The implications of future climate change on the blue water footprint of hydropower in the contiguous US

Gang Zhao, Huilin Gao and Shih-Chieh Kao

1 Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX 77840, United States of America
2 Environmental Sciences Division and Climate Change Science Institute, Oak Ridge National Laboratory, Oak Ridge, TN 37831, United States of America
E-mail: hgao@civil.tamu.edu

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Abstract
As the largest renewable energy source, hydropower is essential to the sustainability of the global energy market. However, a considerable amount of water can be lost in the form of evaporation from the associated multipurpose reservoirs, and hence enlarge the blue water footprint (BWF) of hydropower in a warming climate. To facilitate the sustainable management of both water and energy resources under the impact of climate change in the contiguous United States (CONUS), the BWF values of 143 major multipurpose reservoirs were evaluated during the historical period (1985–2014) and two future periods (2020–2049 and 2070–2099). The historical reservoir evaporation loss was calculated using the Landsat-based reservoir surface area and a new evaporation rate algorithm that considers the heat storage effect. Future projections of runoff availability, hydropower generation, and reservoir evaporation were estimated based on the downscaled climate model ensemble from phase 5 of the Coupled Model Intercomparison Project. It was found that the BWF for the CONUS is highly spatially heterogeneous, with an average value of 26.2 m$^3$ MWh$^{-1}$ in the historical period. In the future, the BWF values are projected to increase under both Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios. This is especially noticeable under RCP 8.5, which has an average BWF value of 30.2 m$^3$ MWh$^{-1}$ for 2070–2099 (increasing by 15.3% from 26.2 m$^3$ MWh$^{-1}$). The uncertainty ranges increase even more, from 3.4 m$^3$ MWh$^{-1}$ during 2020–2049 to 5.7 m$^3$ MWh$^{-1}$ during 2070–2099. These findings can benefit water and energy resources management in identifying suitable environmental, economic, operational, and investment strategies for multipurpose reservoirs in a changing environment.

1. Introduction

Electrical energy is imperative for every aspect of socioeconomic development. With the increases of both population and per capita energy demand, global electricity generation has risen considerably in recent decades (81% from 1990 to 2010) and is projected to keep increasing in the near future (78% from 2010 to 2040) (US Energy Information Administration [USEIA] 2016a). Given the negative impacts of greenhouse gas emissions, the role of renewable energy sources such as solar, wind, hydropower, and bioenergy in the global energy market has become progressively more important (Kao et al 2016, World Energy Council 2016). In 2017, renewable power production contributed 25% of global electricity generation (International Energy Agency 2018). About 4185 terawatt hours was generated from hydropower, which accounts for 65% of the total...
renewable energy output (International Hydropower Association 2018).

Although hydropower generation does not consume water directly, a considerable amount of water can evaporate from the open water surfaces of the associated multipurpose reservoirs. Zhao and Gao (2019) reported that the longterm (1985–2014) annual evaporation from 721 major US reservoirs was estimated to be $3.37 \times 10^9 \text{ m}^3$—which was around 93% of the total US public water supply in 2010. This type of invisible water loss results from a high open water evaporation rate, which is an unavoidable tradeoff for all of the services that a multipurpose reservoir provides (e.g. recreation, flood control, hydropower, irrigation, water supply, navigation, etc.; see the estimated breakdown in figure S1 (available online at stacks.iop.org/ERL/16/034003/media)). With the expectation that evaporation rates will increase significantly in a warming environment, the available water resources will likely become more limited. Specifically, multipurpose reservoirs that are located in water stressed regions will be challenged by rising water and energy demands (Liu et al 2015, Zhang et al 2019), as well as by the need to balance a more diverse renewable energy portfolio (e.g. wind and solar) (Gupta et al 2019). As a result, there is a need to better understand the impacts of climate change on hydropower generation from a water availability perspective.

To quantify the role of water loss from multipurpose reservoirs, the term blue water footprint (BWF; Egan 2011, Hoekstra and Mekonnen 2012) is adopted in this study. Blue water refers to the surface water and/or groundwater which is utilized to generate a product. Following this concept, the BWF of hydropower can be defined as the total volume of evaporation (i.e. average evaporation rate times reservoir surface area) divided by net electricity generation (Hoekstra and Mekonnen 2012), representing the water loss per unit power generation. For instance, by treating all reservoir evaporation as water consumed by hydropower, Torcellini et al (2003) estimated that $\sim 67.7 \text{ m}^2$ of water was lost through evaporation for every megawatt-hour (MWh) hydropower generated in the United States. While BWF can provide an effective way to evaluate the joint influence of generation and water loss, it should also be interpreted with caution. For instance, Bakken et al (2013) suggested a paradox in which a reservoir might report high water consumption/footprint but still be the most feasible method to improve the availability of water in a region. Our focus in this study is hence on understanding the relative changes of regional BWF in different climatic conditions—and not on the specific meaning of BWF at each individual reservoir.

