Integrated model projections of climate change impacts on water-level dynamics in the large Poyang Lake (China)

Yunliang Li, Qi Zhang, Hui Tao and Jing Yao

ABSTRACT

This study outlines a framework for examining potential impacts of future climate change in Poyang Lake water levels using linked models. The catchment hydrological model (WATLAC) was used to simulate river runoffs from a baseline period (1986–2005) and near-future (2020–2035) climate scenarios based on eight global climate models (GCMs). Outputs from the hydrological model combined with the Yangtze River’s effects were fed into a lake water-level model, developing in the back-propagation neural network. Model projections indicate that spring–summer water levels of Poyang Lake are expected to increase by 5–25%, and autumn–winter water levels are likely to be lower and decrease by 5–30%, relative to the baseline period. This amounts to higher lake water levels by as much as 2 m in flood seasons and lower water levels in dry seasons in the range of 0.1–1.3 m, indicating that the lake may be wet-get-wetter and dry-get-drier. The probability of occurrence for both the extreme high and low water levels may exhibit obviously increasing trends by up to 5% more than at present, indicating an increased risk in the severity of lake floods and droughts. Projected changes also include possible shifts in the timing and magnitude of the lake water levels.

Key words | climate change, floods and droughts, hydrological projection, integrated model, Poyang Lake

INTRODUCTION

Increasing atmospheric concentrations of greenhouse gases, especially carbon dioxide, have led to a warming at the earth’s surface. Mean temperatures are expected to increase by as much as 6 °C by the end of the 21st century (Bates et al. 2008; Feng et al. 2014). Climate change is expected to result in significant changes to global and regional hydrological cycles, including changes in amounts and spatial distributions of rainfall and snowfall, and increased storm intensity (Trenberth et al. 2005; Alexander et al. 2006; Huntington 2006; Liuzzo et al. 2010; Me et al. 2018). The general consensus is that the frequency and severity of extreme climate events will increase, enhancing floods and droughts in many regions (IPCC 2007; Déry et al. 2009; Jung et al. 2012; Dai 2013; Xiong et al. 2013; Tal 2019).

Around the world, lakes provide a valuable water resource for irrigation, fishing and recreation, drinking water, aquatic ecosystems, transportation and commerce, and hydropower (Zedler & Kercher 2005). The availability and quality of lake water resources are closely linked to variations in climate (Schindler 2007; Shrestha et al. 2012; Plisnier et al. 2018). Lake water-level changes are a particularly robust signal of changes in catchment water balances, which are otherwise challenging to quantify given the multitude of water sources and their variability in time and space (Soja et al. 2013). In this way, lakes may be considered as sentinels for regional water cycles by exhibiting signals that integrate climate and landscape stresses and that reflect significant changes in these (Williamson et al. 2009; Adams & Sada 2014). Climate change affects lakes both through the direct influence of atmosphere drivers, e.g., temperature, precipitation, and wind speed, and indirectly through changes to catchment hydrology (Taner et al. 2011; Li et al. 2013).
Climate change impacts on lakes are likely to increase in the future (Yu & Shen 2010; Taner et al. 2011; Byun & Hamlet 2018). Consequently, the potential impacts of climate change on lake hydrology are of paramount importance for the management of these systems to support interdependent human and ecosystem communities.

Poyang Lake is the largest freshwater lake in China and the lake is subject to large annual variations in storage levels due to strong seasonality in catchment inflows and lake outflows (Li et al. 2014). The accompanying expansion and contraction of the lake storage area produces periodically inundated areas, which contain unique ecosystems (Hu et al. 2007; Guo et al. 2008; Hui et al. 2008; Feng et al. 2012). Poyang Lake is a region of increasing frequency of floods and droughts due to the combined effects of changes in climate stresses and human activities (Zhang et al. 2020). The largest flood ever recorded was during 1998, when for several consecutive weeks, the lake and river stages exceeded historic highs (Shankman et al. 2006). The largest flood ever recorded was during 1998, when for several consecutive weeks, the lake and river stages exceeded historic highs (Shankman et al. 2012). This resulted in extensive agriculture losses, damage to several cities and many villages, and massive population relocation. All of these floods occurred during or immediately following extreme climatic events in the form of prolonged rainfall across central China (Shankman et al. 2006). In more recent years, Poyang Lake has suffered from sequences of dry years, and water levels are at record lows (Zhang et al. 2014). This has caused considerable negative impacts on the lake ecosystem, including wetland vegetation, fishes, waterbirds, and water quality (Kanai et al. 2002; Zhang et al. 2012b; Li et al. 2019). Additionally, there have been significant issues with water availability for some 4,000 km² of farmland and about 10 million inhabitants in the surrounding area who rely on the lake to meet various water demands (Hu et al. 2007; Hu 2009; Feng et al. 2012). Therefore, change in lake water levels greatly affects the quantity and quality of the lake water resources and considerably impacts both societal activities and the natural ecological environment.

