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Global assessment and hotspots of lake drought

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Many lakes have exhibited substantial variability in recent years, making "lake drought" a growing concern. However, there is no established framework for identifying and studying lake droughts. Here, we propose a reliable definition for it and provide a global assessment of over 160,000 lakes (≥1 km^2) using monthly area data from 1985 to 2018. Our findings show that 15.7% of lakes have experienced statistically significant increasing trends in drought frequency ($p < 0.05$), with hotspots in the Southern United States at 52.7% and Southeast Australia at 70.4%. Furthermore, we identify two severe lake drought events in the Southern United States (2012–2014) and Southeast Australia (2007–2010), posing dramatic threats to water supplies, biodiversity, and ecological health. Rising trends in lake drought are driven by increasing temperature, vapor pressure deficit, and factors associated with the lake water cycle, such as precipitation deficit, increased evaporation, and excessive water withdrawal.

Lakes are crucial components of terrestrial water systems and serve as essential natural resources[1], providing critical functions and services for both ecosystems and human communities[2,3]. These functions are primarily governed by the volume of water they contain[4]. However, under the pressures of global climate change and intensified human activities, more than half the largest lakes worldwide have experienced considerable declines in water storage over the past three decades[4]. This trend has far-reaching consequences, with an estimated 25% of the global population affected, garnering substantial international attention[5].

In addition to long-term reductions in lake storage, short-term deficiencies in lake water availability can also severely influence the ecosystems, society, and the economy. Here, we define the periods when lake water resources fall below a critical threshold, making them unable to support normal ecological and societal functions, as "lake drought". Drought is one of the costliest natural hazards[6]. Under climate change, droughts are projected to become more frequent and impactful[7]. To highlight the deficiency of various water components, droughts have been categorized into different types, such as meteorological drought[8], hydrological drought[9], agricultural drought[10], snow drought[11], groundwater drought[12], and anthropogenic drought[13]. These drought categories have been addressed and discussed in many studies; however, droughts in lakes remain underexplored due to the lack of a universal definition and global assessment.

Lake droughts can result in serious water shortages[14], threaten biodiversity[15], create environmental challenges[16], and even provoke conflicts[17]. The damages caused by lake droughts have been reported recently and frequently; for example, a severe drought in Lake Titicaca (South America's largest lake) in 2023 disrupted regional fishing, agriculture, and tourism, thus affecting more than three million local people who rely on this lake for their livelihoods[18]. Similarly, Lake Mead, the largest reservoir in the United States that supplies drinking water for about 25 million people, faced extreme drought conditions in 2022, resulting in serious water shortages and leaving tens of thousands of farmlands unused[19]. Despite the profound implications of lake droughts, very few studies have focused on this type of extreme event[20]. There is no widely accepted definition and assessment framework for lake droughts. Moreover, analyzes of trends and causes of extreme lake droughts worldwide over recent decades are still missing. Therefore, it is highly imperative to reveal the characteristics of global lake droughts under climate change and discuss the potential drivers of lake droughts.

This study first aims to establish a reliable definition of lake droughts and validate it through sensitivity analysis. Based on this definition, we use a remotely sensed global monthly lake area dataset from 1985 to 2018 to assess lake droughts worldwide. We select the trends in drought frequency to represent long-term changes in lake droughts for each lake. Additionally, focusing on two crucial hotspot regions, we explore the impacts of lake droughts and investigate potential drivers of lake droughts associated with the water cycle and relevant human activities. By providing a foundational definition and a global assessment of lake droughts, this study contributes to a deeper comprehension of this emerging extreme event. Furthermore, it underscores the impacts and causes of lake droughts, attracting more attention to future research and providing important implications for policymakers to manage lake resources efficiently.

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Results

The trends in the frequency of global lake droughts

Similar to other types of droughts[14,21,22], lake droughts signify a deficiency in lake water resources. Due to the limitations of accurate global lake storage data, we used lake area as a proxy for assessing lake storage[23,24] (see "Methods" and "Discussion"). Here, lake drought is defined as periods when the lake area falls below the seasonal normal level. We selected a total number of 162,413 global lakes (≥1 km^2) from a global monthly lake area dataset[25] to investigate lake droughts. We identified lake drought periods as months in which the change ratio of lake area fell below the 20th percentile threshold (see Fig. 1a and "Methods"). The change ratio refers to the monthly area anomaly relative to the climatological mean lake area (1985–2018), thereby avoiding the misclassification of droughts in lake-stable months (see "Discussion" and "Methods"). After comparing different percentile thresholds, we decided on the 20th percentile threshold here, referring to the literature[26,27] (see "Discussion").

The frequency of lake droughts was quantified by the number of months experiencing drought conditions. We evaluated the trends in the frequency of lake droughts using the non-parametric Mann–Kendall (M–K) tests (see Fig. 1a). After testing various window sizes, we applied a 3-year moving window with 1-year intervals (see "Methods" and "Discussion"). Our results reveal that ~15.7% of global lakes show significant upward trends in drought frequency during 1985–2018 ($p < 0.05$; Fig. 1b). Regions with higher percentages of lakes showing increasing drought trends include West Asia (47.1%), South Australia/ New Zeeland (46.6%), West and East Africa (41.2% and 35%), East and Central Asia (35.3% and 31.8%), Central and North Europe (30.3% and 26.1%), and Southeastern South America (31.7%) (see Fig. 1c, S1, and S2, and Table S1). Notably, several large lakes, such as Lake Urmia, Aral Sea, Lake Poyang, Great Salt Lake, and Lake Michigan–Huron, show pronounced increases in drought frequency. Conversely, 37.9% of global lakes exhibit significant downward trends in drought frequency ($p < 0.05$; Fig. 1b). These lakes are primarily located in high-latitude regions, such as Alaska (60.2%), West North America (55.7%), Canada, Greenland, and Iceland (48.5%), as well as high-altitude regions like the Tibetan Plateau (58.6%) (see Fig. 1c and S1, S2, and Table S1). In these areas, lake expansion is often driven by glaciers and snowmelt due to global warming[28–30].

To further characterize global lake droughts, we categorized lakes by size, type, and climate regime. Our findings indicate that larger lakes are more likely to show significant upward trends in drought frequency than smaller lakes (Figs. S3 and S4). Specifically, 36 out of 164 (22%) total super-large lakes (>1000 km^2) display notable increases ($p < 0.05$) in drought frequency, which is about 1.4 times higher than small lakes (1–10 km^2, 15.7%) and medium lakes (10–100 km^2, 15.8%). Figs. S5 and S6 compare natural lakes and reservoirs identified based on the HydroLAKES database[23], indicating that man-made reservoirs (23.6%) built for water management have an 8.1% higher incidence of significant upward trends in drought frequency than natural lakes (15.5%). Interestingly, there are no significant differences in drought frequency trends across climatic regions, with 18.6% of lakes in arid areas and 18.4% in humid areas showing significant increases (Fig. S7). Although less than 20% of lakes have shown significant upward trends in drought frequency over the past decades, this remains a critical issue under climate change and intensified anthropogenic activities, given its profound impacts on human communities and ecosystems.

