

A GIS-Based Interval Fuzzy Linear Programming for Optimal Land Resource Allocation at a City Scale

Changgang Ma^{1,2} · Min Zhou³

Accepted: 21 October 2016 / Published online: 3 November 2016
© Springer Science+Business Media Dordrecht 2016

Abstract A geography information system based interval fuzzy linear programming model for city land resource allocation is developed in this study for dealing with land-use planning. The developed model improves upon the existing land resource allocation model with advantages in uncertainty reflection, model coupling, data availability and spatial analysis. The model can deal with uncertainties expressed as not only discrete interval values but also fuzzy sets. Therefore, it can effectively reflect dynamic, interactive complex, and uncertain characteristics of land-use system without unrealistic simplification. Moreover, the model can be used for supporting spatial allocation of land resources under a variety of ecological, environmental and socio-economic conditions. The developed model is applied to a real case of land resources allocation in Hangzhou City, China. Results demonstrate that the desired system benefit will be between \$ [427.66, 549.83] × 10⁹; The model could help decision makers to generate stable and spatial land resources allocation patterns and strategic land use policies, gain in-depth insights into effects of the uncertainties and analyze trade-offs among economic objective, eco-environmental protection and social demands.

Keywords Land resource allocation · Interval fuzzy linear programming · Geographic information system · Eco-environmental impacts · Social demands

✉ Min Zhou
shijieshandian00@163.com

Changgang Ma
506503930@qq.com

¹ Collaborative Innovation Center for 21st-Century Maritime Silk Road Studies, Research Center for International Trade and Economics, Guangdong University of Foreign Studies, No. 2, North Road of Baiyun Avenue, Baiyun District, Guangzhou 510420, China

² School of Economics and Management, Guangxi Normal University for Nationalities, Chongzuo 532200, China

³ College of Public Administration, Huazhong University of Science and Technology, Number 1037, Luoyu Road, Wuhan, China

1 Introduction

For many decades, the shortage of land resources has continued to be a major obstacle to socio-economic development and people's everyday life, especially in China's big city (Zhou et al. 2015). Such a problem is normally reflected by population growth, climate change (Han et al. 2015), deterioration of land quality, environmental pollution (Oberling et al. 2013), reduction of available land supply, and irrational land resource allocation patterns. For a long time, some above problems were solved by protecting the existing land resources and exploiting new sources of land (Hosseinali et al. 2013). However, the rapidly increasing cost and technological limitations associated with these two means have gradually led to unsustainability of land resources utilization (Verburg et al. 2008; Law et al. 2015). Therefore, pursuing an efficient allocation of land resources is a task engaging both developed and developing countries, across numerous environments and at several spatial scales (Munton 1987; Turner et al. 1994; Carsjens and van der Knap 2002).

Land resource allocation is the systematic assessment of land resources for alternative land uses considering economic and social conditions (Wey and Wei 2016; Cheung and Cheng 2016) in order to select and adopt the best land use options (FAO 1993). Its purpose is to select and put into practice those land uses that will best meet the current needs of the people, while safeguarding resources for the future (Rodriguez-Rosa et al. 2016; Rajaei and Mansourian 2016). The driving force in planning is the need for change, the need for improved management or the need for quite different patterns of land use dictated by changing circumstances (Koomen et al. 2008; Morse 2016). Land resource allocation models are indispensable for sustainable land use planning (Hagoort et al. 2008; McNeill et al. 2014). Previously, there were various models developed for supporting land resource allocation (Richard 2004; Svoray et al. 2005; Uday et al. 2006; Kamusoko et al. 2009; Verburg et al. 2010; Wang et al. 2011; Liu et al. 2013; Pilehforoosha et al. 2014; Zhang et al. 2014; Murray-Rust et al. 2014; Lu et al. 2015; Zhou 2015). In detail, Richard (2004) developed an approach to modelling land use change that links model selection and multi-model inference with empirical models and GIS. The approach was based on analysis and comparison of multiple models of land use patterns using model selection and multi-model inference. Svoray et al. (2005) developed a habitat heterogeneity model (HHM) for urban land-use allocation in a Mediterranean ecotone, where GIS and a multi-criteria mechanism were used for the evaluation of the suitability of ecologically sensitive areas. Uday et al. (2006) applied a soft systems methodology (SSM) to systematically analyze the land-use system of India. Kamusoko et al. (2009) used a Markov-cellular automata model to simulate the future land-use/cover change in Bindura district, Zimbabwe. The Markov-cellular automata model (MCAM) integrates Markovian transition probabilities computed from satellite-derived land use/cover maps and a cellular automata spatial filter. Verburg et al. (2010) provided a typology of land use change in Europe at a high spatial resolution based on a series of different scenarios of land use change for the period 2000–2030. A series of simulation models ranging from the global to the landscape level were used to translate scenario conditions in terms of demographic, economic and policy change into changes in European land use pattern. Wang et al. (2011) constructed a simulation model which combined “top-down” system dynamics model, the “bottom-up” cellular automaton model, and the artificial neural network model for land-use patterns under a drought transition to account for the complexity of both the driving factors behind land-use change and the micro-level changes in land-use patterns. Liu et al. (2013) proposed a novel model (SDHPSO-LA) for land use allocation in a large scope. This model integrated system

dynamics (SD) and hybrid particle swarm optimization (HPSO) to address macro-level socio-economic variables and driving forces. Pilehforooshha et al. (2014) provided a two-stage model for land-use allocation which uses cellular automata, Markov chain, fuzzy rule-based system, goal programming and GIS raster analysis. Zhang et al. (2014) developed a primary development and secondary optimization model for land-use allocation (PDSO-LA model). The model takes both ecological and economic into consideration and emphasizes the trade-offs within and between structural and functional ecological storage. Murray-Rust et al. (2014) presented an agent-based modelling framework (Aporia) to simulate land use change. Aporia was designed to be modular, flexible and open, where a declarative, compositional approach is used to create complex models from subcomponents. Lu et al. (2015) used a vector-based cellular automata model to simulate land use change in downtown of Qidong City, Jiangsu Province, China. Zhou (2015) used an interval fuzzy chance-constrained land-use allocation (IFCC-LUA) model to simulate land-use allocation. The IFCC-LUA model integrated interval parameter programming, fuzzy flexible linear programming and chance-constrained programming techniques, which reflected the complexities in land-use planning management system systematically.

With the help of GIS technique, traditional land resource allocation models combined simulated models and spatial optimization models (Stewart and Janssen 2014; Nguyen et al. 2015). However, most of these models ignored the uncertainties widely existed in the land-use system. In real land-use systems, uncertainties existed in land-use factors such as land-resource availabilities, social land demands, land-use patterns, land price, the cost of land development, as well as environmental and ecological requirements may be presented as fuzzy sets, probabilities, and/or interval values (Messina and Bosetti 2003; Verburg et al. 2013; Nino-Ruiz et al. 2013). These complexities and uncertainties could also be multiplied by dynamic features of the system and interactive feature of the system components. Over the past decades, a number of inexact optimization methods were used for dealing with the complexities and uncertainties associated with resource allocation management problems, such as fuzzy, stochastic and interval programming methods (Chang and Wang 1997; Chanas and Zielinski 2000; Maqsood and Huang 2003; Qin et al. 2007). But few studies referred to the uncertainties in land resource allocation based on integrating above approaches, especially at a city level. Therefore, an uncertainty and GIS based approach for optimal land resource allocation model under the above-mentioned complexities is desired to support decisions of short-term land resource management and long-term strategic land-use planning. Furthermore, previous studies neglected many important environmental, social-economic factors in the land-use allocation system.

Thus, the objective of this study is to develop a GIS-based interval fuzzy linear programming (IFLP) model for land resource allocation at a city level. As an integration of IFLP and GIS, this model can simulate a city's land use change within a variety of ecological, environmental and socio-economic conditions; moreover, the model can simultaneously deal with uncertainties expressed as fuzzy sets and discrete intervals; thirdly, the model can tackle spatial optimization problems based on GIS technique; last but not least, it is capable of evaluating the trade-offs among the expected economic benefit, social demand, environmental objective, and ecological service in the land-use system. The proposed model is applied to a land resource allocation problem of the city of Hangzhou, China, and the results will support decision making of land-use planning in various conditions.

2 The Study System

2.1 The Study Area

The study city named as Hangzhou is the capital of Zhejiang Province, China. It is located between 29°11'N and 30°34'N and between 118°20'E and 120°37'E in the southeast of China (Fig. 1). The city lies on the lower reaches of the Qiantang River and is the southern end of the 1794-kilometre-long Grand Canal (Beijing-Hangzhou Canal). The city's current municipal area is 1,684,075 ha, containing 6 districts with a population of approximately 7,856,300. In 2014, the Urban Planning of Hangzhou divided the city into three areas: Central Construction Zone (district 1 in Fig. 1), New Urban Development Zone (district 2 in Fig. 1) and Eco-environmental Zone (district 3 in Fig. 1), with different development-orient policies in these areas. Hangzhou is the political center, scientific center, educational center, cultural center and economic center of Zhejiang Province. With its famous natural beauty and cultural heritages, Hangzhou is one of the most important tourist venues and famous historical city in China. The city's gross domestic product (GDP) increased rapidly from 4.57 billion RMB in 1996 to 27.38 billion in 2014, in concert with a population increase from 1.67 million to 4.14 million. Tertiary-industry is the main economic growth propelling force of the city, besides, high-tech industry. The population density, the urbanization level, and the economic magnitude in Hangzhou are much higher than most other Chinese cities.

