

Investigating a complex lake-catchment-river system using artificial neural networks: Poyang Lake (China)

Y. L. Li, Q. Zhang, A. D. Werner and J. Yao

ABSTRACT

Lake hydrological simulations using physically based models are cumbersome due to extensive data and computational requirements. Despite an abundance of previous modeling investigations, real-time simulation tools for large lake systems subjected to multiple stressors are lacking. The back-propagation neural network (BPNN) is applied as a first attempt to simulate the water-level variations of a large lake, exemplified by the Poyang Lake (China) case study. The BPNN investigation extends previous modeling efforts by considering the Yangtze River effect and evaluating the influence of the Yangtze River on the lake water levels. Results indicate that the effects of both the lake catchment and the Yangtze River are required to produce reasonable BPNN calibration statistics. Modeling results suggest that the Yangtze River plays a significant role in modifying the lake water-level changes. Comparison of BPNN models to a 2D hydrodynamic model (MIKE 21) shows that comparable accuracies can be obtained from both modeling approaches. This implies that the BPNN approach is well suited to long-term predictions of the water-level responses of Poyang Lake. The findings of this work demonstrate that BPNN can be used as a valuable and computationally efficient tool for future water resource planning and management of the Poyang Lake.

Key words | artificial neural networks, lake–river interaction, lake water level, Poyang Lake, Yangtze River

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INTRODUCTION

A proper understanding of the factors influencing lake water-level fluctuations and an ability to predict these under various future scenarios are important for managing lake resources, in terms of sustaining ecosystem health, providing reliability of water supply, and for the design and operation of lakeshore structures (e.g., Wantzen *et al.* 2008; Cimen & Kisi 2009). Lake water-level changes represent the end result of the complex interplay of various water balance components (Altunkaynak 2007; Pasquini *et al.* 2008). As such, lake hydrographs reflect the history of integrated hydrological changes, often occurring across extensive areas (e.g., Shankman *et al.* 2012; Khatibi *et al.* 2014). In some cases, severe floods and droughts in lake storage behavior can occur, leading to significant socioeconomic losses and environmental stress (Legesse *et al.* 2004; Shankman *et al.* 2012), and the causal factors can be challenging to accurately

determine. It is therefore important to properly understand and quantitatively link the hydrological drivers that govern lake and catchment water balance fluxes to the response dynamics of lake water levels.

Poyang Lake is located in the middle reaches of the Yangtze River and is the largest lake in China, covering some 3,000 km² during wet seasons. The lake is subject to considerable annual variations in water levels (up to 18 m) and surface area, reducing to about one-third its wet season extent during the dry winter period (Hui *et al.* 2008; Feng *et al.* 2012). The seasonality in water levels creates expansive wetlands, which are important conservation sites that provide internationally recognized winter habitats for large numbers of wild water birds, including several endangered species (Kanai *et al.* 2002). The functioning of Poyang Lake wetlands and the associated ecosystems are

particularly sensitive to subtle changes in the lake's water level (Barzen *et al.* 2009). In addition, some 10 million inhabitants depend on the lake for water extraction and farmland management, and land practices are closely linked to the historical seasonality in the lake's extent (Jiang *et al.* 2008; Zhen *et al.* 2011).

Changes in the lake's hydrological regime in the last decade (Shankman *et al.* 2012; Liu *et al.* 2013) have caused considerable impacts on water supply reliability and ecosystem health (Barzen *et al.* 2009; Yu *et al.* 2010; Zhang *et al.* 2012c), and have led to significant research effort to evaluate the driving factors of the lake's hydrology (e.g., Zhang & Xie 2013; Xie *et al.* 2014). The earliest investigations of Poyang Lake's modified hydrology concluded that the lake water level is controlled primarily by seasonal variations in catchment inflows (Shankman *et al.* 2006; Hu *et al.* 2007; Guo *et al.* 2008). However, subsequent research found that changes in the flow regime of the Yangtze River also influence the lake's behavior (Guo *et al.* 2012; Zhang *et al.* 2012b), mostly due to the blocking effect of the Yangtze River in flood seasons (Hu & Xiong 2002; Cui *et al.* 2009).

Previous studies have developed Poyang Lake simulation models to assess causal factors of abnormal water-level variations, and to predict future lake behavior under various climatic and development scenarios. For example, Lai *et al.* (2013), Li *et al.* (2014), and Wang *et al.* (2014) simulated the transient, distributed water-level behavior of Poyang Lake using physically based hydrodynamic models: CHAM (Lai *et al.* 2013), MIKE 21 (DHI (Danish Hydraulic Institute) 2007), and EFDC (Hamrick 1992), respectively. Reasonable matches to observation data were obtained with limited calibration effort, and the models collectively produced important insights into the lake's functioning. However, Poyang Lake's vast extent and the large water-level variability present significant challenges for hydrodynamic simulation, which are computationally expensive and therefore limited to simulations of restricted duration (e.g., two 1-year sequences, Lai *et al.* 2013; 9 years, Li *et al.* 2014; and 9 months, Wang *et al.* 2014). Therefore, hydrodynamic models provide relatively short-term insight into the modifications to Poyang Lake's hydrology, which has changed over several decades under significant shifts in climate stresses and following the construction of numerous structures within the lake's catchment and

along the Yangtze River (Yang *et al.* 2006; Guo *et al.* 2012; Shankman *et al.* 2012).

To study the long-term trends in Poyang Lake's water levels, Min (1995), Wan *et al.* (2003), Huang & Zhong (2004), and Ye *et al.* (2011) developed statistical models to relate Poyang Lake water levels to climate drivers within its catchment. However, the effects of the Yangtze River were neglected in these investigations. To properly evaluate the lake's hydrological regime shift, the effects of both the Poyang Lake catchment and the Yangtze River need to be taken into account, given recent studies that demonstrate their combined roles in controlling lake functioning (Guo *et al.* 2011; Zhang *et al.* 2014).

In this study, artificial neural network (ANN) techniques are applied to the simulation of Poyang Lake water levels, accounting for Yangtze River and Lake catchment controls. ANNs have been successfully applied to simulate the hydrological behavior of several large lake systems, particularly where computational efficiency is of paramount importance (i.e., to allow for long-duration predictions of lake storage behavior) (Lin *et al.* 2008; Cimen & Kisi 2009; Zhang *et al.* 2012a; Sonmez *et al.* 2013). ANN models are simpler and more feasible than many conventional statistical approaches, such as autoregressive and moving average, among others, as demonstrated by the successful application of ANNs to various hydrological problems (Suen & Eheart 2003; Altunkaynak 2007; Panda *et al.* 2010). However, they lack a physical basis and require long historical time series of hydrological responses that are commensurate with the types of predictions that the model will be expected to make (Lin *et al.* 2008; Hashemi *et al.* 2010; Bedri *et al.* 2014). Despite the effectiveness of ANNs in resolving the hydrological responses of various hydrological systems (e.g., rivers, estuaries, lakes, etc.; Altunkaynak 2007; Cimen & Kisi 2009; Yasar *et al.* 2009; Güldal & Tongal 2010; Mpalas *et al.* 2011; Kisi *et al.* 2012; Sonmez *et al.* 2013; Khatibi *et al.* 2014; Mwale *et al.* 2014), there are no examples of ANN applications to a lake-catchment-river hydrological system of the complexity and scale of Poyang Lake.

