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Bottom-up quantification of inter-basin water transfer vulnerability to climate change

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ABSTRACT

Inter-basin water transfer (IBWT) projects offer us a long-term means to minimize the mismatch between water demand and water availability. Climate change may impose significant vulnerability to IBWT projects through perturbations in water availability. However, previous studies of climate change's impacts on IBWT's vulnerability are mainly based on a top-down framework, i.e. forecasting the climate change via a wide range of GCMs, which may underestimate the uncertainty of climate change. In order to address this problem, a bottom-up vulnerability assessment framework is developed to evaluate the vulnerability of IBWT. In this framework, an IBWT vulnerability indicator is proposed based on three dimensions of vulnerability including exposure, sensitivity and adaptive capacity. The framework also highlights the deep uncertainty of climate change by adopting a probabilistic Budyko model, which can estimate the water availability over a broad range of climate futures. The South-to-North Water Transfer Project (SNWTP) in China is adopted as a case study to illustrate the effectiveness of the proposed framework. It shows that the framework is a useful tool for identifying the detrimental climate condition scope for the IBWT's vulnerability, and is valuable to guide long-term water resources management and planning for policymakers.

1. Introduction

With its large capacity to convey water from one river basin (the donor basin) to another (the recipient basin), inter-basin water transfer (IBWT) projects have been promoted for many years to alleviate the problem of the heterogeneous distribution of water resources (Zhang et al., 2015). The key of IBWT's long-term reliable operation lies in whether the transferred water can effectively reduce the scale of mismatch between regional water demand and water availability in each basin involved in IBWT. The mismatch is closely related to climate change. Under climate change, the water availability in each river basin and the possible transferred water from the donor to the recipient basin may be significantly changed (Bates et al., 2008; Pittock et al., 2009). Consequently, climate change has become a key determinant of IBWT project's vulnerability (Zhang et al., 2012).

Vulnerabilities concentrate directly on a system which has weakness that susceptible to climate change which can alter its trajectory to reach its objectives (Vidal and Marle, 2012). A clear understanding of the vulnerability of IBWT is necessary, since the transferred water is typically related to the water availability for human consumption, irrigation, power generation, and industrial uses. Furthermore, systematically identifying vulnerabilities of IBWT can help governments optimize their expenditures and engineering designs for these projects, and also can facilitate water resource managers in the face of climate change.

Current vulnerability analysis frameworks can be classified in two main categories: top-down framework and bottom-up framework (Nazemi and Wheater, 2014; Moody and Brown, 2012). The top-down framework belongs to a scenario-led approach. The basic principle of this approach is to simulate future performance of a system over a set of emission scenarios. Most previous studies of the potential impacts of climate change on IBWT have used these scenario-led approaches (Xi et al., 2010; Gurung and Bharati, 2012; Maknoon et al., 2012). These top-down methods project future conditions from downscaled ocean-atmosphere general circulation models (GCMs) and simulate system responses using hydrological models. However, because of large irreducible uncertainties and poor capacity for representing climatic variability, these methods limit analytical and decision making abilities with respect to water resource management (Brown and Wilby, 2012).

To highlight the deep uncertainty about climate change as well as to avoid uncertainties initiated from downscaling GCMs, decision scaling or robust decision-making approaches to identifying climate change

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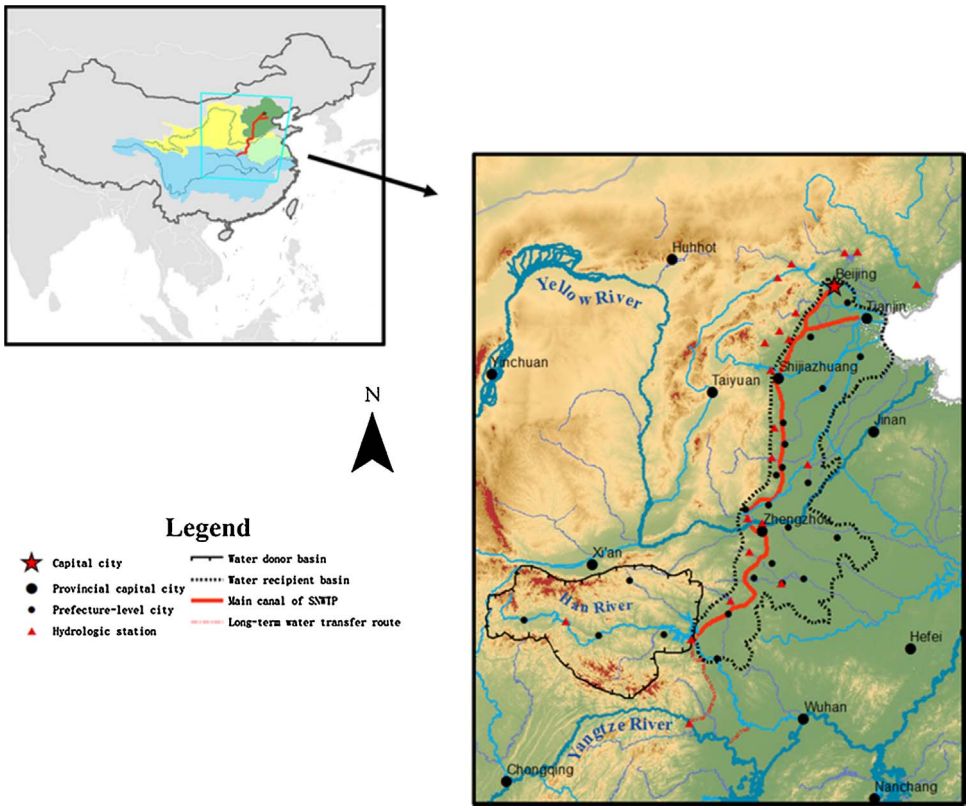

Fig. 1. Location of the Central Route of the SNWTP.

adaptations have been proposed and applied with a bottom-up framework (Brown and Wilby, 2012). Instead of directly assessing system responses to projected climate change, these approaches focus on systematically identifying the greatest vulnerabilities across all future possibilities and considering which suite of climate change adaptations will perform reasonably well across this range. Weaver et al. (2013) also affirmed the value of such frameworks because they are well suited to large-scale integration with climate modeling and have the potential to provide a quantitative, transparent tool to facilitate critical decision-making and may facilitate communication of modeling outcomes to the public and other stakeholders. The general process of bottom-up vulnerability quantification can be divided into five steps: defining system performance criteria, building a system model, conducting vulnerability analysis, evaluating options to inform decision(s), and identifying a preferred decision. Poff et al. (2015) summarized out these steps and applied them to a hypothetical case study of the Iowa River, USA. Most recent bottom-up vulnerability case studies have focused on river basins or water supply systems and have proven these approaches feasible for decision making when projections of the future are highly uncertain (Nazemi et al., 2013; Ghile et al., 2014; Singh et al., 2014).

Despite lots of efforts to examine the climate change induced vulnerabilities in various kinds of water resource systems, only a few studies have been performed on the vulnerability of the IBWT. For example, Gurung and Bharati (2012) quantified the downstream effects of diverting water from the donor basins of the Melamchi Water Supply Project in Nepal under current as well as future climate scenarios. Maknoon et al. (2012) used Dez to Qomrood Inter-Basin Water Transmission Project in Iran as a case study and evaluated the efficiency of different protocols under the effect of climate change. Shrestha et al. (2015) analyzed the impact of climate change on the water diversion plan for the Melamchi Water Supply Project (MWSP) in Nepal. However, the existing studies were all based on the top-down framework mentioned above, i.e. forecasting the climate change via a wide range of GCMs. They cannot avoid the inherent weaknesses of scenario-led approaches.

