The impacts of climate change on water diversion strategies for a water deficit reservoir
Chi Zhang, Xueping Zhu, Guangtao Fu, Huicheng Zhou and Hao Wang

ABSTRACT

This paper presents an assessment framework that analyses the impacts of climate change on the water diversion strategies of a water transfer project in China. A water diversion strategy consists of high and low water levels as well as related diversion flows in four operating periods: pre-flood, flood, post-flood and non-flood periods. The optimal water diversion problem is defined as a multi-objective problem with two conflicting objectives: minimising human and ecological water supply shortages, and solved by the popular non-dominated sorting genetic algorithm II (NSGA-II). The derived Pareto-optimal solutions are then evaluated using the predicted runoffs based on an ensemble of three general circulation models under three climate scenarios. Results obtained from the study catchment show that intra-annual distribution of future runoff changes. The optimal solutions on the Pareto front have greatly varying performance under a climate scenario. It is critical to reveal the different impacts of climate change on the water shortages over the four operating periods, in particular when an increase of water shortage in one period is masked by a reduction in one or more periods. This study illustrates that the framework can be used to identify resilient water diversion strategies to mitigate the potential impacts of climate change on the operation of a water transfer project.

Key words | climate change, impact analysis, multi-objective optimisation, reservoir operation, water diversion, water supply

INTRODUCTION

It has been increasingly recognised that climate change will have a profound impact on management and operation of water infrastructure systems (e.g., Milly et al. 2008; O’Hara & Georgakakos 2008; Mynett & Vojinovic 2009; Wagener et al. 2009; Raje & Mujumdar 2010; Harvey et al. 2012). The potential impacts of climate change should be considered in the planning, design and operation stages of a large water project, which typically lasts for centuries once constructed (Hamlet & Lettenmaier 2000; Yang 2010). Of particular interest in this paper are inter-basin water transfer projects, which divert water from a water-abundant river basin into a water deficit region.

Water transfer projects have been promoted as a real option to relieve water supply pressures and many projects have been constructed in many countries around the world, such as South Africa (Muller 1999), Spain (Azevedo et al. 2005) and Mexico (Dyrnes & Vatn 2005). In particular, China has built more than 20 large water transfer projects since the 1950s (Li 2005), including the huge South-North Water Transfer Project (Ma et al. 2006). These inter-basin water transfer projects normally divert water into a reservoir, from which water is delivered to meet various demands, such as domestic, industrial, agricultural and ecological demands.

Previous research has focused mainly on planning and design of inter-basin water transfer projects due to their wide socio-economic and environmental impacts. For example, Gupta & Zaag (2008) discussed integrated water resources management of water transfers involving engineering, science and politics. Sadegh et al. (2010) studied...
the optimal water allocation problem of a water transfer project. Reservoir operation has been regarded as a classical water resources system analysis problem and many optimisation and evaluation techniques have been developed and applied to different real-world reservoir systems with different system characteristics and purposes (e.g., Suen & Eheart 2006; Kim et al. 2008; O’Hara & Georgakakos 2008; Raje & Mujumdar 2010; Vicuna et al. 2010; Yin et al. 2010; Akbari et al. 2011). However, there is little research on developing water diversion strategies of a water transfer project in conjunction with the operation of the receiving reservoirs.

It is critically important to understand the performance of a water diversion project in a changing future climate, which might affect the water resources available in the supplying and receiving regions. The optimal water diversion strategy based on the current hydrological conditions may not be optimal under future conditions, resulting in excess or shortage of diverted water. Previous research has attempted to investigate the impacts of climate change on future reservoir operation and water supply. Raje & Mujumdar (2010) studied climate change impacts on a multipurpose reservoir performance and derived adaptive policies for possible future scenarios. Li et al. (2009) studied the potential response of runoff and reservoir operation performance to future climate change in a Northern American Prairie watershed. O’Hara & Georgakakos (2008) assessed the ability of an existing reservoir to meet urban water demand under present and projected future climatic scenarios. Lopez et al. (2009) used perturbed physics ensembles of climate models for impact analysis and planning for public water supply under climate change in England. To our knowledge, however, few attempts have been made to investigate the impacts of climate change on inter-basin water transfer strategies.

This paper aims to develop an assessment framework to study the impacts of climate change on optimal water diversion strategies considering multiple conflicting objectives. An ensemble of three global circulation models (GCMs) is used to generate plausible future climate conditions, which are then input into a hydrological model to predict future runoffs. Water diversion strategies are optimised using a multi-objective evolutionary algorithm and a reservoir model. The proposed framework is demonstrated using the water transfer project in the water deficit Biliu River basin, China. The derived water diversion strategies are analysed under three different climate scenarios. Results obtained show that the strategies have greatly varying performance under a climate scenario and that the framework can help the decision-maker to identify resilient strategies that achieve a significant reduction in both human and ecological water shortages under all three climate scenarios.

