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17 Global lakes are warming slower than surface air temperature due to

18

accelerated evaporation

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28 Abstract: Widespread increases in lake surface water temperature (LSWT) have been

- documented in recent decades. Yet our understanding of global lake warming is
- 30 mainly based on summertime measurements and includes relatively few observations
- from high latitudes (> 60° N) where half of the world's lakes are located. Here, we
- 32 provide temporally and spatially detailed high-resolution LSWTs for 92,245 lakes
- 33 (36% are located within the Arctic) based on satellite remote sensing and numerical
- 34 modeling. The global LSWT data suggested a mean increase of +0.24 °C decade⁻¹
- 35 (uncertainty = $0.02 \text{ °C decade}^{-1}$) from 1981 to 2020, which is significantly (P < 0.05)
- slower than the change in surface air temperature (SAT, mean rate: +0.29 °C decade⁻¹)
 during the same period. We show that climatic forces (long-wave radiation, shortwave
- during the same period. We show that climatic forces (long-wave radiation, shortwave
 radiation, and specific humidity) other than SAT contribute more than half of the lake
- warming, and energy loss through accelerated evaporation rate is mainly responsible
- 40 for the slower warming rate. Lake warming is likely to continue from 2021 to 2099
- 41 unless a low-greenhouse-gas-emission scenario is followed. Our dataset provides
- 42 important baseline information to further evaluate the physical and biological
- 43 responses of lakes to past and future warming.

44 Main

45 Lakes comprise only 2.2% of the global land surface area, yet they are extremely important natural resources that play a vital role in global hydrological and 46 biological cycles ^{1,2}. However, lakes are highly vulnerable to climate change ^{3,4}. One 47 of the most pertinent consequences of climate change in lakes is an increase in lake 48 surface water temperature (LSWT)⁵, which can result in a cascade of ecological and 49 environmental impacts. Notably, an increase in LSWT can alter important physical 50 (ice cover, evaporation, stratification, etc.) and biogeochemical (primary production, 51 nutrients, and oxygen concentrations, carbon cycling, etc.) processes in lakes, 52 threatening many key functions of lacustrine ecosystems ^{4,6-8}. For example, the 53 reduction of dissolved oxygen solubility in warmer waters has resulted in the 54 deoxygenation of many temperate lakes ⁶. Warming has also facilitated the increased 55 occurrence of harmful algal blooms ⁹ and contributed to an increase in reported fish 56 die-off events ¹⁰, likewise having a detrimental influence on some of the ecosystem 57 services that lakes provide to society (e.g., drinking water, fisheries, recreation). 58 Unfortunately, under continued global warming, such impacts on lakes are expected 59 to worsen in the future. 60

Global-scale datasets of LSWT have become increasingly available in recent 61 years, due to the availability of extensive in situ and satellite-derived observations ¹¹. 62 A notable example is the synthesis study of summer months' LSWT for 235 globally 63 distributed lakes by ref.⁵, which suggested a higher global average warming rate in 64 lakes (0.34 °C decade⁻¹) compared to surface air temperature (0.25 °C decade⁻¹) 65 between 1985 and 2009⁵. Rapid lake warming was described as a consequence of, 66 among other things, shorter winter ice cover ¹² and changes in cloud cover/incoming 67 solar radiation ¹³. However, the global dataset investigated was based solely on 68 summertime observations ⁵, thus neglecting important changes occurring at other 69 times of the year ¹⁴. More recently, satellite-derived daily observations from 70 thousands of lakes have been compiled into freely-available global datasets (e.g., 71 GloboLakes ¹⁵ and ESA CCI Lakes ¹⁶). These data, which are available from 1995 to 72 the near-present, have been used to examine various lake thermal responses to climate 73 change, including surface warming, mixing regimes alterations, and heatwave 74 enhancement ^{17,18}. However, the comparatively rare coverage of these datasets at high 75 latitudes, and their relatively short temporal coverage, challenge our current 76 understanding of global lake warming. Critically, ~50% of the lakes are located north 77 78 of 60°N¹, and thus need to be resolved in global scale studies. An alternative approach for investigating global lake thermal responses to

An alternative approach for investigating global lake thermal responses to
climate change is to analyze simulations from process-based lake models, which have
become increasingly available in recent years ¹⁹. Global-scale simulations have been
used to investigate historical and future climate change impacts on LSWTs, and to
quantify the anthropogenic contribution to lake temperature changes ^{20,21}. However,
current global-scale lake model simulations, such as those provided by the
Intersectoral Impact Model Intercomparison Project Lake Sector ¹⁹, are typically
provided on a gridded basis by assuming invariant lake morphological (i.e., depth,

8

87 morphology, etc.) and hydrothermal (i.e., heat flux from discharge and sediments)

- features within a relatively large longitude-latitude grid (e.g., 0.1° , 0.25°)^{12,20}.
- 89 Ultimately, these simulations represent an aggregated "typical lake" for each grid cell.
- 90 However, as most lakes are smaller than the size of one grid cell, and lake-specific
- 91 features (e.g., depth) play an important role in their thermal response to climate

92 change $^{22-24}$, these global-scale simulations can be considered uncertain 25 .

To fill the above knowledge gaps, here we integrate satellite remote sensing and numerical modeling to provide hourly LSWTs for 92,245 lakes, and use them to quantify the warming trends of lakes from 1981 to 2099 at a truly global scale. Our study represents the first comprehensive characterization of changes in global LSWT and the associated surface energy redistribution based on a dataset of high spatiotemporal resolution with extensive global coverage.

99 The global lake surface water temperature (GLAST) dataset

100 We established a global lake surface water temperature (GLAST) dataset based on four decades (1981-2020) of Landsat satellite images and a physical model 101 (FLake) ^{26,27} (see Methods and Extended Data Fig. 1). We initially focused on 1.41 102 million lakes, polygons for which were provided in the HydroLAKES database², 103 while the masks for permanent water, narrow channels (to avoid mixing pixels and 104 105 land adjacency effects), and limited observations (< 10 cloud-free images over the study period) reduced the number of target lakes to 92,245 (36% are located within 106 the Arctic) (see Methods). The total surface area of these lakes is 2,116,773.2 km², 107 representing 72.3% of the global lake area ¹. For each lake, the LSWT was retrieved 108 using Landsat thermal observations from 1981 to 2020, and validated with in situ 109 110 observations when available (see Methods). The long-term satellite-derived LSWT 111 was then used to optimize key parameters of the FLake model, which was used to 112 simulate LSWT for all studied lakes. The climate forcing parameters of the FLake model are air temperature, short- and long-wave radiation, wind speed, and specific 113 humidity ¹⁷. Our extensive global validation efforts showed that the optimized FLake 114 model could accurately simulate LSWT, lake surface energy fluxes, evaporation rate, 115 and ice phenology (Extended Data Fig. 2-3, Supplementary Fig. 1). Furthermore, our 116 117 simulated LSWTs demonstrate a much greater accuracy compared to the currently available dataset from ERA5-Land (Extended Data Fig. 4). Following the validation 118 of the FLake model, we then performed historical (1981-2020) and future (2021-119 120 2099) simulations, with the former simulated hourly and the latter at daily timescales, in line with the temporal resolution of the respective climate forcing datasets (see 121 122 Methods). We conducted the future simulations under three different anthropogenic 123 greenhouse gas emission scenarios, including the Representative Concentration 124 Pathway (RCP) 2.6 (low-emissions), RCP 6.0 (medium-emissions), and RCP 8.5 (high-emissions)²⁸. 125

