Identification of optimal strategies for improving eco-resilience to floods in ecologically vulnerable regions of a wetland

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Abstract
In this study, a mixed integer fuzzy interval-stochastic programming model was developed for supporting the improvement of eco-resilience to floods in wetlands. This method allows uncertainties that are associated with eco-resilience improvement and can be presented as both probability distributions and interval values to be incorporated within a general modeling framework. Also, capacity-expansion plans of eco-resilience can be addressed through introducing binary variables. Moreover, penalties due to ecological damages which are associated with the violation of predefined targets can be effectively incorporated within the modeling and decision process. Thus, complexities associated with flood resistance and eco-resilience planning in wetlands can be systematically reflected, highly enhancing robustness of the modeling process. The developed method was then applied to a case of eco-resilience enhancement planning in three ecologically vulnerable regions of a wetland. Interval solutions under different river flow levels and different ecological damages were generated. They could be used for generating decision alternatives and thus help decision makers identify desired eco-resilience schemes to resist floods without causing too much damages. The application indicates that the model is helpful for supporting: (a) adjustment or justification of allocation patterns of ecological flood-resisting capacities, (b) formulation of local policies regarding eco-resilience enhancement options and policy interventions, and (c) analysis of interactions among multiple administrative targets within a wetland.

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1. Introduction

Flood is a strong if not primary influence on composition and processes of wetland plant communities, which have corresponding effects on structure and integrity of ecosystems (Mitsch and Gosselink, 1993; Keddy, 2000; Pivot et al., 2002; Brouwer and Remco van, 2004; Ferrari and Canziani, 2005; Philipp et al., 2006; Fletcher and Hilbert, 2007; Kneis et al., 2009). Also, it is responsible for eco-resilience declination in many ecologically vulnerable regions (EVR) of wetlands (Nicholls et al., 1999; Kercher and Zedler, 2004; Jiang et al., 2007; Carter et al., 2009). Reducing threats and impacts of floods is both a necessary and timely effort for ecological conservation in wetlands, particularly under changing climatic conditions (Schmidt-Thomé et al., 2006a,b). Identification of effective strategies for enhancing eco-resilience to flood is thus desired (Jason and Hall, 2005; Butts, 2000; Madsen et al., 2000). However, there are many complex processes that should be considered for maintaining or building-up eco-resilience, such as intensities of precipitations, occurrence probabilities of floods, interventions of human activities, as well as the related economic implications. Moreover, many factors and parameters (such as the present eco-resilience of an ecologically vulnerable region, the impacts of changing climatic conditions, and the corresponding measures for improving eco-resilience) of these processes may appear dynamic and uncertain that may be presented in fuzzy, probabilistic and/or interval formats. These uncertainties would affect the related decision processes and the generated schemes (Yeomans et al., 2003). Therefore, identifying optimal strategies for improving eco-resilience to flood under uncertainty is desired (Loukas et al., 2002; Shrubsole, 2000; Dean and Kemp, 2004; Blais-Stevens et al., 2003).

Previously, many researchers qualitatively evaluated effects of floods on multiple scales of ecosystems and analyzed their associated vulnerabilities. Also, they proposed a number of measures for mitigating impacts of catastrophic floods, as well as building-up eco-resilience to such disasters. For example, Brouwer and Remco van (2004) advanced an integrated assessment method for evaluating effectiveness of various flooding-control policies through considering a number of hydraulic, hydrological, ecological, eco-
monic and social processes. Ni and Xue (2003) employed artificial neural networks (ANN) to analyze risks associated with flooding events in a number of ecologically vulnerable zones in the Yangtze River. Recently, many geo-techniques were linked with hydro-ecological modeling approaches to assess relationships among ecological strategies, hydrological mechanisms and flooding patterns in wetlands (Zhou et al., 2008). At the same time, a large volume of studies were conducted on the management of ecologically vulnerable regions to reduce risks and damages of floods on ecological integrity at a specific spatial scale (Myers, 1992; Gill et al., 1995; Xu et al., 1996; Tutuncu, 2000; Barnes et al., 2002; Hager, 2002). For instance, Castelletti et al. (2007) proposed a neuro-dynamic programming (NDP) for the management of a multi-purpose water reservoir through generating a series of policies related to flood protection, water supply, hydropower generation and ecological conservation. Also, in order to reflect the compromise of many conflicting targets within the management of ecologically vulnerable regions in a wetland, Cheng and Chau (2002) proposed a multi-objective model. Esohbue (1996) proposed a fuzzy mathematical model to mitigate the adverse effects of floods and storms on ecological conservation in wetlands. Moreover, due to its effectiveness in determining capacity-expansion options, mixed integer linear programming (MILP) was frequently used for flooding mitigation and adaptation planning (Day and Weisz, 1976; Windsor, 1981; Randall et al., 1997; Srinivasan et al., 1999; Needham et al., 2000; Olsen et al., 2000). Though great efforts were made on the studies related to eco-resilience maintenance/improvement and flooding impact mitigation, complexities of their combination within real-world problems are beyond the capacity of the conventional methods, where many system parameters may appear uncertain. In fact, a variety of uncertainties exist in relevant processes and factors, such as stream flows, current eco-resilience capacities of the ecologically vulnerable regions, as well as human intervention intensities and economic/ecological implications. These uncertainties are further complicated by the changing climatic conditions, which are of great significance to ecosystems. Such complexities may further grow by interactions among these uncertain parameters/factors, as well as their association with various economic, environmental and ecological penalties if the predefined targets are violated (or exceeding the limits of eco-resilience).

