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An Uncertain Programming Model for Land Use Structure Optimization to Promote Effectiveness of Land Use Planning

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Abstract: Land use structure optimization (LUSO) is an important issue for land use planning. In order for land use planning to have reasonable flexibility, uncertain optimization should be applied for LUSO. In this paper, the researcher first expounded the uncertainties of LUSO. Based on this, an interval programming model was developed, of which interval variables were to hold land use uncertainties. To solve the model, a heuristics based on Genetic Algorithm was designed according to Pareto Optimum principle with a confidence interval under given significance level to represent LUSO result. Proposed method was applied to a real case of Yangzhou, an eastern city in China. The following conclusions were reached. 1) Different forms of uncertainties ranged from certainty to indeterminacy lay in the five steps of LUSO, indicating necessary need of comprehensive approach to quantify them. 2) With regards to trade-offs of conflicted objectives and preferences to uncertainties, our proposed model displayed good ability of making planning decision process transparent, therefore providing an effective tool for flexible land use planning compiling. 3) Under uncertain conditions, land use planning effectiveness can be primarily enhanced by flexible management with reserved space to percept and hold uncertainties in advance.

Keywords: land use structure optimization (LUSO); uncertainties; flexibility; land use planning; decision support system; effectiveness

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1 Introduction

Resource allocation is an essential issue for human development, especially for land resource that is the carrier of economic activities, human living and the ecological environment. Configuration of land resources is important for achieving the target of sustainable development as well (Cao *et al*., 2012). Land use planning is the concrete policy of land resources allocation, one core work of which is to decide area proportion of different land use types (Liu *et al*., 2002), i.e., regional land use structure that is the reflection of regional socioeconomic structure, and different land use structure corresponding to different economic benefit and ecological benefit. Therefore, to maintain sustainable utilization of land resources, it is important to find the optimal land use structure as scheme of land use planning to regulate future land use activities (Sadeghi *et al*., 2009; Gao *et al*., 2010; Chuai *et al*., 2013). This process is generally called land use structure optimization (LUSO) which is a challenging task due to suffering from potentially conflicting objectives as well as uncertainties.

Most of existing literatures assumed land use system as determinate, thereby ignoring uncertainties management during LUSO, resulting in planning schemes with low scientific credibility and narrowing the horizon of land use managers. One major drawback of employing such determinate methods for LUSO is that when inexact but reasonable land use demand occurs in the future, land use planning without advanced consideration of

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uncertainties will refuse it. In addition, planning will become invalid ultimately under frequent disturbances of uncertainties (Li Xin *et al*., 2013). This helps to explain to the unsatisfactory implementation of general land use planning (1997–2010) in China that was designed with rigid restraints and without reserved space for uncertainties (Zhong *et al*., 2014). As LUSO focuses on land use system which is in the future, and obviously there can be a variety of uncertainties (land use demand for economy and population, influence of climate change and technical progress on land use output, impact of price fluctuations for agricultural products on land use, etc), so we could not forecast parameters accurately (Messina and Bosetti, 2003; Wang *et al*., 2004). In fact, uncertain environment is the real case for LUSO. Land use planning with exact constraints may be constantly violated by uncertainties, increasingly losing its prestige and finally failure. Based on the lessons from previous failures, land use planners in China have reached consensus of making flexible planning to accommodate for those uncertainties. A multitude of uncertain programming models have been employed to deal with LUSO to provide technical assistance for flexible planning making (Li *et al*., 2014).

Uncertain programming is an innovative theme in operational research field in recent years. Multiple new variables have been designed to represent uncertainties with corresponding models built according to different principles, including dependent-chance programming, chance-constrained programming and expected value model (Liu *et al*., 2015). Meanwhile, uncertain programming is widely applied for engineering problems to enhance accuracy and control risk. It has also been used for resource optimized allocation under uncertainties to improve effectiveness of environmental management policy, including water allocation (Nie *et al*., 2008; Li *et al*., 2013), solid waste disposal allocation (Cheng *et al*., 2003), regional energy planning (Li *et al*., 2011), industrial structure optimization (Wang and Zeng, 2013), agricultural plantation optimization (Dong *et al*., 2014), and pollutant disposal allocation (Luo *et al*., 2006). Inspired by such application, scholars started to research LUSO under uncertainties. Thus far, Liu used interval linear programming for uncertain LUSO with economic value maximization as objective (Liu *et al*., 2007; Liu *et al*., 2009); Lu developed a multi-objective interval stochastic programming to address uncertain LUSO, of which some parameters were calculated by GIS spatially (Lu *et al*., 2014; Lu *et al*., 2015); Zhou proposed an interval fuzzy chance-constrained programming and a hybrid programming with interval and stochastic variables to manage uncertain LUSO (Zhou *et al*., 2014; Qiu *et al*., 2015; Zhou, 2015), and Wang established an uncertain interval multiple objective linear programming for LUSO (Wang *et al*., 2010).