Numerous hydrological studies of Poyang Lake have indicated that the changes in accession and recession of the lake storage are attributable to climate anomalies in the lake catchment and the Yangtze River basin (Hu et al. 2007; Woo et al. 2009; Tao et al. 2012; Zhang et al. 2013), while human activities such as land-use changes and modifications to river systems including the Yangtze River have also exerted significant impacts (e.g., Guo et al. 2008, 2012; Zhang et al. 2012a; Ye et al. 2013; Yang et al. 2016). Previous studies regarding historical and projected future response to climate change focus on the lake’s catchment and have drawn a number of consistent conclusions. For example, Guo et al. (2008) used the hydrological model SWAT to explore historical climate and land-use effects on river discharge in the Xinjiang River sub-basin of Poyang Lake and concluded that the role of the climate variability is stronger than the land-use changes. Ye et al. (2011) employed the hydrological model WATLAC to predict catchment discharge and lake water-level changes under future 2011–2050 by adopting the global climate model ECHAM5. Their projections indicate a great likelihood of increasing high flows and decreasing low flows for the catchment rivers, potentially leading to an increase in water levels for the flood seasons and a reduction for the dry seasons. Li et al. (2016) combined the hydrological model WATLAC and the regional climate model COSMO-CLM (for 2016–2035) to arrive at similar conclusions to those reported by Ye et al. (2011). Yan et al. (2015) used the Xin’anjiang model to project future river discharge under the CMIP5 (Coupled Model Inter-comparison Project Phase 5) multi-model ensemble in the Xinjiang River sub-basin of Poyang Lake. These previous studies demonstrate that climate interventions are likely to be more frequent and intensive in the Poyang Lake regions. It is therefore concluded that changes in the hydrology of the region, and the subsequent societal, economic and environmental impacts, have attracted considerable research attention. There are still, however, information gaps. First, a review of these previous studies reveals that most of them mainly focused on river discharge projections within the catchment. Second, a simple regression model was constructed and used to represent the average lake water level (e.g., Ye et al. 2011). This approach was not sufficient to simulate the dynamic changes in the lake water levels (Li et al. 2014). The key innovation of this study was the insight into a complex lake-catchment system and the motivation for filling the existing information gaps in understanding the potential
impacts of future climate change on the water levels and associated floods and droughts of Poyang Lake.

Although process-based models have become popular tools for investigating complex interactions between climate drivers and hydrological systems, assessing lake water-level response to multiple stressors is still a difficult task (Li et al. 2015). Given the hydrological and ecological importance of Poyang Lake, the objective of this study is to assess potential impacts of climate changes on water-level regimes of the lake and associated floods and droughts, using a linked General Circulation Models (GCMs), a catchment hydrological model and a lake water-level prediction model based on the back-propagation neural network (BPNN). The research focuses on the simulation of lake hydrologic behavior under near-future (2020–2035) climate conditions, based on eight GCM scenarios from CMIP5 projections.

**STUDY AREA**

The Poyang Lake catchment has an area of 1.62 × 10^5 km² (Shankman et al. 2006). It is located in the middle reaches of the Yangtze River (Figure 1), with mean annual precipitation and evaporation of 1,600 and 1,000 mm/yr, respectively (Li et al. 2014). The catchment is in a wet, subtropical climate zone. Statistics show that the precipitation exhibits highly seasonal changes, with 45% of annual precipitation concentrated in spring–summer and 16% of rainfall occurring during autumn–winter. Air temperatures vary from the cold winters to the warm summers in the range of 3.9–28.5 °C (averaged across the catchment). The topography within the catchment varies from upstream mountainous areas at elevations of 2,100 m (above sea level) to downstream plain areas around the lake at elevations of about 32 m (Figure 1). The main land-use types include forest (61%), farmland (28%), water bodies (5%), pasture (4%), and urbanization (2%) (Li et al. 2014). The soils in the whole catchment are classified according to the Genetic Soil Classification of China (Shi et al. 2004) and have the following proportions: red soil (43%), latosol (23%), paddy soil (21%), yellow soil (7%), alluvial soil (3%), and others (3%).

