Environmental Research 262 (2024) 119860

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Quantifying water evaporation from large reservoirs: Implications for water management in water-stressed regions

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ABSTRACT

Dam reservoirs are at the core of local water storage and supply, especially in water-stressed regions of the world with acute water shortage problems. However, evaporative losses from these reservoirs and their storage efficiency are often overlooked in water budgeting. We offer a mechanistic approach that combines physically-based modeling with remote sensing information of reservoir characteristics to reliably predict evaporative losses from dam reservoirs. The developed framework is used to predict evaporative water losses from potential dam reservoirs in different basins worldwide. We apply this framework to 10 of the largest dam reservoirs in the world's water-stressed regions to quantify evaporative water losses. Our analysis, spanning from 2000 to 2020, reveals considerable variations in annual evaporation rates in the reservoirs located in water-deprived regions exceeding 3200 mm/year during the study period with the total evaporative loss reaching 26.5 km^3/year. The evaporative water loss accounts up to 15.8% of the storage capacity in one of the dam reservoirs, posing significant challenges for water allocation and conservation strategies, with notable economic and environmental consequences in regions already suffering from water scarcity.

1. Introduction

Global warming, along with increasing water demands, exacerbates the pressure on limited freshwater resources, particularly in water-stressed regions of the world where demands surpass the available water supply (Boretti and Rosa, 2019; Dolan et al., 2021; Huns, 2020; Wada et al., 2016), leading to a state of 'water bankruptcy' with the corresponding socio-economics implications (Madani et al., 2016; Degefu and He, 2016). Moreover, reservoirs are under increasing stress due to the combined effects of climate change and human activities, further compromising their ability to meet water demands (Cooley et al., 2021; Li et al., 2023). Throughout history, local water storages have been crucial for supplying water during dry periods. However, their numbers have drastically been growing during the past decades reaching to over 76,000 reservoirs around the world that are larger than 0.1 km^2 with total storage capacity of more than 7200 km^3 (Lehner et al., 2011). Dam reservoirs are key components of local water storages not only affecting water management and budgeting across scales, but also regulating global fluvial network and ecosystem functioning. Nevertheless, evaporative losses are often overlooked in water balance of dam reservoirs. This could impact the estimation of their storage efficiency, which could exacerbate water shortage problems, and may even intensify conflicts over shared water resources (Gleick, 2019; Oranye and Aremu, 2021; Pacific Institute, 2023; Schillinger et al., 2020; Sivapragasam et al., 2009).

With some estimates, as much as half of the stored water in small water reservoirs (between 2 and 3 m water depth) may be lost via evaporation (Aminzadeh et al., 2024; Bakhtiar et al., 2022; Craig et al., 2005; Mady et al., 2020; Rost et al., 2008). However, the intricate nature of inflows, seepage, and water releases in dam reservoirs makes it difficult to reliably estimate their evaporative losses (Friedrich et al., 2018; McMahon et al., 2013). Nonetheless, reliable estimation of evaporative fluxes from dam reservoirs are crucial for water resource management, mitigating climate change impact, sustainable development, energy production (hydroelectricity generation), understanding ecological consequences, policy making, planning and international cooperation. In particular, climate change influences evaporative fluxes from land and water reservoirs through changes in temperature, wind, and precipitation (Aminzadeh et al., 2023; Konapala et al., 2020). Dam reservoirs, particularly the ones located in water-stressed regions, could be severely influenced by these changes (Rocha et al., 2020). Furthermore, human activities such as land-use changes, urbanization, and

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https://doi.org/10.1016/j.envres.2024.119860
Received 14 July 2024; Received in revised form 23 August 2024; Accepted 26 August 2024
Available online 29 August 2024

increased water withdrawals are compounding the stress on these reservoirs, leading to further depletion of their water resources (Cooley et al., 2021; Li et al., 2023). Strengthening quantitative capabilities to predict and incorporate evaporative losses in the water budget calculations of the dam reservoirs under different climate scenarios enables the development of effective adaptation and mitigation strategies thus protecting people and businesses.

Currently, methods for estimation of evaporative fluxes primarily rely on pan measurements (Sivapragasam et al., 2009), Penman-type estimates with locally calibrated transfer coefficients and heat storage within the water body (Bai and Guo, 2023), eddy covariance (EC) technique (Spank et al., 2020), or measurements of water surface temperature (Zhao et al., 2020, 2022, 2023; Zhao and Gao, 2019). In this study, we seek to provide a mechanistic framework that incorporates physically-based modeling with remote sensing information, utilizing bathymetry and atmospheric data from the MERRA-2 reanalysis (a product based on a combination of models and satellite remote sensing) to reliably predict evaporative losses from dam reservoirs located in different basins worldwide. We thus consider the role of local atmospheric forcing variables and reservoir characteristics including the bathymetry and area to reliably estimate water losses via evaporation. Such mechanistic approach reduces empiricism associated with estimating evaporative losses, which often depends on in situ measurements and local calibrations, and enables trend analysis thus improving local water accounting and management.

To demonstrate the utility of the approach, we focus on the ten largest dam reservoirs in water-stressed regions of the world extended in different climatic zones (Fig. 1a). We opted for dam reservoirs located below 300 m elevation to exclude seasonally frozen reservoirs (primarily limiting the influence of air temperature lapse rate on reservoir's energy balance). High atmospheric evaporative demands in these regions driven by elevated air temperatures and wind speeds, and low humidity levels (as reflected in Fig. 1b), render these reservoirs susceptible to substantial evaporative losses.

