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Simulating Human Water Regulation: The Development of an Optimal Complexity, Climate-Adaptive Reservoir Management Model for an LSM

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ABSTRACT

The widespread influence of reservoirs on global rivers makes representations of reservoir outflow and storage essential components of large-scale hydrology and climate simulations across the land surface and atmosphere. Yet, reservoirs have yet to be commonly integrated into earth system models. This deficiency influences model processes such as evaporation and runoff, which are critical for accurate simulations of the coupled climate system. This study describes the development of a generalized reservoir model capable of reproducing realistic reservoir behavior for future integration in a global land surface model (LSM). Equations of increasing complexity relating reservoir inflow, outflow, and storage were tested for 14 California reservoirs that span a range of spatial and climate regimes. Temperature was employed in model equations to modulate seasonal changes in reservoir management behavior and to allow for the evolution of management seasonality as future climate varies. Optimized parameter values for the best-performing model were generalized based on the ratio of winter inflow to storage capacity so a future LSM user can generate reservoirs in any grid location by specifying the given storage capacity. Model performance statistics show good agreement between observed and simulated reservoir storage and outflow for both calibration (mean normalized RMSE = 0.48; mean coefficient of determination = 0.53) and validation reservoirs (mean normalized RMSE = 0.15; mean coefficient of determination = 0.67). The low complexity of model equations that include climate-adaptive operation features combined with robust model performance show promise for simulations of reservoir impacts on hydrology and climate within an LSM.

1. Introduction

Reservoirs are an important aspect of water resources management worldwide. Although the pace of reservoir creation through dam construction in the United States has slowed (Graf 1999), the number of global dams over 15 m tall has still grown substantially in recent years to over 50 000 (Lehner et al. 2011). The global cumulative reservoir storage capacity behind dams is 7000–8300 km^3, representing over 20% of the total annual discharge to oceans (Syed et al. 2010; Lehner et al. 2011). The proportion of discharge impounded behind reservoirs is even greater in the United States, as reservoir storage amounts to 75% of the annual discharge in this region (Biemans et al. 2011). Assuming an annual mean global river channel storage of 1200–2120 km^3 (Hanasaki et al. 2006), reservoirs increase the amount of standing, natural water by 330%–700% and intercept water from lands covering an area of 53 million km^2, or 40% of the total terrestrial environment (Wisser et al. 2013).

The widespread occurrence of reservoirs is a testament to the associated many societal benefits, but impacts on regional hydrometeorology from these water

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bodies have also been noted. Evaporative losses from reservoirs exceed 5% of total discharge on a global scale, which surpasses the losses from both domestic and industrial water consumption combined (Lehner et al. 2011). Enhanced rates of regional water vapor transport and precipitation have been statistically related to reservoir location, which is strongest for larger reservoirs situated in warmer climates (Hossain 2010; Degu et al. 2011). River fragmentation from dam construction has affected 60% of the world's largest rivers, accounting for approximately 90% of the discharge coming from these fluvial systems (Revenga et al. 2005).

Given the impacts of reservoir management on the water cycle and its close linkage to the energy cycle, these perturbations have an impact on the climate system as well. However, reservoirs have yet to be fully integrated into climate models to better understand the nature of these changes. Inclusion of reservoir behavior in large-scale land surface models (LSMs) that can be used to monitor the impacts on the water and energy cycles and how they interact dynamically is thus critical to better understand such behaviors and the relative impact on the climate system (Nazemi and Wheater 2015a).

In this study, we develop general reservoir operation rule equations that can be used to simulate outflow and storage within an LSM to better represent reservoir management impacts and feedbacks on the climate system. Although the ultimate goal is to use these equations within an LSM, reservoir model coupling to an LSM and subsequent simulations and evaluations are beyond the scope of this paper. Rather, the intent of this study is to generate general reservoir operation rule equations, evaluate the performance of equations in simulating reservoir outflow and storage, and demonstrate applicability of equations for use in an LSM. Furthermore, as other equations have already been developed toward this end, we describe the distinguishing features for the equations used in this study. In particular, we focus on describing the development of simpler, generalized reservoir equations, which is ideal for integration in an LSM, and exhibit how the equations are climate adaptive through conducting and evaluating several experimental simulations. Unique equation properties that were used here as well as equations used in related efforts are discussed in more detail in the sections that follow.

2. Global and California reservoir modeling

Reservoir management is influenced by operation rule curves, which provide an indication of how the storage of water in a given reservoir changes throughout the year. The curves are a function of current and historic hydrologic conditions and the general purpose of the reservoir (Willis et al. 2011). Dam release restrictions and minimum environmental flow thresholds may impose further constraints on how a reservoir is managed. Given the typical high temporal variability in the hydrology and use of reservoirs (Nazemi and Wheater 2015b), rule curves frequently serve as mere guidelines for operators rather than explicit storage thresholds that must be met year-round. Hence, operational criteria to direct modelers with simulations of releases often do not exist (Fekete et al. 2010). Given these considerations, attempting to develop a general system of equations that can accurately simulate outflow for multiple reservoirs remains a difficult task.

Further complicating generalized modeling of reservoir operations is the obsolescence of the assumption that past records in hydrology will hold true in the future because of ongoing environmental alterations caused by climate change (Milly et al. 2008). In the state of California, for example, mean surface air temperatures are projected to increase by 2°–6°C by 2100 (Hayhoe et al. 2004), which is anticipated to exacerbate the already declining trend in annual snowpack and further shift the timing of peak runoff toward earlier in the season (Mote 2006). Rising temperatures coupled with these hydrologic effects are expected to decrease available reservoir storage, promote additional deviations away from the natural flow regime in rivers, and enhance reservoir storage losses due to evaporation (Vanrheenen et al. 2004; Mote 2006; Cayan et al. 2008; Barnett et al. 2008). These changes in the water cycle over both the land and atmosphere, combined with the rise in water demand from population growth, will lead to major water demand and supply shifts over the next century (Haddeland et al. 2014). It is thus essential that transformations such as these are accounted for in the long-term modeling of water management systems.

Despite the importance of including reservoir dynamics in large-scale hydrology models or LSMs, only a limited number of studies have been conducted toward this purpose and all have yet to be fully coupled to a climate model. Descriptions of a more comprehensive list of these studies can be found in Nazemi and Wheater (2015b), but some of the key studies are described in more detail here. The algorithms used to simulate reservoir releases in Hanasaki et al. (2006) to improve global discharge simulations provided the foundation for a number of subsequent studies. Initial releases for an operational year were based on the ratio of storage to total storage capacity so storage could be recovered throughout the year when starting at a low volume. Successive releases were based on release targets, which

changed depending on the downstream agricultural, industrial, and domestic water demands for that month relative to an inflow threshold. The targets were incorporated into actual releases, which were also a function of storage capacity to annual inflow ratios. Biemans et al. (2011) used a similar formulation but excluded industrial and domestic demands to determine releases based exclusively on crop water demands. Döll et al. (2012) used reservoir storage variations in the WaterGAP (Water—Global Assessment and Prognosis) Global Hydrology Model to help with differentiating between surface water and groundwater withdrawals in the agricultural, domestic, and industrial water use sectors. Wisser et al. (2010) simulated reservoir outflow solely from parameterized inflow, which was also used in Fekete et al. (2010) to assess reservoir and irrigation impacts on watershed nutrient exports. In addition, Haddeland et al. (2006) were the first to use a parameter-optimization-based scheme in conjunction with reservoir storage, inflow, evaporation, and dominant reservoir function within the macroscale hydrologic Variable Infiltration Capacity model (VIC) to simulate releases at the continental scale.

While these studies were developed to understand the impacts of reservoir management on streamflow and reservoir storage, not every study explicitly accounts for nonstationarity in the operator's response to changes in hydrology, which would alter model representations of reservoir outflow and storage. The water available to these managed systems is changing because of increasing stresses from population growth and climate change, and the management of these systems will change accordingly. Models thus need to be made more adaptive to integrate these shifts, particularly when used for forecasting future water resource management or climate systems (Wheater and Gober 2013).

Another potential issue is that many of these studies were conducted for reservoirs at large or even global scales without the use of calibrated and validated generalized equations. Although useful for enhancing knowledge about the general Earth system and global water supplies, employment of general equations requiring minimal input is more advantageous for simulating reservoir behavior where no observations are available or for locations where insertion of a theoretical model is desired by a user. Moreover, employing generalized equations provides better justification for regional- or global-scale applications. Such a practice may also help to avoid eliminating localized reservoir management or climate characteristics from becoming part of the model structure.

For example, in the large-scale reservoir modeling studies mentioned above, any combination of storage,

inflow, storage or inflow thresholds, storage capacity, dominant reservoir function, climate information such as evaporation and precipitation, and water demands were used as the basis to determine reservoir releases in the model. Given that the selection of which variables to use was dependent on the intended purpose of the model and the collective management characteristics of the reservoirs being modeled, which are in turn heavily influenced by the spatial scale of the study, some of these variables are more important in determining releases in certain areas over others. Moreover, some of this information might not even be available over large portions of the globe, particularly in developing regions, meaning that large expanses of the land surface with reservoirs would not be simulated if these models were exclusively used. Modeled estimates of these variables could also be represented in the reservoir model, but this introduces additional complexities by resulting in uncertainties that must be quantified. Hence, the better approach involves development of reservoir release algorithms using more general equations to maintain parsimony and ensure model inputs are appropriate to the data available.

