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Sustainable urban water resources management considering life-cycle environmental impacts of water utilization under uncertainty

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ABSTRACT

To improve applicability of life cycle assessment (LCA) in supporting direct and robust decision-making, an integrated approach was developed through incorporating operational research and uncertainty analysis methods within a general LCA framework. The methodology can (a) help comprehensive evaluation of environmental impacts at multiple product-service levels, (b) facilitate the reflections of multiple LCA associated uncertainties and transfer them into consequential decision-making process, and (c) identify desired water allocation schemes for minimizing life-cycle environmental impacts. This represented an improvement upon conventional LCA method, as well as water resources allocation. The developed method was then verified in a water-stressed city (i.e., the City of Dalian), northeastern China. The application indicated that the proposed method was effective in generating desired water supply schemes under uncertainties, reflecting the associated life-cycle environmental impacts, and strengthening capabilities of both LCA and operational research methods. The results also indicated that the top three contributors for life-cycle environmental impacts would be districts of Pulandian and Zhuanghe, and Municipal zone of the city.

1. Introduction

Freshwater is fundamental for maintaining environmental sustainability of human communities. Recently, water demand by municipal, industrial, and agricultural users is continuously increasing across the world due to economic expansion and population explosion. Thus, it is a challenging issue within a water allocation system (WAS) to effectively utilize water resources for satisfying multiple targets without causing too much environmental stress for natural water bodies and the related ecosystems (Ni et al., 2014; Zhang et al., 2014b). Potential conflicts can then arise from increasing demand for limited water resources (Zhang et al., 2014b). Particularly, in many cities across the world, high reliance on freshwater and rapid population growth has resulted in severe water tension in urban water allocation systems (UWAS) (Mankad, 2012). However, many processes and factors need to be comprehensively considered within a UWAS, such as water supply options, water source protection measures, infrastructure capital and operational costs as well as interactions within water-energy nexus systems (Loubet et al., 2014; Xu et al., 2012). The systems which consume intensive energy constantly cause many environmental impacts (Behzadian and Kapelan, 2015). These processes and factors are simultaneously fraught with a variety of uncertainties (e.g., uncertain impacts of water withdraw upon the environment, vague judgments of managers upon water price, and the stochastic distribution of precipitation that is closely related to water availability). This leads to multi-level complexities for relevant decision-making and is posing a major challenge to decision makers. Effective methods are thus desired for helping facilitate impact assessment and decision making of water related activities within UWAS (Le Bars and Le Grusse, 2008).

Conventionally, many system analysis methods were developed for supporting urban water resources management, such as life cycle analysis (LCA), operational research, and system dynamics (SD) modeling. Among them, LCA was widely used to evaluate water footprints (Gu et al., 2014; Zhang et al., 2014a) and the corresponding environmental performances for many water-related activities, such as water extraction, conveyance, and consumption (Mery et al., 2013; Zhang and Anadon, 2013; Zhang et al., 2014a).

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According to ISO (2006), LCA can be used for systematic evaluation of two or more products and processes/services in terms of their economic and environmental implications. A number of researchers assessed environmental performances of multiple water-related activities based on the method of life-cycle analysis (Del Borghi et al., 2013; Sebastian et al., 2011; Stokes and Horvath, 2009). For example, Lim and Park (2007) analyzed environmental impacts and economic costs of a water network system through life-cycle assessment. Zhang and Anadon (2013) evaluated environmental impacts of water extraction and consumption, and wastewater discharge in the energy sector of China through a hybrid input–output model and multiple LCA tools. Hendrickson and Horvath (2014) analyzed emissions and reductions of greenhouse gases (GHG) in current and future water distribution systems for California and Texas, United States. Considering environmental management in compound social-economic-engineering systems (Chung and Lee, 2009), the scope of LCA was broadened from an individual product to multiple products/services. For example, Joore and Brezet (2015) developed a LCA-based multilevel design model to analyze social and product technologies and services, within an urban social system. Guinée et al. (2010) proposed life cycle sustainability analysis, which can be performed efficiently at both product- and economy-wide levels. However, there is a challenge that makes LCA ineffective in some studies. At the stage of post-LCA, the evaluation results of environmental impacts cannot be directly used for tackling the practical problem of water-resource management and environmental-impact control.

To solve the problem of managing water systems and minimizing the associated environmental impacts from a life-cycle perspective, optimization models need to be integrated into an LCA framework. Previously, quantification of life-cycle environmental impacts was incorporated into many optimization models. For instance, Bonnin et al. (2015) established an effective management system for copper scrap recycling through hybrid LCA and multi-objective optimization approaches. Jing et al. (2012) developed a multi-objective optimization model for reflecting life-cycle environmental impacts for a cooling, heating and power generation system within a building. Gebreslassie et al. (2012) proposed a bi-objective non-linear optimization model with the consideration of life-cycle global warming potential for the cooling sector. Vadenbo et al. (2014a,b) introduced a unified framework for waste and resources management in industrial systems through combining multi-objective programming model with life cycle assessment approaches. Specifically, most of the related research considered economic performance as the objective function and did not comprehensively address environmental impacts of relevant products and services within a UWAS (Wang et al., 2013). However, few studies on optimization management were conducted from a life-cycle perspective and could address uncertainties in a UWAS (e.g., water availabilities under multiple precipitation probability levels, and water demand under varying conditions) (van Zelm and Huijbregts, 2013; Wiedmann et al., 2011). For example, Sigel et al. (2010) proposed a conceptual framework for perceiving and tackling uncertainties within the processes of environmental and water-related decision-making. Carmona et al. (2013) developed a methodological framework to support water resources management under uncertain conditions. Some researchers adopted two-stage stochastic programming (TSP) to support decision making considering occurrences of random events with multiple water availabilities (Lv et al., 2013). Moreover, subjective judgments in life-cycle analysis for imprecise or missing data may cause uncertainties that would transfer into consequential optimization models (Arena and Di Gregorio, 2014). Meanwhile, uncertainties of water resources management (e.g., the manager's vague judgments, and water availabilities under multiple probability levels) would also multiply complexities of relevant decision-making process. Traditionally, these uncertainties were quantified by a series of methods. For example, uncertainties caused by imprecise LCI data can be analyzed by Monte Carlo simulation (Leinonen et al., 2013). Variations of water availabilities can be described into probability distributions or fuzzy sets (Wang et al., 2015). Water demands in future could be estimated by interval numbers with unknown distributions (Cai et al., 2011a). Such uncertainties associated with life-cycle analysis and water resources management have been rarely considered by the previous LCA- and optimization- related studies.

Therefore, to improve the applicability of post-LCA for robust decision-making support for UWAS, systematic evaluation tools, optimization modeling, and uncertainty analysis approaches need to be incorporated within a general LCA framework. The objective of this research is to develop an integrated approach for supporting comprehensive decision-making in UWAS through the incorporation of operational research and uncertainty analysis within a general LCA framework. This method will improve capabilities of conventional LCA in terms of their applicability and uncertainty reflection. It can effectively connect life-cycle sustainability assessment with robust decision making and then be used for supporting sustainable urban water resources management, strengthening the capability of post-LCA in generating comprehensive decision alternatives under uncertainties. The methodology can (a) systematically reflect and address complexities of UWAS, and facilitate the comprehensive evaluation of environmental impacts at multiple product service levels, (b) facilitate reflections of multiple uncertainties and incorporate them into a general LCA framework, and (c) identify water allocation and manage robust action for environment-oriented water supply system design. The developed method will then be verified in a water-stressed city (i.e., the City of Dalian) in northeastern China. In detail, the objective entails the following tasks: (i) employment of multi-level life cycle analyses to systematically evaluate environmental impacts of products/services within a UWAS, (ii) adoption of an inexact optimization approach to strengthen applicability of LCA in generating water management options under uncertainties resulting from LCA results and management parameters, and (iii) application of the proposed model in Dalian, China, for demonstrating the applicability of the methodology. In this research, a fuzzy inexact two-stage programming (FITSP) model will be developed and combined with uncertainty and life cycle analysis of urban water systems for supporting decision-making in water resources management. In detail, the paper is organized as follows: (a) explanations of LCA-based decision-making under uncertain conditions will be covered in part 2, (b) specific methods (e.g., uncertainty and life cycle analysis, optimization model, and solution method) that are to be adopted in this research will be described in part 3, and (c) a studying case in Dalian City will be presented in part 4 to demonstrate effectiveness of the proposed methodology. At last, background data for life cycle analysis and case study will be listed in Appendix.

2. A systematic perspective of LCA-based decision-making under uncertainty

For conventional LCA methods, the generated results merely represent environmental impacts of relevant products and/or services in a quantitative way. They can be used for research and development (R&D) to guide emerging technologies in advance toward decreased environmental burden, providing environmental guidance for consideration alongside technical and economic measures of technology readiness (Wender et al., 2014). In terms of mature technologies, these methods can be adopted for reflect and compare environmental effects of varying products and services. In this capacity, LCA could proactively identify environmental opportunities not only for significant investments in any new technologies/facilities, but also for operational arrangements of product/service provision. However, there are at least three critical challenges that make LCA ineffective: (a) environmental emission databases rely on historical data collected predominantly from mature industries. Dynamic changes of relevant parameters and factors may occur for the databases. A variety of uncertainties are thus associated with any LCA results (Liang et al., 2013). This may lead to disparities when the results are used for evaluating environmental impacts; (b) current practices and studies of LCA underemphasized the importance to inform critical management and to support post-LCA decision making. There is a lack of methods that could link decision-support approaches with LCA results, further strengthening its capability in applicability; and (c) existing approaches can hardly be used to interpretation LCA results with high uncertainties that can be transferred to consequential decision-making process. Such challenges contribute to high uncertainties that render LCA and the results impracticable and potentially misleading for consequential decision alternative generation. Moreover, multiple objectives in addition to environmental impact minimization need to be comprehensively analyzed including economic considerations. Complicated tradeoff analysis needs to be maintained in addition to the evaluation results provided by LCA. Thus, strengthening LCA with decision-making and uncertainty analysis methods is desired; such that comprehensive impact of technologies, products, and services can be employed for help identify desired opportunities for minimizing environmental impacts from a systematic view point. In detail, complexities and uncertainties of LCA include LCI (life cycle inventory) data, environmental impacts, vague judgments of water resources managers, and stochastic variations in hydrological cycles. These uncertainties are quantified in the following: (i) uncertainties of environmental emission databases that can be analyzed by Monte Carlo methods, (ii) environmental impacts of technologies, products and services that can be expressed as possibilistic distributions, (iii) human-related parameters that could merely be expressed by intervals without known distributions. Moreover, a variety of uncertain conditions related with decision processes could also be expressed as inexact numbers with unknown distribution information. Such uncertain conditions need to be effectively considered into the planning processes and post-LCA decision making. Therefore, in this research, operational research, and uncertainty analysis will be incorporated within a general LCA framework to facilitate decision making in water resources management.

Advantages of the methodology include: (a) it could systematically address complexities and uncertainties across the life cycle of urban water systems through multiple uncertainty analysis methods (e.g., inexact optimization and Monte Carlo simulation), (b) it could facilitate the comprehensive evaluation of environmental impacts considering uncertain features of the study system, and (c) it could strengthen decision making in water-management level through incorporating uncertain characteristics and environmental impacts of urban water systems into a general modeling framework for identifying optimal water management solutions. Specifically, a fuzzy inexact two-stage programming (FITSP) model will be developed and combined with LCA for supporting the planning of urban water management system in the City of Dalian, China. In detail, a first-stage water-allocation decision is targeted for the planning of water resources management before any random changes of seasonal flows; the economy and population are realized as described in steps 1 to 3; when the uncertainty of the variables are uncovered in steps 4 and 5, a second-stage recourse action can be taken to analyze the extent of environmental impacts in a UWAS; acceptable solutions of water allocation can be identified in a UWAS. Fig. 1 indicates the framework of FITSP for UWASs. The detailed process in this framework can be summarized as follows:

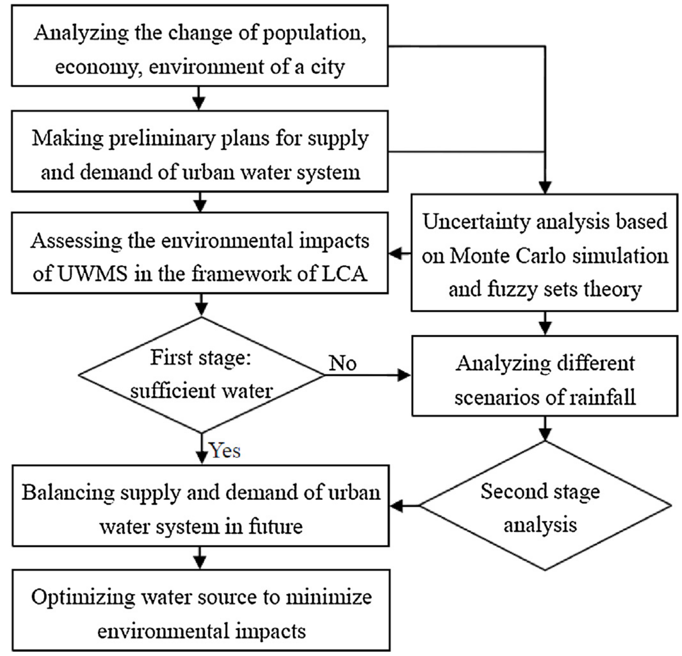

Fig. 1. Framework of fuzzy inexact two-stage programming of UWAS.

Step 1: water demand projection

Many water resources (e.g., surface, underground, recycled, and desalinated water) can be utilized by multiple users (e.g., agricultural, industrial and municipal sectors). The main task of this stage is to estimate water demands by multiple users in the planning period.

Step 2: water allocation targets (the 1st-stage decision)

After estimating the total water demand, water allocation targets for each user should be roughly determined. Such targets can be considered as the 1st-stage decision. At this stage, the main task is to plan water-resource allocation and expand water-supply capacity to meet the projected demands in the planning period.