We selected the simulations over the minimum ice-free period (that is, the
intersection of the non-frozen period between 1981 and 2020) for lakes worldwide,
examined the long-term LSWT trends, and analyzed the drivers and feedbacks on the

distribution of lake surface energy fluxes (see Methods). The average duration of the

- minimum ice-free period for the lakes studied was 187 ± 125 days. We also performed
- trend analysis for different seasons, and our four seasons were defined as winter
- (Months 1-3), spring (4-6), summer (7-9), and autumn (10-12) in the Northern
- Hemisphere, and summer (1-3), autumn (4-6), winter (7-9), and spring (10-12) in the
- 134 Southern Hemisphere, following the same practice as in ref.⁵. For the majority of
- 135 lakes in the southern hemisphere and the middle-to-low latitudes of the northern
- 136 hemisphere, the minimum ice-free period extends throughout all four seasons of the
- 137 year (Supplementary Fig. 2). As latitude increases, the minimum ice-free period
- becomes shorter; for Arctic lakes, 100% of the lakes are covered with ice during
- 139 winter, and 95.4% and 96.6% are ice-covered during spring and autumn, respectively.

140 Four decades of global lake warming

The global LSWT dataset showed a mean warming rate of +0.24 °C decade⁻¹ 141 (uncertainty = $0.02 \degree C$ decade⁻¹) from 1981 to 2020 (Fig. 1). The spatial patterns and 142 143 warming rates were similar between daytime and nighttime (Supplementary Fig. 3). Of all lakes examined, 41.6% experienced a statistically significant warming trend (P 144 < 0.05). Small lakes were warming much faster than large lakes. Notably, the mean 145 warming rate for lakes with a surface area $\leq 1 \text{ km}^2$ was 1.7 times higher than lakes 146 with a surface area $> 100 \text{ km}^2$ (Extended Data Fig. 5a). By contrast, cooling trends 147 were observed in only 2.8% of the lakes, mostly in those located in western Siberia, 148 associated with the stratospheric circulation anomaly near the Ural Mountains ²⁹. A 149 pronounced increase in LSWT was observed in high-latitude regions, with Arctic 150 lakes warming at a rate (+0.48 °C decade⁻¹, uncertainty = 0.03 °C decade⁻¹) twice that 151 152 of lakes situated south of the Arctic Circle (+0.22 °C decade⁻¹, uncertainty = 0.02 °C 153 decade⁻¹). Such amplified warming of LSWT was comparable to that calculated for surface air temperature (SAT), land surface temperature, and ocean surface 154 temperature in the Arctic regions ³⁰⁻³². 155

156 The global LSWT trend was 17% lower than that calculated for SAT (+0.29 °C decade⁻¹, Fig. 1b), and slower LSWT warming rates were found across all latitudes 157 except for the near-polar regions (Fig. 1c). Matched pair t-test also revealed 158 159 significant (P < 0.05) differences between the global trends for LSWT and SAT. As a result, the mean lake-to-air temperature difference has decreased by 0.3 °C (from 160 1.8 °C to 1.5 °C) over the past four decades (85% of the lakes globally showed higher 161 162 LSWT than SAT, see Extended Data Fig. 6a-b). By contrast, the lake-air temperature differences have increased at high latitudes (particularly in Northern Europe) due to 163 the greater LSWT warming, highlighting the differential responses of LSWT and SAT 164 to climate change. 165

Unexpectedly, we found lake warming (+0.64 °C decade⁻¹) and air cooling (0.17 °C decade⁻¹) in the Arctic during spring. This is the season when Arctic lakes
experienced the fastest warming rates, as compared to +0.48 °C decade⁻¹ in summer
and +0.43 °C decade⁻¹ in autumn, respectively (Extended Data Fig. 7). The
substantial increase in LSWT in spring was likely due to the prolonged ice-free

season during the most recent years and thus an increase in the accumulation of solar 171 radiation at the lake surface ^{33,34}, while the slight decrease in SAT was due to the 172 negative anomalies in the high latitudes of East Asia and western Europe ³⁵. 173 174 Moreover, our analysis suggested that the LSWT trend is not only higher in regions 175 with climatologically longer ice duration (i.e., colder regions), but also positively correlates with the loss of ice-cover days (Extended Data Fig. 5b-c). These results 176 177 also agree with a previous study that suggested lake warming during the months of ice-off was 1.4 times greater than during the open water season ¹². In all other 178 seasons, mean LSWT demonstrated slower increasing rates than SAT in both Arctic 179 180 and non-Arctic lakes.

181 Drivers of the global lake warming

182 We quantified the contributions of key external climate forcing parameters to the global LSWT trends using FLake simulations (Fig. 2, Supplementary Fig. 4). This 183 184 was accomplished through six groups of simulations, including one reference 185 simulation with the trends of all forcing parameters retained, and five control 186 simulations with the target parameter kept the long-term trend and others were detrended (see Methods). On average, the increase in SAT represents 47% (+0.112 °C 187 decade⁻¹) of lake warming globally. Substantial contributions were identified from 188 long-wave radiation (+0.061 °C decade⁻¹, or 26%) and specific humidity (+0.059 °C 189 decade⁻¹, or 25%). Although solar brightening was also responsible for 7% (+0.017 °C 190 decade⁻¹) of the global lake warming, marked decreases in solar radiation were found 191 in the Canadian and Russian Arctic, the Tibetan Plateau, and India, offsetting of the 192 warming trends (Supplementary Figs. 5g & 6d). By contrast, despite the potential 193 impacts of wind speed on evaporation and stratification ³⁶⁻³⁸, its contribution to global 194 LSWT trends was minor (-0.005 °C decade⁻¹, -2%). These results corroborate 195 previous findings that other climate variables could considerably influence lake 196 warming besides SAT ^{13,39-41}, whereas the total contribution of the variables to global 197 lake surface warming estimated here (53%) was slightly higher than that by ref. ^{13,39} 198 199 (~40%).