With a high density of reservoirs and a diverse array of climate and spatial regimes, California serves as an ideal setting for generalized reservoir model development. Numerous statewide water management models have already been developed to determine optimum surface water and groundwater allocations given different management objectives. Model drivers included economic considerations (Jenkins et al. 2001); water supply allocation and storage priorities (Draper et al. 2004); human and environmental water demands (Yates et al. 2005); and historical surface water, land use, and water diversions [California Central Valley Groundwater–Surface Water Simulation Model (C2VSim); Brush et al. 2013]. These models typically require either a high number of inputs or parameters. Unfortunately, highly parameterized, multitermed models make model calibration and validation more challenging (Kuczera and Mroczkowski 1998) and thus computationally intensive to run in an LSM framework. Instead, a simpler model structure is required that minimizes the need for extra terms or parameters, while still adequately representing reservoir outflow and storage behavior.

The reservoir management model described herein was developed using California reservoirs as a test case with the intent of ultimately running within a large-scale LSM. As such, the model was designed so that LSM surface runoff at the upstream location of the targeted reservoir to be modeled will serve as reservoir inflow and the primary input. Outputs consist of reservoir outflow and storage, which were estimated through the

optimization of parameter values. Optimal parameter values were generalized across reservoir locations based on the inflow to storage capacity ratio to demonstrate applicability across larger spatial scales. Furthermore, the generalization based on these variables will allow an LSM user to "synthesize" a reservoir at any model grid location given a desired storage capacity to achieve a realistic representation of reservoir management behavior. This will be useful to simulate climate impacts stemming from "hypothetical" reservoirs, which would aid in the testing of potential climate effects from planned reservoir development on a global scale. Because seasonal changes in temperature are closely linked to the agricultural growing season (Nazemi and Wheater 2015a), which in turn heavily influences reservoir behavior in California, temperature was employed to distinguish between the equations used to simulate reservoir outflow and storage. Moreover, this feature was added to better allow for global-scale simulations and represent future reservoir storage and management shifts in response to a warming climate, which is one of the distinguishing characteristics of the model developed in this study relative to previous reservoir modeling schemes designed for global-scale simulations.

The materials and methods section that follows first describes the background for model development, including the study area, data sources, and criteria driving the selection of different components used in the model. Next, we discuss the different equations that were tested for use in the model and the measures employed to select the most appropriate set of equations for this study. This section also involves a detailed rationalization for incorporating temperature into the model. We then describe the optimization of model parameters for each reservoir and how the optimized parameter values were used to create generalized parameters. Finally, we explain the use of three outside reservoirs for model validation and the statistics used for evaluation of model performance.

3. Materials and methods

a. California study area

Reservoirs from California were selected for use in model development. California consists of 1530 dams with a collective storage capacity that is approximately equivalent to the mean annual discharge from its rivers, resulting in a reservoir storage density of $239\,000\,\mathrm{m^3\,km^{-2}}$ that is surpassed by only 2 of the 18 major water resource regions in the continental United States (Graf 1999). Considering the extensive water resource management characteristics of this region and

the access to a wide range of reservoir observations, California serves as an ideal test site for reservoir model development.

b. Data sources

Data used in model development included temperature, as well as reservoir inflow, outflow, and storage. Temperature records were obtained from Parameter-Elevation Regressions on Independent Slopes Model (PRISM) estimates at 2.5-arc-min resolution (PRISM Climate Group 2004). PRISM data were acquired by selecting the grid cells that encompassed the downstream-most location of the reservoir. PRISM was used over in situ station temperature records, as the model is intended for use in an LSM, which also employs the use of grid-based temperature measurements to drive internal physical processes.

Reservoir inflow, storage, and outflow data were obtained from the California Data Exchange Center (CDEC; DWR 2013). This site is managed by the California Department of Water Resources (DWR) and includes data collected by the U.S. Army Corps of Engineers (USACE), U.S. Bureau of Reclamation (USBR), and local county and municipal governments. Data from the 50 largest statewide reservoirs by maximum reservoir capacity with continuous monthly data from the 1995–2013 simulation period were targeted for the study. A total of 14 reservoirs fit the criteria, which account for approximately 50% of the total statewide storage capacity and include the four largest by volume in the state. Summary hydrologic statistics and information for the reservoirs used in model development are included in Table 1. Reservoir locations are provided in Fig. 1.

c. Model criteria

Model development was driven by the need to maintain model parsimony and facilitate integration into an LSM. Inputs to the model thus were kept to a minimum. Those already available to an LSM user consisted of inflow and temperature. Inflow will be derived from upgradient, surface runoff where a river-routing model will be used to transfer water between upstream and downstream reservoirs. Temperature will be used in the equation formulations as described in section 3d. Reservoir storage capacity and an initial storage condition are the only reservoir design variables required by the LSM user that are not currently available within the LSM framework. Model outputs consist of dynamic estimates of reservoir outflow and storage calculated simultaneously at each time step. Simulations in an LSM with river-routing model included will allow reservoir outflow to be routed to downgradient locations,

TABLE 1. Summary of hydrology and spatial information for reservoirs used in model development (source: DWR; http://www.water.ca.gov/damsafety/damlisting).

Reservoir name	River	Operator[a]	Use code[b]	Lat, lon	Drainage area (km^2)	Elev (m)	Storage capacity (km^3)
Shasta	Sacramento	USBR	IMPR	40.72°N, 122.42°W	17 262	378	5.61
Oroville	Feather	DWR	IMPR	39.54°N, 121.49°W	9342	281	4.36
Trinity	Trinity	USBR	IMPR	40.80°N, 122.76°W	1782	730	3.02
New Melones	Stanislaus	USBR	IMPR	37.95°N, 120.53°W	2331	346	2.96
Pine Flat[c]	Kings	USACE	IR	36.83°N, 119.33°W	4002	296	1.23
Folsom	American	USBR	IPR	38.68°N, 121.18°W	4882	146	1.20
Isabella[c]	Kern	USACE	IR	35.65°N, 118.47°W	5372	803	0.70
Millerton	San Joaquin	USBR	IR	37.00°N, 119.71°W	4338	177	0.64
Camanche	Mokelumne	EB MUD	M	38.23°N, 121.02°W	1603	80	0.51
Sonoma	Dry Creek	USACE	IR	38.72°N, 123.01°W	337	158	0.47
New Hogan	Calaveras	USACE	IMR	38.15°N, 120.81°W	940	221	0.39
Eastman	Chowchilla	USACE	IR	37.21°N, 119.97°W	609	187	0.18
Black Butte[c]	Stony	USACE	IR	39.81°N, 122.33°W	1919	157	0.18
Kaweah	Kaweah	USACE	IR	36.42°N, 119.00°W	1453	229	0.18

[a] EB MUD = East Bay Municipal Utilities District.
[b] I = Irrigation; M = Municipal; P = Hydropower; R = Recreation.
[c] Reservoirs used in validation, all others used in model calibration and parameter generalization.

effectively mimicking flow in river channels, and reservoir storage will be linked to the LSM hydrology to allow for evaporation.

Although an initial storage condition was used for model development, once integrated into an LSM this could be achieved using reservoir water levels if the relationship between reservoir storage and elevation is known or could be reasonably estimated. Moreover, reservoir surface area and water level heights from the upcoming NASA Surface Water and Ocean Topography (SWOT) satellite mission could be used to derive change in storage to aid with these estimates. This mission is expected to observe reservoirs down to a surface area of 0.0625 km^2 with an expected launch date of 2020 (Biancamaria et al. 2010).

The reservoir model was run at a monthly time step. Model behavior is thus best captured as broad seasonal variations in reservoir operations that are largely controlled by the timing of crop planting and harvest seasons relative to inputs such as snowmelt within the model development study area. Even still, the current reservoir model formulation permits operation at daily or subdaily time steps once coupled to an LSM to match the temporal scale of LSM output specified by the user. For example, the accumulation of daily LSM output over a given simulated month could be used as reservoir model input and to drive the decision behavior (mode switching, described in section 3d). Releases would then remain constant through time and only shift when reservoir behavior changes (i.e., monthly) according to the reservoir model. In this way, the reservoir management model would operate based on monthly inflow and

temperature values, while still able to communicate with the LSM at submonthly intervals.

The justification for simulating reservoir behavior at a monthly time step stems from the desire to ultimately represent long-time-scale reservoir impacts on the climate while running the model coupled to an LSM. Longer reservoir model time steps are therefore desired to decrease the subdaily variability so the rules governing reservoir management become easier to generalize at these temporal scales, thereby making the associated impacts on the water cycle and climate system less challenging to estimate. Although this exempts management functions such as hydropower generation that occur at smaller time scales from being included, accounting for daily and subdaily variations in reservoir behavior is beyond the scope of this study. More importantly, omitting explicit representations of these functions preserves a simpler model structure with minimal inputs, making it easier to achieve the goal of integration into an LSM.

d. Model development and selection

The model was designed to simulate both reservoir outflow and storage simultaneously, as representing these characteristics is necessary to adequately capture reservoir behavior. Reservoir storage is updated using Eq. (1):

$$S(t) = S(t - \Delta t) + [I(t) - Q(t)], \tag{1}$$

where $S(t)$ is reservoir storage (m^3), $I(t)$ is reservoir inflow (m^3 s^{-1}), $Q(t)$ is reservoir outflow (m^3 s^{-1}), and t is time (s). This equation has been used to simulate

FIG. 1. Locations of reservoirs used in model development. Numbers denote respective statewide storage capacity rank.

reservoir storage in other studies (Hanasaki et al. 2006; Wisser et al. 2010; Fekete et al. 2010).