Step 3: life cycle assessment

Major water sources include rivers, reservoirs, links, and water purifying plants, and the main users are residents, industries and the environment in districts of cities. The following aspects of life cycle assessment need to be considered: (a) two or more units need to be maintained as functional units of the integrated product-service system to facilitate data collection, (b) water sources, services, and end-users need to be contained within the LCA system boundary, and (c) environmental impacts should be assessed by the methodology recommend by a series of ISO 14000s.

Step 4: 2nd-stage decision based on probabilistic events

When the future rainfall probability deviates from the expected value of the first stage, a second-stage decision should be recourse. Conventionally, two types of recourse actions were commonly implemented. The first recourse action is through increasing water-supply capacity of the existing facilities. The second one is importing water from other long-distance areas, usually with higher environmental impacts compared with environmental impacts of water allocation in the 1st stage. Then allocate water to users in different scenarios and assess the environmental impacts of second-stage water conveyance.

Step 5: uncertainty analysis of LCA and optimization

In addition to the recourse issue between supplies and demands, uncertainties may exist in many parameters. Uncertainty analysis should be added in this study, because the future uncertainty cannot be neglected. In LCA of UWASs, the uncertainty of the life cycle inventory should be analyzed by Monte Carlo simulations

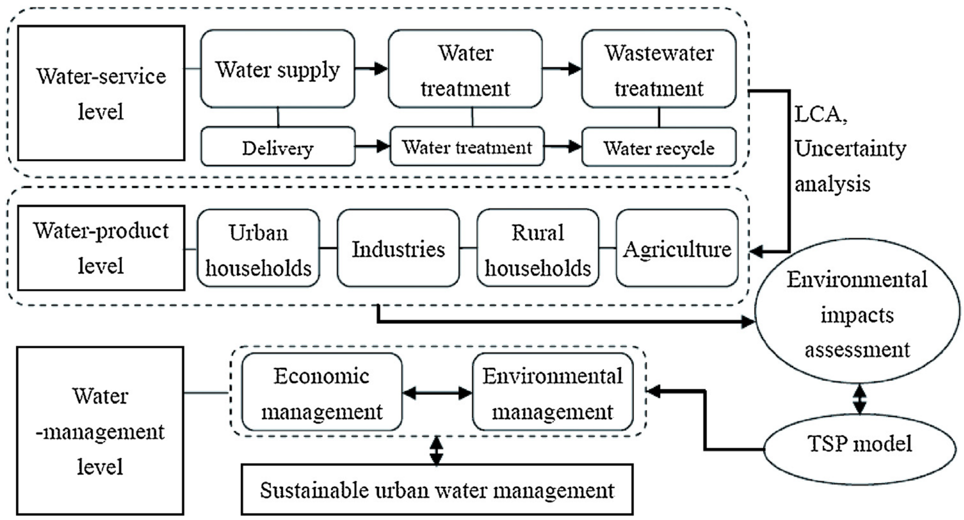

Fig. 2. Multi-level framework for sustainable urban water management.

and fuzzy sets theory. The uncertainties of other parameters, i.e., water demands of different users, can be expressed as interval values. Interval-parameter and fuzzy sets theory can thus be integrated into the two-stage stochastic programming (TSP) model to provide a more robust decision.

Step 6: development of fuzzy inexact two-stage stochastic programming

The objective function for a two-stage recourse problem is to minimize the environmental impacts of water conveyance in the two stages. Water users with conflicting interests and rainfall probability should be the main constraints. The final solution can thus support the decision-making in UWASs. Specifically, an FITSP model will be developed and combined with LCA for supporting the planning of urban water management system in the City of Dalian, China.

3. Methodology

3.1. Multi-level life cycle analysis under uncertainty

Within a real UWAS, a number of subsystems and components are contained, including water supply, transportation, distribution, as well as drainage and sewer networks. Thus, in order to obtain comprehensive LCA results for UWAS, analysis should be conducted through the framework at the following multiple levels (Fig. 2): (a) Water availability, allocation, and consumption are contained into water-product level, in order to fulfill water demands of multiple users in a city; (b) Water supply and treatment, as well as wastewater treatment are incorporated into water-service level, considering service capacity of related infrastructures; and (c) Optimal solutions for water resources allocation are included into water-management level, through minimizing environmental impacts in UWAS. The environmental impacts of the water services and products are analyzed by LCA. Then the environmental impacts of the UWAS are incorporated into the third level to support sustainable urban water resources management. Also, a number of factors, associated with source data, technology database, and their dynamic changes, could lead to uncertainties of LCA results, (van Zelm and Huijbregts, 2013). Especially, the final results of environmental impacts of UWAS in future years will be influenced by the quality of the related LCI data. Thus, these uncertainties may affect decision making in UWAS, if cannot be dealt with properly.

Based on factual information and models of natural processes, LCA is an increasingly important tool for environmental assessment of UWASs. The aim of LCA in this paper is to assess the environmental impacts of multi-level UWASs and support the subsequent solution of water allocation. Thus, the determination of the functional unit is based on multiple levels of urban water, where all of the available supply alternatives are included. The system boundary of a UWAS includes the process of water extraction, production, use, treatment and discharge/reuse (Fig. 3). The production of pipelines and related chemicals is not included in the system boundary. Electricity production for water conveyance and treatment is included in the system boundary.

3.2. Post-LCA decision-making under uncertainty

In conventional LCA processes, a variety of impact evaluation results can be generated, which would be used for anticipatory analysis of technologies, products and/or service. Then, these results can be used for support the identification of their environmental and economic implications. However, this process is commonly difficult for facilitating decision-making in future, due to various uncertainties related with life cycle inventory (LCI) data and consequential management or optimization processes (Wiedmann et al., 2011). The reason is that environmental impact assessment relies on related LCI data which are inevitably estimated from historical or secondary data. It would be a challenge for researchers to analyze environmental impacts in future by vague judgment through historical data. Fuzzy sets theory can simulate the way of decision making characterized by uncertainty and vagueness (Gonzalez et al., 2002). Thus, fuzzy sets theory has been widely used to for solving decision-making problems in life cycle analysis, such as data quality analysis (Weckenmann and Schwan, 2001), environmental impact assessment (Reza et al., 2013), and LCA result interpretation (Ilagan and Tan, 2011). In this research, due to differences in the estimation methods, and the statistical reports, a range of value of LCI data can be obtained for the estimation. At the same time, the statistic errors for relevant parameters of LCA can lead to certain ranges of fluctuation. Such uncertainties can thus be estimated as fuzzy numbers based on Monte Caro results of LCA (Jato-Espino et al., 2014; Yue et al., 2014).

Meanwhile, many economic parameters could barely be evaluated as deterministic values instead of interval numbers in decision-making activities. Moreover, water availabilities could be expressed as probability density functions (PDFs) due to their high

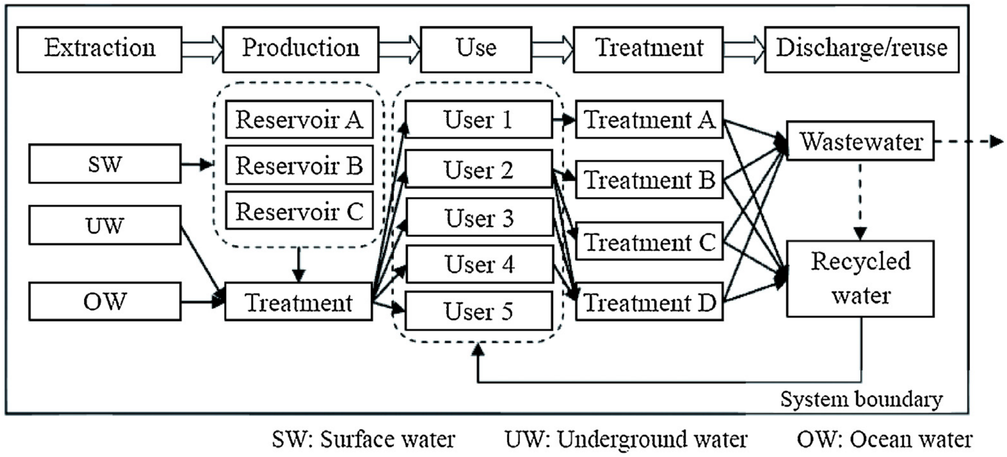

Fig. 3. System boundary of urban water on service-product level.

dependence upon many natural conditions such as random precipitation events (Bieda, 2014). In detail, uncertainty analysis of LCA includes (a) analyzing data quality of life cycle inventory by Data Quality Indicators (DQI) method to determine range endpoints (Wang et al., 2012), (b) estimating the uncertainties of life cycle inventory and environmental impacts by Monte Carlo simulation and fuzzy sets theory (Jato-Espino et al., 2014; Li and Lu, 2014; Dandres et al., 2014), and (c) estimating the uncertainties of economic factors by interval numbers. Such interval or fuzzy parameters from LCA, however, can also hardly be used for supporting decision-making in UWAS. The parameters should be integrated into the two-stage decision making in UWAS.

In detail, DQI uses a group of selected indicators to assess the quality of life cycle inventory, such as reliability of data source, and age of data (Wang and Shen, 2013). Each quality indicator can be described by a number (i.e., q_i). Data quality indicators, e.g., age of data, can be assigned as values 1–5 (represents 0–3 years old, 3–6 years old, 6–10 years old, 10–15 years old, and more than 15 years old respectively). Then, the aggregated scores can be formulated as follows:

$$q = \frac{1}{n}\sum_{i=1}^{n} q_i \tag{1}$$

where q is the aggregated score of n indicators. Then, a factor (R) is used to describe the quality of parameters, which can be presented as follows:

$$R = \frac{q - \min\ q_i}{\max\ q_i - \min\ q_i} \times 100\% \tag{2}$$

where R is the percent of q of the maximized distance among q_i. Then, DQI value can be assigned as values of 1–5 based on the obtained values of R (Table 1). Consequentially, the corresponding range endpoints can be obtained based on the generated aggregated DQI scores. At the same time, a specific distribution can be assigned/fitted to the range endpoints. The shape parameters can be determined (Table 2). Then, assume that there are n variables to analyze uncertainty in a life cycle inventory, i.e., $x = (\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_n)$. The index of $\tilde{x}_i$ can be defined by the membership function $\mu(x_i)$. Suppose $\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_n$ are triangular fuzzy numbers, and for any $i \in n, \tilde{x}_i = (a_i, b_i, c_i)$. After performing Monte Carlo simulation with 8000 iterations, the index a_i and c_i can be obtained by b_i and its range endpoints from DQI. Thus, the final estimate for each parameter (i.e., $\tilde{x}_i$) can be described by the average of the mode values (e.g., b_i) and minimum, and maximum values (i.e., a_i and c_i) (Canizes et al., 2012; Markowski and Siuta, 2014).

3.3. Integration of LCA and inexact optimization

In UWAS, water allocation strategies and facility expansion policies need to be proposed before the occurrence of many water-related random events, representing the first-stage decisions over the planning period. Then, correction decisions may need to be applied to those original first-stage decisions after the occurrences of random water availability, representing the second-stage recourse decisions. Traditionally, two types of recourse actions implemented, which are (i) increasing water-supply capacity of the existing facilities; (ii) importing water from other long-distance areas. The integration of LCA and TSP in UWAS are described as the following.

Consider a problem in which a water manager is responsible for allocating water to multiple users from multiple water resources during a dry season (Huang and Loucks, 2000). The users are expanding their activities and need to know how much water they can expect. The water manager can formulate the problem through minimizing environmental impacts and fulfilling water demands

Table 1
DQI assignment matrix.

R	DQI
$0 \le R < 12{:}5\%$	1
$12{:}5\% \le R < 25\%$	1.5
$25\% \le R < 37{:}5\%$	2
$37{:}5\% \le R < 50\%$	2.5
$50\% \le R < 62{:}5\%$	3
$62{:}5\% \le R < 75\%$	3.5
$75\% \le R < 87{:}5\%$	4
$87{:}5\% \le R < 100\%$	4.5
$R = 100\%$	5

Table 2
Transformation matrix.

Aggregated DQI scores	Beta distribution function	
	Shape parameters (α, β)	Range endpoints ($\pm$%)
5	(5, 5)	10
4.5	(4, 4)	15
4	(3, 3)	20
3.5	(2, 2)	25
3	(1, 1)	30
2.5	(1, 1)	35
2	(1, 1)	40
1.5	(1, 1)	45
1	(1, 1)	50

within a specific UWMS. To reflect uncertain information in water resources management, two-stage programming can be adopted. In the first-stage decision-making process, it is assumed that amount of water supply could meet the demand before any random changes of seasonal flows. Then, environmental impacts of water consumption at this stage need to be analyzed under the predetermined water supply targets. Meanwhile, under occurrences of any random seasonal flows, recourse actions need be taken to compensate for water shortage that may have been experienced as a result of the first-stage decision. Thus, the corresponding enhanced environmental impacts for extra water supply (i.e., recourse actions) of this stage need to be analyzed and taken into consideration for entire decision-making processes. An attribute of two-stage programming is its decision-making capability to deal with recourse strategies and the associated uncertainties (Chu and You, 2013). The two-stage programming is suitable for solving water-related problems, e.g., water quality (Li et al., 2013) and resources management (Xie et al., 2013). The method can be formulated as a two-stage linear programming (Eq. (3)).

$$\min \mathrm{LCA\_}f = \sum_{l=1}^{k}\sum_{i=1}^{n} e_{il}T_{il} + \sum_{l=1}^{k}\sum_{i=1}^{n}[e'_{il}E(D_{iQl})] + \sum_{r=1}^{p}\sum_{i=1}^{n} e''_{ir}T_{ir} \quad (3a)$$

s.t.

$$T_{il} \geq \sum_{r=1}^{n'} D_{iQl} \geq 0, \quad \forall i, l \quad (3b)$$

$$Q_l \geq \sum_{i=1}^{m}(T_{il} - D_{iQl}), \quad \forall l \quad (3c)$$

$$C_l \geq \sum_{i=1}^{m}(T_{il} - D_{iQl}), \quad \forall l \quad (3d)$$

$$T_{i\max} \geq T_{il} + T_{ir}, \quad \forall i, l, r \quad (3e)$$

$$T_{il}, T_{ir}, D_{iQl} \geq 0, \quad \forall i, l, r \quad (3f)$$

where LCA_f: environmental impacts in life-cycle stages in UWAS;

e_{i1}: environmental impact from the supply of 1 t surface water to the ith district from water source in the first stage;
e'_{il}: added environmental impact from the supply of 1 t surface water to the ith district from the lth water source of the second stage;
i_l: added environmental impact from the supply of 1 t surface water to the ith district from the lth water source of the second stage;
T_{il}: fixed water allocation target from the lth water source that is promised to ith district in the first stage;
D_{iQl}: amount of surface water delivered in the second stage of which T_{il}, could not be satisfied when the inflow is Q;
$E(D_{iQl})$: expectation value of $D^{\pm}_{iQl}$;
e''_{il}: environmental impact from the supply of 1 t other sources of water (i.e., ground water, desalinated water, and recycled water) to the ith district from rth water source;
T_{ir}: fixed water allocation target from water source r to district i;
i: districts of a city;
l: surface water sources of a city;
r: other types of water sources to a city;
$T_{i\max}$: maximum allowable allocation of water for district i (t/year);
C_l: water supply capacity of lth river.