The specific objectives of this paper are: (1) to develop and apply an ANN model for the prediction of Poyang Lake water-level changes, incorporating Yangtze River and lake catchment effects; and (2) to evaluate the performance of the ANN model by comparison to a physics-based

hydrodynamic model of the lake. A number of previous studies have compared ANNs to hydrodynamic approaches to provide important insights into model performance, thereby strengthening confidence in model applications. These include a number of river- and lake-stage investigations (e.g., Shrestha *et al.* 2005; Panda *et al.* 2010; Chen *et al.* 2012a, 2012b). For example, Panda *et al.* (2010) compared the performance of an ANN technique to the hydrodynamic model MIKE 11 for Kushabhadra River stage simulation (India). They reported that the ANN model was superior to MIKE 11 in terms of goodness-of-fit indices, and in particular, for the simulation of peak water levels. Liu & Chen (2012) used ANN and 3D hydrodynamic models to predict water temperatures in Yuan-Yang Lake (China). The results indicated that the 3D hydrodynamic model provided a better prediction of depth-dependent water temperatures in the calibration and validation phases, except at 3 m below the water surface, where the ANN approach exhibited more satisfactory results. The current study is the first attempt to compare a data-driven ANN approach to a physically based 2D hydrodynamic model for the simulation of water levels in a large and complex lake-catchment-river system.

STUDY AREA

Poyang Lake (28°4′–29°46′N, 115°49′–116°46′E) is the largest freshwater lake in China, and has an internationally recognized wetland system (Feng *et al.* 2011). The lake and its catchment are located in the mid-to-lower reaches of the Yangtze River (see Figure 1(a)). The lake catchment experiences a wet, subtropical climate with mean annual precipitation and pan evaporation (averaged across the catchment) of 1,666 and 1,034 mm/year, respectively (Li *et al.* 2014). Poyang Lake receives inflows predominantly from five major rivers (Ganjiang, Fuhe, Xinjiang, Raohe, and Xiushui Rivers) within its 16.22×10^4 km² catchment (Shankman *et al.* 2012). Other inflow sources include minor streams around the lake shoreline, rainfall to the lake's surface, and seasonal Yangtze River inflows. The lake discharges to the Yangtze River at Hukou (the junction of the Yangtze River and Poyang Lake) in the north (see Figure 1(a)).

It is a geometrically complex lake with tortuous shorelines and incised bottom morphology, which are shaped

by a combination of lacustrine and riverine morphological processes (Gao *et al.* 2014). The lake bottom elevation decreases from south (upstream) to north (downstream) (see Figure 1(b)), with a difference of about 6.5 m (Li *et al.* 2014). The lake is generally shallow with an average depth of 8 m and maximum depth of 29 m near the downstream extremity of the lake during flood seasons (Wang & Dou 1998). Lake water levels vary by 8–18 m each year in response largely to the seasonality in rainfall. Differences in water surface elevations (across the length of the lake) can reach up to 5 m in dry seasons, while in wet seasons, the lake's water level is almost horizontal (Li *et al.* 2014). The size of Poyang Lake's surface area fluctuates greatly with changes in water level. In the relatively high water-level period in summer, the lake covers an area of roughly 3,000 km², while in the relatively low water-level period in winter, flow is mainly limited to Lake channels and the surface area shrinks to less than 1,000 km² (Hui *et al.* 2008; Feng *et al.* 2012).

MATERIALS AND METHODS

Data availability

Observed daily river discharges at seven river gauging stations in the lake's catchment and the Yangtze River are available (Table 1). The most downstream gauging stations of the Ganjiang, Fuhe, Xinjiang, Raohe, and Xiushui Rivers were selected to represent the discharge from the lake's catchment (Figure 1). The Yangtze River gauging stations of Hankou and Jiujiang, situated 284 and 30 km upstream of the lake, respectively, were used to reflect the River effect (Figure 1(a)). Within the lake, the gauging stations of Hukou, Xingzi, Duchang, Tangyin, and Kangshan, located from the downstream outlet to the most upstream end of the lake, were selected and expected to represent different responses of the lake (Figure 1(b)).

Back-propagation neural network

The back-propagation neural network (BPNN) approach developed by Rumelhart *et al.* (1986) was used in this study. BPNN is the most commonly used of the various

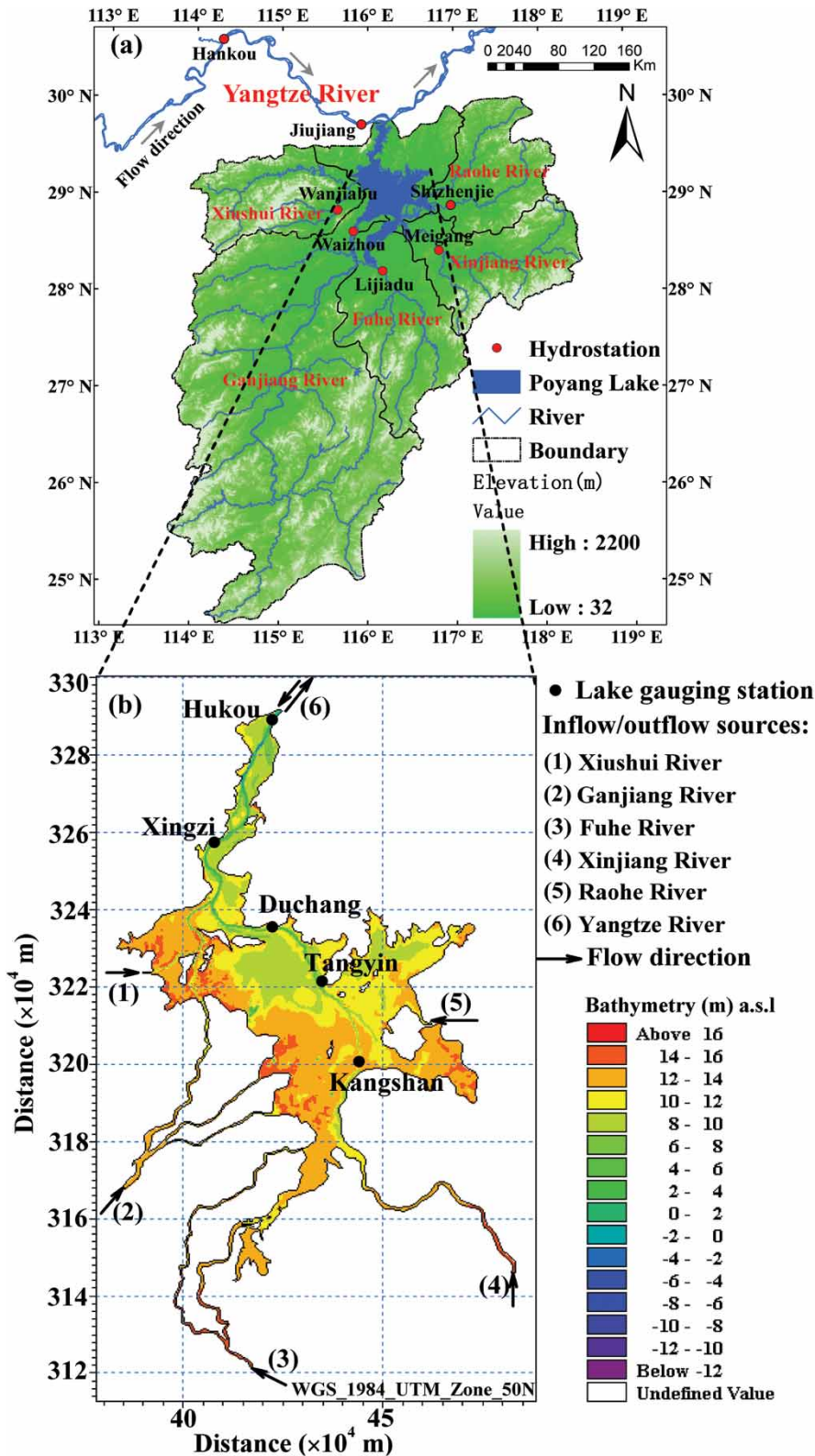


Figure 1 | (a) Location of Poyang Lake and (b) lake bathymetry, lake gauging stations, and major rivers within the lake surroundings (modified from Li et al. 2014).