As highlighted previously, different formulations of reservoir storage and inflow provide the basis for simulating reservoir outflow in other studies (e.g., Hanasaki et al. 2006). Here, we test six different equation arrangements prior to application in this study (Table 2). Model 1 treats outflow as equal to inflow, which effectively ignores any influence of the reservoir on the outflow. For this reason, results from model 1 were included to serve as a performance baseline. As long as the simulated outflow using the other reservoir models demonstrated superior performance over the results from model 1, the overall model performance was considered to be an improvement over the base case where the influence of reservoirs on outflow was ignored. The other models shown use either parameterized fractions of inflow and/or storage to simulate outflow. Model complexity was incrementally enhanced with each subsequent model that was tested by increasing the number of parameters.

As shown in Table 2, reservoir outflow equations were allowed to switch modes within the year to represent seasonal changes that typify California reservoir management behavior (Fig. 2). During the initial stages of model development, the mode switching was achieved using the month of the simulated output. For instance, if the simulation was conducted within the summer months, the release equation was used. Otherwise, the recharge equation was used. However, given that the model was ultimately to be run on a global scale within an LSM, the use of months was less than ideal given the strong link between reservoir behavior and climate and locations across the globe that are not climatically similar during the same month. Ultimately, temperature was selected for this purpose, as many reservoirs exhibited a strong seasonal signal in outflow and storage behavior and this variable produced stronger results compared to other variables that were tested.

Temperature was used in the model by applying the recharge equation during the cooler months when the temperature of the simulated month fell below the baseline temperature, which is given as the mean temperature during the 5-yr period immediately prior to the 1995–2013 model simulation period. During the cooler months, reservoir inflow generally exceeds outflow because of increased runoff from snowmelt, so a parameterized fraction of inflow is used to determine outflow

TABLE 2. Drawdown and recharge season reservoir outflow operating rules tested in model development stage arranged according to increasing model complexity.

Model No. and name	Complexity classification	Parameters per season	Recharge season operating rule[a]	Drawdown season operating rule[a]
1. Natural flow	Zero	Zero	$I(t)$	Annual
2. Annual storage release targets	First	One	$\beta S(t - \Delta t)$	Annual
3. Annual inflow release targets	First	One	$\alpha I(t)$	Annual
4. Seasonal storage release targets	Second	One	$\alpha S(t - \Delta t)$	$\beta S(t - \Delta t)$
5. Winter inflow, summer storage release targets	Second	One	$\alpha I(t)$	$\beta S(t - \Delta t)$
6. Winter inflow and storage, summer inflow and storage release targets	Third	Two	$\alpha_w I(t) + \beta_w S(t - \Delta t)$	$\alpha_s I(t) + \beta_s S(t - \Delta t)$

[a] $I(t)$ = reservoir inflow; $S(t)$ = reservoir storage; α, β, α_w, β_w, α_s, and β_s are parameters.
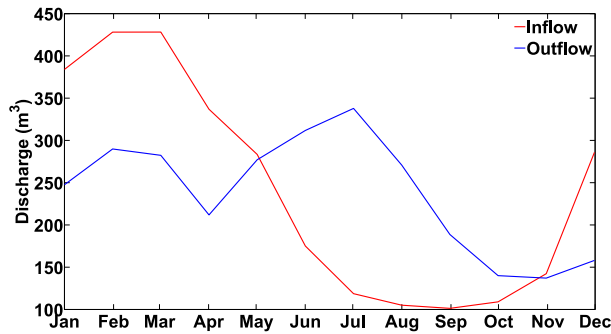
FIG. 2. The 1995–2013 Shasta Reservoir observed inflow and outflow climatology demonstrating typical California seasonal reservoir behavior where inflow exceeds outflow during wet season and outflow exceeds inflow during dry season.

and storage increases. Alternatively, the drawdown equation was applied during the warmer months when the temperature exceeded the baseline temperature. During this time, outflow tends to exceed inflow because of the heightened water demand from agriculture, so a parameterized fraction of storage is used to determine outflow and the storage decreases. It is anticipated that the distribution of monthly temperatures above or below the baseline mean will be identical regardless of reservoir location in the upper or lower reaches of a given watershed. Also, it should be noted that seasonal-based equations have also been applied in other studies to determine reservoir releases (e.g., Hanasaki et al. 2006). The arrangement of temperature is shown in Eqs. (2) and (3):

$$T(t) \leq T_b : \text{Recharge Equation} \qquad (2)$$

and

$$T(t) > T_b : \text{Drawdown Equation}, \qquad (3)$$

where $T(t)$ is monthly temperature (°C) during the simulation period and T_b is the baseline temperature.

Variables other than temperature were tested for use in its place to implement the mode switching within the model. Of those variables, only temperature was found to produce as robust results as the use of months. Intuitively, this makes sense given that temperature is a natural proxy for seasons. Its use in this instance was also preferred given its functional connection with shifts in the length of the California growing season and given that the seasonal snowmelt pulse drives reservoir operations, and this does not always stay constant from one year to the next. Therefore, the way in which temperature is used enables easy adaptation of the model to other regions where agriculture and snowmelt drive reservoir operations, but at different times of the year. This could be critical for reservoirs located in farming

areas around the Andes of South America, which is one of the few regions that have experienced substantial growth in reservoir development over recent years (Wisser et al. 2013). Selection of temperature over time to trigger mode switching is thus more in sync with the stronger link between reservoir operations, agriculture, and snowmelt globally, making it more ideal for use in global simulations within an LSM. Given that temperature is also reproduced with a higher degree of accuracy within this model framework relative to other variables makes it even more suitable for its current use in the model equations. There is also potential for explicitly relating temperature changes in the model to water demands, as it has already been used to help determine crop and livestock water demands in other studies (Nazemi and Wheater 2015a).

Reservoir inflow, storage, and water demand thresholds have also been used to drive reservoir operation rules (Biemans et al. 2011; Wisser et al. 2010; Döll et al. 2009; Haddeland et al. 2006; Hanasaki et al. 2006). Monthly storage and inflow thresholds were tested for use in this study with marginal improvements in results and thus were omitted. Water demands were not used, as these would be difficult to reproduce directly within an LSM, which is the end goal for the model. Although not known to have been used to drive operation rules for large-scale reservoir modeling studies and not tested here, snow coverage, upper watershed rain to snow ratios, regional soil moisture, or reservoir water levels could have potentially been employed in a similar capacity. However, because changes in temperature are more directly linked to climate change and the loss of stationarity in hydrologic models, the use of temperature as a proxy provides a stronger basis for the model adaptivity framework we applied. Moreover, the availability and reliability of temperature data exceeds that of the other variables, making it easier to implement within an LSM structure.

Additional model constraints were added to make the model more realistic by preventing storage from exceeding maximum capacity or falling below zero. In the event that simulated storage surpassed the user-defined storage capacity, outflow was simulated using Eq. (4):

$$Q(t) = I(t) + \frac{S(t - \Delta t) - S_{\max}}{\Delta t}, \qquad (4)$$

where $S_{\max}$ is the maximum storage capacity (m^3) for the given reservoir. An additional constraint was added to prevent reservoir storage from falling below 10% capacity, as this level rarely occurred in any of the observations used in model development and it follows the minimum accepted allowable storage level used by Hanasaki et al. (2006).

Performance of the different models that were tested was evaluated based on the outflow and storage best-fit statistics of the normalized root-mean-square error (nRMSE), where the RMSE is normalized to the mean of the observations; coefficient of determination r^2; and Nash–Sutcliffe efficiency (NSE) during model optimization (Nash and Sutcliffe 1970; Krause et al. 2005). Model complexity was increased incrementally until little improvement could be gained in model performance by applying more complex formulations. This determination was achieved using the Akaike Information Criterion (AIC) shown in Eq. (5):

$$AIC = 2K[\ln(L)], \qquad (5)$$

where K is the number of parameters and L is the likelihood function (Akaike 1974). Here, the likelihood function is assumed to be the difference between one and the nRMSE of observed and simulated reservoir outflow and storage, where the nRMSE has been normalized to the storage or outflow mean. The AIC method was chosen to acknowledge that model selection involves a trade-off between how well the model fits observations and the number of parameters used or model complexity. Thus, lower AIC values indicate a more ideal model in terms of both its best-fit statistics and number of parameters used.

e. Parameter optimization

Parameter optimization was achieved for 11 reservoirs by changing parameter values to minimize the objective function for each reservoir individually. The objective function is defined as the Pareto front between observed and modeled reservoir outflow and storage nRMSE. Pareto optimization was necessary to implement here because the minimum objective function for outflow and storage are conflicting objectives. In other words, changing parameter values to find the minimum nRMSE for either storage or outflow will not necessarily result in the desired cumulative minimum nRMSE for both of these variables (Vrugt et al. 2003). Different initial values were tested to ensure the true optimum parameter values for each reservoir were obtained and to avoid finding local objective function minima. The Nelder–Mead algorithm was used to minimize the objective function (Nelder and Mead 1965), which was solved by placing equal weight on reservoir outflow and storage so the Pareto optimum could be satisfied.

f. Parameter generalization and model validation

Model parameters were generalized from the best-performing model to facilitate the automatic generation of reservoirs within an LSM and to justify the utility of

model equations for large-scale applications. Parameter generalization proceeded by regressing final parameter values to a quantitative reservoir characteristic, which included those already available to an LSM user, or those that could be easily input by a user. Final selection of the reservoir characteristic used in the parameter generalization was achieved by choosing the property with the highest r^2 when regressed against the optimized parameter values obtained from each individual reservoir. Ultimately, the resulting generalized regression equation will be used to generate reservoirs within an LSM.