Conventionally, in order to address the prescribed complexities and uncertainties, many inexact optimization techniques were developed such as stochastic programming, fuzzy programming, and interval-parameter programming, as well as their combinations with MILP. This leads to stochastic integer programming (SIP), fuzzy integer programming (FIP), and interval-parameter integer programming (IIP) methods (Augustine, 1996; Cai et al., 2008, 2009a,b,c,d; Maqsood et al., 2002; Maqsood and Huang, 2003; Maqsood et al., 2004; Tan et al., 2009a,b). The SIP and FIP methods can reflect probabilistic or possibilistic distributions of a linear model's right-hand sides and accommodate integer decision variables. However, they cannot address independent uncertainties of the left-hand sides and cost coefficients within optimization systems. Moreover, they are lack of linkages to consequences of system constraint violations, which are essential for the related policy analyses of flooding control and eco-resilience enhancement. In comparison, IIP method can deal with integer variables as well as uncertainties associated with the model's left-hand sides; however, it has difficulties when the right-hand sides are highly uncertain. Another approach that can deal with flood-related issues is two-stage programming (TSP). It is an effective tool for optimization problems where analysis of policy scenarios is desired and the related data are mostly uncertain. The TSP methods were widely explored over the last decades (Pereira and Pinto, 1991; Schultz et al., 1996; Ruszczynski and Swietanowski, 1997; Seifi and Hipel, 2001). A two-stage stochastic network approach and the corresponding solution method were investigated by Cheung and Chen (1998) for dynamic empty container allocation problems. Darby-Dowman et al. (2000) applied a TSP model to determining robust planting plans in horticulture. However, these previous TSP methods were incapable of facilitating dynamic aspects for system management. Though, in many TSP problems, decision variables may take integer or binary values (e.g., yes or no) in order to choose one or more options from a finite number of alternatives. These conventional methods were deficient in taking the integer components into account. Moreover, most of the previous TSP methods were deterministic, and thus were unable to effectively address uncertainties with the mixture of interval, probabilistic and possibilistic information in the management of ecologically vulnerable regions. In addition, there have been no reports on the applications of TSP methods for improving eco-resilience to natural disasters (particularly floods).

Thus, the objective of this study is to develop a mixed integer fuzzy interval-stochastic programming (MIFISP) model for improving eco-resilience to floods in a number of ecologically vulnerable regions of a wetland. Effects of changing climatic conditions will also be incorporated within the modeling process. The developed model will be employed for quantitatively analyzing eco-resilience capacity management strategies that are associated with different levels of penalties when the predetermined targets are violated. It will also be employed to investigate ecological adaptation strategies to the changing climatic conditions. Also, uncertainties expressed as probability density functions and discrete intervals will be directly incorporated within the model. Moreover, extreme values of the changing climatic conditions will be integrated into the developed MIFISP model to investigate their impacts on wetland flow patterns and the corresponding eco-resilience enhancement plans.

2. Eco-resilience to flooding events

Hydrological conditions, especially flooding regimes, are well known to be a strong influence on structure and integrity of ecosystems in wetlands. Floods cause extensive losses and degradation of critical habitats and the emergence of diseases/insects that might produce severe and irreversible impacts on indigenous ecosystems and ecotopes. When affected by a variety of human activities and changing climatic conditions, hydrologic regimes typically have increased frequency and severity of flooding, lowered water tables and reduced groundwater recharge compared to previous, more natural conditions (Watson et al., 1981; Brinson, 1993; Pitt, 1996; Detenbeck et al., 1999; Kristensen et al., 2003; Rai, 2008; Ribarova et al., 2007). Frequent outbreak of floods in wetlands will lead to a series of negative impacts on indigenous ecosystems, including loss of biodiversity, decreased floristic quality, expansions of invasive species and degradation of indigenous ecosystems (Galatowitsch et al., 2000; Brinson and Malvarez, 2002; Kercher and Zedler, 2004). Particularly, there are a number of ecologically vulnerable regions in wetlands that are succumbing to floods. In these regions, resistance of ecosystems towards floods is poor due to their sensitive ecological structure and integrity that are inflexible to strong external disturbances. Normally, a number of biological species, population, and ecosystems that are sensitive to flooding can be identified in these regions. Biodiversities and habitats can be destructed and lost very easily due to various external disturbances such as floods. That is, eco-resilience to floods is at a low level compared with the disturbance intensity of flooding events, posing great risks to indigenous ecosystems. Without proper human interventions, eco-resilience would be further reduced to the lower limit and then to its threshold value. To the end, indigenous ecosystems would be gradually degraded and replaced by invasive ones, resulting economic and ecological losses to local regions. Moreover,
climate change exacerbates this condition with the rising sea levels and changed river runoff patterns. These factors may lead to more complicated and serous interactions and is thus difficulty to make reasonable and scientific decisions.