As a result of fast economic development, the city was suffered from serious environmental and ecological problems in the past a few years. For example, as the main component of the city's water system, West Lake has been threatening by water degradation, eutrophication and pollution from solid wastes. According to reports from Hangzhou Environmental Monitoring Station, concentrations of many pollutants, such as $\text{NH}_3\text{-N}$, BOD and COD, increased progressively since 1990 along the lake. Field investigations and monitoring data indicate that pollution is mostly discharged from point sources and non-point sources. Moreover, industrial solid wastes and household wastes haven't been disposed properly and posed a threat to the safety of residents' healthy.

According to Hangzhou Land-use Planning (2006–2020), authorized by the Chinese Central Government in 2006, Hangzhou will become a new focus of urbanization in the

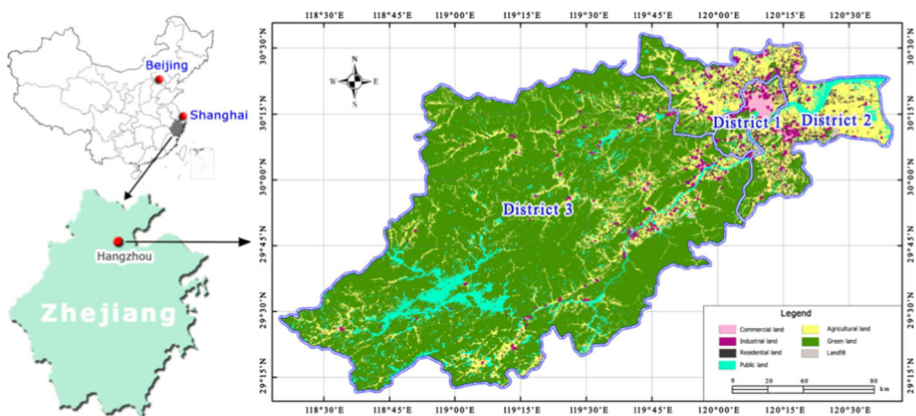


Fig. 1 The study area and existing land use

next several years. Currently, Hangzhou is suffering from problems of disordered land use, deteriorating water quality, and degraded aquatic ecosystems. The land-use structure in this area has changed rapidly since the 2000. In the urban area, industrial land occupies 37.67%, whereas grassland only covers 30.06%. Around 83.10% of the city's entire territory is made up of agriculture land, green land and forest land, and there is still much room to accommodate urban development. In the developed area, residential land, commercial land, grassland, industrial land, landfill land, agricultural land, and public land constitute 305.35 ha, 218.32 ha, 11,484.81 ha, 27.64 ha, 5.39 ha, 3449.99 ha and 1275.55 ha, respectively. The existing land-use planning of Hangzhou is showed in Fig. 1.

2.2 Problem Identification

Land resource allocation involves many stakeholders, such as governments, land agents, residents, farmers and environmental groups. It refers to a sequence of events: (1) land development and economic growth; (2) land degradation, consolidation and conversion; (3) eco-environment pollution and protection. For the city of Hangzhou, land-use system is characterized by high utilization strength, rapid economic growth, serious eco-environmental pollution and limited land reserve, leading to sharp contradiction among relevant stakeholders and high system complexities and uncertainties. There are four main factors affecting land-use planning in Hangzhou: (1) geographical/geophysical factors, such as geographical location, soil erosion process, and so on; (2) socio-economic factors, such as economic benefit, social service, and so on; (3) eco-environmental factors, such as wastewater, solid wastes, and so on; (4) institutional factors, such as government policy.

Therefore, the key point of this problem is to allocate the land areas in Hangzhou in an optimal way based on an appropriate land resource allocation model, which can give a response to above challenges, considering the above four factors affecting land-use planning of Hangzhou. The results of the model could provide the local government insights to understand and deal with the complex land-use issues and will also provide suggestions for optimal land resource allocation and management in the near future. The main problems are identified as follows:

Question A How much areas should be allocated to every type of land use?

Question B Where should land resources be allocated in the real world?

Question C How to handle the complexities and uncertainties in the land-use system?

In general, the problem under consideration is how to effectively plan land resources under a number of environmental, economic, ecological, social and treatment/disposal capacity-availability constraints in order to maximize the overall system benefit.

In the next section, we will use three methods to answer above questions: linear programming will be used to proceed quantity optimization and answer question A; GIS model will be used to support spatial optimization and answer question B; IFLP will be used to handle system complexities and uncertainties and answer question C.

3 GIS-Based IFLP Model for Land Resource Allocation in Hangzhou

3.1 GIS-Based Land Resource Allocation Model for Hangzhou

Spatially explicit land resource allocation models are indispensable for sustainable land use planning, particularly in South China which is experiencing rapid land use/cover changes.

GIS is an important tool for analyzing, simplifying, simulating, communicating and presenting spatial and/or temporal trends in land use change (Siripun 2001). In order to achieve the economic and/or eco-environmental goals, existing types of land use would transform into new land types based on a few conversion rules. GIS can help us to make these rules through 4 steps as follows:

- Step 1* Analyze the existing land use in Hangzhou;
- Step 2* Analyze the factors influencing land suitability;
- Step 3* Factor weighting and overlay analysis;
- Step 4* Formulate conversion rules.

3.1.1 Existing Land Use in Hangzhou

From a system point of view, changes in land use should be made so that lands with new types are as close as possible to land with the same type. For example, an addition of land for commercial use must be adjacent to existing commercial land. The study area is primarily an urban area with very little agricultural land use. It is unrealistic to reduce the agricultural land use to any other uses because of the basic policy of China. Therefore, such conversion is not allowed. Landfill is defined in this study, referring to areas used for municipal solid waste disposal. Since Hangzhou has been determined to reduce landfill and build more incinerators to dispose MSW, none of the land uses will be converted to landfill. This spatial relation to existing land use becomes the first rule for identifying available land for future land conversion.

3.1.2 Factors Influencing Land Suitability

The purpose of land suitability assessment is to analyze the physical, locational, or institutional attributes of the study area in relation to a particular land use (Wang et al. 2004). Based on such analysis, the location for future land use in the study area can be identified so as to get maximum economic benefits with minimum degradation of environmental quality.

In addition to the compatibility with existing land uses, land suitability assessment is based on some key features of the land and influenced by geographical (such as location), economic (such as land development cost and benefit), environmental (such as water quality) factors (Overmars et al. 2007). Different land uses lead to different selections of these factors. For example, land suitability assessment for agricultural land main involves such factors: slope, proximity to water, soil type, precipitation, and temperature, while land suitability assessment for commercial land main involves distance to central business district (CBD), cost and benefit for land development, and so on. It is a systematic procedure for examining the combined effects of a related set of factors that the analyst assumes to be important determinants of locational suitability (Kaiser et al. 1995). In this study, two factors are considered in the commercial land suitability assessment: slope and distance to downtown. Each factor map is developed separately using Arc GIS. In detail, the Arc GIS slope operation employs a four point slope estimation function, which calculates a slope value in degree for each map cell (200 m × 200 m). The assessment results of slope factor are showed in Fig. 2; in calculating the distance to downtown factor, the locations of the CBD of the city on the map are used as starting points while the boundaries of both maps are used as end points. The calculation is carried out across the whole map

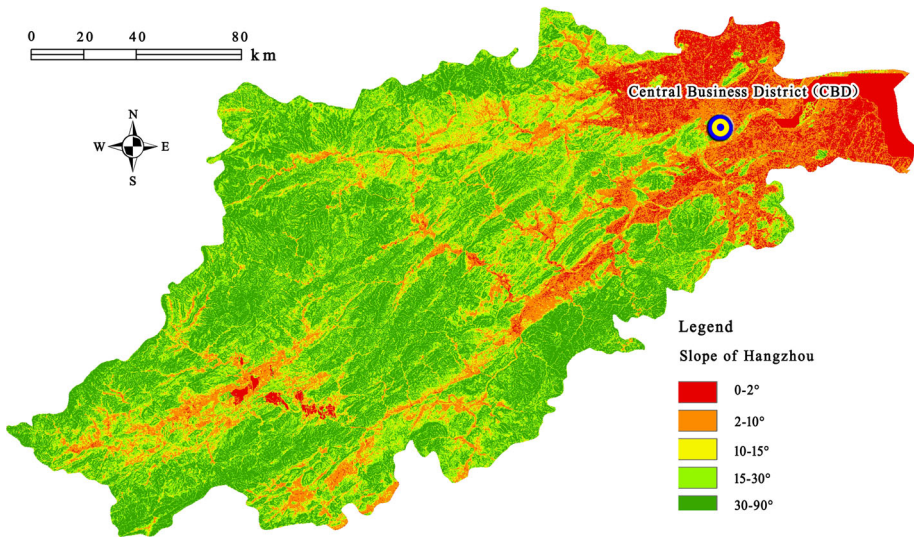


Fig. 2 Suitability assessment of slope factor

with cell values representing the distance to the CBD. The assessment results of distance to CBD factor are showed in Fig. 3.

