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Ensemble modeling of global lake evaporation under climate change

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ABSTRACT

Global projections of lake evaporation are typically based on simulations using single mechanistic models. However, because of its complex interactions with various lake physical properties, environmental and anthropogenic drivers, lake evaporation is highly variable and sensitive to the choice of model used. In this study, we present a multi-model analysis to investigate differences across global simulations of lake evaporation during the warm-season using three different lake models driven by outputs from four general circulation models (GCM) (i.e. 12 model combinations in total) for historic and future scenarios. Our results suggest substantial differences among lake-climate model simulations of lake evaporation. These differences varied throughout the 20th and 21st century, with model driver data explaining 74% of the variance in future projections of warm-season lake evaporation. Our projections indicate that, by the end of the 21st century (2070–2099), global annual lake evaporation rates will increase by 10–27% under Representative Concentration Pathways (RCPs) 2.6–8.5. We highlight the importance of using a multi-model approach for the prediction of future global lake evaporation responses to climate change.

1. Introduction

Water is a fundamental and finite resource that is essential to human well-being (United Nations, 2021). However, only ~3 % of Earth's water is fresh, and only a small fraction (~1%) can be used as drinking water; the remainder is locked up in glaciers, ice caps, and permafrost, or buried deep underground. Of the fraction of remaining fresh water, more than 87 % resides in lakes (Gleick, 1993; Messager et al., 2016), making them a critical resource of fresh water for, among other things, human consumption. In lakes, water storage variability is influenced by both anthropogenic and natural factors, primarily by changing water availability within a lake's catchment as well as changes in over-lake precipitation and within-lake processes such as surface and groundwater outflow and open-water evaporation (Cooley et al., 2021; Vystavna et al., 2021; Wurtsbaugh et al., 2017). Importantly, open-water evaporation is a key component of freshwater loss and the resulting variations in lake level and surface extent (Friedrich et al., 2018; Zhao et al., 2022). In fact, due to their large open-water areas and typically strong air–water vapour pressure gradients, lakes can lose a large proportion of their water via evaporation (Lenters et al., 2005; Zhao et al., 2022). Lake evaporation also plays a fundamental role in the energy budget of lakes, and is central to the modification of lake temperature and related processes such as stratification and mixing (Lenters et al., 2013; MacIntyre et al., 2009; Mishra et al., 2011; Spence et al., 2013; Ye et al., 2019). In turn, lake evaporation is crucial for the basic functioning of lakes and is often considered as one of the most important processes influencing their physical environment (Friedrich et al., 2018; Lenters et al., 2005; Woolway et al., 2020).

The volume of evaporative water loss from a lake is governed by its surface area and the rate of evaporation (Wang et al., 2020; Zhao et al., 2022; Zhao and Gao, 2019). The latter can vary widely among geographical regions and is highly sensitive to climatic variations (Wang

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et al., 2018; Woolway et al., 2018; Zhao et al., 2022; Zhou et al., 2021). Some of the most direct atmospheric drivers of lake evaporation are wind speed and absolute humidity (Lenters et al., 2014; McVicar et al., 2012; Van Cleave et al., 2014). However, due to the influence of lake surface temperature on the vapour pressure gradient, other atmospheric and limnological factors also play a considerable role in the evaporation rate (Brutsaert, 1982; Friedrich et al., 2018; Lenters et al., 2005). The lake surface energy budget components that influence evaporation are numerous including, among other things, incoming and outgoing short- and long-wave radiation and the exchange of sensible heat at the air–-water interface (Friedrich et al., 2018). Several lake-specific features, such as lake depth, water colour, and the influence of terrestrial sheltering (e.g., tall tree canopy) can also modify the magnitude and timing of lake evaporation, primarily through their influences on surface water temperature and the intensity of near-surface turbulence (McVicar et al., 2012; Read et al., 2012; Wang et al., 2020).

Given the importance of lake evaporation, as well as its influence on other within-lake processes, simulating and understanding its response to climate change is of paramount importance. With the use of one-dimensional process-based lake models, previous studies have suggested that global lake evaporation has increased substantially in recent decades, with future projections suggesting a continued increase in many regions within a warming world (Helfer et al., 2012; La Fuente et al., 2022; Wang et al., 2018; Zhou et al., 2021). Specifically, by the end of this century, global mean annual lake evaporation is expected to increase by 16 %, and at a rate of ~4 % per degree increase in global-mean surface air temperatures (Wang et al., 2018). The largest increases in annual evaporation are expected at low latitudes, where evaporation rates are already high (Wang et al., 2018; Zhou et al., 2021), but also in lakes that will transition to becoming ice-free, allowing the potential for evaporation to occur year-round (Sharma et al., 2019; Woolway et al., 2020). Moreover, lake evaporation is expected to increase rapidly in regions that will experience a drying hydroclimate, which will amplify evaporation increase by enlarging the surface vapor pressure deficit (Farooq et al., 2022; Zhou et al., 2021). The amplified evaporative loss combined with a decrease in precipitation, will likely reduce lake volumes and, in turn, the quantity of freshwater this century (La Fuente et al., 2022; Zhou et al., 2021).

Previous studies have undoubtedly improved our understanding of lake evaporation responses to climate change. However, most of these studies are based on simulations from a single one-dimensional model (Wang et al., 2018; Zhao et al., 2022). While numerous methods have been developed to estimate evaporation from lakes (Finch and Calver, 2008), process-based models have been, in recent years, more frequently used to simulate processes occurring in lakes (Moore et al., 2021). Despite being based on decades of theory, observation, and experimentation, process-based lake models implement approximate forms of relationships, which can depend heavily on tuneable parameters, either due to incomplete knowledge of some processes or for practical computing purposes. Indeed, lake evaporation projections can be sensitive to these limitations and, in turn, to the choice of lake model used (La Fuente et al., 2022; Liu, 2022; Pillco Zolá et al., 2019; Rosenberry et al., 2007). An alternative approach, which can combine the wealth of information provided by multiple lake models, is to follow an ensemble approach, that is, to consider outputs from multiple independently developed models. The main advantage of a multi-model approach is that the uncertainty in the individual model predictions can be quantified, allowing the modeller to better assess the likelihood of occurrence of the projections (Moore et al., 2021). In addition, the multi-model ensemble (e.g., average) can often provide a more robust simulation than any single-model realization (La Fuente et al., 2022; Trolle et al., 2014). Previous studies have demonstrated the robustness of ensemble modelling in lakes (Golub et al., 2022; Grant et al., 2021; Moore et al., 2021; Trolle et al., 2014). Importantly, the development of strategies to mitigate the effects of climate change on lakes not only requires robust projections, but also knowledge of uncertainty of model projections. However, the use of ensemble modelling for simulating climate-induced changes in lake evaporation and the quantification of the associated uncertainties have not previously been investigated.

The overarching aim of this study is to investigate differences in global lake evaporation changes using a suite of independently developed lake models forced with multiple General Circulation Models (GCMs) to produce an ensemble of lake-climate model projections. We use an ensemble of three one-dimensional lake models driven by four GCMs (i.e., 12 model realizations) to investigate differences across simulated global lake evaporation. Here we (i) quantify global lake evaporation rates using a multi-model approach; (ii) evaluate the differences across the model ensemble; (iii) assess future projections of lake evaporation under different climate change scenarios by the end of the 21st century, and related these to projected changes in over-lake precipitation; and (iv) quantify lake model and GCM uncertainty for our future projections of warm-season lake evaporation using the model ensemble.