There are many strategies that can enhance eco-resilience towards floods, such as soil and water conservation, wetland restoration as well as many other ecological and human intervention measures (Wu and Feng, 2006). They are helpful in recovering the indigenous ecosystems, the environment, the associated habitats, and thus maintaining ecological structure and integrity in relevant regions of a wetland. Particularly, in ecologically vulnerable regions that are prone to flooding events, wherein eco-resilience capacity to floods might need to be expanded, this is done through various ecological engineering measures across the bed of the main water-courses. During high water flows in wet season, the regions with limited eco-resilience capacities towards floods may be overflowed and cause damages to local ecosystems. Normally, the existing eco-resilience capacities of the regions are evaluated and predefined and the fixed floods-resisting targets have been evaluated and assigned. This could be helpful in protecting valuable riverine ecosystems. Thus, if the water level is lower than the warning one, then the fixed flood-resisting targets are to be realized, which are associated with regular costs. However, when a flooding event occurs, the excess flow will raise the water level of river. Although the buffer capacity of ecosystem might allow a slight expansion, the total resilience capacities to floods are still insufficient. Consequently, floods will exceed the resilience capacities and cause irreversible effects on indigenous ecosystems, leading to economic and environmental costs in the ecologically vulnerable regions. Thus, the total resilience capacity would be the sum of the existing and the expanded ones.

3. Modeling formulation

3.1. Formulation of the MITSP model

In an ecologically vulnerable region which is frequently suffering from floods, the present eco-resilience capacity is evaluated and determined. In the future, when the uncertainties of climatic changing conditions and relevant river flows are quantified, a recourse action can then be taken to mitigate impacts of floods on ecosystems in the region. Thus decision of maintaining current eco-resilience capacity is called the first-stage decision, and the recourse decision is called the second-stage decision. This leads to a general TSP programming problem as follows:

\[
\text{Min } f = \sum_{i=1}^{m} C_i W_i + E \left( \sum_{i=1}^{m} D_i S_{ij} \right) 
\]

subject to:

\[
\sum_{i=1}^{m} (W_i + S_{ij}) \geq Q \quad (1b)
\]

\[
S_{ij} \leq W_i, \quad \forall i 
\]

\[
W_i \leq W_{\text{max}}, \quad \forall i 
\]

\[
S_{ij} \geq 0, \quad \forall i, j 
\]

\[
S_{ij} = k h_{ij}, \quad \forall i, j 
\]

where \( f \) is the total system costs for maintaining eco-resilience ($); \( C_i \) is the cost to maintain the present eco-resilience capacity for the predefined flooding levels in ecologically vulnerable region \( i \), which means the first-stage cost parameter ($/m^3/s$); \( W_i \) is the predefined flood-resisting levels in ecologically vulnerable region \( i \) (m$^3$/s); \( E \) is the expected value of a random variable \( x \); \( D_i \) is the loss of in region \( i \) per m$^3$/s due to a certain amount of surplus water, evidently, \( D_i > C_i \ ($/m^3/s) \), which is the second-stage cost parameter; \( S_{ij} \) is recourse actions, which represents surplus water flows to ecologically vulnerable region \( i \) under the extreme events in wet season in reference to \( W_i \) when the peak water flow is \( Q \) (m$^3$/s); the second-stage decision variable; \( Q \) is quantity of random water flows under varied climatic scenarios (m$^3$/s); \( W_{\text{max}} \) is maximum allowable floods can be resisted within the limit of eco-resilience capacity in ecologically vulnerable region \( i \) (m$^3$/s); \( i \) is an index of ecologically vulnerable region, and \( m \) is total number of the studied regions within the wetland. In model (1), \( Q \) is a random variable. The continuous distribution of \( Q \) is converted into an equivalent of discrete values in order to change model (1) into conventional linear programming methods. As proposed by Loucks et al. (1981), \( Q \) can take values \( q_j \) with probabilities \( p_j \), where \( j \) defines \( p \) levels of flows of the studied wetland. Model (1) can be reformulated as follows:

\[
\text{Min } f = \sum_{i=1}^{m} C_i W_i + \sum_{j=1}^{n} p_j D_i S_{ij} 
\]

subject to:

\[
\sum_{i=1}^{m} (W_i + S_{ij}) \geq q_j, \quad \forall j 
\]

\[
S_{ij} \leq W_i, \quad \forall i, j 
\]

\[
W_i \leq W_{\text{max}}, \quad \forall i 
\]

\[
S_{ij} \geq 0, \quad \forall i, j 
\]