200 Increased evaporation slows down lake warming

Simulations of the lake surface energy fluxes demonstrated that the slower 201 202 warming of LSWT relative to SAT was primarily due to the energy loss through increased evaporation. From 1981 to 2020, the increasing rate in annual latent heat 203 flux (+1.41 W/m² decade⁻¹) was almost three times the increase of incoming net 204 205 radiation (+0.51 W/m² decade⁻¹) (Fig. 3a, c). The rapid increases in latent heat flux 206 can be translated into a mean increase of 7% in the evaporation rate of global lakes during the past four decades, which agrees with previous findings that more energy 207 would be reallocated for evaporation under higher air temperatures ³³. The critical role 208 of evaporation in reducing lake warming is also suggested by the significant negative 209 feedback ($R^2 = 0.58$, P < 0.05) between evaporation rate and lake-to-air warming 210 difference for permanently ice-free lakes (Extended Data Fig. 8); such effect of 211 evaporative cooling has also been identified previously in individual lakes ⁴²⁻⁴⁵. This 212

213 mechanism is also similar to the slower warming rate of the ocean than the land 214 surface, which was attributed primarily to the equilibrium associated with accelerated evaporation over the ocean surface; in contrast, the larger heat capacity of the oceans 215 only represents a transient effect ⁴⁶. Meanwhile, the positive sensible heat flux (Fig. 216 3f) is also responsible for the excessive heat loss from the lake to the air, albeit with a 217 decreasing trend (-0.38 W/m^2 decade⁻¹, Fig. 3e) and a much smaller annual mean 218 value than latent heat flux. Furthermore, heat storage change (ΔG) decreased by 0.52 219 W/m^2 decade⁻¹ over the past four decades (Fig. 3g), indicating a deceleration in both 220 the accumulation of heat storage within lakes and the warming of the lake water 221 column. These changes could have additional implications for the rate of lake 222 stratification and the associated physical and biological processes ⁴⁷. 223

224 The increase in latent heat flux in Arctic lakes during the past four decades 225 $(+1.63 \text{ W/m}^2 \text{ decade}^{-1})$ was higher than in lakes situated elsewhere $(+1.39 \text{ W/m}^2)$ 226 decade⁻¹), even if the non-Arctic lakes showed approximately twice the value of the 227 annual mean latent heat flux than those in the Arctic (Fig. 3d). Such disproportional increases represented a net evaporation rate increase of 14% in Arctic lakes during the 228 past four decades. To compensate for the excess energy loss of evaporation as well as 229 the substantial decreases in net radiation, ΔG in Arctic lakes demonstrated a mean 230 decreasing rate of -2.12 W/m² decade⁻¹, which was four times the global average (-231 $0.52 \text{ W/m}^2 \text{ decade}^{-1}$). 232

233 Future trends and implications of global lake warming

234 Under a medium-emissions scenario (RCP 6.0), global LSWTs are projected to increase at a rate of +0.30 °C decade⁻¹ from 2021 to 2099 (Fig. 4), which is 25% 235 higher than those calculated during the historical period (Fig. 1). Meanwhile, the 236 237 warming trend would be decelerated in Arctic lakes by -21%. The increase in latent 238 heat flux would be stabilized for global lakes under RCP 6.0, albeit at a rapidly decreased rate (-48%) in Arctic lakes. The sensible heat flux (-0.33 W/m² decade⁻¹) 239 and ΔG (-0.25 W/m² decade⁻¹) are projected to decrease for global lakes, as the 240 increase of net radiation (+0.78 W/m² decade⁻¹) would be insufficient to support the 241 energy loss through latent heat (+1.36 W/m² decade⁻¹). The air-to-lake temperature 242 difference is projected to decrease at a slightly slower rate of 0.038 °C decade⁻¹ 243 (Extended Data Fig. 6c). Our projection also indicates that the change in LSWT and 244 the energy fluxes under RCP 8.5 will be more pronounced than those seen in the past 245 four decades, especially for Arctic lakes (Supplementary Fig. 7). Nevertheless, 246 247 negligible future warming in both lakes and air can be expected under a low-248 emissions scenario (RCP 2.6) (Extended Data Fig. 9).

Our GLAST dataset provides spatially and temporally detailed information on
global LSWT changes from 1981 to 2099 (with particularly increased coverage over
high latitude regions compared to the existing datasets), providing more
comprehensive insights into global lake warming and the associated impacts. For
example, our comparison between SAT and LSWT demonstrated significantly slower
warming of lakes, which is different from a previous global-scale study where

globally indistinguishable trends were found between air and lake temperatures ⁵. Our 255 256 different finding is likely due to the substantial increase in the number of lakes in our 257 study as well as the temporal coverage. Likewise, our increased coverage in cold 258 regions has resulted in a greater projected increase in evaporation rate (27%) by the end of this century compared to Wang et al. (15.7%)³³, while our projections were 259 similar to theirs in tropical and temperate regions (Extended Data Fig. 10). Such 260 detailed mapping of the changes in global lake evaporation rate could help to identify 261 the lake-warming induced increases in drought ⁴⁸. In addition, our GLAST dataset can 262 help shed light on the contribution of warming as a major factor driving the observed 263 increase in harmful algal blooms in numerous lakes during recent decades ^{7-9,49-51}. 264

265 The responses of lakes to global warming are complex. For example, rising lake temperatures could change not only the solubility and consumption of oxygen and 266 nutrients (the two fundamental processes that sustain lake ecosystems ^{6,7}), but it could 267 also result in a strengthening of thermal stratification ³⁸. By limiting the transport of 268 oxygen from surface to bottom waters and the transport of dissolved nutrients in the 269 opposite direction, stratification can lead to further declines in oxygen concentrations, 270 with anoxic conditions at depth having the potential to result in substantial nutrient 271 leakage from the sediments ⁵², as well as increased production of potent greenhouse 272 gases ⁵³. Our dataset provides a vital baseline to evaluate the changes in these critical 273 ecological processes and the potential consequences of past and future lake warming. 274

275 Methods

276 Data sources

HydroLAKES. The HydroLAKES database (Version 1.0) provides polygons for 1.4
 million lakes and reservoirs worldwide ², along with various site-specific information,

such as lake surface area, mean depth, elevation, etc. These lake-specific attributes are

essential for our lake thermodynamic simulations using the FLake model 26,27 (see

281 below). The HydroLAKES dataset was downloaded via

282 https://www.hydrosheds.org/products/hydrolakes.

283 *Global Surface Water (GSW) dataset.* We used the 30-m resolution Global Surface

284 Water Occurrence (GSWO) dataset ⁵⁴ to delineate the extent of our examined global

lakes. The GSWO dataset provides the probability of water presence (or water

occurrence, ranging from 0 to 100%) for the entire globe over the past four decades,

based on millions of historical Landsat satellite images. We also used the monthly

- history collection of the GSWO dataset to determine the dynamic water masks for
- 289 lakes with substantial seasonality (see below). The GSW dataset can be freely
- 290 accessed in Google Earth Engine (GEE) via <u>https://developers.google.com/earth-</u>
- 291 <u>engine/tutorials/tutorial_global_surface_water_02</u>.