Although a number of studies have been conducted to quantify the historical hydropower BWF in various regions (Torcellini et al 2003, Herath et al 2011, Mekonnen and Hoekstra, 2012, Lampert et al 2015, Grubert 2016, Bakken et al 2017, Sanchez et al 2020), a systematic investigation on the impacts of future climate change on BWF is lacking. In particular, while the amount of lake/reservoir evaporation is expected to increase (Wang et al 2018), the amount of annual hydropower generation that is governed by runoff availability is also expected to change (Kao et al 2015). A holistic study that involves both large scale hydroclimate modeling and reservoir level evaporative loss evaluation is required, but has not been conducted. Given the competing water-energy management objectives (Liu et al 2015), adaptive optimization of reservoir operation rules is warranted. Implementation of such optimization practices requires a quantitative understanding (with measurement of uncertainty) of how the potential climate change will impact reservoir evaporation and the future hydropower BWF.

Therefore, the objectives of this study are: (a) to quantify the historical BWF of hydropower in the contiguous United States (CONUS) by considering both reservoir evaporation rates and area variations; and (b) to evaluate the impacts of future climate change on runoff, generation, evaporation, and BWF in the context of uncertain climate projections and emission scenarios. For the historical period (1985–2014), the satellite-based surface areas and model-based evaporation rates were generated by Zhao and Gao (2019). For the two future periods (2020–2049 and 2070–2099), downscaled climate projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5) were used to estimate the evaporation rate, reservoir surface area, hydropower generation, and then BWF. Multiple general circulation models (GCMs) from two emission scenarios (Representative Concentration Pathway [RCP] 4.5 and 8.5) were used to account for the projections’ uncertainties. The results and implications across different CONUS regions are then discussed.

2. Method and data

2.1. Scope of the study

In this study, we selected 143 major multipurpose reservoirs with hydropower generation capability in the CONUS from the USEIA-923 (USEIA 2016b) dataset. The total hydroelectric capacity of these reservoirs is 55 730 MW, which accounts for 69% of the hydroelectric capacity in the United States (USEIA 2016b). Among the 159 US reservoirs which have a capacity larger than 100 MW, 14 reservoirs fed by long-distance water diversion and two by the Great Lakes were removed. We focused on these larger multipurpose reservoirs since they represent the majority of the hydropower generation capacity in the US Data for the other 2000+ relatively smaller hydropower plants are harder to gather, and involve more uncertainty. Figure 1 shows the location of these
2. Bluewaterfootprint (BWF)
With the goal of evaluating the impacts of climate change on evaporation, we used the term gross BWF instead of net BWF, whereby evaporation is represented as the net value (lake evaporation minus land evapotranspiration). The BWF is thus defined as the evaporative water losses per unit of net power generation (equation (1)):

$$BWF = \frac{\sum \alpha \cdot E(t) \cdot A(t)}{\sum W(t)}$$

where $\alpha$ is the allocating factor for hydropower; $E(t)$ is evaporation rate at time $t$; $A(t)$ is the surface area at time $t$; and $W(t)$ is the net power generation at time $t$. Because reservoirs generally serve multiple purposes, the allocation of all the evaporative losses to hydropower can overestimate the hydropower water usage (Grubert 2016). Therefore, $\alpha$ is used to represent the evaporative losses associated with hydropower generation. Because it is difficult to accurately attribute the evaporative losses to different functions, we simply defined $\alpha$ as one over the number of reservoir functions (an even breakdown of evaporative losses among all of purposes a reservoir serves). The reservoir purpose data (i.e. flood control, water supply, hydropower, irrigation, and others) were collected from the National Inventory of Dams (NID) (USACE, 2016, Grubert 2020; figure S2 and table S1). Following the flowchart in figure 2, the historical and future BWF values for each of the 143 reservoirs were quantified.

