Supplementary Materials

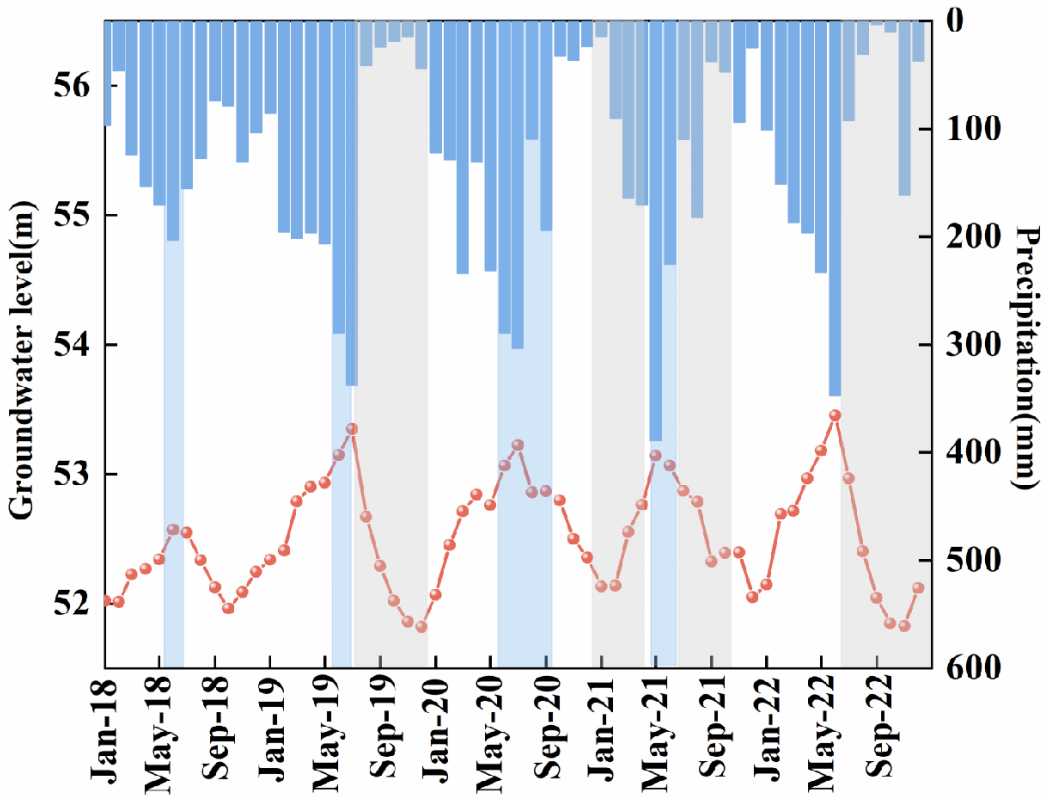

Figure S1. Monthly precipitation and groundwater level data for the Poyang Lake area (2018-2022), with shaded blue and gray areas indicating extreme flooding and drought periods, respectively.

During the model training process, an excessive number of input variables can lead to overfitting. To reduce model complexity, lower computational costs, and mitigate the impact of noise on the model, Partial Least Squares Regression (PLSR) is used to assess the contributions of different predictor factors to the GRACE TWSA in Poyang Lake. As a powerful analytical tool, PLSR combines two techniques: Principal Component Analysis (PCA) and Multiple Linear Regression (MLR) [102]. It not only takes into account the information from the explanatory variables in PCA but also incorporates information from the response variables. This allows PLSR to effectively extract the majority of the explanatory variables. Shi et al. [103] used PLSR to model TWS changes and quantify the relative contributions of various factors to the changes in TWS. The Variable Importance in Projection (VIP) scores and regression coefficients (RC) are used to explain the relative influence of each independent variable. Generally, independent variables with VIP values greater than 0.8 are considered most relevant and important for explaining the dependent variable, while those with values less than 0.5 indicate that the variable does not significantly explain the dependent variable [104–106]. The basic PLSR algorithm can be referenced in Shi et al. [107] and Ma et al. [108]. The VIP score for the i-th variable is calculated as follows:

$$VIP_i = \left[\frac{q \cdot \sum_{n=1}^{h} R\left(Y, t_n\right) \cdot w_{ni}^2}{\sum_{n=1}^{h} R\left(Y, t_n\right)}\right]^{\frac{1}{2}} \quad \text{(S1)}$$

where h represents the number of extracted components, q denotes the number of predictor factors, and t_n is the n-th component. $R(Y, t_n)$ indicates the explanatory power of the n-th component for the predicted variable Y, and w_{ni} represents the marginal contribution of the predictor factor to Y.