2. Methods

2.1. Multi-model projections of global lake evaporation

The simulations used in this study consisted of a lake-climate model ensemble of 12 model realizations (i.e., three lake models, each driven by outputs from four different GCMs). The lake models, namely ALBM (Tan et al., 2015), SIMSTRAT-UoG (Goudsmit et al., 2002) and VIC-LAKE (Bowling and Lettenmaier, 2010) (Text S1, Table S1), contributed to the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) phase 2b Lake Sector (Golub et al., 2022). The ISIMIP is an international network of climate-impact modelers who contribute to a comprehensive and consistent picture of the world under different scenarios of climate change. Given that, in many cases, sector-specific impact models are constructed independently and lack interaction with other sectors (water, forest, lakes, etc), the ISIMIP aims to address this challenge by forcing a wide range of climate-impact models with the same climate and socio-economic input data, and making the projections publicly available (Frieler et al., 2017). In addition, the lake models used in this study have been tested and validated in a number of limnological assessments (Bowling and Lettenmaier, 2010; Guo et al., 2021a, 2021b; Janssen et al., 2021; Mishra et al., 2011; Stepanenko et al., 2014, 2013; Thiery et al., 2014), making them suitable for global assessments. For further information on these models, see the supplementary material. The global lake ISIMIP2b simulations are openly accessible and can be found at https://doi.org/10.48364/ISIMIP.931371.

2.2. Input data

To drive each of the lake models, bias-corrected climate model projections from ISIMIP2b were used (Text S2, Table S2), specifically CMIP5 projections from GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5 for historical and future periods (Lange, 2019). These four GCMs were selected as they best met the needs of all sectors participating in the ISIMIP, providing the necessary scenario length at daily temporal resolution (Frieler et al., 2017). In addition these GCMs had a wide range of projected warming rates, with GFDL-ESM2M and HadGEM2-ES representing the lower and higher ends of the warming spectrum, respectively (Golub et al., 2022). Historical simulations used anthropogenic greenhouse gas and aerosol forcing in addition to natural forcing, covering the period 1901 to 2005. Future projections, which represent the evolution of the climate system subject to three different anthropogenic greenhouse gas emission scenarios covering the period 2006 to 2099, RCP 2.6 (the low-emission scenario), RCP 6.0 (the medium–high emission scenario), and RCP 8.5 (the high-emission scenario), were also investigated. The lake models in ISIMIP2b simulated historic and future projections of various lake physical properties, including lake surface water temperature and the latent heat flux at the air–water interface. These two variables were then used to calculate evaporative water loss from latent heat flux using the relationship:

$$E = \frac{Q_e}{\rho_o L_v} \tag{1}$$

where E is evaporation rate (m s^{-1}), Q_e is the latent heat flux (W m^{-2}), ρ_o is density of surface water (kg m^{-3}), calculated as a function of surface water temperature, T_0 (°C), and $L_v = 2.501 \times 10^6 - 2370T_0$ is the latent heat of vaporization (J kg^{-1}) (Henderson-Sellers, 1986). In this study, evaporation rates were estimated only for the warm-season and are presented in mm day^{-1}. Warm-season average evaporation rates were defined as the average over the months Jul-Sep for lakes located north of 30°N, and Dec-Feb for lakes located south of 30°S. For lakes located between 30°N and 30°S, we used all months for estimating average evaporation rates. In this study, we excluded times during the warm season when lakes experience ice cover. More specifically, we omit all negative values of lake surface water temperature and latent heat flux for each lake, thus excluding them from the analysis (Fig. S1).

2.3. Analysis

From our 12 unique model projections we calculated the ensemble mean and standard deviation under both historical and future climatic forcing. More specifically, we calculated the mean and standard deviation for (i) a single lake model forced by multiple climate model projections (e.g. the mean of all four GCMs × VIC-LAKE) and (ii) multiple lake models forced by a single climate model (e.g. the mean of all three lake models × GFDL-ESM2M). For this analysis, we used JASMIN, the UK's collaborative data analysis environment (Lawrence et al., 2013). To investigate the across-lake differences in simulated lake evaporation rates, we grouped the studied lakes according to the 'lake thermal region' in which they are located (Gong et al., 2022; Maberly et al., 2020).

To complement our lake evaporation analyses, we used global historic and future projections of precipitation (P) available from ISIMIP2b (Frieler et al., 2017). This precipitation data consisted of daily values for historic and future scenarios available for the four GCMs and three RCPs used in projecting future changes in lake evaporation. Notably, we used the same definition for warm-season evaporation and defined the annual average P over the months Jul-Sep for lakes located north of 30°N, and Dec-Feb for lakes located south of 30°S, and for lakes located in the tropical areas (i.e. between 30°N and 30°S). Then, we calculated the net flux of water between the overlying atmosphere and the surface of each representative lake ($P - E$) during the historic and future periods. Precipitation data used in this study is freely available at https://data.isimip.org/search/page/2/tree/ISIMIP2b/InputData/query/pr_day/.

2.4. Uncertainty quantification in future projections of lake evaporation

We used the analysis of variance (ANOVA) to quantify lake and climate model uncertainty on future projections of lake evaporation. First, we calculated the climate change signals (ΔE) (i.e., the difference between lake evaporation in a given time period relative to the base period [1970–1999] average) for each lake-climate model combination and RCP scenario (i.e. three lake models, four GCMs and three RCPs). In the ANOVA, the total sum of squares (SST) was divided into the effects due to GCM (SSA), lake model (SSB), and the interactions between lake model and GCM (SSI).

$$SST = SSA + SSB + SSI \tag{2}$$

Given the inconsistency in GCM and lake model populations, we performed a subsampling method as explained in Bosshard et al. (2013). For each subsampling iteration (i), we selected three GCMs out of the four to equal the number of lake models, resulting in a total of four GCM trios. Thus, each subsampling iteration had three lake models and three GCMs.

Then the variance fraction (η^2) effect was derived as:

$$\eta^2_{GCM} = \frac{1}{I}\sum_{i=1}^{I}\frac{SSA_i}{SST_i} \tag{3}$$

$$\eta^2_{lakemodel} = \frac{1}{I}\sum_{i=1}^{I}\frac{SSB_i}{SST_i} \tag{4}$$

$$\eta^2_{interactions} = \frac{1}{I}\sum_{i=1}^{I}\frac{SSI_i}{SST_i} \tag{5}$$

This analysis was performed for each representative lake and RCP scenario. The variance fraction η^2 corresponds to the contribution of an effect (e.g. lake model) to the total ensemble variance (uncertainty) that can range between 0 % and 100 %.

3. Results

3.1. Global warm-season lake evaporation during the historic period

We began our investigation by calculating the historic (1970–1999) warm-season average evaporation rates (i.e., the areal mean of all warm-season evaporation rates during the 30-year period) for lakes worldwide using the lake-climate model ensemble projections. Following the IPCC climate reference regions (Iturbide et al., 2020), our simulations suggested that across the studied sites, the historic warm-season evaporation rates were typically highest in the tropics, western central Asia, western and central North America and were lowest in the Siberian arctic region and northwest and northeast regions of North America (Fig. 1). Ultimately, our simulations showed considerable regional differences during the period of interest (1970–1999). To more clearly evaluate the spatial differences in evaporation rates, we grouped lakes according to the thermal regions in which they are found (Fig. S2). Our simulations suggested that the highest evaporation rates occurred in the southern warm thermal region, varying between 3.5 and 5.5 mm day^{-1} (these values represent the 25th and 75th percentiles of all simulated warm-season evaporation rates within the thermal region). Similar results were found for the northern warm (between 3.5 and 5.2 mm day^{-1}), and for the northern hot thermal regions (between 3.1 and 5.0 mm day^{-1}). Northern cool and northern frigid thermal regions experienced the lowest warm-season evaporation rates, between 1.6 and 2.8 mm day^{-1}, and 1.1 to 2.2 mm day^{-1}, respectively (Table S3).