Table 1 | Data used in this study

Data description	Gauging station	Location and coordinates	Time duration
Catchment inflow	Waizhou	Ganjiang River (115.83°, 28.63°)	1960–2008
	Lijiadu	Fuhe River (116.17°, 28.22°)	1960–2008
	Meigang	Xinjiang River (116.82°, 28.43°)	1960–2008
	Shizhenjie	Raohe River (116.97°, 28.85°)	1960–2008
	Wanjiabu	Xiushui River (115.65°, 28.85°)	1960–2008
Yangtze River discharge	Hankou	River middle reach (114.28°, 30.63°)	1960–2008
	Jiujiang	River middle reach (115.97°, 29.71°)	1988–2008
Poyang Lake water level	Hukou	Lake downstream (116.22°, 29.75°)	1960–2008
	Xingzi	Lake downstream (116.03°, 29.45°)	1960–2008
	Duchang	Lake midstream (116.18°, 29.27°)	1960–2008
	Tangyin	Lake midstream (116.23°, 29.06°)	1964–2008
	Kangshan	Lake upstream (116.42°, 28.88°)	1960–2008

ANNs (Chen *et al.* 2012a), which are structured on biological neural systems in a highly simplified form. They provide a statistical tool for simulating dependent variables for a wide range of engineering problems, especially where highly complex relationships define the physical processes of the problem (ASCE (American Society of Civil Engineers) Task Committee 2000). The development of neural network

theory was discussed by Pham & Liu (1995) and Graupe (1997), and a review of ANN applications in hydrology was presented by the ASCE Task Committee (2000) and Maier & Dandy (2000), and hence the fundamental aspects of ANN are described here in only a summarized manner.

Standard three-layer feed-forward networks (Figure 2(a)) were employed, with a hyperbolic tangent sigmoid

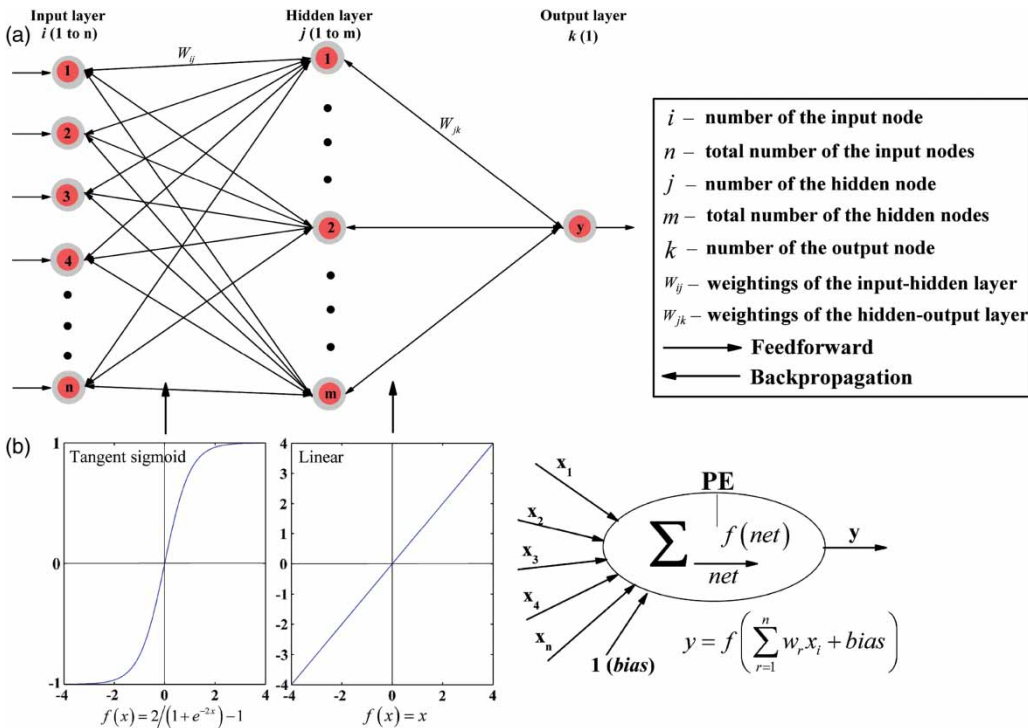


Figure 2 | (a) Architecture of the three-layer BPNN model and (b) processing element showing graphically the transfer functions.

transfer function in the hidden layer, and a linear transfer function in the output layer (Figure 2(b)). This arrangement is well suited to complex relationships between input and output time series (Shrestha et al. 2005; Herman et al. 2007). The input layer receives incoming information, which is processed by hidden layers. The target or output layer (only one node in this study) contains the simulation results. During the learning process, the weightings of the interconnections and the neural biases are iteratively adjusted to minimize the difference between the model's output vector and the desired output vector (based on field observations). The objective function for evaluating the network performance is quantified by the mean-square error (MSE). When the learning performance is less than a specific tolerance ($MSE < 10^{-3} \text{ m}^2$ in this work), the iteration terminates. The Levenberg–Marquardt algorithm is used to determine the weighting and bias matrices for each iteration. The optimal network architecture (i.e., number of hidden nodes, number of iterations, learning rate, and momentum coefficient; see Graupe (1997)) is obtained by trial and error based on the statistical values from the BPNN model training phases. BPNN programming was implemented in MATLAB®.

Data preparation

The input and target data for the BPNN model were normalized using

$$x' = a(x_i - x_{\min}) / (x_{\max} - x_{\min}) + b \quad (1)$$

Here, x' is the parameter/output value after normalization, and x_{\min} and x_{\max} denote the data set minimum and maximum, respectively. The scaling factors a and b were taken as 2 and -1 , respectively, so that normalized values always fall within the range $[-1, 1]$, corresponding to the hyperbolic tangent sigmoid transfer function (Figure 2(b)). The outputs of the model were later converted back to their original scale using the POSTMNMX conversion function in MATLAB®. BPNN modeling was carried out in two phases: training and testing, and hence available data sets (see Table 1) covering a range of hydrological conditions were subdivided accordingly. The time period 1960–2000 was used for model training, during which the optimal set

of connection weightings was sought. The period 2001–2008 was used to test the model's predictive capability. The terms 'training' and 'testing' of the BPNN model were used as analogous to calibration and validation of the physics-based hydrodynamic model.

