Water Resour Manage (2016) 30:5421–5435
DOI 10.1007/s11269-016-1498-0

Identifying and Assessing Robust Water Allocation Plans for Deltas Under Climate Change

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Received: 22 November 2015 / Accepted: 7 September 2016 /
Published online: 21 September 2016

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 salt water 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 10 days based on observed discharge and storage in key reservoirs.

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.

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Keywords Water allocation · Robustness assessment · Climate change · The Pearl River basin · RCP scenarios

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 presents 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 algorithms, 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.

2 Methodology

The methodology for water allocation and robustness evaluation in RAMWA builds on Lempert and Groves (2010), and consists of four steps: problem formulation, assessment framework development, water strategies formalization, robustness and sensitivity assessment (Fig. 1).

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

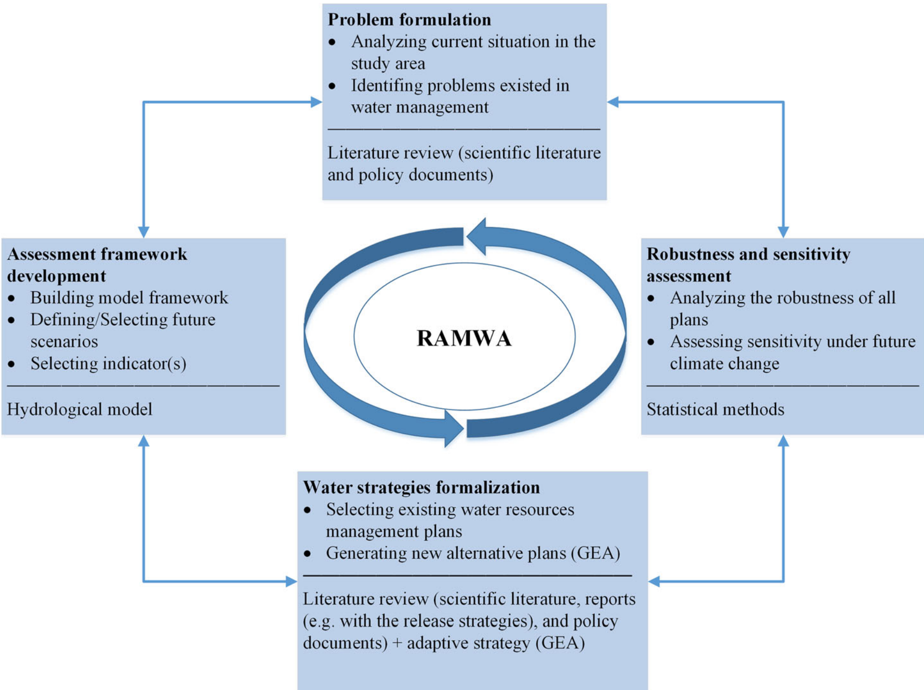

Fig. 1 Four steps of the robustness assessment in the Robust Assessment Model for Water Allocation (RAMWA)

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.

2.2 Assessment Framework Development

The integrated framework is the main element of RAMWA, and responsible for hydrological processes simulation and river routing. In our framework, we use an existing hydrological model (c.f. Lempert and Groves (2010)). The optional models are listed in Appendix A. 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.

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.

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 A Case Study for the Pearl River Delta

3.1 Problem Formulation

The Pearl River in southern China is the second largest river in China in terms of streamflow (Fig. 2). The Pearl River delta is the world's largest urban area (World Bank Group 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, has 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 salt water intrusion.

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.

3.2 Assessment Framework Development

As mentioned in Section 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.

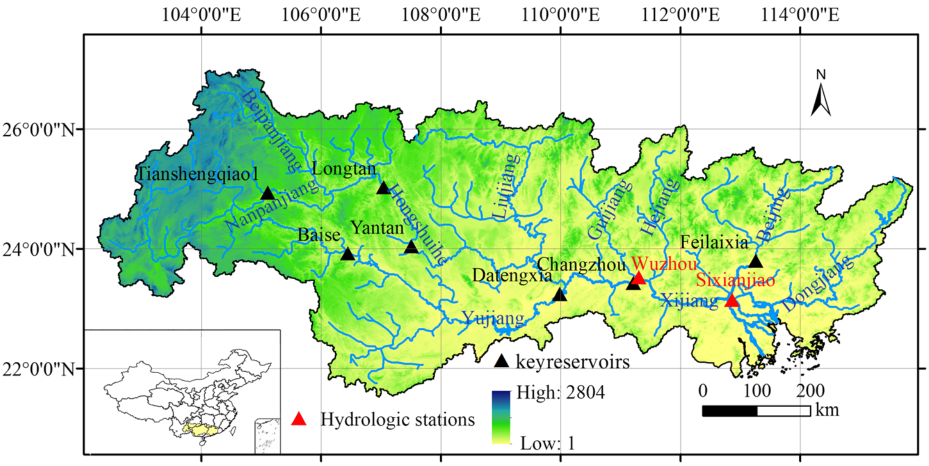

Fig. 2 Location of the Pearl River basin, key reservoirs and hydrological stations used in this study

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. (2006) 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).