3.1.3 Factor Weighting and Overlap Analysis

Factor weighting is an important step because it captures the level of influence that each factor has in the development of the spatial allocation map. The weighting of factors imposes the relative importance of each factor on the suitability of the study area for land

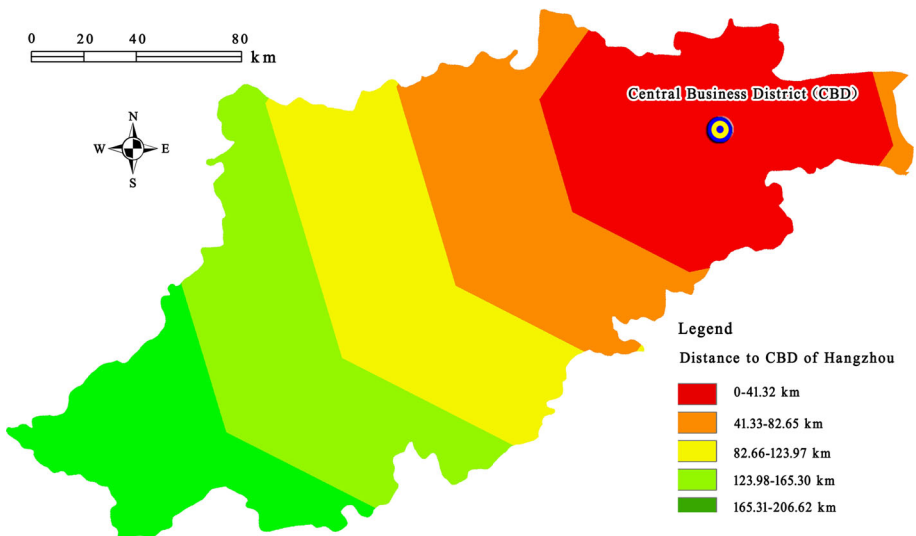


Fig. 3 Suitability assessment of distance to CBD factor

conversion preference. In Arc GIS, there is a weight function which can calculate the weights of each factor (Saaty 1977). The weights of each factor are depended on its importance in the evaluation system.

After both slope and distance to downtown factors are weighted, the overlay function in IDRISI is used to combine them with the existing land use. Based on factor weighting, we can assess land suitability through the formula as follows:

$$S = \sum_n^2 w_n s_n$$

where S represents suitability scores (0–100); w_n (0–1) represents weight for factor n ($n = 1$ for slope factor and $n = 2$ for distance to downtown factor); s_n represents score for factor n . The values of w_n and s_n are presented in Table 1. Figure 4 shows the final land suitability results for commercial land, the suitability of other land types could be assessed in the same way.

3.1.4 Conversion Rules

Three spatial-conversion rules for Hangzhou land use are generated based on above analysis and eco-environmental considerations:

Rule 1 The spatial conversion must accord with existing land use;

Rule 2 The spatial-conversion preference is determined by suitability scores of each cell of land use;

Rule 3 When the scores are similar, “ecological land uses” have the conversion preference.

The spatial optimization of lands can be implemented by above rules. However, these rules couldn’t provide the detailed area value of conversion. Therefore, an IFLP model is developed to calculate this value in various uncertain inputs.

3.2 IFLP for Land Resource Allocation of Hangzhou

A GIS-based IFLP model (the details of IFLP can be found in Appendix 1) is developed here by coupling the GIS with the IFLP. Base on GIS, the maximum area of every type of land and spatial conversion rules are provided by the outcomes of land suitability assessment and spatial analysis. Therefore, GIS is an important technique for guiding future land-use spatial allocation and providing key constraints and parameters in the IFLP model. Based on IFLP, uncertainties existed in various economic, environmental, ecological and social conditions and expressed as discrete intervals and fuzzy sets can be reflected. Moreover, land resource can be allocated in an optimized way, and decision-makers can get in-depth insights into trade-offs between economic objective and eco-environmental penalties. In detail, the IFLP model can be conceptualized as follows:

1. The objective is to maximize the net economic benefit of the land-use system;
2. The social demand must be satisfied; thus, enough land needs to be released for social use;
3. The ecological system should be balanced and the environment should be protected; thus enough land needs to be released for environmental and ecological use;

Table 1 Values of w_n and s_n

Symbol	Land suitability				
	S ₁	S ₂	S ₃	N ₁	N ₂
s_1 (slop)	0–2°	2–10°	10–15°	15–30°	30–90°
s_2 (distance to CBD)	0–41.32 km	41.33–82.65 km	82.66–123.97 km	123.98–165.30 km	165.31–206.62 km
w_1 (slop)	0.4				
w_2 (distance to CBD)	0.6				

4. Decisions need to be made periodically over time and spatial analysis and conversion should be considered.

The IFLP model for land-use planning of Hangzhou can be formulated as follows:

(a) Economic objective

$$\begin{aligned}
 \text{Max}f(x)^\pm = & \sum_{i=1}^I \sum_{t=1}^T (BP_{ij=2,t}^\pm \times x_{ij=2,t}^\pm) + \sum_{i=1}^I \sum_{t=1}^T (BP_{ij=3,t}^\pm \times x_{ij=3,t}^\pm) \\
 & + \sum_{i=1}^I \sum_{t=1}^T (BP_{ij=6,t}^\pm \times x_{ij=6,t}^\pm) - \sum_{i=1}^I \sum_{t=1}^T [(WC_{ij=2,t}^\pm + SC_{ij=2,t}^\pm) \times x_{ij=2,t}^\pm] \\
 & - \sum_{i=1}^I \sum_{t=1}^T [(WC_{ij=3,t}^\pm + SC_{ij=3,t}^\pm) \times x_{ij=3,t}^\pm] - \sum_{i=1}^I \sum_{t=1}^T [(WC_{ij=6,t}^\pm + SC_{ij=6,t}^\pm) \times x_{ij=6,t}^\pm] \\
 & - \sum_{i=1}^I \sum_{t=1}^T (GC_{ij=4,t}^\pm \times x_{ij=4,t}^\pm) - \sum_{i=1}^I \sum_{t=1}^T (PC_{ij=5,t}^\pm \times x_{ij=5,t}^\pm)
 \end{aligned}$$

(b) Social-economic constraints

(1) Government investment constraints

$$\begin{aligned}
 & \sum_{i=1}^I \sum_{t=1}^T [(WC_{ij=2,t}^\pm + SC_{ij=2,t}^\pm) \times x_{ij=2,t}^\pm] + \sum_{i=1}^I \sum_{t=1}^T [(WC_{ij=3,t}^\pm + SC_{ij=3,t}^\pm) \times x_{ij=3,t}^\pm] \\
 & + \sum_{i=1}^I \sum_{t=1}^T [(WC_{ij=6,t}^\pm + SC_{ij=6,t}^\pm) \times x_{ij=6,t}^\pm] + \sum_{i=1}^I \sum_{t=1}^T (GC_{ij=4,t}^\pm \times x_{ij=4,t}^\pm) \\
 & + \sum_{i=1}^I \sum_{t=1}^T (PC_{ij=5,t}^\pm \times x_{ij=5,t}^\pm) \leq MGI_{i,t}^\pm
 \end{aligned}$$

(2) Water consumption constraints

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{t=1}^T (UWP_{i,j,t}^\pm \times x_{i,j,t}^\pm) \leq MAW_{i,t}^\pm$$

(3) Energy consumption constraints

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{t=1}^T (UEP_{i,j,t}^\pm \times x_{i,j,t}^\pm) \leq MAE_{i,t}^\pm$$