The bottom-up framework can partly resolve these problems. However, to date there are no studies on IBWT's vulnerability quantification based on the bottom-up framework. Furthermore, no studies have put forward system performance criteria or selected a water system model which is really suitable for the IBWT. Due to the significant difference in scale and complexity between the ordinary water supply systems and IBWT, the bottom-up vulnerability assessment framework established for the ordinary water supply systems is not suitable for the IBWT.

In this paper, we provide a framework of vulnerability quantification of an inter-basin water diversion system. Beginning with identifying hazards which bring the key vulnerability of future climate to IBWT, a performance indicator is then developed to quantitatively measure vulnerability. Next, a water system model is chosen to predict annual water availability under the identified hazards, and we further combine the indicator and the model as a whole to involve greater complexity for the water transfer system and accurately reflect vulnerability for the bottom-up decision making. In order to show the practicality and feasibility of the framework, this study provide a demonstration of bottom-up quantification of future vulnerability for the Central Route of the South-to-North Water Transfer Project (SNWTP). Quantifying vulnerability of IBWT will help people to reexamine the performance of this kind of project under climate change, and provides a reference for water resource managers to face future climate effects wisely.

2. Central Route of the South-to-North Water Transfer Project

2.1. Description of the project

The SNWTP in China is the largest and the most strategic water transfer project ever undertaken. The SNWTP diverts water from the water rich south-central China to the arid North China plain through a large canal (Fig. 1). The total length of the canal is approximately

1264 km. With huge land but uneven distributed water resources, the entire study area includes both the donor and recipient basins involved in SNWTP. The project initially provides 9.5 billion m^3 of water annually. By 2030, the mean annual water quantity to be diverted is expected to increase to 12 ~ 13 billion m^3. The Central Route of SNWTP mainly supply water to more than 20 large- and medium-sized cities in the middle and western parts of the Huang-Huai-Hai Plain. The mega project has achieved initial success. As of mid-July 2015, the water supply for the first phase of the Central Route had exceeded 1 billion m^3. Receiving areas included Dengzhou, Nanyang, Luohe, Pingdingshan, Xuchang, Zhengzhou, Jiaozuo, Puyang, Hebi, and Xinxiang cities in Henan Province, reaching a beneficiary population of 10 million. Approximately 5 million people in Handan, Xingtai, Shijiazhuang, and Baoding cities in Hebei Province also benefited. In the Beijing and Tianjin regions, daily water supplies were about 2.2 and 1.3 million m^3, accounting for 70% and 80% of urban water consumption respectively; the total beneficiary population is approximately 17 million. In the near future, water supply will increase along as more conveyance system and water plants put into operation.

As a mega project of IBWT, the Central Route traverses China's four main river basins − the Yangtze river, Yellow river, Huaihe river and Haihe river basins and numerous sub-basins. Considering the integrity of river basin or sub-basin and administrative divisions and the spatial characteristics of water diversion, the entire study area involved in the project is divided into 10 regions for the convenience of research (Fig. 2). Two regions (Regions 1 and 2) are located in the donor basin for the Central Route of the SNWTP, whereas others (Region 3 to 10) are in the recipient basins. Some additional details including the cities located within the region, water allocation quota, water resource conditions and economic situation of these regions are listed in Table 1. Because of the division of the study area, the varying hydrological conditions and vulnerabilities could be easily examined and contrasted among regions.

2.2. Data sources

Runoff and meteorological data for this study were collected and processed as follows: streamflow data for 21 hydrological stations are collected for the period of 1950 to 2010 from the Hydrological Year Book of China. A summary of the hydrological station location and data collection period can be found in Table 2. Climate data for 1950 to 2010, including precipitation, air temperature, wind speed, solar radiation, and relative humidity, were acquired from the National Meteorological Information Center of the China Meteorological Administration. Potential evapotranspiration amounts were calculated from the Penman-Monteith equations (Allen et al., 1994; Allen et al., 1998). The units of streamflow, precipitation, and evapotranspiration are converted into mm. All the streamflow and meteorological data were spatially averaged over the 10 regions of our study area. Some statistics data such as population density and per capita GDP are from China City Statistical Yearbook (2016). The scheme of water allocation is based on the Master Plan for South-to North Water Transfer Project.

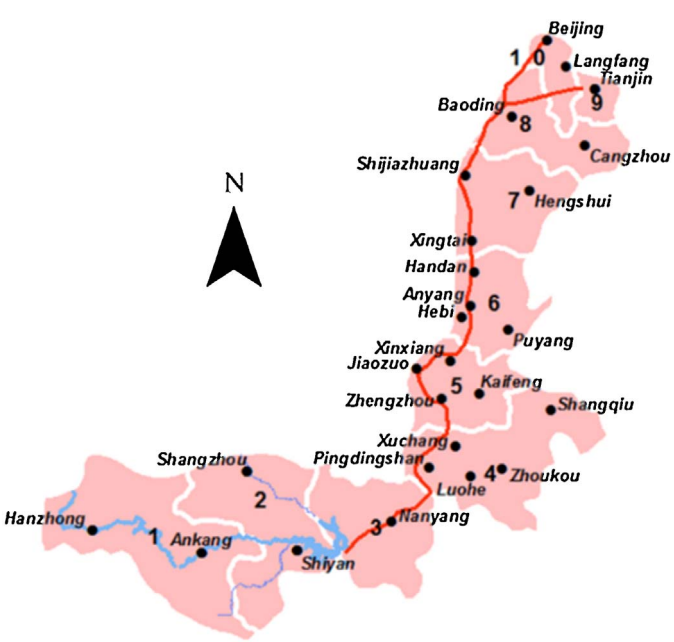

Fig. 2. The spatial division of the study area.

3. Methodology

Our application follows the framework of the vulnerability-based bottom-up approach, with some modifications to make it suitable for IBWT. Inspired by Nazemi and Wheater (2014), our new framework takes a four-step procedure to evaluate the vulnerability of IBWT to climate change. We start with an identification process of the key hazards and critical climate variables. The key hazards are the most essential meteorological events influencing the vulnerability of the IBWT, and the critical climate variables are the dominant factors leading to the key hazard. After the key hazard is identified, we develop a new IBWT performance indicator to measure IBWT performance related to the key hazard. Then, a water system model is chosen to connect the whole framework. Finally, we input the feasible range of critical climate variables to represent the various degree of future key hazard and conduct an IBWT vulnerability analysis by analyzing the output of performance indicator.

3.1. Identification of key hazard and critical climate variables

Hazard identification is always a prerequisite for better understanding of vulnerability. Full awareness of the hazards associated with a water resource system is always part of the bottom-up vulnerability assessment framework and, in this study, we focus only on the key hazard resulting in the most primary and critical vulnerability since only certain kinds of vulnerabilities capture the attention of policy makers. Critical climate variables mean a set of climate variables which are the major driving factors of key vulnerability. This section includes the process of correlating the key hazard to key vulnerability and identifying the critical climate variables which could lead to the key hazard.

The primary goal of water transfer projects is to redistribute water resources to increase the water availability in the receiving basins. Although IBWT is considered as an adaptation strategy to inadequate water availability, its long term operation also depends heavily on a reliable, stable water availability condition. Water availability is important to IBWT. Any perturbation in regional water availability can influence the target of the project and threaten the project benefit. From the prospective of vulnerability, the vulnerabilities of IBWT lie in the process of water availability perturbation.

In the context of climate change, changing water availability is inevitable. The amount of water availability could be limited by more serious water-related hazards like droughts. The occurrence probability of droughts may increase along with the impacts of climate change (Winstanley et al., 2006). Drought is considered as the key hazard of IBWT to climate change which will significantly affected water availability. Meanwhile, higher temperature (leading to increased evaporation) and less precipitation (leading to less water provisions), may result in more frequent and severe droughts. So, precipitation and temperature are the critical climate variables.

Changes in runoff patterns can significantly affect water availability for human consumption and to some extent represent the degree of drought. In order to verify whether climate change really has a significant impact on the water availability, we adopt several statistical

Table 1
Summary of the basic conditions of the 10 study regions.