Model 3 cannot solve water allocation problem when water inflows are random variables. Thus, distributions of water inflows, i.e., parameter Q, should be expressed as discrete values. Let water inflows be described as values q_j in probabilities p_j:

$$E(D_{iQl}) = \sum_{j=1}^{n} p_{jl}D_{ijl} \quad (4)$$

Thus, Model 3 can be reformulated as two-stage stochastic programming (Eq. (5)):

$$\min \mathrm{LCA\_}f = \sum_{l=1}^{k}\sum_{i=1}^{n} e_{il}T_{il} + \sum_{l=1}^{k}\sum_{i=1}^{n}\left[e'_{il}\sum_{j=1}^{m} p_{jl}D_{ijl}\right] + \sum_{r=1}^{p}\sum_{i=1}^{n} e''_{ir}T_{ir} \quad (5a)$$

s.t.

$$T^{il} \geq D_{ijl} \geq 0, \quad \forall i, j, l \quad (5b)$$

$$q_{jl} \geq \sum_{i=1}^{m}(T_{il} - D_{ijl}), \quad \forall j, l \quad (5c)$$

$$C_l \geq \sum_{i=1}^{m}(T_{il} - D_{ijl}), \quad \forall l, j \quad (5d)$$

$$T_{i\max} \geq T_{il} + T_{ir}, \quad \forall i, l, r \quad (5e)$$

$$T_{il}, D_{ijl} \geq 0, \quad \forall i, j, l \quad (5f)$$

$$T_{il}, T_{ir}, D_{ijl} \geq 0, \quad \forall i, j, l, r \quad (5g)$$

Practically, quite a lot of information related with decision processes in UWASs has dynamic features, e.g., the amount of water demands and supply with time. The variations of the parameters can be reflected as uncertain or inexact numbers with unknown distribution information (Guo et al., 2008). In detail, an inexact number (e.g., $x^{\pm}$) is an interval with deterministic lower and upper bounds and with unknown distribution information (Huang et al., 1996). In this research, detailed parameters of model 5 can hardly reflect such uncertain information. Thus, with the consideration of uncertain parameters, model 5 needs to be transformed into an interval linear programming (ILP) model that can also be considered as inexact programming according the traditional methods. In the past decades, method of interval linear programming or inexact programming has been widely used in water resources management (Tan et al., 2013), water pollution reduction (Tan et al., 2011) and solid waste management (Cai et al., 2007). As a result, interval parameters could be incorporated into the TSP model. This leads to an inexact two-stage programming (ITSP) model as follows (Huang and Loucks, 2000):

$$\min \mathrm{LCA\_}f = \sum_{l=1}^{k}\sum_{i=1}^{n} e^{\pm}_{il}T^{\pm}_{il} + \sum_{l=1}^{k}\sum_{i=1}^{n}\left[e'^{\pm}_{il}\sum_{j=1}^{m} p_{jl}D^{\pm}_{ijl}\right] + \sum_{r=1}^{p}\sum_{i=1}^{n} e''^{\pm}_{ir}T^{\pm}_{ir} \quad (6a)$$

s.t.

$$T^{\pm}_{il} \geq D^{\pm}_{ijl} \geq 0, \quad \forall i, j, l \quad (6b)$$

$$q^{\pm}_{jl} \geq \sum_{i=1}^{m}(T^{\pm}_{il} - D^{\pm}_{ijl}), \quad \forall i, j, l \quad (6c)$$

$$C_l \geq \sum_{i=1}^{m}(T^{\pm}_{il} - D^{\pm}_{ijl}), \quad \forall l, j \quad (6d)$$

$$T^{\pm}_{i\max} \geq T^{\pm}_{il} + T^{\pm}_{ir}, \quad \forall i, l, r \tag{6e}$$

$$T^{\pm}_{il}, T^{\pm}_{ir}, D^{\pm}_{ijl} \geq 0, \quad \forall i, j, l, r \tag{6f}$$

where $f^{\pm}$, $e^{\pm}_{il}$, $T^{\pm}_{il}$, $T^{\pm}_{ir}$, $e'^{\pm}_{il}$, $e''^{\pm}_{ir}$, $D^{\pm}_{ijl}$, $q^{\pm}_{jl}$ and $T^{\pm}_{il\max}$ are interval parameters and variables.

Data unavailability and incompleteness in life-cycle analysis of urban water management lead to high degree of uncertainty. Model 6 still cannot be used to deal with the water allocation problem with uncertain variables generated by LCA. To reflect the uncertainty in life cycle analysis, environmental-impact coefficients could be converted to fuzzy numbers. Thus, Model 6 can be reformulated as a fuzzy inexact two-stage programming (FITSP) model (Huang and Loucks, 2000):

$$\min \mathrm{LCA}\_\tilde{f} = \sum_{l=1}^{k}\sum_{i=1}^{n}\tilde{e}^{\pm}_{il}T^{\pm}_{il} + \sum_{l=1}^{k}\sum_{i=1}^{n}\left[\tilde{e}'^{\pm}_{il}\sum_{j=1}^{m}p_{jl}D^{\pm}_{ijl}\right] + \sum_{r=1}^{p}\sum_{i=1}^{n}\tilde{e}''^{\pm}_{ir}T^{\pm}_{ir} \tag{7a}$$

s.t.

$$T^{\pm}_{il} \geq D^{\pm}_{ijl} \geq 0, \quad \forall i, j, l \tag{7b}$$

$$q^{\pm}_{jl} \geq \sum_{i=1}^{m}(T^{\pm}_{il} - D^{\pm}_{ijl}), \quad \forall i, j, l \tag{7c}$$

$$C_l \geq \sum_{i=1}^{m}(T^{\pm}_{il} - D^{\pm}_{ijl}), \quad \forall l, j \tag{7d}$$

$$T^{\pm}_{i\max} \geq T^{\pm}_{il} + T^{\pm}_{ir}, \quad \forall i, l, r \tag{7e}$$

$$T^{\pm}_{il}, T^{\pm}_{ir}, D^{\pm}_{ijl} \geq 0, \quad \forall i, j, l, r \tag{7f}$$

where $\tilde{f}^{\pm}$, $\tilde{e}^{\pm}_{il}$, $\tilde{e}'^{\pm}_{il}$ and $\tilde{e}''^{\pm}_{il}$ are fuzzy and interval parameters.

3.4. Solution method

Solution of a fuzzy inexact linear programming model (Eq. (8)) is composed of the following two steps.

$$\mathrm{Min}\, \tilde{z}^{\pm} = \tilde{c}^{\pm}x^{\pm} \tag{8a}$$

$$a^{\pm}_{i}x^{\pm} \geq b^{\pm}_{i}, \quad i = 1, 2, \ldots, m \tag{8b}$$

$$\tilde{z}^{\pm} > 0 \tag{8c}$$

$$x^{\pm} \geq 0 \tag{8d}$$

3.4.1. Step 1 Solution method for interval programming

According to the algorithms for objective to minimize $\tilde{z}^{\pm}$ (Cai et al., 2011b; Huang et al., 1995), inexact linear programming (ILP) model can be converted into two sub-models (i.e., Models 9 and 10). Model 9 corresponding to $\tilde{z}^{-}$ is first solved, and then Model 10 corresponding to $\tilde{z}^{+}$ can be solved based on the solution of model 9. In detail, the solution models for interval programming can be formulated as follows.

$$\mathrm{Min}\, \tilde{z}^{-} = \sum_{j=1}^{k_1} c^{-}_{j}x^{-}_{j} + \sum_{j=k_1+1}^{n} c^{-}_{j}x^{+}_{j} \tag{9a}$$

s.t.

$$\sum_{j=1}^{k_1}|a_{ij}|^{+}\mathrm{Sign}(a^{+}_{ij})x^{-}_{j} + \sum_{j=k_1+1}^{n}|a_{ij}|^{-}\mathrm{Sign}(a^{-}_{ij})x^{+}_{j} \leq b^{-}_{j}, \quad \forall j \tag{9b}$$

$$x^{-}_{j}, x^{+}_{j} \geq 0 \tag{9c}$$

where $x^{-}_{j}(j = 1, 2, \ldots, k_1)$ and $x^{+}_{j}(j = k_1 + 1, k_1 + 2, \ldots, n)$ are interval variables with negative and positive coefficients in the objective function. Thus, $x^{-}_{j\mathrm{opt}}(j = 1, 2, \ldots, k_1)$ and $x^{+}_{j\mathrm{opt}}(j = k_1 + 1, k_1 + 2, \ldots, n)$ are the solution of model 9.

$$\mathrm{Min}\, \tilde{z}^{+} = \sum_{j=1}^{k_1} c^{+}_{j}x^{+}_{j} + \sum_{j=k_1+1}^{n} c^{+}_{j}x^{-}_{j} \tag{10a}$$

s.t.

$$\sum_{j=1}^{k_1}|a_{ij}|^{-}\mathrm{Sign}(a^{-}_{ij})x^{+}_{j} + \sum_{j=k_1+1}^{n}|a_{ij}|^{+}\mathrm{Sign}(a^{+}_{ij})x^{-}_{j} \leq b^{+}_{j}, \quad \forall j \tag{10b}$$

$$x^{\pm} \geq 0 \tag{10c}$$

$$0 \leq x^{+}_{j} \geq x^{-}_{j\mathrm{opt}}, \quad \forall j = 1, 2, \ldots, k_1 \tag{10d}$$

$$x^{-}_{j} \leq x^{+}_{j\mathrm{opt}}, \quad \forall j = k_1 + 1, k_2 + 2, \ldots, n \tag{10e}$$

3.4.2. Step 2 Solution method for fuzzy-sets programming

The solution method for fuzzy parameters is referred to the (Jimenez, 1996) method, which is based on the definition of the expected value of a fuzzy number (Pishvaee and Razmi, 2012). Assuming a triangular fuzzy number ($\tilde{c}$), the membership function of $\tilde{c}$ can be described as Eq. (11) (Pishvaee and Razmi, 2012).

$$\mu_{\tilde{c}} = \begin{cases} f_c(x) = \dfrac{x - c^{\mathrm{pes}}}{c^{\mathrm{mos}} - c^{\mathrm{pes}}}, & \text{if } c^{\mathrm{pes}} \leq x \leq c^{\mathrm{mos}} \\ 1, & \text{if } x = c^{\mathrm{mos}} \\ g_c(x) = \dfrac{c^{\mathrm{opt}} - x}{c^{\mathrm{opt}} - c^{\mathrm{mos}}}, & \text{if } c^{\mathrm{mos}} \leq x \leq c^{\mathrm{opt}} \\ 0, & \text{if } x \leq c^{\mathrm{pes}} \text{ or } x \geq c^{\mathrm{opt}} \end{cases} \tag{11}$$

where c^{mos}, c^{pes} and c^{opt} are the three prominent points (the most likely, the most pessimistic and the most optimistic values), respectively. Expected interval (i.e., EI) can be described by Eq. (12).

$$\mathrm{EI}(\tilde{c}) = [E^{c}_{1}, E^{c}_{2}] = \left[\int_{0}^{1} f^{-1}_{c}(x)dx, \int_{0}^{1} g^{-1}_{c}(x)dx\right] = \left[\frac{c^{\mathrm{pes}} + c^{\mathrm{mos}}}{2}, \frac{c^{\mathrm{mos}} + c^{\mathrm{opt}}}{2}\right] \tag{12}$$

And thus, the index of expected value (i.e., EV) can be estimated as the value of fuzzy number (Pishvaee and Razmi, 2012).

$$\mathrm{EV}(\tilde{c}) = \frac{E^{c}_{1} + E^{c}_{2}}{2} = \frac{c^{\mathrm{pes}} + 2c^{\mathrm{mos}} + c^{\mathrm{opt}}}{4} \tag{13}$$

Thus, Eqs. (9a) and (10a) can be changed into the following equations.

$$\mathrm{Min}\, \tilde{z}^{-} = \sum_{l=1}^{k}\left(\sum_{j=1}^{k_1}\frac{E^{c-}_{j1l} + E^{c-}_{j2l}}{2}x^{-}_{jl} + \sum_{j=k_1+1}^{n}\frac{E^{c-}_{j1l} + E^{c-}_{j2l}}{2}x^{+}_{jl}\right) \tag{14a}$$

$$\mathrm{Min}\, \tilde{z}^{+} = \sum_{l=1}^{k}\left(\sum_{j=1}^{k_1}\frac{E^{c+}_{j1l} + E^{c+}_{j2l}}{2}x^{+}_{jl} + \sum_{j=k_1+1}^{n}\frac{E^{c+}_{j1l} + E^{c+}_{j2l}}{2}x^{-}_{jl}\right) \tag{14b}$$