(c) Land suitability constraints

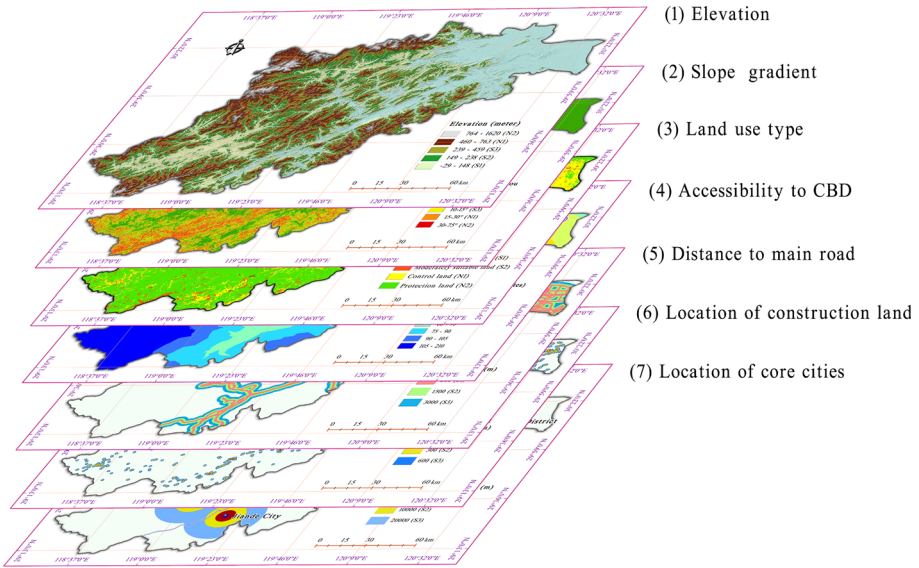


Fig. 4 Final results of land suitability assessment for commercial land

- (1) Minimum green land per capita constraint

$$\sum_{i=1}^I \sum_{t=1}^T x_{i,j=4,t}^{\pm} / P_{i,t}^{\pm} \geq MIGL^{\pm}$$

- (2) Minimum public land per capita constraint

$$\sum_{i=1}^I \sum_{t=1}^T x_{i,j=5,t}^{\pm} / P_{i,t}^{\pm} \geq MIPL^{\pm}$$

- (3) Minimum residential land constraint

$$\sum_{i=1}^I \sum_{t=1}^T x_{i,j=1,t}^{\pm} \geq MIRL^{\pm}$$

- (4) Minimum agriculture land constraint

$$\sum_{i=1}^I \sum_{t=1}^T x_{i,j=6,t}^{\pm} \geq MIAL^{\pm}$$

- (5) Minimum industrial land constraint

$$\sum_{i=1}^I \sum_{t=1}^T x_{i,j=2,t}^{\pm} \geq MIIL^{\pm}$$

- (6) Minimum commercial land constraint

$$\sum_{i=1}^I \sum_{t=1}^T x_{i,j=3,t}^{\pm} \geq MICL^{\pm}$$

(d) Environmental constraints

(1) Wastewater treatment capacity constraint

$$\begin{aligned} &\sum_{i=1}^I \sum_{t=1}^T (RWP_{i,j=1,t}^{\pm} \times x_{i,j=1,t}^{\pm}) + \sum_{i=1}^I \sum_{t=1}^T (IWP_{i,j=2,t}^{\pm} \times x_{i,j=2,t}^{\pm}) \\ &+ \sum_{i=1}^I \sum_{t=1}^T (CWP_{i,j=3,t}^{\pm} \times x_{i,j=3,t}^{\pm}) + \sum_{i=1}^I \sum_{t=1}^T (AWP_{i,j=6,t}^{\pm} \times x_{i,j=6,t}^{\pm}) \leq MAWC_{i,t}^{\pm} \end{aligned}$$

(2) Solid-waste treatment capacity constraint

$$\begin{aligned} &\sum_{i=1}^I \sum_{t=1}^T (RSP_{i,j=1,t}^{\pm} \times x_{i,j=1,t}^{\pm}) + \sum_{i=1}^I \sum_{t=1}^T (ISP_{i,j=2,t}^{\pm} \times x_{i,j=2,t}^{\pm}) + \sum_{i=1}^I \sum_{t=1}^T (CSP_{i,j=3,t}^{\pm} \times x_{i,j=3,t}^{\pm}) \\ &+ \sum_{i=1}^I \sum_{t=1}^T (ASP_{i,j=6,t}^{\pm} \times x_{i,j=6,t}^{\pm}) - \sum_{i=1}^I \sum_{t=1}^T (LSP_{i,t}^{\pm} \times x_{i,j=7,t}^{\pm}) \leq MASC_{i,t}^{\pm} \end{aligned}$$

(e) Technical constraints

(1) Total land areas constraint

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{t=1}^T x_{i,j,t}^{\pm} = TLA_{i,j,t}^{\pm}$$

(Total land areas constraint)

(2) Non-negative constraint

$$x_{i,j,t}^{\pm} \geq 0$$

x are the decision variables, which mean allocation to all kinds of land uses. The detailed nomenclatures for the variables and parameters are provided in Appendix 2 to this paper. According to Appendix 1, this IFLP model can be transformed into two deterministic sub-models, which correspond to the upper and lower bounds for the desired objective function value.

Figure 5 illustrates the general framework of the GIS-based IFLP model. The modelling approach is based on GIS and IFLP. Each technique has a unique contribution in enhancing the model’s capability in dealing with complexities and uncertainties in land resource allocation. For example, GIS can reflect the spatial features of land use in the urban area of Hangzhou and provide parameter inputs for IFLP model through land suitability assessment. The understanding of such spatial optimization is of crucial importance for land resources planning and management; in addition, the recursiveness and uncertainties generated by system conditions in analyzing the land-use allocation plan are handled through IFLP model. Tables 2 and 3 present the benefit and cost data from the land system, which are obtained through land evaluation. These parameters comes from statisticyearbook (1992–2011) of Hangzhou city (Nanjing Statistical Bureau 1992–2011); Table 4 shows the governmental investment, total population, the city’s land area, and minimum

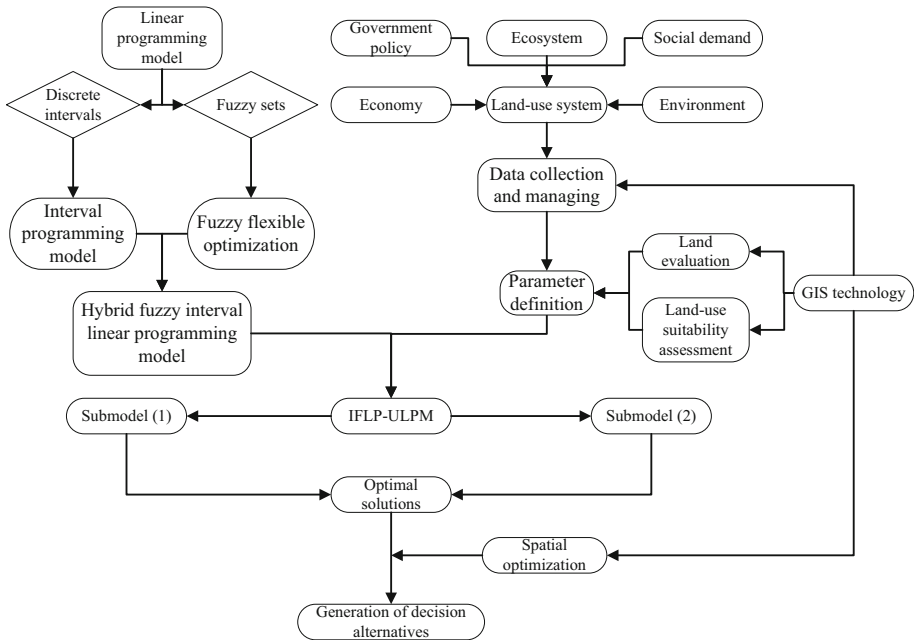


Fig. 5 Framework for the GIS-based IFLP

Table 2 Benefit for different land-use types

Symbol	Period		
	t = 1	t = 2	t = 3
$BP_{i=1, j=2}$ (10^6 \$/ha)	[8.6, 8.9]	[10.0, 11.8]	[11.0, 13.9]
$BP_{i=2, j=2}$ (10^6 \$/ha)	[8.4, 8.6]	[10.1, 11.6]	[11.4, 13.6]
$BP_{i=3, j=2}$ (10^6 \$/ha)	[7.9, 8.4]	[9.2, 10.4]	[10.4, 13.4]
$BP_{i=1, j=3}$ (10^6 \$/ha)	[5.1, 5.4]	[6.5, 6.8]	[8.3, 8.4]
$BP_{i=2, j=3}$ (10^6 \$/ha)	[4.8, 5.6]	[5.7, 6.2]	[7.5, 7.6]
$BP_{i=3, j=3}$ (10^6 \$/ha)	[3.7, 3.8]	[4.5, 4.6]	[5.1, 5.2]
$BP_{i=1, j=6}$ (10^3 \$/ha)	[19.0, 23.4]	[24.9, 28.4]	[38.1, 39.6]
$BP_{i=2, j=6}$ (10^3 \$/ha)	[16.1, 17.8]	[22.0, 25.6]	[30.8, 35.6]
$BP_{i=3, j=6}$ (10^3 \$/ha)	[13.2, 14.5]	[17.6, 18.9]	[26.4, 29.4]

$BP_{i,j,t}^{\pm}$ Unit benefit of land-use type j in district i in period t (\$/ha)

land area constraints through land suitability assessment using GIS. These parameters comes from Hangzhou Association of Solid Waste Recycle and Disposal (1992–2011). The solution algorithm of IFLP can then be summarized by using the following pseudo-code:

- Step 1 Analyze the urban land-use system and formulate the IFLP model;
- Step 2 Use GIS to assess the land suitability of every type of land use;
- Step 3 Obtain the parameter values for the IFLP model based on the results of land suitability assessment and various real constraints and conditions;