**METHODOLOGY**

The framework consists of a downscaling method, a hydrological model, a water transfer strategy optimisation model and a multi-objective evolutionary algorithm. The structure of the integrated framework is described in Figure 1. The
outputs from GCMs are analysed and downscaled to regional daily climate variables using the downscaling method. The future runoff conditions are generated using the hydrological model based on the predicted regional climate variables. Water diversion strategies are developed using the water transfer strategy optimisation model under current hydrological conditions and evaluated under future climate conditions.

**Water diversion strategy**

Development of optimal water diversion strategies has to consider the water shortage characteristics of the receiving basin, in order to achieve an efficient use of water resources available in the supplying and receiving river basins.

**Diversion strategy**

Reservoir operating rule curves are the most common tool currently used to manage reservoir operations (Yin et al. 2010). Figure 2 illustrates the monthly water diversion operating rule curves for the case study reservoir. In a hydrological year, the 12 months are divided into four operating periods according to the characteristic of water deficit for a specific study area, i.e., pre-flood, flood, post-flood and non-flood periods. Between the reservoir maximum and minimum water levels, the high and low water level curves are employed here to construct the water diversion rule curves. Each curve can be described by four water level variables, i.e., $ZH_i$ and $ZL_i$, $i = 1, 2, 3, 4$, for the high and low water level curves, respectively. The water diversion rule curves divide the reservoir storage into three zones: high zone, middle zone and low zone. A water diversion strategy is determined according to the following rules: when the actual reservoir water level is in the high zone, no water is diverted; when in the middle zone, the diversion flows are $IM_i$, $i = 1, 2, 3, 4$ for the four operating periods; when in the low zone, the diversion flows are $IL_i$, $i = 1, 2, 3, 4$. The maximum and minimum water levels, which are defined during the reservoir design stage, will not be changed. The variables $ZH_i$, $ZL_i$, $IM_i$ and $IL_i$ ($i = 1, 2, 3, 4$) will be optimised in this study. During the operating process, when there is insufficient water to meet all the demands of the users, the water supplies are reduced proportionally for all users according to empirically determined hedging rates (Yin et al. 2010). More specifically, when the reservoir water level is in the low zone, the water supplies (out flows) for the three water users are with water demands multiplied by coefficients of 0.98, 0.90 and 0.90 for the domestic, agricultural and ecological water users, respectively. When in the high and middle zones, the supplies are the demands (Zhu et al. 2014).

![Figure 2](https://iwaponline.com/jh/article-pdf/16/4/872/387389/872.pdf)
Objective functions

Many reservoirs are built with multiple purposes and reservoir operation is a multi-objective optimisation problem (Kim et al. 2008; Akbari et al. 2011). The goal of the water transfer project is to meet water demands, including the public and agricultural water demands, and ecological water demands. Thus the water supply objectives are to minimise the water shortage ratios corresponding to the two demands, as shown below.

**Human water supply objective**

\[
Z_{\text{hum}} = \min \left\{ \alpha_1 \times \frac{1}{T} \sum_{t=1}^{T} \left[ \max \left( 0, \frac{Q_{\text{pub}}^t - R_{\text{pub}}^t}{Q_{\text{pub}}^t} \right) \right] + \alpha_2 \times \frac{1}{T} \sum_{t=1}^{T} \left[ \beta_t \times \max \left( 0, \frac{Q_{\text{irr}}^t - R_{\text{irr}}^t}{Q_{\text{irr}}^t} \right) \right] \right\}
\]

**Ecological water supply objective**

\[
Z_{\text{eco}} = \min \left\{ \frac{1}{T} \sum_{t=1}^{T} \left[ \max \left( 0, \frac{Q_{\text{eco}}^t - R_{\text{eco}}^t}{Q_{\text{eco}}^t} \right) \right] \right\}
\]

\(Z_{\text{hum}}\) is the human water need objective and \(Z_{\text{eco}}\) is the ecological water need objective. The human objective includes the public and agricultural components. The \(\alpha\) terms are the weighting factors for public and agricultural demands (\(\alpha_1 = \alpha_2 = 1/2\) in this research). The ecological objective refers to the water shortage ratio of meeting the ecological water demands. The water shortage ratios are defined as the average ratio of the water deficit to the relevant demands over the study periods. \(T\) is the total number of months in a study period. \(Q_i^t\) is the demand of sector \(x\) (where \(x\) is replaced by pub, irr and eco in this paper, representing the public, agricultural and ecological water use, respectively) in the \(t\)th study period; \(R_x^t\) is the actual water release for sector \(x\) in the \(t\)th study period. \(\beta_t\) is used to represent the time sensitivity of the crop growth according to the distribution of the agricultural water demand during a year. \(\beta_t\) is large during crop growth-sensitive periods, small during crop growth-insensitive periods and zero during non-crop growth periods. The factor \(\beta_t\) is the average ratio of the water use in the \(t\)th month to the total water use in an entire year, calculated using the historical data.

The water balance in the reservoir is represented by a continuity equation. The reservoir water levels and volumes are constrained according to their design limitations.