2. Materials and methods

2.1. Reservoir characteristics and meteorological data

Water stress was calculated using the WaterGAP model and its indicators (Alcamo et al., 2003; Döll et al., 2003), which estimates runoff and water allocation based on variables such as precipitation, temperature, reservoirs, lakes, and sector-specific water use. The model operates at a spatial resolution of 0.5° (~55 km per grid cell). The water stress index was calculated by aggregating runoff and water use with ecoregion and determining the ratio of water demand to availability.

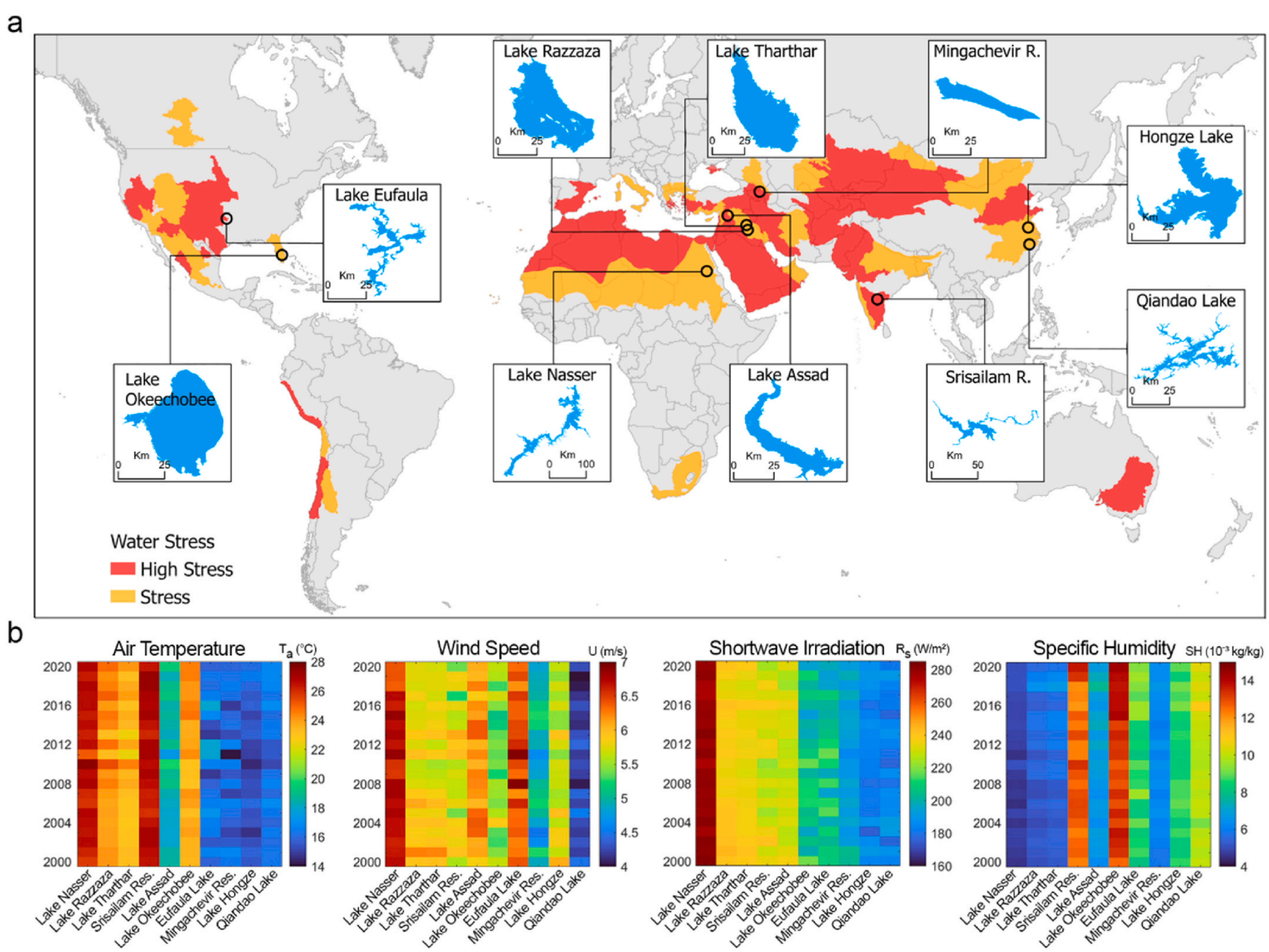

Fig. 1. (a) The largest dam reservoirs in water-stressed regions of the world (Table 1). Water stress is defined as the ratio of water withdrawal to water availability within an ecoregion, where higher values indicate greater stress on water resources (the extent of the water-stressed regions was extracted based on the data provided in the Atlas of Global Conservation (Hoekstra et al., 2010).) (b) Mean annual air temperature, wind speed, shortwave irradiation, and specific humidity of reservoirs from 2000 to 2020 extracted from MERRA-2 reanalysis datasets (Global Modeling And Assimilation Office, 2015a; Global Modeling And Assimilation Office, 2015b).

