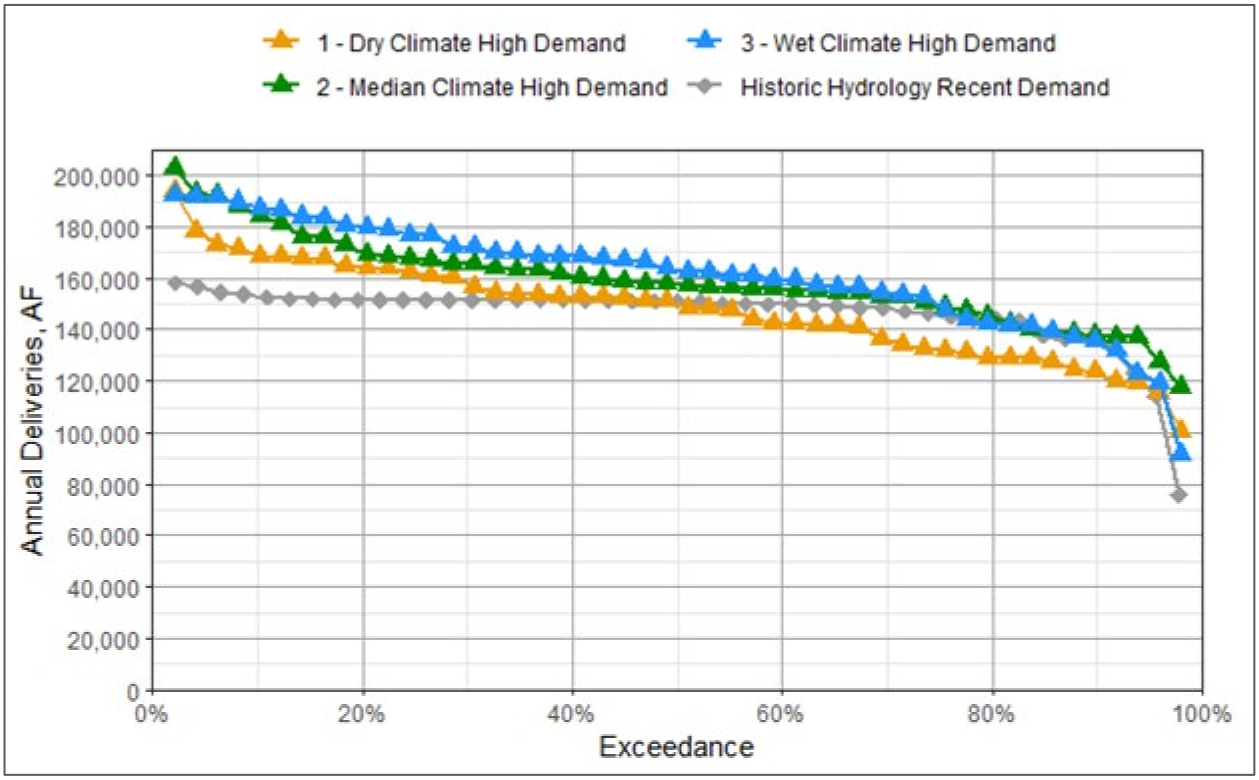


Figure 5-31. Annual Delivery Exceedance, High Demand Existing Operations Studies

Each baseline study results in some amount of unmet demands. Average annual unmet demands are shown in Table 5-13.

Table 5-13. Average Annual Unmet Demands in Existing Operations Studies, AF

	Dry Climate	Median Climate	Wet Climate
Low Demand	9,014	5,740	5,763
Baseline Demand	20,663	14,099	14,683
High Demand	35,158	24,112	23,027

Exceedance charts of annual unmet demand, separated by demand level, are shown in Figure 5-32, Figure 5-33, and Figure 5-34.

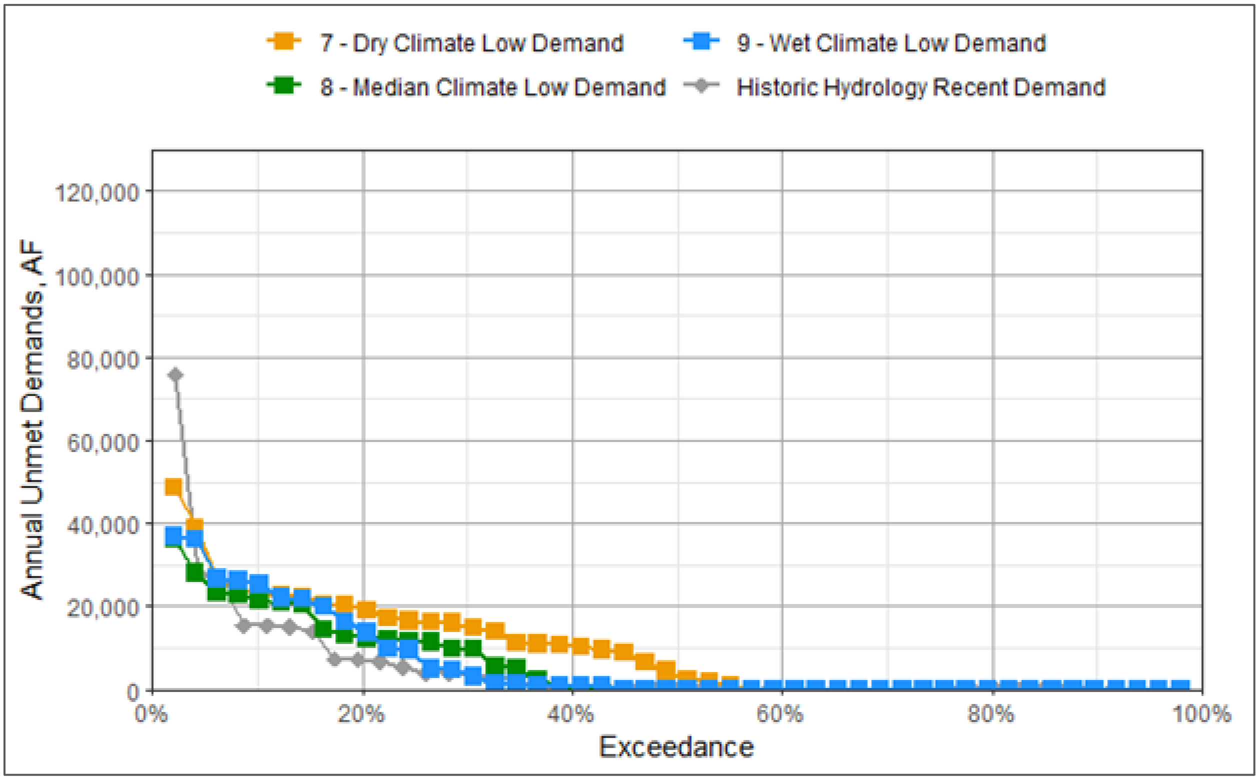


Figure 5-32. Unmet Demands Exceedance, Low Demand Existing Operations Studies

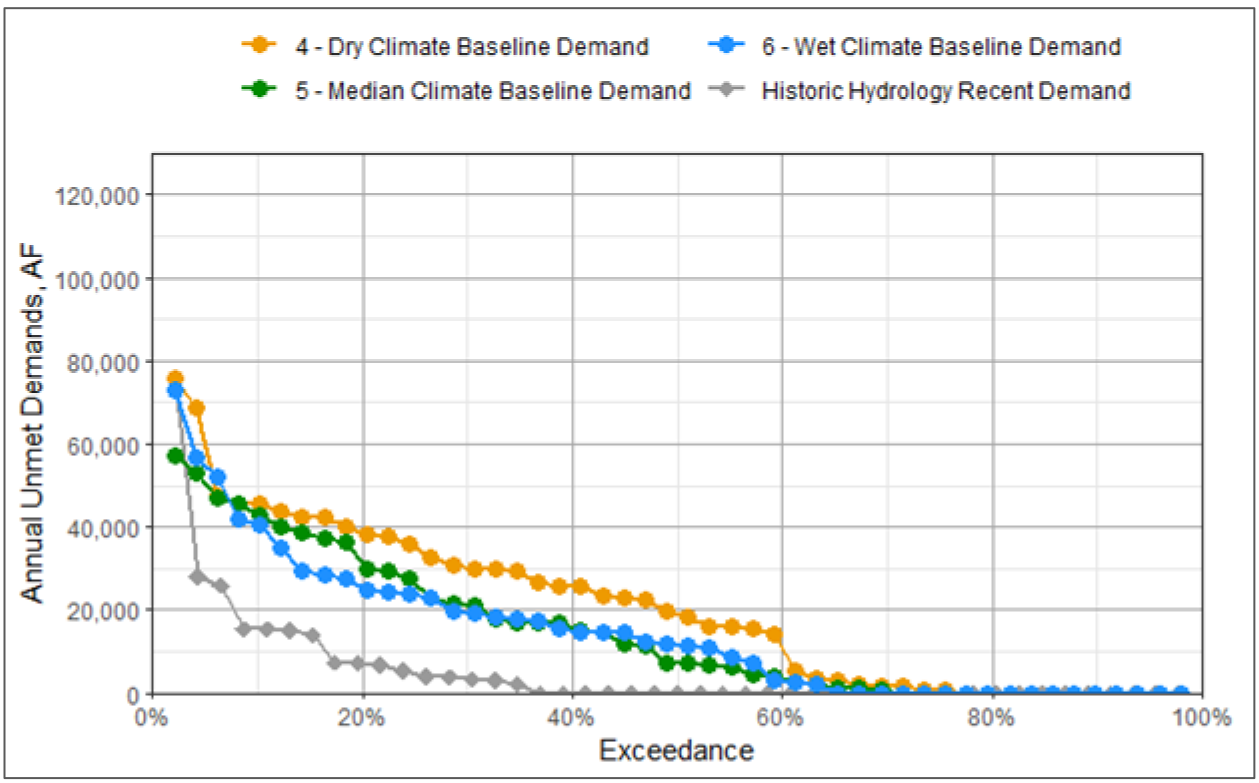


Figure 5-33. Unmet Demands Exceedance, Baseline Demand Existing Operations Studies

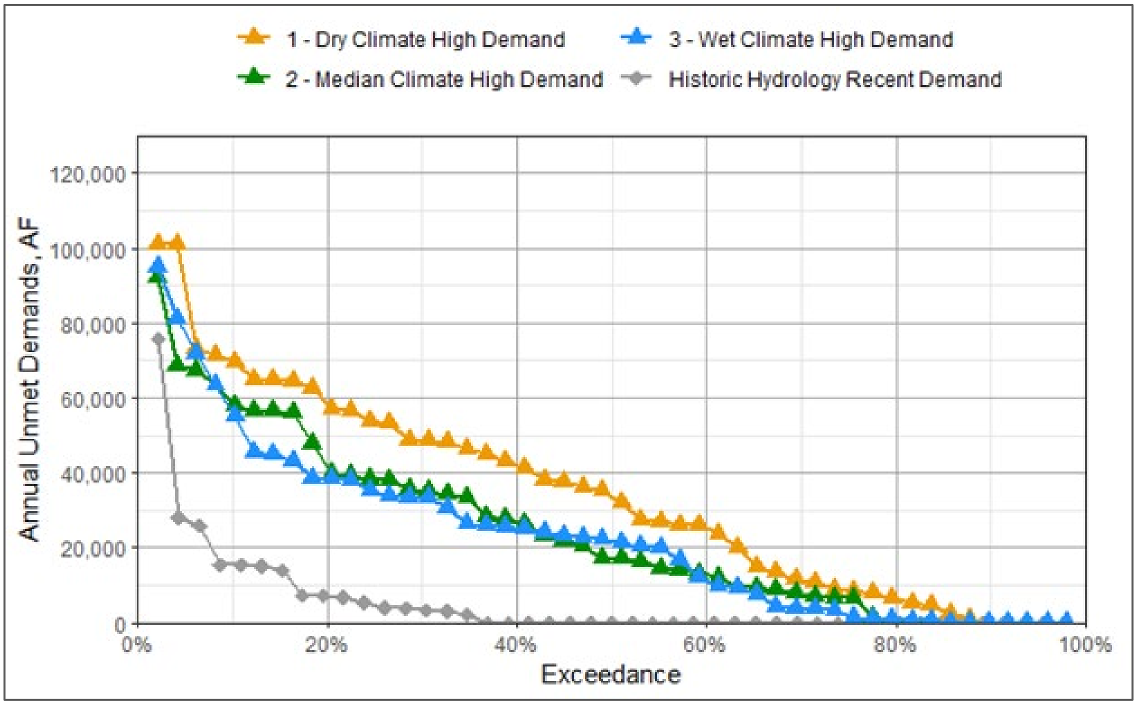


Figure 5-34. Unmet Demands Exceedance, High Demand Existing Operations Studies

5.6.2.4 Generation

Annual average power generation in the baseline studies is shown in Table 5-14. For comparison, the average annual generation in the historic hydrology calibration study is 251.4 GWh.

Table 5-14. Average Annual NID Generation, Existing Operations Studies, GWh

	Dry Climate	Median Climate	Wet Climate
Low Demand	205.7	238.2	254.0
Baseline Demand	205.0	237.5	258.7
High Demand	203.7	236.4	250.0

5.6.3. Results Summary

The results of the nine Existing Operations studies were presented to the NID BOD and stakeholders for consideration to carry forward for evaluation of strategic alternatives. For this evaluation, three of the nine Existing Operations scenarios were chosen. The chosen scenarios were:

- Dry Climate with High Demands
- Median Climate with Baseline Demands
- Wet Climate with Low Demands

These scenarios provide dry and wet bookends with a median climate scenario to represent a mid-point. Use of these scenarios provides a wide range of hydrologic conditions and consumptive demands; the scenarios are suitable for testing the strategic alternatives designed to improve NID's water supply security in the face of shifting runoff patterns and volumes in the projected climate scenarios.

Chapter 6. Strategic Alternatives

Seven strategic alternatives were selected as potential measures to increase NID's future water security. Each strategic alternative was layered onto each of the three Existing Operations scenarios. The benefits of the strategic alternatives were then determined by comparing them to each of the selected Existing Operations studies.

6.1. Existing Operations Studies

As discussed in Section 1.6.3, three Existing Operations scenarios were chosen for measuring the benefit of each of the strategic alternatives.

To establish a basis for measuring benefit, exceedance curves of unmet demands, total NID carryover storage, and total NID generation for these selected Existing Operations scenarios are shown as Figure 6-1 through Figure 6-3. Exceedance curves are graphical representations used to analyze and visualize the likelihood of exceeding a certain threshold or level for a given variable. As an example (Example 1), if one wanted to know how often Annual Unmet Demand exceeds 60,000 AF under the Dry Climate High Demand Scenario, based on Figure 6-1, the answer is 20% of the time.

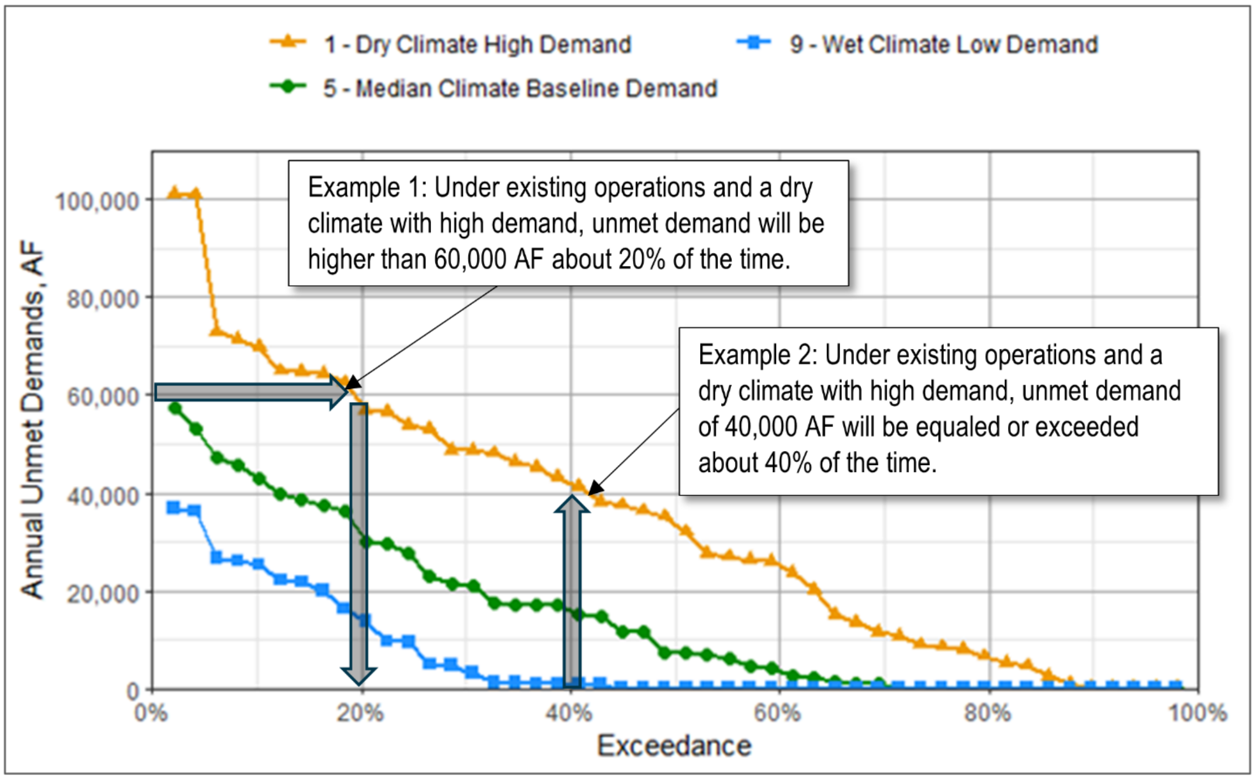


Figure 6-1. Annual Unmet Demands Exceedance, Selected Existing Operations Scenarios

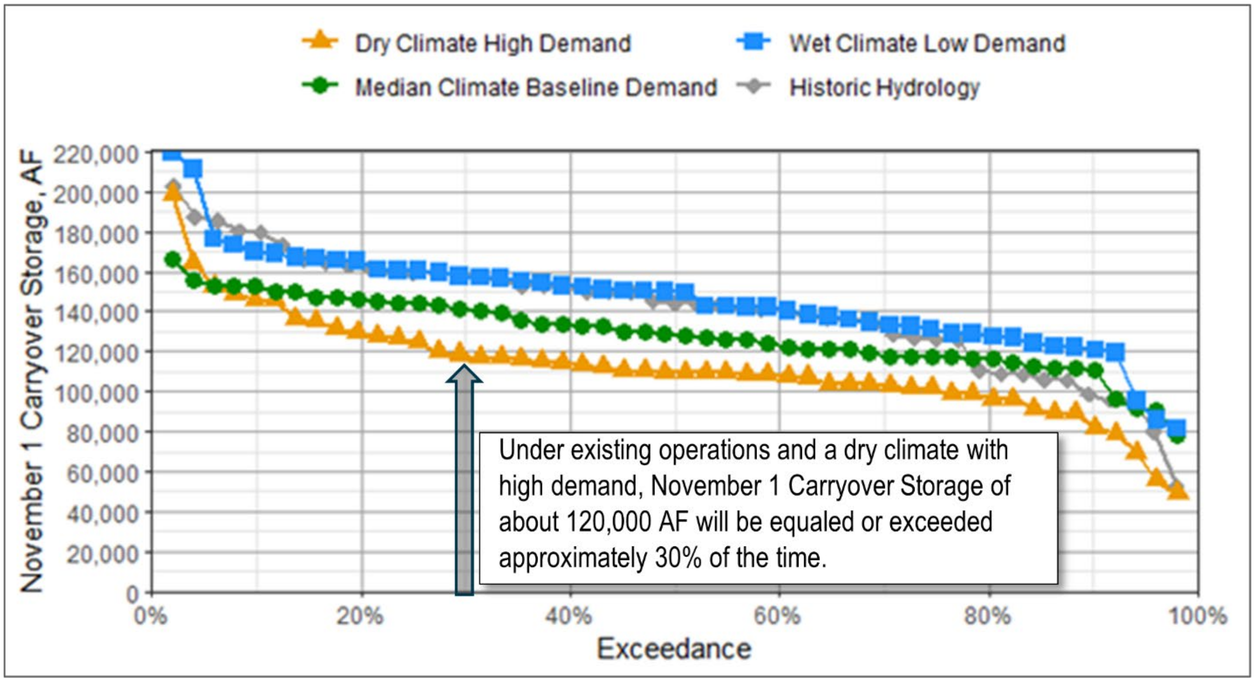


Figure 6-2. November 1 Carryover Storage Exceedance, Selected Existing Operations Scenarios

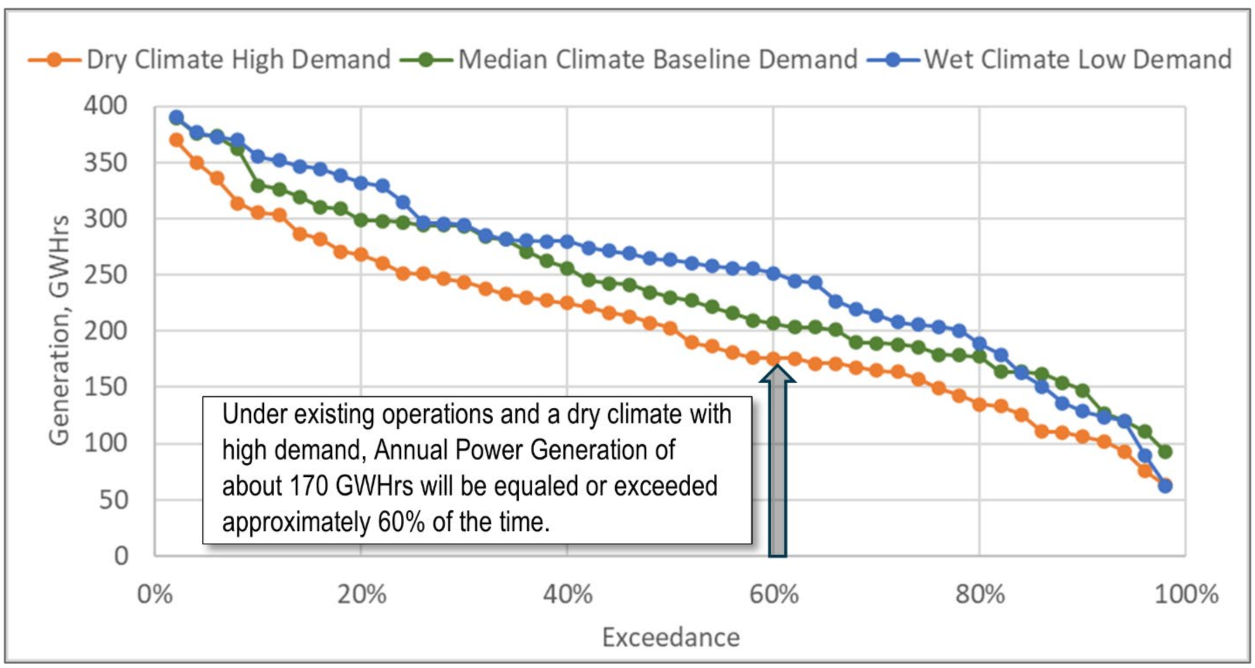


Figure 6-3. Annual NID Generation Exceedance, Selected Existing Operations Scenarios

6.2. Strategic Alternatives Chosen for Modeling

Seven strategic alternatives were chosen for modeling:

- Extended Irrigation Season
- Rollins Reservoir 10,000 AF Storage Increase
- Rollins Reservoir 50,000 AF Storage Increase
- Centennial Reservoir
- Revised Carryover Targets
- Water Purchases from PG&E
- Revised Carryover Targets + Water Purchases from PG&E

Sections 6.3 through 6.9 describe each alternative and provide summary modeling results.

6.3. Extended Irrigation Season

NID's current irrigation season runs through October 15th. The extended irrigation season strategic alternative extends the end of the irrigation season through October 31st. Irrigation deliveries in the second half of October are assumed to match irrigation deliveries in the first half of October. Municipal Deliveries to water treatment plants are left unchanged. Average annual demands are shown in Table 6-1.

Table 6-1. Average Annual Demands, Regular Irrigation Season and Extended Irrigation Season

Scenario	Average Annual Demand, Current Irrigation Season (AF)	Average Annual Demand, Extended Irrigation Season (AF)	Difference (AF)
Dry Climate High Demand	181,616	188,055	6,439
Median Climate Baseline Demand	151,806	157,318	5,512
Wet Climate Low Demand	109,705	113,531	3,826

Modeling of the extended irrigation season shows that this alternative would result in more irrigation deliveries but a reduction in the November 1 carryover storage. This is summarized in Table 6-2. Demand, delivery, and unmet demands for each scenario are shown in Table 6-3. Resulting unmet demand exceedance for the Extended Irrigation Season Alternative is shown in Figure 6-4.

Table 6-2. Increase in Demand and Deliveries in Extended Irrigation Season

Scenario	Increase in Demand	Increase in Deliveries	Change in Carryover Storage
Dry Climate High Demand	6,439	5,193	-265
Median Climate Baseline Demand	5,512	4,001	-2,078
Wet Climate Low Demand	3,826	3,334	-2,656

Table 6-3. Deliveries and Unmet Demand, Extended Irrigation Alternative

Scenario	Project Condition	Demand	Delivery	Unmet Demand
Dry Climate High Demand	Regular Irrigation Season	181,616	146,458	35,158
	Extended Irrigation Season	188,055	151,651	36,405
Median Climate Baseline Demand	Regular Irrigation Season	151,806	137,706	14,099
	Extended Irrigation Season	157,318	141,707	15,611
Wet Climate Low Demand	Regular Irrigation Season	109,705	103,941	5,763
	Extended Irrigation Season	113,531	107,275	6,256

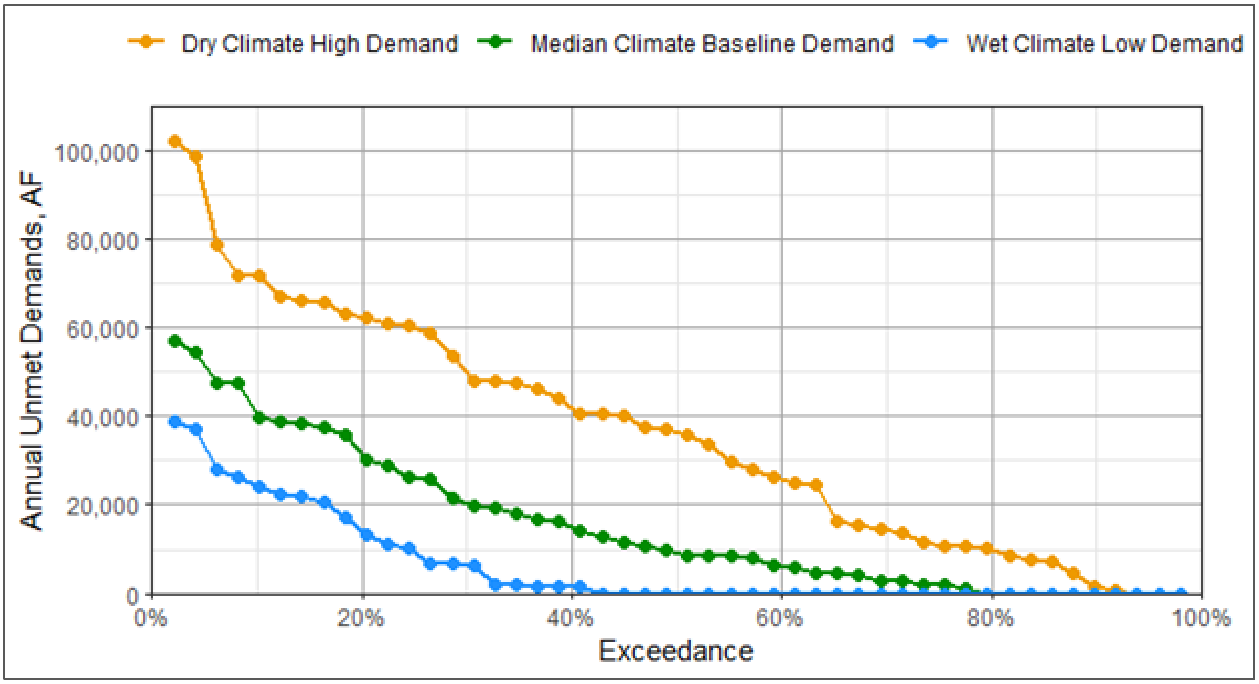


Figure 6-4. Annual Unmet Demand Exceedance, Extended Irrigation Season Alternative

6.4. Rollins Reservoir 10,000 AF Storage Capacity Increase

A modified Rollins Reservoir was built into the model simulating an additional 10,000 AF of usable storage capacity at Rollins Reservoir. All outlet works are assumed to have the same capacities as the current Rollins Reservoir outlet works. Proposed future FERC minimum flow requirements and minimum pool requirements were also assumed.

This strategic alternative allows for more water to be stored in Rollins Reservoir ahead of the summer storage dispatch season, allowing a larger buffer from minimum pool levels. Currently, Rollins Reservoir spills most years, and there is water available to be stored in nearly all years. Rollins Reservoir storage with this strategic alternative is shown for the Dry Climate High Demand scenario in Figure 6-5, for the Median Climate Baseline Demand scenario in Figure 6-6, and for the Wet Climate Low Demand scenario in Figure 6-7. These figures all show that Rollins Reservoir continues to fill and spill in most years with the expanded storage capacity.

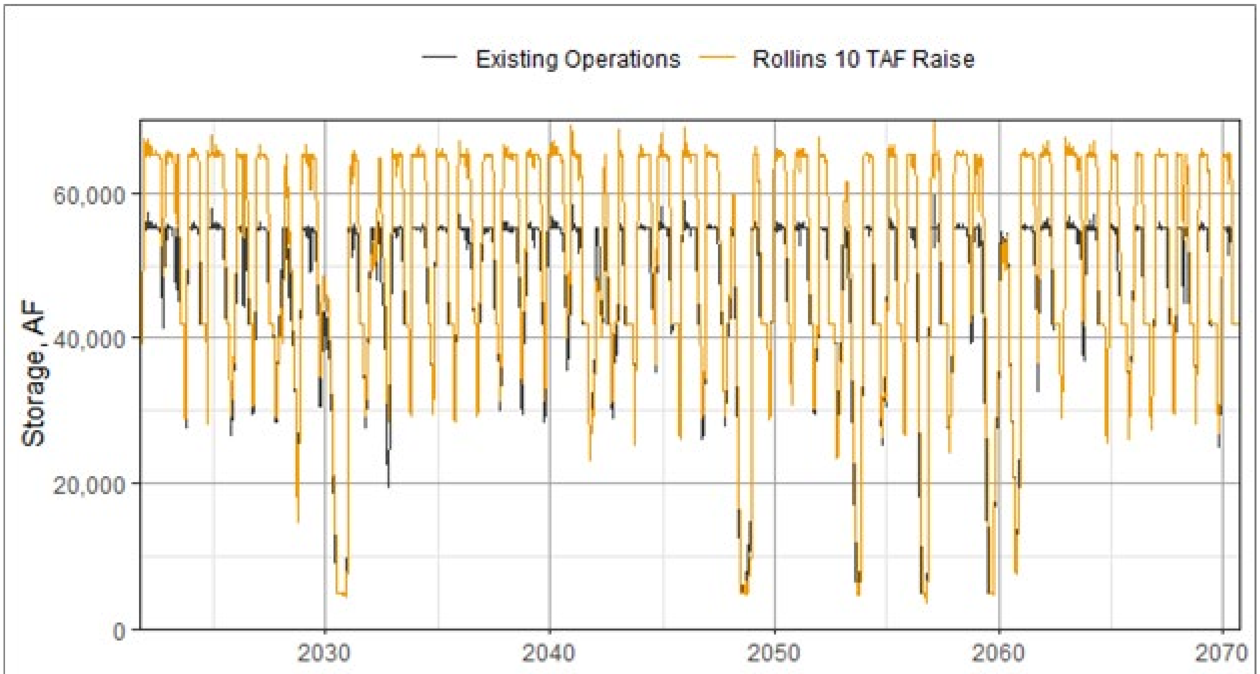


Figure 6-5. Rollins Reservoir Storage, Rollins 10 TAF Raise Alternative, Dry Climate High Demands Scenario

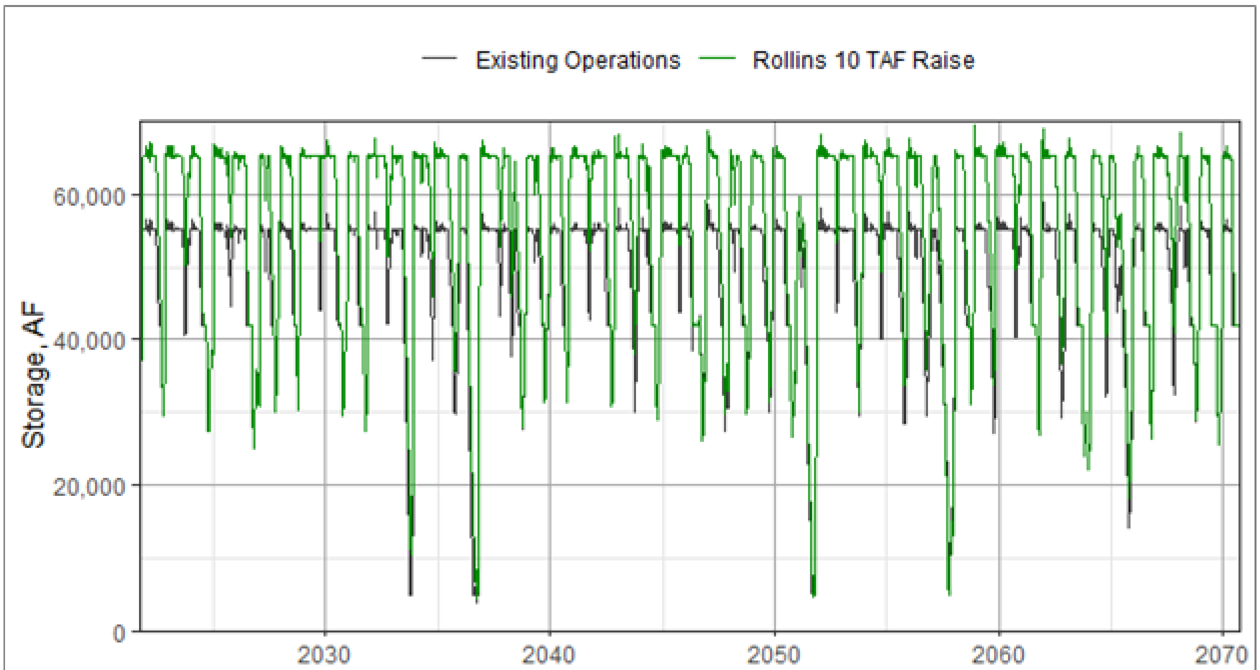


Figure 6-6. Rollins Reservoir Storage, Rollins 10 TAF Raise Alternative,
Median Climate Baseline Demands Scenario

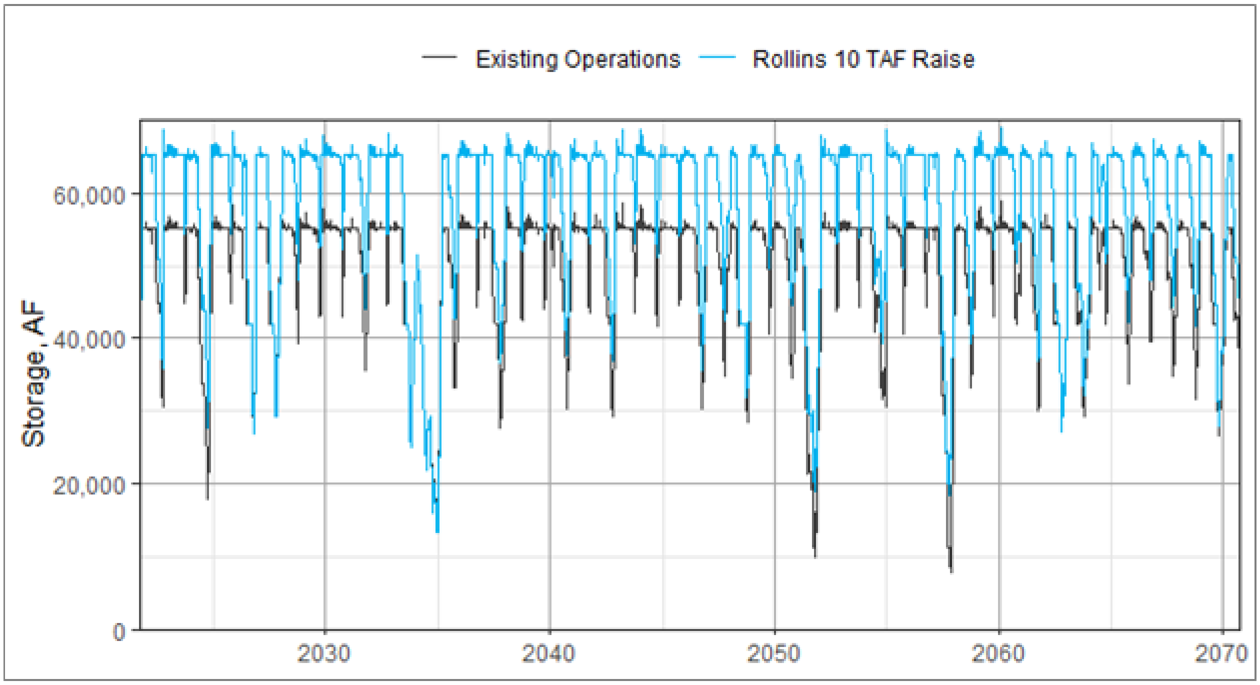


Figure 6-7. Rollins Reservoir Storage, Rollins 10 TAF Raise Alternative, Wet Climate Low Demands Scenario

This additional storage on the Bear River increases NID's ability to make deliveries by increasing delivery allocations and reducing storage constraints at Rollins Reservoir. Demands, deliveries, and unmet demands are shown in Table 6-4. An exceedance plot of the annual unmet demand is shown in Figure 6-8.

Table 6-4. Demand, Delivery, and Unmet Demands, AF, Rollins 10 TAF Raise Alternative

Scenario	Project Condition	Demand	Delivery	Unmet Demand
Dry Climate High Demand	Existing Operations	181,616	146,458	35,158
	Rollins 10 TAF increase	181,616	152,544	29,072
Median Climate Baseline Demand	Existing Operations	151,806	137,706	14,099
	Rollins 10 TAF increase	151,806	142,221	9,585
Wet Climate Low Demand	Existing Operations	109,705	103,941	5,763
	Rollins 10 TAF increase	109,705	105,485	4,220

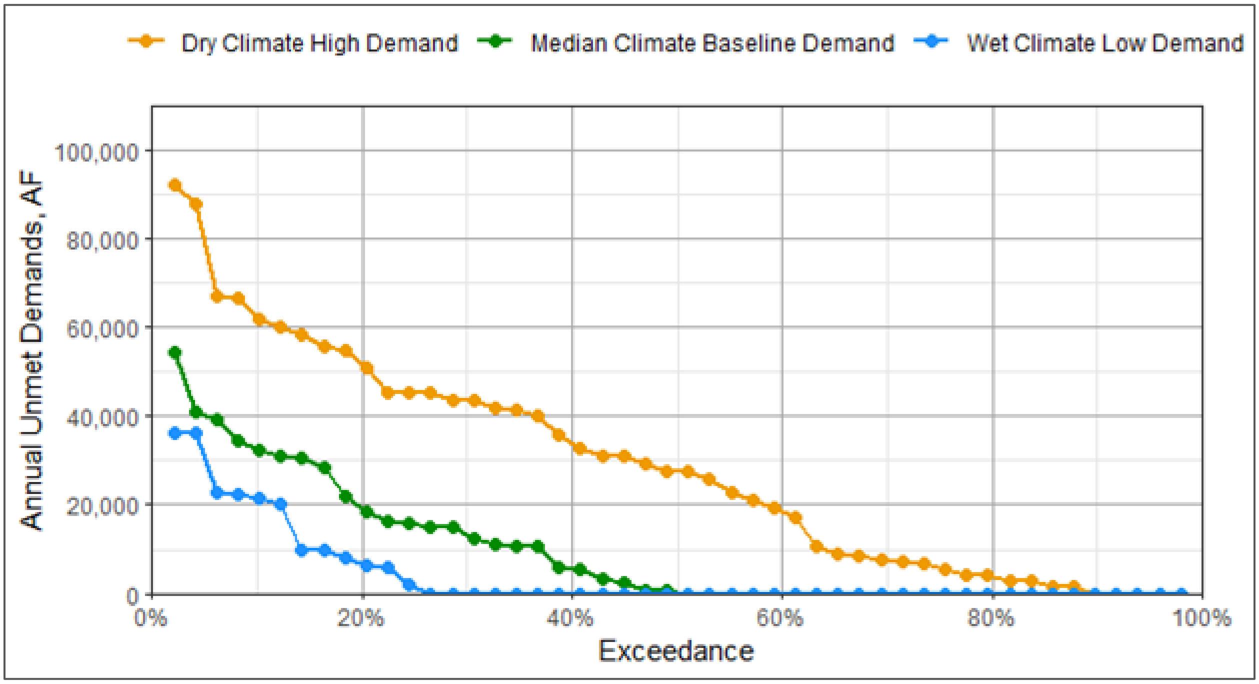


Figure 6-8. Annual Unmet Demand Exceedance, Rollins 10 TAF Raise Alternative

6.5. Rollins Reservoir 50,000 AF Storage Capacity Increase

A modified Rollins Reservoir was built into the model that simulates an additional 50,000 AF of usable storage capacity at Rollins Reservoir. All outlet works are assumed to have the same capacities as the current Rollins Reservoir outlet works. Proposed future FERC minimum flow requirements and minimum pool requirements were also assumed.

This strategic alternative allows for more water to be stored in Rollins Reservoir ahead of the summer storage dispatch season, which allows a larger buffer from minimum pool levels. Currently, Rollins Reservoir spills most years, and there is water available to be stored in nearly all years. Rollins Reservoir storage with the Rollins Reservoir 50 TAF storage increase strategic alternative is shown for the Dry Climate High Demand scenario in Figure 6-9, for the Median Climate Baseline Demand scenario in Figure 6-10, and for the Wet Climate Low Demand scenario in Figure 6-11. These figures show that, under this scenario, Rollins reservoir will not be filled every single year by the additional capacity of 50,000 AF, but storage is higher than the current capacity every year.

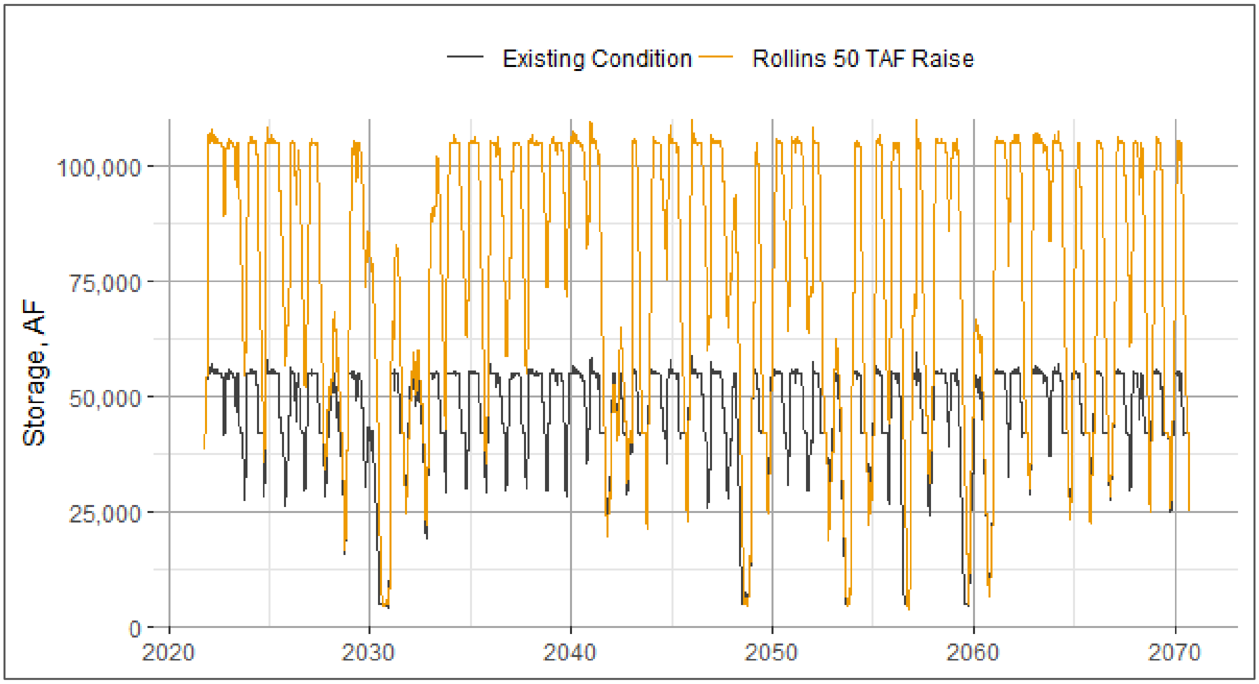


Figure 6-9. Rollins Reservoir Storage, Rollins 50 TAF Raise Alternative, Dry Climate High Demands Scenario

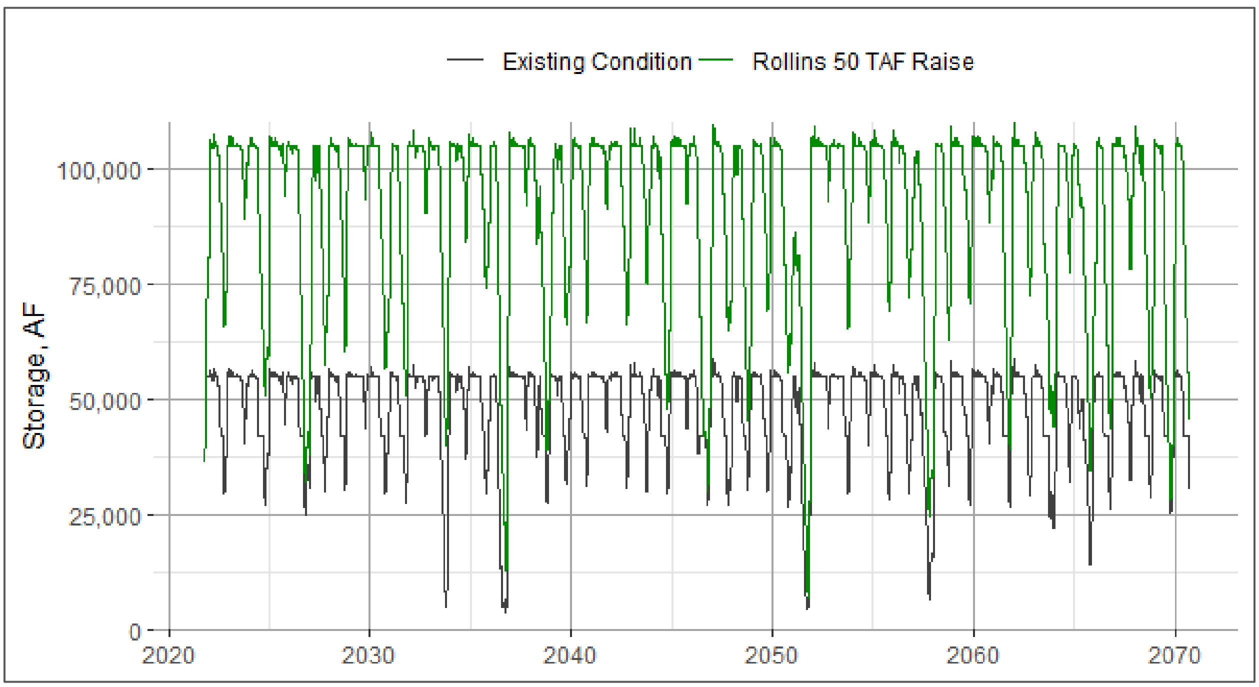


Figure 6-10. Rollins Reservoir Storage, Rollins 50 TAF Raise Alternative, Median Climate Baseline Demands Scenario

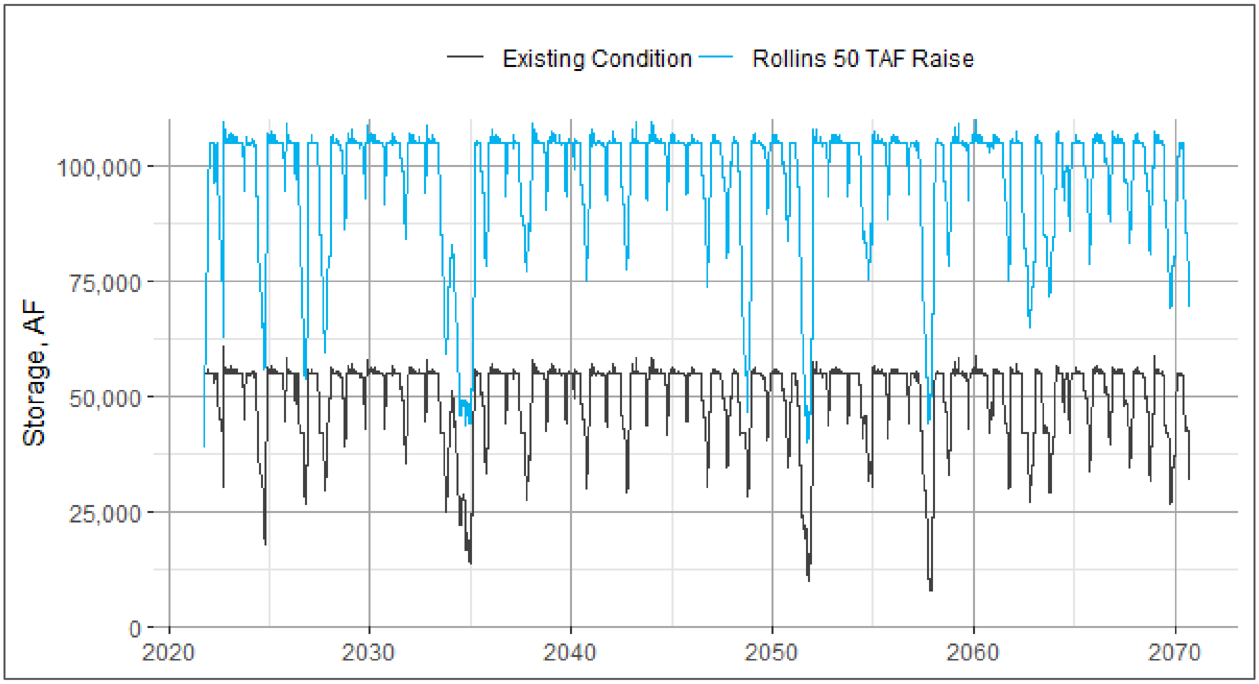


Figure 6-11. Rollins Reservoir Storage, Rollins 50 TAF Raise Alternative, High Climate Low Demands Scenario

Demand, delivery, and unmet demands for the Rollins 50 TAF Raise Alternative are shown in Table 6-5, and an exceedance plot of unmet demands for the Rollins 50 TAF Raise Alternative is shown in Figure 6-12.

Table 6-5. Demand, Delivery, and Unmet Demands, AF, Rollins 50 TAF Raise Alternative.

Scenario	Project Condition	Demand	Delivery	Unmet Demand
Dry Climate High Demand	Existing Operations	181,616	146,458	35,158
	Rollins 50 TAF increase	181,616	167,384	14,232
Median Climate Baseline Demand	Existing Operations	151,806	137,706	14,099
	Rollins 50 TAF increase	151,806	150,092	1,714
Wet Climate Low Demand	Existing Operations	109,705	103,941	5,763
	Rollins 50 TAF increase	109,705	108,892	813

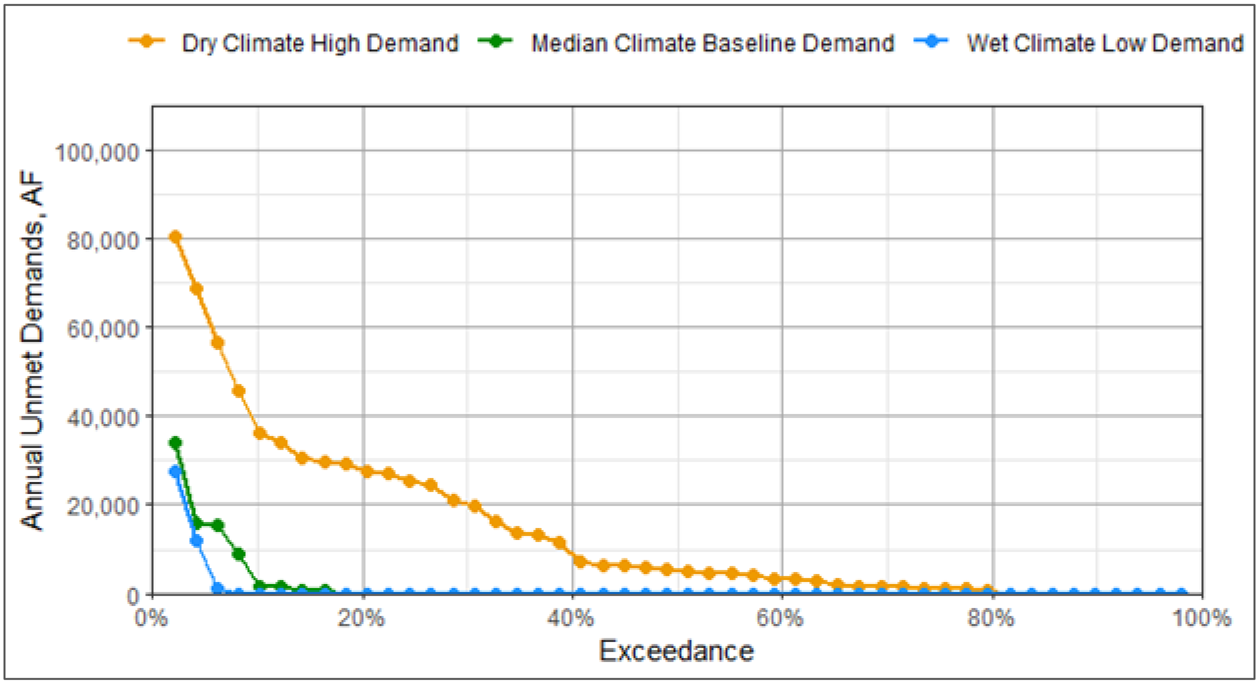
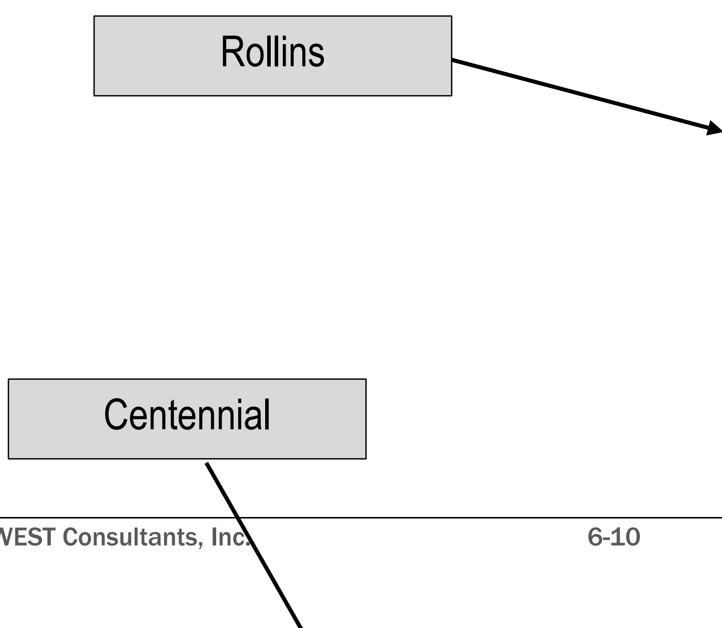


Figure 6-12. Unmet Demands Exceedance, Rollins 50 TAF Raise Alternative

6.6. Centennial Reservoir

A potential Centennial Reservoir was built into the model that provides for 96,660 AF of usable storage on the Bear River below Rollins Reservoir and above Lake Combie. The location of Centennial Reservoir in the Project schematic is shown in Figure 6-13. The reservoir was modeled with a low-level outlet with 300 cfs of capacity, an ungated spillway with a maximum capacity of 30,000 cfs, and no powerhouse. Minimum flow requirements below Centennial Reservoir were assumed to be the same as Lake Combie. Centennial Reservoir would be used to store water in the winter and spring and provide water to Lake Combie for deliveries into the Combie Phase I and Magnolia III canals in the summer and fall. Lake Combie can only drop 5 ft throughout the summer, and currently, these deliveries are made to Lake Combie from Rollins Reservoir. With Centennial Reservoir making these deliveries, Rollins Reservoir inflows and storage can be used exclusively in the Bear River Canal.



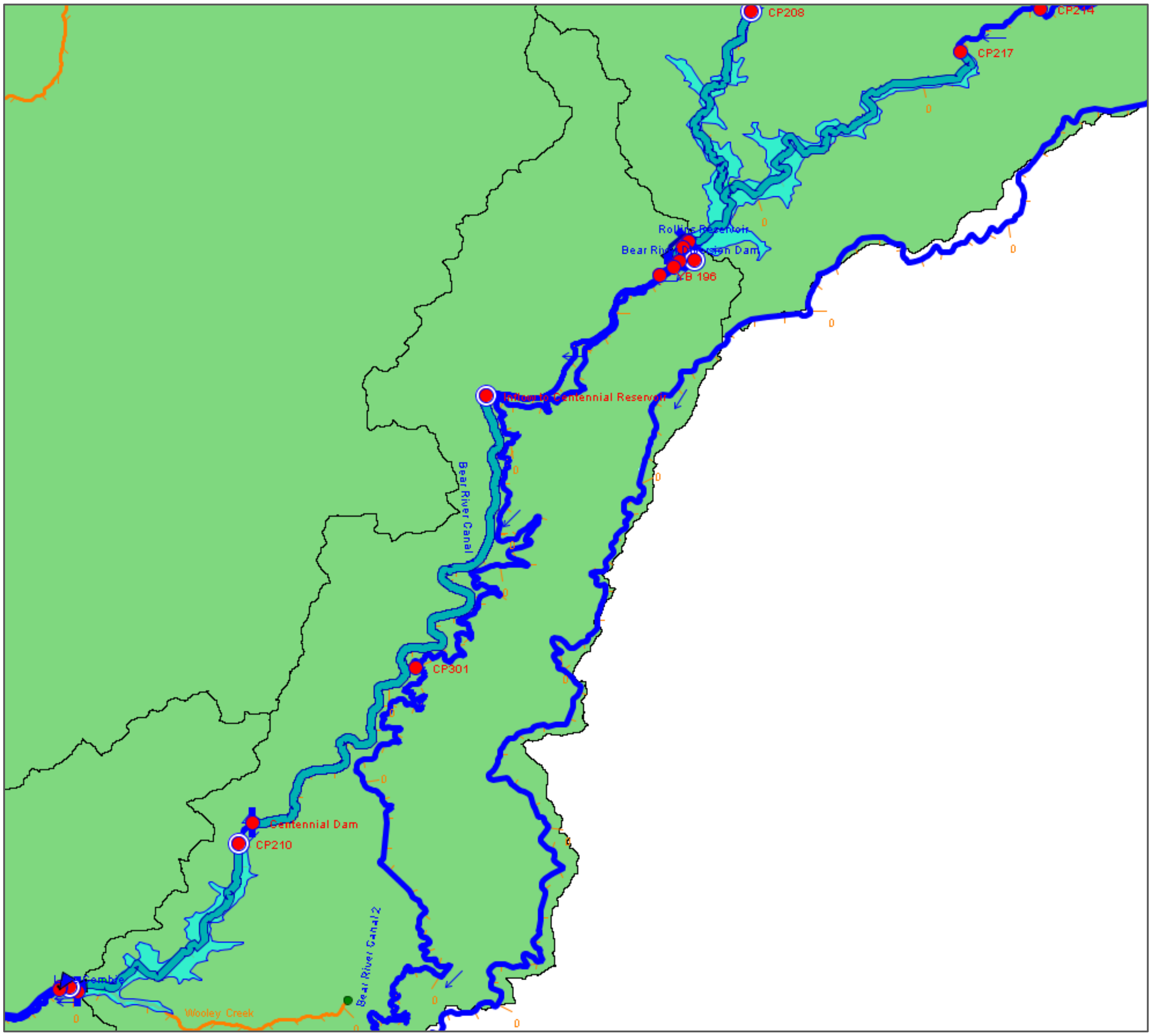


Figure 6-13. Centennial Reservoir Project Schematic

Centennial Reservoir storage is shown in Figure 6-14. The additional delivery and resulting reduction in unmet demand is shown in Table 6-6, and an exceedance plot of unmet demands for the Centennial Reservoir Alternative is shown in Figure 6-15.

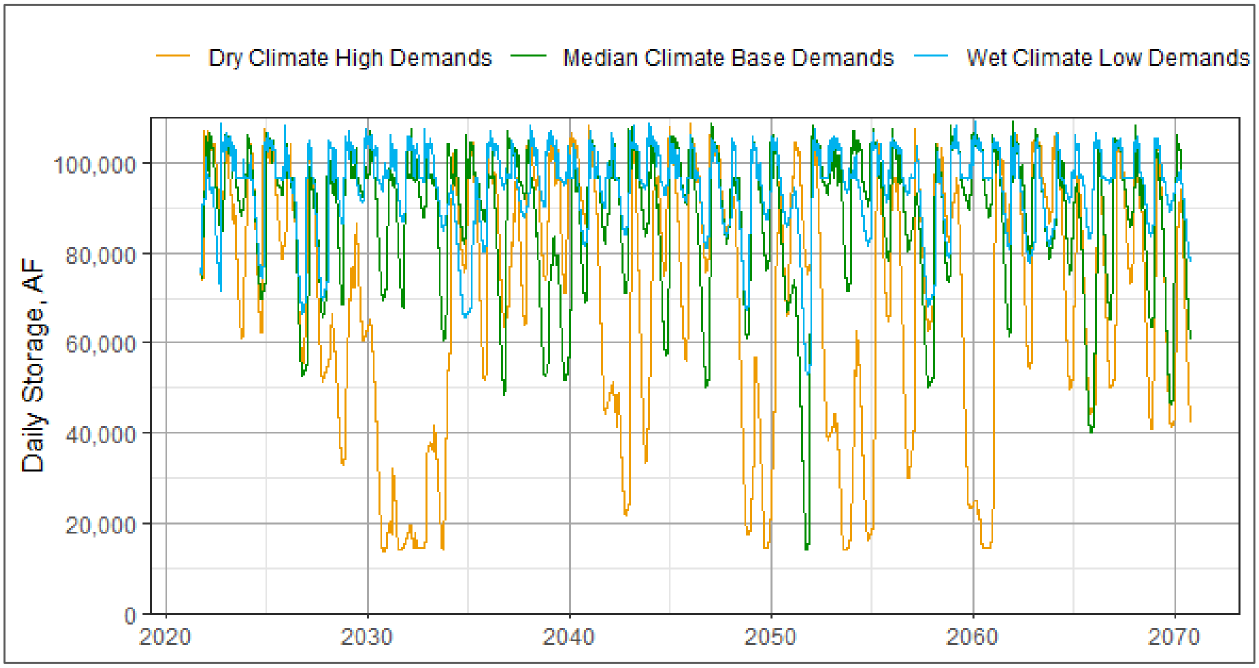


Figure 6-14. Centennial Reservoir Storage

Table 6-6. Demand, Delivery, and Unmet Demands, AF, Centennial Reservoir Alternative

Scenario	Project Condition	Demand	Delivery	Unmet Demand
Dry Climate High Demand	Existing Operations	181,616	146,458	35,158
	Centennial Reservoir	181,616	165,322	16,294
Median Climate Baseline Demand	Existing Operations	151,806	137,706	14,099
	Centennial Reservoir	151,806	144,332	7,473
Wet Climate Low Demand	Existing Operations	109,705	103,941	5,763
	Centennial Reservoir	109,705	108,815	890

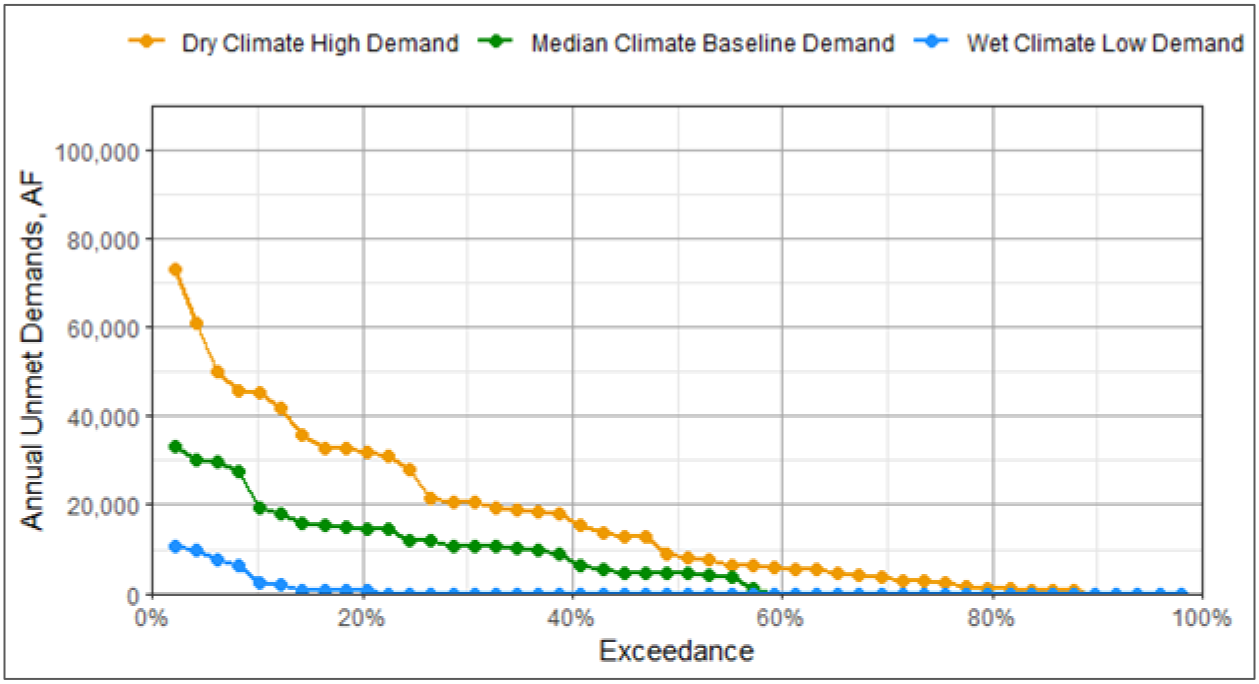


Figure 6-15. Unmet Demands Exceedance, Centennial Reservoir Alternative

6.7. Revised Carryover Targets

The revised carryover targets alternative lowers carryover targets at NID reservoirs. Existing Operations carryover targets use the average historical reservoir carryover level. In dry years, NID draws their reservoirs lower than the average carryover level. The revised carryover targets represent the level that NID would set reservoir carryover levels in a drought and better represent unmet demands in dry years. Existing Operations carryover targets and revised carryover targets are listed in Table 6-7.

Table 6-7. Revised Carryover Targets

Reservoir	Existing Operations Carryover Target	Revised Carryover Target
Jackson Meadows Reservoir	35,000	21,000
Bowman Reservoir	30,000	14,500
Sawmill Lake	1,500	1,000
French Lake	7,000	5,000
Faucherie Lake	2,100	1,500
Jackson Lake	600	1,000
Rollins Reservoir	40,000	25,000
Scotts Flat Reservoir	23,000	17,000
Lake Combie	2,500	2,500
Total	**141,700**	**88,500**

The revised carryover targets result in further drawdown of the reservoirs by the end of the year, and more storage capture in the winter and spring before the initiation of spill. These revised carryover targets did not significantly affect the ability of these reservoirs to fill in most years.

The additional delivery and resulting reduction in unmet demand is shown in Table 6-8, and an exceedance plot of unmet demands for the Centennial Reservoir Alternative is shown in Figure 6-16.

Table 6-8. Demand, Delivery, and Unmet Demands, AF, Revised Carryover Targets Alternative

Scenario	Project Condition	Demand	Delivery	Unmet Demand
Dry Climate High Demand	Existing Operations	181,616	146,458	35,158
	Revised Carryover Targets	181,616	150,528	27,715
Median Climate Baseline Demand	Existing Operations	151,806	137,706	14,099
	Revised Carryover Targets	151,806	138,963	9,814
Wet Climate Low Demand	Existing Operations	109,705	103,941	5,763
	Revised Carryover Targets	109,705	104,218	3,079

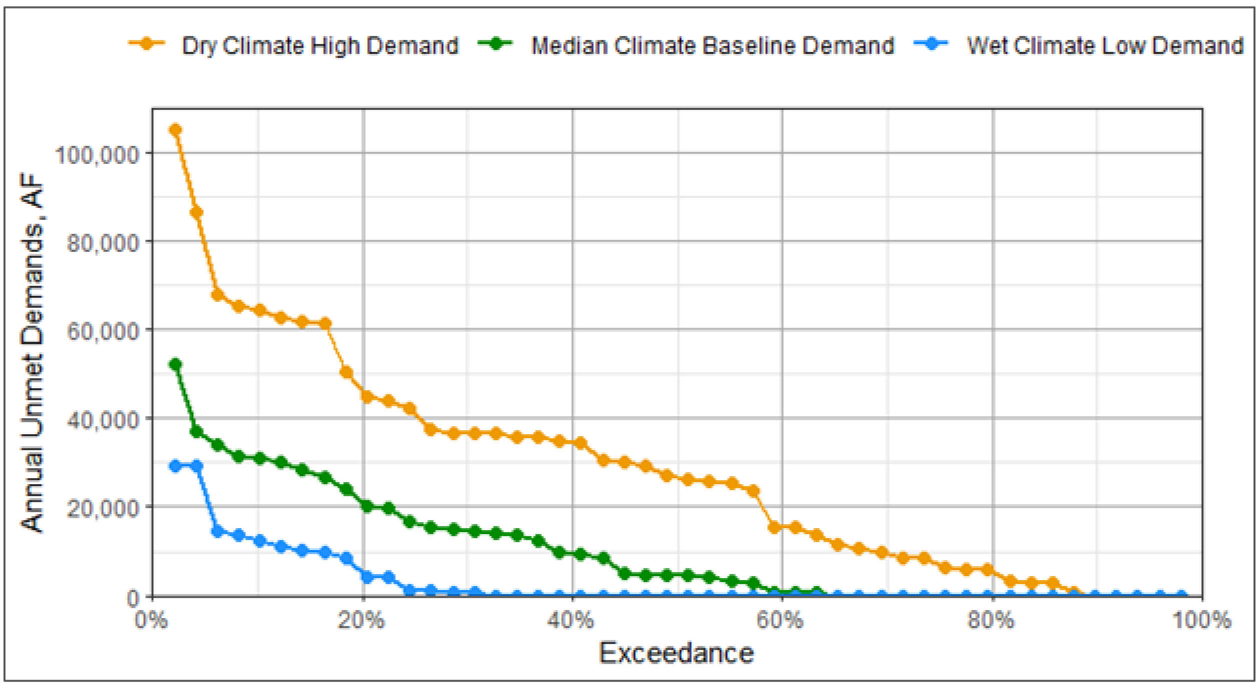


Figure 6-16. Unmet Demands Exceedance, Revised Carryover Targets Alternative

6.8. Purchase of Additional Supply from PG&E

The COA (NID 2018) specifies amounts of water that will be made available for purchase by NID from PG&E. These monthly purchase volumes and maximum flow rates are based on the Sacramento Valley Index, a water year type index defined and calculated by the DWR. Available monthly purchase volumes at the Deer Creek Powerhouse are shown in Figure 6-17, and available monthly purchase volumes on the Bear River Canal are shown in Figure 6-18. In Dry and Critically Dry Years the amount of water available for purchase in July through December are the volumes shown multiplied by the Sacramento Valley Index divided by the 50-year average of the Sacramento Valley Index.

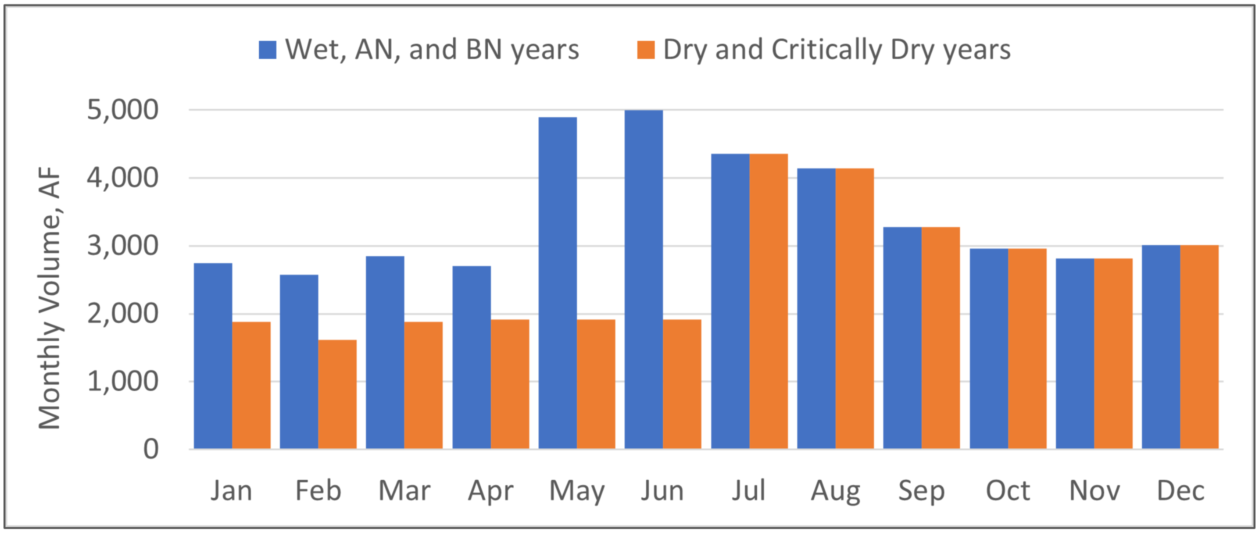


Figure 6-17. Available Monthly Purchase Volumes at the Deer Creek Powerhouse

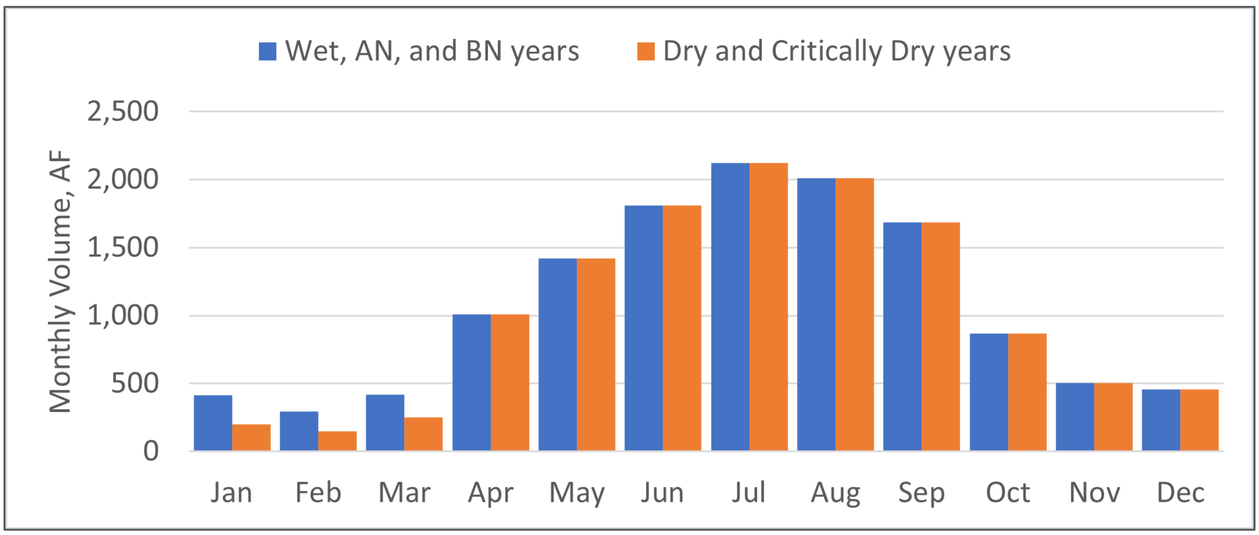


Figure 6-18. Available Monthly Purchase Volumes on the Bear River Canal

Monthly water volumes available for purchase were estimated using a regression for each of the developed climate change hydrology datasets. Current operations modeling study results were used to determine when unmet demands were occurring and identify water that could be purchased to meet or reduce those unmet demands. Identified useful water purchase annual volumes are shown in Figure 6-19.

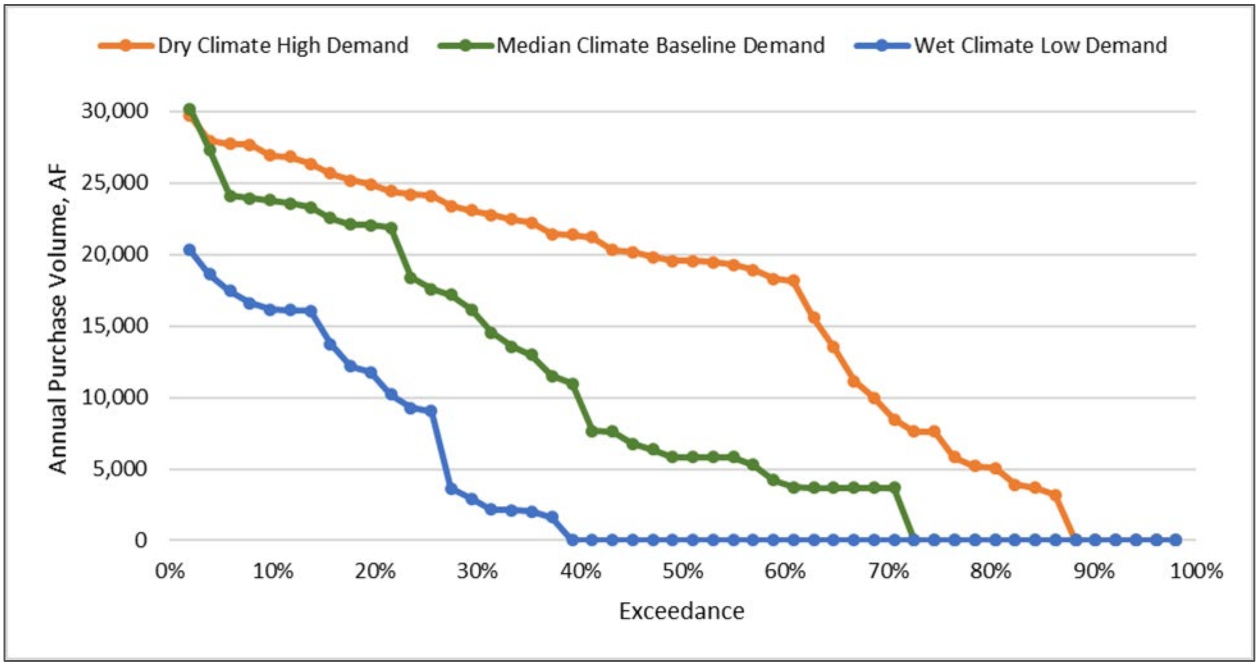


Figure 6-19. Annual Purchase Volumes Exceedance; Purchase of Additional Supply from PG&E Alternative

The model was run adding the identified useful water purchases at Deer Creek Powerhouse to NID diversions to Deer Creek, or displacing NID diversions to Deer Creek with purchase water results in more NID water available to be moved to the Bear River. Water purchases on the Bear River Canal are incorporated into the water balance calculations at Rollins Reservoir. NID allocation calculations incorporated the additional supply when determining annual delivery allocations.

The additional delivery and resulting reduction in unmet demand is shown in Table 6-9, and an exceedance plot of unmet demands for the Centennial Reservoir Alternative is shown in Figure 6-20.

Table 6-9. Demand, Delivery, and Unmet Demands, AF, Water Purchases from PG&E Alternative

Scenario	Project Condition	Demand	Delivery	Unmet Demand
Dry Climate High Demand	Existing Operations	181,616	146,458	35,158
	Purchase of additional supply	181,616	152,344	29,272
Median Climate Baseline Demand	Existing Operations	151,806	137,706	14,099
	Purchase of additional supply	151,806	141,892	9,914
Wet Climate Low Demand	Existing Operations	109,705	103,941	5,763
	Purchase of additional supply	109,705	105,868	3,837

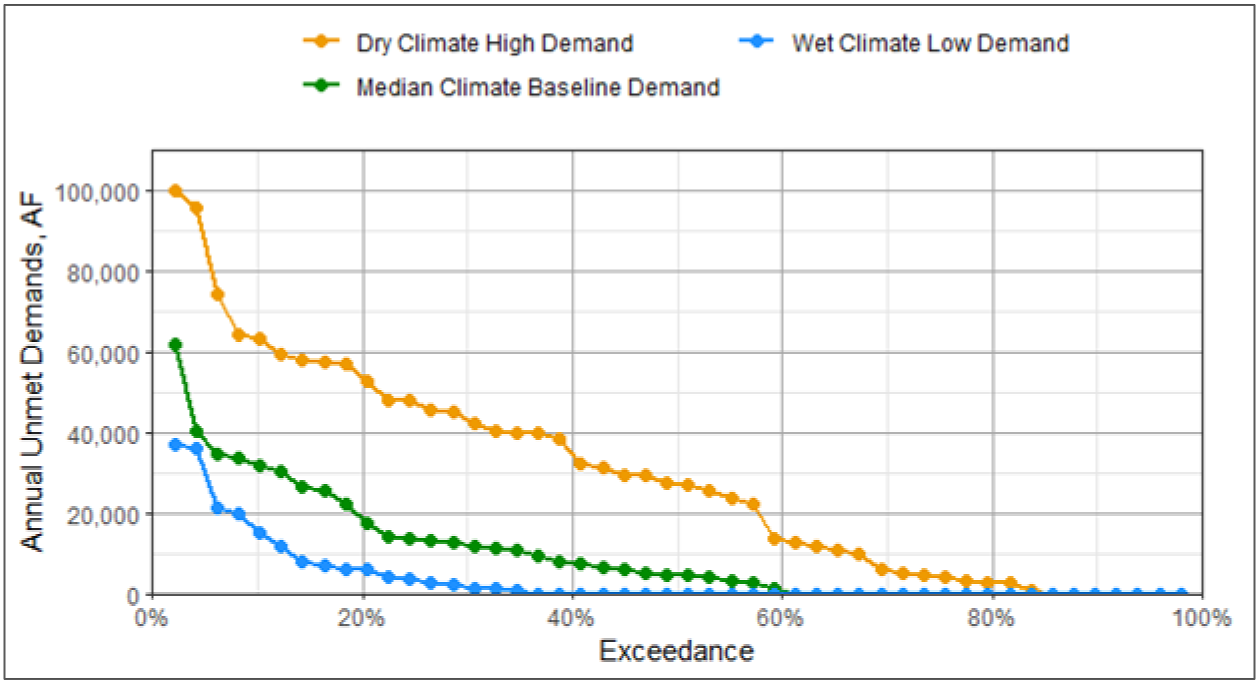


Figure 6-20. Annual Unmet Demands Exceedance, Purchase of Additional Supply from PG&E Scenario

6.9. Revised Carryover Targets and Purchase of Additional Supply from PG&E

An additional modeling study was performed that combined the revised carryover targets with the purchase of additional supply from PG&E. These alternatives work together to reduce the unmet demand further than the individual alternatives. Purchase volumes are reduced slightly, shown in the exceedance plot in Figure 6-21.

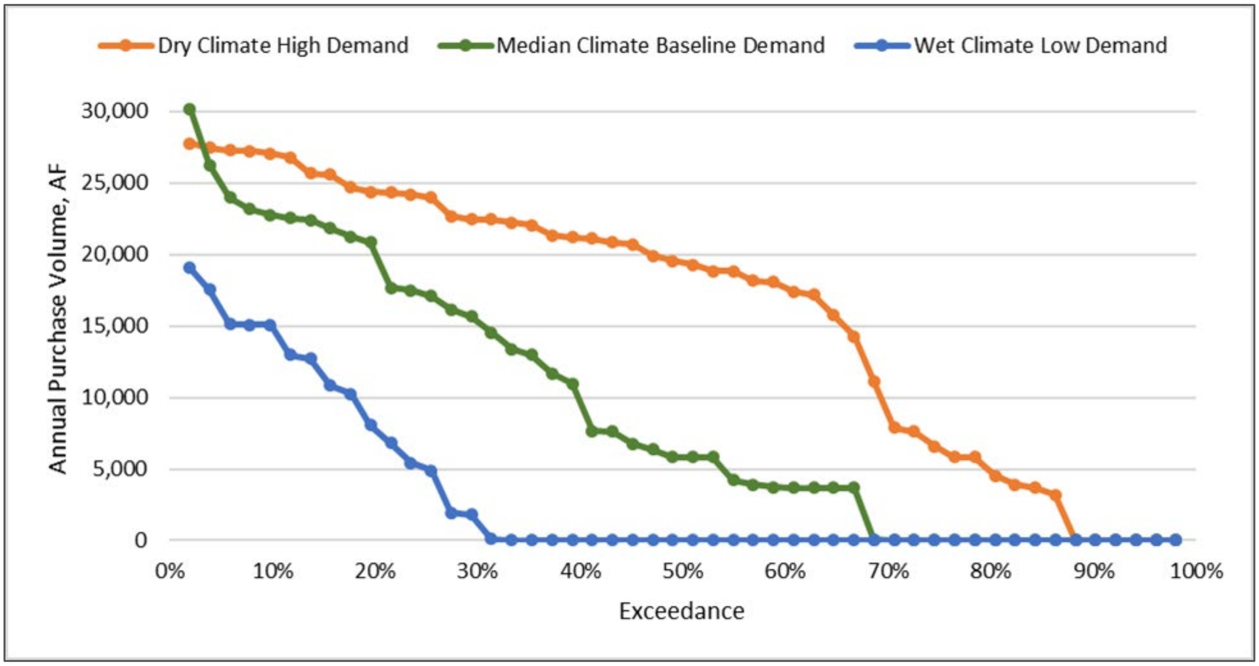


Figure 6-21. Annual purchase volumes exceedance, Revised Carryover Targets and Purchase of additional supply from PG&E alternative

The additional delivery and resulting reduction in unmet demand is shown in Table 6-10, and an exceedance plot of unmet demands for the Centennial Reservoir Alternative is shown in Figure 6-22.

