

An integrated GIS-based interval-probabilistic programming model for land-use planning management under uncertainty—a case study at Suzhou, China

Shasha Lu · Min Zhou · Xingliang Guan · Lizao Tao

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Abstract A large number of mathematical models have been developed for supporting optimization of land-use allocation; however, few of them simultaneously consider land suitability (e.g., physical features and spatial information) and various uncertainties existing in many factors (e.g., land availabilities, land demands, land-use patterns, and ecological requirements). This paper incorporates geographic information system (GIS) technology into interval-probabilistic programming (IPP) for land-use planning management (IPP-LUPM). GIS is utilized to assemble data for the aggregated land-use alternatives, and IPP is developed for tackling uncertainties presented as discrete intervals and probability distribution. Based on GIS, the suitability maps of different land users are provided by the outcomes of land suitability assessment and spatial analysis. The maximum area of every type of land use

obtained from the suitability maps, as well as various objectives/constraints (i.e., land supply, land demand of socioeconomic development, future development strategies, and environmental capacity), is used as input data for the optimization of land-use areas with IPP-LUPM model. The proposed model not only considers the outcomes of land suitability evaluation (i.e., topography, ground conditions, hydrology, and spatial location) but also involves economic factors, food security, and eco-environmental constraints, which can effectively reflect various interrelations among different aspects in a land-use planning management system. The case study results at Suzhou, China, demonstrate that the model can help to examine the reliability of satisfying (or risk of violating) system constraints under uncertainty. Moreover, it may identify the quantitative relationship between land suitability and system benefits. Willingness to arrange the land areas based on the condition of highly suitable land will not only reduce the potential conflicts on the environmental system but also lead to a lower economic benefit. However, a strong desire to develop lower suitable land areas will bring not only a higher economic benefit but also higher risks of violating environmental and ecological constraints. The land manager should make decisions through trade-offs between economic objectives and environmental/ecological objectives.

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Shasha Lu and Min Zhou equally contributed to this work.

S. Lu (✉)
School of Economics and Management, Beijing Forestry University,
Beijing 100083, China
e-mail: sasafly0505@163.com

M. Zhou (✉)
College of Public Administration, Huazhong University of Science
and Technology, Wuhan 430074, China
e-mail: shijieshandian00@163.com

X. Guan
National Academy for Mayors of China, Beijing 100029, China
e-mail: guanxingliang@126.com

L. Tao
Institute of International Law, Wuhan University,
Wuhan 430072, China
e-mail: yolandatao@qq.com

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Introduction

In the real world, there are a large number of uncertain factors (gray factors) during the resources management and decision-making process (Huang and Moore 1993). The inherent complexities and uncertainties that exist in the real world have

been beyond the conventional deterministic optimization methods (Han et al. 2011). Previously, researchers have developed many inexact optimization methods to deal with uncertainties—including fuzzy programming model (FPM), stochastic programming model (SPM), and interval linear programming (ILP) (Huang et al. 1992). These inexact methods are used for dealing with the complexities and uncertainties in the pollution control planning (Luo et al. 2006), soil erosion control (Han et al. 2013), environmental management (Guo and Huang 2010), solid waste management (Zhang et al. 2010; Tan et al. 2010), water resources management (Lin and Huang 2008), water quality management (Qin et al. 2009; Xie et al. 2011), coupled coal and power management (Liu et al. 2009), regional energy planning (Li et al. 2011), industrial structure optimization (Zhou et al. 2013), agricultural production structure optimization (Lu et al. 2013), and other economic-environment sustainable development management problems.

In recent years, land-use problems associated with land-use change, socioeconomic development, and environmental protection have been growing concerns faced by many regional and/or national authorities (Fang et al. 2013; Long 2014; Zhang et al. 2014). Similarly, uncertainties are ubiquitous within many system parameters and their interrelationships in a land-use management system, posing a pressing challenge for decision makers in generating economically sound and environmentally responsible schemes (Messina and Bosetti 2003; Wang et al. 2004). The random characteristics of natural processes (e.g., climate change) and land-use conditions (e.g., land-use patterns, land supply, land demand, and land-quality requirement), the errors in estimated modeling parameters (e.g., benefit and/or cost parameters), and the vagueness of system objectives and constraints (economic benefits maximization, social development objectives, and eco-environmental requirements) are all possible sources of uncertainties (Lu et al. 2014a, b). In order to support land resource allocation decisions and land management needs, many researchers have employed inexact optimization methods for dealing with uncertainties in land resource allocation systems. For example, Liu et al. (2007a, b) developed an inexact chance-constrained linear programming (ICCLP) model for land-use management of lake areas at urban fringes. Wang et al. (2010) established an interval multi-objective linear programming model to optimizing and adjusting land-use structure in Pi County of Sichuan Province in China. Lu et al. (2014a, b) applied a multi-objective interval-stochastic land resource allocation model (MOISLAM) to identify a desirable land resource allocation strategy in an urban area under uncertainty. Zhou et al. (2014) developed an integration of existing ILP and fuzzy flexible programming (FFP) for optimizing national-scale land systems of China.

Undoubtedly, the inexact optimization model for land-use allocation allows system uncertainties and decision makers'

aspirations to be effectively communicated into the programming process. The solutions obtained from the optimization model provide lower and upper bounds of the interval numbers (gray numbers) in relation to the decision variables and objective function values, which are useful for generating a range of decision alternatives under various system benefit conditions (Lu et al. 2014a, b). Unfortunately, inexact optimization models for land-use allocation in the previous studies lacked an effective suitability assessment. Most of the models developed to support land resource allocation decisions and land management need to have economic, social, environmental, and technical parameters; furthermore, the location of existing land use and suitability of physical features (slope, surficial geological type, surface erosion, and distance to main road) also need to be considered. In fact, land-use suitability mapping and analysis are the fundamental processes for identifying the appropriate area as well as the best site for some activity given the set of potential sites (Malczewski 2004; Liu et al. 2006; Liu et al. 2007a). Over the past decades, multi-criteria decision analysis (MCDA) and geographic information system (GIS) techniques have increasingly become integral components for performing such a task (Collins et al. 2001). The spatial patterns and corresponding land values derived from land-use suitability analysis are directly related to solutions of land allocations and should be projected as a criteria used in constraints of optimization models (Liu et al. 2007a). It is essential therefore to incorporate the proper land-use suitability into the optimization model formulations, which would be helpful for decision makers to identify a desirable land resource allocation strategy under uncertainty.

As an extension of previous approaches, the objective of this study is to develop a GIS-based interval-probabilistic programming model for land-use planning management (IPP-LUPM). As an integration of the interval-probabilistic programming method and GIS, this method may better account for complicated interactions, trade-offs, uncertainties, and system reliabilities in a land resources allocation system. The detailed tasks include the following: (1) conducting the land suitability evaluation of each land-use category based on GIS, multi-criteria evaluation model and the FAO's (1976) framework, (2) constructing hybrid interval-probabilistic linear programming (IPLP) based on land suitability evaluation results, and (3) applying the developed method to the optimization of land-use allocation in the city of Suzhou, in the Yangtze River Delta of China.

The study area and research material

The study area

The study area named as Suzhou is the central city of Yangtze River Delta Economic Zone of China. It is located between

30° 45' N and 32° 05' N and between 119° 55' E and 121° 20' E in the southern part of Jiangsu Province, bordering Shanghai on the east, Hangzhou (the capital of Zhejiang Province) in the south, the Taihu Lake in the west, and the Yangtze River in the north (Fig. 1). Situated at the temperate zone and with subtropical oceanic monsoon climate, the city enjoys four distinct seasons, a mild temperature and abundant rainfall. The annual temperature of Suzhou is 16 °C and the annual precipitation is 1,100 mm (Suzhou Statistical Bureau 2012). With a network of rivers and canals as well as a fertile land, the city is rich in a variety of agricultural products. As a well-known “Land of Fish and Rice” as well as “Silk Capital,” Suzhou enjoys a fame of “Paradise on Earth.”