292 In situ data. Extensive in situ datasets were compiled to validate the lake thermal

- 293 parameters derived from satellites or simulated by model in this study. Specifically,
- we compiled hourly recorded field measurements of lake temperature sampled near
- the water surface (depth ≤ 1 m) through various sources (see Supplementary Table 1)

- to evaluate the performance of the Landsat-retrieved water surface temperature (see
- below). A total of 6,755,222 hourly records were obtained, which are distributed at
- 403 sites worldwide. We also collated observed lake surface heat flux and evaporation
- rate data, which were available at various temporal resolutions (monthly, seasonal,
- and annual), from the published literature to validate the model-simulated surface
- 301 energy budget (Supplementary Table 2). We downloaded *in situ* lake ice phenology
- records (i.e., the Global Lake and River Ice Phenology Database (GLRIPD, version
- 3031)) from the National Snow and Ice Data Center 55 to validate the model-simulated
- lake ice freeze-up day, break-up day, and ice duration (see below). The dataset covers
- approximately 700 lakes in the Northern Hemisphere and is freely available at
- 306 <u>https://nsidc.org/data/G01377/versions/1</u>.
- *Landsat satellite data.* We used all Collection 1 Tier 1 Landsat 4, 5, 7, and 8 images
- from 1981-2020 to retrieve global LSWTs. The satellite-derived LSWTs were further
- used for calibrating the FLake model (see below). The Landsat brightness temperature
- datasets have spatial resolutions of 120 m, 60 m, and 100 m for Landsat 4/5 Thematic
- Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8
- Thermal InfraRed Sensor (TIRS), respectively. The Landsat data are available at
- $\label{eq:linear} {\tt 313} \qquad \underline{\tt https://developers.google.com/earth-engine/datasets/catalog/landsat}.$
- 314 *Total Column Water Vapor (TCWV) data.* We used the TCWV from NCEP/NCAR
- Reanalysis data ⁵⁶ to estimate the atmospheric contribution, which represents a key
- 316 process in retrieving LSWT using Landsat satellite images. The data is available in
- 317 GEE at <u>https://developers.google.com/earth-</u>
- 318 <u>engine/datasets/catalog/NCEP_RE_surface_wv</u>), at a spatial resolution of 2.5° and a
- temporal resolution of six hours (i.e., four observations provided at 00:00, 06:00,
- 320 12:00, and 18:00 UTC each day).
- 321 *ERA5-Land reanalysis dataset.* The European Centre for Medium-Range Weather
- 322 Forecasts (ECMWF) Re-Analysis v5-Land (ERA5-Land) dataset ⁵⁷ provides global-
- land gridded climate forcing data from 1981 to the near present, at hourly temporal
- resolution and $0.1^{\circ} \times 0.1^{\circ}$ spatial resolution. Various climate forcing variables of the
- hourly ERA5-Land dataset were used to calibrate the lake-specific FLake model,
- 326 including 2-m surface air temperature (SAT, in K), 2-m dew-point temperature (in K),
- 327 downward surface shortwave radiation (SWdown, in W/m²), downward surface long-
- 328 wave radiation (LWdown, W/m²), surface pressure (Pa), and surface 10-m u and v
- components of wind (m/s). ERA5-Land provides LSWT data based on grid cells,
- 330 which were also simulated using the FLake model; however, these simulations were
- performed by assuming invariant lake morphological (depth, morphology, fetch, etc.)
- and hydrothermal (heat flux from estuaries and bottom sediments) features within a
- relatively large grid (i.e., 0.1°). We compared the accuracies of the LSWT between
- ERA5-Land and our lake-specific simulations (see below). The ERA5-Land dataset
- can be accessed in GEE at <u>https://developers.google.com/earth-</u>
- 336 <u>engine/datasets/catalog/ECMWF_ERA5_LAND_HOURLY</u>.
- 337 *Global ocean surface temperature data.* We downloaded the annual anomalies of

- 338 global ocean surface temperature from 1981 to 2020 to compare with lake surface
- 339 warming (Fig. 1b). The data was provided by the NOAA National Centers for

340 Environmental Information and available at

- 341 <u>https://www.ncei.noaa.gov/cag/global/time-series/globe/ocean/ann/3/1981-2020</u>.
- 342 The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b) dataset. We
- downloaded future (i.e., 2021-2099) climate-forcing datasets to simulate the future
- response of lakes to climate change from ISIMIP2b (<u>https://www.isimip.org/</u>)²⁸. The
- 345 datasets include simulations from four bias-corrected climate models (i.e., IPSL-
- 346 CM5A-LR, GFDL ESM2M, MIROC5, and HadGEM2-ES) under three different
- 347 greenhouse gas emissions scenarios (RCP 2.6, low emissions; RCP 6.0, moderate-
- high emissions; RCP 8.5, high emissions), which are provided daily with a spatial
- resolution of $0.5^{\circ 28,58}$. The variables we used include air temperature at 2 m, wind
- speed at 10 m, surface solar, thermal radiation, and specific humidity.

351 Selection of studied lakes

We used the water occurrence provided by the GSWO dataset to delineate permanent 352 water surfaces within the lake boundaries defined by HydroLAKES, where only 353 pixels with the probability of water presence > 70% were considered permanent 354 water. We further determined the lake center as the point with the largest distance to 355 the shoreline of the permanent water within a lake (D). Note that, when multiple 356 permanent water polygons are available within one lake, we selected the lake center 357 with maximum D. To minimize the potential impacts of mixing pixels ⁵⁹, land-358 adjacent effects, and geometric errors 60 on the LSWT retrievals, we only selected 359 360 lakes with D larger than 3 pixels. For example, we excluded lakes with D < 300 m for Landsat 8 TIRS, as the spatial resolution of TIRS is 100 m. We further excluded lakes 361 362 with insufficient satellite-derived LSWTs (< 10 valid satellite observations over the 363 past four decades) or without climate-forcing data from ERA5-Land (i.e., lakes located near the coast). The final number of lakes selected is 92,245, with 62% 364 located at high latitudes (north of 60°N) and 36% located in the Arctic (north of 365 66.5°N). The combined area of these lakes is 2,116,773.2 km², which accounts for 366 72.3% of the global lake area. Specifically, the total areas of the studied lakes located 367 north of 60° and in the Arctic region are 437,201.18 km² and 140,763.9 km², 368 369 respectively; these areas represent 62% and 54% of the global lake areas at high 370 latitudes and Arctic lakes, respectively. Moreover, the latitudinal distributions of the selected lakes are similar to the patterns of all global lakes, in terms of the lake area 371 372 and lake number (Supplementary Fig. 8), indicating that the thermal dynamics of 373 global lakes can be well represented using our studied lakes.