As well as demonstrating clear differences in lake evaporation rates across thermal regions, our global-scale simulations demonstrated noticeable differences in evaporation rates across the lake-climate model ensemble. Most of the differences between models were evident in North America, northern South America, and central Africa (Fig. 1). Critically, this suggests that the choice of model used can have a considerable influence on the simulated evaporation rates during the historic period. To explore this effect further, we investigated the differences in the spatial distribution of average lake evaporation across the lake-climate model ensemble and lake thermal regions. The variability in simulated lake evaporation (here denoted by the difference between the quantiles) was more evident across lake models (i.e., the mean of all GCMs) than across GCMs (i.e., the mean of all lake models) (Fig. S3). Some examples include the evaporation estimates for the tropical hot region ranging between 2 ± 2 mm day^{-1} and 4 ± 1 mm day^{-1} for lake models, whereas almost all GCMs had an evaporation estimate of 3 ± 1 mm day^{-1} for this thermal region. In addition, the northern hot (ALBM: 4 ± 2 mm day^{-1}; VIC-LAKE: 4 ± 1 mm day^{-1}; SIMSTRAT-UoG: 5 ± 1 mm day^{-1}) and southern hot (ALBM: 3 ± 1 mm day^{-1}; VIC-LAKE and SIMSTRAT-UoG 4 ± 1 mm day^{-1}) thermal regions also showed differences across lake models, contrary to the climate models, where all GCMs reported an evaporation rate of 4 ± 2 mm day^{-1} for the northern hot and 4 ± 1 mm day^{-1} for the southern hot region

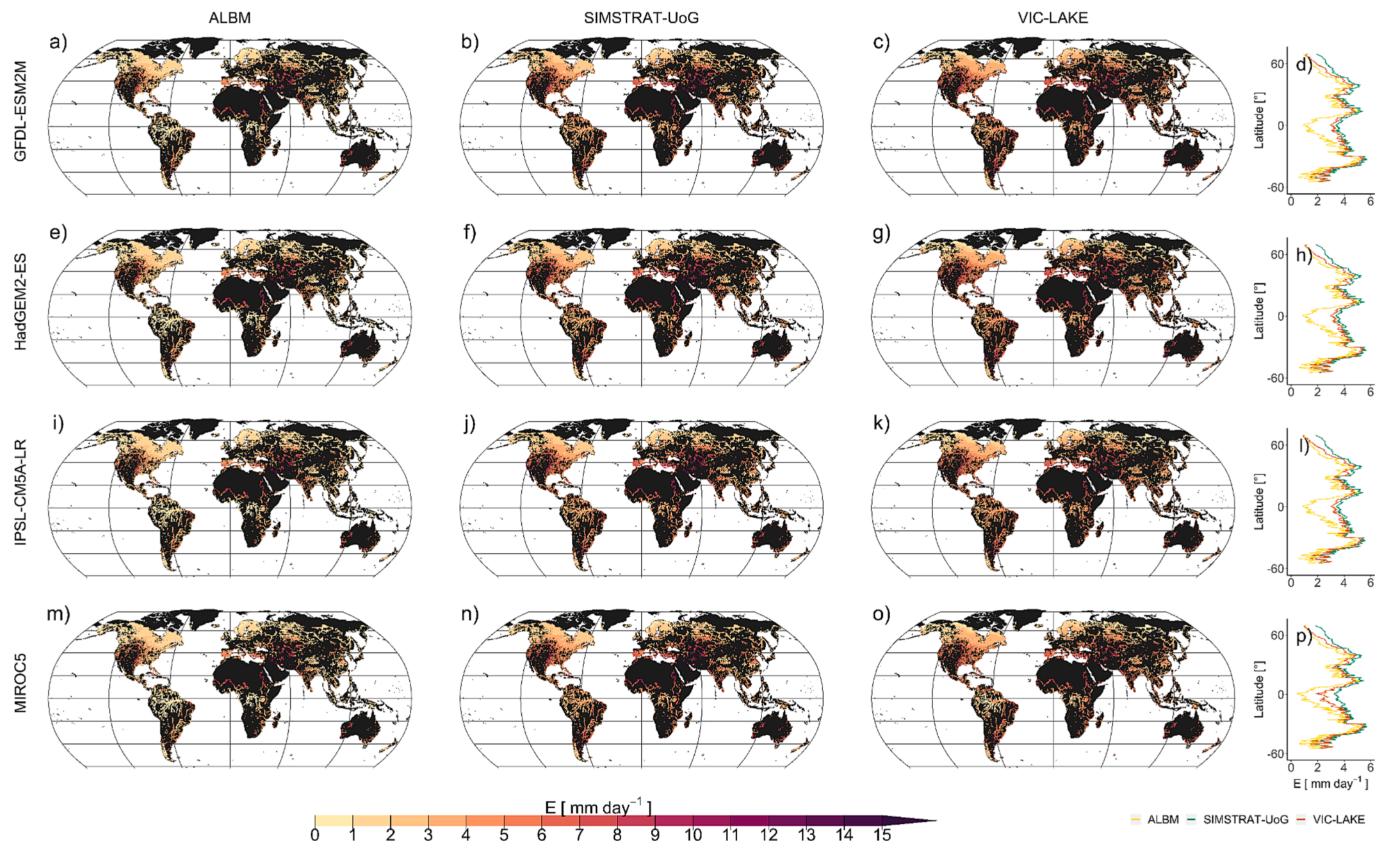

Fig. 1. Warm-season lake evaporation rates in mm day^{-1} averaged over the 1970–1999 period for each lake model and General Circulation Model (GCM) combination, shown are: (a, e, i, m) ALBM, (b, f, j, n) SIMSTRAT-UoG, (c, g, k, o) VIC-LAKE. Each lake model was driven by GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC5. Latitudinal plots show warm-season evaporation simulations across lake models (d, h, l, p).

(Tables S4 and S5).

3.2. Multi-model projections of global lake evaporation during the 21st century

Having investigated historic warm-season lake evaporation rates and the discrepancies across the lake-climate model ensemble, we then investigated projected changes under future climatic forcing (RCPs 2.6, 6.0 and 8.5) from 2006 to 2099. Our projections demonstrated noticeable changes in global lake evaporation anomalies (ΔE) (i.e., the difference between lake evaporation in a given time period relative to the base period [1970–1999] average). All models projected an increase in warm-season lake evaporation by the end of the 21st century. However, the magnitude of change in evaporation rates varied considerably across the model ensemble, particularly at high latitudes. Contrary to the results of the historic period, the evaporation projections from ALBM and SIMSTRAT-UoG were very similar, particularly across latitudinal gradients for the RCP 8.5 scenario (Fig. 2 d, h, l, p). The largest discrepancies among lake models were found at higher latitudes, where evaporation projections from VIC-LAKE were consistently higher. In contrast to the other lake models (i.e. ALBM and SIMSTRAT-UoG), VIC-LAKE showed the largest changes in warm-season evaporation at high latitudes (Fig. 2). Furthermore, when we compared the differences in lake evaporation anomalies among the GCMs, we found that there was stronger spatial heterogeneity compared to the historic period. A notable example are the GFDL-ESM2M-driven simulations where there were particularly large differences (Fig. 2 a-c), such as in eastern North America and Siberia. Moreover, the MIROC5-driven simulations were also highly influenced by the lake model used, especially in North America, eastern Europe and western Siberia (Fig. 2 m-o).