**Constraints**

The model constraints are shown below

\[
S_{t-1} + W_{t}^0 + W_{t}^{\text{in}} - \left( W_{t}^{\text{eco}} + W_{t}^{\text{pub}} + W_{t}^{\text{irr}} \right) - W_{t}^{\text{w}} - S U_t = S_t \tag{3}
\]

\[
\begin{align*}
Z_0 & \leq Z_t \leq Z_c, \quad \text{during the flood and post – flood period} \\
Z_0 & \leq Z_t \leq Z_m, \quad \text{during the pre – flood and non – flood period} \\
\end{align*}
\]

\[
\begin{align*}
S_0 & \leq S_t \leq S_c, \quad \text{during the flood and post – flood period} \\
S_0 & \leq S_t \leq S_m, \quad \text{during the pre – flood and non – flood period} \\
\end{align*}
\]

\[
0 \leq W_{t}^{\text{in}} \leq W_{t}^{\text{in, max}} \tag{6}
\]

\[
\begin{align*}
Z_0 & \leq ZL_{t}^{\text{f}} \leq ZL_{t}^{\text{u}} \leq Z_c, \quad \text{during the flood and post – flood period} \\
Z_0 & \leq ZL_{t}^{\text{f}} \leq ZL_{t}^{\text{u}} \leq Z_m, \quad \text{during the pre – flood and non – flood period} \\
\end{align*}
\]

Equation (3), which is referred to as the continuity equation, is the constraint on the water balance. Equations (4) and (5) are the constraints on the water level and allowable storage. Equation (6) is the constraint on the amount of annual water diversion. Equation (7) is the constraint on the upper and lower water diversion levels. Herein, \(S_t\) (m³) is the storage at the end of \(t\)th study period; \(W_{t}^0\) (m³) is the natural inflow during the \(t\)th study period; \(W_{t}^{\text{in}}\) (m³) is the actual amount of diverted water; \(W_{t}^{\text{w}}\) (m³) is the actual amount of water supply for water user \(x\) (\(x\) is pub, irr, eco, representing the public, agricultural and ecological water users); \(W_{t}^{\text{w}}\) (m³) is the reservoir surplus water during the \(t\)th study period; \(z_t\) (m) is the ended water level during the \(t\)th study period; \(Z_0\), \(Z_c\) and \(Z_m\) (m) are the dead storage water level, flood...
control level and the allowable water level during the dry stage; $S_0$, $S_c$ and $S_n$ (m$^3$) are the reservoir storage corresponding to the $Z_0$, $Z_c$ and $Z_n$; $W_{0,\text{max}}^{\text{in}}$ (m$^3$) is the maximum amount of annual water diversion, which is $500 \times 10^6$ m$^3$ here; $ZL_i$ and $Zl_i$ (m) are the upper and lower water diversion levels, and they also varied in the range of $Z_0$, $Z_c$ and $Z_n$, $i = 1,2,3,4$.

**Multi-objective optimisation method**

The non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al. 2002) is selected to solve the above water transfer optimisation problem. It uses an elite-preservation strategy and an explicit diversity-preserving mechanism in order to provide fast non-dominated sorting and get good coverage of the Pareto front. It has been widely used for solving multi-objective optimisation problems, and has been proved to be efficient for such problems (e.g., Suen & Eheart 2006; Fu et al. 2008; Alvisi et al. 2011; Creaco & Franchini 2012).

**Future runoff generation**

**Global climate change scenarios**

The future climate conditions can be represented by climate scenarios. The IPCC Special Report of Emission Scenarios (2000) developed various emission scenarios, based on different assumptions of social, economic and technological developments. Three scenarios, A1B, A2 and B1 are considered. A1B describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. A1B has the highest rates of technological change and economic development, and it describes balance across all sources of technological change in the energy system. A2 describes a very heterogeneous world, in which the underlying theme is self-reliance and preservation of local identities. B1 describes a convergent world with the same global population that peaks in mid-century and declines thereafter, as the A1B, but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social and environmental sustainability, including improved equity, but without additional climate initiatives. The three climate scenarios are considered because they can capture the range of uncertainties and are typically chosen by other studies (Raje & Mujumdar 2010; Vicuna et al. 2010).

Lopez et al. (2009) found that additional information contained in an ensemble of climate models can provide a better understanding of the possible ranges of future conditions, compared to the use of a single model. Thus, the monthly data from three GCMs are used to consider the uncertainties of global climate prediction in each of the three scenarios (A1B, A2 and B1). The used GCMs include BCCR_BCM2_0 (Norway), CSIRO_MK3_0 (Australia) and NCAR_CCSM3 (USA). They are chosen because the required climate variable data are available in the study river basins for all the scenarios. The GCMs used typically have a grid cell size of $1^\circ \times 1^\circ$. The study area is largely located within one cell. The regional monthly precipitations of the study area are calculated by averaging the data at the four nearest grid nodes.