Poyang Lake is the largest freshwater lake in China and has an internationally recognized wetland system (Feng et al. 2011). It receives inflows predominantly from five major rivers (i.e., the Ganjiang, Fuhe, Xinjiang, Raohe, and Xiushui Rivers) within its drainage catchment (Figure 1). The Ganjiang, Fuhe, and Xinjiang Rivers contribute approximately 89% of the lake’s inflow from its drainage catchment area, and the remaining 11% is mainly made up of inflows from the Raohe and Xiushui Rivers (Ye et al. 2013). Poyang Lake is connected to the Yangtze River through a narrow channel at Hukou at its northern end (Figure 1), and the Yangtze River plays a complementary role in controlling outflows (Hu et al. 2007; Cui et al. 2009; Guo et al. 2012; Li et al. 2017). Therefore, Hukou is an important gauging station to represent this complex lake system (Figure 1) due to its water-level variations representing the combined effects of the drainage catchment rivers and the Yangtze River (Hu et al. 2007; Li et al. 2015). Much of the lake is shallow with an average (across the lake area) depth of 6 m across the whole space and maximum depth of ~30 m during flood seasons (Li et al. 2017). Lake water levels vary by 8–18 m each year in response largely to seasonal climate variability and hydrological regime (Li et al. 2014, 2015). 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 from the relatively high water-level period in summer (>3,000 km²) to the relatively low water-level period in winter (shrinks to <1,000 km²) (Hui et al. 2008; Feng et al. 2012).

**MATERIALS AND METHODS**

**Data availability**

Observed daily precipitation and temperature were obtained from 13 national weather stations within the Poyang Lake catchment (Figure 1). Observations of daily river discharge at the downstream gauging stations of the Ganjiang, Fuhe, Xinjiang, Raohe, and Xiushui Rivers (Figure 1) were used to represent catchment inflows and validate the hydrological model. These hydrometeorological data were obtained from the Hydrological Bureau of Jiangxi Province and the Hydrological Bureau of the Yangtze River Water Resources Commission of the Ministry of Water Resources of China.
Integrated modeling framework

The current study adopts climate predictions from GCMs as an input to a hydrological model (WATLAC) of the Poyang Lake catchment to produce catchment discharge estimates. The WATLAC model and the output from GCMs are used as inputs into a statistical lake water-level prediction model (BPNN) (Figure 2). The downscaled time series

Figure 1 | (a) Location of Poyang Lake and its catchment, and (b) major surrounding rivers and hydrometeorological gauging stations.
precipitation and temperature from GCMs were used as input to a grid-based lake catchment hydrological modeling system. The hydrological model was used to simulate rainfall-runoff processes, which produces river discharges to the lake. It is almost impossible to use the flows of the Yangtze River to estimate climate impacts on the lake water levels due to the outputs of GCMs. Therefore, the resulting catchment river discharges in combination with the Yangtze River climate drivers (precipitation and temperature) are then linked to a BPNN lake model to estimate the lake water level in response to climate variability. Figure 2 shows the conceptual flow chart for the integrated model framework using an input–output approach.

General circulation models

The World Climate Research Program developed the CMIP, which provides coordinated simulations from state-of-the-art GCMs around the world. The fifth experiment of this project (CMIP5), used for the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report, is now available. The efforts of CMIP5 are enormous, with a larger number of more complex models run at higher resolution, with more complete representations of external forcings, and more types of scenario and more diagnostics stored. Unlike the Special Report on Emission Scenarios (SRES) B1, A1B and A2 scenarios used in previous CMIP3, CMIP5 uses the new Representative Concentrations Pathways (RCPs) (Taylor et al. 2012). There are three emission scenarios (i.e., a low emission scenario RCP2.6, an intermediate emission scenario RCP4.5, and a moderate high emission scenario RCP8.5) for each climate model. Consequently, the use of the newest CMIP5 data makes a great contribution to the estimation of future climate-induced hydrologic changes (Taylor et al. 2012). In view of the underlying principles and descriptions of CMIP5 are provided in the above references; therefore, only a brief description is given here.