\[
S_{ij} = k h_{ij}, \quad \forall i, j 
\]

where \( S_{ij} \) are decision variables representing surplus water amount (in reference to \( W_i \) that is supposed to be contained by ecologically vulnerable region \( i \) under flow level \( j \) (m$^3$/s), \( q_j \) is river water quantity to be contained within the regions under flow level \( j \) (m$^3$/s), \( p_j \) is probability of occurrence under a flow level \( j \) (%), \( j \) is an index of flow level, \( n \) is the total number of flow levels (\( n = 5 \), where \( j \) is 1–5 for low, low-medium, medium, medium-high and high levels). Thus, the developed TSP model can effectively deal with the probabilistic uncertainties presented in the flow levels. However, the above model cannot address the aspects for improving eco-resilience capacity. To accommodate planning of such expansion schemes within the developed TSP model, integer variables are incorporated within the framework of model (2). This leads to a mixed integer two-stage programming (MITSP) model as follows:

minimize system cost for maintaining and expanding eco-resilience under various water-flow levels

\[
\text{Min } f = \sum_{i=1}^{m} C_i W_i + \sum_{j=1}^{n} p_j D_i S_{ij} + \sum_{i=1}^{m} \sum_{j=1}^{w} \sum_{k=1}^{m} E_{ijk} y_{ijk} 
\]

subject to:

water-flow constraints

\[
\sum_{i=1}^{m} (W_i + S_{ij}) \geq q_j, \quad \forall j 
\]

the existing and enhanced eco-resilience constraints

\[
\sum_{i=1}^{m} (W_i + S_{ij}) \leq \sum_{i=1}^{m} \sum_{k=1}^{m} R_{ik} y_{ijk} + \sum_{i=1}^{m} R_i, \quad (W \neq w) \forall j 
\]

allowable flood-resisting capacity constraints

\[
S_{ij} \leq W_i, \quad \forall i, j 
\]
3.2. Formulation of the IMITSP model

Model (3) can effectively address issue of optimal expansion schemes and deal with uncertainties in the probabilistic water-levels, as well as incorporate the related strategies within the modeling systems, which can be solved through conventional deterministic approaches. However, uncertainties may also exist in other parameters such as costs, expansion capacities, and flood-retention targets. In fact, uncertainties in many practical problems may exist as ambiguous intervals. Decision makers may find it harder to specify probabilities than to define fluctuation ranges (Huang and Loucks, 2000). For example, implicit judgment of a decision maker on the target of eco-resilience can hardly be expressed as a probability density function (PDF); however, it can be easily defined as an interval. Moreover, the deterministic model in the above can only obtain solution under one climatic condition, which is appropriate to reflect optimal options with current climatic condition. As a comparison, there are plenty of complexities and uncertainties existing within the process of the forecasting of future climatic conditions. Also, it is more reasonable and scientific to obtain optimal solutions with continuous interval values than discrete scenario analysis or best-worst solutions, reflecting imbedded uncertainties in forecasting future climatic variations. To remedy these problems, interval parameters (Huang et al., 1995) are therefore introduced into model (3). This result in the development of an inexact mixed integer two-stage programming (IMITSP) model as follows:

\[
\min f^+ = \sum_{i=1}^{m} C^+_i W_{i}^+ + \sum_{j=1}^{n} \sum_{k=1}^{w} p_j D^{+}_{ij} S^+_j + \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{w} E_{ik} Y_{ik}^+ \quad (4a)
\]

subject to:

\[
\sum_{i=1}^{m} (W_{i}^+ + S^+_j) \geq q^+_j, \quad \forall j \quad (4b)
\]

\[
\sum_{i=1}^{m} (W_{i}^+ + S^+_j) \leq \sum_{k=1}^{w} \Delta R_{ik} Y_{ik}^+ + \sum_{i=1}^{m} R_{ik}^+, \quad (W \neq w) \forall j \quad (4c)
\]

\[
S^+ \leq W_{i}^+, \quad \forall i, j \quad (4d)
\]

\[
W_{i}^+ \leq W_{imax}^+, \quad \forall i \quad (4e)
\]

\[
S^+_j \geq 0, \quad \forall i, j \quad (4f)
\]

\[
y_{ijk}^+ = 0 \text{ or } 1, \quad \forall i, j, k \quad (4g)
\]

where the symbol ‘−’ and ‘+’ superscripts represent lower and upper-bounds of the parameters, respectively. According to Huang et al. (1995), the developed interval model can be transformed into two sets of deterministic sub-models, which correspond to the lower and upper-bounds of the desired objective. The sub-model corresponding to the lower-bound of the objective-function value (i.e., \(f^−\)) should be first formulated as follows:

\[
\min f^− = \sum_{i=1}^{m} C_i W_{i}^− + \sum_{j=1}^{n} \sum_{k=1}^{w} p_j D^{−}_{ij} S_{ij}^− + \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{w} E_{ik} Y_{ik}^− \quad (5a)
\]

subject to:

\[
\sum_{i=1}^{m} (W_{i}^− + S_{ij}^−) \geq q_{ij}^−, \quad \forall j \quad (5b)
\]

\[
\sum_{i=1}^{m} (W_{i}^− + S_{ij}^−) \leq \sum_{k=1}^{w} \Delta R_{ik} Y_{ik}^\pm + \sum_{i=1}^{m} R_{ik}^−, \quad (W \neq w) \forall j \quad (5c)
\]

\[
S_{ij}^− \leq W_{i}^−, \quad \forall i, j \quad (5d)
\]

\[
W_{i}^− \leq W_{imax}^−, \quad \forall i \quad (5e)
\]

\[
S_{ij}^− \geq 0, \quad \forall i, j \quad (5f)
\]

\[
y_{ijk}^− = 0 \text{ or } 1, \quad \forall i, j, k \quad (5g)
\]

\[
\sum_{j=1}^{n} \sum_{k=1}^{w} Y_{ijk}^− \leq n, \quad \forall i \quad (5h)
\]

where \(S_{ij}^−\) and \(y_{ijk}^−\) are decision variables. Let \(S_{ij}^{opt}\) and \(y_{ijk}^{opt}\) are solutions of model (5). The second sub-model corresponding to the upper bound of the objective-function value (i.e., \(f^+\)) is:

\[
\min f^+ = \sum_{i=1}^{m} C_i W_{i}^+ + \sum_{j=1}^{n} \sum_{k=1}^{w} p_j D^{+}_{ij} S_{ij}^+ + \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{w} E_{ik} Y_{ik}^+ \quad (6a)
\]

subject to:

\[
\sum_{i=1}^{m} (W_{i}^+ + S_{ij}^+ ) \geq q_{ij}^+, \quad \forall j \quad (6b)
\]

\[
\sum_{i=1}^{m} (W_{i}^+ + S_{ij}^+ ) \leq \sum_{k=1}^{w} \Delta R_{ik} Y_{ik}^+, \sum_{i=1}^{m} R_{ik}^+, \quad (W \neq w) \forall j \quad (6c)
\]

\[
S_{ij}^+ \leq W_{i}^+, \quad \forall i, j \quad (6d)
\]

\[
W_{i}^+ \leq W_{imax}^+, \quad \forall i \quad (6e)
\]

\[
S_{ij}^+ \geq S_{ij}^{opt}, \quad \forall i, j \quad (6f)
\]

\[
y_{ijk}^+ = 0 \text{ or } 1, \quad \forall i, j, k \quad (6g)
\]

\[
y_{ijk}^+ = y_{ijk}^{opt}, \quad \forall i, j, k \quad (6h)
\]

\[
\sum_{j=1}^{n} \sum_{k=1}^{w} Y_{ijk}^+ \leq n, \quad \forall i \quad (6i)
\]
where $S_{ij}^+$ and $y_{ijk}^+$ are decision variables. Let $S_{ij}^{opt}$ and $y_{ijk}^{opt}$ are solutions of model (6). The solutions of the developed model [i.e., model (4)] are obtained by integration of the resulting solutions from its sub-models (5) and (6). The obtained solutions provide stable intervals for the objective function and decision variables with different levels of risk in violating the constraints. They can be easily interpreted for generating decision alternatives. Thus, solutions for the model with optimized flood-resisting patterns and capacity-expansion options are:

$$f_{opt} = [f_{opt}^+, f_{opt}^-]$$

$$S_{ij}^{opt} = [S_{ij}^+, S_{ij}^-], \quad \forall i, j$$

$$y_{ijk}^{opt} = [y_{ijk}^+, y_{ijk}^-], \quad \forall i, j, k$$

Thus, the optimum interval flood-retention adaptation patterns are:

$$A_{ij}^{opt} = \begin{cases} W_i^+ + S_{ij}^{opt}, & \text{if } q_j \geq \sum_{i=1}^u W_i, \quad \forall i, j \\ 0, & \text{if } q_j < \sum_{i=1}^u W_i, \quad \forall i, j \end{cases}$$

where $A_{ij}^{opt}$ is the optimal water allocation to region $i$ under flow level $j$, which is obtained by adding the optimal surplus water $S_{ij}^{opt}$ to the flood retention target $W_i^+$.

### 3.3. Formulation of the MIFISP model

One potential approach for further decreasing solution uncertainties existing as vague information and thus increasing system effectiveness and robustness is to more carefully consider the stipulations existing as vague information and thus increasing system robustness. A satisficing approach of MILP can be formulated wherein solutions with interval values obtained from interval-parameter programming framework. An FLP model can be formulated wherein solutions are effective to communicate membership information for admissible uncertain characteristics with a certain degree of flexibility.