Reservoir characteristics that were tested empirically for use in parameter generalization consisted of both observed and modeled data. Observations were obtained from CDEC (www.cdec.water.ca.gov) and included reservoir storage capacity, elevation, latitude, longitude, coefficient of variation of monthly inflow, and inflow to reservoir storage capacity ratios (I:SC) calculated using Eq. (6):

$$I:SC = \frac{I_{\text{win}}}{S_{\text{max}}}, \qquad (6)$$

where I_{win} is the mean total winter (October–May) inflow over the simulation period. It should be noted that annual inflow to storage capacity ratio was also tested here. Moreover, the inverse of this ratio was used to dampen simulations of releases and avoid overflow for small reservoirs in Hanasaki et al. (2006). Modeled records that were tested for use in parameter generalization consisted of seasonal or annual precipitation and seasonal temperature obtained from 2.5-arc-min-resolution PRISM-gridded data that encompassed the geographic coordinates of the reservoir. Note that although temperature was tested for use in parameter generalization, it does not necessarily have to be employed in the final model to maintain consistency with the use of temperature to select model equations, as these are two entirely different features of the model.

Following parameter generalization, additional model simulations were conducted for the same 11 reservoirs as well as three additional reservoirs to test the performance of the generalized parameters and for model validation. Model simulations for each of the calibration reservoirs were conducted using the generalized parameters so the results could be compared to the original parameter results optimized for each reservoir individually. Model validation was achieved using the generalized parameters to run the model for three additional reservoirs outside of those used in the development of the generalized parameters. Selection of validation reservoirs was based on availability of

TABLE 3. The 11 reservoir mean (std dev) model performance statistics obtained during calibration.

Model No.	Optimized parameter values	ΔAIC[a]	Mean $S + Q$ nRMSE[b]	Mean $S + Q$ nRMSE climatology[b]	Mean $S + Q$ r^2	Mean Q NSE
1	Nc[c]	Nc[c]	0.13 (0.06)[d]	0.41 (0.17)[d]	0.52 (0.22)[d]	0.24 (0.52)
2	β = 0.24 (0.03)	0.07	0.18 (0.07)	0.26 (0.06)	0.51 (0.14)	0.15 (0.22)
3	α = 0.31 (0.37)	0.54	0.35 (0.08)	0.85 (0.33)	0.26 (0.10)	−0.76 (0.88)
4	α = 0.19 (0.27) β = 0.21 (0.25)	0.05	0.17 (0.06)	0.23 (0.07)	0.54 (0.12)	0.20 (0.23)
5	α = 0.48 (0.22) β = 0.08 (0.04)	0	0.15 (0.03)	0.25 (0.09)	0.56 (0.10)	0.33 (0.51)
6	α_w = 0.15 (0.12) β_w = 0.08 (0.05) α_s = 0.17 (0.38) β_s = 0.13 (0.07)	2.05	0.17 (0.08)	0.23 (0.10)	0.51 (0.19)	0.24 (0.35)

[a] AIC reported as the difference from the best-performing (lowest) value.
[b] RMSE normalized to mean values.
[c] Nc = not calculated because no storage simulations or parameters for baseline model.
[d] Represents value obtained from outflow simulation only.

continuous records that matched the length of calibration reservoir records, as well as possession of diverse spatial and hydrological characteristics relative to the calibration reservoirs shown in section 3b.

4. Results

Average model performance statistics tested for the six models are shown in Table 3. Model 5 performed best in terms of the AIC, while models 4 and 2 performed only slightly worse with ΔAIC values of 0.05 and 0.07, respectively. Model 5 also had the highest mean outflow and storage r^2 of 0.56 and highest mean outflow NSE of 0.33. The next highest-performing model for these statistics was model 4 with a mean outflow and storage r^2 of 0.54 and model 6 with an outflow NSE of 0.24. Model 4 also had the lowest mean outflow and storage nRMSE climatology of

0.23, while the value for model 5 was slightly higher at 0.25. Only the outflow performance from models 5 and 6 universally exceeded the baseline performance from model 1 where outflow was treated as inflow.

Given its overall superior performance in the testing of the different models, model 5 was used for all subsequent analyses. Model calibration results for the individual reservoir parameter optimization are shown in Table 4. For the 11 calibration reservoirs, the overall mean outflow and storage nRMSE and climatology nRMSE ranged from 0.11 to 0.20 and 0.15 to 0.44, respectively. The mean outflow and storage r^2 ranged from 0.41 to 0.68, while the outflow NSE ranged from −0.97 to 0.76. The accompanying 1995–2013 modeled and observed outflow and storage time series for the three largest reservoirs are provided in Fig. 3 with climatologies in Fig. 4.

TABLE 4. Model performance statistics obtained using optimized parameters for individual reservoirs.[a]

Reservoir	α	β	Mean $S + Q$ nRMSE[b]	Mean $S + Q$ nRMSE climatology[b]	Mean $S + Q$ r^2	Q NSE
Shasta	0.58	0.08	0.12	0.18	0.63	0.51
Oroville	0.64	0.06	0.13	0.28	0.60	0.49
Trinity	0.24	0.06	0.16	0.18	0.57	−0.27
New Melones	0.02	0.05	0.18	0.44	0.47	−0.97
Folsom	0.75	0.09	0.12	0.26	0.58	0.76
Millerton	0.65	0.07	0.16	0.15	0.62	0.77
Camanche	0.60	0.04	0.16	0.36	0.41	0.52
Sonoma	0.46	0.06	0.19	0.32	0.45	0.41
New Hogan	0.45	0.09	0.11	0.17	0.67	0.63
Eastman	0.29	0.10	0.12	0.20	0.68	0.42
Kaweah	0.62	0.20	0.20	0.25	0.46	0.40
Mean (std dev)	0.48 (0.22)	0.08 (0.04)	0.15 (0.03)	0.25 (0.09)	0.56 (0.10)	0.33 (0.51)

[a] Outflow calculated using model 5 from Table 2.
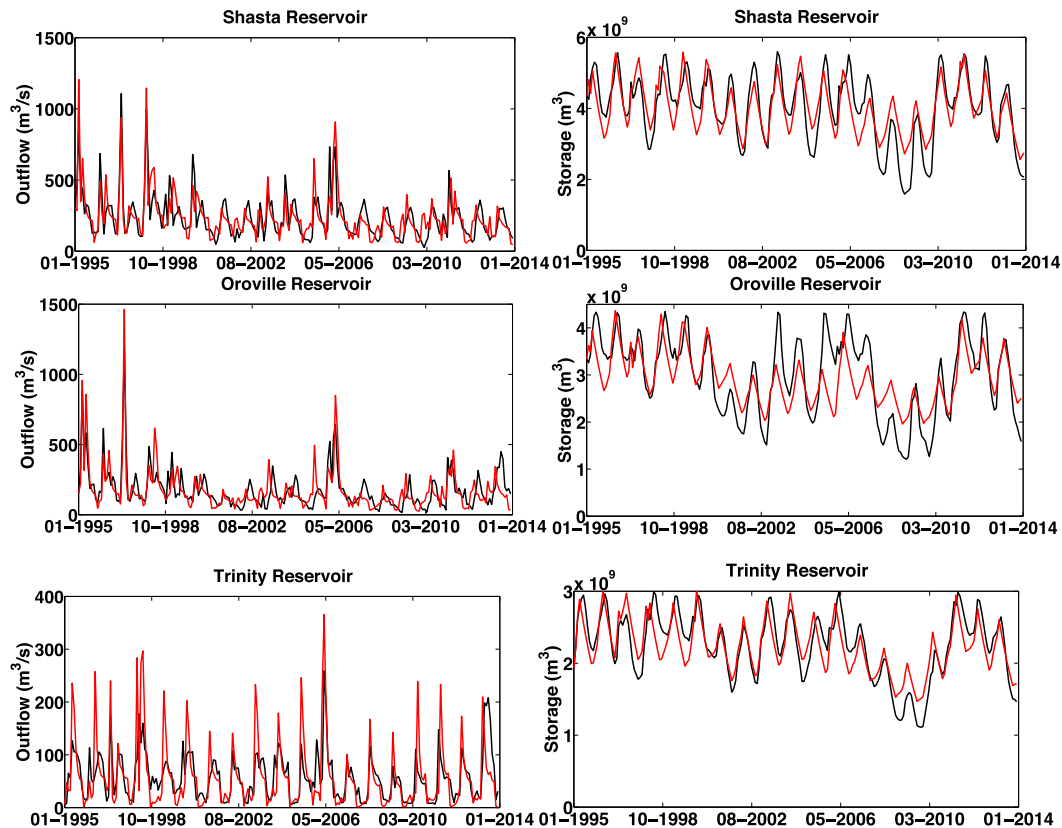[b] RMSE normalized to mean values.

FIG. 3. The 1995–2013 observed and simulated reservoir (left) outflow and (right) storage time series for the three largest calibration reservoirs: (top) Shasta, (middle) Oroville, and (bottom) Trinity. Simulations were performed using individually optimized parameters for each reservoir.

The optimized parameter response surfaces with respect to the objective function of both outflow and storage for the three largest reservoirs are shown in Fig. 5. The response surface gradient was larger for that of outflow than storage, suggesting the minimum objective function was found more quickly for reservoir outflow. The absence of many heterogeneities and local minima in both the outflow and storage response surfaces suggests that the optimum parameter values could readily be obtained using the Nelder–Mead algorithm as long as a few different combinations of initial parameter values were tested to adequately cover the parameter domain.