Set

$$\mu_{\tilde{e}^+}(x)=\begin{cases} f_{e^+}(x)=\dfrac{x-e^{\text{pes}+}}{e^{\text{mos}+}-e^{\text{pes}+}}, & \text{if } e^{\text{pes}+}\le x\le e^{\text{mos}+}\\ 1, \quad \text{if } x=e^{\text{mos}+} & \\ g_{e^+}(x)=\dfrac{e^{\text{opt}+}-x}{e^{\text{opt}+}-e^{\text{mos}+}}, & \text{if } e^{\text{mos}+}\le x\le e^{\text{opt}+}\\ 0, \quad \text{if } x\le e^{\text{pes}+} \text{ or } x\ge e^{\text{opt}+} & \end{cases} \tag{15}$$

$$\mu_{\tilde{e}^-}(x)=\begin{cases} f_{e^-}(x)=\dfrac{x-e^{\text{pes}-}}{e^{\text{mos}-}-e^{\text{pes}-}}, & \text{if } e^{\text{pes}-}\le x\le e^{\text{mos}-}\\ 1, \quad \text{if } x=e^{\text{mos}-} & \\ g_{e^-}(x)=\dfrac{e^{\text{opt}-}-x}{e^{\text{opt}-}-e^{\text{mos}-}}, & \text{if } e^{\text{mos}-}\le x\le e^{\text{opt}-}\\ 0, \quad \text{if } x\le e^{\text{pes}-} \text{ or } x\ge e^{\text{opt}-} & \end{cases} \tag{16}$$

$$E^-_{i_1l(N)}=\frac{1}{2}(e^{\text{pes}-}_{i_1l(N)}+e^{\text{opt}-}_{i_1l(N)}) \tag{17}$$

$$E^-_{i_2l(N)}=\frac{1}{2}(e^{\text{pes}-}_{i_2l(N)}+e^{\text{opt}-}_{i_2l(N)}) \tag{18}$$

$$E^+_{i_1l(N)}=\frac{1}{2}(e^{\text{pes}+}_{i_1l(N)}+e^{\text{opt}+}_{i_1l(N)}) \tag{19}$$

$$E^+_{i_2l(N)}=\frac{1}{2}(e^{\text{pes}+}_{i_2l(N)}+e^{\text{opt}+}_{i_2l(N)}) \tag{20}$$

where $e^{\text{mos}\pm}$, $e^{\text{pes}\pm}$ and $e^{\text{opt}\pm}$ are prominent points of environmental impact. Water allocation optimization can be formulated as the following FITSP model (Eqs. (21) and (22)).

$$\begin{aligned}\min \text{LCA}\_\tilde{f}^-_{(N)} =& \sum_{l=1}^{k}\sum_{i=1}^{n}\frac{E^-_{i_1l(N)}+E^-_{i_2l(N)}}{2}T^-_{il(N)}\\ &+\sum_{l=1}^{k}\sum_{i=1}^{n}\left(\frac{E'^-_{i_1l(N)}+E'^-_{i_2l(N)}}{2}\sum_{j=1}^{n}p_{jl}D^-_{ijl(N)}\right)\\ &+\sum_{r=1}^{p}\sum_{i=1}^{n}\frac{E''^-_{i_1r(N)}+E''^-_{i_2r(N)}}{2}T^-_{ir(N)}\end{aligned} \tag{21a}$$

s.t.

$$T^-_{il}\ge D^-_{ijl}\ge 0,\quad \forall i,j,l \tag{21b}$$

$$q^+_{jl}\ge\sum_{i=1}^{m}(T^-_{il}-D^-_{ijl}),\quad \forall i,j,l \tag{21c}$$

$$C_l\ge\sum_{i=1}^{m}(T^-_{il}-D^-_{ijl}),\quad \forall l,j \tag{21d}$$

$$T^+_{i\max}\ge T^-_{il}+T^-_{ir},\quad \forall i,l,r \tag{21e}$$

$$T^-_{il},T^-_{ir},D^-_{ijl}\ge 0,\quad \forall i,j,l,r \tag{21f}$$

$$\begin{aligned}\min \text{LCA}\_\tilde{f}^+_{(N)} =& \sum_{l=1}^{k}\sum_{i=1}^{n}\frac{E^+_{i_1l(N)}+E^+_{i_2l(N)}}{2}T^+_{il(N)}\\ &+\sum_{l=1}^{k}\sum_{i=1}^{n}\left(\frac{E'^+_{i_1l(N)}+E'^+_{i_2l(N)}}{2}\sum_{j=1}^{n}p_{jl}D^+_{ijl(N)}\right)\\ &+\sum_{r=1}^{p}\sum_{i=1}^{n}\frac{E''^+_{i_1l(N)}+E''^+_{i_2l(N)}}{2}T^+_{ir(N)}\end{aligned} \tag{22a}$$

s.t.

$$T^+_{il}\ge D^+_{ijl}\ge 0,\quad \forall i,j,l \tag{22b}$$

$$q^-_{jl}\ge\sum_{i=1}^{m}(T^+_{il}-D^+_{ijl}),\quad \forall i,j,l \tag{22c}$$

$$C_l\ge\sum_{i=1}^{m}(T^+_{il}-D^+_{ijl}),\quad \forall l,j \tag{22d}$$

$$T^-_{i\max}\ge T^+_{il}+T^+_{ir},\quad \forall i,l,r \tag{22e}$$

$$D^+_{ijl}\ge D^-_{ijlopt},\quad \forall i,j \tag{22f}$$

$$T^+_{il},T^+_{ir},D^+_{ijl}\ge 0,\quad \forall i,j,l,r \tag{22g}$$

4. Case study: Water resources management of Dalian City

As an important coastal city in northeastern China, Dalian City stands on the southern tip of the Liaodong Peninsula (Han et al., 2011). The city is composed of eight districts, i.e., Municipal zone, Jinzhou, Pulandian, Wafangdian, Changxingdao, Zhuanghe, Huayuankou, and Changhai (Fig. 4). The annual average precipitation in the city is from 600 to 800 mm. In past years, water supply mostly depends on rivers flowing through the city, such as Yingna, Biliu, and Dasha Rivers. However, Dalian has an inherently small fresh water supply. The per capita water resources supply in Dalian City was about 6.54 t in 2013 (Han et al., 2011). It was less than a quarter of per capita water resources supply of China.

With the development of the population and economy, local water sources would not fulfill the demands of the city. According to the Dalian water sources plan, Hun River in Fushun City will become a main water source outside of the city. The UWAS of Dalian is composed of rivers, reservoirs, links, and water purifying plants (Fig. 5).

The system boundary of the UWAS in Dalian City includes the following parts: electricity consumption in the stage of water transfer from reservoirs to the water treatment plants, electricity consumption in the stage of water and the wastewater treatment plants (Fig. 6). The functional units are 1000 kg water in product level; and supply 1000 kg water to users in service level. The Eco-indicator 99 method is chosen to assess the environmental impacts of the UWAS of Dalian. Three planning horizons are considered in this study, with the base year of 2010, and the planning years of 2015, 2020 and 2030. The objective of TSP is minimizing the environmental impacts in the life cycle stages of the UWAS. The total available water in Dalian is random variables. If local water resources cannot fulfill the demands of water users, a certain amount of water must be obtained from Hun River. The maximum water allocation and supply capacity of each river and allocation target for eight districts of Dalian are considered as constraints. The background data of the UWAS in Dalian are listed in section of Appendix.

4.1. Life cycle inventory

According to the statistics data of Dalian City, the amount of energy consumption for water services in Dalian City was 58,279 standard coal in 2010 (NBS and DBS, 2013). The amount is allocated by the amount of water consumption based on different sources. The amount of energy consumption in different areas of Dalian City is described in Table 3. The data is calculated through the secondary data from Stokes and Horvath (2009) and activity emission inventory of electricity in China (IPCC, 2006; Cui et al., 2012) listed in Table A.2 of Appendix.

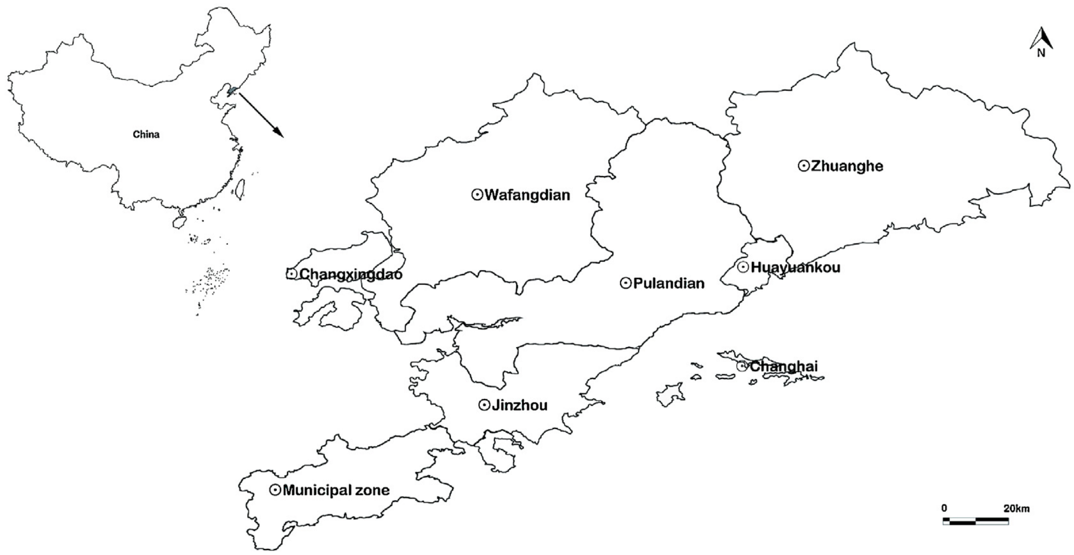

Fig. 4. The position of Dalian City.

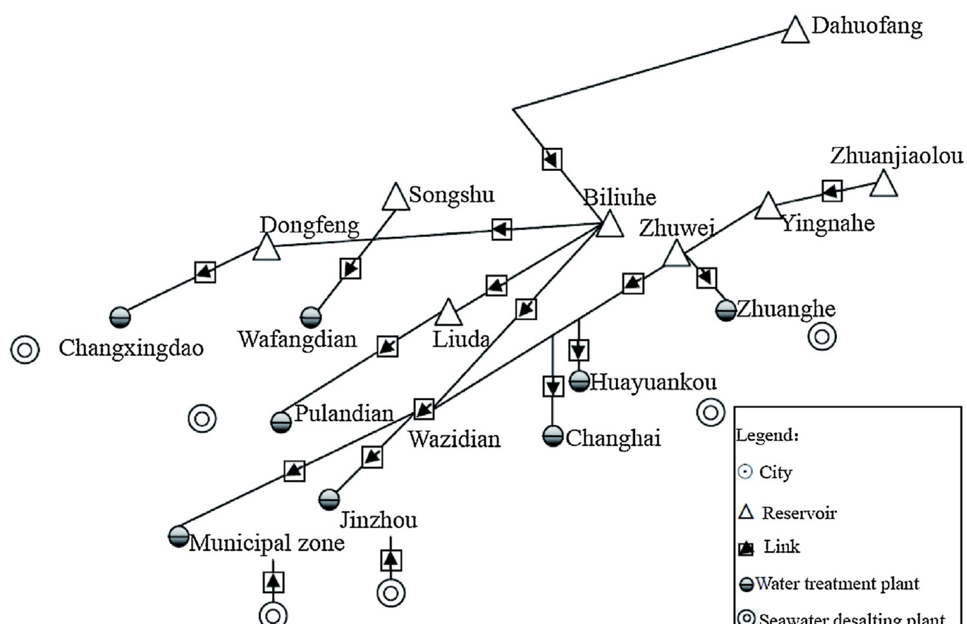

Fig. 5. Urban water management system in Dalian City.

Table 3
Energy consumption for the service of water conveyance in Dalian City.

Area[a]	Rivers (reservoirs)	Surface water ($\times10^{-3}$ MWh/t)	Desalinated water ($\times10^{-3}$ MWh/t)	Recycled water ($\times10^{-3}$ MWh/t)	Second stage conveyance ($\times10^{-3}$ MWh/t)
$I_{1\text{-a}}$	Yingna River (Yingnahe)	1.05	7.50	4.72	167.00
$I_{1\text{-b}}$	Biliu River (Biliuhe)	0.59			
$I_{2\text{-a}}$	Yingna River (Yingnahe)	1.05	7.50	4.72	167.00
$I_{2\text{-b}}$	Biliu River (Biliuhe)	0.59			
I_3	Dasha River (Liuda)	0.27	7.50	4.72	172.00
$I_{4\text{-c}}$	Fuzhou River (Songshu)	0.17	7.50	4.72	145.00
$I_{4\text{-d}}$	Fuzhou River (Dongfeng)	0.16			
I_5	Fuzhou River (Dongfeng)	0.51	7.50	4.72	212.00
I_6	Zhuang River (Zhuwei)	0.15	7.50	4.72	214.00
I_7	Yingna River (Yingnahe)	0.62	7.50	4.72	246.00
I_8	Yingna River (Yingnahe)	4.67	7.50	4.72	278.00

[a] I_1 means Municipal zone of Dalian. Similarly, I_2 means Jinzhou, I_3 means Pulandian, I_4 means Wafangdian, I_5 means Changxingdao, I_6 means Zhuanghe, I_7 means Huayuankou, and I_8 means Changhai.