In this study, scenarios were constructed from eight well-known climate models (Table 1): BCC, BNU, CNRM, FGOALS, GISS, MIROC, MPI and MRI, which are adopted to characterize the changes from the 20-year climate period 1986–2005 to the near-term future 2020–2035. These GCMs

### Table 1 | CMIP5 models evaluated and their attributes

<table>
<thead>
<tr>
<th>Model (country)</th>
<th>Model center (or group)</th>
<th>Grid points</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC (China)</td>
<td>Beijing Climate Center, China Meteorological Administration</td>
<td>128 × 64</td>
<td>Xin et al. (2013)</td>
</tr>
<tr>
<td>BNU (China)</td>
<td>College of Global Change and Earth System Science, Beijing Normal University</td>
<td>128 × 64</td>
<td>Wu et al. (2013)</td>
</tr>
<tr>
<td>CNRM (France)</td>
<td>Center National de Recherches Meteorologiques/Center Europeen de Recherche et</td>
<td>256 × 128</td>
<td>Voldoire et al. (2013)</td>
</tr>
<tr>
<td></td>
<td>Formation Avancee en Calcul Scientifique</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FGOALS (China)</td>
<td>LASG, Institute of Atmosphere Physics, Chinese Academy of Sciences</td>
<td>128 × 60</td>
<td>Bao et al. (2013)</td>
</tr>
<tr>
<td>GISS (USA)</td>
<td>NASA Goddard Institute for Space Studies</td>
<td>144 × 90</td>
<td>Kim et al. (2012)</td>
</tr>
<tr>
<td>MIROC (Japan)</td>
<td>Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and Japan Agency for Marine-Earth Science and Technology</td>
<td>128 × 64</td>
<td>Watanabe et al. (2010)</td>
</tr>
<tr>
<td>MPI (Germany)</td>
<td>Max Planck Institute for Meteorology</td>
<td>192 × 96</td>
<td>Zanchettin et al. (2012)</td>
</tr>
<tr>
<td>MRI (Japan)</td>
<td>Meteorological Research Institute</td>
<td>320 × 160</td>
<td>Yukimoto et al. (2012)</td>
</tr>
</tbody>
</table>
have been selected to represent different future climates considering variations to key global climate features. The downscaled approach used in this work was a simple interpolation method based on 13 national meteorological stations within the Poyang Lake catchment (Figure 1).

**Bias correction**

It is to be noted that monthly precipitation and temperature outputs of GCMs typically have some systematic biases, which is partly due to the fact that the climate models are not calibrated/validated at the catchment scale. For example, the GCMs’ outputs and observations have large differences both in temporal distribution and magnitudes (Pearson’s $r = 0.76$; Figure 3(a) and 3(c)). These can lead to considerable deviation when applied to a hydrological model (Graham et al. 2010). In this study, the bias correction approach proposed by Li et al. (2010) is used to account for the biases from the GCM outputs. This method is termed the equidistant CDF matching method. It considers changes in the distribution of the future climate, including the tails of the distribution, which are most pertinent for climate impact and assessment studies. The method is simple to implement and does not require substantial computational time, and can be used to produce auxiliary ensemble scenarios for various climate impact-oriented applications (Li et al. 2010). The bias correction method is demonstrated by comparing GCMs’ outputs with the observations in the baseline period (1986–2005), as shown in Figure 3. After bias correction, the monthly precipitation and average temperature tend to cluster more tightly compared to the observed data (Pearson’s $r = 0.99$; Figure 3(b) and 3(d)), indicating a very effective method and greatly reduced model biases.

**Weather generator**

Weather generator (Liao et al. 2004) is a stochastic model that can be used to simulate daily weather based on parameters determined by historic observations. It has the advantage to be able to statistically simulate weather over an extensive period based using parameters determined from the relatively short historic records. The focus is on precipitation simulation since the determination of other weather variables such as temperature is dependent on precipitation simulation. Stochastic simulation of daily precipitation at each gauging station can be simulated by four parameters which include transition probabilities of wet day to wet day and dry day to wet day, shape parameter

![Figure 3](https://iwaponline.com/hr/article-pdf/doi/10.2166/nh.2019.064/616054/nh2019064.pdf)

Figure 3 | Comparisons between climate observations and GCM outputs (averaged over the 13 weather gauging stations across the baseline period 1986–2005): (a and c) monthly average precipitation and temperature before bias correction; (b and d) monthly average precipitation temperature after bias correction.

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and scale parameter of Gamma distribution. Consequently, this approach based on first-order Markov Chain with Gamma distribution for daily precipitation simulation is used in this study (Liao et al. 2004). The weather generator has proved to be a useful tool to study the impact of climate change, as its results can be used directly in daily step simulation models. The underlying principles and mathematical descriptions of weather generator are provided in detail in Liao et al. (2004).