**Downscaling using historical information**

The meteorological outputs from each GCM are from 1901 to 2099. Several climate variables impact the hydrologic cycle, such as precipitation and temperature, etc. As the main source of runoff, precipitation affects the runoff generation. According to the historical information, the daily average temperature varies substantially from below zero to nearly 20°C in the case study catchment. The future temperature changes have little impact on runoff and thus are not considered.

The monthly output data from the GCMs need to be downscaled to daily data for future runoff prediction using a hydrological model. Milzow et al. (2010) applied a downscaling method based on past climate data time series according to monthly relative variations. The method is used here and described in detail as follows. First, a baseline period, which refers to a past period, and a future period are chosen based on the whole study periods. The GCM outputs are monthly time series for both the baseline and future periods, while the historical daily climate data are available.
for the baseline period only. Second, on the basis of the monthly climate data of GCMs outputs, monthly variation ratios can be calculated by dividing the future period monthly climate data by the baseline period monthly climate data. Third, the future daily climate data can be calculated by multiplying the historical daily climate data of the baseline period by the monthly variation ratios. The downscaling method used here is simple but can effectively represent the monthly variations in climate variables (Milzow et al. 2010).

Hydrological model

Model description

The Soil and Water Assessment Tool (SWAT) is a continuous and physically based distributed hydrological model (Winchell et al. 2008). It was developed to simulate hydrological processes with an aim to assessing the impact of land management practices on water quantity and quality in response to complex soils and land use conditions in watersheds (Arnold et al. 1998). The SWAT model can simulate a variety of hydro-physical processes within the catchments. The model has been widely applied to national projects in the USA (US Environmental Protection Agency 1999) and a number of research projects on different scales in different countries (Kang et al. 2006; Abbaspour et al. 2007; Guo et al. 2008; Marshall & Randhir 2008; Li et al. 2009b; Zhang et al. 2013). In addition, SWAT can be used for climate impact analysis by simply using proportional changes of climate elements.

Model calibration and validation

Model calibration and validation are necessary to identify the SWAT model parameters before it can be used for prediction. The Latin Hypercube sampling based on One Factor at a Time (LH-OAT) method (van Griensven et al. 2006) incorporated in SWAT was used to identify the sensitive parameters. Then model calibration was carried out by optimising the sensitive parameters according to the following model performance metrics below: the average relative error (Re), the coefficient of determination ($R^2$) and the Nash–Sutcliffe model efficiency ($Ens$). These metrics are defined as follows:

$$Ens = 1 - \frac{\sum_{t=1}^{T} (Q_{mt} - Q_{st})^2}{\sum_{t=1}^{T} (Q_{mt} - Q_{avg})^2} \quad (8)$$

$$Re = \frac{(Q_{avg} - Q_{avg})}{Q_{avg}} \times 100\% \quad (9)$$

$$R^2 = \frac{\sum_{t=1}^{T} (Q_{st} - Q_{avg})(Q_{mt} - Q_{avg})}{\left\{ \sum_{t=1}^{T} (Q_{st} - Q_{avg})^2 \right\}^{1/2} \times \left\{ \sum_{t=1}^{T} (Q_{mt} - Q_{avg})^2 \right\}^{1/2}} \quad (10)$$

where $Q_{mt}$ and $Q_{st}$ are the measured and simulated flow rates at time $t$, respectively; $Q_{avg}$ are the average measured and simulated flow rates over the simulated period, respectively; while $T$ is the total number of time steps. A higher $Ens$ value represents a better goodness-of-fit of the SWAT model. A $Re$ value closer to zero represents a better performance of the model and $Re = 0$ represents a perfect match between the average measured and simulated data. A smaller $R^2$ value reflects a worse goodness-of-fit with $R^2 = 1$ meaning a perfect fit.

CASE STUDY

Biliu River basin

The Biliu River reservoir was built primarily for water supply and flood control. It is located in the Liaoning Province of China (Figure 3) and is the most important water source for Dalian City. The drainage area of the reservoir is 2,085 km² with a total storage capacity of $934 \times 10^6$ m$^3$. Its accumulated water supply for Dalian City has been $4,000 \times 10^6$ m$^3$ since it was built. However, in recent years, the Biliu River reservoir has experienced severe water shortage problems, which have been regarded as a bottleneck for the economic and social development of the city. Water transfer from a basin of abundant water resources is a potential solution to reduce the gap between the water demand and the water supply.
The water transfer project from Dahuofang reservoir to Biliu River reservoir is currently being constructed to transfer water to meet the increasing demands in Dalian. The source basin, Dahuofang reservoir, has a total storage capacity of $2.19 \times 10^9$ m$^3$ and its average annual reservoir inflow is about $1.49 \times 10^9$ m$^3$. It serves as a main, controlling reservoir for the large water transfer projects in Liaoning Province with a maximum water diversion capacity of $1.910 \times 10^9$ m$^3$ per year. However, the planned water supply is $1.27 \times 10^9$ m$^3$ in 2015, so there is still $642 \times 10^6$ m$^3$ spare capacity. This
sparing capacity is used to supply water for Dalian City, through
the water transfer project to Biliu River reservoir. The water
transfer project from Dahuofang reservoir to Biliu River reser-
voir was designed to have a maximum water diversion
capacity of $300 \times 10^6$ m$^3$ per year, which is $288 \times 10^6$ m$^3$ after
loss. The mentioned spare capacity is twice the current maxi-
mum water diversion capacity. The source region has
sufficient water even under climate change in the future.
According to the variations in water resources available
within a year, the maximum diversion flows are determined
for the four operation periods (see Table 1). Dahuofang reser-
voir is linked with some other reservoirs in Liaoning Province,
offering the flexibility of integrated control to maximise the use
of water resources. Thus the available water in Dahuofang
reservoir is regarded as sufficient for transferring to Biliu
River reservoir even considering future climate change.