Region no.	City	Water transfer allocation in SNWTP (10^9 m^3/year)	Per capita water resources (m^3)	Population density (persons/km^2)	Annual average population (10,000 persons)	Total water supply (1000 tons)	Water consumption for residential use (1000 tons)	Per capita GDP (yuan)
1	Hanzhong	–	3872	140.78	385.2	2588	1280	28908
	Ankang	–	3964	130.10	264.0	1358	911	26117
2	Shangzhou	–	2142	130.49	251.2	930	538	24538
	Shiyan	–	1969	146.52	346.8	11007	4641	35604
3	Nanyang	3.99	790	445.66	1178.0	9545	2726	26651
4	Luohe	1.06	320	990.60	270.4	9923	1665	36671
	Zhoukou	1.03	257	1034.10	1230.4	3681	970	22651
	Pingdingshan	2.50	372	706.83	554.2	10322	3412	33014
	Xuchang	2.26	228	1003.90	498.2	4612	1556	48471
	Shangqiu	–	280	887.19	946.1	4335	1791	23359
5	Zhengzhou	5.40	178	1259.47	956.9	34131	15488	72991
	Kaifeng	–	294	885.62	551.0	7961	2725	32454
	Jiaozuo	2.69	223	907.93	368.7	8013	2488	52421
	Xinxiang	3.92	380	727.59	627.8	7716	3174	33699
6	Puyang	1.19	178	1013.54	420.9	5467	1530	34895
	Hebi	1.64	423	764.85	166.4	5753	1926	42550
	Anyang	2.83	322	831.56	597.8	5185	2618	35210
	Handan	3.52	192	853.28	1020.7	14633	4800	32945
7	Xingtai	3.30	220	621.64	767.9	5206	1937	22758
	Hengshui	3.10	148	513.40	450.3	2464	1171	26022
	Shijiazhuang	7.82	229	781.85	1020.1	19098	8073	48970
8	Baoding	5.50	282	539.37	1145.3	8796	3369	26501
	Cangzhou	4.83	180	547.47	758.5	3952	1492	42676
9	Tianjin	10.20	134	853.12	1517.0	81249	35691	105231
10	Beijing	12.40	130	812.5	2152.0	182419	35691	99995
	Langfang	2.58	195	705.75	436.4	5001	2249	48407

tests to identify the trends and change points of the mean annual runoff under the past climate condition. The Mann–Kendall modified trend test (Hamed and Ramachandra Rao, 1998; Yue and Wang, 2004) for auto-correlated series was implemented to evaluate the monotonic trend in runoff series. Sen's Slope test (Sen, 1968) which is a nonparametric alternative for assessing the slope of a univariate time series, was also be used to detect trends in the runoff series. Pettit's test (Pettitt, 1979) was applied for change point detection. Excellent introductions to these statistical tests are found in the references cited here. Some results obtained from these statistical tests will support the following analysis. Spatial correlations of runoff, precipitation, and potential evapotranspiration among the all regions were explored in this study, which help to reveal the spatial characteristics of hazards.

The identification of key hazard and critical climate variables is closely related to the next few steps. In the second step, water availability perturbation caused by drought hazard will be chosen and integrated into a performance indicator to quantify vulnerability of IBWT under climate change. In the third step, the critical variables are then given within a feasible range which can reflects various degree of future drought, and will be taken as the input of water system model to generate water availability. A better understanding of hazards not only provides insights for the current situation of a system and the extent of climate change, but also supports the process of decision making.

3.2. IBWT performance indicator

Detecting the vulnerability of water resource system under climate change is important for adaptation of strategies, such as investments in

Table 2
Summary hydrological station characteristics.

Hydrological station	River	Lon. (°E)	Lat. (°N)	Drainage area(km^2)	Record period
Zhangjiafen	Bai River	116.78	40.62	8506	1956–2005
Xiahui	Chao River	117.17	40.62	5340	1960–2012
Xiangshuibao	Yang River	115.18	40.51	14600	1956–2005
Shixiali	Sanggan River	114.73	40.25	25533	1956–2005
Luanxian	Luan River	118.76	39.73	44100	1954–2008
Zijinguan	Juma River	115.17	39.43	1760	1954–2002
Daomaguan	Tang River	114.63	39.08	2950	1957–2002
Zhongtangmei	Tang River	114.88	38.88	4990	1960–2008
Fuping	Sha River	114.18	38.85	4061	1958–2010
Huangbizhuang	Hutuo River	114.30	38.25	23400	1954–2012
Zhuzhuang	Sha River	114.23	36.98	1220	1954–2000
Guantai	Zhang River	114.08	36.33	17800	1956–2010
Yuancun	Wei River	115.06	36.11	14286	1956–2010
Wuzhi	Qin River	113.27	35.07	12880	1956–2007
Huayuankou	Yellow River	113.65	34.93	730036	1954–2008
Baisha	Ying River	113.25	34.34	985	1954–2009
Luohe	Shaying River	114.03	33.58	12150	1954–2010
Yahekou	Bai River	112.63	33.30	3030	1960–2007
Shiquan	Han River	108.18	33.04	23800	1954–2007
Danjiangkou	Han River	111.50	32.52	95217	1956–2012
Yichang	Yangtze River	111.30	30.68	1006000	1954–2010

and construction of infrastructure. There is widespread interest in developing a performance indicator to quantify climate change vulnerability as part of a vulnerability assessment process, but few attempts to define or quantify indicators have focused on complex, large-scale IBWT. Existing performance indicators are not ideally suited to mega water transfer projects. We propose a performance indicator for quantitative evaluation of IBWT vulnerability that originates from a traditional vulnerability assessment, with particular relevance to various possibilities for future climate change.

There are various forms of vulnerability indices exist. Climate change studies have broadly evaluated vulnerability through the sensitivity, adaptive capacity, and exposure to climate variations (Adger, 2006; Birkmann et al., 2013; Dong et al., 2015). In this view, McCarthy et al. (2001) suggested to quantitatively analyze vulnerability with a three parameters function which based on the three dimensions of vulnerability including exposure, sensitivity and adaptive capacity. Here we follow the conceptual model of vulnerability established by Dong et al. (2015). The model was used to quantitatively evaluate the agricultural vulnerability to climate change. The conceptual model of IBWT vulnerability quantification in a specific climate change could be established as:

$$Vulnerability = \frac{Sensitivity \times ExposureDegree}{AdaptiveCapacity} \tag{1}$$

Sensitivity is the degree to which the system will be affected by, or responsive to climate-related stimuli (Füssel and Klein, 2006). Adaptive capacity, is the ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a hazardous event, and exposure has been defined as the presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, and cultural assets in places that could be adversely affected climatic hazards (Cabinet Office, 2011; IPCC, 2012).

Some researchers have used the conceptual equation to describe how different elements of vulnerability are related, providing an objective and quantitative approach for evaluating vulnerability. In our study, we assume that vulnerability is proportional to the product of sensitivity and exposure degree, and is inversely proportional to the system adaptive capacity. These three terms are determined by an equation which could allow us to quantitatively analyze vulnerability in a system under climate change. In this brief article, we use the broad and established definition of vulnerability. We explain how to use Eq. (1) with IBWT and give a quantitative method to assess sensitivity, adaptive capacity, and exposure degree.

We have pointed that IBWT aims to solve the problem of uneven distribution of water resources, which is a matter of the lack of sufficient available water resources to meet water needs within one or more regions. Therefore, we start to express and quantify vulnerability with the calculation of regional water availability (*WA*).

For sufficiently large temporal and spatial scales, the change in water storage could be treated as zero, and the water exchange of groundwater can also be regarded as zero. *WA* can be directly regarded as the runoff measured at hydrological station since we are study the basin scale annual water availability.