As the neural network is data-driven, the input–output data analysis is very important prior to any model-building operation (Ghorbani et al. 2010). In the current study, a cross-correlation function (Box et al. 1994) was employed to determine the appropriate structure of the input vectors. Cross-correlation functions are used to establish relationships between the input and output time series, and can be written as follows:

$$C_{xy}(k) = \begin{cases} \frac{1}{L} \sum_{t=1}^{L-k} (x_t - \bar{x})(y_{t+k} - \bar{y}) & k = 0, 1, 2, \dots \\ \frac{1}{L} \sum_{t=1}^{L+k} (y_t - \bar{y})(x_{t-k} - \bar{x}) & k = 0, -1, -2, \dots \end{cases} \quad (2)$$

$$r_{xy}(k) = C_{xy}(k) / \sigma_x \sigma_y \quad k = 0, \pm 1, \pm 2, \pm \dots \quad (3)$$

where k is the time lag, L is the length of the time series, x_t and y_t are input and output time series, respectively, \bar{x} and \bar{y} are the means of the input and output series, $r_{xy}(k)$ is the cross-correlation function, σ_x and σ_y are the standard deviations of the time series, and $C_{xy}(k)$ is the cross-correlogram (Box et al. 1994). If $C_{xy}(k)$ is not symmetrical and if the maximum or minimum $r_{xy}(k)$ value is obtained for a positive lag, the input signal influences the output signal. The response time is the lag time that corresponds to the maximum $r_{xy}(k)$ value (Box et al. 1994). The average times for Lake water levels to respond to flows in the catchment rivers and in the Yangtze River were computed using this method (see Figure 3).

The cross-correlation analysis shows the significant correlation between Lake water levels and the Yangtze River discharge (at both Hankou and Jiujiang), with a time lag of approximately 2 days (Figure 3). A relatively weak correlation, with a time lag of around 10 days (ranging between 9 and 14 days) is obtained for lake water-level responses to changes in flows in the catchment rivers (Figure 3). Given the weak correlation, the choice of 10 days was

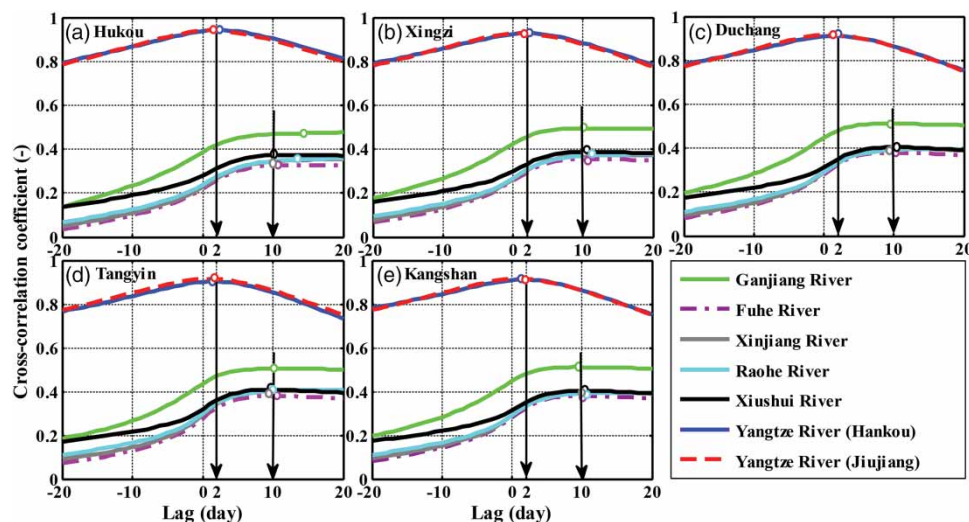


Figure 3 | Plots of the cross-correlation function for lake water-level responses to discharges from catchment rivers and the Yangtze River. The arrows correspond to the maximum cross-correlation coefficient and indicate the associated time lag.

further evaluated during sensitivity testing (see ‘BPNN sensitivity analyses’).

BPNN model construction and scenarios

Five BPNN models of similar structure were built to simulate the lake water-level time series at Hukou, Xingzi, Duchang, Tangyin, and Kangshan gauging stations. Three variations to each model were developed, in order to explore the influence of the Yangtze River representation on the models’ capability to reproduce lake water-level changes. Three model scenarios were considered as follows.

S1: The influence of Yangtze River discharge on lake water levels is neglected. The period 1960–2000 (14,976 data points) was used for BPNN training, with the exception of the Tangyin water-level simulation, for which the period 1964–2000 (13,515 data points) was adopted for the model training phase due to data limitations. Data from 2001 to 2008 (2,922 data points) were used for model testing (see Table 1).

S2: The discharge hydrograph for Hankou was added to incorporate Yangtze River effects.

S3: Yangtze River effects were incorporated using the discharge hydrograph for Jiujiang. The period 1988–2000

(4,749 data points) was used for BPNN training, and data from 2001–2008 were used for model testing (see Table 1).

BPNN model structure

To minimize the influence of lag times in BPNN modeling, the times assigned to daily discharge rates were delayed by 10 days for catchment rivers, and by 2 days for Yangtze River flows (based on cross-correlation analysis). For scenario S1, the BPNN formulation for simulating Lake water levels is expressed by

$$L(t) = f\{Q_{1(t-10)}, Q_{2(t-10)}, Q_{3(t-10)}, Q_{4(t-10)}, Q_{5(t-10)}\} \quad (4)$$

where $L(t)$ is the water level at current time t and $Q_{1(t-10)}$, $Q_{2(t-10)}$, $Q_{3(t-10)}$, $Q_{4(t-10)}$, and $Q_{5(t-10)}$ are the discharge rates (10 days prior) for the Ganjiang, Fuhe, Xinjiang, Raohe, and Xiushui Rivers, respectively. S2 is otherwise the same as S1, and hence the BPNN formulation for S2 is obtained by adding $Q_{6(t-2)}$ (i.e., the 2-day delayed flows at Hankou) to the arguments of f in Equation (4). The BPNN formulation for S3 is obtained by adding $Q_{7(t-2)}$ (i.e., the 2-day delayed flows at Jiujiang) to the arguments of f in Equation (4).

MIKE 21 hydrodynamic model

Model description

A depth-averaged hydrodynamic model of Poyang Lake was constructed using the MIKE 21 code (DHI 2007), which is best suited to two-dimensional free-surface flows where stratification can be neglected. MIKE 21 is a finite-volume model that can be used to determine the temporal and spatial changes in both water surface elevations and depth-averaged velocities, in response to wind, river inputs, and a variety of other surface-water forcing functions. The model employs an unstructured triangular grid in the horizontal plane to resolve the complex shoreline and flow geometries. MIKE 21 has an extensive history of successful applications to similar areas, e.g., Lido Entrance (Italy; Warren & Bach 1992), Lough Neagh (Northern Ireland; Bell *et al.* 2005), Alberni Inlet (Canada; Barua *et al.* 2006), Skallingen Ende spit/platform (Denmark; Niemann *et al.* 2006), Emilia Romagna coastal area (Italy; Martinelli *et al.* 2010), and Poyang Lake (China; Li *et al.* 2014), demonstrating that the model can reproduce the dominant physical processes of similar settings. The underlying principles and a mathematical description of MIKE 21 are provided by DHI (2007) and in the above references, and therefore only a brief description of the code is given here.

