WATER ALLOCATION UNDER FUTURE CLIMATE CHANGE AND SOCIO-ECONOMIC DEVELOPMENT

The case of Pearl River Basin

Dan Yan

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WATER ALLOCATION UNDER FUTURE CLIMATE CHANGE AND SOCIO-ECONOMIC DEVELOPMENT

The case of Pearl River Basin

Dan Yan

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Abstract

Water shortage has become a major challenge in many parts of the world due to climate change and socio-economic development. Allocating water is critical to meet human and ecosystem needs in these regions now and in the future. However, water allocation is being challenged by uncertainties associated with climate change and socio-economic development. This thesis aims to assess the combined effects of climate change and socio-economic development on water supply and demand in the Pearl River Basin (PRB) in China, and identify water allocation plans, which are robust to future climate change and socio-economic development. To do so, the impact of climate change on future water availability is first assessed. Next, different model frameworks are developed to identify robust water allocation plans for improving reservoir management, ensuring sufficient flow into the delta to reduce salt intrusion, and providing sufficient freshwater for human and industrial consumption under future climate change and socio-economic development.

Results show that water availability is becoming more variable throughout the basin due to climate change. River discharge in the dry season is projected to decrease throughout the basin. For a moderate climate change scenario (RCP4.5), low flows reduce between 6 and 48 % depending on locations. For a high climate change scenario (RCP8.5), the decreases of low flows can reach up to 72%. In the wet season, river discharge tends to increase in the middle and lower reaches and decreases in the upper reach of the Pearl River Basin. The variation of river discharge is likely to aggravate water stress. Especially the reduction of low flow is problematic as already the basin experiences water shortages during the dry season in the delta. The model frameworks developed in this study not only evaluate the performance of existing water allocation plans in the past, but also the impact of future climate change on robustness of previous and newly generated water allocation plans. The performance of the four existing water allocation plans reduces under climate change. New water allocation plans generated by the two model frameworks perform much better than the existing plans. Optimising water allocation using carefully selected state-of-the-art multi-objective evolutionary algorithms in the Pearl River Basin can help limit water shortage and salt intrusion in the delta region. However, the current water allocation system with six key reservoirs is insufficient in maintaining the required minimum discharge at two selected gauge stations under future climate change. More reservoirs, especially in the middle and lower reaches of the Pearl River, could potentially improve the future low flow into the delta.

This study also explored future water shortage in the Pearl River Basin under different water availability and water use scenarios. Four different strategies to allocate water were defined. These water allocation strategies prioritize upstream water use, Pearl River Delta water use, irrigation water use, and manufacturing water use, respectively. Results show that almost all the regions in the Pearl River Basin are likely to face temporary water shortage under the four strategies. The increasing water demand contributes twice as much as the decreasing water availability to water shortage. All four water allocation strategies are insufficient to solve the water scarcity in the Pearl River Basin. The economic losses differ greatly under the four water

allocation strategies. Prioritizing the delta region or manufacturing production would result in lower economic losses than the other two strategies. However, all of them are rather extreme strategies. Development of water resources management strategies requires a compromise between different water users. Optimization algorithms prove to be flexible and useful tool in adaptive water resources allocation for providing multiple approximate Pareto solutions. In addition, new technologies and increasing water use efficiency will be important to deal with future water shortage in the Pearl River Basin.

Table of Content

1

Introduction

Chapter 1

Introduction

1.1 Background

Rivers are the most important source of water for human use. Historically, most of the world's major civilizations have developed along rivers. Today, much of the world's population lives along large rivers, relying on them for industrial, agricultural, and domestic water supply (Gibson et al., 2002). People have been attracted especially to delta regions due to fertile soils, abundant food supply and more recently due to rapid economic development (Essink et al., 2010). The combination of rapid population growth, urbanization and industrialization has resulted in increased water demand, and conflicts between different water users in delta regions (Liu et al., 2010). Climate change is likely to further aggravate water stress in these regions. In addition, saltwater intrusion is increasing due to sea level rise and human activities, which can deteriorate water quality and reduce freshwater availability in delta regions (Chang and Clement, 2012).

For river basins and deltas under severe water stress, better management of water resources can potentially improve water availability for domestic, agricultural, industrial and environmental uses (Cosgrove and Loucks, 2015; Marcell, 2016). Water resource management is the activity of planning, developing, distributing and managing the optimum use of water resources (Loucks et al., 2005). It covers a variety of activities and disciplines, of which water resources allocation is particularly important for basins with uneven distribution of water resources. Water resources allocation is defined as a process of changing the natural or status quo distribution of water resources to meet requirements for economic and social development (Shen and Speed, 2009).

Water resources allocation is facing major challenges due to increased variation in water availability caused by climate change and increased water demand caused by socio-economic development (Alcamo et al., 2007). Traditionally water managers assume that future water availability is predictable in water resources allocation (Kwakkel et al., 2015). However, climate variability and change influence the global and regional hydrological cycle resulting in large scale impacts on water availability (Hagemann et al., 2013), which lead to large uncertainties in quantification of future water availability. In addition to uncertainties in water availability, water demand studies raise similar doubts about how population growth and socio-economic development contribute to patterns of consumption.

Due to changing water supplies and increased water demands, tools and methods for water allocation have become an important area of study (Ghimire and Reddy, 2014; Kim and Wurbs, 2011; Kumphon, 2013; Liu et al., 2010; Perera et al., 2005; Qtaishat, 2013; Rani and Moreira, 2010; Wurbs, 2005). For example, Liu et al. (2010) presented an optimization model, which is capable of allocating water among different sectors in saltwater intrusion areas. The model employed a genetic algorithm to optimize release flows for different reservoirs and can be a useful tool for water managers for integrated water resource management. Perera et al. (2005) described the software tool REALM (REsource ALlocation Model), which used a fast network linear programming algorithm to optimise the water allocation. Wurbs (2005) used a generalized WRAP (Water Rights Analysis Package) modeling system to evaluate reservoir system management, water allocation and supply reliability.

Previous studies typically addressed water allocation through mathematical optimization models (Pallottino et al., 2005). Reservoirs operation often plays an important part in these water allocation studies. Different linear and non-linear algorithms have been developed to obtain optimized operations of multiple-reservoir systems (Alicki et al., 2002; Fayaed et al., 2013; Froehlich et al., 2009; Ghimire and Reddy, 2014). However, few studies considered uncertainties, especially in future water availability. Since climate change and its potential impacts on the hydrological cycle are increasingly contributing to future water availability uncertainties (Oki and Kanae, 2006), it is important to allocate water resources in a changing climate. This has inspired methodological advances to assess the robustness of water management strategies under future climate change (Kasprzyk et al., 2013; Lempert and Mckay, 2011; Lempert and Groves, 2010; McInerney et al., 2012; Nassopoulos et al., 2012).

Robust Decision Making (RDM) is an analytic framework developed by Lempert and Groves (2010) to help decision makers identifying potential robust strategies, characterizing the vulnerabilities of such strategies, and evaluating trade-offs among them. It is now widely used in water resource management and allocation (Hadka et al., 2015; Kasprzyk et al., 2013; Matrosov et al., 2013; Singh et al., 2015). Lempert and Groves (2010) used Robust Decision Making (RDM) to evaluate the performance of water agency plans over thousands of plausible futures. The plausible range of climate changes used in RDM are generated based on K-nearest neighbour (KNN) bootstrapping technique. Matrosov et al. (2013) used RDM to assess propagation of uncertainties, and to rank different infrastructure portfolios for 2035. Climate change uncertainty was represented using monthly climate change perturbation factors that are multiplied by historical river flow time series. These previous studies used statistical methods to generated future climate scenarios. This is a severe underutilization of climate models as tools for supporting decision making (Weaver et al., 2013).

Global climate models (GCMs) are the primary tools for studying climate change in the future, and are widely used in water resources management to help identify potential water availability in the future (IPCC, 2013; Wang and Chen, 2014). The output of GCMs show consistent projections of changes in precipitation for several regions. However, for India, China, West Africa and south America, the changes in precipitation are highly uncertain (IPCC, 2013). The output of GCMs further indicates that climate change is likely to result in increased variability in precipitation. Therefore, to manage water resources under climate change uncertainty, it is necessary to use a range of projections for different emissions scenarios derived from multiple GCMs (Pierce et al., 2009; Teutschbein et al., 2015).

In addition to increased variation in water availability caused by climate change and increased water demand as a result of socio-economic development (Alcamo et al., 2007), problems of water resources allocation are brought into sharp focus when river basins cross political boundaries. In a transboundary river basin, upstream water use is expected to lead to increased water scarcity in downstream regions of the basin (Munia et al., 2016). Therefore, allocating water in a basin should also consider and quantify the impact of upstream water use on downstream water availability.

The central question of this thesis is to what extent can water resources allocation strategies help large river basins addressing water shortage problem under climate change and socio-economic development? To answer this question, a large basin in China is selected to be the case study area.

1.2 Study basin

The study basin for this research is the Pearl River Basin located in the south of China. In terms of basin area, it is the third largest river in China (Figure 1.1). It has the second largest total discharge in China following the Yangtze River. The drainage area is 4.54×10^5 km^2 of which 4.42×10^5 km^2 is located in China (PRWRC, 2005; Zhang et al., 2009a). The Pearl River is composed of three major rivers, Xijiang, Beijiang, and Dongjiang. The largest river is Xijiang. The total length of Xijiang is 2075 km with a drainage area accounting for 77.8 percent of the entire Pearl River Basin (Zhang et al., 2009a). The Pearl River Basin is situated at subtropical monsoon zone, and the climate is characterized by mild temperature and sufficient rainfall. The annual average temperature is from 14 to 22 °C, and the annual average precipitation ranges from 1200 to 2200 mm.

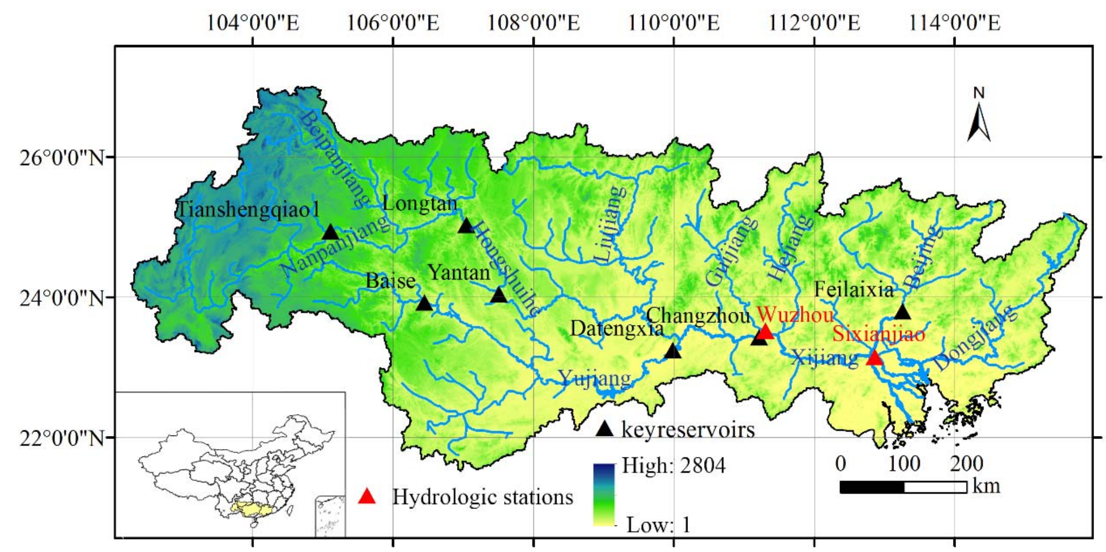

Figure 1.1 Location of the Pearl River Basin, key reservoirs and hydrological stations used in this study

This basin has been selected because it is an example of a river basin experiencing rapid economic growth and urbanization, and increasing the competition between water users that directly or indirectly depend on the river runoff for drinking, irrigation, manufacturing and industrial processes (PRWRC, 2010). Since the economic reform in 1979, China has become the world's most dynamic large economy. The Pearl River Delta, including HongKong, Macao, and the Pearl River Delta Economic Zone, is the largest and most export-oriented region in China experiencing rapid urbanization and industrialization (Enright et al., 2005). The Pearl River plays a key role for fresh water supply in the Pearl River Delta (Yao et al., 2016). However, the Pearl River is influenced by a subtropical monsoon climate. About 80 percent of the streamflow occurs during the monsoon season from April to September, with peak flows during May and July (PRWRC, 2010). Due to highly uneven spatial and temporal distribution of flows, there are frequent floods and droughts in the basin (Zhang et al., 2012; Zhang et al., 2009a). In addition, the increasing water demand in combination with low water availability in the dry season is causing increased seasonal water shortages (Zhu et al., 2002). In recent years, saltwater intrusion has become another major issue in the Pearl River Delta. This increased salinity poses a potential threat to water supply and freshwater ecosystems.

To improve water security in the region, the government in 2005 launched the 'Key Reservoirs Operational Project for Pearl River Basin', to maintain low flow in the dry season by releasing additional water from upstream reservoirs (He et al., 2007; Xie, 2007). This water allocation project aims to improve the operational effectiveness and efficiency of six key reservoirs: Tianshengqiao I, Longtan, Yantan, Feilaixia, Changzhou, and Baise, and thus to maximize the benefits for different water users in the basin (Qian, 2007). The implementation of the policy alleviated salt intrusion to some extent (Liu, 2007b). Yet, despite the releases, there was severe saltwater intrusion in 2009 and 2011 due to unusually low precipitation (Wang and Jiao, 2012).

Socio-economic development and water consumption differ greatly across the regions in the Pearl River Basin. The delta is one of the leading economic regions and a major manufacturing center of China. Some of the poorest regions in China are in the upstream part of the basin. (Jalan and Ravallion, 2000). However, the poorer upstream regions are starting to catch up with the economic development in the delta since the Chinese government launched the "Western Development Program" in 1999. The program aims to boost the socio-economic development in western China (Lai, 2002) including three provinces in the Pearl River Basin, Yunnan, Guizhou and Guangxi. The western development program has substantially accelerated the economic growth of these three provinces resulting in increased industrial and domestic water use in the upstream regions (PRWRC, 2015). This has resulted in reduced water supply to the delta and caused severe water use conflicts between upstream and downstream regions.

For both scientific and socio-economic reasons it is important to develop water allocation plans among different regions and water users in the Pearl River Basin, which are robust to both climate change and socio-economic development.

1.3 Methodology

Allocating water among different regions and users is a complex process, which requires a clear identification and appropriate modeling of the allocating plans that are robust to a wide range of combination of supply and demand conditions. To allocate water resources in a large river basin, this study developed an integrated framework combining a hydrological model, reservoir and routing model, multi-objective evolutionary algorithm, and robust decision making.

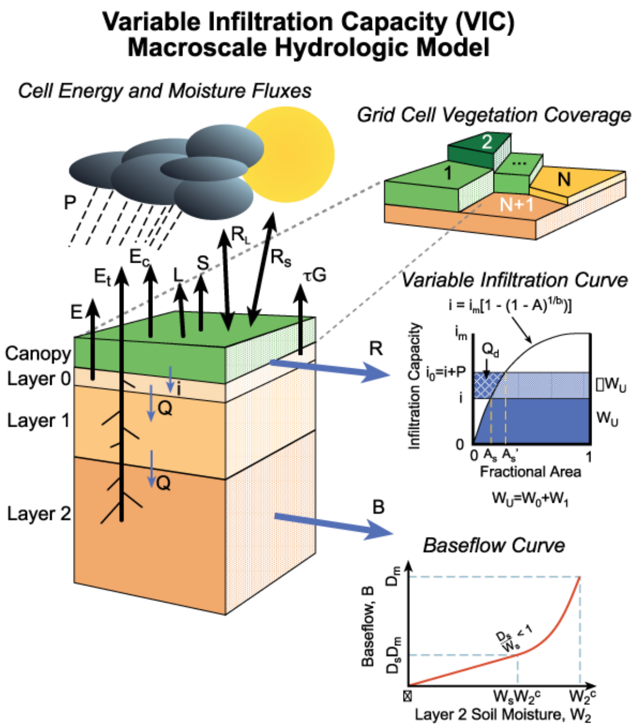

Figure 1.2 VIC land cover tiles and soil column, with major water and energy fluxes (source: Gao et al., 2010)

As hydrological model, the Variable Infiltration Capacity (VIC) was selected to simulate the hydrological response to future climate change and build water availability scenarios (Figure 1.2). The VIC model is a semi-distributed macroscale hydrological model, which balances both water and surface energy within the grid cell (Gao et al., 2010). It was originally developed by Liang et al. (1994) and comprised of two soil layers. The upper layer is characterized by the usual VIC spatial distribution of soil moisture capacities, and the lower layer is spatially lumped. The surface is described by N+1 land cover types. They are differentiated by leaf area index (LAI), canopy resistance, and relative fraction of roots in each soil layer. Three modifications were made to improve the model in 1996, including allowing diffusion of moisture between soil layers, variations of LAI and the fraction vegetation cover at each time step, and the last but not the least, adding 0.1 m thin layer on top of the previous upper layer which announced the generation of VIC-3L (Figure 1.2) (Liang et al., 1996). A number of modifications have been made to improve VIC since then, such as routing model (Lohmann et al., 1996; Lohmann et al., 1998), snow model (Bowling et al., 2004; Andreadis et al., 2009), elevation bands (Nijssen et al., 2001b), frozen soil formulation (Cherkauer and Lettenmaier, 1999; Cherkauer et al., 2003), blowing snow algorithm (Bowling et al., 2004), lake and wetland algorithm (Bowling et al., 2003; Cherkauer et al., 2003; Bowling and Lettenmaier, 2010; Gao et al., 2011), and reservoir module (Haddeland et al., 2006a).

The VIC model has been successfully applied in estimating climate change impacts on hydrological process at different spatial and temporal scales. For example, Christensen et al. (2004) and Christensen and Lettenmaier (2007) used the VIC model to assess the sensitivity of the reservoir system (flood control, water supply, hydropower, etc.) to projected climate changes in the Colorado River basin. Hurkmans et al. (2010) employed the VIC model, forced by three high-resolution climate scenarios (0.088 degree), to examine changes in streamflow at various locations throughout the Rhine River basin. Vicuna et al. (2007) used a set of downscaled GCM outputs and VIC to project the impacts of climate change on California's major managed water resources systems. The above applications show that the VIC model is capable of estimating variations in water resource under future climate change. Therefore, the VIC model is used in this study.

VIC uses a separate routing model based on a linear transfer function to simulate the streamflow (Lohmann et al., 1996; Lohmann et al., 1998a; Lohmann et al., 1998b). Adaptations to the routing model are implemented in VIC to allow representation of water management impacts (Gao et al., 2010). Haddeland et al. (2006b) developed a reservoir model to simulate reservoir operation and irrigation water withdrawals. The VIC model is modified to allow for irrigation water use, based on the model's predicted soil moisture deficit (Haddeland et al., 2006a; Haddeland et al., 2006b). This reservoir model is a generic model, which is implemented within the routing model. An optimization scheme based on SCEM-UA algorithm is used to calculate the original optimal releases given by reservoir inflow, storage capacity, installed capacity and efficiency. Irrigation demands are calculated based on simulated irrigation water requirements downstream of the dam. In this thesis, this reservoir model is used to implement water allocation plans generated by the Multi-objective Evolutionary Algorithms (MOEAs).

An evolutionary algorithm is a generic population-based metaheuristic optimization algorithm and uses mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection (Coello Coello et al., 2007). Over the past decades, a number of MOEAs have been developed (Deb et al., 2000), of which the Vector Evaluated Genetic Algorithm (VEGA) induced by Schaffer (1984) was the first MOEA to search for multiple Pareto optimal solutions. Fonseca and Fleming (1993) first used Pareto-based selection in the Multi-objective Genetic Algorithm (MOGA). Several design concepts were introduced between 1993 and 2003, for example, elitism, diversity maintenance and external archiving. The first generation of notable algorithms include the Niched-Pareto Genetic Algorithm (NPGA) (Horn and Nafpliotis, 1993), the Non-dominated Sorting Genetic Algorithm (NAGA) (Srinivas and Deb, 1994), the Strength Pareto Evolutionary Algorithm (SPEA) (Zitzler and Thiele, 1999) etc. To date, more than two dozen of the MOEAs have been proposed. The Borg, NSGAII, NSGAIII, eMOEA, eNSGAII, PGDE3, SMPSO, OMOPSO, and MOEAD are considered as start-of-the-art algorithms (Reed et al., 2013).

Robust Decision making (RDM) is a quantitative approach for supporting decisions under deep uncertainties (Figure 1.3). It uses multiple futures, robustness criteria, and adaptivity to hedge against uncertainty. The RDM can evaluate the performance of proposed strategies over thousands of plausible futures, use "scenario discovery" to characterize the vulnerabilities of these proposed strategies, and obtain information from the results to identify and compare options for reducing the vulnerabilities (Lempert and Groves 2010). Kasprzyk et al. (2013) proposed a Many-objective Robust Decision Making (MORDM) framework combing the MOEA optimization and RDM. MORDM uses a multi-objective evolutionary algorithm to solve multi-objective problems, and provide a large set of alternatives as input strategies to RDM. Hadka et al. (2015) developed an open source many objective robust decision making (OpenMORDM) framework in R programme language to support bottom-up decision making under deep uncertainty. The OpenMORDM can employ multi-objective evolutionary search to identify trade-offs between strategies, re-evaluate their performance under deep uncertainty, and use interactive visual analytics to support the selection of robust management strategies. Therefore it is used in this thesis.

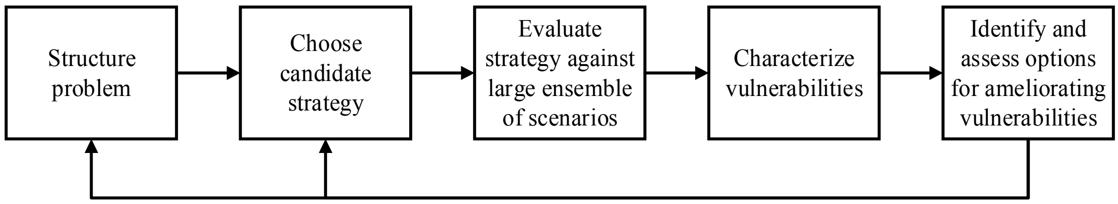

Figure 1.3 Steps in a robust decision making analysis (source: Lempert and Groves, 2010)

1.4 Objectives

The research objective of this thesis is to assess combined effects of climate change and socio-economic development on water supply and demand in the Pearl River Basin, and identify water allocation plans, which are robust to climate change and socio-economic development in this basin. In order to reach this objective, four research steps and corresponding questions were formulated:

- How will water availability change as a result of climate change in the Pearl River Basin?
- Can water allocation reduce saltwater intrusion in the Pearl River Delta?
- How will socio-economic development affect water shortage in the Pearl River Basin?
- Whether robust decision making (RDM) is appropriate for generating water allocation and management strategies in the Pearl River Basin under climate change and socio-economic development?

1.5 Outline of the thesis

This thesis comprises of six chapters, including the introduction. Each of the subsequent chapters addresses at least one of the research questions and builds upon results and conclusions of the previous chapter.

Chapter 2 assesses the impact of climate change on water availability and hydrological extremes in the Pearl River Basin. To do this we use the VIC Model forced by bias corrected climate model output using the new IPCC scenarios RCP 4.5 and 8.5. The model simulations are used to quantify run-off, seasonal variations in river discharge, and characterize the sensitivity of hydrological extremes to climate change.

Chapter 3 combines multi-objective generic evolutionary algorithm, robust decision making, and biophysical modelling by developing a Robust Assessment Model for Water Allocation (RAMWA) to facilitate sustainable water management and allocation in delta regions. The

RAMWA approach is specifically developed for deltas where flows tend to be (too) low in the dry season but there is sufficient water supply during the wet season, which can be stored in upstream reservoirs for later release. With this new model, the study aims to help water managers to evaluate the robustness of existing water allocation plans, as well as to identify an improved set of options.

Chapter 4 improves the model developed in chapter 3. Ten state-of-the-art MOEAs are evaluated for the water allocation problem in the Pearl River Basin. The MOEA with the best performance is used to generate future water allocation plans. Key trade-offs among different objectives and robustness of different water allocation plans under future climate scenarios are explored.

Chapter 5 builds two water availability scenarios and three water use scenarios under future climate change and socio-economic development, identifies four different water resources allocation strategies in the Pearl River Basin, and evaluates future water shortages and economic development for each region in the Pearl River Basin under these scenarios and strategies.

Chapter 6 presents a compilation of the key findings of this thesis. The uncertainties and limitations of the chosen approach are discussed. Furthermore, this chapter also gives an outlook to a new agenda for robust decision making under deep uncertainties and concludes with the main messages drawn from this work.

2

Hydrological Response to Climate Change: the Pearl River, China under Different RCP Scenarios

Chapter 2

Hydrological Response to Climate Change: the Pearl River, China under Different RCP Scenarios

Abstract

The Pearl River Basin in China is a rapidly developing region and changes in river discharge and frequency of hydrological extreme events are likely to affect its future development. To improve our understanding of current and future water resources in the Pearl River Basin we simulated the basin's hydrological response to atmospheric climate change using the VIC model (Variable Infiltration Capacity). We aimed to assess the impact of climate change on seasonal discharge and extreme flows. For the climate change assessment we used bias-corrected results of five different climate models under the IPCC scenarios RCP4.5 and 8.5. The results indicate a reduction in average low flow of the five climate models. The reduction depends on location and lies between 6 and 48% for RCP4.5. For RCP8.5, low flows show a 22 - 72% decrease. High flows are projected to decrease in the upstream part of the Basin and to increase in the central part under both RCP4.5 (-6 to 20%) and 8.5 (-16 to 31%). River discharge in the dry seasons is projected to decrease throughout the basin. In the wet seasons, river discharge tends to increase in the middle and lower reaches and decrease in the upper reach of the Pearl River Basin. The variation of river discharge is likely to increase the flood frequencies and aggravate drought stress. Especially the reduction of low flow is worrying as already the basin experiences temporary water shortages and increasing salt intrusion in the delta. Our results clearly indicate that the rivers flow within the Pearl River Basin will become more variable in the future.

This chapter has been published as:

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2.1 Introduction

Global warming due to increasing concentration of greenhouse gases is likely to have a significant impact on precipitation, run-off processes and water resources (Arnell and Reynard, 1996; Cuo et al., 2015; Haddeland et al., 2012; Pervez and Henebry, 2015; Zhang et al., 2010b). This raises the question whether climate change is a threat to human water security or not. Previous studies have shown that simulated climate change impacts vary substantially depending on climate model and emission scenarios used (Arnell, 1999; Bronstert, 2004; Bronstert et al., 2002; Hurkmans et al., 2008; Montenegro and Ragab, 2010; Wang et al., 2008; Wentz et al., 2007). However, most of them focused on shifts in the timing of hydrological regimes where runoff is dominated by snow melt (e. g. Adam et al., 2007; Arnell and Gosling, 2013; Hurkmans et al., 2010) or long-term mean annual streamflow and water availability (e. g. Christensen et al., 2004; Kling et al., 2014). Few studies have reported if climate change can alter the risk of hydrological extremes at regional scales (Lehner et al., 2006) even though developed basins with a dense population are highly vulnerable to hydrological extremes.

The Pearl River in southern China is the second largest river in China in terms of streamflow. Since the late 1970s, the Pearl River Basin plays an important role in Chinese economic development. The delta in particular has become one of the leading economic regions and a major manufacturing center of China. In about 0.4% of China's land territory, the delta produces about 20% of the national GDP, and attracts 40% of foreign investment (Chen et al., 2010). The Pearl River is influenced by a subtropical monsoon climate. About 80% of the streamflow occurs during the monsoon season from April to September, with peak flows during May and July (PRWRC, 2010). Due to highly uneven spatial and temporal distribution of flows, there are frequent floods and droughts in the basin. The extreme events have caused large life and property losses (Zhang et al., 2012; Zhang et al., 2009b). In addition, the increasing water demand in combination with low water availability in the dry season is causing increased seasonal water shortages (Zhu et al., 2002). Reduced flows in the dry season, in combination with seas level rise have resulted in increasing saltwater intrusion in the delta. This increased salinity poses a potential threat to water supply and freshwater ecosystems. Seasonal variation in river discharge is a key factor determining salt intrusion in the delta (Gong et al., 2013). Saltwater intrusion could further increase in the future if low flows continue to reduce. Therefore it is important to assess the impact of future climate change on river discharge.

Several previous studies have estimated hydrological changes over the Pearl River Basin, among which a large number of studies focused on the hydrological models used and the calibration process (Deng et al., 2009; Li et al., 2012; Liao et al., 2013; Lin et al., 2013; Lv et al., 2014). Only few studies have evaluated impact of climate change on river discharge and even less tried to look further into the future (Jiang et al., 2007). In terms of future climate change, some studies preferred hypothetical climate change scenarios (Jiang et al., 2007; Li et al., 2011). Few studies used the output of GCMs to force the hydrological models in the Pearl River Basin (Liu et al., 2012; Wu et al., 2014; Xiao et al., 2013). However, more attention was paid to annual discharge and extreme flood events (Wu et al., 2014). For a basin which is suffering from water shortage and saltwater intrusion in the dry seasons, it is in particular important to assess variations in low flow over the basin. Unlike the previous studies, the impacts of future climate change on both high and low flows have been evaluated in this paper.

Two types of hydrological models have been used in the basin: 1) catchment-based models that only consider water balances (e. g. Jiang et al., 2007; Lin et al., 2013; Wang and Xia, 2004; Xiong and Guo, 1999; Yang and Xu, 2011). These catchment-based models run at a basin scale, and have a good representation of lateral transfers but are weaker in energy and carbon linkages. 2) Non-calibrated global hydrological models with a coarse resolution (e. g. Deng et al., 2009; Guo et al., 2002; Li et al., 2012; Niu and Chen, 2009). Both of these model types have their limitations in assessing the hydrological regime of the Pearl River.

The variable infiltration capacity (VIC) model is a macro-scale hydrologic model originally developed by Liang et al. (1994). It has been successfully applied in estimating climate change impacts on hydrological process at different spatial and temporal scales. For example, Christensen and Lettenmaier (2007) used the VIC model to assess the sensitivity of the reservoir system (flood control, water supply, and hydropower, etc.) to projected climate change in the Colorado River basin. Hurkmans et al. (2008) employed the VIC model, forced by three high-resolution climate scenarios, to examine changes in streamflow of the Rhine River. Vicuna et al. (2007) used a set of downscaled GCM outputs to force the VIC model to study the impact of climate change on California's major managed water resources systems. Van Vliet et al. (2013) used a global physically based hydrological-water temperature modeling framework including VIC and streamflow temperature model (RBM) to assess the impact of climate change on global river flows and river water temperatures under SRES A2 and B1 emissions scenarios. The above applications show that the VIC model is capable of estimating variations in river discharge under future climate change. Therefore we used the Variable Infiltration Capacity (VIC) Model in this study.

The objective of this study is to assess the impact of climate change on water availability and hydrological extremes in the Pearl River Basin. To do this we used the VIC Model forced by bias corrected climate model output using the new IPCC scenarios RCP 4.5 and 8.5. The model simulations were used to quantify run-off, seasonal variations in river discharge, and characterize the sensitivity of hydrological extremes to climate change.

2.2 Study area and data selection

2.2.1 Study area

The Pearl River is the third largest river in China in terms of drainage area (Figure 2.1). The drainage area is 4.54×10^5 km^2 of which 4.42×10^5 km^2 is located in China (PRWRC, 2005; Zhang et al., 2009b). The Pearl River is composed of three major rivers: Xijiang, Beijiang, and Dongjiang. The largest is Xijiang which is 2075 km long and has a drainage area accounting for 78% of the entire Pearl River Basin. The Pearl River Basin is situated at subtropical monsoon zone. The annual average temperature is between 14 and 22 °C, and the annual average precipitation ranges from 1200 to 2200 mm.

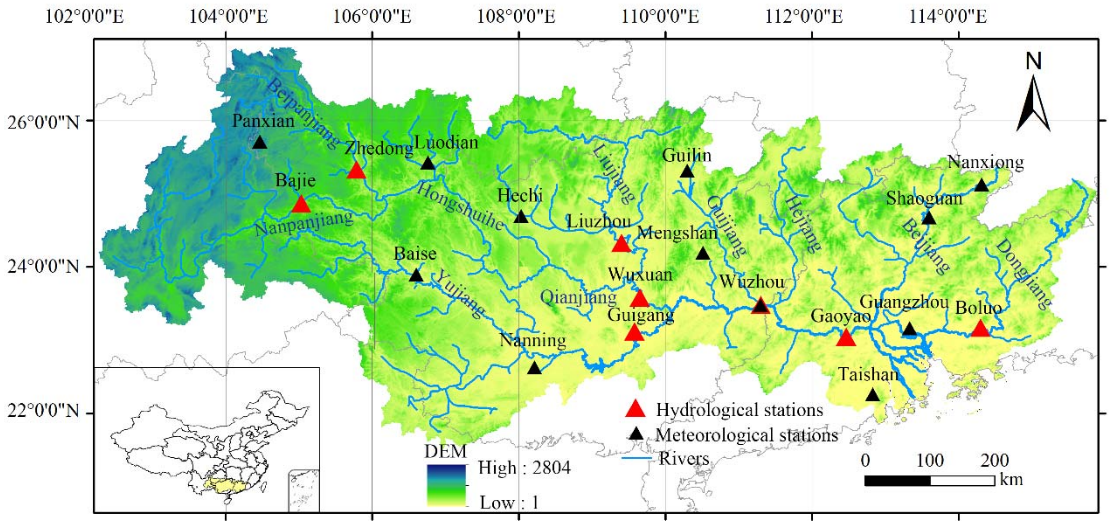

Figure 2.1 The location of the Pearl River Basin

2.2.2 Data and model selection

We prepared different datasets, including elevation band file, vegetation file, soil file, and meteorological forcing file as input data for our hydrological simulation in the VIC model. The elevation and land cover classification are described in Nijssen et al. (2001a). The DDM30 routing network for routing the runoff were obtained from Döll and Lehner (2002).

VIC uses eight meteorological variables including precipitation, minimum and maximum temperature (T_{min} and T_{max}), wind speed, incoming shortwave (radiation) radiation, incoming longwave (thermal infrared) radiation, atmospheric pressure and specific pressure as input variables. The observed data obtained from the China Meteorological Data Sharing Service System have only four variables: precipitation, T_{min} , T_{max} and wind speed. Hence a substitute dataset is needed. The WATCH Forcing Data (WFD) (1958-2001) and WATCH Forcing Data ERA Interim (WFDEI) (1979-2012) were selected because they were created particularly for the purpose of driving land surface models and hydrological models (Weedon et al., 2011). The WFD are derived from the ERA-40 reanalysis data via sequential interpolation to 0.5°×0.5° resolution, elevation correction and bias correction based on monthly observations. The WFDEI are generated using the same methodology as the WFD (Weedon et al., 2014). They are mixed products of reanalysis data and observations, and have all the eight parameters needed in VIC.