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3.4. Method of solution

According to Huang et al. (1995), the solution algorithm of the developed model can be presented as follows:

(a) Formulate the model;
(b) Transform the IMITSP model into two sub-models, where the lower-bound of $f^-$ is first desired since the objective is to minimize $f^-$;
(c) Formulate the $f^-$ sub-model [i.e., model 5a(5)], including formulation of the $f^-$ objective function and the related constraints for this objective function;
(d) Solve the $f^-$ sub-model according to conventional LP (linear programming) methods and get the solution for $S^-$opt and $y^{ijk}_{opt}$;
(e) Then the objective function corresponding to $f^-$ can be obtained as $f^-_{opt}$;
(f) Formulate the $f^+$ sub-model [i.e., model (6)], including formulation of the $f^+$ objective function and the related constraints for this objective function, as well as the second set of constraints for bounds of the decision variables;
(g) Solve the $f^+$ sub-model according to conventional LP (linear programming) methods and get the solution for $S^+$ and $y^+$;
(h) Then the objective function corresponding to $f^+$ can be obtained as $f^+_{opt}$;
(i) Formulate the MIFISP model [i.e., model (7)];
(j) Transform the MIFISP model into two sub-models and solve these two models according to the steps (b)–(h);
(k) Then the solution for $S^\pm_{opt}$, $y^{\pm}_{ijk}$, and $\lambda^\pm_{opt}$, which are probably different to the solutions in the original IMITSP model;
(l) Thus, the optimal adaptation pattern for flood retention in a wetland can be obtained as follows:

$$A^\pm_{ij_{opt}} = W^\pm_i + S^\pm_{ij_{opt}}, \quad \text{if} \quad q_j \geq \sum_{i=1}^{m} W_i, \quad \forall i, j, \quad \text{and} \quad A^\pm_{ij_{opt}} = 0, \quad \text{if} \quad q_j \leq \sum_{i=1}^{m} W_i, \quad \forall i, j.$$

4. Case study

The developed MIFISP model is applied in a semi-hypothetical wetland, which is established based on typical ones in north China. The study system consists of three ecologically vulnerable regions with diverse eco-resilience capacities (i.e., $i = 3$). The schematic figure of the study system is displayed in Fig. 1. Currently, given the present eco-resilience capacities, regions 1–3 can resist floods under $\{130, 150\}$, $\{170, 190\}$ and $\{30, 50\}$ m$^3$/s, respectively.

The flood-resisting capacity under current eco-resilience, maximum allowable water-flow levels, and relevant costs are varied among the three regions, which are shown in Table 1. Table 2 presents the eco-resilience enhancement options and the associated costs in the regions. It is indicated that eco-resilience to floods in region 1 can be expanded once under any of the three options, with a maximum expansion capacity of $210$ m$^3$/s, while the resilience of region 2 has a maximum expansion capacity of $270$ m$^3$/s. In comparison, the resilience...

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<td>Allowable flood-resisting capacity and the related economic data.</td>
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<tr>
<td>Maximum allowable flood/peak flows under current ecological resilience ($W^\pm_i$) [m$^3$/s]</td>
</tr>
<tr>
<td>Current flood-resisting target ($W^\pm_i$) [m$^3$/s]</td>
</tr>
<tr>
<td>Cost of flood resistance to maintain current ecological resilience ($C^\pm_i$) [10$^3$ $$/m^3$/s]</td>
</tr>
<tr>
<td>Penalty due to ecological damages ($D^\pm_i$) [10$^3$ $$/m^3$/s]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ecological resilience improvement options and the associated costs.</td>
</tr>
<tr>
<td>Ecological vulnerable region</td>
</tr>
<tr>
<td>Existing flood-resisting capacity (m$^3$/s)</td>
</tr>
<tr>
<td>Ecological resilience improvement options (m$^3$/s)</td>
</tr>
<tr>
<td>$\Delta R_1$ (option 1)</td>
</tr>
<tr>
<td>$\Delta R_2$ (option 2)</td>
</tr>
<tr>
<td>$\Delta R_3$ (option 3)</td>
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<tr>
<td>Capital cost of the options (10$^3$ $$/m^3$/s)</td>
</tr>
<tr>
<td>$E_1$ (option 1)</td>
</tr>
<tr>
<td>$E_2$ (option 2)</td>
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<tr>
<td>$E_3$ (option 3)</td>
</tr>
</tbody>
</table>
of region 3 cannot be expanded. Also, various water-flow levels and the associated probabilities of occurrences are provided in Table 3. Accordingly, the problem under consideration is to determine: (i) how to select preferred expansion schemes of the eco-resilience for the study three ecologically vulnerable regions, (ii) how to effectively divert surplus water flows to the three regions according to the present and the expanded eco-resilience capacities, (iii) how to accurately take effects of the changing climatic conditions into consideration, and (iv) how to incorporate predefined eco-resilience capacities in terms of allowable flood-resisting targets with the least risk of system disruption. Accordingly, optimal strategies of eco-resilience maintenance/improvement to floods in the study regions can be obtained.

Table 3
Peak flow distribution and the relevant probabilities.