Table 6-10. Demand, Delivery, and Unmet Demands, AF, Revised Carryover Targets and Water Purchases from PG&E Alternative

Scenario	Project Condition	Demand	Delivery	Unmet Demand
Dry Climate High Demand	Existing Operations	181,616	146,458	35,158
	Revised Carryover Targets and Purchase of additional supply	181,616	158,277	23,338
Median Climate Baseline Demand	Existing Operations	151,806	137,706	14,099
	Revised Carryover Targets and Purchase of additional supply	151,806	145,636	6,170
Wet Climate Low Demand	Existing Operations	109,705	103,941	5,763
	Revised Carryover Targets and Purchase of additional supply	109,705	107,762	1,943

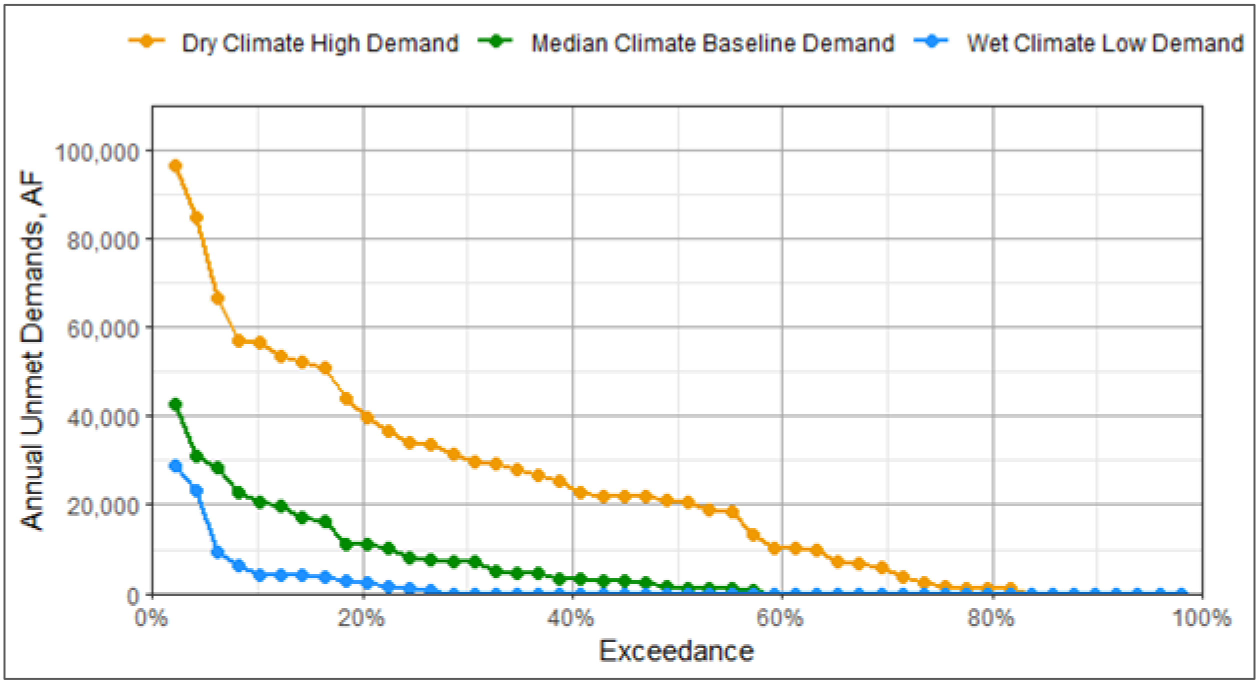


Figure 6-22. Annual Unmet Demands Exceedance, Revised Carryover Targets and Purchase of Additional Supply from PG&E Scenario

6.10. Summary

Deliveries, unmet demands, and carryover storage are summarized for the strategic alternatives for the Wet Climate Low Demand scenarios in Table 6-11, for the Median Climate Low Demand scenarios in Table 6-12, and for the Dry Climate Low Demand scenarios in Table 6-13.

Table 6-11. Strategic Alternatives Deliveries, Unmet Demands, and Carryover Storage, Wet Climate Low Demand Scenarios

Strategic Alternative	Average Annual Delivery (AF)	Average Annual Unmet Demand (AF)	Carryover Storage (AF)
Existing Operations	103,941	5,763	147,800
Extended Irrigation Season	107,275	6,256	144,800
Rollins Reservoir 10,000 AF Storage Incr.	105,485	4,220	154,200
Rollins Reservoir 50,000 AF Storage Incr.	108,892	813	190,200
Centennial Reservoir	108,815	890	231,400
Revised Carryover Targets	104,218	3,079	134,300
Water Purchases from PG&E	105,868	3,837	146,700
Revised Carryover Targets + Water Purchases from PG&E	107,762	1,943	135,500

Table 6-12. Strategic Alternatives Deliveries, Unmet Demands, and Carryover Storage, Median Climate Baseline Demand Scenarios

Strategic Alternative	Average Annual Delivery (AF)	Average Annual Unmet Demand (AF)	Carryover Storage (AF)
Existing Operations	137,706	14,099	131,400
Extended Irrigation Season	141,707	15,611	126,500
Rollins Reservoir 10,000 AF Storage Incr.	142,221	9,585	132,400
Rollins Reservoir 50,000 AF Storage Incr.	150,092	1,714	162,800
Centennial Reservoir	144,332	7,473	205,900
Revised Carryover Targets	138,963	9,814	114,700
Water Purchases from PG&E	141,892	9,914	129,200
Revised Carryover Targets + Water Purchases from PG&E	145,636	6,170	116,300

Table 6-13. Strategic Alternatives Deliveries, Unmet Demands, and Carryover Storage, Dry Climate High Demand Scenarios

Strategic Alternative	Average Annual Delivery (AF)	Average Annual Unmet Demand (AF)	Carryover Storage (AF)
Existing Operations	146,458	35,158	110,800
Extended Irrigation Season	151,651	36,405	106,300
Rollins Reservoir 10,000 AF Storage Incr.	152,544	29,072	117,000
Rollins Reservoir 50,000 AF Storage Incr.	167,384	14,232	129,700
Centennial Reservoir	165,322	16,294	163,100
Revised Carryover Targets	150,528	27,715	91,700
Water Purchases from PG&E	152,344	29,272	115,100
Revised Carryover Targets + Water Purchases from PG&E	158,277	23,338	93,200

Deliveries across all strategic alternatives for the wet hydrology low demand scenarios is shown in Figure 6-23, for the median hydrology baseline demand scenarios in Figure 6-24, and in the dry hydrology low demand scenarios in Figure 6-25.

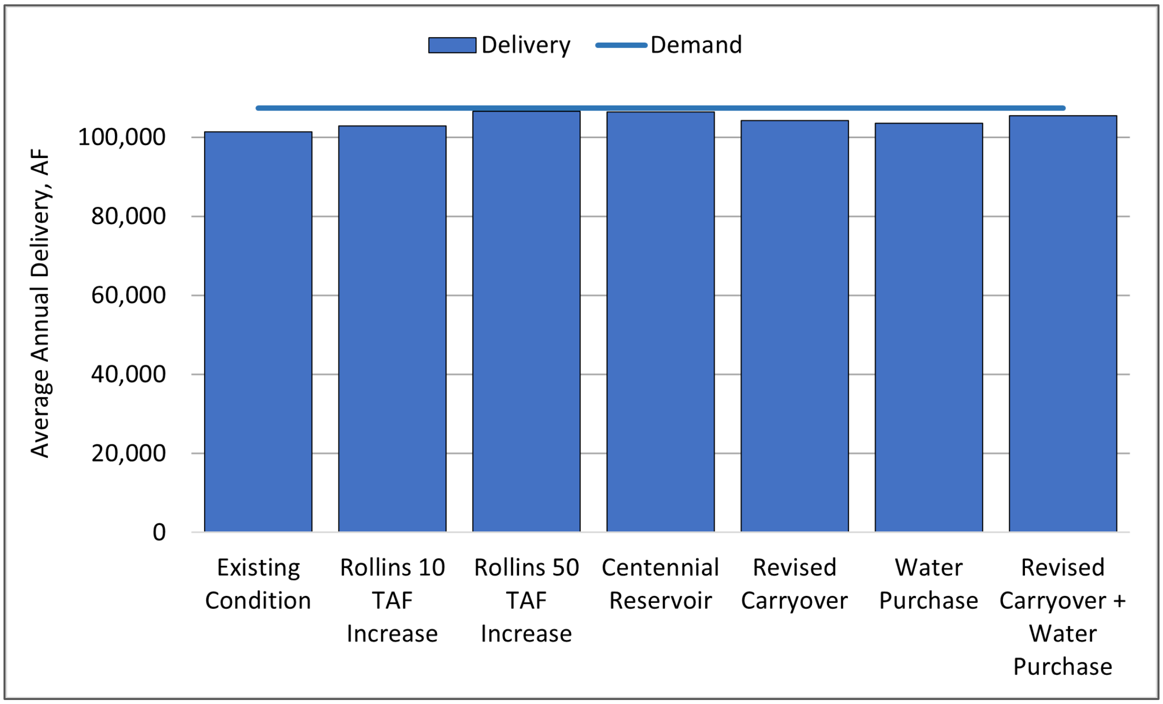


Figure 6-23. Deliveries in Strategic Alternatives, Wet Climate Low Demand Scenarios

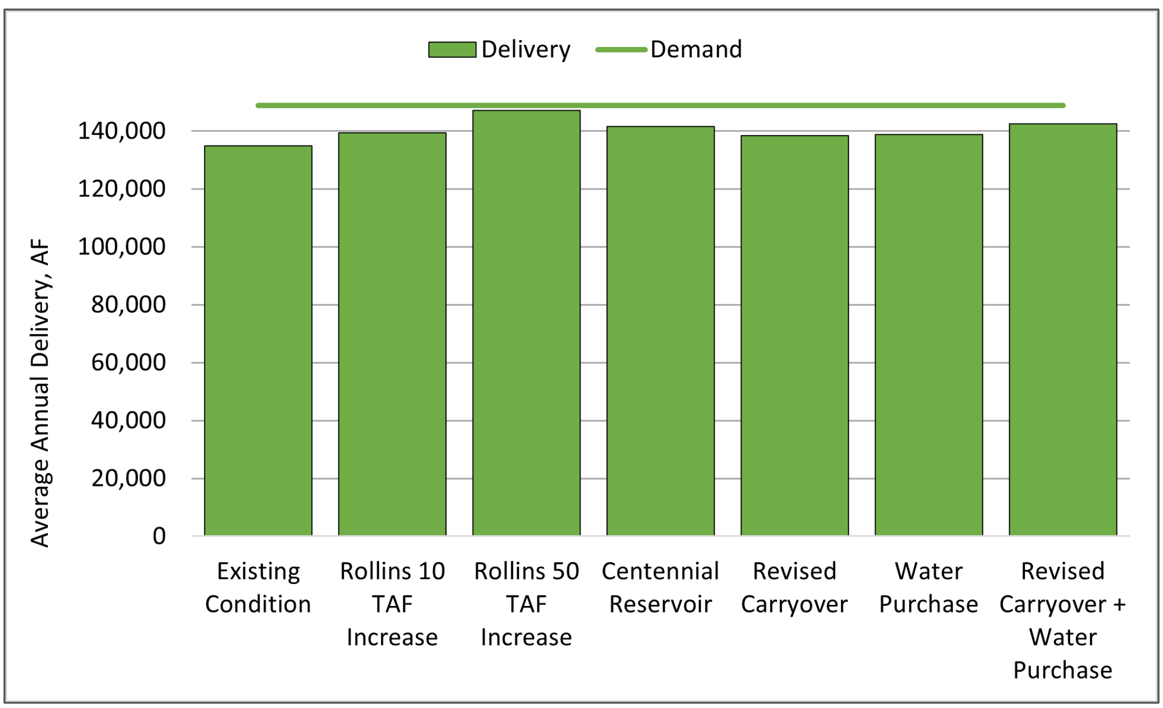


Figure 6-24. Deliveries in Strategic Alternatives, Median Climate Baseline Demand Scenarios

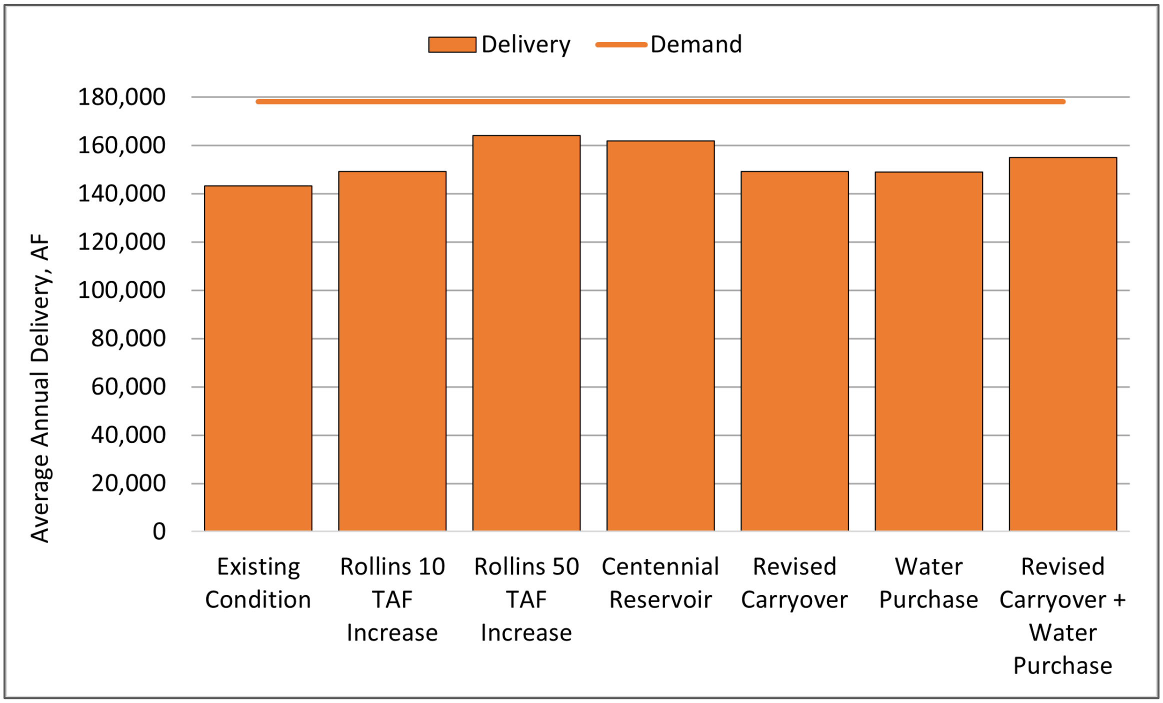


Figure 6-25. Deliveries in Strategic Alternatives, Dry Climate High Demand Scenarios

Unmet demands across all strategic alternatives for the wet hydrology low demand scenarios is shown in Figure 6-26, for the median hydrology baseline demand scenarios in Figure 6-27, and in the dry hydrology low demand scenarios in Figure 6-28.

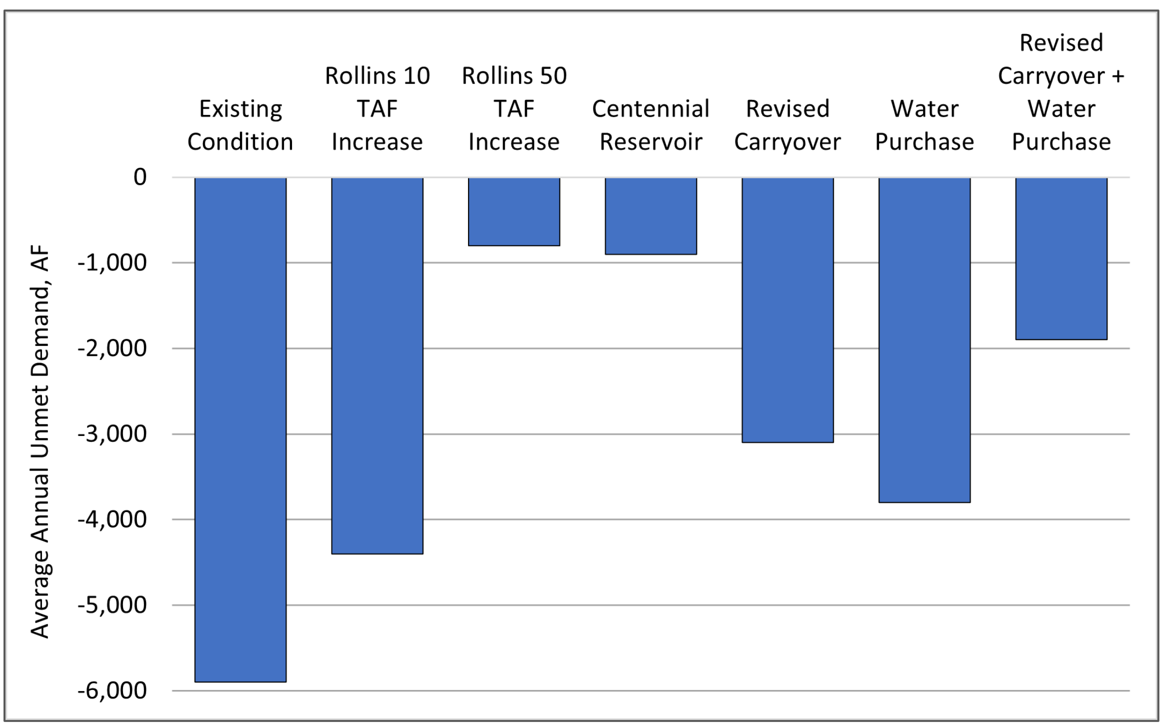


Figure 6-26. Unmet Demands in Strategic Alternatives, Wet Climate Low Demand Scenarios

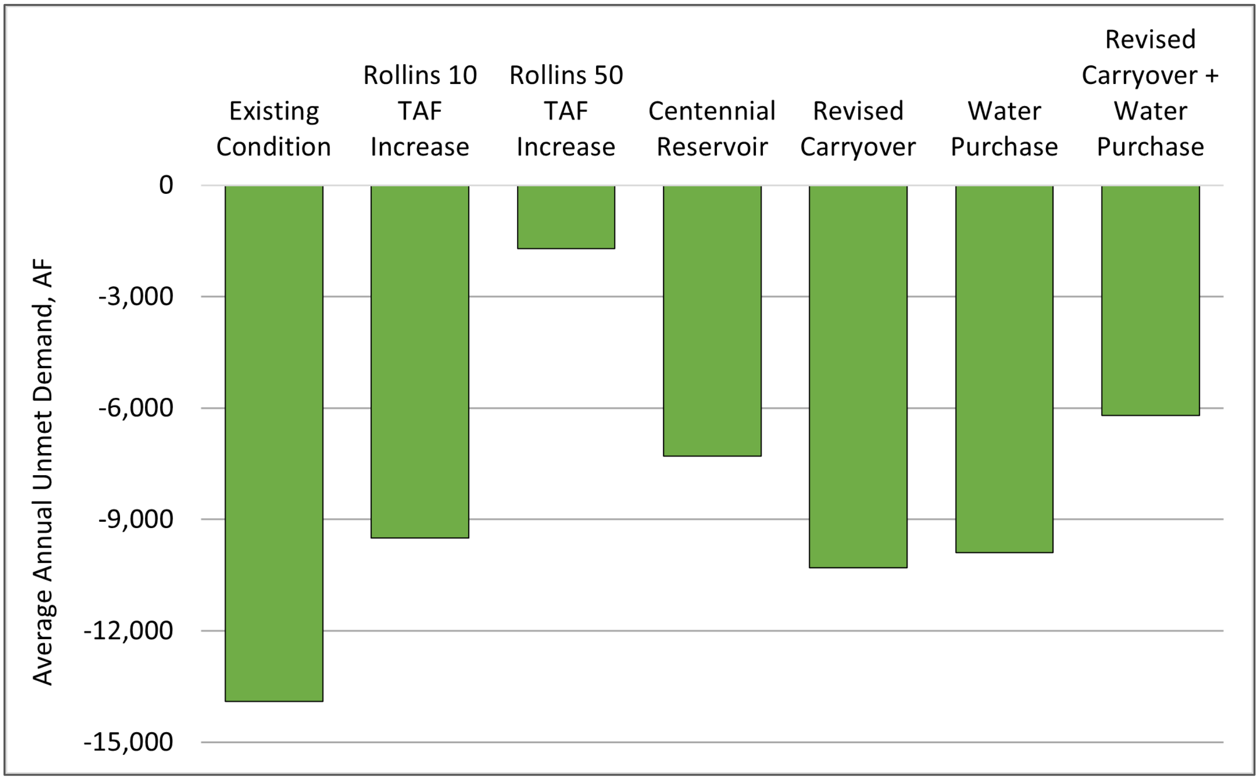


Figure 6-27. Unmet Demands in Strategic Alternatives, Median Climate Baseline Demand Scenarios

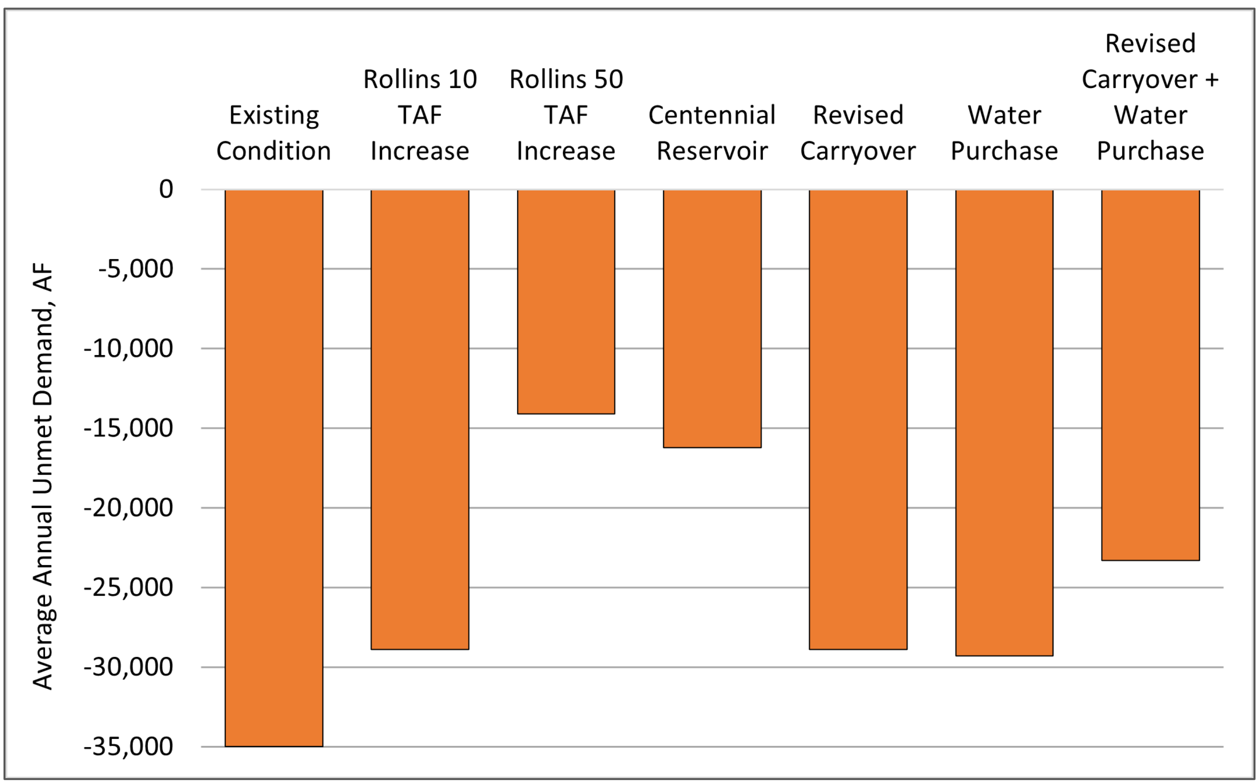


Figure 6-28. Unmet Demands in Strategic Alternatives, Dry Climate High Demand Scenarios

Average November 1 carryover storage across all strategic alternatives for the wet hydrology low demand scenarios is shown in Figure 6-29, for the median hydrology baseline demand scenarios in Figure 6-30, and in the dry hydrology low demand scenarios in Figure 6-31.

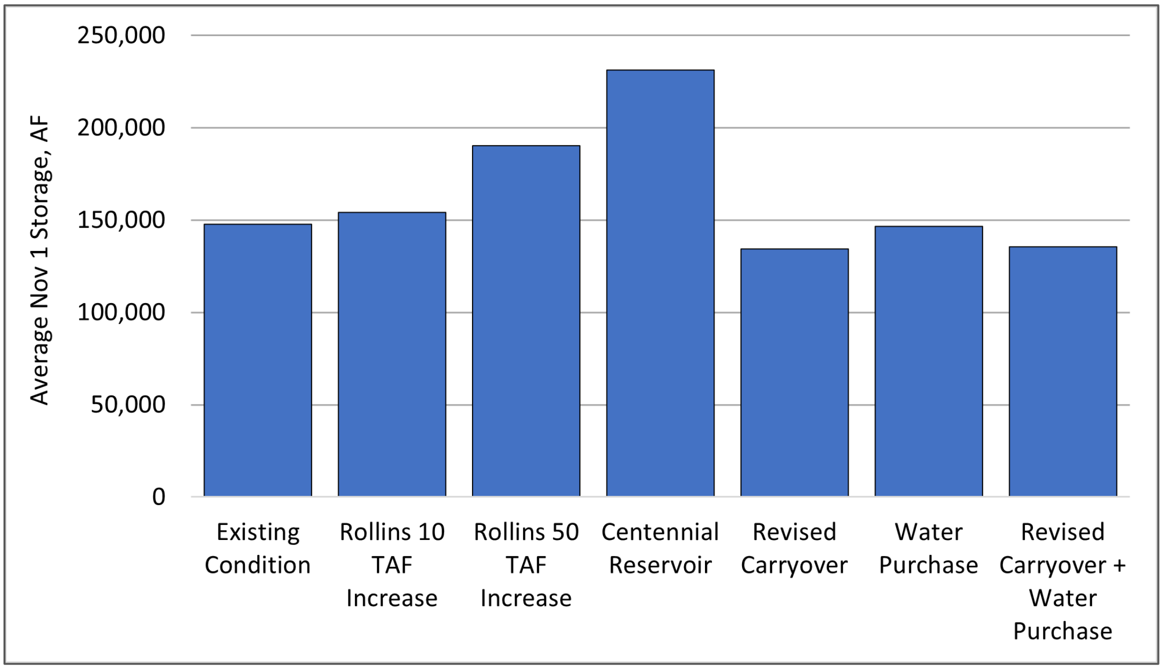


Figure 6-29. Average November 1 Carryover Storage in Strategic Alternatives, Wet Climate Low Demand Scenarios

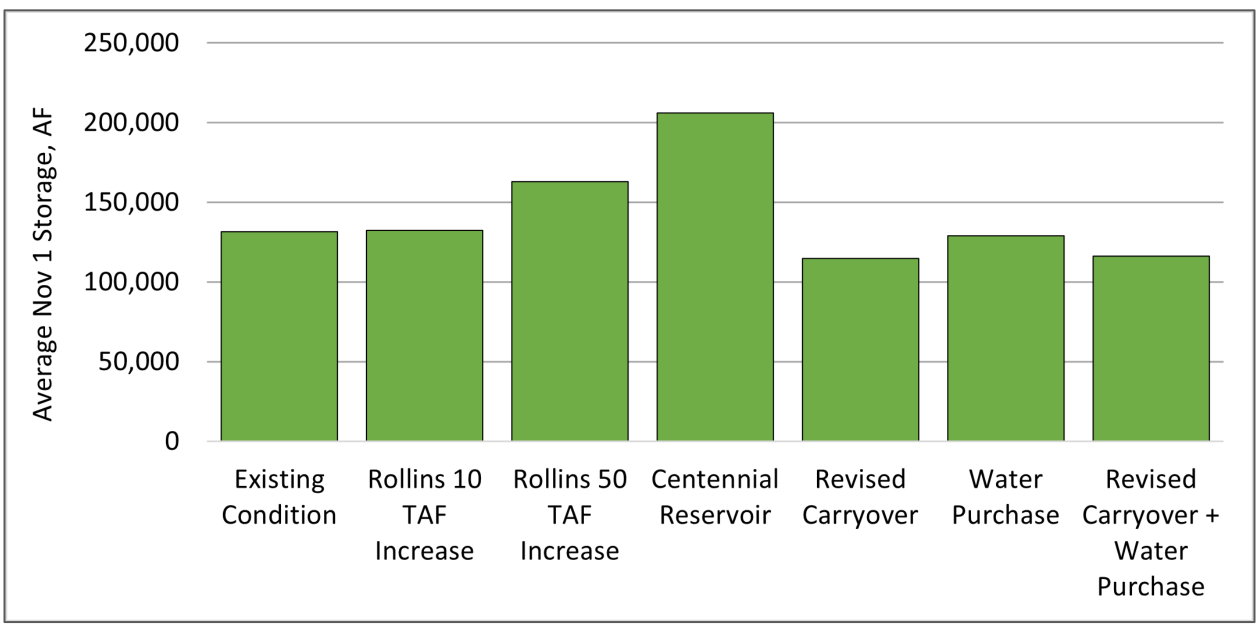


Figure 6-30. Average November 1 Carryover Storage in Strategic Alternatives, Median Climate Baseline Demand Scenarios

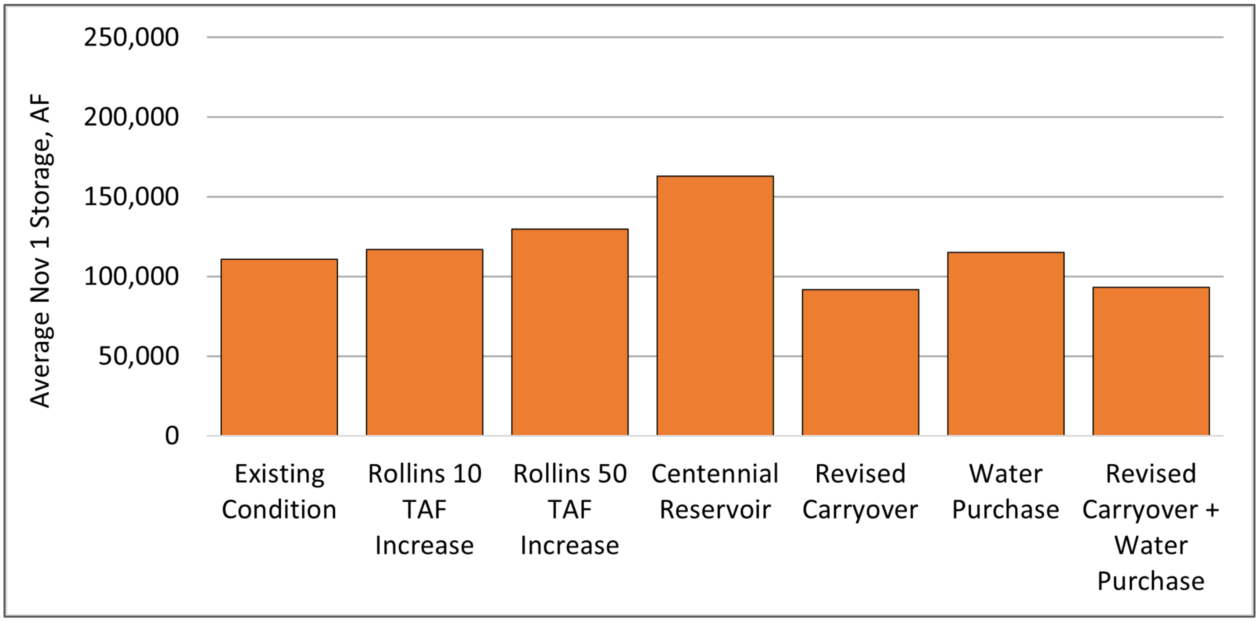


Figure 6-31. Average November 1 Carryover Storage in Strategic Alternatives, Dry Climate High Demand Scenarios

Chapter 7. Summary and Recommendations

The goal of the PFW is to help guide NID's future water management under anticipated changes in climate, runoff, water use, and regulation. The PFW offers a range of potential scenarios for the NID's BOD to consider when assessing ways to best meet customer demands for water over the next 50 years. This report documents the analyses performed to provide actionable information on NID's historical and projected water supply and demand to support the BOD's decision making.

Nine scenarios were initially developed representing various combinations of climate change projections, Dry, Median and Wet, and various combinations of projected customer demands, Low, Baseline and High (Table 5-9). The BOD selected 3 scenarios for further analysis:

- Dry Climate with High Demands
- Median Climate with Baseline Demands
- Wet Climate with Low Demands

These scenarios provide a dry and wet bookend with a median climate scenario to represent a mid-point, and they provide a wide range of hydrologic conditions and consumptive demands. Results of all three scenarios indicate that the ability to meet full customer demands in the future will likely be diminished under existing conditions because of climate change (Figure 6-1).

Seven strategic alternatives were identified by the NID's BOD for investigation to better meet projected customer water demand. The three existing conditions scenarios selected by the BOD for further analysis were used to estimate the relative benefits gained from each of the seven strategic alternatives. The Strategic alternatives analyzed were:

- Extended Irrigation Season
- Rollins Reservoir 10,000 AF Storage Increase
- Rollins Reservoir 50,000 AF Storage Increase
- Centennial Reservoir
- Revised Carryover Targets
- Water Purchases from PG&E
- Revised Carryover Targets + Water Purchases from PG&E

Comparisons of average annual delivery, average annual unmet demand, and carryover were made relative to the three projected climate existing operations scenarios (Table 6-11, Table 6-12, and Table 6-13). While each of the strategic alternatives increased average annual deliveries, some alternatives also resulted in a reduction in carryover storage. A decrease in carryover storage indicates a reduction in available NID water supply in subsequent years. Alternatives that both increase water deliveries and increase carryover storage are much more valuable, from a water supply perspective, than an increase in water deliveries alone.

With the results of the analysis presented in this report, NID's board and directions and community have the necessary information to make scientifically informed decisions.

It is acknowledged that estimating projected water supply and customer demands inherently involves high uncertainties. Uncertainties are also inherent in the social, political, and policy aspects that might influence water resources management. While the most current data and recommended methods were applied in the analysis, uncertainties still exist, and cannot be completely removed from the process. To minimize the effects of uncertainties in decision-making, it is recommended that NID update the analyses in this report as new methods and data become available or policies change. PFW updates every five years is a reasonable and prudent plan going forward.

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Appendix A:

Chapter 2 Supplemental Information

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FIGURES

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Appendix A. Chapter 2 Supplemental Information

A.1. HEC-HMS Subbasin

Table A-1 presents subbasin names and their respective drainage areas, detailed in Appendix A.

Table A-1. HEC-HMS Model—Subbasin Summary

Name	Area (sq. mi.)	Name	Area (sq. mi.)
NY_NorthYuba_S10	33.729	SY_SouthYuba_S80	11.616
NY_NorthYuba_S20	17.091	SY_SouthYuba_S90	22.299
NY_HayPressCreek_S10	31.489	SY_HumbugCreek_S10	10.818
NY_NorthYuba_S30	4.480	SY_SouthYuba_S100	44.248
NY_LavezzolaCreek_S10	28.547	SY_SouthYuba_S110	34.606
NY_DownieRiver_S10	17.511	YR_YubaRiver_S20	18.265
NY_PauleyCreek_S10	25.361	SY_SouthYuba_S120	6.988
NY_DownieRiver_S20	0.556	YR_YubaRiver_S30	23.666
NY_NorthYuba_S40	54.639	YR_DeerCreek_S10	5.761
NY_DownieRiver_S30	0.517	YR_DeerCreek_S20	14.529
NY_NorthYuba_S50	36.229	YR_DeerCreek_S30	13.959
NY_CanyonCreek_S10	60.982	YR_DeerCreek_S40	10.855
NY_NorthYuba_S60	36.442	YR_DeerCreek_S50	10.599
NY_SlateCreek_S10	49.480	DC_SquirrelCreek_S10	25.045
NY_SlateCreek_S20	11.942	YR_DeerCreek_S60	1.462
NY_NorthYuba_S70	2.930	YR_DeerCreek_S70	7.615
NY_NorthYuba_S80	39.059	YR_DryCreek_S10	107.900
NY_BridgerCreek_S10	22.526	YR_YubaRiver_S40	15.403
NY_NorthYuba_S90	15.693	YR_YubaRiver_S50	22.534
MY_PassCreek_S10	18.704	BR_DryCreek_S10	33.032
MY_MiddleYuba_S10	17.706	BR_BestSlough_S10	99.463
MY_MiddleYuba_S20	0.682	BR_BestSlough_S20	45.665
MY_MiddleYuba_S30	2.456	BR_BearRiver_S140	0.438
MY_MiddleYuba_S40	1.052	BR_BearRiver_S150	0.361
MY_MiddleYuba_S50	19.458	BR_BearRiver_S10	1.591
MY_EastForkCreek_S10	13.201	BR_BearRiver_S20	10.637
MY_MiddleYuba_S60	12.964	BR_LittleBearCreek_S10	1.588
MY_WolfCreek_S10	8.693	BR_BearRiver_S30	7.292
MY_MiddleYuba_S70	21.582	BR_BearRiver_S40	0.369
MY_KanakaCreek_S10	17.961	BR_SteephollowCreek_S10	23.798
MY_MiddleYuba_S80	9.734	BR_BearRiver_S50	6.963
MY_OregonCreek_S10	29.175	BR_GreenhornCreek_S10	40.786
MY_MiddleYuba_S90	17.136	BR_BearRiver_S60	4.483
MY_OregonCreek_S20	6.097	BR_BearRiver_S70	5.953

Name	Area (sq. mi.)
MY_MiddleYuba_S100	13.485
NY_NorthYuba_S100	1.698
YR_YubaRiver_S10	14.534
SY_SouthYuba_S10	0.735
SY_SouthYuba_S20	0.289
SY_SouthYuba_S30	0.538
SY_SouthYuba_S40	51.161
SY_FordyceCreek_S10	1.270
NC_WhiteRockCreek_S10	1.147
SY_FordyceCreek_S20	1.009
SY_FordyceCreek_S30	27.502
SY_FordyceCreek_S40	22.538
SY_SouthYuba_S50	6.415
SY_JordanCreek_S10	0.575
SY_JordanCreek_S20	0.246
SY_RuckerCreek_S10	0.282
SY_RuckerCreek_S20	1.226
SY_RuckerCreek_S30	0.291
CC_LakeCreek_S30	5.063
TC_LindseyCreek_S10	0.162
TC_LindseyCreek_S20	0.247
TC_LindseyCreek_S30	0.510
TC_TexasCreek_S10	0.447
TC_TexasCreek_S20	0.186
TC_TexasCreek_S30	0.098
TC_TexasCreek_S40	3.828
SY_ClearCreek_S10	1.765
SY_FallCreek_S10	0.614
CC_LakeCreek_S10	0.433
CC_LakeCreek_S20	0.081
SY_SouthYuba_S60	5.081
CC_CanyonCreek_S10	4.997
CC_CanyonCreek_S20	4.500
CC_CanyonCreek_S30	7.869
CC_JacksonCreek_S10	0.642
CC_CanyonCreek_S40	10.486
SY_SouthYuba_S70	18.625
CC_CanyonCreek_S50	16.498
SY_Poorman_Creek_S10	23.308

Name	Area (sq. mi.)
BR_BearRiver_S80	19.717
BR_BearRiver_S85	12.534
BR_WolfCreek_S10	37.513
WC_SouthWoolfCreek_S10	33.423
BR_BearRiver_S90	13.478
BR_WolfCreek_S20	7.106
BR_BearRiver_S100	30.529
BR_BearRiver_S120	17.705
BR_BearRiver_S110	0.351
BR_BearRiver_S130	16.527
RC_DryCreek_S10	0.978
RC_DryCreek_S20	0.693
RC_DryCreek_S30	1.434
RC_DryCreek_S40	2.148
RC_RaccoonCreek_S10	49.579
RC_DotyCreek_S10	24.846
RC_RaccoonCreek_S20	29.761
RC_BunkhamSlough_S10	26.829
RC_AuburnRavine_S10	36.080
RC_OrchardCreek_S10	22.356
RC_OrchardCreek_S20	18.214
RC_RaccoonCreek_S30	11.270
RC_PleasantGroveCreek_S10	46.578
RC_CurryCreek_S10	16.793
RC_PleasantGroveCreek_S20	6.087
RC_PleasantGroveCreek_S30	1.592
NFA_NFAmerican_S10	75.531
NFA_BigGraniteCreek_S10	17.952
NFA_NFNorthAmerican_S10	4.374
NFA_NFNorthAmerican_S20	0.611
NFA_NFNorthAmerican_S30	3.882
NFNA_EastForkNFAmerican_S10	17.559
NFA_NFNorthAmerican_S40	6.457
NFA_NFAmerican_S20	47.669
NFA_NFNorthAmerican_S50	21.796
NFA_CanyonCreek_S10	1.533
NFA_CanyonCreek_S20	4.095
NFA_NFAmerican_S30	15.897

A.2. USGS Schematics

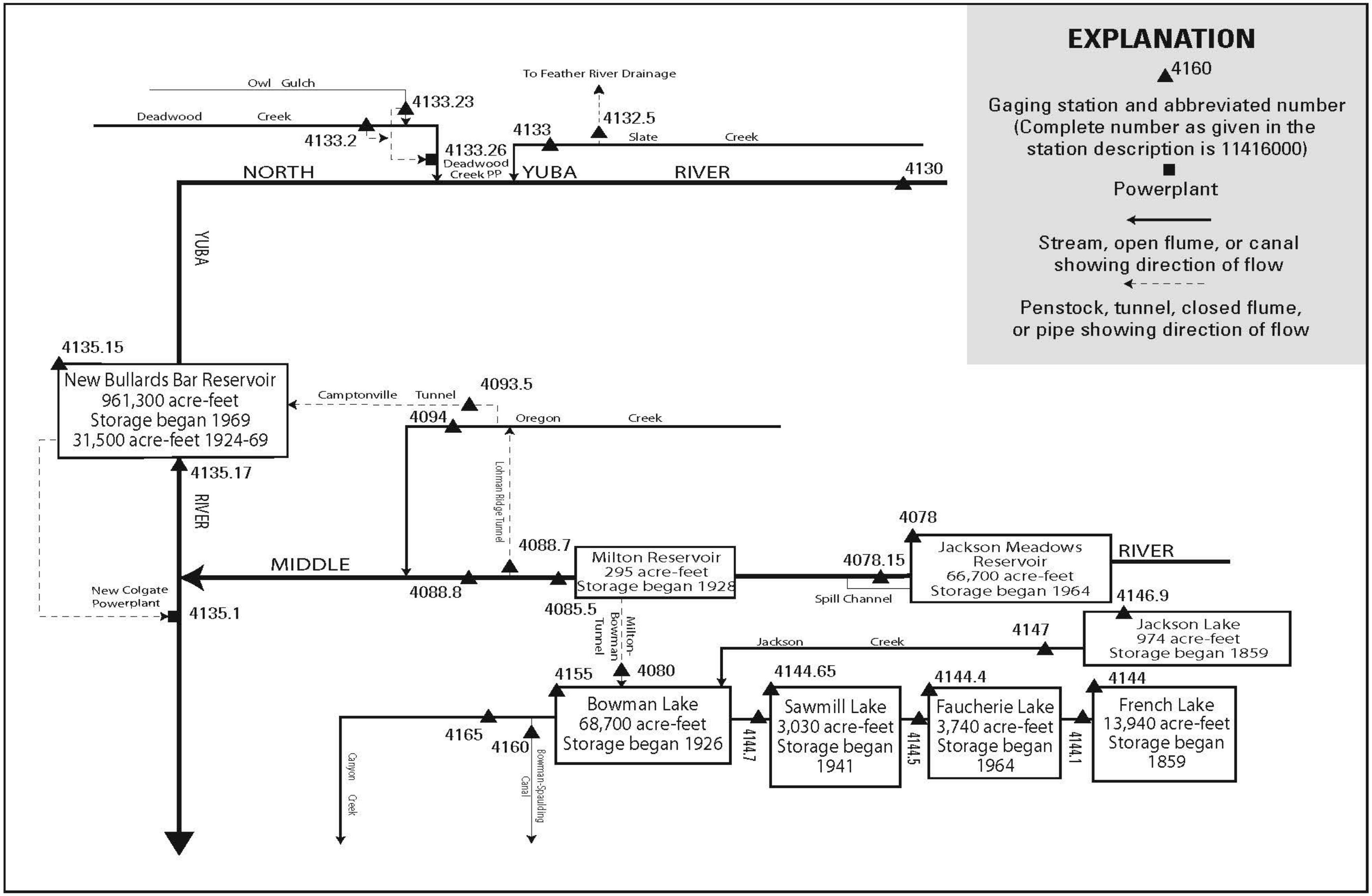


Figure A-1. Diversions and Storage in North and Middle Yuba River Basins, WY2010

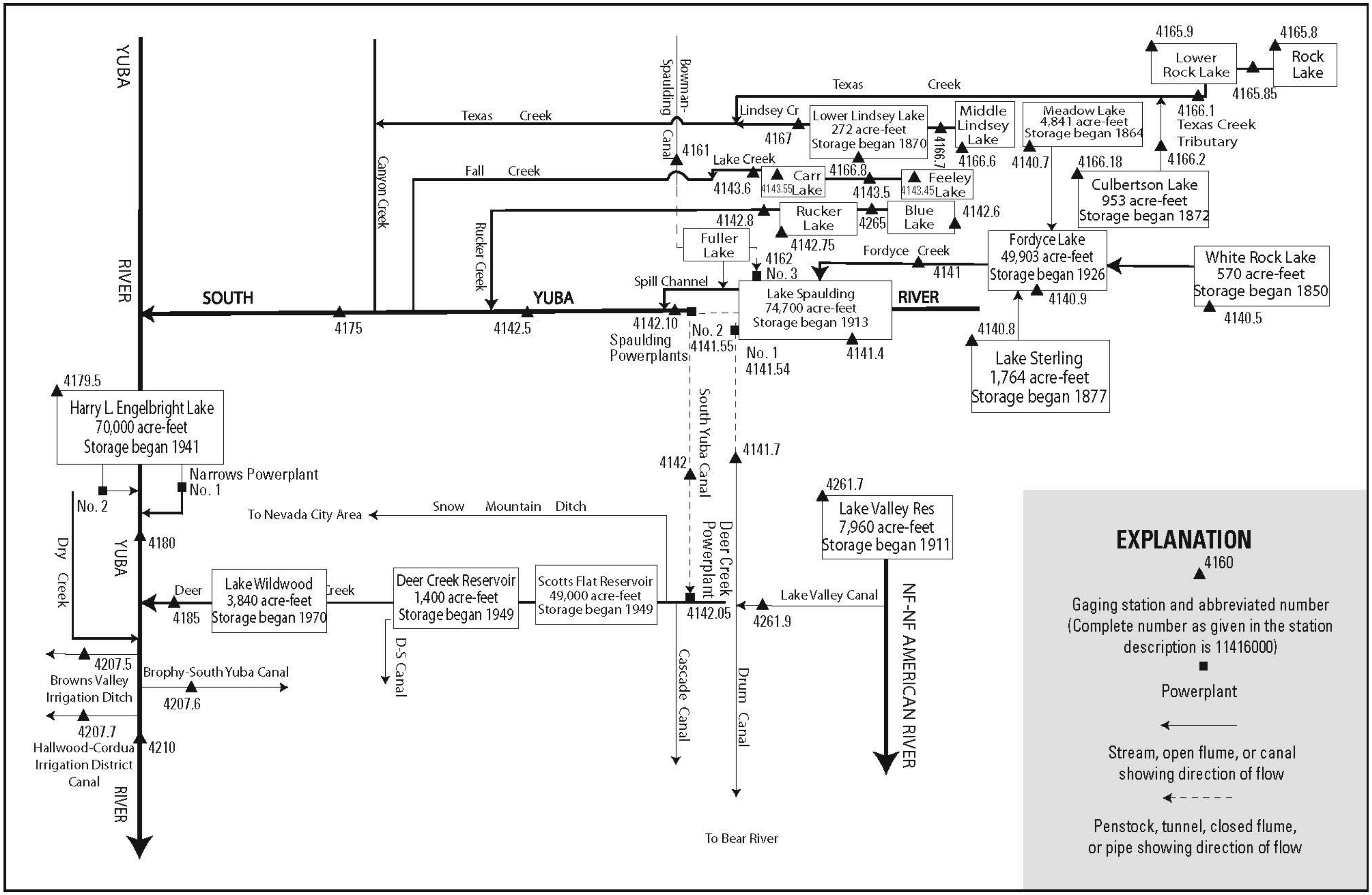


Figure A-2. Diversions and Storage in South Yuba River Basin, WY2010

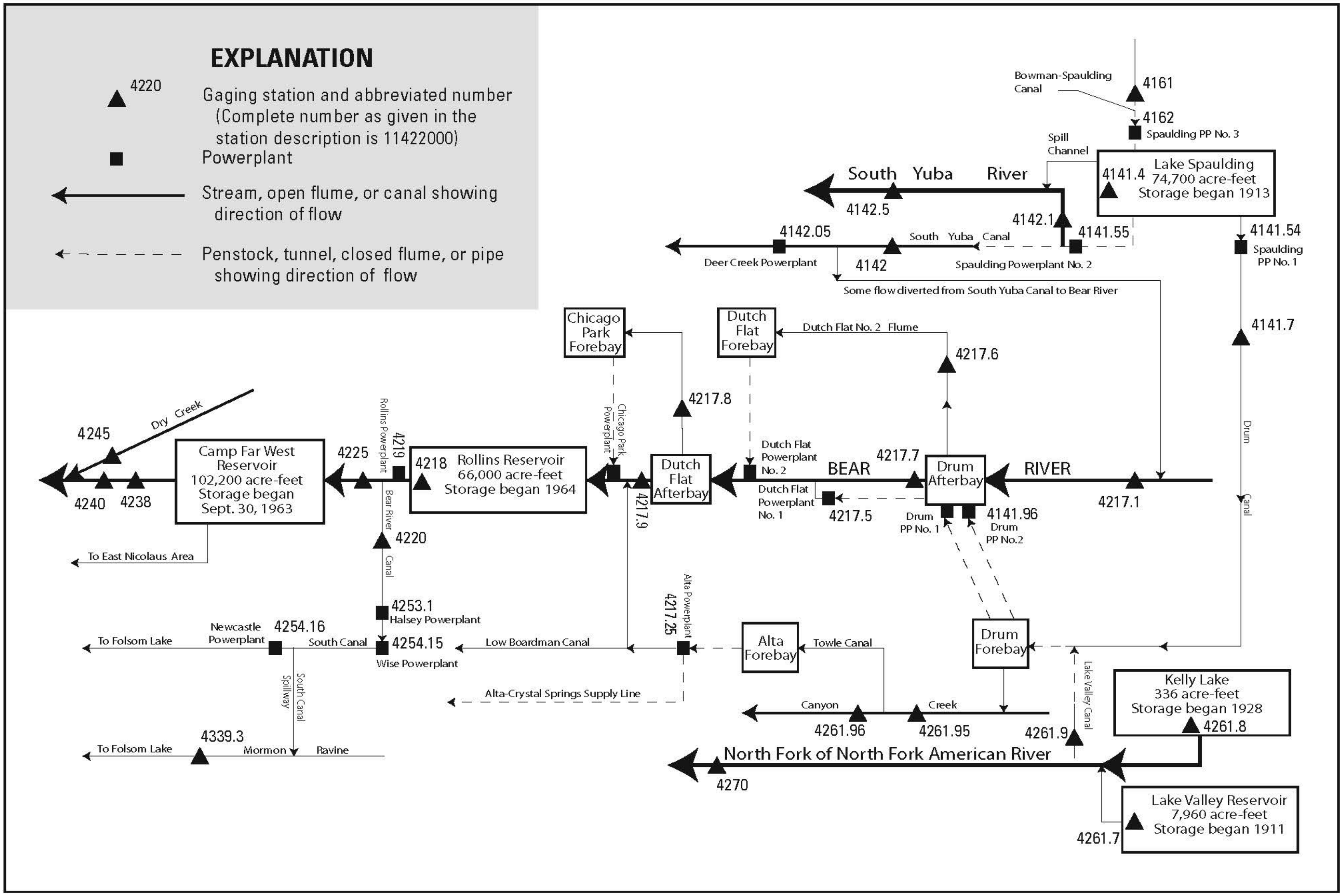


Figure A-3. Diversions and Storage in Bear River Basin, WY2010

A.3. Calibration Parameters

Sensitivity analysis was performed to determine the most sensitive model parameters to improve calibration. The results indicated that the calibration procedure should focus on baseflow groundwater fractions, snow parameters (PX and base temperatures and Wet Meltrate coefficient), and constant loss rate.

Table A-2. HEC-HMS Calibration Parameters

Process	Parameter	Calibration Approach
Streamflow Routing	Length	Not adjusted during model calibration.
	Slope	Not adjusted during model calibration.
	Manning's n	Not adjusted during model calibration.
	Index Celerity	Set to 5 ft/s. Not adjusted during model calibration.
	8-point Cross Section Shape	Not adjusted during model calibration.
	Manning's n (Left and Right)	Set to 0.07. Not adjusted during model calibration.
Evapotranspiration and Canopy	Initial Storage	Set to 0% for each subbasin. Not adjusted during model calibration.
	Max Storage	Specified for each subbasin. Estimated by the Canopy Storage Depths for NLCD Land Cover Classifications. Not adjusted during model calibration.
	Crop Coefficient	Set to 1. Not adjusted during model calibration.
	Hamon Coefficient	Set to 0.0065. Not adjusted during model calibration.
Runoff Transform	Time of Concentration (T_c)	Due to the use of daily average precipitation and a relatively long computational interval, little to no overland flow was generated during any simulation. Therefore, runoff transform parameters were not calibrated as part of this modeling effort.
	Storage Coefficient (R)	Due to the use of daily average precipitation and a relatively long computational interval, little to no overland flow was generated during any simulation. Therefore, runoff transform parameters were not calibrated as part of this modeling effort.
Snowmelt	PX Temperature	This value was initially calibrated for four stations during the snowmelt calibration (refer to Section 6). Further refinement was implemented to better match runoff generation in certain upstream subbasins during model calibration.
	Base Temperature	This value was initially calibrated for four stations during the snowmelt calibration (refer to Section 6). Further refinement was implemented to better match runoff generation in certain upstream subbasins during model calibration.
	Wet Meltrate	This value was initially calibrated for four stations during the snowmelt calibration (refer to Section 6). Further refinement was implemented to better match runoff generation in certain upstream subbasins during model calibration.
	Rain Rate Limit	Set during snow model calibration. Not adjusted during HEC-HMS model calibration.

Process	Parameter	Calibration Approach
Snowmelt, continued	ATI-Meltrate Function	This value was initially calibrated for four stations during the snowmelt calibration (refer to Section 6). Further refinement was implemented to better match runoff generation in certain upstream subbasins during model calibration.
	ATI-Coldrate Function	Set during snow model calibration. Not adjusted during HEC-HMS model calibration.
	Snowpack Water Capacity	Set during snow model calibration. Not adjusted during HEC-HMS model calibration.
	Ground melt	Set during snow model calibration. Not adjusted during HEC-HMS model calibration.
Infiltration	Initial Deficit	Set to 0. Not adjusted during calibration.
	Maximum Deficit	Set to 2 inches. over the active soil layer depth. Not adjusted during HEC-HMS model calibration.
	Constant Loss Rate	Initially set to 0.1 in/hr. Adjusted to guarantee the generation of minimal to no excess precipitation and maximize runoff using the linear reservoir baseflow routine. The final values all fall between 0.06 and 0.13 in/hr.
	% Impervious Cover	Not adjusted during model calibration
Baseflow	GW 1 Initial Discharge	Initial discharge set to 0.
	GW 1 Fraction	Set to 0.5 adjusted between 0 and 0.5 during HEC-HMS model calibration. Whenever the GW 1 and GW 2 fractions do not equal 1.0, the difference between 1.0 and the sum is the percentage that does not contribute to runoff and is instead lost to a deep aquifer.
	GW 1 Storage Coefficient	GW 1 was conceptualized to represent the fast-responding portion of baseflow. Therefore, this coefficient was set to a smaller value than the GW 2 storage coefficient. This value was set to 2 times the storage coefficient. Minor modifications to this parameter were made during modeling calibration.
	GW 1 # of Reservoirs	Set to 1. Not adjusted during model calibration.
	GW 2 Initial Discharge	Initial discharge is event specific and can vary throughout the year within a single subbasin. Parameter was set to an appropriate value within each subbasin for each water year that provided adequate agreement with observed data.
	GW 2 Fraction	Set to 0.5 and varied between 0 and 0.5 during HEC-HMS model calibration. Whenever the GW 1 and GW 2 fractions do not equal 1.0, the difference between 1.0 and the sum is the percentage that does not contribute to runoff and is instead lost to a deep aquifer.
	GW 2 Storage Coefficient	Set to a larger value than the GW 1 storage coefficient. Minor modifications to this parameter were made during modeling calibration.
	GW 2 # of Reservoirs	Set to 1. Not varied during model calibration.

A.4. Calibration Results for Selected Water Years

A.4.1. Calibration Results for WY1997

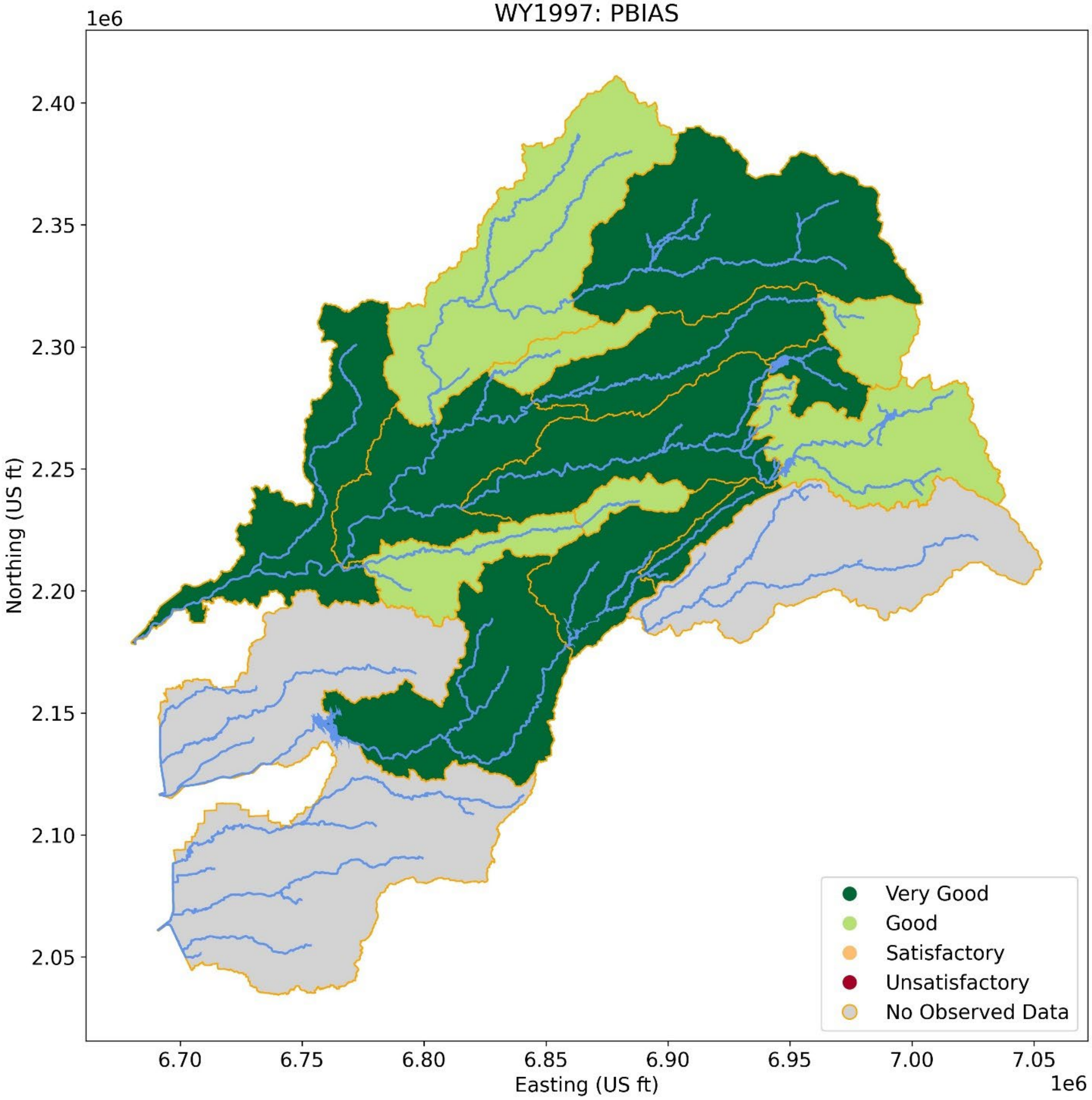


Figure A-4. WY1997 Percent Bias (PBIAS) Calibration Results for the Entire Calibrated Watersheds

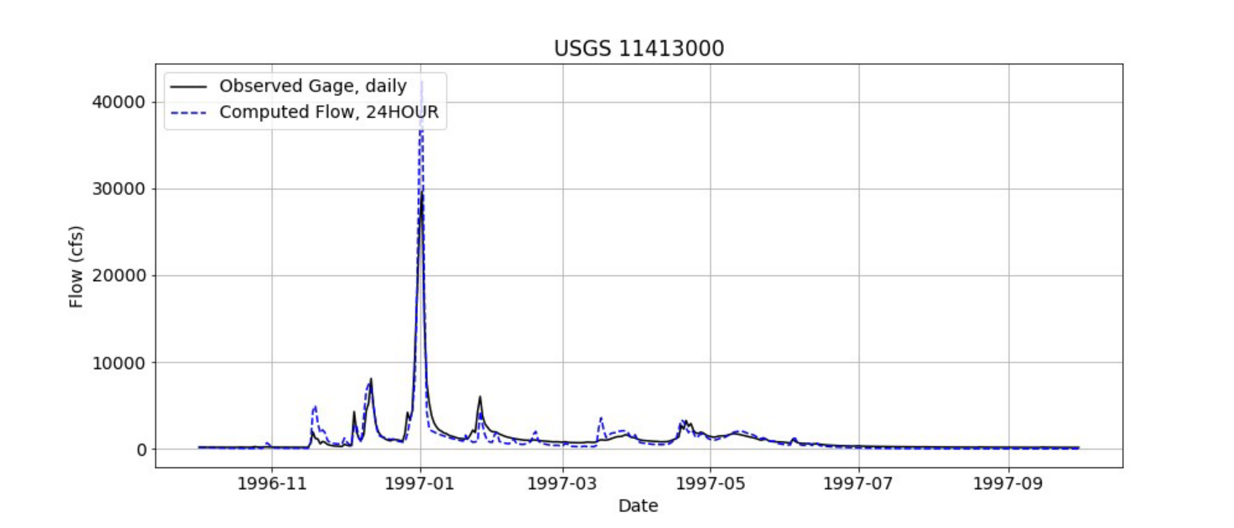


Figure A-5. WY1997 Calibration Results for Calibration Location USGS Gage 11413000

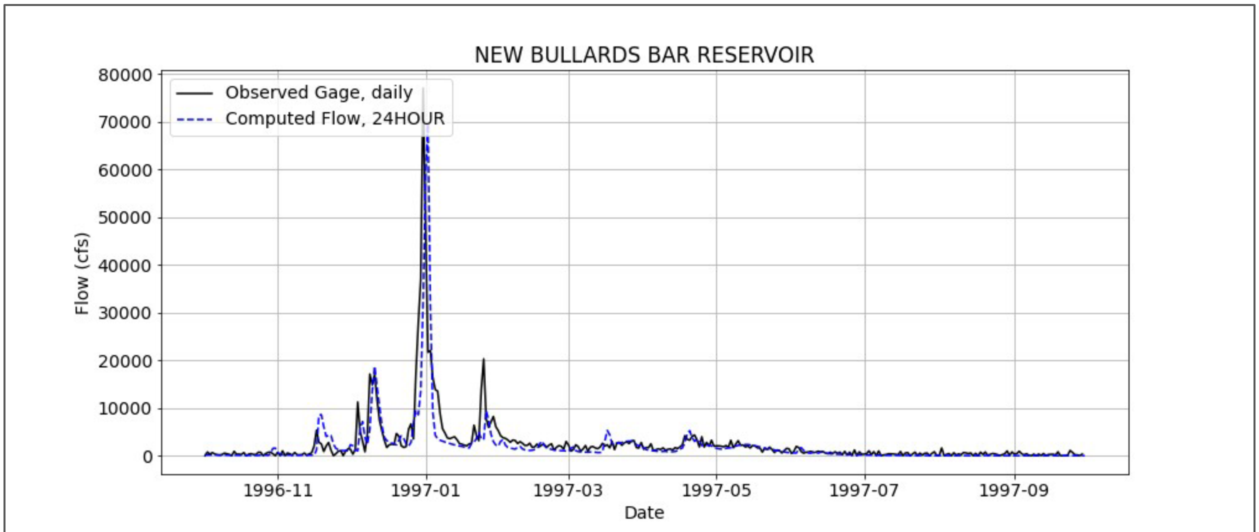


Figure A-6. WY1997 Calibration Results for Calibration Location New Bullards Bar Reservoir

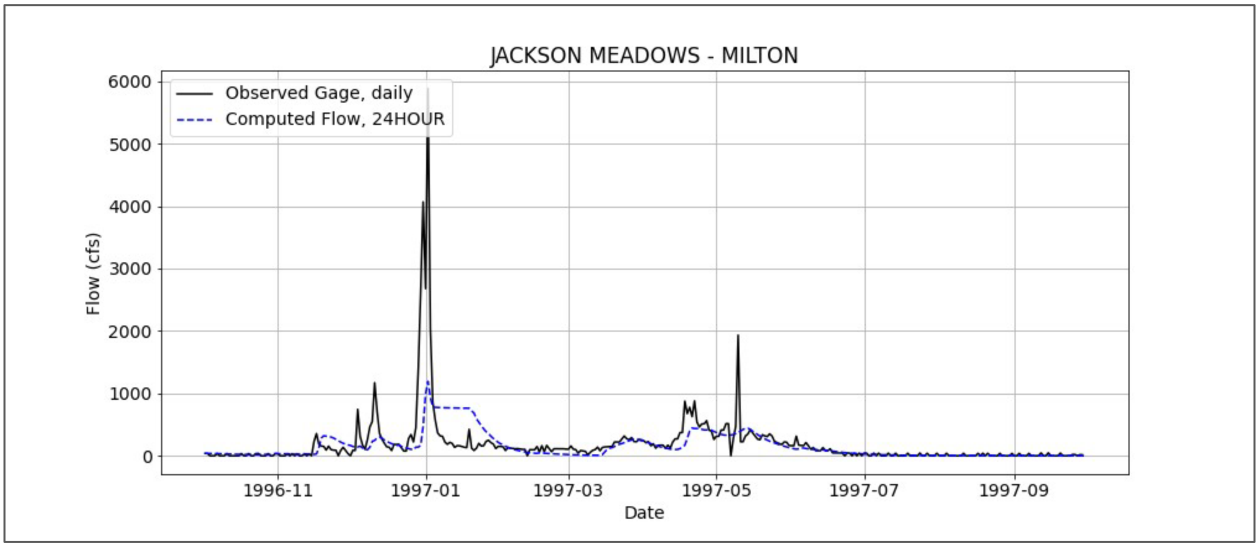


Figure A-7. WY1997 Calibration Results for Calibration Location Jackson Meadows and Milton Reservoirs

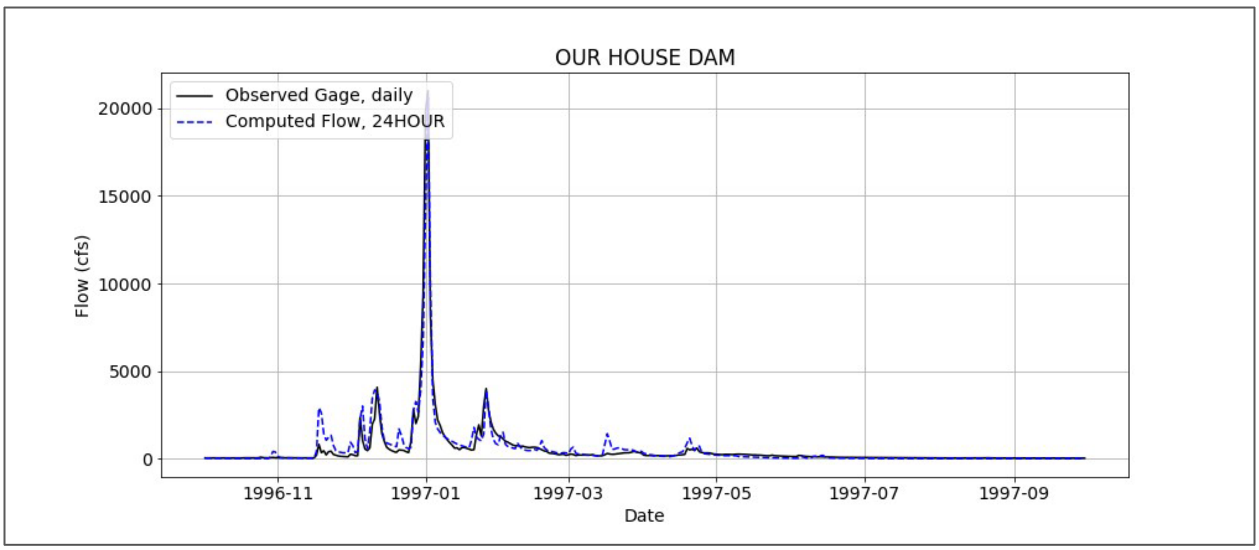


Figure A-8. WY1997 Calibration Results for Calibration Location Our House Dam

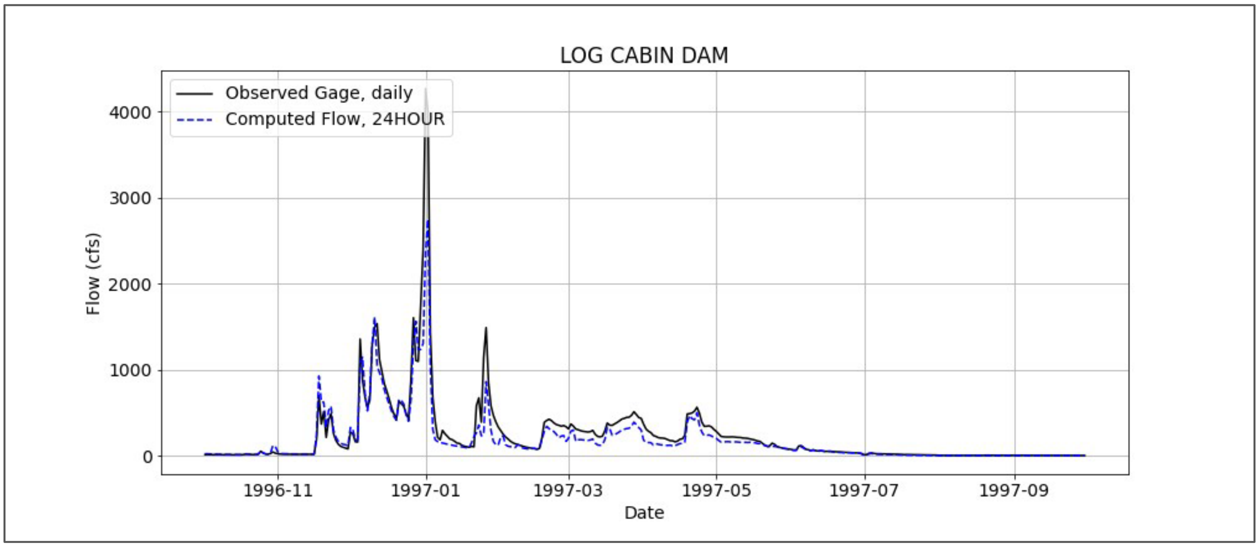


Figure A-9. WY1997 Calibration Results for Calibration Location Log Cabin Dam

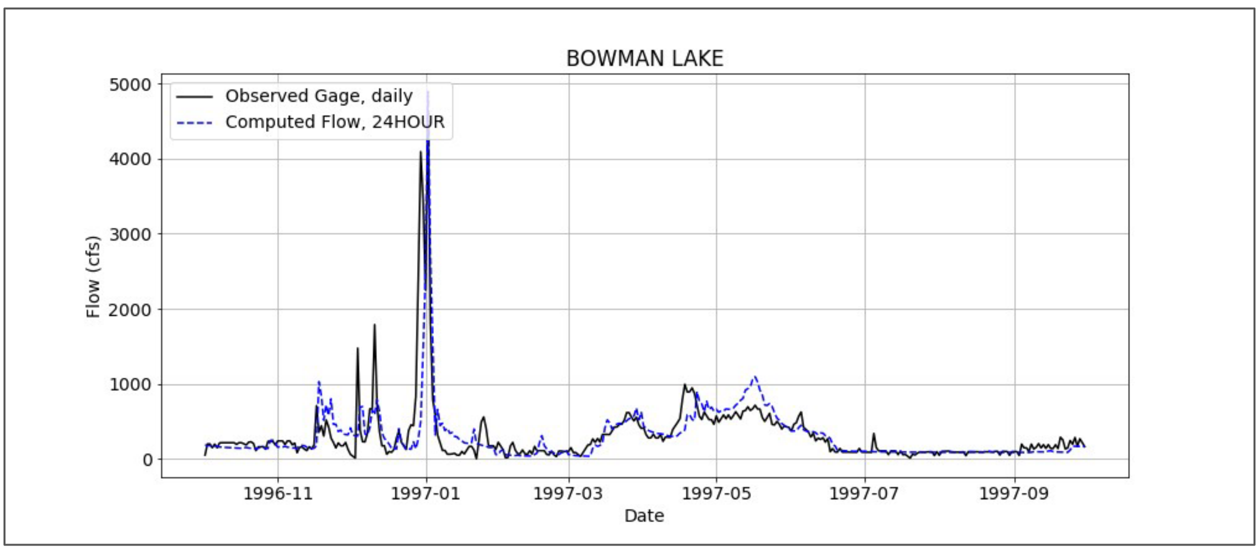


Figure A-10. WY1997 Calibration Results for Calibration Location Bowman Lake

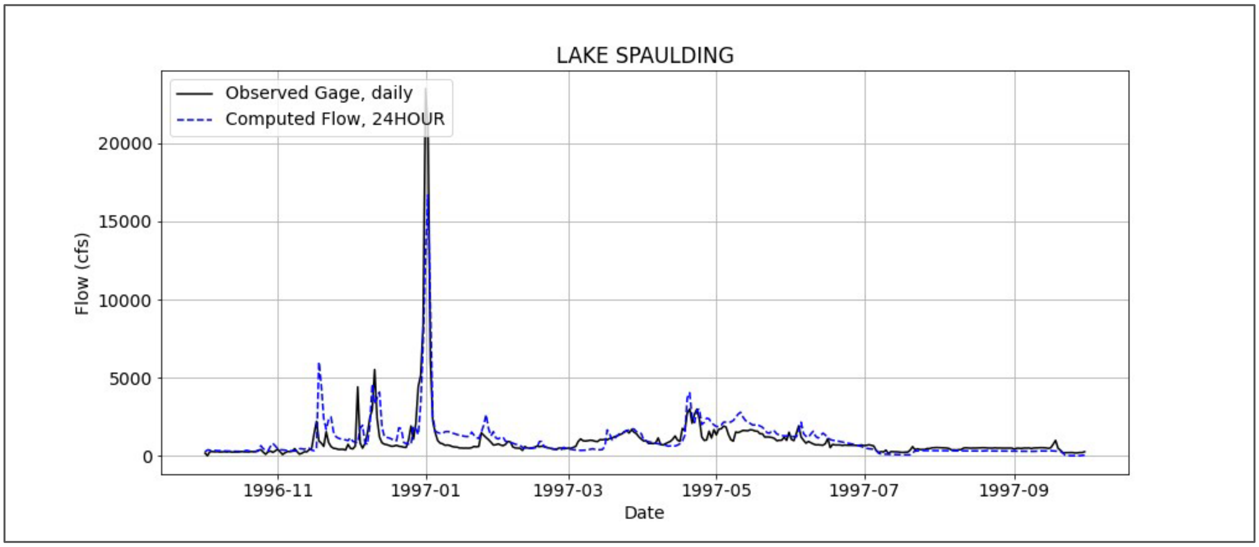


Figure A-11. WY1997 Calibration Results for Calibration Location Lake Spaulding

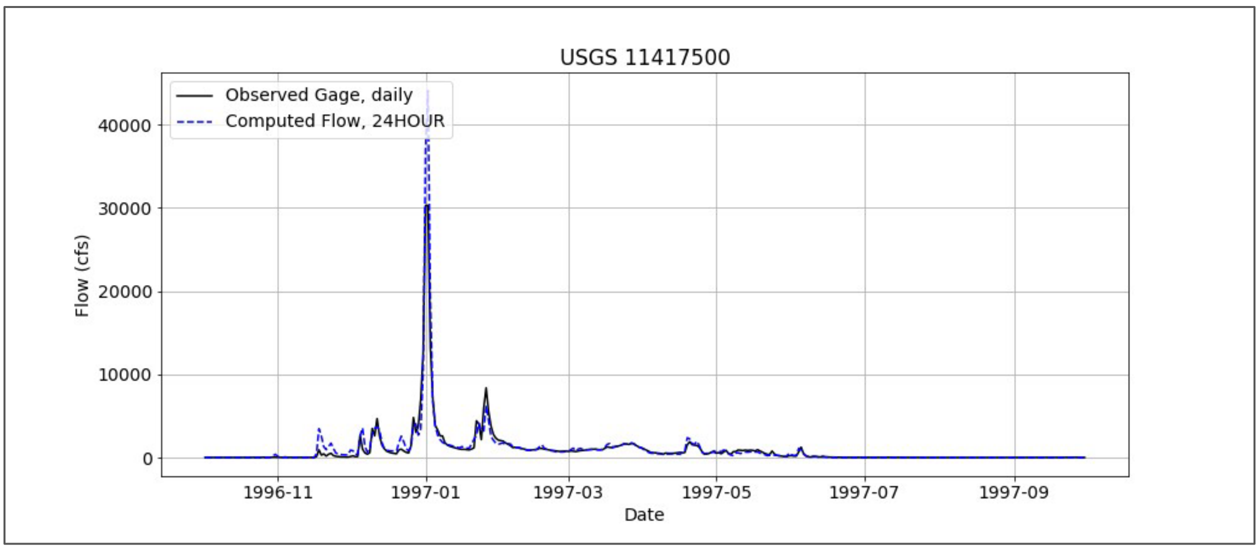


Figure A-12. WY1997 Calibration Results for Calibration Location USGS Gage 11417500

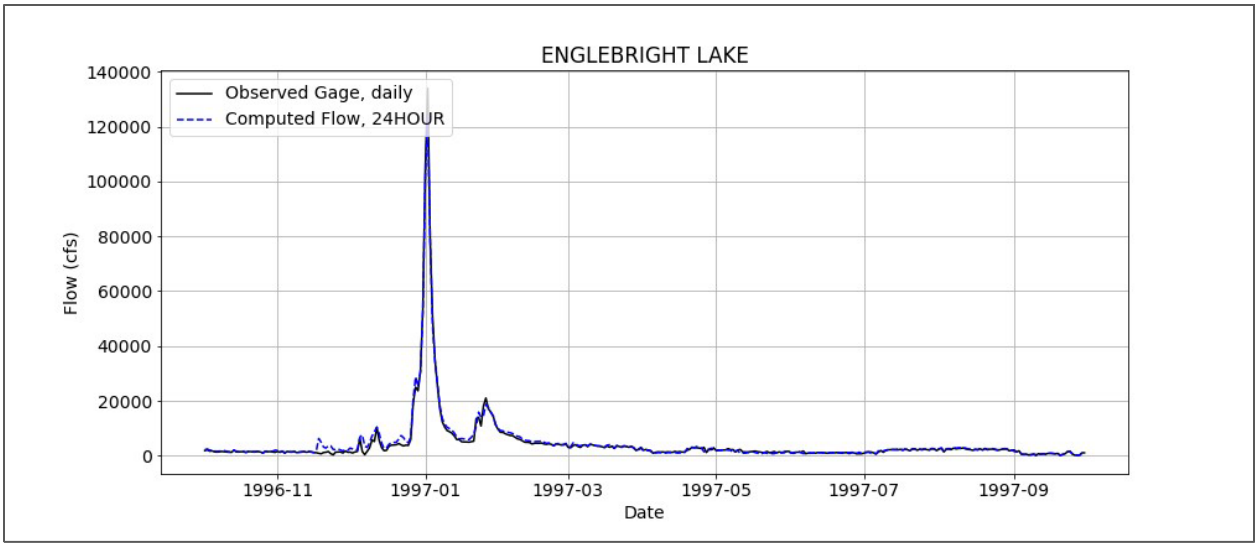


Figure A-13. WY1997 Calibration Results for Calibration Location Englebright Lake

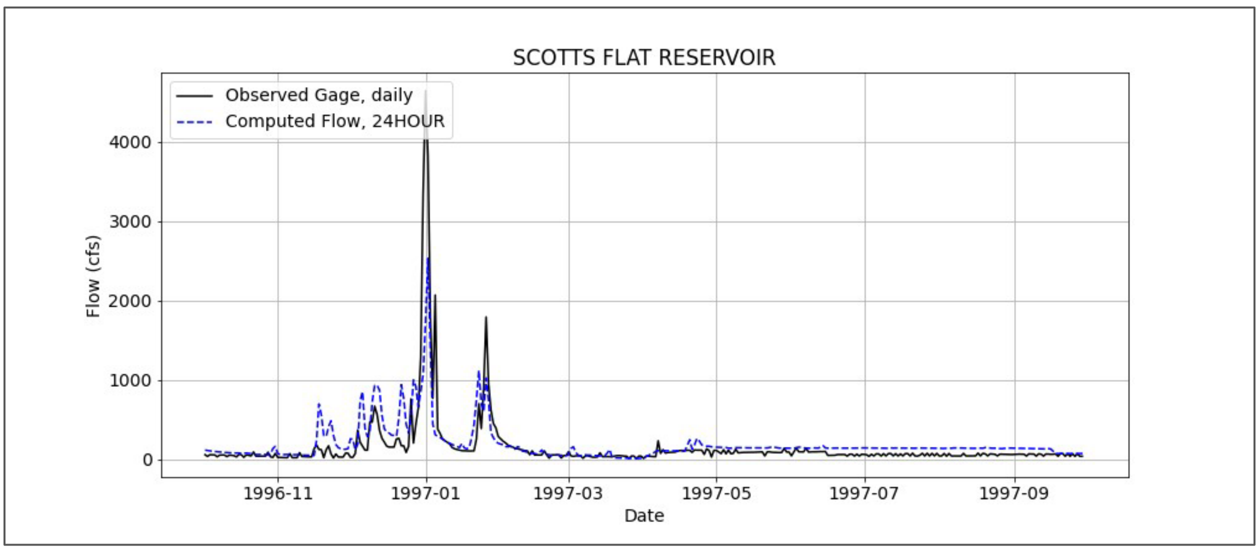


Figure A-14. WY1997 Calibration Results for Calibration Location Scotts Flat Reservoir

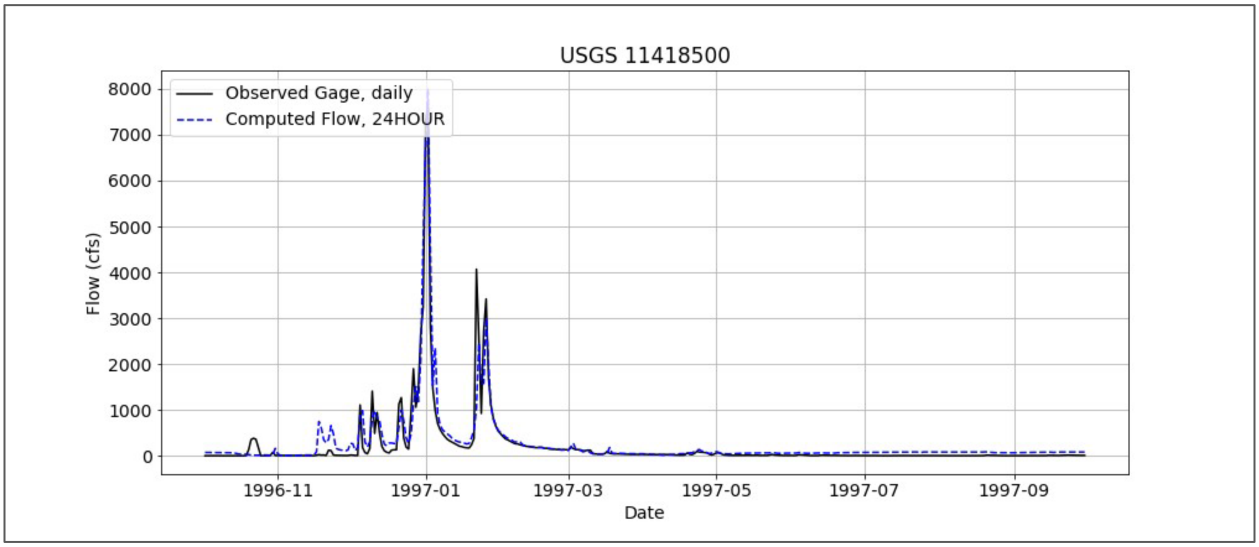


Figure A-15. WY1997 Calibration Results for Calibration Location USGS Gage 11418500