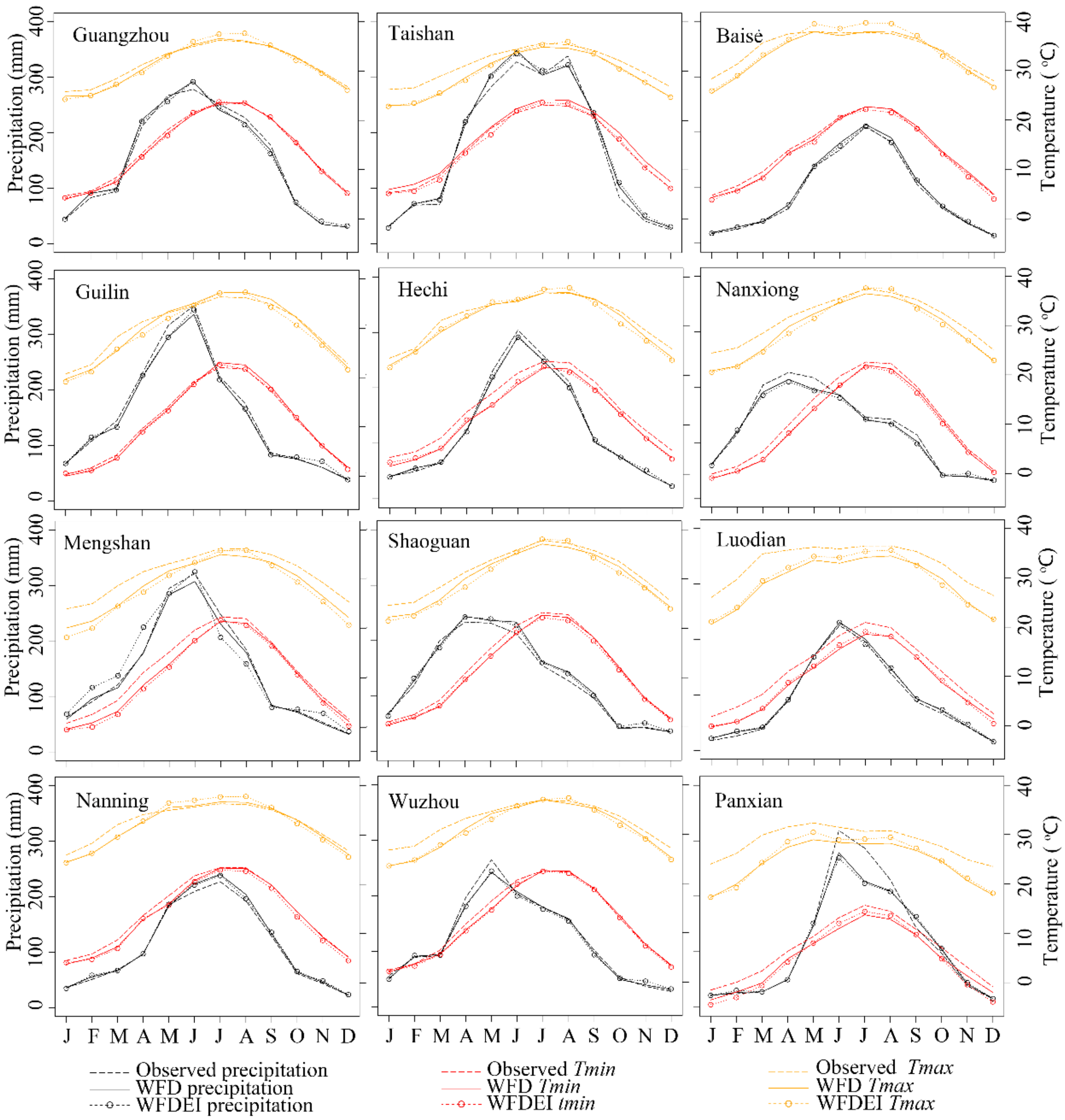

Figure 2.2 The average monthly precipitation and temperature of selected stations for the period 1979-2001

If the WFD and WFDEI match well with the observations, it is more coherent to use the WFD and WFDEI because the outputs of the five GCMs used in the study are bias corrected based on the WFD. To check the quality of the WFD and WFDEI, we compared them against the observations for twelve randomly selected meteorological stations. Figure 2.2 shows the WFD and WFDEI have good performances on T_{min}, T_{max} and precipitation. The WFD and WFDEI show the best and worst performance at Guangzhou and Panxian station. Taylor diagrams were used to display the quality of the WFD and WFDEI at these two stations against the observed data (Figure 2.3). The correlations of precipitation, T_{min} and T_{max} with observations are above 0.90, the centered root-mean-square (RMS) deviations are about 0.5, and the standard deviations of all the variables are close to the observed standard deviation at both the stations. Based on this analysis, we conclude that the WFD and WFDEI products do represent the observations well, hence we decided to use the WFD and WFDEI for calibration and validation in the study.

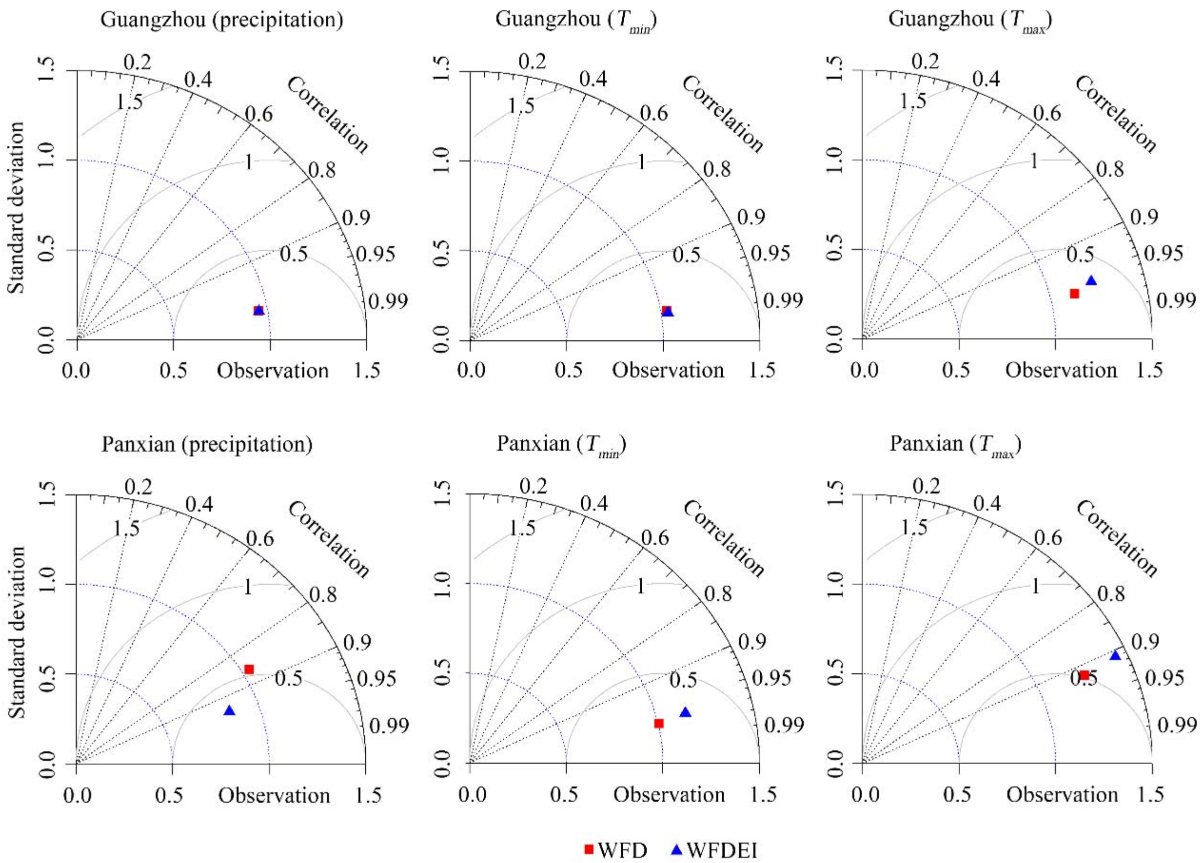

Figure 2.3 Taylor diagram for precipitation, minimum and maximum of temperature at Guangzhou and Panxian station

Future climate change scenarios were prepared using data from the Coupled Model Intercomparison Project5 (CMIP5). The CMIP5 projections of climate change are driven by concentration or emission scenarios consistent with the RCPs (Representative Concentration Pathways) described in Moss et al. (2010). Pierce et al. (2009) showed that the superiority of the multi-model ensemble average to any one individual model, already found in global studies, is also true in their regional study, including measures of variability. They found model skill to asymptote after including approximately 5 different models. They also found selecting models based on the quality of their simulation in the region of interest did not result in systematically different conclusions than those obtained by picking models randomly. We decided to select five GCMs for our study. The selection criteria were 1) use frequency in model studies for Asia; 2) relative independence and good performance in precipitation and temperature simulation; 3) downscaled data available for use in our hydrological model. The criteria were assessed from literature (Deng et al., 2013; Ogata et al., 2014; Seth et al., 2013; Sperber et al., 2013; Su et al., 2013; Wang et al., 2014; Zhou et al., 2014). CNRM-CM5, HadGEM2-ES, IPSL-CM5A-LR, and MPI-ESM-LR were found to be the most commonly used models in climate change and hydrologic studies over Asia (Table 1.1). According to the family tree for projected climate change under future scenarios constructed by Knutti et al. (2013), CNRM-CM5, HadGEM2-ES, IPSL-CM5A-LR, and MPI-ESM-LR are relatively independent models. Wang and Chen (2014) have investigated the performance of GCMs in China using mean absolute error (MAE) between the simulated and observed monthly mean temperature and precipitation (Figure 2.4). They found MPI-ESM-LR and HadGEM2-ES perform well on reproducing temperature while IPSL-CM5A-LR, HadGEM2-ES, CNRM-CM5 have higher skill in simulating precipitation. EC-EARTH is close to CNRM-CM5 on the family tree, but it was still selected as a complement for the other four models already selected in the study, because EC-EARTH has been demonstrated to have good performance in simulating annual temperature and precipitation on regional and global scales (Bintanja et al., 2013; Hazeleger et al., 2012; Huang et al., 2014; Wang and Chen, 2014).

Table 1.1 Detailed information of the five selected GCMs

GCM	Model	Resolution	Source
1	CNRM-CM5	256 × 128	Centre National de Recherches Meteorologiques
2	EC-EARTH	320 × 160	Royal Netherlands Meteorological Institute, De Bilt, The Netherlands
3	HadGEM2-ES	192 × 145	Met Office Hadley Centre, UK
4	IPSL-CM5A-LR	96 × 96	Institut Pierre-Simon Laplace, France
5	MPI-ESM-LR	192 × 96	Max Planck Institute for Meteorology (MPI-M), Germany

The Mann-Kendall test was used to detect trends in annual precipitation in the Pearl River Basin, but very few grids show significant trends under all five selected GCMs. Our results about annual precipitation trends are consistent with the works of Zhang et al. (2012) and Gemmer et al. (2004). For the seasonal timescale, our findings are supported by Liu et al. (2009), who found that the precipitation of spring, summer, and winter increased, but autumn precipitation decreased during the period of 1961-2007. The coefficient of variation (C_v) was calculated for all five GCMs. The values of three models (CNRM-CM5, HadGEM2-ES, and MPI-ESM-LR) are 11% which is the same as the result of Chen et al. (2005). The accumulated precipitation anomalies of the ensemble average of the five GCMs show that the Pearl River Basin has experienced cycles of wet and dry periods. After a period of abundant rain in the 1970s, the basin entered a dry period in the 1980s. During the 1990s, the precipitation was increasing (Ren, 2007).

The temperature, precipitation and snowfall of the five selected GCMs were bias corrected using the method developed by Piani et al. (2010). The radiation and wind speed data series were bias corrected with the method from Haddeland et al. (2012). The WATCH Forcing Data series (1960-1999) were used as a reference for the bias correction. Figure 2.5 shows all the meteorological datasets used in this study and how they are used.

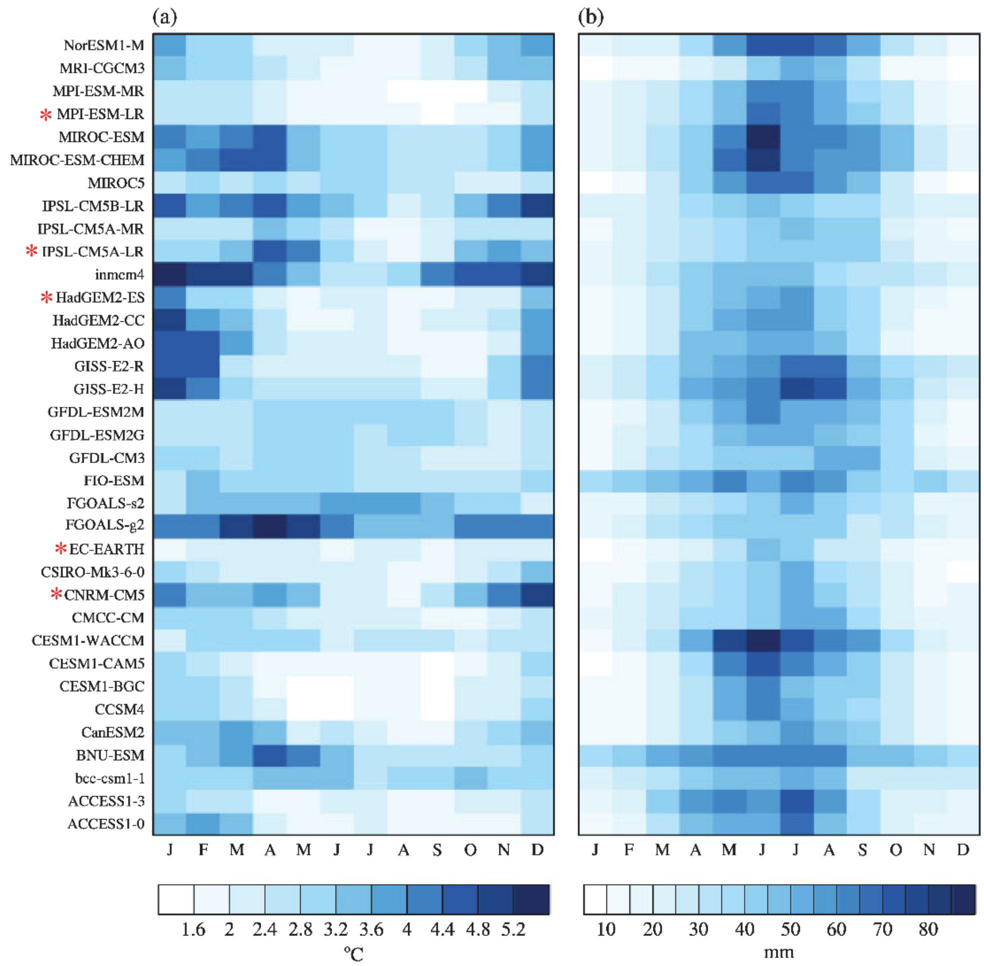

Figure 2.4 Biases of simulated (a) monthly mean temperature (℃) and (b) precipitation (mm) expressed in mean absolute error during the period of 1961-2005 for each calendar month and individual model (* represents the model used in the study) (source: Wang and Chen, 2014)

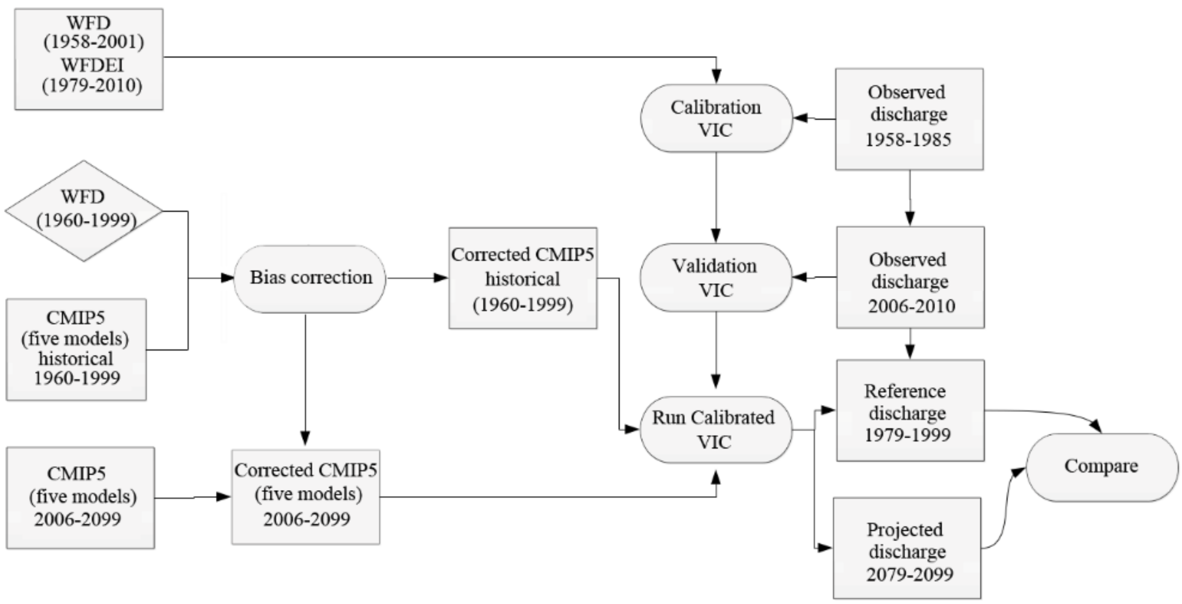

Figure 2.5 Schematic representation of all datasets used in this study and how they are used

The observed discharge data for calibration and validation were obtained from the hydrologic year books of the Pearl River. Eight gauge stations, Zhedong, Bajie, Wuxuan, Liuzhou, Guixian (another name is Guigang), Gaoyao, Wuzhou, and Boluo, were selected for this study (Figure 2.1).

2.3 Model calibration and validation

The VIC model is a semi-distributed macro-scale model characterized by heterogeneous vegetation and multiple soil layers with non-linear base flow and variable infiltration. VIC can be run in either a water balance mode or a water-and-energy balance mode. It has been successfully applied in assessing climate change impact on hydrological process at different spatial and temporal scales (Cherkauer and Lettenmaier, 1999; Gao et al., 2010; Liang et al., 1999; Liang et al., 2003; Wood et al., 1992).

Before using the model for future simulations, the VIC model was calibrated. For this study, the VIC model was calibrated using the WATCH Forcing Data (see Section 2.2.2), in combination with monthly observed discharge data of eight stations in the Pearl River Basin for the period of 1958-1985. Six parameters were used for calibration: (1) b_{infilt} is the parameter of variable infiltration curve and ranges from 0 to 0.5. Higher value of b_{infilt} can cause higher surface runoff. (2) Ds_{max} is the maximum velocity of baseflow ranging from 0 to 30 mm/day. (3) D_s is the fraction of Ds_{max} where linear baseflow ends, ranges from 0 to 1. Higher value will lead to higher water content in the third layer. (4) W_s is the fraction of maximum soil moisture where non-linear baseflow occurs, ranges from 0 to 1. Higher value of W_s tends to delay the peaks. (5) d_2 and d_3 are the thickness of layer 2 and 3, ranging from 0.2 to 2.5 m in the Pearl River Basin. The thickness of the soil layers can slow down seasonal peak flows and increase evapotranspiration. First these six parameters were subjected to a sensitivity analysis to understand how variability in soil parameters affects discharge and baseflow. The parameters D_s, W_s, and Ds_{max} were found to have negligible influence on discharge, and were eliminated to save computation time.

After sensitivity analysis, the VIC model was calibrated and evaluated automatically using monthly observed discharge. Nash–Sutcliffe model efficiency coefficient (E), correlation coefficient (R), and normalized root mean square deviation (NRMSD) were used in the calibration. The Nash–Sutcliffe model efficiency coefficient is an indicator widely used to evaluate the performance of hydrological model. Its value ranges from −∞ to 1. A value of 1.0 indicates a perfect match between simulated and observed discharge. It is calculated as:

$$E = 1 - \frac{\sum_{t=1}^{T}\left(Q_o^t - Q_m^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q_o}\right)^2} \qquad (2.1)$$

where Q_o is the observed discharge, the Q_m is the simulated discharge, and the overbar denotes the average over the considered period.

Normalized Root Mean Square Deviation (NRMSD) indicates the standard deviation of the differences between simulations and observations. NRMSD is represented as a percentage, where lower values refer to less residual variance (Lombard et al., 2009).

The equation of NRMSD is given as follow:

$$NRMSD = \frac{\sqrt{\frac{\sum_{t=1}^{N}(Q_o^t - Q_m^t)^2}{N}}}{Q_{max} - Q_{min}} \quad (2.2)$$

Where Q_{max} is the maximum value of the observation, and Q_{min} is the minimum of the observation.

Two different methods were used to calibrate the VIC model. The first one is based on Monte Carlo method with Latin hypercube sampling (LHS) (McKay, 1979; Sieber and Uhlenbrook, 2005). The range of each parameters (b_{infilt}, , d_2 and d_3) was divided into 4 intervals. Those intervals were set to equal size. One value was chosen from each interval by Monte Carlo method, and then combined with the other two parameters randomly. It took 576 model runs to obtain the optimal parameters. The second method is to narrow down the ranges of the parameters first. Actually this step has been done in the sensitivity analysis. Then Monte Carlo method is applied to select the optimal parameters randomly. The second method plus the sensitivity analysis for each sub-basin requires only half of the runs of the first method, and yields better results (Figure 2.6). When considering Guixian, Liuzhou, Gaoyao, Wuzhou, and Wuxuan, a significant improvement (about 5%) of Nash–Sutcliffe model efficiency coefficient was found. In particular for Boluo, the Nash-Sutcliff model efficiency coefficient increased by 74%.

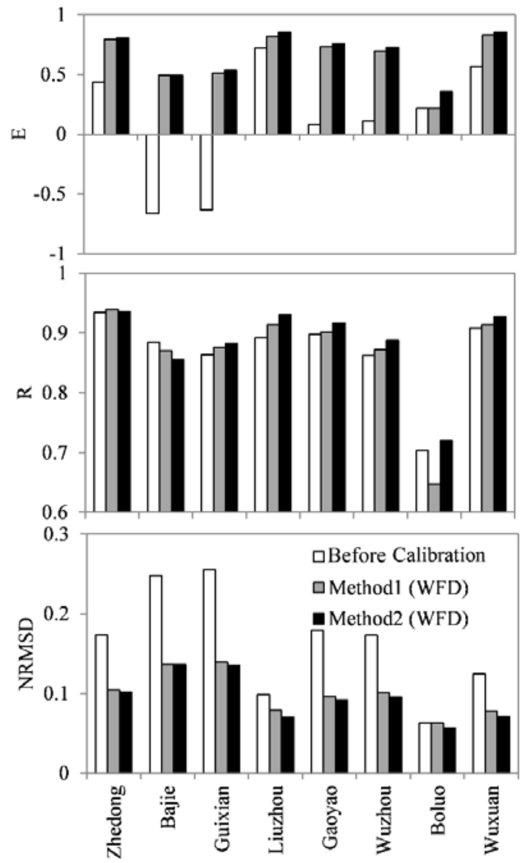

Figure 2.6 Statistics for eight stations under two calibration methods. The VIC model was forced by the WATCH Forcing Data (1958-1985)

The performance of the VIC model used in this study has been compared with other hydrological models used in previous studies. As a matter of fact, all these models can produce good results in simulating historical river discharge. Some models applied to smaller sub basin may perform better because of higher resolution (Lv et al., 2014).

After calibration, the VIC model was evaluated by comparing with observed discharge data from Gaoyao and Wuzhou stations for the period 2006-2010. The slightly reduced Nash-Sutcliff model efficiency coefficients of the two stations (Gaoyao: 0.10; Wuzhou: 0.08) for the validation period indicate that the performance of VIC is fairly stable. In general, the discharge is overestimated by VIC (Figure 2.7). See section 2.5 for further discuss of the overestimation.

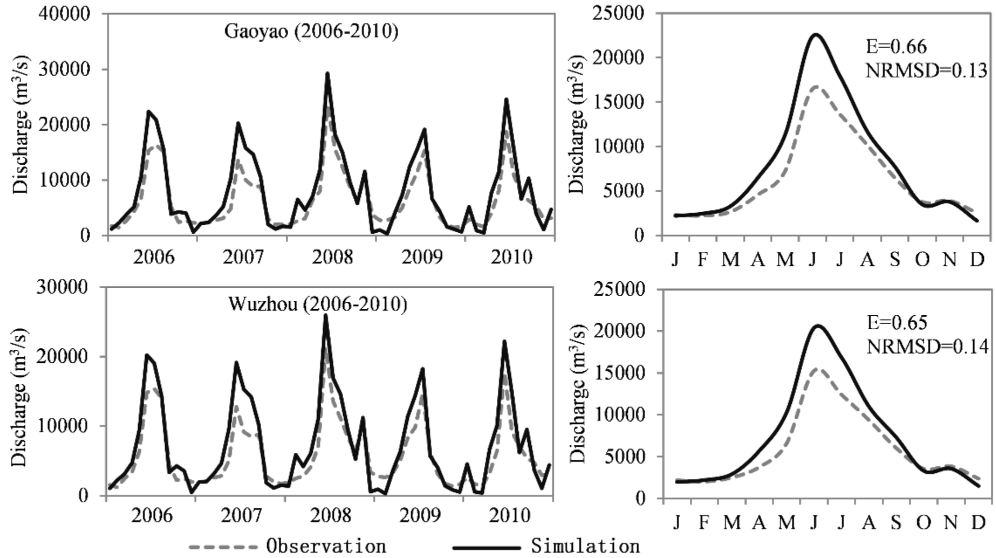

Figure 2.7 Monthly time series for 2006-2010 and mean annual cycle of observed and simulated monthly river discharge for Gaoyao and Wuzhou station for the period 2006-2010. The stations are located in the midstream of the Pearl River. The Nash–Sutcliffe model efficiency coefficient (E), correlation coefficient (R), and normalized root mean square deviation (NRMSD) are calculated for monthly series for 2006-2010.

2.4 Projection of river discharge variation under future climate

2.4.1 Simulations of historic river discharge

Two methods were used to bias correct the output of five different CMIP5 models (see Section 2.2.2). The WATCH Forcing Data (1960-1999) were used as a reference for the bias corrections. From Section 2.3, we know that the VIC model performed well in historic river discharge simulation forced by the WATCH Forcing Data and WATCH Forcing Data ERA Interim. Therefore, to evaluate the performance of bias corrections on climate model output, the historic discharges based on bias corrected output of the five CMIP5 models were compared with those based on the WATCH Forcing Data and WATCH Forcing Data ERA Interim. The results indicated that although the maximums of simulated discharge are slightly different from the observations, the medians, quartiles, and minimums correspond well with the simulated values based on WFD and WFDEI (Figure 2.8). The bias correction methods have proven to be useful for adjusting climate model bias.

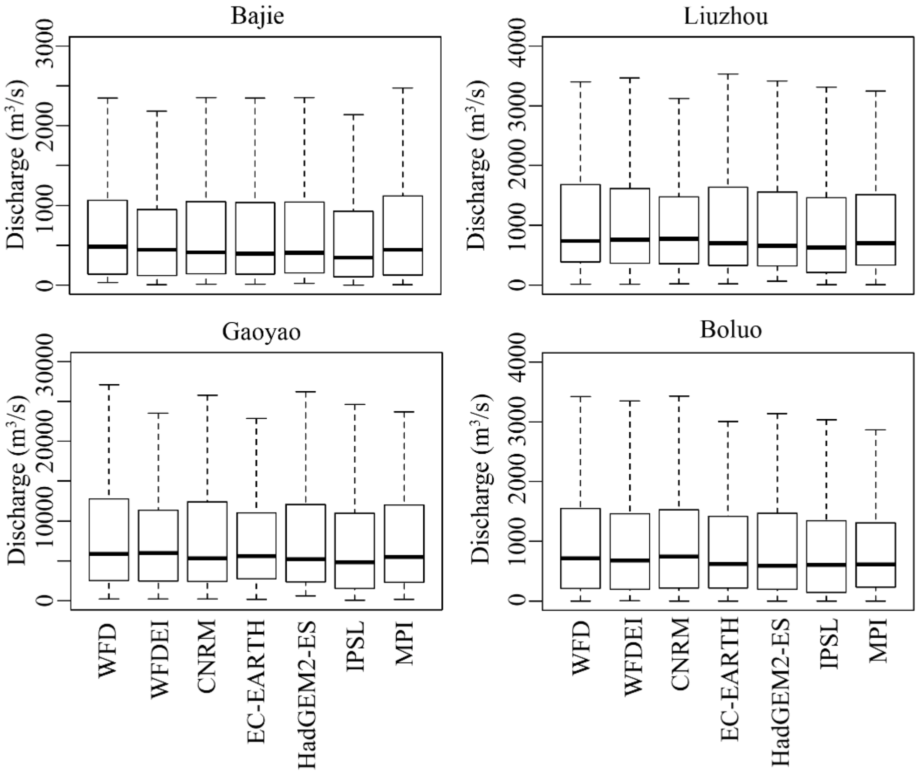

Figure 2.8 Simulated average annual discharge forced by the WATCH Forcing Data, the WATCH Forcing Data ERA Interim, and bias corrected output of five different climate models for the period 1979-1999

2.4.2 Climate change impacts on average and extreme river flows

The changes in high, low and mean flows for the period 2079-2099 relative to 1979-1999 were calculated for all five GCM experiments under RCP4.5 and 8.5 scenarios (Figure 2.9). The 95th percentile of the monthly discharge distribution (Q_{95}) is an index of high flow. For low flow, we used the 10th percentile of the discharge distribution (Q_{10}). Both Q_{95} and Q_{10} are widely used flow indices (Smakhtin, 2001; Tharme, 2003; van Vliet et al., 2013).

The differences between future climate scenarios will be discussed in Section 2.5.2. Here we focus on mean values of the five CMIP5 models. Our results show that climate change is projected to have a significant impact on water availability in the Pearl River Basin (Figure 2.9). Low flows are projected to decrease throughout the Pearl River Basin. All climate models indicate a reduction of low flows. Lows flows were reducing more for RCP8.5 compared to RCP4.5. For RCP4.5, low flows reduce between 6 and 48 % depending on locations. For RCP8.5, the decreases of low flows can reach up to 72%. Moderate changes in mean flows are found in the central basin (between -10 and 10%). In the upstream region, mean flows slightly reduce under RCP4.5 (up to 9%). For RCP8.5, the maximum reduction in mean flow is 24%. In the southern part of the basin, mean flows are projected to increase, with similar patterns as for changes in high flows. High flows are projected to decrease in the upstream region and to increase in the midstream region under both RCP4.5 and 8.5 scenarios. In other words, the spatial patterns of river discharge changes under RCP4.5 and 8.5 scenarios are very similar, only the magnitude is different. The period of 2079-2099 is much drier for RCP8.5 compared to RCP4.5 relative to 1979-1999.

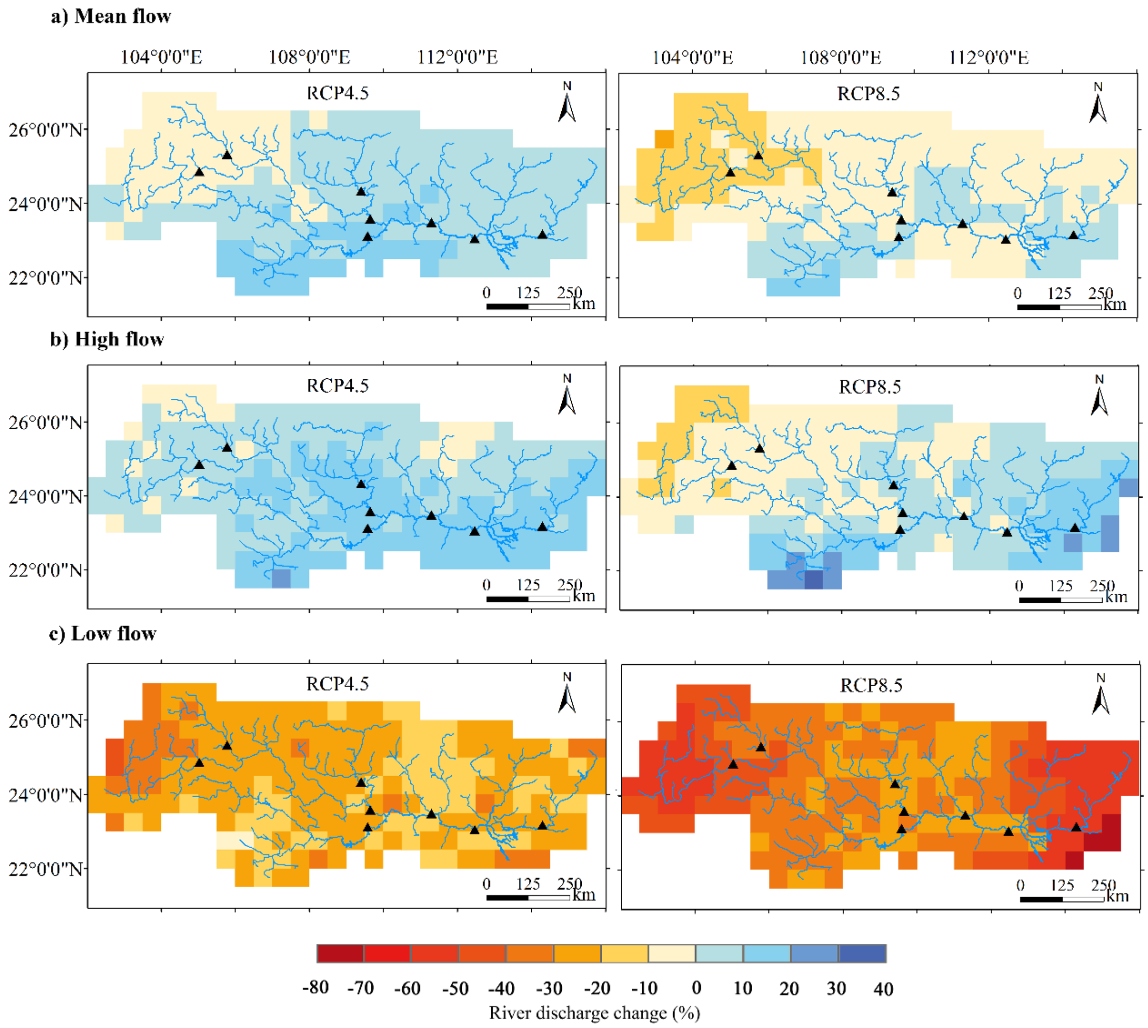

Figure 2.9 Mean projected changes in high flow (Q_{95}), low flow (Q_{10}) and mean flow for 2079-2099 relative to 1979 -1999 for the Pearl River Basin under two RCP scenarios (model mean of five GCMs)

2.4.3 Seasonal variations in river discharge under future climate change

Mean annual cycles of projected changes in river discharge were calculated for four selected stations situated in different sub-basins (Figure 2.10). The results show that the mean onset of the East Asian Monsoon is delayed at all four stations under climate change. At Bajie station, discharge is projected to decrease for most of the year. Only moderate increases are found in October and December under RCP8.5 and November under RCP4.5. Similar temporal patterns have been detected for Liuzhou, Gaoyao and Boluo station for RCP4.5 and 8.5 respectively. For RCP4.5, the discharge is projected to decrease from January to May, then to increase for the rest of the year except October. For RCP8.5, the period of decreasing discharge lasts until July, and then two downstream stations (Gaoyao and Boluo) have a period of increasing discharge until the end of the year. Liuzhou station, located in the middle reaches of the Pearl River, has an increasing period of about three months (August-October), then goes down again. The results show that the wet season is likely to become wetter, and the dry season will become drier in the middle and lower reaches of the Pearl River Basin. For upstream stations, both the dry and wet seasons are becoming drier.

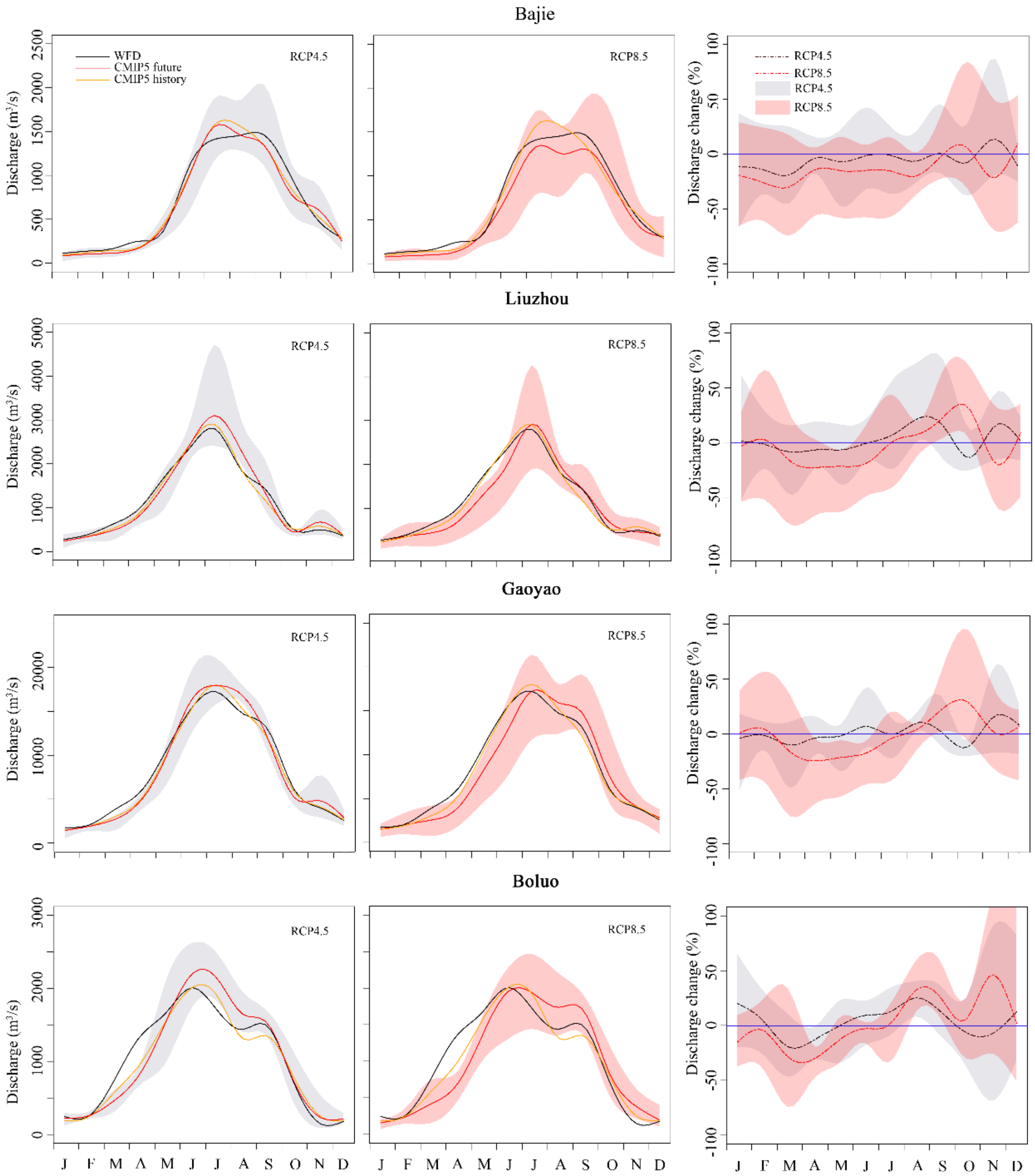

Figure 2.10 Mean annual cycle of projected changes in 30-day moving average of river discharge for selected stations in the Pearl River Basin for 2079-2099 relative to 1979-1999

2.5 Discussion

2.5.1 Model performance

Eight stations have been selected for analysing impacts of climate change on water availability in the Pearl River Basin. Simulated and observed discharges are considered to be satisfactorily matching if the Nash-Sutcliffe index is higher than 0.6 (Bennis and Crobeddu, 2007). Three stations (Bajie, Guixian and Boluo) have a Nash-Sutcliffe index slightly below 0.6 which indicates a relatively weak performance of VIC for those stations. All three stations are located in the lower reaches of different tributaries. Previous studies have shown that at downstream stations hydrological and land surface models tend to overestimate river discharge. This is mainly due to anthropogenic water withdrawals, such as agriculture, energy, manufacturing and domestic water use (e. g. van Vliet et al., 2012). Also in the Pearl River water withdrawals could have caused a flow reduction. These anthropogenic effects on Pearl River discharge will be a subject of future study.

