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Key Points:

- The propagation from atmospheric water deficit to lake drought was enhanced at 28% of the selected lake basins in China
- Reservoirs are more susceptible to atmospheric water deficits than natural lakes
- Lake droughts were determined by lake-specific hydrological conditions at 37% of the selected lake basins

Supporting Information:

Supporting Information may be found in the online version of this article.

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Propagation From Atmospheric Water Deficit to Lake Drought in Lake Basins Across China: Implications for Lake Drought Management

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Abstract Global lakes are expected to witness a growing incidence of droughts under climate warming, but the propagation from atmospheric water deficit (AWD) to lake drought, mediated by basin water deficit (BWD) as a key intermediary, remains underexplored at the lake basin scale. This study investigated the propagation from AWD to lake drought in 1,617 lake basins across China using a copula-based approach. 19% of AWD events cascaded to lake droughts via BWD, while 57% of lake droughts were traceable to antecedent AWDs. These results underscore the significance of basin modulation in determining the responses of lake droughts to climate variability. Notably, the propagation ability for reservoir basins was higher than that of natural lake basins, indicating that reservoirs are more susceptible to AWDs than natural lakes. A classification framework for China's lake basins was further proposed for lake drought management. 28% of lake basins exhibited lake drought intensification through the AWD-to-BWD path, necessitating climate-adaptive measures. 6% of lake basins faced lake drought intensification driven by BWD with no AWD occurrence, requiring integrated lake basin management. 18% of basins with lake drought intensification were controlled by lake-specific hydrological conditions, demanding localized strategies to maintain water stability. The remaining lake basins exhibited a reduced probability of lake drought occurrence. This study provides actionable guidance to tailor lake drought management, prioritizing climate-vulnerable basins or lake-specific interventions.

Plain Language Summary Although lakes cover only 3% of the global land area, they are essential to the global hydrological and biogeochemical cycles. Recently, an increasing number of lakes have suffered droughts under climate warming, yet the propagation from atmospheric water deficit to lake drought remains poorly understood at large scales. Lake drought is initially triggered by an atmospheric water deficit and further modulated by basin hydrological processes. Few studies have focused on hydrological propagation in specific lake basins using hydrological-hydrodynamic models, which are highly data-intensive and time-consuming. In this study, we investigated the propagation chain from atmospheric water deficit to basin water deficit to lake drought in 1,617 lake basins across China using a copula-based approach. Then, a lake basin classification framework for lake drought management was proposed according to the changes in this propagation chain. The results of this study provide decision support for prioritizing lake basins requiring climate-adaptive policies and lake-specific interventions.

1. Introduction

Although lakes cover only 3% of the global land area, they harbor a substantial portion of terrestrial water resources, which are crucial for socio-economic development and ecosystem sustainability (Weyhenmeyer et al., 2024; Yao et al., 2023). In a warming climate, these functions are anticipated to be at risk from the increasingly frequent lake drought, which is identified by combining a specific threshold with the lake water deficit status, as indicated by a drop in water level, surface area, or storage below normal conditions (Woolway et al., 2020). Generally, lake drought is initially triggered by an atmospheric water (precipitation) deficit, which subsequently propagates to a lake water deficit through basin hydrological processes, and can be further intensified by human water withdrawal (Cooley et al., 2021; Perales et al., 2020; Zhang, Li, et al., 2023). The propagation from atmospheric water deficit (AWD) to lake drought reflects water shortage propagation processes from the atmosphere to the land and from the basin to the lake, which directly affect the water availability, nutrient concentration, and ecological health of lakes (Saber et al., 2020; Tong et al., 2023). Yet, this important process of atmosphere–basin–lake water shortage propagation has received little attention from limnologists, hydrologists, meteorologists, and remote sensing scientists.

Few limnologists have investigated the propagation from AWD to lake drought in specific large lake basins and lake basins that significantly impact local socioeconomics using hydrological models in combination with lake hydrodynamic models (Kummu et al., 2014; Lai et al., 2013). Such a process-based method can depict water transfer processes in lake basins at different time scales, but exhibits two disadvantages. On one hand, this method is highly data-intensive, with its accuracy heavily dependent on precise lake bathymetry (Yao et al., 2018). Despite the rapid development of remote sensing technology, retrieving underwater bathymetry remains a challenge (Liu & Song, 2022; Luo et al., 2022). On the other hand, the lake model needs to be customized and the computation is time-consuming. These limitations make the method impractical for large-scale studies. Instead, statistical approaches can circumvent these disadvantages, including correlation analysis, machine learning, and copula-based approach, of which the copula-based approach has been used to model nonlinear dependencies between continuous hydro-meteorological variables (Gaupp et al., 2020; Jiang et al., 2023; Qing et al., 2023). For example, it is assumed that there is a propagation from meteorological drought to hydrological drought when the two types of droughts co-occurred (Zhang et al., 2017). Moreover, the copula-based approach overcomes the shortcoming of assessing the relationship between hydro-meteorological extremes with few samples, making it possible to investigate hydrological propagation relationships in lake basins with limited observational data.

Hydrology and remote sensing researchers are concerned with the dynamics of hydrological variables in lakes, such as lake water area, storage, and depth, but the research on hydrological extremes of lakes and their connections with atmospheric conditions through basin modulation remains underexplored (Cooley et al., 2021; Pekel et al., 2016; Tong et al., 2023). For example, Yao et al. (2023) constructed time-varying water storage in 1,972 global largest lakes from 1992 to 2020, and the relationships between lake water storage and precipitation were only subsidiary outcomes. Xu et al. (2024) found that the projected lake expansion in the Tibetan Plateau is primarily fueled by amplified water inputs from increased precipitation and glacier meltwater, profoundly reshaping the hydrological connectivity of lake basins. These studies focused on the inversion techniques and approaches of lake variables. As a crucial hydrological relationship in lake basins, the propagation from AWD to lake drought through basin water deficit (BWD) reflects the water shortage transfer processes in atmosphere–basin–lake systems, emphasizing the role of atmospheric forcing and basin-scale processes in driving lake droughts. This propagation is initiated by atmospheric forcing and modulated by basin- and lake-scale processes. Understanding such hydrological propagation mechanisms is a prerequisite for integrated lake basin management to achieve effective drought governance (Awange et al., 2008; Soeprobowati, 2015).

In this light, this study takes 1,617 lake basins of China as an example and combines satellite products and a copula-based approach to: (a) analyze the spatial patterns of propagation from AWD to lake drought, (b) investigate the temporal changes in the propagation from AWD to lake drought during the past 40 years, and (c) propose a lake basin classification framework for effective lake drought management. The results are of great significance for understanding the hydrological transfer mechanism in atmosphere–basin–lake systems, which are expected to assist the lake drought management in lake basins under climate change.

2. Methods and Materials

2.1. Methods

2.1.1. Definitions of AWD, BWD, and Lake Drought

Many definitions of drought and water deficit have been proposed in previous studies, among which the standard precipitation index (SPI) has been widely used and extended to other hydrological variables, such as river runoff, soil moisture, groundwater levels, and lake water area (AghaKouchak et al., 2021; Guttman, 1999; McKee et al., 1993). The SPI usually employs the Gamma distribution to calculate the cumulative probability distribution of precipitation $F(x)$:

$$F(x) = \begin{cases} \int_0^x \frac{t^{\alpha-1} e^{-t/\beta}}{\beta^\alpha \Gamma(\alpha)} dt & (x > 0) \\ N_{zero} / N_{total} & (x = 0) \end{cases} \tag{1}$$

where x represents precipitation, α is the shape parameter, β is the scale parameter, Γ is the Gamma function, N_{zero} is the number of months with zero precipitation, and N_{total} is the total number of months. $F(x)$ is then transformed into the standard normal distribution quantile to derive the SPI value.