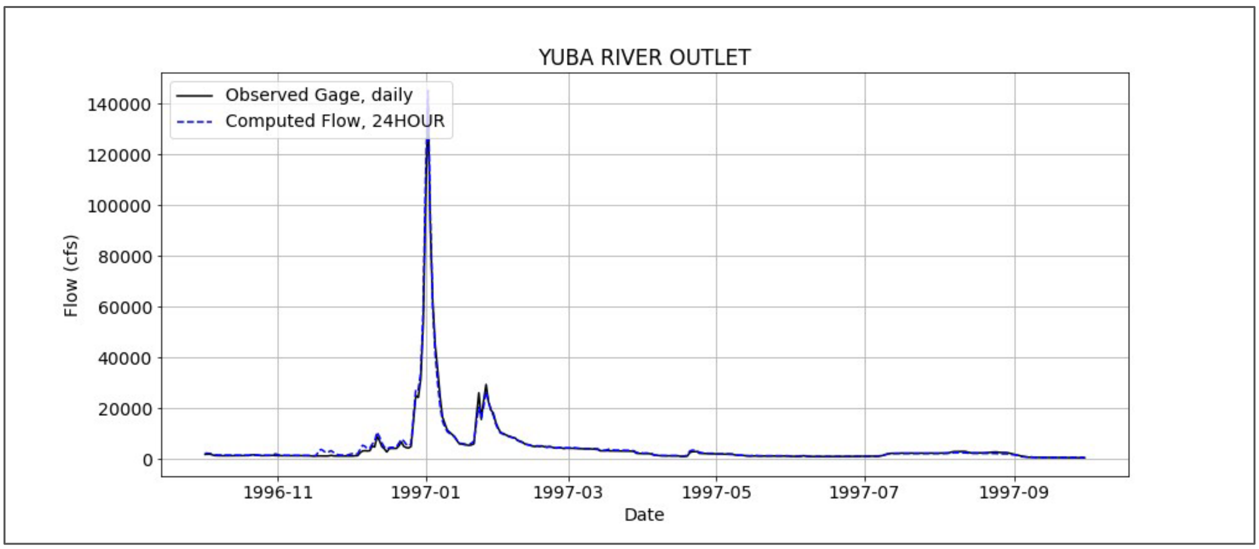


Figure A-16. WY1997 Calibration Results for Calibration Location Yuba River Outlet

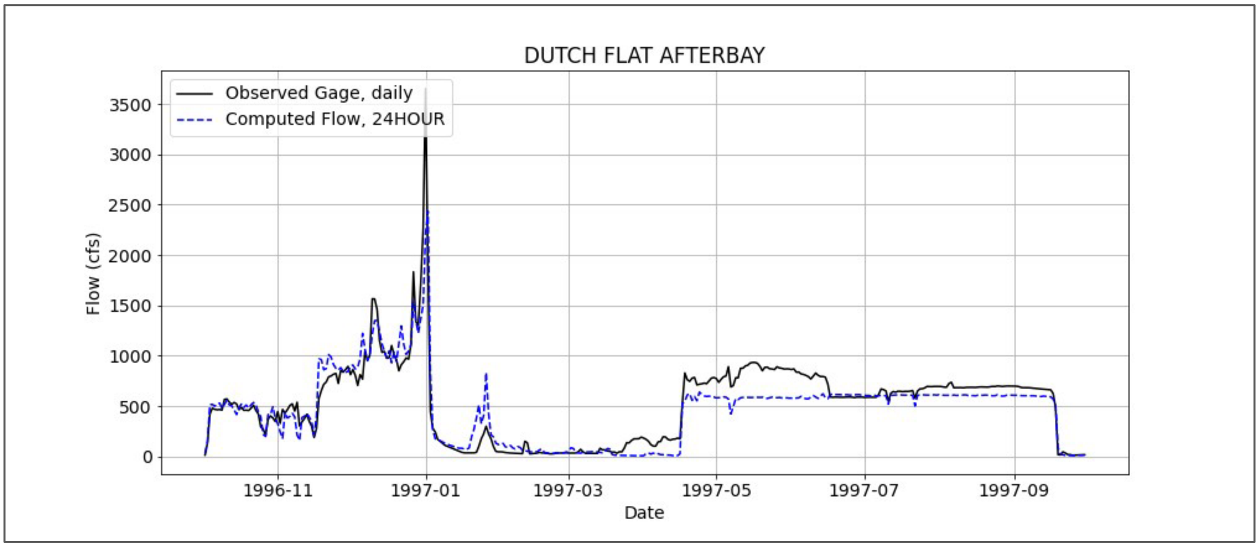


Figure A-17. WY1997 Calibration Results for Calibration Location Dutch Flat Afterbay

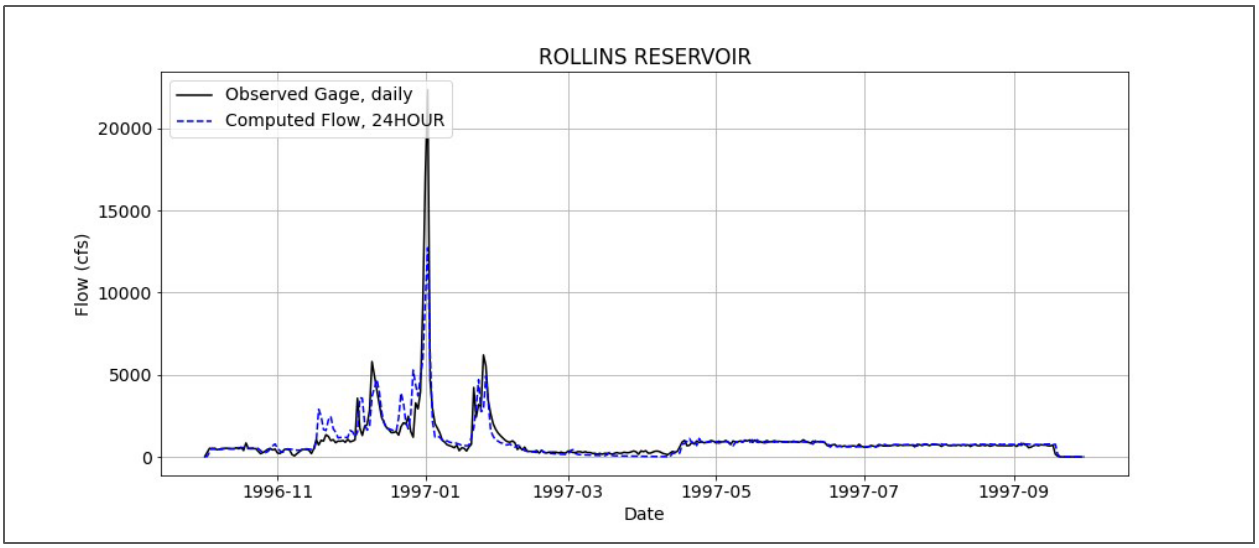


Figure A-18. WY1997 Calibration Results for Calibration Location Rollins Reservoir

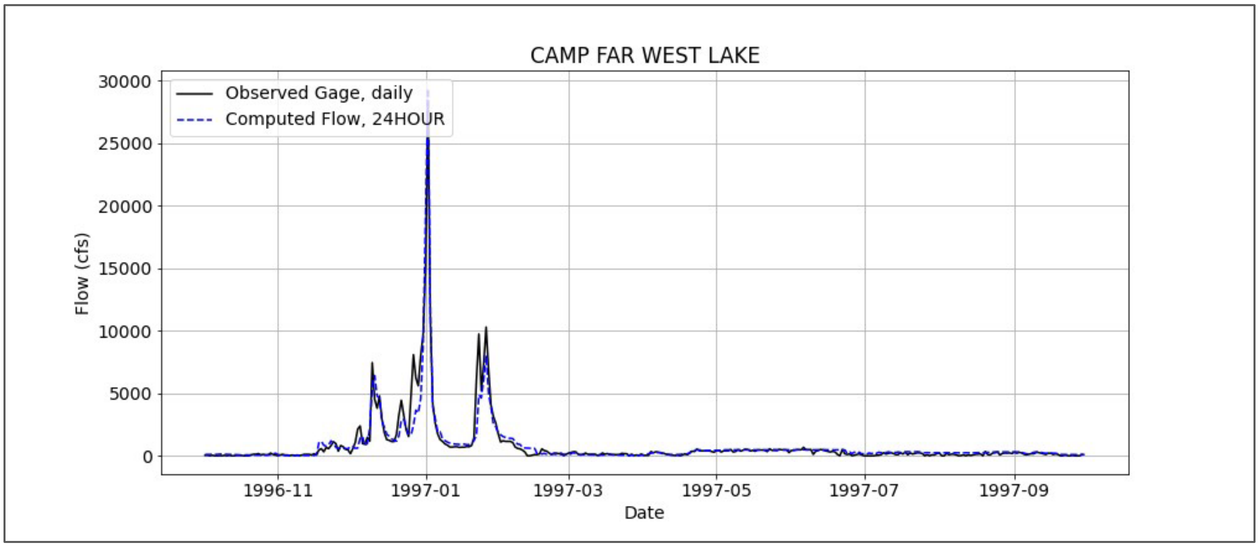


Figure A-19. WY1997 Calibration Results for Calibration Location Camp Far West Lake

A.4.2. Calibration Results for WY2004

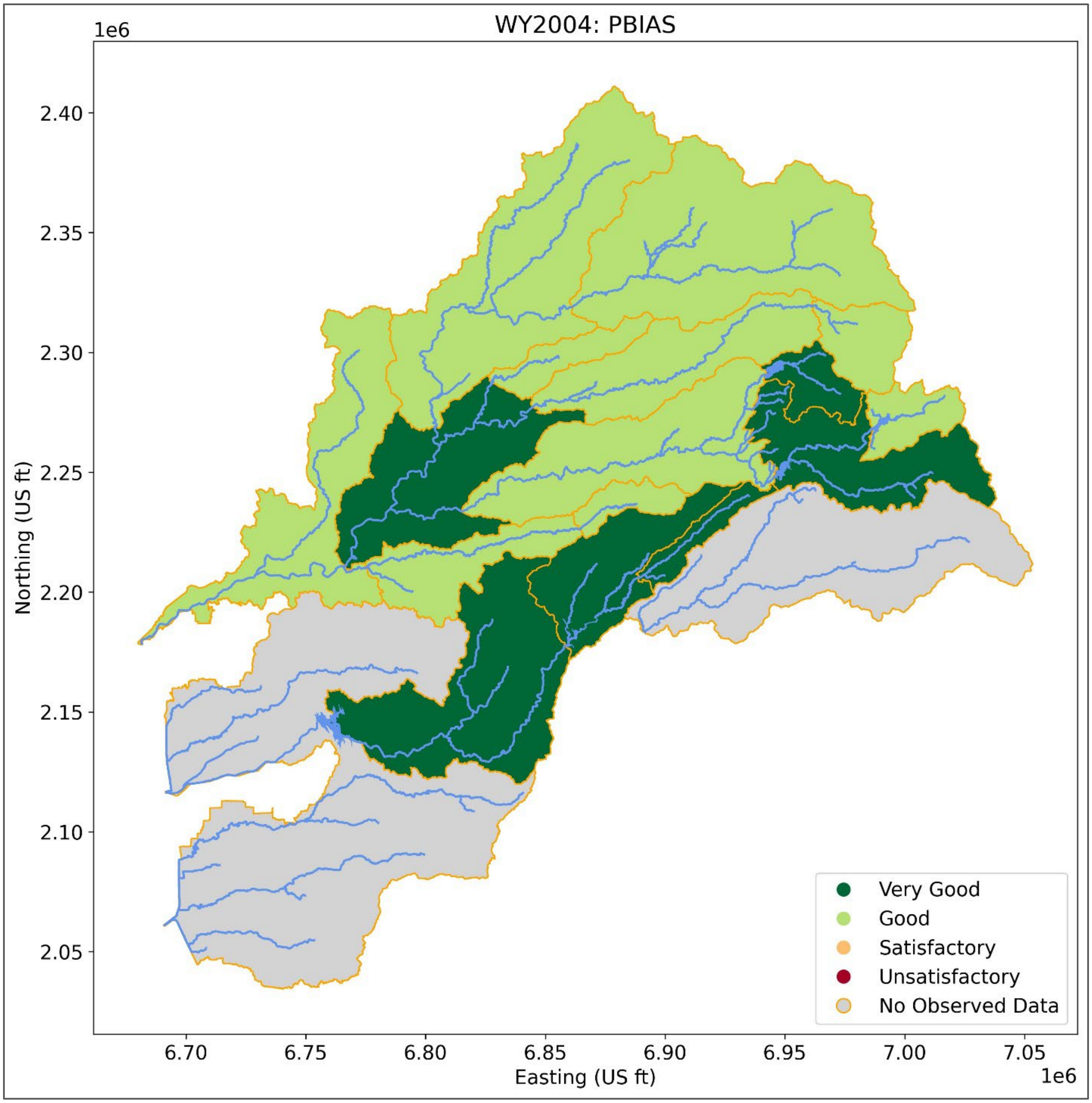


Figure A-20. WY2004 Percent Bias (PBIAS) Calibration Results for the Entire Calibrated Watersheds

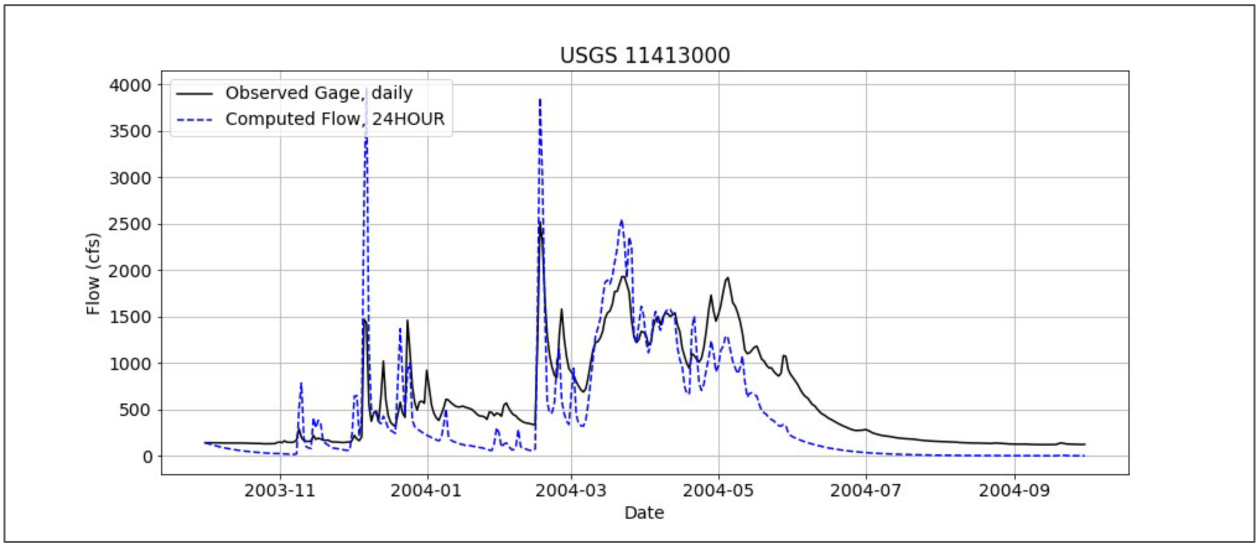


Figure A-21. WY2004 Calibration Results for Calibration Location USGS Gage 11413000

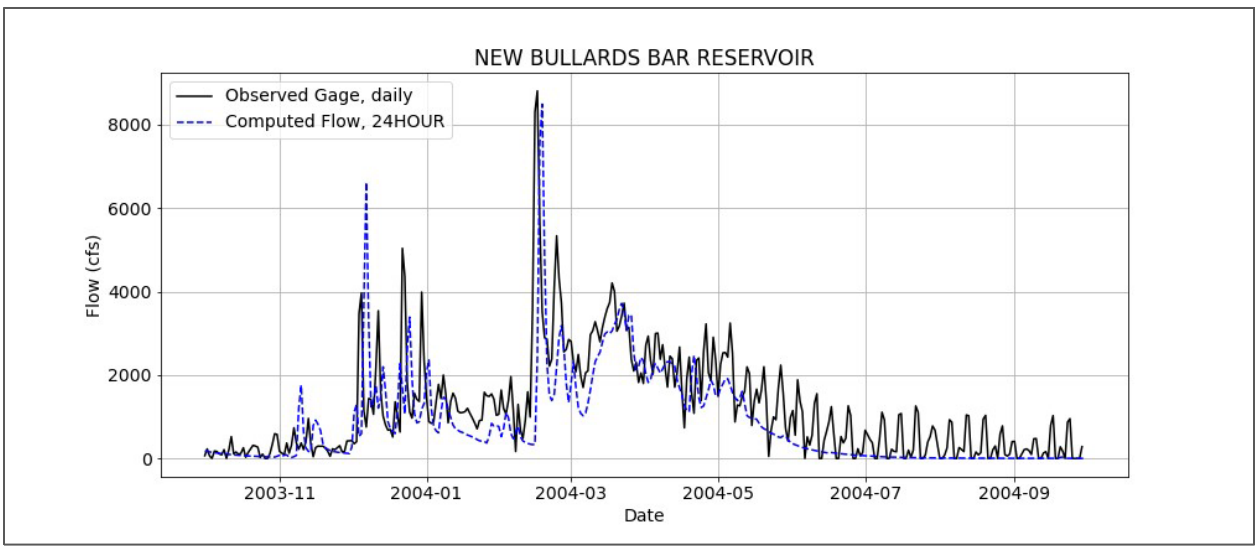


Figure A-22. WY2004 Calibration Results for Calibration Location New Bullards Bar Reservoir

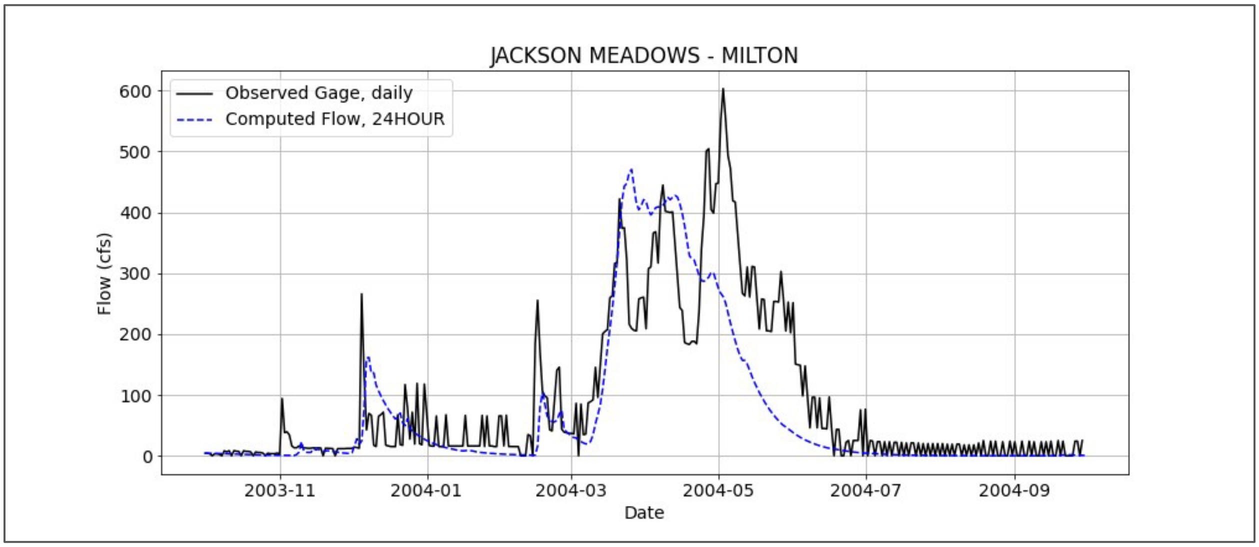


Figure A-23. WY2004 Calibration Results for Calibration Location Jackson Meadows and Milton Reservoirs

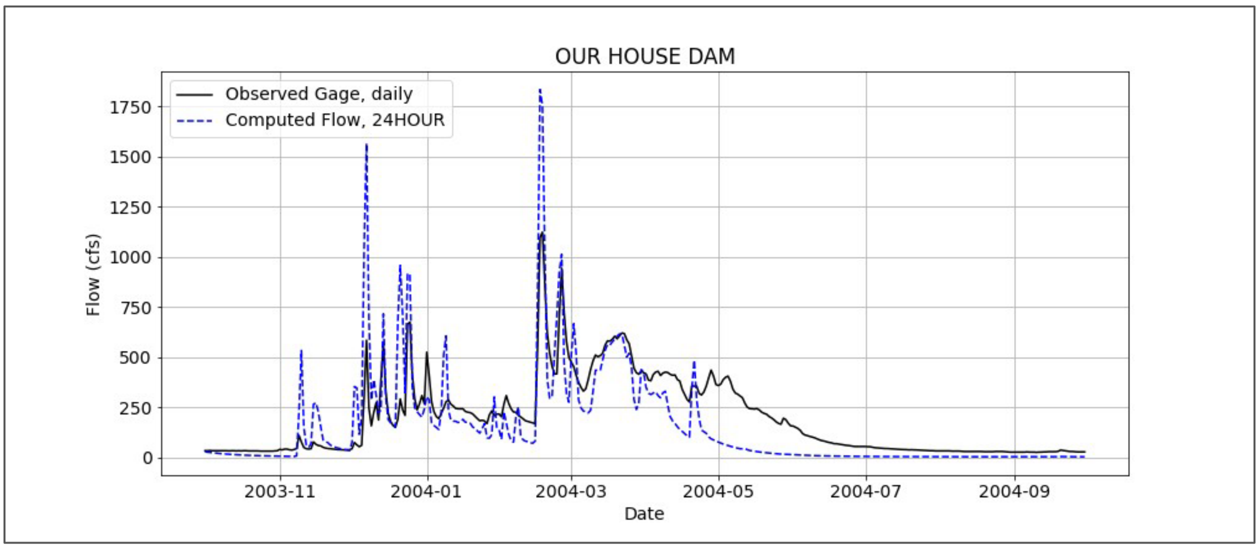


Figure A-24. WY2004 Calibration Results for Calibration Location Our House Dam

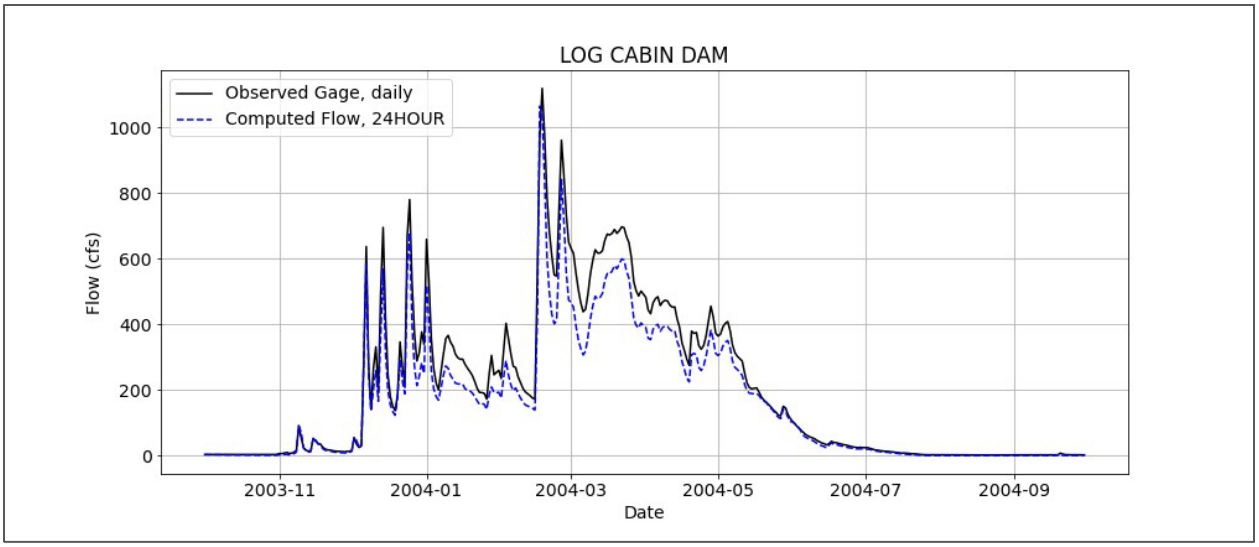


Figure A-25. WY2004 Calibration Results for Calibration Location Log Cabin Dam

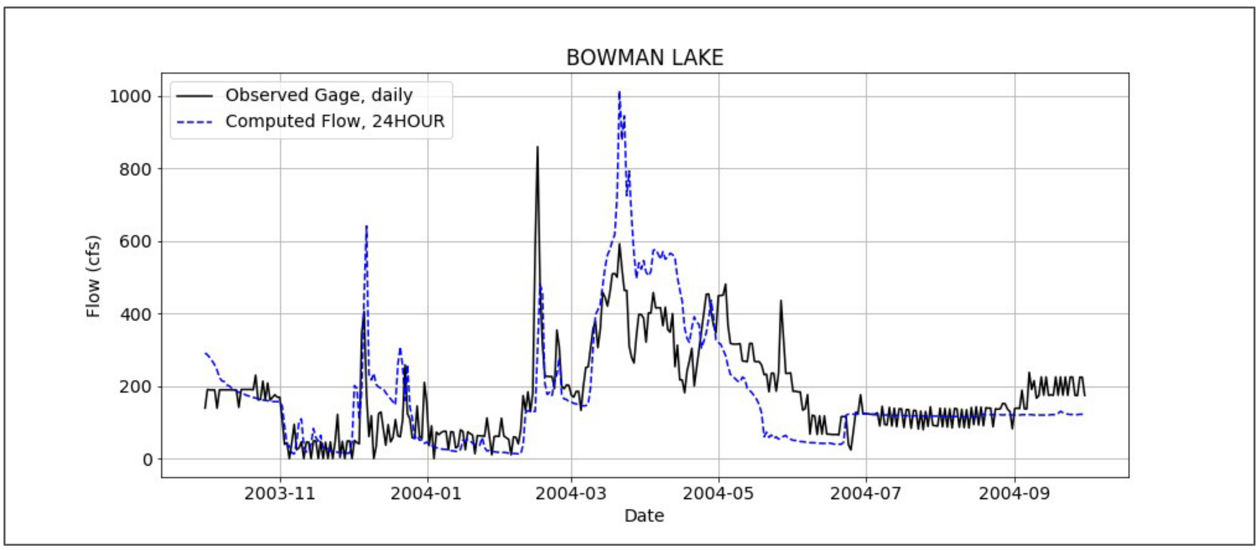


Figure A-26. WY2004 Calibration Results for Calibration Location Bowman Lake

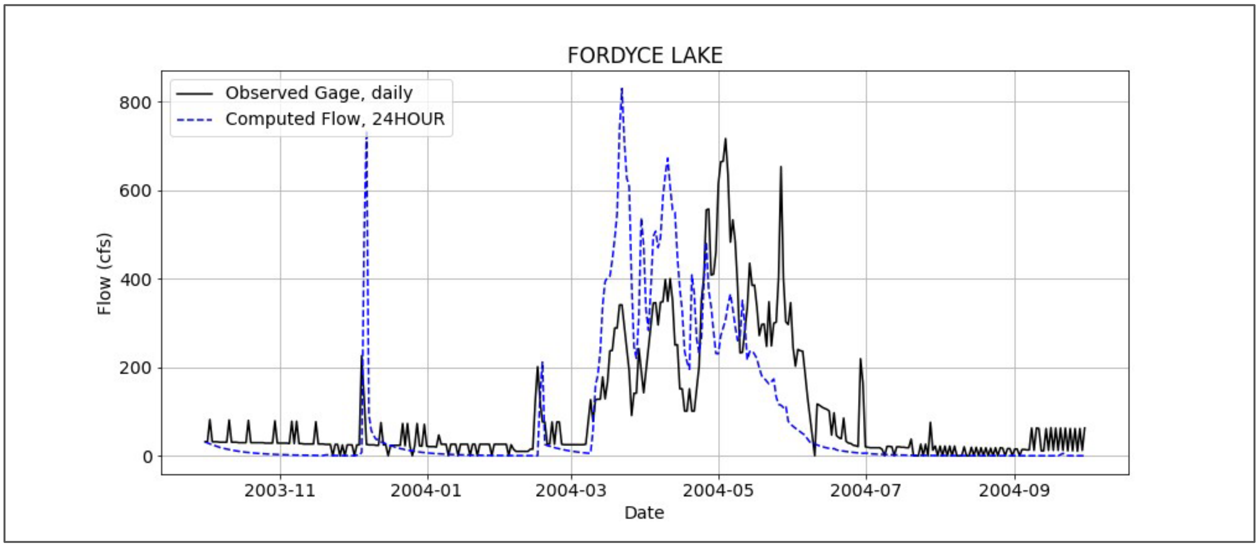


Figure A-27. WY2004 Calibration Results for Calibration Location Fordyce Lake

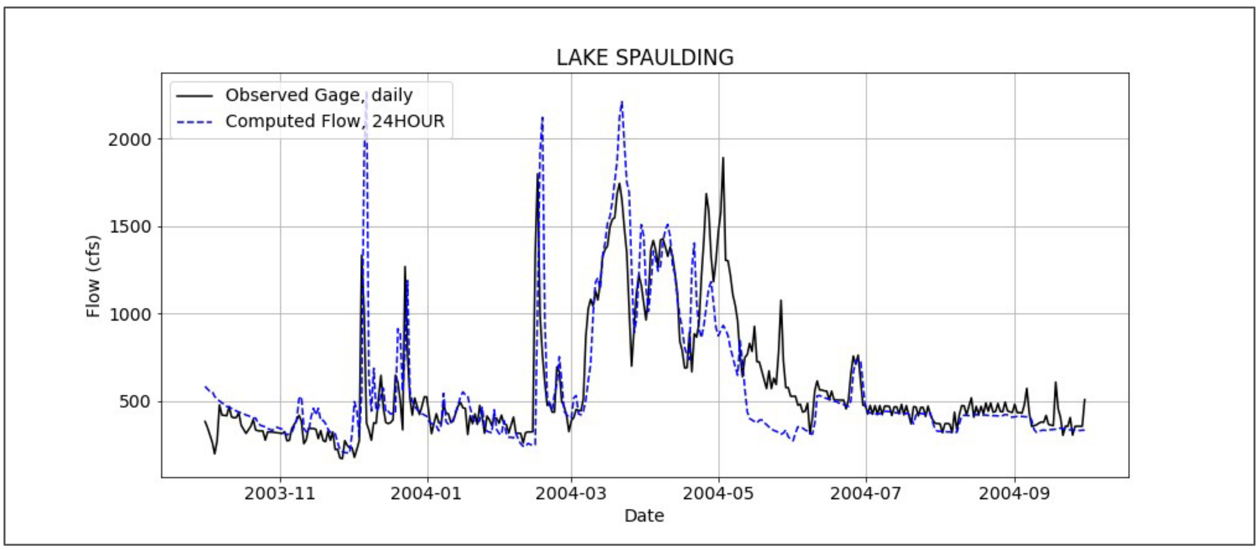


Figure A-28. WY2004 Calibration Results for Calibration Location Lake Spaulding

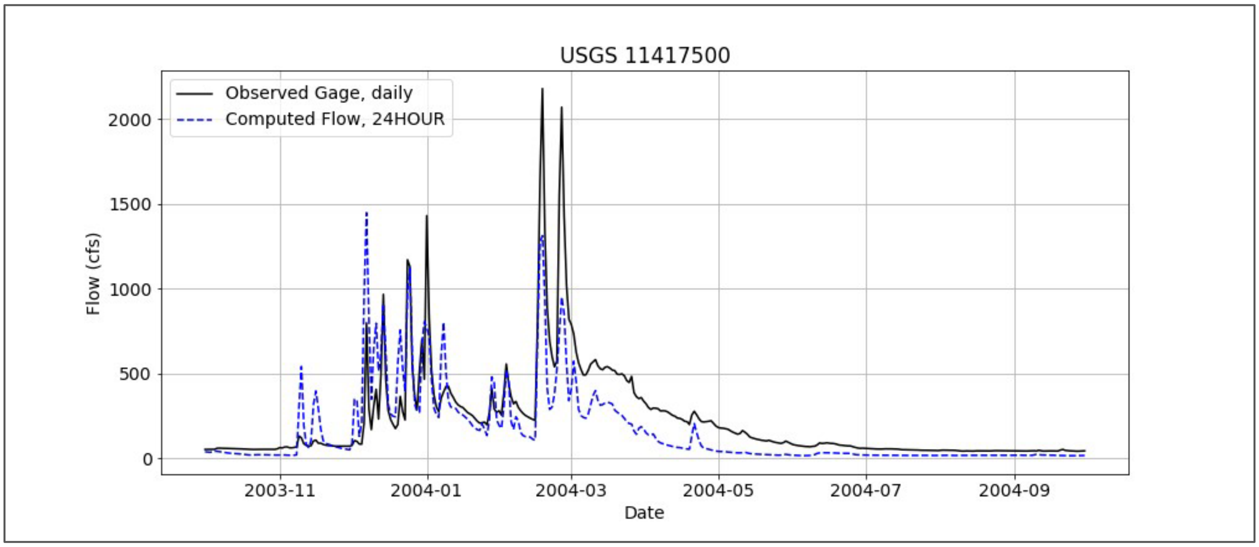


Figure A-29. WY2004 Calibration Results for Calibration Location USGS Gage 11417500

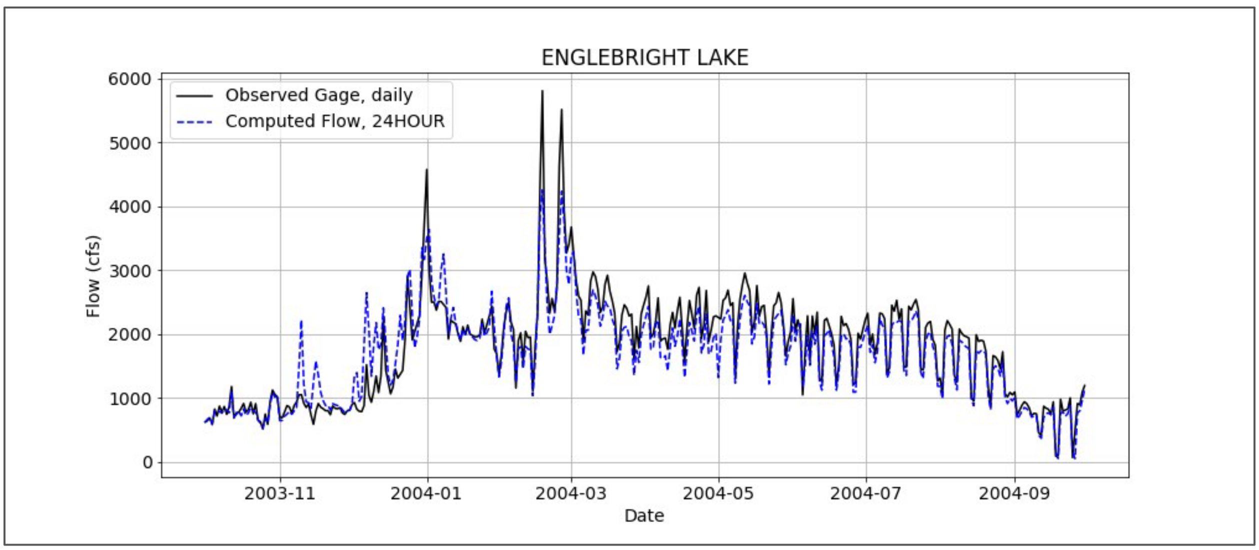


Figure A-30. WY2004 Calibration Results for Calibration Location Englebright Lake

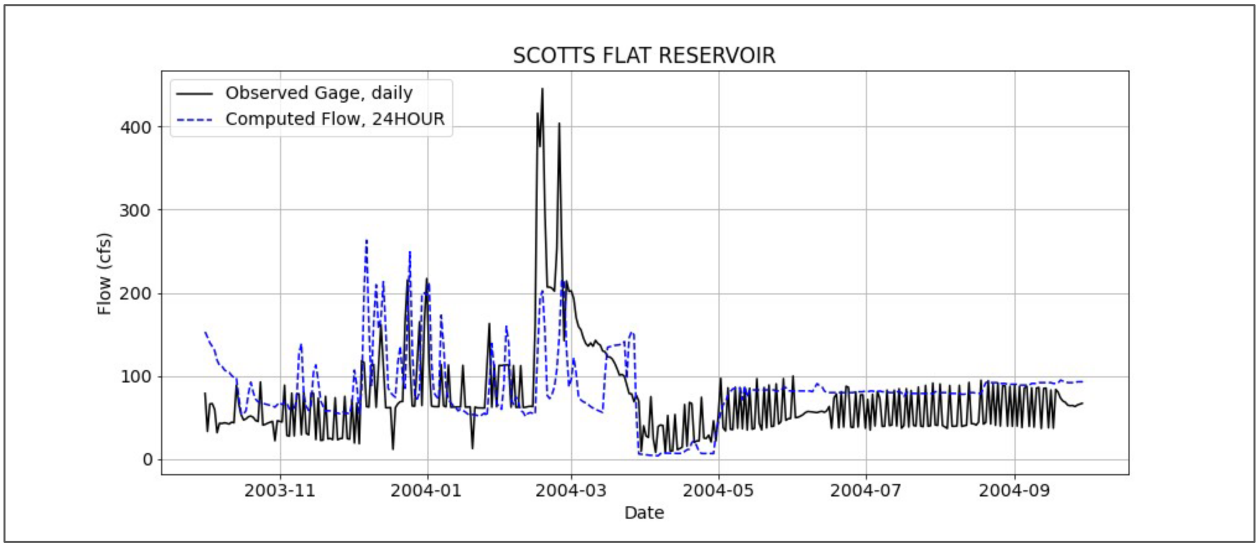


Figure A-31. WY2004 Calibration Results for Calibration Location Scotts Flat Reservoir

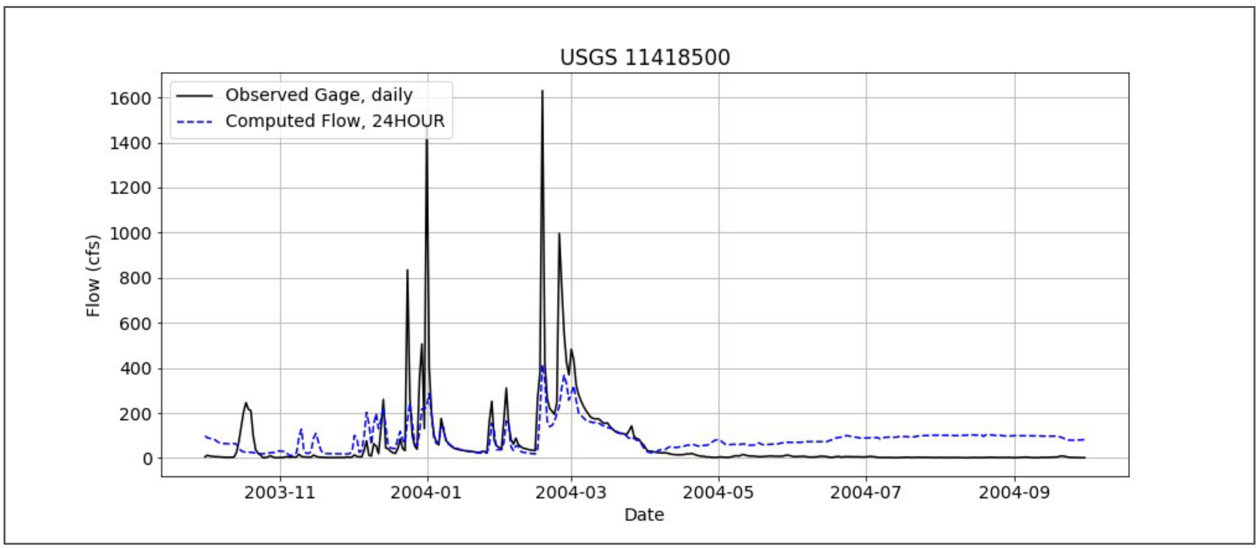


Figure A-32. WY2004 Calibration Results for Calibration Location USGS Gage 11418500

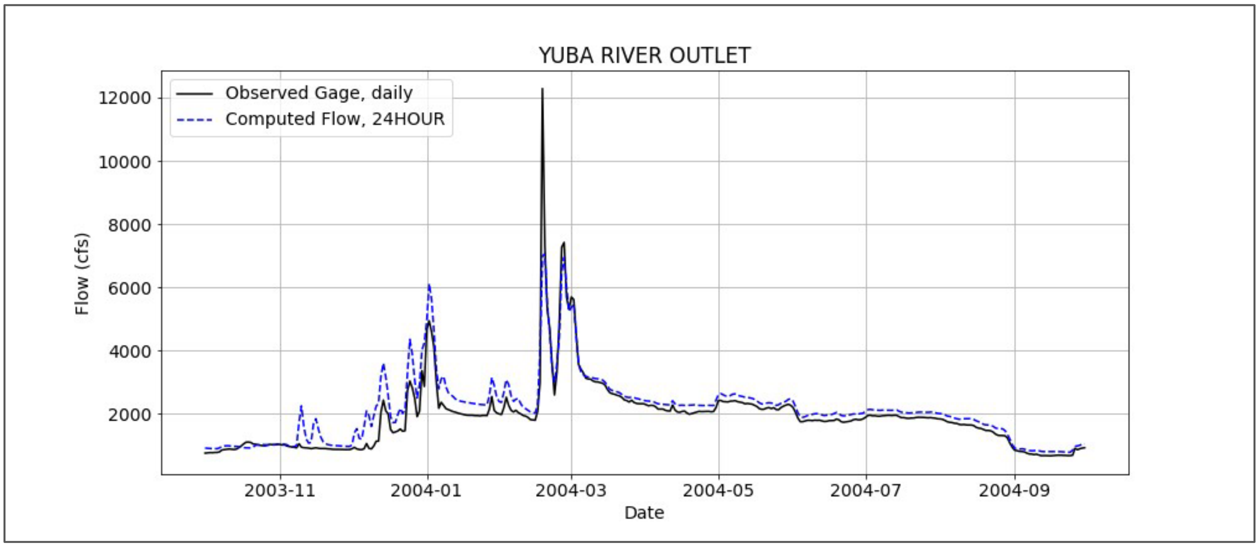


Figure A-33. WY2004 Calibration Results for Calibration Location Yuba River Outlet

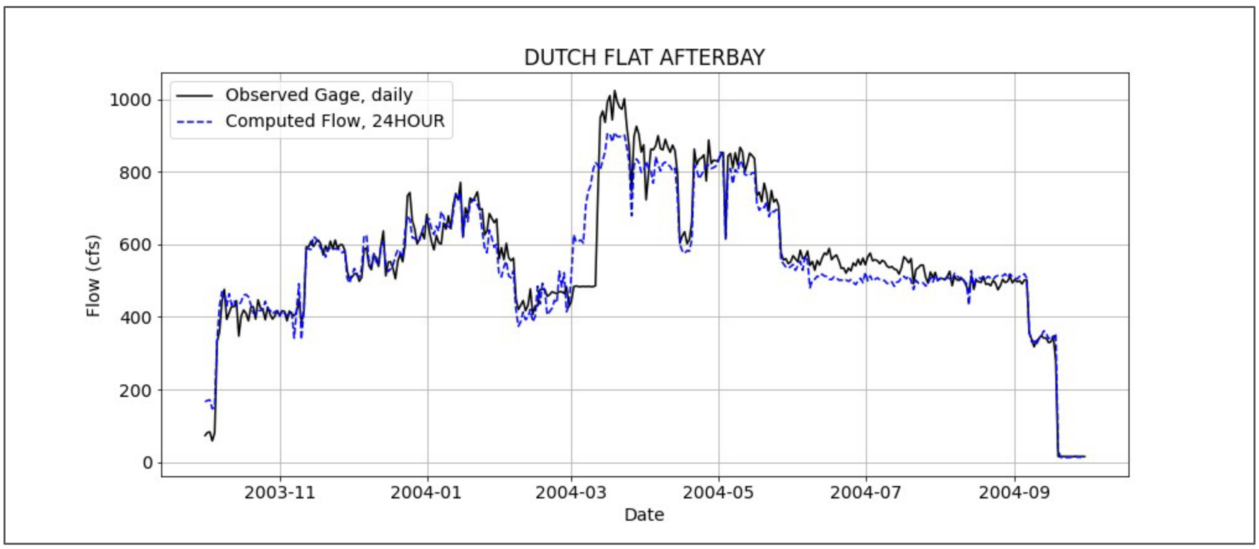


Figure A-34. WY2004 Calibration Results for Calibration Location Dutch Flat Afterbay

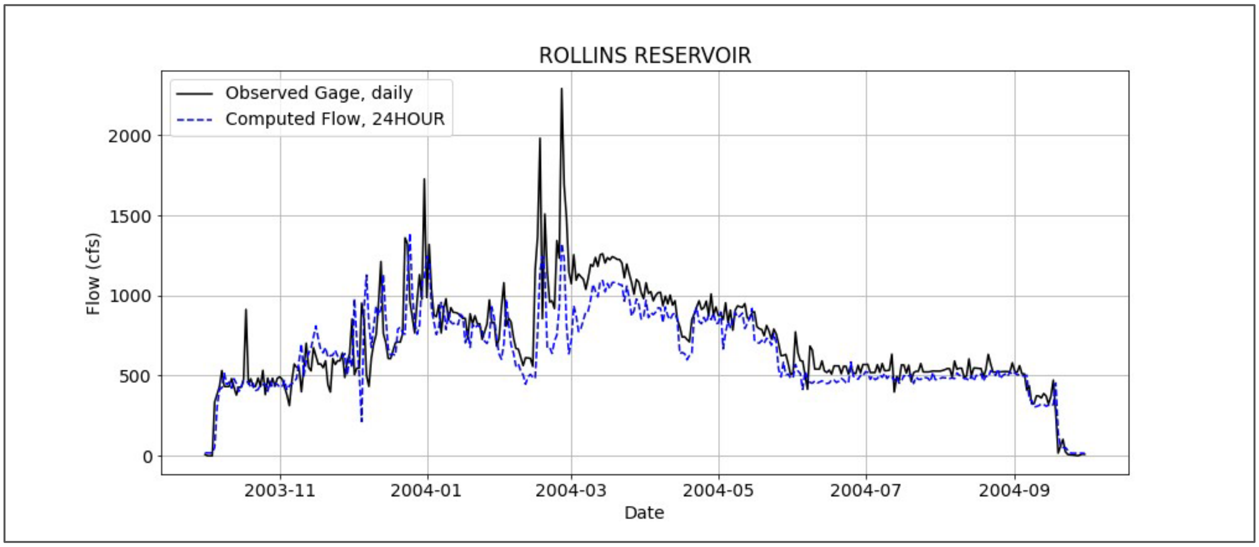


Figure A-35. WY2004 Calibration Results for Calibration Location Rollins Reservoir

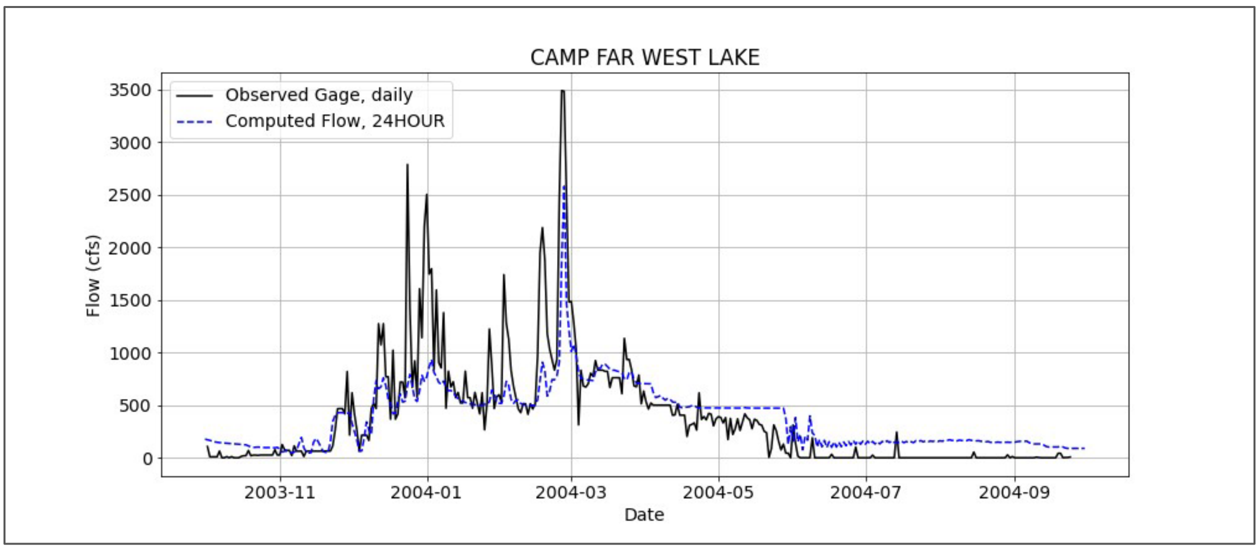


Figure A-36. WY2004 Calibration Results for Calibration Location Camp Far West Lake

A.4.3. Calibration Results for WY2006

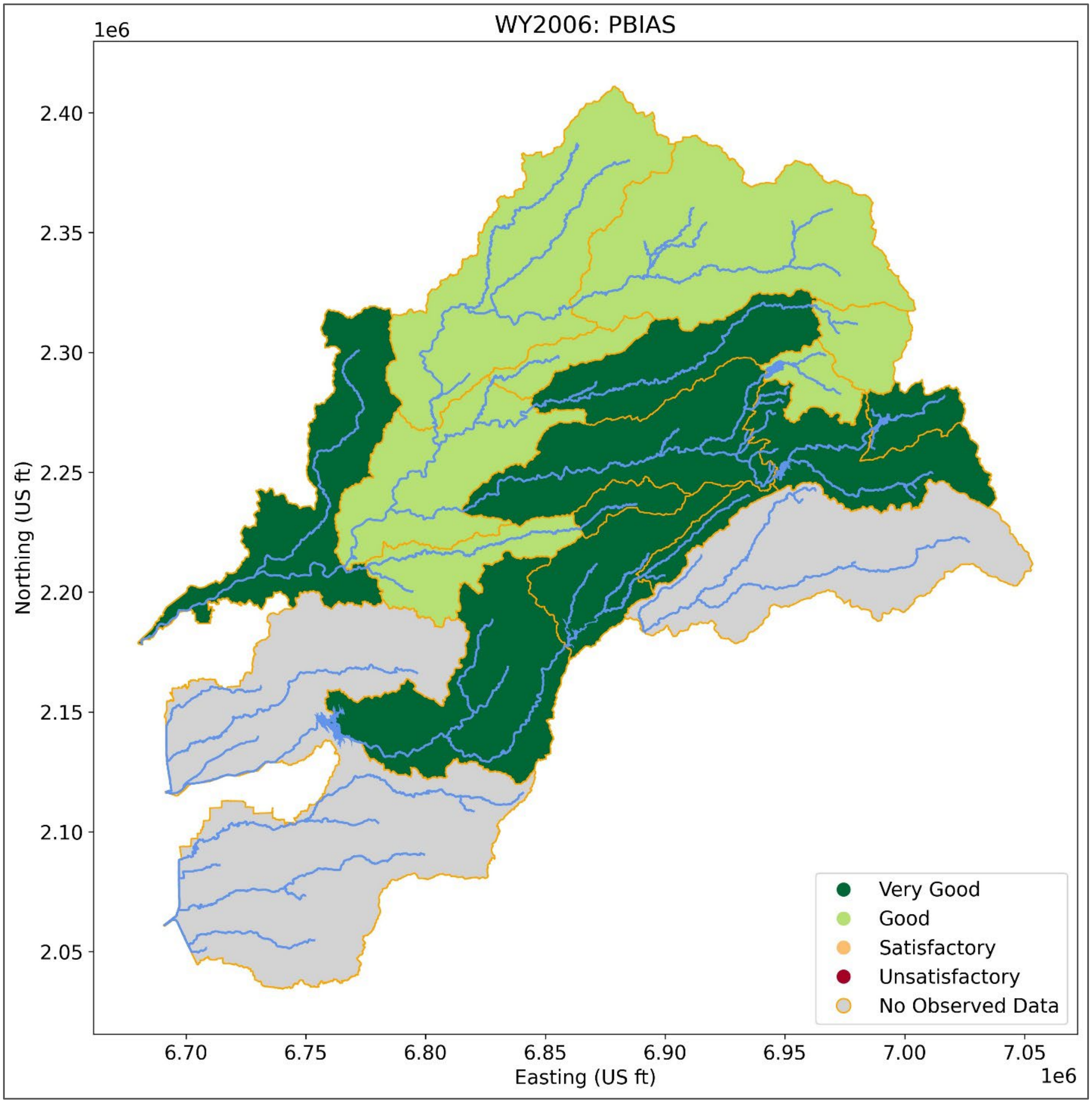


Figure A-37. WY2006 Percent Bias (PBIAS) Calibration Results for the Entire Calibrated Watersheds

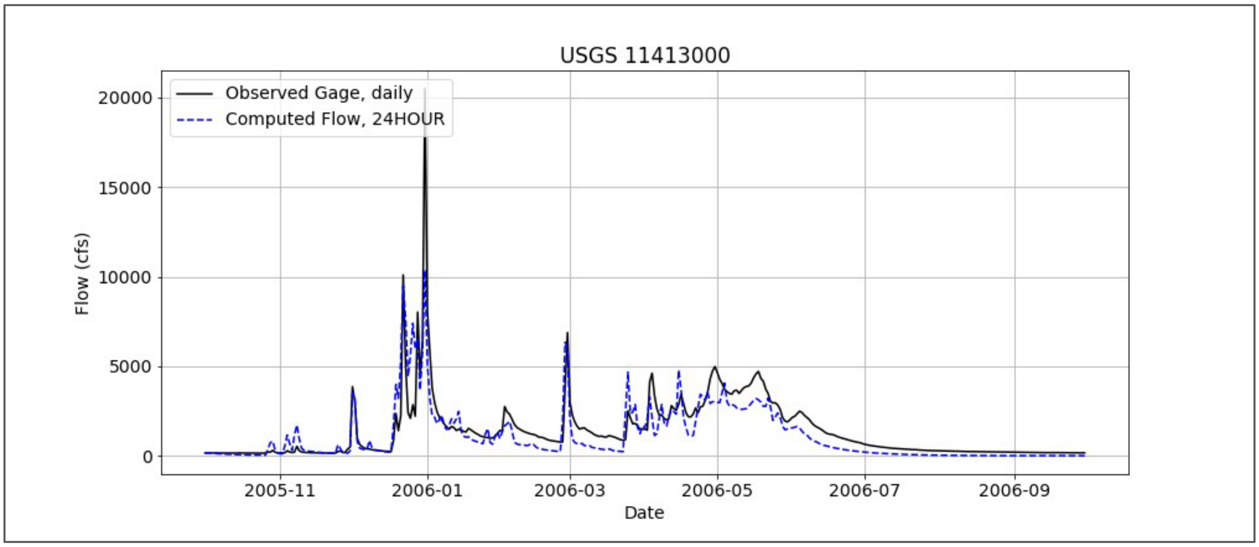


Figure A-38. WY2006 Calibration Results for Calibration Location USGS Gage 11413000

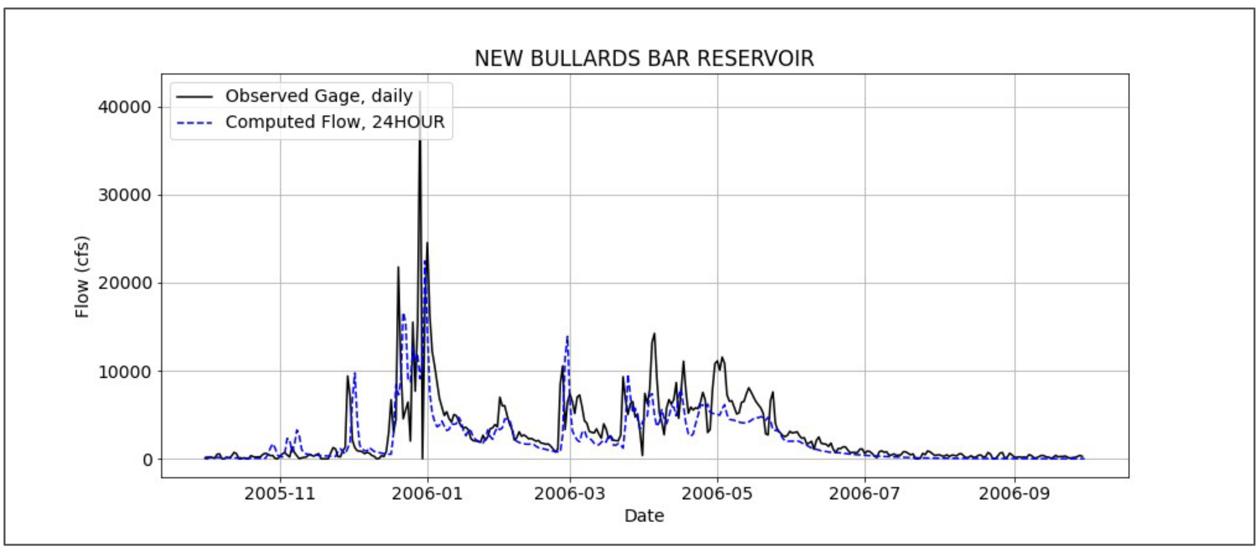


Figure A-39. WY2006 Calibration Results for Calibration Location New Bullards Bar Reservoir

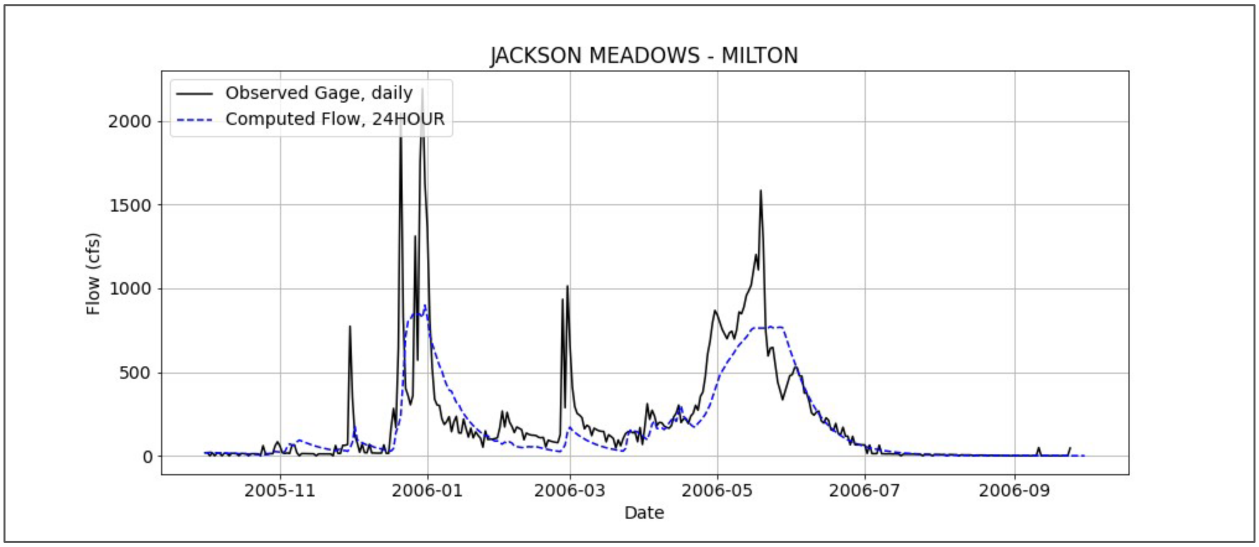


Figure A-40. WY2006 Calibration Results for Calibration Location Jackson Meadows and Milton Reservoirs

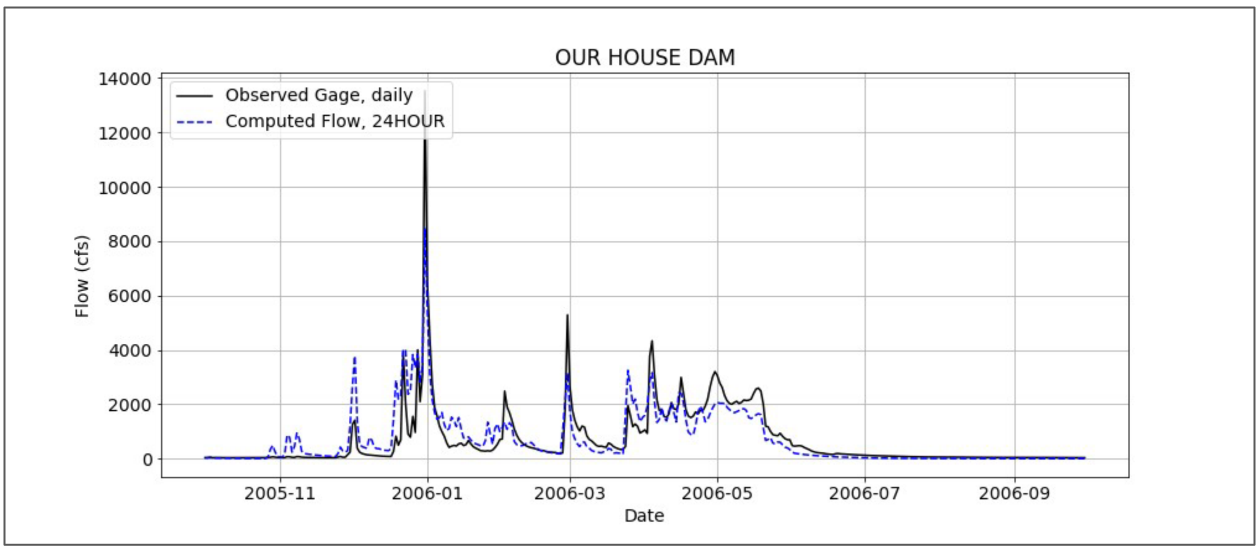


Figure A-41. WY2006 Calibration Results for Calibration Location Our House Dam

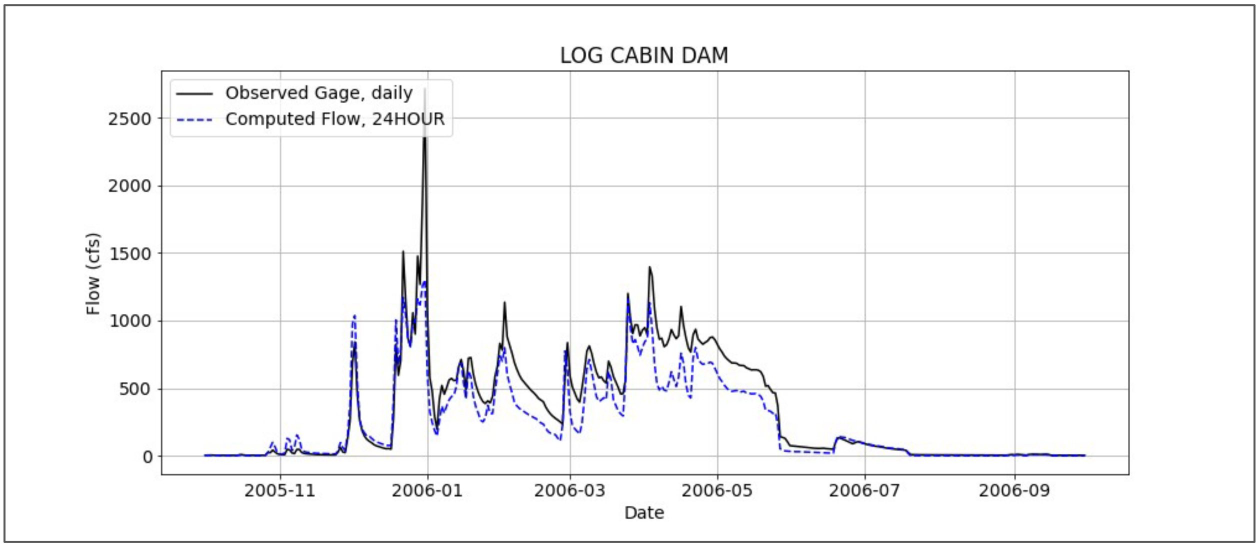


Figure A-42. WY2006 Calibration Results for Calibration Location Log Cabin Dam

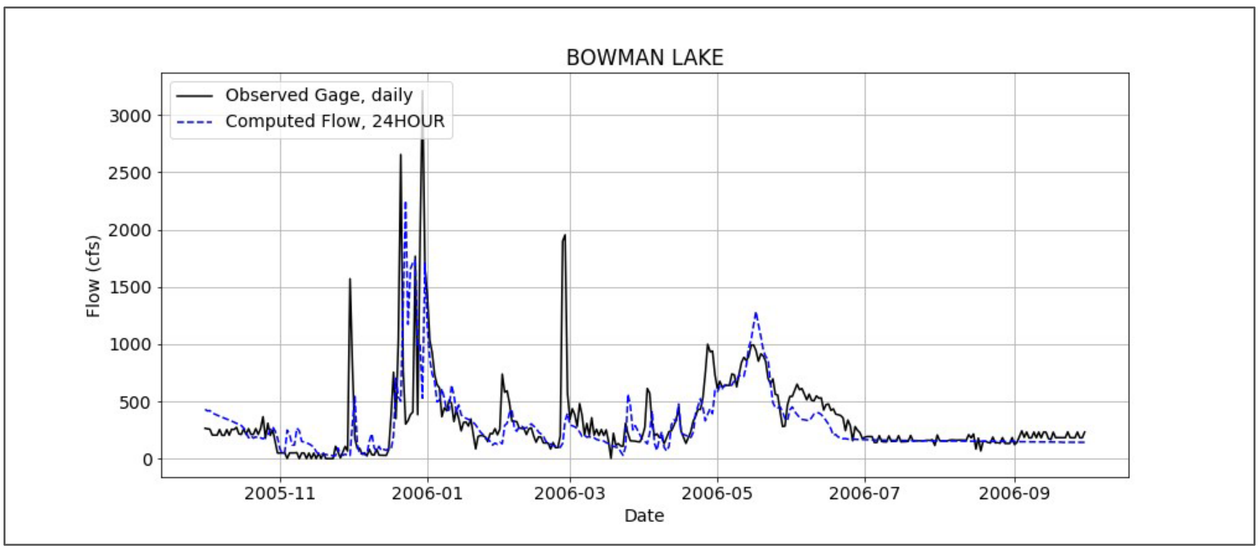


Figure A-43. WY2006 Calibration Results for Calibration Location Bowman Lake

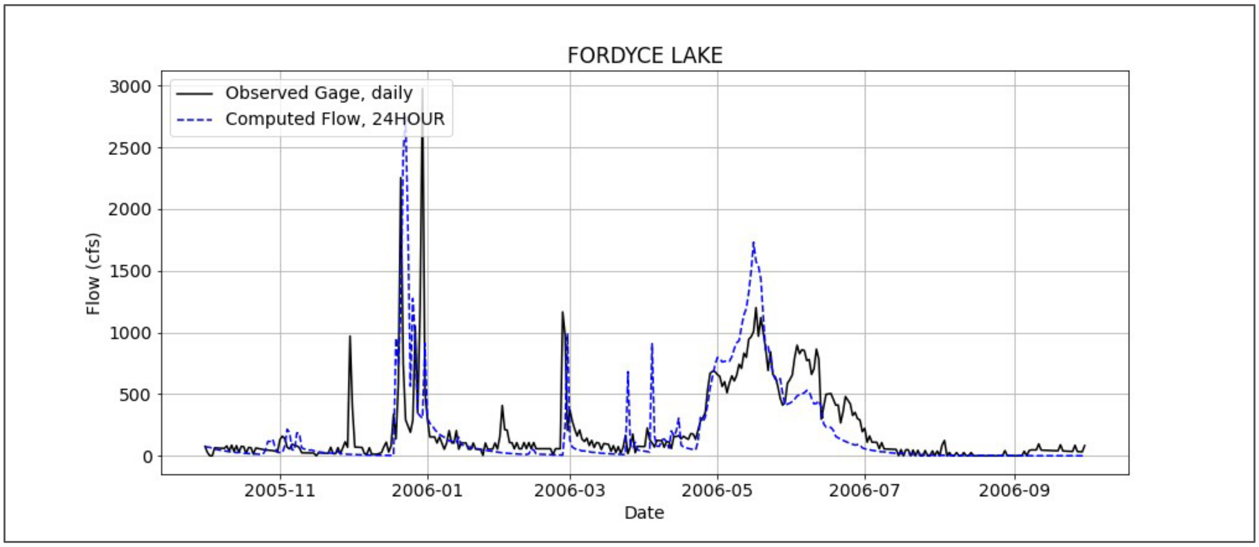


Figure A-44. WY2006 Calibration Results for Calibration Location Fordyce Lake

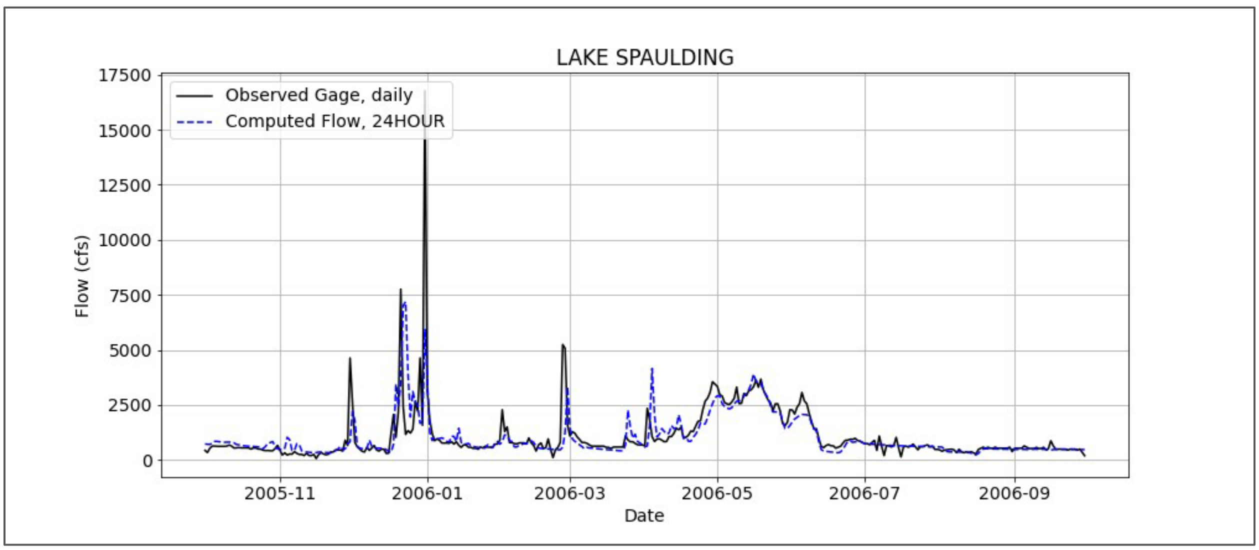


Figure A-45. WY2006 Calibration Results for Calibration Location Lake Spaulding

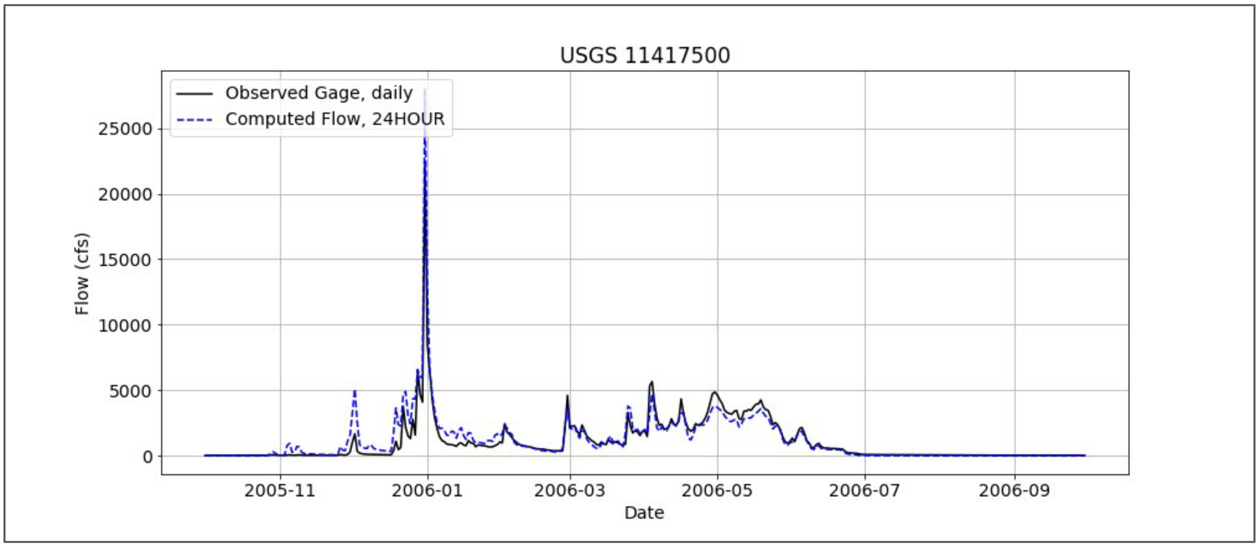


Figure A-46. WY2006 Calibration Results for Calibration Location USGS Gage 11417500

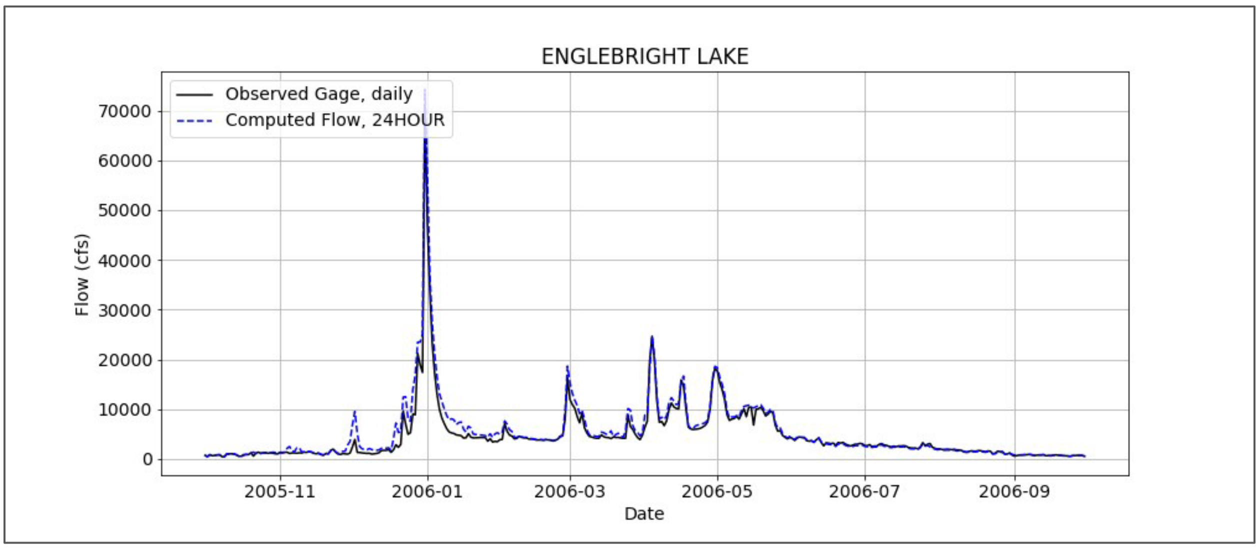


Figure A-47. WY2006 Calibration Results for Calibration Location Englebright Lake

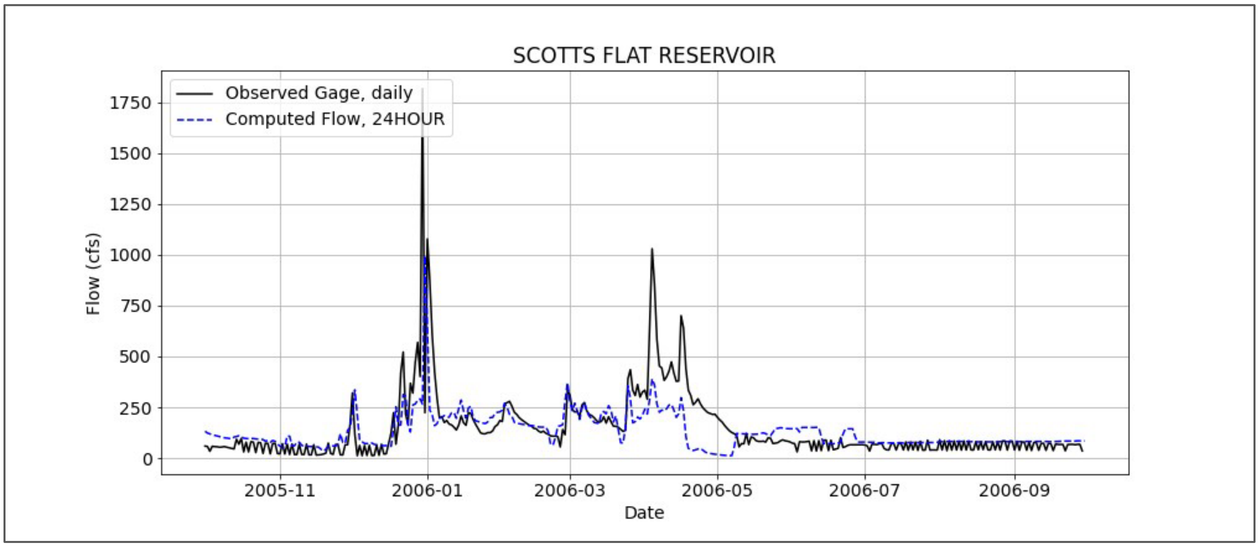


Figure A-48. WY2006 Calibration Results for Calibration Location Scotts Flat Reservoir

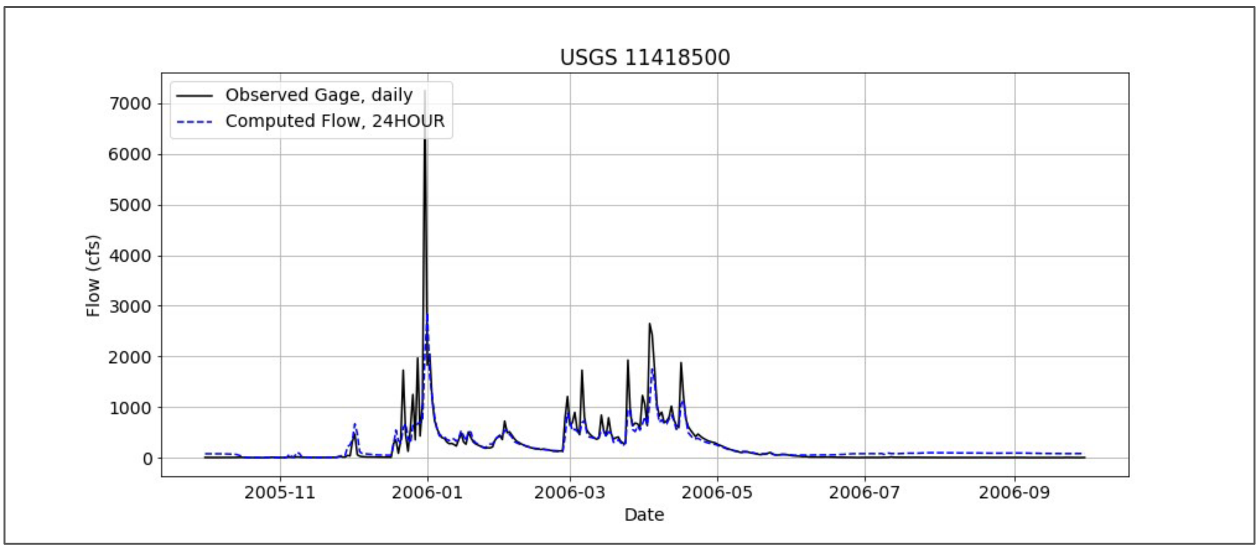


Figure A-49. WY2006 Calibration Results for Calibration Location USGS Gage 11418500

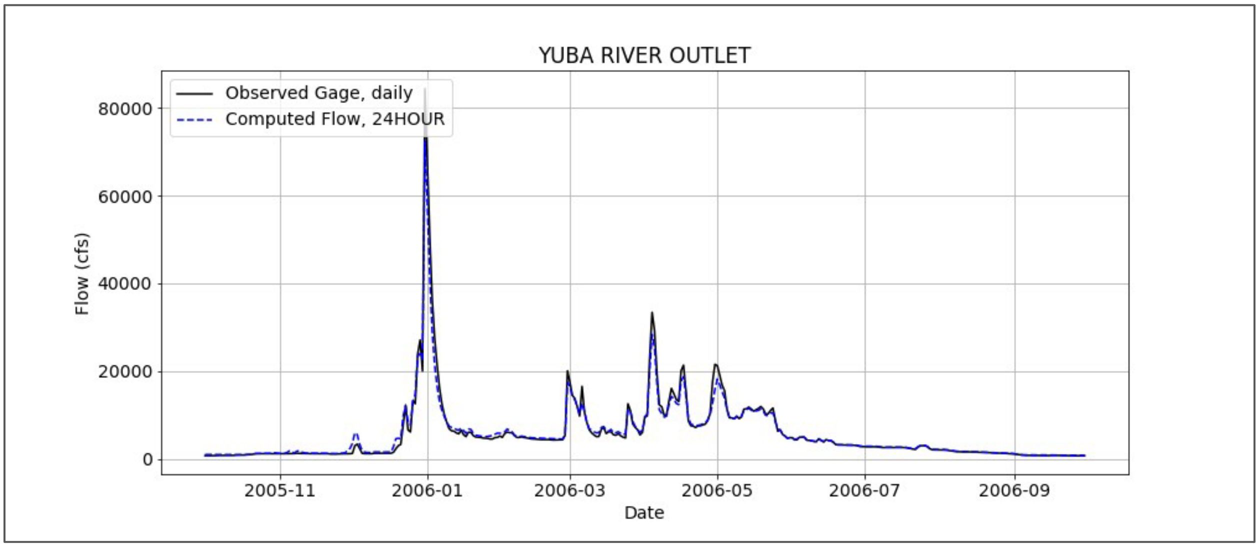


Figure A-50. WY2006 Calibration Results for Calibration Location Yuba River Outlet

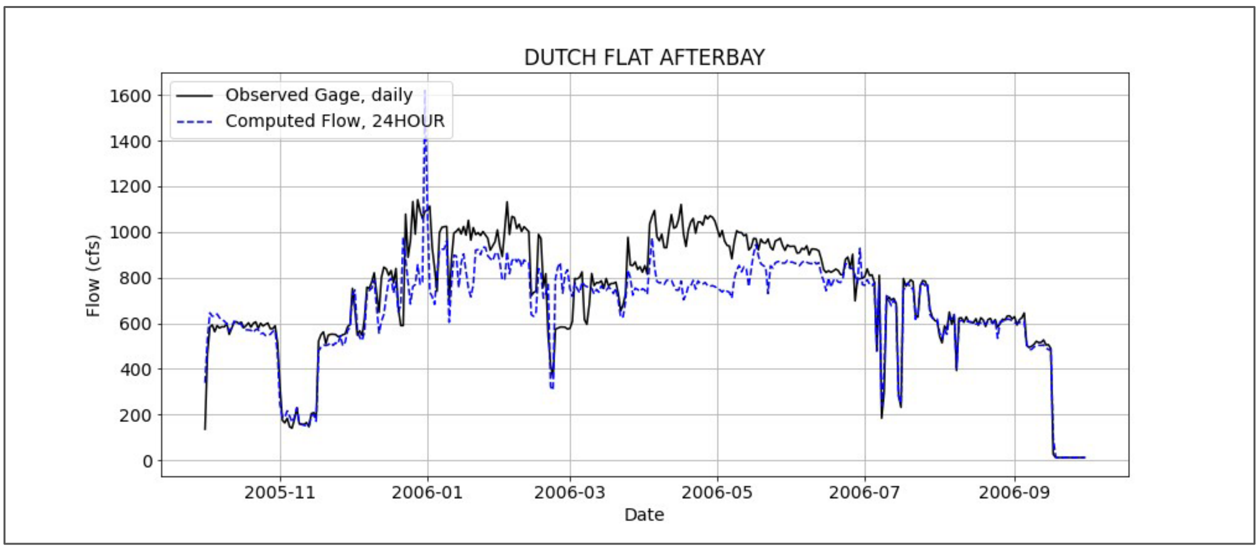


Figure A-51. WY2006 Calibration Results for Calibration Location Dutch Flat Afterbay

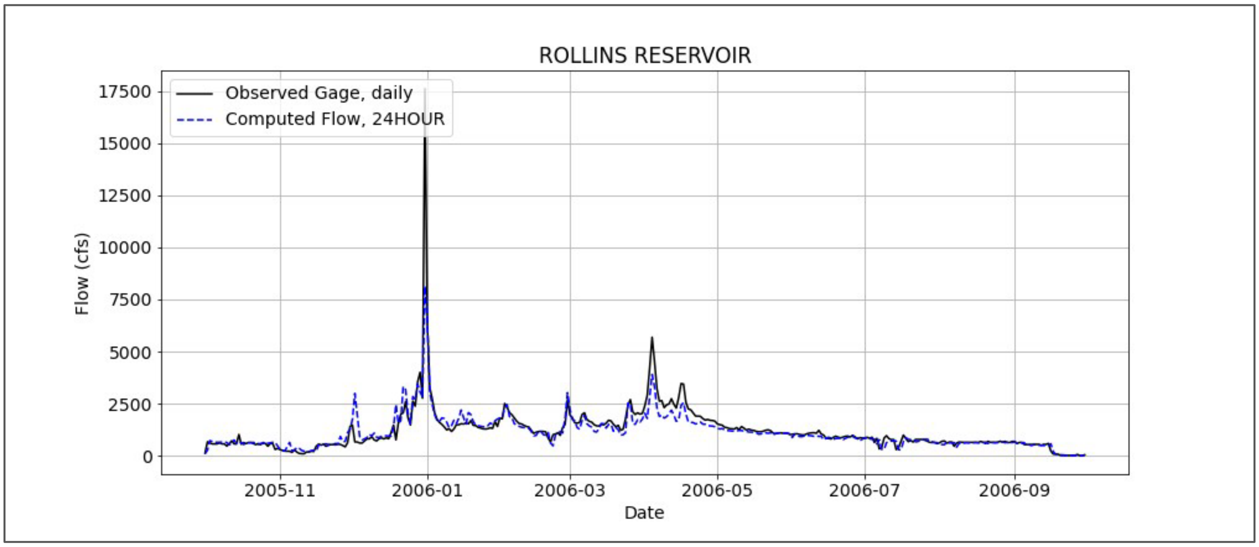


Figure A-52. WY2006 Calibration Results for Calibration Location Rollins Reservoir