Table 1 | The variable ranges used in the optimisation process

<table>
<thead>
<tr>
<th>Variables</th>
<th>Range</th>
<th>Pre-flood period</th>
<th>Flood period</th>
<th>Post-flood period</th>
<th>Non-flood period</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZH (m)</td>
<td>Upper</td>
<td>69.0</td>
<td>68.5</td>
<td>68.5</td>
<td>69.0</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>47.0</td>
<td>47.0</td>
<td>47.0</td>
<td>47.0</td>
</tr>
<tr>
<td>ZL (m)</td>
<td>Upper</td>
<td>ZH</td>
<td>ZH$_2$</td>
<td>ZH$_3$</td>
<td>ZH$_4$</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>47.0</td>
<td>47.0</td>
<td>47.0</td>
<td>47.0</td>
</tr>
<tr>
<td>IM (m$^3$/s)</td>
<td>Upper</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>IL (m$^3$/s)</td>
<td>Upper</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Lower</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

The average historical water deficits during the four
operating periods are represented in Figure 4. The operating
periods, the months in each period have similar water condi-
tions and can be operated with similar rules, are used to
decide the period diversion flows. The operating periods
also result in fewer decision variables, which make the opti-
mising calculation more efficient. The maximum water
deficit occurs in May and June, because the period is the
crop growth-sensitive period and the agricultural water
demand is large, and this is taken as the pre-flood period.
In July and August, there is no water deficit but excess
flood water, and this is taken as the flood period. In Septem-
ber and October, there is a small quantity of water deficit or
surplus, and this is taken as the post-flood period. The
remaining months, the non-flood period, have a rather uni-
form distribution of water deficit, which is largely from the

Figure 4 | The historical water deficits in the Biliu River reservoir.
uniform public and ecological water demands as the agricultural water demand is rather low during this period. The variable ranges used for the four operating periods in the optimisation process are listed in Table 1.

### Dataset

The available monthly historical runoff records of 1958–2005 are used for optimising water diversion strategy. Years 1980–2004 are taken as the baseline period for future runoff prediction. The climate dates of 1901–2099 for three climate change scenarios (A1B, A2 and B1) were downloaded from the National Climate Center (http://ncc.cma.gov.cn) and extracted for the baseline period (1980–2004) and two future periods 2016–2040 and 2041–2065. Predictor precipitation data output from the three GCMs of the future time slices for the A1B, A2 and B1 scenarios are used to project future runoff.

Historical hydrological data were obtained from different sources as described below. Daily and monthly runoff data for the Biliu River were obtained from the Biliu River Reservoir Administration. Daily precipitation data were provided by the Hydrology Bureau of Liaoning Province. Historical meteorological data, which include daily solar radiation, humidity, maximum and minimum temperature, wind speed and direction, were collected from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/index.jsp) and were used in the hydrological model.

The SWAT model also requires topographic, land use and soil data for the case study areas. The Digital Elevation Model data with a resolution of 90 m × 90 m were provided by the CGIAR Consortium for Spatial Information (http://srtm.cgiar.org). Soil type and land use maps were provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn/first.asp).

Water demand data were obtained from the Biliu River Reservoir Administration. The historical water demands of the domestic and agricultural water users are 220.5 and 22.4 × 10^6 m³ per year, respectively. Historically, there were zero-flow conditions downstream of the Biliu River reservoir during an extended period of a year. To avoid unreasonable zero-flow conditions, we consider the use of ‘good’ ecological flow in the optimisation process. The ‘good’ ecological flow is defined according to the approach by Tennant (1976), which is 40% of the historical average annual flow for the months from June to August, the critical period for fish to lay eggs, and 20% for the other months. The corresponding annual ecological water demand for the study area is 151.4 × 10^6 m³. The domestic water demand in 2015 is projected to increase from 220.5 to 508.5 × 10^6 m³, the increased demand (288 × 10^6 m³) will be supplied through the diversion project, while the agricultural and ecological water demands remain unchanged. Furthermore, the public water demand is typically evenly distributed within a year, while the agricultural water demand has an uneven distribution.