2.5.2 Scenarios uncertainty on river discharge simulation

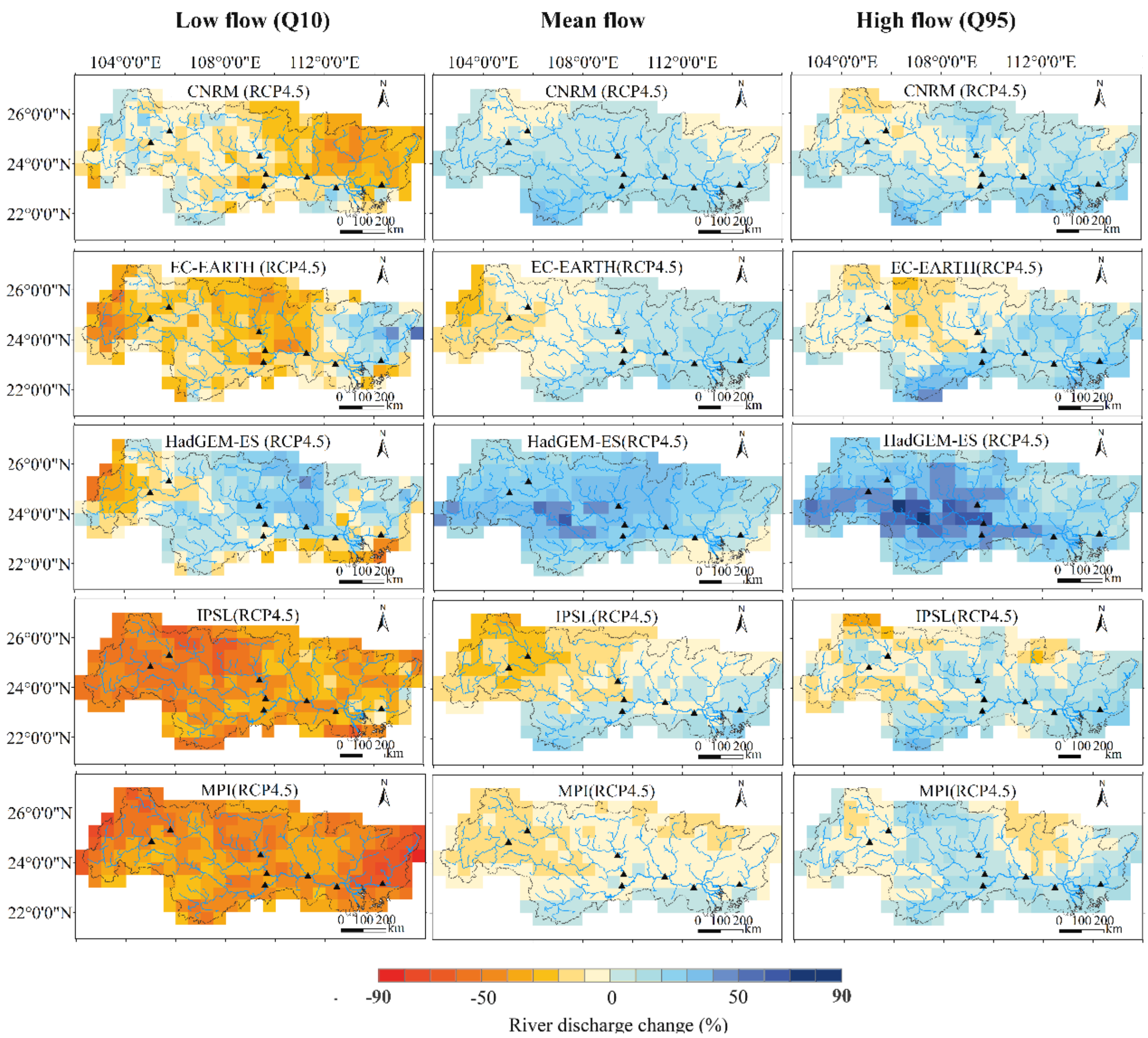

Figure 2.11 Projected changes in low flow (Q10), high flow (Q95) and mean flow for 2079-2099 relative to 1979 -1999 for five selected GCMs under RCP4.5

For studies exploring climate change impact on river discharge, one of the main uncertainties arises from the climate change models (Teng et al., 2012). The uncertainties are highly relevant to the structure, parameterization and spatial resolution of corresponding GCMs. Using multiple models forced by multiple scenarios would lead to a better understanding of the uncertainties in climate models (Biemans et al., 2009). Therefore the VIC model was forced by bias corrected output of five selected CMIP5 models (see section 2.2.2) under two emission scenarios for the period 2079-2099 to investigate the impacts of uncertainties resulting from climate models on river discharge simulations (Figure 2.11).

For the Pearl River Basin the projected climate differs greatly depending on the climate model used. When using the HadGEM2-ES model, the river discharge was generally very high due to the large increase in precipitation (Figure A1). The HadGEM2-ES model is known to produce more extreme scenarios due to its relatively high climate sensitivity (Figure A2) (IPCC, 2013). For mean and high flows, the spatial patterns are quite similar for all the climate models except HadGEM2-ES. High and mean flows are projected to decrease for the upper reach, and to increase in the south and southeast of the basin. Moderate changes in high and mean flows are found in the midstream of the basin. Low flows are projected to decrease in the upper and lower reaches under all the scenarios including HadGEM2-ES. Inconsistent low flow changes were only found in the upstream of the Dongjiang River when the EC-EARTH model was used for the simulation. To sum up, the GCM models are found to be relatively robust when simulating low, high and mean flows.

2.5.3 Impact of changes in river discharge on water resources

The VIC model was forced with bias corrected output of five different CMIP5 models (1960-2099) to quantify the impact of climate change on water resources. Our results show that climate change can affect timing and magnitude of high, low and mean flows in the Pearl River Basin. High flows are projected to increase in the downstream part of the basin. Relative increases in high flows are larger than projected increases in mean flows. This is likely to increase flood risks in the lower part of the basin. Zhang et al. (2012) showed similar results in their study on the precipitation structure in terms of annual total rain days, annual total precipitation amount, annual precipitation intensity and annual mean precipitation days over the Pearl River Basin. Liu et al. (2012) concluded that a substantial increase in annual discharge and increasing trend in discharge during high flow were detected using output of three GCMs under A1B, A2 and B1 scenarios in the West River (Xijiang) basin. The results are consistent with our findings under RCP4.5. However, for RCP8.5, high flow is projected to decrease in the upper reach and increase in the middle and lower reaches of the basin. Similar conclusions were drawn recently by Xiao et al. (2013) for the West River, the Yujiang River, the Guijiang River, Hongshuihe River, and the North River (Beijiang) using five different GCMs under RCP4.5. Only Wu et al. (2014) yielded different conclusions; they found low likelihood of increasing treads in high flow under the RCP4.5 scenario in the North River. Decreases in annual average low flows are projected for the whole basin. This reduced water availability during dry periods is likely to have a negative impact on water security in the basin.

Climate change is also projected to affect seasonal variations in river discharge. In the lower reaches of the Pearl River Basin, river discharge is increasing in the wet seasons and decreasing in the dry seasons. The variation is likely to increase the flood frequencies and aggravate drought stress. These changes could especially have an impact on the Delta which is one of the leading economic regions and a major manufacturing centre of China. Here, more floods and droughts could potentially have a major impact on the economy and society. The reduced flow during the dry season could potentially increase saltwater intrusion in the delta. Especially as the increasing water consumption due to economic development and population growth is likely to further reduce dry season flows. In the upstream part of the basin, river discharge is decreasing during both the dry and wet seasons. Consistent low flows may increase levels of water scarcity and climate change may also reduce production of the hydropower stations in the upstream of the Pearl River Basin (e. g. Christensen et al., 2004; Schaefli et al., 2007).

2.6 Conclusion

Our simulation results show that climate change is likely to impact future flows of the Pearl River. Not only the average flows are affected by climate change but also the extremes. In the downstream part of the basin the high flows are increasing and the low flows are reducing. In the upstream part, both the high and low flows tend to decrease. Results clearly indicate that river flows are becoming more variable throughout the basin. There are substantial differences in results between the different climate models, e. g. all the models point into the same direction in term of flow changes with the exception of HadGEM2-ES. This model shows much higher precipitation and thus runoff compared to the other four GCMs. The main conclusion of our work is that dry seasons are projected to become drier throughout the basin. Wet seasons are projected to become drier in the upper reach and wetter in the middle and lower reaches of the Pearl River Basin. Uneven spatial and temporal distribution of water resources may aggravate water shortages as well as flood events in the basin. Although previous studies have focused on high flow events, this study shows that, also for monsoon climate, it is important to simulate both high and low discharge.

Acknowledgements

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Appendix A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, atdoi:10.1016/j.ejrh.2015.

3

Identifying and assessing robust water allocation plans for deltas under climate change

Chapter 3

Identifying and assessing robust water allocation plans for deltas under climate change

Abstract

Water scarcity threatens economic growth, social cohesion, and environmental sustainability in many deltas. This situation is likely to worsen due to future climate change. To reduce water scarcity and limit saltwater intrusion in deltas, many countries have launched policies to allocate water resources. However, it is difficult to develop long-term adaptive water management policies due to large uncertainties. In this paper, we present a Robust Assessment Model for Water Allocation (RAMWA) to support decision making about water release of different key reservoirs under future climate change. The model was applied in the Pearl River Basin, China to improve reservoir management, to ensure sufficient flow into the delta to reduce salt intrusion, and to provide sufficient freshwater for human and industrial consumption. Results show that performance of the existing water allocation plans reduces under climate change, as the plans are unable to sustain the required minimum river discharge. However alternatives generated by a Generic Evolutionary Algorithm (GEA) suggest that new plans can be developed which ensure minimum flows into the delta under most future climate change scenarios. The GEA plans perform better than existing plans because rather than following a fixed allocation schedule, the optimal water release for each reservoir is recalculated every ten days based on observed discharge and storage in key reservoirs.

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3.1 Introduction

Water is a fundamental human need, and essential for socio-economic development and environmental protection (Oki and Kanae, 2006). However, both human population and water resources are distributed unevenly. High population density regions do not always overlap with abundant water resources regions and as a result one third of the global population currently lives under water scarcity (Vörösmarty et al., 2000). The latest IPCC report (2013) reaffirms that global climate change is likely to have substantial impacts on water resources across the globe. Impacts vary among different regions throughout the world. In some places water availability will increase but in many densely populated areas, such as urbanizing delta regions with intensive conflicts between different water users, water scarcity will increase (Vicuna and Dracup, 2007).

Insufficient water resources in deltas have negative impacts on the environment and socio-economic development. One of the solutions to reduce impacts of water scarcity is to improve water allocation systems and policy. To guarantee water security in the deltas, different countries have launched improved policies to allocate water, e. g. the Chatfield Reservoir Reallocation Project in America (Bark et al., 2014) and the Key Reservoirs Operational Project in China (Xie, 2007).

Many optimization techniques for water allocation have been proposed, e.g. linear programming, nonlinear programming, genetic algorithms, and artificial neural networks (Chang et al., 2016; Li et al., 2015; Zarghami et al., 2015). However, most previous studies address water allocation problems based on hypothetical water distribution networks and run at course temporal resolutions from weekly, to even annual time scales (Xiao et al., 2016). Nodes (e. g. reservoirs and demand centres) and links/carriers (e. g. rivers and pipes) are used to represent water supply systems and often no flow routing has been incorporated. Most previous studies also use only historic data and neglect future climate change. Very few studies incorporate changes and uncertainties in future water availability (Davijani et al., 2016; Sechi and Zucca, 2015).

Robust Decision making (RDM) is a quantitative approach for supporting decisions under deep uncertainties (Lempert and Groves, 2010). It uses simulations to assess the performance of water agency plans over many plausible futures, and present the results to water managers to help them improve their plans. Inspired by Lempert and Groves (2010), we also use robustness evaluation of water allocation plans over different climate scenarios to address future uncertainties in water availability. Robustness is defined here as good performance across different future scenarios. In other words, a water allocation plan will be considered to be robust if it satisfies certain performance criteria under all or most scenarios. Previously statistical methods were used to randomly generate scenarios. However, to better include uncertainties in future climate in the analyses, it is often more appropriate to use outcomes of climate models in combination with biophysical hydrological models (Yan et al., 2015).

This study combines multi-objective generic evolutionary algorithm, robust decision making, and biophysical modelling by developing a Robust Assessment Model for Water Allocation (RAMWA) to facilitate sustainable water management and allocation in delta regions. The

RAMWA approach is specifically developed for deltas where flows tend to be (too) low in the dry season but there is sufficient water supply during the wet season, which can be stored in upstream reservoirs for later release. With this new model, the study aims to help water managers to evaluate the robustness of existing water allocation plans, as well as to identify an improved set of options.

The model developed for this study uses a physically based routing model to distribute water in a real river network at a daily scale. It not only evaluates the performance of existing water allocation plans in the past, but also the impact of future climate change on robustness of previous and newly generated water allocation plans. In addition, the future scenarios used in this study are generated by coupling biophysical climate, hydrological and routing model instead of statistical models.

3.2 Methodology

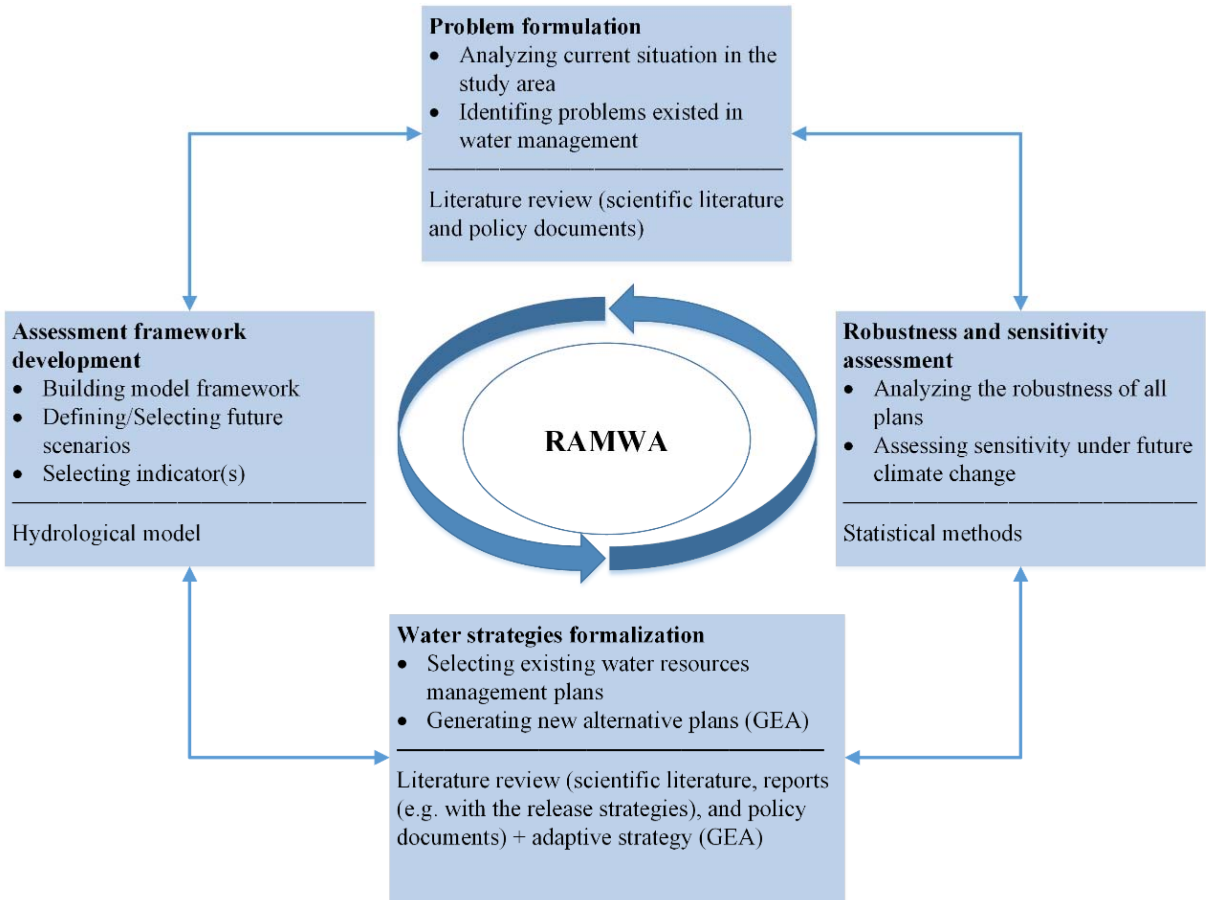

Figure 3.1 Four steps of the robustness assessment in the Robust Assessment Model for Water Allocation (RAMWA)

The methodology for water allocation and robustness evaluation in RAMWA builds on Lempert et al. (2010), and consists of four steps: problem formulation, assessment framework development, water strategies formalization, robustness and sensitivity assessment (Figure 3.1).

3.2.1 Problem formulation

In this step, the main causes of water scarcity and saltwater intrusion are identified and it is determined whether future development is likely to aggravate the situation. Next variation in future water demand and supply in the study area is reviewed and water management policies related to water allocation, water scarcity and saltwater intrusion are collected. In addition, the current performance of water management policies and plans is assessed through literature review.

3.2.2 Assessment framework development

The integrated framework is the main element of RAMWA, and responsible for hydrological processes simulation and river routing. In this framework, we use an existing hydrological model (c.f. Lempert and Groves (2010)). The optional models are listed in Appendix B. Model selection is a crucial step in the assessment, in which model performance as well as regional applicability should be considered.

Performance metrics are built to quantify the performance of different water allocation plans. Performance is defined to relate to the main goal of water allocation plans, *e.g.* to guarantee minimum water flows during the dry season, to prevent excessive salt-water intrusion and to provide sufficient fresh water resources for different users in the delta. Metrics are used to reflect whether goals are achieved. For example, a performance metric could be the duration over which the discharge in the lower reach of the river is above a certain threshold.

3.2.3 Water management plans selection and formalization

In this step, first existing water management plans are selected. They can be operational plans developed by local government to guarantee sufficient water supply for different users. Ideally, the plans are based on the best available information, consideration of environmental issues, recognition of existing water use and consultation with the water resources administrative department.

Next to the evaluation of existing plans, the RAMWA approach presented in this study aims to identify whether potentially more robust alternatives exist. A generic evolutionary algorithm (GEA) for multi-objective and multi-optima optimization problems is used in RAMWA to generate alternatives for the water allocation problem. For the GEA, we consider the water allocation problem can be defined as constrained N-objective ($N \geq 1$) minimization problem.

3.2.4 Robustness and sensitivity assessment

In this step, the performance of each candidate plan is assessed under future climate scenarios. Next the robustness of the candidate plans is characterized. Similar to Lempert and Groves (2010), a set of thresholds is set for each indicator of the performance in accordance with water managers' preferences. Candidate plans that violate thresholds are considered as plans with poor performance. If a plan performs well under all or most of the climate scenarios, it is considered to be robust.

In order to identify which input parameter affects robustness most, a sensitivity analysis is performed. RAMWA uses the top marginal variable to check relative importance of individual input parameters on output variables. The top marginal variable indicates the uncertainty contribution of a subset of inputs, also known as the percentage of output variance accounted for by the subsets (Berger et al., 2010).

3.3 A case study for the Pearl River Delta

3.3.1 Problem formulation

The Pearl River in southern China is the second largest river in China in terms of streamflow (Figure 3.2). The Pearl River Delta is the world's largest urban area (World Bank, 2015) and its rapid regional socio-economic development is challenged by reduced availability of water resources (Jiang, 2009). Reduced low flow, in combination with rising sea levels, have caused severe saltwater intrusion in the delta (Li and Ao, 2000). Increasing salinity poses a potential threat to water supply in the delta (Liu et al., 2010). In a previous study, we showed that throughout the basin dry season rainfall and discharge are likely to reduce in the future due to climate change (Yan et al., 2015). This may result in a further increase of saltwater intrusion.

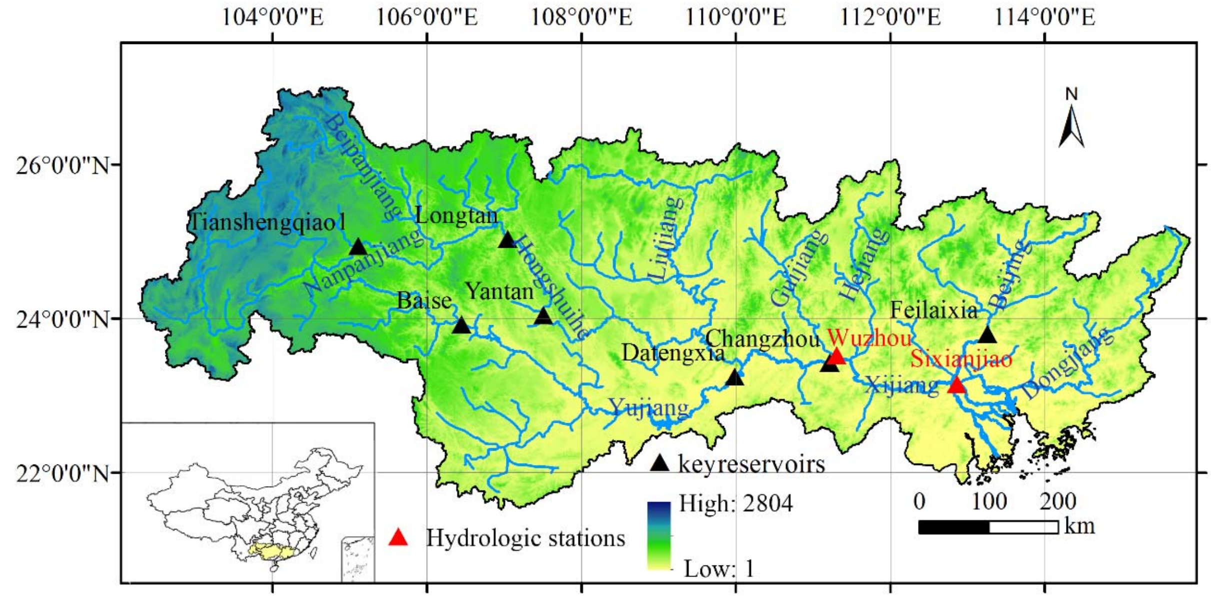

Figure 3.2 Location of the Pearl River Basin, key reservoirs and hydrological stations used in this study

To improve water security in the region, the government in 2005 launched the 'Key Reservoirs Operational Project for Pearl River Basin', to maintain low flow in the dry season by releasing additional water from upstream reservoirs (He et al., 2007; Xie, 2007). This water allocation project aims to improve the operational effectiveness and efficiency of the key reservoirs: Tianshengqiao I, Longtan, Yantan, Feilaixia, Changzhou, and Baise, and thus to maximize the benefits for different water users in the basin (Qian, 2007). The implementation of the policy alleviated salt intrusion to some extent (Liu, 2007b). Yet, despite the releases, severe saltwater intrusion reappeared in 2009 and 2011 due to unusually low precipitation (Wang and Jiao, 2012). In addition, projected low flows reduced under climate change (Yan et al., 2015) are likely to affect the performance of the water allocation project and represent a major challenge to water management. The robustness of the water allocation project under climate change is selected as the main issue to be addressed in this case study.

3.3.2 Assessment framework development

As mentioned in Section 3.2.2, the assessment framework development consists of three steps: (1) developing an integrated framework for hydrological simulation; (2) selecting future scenarios; (3) defining indicators to quantify the performance of water allocation plans.

For the hydrological simulation we select the variable infiltration capacity (VIC) model which is a macro-scale hydrologic model originally developed by Liang et al. (1994). Previous studies have demonstrated good performance of VIC on hydrologic processes simulation in the Pearl River Basin (Niu and Chen, 2009; Yan et al., 2015). Therefore we use the VIC model as the centrepiece of the integrated framework to balance both water and surface energy budgets within each gird cell. A reservoir model developed by Haddeland et al. (2006a) is used to simulate reservoir operations and irrigation water withdrawals. Water releases from the key reservoirs are modelled using existing water allocation plans (see Section 3.3.3).

Future climate change scenarios can be selected from different climate models. We selected from over 30 general circulation models (GCMs) used for IPCC AR5. Using the following criteria 1) performance in the study area and 2) being representative for the range of projected future climate change. Based on these criteria, we select CNRM-CM5, HadGEM2-ES, IPSL-CM5A-LR, MPI-ESM-LR and EC-EARTH for future projections (for details on GCM selection see Yan et al. (2015)).

For the Pearl River Basin, water allocation plans aim to maintain minimum river flows to prevent excessive saltwater intrusion. Ideally, the chlorinity of water should be lower than 250 mg/l. To achieve this objective, the Chinese government decrees that the discharge should be at least 1800 m^3/s at the measurement station near Wuzhou and 2200 m^3/s at the Sixianijiao station (Xie, 2007) (Figure 3.2). Therefore selected performance indicators are the number of days discharge < 1800 m^3/s at Wuzhou and number of days discharge < 2200 m^3/s at Sixianjiao.

3.3.3 Candidate plans selection

Four water allocation plans are identified based on the government report (PRWRC, 2006). These four plans were developed in 2006 to deal with two different inflow conditions (p>90% and p>97%, where p represents the probability of inflow conditions) at Wuzhou station (Table 3.1). Table 3.1 shows the corresponding discharges of these two inflow conditions at Wuzhou station from October to March. Plan 1 and 2 are developed for condition 1 (p>90%). Plan 1 is a so-called continuous release plan in which extra water is released continuously after 20th December. Plan 2 is an interval plan in which extra water is released at intervals. Plan 3 and 4 are the continuous and interval plans developed for inflow condition 2 (p>97%).

Under plan 1 and 3, the key reservoirs release more water than under plan 2 and 4 (Figure 3.3).

Water allocation starts from November. For each month, we check whether to release water by calculating the average discharge of the previous month and comparing it with the average discharges of the two inflow conditions (Table 3.1).

Table 3.1 Corresponding discharge of two inflow conditions at Wuzhou station (2005-2006 and 1992-1993 are typical years for two inflow conditions respectively) (unit: m^3/s)

Inflow condition	2006			2007		
	Oct	Nov	Dec	Jan	Feb	March
2005-2006 (90%)	3140	2300	1700	1590	1210	2540
1992-1993 (97%)	2040	1416	1110	1266	1308	2023

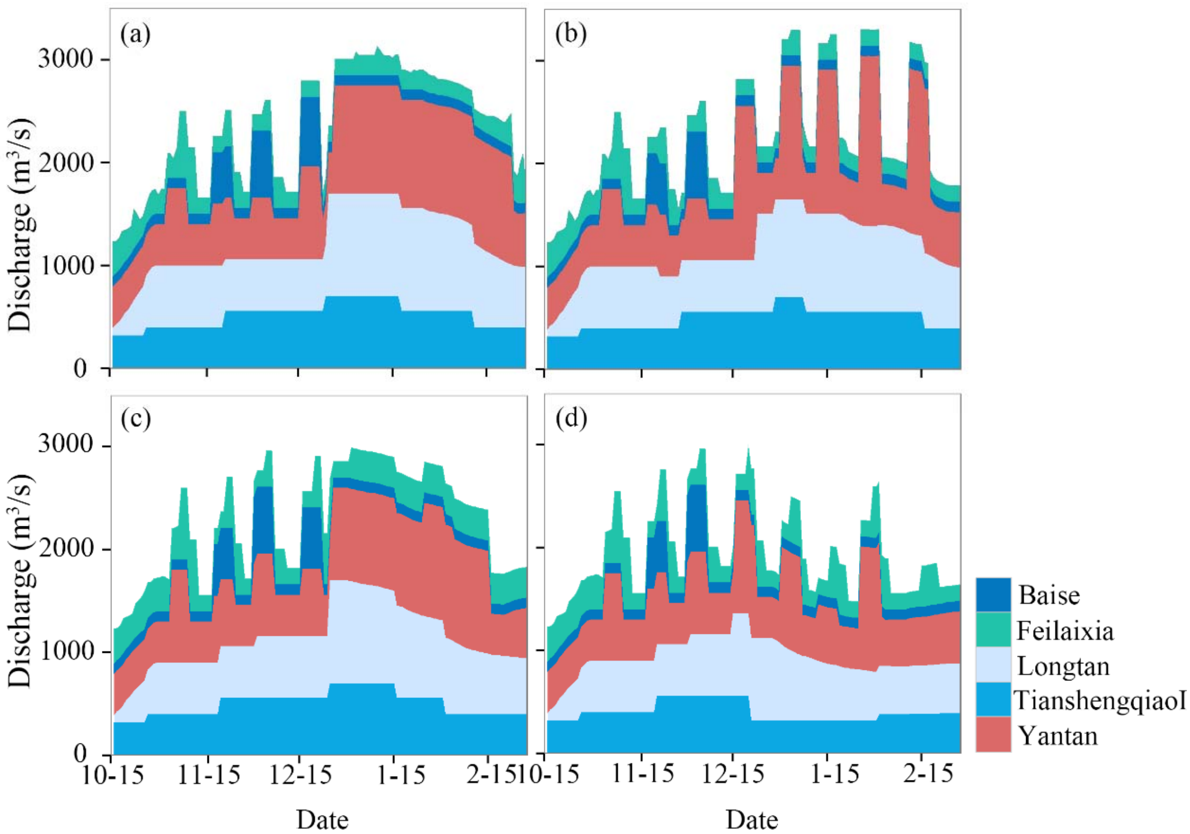

Figure 3.3 Water releases of key reservoirs under four existing 2006 water allocation plans in the Pearl River Basin (a) plan 1; (b) plan 2; (c) plan 3; (d) plan 4

A GEA named omni-optimizer based on NSGA-II (Deb and Tiwari, 2008) is chosen to generate additional plans. The omni-optimizer was selected as previous studies (McClymont and Keedwell, 2012) suggested it provides an effective way to discover solutions for multiple reservoir systems. Its population-based search yields approximations to the Pareto optimal front in a single algorithm. We slightly modify the omni-optimizer by using different Latin hypercube sampling algorithm to generate a diverse set of plans. The omni-optimizer starts with 100 plans created randomly by Latin hypercube sampling. The diversity of plans is warranted by using a nearest neighbour based strategy (Deb and Tiwari, 2008). The plan optimization procedure works as follows: selected plans are recombined and mutated to obtain two offspring plans. Both parent and offspring are combined together to preserve the elites. A good parent plan will remain in the subsequent plan. A modified domination principle is used to classify the entire set of plans into different classes (Deb and Tiwari, 2008).

The omni-optimizer uses two objectives and twelve constraints to evaluate the performance of the plans. The objective functions are given as follow:

$$min \sum_{i=1}^{i=N} |Q_{wuzhou,i} - 1800| \quad (3.1)$$

$$min \sum_{i=1}^{i=N} \left|Q_{sixianjiao,i} - 2200\right| \quad (3.2)$$

where N represents number of days during dry season, $Q_{wuzhou,i}$ and $Q_{sixianjiao,i}$ are the daily discharge at Wuzhou and Sixianjiao. Capacity (S_{max}) and dead storage (S_{dead}) of the six key reservoirs were used as constraints (see also Table B2 in Appendix B).

$$S_{dead} < S_{t,k} < S_{max} \quad (3.3)$$

$$S_t = S_{t-1} + Q_{in} - Q_{out} - E_{res} \quad (3.4)$$

where S_{t-1} is reservoir storage at the end of previous day, Q_{in} is simulated inflow to the reservoir, Q_{out} is the release of reservoir, E_{res} is the evaporation of the reservoir.

3.3.4 Candidate plans evaluation and sensitivity analysis

During the period 1980-1985, before implementation of the allocation plans, the simulations without any allocation plan match well with the observations. After the implementation of water allocation plans, the observations are closer to simulations with water plans. However number of days that discharge is less than 1800 m^3/s at Wuzhou station (N_w) is underestimated for all water plans during 2009-2010 (Figure 3.4a). Due to extremely low inflow in the dry season, only two reservoirs were used for water allocation during 2009-2010.

Taking $N_w$as the main indicator, the performance of the GEA plans is superior to the 2006 water allocation plans. Peak values (lowest performance) of GEA plans are less than the peak values of the 2006 water allocation plans. More than 75 percent of the GEA plans perform better than plan 1, 3, and 4, and at least five percent of the GEA plans outperform plan 2 (Figure 3.4b).

Due to climate change, there will be about 90 days in which the discharge is less than 1800 m^3/s at Wuzhou by the end of this century if there is no water allocation plan. N_w values are consistently high for the period of 2080-2099, indicating increased water scarcity in the delta (Figure 3.4c and d).