Similarly, the Standard Runoff Index (SRI) and Standard lake Water area Index (SWI) were employed to quantify basin and lake water shortage (Shukla & Wood, 2008; Zhang et al., 2017). This study utilized 12-month-scale SPI, SRI, and SWI to assess AWD, BWD, and lake drought, respectively. Lake drought was defined as SWI ≤ -1, while AWD and BWD were identified when SPI and SRI values fall below zero, indicating water deficit conditions (McKee et al., 1993). The SWI threshold of -1 follows standardized index conventions such as the SPI, corresponding to one standard deviation below the mean (15.9% cumulative probability). This ensures cross-variable drought assessment consistency (e.g., precipitation, runoff). This study defines AWD and BWD with thresholds of 0 (SPI ≤ 0, SRI ≤ 0), contrasting with conventional drought thresholds (SPI ≤ -1, SRI ≤ -1), to fully characterize basin-mediated water shortage propagation. Even under non-drought atmospheric and basin conditions (SPI > -1, SRI > -1), persistent AWD and BWD can trigger lake droughts through cumulative hydrological feedbacks—a process traditional drought-focused methods often overlook. By extending these definitions, the approach enhances detection of AWD–BWD–lake drought dynamics in lake basins.

Moreover, the Gamma, Generalized Extreme Value (GEV), and Pearson Type III distributions were applied to fit the precipitation, runoff, and lake water area series using L-moment estimation, aiming to accurately characterize the probability distributions of these variables (Wang et al., 2021; Xu et al., 2015). If a distribution passes the Kolmogorov-Smirnov test at the 95% confidence level, the candidate distributions are further compared using the Bayesian Information Criterion (BIC) (Kole et al., 2007; Neath & Cavanaugh, 2012).

2.1.2. Calculation of Propagation Probability From AWD to Lake Drought

Within the Copula framework, we assumed a propagation from AWD to lake drought when the AWD, BWD, and lake drought coincide in a given lake basin (Figure 1a). The concurrent probability (P_{vine}) of AWD, BWD, and lake drought was estimated using a copula method based on Sklar's theorem (Sklar, 1959):

$$P_{vine}(\mathrm{SPI} \leq 0, \mathrm{SRI} \leq 0, \mathrm{SWI} \leq -1) = C[F_{\mathrm{SPI}}(0), F_{\mathrm{SRI}}(0), F_{\mathrm{SWI}}(-1)] \tag{2}$$

where P_{vine} is concurrent probability of SPI ≤ 0, SRI ≤ 0, and SWI ≤ -1, F_{SPI}, F_{SRI}, and F_{SWI} are the marginal probability distributions of SPI, SRI, and SWI, and $C \rightarrow [0,1]$ is a copula function. Regular vine tree structures were employed to model the complex dependencies of the SPI, SRI, and SWI (Bedford & Cooke, 2002). For each copula pair, copula families with a single parameter of Kendall's tau were employed, including Gaussian, Clayton, Gumbel, Frank, and Joe copulas. The maximum likelihood estimation was used to calculate the parameter for each bivariate copula and the BIC was used to select the optimal copula model for each copula pair. Notably, $P(\mathrm{AWD} \cap \mathrm{LDT})$ in Figure 1a doesn't represent the propagation from AWD to lake drought. This is because the basin serves as the critical intermediary linking atmospheric and lake processes. When AWD occurs, it first alters basin hydrological dynamics—such as reducing runoff and soil moisture. These changes subsequently impact lake hydrology through surface and subsurface flow pathways, forming a cascading atmosphere–basin–lake water shortage response. If AWD is not accompanied by BWD, lake drought in such cases is likely dominated by internal hydrological processes, such as excessive evaporation or anthropogenic outflow regulation.

According to the graphical relationship in Figure 1a, the conditional probability of P_{vine} given AWD significantly differs from that given lake drought, indicating two critical insights: (a) not all AWDs propagate to lake droughts due to basin-scale buffering effects, and (b) not all lake droughts originate from AWDs (e.g., anthropogenic withdrawals). To disentangle these dual dynamics, two probabilistic metrics were formalized:

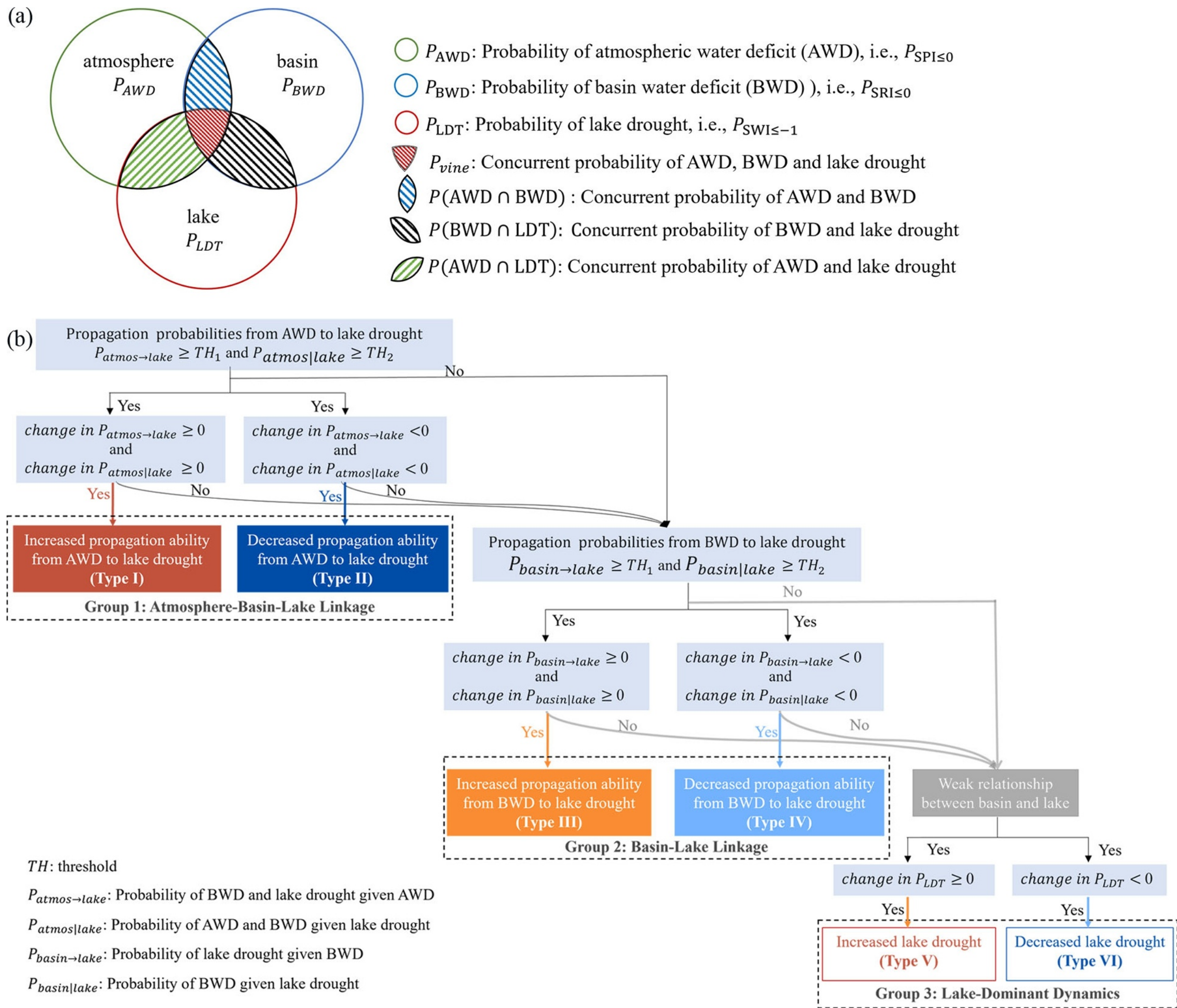

Figure 1. (a) Venn diagram of propagation from AWD to lake drought. (b) Conceptual classification framework of lake basins based on propagation ability from AWD to lake drought.