Model construction, calibration, and validation

A modified version of the MIKE 21 model applied to a previous Poyang Lake investigation by Li *et al.* (2014) is used. They focused mainly on the combination of catchment and Lake models. We adopt field observations of river inflows rather than the results of catchment simulation to represent the upstream boundary conditions of the lake model, since future predictions of catchment runoff are not required for the purposes of the current investigation. Li *et al.* (2014) used geographic information system techniques and considered the historic flood event of 1998 to generate the irregular lake shorelines, which define the hydrodynamic model domain. The wet-dry point treatment method of MIKE 21 (DHI 2007) is well suited to simulate the wetting and drying processes associated with the considerable variations in the lake

area. MIKE 21 converts all rainfall to runoff across land surface areas that are not inundated (DHI 2007). To better capture the complex Lake bathymetry and also to improve the model's computational efficiency, Li *et al.* (2014) adopted a variable mesh resolution, i.e., a coarse mesh covers the Lake floodplains, and a fine mesh is applied to the relatively deep and narrow flow channels. The mesh elements vary in size from 70 to 1,500 m, resulting in a total of 20,450 triangular elements.

Catchment inflows to the model occur via the upstream boundary conditions, which include five inflow points at which observations of daily flows from the major catchment rivers are used to represent lake-catchment interactions. The lake's lower boundary condition is specified as daily water levels from Hukou gauging station, to simulate Yangtze River-Poyang Lake interactions. Direct precipitation and evaporation to/from the lake surface are also included, although these were found to be a relatively minor component of the lake water balance. The observed series of lake water levels at Xingzi, Duchang, Tangyin, and Kangshan gauging stations, and flow rates at Hukou gauging station were used to calibrate (2000–2005) and validate (2006–2008) the model. Other aspects including the model construction and calibrated parameters are the same as the approach of Li *et al.* (2014), and are described in detail therein.

Evaluation criteria

The determination coefficient (R^2), Nash-Sutcliffe efficiency coefficient (E_{ns}) and root-mean-square error (RMSE) were used to evaluate the performances of the BPNN and MIKE 21 models, both in training/calibration and testing/validation phases of the investigation. The formulations are given as follows:

$$R^2 = \frac{\left[\sum_{l=1}^N (h_{obs} - \bar{h}_{ops})(h_{sim} - \bar{h}_{sim}) \right]^2}{\left[\sum_{l=1}^N (h_{obs} - \bar{h}_{ops})^2 \sum_{l=1}^N (h_{sim} - \bar{h}_{sim})^2 \right]} \quad (5)$$

$$E_{ns} = 1 - \frac{\sum_{l=1}^N (h_{obs} - h_{sim})^2}{\sum_{l=1}^N (h_{obs} - \bar{h}_{obs})^2} \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{l=1}^N (h_{\text{obs}} - h_{\text{sim}})^2}{N}} \quad (7)$$

where h_{obs} (m) is the observed water level, h_{sim} (m) is the predicted water level, \bar{h}_{obs} (m) and \bar{h}_{sim} (m) represent the average values of observed and predicted water levels, respectively, l denotes the current time step, and N is the total number of time steps. The ideal value for R^2 and E_{ns} is 1, and the ideal value for RMSE is 0 m.

RESULTS AND DISCUSSION

BPNN model training and testing

The BPNN learning rate and momentum coefficient are found to be 0.01 and 0.95–1.0, respectively (Table 2). Reasonable model-field measurement matches (see below for a description of the model performance statistics) are obtained from the Hukou model after 3,000 iterations (Table 2). Hence, the same number of iterations is used for training other BPNN models, and convergence (based on MSE) to an optimal set of parameters was tested in each case. The closeness of the learning rate, momentum coefficient, and number of iterations for all models (and

scenarios) demonstrates that the model results are not especially sensitive to these parameters. The number of neurons in the hidden layer is the main parameter that varies between models, ranging from 21 to 33 neurons to predict lake water levels with acceptable accuracy (Table 2). The sensitivity of the model to the optimal parameters in this study is consistent with previous BPNN modeling by Chen *et al.* (2012a, b), who found that the optimal number of nodes in the hidden layer was important for obtaining the best network architecture.

Table 3 summarizes the performance results for the three BPNN model scenarios. R^2 and E_{ns} for the five gauging stations are relatively low (<0.46), and the RMSE errors are correspondingly large (>1.0 m) for scenario S1. These performance statistics, including the RMSE of 2.88 m at Hukou, indicate that the BPNN models of S1 failed to reproduce the observed time series of lake water levels. The simulation of lake water levels is clearly improved in scenarios S2 and S3 (Table 3). The values of R^2 and E_{ns} improve to >0.90, and RMSE errors decrease significantly to <1.0 m with the introduction of Yangtze River flows. In particular, the lake water-level simulation accuracy for the downstream gauging stations is significantly enhanced (Table 3). These results indicate that Yangtze River discharges play an important role in Poyang Lake water-level behavior, in support of the cross-correlation

Table 2 | Neural network parameters in BPNN models

BPNN model	Model scenario	Model parameters				
		Learning rate	Momentum coefficient	Iteration number	Input nodes	Hidden nodes
Hukou	S1	0.01	1.0	3,000	5	22
	S2	0.01	1.0	3,000	6	22
	S3	0.01	1.0	3,000	6	21
Xingzi	S1	0.01	1.0	3,000	5	28
	S2	0.01	1.0	3,000	6	25
	S3	0.01	1.0	3,000	6	25
Duchang	S1	0.01	0.98	3,000	5	22
	S2	0.01	0.98	3,000	6	22
	S3	0.01	0.98	3,000	6	21
Tangyin	S1	0.01	0.95	3,000	5	22
	S2	0.01	1.0	3,000	6	24
	S3	0.01	1.0	3,000	6	21
Kangshan	S1	0.01	0.98	3,000	5	22
	S2	0.01	0.98	3,000	6	33
	S3	0.01	0.98	3,000	6	23

Table 3 | Performance evaluation of BPNN models

BPNN	Performance	Location				
		Hukou	Xingzi	Duchang	Tangyin	Kangshan
S1	Training – R^2	0.43	0.45	0.46	0.45	0.44
	Training – E_{ns}	0.43	0.45	0.46	0.45	0.44
	Training – RMSE (m)	2.88	2.52	2.08	1.73	1.39
	Testing – R^2	0.47	0.48	0.49	0.51	0.50
	Testing – E_{ns}	0.39	0.36	0.37	0.42	0.39
	Testing – RMSE (m)	2.66	2.56	2.16	1.62	1.24
S2	Training – R^2	0.98	0.97	0.95	0.92	0.90
	Training – E_{ns}	0.98	0.96	0.95	0.92	0.90
	Training – RMSE (m)	0.58	0.64	0.61	0.66	0.61
	Testing – R^2	0.96	0.95	0.93	0.92	0.90
	Testing – E_{ns}	0.96	0.92	0.87	0.86	0.81
	Testing – RMSE (m)	0.70	0.91	1.02	0.82	0.71
S3	Training – R^2	0.98	0.97	0.96	0.95	0.94
	Training – E_{ns}	0.98	0.97	0.96	0.95	0.94
	Training – RMSE (m)	0.59	0.60	0.58	0.55	0.50
	Testing – R^2	0.97	0.96	0.94	0.93	0.90
	Testing – E_{ns}	0.93	0.90	0.86	0.87	0.83
	Testing – RMSE (m)	0.89	1.01	0.96	0.77	0.65

analysis (Figure 3). The decrease in RMSE values from the lake outlet to the most upstream gauging station, obtained for S1 models (see Table 3), provides evidence that the contribution of the Yangtze River (to lake water levels) reduces gradually in the upstream direction from the lake outlet, as expected.