The city’s current municipal area is 8,404 km², containing seven districts (i.e., Canglang, Jinchang, Pingjiang, Suzhou Industrial Park, Suzhou High & New Technology Development Zone, Xiangcheng, and Wuzhong) and five satellite cities (namely Kunshan, Changshu, Taicang, Wujiang, and Zhangjiagang) with a population of approximately 10.55 million in 2012. With the famous Suzhou gardens and cultural heritages, the city is a national excellent tourism venue and famous historical city in China. Since China adopted reform and opening up policy, Suzhou has grown more and more internationalized, industrialized, modernized, and harmonious and has become a model in China for building a moderately prosperous society in all respects. In 2012, the gross domestic product (GDP) as well as GDP per capita of the city was about 1,201.17 billion yuan and 186,207

yuan (yuan (¥) to US\$: 6.25:1), respectively; the governmental financial revenue was 256.17 billion yuan. High-technology industry is the main economic growth propelling force of the city, besides tertiary industry, possessing 13,000 enterprises with foreign investment and 128 of the world’s top 500 enterprises. Suzhou is the city with the best development potentiality and economic vitality and the most charming and competitive city in China.

While the growth of the secondary and tourist industry has increased the proportion of total income, it has also resulted in overuse of large areas of land traditionally devoted to agriculture and forests. The demand for industrial water to support secondary industry aggravates existing conflicts between water supply and demand. The environmental problems in the area are mainly derived from discharge of industrial wastewater. Seepage and runoff of pesticides and fertilizers from agricultural activities and discharge of wastewater from farmers and livestock are also resulting in nonpoint pollution and eutrophication. For example, as the main component of the city’s water system, Taihu Lake has been threatened by water degradation, eutrophication, and pollution from solid wastes. According to reports from Suzhou Environmental Monitoring Station, concentrations of many pollutants, such as NH₃-N, BOD, and COD, have increased progressively since 1990 along the lake. Moreover, industrial solid wastes and household wastes have not been disposed properly and posed a threat to the safety of residents’ health.

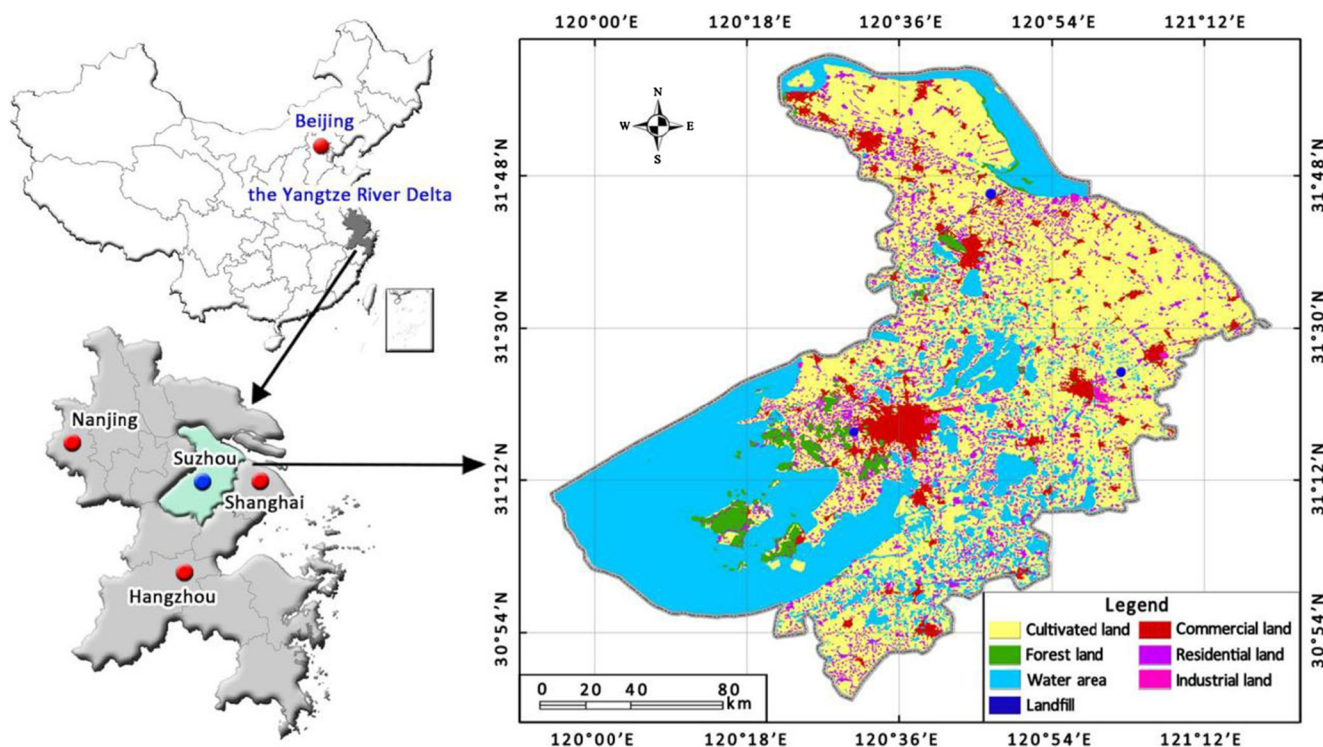


Fig. 1 The study area

Data acquisition

The dataset of this study included the area and distribution pattern of different land-use types, the physical characteristics containing topography, ground conditions, geologic hazards, and hydrology conditions, the existing digitized databases of traffic maps, and economic and environmental information from tables and reports.

1. Data on existing land-uses were obtained from the land-use and land-cover change (LUCC) database established by Chinese Academy of Sciences (CAS), which produces thematic maps at a scale of 1:100,000 (Liu et al. 2002). These LUCC data were obtained through visual interpretation and digitization of satellite remote sensing data provided by the US Landsat TM/ETM images, with a hierarchical classification system of 25 land-cover classes (Deng et al. 2010). During the process of interpretation and land-cover classifications, CAS has verified that the average interpretation accuracies for the LUCC data were more than 92 % through an outdoor survey and random sample check (covering a line survey of 70,000 km and 13,300 patches) (Liu et al. 2002; Lu et al. 2014a, b). Considering the convenience for the land managers and having consulted the local urban planning authority, we distinguished the types of land-use into seven categories: commercial land, residential land, and industrial land, cultivated land, forest land, water area, and landfill.
2. Topographic attributes, i.e., slope and aspect layers, were calculated from the 30-m resolution, contour-based, digital elevation model (DEM) available at no charge to users via electronic download from NASA's Land Processes Distributed Active Archive Center (LP DAAC).
3. Surficial geology, soil thickness, and hydrology attribute were obtained from the Hydrogeology and Engineering Geology Team of Jiangsu Province.
4. Land transport network data, including railways, highways, state and provincial roads, and general level of road, were obtained from the Department of Transportation of Suzhou.
5. The socioeconomic data (e.g., manuals, local planning reports) were collected from the local government and Suzhou Statistical Yearbook.

Methodology

Model architecture of the GIS-based IPP-LUPM

An integrated GIS-based interval-probabilistic programming model is a decision support model suited for land-use

planning management. Its main objective is to help land planners and decision makers to obtain optimal areas of different land-users. The framework of the GIS-based IPP-LUPM model is shown in Fig. 2, which includes three main components.

1. Geographical database (GDB) management system, which manages the database describing the study area and includes data acquisition, storage, retrieval, manipulation, and analysis.
2. Land suitability assessment module based on GIS technology and multi-criteria decision-making methods (Malczewski 2004; Liu et al. 2006). Land suitability assessment procedures involve the utilization of geographical database and the decision makers' preferences; correspondingly, land suitability map and the maximum area of each land-use category are provided by the outcomes of land suitability assessment and spatial analysis.
3. A hybrid interval-probabilistic programming model (IPPM). The IPPM can effectively reflect uncertainties existed in various economic, environmental, ecological, and social conditions and expressed as discrete intervals and probability distribution (Huang et al. 1992; Liu et al. 2007b). 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.