Reservoir characteristics, encompassing bathymetry, area, capacity, and elevation, were extracted from Global Reservoir and Dam Database (GRanD) and GLOBathy (Khazaei et al., 2022; Lehner et al., 2011). In this analysis, we used information on dams and reservoirs from GRanD version 1.3 consisting of 7320 records of reservoirs and dams. Each dam in the database is geospatially referenced and linked to reservoir outlines at a high spatial resolution. To obtain bathymetry information for the selected dam reservoirs, we utilized the GLOBathy dataset (Khazaei et al., 2022) created using a GIS-based framework, aligning with the widely recognized HydroLAKES global dataset (Messager et al., 2016). GLOBathy covers over 1.4 million waterbodies, including natural lakes and reservoirs. These waterbodies play a crucial role in the ecological and hydrological balance of watersheds, and their morphology and geophysical characteristics, defined by bathymetry, are vital for understanding dynamics of the waterbody. Bathymetric maps were generated based on the maximum depth estimates of waterbodies and the geometric/geophysical attributes from HydroLAKES. The accuracy of maximum depth estimates was validated using data from 1503 waterbodies, incorporating multiple observed sources.

The atmospheric forcing variables required for quantification of evaporative losses were obtained from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) reanalyses dataset (Global Modeling And Assimilation Office, 2015a; 2015b). We thus extracted hourly meteorological data including wind speed, radiation, air temperature, and specific humidity at spatial resolution of 0.5° longitude by 0.625° latitude (approximately 55 km by 70 km).

Reservoirs located at elevations exceeding 300 m were subsequently excluded from our analysis. From the remaining reservoirs, we identified the ten largest reservoirs by surface area for further investigation as these tend to experience higher rates of evaporation (Fig. 1). This approach ensured that our study focused on dam reservoirs within water-stressed areas and prioritized those with substantial potential for water loss due to evaporation.

2.2. Physically-based modeling of evaporation rate in dam reservoirs

We used the physically-based model of Aminzadeh et al. (2018) to quantify evaporation rate from water reservoirs. This model solves the 1D energy balance equation considering the radiation adsorption in the depth of the water body to quantify vertical temperature profile in depth of the reservoirs:

$$\frac{\partial T_w}{\partial t} = \frac{\partial}{\partial z}\left(\left(\alpha_{T,w} + D_w\right)\frac{\partial T_w}{\partial z}\right) + \frac{Q(z,t)}{\rho_w c_w} \quad (1)$$

here, T_w [K] is the water temperature at depth z [m], $\alpha_{T,w}$ [m^2/s] is molecular thermal diffusion, D_w [m^2/s] is eddy thermal diffusivity, and ρ_w [kg/m^3] and c_w [J/kgK] are the water density and specific heat, respectively. According to Dake and Harleman (1969), the heat source (Q [W/m^3]) which is responsible for the absorption of radiative flux within the water body, is a function of depth (light attenuation) and time (diurnal or seasonal fluctuation of incoming radiation). The upper boundary condition for Eq. (1) is defined based on sensible, radiative, and latent heat fluxes at the surface, while the bottom boundary condition considers thermal exchanges with the underlying soil layer and radiation interception at the bottom of the water column. This approach allows quantification of surface temperature defining saturated vapor pressure over the surface of the evaporating water body. Hence, evaporative flux can be quantified as:

$$E = 86.4 \times 10^6 \frac{0.622\,\kappa^2\,U}{\rho_w\,R_d\,T_a\left[\ln\left(\frac{z}{z_0}\right)\right]^2}\left(e_s(T_{ws}) - e_a\right) \quad (2)$$

where E represents the evaporation rate [mm/day], κ is von Karman's constant, U is the wind speed [m/s], R_d is the gas constant for dry air (~287 [J/kgK]), T_a is the air temperature [K] and T_{ws} is the water surface temperature [K]. The parameter z_0 represents the roughness length [m], and z is the measurement height for wind speed and air temperature [m]. Finally, e_s and e_a [Pa], represent the saturated vapor pressure at the water surface and the vapor pressure within the air, respectively. Through this methodology, we were able to estimate and analyze the evaporation rates in an hourly resolution, providing essential information for our comprehensive assessment of water loss from dam reservoirs in water-stressed regions.

To calculate annual evaporation rates, we adopted a method of averaging the area of MERRA-2 cells that fell entirely or partially within a specific basin. It is important to highlight that the impact of inflows and outflows on changing energy balance of the water body was tacitly ignored. The presence of such detailed information would facilitate a more precise assessment of the water temperature within the reservoir, thereby enhancing the precision of estimates of evaporative losses and the dynamics of the energy balance.

3. Results

3.1. Model evaluation using Lake Mead data

Our model predictions of water temperature and evaporation dynamics were primarily evaluated with measurements in Lake Mead, USA, due to the availability of comprehensive, high-quality data for the selected time period (Fig. 2). With more than 640 km^2 surface area and 32 km^3 storage capacity (Ferrari, 2008), it plays a key role in supplying water demands of Nevada, Arizona, and California, which are amongst the driest states in the USA (Bartels et al., 2020; Easterling et al., 2017). The average annual precipitation (based on data from several weather stations around the lake) and temperature (measured at Lake Mead Boulder Basin ET Station, 2011–2021) of 146 mm/year and 23 °C highlight high atmospheric evaporative demands in Lake Mead (Rosen et al., 2012; USGS Surface-Water Daily Data for Nevada, 2023).