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 salt water 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) (Fig. 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 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 1). Table 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 (Fig. 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 1).

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

Table 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

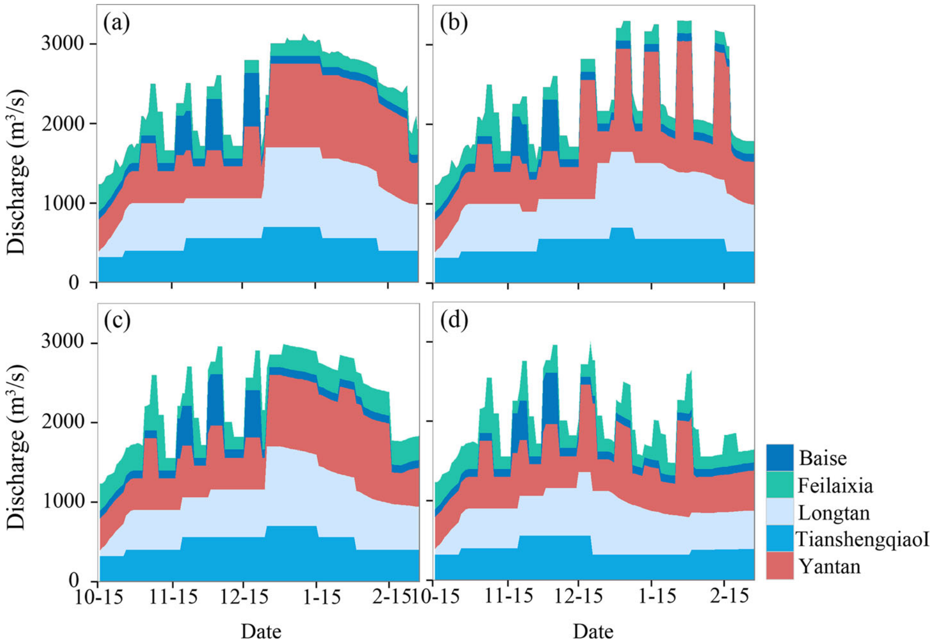

Fig. 3 Water releases of key reservoirs under four existing 2006 water allocation plans in the Pearl River basin **a** plan 1; **b** plan 2; **c** plan 3; **d** plan 4

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:

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

$$min \sum_{i=1}^{i=N} \left| Q_{sixianjiao,i} - 2200 \right| \quad (2)$$

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 4 in Appendix A).

$$S_{dead} < S_{t,k} < S_{max} \tag{3}$$

$$S_t = S_{t-1} + Q_{in} - Q_{out} - E_{res} \tag{4}$$

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.

3.4 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) are underestimated for all water plans during 2009–2010 (Fig. 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