$$P_{atmos\rightarrow lake}(\mathrm{BWD} \cap \mathrm{LDT}|\mathrm{AWD}) = \frac{P_{vine}}{P_{\mathrm{AWD}}} \tag{3}$$

$$P_{atmos|lake}(\mathrm{AWD} \cap \mathrm{BWD}|\mathrm{LDT}) = \frac{P_{vine}}{P_{\mathrm{LDT}}} \tag{4}$$

where P_{AWD} and P_{LDT} are the probabilities of AWD (SPI ≤ 0) and lake drought (SWI ≤ -1), respectively, estimated by the marginal probability distributions using the GEV. $P_{atmos\rightarrow lake}$ is the conditional probability of the simultaneous occurrence of BWD and lake drought given the occurrence of AWD, representing the likelihood of AWD propagating to lake drought via BWD. $P_{atmos|lake}$ is the conditional probability of the simultaneous occurrence of AWD and BWD given the occurrence of lake drought, representing the proportion of lake drought events linked to AWD. These two propagation probabilities were used to evaluate the propagation ability of water shortage transfer within the atmosphere–basin–lake system. Higher values indicate stronger atmosphere–land coupling in the lake basin.

Similarly, the propagation probabilities from AWD to BWD and from BWD to lake drought were estimated to explore the water shortage transfer processes from the atmosphere to the basin and hence to the lake, calculated as follows:

$$P_{atmos\rightarrow basin}(\mathrm{BWD}|\mathrm{AWD}) = \frac{P(\mathrm{AWD}\cap \mathrm{BWD})}{P_{\mathrm{AWD}}} \tag{5}$$

$$P_{atmos|basin}(\mathrm{AWD}|\mathrm{BWD}) = \frac{P(\mathrm{AWD}\cap \mathrm{BWD})}{P_{\mathrm{BWD}}} \tag{6}$$

$$P_{basin\rightarrow lake}(\mathrm{LDT}|\mathrm{BWD}) = \frac{P(\mathrm{BWD}\cap \mathrm{LDT})}{P_{\mathrm{BWD}}} \tag{7}$$

$$P_{basin|lake}(\mathrm{BWD}|\mathrm{LDT}) = \frac{P(\mathrm{BWD}\cap \mathrm{LDT})}{P_{\mathrm{LDT}}} \tag{8}$$

where P_{BWD} is the probability of BWD (SRI ≤ 0), $P(\mathrm{AWD}\cap \mathrm{BWD})$ and $P(\mathrm{BWD}\cap \mathrm{LDT})$ are the concurrent probabilities of AWD-BWD and BWD-lake drought, as illustrated in Figure 1a.

The changes in the propagation probabilities were calculated as the difference between the changed period 2000–2018 and the whole period 1985–2018 (see details in the Materials). For SPI, SRI, and SWI calculations in each period, distribution parameters fitted over the whole period were used to characterize water deficit and drought changes. This study selected the period 1985–2018 for probabilistic model fitting to enhance analytical reliability. Given the lower frequency of remote sensing observations during 1985–1999, the reconstructed monthly lake water area data from this earlier period may contain greater uncertainties in capturing extreme lake drought events. By maintaining original data standards (1985–2018), the increased effective sample size improves the statistical representativeness of hydrological time series. The whole period better captures hydrological variability characteristics, thereby enhancing the stability of probability distribution fitting for lake water area and reducing parameter estimation biases caused by small sample sizes.

2.1.3. Lake Basin Classification for Lake Drought Management

This study proposes a novel lake basin classification framework for lake drought management based on water shortage propagation within the atmosphere–basin–lake system. Lake basins are classified into three groups with six subtypes through a three-tiered decision process (Figure 1b). This process evaluates directional consistency of the changes in propagation probabilities (e.g., $P_{atmos\rightarrow lake}$ and $P_{atmos|lake}$) in each lake basin.

1. Group 1 (Atmosphere–Basin–Lake Linkage): a lake basin is assigned to Type I (increased propagation ability from AWD to lake drought via BWD) if both $P_{atmos\rightarrow lake}$ and $P_{atmos|lake}$ exceed certain thresholds (set 0.1 and 0.3 in this study, respectively), and exhibit positive changes. Conversely, if both probabilities show negative changes, it is classified as Type II (decreased propagation ability from AWD to lake drought via BWD). This group highlights atmospheric forcing mediated through basin processes.
2. Group 2 (Basin–Lake Linkage): Unclassified lake basins are re-evaluated using the $P_{basin\rightarrow lake}$ and $P_{basin|lake}$. Type III (increased propagation ability from BWD to lake drought) or Type IV (decreased propagation ability from BWD to lake drought) is assigned based on positive or negative changes. This group emphasizes basin-regulated propagation independent of AWD.
3. Group 3 (Lake-Dominant Dynamics): Remaining lake basins are classified as Type V (increased lake drought) or Type VI (decreased lake drought) based on changes in P_{LDT}. Lake drought dynamics here are governed by lake-specific factors (e.g., evaporation, outflow regulation) without BWD.

This classification framework delineates AWD–BWD–lake drought propagation pathways (Figure 1b), providing a decision-support tool for prioritizing lake basins requiring climate-adaptive policies (e.g., Type I) versus lake-specific interventions (e.g., Type V).

2.2. Materials

The lake data of China were obtained from the HydroLAKES dataset (Messager et al., 2016). 1,617 lakes were chosen to investigate the propagation from AWD to lake droughts subject to the following selection criteria. First,

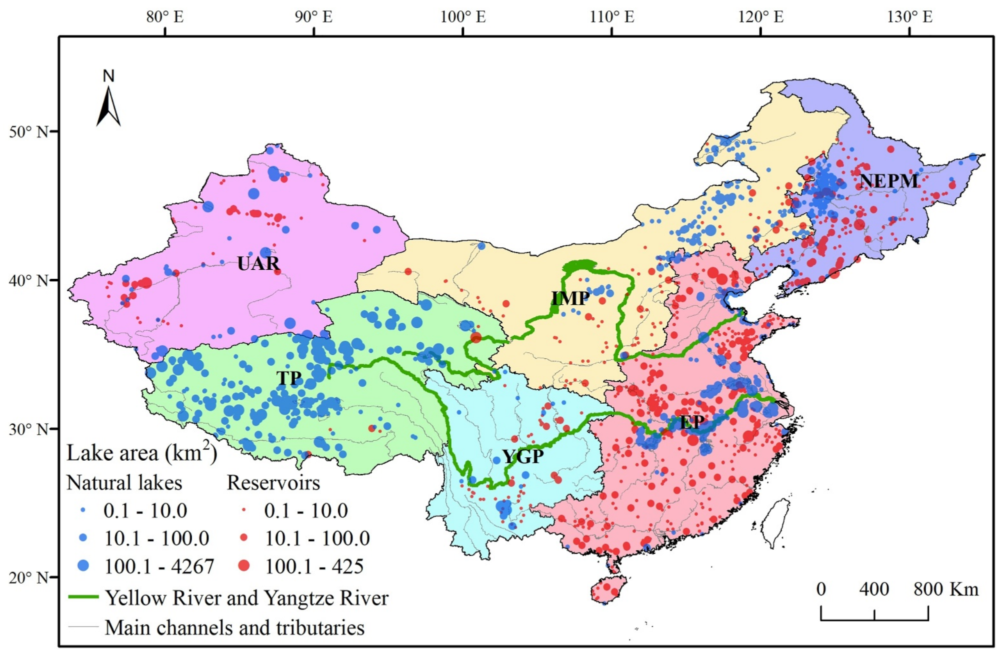

Figure 2. Sketch map of the selected lakes. The points are the lake outlets in their basins.