The variability in lake evaporation anomalies among GCMs was much greater than among lake models under the RCP 8.5 scenario when compared to the historical period (Fig. S4). This was most evident when the studied lakes were grouped by thermal region. The most notable examples were found in the tropical hot regions with evaporation anomalies varying between GFDL-ESM2M: 0.4 $\pm$ 0.3 mm day^{-1} and HadGEM2-ES: 1.1 $\pm$ 0.6 mm day^{-1} for GCMs, and between SIMSTRAT-UoG: 0.7 $\pm$ 0.4 mm day^{-1} and ALBM: 0.9 $\pm$ 0.8 mm day^{-1} for lake models. In the southern warm region, evaporation anomalies were between GFDL-ESM2M: 0.5 $\pm$ 0.4 mm day^{-1} and IPSL-CM5A-LR: 1.3 $\pm$ 0.6 mm day^{-1} for the climate models, and between VIC-LAKE: 0.7 $\pm$ 0.4 mm day^{-1} and ALBM: 0.9 $\pm$ 0.7 mm day^{-1} for lake models. Similar results were found in the northern temperate region GFDL-ESM2M: 0.6 $\pm$ 0.3 mm day^{-1} and HadGEM2-ES: 1.5 $\pm$ 0.6 mm day^{-1} and between VIC-LAKE: 0.9 $\pm$ 0.4 mm day^{-1} and ALBM: 1.2 $\pm$ 0.7 mm day^{-1} (Tables S6, S7). Global warm-season evaporation maps for RCPs 2.6 and 6.0 are included in the supplementary material (Fig. S5, S6). Thus, unlike the results for the historic period (where lake evaporation projections among GCMs were comparable), we found that for the future projections, all GCMs resulted in notoriously different changes in lake evaporation.

When we estimated global average warm-season evaporation changes, it was evident that the influence of GCM models was more important than that of lake models, particularly in the future scenarios (Fig. 3). More specifically, when comparing the global average change in evaporation by the end of the century (2070–2099) (i.e. the increase in lake evaporation relative to the base period [1970–1999]), we found that there was a large spread in the projections, particularly for the high-emissions RCP 8.5 scenario. For instance, SIMSTRAT-UoG projected evaporation changes that ranged between 13 % and 29 %, ALBM evaporation changes varied between 23 % and 52 %, and VIC-LAKE projections varied between 16 % and 33 % (Fig. 3, Table S8). Thus,

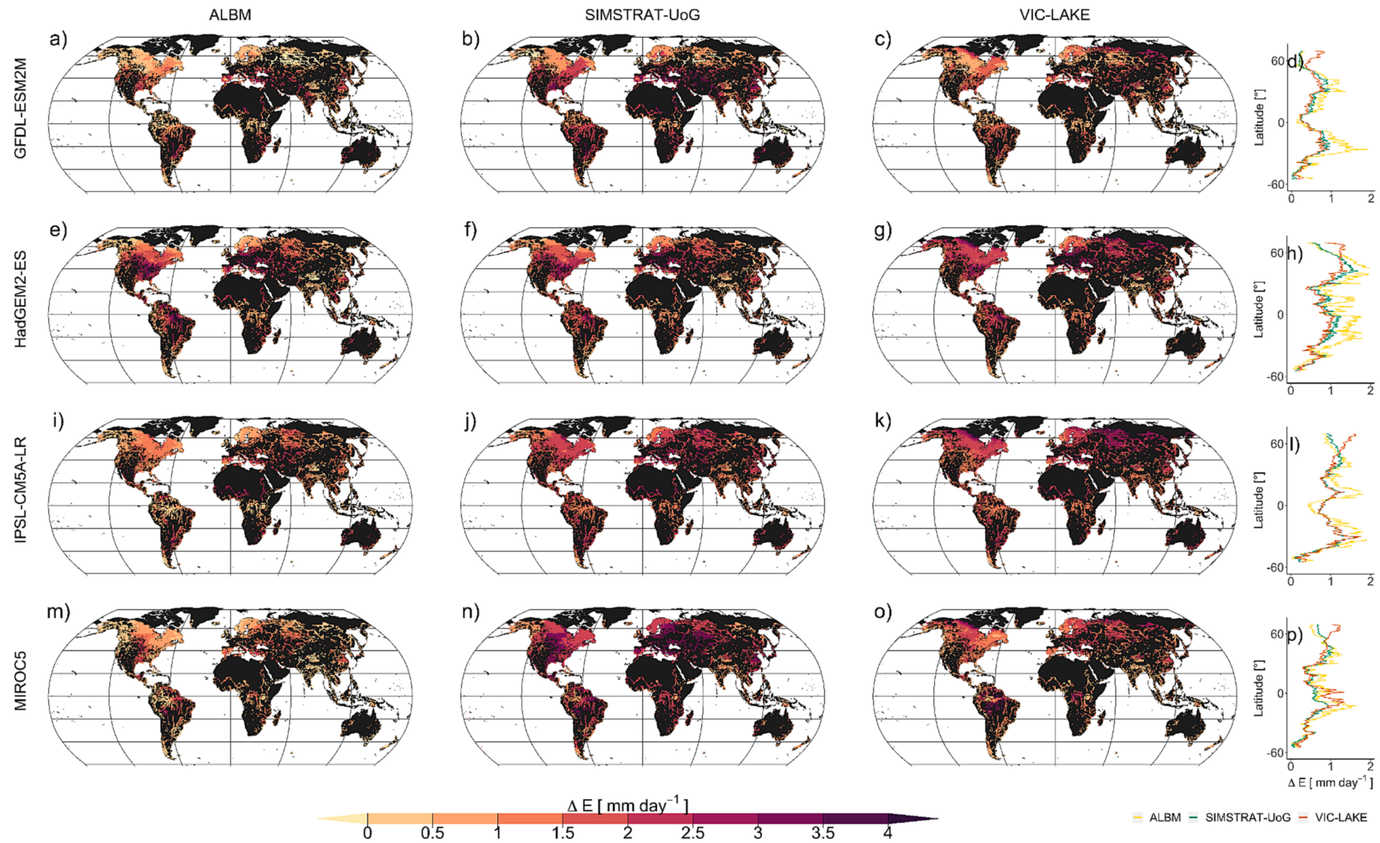

Fig. 2. Projected changes in warm-season lake evaporation rates in mm day^{-1} by the end of the 21st century (2070–2099) under Representative Concentration Pathway (RCP) 8.5. Projections are shown for each lake-model combination namely (a, e, i, m) ALBM, (b, f, j, n) SIMSTRAT-UoG and (c, g, k, o) VIC-LAKE. Each lake model was driven by GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC5. Latitudinal plots show warm-season evaporation simulations across lake models (d, h, l, p). Anomalies (ΔE) are quoted relative to the 1970–1999 base-period average.

unlike the historic period (where GCM models predicted a similar global average rate of lake evaporation), we found that for the future projections of lake evaporation, the climate models differed considerably from each other in their results.

Due to differences in simulated evaporation rates among the model ensemble, particularly across climate model simulations, using a multi-model average with quoted uncertainties can provide more robust predictions. At a regional scale, we found considerable variability in lake evaporation rates across lake thermal regions. For instance, lake evaporation for the base period (1970–1999) ranged between 1.8 $\pm$ 0.5 mm day^{-1} and 4.5 $\pm$ 0.28 mm day^{-1} for the northern frigid and southern warm regions respectively (quoted uncertainties represent the standard deviation of the model ensemble). Similarly to the historic period, by the end of the century (2070–2099), evaporation increases varied strongly across thermal regions. Under the most pessimistic scenario RCP 8.5, evaporation increased between 0.3 $\pm$ 0.2 mm day^{-1} and 1.2 $\pm$ 0.41 mm day^{-1} for the southern temperate and northern warm regions, respectively. These changes represented an increase of 42 % for the northern frigid lakes and 12 % for the southern temperate lakes, demonstrating that lakes in the northern hemisphere will experience the largest increases in evaporation compared to the base period (Fig. 4, Table S9).