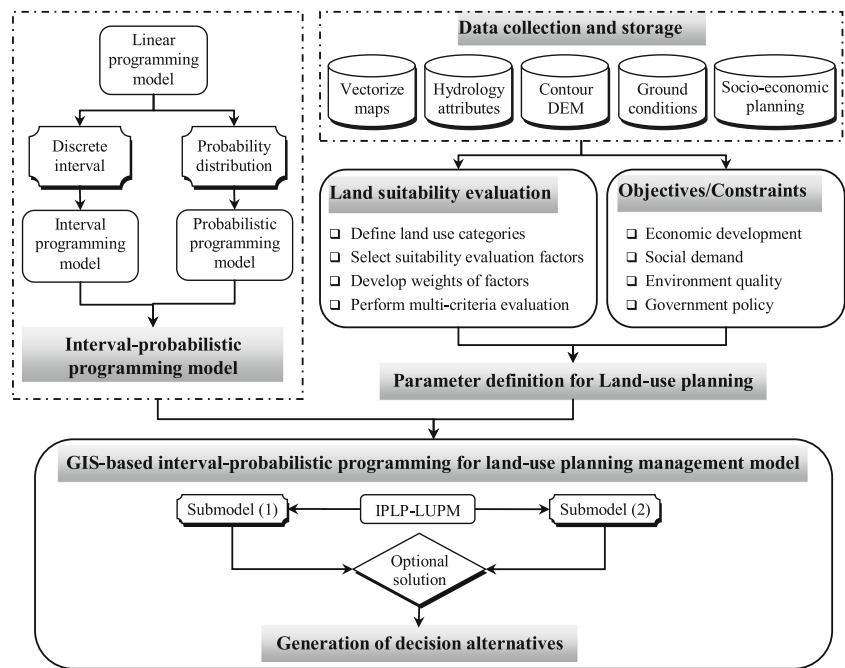
It should be noted that land suitability plays two important roles in the IPP-LUPM. Firstly, different land suitability conditions are related to different maintenance costs for nonbeneficial land-use types, which would result in different land-use patterns and objective function values. Secondly, maximum area of each type of land use is determined by the results from GIS-based land suitability evaluation model; land suitability parameters are important in determining the quantity optimization in the hybrid interval-probabilistic programming model.

The proposed GIS-based IPP-LUPM can effectively reflect interactive, complex, dynamic, and uncertain features of land-use allocation problems. The model can help to generate desired decision alternatives for land-use allocation optimization based on the given objectives/constraints.

GIS-based land suitability evaluation model

Land suitability evaluation is a fundamental part of the land-use management process (FAO 1976), aiming at analyzing the physical, spatial, and/or institutional attributes of a parcel of land and providing a scientific basis for land-use planning and redevelopment. Based on such analysis, land suitability map of individual land-use categories can be identified. The determination of the suitability level for each land use and spatial

Fig. 2 Framework for the IPP-LUPM



unit is the basis for subsequent optimization of the land-use areas (Dai et al. 2001).

Suitability evaluation factors

It is essential to select a set of suitability factors that provides a basis for determining the suitability of land. Evaluation factors should be identified on the basis of available literatures (e.g., manuals, local planning reports, and general planning standard), expert knowledge, and fieldwork; the planners need to make sure that the selected factors are comprehensive, measurable, nonredundant, decomposable, and operational (Malczewski 1999; Zhang et al. 2013). In fact, this is the most critical part in the overall procedure and is also the most time-consuming part because it involves the collection and preparation of the data. In this paper, the most pertinent factors for the major land-use categories were found to be as follows (Table 1):

1. Suitability factors for cultivated land; these include four factor groups comprising eight separate sets of geo-environmental attributes. Topography, including elevation and slope gradient, forms an important determinant of suitability assessment for different land users. Ground conditions, including surficial geology and soil thickness, may pose the likelihood for agricultural production activities to be encountered. Geologic hazards, including surface erosion and distance to fault, may pose actual or potential threats to agricultural production activities and thus must be taken into consideration. Hydrology attribute, including underground water depth and surface

runoff, may affect land natural productivity, which should be also incorporated into the evaluation system.

2. Suitability factors for commercial land, residential land, and industrial land; these include four factor groups comprising eight separate sets of geo-environmental attributes. Topography, including elevation and slope gradient, forms an important determinant of suitability assessment for construction land. Ground conditions, including surficial geology and existing land use, may pose the likelihood for construction problems to be encountered. Geologic hazards, including surface erosion and distance to fault, may pose actual or potential threats to engineering construction and maintenance. Spatial location, including distance to main road and distance to central business district (CBD), is important in the evaluation of the ease in relation to accessibility and basic urban facilities.

Criterion of suitability factors

Table 1 presents the class boundaries and standardized measurements employed for each factor. Based on the literature information and expert knowledge, the criterion values in each factor were standardized in accordance with the five levels of adaptability for each land-use category. As a general guideline, a positive correlation between the criterion values and adaptability levels is employed. These integer numbers (scores) ranging from 100 to 0 were assigned to highly suitable (S1), moderately suitable (S2), marginally suitable (S3), currently not suitable (N1), and permanently not suitable (N2)

Table 1 Selection of suitability factors for each land-use category and its weights

Physical characteristics	Suitability rating Score	S1 100–90	S2 90–80	S3 80–60	N1 60–30	N2 30
Cultivated land						
Topography	Slope gradient (°) (0.6)	<1.0 (100)	1.0–2.0 (90)	2.0–5.0 (80)	5.0–15.0 (40)	>15.0 (0)
	Elevation (meter) (0.4)	<30 (90)	30–50 (80)	50–100 (70)	100–200 (50)	>200 (10)
Ground conditions	Surficial geological type (0.5)	Anthrosol (95)	Hydromorphic soil (85)	Semi-hydromorphic soil (70)	Alfisols, entisols (30)	Lakes, river (5)
	Soil thickness (centimeter) (0.5)	>80 (90)	50–80 (70)	30–50 (70)	15–30 (30)	<15 (10)
Geologic hazards	Surface erosion (0.5)	Absent (100)	Sheet (80)	Rill (70)	Gully (35)	Deep gully (20)
	Distance to fault (meter) (0.5)	>300 (100)	100–300 (90)	50–100 (60)	30–50 (30)	<30 (10)
Hydrology conditions	Underground water depth (meter) (0.40)	>500 (90)	300–500 (85)	100–300 (70)	10–100 (40)	<10 (20)
	Surface runoff (millimeter) (0.60)	>1,000 (100)	900–1,000 (85)	800–900 (70)	600–800 (50)	<600 (40)
Commercial land, residential land, and industrial land						
Topography	Slope gradient (°) (0.8)	<1.0 (100)	1.0–2.0 (90)	2.0–5.0 (60)	5.0–15.0 (30)	>15.0 (0)
	Elevation (meter) (0.2)	<30 (90)	30–50 (80)	50–100 (60)	100–200 (50)	>200 (20)
Ground conditions	Surficial geological type (0.4)	Anthrosol (100)	Hydromorphic soil (85)	Semi-hydromorphic soil (70)	Alfisols, entisols (30)	Lakes, river (5)
	Existing land use (0.6)	Construction land (100)	Cultivated land (90)	–	Water area (40)	Forest land (30)
Geologic hazards	Surface erosion (0.5)	Absent (100)	Sheet (80)	Rill (70)	Gully (35)	Deep gully (20)
	Distance to fault (meter) (0.5)	>300 (100)	100–300 (90)	50–100 (60)	30–50 (30)	<30 (10)
Spatial location	Distance to main road (meter) (0.6)	<100 (95)	100–300 (85)	300–800 (70)	800–1,500 (40)	>1,500 (10)
	Distance to CBD (minutes) (0.4)	<5 (100)	5–10 (90)	10–30 (80)	30–60 (50)	>60 (20)

Class S1—highly suitable: land having no significant limitations for sustained applications. Class S2—moderately suitable: land having limitations that in the aggregate are moderately severe for sustained application. Class S3—marginally suitable: land with limitations that in the aggregate are severe for sustained application. Class N1—currently not suitable: land that has qualities that appear to preclude sustained use. Class N2—permanently not suitable (FAO 1976)

classes, respectively. For example, the slope index was divided into five levels of adaptability to cultivated land as follows: <1.0, 1.0–2.0, 2.0–5.0, 5.0–15.0, and >15.0. Correspondingly, the criterion values were 100, 90, 80, 40, and 0, respectively. The assessment maps for each suitability factor are seen in Fig. 3.

Development of weights

Factor weighting is a primary issue because it imposes the relative importance of each factor on the suitability of the study area for different land users. The analytic hierarchy process (AHP) proposed by Saaty (1977), a multi-objective, multi-criteria decision-making approach, gained wide application in site selection, suitability analysis, and regional planning. The AHP weighting method can, although rationally defensible, be fairly arbitrarily applied and depends entirely on the perceptions and priorities of the evaluators (Dai et al. 2001). The Delphi survey technique is a flexible approach, which can contribute significantly to broadening knowledge if used correctly and rigorously and designed to transform opinion into group consensus (Hasson et al. 2000). In this study, the Delphi approach is used to determine the relative importance of each factor based on the expert knowledge; 15 experts, independently of one another, were asked to place a value on each factor. The average was used as the final weight (Table 1).