Fig. 2 compares model predictions of water temperature and evaporation dynamics with measurements of vertical temperature profile using an array of temperature sensors mounted on a floating platform and surface fluxes obtained from an eddy covariance tower in Lake Mead from March 2010 to March 2011 (Moreo and Swancar, 2013). The required atmospheric forcing variables including radiation, wind, air temperature, and humidity were extracted from a weather station in Lake Mead. The model incorporated the influence of bathymetry and variations in the reservoir's depth, enabling to estimate radiative energy absorption within the water body and subsequent determination of surface fluxes. The results in Fig. 2 indicate that the physically-based model captures dynamics of evaporative losses and temperature variations in the lake. Our model estimates of cumulative annual evaporative loss (1688 mm) is comparable with measurements (~1950 mm). The difference (~15%) between modeled and measured evaporative losses could primarily be attributed to the impact of water inflows with different temperatures affecting energy balance of the water body (currently neglected due to the lack of the reliable data). However, model estimates could be improved wherever reliable temperature data for inflows are available.

3.2. Evaporative loss from dam reservoirs in water-stressed regions

Although dam reservoirs play a key role in addressing seasonal water demands in regions with acute water shortages, their impacts can vary depending on local conditions and management practices affecting their storage efficiency. We employed a physically-based model to quantify evaporative losses from the ten largest dam reservoirs in water-stressed regions of the world from 2000 to 2020 (located at elevations below 300 m). The area of the selected largest reservoirs ranged from 354 km^2 (Eufaula Lake, USA) to 5385 km^2 (Lake Nasser, Egypt) with average depths varying from 2.7 m (Lake Okeechobee, USA) to 50.9 m (Qiandao Lake, China) (Table 1). The largest dam reservoir is Lake Nasser in Egypt

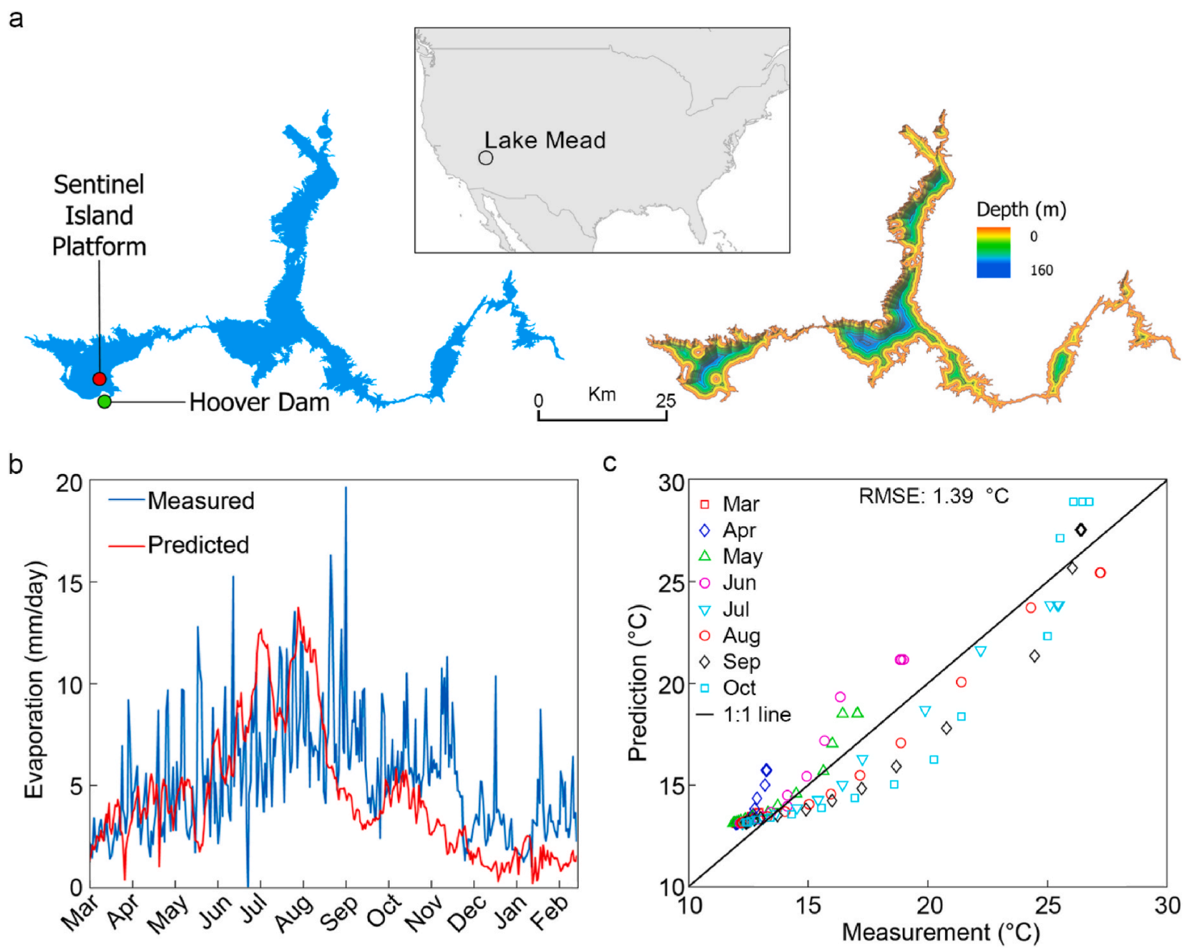

Fig. 2. (a) Lake Mead (USA) with ~640 km^2 surface area and a maximum depth of ~162 m. (b) Comparison between our model predictions of evaporation rate from March 2010 to March 2011 with measurements obtained from an Eddy Covariance (EC) tower at Sentinel Island of the lake. (c) Physically-based modeled water temperature at depths of the reservoir compared with vertical measurements using a multi-parameter water-quality sonde.