WA fluctuates over time and can be referred to as a time series. A time series can consist of trend part, periodic term and stochastic part. Here we borrowed the concept of time series and decomposed *WA* into three components: the long-run trend or long-term average component (WA_T), a fluctuating component (WA_C) affected by climatic factors, and a remainder (or irregular or error) component affected by other random factors, which is micro and can be ignored. We chose years as the period of time, all these variables are expressed in mm per year and a time series of annual *WA* is written as:

$$WA_t = WA_T + WA_{C,t} \tag{2}$$

where WA_t is the volume of water availability at year t, WA_T is the long-term average component, and $WA_{C,t}$ is climate affected water availability at period *t*.

From previous Pettit's test in section 3.1, the break points of annual runoff, which indicate abrupt changes in water availability, have been detected. According the break point, the runoff series can be divided into two periods: natural period and impacted period. The long-term average components of water availability (WA_T) for each period are denoted by $WA_{T,natural}$ and $WA_{T,impacted}$, respectively.

Sensitivity is expressed by the range of the volume of WA_t relative to the WA_T in a period under a specific degree of climate change, called sensitive water availability. We assume that it is proportional to the difference between the minimum and maximum values of $WA_{C,t}$ then is divided by $WA_{T,impacted}$ and modified by adding one unit, as in the following equation:

$$Sensitive\ Water\ Availability = 1 + \frac{WA_{C,max} - WA_{C,min}}{WA_{T,impacted}} \tag{3}$$

We also argue that the closer the values for impacted period runoff and natural runoff are, the water diversion system more adaptable to climate change. However, IBWT movement of vast volumes of water from the donor basin to several recipient basins changes the local water availability in the region. We need appropriate variables to quantitatively evaluate adaptive capacity:

$$Adaptive\ Water\ Availability = \frac{WA_{T,impacted} \pm WT}{WA_{T,natural}} \tag{4}$$

where *WT* is the volume of water transferred into or out of the region. The total amount of water diverted from the donor basin should equal the volume of water inflow to the recipient basins.

According to the original project design, most of the water is supplied for urban living and industrial production, and some is for other uses. So, if hazard occur, populations, economies, ecologies, and environments could be affected by climate change. This study is mainly concerned with people and the economy; therefore, population density (*PD*) and per capita GDP (GDP_p) of each region are selected for the characterization of exposure degree. We also set the donor region (an average of region 1 and 2) population density (PD_0) and per capita GDP ($GDP_{p,o}$) as benchmarks to facilitate a comprehensive comparison among all regions. Thus, water availability exposure can be denoted by:

$$Water\ Availability\ Exposure = \frac{1}{2} \times \left(\sqrt{\frac{PD}{PD_0}} + \sqrt{\frac{GDP_p}{GDP_{p,0}}} \right) \tag{5}$$

Water Availability Exposure is a multiplier in the formula. Its value will have a great impact on the results of vulnerability of IBWT. There are square root transformations and coefficient multiplications to handle the value water availability exposure in a reasonable range. Thus, the regional water availability vulnerability under a climate change scenario can be further interpreted as:

$$Vulnerability = \frac{Sensitive\ Water\ Availability\ \times\ Water\ Availability\ Exposure}{Adaptive\ Water\ Availability} \tag{6}$$

When each variable is assigned values, the base equation listed above is used to calculate a non-dimensional score ranging from several to dozens. Increasing vulnerability values will cause a system to shift from one major state to another and eventually may lead to large and widespread consequences that may endanger the water diversion project.

3.3. Water resource system model

Prior procedures in this research have identified key hazard of the IBWT, and a performance indicator to quantify vulnerability based on regional water availability was also developed. In this section we choose a hydrological model called a probabilistic Budyko framework that serves as a quantitative link between climate variables and their

impacts on water availability. The model can be used in the bottom-up framework with projections of various degree key hazards by using different combinations of critical climate variables.

The Budyko framework (Budyko, 1948; Budyko, 1974) is a quantitative framework that treats the partitioning of water supply (P) between evapotranspiration (E) and streamflow (Q) at mean annual catchment scales as a functional balance between water supply and demand (E_p, potential evaporation). This framework has been successfully used to predict long-term or mean annual water availability for a wide range of hydroclimatic conditions. It serves as a semi-empirical model that provides a simple first-order relationship to estimate the evaporation ratio E/P as a function of the aridity index (E_p/P).

The Budyko framework origin from the original curve which was derived by Budyko. This framework assumed that a curve without any parameters was appropriate for large basins and long-term averages. However, it was later shown that a variety of catchment and climate characteristics can affect the shape and position of the curve to a basin (Donohue et al., 2006). To account for these factors, several other mathematical functions have been proposed to represent the Budyko hypothesis. One of the more popular forms, which we used in this study, is the Fu (1981) rational function equation (Zhang et al., 2004), which takes the form :

$$\frac{E}{P} = 1 + \frac{E_p}{P} - \left(1 + \left(\frac{E_p}{P}\right)^{\omega}\right)^{\frac{1}{\omega}} \tag{7}$$

where the single parameter ω in Fu's equation represents the sum effect of all processes not encapsulated in P and E_p, such as soil properties, slope, vegetation cover, and climate seasonality, which can alter the partitioning of P between E and Q. Although Fu's equation is more flexible to adapt to different watershed characteristics, these modified Budyko curves remain deterministic. Adjustable parameters are calibrated against local data and must always be treated as constants, thus, cannot quite explain the systematic deviations and large scatter that occurs between actual and expected values of the curve. On the basis of analytically derived Fu equation, Greve et al. (2015) proposed a way to account for systematic variations from the original deterministic curve and for the nonlinearity of the underlying Budyko space, thus extending the deterministic formulation of the curve to a probabilistic one to embody the parametric uncertainty in the Budyko curve. The existing research on probabilistic Budyko framework has fully explained the performance of it under various climatic conditions (Greve et al., 2015; Singh and Kumar, 2015; Gudmundsson et al., 2016).

In this study, we calibrate the Fu's equation using historically available data sets to obtain optimal estimates of ω for each control volume (district) in each year. Each region presents a different distribution of ω, and value ranges and centralizing trends for ω and E_p/P vary in different hydrological features. Greve et al. (2015) assumed ω follows a certain one dimensional distribution. Following the proposed probabilistic ideology but not replicating the method of Greve et al. (2015), the evaluated parameters were assembled to model the dependence structure and underlying joint distribution between ω and E_p/P by a copula-based method (Bárdossy and Pegram, 2009). The copula-based method has been commonly used for modeling the dependence structure of multivariate random variables and also for the multisite stochastic simulation.

The water system model's comprehensiveness and effectiveness for studying the effects of global change on water resources also facilitated our vulnerability quantification work, because future water availability as a result of changing climate can be derived easily from the model. Climate change, represented by changes in critical climate variable, can be illustrated by shifts in formula parameters. For example, extreme climate conditions with scant rainfall and high temperature could be manifested by increasing the value of E_p as well as decreasing the value of P, and eventually shift the value of E_p/P. With this probabilistic approach, we can simulate reasonable data sets of water availability in a given climate change scenario and assess regional system vulnerability follow the IBWT performance indicator we developed in section 3.2.

3.4. Quantification of climate change vulnerability

After determining the scope of the changes in temperature and precipitation respectively, we evenly alter the value of critical climate variables within the scope. We use this two-parameter representation of key hazard as input to the water system model to generate a large number of stochastic water availability series within the feasible future drought envelope in each region. Then the water availability series are converted to vulnerabilities of IBWT using the developed IBWT performance indicator. As a bottom-up vulnerability-based work, we do not seek to provide probabilities for the climate conditions that lead the system into an unsatisfactory state, but to generate different feasible climates as a climate space using a set of climate variables. The IBWT vulnerability response to hazard conditions can be quantified and visualized to improve insights about possible IBWT responses and provide a guide for adaptive management in the future.