Performing suitability assessment

Multi-criteria evaluation is used to combine a set of criteria to form a single suitability map according to a specific land-use category. The weighted linear combination (WLC), a common

compensatory method, is used for the estimation and implementation of numerous criteria in GIS. The combination of the components, according to the WLC model, is carried out as follows:

$$S_j = \sum_{i=1}^n W_{ij}X_{ij}$$

where S_j is defined as the level of adaptability to land-use category j , n is the number of criteria related to category j , W_{ij} is the weight of criterion i of category j , and X_{ij} is the rank of criterion i of category j according to the range of criterion (i) values.

After completing the suitability calculation, the final suitability assessment could easily be mapped using GIS mapping capability. The WLC is repeated for each land-use category separately to create a suitability map with a value range of (0–100) per cell. Since composite score is a real number, it is possible to show as many levels of suitability as desired. For each suitability map here, a three specific interval classification between the minimum and the maximum cell values calculated is employed, i.e., assigning the three ranges in an order to highly suitable (75–100), moderately suitable (35–75), and not suitable (0–35), respectively. The resultant raster maps are then vectorized and zoned. In the case of the city of Suzhou, two suitability assessment maps have been developed. Figure 4 presents the results for cultivated land and construction land investigated here.

IPP-LUPM model for Suzhou

Land suitability evaluation model provides the best location for various land types (Liu et al. 2006). Therefore, it can effectively support spatial optimization for land-use management. However, the suitability evaluation model cannot depict the optimum land-use pattern under uncertain conditions. It can only deal with negative or positive aspects related to land capability (the supply side) without consideration of the relative demand for activities. For example, if an area is suitable for both cultivated land and forest land, the land manager will be confused about how to allocate this area. A simultaneous consideration of land supply and demand is required in order to optimize the allocation of land resources in a land-use planning system. In short, the problem can be stated as how to achieve a land-use allocation so as to satisfy the space requirement for each land use (the demand site) and simultaneously benefit from the land capability to the maximum possible extent.

Interval linear programming is a good tool to deal with uncertainties expressed as interval values (Huang et al. 1992). Probabilistic programming is an effective method for handling uncertainties expressed as probability distributions existing in

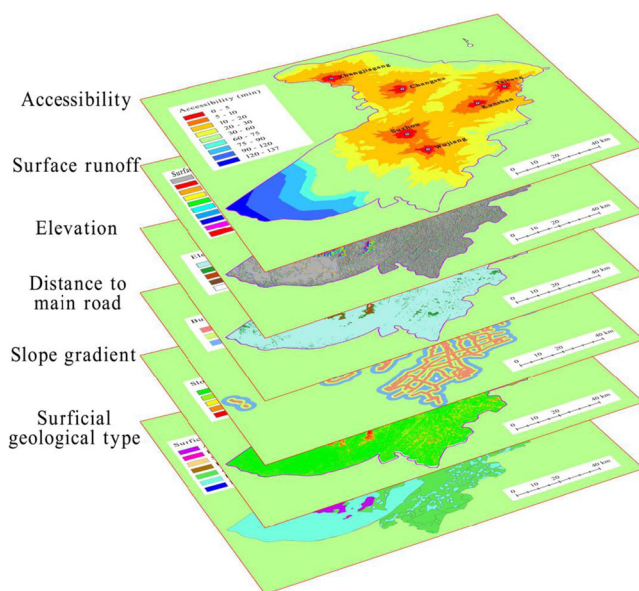
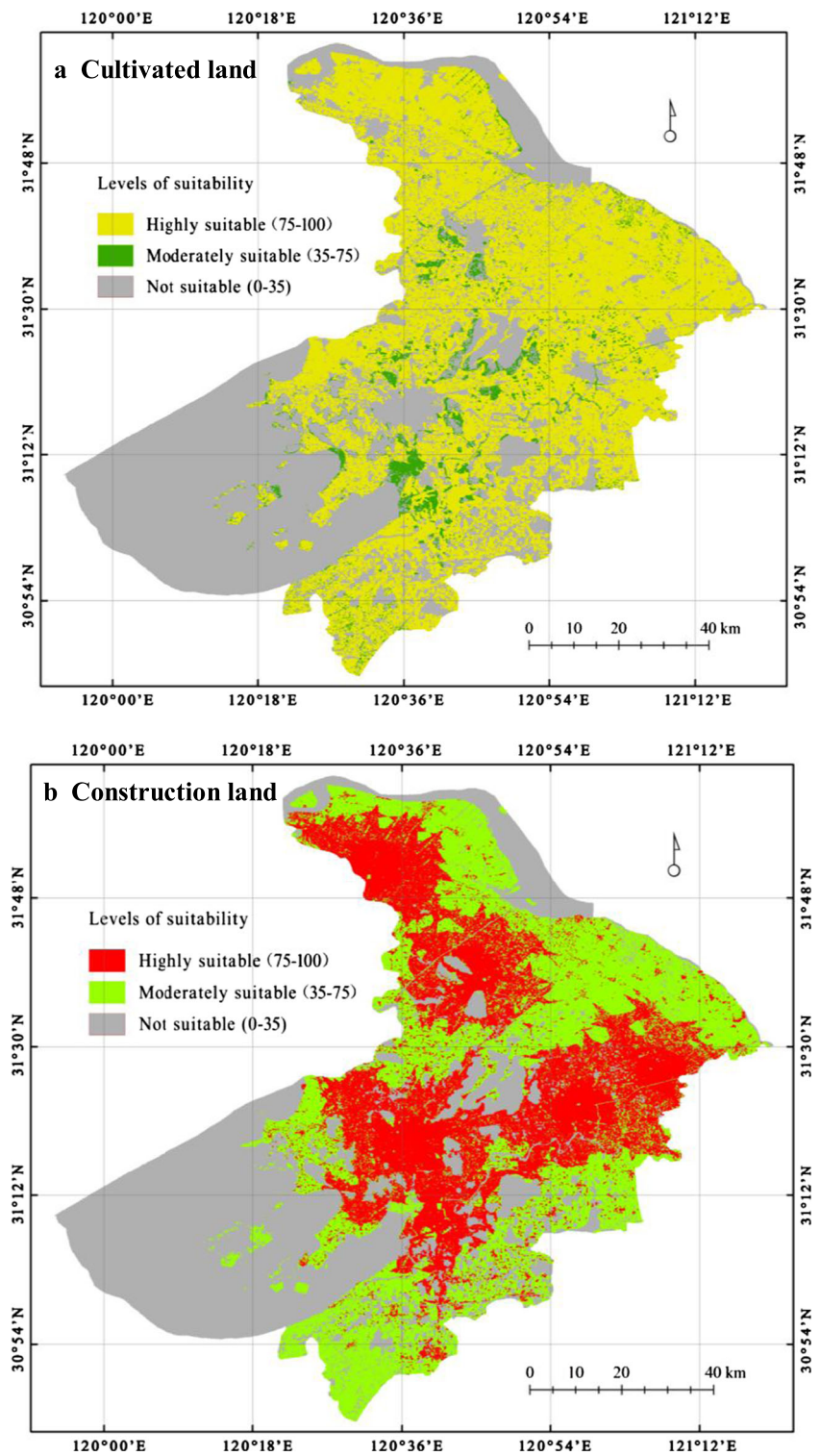


Fig. 3 Assessment maps for each suitability factor

Fig. 4 Suitability assessment maps for each of the land-use categories



the decision-making problems (Li et al. 2009). Interval-probabilistic programming (IPP) model which incorporates the two methods within a general optimization framework is a good tool to handle uncertainties expressed as discrete interval values and probability distribution in a land-use system. Based on results from land suitability evaluation in GIS-

based land suitability evaluation model and some existing IPP-based land-use allocation models (Wang et al. 2004; Liu et al. 2007b; Lu et al. 2014a, b), we choose economic benefit as the objective function and the land areas of different land types under different land suitability conditions as the decision variables. The constraints include six types: economic

constrains, social constrains, land suitability constrains, environmental constrains, ecological constrains, and technical constrains. The proposed IPP-LUPM can be expressed as follows (planning period is 2015):