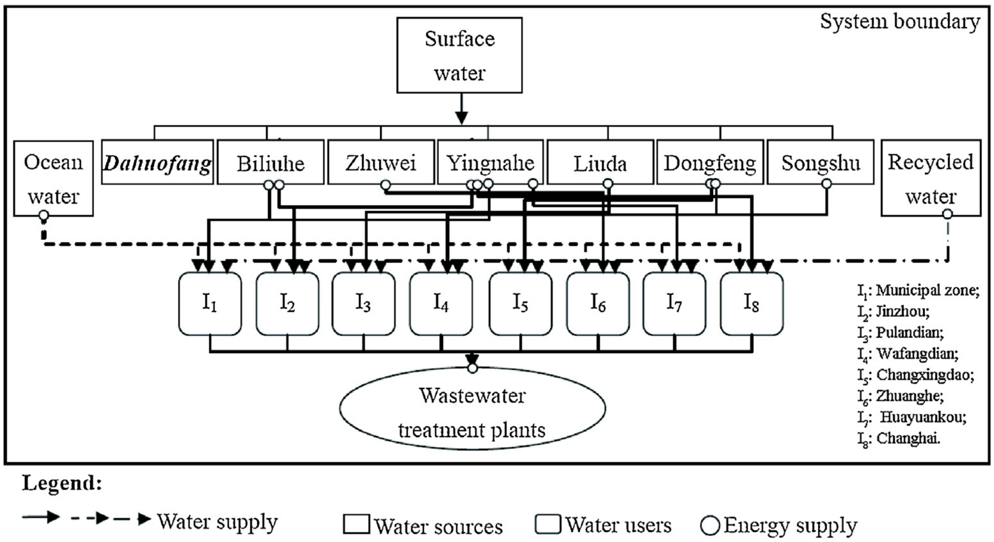

Fig. 6. System boundary of water service in Dalian City.

4.2. Environmental impacts analysis

The environmental impacts and water demands of the UWAS in the planning years will be influenced by changes in population, the economy and the environment. The analysis of environmental impacts is based on the method of Eco-indicator 99 for life-cycle analysis of UWAS. Referred to related research from Pishvaee and Razmi (2012), the average Hierarchist version of Eco-indicator 99 is chosen to evaluate environmental impact of UWMS in Dalian City. The uncertainty analysis of life cycle inventory is based on the methodology of data quality indicators (DQI). A Monte Carlo procedure can generate variability of pollutant emissions and water requirements. Fuzzy set theory can then be introduced to analyze the uncertainty of environmental impacts. The uncertainty of the life cycle inventory of the UWAS in Dalian is listed in Table 4. The results of environmental impacts are listed in Tables 5 and 6. Generally, environmental impacts for 1000 kg surface water conveyance in two stages would vary largely with the different districts of Dalian City. Compared with other districts, the largest environmental impacts based on functional units of the first and second stages would occur in Changhai, the least one in the stages would happen in Zhuanghe and Wafangdian.

4.3. Two-stage stochastic programming

Three planning horizons are considered in this study, with the base year of 2010, and the planning years of 2015, 2020 and 2030. When consider the features of Dalian City, the Eqs. (22) and (23) are changed to the following equations:

$$\begin{aligned}\min \mathrm{LCA}\,\tilde{f}^{-}_{(N)} = {} & \sum_{l=1}^{6}\sum_{i=1}^{8}\frac{E^{-}_{i_1 l(N)}+E^{-}_{i_2 l(N)}}{2}T^{-}_{il(N)} \\ & +\sum_{l=1}^{6}\sum_{i=1}^{8}\left(\frac{E'^{-}_{i_1 l(N)}+E'^{-}_{i_2 l(N)}}{2}\sum_{j=1}^{3}p_{jl}D^{-}_{ijl(N)}\right) \\ & +\sum_{r=1}^{2}\sum_{i=1}^{8}\frac{E''^{-}_{i_1 r(N)}+E''^{-}_{i_2 r(N)}}{2}T^{-}_{ir(N)} \end{aligned} \tag{23a}$$

s.t.

$$T^{-}_{il} \geq D^{-}_{ijl} \geq 0, \quad \forall i, j, l \tag{23b}$$

$$q^{+}_{jl} \geq \sum_{i=1}^{8}(T^{-}_{il} - D^{-}_{ijl}), \quad \forall i, j, l \tag{23c}$$

$$C_l \geq \sum_{i=1}^{8}(T^{-}_{il} - D^{-}_{ijl}), \quad \forall l, j \tag{23d}$$

$$T^{+}_{i\max} \geq T^{-}_{il} + T^{-}_{ir}, \quad \forall i, l, r \tag{23e}$$

$$T^{-}_{il}, T^{-}_{ir}, D^{-}_{ijl} \geq 0, \quad \forall i, j, l, r \tag{23f}$$

Table 4
Uncertainty analysis of life cycle inventory.

Item		DQI	R	DQI	Range endpoints
Electricity for two stages	2015	(3, 2, 1, 3, 2, 3)	66.67%	3.5	±25%
	2020	(3, 2, 1, 2, 2, 3)	58.33%	3	±30%
	2030	(3, 2, 1, 1, 2, 3)	50.00%	3	±30%
Water supply	2015	(4, 5, 5, 4, 5, 4)	50.00%	3	±30%
	2020	(4, 5, 5, 3, 5, 4)	66.67%	3.5	±25%
	2030	(4, 5, 5, 2, 5, 4)	72.22%	3.5	±25%
Water demand	2015	(4, 5, 5, 4, 5, 4)	50.00%	3	±30%
	2020	(4, 5, 5, 3, 5, 4)	66.67%	3.5	±25%
	2030	(4, 5, 5, 2, 5, 4)	72.22%	3.5	±25%

Table 5
Environmental impacts of 1000 kg surface water conveyance for Dalian.

Year	Area	$\tilde{e}(a,b,c)\,(\times 10^{-6})$			$\tilde{e}'(a,b,c)\,(\times 10^{-6})$		
		a	b	c	a	b	c
2015	$I_{1\text{-}a}$	[22.9, 23.0]	[30.7, 31.0]	[178.4, 185.0]	[3598.7, 3657.3]	[4850.1, 4915.8]	[28,632.4, 28,825.3]
	$I_{1\text{-}b}$	[13.0, 13.1]	[17.4, 17.6]	[101.2, 103.4]	[3608.6, 3667.2]	[4863.5, 4929.2]	[28,709.6, 28,906.9]
	$I_{2\text{-}a}$	[22.9, 23.0]	[30.7, 31.0]	[178.4, 185.0]	[3598.7, 3657.3]	[4850.1, 4915.8]	[28,632.4, 28,825.3]
	$I_{2\text{-}b}$	[13.0, 13.1]	[17.4, 17.6]	[101.2, 103.4]	[3608.6, 3667.2]	[4863.5, 4929.2]	[28,709.6, 28,906.9]
	I_3	[5.7, 5.9]	[8.0, 8.1]	[47.6, 55.0]	[3740.9, 3780.9]	[5047.5, 5090.4]	[29,871.6, 29,993.9]
	$I_{4\text{-}c}$	[3.6, 3.7]	[4.9, 5.0]	[29.0, 28.9]	[3160.9, 3171.3]	[4232.6, 4266.4]	[24,641.8, 25,076.2]
	$I_{4\text{-}d}$	[3.4, 3.5]	[4.6, 4.7]	[27.3, 27.7]	[3161.1, 3171.5]	[4232.8, 4266.6]	[24,643.6, 25,077.4]
	I_5	[11.1, 11.3]	[14.9, 15.1]	[87.6, 87.7]	[4583.5, 4599.0]	[6189.9, 6248.6]	[36,699.0, 37,601.0]
	I_6	[3.3, 3.3]	[4.4, 4.5]	[26.5, 26.7]	[4632.5, 4690.4]	[6247.1, 6306.4]	[36,927.0, 36,993.0]
	I_7	[13.4, 13.5]	[18.0, 18.1]	[104.9, 106.7]	[5303.1, 5391.0]	[7164.8, 7239.7]	[42,430.2, 42,552.5]
	I_8	[100.9, 102.6]	[136.5, 138.1]	[812.5, 812.8]	[5925.1, 5984.4]	[8008.5, 8090.1]	[47,598.9, 48,185.2]
2020 and 2030	$I_{1\text{-}a}$	[21.0, 21.5]	[30.7, 31.1]	[212.9, 214.6]	[3356.6, 3391.7]	[4864.2, 4920.5]	[33,569.8, 33,960.1]
	$I_{1\text{-}b}$	[12.1, 12.2]	[17.4, 17.6]	[118.1, 120.0]	[3365.5, 3401.1]	[4877.5, 4934.0]	[33,666.2, 34,053.0]
	$I_{2\text{-}a}$	[21.0, 21.5]	[30.7, 31.1]	[212.9, 214.6]	[3356.6, 3391.7]	[4864.2, 4920.5]	[33,569.8, 33,960.1]
	$I_{2\text{-}b}$	[12.1, 12.2]	[17.4, 17.6]	[118.1, 120.0]	[3365.5, 3401.1]	[4877.5, 4934.0]	[33,666.2, 34,053.0]
	I_3	[5.5, 5.6]	[8.0, 8.1]	[55.2, 55.9]	[3461.3, 3526.3]	[5016.1, 5086.4]	[34,592.4, 34,742.5]
	$I_{4\text{-}c}$	[3.4, 3.4]	[4.9, 5.0]	[34.0, 34.2]	[2907.6, 2946.7]	[4237.8, 4280.0]	[29,516.7, 29,699.2]
	$I_{4\text{-}d}$	[3.2, 3.3]	[4.7, 4.7]	[31.7, 32.4]	[2907.8, 2946.9]	[4238.0, 4280.3]	[29,519.0, 29,701.1]
	I_5	[10.3, 10.4]	[14.9, 15.1]	[103.1, 104.7]	[4299.0, 4304.6]	[6186.2, 6247.2]	[42,073.8, 43,137.9]
	I_6	[3.0, 3.1]	[4.4, 4.5]	[30.7, 30.7]	[4291.1, 4370.2]	[6232.0, 6341.0]	[43,031.5, 43,800.8]
	I_7	[12.4, 12.6]	[18.0, 18.2]	[124.1, 124.2]	[4936.7, 5060.3]	[7177.3, 7279.9]	[49,770.2, 49,452.1]
	I_8	[94.0, 94.6]	[136.5, 138.2]	[945.5, 965.6]	[5516.1, 5621.3]	[7996.8, 8086.7]	[55,130.4, 55,203.3]

Table 6
Environmental impacts of 1000 kg desalinated and recycled water conveyance for Dalian.

	$\tilde{e}''_{i1}(a,b,c)\,(\times 10^{-4})$[a]			$\tilde{e}''_{i2}(a,b,c)\,(\times 10^{-4})$[b]		
	a	b	c	a	b	c
2015	[1.63, 1.65]	[2.20, 2.22]	[13, 13]	[1.03, 1.04]	[1.38, 1.4]	[8.13, 8.15]
2020	[1.53, 1.54]	[2.19, 2.22]	[14.9, 15]	[0.96, 0.97]	[1.39, 1.4]	[9.45, 9.56]
2030	[1.53, 1.54]	[2.19, 2.22]	[14.9, 15]	[0.96, 0.97]	[1.39, 1.4]	[9.45, 9.56]

[a] The index of $\tilde{e}''_{i1}$ represents the environmental impacts of 1000 kg desalinated water conveyance.
[b] The index of $\tilde{e}''_{i2}$ represents the environmental impacts of 1000 kg recycled water conveyance.

$$\min \mathrm{LCA}\_\tilde{f}^{+}_{(N)} = \sum_{l=1}^{6}\sum_{i=1}^{8}\frac{E^{+}_{i_1 l(N)}+E^{+}_{i_2 l(N)}}{2}T^{+}_{il(N)} + \sum_{l=1}^{6}\sum_{i=1}^{8}\left(\frac{E'^{+}_{i_1 l(N)}+E'^{+}_{i_2 l(N)}}{2}\sum_{j=1}^{3}p_{jl}D^{+}_{ijl(N)}\right) + \sum_{r=1}^{2}\sum_{i=1}^{8}\frac{E''^{+}_{i_1 l(N)}+E''^{+}_{i_2 l(N)}}{2}T^{+}_{ir(N)} \tag{24a}$$

s.t.

$$T^{+}_{il} \geq D^{+}_{ijl} \geq 0, \quad \forall i,j,l \tag{24b}$$

$$q^{-}_{jl} \geq \sum_{i=1}^{8}(T^{+}_{il}-D^{+}_{ijl}), \quad \forall i,j,l \tag{24c}$$

$$C_l \geq \sum_{i=1}^{8}(T^{+}_{il}-D^{+}_{ijl}), \quad \forall l,j \tag{24d}$$

$$T^{-}_{i\,\max} \geq T^{+}_{il}+T^{+}_{ir}, \quad \forall i,l,r \tag{24e}$$

$$D^{+}_{ijl} \geq D^{-}_{ijlopt}, \quad \forall i,j \tag{24f}$$

$$T^{+}_{il}, T^{+}_{ir}, D^{+}_{ijl} \geq 0, \quad \forall i,j,l,r \tag{24g}$$

5. Results and discussion

Considering uncertainties of the water supply system, two scenarios are established in this research. In detail, scenario 1 represents the baseline of water supply options in Dalian with considering physical restrictions of the existing water supply infrastructure capacities. Scenario 2 considers possible expansions of the existing infrastructures under random water availabilities.

5.1. Environmental impact analysis under scenarios 1 and 2

Based on the optimal solutions of models 23 and 24, environmental impacts of water allocation system in Dalian are shown in Table A.7 and Fig. 7 under two scenarios. On the whole, the minimized environmental impacts of the UWAS in Dalian would be $[1.09\times10^7, 2.29\times10^7]$ in 2015, $[1.57\times10^7, 1.87\times10^7]$ in 2020, and $[2.80\times10^7, 3.17\times10^7]$ in 2030 under scenario 1; Meanwhile, the values would be $[6.59\times10^6, 9.58\times10^6]$ in 2015, $[9.58\times10^6, 1.70\times10^7]$ in 2020, and $[1.55\times10^7, 2.83\times10^7]$ in 2030 under scenario 2.