Figure 6 shows the Pareto fronts for the objective function of both outflow and storage for the three largest reservoirs. The results from this figure represent the objective functions using all combinations of parameter values covering the parameter domain that are divisible by 0.05. All three reservoirs display a similar shape where there is a greater spread of data at midrange nRMSE storage values (~0.5–0.6) but a smaller spread of data as the nRMSE falls outside this range. The

results indicate that there were not as many combinations of parameter values that could reproduce the optimum outflow and storage simultaneously for the reservoirs.

Of all the reservoir characteristics that were tested empirically to determine the best-fit regression relationship with the individually optimized parameters for the generation of generalized parameter equations, the winter inflow to storage capacity ratios showed the strongest correlation. Further empirical testing showed a logarithmic fit best described the relationship between the winter inflow to storage capacity ratio and the optimized alpha parameter values, while a linear relationship best described the relationship between the winter inflow to storage capacity ratio and the optimized beta parameter values. The newly developed generalized parameter equations showing these relationships are provided in Eqs. (7) and (8):

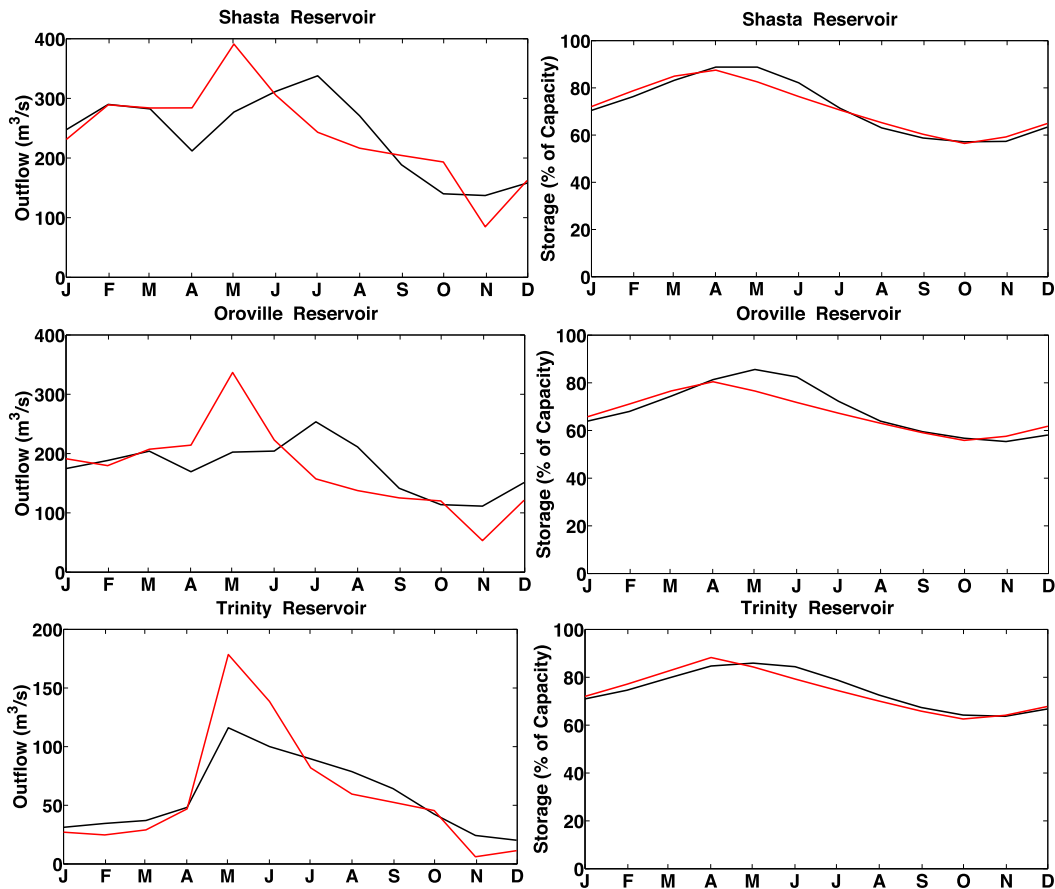$$\alpha = 0.2728 \left[\ln\left(\frac{I_{\text{win}}}{S_{\text{max}}}\right) \right] + 0.5185 \qquad (7)$$

FIG. 4. The 1995–2013 observed (black line) and simulated (red line) reservoir (left) outflow ($m^3 s^{-1}$) and (right) storage climatologies (% of total capacity) for the three largest calibration reservoirs: (top) Shasta, (middle) Oroville, and (bottom) Trinity. Simulations were performed using individually optimized parameters.

and

$$\beta = 0.031\,27\left(\frac{I_{\text{win}}}{S_{\text{max}}}\right) + 0.047\,81,\qquad(8)$$

where and α and β are the model parameters. Final generalized parameter curves with accompanying 95% confidence intervals generated from these equations are shown in Fig. 7.

Final parameter values and model performance statistics using the generalized parameter values from the outflow model 5 for each of the 11 calibration and three validation reservoirs are shown in Table 5. As evidenced by the nRMSE, r^2, and NSE values, the model performed better overall for the validation reservoirs than those used in the parameter generalization. The collective mean outflow and storage nRMSE and nRMSE climatology for both the calibration and validation reservoirs ranged from 0.11 to 0.23 and 0.17 to 1.01, respectively. The outflow and storage r^2 and outflow NSE ranged from 0.37 to 0.72 and −0.74 to 0.93, respectively. The accompanying

1995–2013 time series of modeled and observed outflow and storage for the three validation reservoirs are provided in Fig. 8 with climatologies shown in Fig. 9.

5. Discussion

a. Model selection

Several of the outflow equations were under consideration for use in the study based on the similarities obtained during preliminary testing. Model 6 compared favorably to model 5 in terms of the nRMSE, r^2, and NSE, but because of the use of more parameters it did not perform as well with the AIC. Model 4 performed better in terms of the mean outflow and storage climatology nRMSE, but model 5 outperformed model 4 for all other statistics shown in Table 3. Based on its overall superior performance, model simulation and parameter generalization were achieved using model 5 where reservoir outflow is simulated using a parameterized fraction of inflow during the cooler winter months and a
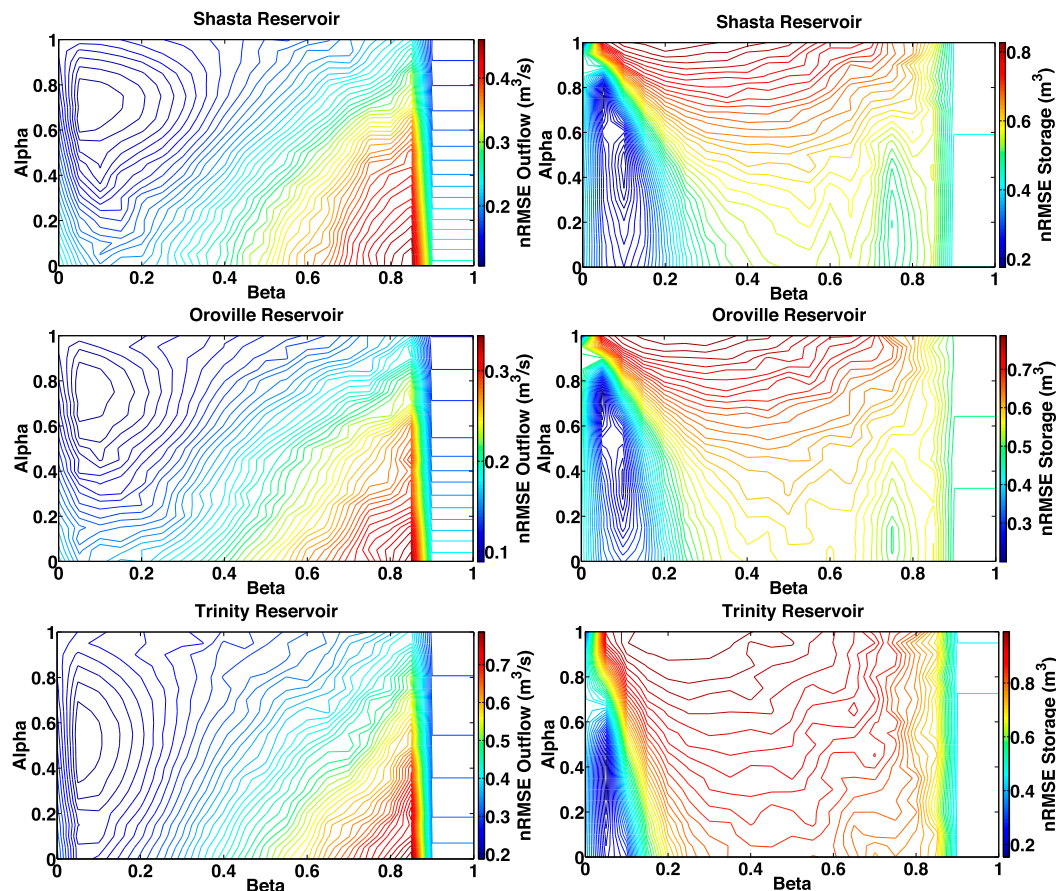
FIG. 5. Reservoir (left) outflow and (right) storage parameter domain plots with respect to RMSE for the three largest reservoirs: (top) Shasta, (middle) Oroville, and (bottom) Trinity.

parameterized fraction of storage during the warmer summer months.

b. Model calibration and generalization

The model performance for the 11 calibration reservoirs using the optimized parameters is similar to that of all reservoirs where the generalized parameters were used. The mean α and β parameters were identical for the two reservoir groups, while the mean outflow and storage nRMSE values increased slightly and the mean outflow and storage r^2 and NSE decreased slightly for the reservoir group using the generalized parameters. The greatest difference in model performance statistics occurred with the mean outflow and storage nRMSE of the climatologies, which nearly doubled from 0.25 to 0.48 for the generalized parameter reservoir group. Use of generalized parameter values increased this statistic for each of the individual reservoirs by a minimum of 12% relative to the results where the parameter values were optimized for each reservoir individually. This decrease in model performance was expected, as the

ability to reproduce the heterogeneities of reservoir management on an individual level becomes more difficult when parameters are used that better match collective over individual reservoir behavior. Similarly, the higher RMSE observed during low-storage periods in the Isabella and Pine Flat Reservoirs likely occurred from this phenomenon, as the reservoirs used to develop generalized parameters had lower levels of interannual variability in storage and the model performance is higher for these types of reservoirs.