Economic objective

$$\text{Max } f(x)^\pm = \sum_{i=1}^3 \sum_{j=1}^3 (CP_{i,j}^\pm \times x_{i,j}^\pm) - \sum_{i=1}^3 \sum_{k=1}^3 (CN_{i,k}^\pm \times x_{i,k}^\pm) - CN_{k=4}^\pm \times x_{k=4}^\pm$$

where \pm is the interval values; $f(x)^\pm$ is the net system benefit over the planning horizon (yuan); i =land-use suitability, where $i=1$ means highly suitable, $i=2$ means moderately suitable, and $i=3$ means not suitable; j =type of beneficial land use, where $j=1$ for commercial land, $j=2$ for residential land, and $j=3$ for industrial land; k =type of nonbeneficial land use, where $k=1$ for cultivated land, $k=2$ for forest land, $k=3$ for water land, and $k=4$ for landfill (note that forest land, water land, and landfill are not relevant to land suitability); $CP_{i,j}^\pm$ is the unit benefit of land-use type j (yuan/ha); $CN_{i,k}^\pm$ is the unit cost of land-use type k (yuan/ha). $\sum_{i=1}^3 \sum_{j=1}^3 CP_{i,j}^\pm \times x_{i,j}^\pm$ means benefit from land-use system, and $\sum_{i=1}^3 \sum_{k=1}^3 (CN_{i,k}^\pm \times x_{i,k}^\pm) + CN_{k=4}^\pm \times x_{k=4}^\pm$ means cost from land-use system.

Economic constraints

Constraint (a): government investment constraint

$$\sum_{i=1}^3 \sum_{k=1}^3 (CN_{i,k}^\pm \times x_{i,k}^\pm) + CN_{k=4}^\pm \times x_{k=4}^\pm + TI^\pm - TO^\pm \geq TD^\pm$$

where TI^\pm is the input capital (yuan), TO^\pm is the output capital (yuan), and TD^\pm is the demand capital (yuan).

Constraint (b): agricultural production input-output constraint

$$\sum_{i=1}^3 (YPU_i^\pm \times x_{i,k=1}^\pm) + YI^\pm - YO^\pm \geq YD^\pm$$

where YPU_i^\pm is the unit production from agriculture land (ton/ha), YI^\pm is the input agricultural production (ton), YO^\pm is

the output agricultural production (ton), and YD^\pm is the demand agricultural production (ton).

Constraint (c): water production input-output constraint

$$\sum_{i=1}^3 (WPU_i^\pm \times x_{i,k=3}^\pm) + WI^\pm - WO^\pm \geq WD^\pm$$

where WPU_i^\pm is the unit production from water land (ton/ha), WI^\pm is the input aquatic production (ton), WO^\pm is the output aquatic production (ton), and WD^\pm is the demand aquatic production (ton).

Constraint (d): available water consumption constraint

$$\sum_{i=1}^3 \sum_{j=1}^3 (WC_i^\pm \times x_{i,j}^\pm) + \sum_{i=1}^3 \sum_{k=1}^3 (WC_i^\pm \times x_{i,k}^\pm) + WC_i^\pm \times x_{k=4}^\pm \leq AWA^\pm$$

where WC_i^\pm is the unit water consumption of land-use j or k (ton/ha) and AW^\pm is the available water (ton).

Constraint (e): available electricity power consumption constraint

$$\sum_{i=1}^3 \sum_{j=1}^3 (EC_i^\pm \times x_{i,j}^\pm) + \sum_{i=1}^3 \sum_{k=1}^3 (EC_i^\pm \times x_{i,k}^\pm) + EC_i^\pm \times x_{k=4}^\pm \leq AE^\pm$$

where EC_i^\pm is the unit electric power consumption of land-use j or k (kilowatt hour/ha (kWh/ha)) and AE^\pm is the available electric power (kilowatt hour (kWh)).

Social constraints

Constraint (f): maximum people in a unit land area constraint

$$TP^\pm / \left(\sum_{i=1}^3 \sum_{j=1}^3 x_{i,j}^\pm + \sum_{i=1}^3 \sum_{k=1}^3 x_{i,k}^\pm + x_{k=4}^\pm \right) \leq MIP^\pm$$

where TP^\pm is the total population (person) and MIP^\pm is the minimum population in a unit area of land-use j or k (person/ha).

Constraint (g): available labor constraint

$$\sum_{i=1}^3 \sum_{j=1}^3 (LC_i^\pm \times x_{i,j}^\pm) + \sum_{i=1}^3 \sum_{k=1}^3 (LC_i^\pm \times x_{i,k}^\pm) + LC_i^\pm \times x_{k=4}^\pm \leq AL^\pm$$

where LC_i^\pm is the unit labors of land-use j or k (person/ha) and AL^\pm is the available labors (person).

Land suitability constraints

Constraint (h): land suitability constraint for beneficial land-use types

$$\sum_{i=1}^3 \sum_{j=1}^3 x_{i,j}^\pm \leq MIL_j^\pm$$

Constraint (i): land suitability constraint for nonbeneficial land-use types

$$\sum_{i=1}^3 \sum_{k=1}^3 x_{i,k}^\pm + x_{k=4}^\pm \leq MIL_k^\pm$$

where MIL_j^\pm is the maximum area of land-use j (ha) and MIL_k^\pm is the maximum area of land-use k (ha). The maximum area of land-use j or k can be obtained from the land-use suitable evaluation model in [GIS-based land suitability evaluation model](#). The highly suitable area is set as the maximum area.

Environmental constraints

Constraint (j): wastewater treatment capacity constraint

$$\sum_{i=1}^3 (CWC_{i,j=1}^\pm \times x_{i,j=1}^\pm) + \sum_{i=1}^3 (RWC_{i,j=2}^\pm \times x_{i,j=2}^\pm) + \sum_{i=1}^3 (IWC_{i,j=3}^\pm \times x_{i,j=3}^\pm) + \sum_{i=1}^3 (AWC_{i,k=1}^\pm \times x_{i,k=1}^\pm) \leq AWD^p$$

where $CWC_{i,j=1}^\pm$ is the wastewater discharging factor of commercial land (ton/ha), $RWC_{i,j=2}^\pm$ is the wastewater discharging factor of residential land (ton/ha), $IWC_{i,j=3}^\pm$ is the wastewater discharging factor of industrial land (ton/ha), $AWC_{i,k=1}^\pm$ is the wastewater discharging factor of cultivated land (ton/ha),

AWD is the wastewater treatment plant capacity (ton), p is the probability of violating the constraints of environmental capacities, and p is the $[0, 1]$.

Constraint (k): solid-waste treatment capacity constraint

$$\sum_{i=1}^3 (CSC_{i,j=1}^\pm \times x_{i,j=1}^\pm) + \sum_{i=1}^3 (RSC_{i,j=2}^\pm \times x_{i,j=2}^\pm) + \sum_{i=1}^3 (ISC_{i,j=3}^\pm \times x_{i,j=3}^\pm) + \sum_{i=1}^3 (ASC_{i,k=1}^\pm \times x_{i,k=1}^\pm) - LHC^\pm \times x_{k=4}^\pm \leq ASDASD^p$$

where $CSC_{i,j=1}^\pm$ is the solid-waste discharging factor of commercial land (ton/ha), $RSC_{i,j=2}^\pm$ is the solid-waste discharging factor of residential land (ton/ha), $ISC_{i,j=3}^\pm$ is the solid-waste discharging factor of industrial land (ton/ha), $ASC_{i,k=1}^\pm$ is the solid-waste discharging factor of cultivated land (ton/ha), ASD is the solid-waste treatment plant capacity (except landfill) (ton), and LHC^\pm is the solid-waste treatment plant capacity (landfill) (ton).

Ecological constraints

Constraint (l): available soil erosion constraint

$$\sum_{i=1}^3 \sum_{j=1}^3 (OC_i^\pm \times x_{i,j}^\pm) + \sum_{i=1}^3 \sum_{k=1}^3 (OC_i^\pm \times x_{i,k}^\pm) + OC_i^\pm \times x_{k=4}^\pm \leq AO^\pm$$

where OC_i^\pm is the soil erosion rate of land-use j or k (ha) and AO^\pm is the available soil erosion area (ha).

Constraint (m): forests cover rate constraints

$$\left(\sum_{i=1}^3 x_{k=2}^\pm \right) / \left(\sum_{i=1}^3 \sum_{j=1}^3 x_{i,j}^\pm + \sum_{i=1}^3 \sum_{k=1}^3 x_{i,k}^\pm + x_{k=4}^\pm \right) \geq MFR^\pm$$

where MFR^\pm is the minimum forest cover rate.