the basin area is larger than 100 km^2 and the lake area is larger than 1 km^2 to ensure a hydrological propagation from the basin to the lake. Second, the marginal distribution of each variable passes the Kolmogorov-Smirnov test at the 95% confidence level. Third, the P_{AWD}, P_{BWD} and P_{LDT} are greater than 0.01 (return period of one-hundred-year) for the probability below this threshold might lead to unreliable results. The area of selected lakes ranges from 1 to 4,267 km^2, with a total coverage of 55,255 km^2, accounting for 56.8% of China's total lake area. The basin area ranges from 100 to 657,165 km^2. This study did not adopt pre-defined sub-basins from HydroBASINS due to their inconsistency with actual lake drainage boundaries. Instead, an automated watershed delineation approach was employed to independently extract the basin area for each lake by treating the lake pour point as the basin outlet (Xie et al., 2022). This refined delineation accurately characterizes the hydro-connectivity topology of the lake and its basin, providing reliable geographic units to investigate the hydrological transport processes in the atmosphere–basin–lake system. The ratio of basin area to lake area ranges from 1.3 to 341,802. The selected 1,617 lakes were classified as natural lakes and reservoirs according to a comprehensive reservoir dataset (CRD) of China released by Song et al. (2022b). For a certain lake of HydroLAKES, the boundaries of HydroLAKES and CRD overlapped first. When the overlapping area exceeded 70% of HydroLAKES, the lake type was assigned as reservoirs. The other lakes were assigned to natural lakes. Finally, 882 natural lakes and 735 reservoirs were classified, accounting for 83% and 17% of the total area of selected lakes, respectively (Figure 2). All the lakes were categorized into six zones according to the geographical division of China, including Yunnan-Guizhou Plateau (YGP), Tibetan Plateau (TP), Uygur Autonomous Region (UAR), Inner Mongolia Plateau (IMP), Northeast Plains and Mountains (NEPM), and Eastern Plains (EP).

The monthly lake water area from 1985 to 2018 was reconstructed by Zhao et al. (2022), using a robust image enhancement algorithm based on the dynamic Landsat-based global surface water dataset and the static HydroLAKES boundaries. The data spanned from 1985 to 2018, that is, the whole observation period. The period from 2000 to 2018 was considered as the changed period due to intensified human activities and high-frequency satellite observations. The precipitation and runoff (sum of surface and subsurface runoffs) of each lake basin were obtained from the Inter-Sectoral Impact Model Intercomparison Project phase 3a (ISIMIP3a) (Frieler et al., 2024). Runoff from five terrestrial hydrology models was employed, including four global hydrological models (GHMs; CWatM, H08, HydroPy, and WaterGAP2-2e) and one global land surface model (MIROC-INTEG-LAND). The spatial resolution of ISIMIP data is 0.5° × 0.5°. The population and Gross Domestic Product (GDP) datasets of China in 2015 with a resolution of 1 km × 1 km were employed to estimate the impacts of propagation from AWD to lake drought on socioeconomic systems (Wang & Wang, 2022a; Wang

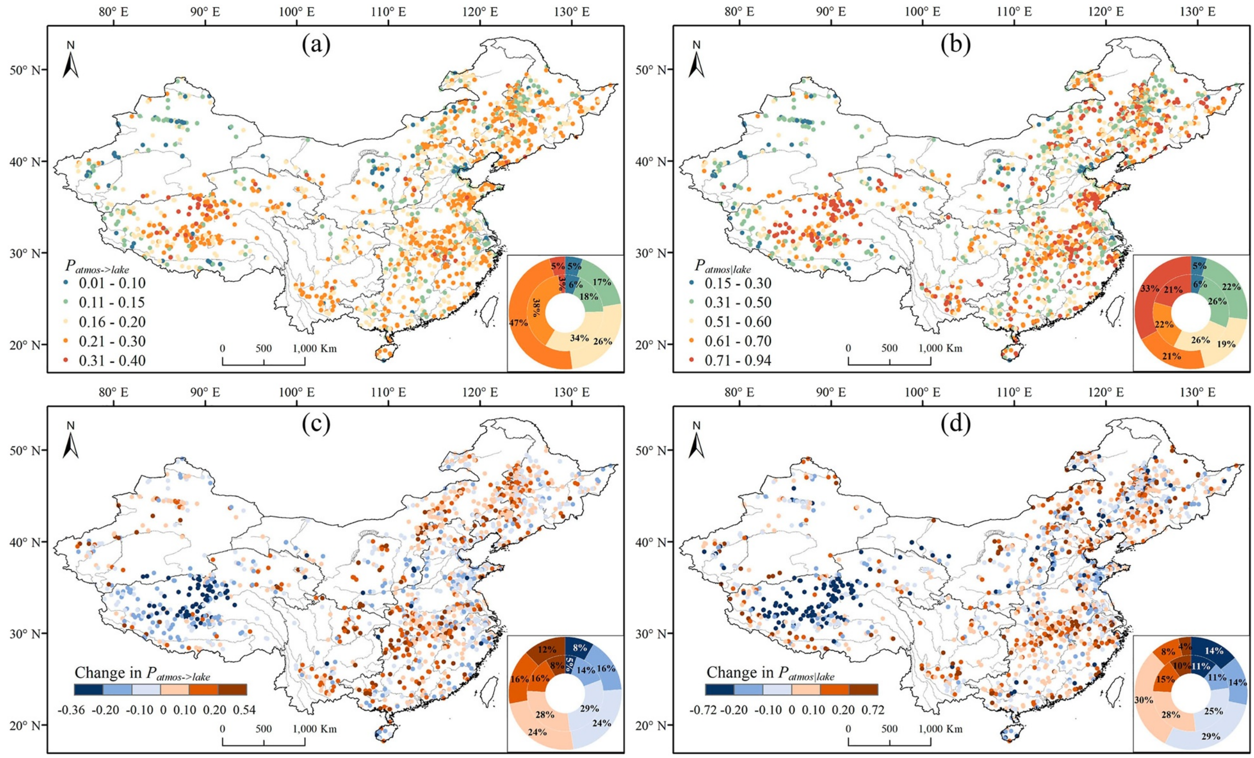

Figure 3. Spatial distributions of propagation probabilities (a) $P_{atmos\rightarrow lake}$ and (b) $P_{atmos|lake}$ from AWD to lake drought in China. Changes in (c) $P_{atmos\rightarrow lake}$ and (d) $P_{atmos|lake}$, calculated as the difference between each variable during 2000–2018 and 1985–2018. The points are the lake outlets of lake basins. The inner and outer rings of the donut represent the proportions of the lake number and area to the total values, respectively.

& Wang, 2022b). The land use dataset of China in 2015 with a resolution of 1 km × 1 km was used to analyze the impacts of different land use types on the propagation. A lake basin was classified as cropland-, forest-, or grassland-dominated if any single land cover type exceeded 50% of its total area. In addition, lake basins with >10% residential land cover was categorized as residential-influenced, reflecting urbanization impacts on water shortage propagation.