Lake droughts in hotspot regions and their impacts

To examine the impacts of lake droughts, we selected two regions as illustrative cases: the Southern United States (SUS; 31.7–36° N, 95–102° W; parts of Texas and Oklahoma; Fig. S8) and Southeast Australia (SEA; 32–39° S, 139–147° E; parts of South Australia, New South Wales, and Victoria; Fig. S8). These hotspots were chosen mainly due to the higher proportion of lakes exhibiting significant increases in drought frequency. Furthermore, both regions are confronted with elevated water demands due to population growth (particularly in SUS) and extensive cropland areas, with over 15% in SUS and over 20% in SEA. According to water scarcity hotspot maps, these regions have experienced water shortages and are projected to continue facing them[31]. Furthermore, the predominant types of lakes in the two regions exhibit obvious differences, indicating different impacts on human societies and ecological environments. Most lakes (62.4%) in SUS are

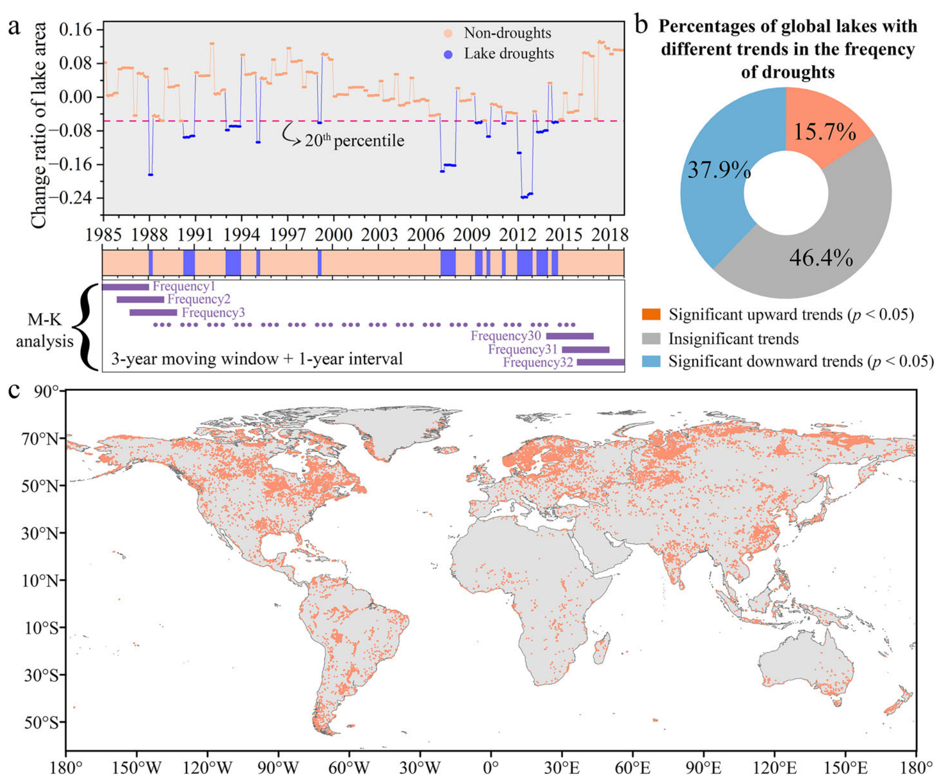

Fig. 1 | Definition and trends in the frequency of lake droughts. **a** Identification of lake droughts and calculation of trends in the frequency of lake droughts. The change ratio refers to the lake area anomaly to the climatological mean lake area. The red dashed line indicates the 20th percentile threshold. The blue color indicates lake droughts, while the light orange color indicates normal conditions. The purple rectangles in the lower subplot indicate the frequency of lake droughts using a 3-year moving window with a 1-year interval. **b** Percentages of global lakes with different trends in the frequency of lake droughts, including significant upward trends ($p < 0.05$), significant downward trends ($p < 0.05$), and insignificant trends. **c** Spatial distribution of global lakes with significant upward trends in the frequency of droughts ($p < 0.05$). Only lakes with significant upward trends in drought frequency are shown here. The distribution of lakes with insignificant trends and significant downward trends is shown in Fig. S1.

artificial reservoirs, whereas a higher percentage of lakes (75.3%) in SEA are natural. Beyond SUS and SEA, our analysis encompassed lake droughts in four additional hotspot regions globally: Eastern Europe & Western Asia (EEWA), Western Africa (WAFR), Eastern South America (ESAM), and Central China (CC). The results from these regions align closely with those from SUS and SEA (see Fig. S9).

Our findings reveal that nearly 52.7% of lakes in SUS and 70.4% in SEA exhibit notable increases in drought frequency (Fig. 2a). Using the Kolmogorov–Smirnov (K–S) test, we found statistically significant differences ($p < 0.01$) in lake drought frequencies (in months) when contrasting the first half of the study period (1985–2001) with the second half (2002–2018) in both regions (Fig. 2b, c). Notably, lake drought frequencies are considerably higher in the second half period, especially in SEA (over 90% of the lakes), highlighting an escalating risk in recent years. We also analyzed trends in the proportion of lake droughts, defined as the ratio of lakes undergoing drought to the total number of lakes, which reflects the regional magnitude of lake droughts. Results show increasing trends ($p < 0.01$) in both SUS (since 1995) and SEA (since 1997), further exacerbating water stress in these hotspot areas (Fig. 2d, e). Severe drought events have occurred in both regions over the past two decades. Specifically, over 50% of lakes in SUS were subjected to extreme drought conditions in 2006 and from 2012 to 2014, while SEA similarly endured such conditions from 2007 to 2010. These events greatly impacted local communities due to critically low lake water availability.

We also observed that severe lake droughts frequently occur after megadroughts in both regions (Fig. S10). A pertinent example is SUS, which was highly affected by the exceptional 2010–2013 Southern United States and Mexico drought. Since August 2011, this region has faced extensive lake droughts. High water demand during drought accelerates lake water extraction, resulting in a more pronounced reduction in lake levels[32]. SUS contains more reservoirs (116 out of 186 total lakes) that are essential water supply sources. However, in recent decades, most reservoirs in this region have reached record low levels[33], failing to meet local water demands and placing substantial strain on available water resources. This situation has had devastating repercussions for agricultural, industrial, and domestic sectors. The megadrought in 2011 was revealed to cause an estimated loss of over 7 billion US dollars in crops and livestock in Texas, linked to lake droughts[34]. Oklahoma reported ~2 billion US dollars in losses from the 2011 to 2012 drought[35].

During 2007–2010, SEA experienced intense lake droughts that aligned with the Millennium drought, often referred to as the 'Big Dry' of the 2000s. When the River Murray, a major water source, dried up, over 70% of lakes in the region also experienced drought conditions, severely threatening water availability for agriculture and domestic use[36]. Lakes can also provide vital ecosystem services and maintain biodiversity; therefore, the sharp drop in lake levels poses critical ecological and environmental issues[37–39]. Notable biodiversity loss (e.g., aquatic flora and fauna) was revealed during the Millennium Drought[40], including obvious declines in fish growth and productivity in lakes such as Lake Mokoan and Lake Eppalock due to habitat loss and nutrient deficits caused by lake droughts[41]. Furthermore, extremely low levels of lakes are also likely to lead to environmental pollution. Given the exposure of lake beds (rich in iron sulfides) during lake droughts[42], the salinity level in Lake Alexandrina, SEA, increased ~7 times during 2006–2009 due to the release of metals and sulfuric acid, posing severe threats to the local ecology and environment[43]. Thus, these findings underscore the urgent need to understand and address the underlying causes of lake droughts, particularly in regions facing increasing water demands and shortages.

