Use of many-objective visual analytics to analyze water supply objective tradeoffs with water transfer

Chi Zhang[1] ·Yu Li[2] · Jinggang Chu[3] · Guangtao Fu[4] · Rong Tang[5] Wei Qi[6]

Abstract: The construction of water transfer projects can have a considerable impact on the operation of the receiving reservoir. This study investigates the change of the objective tradeoffs in multi-objective reservoir operation problems due to the introduction of water transfer using a case study of the East-to-West Water Transfer project in northeastern China. Two optimization cases are constructed to analyze the tradeoff changes: a base case with no water transfer which considers four objectives, i.e., minimizing industry water shortage, minimizing agriculture water shortage, minimizing water spillage, and maximizing ecological satisfaction; a future post-construction case which considers an additional objective to minimize the amount of water transferred. Results obtained from the case study show increasing water transfer substantially reduces the intensity of the competition between industrial and agricultural water shortages, and the objective tradeoffs among water spillage, ecological satisfaction and agricultural shortage index are substantially changed because of water transfer. In addition, the amount of water transferred with high efficiency regarding each objective is identified, and three solutions of different orders of magnitude in diverted water have been recommended for informed decision making considering efficiency and

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1 Professor, School of Hydraulic Engineering, Dalian University of Technology, Dalian, Liaoning 116023, PRC; E-mail: czhang@dlut.edu.cn.

2 Senior Lecturer, School of Hydraulic Engineering, Dalian University of Technology, Dalian, Liaoning 116023, PRC (corresponding author); E-mail: dagongliyu@mail.dlut.edu.cn.

3 Associate Professor. School of Hydraulic Engineering, Dalian University of Technology, Dalian, Liaoning 116023, PRC; E-mail: jgchu@mail.dlut.edu.cn.

4 Associate Professor, Center for Water Systems, College of Engineering, Mathematics, and Physical Sciences, University of Exeter, North Park Rd., Exeter EX4 4QF, UK. E-mail: g.fu@exeter.ac.uk.

5 Ph.D. student, School of Hydraulic Engineering, Dalian University of Technology, Dalian, Liaoning 116023, PRC; E-mail: tangrong514@mail.dlut.edu.cn.

6 Ph.D. student, School of Hydraulic Engineering, Dalian University of Technology, Dalian, Liaoning 116023, PRC; E-mail: QiWei_WaterResources@hotmail.com.

benefit. This study implies that many-objective visual analytics can be used to determine the optimal amount of water transferred in terms of water efficiency revealed in different objective tradeoff spaces.

Key words: Many-objective optimization; Objective tradeoffs; Reservoir operation; Visual analytics; Water efficiency; Water transfer

Introduction

Reservoirs play an important role in water resources management to meet various demands such as water supply, hydropower generation and minimum ecological flow (Chang and Chang 2009). With rapid economic development and urbanization, however, water demand has increased substantially and thus outstripped supply in many regions worldwide. To overcome water shortage, many inter-basin water transfer projects across national, regional and local boundaries have been constructed in recent years (Sadegh et al. 2010; Zhu et al. 2014; Bonacci and Andrić 2010). It is suggested that the development of reservoirs and water transfer projects can potentially increase the resilience of water supply and reduce the risk of water shortage (Jain et al. 2007).

The amount of diverted water, which affects the scale of water transfer projects, is determined mainly based on economic measures and water availability (demand). For example, Jain et al. (2005) determined the amount of diverted water according to the demands with desired reliability. Sadegh et al. (2010) allocated inter-basin water resources aiming to achieve the maximum total net benefit. However, the marginal benefit of water transfer usually decreases with an increase of water transferred (Booker and Neill 2006;

Draper and Lund 2004). The efficiency of water transfer, i.e., the ratio of utilized water to the total imported water, has not been considered explicitly in the decision making process.

Many-objective (i.e., greater than three objectives) analysis which allows the consideration of a suite of objectives that represent concerns from different stakeholders has been increasingly used in engineering fields as diverse as water supply risk management (Kasprzyk et al. 2009; Hurford et al. 2014), groundwater monitoring network design (Kollat et al. 2011), water distribution systems optimal design (Fu et al. 2013; Smith et al. 2015). These applications have illustrated that many-objective analysis can yield new design insights and avoid the potentially highly negative consequences that could result from lower dimensional formulations.

Reservoir operation with water transfers usually involve different stakeholders, thus it is typically a complex decision-making problem (Oliveira and Loucks 1997; Watkins and McKinney 1997). Previous studies have investigated reservoir operation problems using Multi-objective Evolutionary algorithms, and analyzed the tradeoffs among different objectives in water supply problems considering water transfer options. For example, Zeff et al. (2014) analyzed objective tradeoffs in developing regional water supply portfolios for four water utilities. However there are few attempts to consider the impacts of water transfer on multi-objective reservoir operation problems. In particular, there is lack of understanding of how the operation of the water transfer scheme (i.e., the amount of water transfer) will affect the water spillage and ecological objectives from the receiving reservoir and how the water transfer scheme and receiving reservoir could be operated jointly to achieve an overall high performance.

This paper aims to analyze the impacts of water transfer on multi-objective tradeoffs in a reservoir operation problem. The East-to-West Water Transfer (EWWT) project, which transfers water from the Huanren Reservoir to the Dahuofang Reservoir in northeastern China, is used as a case study. Two cases are constructed to analyze the tradeoff changes, i.e., the changes in the relationships between objectives under different conditions such as the construction of the water transfer project. The Base Case represents the prior construction situation, in which no water is transferred into the Dahuofang reservoir, and the Future Case represents the post-construction situation, in which water can be transferred from other reservoirs. Visual analytics are used to explore the difference between the Base Case and the Future Case, and provide an understanding of the change of tradeoffs. This study provides new insights on how reservoir operation objectives including water spillage, water shortage and ecological objectives are affected by water transfer.

Case study

The Dahuofang Reservoir is located in the main stream of the Hunhe River, with a drainage area of 5437km^2. It was built with purposes of industrial and domestic water supplies to two cities, Fushun and Shenyang in central Liaoning province and agricultural water supply downstream. The industrial water demand is 5.98×10^8m^3 and the agricultural water demand is 1.64×10^8m^3 in 2005. The water demands are basic data for the Base Case which will be described in the following section. The reservoir characteristics and inflow statistics of 51 years' data from 1956 to 2006 are illustrated in Table 1.

Table 1. Reservoir characteristics and inflow statistics.

Reservoir properties		Inflow statistics	
Dead storage capacity (10^8m^3)	1.34	Annual average (10^8m^3)	14.90
Dry season active storage capacity (10^8m^3)	14.30	Standard deviation(10^8m^3)	7.96
Flood season active storage capacity (10^8m^3)	10.00	Coefficient of variation	0.53
Evaporation and leakage loss (m/year)	0.90	Coefficient of skewness	1.28

With the rapid economic development and urbanization, the industrial and domestic water demands have been increasing over recent years and are projected to continue to increase in the future. According to the Dahuofang Reservoir Water Transfer Planning (Li et al. 2009), a water supply of $24.64\times10^8m^3$ is required in 2030, considering the demands from other five cities, Benxi, Liaoyang, Anshan, Yingkou and Dalian, in addition to the two cities Fushun and Shenyang. A long distance water transfer project, the East-to-West Water Transfer (EWWT) project, has been promoted as a long-term water supply strategy for Liaoning province to meet the increasing water demand. The donor reservoir of EWWT is the Huanren Reservoir, which is located in Hunjiang River basin with a total storage capacity of $34.6\times10^8m^3$. Its average annual inflow is $37.15\times10^8m^3$, which is much higher than the water demands, $8.61\times10^8m^3$, in its own water supply region. Thus the Huanren Reservoir has a sufficient capacity to transfer water to the Dahuofang Reservoir through the EWWT project (shown in Fig. 1). The conveyance capacity of this tunnel is 60 m^3/s and the leakage loss during transfer is 4%, and this means the carrying efficiency of the tunnel is 96%. Whether the water transfer is essential for this area and how much diverted water is recommended are the most concerned problems for decision makers.