4. Results

4.1. Hazard analysis for the SNWTP

The preliminary analysis of key hazard for this study included several statistical tests computed from annual runoff time series for each region. Table 3 shows the statistic result in runoff based on the Mann–Kendall test, Sen's slope test, and Pettitt's test. Observed runoff (Fig. 3, black dotted line), 5-year averages (Fig. 3, blue line), and trend lines (Fig. 3, red line) based on the Pettitt's test have been plotted for the 10 regions. Although all the catchments exhibited large variations in runoff, most experienced a more or less declining trend. Mean annual runoffs originally varied more than 400 mm between averages in the two donor regions, while in recent year runoffs have been less than 400 mm. For most of the northern regions, decreases in average annual runoff to less than 200 mm can be seen.

As Table 3 shows, the z statistic varied from −6.827 to 0.613 and Sen's slope varied between −1.630 and 0.565. Test results were positive in only one case (Region 3) and negative in all the other regions. In the donor basin statistically significant declining trends can only be identified in Region 1, with a confidence level of 95%. Similarly, except for Region 3 for which a trend couldn't be identified, the other receiving regions were dominated by significant trends (more than 95% confidence level) in runoff and a sudden change occurred around 1980. Trend lines give average runoffs before and after the mutation point. In the past two or three decades, several northern

Table 3
Summary of trend analysis for annual streamflow by Mann–Kendall modified trend test and Pettitt's test.

Region no.	Z statistic	Mann-Kendall test significance[a]	Sen's slope	Probable change year	Pettitt's test significance[a]
1	−2.067	**	−2.555	1991	**
2	−0.847	ns	−0.738	1986	ns
3	0.613	ns	0.565	1975	ns
4	−2.942	***	−1.282	1986	***
5	−4.885	***	−0.419	1978	***
6	−3.407	***	−2.095	1978	***
7	−3.493	***	−2.663	1979	***
8	−3.349	***	−1.329	1980	***
9	−6.208	***	−1.630	1980	***
10	−6.827	***	−1.554	1983	***

[a] ***, ** and * indicate confidence levels of 99%, 95% and 90%, respectively; ns indicates confidence level under 90%.

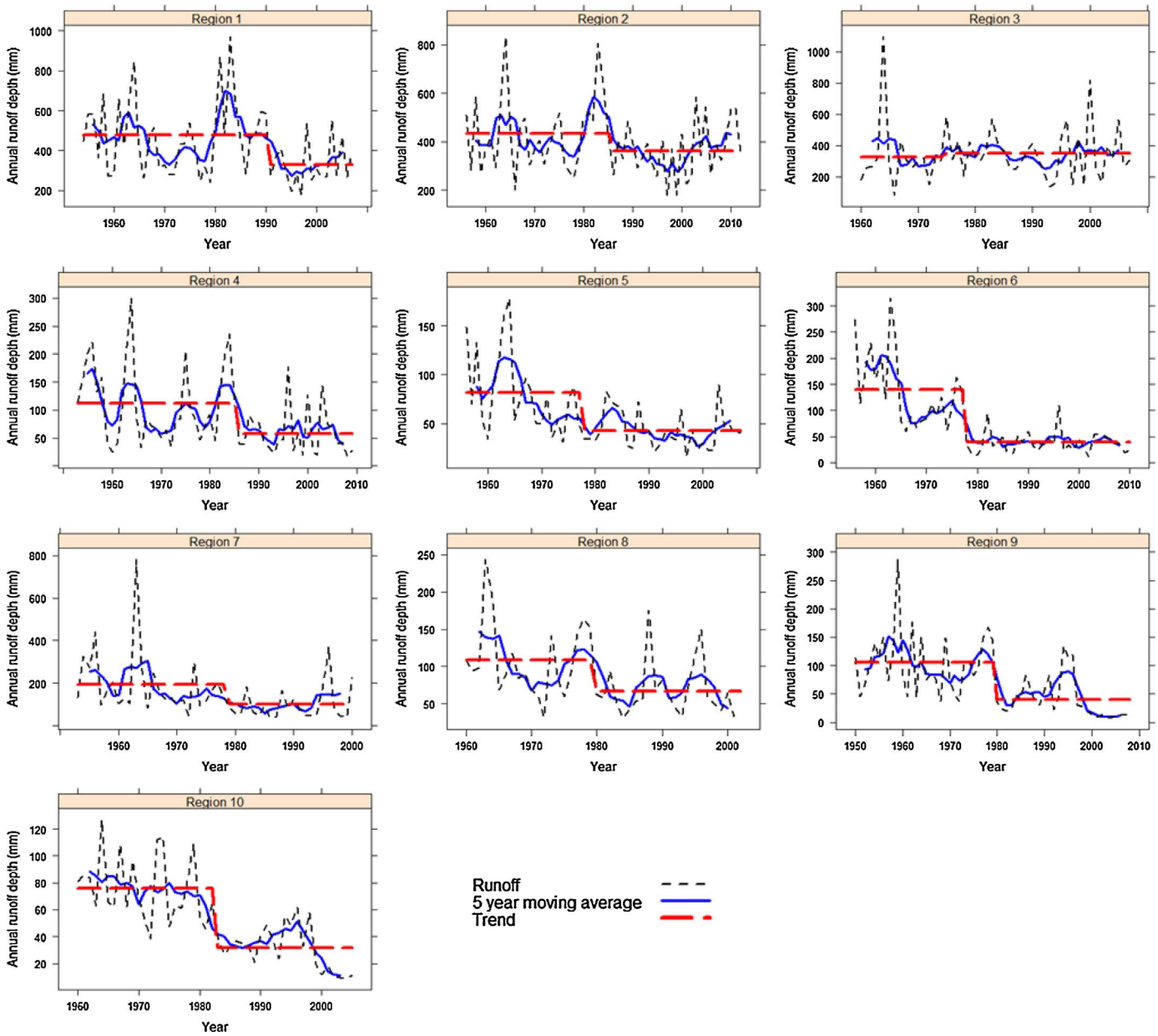

Fig. 3. Long-term variations, 5-year moving averages, and trend lines for runoff in each region. The trend lines give provide information about runoff averages before and after sudden change of runoff occurred.

regions that have already faced severe water shortages suffered even further reductions of water quantity at the same time. Some recent studies have claimed that the cause of sharply reduced water availability is a conjunction of climate change and human activities.

Fig. 4 provides a graphical display of the correlation matrix for runoff, precipitation, and potential evapotranspiration in the 10 regions. The three correlograms are almost consistent. It is reasonably clear that there are strong correlations between adjacent regions; additionally, some separated regions are mutually correlative to a certain degree, particularly in water recipient areas. A statistically positive correlation is exhibited here, suggesting that the concurrent occurrence of a dry year in several recipient regions or in both water-donating areas would be the most adverse combination for operation of the SNWTP. Regional drought or even widespread drought may become endemic because of climate change. Drought is a key hazard that exposes the entire region to the risk of water scarcity.

Key hazard identification proves that water availability is an indicative element to future vulnerability and that both increasing air temperature and decreasing precipitation are key factors that are symptoms of climate change.

4.2. Implementation of the probabilistic Budyko model

From the probabilistic Budyko framework, we mapped aridity index and ω onto the same surface, as shown in Fig. 5. Each point represents one year in a region. The clustering can be interpreted as the likelihood that these conditions will occur. There is substantial scatter in the values of ω and E_p/P, and broader ranges of these parameters are mostly observed in northern regions. For example, in the two donor regions, the values of E_p/P range from 0.5 to 2.0 and values of ω range from 1.2 to 2.2, while for northern regions with dramatic changes in water availability, the ranges of these parameters increase over time. Outliers in the upper part of the plots are assumed to have low probabilities for these conditions.