### RESULTS AND DISCUSSION

#### Optimised diversion strategies

The Pareto optimal front obtained for the two water supply objectives under the current hydrology conditions is shown in Figure 5. Since both objectives are minimisation objectives, the ideal solution should be as close to the left-bottom corner as possible in the two-dimensional objective space. It can be seen that there is a clear tradeoff between the two objectives, that is, an improvement in the ecological objective results in an increase in the human objective.

In order to demonstrate the efficiency of water diversion, we compare the Pareto front in Figure 5 to the water deficits in the historical water demand scenario. We optimised the reservoir operation with historical water demand but without...
water diversion. The domestic, agricultural and ecological demands are 220.5, 22.4 and $151.4 \times 10^6$ m$^3$ per year, respectively. The optimised Pareto front without water diversion is also shown in Figure 5. It shows that the water shortage ratios are larger than the Pareto front with water diversion. These ratios are expected to increase further when domestic water demand is increased to $508.5 \times 10^6$ m$^3$.

The curve can be divided into three sections as circled in Figure 5: the top section represents solutions with a good performance in the human water supply objective, the bottom section represents solutions with a good performance in the ecological water supply objective, and the middle section represents solutions with balanced objectives. Decision-makers may choose a water diversion strategy solution based on their preference structures. Three solutions SA, SB and SC are selected from the top, bottom and middle sections for detailed analyses, respectively. Their human and ecological water supply objective values are shown in Figure 5.

Recall that the water level and diversion flow decision variables are not only constrained by the allowable ranges (Table 1), but also constrained within the maximum amount of annual water diversion. Results obtained show that the Pareto-optimal solutions are feasible: their water levels are within reservoir allowable storages and the average annual diverted water reasonably less than the maximum amount of annual water diversion, e.g., the average annual diverted water of SA, SB and SC are 186.8, 217.2 and $178.6 \times 10^6$ m$^3$ respectively, smaller than $300 \times 10^6$ m$^3$.

The high and low water level curves, as well as the eight diversion flows for different water level zones are shown for the three solutions in Figure 6. Their diversion water levels are high during the non-flood period and much lower during the flood and post-flood period, because the water deficits are large during the former period and small during the latter periods. During the pre-flood period, the low water levels are similar while the high water levels are significantly different. The high water level of SA during the pre-flood period is much higher than SB, and SC balances them.

The diversion flows of SA are the highest during the pre-flood period, i.e., 16 m$^3$/s for the middle and low zone. SA also has a higher flow than the other two solutions during the flood period, i.e., 3.5 and 8 m$^3$/s for the middle and low zones. This is because from May to August are the crop growth-sensitive periods and SA represents an emphasis on human needs. However, the largest diversion flows of SB happen during the non-flood period, i.e., 16.5 m$^3$/s for the middle zone and 17 m$^3$/s for the low zone. The ecological needs are high during the flood and post-flood periods and there is a small amount of water diverted during the flood period, so the diversion flow

![Figure 6](https://iwaponline.com/jh/article-pdf/16/4/872/387389/872.pdf)
during the post-flood period is the highest in the three solutions. But it is still too low, 4 m³/s for the middle zone and 4.5 m³/s for the low zone. The water consumption in the two periods causes a high water diversion flow during the non-flood period for SB. The emphasis of ecological water supply causes the large diversion flow of SB during the post-flood and non-flood period. The high water diversion flows supplement the reservoir storage. The diversion flows of SC seem to balance those of SA and SB.

From Point SA to Point SB along the Pareto curve, the corresponding diversion flows during the pre-flood and flood period have a decreasing trend while during the post-flood and non-flood period have an increasing trend. SC diverts a medium flow between those of the two extreme strategies and is relatively more uniform. The advantage of the large flow diversion, compared to the medium flow, is that the flows in other periods are reduced, with one period having a flow rate of zero, which might reduce the water loss in the transfer process. However, the medium flow diversion fits the characteristics of water deficit better than the high flow diversion form. Further, the medium flow diversion reduces the flood risks by avoiding a high water level in the reservoir prior to the flood period.

The distribution of human and ecological water shortage ratios over the four operating periods are shown for the three selected solutions in Figure 7. The human water shortage ratios are very large during the pre-flood period; however, they are very small (<2.52%) during the other three periods. The ecological water shortage ratios are more evenly distributed over the four operating periods than human water shortage ratios, with a maximum of 8.61%. The large diversion flow of SA during the pre-flood period first relieves the agricultural water shortage and reduces the water shortage ratios. Although the human water shortage ratio of SA in the pre-flood period is the largest (1.43%) among the four periods, it is much smaller than the ratios of the other two diversion strategies. Conversely, the ecological water shortage ratio of SA in the pre-flood period is the smallest, but increases gradually and reaches the peak until the non-flood period. The human and ecological water shortage ratios of SB are the largest during the pre-flood period and then decrease gradually and reach the bottom until the non-flood period. Although there is excess water in the flood period (Figure 4), there are water shortages in this flood period, as shown in Figure 7. It is because both figures show average conditions over long periods. Further analysis shows that most years have excess water in the flood period, resulting in the average excess water as shown in Figure 4. However, several continuous dry years, such as 1990–1993 and 1999–2004, do not have sufficient water resulting in the water shortage ratios in this period. The different distributions of water shortage ratios under SA and SB result from the different distributions of diversion flows at different periods: during the pre-flood and flood periods, the water shortage ratios under SA are the smallest while under SB are the largest; conversely, during the non-flood period, the water shortage ratios under SA are the largest while under SB are the smallest. Since SB diverts larger flow than the other two strategies.