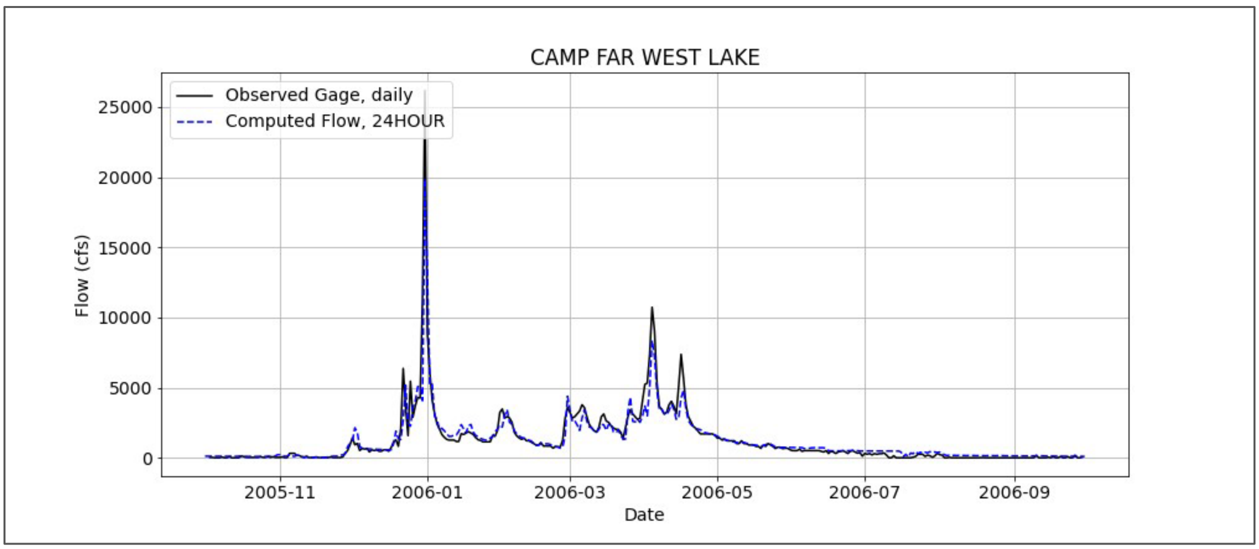


Figure A-53. WY2006 Calibration Results for Calibration Location Camp Far West Lake

A.4.4. Calibration Results for WY2015

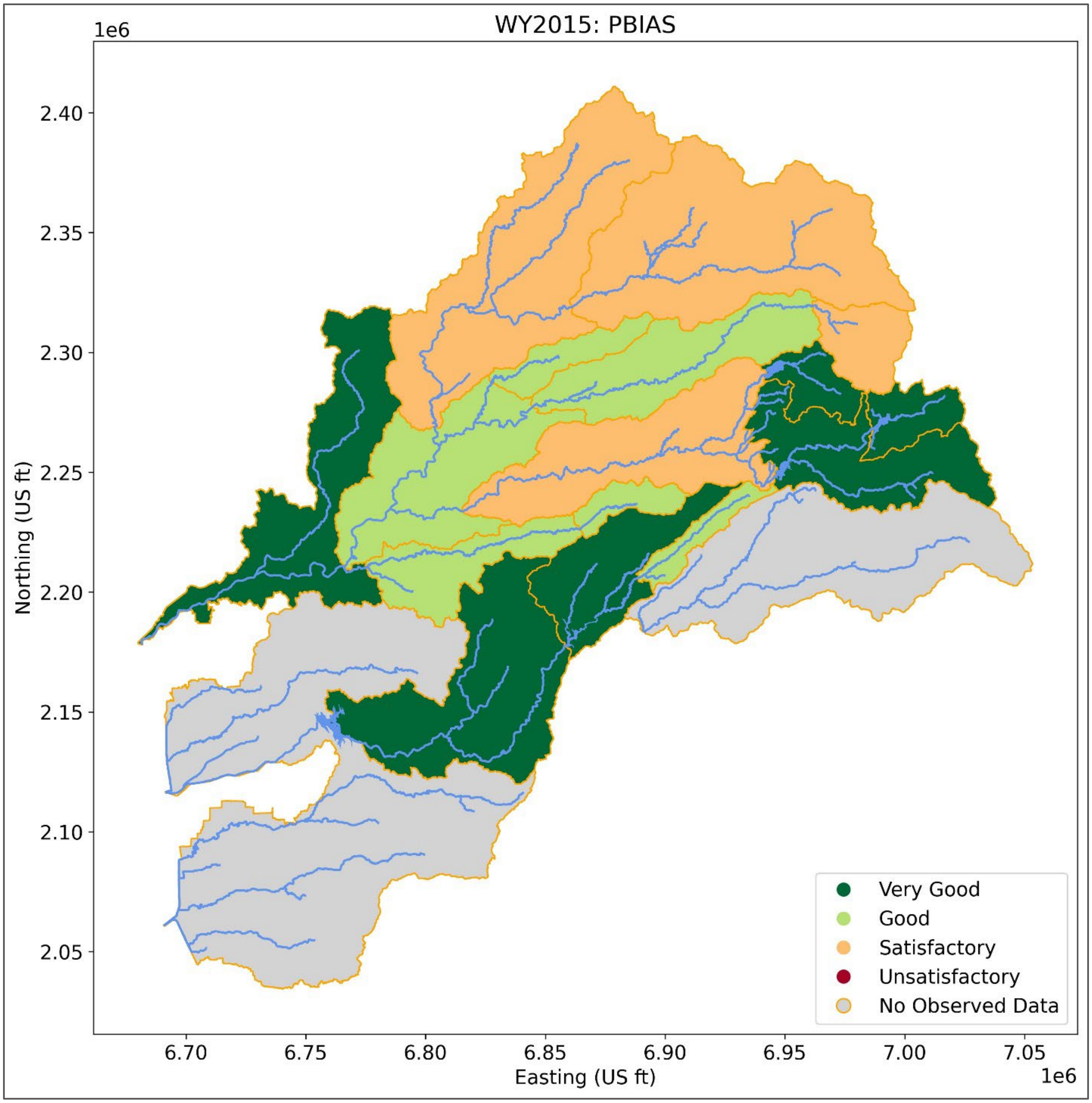


Figure A-54. WY2015 Percent Bias (PBIAS) Calibration Results for the Entire Calibrated Watersheds

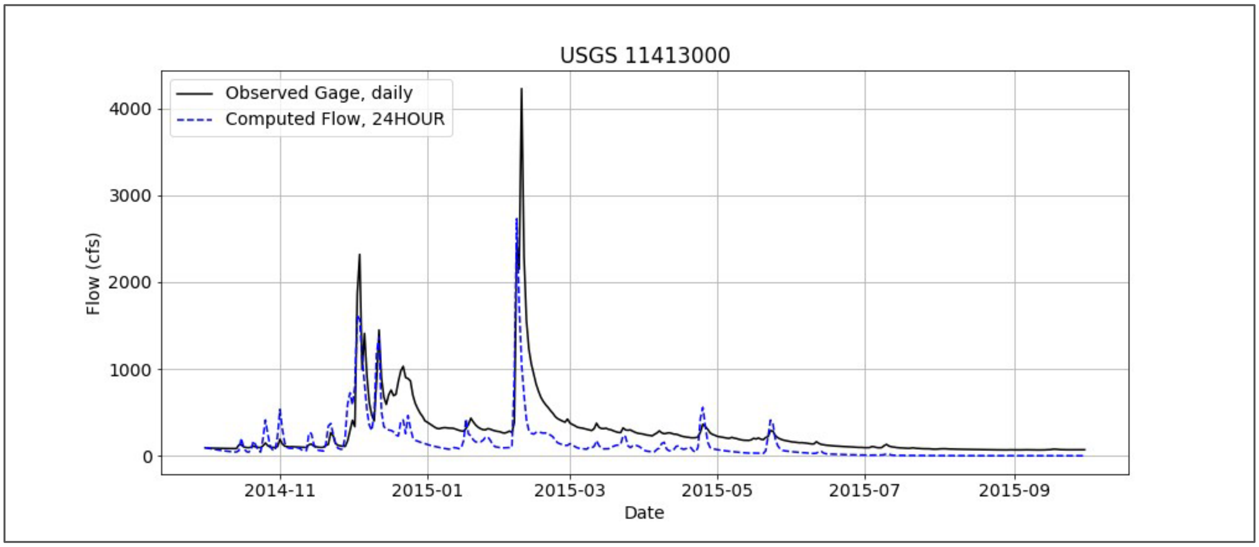


Figure A-55. WY2015 Calibration Results for Calibration Location USGS Gage 11413000

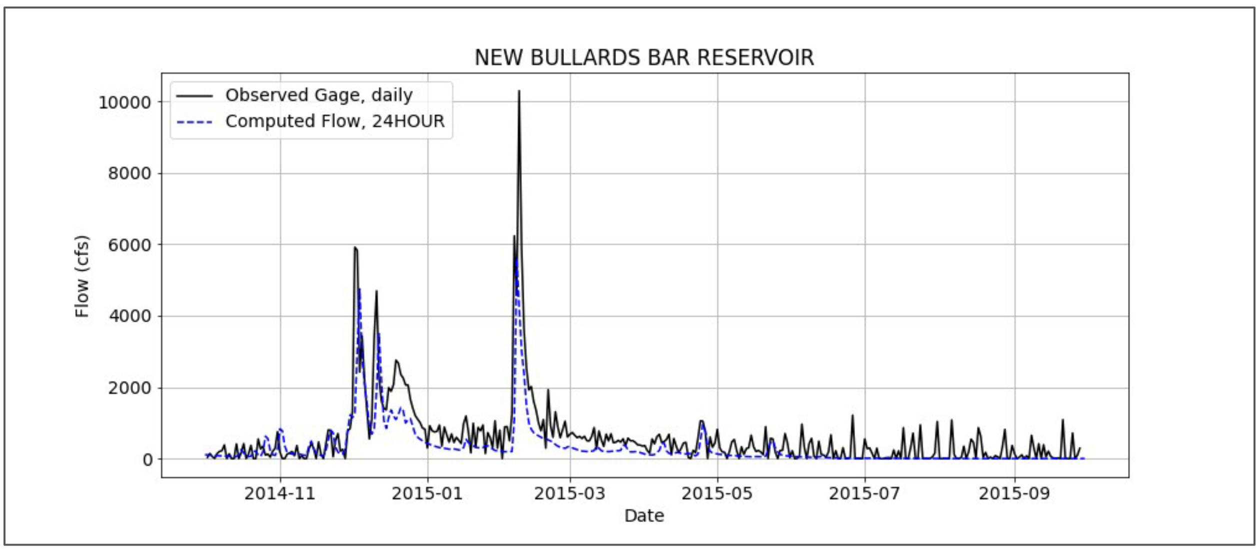


Figure A-56. WY2015 Calibration Results for Calibration Location New Bullards Bar Reservoir

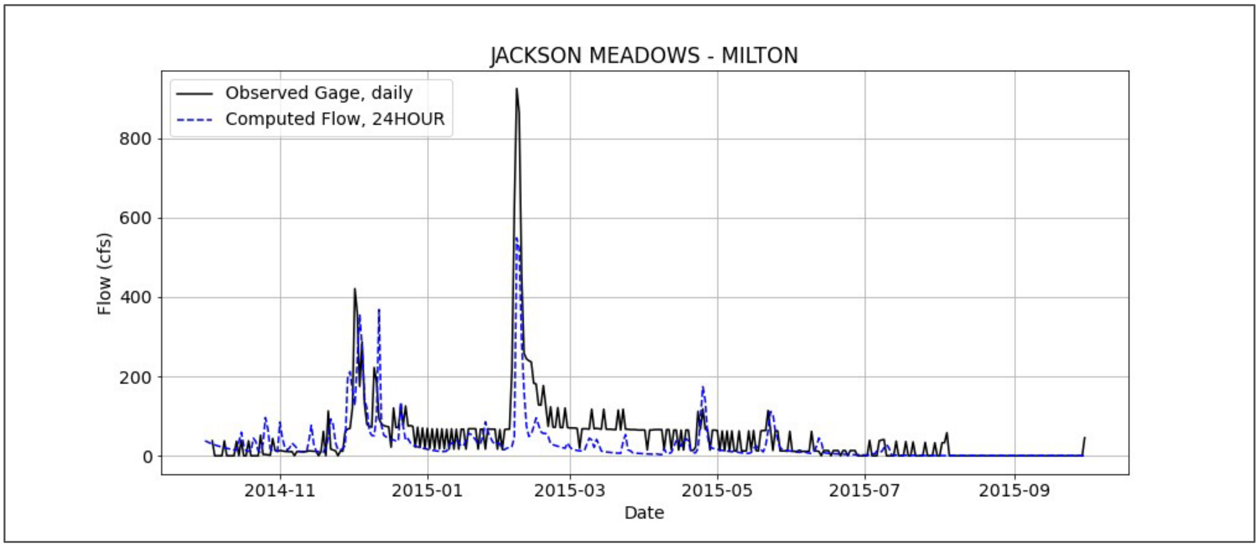


Figure A-57. WY2015 Calibration Results for Calibration Location Jackson Meadows and Milton Reservoirs

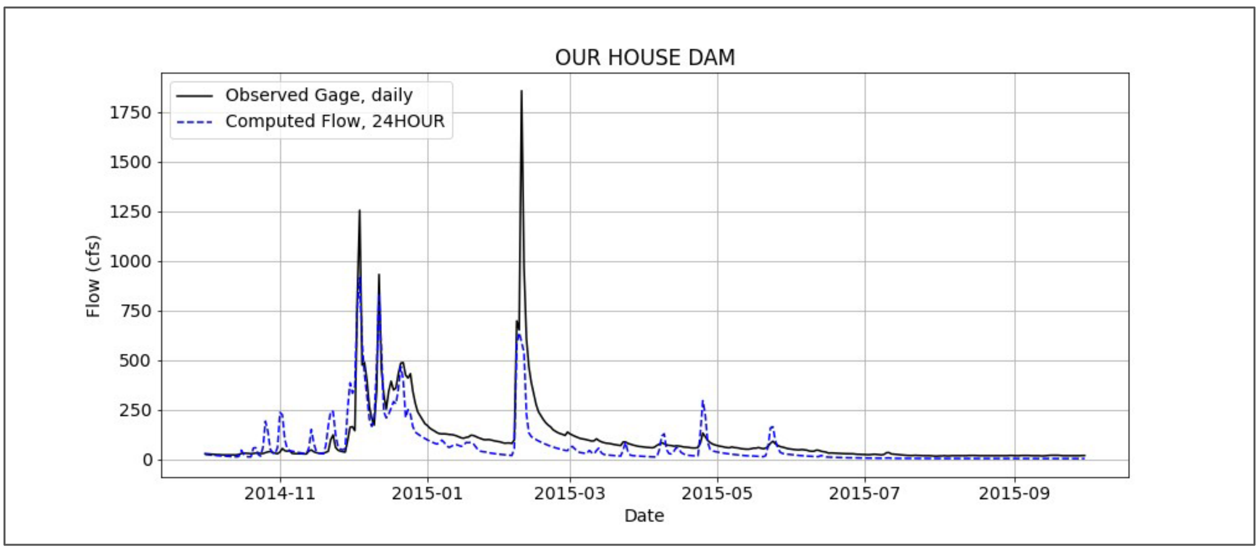


Figure A-58. WY2015 Calibration Results for Calibration Location Our House Dam

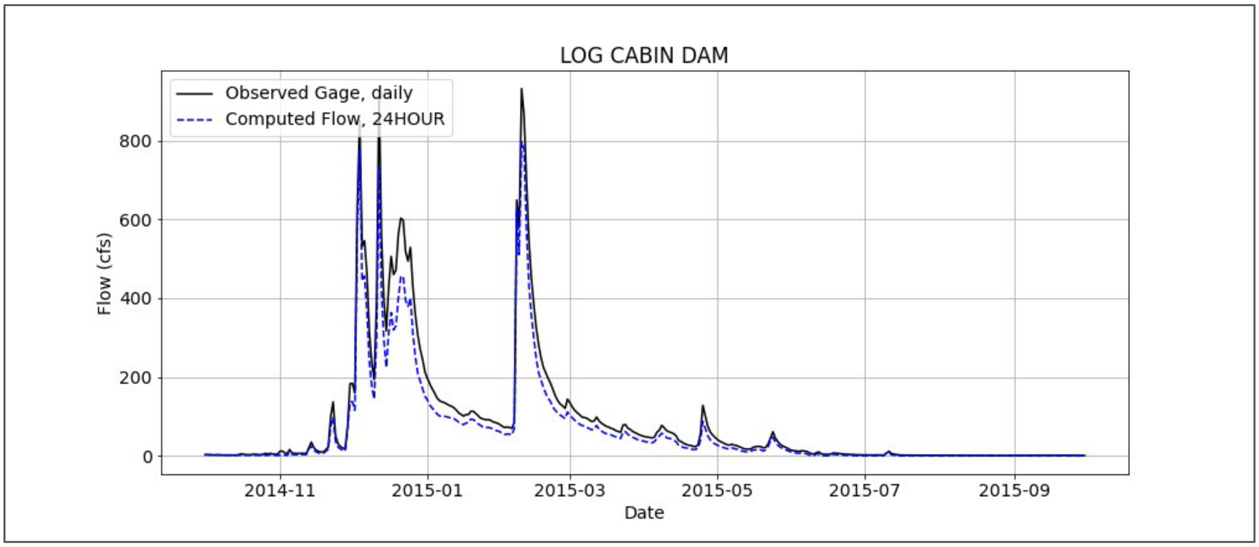


Figure A-59. WY2015 Calibration Results for Calibration Location Log Cabin Dam

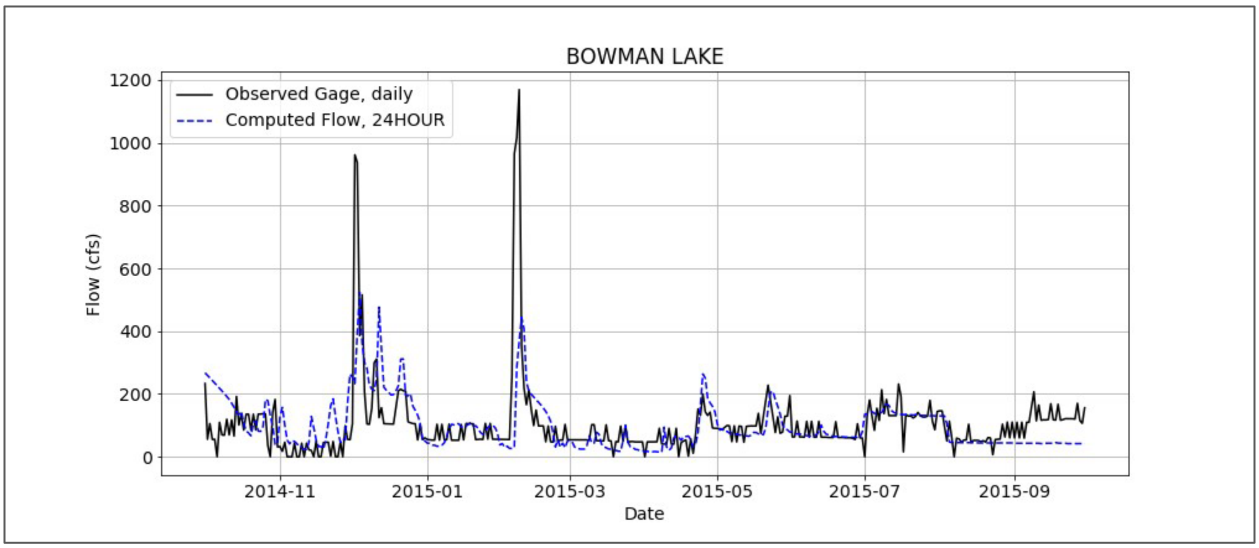


Figure A-60. WY2015 Calibration Results for Calibration Location Bowman Lake

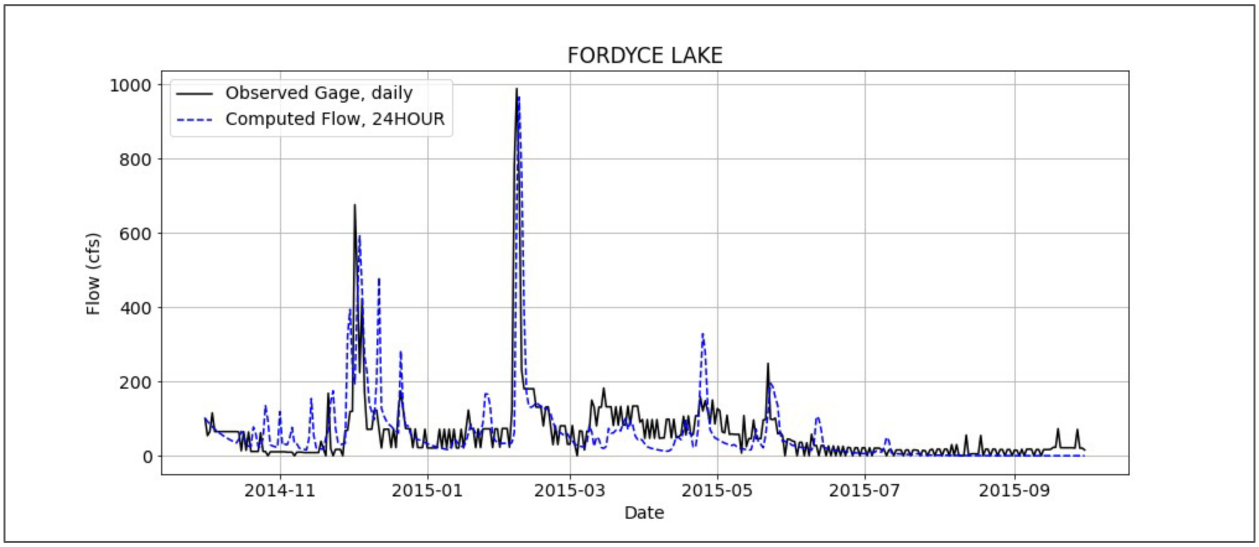


Figure A-61. WY2015 Calibration Results for Calibration Location Fordyce Lake

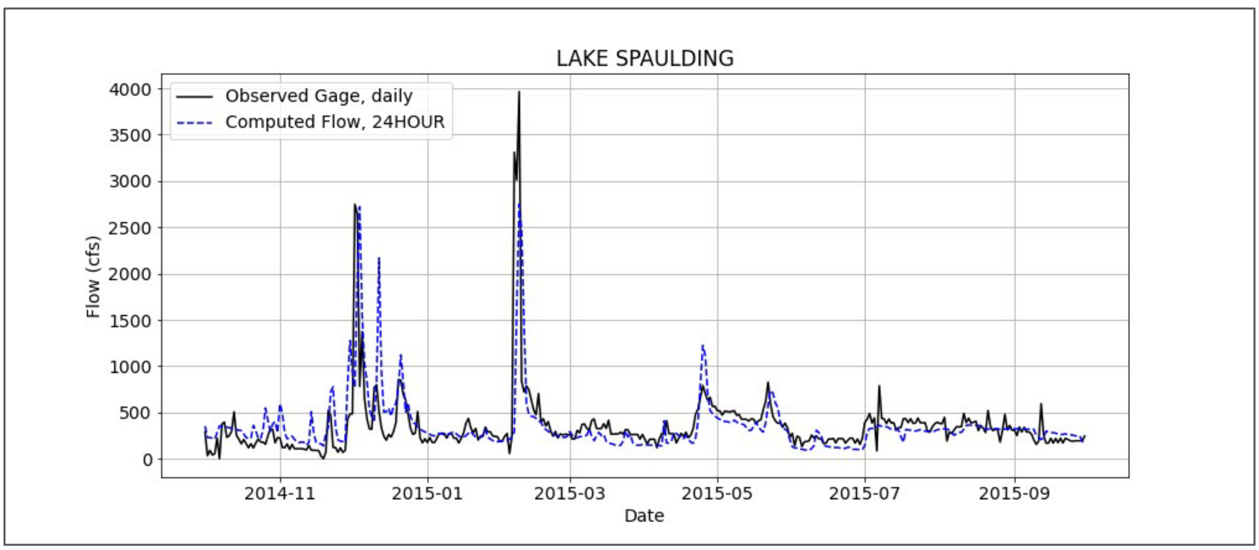


Figure A-62. WY2015 Calibration Results for Calibration Location Lake Spaulding

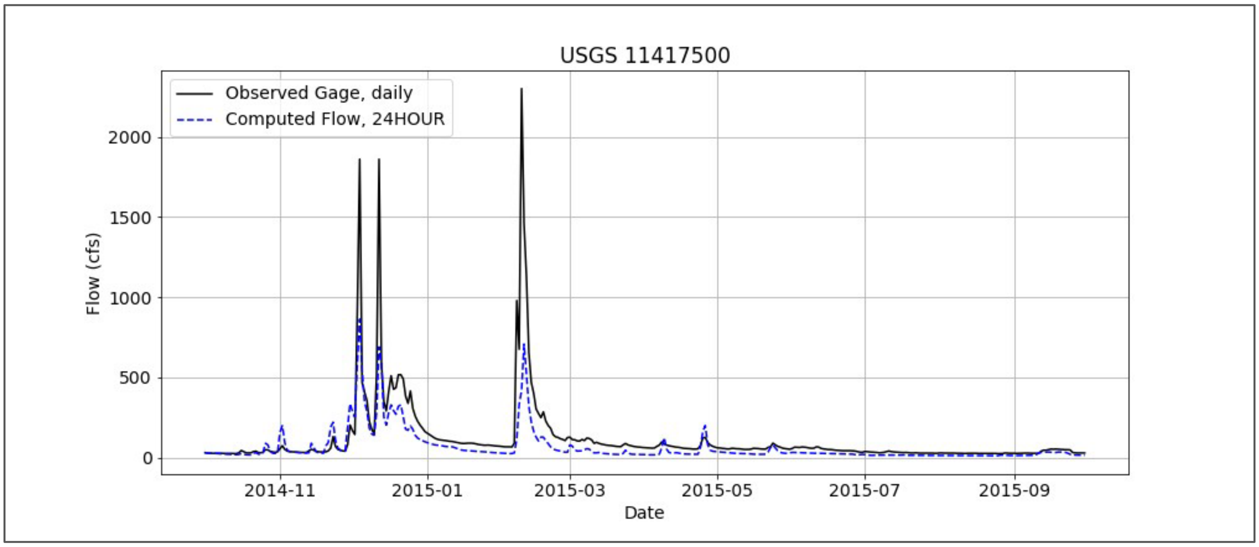


Figure A-63. WY2015 Calibration Results for Calibration Location USGS Gage 11417500

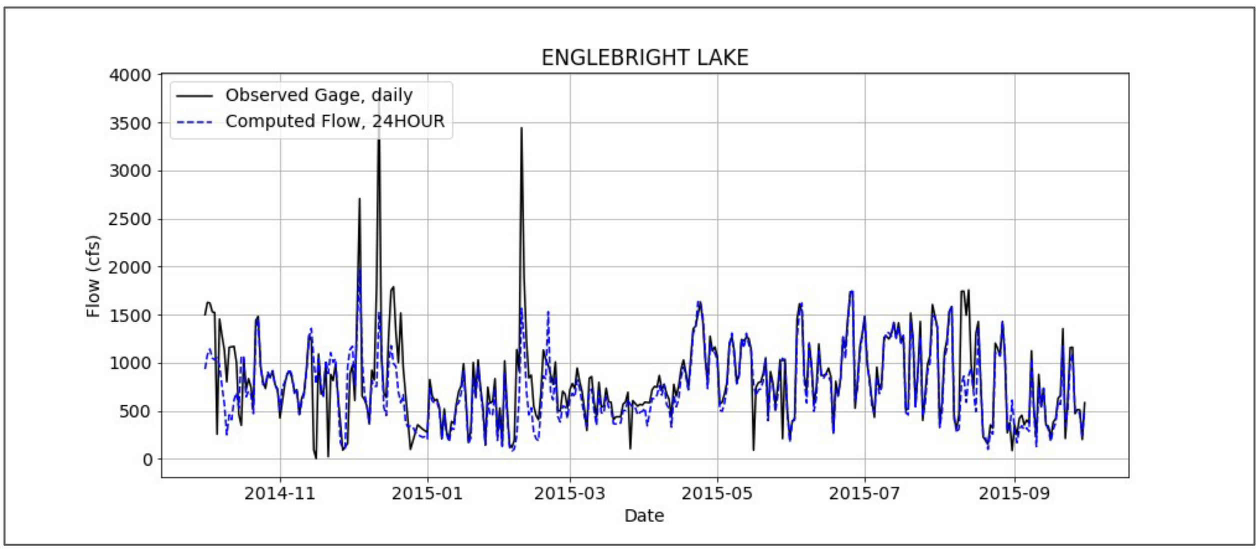


Figure A-64. WY2015 Calibration Results for Calibration Location Englebright Lake

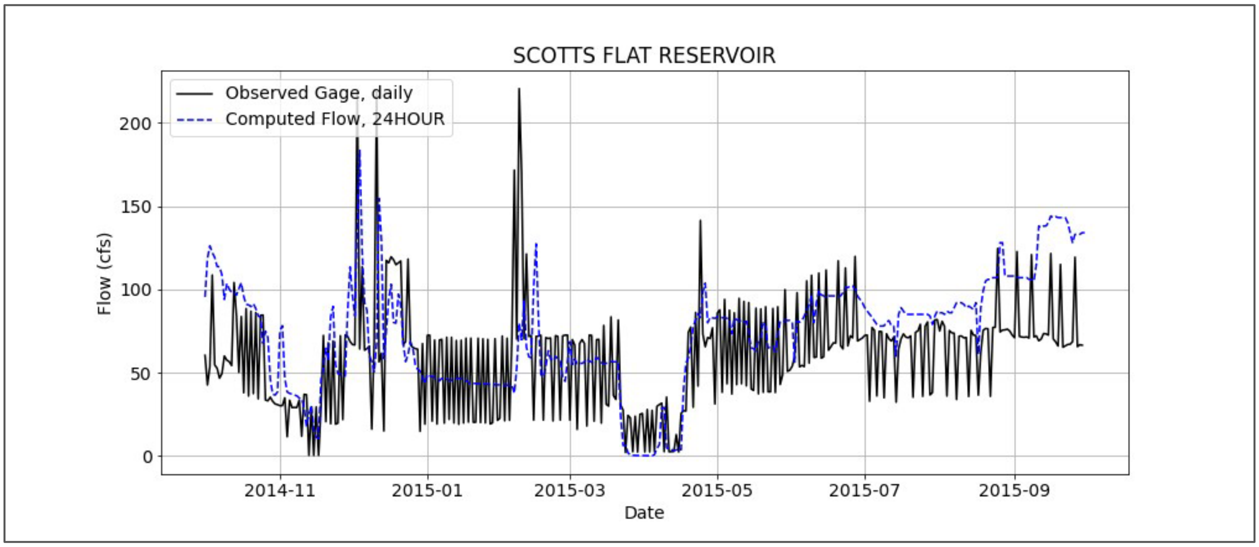


Figure A-65. WY2015 Calibration Results for Calibration Location Scotts Flat Reservoir

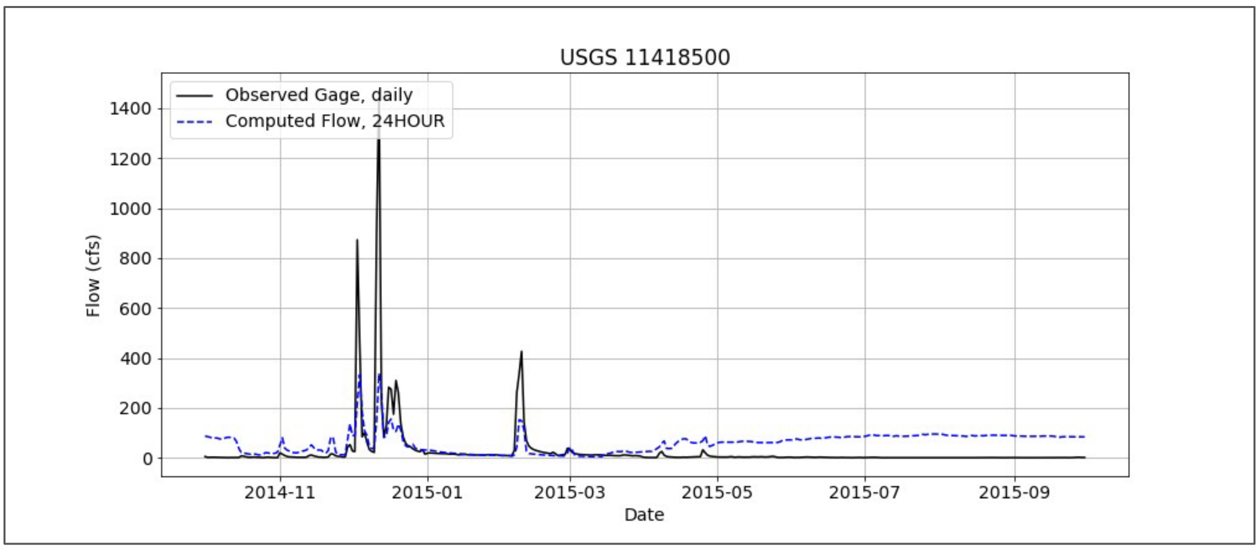


Figure A-66. WY2015 Calibration Results for Calibration Location USGS Gage 11418500

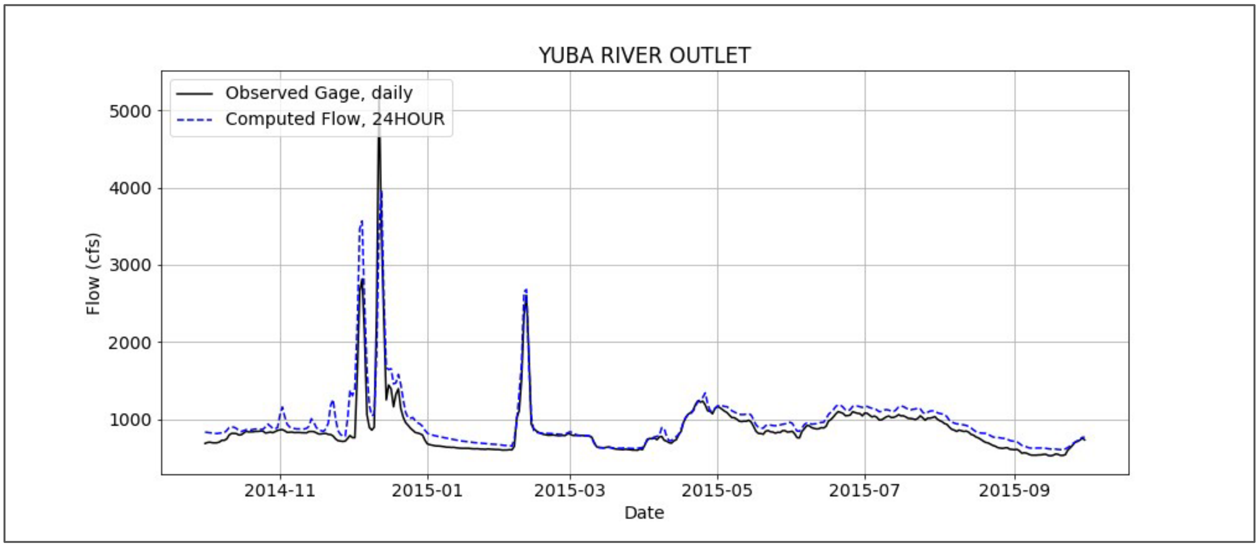


Figure A-67. WY2015 Calibration Results for Calibration Location Yuba River Outlet

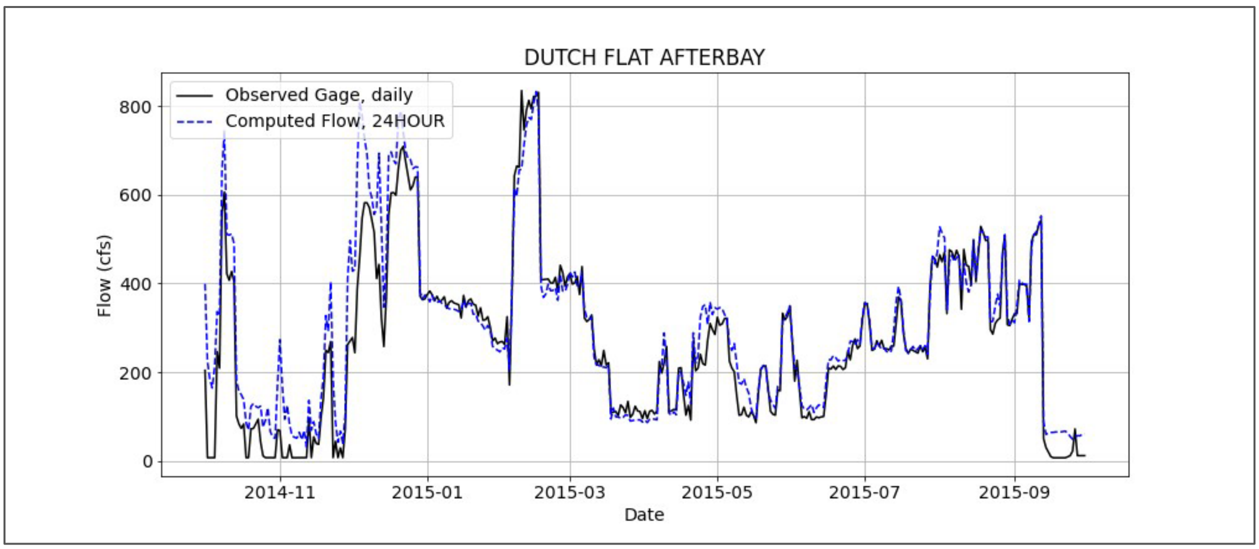


Figure A-68. WY2015 Calibration Results for Calibration Location Dutch Flat Afterbay

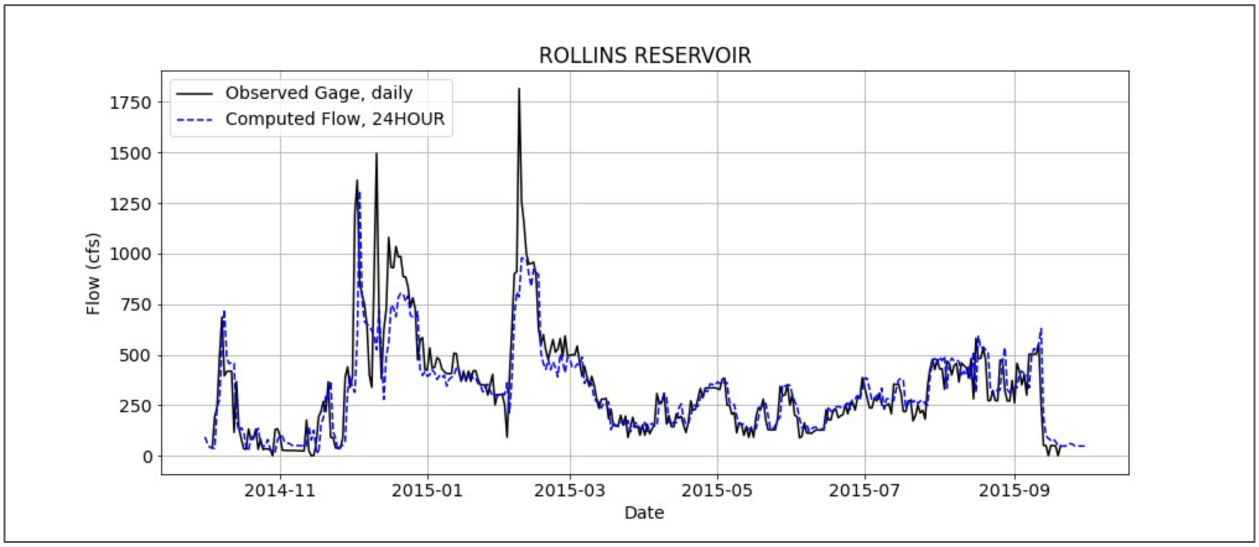


Figure A-69. WY2015 Calibration Results for Calibration Location Rollins Reservoir

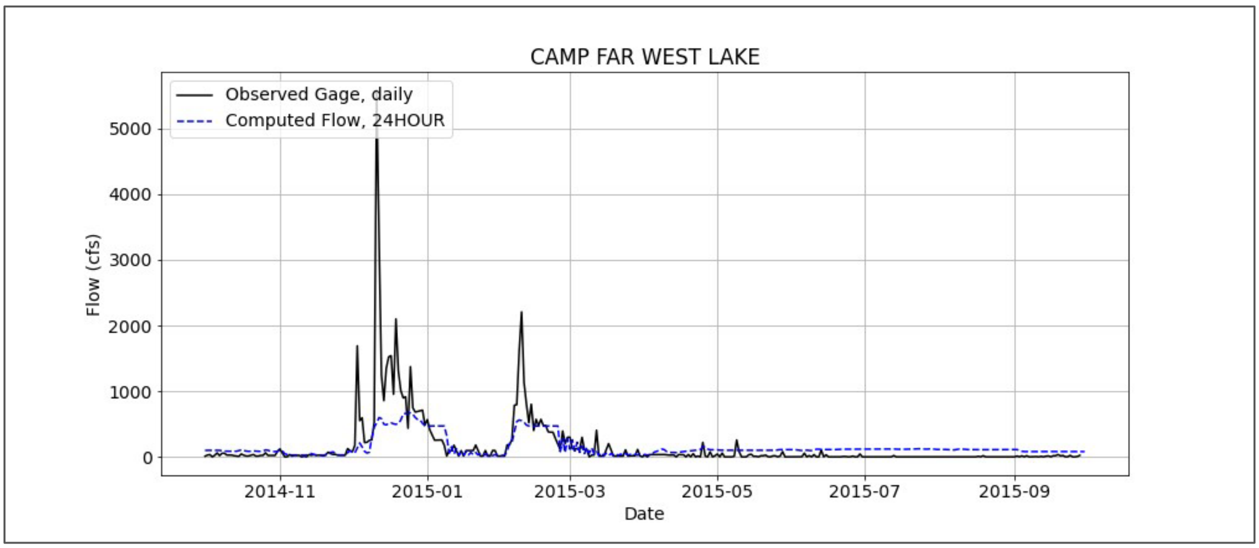


Figure A-70. WY2015 Calibration Results for Calibration Location Camp Far West Lake

A.4.5. Calibration Results for WY2021

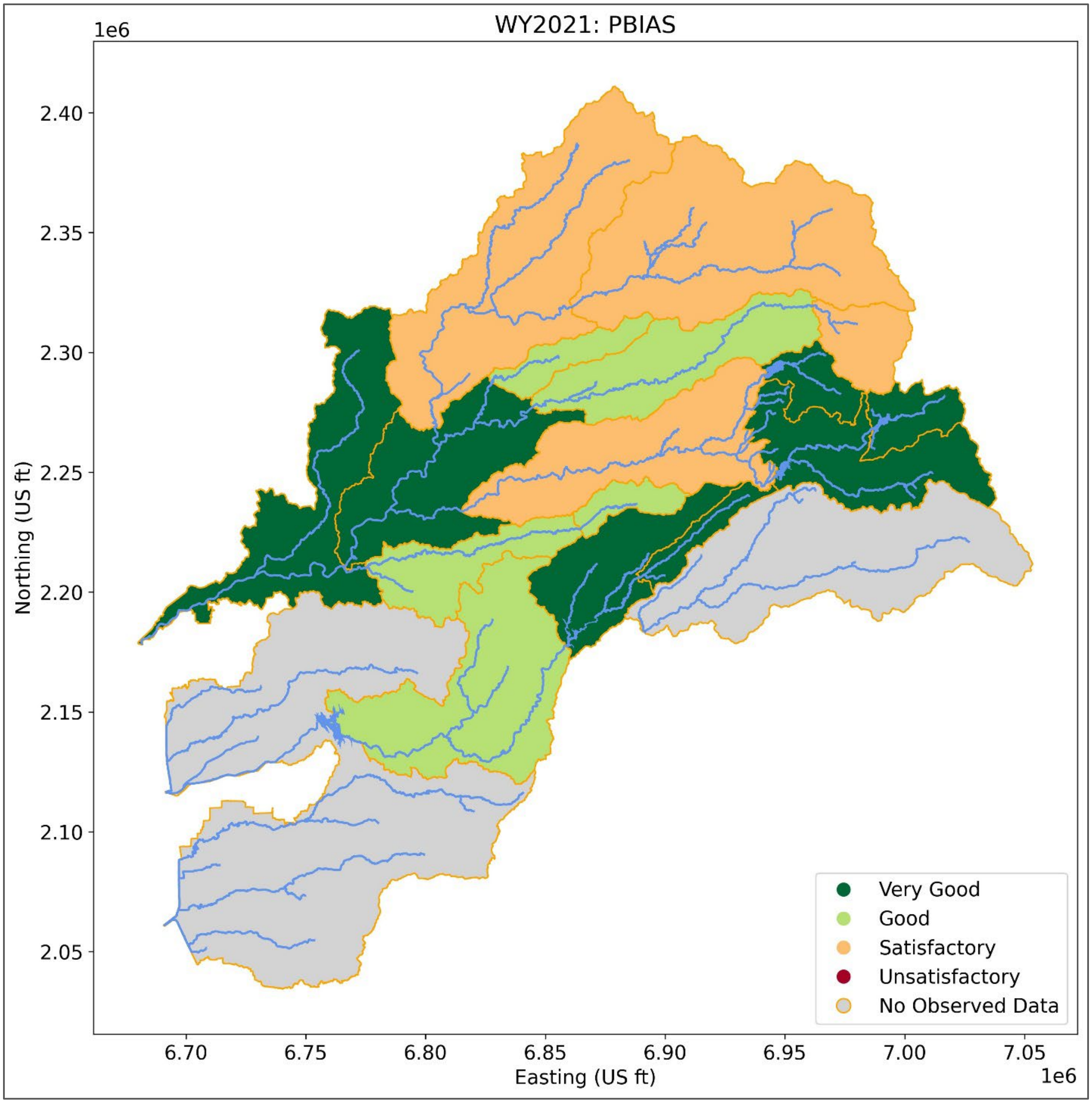


Figure A-71. WY2021 Percent Bias (PBIAS) Calibration Results for the Entire Calibrated Watersheds

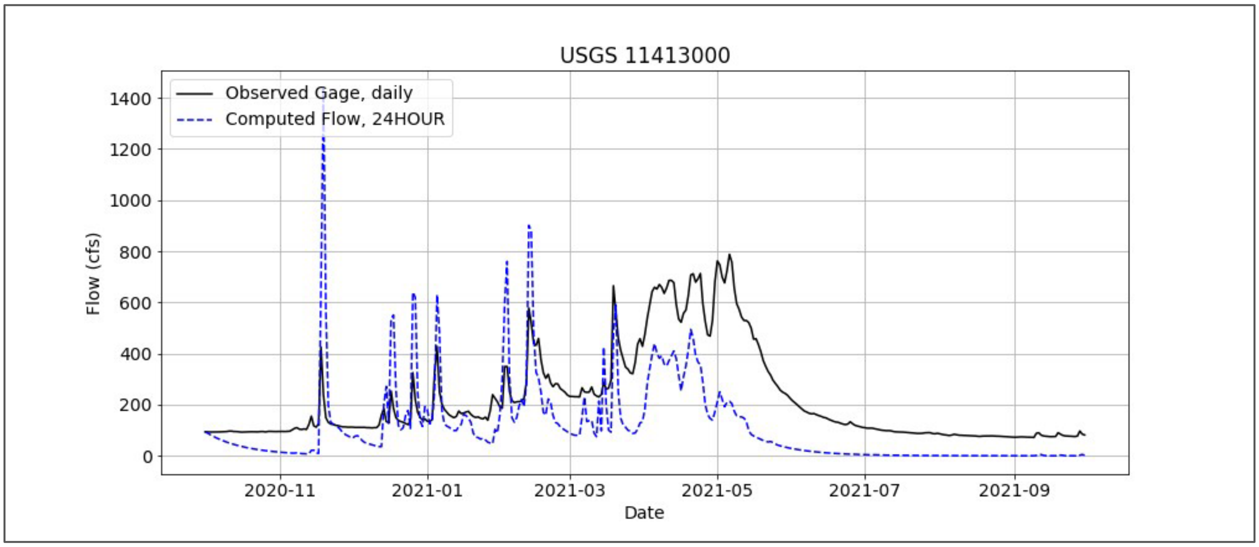


Figure A-72. WY2021 Calibration Results for Calibration Location USGS Gage 11413000

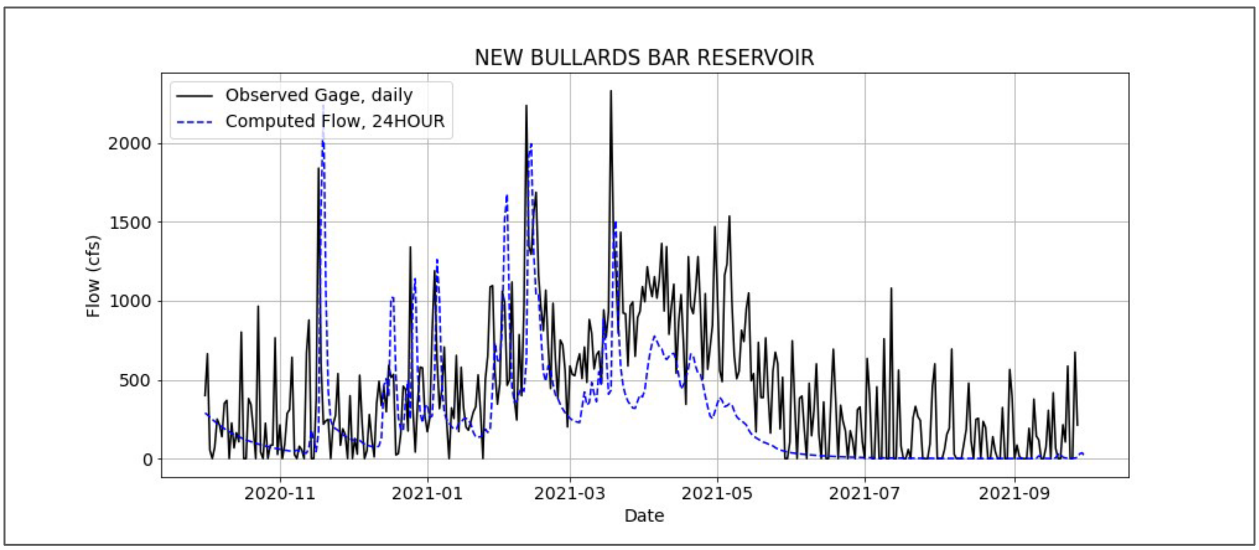


Figure A-73. WY2021 Calibration Results for Calibration Location New Bullards Bar Reservoir

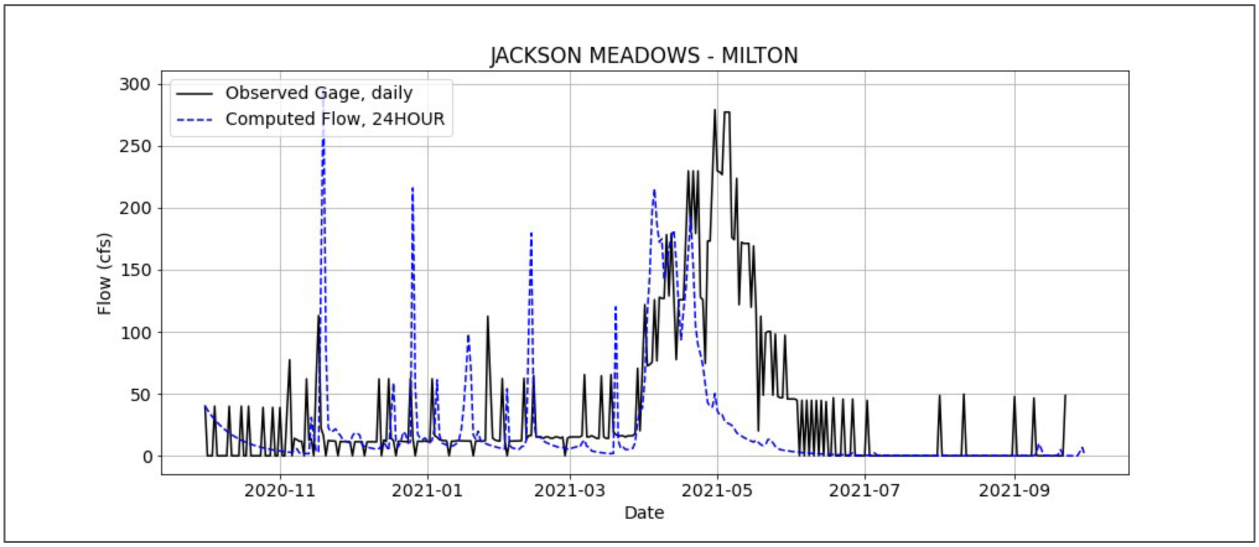
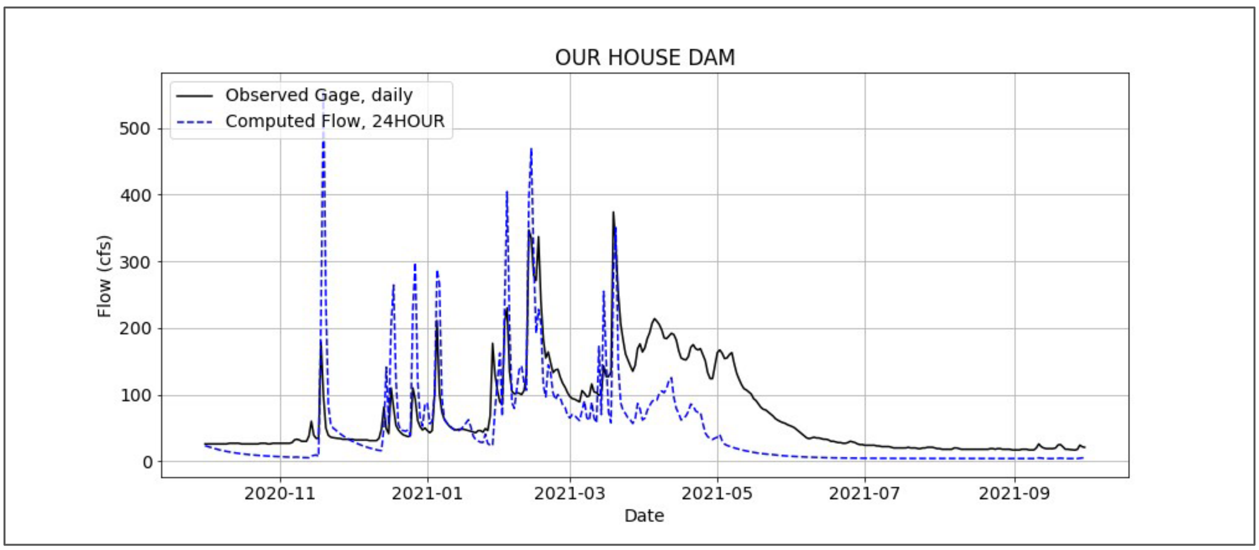


Figure A-74. WY2021 Calibration Results for Calibration Location Jackson Meadows and Milton Reservoirs



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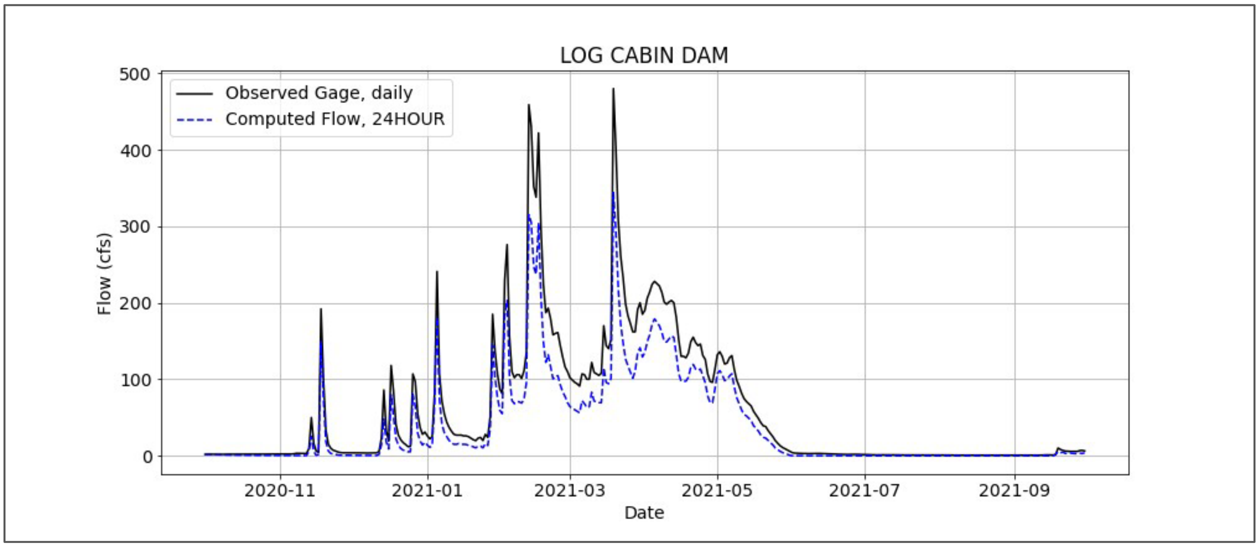

Figure A-76. WY2021 Calibration Results for Calibration Location Log Cabin Dam

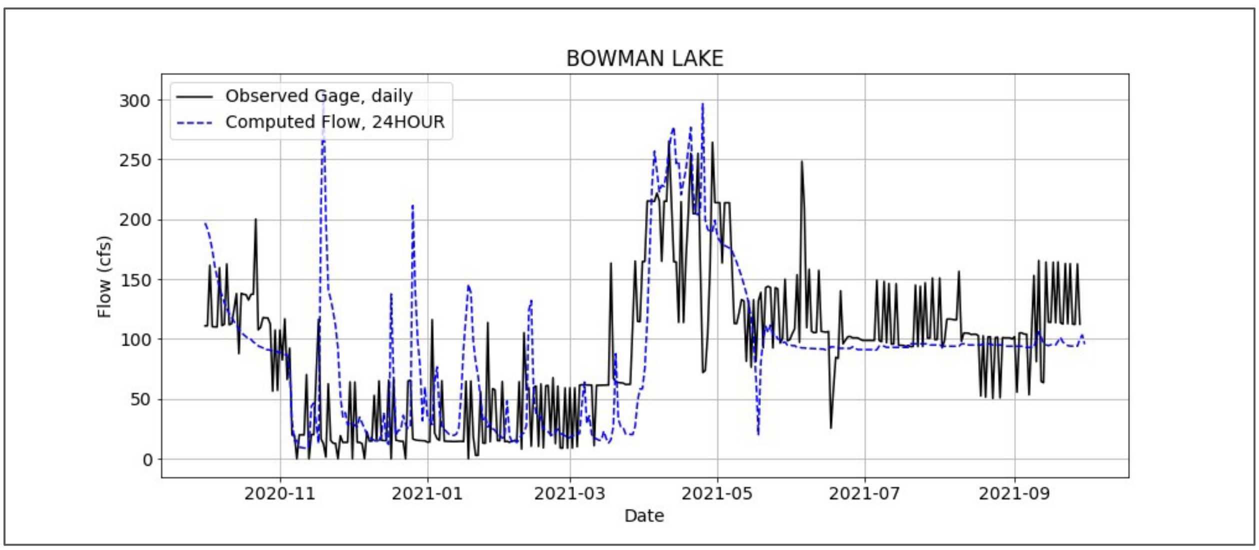

Figure A-77. WY2021 Calibration Results for Calibration Location Bowman Lake

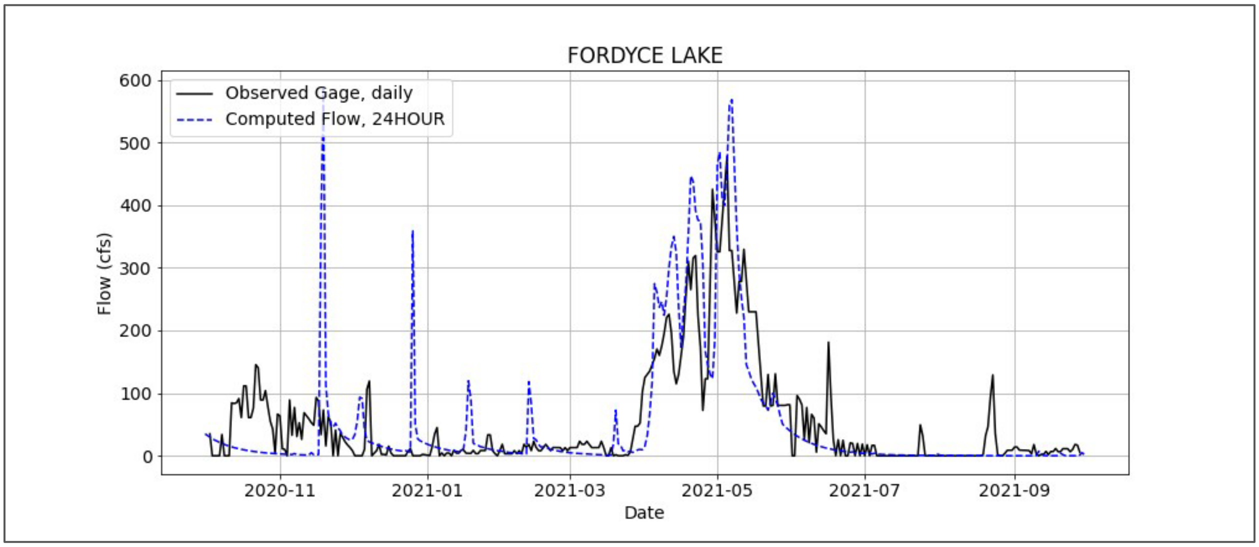

Figure A-78. WY2021 Calibration Results for Calibration Location Fordyce Lake

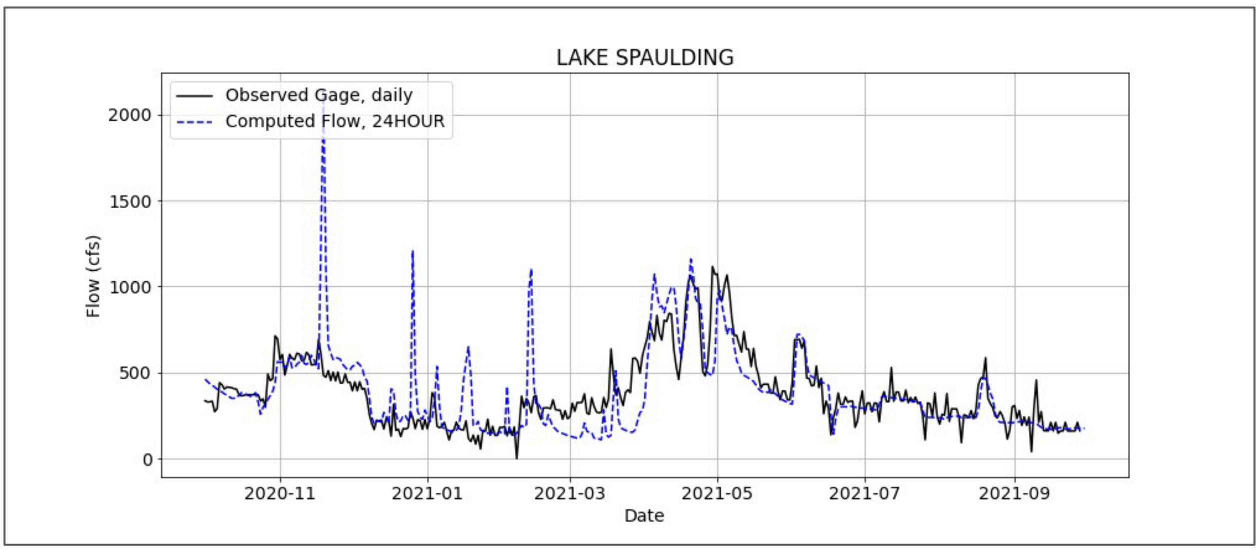

Figure A-79. WY2021 Calibration Results for Calibration Location Lake Spaulding

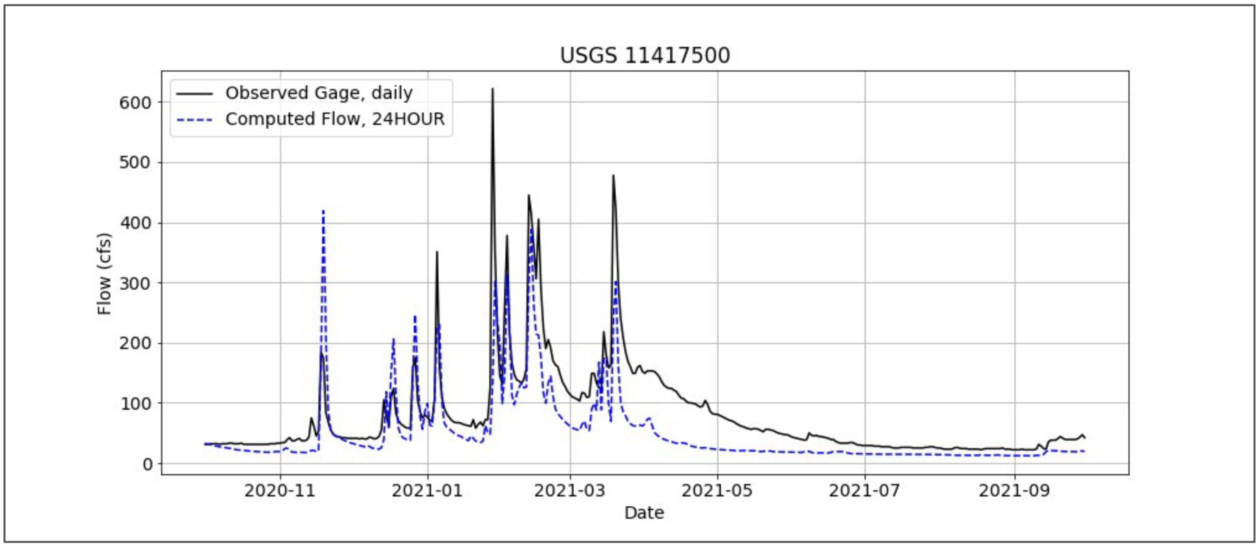

Figure A-80. WY2021 Calibration Results for Calibration Location USGS Gage 11417500

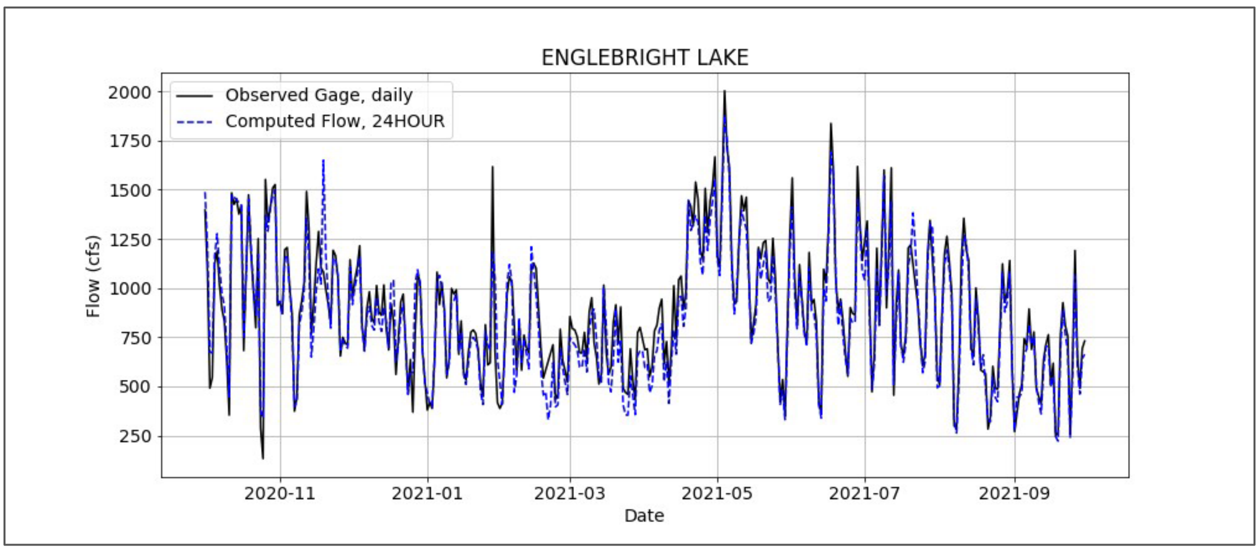

Figure A-81. WY2021 Calibration Results for Calibration Location Englebright Lake

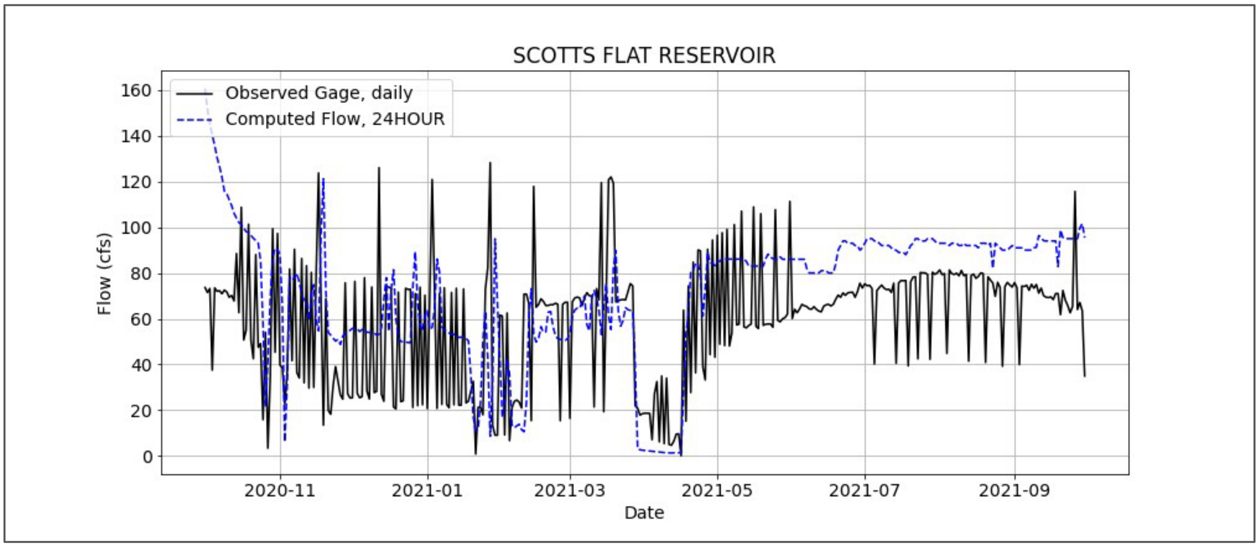

Figure A-82. WY2021 Calibration Results for Calibration Location Scotts Flat Reservoir

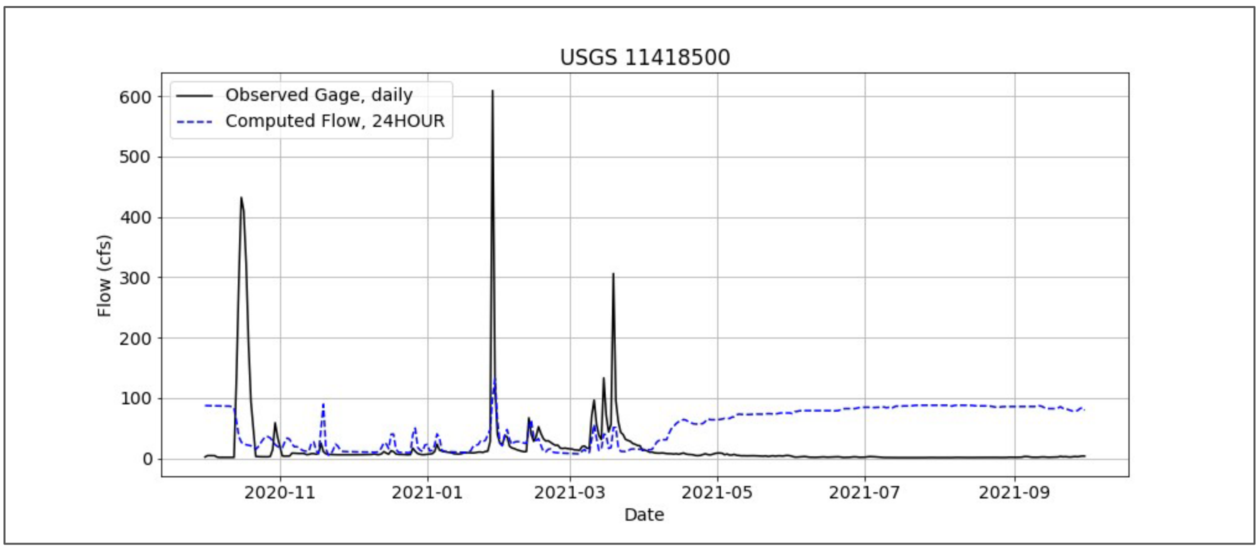

Figure A-83. WY2021 Calibration Results for Calibration Location USGS Gage 11418500

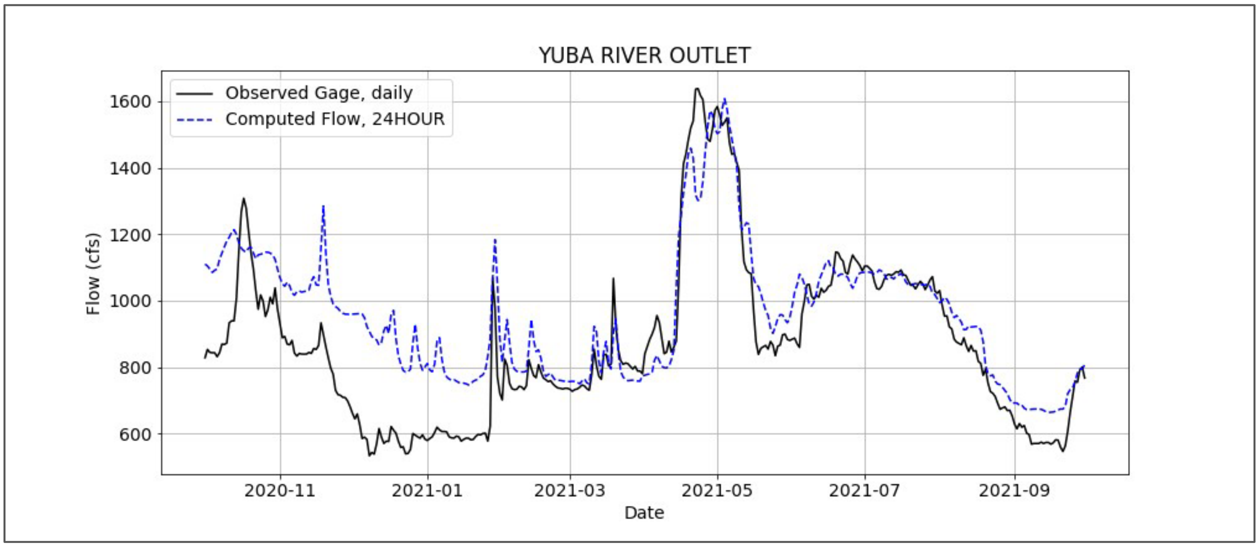

Figure A-84. WY2021 Calibration Results for Calibration Location Yuba River Outlet

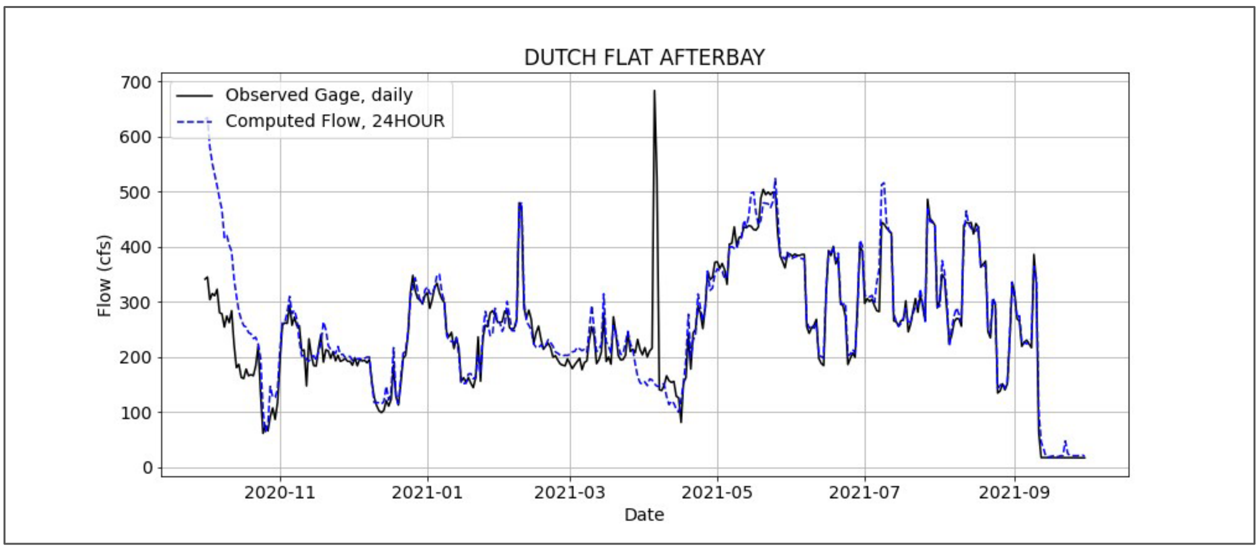

Figure A-85. WY2021 Calibration Results for Calibration Location Dutch Flat Afterbay

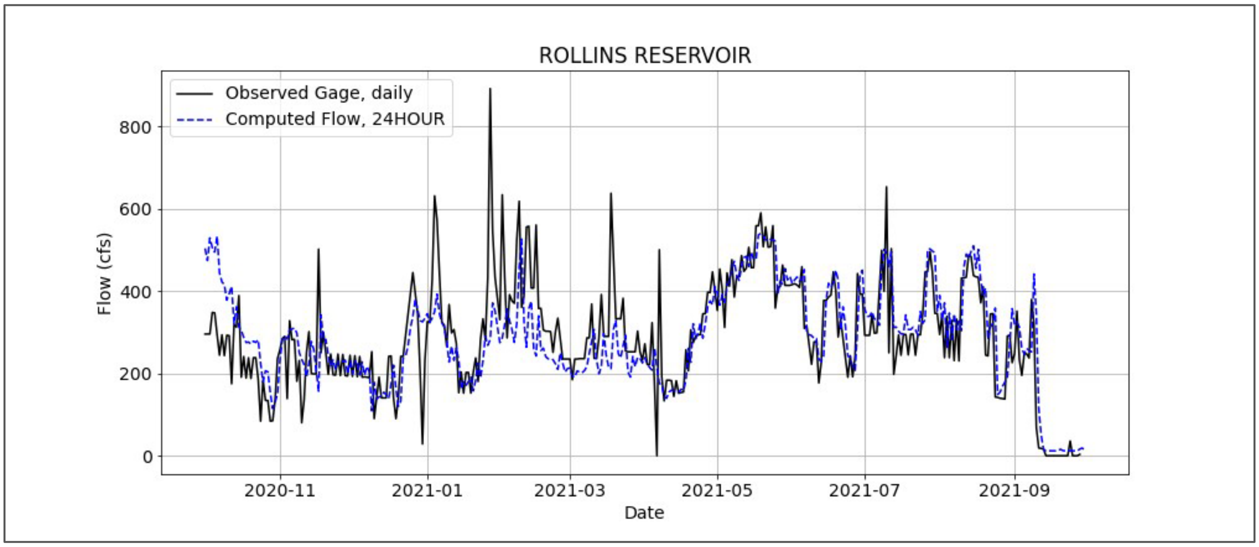

Figure A-86. WY2021 Calibration Results for Calibration Location Rollins Reservoir

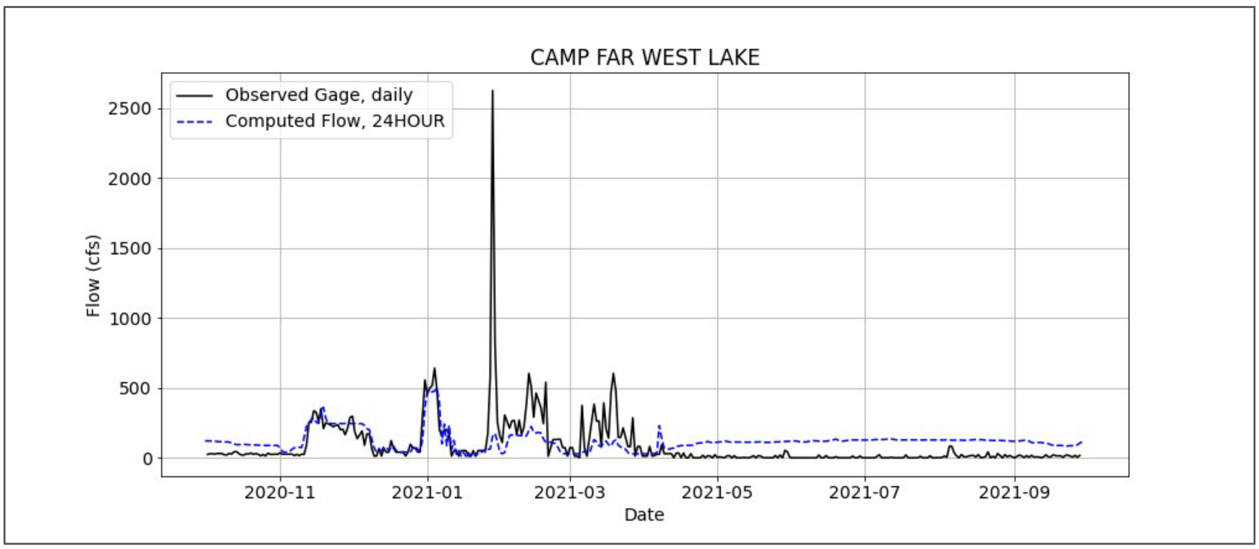

Figure A-87. WY2021 Calibration Results for Calibration Location Camp Far West Lake

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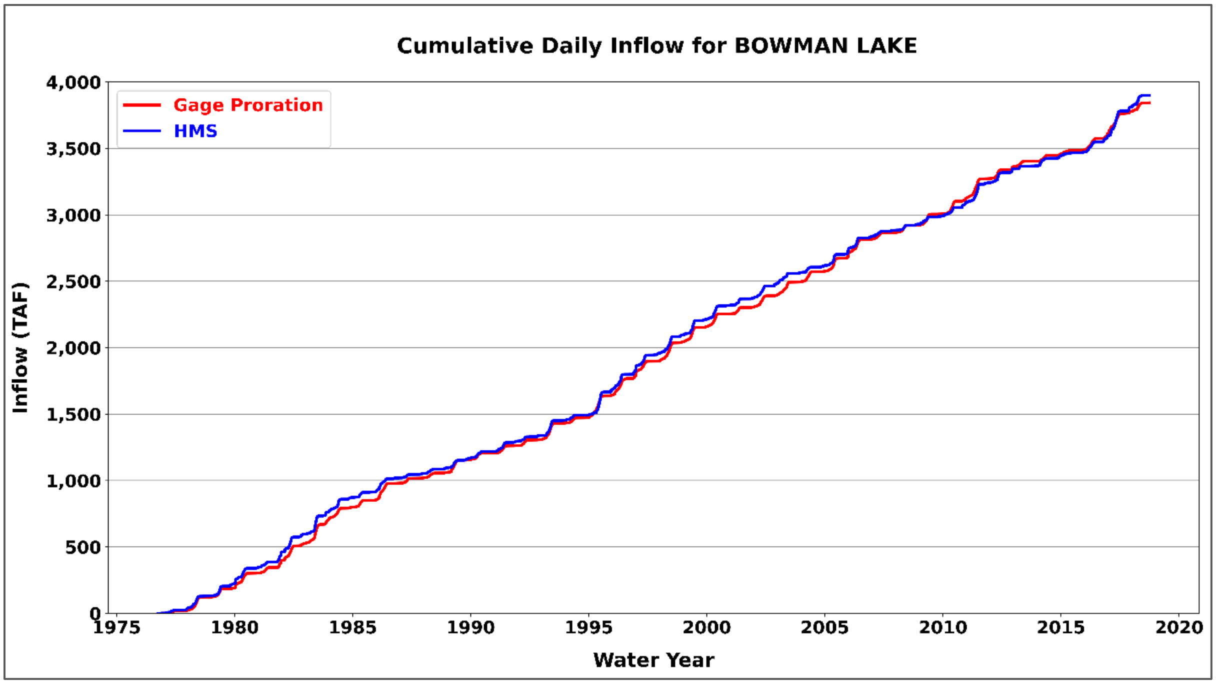
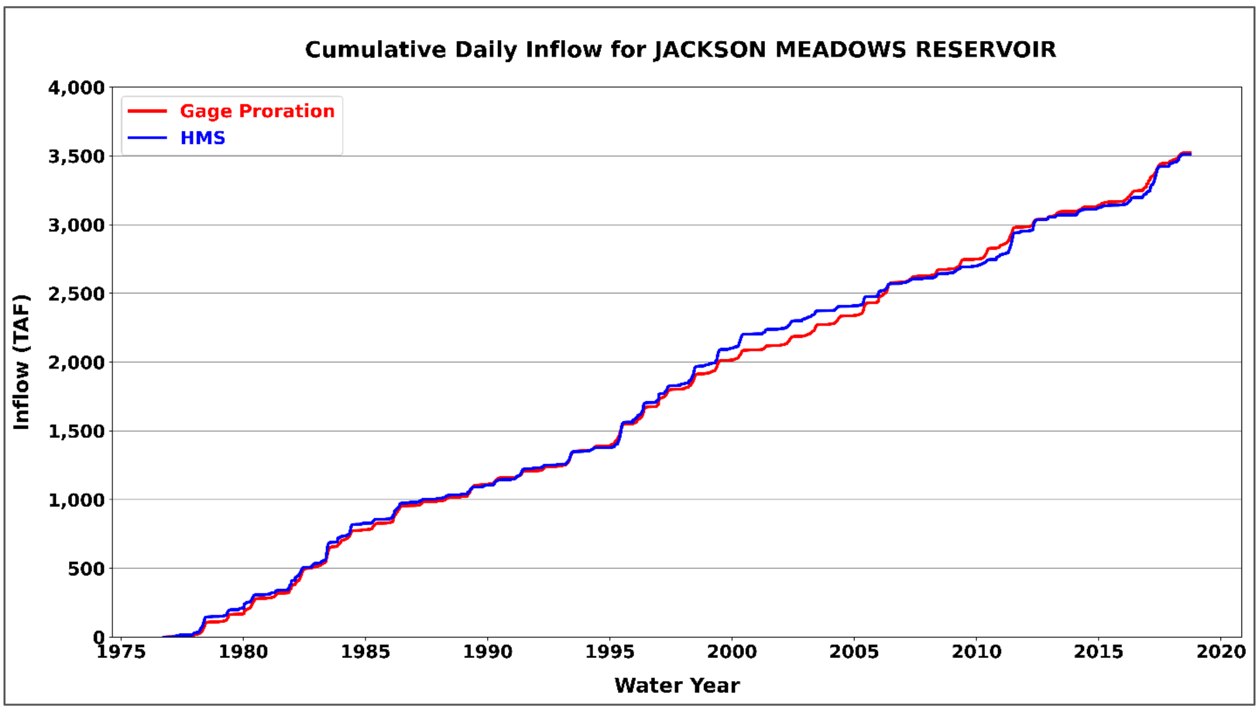