The model did not perform as well for the New Melones, Trinity, Sonoma, and Camanche Reservoirs. As shown in Table 6, the generalized parameter performance statistics from these four reservoirs represent three out of the four highest mean outflow and storage nRMSE values, three of the five highest mean outflow and storage climatology values, and the three lowest mean outflow and storage r^2 values when simulations are run using the generalized parameters. Furthermore, this group of reservoirs includes the only two with a negative NSE and the three lowest NSE values
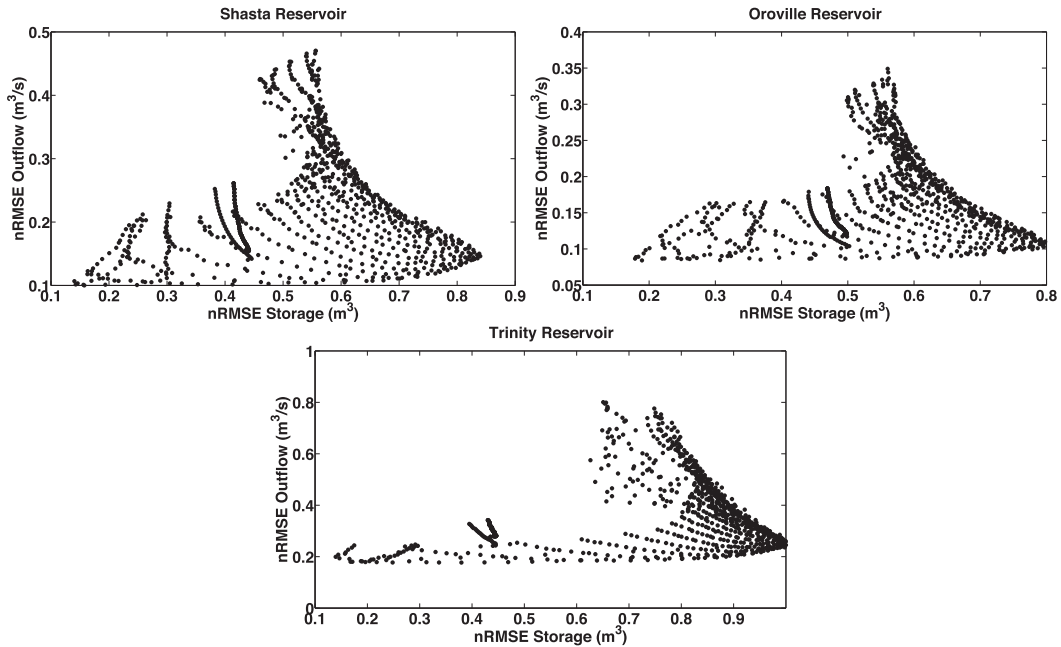
FIG. 6. Pareto fronts for combinations of parameter values between zero and one showing RMSE outflow and storage for (top left) Shasta, (top right) Oroville, and (bottom) Trinity.

overall. To demonstrate the impacts that these reservoirs have on model performance, when they are excluded from the analysis, the mean performance statistics presented in Table 5 improve by 11% for nRMSE, 13% for the nRMSE climatologies, 6% for r^2, and 40% for NSE.

As these four reservoirs also had small storage coefficient of variation S_{cv} values and winter inflow to storage capacity ratios (I:SC) relative to the others in the study, the strength of model performance is closely related to the management intensity of the given reservoir. As shown in Table 6, the four reservoirs accounted for the four lowest S_{cv} values and three of the four lowest winter inflow to storage capacity ratios of the 14 reservoirs that were tested. Lower S_{cv} values are

indicative of smaller changes in monthly storage, which suggest more water must either be released or held back so outflow and inflow are closely aligned and storage remains closer to constant through time. Similarly, lower winter I:SC ratios are exemplified by reservoirs with larger storage capacities and thus higher storage to streamflow ratios and a greater degree of management intensity (Vörösmarty et al. 1997). Both scenarios suggest the degree of management intensity is enhanced for the four lower-performing reservoirs.

Given these considerations, although the model performs well for the majority of management reservoirs, those with higher management intensity are expected to be represented with lower accuracies. Based on the
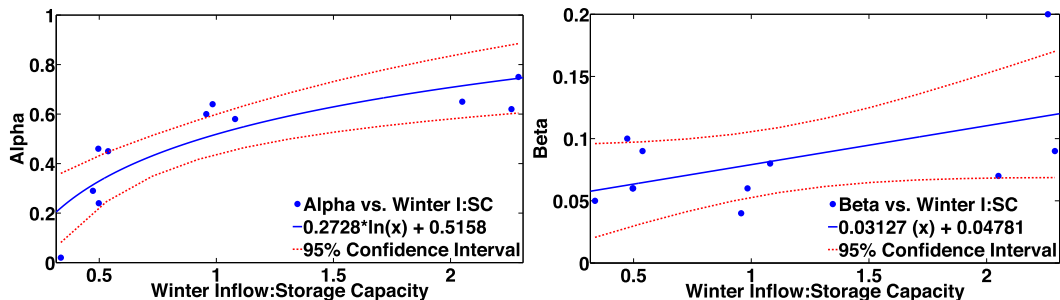

FIG. 7. Generalized parameter curves showing results of regression between final (left) α and (right) β parameter values optimized for each reservoir individually against the October–May winter I:SC for the 11 calibration reservoirs.

TABLE 5. Model performance statistics obtained using generalized parameters.[a]

	α	β	Mean $S + Q$ nRMSE[b]	Mean $S + Q$ nRMSE climatology[b]	Mean $S + Q$ r^2	Q NSE
Calibration reservoirs						
Shasta	0.54	0.08	0.13	0.37	0.59	0.41
Oroville	0.51	0.08	0.15	0.46	0.57	0.36
Trinity	0.33	0.06	0.18	0.43	0.55	−0.04
New Melones	0.22	0.06	0.23	1.01	0.43	−0.74
Folsom	0.75	0.12	0.14	0.33	0.57	0.76
Millerton	0.71	0.11	0.23	0.28	0.51	0.73
Camanche	0.51	0.08	0.23	0.63	0.37	0.43
Sonoma	0.33	0.06	0.21	0.47	0.44	0.23
New Hogan	0.35	0.06	0.13	0.54	0.64	0.51
Eastman	0.32	0.06	0.15	0.44	0.69	0.40
Kaweah	0.74	0.12	0.21	0.28	0.42	0.42
Mean (std dev)	0.48 (0.19)	0.08 (0.02)	0.18 (0.04)	0.48 (0.21)	0.53 (0.10)	0.32 (0.41)
Validation reservoirs						
Pine Flat	0.53	0.08	0.17	0.22	0.64	0.59
Isabella	0.47	0.07	0.18	0.51	0.64	0.47
Black Butte	0.82	0.14	0.11	0.17	0.72	0.93
Mean (std dev)	0.60 (0.19)	0.10 (0.04)	0.15 (0.04)	0.30 (0.18)	0.67 (0.04)	0.66 (0.24)

[a] Outflow calculated using model 5 from Table 2.
[b] RMSE normalized to difference between max and min values.

range of S_{cv} values and winter I:SC ratios for the four reservoirs relative to model performance, the accuracy of model simulations improved for reservoirs with S_{cv} values greater than 0.22 and winter I:SC ratios above 2×10^{-7} s^{-1}. Despite these deficiencies in model performance, the results presented in Table 3 reveal the mean of performance statistics using model 5 far exceeded that when the baseline model 1 was applied, thereby indicating the simulation of discharge is still markedly improved overall when model 5 is used.

c. Model caveats and omissions

The omission of the Whiskeytown Reservoir from this analysis further provides support for the better model performance above a threshold S_{cv} value. Storage from this Northern California reservoir is maintained at capacity during the summer months for recreational purposes, resulting in an S_{cv} value of 0.07, which is lower than all but one of the reservoirs listed in Table 5 and indicates a high degree of management intensity. Thus, despite meeting the targeted source data criteria in model development, observations from this reservoir were excluded, as attempting to account for the unique management characteristic of this reservoir while still capturing the more typical summer operation regime in California reservoirs was not possible given the model development criteria aim of maintaining parsimony. It is likely that similar or different management conditions exist for other global reservoirs that would make model application to those reservoirs less than ideal.

Constraints on releases from environmental flow requirements were not included because of the gross disparity in how these flows are managed worldwide and the lack of availability of this data. Although the model was developed in California where this might be feasible, it is ultimately intended for use at the global scale. In addition, because of the wide variability of environmental flow requirements from one river system to the next, this would still be a difficult task even if only conducted within California.