At a global scale, the model ensemble from this study indicated an average warm-season evaporation rate of 3.2 $\pm$ 0.5 mm day^{-1} (quoted uncertainties represent the standard deviation of the model ensemble) during the last decades of the 20th century (1970–1999). During the 21st century (2006–2099) all lake models projected an increase in global lake evaporation. Under the low-emissions scenario (RCP 2.6), global lake evaporation was projected to increase by 0.3 $\pm$ 0.1 mm day^{-1} by the end of the 21st century. For the medium–high emissions scenario (RCP 6.0), global lake evaporation was projected to increase by twice as much (i.e., 0.6 $\pm$ 0.2 mm day^{-1}). The largest change in global lake evaporation was projected under the high-emissions scenario (RCP 8.5) with evaporation rates increasing by 0.9 $\pm$ 0.3 mm day^{-1}, i.e., three times higher than RCP 2.6. These projected changes correspond to an average (although highly variable across the ensemble) percent increase of 10 %, 18 %, and 27 %, for RCP 2.6, 6.0, and 8.5 respectively, compared to the base-period average (Fig. 5, Table S10).

To evaluate the combined effects of warm-season evaporation and precipitation on lakes, we estimated the difference between precipitation and evaporation ($P - E$) (Fig. S7). Our analysis revealed that under all RCP scenarios the multi-model average evaporation projections exceeded the multi-model average change in precipitation (Fig. 6). For the low-emissions scenario RCP 2.6 some regions in western North America, north South America and the Mediterranean exhibited deficits in P-E. The most pessimistic RCP 8.5 scenario showed a higher deficit in various regions of North America, northern South America, the Mediterranean, western and central Europe, as well as central Asia (Fig. 6). Notably, these results reflect the rapid increase in evaporation and the simultaneous decrease in precipitation this century in many lake-rich regions. Relative to the 1970–1999 base period average (0 $\pm$ 0.5 mm day^{-1}), P-E continuously decreased throughout the 21st century. For instance, our projections suggest that P-E will decrease by -0.2 ± 0.19 mm day^{-1}, -0.5 ± 0.24 mm day^{-1}, -0.8 ± 0.4 mm day^{-1} under RCPs 2.6, 6.0 and 8.5, respectively by the end of the 21st century (2070–2099) (Fig. 6, Table S11).

3.3. Uncertainty in future projections of warm-season evaporation

We quantified the percentage of total variance explained by GCM and lake model for projections of warm-season lake evaporation during