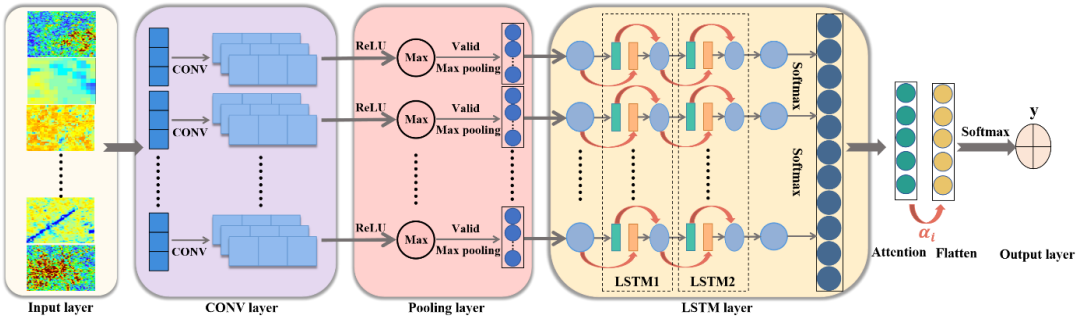

Figure S2. CNN-LSTM-Attention Downscaling Model Framework.

Table S1. Groundwater Drought Classification Based on SGSAI.

Categorization	Drought severity	Range
W3	Extreme wet	（2.0,∞）
W2	Severe wet	（1.5,2.0）
W1	Moderate wet	（1.0,1.5）
W0	Mild wet	（0.5,1.0）
WD	No drought and no wet	（-0.5,0.5）
D0	Mild drought	（-1.0,-0.5）
D1	Moderate drought	（-1.5,-1.0）
D2	Severe drought	（-2.0,-1.5）
D3	Extreme drought	（-∞,-2.0）

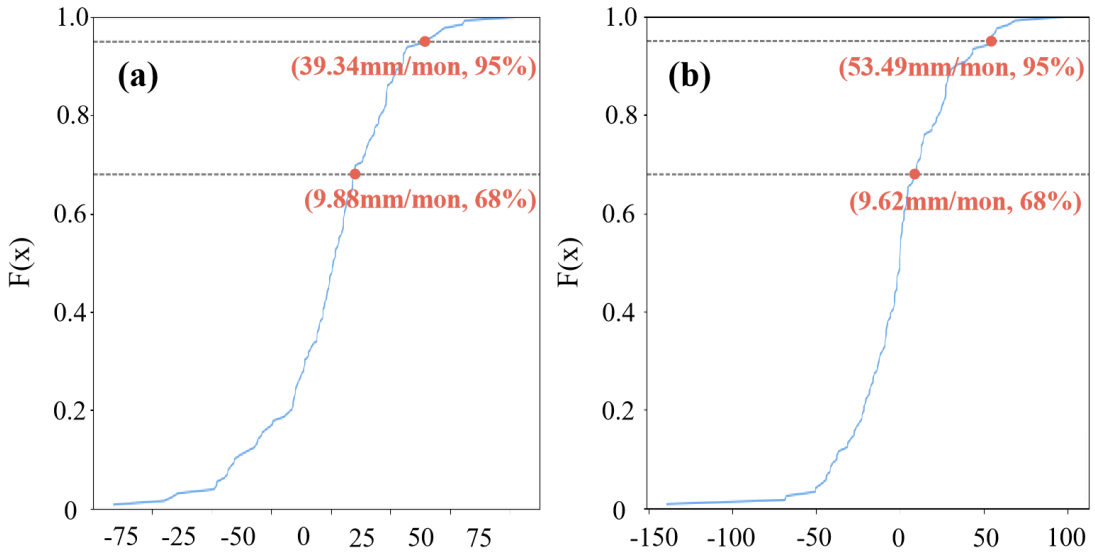

Figure S3. The empirical cumulative distribution function (eCDF) curves of the monthly gap change rate (dM/dt) based on GWS. (a) and (b) represent the function curves for drought and flood, respectively.

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