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Identification of optimal placements of best management practices through an interval-fuzzy possibilistic programming model

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ABSTRACT

In this research, an interval-fuzzy possibilistic programming (IFPP) method was developed by integrating interval parameter programming (IPP), fuzzy possibilistic programming (FPP), and a fuzzy expected value equation within a general optimization framework. The developed IFPP method can not only effectively address uncertainties presented in terms of crisp intervals and fuzzy-boundary intervals in both the objective function and constraints, but it can also improve the traditional fuzzy mathematical programming by choosing the credibility degree of constraints based on the decision maker's preference and avoiding complicated intermediate models with high computational efficiency. The developed method was applied to identify optimal placements for best management practices (BMPs) to control nutrient pollution in the Baoxianghe River watershed in China, in which a GIS-aided export coefficient model (ECM) was employed to estimate the phosphorus loads from a nonpoint source (NPS). The optimization results showed that the hybrid approach could be used to generate a series of implementation levels for BMPs under multiple credibility levels, ensuring that the NPS phosphorus loads discharged into rivers reduce to an allowable level and considering a proper balance between expected system costs and risks of violating the constraints. Relaxing the sub-basin discharge permits suggests a global discharge permit for the entire watershed, which may allow managers to shift BMP implementation among sub-basins to meet the overall discharge permit at a lower cost.

1. Introduction

Excessive nutrients, such as nitrogen and phosphorus, in natural water bodies significantly degrade the aquatic environment by stimulating algae growth and depleting dissolved oxygen, and they may eventually result in eutrophication in the water bodies (Guo, 2007; Ongley et al., 2010; Potter et al., 2004). Over the past few decades, the total maximum daily load (TMDL) program has provided a guideline to improve the water quality of impaired water bodies and to protect or restore the original beneficial uses. The utilization of TMDL mostly requires the implementation of best management practices (BMPs) in the watershed upstream of a lake to reduce nutrient loads from nonpoint sources (NPS) before they enter the receiving water bodies (Alminagorta et al., 2012). In this case, the identification of BMP placement schemes is desired to achieve multiple targets, such as the minimization of BMP costs and the maximization of nutrient reduction. However, such a process is fraught with complexities due to the diverse costs and efficiencies of BMPs and the tradeoffs among nonpoint sources, nutrient discharge permits, and the available farmland areas and stream length for BMP implementation. These factors lead to many challenges for watershed managers. Thus, it is necessary to develop a systems approach for analyzing the BMP placement management system to support the decisions of nutrient reduction planning.

In recent years, a number of optimization techniques have been developed to identify BMP placement and to determine load reduction strategies (Alminagorta et al., 2012; Chen et al., 2015; Ciou et al., 2012; Gaddis et al., 2014; Jha et al., 2009; Kaini et al., 2012; Limbrunner et al., 2013; Perez-Pedini et al., 2005; Rabotyagov

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et al., 2012; Rodriguez et al., 2011). For example, Rabotyagov et al. (2010) applied an integrated simulation-optimization framework to search for a cost-effective mix and location of agricultural conservation practices in a typical agricultural watershed in consideration of nitrogen reduction targets. Panagopoulos et al. (2012) used a genetic algorithm to facilitate the evaluation of the optimal location for placing BMPs to minimize diffuse surface water pollution in the Arachtos watershed in Greece. Alminagorta et al. (2012) developed and applied a simple linear programming model to identify cost-effective BMPs to reduce phosphorus loading in the Echo Reservoir in Utah. Ahmadi et al. (2013) coupled a multi-objective genetic algorithm (NSGA-II) with a distributed watershed model (i.e., soil and water assessment tool) to identify the optimal types and locations of conservation practices for nutrient and pesticide control. Chen et al. (2015) developed a preference-based multi-objective optimization model by modifying the NSGA-II to optimize the locations of BMPs for the cost-effective nutrient reduction in the Three Gorges Reservoir watershed. In practical BMP placement management systems, uncertainties may exist in the related BMP costs, nutrient-reduction efficiencies and nutrient discharge permits (Dong et al., 2014; Hernandez and Uddameri, 2010). Such uncertainties may be further multiplied by the site-specific features of many system components, factors, and parameters, which bring significant difficulties to the formulation of waste management models and the generation of effective solutions (Dai et al., 2013). These multi-form uncertainties have raised concerns over the reliability and sustainability of BMP placement projects, attracting wide interest in prospective technologies. A proper understanding of the sources and effects of uncertainty is needed.