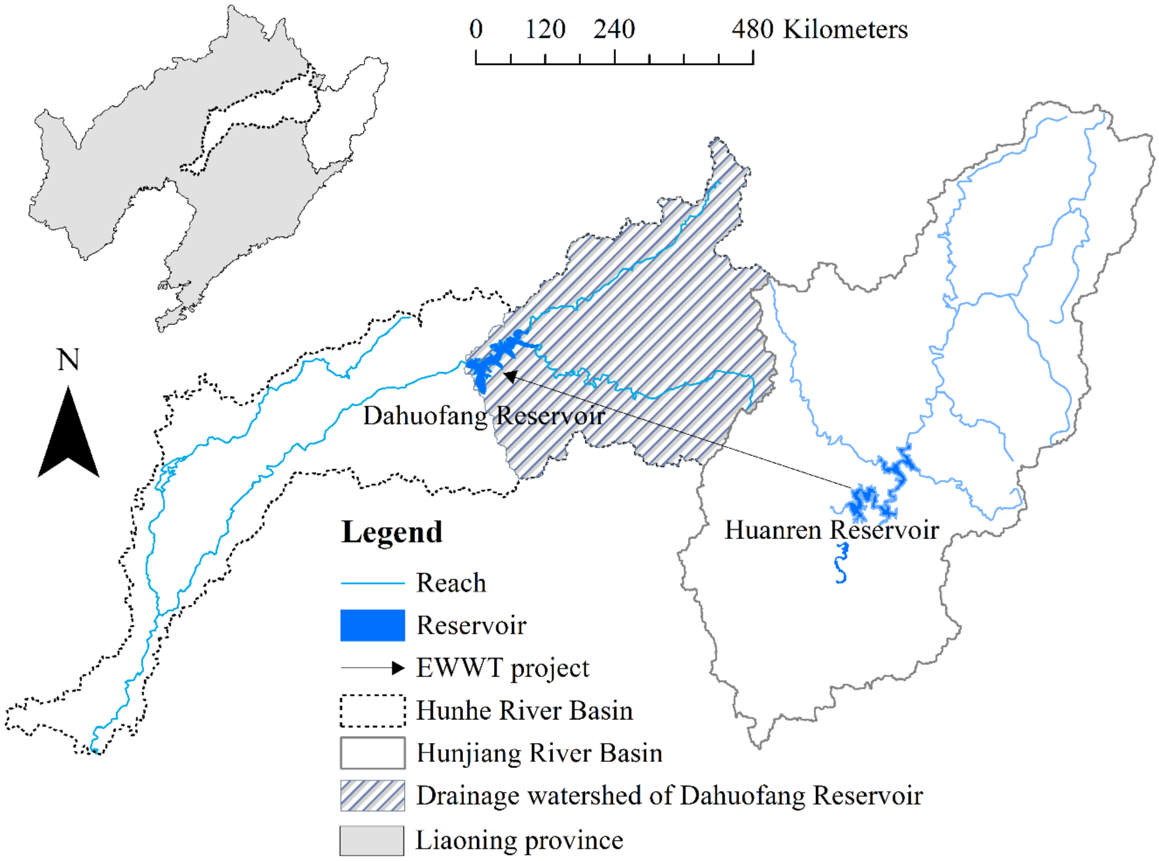

Fig.1 Location and main features of the Dahuofang reservoir and East-to-West Water Transfer project.

Methodology

To provide an insight into the potential planning and operation of the water transfer project, we used a similar Many-Objective Visual Analytics framework proposed by Woodruff et al. (2013) to analyze the Pareto solutions of reservoir optimal operation. We first constructed two optimization cases with and without the water transfer project, Pareto solutions were then obtained with a many-objective optimization algorithm, i.e., ε-NSGAII in this case study, and finally the Pareto solutions of the two cases were visualized with visual analytics to explore the Pareto tradeoff changes brought by water transfer. The framework is illustrated in Fig. 2, and the case set-up, objective functions, constraints, decision variables, optimization algorithm and visual analytics involved are described as follows.

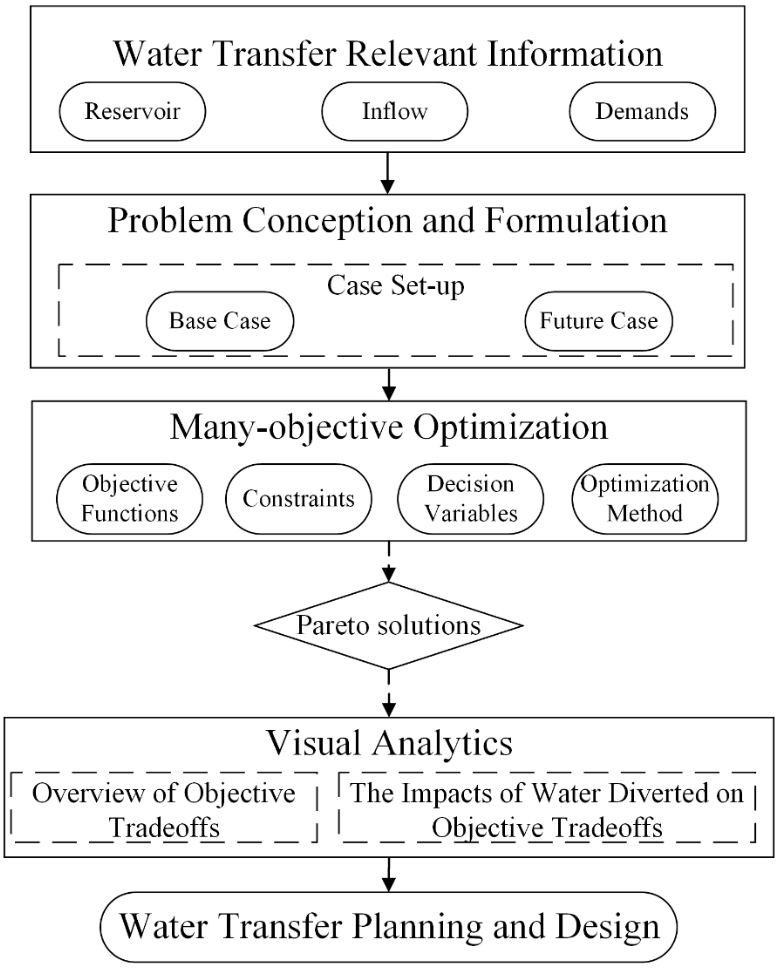

Fig.2 Many-objective visual analytics framework for the water transfer problem.

Case set-up

To evaluate the potential influence of water transfer, two cases with and without water transfer, i.e., the Base Case and the Future Case, are set up. In the Base Case, the Dahuofang Reservoir is the only water source for water supply without water transfer from other reservoir. In the Future Case, EWWT project would have been constructed and water can be transferred from the Huanren Reservoir to the Dahuofang Reservoir for water supply in 2030. The demands vary across the 36 periods in one year. The demand allocation ratios for the 36 periods are provided in the Supplemental Materials.

In the Base Case, the Dahuofang Reservoir is operated according to water supply operation rule curves, established at the planning stage to provide long-term operation guidelines for reservoir managers to meet expected water demand. The reservoir operation rule curve approach is widely applied in reservoir operation for their easy implementation in China (Hsu et al. 2004; Liu et al. 2011; Guo et al. 2013; Li et al. 2015). Although this approach does not directly consider the economic value of each use in the operation process, it does consider the priority of each use with the priority order reduced from the top to the bottom. In this paper, the rule curves for industrial and agricultural water demand shown schematically in Fig. 3(a) are defined according to reservoir storage, that is, the dynamic water storage of reservoir is taken as the single, influential factor for water supply. The active water storage of reservoir is divided into three parts: zone 1, zone 2 and zone 3 by the two water supply rule curves, both of which are used to decide if water demand is satisfied fully or partly with different rationing factors. The industrial water rationing factor, $\alpha 1 = 0.9$, is higher than the agricultural water rationing factor, $\alpha 2 = 0.7$ in this paper. These alpha values are related to the priority order of each water use and thus are fixed for each water use according to water reservoir regulations. When the water storage of reservoir lies in zone 1, industrial water demand D^1 and agricultural water demand D^2 are fully met, i.e., the total amount of water supply is D^1+D^2. When the water storage of reservoir is in zone 2, industrial water demand D^1 is fully met and agricultural water demand D^2 needs to be multiplied by the agricultural rationing factor $\alpha 2$, i.e., the total amount of water supply is D^1+ $\alpha 2$*D^2. When the water storage of reservoir is in zone 3, industrial water demand D^1 and agricultural water demand D^2 needs to be multiplied by the rationing factors, i.e., the amount of water supply is $\alpha 1*D^1+\alpha 2*D^2$. When water availability is smaller than $\alpha 1$*D1+ $\alpha 2$*D2, industrial water demand should be satisfied first, and the surplus water is supplied to agriculture, due to the higher priority on industrial demand.