<table>
<thead>
<tr>
<th>Flow level (j)</th>
<th>Flow volume (q±)</th>
<th>Probability (pj) (m³/s) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low (j=1)</td>
<td>[224.96, 246.56]</td>
<td>10</td>
</tr>
<tr>
<td>Low-medium (j=2)</td>
<td>[282.60, 310.37]</td>
<td>20</td>
</tr>
<tr>
<td>Medium (j=3)</td>
<td>[337.85, 415.97]</td>
<td>40</td>
</tr>
<tr>
<td>Medium-high (j=4)</td>
<td>[459.41, 505.40]</td>
<td>20</td>
</tr>
<tr>
<td>High (j=5)</td>
<td>[586.75, 648.01]</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 4 displays results of binary decision variables obtained through the developed MIFISP model. Generally speaking, the solutions indicate that the eco-resilience of region 1 would be expanded under all of the expected peak levels except the medium water flow. Also, under the low and low-medium flow levels, the eco-resilience expansion scheme would be [0, 1], representing that it would be enhanced in region 1 with option 1 under the disadvantageous scenario (i.e., upper peak flow level under extreme climate change events) and would not be improved under optimistic scenario (i.e., lower peak flow level under extreme climate change events). As a comparison, the eco-resilience in region 2 would not be improved under low and low-medium peak flow levels. Similar to region 1, the eco-resilience in region 2 would be expanded under disadvantageous peak levels such as medium-high and high levels with interval-valued options, i.e., the lower-bound (0) means no expansion under optimistic scenarios and the upper-bound (1) means an expansion under pessimistic scenarios of the changing climatic conditions. Moreover, the eco-resilience to floods in region 3 would not be expanded. In details, Fig. 2 and Table 5 present the improvement schemes for the 3 regions under the five-peak flow levels. It is indicated that the improvement strategies for regions 1 and 2 are totally different. Mostly, the eco-resilience in region 1 would not be improved under optimistic scenario except under medium-high and high peak flow levels with a probability
of occurrence being between 10 to 20%, and would be forced to be enhanced under pessimistic scenario (upper bound). Under the low peak flow level, the improvement of eco-resilience as resistance to floods would be \([0, 80]\) m\(^3\)/s, i.e., this indicates that no enhancement would be necessary under very optimistic settings in the region, but an enhancement of up to 80 m\(^3\)/s would be required for attaining regional goals of flood control. Under medium-high flow level, and eco-resilience enhancement for additional 140 m\(^3\)/s of flood would be required in region 1, implying that both the advantageous and conservative options would require improvements to resist floods in region 1.

Solutions of continuous decision variables through the developed inexact model are displayed in Table 5. In case of flooding events, the surplus water would firstly be allocated to region 2 due to relatively low penalty cost in the region. Secondly the eco-resilience to floods in regions 1 and 3 would be expanded. This is because region 2 has the highest flood-resisting capacity. Region 2 is also subject to the lowest penalty when accepting the surplus water. In comparison, regions 1 and 3 correspond to higher costs and penalties. However, at most times, the three regions would make resilience improvement as the first priority due to low capital cost of the improvement. If the peak flow level at extreme times were still higher than total resisting capacities of the three regions, surplus flooding with higher penalty cost (with damages to local ecosystems) would thus occur. Table 5 presents the optimized surplus flooding patterns and the relevant maximum allowable flood containing amounts. Corresponding to the advantageous and demanding scenarios (i.e., pessimistic and optimistic ones), the interval values of the solutions can be obtained and can be displayed in this table. The solutions of surplus flooding capacity for region 1 would be 56.30 m\(^3\)/s under high peak flow level, with a probability of 10%. As a comparison, the solutions for regions 2 would be [9.87, 24.25], 130.60, and 170.52 m\(^3\)/s under medium, medium-high, and high peak flow levels, respectively. In region 3, the only surplus flood-retention capacity (30.52 m\(^3\)/s) would be occurred under high peak flow level with a probability of 10%.

As mentioned in the above sections, solutions of the second stage can be obtained after the first-stage solutions. The solutions for region 1 are \(S_{1i}^{\text{opt}}\) to \(S_{14}^{\text{opt}} = 0.00\) and \(S_{15}^{\text{opt}} = [56.30, 56.30]\). The relevant flood-retention pattern under low to medium-high peak flows would be \(A_{11}^{\text{opt}}\) to \(A_{14}^{\text{opt}} = 0.00\) since the total available resilience to flood would be higher than the water-flow level (i.e., as mention in the previous section, \(q_i^e \leq \sum_{i=1}^n W_i^e\)). And the total potential flood-resisting pattern under high peak flows would then be \(A_{11}^{\text{opt}}\) to \(A_{14}^{\text{opt}} = 0.00\) since the total available resilience to flood would be higher than the water-flow level (i.e., as mention in the previous section, \(q_i^e \leq \sum_{i=1}^n W_i^e\)). Similarly, the results of \(S_{21}^{\text{opt}}\) to \(S_{24}^{\text{opt}} = 0.00\), \(S_{23}^{\text{opt}} = [9.87, 24.25]\), \(S_{24}^{\text{opt}} = [130.60, 130.60]\), and \(S_{25}^{\text{opt}} = [170.52, 170.52]\) m\(^3\)/s, respectively, indicating for region 2, no surplus flood-resisting pattern would be occurred under low, low-medium, medium, and medium-high peak flow levels. However, some surplus flood-resisting patterns might be observed under high peak flow level with a probability of 10%. Also, the solutions for \(S_{31}^{\text{opt}}\) to \(S_{34}^{\text{opt}} = 0.00\) and \(S_{35}^{\text{opt}} = 30.52\) m\(^3\)/s, implying that there would be no surpluses under low to medium-high flows for region 3. However, the surplus flood-resisting capacity would probably be needed under high flows with a probability of 10%. The objective-function value for the developed model would be \([40,379.55, 61,381.28] \times 10^2\), which is composed of the costs for maintaining current eco-resilience, penalties due to surplus flood retention, and capacity expansions of eco-resilience of the 3 regions.