374 Satellite retrieved LSWT dataset

Landsat-retrieved LSWT data from 1981-2020 were used to calibrate lake-specific

- 376 FLake models (see below). Based on extensive *in situ* data collected worldwide, we
- validated three widely used LSWT retrieval algorithms, including the generalized
- single-channel (GSC) algorithm ⁶¹⁻⁶³, the practical single-channel (PSC) algorithm

^{64,65}, and the statistical mono-window (SMW) algorithm ^{66,67}. We used the TCWV 379 380 from the NCEP/NCAR Reanalysis dataset to estimate the atmospheric contribution 381 when performing the satellite retrieval. The satellite-in situ match-ups used for the 382 validations were selected via the following criteria: (1) the sampling time difference 383 between *in situ* measurements and satellite overpasses was within 1 h; and (2) no fewer than 50% (that is, 5) of the pixels within the 3×3 -pixel window centered at the 384 385 in situ stations were valid, and the standard deviation was not higher than $0.5 \,^{\circ}\text{C}$ within the window. We considered the satellite LSWT retrieval invalid when (i) the 386 pixel was labeled as high-confidence cloud/cloud shadow or snow/ice or high aerosols 387 or radiometric saturation by the CFMask algorithm ⁶⁸, (ii) the LSWT retrieval was 388 below 0 °C, or (iii) masked as "land" by the GSW monthly water mask (with auxiliary 389 criteria of MNDWI < 0.05 for "no data"-labeled water mask, where MNDWI = 390 391 (Green - SWIR)/(Green + SWIR)). A total of 9,948 satellite-*in situ* match-ups were obtained, and the satellite LSWT retrievals were represented by the mean LSWTs of 392 393 the valid pixels within a 3×3 -pixel window centered at the *in situ* stations. Our 394 results showed that the SMW algorithm performed best (Supplementary Fig. 9) among the three LSWT retrieval algorithms, with high agreements between the 395 satellite and *in situ* measurements (slope = 0.98, MAE = 0.93 °C, R² = 0.99). 396 Comparisons of the time-series of satellite retrievals and continuous buoy 397 observations also revealed that the SMW-derived satellite LSWTs could accurately 398 399 capture the seasonal dynamics in water surface temperature (Supplementary Fig. 10). 400 Applying the SMW algorithm to global Landsat images over the past four decades, 401 we derived long-term LSWT datasets over global lakes, where the data represent the 402 surface temperature at the time of satellite overpasses (i.e., around 10:00 am local 403 time). For each Landsat observation over a lake, a 3×3 -pixel kernel around the 404 predefined lake center point was extracted, and the corresponding mean LSWT of the 405 valid pixels within this window was used to represent the LSWT for the lake. We excluded lakes with < 10 Landsat observations, and 91.3% of our finally examined 406 407 lakes (i.e., 92,245) have at least 100 LSWT satellite retrievals (Supplementary Fig. 11). Such datasets of satellite-derived LSWT "snapshots" allow us to calibrate lake-408 specific thermodynamic models, which can be used to produce hourly uninterrupted 409

410 LSWT simulations.

411 Simulations and validations of LSWTs and heat fluxes

To simulate hourly LSWT and surface heat fluxes, we adopted the one-dimensional 412 thermodynamic lake model FLake ^{26,27}. The FLake model parameterizes a two-layer 413 414 water vertical temperature profile, including a vertically homogeneous upper layer (i.e., a mixed layer at the surface) and a lower, stably-stratified layer (i.e., thermally 415 active layer above bottom sediments)⁶⁹. Additional layers are considered when the 416 lake is covered with ice and snow. FLake is capable of simulating temperature 417 profiles and the surface heat flux components in a lake, and the simulations can be 418 419 performed at hourly to annual scales. The model has been widely used in previous studies to accurately reproduce LSWTs ^{70,71}, lake mixing regimes ¹⁸, and ice cover 420

421 phenologies ^{18,71-73} at both regional and global scales.

422 The FLake model requires information on lake-specific characteristics and five 423 climate forcing variables, including SAT, wind speed, short- (solar) wave radiation, 424 long-wave radiation, and specific humidity (estimated directly using dew-point 425 temperature and surface pressure). The long-term climate variables were obtained 426 from the hourly gridded ERA5-Land product (1981-2020), and we extracted the data 427 from the grid cell located at the predetermined lake center. The lake-specific 428 parameters comprise fetch, latitude, lake depth, the light attenuation coefficient (K_d) , lake ice albedo (α), and the snow accumulation rate. The lake fetch was fixed as the 429 square root of the lake surface area (provided by the HydroLAKES dataset), and the 430 431 latitude corresponds to the location of the lake center. However, the other lake-432 specific parameters for global lakes are either not available or suffer from large 433 uncertainties. Likewise, the wind speed provided by the ERA5-Land dataset is often 434 highly uncertain at the lake surface, as they were based on assimilated data over land instead of lake surfaces ⁷¹. To address this issue, we tuned the lake parameters and 435 wind speed using a total of 2,880 combinations for each lake following a similar 436 method to ref.⁷¹. We find the optimal set of parameters associated with the minimum 437 median absolute errors (MAE, Supplementary Fig. 12) between the Landsat-retrieved 438 LSWTs and the FLake simulations (i.e., mixed-layer temperature) at the Landsat 439 overpassing time. The selection of trials for the 2,880 combinations was based on 440 previous studies ^{27,71,74}. For example, the initial lake depth was obtained from the 441 HydroLAKES dataset, which was based on a combination of observations and 442 interpolated DEM ². We selected a set of K_d values that represent global ocean waters 443 with varying transparency as referred to ref.⁷¹, and we also provided three additional 444 higher values (up to 3 m⁻¹, a default value widely used for inland lake simulations 445 ^{27,74}) considering the relatively higher turbidity of many lakes. We set four 446 combinations of snow and ice albedo, as recommended by ref.⁷¹. Further information 447 on the 2,880 combinations is given in Supplementary Table 3. Note that we also used 448 449 a perpetual-year solution to determine the initialized prognostic variables (e.g., mixed-layer depth, mixed-layer temperature, mean temperature of the water column) 450 for the FLake model, which is achieved by repeating the forcing data from a 451 452 representative period (i.e., 1981-1985) and running the FLake model until the simulated annual cycle is stabilized ¹⁸. We examined the calibration performance of 453 the lake-specific FLake models (Supplementary Fig. 12), which showed that the 454 455 simulated LSWTs agreed well with the satellite retrievals, with a global MAE of 456 1.2 °C and a median ratio of \sim 1 (a metric of assessing the extent of over- or underestimation by comparing the model simulations to Landsat observations). The MAE 457 458 for deep lakes (water depth > 50 m) was slightly larger than shallower lakes, possibly due to the limitations of the FLake model (2-layer representation of the lake)⁶⁹; while 459 only a small number of lakes have such a depth ($\sim 0.7\%$), and our further validation 460 461 using in situ observations showed high accuracy levels of the globally simulated 462 LSWTs. The satisfactory calibration performance over different types (large/small, deep/shallow, cold/temperate) of lakes could also be revealed by the consistent time-463 series between satellite retrievals and FLake simulations (Supplementary Fig. 13). 464