Attribution of lake droughts and lake water cycle

Lakes are critical indicators of both climate change and human activities, as their changes are closely linked to climatic variables[44–47] and water withdrawal[48–50]. To explore the climatic drivers of lake droughts, we assessed annual anomalies of the proportion of lake droughts, total precipitation (P), mean temperature (T), and mean vapor pressure deficit (VPD) in two hotspot regions (SUS and SEA). Our results reveal that increased lake

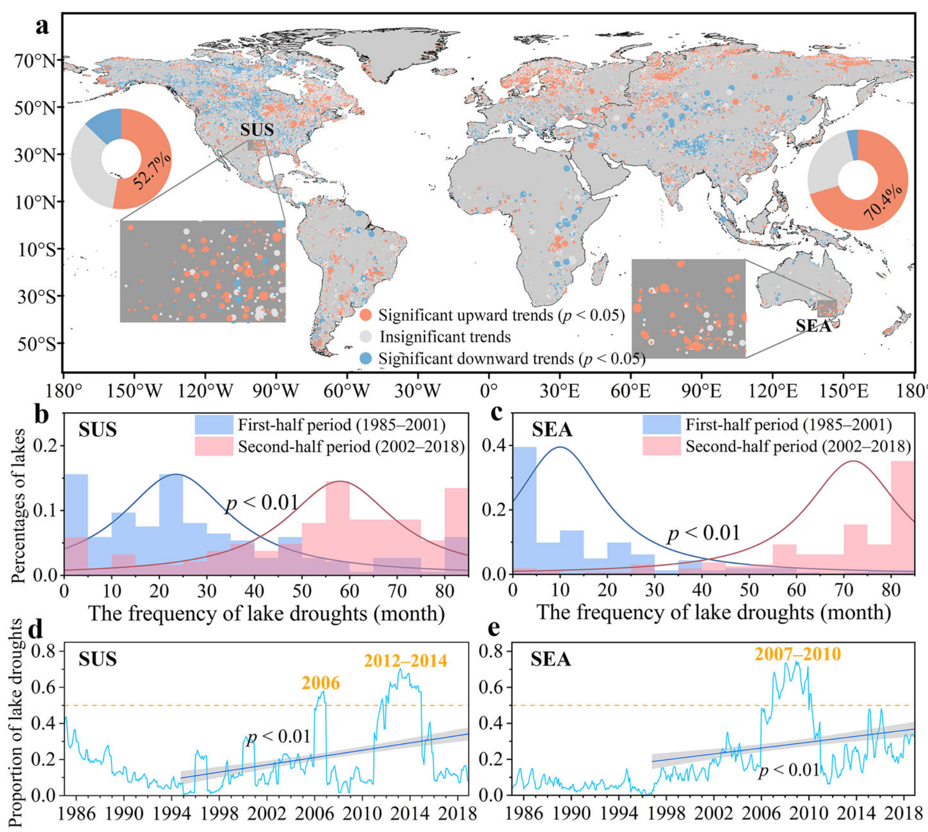

Fig. 2 | Characteristics of lake droughts in SUS and SEA during 1985–2018. a Global map of trends in the frequency of lake droughts, including significant upward trends (in orange), significant downward trends (in blue), and insignificant trends (in gray). Two hotspot regions are highlighted and zoomed in on the map. The pie charts indicate the percentages of lakes with different trends in the frequency of lake droughts in SUS and SEA, respectively. **b**, **c** Distribution of lakes with different frequencies of lake droughts (in months) during the first half (1985–2001) and the second half period (2002–2018) in SUS and SEA, respectively. The statistical significance levels (p-values) of the differences in these two distributions between the two time periods are provided. **d**, **e** Monthly variations in the proportion of lakes experiencing drought conditions. The trend lines with shaded 95% confidence regions are highlighted in SUS (1995–2018) and SEA (1997–2018). The significance levels (p-values) are also provided. Periods with a high proportion of lake droughts are marked in orange.

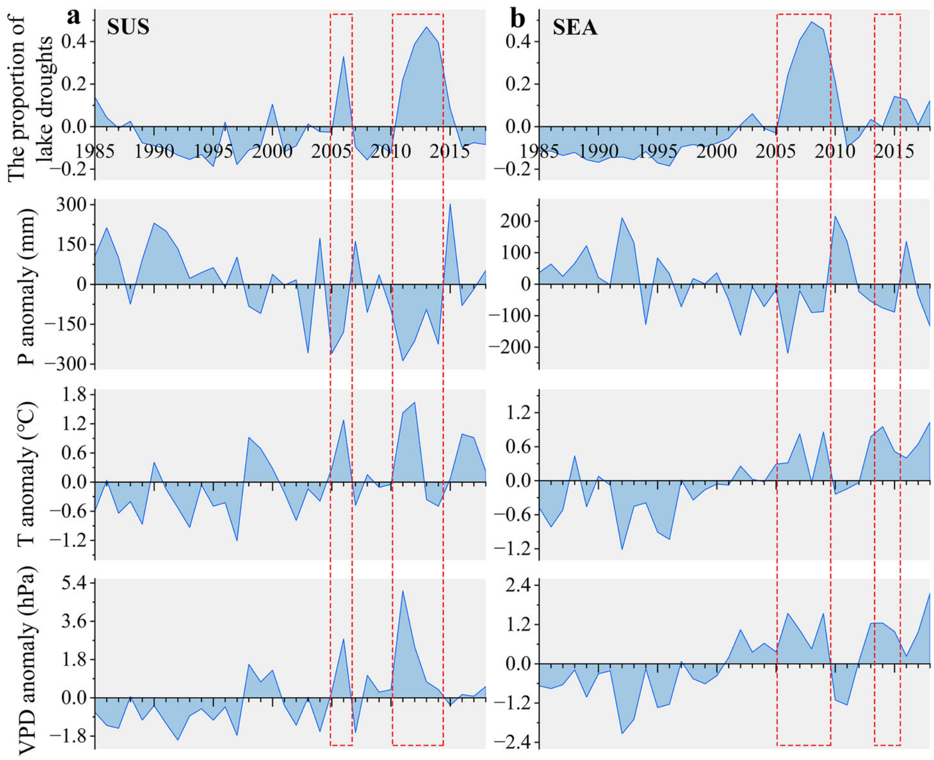

Fig. 3 | Interannual variations of lake droughts and related climatic variables in SUS and SEA from 1985 to 2018. a, **b** From top to bottom, yearly anomalies of the monthly average proportion of lake droughts, annual total *P* (mm), annual mean *T* (°C), and annual mean VPD (hPa) in SUS and SEA, respectively. The monthly average proportion of lake droughts represents the monthly average ratio of lakes experiencing drought conditions to the total number of lakes in the region. The red rectangles highlight periods when there is a locally high proportion of lake droughts and the corresponding climatic factors.

drought occurrences are frequently associated with *P* deficits, elevated *T*, and high VPD in both regions (Fig. 3). For instance, positive anomalies in the proportion of lake droughts correspond to low *P*, warm *T*, and high VPD in SUS during 2010–2014, as well as in SEA during 2005–2009. Monthly variations in lake drought occurrences and related climatic factors also suggest a close consistency between high lake drought risks and low *P*, warm *T*, and high VPD (Fig. S11). However, the elevated risks of lake droughts are not solely determined by these three variables. For example, a notable increase in the incidence of lake droughts, exceeding 50%, along with *T* anomalies and VPD anomalies, was observed around 2006 in SUS. This suggests the primary contribution of warm *T* and high VPD. In contrast, a local peak in lake droughts around 2015 in SEA was accompanied by a local trough in *P* instead of *T* and VPD, indicating the dominant role of *P*.