In general, uncertain parameters can be represented as intervals, fuzzy sets and probability density functions (Cai et al., 2011; Dai et al., 2015). An interval number has only a lower and an upper bound, which are used to approximate uncertainties when available data are insufficient to create distribution or membership functions. Huang (1998) developed an interval parameter programming (IPP) model to address system optimization problems, where IPP is an effective tool to handle interval numbers in objective function coefficients and constraint parameters. Over the past few years, IPP models have frequently been used in water resource management (Hu et al., 2012; Huang and Loucks, 2000; Karmakar and Mujumdar, 2006; Luo et al., 2003; Lv et al., 2010; Maqsood et al., 2005; Marques et al., 2005; Rosenberg and Lund, 2009; Tan et al., 2011). Fuzzy possibilistic programming (FPP) is an attractive tool to address decision problems of BMP placement under fuzzy goals and constraints, and it can handle epistemic uncertainty in the form of ambiguous parameters presented as fuzzy membership functions (Inuiguchi et al., 2003). Previously, Iwamura and Liu (1998) developed a fuzzy chance-constrained programming method using the possibility to measure the occurrence chance of a fuzzy event. Comparatively, Huang (2006) advanced a credibility chance-constrained programming method by extending the chance-constrained programming idea to the fuzzy environment based on the credibility measure averaging of the possibility and necessity measures. More recently, Zhang and Huang (2011) applied the credibility chance-constrained programming model to water resource management. As a new method of FPP, no applications of credibility chance-constrained programming to reflect and address the uncertainties associated with BMP placement management have been reported. Additionally, due to the inherent economic fluctuations, lower and upper bounds of BMP cost parameters may be provided as subjective judgments from a number of stakeholders and decision makers. At the same time, with regard to unavailable stochastic distribution information and various influence factors, nutrient reduction efficiency parameters on the left-hand side of constraints are acquired by limited data and presented by fuzzy membership functions. As a result, the conventional IPP and FPP may be unavailable and may lose information when two bounds of intervals in the objective function and constraints are presented by possibility distributions (i.e., fuzzy-boundary intervals) (Zhang et al., 2014). One potential approach for better accounting for uncertainties and BMP placement issues is to develop an interval-fuzzy possibilistic programming (IFPP) method by coupling the IPP and FPP models.

Therefore, the objective of this study is to develop an interval-fuzzy possibilistic programming (IFPP) method for solving such complexities and uncertainties. The proposed IFPP method can not only effectively address uncertainties presented in terms of crisp intervals and fuzzy-boundary intervals in both the objective function and constraints, but it can also improve the traditional fuzzy mathematical programming by choosing the credibility degree of constraints based on the decision maker's preference and avoiding complicated intermediate models with high computational efficiency. Then, the developed method will be applied to identify, evaluate and locate BMPs to control the nutrient pollution of nonpoint sources in the Baoxianghe River watershed in China. Cost-effective strategies for BMP placement for sub-basins and trade-offs between system costs and violation risks of fuzzy credibility constraints under different confidence levels are to be investigated and analyzed.

2. Modeling development

In a practical decision making process, parameter uncertainty (i.e., cost coefficients) could be presented as ambiguous coefficients with possibility distributions in the optimization model. Thus, the related system characterizes epistemic uncertainty due to incomplete, unavailable and subjective information on the decision makers and stakeholders. Such an imprecise problem can be solved by fuzzy possibilistic programming (FPP) (Hsu and Wang, 2001; Tanaka et al., 2000). An FPP model can be formulated as follows:

$$\text{Min} \sum_{j=1}^{n} \underset{\sim}{C}_j x_j \tag{1a}$$

subject to:

$$\sum_{j=1}^{n} \underset{\sim}{a}_{ij} x_j \geq b_i, \; i = 1, 2, \ldots, m \tag{1b}$$

$$\sum_{j=1}^{n} \underset{\sim}{a}_{ij} x_j \leq d_i, \; i = 1, 2, \ldots, m \tag{1c}$$

$$x_j \geq 0, j = 1, 2, \ldots, n \tag{1d}$$

where $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$ is the vector of non-fuzzy decision variables; b_i and d_i are the right-hand side coefficients; and $\underset{\sim}{C}_j$ and $\underset{\sim}{a}_{ij}$ are the fuzzy possibilistic vectors with possibility distributions that can be treated as fuzzy membership functions.

Assume that $\underset{\sim}{C}_j$ is a trapezoidal fuzzy variable that can be expressed as $\underset{\sim}{C}_j = \left(c_{\mathrm{I},j}, c_{\mathrm{II},j}, c_{\mathrm{III},j}, c_{\mathrm{IV},j}\right)$ of crisp numbers with $c_{\mathrm{I},j} \leq c_{\mathrm{II},j} \leq c_{\mathrm{III},j} \leq c_{\mathrm{IV},j}$. Then, the expected values of $\underset{\sim}{C}_j$ (i.e., $E\left(\underset{\sim}{C}_j\right)$) can be calculated as follows:

$$E\left(\underset{\sim}{c}_j\right) = \frac{c_{\mathrm{I},j} + c_{\mathrm{II},j} + c_{\mathrm{III},j} + c_{\mathrm{IV},j}}{4} \tag{2}$$

Section S1 of the Supplementary material shows the method for calculating the expected value of a fuzzy number. Based on Eq. (2),