465 Using the optimized lake-specific FLake models, we simulated the historical (1981-

- 466 2020) and future (2021-2099) LSWTs and heat fluxes (i.e., net radiation, latent heat
- 467 flux, sensible heat flux, and heat storage change (ΔG)) for lakes worldwide. The
- historical simulations were on an hourly basis, which was based on the climate
- 469 forcing data from the ERA5-Land dataset. In contrast, the future simulations were
- 470 performed on a daily timescale, using the climate data from four bias-corrected
- 471 climate models (i.e., IPSL-CM5A-LR, GFDL ESM2M, MIROC5, and HadGEM2-
- ES) under three different greenhouse gas emissions scenarios (RCP 2.6, RCP 6.0, and
- 473 RCP 8.5). Under each scenario, we used FLake to perform simulations for each of the
- four climate models, and the associated mean and standard deviation were estimated
- 475 (Fig. 4, Extended Data Fig. 9).

We further validated the FLake-simulated LSWT, heat flux, and evaporation rate 476 477 simulations using extensive independent in situ measurements (see Supplementary 478 Tables 1&2). LSWTs were validated at three different temporal scales (hourly, daily, 479 seasonal, and annual). We compared in situ LSWT records across 29 lakes and 480 concurrently (time difference < 1 h) simulated LSWT by FLake, which showed good 481 agreement at hourly, daily, seasonal, and annual scales (Extended Data Fig. 2a-d). 482 Consistent temporal changes between FLake simulated LSWTs and independent in 483 situ LSWTs over various types of lakes in Supplementary Fig. 14 clearly demonstrated the validity of our simulations. Comparisons with global or regional 484 LSWT products are summarized in Supplementary Table 4. Satisfactory results were 485 486 also obtained for the net radiation flux, latent heat flux/evaporation rate, sensible heat flux, and heat storage change (Extended Data Fig. 3), which are comparable to or 487 better than other products ^{33,75,76}. Consistent seasonal dynamics between FLake 488 489 simulations and *in situ* evaporation rate measurements revealed in Supplementary Fig. 490 15 could further support the reliability of our simulated evaporation rate data. We also 491 compared the evaporation rate against annual mean data from existing literature 492 (Supplementary Table 5), which also demonstrated good agreements over different 493 lakes. Moreover, the high performance of our lake-specific models can be further verified through their ability to reproduce the lake ice phenologies measured in the 494 495 GLRIPD dataset (Supplementary Fig. 1). The simulation-based ice phenologies 496 (freeze-up day, break-up day, and duration) were calculated by time-series daily averaged LSWTs (see below), as described in previous studies ^{19,68,75}. 497

498 We also compared the accuracy levels of the FLake simulated LSWT with the gridded 499 LSWT product provided by ERA5-Land; ERA5-Land simulations are based on grid 500 cells $(0.1^{\circ} \times 0.1^{\circ})^{76}$, while our optimized simulations were specifically performed for 501 individual lakes. Our simulations demonstrated substantially reduced uncertainties 502 (MAE decreased by ~1 °C or ~50%) compared to the ERA5-Land LSWT (Extended 503 Data Fig. 4). Such marked improvements highlight the importance of considering 504 lake-specific characteristics with satellite observations as an ideal boundary condition

- 505 in simulating lake thermodynamics.
- 506 We acknowledge that temporal variations in water level can influence lake
- 507 thermodynamics, including the distribution of incoming solar radiation, heat storage

in deeper layers, and temperature profiles within the water column ^{22,77}. However, 508 509 incorporating spatial variations in lake depth would introduce further complexity and 510 necessitate a three-dimensional model, which goes beyond the scope of our study. 511 Additionally, obtaining long-term time-series data on lake water levels at a global 512 scale poses a separate challenge. Furthermore, it is important to note that the FLake model we employed in our study does not include water balance processes ⁷⁴, which 513 prevents the incorporation of water levels when simulating lake thermal dynamics. 514 Despite these limitations, our results are based on the calibration of the lake-specific 515 516 FLake model using long-term remote sensing observations. This calibration helps to 517 compensate for uncertainties in the simulation of LSWT stemming from various 518 sources (including those associated with lake level dynamics), as demonstrated by the 519 high accuracies of the simulated LSWT and other thermal variables (see above). 520 It is also worth noting that our optimization process aimed to derive a lake-specific 521 FLake model by optimizing five parameters (i.e., wind speed, lake depth, α , K_d , and the snow accumulation rate). However, these optimized parameters may not 522 necessarily represent the true values for a specific lake. The primary objective of our 523 optimization was to find a set of fixed parameters among the 2,880 combinations that 524 525 minimize the differences between the simulated LSWTs by FLake and those retrieved by Landsat. However, in reality, some parameters may exhibit significant temporal 526 527 variations. For instance, K_d in lakes are influenced by the concentrations of chlorophyll and suspended sediments in the water column ⁷⁸, which can undergo 528 substantial changes over short periods (daily to weekly) due to highly dynamic 529 hydrological and biogeochemical processes within the lake ^{51,79}. Indeed, to examine 530 the potential impacts of temporal variations in lake parameters on the FLake 531 532 simulations, we conducted comprehensive validation analyses to assess the 533 performance of our optimized parameter set. The results demonstrated that the 534 optimized FLake model not only achieved high accuracy in simulating LSWTs but also effectively captured lake ice phenology, heat flux, and evaporation rate. 535 536 Importantly, the model exhibited good performance across different temporal scales, indicating its robustness and ability to capture the dynamics of these variables under 537 varying conditions. These findings further reinforce the reliability and versatility of 538 539 the FLake model with the optimized parameter set, making it a valuable tool for studying lake thermal dynamics. 540

541 Examination of long-term changes

542 Our analysis of long-term changes in LSWT and heat fluxes only focused on ice-free 543 periods. In this study, we defined the ice-free duration as the period in which the daily mean LSWT is > 1 °C, following the same method as previous studies ^{18,71,80}. The 544 545 freeze-up day was determined as the date when the temperature started to drop below 1 °C in the autumn/winter season, while the break-up day was identified as the date 546 when the temperature exceeded 1 °C in the following spring/summer season. The ice-547 548 duration period was calculated as the time between these two dates. Our analysis 549 revealed that our lake-specific FLake model effectively reproduces lake ice

550 phenologies, as demonstrated through comparisons with global *in situ* data from the 551 GLRIPD dataset. The slopes between the *in situ* observed and FLake-simulated 552 freeze-up date, break-up date, and ice duration were found to be 0.90, 1.00, and 1.07, 553 respectively. Furthermore, the MAE values for these simulations were 14.0, 6.0, and 554 13.0 days, respectively (Supplementary Fig. 1). It is important to note that the data 555 from different locations within the GLRIPD dataset may vary in temporal resolution 556 due to its compilation from several individual collections, including records contributed by both citizens and scientists. In general, these matrices indicate 557 comparable levels of accuracy in capturing lake ice phenologies as previous studies 558 ^{25,81}. We further estimated the changes in ice duration for individual lakes by 559 multiplying the long-term linear regression slope of ice duration by the number of 560 examined years, and used them to explore the potential impacts of ice loss on lake 561 562 warming (Extended Data Fig. 5c).

