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Many-objective robust decision making for water allocation under climate change

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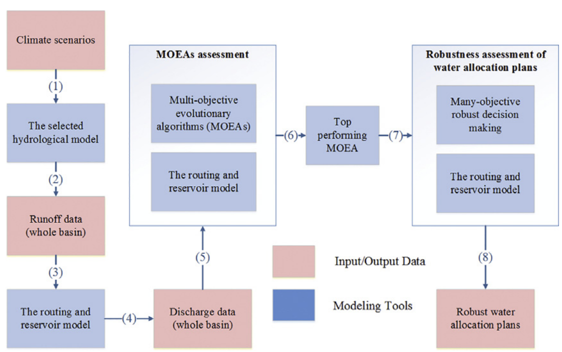
HIGHLIGHTS

- A model framework is developed for identifying robust water allocation plans in large river basins.
- The Borg is the top performing algorithm for water allocation in the Pearl River basin.
- Robust decision making using carefully selected MOEAs can help limit salt intrusion.

GRAPHICAL ABSTRACT



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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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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) (Reed 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 modeling 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 addressed 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., 2006) 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 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 3. Section 4 discusses the performance of the MOEAs and uncertainties existed in the input parameters. Section 5 concludes the paper, including lessons learned from this study and suggestions for future research.

2. Methodology

2.1. Model framework

Fig. 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