After using the copula method to model the dependence structure of the bivariate random variables ω and E_p/P, we validated the probabil-

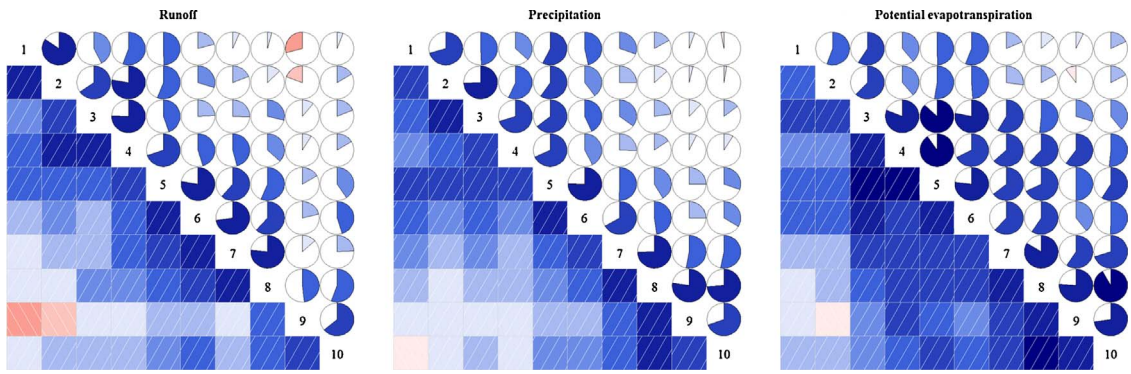

Fig. 4. (left to right) Correlograms of annual runoff, potential evapotranspiration, and precipitation intercorrelations in each region. Figures on the diagonal represent regions 1 to 10. Positive correlations are shown in blue, while negative correlations are shown in red. The darker the hue, the greater the magnitude of the correlation. It is also possible to use pie charts for visualizing correlation values.

istic Budyko framework and estimated the simulated ω and E_p/P values. The probabilistic Budyko framework does well in each region. Taking the Region 1 as an example, Fig. 6 shows that the distribution of points obtained from hundreds of simulations coincides well with the observed values. Climate change is illustrated by shifts in rainfall and temperature that change the values of E_p/P, so with this probabilistic approach, in the final step we can simulate reasonable data sets for water availability. For a given climate change scenario, we also can assess regional vulnerability based on an average of the data sets, following the IBWT performance indicator we developed in section 3.2.

4.3. Vulnerability quantification

We choose precipitation and temperature as climate variables critical to water availability. We vary precipitation from −40% to +10% of historical estimates and temperature increases from 0 °C to 5.0 °C as a two-parameter representation for different future drought severity. This identified climate conditions domain can be converted easily to corresponding water availability ensembles, using a probabilistic Budyko model.

We simulated our stochastic Budyko framework enough times so that nearly every climate change scenario could be covered. Water availability and regional vulnerability are derived from the averages of model outputs, and visualized in high-resolution, two-dimensional maps. Fig. 7 show modelled changes in annual water availability under climate change without considering SNWTP. The relative change rate of annual water availability in each of the 10 regions was estimated as a function of precipitation change and potential evapotranspiration change. Fig. 8. Show the vulnerabilities mapped in variable future climate spaces without considering SNWTP. The climate space is defined by precipitation change and potential evapotranspiration change in each of the 10 regions. The contours in Fig. 7 indicate the mean values for the water availability change rate in a future impact period, compared with average water availability in the current impact period. As temperatures increase, evaporation increases and rainfall decreases, resulting in decreased water availability. Fig. 8 describes system vulnerability as obtained from the IBWT performance indicator. It can be seen that vulnerability values may double and redouble, signaling high risk of droughts and water scarcities. Figs. 7 and 8 demonstrate that it is a matter of the utmost urgency to take measures to handle water stress, as the northern regions are affected the worst by both drought and warming. In some extreme climate change scenarios, water availability in some regions should have a sharp decrease based on the bottom-up framework predictions. This may expose populations and economies to mortal threats. Further observation also reveals that precipitation change has a much stronger influence on water availability than temperature change. From the perspective of vulnerability, the water source of the SNWTP Central Route is a comparatively ideal basin, with lower vulnerabilities. Vulnerability values were below 4 for most cases we have simulated in these regions.

Taking the SNWTP into account, there are significant shifts in water availability change rates in all regions. As shown in Fig. 9, the transfer project will supply additional water to cope with water scarcity. Especially in regions 9 and 10, the water availability change rate may be more than three times greater compared with the average volume available in the current impact period. In southern part of the project area, future projections for lower total annual rainfall and higher temperatures mean that less water will likely be available in the donor basins. When we use the volume of water diversion based on the scheme of the first phase of the Central Route project, the water diversion produces profound changes in local water supplies in the source area under the common action of climate change. Looking at the vulnerability values in Fig. 10, nearly all the recipient region vulnerabilities decrease compared with those without the diversion project. In some modest climate change scenarios, SNWTP could mitigate the effects of uneven distribution of water resources while maintaining a relatively low level of vulnerability. However, the transfer scheme will divert approximately 13 billion m^3 of water annually from the Danjiangkou reservoir on the Hanjiang, which is 1.5 times greater than diversion of the first phase, and climate change will not always be moderate. The vulnerability simulations in Fig. 10 indicate that with water transfer quantity of the first phase, severe climate changes could increase source area vulnerabilities significantly. The max vulnerability with SNWTP can be five to six times the value of the max vulnerability without SNWTP. Thus, whether these mega water transfer projects will be able to always satisfy human needs remains unknown.

5. Discussion

In this paper we have drawn attention to IBWT performance against the background of global climate change, generated reliable projections of future water availability under changing environmental conditions, and provided a bottom-up vulnerability assessment. This assessment framework also provides decision-relevant information about potential future climate change that lead to better decision making and help to guide long-term water resources management and planning. The key hazard identification process has shown a statistically significant positive correlation and declining trend in historical water availability data among relative areas of the water diversion project. This implies that we should pay special attention to drought and water scarcity in a regional perspective. Finally, our analysis suggests that SNWTP could relieve a water resource crisis to some extent, without causing a high level of vulnerability if climate change is not severe. Under some extreme climatic conditions, the situation will be complicated because the donor basin will display a high level of vulnerability.