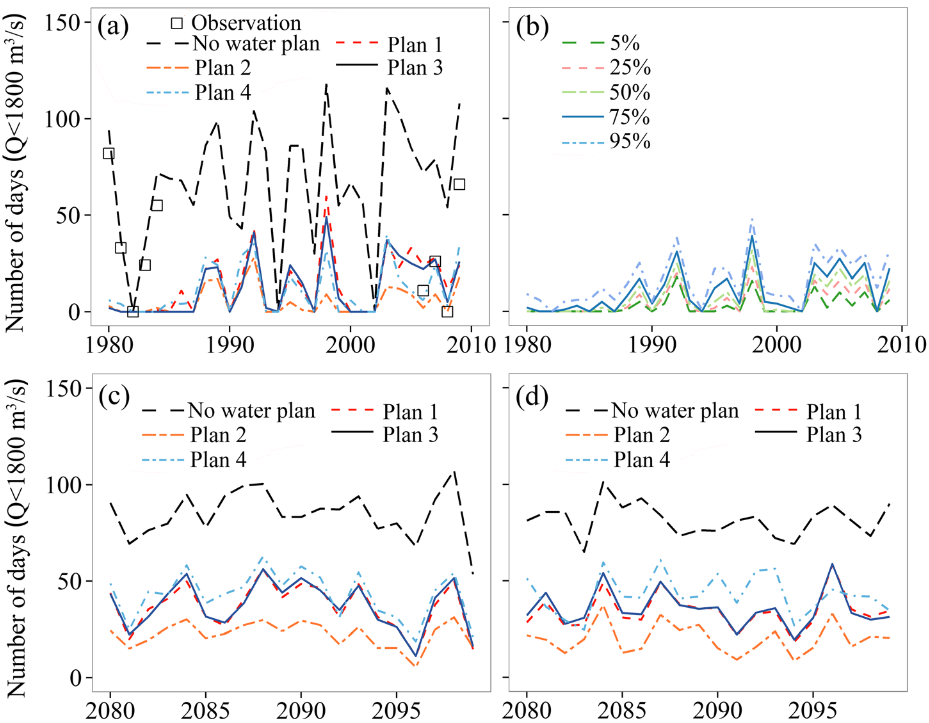

Fig. 4 Assessment of water allocation plans **a** Observed and simulated number of days at which the discharge is less than 1800 m^3/s at Wuzhou station (N_w). Simulated values with and without the operation of different water allocation plans (Observations are available for 1980–1985 (no water allocation 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

values of the 2006 water allocation plans. More than 75 % of the GEA plans perform better than plan 1, 3, and 4, and at least five percent of the GEA plans outperform plan 2 (Fig. 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 (Fig. 4c and d).

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 10 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.

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 (Fig. 5a–d). Plan 2 performs the best and performs well for all GCMs except IPSL. Based on our definition of robustness in Section 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 (Fig. 5e). The median of N_w for the GCM model scenarios is below 30 days for all climate models except for IPSL.

Figure 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 % of the points are in the square.

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 % 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) (Fig. 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 (Fig. 7 in Appendix C).

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

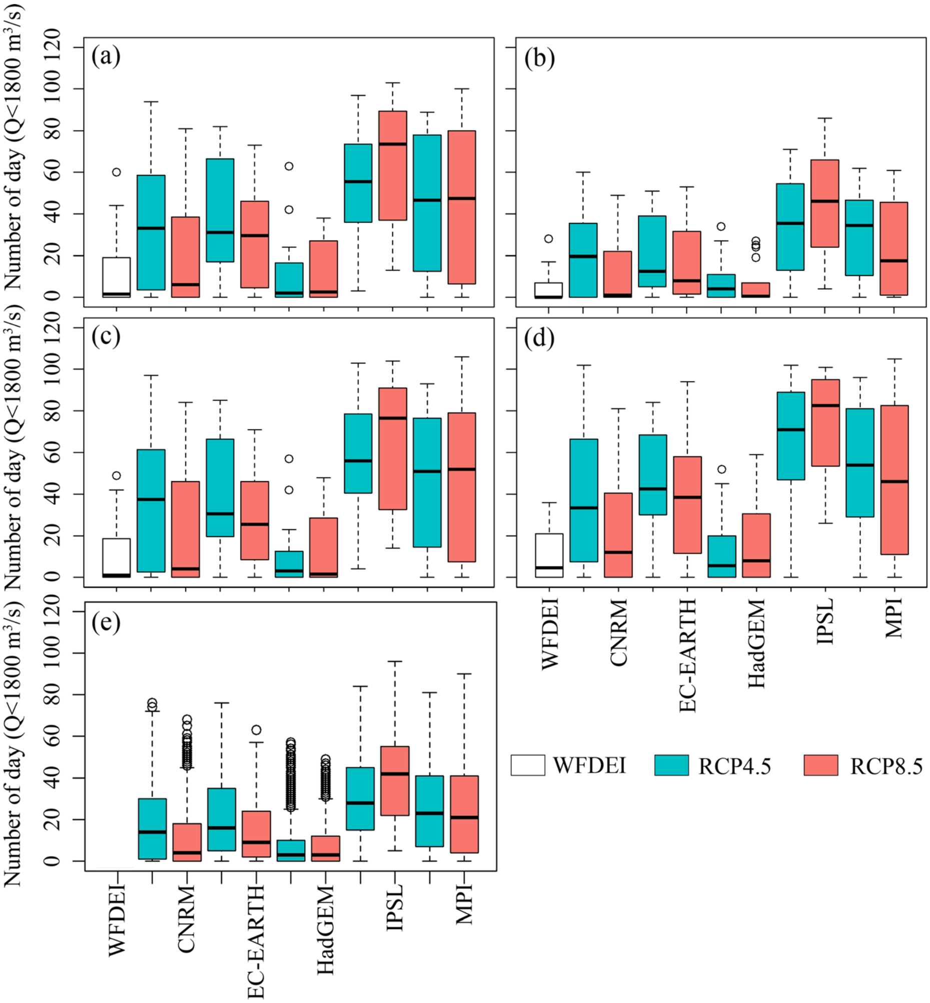

Fig. 5 N_w under four different 2006 water allocation plans driven by different future climate scenarios (2080–2099) **a** plan 1; **b** plan 2; **c** plan 3; **d** plan 4 and **e** 100 GEA plans also driven by different future climate scenarios (2080–2099)

of the reservoir releases was at least 83 % (Table 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 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.