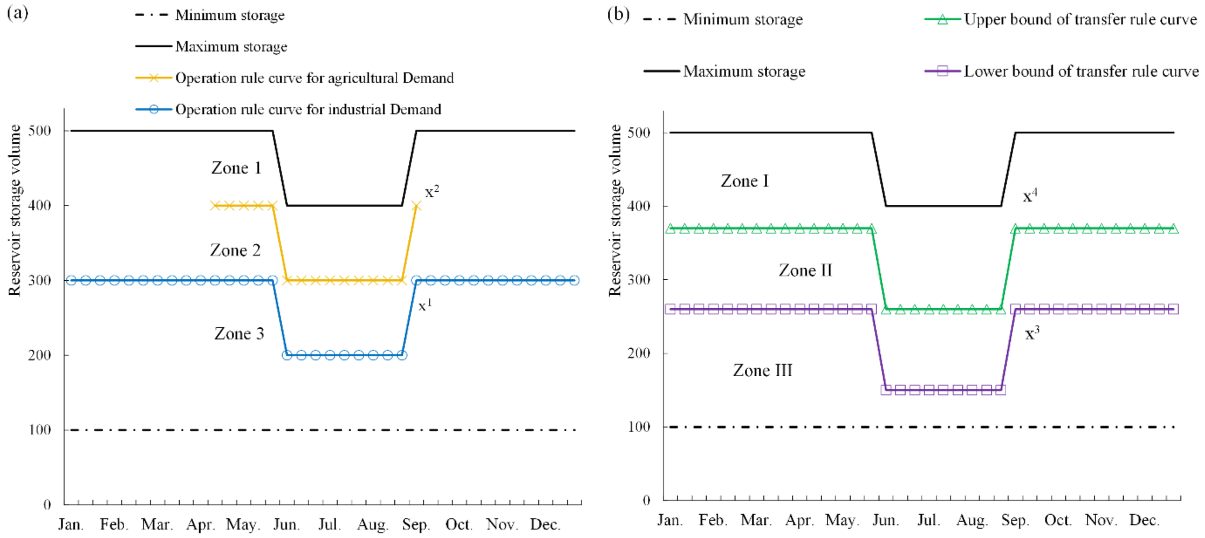

Fig. 3 Reservoir operational rule curves. (a): water supply rule curves, and (b): water transfer rule curves.

In the Future Case, besides the same water supply policy, water transfer is operated according to water transfer rule curves based on reservoir storage. The forms of water transfer rule curves are shown schematically in Fig. 3(b) and one of the real optimal reservoir operation rule curves is shown in Supplemental Materials. The active water storage of reservoir is divided into three parts: zone I, zone II and zone III by upper and lower water-transfer rule curves, as shown in Fig. 3(b). The amount of water transferred depends on where the initial reservoir storage lies at the beginning of a specified operation period: When the water storage of reservoir lies in zone I, no water is transferred. When the water storage of reservoir is in zone III, it diverts water with the diversion capacity of the pipes, that is the water transferred is 60 $m^3/s \times 0.96$ where 60 m^3/s is the conveyance capacity of the water transfer tunnel and 0.96 is the carrying efficiency of the tunnel; when the water storage of reservoir lies in zone II, a rationing factor Θ is applied to determine the amount of transferred water (the transferring amount is $60\times0.96\times\Theta$ m^3/s), and Θ is determined by the water storage of receiving reservoir as:

$$\theta = \frac{Upper_t - S_t}{Upper_t - Lower_t} \tag{1}$$

where $Upper_t$ and $Lower_t$ represent the upper and lower storages of transfer rule curves at study period t; S_t represents water storage of reservoir at study period t.

Objective functions

To analyze the objective tradeoff changes for investigating the impacts of water transfer on water supply, we have to obtain the Pareto solutions of such a many-objective optimization problem. The objectives investigated are minimizing industry water shortage, minimizing agriculture water shortage, minimizing water spillage, maximizing ecological satisfaction, and minimizing the amount of water transferred. There are tradeoffs among these objectives. The limited water available makes it impossible to meet all the demands, i.e., industrial, agricultural and ecological demands at the same time, and so they are in conflict with each other. Reducing the amount of water spillage can increase the amount of water supply. That is, there is a tradeoff between water spillage and total water supply. When considering water transfer, the objective of minimizing the amount of water transferred is obvious to reduce water transfer cost, which is contrary to transferring as much as water to meet all water demands. Thus, the objective of minimizing the amount of water transfer is in conflict with minimizing the water shortages.

The shortage index (SI) proposed by the US Army Corps of Engineer (HEC 1975) represents the lumped water supply shortage and reflects the severity of water shortage, and could be adopted as an indicator to reflect water supply efficiency for water demand (Chang et al. 2005). In this study, industrial and agricultural water demands are considered, and correspondingly, industrial and agricultural shortage indices are used as two separate objectives. The industrial shortage index is defined as:

$$\min INSI = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{D_{1,j}-R_{1,j}(\boldsymbol{x})}{D_{1,j}}\right)^2 \quad (2)$$

where $INSI$ is industrial shortage index, occurred during system operation over N years; $\boldsymbol{x}$ is the decision variable vector of the many-objective optimization model denoting the water-supply rule curves; N is the total number of simulation years; $D_{1,j}$ is the industrial water demand during the jth year; $R_{1,j}(\boldsymbol{x})$ is the industrial water supply during the jth year.

The agricultural shortage index is defined as:

$$\min AGSI = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{D_{2,j}-R_{2,j}(\boldsymbol{x})}{D_{2,j}}\right)^2 \quad (3)$$

where $AGSI$ is agricultural shortage index, occurred during system operation over N years; $D_{2,j}$ is the agricultural water demand during the jth year; $R_{2,j}(\boldsymbol{x})$ is the agricultural water supply during the jth year.

The historical range of variation (RVA) approach (Richter et al. 1998) is used to define the ecological objective (Shiau and Wu 2004; Suen and Eheart 2006), which considers five aspects (indicators), i.e., average monthly flow, 10-day maximum flow during wet season, Julian date of the maximum flow, the number of high pulses and rising rate during wet season. The ecological objective is written as:

$$\max ECOS = \{w_1 \times \mu_{avgf} + w_2 \times \mu_{Max10} + w_3 \times \mu_{DH} + w_4 \times \mu_{HE} + w_5 \times \mu_{RR}\} \quad (4)$$

where $ECOS$ is the ecosystem need fitness function; μ is the satisfaction degree of each ecological indicator and $w_i(i = 1\sim5)$ is the weighting factor ($w_i = 1/5$ in the case study); μ_{avgf} is the satisfaction degree of average monthly flow, μ_{Max10} is the satisfaction degree of 10-day maximum flow during wet season, μ_{DH} is the satisfaction degree of Julian date of the maximum flow, μ_{HE} is the satisfaction degree of the number of high pulses and μ_{RR} is the satisfaction degree of rising rate during wet season. For each ecological indicator, the satisfaction degree is calculated by a Gaussian shape membership (Suen and Eheart 2006; Suen et al. 2009). It assumes that species diversity is best kept when the flow conditions are as close as to the target flows, i.e., with an intermediate frequency of disturbance as opposed to light or heavy disturbance (Connell 1978).

$$\mu_i = e^{\frac{-(h_i - m_i)^2}{2\sigma_i^2}} \quad (5)$$

where μ_i is the satisfaction degree of the ith ecological indicator; h_i is the value of the ith ecological indicator; m_i and σ_i^2 are the mean and variance of the ith ecological indicator original values respectively, which are provided in Supplemental Materials (shown in Table S1).

Reducing water spillage, which potentially increases the amount of water to meet the demand, is a major objective for water supply reservoirs, so water spillage has been widely used in reservoir operation to evaluate reservoir operation performance (Guo et al. 2012). It is defined as:

$$\min WSP = \frac{1}{N}\sum_{j=1}^{N} WSP_j(\boldsymbol{x}) \tag{6}$$

where WSP is water spillage, occurred during system operation over N years; $WSP_j(\boldsymbol{x})$ is the water spillage during the jth year.