Table 3 Costs for different land-use types

Symbol	Period		
	t = 1	t = 2	t = 3
$WC_{i=1, j=2}$ (\$/ha)	[613.8, 678.4]	[766.2, 816.3]	[874.6, 902.4]
$WC_{i=2, j=2}$ (\$/ha)	[587.5, 673.3]	[729.6, 784.3]	[830.6, 942.0]
$WC_{i=3, j=2}$ (\$/ha)	[449.8, 489.7]	[562.6, 618.3]	[716.3, 752.2]
$SC_{i=1, j=2}$ (10^3 /ha)	[5.2, 6.2]	[7.3, 7.9]	[8.6, 9.4]
$SC_{i=2, j=2}$ (10^3 /ha)	[4.8, 5.3]	[6.7, 7.0]	[8.4, 9.0]
$SC_{i=3, j=2}$ (10^3 /ha)	[4.4, 4.6]	[5.7, 6.0]	[7.2, 8.0]
$WC_{i=1, j=3}$ (\$/ha)	[779.4, 842.7]	[862.9, 941.3]	[942.0, 1068.3]
$WC_{i=2, j=3}$ (\$/ha)	[763.3, 854.1]	[838.0, 859.6]	[930.3, 998.4]
$WC_{i=3, j=3}$ (\$/ha)	[716.4, 778.7]	[782.3, 856.2]	[909.8, 984.3]
$SC_{i=1, j=3}$ (10^3 /ha)	[7.1, 7.5]	[8.8, 9.6]	[9.6, 10.3]
$SC_{i=2, j=3}$ (10^3 /ha)	[6.7, 6.9]	[8.6, 9.0]	[10.0, 10.3]
$SC_{i=3, j=3}$ (10^3 /ha)	[6.2, 6.5]	[7.6, 8.1]	[9.3, 11.3]
$WC_{i=1, j=6}$ (\$/ha)	[5.1, 7.6]	[6.2, 8.6]	[8.4, 9.7]
$WC_{i=2, j=6}$ (\$/ha)	[4.7, 5.3]	[6.0, 6.4]	[8.1, 8.6]
$WC_{i=3, j=6}$ (\$/ha)	[4.3, 6.5]	[5.6, 6.9]	[7.6, 8.3]
$SC_{i=1, j=6}$ (\$/ha)	[640.2, 689.3]	[695.9, 784.3]	[854.1, 894.6]
$SC_{i=2, j=6}$ (\$/ha)	[609.4, 684.3]	[656.3, 753.5]	[794.0, 847.3]
$SC_{i=3, j=6}$ (\$/ha)	[581.6, 642.2]	[608.0, 679.4]	[745.7, 825.6]
$GC_{i=1, j=4}$ (10^3 /ha)	[4.0, 4.3]	[5.1, 5.4]	[6.2, 6.9]
$GC_{i=2, j=4}$ (10^3 /ha)	[3.7, 4.0]	[4.7, 5.0]	[5.9, 6.5]
$GC_{i=3, j=4}$ (10^3 /ha)	[3.4, 4.0]	[4.5, 4.9]	[5.6, 6.0]
$PC_{i=1, j=5}$ (10^3 /ha)	[8.5, 9.0]	[9.8, 12.5]	[10.8, 14.7]
$PC_{i=2, j=5}$ (10^3 /ha)	[7.9, 8.3]	[9.1, 9.6]	[10.3, 13.7]
$PC_{i=3, j=5}$ (10^3 /ha)	[7.6, 8.1]	[7.0, 8.8]	[10.1, 13.7]

$WC_{ij,t}^{\pm}$ Unit wastewater-tackling cost of land-use type j in district i in period t (\$/ha)

$SC_{ij,t}^{\pm}$ Unit solid-waste-tackling cost of land-use type j in district i in period t (\$/ha)

$GC_{ij=4,t}^{\pm}$ Unit maintenance costs of green land in district i in period t (\$/ha)

$PC_{ij=5,t}^{\pm}$ Unit maintenance costs of public land in district i in period t (\$/ha)

Step 4 Transform the IFLP model into two sub-models corresponding to the up bound and low bound objective- function values;

Step 5 Solve two sub-models and obtain their solutions;

Step 6 Obtain the solutions of the IFLP model and get the optimal land areas for each user;

Step 7 Formulate the spatial conversion rules through GIS;

Step 8 Allocate the land resource to each user in the map based on above quantity optimization and spatial optimization;

Step 9 Analyze the results and generate decision alternatives.

Table 4 Economic and technical data

Symbol	Period		
	t = 1	t = 2	t = 3
MGI_i (10^6 \$)	[456.4, 892.5]	[1032.6, 1372.5]	[1638.3, 2347.6]
TLA_i (10^3 ha)	[17.3, 17.6]	[17.8, 18.5]	[18.3, 19.4]
P_t (10^6 people)	[5.68, 5.70]	[5.78, 5.80]	[6.22, 6.24]
$MIRL$ (10^3 ha)	[2.3, 2.7]	[2.7, 3.4]	[3.4, 4.1]
$MIGL$ (ha/person)	[13, 15]	[16, 18]	[20, 22]
$MIPL$ (ha/person)	[23, 25]	[26, 28]	[31, 33]
$MIAL$ (10^3 ha)	[1.10, 1.20]	[1.05, 1.15]	[0.90, 1.00]
$MAWC_t$ (10^3 ton)	127.6	127.9	128.1
LSP_i (10^3 ton)	[0.7, 1.2]	[0.8, 1.6]	[0.9, 2.0]
$MASC_i$ (10^6 ton)	1.239	1.241	1.272

MGI_t^\pm Maximum government investment in period t (\$)

TLA_t^\pm Total land area in period t , including residential land, industrial land, commercial land, green land, public land, agricultural land and landfill (ha)

P_{it}^\pm Total population until period t (people)

$MIGL^\pm$ Minimum area of green land per capita in period t (ha/person)

$MIPL^\pm$ Minimum area of public land per capita in period t (ha/person)

$MIRL^\pm$ Minimum area of residential land in period t (ha)

$MIAL^\pm$ Minimum area of agricultural land in period t (ha)

$MAWC_t$ Wastewater treatment plant capacity in period t (ton)

LSP_{it}^\pm Solid-waste treatment plant capacity (landfill) in district i in period t (ton)

$MASC_t$ Solid-waste treatment plant capacity (except landfill) in period t (ton)

4 Results Analysis

Solutions to the GIS-based IFLP model of Hangzhou are presented in Figs. 6 and 7. The objective function and decision variables are interval, indicating that multiple alternatives exist, and the objective (net system benefit) is sensitive to variation of uncertain inputs. The temporal and spatial variations of economic, social, ecological and environmental conditions would result in varied land resource allocation patterns. By explicitly considering a number of land management plans and GIS technique, the IFLP model could not only handle multiple uncertainties and help identify a desired quantity allocation, but also reflect spatial features of the land-use system. The results indicate that reasonable interval allocations of land use were generated and thus a number of decision alternatives would be generated. Detailed analysis of the modeling solutions are provided below

4.1 Optimized Industrial and Commercial Land Resource Allocation

The optimized allocation for the industrial and commercial land of the three districts is presented in Fig. 6. The results indicate that the land areas of industrial sector in the three districts would decrease with the time periods. Although the benefit from the industrial land will increase with the time periods, the environmental penalties along with this

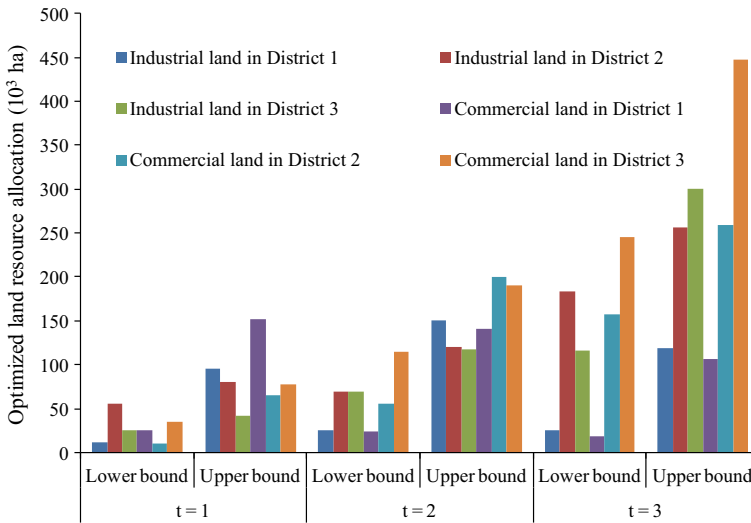


Fig. 6 Optimized land resource allocation to industrial land and commercial land

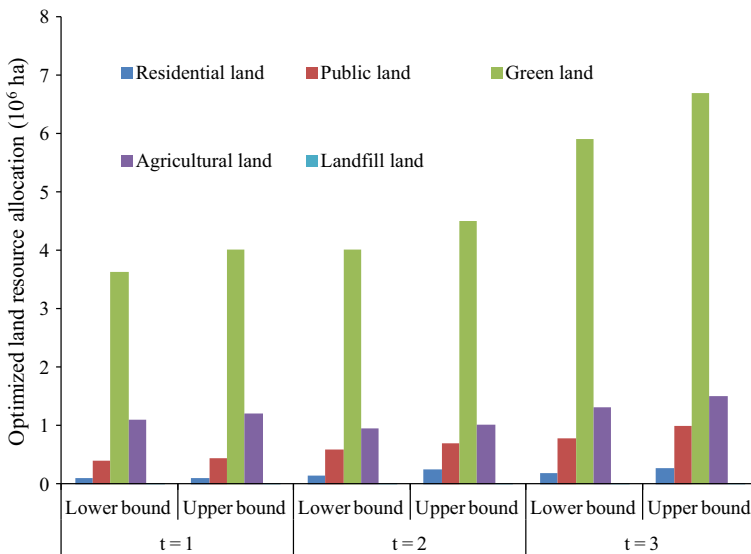


Fig. 7 Optimized land resource allocation to other land types

increase would bring about more cost for the objective function. The results also indicate that the land areas of commercial sector would also decrease along with the time periods, and the decrement is above that of industrial land. In fact, the commercial land has higher development costs and lower benefit for their operations in Hangzhou, decreasing more commercial land would become more beneficial.