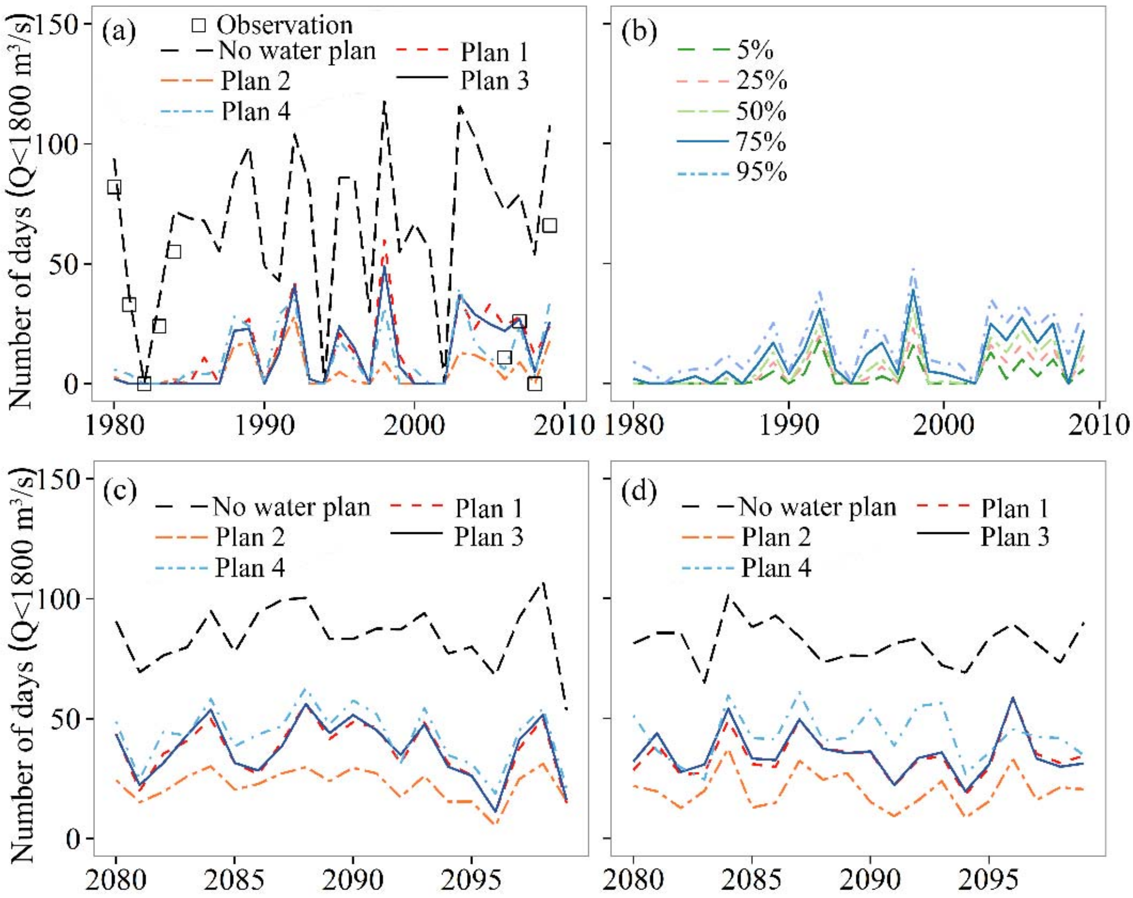

Figure 3.4 Assessment of water allocation plans (a) Observed and simulated number of days at which the discharge is less than 1800 m^3/s at Wuzhou station (N_w). Simulated values with and without the operation of different water allocation plans (Observations are available for 1980-1985 (no water allocation plan operational) and 2006-2010 (including water allocation)); (b) different percentiles of N_w under 100 GEA plans; (c) average N_w with and without water allocation implemented under RCP 4.5; (d) average N_w with and without water allocation implemented under RCP 8.5. Each line in panel (c) and (d) represents the average of five GCMs

Results also show large disparity in the performance of the different water plans for future climate scenarios. Plan 2 has the highest performance (N_w ~ 20 days). Plan 1 and plan 3 have similar performance (N_w ~ 40 days). Plan 2 and 4 are the best and worst plans among the four 2006 water allocation plans. They are both interval water allocation plans. Key reservoirs release more water under plan 4 until 20th, December. However, the water release of plan 4 is lower than plan 2 after 20th, December. Plan 1 and 3 are continuous water allocation plans. The total water release of plan 2 is less than plan1 and 3, but the peak flow of plan 2 is higher than plan 1 and 3. Plan 2 is a more efficient and water-saving strategy compared with the other existing water allocation plans. The GEA plans on average perform better than Plan 2. The main reason is that GEA plans are more adaptive strategies. The GEA recalculates the optimal water release for each reservoir every ten days based on discharge at Wuzhou and Sixianjiao station and storage of the key reservoirs. Unlike the GEA plans, the 2006 water allocation plans are developed in advance.

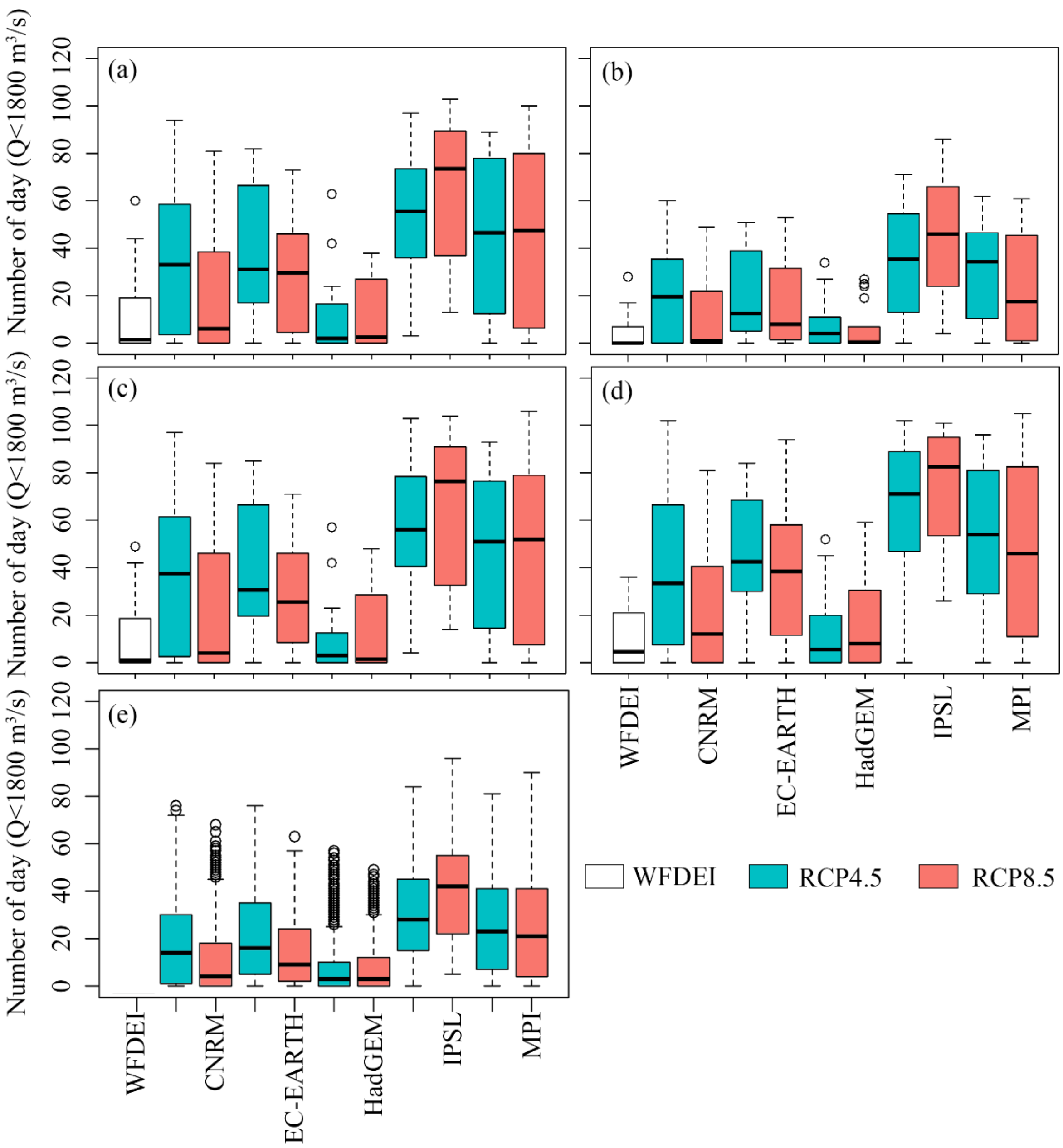

Figure 3.5 N_w under four different 2006 water allocation plans driven by different future climate scenarios (2080-2099) (a) plan 1; (b) plan 2; (c) plan 3; (d) plan 4 and (e)100 GEA plans also driven by different future climate scenarios (2080-2099)

Assessing the performance of the four plans under different climate models shows that performance is the best under the HadGEM2 model and the worst for IPSL (Figure 3.5a-d). Plan 2 performs the best and performs well for all GCMs except IPSL. Based on our definition of robustness in Section 3.1, none of the four water allocation plans is robust for the period 2080-2099. But in relative terms, plan 2 is the most robust plan.

The GEA plans perform substantially better than the four predefined water allocation plans (Figure 3.5e). The median of N_w for the GCM model scenarios is below 30 days for all climate models except for IPSL.

Figure 3.6 uses squares with side length of 50 days to compare plans as the medium of plan 2 is around 50 days under IPSL RCP8.5. All plans perform relatively well for all climate models except IPSL with 65 percent of the points are in the square.

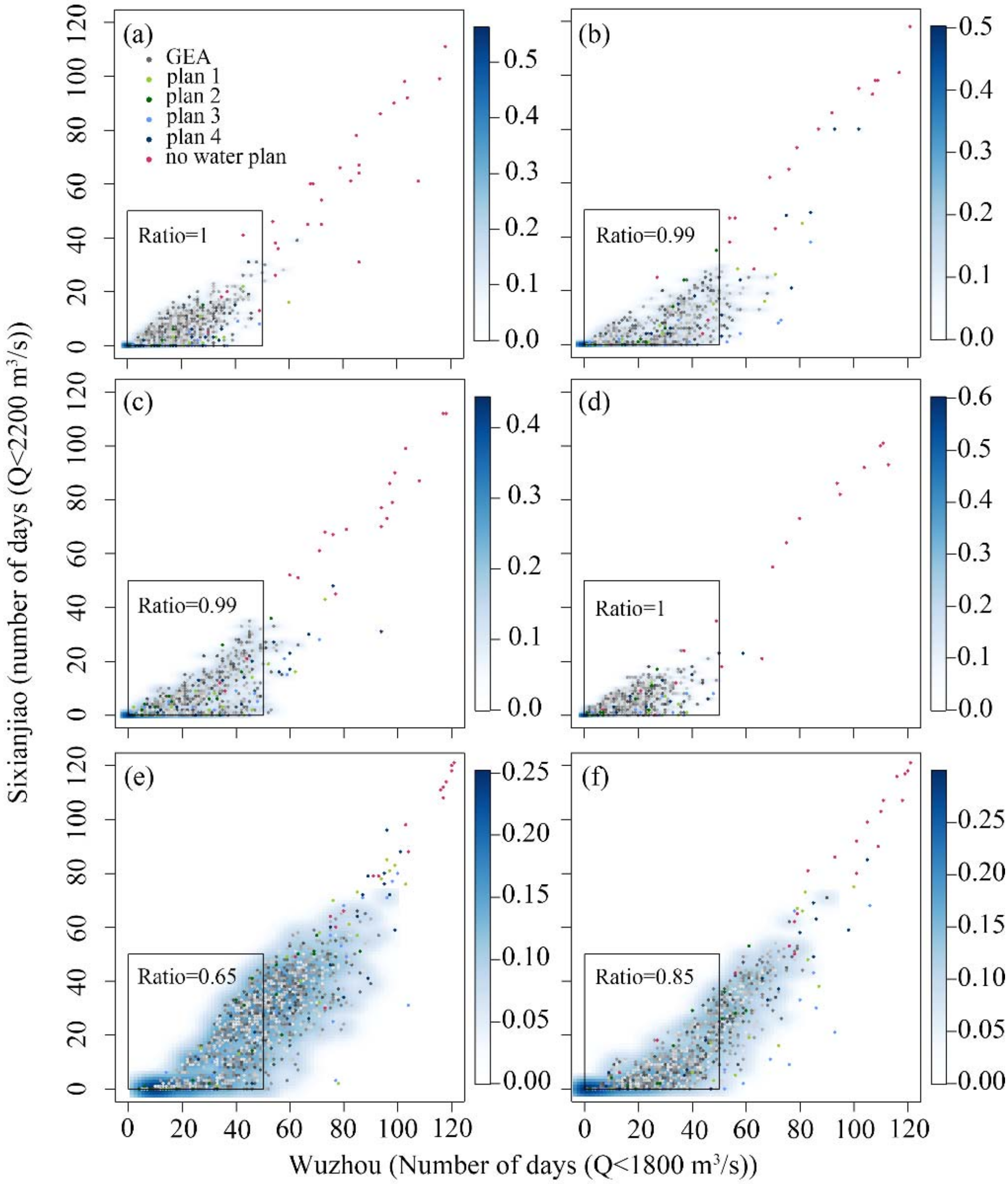

Figure 3.6 Robustness assessment of all selected water allocation plans driven by WFDEI (1980-2010) and five selected GCMs under RCP8.5 (2080-2099) (a) WFDEI; (b) CNRM; (c) EC-EARTH; (d) HadGEM; (e) IPSL; (f) MPI (Points in different shades of grey represent results under GEA plans in different years; blue represents the density of points)

Yan et al. (2015) showed that low flow at Wuzhou and Sixianjiao station for the period of 2079-2099 relative to 1979-1999 would decrease by about 40 percent under IPSL RCP8.5. From the results, it is apparently that neither the 2006 water allocation plans nor the GEA plans can cope with a future as projected by the IPSL model. Yet, the GEA plans are found to offer more robust alternatives than the four water allocation plans.

To improve the current performance of the water allocation policy, a new reservoir called Datengxia is currently under construction in the upstream of Qianjiang River (Liu, 2007a)

(Figure 3.2). Our analysis shows that the performance of the GEA plans improves substantially if this new reservoir is added to the system. The fractions of plans which are within the 50 day threshold increases to 0.93 under IPSL RCP 4.5 and to 0.83 under IPSL RCP 8.5 (Figure 3.7).

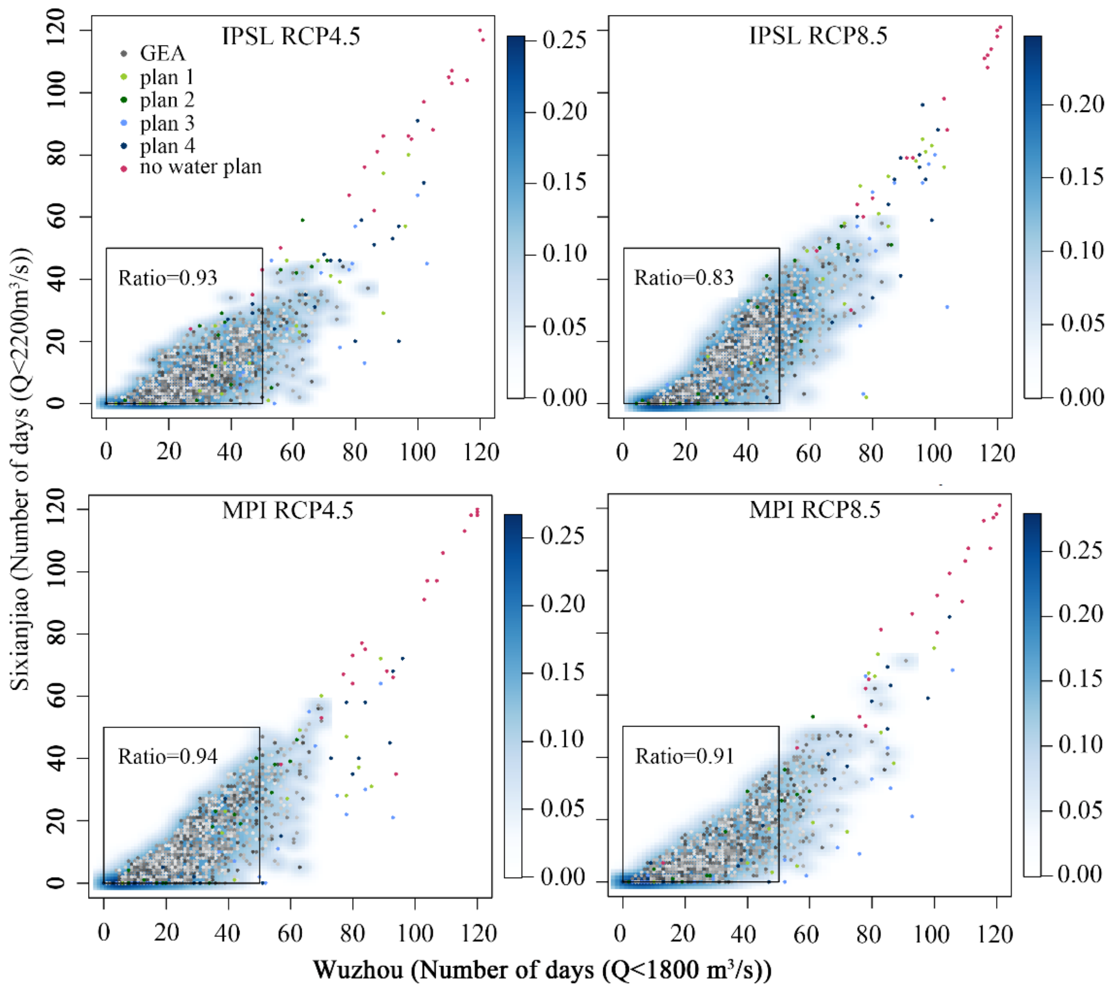

Figure 3.7 Robustness assessment of four 2006 water allocation plans and modified GEA plans for 2080-2099 driven by IPSL and MPI RCP 4.5 and 8.5 after adding the Datengxia reservoir to the key reservoir system (a) IPSL RCP4.5; (b) IPSL RCP8.5; (c) MPI RCP4.5; (d) MPI RCP8.5 (Points in different shades of grey represent results under GEA plans in different years; blue represents the density of points)

The sensitivity analysis aims to quantify the impact of uncertainty in reservoir operation on overall study output. We apply a Monte Carlo method in association with Latin Hypercube Sampling (LHS) (van den Brink et al., 2008) to the operations of different reservoirs. The relative importance of the individual reservoir is assessed using the top marginal variable. The top marginal variable of an input is the variance reduction which would occur if the input would become fully known. The adjusted R^2 of the reservoir releases was at least 83 percent (Table 3.2).This indicates that most variance in the output is accounted for and that there was no significant interaction between the model inputs.

The uncertainties in Yantan and Longtan reservoir releases contribute most to the variance in discharge at Wuzhou station (Table 3.2). Feilaixia reservoir does not add to the variance at Wuzhou station as it is located in another river branch. With the completion of Datengxia, the relative contribution of the other reservoirs to the variance of the discharge at Wuzhou decreases, especially for the Baise and TianshengqiaoI reservoir.

As the Changzhou reservoir was not included in the water allocation plans of 2006 and a sensitivity analysis showed little effect of Changzhou reservoir on discharge, it was excluded from the analysis.

Table 3.2 Top marginal variance of the releases for different reservoirs (expressed as percentage of total variance at Wuzhou station)

		R2 adjust based on a linear fit	R_{Baise}	$R_{TianshengqiaoI}$	R_{yantan}	$R_{Longtan}$	$R_{Datengxia}$
Mean values of the five GCMs	RCP 4.5	87	15	15	37	32	*
	RCP 8.5	86	19	14	36	30	*
IPSL	RCP 4.5	83	6	9	32	24	30
	RCP 8.5	83	6	4	30	27	32

*means this reservoir is not selected for water allocation

3.4 Discussion

3.4.1 Effect of design choices on the performance of RAMWA

The study provides an example of evaluation and selection of robust plans for the operation of key reservoirs during the dry season. Furthermore, the model can show water managers the performance of different combinations of water release from key reservoirs under an uncertain future. To do so, the RAMWA approach requires several design choices from the researchers and/or water managers, for example, how to develop alternative water management plans, how to construct performance criteria or how to set threshold levels.

For this study, the choices were made by the authors, but water managers can potentially participate in the design choices of the robustness evaluation. For example, the minimum discharges are set to 1800 and 2200 m^3/s at Wuzhou and Sixianjiao station in this study. However, the thresholds may become inappropriate in the future due to sea level rising and decreasing precipitation. Water managers can adjust their setting and strategies in accordance with their goals at any time during the process. The interaction between models analysts and water managers could potentially improve the ability of RAMWA in identifying and assessing robust water allocation plans for deltas under climate change.

Future climate scenario selection is also an important design choice for water managers. In this study, our robustness assessment is based on five GCMs. Using a higher number of climate models could affect our results because there are more than 30 GCMs used in CMIP5 (Taylor et al., 2012). Although we select these five models to cover a wide range of changes in temperature and precipitation, parts of the uncertainties in future climate change may still be unrepresented.

3.4.2 Multi-objective evolutionary algorithms selection

The optimization algorithm is an important component in RAMWA as algorithm selection influences the performance of RAMWA in assessing water allocation plans.

We selected the omni-optimizer, which is based on the well-known NSGA-II (Reddy and Kumar, 2006), to generate alternative plans in RAMWA. The capability of the omni-optimizer has been demonstrated by its applications in a number of optimization problems (Deb and Tiwari, 2008). In general, it is difficult to find Pareto approximate alternatives for complicated environmental systems due to multiple conflicting performance constraints. However, in this study, omni-optimizer managed to generate high-quality planning alternatives for water allocation. Each alternative is non-dominated with respect to multiple performance measures. Non-dominated means that no objective function can be improved in value without reducing some of the other objective values (Deb and Gupta, 2006).

In addition, omni-optimizer uses $\epsilon - domination$ to maintain the diversity of the solutions. The ϵ-domination is a modified domination principle to classify the entire combined population into different classes (Deb and Tiwari, 2008). High diversity of the alternatives cannot only help water managers to select an optimized solution, but also inspire them by showing them a set of high quality optional alternatives.

The performance of omni-optimizer seems to be good for searching robust water allocation plans in the decision space in this study. However, it is unclear whether these plans cover the whole Pareto optimal frontier or only a small island with good performance. If other multi-objective evolutionary algorithms were used in RAMWA, the allocation plans may be completely different but with good performance. In order to detect the most robust strategy in water allocation system, it is worth to try different MOEAs and do a comparison. This question will be addressed in our future work.

3.5 Conclusion

In this study, a robustness assessment model for water allocation is developed to facilitate sustainable water management in delta regions. The model is specifically developed for deltas where flows tend to be (too) low in the dry season but where there is sufficient water supply during the wet season, which can be stored in upstream reservoirs for later release. This model is applied in the Pearl River Basin to assess the robustness of reservoir management, which aims to ensure sufficient flow into the delta to reduce salt intrusion, and to provide sufficient freshwater for human and industrial consumption under climate change. The model assesses the robustness of four existing water allocation plans under future climate scenarios. Results show that performance of existing water allocation plans reduces under climate change. The plans differ in how the water is released. The plan, which releases high volumes of water at intervals, is found to be the most robust. None of the existing plans can maintain the required minimum river discharge under all future scenarios.

In addition, we use the model to assess whether more robust alternative plans exist. For this we use an advanced generic evolutionary algorithm (GEA). More robust GEA plans could be found, ensuring minimum flows into the delta under most future climate change scenarios. The main reason is that GEA plans are more adaptive strategies. They perform better than existing plans because the optimal water release for each reservoir is recalculated every ten days based on observed discharge and reservoir storage. Nevertheless, neither the 2006 water allocation plan nor the GEA plans can deal with the extreme dry years projected by the IPSL climate model. The performance of the plans improves substantially if a new key reservoir is added to the reservoir system. In conclusion, RAMWA can be a useful tool for adaptive water management in deltas regions because of its ability to search and evaluate robust water allocation plans.

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Electronic supplementary material

The online version of this article (doi:10.1007/s11269-016-1498-0) contains supplementary material, which is available to authorized users.

4

Many-objective Robust Decision Making for Water Allocation under Climate Change

Chapter 4

Many-objective Robust Decision Making for Water Allocation under Climate Change

Abstract

Water allocation is facing profound challenges due to climate change uncertainties. To identify adaptive water allocation strategies that are robust to climate change uncertainties, a model framework combining many-objective robust decision making and biophysical modeling is developed for large rivers. The framework was applied to the Pearl River Basin (PRB), China where sufficient flow to the delta is required to reduce saltwater intrusion in the dry season. Before identifying and assessing robust water allocation plans for the future, the performance of ten state-of-the-art MOEAs (multi-objective evolutionary algorithms) is evaluated for the water allocation problem in the PRB. The Borg multi-objective evolutionary algorithm (Borg MOEA), which is a self-adaptive optimization algorithm, has the best performance during the historical periods. Therefore it is selected to generate new water allocation plans for the future (2079-2099). This study shows that robust decision making using carefully selected MOEAs can help limit saltwater intrusion in the Pearl River Delta. However, the framework could perform poorly due to larger than expected climate change impacts on water availability. Results also show that subjective design choices from the researchers and/or water managers could potentially affect the ability of the model framework, and cause the most robust water allocation plans to fail under future climate change. Developing robust allocation plans in a river basin suffering from increasing water shortage requires the researchers and water managers to well characterize future climate change of the study regions and vulnerabilities of their tools.

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4.1 Introduction

Water resources are essential for life and socio-economic development (Oki and Kanae, 2006). Due to climate change and population growth, water resources in many parts of the world have been pushed to their natural limits (Vörösmarty et al., 2000; Wang et al., 2017). Water shortage has become a major challenge in these regions causing a bottleneck for socio-economic development. Allocating water resources is critical to meet human and ecosystem needs now and in the future *(Bangash et al., 2012; Null and Prudencio, 2016)*. However, water resources allocation and management are being challenged by uncertainties associated with climate change.

Different new methods to deal with uncertainties in water resources management have been developed in recent years. For example, Lempert and Groves (2010) developed Robust Decision Making (RDM) which uses multiple futures, robustness criteria, and adaptivity to hedge against uncertainty. A large ensemble of monthly temperature and precipitation sequences were generated based on the Atmosphere-Ocean General Circulation Models (AOGCM) using K-nearest neighbour (KNN) bootstrapping technique to represent a plausible range of climate changes. Matrosov et al. (2013) used an information-gap theory to propagate uncertainties, and to rank different infrastructure portfolios for 2035. Climate change uncertainty is represented using monthly climate change perturbation factors that are multiplied by historical river flow time series. Mortazavi-Naeini et al. (2015) used robust optimization to secure urban bulk water supply against extreme drought and uncertainties associated to climate change. They obtained the ranges of future rainfall and potential evapotranspiration (PET) for 23 GCMs from a previous study CSIRO-BoM (2007), then used a stochastic multi-site model to generate 10,000 50-year replicate of daily rainfall and PET based on these ranges. However, only one emission scenario (A1F1) was involved in their study. Culley et al. (2016) developed a bottom-up approach to identify the maximum operational adaptive capacity of water resource systems with respect to a future climate exposure space. The climate exposure space used in their study is generated based on seven general circulation models and six regional climate models under three representative concentration pathways (RCPs).

Several previous studies used statistical methods to generated future climate scenarios. This is a severe underutilization of climate models as tools for supporting decision making (Weaver et al., 2013). Recently, climate change projections derived from general circulation models (GCMs) are considered as an important source of knowledge for water managers to adapt their strategies to a changing hydrological cycle due to climate change (IPCC, 2013; van Pelt et al., 2015). However, the GCMs are not designed, or intended to be used as a tool for water resources management. The output of GCMs is delivered in coarse grids, and associates with significant biases. Downscaling and bias correction are necessary before application at a regional scale (Kiem et al., 2016; Kiem and Verdon-Kidd, 2011). In addition, the projections of future climate change are also plagued with uncertainties (Dessai and Hulme, 2007). For example, Lim and Roderick (2009) showed that when 20 GCMs were used to produce 39 runs of the 21st century for the Murray-Darling Basin, 22 runs showed increase trends in annual average precipitation to the end of the 21st century, while 17 showed decreases. There is no consensus on what will happen to future climate, which causes difficulties in decision making for efficient water resources management. It is unlikely that uncertainties in future climate projections will significantly reduce in the near future. To manage water resources under climate change uncertainty, it is necessary to use projections for different emissions scenarios derived from multiple GCMs (Pierce et al., 2009; Teutschbein et al., 2015).

Optimization algorithms are often considered as an important component of many decision making approaches in water allocation (Chang et al., 2016; Davijani et al., 2016; Zuo et al., 2015). However, it is difficult to optimize the real-world water allocation problems due to multiple conflicting objectives. For multi-objective optimization, improvement of one objective may lead to deterioration of some of the other objective values (Deb and Gupta, 2006). Recently, much attention has been paid to Multi-objective Evolutionary Algorithms (MOEAs) (Kasprzyk et al., 2013). Instead of finding a solution, which can optimize all objectives simultaneously, the MOEAs are developed to capture the best trade-off solutions (Coello Coello et al., 2007). Due to the inherent parallelism and capability to exploit similarities of solutions by recombination, the MOEAs are capable of searching for multiple Pareto-optimal solutions concurrently in a highly complex search space (Zitzler and Thiele, 1999). However, Reed et al. (2013) evaluated performance of ten state-of-the-art MOEAs on three different test problems, and found the MOEAs performed differently for different test problems. Therefore, it is necessary to do a pre-assessment of different MOEAs, and select one or more suitable MOEAs for a multi-objective water allocation problem.

With the help of MOEAs, the result of an optimization for a complex water allocation problem changes from a single best solution to a Pareto approximate set of solutions. Selecting the most robust set of solutions among all these non-dominant solutions poses a new challenges to decision makers. Previous studies used different methods to negotiate trade-offs and selected robust solutions in water resources management, e. g. visually interactive decision-making and design using evolutionary multi-objective optimization (Kollat and Reed, 2007), geometric angle-based pruning algorithm (Sudeng and Wattanapongsakorn, 2014), and many-objective robust decision making (Kasprzyk et al., 2013). Among these methods, many-objective robust decision making can identify trade-offs between different solutions, assess their performance under deep uncertainties, and use interactive visual analytics to explore robust solutions efficiently (Kasprzyk et al., 2013). It has been successfully applied to solve a number of water resources management problems (Singh et al., 2015). Therefore, it is used in this study.

This paper aims to develop a model framework combining many-objective robust decision making with biophysical modelling to identify robust water allocation plans under future climate change. Multiple GCMs under RCP4.5 and 8.5 are viewed as sources of insight into complex system behaviour, and aid to thinking within robust decision framework. Unlike previous studies which address water allocation problems based on hypothetical water distribution networks and run at course temporal resolutions (weekly, to annual time scales) (Xiao et al., 2016), our framework uses a physically based routing model (Haddeland et al., 2006a) to distribute water in a real river network at a finer temporal resolution (daily scale). In addition, the performance of different start-of-the-art MOEAs is evaluated before identifying and assessing robust water allocation plans. The MOEA(s) with the best performance is selected for future computation. This is the first study assessing the performance of different MOEAs before using. Previous studies selected MOEA based on its historical applications for other problems (Kasprzyk et al., 2013; Vink and Schot, 2002; Yan et al., 2016). However, the MOEAs perform differently for different optimization problems.

The rest of the paper is organized as follows. In Section 4.2, we describe the model framework that combines models and datasets used in this study. A case study of the Pearl River Basin, China is presented in Section 4.3. Section 4.4 discusses the performance of the MOEAs and uncertainties existed in the input parameters. Section 4.5 concludes the paper, including lessons learned from this study and suggestions for future research.

4.2 Methodology

4.2.1 Model framework

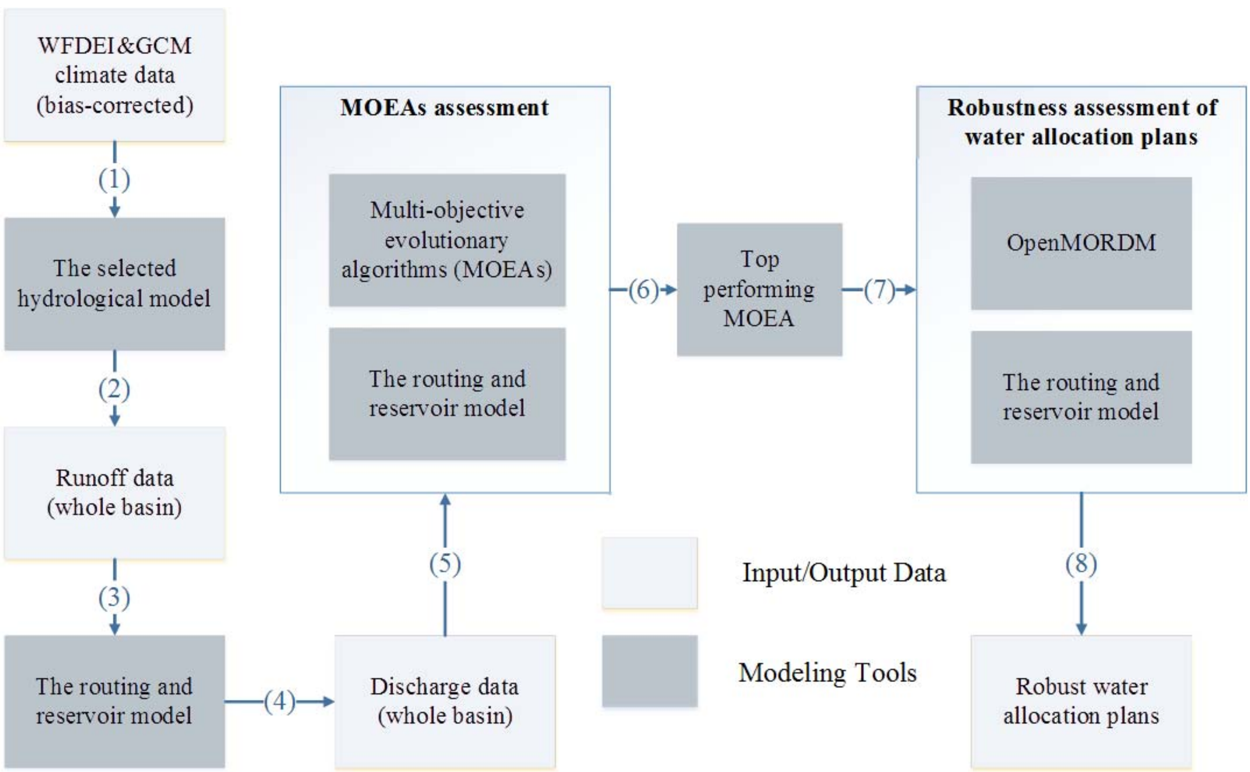

Figure 4.1 Model framework integrating different models and datasets used in this study

Figure 4.1 illustrates the model framework integrating different models and datasets used in this study. The model framework is a complex tool to facilitate sustainable water allocation in delta regions, which includes a hydrological model, a routing and reservoir model, ten different Multi-objective Evolutionary Algorithms (MOEAs), and an open source software for many-objective robust decision making (OpenMORDM) (see below for more details).

The WATCH Forcing Data for ERA Interim (WFDEI) (Puccini et al., 2016) and downscaled climate data from five GCMs under two RCPs are used to drive a hydrological model (chain 1). Five GCMs selected in this study are the CNRM-CM5, HadGEM2-ES, IPSL-CM5A-LR, MPI-ESM-LR and EC-EARTH. They were selected using the following criteria 1) good performance in historical precipitation and temperature simulation, and 2) data available at a resolution suitable for the hydrological modeling (for more details see Yan et al., 2015). For each GCM, we obtain climate data for two RCPs (RCP4.5 and 8.5). The RCP4.5 is a medium-low emission pathway in which total radiative forcing is stabilized at roughly 4.5 Wm^{-2} before 2100 (Thomson et al., 2011). RCP8.5 is a high emission scenario. The greenhouse gas emissions and concentrations in this scenario increase considerably over time, leading to a radiative forcing of 8.5 Wm^{-2} in 2100 (Riahi et al., 2011). By selecting these two scenarios, we expect to capture a reasonable range in climatic and hydrological projections for the Pearl River Basin. RCP2.6 is the only scenario complying the internationally agreed 2 °C warming projection. Given the current pace of greenhouse gases emissions, it is not a realistic target (Hoang et al., 2016). Therefore, RCP2.6 is not used in this study.

As hydrological model, we use the variable infiltration capacity (VIC) model (Liang et al., 1994; Liang et al., 1996). The parameterisation of the VIC model for the Pearl River Basin has been described in more detail in Yan et al. (2015). The VIC model simulates daily runoff data (chain 2). Next the runoff data are used as input in a routing and reservoir model developed by (Haddeland et al., 2006a) (chain 3) to generate discharge data for the whole basin (chain 4). Subsequently, ten MOEAs are employed to generate candidate water allocation plans under historical discharge scenarios (chain 5 and 6). Three historical periods are selected, which are correspond to the 1st, 5th, and 10th percentiles of the mean discharge over all the historical periods at Wuzhou station. We compare the performance of these ten MOEAs in the historical periods, and select the top performing algorithm.

Finally, we combined an open source software for many-objective robust decision making (OpenMORDM) developed by Hadka et al. (2015) with the routing model to generate multiple water allocation plans, and identify the robustness of each plan (chain 7 and 8). Multiple robustness measures are necessary because their averaging tends to ignore outliers (Hadka et al., 2015). Therefore we use two different methods: regret and satisficing to measure robustness in this study. The regret-based robustness is obtained by minimizing the deviations in performance caused by uncertainties compared to an ideal solution, while the satisficing-based robustness is obtained by calculating the fraction of scenarios that satisfy the designed criteria (Hadka et al., 2015). The functions are given as follow:

$$R_{Regret} = \min_{i}\left\{\underset{s\in S}{quantile}\left(\left|\frac{f_i(x;s) - \sup_{y\in P} f_i(y;s)}{f_i(x;s)}\right|, 0.9\right)\right\} \quad (4.1)$$

where S represents the set of ten climate scenarios from five GCMs under RCP 4.5 and 8.5 for the period of 2079-2099, P represent alternative plans generated by the MOEA, $\sup_{y\in P} f_i(y;s)$ is the ideal point in P within all the future scenarios, y indicates that the plan is the ideal point. The ideal point marks the best value achieved in each objective. $f_i(x;s)$ is the value of the ith objective in future scenarios, x indicates that the plan is one of the alternatives. $\underset{s\in S}{quantile}(, 0.9)$ computes the 90th percentile value across all sampled future scenarios.

$$R_{satisficing} = \frac{1}{|S|}\sum_{s \in S} I_S\big(f(x;s)\big) \quad (4.2)$$

where $I_S()$ is a satisficing indicator function. The designed evaluation criteria are encoded in this function. If all evaluation criteria are satisfied, the indicator equals to 1, and 0 otherwise. These two methods measure different criteria, we consider water allocation plans that score high on both measures most robust.