with 5385 km^2 surface area, 160 km^3 storage capacity and maximum depth of 130 m, while Eufaula Lake possesses the smallest storage capacity, measuring 4.7 km^3. With only 3.7 m maximum depth, Lake Okeechobee is the shallowest reservoir, while deepest points of Qiandao Lake reach to 176 m. Detailed specifications for each reservoir can be found in Table 1.

Characteristics of the reservoirs including surface area and bathymetry were extracted from GranD (Lehner et al., 2011) and GLOBathy (Khazaei et al., 2022), while local atmospheric forcing variables providing above surface boundary conditions were obtained from MERRA-2 (Global Modeling And Assimilation Office, 2015a; Global Modeling And Assimilation Office, 2015b). The results of our study reveal significant variations in the yearly evaporation rate from the dam reservoirs in water-stressed regions across different climatic conditions (Fig. 3a). Lake Nasser exhibits the highest evaporation rate, ranging from 2350 mm/year to 3200 mm/year, while Qiandao Lake shows the lowest evaporation rate, ranging from 383 mm/year to 692 mm/year. Fig. 3b depicts the evaporation rates for each reservoir during the study period from 2000 to 2020. To gain more profound insights, we explored the relationships between the yearly evaporation rate and first order climatic parameters, including mean annual air temperature, wind speed, shortwave irradiation, and specific humidity (Fig. 3c). Our results demonstrate that the yearly evaporation rate exhibits a positive correlation with air temperature across different climatic zones. The observed increase in the evaporation rate is approximately 122 mm/year per degree rise in temperature. Additionally, an average increase of 1 m/s in wind speed results in a notable rise of over 600 mm/year in evaporation rate. A 1 W/m^2 intensification in average shortwave irradiation causes a

Table 1
Characteristics of dam reservoirs.

Reservoir Name	Dam Name	Country	Area (km^2)	Capacity (mio m^3)	Depth avg. (m)	Depth max. (m)	Elevation ASL (m)
Lake Nasser	High Aswan Dam	Egypt	5385.34	162000	30.1	130	179
Lake Razzaza	Raza Dike	Iraq	1330.22	26000	19.5	45	29
Lake Tharthar	Thartar	Iraq	1698.86	43500	25.6	98	44
Srisailam Res.	Srisailam	India	536.42	8722	16.3	60	263
Lake Assad	Tabqa	Syria	636.77	11600	18.2	48	302
Lake Okeechobee	Structure 193	United States	1418.77	10510	2.7	4	3
Eufaula Lake	Eufaula Lake	United States	354.96	4719	13.3	27	179
Mingachevir Res.	Mingechaur	Azerbaijan	415.51	16000	38.5	130	70
Lake Hongze	Sanhezha	China	1374.36	13500	5.0	6	10
Qiandao Lake	Xinanjiang	China	424.57	21626	50.9	176	100