As discussed before, the developed model is suitable for identifying optimal strategies for improving eco-resilience of wetlands to floods under changing climatic conditions. The inexact model is applicable and effective in generating different decision alterna-
tives through interval value. Such alternatives may be desired by decision makers when making long-term planning under changing climatic conditions, which is required in many wetlands. For examples, the solutions of the binary variables of the inexact model have three possible presentations including \([0, 0]\), \([1, 1]\), and \([0, 1]\). The binary variables are deterministic numbers if the solution is \([0, 0]\) or \([1, 1]\), which implies that the relevant scheme of eco-resilience enhancement would not or would be adopted with certainty. In comparison, \([0, 1]\) and \([1, 0]\) solutions represent interval expansion decisions, which can be interpreted to provide decision alternatives reflecting potential system condition variations by the input uncertainties (Huang et al., 1995). The lower-bound expansion value and thus lower capital cost could be used under advantageous system conditions when the flow levels are very-low. Conversely, the upper expansion values and thus higher capital costs could be used under more demanding system conditions when the flow levels are very-high. The developed model is successfully used in the wetland with three ecologically vulnerable regions. The solutions pose as effective policy alternatives for improving eco-resilience in the wetland. It is evident from the models that the flood-resisting patterns and eco-resilience improvement schemes under the changing climatic conditions can be examined continuously. The eco-resilience would be expanded to the maximum allowable limits under the demanding cases (the upper bound of water-flow levels), while most of the capacity expansions would not be occurred under the advantageous cases. Most of the potential capacity expansions in the wetland would be idling under favorable cases. Similarly, region 1 would be chosen as the priority region for enhance its resilience due to its lower cost, while region 2 would be the first option for surplus flood because of its lower penalty. Mostly, the surplus flood allocation would stable in the wetland, the flood-resisting patterns would be similar for the three regions. Furthermore, the interval values for the future climatic conditions are stable, indicating a number of decision alternatives for the study wetland. The developed models can provide a considerable insight into various aspects of a problem under consideration. They can help investigate interactive relationships between different flooding events among the study regions of the wetland.

5. Conclusions

In this study, a mixed integer fuzzy interval-stochastic programming model (MIFISP) was developed through incorporation of interval-parameter programming, fuzzy linear programming, two-stage programming techniques within a general mixed integer programming framework. Through the developed model, relevant penalties (i.e., economic, environmental and ecological ones) associated with violation of various predetermined policies which can be expressed as allowable flood-resisting capacities could be effectively quantified. Solutions were then obtained by solving the two sub-models sequentially. The interval solutions were stable in the given decision space with an associated level of system-failure risk. Also, expansion planning issues of flood-resisting capacity of eco-resilience improvement can be addressed through the adoption of binary variables. Through this approach, policies expressed as allowable flood-resisting targets can be effectively incorporated within a general optimization framework. The model allows uncertainties to be presented as random distributions and discrete intervals. Moreover, the model provides insights into the impacts of varied changing climatic conditions on wetlands through expressing water level as intervals in which the lower- and upper-bounds indicate two extreme values under various climate change scenarios.

The MIFISP model is successfully applied to a wetland with three ecologically vulnerable regions that are frequently suffering from floods. The results indicate that the model can be employed as an effective tool in analyzing complex relationships between various flood events, economic implications and the associated eco-resilience improvement. The binary variable solutions represented decisions of flood-resisting capacity expansion through the improvement of eco-resilience in relevant regions. Also, uncertain but useful information from decision makers, stakeholders, third-party researchers, and local residents can be efficiently reflected in this method, which would be an effective tool for achieving satisfactory compromise policies. Although the developed method was successfully applied to a semi-hypothetical wetland with three ecologically vulnerable regions, real-world applications are still necessary for further demonstrating its effectiveness and applicability. However, there will be a number of challenges associated with real-world applications of the method, including (a) determination of economic penalties associated with ecological damages due to flooding, (b) investigation of extreme values of hydrological process under climate change, and (c) quantitative reflection of ecological resilience within a specific wetland.

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