Minimizing the amount of water transferred can reduce water transfer cost and environmental impacts on the water source basin, so this indicator is needed in reservoir operation related to water transfer. It is defined as:

$$\min WIM = \frac{1}{N}\sum_{j=1}^{N} WIM_j(\boldsymbol{x}) \tag{7}$$

where WIM is the total amount of water imported, occurred during system operation over N years; $WIM_j(x)$ is the sum of water imported during the jth year.

The Base Case represents the prior construction situation, in which no water is imported into the Dahuofang reservoir. In this case, the reservoir optimization problem is formulated as a four-objective optimization problem that seeks to minimize industrial shortage index, minimize agricultural shortage index, minimize water spillage, and maximize ecological satisfaction. The four objective functions are described in Equations (2), (3), (4), and (6), respectively. The Future Case represents the post-construction situation, in which water is transferred from the Huanren Reservoir to the Dahuofang Reservoir. In this case, the reservoir optimization problem is formulated as a five-objective optimization problem that seeks to minimize industrial shortage index, minimize agriculture shortage index, minimize water spillage, maximize ecological satisfaction and minimize the amount of water transferred. The five objective functions are described using Equations (2), (3), (4), (6) and

(7), respectively.

Constraints

For the reservoir operation system optimization problem, the constraints include:

$$S_{t+1} - S_t = I_t + WIM_t - R_t - WSP_t - E_t \tag{8}$$

$$ST_t^{\min} \le S_t \le ST_t^{\max} \tag{9}$$

$$0 \le WIM_t \le WIM_t^{\max} \tag{10}$$

where S_t is the initial water storage at the beginning of period t; S_{t+1} is the ending water storage at the end of period t; I_t, WIM_t, R_t, WSP_t and E_t are inflow, water imported, water supply, water spillage and evaporation loss, respectively; and $ST_t^{\max}$, $ST_t^{\min}$, $WIM_t^{\max}$are the maximum storage, minimum storage, and maximum water transfer capacity in period *t* respectively.

Decision Variables

In the Base Case, the decision variables are water storage volumes at different time periods on water supply operation rule curves for industrial and agricultural water demands. Each simulation year is divided into 36 time periods (with ten days as a time period). On the operation rule curve of industrial water demand there are 36 decision variables, one for each time period from January to December. On the operation rule curve of agricultural water demand, there are 15 decision variables from the second 10 days of April to the first 10 days of September as there are no crops and no agricultural water demand with the low temperature of the study area except during these time. Therefore, there are 51 decision variables in total. In the Future case, there are 72 water storage volumes at different time periods on water transfer rule curves to be decision variables in addition to the 51 decision variables on water supply operation rule curves. Therefore, there are 123 decision variables in total. A table of decision variables are shown in Supplemental Materials.

Optimization Method

Evolutionary algorithms have emerged as a widely-used method for solving problems in complex engineering systems characterized by conflicting objectives (Wu et al. 2010; Nicklow et al. 2010; Bozorg-Haddad et al. 2016). On the basis of the concept of Pareto-based selection, between 1993 and 2003, several first-generation MOEAs were developed considering different techniques such as elitism, diversity maintenance, and external archiving, including SPEA (Zitzler and Thiele 2000), PESA (Corne et al. 2000) and PAES (Knowles and Corne 2000). In the following years, second generation MOEAs were proposed with strategies such as ε-dominance, invariant operators, aggregate functions and auto-adaptive operators including IBEA (Zitzler and Künzli 2004), ε-MOEA (Deb et al. 2002), ε-NSGAII (Kollat and Reed 2006), GDE3 (Kukkonen and Lampinen 2005), MOEA/D (Zhang et al. 2009) and Borg MOEA (Hadka and Reed 2012a). Among these MOEAs, ε-NSGAII has been proved efficient, reliable, and easy-to-use for water resources applications (Kollat and Reed 2006; Kasprzyk et al. 2009; Hadka and Reed 2012b), and it was selected in this study. A flow chart of this algorithm and more detail can be found in the previous studies (Kollat and Reed 2006; Reed and Minsker 2004) .The ε-NSGAII's parameter values used in this study are shown in Table 2. ε plays a key role in ε-NSGAII and preliminary analysis sensitivity analysis on ε is shown in Supplemental Materials. Other parameters settings are based on previous studies' recommendations (Reed and Minsker 2004). Ten random seed runs are used because of the random nature of genetic algorithms. For each random seed, one million model evaluations are carried out as beyond one million evaluations there is little improvement in the Pareto approximate sets attained. The Pareto approximate set analyzed is generated across all ten random seed optimization runs.

Table 2. Parameter values of the ε-NSGAII algorithm

Symbol	Value	Description
$n_{initial}$	12	Initial population size
$n_{generation}$	250	The maximum number of generation in each run
$n_{maximum}$	1 million	The maximum number of model simulations
p_c	1.0	Probability of crossover
p_m	1/n	Probability of mutation, n is the number of decision variables
η_m	20	Distribution index for mutation
η_c	15	Distribution index for crossover
ε	$3 \times 10^4 m^3$	Objective precision: industry water shortage
	$3 \times 10^4 m^3$	Objective precision: agriculture water shortage
	$5 \times 10^4 m^3$	Objective precision: water imported
	$5 \times 10^4 m^3$	Objective precision: water spillage
	0.01	Objective precision: ecological satisfaction

Visual Analytics

This paper used a visualization software, DecisionVis (https://www.decisionvis.com/discover-ydv/), which is a fully interactive, multi-dimensional data visualization and analysis tool that allows for visual exploration of the relationships between different objectives using Pareto optimal solutions obtained. This tool is capable of taking extremely complex spaces of design possibilities and translating them into meaningful visual representations (Kollat and Reed 2007; Kasprzyk et al. 2009; Kollat et al. 2011). It can handle many objectives explicitly, show the changing trend of each objective, keenly identify inflection points, and help to understand where performance tradeoffs exist, their severity, and their shape. Seeking to understand these relationships provides a more informed and data driven approach to decision making, which are unimaginable in traditional decision-making analytical methods.

To use DecisionVis, the Pareto solutions obtained by the optimization runs need to be imported according to DecisionVis data format, and the axes can be changed to show different multi-dimensional display as needed. Besides, the functionalities, such as doing Pareto Sorting to identify tradeoffs between objectives, marking points interactively in the plot window, brushing data to filter out portions of the data to concentrate on important data make the tool easy to interact with the user.

Results and discussion

The purpose of this section is to analyze the differences in objective tradeoffs between the Base Case and the Future Case, explore the changes caused by water transfer, and then determine the amount of water transferred in terms of the efficiency of the other objectives.

Overview of objective tradeoffs

Fig. 4 shows the Pareto approximate sets of solutions from the Base Case and the Future Case, which represent the best approximation to the true Pareto-optimal set from a total of ten million model simulations. In Fig. 4: x, y and z axis represent the value of AGSI, INSI, and WSP, respectively. The color of the cones represents the value of ecological satisfaction from

0.49 to 0.86: the blue and red cones represent high and low ecological satisfaction. The sizes of the cones represent the value of WIM, which ranges from $7.94\times10^8m^3$ to $16.38\times10^8m^3$; the arrows represent the optimization direction of corresponding objectives. As ecological satisfaction objective is the maximization objective and the others are the minimization objectives, an ideal solution would be located towards the rear lower corner (low industrial water shortage, low agricultural water shortage, and low water spillage) of the plot and represented by a small (low water imported), blue (high ecological satisfaction) cone.