Trend analyses reveal a significant increase in the proportion of lake droughts ($p < 0.01$), which coincides with marked increases in both *T*[51] ($p < 0.01$) and VPD[52] ($p < 0.01$) in SUS from 1995 to 2018 (Fig. S12a). This observation occurs despite a statistically insignificant decline in *P* ($p = 0.6$). Similarly, the SEA region has experienced a notable and consistent increase in the proportion of lake droughts ($p < 0.01$), alongside significant upward trends in *T*[53] ($p < 0.01$) and VPD[54] ($p < 0.01$) since 1997. Conversely, *P* has shown a downward but statistically insignificant trend ($p = 0.68$, Fig. S12b). Future projections further indicate that *T* and VPD will continue to rise, while P is expected to decline over the coming decades[54,55]. Using linear regression to isolate the effects of individual and combined climatic factors, we assessed their relative contributions to lake drought trends (see "Methods"). The results show that the significant upward trends in the proportion of lake droughts in SUS transition to negligible trends after removing the impacts of *T* and VPD, as evidenced by both linear regression and the M–K test (Figs. S13a and S13b). In contrast, the trends in the proportion of lake droughts remained largely unchanged after the removal of *P* effects. Notably, the combined influence of *P* and VPD mainly contributes to lake drought trends in SUS. In SEA, substantial changes in lake drought trends are observed after removing the effects of *T*, VPD, and their combinations, but not *P* (Fig. S13c and 13d). These findings suggest that the rise in lake droughts in SUS is primarily driven by increasing VPD and *T* rather than changes in *P*. Similarly, the increasing frequency of lake droughts in SEA is closely linked to global warming, underscoring the dominant role of rising temperatures over precipitation in driving lake drought trends.

Lake droughts arise from complex interactions among lakes, surrounding land, and the atmosphere (Fig. 4). At the watershed scale, a critical water cycle governs regional water balance (Fig. S14). *P* (rainfall and snowfall) serves as the primary direct water resources for watersheds and most lakes. It also dramatically influences surface runoff and streamflow, which replenish lake water from surrounding land, rivers, and groundwater. Consequently, deficient *P* can markedly increase the probability of lake droughts. *T* and VPD further modulate the water cycle by regulating regional evapotranspiration (ET), including evaporation (*E*) from lakes, rivers, and soils, as well as transpiration from vegetation. Warmer *T* typically indicates greater radiation energy, thus triggering a higher ET rate[56]. VPD, reflecting atmospheric dryness and *E* demand[57], enhances ET when energy is sufficient[58]. Therefore, high *T* and VPD contribute to the depletion of regional water resources through increased ET. Among these processes, lake *E* is the primary pathway for water loss in most lakes[58,59], making increased *E* a key climatic driver of heightened lake drought risks. Additionally, elevated ET from rivers, soils, and vegetation can diminish discharge flow to lakes, resulting in dry lakes. Infiltration, another mechanism of water loss, is particularly important for lakes in karstic environments. Apart from *E*, infiltration was the most influential driver of Lake Chad's notable recession during 1973–1975[60].

Human activities can also profoundly affect lake water balances[13,48–50], contributing to the preferential occurrence of lake droughts, especially in regions where lakes are crucial water resources. Over-exploitation of lake water for human use can lead to abrupt lake shrinkage[61]. For instance, excessive agricultural water use was a primary factor in the extreme decline of Urmia Lake's water levels since 1996[48,50,62]. Land reclamation can also cause sudden drops in lake levels. Moreover, for lakes interconnected with rivers or influenced by dam construction, disruptions in water balance are common. Specifically, when river water levels fall heavily below those of the lake, outflow increases while inflow decreases, exacerbating lake drought conditions[20]. A notable example is the dramatic decline in Lake Victoria's

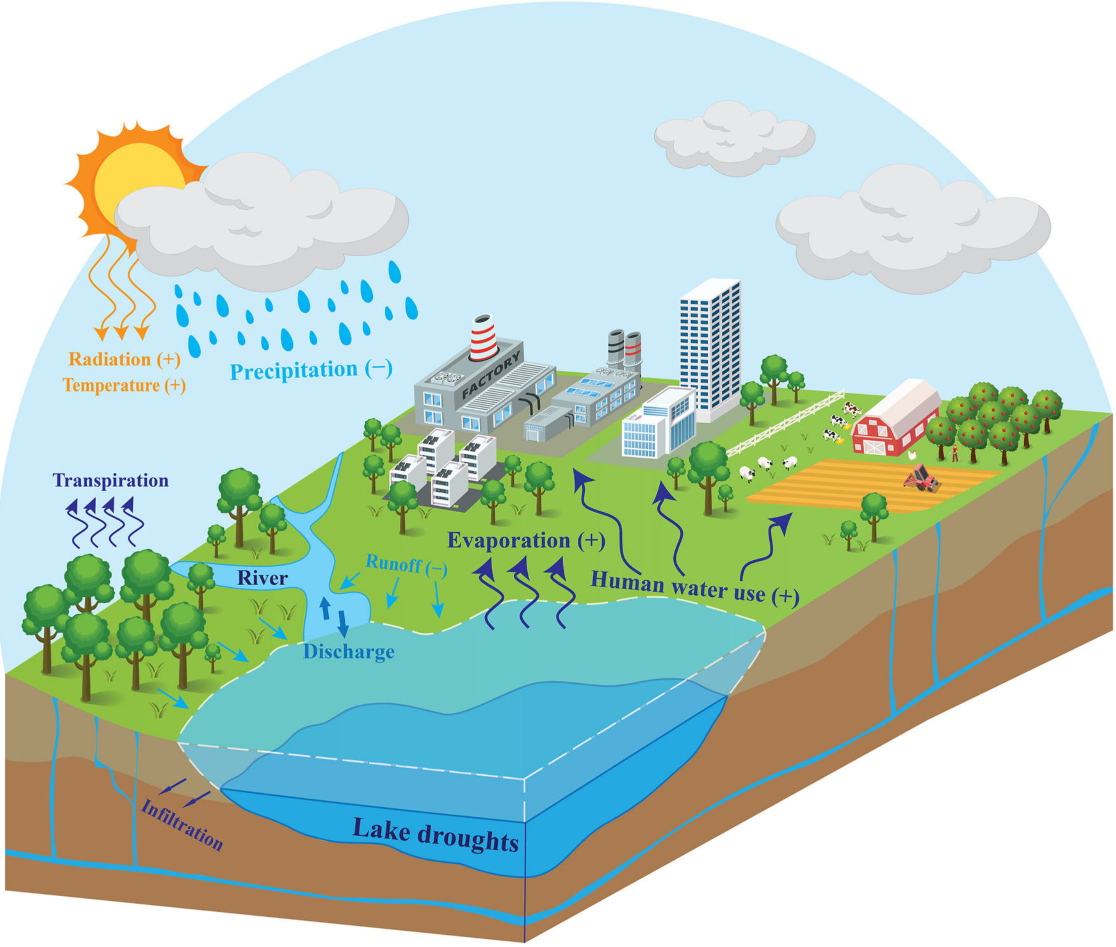

Fig. 4 | The physical mechanism of lake droughts. This diagram illustrates the complex water interactions between a lake, its surrounding land, and the atmosphere. Multiple variables connected to the lake water cycle are highlighted, including precipitation, temperature, evaporation, human water use, river discharge, runoff, infiltration, and transpiration. The arrows reflect the transport direction of these variables. The dotted line in the lake indicates the occurrence of a lake drought. The plus (+) or minus (−) symbols in brackets indicate an increase or decrease in the dominant variables resulting in lake droughts. For example, decreased precipitation (−) and increased evaporation (+) can lead to a lake drought.