Constraint (n): fertilizer consumption constraints

$$\sum_{i=1}^3 (FP_i^\pm \times x_{k=1}^\pm) / \left(\sum_{i=1}^3 \sum_{j=1}^3 x_{i,j}^\pm + \sum_{i=1}^3 \sum_{k=1}^3 x_{i,k}^\pm + x_{k=4}^\pm \right) \leq MFP^\pm$$

where FP_i^\pm is the fertilizer consumption for unit cultivated land and MFP^\pm is the maximum fertilizer consumption.

Technical constraints

Constraint (o): total land areas constraint

$$\sum_{i=1}^3 \sum_{j=1}^3 x_{i,j}^{\pm} + \sum_{i=1}^3 \sum_{k=1}^3 x_{i,k}^{\pm} + x_{k=4}^{\pm} = TUL^{\pm}$$

where TUL^{\pm} is the total land area of Suzhou (ha).

Constraints (p): nonnegative constraints

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

$$x_{i,k}^{\pm} \geq 0$$

According to the IPP solution algorithm in the references (Huang et al. 1992; Huang 1998), the above IPP-LUPM model can be transformed into two deterministic sub-models, which correspond to the upper and lower bounds for the desired objective function value. Then, we can calculate the two linear models in the software of Microsoft Office Excel. Tables 2, 3, and 4 provide the economic, social, environmental, and technical data which were obtained from Chinese Academy of Sciences (CAS), Suzhou Statistical Yearbook and the local government mentioned in Data acquisition.

Results analysis

As mentioned above, every land-use suitability level of every land-use type will be corresponding to different cost parameters, thus corresponding to different modeling results. There will be 12 (three land suitability levels multiply four land-use types) model results. First, we discuss the situation that $i=1$ (for all j and k). Other results can be discussed in the same way.

The relationship between land-use patterns and system benefits/strategic land-use policy

Based on the proposed IPP-LUPM model, under $i=1$, the interval land-use patterns for Suzhou in 2015 under different p levels would be generated (Table 5), which are helpful in solving the land-use management problem. IPP-LUPM solutions could provide stable ranges for land-use patterns ($x_{i,j}^{\pm}$ and $x_{i,k}^{\pm}$) and system benefits ($f(x)^{\pm}$) under different p levels. Solutions for the lower bounds of the decision variables $x_{i,j}^{\pm}$

and upper bounds of decision variables $x_{i,k}^{\pm}$ correspond to the lower system benefit, which could guarantee that social demands, ecological balance, and environmental criteria be met, and imply a conservative land-use management strategy. When the decision variable $x_{i,j}^{\pm}$ aims toward the upper bounds and decision variable $x_{i,k}^{\pm}$ 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 ($f(x)^{\pm}$) provides two extremes of system benefit over the planning horizon. For example, under $p=0.01$, which means that the environmental violating probability is the lowest, the environmental constraints will be most strict, and the optimized $f(x)^{\pm}$ will be $[25.62, 31.02] \times 10^{12}$ yuan, which means that the expected system benefit would change between 25.62×10^{12} yuan and 31.02×10^{12} yuan with varied reliability levels, implying that the actual value of each continuous variable varies within its lower and upper bounds. In detail, the lower-bound benefit ($f(x)^- = 25.62 \times 10^{12}$ yuan) would correspond to lower bounds of beneficial decision-variable values ($x_{i=1,j=1}^- = 474.1 \times 10^2$ ha; $x_{i=1,j=2}^- = 555.7 \times 10^2$ ha; $x_{i=1,j=3}^- = 49.1 \times 10^2$ ha) and upper bounds of nonbeneficial decision-variable values ($x_{i=1,k=1}^+ = 4336.5 \times 10^2$ ha; $x_{i=1,k=2}^+ = 220.8 \times 10^2$ ha; $x_{i=1,k=3}^+ = 2844.7 \times 10^2$ ha; $x_{i=1,k=4}^+ = 10.0 \times 10^2$ ha) under demand conditions (e.g., lower wastewater treatment efficiency, lower revenues, higher discharge rates, and stricter environmental requirements). In comparison, the upper-bound system benefit ($f(x)^+ = 31.02 \times 10^{12}$ yuan) would be linked to the upper bounds of beneficial decision-variable values ($x_{i=1,j=1}^+ = 488.5 \times 10^2$ ha; $x_{i=1,j=2}^+ = 571.5 \times 10^2$ ha; $x_{i=1,j=3}^+ = 50.1 \times 10^2$ ha) and lower bounds of nonbeneficial decision-variable values ($x_{i=1,k=1}^- = 4272.1 \times 10^2$ ha; $x_{i=1,k=2}^- = 216.5 \times 10^2$ ha; $x_{i=1,k=3}^- = 2800.6 \times 10^2$ ha; $x_{i=1,k=4}^- = 9.8 \times 10^2$ ha) under advantageous conditions. In general, 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 IPP-LUPM 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 IPP-LUPM approach allows decision makers to incorporate

Table 2 Economic, social, environmental, and technical parameters ($i=1$)

Symbol	Lower bound	Upper bound	Symbol	Lower bound	Upper bound
TUL^\pm (km ²)	5,607.45	7,586.55	WC^\pm (10 ³ m ³ /km ²)	197.94	267.80
TP^\pm (10 ⁶ people)	6.89	9.33	AW^\pm (10 ⁹ m ³)	1.31	1.77
MIP^\pm (people/km ²)	984.00	1,032.00	EC^\pm (10 ⁶ kWh/km ²)	3.13	4.23
TI^\pm (10 ⁹ yuan)	3,408.53	4,611.53	AE^\pm (10 ⁹ kWh)	20.62	27.90
TO^\pm (10 ⁹ yuan)	2,292.45	3,101.55	OC^\pm	3 %	4 %
TD^\pm (10 ⁹ yuan)	6,675.90	9,032.10	AO^\pm (km ²)	177.65	240.35
YPU^\pm (ton/km ²)	2.50	3.38	CWC^\pm (10 ³ ton/km ²)	7.60	10.28
YT^\pm (10 ³ ton)	588.20	795.80	IWC^\pm (10 ⁶ ton/km ²)	10.39	14.05
YO^\pm (10 ³ ton)	392.70	531.30	AWC^\pm (10 ³ ton/km ²)	109.13	147.65
YD^\pm (10 ³ ton)	1,163.65	1,574.35	TWC^\pm (10 ³ ton/km ²)	30.55	41.33
WPU^\pm (ton/km ²)	1.20	1.62	RWC^\pm (10 ⁶ ton/km ²)	3.11	4.21
WT^\pm (10 ³ ton)	175.10	236.90	CSC^\pm (ton/km ²)	53.76	72.74
WO^\pm (10 ³ ton)	96.05	129.95	ISC^\pm (10 ³ ton/km ²)	73.49	99.43
WD^\pm (10 ³ ton)	166.60	225.40	ASC^\pm (ton/km ²)	772.12	1,044.63
LC^\pm (people/km ²)	603.50	816.50	TSC^\pm (ton/km ²)	216.14	292.42
AL^\pm (10 ³ people)	3,980.55	5,385.45	RSC^\pm (10 ³ ton/km ²)	22.01	29.78
MFP^\pm	55 %	60 %	LHC^\pm (ton)	1,306.45	1,767.55

implicit knowledge within the problem and thus obtain satisfactory and applicable decision schemes.