The model results obtained for scenarios S2 and S3 are generally similar (Table 3). The calibration statistics of S3 are slightly superior for most of the lake gauging stations, which could be attributed to the closer proximity of S3's Jiujiang station (roughly 30 km from Poyang Lake outlet; Figure 1(a)) relative to S2's Hankou station (284 km), although the calibration differences are subtle and could be due to numerous factors.

Figure 4 shows the comparison of observed and simulated lake water levels of the five gauging stations in training and testing phases for scenario S3. It can be seen that the observed highs and lows in water levels are successfully captured in both the training and testing time periods. The model-to-measurement match during the testing phase is generally poorer than those of the training phase (see Table 3 and Figure 4), which is an expected outcome given that training phase outputs are the focus of the calibration effort (e.g., Panda *et al.* 2010). This may also be

due partly to changes in the lake hydrology following the impact of the Three Gorges Dam (Liu *et al.* 2013; Zhang *et al.* 2014).

BPNN sensitivity analyses

Sensitivity analyses were performed for each BPNN input variable. For each input variable, relative changes of –50, –25, 25, and 50% were made, and corresponding outputs were obtained. The sensitivity of each input variable was defined using (Lee *et al.* 2003)

$$\text{Sensitivity (\%)} = \frac{1}{N_p} \sum_{p_i} \left(\frac{\text{change in output (\%)}}{\text{change in input (\%)}} \right) \times 100 \quad (8)$$

In Equation (8), N_p denotes the number of values for which the sensitivity is obtained (i.e., $N_p = 4$ in this case), constructed with inputs and corresponding outputs using the training data set. The sensitivity analysis included testing of the BPNN lag time. An alternative and arguably more realistic lag time (to the optimal value of 10 days; Figure 4) of 3 days was evaluated, albeit the cross-correlation coefficients for lake water-level responses to

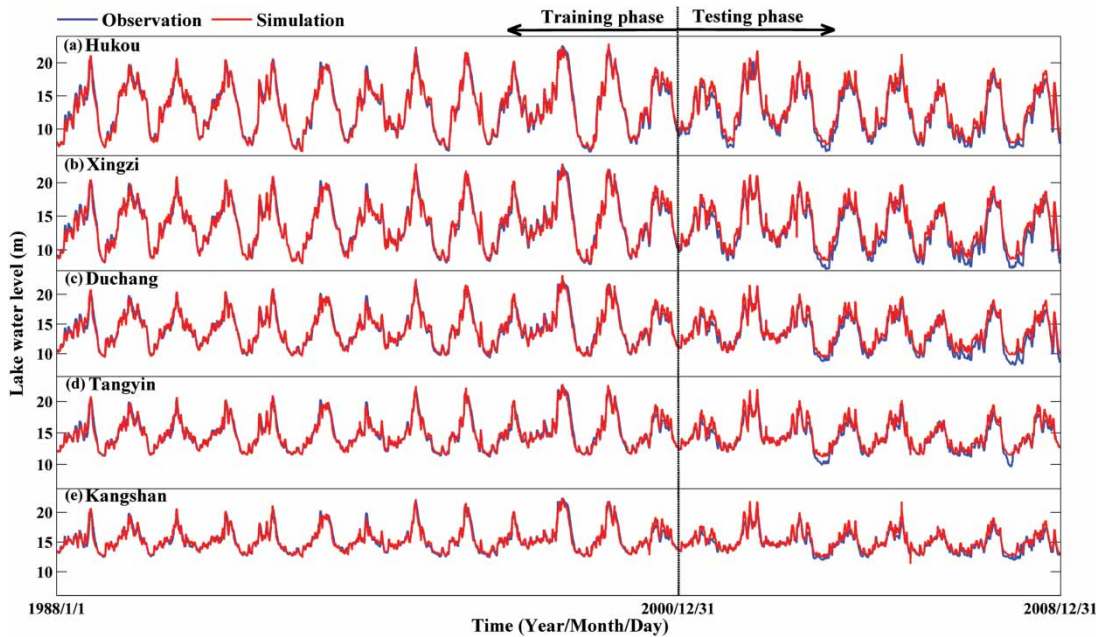


Figure 4 | Comparison of observed (blue line) and simulated (red line) Lake water levels for scenario S3. Please refer to the online version of this paper to see this figure in colour.

catchment inflows were small for this value (Figure 3). The resulting sensitivities shown in Figure 5(a) and (b) highlight the significant role of the Yangtze River in the prediction of lake water levels, in particular for the more downstream lake gauging stations. The prediction of lake water levels is also sensitive to the Ganjiang River, whose inflow is the largest among the five catchment rivers, which otherwise

produced only minor sensitivities (sensitivity indices <1%). The sensitivity analysis also indicates that the 3- and 10-day time lags between lake water-level responses and catchment discharges produce similar results (Figure 5(a) and (b)). This implies that the BPNN model is rather insensitive to the lag times in the lake’s response to catchment discharge.

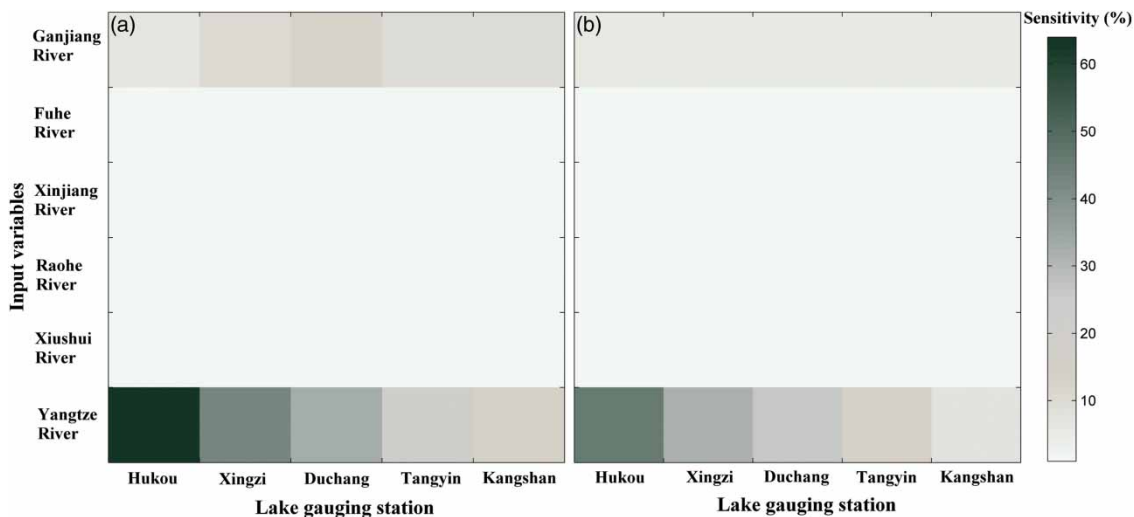


Figure 5 | Sensitivity of lake water levels to input variables, for the BPNN model of (a) 10-day delay and (b) 3-day delay.

Comparison of BPNN and MIKE 21 results

The performance evaluation of the BPNN and MIKE 21 models required consistent simulation periods to be adopted in both approaches. The BPNN model (incorporating Hankou hydrograph) was therefore re-run to repeat the model training and testing phases such that these corresponded with the MIKE 21 calibration (2000–2005) and validation (2006–2008) periods, respectively.