2.3. Quantification of historical BWF
The evaporation volume was quantified for each reservoir during the historical period. The monthly water area time series were generated by improving the Landsat-based global surface water classifications from Pekel et al (2016) using an image enhancement algorithm (Zhao and Gao 2018). The evaporation rate time series were calculated after equation (2) using the Penman equation, taking the lake heat storage effects into consideration (Zhao and Gao 2019).

$$E = \frac{s(R_\text{net} - \Delta U) + \gamma f(u) (e_s - e_a)}{\lambda_v (s + \gamma)}$$

where $E$ is the evaporation rate (mm d$^{-1}$); $s$ is the slope of the saturation vapor pressure curve (kPa °C$^{-1}$); $R_\text{net}$ is the net radiation (MJ m$^{-2}$ d$^{-1}$); $\Delta U$ is the heat storage changes of the water body (MJ m$^{-2}$ d$^{-1}$); $f(u)$ is the wind function with $u$ as the screen height (2 m) wind speed (m s$^{-1}$); $e_s$ is the saturated vapor pressure at air temperature (kPa); $e_a$ is the air vapor pressure (kPa); $\lambda_v$ is the latent heat of vaporization (MJ kg$^{-1}$); and $\gamma$ is the psychrometric constant (kPa °C$^{-1}$). While equation (2) addresses...
the heat storage effect for reservoirs, caution is needed when the water surface is highly turbulent (Reynolds number greater than 2000), as heat stored by such water can be quickly released through sensible heat flux.

Meteorological data for calculating the evaporation rate include four variables: shortwave radiation, air temperature, vapor pressure deficit, and wind speed. These data were collected from Phase 2 of the North American Land Data Assimilation System (NLDAS-2; Xia et al. 2012) monthly product (at 1/8th degree resolution). For any reservoir covering multiple NLDAS-2 grids, the meteorological forcings were first averaged over those grids. For calculating the heat storage change (ΔU), average reservoir depth from NID was used and reservoir monthly fetch length was calculated following Zhao and Gao (2019). Lastly, the monthly evaporation volume time series were estimated from the area and evaporation rates. Monthly net power generation data for each hydroelectric plant were collected from the USEIA-923 dataset (USEIA 2016b). Both the evaporation volume and electricity data were aggregated to annual values for calculating the BWF values after equation (1).

2.4. Quantification of future BWF

The future evaporation rate, surface area, and power generation were projected to estimate the future BWF. The statistically downscaled future hydroclimate projections were collected from the downscaled CMIP5 Climate and Hydrology Projections (DCCHP; Reclamation 2013) dataset, which employed the Bias-Correction Spatial Disaggregation method to downscale the original climate outputs to 1/8th degree. To account for the uncertainties, outputs from 13 GCMs were employed: CCSM4, CESM1-CAM5, CSIRO-MK3-6-0, FIO-ESM, GFDL-ESM2M, GISS-E2-R, HADGEM2-AO, HADGEM2-ES, IPSL-CM5A-MR, MIROC-ESM, MIROC-ESM-CHEM, MIROC5, and NORESM1-M. These models were selected because they include all four RCP scenarios (i.e. RCP2.6, RCP4.5, RCP6.0, and RCP8.5). In this study, we primarily focused on analyzing the results from the median (RCP4.5) and high emission (RCP8.5) scenarios, as these are commonly used by climate change impact studies (Moore et al. 2013, Fix et al. 2018). For RCP4.5, these models correspond to a warming level of 1.5 °C in 2020–2049 and 2.9 °C in 2070–2099. For RCP8.5, the values in the two periods are 1.8 °C and 4.0 °C, respectively.

2.4.1. Future evaporation rate

With regard to the four forcing variables required to estimate evaporation rate, the DCCHP only provides the downscaled maximum air temperature, the minimum air temperature, and the wind speed data. Thus, we used the MT-CLIM algorithms (Kimball et al. 1997, Thornton and Running 1999) to derive the vapor pressure deficit and the incoming evaporation.
shortwave radiation from DCCHP data using geographic information. All of these modeled forcing variables were then bias-corrected against historical observations using a delta change method (Arnell 1996). Compared to the distribution-preserving bias-correction methods (e.g. quantile mapping), the delta change method is simple yet appropriate for climate bias-correction on a monthly scale (Bosshard et al 2011, Teutschbein and Seibert 2012). First, the biases were quantified as the long-term difference between the observed and modeled data during the historical period. Then these biases were applied to the future modeled data. Following Abatzoglou et al (2018), the differences were computed as additive for air temperature, wind speed, and radiation, and multiplicative for vapor pressure. Finally, after the same process described in section 2.3, the monthly evaporation rates were calculated for each reservoir.