The relationship between p level and system benefits/environmental policy analysis

The p levels represent the probability of violating the constraints of environmental capacities. The results in Fig. 5 also indicate that any change in p would yield different waste management capacities and thus results in different land-use patterns and different system benefits. For example, when $p=0.01$, results are showed in above section; in comparison,

when $p=0.10$, system benefit will be $[28.34, 36.81] \times 10^{12}$ yuan; beneficial land-use allocation will be $x_{i=1,j=1}^\pm = [480.0, 510.9] \times 10^2$ ha, $x_{i=1,j=2}^\pm = [558.3, 600.2] \times 10^2$ ha, and $x_{i=1,j=3}^\pm = [47.8, 50.0] \times 10^2$ ha; and nonbeneficial land-use allocation will be $x_{i=1,k=1}^\pm = [4143.0, 4228.5] \times 10^2$ ha, $x_{i=1,k=2}^\pm = [208.7, 214.0] \times 10^2$ ha, $x_{i=1,k=3}^\pm = [2713.7, 2773.5] \times 10^2$ ha, and $x_{i=1,k=4}^\pm = [9.5, 9.7] \times 10^2$ ha. Similar characteristics exist in solutions under the other significance levels ($p=0.30, 0.40, \text{ and } 0.50$). It is obvious that the beneficial land areas and system benefit will increase along with the p level, while the nonbeneficial land areas will decrease along with the p level. In general, if

Table 3 Benefits and costs for different land-use types ($i=1, 2$; yuan/hm²)

Land-use type	Symbol	Lower bound	Upper bound
Benefits of beneficial land use	$CP_{i=1,j=1}$ (10 ⁶)	53.58	55.45
	$CP_{i=1,j=2}$ (10 ⁶)	8.10	11.21
	$CP_{i=1,j=3}$ (10 ⁶)	31.77	33.64
	$CP_{i=2,j=1}$ (10 ⁶)	81.23	100.32
	$CP_{i=2,j=2}$ (10 ⁶)	15.26	26.37
	$CP_{i=2,j=3}$ (10 ⁶)	45.67	60.58
Costs of nonbeneficial land use	$CN_{i=1,j=1}$ (10 ³)	12.01	15.94
	$CN_{i=1,j=2}$ (10 ³)	79.74	83.48
	$CN_{i=1,j=3}$ (10 ³)	9.32	15.96
	$CN_{i=1,j=4}$ (10 ³)	5.21	6.15
	$CN_{i=2,j=1}$ (10 ³)	13.25	18.36
	$CN_{i=2,j=2}$ (10 ³)	89.36	99.32
	$CN_{i=2,j=3}$ (10 ³)	15.36	25.19
	$CN_{i=2,j=4}$ (10 ³)	6.35	7.91

Table 4 Environmental capacity under different p levels

Environmental capacity	p level					
	$p=0.01$	$p=0.10$	$p=0.20$	$p=0.30$	$p=0.40$	$p=0.50$
AWD (10^9 ton)	17.72	19.25	29.34	33.18	38.64	42.68
ASD (10^6 ton)	146.79	168.95	198.25	215.34	239.14	249.67

the environmental risk increases at 10 %, the system benefit will increase at 5.0×10^{12} yuan.

Since the p levels represent probabilities at which the environmental constraints will be violated, relation between system benefit and p demonstrates a trade-off between economic efficiency and system risk. An increased p level means an increased risk of environmental constraint violation; at the same time, it will lead to a decreased strictness for the constraints (and thus an expanded decision space, e.g., increased waste treatment/disposal capacity). That is, a higher system benefit (under a high p level) represents an alternative with higher waste generation rates and a higher waste treatment/disposal capacity, while a lower system benefit (under a lower p level) represents an alternative with lower waste generation rates and a lower environmental capacity. Usually, planning with lower system benefit can guarantee that waste management requirements and

environmental regulations be met; in comparison, with planning aiming toward higher system benefit, these requirements may not be met. Thus, with the increased p level, the reliability of meeting waste treatment/disposal capacity requirements and environmental requirements would decrease. Therefore, in practical problems, lower $x_{i,j}^{\pm}$ values and higher $x_{i,k}^{\pm}$ values generally should be used under advantageous environmental conditions (e.g., conditions with lower waste generation) since they correspond to the lower system benefit; in comparison, higher $x_{i,j}^{\pm}$ values and lower $x_{i,k}^{\pm}$ values are suitable for more demanding environmental conditions.

The relationship between system benefits and social and ecological constraints

If we change the social conditions, the model results will be different. In IPP-LUPM, social constraints are maximum

Table 5 Optimized land-use patterns for Suzhou in 2015 under different p levels and different land-use suitability levels (100 ha)

Levels of land-use suitability	Land-use type	$p=0.01$	$p=0.10$	$p=0.20$	$p=0.30$	$p=0.40$	$p=0.50$
$i=1$	$j=1$	[474.1, 488.5]	[480.0, 510.9]	[489.3, 536.6]	[518.5, 549.1]	[521.3, 605.4]	[526.4, 636.8]
	$j=2$	[555.7, 571.5]	[558.3, 600.2]	[572.3, 622.3]	[601.8, 643.2]	[608.0, 706.8]	[612.2, 739.8]
	$j=3$	[49.1, 50.1]	[47.8, 50.0]	[48.4, 53.5]	[52.8, 54.7]	[49.8, 58.6]	[51.0, 63.4]
	$k=1$	[4,272.1, 4,336.5]	[4,143.0, 4,228.5]	[3,966.8, 4,184.3]	[3,889.1, 4,097.4]	[3,924.6, 3,966.1]	[3,834.8, 3,878.7]
	$k=2$	[216.5, 220.8]	[208.7, 214.0]	[200.6, 211.4]	[196.0, 206.6]	[199.2, 208.7]	[194.3, 196.1]
	$k=3$	[2,800.6, 2,844.7]	[2,713.7, 2,773.5]	[2,599.9, 2,742.8]	[2,547.8, 2,685.4]	[2,571.9, 2,599.7]	[2,513.7, 2,543.7]
	$k=4$	[9.8, 10.0]	[9.5, 9.7]	[9.1, 9.4]	[8.7, 8.8]	[3.5, 4.5]	[0, 1.1]
$i=2$	$j=1$	[499.2, 520.0]	[491.7, 539.5]	[512.2, 570.0]	[542.8, 583.1]	[550.9, 651.4]	[555.2, 687.2]
	$j=2$	[581.1, 607.2]	[574.6, 629.3]	[598.9, 668.0]	[631.9, 679.1]	[641.8, 765.4]	[652.5, 803.6]
	$j=3$	[48.1, 49.5]	[49.0, 53.4]	[51.0, 59.5]	[56.2, 58.0]	[55.5, 62.1]	[57.3, 69.2]
	$k=1$	[4,699.8, 4,816.2]	[4,636.5, 4,779.9]	[4,444.9, 4,730.0]	[4,394.1, 4,669.7]	[4,432.0, 4,561.9]	[4,332.9, 4,421.9]
	$k=2$	[238.1, 244.9]	[234.3, 240.6]	[223.8, 237.4]	[221.6, 237.5]	[223.7, 230.2]	[218.1, 224.2]
	$k=3$	[3,079.8, 3,156.5]	[3,040.6, 3,131.7]	[2,911.6, 3,100.9]	[2,881.0, 3,062.9]	[2,906.9, 2,991.9]	[2,841.9, 2,898.4]
	$k=4$	[9.8, 10.0]	[9.5, 9.7]	[9.1, 9.4]	[8.7, 8.8]	[3.5, 4.5]	[0, 1.1]
$i=3$	$j=1$	[549.9, 577.8]	[545.4, 606.8]	[579.5, 651.8]	[613.9, 664.1]	[636.6, 756.7]	[659.0, 823.6]
	$j=2$	[638.5, 677.9]	[636.8, 710.8]	[674.9, 763.6]	[714.3, 776.4]	[739.0, 880.4]	[765.8, 961.7]
	$j=3$	[55.9, 58.1]	[53.0, 60.9]	[57.5, 62.3]	[63.3, 64.0]	[63.5, 77.5]	[64.1, 80.7]
	$k=1$	[5,167.2, 5,391.6]	[5,149.8, 5,397.8]	[5,019.3, 5,391.2]	[4,962.7, 5,324.7]	[5,097.3, 5,291.1]	[5,115.2, 5,307.7]
	$k=2$	[260.9, 271.9]	[258.5, 271.9]	[252.5, 271.2]	[250.1, 268.5]	[257.0, 267.3]	[258.4, 266.5]
	$k=3$	[3,389.5, 3,534.4]	[3,373.6, 3,539.4]	[3,291.7, 3,534.1]	[3,253.5, 3,490.7]	[3,342.6, 3,467.7]	[3,352.3, 3,477.8]
	$k=4$	[9.8, 10.0]	[9.5, 9.7]	[9.1, 9.4]	[8.7, 8.8]	[3.5, 4.5]	[0, 1.1]