**Catchment hydrological model**

The catchment model WATLAC (Zhang & Li 2009; Zhang & Werner 2009) is a spatially distributed hydrological model that was developed for large-scale, physically based, continuous rainfall-runoff simulation. WATLAC represents landscape and stream flow hydrology at daily time step. The model used in the present study is a modified version of the model used in a previous Poyang Lake investigation by Li et al. (2014). They focused mainly on the integrated approach of catchment hydrology and lake hydrodynamic models. In this study, the WATLAC hydrological model is uncoupled from the hydrodynamic lake simulator (developed using MIKE 21) for two major reasons. One is that the hydrodynamic model is not adequate to allow for the long time-frames of 20-year climate change simulations due to its computational expense even using a modern computer. In addition, the time-series water-level boundary condition under future climate changes, representing the Yangtze River–Poyang Lake interactions, is difficult to specify. Therefore, a BPNN model was employed as an alternative to the hydrodynamic model of Li et al. (2014) (see the next section). Li et al. (2014) calibrated and validated the Poyang Lake catchment model using the time sequence 2000–2008 and produced a reasonable reproduction of the river discharge at Shizhenjie, Wanjiabu, Waizhou, Meigang, Lijiadu, and Xiajiang gauging stations (Figure 1). Details of data availability and calibration/validation of the hydrological model are provided by Li et al. (2014).

In the current study, the previous WATLAC model was recalibrated using the extended time series of precipitation and temperature derived from 13 national meteorological stations as forcing data in the calibration period 1986–2000 and the validation period 2001–2005. In order to better reflect the effects of climate change, a temperature-based approach was employed to estimate the potential evapotranspiration for WATLAC input (i.e., Hamon 1961), rather than pan evaporation (as used by Li et al. 2014). This was the primary reason for recalibrating the WATLAC model. The river discharges at Waizhou, Lijiadu, Meigang, Shizhenjie, and Wanjiabu gauging stations, representing the Ganjiang, Fuhe, Xinjiang, Raohe, and Xiushui River discharges (Figure 1), respectively, were selected to calibrate and validate the WATLAC model. Other WATLAC model aspects are the same as the approach of Li et al. (2014) and are described in detail therein.

**Lake water-level model**

The BPNN method, developed by Rumelhart et al. (1986), is the most commonly used ANN approach (Chen et al. 2012). In the current study, standard three-layer feed-forward networks were employed, with a hyperbolic tangent sigmoid transfer function in the hidden layer and a linear transfer function in the output layer, which is well suited to non-linear problems (Herman et al. 2007). The input layer receives incoming information, which is processed by hidden layers. The target or output layer (only lake water level 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. The objective function for evaluating the network performance is quantified by the mean-square error. When the learning performance is less than a specific tolerance ($10^{-3}$ m$^2$ in this work), the iteration terminates.

The BPNN model was built to simulate the lake water-level time series at the Hukou gauging station. The monthly total discharges (calculated from the WATLAC simulation results) from the Ganjiang, Fuhe, Xinjiang, Raohe and Xiushui Rivers (see Figure 1(b)) as well as monthly precipitation and mean temperature from the gauging stations of the Yangtze River (obtained from the GCMs output) were used as inputs in building the BPNN model. The monthly mean lake water levels (based on field observations) at Hukou gauging stations were included as target variables. In the present study, the corresponding time period 1986–2000 was used for model training, during which the optimal
set of connection weightings was sought, and the period 2001–2005 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 WATLAC model.

**Model evaluation criteria**

The performances of both catchment and lake models were evaluated by comparing simulation results to field observations (i.e., river discharge and lake water levels during 1986–2005). The determination coefficient ($R^2$), Nash-Sutcliffe efficiency coefficient ($E_{ns}$), and relative error ($R_e$) were used to evaluate the model-observation match (Li et al. 2014), both in calibration/training and validation/testing phases. The ideal value for $E_{ns}$ and $R^2$ is 1, and the ideal value for $R_e$ is 0.