Explicitly accounting for reservoir functions such as hydropower generation, flood control, and agricultural or domestic water supplies was avoided to maintain model parsimony and focus modeling efforts and representing reservoir behavior better over longer time scales, which was deemed necessary given the ultimate goal of integration into an LSM and evaluation of climate impacts. For the same reason, monthly rather than daily time steps were used. Use of more complicated release equations or a finer temporal resolution to account for various reservoir functions might be ideal if the purpose of the study was to better represent reservoir outflow in a regional or global hydrology model. However, the purpose here was to find the minimal complexity equations that could be used to represent general reservoir behavior for use in an LSM so simulations of up to 100 years can be run to evaluate reservoir impacts on the climate. Considering these goals, shorter time steps are not needed, but monthly rules can still be decimated into a daily time step, as necessary, to match temporal scales if run within a coupled LSM framework.
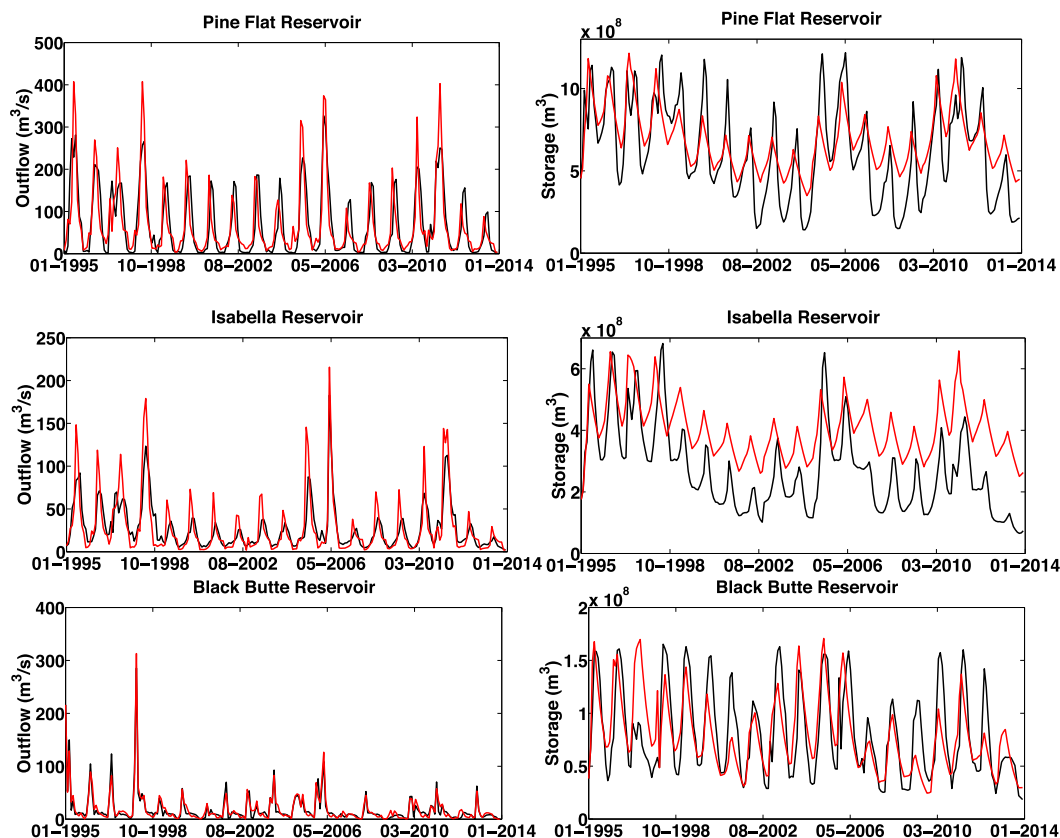
FIG. 8. The 1995–2013 observed and simulated reservoir (left) outflow and (right) storage time series for the three validation reservoirs: (top) Pine Flat, (middle) Isabella, and (bottom) Black Butte. Simulations performed using generalized parameters.

The use of only California reservoirs for model calibration and validation when the model is ultimately intended for the global scale represents another shortcoming. However, given that similar practices were conducted in other studies (i.e., Hanasaki et al. 2006) and that the focus of this research was to represent general reservoir behavior over longer time scales to analyze climate impacts, the use of regionally concentrated reservoirs for model development was viewed as justified. Moreover, reservoirs with a minimum of 19 years of continuous monthly data available were targeted for this study to better determine how model performance varies under different climate conditions, and the selected reservoirs fit these criteria. Use of reservoir records that have a higher degree of variability in climate is ideal in model development given the intended end use of the model to evaluate climate impacts in an LSM.

Other omissions from the model included storage losses due to evaporation, seepage, or sedimentation. An attempt was made to incorporate storage loss terms into the model for these variables with minimal

improvement to model performance likely because of the strong spatial heterogeneity in how these processes behave that highlights the difficulty in incorporating them into a generalized model of reservoir behavior. Moreover, the contribution of these losses to the overall water budget of a reservoir is generally small, meaning little can be gained in model performance by adding them. For example, evaporative losses generally only represent 5% of the total annual storage for large reservoirs, while seepage and sedimentation losses are typically at or below these levels (Gleick 1992; Minear and Kondolf 2009). Thus, the use of these loss estimates was avoided to maintain model simplicity. It should be noted that loss estimates from these variables were also not explicitly accounted for in simulations of reservoir releases in a number of other studies (e.g., Hanasaki et al. 2006; Wisser et al. 2010; Fekete et al. 2010; Biemans et al. 2011).

d. Climate-adaptive capability

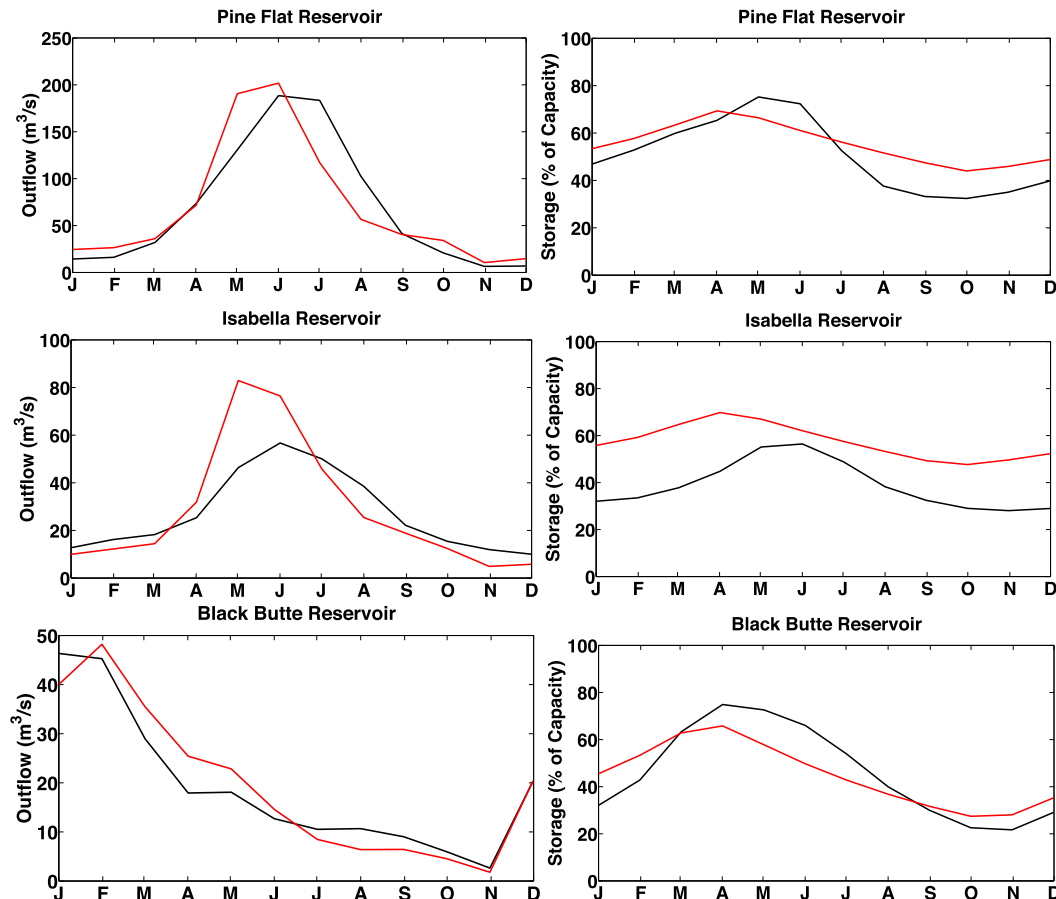The utilization of temperature as a proxy to select the model outflow equation, as shown in Eqs. (2) and (3),

FIG. 9. The 1995–2013 observed and simulated reservoir (left) outflow ($m^3 s^{-1}$) and (right) storage climatologies (% of total capacity) for the validation reservoirs: (top) Pine Flat, (middle) Isabella, and (bottom) Black Butte. Simulations performed using generalized parameters.

has important implications for incorporating climate change impacts into model simulations. Assuming a warmer future from climate change, holding the 5-yr baseline temperature constant in this equation means that as the model advances, the monthly mean temperature for a greater proportion of simulated months will be above this baseline. Consequently, the summer drawdown equation would be favored over the winter recharge equation in model simulations. Ignoring the impacts on model simulations due to the changes in snowpack and surface runoff that would likely occur under such a warming scenario to only determine how reservoirs would change if reservoir management was held constant, one can anticipate simulated reservoir storage to diminish or even dry up.