4.2 Optimized Land Resource Allocation of Other Land Types

The optimized allocation for the residential land, public land, green land, agricultural land and landfill land of the three districts is also presented in Fig. 7. The results indicate that the areas of residential land, public land and green land in the three districts would increase with the time periods. This increase is due to the strict political constraints. Since the orientation of Hangzhou is to develop a livable and ecological city, industrial land and commercial land will convert into residential land, public land and green land. The areas of agricultural land and landfill land in the three districts would decrease with the time periods. The reason of the decrease of agricultural land is the fact that its economic benefit is low and its environmental effect is not very significant. The decreasing of landfill land indicates that this controlled method for municipal solid waste disposal is not good enough for future environmental management. The inefficient handling ability and expensive costs are the main causes of this conversion.

4.3 Social Implication of the Allocation Results

The proposed model is useful for land use policy making. First, the model provides quantitative results for land-use planning. The area of every type of land use is got through model computing. Thus, the land manager can determine the land-use pattern in Hangzhou, as well as the land use policy they like. Second, the interval results are useful for integrating different land-use patterns. Every result is a stable range, and the area of the land-use can float between the lower bound and the upper bound. The land manager can formulate different land-use combination through choose different land area values between there intervals. In detail, solutions for the lower bounds of the industrial land, commercial land, agricultural land and the upper bounds of the green land, public land, residential land and landfill correspond to the lower system benefit, which could guarantee social demands, ecological balance and environmental criteria be met, and imply a conservative land-use management strategy. When the industrial land, commercial land, agricultural land aims toward the upper bounds and green land, public land, residential land and landfill aims toward the lower bounds, the land-use system will get a higher benefit level. However, the social demands, ecological risk and environmental criteria will be increased, implying a more radical economic strategy. Solution of the objective function provides two extremes of system benefit over the planning horizon. Planning with a lower system benefit will be associated with a lower risk of violating the system constraints. Conversely, a plan targeting a higher system benefit may be associated with a higher risk of violating system constraints.

When land-use patterns are selected through combining land-use area values within their interval solutions, the system benefit value will change within its interval correspondingly. Therefore, decision alternatives can be generated by adjusting different land-use combinations according to projected applicable conditions. This could effectively reflect potential variations of system conditions caused by the existence of parameter uncertainties. The feasible ranges for the decision variables provided by the GIS-based IFLP solutions are also useful for decision makers to justify the generated alternatives directly, or to potentially adjust the decision variable values when they are not satisfied with the provided alternatives. Therefore, the GIS-based IFLP approach allows decision makers to incorporate implicit knowledge within the problem, and thus obtain satisfactory and applicable decision schemes.

Moreover, the λ results also can help decision maker to analyze the relationship between economic development and eco-environment demand. Thus the corresponding economic policies and eco-environmental policies can be made with the help of these quantitative analyses. The λ represents the possibility of satisfying all objectives and constraints under the given system conditions. The solutions correspond to conservative strategies when their λ values tend to the lower bound; in comparison, the solutions become more optimistic when their λ values tend to the upper bound. The λ value and the system benefit have a relationship of positive correlation. It indicates the tradeoff between system benefit and all the constraints. A lower λ values would guarantee all the requirements are met, result in a more strict constraints and a lower system benefit; in comparison, a higher λ values lead to a more flexible constraints and a higher system benefit.

4.4 Summary

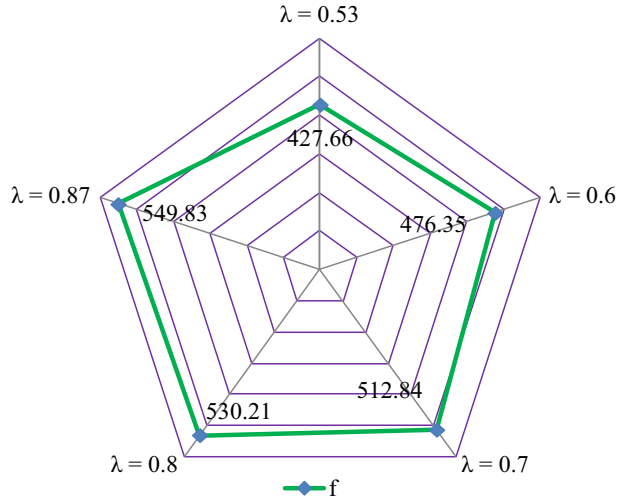
Although allocating more industrial land or commercial land might bring higher benefits, costs for tackling wastes produced by them and ecological risk would also be increased. Therefore, a tradeoff exists among allocating more industrial/commercial/agricultural land for obtaining high benefits and allocating more green land to avoid high ecological risk and allocating more residential/public land to satisfy social demand and allocating more landfill land to dispose more solid wastes.

The results indicate that the GIS-based IFLP solutions could provide stable ranges for land-use patterns x_{ij}^{\pm} and system benefit $f(x)^{\pm}$. The expected system net benefit ($f(x)^{\pm}$) is \$ $[427.66, 549.83] \times 10^9$. Thus, when different land-use patterns are selected through combining land area values within their interval solutions, the system benefit value will change within its interval correspondingly. Therefore, decision alternatives can be generated by adjusting different land area combinations according to projected applicable conditions. This could effectively reflect potential variations of system conditions caused by the existence of parameter uncertainties. The feasible ranges for the decision variables provided by the GIS-based IFLP solutions are also useful for decision makers to justify the generated alternatives directly, or to potentially adjust the decision variable values when they are not satisfied with the provided alternatives. Therefore, the GIS-based IFLP model allows decision makers to incorporate implicit knowledge within the problem, and thus obtain satisfactory and applicable decision schemes.

The results also indicate that the expected λ^{\pm} values is $[0.53, 0.87]$. The λ^{\pm} level represents the possibility of satisfying all objective and constraints under the given system conditions. It corresponds to the decision makers' preference regarding economic and environmental tradeoffs. In detail, λ^+ corresponds to a high system benefit ($f^+ = \$ 549.83 \times 10^9$) and optimistic strategies for land-use allocation, representing the maximum degree of overall satisfaction under loose environmental and ecological constraints. In comparison, λ^- corresponds to a low system benefit ($f^- = \$ 427.66 \times 10^9$) and conservative strategies for land-use allocation, representing the maximum degree of overall satisfaction under strict environmental and ecological constraints. The quantitative relationship between λ^{\pm} and f^{\pm} is showed in Fig. 8.

The obtained results indicate that uncertainties that exist in the system parameters can be effectively reflected as intervals and membership functions in the IFLP model, with reasonable solutions generated. Moreover, the spatial land-use patterns can be generated by GIS-supported land conversion rules. Thus, the hybrid model can help generate desired

Fig. 8 The quantitative relationship between λ^\pm and f^\pm (\$10⁹)



policies for land-use allocation with a maximized economic benefit and minimized environmental and ecological violation risk.

5 Conclusions

In this study, a GIS-based interval fuzzy linear programming for land resource allocation model has been developed, which is based on approaches of IFLP and GIS technique, by allowing uncertainties expressed as both fuzzy sets and discrete intervals to be incorporated within the optimization framework. In its solution process, the model is transformed into two deterministic sub-models, which correspond to the lower and upper bounds of the objective-function value. Interval solutions can then be generated by solving the two sub-models sequentially. The coupled model improves upon the previous approaches with advantageous capabilities in uncertainty reflection, policy analysis and spatial optimization. Social policies can be easy get through the proposed model.

The developed GIS-based IFLP model has been applied to planning land resource allocation in Hangzhou, China. A number of ecological, social, environmental and economic factors have been integrated into the modeling framework. The results indicate that reasonable solutions have been generated. The solutions correspond to conservative strategies when their λ values tend to the lower bound; in comparison, the solutions become more optimistic when their λ values tend to the upper bound. Under the conservative strategies for land resource allocation, the system will achieve a minimum benefit, at the same time, the environmental and ecological penalties and costs would both be minimized. Therefore, the generated solutions can provide desired land resource allocation plans with maximized system reliability.

Although reasonable solutions have been obtained in this study, more research extensions have to be done. For example, for large-scale land resource management problems, dynamic feature of system conditions is needed. Under such a situation, more complex

models, such as nonlinear IFLP, stochastic IFLP, inexact multi-stage programming, and many other hybrid approaches should be developed for obtaining improved applicability.

Acknowledgements This research was supported by the Key discipline construction project of high level university of Guangdong province “service in integration-innovation system construction of the management discipline about the major strategic needs of Maritime Silk Road in twenty-first Century”, 2014 annual scientific research project of State Ethnic Affairs Commission (No:14GSZ004) and 2014 annual key research project of Guangxi university (No ZD2014142). The insightful and constructive comments of editors and three anonymous reviewers are greatly appreciated.