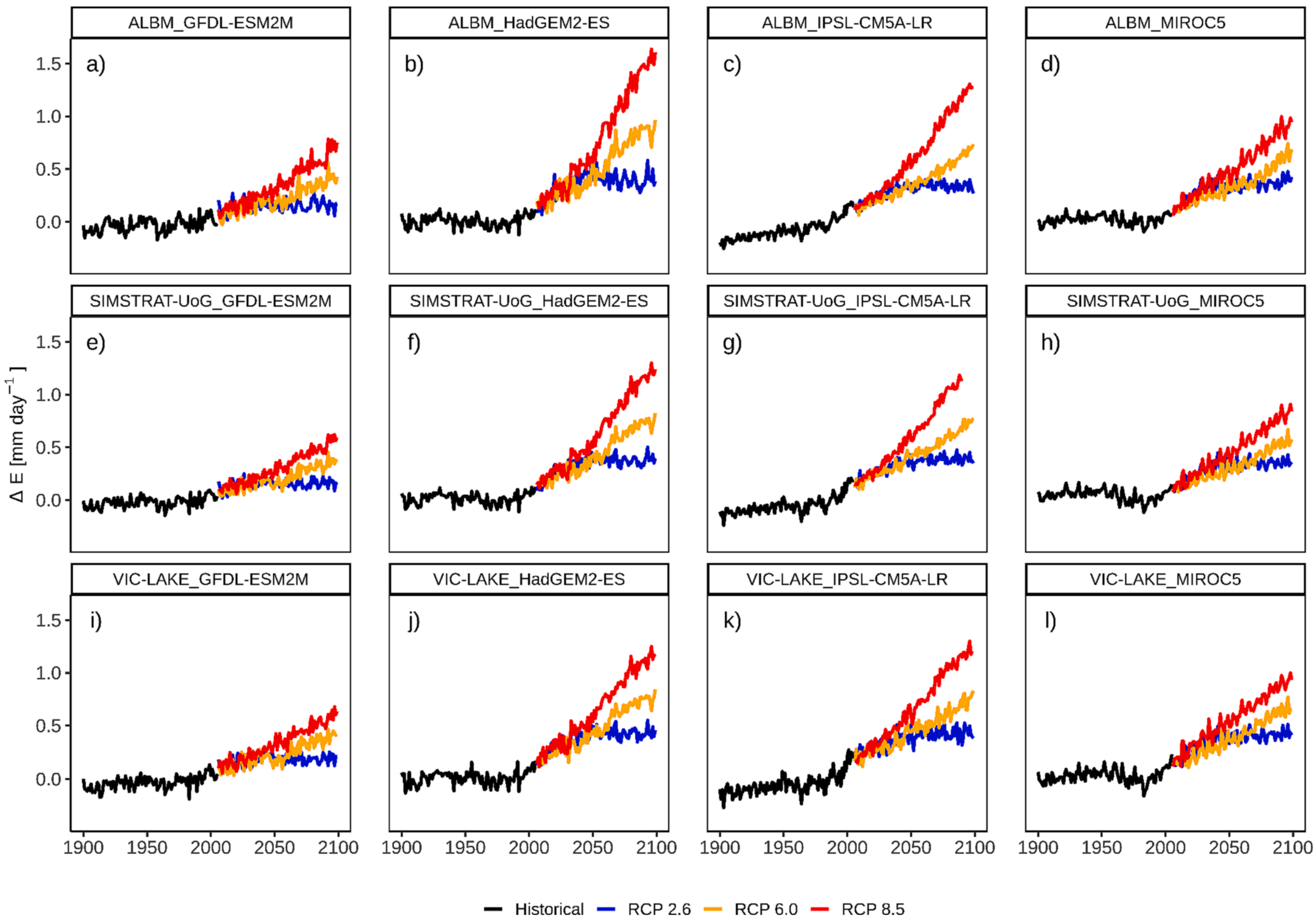

Fig. 3. Projected changes in global warm-season lake evaporation in mm day^{-1} during the historic (1901–2005) and future (2006–2099) periods. Projections are shown for each of the individual lake-climate models, namely for (a-d) ALBM, (e-h) SIMSTRAT-UoG and (i-l) VIC-LAKE, driven by the four General Circulation Models included in this study. Black lines represent the historical period, and the coloured lines represent the future period, with the blue, orange and red representing the projected change under RCP (Representative Concentration Pathway) 2.6, 6.0, and 8.5, respectively. Anomalies (ΔE) are quoted relative to the 1970–1999 base-period average. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the 21st century under RCP 2.6, 6.0 and 8.5 (Fig. S8, Fig. S9 and Fig. 7). For the aim of this study, we only show the results for GCM and lake model uncertainty and, unlike Bosshard et al. (2013), do not show the interactions between lake model and GCM, which is outside the scope of this study. Fig. 7 shows the variance explained by both GCM and lake model over the 2070–2099 period for the RCP 8.5 scenario. GCMs accounted for most of the variance (~74 %) on global lake evaporation projections (Fig. 8), dominating in nearly all regions except some regions of North America, the Tibetan-Plateau, Siberia and West Central Asia (Fig. 7). However, it must be noted that the sources of uncertainty varied, particularly when comparing across lake thermal regions (Fig. 8), where lake model variance became greater by the end of this century in the northern regions. We found that for the northern frigid thermal region, GCMs and lake models contributed equally to the variance in lake evaporation estimates at 51 % and 49 % for the RCP 8.5 scenario, respectively. Increasing trends in variance resulting from the lake models were found in the northern warm, northern hot, and southern temperate regions and to a lesser extent in northern frigid and southern hot regions (Fig. 8). GCM variance was mostly dominant in northern temperate, southern warm, and tropical hot regions but was also high in some lakes situated in the southern temperate region. Given that GCM explained most of the variance in future projections of lake evaporation, we further quantified the variability in key meteorological forcings across these models (Fig. S10). We found that short- and longwave radiation as well as air temperature, showed a stronger variability than relative humidity, precipitation and wind speed. The highest variability was detected in regions of North America and Siberia, where northern cool and temperate lakes were located and to a lesser extent in northern South America.

4. Discussion

To the best of our knowledge, this is the first study to evaluate differences in projections of global lake evaporation using an ensemble approach (i.e. a combination of three lake models driven by four GCMs). In line with previous research (La Fuente et al., 2022; Liu, 2022; Pillco Zolá et al., 2019), our comparative analyses suggest that lake evaporation is sensitive to the choice of model used. Differences in spatial patterns of lake evaporation were evident across lake models and GCMs throughout the 20th and 21st century. Moreover, while previous studies using observational data and/or simulations from a single model suggest a latitudinal dependence on lake evaporation, with higher evaporation rates at low latitudes (Wang et al., 2018; Zhao and Gao, 2019), our study demonstrates that not only the choice of lake model, but also the choice of driver data (i.e., the climate model) used can play a considerable role in the magnitude of projected evaporation in this climatic region. In fact, in agreement with recent assessments (Zhao et al., 2023), our uncertainty analysis on future projections of lake evaporation suggests that GCM model uncertainty (i.e., variance in estimates of climate models) was greater than lake model uncertainty (i.e., variance in the modeled

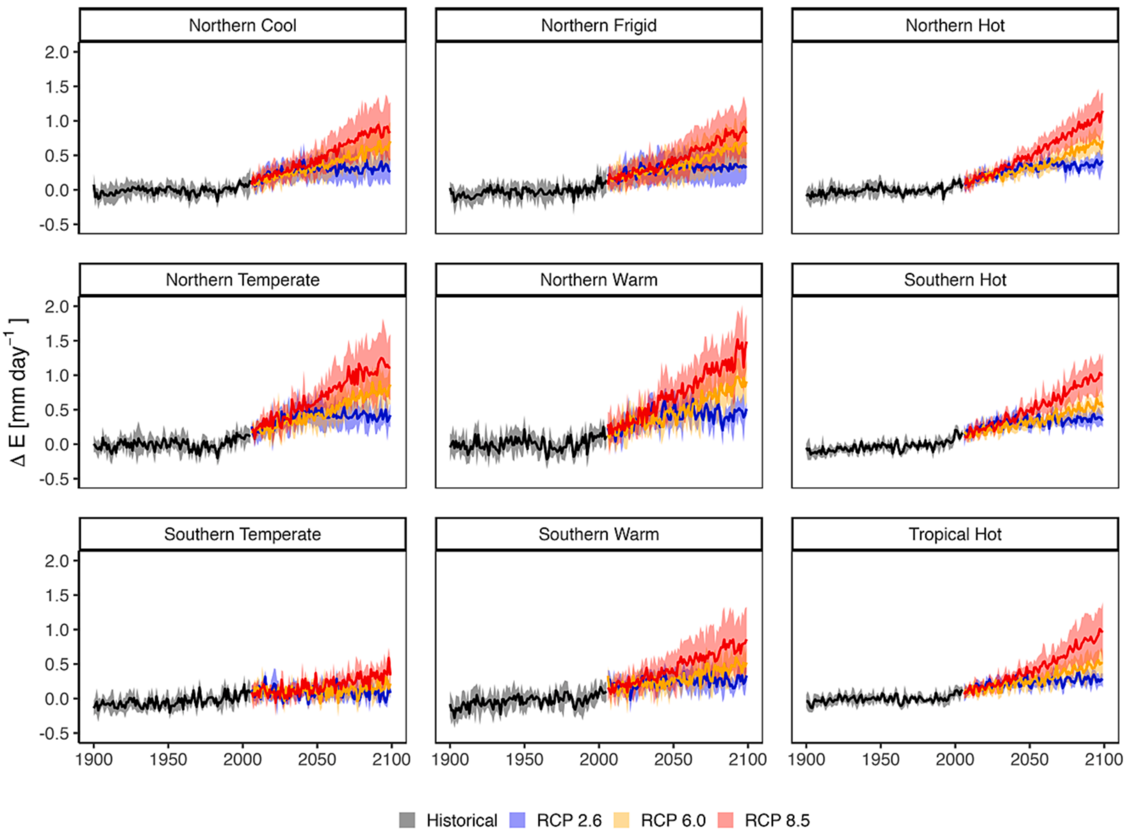

Fig. 4. Model ensemble projected changes in global warm-season lake evaporation during the historic (1901–2005) and future (2006–2099) periods across lake thermal regions. Anomalies (ΔE) are quoted relative to the 1970–1999 base-period average.

representation of lake evaporation), explaining 74 % of the total variance. Importantly, we found that the lake model and GCM uncertainty contributions were variable across lake thermal regions, with lakes located in northern thermal regions exhibiting an equal uncertainty contribution from lake model and GCM. Other warm and hot thermal regions exhibited increasing trends in lake model uncertainty contribution during the 21st century, suggesting that uncertainty contribution from lake models and GCMs can be influenced by lake-specific characteristics. Despite the differences in time periods used to estimate evaporation change, our ensemble projections align with those reported by Wang et al. (2018), who estimated a global lake evaporation increase of 16 % by 2091–2100 with reference to 2006–2015 under RCP 8.5, comparable to the 27 % estimated by our model ensemble by 2070–2099 with reference to the 1970–1999 period. Therefore, our analyses demonstrated that using a single model realization may be problematic for capturing the strong spatial and temporal variability that evaporation rates exhibit at both regional and global scales.