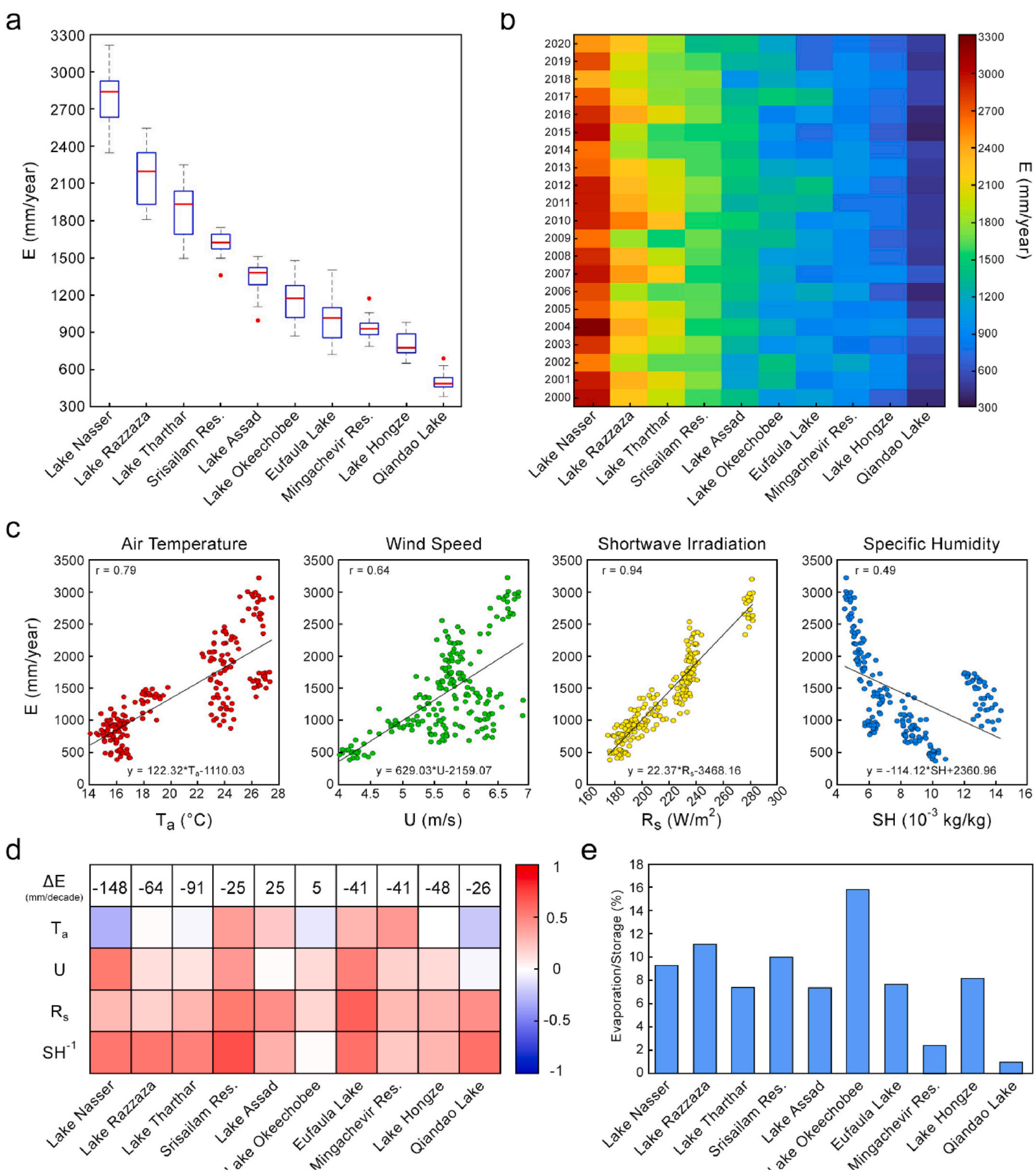

Fig. 3. Analysis of evaporation rates for 10 selected lakes in water stressed-regions of the world marked in Fig. 1. Box plot displaying the evaporation rates (a), and yearly evaporation rate from 2000 to 2020 (b). The relationship between atmospheric forcing variables (i.e., mean annual air temperature, wind speed, shortwave irradiation, and specific humidity), and yearly evaporation rate. Pearson correlation coefficients (r-values) are displayed within each plot, and the p-values are nearly 0 for all plots(c). Model estimates of the variation of evaporation rate and its correlation with local climatological factors (SH^{-1} indicates the inverse of the specific humidity) (d). The relationship between yearly evaporation volume and the total storage volume of the reservoir, expressed as a percentage (e).

rise of 22 mm/year evaporation rate. Evaporation is negatively correlated with atmospheric humidity where an increase of 10^{-3} kg/kg in specific humidity is associated with a decrease of ~115 mm/year in evaporation rate.

As demonstrated in the top row of Fig. 3d, evaporation estimates for eight reservoirs over the 21-year period (2000–2020) reveals a declining trend. This finding may deviate from the prevailing insights into the impact of global warming on heightened evaporative losses from reservoirs (Zhao et al., 2022). Consequently, we conducted additional investigations into the influence of climatic variables to offer a more comprehensive understanding of the intricate relationships governing evaporation rates in these reservoirs. Lake Nasser demonstrated the most notable decrease of ~150 mm/decade. Lake Tharthar experienced a decline of 91 mm/decade, while Lake Razzaza showed a diminishing trend of ~60 mm/decade. Eufaula Lake, Mingachevir Reservoir and Lake Hongze experience comparable decreasing trends of ~40mm/decade. Qiandao lake and Srisailam Reservoir exhibited relatively modest decreases in their evaporation rates, with a reduction of 26 and 25 mm/decade decrease, respectively. In contrast, our analysis showed that Lake Assad and Lake Okeechobee demonstrated increasing trends in their evaporative losses (25 and 5 mm/decade, respectively). Subsequent rows (2 through 5) of Fig. 3d depict the Pearson correlation coefficients between evaporation rate and mean climatic variables in each reservoir, i.e., air temperature, wind speed, shortwave irradiation, and atmospheric humidity. Considering the negative impact of humidity changes on evaporation trends, we opted to calculate the correlation based on the inverse of the specific humidity. A distinct negative correlation between evaporation rates and mean annual air temperature was observed in Lake Nasser, Lake Tharthar, and Qiandao Lake. This suggests that despite increasing air temperatures during the study period, these reservoirs encountered a reduction in evaporation rates. This underscores the complex interplay of local climatological factors influencing evaporation dynamics where the decline in evaporation patterns is primarily attributed to a decrease in wind speed and radiation and an increase in humidity levels.

We elucidated the influence of evaporation on the storage efficiency of these dam reservoirs by calculating the ratio of evaporative loss to total storage for each reservoir. Our results obtained for 2020 suggest that evaporation accounts for up to 15.8% of annual losses in dam reservoirs of water-stressed regions (Fig. 3e). Notably, shallow reservoirs such as Lake Okeechobee, Lake Razzaza, and Srisailam Reservoir exhibit high ratios of evaporative losses to storage capacity, while deep reservoirs like Qiandao Lake and Mingachevir Reservoir appear to be more efficient for water storage purposes.