Under scenario 1, as shown in Fig. 8, the districts of Municipal zone, Pulandian, Wafangdian, Changxingdao, and Zhuanghe, would suffer more environmental impacts from UWAS than the other four districts. Meanwhile, the district of Zhuanghe would also be the biggest environmental impact area in Dalian. Compared with scenario 1, a smaller amount of second-stage water would need to be transferred from Hun River under scenario 2. This means the environmental impacts of scenario 2 would be lower than those of scenario 1. Under this scenario, the amounts of water supply would vary with the planning year and precipitation probabilities in both

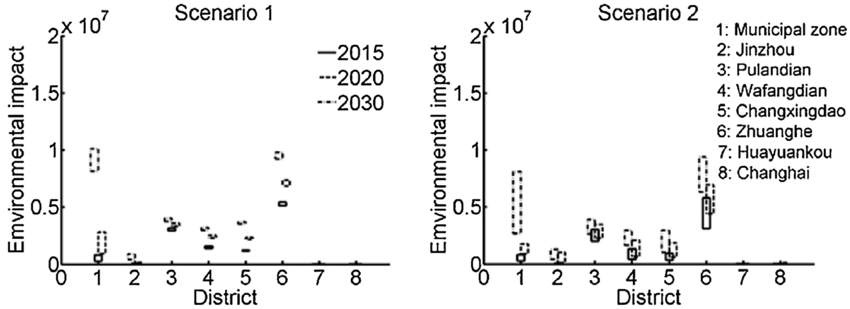

Fig. 7. Environmental impacts of optimal water allocation options in Dalian.

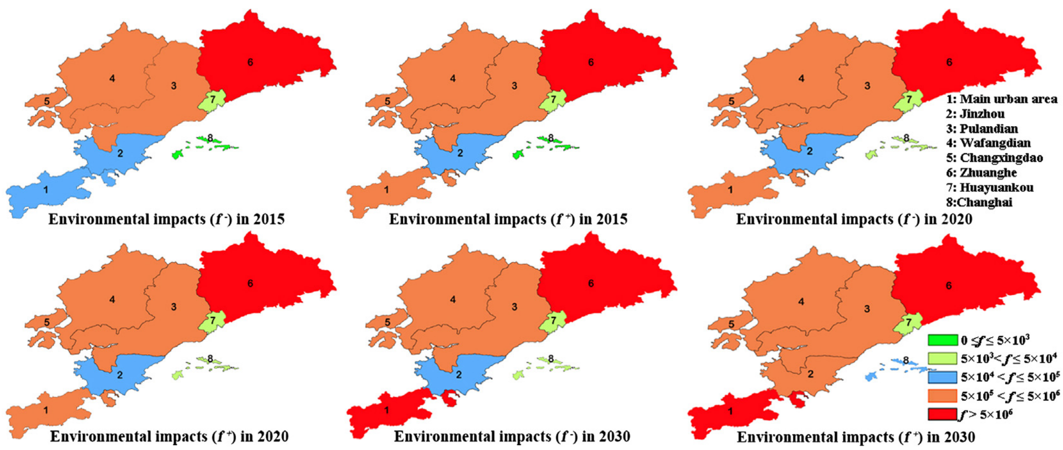

Fig. 8. Environmental impacts of water allocation system in Dalian under scenario 1.

water supply stages. On the whole, the water supply in the first stage can basically fulfill the demands from the districts of Municipal zone, Jinzhou, Huayuankou, and Changhai. Other districts would be relied on the second stage water conveyance. Under scenario 2, as shown in Fig. 9, the districts of municipal zone, Pulandian, and Zhuanghe would suffer more obvious environmental impacts from UWAS than the other five districts. Meanwhile, the district of Zhuanghe would become the biggest environmental-impact contributor area in Dalian.

The detail of environmental impacts under scenario 1 in eight districts is described as follows. (a) In 2015, the total amount of environmental impacts in Dalian would be [6.2×10^6, 1.2×10^7]. The environmental impacts in Pulandian and Zhuanghe would be the most obvious in eight districts. The environmental impacts of these two districts would be [2.0×10^6, 3.0×10^6] and [3.1×10^6, 5.8×10^6]. On the contrary, the environmental impacts in Jinzhou, Huayuankou, and Changhai would be the least obvious in eight districts. The environmental impacts of these three districts would be [5.2×10^4, 6.5×10^4], 6×10^3, and [4×10^3, 5×10^3]. The environmental impacts of UWAS in Municipal zone, Wafangdian, and Changxingdao would be [2.7×10^5, 8.0×10^5], [4.1×10^5, 1.3×10^6], and [3.2×10^5, 9.5×10^5]. (b) In 2020, the total amount of environmental impacts in Dalian would be [9×10^6, 1.72×10^7]. Similarly with the environmental impacts in 2015, the environmental impacts in Pulandian and Zhuanghe would also be the most obvious in eight districts. The environmental impacts of these two districts

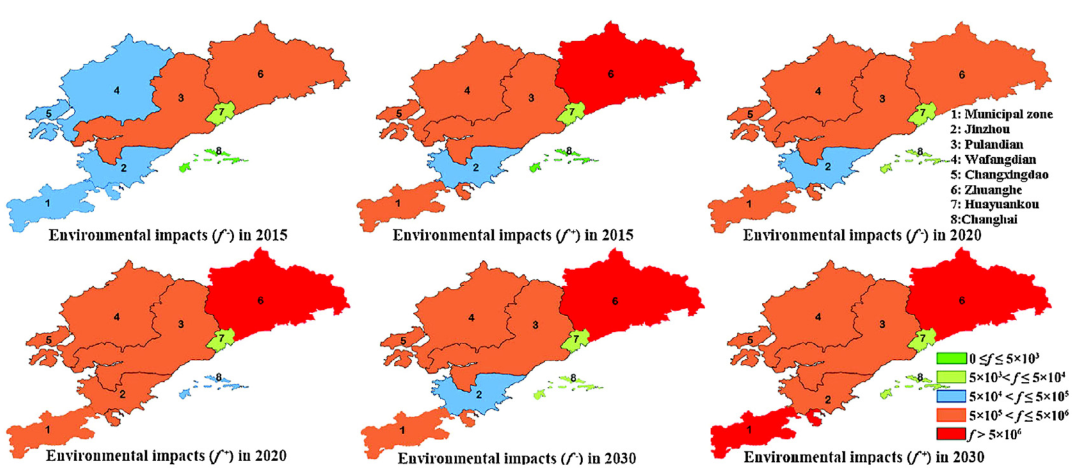

Fig. 9. Environmental impacts of water allocation system in Dalian under scenario 2.

would be [2.3×10^6, 3.5×10^6] and [4.4×10^6, 7.0×10^6]. On the contrary, the environmental impacts in Jinzhou, Huayuankou, and Changhai would also be the least obvious in eight districts. The environmental impacts of these three districts would be [1.2×10^5, 1.0×10^6], 1.3×10^4, and [8.0×10^3, 9.1×10^4]. The environmental impacts of UWAS in Municipal zone, Wafangdian, and Changxingdao would be [9.1×10^5, 1.8×10^6], [6.6×10^5, 2.1×10^6], and [6.2×10^5, 1.8×10^6]. (c) In 2030, the total amount of environmental impacts of UWAS in Dalian would be [1.5×10^7, 2.9×10^7]. The environmental impacts in Zhuanghe would also be the most obvious in eight districts. The environmental impacts of the district would be [6.3×10^6, 9.4×10^6]. On the contrary, the environmental impacts in Jinzhou, Huayuankou, and Changhai would also be the least obvious in eight districts. The environmental impacts of these three districts would be [4.0×10^5, 1.3×10^6], 2.6×10^4, 1.3×10^4. Compared with the environmental impacts of UWAS in 2015 and 2020, Municipal zone would become the biggest growth district. Its environmental impact in 2030 would reach [2.7×10^6, 8.1×10^6].

The detail of environmental impacts under scenario 2 in eight districts is described as follows. (a) In 2015, the total amount of environmental impacts in Dalian would be [1.1×10^7, 1.2×10^7]. The environmental impacts in Pulandian and Zhuanghe would be the most obvious in eight districts. The environmental impacts of these two districts would be [2.9×10^6, 3.2×10^6] and [5.1×10^6, 5.5×10^6]. On the contrary, the environmental impacts in Jinzhou, Huayuankou, and Changhai would be the least obvious in eight districts. The environmental impacts of these three districts would be [0.52×10^4, 0.65×10^4], 6×10^3, and [4×10^3, 5×10^3]. The environmental impacts of UWAS in Municipal zone, Wafangdian, and Changxingdao would be [2.7×10^5, 8.0×10^5], [1.4×10^6, 1.6×10^6], and [1.1×10^6, 1.2×10^6]. (b) In 2020, the total amount of environmental impacts in Dalian would be [1.6×10^7, 1.9×10^7]. Similarly with the environmental impacts in 2015, the environmental impacts in Pulandian and Zhuanghe would also be the most obvious in eight districts. The environmental impacts of these two districts would be [3.3×10^6, 3.6×10^6] and [6.8×10^6, 7.4×10^6]. On the contrary, the environmental impacts in Jinzhou, Huayuankou, and Changhai would also be the least obvious in eight districts. The environmental impacts of these three districts would be [1.2×10^5, 1.3×10^5], 1.3×10^4, 8×10^3. The environmental impacts of UWAS in Municipal zone, Wafangdian, and Changxingdao would be [9.1×10^5, 2.8×10^6], [2.3×10^6, 2.5×10^6], and [2.2×10^6, 2.4×10^6]. (c) In 2030, the total amount of environmental impacts in Dalian would be [2.8×10^7, 3.2×10^7]. The environmental impacts in Municipal zone and Zhuanghe would be the most obvious in eight districts. The environmental impacts of these districts would be [8.1×10^6, 1.0×10^7] and [9.2×10^6, 9.8×10^6]. On the contrary, the environmental impacts in Jinzhou, Huayuankou, and Changhai would also be the least obvious in eight districts. The environmental impacts of these three districts would be [4.0×10^5, 8.9×10^5], 2.6×10^4, and 1.3×10^4. Compared with the environmental impacts of UWAS in 2015 and 2020, Municipal zone would become the biggest growth district. The environmental impacts of UWAS in Pulandian, Wafangdian, and Changxingdao would reach [3.7×10^6, 4.0×10^6], [3.0×10^6, 3.2×10^6], and [3.5×10^6, 3.7×10^6].

5.2. *Water allocation strategies*

In this research, a fuzzy inexact two-stage programming (FITSP) model was integrated into uncertainty and life-cycle analysis methods to identify desired strategies for urban water allocation under minimized life-cycle environmental impacts of water consumption. The proposed FITSP model improved conventional studies in the following three aspects: (a) This research could strengthen capabilities in robust and direct decision-making of previous LCA studies on uncertain reflections. For conventional LCA research, the generated results merely represented environmental impacts of water consumptions in a quantitative way (e.g., Lim and Park, 2007; Zhang and Anadon, 2013). However, uncertainties of LCI data and dynamics of water availabilities could make post-LCA decision-making ineffective. The methodology proposed in this research could systematically tackle the uncertainties in supporting decision making in water resources management; (b) This study could also incorporate life-cycle environmental impacts of water consumptions into programming models for generating desired water management strategies. In previous studies for water resources, economic performances were commonly considered as objective functions (e.g., Xie et al., 2013; Wang and Huang, 2011). The environmental impacts were not yet comprehensively addressed. With employment of LCA and optimization approaches, this study could deal with water management options, taking into consideration of environmental impacts of water consumption and water demands of multiple users; (c) Finally, compared with the related study for Dalian (e.g., Han et al., 2011), this research could establish practical and desired strategies of water resources management, in consideration of update plans for water resources of Dalian (WABD, 2012) (Table A.6). In detail, based on the assumptions of recourse actions in future, this study could emphasize allocation of local and external water sources for eight districts of Dalian upon two scenarios, improving the capabilities for decision-making support in uncertain conditions. For example, it could be obtained that amount of water delivered from external water sources (e.g., from Hun River in Fushun City) would be 1070–1190 Mt in 2030 upon scenario 1, if Dalian is in median water year. Meanwhile, optimal water allocations for eight districts could be described as follows: 330–413 Mt for Municipal zone, 0–36 Mt for Jinzhou, 155–161 Mt for Pulandian, 144–152 Mt for Wafangdian, 112–117 Mt for Changxingdao, 0 Mt for Huayuankou, 317 Mt for Zhuanghe, and 0–13.4 Mt for Changhai. Thus, compared with previous studies, this study could strengthen the capabilities of robust decision-making and indications of uncertain conditions for water resources management in environmental perspectives. In detail, the first- and second-stage decisions would represent responses of water allocation plans under uncertain water demands, mainly presented as interval numbers in this research. According to Eqs. (22) and (23), solutions for water conveyance in the city of Dalian can be obtained (Table 7), which cover decision alternatives for the first and second decision stages. The first-stage decision is preliminarily determined by local water authorities and is mainly assigned as certain water allocation targets which are met merely by local water sources. Comparatively, the second-stage decision alternatives mainly related to water conveyance from the Hun River under the occurrence of random hydrological events in the city. The results of second-stage solutions of surface water conveyance are shown in Table 8.

Solutions of the two scenarios can thus reflect applicability of the methodology in strengthening the applicability of post-LCA for comprehensive decision alternatives under uncertainties (i.e., first-stage strategy showed in Fig. 10 and second-stage strategy showed in Fig. 11). Under the two scenarios, similar decision alternatives can be obtained with slight disparities. This represents detailed active plans for minimizing the impacts based on anticipatory LCA results. In detail, under scenario 1 the reservoirs of Biliu and Yingna Rivers would support more than 70% of the first-stage water supply of Dalian. Meanwhile, solutions of this scenario in both stages indicate the main local water source of the city is Biliu and Yingna Rivers. Compared with the other seven districts in Dalian, Zhuanghe district is the most sensitive to uncertain conditions. The reasons of its sensibilities to uncertainties lie in the following aspects: (i) surface water from local supply is far from enough to meet the

Table 7
Solutions of surface water conveyance of rivers in Dalian.