2.4.2. Future surface area

The future surface areas of a reservoir of interest were estimated from projected runoff values using an empirical relationship. This runoff projection method was adopted from Kao et al (2015), with the average runoff rate calculated over the contributing area. For each reservoir, a linear regression between the annual runoff rate (mm yr$^{-1}$) and annual surface area (km$^2$) was established during the historical period (1985–2014). Following Kao et al (2015), we optimized the regression equation by using a multi-year running average of the runoff rate. For a given reservoir, a series of moving windows with different sizes were tested, and the one which led to the largest $R^2$ between area and runoff was selected. This regression equation was used to calculate future annual surface areas (2020–2049 and 2070–2099) using bias-corrected future annual runoff rates from DCCHP. Detailed steps can be found in text S1, with an example for Logan Martin Lake, Alabama provided (figure S3). The regression equations, their corresponding $R^2$ values, and the relative root mean square error (RRMSE) values of these 143 reservoirs can be found in table S2. The generally low $R^2$ values (the average is 0.21, and the standard deviation [SD] is 0.17) for the runoff-area relationships are mainly caused by the small variation of surface area of some reservoirs, especially for the run-of-river types (figure S4). However, given the small RRMSE values (average of 3.7%, with SD of 3.8%), the sensitivity of surface area on BWF is rather small (figure S5).

2.4.3. Future hydropower generation

To project the future power generation, a linear relationship between the annual runoff rates (mm yr$^{-1}$) and the annual net power generation (MWh yr$^{-1}$) was first established during the historical period (figure S3(b)). Then, future annual power generation values were projected by applying the future annual runoff (bias-corrected) to the linear relationship (figure S3(c)). The regression equations between historical power generation and runoff, their corresponding $R^2$ values (average 0.70 with SD 0.25), and the RRMSE values (average 14.6% and SD 8.7%) of these 143 reservoirs are provided in the table S2.

3. Results

The results were analyzed over the four regions following Naz et al (2016): the Western US, the Northern US, the Southern US, and the Eastern US (figure 3). The rationale for using these four regions is to be consistent with the two-digit hydrologic regions (HUC2) while considering the large scale climate regions (Karl and Koss 1984). The total generation capacity (and the number of reservoirs) of each region is 40 300 MW (75), 3065 MW (9), 1666 MW (11), and 10 700 MW (48), respectively. The overall BWF in each region was calculated by dividing the regional total evaporation volume by the regional total power generation.

3.1. Historical BWF

Figure 3 shows the distributed BWF over historical period. Overall, the total CONUS hydropower BWF is 26.2 m$^3$ MWh$^{-1}$. This result is smaller than other studies (68.0 m$^3$ MWh$^{-1}$ from Torcellini et al 2003; 38.5 m$^3$ MWh$^{-1}$ from, Lampert et al 2015; 80.0 m$^3$ MWh$^{-1}$ for the entire globe from, Gerbens-Leenes et al 2009). This is because the evaporative loss was equally allocated to different functions in this study, while it was solely allocated to hydropower in most previous studies (as concluded in Zhang et al 2019).

For the 143 reservoirs, their individual BWF values range from 0.02 to 1200 m$^3$ MW h$^{-1}$, showing a large spatial heterogeneity. The Western US—which contains the Columbia River Basin, the Sacramento-San Joaquin Rivers Basin, and the Colorado River Basin—has an average BWF of 11.6 m$^3$ MWh$^{-1}$. In this region, the hydropower reservoirs located on the Snake–Columbia Rivers contribute 78% of the generation capacity. Because the climate in this region is humid—and because the surface areas of most of these reservoirs are relatively small—their evaporative losses are small. In addition, their hydropower capacities are in general high (due to steep gradients of the topography). Thus, they tend to have small BWF values. For instance, the BWF for the Columbia River Basin is 6.8 m$^3$ MWh$^{-1}$. In contrast, the reservoirs located in the semi-arid Colorado River Basin have large surface areas. As a result, the BWF value for this river basin is relatively high (i.e. 80 m$^3$ MWh$^{-1}$). The Northern US contains the Missouri River Basin and the Upper Mississippi River Basin. Among the nine reservoirs in this region, only two of them have hydropower electricity as their primary purpose, while others were mainly constructed for flood control (US Army Corps of
Thus, with low hydroelectricity generation, this region has shown a high BWF value (i.e. 84 m³ MWh⁻¹). Of the four regions, the Southern US has the largest averaged BWF (121 m³ MWh⁻¹) due to its high evaporation rate and relatively low level of hydropower generation. The Eastern US consists of 48 reservoirs located in many small river basins (figure 3). Its BWF is characterized by a large spatial heterogeneity (with an SD of 184 m³ MWh⁻¹, as compared to the average of 66 m³ MWh⁻¹).