563 For each lake, the above three ice phenologies were computed for multiple years, and 564 the minimum ice-free period (that is, the intersection of the non-frozen period between 1981 and 2020) was considered as our focal time period (i.e., FLake 565 simulations were analyzed only within this period). The minimum ice-free period 566 represents the time span from the latest break-up day to the earliest freeze-up day 567 during the 40-year period. The average duration of the minimum ice-free period for 568 569 the lakes studied was 187 ± 125 days. For most lakes in the southern hemisphere and the low- and mid-latitudes of the northern hemisphere, the ice-free period extends 570 571 throughout all four seasons of the year (Supplementary Fig. 2). As latitude increases, 572 the minimum ice-free period becomes shorter; for Arctic lakes, 100% of the lakes are covered with ice during winter, and 95.4% and 96.6% of the lakes remain ice-covered 573 574 during spring and autumn, respectively.

575 We calculated the monthly, seasonal, and annual mean LSWT and heat fluxes based 576 on daily simulations within the minimum ice-free period for all examined lakes. To determine the trends of LSWT and heat fluxes, we first estimated their monthly 577 578 anomalies as the differences from the long-term mean values during 1981-2020, and 579 then estimated the annual mean anomalies across the examined period (1981-2099). We used the linear slope through the annual mean anomalies within a time period (i.e., 580 1981-2020 or 2021-2099) to represent the trend within the period. We also performed 581 582 the same trend analysis for different seasons, and our four seasons were defined as winter (Months 1-3), spring (4-6), summer (7-9), and autumn (10-12) in the Northern 583 Hemisphere, and summer (1-3), autumn (4-6), winter (7-9), and spring (10-12) in the 584 585 Southern Hemisphere, following the same practice as a previous research ⁵.

586 We further integrated the global time-series data into $1^{\circ} \times 1^{\circ}$ grid cells (see Fig. 1a,

587 Fig. 3) and performed the above slope calculations for each grid cell. We adopted a

lake area weighted method to estimate the time-series LSWT and heat fluxes within a
grid cell (S_{gird}), which can be expressed as

590
$$S_{grid} = \sum_{i=1}^{m} S_{lake,i} A_{lake,i} / \sum_{i=1}^{m} A_{lake,i}$$
(1)

591 where $S_{lake,i}$ and $A_{lake,i}$ are the time-series anomalies and lake surface area for the ith

lake within this grid, respectively, and m is the number of our examined lakes within this grid. Then, the mean trends over global or regional (i.e., Arctic or non-Arctic) scales (S_g) were also estimated using a similar area-weighted scheme, which can be expressed as:

596
$$S_g = \sum_{j=1}^n S_{grid,j} A_{grid,j} / \sum_{j=1}^n A_{grid,j} \quad (2)$$

where S_{grid,j} and A_{grid,j} are the time-series anomalies and grid area of the jth grid cell 597 within the examined region (i.e., globe, Arctic, or non-Arctic regions), respectively, 598 and *n* is the number of grid cells within the target region. The daytime/nighttime lake 599 warming trends were calculated using the same method. Daytime and nighttime were 600 defined as the time periods from local 6 am to 6 pm and from local 6 pm to 6 am of 601 602 the next day, respectively. LSWT trends were also compared with the SATs above the 603 lakes (Fig. 1b). We adopted the same method as LSWT to calculate long-term SAT 604 changes, and only grid cells that cover the studied lakes were included.

605 We performed the following sensitivity analysis to quantify how could the uncertainty 606 of the daily LSWT simulations propagated into the long-term trends. We first generated random noises with a distribution matching the uncertainty of the daily FLake 607 simulations (median absolute error or MAE = $1.16 \,^{\circ}$ C) (see Supplementary Fig. 16a). 608 609 These noises were then added to the daily simulated LSWT time series dataset for each lake. Results show that trends between the noise-added and original data are almost the 610 611 same for all lakes (Supplementary Fig. 16b). We further calculated the standard 612 deviation of these differences across all lakes as the uncertainty propagated by the FLake simulation, and revealed a small uncertainty value ($0.02 \, ^{\circ}$ C decade⁻¹) relative to 613 614 the global LSWT trend (0.24 °C decade⁻¹). The uncertainty values were also small when 615 calculated separately for Arctic (0.03 °C decade⁻¹) and non-Arctic lakes (0.02 °C 616 decade⁻¹). Furthermore, considering the limited data availability of Landsat in certain seasons due to cloud cover, we performed optimization of the FLake models by 617 618 excluding data from one of the four seasons. Our results revealed consistent MAE and trends between the models trained on three seasons and those trained on all four seasons. 619 As such, the impact of reduced data availability in certain seasons on the accuracy of 620 621 the FLake model is limited.

622 Attribution of historical lake warming

623 We quantified the contributions of five individual climate forcing parameters (SAT,

wind speed, downward short- and long-wave radiation, and specific humidity) to the

historical LSWT trend from 1981 to 2020. The dominant drivers could be determined

as the variables with the maximum contributions. In practice, we designed six groups

of simulations, with one reference simulation (S1) where all climate parameters

changed from 1981 to 2020 (i.e., the same as the above historical simulations), and

629 five control simulations (S2-S6) where one parameter kept the long-term trend and

others were detrended by repeating the data in the first year (i.e., 1981) across the four

decades. Such a method was similar to those adopted for regional studies 36,40,82 , and

the detailed parameterizations for the six simulations are listed in Supplementary

- Table 6. In theory, the LSWT trends from the control simulations are the contributions
- of the corresponding changed climate parameter to the long-term trend. Indeed, our
- results showed that the summarized trend (0.244 $^{\circ}$ C decade⁻¹) from the five control
- simulations was almost identical to the reference simulation (0.236 °C decade⁻¹) (Fig.
- 637 2), further indicating the validity of our attribution analysis.