4. Discussion

4.1. Implication of evaporative losses from dam reservoirs located in water-stressed regions

The estimated evaporation rates, surpassing 3000 mm/year in the studied water-stressed regions, underscore the significant water loss taking place in dam reservoirs. These losses amplify overall water stress, exacerbating the challenges faced in water-stressed regions in fulfilling water demands. The cumulative evaporative loss from the top 10 largest dam reservoirs, exceeding 26.5 km^3/year over this 21-year analysis, highlights the significant impact of evaporation on water availability. Considering the global freshwater withdrawal of 3900 km^3 in 2020 (FAO, 2021), the cumulative evaporative losses from the 10 selected dam reservoirs located in the water-stressed regions in this study account for more than 0.68% of the total freshwater demands. To mitigate the evaporative losses, the implementation of effective strategies is essential. Modular floating elements have proven to be a potential solution for reducing evaporation from small water reservoirs (Aminzadeh et al., 2018; Bakhtiar et al., 2022; Jin et al., 2022; Lehmann et al., 2019, Pourmand et al., 2022; Rezazadeh et al., 2020). However, for larger water bodies like dam reservoirs, alternative methods such as chemical monolayers are often used. Laboratory studies have shown that molecularly thin films of compounds like hexadecanol and octadecanol can significantly reduce water evaporation (Barnes, 2008). Despite their potential cost-effectiveness, these monolayers face challenges such as limited lifespans and uneven distribution across large water surfaces (e.g., due to the wind effect), which diminish their efficiency under real environmental conditions (Barnes, 2008; Karimzadeh et al., 2023).

The economic significance of evaporative losses of stored blue water, i.e. liquid water in surface and groundwater reservoirs (Madani and Khatami, 2015), from dam reservoirs can be further assessed by comparing them with the costs of alternative freshwater resources, such as desalination. The cost of desalinated water production could reach to 2 USD/m^3 in some areas of the world depending on the type and capacity of the desalination plants. Accordingly, direct economic cost of 26.5 km^3 evaporative water loss may exceed 53 billion USD/year (Caldera et al., 2018; Pistocchi et al., 2020). This amount of water may alternatively support livestock or additional crop production. Considering the water footprint of wheat, rice, and maize (approximately 1827, 1673, and 1222 l/kg, respectively (Mekonnen and Hoekstra, 2011a; Mekonnen and Hoekstra, 2011b), 26.5 km^3 yearly evaporative losses could provide the necessary water demands for production of ~15 million tons of wheat, 16 million tons of rice, and 21 million tons of maize. These numbers would change if different crops with varying water demands were considered in the calculation. Additionally, since the crops are not produced using only blue water, this also affects the reported values.

4.2. Global estimates of evaporative loss from dam reservoirs in different basins

Significant evaporative water losses from dam reservoirs in water-stressed regions highlight the importance of accurately estimating evaporation dynamics from such reservoirs worldwide. Therefore, we used the developed methodology to predict evaporative losses from potential dam reservoirs worldwide with the results presented in Fig. 4 depicting our model predictions for potential dam reservoirs (assuming 30 m average depth, consistent with existing estimates for large dam reservoirs) in different basins worldwide. We tacitly ignored freezing periods and condensation process to provide a conservative estimate for upper bound of potential evaporative losses. Spatially averaged atmospheric forcing variables in each basin were used to obtain the results reported in Fig. 4.

Our approach enables a deeper understanding of the intricate interplay between local environmental factors (air temperature, wind speed, solar irradiation and humidity) and their effects on evaporative losses, fostering a more accurate and reliable assessment of water resources management globally. The results presented in Fig. 4 offer quantitative tools for making informed decisions for the design and construction of water storage infrastructures. In the presence of reliable climate data with high spatial and temporal resolutions (Bauer et al., 2021), one could utilize the methodology proposed here to design and construct more resilient dam reservoirs in the face of projected climate changes. Such efforts contribute to several United Nations Sustainable Development Goals (UN SDGs), The European Green Deal and the Paris Agreement.

4.3. Model limitations and future improvements

The proposed mechanistic framework enables the prediction of evaporative losses from dam reservoirs under different climatic and reservoir conditions. However, our modeling approach has some limitations that could be addressed in future investigations. Snowmelt and surface run off with different temperatures (Roberts et al., 2018), water release from the dam reservoirs, and varying water levels throughout the year can affect energy balance and thus water temperature within the