Figure A-88. Cumulative Daily Inflow (1975–2018) for Bowman Lake After Calibration Refinements



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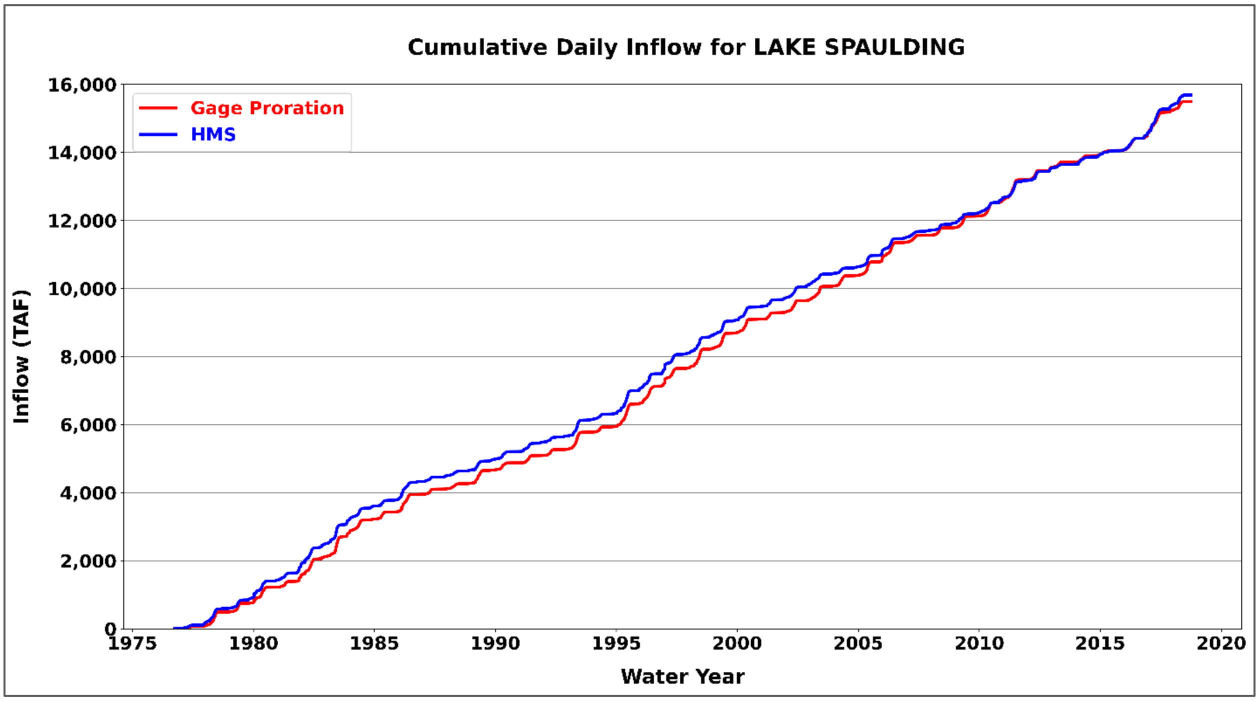

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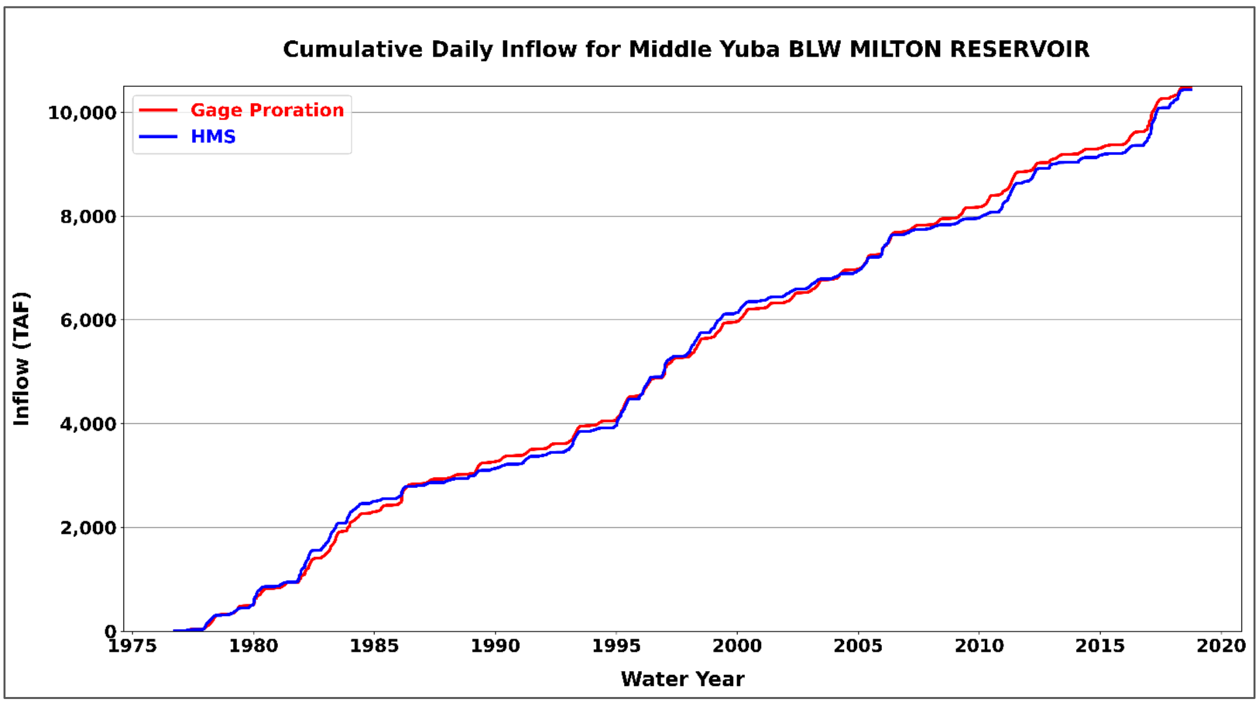

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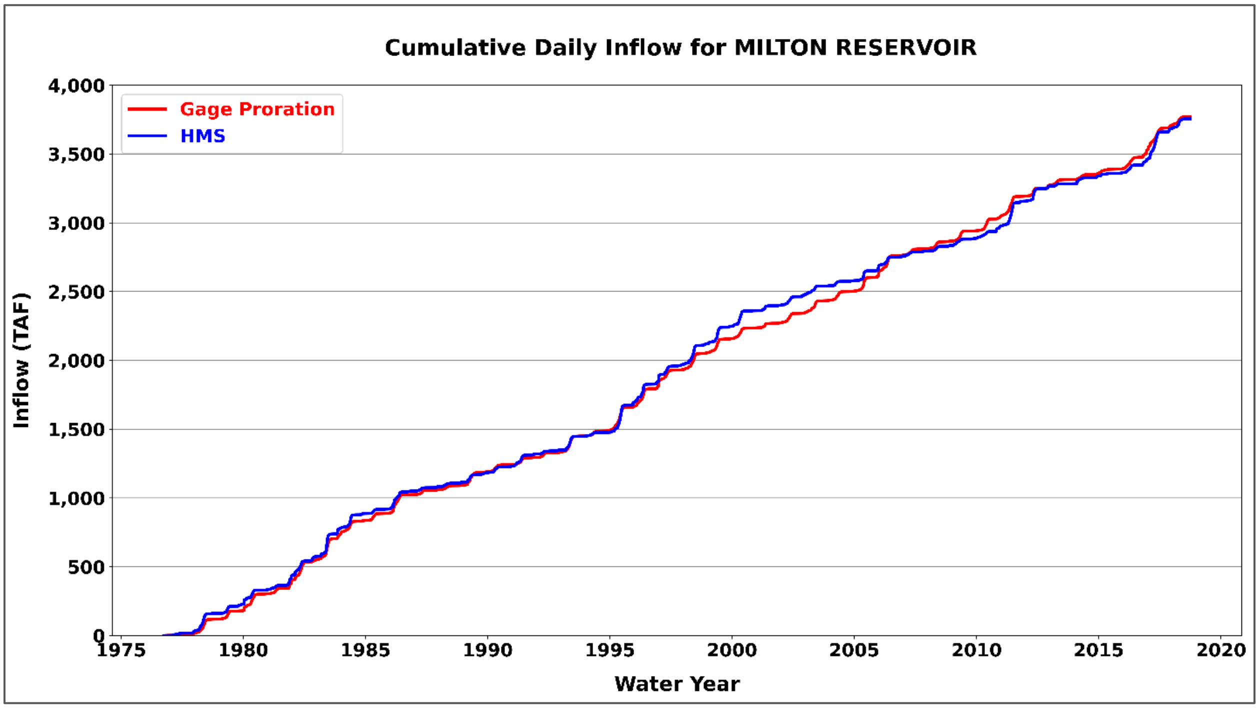
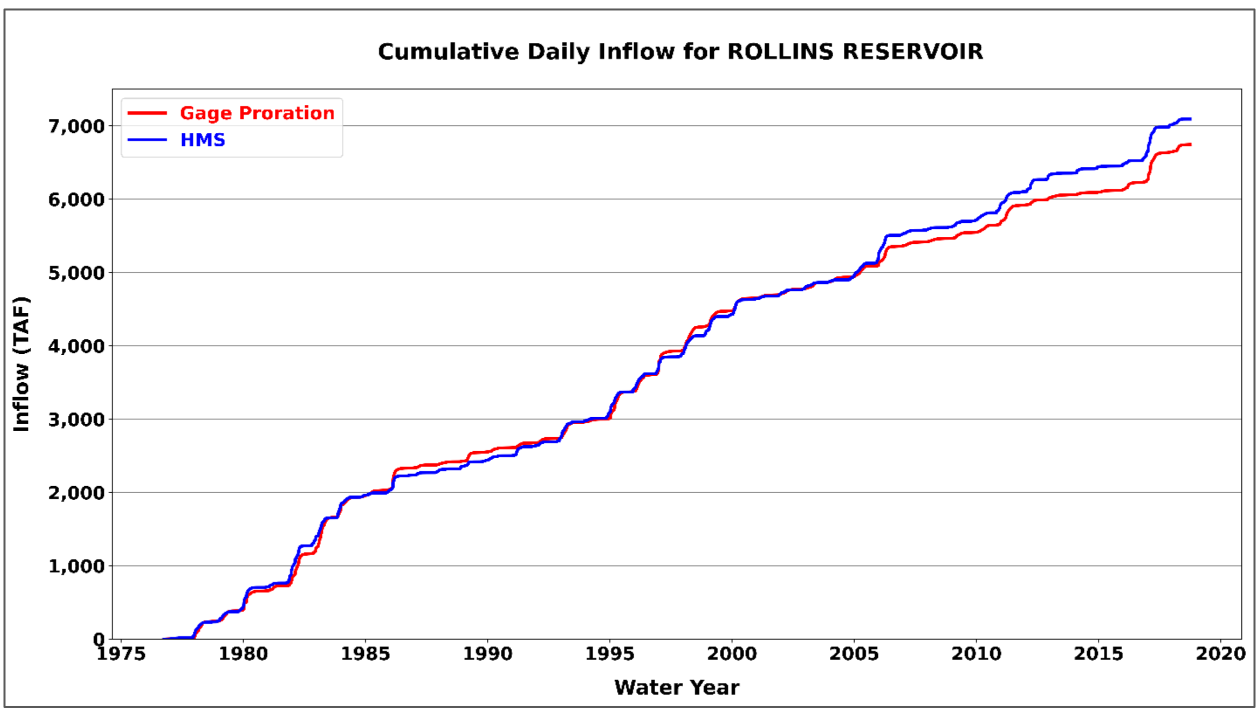


Figure A-92. Cumulative Daily Inflow (1975–2018) for Middle Yuba- Milton Reservoir After Calibration Refinements



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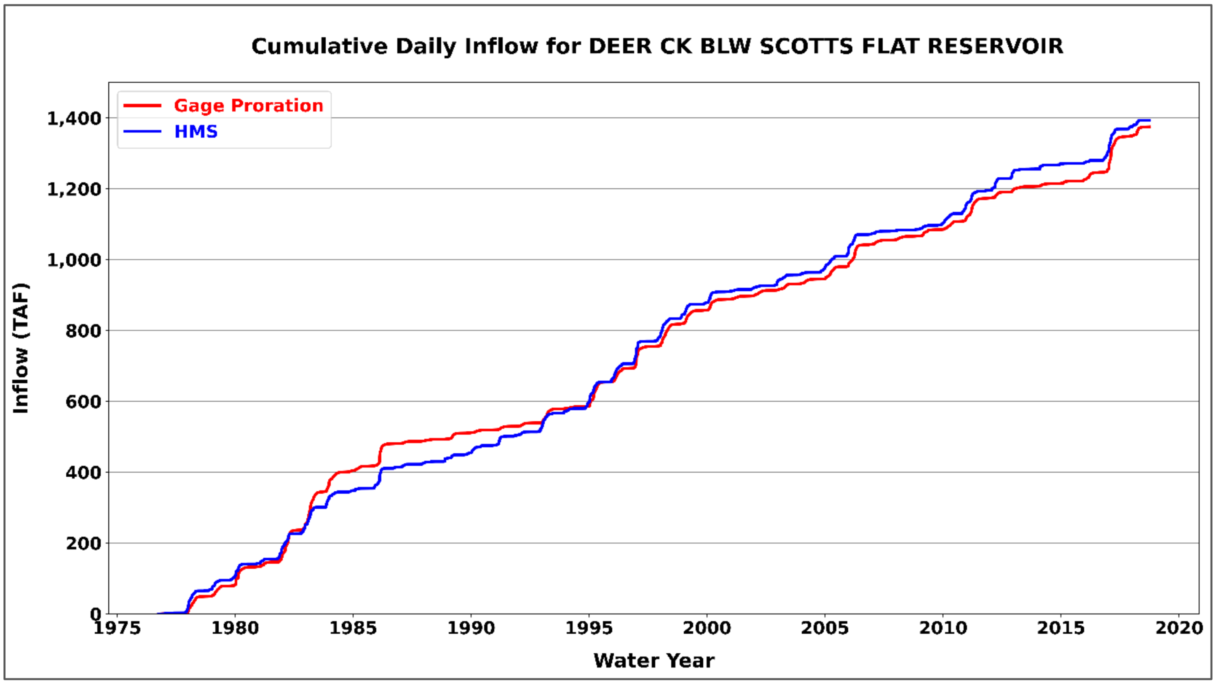

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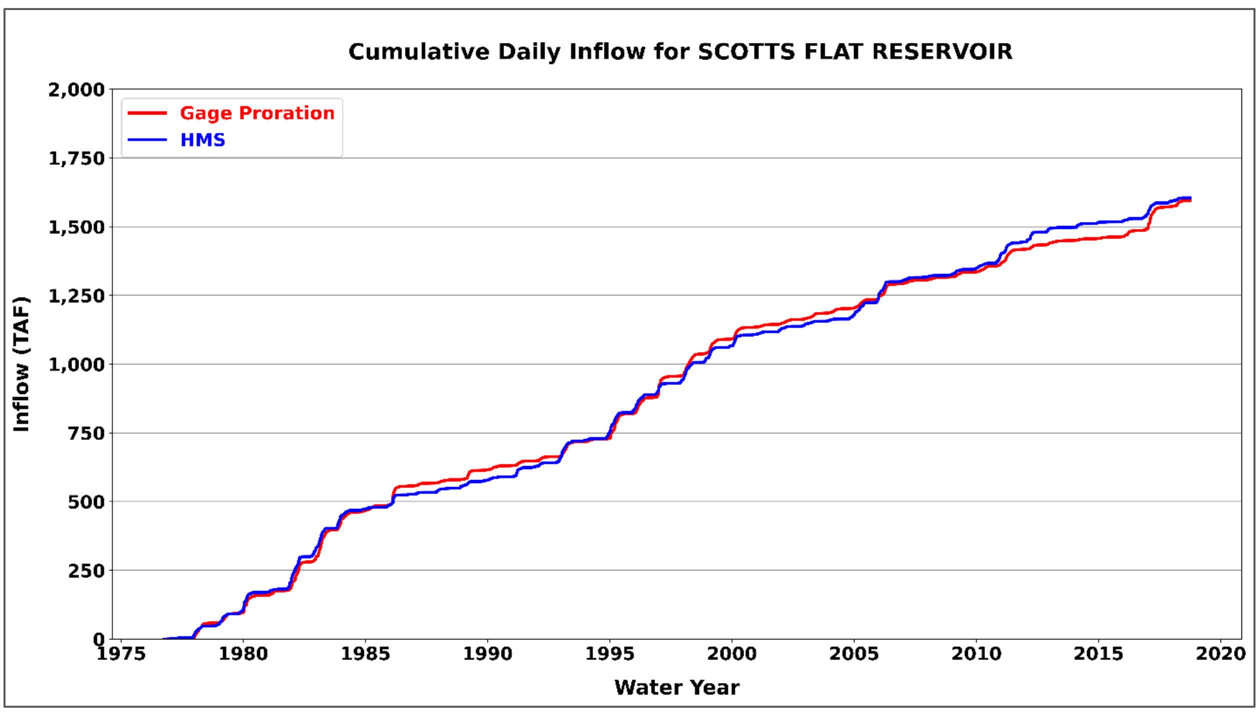

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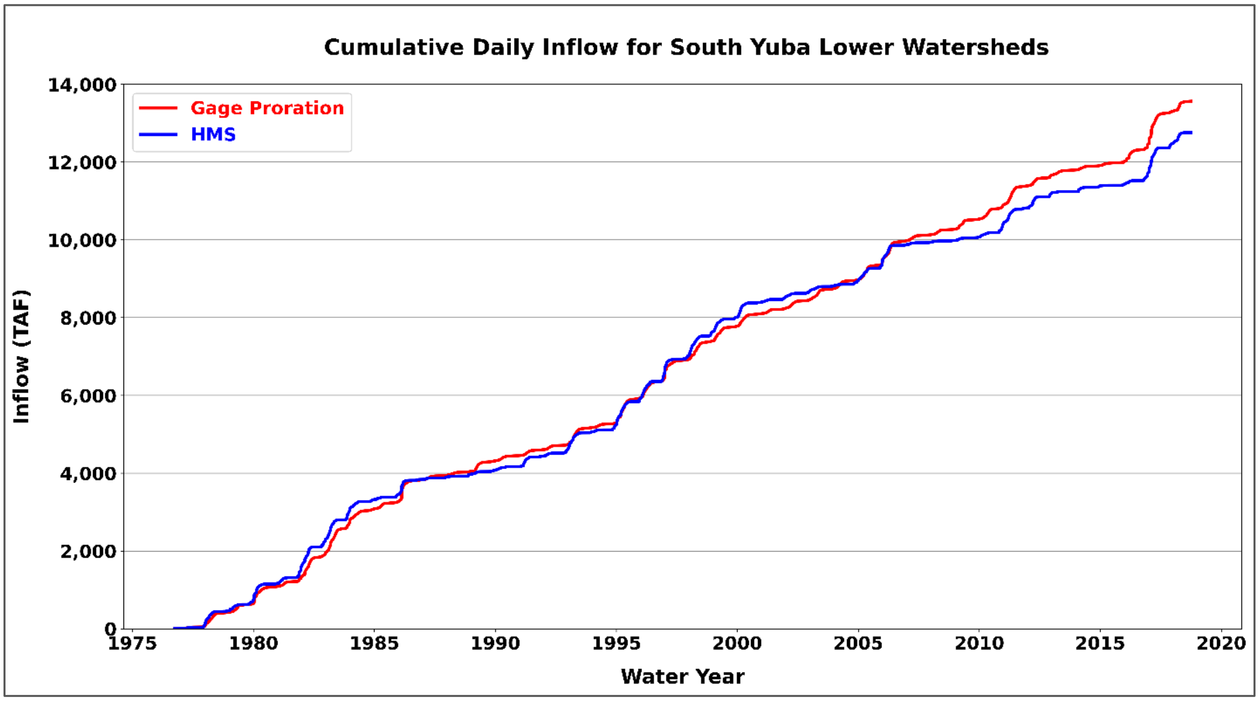
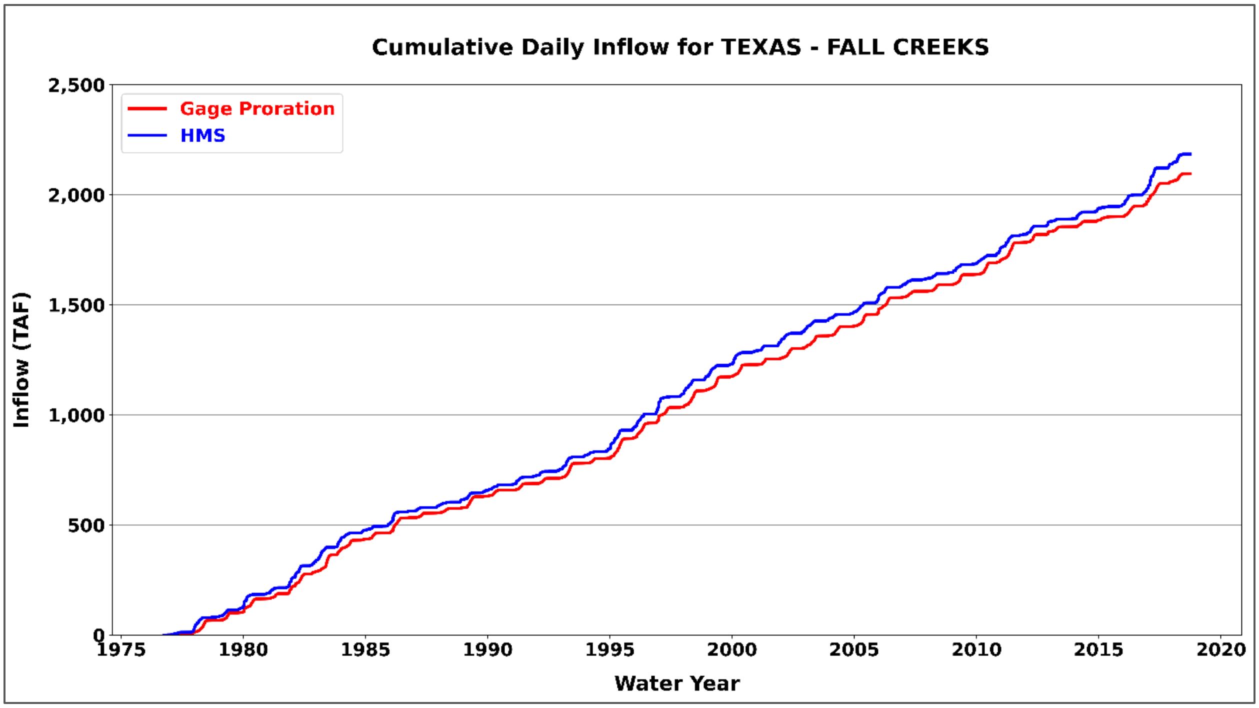


Figure A-96. Cumulative Daily Inflow (1975–2018) for South Yuba Lower Watersheds After Calibration Refinements



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Appendix B:

Chapter 4 Supplemental Information

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Appendix B. Chapter 4 Supplemental Information

B.1. Assumptions Used to Develop the Model

Table B-1. General Data Sources and Assumptions

Category	Parameter	Current Scenario (Recent Historical) Data Sources, Assumptions	Projected Scenario General Data Sources, Assumptions	Additional Details	References
Demand Model Setup	Demand model platform	Integrated Water Flow Model Demand Calculator (IDC) demand model, linked to a canal system balance model.	Same platform as current scenario.	An IDC demand model was used to quantify treated and raw water demand in NID. Results were linked by parcels to canals to quantify upstream demand at NID's water supply sources (factoring in conveyance system losses and municipal purchases).	[1]
Demand Model Setup	Demand model time step	Monthly	Monthly	IDC was used to simulate demand on a monthly time step. A monthly time step captures intra-annual conditions and interdependencies among different factors that influence demand.	[2] (Section 2.7)
Demand Model Setup	Demand model grid	Unitized grid, results linked to parcels.	Same approach as current scenario.	Demand was simulated in IDC for different combinations of land use, soil, and climate zone characteristics found in NID that impact demand. The IDC results were calculated first on a "unit" depth basis (e.g., feet/month) and were then linked to parcels that most closely matched those combinations of characteristics to quantify the demand "volume" (e.g., acre-feet/month).	[3]
Land Use	Land use types and areas	Summarized from available spatial land use mapping data (DWR, Land IQ, USDA) and survey or crop report data (DWR, counties, NID).	Land use area changes estimated based on county general plan and zoning information, NID "soft service areas" (i.e., areas of potential growth), and recent historical trends (methodologies and/or results verified with counties and NID staff).	Recent historical land use was summarized from available spatial data sources and linked to specific parcels in NID. Projected land use was developed based on recent historical trends in land use, with spatial land use changes informed by county general plan and zoning data and fill in of "soft service areas" where growth opportunities exist within NID. The effects of potential alternate projected scenarios on demand were evaluated through sensitivity analyses to identify "bookend" projected scenarios.	[4]-[17]
Precipitation Simulation	Precipitation	PRISM gridded historical precipitation data, consistent with HEC-HMS model.	Climate change-adjusted precipitation projections, consistent with HEC-HMS model.	Precipitation was simulated for climate zones in NID that share similar historical precipitation rates. Data sources used for the current and projected scenarios were consistent with the data sources used to simulate precipitation in the HEC-HMS model.	[2] (Section 9) [18]-[19]
Precipitation Simulation	Precipitation runoff	Calculated using the modified Soil Conservation Service (SCS) curve number method, routing runoff to the nearest waterway.	Same approach as current scenario, but assuming projected precipitation and projected land use changes.	IDC was used to simulate precipitation runoff using a modification of the United States Department of Agriculture (USDA) SCS curve number method. Curve numbers were derived from technical literature, depending on land use types, soil textures, and typical hydrologic conditions.	[20]
Evapotranspiration	Evapotranspiration (ET)	Calculated from spatial OpenET data, summarized by land use type and climate zones in NID. OpenET data was evaluated in comparison to other technical literature and ET data sources and was used to develop local crop coefficients (Kc) to facilitate estimation of ET in the projected scenarios.	Calculated from reference ET (ETo) and crop coefficients (Kc) following the FAO 56 guidelines. Kc for different land uses was calculated from historical OpenET ETc and spatial CIMIS ETo. Projected ETo was estimated through climate change adjustments, consistent with the climate change scenarios used in the HEC-HMS model.	ET was simulated for different land uses across climate zones in NID that share similar historical ETo rates. The industry-standard crop coefficient approach, documented in FAO 56, was used to estimate ET due to land use characteristics (captured in Kc) and climate effects (captured in ETo). Local Kc values were developed using the available information about local ET and crop water use (e.g., satellite-based ET information from OpenET) to provide locally-accurate representations of ET that account for deficit irrigation or other local factors that impact water needs for different land uses in NID.	[21]-[24], [38]-[39]
Soil Moisture Simulation	Soil textures and soil parameters (wilting point, field capacity, total porosity, pore size distribution, saturated hydraulic conductivity)	Summarized from SSURGO and STATSGO soil data and technical literature. Soil parameters were evaluated and calibrated using industry-standard approaches (e.g., pedotransfer functions) to ensure physically realistic soil water characteristics.	Same approach as current scenario.	Simulated soil textures in NID were classified from USDA National Cooperative Soil Survey (NCSS) SSURGO/STATSGO data. Initial soil parameters were assigned from SSURGO/STATSGO data. Final soil parameters were refined through calibration using pedotransfer functions (standard, predictive methods for translating raw soil data into soil water characteristics that are physically realistic) and were compared with values from technical literature.	[25]-[27]
Soil Moisture Simulation	Initial soil moisture (i.e., soil moisture at the first model time step)	Estimated to be equal to the soil field capacity.	Same approach as current scenario.	Initial soil moisture simulated in IDC depends on irrigation and hydrologic conditions preceding the simulation period. The first model time step was initiated more than one year prior to the current and projected scenario analysis period. This allowed sufficient time for IDC to simulate soil moisture with respect to irrigation and hydrologic conditions preceding the analysis period.	[25]-[26]
Soil Moisture Simulation	Minimum soil moisture (i.e., soil moisture at which irrigation is triggered)	Estimated to be equal to 50% of the available soil moisture.	Same approach as current scenario.	IDC simulates irrigation once the minimum soil moisture is reached. The minimum soil moisture was set to 50% of the available soil moisture to represent typical conditions in California and to avoid simulation of additional water stress within IDC (local Kc values already account for typical water stress, as applicable; see parameter "Evapotranspiration").	[25]-[26]
Agricultural Water Use Inputs	Root depth	Defined for each simulated land use type based on representative values in technical literature.	Same approach as current scenario.	Different land use types have different characteristic root depths, determining where in the soil vegetation can extract moisture. Typical root depths for different land use types are documented in technical literature.	[28]
Agricultural Water Use Inputs	Irrigation period (i.e., months when irrigation occurs)	Defined based on NID's historical irrigation delivery records.	Estimated based on recent historical information with consideration for potential future changes to the irrigation season start/end.	Typical irrigation periods were identified from NID delivery records and through discussion with NID staff.	[29]
Agricultural Water Use Inputs	Tailwater (i.e., runoff of irrigation applied water)	Tailwater for each irrigated land use was simulated as a fraction of the total irrigation applied water (approximately 5% for irrigated land uses in NID).	Estimated to be similar to the current scenario.	Tailwater depends mainly on customer irrigation practices and irrigation methods for different crops and field conditions. Model inputs were set at levels typical of land uses and irrigation methods in NID, with comparison of recent historical demands simulated in IDC to NID delivery records.	
Urban Water Use Inputs	Population	Estimated from California Department of Finance (DOF) population estimates for cities, counties.	Estimated with respect to California DOF population projections for counties, county General Plan information and transportation studies, and NID's projected connections for treated water customers (e.g., from NID's 2020 Urban Water Management Plan).	California DOF population estimates and projections were consistent with methods used to evaluate projected water demands in NID's 2020 Urban Water Management Plan and in county transportation studies.	[30]-[31]

Category	Parameter	Current Scenario (Recent Historical) Data Sources, Assumptions	Projected Scenario General Data Sources, Assumptions	Additional Details	References
Urban Water Use Inputs	Per capita water use	Estimated based on population estimates and potable water production data from NID, cities, and the State Water Resources Control Board (SWRCB).	Estimated to be similar to the current scenario (changes to urban demand were simulated through changes to population and other inputs).	Per capita water use (together with population) drives the IDC simulation of urban demand. Estimates and trends were derived from NID, state, and city data.	[32]-[34]
Urban Water Use Inputs	Urban indoor water use fraction	Estimated based on urban water production and deliveries during winter months, assuming that the minimum monthly use (typically February) is primarily used indoors.	Estimated to be similar to the current scenario.	The urban indoor water use fraction is the fraction of treated water that is assumed to be used indoors (i.e., for drinking water, sanitation, etc.). Urban indoor water use is simulated in IDC separately from urban outdoor water use (i.e., for landscape irrigation).	[32]-[33]
Urban Water Use Inputs	Urban return flow fraction (i.e., urban wastewater and runoff of applied water)	Indoor use is assumed to be approximately 100% return flow (i.e., 100% wastewater inflow). Outdoor use is assumed to have approximately 5% return flow (i.e., tailwater), typical of landscape irrigation.	Estimated to be similar to the current scenario.	Return flow is simulated in IDC as a fraction of the total urban water use. Model inputs were set at levels typical of urban water use, land uses, and irrigation methods in NID.	[1], [35]
Raw Water Demand	Raw water demand	Calculated using IDC as the amount of water needed to meet irrigation demand, after accounting for soil moisture, precipitation, tailwater, ET, etc.	Same approach as current scenario but calculated with projection scenario information.	Irrigation applied water was adaptively calculated using the IDC model, based in part on local land use in NID in conjunction with local ET information and other IDC input data described above. IDC inputs were defined unique to specific, local characteristics observed in NID, to the extent possible. Model inputs were refined to provide for consistency between model results and recent historical delivery records.	[36]
Treated Water Demand	Treated water demand	Calculated as the amount of water needed to meet urban water use requirements, after accounting for population, per capita water use, return flow, etc.	Same approach as current scenario but calculated with projection scenario information.	Urban water demand was adaptively calculated using the IDC model. Model inputs were refined to provide for consistency between model results and recent historical delivery records.	[36]
Municipal Water Demand	Municipal water demand	Summarized from historical municipal purchase records from NID.	Estimated consistent with other NID projections.	Future projections of municipal water purchases from NID were defined consistent with projections in NID's 2020 Urban Water Management Plan.	[36]
Environmental Flows	Environmental flows	***Simulated as part of the ResSim reservoir operations model.***	***Simulated as part of the ResSim reservoir operations model.***	Environmental flows are NID's in-stream flow requirements, as specified in the FERC Final Environmental Impact Statement for Hydropower License. Environmental flows are simulated as part of the ResSim reservoir operations model.	[36]
Conveyance System Losses (Below NID Reservoirs)	Conveyance system losses (below NID reservoirs)	Estimated as a fraction of canal inflows, based on NID operations data.	Same approach as current scenario, with adjustment for different projected scenarios.	System losses from NID conveyance infrastructure (below NID's reservoirs) was estimated as a fraction of NID's canal inflows. Estimates were consistent with previous NID analyses based on NID operations data, calculated from inflows and outflows. These losses include all evaporation, seepage, and other losses from the conveyance system below NID's reservoirs. Evaporation from NID's reservoirs are simulated as part of the ResSim reservoir operations model.	[25]-[26], [36]-[39]

Reference **Source**

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B.2. Evapotranspiration and Crop Coefficient Development Process

B.2.1. Introduction

Evapotranspiration (ET), or consumptive water use, is the major driver of agricultural water use, and is impacted by many factors, including:

- The types of crops and vegetation that are grown (reflecting the inherent differences in water needs of different crops and vegetation);
- The quality of crops, vegetation, and land use (including water availability, nutrient and pest management, and other factors); and
- Environment-driven demand for evaporation (related to weather and climate parameters, as a function of temperature, solar radiation, wind speed, and humidity).

Each of these factors are accounted for in the methods used to quantify ET.

In the Nevada Irrigation District (NID) Plan for Water (PFW) demand model, ET was quantified for different land uses and different climate zones in NID for each of the demand model scenarios using the best available local information and standard technical approaches (ASCE 2016). Two key approaches used to quantify ET were:

- **Open ET data**: In the current demand scenario, ET was quantified based on representative ET curves developed for different land uses and climate zones in NID using OpenET data.
- **Crop coefficient approach**: In the projected demand scenarios, ET was calculated following the standard crop coefficient approach described in the United Nations Food and Agriculture Organization (FAO) Irrigation and Drainage Paper 56 (Allen et al. 1998). In this approach, ET is calculated by multiplying a reference evapotranspiration (ETo) value by a crop coefficient (Kc) as seen in Equation 1. ETo captures the environment-driven demand for evaporation, while Kc represents the unique properties of crops and vegetation to accurately estimate the specific crop water use characteristics. Kc thus serves as a scaling factor for modifying ETo, tailoring ET calculations to the unique demands of different land uses under specific climatic and environmental conditions.

$$\mathbf{ET} = \mathbf{Kc} \times \mathbf{ETo} \quad [1]$$

The purpose of this appendix is to document the processes used in analyzing OpenET data and developing Kc values specific to the local conditions within NID. NID covers a diverse landscape, necessitating approaches for quantifying ET that account for local conditions within NID with respect to climate and crop water use characteristics. The approaches described in this appendix aim to provide accurate estimates of crop water use in the NID PFW demand model.

B.2.2. Data Sources

Accurate estimation of crop water use in NID requires comprehensive and reliable data sources that reflect the diverse landscape within the NID service area. This section outlines the primary data sources used in the ET analysis and Kc development process.

B.2.2.1 OpenET

OpenET is a multi-agency web-based geospatial utility that leverages satellite-based remote-sensing technology to provide spatially distributed and continuous ET estimates over vast, diverse regions. While OpenET is a new utility, the underlying methodologies to quantify ET apply a variety of well-established modeling approaches that are widely used in local, state, and Federal government and research applications. Additional information about the OpenET team, data sources, and methodologies are available at: https://openetdata.org/.

The capability of OpenET to deliver timely and large-scale ET datasets played a crucial role in developing ET and Kc estimates that capture the unique crop water use conditions observed within NID in recent years. OpenET information is available in raster coverages of the NID service area with a spatial resolution of 30 meters (m) x 30 m (approximately 0.22 acres). Data is available on both a daily and monthly timestep from 2016 through present. Monthly ensemble mean ET data for the entire NID service area in 2016–2022 was extracted from OpenET and analyzed to support development of the NID PFW demand model.

B.2.2.2 Spatial California Irrigation Management Information System (CIMIS)

Spatial CIMIS is a geospatial data product produced and released by the CIMIS. CIMIS operates an extensive network of weather stations strategically distributed across California that collect and report weather and climate parameters, including ETo estimates. Spatial CIMIS provides spatially continuous ETo estimates throughout California, which are calculated based on available quality-controlled CIMIS station data using advanced interpolation techniques with reference to topography and other factors that impact climate conditions. This approach enables the creation of ETo estimates throughout California, even where direct measurement may not exist. Additional information about the spatial CIMIS data sources and methodologies is available at: https://cimis.water.ca.gov/SpatialData.aspx.

Spatial CIMIS data was used together with OpenET data to calculate Kc curves representing specific land uses and climate conditions within NID. Spatial CIMIS ETo information is available in raster coverages of the NID service area with a spatial resolution of 2 km x 2 km. ETo estimates were extracted from spatial CIMIS on a daily timestep from 2016–2022 and were aggregated to monthly ETo totals to support development of monthly Kc curves.

B.2.3. Methods

B.2.3.1 Representative ET Curves

OpenET data was used to observe recent historical ET trends and develop representative ET curves for each land use category in each climate zone simulated in the demand model. Additional information about the land use categories and climate zones simulated in the demand model are discussed in Chapter 4 of the NID PFW report. The representative ET curves are meant to capture the range of observed ET rates across all pixels (i.e., 30 m x 30 m areas) within each climate zone that correspond to each respective land use category. The representative ET curves were used to determine the average ET and ET percentiles across tens to thousands of pixels in NID, depending on the distribution of each land use within each climate zone in NID. Importantly, OpenET data was not used to directly assign an ET value representing any single point within NID in the demand model, but rather to identify and simulate ET trends.

The development of representative ET curves involved a series of geographic information system (GIS) analyses. The following steps were taken to calculate the representative ET curves:

- **<u>Data Collection</u>**:
  - **ET**: Ensemble mean ET data was downloaded from OpenET for the entire NID service area (monthly timestep, 2016–2022).
  - **Land use**: Spatial land use information was summarized for the entire NID service area (annual timestep, 2016–2022). This information was developed through a land use analysis process based on:
    - Statewide land use mapping, available from the California Department of Water Resources (DWR) (DWR 2023)
    - CropScape Cropland Data Layer coverage, available from the U.S. Department of Agriculture (USDA 2023)

    In total, 11 land use categories were simulated in the demand model. The land use analysis and land use categories are discussed in Chapter 4 of the NID PFW report.
  - **Climate zones**: Climate zones delineated based on analyses of climate-related data to identify regions with similar precipitation and ETo characteristics within the NID service area. In total, three climate zones were simulated in the demand model. The climate zones are discussed in the Chapter 4 of the NID PFW report.
- **<u>ET Summary by Land Use and Climate Zone:</u>**
  - The ET data, land use data, and climate zone boundaries were imported into the same GIS analysis process and were scaled, as necessary, to 30 m x 30 m.
  - Through a month-by-month process, the ET, land use, and climate zones were spatially linked together by location to create a compiled ET dataset containing the monthly ET rate within each 30 m x 30 m pixel, with indicators of the land use and climate zone corresponding to that pixel.
  - An array was created of all ET rates within all pixels, summarized by:
    - Land use
    - Climate zone
    - Year and month
- **<u>Representative ET Curve Calculation and Use in the Demand Model:</u>**

  - Representative ET curves (ET rates per month, from 2016–2022) were calculated for each land use and climate zone by calculating the following summary statistics from all pixels linked to each land use and climate zone:
    - 10th percentile
    - 25th percentile
    - 50th percentile (median)
    - 75th percentile
    - 90th percentile
    - Mean
  - The representative ET curve for each land use and climate zone was compared against other representative ET curves reported from other sources – including DWR's Cal-SIMETAW (DWR 2022a) and the Irrigation Training and Research Center (ITRC) at California Polytechnic State University – San Luis Obispo (ITRC 2023) – to verify their general consistency with ET trends reported in technical literature.
  - The representative ET curve for each land use and climate zone was used within the demand model to represent the monthly ET rates for all areas corresponding to that land use and climate zone between 2016–2022. In earlier years, monthly ET rates from the same month in a hydrologically similar year were used in lieu of available data from OpenET. The 50th percentile (median) ET curve was used in the current demand scenario, and the relative impacts of other percentile curves on demand were evaluated through sensitivity analyses (discussed in the NID PFW report).

B.2.3.2 Representative Kc Curves

OpenET and spatial CIMIS data were combined and used to develop representative Kc curves for each land use category in all climate zones in the demand model. Additional information about the land use categories and climate zones simulated in the demand model are discussed in Chapter 4 of the NID PFW report. The representative Kc curves were developed to capture the range of observed crop-related water use requirements within NID. The representative Kc curves were used to estimate future crop water use requirements for each land use category in NID in the projected demand scenarios.

The development of representative Kc curves involved a series of GIS analyses, building off those used to develop the representative ET curves. The following steps were taken to calculate representative Kc curves:

- <u>**Data Collection:**</u>
  - **ETo**: ETo data was downloaded from spatial CIMIS for the entire NID service area (daily timestep aggregated to monthly values, 2016–2022)
  - **ET**: Ensemble mean ET data was downloaded from OpenET for the entire NID service area (monthly timestep, 2016–2022). See Section B.2.3.1.

- **Land use and climate zones**: Spatial land use information was summarized (annual timestep, 2016–2022), and climate zones were delineated for the entire NID service area. See Section B.2.3.1.

- **Kc Summary by Land Use and Climate Zone:**
  - The ETo data was imported into a GIS analysis process and was downscaled to 30 m x 30 m, consistent with the ET data. Units were converted, as needed, for consistency.
  - The compiled ET data containing monthly ET rates with indicators of the land use and climate zone (developed through the process described in Section B.2.3.1) was imported into the same GIS analysis process.
  - An array was created containing Kc values for each pixel in the NID service area, calculated based on the ratio of ET to ETo (rearranging Equation 1 to solve for Kc). Kc values within all pixels were summarized by:
    - Land use
    - Climate zone
    - Year and month
- **Representative Kc Curve Calculation and Use in the Demand Model:**
  - Representative Kc curves (Kc values each month, summarized across 2016–2022) were calculated for each land use across all climate zones by calculating the following summary statistics from all pixels linked to the corresponding land use:
    - 25th percentile
    - 50th percentile (median)
    - 75th percentile
  - The representative Kc curves for each land use in water year 2022 (October 2021 through September 2022) were used together with projected monthly ETo estimates to calculate monthly ET estimates for all projected demand scenarios following Equation 1. Projected monthly ETo estimates were estimated following the standard Hargreaves-Samani approach (Hargreaves and Samani 1985, Allen et al. 1998), based on spatial projected temperature information in the NID service area derived from the climate change analyses used in the hydrology scenarios (see Chapter 4 of the NID PFW report for more information).

    The following Kc curves were used within each projected demand scenario:
    - Low Demand: 25th percentile
    - Baseline Demand: 50th percentile (median)
    - High Demand: 75th percentile

    The selection of these percentiles is discussed in Section B.2.4.3.

B.2.4. Results and Conclusions

These analyses of representative ET curves and representative Kc curves provide valuable insights into local water use requirements within the NID service area and serve as a solid foundation for water management planning in the NID PFW process. The subsections below present and discuss results of the ET and Kc development process.

B.2.4.1 ET and Representative ET Curves

Figure 1 presents the spatial distribution of ET within NID in July 2022, as an example. The ET values were derived from OpenET data, which provides spatially distributed and continuous ET estimates. The map highlights the diverse consumptive water use patterns across different areas in NID. ET values reflect both the variability in climate conditions across NID as well as the monthly water needs of crops and vegetation, accounting for differences in inherent characteristics, growth stages, agronomic and irrigation practices, and environments across NID. Accurate representation of these qualities is crucial for accurately simulating demand within NID with respect to local, observed conditions.

Figure 2 presents a sample, representative ET curve developed for pasture in climate zone 3 (the lowest elevation zone). As discussed above, the representative ET curves were compared to other representative ET curves reported from other sources (e.g., Cal-SIMETAW, ITRC) to verify their general consistency with ET trends reported in technical literature. In contrast with OpenET, many ET estimation approaches do not directly account for crop stress, which is caused by a variety of factors, and if present, will reduce ET. Consequently, many ET approaches and estimates in technical literature overestimate actual ET. One benefit of using OpenET data to quantify ET is that it captures the variability of ET observed within NID for each land use category, including those factors that may lead to differences in ET values compared to those reported in technical literature. The ET curves from other sources (e.g., Cal-SIMETAW, ITRC) tend to be higher than the OpenET results, especially in the mid- to late-summer period when evaporative demand is highest and when crop stress, if present, will be most noticeable. Differences observed between other sources and OpenET are influenced by those factors, which are captured within this ET analysis.

B.2.4.2 ETo

As described above, ETo serves as a critical parameter for estimating crop water use requirements. Figure 3 shows the spatial distribution of ETo from spatial CIMIS within NID in July 2022, as an example, revealing significant spatial variability in ETo across the NID service area. Differences in ETo across the landscape are influenced by climate and weather-related parameters, as a function of temperature, solar radiation, wind speed, and humidity. Regions with higher ETo values indicate areas with relatively higher consumptive water use requirements (all else equal), whereas lower ETo values correspond to relatively lower consumptive water use requirements. Factoring spatial estimates of ETo into the development of representative ET curves helps to capture these differences across the NID service area.

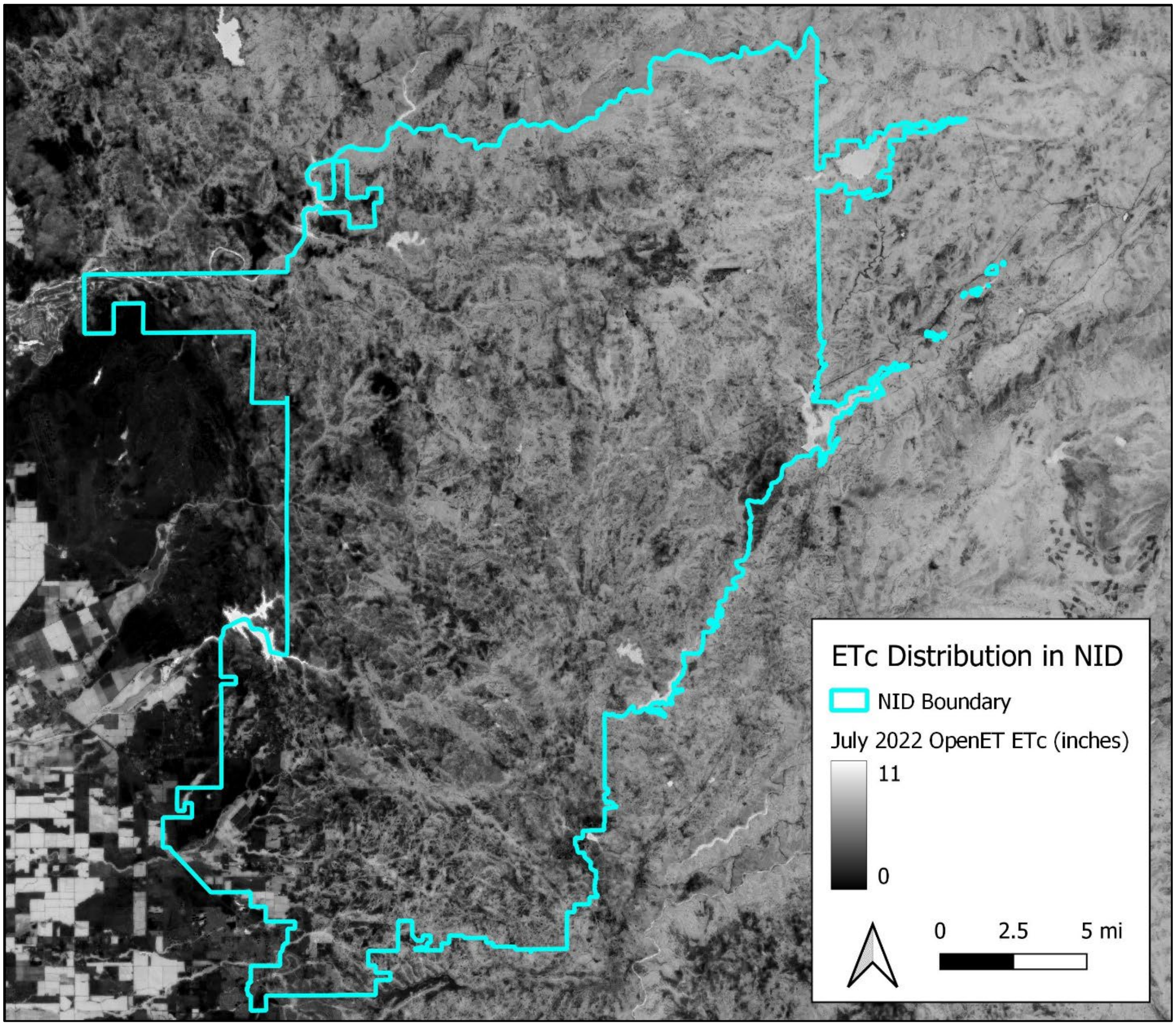

Figure B-1. Crop Evapotranspiration (ET) in July 2022 from OpenET.

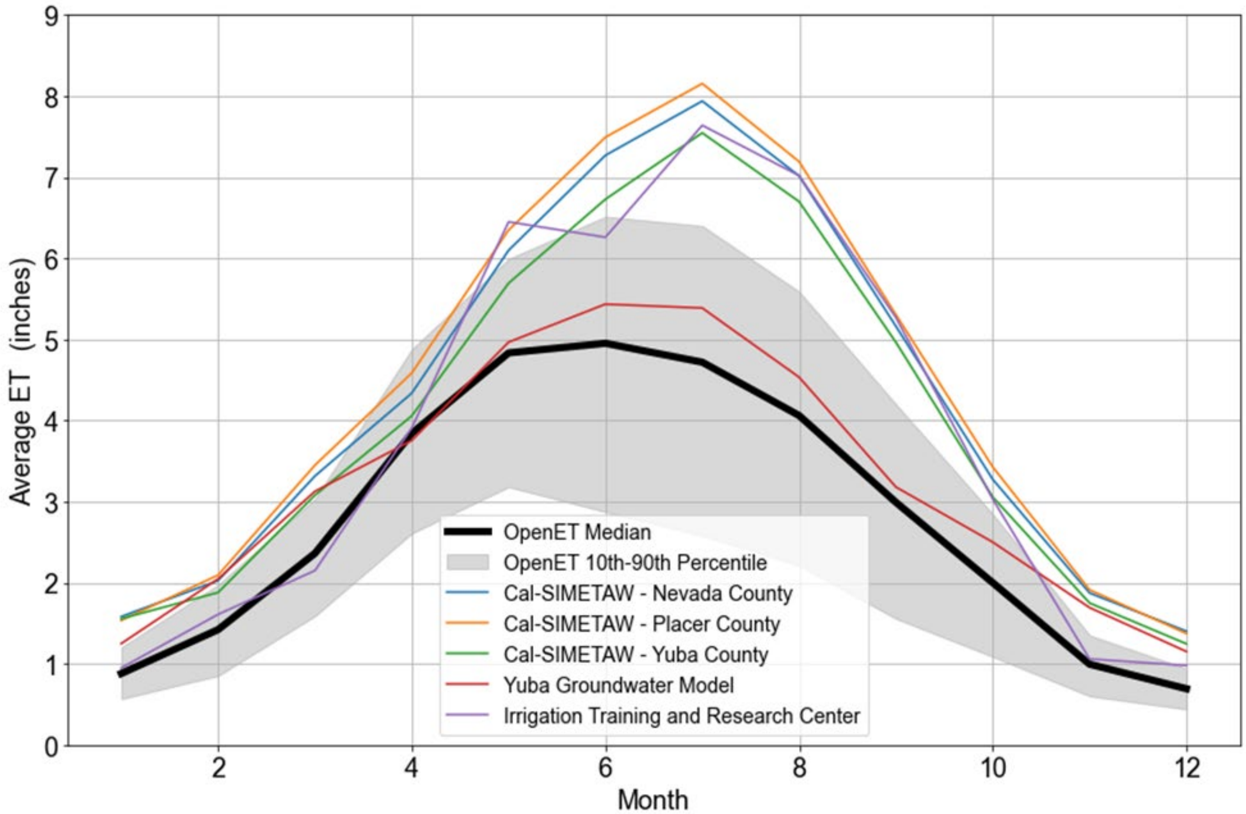

Figure B-2. Sample ET Curve Summarized for all Parcels Categorized as Pasture in Climate Zone 3 (2021), with Comparisons to Other Representative ET Estimates for Pasture from Cal-SIMETAW (DWR 2022a), the Yuba Groundwater Model (YWA 2019), and the Irrigation Training and Research Center ET Data for Water Budget Applications (ITRC 2023).

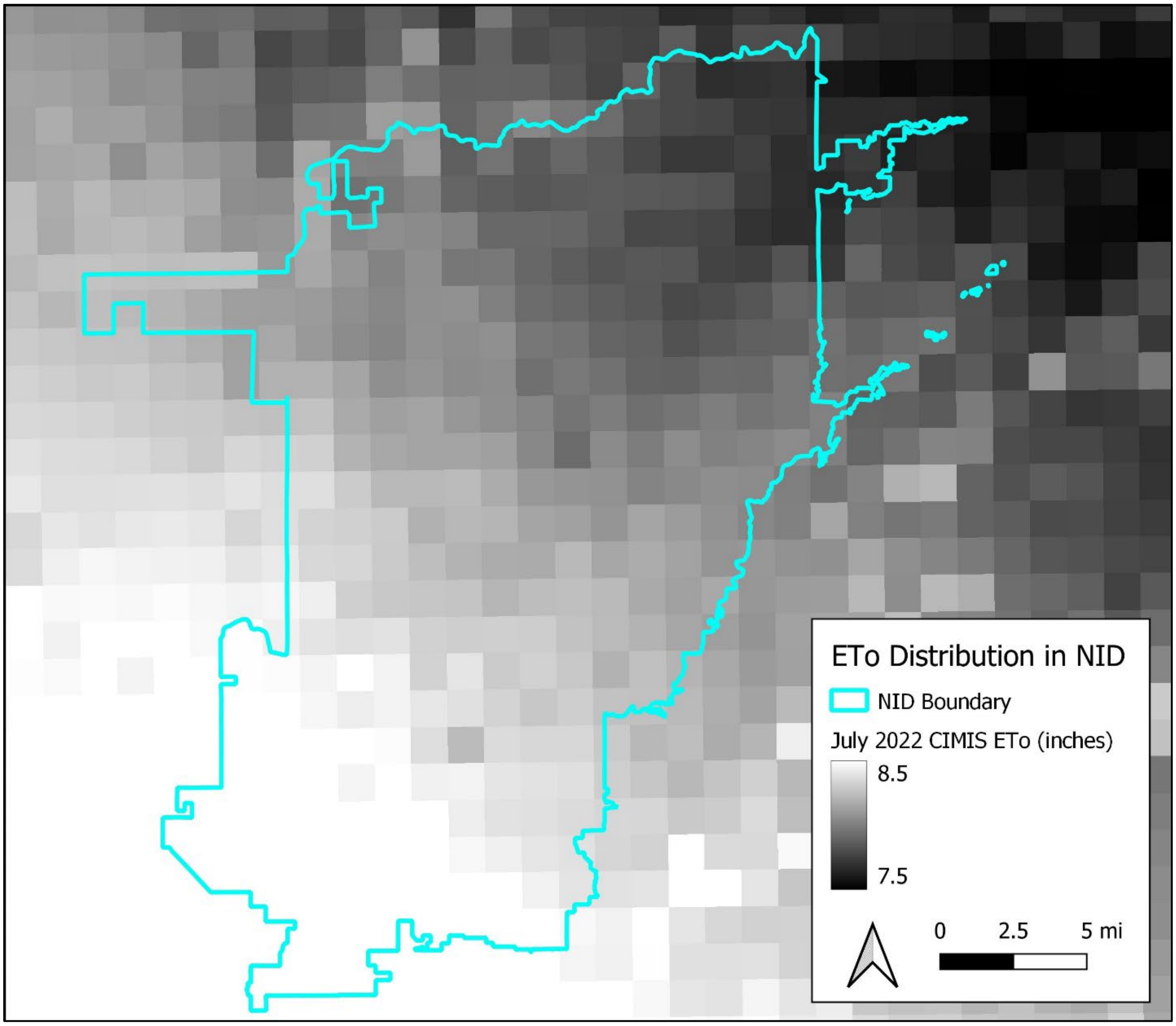

Figure B-3. Reference Evapotranspiration (ETo) in July 2022 from Spatial CIMIS.

B.2.4.3 Representative Kc Curves

Figure 4 illustrates the median Kc values for various land use categories within the NID service area in water year 2022 (October 2021 through September 2022), summarized across all climate zones. The figure showcases the variations in Kc values for different land use categories over the course of the year, as well as relative differences between land use categories. The representative Kc values, such as those depicted in Figure 4, were considered in the demand model development process to quantify ET in the projected scenarios.

Figure 5 provides a comparison of ET values calculated for pasture using the representative Kc curves, versus ET values summarized from OpenET data for pixels representing pasture. The comparison is made for 2016–2022, a period when OpenET data is available, although it is noted that the representative Kc curves shown are those that are also used in the projected demand scenarios:

- Low Demand: 25th percentile (ET in Figure 5 is calculated using ETo summarized from the wet hydrology scenario)
- Baseline Demand: 50th percentile, or median (ET in Figure 5 is calculated using ETo summarized from the median hydrology scenario)
- High Demand: 75th percentile (ET in Figure 5 is calculated using ETo summarized from the dry hydrology scenario)

The comparison in Figure 5 indicates that ET estimates generated by the representative Kc curves are within the range of ET estimates observed from OpenET data during the irrigation season (generally March-October). Additionally, ET estimates calculated using the 25th and 75th percentile Kc curves reflect a reasonable range within the upper and lower bounds of the 25th and 75th percentile ET values observed from OpenET data.

Table 1 summarizes the relative changes in total annual ET from the median Kc for different land use categories if the 25th percentile or 75th percentile Kc curves are used. As compared to ET generated using the median Kc values, these percentiles result in an average change of approximately -18% of total ET (using the 25th percentile Kc values) or +15% of total ET (using the 75th percentile Kc values) overall.

The selection of the 25th percentile and 75th percentile for the “low” and “high” projected demand scenarios was informed by comparison of these ET changes to typical differences in ET under reasonable changes in cultivation and irrigation practices where ET is reduced (in the low bookend scenario) or ET is increased (in the high bookend scenario). Typical differences range from +/-15% or more, depending on conditions. A sample of references considered in this comparison is provided below. Many of the references provided evaluate ET of alfalfa, which serves as a proxy for evaluating ET of pasture – the primary agricultural land use in NID.

- Sanden et al. 2011: Review of alfalfa water requirements and recommendations for irrigation planning from the University of California Cooperative Extension. Normal year ET is considered a good guideline for planning irrigations, but actual ET can be +/-15% of that.
- Andales et al. 2010: ~12% decrease in ET observed between two growing seasons (2008–2009) for alfalfa cultivated under similar conditions each year, but with water stress early in the season when the decrease in ET was observed. ET differences were measured using weighing lysimeters, which are considered to be one of the most accurate ways to measure ET over a small area (ASCE 2016).
- Hunsaker et al. 2002: ~10-30% difference in ET observed between well-watered and water-stressed treatment conditions during the same growing season (1985) for alfalfa cultivated under otherwise similar conditions. A 30% difference in ET from well-watered to water-stressed conditions likely represents +/-15% difference from a "median" condition between those bookend conditions. ET differences were measured using weighing lysimeters.
- Djaman and Irmak 2013: ~5-10% change in ET observed between full irrigation and 50% reduced irrigation conditions during two growing seasons (2009–2010) for corn cultivated under otherwise similar conditions. ET differences were estimated using a soil water balance.
- Tasumi et al. 2005: +/- 10-20% difference in daily Kc values during peak-season irrigation of beans and corn under different cloud cover conditions (higher values in clear sky, lower values in cloudy

conditions). ET differences used to calculate the Kc values were measured using weighing lysimeters.

- Samani et al. 2013: ET was quantified for 751 alfalfa fields in New Mexico using a remote-sensing approach (similar to OpenET) and the range of total ET was observed between ~700-1200 mm/year (27.6-47.2 inches/year, with some outliers). This range translates to a difference in ET of approximately +/- 20-30% around the average, and the 25th and 75th percentiles are approximately 10-15% around the average. Potential reasons cited for ET and Kc variability was determined to include "irrigation methods and technology, lack of knowledge of irrigation scheduling, limited water supply, interference of harvesting schedule with irrigation, cultural practices, and economic factors."

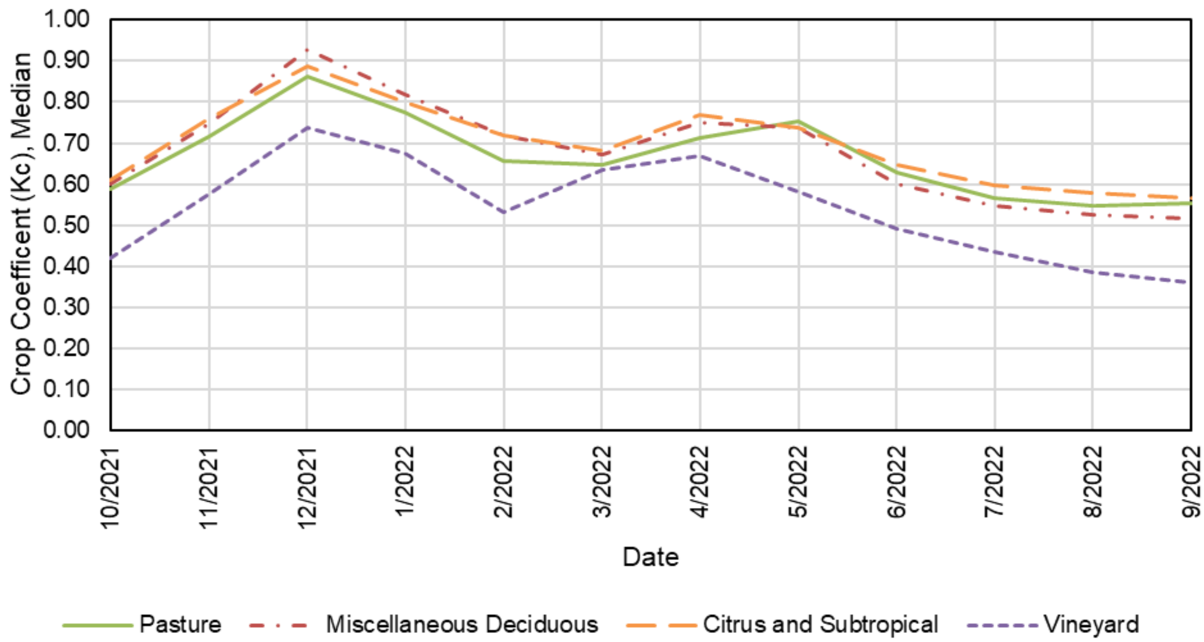

Figure B-4. Median Crop Coefficients for Various Land Use Categories in Water Year 2022, Summarized Across all Climate Zones.

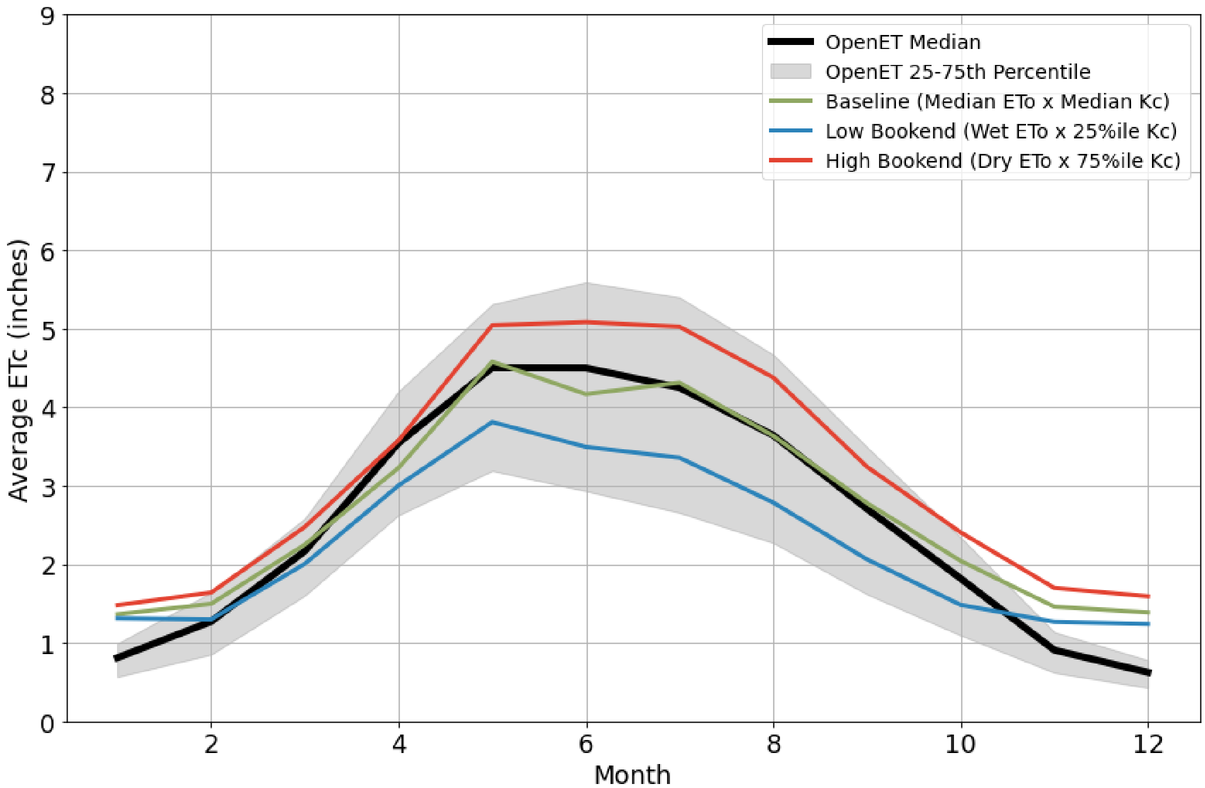

Figure B-5. Comparison of ET Calculated from Representative Kc Curves with OpenET ET for Pasture (2016–2022).

Table B-2. Percent Difference from Median ET Calculated Using the 25th Percentile and 75th Percentile Kc Values for Agricultural Land Use Categories in NID.

Agricultural Land Use Category	Fraction of Total Agricultural Land Use Area Evaluated	Percent Difference in ET in Water Year 2022 (%)	
		25th Percentile Kc vs Median Kc	75th Percentile Kc vs Median Kc
Pasture	88%	-17%	14%
Vineyard	6%	-16%	16%
Misc. Deciduous	3%	-18%	14%
Misc. Truck Crops	2%	-27%	30%
Citrus and Subtropical	1%	-15%	12%
Average (Area-Weighted)		**-18%**	**15%**

B.3. Land Use Analysis Process

B.3.1. Introduction

The purpose of this appendix is to document the process used to analyze and summarize spatial land use information for the NID service area. This information was used to assemble an annual spatial land use and land cover (LULC) dataset for use in the NID PFW demand model. The spatial LULC dataset was used for a variety of purposes in the demand model, including identifying typical land uses within NID to simulate in the demand model, and identifying where those land uses occur. This spatial representation and understanding of land use provides a crucial linkage between the demand model results and the locations within NID where demand occurs.

B.3.2. Data Sources

The annual spatial LULC dataset was developed primarily using geospatial land use information obtained from the California DWR and the USDA. Both data sources are described below.

B.3.2.1 DWR Statewide Land Use Mapping

DWR provides a statewide land use mapping dataset covering all developed land in California, including cultivated agricultural land, idle agricultural land, and urban areas (DWR 2023). The dataset is generated by Land IQ, in cooperation with DWR, using remotely-sensed imagery and associated analytical techniques. The data is provided in vector-based GIS formats with field-by-field classification of each appropriate land use. The data does not generally include non-developed land (e.g., native vegetation), and leaves gaps outside of areas where developed land uses exist. Currently, statewide land use mapping data is available in 2014, 2016, 2018, 2019, 2020, 2021 and provisionally for 2022. The statewide land use mapping dataset undergoes extensive quality assurance, quality control, and validation processes by Land IQ and DWR to ensure that there is appropriate classification of different land uses throughout California. Additional information about the DWR statewide land use mapping dataset is available online at: https://data.cnra.ca.gov/dataset/statewide-crop-mapping.

B.3.2.2 USDA CropScape Cropland Data Layer

The USDA's CropScape Cropland Data Layer (CDL) is a raster-based data product that allows visualization of land uses throughout the United States (USDA 2023). The CDL dataset is generated using remotely-sensed imagery and analytical methodologies to provide a continuous nationwide land use coverage. Updates are released annually, with new CDL data becoming available each spring for the preceding year. Although validation of the CDL data does occur at the national level, issues have been identified in agricultural land use designations in California through independent, local checks. For this reason, the CDL data is used primarily for identifying non-developed land uses where gaps exist in the DWR statewide land use mapping dataset. Additional information about the USDA CDL data is available online at: https://nassgeodata.gmu.edu/CropScape/.

B.3.3. Methods

The DWR and USDA data were combined through an analysis process to develop the spatial LULC dataset used in the NID PFW demand model. The result was a spatially continuous annual representation of land use in the NID service area for 2013–2022, during the current demand scenario simulation period. As the DWR data is considered the most accurate spatial data source available within the NID service area, the DWR data was prioritized in development of the spatial LULC dataset, while the USDA data was used to fill in gaps in the DWR dataset.

The general process used to create the combined spatial LULC dataset was as follows:

1. The DWR data was rasterized and reprojected to match the USDA data projection and spatial resolution (30 meters (m) x 30 m).
2. The USDA data was masked to exclude any values where DWR data was available (i.e., to include only gaps within the DWR data).
3. For each year of available data, the DWR data and USDA data were combined to create one continuous raster coverage of NID, using:
4. The DWR data for that year (if available), or the DWR data for the most recent or hydrologically similar year (if data for that year was not available).
5. The USDA data for that year, filling in gaps in the DWR data.
6. Land uses in the combined spatial LULC dataset were linked to the appropriate land uses simulated in the demand model.
7. Land use areas (acres) were summarized from the spatial LULC dataset by converting the area of each pixel in continuous raster (30 m x 30 m) to acres.

Results of this analysis process were summarized and used in both raster and tabular format.

B.3.4. Results

Sample results of the land use analysis process are provided in Figure 1 and Table 1 for 2019 and 2022, respectively. Based on this analysis, the majority of land within the NID service area is categorized as either native vegetation or urban (Figure 1). In 2022, pasture was the predominant agricultural land use, encompassing 67% of all agricultural land (Table 1).

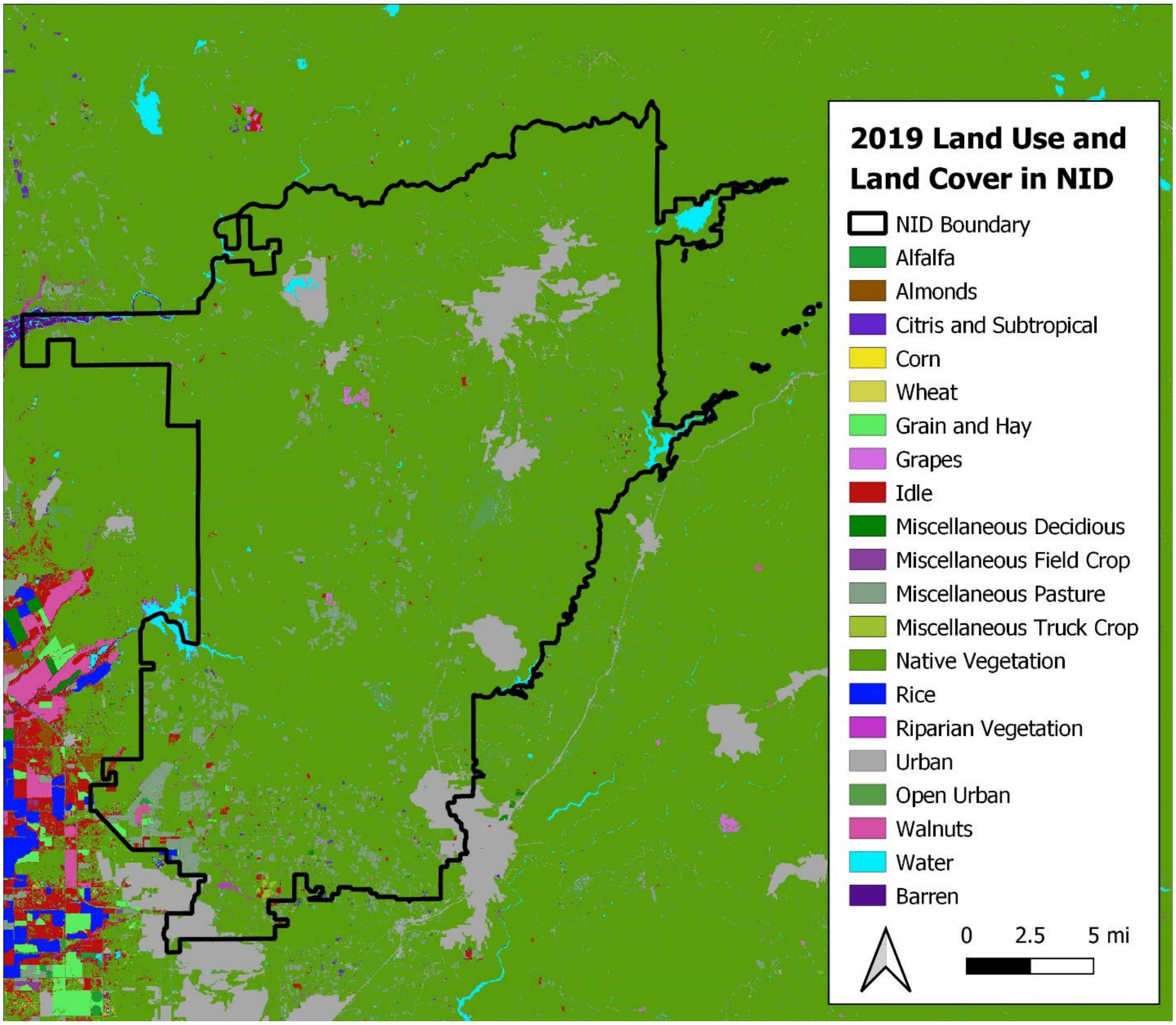

Figure B-6. Land Use Class in the LULC Dataset in 2019

Table B-3. Average Land Use Acreage in NID in Water Year 2022.

Land Use Sector in the Demand Model	Land Use Category in the Demand Model	Land Use Class in the Spatial LULC Dataset	Acres
Agricultural	Citrus and Subtropical	Citrus and Subtropical	68
	Idle	Idle and Barren	804
	Miscellaneous Deciduous	Almond	59
		Miscellaneous Deciduous	144
		Walnuts	115
	Miscellaneous Truck and Nursery	Miscellaneous Field Crops	24
		Miscellaneous Truck Crops	95
		Other Crops	570
	Pasture	Alfalfa	39
		Miscellaneous Pasture	4,432
	Vineyard	Grapes	297
Native and Riparian Vegetation	Native and Riparian Vegetation	Native and Riparian Vegetation	104,933
	Water	Water	1,663
Urban	Urban and Residential	Urban	16,771
		Total	130,014

B.4. Demand Model Input Parameter Sensitivity Analyses

B.4.1. Introduction

The purpose of this appendix is to document the sensitivity analyses that were conducted to test the relative impacts of different input parameters within the demand model that was developed and used to support the NID PFW process. The NID PFW is a public collaboration process to determine the best ways to meet the NID community's demand for water over the coming 50 years and involves a review of NID's available water supply and the long-term impacts on varying water demands. As part of the NID PFW process, a demand model was developed to simulate and test the water demands experienced under potential future demand scenarios – referred to as projected demand scenarios. The projected demand scenarios were developed to simulate a range of high and low demand conditions that may be experienced within the NID service area over the next 50 years.

The objectives of the sensitivity analyses documented in this appendix were to:

- Identify which factors most significantly impact demand, and should be considered in the development of the projected demand scenarios, and to
- Evaluate potential demand changes from current conditions in different "bookend" scenarios (i.e., a potential future range of high demand and low demand conditions), helping to identify reasonable bounds for developing input parameters in the projected demand scenarios.

The input parameters considered in the sensitivity analyses included:

- Raw water customers (with respect to changes in NID's customer base and areas receiving raw water)
- Treated water customers (with respect to changes in NID's customer base and parcels receiving treated water)
- Evapotranspiration (ET), with respect to changes in:
  - Climate-related impacts to environment-driven demand for evaporation
  - Crop cultivation practices and environmental stresses
- System losses (in NID's canals and distribution system downstream of NID's reservoirs)

In total, five levels of demand conditions were considered in each sensitivity analysis, with incrementally higher and lower demand conditions simulated around a baseline current demand condition (Figure B-7). The baseline current demand condition was developed starting from a historical demand model calibrated within approximately two percent, on average, of recent historical demand (2013–2022) across the NID service area, and was then refined for current conditions assuming: continuation of current land use (2022), current population and urban water use (2022), recent average precipitation (2013–2022) and ET (2016–2022), and 15% system losses (representing NID's current estimate of canal system losses based on findings from NID's Raw Water Master Plan and associated analyses by NID of water that is released into NID canals that is not delivered to NID customers).

The sections below identify the assumptions that were used to develop each level of demand conditions in each sensitivity analysis and the equivalent results for each. Results of the sensitivity analyses reported below are the "average water requirement" of NID's customers, which includes the sum of raw water demand and treated water demand, as well as the system losses in NID's canals and distribution system downstream of NID's reservoirs that occur delivering water to NID's customers (Figure B-7). These sensitivity analysis results do not include municipal water demand or environmental flows. Changes to municipal water demand were included in the projected demand scenarios based on five-year projected changes to municipal water use (2020–2040) from NID's Urban Water Management Plan, with interpolation or extrapolation in the intervening and following years through the end of the projected period. Regulatory-required environmental flows were included in the reservoir operations model (i.e., the ResSim model) that was developed and used in coordination with the demand model to simulate water supply versus demand and conditions of unmet demand under potential projected scenarios. Additional information about the projected demand scenarios and demand model is provided in the NID PFW report.

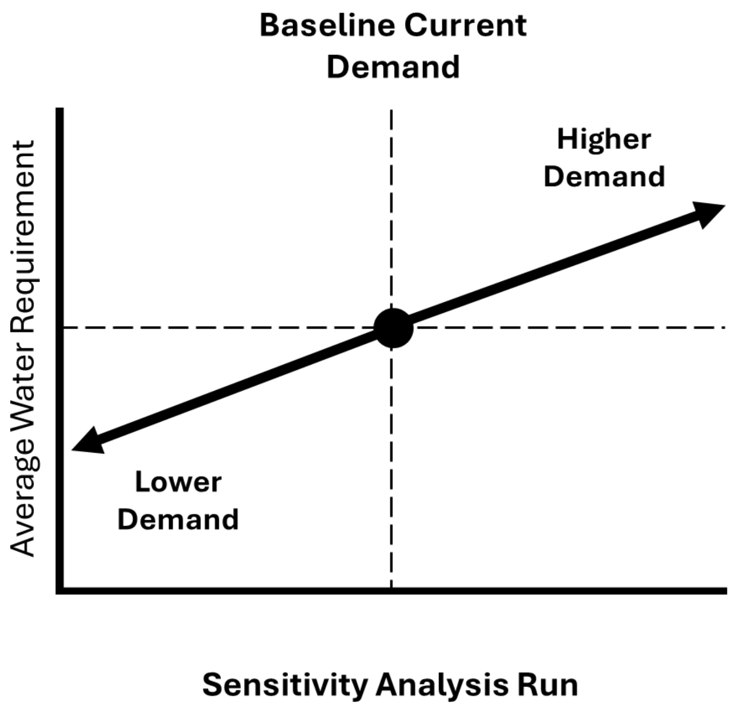

Figure B-7. Layout of Sensitivity Analysis Runs and Results Summaries.

B.4.2. Sensitivity Analyses

B.4.2.1 Raw Water Customers

The first analysis was conducted to evaluate the sensitivity of the demand model to changes in NID's raw water customers, as related to changes in NID's customer base and areas receiving raw water. Around the baseline current demand condition (analysis run 3):

- Higher demand conditions were evaluated through expansion of raw water customers into parcels within 1,000 feet of NID canals that (1) were not already NID customers, per NID delivery records, and (2) have historically been associated with agriculture or irrigated land uses, as identified from land use analyses. Expansion was tested through 50% fill-in to those areas (analysis run 4) and through 100% fill-in to those areas (analysis run 5). These levels of expansion were selected to test potential high-demand bookend scenarios, although actual future growth of NID's raw water customer base is likely to be less than this.
- Lower demand conditions were evaluated through reduction of land irrigated by raw water customers, with no fill-in to additional parcels in the NID service area. The analysis tested 25% reduction (analysis run 2) and 50% reduction (analysis run 1) of non-permanent crop areas. These reductions were selected to test the demand model sensitivity to potential low-demand bookend scenarios. However, potential future reductions in irrigated areas are likely to be less than these changes.

Changes in the average water requirement resulting from this analysis ranged between approximately -55,000 acre-feet per year (AF/yr) and +52,000 AF/yr, as compared to the baseline current demand condition (Figure B-8 and Table B-4).

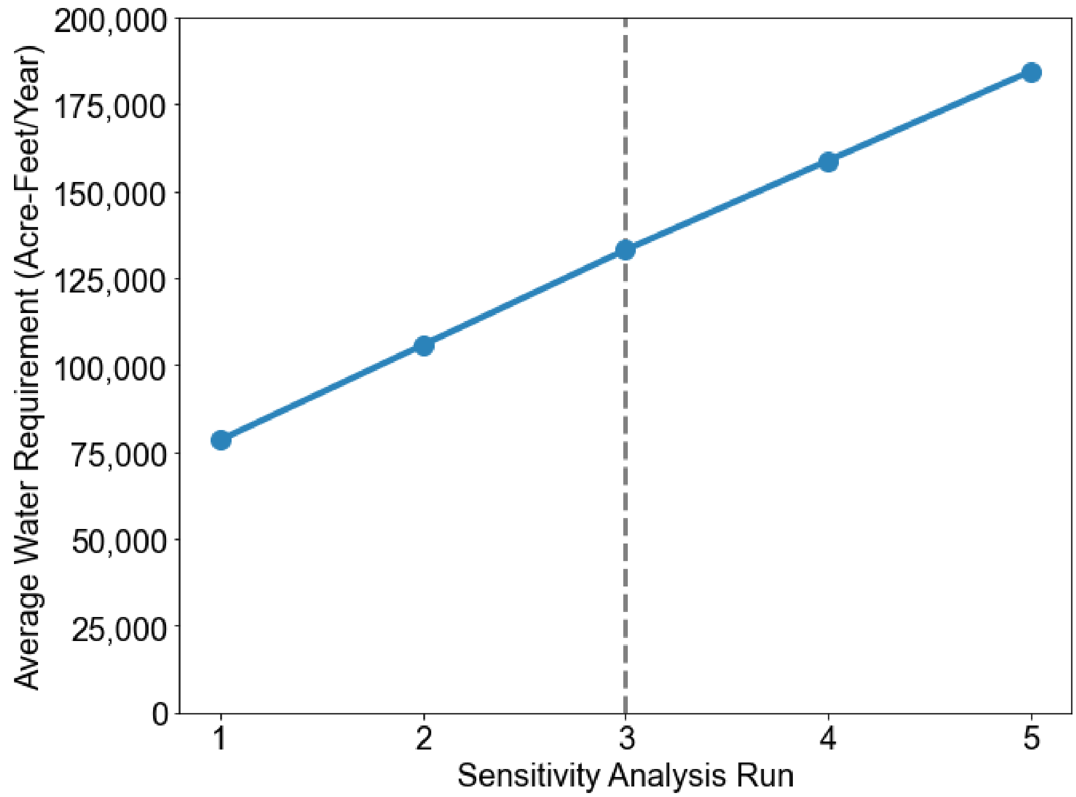

Figure B-8. Sensitivity Analysis Summary: Raw Water Customers.