638 Impact of lake warming on energy budget

The changes in climate-forcing variables influence various heat exchange processes at
the lake-air interface. These processes encompass the absorption of incoming solar
radiation (SWdown) and long-wave atmospheric radiation (LWdown), the reflection
of solar radiation (SWup), the emission of long-wave lake-surface radiation (LWup),
and the exchange of evaporative latent heat and conductive sensible heat ⁸³. These

644 processes collectively determine the net radiation (Rn, Eq. (3)), which is a

fundamental component in the lake surface energy budget 4,84 . The net radiation can

be utilized for two heat loss processes: latent heat flux (LE), which serves as the

647 primary energy source for evaporation and is proportional to the evaporation rate ⁸⁵;

- and sensible heat flux (H). Additionally, the net radiation also contributes to heat
- transfer to deeper layers through heat storage change (ΔG , see Eq. (4)).

$$Rn = SWdown + LWdown - SWup - LWup (3)$$

$$Rn = LE + H + \Delta G \qquad (4)$$

652 We investigated the potential role of increasing evaporation rate on the different

- warming rates between LSWT and SAT using a climate elasticity model ⁸⁶. This
- model has been extensively employed to quantify the responses of diverse parameters
 to climate change ⁸⁷⁻⁸⁹, which can be expressed as

$$e = (dLSWT - dSAT)/dLE$$
(5)

where the elasticity (e) represents the difference of changes in the lake and air

temperature (dLSWT–dSAT) in response to the changes in latent heat flux (dLE).

We utilized the four-decade time series data from 1981 to 2020, focusing on permanently ice-free lakes, to calculate changes in two consecutive years in the

respective variables (i.e., dLSWT, dSAT, dLE) for the elasticity calculation. The

selection of permanently ice-free lakes is because the energy fluxes of frozen lakes

663 could be modulated substantially by the changes in ice cover over a long-term period

- ³³, complicating the response of the latent heat loss on the different warming rates
- between lakes and air temperatures. The elasticity (e) was calculated as the linear
- slope of the scatter plot that includes 39 pairs of matched dLSWT–dSAT and dLE

667 (Extended Data Fig. 8). We found significant negative correlations between the long-

term dLSWT – dSAT and dLE ($R^2 = 0.58$, P < 0.05), indicating the substantial

669 impacts of evaporation rate increase on the slower rates of LSWT than SAT.

670 Analyzing the impacts of lake warming on evaporation

- To examine the potential historical and future impacts of lake warming on evaporation,
- 672 we quantified changes in evaporation rate based on the simulated latent heat fluxes
- 673 (Extended Data Fig. 10). We compared our estimated evaporation rate to that of Wang
- et al. ³³, and the latter includes datasets from both ice-free and ice-covered seasons. The
- 675 comparisons were conducted using temporally consistent mean annual values for two
- periods: the past (2006-2015) and the future (2090-2099, representing the end of the
- 21st century, following a similar practice as previous studies ^{17,18,33}). The comparisons
- were performed at both global and regional scales, including tropical, temperate, arid, cold, and polar regions. Global and regional changes were calculated by integrating the
- 680 differences using a similar lake area-weighted method as in Eq. (2) 90 .
- 681 **Data Availability:** The developed GLAST dataset can be accessed through
- 682 https://zenodo.org/record/8322038.
- 683 Code Availability: The source code for the FLake model is opening accessible at
 684 http://www.flake.igb-berlin.de/.
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- 696 L.F.: conceptualization, methodology, funding acquisition, supervision, and writing.
- 697 X.W. and X.P.: data processing. W.X. and R.I.W. participated in interpreting the
- 698 results and refining the manuscript.
- 699 **Competing Interests:** The authors declare no competing interests.
- 700 Figure Captions:
- 701 Fig. 1 | Global patterns of lake warming from 1981 to 2020. (a) Global trends in lake surface water temperature (LSWT) from 1981 to 2020. The time-series data used to 702 703 calculate the LSWT trend are aggregated into 1°×1° grid cells, and a lake area weighted 704 method was adopted to estimate the LSWT time series for each grid (see Methods). 705 Grey indicates regions without examined lakes. The bar charts within the panel show 706 the trends for LSWT and surface air temperature (SAT) for global (G), Arctic (A), and 707 non-Arctic (NA) lakes. (b) Comparison of the long-term anomalies (relative to 1981-708 2020 mean) for global LSWT, ocean surface temperature, and SAT. Their trends over 709 the past decades are annotated. (c) Latitudinal profiles of the trends for LSWT and SAT. 710
- 711 Fig. 2 | Attribution of global lake warming over the past four decades. Latitudinal

712 profiles (curves) and globally averaged (bars) contributions to lake warming from five 713 different climate forcing variables, including surface air temperature (SAT), downward 714 surface long-wave radiation (LWdown), specific humidity (SH), downward surface 715 shortwave radiation (SWdown), and surface wind speed (U). The numbers outside and within (if applicable) the parentheses are the absolute (°C decade⁻¹) and relative 716 717 contributions (%) to global lake warming for each variable. The grey bar (labeled as 718 "sum") and grey curve indicate the sum of individual contributions of each variable, and the black bar (labeled as "reference") and black curve show the results of the 719 reference simulation (see Methods). The reference simulation represents the FLake 720 simulation with the trends of all forcing variables retained. The contributions of five 721 722 variables were estimated through control simulations where the target variable kept the 723 long-term trend and others were detrended.

724

Fig. 3 | Global patterns of lake surface heat fluxes and their trends. Left panels: long-term trends from 1981 to 2020 (in W/m² decade⁻¹). Right panels: climatological annual mean values (in W/m²). (**a**, **b**) Rn: net radiation flux, (**c**, **d**) LE: latent heat flux, (**e**, **f**) H: sensible heat flux, and (**g**, **h**) Δ G: heat storage change. The bar chart within each panel demonstrates the average values for global (G), Arctic (A), and non-Arctic (NA) lakes.

731

732 Fig. 4 | Long-term changes in LSWT, SAT, and heat fluxes from 1981 to 2099. (a) LSWT, (b) SAT, (c) Net radiation flux (Rn), (d) Latent heat flux (LE), (e) Sensible heat 733 flux (H), and (f) Heat storage change (ΔG). The data are presented as the anomalies 734 735 relative to 1981-2020 mean, with the results for global, Arctic, and non-Arctic lakes 736 shown separately. Future (2021-2099) conditions were simulated under a high 737 emissions scenario (RCP 6.0). Other RCP scenarios are shown in Extended Data Fig. 9. The linear slopes (units: °C decade⁻¹ in **a-b**, W/m^2 decade⁻¹ in **c-f**) for historical (1981-738 739 2020) and future (2021-2099) periods are annotated (the font colors correspond to the respective curves), and statistically significant trends are indicated by "*". The shadings 740 associated with the future data represent the standard deviations across the four climate 741 742 model projections.

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