3. Results

3.1. Distributions of Propagation Probabilities From AWD to Lake Drought

The propagation probabilities from AWD to lake drought calculated from the five terrestrial hydrology models were first compared (Figure S1 in Supporting Information S1). Equations 3 and 4 demonstrate that differences in propagation probabilities between models primarily stem from P_{vine} variations, that is, the concurrent probability of AWD, BWD, and lake drought. Figure S1 in Supporting Information S1 shows that the P_{vine} from different models correlates well, with Pearson correlation coefficients exceeding 0.78. Therefore, it is reasonable to use the average values from the five models to reduce uncertainties in propagation probability calculations. Figures 3a and 3b show the spatial distributions of propagation probabilities from AWD to lake drought in China's lake basins. Generally, high propagation probabilities mainly occurred in the Tibetan Plateau and the low values occurred in Northwestern China. The $P_{atmos\rightarrow lake}$ averaged from the selected lake basins was 0.19 ± 0.06 (one standard deviation), meaning that 19% of AWDs propagated to lake droughts at the national scale. The $P_{atmos|lake}$ averaged from the selected lake basins was 0.57 ± 0.15, meaning that 57% of lake droughts were related to AWDs. The $P_{atmos|lake}$ values were larger than $P_{atmos\rightarrow lake}$ because the P_{LDT} values were smaller than the P_{AWD}. Among the six lake zones, the high propagation probabilities occurred in the TP and YGP zones during 1985–2018, as shown by blue bars in Figures 4a and 4b. The high propagation probabilities in these two zones are primarily driven by intense land-atmosphere coupling characteristic of high-altitude regions, where strong

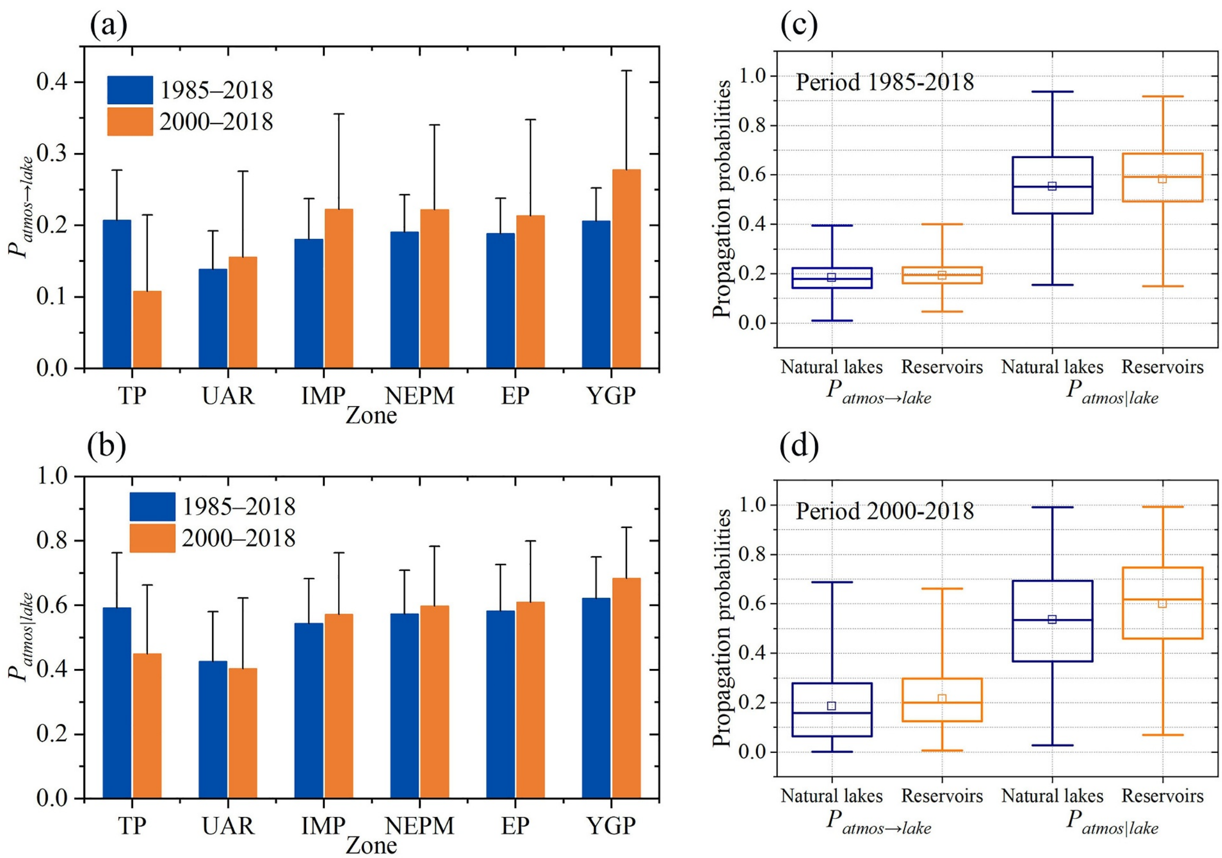

Figure 4. Propagation probabilities (a) $P_{atmos\rightarrow lake}$, and (b) $P_{atmos|lake}$ from AWD to lake drought for the six lake zones during 1985–2018 and 2000–2018. The black bar is one standard deviation. Comparison of propagation probabilities between natural lakes and reservoirs (c) from 1985 to 2018 and (d) from 2000 to 2018. On each box, the central mark is the median, the square is the average, the edges of the box are the 25th and 75th percentiles, and the whiskers are the most extreme values.

interactions between surface hydrology and atmospheric dynamics amplify water shortage transmission to lakes (Long et al., 2014; Yang et al., 2025; Zhu et al., 2023).

It is worth noting that reservoir basins exhibited higher propagation probabilities compared to natural lake basins during 1985–2018, indicating their greater susceptibility to AWDs (Figure 4c). This divergence primarily stems from contrasting hydrological regulation mechanisms: reservoirs experience accelerated water level fluctuations due to anthropogenic controls (e.g., irrigation releases, hydropeaking), which degrade their natural buffering capacity against AWDs, while natural lakes maintain gradual water level dynamics through delayed groundwater recharge and snowmelt-dominated hydrological cycles, with wetland ecosystems further attenuating water shortage propagation signals (Hughes et al., 2012; Xi et al., 2021). In addition, land use patterns in lake basins also influence the propagation probabilities from AWD to lake drought. As shown in Figure 5, the forest-dominated lake basins exhibit the highest drought propagation probability, followed by cropland- and grassland-dominated lake basins, while residential-influenced lake basins show the lowest probability. This difference arises from distinct hydrological regulation mechanisms across ecosystems: the strong evapotranspiration from forest canopies and soil moisture depletion caused by deep root systems intensifies the cascading transmission of atmospheric water shortage to soil and lake systems at the annual scale (Peterson et al., 2021; Yang et al., 2017). In contrast, cropland irrigation and grasslands' shallow water retention partially mitigates drought signal accumulation, creating moderate buffering effects. Conversely, impervious surfaces in residential areas promote rapid runoff generation, and artificial drainage systems disrupt natural hydrological connectivity, thereby weakening AWD–BWD–lake drought cascading effects (Rachunok & Fletcher, 2023; Salvadore et al., 2015).