**RESULTS**

**Model calibration and validation**

The optimized values of parameters for both WATLAC and BPNN models are presented in Table 2. WATLAC calibration was based on the procedure of PEST software (Doherty 2005), and details of the selection of parameters for calibration are described in Li et al. (2014). Trial-and-error was used to calibrate the BPNN parameters (see Anderson 1996; Graupe 1997). Both visual comparison and statistical results of the model calibration/training and validation/testing are represented in Figures 4 and 5. For the WATLAC model, the value of $R^2$ ranges from 0.67 to 0.86, and the value of $E_{ns}$ varies from 0.67 to 0.82, indicating an acceptable level of agreement with field observations in both the calibration and validation periods. For all the five gauging stations, scatter plots demonstrate that the WATLAC model is reasonably consistent in describing the catchment’s rainfall-runoff behavior more generally, although the model slightly over- and underestimated the river discharges especially for the capture of peak values (Figure 4).

For the BPNN lake water-level prediction, the results show that both amplitude and phase of monthly lake water levels are reasonably represented (Figure 5), although peak values proved somewhat difficult to accurately reproduce, as illustrated by the underestimation of flood water levels and overestimation of low lake water levels. Additionally, the statistical results indicate that an overall better BPNN model performance from the training phase to the testing phase, i.e., the $R^2$, $E_{ns}$, and $R_e$ for the testing phase are 0.83, 0.81, and 5.1%, respectively, is largely consistent with the training phase with the corresponding values of 0.84, 0.83, and 0.1% (Figure 5). Better results show that the BPNN approach was able to predict the nonlinear water-level responses of Poyang Lake. Therefore, BPNN is suggested as an insightful and efficient modeling tool for water-level prediction under future climate changes.

**Lake water-level changes**

Changes in the river inflows in the catchment of Poyang Lake are inextricably linked to the dynamic changes of lake water levels (Figure 6). On average, hydrological projections show that climate change causes distinctly decreasing river discharge in the catchment in dry seasons (i.e., up to

<table>
<thead>
<tr>
<th>Model</th>
<th>Parameter and unit</th>
<th>Description</th>
<th>Initial value</th>
<th>Bounds</th>
<th>Optimal value</th>
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<tbody>
<tr>
<td>WATLAC</td>
<td>$\alpha$ (−)</td>
<td>Overland runoff lag coefficient</td>
<td>1.87</td>
<td>0.01–5.0</td>
<td>2.2</td>
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<td></td>
<td>$\omega$ (−)</td>
<td>Muskingum weighting factor</td>
<td>0.01</td>
<td>0.01–1.0</td>
<td>0.1</td>
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<tr>
<td></td>
<td>$k$ (day)</td>
<td>Flood travel time in the Muskingum method</td>
<td>1.6</td>
<td>0.01–5.0</td>
<td>4.74</td>
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<tr>
<td></td>
<td>$\beta_1$ (−)</td>
<td>Soil infiltration coefficient</td>
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<td>0.01–5.0</td>
<td>2.0</td>
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<tr>
<td></td>
<td>$\beta_2$ (−)</td>
<td>Groundwater recharge coefficient</td>
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<td>0.01–5.0</td>
<td>2.1</td>
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<td>BPNN</td>
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<td>Learning rate</td>
<td>0.01</td>
<td>0–1.0</td>
<td>0.02</td>
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<td></td>
<td>$\mu$ (−)</td>
<td>Momentum coefficient</td>
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<td>0–1.0</td>
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<td></td>
<td>$n$ (−)</td>
<td>Hidden nodes</td>
<td>7</td>
<td>1–30</td>
<td>10</td>
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</tbody>
</table>
Figure 4 | Scatter plots of simulated daily discharges against the observed daily discharges for the calibration period 1986–2000 (left) and the validation period 2001–2005 (right) at the five gauging stations.
but increasing trend in flood seasons (i.e., up to 29% in June) (Figure 6). It is necessary to quantitatively identify the seasonal changes of lake water levels between each climate scenario and the baseline (Figure 7(a)–7(c)). Predicted lake water levels for the current (1986–2005) and future climate scenarios (2020–2035) were averaged for each month. For all the three emission scenarios (RCP2.6, RCP4.5, and RCP8.5), the result tends to show a noticeable reduction in monthly lake water levels, particularly in autumn and winter months (i.e., from September to February; Figure 7(a)–7(c)). Accordingly, the percentage change of lake water levels varies from −5% to −30%, except for GISS which exhibits <15% increases in lake water level (Figure 6(d)–6(f)). The distinct increases in
Lake water levels are observed from 5% to 25% in spring and summer months (i.e., from March to August), especially for the RCP2.6 scenario (except BCC which exhibits <10% decreases in lake level; Figure 6(d)–(f)). Although the results show substantial differences between different GCMs, as expected, all model simulations estimate a consistent pattern in seasonal lake-level distributions as compared with the baseline condition (Figure 7(a)–7(c)). It also can be found that the future BNU projections exhibit sharp rise and a very significant time shift occurring in the peak water levels for late spring and summer months (see red lines in Figure 7(b)–7(c)), indicating the variability of hydrological behavior in seasonality. From the point of view of the extreme flooding and droughts, Figure 7(a)–7(c) also shows that the highest water level of Poyang Lake may be up to around 19.5 m in June or July, and the lake level can drop down to the lowest value of 7.0 m in winter. That is, the water-level changes estimated by the eight climate models are likely to increase during the wet season and decrease in the dry season. In addition, the impacts of future climate
changes on the water-level regimes of Poyang Lake tend to prolong the duration of flooding water levels and enhance the hydrological deficits leading to lower water levels than at present (Figure 7(a)–7(c)).