Despite this quantification of vulnerability, it is still noted that there

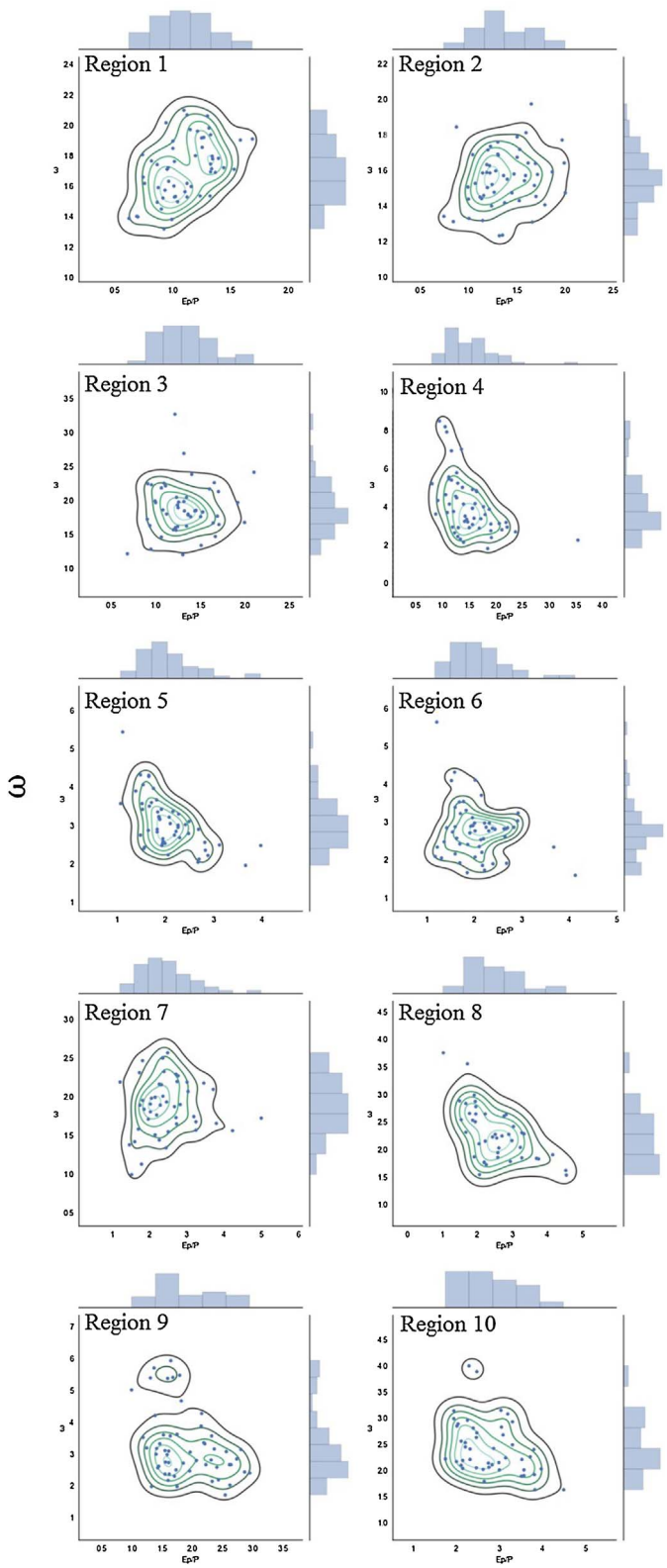

Fig. 5. Scatterplots of E_p/P (x-axis) and ω (y-axis) in each region. Marginal distributions of the points are shown as histograms and the contours represent density. Scatterplots for regions 1 to 10 are arranged from left to right and top to bottom.

are wide ranging sources of uncertainty associated with our choices of this quantification framework, the subsequent hydrological model employed, and the climate conditions for analysis. For example, in contrast to the traditional Budyko and Fu equations, the probabilistic model in the bottom-up framework is better able to deal with

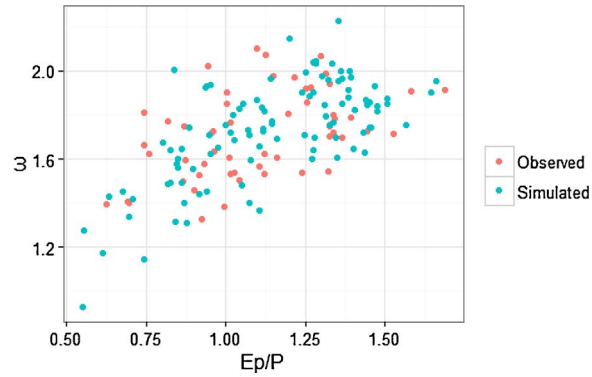

Fig. 6. Scatterplots for observed and simulated annual water availability in Region 1.

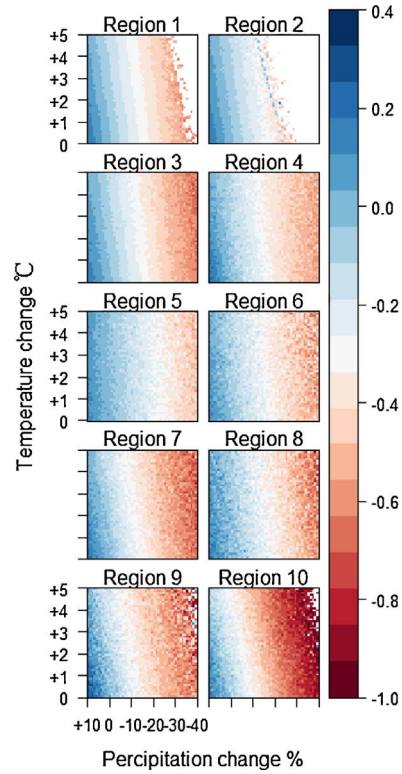

Fig. 7. The relative change rate of annual water availability under climate change in each of the 10 regions without considering SNWTP. The annual water availability was estimated using the Budyko framework as a function of precipitation change and potential evapotranspiration change.

uncertainty. However, this probabilistic model is remain limited to estimating the change in water availability for a given extreme climatic conditions. Fig. 7–10 that illustrate the change rates of water availability and vulnerabilities always exhibit some white space in the upper right corner, particularly in the donor regions. This is due to the relatively stable historic conditions with respect to the basin characteristics ω and aridity index (E_p/P) only changed within a narrow range, which limits the predictive capability in some extreme climatic conditions. Uncertainties are especially important for considering future major IBWT projects. The rate and magnitude of climate change may vary in the receiving basin as well as the donor basin, which makes assessment more complex. In addition, when the donor and receiving areas experience drought simultaneously, the demand for water in the donor areas also increases. Whether there is adequate amount of water to supply the water receiving areas is uncertain, particularly for the northern areas of the study area, such as the cities of Beijing and Tianjin.

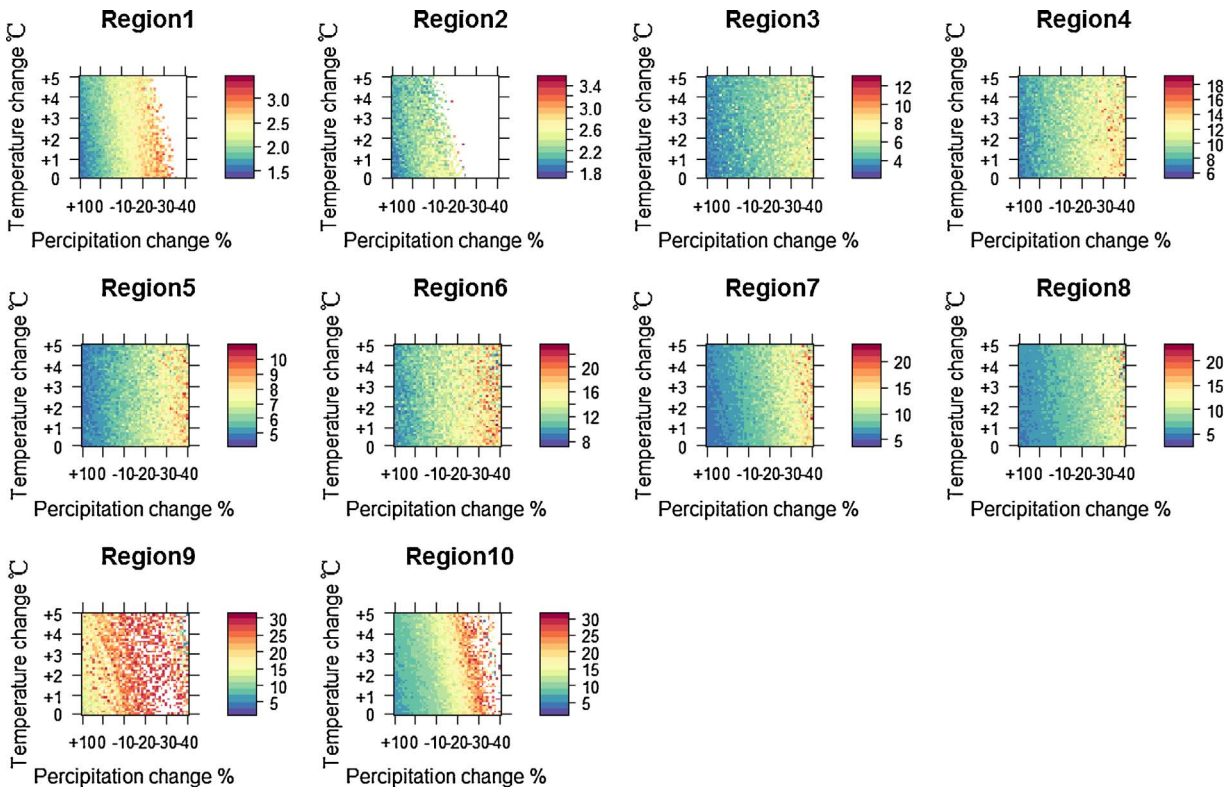

Fig. 8. IBWT vulnerabilities mapped in variable future climate spaces without considering SNWTP. The variable climate space is defined by precipitation change and temperature change in each of the 10 regions.