However, we think those uncertain programming models still can not provide effective decision support tool for land use planning making under uncertain environment. One side, those studies have not analyzed the sources and types of uncertainties during LUSO systematically, and thus uncertain variable selection lacks enough evidences. More importantly, on the other hand, such models did not provide a transparent process for the stakeholders to decide LUSO scheme with respect to conflicted objectives and uncertainties. The effectiveness of land use planning largely depends on the extent of transparency for decision making. Stakeholders always have different interests on suggested objectives and different attitudes towards uncertainties, so firstly they should be able to obtain LUSO schemes of different trade-offs between economic and ecological objectives under different levels of uncertainties. Informed decision can be made only if advantages and disadvantages of any particular LUSO scheme are carefully weighted against each other, taking into account their preferences on the conflicted objectives and uncertainties (Linkov *et al*., 2006). However, few of previous studies have developed uncertain LUSO models to meet such demands for land use planning decision to promote its effectiveness.

This paper aims to develop an uncertain LUSO model to meet demands of transparency in land use flexible planning decision-making with respect to various uncertainties and conflicted objectives. Firstly the sources and types of uncertainties during different LUSO steps were systematically analyzed; secondly the interval programming model was established to deal with uncertain LUSO, of which a heuristic algorithm with Pareto Optimum principle and stochastic simulation was proposed to solve it; lastly, Yangzhou a rapidly growing city in eastern China was taken as a case study to demonstrate the application of proposed method and provide considerable land use management knowledge for local government. This study presents an effective tool for flexible land use planning decision-making under uncertain conditions, thus can improve the effectiveness of land use planning primarily.

2 Materials and Methods

2.1 Study area and data sources

Yangzhou City is in the middle of Jiangsu, an eastern province of China, at the intersection of the Yangtze River and the Great Canal (Fig. 1). Its geographical extent is 31°56′N–133°25′N and 119°01′E–119°54′E, only 230 km away from Shanghai—the biggest Municipality in China and 70 km away from Nanjing—the capital of Jiangsu Province. The municipal area is 6.59×10^5 ha with a population of 4.61×10^5 of which 61.2% live in urban area and with Gross Domestic Product (GDP) of 3.7×10^{11} yuan (RMB) in 2013. Yangzhou City, with an abundance of historic cultural monuments, is a famous tourism city; however in recent years its building industry and industrial manufacturing grew with an annual average rate of 10%. This has brought about lots of environmental problems, such as industrial wastewater pollution, occupation of public space, and forest encroachment, posing serious threat to its tourism advantage. Additionally, urban expansion has taken up a large amount of agricultural land, which has a global impact on economic and social sustainable development. As land resources provides a carrier for human activities, it is always important to employ land resource allocation policy to balance economic growth, arable land protection, and ecological environmental maintenance, which is particularly important for Yangzhou to realize sustainable development. Yangzhou is currently undergoing a rapid urbanization and industrialization. There is serious contradiction for land resources between economic development and ecological protection, and also due to exhausted demographic dividend, economic structure transition pressures, and unpredictable natural hazards, there are considerable challenges and uncertainties for land use in the future. In this context, to provide effective reference for land resource allocation in respect to uncertainties and trade-offs between economic and ecological benefits, the established model was applied for Yangzhou to generate informed LUSO scheme under uncertain conditions, thus contributed to the land use planning effectiveness.

Generally, three types of data are needed in this manuscript, of which land use data (including vector format) was provided by Land Resources Bureau of Yangzhou (http://gtj.yangzhou.gov.cn/); relevant socio-economic data such as population, GDP, economic output of different industries was obtained from Yangzhou Statistical Yearbook (Yangzhou Statistics Bureau, 2007–2014) and Jiangsu Statistical Yearbook (Jiangsu Statistics Bureau, 2007–2014); relevant regulated data such as per capita urban land, land use intensity criterion, forest acreage was collected from National Economic Development Planning, General Land Use Planning, Urban and Rural Planning of Yangzhou, and other strategic planning.

2.2 Analysis of LUSO uncertainties

Integrated land use and social-economic systems always suffer from high levels of uncertainties, certainly communication of these uncertainties helps for risk perception and effectiveness improvement of land use measures (Polasky *et al*., 2011; Verburg *et al*., 2013). Currently, there are many classifications for uncertainties in integrated environmental assessment according to different purposes, and it is difficult to reconcile these taxonomies. Matott provided a comprehensive overview about sources and types of uncertainties, as well as model evaluation methods to alleviate such uncertainties (Matott *et al*., 2009), so here there is no need to narrate again. Among existing classifications, the three dimensional concept framework from Asselt was selected to describe LUSO uncertainty in this paper (Walker *et al*., 2003), where uncertainty was defined in three dimensions: location, level and nature. Location is the identification where uncertainty happens in model assessment process; level of uncertainty is to manifest uncertainty along the spectrum between deterministic knowledge and complete ignorance; and nature of uncertainty is to distinguish between uncertainty caused by the imperfection of knowledge and uncertainty due to inherent variability of studied phenomena. It is easy to understand uncertainty classification of location and nature dimensions, but for the level dimension, Brown (2004) and Refsgaard et al. (2007) gave a more detailed uncertainty taxonomy based on deterministic degree of knowledge, as shown in Fig. 2, which was used to supplement the three dimensional concept framework of Asselt (Walker *et al*., 2003). Next the presented three dimensional concept framework was used to analyze the types and sources of uncertainties during different LUSO steps, as