The normalized probability distribution functions (PDFs) of the RCP2.6, RCP4.5, and RCP8.5 are calculated in relation to the 1986–2005 baseline as shown in Figure 8. It is evident that the probability of occurrence for both the high (>16 m) and low (<9 m) lake water levels exhibits an increasing trend (i.e., up to 5%), but the probability of occurrence for other different water levels (~12–17 m) by the eight models tends to decrease (i.e., up to 6%) (Figure 8(a)–8(c)) relative to the baseline scenario. Overall, these predicted changes indicate that future climate changes are more likely to affect the lake water levels both on temporal distribution and magnitudes, despite a similar seasonal pattern.

Climate change impacts on lake floods and droughts

In order to further evaluate the impacts of future climate changes on Poyang Lake floods and droughts, it is necessary to clearly quantify the changes of the high (Q10) and low (Q90) lake water level (Figure 9). Except for the BCC and MRI models, all other GCM simulations tend to suggest that the increases in the severity of future flood events are due to large relative changes (e.g., up to 2.0 m for BNU under RCP8.5; Figure 9(a)). However, the FGOALS, GISS, and MIROC produce some negative changes. Figure 9(b) shows that the future lake water level will be considerably lower at dry seasons due to all the GCM projections with the noticeable reduction in lake levels in the magnitudes of 0.1–1.5 m (except GISS which exhibits <0.6 m increases in lake level), indicating that the droughts of Poyang Lake are more likely to intensify in the future.

Figure 10 provides a side-by-side comparison of the maximum and minimum annual lake-water-level changes across the future periods for all eight GCMs averaged over the RCP2.6, RCP4.5, and RCP8.5 emission scenarios. For the maximum annual water-level distribution, box-plots show that the majority of GCMs yield a distribution with increased median changes compared to the baseline scenario (except the BCC model; Figure 10(a)). Results indicate the significant risk in the severity of floods in future climate change, despite the noticeable reduction in interannual variability due to the considerably narrower range. All the GCM projections yield decreased median changes with a narrower range, indicating that the lake droughts are likely to intensify (except the GISS model; Figure 10(b)). These predicted changes for the period 2020–2035 fully indicated that there may be significant risk in the severity of floods and droughts in Poyang Lake, leading to higher and lower water levels than present seasons.

DISCUSSION

Climate change plays an important role in affecting terrestrial and aquatic ecosystems via various physical and biological processes, particularly for some highly fluctuating lakes (Tanner et al. 2011; Tal 2019). However, projecting lake water-level response to multiple stressors is still difficult, because forcing factors may change simultaneously and unevenly (Tanner et al. 2011; Li et al. 2015). Our study examines the impacts of future climate change on lake water levels through the utility of linked lake-catchment models, exemplified by the large Poyang Lake (China) case study. The WATLAC hydrological model was driven by current climatology and climate change scenario temperature and precipitation data from eight selected GCMs to provide the river discharges. Considering the findings of this work and previous relevant studies (e.g., Ye et al. 2011; Li et al. 2016), the decreasing river discharge during the dry winter months and the increasing river discharge during the wet summer may have important effects on the water resource planning, water availability, and other aspects of the catchment. The river discharges together with the Yangtze River’s effects were used as input for the BPNN lake water-level prediction model for historic (1986–2005) and future periods (2020–2035). The BPNN model is simpler and more feasible than many conventional statistical models and physically based hydrodynamic models in Poyang Lake (e.g., Ye et al. 2011; Li et al. 2015).