To test this theory in the model, an experimental set of simulations were run for the Shasta Reservoir where the baseline temperature was maintained as the 5-yr 1990–95 baseline and the monthly temperature input in the model from PRISM was artificially

increased by increments of 0.5°C for each subsequent model run. As shown in Fig. 10, the summer drawdown equation is increasingly favored with each incremental rise in temperature until the temperature increase reaches 11.5°C, which is when the summer drawdown equation is used exclusively to compute reservoir outflow. Ignoring any effects that warming might have on runoff, the shift in equation usage resulted in a corresponding mean annual storage decrease of approximately 55%.

In an attempt to incorporate the increased temperature effects on runoff as well, the model was rerun for the Shasta Reservoir under the same incrementally warming scenario while simultaneously decreasing reservoir inflow by 5% for each 0.5°C rise in temperature. The justification for the decrease in inflow is that the volume of water available to reservoirs is expected to decrease because of shifts in runoff toward earlier in the season (Mote 2006) and slight decreases in projected California precipitation (Cayan et al. 2008). As a

TABLE 6. Storage coefficient of variation and winter inflow to storage capacity ratios and rank relative to model performance for the 14 calibration and validation reservoirs using generalized parameters.

Reservoir name	S_{cv} (rank)[a]	Winter I:SC (rank)[a]	$S + Q$ nRMSE rank[a]	$S + Q$ nRMSE climatology rank[a]	$S + Q$ r^2 rank[a]
Shasta	0.24 (10)	1.08 (5)	13	9	6
Oroville	0.28 (9)	0.98 (7)	11	7	7
Trinity	0.20 (12)	0.50 (12)	8	8	9
New Melones	0.22 (11)	0.34 (14)	5	1	13
Folsom	0.32 (6)	2.29 (2)	10	10	8
Millerton	0.31 (7)	2.05 (4)	3	12	10
Camanche	0.19 (13)	0.96 (8)	2	2	14
Sonoma	0.10 (14)	0.50 (11)	1	3	12
New Hogan	0.30 (8)	0.54 (10)	12	4	3
Eastman	0.62 (2)	0.47 (13)	9	6	2
Kaweah	0.98 (1)	2.26 (3)	4	11	11
Pine Flat[b]	0.46 (5)	3.98 (6)	7	13	5
Isabella[b]	0.51 (3)	3.14 (9)	6	5	4
Black Butte[b]	0.50 (4)	10.13 (1)	14	14	1

[a] Ranking from highest to lowest value.
[b] Validation reservoirs.

part of this experiment, the parameter values were allowed to change dynamically with the reductions in inflow, as the parameters are calculated based on the winter inflow to storage capacity ratios. Hence, this feature effectively represents the implementation of a modification to operation procedures in response to climate-induced shifts in hydrology. An additional experiment was run where the parameter values were held constant to the initial values to better mimic no change in management operations to accommodate changes in inflow. As shown in Fig. 10, only slight additional decreases in annual storage resulted from the experiment where dynamic parameters were used relative to the shift in equation usage. Alternatively, the results where constant parameter values were used show a substantial additional decrease in mean annual storage. Thus, when the parameter values are allowed to update with decreases in inflow, the losses in storage resulting from decreases in inflow are offset by reductions in outflow resulting from the decline in the magnitude of parameter values.

This experiment should not be used to imply that a 20% reduction in annual reservoir storage is imminent by 2100 because of the projected 4°C increase in temperature for California by the same year. Although an increase in the growing season and simultaneous rise in agricultural water demand is anticipated with additional warming, a more advanced analysis that examines these shifts on a per-crop or per-climate-regime basis is required to determine how the growing season will truly be altered to impact the relative lengths of the reservoir recharge and release seasons with each incremental rise in temperature. Furthermore, more robust estimates of

projected climate data or hydrologic changes under different warming scenarios would be necessary to determine how the reservoir inflow used as input might shift. Fixed decreases in inflow were used for this analysis because the intent was merely to show how model simulations might change because of a decrease in runoff that is expected under a warming climate.

By allowing simulated operations to change with a shift in the temperature regime, the use of temperature in the model accounts for the obsolescence of the former assumption in hydrology that past records will hold true in the future because of climate change. As this change in stationarity is not expected to be temporary because of the long lifetimes of atmospheric CO_2 and thermal resistance of the Earth system (Milly et al. 2008),
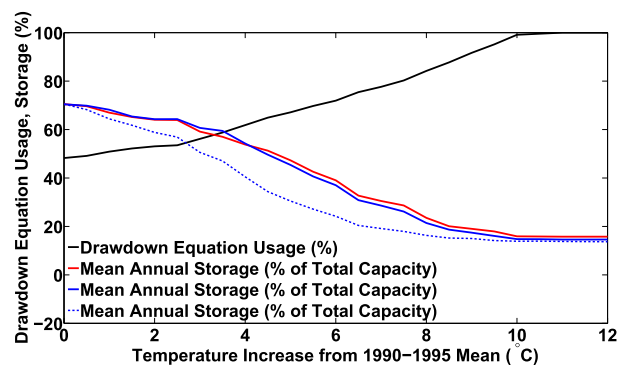

FIG. 10. Effects of temperature increase on model simulations in terms of drawdown equation usage (black line) and on mean annual reservoir storage due to operation impacts (red line), and combined inflow and reservoir operation with (solid blue line) and without (dotted blue line) dynamic parameters. Analysis based on 1995–2013 simulations for Shasta Reservoir.

inclusion of potential effects from climate change in reservoir models as is done here is critical. Moreover, allowing the parameters to update to address changes stemming from nonstationarity has yet to be implemented in previous works (Nazemi and Wheater 2015b). Assuming that operations are as strongly linked to temperature and the growing season as they are today, a modeling adaptation measure such as this allows for simulated operations to adapt with climate-change-induced shifts in hydrology, effectively simulating the human operator response and making these models more realistic. Failing to update this information would wrongly ignore the potential for excessive reservoir drawdown resulting from warming when the severity of such problems is expected to worsen because of climate change.

e. Expected utility in a land surface scheme

The ultimate goal of integrating the newly developed reservoir management model into an LSM is crucial to understanding how reservoirs interact with both the climate and the water cycle. Once coupled, the surface runoff routed downstream through a river-routing model will serve as inflow to the reservoir model. Inflow will be partitioned between reservoir outflow (to be treated as existing surface runoff in the LSM) and reservoir storage (linked to the atmosphere component of the LSM through evaporation). The simple structure of the model equations combined with generalized parameters that are numerically related to reservoir inflow and storage capacity means that the reservoir management model will support this capability, enabling reservoirs to be generated automatically based on the cumulative gridcell reservoir storage capacity defined by the user. The next phase of this work will involve coupling the two models and investigating the impacts that reservoirs have on the climate and hydrology.

Although the reservoir model parameters were optimized to produce generalized parameters that were validated regionally within California, the selected reservoirs matched the data availability criteria of having a long, continuous time series of variable climate conditions, making them ideal for use in model development when the end goal is to integrate into a climate model. In addition, based on the way temperature is used in the equations, more robust model performance will occur in regions with distinct reservoir recharge and drawdown seasons. Similar to California, this could occur in areas with comparable climate patterns, management practices that are heavily influenced by agricultural water demands, or snowmelt-dominant runoff. Furthermore, the recharge and drawdown seasons for the targeted

location to be modeled would not have to coincide exactly with the time of year as those in California. Rather, they need to be merely be somehow related to temperature, as is shown in this study. For example, this could be accomplished by running the model in areas receiving increased recharge from elevated inflow during the cooler season due to elevated precipitation and/or runoff from snowmelt, and increased drawdown from higher agricultural demands during the warmer season. Potential examples of such areas throughout the globe include agricultural regions in the vicinity of the Andes in South America; the Murray–Darling agricultural region of Australia; and the continental United States, where agriculture heavily influences reservoir management and seasonal snowmelt plays a large role in inflows. The model performance thresholds identified for the reservoir storage coefficient of variation and winter I:SC will be used to provide additional guidance on which reservoirs within these regions are most appropriate for model simulations.

6. Conclusions

In summary, this study made several important contributions toward including reservoir management in an LSM. First, it tested a set of different equations that represent reservoir outflow and storage dynamics simultaneously. The group of equations yielding the highest overall model performance, as determined from the collective AIC, r^2, nRMSE, and NSE values, was selected for use in the reservoir model. Second, the model was designed to use temperature to better mimic the dual reservoir operation in California that is driven by the agricultural growing season and to account for future climate-change-induced alterations in hydrology. As demonstrated through several experiments, the adaptation measure is capable of reproducing anticipated changes in storage from an increase in temperature and/or subsequent water demands, making it ideal for simulations of the future climate system. Third, the parameters were generalized to exhibit the utility of model applications at the global scales and for automatic generation of reservoirs within an LSM based on the specified storage capacity. Finally, although model performance caveats were highlighted for reservoirs with higher management intensities (e.g., $S_{cv} < 0.22$ or winter I:SC $< 2 \times 10^{-7}\,\mathrm{s}^{-1}$), strong model validation results (mean reservoir outflow and storage $r^2 = 0.67$) and simple model structure requiring minimal inputs show promise for intended application of the model within an LSM. The new, climate-adaptive reservoir management model thus provides a great first step toward future use in conjunction with other rigorously calibrated and

validated reservoir models within an LSM to evaluate human impacts on the terrestrial water cycle and climate system due to reservoir management.

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