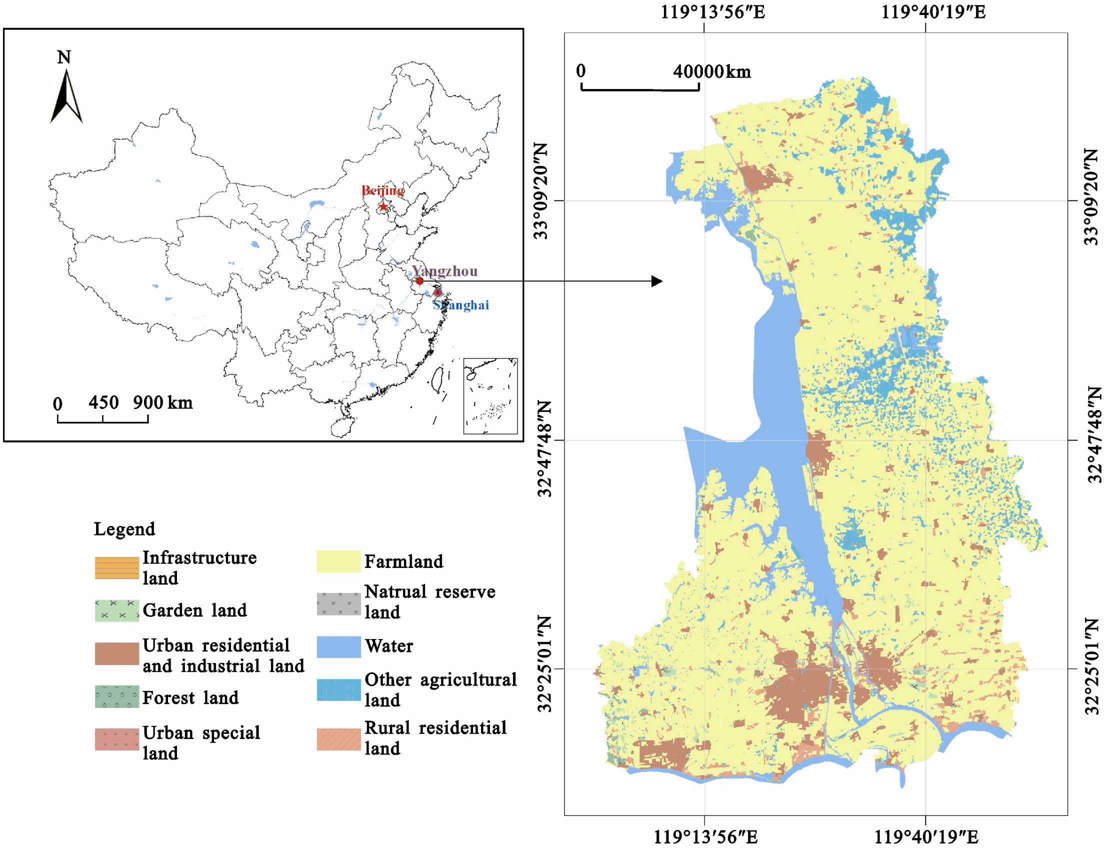

Fig. 1 Location and land use patterns of Yangzhou City, China

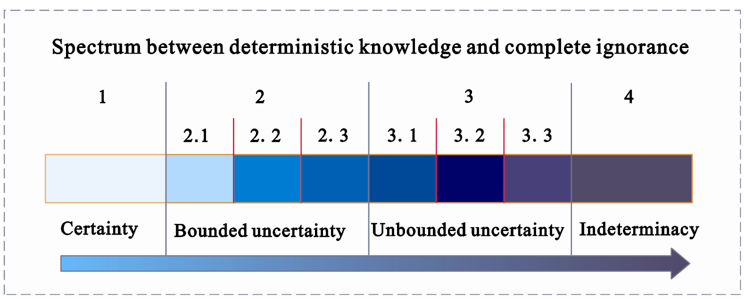

Fig. 2 Uncertainties taxonomy for level dimension in three dimensional concept framework. 2.1—All possible outcomes and all probabilities known; 2.2—All possible outcomes and some probabilities known; 2.3—All possible outcomes but no probabilities known; 3.1—Some possible outcomes and probabilities known; 3.2—Some possible outcomes, but no probabilities known; 3.3—No possible outcomes known ('do not know'); 4—Indeterminacy ('can not know')

shown in Table 1. The search for land use structure with the highest benefits under relevant constraints is LUSO process which we can divide into the following steps, and each step suffers from uncertainties.

Step 1: Determination of objectives and constraints. Usually macro objectives for LUSO include maximizing economic value, and ecological and social benefit. In contrast, concrete objectives due to decomposition and elaboration of macro objective are with various contexts, e.g., minimum soil erosion, pollutant emission, land development cost, maximum income, water efficiency, and so on. Constraints include specific requirements of strategy planning to regional land use, e.g., intensity of development, population density, and quantities of agricultural land and parkland. It was observed that when research purpose was to demonstrate method application, macro objectives were always selected; while when purpose was to resolve serious problem of study area, corresponding specific objectives were adopted. In this process, uncertainties were selected as different combinations of objectives and constraints adopted by different researchers. This is due to the lack of perfect knowledge for LUSO. The more informed one is, the more likely one will select the most appropriate objectives and constraints, resulting in less uncertainty. In level dimension of proposed concept framework, these uncertainties belong to bounded uncertainty, due to all possible combinations of objectives and constraints known, yet corresponding probabilities to be applied unknown.