**Future climate scenarios**

Recall that the monthly variation ratios use for downscaling are calculated by the average precipitations of the future...
periods 2016–2040 and 2041–2065 compared to the baseline period 1980–2004. The average monthly precipitation data of these periods are averaged over the three GCMs. The distributions of monthly and periodical precipitation in the future period are shown in the top half of Figures 8(a) and 8(b).

Compared to the baseline period, the average annual precipitation for A1B, A2 and B1 increases by 10.60, 6.22 and 5.18%, respectively. The results indicate that the changes in the total amount of precipitation vary significantly within a year. During the three operating periods (from May to October), precipitation is predicted to increase in all the three scenarios except for a decrease of 3.43% for June in B1. There is a generally decreasing trend during the non-flood period (November to February) in all the three scenarios. The greatest increase (25.59%) in precipitation occurs in September under A1B. The greatest increase of 14.56% under A2 occurs in July, and 17.21% under B1 occurs in May.

**Runoff forecast**

Based on the LH-OAT method incorporated into SWAT, the parameters that have a significant influence on the efficiency are first identified. Then the model’s calibration is performed manually by varying the sensitive parameters in
order of significance and in order of the flow station controlled sub-basins from the upstream to the downstream. The ranges of the main SWAT parameters for the study area are listed in Table 2.

The simulated and measured monthly runoffs during the calibration and validation periods at the station of Biliu River reservoir are shown in Figure 9. The values of $E_n$ and $R^2$ exceed 0.85 and 0.90, respectively, and the absolute value of $R_e$ is less than 10% during both periods. Model identification and evaluation remains a challenging area, in particular for complex hydrological models (Giustolisi & Savic 2009; Wagener et al. 2009). Thus, the model performance can be regarded as reasonable when $E_n > 0.50$, $R^2 > 0.60$ and $R_e < 20\%$ according to Hao et al. (2006). Therefore, the results in Figure 9 show a good agreement between measured and simulated data, suggesting that the model is suitable for runoff prediction.

The annual runoffs of three scenarios in the future period are simulated by the validated SWAT model using the daily precipitation data generated from downscaling. The predicted runoff percentage differences relative to the baseline period are shown in Figure 10. It clearly shows the differences between the three scenarios and with the baseline. The annual runoffs in the entire simulation period under A1B are larger than those of the baseline period. The future runoffs in most years under A2 and B1 are larger than the baseline period runoff, but smaller runoff happens frequently after 2041 under B1. The mean annual runoff under A1B, A2 and B1 over the simulation period increases by 14.44, 5.82 and 3.34%, respectively, compared to the baseline period.

The distributions of monthly and periodical runoffs are shown in the bottom half of Figure 8(a). The maximum increase of future runoff occurs in September under A1B (27.62%) and in July under A2 (11.50%) caused by the maximum increase in precipitation. The precipitations in July and August are similar but the runoff generated in July is much less than that in August because the antecedent soil moisture is small in July due to a long period of dry months. For example, the runoff of B1 decreases by 9.91% when the precipitation increases by 2.29% in July. Figure 8(b) shows that the future runoff increases in all the four periods in A1B. In A2 and B1, however, the runoff increases during the flood and post-flood periods and decreases during the other two periods. The results indicate that the annual precipitation and runoff increase to different extents in the three scenarios. The human and ecological water supply objectives under future scenarios may be influenced by the varied quantity and distribution of future runoffs.