	Scenario 1 (Mt)			Scenario 2 (Mt)		
	q[a] = 20%	q = 55%	q = 25%	q = 20%	q = 55%	q = 25%
Biliuhe and above river						
2015	[373, 392]	[346, 373]	[346, 365]	[373, 392]	[346, 373]	[346, 365]
2020	450	[346, 450]	346	[469, 479]	[346, 469]	[346, 356]
2030	450	[346, 450]	346	[795, 813]	[346, 795]	[346, 364]
Yingnahe and above river						
2015	208	208	208	208	208	208
2020	[227, 241]	[208, 227]	[208, 228]	[208, 218]	208	[208, 218]
2030	[228, 241]	[195, 241]	[208, 240]	[208, 221]	[195, 208]	[208, 221]
Dongfeng and above river						
2015	67	67	67	[192, 195]	[69, 192]	[69, 72]
2020	67	67	67	197	[69, 197]	[69, 73]
2030	67	67	67	[197, 268]	[69, 197]	[69, 74]
Songshu and above river						
2015	47	[34, 47]	[34, 38]	[34, 39]	34	[34, 39]
2020	47	[34, 47]	[34, 38]	[95, 97]	[34, 95]	[34, 38]
2030	47	[34, 47]	[34, 39]	[97, 97]	[34, 97]	[34, 39]
Liuda and above river						
2015	49	[37, 49]	[37, 42]	[79, 178]	[37, 79]	[37, 42]
2020	49	[37, 49]	[37, 43]	[79, 181]	[37, 79]	[37, 43]
2030	[49, 89]	[89, 89]	[89, 89]	[132, 198]	[91, 129]	[91, 94]
Zhuwei and above river						
2015	81	[70, 81]	[70, 78]	[147, 266]	[70, 147]	[70, 78]
2020	81	[70, 81]	[70, 79]	[147, 306]	[70, 147]	[70, 79]
2030	81	[70, 81]	[70, 81]	[147, 384]	[70, 147]	[70, 81]

[a] The index of q represents precipitation probability level of water availabilities. In detail, when q is 20%, it means precipitation probability would be 20% in high-flow year; when q is 55%, it means precipitation probability would be 55% in median-flow year; when q is 25%, it means precipitation probability would be 25% in low-flow year.

demands of the district. In detail, the source of local surface water would support only 26–54%, 8–17%, and 2–4% in the years of 2015, 2020 and 2030, with median-flow year of runoff; (ii) Zhuanghe district would have to transfer a large amount of water from the external areas of the city. In detail, amount of water allocated from Hun River for Zhuanghe district would be193–196, 234–236, and 314 Mt when precipitation probability is 55%. Other districts of Dalian would also experience certain degrees of water scarcity, such as Municipal zone, Pulandian, and Wafangdian. The detail of solutions for surface water conveyance of Dalian City in first- and second-stages is described as the following.

5.2.1. Scenario 1

In the first stage, water supply from local rivers is described as follows. (a) In high flow year, Biliu River would afford 373–450 Mt water supply; Yingna River 208–241 Mt water supply; Fuzhou River would afford 114 Mt water supply; Dasha River would afford 49–89 Mt water supply; and Zhuang River would afford 81 Mt

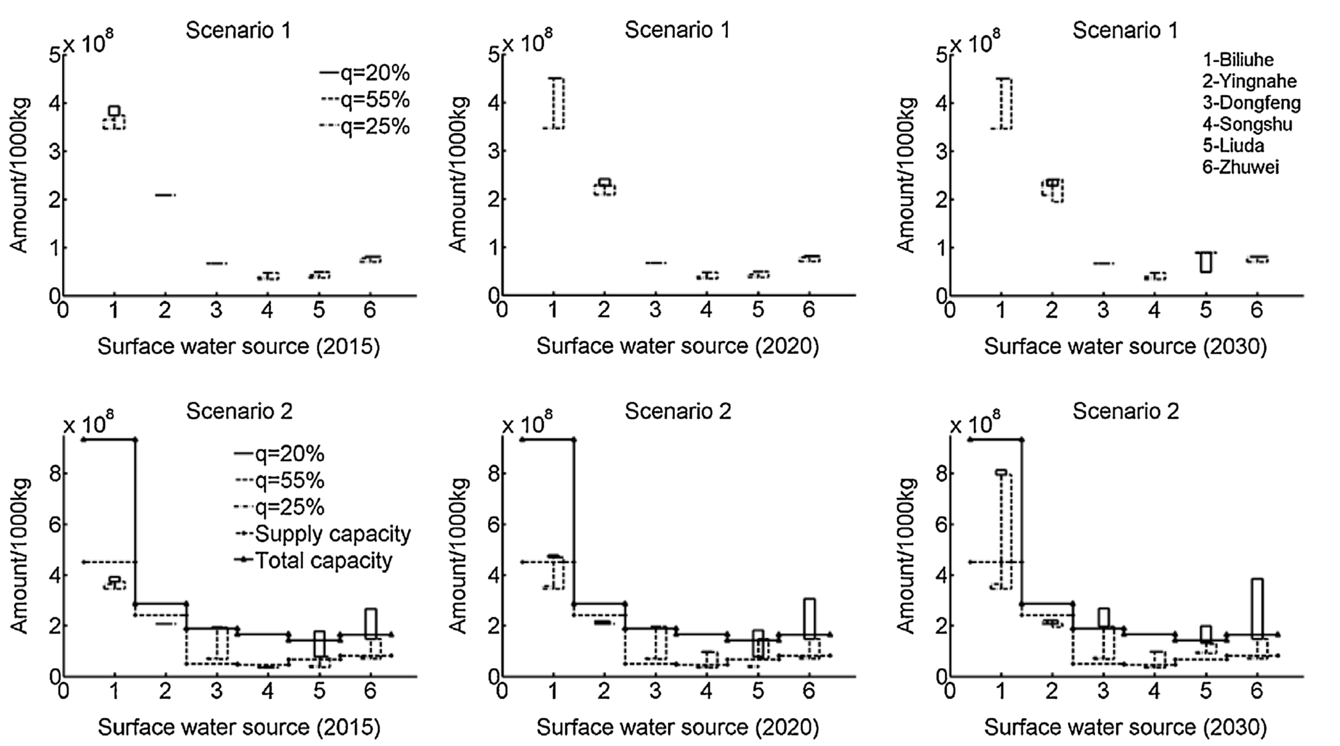

Fig. 10. Optional water conveyance solutions from local sources for Dalian.

Table 8
Second-stage solutions of surface water conveyance in scenarios 1 and 2.

	Scenario 1 (Mt)			Scenario 2 (Mt)		
	q = 20%	q = 55%	q = 25%	q = 20%	q = 55%	q = 25%
$I_{1\text{-}a}$						
2015	0	0	0	0	0	0
2020	0	[0, 18.8]	[18.8, 29.5]	0	0	0
2030	312	[330, 345]	[345, 363]	0	0	0
$I_{1\text{-}b}$						
2015	0	[0, 27.4]	[27.4, 46.2]	0	[0, 46.2]	27.4
2020	0	[0, 104]	[36.5, 104]	0	[0, 66]	123
2030	0	[0, 68]	[0, 68]	0	[0, 413]	413
$I_{2\text{-}a}$						
2015	0	0	0	0	0	0
2020	0	0	0	0	0	0
2030	0	0	0	0	0	0
$I_{2\text{-}b}$						
2015	0	0	0	0	0	0
2020	0	0	[0, 67.5]	0	[0, 67.5]	0
2030	0	[0, 36]	[36, 104]	0	[0, 67.5]	36
I_3						
2015	129	[134, 141]	[141, 146]	[0, 104]	[99, 146]	141
2020	132	[138, 144]	[144, 150]	[0, 108]	[102, 150]	144
2030	149	[155, 161]	[161, 167]	[0, 125]	[119, 167]	161
$I_{4\text{-}c}$						
2015	0	[4, 13]	13	0	[0, 5]	0
2020	0	[4, 13]	13	[0, 2]	[0, 65]	61
2030	0	[5, 13]	13	[0, 5]	[0, 68]	63
$I_{4\text{-}d}$						
2015	72	72	72	0	[0, 85]	85
2020	107	107	107	[0, 4]	[0, 59]	59
2030	139	139	139	[0, 76]	[71, 89]	89
I_5						
2015	40	[40, 43]	43	0	[0, 41]	38
2020	71	[71, 75]	75	0	[0, 73]	69
2030	112	[112, 117]	117	0	[0, 115]	110
I_6						
2015	185	[193, 196]	[196, 204]	[0, 127]	[119, 204]	196
2020	225	[234, 236]	[236, 245]	[0, 168]	[159, 245]	236
2030	303	314	[314, 325]	[0, 248]	[237, 325]	314
I_7						
2015	0	0	0	0	0	0
2020	0	0	0	0	0	0
2030	0	0	0	0	0	0
I_8						
2015	0	0	0	0	0	0
2020	0	[0, 6.1]	[0, 9.61]	0	[0, 9.61]	0
2030	0	[0, 13.4]	[0, 13.4]	0	[0, 13.4]	0
Total						
2015	426	[446, 489]	[492, 528]	[0, 231]	[218, 527]	487
2020	535	[564, 694]	[698, 737]	[0, 282]	[261, 735]	692
2030	1020	[1070, 1190]	[1190, 1250]	[0, 454]	[427, 1240]	1190

water supply in the three planning years. (b) In median flow water year, Biliu River would afford 346–450 Mt water supply; Yingna River 195–241 Mt water supply; Fuzhou River would afford 101–114 Mt water supply; Dasha River would afford 37–89 Mt water supply; and Zhuang River would afford 70–81 Mt water supply in the three planning years. (c) In low flow year, Biliu River would afford 346–365 Mt water supply; Yingna River 208–240 Mt water supply; Fuzhou River would afford 101–106 Mt water supply; and Dasha River would afford 37–89 Mt water supply; Zhuang River would afford 70–81 Mt water supply in the three planning years.

The strategy of water supply to these districts is described as follows: (a) If Dalian is in high flow year, Hun River would deliver 312 Mt water to Municipal zone; 129, 132, and 149 Mt water to Pulandian, 72, 107, and 139 Mt water to Wafangdian, 40, 71, and 112 Mt water to Changxingdao, 185, 225, and 303 Mt water to Zhuanghe in the three planning year. (b) If Dalian is in median water year, Hun River would deliver [0, 27.4], [0, 122.8], and [330, 413] Mt water to Municipal zone; [134, 141], [138, 144], and [155, 161] Mt water to Pulandian, [76, 85], [111, 120] and [144, 152] Mt water to Wafangdian, [40, 43], [71, 75], and [112, 117] Mt water to Changxingdao, [193, 196], [234, 236], and 314 Mt water to Zhuanghe in the three planning year. (c) If Dalian is in low flow year, Hun River would deliver [27.4, 46.2], [55.3, 133.5], [345, 431] Mt water to Municipal zone; [141, 146], [144, 150], and [161, 167] Mt water to Pulandian, 85, 120, and 152 Mt water to Wafangdian, 43, 75, and 117 Mt water to Changxingdao, [196, 204], [236, 245], and [314, 325] Mt water to Zhuanghe in the planning years.

5.2.2. *Scenario 2*

The strategy for water conveyance in both stages is described as follows: In first stage conveyance, Biliu River is the main water source. In high flow year, Biliu River would afford [373, 392], [469, 479], and [795, 813] Mt water supply in 2015, 2020, and 2030. In median water year, Biliu River would afford [346, 373], [346, 469], and [346, 795] Mt water supply in 2015, 2020, and 2030. In low flow year, Biliu River would afford [346, 365], [346, 356], and [346, 364] Mt water supply in 2015, 2020, and 2030. Yingna River

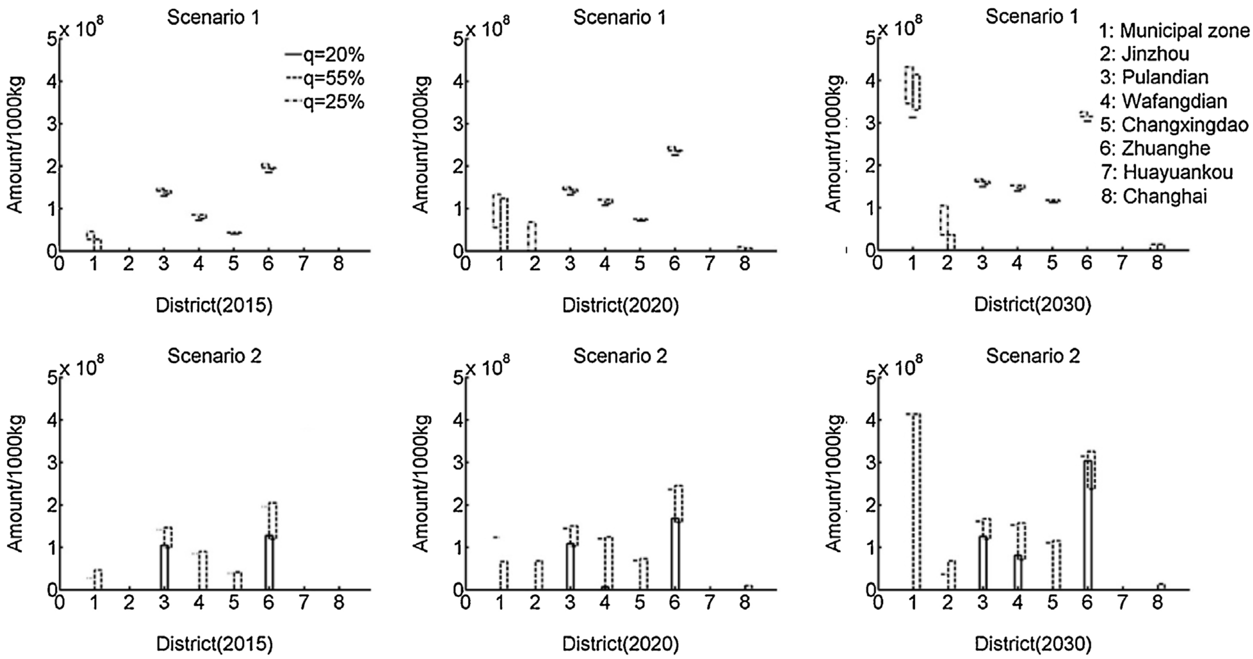

Fig. 11. Optimal water conveyance solutions from external sources for Dalian.

is another important water source in Dalian. For example, Yingna River would afford 208 and [208, 218] Mt water supply in 2015 and 2020. Yingna River would afford [208, 221], [195, 208], and [208, 221] Mt water supply in 2030 with the three inflow conditions. The above two main rivers in Dalian, i.e., Biliu and Yingna Rivers, would supply nearly 60% water resources. The water supply from other rivers is described as follows: (a) In high flow year, Fuzhou River would afford 226–365 Mt water supply; Dasha River would afford 79–198 Mt water supply; Zhuang River would afford [147, 266], [147, 306], and [147, 384] Mt water supply in 2015, 2020, and 2030. (b) In median water year, Fuzhou River would afford 103–294 Mt water supply; Dasha River would afford 37–129 Mt water supply; Zhuang River would afford 70–147 Mt water supply in the three planning years. (c) In low flow year, Fuzhou River would afford 105–113 Mt water supply; Dasha River would afford 37–94 Mt water supply; Zhuang River would afford 70–81 Mt water supply in the three planning years. As above, local rivers in Dalian can support a half of water demand of Dalian City. As showed in Fig. 10, however, at least five rivers in this scenario need to improve the water supply of the planning years. In other words, the solutions of the water supply would exceed the present level of water supply capacity of the rivers.