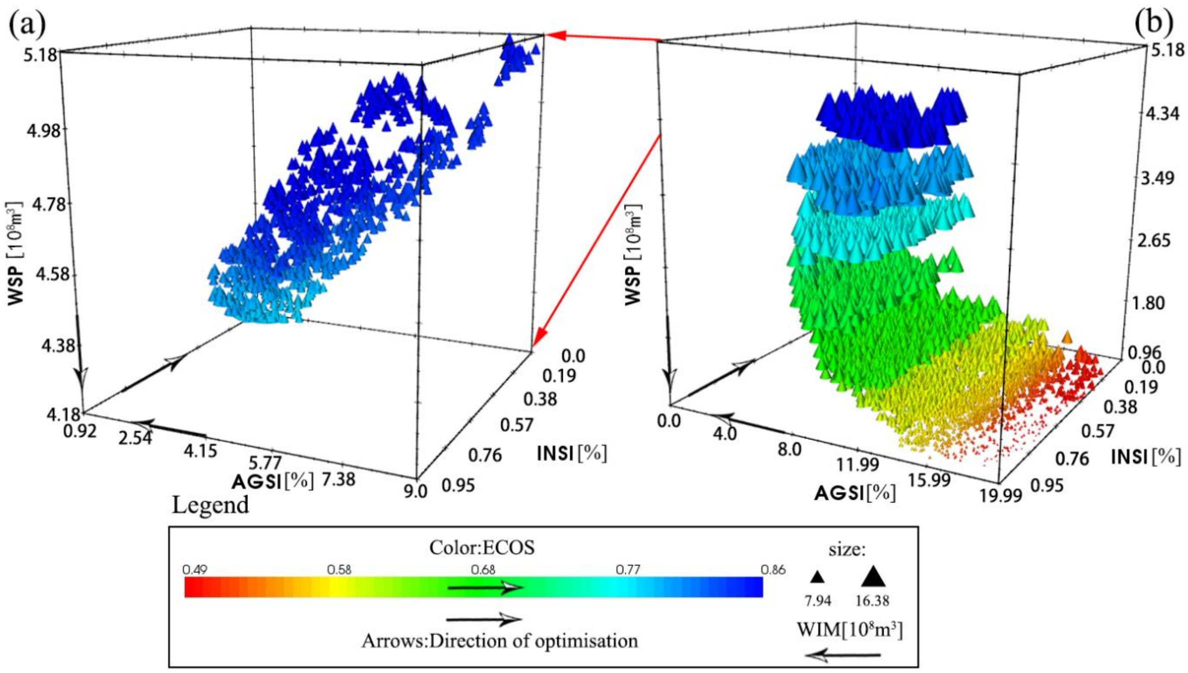

Fig. 4 Approximate Pareto sets of the Base and Future cases. (a) the Base Case with four objectives [industrial water shortage index (INSI), agricultural water shortage index (AGSI), water spillage (WSP) and ecological satisfaction (ECOS)], and (b) the Future Case with five objectives [the 5th objective is water transferred (WIM)].

There are 1215 Pareto solutions in the Base Case and 4942 solutions in the Future Case. As shown in Fig. 4: WSP in the Base Case varies in the range of $4.18\times10^8m^3$ to $5.18\times$

$10^8 m^3$, which is the higher part of the range in the Future Case, i.e., $0m^3$ to $5.18\times10^8m^3$; the range of ECOS(> 0.75) in the Base Case is the higher part of that in the Future Case; the ranges of AGSI in the Base Case is the lower part of that in the Future case. The wider ranges of WSP, ECOS, AGSI in the Future Case means more intense competition of different water users. The massive increase of water demand means that it cannot be met with an acceptable level of reliability without water transfer in the Future Case. The water supply stress in the future could be higher when the amount of water transfer is less than a certain quantity.

As can be seen from Fig. 4(a) and Fig. 4(b), there are some complex relationships between the objectives: (1) WSP has a positive relationship with ECOS (positive relationship, i.e., the former increases with the increase of the later) in the Base Case and the Future Case, because higher ECOS means more water for downriver, and this results in more water spilled to the downstream river; (2) ECOS has a positive relationship with AGSI in the Base Case with the fixed water resources but a negative relationship, i.e., increasing ECOS can be achieved with decreasing AGSI because of an increasing amount of water transferred in the Future Case; (3) INSI has no obvious relationship with ECOS and WSP as solutions with a wide range of ECOS and WSP can achieve the same INSI objective values in both cases; (4) WSP has a positive relationship with WIM in the Future Case. In conclusion, in the Base Case, solutions features that the higher ECOS is, the higher AGSI and WSP are, due to the fixed water resources. In the Future Case, with an increasing amount of water transferred, higher ECOS and WSP can be achieved with lower AGSI. In Fig4. (b), it is clearly shown that the sizes of the cones which represent the amount of water transferred (WIM) gradually become larger with decreasing AGSI. To increase water supply for the massive water demands in the future, it has to increase the water amount transferred (i.e., higher WIM) by lifting the position of points on water transfer rule curves. An unintended impact, thus, is the increased water spillage during water sufficient years. Meanwhile higher WIM suggests more water resources for supply, and further suggests more water for industrial, agricultural and ecological water demands (lower AGSI). The tradeoff relationships among the objectives, WSP, ECOS and AGSI, change from the pre-EWWT case to the post-EWWT case.

The impacts of WIM on objective tradeoffs

The Pareto approximate set obtained from the four-objective problem and five-objective problem contain all of the solutions for the sub-problems, i.e., four-objective optimization problems, three-objective optimization problems, two-objective problems, and single-objective problems. This allows the analysis of the solution sets from lower-dimensional problem definitions with the results from the full many-objective optimization; thus some lower dimensional tradeoffs are selected below to highlight the tradeoff changes with the variation of WIM values.

The tradeoff between INSI and AGSI

Fig. 5 shows the tradeoffs in the objective space of industrial water shortage index and agricultural water shortage index; the solutions in the Base Case are shown in Fig 5(a) and the Future Case is in Fig. 5(b). A tradeoff curve between INSI and AGSI can be observed in the Base Case without water transfer in Fig. 5(a), and shows tradeoffs between the two objectives (highlighted with red squares). This illustrated the relationship between industrial water demand and agriculture water demand is competitive with fixed water resources, i.e., the increase in water supply for industrial water inevitably leads to the reduction of agricultural water supply.

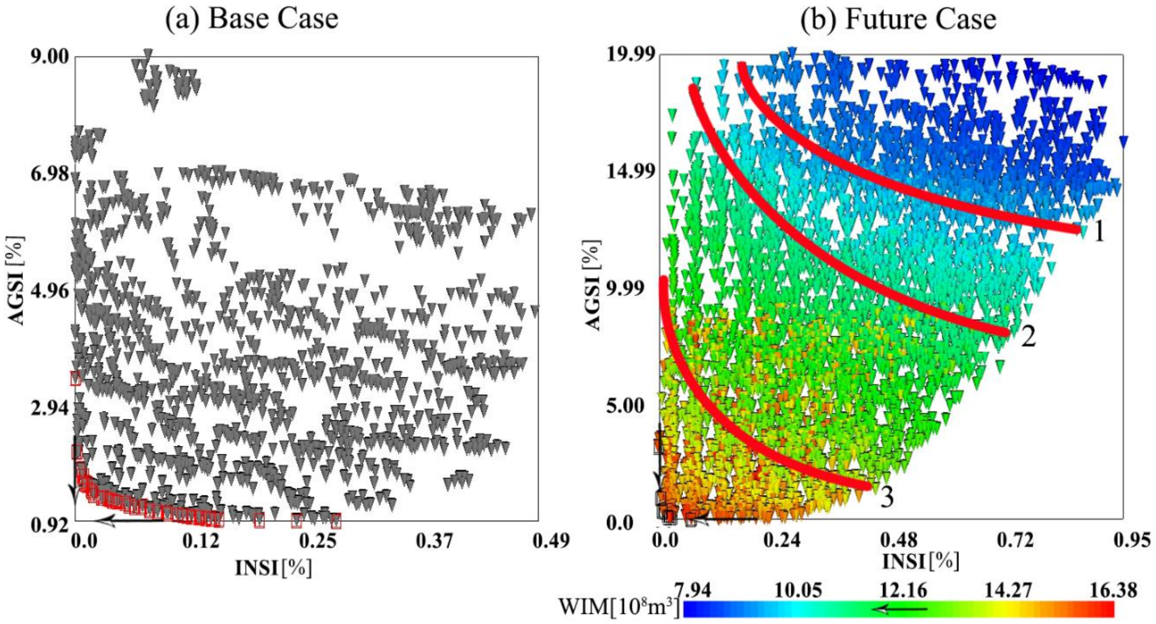

Fig. 5 The tradeoffs in the objective space of industrial water shortage index and agricultural water shortage index with the Pareto approximate solutions highlighted with squares.