The propagation processes were further disentangled by comparing propagation probabilities from the atmosphere to the basin and from the basin to the lake (Figures 6a and 6b). About 87% of AWDs converted to BWDs whereas only 21% of BWDs converted to lake droughts, indicating that AWDs strongly influenced BWDs,

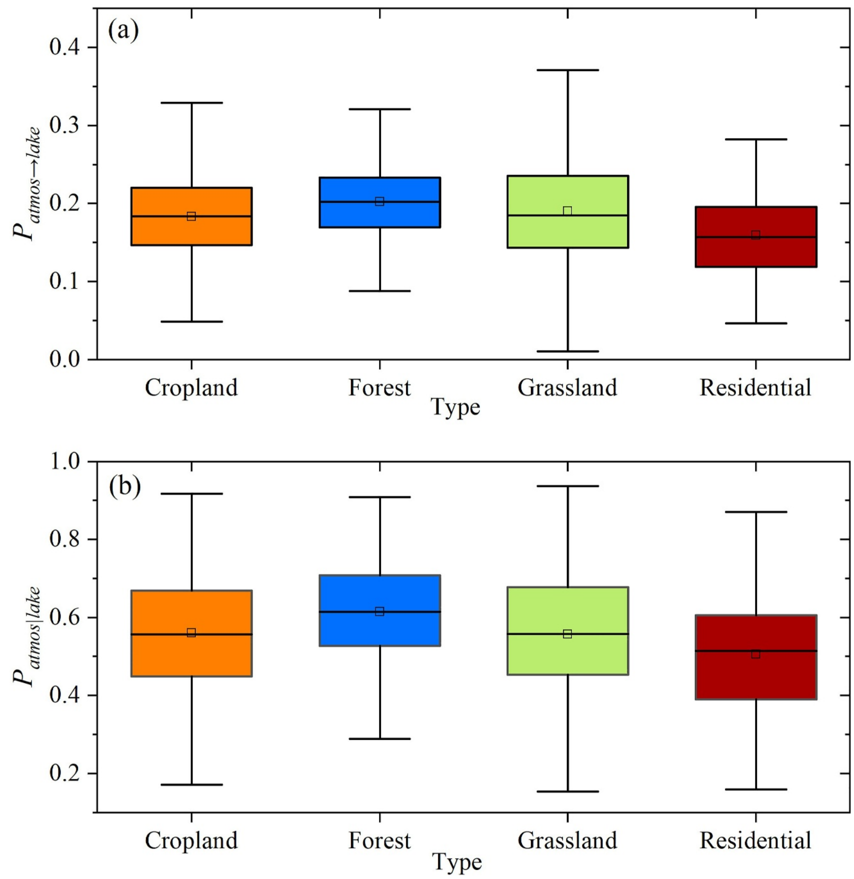

Figure 5. Propagation probabilities (a) $P_{atmos\to lake}$, and (b) $P_{atmos|lake}$ from AWD to lake drought for different land use types during 1985–2018. On each box, the central mark is the median, the square is the average, the edges of the box are the 25th and 75th percentiles, and the whiskers are the most extreme values.

whereas BWDs had a weaker influence on lake droughts at the annual scale. To reduce the impact of different water deficit thresholds of the atmosphere, the basin, and the lake, we set these three thresholds to the same value of −1 (Figures 6c and 6d). The propagation probabilities from AWD to BWD ($P_{atmos\to basin}$, $P_{atmos|basin}$) were (0.70 ± 0.14, 0.72 ± 0.14), whereas the propagation probabilities from BWD to lake drought ($P_{basin\to lake}$, $P_{basin|lake}$) were (0.30 ± 0.14, 0.27 ± 0.13). The results confirm that the propagation from AWD to BWD is robust, whereas the propagation from BWD to lake drought is significantly weaker, reflecting the complexity of lake drought dynamics.

3.2. Changes in Propagation Probabilities From AWD to Lake Drought

Figures 3c and 3d show the changes in $P_{atmos\to lake}$ and $P_{atmos|lake}$ in lake basins across China during 2000–2018 compared with 1985–2018. The changes in these two propagation probabilities had distinct regional characteristics. The positive values occurred in Northeast China and the south of 30–31°N, whereas the negative values occurred in the Tibetan Plateau and the plains of the Yellow, Huai, and Hai rivers. Although the spatial patterns of changes in $P_{atmos\to lake}$ and $P_{atmos|lake}$ are similar, the correlation coefficient between them is only 0.28, which is caused by the low relationship between P_{AWD} and P_{LDT} (Figure S2 in Supporting Information S1). The changes in P_{LDT} explained 81% of the changes in $P_{atmos\to lake}$ and the changes in P_{AWD} explained 22% of the changes in $P_{atmos|lake}$ (Figure S3 in Supporting Information S1). For the six zones, the changes in the propagation probabilities increased in the IMP, NEPM, EP, and YGP zones, indicating widespread enhanced propagation ability from AWD to lake drought in lake basins over the eastern regions of China (Figures 4a and 4b). In addition, the changes in propagation probabilities for the reservoir basins increased, indicating that the propagation from AWD to lake drought was enhanced for the reservoir basins (Figure 4d).

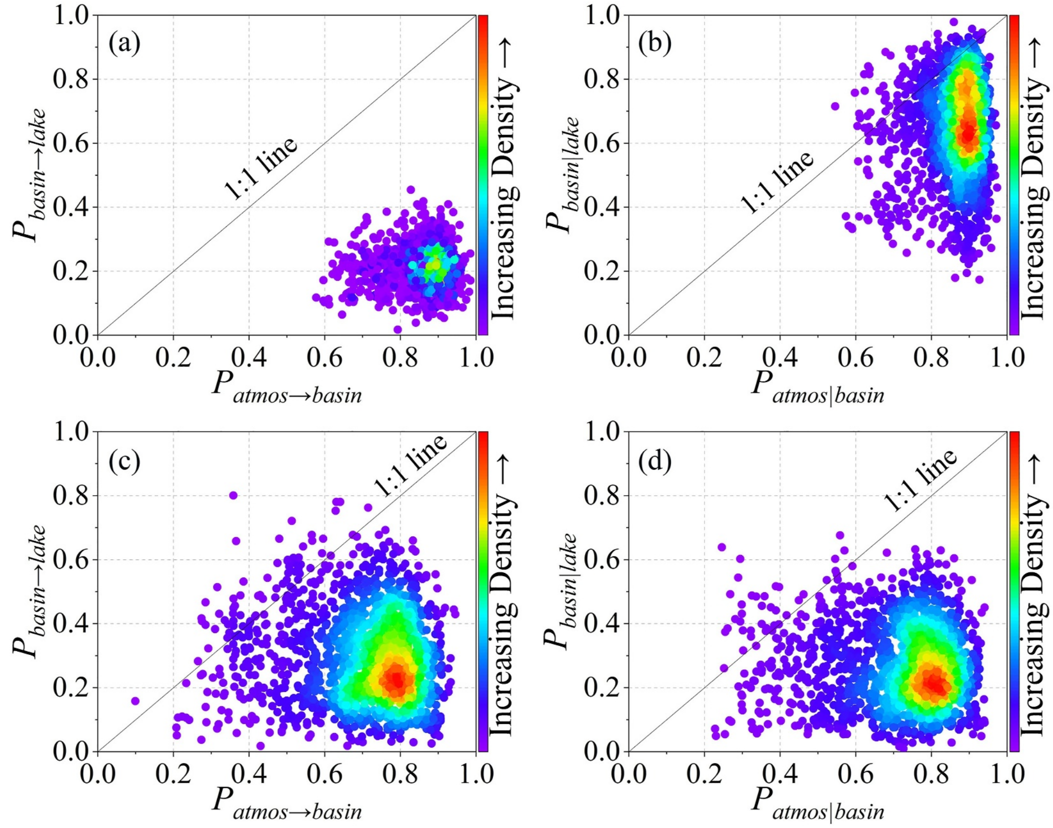

Figure 6. Propagation probabilities (a) from AWD to BWD and (b) from BWD to lake drought. (c)–(d) are similar to (a)–(b), but the water deficit thresholds of the atmosphere, the basin, and the lake were set to the same value of −1, that is, SPI ≤ −1, SRI ≤ −1, and SWI ≤ −1.