### Climate impacts on optimised water diversion strategies

#### Objective values

All the Pareto-optimal solutions shown in Figure 5 were re-evaluated under the three climate scenarios A1B, A2 and B1. Figure 11 shows the re-evaluated human and ecological water supply objectives under the three scenarios. Under Scenario A1B, the performance of Pareto-optimal solutions is much improved, which implies that the water deficit can be relieved under A1B. Under scenarios A2 and B1, some solutions perform worse, with an increase in both water supply shortage ratios. However, some solutions have an improved performance, with a reduction in both water supply shortage ratios. This implies that the varying distribution of future runoff within a year under different scenarios has a substantial influence on the water supply of the reservoir, although an increase in annual future runoff is observed in all the three scenarios (in the section Runoff forecast). The results reveal that some solutions on the Pareto front are more resilient to future climate changes. This finding might help decision-makers to establish a preference structure and make an informed decision.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Default range of variation</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN2</td>
<td>SCS runoff curve number</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>ESCO</td>
<td>Compensation coefficient of soil evaporation</td>
<td>0–1</td>
<td>–</td>
</tr>
<tr>
<td>ALPHA_BF</td>
<td>Base flow recession constant</td>
<td>0–1</td>
<td>days</td>
</tr>
<tr>
<td>GW_DELAY</td>
<td>Delay time for aquifer recharge</td>
<td>0–500</td>
<td>days</td>
</tr>
<tr>
<td>REVAPMN</td>
<td>Threshold water level in shallow aquifer for re-evaporation</td>
<td>0.02–0.2</td>
<td>–</td>
</tr>
<tr>
<td>CANMX</td>
<td>Maximum canopy storage</td>
<td>–</td>
<td>mm</td>
</tr>
</tbody>
</table>
Figure 9 | Simulated monthly runoff at Biliu River reservoir station: (a) calibration period of 1980–1989; (b) validation period of 1990–1999.

Figure 10 | The predicted runoff percentage differences relative to the baseline period.
The three selected solutions are further analysed. Table 3 shows the solutions’ performance improvements, represented by the relative reduction in each objective compared to its original values. The results indicated that SB has good performance in the three future climate scenarios, while SA and SC improve under scenario A1B only. Recall that solution SB has a very low ecological deficit, and as a compromise it has a high human water supply deficit. However, the human water supply deficit can be reduced significantly under the three scenarios, with a maximum of 86.44% under A1B. Overall, solution SB is the most resilient solution to future climate change, which might be preferred by a decision-maker to mitigate the climate change impacts.

Distribution of human and ecological water shortage ratios

Figure 12 shows the breakdown of the average changes of human and ecological water shortage ratios into four operating periods. The x-axis represents the three selected solutions grouped for each operating period.

Recall that solution SB has a significant reduction in human water shortage under the three climate scenarios in comparison to the baseline scenario. It can be observed from Figure 12(a) that the reduction results from the pre-flood and flood periods and there is little change in the post-flood and non-flood periods. For solution SA, it has a significant reduction in human water shortage under all three scenarios, but it is offset by an increase in the non-flood period under A2 and B1, actually resulting in a deterioration in this objective. For solution SC, there is an increase of human water shortage in all the four periods except for the flood period under A2 and B1, and a decrease of human water shortage in all the four periods under A1B.

Similar observations can be made for the ecological water shortage objective. Solution SA has an increased ecological water shortage in the non-flood period under A2 and B1. Solution SB has a slight increase of ecological water shortage in the non-flood period but has a reduction in all the other periods.

Figure 12 highlights the substantial variations of the human and ecological water shortages in the four operating periods under future runoffs. It is particularly critical to reveal the variations when they are masked by the average
water shortages over the simulated period. This information will help a decision-maker to fully understand the implications of a water diversion strategy, and support informed decision-making in the water transfer operation and management process.

**CONCLUSIONS**

This study has developed a framework for analysing the impact of climate change on water diversion strategies from a water-abundant river basin into a water deficit reservoir. The framework is applied in a real world case study of Biliu River reservoir basin, China. The optimal water diversion problem is defined as a multi-objective problem, with two conflicting objectives: minimising human and ecological water supply deficits. The Pareto-optimal solutions derived are evaluated using the predicted runoffs based on an ensemble of three GCMs under three climate scenarios (A1B, A2 and B1). Specifically, the main findings from this study are summarised below.

1. The distributions of water shortage over the four operating periods differ significantly in the human and ecological objectives. The human water shortage mainly occurs in the pre-flood period; however, the ecological water
shortage is more evenly distributed over the four periods. Further, there is a clear tradeoff between the human and ecological water shortage objectives as expected.

(2) The predicted runoff variations between the baseline and future periods vary in the four operating periods. An increase in future runoff is predicted for the flood and post-flood periods and a decrease is predicted for the pre-flood and non-flood periods.

(3) The optimal solutions on the Pareto front have greatly varying performance under a climate scenario, with some solutions having an improved performance in both human and ecological water shortages under all three climate scenarios. In particular, the solution at the bottom of the Pareto front, which has the greatest human water shortage and the smallest ecological water shortage among all solutions, is rather resilient under all three scenarios, achieving a significant reduction in both water shortages.

(4) The impacts of climate change on the human and ecological water shortages vary in the four operating periods. The increase of water shortage in one operating period may be masked by a reduction in one or more periods, highlighting the importance of revealing the variations of water shortage in the four periods in addition to the average water shortage over the future period simulated.

This study provides an in-depth understanding of the potential impacts of climate change on a water transfer project in China, and also provides a useful tool for the decision-maker to identify more resilient water diversion strategies to mitigate potential climate impacts in the future. The proposed framework will be tested on more case studies and the uncertainties related to various components will be analysed in a future study.

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