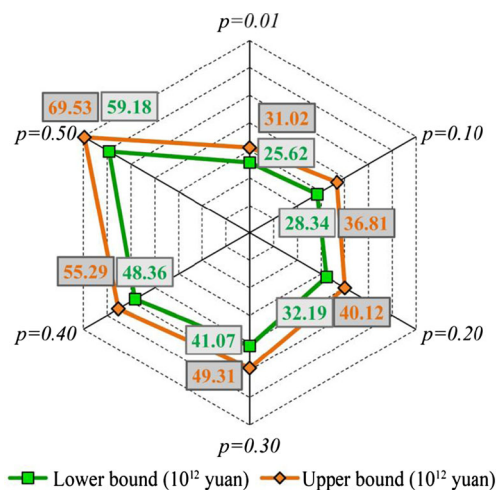


Fig. 5 System benefit under different probability levels

people in a unit area constraint and available labor constraint. If the maximum people in a unit area (is a constant) changes, the land-use patterns and system benefit will change too. We discuss the quantitative trade-offs between them here. Figure 6 shows the relationship between maximum people in a unit area/available labors and the system benefit. We can clearly see that more allowable people in a unit area will lead to more available labor and thus make more system benefit. In detail, when maximum people in a unit area are 13 person/ha and the available labors are 5.8×10^{12} person, the system benefit will be $[25.62, 31.02] \times 10^{12}$ yuan; in comparison, when maximum people in a unit area are 14 person/ha and the available labors are 6.0×10^{12} person, the system benefit will be $[27.94, 35.19] \times 10^{12}$ yuan. Similar characteristics exist in solutions under the other social conditions. In general, a worse social condition (more people in a unit area) could lead to a higher system benefit, and vice versa. However, a city has its planning for maximum people in a unit area, and the value could not be too high. Thus, the government can make decisions through trade-offs between social and economic objectives and between increased certainties and decreased safeties.

Trade-off between system benefits and land suitability

Above results analysis is based on the condition of high land suitability ($i=1$). Under $i=2$, the cost parameter of nonbeneficial land-use types (CN_k^*) will increase, and the maximum allowable area for every land type will also increase. In this situation, we calculate the IPP-LUPM again and could get the quantitative relationship between land suitability and system benefit. This result is shown in Fig. 7. The figure shows that the net system benefit will increase with the value of i , although the cost will increase in this case. The reason is that more available beneficial land area will bring more benefit, and this benefit is more than the developing cost for nonbeneficial land-use types. This means that developing

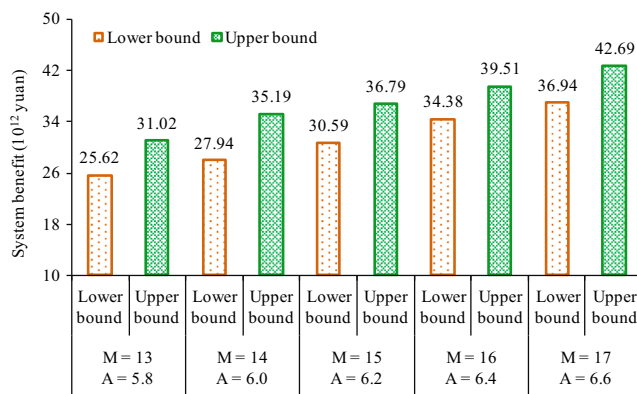


Fig. 6 System benefit under different social conditions

lower suitable land areas will bring more benefit than only developing highly suitable land areas. However, it is obvious that developing lower suitable area will lead to more environmental and ecological problems (the value of p will increase). The land manager can make decisions through trade-offs between economic objectives and environmental/ecological objectives and between increased certainty and decreased safety. A detailed quantitative analysis is as follows: Under $i=1$, the system benefit is $[25.62, 31.02] \times 10^{12}$ yuan, while under $i=2$, the values change to $[36.98, 42.65] \times 10^{12}$ yuan; when $i=3$, the system benefit will be $[45.98, 56.92] \times 10^{12}$ yuan, which is much more than the case $i=1$. However, by means of calculating all other nine scenarios, we will find that the most sensible strategy is taking $i=3$ when $j=1, 2$, and 3 and $i=1$ when $k=1, 2, 3$, and 4. In this situation, the comprehensive benefit will be the most optimized, but the premise

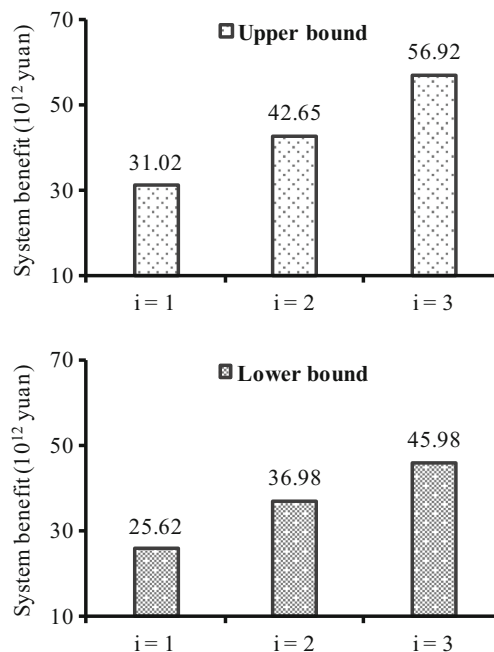


Fig. 7 System benefit under different land suitability conditions

condition will be strictest. This implies enough available land area and perfect environmental/ecological efficiency.

The obtained results indicate that uncertainties that exist in the system parameters can be effectively reflected as intervals and probability distributions in the IPP-LUPM model, with reasonable solutions and land-use policies generated. The quantitative interactions among land areas, system benefit, and environmental capacities can be studied more clearly.

Conclusions

A GIS-based interval probabilistic programming for urban land-use planning management (IPP-LUPM) model is developed by coupling the GIS technology with the IPP model. The GIS-based IPP-LUPM model not only considers the outcomes of land suitability assessment (i.e., topography, ground conditions, hydrology, and spatial location) but also involves socio-economic factors and eco-environmental constraints, which can effectively reflect various interrelations among different aspects in a land-use planning management system. Moreover, it can also help examining the reliability of satisfying (or risk of violating) system constraints under uncertainty. The proposed model has been applied to a real case of optimal land-use planning management in the city of Suzhou, the Yangtze River Delta of China. The results demonstrated that the model has generated a range of decision alternatives under various system conditions and thus could help decision makers to identify strategic land-use allocation strategies under uncertainty.

In comparison with the previous inexact optimization models, the main contribution of this paper is the incorporation of land-use suitability evaluation into the optimization process. Land-use suitability analysis can effectively identify the appropriate spatial pattern and the corresponding land area for every land-use type, which would be helpful for obtaining the objective and alternative solutions of land resources allocation. The suitability maps of different land-uses can be provided by land suitability evaluation based on GIS technology. The area of every land-use type under different land-use suitability levels, as well as various objectives/constraints (i.e., land supply, land demand of socio-economic development, future development strategies, and environmental restrictions), is used as input parameter for the optimization model. The case study results at Suzhou, China, indicate that the GIS-based IPP-LUPM could identify the quantitative relationship between land suitability and system benefit. Willingness to arrange the land areas based on the condition of highly suitable land will not only reduce the potential conflicts on the environmental system but also lead to a lower economic benefit. However, a strong desire to develop lower suitable land areas will bring not only a higher economic benefit but

also higher risks of violating environmental and ecological constraints.

We argue that the merging of the technologies of GIS and IPP is a promising research tool attracting planners and other resources managers, including solid waste treatment (Jiao et al. 2013), nonpoint source pollution control (Luo et al. 2006), and water quality management (Fleifle et al. 2014). As for a municipal solid waste (MSW) treatment system, uncertainties may exist in waste treatment options, waste-generation amounts, transportation and operation costs, local waste management policies, and the allowable waste-flow levels, which might be presented in interval and probabilistic formats. Meanwhile, the topography, landforms, soil conditions, and the location and accessibility in relation to transfer station, landfill site, and composting plant within a solid waste treatment system should also be taken into consideration. Consequently, the incorporation of GIS and inexact methods could be widely used to the related optimization processes of an MSW management system. In this study, it should be noted that the modeling results directly answer the question of “what to do?” for a variety of objectives/constraints in different spatial units. However, spatial units applied in the optimization modeling are not detailed enough for managers and decision makers to implement the optimization modeling results. Consequently, GIS-based multi-objective land-use spatial allocation model focusing on the “how do I do it?” would be interesting topics that deserve future research efforts.

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