3.3. Lake Basin Classification for Lake Drought Management

The selected lake basins were classified into three groups with six subtypes based on our proposed framework (Figure 7a). 28% of the selected lake basins belonged to Type I, mainly located in northeast China and the middle-lower reaches of the Yangtze River. The propagation ability from AWD to lake drought in these lake basins increased, resulting in a risk of lake shrinkage. Specifically, the lake basins in northeast China need to be alert to the risk of water scarcity, and the lake basins in the middle-lower reaches of the Yangtze River need to be alert to the crisis of ecosystem degradation (Cai et al., 2016; Li et al., 2024). These lake basins require an urgent response to address the adverse effects of climate change. Notably, Type I accounts for 33% (by number) of reservoir basins and 25% (by number) of natural lake basins (Figure 8), confirming that reservoirs are more susceptible to AWDs than natural lakes. 25% of the selected lake basins belong to Type II, which were mainly located in the Tibetan Plateau and the plains of the Yellow, Huai, and Hai rivers. The propagation ability from AWD to lake drought in these lake basins decreased. Taking the Tibetan Plateau as an example, lake basins in this region have mainly faced the problem of lake expansion in recent years (Xu et al., 2024). The propagation chain of Type I and Type II lake basins was AWD−BWD−lake drought. The increased (Type III) and decreased (Type IV) propagation ability from BWD to lake drought accounted for small proportions of the selected lake basins. Lake droughts of these two types were mainly related to BWDs, indicating that integrated lake basin management would be effective. The propagation chain of Type III and Type IV was non-AWD−BWD−lake drought. 18% and 19% of the selected lake basins belonged to Type V and Type VI, respectively. These lake basins were widely distributed throughout China. Drought changes in these lakes were predominantly governed by lake-specific hydrological conditions rather than basin-scale processes. These lake basins need to pay more attention to the impact of human activities or natural changes on the lakes themselves, as the basins' influence on lakes is limited.

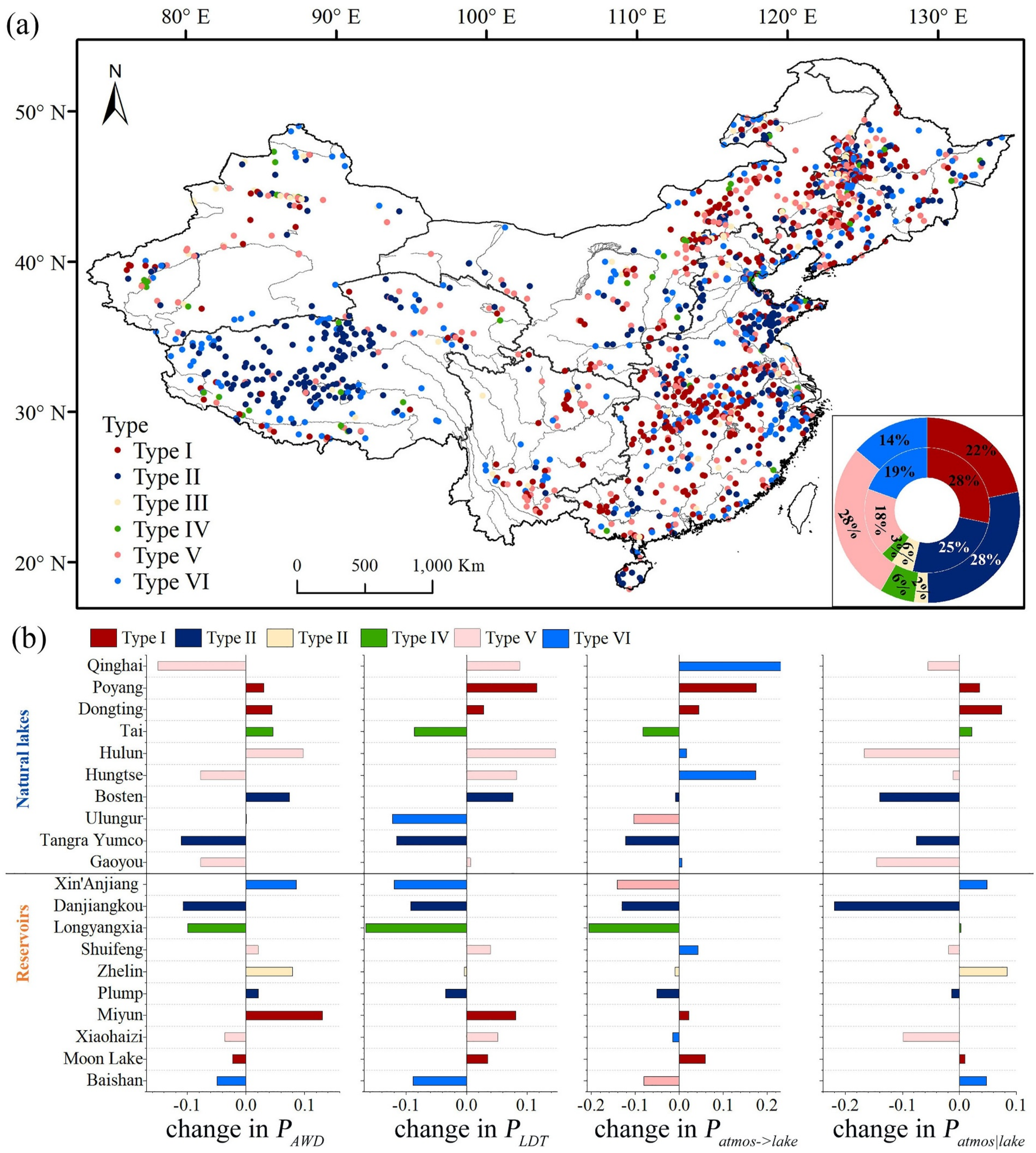

Figure 7. (a) Lake basin classification across China. The inner and outer rings of the donut represent the proportions of the lake number and area of each type to the total values, respectively. (b) Types for the top 10 largest natural lakes and reservoirs according to the water area of the selected lake basins. The water area of the natural lakes and reservoirs from top to bottom decreases.

4. Discussion

4.1. Implications for Lake Drought Management

Although integrated lake basin management toward effective water governance has been advocated in many countries and organizations, this issue has not received sufficient attention in global water policies (Avramoski, 2004; Cheng & You, 2019; Soeprobowati, 2015). China has proposed integrated lake basin management since 2017, named "a holistic approach to conserving mountains, rivers, forests, farmlands, lakes, and grasslands"

Figure 8. Classification heatmaps of the proportions of the lake number of each type to the total values for (a) natural lake basins and (b) reservoir basins. (c) And (d) are similar to (a) and (b), but for the proportions of lake area of each type to the total values.

(Cheng & You, 2019; Kong et al., 2019). According to our proposed lake basin classification framework, this study divided lake basins into three groups with six subtypes based on natural physical process of water shortage propagation in the atmosphere−basin−lake system, which provides new insights into effectively managing lake droughts in China.