The BPNN and MIKE 21 models were compared based on R^2 , E_{ns} , and RMSE values (see Table 4). The water levels at Hukou could not be used for the evaluation of model performance, because these were assigned as the lower boundary condition for the MIKE 21 model, as per Li *et al.* (2014). It is common for physical models to be judged also on the match between calibrated and field-measured model parameters (Doherty & Johnston 2003), but here, there is a lack of knowledge pertaining to the ‘true’ values of model parameters, and rather, we ensure that MIKE 21 model parameters fall within acceptable ranges. The model-measurement RMSE values (Table 4) indicate that the MIKE 21 model is superior to the BPNN approach in reproducing lake water levels at Xingzi, Duchang, and Tangyin gauging stations, whereas the reverse is true for Kangshan gauging station. In general terms, the MIKE 21 and BPNN models produce largely similar model-measurement performance statistics across all four gauging stations and for the period of simulation.

Scatter plots of the match between simulated and observed water levels at the various gauging stations, for both the BPNN and MIKE 21 models, are presented in Figure 6 (training phase) and Figure 7 (testing phase). The comparison of observed and simulated results from both BPNN and MIKE 21 models is explored further in Figure 8, which differentiates four characteristic periods, reflecting low water levels, rising water levels, high water levels, and falling water levels. In the training phase, the BPNN-simulated water levels are generally distributed uniformly about the line of best fit (Figure 6). Both the BPNN and MIKE 21 models over-predict the lowest lake water levels, and the RMSE errors are correspondingly larger during low water-level periods (Figures 6 and 8). This is most prominent for the MIKE 21 model, and in particular for Kangshan station, with RMSE values >1.2 m (see Figures 6(d) and 8(d)), in which the BPNN model clearly outperforms the MIKE 21 model. Similar model discrepancies were obtained for both the BPNN and MIKE 21 models (for low water levels) during model testing (Figure 7). The superior calibration match (for low water-level periods) for the BPNN model, relative to the MIKE 21 model, is apparent in the values of R^2 , E_{ns} , and RMSE, for all the four gauging stations (Figure 8). Conversely, the MIKE 21 model outperforms the BPNN model for other water-level regimes (see Figure 8).

The BPNN model is best suited to the simulation of falling water-level periods, but is weakest in reproducing

Table 4 | Performance evaluation of BPNN and MIKE 21 models in training and testing phases (2000–2008) at five gauging stations

Method	Performance	Location				
		Hukou	Xingzi	Duchang	Tangyin	Kangshan
BPNN	Training R^2	0.98	0.97	0.96	0.95	0.94
	Training E_{ns}	0.98	0.97	0.96	0.95	0.94
	Training RMSE (m)	0.53	0.55	0.53	0.48	0.42
	Testing R^2	0.97	0.97	0.95	0.93	0.88
	Testing E_{ns}	0.97	0.95	0.91	0.90	0.90
	Testing RMSE (m)	0.59	0.75	0.98	0.63	0.54
MIKE 21	Training R^2	–	0.99	0.98	0.97	0.96
	Training E_{ns}	–	0.97	0.98	0.94	0.88
	Training RMSE (m)	–	0.45	0.36	0.48	0.52
	Testing R^2	–	0.98	0.98	0.97	0.94
	Testing E_{ns}	–	0.95	0.93	0.97	0.80
	Testing RMSE (m)	–	0.62	0.64	0.34	0.58

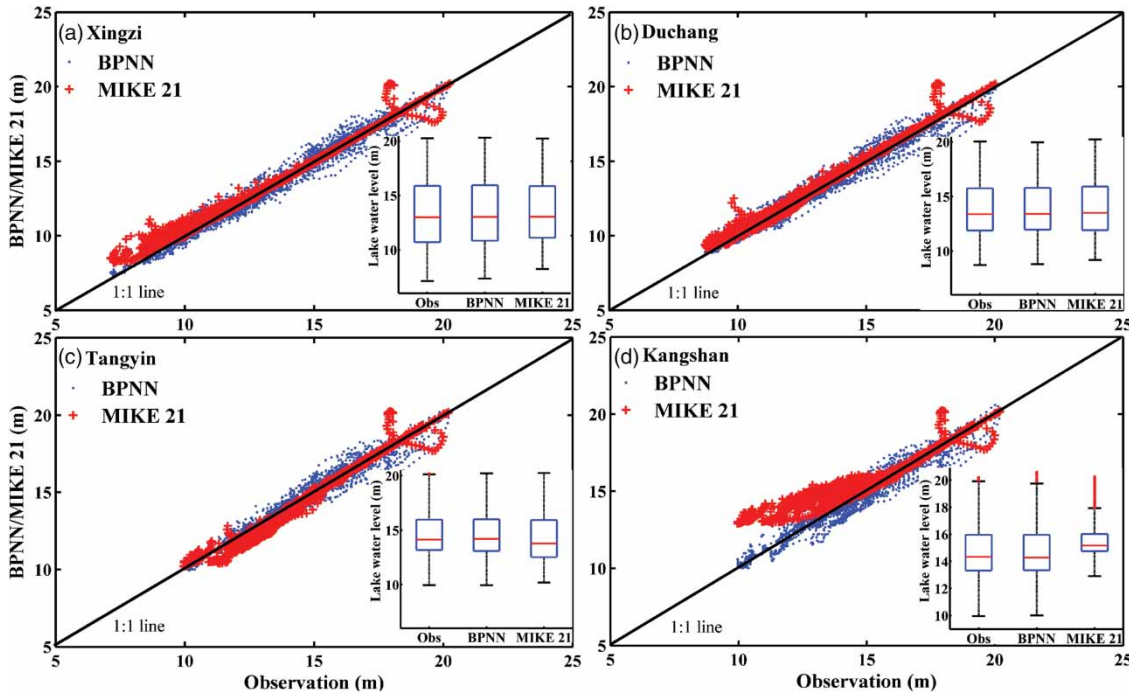


Figure 6 | Scatter plots of simulated versus observed water levels from the BPNN and MIKE 21 models of the four gauging stations (training phase). Box plots represent the comparison between observation (Obs), BPNN, and MIKE 21. The line in the box represents the median (50th percentile), and the top and bottom of each box represent the 25th and 75th percentile values, respectively, and outliers are plotted individually.