water levels between 2001 and 2006, which was largely attributed to reduced water inflow following dam expansion[63]. Additionally, it is important to acknowledge the drought observed in reservoirs in CC around 2002, during which no severe climatic anomalies were noted; this event is likely linked to the construction of the Three Gorges Dam[64,65] (Fig. S15).

However, in most cases, human activities are likely the dominant factor driving persistent changes in lakes. While extreme climatic anomalies are the primary trigger for lake droughts, human activities often exacerbate these conditions rather than acting as the direct cause. For example, in SUS during 2010–2013, warmer T, higher VPD, and lower P led to notable declines in soil moisture and surface water levels (including lakes, rivers, and streams), resulting in exceptional megadroughts. During these droughts, heightened water demand for agricultural, domestic, and industrial use further reduced lake levels, intensifying the severity of lake drought conditions. To investigate this further, we divided lakes into natural lakes and artificial reservoirs. Given that most artificial reservoirs are managed to meet water supply, flood control, and other human needs, they are more susceptible to human influence than natural lakes. Therefore, we compared drought occurrence between the two types of lakes across hotspot regions, assuming consistent climatic conditions within each region, to elucidate the role of human activities. Our results demonstrate that human activities exacerbate regional lake droughts to some extent, although they are not the dominant driver. For instance, in SUS, where over 60% of artificial reservoirs serve as critical water resources, more reservoirs (59%) exhibit a significantly increasing trend in drought frequency compared to natural lakes (39%). Similar trends were observed in ESAM and WAFR (Fig. S16). By contrast, SEA and CC show more lakes with increasing drought trends overall. However, within each hotspot region, the temporal patterns of drought for natural and artificial lakes are remarkably consistent, both strongly correlated with climatic anomalies (Fig. S15). This close alignment underscores the predominant role of climatic factors in driving lake droughts. Notably, the proportion of drought occurrences in reservoirs is slightly higher than in natural lakes, likely demonstrating the influence of human regulation. Furthermore, our global analysis also reveals that more reservoirs experience significant upward trends in drought frequency compared to natural lakes (Fig. S5). For example, most reservoirs and dams mainly located at middle latitudes, such as in China, India, the United States, and the Middle East (Fig. S5), are constructed to support community needs[66]. Consequently, climatic factors play a dominant role in lake droughts, while human activities (e.g., dam construction and regulation[67,68]) also contribute to reservoir droughts.

Discussion

Building upon established definitions of various drought types[69], this study initially introduces the concept of "lake drought". Lake storage is the most direct and efficient indicator of regional water mass balance[70]. Given the limited availability of comprehensive global lake storage data, we turned to a global monthly lake area database, employing lake surface area as a proxy to assess lake water quantity and identify drought conditions. To validate the reliability of using lake area as a proxy, we collected global lake storage data (1972 global lakes) and compared it to the corresponding lake surface area data (see Methods). Results reveal that over 70% of lakes exhibit a statistically significant correlation between area and volume ($p < 0.05$). Among these, ~55.7% exhibit a strong positive correlation, characterized by correlation coefficients that exceed 0.5 (Fig. S17). To further substantiate the reliability of the lake area data, we compared it against an independent global yearly lake area dataset (see "Methods"). The comparison revealed a high level of consistency, with more than 70% of the 162,413 lakes showing strong positive correlations (coefficients > 0.5; $p < 0.05$; see Fig. S18).

Subsequently, we conducted sensitivity analyses to ensure the robustness of our lake drought identification. Here, we assessed lake droughts on a monthly scale, as most lakes exhibit obvious monthly variations in volume[71]. Consequently, calculating thresholds using a multi-month moving window would be inappropriate. Meanwhile, relying solely on a single month is also problematic, as the sample size for setting thresholds (total sample = 34 months in this study) is insufficient, potentially leading to misidentification of droughts during stable seasons with minimal fluctuations. To address these issues, we utilized change ratios of lake area, calculated based on seasonal anomalies (see "Methods"). Anomalies reflect absolute changes in lake area, while change ratios illustrate relative changes, allowing for comparisons throughout the entire studied period. This approach allows for more appropriate threshold establishment (total sample = 34 × 12 = 408 months), minimizing the risk of misidentifying drought months. Our results from these two methods, namely anomalies and change ratios, reveal a significant degree of consistency in spatial distribution, accompanied by a robust correlation ($R^2 = 0.87$, $p < 0.01$). Approximately 88.2% of global lakes exhibit consistent trends in drought frequency (Fig. S19), which supports the soundness of the method implemented in this study.

The determination of appropriate thresholds is another crucial issue in identifying extreme events, with percentile thresholds being the most commonly used[72,73]. Different percentile thresholds can impact the detection of extremes; therefore, we compared the characteristics (trends in the frequency of lake droughts) using five different percentiles, ranging from the 10th to the 30th in 5% increments. The results reveal a pronounced consistency in the spatial distribution of global lake drought frequency trends across these thresholds (Fig. S20), supported by strong correlation coefficients, generally exceeding 0.8 ($p < 0.01$; Fig. S21). As the threshold increases from the 10th to the 30th percentile, the number of identified drought months rises ((10% ~30%) × 408 months = 40 ~ 120 months), leading to an increase in the percentage of lakes with significant trends (both upward and downward). Specifically, about 12% of global lakes show significant increases in drought frequency at the 10th percentile, while this percentage increases to 17.2% using the 30th percentile. Given the focus of this study on monthly-scale lake droughts and the need to ensure a sufficient sample size of drought months (20% × 408 = 81 months), we determined the 20th percentile threshold to identify lake droughts. This threshold is also consistent with established practices for identifying traditional droughts[26,27,74].

Following the identification of lake droughts, we analyzed trends in drought frequency to characterize global patterns (see "Methods"). To assess the influence of varying window sizes on trend calculations, we tested six moving window sizes: 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year. Our findings reveal that global patterns of lake drought frequency trends remain relatively consistent across different window sizes (Fig. S22), alongside close correlations ($R^2 > 0.85$, $p < 0.01$; Fig. S23). However, as the window size increases, the proportion of lakes exhibiting significant trends (both upward and downward) also rises. Specifically, smaller window sizes (e.g., 1-year and 2-year) often fail to adequately capture drought events, leading to a higher proportion of lakes with insignificant frequency trends and reduced reliability. Conversely, larger window sizes (e.g., 7-year and 10-year) are constrained by the limited study period from 1985 to 2018, leading to insufficient data samples and increased uncertainty in trend calculations. Balancing these considerations, we selected the 3-year moving window to illustrate changes in drought frequency in this study.