Table B-4. Sensitivity Analysis Summary: Raw Water Customers.

Sensitivity Analysis Run	Change from Baseline	Average Water Requirement (AF/yr)	Difference from Baseline (AF/yr)
1	50% reduction in non-permanent crop areas, no fill-in to additional parcels	78,000	-55,000
2	25% reduction in non-permanent crop areas, no fill-in to additional parcels	106,000	-27,000
3 (Baseline)	No change (2022 land use)	133,000	--
4	Land use in 2022, plus fill-in to 50% parcels within 1000 feet of NID canals	159,000	26,000
5	Land use in 2022, plus fill-in to 100% parcels within 1000 feet of NID canals	185,000	52,000

B.4.2.2 Treated Water Customers

The second analysis was conducted to evaluate the sensitivity of the demand model to changes in NID's treated water customers, as related to changes in NID's customer base and parcels receiving treated water. Around the baseline current demand condition (analysis run 3):

- Higher demand conditions were evaluated through expansion of treated water customers into soft service areas (i.e., areas where NID has identified potential future growth opportunities for treated water customer service). Expansion was confined to parcels that were not already associated with NID customers, per NID delivery records. Expansion was tested through 50% fill-in (analysis run 4) and 100% fill-in (analysis run 5) to the soft service areas. These levels of expansion were selected to test potential high-demand bookend scenarios, although actual future growth of NID's treated water customer base is likely to be less than this.
- Lower demand conditions were evaluated through population decline in the NID service area, resulting in reduction in NID's treated water customers. The analysis tested population decline to the 2015–2019 average, representing the average population prior to the COVID-19 pandemic (analysis run 2), as well as population decline to the minimum population in the NID service area since 2000 (analysis run 1). These reductions were selected to test the demand model sensitivity to potential low-demand bookend scenarios. However, potential future reductions in NID's treated water customer base is likely to be less than these changes.

This analysis resulted in minimal changes to the average water requirement in NID, representing +/-3,000 AF/yr or less as compared to the baseline current demand condition (Figure B-9 and Table B-5).

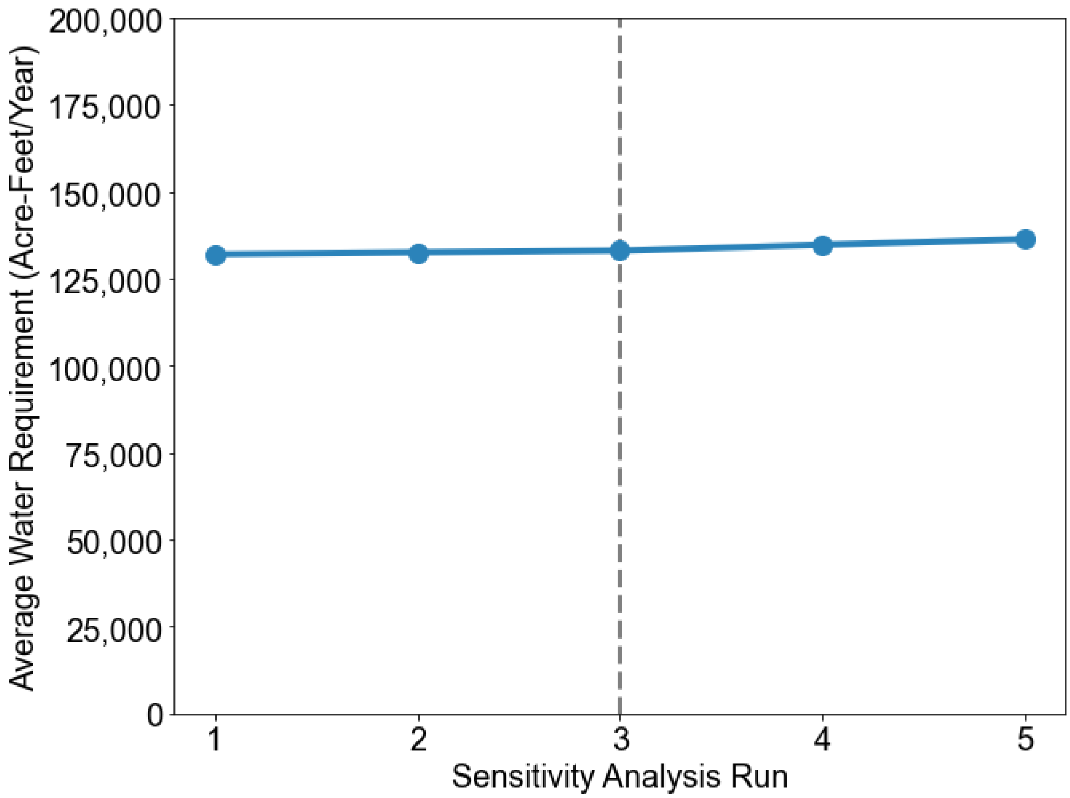

Figure B-9. Sensitivity Analysis Summary: Treated Water Customers.

Table B-5. Sensitivity Analysis Summary: Treated Water Customers.

Sensitivity Analysis Run	Change from Baseline	Average Water Requirement (AF/yr)	Difference from Baseline (AF/yr)
1	Population decline to minimum since 2000 (depending on location, ~80-90% of current)	132,000	-1,000
2	Population decline to 2015–2019 average (pre-pandemic average, ~95% of current)	133,000	0
3 (Baseline)	No change (2022 population)	133,000	--
4	Expansion to fill 50% of soft service areas (~ +20% of current treated water customers)	135,000	2,000
5	Expansion to fill 100% of soft service areas (~ +40% of current treated water customers)	136,000	3,000

B.4.2.3 Evapotranspiration with Changes to Climate

The third analysis was conducted to evaluate the sensitivity of the demand model to changes in ET, as related to potential changes in climate (specifically temperature) within the NID service area. ET and its relationship to climate parameters is described further in Chapter 4 of the NID PFW report. Around the baseline current demand condition (analysis run 2), higher and lower demand conditions were evaluated through increases or decreases (respectively) in the average daily temperature in the NID service area. Temperature changes were used to adjust the median historical ET in the NID service area based on the relationship between ET and temperature described by Hargreaves and Samani. Additional information about the Hargreaves-Samani approach is described in the NID PFW report. The following temperature changes were tested:

- Lower demand:
  - Adjusted for an average -2.2°F (-1.2°C) temperature change (analysis run 1)
- Higher demand:
  - Adjusted for an average +2.2°F (+1.2°C) temperature change (analysis run 3)
  - Adjusted for an average +4.3°F (+2.4°C) temperature change (analysis run 4)
  - Adjusted for an average +6.5°F (+3.6°C) temperature change (analysis run 5)

These changes were selected to test the demand model sensitivity to potential temperature changes in bookend climate change scenarios. However, potential future changes in temperature may be greater or less than these changes. This analysis resulted in changes in the average water requirement ranging between approximately -4,000 AF/yr to +16,000 AF/yr, as compared to the baseline current demand condition (Figure B-10 and Table B-6).

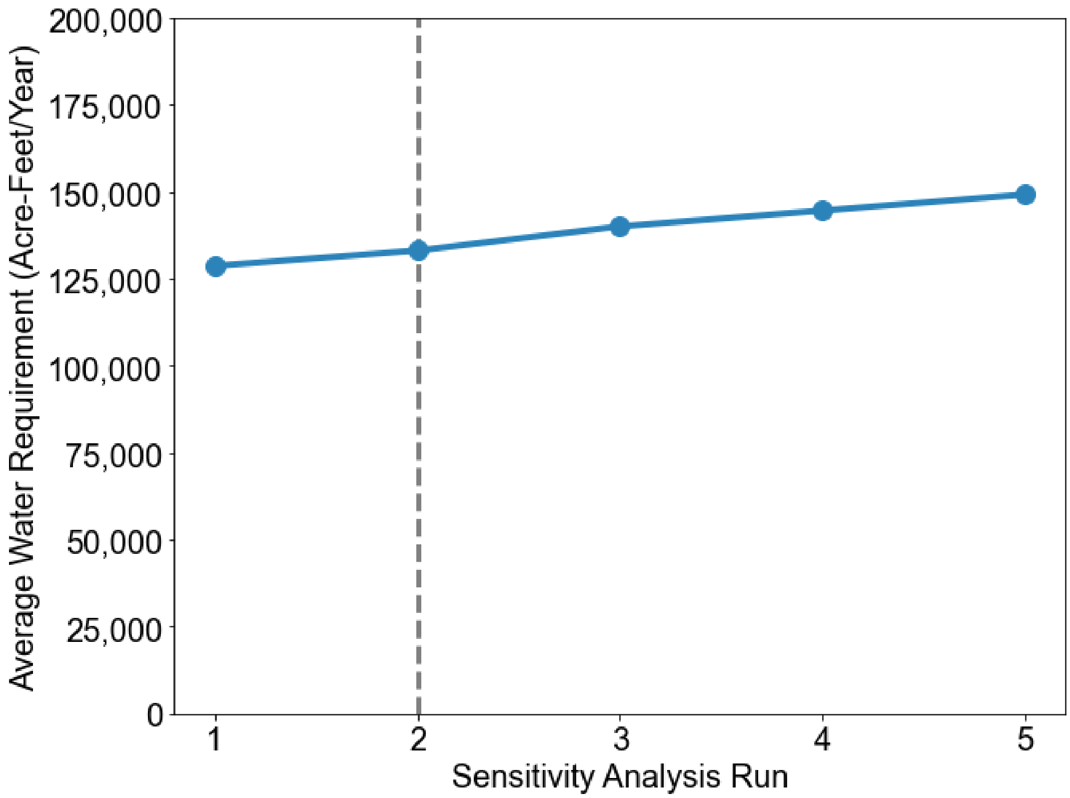

Figure B-10. Sensitivity Analysis Summary: Evapotranspiration with Changes to Climate.

Table B-6. Sensitivity Analysis Summary: Evapotranspiration with Changes to Climate.

Sensitivity Analysis Run	Change from Baseline	Average Water Requirement (AF/yr)	Difference from Baseline (AF/yr)
1	Median historical ET adjusted for -2.2°F (-1.2°C)	129,000	-4,000
2 (Baseline)	No change (median historical ET)	133,000	--
3	Median historical ET adjusted for +2.2°F (+1.2°C)	140,000	7,000
4	Median historical ET adjusted for +4.3°F (+2.4°C)	145,000	12,000
5	Median historical ET adjusted for +6.5°F (+3.6°C)	149,000	16,000

B.4.2.4 Total Evapotranspiration

The fourth analysis was conducted to evaluate the sensitivity of the demand model to changes in total ET. ET is impacted by:

- the types of crops or vegetation that are grown (reflecting the inherent differences in water needs of different crops and vegetation);
- the quality of crops, vegetation, or land use, including water availability, nutrient and pest management, and other factors; and
- the environmental demand for evaporation related to weather and climate parameters, as a function of temperature, solar radiation, wind speed, and humidity.

Each of these factors is accounted for in the methods used to quantify ET in the demand model. Changes in total ET in this analysis were determined through ET data summarized from OpenET. OpenET is a multi-agency web-based geospatial utility that uses satellite imagery to quantify ET over time with a spatial resolution of 30 meters x 30 meters (approximately 0.22 acres). For the NID demand model, OpenET data was used to observe recent historical ET trends and evaluate representative ET rates for land uses in NID (e.g., average ET and percentiles across tens to thousands of pixels in NID). Additional information about OpenET and its application in the demand model is described in the NID PFW report.

Around the baseline current demand condition (analysis run 3), higher and lower demand conditions were evaluated through increases or decreases (respectively) in the average ET value simulated in NID. Potential high and low demand conditions were determined from OpenET data as follows:

- Lower demand:
  - 10th percentile ET from OpenET analyses (analysis run 1)
  - 25th percentile ET from OpenET analyses (analysis run 2)
- Higher demand:
  - 75th percentile ET from OpenET analyses (analysis run 4)
  - 90th percentile ET from OpenET analyses (analysis run 5)

These changes were selected to test the demand model sensitivity to potential ET changes over the range of conditions experienced in NID historically. However, potential future ET changes may be less than these changes. This analysis resulted in changes in the average water requirement ranging between approximately -40,000 AF/yr to +42,000 AF/yr, as compared to the baseline current demand condition (Figure B-11 and Table B-7).

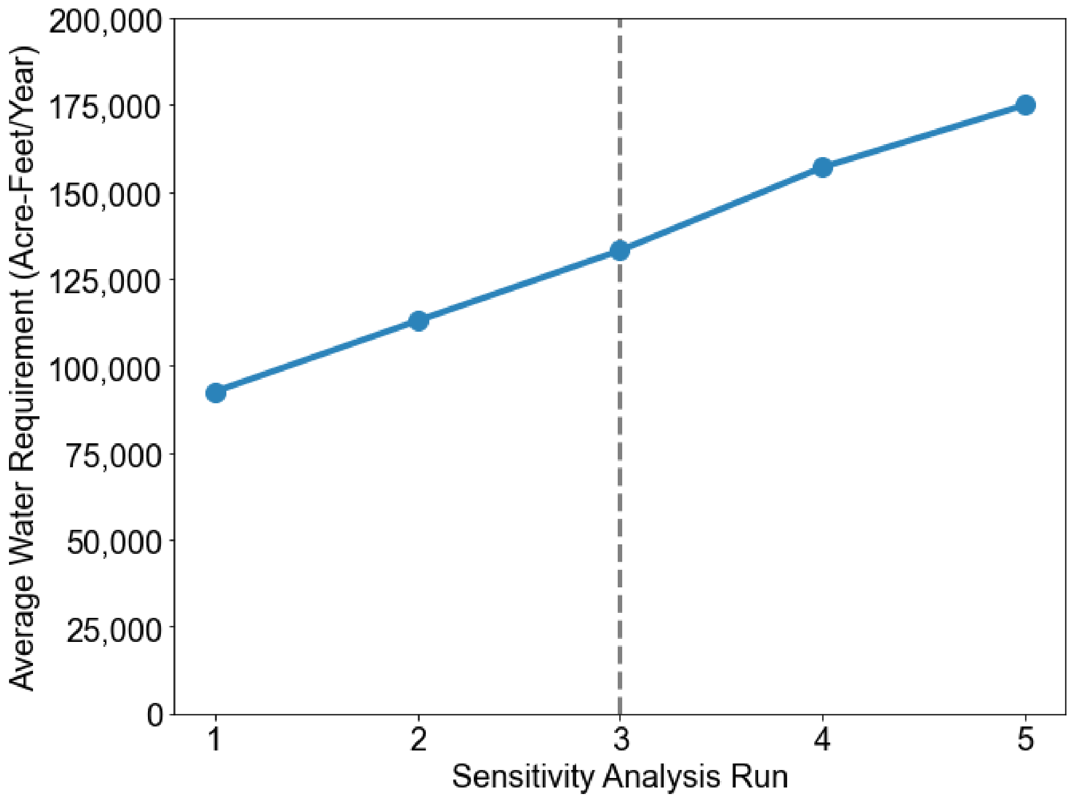

Figure B-11. Sensitivity Analysis Summary: Total Evapotranspiration.

Table B-7. Sensitivity Analysis Summary: Total Evapotranspiration.

Sensitivity Analysis Run	Change from Baseline[1]	Average Water Requirement (AF/yr)	Difference from Baseline (AF/yr)
1	10th percentile ET	93,000	-40,000
2	25th percentile ET	113,000	-20,000
3 (Baseline)	No change (50th percentile ET)	133,000	--
4	75th percentile ET	157,000	24,000
5	90th percentile ET	175,000	42,000

[1]By percent of parcels, by land use category and climate zone.

B.4.2.5 System Losses

The fifth analysis was conducted to evaluate the sensitivity of the demand model to changes in system losses. In this context, system losses represent water that is lost (whether through seepage, evaporation, or other outflows) from NID's canals and distribution system downstream of NID's reservoirs that occur delivering water to NID's customers.

Around the baseline current demand condition (analysis run 2), higher and lower demand conditions were evaluated through increases or decreases (respectively) in average system losses. The following system losses were tested:

- Lower demand:
  - System losses representing 10% of canal inflows (analysis run 1)
- Higher demand:
  - System losses representing 20% of canal inflows (analysis run 3)
  - System losses representing 30% of canal inflows (analysis run 4)
  - System losses representing 40% of canal inflows (analysis run 5)

These changes were selected to test the demand model sensitivity to uncertainties and potential changes in system losses across a range of conditions. The actual system losses likely differ from these conditions but are expected to generally fall within this range. This analysis resulted in changes in the average water requirement ranging between approximately -7,000 AF/yr to +56,000 AF/yr, as compared to the baseline current demand condition (Figure B-12 and Table B-8).

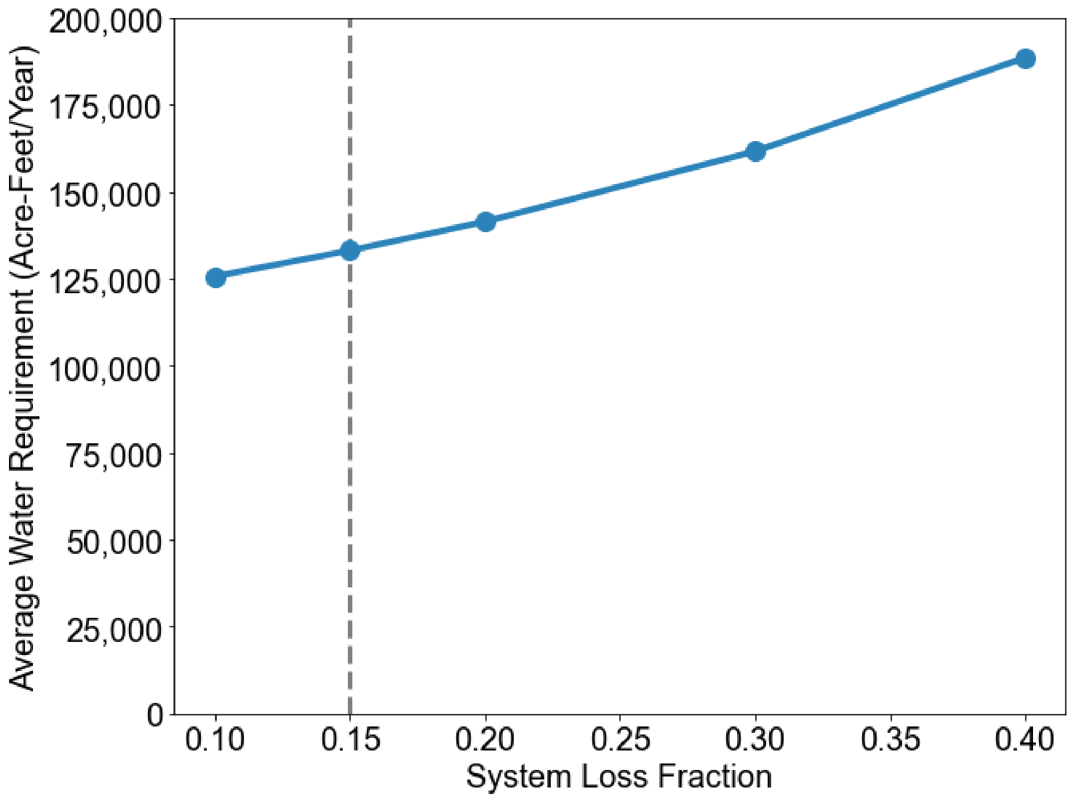

Figure B-12. Sensitivity Analysis Summary: System Losses.

Table B-8. Sensitivity Analysis Summary: System Losses.

Sensitivity Analysis Run	Change from Baseline	Average Water Requirement (AF/yr)	Difference from Baseline (AF/yr)
1	10% system losses	126,000	-7,000
2 (Baseline)	No change (15% system losses)	133,000	--
3	20% system losses	141,000	8,000
4	30% system losses	162,000	29,000
5	40% system losses	189,000	56,000

B.4.3. Comparison of Sensitivity Analyses

Figure B-13 provides a comparison of the results across all five sensitivity analyses, sorted generally from the greatest sensitivity and potential impacts to average water requirements in NID to the lowest sensitivity and potential impacts. This comparison indicates that changes to the raw water customer demand in NID (under those conditions tested) have the most significant potential impacts to the average water requirement. This reflects the significance of raw water use in NID, which represents approximately 90% of NID's annual demand. Following raw water customers, other factors with potentially significant impacts to the average water requirement include system losses and total ET changes. System losses are currently calculated in NID (and in the NID demand model) as a fraction of the total canal inflows, based on the best information currently available. Thus, significant changes to the estimated system losses have widespread effects on the water required in the NID system. Total ET changes are also impactful, mirroring the model sensitivity to raw water customer demand, which is primarily driven by ET. In contrast, temperature-related impacts to ET alone are less impactful than considering the effects of all factors that impact total ET. Treated water customer demand has the lowest potential impact to the demand model results among those parameters tested, as treated water use represents a much smaller portion of NID's demand.

The results of these sensitivity analyses were considered in the development of the projected demand scenarios. Please see Chapter 4 of the NID PFW report for more information about the projected demand scenarios and the assumptions and data sources that were used to develop those.

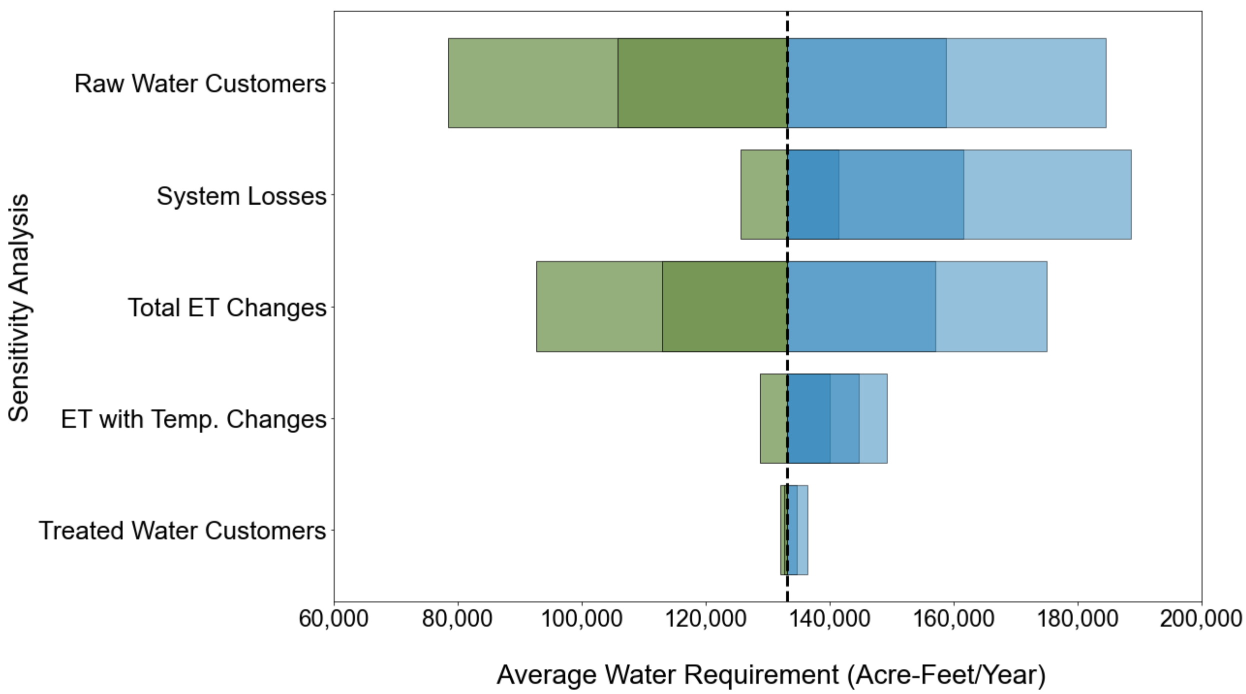

Figure B-13. Comparison of Sensitivity Analyses.

B.5. References

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Appendix C:

Chapter 5 Supplemental Information

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FIGURES

Appendix C. Chapter 5 Supplemental Information

C.1. Middle Yuba River

C.1.1. Jackson Meadows Reservoir

Jackson Meadows Reservoir daily storage matches historical storage well over the calibration period, as shown in Figure C-1. Releases from Milton Reservoir to the Middle Yuba River are shown in Figure C-2 and to the Milton-Bowman Conduit in Figure C-3.

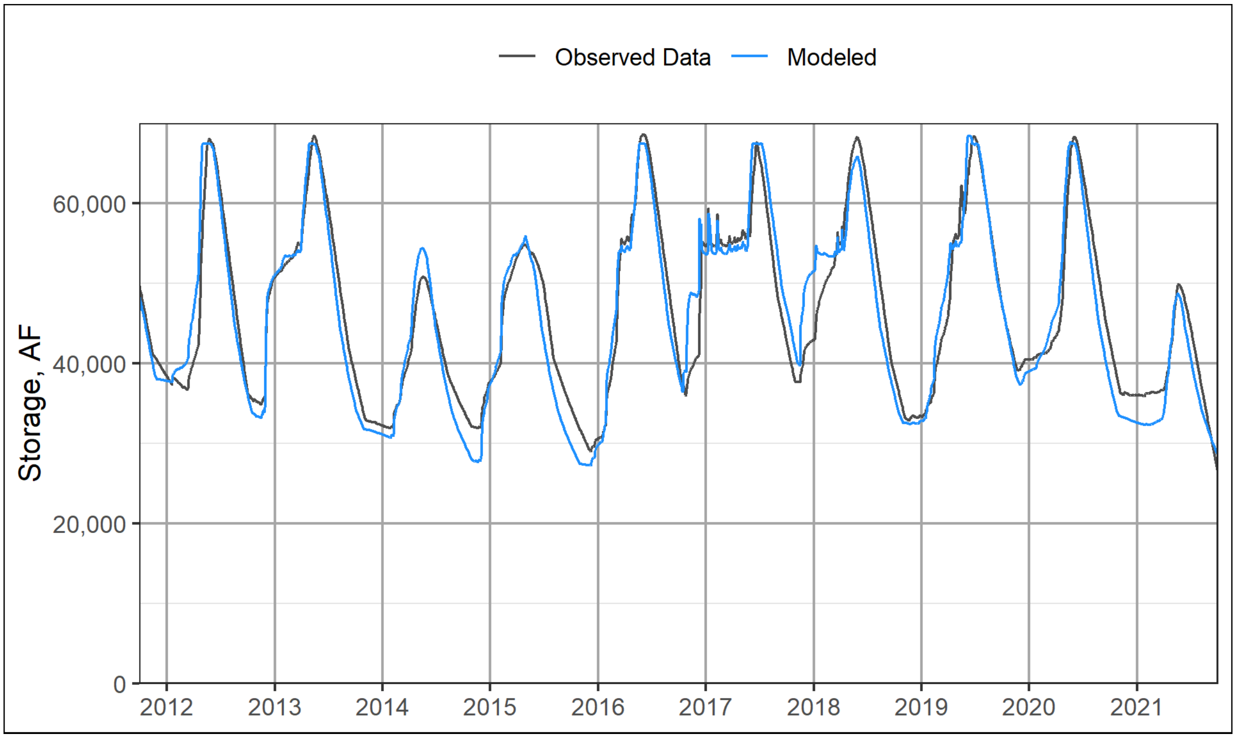

Figure C-1. Jackson Meadows Reservoir Storage, Water Years 2012–2021

C.1.2. Milton Reservoir

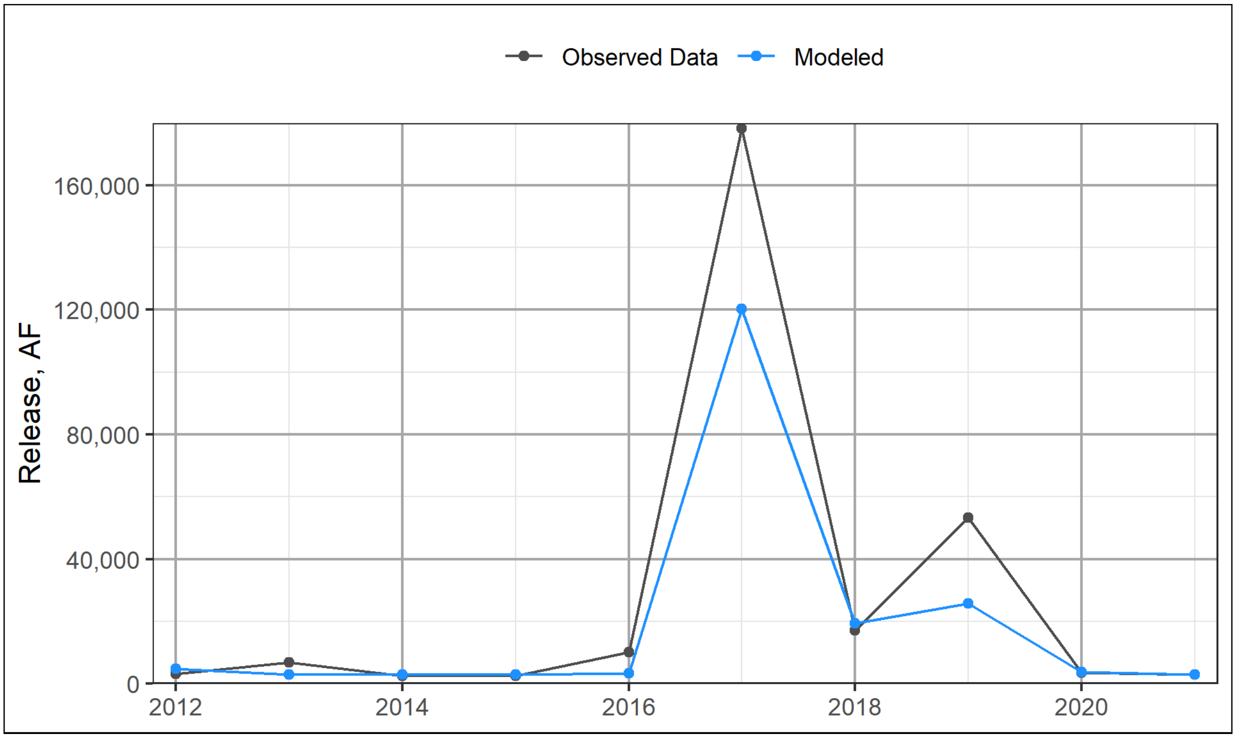

Figure C-2. Release from Milton Reservoir to Middle Yuba River, Water Years 2012–2021

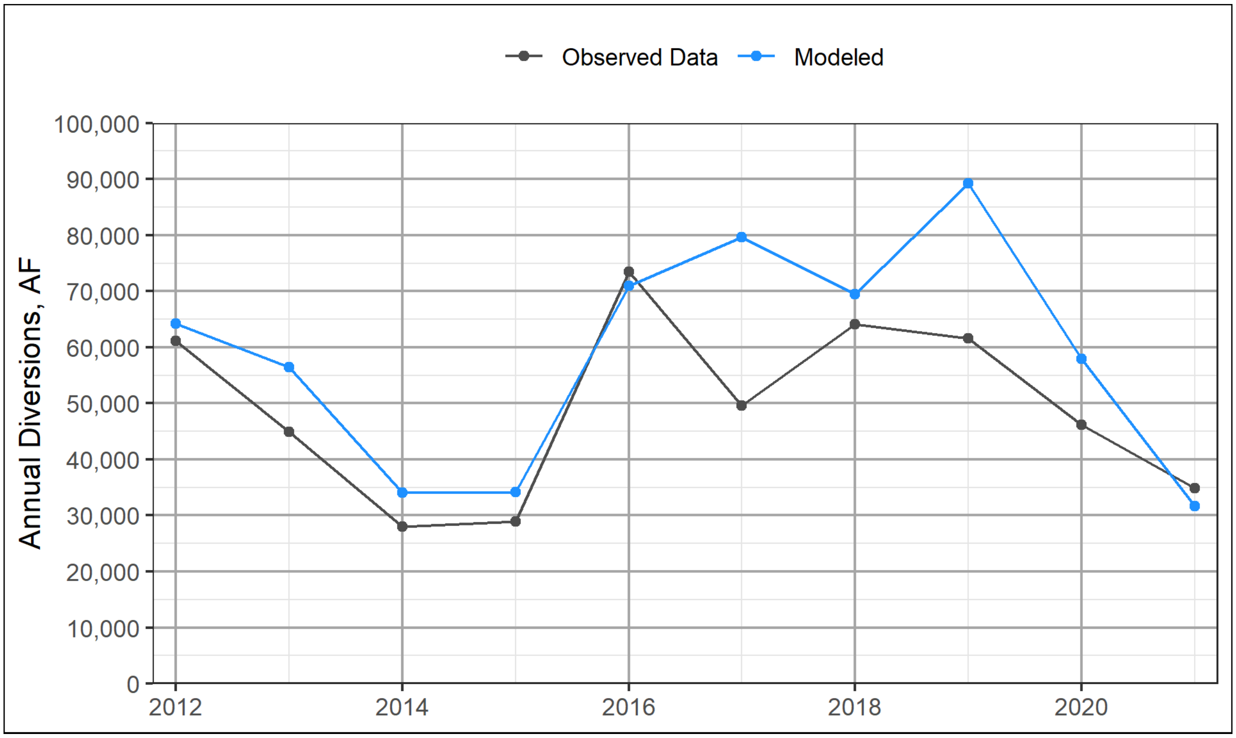

Figure C-3. Diversions to Milton-Bowman Conduit, Water Years 2012–2021

C.2. Canyon Creek

Reservoirs upstream of Bowman Reservoir have daily storage traces that match recent observed data fairly well, as shown in Figure C-4 through Figure C-7. Releases from these reservoirs have limited gauge data with all reservoirs' spills not included in the recorded observed data; therefore, it is not possible to compare reservoir release volumes.

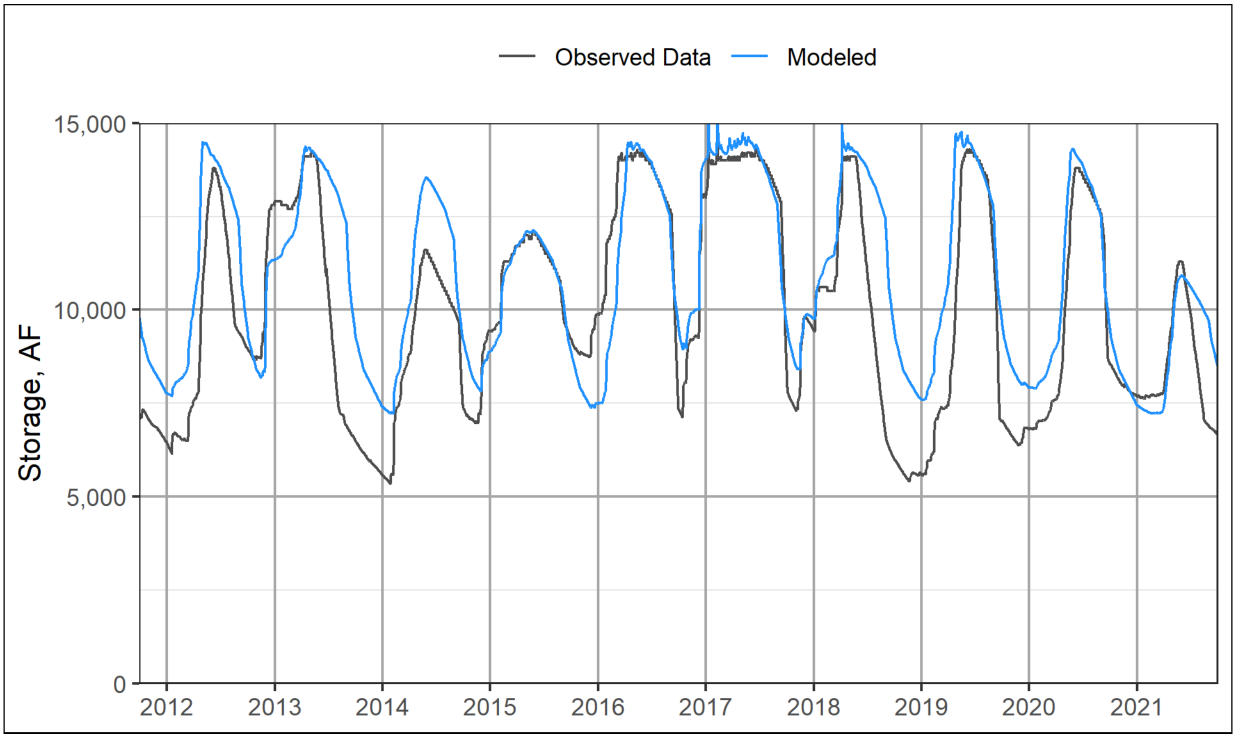

Figure C-4. French Lake Storage, Water Years 2012–2021

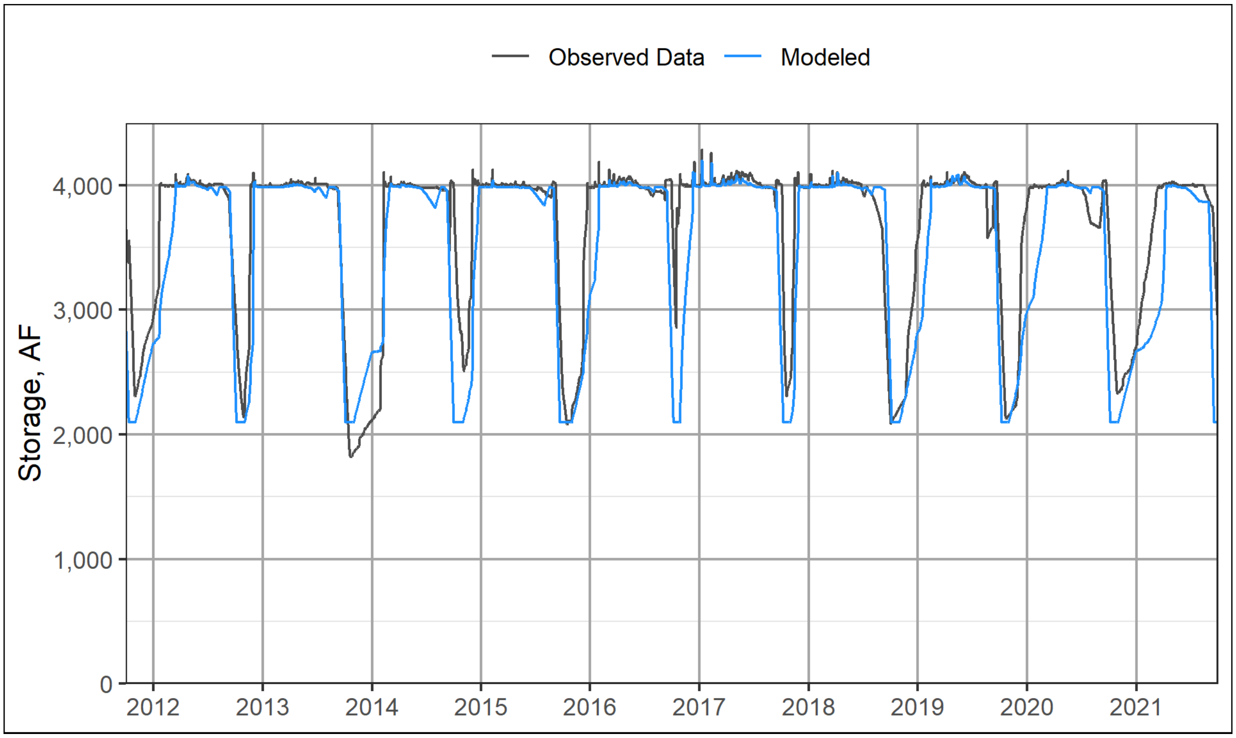

Figure C-5. Faucherie Lake Storage, Water Years 2012–2021

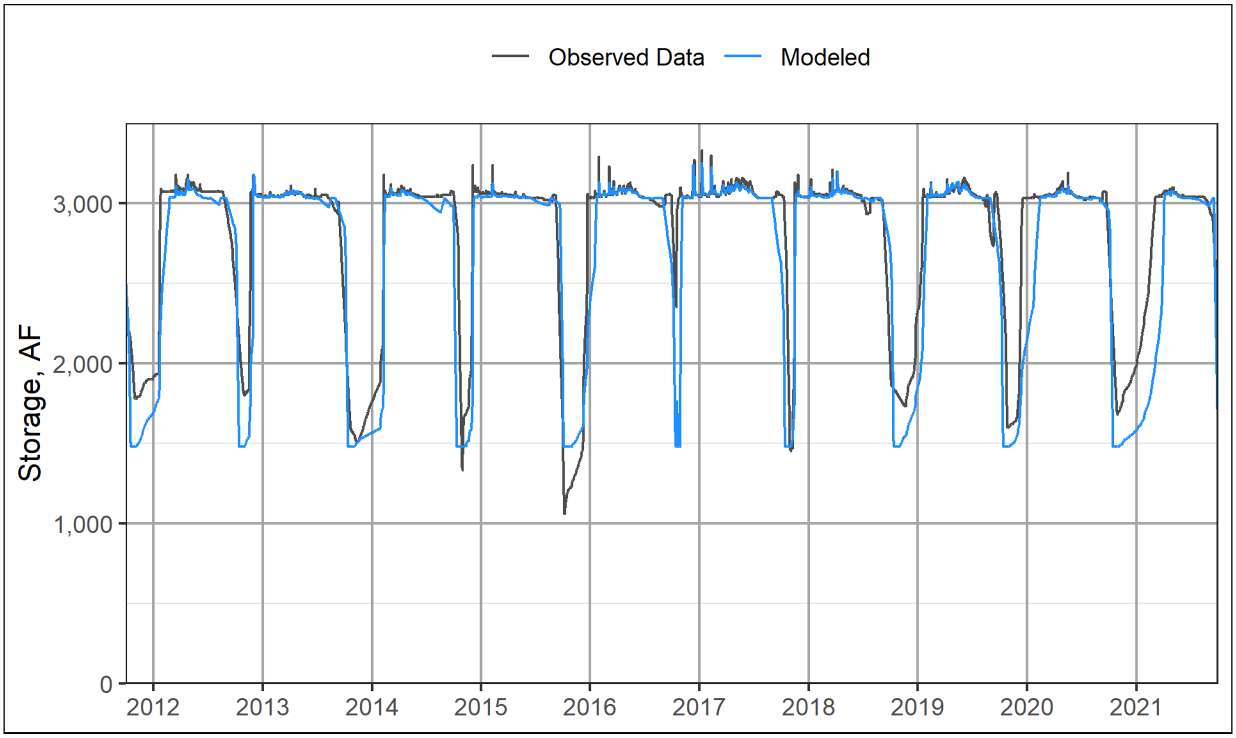

Figure C-6. Sawmill Lake Storage, Water Years 2012–2021

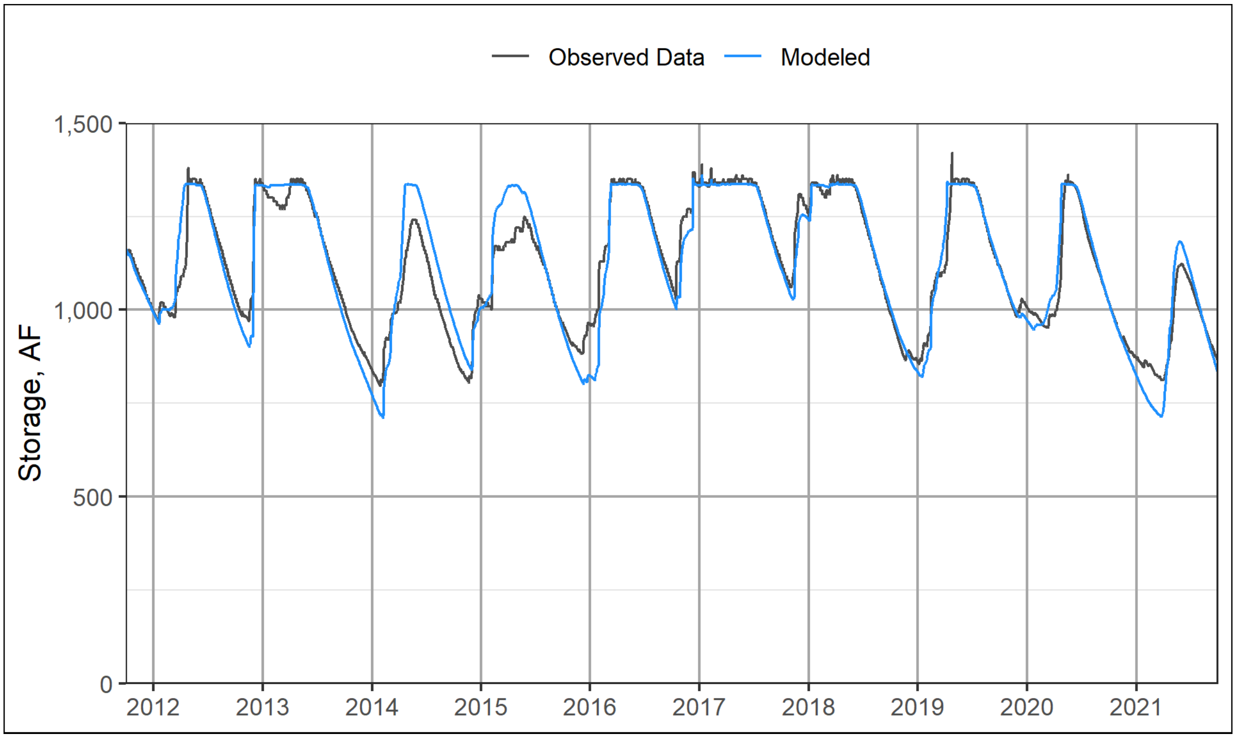

Figure C-7. Jackson Lake Storage, Water Years 2012–2021

Daily storage at Bowman Reservoir matches the recent observed data over the validation period fairly well, as shown in Figure C-8. Releases to Canyon Creek are shown in Figure C-9, and diversions to the Bowman-Spaulding Conduit are shown in Figure C-10.

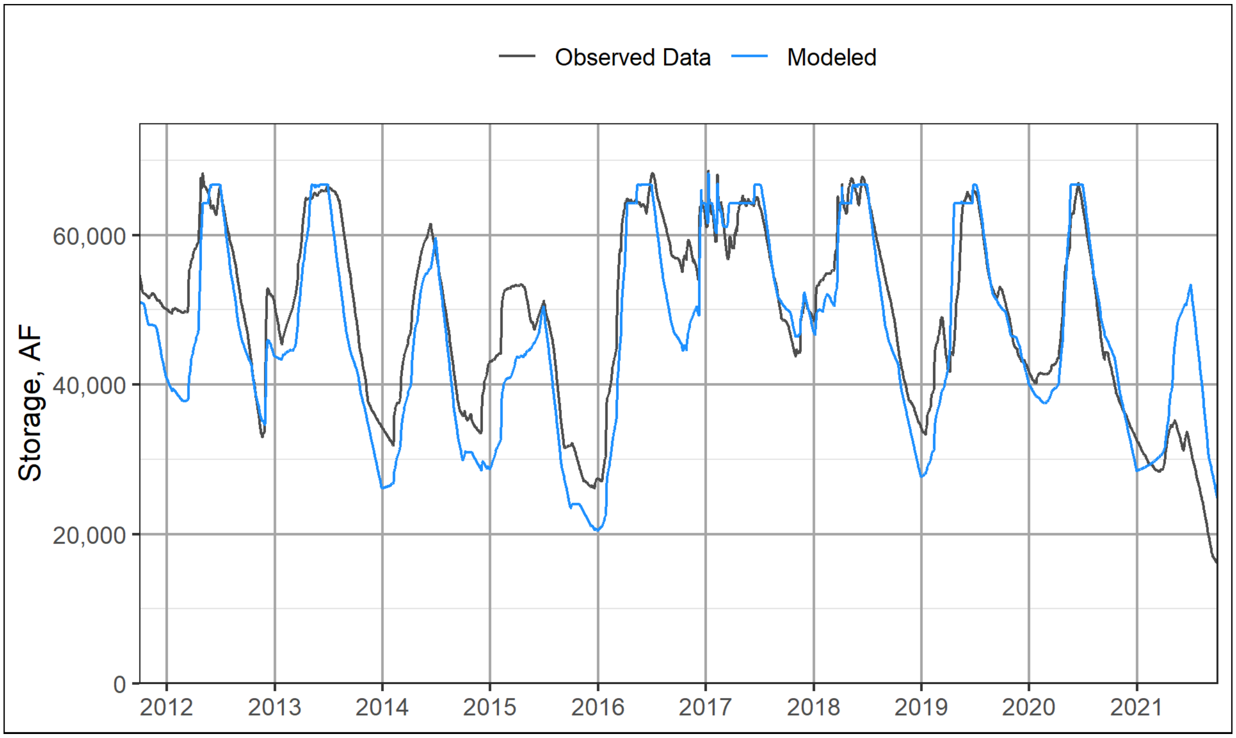

Figure C-8. Bowman Reservoir Storage, Water Years 2012–2021

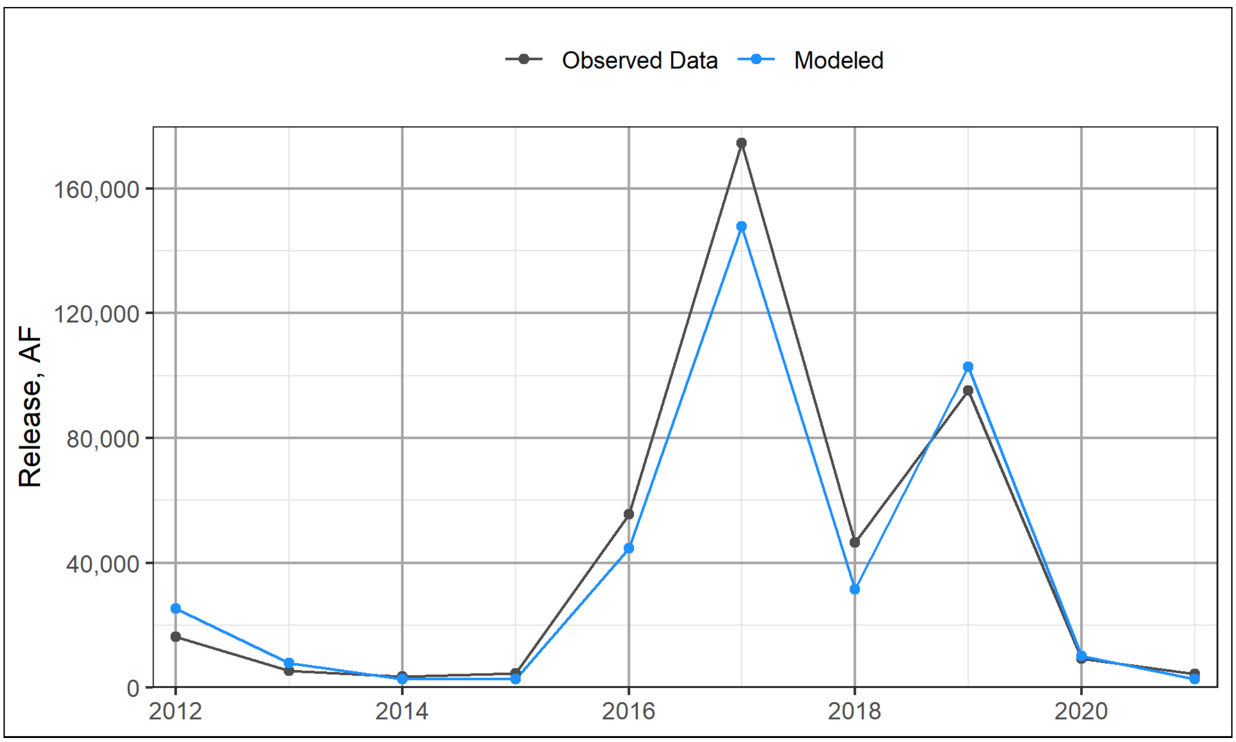

Figure C-9. Bowman Reservoir releases to Canyon Creek, Water Years 2012–2021

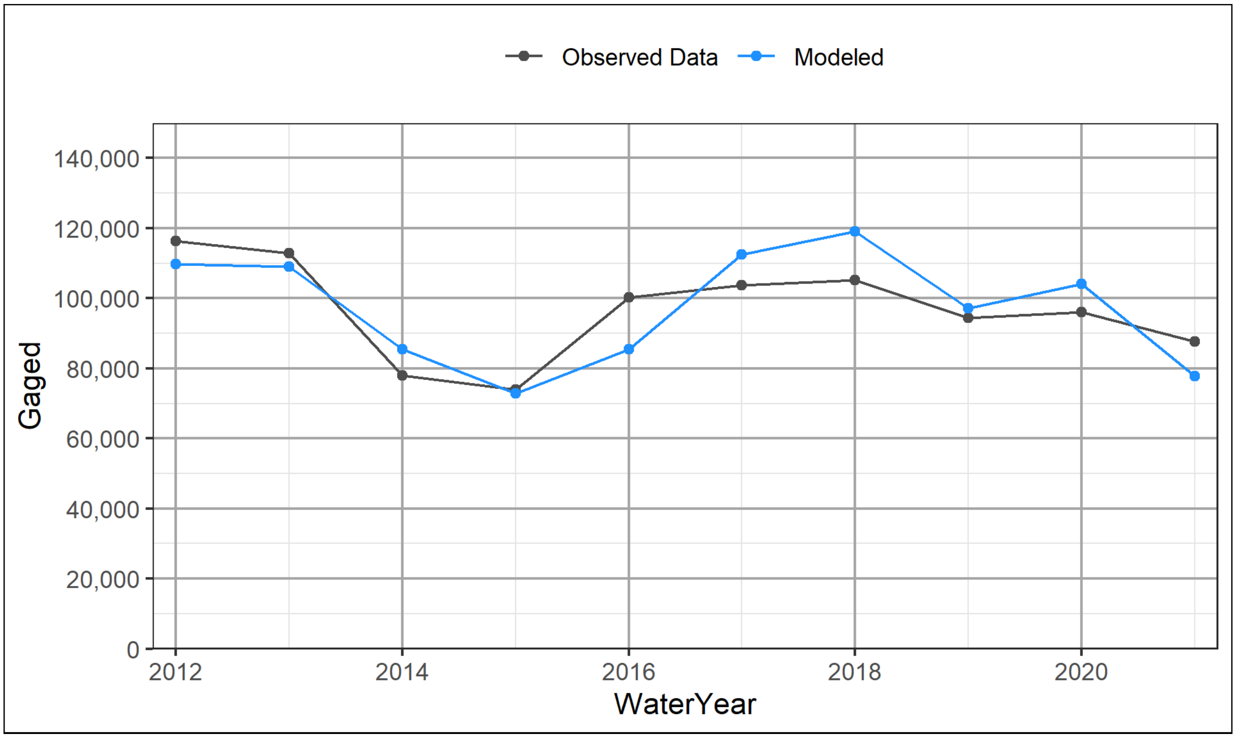

Figure C-10. Bowman Reservoir Diversions to Bowman-Spaulding Conduit, Water Years 2012–2021

C.3. Texas Fall Creeks

C.3.1. PG&E Reservoirs

Many PG&E Reservoirs upstream of the diversions along the Bowman-Spaulding conduit on the collection of streams referred to as the Texas-Fall Creeks are not gauged throughout the year or are not gauged at all. Comparisons to historical observed data are shown where possible. Most reservoirs match the observed data reasonably well, with the exception of Blue Lake. The simple nature of Blue Lake operations, in which the lake only releases discretionary water in wet years and can go 10 years between discretionary releases, suggests that the storage discrepancy is due to the unimpaired hydrology and not reservoir operations. Blue Lake has a very small watershed area, and its unimpaired hydrology could be affected by precision in its estimation parameters.

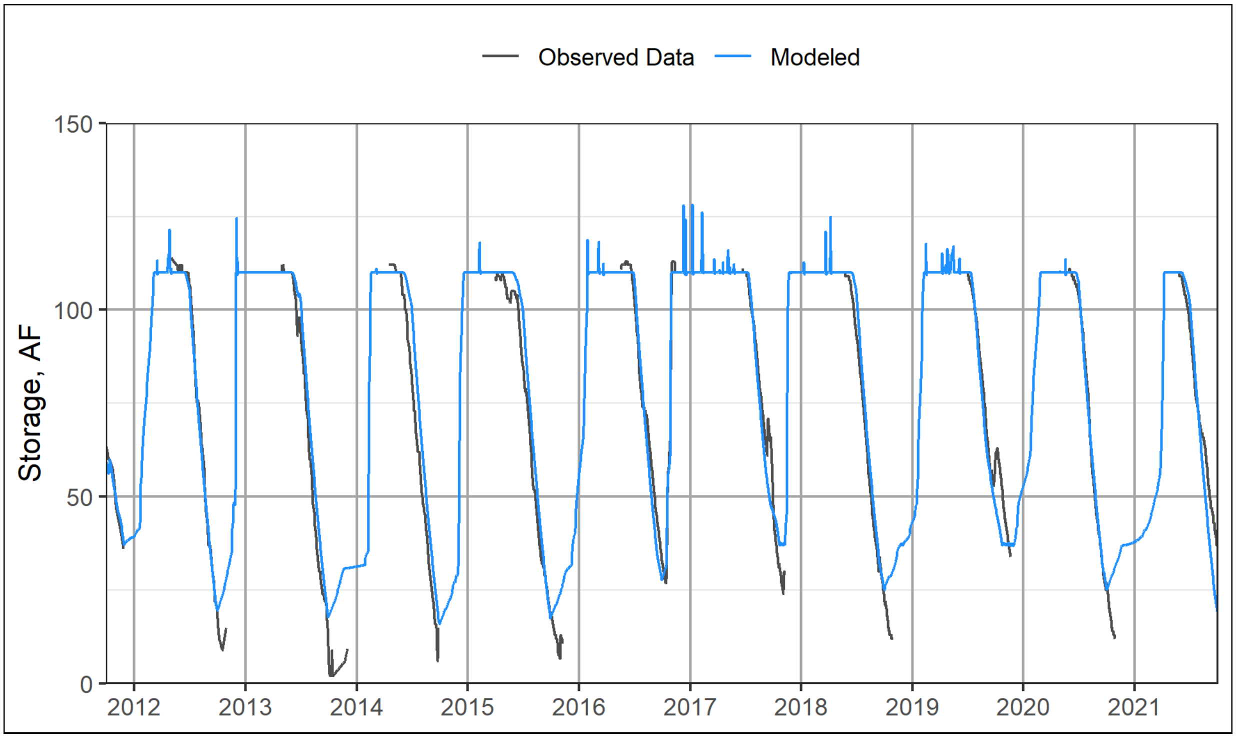

Figure C-11. Middle Lindsey Lake Storage, Water Years 2012–2021

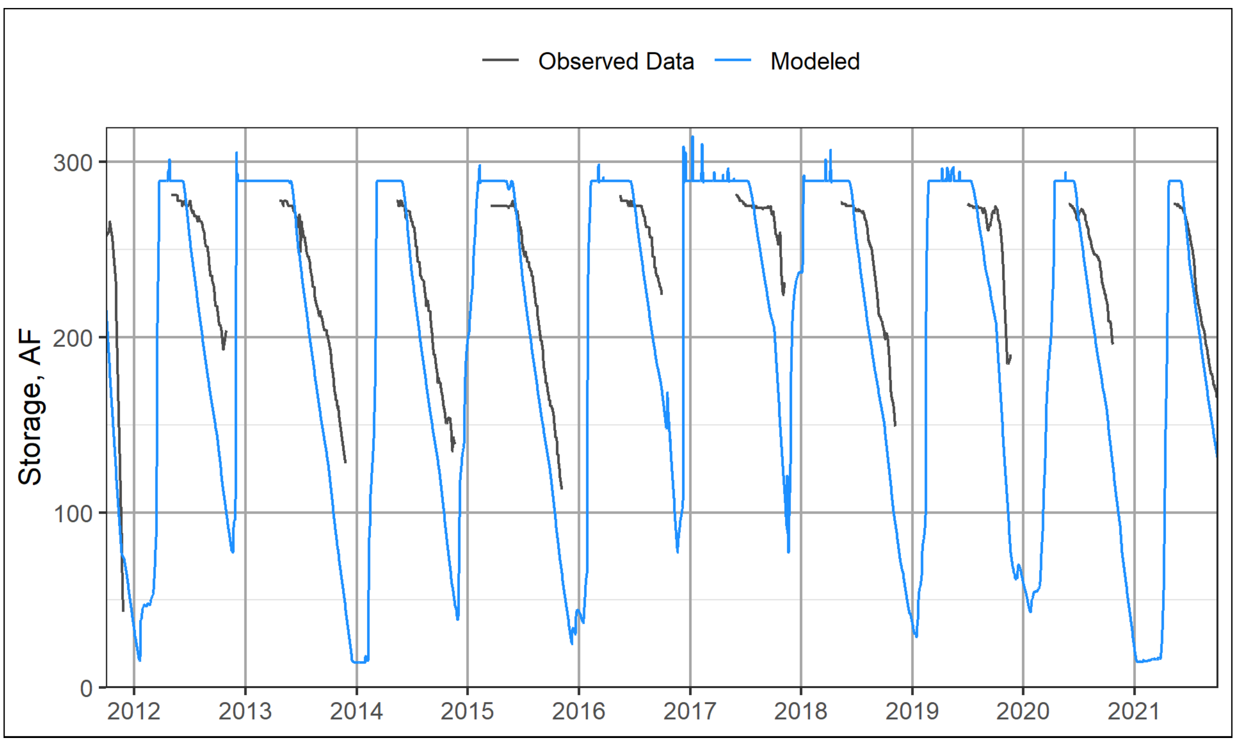

Figure C-12. Lower Lindsey Lake Storage, Water Years 2012–2021

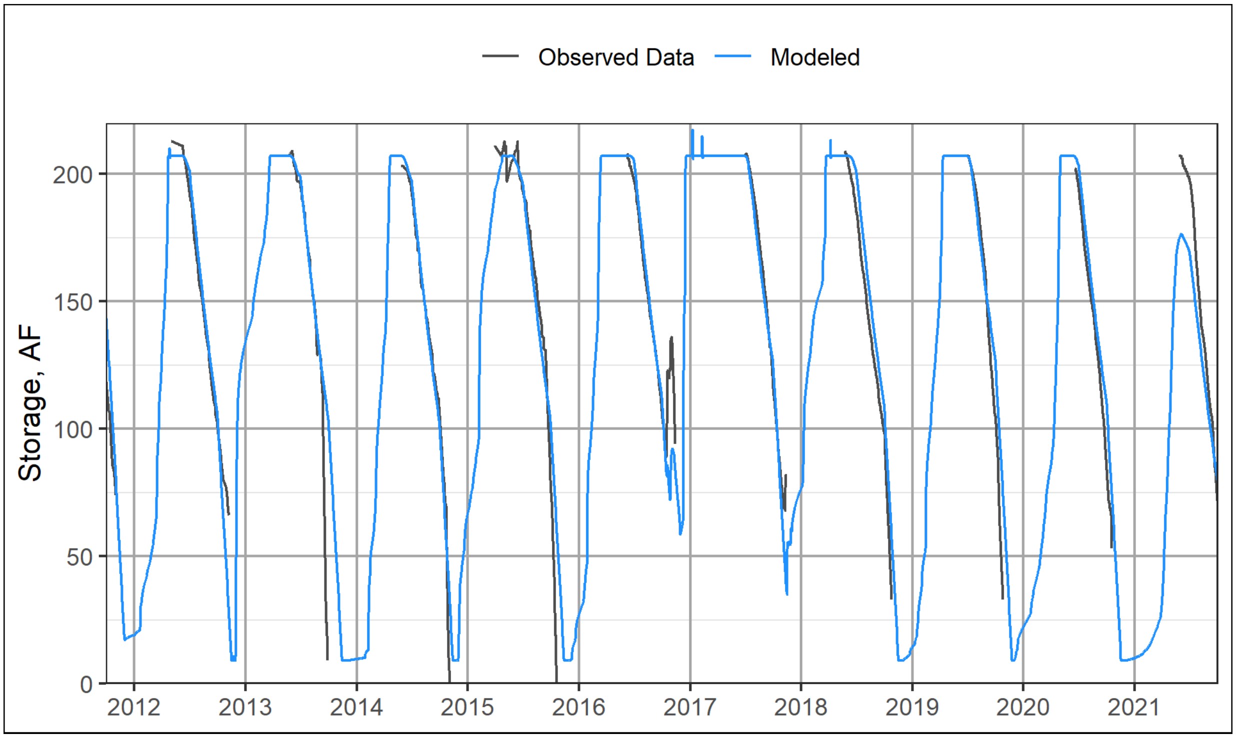

Figure C-13. Upper Rock Lake Storage, Water Years 2012–2021

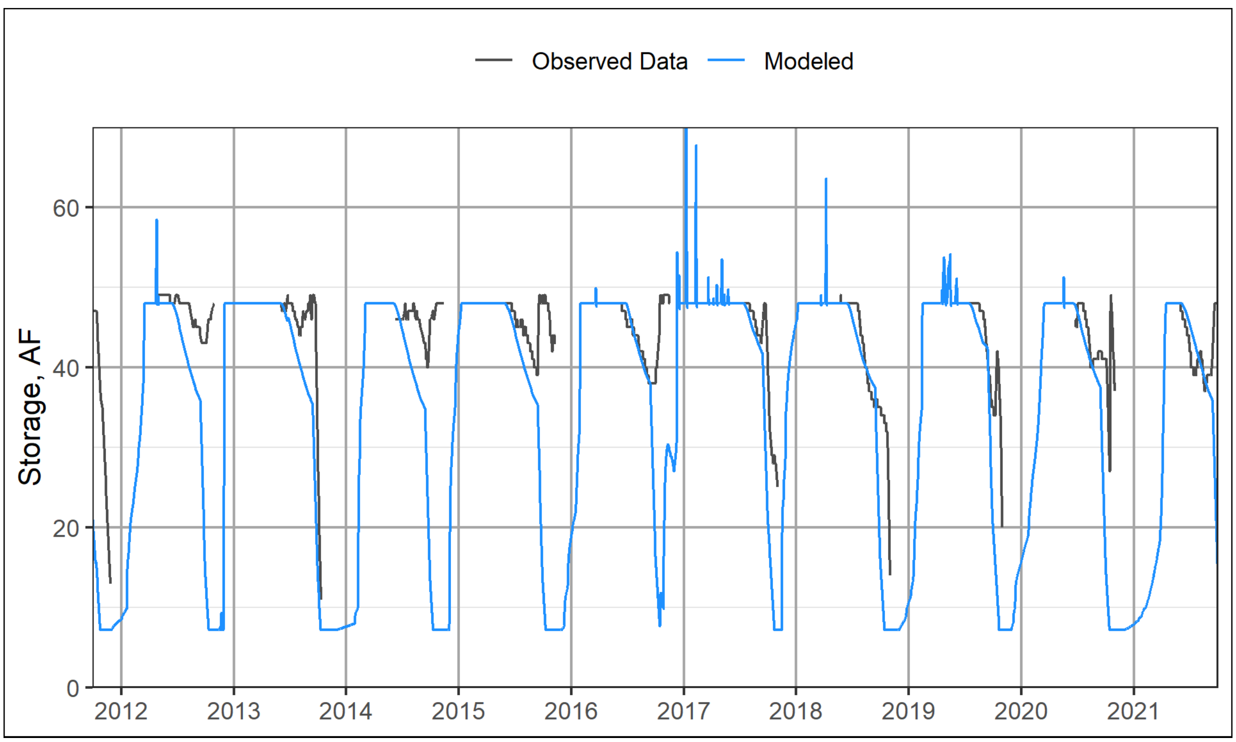

Figure C-14. Lower Rock Lake Storage, Water Years 2012–2021

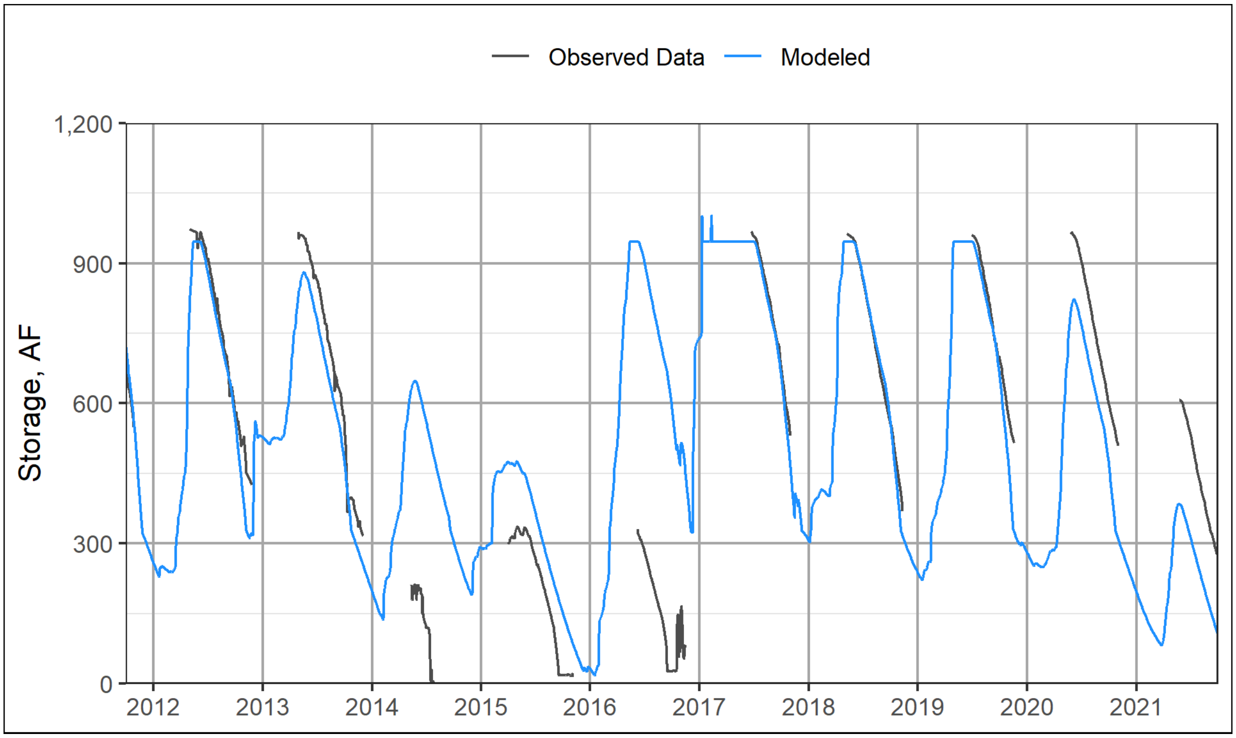

Figure C-15. Culbertson Lake Storage, Water Years 2012–2021

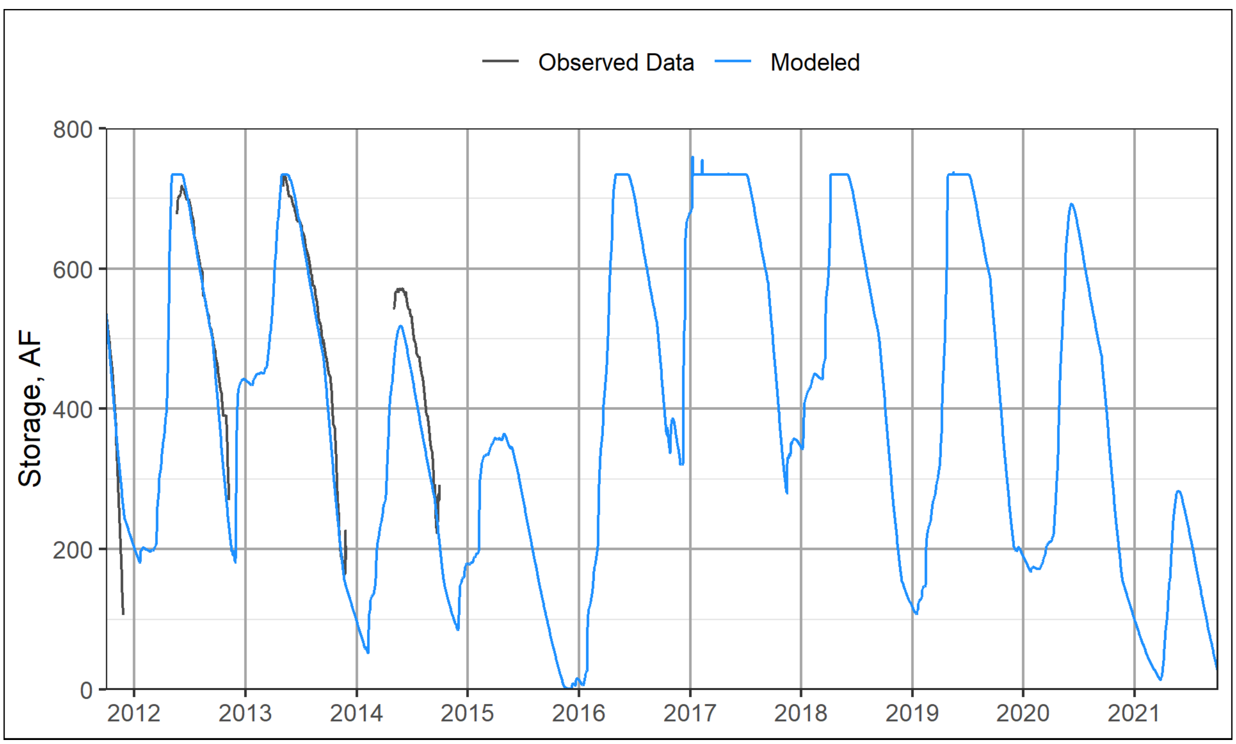

Figure C-16. Feely Lake Storage, Water Years 2012–2021

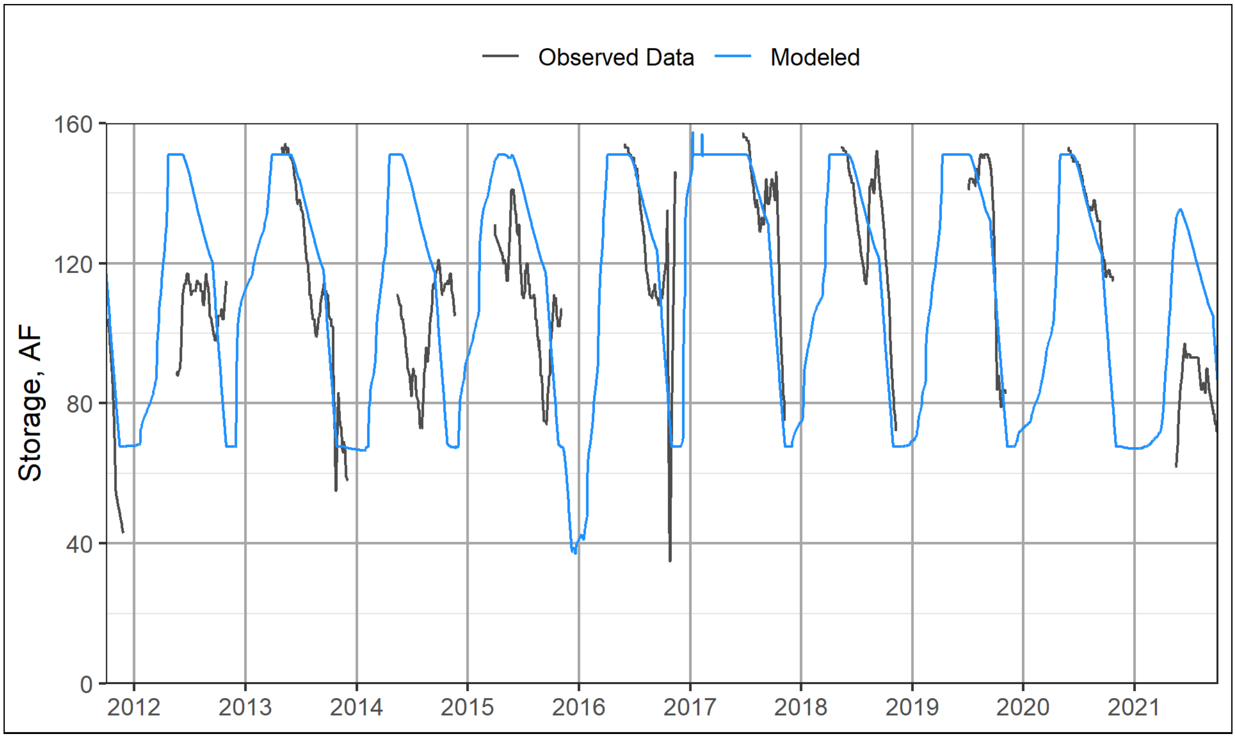

Figure C-17. Carr Lake Storage, Water Years 2012–2021

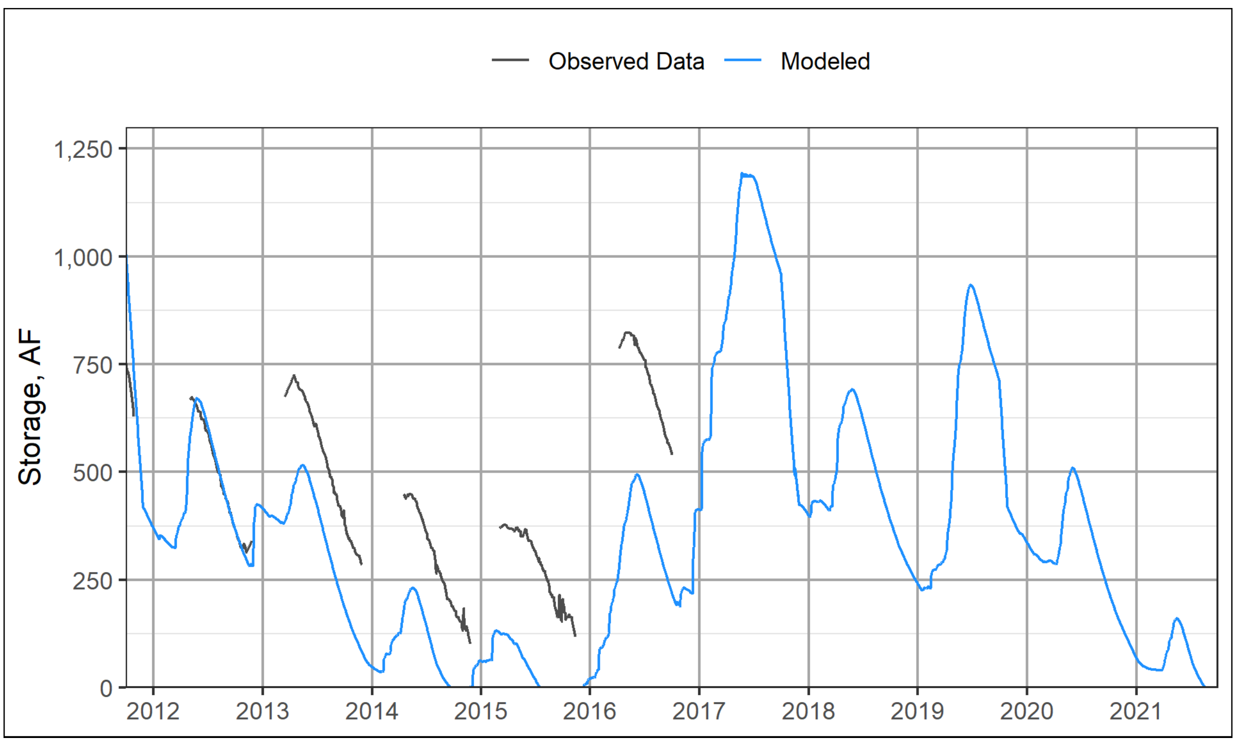

Figure C-18. Blue Lake Storage, Water Years 2012–2021

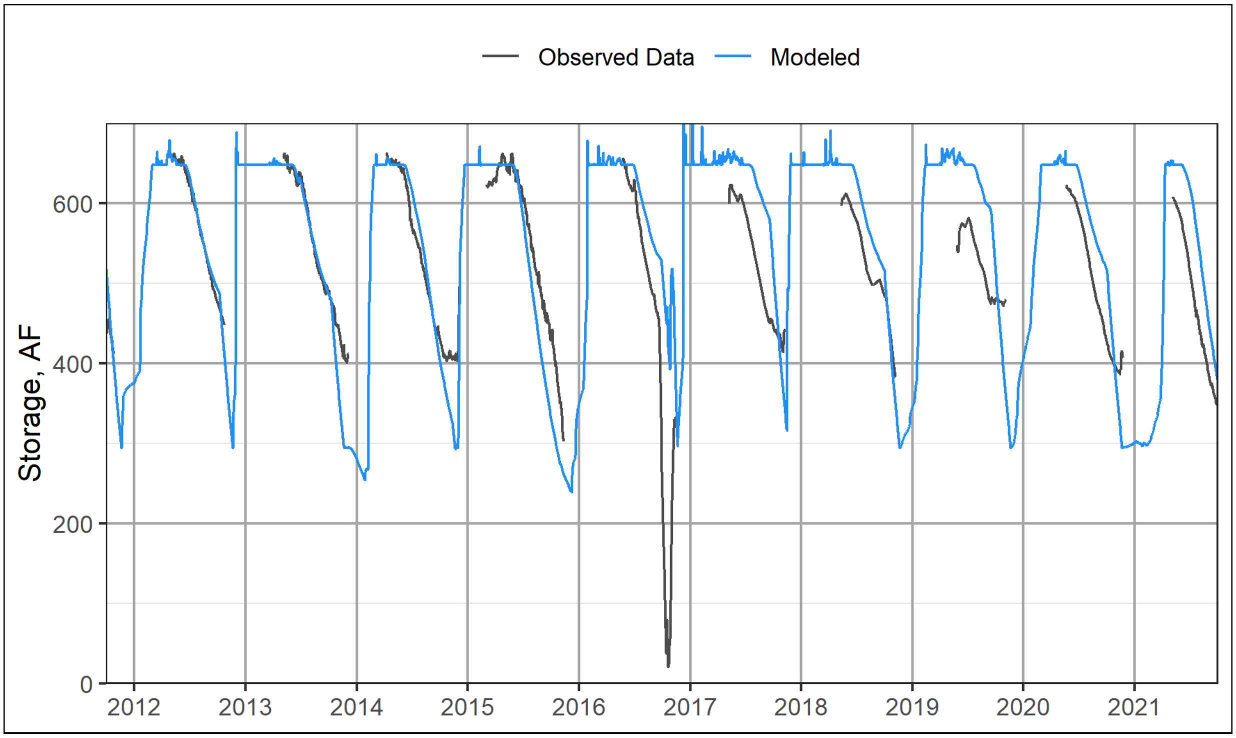

Figure C-19. Rucker Lake Storage, Water Years 2012–2021

Fuller Lake does not have available observed storage, but the reservoir must generally be kept full to maintain head on Spaulding PH No 3.

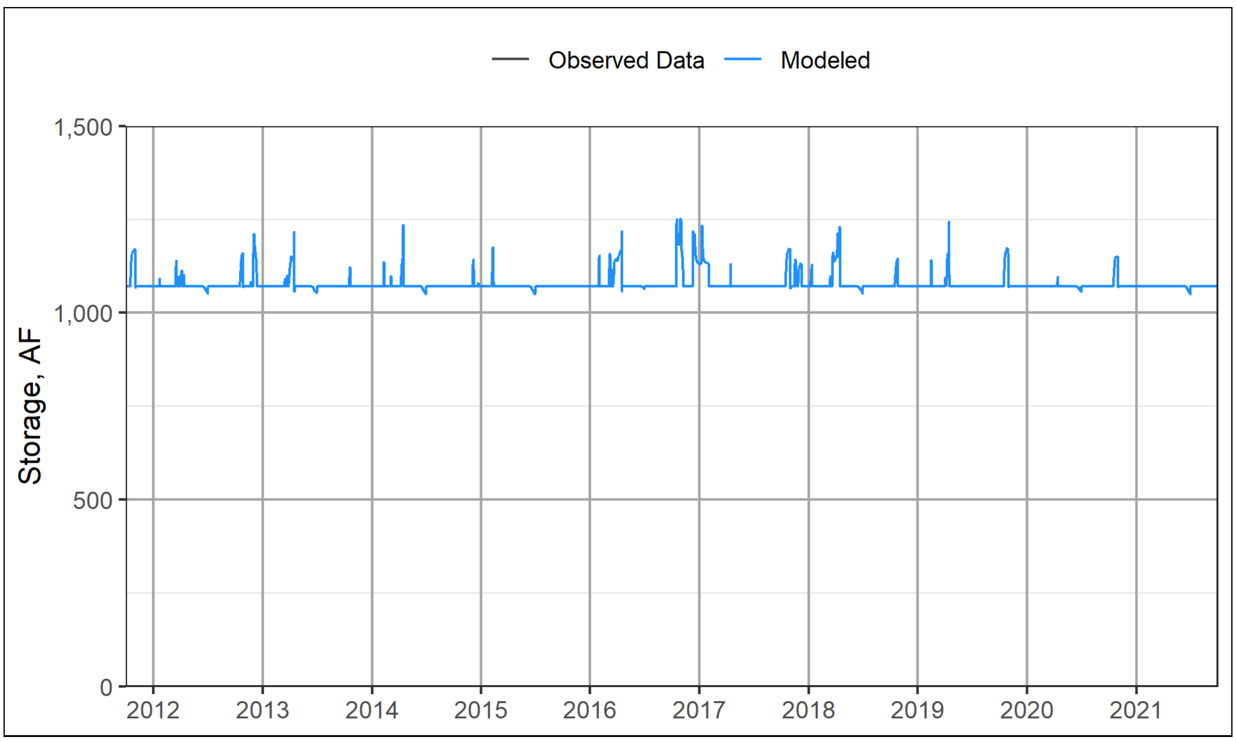

Figure C-20. Fuller Lake Storage, Water Years 2012–2021

C.3.2. Spaulding Powerhouse No. 3

Annual diversions into Spaulding at the end of the Bowman-Spaulding Conduit through Spaulding Powerhouse No 3 are shown in Figure C-21 and Figure C-22.