Lake droughts in Type I lake basins were aggravated by AWD variations, reminding the decision-makers to be aware of lake shrinkage risks caused by atmospheric and runoff deficits. Figure 9 shows that Type I lake basins influenced 21% of the national land area, 16% of the population, and 13% of the GDP. In other words, the strong human interventions reflected by the population and GDP might also exacerbate the crisis of lake drought, such as irrigation, domestic water use, and reservoir operation (Apurv & Cai, 2021; Zhang et al., 2018). For example, Poyang Lake (Type I; Figure 7b), the largest freshwater lake in China, experienced record-breaking droughts in the summer of 2022 due to abnormal atmospheric precipitation (Zhang, Xue, & Xia, 2023). The operation of the Three Gorges Dam (TGD) exacerbated this drought, as it down-cut river channel and decreased runoff of the mainstream Yangtze River (Lai et al., 2014). Although the TGD has a function of drought alleviation, its regulation effect on this drought was limited due to the water released before the flood season. In addition, there are very high-density reservoirs in the Poyang Lake basin, but their main functions are flood control, power generation, and irrigation. It is necessary to strengthen the medium- and long-term hydrological forecasting capabilities for rivers and lakes and improve the regulating function of reservoirs during drought. From broader geophysical and climatic perspectives, reduced lake area and water storage may weaken evaporative cooling effects, thereby exacerbating regional heatwaves and altering local hydrological cycles (Fan et al., 2024; Wang et al., 2024). Such feedbacks could amplify atmosphere–land interactions, particularly in densely populated basins where human activities intersect with natural processes (Woolway et al., 2018). However, current Earth system models often oversimplify these coupled dynamics, limiting their capacity to predict cascading hydro-climatic impacts.

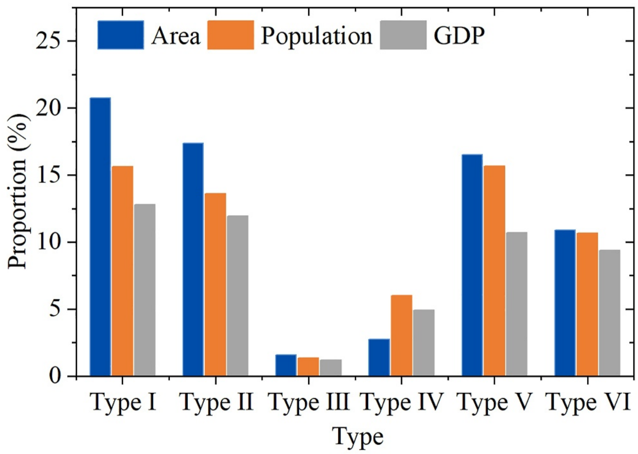

Figure 9. Proportions of area, population, and GDP affected by different lake basin types relative to national totals.

Compared to Type I lake basins, lake drought caused by AWD has been mitigated in Type II lake basins. Most of these lake basins are in the TP zone, where drought mitigation is primarily attributed to the increased precipitation resulting from climate warming (Xu et al., 2024). Lake drought management in these basins can be temporarily de-prioritized. However, the risk of lake shrinking in the other lake basins is still high. For instance, P_{LDT} in Bosten Lake (Type II; Figure 7b), the largest freshwater lake in Northwest China, increased from 0.14 in 1985–2018 to 0.22 in 2000–2018, reflecting decoupled atmospheric forcing and heightened anthropogenic impacts. The management strategy for these lake basins aligns with that of Type V lake basins, as lake droughts in Type V are predominantly governed by lake-specific hydrological conditions, including precipitation, evaporation, outflow regulation, and consumptive water use, rather than basin-scale processes. Hulun Lake, Hungtze Lake, and Gaoyou Lake belonged to this type (Figure 7b). Drought changes in these three lakes were mainly affected by human activities, and it is urgent to prevent water quality deterioration and ecosystem degradation (Cui & Li, 2016; Huang et al., 2023). In addition, attention should be paid to the drought changes in the Miyun Reservoir, which is the water destination region of the central South−to−North Water Diversion project (Long et al., 2020). Although the water area of this reservoir has been recovered since 2015 due to the Water Diversion project, climate-driven risks require proactive mitigation (Zheng et al., 2016) (Figure S4 in Supporting Information S1).

4.2. Limitations

The lake water area data used in this study have limitations that require future improvements. These data were reconstructed from remote sensing imagery (Zhao, 2021). Pre-2000 Landsat images suffered from low observation frequency and contamination by clouds, cloud shadows, and terrain shadows, resulting in substantial data gaps (Pekel et al., 2016; Vicente-Serrano et al., 2008). These gaps may underestimate lake hydrological fluctuations, such as rapid expansion following intense precipitation events. For example, Zhao and Gao (2018) demonstrated that correcting contaminated images for 6,817 global reservoirs (1984–2015) increased estimated reservoir surface area from 1.73×10^5 km^2 to 3.94×10^5 km^2. In addition, the lake water area extraction relies on the buffered HydroLAKES database's static water body boundaries, but climate warming-driven lake expansion and basin reorganization have caused significant water area changes in high-altitude regions like the Qinghai-Tibet Plateau (Liu et al., 2021; Vacherat et al., 2018; Xu et al., 2024), potentially introducing inaccuracies in maximum lake water area estimates for these reorganized basins. Up to now, most lake modules in ecological, hydrological, water quality, and Earth system models parameterize lakes as static entities with fixed sizes (Frieler et al., 2024; Müller Schmied et al., 2023). This oversimplification severely constrains predictive capabilities for future evolution trends of large-scale hydrological processes in lake basins.

Second, the study analyzed the propagation from AWD to lake drought using SPI and SWI over the same 12-month period, potentially underestimating the complexity of water shortage propagation in atmosphere–basin–lake systems (Sattar et al., 2019; Yang et al., 2024). We calculated correlation coefficients between SPI and SWI with lags of 1–12 months. Results show a maximum average correlation of 0.29 (Figure S5 in Supporting Information S1), explaining only 8% of SWI variability. This indicates that lagged effects were weak compared to dominant drivers like groundwater recharge and human activities. At annual or multi-year scales, SWI-SPI lagged relationships are masked by interacting hydrological processes (e.g., vegetation transpiration delays, irrigation withdrawals), which may generate spurious correlations (Peterson et al., 2021). This study used a probability statistical method focused on annual-scale analysis to avoid overinterpreting noise-driven signals, providing a robust framework for lake drought assessment.

Third, the lake basin classification did not consider the lake outflow due to the lack of observation records. The lake outflow is influenced by the hydrological conditions of the river where the lake flows, which cannot be ignored in some lake basins. Taking Poyang Lake, flowing into the Yangtze River, as an example, the decrease in water level of the Yangtze River leads to an increase in lake outflow and hence aggravates lake drought (Zhang et al., 2017). Exploring lake outflow dynamics through an integrated framework combining Earth system models, high-resolution river network topology, and lake bathymetry would advance understanding of how climate–land–human interactions modulate water shortage propagation in atmosphere–basin–lake systems (Baydaroğlu et al., 2023; Shen, 2018). This study emphasizes the water transfer processes from the atmosphere to the basin and to the lake, so a tentative classification was conducted toward this objective. More classifications can be designed toward different goals.

5. Conclusions

This study investigated the propagation from AWD to lake drought in 1,617 lake basins of China and proposed a novel lake basin classification framework for lake drought management for the first time. This study emphasized the water shortage propagation from the atmosphere to the basin and to the lake, highlighting the importance of simultaneously addressing the adverse effects of climate change and strengthening lake management. The finding of this study extends current hydrological research of lakes, providing new insight into coping with lake drought under climate change.

Data Availability Statement

We are grateful to Lange et al. (2023) for providing the ISIMIP3a precipitation dataset, Gosling et al. (2024) for providing the ISIMIP3a runoff dataset, Zhao (2021) for providing the lake water surface area dataset, Song et al. (2022a) for providing the geospatial database of nearly 100,000 reservoirs in China, Wang and Wang (2022b) for providing the GDP, and Wang and Wang (2022a) for providing the population dataset, and Xu et al. (2019) for providing the land use dataset.

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