In Fig. 5(b), the colors of cones represent the variation of WIM objective values. The blue represents less water transferred and the red represents more water transferred, and their color varies from blue in the upper right where the solutions have larger INSI and AGSI to red in the lower left where the solutions have smaller INSI and AGSI. When WIM is lower than $9.0 \times 10^8 \mathrm{m}^3$, there is an obvious tradeoff curve between INSI and AGSI, which is marked with red curve No. 1. When WIM is limited to $11.0 \times 10^8 \mathrm{m}^3$ and $13.0 \times 10^8 \mathrm{m}^3$, obvious tradeoff curves also exist, which are marked with red curves No. 2 and No. 3, respectively. When the WIM objective is larger than $14.0 \times 10^8 \mathrm{m}^3$ (the color of cones becomes yellow and red), there is no obvious tradeoff curve between these two objectives.

The first red curve has the widest range in the lower tail which means that INSI is most sensitive to the variation of AGSI, that is, a small increase in AGSI could lead to a significant reduction in INSI. The third curve, on the contrary, has a wide range in AGSI. The second curve is reasonably balance across the two objectives. These revealed that with increment of water transferred, the competition between INSI and AGSI objectives becomes less intense.

The tradeoff between AGSI and WSP

Fig. 6 shows the tradeoffs in the objective space of AGSI and WSP with the Pareto approximate solutions highlighted with squares. Similarly, the solutions in the Base Case are shown in Fig. 6(a), and the Future Case is in Fig. 6(b). There is a narrow tradeoff curve between these two objectives in the Base Case, and the Pareto approximate solutions are distributed in the region that AGSI and WSP are relatively small. For most of the solutions, the two objectives present a positively correlated relationship, that is, water spillage increases with increasing AGSI. Due to the competition between industrial and agricultural water demand, with the increase of AGSI, industrial water shortage index decreases which leads to the decrease of WSP. However, when AGSI keeps increasing, the water has to be abandoned to improve the ECOS, resulting in an increase in water spillage.

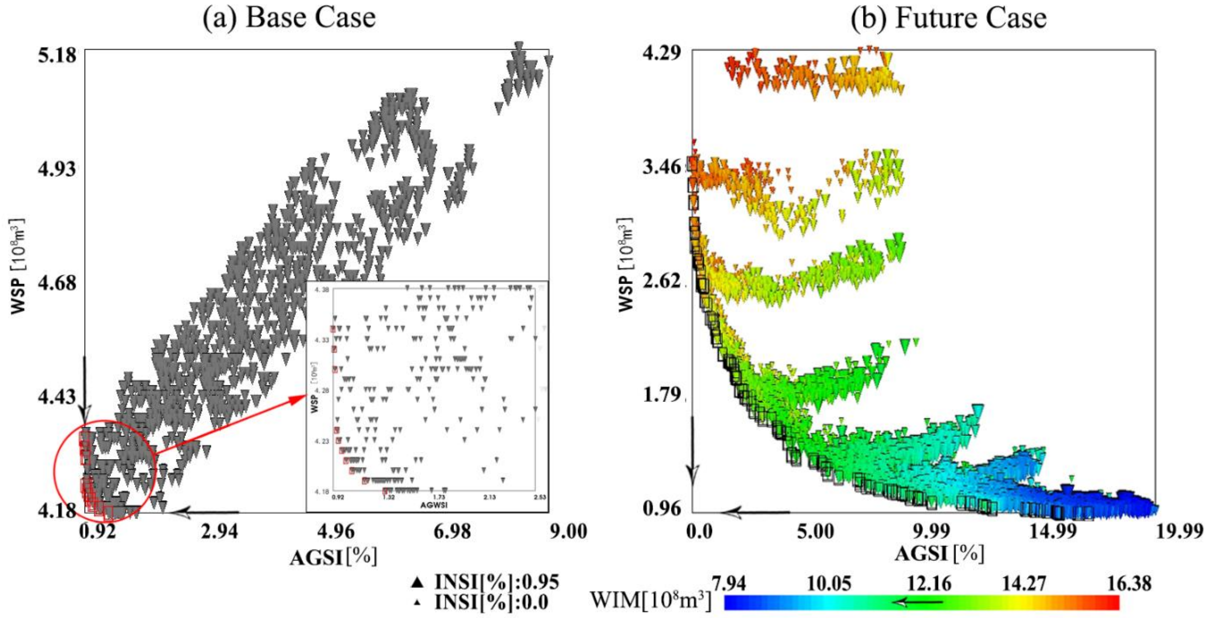

Fig. 6 The tradeoffs in the objective space of agricultural water shortage index and water spillage with the Pareto approximate solutions highlighted with squares.

Fig. 6(b) shows that there is a clear and wide tradeoff curve between AGSI and WSP in the Future Case, which distributes almost in all ranges of these two objectives. And when the water transferred is the same, i.e., the color of the cones are the same, AGSI and WSP have a positively correlated relationship and the objective values when optimization between them are tradeoffs. This is the same as it in the Base Case. Moreover, it is obvious that when water transferred is less than 11×10^8m^3, the amount of water spillage is stable because most of water is used for water supply with less water transferred. This illustrated the highest water imported utilization efficiency considering water spillage.

The relationship between the WIM and other objectives

This section aims to determine the optimal amount of water transferred based on the tradeoffs among the objectives. The impacts of imported water on different demands are very different, so each demand corresponds to an efficient amount of diverted water, which will be explicitly explored for decision-making. Interactive visual analytics helps decision makers to understand where performance tradeoffs exist, their severity and shape, especially the inflection points on the tradeoff curves, after which the trends and characteristics are changed. Thus, a visualization analysis software, DecisionVis, is used to identify critical points, of which the slope changes obviously. These points have diminishing return, beyond which it becomes too costly to obtain extra benefits. These key points can represent the critical solutions considering two-objective tradeoffs and could be the most concerned points for decision makers. We quantify the amount of water transferred in these points.

In Fig. 7(a), a clear tradeoff curve between imported water and industrial water shortage index can be observed and the approximate Pareto front is highlighted with black squares. It shows as water transferred increases, the industrial water shortage index decreases (benefit). In addition, the cones are shown in colors to represent the ecological satisfaction objective. Note that the cones in the Pareto approximate front have very different colors varying from red to light blue, representing a significant variation in the ECOS objective. Considering the tradeoff between the two objectives, we chose the point marked with S1, beyond which slope almost does not decrease. This means beyond S1 it is too costly to further decrease the industrial water shortage index, that is, too much diverted water is needed to diminish industrial water shortage index. Then, S1 has an amount of diverted water of $11.0\times10^8 m^3$.