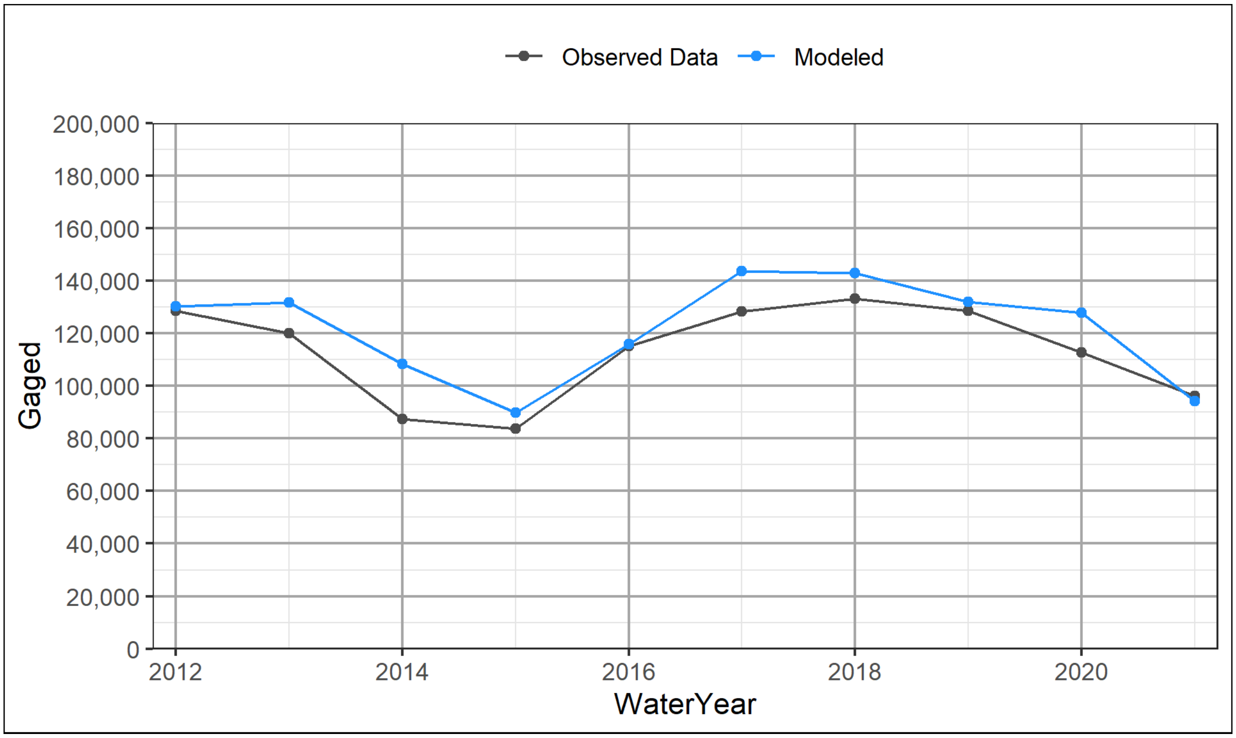

Figure C-21. Annual Flows through Spaulding Powerhouse No. 3, Water Years 2012–2021

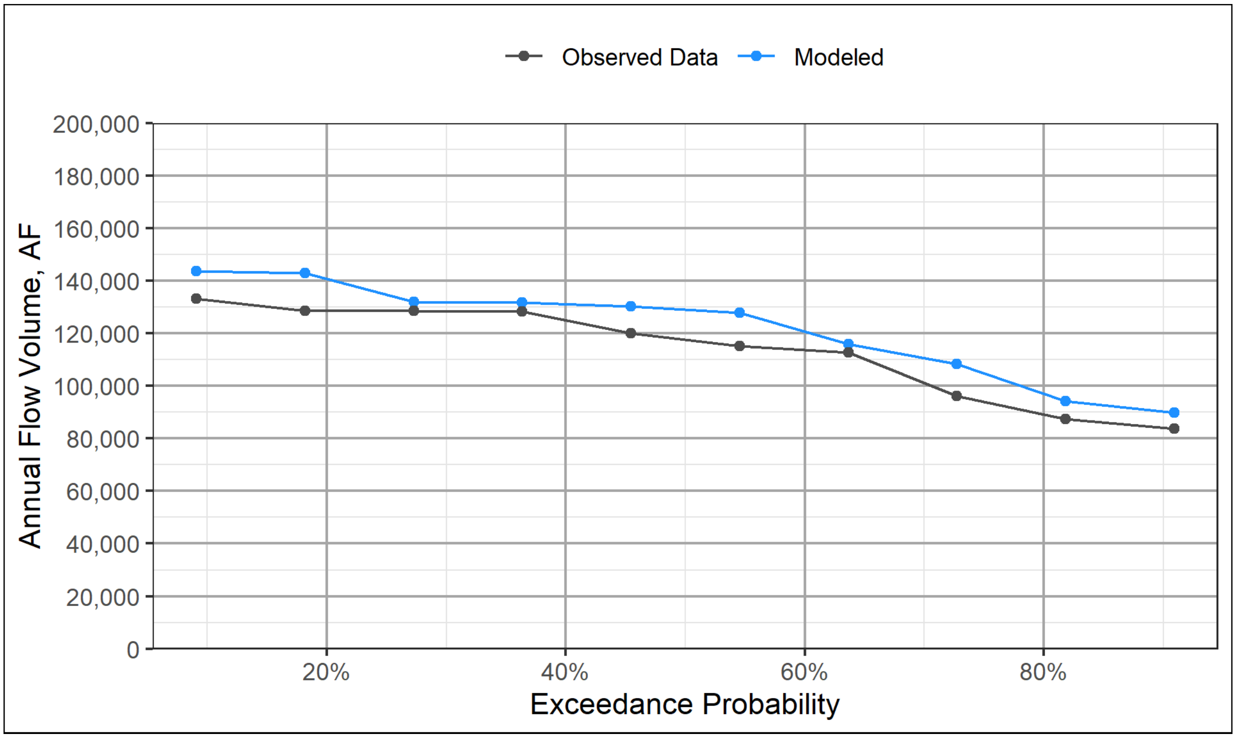

Figure C-22. Annual Flow Exceedance through Spaulding Powerhouse No. 3, Water Years 2012–2021

C.4. South Yuba River

C.4.1. Upstream of Fordyce Lake

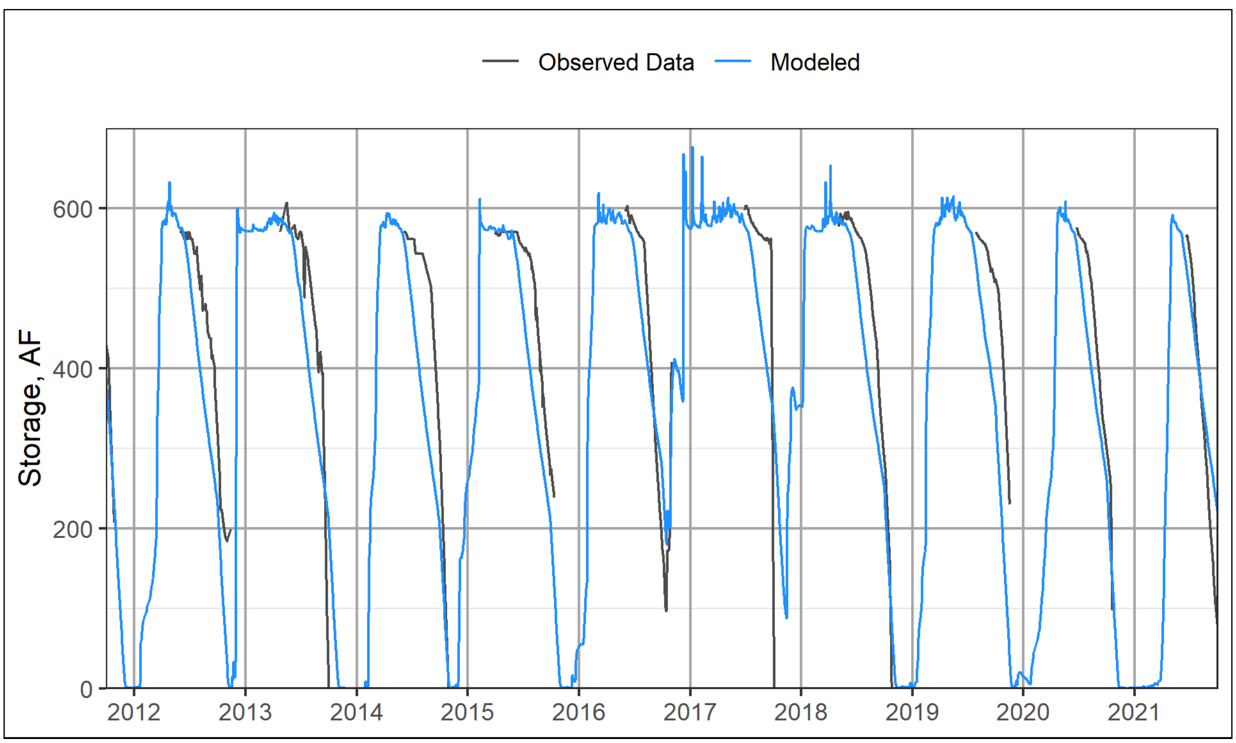

Figure C-23. White Rock Lake Storage, Water Years 2012–2021

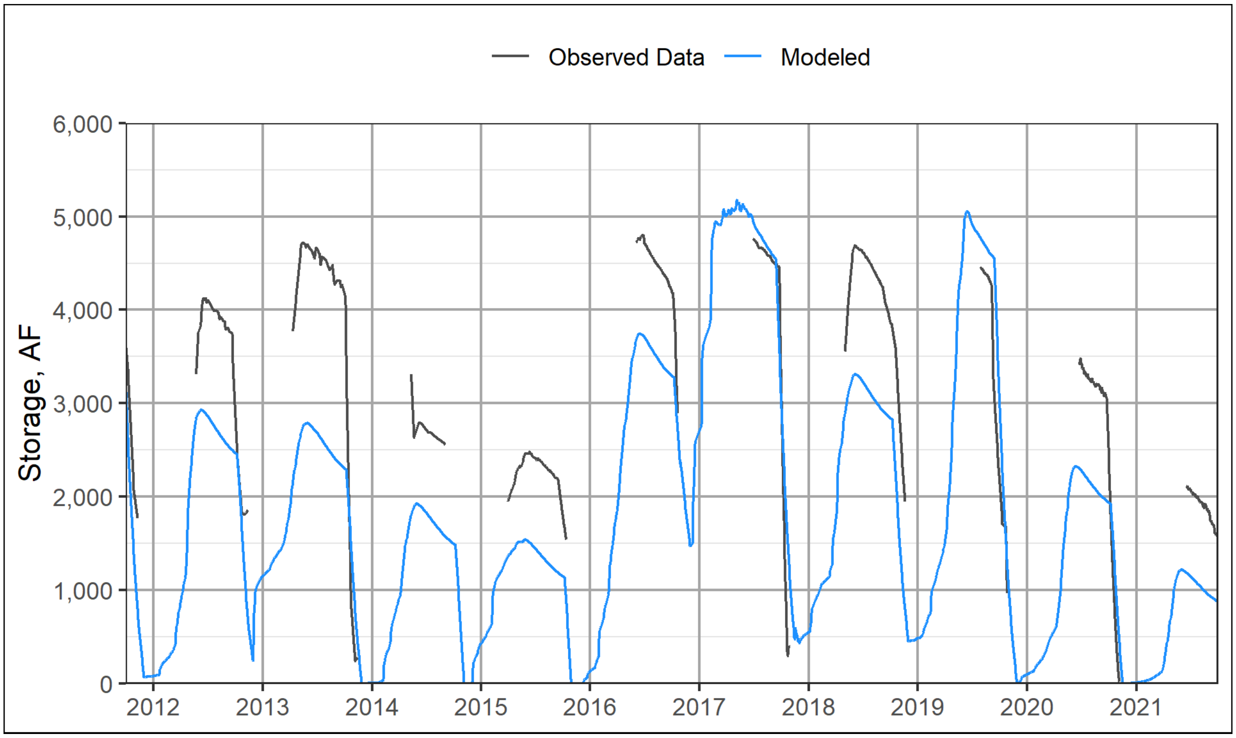

Figure C-24. Meadow Lake Storage, Water Years 2012–2021

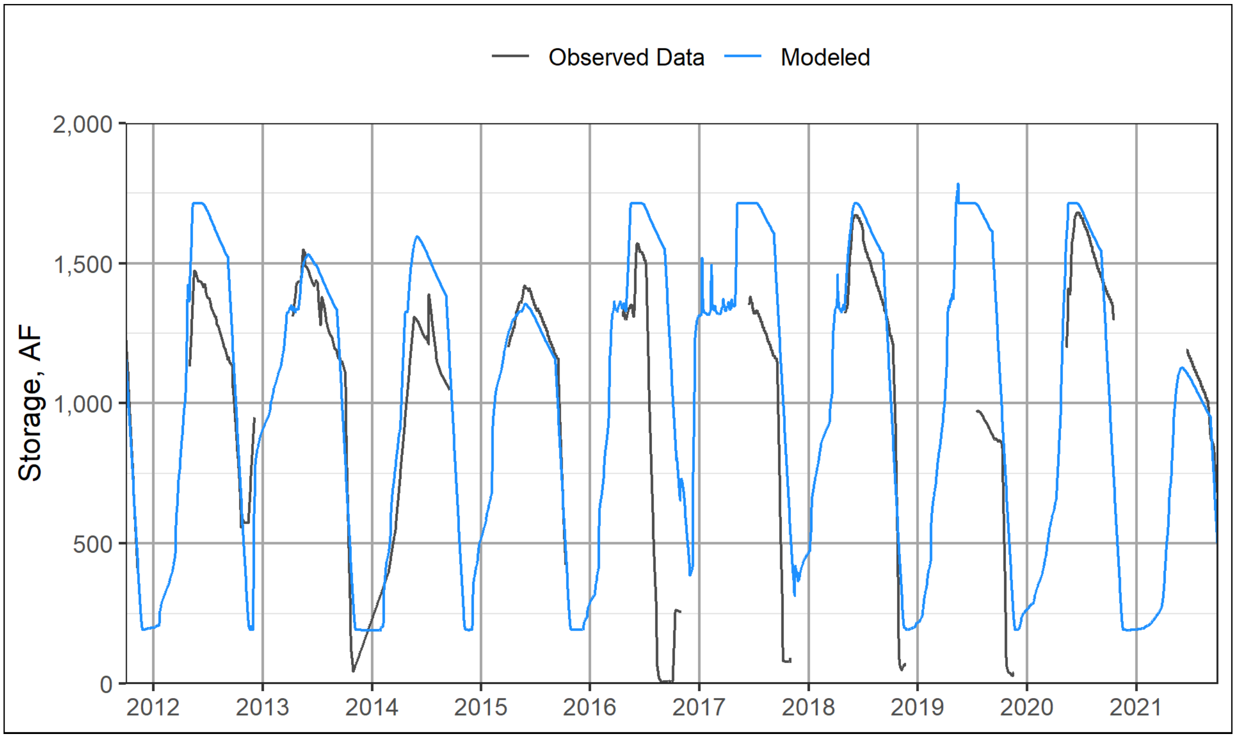

Figure C-25. Lake Sterling Storage, Water Years 2012–2021

C.4.2. Fordyce Lake

Fordyce Lake Operations are difficult to capture. Historical carryover ranges from 4–20 TAF, with no consistency regarding year type. Reservoir fill levels generally match observed values with the notable exception of 2021.

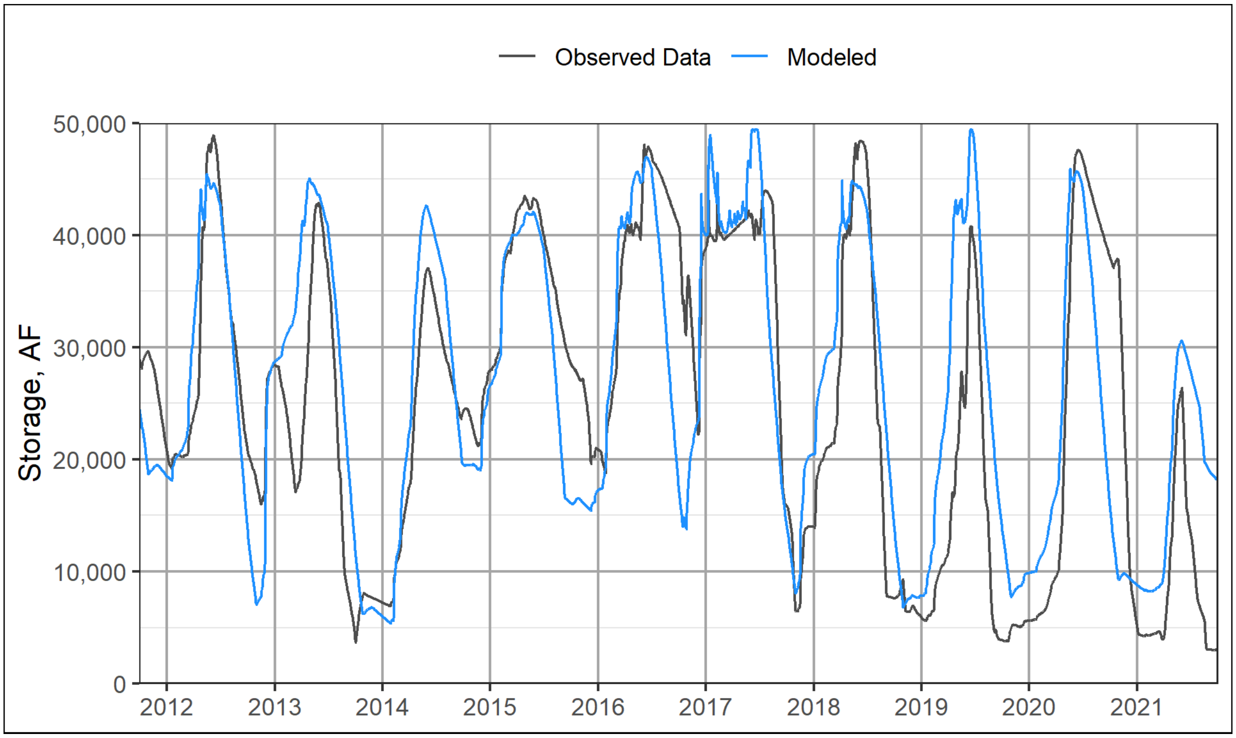

Figure C-26. Fordyce Lake Storage, Water Years 2012–2021

C.4.3. Lake Spaulding

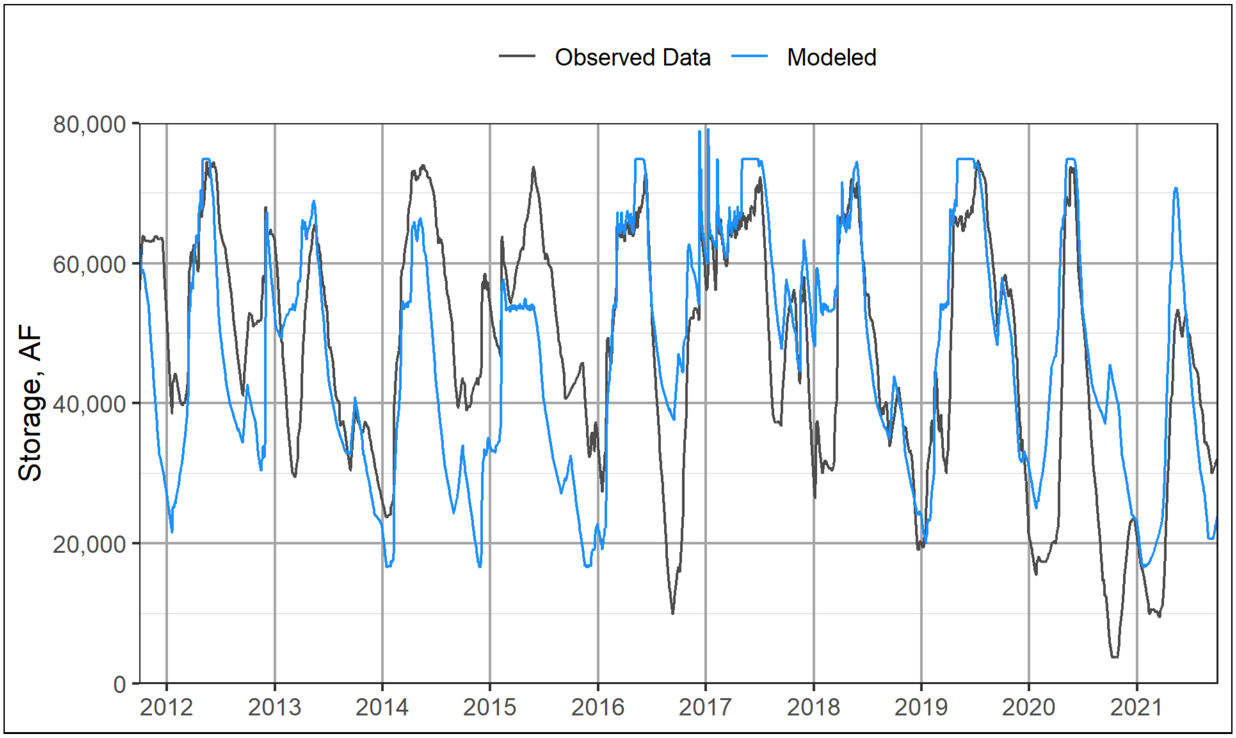

Figure C-27. Lake Spaulding Storage, Water Years 2012–2021

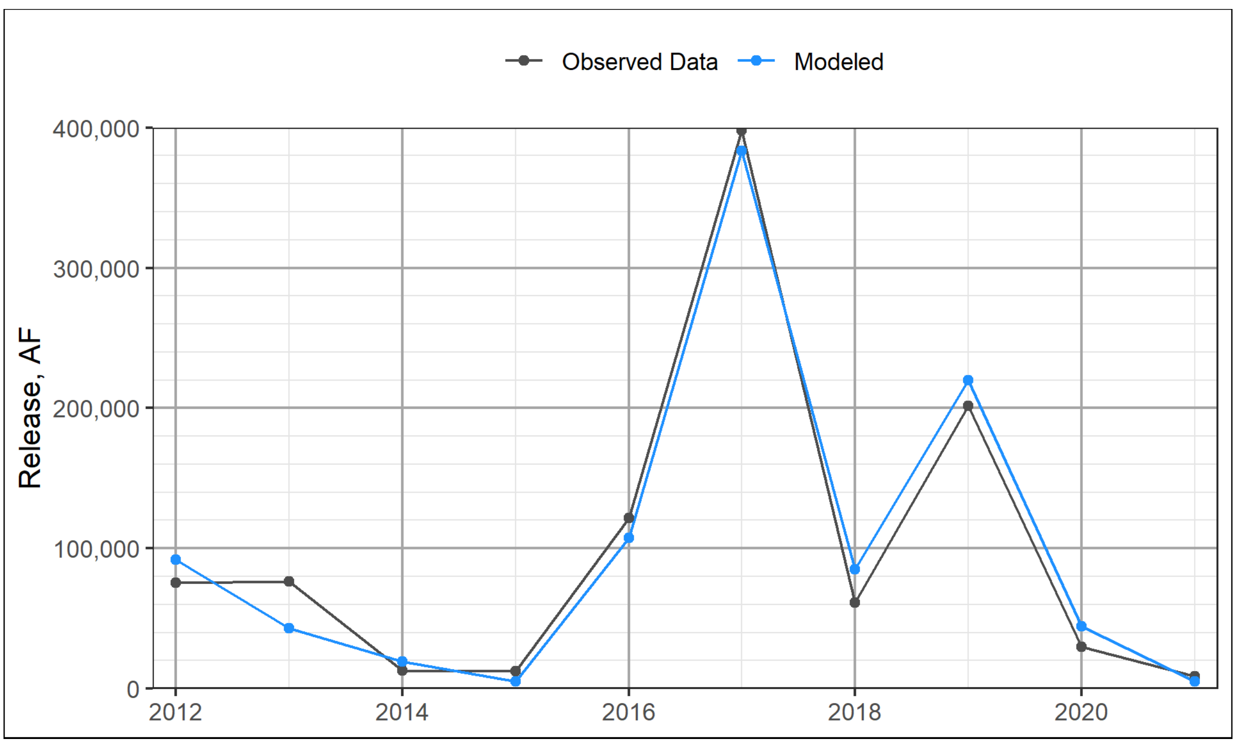

Figure C-28. Release from Lake Spaulding to South Yuba River, Water Years 2012–2021

Annual diversions into Spaulding Powerhouse No. 1 are shown in Figure C-29 and Figure C-30. Annual diversions into Spaulding Powerhouse No. 2 are shown in Figure C-31 and Figure C-32.

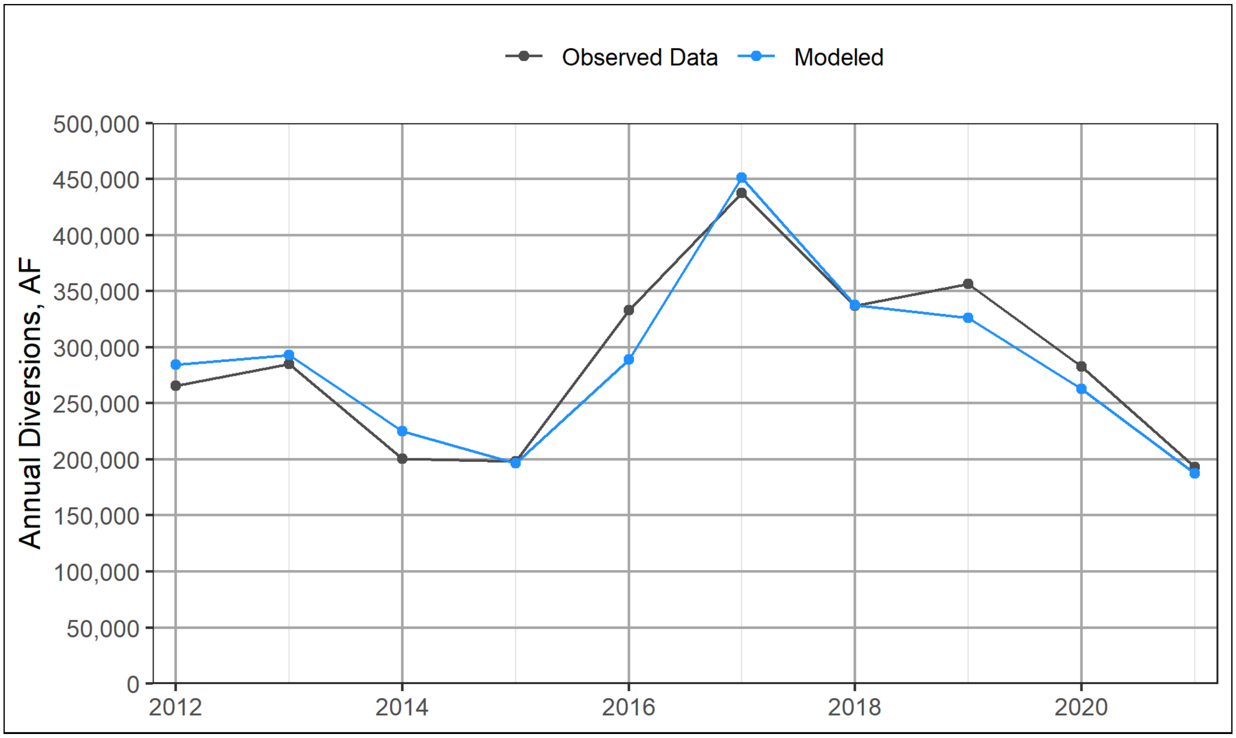

Figure C-29. Annual Flows through Spaulding Powerhouse No. 1, Water Years 2012–2021

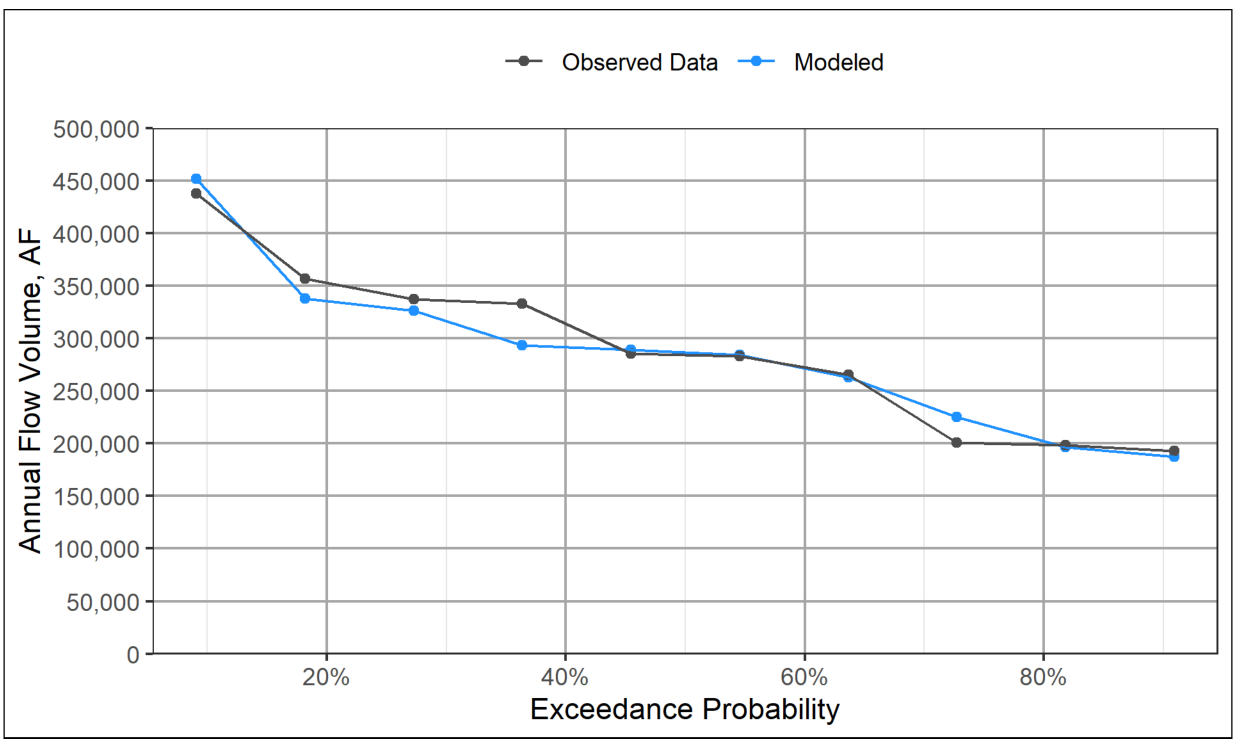

Figure C-30. Annual Flow Exceedance through Spaulding Powerhouse No. 1, Water Years 2012–2021

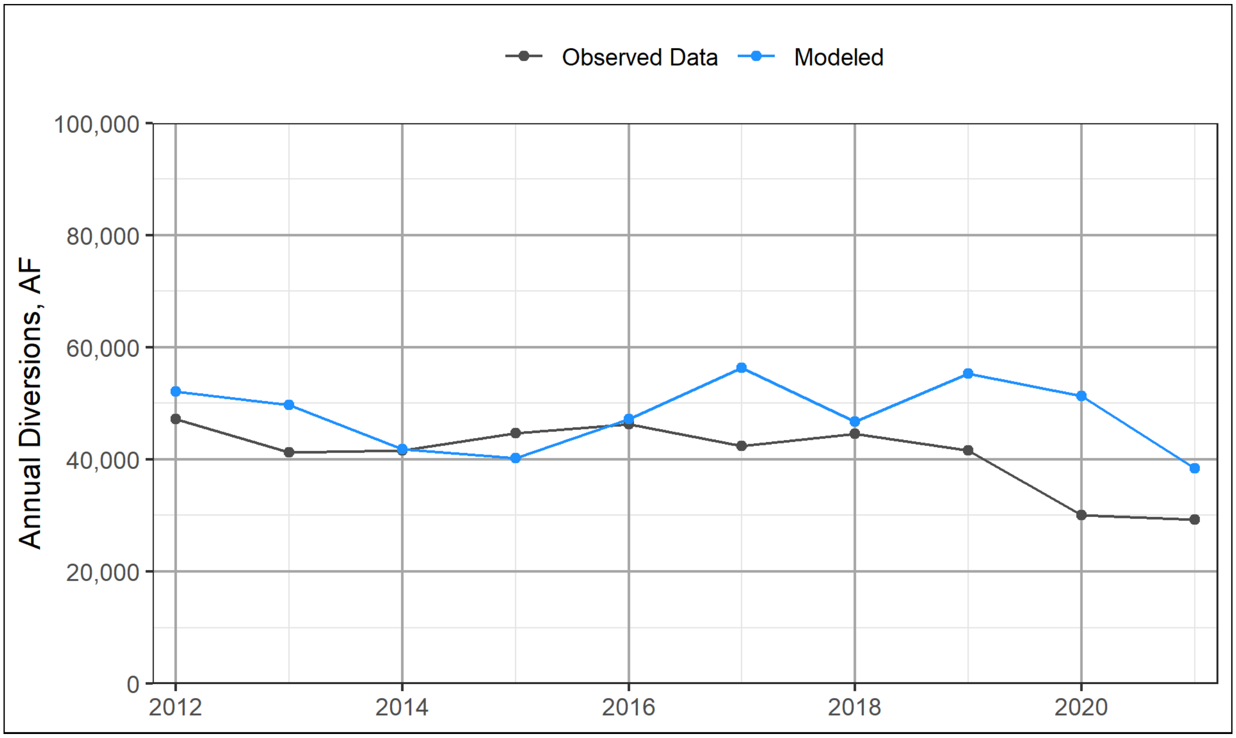

Figure C-31. Annual Flows through Spaulding Powerhouse No. 2, Water Years 2012–2021

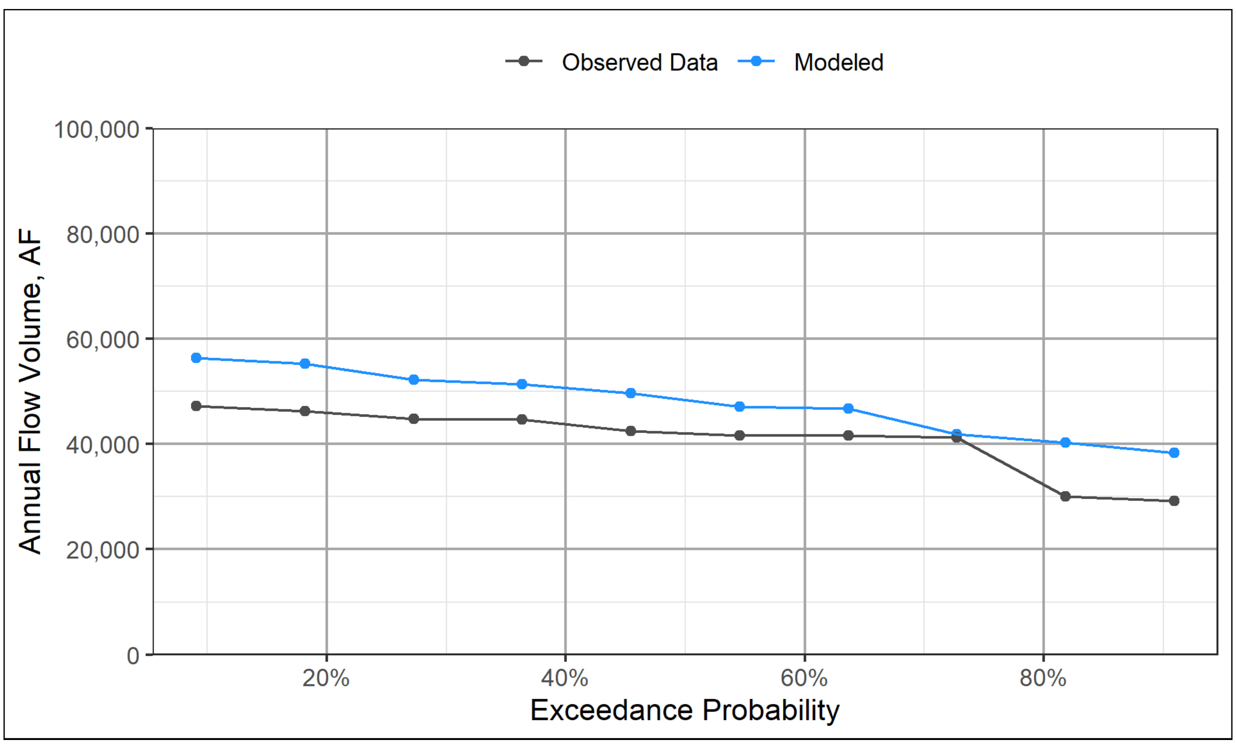

Figure C-32. Annual Flow Exceedance through Spaulding Powerhouse No. 2, Water Years 2012–2021

C.5. North Fork American River

C.5.1. Lake Valley Reservoir

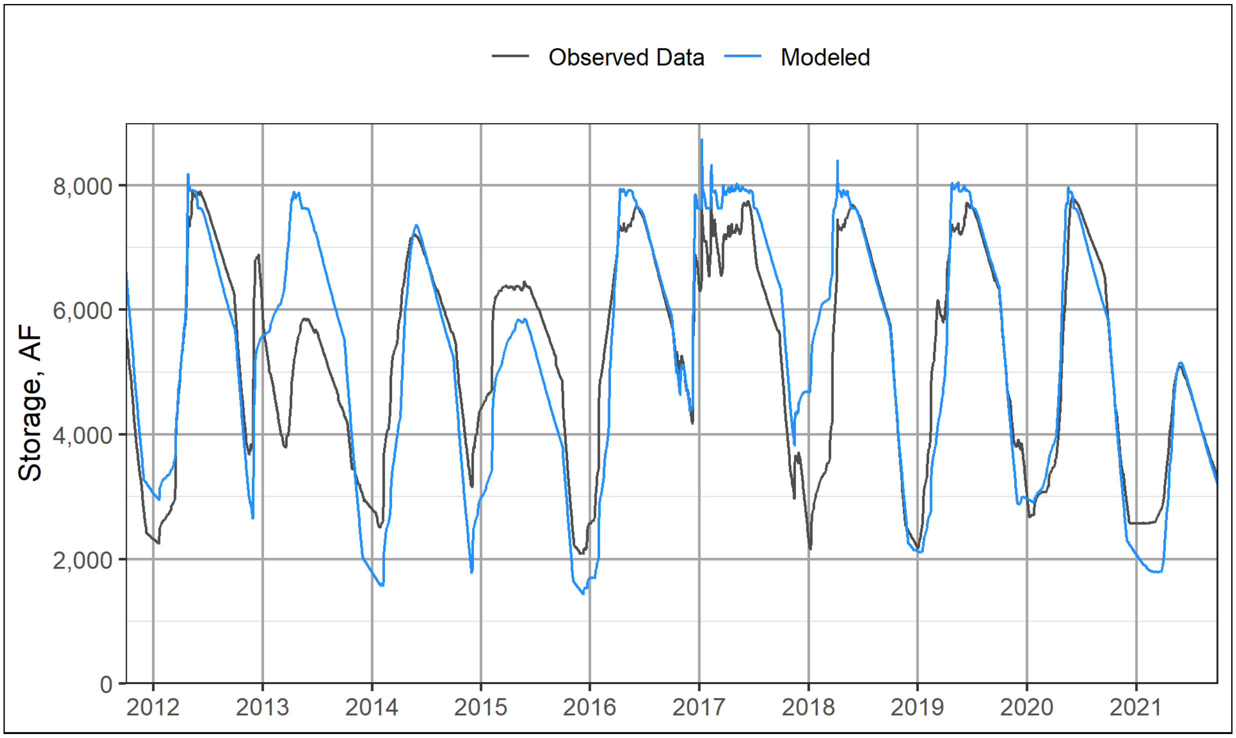

Figure C-33. Lake Valley Reservoir Storage, Water Years 2012–2021

C.5.2. Kelly Lake

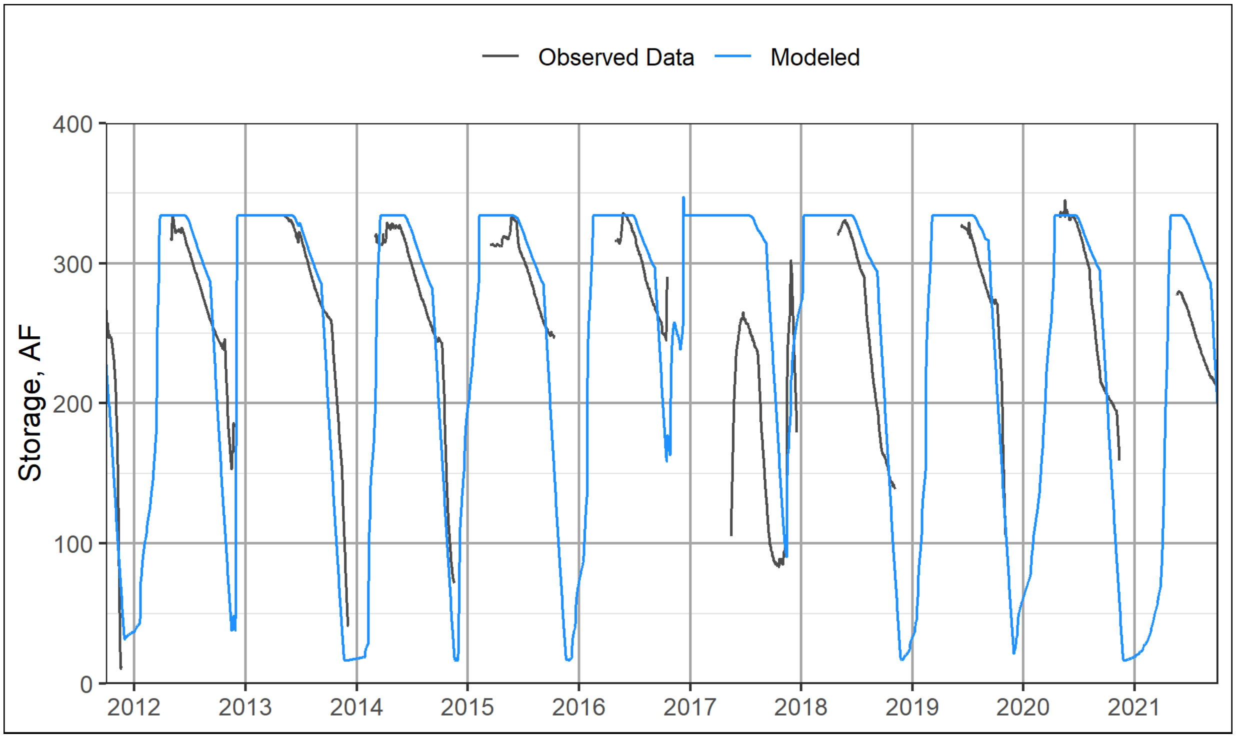

Figure C-34. Kelly Lake Storage, Water Years 2012–2021

C.5.3. Lake Valley Canal Flows

The Lake Valley Canal was piped in 2014, which resulted in a reduced capacity for the conduit. The model reflects the current capacity of the conduit and does not match flows pre-canal piping. For this reason, flows in the Lake Valley Canal are only compared for the period of water years 2015–2021.

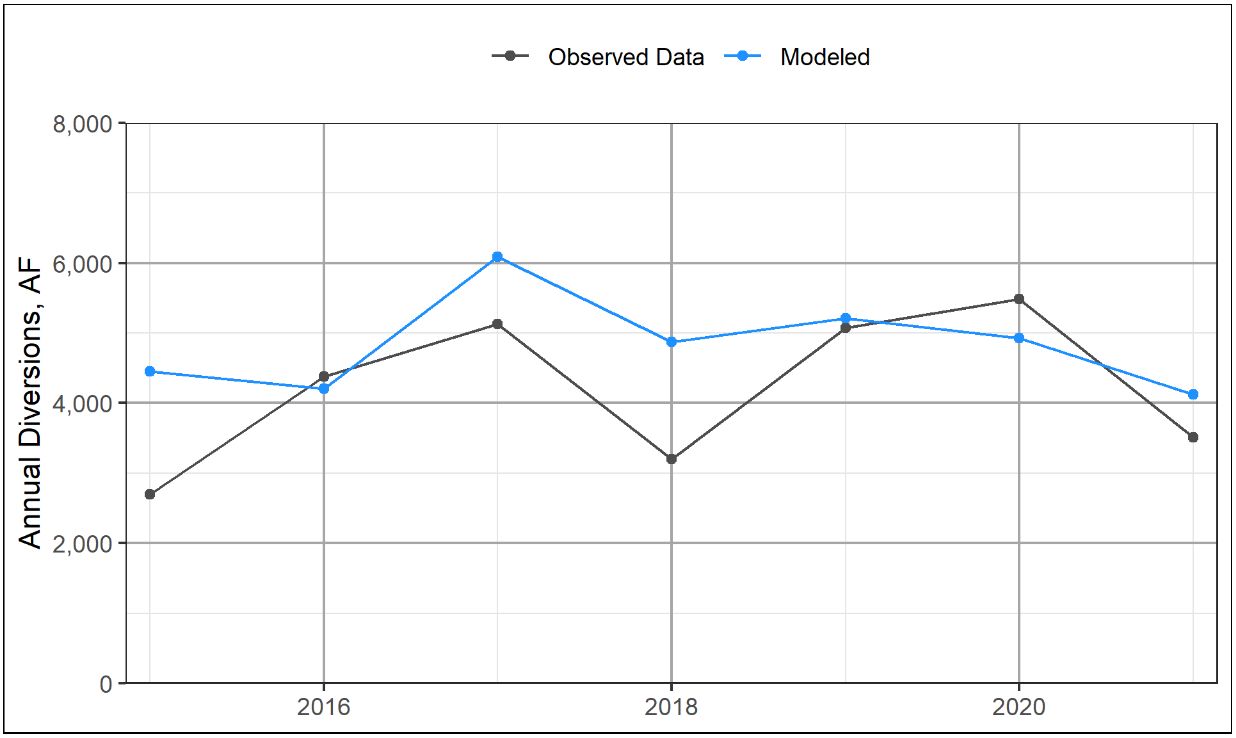

Figure C-35. Annual Diversions into Lake Valley Canal, Water Years 2015–2021

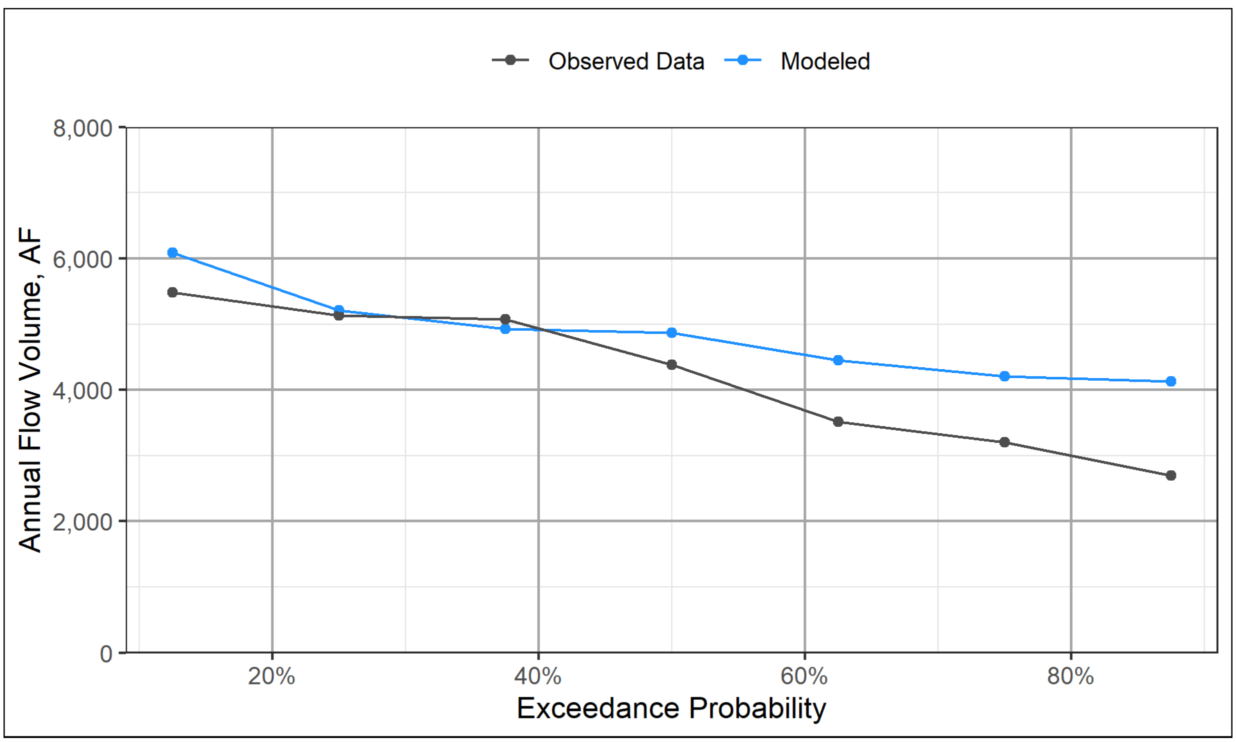

Figure C-36. Annual Diversions into Lake Valley Canal Exceedance, Water Years 2015–2021

C.5.4. Diversions from Canyon Creek into the Towle Canal

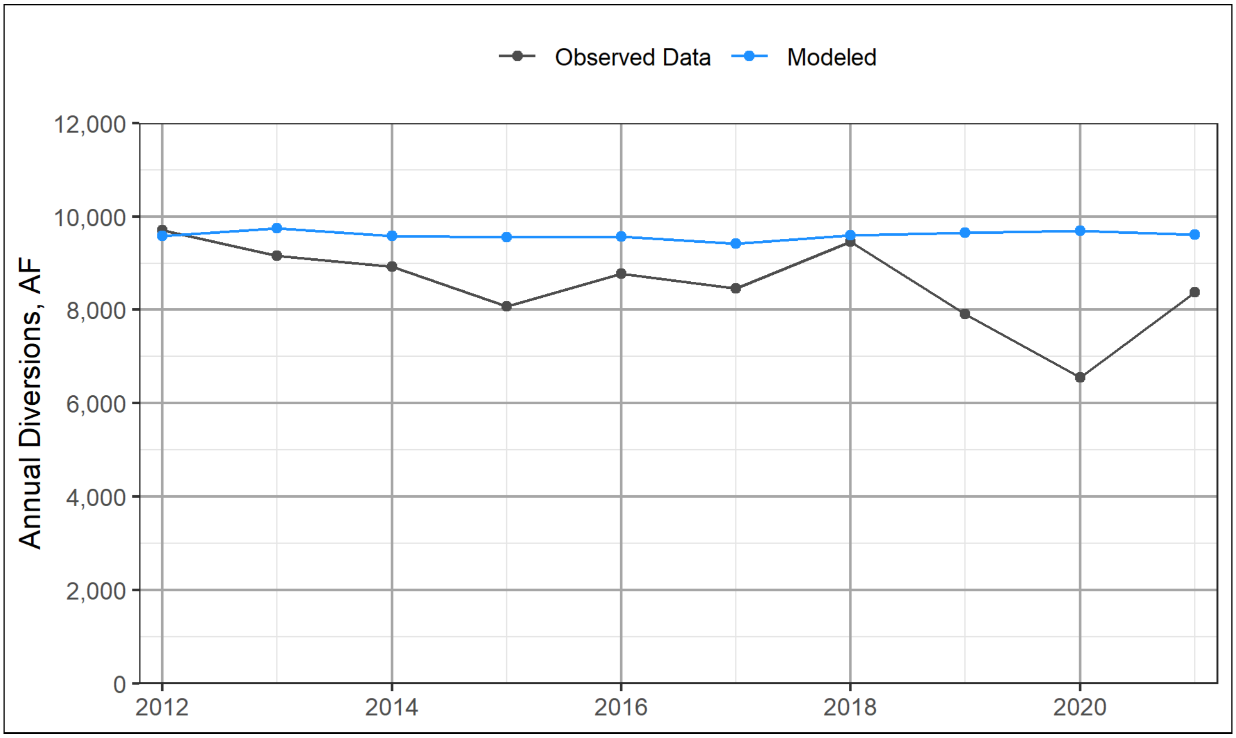

Figure C-37. Annual Diversions into Towle Canal, Water Years 2012–2021

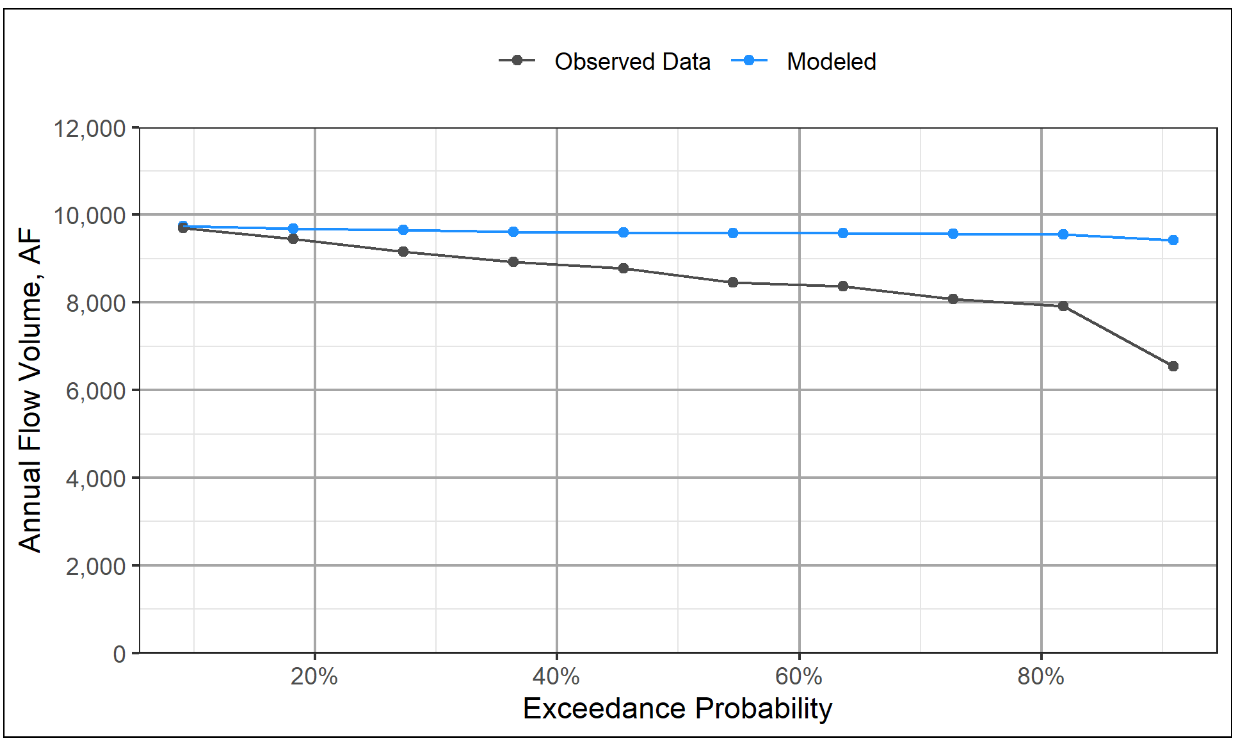

Figure C-38. Annual Diversions into Towle Canal Exceedance, Water Years 2012–2021

C.6. Bear River

C.6.1. Drum Forebay

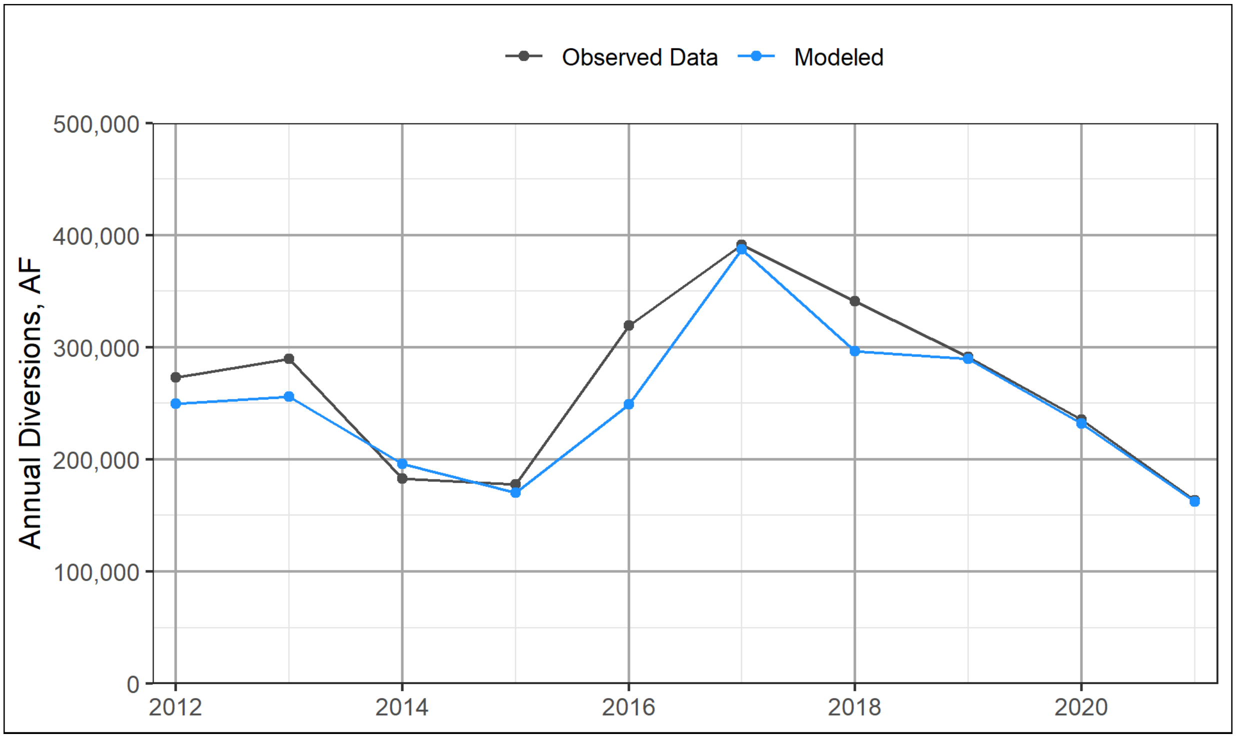

Figure C-39. Annual Flows through Combined Drum Powerhouses, Water Years 2012–2021

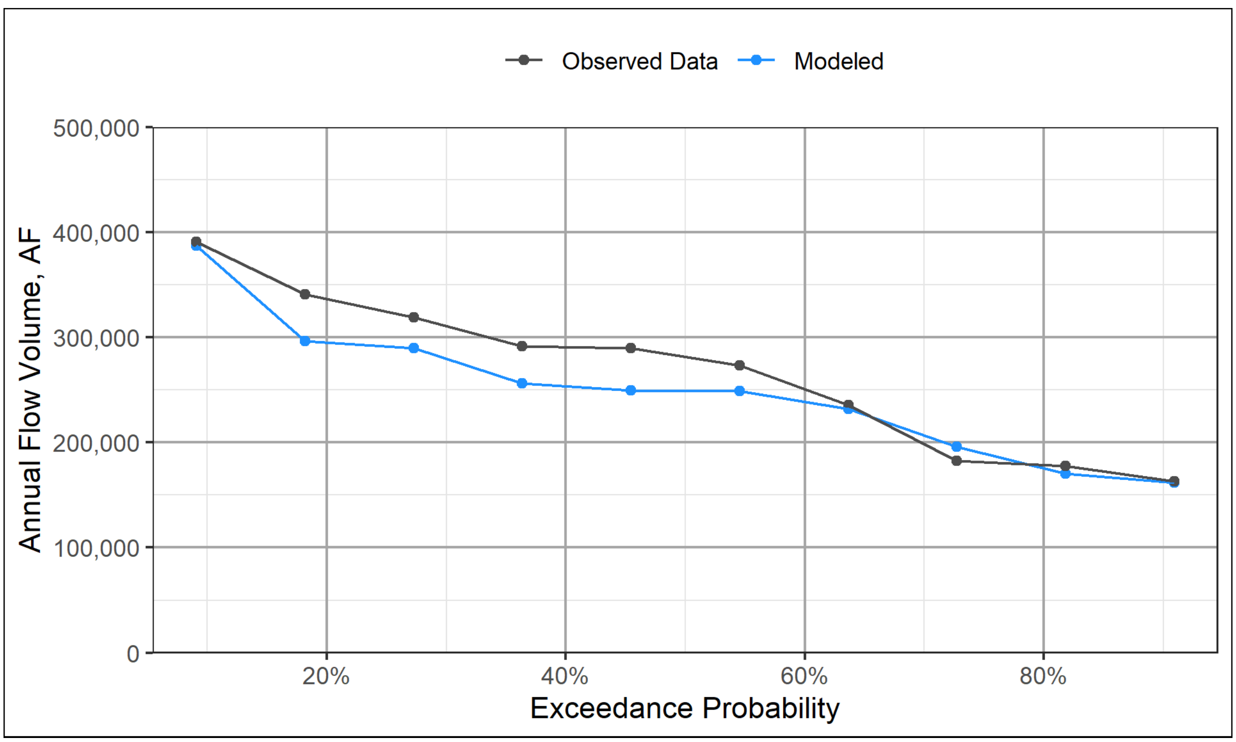

Figure C-40. Annual Flow Exceedance through Combined Drum Powerhouses, Water Years 2012–2021

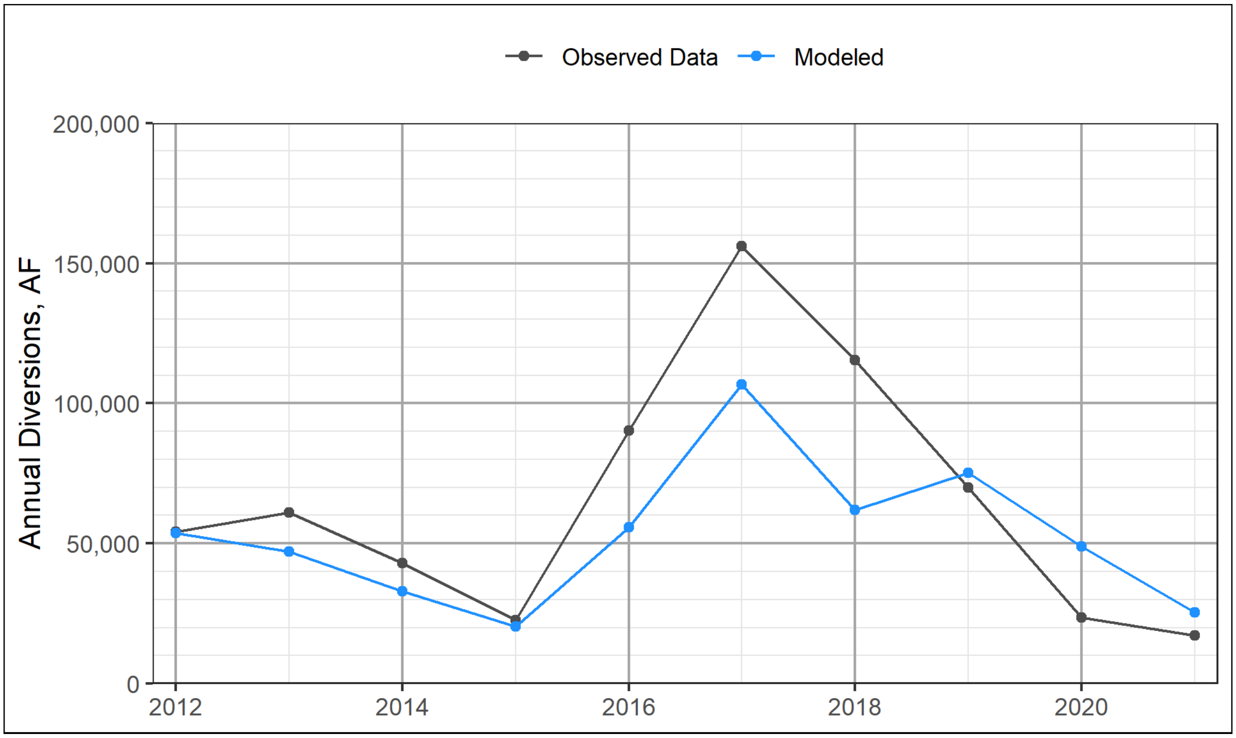

Figure C-41. Annual Flows through Drum Powerhouse No. 1, Water Years 2012–2021

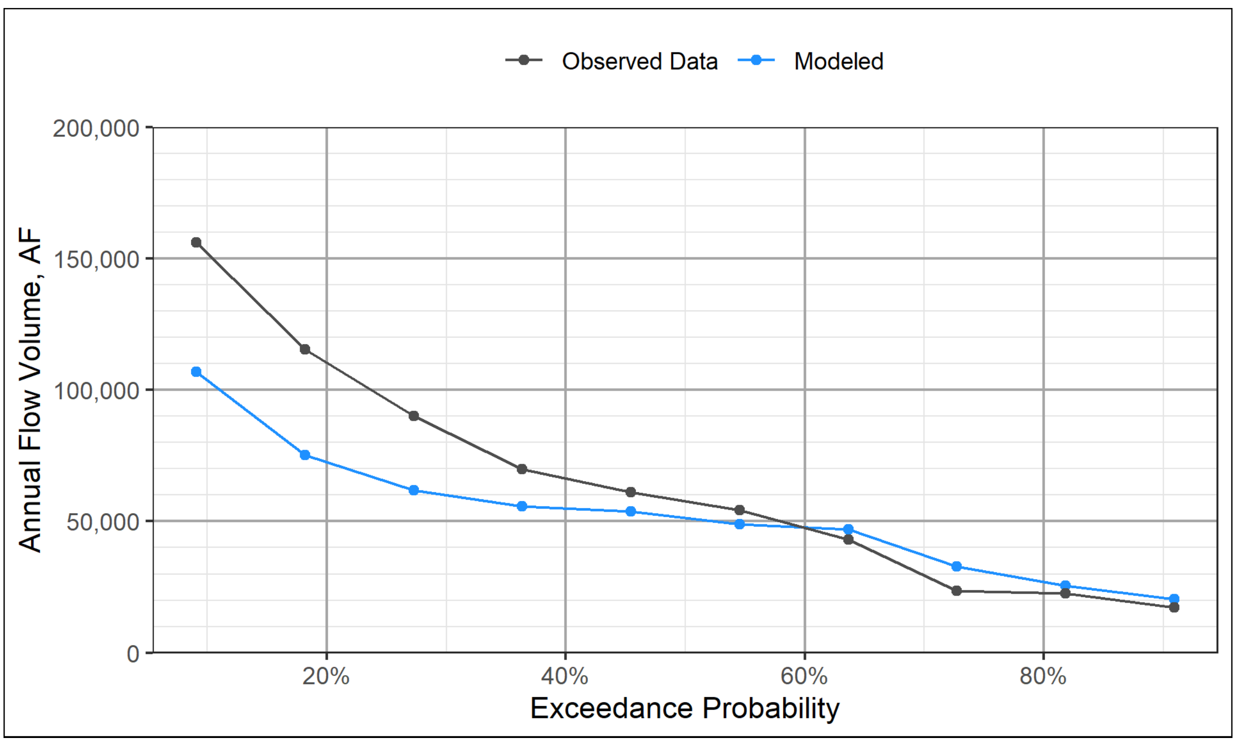

Figure C-42. Annual Flow Exceedance through Drum Powerhouse No. 1, Water Years 2012–2021

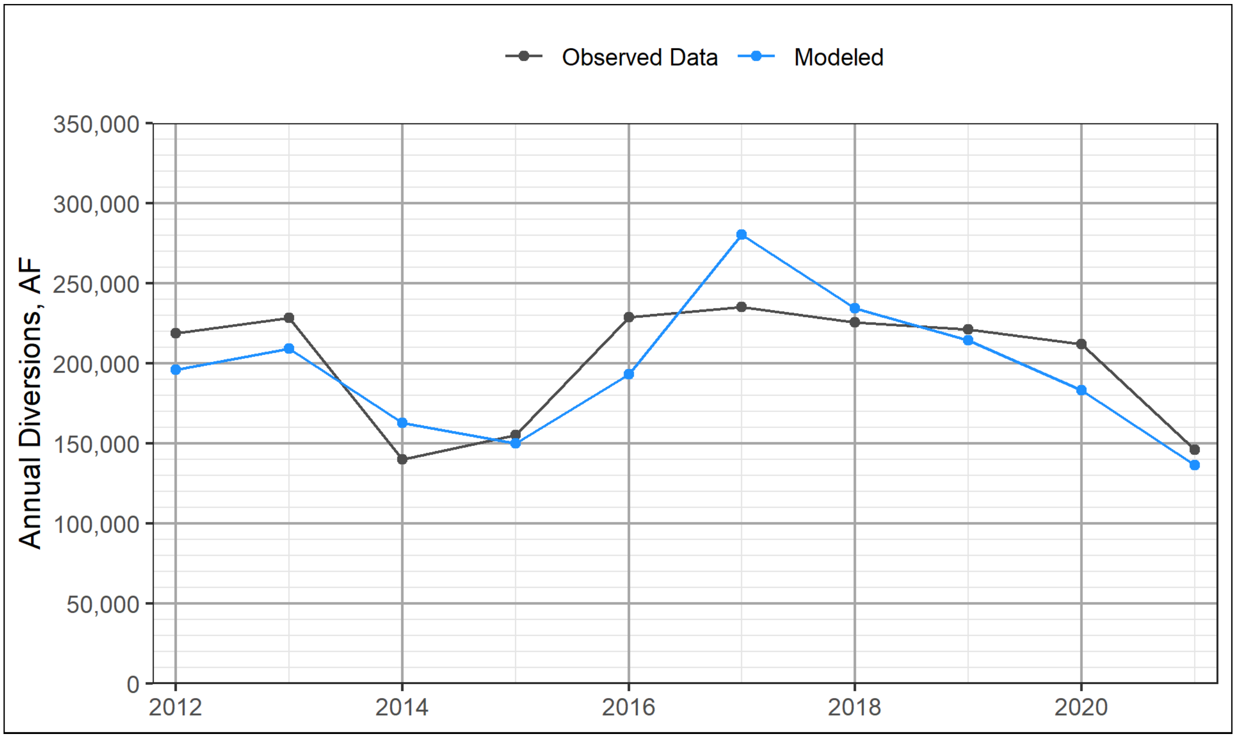

Figure C-43. Annual Flows through Drum Powerhouse No. 2, Water Years 2012–2021

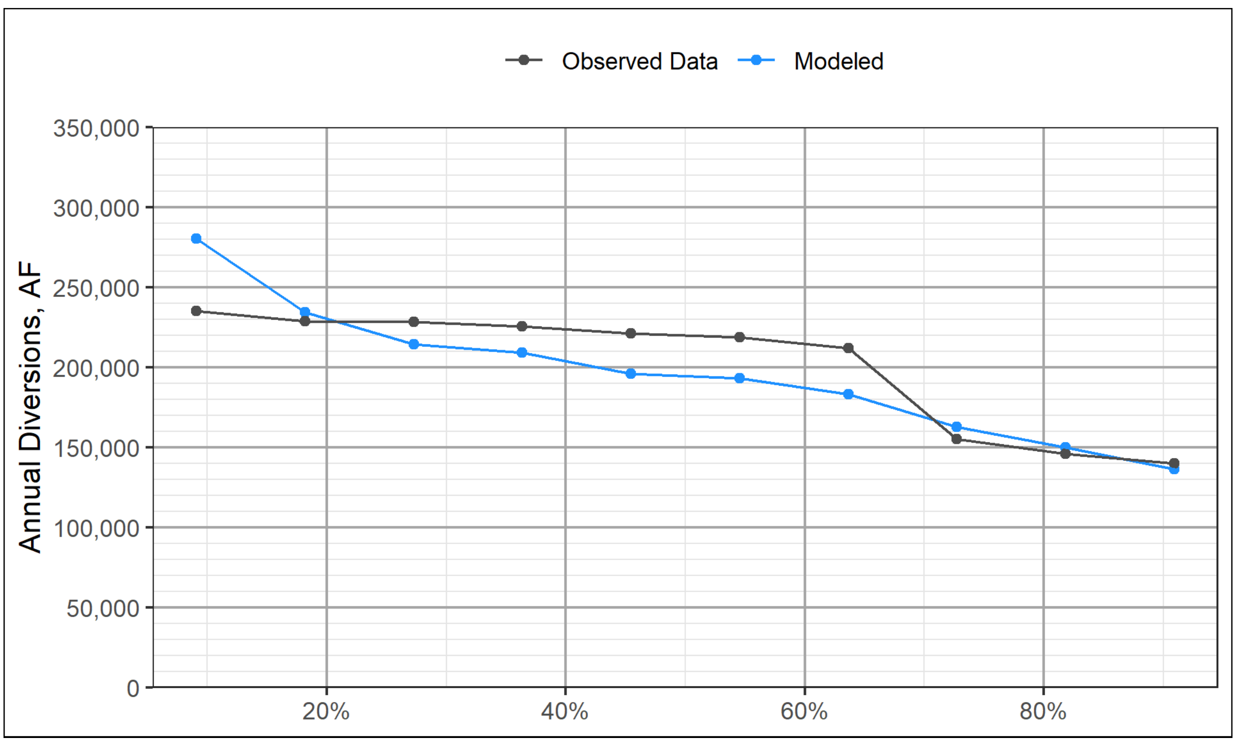

Figure C-44. Annual Flow Exceedance through Drum Powerhouse No. 2, Water Years 2012–2021

C.6.2. Drum Afterbay

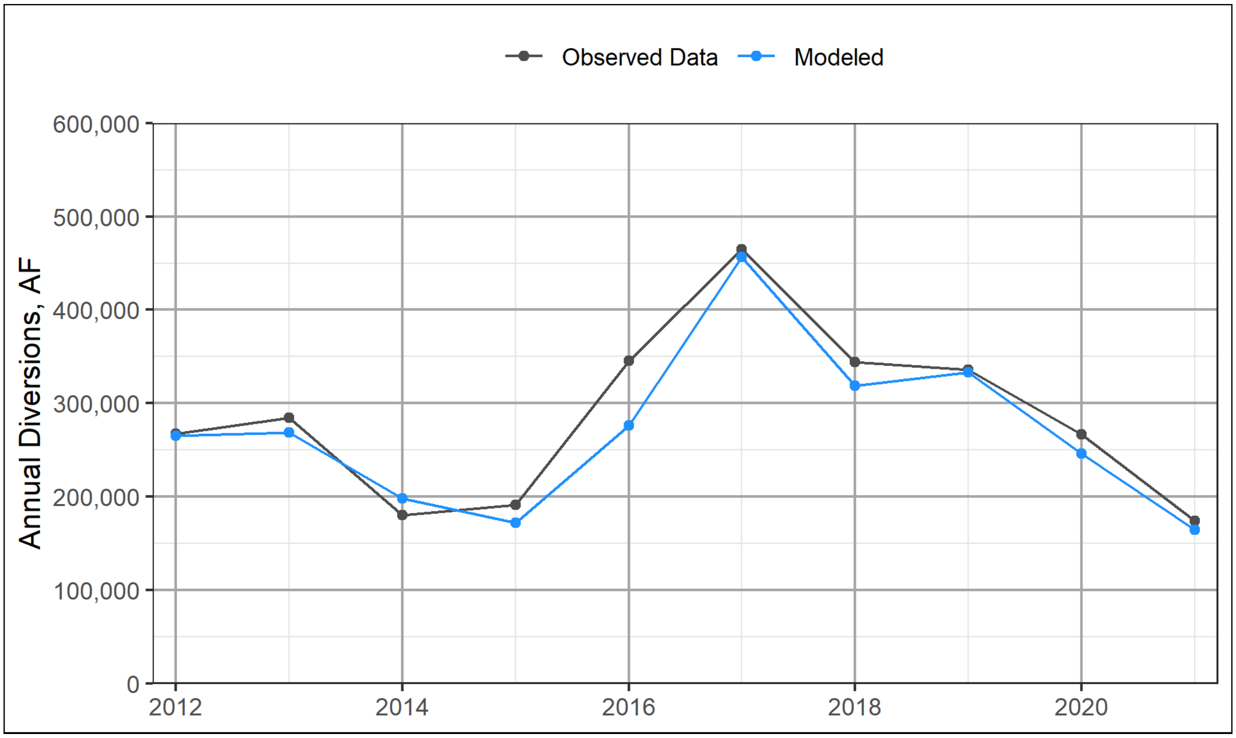

Figure C-45. Annual Flows through Combined Dutch Flat Powerhouses, Water Years 2012–2021

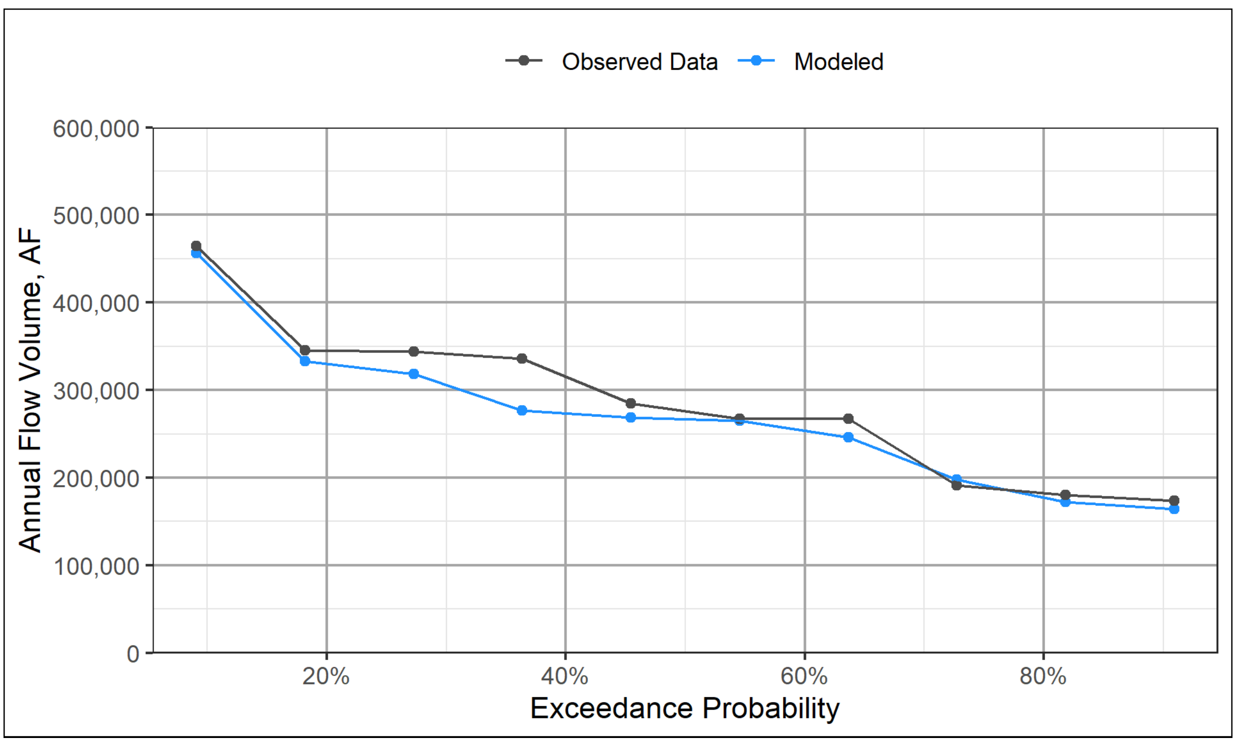

Figure C-46. Annual Flow Exceedance through Combined Dutch Flat Powerhouses, Water Years 2012–2021

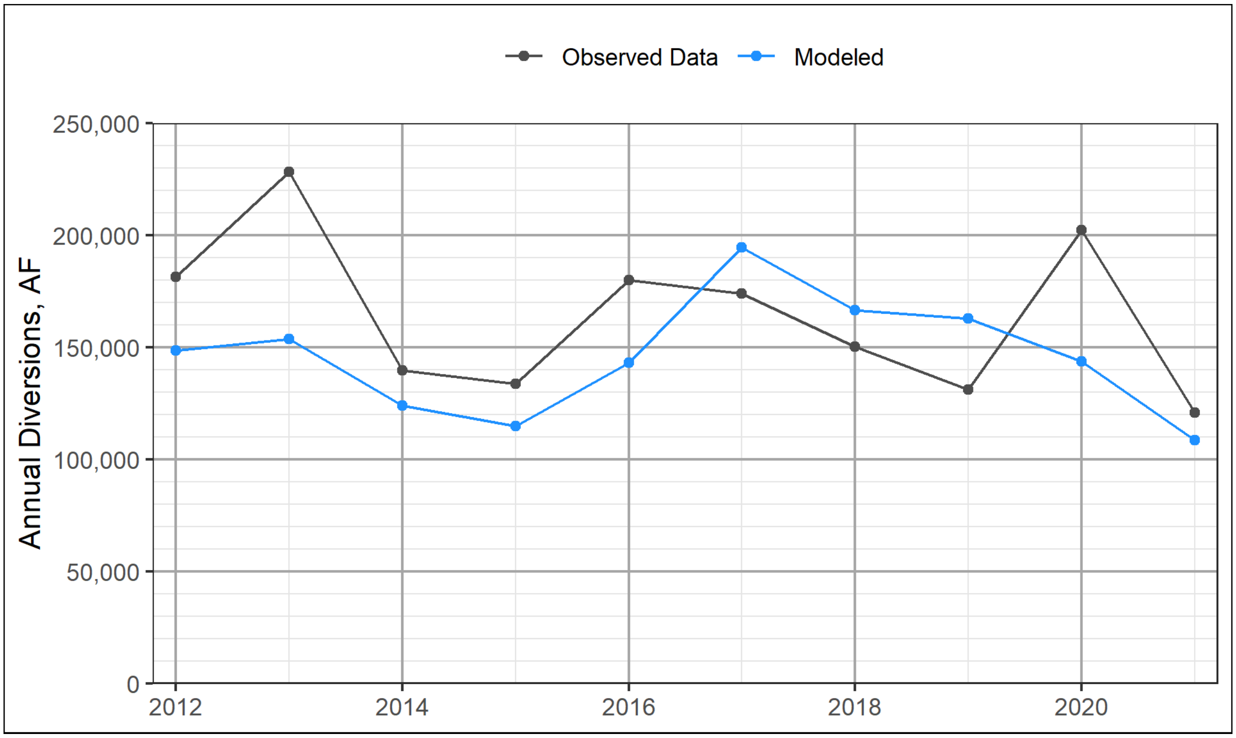

Figure C-47. Annual Flows through Dutch Flat Powerhouse No. 1, Water Years 2012–2021

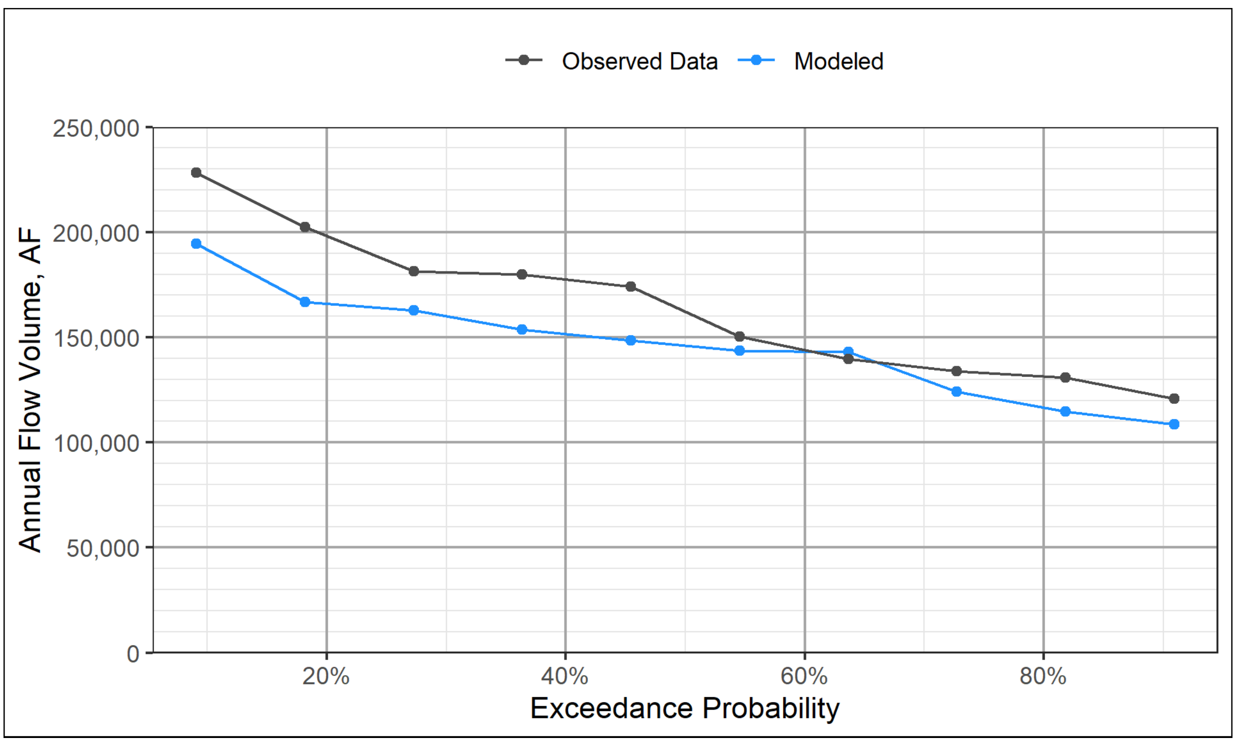

Figure C-48. Annual Flow Exceedance through Dutch Flat Powerhouse No. 1, Water Years 2012–2021

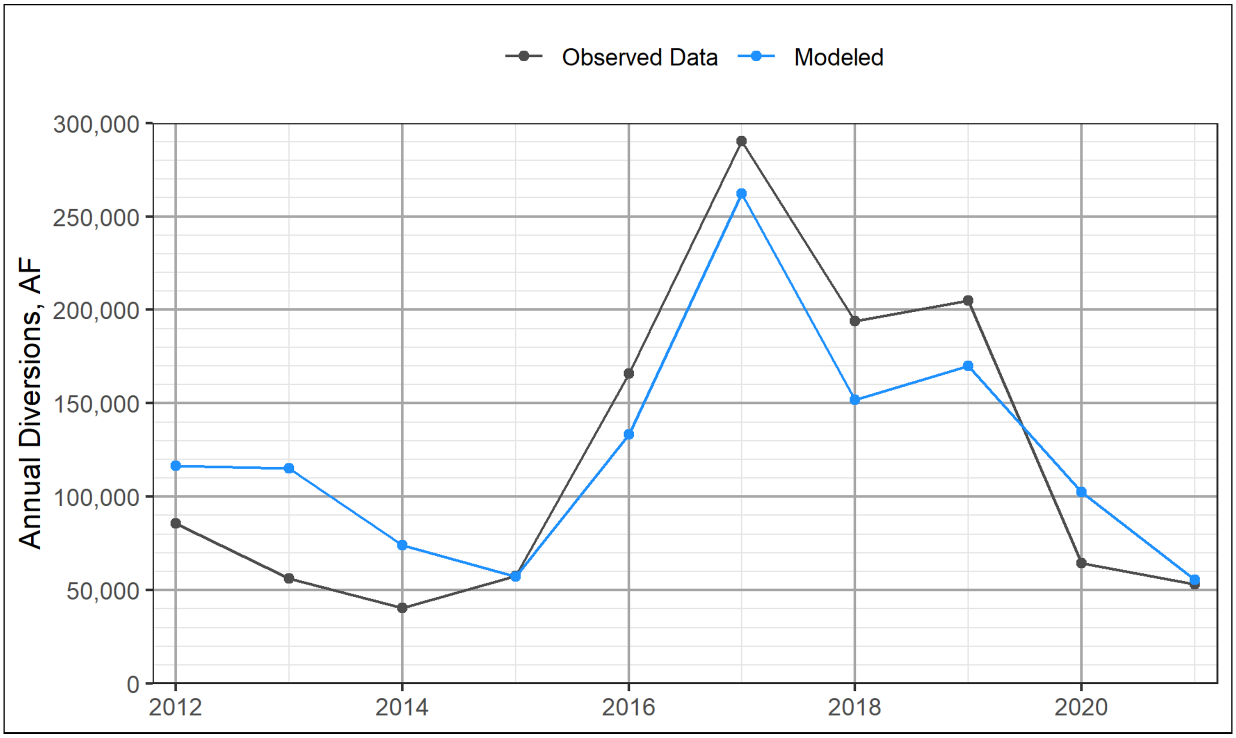

Figure C-49. Annual Flows through Dutch Flat Powerhouse No. 2, Water Years 2012–2021

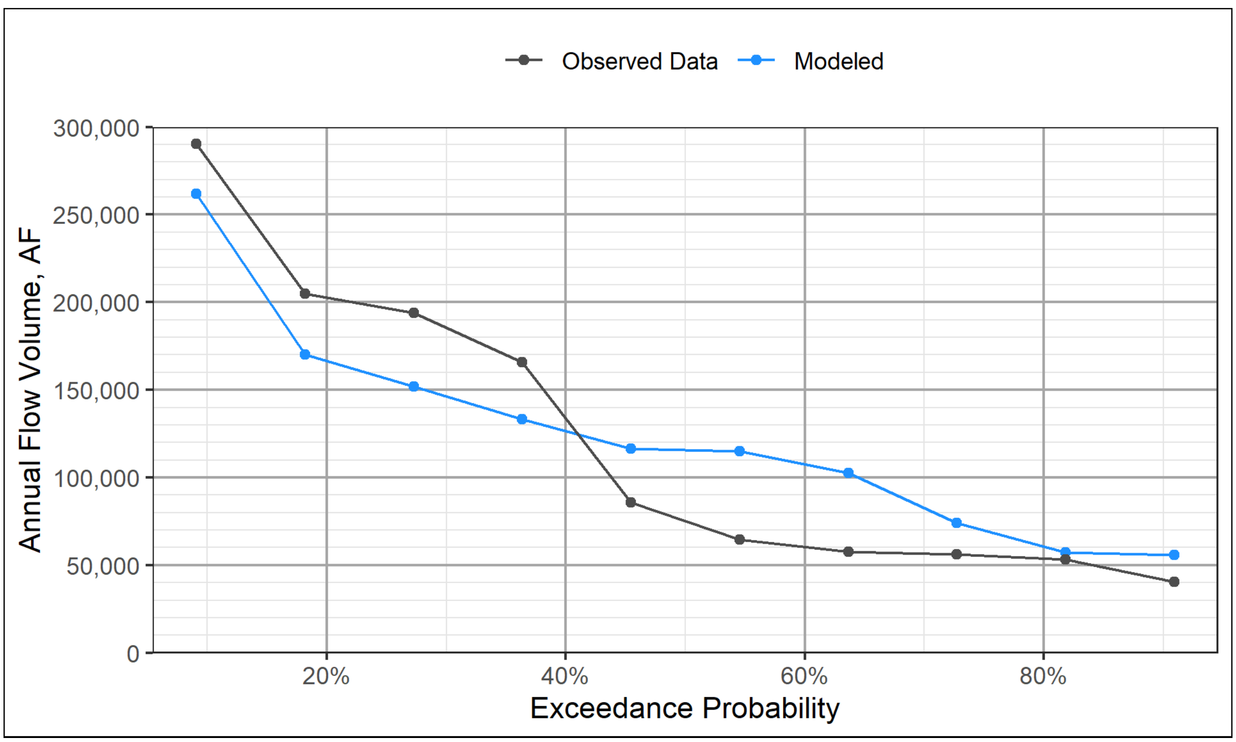

Figure C-50. Annual Flow Exceedance through Dutch Flat Powerhouse No. 2, Water Years 2012–2021

C.6.3. Dutch Flat Afterbay

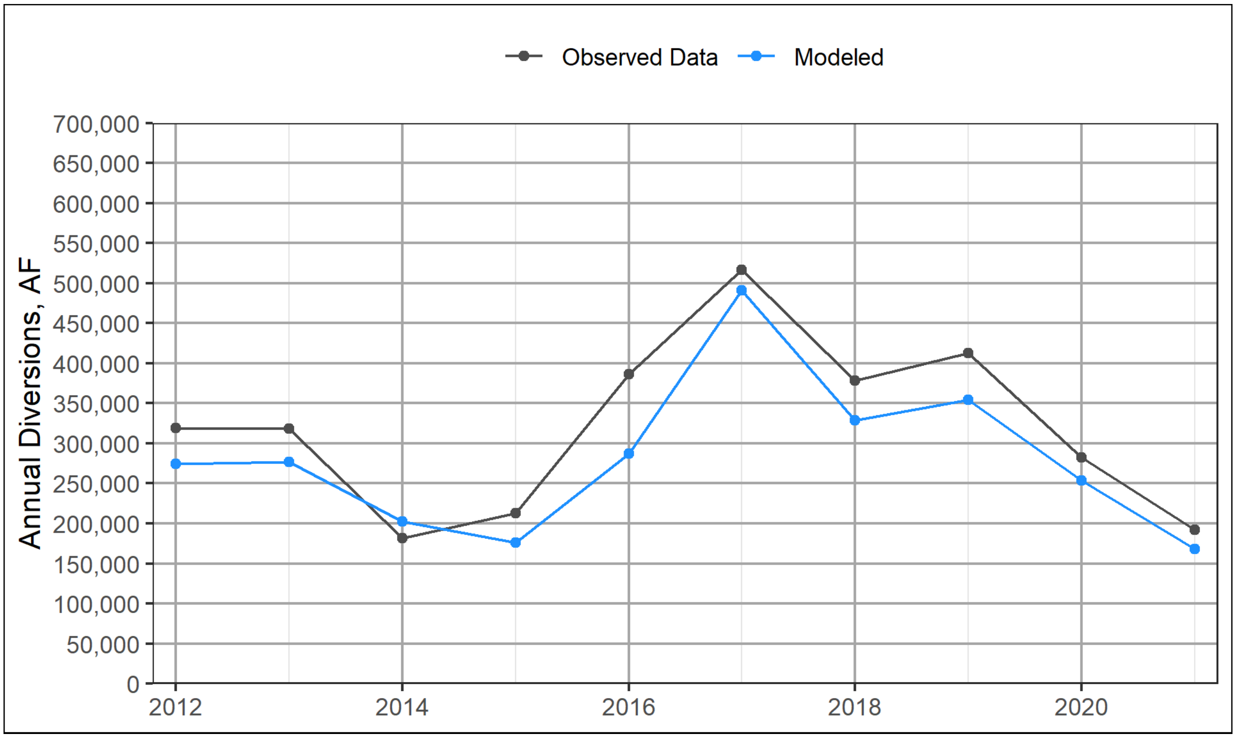

Figure C-51. Annual Flows through Chicago Park Powerhouse, Water Years 2012–2021

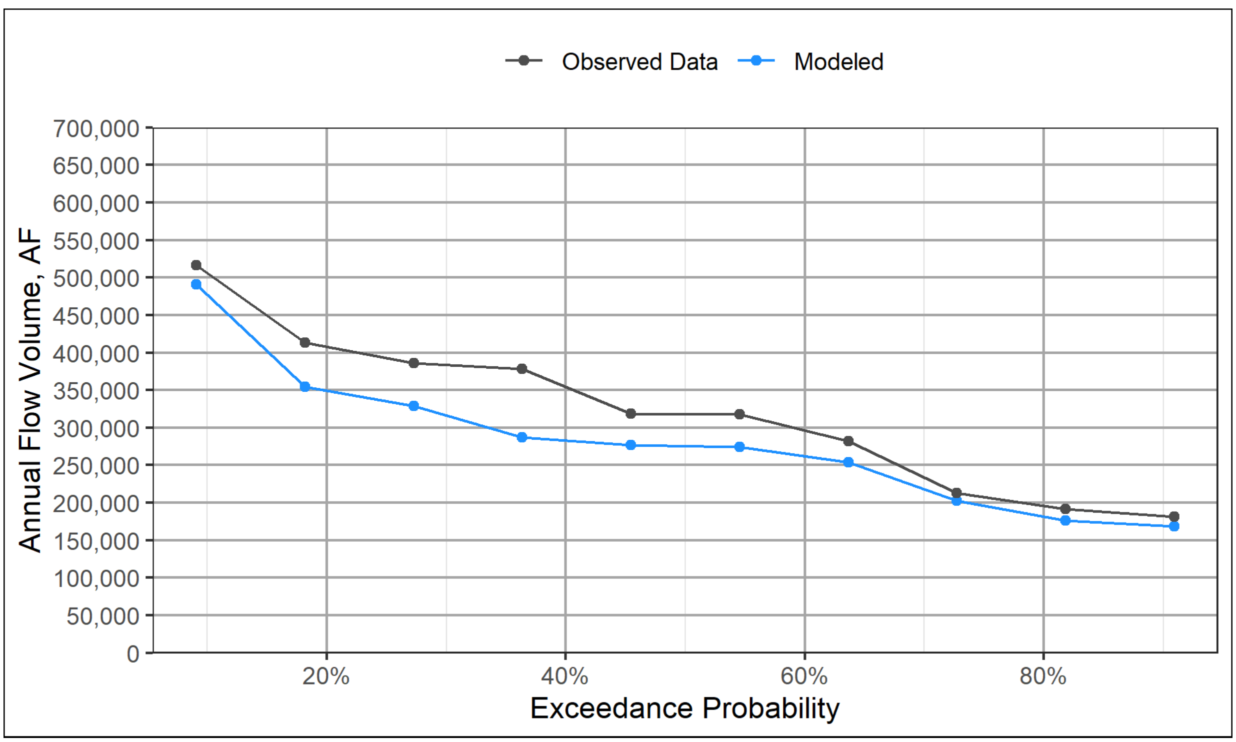

Figure C-52. Annual Flow Exceedance through Chicago Park Powerhouse, Water Years 2012–2021

C.6.4. Rollins Lake

Rollins Lake had a bathymetric survey in 2021, which changed the estimate of storage capacity of the Reservoir. The model uses the new storage-elevation relationship from the updated bathymetric survey, while USGS storage data before 2021 uses the previous storage-elevation relationship. For this reason, Rollins Lake validation uses reservoir elevation rather than storage.