Step 2: Model selection. In this step, according to different understandings of LUSO, optimization models will be chosen as linear or nonlinear with inexact or traditional programming. Moreover, multiple objective decision making technique also needs to be decided for multi-objective LUSO. Mostly it is assumed that optimization goal values have linear relationships with quantities of land use types, therefore linear programming was always selected. However, when conducting multi-objective decision, it is necessary to implant linear formulations into a nonlinear model to obtain trade-off solutions. Uncertainties in this step are similar to model uncertainty in environmental assessment, where each time the applied model may be different in structure, which leads to uncertain results. As in step 1, uncertainties within this step are rooted in knowledge imperfection of researchers for programming models and LUSO itself.

Step 3: Data collection. Based on steps 1 and 2, data were collected to determine related land use parameters of target year. Commonly, historical data are required to forecast corresponding parameters, e.g., population size, urbanization level, output abilities of different land use types, and so on, while for some parameters in constraints of uncertain model, information is obtained from regional strategic planning and other higher level planning. The accuracy of result of LUSO relies heavily on the quality of basic data. While occasionally data were obtained by approximation or estimation, mistaken calculations are also included. Thus, original data material is uncertain instead of accurate to some extent. Some possible outcomes of basic data may be known, but all possible outcomes cannot be known, hence deemed as unbounded uncertainty category.

Step 4: Parameters forecast and input. In this step, parameters of target year were forested according to historical tendency with various methods, and these predicted values were used to describe land use. However, future land use situations may encounter many cases and it is not known what will happen in the future. As a result, there are uncertainties, and parameters should have corresponding intervals to accommodate possible cases. That is to say parameter uncertainties reflect uncertain land use phenomenon which is affected by various uncertain factors (such as physical, socio-economic and even spatial factors). Therefore, we could not know all the possible outcomes. In such an instance, according to the three dimensional concept framework, most parameters uncertainties belong to the unbounded uncertainty in Fig. 1. While some parameters, particularly in constraint condition, are certain or with probability distribution functions already known and are therefore identified as bounded uncertainty. We consider parameter uncertainties of LUSO mostly caused by inherent variation of land use system. However, imperfect knowledge of researchers could also enlarge that.

Step 5: Representation of model results. Theoretically, because input parameters are uncertain, outputs of LUSO model should also be uncertain (i.e., uncertainties propagated from input to output through programming model). Although corresponding results can be obtained under different scenarios by input parameter adjustment, it is difficult to know all possible LUSO results. For uncertainties within this step, more attention should be paid to make land use planning account for underlying risks and maintain flexibility to hold them.

Above we analyzed LUSO uncertainties systematically. Once researchers begin to do LUSO, uncertainties appear as researcher must decide optimized objectives, choose a model structure, and collect basic data, and these procedures could bring about considerable uncertainties. There is no useful method to address this challenge,

Table 1 Analysis of Land use structure optimization (LUSO) uncertainties with proposed three dimensional concept framework

Content of uncertainties	Location dimension	Level dimension	Nature dimension
Uncertainties of objective and constraint	Step 1	2.3	1
Model selection uncertainties	Step 2	2.3	1
Data collection uncertainties	Step 3	3	1
Input parameters uncertainties	Step 4	1, 2 or 3	1 or 2
Result uncertainties	Step 5	2	2

Notes: Column 4: 1—Imperfect knowledge of researchers; 2—Inherent variability of land use system Column 3: Symbols are the same as those in Fig. 2

except to enhance related knowledge to help make an informed decision. In this case, uncertainties in steps 1, 2 and 3 are not the object to be dealt with in this research. Input parameters of LUSO are various, and for such uncertainties, there are both bounded and unbounded uncertainties, i.e., only partially possible outcomes or sometimes with all possibilities known. Therefore, it can not be decided which type of uncertain variable should be selected to describe—fuzzy, rough or stochastic, and what is more important is that it is difficult to find corresponding or relevant mathematical functions. Although interval number is a coarse method to represent uncertainties, it can avert the search for mathematical function of uncertain variables. Given this, interval number was applied to represent input parameter uncertainties as input for LUSO programming model. How to obtain the lower and upper limits of such intervals will be introduced following, and for uncertainties of LUSO results, stochastic simulation was used to determine interval size of optimized land use structure under different significance levels.

2.3 Methodology

2.3.1 Generic uncertain programming model

Making part or all parameters of common programming model replaced by uncertain parameter, then it becomes uncertain programming model which was developed to manage uncertainties and complexities in operational research field. The generic uncertain programming model is like Equation (1), where there are n optimized objectives with Z constraints set, and $f_n(\xi_n, X)$, $g_z(\varphi_z, X)$ are the expressions of objective n and constraint z respectively, of which ξ_n, φ_z are their uncertain parameters, and X is the vector of independent variables. The parameter can be interval, rough and stochastic or other type of uncertain variable. Combined with different uncertain variable, generic uncertain programming model can further be subdivided into dependent-chance programming, chance-constrained programming, interval programming, and so on. Here, as we described above, interval number has some advantage for uncertain LUSO, thus was adopted along with interval programming, and specific formulation will be established following.