In addition, uncertainties existed in input parameters are analysed. We use the Patient Rule Induction Method (PRIM) to find regions of input parameters at which higher quality values are found. The PRIM is originally proposed by Friedman and Fisher (1999). It works by iteratively removing a small portion of samples with lowest (or highest) response value (Hadka et al., 2015).

4.2.2 Multi-Objective Evolutionary Algorithms selection

In general, a multi-objective evolutionary algorithm can be described as

$$\mathrm{P}(\mathrm{t}+1) = \mathrm{S_s}\left(\mathrm{v}\left(\mathrm{S_v}\big(\mathrm{P}(\mathrm{t})\big)\right), \mathrm{P}(\mathrm{t})\right) \quad (4.3)$$

where $P(t)$ represent candidate solutions at iteration t, S_v represents the selection for variation operator, v is the genetic-variation (recombination and mutation) operator, S_s is the environment-selection operator, and $P(t+1)$ are the new solutions (Purshouse and Fleming, 2007).

Multi-objective evolutionary algorithms have proven to be effective in obtaining a set of trade-off solutions for multi-objective problems with mutual conflicting objectives (Coello Coello et al., 2007). However there are more than two dozen of the MOEAs have been proposed over the last decade. Through a literature review on current state-of-the-art MOEAs with high performance (Kasprzyk et al., 2013; Kollat and Reed, 2006), we found ten algorithms, reported the top performing modern tools (see Table D1 in Appendix D).

Therefore, we selected these ten algorithms to generate candidate water allocation plans (see Table D2 in Appendix D for the parameterisation of these MOEAs). Source codes of the algorithms were obtained from an open source Java library for multi-objective optimization[1]. The library supports genetic algorithms, differential evolution, particle swarm optimization, and more.

The hypervolume indicator is selected for assessing different MOEAs. Hypervolume is the volume of objective space dominated by an approximation set which is first proposed by Zitzler and Thiele (1998). It is a frequently applied measure for comparing quality of solution sets that generated by different MOEAs (Beume et al., 2007). High value of hypervolume means a solution set is both converged and diverse. The hypervolume indicator represents the difference

[1] http://moeaframework.org/

in hypervolume between the solution set captured by a given MOEA and the reference Pareto approximate set. It helps researchers identify whether the selected water allocation plans cover the whole Pareto optimal frontier or only a small island with good performance.

4.3 Case study: the Pearl River Basin

4.3.1 Pearl River Basin

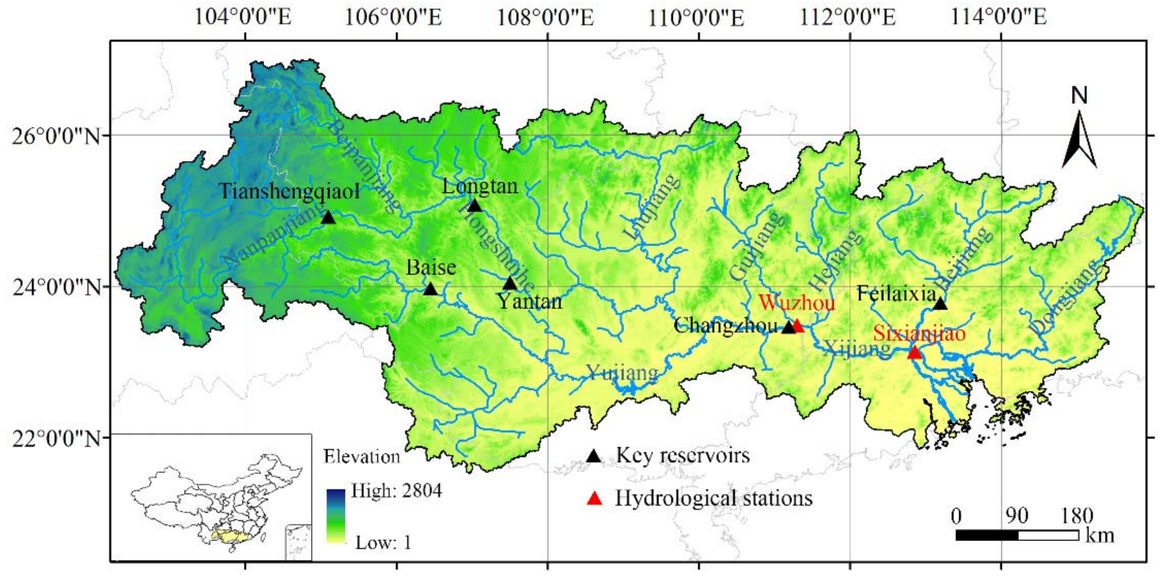

Figure 4.2 Location of the Pearl River Basin, key reservoirs and hydrological stations used in this study

The Pearl River in southern China is the third largest river in China in terms of drainage basin area (Figure 4.2), and its delta is the world's largest urban area in both size and population (World Bank, 2015). Frequent saltwater intrusion has occurred in recent years, and poses a threat to water supply in the delta (Chen et al., 2009). In a previous study, we found that dry season rainfall and discharge are likely to reduce throughout the basin in the future due to climate change (Yan et al., 2016). This may result in a further increase of saltwater intrusion.

To reduce saltwater intrusion, the Chinese government has launched a policy named "Key Reservoirs Operational Project for Pearl River Basin" to sustain minimum flow in the channel during the dry season by releasing extra water from selected upstream key reservoirs (He et al., 2007; Xie, 2007). Discharge is monitored at two important gauge stations: Wuzhou and Sixianjiao (Figure 4.2). The Chinese government decrees that the discharge should be at least 1800 m^3/s at the measurement station near Wuzhou and 2200 m^3/s at the Sixianijiao station respectively (Xie, 2007). The key reservoirs are Tianshengqiao I, Longtan, Yantan, Feilaixia, Changzhou, and Baise (Qian, 2007). The implementation of the policy alleviated the problem of salt intrusion to some extent (Liu, 2007b). However, climate variability affects the performance of the water allocation project and represents a major challenge to water management (Yan et al., 2015).

4.3.2 Formulating the optimization problem

The main goal of the water allocation plan is to ensure sufficient water flows into the delta. This is realised by releasing additional water from the key reservoirs. The MOEAs are selected to generate the candidate water allocation plans. Based on time period partition from the existing water allocation plans (PRWRC, 2006), we also split the dry season into six sub periods of 20 days. For each sub period, the key reservoirs release certain amount of water based on calculations of the MOEAs during the first ten days, and an equal amount of water as the natural flow for the second ten days. Five objectives and twelve constraints are used in the MOEAs to evaluate the performance of the plans. The conflicting objectives are to minimize variations between required minimum flow and discharge at two selected hydrological stations (Wuzhou and Sixianjiao), to maximize hydropower potential of the key reservoirs (instead of maximizing hydropower potential, we actually minimize $\frac{1}{hydropower\ potential}$ in this study), and to minimize the average numbers of days that discharge is less than the required minimum flows at Wuzhou and Sixianjiao station (Table 4.1). These objective functions are given as follow:

$$f_{var,wuzhou} = min\ (\frac{1}{|S||N||M|}\sum_{s\in S}\sum_{t\in T}|Q_{wuzhou,i} - \alpha|) \qquad (4.4)$$

$$f_{var,sixianjiao} = min\ (\frac{1}{|S||N||M|}\sum_{s\in S}\sum_{t\in T}|Q_{sixianjiao,i} - \beta|) \qquad (4.5)$$

$$f_{hydropower} = min(\sum_{i=1}^{i=n}\frac{10e^{11}|S||N|}{Q_{r_i}\rho\eta hg}) \qquad (4.6)$$

$$f_{Nr,wuzhou} = min\left(\frac{1}{|S||N|}Nr_{wuzhou}\right) \qquad (4.7)$$

$$f_{Nr,sixianjiao} = min\left(\frac{1}{|S||N|}Nr_{sixianjiao}\right) \qquad (4.8)$$

Table 4.1 Objectives and constraints used in this study

ID	Objectives and constraints	Description
Objective 1	$f_{var,wuzhou}$	To minimize variations between required minimum flow and discharge at Wuzhou
Objective 2	$f_{var,sixianjiao}$	To minimize variations between required minimum flow and discharge at Sixianjiao
Objective 3	$f_{hydropower}$	To maximize hydropower potential of the key reservoirs
Objective 4	$f_{Nr,wuzhou}$	to minimize the average numbers of days that discharge is less than the required minimum

		flows at Wuzhou
Objective 5	$f_{Nr,sixianjiao}$	to minimize the average numbers of days that discharge is less than the required minimum flows at Sixianjiao
Constraint 1-12	$S_{dead,k} < S_{t,k} < S_{max,k}$	Constraint 1-12 represent a group of constraints to keep the storage of the six key reservoirs between their dead storage and capacity

where *S* represents the set of ten climate scenarios from five GCMs under RCP 4.5 and 8.5 for the period of 2079-2099, *T* is the set of time steps (daily), *N* is the number of year during the research period. *M* is the number of sub periods in a year. $Q_{wuzhou,i}$ and $Q_{sixianjiao,i}$ are the daily discharge at Wuzhou and Sixianjiao. α and β are the required minimum flows at Wuzhou and Sixianjiao during dry season. Nr_{wuzhou} and $Nr_{sixianjiao}$ represent number of days that discharge is less than the minimum flows at Wuzhou and Sixianjiao station. ρ is the density of water, η is the efficiency of the power generating system, h is the hydrostatic pressure head, g is acceleration due to gravity. Capacity (S_{max}) and dead storage (S_{dead}) of the six key reservoirs are used as constraints in the MOEAs. Equation (4.10) shows how to calculate the storage of a reservoir at day t.

$$S_{dead,k} < S_{t,k} < S_{max,k} \quad (4.9)$$

$$S_t = S_{t-1} + Q_{in} - Q_{out} - E_{res} \quad (4.10)$$

where S_{t-1} is reservoir storage at the end of previous day, Q_{in} is simulated inflow to the reservoir, Q_{out} is the release of reservoir, E_{res} is the evaporation of the reservoir.

4.3.3 Selecting typical dry periods for assessing the MOEAs

Next the performance of ten state-of-the-art MOEAs is evaluated. We select three historical dry sub periods for the MOEAs assessment. These three selected historical periods (1997-1998, 2008-2009, and 1988-1989) correspond to the 1st, 5th, and 10th percentiles of the mean discharge over all the historical periods at Wuzhou station. The values of *S* and *N* in the objective functions are set to 1 during the evaluation.

4.3.4 Robustness assessment of water allocation plans

The values of required minimum flow at Wuzhou and Sixianjiao (α and β) are set to be 1800 and 2200 m^3/s at present. These two numbers are given by the local government based on consideration of current water use and saltwater intrusion in the Pearl River Basin. They may become inappropriate in the future due to changes in sea level and water use in the delta. Since values of required minimum flow at Wuzhou and Sixianjiao are uncertain, the OpenMORDM is used to quantify the impact of these uncertainties on robustness of different water allocation plans.

First a range of plausible values is selected for these two parameters, and Latin hypercube sampling is used to create 1000 randomly samples for each of them. Next the performance of different parameter combinations across all the climate scenarios is used to calculate the two robustness indicators (Section 4.2.1). The satisficing function in Equation 4.2 is designed with two criteria: (1) preserve a maximum variation between discharge and required minimum flow at Wuzhou station of 140 m^3/s; (2) preserve a maximum variation between discharge and required minimum flow at Sixianjiao of 180 m^3/s (PRWRC, 2006).

4.3.5 Results

4.3.5.1 MOEAs performance and selection

As mentioned in Section 4.2.2, the hypervolume indicator is selected for assessing different MOEAs (Figure 4.3a). The hypervolume indicator represents the difference in hypervolume between the solution set captured by a given MOEA and the reference Pareto approximate set. It ranges from 0 to 1. A higher value indicates a better performance.

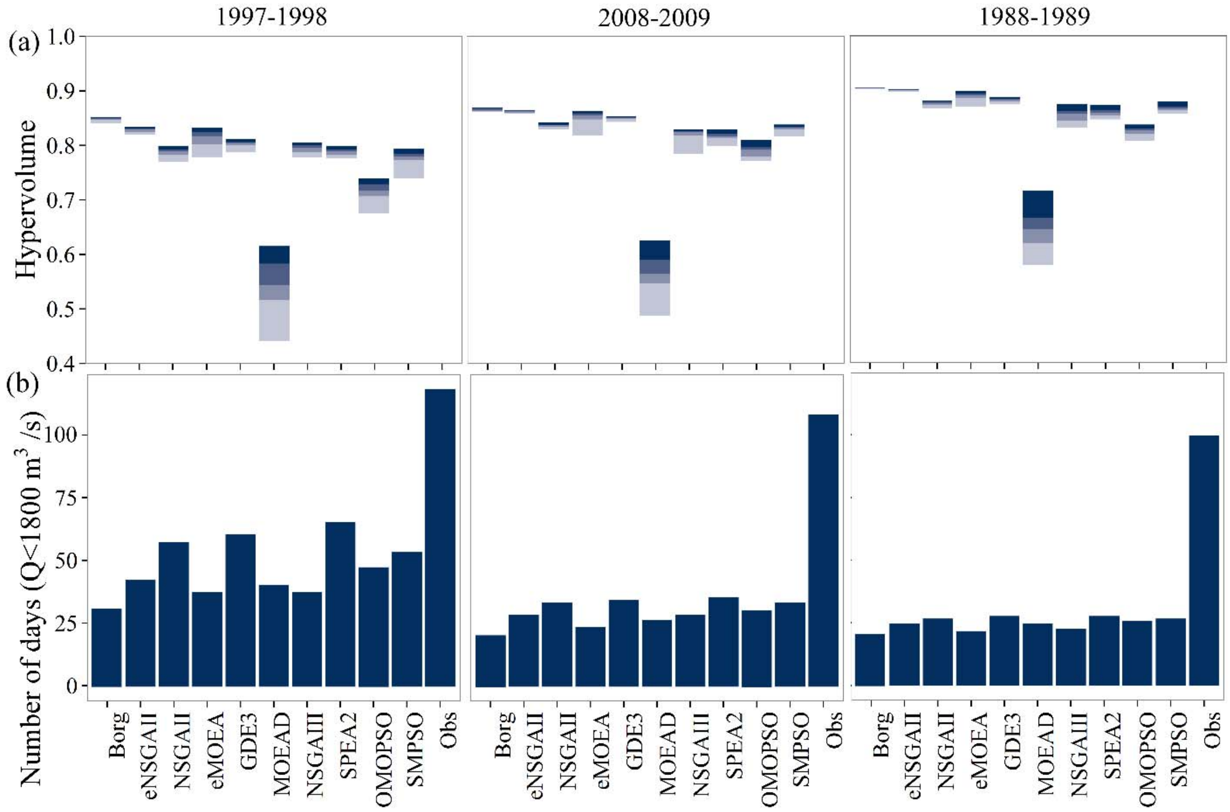

Figure 4.3 Performance assessment of ten different MOEAs in terms of (a) percentile of hypervolume indicator across all runs (50 seeds) of all the selected MOEAs, (b) number of days at which the discharge is less than 1800 m^3/s at Wuzhou station for three selected sub periods

We run the MOEAs 50 times with different seeds, and obtain the range of hypervolume indicator for all the MOEAs. For the driest period (1997-1998), the hypervolume indicators of all the MOEAs are above 70 percent except the MOEAD and OMOPSO. Borg and eNSGAII have the best performance. During the period of 2008-2009 and 1988-1989, the differences in hypervolume indicators are smaller than for the driest period for all MOEAs. Borg still perform the best followed by the eNSGAII and GDE.

Since the main purpose of the water allocation in the Pearl River Basin is to maintain sufficient flow in the channel during the dry seasons, we also select the objective 4, number of days that discharge<1800 m^3/s at Wuzhou station ($\mathrm{Nr_{wuzhou}}$), as another indicator for algorithm assessment (Figure 4.3b). Results show that all the algorithms can find solutions that substantially reduce $\mathrm{Nr_{wuzhou}}$ during the three selected periods. The largest difference between the algorithms is found in the driest period. The Borg algorithm has the best performance during this period. There is no substantial difference between the algorithms for the other two periods.

Overall, the Borg is the top performing algorithm for water allocation in the Pearl River Basin. Therefore, we select the Borg to generate new alternative water allocation plans in the future.

4.3.5.2 Water allocation in the future

Future period are divided into four sub periods of five years: 2079-2084, 2084-2089, 2089-2094, and 2094-2099. Figure 4.4 illustrates multi-objective trade-offs generated by the Borg for water allocation in the Pearl River Basin during the period of 2079-2084 (driest) and 2094-2099 (wettest). Results show that the Borg has better performance for wetter period than drier period with respect to objective 3, 4 and 5: maximizing hydropower potential, minimizing Nr_{wuzhou}, and $Nr_{sixianjiao}$. However, no plan can maintain the required flow at Wuzhou and Sixianjiao station for the whole dry season under all the climate scenarios for both 2079-2084 and 2094-2099. There are 46-78 days that the discharge at Wuzhou station is less than the required minimum flow and 18-46 days at Sixianjiao station during the period 2079-2084.

Figure 4.4b and d show the existence of conflicts between the five objectives. None of the plans score high for all the objectives. To keep water level as close as possible to the required minimum flow at Wuzhou and Sixianjiao is negatively correlated with maximizing hydropower potential (instead of maximizing hydropower potential, we actually minimize $\frac{1}{hydropower\ potential}$ in this study, details see Function 6), and minimizing Nr_{wuzhou}, and $Nr_{sixianjiao}$. For example, a decision maker pursuing high hydropower potential must accept that high variations between required minimum flow and discharge at two selected hydrological stations. On the contrary, a stakeholder from waterway transport industry (navigation requires the water level to stay within a certain range) may prefer plans which have a good performance on minimizing variations between the required minimum flow and discharge at these two stations. Consequently, these plans have poor performance with respect to maximize hydropower potential, and minimize Nr_{wuzhou}, and $Nr_{sixianjiao}$. Therefore, selection of water allocation plans requires stakeholders from different sectors to reach a compromise between the objectives.

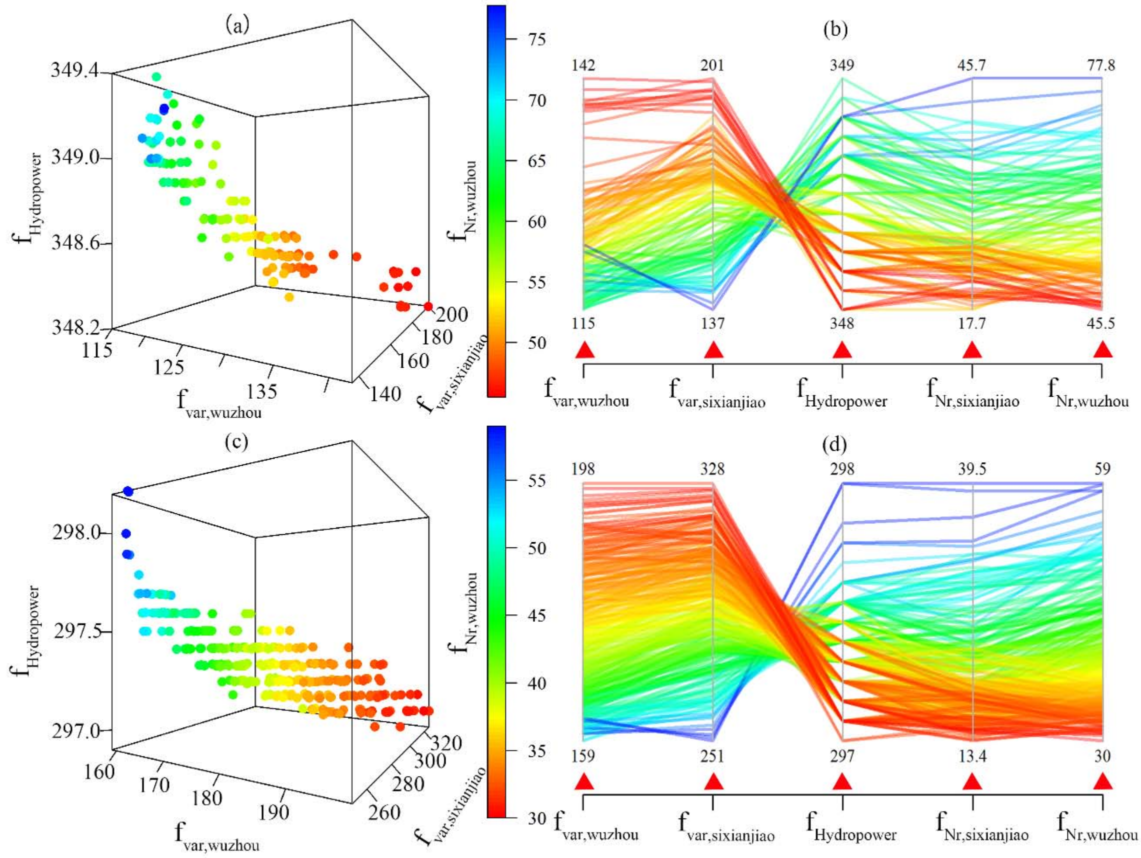

Figure 4.4 Performance of different water allocation plans that generated by the Borg. Each point in panel (a) and (c) represents a water allocation plan for the period of 2079-2084 and 2095-2099 respectively. Panel (b) and (d) provide an alternative visualization of the water allocation trade-offs using a parallel coordinates plot for 2079-2084 and 2095-2099. Each line also represents a single plan where its intersections on the vertical axes represent the relative objective values. The red triangles represent ideal axis values for the corresponding objectives. Plans are colored based on number of days that discharge is less than the required minimum flow at Wuzhou station

4.3.5.3 Robustness assessment of water allocation plans

Figure 4.5 shows two different types of robustness measures (see Section 4.3.4) in panel (a) and (b). These two measures identify similar regions with weak and strong robustness. Blue points that located in the right hand side of the figures are more robust water allocation plans. These robust plans have higher hydropower potential and lower Nr_{wuzhou}, and $Nr_{sixianjiao}$ values. They are also the plans with relatively more water release from the upstream reservoirs, in which all the key reservoirs release high volume of water. There are several plans in which the key reservoirs release even more water than the robust plans. However, the performance of these plans in regret-based robustness measure is poor. By implementing these plans, the TianshengqiaoI reservoir only releases half of the water compared with the robust plans. Extra water mainly come from Yantan and Longtan reservoir.

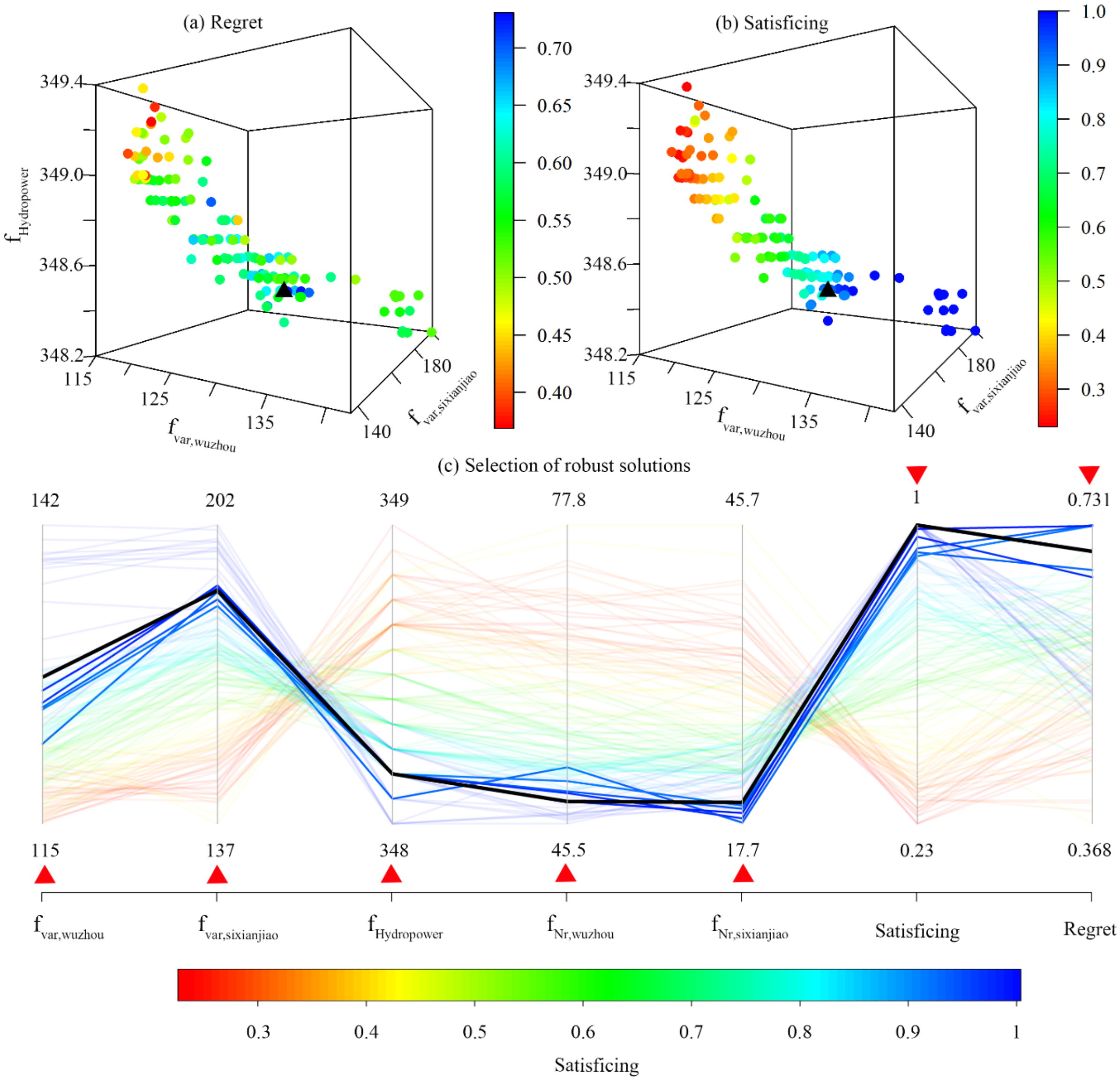

Figure 4.5 Robustness assessment of water allocation plans under climate change uncertainties during the period of 2079-2084. Panel (a) and (b) show two different robust measures: regret (a) and satisficing (b). Regret-based robustness computes the performance deviation from the ideal point under all the Scenarios. Satisficing-based robustness measures the fraction of scenarios that satisfies the stakeholder's criteria. Panel (c) shows the selected robust water allocation plans. Two more axis are added to the parallel coordinates plot. The Line's vertical positon on each axis represents value of different robustness measure. The red triangle represents ideal axis value for the corresponding objective. Plans which have a regret-based robustness value<0.65 or a satisficing-based robustness value < 0.9 are shown by transparent lines. Black triangles and line represent a randomly selected robust water allocation plan used for further analysis

Subtle difference was found between regret and satisficing-based robustness measures. The right-most points in panel (b) represent the most robust water allocation plans under the satisficing-based robustness measure. These plans have the highest water releases from the key reservoirs. The corresponding points in panel (a) also have strong robustness. However, points in the middle slightly to the right have higher robustness under the regret-based robustness measure. In panel (c), water allocation plans with a regret-based robustness measure>0.65 and a satisficing-based robustness measure>0.9 (the values of 0.65 and 0.9 correspond to the 90th percentile of regret-based and satisficing-based robustness) are highlighted. Results show that the highlighted robust water allocation plans also have relative good performance for almost all the objectives expect minimizing average variation between required minimum flow and discharge at Sixianjiao station.

We identified the set of robust water allocation plans for the Pearl River Basin during the period of 2079-2084. However, values of required minimum flow at Wuzhou and Sixianjiao are uncertain, which means a plan with high robustness may fail in some of the scenarios. Therefore, we randomly select a robust plan (see black triangles and line in Figure 4.5), and use the PRIM (see also Section 4.2.1) to identify ranges of the two uncertain parameters leading to poor performance in minimizing Nr_{wuzhou}. In Figure 4.6, each of the vertical bar corresponds to one of the uncertainty parameterizations (α and β). The black overlaid boxes represent the ranges of each parameter that lead to poor performance in minimizing Nr_{wuzhou}. Figure 4.6 shows that if α and β are larger than 1810 and 2390 m^3/s in the future, there is a higher likelihood that the values of Nr_{wuzhou} will increase (also see in Section 4.4).

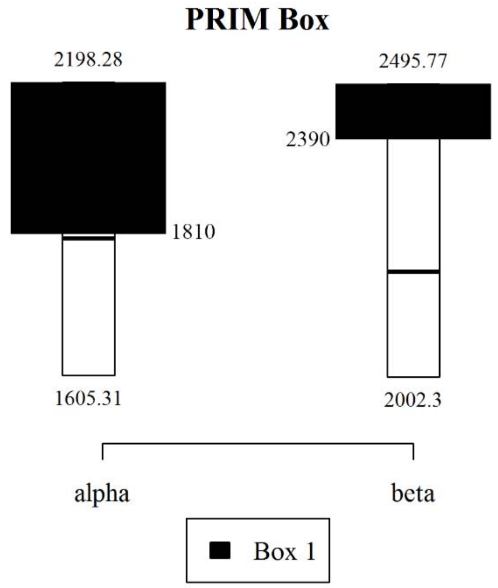

Figure 4.6 Uncertainty analysis for the required minimum flows at Wuzhou and Sixianjiao. The black horizontal bars indicate the baseline parameters (1800 and 2200 m^3/s) under well-characterized uncertainties. The black boxes represent the ranges of each parameter that lead to poor performance in minimizing Nr_{wuzhou}

4.4 Discussion

This study first assessed how ten different state-of-the-art MOEAs perform in identifying water allocation plans for large rivers. Two indicators are selected for the assessment. Maintaining sufficient flow into the delta is our main objective, and thus an important indicator.

Hypervolume indicator represents how well the MOEAs perform in searching solutions in the objective space, and is a frequently applied measure for comparing quality of solution sets that generated by different MOEAs (Beume et al., 2007). Therefore it is considered as another important indicator. Based on the two indicators above, Borg has the best performance compared with other selected MOEAs. This result is similar to the conclusion of Kollat and Reed (2006) and Kasprzyk et al. (2013) who also found the Borg represents a top performing MOEA that could strongly support many-objective water resources applications.

However, even the Borg algorithm cannot find solutions under all possible future climate scenarios for the current water allocation system. New elements would have to be added to this system. Historically, the additional water mainly came from upstream reservoirs in the Pearl River Basin. These upstream reservoirs only controlled one third of the water resource in the Pearl River Basin. Water resources in the middle and lower reaches of the Pearl River are not regulated (Qian, 2007).

The required minimum flows at Wuzhou and Sixianjiao station are currently 1800 and 2200 m^3/s. These two values are determined by the Pearl River Flood Control and Drought Relief Administration during the initial period of controlling saltwater in 2006 based on the best available information on current water use requirements in the Pearl River Delta, including domestic, manufactural and agricultural water use (Xie, 2007). Recent studies indicate that the future water use demand of the delta may increase substantially (Zhu et al., 2004), while at the same time the Pearl River Basin is likely to become drier in the dry season (Yan et al., 2015). Reduced low flow, in combination with increased water use demand and rising sea levels, is likely to increase saltwater intrusion in the delta (Yan et al., 2016; Yao et al., 2015). Therefore, the currently agreed minimum flow requirements at Wuzhou and Sixianjiao may not be sufficient to combat salt intrusion in the future. However, it will be hard to meet higher flow requirements as we show that above 1810 and 2390 m^3/s at Wuzhou and Sixianjiao station, it becomes increasingly hard to find solutions. In the future, water resources from another branch (the East River) may become more important for the delta region. New technologies, water saving and increasing water use efficiency can also be part of the solution to prevent future water crisis (Yao et al., 2016).

In Section 4.3.5.2, we mentioned that selection of water allocation plans requires stakeholders from different sectors to reach a compromise between the objectives. However, decision making in China is more complicated. The water management strategies are made by the Chinese government. During a decision making process, the interests of some stakeholders could be neglected because of the overall interests of society. For example, the project “Key Reservoirs Operational Project for the Pearl River Basin” studied in the paper, is a transboundary water allocation project. The purpose of this project is to ensure water security in the Pearl River Delta, which is the world’s largest urban area. When water use in the Pearl River Delta is at risk, the performance of other objectives tend to be ignored by the government. The government can decide which stakeholder should compromise.

The model framework is a useful tool to help water managers for adaptive water management in delta regions. It uses 3D scatter plot and parallel coordinates plot to visualize the trade-offs between different objectives. By exploring the effects of trade-offs, water managers can obtain the dependencies between their decisions and the performance of the objectives, and discover the cost-benefit compromise offered by different strategies. In addition, water managers can also use a weighting scheme to identify the most-preferred designs.

4.5 Conclusion

This study developed a model framework combining many-objective robust decision making with biophysical modelling to identify robust water allocation plans under future climate change. It was applied in the Pearl River Basin to develop and appraise the release plans of large reservoirs with the objective to maintain flow into the delta to reduce salt intrusion in dry seasons. This study not only discussed many-objective robust decision making for water allocation under climate change, but also evaluate the performance of ten state-of-the-art MOEAs for the water allocation problem in the Pearl River Basin.

Results also show that optimising water allocation using carefully selected state-of-the-art MOEAs in the Pearl River Basin can help limit water shortage and salt intrusion in the Delta region. The number of days that discharge is less than the required minimum flow at Wuzhou has a substantial reduction (up to 46.5%) during 2079-2084. However the current water allocation system with six key reservoirs is insufficient in maintaining the required minimum discharge for future climate scenarios. More reservoirs, especially in the middle and lower reaches of the Pearl River, could potentially improve the future low flow into the delta. In addition, new technologies and increasing water use efficiency will be important to deal with future water shortage in the Pearl River Basin.

This application shows that subjective design choices from the researchers and/or water managers could potentially affect the ability of the model framework, and cause the most robust water allocation plans to fail under future climate change. Developing robust allocation plans in a river basin suffering from increasing water shortage requires the researchers and water managers to well characterize future climate change of the study regions and vulnerabilities of their tools.

Acknowledgments

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Appendix D. Supplementary data

Supplementary data associated with this article can be found in the online version, at doi: http://dx.doi.org/10.1016/j.scitotenv.2017.06.265. These data include the Google map of the most important areas described in this article.

5

Exploring future water shortage for the Pearl River Basin, China under different water allocation strategies

Chapter 5

Exploring future water shortage for the Pearl River Basin, China under different water allocation strategies

Abstract

Climate change and socio-economic development increase variations in water availability and demands for water resources in the Pearl River Basin (PRB), China respectively. This can potentially result in conflicts over fresh water resources between different water users, and cause water shortage in the dry season. To assess and manage water shortage in the PRB, two water availability and three water use scenarios were first explored. Next, four different strategies to allocate water were defined. These water allocation strategies prioritized upstream water use, Pearl River Delta water use, irrigation water use, and manufacturing water use, respectively. The impact of the four strategies on water use and related economic output was assessed under different water availability and water use scenarios. Results show that almost all the regions in the PRB are likely to face water shortage under the four strategies. The increasing water demand contributes twice as much as the decreasing water availability to water shortage. All four water allocation strategies are insufficient to solve the water scarcity in the PRB. The economic losses differ greatly under the four water allocation strategies. Prioritizing the delta region or manufacturing production would result in lower economic losses than the other two strategies. However, all of them are rather extreme strategies. Development of water resources management strategies requires a compromise between different water users.

This chapter is based on:

Yan D, Yao M T, Huang H Q, Kabat P, Hutjes R, Ludwig F, Werner S E. Exploring future water shortage in the Pearl River Basin, China under different water allocation strategies, Water Resources Management, submitted.

5.1 Introduction

As a fundamental resource, water is essential for human survival and all water users (Oki and Kanae, 2006). However, fresh water resources are unevenly distributed in both time and space, which causes serious water shortage in many parts of the world (Piao et al., 2010; Yang et al., 2008). In addition, population growth and socio-economic development have exponentially increased global water use during the last few centuries. This intensified the competition over the fresh water resources between different regions and sectors (Dong et al., 2016; Liu et al., 2017; Vörösmarty et al., 2000). Solutions to water stress problems depend not only on water availability, but also on processes through which water is managed and allocated to different users or sectors (Biswas, 2004). However, water resources management and allocation are facing major challenges due to increased variations in water availability caused by climate change and increased water demand because of socio-economic development (Alcamo et al., 2007).