Although we consider our results robust and believe that they bridge an important knowledge gap in climate change assessments, there are some limitations to consider when interpreting our key findings, particularly in terms of the magnitude of projected change from the 12 model realisations. Firstly, similar to both Wang et al. (2018) and Zhou et al. (2021), our simulations represent an aggregated 'typical lake' for each 0.5° longitude-latitude grid, where the modelled representative lake is characterized by the average surface area and depth of all known lakes in that grid. Individual lakes within a 0.5° grid will likely behave differently to the typical lake considered as, for example, lake surface area and depth are known to strongly modulate lake evaporation rates (Wang et al., 2020; Zhao et al., 2022; Zhao and Gao, 2019). However, such representations of lakes (i.e., at a gridded scale) are necessary for their inclusion in Earth system models and for global scale projections (Subin et al., 2012; Vanderkelen et al., 2021; Wang et al., 2018; Zhou et al., 2021). Importantly, due to the spatial mismatch between real world lakes and our definition of a 'representative lake' a thorough validation of our results is not feasible and falls beyond the scope of this manuscript. Moreover, as our projections are generated using 1-D process-based lake models, which largely represent average lake conditions (Råman Vinnå et al., 2021; Ulloa et al., 2019), horizontal features within a lake and the intra-lake responses to climate change will not be captured (Calamita et al., 2021; Mason et al., 2016; Woolway and Merchant, 2018). In turn, the spatial variability in evaporation (Lenters et al., 2013; Mahrer and Assouline, 1993; Spence et al., 2013), which can be large in some lakes, is not included in our projections. In addition, we highlight that our uncertainty estimations are likely biased due to the unequal number of GCMs and lake models, and thus result in a larger contribution of GCM variance. To address this limitation, we included a subsampling method in our uncertainty analysis, and thus demonstrated that the variance in future lake evaporation projections is mostly dominated by GCM data (Zhao et al., 2023). Furthermore, while this study provides important insights into lake evaporation responses to climate change, we focused solely on the warm season, thus we are neglecting evaporation rates at other times of the year. In some lakes, for example, the high evaporation season occurs during the autumn and winter (e.g., the Laurentian Great Lakes). However, for consistency across a global lake distribution, effects outside the warm seasons were not considered in this study. In addition, our ISIMIP2b simulations assume a constant light attenuation coefficient. While this is common in 1-D global lake simulations (Golub et al., 2022; Grant et al., 2021; Wang et al., 2018), it does mean that changes in water transparency during the 20th and 21st centuries are not considered. Transparency can either increase or decrease in the future, as it has during the historic period (de Farias Mesquita et al., 2020; Heiskanen et al., 2015). These changes in transparency can either amplify or suppress lake evaporation under climate change via its influence on lake surface water temperature (Rose

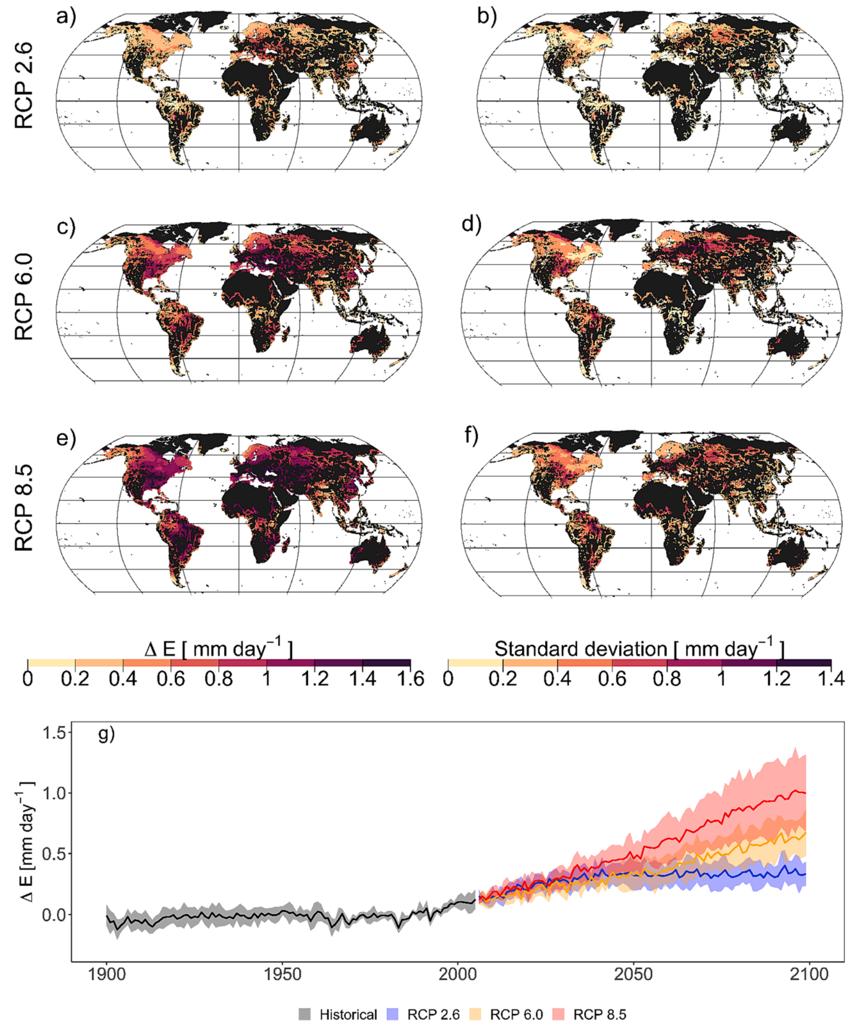

Fig. 5. Projected changes in warm-season lake evaporation rates in mm day^{-1} (ΔE) by the end of the 21st century (2070–2099) for Representative Concentration Pathway (a-b) RCP 2.6, (c-d) RCP 6.0 and (e-f) RCP 8.5, averaged across lake and climate models. Shown are the mean (left column) and the standard deviation (right column), and (g) model ensemble projected changes in global warm-season lake evaporation during the historic (1901–2005) and future (2006–2099) periods. Anomalies (ΔE) are quoted relative to the 1970–1999 base-period average.

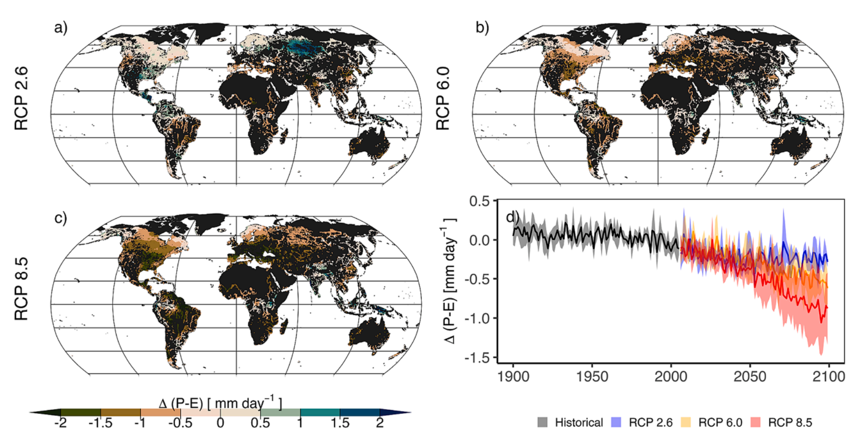

Fig. 6. Projected changes in warm-season precipitation minus evaporation rates in mm day^{-1} $\Delta(P - E)$ by the end of the 21st century (2070–2099) for Representative Concentration Pathway (a) RCP 2.6,(b) RCP 6.0 and (c) RCP 8.5, averaged across lake and climate models, and (d) model ensemble projected changes in global warm-season precipitation minus evaporation during the historic (1901–2005) and future (2006–2099) periods. Anomalies Δ(P-E) are quoted relative to the 1970–1999 base-period average.