$$\begin{aligned} &\max\left[f_1(\xi_1,X),f_2(\xi_2,X),\cdots,f_n(\xi_n,X)\right] \\ &s.t.\quad g_z(\varphi_z,X)\le 0,\quad j=1,2,\ldots,Z \end{aligned} \tag{1}$$

2.3.2 Specific formulation

As land use structure reflects regional development structure, so conversely it could be used to guide socio-economic activities for promotion of land use sustainability. The concept of sustainable development from Word Commission on Environment and Development captures both economic and environmental dimensions of development, mainly emphasizing economic and ecological benefits (Singh, 1999). However, social benefit is also important for land use planning, but it is a comprehensive concept involving different connotations and difficult to quantify, therefore it is hard to get identified indicators and criteria to denote social benefit. In addition, social benefit has close relationship with economic and ecological benefits, when these two objectives are at high levels, human well-being satisfied to a large extent. The main form of social benefit is residential demand which will be guaranteed at the stage of constrains setting. Thus, only economic and ecological benefits are set as optimized objectives in this study. Constraints are defined from land use intensity, residential land demand, land use conversion cost, arable land protection, and other aspects.

(1) Objectives formulation

Economic benefit maximization. Different land use types have corresponding GDP output abilities. Although it is difficult to accurately identify the GDP belong to different types of land uses, an appropriate estimation was obtained based on relevant statistic data. The formula is as follows:

$$\max f_1^{\mp}(X)=\sum_{i=1}^{12} ecoc_i^{\mp}\times x_i^{\mp} \tag{2}$$

where $f_1^{\mp}$ refers to upper and lower limits of optimized economic benefit of 2030 year and $ecoc_i^{\mp}$ is interval size of GDP output ability for land use i, and $x_i^{\mp}$ is the solution element, referring to quantity of land use i, meanwhile $X=[x_1, x_2,\ldots, x_{12}]$.

Ecological benefit maximization. Natural capital provides humans with a range of provisioning, regulating, and cultural services upon which humans depend for our quality of life and well-being. This was used as representation of ecological benefit. We coarsely calculated the natural capital value of different land use types based on unit monetary values of global ecosystem services from a previous study (Costanza *et al*., 2014) and matchup of unit values between our land use taxonomy and biome classification of Costanza is in Table 2. Following equation is used to measure aggregate ecological benefit of target year.

$$\max f_2^{\mp}(X) = \sum_{i=1}^{12} ecog_i^{\mp} \times x_i^{\mp} \quad (3)$$

where $f_2^{\mp}$ is the interval size of ecological benefit, and $ecog_i^{\mp}$ is the interval of natural capital value for land use *i*. Although Costanza *et al*. (2014) estimated the monetary value of global ecosystem services, in case of the studied area, there are maybe some differences due to specific geographical conditions, therefore we correct existing standard to obtain the interval values, i.e., $ecog_i^{\mp}$, and these intervals accommodate relevant uncertainties.

(2) Constraints formulation

Arable land protection constraint. In view of food security, Chinese central government stipulates subordinate administrative districts have political duty to protect certain amount of arable land. For Yangzhou, the arable land quantity of 2030 has to be greater than *gb* which is the least cultivated land quantity regulated by Jiangsu Province government, as follows:

$$x_1 \geq gb \quad (4)$$

Ratio of urban green space constraint. Urban green land can absorb polluted air, balance urban heat island effect, improve human wellbeing and maintain urban ecosystem health. Within urban range, ratio of green space should be greater than $ld^{\mp}$, which is an interval number obtained from urban planning knowledge.

$$x_9 / (x_6 + x_9) \geq ld^{\mp} \quad (5)$$

Ratio of developed space constraint. For a region, developed space with an exceeded threshold may cause serious environmental issues, e.g., urban landscape could hinder the hydrologic cycle, leading to groundwater level declining, resulting in land subsidence. Additionally, it compresses space for biological species, threatening biodiversity (Berke and Kaiser, 2006). Therefore, it is important to limit developed space at certain level as:

$$(x_6 + x_7 + x_8 + x_9) / Area \leq dR \quad (6)$$

where *Area* is total area of Yangzhou City, and *dR* is land development intensity criterion set by Jiangsu Province government from perspective of sustainable development of whole province.

Residential land demand constraint. The basic function of land use is to accommodate population, while in China due to different patterns of life and productions, urban and rural regions are with different per capita residential land standards, and thus rural and urban residential land areas in Yangzhou of 2030 are restricted like this:

$$\begin{aligned} popr^{\mp} \times Ar^{l} \leq x_7 \leq popr^{\mp} \times Ar^{h} \\ popu^{\mp} \times Au^{l} \leq \rho^{\mp} \times x_6 \leq popu^{\mp} \times Au^{h} \end{aligned} \quad (7)$$

where $popr^{\mp}$ is the rural population interval of 2030, $popu^{\mp}$ referring to urban population interval, and Ar^{l}, Ar^{h} are lower and upper limits of per average rural residential area, and Au^{l}, Au^{h} are those of urban residential land, while $\rho^{\mp}$ is the ratio of urban residential land to land use x_6.