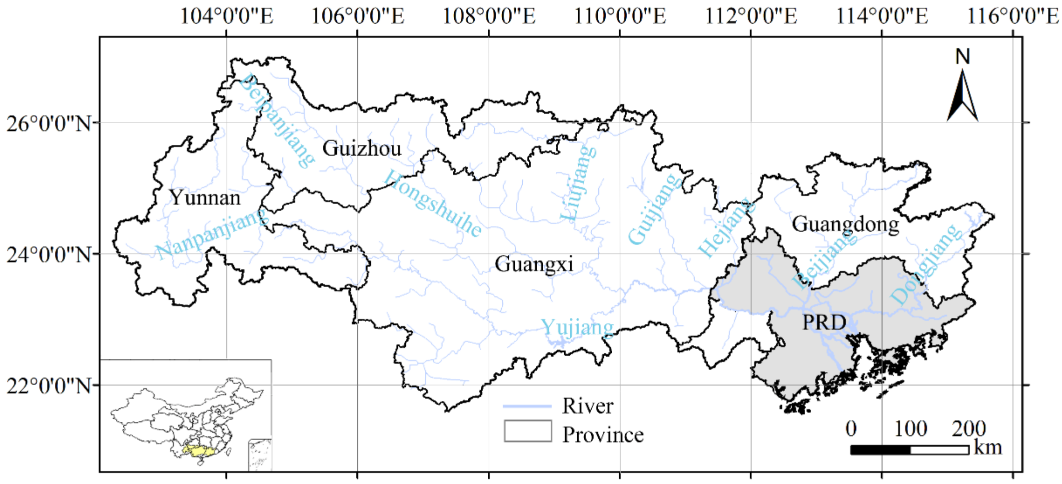

Figure 5.1 Location of the Pearl River Basin. The PRB mainly covers 4 provinces (Yunnan, Guizhou, Guangxi, Guangdong) in southern China. The Pearl River Delta (PRD), which is located in Guangdong province, is the largest urban complex in the world consists 11 important cities, include Hong Kong and Macau (Hong Kong and Macau are not include in the present study)

The Pearl River is the second largest river in terms of streamflow and the third largest river in terms of drainage basin area in China (Figure 5.1). It mainly flows through Yunnan, Guizhou, Guangxi, and Guangdong provinces, and enters the South China Sea through the Pearl River Delta in Guangdong province (Zhang et al., 2007). The Pearl River Basin (PRB) is situated in a subtropical monsoon climate zone. About 80% of the streamflow occurs during the wet season between April and September (Zhang et al., 2012). Highly uneven spatial and temporal distribution of streamflow has caused seasonal water shortages in the basin (Zhang et al., 2009b). In my previous study, rainfall and discharge during the dry season are projected to reduce because of climate change (Yan et al., 2015). Without any interventions, reduced future low flows may further aggravate seasonal water shortages in the PRB.

Socio-economic development and water consumption differ greatly across the regions in the PRB. The Pearl River Delta (PRD) accounts for 12% of the total area of the PRB and is the world's largest urban region in both population and area (World Bank, 2015). It is also one of the leading economic regions and a major manufacturing center in China (Liu et al., 2010). In 2000, the PRD used 21.3 billion m^3 water, accounting for 25.3% of the total water use of the PRB. The upstream basin, however, consists of the poorest regions in China (Jalan and Ravallion, 2000). Guizhou, for instance, is the poorest province in China. Guizhou (the part within the PRB that uses water from Pearl River tributaries) is 50% larger in area than the PRD, but only used 12% of the PRD's total water use in 2000 due to the limited socio-economic activities (PRWRC, 2001).

However, the poorer upstream regions are starting to catch up with the economic development in the delta since the Chinese government launched the "Western Development Program" in 1999. The program aims to boost the socio-economic development in western China (Lai, 2002) including three provinces in the PRB, Yunnan, Guizhou, and Guangxi. The western development program substantially accelerated the economic growth of these three provinces resulting in increasing industrial and domestic water use in the upstream regions (PRWRC, 2015). This has resulted in reducing streamflows in the Pearl River, and reduced water supply to the delta (Zheng et al., 2016). On the other hand, water use in the delta is likely to gradually increase in the near future (Yao et al., 2017), while the upstream parts of the PRB would require more water for its future development. This could result in water use conflicts between upstream and downstream regions.

In addition, saltwater intrusion is likely to further aggravate water conflicts between upstream and downstream regions. In recent years, saltwater intrusion has become a major problem in the delta. Duration of intrusion episodes is getting longer, the affected area is getting larger, and the intensity is increasing (Yan et al., 2016; Zhang et al., 2010a). To reduce saltwater intrusion, the Chinese government has launched a policy named "Key Reservoirs Operational Project for Pearl River Basin" to reduce saltwater intrusion by releasing additional water from selected upstream reservoirs (He, 2007; Xie, 2007). The implementation of this policy reduced salt intrusion to some extent, but requires large amounts of fresh water from upstream, where water resources are already insufficient in some regions (Cai et al., 2011). Further implementation of this policy means less water to be allocated in the upstream region, thus may exacerbate the already existing water scarcity in the upstream part of the basin.

Competition for water not only exists between upstream and downstream regions, but also exists between different water use sectors. Irrigation water use accounted for 57% of total water consumption in 2000, but only 46% in 2014 (PRWRC, 2001; PRWRC, 2015). Meanwhile, the industrial water use increased by 3 billion m^3 (from 18% in 2000 to 22.7% in 2014).

Although it is clear that competition for water will increase in the future, the extent of the problems, the economic impacts and possible strategies to reduce competition are still unclear. To address this knowledge gap, My colleague M. T. Yao and I focussed on three different research questions:

1. How severe are water shortages during the dry season in the PRB under future climate change and socio-economic development?

2. How do the water shortages affect economic development in the PRB?

3. Can water allocation strategies alleviate competition over limited water resource in the PRB?

To answer these questions, M. T. Yao developed future water use scenarios using the Shared Socio-economic Pathways (SSPs) framework (O'Neill et al., 2015). Future water availability scenarios, consistent with the Representative Concentration Pathways (RCPs) (Moss et al., 2010; van Vuuren et al., 2011) are adopted from my previous study (Yan et al., 2015). These scenarios are used to assess the impact of different water allocation strategies on future water shortage in the dry season.

5.2 Methodology

The methodology of this study builds on my previous study (Yan et al., 2017; Yan et al., 2015) and M. T. Yao's previous studies (Yao et al., 2017; Yao et al., 2016), and consists of building water availability and water use scenarios, and developing water allocation strategies for the PRB. The scenarios are developed following a scenario matrix architecture, consisting of: 1) the level of radiative forcing of the climate system characterised by different Representative Concentration Pathways (RCPs) (van Vuuren et al., 2011); and 2) a set of underline alternative futures of societal development, the Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2015). SSPs and RCPs were independently developed in the context of the Intergovernmental Panel on Climate Change (IPCC) fifth Assessment Report framework (O'Neill et al., 2014; van Vuuren et al., 2014).

5.2.1 Water availability scenarios

Future water availability scenarios are adopted from my previous study (Yan et al., 2015). The scenarios are generated using the variable infiltration capacity (VIC) hydrological model in combination with five different global climate models (GCMs) under different RCPs (4.5 and 8.5). The VIC model is a semi-distributed macro-scale model, which is characterized by heterogeneous vegetation and multiple soil layers with non-linear base flow and variable infiltration (Hamman et al., 2016; Liang et al., 1994). The five GCMs used in this study are CNRM-CM5, EC-EARTH, HadGEM2-ES, IPSL-CM5A-LR, and MPI-ESM-LR. These five GCMs can well represent future climate change in the PRB (Wang and Chen, 2014; Yan et al., 2015). See Yan et al. (2015) for details on the hydrological modelling and the development of the future water availability scenarios.

5.2.2 Water use scenarios

5.2.2.1 Socio-economic scenarios

To project future water use in the PRB, a set of regional water use scenarios consistent with the SSPs was developed by M. T. Yao. The SSPs describe a set of plausible alternative trends in the evolution of society and natural systems over the 21st century, in the absence of climate change or climate policies (O'Neill et al., 2014). Three SSPs scenarios (SSP1, 2, and 3) are used in this studies. SSP1 depicts a sustainable world in which the challenges for mitigation and adaptation are both low. This world is characterized by rapid technology, high environmental awareness, low energy demand, medium-high economic growth and low population. SSP3 represents a world where it is difficult to mitigate and adapt to climate change because of slow technology development, extreme poverty, and a very high population. SSP2 is characterized by development similar to historical trends, which represents an intermediate world between SSP1 and SSP3 (O'Neill et al., 2015; O'Neill et al., 2014).

The development of the water use scenarios follows the method developed in Yao et al. (2016), which links region-specific historical trends and future development targets with China's national SSPs scenarios. The water use scenarios for the upstream regions, i.e. Guangxi, Guizhou, Yunnan, and Guangdong without the delta, are generating using the national assumptions and planning targets for China during the period 2010-2050 (Wada et al., 2016). Quantitative assumptions for China's population and GDP growth are compiled from the SSPs database (www.iiasa.ac.at/web/home/research/researchPrograms/Energy/SSP_Scenario_Database.html), the IIASA-VIC v9 and OECD Env-Growth v9, respectively. Changes in value-added manufacturing are derived from the UNEP GEO4 Driver Scenarios (Rothman et al. 2007).

Scenarios for the delta are adopted from Yao et al. (2017), which constructed these scenarios within the context of China's overall development, but adjusted the national assumptions by taking the PRD-specific historic trajectories and planning targets into account.

5.2.2.2 Water use projections

When we refer to "SSP scenarios" below, it indicates the sub-basin scenarios developed for the present study, rather than the original SSP scenario descriptions (O'Neill et al., 2015).

Sectoral water use for upstream regions and the PRD is projected using the SSP Scenarios. For each of the three SSPs, four socio-economic indicators are used to project the future sectoral water use: (1) economic development (GDP), (2) population growth, (3) structural GDP changes determined by the share of the manufacturing value-added in the total GDP, and (4) annual technological change rate. Water use is calculated for each region for three different sectors: manufacturing water use (MWU), domestic water use (DWU), and irrigation water use (IWU).

Equations from the WaterGAP 2.2 are used (Flörke et al., 2013; Muller Schmied et al., 2014) to quantify the future pathways of domestic and manufacturing water use for each upstream province and the PRD. Parameters for calculating the domestic water use were calibrated with respect to historical water use data following the methods reported in the previous study (Yao et al., 2015).

The provincial manufacturing water use intensity of 2010 (the base year) is used to project the future manufacturing water uses. M. T. Yao's projection only captures part of the industrial water use in the PRB, because the industrial water use includes also the water use for thermal electricity generation. For instance, in the PRD, the thermal electricity generation uses about half of the total industrial water.

Water use for electricity generation is not included in this study because none of the essential data required for estimating water use in the electricity generation sector is sufficiently available for the PRB (Yao et al., 2017). One of the reason M. T. Yao uses the WaterGAP is that it can disaggregate the manufacturing sector into an industrial sector and electricity generation sector.

Irrigation dominates the agricultural water use in the PRB. Although the details such as land use change, and irrigation system adopted are not reported comprehensively, the irrigation water use intensity in m^3 per hectare is well reported for each region within the PRB. Thus, here M. T. Yao uses the improvement of the reported irrigation water use intensity (IWI) of the base year (per hectare water use) to estimate the effects of technology on irrigation water uses. The technological transition for irrigation was assumed following a similar rate as the manufacturing sector following a previous study (Yao et al., 2017). The irrigation water use is then calculated by multiplying irrigation water use intensity (IWI) with the irrigated area. In addition, irrigation land use change scenarios are gathered from the 30-meter Global Land Cover Dataset (GlobeLand30) projection for three different SSPs (Brovelli et al., 2015). See Yao et al. (2017) for details on how to calculate irrigation water use for each region in the PRB.

The socio-economic status of the basin in 2010 and overview of quantitative scenario assumptions of GDP, manufacturing value-added, population and irrigated area are provided in the Appendix E.

5.2.2.3 Technological improvement

All three water use sectors, irrigation, domestic and manufacturing are affected by technological change (TC), leading to improvements in water use efficiency (i.e. output per unit of water) and thereby decreasing water use intensity (i.e. water use per unit of output in the respective sector). TC estimation was quantified as annual technological improvement rates for each of the combinations of SSPs and Hydro-Economic (HE) classifications using a range of historically observations (Wada et al., 2015). See Yao et al. (2017) for details on how to quantify TC estimation.

5.2.3 Water allocation strategies in the PRB

Four different water allocation strategies are defined. The first two strategies reflect the competition between upstream regions and the Delta, and the third and fourth strategies are two economic-driven strategies that reflect the competition between different water use sectors. All four strategies assume that all the requirements for domestic and environmental water use are fulfilled. First, environmental flow is calculated using a simple Tennant method (Pastor et al., 2013). Additional water to prevent saltwater intrusion is not included in the environmental flow calculation in this study.

The four strategies are:

1. upstream-prioritized (UP) strategy. The upstream region preferentially uses the amount of water as projected under water use scenarios. If its projected water use is larger than projected water availability, the upstream region would take all the available water in this region.

2. delta-prioritized (DP) strategy. In this strategy, the upstream regions release additional water to the Delta, which can satisfy irrigation and manufacturing water demand in the Delta. I had planned to satisfy water demand of the Delta first, and optimized the remaining water resources between different upstream regions. However, transferring water from downstream to upstream region over a long distance is very difficult to implement (Zhong, 2004). Therefore, the DP strategy is simplified. In the new DP strategy, I assume that each upstream region releases the same absolute amount of additional water to the Delta.

3. irrigation- prioritized (IrrP) strategy. In this strategy, the overall agricultural profit of the PRB is maximized using an open source framework for many-objective robust decision making (OpenMORDM) developed by Hadka et al. (2015). The plan with the highest agricultural profit is selected as the IrrP strategy.

4. manufacture-prioritized (ManP) strategy. This strategy is also generated by the OpenMORDM. The difference between the IrrP and ManP strategy is that the ManP strategy pursues the highest manufacturing profit.

Both the IrrP and ManP strategy are generated by the OpenMORDM. The OpenMORDM is a useful tool to help decision makers for adaptive water management in river basins (Hadka et al., 2015). It uses 3D scatter plots and parallel coordinates plots to visualize the trade-offs between different objectives (Hadka et al., 2015). The advantage of the OpenMORDM is tested in Yan et al. (2017). In this study, the OpenMORDM employs the Borg multi-objective evolutionary algorithm (Borg MOEA) to capture the set of best trade-off solutions. The Borg MOEA is one of the top performing multi-objective evolutionary algorithms (Reed et al., 2013; Yan et al., 2017). Two objectives and three constraints are used in the OpenMORDM to evaluate the performance of the plans generated by the Borg MOEA. The two objectives are to maximize profits from agricultural and manufacturing water use. The OpenMORDM considers the two conflicting objectives explicitly and simultaneously, and discovers the Pareto approximation trade-off sets among them. The objective functions are given as follow:

$$f_{irr\_profit} = max\left(\frac{1}{|S|T}\left(\sum_{j=1}^{M}\sum_{i=1}^{N} IWU_{i,j} * X_i * I_i\right)\right) \quad (5.1)$$

$$f_{man\_profit} = max\left(\frac{1}{|S|T}\left(\sum_{j=1}^{M}\sum_{i=1}^{N} \frac{MWU_{i,j} * Y_i}{MVA_t \times TC_t}\right)\right) \quad (5.2)$$

where f_{irr_profit} and f_{man_profit} represent profits from agricultural and manufacturing water use. M is the number of months from 2010 to 2050, N represents numbers of regions in the PRB, $IWU_{i,j}$ and $MWU_{i,j}$ are the projected irrigation and manufacturing water use in the i^{th} region at time j, MVA_t is the manufacturing value added in year t, X_i and Y_i represent the percentage of irrigation and manufacturing water use, which are used by the i^{th} region at time j, I_i represents irrigation index, S represents the set of all sampled climate scenarios. T represents the number of years during 2010-2050.

Three constraints are used in this study. These three constraints are the actual irrigation and manufacturing water uses should be less than the total projected irrigation and manufacturing water uses, and the total water use of all water use sectors should be less than the water availability of the PRB given as follow:

$$IWU_{total,j} \geq \sum_{i=1}^{N} IWU_{i,j} * X_i \quad (5.3)$$

$$MWU_{total,j} \geq \sum_{i=1}^{N} MWU_{i,j} * Y_i \quad (5.4)$$

$$Q_{total,j} \geq \sum_{i=1}^{N} ENV_{i,j} + \sum_{i=1}^{N} DOM_{i,j} + \sum_{i=1}^{N} IRR_{i,j} * X_i + \sum_{i=1}^{N} MAN_{i,j} * Y_i - \sum_{I=1}^{N} RET_{i,j}$$

(5.5)

where $Q_{total,j}$ represents water availability in the PRB at time j, $IWU_{total,j}$ and $MWU_{total,j}$ represent the projected total irrigation and manufacture water use of the whole basin at time j. $ENV_{i,j}$ and $DOM_{i,j}$ represent environmental flow and domestic water use of the i^{th} region at time j respectively, $RET_{i,j}$ is the amount of water returned by the i^{th} region at time j.

5.2.4 Water shortage in the PRB

Water shortages under the four water allocation strategies are estimated for each region during the dry months when projected water use is higher than water availability. As the purpose of this study is to quantify how severe the water shortage is during the dry season, more attention is paid to the drier climate change scenario (RCP8.5), for which water shortages are likely to be more severe.

For the UP strategy, water shortage of each region is calculated according to Equation 5.6 and 5.7. Equation 5.6 is developed for regions without upstream region, for example, Yunnan.

$$WD_m = \sum_{t=1}^{T} (AW_{m,t} - WU_{m,t})/T$$

$$WS_m = \begin{cases} 0 & , WD_m > 0 \\ WD_m, & WD_m < 0 \end{cases} \quad (5.6)$$

where WD_m is the monthly mean difference between water availability and water use for a upstream region during 2010-2050, WS_m represents the monthly mean water shortage for the upstream region, m represents each month during a year (from January to December), $AW_{m,t}$ and $WU_{m,t}$ are water availability and water use for month m in year t, T represents the number of years during 2010-2050.

To estimate water shortage in Yunnan, the first step is to calculate the difference between water availability and water use of Yunnan. If the difference is negative, its value is considered to be the water shortage of Yunnan province. Otherwise, water shortage in Yunnan is set to be zero, and the excess water goes to its downstream region.

Equation 5.7 is developed for regions with upstream region(s), for example, Guangxi.

$$WD_m = \sum_{t=1}^{T}\left(\sum_{x=1}^{X} EW_{m,t,x} + AW_{m,t} - WU_{m,t}\right)/T$$

$$WS_m = \begin{cases} 0 & , WD_m > 0 \\ WD_m, & WD_m < 0 \end{cases} \qquad (5.7)$$

where $EW_{m,t,x}$ represents excess water from upstream region x for month m in year t.

To estimate water shortage in Guangxi, the summary of excess water from all the upstream regions is first calculated. Next, I compare the total water income (water availability and excess water from upstream regions) and projected water use. If the total water income is larger than the projected water use, water shortage in Guangxi is zero. The excess water goes to downstream regions of Guangxi. Otherwise, water shortage of Guangxi equals to total water income minus projected water use, and no water is transferred to its downstream regions.

In the DP strategy, water shortage of the PRD is first calculated using Equation 5.6. To provide enough water resource for the PRD, each upstream region releases the same absolute amount of water to the Delta. Therefore, new water uses in these upstream regions are the original projected water uses plus the mount of water released to the Delta. The rest of the calculations are the same as in the UP strategy. For the IrrP and ManP strategy, new water use for each region is generated by the OpenMORDM. Water shortage of the whole basin is then calculated based Equation 5.6 and 5.7.

5.3 Results

In this section, the projections of sectoral water use and water availability for the PRB are presented, four water allocation strategies are identified, followed by the projected water shortage, and economic development under different water allocation strategies.

5.3.1 Water scarcity in the PRB

5.3.1.1 Regional water use in the PRB

Figure 5.2 presents different trends of future water use projected for the PRD and the upstream basin. The PRD's annual water use peaks around 2030 then curves. By 2050, the total water use of the PRD increases by 10% to 22 billion m^3 on average from 20 billion m^3 in 2010.The upstream basin exhibits a steep increase of total water use in all three paths. The total water use of the upstream basin increases with more than 50% from 45 billion m^3 in 2010 to 70 billion m^3 in 2050.

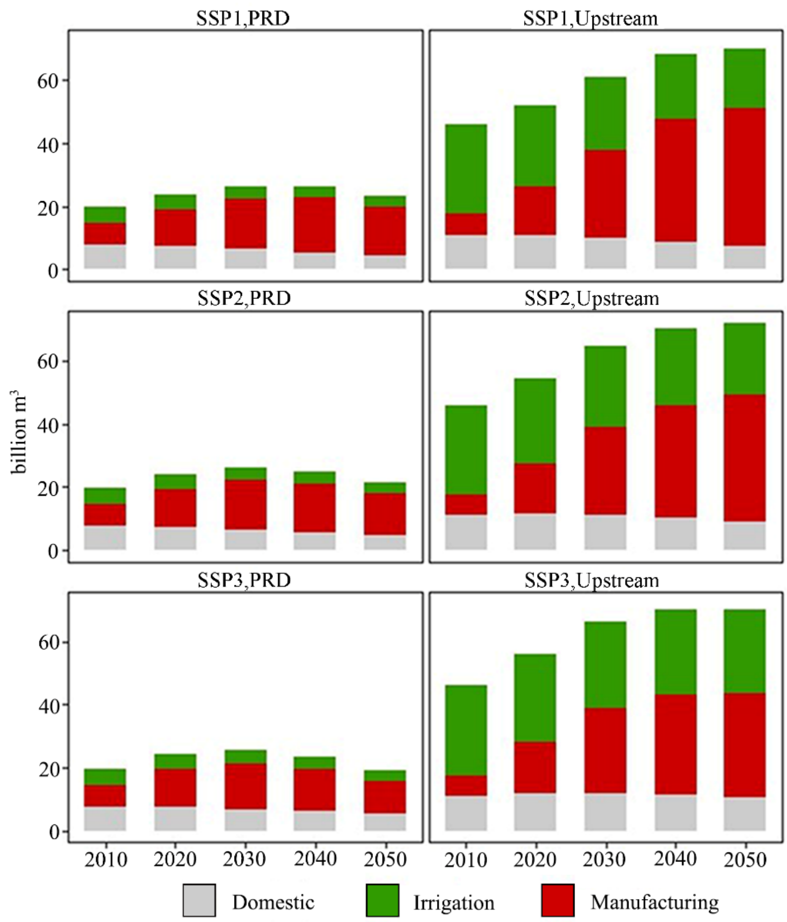

Figure 5.2 Sectorial water use projections for the PRD and the upstream PRB under different scenarios

Within the upstream areas, Guangxi and Guangdong (without the PRD) are the dominant water users, account for 54 and 30% total water use in 2010 and 43 and 33% total water use in 2050 respectively (Figure 5.3).

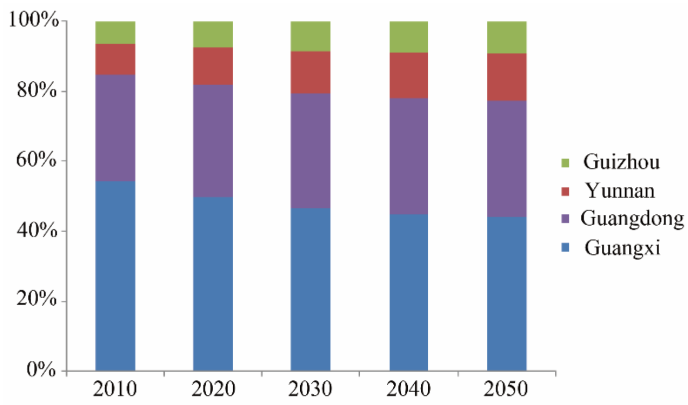

Figure 5.3 Average change in composition of regional water use in upstream basin (Guangdong in this figure is the Guangdong province without the PRD)

5.3.1.2 Sectoral water use in the PRB

The changes in future water use are largely driven by the manufacturing sector, the only sector where water use increases by 2050. By 2050, the manufacturing sector is responsible for 45% of estimated total water use in the basin.

Projections for the domestic and irrigation water use follow a consistent decreasing trend under all the scenarios across the PRB (Figure 5.2). By 2050, domestic water use will decrease by 37% (PRD) and 19% (Upstream) due to a combination of population change (the population in PRB first increases then decreases. The turning point is around 2030) and technological improvement. Irrigation water use will decrease by 36% (PRD) and 20% (Upstream) due to improved water use efficiency as a result of technological development and a reduction of irrigated land. By 2050, the manufacturing sector dominates the total water use in the PRD, whereas irrigation water use still is a considerable fraction of the total water use in the upstream areas.

The large differences between the PRD and the upstream area are because of the different scale of irrigation sector in the base year. As the national SSP assumptions indicate, the upstream basin will continue to show rapid economic growth while retaining most of its irrigated lands. This results in a continuous increase of water use during the study period. Although the speed of increase levels off, M. T. Yao's result do not show a clear saturation of total water use in the upstream basin by 2050.

The Delta has its own development path, where the sectoral water use will maximize around 2030 and then gradually decrease (Yao et al., 2017). By 2050, the total water use in the PRD is comparable to the level of 2010.

5.3.1.3 Water availability changes in the PRB

The decadal changes of the water availability in the PRB show a decreasing trend from the 2010s to 2040s under both RCP4.5 and 8.5 (Figure 5.4). At present about 280 billion m^3 of water is available for the upstream and about 47 billion m^3 is available for the PRD (including dry season and wet season). This means that water use is presently at 25-30% of available amounts in the upstream and at 50-60% in the downstream. In the 2040s, the total water availability of the upstream regions is 15.2 billion m^3 lower than the water availability in the 2010s under RCP4.5. Water availability in the delta reduces by 1.69 billion m^3 from the 2010s to 2040s under RCP4.5. Under RCP8.5, the water availability of the upstream regions and the Delta reduces by 10.4 and 2.25 billion m^3 from the 2010s to 2040s respectively. The water availability under RCP8.5 for each decade is lower than the water availability under RCP4.5 for the whole basin. In the upstream regions, the difference in water availability can reach up to 4.68 billion m^3 between RCP4.5 and 8.5.

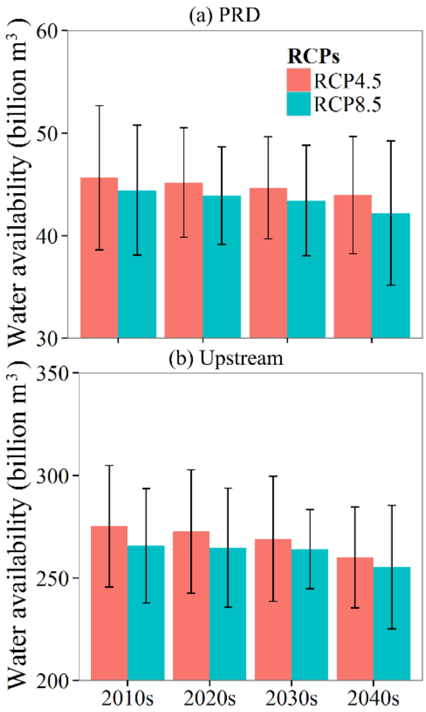

Figure 5.4 Annual average water availability for each decade from 2010s to 2040s under RCP4.5 and 8.5. The error bars indicate minimum and maximum values of the five climate models

5.3.1.4 Water shortages in the PRB

Future water availability and water use projected for the PRD and the upstream regions are compared in this study. The comparison only focuses on the dry months when projected water use is higher than water availability. The comparison reveals water shortages exist for the period of 2010-2050. The average decadal water shortages of the upstream regions and the Delta show an increasing trend, which is opposite to the trend of the water availability. The annual average water shortages for the whole upstream region and the Delta under the assumption that each region in the PRB is an independent system are shown in Figure 5.5. For the Delta, water shortages are around 500 million m^3 per year. The upstream region's total water shortage is twice as much as the water shortage in the PRD. Results also show that water shortages under RCP8.5 are much higher than water shortages under RCP4.5 for the whole basin under all the SSPs. However, the differences in water shortage between different SSPs are not substantial in the PRD. For the upstream region, water shortages under SSP3 are clearly higher than water shortages under SSP1 and 2.

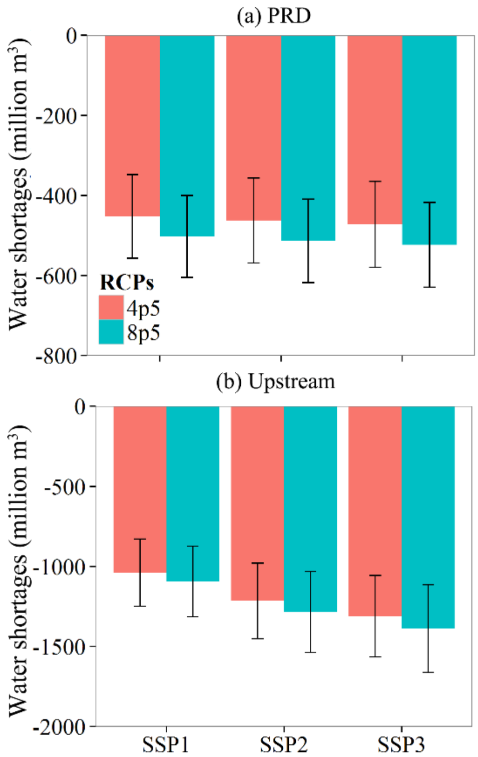

Figure 5.5 Annual average water shortages for the PRD and the upstream PRB under different RCPs and SSPs (2010-2050). The error bars indicate minimum and maximum values of the five climate models

5.3.2 Identifying water allocation strategies

Figure 5.6 illustrates an example how to identify the IrrP and ManP strategy using the OpenMORDM under RCP8.5 and SSP1. The OpenMORDM generates a set of alternative plans with different agricultural and manufacturing profits based on the two objectives and three constraints mentioned in Section 5.2.3. Since the main purposes of the IrrP and ManP strategy in this study are to pursue maximum agricultural and manufacturing profits, two plans that yield the highest agricultural and manufacturing profits were manually selected as the IrrP and ManP strategy respectively. In other words, the OpenMORDM generates many possible plans, but only the most extreme plans are discussed in this Chapter. I use the same method to obtain the strategies for SSP2 and SSP3.

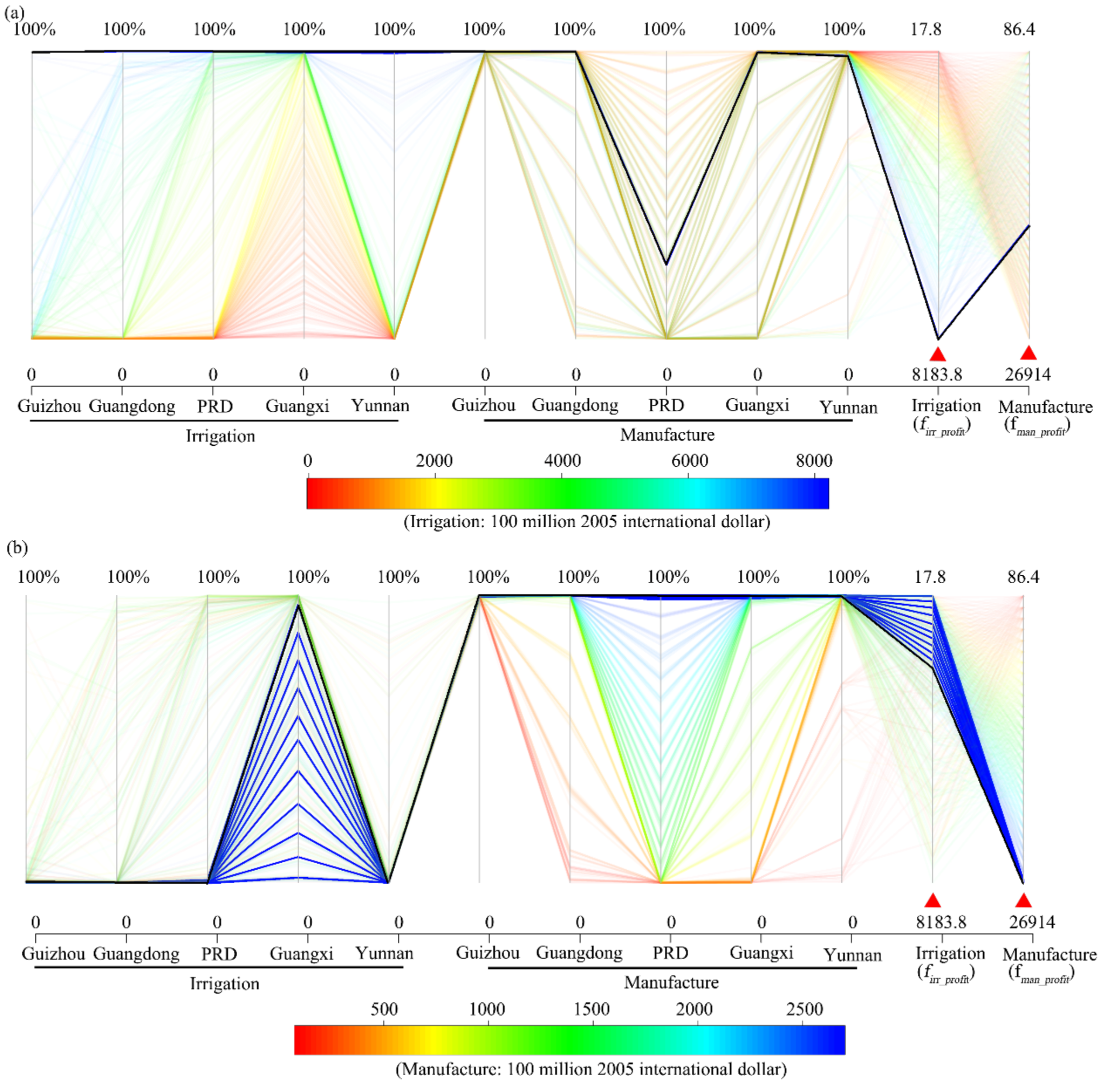

Figure 5.6 Selection of the IrrP and ManP strategy under SSP1 and RCP8.5: (a) the IrrP strategy, (b) the ManP strategy. Each line represents an alternative plan where its intersections on the vertical axes represent the percentages of projected water use, which would be used in different regions for different purposes. The red triangles represent ideal values for the corresponding objectives. Plans are colored based on (a) irrigation and (b) manufacturing profits respectively. The black line is the selected plan

5.3.3 Water shortages under different water allocation strategies in the PRB

As shown in Figure 5.7, Yunnan, Guangxi, Guangdong and the PRD are likely to face severe water shortages under the UP strategy. Yunnan is the province with the highest water shortage, where an additional 300 million m^3 of water is needed each month during January-April period for all SSPs. For Guangxi, Guangdong and the PRD, water shortage is higher during the period of November-December than January-April. In the PRD, water shortage can reach up to 255 million m^3 in December under SSP3. Results also show that only subtle differences in water shortage are found between different SSPs. Water shortages for all the regions except Guizhou are lower under SSP1 compared to SSP2 and 3.