In second stage, Hun River would mainly support the water demands from the districts of Pulandian, Wafangdian, Changxingdao, and Zhuanghe. The strategy of water supply to these districts is described as follows: (a) If Dalian is in high flow year, Hun River would deliver [0, 104], [0, 108], and [0, 125] Mt water to Pulandian in 2015, 2020 and 2030; [0, 6] and [0, 81] Mt water to Wafangdian in 2020 and 2030; [0, 127], [0, 168], and [0, 248] Mt water to Zhuanghe in 2015, 2020 and 2030. (b) If Dalian is in median water year, Hun River would deliver [99, 146], [102, 150], and [119, 167] Mt water to Pulandian; [0, 90], [0, 124], and [0, 157] Mt water to Wafangdian; [0, 41], [0, 73], and [0, 115] Mt water to Changxingdao; [119, 204], [159, 245], and [237, 325] Mt water to Zhuanghe in the planning years. (c) If Dalian is in low flow year, Hun River would deliver 141–161 Mt water to Pulandian; 85–152 Mt water to Wafangdian; 38–110 Mt water to Changxingdao; 196–314 Mt water to Zhuanghe in the planning years.

6. Conclusions

In this research, three limitations of traditional life cycle analysis were improved through the integration of operational research and uncertainty analysis methods into a general LCA framework. This improved conventional LCA in (a) evaluation of life-cycle environmental impacts at multiple product-service levels, (b) robust and direct decision-making, and (c) managing uncertainties associated with environmental impact and the consequential decision-making. The framework could systematically explore uncertainties that could be described by fuzzy sets, probability density functions, and interval numbers across the life cycle of urban water systems considering environmental impacts. In detail, a hybrid LCA and two-stage stochastic programming (TSP) models was proposed to analyze the environmental impacts based on a complicated urban water allocation system (UWAS) in an uncertain environment. Coupled with inexact numbers, fuzzy sets theory and Monte Carlo simulation, the improved methodology could optimize water allocation in consideration of uncertain conditions. The developed method was then verified by a case study in water-stressed city (i.e., the City of Dalian), northeastern China. The application indicated that the proposed method was effective in generating desired water supply schemes under uncertainties and reflecting the associated life-cycle environmental impacts, strengthening capabilities of both LCA and operational research methods. The results indicated that the top three contributors for life-cycle environmental impacts would be districts of Pulandian and Zhuanghe, and Municipal zone of the city.

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Appendix A. Background data

See Table A.1.

Table A.1
The LCI of electricity generated by power stations of China in 2009.

Item		Amount (kg/kWh)
Raw material	Coal	6.60×10^{-1}
	Fuel oil	2.50×10^{-4}
	H_2SO_4	2.30×10^{-4}
	HCl	6.22×10^{-5}
	NaOH	5.82×10^{-5}
	Limestone	4.96×10^{-3}
	Freshwater	8.47×10^{-2}
Direct emissions	CO_2	8.00×10^{-1}
	SO_2	1.67×10^{-3}
	NO_x	8.05×10^{-3}
	Particulates	2.00×10^{-5}
	CO	1.04×10^{-3}
	CH_4	7.90×10^{-6}
	NMVOC	2.40×10^{-4}
	As	1.86×10^{-8}
	Cr	1.42×10^{-9}
	Cd	2.40×10^{-10}
	Ni	1.83×10^{-9}
	Pb	4.81×10^{-8}
	V	2.42×10^{-8}
	Zn	6.51×10^{-8}
	Hg	4.13×10^{-8}
Waste disposal	Wastewater	8.47×10^{-2}
	Landfill	2.64×10^{-1}

According to the plan of water consumption of Dalian, the water consumption of eight districts in three planning years is listed in Table A.2.

Water is conveyed through links between reservoirs and water treatment plants (WTPs) by electricity. The distance between the reservoir and the WTP of Dalian City is described in Table A.3. The parameters of the reservoirs for Dalian City are listed in Table A.4. Also, water availability in different precipitation probabilities of Dalian City is listed in Table A.4. As showed in Table A.4, the value of capacity in Biliuhe and above river is referred to (Liu, 2008). The values of water supply capacity in Biliuhe, Dongfeng, Songshu, Liuda, and Zhuwei with their above rivers are referred to Lu (2008). The values of capacity and water supply capacity in Yingnahe and above river are referred to Zhang (2013). The values of capacity in Songshu, Liuda, and Zhuwei with their above rivers are referred to Liu and Li (2009), Liu et al. (2014), Tan and Zhang (2014), and Song and Ye (2010), respectively.

The water demands of the three planning years were predicted as interval parameters to reflect the related future change (Table A.5).

Table A.2
The plan of water supply and demand of Dalian City in the planning years of 2015, 2020 and 2030.

	Year	I_1 (Mt)	I_2 (Mt)	I_3 (Mt)	I_4 (Mt)	I_5 (Mt)	I_6 (Mt)	I_7 (Mt)	I_8 (Mt)
Supply									
Surface water	2015	350	210	180	120	110	270	22	5.8
	2020	400	240	190	150	140	310	34	9.6
	2030	550	380	200	190	180	380	60	13
Desalinated water	2015	17	5.3	27	12	54	11	1.3	0.6
	2020	40	37	40	24	66	16	2.7	0.6
	2030	45	53	53	27	120	21	5.3	1.9
Recycled water	2015	120	54	19	13	16	14	5.4	0.9
	2020	160	86	29	24	43	24	11	1.7
	2030	220	160	43	39	120	53	23	3.3
Total	2015	487	269	226	145	180	295	29	7
	2020	600	363	259	198	249	350	48	12
	2030	815	593	296	256	420	454	88	18
Demand	2015	487	269	226	145	180	295	29	7
	2020	600	363	259	198	249	350	48	12
	2030	815	593	296	256	420	454	88	18

Table A.3
The distance between reservoir and WTP of Dalian City.

Area	First stage		Second stage	
	Rivers (reservoirs)	Distance (km)	Rivers (reservoirs)	Distance (km)
$I_{1\text{-}a}$	Yingna River (Yingnahe),	121	Hun River (Dahuofang)	190.5
$I_{1\text{-}b}$	Biliu River (Biliuhe)			
$I_{2\text{-}a}$	Yingna River (Yingnahe),	121		190.5
$I_{2\text{-}b}$	Biliu River (Biliuhe)			
I_3	Dasha River (Liuda)	31		197
$I_{4\text{-}c}$	Fuzhou River (Songshu,)	19		165.1
$I_{4\text{-}d}$	Fuzhou River (Dongfeng)			
I_5	Fuzhou River (Dongfeng)	59		242
I_6	Zhuang River (Zhuwei)	17		244
I_7	Yingna River (Yingnahe)	71		280
I_8	Yingna River (Yingnahe)	108		317

Table A.4
The related hydrologic parameters of Dalian City.

Reservoirs and rivers	Capacity (Mt)	Water availability (q_j) in different probabilities (Mt)			Water supply capacity (Mt)
		20%	55%	25%	
Biliuhe and above river	934	[848, 1348]	[346, 848]	[0, 346]	450
Yingnahe and above river	287	[416, 916]	[208, 416]	[0, 208]	241
Dongfeng and above river	142	[197, 697]	[69, 197]	[0, 69]	67
Songshu and above river	167	[97, 597]	[34, 97]	[0, 34]	47
Liuda and above river	189	[79, 579]	[37, 79]	[0, 37]	49
Zhuwei and above river	165	[147, 647]	[70, 147]	[0, 70]	81

Table A.5
Water demand prediction of Dalian City in 2015, 2020 and 2030.

	2015			2020			2030		
	Surface water (Mt)	Desalinated water (Mt)	Recycled water (Mt)	Surface water (Mt)	Desalinated water (Mt)	Recycled water (Mt)	Surface water (Mt)	Desalinated water (Mt)	Recycled water (Mt)
I_1	[349, 360]	[16.5, 17]	[117, 121]	[400, 412]	[39.9, 41.1]	[157, 162]	[548, 565]	[45.2, 46.5]	[225, 232]
I_2	[205, 212]	[5.3, 5.5]	[53.9, 55.5]	[233, 240]	[37.2, 38.3]	[86.1, 88.7]	[382, 394]	[53.1, 54.7]	[160, 164]
I_3	[178, 183]	[26.6, 27.4]	[19.3, 19.9]	[181, 187]	[39.9, 41.1]	[28.6, 29.4]	[198, 204]	[53.1, 54.7]	[43.1, 44.4]
I_4	[119, 124]	[11.9, 12.3]	[13.3, 13.7]	[154, 158]	[23.9, 24.6]	[24.5, 25.2]	[186, 191]	[26.6, 27.4]	[39, 40.2]
I_5	[107, 110]	[54.3, 55.9]	[16.2, 16.7]	[138, 142]	[66.4, 68.4]	[43.3, 44.6]	[179, 184]	[120, 123]	[122, 125]
I_6	[266, 274]	[11.2, 11.5]	[14, 14.4]	[306, 315]	[15.9, 16.4]	[24, 24.7]	[384, 395]	[21.3, 21.9]	[53.5, 55.1]
I_7	[21.6, 22.2]	[1.3, 1.4]	[5.4, 5.5]	[34.2, 35.2]	2.7	[11.1, 11.4]	[59.9, 61.7]	[5.3, 5.5]	[22.6, 23.2]
I_8	[5.8, 6]	0.6	0.9	[9.6, 9.9]	0.6	1.7	[13.4, 13.8]	[1.9, 2]	[3.3, 3.4]
Total	[1250, 1290]	[128, 132]	[240, 247]	[1460, 1500]	[226, 233]	[376, 387]	[1950, 2010]	[326, 336]	[668, 688]

Table A.6
Original surface water plan of Dalian City without considering uncertainties.

Districts and planning year		Surface water allocation (100 Mt)	
		The 1st stage	The 2nd stage
Municipal zone	2015	299.54	43.46
	2020	271.74	128.26
	2030	200.21	304.95
Jinzhou	2015	69.51	131.19
	2020	63.53	173.47
	2030	33.12	393.72
Pulandian	2015	164.44	9.56
	2020	175.14	5.86
	2030	188.27	5.73
Wafangdian	2015	115	0
	2020	141.85	10.15
	2030	148.91	35.09
Changxingdao	2015	8.54	101.46
	2020	9.17	131.83
	2030	9.11	170.89
Zhuanghe	2015	265	0
	2020	310	0
	2030	386	0
Huayuankou	2015	21.3	0
	2020	34.3	0
	2030	59.7	0
Changhai	2015	5.7	0
	2020	9.7	0
	2030	13.8	0
Total	2015	949.03	285.67
	2020	1015.43	449.57
	2030	1039.12	910.38

Source: WABD (2012).

Table A.7
Environmental impacts of water allocation system in Dalian based on optimal solutions.

	Scenario 1 ($\times 10^5$)			Scenario 2 ($\times 10^5$)		
	2015	2020	2030	2015	2020	2030
I_1	[2.65, 7.99]	[9.07, 27.78]	[26.67, 80.79]	[2.65, 7.99]	[9.08, 28.05]	[81.39, 101.06]
I_2	[0.52, 0.65]	[1.15, 1.28]	[4.03, 13.00]	[0.52, 0.65]	[1.15, 1.28]	[4.03, 8.89]
I_3	[20.07, 30.31]	[22.78, 34.60]	[26.28, 38.96]	[29.34, 31.63]	[33.07, 36.05]	[37.39, 40.41]
I_4	[4.08, 13.24]	[6.60, 20.94]	[16.37, 29.55]	[13.91, 15.94]	[23.05, 25.26]	[29.74, 32.14]
I_5	[3.23, 9.45]	[6.15, 18.27]	[10.27, 29.37]	[11.40, 12.44]	[21.95, 23.53]	[35.11, 37.22]
I_6	[31.26, 57.9]	[44.18, 69.52]	[63.10, 93.96]	[51.12, 54.6]	[68.49, 73.53]	[92.08, 97.97]
I_7	[0.06, 0.06]	[0.13, 0.13]	[0.26, 0.26]	[0.06, 0.06]	[0.13, 0.13]	[0.26, 0.26]
I_8	[0.04, 0.05]	[0.08, 0.08]	[0.13, 0.13]	[0.04, 0.05]	[0.08, 0.08]	[0.13, 0.13]

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