Conversion cost constraint. In the process of land consolidation, portions of other agricultural land, natural reserve land, and water are always converted to arable land for grain safety guarantee, while with remaining quantities lesser, marginal conversion cost increases drastically, meaning that conversion quantity should be limited at a reasonable level.

$$x_5 \geq 122658.65\text{-}og^{\mp}, x_{10} \geq 97400.22 - wa^{\mp}, x_{12} \geq 770.31 - ns^{\mp} \quad (8)$$

Table 2 Natural capital value standard of different land use types

Variable	Land use type	Unit natural capital value (Costanza *et al*., 2014)
x_1	Arable land	Cropland
x_2	Garden land	Average of cropland and temperate forest
x_3	Forest land	Temperate forest
x_4	Grassland	Grass
x_5	Other agricultural land	Cropland
x_6	Urban residential and industrial land	0
x_7	Rural residential land	0
x_8	Infrastructure land	0
x_9	Urban special land	urban
x_{10}	Water	Lake
x_{11}	Beach and moor	Tidal Marsh
x_{12}	Natural reserve land	0

where $og^{\mp}$, $wa^{\mp}$, $ns^{\mp}$ are potential consolidation quantities of above three land use types according to the trend of investment for land consolidation projects.

Macro strategy constraint. To promote sustainability level and provide space for agricultural structural adjustment, there should be enough land for generalized agricultural activities. Also proportion of infrastructure land to urban land should be harmonious, because Chinese local governments have enthusiasm for infrastructure construction, always resulting in excessive infrastructure.

$$\sum_{i=1}^{5} x_i \geq bag^{\mp}, ju^{\mathrm{l}} \leq x_8 / x_6 \leq ju^{\mathrm{h}} \tag{9}$$

where $bag^{\mp}$ is area interval for generalized agricultural production, and ju^{l}, ju^{h} are lower and upper limits of ratio of infrastructure to urban land.

Other constraints. The basic constraints are the total area and non-negative variable constraints as follows:

$$\sum_{i=1}^{12} x_i = Area,\ x_i \geq 0 \tag{10}$$

2.3.3 Interval size determination

As observed above there are determinate and uncertain variables in proposed programming model. For determinate variables, values were obtained from related strategy planning and professional standardization materials. While setting interval size of uncertain variables was a challenge. Verburg noted there are two approaches of defining the band-width of uncertain variable value (Verburg *et al.*, 2013). One is using the standard deviations of historic data to denote, and the other is combining expert knowledge with historic trends to determine band-width. The second approach was considered to percept the underlying uncertainties stemmed from imperfect human knowledge, and therefore be more suitable for estimating uncertain LUSO variables values.

Because grey theory assumed that world system was grey and full of uncertain, incomplete information, it has been proved to have an obvious advantage of making grey system clear (Liu and Lin, 2006). The grey prediction method was applied to forecast uncertain LUSO variables' value of 2030 year based on historic data. Although the predicted value was considered to be a result of internal uncertainties of indicated phenomenon, land use also suffers from outside uncertainties, e.g., population policy influence, economic cycle affect, even impact of natural disasters. Therefore, expert investigation method was applied in the second stage to address these uncertainties. Secondly, 100 experts from relevant fields were surveyed to understand biases of real value versus the grey predicted value with measure of standard deviation of historic data. Experts came from Land Resource Bureau, local government of Yangzhou City and some research institutes. Those experts all had enough land use knowledge and were familiar with situation of Yangzhou development. The materials including grey predicted results, historic data of uncertain variables, uncertainties analysis, as well as basic land use and socioeconomic situation of Yangzhou City were provided to the experts based on which experts estimated deviations of uncertain variables. Expectations of negative and positive deviations were respectively regarded as lower and upper bounds of interval number, which are shown in Table 3. The ratio of interval size to its lower limit is assumed as relative width of interval, which in reality reflects the influence extent of uncertainties, e.g., the relative width of $ecoc_1^{\mp}$ is larger than that of $ecoc_2^{\mp}$, so we consider variable $ecoc_1^{\mp}$ with higher uncertainties and is more likely to be impacted by uncertain factors.

2.3.4 Solving algorithm

Interval numbers and conflicted objectives decision need to be dealt with for uncertain programming. However, traditional methods with serious simplification are not sufficient. Therefore, a heuristic approach was developed to resolve it, mostly based on GA, featured in Fig. 3. Based on the hypothesis that uncertain variable presented as average distribution on interval from which we randomly select a value to determine uncertain variable, and it accordingly becomes common programming model; then we could use GA method to solve it and obtain the excellent solution. The above process was repeated 10 000 times resulting in 10 000 excellent solutions. Bootstrap statistic approach was then employed to study distribution characteristics of excellent solutions to gain confidence interval under a given significant level as follows:

$$\Pr\left(X_{w,\alpha/2}^{*} \leq X_{w}^{*} \leq X_{w,(1-\alpha/2)}^{*}\right) = 1 - \alpha \tag{11}$$

where X_w^* is the excellent solution selected from non-dominated set and α is significant level, meaning $100 \times (1 - \alpha)$ percentage of the future uncertainties considered. The smaller it is, the wider confidence interval