Appendix 1: Interval Fuzzy Linear Programming

Interval fuzzy linear programming (IFLP) involves the optimization of an objective function subject to a fuzzy decision space delimited by constraints with fuzzy coefficients and fuzzy capacities (Liu et al. 2003). A general IFLP problem can be defined as follows:

$$Max f^\pm \cong C^\pm X^\pm \tag{1a}$$

subject to

$$A^\pm X^\pm \lesseqgtr B^\pm \tag{1b}$$

$$X^\pm \ge 0 \tag{1c}$$

where $A^\pm \in \{R^\pm\}^{m \times n}$, $B^\pm \in \{R^\pm\}^{m \times 1}$, $C^\pm \in \{R^\pm\}^{1 \times n}$, $X^\pm \in \{R^\pm\}^{n \times 1}$, $\{R^\pm\}$ denote a set of interval numbers; symbols ‘ \cong ’ and ‘ \lesseqgtr ’ represent fuzzy equality and inequality. On the basis of the principle of fuzzy flexible programming, let λ^\pm value correspond to the membership grade of satisfaction for a fuzzy decision. Specifically, the flexibility in the constraints and fuzziness in the system objective, which are represented by fuzzy sets and denoted as “fuzzy constraints” and a “fuzzy goal”, respectively, are expressed as membership grades λ^\pm corresponding to the degrees of overall satisfaction for the constraints/objective. Thus, model (1) can be converted to

$$Max \lambda^\pm \tag{2a}$$

subject to

$$C^\pm X^\pm \leq f_d^- + (1 - \lambda^\pm)(f_d^+ - f_d^-) \tag{2b}$$

$$A^\pm X^\pm \leq B^- + (1 - \lambda^\pm)(B^+ - B^-) \tag{2c}$$

$$X^\pm \ge 0 \tag{2d}$$

$$0 \leq \lambda^\pm \leq 1 \tag{2e}$$

where x_j^\pm denotes interval decision variables and $x_j^\pm \in X^\pm$; f_d^+ and f_d^- denote the upper and lower bounds of the objective’s aspiration level as designated by decision makers, respectively; λ^\pm denotes the control decision variable corresponding to the degree (membership grade) to which X^\pm solution fulfils the fuzzy objective or constraints. IFLP model can be transformed into two deterministic sub-models, which corresponding to the upper and lower bounds for the desired objective function value. In detail, the sub-model corresponding to λ^- is first formulated and solved. This is based on the fact that the λ^-

corresponds f^- and the system objective is to be minimized. If $b_i^\pm \geq 0$ and $f^\pm \geq 0$, the sub-model corresponding to λ^- can be formulated as follows:

$$\text{Max } \lambda^- \tag{3a}$$

subject to:

$$\sum_{j=1}^{k_1} c_j^+ x_j^+ + \sum_{j=k_1+1}^n c_j^+ x_j^- \leq f_d^- + (1 - \lambda^-)(f_d^+ - f_d^-) \tag{3b}$$

$$\sum_{j=1}^{k_1} |a_{ij}|^- \text{Sign}(a_{ij}^-) x_j^+ + \sum_{j=k_1+1}^n |a_{ij}|^+ \text{Sign}(a_{ij}^+) x_j^- \leq b_i^- + (1 - \lambda^-)(b_i^+ - b_i^-), \quad \forall i \tag{3c}$$

$$0 \leq \lambda^- \leq 1 \tag{3d}$$

$$x_j^- \geq 0, \quad j = 1, 2, \dots, k_1 \tag{3e}$$

$$x_j^+ \geq 0, \quad j = k_1 + 1, k_1 + 2, \dots, n \tag{3f}$$

Sign is a signal function, which is defined as:

$$\text{Sign}(x^\pm) = \begin{cases} 1 & \text{if } x^\pm \geq 0 \\ -1 & \text{if } x^\pm \leq 0 \end{cases}$$

Let $x_{j\text{opt}}^+$ ($j = 1, 2, \dots, k_1$) and $x_{j\text{opt}}^-$ ($j = k_1 + 1, k_1 + 2, \dots, n$) be solutions of sub-model (3). Then, the second sub-model corresponding to λ^+ can be formulated supported by the solution of sub-model (3):

$$\text{Max } \lambda^+ \tag{4a}$$

subject to:

$$\sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^n c_j^- x_j^+ \leq f_d^- + (1 - \lambda^+)(f_d^+ - f_d^-) \tag{4b}$$

$$\sum_{j=1}^{k_1} |a_{ij}|^+ \text{Sign}(a_{ij}^+) x_j^- + \sum_{j=k_1+1}^n |a_{ij}|^- \text{Sign}(a_{ij}^-) x_j^+ \leq b_i^- + (1 - \lambda^+)(b_i^+ - b_i^-), \quad \forall i \tag{4c}$$

$$0 \leq \lambda^+ \leq 1 \tag{4d}$$

$$x_{j\text{opt}}^+ \geq x_j^- \geq 0, \quad j = 1, 2, \dots, k_1 \tag{4e}$$

$$x_j^+ \geq x_{j\text{opt}}^-, \quad j = k_1 + 1, k_1 + 2, \dots, n \tag{4f}$$

Let $x_{j\text{opt}}^-$ ($j = 1, 2, \dots, k_1$) and $x_{j\text{opt}}^+$ ($j = k_1 + 1, k_1 + 2, \dots, n$) be solutions of sub-model (4). Thus, we can obtain the interval solutions as follows:

$$\lambda_{\text{opt}}^\pm = [\lambda_{\text{opt}}^-, \lambda_{\text{opt}}^+] \tag{5a}$$

$$x_{j\ opt}^{\pm} = [x_{j\ opt}^{-}, x_{j\ opt}^{+}], \quad \forall j \tag{5b}$$

Then, f_{opt}^{-} and f_{opt}^{+} can be calculated as follows:

$$f_{opt}^{-} = \sum_{j=1}^{k_1} c_j^{-} x_j^{-} + \sum_{j=k_1+1}^n c_j^{-} x_j^{+} \tag{6a}$$

$$f_{opt}^{+} = \sum_{j=1}^{k_1} c_j^{+} x_j^{+} + \sum_{j=k_1+1}^n c_j^{+} x_j^{-} \tag{6b}$$

Thus, we have

$$f_{j\ opt}^{\pm} = [f_{opt}^{-}, f_{opt}^{+}], \quad \forall j. \tag{7}$$

Appendix 2: Nomenclatures

$f(x)^{\pm}$	Net system benefit over the planning horizon (\$)
i	Name of district, where $i = 1$ for Central Construction Zone (district 1), $i = 2$ for New Urban Development Zone (district 2), and $i = 3$ for Eco-environmental Zone (district 3)
j	Type of land use, where $j = 1$ for residential land, $j = 2$ for industrial land, $j = 3$ for commercial land, $j = 4$ for green land, $j = 5$ for public land, $j = 6$ for agricultural land, and $j = 7$ for landfill
t	Time of planning, where $t = 1$ for period 1 (2011–2015), $t = 2$ for period 2 (2016–2020), and $t = 3$ for period 3 (2021–2025)
$BP_{i,j,t}^{\pm}$	Unit benefit of land-use type j in district i in period t (\$/ha)
$WC_{i,j,t}^{\pm}$	Unit wastewater-tackling cost of land-use type j in district i in period t (\$/ha)
$SC_{i,j,t}^{\pm}$	Unit solid-waste-tackling cost of land-use type j in district i in period t (\$/ha)
$GC_{i,j=4,t}^{\pm}$	Unit maintenance costs of green land in district i in period t (\$/ha)
$PC_{i,j=5,t}^{\pm}$	Unit maintenance costs of public land in district i in period t (\$/ha)
MGI_t^{\pm}	Maximum government investment in period t (\$)
TLA_t^{\pm}	Total land area in period t , including residential land, industrial land, commercial land, green land, public land, agricultural land and landfill (ha)
$P_{i,t}^{\pm}$	Total population until period t (people)
$MIGL^{\pm}$	Minimum area of green land per capita in period t (ha/people)
$MIPL^{\pm}$	Minimum area of public land per capita in period t (ha/people)
$MIRL^{\pm}$	Minimum area of residential land in period t (ha)
$MIAL^{\pm}$	Minimum area of agricultural land in period t (ha)
$MIIL^{\pm}$	Minimum area of industrial land in period t (ha)
$MICL^{\pm}$	Minimum area of commercial land in period t (ha)
$UWP_{i,j,t}^{\pm}$	Unit water consumption of land-use type j in district i in period t (ton/ha)
$MAW_{i,j,t}^{\pm}$	Water supply capacity in period t (ton)
$UEP_{i,j,t}^{\pm}$	Unit quantity of electricity consumption of land-use type j in districts i in period t (kilowatt-hour/ha)

$MAE_{i,j,t}^{\pm}$	Electricity supply capacity in period t (kilowatt-hour)
$RWP_{ij=1,t}^{\pm}$	Wastewater discharging factor of residential land in district i in period t (ton/ha)
$IWP_{ij=2,t}^{\pm}$	Wastewater discharging factor of industrial land in district i in period t (ton/ha)
$CWP_{ij=3,t}^{\pm}$	Wastewater discharging factor of commercial land in district i in period t (ton/ha)
$AWP_{ij=6,t}^{\pm}$	Wastewater discharging factor of agricultural land in district i in period t (ton/ha)
$MAWC_t$	Wastewater treatment plant capacity in period t (ton)
$RSP_{ij=1,t}^{\pm}$	Solid-waste discharging factor of residential land in district i in period t (ton/ha)
$ISP_{ij=2,t}^{\pm}$	Solid-waste discharging factor of industrial land in district i in period t (ton/ha)
$CSP_{ij=3,t}^{\pm}$	Solid-waste discharging factor of commercial land in district i in period t (ton/ha)
$ASP_{ij=6,t}^{\pm}$	Solid-waste discharging factor of agriculture land in district i in period t (ton/ha)
$LSP_{i,t}^{\pm}$	Solid-waste treatment plant capacity (landfill) in district i in period t (ton)
$MASC_t$	Solid-waste treatment plant capacity (except landfill) in period t (ton)