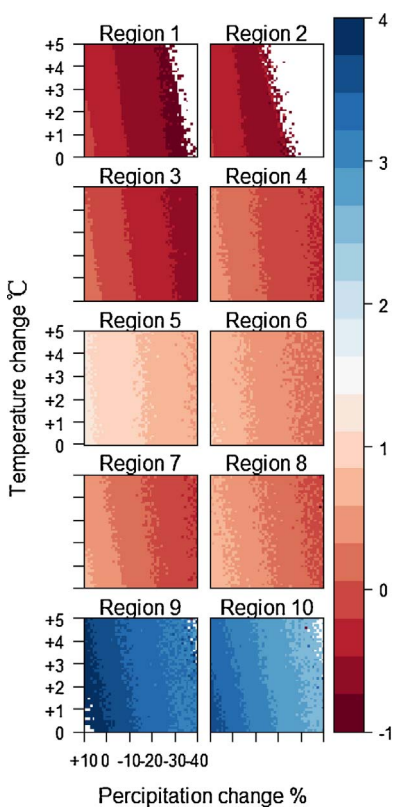

Fig. 9. The relative change rate of annual water availability under climate change in each of the 10 regions when considering SNWTP. The annual water availability was estimated using the Budyko framework as a function of precipitation change and potential evapotranspiration change.

The future is full of uncertainties, and climate change calls for a more flexible and forward-looking approach. Large-scale water infrastructures must be able to meet a wide range of changing conditions, and we should meet the future with foresight, insight, and action. Faced with this reality, a long-term water transfer scheme has been proposed to make the Yangtze River a second source of water to ensure an adequate water supply. As a most important policy lever, we urge water resources managers to focus on sustainable water management, such as increasing water use efficiency and addressing water pollution problems to ensure the highest reliability and lowest vulnerability within this water diversion system.

6. Conclusion

Hazards associated with climate change raise concerns for the vulnerability assessment of IBWT. In our study, a methodology for conducting a bottom-up vulnerability quantification was introduced and successfully applied to the SNWTP, which is a strategic infrastructure project in China. We developed a new performance indicator based on the hazard discovery process. Because IBWT is designed to handle temporal or spatial imbalances between available water resources and demand, this indicator could comprehensively represent the vulnerability of water availability by quantifying and integrating sensitivity, adaptability, and exposure from the perspective of conventional vulnerability. To fully represent the different degree of hazard of climate change, we also produced a range of climate change scenarios associated with each trajectory of change in average surface temperature and annual precipitation. Each of the scenarios can then be input to a water resource model. This useful analytical methodology captures the most sensitive climate conditions that lead to unsatisfactory performance for the water supply system and allows water managers to gain insight about the characteristics of vulnerability. The results of this study show that construction of the SNWTP can to some extent ease conflicts of water supply and demand in northern China under mild

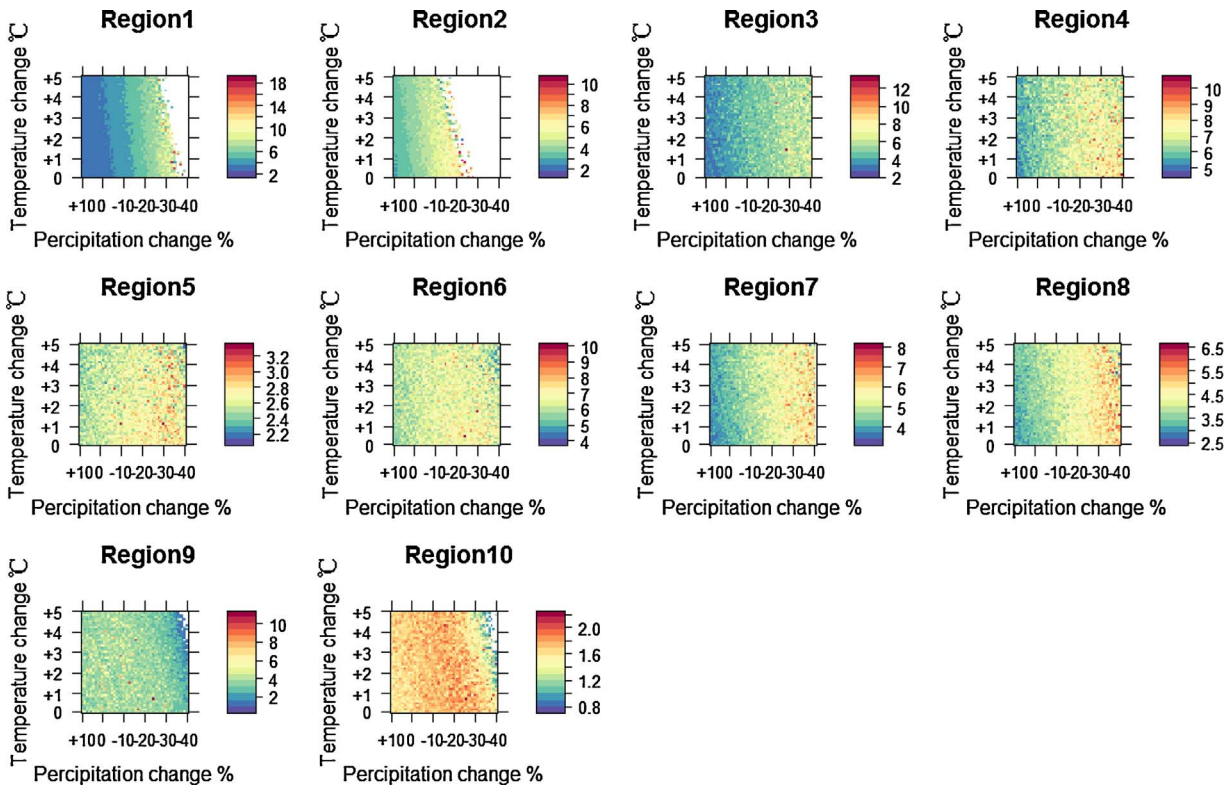

Fig. 10. IBWT vulnerabilities mapped in a variable future climate space when considering SNWTP. The variable climate space was defined by precipitation change and temperature change in each of the 10 regions.

climate change scenarios. If severe climate change with high uncertainty takes place, policymakers and project managers should comprehensively reconsider strategies and policies for water resources management.

Further investigations are needed to improve the proposed vulnerability assessment framework of IBWT, for example with respect to the performance indicator, to make the assessment more applicable to extreme climates over diverse regions. Also, this indicator could be considered to account for additional aspects other than water availability, such as ecological, economic, and social dimensions, which have kindled much controversy and debate in the world and may be of equal importance to the IBWT. There is always room for improvement in the other parts of this bottom-up framework methodology, such as enhancing predictability, improving accuracy and feasibility of the water system model, and choosing scientific and reasonable evaluation criteria. In conclusion, the implementation of a scientifically credible vulnerability assessment for large hydraulic engineering works like IBWT will undoubtedly underpin a thoughtful, proactive, and positive water management approach to maintaining sustainable human development.

Acknowledgments

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