To further validate our results, we calculated long-term trends in lake area from 1985 to 2018 for each lake. As expected, a strong negative correlation exists between trends in lake drought frequency and lake area ($R^2 = 0.51$, $p < 0.01$; Fig. S24). Specifically, increasing (decreasing) trends in drought frequency are typically associated with decreasing (increasing) trends in lake area. The results reveal that over 80% of lakes exhibiting upward trends in drought frequency concurrently exhibited significant downward trends in lake area. However, a decrease (increase) in lake area does not inherently suggest a corresponding increase (decrease) in drought frequency, as lake droughts reflect extreme conditions rather than gradual changes. This is supported by the observation that the fraction of lakes with upward (downward) trends in drought frequency is smaller than the fraction of lakes with downward (upward) trends in lake area (Fig. S24). In addition, we also observed that there is a close connection between lake droughts and meteorological droughts in both hotspot regions (see Figs. S10, S25, and S26), further corroborating the reliability of our findings.

However, it should also be noted that meteorological and lake droughts do not always exhibit perfect linear consistency. As a type of hydrological drought, lake droughts are influenced by the propagation of meteorological droughts through the water cycle, akin to the interactions observed in hydrological droughts[75–77]. As illustrated in Fig. S10, lake droughts generally occur following meteorological droughts. However, the propagation rate is less than 100%[78], indicating that not all meteorological droughts result in hydrological droughts. This can lead to situations where meteorological droughts occur without corresponding lake droughts, as seen in April 1987, May 1998, and December 2005 in SUS, as well as in March 1986, February 1991, and May 2005 in SEA (see Figs. S27 and S28). Generally, severe meteorological droughts (characterized by longer duration and higher intensity) are more likely to induce lake droughts. Nonetheless, such intense meteorological droughts can also lead to prolonged lake droughts, causing hydrological droughts to persist even after meteorological droughts have ended. Additionally, factors such as excessive human water usage and land cover changes, independent of climatic conditions, can also induce lake droughts[79]. Therefore, hydrological droughts may occur independently of meteorological droughts, as illustrated by occurrences in October 2006 and October 2013 in SUS, and October 2009 and March 2010 in SEA (see Figs. S27 and S28).

It is important to acknowledge several limitations and uncertainties in this study. Firstly, the extent of a small proportion of lakes may not accurately reflect their volume due to factors such as sediment accumulation[4], which can reduce storage capacity even when the lake extent remains unchanged. Limitations also arise from the monthly lake area dataset, as a higher-resolution dataset would better capture changes in extremes. Thus, there is an urgent need for a global lake storage dataset with higher spatial-temporal resolution (i.e. weekly) in the future. In addition, the setting of the 20th percentile threshold may induce uncertainties. Huge differences in area changes exist across lakes of various regions, types, and sizes[80]. For example, some lakes remained relatively unchanged throughout the entire period, while others experienced dramatic fluctuations. While employing lake-specific percentile thresholds may be more appropriate for local-scale applications, this approach is challenging for a global study encompassing over 160,000 lakes. As a result, the chosen threshold represents a compromise between practicality and methodological rigor.

Despite these limitations and uncertainties, defining and identifying lake droughts hold meaningful value, as they provide critical insights into different aspects of hydrological dryness[81]. Here, lake droughts primarily indicate extremely low water availability in lakes for a given duration. Unlike gradual declines in lake water resources, which may not immediately harm society as long as water levels remain above critical thresholds, extreme lake droughts can have severe and immediate detrimental effects. Moreover, akin to other types of droughts[82], lake droughts may take a long time to recover from, as the damage can be extensive and long-lasting. Lake droughts are also a critical issue for global water security. Rapid population growth, urbanization, and climate change have exacerbated water pressures and challenges globally over the past few decades[83,84]. Over 2 billion people lack access to sufficient safe water[85,86], and water scarcity is projected to worsen in the future[87]. Consequently, the concept of water security has gained worldwide attention in recent decades. Water security is interconnected with various sectors, including human society, economic stability, food and agriculture, environmental and ecological health, and even military security[88,89]. Many countries in the Middle East, Asia, and Africa are already facing water scarcity and heightened vulnerability to water shortages[84]. Notably, these regions align closely with hotspots showing increasing trends in lake droughts (Figs. S1 and S2), such as the Middle East (47.1%), West and East Africa (41.2% and 35%), as well as East and Central Asia (35.3% and 31.8%).

Lake droughts can severely impact water security in several ways. As vital water resources, lakes (natural lakes and reservoirs) hold ~87% of the Earth's available liquid freshwater[90,91]. Lake droughts indicate extreme short-term water shortages, directly impacting communities and human activities such as agriculture, tourism, and industry[92]. Moreover, lake droughts often follow regional megadroughts (characterized by high T and VPD) with high water demand for both human and ecological needs (Figs. S10 and S11). Therefore, lake droughts can further reduce water supply (e.g., drinking water), triggering severe water crises and threatening public health. Additionally, agricultural production and food security can be highly impacted, particularly in key farming regions, where reduced irrigation water can hinder crop growth, reduce yields, and cause substantial economic losses. Low water levels in lakes can disrupt fishing, shipping, hydropower generation, and tourism, undermining regional financial stability. For instance, the Great Lakes region experienced severe economic impacts during low water levels in 2012[93], with shipping activities incurring additional costs of ~$20,000 per freighter due to reduced cargo capacity[94]. In regions where multiple countries share lake resources, water shortages caused by lake droughts can escalate tensions and increase the risk of conflicts over water access. A notable example is Lake Chad in Africa, which sustains 37 million people across four littoral states[95]. Its ongoing decline exemplifies the socio-political risks associated with lake droughts[96].

Beyond their direct impacts on water availability, lake droughts pose large ecological and environmental challenges, including enhanced levels of pollutants[37], altered stratification and lake structure[38], and habitat loss[15,39]. During lake droughts, exposed lakebeds increase the risk of spreading dust, chemicals, and heavy metals, which can disperse through atmospheric and hydrological cycles, exacerbating environmental pollution and degrading water quality[97]. This, in turn, indirectly threatens water security and human health. For example, Lake Urmia, the largest inland lake in Iran, has seen public health risks and disease outbreaks affecting 13 million people due to lake droughts[98]. Similarly, harmful dust from the exposed bed of the Great Salt Lake has spread to surrounding areas driven by wind, severely impacting public health and increasing disease risks[99]. The rapid shrinkage of the Aral Sea has also caused numerous environmental problems, including a drastic increase in salt and mineral content, reduced clean water resources, and heightened cancer risks for locals[100]. Given the growing threats, there is an urgent need to study lake droughts and develop effective strategies to mitigate their impacts and ensure sustainable lake water resources.