3.2. Future BWF

Using the method described in section 2.4, the future evaporation rate, runoff rate, surface area, and power generation were estimated (figure 4). The projected average evaporation rates of these 143 reservoirs from the ensemble-median (of the 13-member climate models) show a continuous increase from the historical period to the two future periods. The average evaporation rate during the historical period is 1033 mm yr⁻¹. Under the RCP8.5 scenario, the average evaporation rate from the ensemble-median will be elevated to 1091 mm yr⁻¹ (a 5.5% increase, p < 0.05 according to the ANOVA test) in Period 1, and 1193 mm yr⁻¹ in Period 2 (a 15.5% increase, p < 0.05). These changes are mainly driven by the projected temperature increase (1.8 °C in Period 1, and 4.0 °C in Period 2). Unlike the evaporation rate, there is no clear trend for the future runoff rate concerning the ensemble-median values, but there are large uncertainties. This is because the change of runoff rate is driven by both precipitation and evapotranspiration, which vary significantly among the different climate models. As a result, the future surface area and power generation follow similar patterns (i.e. no clear increasing trends, but large uncertainties). With respect to inter-annual variability, there is no consistent increase or decrease in trend in terms of the median values from the 13 climate models (figure S6).

With respect to future BWF values, the results suggest clear increasing trends (p < 0.05) over all regions (figure 5). For example, the predicted median BWF in the Western US will increase by 0.4 m³ MWh⁻¹ from the Historical Period to Period 1, and then by 1.2 m³ MWh⁻¹ from Period 1 to Period 2 under RCP8.5. On one hand, these continuous increments (in terms of model median value) are consistent with the increasing evaporation rate (figure 4(a)). On the other hand, however, changes in power generation (due to changes in the runoff rate) also play an important role. For instance, the BWF could decrease in the most distant Period 2 (11.6 to 11.4 m³ MWh⁻¹) according the GISS-E2-R model under the RCP4.5 scenario, when the projected increment of power generation outweighs the increment of evaporation volume.

For the entire CONUS (figure 5(e)), future BWF values are likely to increase—but with large uncertainties. The median BWF value increases from 26.2 m³ MWh⁻¹ (Historical Period) to 27.4 m³ MWh⁻¹ (Period 1, by 4.6%, p = 0.02) and
then to 27.8 m$^3$ MWh$^{-1}$ (Period 2, by 6.1%, $p < 0.01$) under the RCP4.5 scenario. The numbers for the RCP8.5 scenario increase from 26.2 m$^3$ MWh$^{-1}$ to 26.9 m$^3$ MWh$^{-1}$ (2.7%, $p < 0.01$) and to 30.2 m$^3$ MWh$^{-1}$ (15.3%, $p < 0.01$). Meanwhile, the BWF uncertainties are likely to propagate to larger ranges for both scenarios. Taking RCP8.5 as an example, the range of the BWF values is 3.4 m$^3$ MWh$^{-1}$ (from 25.6 to 29.1 m$^3$ MWh$^{-1}$) in Period 1, while it is 5.7 m$^3$ MWh$^{-1}$ (from 26.7 to 32.4 m$^3$ MWh$^{-1}$) in Period 2.

Despite the consistently increasing trends for the entire CONUS, some spatial heterogeneities related to the percentage increases of BWF can be observed (figure 6). Using Period 2 under the RCP8.5 scenario as an example (figure 6(d)), the percentage increase of BWF ranges from 7% to 25%. In particular, the hydroelectric plants in the Western US have larger percentage increases than those at other locations. For instance, the Columbia River Basin has an average percentage increase value of 19% ($p < 0.01$). This result is consistent with other climate change impact studies, which found that the Western US is more vulnerable to global warming (Leung et al. 2004, Diffenbaugh et al. 2008, Abatzoglou and Williams 2016). In contrast, the Eastern US shows relatively smaller percentage increase values (average of 13%, $p < 0.01$).

During Period 1, the changes under the two RCP scenarios are quite similar. However, during Period 2, the negative effect of climate change on BWF is much more substantial under RCP8.5.