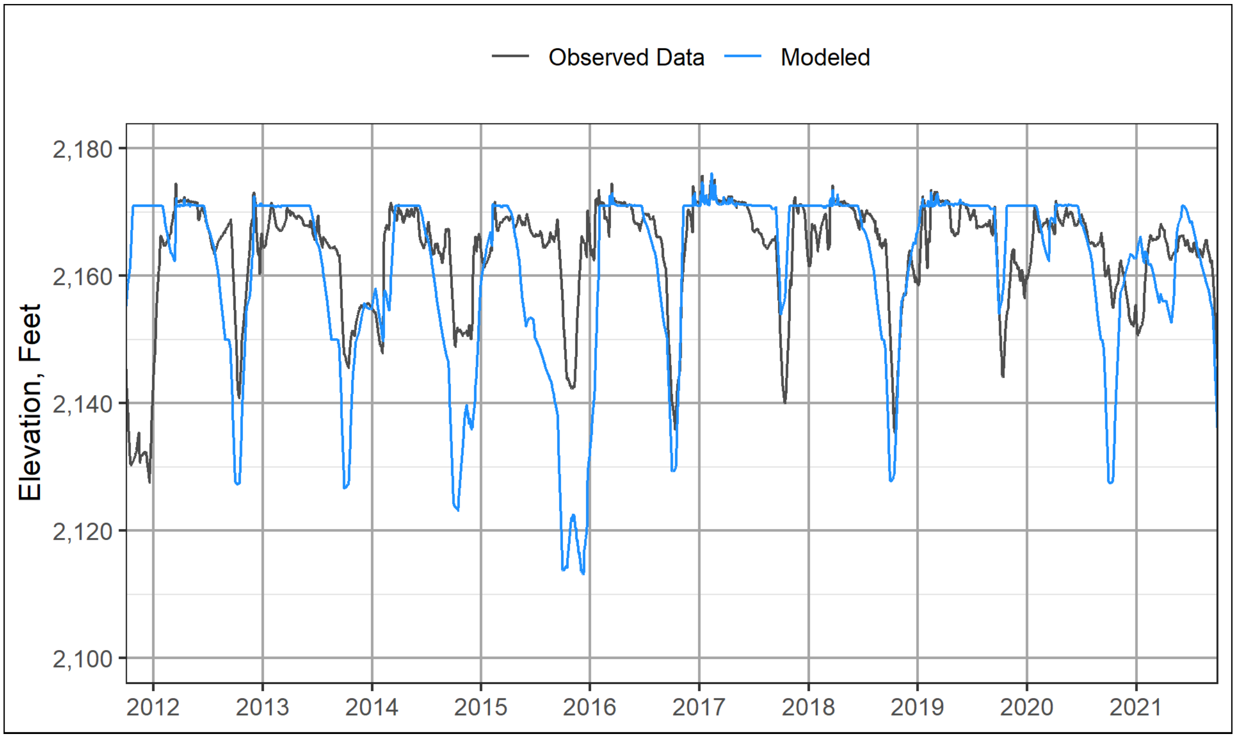

Figure C-53. Rollins Lake Elevation, Water Years 2012–2021

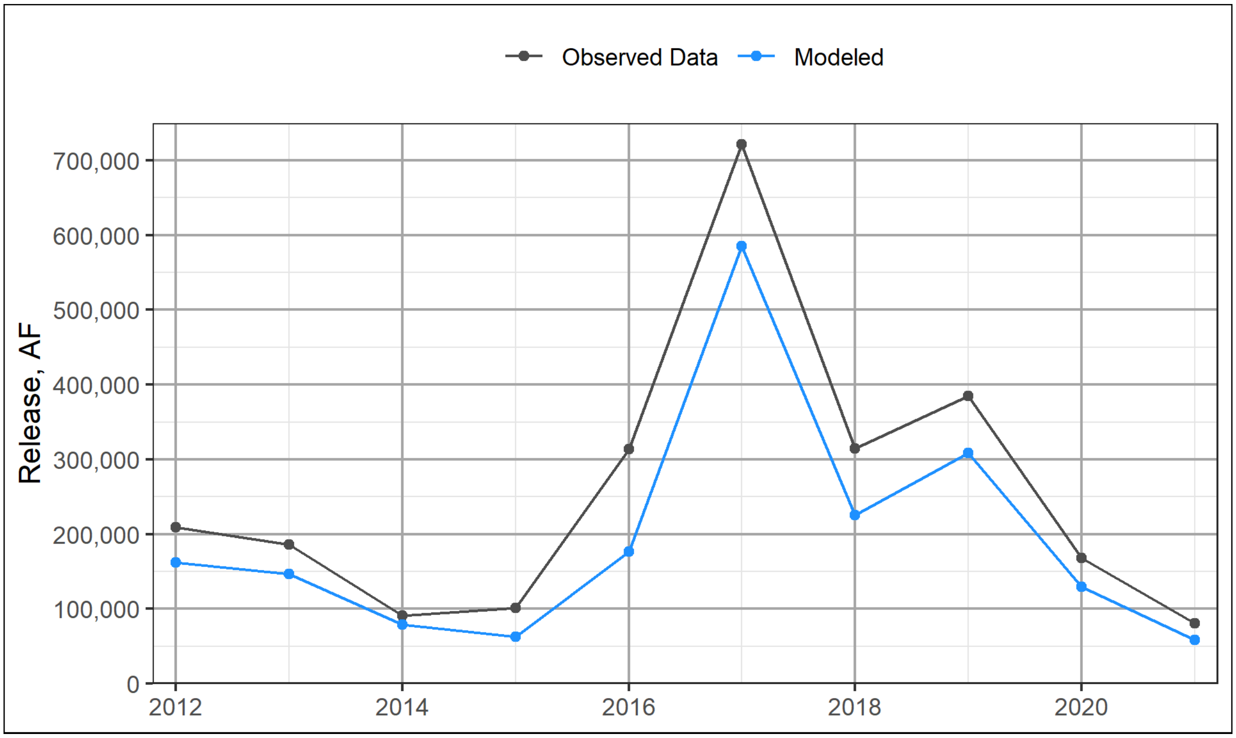

Figure C-54. Rollins Lake releases to Bear River, Water Years 2012–2021

C.6.5. Bear River Canal

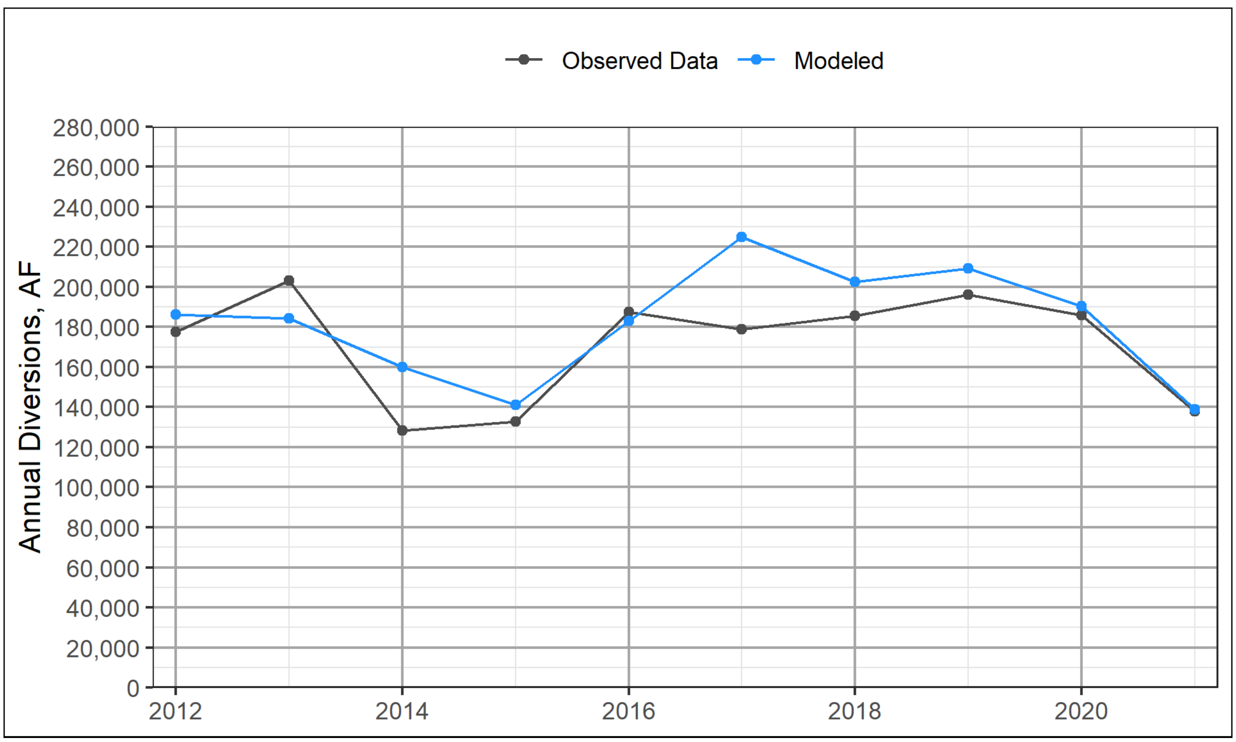

Figure C-55. Rollins Lake Diversions to Bear River Canal, Water Years 2012–2021

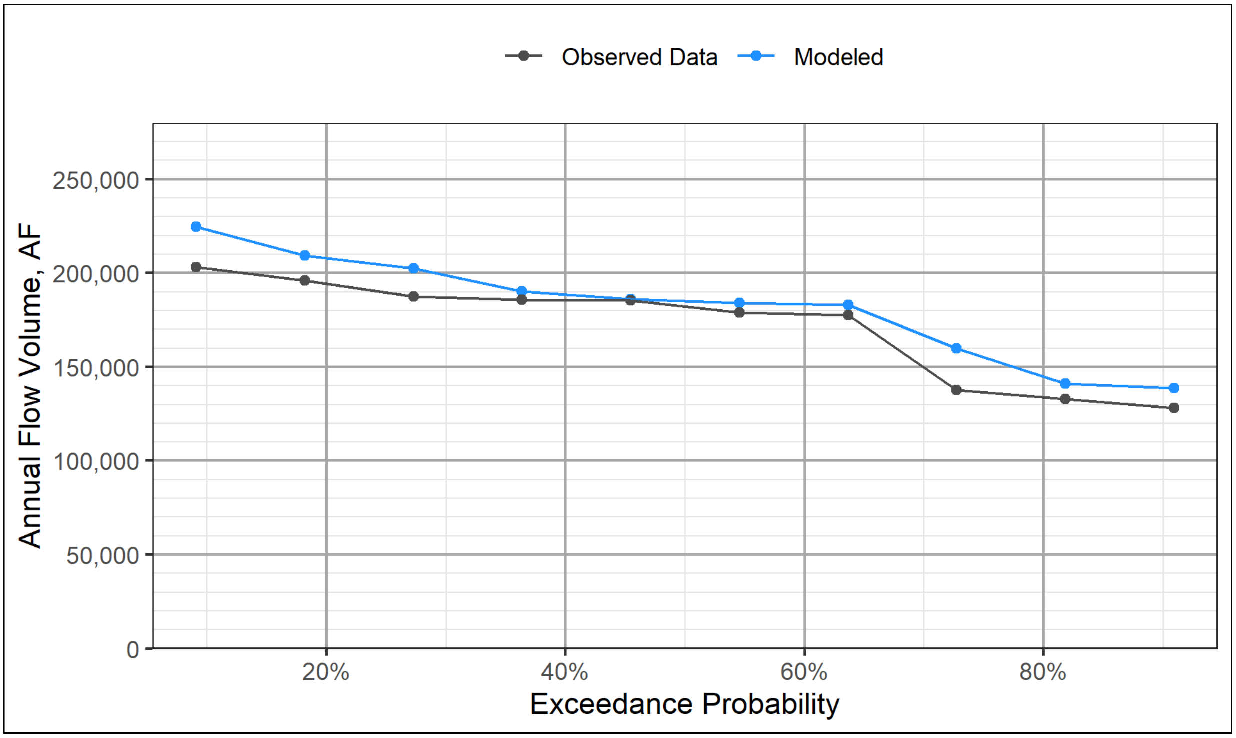

Figure C-56. Annual Diversion Exceedance to Bear River Canal, Water Years 2012–2021

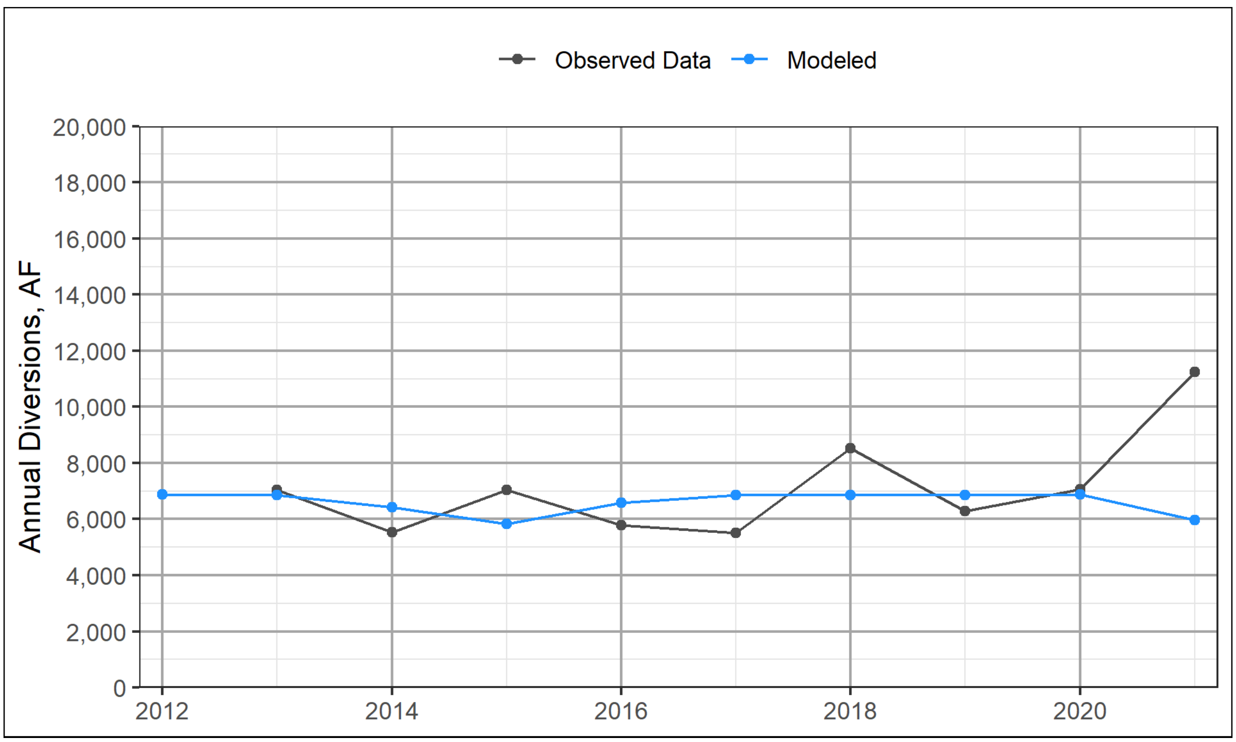

Figure C-57. NID Diversions from Rock Creek Reservoir, Water Years 2012–2021

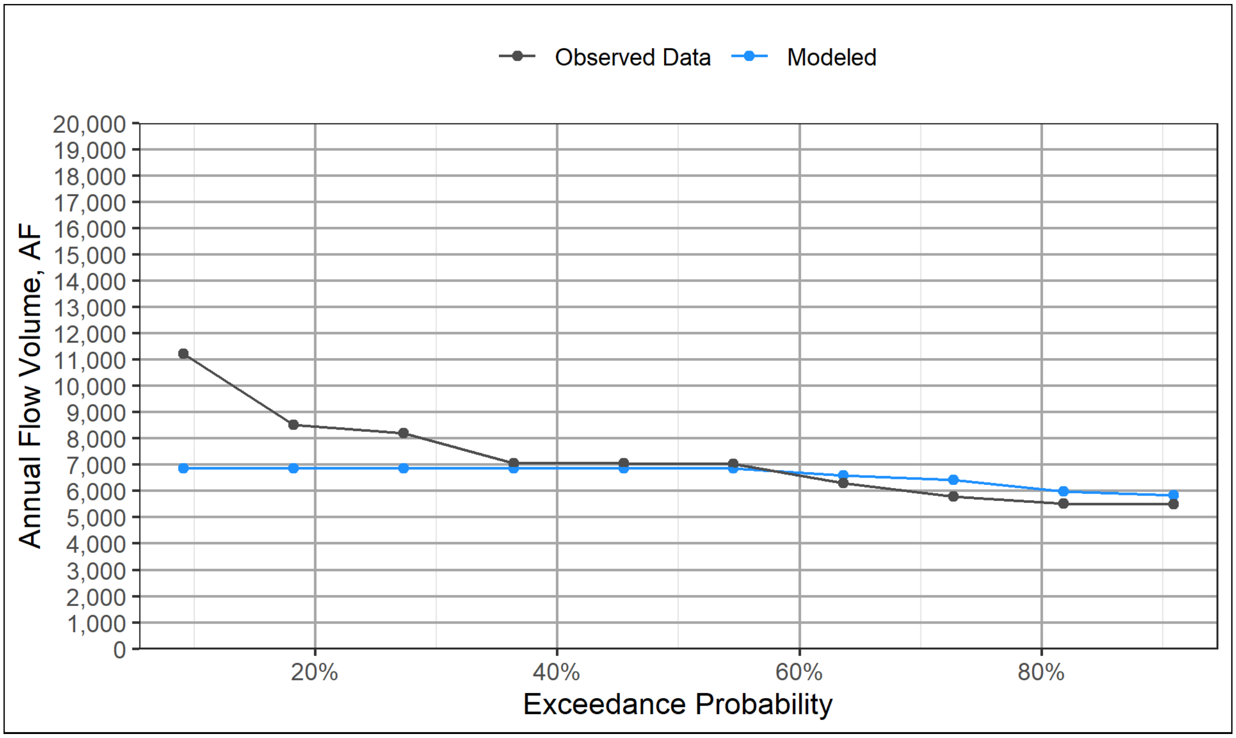

Figure C-58. Annual Diversion Exceedance to NID from Rock Creek Reservoir, Water Years 2012–2021

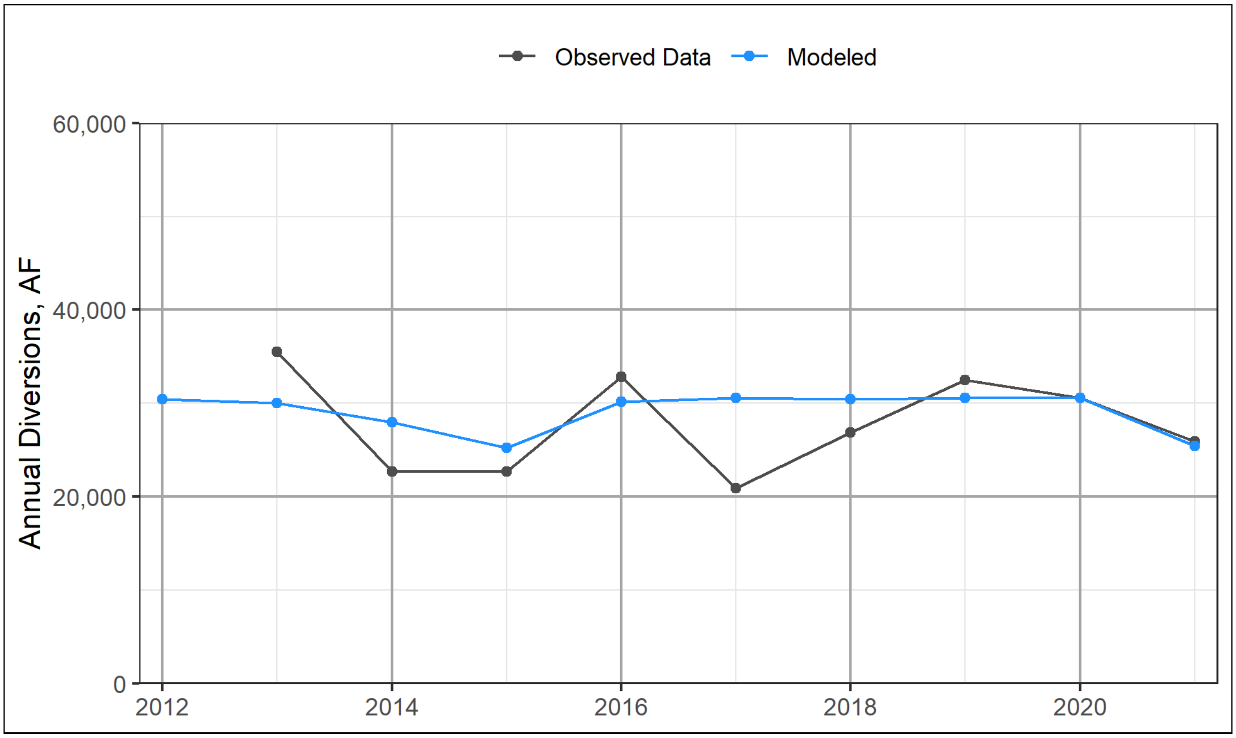

Figure C-59. NID Diversions into Auburn Ravine, Water Years 2012–2021

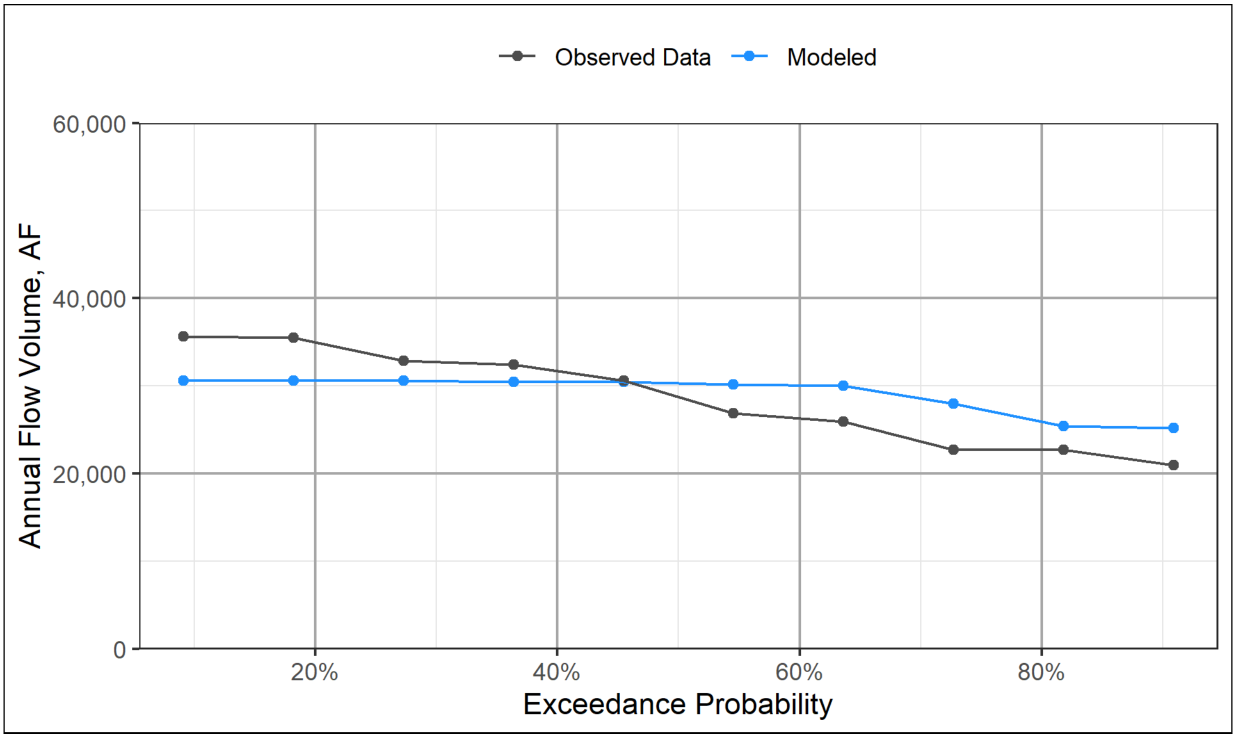

Figure C-60. Annual Diversion Exceedance NID into Auburn Ravine, Water Years 2012–2021

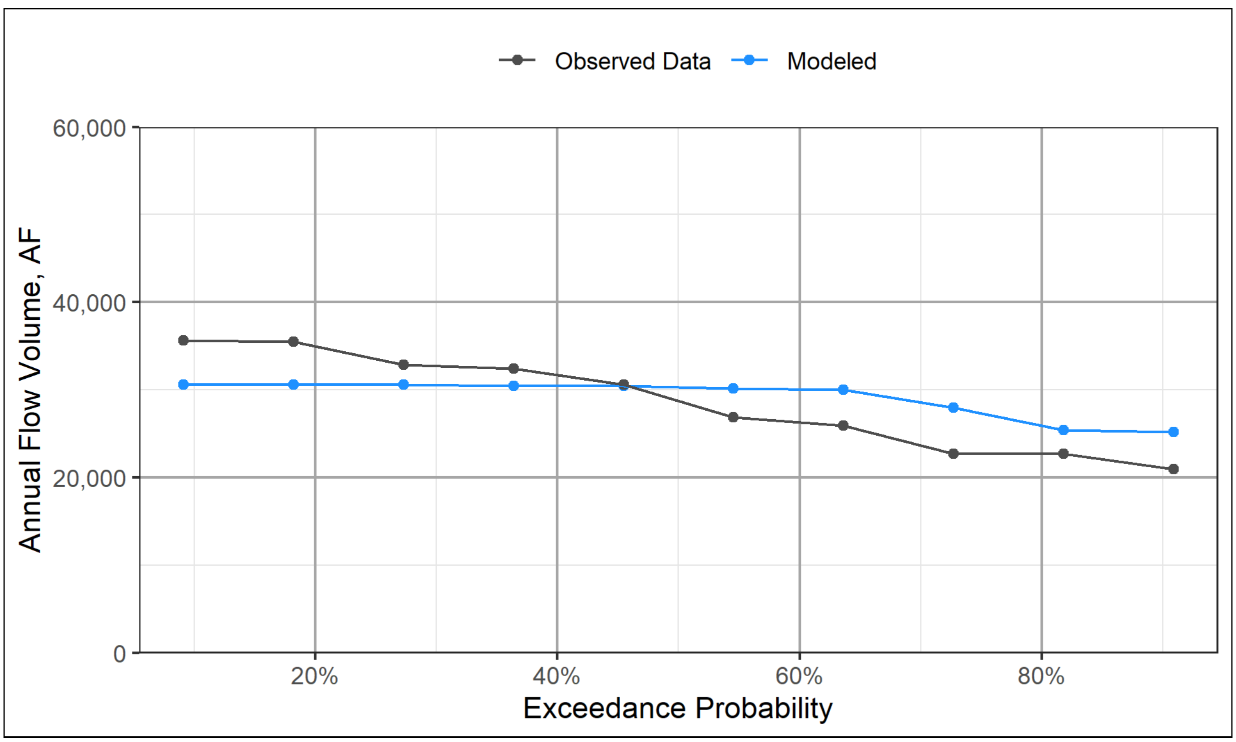

Figure C-61. Annual Diversion Exceedance NID into Auburn Ravine, Water Years 2012–2021

C.6.6. Lake Combie

Lake Combie had a bathymetric survey in 2021, which changed the estimate of storage capacity of the Reservoir. The model uses the new storage-elevation relationship from the updated bathymetric survey, while USGS storage data before 2021 uses the old storage-elevation relationship. For this reason, Lake Combie validation uses reservoir elevation rather than storage.

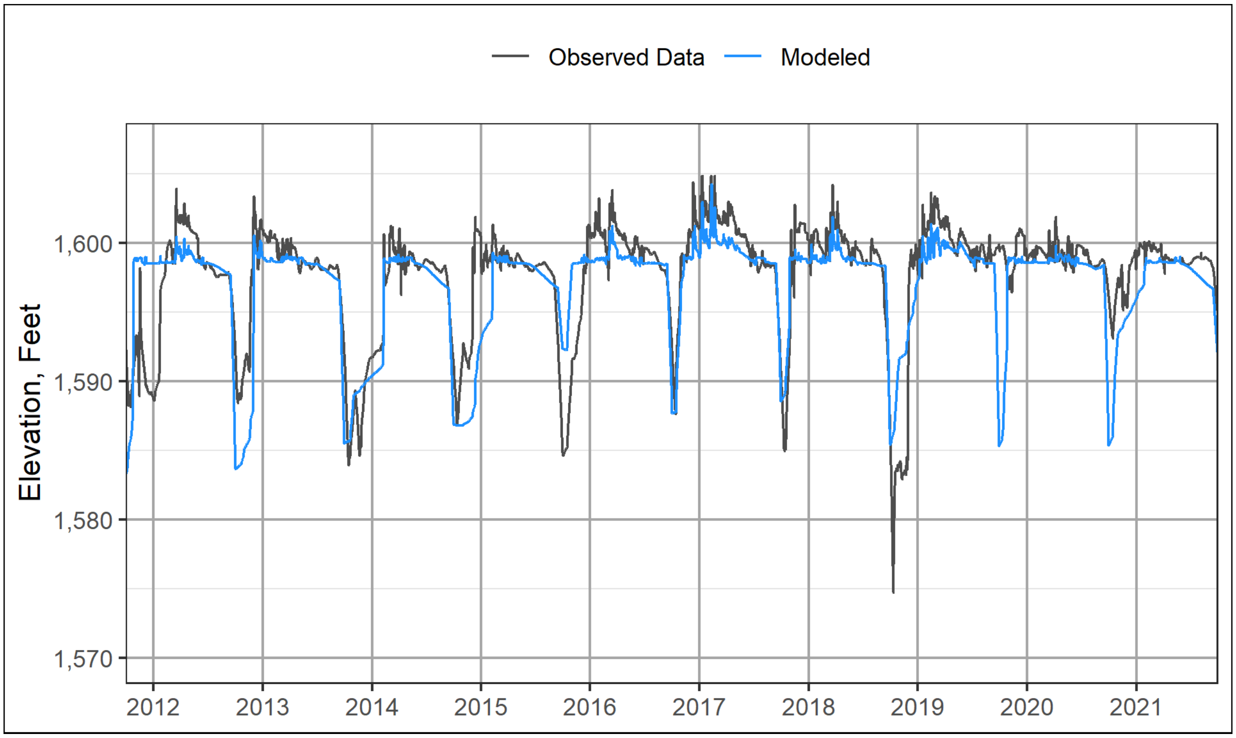

Figure C-62. Combie Lake Storage, Water Years 2012–2021

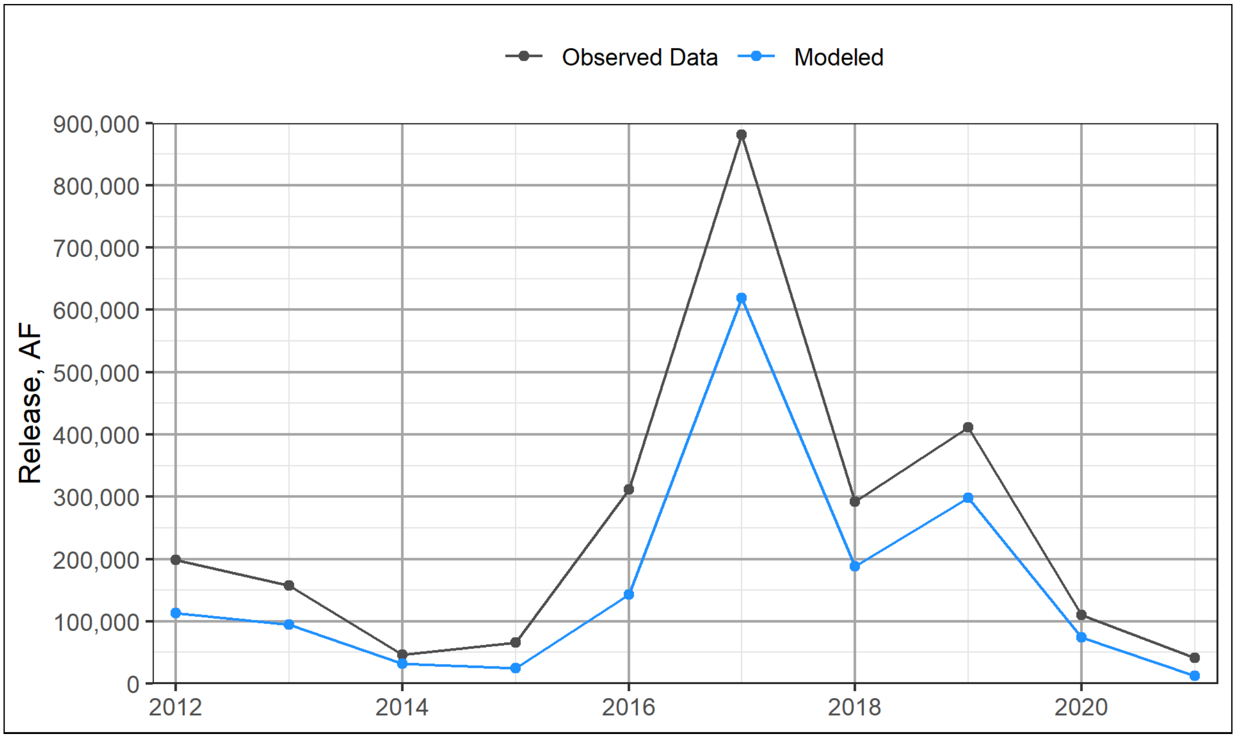

Figure C-63. Combie Lake releases to Bear River, Water Years 2012–2021

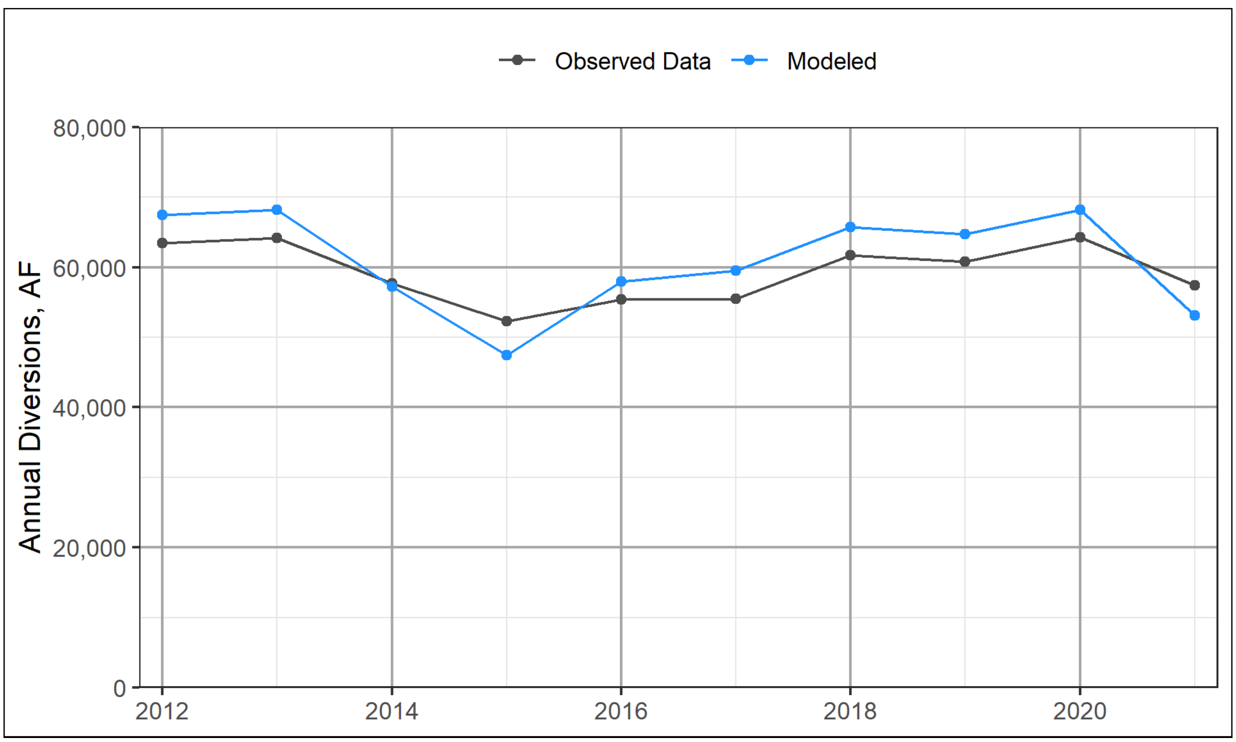

Figure C-64. Combie Lake Diversions to Phase I Canal and Magnolia III Canal, Water Years 2012–2021

C.7. Deer Creek

C.7.1. Deer Creek Powerhouse

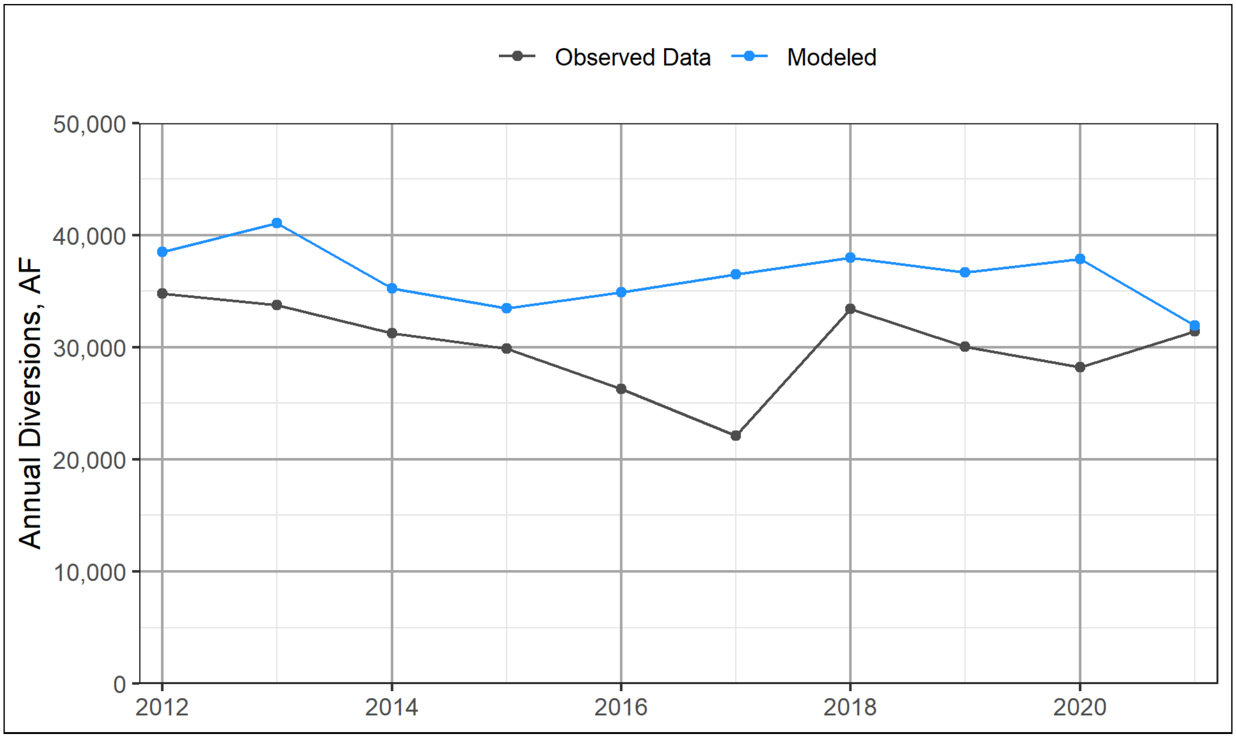

Figure C-65. Annual Flow through Deer Creek Powerhouse, Water Years 2012–2021

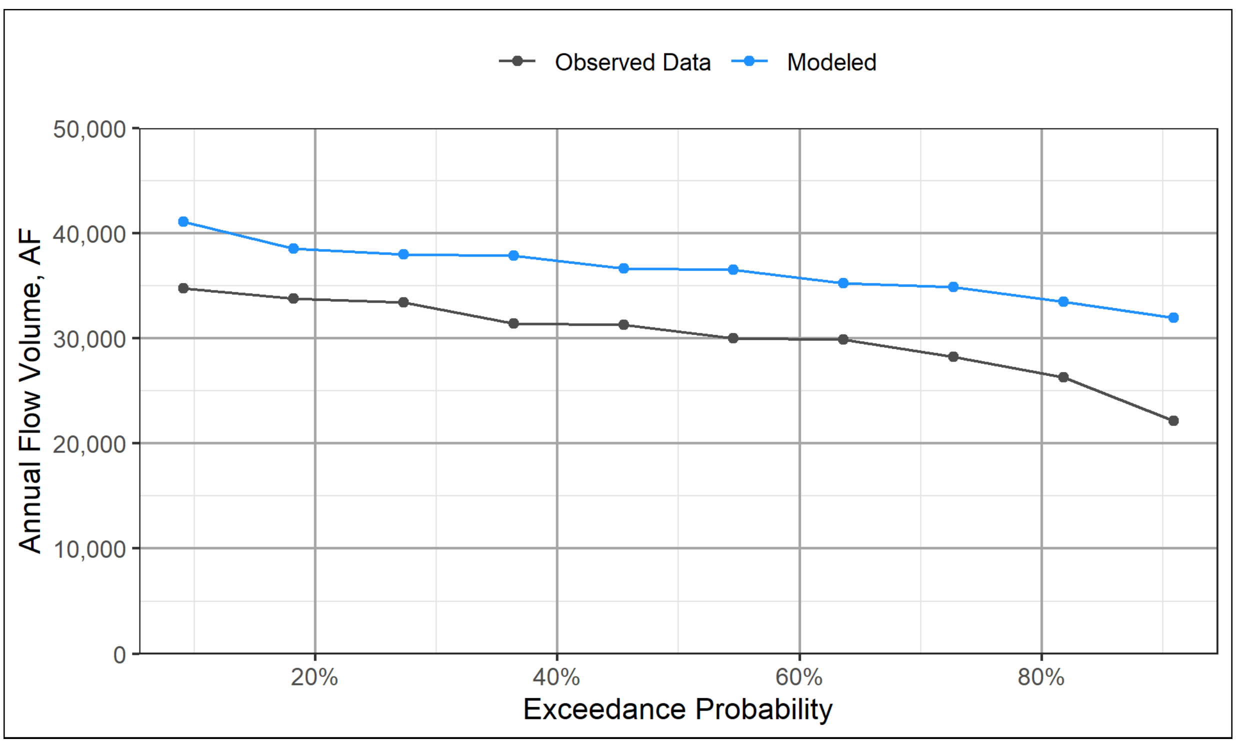

Figure C-66. Annual Flow Exceedance through Deer Creek Powerhouse, Water Years 2012–2021

C.7.2. Scotts Flat Reservoir

Scotts Flat Reservoir had a bathymetric survey in 2021, which changed the estimate of storage capacity of the Reservoir. The model uses the new storage-elevation relationship from the updated bathymetric survey, while USGS storage data before 2021 uses the old storage-elevation relationship. For this reason, Scotts Flat Reservoir validation uses reservoir elevation rather than storage.

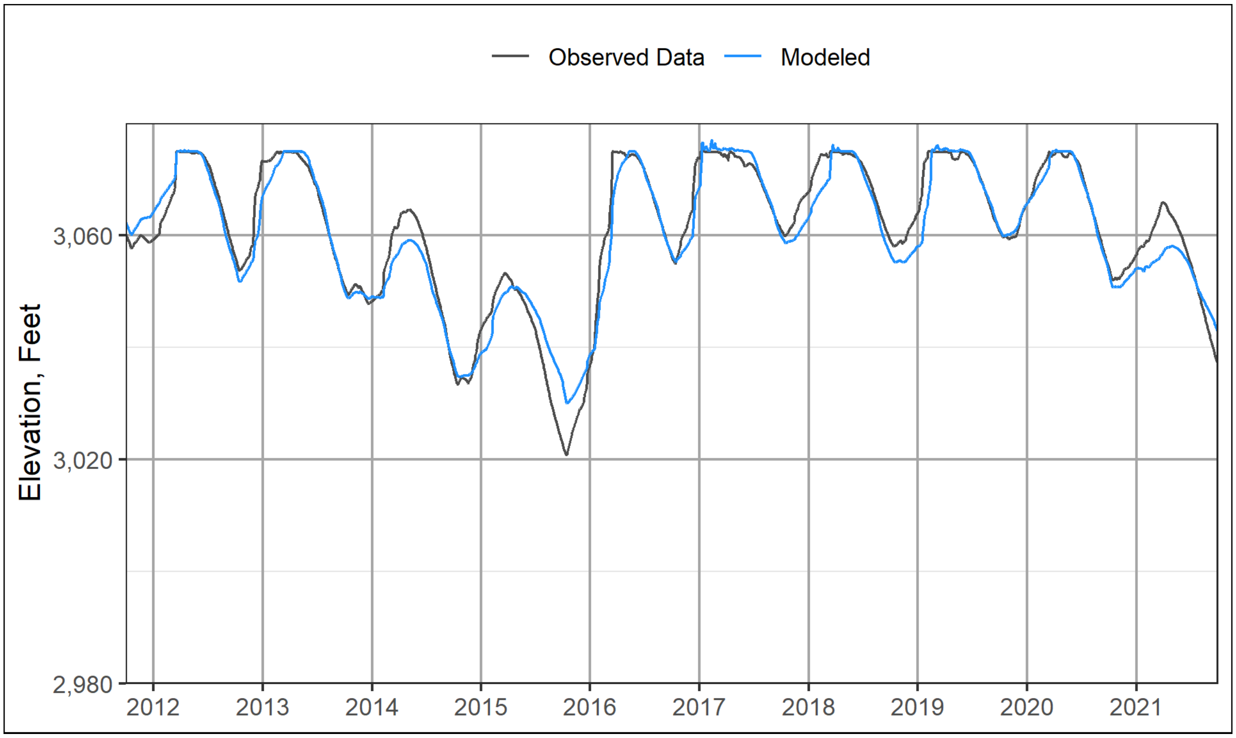

Figure C-67. Scotts Flat Reservoir Elevation, Water Years 2012–2021

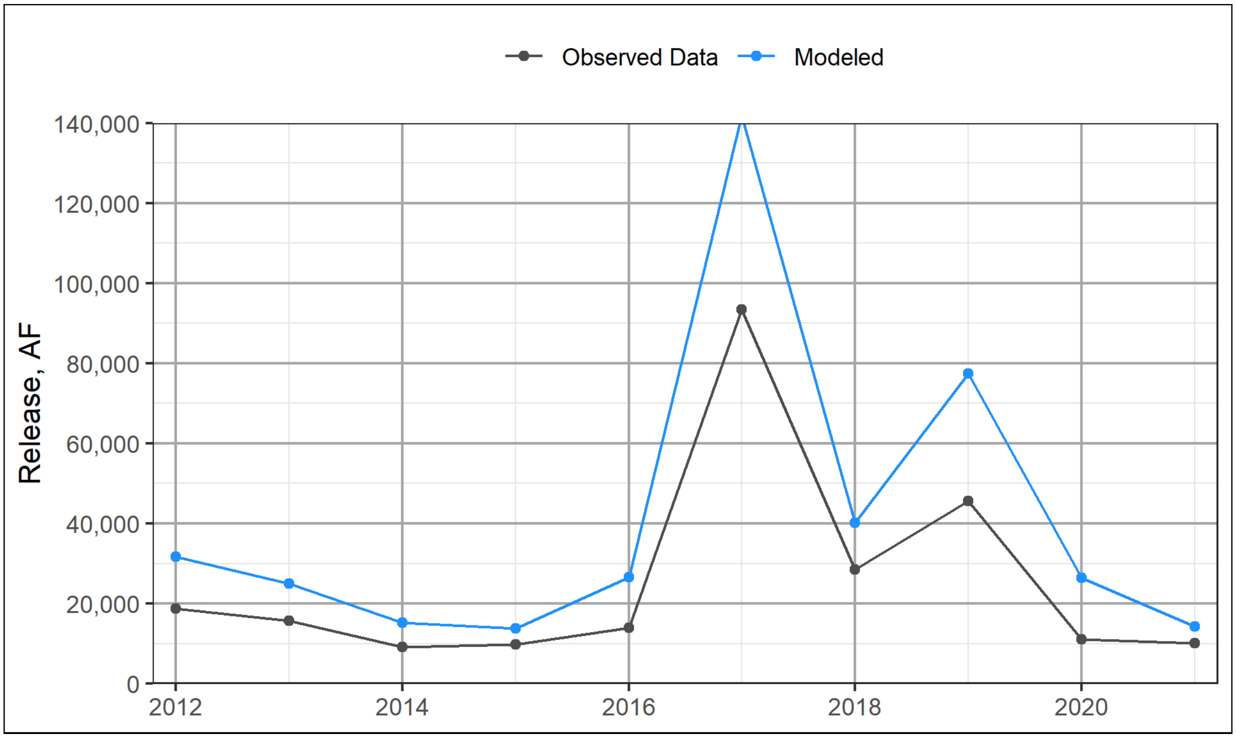

Figure C-68. Scotts Flat releases to Deer Creek, Water Years 2012–2021

C.7.3. Cascade Canal

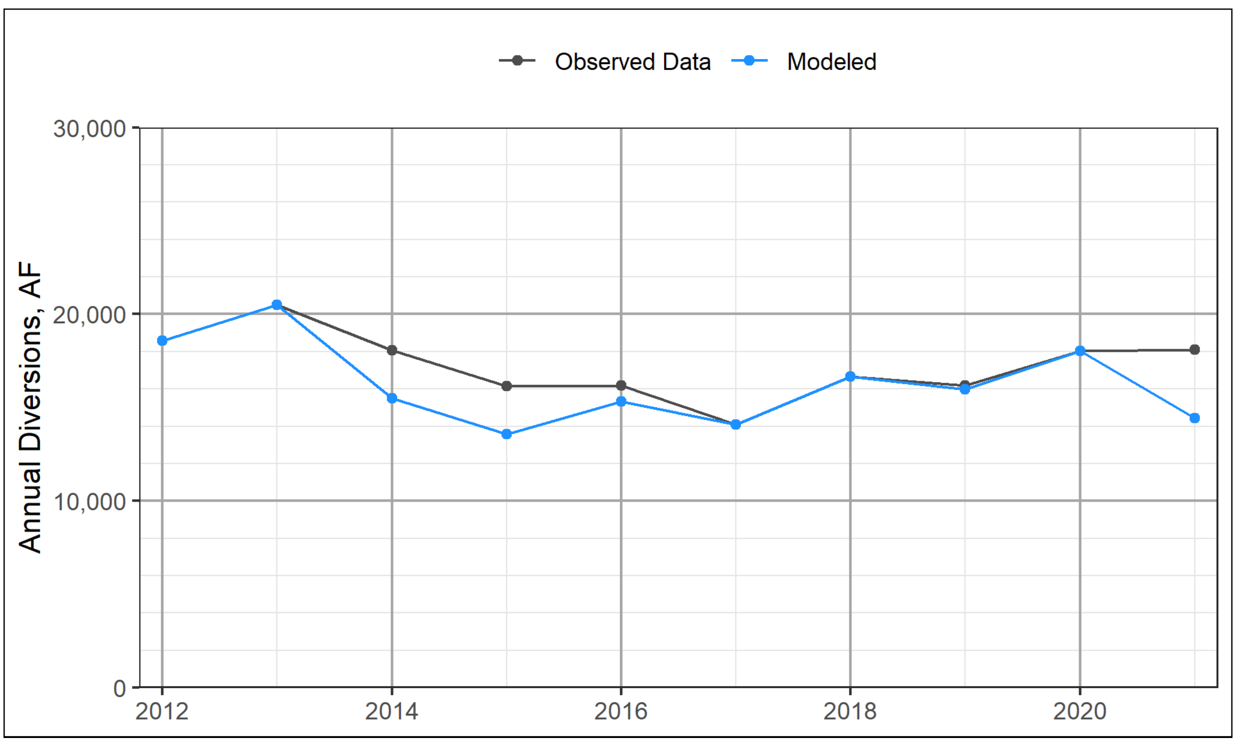

Figure C-69. Diversions to Cascade Canal, Water Years 2012–2021

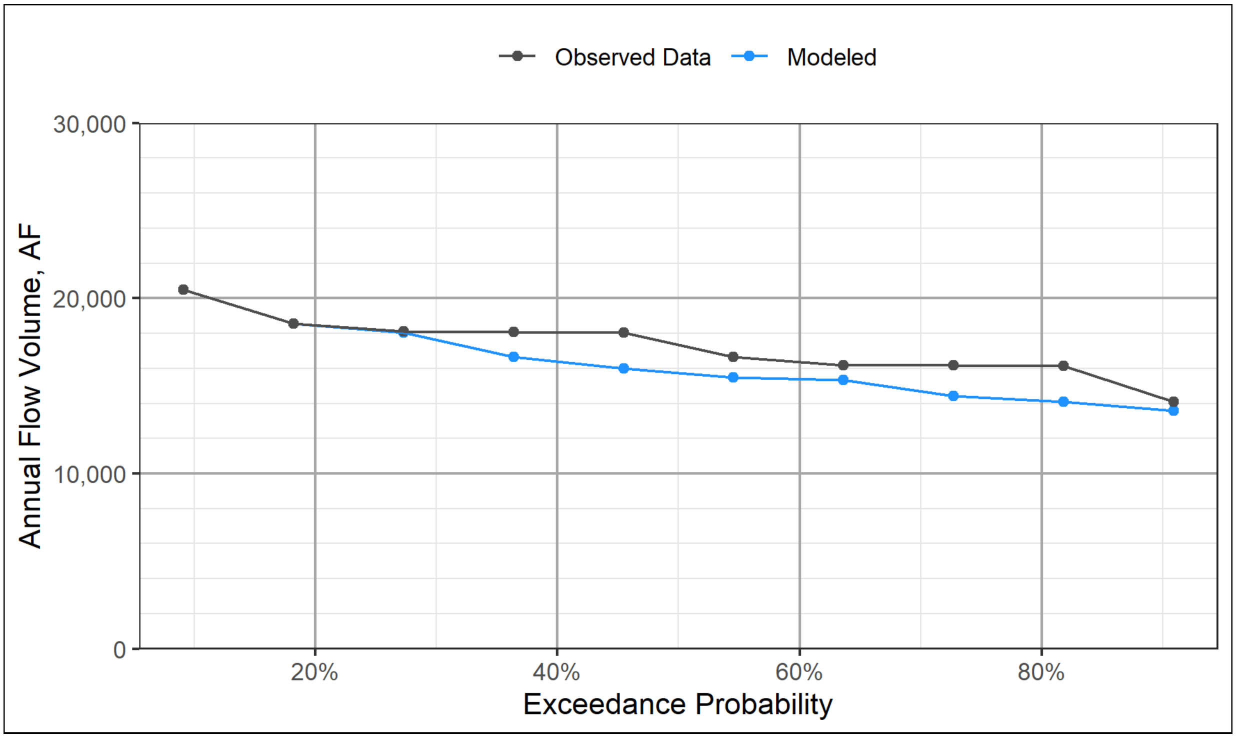

Figure C-70. Annual Diversion Exceedance to Cascade Canal, Water Years 2012–2021

C.7.4. DS Canal

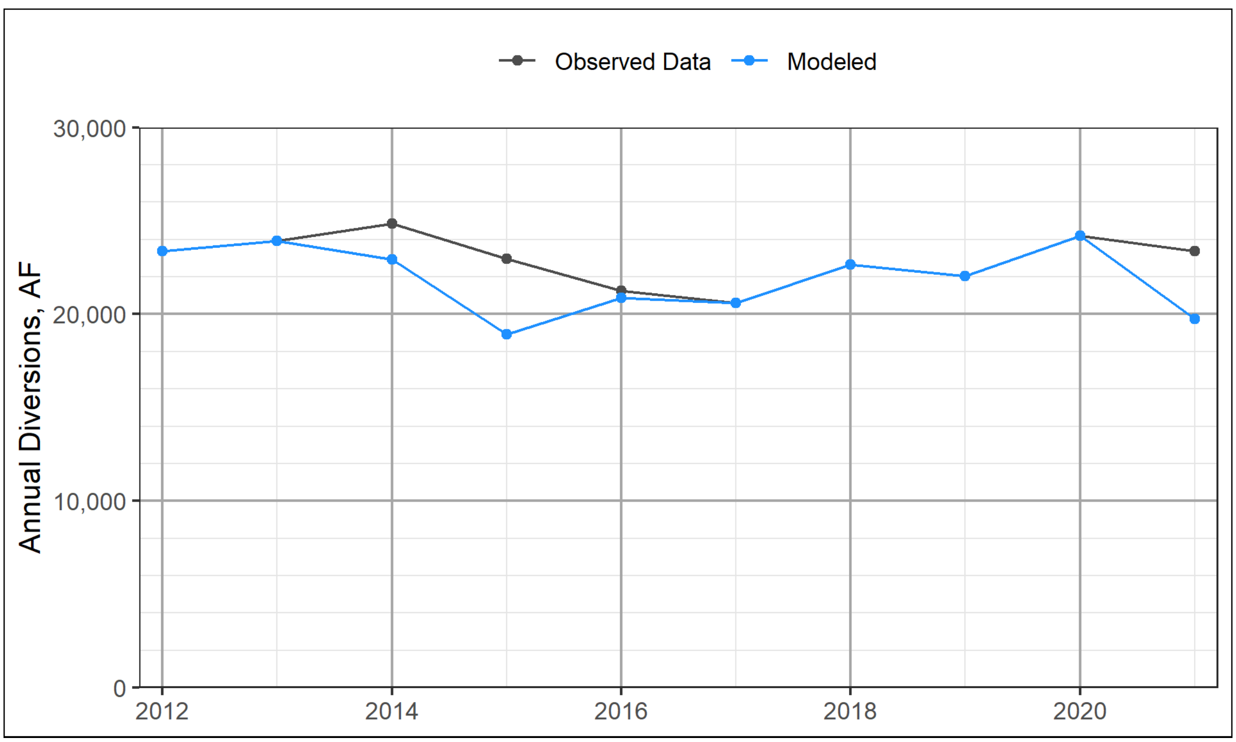

Figure C-71. Diversions to DS Canal, Water Years 2012–2021

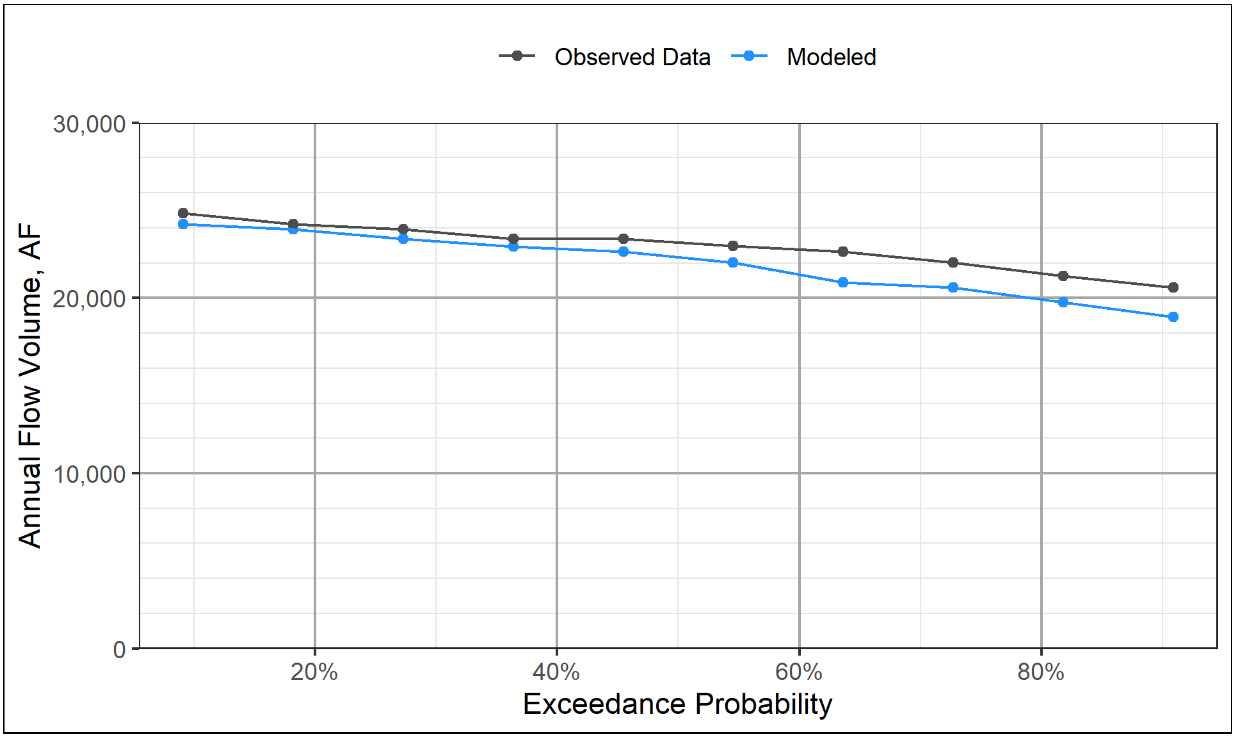

Figure C-72. Annual Diversion Exceedance to DS Canal, Water Years 2012–2021

C.7.5. Newtown Canal

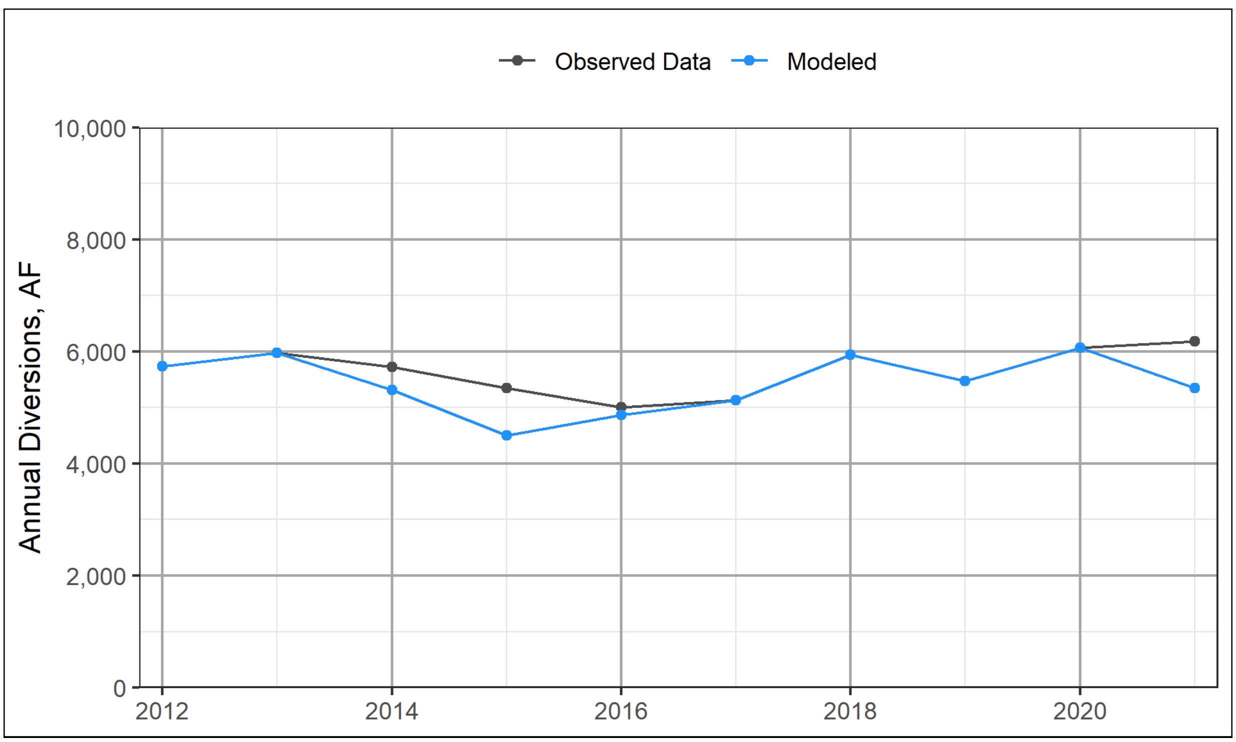

Figure C-73. Diversions to Newtown Canal, Water Years 2012–2021

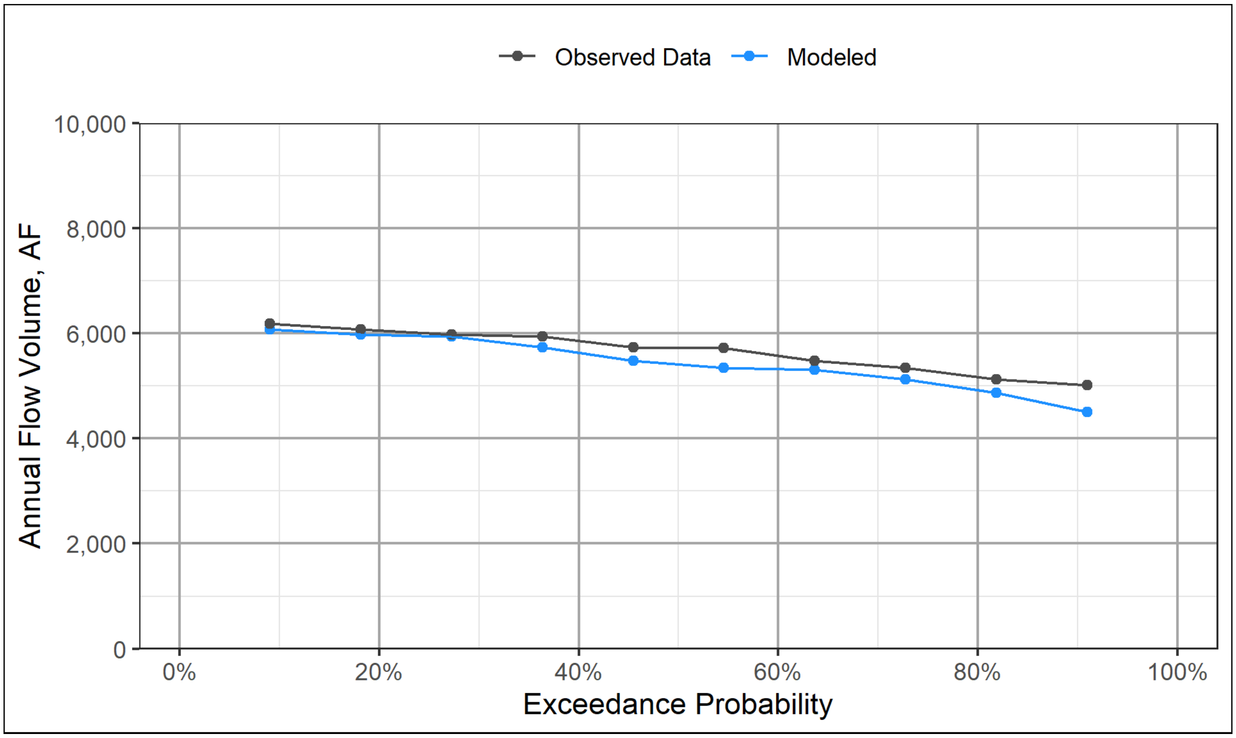

Figure C-74. Annual Diversion Exceedance to Newtown Canal, Water Years 2012–2021

C.7.6. Tunnel Canal

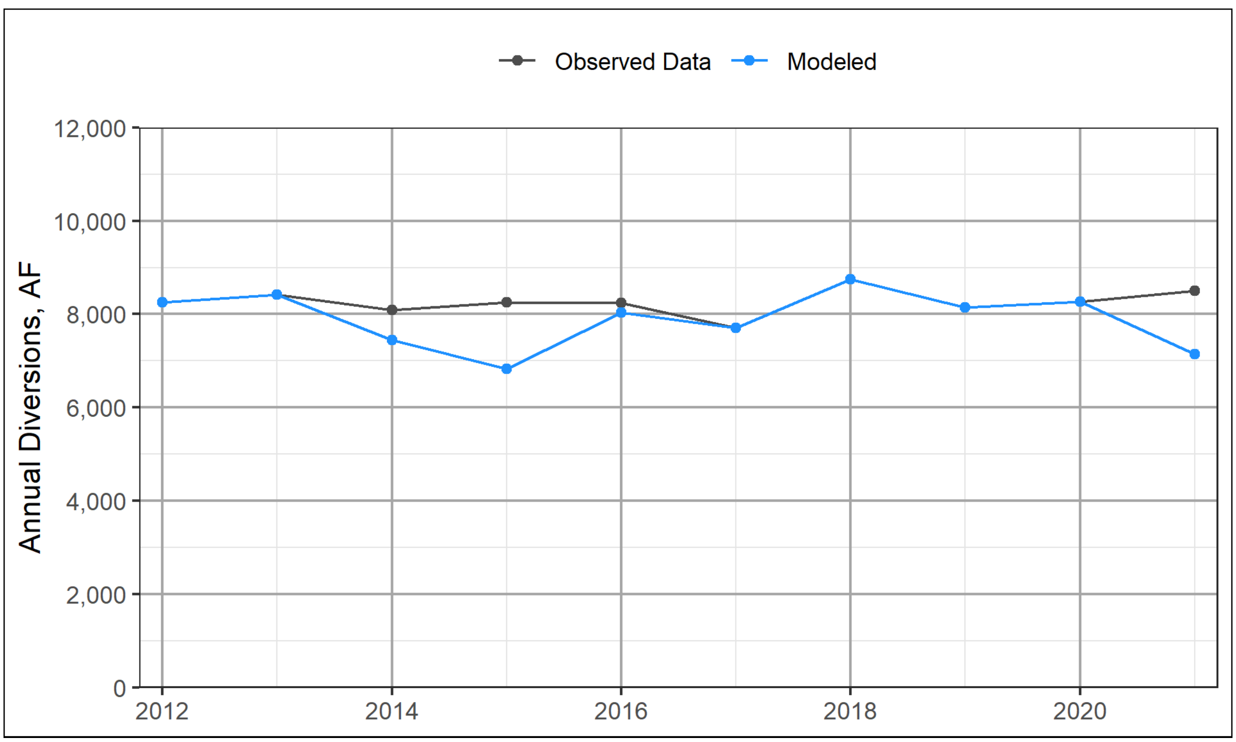

Figure C-75. Diversions to Tunnel Canal, Water Years 2012–2021

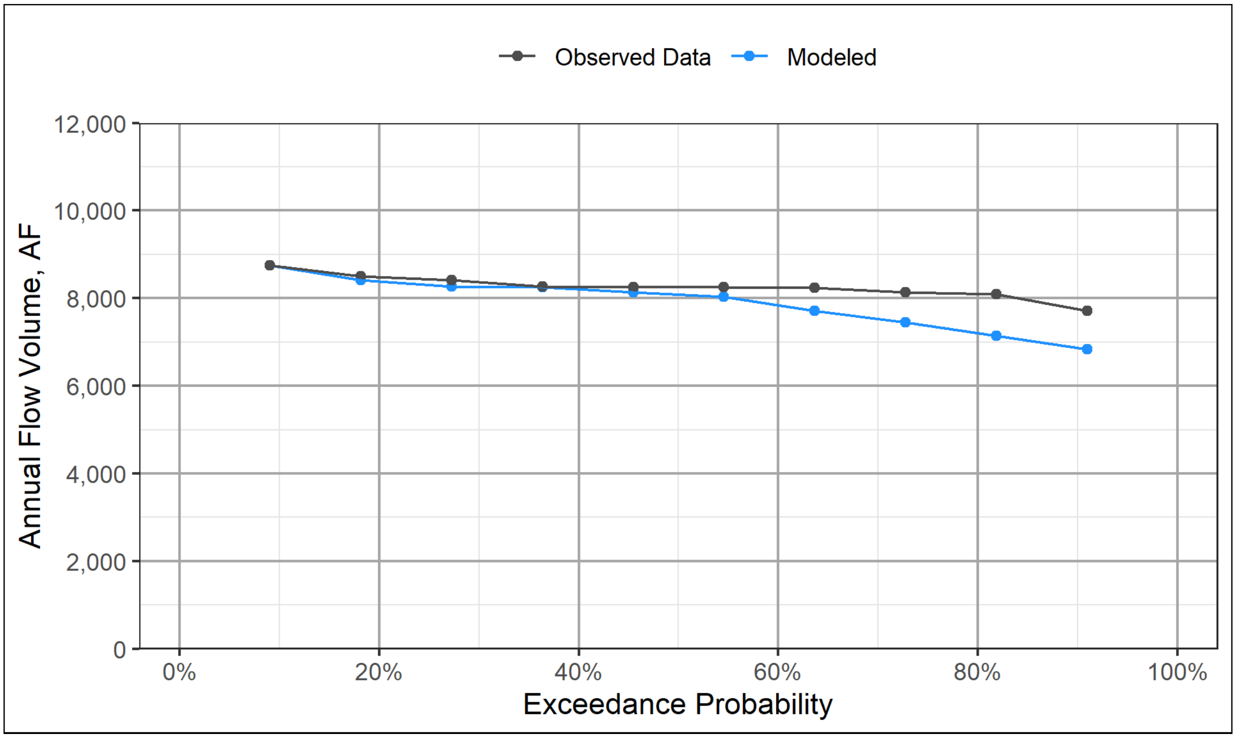

Figure C-76. Annual Diversion Exceedance to Tunnel Canal, Water Years 2012–2021