Table 3 Values of variables in proposed uncertain programming model

Variable	Interval size	Variable	Interval size	Variable	Interval size	Variable	Interval size
$ecoc_1^{\mp}$	[4.45, 6.76]	$ecoc_{11}^{\mp}$	0	$ecog_9^{\mp}$	[3.98, 4.83]	Ar^{l}	100
$ecoc_2^{\mp}$	[3.92, 5.11]	$ecoc_{12}^{\mp}$	0	$ecog_{10}^{\mp}$	[6.99, 8.44]	Ar^{h}	220
$ecoc_3^{\mp}$	[7.87, 11.09]	$ecog_1^{\mp}$	[2.84, 3.89]	$ecog_{11}^{\mp}$	[100.09, 129.52]	Au^{l}	60
$ecoc_4^{\mp}$	–	$ecog_2^{\mp}$	[2.01, 3.29]	$\rho^{\mp}$	[0.55, 0.68]	Au^{h}	120
$ecoc_5^{\mp}$	[1.81, 2.29]	$ecog_3^{\mp}$	[1.67, 2.66]	gb	314391	$og^{\mp}$	[12093, 17668]
$ecoc_6^{\mp}$	[948.91, 1211.06]	$ecog_4^{\mp}$	–	$ld^{\mp}$	[0.0366, 0.0432]	$wa^{\mp}$	[6719, 8803]
$ecoc_7^{\mp}$	[19.98, 23.77]	$ecog_5^{\mp}$	[2.35, 3.44]	dR	0.2314	$ns^{\mp}$	[109, 145]
$ecoc_8^{\mp}$	[880.35, 1105.14]	$ecog_6^{\mp}$	0	$Area$	6519121	$bag^{\mp}$	[370291, 410874]
$ecoc_9^{\mp}$	[98.88, 154.07]	$ecog_7^{\mp}$	0	$popr^{\mp}$	[140.27, 178.03]	ju^{l}	0.52
$ecoc_{10}^{\mp}$	[5.11, 6.66]	$ecog_8^{\mp}$	0	$popu^{\mp}$	[299.02, 342.76]	ju^{h}	0.65

Notes: Zero indicating there is no ecological benefit for those landscapes; some variables with certain rather than interval numbers manifest they are mandatory indicators for land use planning. Meanings of all abbreviations see equations

will be, $X^*_{w,\alpha/2}$ and $X^*_{w,(1-\alpha/2)}$ are lower and upper quartiles, respectively. Here confidence interval was considered to be a solution distribution as result of LUSO to accommodate uncertainties. Because confidence interval band was decided by α, and with adjustment of it the result of uncertain LUSO can be controlled. This completely depends on decision maker's attitudes, where if risk is preferred, and then α is assigned with large value to narrow interval size, with the possibility of uncertainties to violate interval restriction increased, whereas if it is risk prudent, interval will be wide to hold most of uncertainties.

Pareto Optimum principle was applied for trade-offs making, where only both economic benefit $f_1(X^*)$ and ecological benefit $f_2(X^*)$ of X^* are better than that of X, X^* is considered better than X. With this rule to evolve solutions, ultimately non-dominated solution set can be obtained, which forms the so-called efficiency frontier. However, non-inferior solutions in non-dominated set do not conform to the rule of Equation (12), and therefore could not be compared to determine which is best. To provide assistance for trade-offs making between ecological and economic benefits, this paper presents a skill to distinguish these solutions. For each of the non-inferior solutions, ratio of its economic objective to ecological objective was calculated, listed in descending order with the sequence number to mark them, i.e., non-dominated solution with the largest ratio value is denoted by X^*_1, and with the wth large ratio value is denoted by X^*_w. Finally, one of non-inferior solutions is used as a land use planning scheme. However, which solution to be adopted depends on the preference of stakeholders that is represented by w value; the larger it is, the more preferred ecological objective is, while the smaller it is, the more preferred economic objective is.

$$If\left[f_1\left(X^*\right) \geq f_1\left(X\right) \text{ and} f_2\left(X^*\right) \geq f_2\left(X\right)\right], \text{ then } X^* \geq X \tag{12}$$

The evolutionary process of pursuing non-inferior solutions is achieved by GA, which was proven to have good global optimum ability for both linear and nonlinear programming. Usually GA has four steps: initialization, selection, crossover, and mutation. Firstly, parent solutions are randomly generated in binary format, where a solution is a chromosome, the binary characters on which are genes. Secondly, their economic and ecological objective values are calculated, after that we select the best 10 solutions into non-dominated set. Thirdly, according to crossover rate, some pairs of chromosomes are chosen to create offspring by swapping part of their genes. Fourthly, to promote diversity, some chromosomes are selected to mutate genes into another binary character. The above four steps are an iterative process of GA of producing the next generation, and for each loop, new generation was compared with the solutions already in non-dominated set to make non-dominated set updated. During the whole process, penalty function tool is applied to guarantee all solutions within constraints, and when cycle index reaches given number of times, programming will cease. Non-dominated set is then exported, from which the ideal solution is selected according to the w value of stakeholders.