4. Discussion

The optimization of water resources requires disentangling the tradeoffs between energy production, drinking water supply, irrigation, and other factors (González et al. 2016). For example, reduced water impoundment in upstream watersheds (due to enhanced evaporation) might limit the amount of available water for downstream water users (Bakken et al. 2013). To fully consider the tradeoffs, the evaporative loss should be quantified with respect to the value of electricity production and other reservoir uses—which requires implementing socio-hydrological models to quantify the economic values of the different reservoir purposes. This would also lead to a more accurate assignment of the allocating factor ($\alpha$) for multipurpose reservoirs. However, the development of reliable socio-hydrological models first depends on a robust understanding of the hydrology. Therefore, in this paper we only used simplified allocation factors to estimate the BWF of hydropower. Regardless of different BWF assessment approaches,
the relative impacts due to climate change remain similar, so it will not affect our overall findings.

Although the annual hydropower generation was found to correlate well with the upstream runoff rate (average $R^2 = 0.70$), the correlation between reservoir surface area and upstream runoff rate is relatively low (average $R^2 = 0.21$). Specifically, reservoirs with complex upstream hydrology and operations (e.g., Lake Sakakawea) have shown low $R^2$ values. On one hand, a well-calibrated hydrologic and reservoir-management model can be leveraged to better simulate future conditions under projected changes of climate, land cover, and flow regulation (Prowse et al. 2006, Zhao et al. 2018). On the other hand, we have found that the RRMSE values (average of 3.7%) of these regression based areas are quite small and result in a low sensitivity for the BWF estimates (figure S5).

During the historical period, our calculated BWF values are relatively small compared to those of other studies (Torcellini et al. 2003, Gerbens-Leenes et al. 2009) due to the use of uniform allocation factors. This finding is consistent with Zhang et al. (2019), which also concluded that consideration of allocation coefficients significantly reduces the BWF values. Depending on the definition of 'BWF for hydropower', the BWF values could be even smaller if 'net' evaporation values (lake evaporation minus land evapotranspiration) are used, or they could be larger if the seepage of the reservoir was considered.
Figure 6. The change of BWF (in percentage) compared with the historical period for (a) Period 1 under the RCP4.5 scenario, (b) Period 2 under the RCP4.5 scenario, (c) Period 1 under the RCP8.5 scenario, and (d) Period 2 under the RCP8.5 scenario. The results were calculated based on the median values of 13 models.

(Sivapragasam et al 2009, Bakken et al 2013). With respect to the future BWF of hydropower, results from both regional and individual reservoirs suggest that the overall water loss from open water evaporation is expected to increase, which may challenge hydroelectric production and all other services. In water stress regions, this issue becomes more complicated due to increasing water demand, thus requiring comprehensive socioeconomic evaluation of the energy and water sectors (Liu et al 2015, Scherer and Pfister 2016). Although several geo-engineering measures (e.g. water covering, water recharge to aquifers, and reservoir relocation) have been developed to mitigate open water evaporation, limitations of each measure hinder their general application (Assouline et al 2011).

5. Summary and conclusion

To accurately assess historical reservoir evaporative losses—and to project future hydropower BWF under a changing climate—we developed a modeling framework to quantify the BWF of 143 major multipurpose reservoirs in the CONUS. From 1985 to 2014, the average BWF value for these reservoirs was 26.2 m³ MWh⁻¹. Towards the end of this century, the average BWF of the CONUS is projected to increase to 30.2 m³ MWh⁻¹ (up by 15.3%) due to an increase of the evaporation rate under the RCP8.5 scenario.

While the model median indicates an increasing trend, different models and scenarios reveal large uncertainties. For instance, the projected BWF at the end of this century ranges from 25.3 m³ MWh⁻¹ (−3.4%) to 32.4 m³ MWh⁻¹ (23.7%).

Recognizing that these CONUS reservoirs have been providing broader benefits (other than just hydropower), it is important to understand the potential impacts of climate change on our valuable fresh water resources. By estimating the historical BWF using dynamic reservoir areas, and by assessing the impacts of climate change on the future BWF using an ensemble of future hydroclimate projections, this study provides a new perspective for understanding the tradeoffs between water and energy. Meanwhile, for the many new multipurpose reservoirs planned worldwide, the large amount of evaporative losses introduced by new impoundments—and how this situation might be impacted by climate change—should be evaluated in advance. We expect that such analysis can be beneficial to resource managers with regard to identifying suitable environmental, economic, operation, and investment strategies in a changing environment.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.
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ORCID iDs

Gang Zhao 🌐 https://orcid.org/0000-0003-2737-0530
Huilin Gao 🌐 https://orcid.org/0000-0001-7009-8005
Shih-Chieh Kao 🌐 https://orcid.org/0000-0002-3207-5328

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