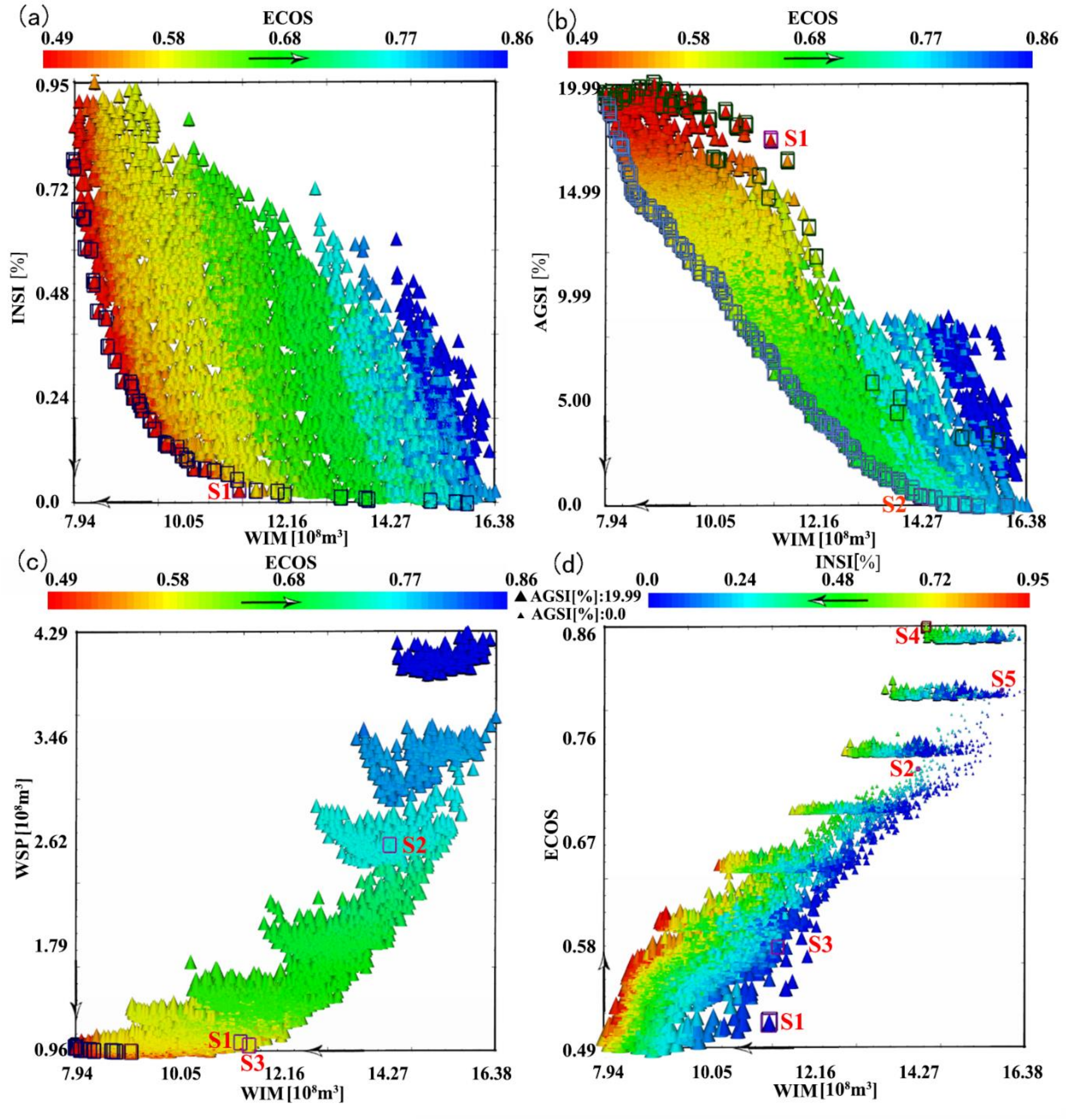

Fig. 7 The tradeoffs in the objective space of water transferred and each other objective: (a) water transferred versus industrial water shortage index; (b) water transferred versus agricultural water shortage index; (c) water transferred versus water spillage; (d) water transferred versus ecological satisfaction.

Fig. 7(b) shows the tradeoff in the objective space of water transferred and agricultural water shortage index with the Pareto approximate solutions highlighted with light blue squares. The Pareto approximate solutions for the WIM-INSI sub-problem highlighted in Fig. 7(a) are also shown in Fig. 7(b) (highlighted with black squares). Most of these solutions are not non-dominated in the space of imported water and agricultural water shortage index. The two objectives are correlated and they have a similar tradeoff relationship with water imported, as revealed by Fig. 7(a) and Fig. 7(b). Similarly, we chose a point marked with S2, beyond which slope almost does not decrease, that is, too much diverted water is needed to diminish agricultural water shortage index. The marked point which is the highest point on the efficiency of water transfer for AGSI shows the amount of diverted water should be set to around $14.0 \times 10^8 m^3$, higher than $11.0 \times 10^8 m^3$ quantified based on the WIM-AGSI tradeoff curve. The cause of higher water diverted is that industry water demand is more urgent than agricultural water demand on reservoir operation, and water would be supplied for the industry water demand primarily. Thus, more water transferred is needed for reducing INSI firstly and then AGSI, which also can indicate the differences among the three red curves in Fig. 5(b).

Fig. 7(c) shows the tradeoff in the objective space of imported water and water spillage with the Pareto approximate solutions highlighted with black squares. In general, the two objectives have a positive relationship, that is, an increase in imported water leads to an increase with water spillage. Specially, we choose a point marked with S3, where the slope begins to increase markedly. Beyond this point, a little increment of water diverted leads to a large amount of water spillage. The value of WIM in the critical point is $11.0 \times 10^8 m^3$ for the highest water imported utilization efficiency considering WSP. When WIM is more than this value, water is transferred even during water sufficient periods not for supply but water spillage. Thus, the amount of diverted water should be set to around $11.0\times10^8m^3$.

Fig. 7(d) shows the tradeoff in the objective space of imported water and ecological satisfaction. Point S4, chosen from the end of the WIM-ECOS tradeoff curve is the points with largest slope, which means when diverted water brings about the maximum increment of ecological satisfaction and the values of WIM are $14.0 \times 10^8m^3$. In addition, S5 with the most water transferred which represented by a small, blue cone with high ECOS objective features a best balance on other objectives, that is, low agricultural water shortage, low industrial water shortage and high ecological satisfaction. This point is also a most concerned point and the amount of water transferred reaches up to $16.0\times10^8m^3$.

Based on the analysis above, three solutions of different orders of magnitude in diverted water can be identified regarding high efficiency of each objective. The optimized, efficient amount of water transfer is 11.0×10^8 m^3 for industrial water shortage and water spillage, that is, there are little decrease in industrial water shortage and exponential increase in water spillage with further increase of water imported beyond this point. If the decision maker seeks to improve the performance of each objective regardless of the cost and impacts on the source reservoir, the amount of water transfer can be set at $16.0\times10^8m^3$. In this case, low industrial and agricultural water shortages and high ecological satisfaction can be obtained, however, the value of water spillage is very high. This suggests that if the decision maker seeks to obtain a higher benefit of water supply, it might lead to lowering efficiency in imported water utilization. If the decision maker seeks to obtain a balance between a high benefit of water supply and the cost, the amount of water transfer should be set at 14.0×$10^8$$m^3$. In this case, the decision maker can obtain low industrial and agricultural water shortages or high ecological satisfaction with appropriately reducing industrial and agricultural water supply through proper operations of water discharge, which suggests the ECOS is affected by both water imported and reservoir operation.

Conclusions

This paper has analyzed the objective tradeoff changes to reveal the impacts of water transfers on reservoir operation. Based on this, we provided an approach to determine the optimal amount of diverted water with different water uses. This could provide more informed decision making on the water transfer project. This approach was demonstrated using the Dahuofang Reservoir and the EWWT project as a case study. Two optimization cases were constructed to analyze the changes. The Base Case with no water imported into reservoir was formulated as a four-objective optimization problem that seeks to minimize industry and agriculture water shortages, minimize water spillage, and maximize ecological satisfaction. The Future Case represents the post-construction situation, in which water is imported, and an additional objective was used to minimize the amount of water transferred.

The results obtained demonstrate that the construction of the water transfer project has led to the change of the tradeoffs between water supply objectives. It is shown that increasing water transferred dramatically reduces the intensity of the competition between industrial and agricultural water shortages, and changes the tradeoff relationships among the objectives, water spillage, ecological satisfaction and agricultural shortage index.

The impacts of water transferred on each water supply are explored through the use of visual analytics, and the amount of water imported with high efficiency regarding each objective can be identified. Three solutions of orders of magnitude in diverted water have been selected for informed decision making, the solution with low diverted water pursues the efficiency of water diversion, the solution with high diverted water seeks to maximize the benefit of water diversion in water supply of receiving reservoir, and the solution with medium diverted water aims to achieve the best balance between efficiency and benefit.

The many-objective visual analytics approach provides a powerful tool for analyzing the tradeoffs between water use objectives considered, and it can be used to support planning and design in the water transfer project. Thus, this approach is suggested as one way forward to address the challenges in the context of the optimal operation of water transfer projects, particularly in revealing and balancing the tradeoffs between various design objectives. However, the EWWT scheme and the Dahuofang reservoir represent a simple example and it cannot fully represent the complexity of the real world water transfer projects. Future work will investigate how water transfer is affected by future demand uncertainty, different operation policies, and different problem formulations considering more or different objectives. Besides, the many-objective visual analytics approach can be further improved from the following two aspects. First, it is computationally expensive especially for complex, cascaded reservoir systems and parallel computing techniques could be incorporated into multi-objective evolutionary algorithms such as Borg (Hadka and Reed 2012a, 2012b; Woodruff et al. 2013). Second, though the visual analytics can visually represent the Pareto solutions and their spatial relationships, it is challenging to identify high performing solutions from a rather large set of Pareto optimal solutions through an interactive process while balancing the trade-offs between different objectives and the decision maker’s preferences could be better captured for solution screening.