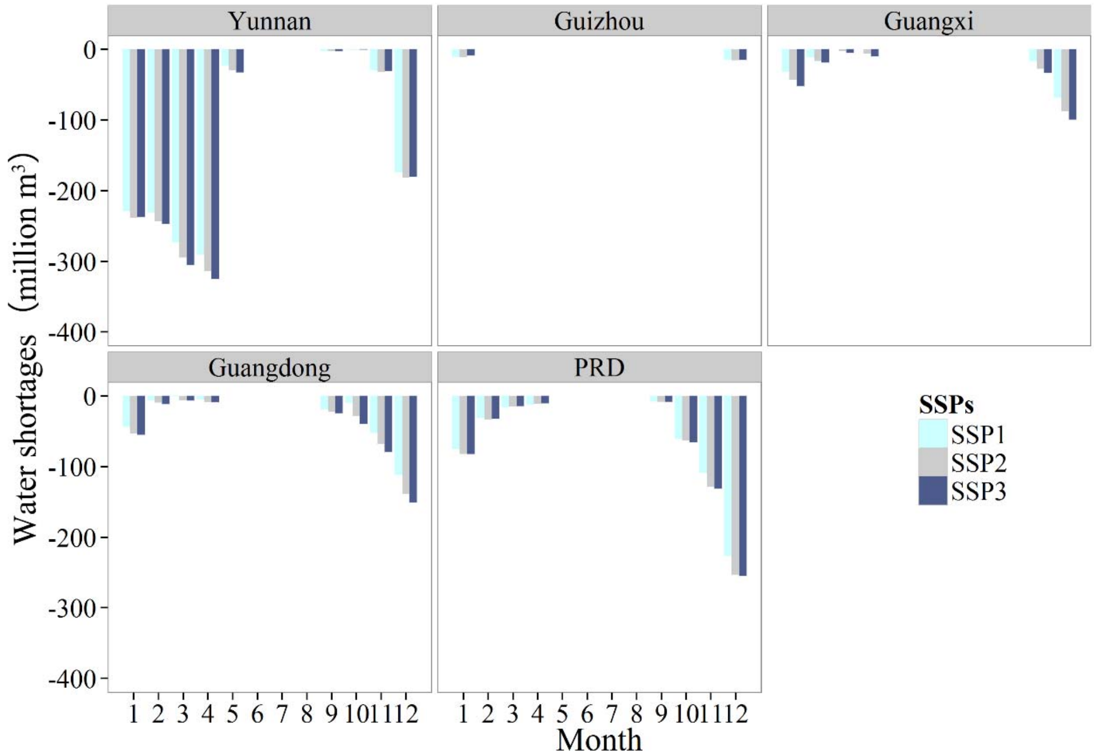

Figure 5.7 Average monthly water shortages for different regions in the PRB under the upstream-prioritized strategies for the period of 2010-2050 (RCP8.5)

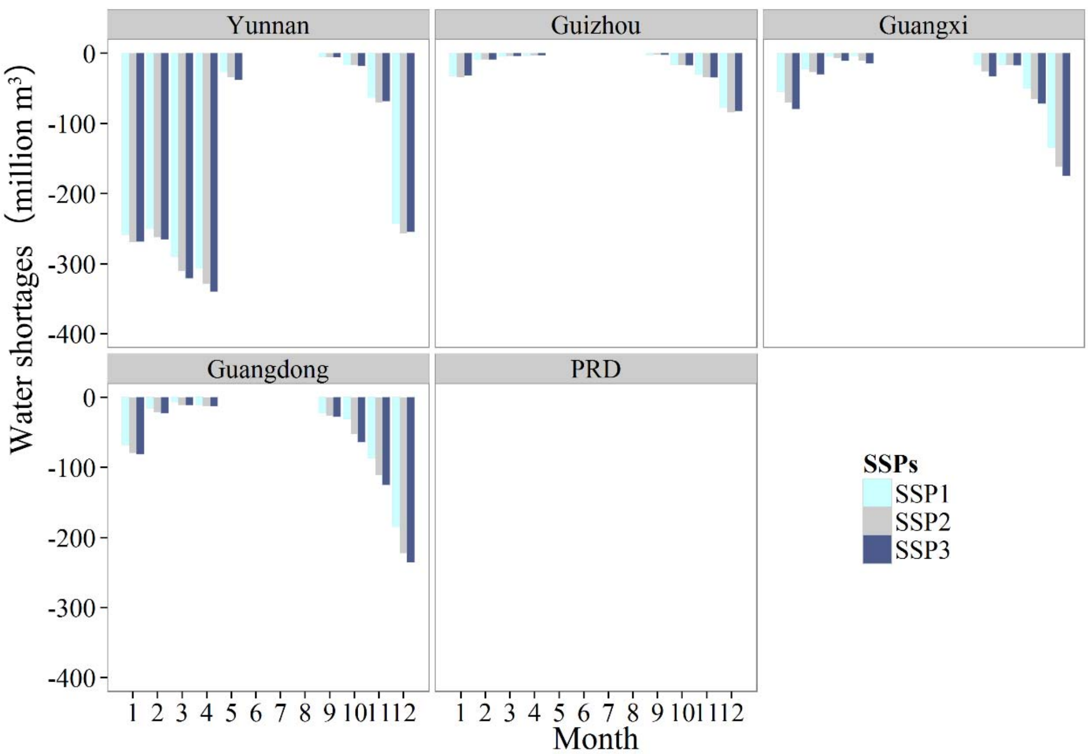

Figure 5.8 Average monthly water shortages for different regions in the PRB under the Delta-prioritized strategies for the period of 2010-2050 (RCP8.5)

Under the DP strategy, water shortages for all the upstream regions have become larger compared to water shortages under the UP strategy, except for the PRD (Figure 5.8). Additional water from the upstream regions is sufficient to supply all the water uses in the delta, but increases upstream shortages. Under SSP3, all the upstream regions expect Guizhou have the highest water shortages. In Guizhou, water shortages under SSP2 are higher than water shortages under SSP3. Figure 5.6 shows what percentages of projected irrigation and manufacturing water uses can be satisfied for each region under the IrrP and ManP strategy. The part that cannot be satisfied under the projected water availability is considered as water shortage of the region (see Section 5.2.4). Figure 5.9 shows the annual average water shortages for the whole basin under three SSPs. Water shortages range from 800 to 1500 million m^3 under both IrrP and ManP strategy. Under SSP3, water shortage in the PRB is more severe than under SSP1 and SSP2. Under all three SSPs, water resources in the PRB are insufficient to satisfy both irrigation and manufacturing water uses.

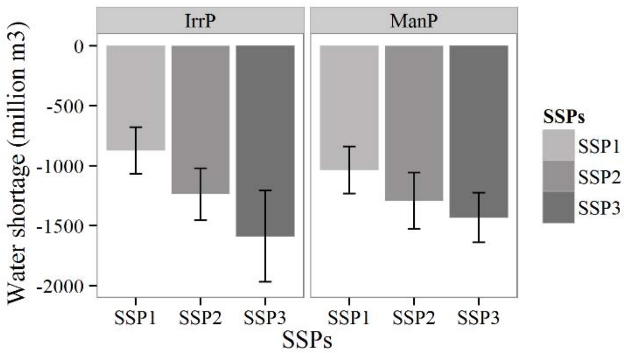

Figure 5.9 Annual average water shortages under the IrrP and ManP strategy for the period of 2010-2050 (RCP8.5)

5.3.4 Economic development under different water allocation strategies

The economic profits of agriculture and manufacturing sector under the condition with no water stress are selected as the baseline, i.e. under the baseline, both the upstream and the PRD will achieve the socio-economic development suggested by the SSPs scenarios (on average 4682 and 4146 billion international $2005 for the upstream regions and the PRD respectively), regardless if enough water is available in future.

Figure 5.10 shows the average economic losses due to water shortages compared to the baseline under different water allocation strategies. The error bars indicate minimum and maximum values of the five climate models. We found that economic losses for the PRB differ greatly under the four water allocation strategies. The PRB has the highest economic losses under the IrrP strategy, up to 14% of the total projected GDP of the whole PRB in 2050. For two strategies that reflect the competition between the upstream regions and the Delta (the UP and DP strategy), the PRB has higher economic losses under the UP strategy. The economic difference between the UP and DP strategy can reach up to 450 billion US$ under SSP1. Results confirm that although the economic growth rate of the upstream region is projected to have a large increase in the future, it is still weak when facing the competition from the PRD. Another interesting finding is that the economic losses under the DP strategies is higher than economic losses under the ManP strategies. The result is different from what we have expected. The reason will be discussed in Section 5.4.

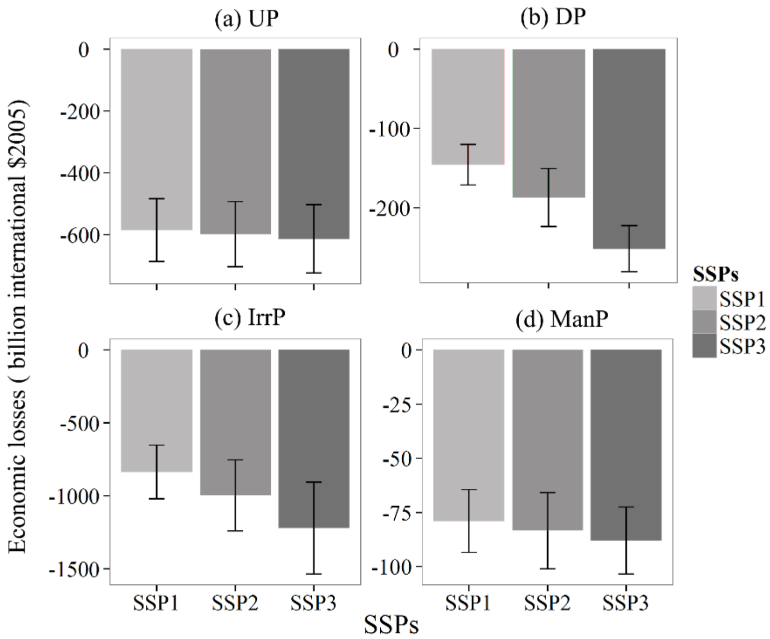

Figure 5.10 Average economic losses for the whole Pearl River Basin under four different water allocation strategies in 2050 (RCP8.5) (a) the upstream-prioritized, (b) the PRD-prioritized, (c) the irrigation-prioritized, and (d) the manufacture-prioritized strategy. Note different scale of y-axis of the different panels

5.4 Discussion

5.4.1 Projected water shortage

This study shows that the PRB is likely to face water shortages under all projected scenarios (Figure 5.5). It is the result of both increasing water demand and decreasing water availability. For example, water demand of the upstream regions increases by 25 billion m^3 from 2010 to 2050. During the same period, the total water availability of these regions decrease by 10.38 billion m^3 under RCP8.5. The increasing water demand contributes twice as much as the decreasing water availability to water shortage. The result is consistent with previous studies about the PRB. For example, Yang et al. (2008) concluded that water shortages in the East River basin (a major branch of the PRB) are aggravated by both climate change and human activities. Similar conclusions about the causes of water shortage in the Delta are drawn by Yao et al. (2016). It should be noted that water shortages in the PRB are seasonal events. There is sufficient water supply for the PRB during the wet season. However, storing large amount of water in reservoirs may lead to increasing flood risk as more than 80% of streamflow in the PRB occurs during the wet season.

Figure 5.5 suggests the differences in water shortage between RCPs are larger than differences between SSPs. The error bars in Figure 5.5 indicate that uncertainty in GCMs are larger than uncertainty in RCPs. To sum up, uncertainty in SSPs < RCPs < GCMs. My previous study explored uncertainties existed in different GCMs and RCPs (Yan et al., 2015). In this study, more attentions were paid to the three SSPs. Furthermore, in order to obtain the upper limits of the water shortage, the results under RCP8.5 were selected for further analysis in Section 5.3. Differences in water shortage between different SSPs are not significant based on M. T. Yao's water demand projections. Because the study period is relatively short spanning for only 40 years during which the socio-economic development under different SSPs pathways are not diverged significantly from each other. The water shortages are slightly higher under SSP3 (Figure 5.5). This is consistent with the narrative of the shared socio-economic pathways. The SSP3 is a pathway that faces high challenges both in mitigation and adaptation. Under SSP3, the economic development is primarily regionally oriented, and economic development and technological change are more fragmented and slower than SSP1 and 2 (O'Neill et al., 2014). In addition, the SSP3 is also characterized by rapid population grow. Low water use intensity due to slow technological change, together with high domestic water demand, make SSP3 the most water consuming scenario.

The OpenMORDM generated many possible water allocation strategies. In the real world, selection of water allocation plans requires stakeholders from different sectors to reach a compromise between the objectives. All the water users in the PRB should be given a fair treatment. But in this paper, only the most extremes ones were discussed. The performance of the four water allocation strategies were evaluated in this study. Results show that none of the prioritization strategy is sufficient to avoid all economic losses caused by water scarcity in the PRB (see Section 5.3.4). Prioritizing water for the delta and manufacture sector are the most profitable water allocation strategies.

The purpose of the "Key Reservoirs Operational Project for the Pearl River Basin" is to transfer upstream fresh water to the delta to repel saltwater intrusion and ensure water supply safety for the delta (He, 2007; Xie, 2007). This policy is actually a delta-prioritized strategy. In this study, I also defined a delta-prioritized strategy, which is upstream regions give sufficient water to the PRD. Each upstream region share the same absolute amount of additional water. In this case, the pressure for Yunnan is much higher than Guangxi. Figure 5.7 and 5.8 show that Yunnan province is likely to face the worst water scarcity compared to other regions in the PRB, especially in spring. This result is consistent with some previous studies (Jia and Pan, 2016; Wang and Meng, 2013). As a matter of fact, drought in spring is a major and frequent natural disaster in Yunnan province. Over the last three decades more droughts have been observed in Yunnan province (Abbas et al., 2014). Hence, it is likely that Yunnan does not have the ability to provide more water for the downstream regions in the future.

Figure 5.10 shows that the ManP strategy has lower economic losses compared to the delta-prioritized strategy. It is because the additional water from the upstream regions is also used to satisfy the agricultural water uses in the Delta under the delta-prioritized strategy. In 1979, the area of irrigated land in the PRD was 13838 km^2, accounting for 25.5% of the total area. The proportion of irrigated land in the PRD decreased from 25.5% in 1979 to 16% in 2009, accompany with a rapid increase of construction land (Liu et al., 2016). In Section 5.3.1, agricultural water uses in 2050s reduce around 60% compared to agricultural water uses in

2010s due to improved water use efficiency as a result technological development and a reduction of irrigated land. Nevertheless, the agricultural water use still accounts for more than 10% total water use in 2050s (Figure 5.2). Water allocation between upstream regions and the PRD requires a compromise between economic profits and social equity in the future. In addition, food security is also a high priority in China. Water resources tend to be transferred from low-value agricultural uses to high-value manufacturing uses in the PRB. In many parts of the PRB, Water shortages are limiting agricultural development (Khan et al., 2009). Since the PRB is one of the most important granaries in China, the local government must first consider the increasing food demands before implementing a policy.

5.4.2 Some study limitations and outlook

The primary limitation comes from the missing sectors and detailed sub-sectoral information. Data limitations for the thermo-electricity sector make it very difficult to associate this sector with the SSP storylines in a consistent way. However, this maybe more important for water quality (i.e. temperature) considerations than for water quantity stress, since most of cooling water intake returns to the river again (Fthenakis and Kim, 2010; Inhaber, 2004).

Moreover, uncertainty lies in both estimation of manufacturing water use intensity and manufacturing products. Manufacturing water use intensity and economic gains heavily depend on the structural composition of this sector and the corresponding technology it adopts. However, no sub-sector water-use data is available. And it is unlikely that the industrial structure in the upstream basin will remain the same for the coming few decades given its fast industrialization process. Thus, the current projection of manufacturing water use and products may need to be updated when future long term plans become available.

As the two-child policy has recently been issued, it is unclear how much the projected population growth may differ from the real development in the coming few decades. Although, the possible estimated domestic water use may have only limited impact on future water deficit in the PRB, because the total water use is dominated by agricultural and manufacturing uses for the whole PRB.

5.5 Conclusion

In this Chapter, the effect of four water allocation strategies on water resources and economic development in the PRB was simulated under regional scenarios that are consistent with the global scenarios developed in the context of the fifth IPCC Assessment Report framework.

Results show that future demands for water are much higher than supply. Large scale increases in water demand are mainly from manufacture factor in the upstream Pearl River Basin. Furthermore, differences in water use and shortage are not substantial between the SSPs for the whole basin. Under SSP3, the basin has the highest water shortage. Results also show that almost all the regions in the PRB are likely to face water shortage under the four water allocation strategies due to combined effects of climate change and socio-economic development in the future. The delta region only has sufficient water resources under the delta-prioritized strategy. The economic losses differ greatly under the four strategies. Prioritizing the delta region or manufacturing production would result in lower economic losses than the other two strategies, whereas the economic loss is the highest when water for irrigation has the priority. All four water allocation strategies are insufficient to solve the water scarcity in the PRB. However, all of them are rather extreme strategies. Development of water resources management strategies requires a compromise between different water users. In addition, new technologies and increasing water use efficiency is important to deal with future water shortage in the PRB.

Acknowledgments

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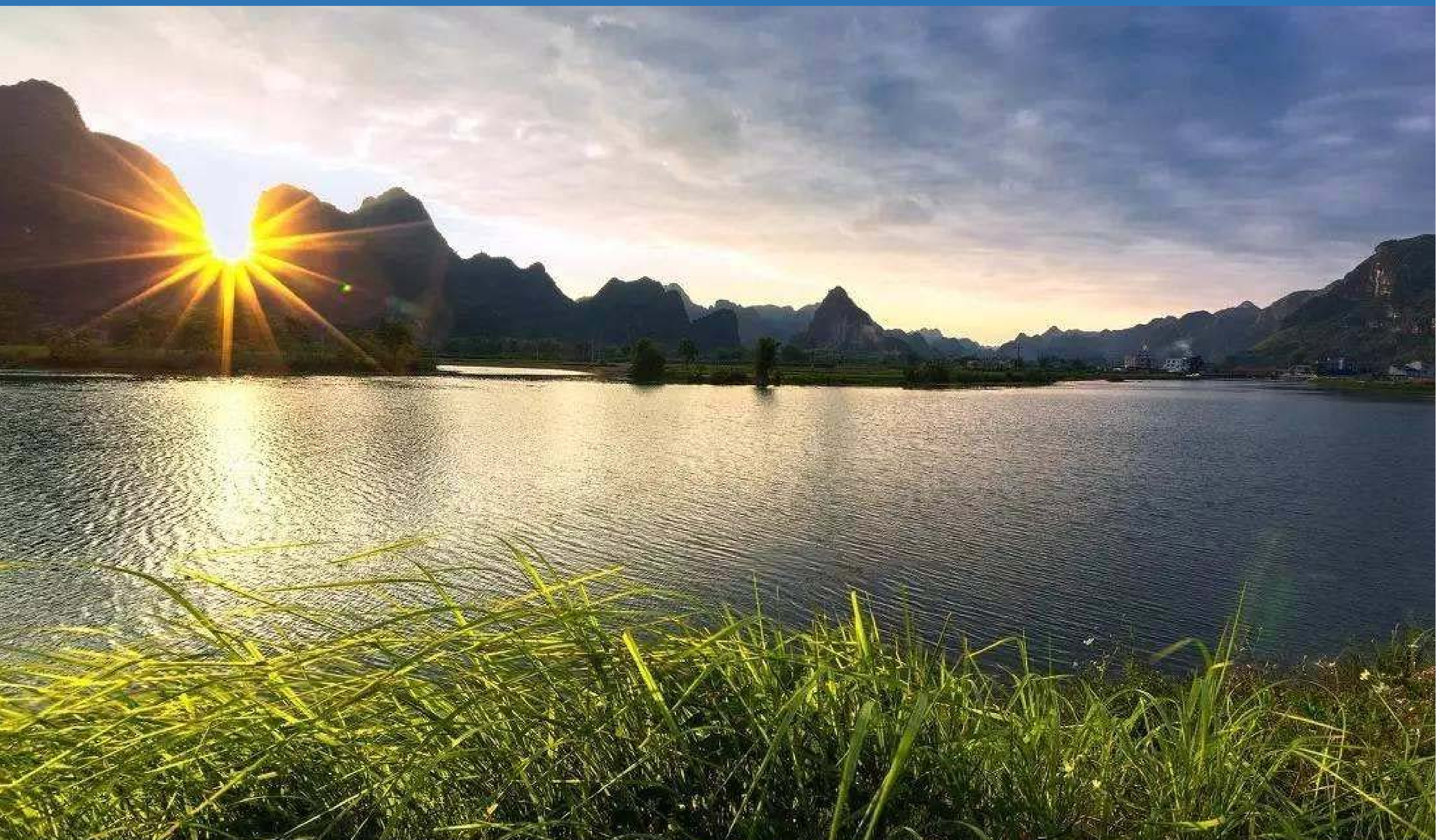
6

General Discussion



Chapter 6

General Discussion

6.1 Introduction

Population growth and socio-economic development have increased pressure on water resources in many parts of the world, especially in some transboundary and densely populated river basins like the Mekong River basin, Rhine River basin and Pearl River Basin. This situation is likely to be aggravated over the next decades by decreasing water availability due to climate change (Alcamo et al., 2007; Arnell, 2011; Milly et al., 2005). Allocating water resources is critical to meet human and ecosystem needs now and in the future (Bangash et al., 2012; Null and Prudencio, 2016). However, water resource allocation in river basins are being challenged by uncertainties associated with climate change and socio-economic development. This thesis explores how to develop robust water allocation strategies in a large river basin with water competition between regions under future uncertainties. The Pearl River Basin (PRB), which is presently confronted with insufficient water resources to sustain its rapid regional socio-economic development, is selected to be the case study area.

This thesis is a part of a joint scientific thematic research programme (JSTP) “Working with Water: adaptive land use and water management in the Pearl River Delta under climate change and sea level rise”. The overall aim of the project is to improve our understanding of seasonal dynamics of hydrological extremes under climate change, and to identify response strategies by studying the complex feedback mechanisms between climate extremes and the integrated socio-hydrological system. In this project, I am responsible for assessing the impact of climate change on water availability and hydrological extremes, and identifying robust water allocation strategies for different purposes in the Pearl River basin under future uncertainties. My colleague M. T. Yao focuses on water use/consumption in the Pearl River Delta. And we also worked together to explore water shortage in the Pearl River basin under combined effects of climate change and socio-economic develop (Chapter 5). Within this project the central question of this thesis is:

To what extent can water resources allocation strategies help large river basins addressing water shortage problem under climate change and socio-economic development?

Four more detailed research questions were defined, each of which is addressed in one or more chapters in this thesis:

1. How will water availability change as a result of climate change in the Pearl River Basin?
2. Can water allocation reduce saltwater intrusion in the Pearl River Delta?
3. How will socio-economic development affect water shortage in the Pearl River Basin?
4. Whether robust decision making (RDM) is appropriate for generating water allocation and management strategies in the Pearl River Basin under climate change and socio-economic

development?

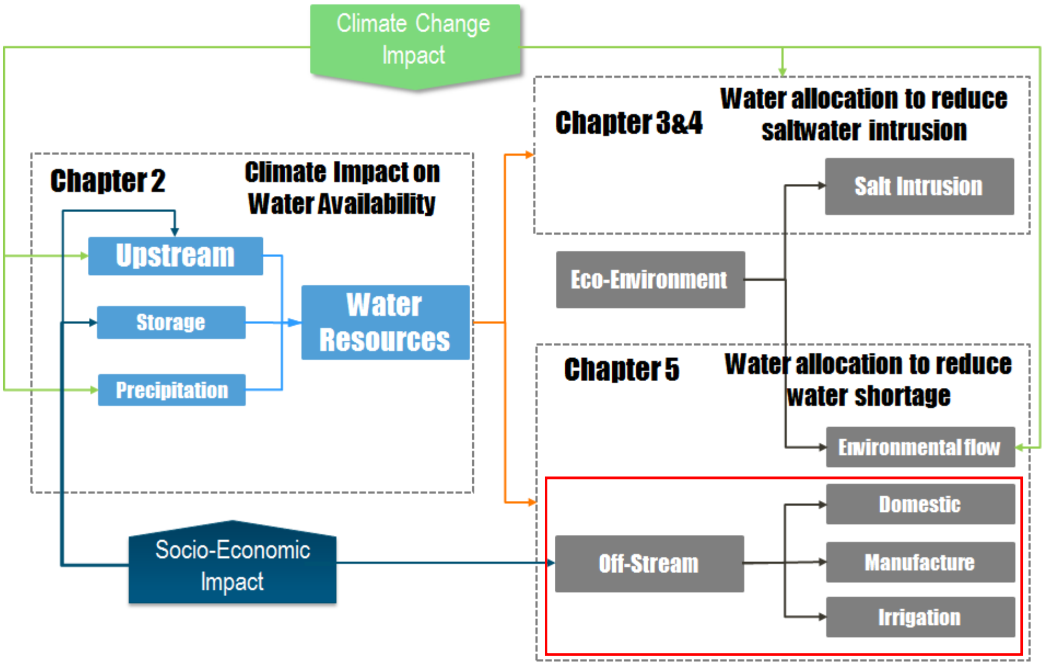


Figure 6.1 Main elements of this thesis (The contents in the red rectangle were done by my colleague M. T. Yao)

Figure 6.1 illustrates the main elements of this thesis. In answering the above research questions, the thesis first assessed the impact of climate change on seasonal discharge and extreme flows in the Pearl River Basin during the period 1960-2099 to gain a better understanding of future water availability (Chapter 2). A Robust Assessment Model for Water Allocation (RAMWA) combining multi-objective generic evolutionary algorithm, robust decision making, and biophysical modelling was developed to facilitate sustainable water management and allocation in delta regions (Chapter 3). The performance of different state-of-the-art multi-objective evolutionary algorithms were evaluated in Chapter 4. In Chapter 4, I also modified the modeling framework to identify adaptive water allocation strategies that are robust to future climate change. Chapter 5 assessed water conflicts between different water users in the Pearl River Basin. I built two water availability scenarios under future climate change, while M. T. Yao built three water use scenarios under future socio-economic development. Together, we explore water shortage in the Pearl River basin under four extreme water allocation strategies.

6.2 Research questions

Q1: How will water availability change as a result of climate change in the Pearl River Basin?

To answer this question, I used the VIC model driven by bias-corrected results of five different climate models under the IPCC scenarios RCP4.5 and 8.5. My simulation results clearly indicated that water availability is becoming more variable throughout the basin due to climate change. In the downstream part of the PRB, river discharge is increasing in the wet seasons and decreasing in the dry seasons. In the upper reaches of the basin, river discharge is decreasing during both the dry and wet seasons. The findings are comparable to conclusions drawn recently by Xiao et al. (2013) for the West River, the Yujiang River, the Guijiang River, Hongshuihe River, and the North River (Beijiang) using five different Global Climate Models (GCMs) under RCP4.5. Zhang et al. (2012) showed similar results in their study on the precipitation structure in terms of annual total rain days, annual total precipitation amount, annual precipitation intensity and annual mean precipitation days over the Pearl River Basin. Du et al. (2014) also found that water availability will decrease in Winter and Spring, and increase in Summer and Autumn by 2080s.

The variation in river discharge is likely to increase flood frequencies and aggravate drought stress in the lower reaches of the Pearl River Basin. These changes could especially have an impact on the Delta which is one of the leading economic regions and a major manufacturing center of China. Here, more floods and droughts could potentially have a major impact on the economy and society. Additionally, the reduced flow during the dry season may increase saltwater intrusion in the delta. In the upper reaches of the basin, consistent low flows may increase levels of water scarcity and climate change may also reduce production of the hydropower stations in the upstream of the Pearl River Basin (e.g. Christensen et al., 2004; Schaefli et al., 2007). Thus, water resources management is facing major challenges due to increased variation in water availability caused by climate change.

For Chapter 2, the main uncertainties arise from the usage of climate change scenarios. These scenarios were constructed using GCMs output under different Representative Concentration Pathways (RCPs). RCPs are a set of four new scenarios developed for modelling climate change. However, the output of GCMs is delivered in coarse grids, and associates with significant biases. Downscaling and bias correction are necessary before application at a regional scale (Kiem et al., 2016; Kiem and Verdon-Kidd, 2011). In addition, the projections of future climate change are also plagued with uncertainties (Dessai and Hulme, 2007). The uncertainties are highly relevant to the structure, parameterization and spatial resolution of corresponding GCMs. Projected patterns of climate change vary substantially between GCMs, even when the same emission scenario is used. This is especially the case for precipitation. For example, Lim and Roderick (2009) showed that when 20 GCMs were used to produce 39 runs of the 21st century for the Murray-Darling Basin, 22 runs showed increase trends in annual average precipitation to the end of the 21st century, while 17 showed decreases. There is no consensus on what will happen to future climate. It is unlikely that uncertainties in future climate projections will significantly reduce in the near future. Using multiple models forced by multiple scenarios would lead to a better understanding of the uncertainties in climate models (Biemans et al., 2009). Therefore the VIC model was forced by bias corrected output of five selected CMIP5 models under two emission scenarios for the period 2079-2099 to investigate the impacts of uncertainties resulting from climate models on river discharge simulations.

The simulated discharge provided the necessary data base required for developing water allocation model in Chapter 3, 4, and 5. Also, my analysis showed that higher risk of floods and droughts in the lower basin and reduction of water supply from the upper basin as a result of decreasing discharge will combine to enhance uncertainty of water supply in the lower basin.

All these point to new challenges for water availability and for water resources management under climate change. This study may also act as a typical case study for other regions of the world in terms of water security under changing climate.

Q2: Can water allocation reduce saltwater intrusion in the Pearl River Delta?

This question is answered in two chapters (Chapter 3 and 4). In chapter 3, I developed a model framework called the Robust Assessment Model for Water Allocation (RAMWA) to identify and assess robust water allocation plans for the Pearl River Delta under climate change. The RAMWA not only evaluated the performance of existing water allocation plans in the past, but also the impact of future climate change on robustness of previous and newly generated water allocation plans. Results showed that performance of the existing water allocation plans reduces under climate change, as the plans are unable to sustain the required minimum river discharge. However, alternatives generated by a Generic Evolutionary Algorithm (GEA) suggested that new plans can be developed which ensure minimum flows into the delta under most future climate change scenarios. The GEA plans performed better than the four 2006 water allocation plans. Nevertheless, neither the 2006 water allocation plan nor the GEA plans can deal with the extreme dry years projected by the IPSL climate model.

To obtain improved water allocation plans, the model framework was updated in Chapter 4. New framework combines an open source software for many-objective robust decision making (OpenMORDM) (Hadka et al., 2015) with a physically based routing model (Haddeland et al., 2006a) that distributes water in a real river network at a daily scale. More advanced optimization algorithms were used in the new framework. Before implementation of the new framework, the performance of ten different state-of-the-art multi-objective evolutionary algorithms (MOEAs) was evaluated. The best performing MOEA, Borg, was selected to generate new water allocation plans.

There are many other differences between the old and new model framework. The old framework defined robustness as good performance across different future scenarios. In other words, a water allocation plan will be considered to be robust if it satisfies certain performance criteria under all or most scenarios. In this study, the selected performance criteria are the number of days with discharge < 1800 m^3/s at Wuzhou and number of days with discharge < 2200 m^3/s at Sixianjiao. The new framework used two different methods, regret and satisficing, to measure the robustness of water allocation plans. Using multiple robustness measures are necessary because their averaging tends to ignore outliers (Hadka et al., 2015).

The old framework uses two objectives to evaluate the performance of the newly generated water allocation plans. These two objectives are to minimizing the average numbers of days that discharge is less than the required minimum flows at Wuzhou and Sixianjiao station. In addition to the two above objectives, three new conflicting objectives were added into the new framework. They are to minimize variations between required minimum flow and discharge at two selected hydrological stations (Wuzhou and Sixianjiao), and to maximize hydropower potential of the reservoirs. Involving more conflicting objectives increased running time. However, in the real-world water allocation problems, water managers likes to pursue more than one target (Farahani et al., 2010). It is more realistic to explore trade-offs among different objectives than to obtain one single optimal solution.

The new framework performed better than the old one in finding water allocation plans with high performance. However, even the evolutionary algorithm Borg could not find solutions that can maintain sufficient flow at Wuzhou and Sixianjiao for the entire dry seasons under all possible future climate scenarios using the current water allocation system. The current water allocation system involves six reservoirs (labelled as key reservoirs in the water allocation policy): Tianshengqiao I, Longtan, Yantan, Feilaixia, Changzhou, and Baise. The most important four key reservoirs (Tianshengqiao I, Longtan, Yantan, and Baise) are located in the upstream part of the Xijiang River. The nearest reservoir (Yantan) to the delta is 855 km away. It takes at least seven days for water released from Yantan reservoir to travel to the estuary. These upstream reservoirs control one third of the water resource in the Pearl River Basin. Water resources in the middle and lower reaches of the Pearl River are not regulated (Qian, 2007). The analysis showed that the current water allocation system with six key reservoirs is insufficient in maintaining the required minimum discharge for future climate scenarios. More reservoirs, especially in the Yujiang Sub-river basin and the middle reach of the Xijiang River, could potentially improve the future low flow into the delta.

To improve the current performance of the water allocation policy, a new reservoir called Datengxia is currently under construction in the upstream of Qianjiang River (Liu, 2007a). Datengxia is designed as a large reservoir for water allocation, hydropower and flood control (Liu, 2007b). The government expects that Datengxia can play an important role in solving saltwater intrusion problem in the dry season (Liu, 2007b). In Chapter 3, I added the Datengxia reservoir to the key reservoir system, and evaluated its effect on maintaining sufficient flows during the dry season. The results showed that adding the Datengxia reservoir can substantially improve the performance of the water allocation plans. The fractions of plans which are within the 50 day threshold increases to 0.93 under IPSL RCP 4.5 and to 0.83 under IPSL RCP 8.5.

The required minimum flows at Wuzhou and Sixianjiao station are currently 1800 and 2200 m^3/s. Yao et al. (2016) indicates that the future water use demand of the delta may increase substantially, while at the same time the Pearl River Basin is likely to become drier in the dry season (Yan et al., 2015) . Therefore, the currently agreed minimum flow requirements at Wuzhou and Sixianjiao may not be sufficient to combat salt intrusion in the future. Moreover, channel incision can contribute to saltwater intrusion and subsequent water shortage in the delta due to increasing channel depth and sea level (Lu et al., 2007). The rapid channel incision was mainly the result of extensive sand mining in the lower reaches of the Pearl River. It has caused changes both in the channel geometry and in the river hydraulics. Since 1990s, the channel depth of the lower Pearl River increased up to 10m in the deepest cut. In addition, sea level rise caused by climate change is further aggravated saltwater intrusion (Kong and Chen, 2012). Therefore, the thresholds of the minimum flows (1800 m^3/s at Wuzhou and 2100 m^3/s at Sixianjiao) used in the model framework may be inappropriate in the near future. The uncertainty of these two thresholds is analysed using the Patient Rule Induction Method (PRIM) in Chapter 4.

Q3: How will socio-economic development affect water shortage in the Pearl River Basin?

Chapter 3 and 4 mainly focused on water allocation among different regions and users under climate change. Chapter 5 paid more attention to how socio-economic development affects future water demand (done by M. T. Yao) and how severe water shortage can be under both climate change and socio-economic development? To do so, two water availability scenarios and three water use scenarios were developed consistent with the RCPs and the Shared Socio-economic Pathways (SSPs) respectively. SSPs describe a set of plausible alternative scenarios in the evolution of society and natural systems over the 21st century, in the absence of climate change or climate policies (O'Neill et al., 2014). Results shows that the Pearl River Basin is likely to face severe water shortage under all the climate change and socio-economic scenarios (Figure 5.5). It is the result of both increasing water demand and decreasing water availability. For example, water demand of the upstream regions increases by 25 billion m^3 from 2010 to 2050. During the same period, the total water availability of these regions decreased by 10.38 billion m^3 under RCP8.5. The increasing water demand due to socio-economic development contributes twice as much to water shortage as the decreasing water availability due to climate change. The result is consistent with previous studies about the Pearl River Basin. For example, Yang et al. (2008) concluded that water shortages in the East River basin (a major branch of the Pearl River Basin) are aggravated by both climate change and human activities.

Four water allocation strategies were assessed in Chapter 5. The first one is an upstream prioritized strategy, in which upstream region preferentially uses the amount of water as projected under water use scenarios. If its projected water use is larger than projected water availability, the upstream region would take all the available water in this region. The second one is a delta prioritized strategy. In this strategy, the upstream regions release additional water to the Delta, which is sufficient for irrigation and manufacturing water use in the Delta. Each region release the same absolute amount of additional water to the Delta. The third one is an irrigation-priority strategy, while the fourth one is a manufacture-priority strategy. Under the upstream prioritized strategy, Yunnan, Guangxi, Guangdong and the PRD are likely to face severe water shortages. Under the delta prioritized strategy, water shortages for all the upstream regions have become even larger compared to water shortages under the upstream prioritized strategy. Water shortages range from 800 to 1500 million m^3 under both upstream-priority and manufacture-priority strategy. Prioritizing water for the delta and manufacture sector are the most profitable water allocation strategies. However, water allocation among these water use sectors does not only depend on economic profit. Another factor to consider is that all the water users in the Pearl River Basin should be given a fair treatment. Water allocation between upstream region and the PRD requires a compromise among economic profit, sustainability and food security in the future.

Q4: Whether robust decision making (RDM) is appropriate for generating water allocation and management strategies in the Pearl River Basin under climate change and socio-economic development?

The purpose of water resources management is to provide adequate amounts of water of proper quality for the various water-related services (Serageldin, 1995). In recent years, extreme floods, water shortage, the need for ecological rehabilitation of rivers, and the prospect of future global change has raised the awareness that new water management strategies might be needed over the forthcoming years to ensure sustainable use of the water system over the 21st century (Haasnoot et al., 2012). However, the future is surrounded by large uncertainties. Climate change and the hydrologic response are major causes of these uncertainties, as they may affect water availability. In addition, socio-economic developments will affect the hydrological cycle through growing water demand. The complexity of the water systems and uncertainties associated with climate change and socio-economic development make it is different to develop robust water management strategies.