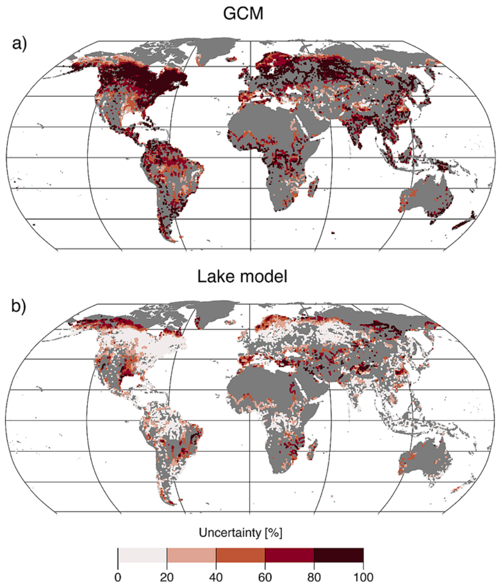

Fig. 7. Percentage of total uncertainty explained by (a) GCM and (b) lake model in future projections of warm-season lake evaporation over the period 2070–2099 for the Representative Concentration Pathway (RCP) 8.5.

et al., 2016). As it is uncertain how water transparency will change during the 21st century, the ISIMIP2b projections focused solely on the more robust future projections of climate change. While the limitations described above will influence the robustness of our simulations in terms of the projected magnitude of change at local scales (e.g., for individual lakes), we believe that these simulations are extremely useful to answer some of the core questions of this study, notably regarding quantifying differences across a lake and climate model ensemble.

An ensemble mean is typically considered to provide an optimal prediction of lake responses to climate change (La Fuente et al., 2022; Trolle et al., 2014), with the underlying assumption that different models provide statistically independent information evenly distributed around the true state (Pennell and Reichler, 2011). Ensemble modelling has become increasingly popular in climate change impact assessments in recent years. However, its application should include, when possible, detailed uncertainty quantification. This is important due to the high variability that different sources of error and uncertainty (i.e. lake model, climate model, model parameter, initial conditions, etc.) can have on projected historical and future change. Here, we have considered only two sources of uncertainty (i.e., due to lake and climate models), but others could also be important. Specifically, recent studies have highlighted the benefit of using large ensemble simulations (i.e., a set of projections starting from different initial conditions but produced with a single model and identical external forcing; Deser et al., 2020). Given the important role that GCMs play in the uncertainty of lake evaporation, future research could investigate the contribution of key forcings (i.e. wind speed, relative humidity, solar radiation, etc.) to the overall GCM uncertainty, and thus provide valuable information not only for water managers but also for modelers.

The use of large ensembles in lakes is not common, given its computational expense. However, some recent studies have used large ensembles to investigate lake responses to climate change, notably to investigate the contribution of natural vs anthropogenic forcing to changes in lake ice cover (Huang et al., 2022). Similar large ensemble simulations have also been used in terrestrial and marine ecosystems to investigate long-term temperature changes (Mora et al., 2013; Schlunegger et al., 2020; Silvy et al., 2020). Future studies could benefit from investigating lake evaporation responses to climate with the use of large ensembles. In practice no single model can be identified as being the best performing due to the lack of global lake evaporation observations, which limits a detailed validation of these simulations. Our study quantifies the uncertainties associated with our results and thus highlights the advantages of using a multi-model approach. Future studies could benefit from more extensive validation of these global simulations. However, given the cost, accessibility, and technical challenges of obtaining direct measurements of lake evaporation at local, and even more so at global scales, the validation of evaporation estimates is often limited to specific lake sites (Wang et al., 2018; Zhao et al., 2022).

Accurate evaporation quantification is crucial for adaptation and mitigation planning, particularly in regions that rely heavily on the ecosystem services that lakes provide. Indeed, evaporation from lakes is increasing at alarming rates, however it is in fact the P-E (precipitation minus evaporation) relationship that primarily influences the water budget of many lakes. Our results suggest that the increase in evaporation will likely exceed precipitation, particularly in regions where precipitation is projected to decrease this century. More specifically, all RCP scenarios projected a global decrease in the P-E relationship, with the P-E spatial distribution suggesting that more and more lakes are likely to experience a deficit in their water balance. As two key lake ecosystem threats (i.e. reduced water quantity and water quality deterioration) are directly linked to evaporation, robust model projections with quantified uncertainties are critical to increase the confidence in future projections

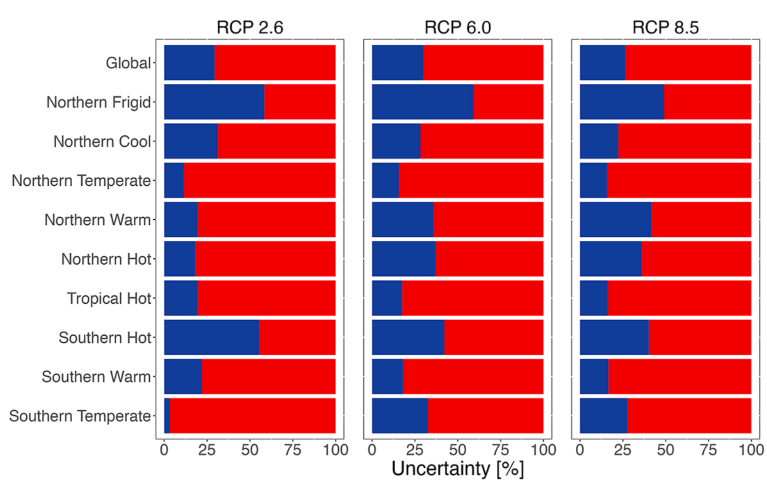

Fig. 8. Percentage of uncertainty explained by GCM and lake model in projections of warm-season lake evaporation over the 2070–2099 period for the global average, and for the lake thermal regions under Representative Concentration Pathway (RCP) 2.6, 6.0 and 8.5.

for decision-making. In a recent assessment of lake Sunapee, Wynne et al. (2023) highlighted the large variability in uncertainty sources for various lake thermal metrics. As a complex physical process related to, among others, surface water temperature and lake heat storage, evaporation is likely to exhibit variability in uncertainty sources across different lake types. Recent studies have highlighted the benefit of investigating climate change impacts in lakes with the use of multiple lake-climate model combinations (Golub et al., 2022; La Fuente et al., 2022; Moore et al., 2021). Indeed, multi-lake-model simulations are increasingly used to provide robust assessments of freshwater ecosystem responses to climatic variations. In addition, multi-model comparisons are powerful methods to explore reliable scientific findings and yield robust policy conclusions (Duan et al., 2019). Our model simulations were part of the ISIMIP framework, and thus open the possibility to link the implications of our results with other relevant sectors (Frieler et al., 2017; Rosenzweig et al., 2017; Warszawski et al., 2014). More specifically, our evaporation simulations can be utilized in studies of regional water availability and water quality, population health, fisheries and marine ecosystems, and agriculture (Friedrich et al., 2018; Li et al., 2013; Marsh and Bigras, 1988; Zhao et al., 2022).

5. Conclusions

In this study, we used an ensemble of lake-climate models to project future global lake evaporation changes under scenarios of climate change. We found substantial differences in projected global lake evaporation across the model ensemble. These differences indicated that a single-model realisation cannot capture the strong spatial and temporal variability that global lake evaporation exhibits. Furthermore, our results projected that global annual lake evaporation rates will increase by 27 % under the Representative Concentration Pathway (RCP) 8.5, higher than the 16 % increase predicted by earlier studies. Our uncertainty analysis revealed that GCM driver data had a greater contribution than lake model to the variance in future projections of lake evaporation. Using a multi-model approach is essential for providing robust evaporation projections, and quantifying the uncertainties associated to these projections. The findings of this study have important implications for the water management of lake-rich regions, and provides important insights for the lake modeling community.

CRediT authorship contribution statement

Sofia La Fuente: Conceptualization, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Eleanor Jennings:** . **John D. Lenters:** . **Piet Verburg:** Conceptualization, Writing – original draft, Writing – review & editing. **Zeli Tan:** . **Marjorie Perroud:** . **Annette B.G. Janssen:** Data curation, Formal analysis, Methodology, Writing – review & editing. **R. Iestyn Woolway:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing.

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 lake model simulations and input data are available at https://doi.org/10.48364/ISIMIP.931371.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2024.130647.

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