This study offers a global picture of changes in lake droughts from 1985 to 2018, revealing that ~15.7% of global lakes witness obvious increasing trends in drought frequency. As shown in Figs. S1 and S2, there are relatively higher percentages of lakes with increased drought frequency in the Middle East, Southeast Australia, West and East Africa, Central and North Europe, East and Central Asia, and Southeastern South America. In contrast, high-latitude regions (e.g., Alaska, Western North America, Canada, Greenland, and Iceland) and high-altitude regions (e.g., the Tibetan Plateau), which host a large number of natural lakes, show significant downward trends in drought frequency over the past decades (Figs. S5 and S6). In alignment with the association between climate change and other extreme events[101–103], this study highlights a strong association between climate change (global warming) and the increasing prevalence of lake droughts in two hotspot regions (SUS and SEA). Lake droughts are closely associated with the dynamics of the lake water cycle and are influenced by multiple factors. Key drivers include P, E, T, VPD, discharge with rivers, runoff, and human water use. P and E are crucial components of the lake water cycle[104] and the largest forms of lake water gain and loss for most lakes, serving as primary drivers of changes in lake levels[58]. For lakes that are the main water supplies for human communities, excessive water withdrawal is another critical factor leading to lake droughts[105].

Beyond lake droughts, other lake extremes such as lake heatwaves[72,106], algal bloom[107], and deoxygenation[108,109], which are closely associated with lake water resources, have also attracted increasing attention recently. There are potential connections between these lake extremes, as events like lake heatwaves may affect water levels in lakes by elevating lake E[72], thereby inducing lake droughts. The compounding impacts of such extremes are often more severe than individual extreme event involved[92], underscoring the need to further explore the linkages between interdependent compound hazards in the future. Further, future research on lake droughts needs to focus more on quantifying human causes and drivers[13,81]. Accurate monitoring, prediction, and projection of lake resources under various future climate and development scenarios is also an urgent need to better analyze lake droughts in the future.

Methods

Data

We collected monthly lake area data from the Global Lake Evaporation Volume (GLEV) dataset[25] to investigate global lake droughts. This dataset, derived from satellite observation images, includes monthly lake surface area time series for over 1.42 million lakes (≥ 0.1 km^2) globally from January 1985 to December 2018 (408 months). We obtained the shapefiles and other auxiliary information (e.g., classification of reservoirs and natural lakes, latitude, and longitude) from the HydroLAKES dataset[23], using consistent lake ID between these two datasets. To validate the lake area series from the GLEV dataset, we gathered yearly lake area data from the Global Lake Area, Climate, and Population (GLCP) database[110]. This dataset provides annual total surface area (the addition of seasonal and permanent water area) for 1.42+ million worldwide lakes from 1995 to 2015 with the same ID as lakes from the GLEV dataset; therefore, the area from these two datasets can be compared directly for each lake. Additionally, we accessed global lake storage data from the Global Database of Lake Water Storage (GLWS) dataset[4]. This dataset contains near-monthly lake areas, levels, storages for 1972 global lakes from 1992 to 2020, shapefiles for the locations, and other information.

To explore the relationship between lake droughts and climate change, we used meteorological data (2-m air T, 2-m dewpoint T, and total P) derived from the ERA5-Land monthly averaged reanalysis dataset[111]. This dataset, produced for analyzing global land components, has a spatial resolution of 0.1 degrees and spans from 1950 to the present[112]. We used 2-m dewpoint T and 2-m air T from this dataset to calculate VPD. VPD is defined as the difference between the saturated water vapor pressure (SVP) and actual water vapor pressure (AVP)[113]. The calculation of VPD based on the ERA5 dataset is as follows[114].

$$\mathrm{VPD} = \mathrm{SVP} - \mathrm{AVP} \tag{1}$$

where SVP (determined by 2-m air T (t, °C)) and AVP (determined by 2-m dewpoint T (t_d, °C)) are calculated as follows.

$$SVP = 6.112 \times f_w \times e^{17.67t/(t+243.5)} \tag{2}$$

$$AVP = 6.112 \times f_w \times e^{17.67t_d/(t_d+243.5)} \tag{3}$$

$$f_w = 1 + 7 \times 10^{-4} + 3.46 \times 10^{-6} \times P_{mst} \tag{4}$$

$$P_{mst} = P_{msl} \times \left((t + 273.16)/(t_d + 273.16 + 0.0065 \times A)\right)^{5.625} \tag{5}$$

where P_{mst} indicates the air pressure (hPa) in a region with the altitude of A (m) and P_{msl} indicates the air pressure at mean sea level (1013.25 hPa). The altitude information was derived from the Shuttle Radar Topography Mission (SRTM) digital elevation dataset[115].

We applied monthly P and potential ET (PET) data from the Climatic Research Unit gridded Time Series (CRU TS)[116] to calculate the aridity index. This dataset consists of ten meteorological variables from 1901 with a spatial resolution of 0.5 degrees, supporting large-scale climate research. The aridity index was proposed to identify climate regimes with various dryness levels. This index is defined as the ratio of the annual average PET to P for a long-term period; in this study, we used the period from 1985 to 2018. Based on the value of the index, the land can be classified into arid regions (>2.25), transitional regions (0.9–2.25), and humid regions (≤0.9)[57].

Identification of lake droughts

Lake droughts are rarely addressed in the literature, resulting in a lack of a clear and commonly accepted definition. Therefore, in this study, we proposed a robust and reasonable definition and calculation method for lake droughts, referring to existing research related to other extreme events[72,106,117,118]. Here, we define lake droughts as periods (months) when the lake surface area is lower than the seasonally normal value. Limited to the availability and completeness of global monthly lake storage and level datasets, we used the surface area to reflect lake water resources since it is commonly acknowledged that lake area is statistically correlated to lake storage and extensively used to estimate lake storage[119–122].

Before identifying global lake droughts, we performed preprocessing (filtering and filling) of the lake area data. First, we filtered out lakes with a multi-year mean area of smaller than 1 km^2 during the studied period. We also removed lakes with more than 2% missing data throughout the whole period. For lakes with 2% or less missing data, we applied linear interpolation with five adjacent data points to fill in the gaps. Last, we selected a total number of 162,413 lakes (≥1 km^2, excluding the Caspian Sea) in this study to investigate the characteristics of droughts.

According to the definition, the key to identifying lake drought months is to determine the seasonally normal value. In the first step, we eliminated the effects of the seasonal cycle, to ensure climate extremes (departures from normal) are relative to the time of the year[72,123–125]. The most common approach is to calculate the seasonal anomalies (e.g., monthly anomalies in this study) and compare these anomalies within the same season (month). Then, extreme values exceeding a defined threshold in each season can be captured (e.g., the identification of lake heatwaves[72]), which means the extreme events will be identified every season. However, lakes exhibit distinct periods of low, stable, and high water volumes[38], which can lead to misidentifications of droughts during stable periods compared to other seasons. To enhance the accuracy and robustness of results, we proposed using the change ratio of lake area based on anomalies ("Discussion"). It is calculated as the ratio of lake area anomalies to the climatological mean lake area (Eq. 6); therefore, it removes the seasonality and can reflect the relative change rate (%) in each month of the year, which can be compared throughout the whole period from 1985 to 2018.

$$Change\ ratio = \frac{Lake\ area\ anomaly}{Climatological\ mean\ lake\ area} \tag{6}$$

Then, we determined a threshold in change ratio to identify lake droughts. We used different thresholds ranging from the 10th to the 30th percentile with 5% intervals. Considering the monthly temporal resolution and the 34-year data length, we finally selected the 20th percentile threshold for this study. As shown in the upper part of Fig. 1a, droughts (months) were identified and highlighted in blue when the change ratio was lower than the 20th percentile threshold for each lake.