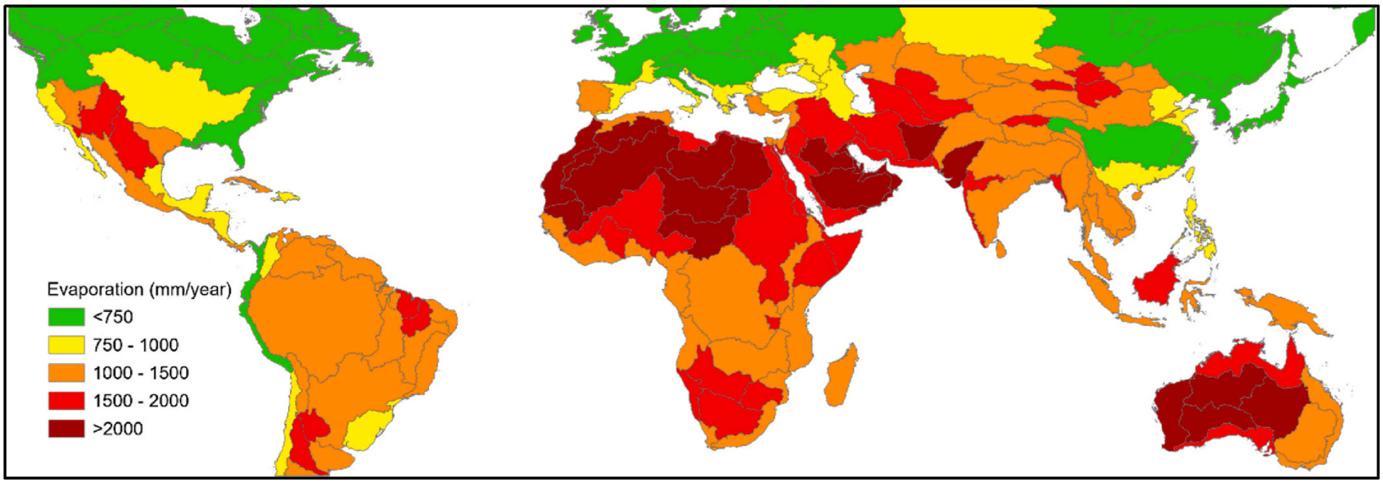

Fig. 4. Modeled yearly evaporation rates from hypothetical representative dam reservoirs (with average depth of 30 m) in 185 basins worldwide. Model results were obtained based on the average meteorological data of 2020 over each basin.

reservoirs (Wright et al., 2009). In the present study, we implicitly neglected the role of water inflows and outflows to the reservoir to maintain the model's applicability for estimating evaporative losses globally. Presence of such detailed information of water flows and their associated temperatures will improve our model estimations. In addition, the relatively coarse resolution of MERRA-2 reanalysis meteorological datasets ($0.5^\circ \times 0.625^\circ$) may not fully represent atmospheric boundary conditions above the reservoirs. Having highly resolved atmospheric forcing variables would enable us to improve our model estimates of water evaporation (Bauer et al., 2021; Shokri et al., 2023).

Uncertainties associated with bathymetric datasets may further influence our model estimations. Current global bathymetry models, including GLOBathy, are known to have relatively large uncertainties, especially when applied at the scale of individual reservoirs (Hao et al., 2024). The lack of high-resolution and accurate bathymetric data for many global reservoirs introduces additional uncertainty into our model's ability to precisely estimate evaporative losses. These inaccuracies can influence water volume estimations, surface area calculations, and, consequently, evaporation predictions. To enhance the model, future studies should consider integrating advanced bathymetric technologies, such as satellite-based altimetry and high-resolution sonar mapping, which are improving the accuracy of bathymetric datasets (Li et al., 2020). The development of these technologies and the refinement of bathymetric data will help to reduce uncertainties in water depth and surface area estimations, leading to more precise predictions of water temperature and evaporation rates.

5. Summary and conclusions

We developed and applied a mechanistic approach to estimate evaporative losses from the largest dam reservoirs in water-stressed regions of the world from 2000 to 2020. The model results revealed that evaporation rates in these regions may exceed 3000 mm/year with cumulative evaporative losses reaching as high as 26.5 km^3/year. Among the studied regions, Lake Nasser, with its hot and dry climate, exhibited the highest evaporation rate (3221 mm/year in 2004), while Qiandao Lake had the lowest rate (383 mm/year in 2015).

Our study highlights the significance of evaporative water losses from large reservoirs, especially in regions with limited water availability and in the state of water bankruptcy. The importance of such losses is better understood when gauged with the cost of conventional water production methods like desalination (with considerable adverse environmental influences (Jones et al., 2019)) or resulting lost opportunities (e.g. crop production with additional water availability) (Caldera et al., 2018). This highlights the urgent need for effective water management strategies to mitigate water loss and ensure the sustainability of water resources around the world, particularly in water-stressed regions. Our analyses unveiled valuable insights into the relationship between evaporation loss from dam reservoirs and meteorological factors. We observed that evaporation increases by 122 mm per 1 °C increase in air temperature, 629 mm per 1 m/s increase in wind speed, and 22 mm per 1 W/m^2 rise in shortwave radiation flux. These identified correlations lay the groundwork for projecting future evaporation rates and devising necessary actions to cope with water shortages in water-stressed regions. The proposed approach further enabled us to delineate potential evaporative losses from typical dam reservoirs across different climatic zones around the world thus highlighted the significance of evaporative losses and their potential implications for improving water management and budgeting.

CRediT authorship contribution statement

Hannes Nevermann: Writing – original draft, Methodology, Formal analysis, Data curation. **Milad Aminzadeh:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Kaveh Madani:** Writing – review & editing, Conceptualization. **Nima Shokri:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All the data used in this analysis are listed in the acknowledgements and are sourced from publicly available resources.

Acknowledgements

We gratefully acknowledge the funding and resources provided by the Institute of Geo-Hydroinformatics at Hamburg University of Technology (TUHH). The authors would also like to express their appreciation for the valuable access to the datasets of MERRA-2, GRanD, GLOBathy, and HydroLAKES.

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