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Figure captions

Supplemental Materials

Sensitivity analysis of parameters values used in the optimization model

Fig. S1 shows the Pareto optimal solutions from different ε values of 0.03, 0.02, 0.01 and 0.005. The results indicate that the number of the Pareto solutions increases and the optimal solution space becomes larger with the value of ε decreasing. The impact of ε values on the number and distribution of the Pareto approximate solutions is reduced significantly when ε is less than 0.01. Thus we chose 0.01 as the value of ε in this study.

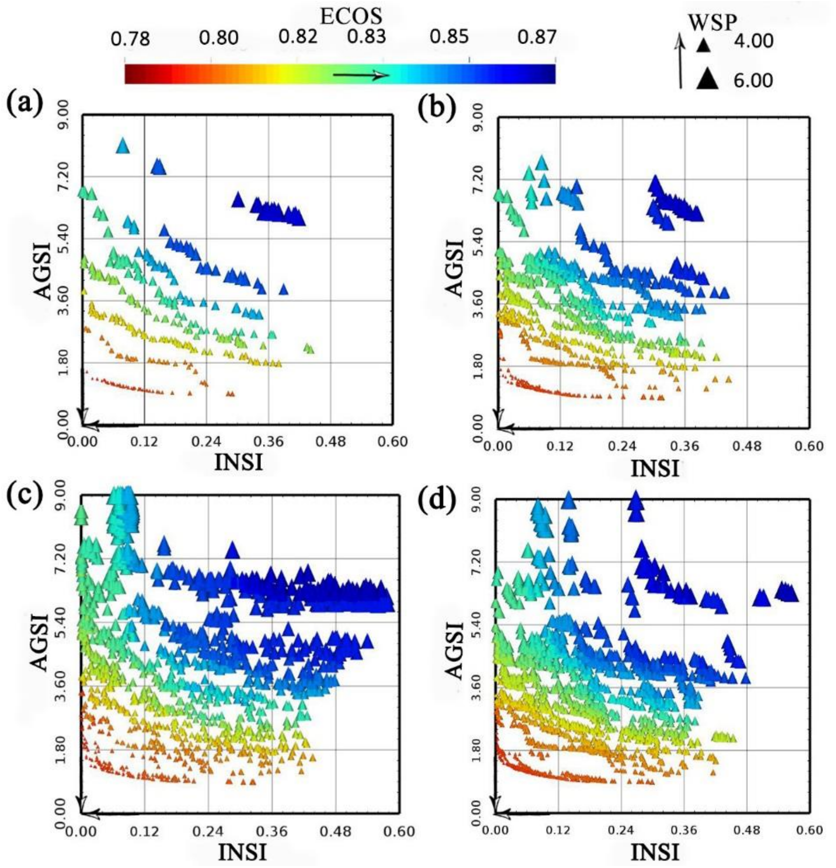

Fig. S1 Pareto optimal solution sets from different ε values: (a) ε=0.03; (b) ε=0.02; (c) ε=0.01; (d) ε=0.005.

Statistics of ecological indicators

Table S1. Mean and variance of ecological indicators.

Ecological indicators	Mean	Variance
Average monthly flow ($10^8 m^3$)	1.24	0.43
10-day maximum flow during wet season ($10^8 m^3$)	3.19	8.74
Julian date of the maximum flow	20.53	8.35
Number of high pulses	2.00	1.21
Rising rate during wet season ($10^8 m^3$/day)	0.31	0.06

Decision variables

The decision variables are shown in Table S2:

Table S2. Decision variables.

Decision variables	Base Case	Future Case
Reservoir storage volume(m^3)：operation rule curve for industrial water demand	$x_i^1, i = 1, 2, \ldots, 36$	$x_i^1, i = 1, 2, \ldots, 36$
Reservoir storage volume(m^3)：operation rule curve for agricultural water demand	$x_i^2, i = 12, 13, \ldots, 26$	$x_i^2, i = 12, 13, \ldots, 26$
Reservoir storage volume(m^3)：lower water-transfer rule curve	-	$x_i^3, i = 1, 2, \ldots, 36$
Reservoir storage volume(m^3)：upper water-transfer rule curve	-	$x_i^4, i = 1, 2, \ldots, 36$

Remarks: *i* represents time periods of operation. Each simulation year is divided into 36 time periods (with ten days as a time period). Each of three rule curves, operation rule curve for industrial water demand, lower water-transfer rule curve, and upper water-transfer rule curve consists of 36 decision variables (from January to December), and the operation rule curve for agricultural water demand consists of 15 decision variables (from the second 10 days of April to the first 10 days of September).

Water demands dispatching ratios

Table S3. Water demands dispatching ratios

Periods	Ratio
1	0.022
2	0.022
3	0.024
4	0.022
5	0.022
6	0.017
7	0.022
8	0.022
9	0.024
10	0.022
11	0.023

Periods	Ratio
12	0.025
13	0.029
14	0.049
15	0.061
16	0.043
17	0.040
18	0.040
19	0.022
20	0.032
21	0.042
22	0.037
23	0.038
24	0.032
25	0.030
26	0.022
27	0.022
28	0.022
29	0.022
30	0.024
31	0.022
32	0.022
33	0.022
34	0.022
35	0.022
36	0.024

Pareto solutions of Future Case

The Pareto solutions of the Future Case can be seen in supplemental text named Pareto solutions.txt. To make the optimal reservoir operation rule curves easy to be understood, we chose one Pareto solution from the numerous solutions in the Future Case, shown in Figure S2. The figure shows: (1) the operation rule curves are as flat as possible for practical operability; (2) the points of reservoir operation rule curves are lower in wet periods to restrict diversion and increase water supply as much as possible while higher in dry periods for reasonability; (3) the points of operation rule curves for agricultural demand are higher than that for industrial demand own to lower priority.

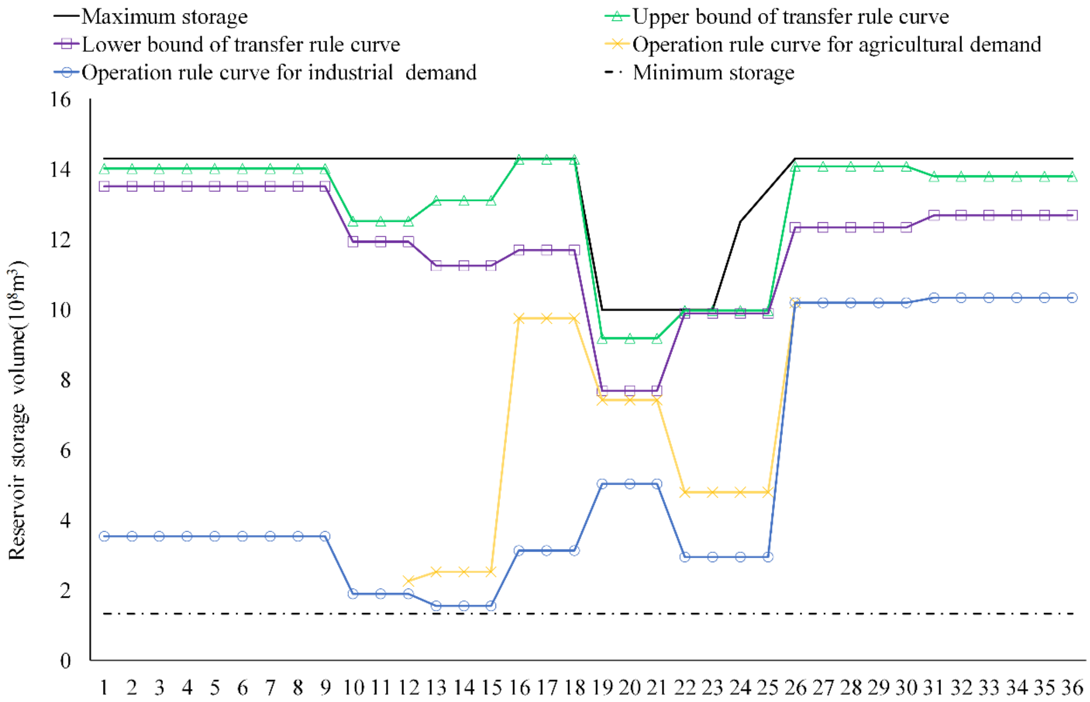

Fig.S2 One of optimal reservoir operation rule curves in the Future Case.

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