Although the results of this study represent successfully the temporal behaviors of the future lake levels, it is important to keep in mind that the current integrated model projection necessitated some simplifications. Several atmospheric variables including solar radiation, wind speed,
Figure 8 | PDFs for projected monthly lake water-level anomalies (compared with the baseline period) by multi-model assessment under (a) RCP2.6, (b) RCP4.5, and (c) RCP8.5 scenarios for the period 2020–2035. Arrows indicate the significant changes in lake water levels during representative water-level periods of the lake.
Dew point temperature were not considered for the WATLAC hydrological model due to the lack of projected values of different GCMs. For the catchment model, land-use patterns in Poyang Lake’s catchment were kept unchanged for the purpose of distinguishing the climate impacts on river discharge. Although the BPNN model used some key climate factors (e.g., precipitation and temperature) to consider the impacts of climate conditions of the Yangtze River on the water-level changes of Poyang Lake, it is not the best way to represent the hydrological regime in the mainstem of the Yangtze River under future climate changes. Additionally, the Three Gorges Dam in the upstream of the river may exert some impacts on the mainstream flows (Zhang et al. 2012a; Yang et al. 2016), which was beyond the scope of this research. Future work should develop numerical models for projecting the flow regime of the Yangtze River and the associated climate impacts. While a majority of the model runs were used for the

Figure 9 | GCM projections of future 2020–2035. (a) Q10 and (b) Q90 lake water-level change under the three emission scenarios relative to baseline 1986–2005. Q10 and Q90 are the 10% and 90% values and used as proxy indicators of changes in flood and drought conditions, respectively.

Figure 10 | Comparison of the maximum (a) and minimum (b) annual water-level distributions for Poyang Lake from eight GCMs in the future (2020–2035) with the baseline period (1986–2005). The line in the box represents the median (50th percentile) of all climate change scenarios. The top and bottom of each box represent the 25th and 75th percentile values.
prediction of lake water levels, these results contained a high degree of uncertainty in the projection of future lake levels, but it seems reasonable to rely on simulated trends assuming that model error predictions are similar among different scenario simulations. The major sources of uncertainty are the path of future emissions and differences between GCMs used in this study. However, there is no universally accepted methodology for evaluating the relative quality of GCMs with regard to their ability in projecting the future climate (Bader et al. 2008).

In order to utilize the integrated model framework for regulatory or planning purposes, potential improvements could include: (1) the development of downscaled climate change scenarios incorporating additional atmospheric drivers (e.g., dew point temperature) for catchment hydrological model input and (2) improvement in the temporal span of the integrated simulation, providing long-term modeling results. Further improvements in the study could include a sensitivity analysis implemented in both the hydrological and lake models for the key drivers, using synthetic scenarios through changing the drivers by arbitrary amounts within realistic ranges. Linking models through an input–output approach (i.e., loose coupling), as done in this study, inherently neglects certain feedback loops that might have significant impacts on long-term lake system behavior (Li et al. 2014).

CONCLUSIONS

Changes in lake water levels play a key role in affecting the quantity and quality of the Poyang Lake water resources and the natural ecological environment. The linking of GCMs, WATLAC, and BPNN shows promise as a modeling tool for projecting combined impacts of climate changes on water levels of Poyang Lake. Catchment hydrological projections reveal that climate change leads to distinctly decreasing river discharge in dry seasons and increasing trend in flood seasons, varying between −26% and 29%. In general, the lake simulation results show a consistent pattern in seasonal water-level dynamics as compared with the baseline condition (1986–2005). The future water levels tend to increase in spring and summer within the range of 5–25%, while a noticeable reduction in lake water levels in autumn and early winter with magnitudes ranging from −5% to −50%. Overall, the GCM simulations suggest increases in the severity of future floods due to large relative changes by up to 2.0 m, while the future lake water level will be considerably lower at dry seasons due to all the GCM projections with the noticeable reduction in lake levels in the magnitudes of 0.1–1.3 m, relative to the maximum- and minimum-recorded water levels from 1986 to 2005. The probability of occurrence of both the high and low water levels exhibits an increasing trend by up to 5%, indicating a significant risk in the severity of floods and droughts in Poyang Lake. All of these changes are likely to have a considerable impact on the region’s character, its cities, economy, and climate-sensitive sectors of its hydrology and ecosystem. For this reason, the climate change scenarios combined with the linked modeling approach used here may be applied to other similar hydrological systems to assess their potential response to climate change and other external forcings.

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