Generating high quality water management strategies for complex water systems under future uncertainties poses several major challenges. First, the systems are often characterized by multiple, conflicting performance measures (Kasprzyk et al., 2013). Traditional approaches often aggregate the multiple measures into a single metric of performance (e. g. Banzhaf, 2009; Franssen, 2005). As an iterative decision analytic framework, the RDM considers multiple conflicting performance measures explicitly and simultaneously (Kasprzyk et al., 2013). The solution to a multi-objective problem formulation is a set of trade-offs. Each of them is non-dominated with respect to multiple performance measures. The trade-offs are considered as a whole allows water managers to learn about trends and properties of their modeled systems, e. g. how sensitive it is to change, how it responds to extreme events, what its performance is with respect to multiple measures (Haimes and Hall, 1977; Kasprzyk et al., 2013). In Chapter 4, the trade-offs for water allocation in the Pearl River Basin, for example, showed that the key reservoirs can lower hydropower production in order to obtain lower variations between required minimum flow and discharge at two selected hydrological stations (Wuzhou and Sixianjiao). Second, to identify Pareto-optimal strategies for water management problems with multiple conflicting objectives and constraints poses significant computational challenges. This study used a high performance computing cluster (HPC) to perform all the calculations in the thesis. The HPC currently contains 900 cores, 600 TB of parallel storage and a fast internal infiniband network.

RDM is an iterative decision analytic framework that aims to help decision maker to identify potential strategies, characterize the vulnerabilities of such strategies, and evaluate the trade-off among them (Lempert and Collins, 2007). It is particularly suitable for three conditions: when the uncertainty cannot be well characterized, when there is a large set of decision alternatives, and the decision challenge is complex that decision makers need simulation models to trace the potential consequences of their actions over many plausible scenarios (Kasprzyk et al., 2013; Lempert and Groves, 2010). The PRB is a transboundary river basin with competing water users. Large uncertainties exist in future water availability and water use of the PRB (Chapter 5). There were several existing water allocation strategies in the PRB. The MOEAs also generated hundreds and even thousands of new strategies performing better than the existing plans. In Chapter 3, I compared the performance of the existing strategies and new strategies generated by a multi-objective evolutionary algorithm. Results showed that performance of the existing water allocation strategies reduces under climate change, as the plans are unable to sustain the required minimum river discharge. However alternatives generated by a multi-objective evolutionary algorithm suggest that new plans can be developed which ensure minimum flows into the delta under most future climate change scenarios. Selecting a robust strategy from thousands of alternatives is a key challenge to tackle in water allocation in the Pearl River Basin. To evaluate the potential consequences of these strategies over many scenarios, a simulation model of water distribution is needed. The above analysis suggests that the RDM may be a suitable approach for the PRB to identify robust water allocation and management strategies. Therefore, an open source software for many-objective robust decision making (OpenMORDM) (Hadka et al., 2015) is selected in this thesis to identify and evaluate water allocation strategies in the PRB.

The advantage of the OpenMORDM was tested in Chapter 4 and 5. In Chapter 4, I developed a model framework combined the OpenMORDM with a reservoir and routing model (Haddeland et al., 2006a) that distributes water in a real river network at a daily scale. The new framework is able to generate water allocation alternatives, quantify the trade-offs between robustness and the five performance objectives of water allocation in the PRB, explore dependencies between uncertainties and framework performance, and identify the vulnerable states of the framework. In Chapter 5, I used the OpenMORDM to generate the irrigation-prioritized (IrrP) strategy and manufacture-prioritized (ManP) strategy. In addition to the two extreme strategies, the OpenMORDM also generated many other possible water allocation strategies, which can be used for further discussion. The two case studies in this thesis show that the OpenMORDM can be easily applied to multi-objective water resources management and allocation problems in the PRB.

6.3 Scientific contributions

Water allocation in large river basins is a highly challenging topic requiring knowledge, tools and approaches that often stand at the forefronts of several scientific disciplines including hydrology, climatology, statistics, and socioeconomics. This thesis provides an important step forward in water allocation under climate change and socio-economic development. Contributions were made in the following areas: (1) advancing knowledge and better understandings about changes in both high flow and low flow, and related risks; (2) a more adaptive reservoir management, based on a network of observation, forecasts and optimization; (3) strategic long-term planning to include socio-economic and climate change scenarios and their impact on water allocation; (4) integration of supply and demand management.

Previous studies focussed on quantifying variations in annual, seasonal and monthly discharge and extreme flood events in the Pearl River Basin (Chen et al., 2012; Chen et al., 2010; Liu et al., 2012; Wu et al., 2014; Xiao et al., 2013). However it is also important to assess variations in low flow across the basin, because it is suffering from water shortage and saltwater intrusion in the dry season. This is the first study to explicitly quantify future changes in high flows, mean flows and low flows over the whole Pearl River Basin. The WATCH Forcing Data (WFD) (1958–2001) (Weedon et al., 2011), WATCH Forcing Data ERA Interim (WFDEI) (1979–2012) (Weedon et al., 2015) and downscaled and bias corrected CMIP5 climate projections (Taylor et al., 2012) were used to drive the VIC model in this study. Before simulating hydrological response to climate change in the Pearl River Basin, the selection criteria for climate data were described and the quality of the selected data sets in the Pearl River Basin was checked at first. Climate data selection is essential for hydrologic climate change impact assessment. This study give an example how to select appropriate climate forcing data for future hydrology studies.

With climate change now generally perceived inevitable, the policy attention is shifting from mitigation to adaptation (IPCC, 2013). Therefore, research on how to cope with hydrological changes due to climate change becomes increasing relevant in water resources management. This study represents an important contribution to adaptive reservoir management by developing two model frameworks (Chapter 3 and 4) based on a network of observation, forecasts and optimization. New water allocation plans generated by the two model frameworks perform better than the existing plans because rather than following a fixed allocation schedule, the optimal water release for each reservoir is recalculated every 10 days based on observed discharge and storage in key reservoirs. The two model frameworks demonstrate an useful approach to help water managers determine how changes in their assumptions about exogenous factors, such as required minimum flows at Wuzhou and Sixianjiao (Chapter 4), affect the performance of the planning strategies. For complex multiple reservoir systems, this is particularly useful because it can help water managers determine the impacts of their assumptions and decision choices on the decision making process. Additionally, multi-objective evolutionary algorithms were embedded in the model frameworks to generate new alternatives under climate change uncertainty. Results indicate that there is large potential for application of multi-objective evolutionary algorithms to complex multiple reservoirs system problems.

Water resources management are facing major challenges due to increased variations in water availability caused by climate change and increased water demand caused by socio-economic development (Alcamo et al., 2007). Therefore, developing socio-economic and climate change scenarios is of great importance for water resources management in a changing and complex environment. This study made a contribution in strategic long-term planning to include socio-economic and climate change scenarios and their impact on water allocation. My colleague M. T. Yao and I demonstrated how to develop globally-consistent regional socio-economic and climate change scenarios for the Pearl River Basin in Chapter 5. The regional scenarios provide a useful tool that works across different disciplines and different sectors of society, and merging different temporal and spatial scales. Additionally, the utility of combined regional socio-economic and climate scenarios can also help water managers understand future societal responses to the unfolding impacts of climate change.

Many countries pay more attention on water demand management, for example, China's most stringent water resources management for water quantity and quality control (Ge et al., 2017). However, adapting to water shortages requires considering both water supply and demand. Through assessing the combined effects of climate change and socio-economic development on water supply and demand in the Pearl River Basin, and identify adaptation strategies to alleviate competition over limited water resource in the PRB, this study represents an important contribution to integration of supply and demand management. Regarding scientific approach, the developed model frameworks comprising of many-objective robust decision making with biophysical modelling can be applied to large river basins where flows tend to be (too) low in the dry season but there is sufficient water supply during the wet season, which can be stored in the upstream reservoirs for later release.

6.4 Outlook and recommendations for future research

This multidisciplinary research contributes an integrated approach for more robust water resources allocation, and for adaptation to future water shortage as one of the most important challenges in densely populated river basins, yet highly vulnerable Pearl River Basin. First, a comprehensive analysis of river discharge provides advancing knowledge and better understandings about changes in both high flow and low flow, and related risks in the Pearl

River Basin. Based on a network of observation, forecasts and optimization, more adaptive reservoir management is then provided. Furthermore, this thesis also highlights strategic long-term planning to include socio-economic and climate change scenarios and their impact on water allocation and integration of supply and demand management. To further advance this important approach, several recommendations for water allocation under future uncertainties are formulated as below:

The integrated approach developed in this thesis has been validated in the Pearl River Basin. It performed well for water allocation and management in the Pearl River Basin under future climate change and socio-economic changes. There are potentials for applying this integrated approach to other large river basins, which are also suffering from water shortage, for example, the Yellow River in northern China. Compared to the Pearl River Basin, water shortage in the Yellow River basin is even worse. During 1972-2000, there were 22 years that the Yellow River failed to reach the sea for a period of different length each year (Magee, 2011). By implementing a water allocation policy named the water–sediment regulation since 2002, drying up of the Yellow River was alleviated (Kong et al., 2015). However, the basin is still facing severe water shortage in recent years (Zhuo et al., 2016). Unlike in the Pearl River Basin, future climate change is likely to yield a positive effect in the Yellow River basin as discharge is projected to have a consistent increase in early Spring (Immerzeel et al., 2010). Retained in reservoirs, the additional water could enhance water availability for irrigated agriculture and food security. There is no previous study exploring water allocation in the Yellow River basin under consideration of both socio-economic and climate change scenarios and their impact. Therefore, applying this approach in the Yellow River basin is recommended for future studies. In addition, it is also interesting to modify this approach to identify and assess robust water allocation plans for large water transfer projects, such as the South-to-North water transfer project in China.

Results show that the increasing water demand contributes twice as much as the decreasing water availability to water shortage in the Pearl River Basin. Integration of supply and demand management is thus highlighted in this thesis. However, water allocation at the basin scale means that we have to look not only at water supply and demand for cross-sectoral and upstream-downstream water users, but also institutional issue involved with the provision of water services (Rijsberman and Molden, 2001). A more extensive analysis about institutional issues, including better insights into the impacts of planning, policies, regulations, and allocation procedures on water supply and use would be needed for future modeling. To develop a new framework involving institutional interventions would constitute an important breakthrough in decision making under future uncertainties.

Water security in the Pearl River Basin is facing major challenges due to increased variation in water availability caused by climate change and increased water demand caused by socio-economic development. Developing effective and efficient tool to identify robust water allocation strategies that strengthen the coordinated management of the water resources in the Pearl River Basin are therefore extremely important for water security in the delta region and the entire basin.

Appendix A. Supplementary data

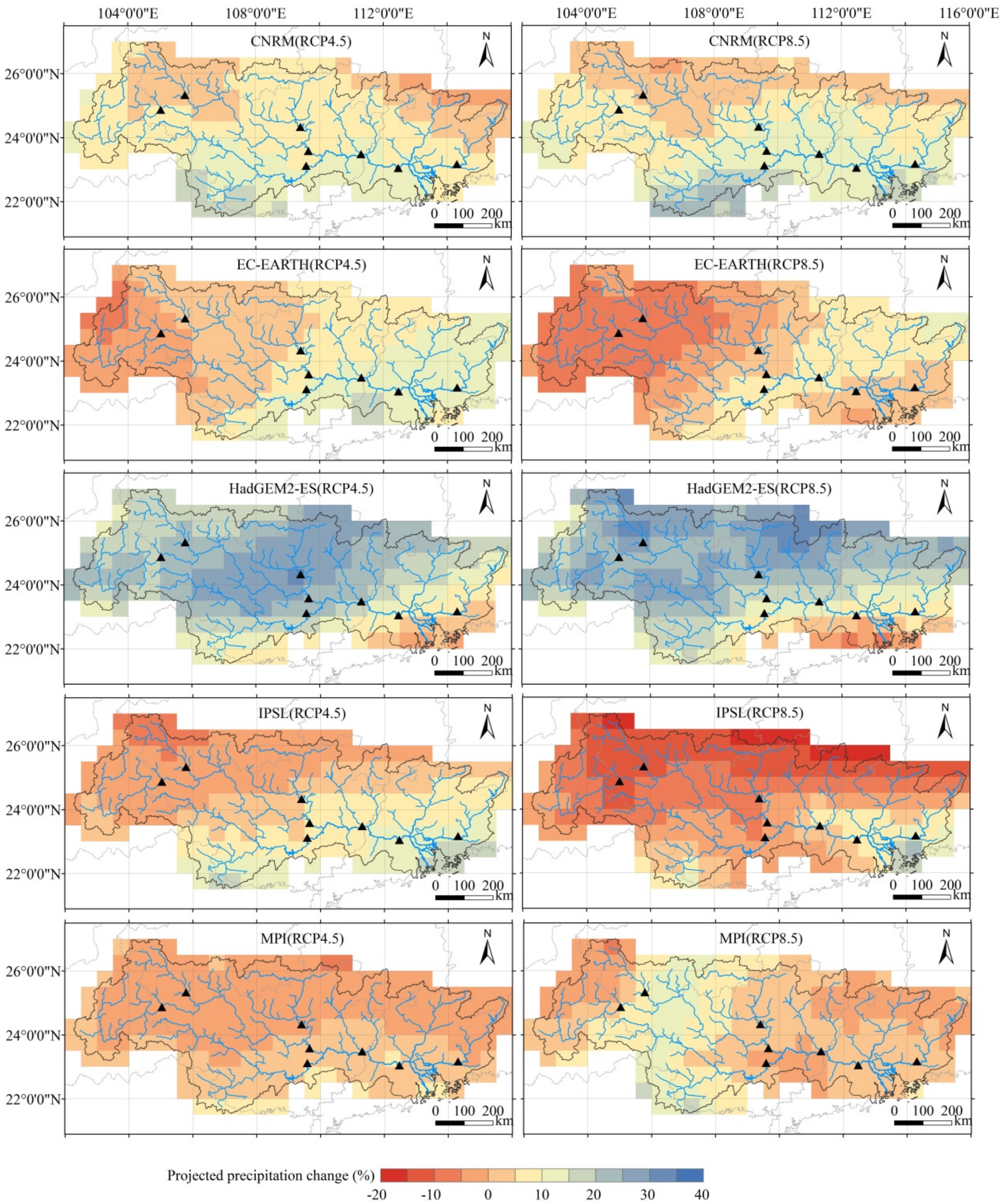


Figure A1 The mean precipitation change (%) for 2079-2099 relative to 1979 -1999 for ten scenarios from five selected GCMs under two RCP emissions.

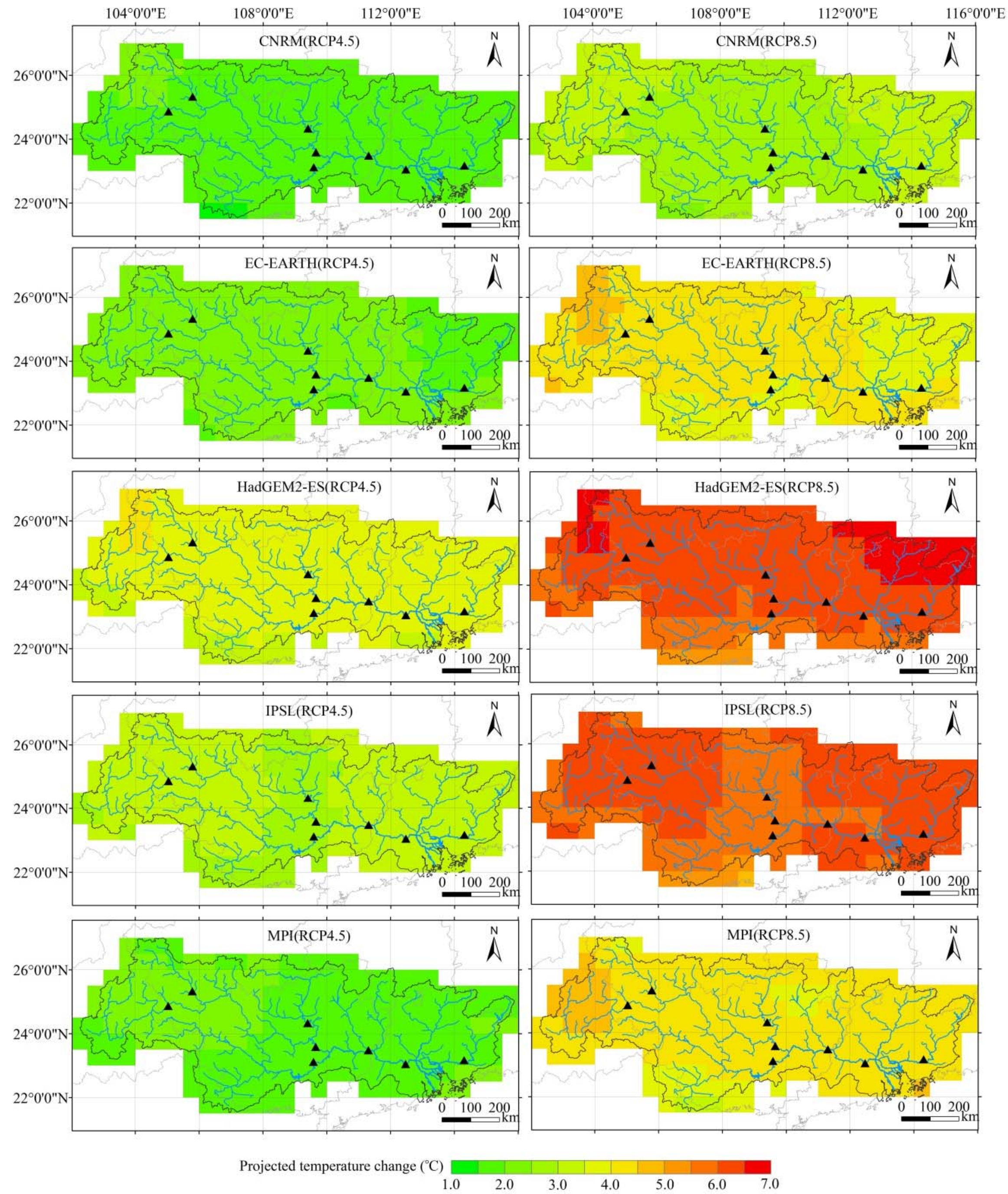


Figure A2 Projected changes (℃) in mean temperature for 2079-2099 relative to 1979-1999 for the five GCMs under two RCP emissions.

Appendix B. Supplementary data

Table B1 The optional hydrological models

Model name	Model time step	Meteorological forcing variables[1]	Energy balance	Evapotranspiration scheme[2]	Runoff scheme[3]	Snow scheme	Reference(s)
GWAVA	Daily	P,T,W,Q,LW,SW,SP	No	Penman-Monteith	Saturation excess /Beta function	Degree day	Meigh et al.(1999)
H08	6h	R,S,T,W,Q,LW,SW,SP	Yes	Bulk formula	Saturation excess /Beta function	Energy balance	Hanasaki et al.(2008a)
HTESSEL	1h	R,S,T,W,Q,LW,SW,SP	Yes	Penman-Monteith	Variable infiltration capacity/Darcy	Energy balance	Balsamo et al.(2009)
JULES	1h	R,S,T,W,Q,LW,SW,SP	Yes	Penman-Monteith	Infiltration excess/Darcy	Energy balance	Coxetal.(1999), Essery et al.(2003)
LPJmL	Daily	P,T,LWn,SW	No	Priestley-Taylor	Saturation excess	Degree day	Sitch et al.(2003)
MacPDM	Daily	P,T,W,Q,LWn,SW	No	Penman-Monteith	Saturation excess /Beta function	Degree day	Arnell (1999)
Matsiro	1h	R,S,T,W,LW,SW,SP	Yes	Bulk formula	Infiltration and saturation excess/GW	Energy balance	Takata et al.(2003)
MPI-HM	Daily	P,T	No	Thorntwaite	Saturation excess /Beta function	Degree day	Hagemann and Dümenil Gates(2003),Hagemann and Dümenil(1998)
Orchidee	15min	R,S,T,W,Q,SW,LW,SP	Yes	Bulk formula	Saturation excess	Energy balance	De Rosnay and Polcher (1998)

Appendix

VIC	Daily/3h	P,Tmax,Tmin,W,Q,LW, SW,SP	Snow season	Penman-Monteith	Saturation excess /Beta function	Energy balance	Liang et al.(1994)

1: R: Rainfall, S: Snowfall, P: Precipitation, T: Air temperature, Tmax: Maximum daily air temperature, Tmin: Minimum daily air temperature, W: Wind speed, Q: Specific humidity, LW: Longwave radiation (downward), LWn: Longwave radiation (net), SW: Shortwave radiation (downward), SP: Surface pressure

2: Bulk formula: Bulk transfer coefficients are used when calculating the turbulent heat fluxes.

3: Beta function: Runoff is a nonlinear function of soil moisture.

Table B2 Detailed information of key reservoirs

	Latitude (degree)	Longitude (degree)	Capacity (10^9 m^3)	Dead storage (10^9 m^3)	Normal storage (10^9 m^3)
Tianshengqiao I	105.11	24.94	10.26	2.60	8.395
Yantan	107.51	24.04	3.35	1.04	2.6
Longtan	107.05	25.03	27.27	5.06	16.21
Baise	106.45	23.92	5.66	2.18	4.8
Feilaixia	113.26	23.80	1.9	0.11	0.423
Changzhou	111.22	23.43	5.6	1.52	1.86
Datengxia	110.00	23.50	3.43	1.206	2.813

Appendix C. Data sources

The VIC model uses several datasets including elevation band file, vegetation file, soil file, and meteorological forcing file as input. The elevation and land cover classification were described in Nijssen et al. (Nijssen et al., 2001b). The DDM30 routing network was obtained from Döll and Lehner (Döll and Lehner, 2002).

The WATCH Forcing Data ERA Interim (WFDEI) (1979-2012) were selected as the historic forcing data. The WFDEI are derived from the ERA-Interim reanalysis data via sequential interpolation to 0.5°×0.5° resolution, elevation correction and bias correction based on monthly observations. They were mixed products of reanalysis data and observations and have all the eight parameters needed in VIC. The WFDEI were compared against the observations for the Pearl River Basin by Yan et al. (2015). The WFDEI have good performances for T_{min}, T_{max} and precipitation.

Information about irrigated areas was obtained from Siebert et al. (2005),while crop information was from Haddeland et al. (2006a). Dam information was obtained from the Chinese Large- and Medium - Sized Reservoir Database (Table B2 in appendix B).

The observed discharge data for calibration and validation were obtained from the hydrologic year books of the Pearl River. Two gauge stations: Wuzhou and Sixianjiao were selected for this study.

Appendix D Supplementary data

Table D1 Selected Multi-objectives Evolutionary Algorithms in this study including key references describing the algorithms

MOEAs	Source
Non-dominated Sorting Genetic Algorithm II (NSGAII)	Deb et al. (2000)
Epsilon Non-dominated Sorting Genetic Algorithm II (eNSGAII)	Kollat and Reed (2006b)
Epsilon Multi-Objective Evolutionary Algorithm (eMOEA)	Deb et al. (2003)
Generalized Differential Evolution 3 (GDE3)	Kukkonen and Deb (2006)
Multi-objective Particle Swarm Optimization (MOPSO)	Sierra and Coello Coello (2005)
Multi-objective Evolutionary Algorithm Based on Decomposition (MOEAD)	Zhang et al. (2009)
The Borg MOEA	Hadka and Reed (2013)
The Speed-constrained Multi-objective Particle Swarm Optimizer (SMPSO)	Nebro et al. (2009)
Strength Pareto Evolutionary Algorithm 2 (SPEA2)	Zitzler et al. (2002)
Non-dominated Sorting Genetic Algorithm III (NSGAIII)	Deb and Jain (2014)

Table D2 Parameters for MOEA search (Detailed information about these parameters please find in Reed et al. (2013).)

Parameters	Value
PM rate	0.2
PM distribution	20
SBX rate	1
SBX distribution	15
DE crossover rate	0.1
DE step size	0.5
UM rate	0.2
SPX parent	10
SPX epsilon	3
PCX parent	10
PCX eta	0.1
PCX zeta	0.1
UNDX parent	10
UNDX zeta	0.5
UNDX eta	0.35
Initial Population Size	100
Minimum Population Size	100
Maximum Population Size	10000
Injection Rate	0.25
Selection rate	0.02
Max Mutation Index	10

Appendix E Supplementary data

Table E1 Socio-economic status of the study area in 2010

	Guangxi	Yunnan	Guizhou	Guangdong	PRD
GDP, PPP *(100 million International $2005)*	2,175	1,642	1,046	1,901	8,426
MAN value-added *(100 million International $2005)*	877	592	345	611	3,999
GDP/ca *(international $2005/person)*	4,216	3,568	3,006	3,940	15,046
Population *(million)*	51.6	46.0	34.8	48.2	56.2

Table E2 Overview of quantitative scenario assumption of GDP in 100 million International $2005

	SSP1					SSP2					SSP3				
	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD
2010	2,175	1,642	1,046	1,901	8,426	2,175	1,642	1,046	1,901	8,426	2,175	1,642	1,046	1,901	8,426
2020	5,016	3,787	2,412	4,384	18,231	5,038	3,803	2,423	4,403	18,311	5,054	3,815	2,431	4,417	18,268
2030	9,902	7,475	4,762	8,653	30,107	9,007	6,799	4,332	7,871	29,395	8,539	6,446	4,106	7,462	28,243
2040	15,419	11,640	7,415	13,474	39,885	12,090	9,126	5,814	10,565	36,987	10,254	7,741	4,931	8,961	34,073
2050	19,555	14,762	9,404	17,089	46,048	14,489	10,938	6,968	12,662	41,944	11,120	8,394	5,348	9,718	36,375

Table E3 Overview of quantitative scenario assumption of manufacturing value-added in 100 million International $2005

	SSP1					SSP2					SSP3				
	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD
2010	877	592	345	611	3,999	877	592	345	611	3,999	877	592	345	611	3,999
2020	2,255	1,521	886	1,571	7,781	2,251	1,518	885	1,569	7,835	2,190	1,477	860	1,526	7,803
2030	4,609	3,109	1,811	3,212	11,772	4,206	2,837	1,653	2,931	11,206	3,797	2,561	1,492	2,646	10,362
2040	7,199	4,856	2,829	5,016	14,388	5,648	3,810	2,219	3,935	12,374	4,626	3,120	1,818	3,223	10,467
2050	9,045	6,101	3,554	6,303	14,597	6,748	4,552	2,652	4,702	12,073	4,961	3,346	1,949	3,457	9,077

Table E4 Overview of quantitative scenario assumption of population in million people

	SSP1					SSP2					SSP3				
	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD
2010	51.6	46.0	34.8	48.2	56.0	51.6	46.0	34.8	48.2	56.0	51.6	46.0	34.8	48.2	56.0
2020	53.1	47.3	35.8	49.6	59.4	53.3	47.5	35.9	49.8	60.0	53.5	47.7	36.1	50.0	60.6
2030	53.0	47.3	35.8	49.6	58.6	53.8	48.0	36.3	50.3	60.1	54.4	48.5	36.7	50.8	61.9
2040	51.5	45.9	34.7	48.1	56.0	52.6	46.9	35.5	49.2	58.4	53.6	47.8	36.1	50.1	61.1
2050	48.5	43.2	32.7	45.3	52.1	49.9	44.5	33.6	46.7	54.9	51.4	45.9	34.7	48.1	59.0

Table E5 Overview of quantitative scenario assumption of irrigated area in ha

	SSP1					SSP2					SSP3				
Year	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD	Guangxi	Yunnan	Guizhou	Guangdong	PRD
2010	1,285,738	321,728	237,120	560,730	614,882	1,285,738	321,728	237,120	560,730	614,882	1,285,738	321,728	237,120	560,730	614,882
2020	1,292,831	340,113	238,170	561,329	610,120	1,293,498	340,238	238,174	561,471	611,509	1,295,188	343,904	238,343	561,639	612,963
2030	1,300,681	353,630	239,136	561,979	608,233	1,303,463	355,541	239,303	562,442	610,807	1,310,105	365,636	239,987	563,187	613,919
2040	1,305,729	362,019	239,754	562,430	607,708	1,311,149	366,965	240,172	563,245	611,205	1,323,446	384,249	241,462	564,682	615,875
2050	1,308,014	365,248	240,031	562,670	608,017	1,317,463	374,890	240,877	563,987	612,229	1,335,410	398,240	242,772	566,166	617,821

Table E6 Overview of quantitative scenario assumption of technological change rate (TC)

	SSP-Upstream	SSP-PRD
SSP1	1.10%	1.20%
SSP2	0.60%	1.10%
SSP3	0.30%	1.00%

Reference

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Summary

The Pearl River in southern China provides important water resources for agriculture, industry, hydropower generation and domestic use within its drainage basin. Particularly, it plays a key role for water supply to large cities in the Pearl River Delta, such as Macau, Hong Kong, Guangzhou. Population growth and socio-economic development have increased pressure on water resources in the Pearl River Basin (PRB). This situation is likely to be aggravated by decreasing water availability due to climate change. Allocating water is critical to meet human and ecosystem needs in the PRB now and in the future. However, water resources allocation in the PRB is being challenged by uncertainties associated with climate change and socio-economic development. This study assessed the combined effects of climate change and socio-economic development on water supply and use in the PRB, and identified water allocation plans, which are robust to climate change and socio-economic development in this basin.

This study first assessed the impact of climate change on seasonal discharge and extreme flows in the PRB (Chapter 2). The variable infiltration capacity (VIC) model driven by bias-corrected results of five different climate models under the IPCC scenarios RCP4.5 and 8.5 was used for the assessment. Results indicate a reduction in average low flow under the five climate models. The reduction varies across the basin and is between 6 and 48% for RCP4.5. For RCP8.5, low flows show a 22 - 72% decrease. High flows are projected to decrease in the upstream part of the basin and to increase in the central part under both RCP4.5 (-6 to 20%) and 8.5 (-16 to 31%). River discharge in the dry season is projected to decrease throughout the basin. In the wet season, river discharge tends to increase in the middle and lower reaches and decreases in the upper reach of the PRB. The variation of river discharge is likely to aggravate water stress. Especially the reduction of low flow is problematic as already now the basin experiences temporary water shortages in the delta.

In the second part (Chapter 3), this study developed a Robust Assessment Model for Water Allocation (RAMWA) to support decision making about water release of different key reservoirs under future climate change. The model was applied in the PRB to improve reservoir management, to ensure sufficient flow into the delta to reduce salt intrusion, and to provide sufficient freshwater for human and industrial consumption. Results show that performance of the existing water allocation plans reduces under climate change, as the plans are unable to sustain the required minimum river discharge. The plan, which releases high volumes of water at intervals, is found to be the most robust. However alternatives generated by a Generic Evolutionary Algorithm (GEA) suggest that new plans can be developed which ensure minimum flows into the delta under most future climate change scenarios. The GEA plans perform better than existing plans because rather than following a fixed allocation schedule, the optimal water release for each reservoir is recalculated every ten days based on observed discharge and storage in key reservoirs. Additionally, the performance of the plans improves substantially if a new key reservoir is added to the reservoir system.

Next, a model framework combining many-objective robust decision making with biophysical modelling is developed to identify robust water allocation plans under future climate change (Chapter 4). It was applied in the PRB to develop and appraise the release plans of large

reservoirs with the objective to maintain flow into the delta to reduce salt intrusion in dry seasons. Before identifying and assessing robust water allocation plans for the future, the performance of ten state-of-the-art MOEAs (multi-objective evolutionary algorithms) is evaluated for the water allocation problem in the PRB. The Borg multi-objective evolutionary algorithm (Borg MOEA), which is a self-adaptive optimization algorithm, has the best performance during the historical periods. Therefore it is selected to generate new water allocation plans for the future (2079-2099). This study shows that robust decision making using carefully selected MOEAs can help limit saltwater intrusion in the Pearl River Delta. However, the framework could perform poorly due to larger than expected climate change impacts on water availability. Results also show that subjective design choices from the researchers and/or water managers could potentially affect the ability of the model framework, and cause the most robust water allocation plans to fail under future climate change. Developing robust allocation plans in a river basin suffering from increasing water shortage requires the researchers and water managers to well characterize future climate change of the study regions and vulnerabilities of their tools.

Finally, future water shortage for the PRB is explored under four different water allocation strategies (Chapter 5). First, two water availability and three water use scenarios consistent with the global scenarios were explored in the context of the fifth IPCC Assessment Report framework. Next, four different strategies to allocate water were defined. These water allocation strategies prioritized upstream water use, Pearl River Delta water use, irrigation water use, and manufacturing water use, respectively. The impact of the four strategies on water use and related economic output was assessed under different water availability and water use scenarios. Results show that almost all the regions in the PRB are likely to face water shortage under the four strategies. The increasing water demand contributes twice as much as the decreasing water availability to water shortage. All four water allocation strategies are insufficient to solve the water scarcity in the PRB. The economic losses differ greatly under the four water allocation strategies. Prioritizing the delta region or manufacturing production would result in lower economic losses than the other two strategies. However, all of them are rather extreme strategies. Development of water resources management strategies requires a compromise between different water users.

This thesis provides an important step forward in water allocation under climate change and socio-economic development. Contributions were made in the following areas: (1) advancing knowledge and better understandings about changes in both high flow and low flow, and related risks; (2) strategic long-term planning to include socio-economic and climate change scenarios and their impact on water allocation; (3) integration of water supply and use management. A key prospect for this work is a more adaptive reservoir management, based on a network of observation, forecasts and optimization.

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It was an autumn evening when I first stepped out Ede-Wageningen. My friend who came to pick me up was late. I sat on my suitcase waiting for him. After people who shared the same train with me left, the neighborhood of Ede-Wageningen was quiet and peaceful. The sky was bright orange. Warm autumn sun shining through the golden canopy of tall oak trees. The whole scene looked like an oil painting of Vincent van Gogh. I fell in love with the Netherlands from that moment. Five year later, I still love the Netherlands. PhD is a long journey full of ups and downs. The goodwill I received from all the colleagues, friends, and even strangers at the footpath made my journey wonderful. I am thankful to all the people who has supported me, uplifted me, and comforted me. And I am particularly thankful to some of them.

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Curriculum Vitae

Dan Yan was born on 18th April 1982 in Henan Province, China. She started her Bachelor's program of Geographical Information System at Henan University in 2000. She received her Bachelor's degree in 2004 and continued with her MSc study focusing geo-computation at East China Normal University. She wrote her MSc thesis on strategic planning for sustainable tourism in Shanghai. She developed an analytic model based on market, traffic, environment and tourism resources to help decision makers make tourism plans. She graduated in 2007 for her Master's degree. Dan started her first PhD at Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences in 2008. Dan attended a joint doctoral training program between Chinese Academy of Sciences and Max Planck Gesellschaft in 2010, and spent one year at Max Planck Institute for Meteorology in Hamburg, Germany. In 2012, she completed her PhD thesis on Interactions between Land Use Change, Regional Development, and Climate Change in the Poyang Lake District. In 2012, Dan started her PhD in the Water Systems and Global Change Group (back then Earth System Science), Wageningen University and Research. Her research focused on assessing the combined effects of climate change and socio-economic development on water supply and demand in the Pearl River basin (PRB), and identifying water allocation plans, which are robust to future climate change and socio-economic development.

List of publications

Publications in peer-reviewed journals

Yan D, Huang H Q, Ludwig, F, Werners, S E, Many-objective Robust Decision Making for Water Allocation under Climate Change. Science of the Total Environment, 2017, 607-608: 294-303.

Yan D, Werners, S E, Huang H Q, Ludwig, F. Identifying and assessing robust water allocation plans for deltas under climate change. Water Resources Management, 2016, 30 (14), 5421–5435.

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Submitted papers for publication

Yan D, Yao M T, Huang H Q, Kabat P, Hutjes R, Ludwig F, Werner S E. Exploring future water shortage in the Pearl River Basin, China under different water allocation strategies, Water Resources Management, major revision.

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- Research in context activity: 'Writing research proposal on: 'Adaptive Water Resources Management in Irrigation Districts along the Lower Yellow River under New Incoming Water and Sediment Conditions' and writing Press Release on publication of PhD research' (2017)

Other PhD and Advanced MSc Courses

- Scientific writing, Wageningen University (2015)

Management and Didactic Skills Training

- Assisting practical of the MSc course 'Adaptation to climate change' (2015-2016)

Oral Presentations

- *Hydrological response to climate change: The Pearl River, China under different RCP scenarios*. The 2nd Wageningen PhD Symposiums, 6 May 2015, Wageningen, The Netherlands
- *Comparing different multi-objective evolutionary algorithms for water allocation under different climate scenarios*. The 8th International Congress on Environmental Modelling and Software (iEMSs), 10-13 July 2016, Toulouse, France
- *Adaptive management of land and water for mitigating climate hazards in river deltas.* Global Land Programme 3rd Open Science Meeting, 24-26 October 2016, Beijing, China

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