The trends in the frequency of lake droughts

Given the notable variability in global lake changes, evaluating the intensity and severity of lake droughts collectively poses challenges. Therefore, after identifying all drought months from 1985 to 2018, we used drought frequency trends to characterize dynamic changes in lake droughts. Frequency is one of the most widely used metrics for assessing extreme events in many studies[126–129]. In this study, we define the frequency of lake droughts as the number of months in droughts. We chose not to combine adjacent drought months into a single event, as the limited data at the monthly scale resulted in too few events for trend analysis.

As shown in the lower part of Fig. 1a, we calculated trends in the frequency of droughts for global lakes. First, the identified monthly drought series (comprising drought and non-drought months) was transferred into a frequency series. Then, we compared different moving window sizes, including 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year windows. Considering the reliability and data length, we finally counted frequencies using a 3-year moving window with a 1-year interval (e.g., the first value is the lake drought frequency from 1985 to 1987; the last value is the lake drought frequency from 2016 to 2018). Based on this frequency series, we applied the M–K trend analysis[130,131] to obtain trends and significance levels. The non-parametric M–K test is aimed at robust nonlinear trend analysis[132]. The calculation is as follows for a given time series ($x_i, i = 1, 2, 3, \ldots, n$).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{7}$$

$$\mathrm{sgn}\left(x(j) - x(i)\right) = \begin{cases} 1, & x_j > x_i \\ 0, & x_j = x_i \\ -1, & x_j < x_i \end{cases} \tag{8}$$

where S with a value of > 0 (< 0) reflects an upward (a downward) trend.

$$Z = \begin{cases} (S-1)/Var(S), & S > 0 \\ 0, & S = 0 \\ (S+1)/Var(S), & S < 0 \end{cases} \tag{9}$$

$$Var(S) = n(n-1)(2n+5)/18 \tag{10}$$

where Z can indicate the trends and significance level. A positive (negative) value of Z indicates an upward (downward) trend. $|Z| \geq 1.96$ (the absolute value of Z) indicates that the trend satisfies the significance level of $p < 0.05$.

The impacts of climatic factors on lake drought trends

We further compared the relative contributions of individual climatic factors (P, T, and VPD) and their combined factors (P and T, P and VPD, T and VPD, and P and T and VPD) to lake drought trends in two hotspot regions. To achieve this, we employed two methods: linear regression analysis and the Partial M–K (PMK) test. Similar to the M–K estimation, the PMK test is a non-parametric method that detects trends while controlling for the influence of covariates[133]. Both methods operate on the principle of first removing the influence of individual or combined factors on long-term trends and then comparing the trends (slope and p-values) before and after accounting for these influences[134,135].

To remove the effects of various factor combinations (X, with a total of seven combinations) on the proportion of lake droughts (Y), we established linear relationships between X and Y using least squares estimation. The linear equation can be expressed as:

$$Y = k_1X_1 + k_2X_2 + k_3X_3 + b \tag{11}$$

$$Residual = Y - Y_{fitting} \tag{12}$$

where X_1, X_2, and X_3 indicate P, T, and VPD, respectively. k_1, k_2, and k_3 may assume a value of zero but cannot all be zero simultaneously, representing different factor combinations. For example, it shows the combination of P and T when k_3 is equal to 0. Based on the optimal linear model, we obtained the residual time series (Eq. 12), where $Y_{fitting}$ represents the fitted values, and Y represents the original values. The residual time series represents the Y time series after removing the influence of the factors (X). We then compared the trends of the residual series with those of the original series using both linear regression and M–K analysis. The M–K trend results are reflected by τ, which ranges from −1 to 1. A larger absolute value of τ indicates a larger slope, while $\tau = 0$ indicates no trend. Positive and negative values of τ represent upward and downward trends, respectively. The calculation of τ is as follows, where S and n are defined in accordance with the M–K analysis.

$$\tau = 2S/n(n-1) \tag{13}$$

Validation

To ensure the accuracy of our results, we first validated the datasets used in this study. We collected additional lake area data derived from the GLCP database, which provides the total yearly lake surface area for all studied lakes. The annual total lake area is defined as the sum of permanent and seasonal water areas within a given year. Therefore, we selected the annual maximum lake area to align the monthly lake area from the GLEV dataset with the yearly area, as it most closely matches the total area. We removed any missing data for each lake and conducted a correlation analysis between the area series from these two datasets. In addition, since a large proportion of lakes from the GLWS dataset include over 10% of missing data, it is insufficient to analyze droughts. Therefore, we only compared the lake area series from the GLEV dataset with the lake storage series from the GLWS dataset for each lake. Due to inconsistent lake IDs across the GLEV and GLWS datasets, we used geographical coordinates (latitude and longitude) to pair up the lakes.

Given the lack of a universally accepted definition and methodology for calculating lake droughts, it was essential to validate the rationality and reliability of our approach. Based on the definition used in this study, we first conducted sensitivity analyses focusing on two key aspects: calculating seasonal changes and selecting the threshold. We applied different methods to calculate seasonal changes in the lake area: anomalies (the widely used approach) and change ratios (as proposed in this study). We then calculated and compared the trends in lake drought frequency based on these two methods, using the 20th percentile threshold. Regarding the threshold selection for identifying lake droughts, we characterized and compared the trends in lake drought frequency based on five thresholds ranging from the 10th to 30th percentile with 5% intervals (10th, 15th, 20th, 25th, and 30th). Meanwhile, we applied different moving windows (1-year, 2-year, 3-year, 5-year, 7-year, and 10-year windows) to assess the trends in lake drought frequency. Finally, we compared the long-term trends in the lake area with those in lake drought frequency to further validate our results.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All the data supporting this study is freely available to the public. The monthly lake surface area series from the GLEV dataset can be obtained from https://zenodo.org/records/4646621. The point shapefiles and additional information for global lakes collected from the HydroLAKES dataset can be found at https://www.hydrosheds.org/products/hydrolakes. The yearly lake surface area series from the GLCP dataset is available at https://portal.edirepository.org/nis/mapbrowse?scope=edi&identifier=394&revision=5. The lake water storage from the GLWS v1.1 dataset can be obtained from https://zenodo.org/records/7946043. The ERA5-Land reanalysis dataset of total precipitation, 2-m air temperature, and 2-m dewpoint temperature can be obtained from https://cds.climate.copernicus.eu/. The SRTM DEM data can be downloaded from the Google Earth Engine platform https://code.earthengine.google.com/. The CRU TS Version 4.07 dataset of precipitation and potential evapotranspiration for the calculation of VPD can be obtained from https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.07/. The monthly 0.5-degree SPEI-01 data is available from 1901 to 2018 at https://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=spei_01. The global 1-km gridded total population data from 2001 to 2020 was derived from the WorldPop Hub at https://hub.worldpop.org/. The 0.00025-degree cropland area data in 2003, 2007, 2011, 2015, and 2019 was collected from the Global Land Analysis and Discovery (GLAD, https://glad.umd.edu/dataset/croplands).

Code availability

The code for identifying and assessing global lake droughts and related data is publicly available at https://zenodo.org/records/14997634.

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Author contributions

X.C. and S.W. conceived and designed the study. X.C. carried out the calculation and analysis and then drafted the manuscript. J.C. and S.W. supported and supervised the study. Then, J.C., S.W., and A.A. contributed to the improvement and modification of the draft. X.C. revised and edited the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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