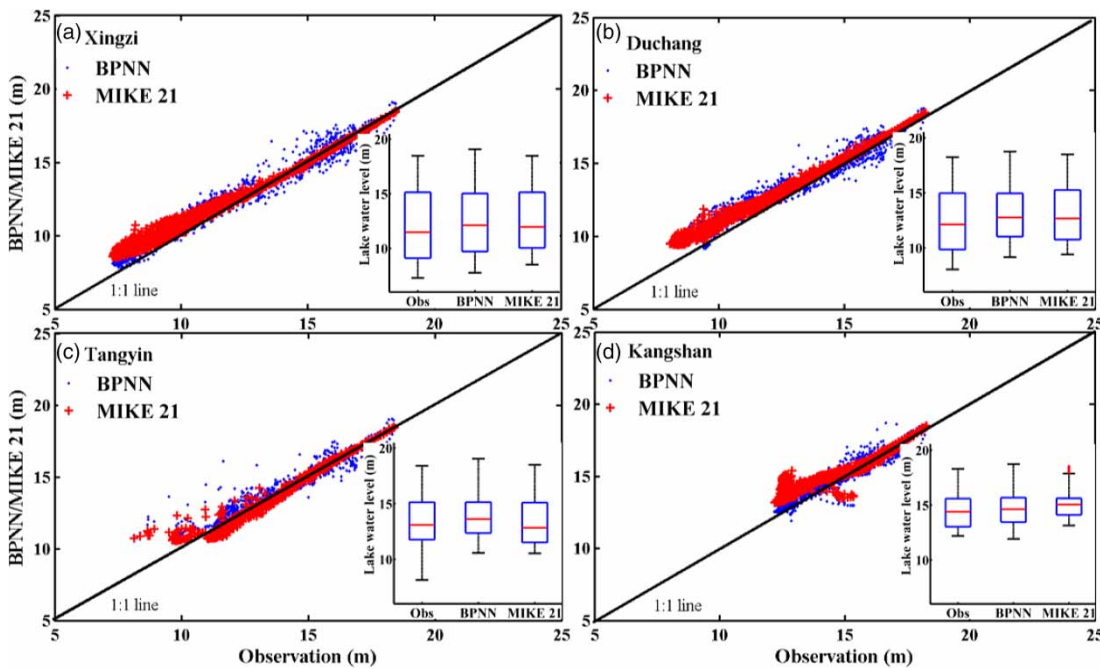


Figure 7 | Scatter plots of simulated versus observed water levels from the BPNN and MIKE 21 models of the four gauging stations (testing phase). Box plots represent the comparison between observation (Obs), BPNN, and MIKE 21. The line in the box represents the median (50th percentile), and the top and bottom of each box represent the 25th and 75th percentile values, respectively, and outliers are plotted individually.

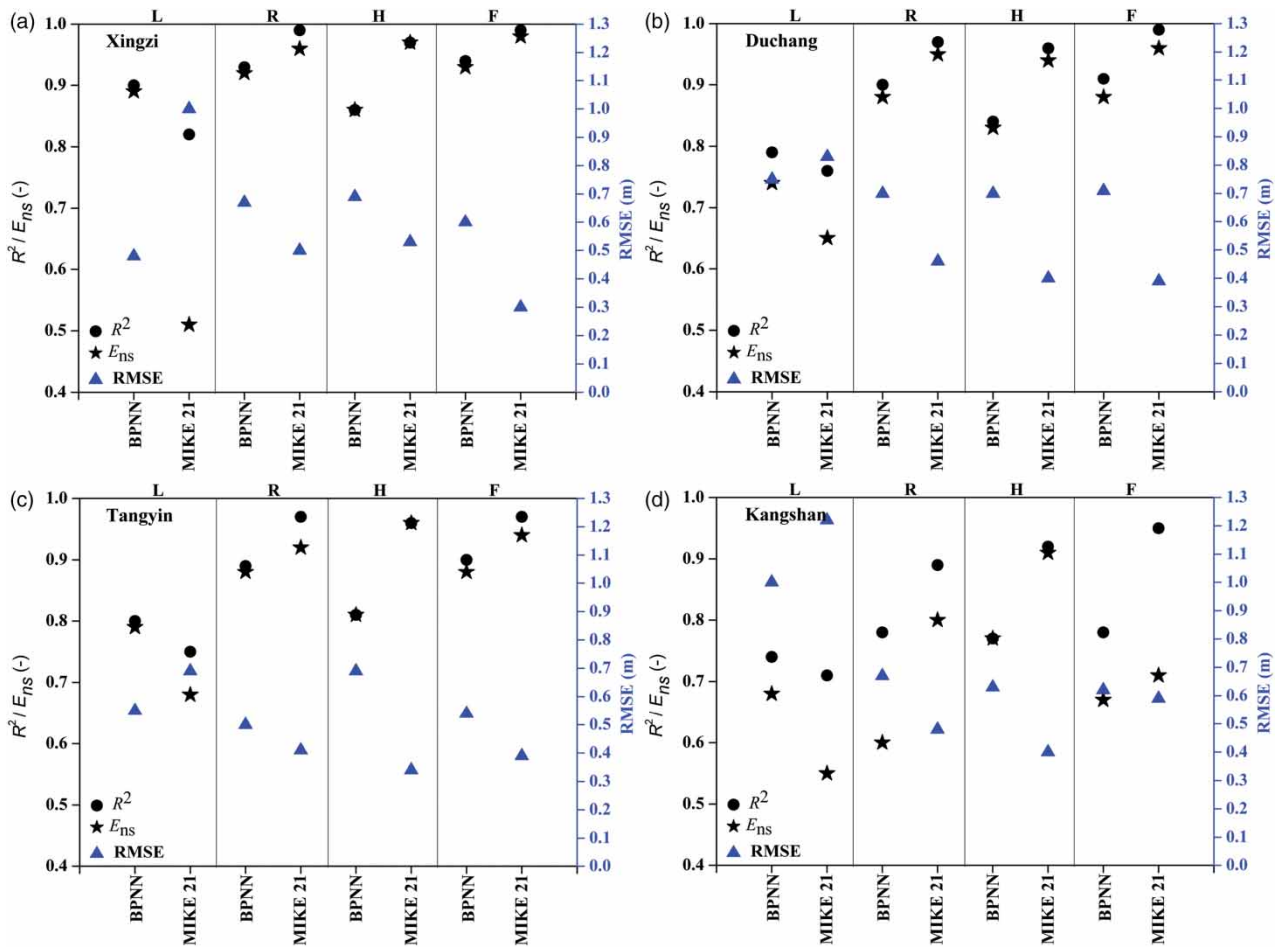


Figure 8 | Performance evaluation of BPNN and MIKE 21 models for four different water-level regimes: L = low water-level period (December–February), R = rising water-level period (March–June), H = high water-level period (July–September), and F = falling water-level period (October–November).

the highest and lowest water levels (Figure 8). The MIKE 21 model performs equally well in capturing the dynamics of rising, falling, and the highest water-level periods, and is weakest during low water levels (Figure 8). While it is difficult to attribute these trends in model-measurement performance to specific elements of each model, the complex lake bathymetry and the complicated nature of shallow flows in the lake may exert more influence on the MIKE 21 model's capability to simulate low water levels rather than high water levels. The same hypothesis was drawn by Li *et al.* (2014). Also, the specification of the boundary condition may not be suitable for the low lake water-level regime due to the 'river behavior' of the lake.

CONCLUSIONS

Poyang Lake is a prominent example of a highly valued water resource with especially complex hydrological controls, which have proven challenging to characterize and accurately quantify. In this study, the water-level variations of Poyang Lake are simulated using BPNN. The effects of both the lake's catchment and the Yangtze River are required to produce reasonable BPNN calibration statistics. This is consistent with previous studies that show that the river has strong controls on lake water-level recession (Guo *et al.* 2012; Zhang *et al.* 2012b, 2014). Comparison between the BPNN and hydrodynamic modeling approaches shows that comparable accuracies were

obtained for both approaches. The 1-year simulation of lake water levels using MIKE 21 requires about 28 h of central processing unit time (on an Intel Core I5 PC), while the BPNN model takes only 1.4 min. This implies that the BPNN may be used as a computationally efficient alternative that is well suited to long-term simulations. However, the lack of physical representation of internal processes in the lake is a limitation of the BPNN model. This paper is the first time that an ANN method has been applied to simulate the water-level changes of a highly dynamic lake-catchment-river system, exemplified by the Poyang Lake case study. While designed specifically for Poyang Lake, the versatility of the ANN approach offers an alternative methodology for the simulation of other river-connected lakes, for which limitations apply to more computationally demanding hydrodynamic modeling methodologies.

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