References

- Carsjens, G. J., & van der Knapp, W. (2002). Strategic land-use allocation: dealing with spatial relationships and fragmentation of agriculture. *Landscape and Urban Planning*, *58*, 171–179.
- Chanas, S., & Zielinski, P. (2000). On the equivalence of two optimization methods for fuzzy linear programming problems. *European Journal of Operational Research*, *121*, 56–63.
- Chang, N. B., & Wang, S. F. (1997). A fuzzy goal programming approach for the optimal planning of metropolitan solid waste management systems. *European Journal of Operational Research*, *32*, 303–321.
- Cheung, C., & Cheng, J. Y. (2016). Resources and norms as conditions for well-being in Hong Kong. *Social Indicators Research*, *126*, 757–775.
- FAO. (1993). Guidelines for land use planning Development Series 1, Rome.
- Hagoort, M., Geertman, S., & Ottens, H. (2008). Spatial externalities, neighbourhood rules and CA land-use modelling. *The Annals of Regional Science*, *42*, 39–56.
- Han, H., Hwang, Y. S., Ha, S. R., & Kim, B. S. (2015). Modeling future land use scenarios in South Korea: Applying the IPCC special report on emissions scenarios and the SLEUTH model on a local scale. *Environmental Management*, *55*, 1064–1079.
- Hosseinali, F., Alesheikh, A. A., & Nourian, F. (2013). Agent-based modeling of urban land-use development, case study: Simulating future scenarios of Qazvin city. *Cities*, *31*, 105–113.
- Kaiser, E. J., Godschalk, D. R., & Chaping, J. F. S. (1995). *Urban land use planning* (4th ed.). Urbana, USA: University of Illinois Press.
- Kamusoko, C., Aniya, M., Adi, B., & Manjoro, M. (2009). Rural sustainability under threat in Zimbabwe—Simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. *Applied Geography*, *29*, 435–447.
- Koomen, E., Rietveld, P., & de Nijs, T. (2008). Modelling land-use change for spatial planning support. *The Annals of Regional Science*, *42*, 1–10.
- Law, E. A., Meijaard, E., Bryan, B. A., Mallawaarachchi, T., Koh, L. P., & Wilson, K. A. (2015). Better land-use allocation outperforms land sparing and land sharing approaches to conservation in Central Kalimantan, Indonesia. *Biological Conservation*, *186*, 276–286.
- Liu, L., Huang, G. H., Liu, Y., Fuller, G. A., & Zeng, G. M. (2003). A fuzzy-stochastic robust programming model for regional air quality management under uncertainty. *Engineering Optimization*, *35*, 177–199.
- Liu, X., Ou, J., Li, X., & Ai, B. (2013). Combining system dynamics and hybrid particle swarm optimization for land use allocation. *Ecological Modelling*, *257*, 11–24.

- Lu, Y., Cao, M., & Zhang, L. (2015). A vector-based cellular automata model for simulating urban land use change. *Chinese Geographical Science*, 25, 74–84.
- Maqsood, I., & Huang, G. H. (2003). A two-stage interval-stochastic programming model for waste management under uncertainty. *Journal of the Air and Waste Management Association*, 53, 540–552.
- McNeill, D., Bursztyn, M., Novira, N., Purushothaman, S., Verburg, R., & Rodrigues-Filho, S. (2014). Taking account of governance: The challenge for land-use planning models. *Land Use Policy*, 37, 6–13.
- Messina, V., & Bosetti, V. (2003). Uncertainty and option value in land allocation problems. *Annals of Operations Research*, 124, 165–181.
- Morse, S. (2016). Measuring the success of sustainable development indices in terms of reporting by the global press. *Social Indicators Research*, 125, 359–375.
- Munton, R. (1987). The conflict between conservation and food production in Great Britain. In C. Cocklin, B. Smit, & T. Johnston (Eds.), *Demand on rural land*. London, England: Westview Press.
- Murray-Rust, D., Robinson, D. T., Guillem, E., Karali, E., & Rounsevell, M. (2014). An open framework for agent based modelling of agricultural land use change. *Environment Modelling and Software*, 61, 19–38.
- Nguyen, T. T., Verdoodt, A., Tran, V. Y., Delbecque, N., Tran, T. C., & Ranst, E. V. (2015). Design of a GIS and multi-criteria based land evaluation procedure for sustainable land-use planning at the regional level. *Agriculture Ecosystems and Environment*, 200, 1–11.
- Nino-Ruiz, M., Bishop, I., & Pettit, C. (2013). Spatial model steering, an exploratory approach to uncertainty awareness in land use allocation. *Environment Modelling and Software*, 39, 70–80.
- Oberling, D. F., la Rovere, E. L., & de Oliveira Silva, H. V. (2013). SEA making inroads in land-use planning in Brazil: The case of the Extreme South of Bahia with forestry and biofuels. *Land Use Policy*, 35, 341–358.
- Overmars, K. P., Verburg, P. H., & Veldkamp, T. (2007). Comparison of a deductive and an inductive approach to specify land suitability in a spatially explicit land use model. *Land Use Policy*, 24, 584–599.
- Pilehforoosha, P., Karimi, M., & Taleai, M. (2014). A GIS-based agricultural land-use allocation model coupling increase and decrease in land demand. *Agricultural Systems*, 130, 116–125.
- Qin, X. S., Huang, G. H., Zeng, G. M., Chakma, A., & Huang, Y. F. (2007). An interval-parameter fuzzy nonlinear optimization model for stream water quality management under uncertainty. *European Journal of Operational Research*, 180, 1331–1357.
- Rajaei, S. A., & Mansourian, H. (2016). Urban growth and housing quality in Iran. *Social Indicators Research*. doi:10.1007/s11205-016-1260-2.
- Richard, A. (2004). Modelling land use change with generalized linear models—a multi-model analysis of change between 1860 and 2000 in Gallatin Valley, Montana. *Journal of Environmental Management*, 72, 91–103.
- Rodriguez-Rosa, M., Gallego-Alvarez, I., Vicente-Galindo, M. P., & Galindo-Villardón, M. P. (2016). Are social, economic and environmental well-being equally important in all countries around the world? a study by income levels. *Social Indicators Research*. doi:10.1007/s11205-016-1257-x.
- Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology*, 15, 234–281.
- Siripun, T. (2001). *Dynamic simulation modeling of the land use, economy and environment in Chiang Mai, Thailand using GIS and remote sensing*. New York, USA: State University of New York Press.
- Stewart, T. J., & Janssen, R. (2014). A multiobjective GIS-based land use planning algorithm. *Computers Environment and Urban Systems*, 46, 25–34.
- Svoray, T., Kutiel, P. B., & Bannet, T. (2005). Urban land-use allocation in a editerranean ecotone: Habitat Heterogeneity Model incorporated in a GIS using a multi-criteria mechanism. *Landscape and Urban Planning*, 72, 337–351.
- Turner, B. L., Meyer, W. B., & Skole, D. L. (1994). Global land-use/land cover change: towards an integrated study. *Ambio*, 23, 91–99.
- Uday, B. N., de Bie, C., van Keulen, H., Skidmore, A. K., & Harmsen, K. (2006). Review of a land use planning programme through the soft systems methodology. *Land Use Policy*, 23, 187–203.
- Verburg, P. H., Eickhout, B., & van Meijl, H. (2008). A multi-scale, multi-model approach for analyzing the future dynamics of European land use. *The Annals of Regional Science*, 42, 57–77.
- Verburg, P. H., Tabeau, A., & Hatna, E. (2013). Assessing spatial uncertainties of land allocation using a scenario approach and sensitivity analysis: A study for land use in Europ. *Journal of Environmental Management*, 127, S132–S144.

- Verburg, P. H., van Berkel, D. B., van Doorn, D. B., van Eupen, M., & van den Heiligenberg, H. A. (2010). Trajectories of land use change in Europe: a model-based exploration of rural futures. *Landscape Ecology*, *25*, 217–232.
- Wang, H., Li, X. B., Long, H. L., Qiao, Y. W., & Li, Y. (2011). Development and application of a simulation model for changes in land-use patterns under drought scenarios. *Computers and Geosciences*, *37*, 831–843.
- Wang, X. H., Yu, S., & Huang, G. H. (2004). Land allocation based on integrated GIS-optimization modeling at a watershed level. *Landscape and Urban Planning*, *66*, 61–74.
- Wey, W. M., & Wei, W. L. (2016). Urban growth and housing quality in Iran. *Social Indicators Research*, *126*, 161–186.
- Zhang, J., Fu, M., Zhang, Z., Tao, J., & Fu, W. (2014). A trade-off approach of optimal land allocation between socio-economic development and ecological stability. *Ecological Modeling*, *272*, 175–187.
- Zhou, M. (2015). An interval fuzzy chance-constrained programming model for sustainable urban land-use planning and land use policy analysis. *Land Use Policy*, *42*, 479–491.