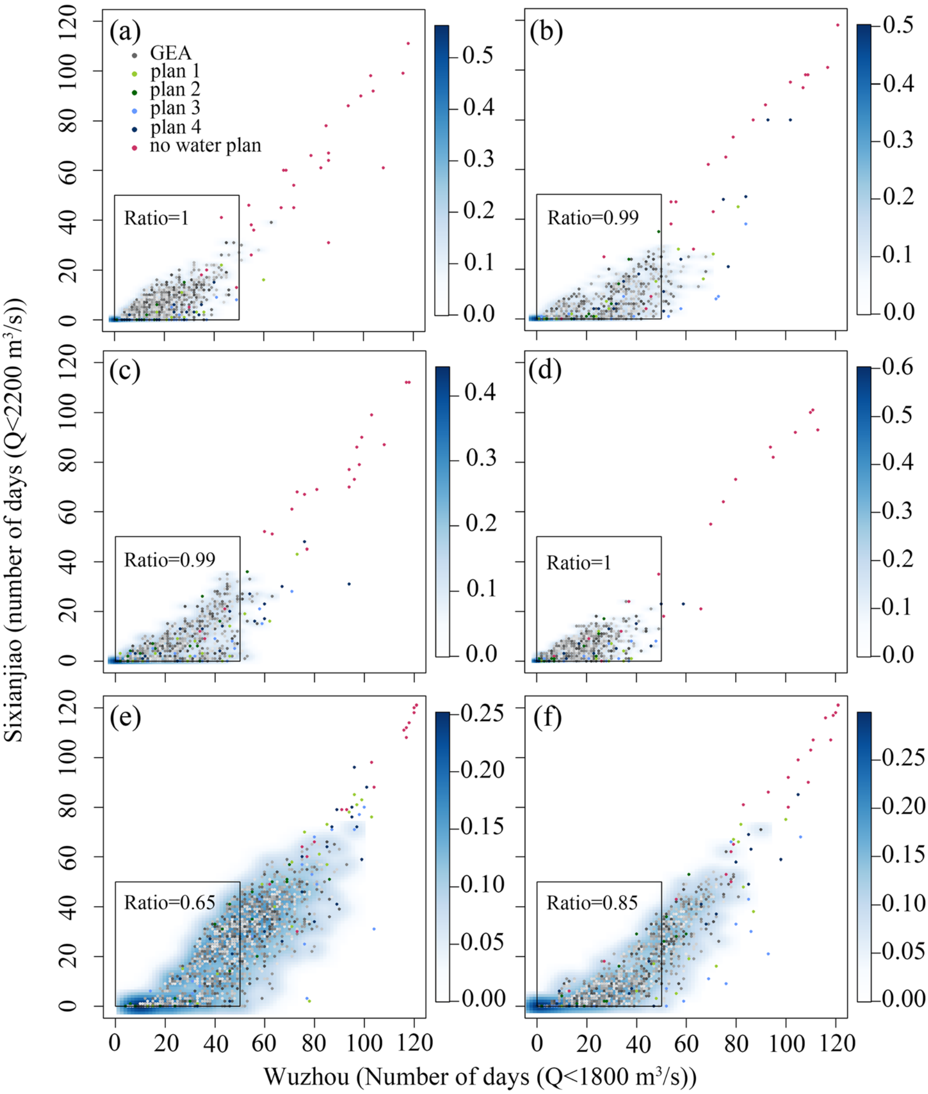

Fig. 6 Robustness assessment of all selected water allocation plans driven by WFDEI (1980–2010) and five selected GCMs under RCP8.5 (2080–2099) **a** WFDEI; **b** CNRM; **c** EC-EARTH; **d** HadGEM; **e** IPSL; **f** MPI (Points in different shades of grey represent results under GEA plans in different years; blue represents the density of points)

4 Discussion

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

Table 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

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.

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 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.

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 10 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.

Acknowledgments The authors would like to thank Ronald Hutjes from Wageningen UR. This work was financially supported by Joint Scientific Thematic Research Programme “Working with Water: adaptive land use and water management in the Pearl River Delta under climate change and sea level rise” (the Netherlands Organisation for Scientific Research), National Natural Science Foundation of China (No. 41330751), External Cooperation Program of Chinese Academy of Sciences (No. GJHZ1019) and China Postdoctoral Science Foundation (No. 2013M540135).

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