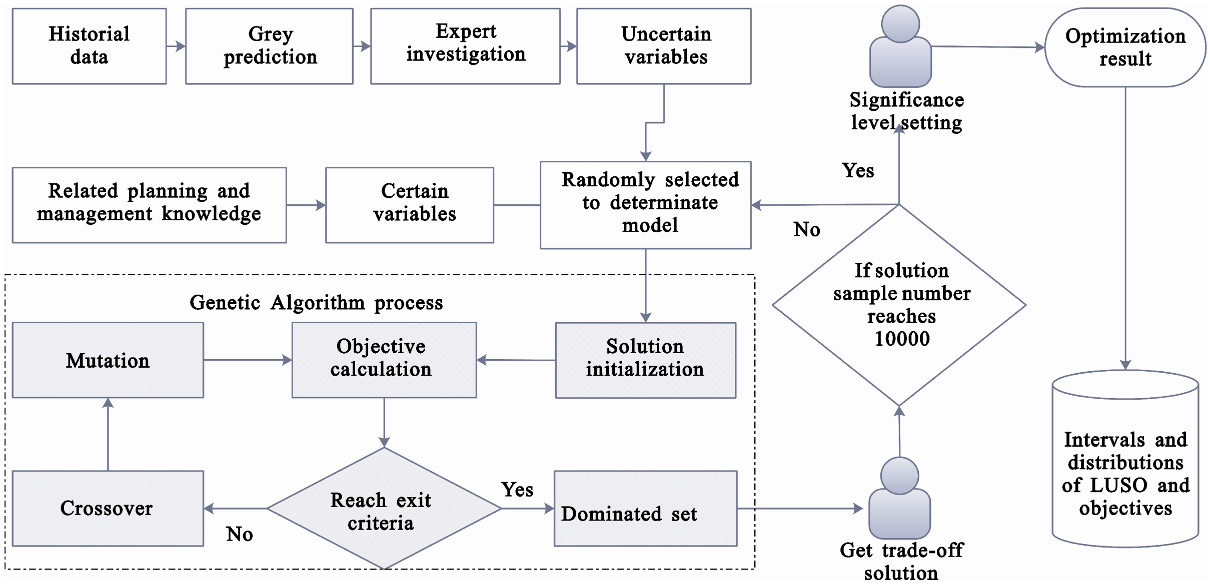

Fig. 3 Flowchart of heuristic algorithm for uncertain Land use structure optimization (LUSO)

Above is our proposed approach to solve the uncertain programming model, which could be briefly described as follows. Uncertain variable values are randomly selected from intervals to determinate uncertain model, and GA resolves it; this process repeats 10 000 times, and every time one sample solution was acquired; the confidence interval of LUSO is then obtained based on 10 000 solution samples selected from dominated set with w value. In all, two control parameters (α and w) are presented for stakeholders to adjust preferences on uncertainties and trade-offs between conflicted objectives interactively, and makes LUSO decision transparent, thus could get the informed scheme for land use planning and then promote its effectiveness.

3 Results

The proposed approach provides an interactive tool to deal with uncertain LUSO with help of two parameters. One was significance level α, on behalf of attitude to uncertainties, meaning interval result to hold percentage of $100 \times (1-\alpha)$ land use uncertainties in the future. The other was sequence number w, representing relative preference to the two objectives, of which value range is 1–10, because there are 10 solutions in dominated set, and the smaller of it, the more preferred economic objective is. Thus design makers can attempt the two parameters constantly until get the ideal solution. Here results were calculated under various scenarios with different combinations of these two parameters and for each circumstance the result can be observed in Table 4, while computation time for solution was approximately 8 hours on a Lenovo laptop with an Intel(R) Core (TM)i-3 CPU @1.9GHz.

The economic and ecological objectives of land use structure in 2013 of Yangzhou City were calculated as 6.555×10^{11} and 3.397×10^{10} yuan (RMB), respectively. Contrasting to any circumstances of 2030 year in Table 4, of which lower limits of economic objective are 8.234×10^{11}, 7.741×10^{11}, 6.819×10^{11} and 7.335×10^{11} yuan, respectively, and the expected values of ecological objective are 3.454×10^{10}, 3.473×10^{10}, 3.489×10^{10} and 3.471×10^{10} yuan, respectively. There is much room to improve current land use structure. To obtain better economic and ecological benefits, meanwhile, to satisfy suggested constrains, general orientation of land use change for Yangzhou in the future could be as follows: as farmers moving into urban, rural residential land should be reduced gradually, which can be reclaimed into arable land, because present arable land is only 284 065 ha, with a certain gap to the regulated quantity of 314 391 ha, thus one emphasis of land use policy for Yangzhou is the consolidation of rural settlement to supplement arable land; along with the progress of urbanization and industrialization, urban and infrastructure land will increase drastically, e.g., if α=0.5 and w=2, urban land increases at least 28.52% to reach its lower limit, however, to avoid its excessive expansion,

Table 4 Uncertain Land use structure optimization (LUSO) results for Yangzhou City of China in year of 2030

Variables	α=0.5		α=0.1		Present land use structure
	w=2	w=5	w=8	w=5	
$x_1^{\pm}$ (ha)	[315654, 318528]	[318230, 323120]	[316628, 331716]	[315360, 326440]	284065
$x_2^{\pm}$ (ha)	[6593, 8214]	[6638, 8288]	[6145, 9504]	[6135, 9556]	13083
$x_3^{\pm}$ (ha)	[6844, 8211]	[6854, 8211]	[6477, 9323]	[6474, 9400]	5129
$x_4^{\pm}$ (ha)	[0, 0]	[0, 0]	[0, 0]	[0, 0]	0
$x_5^{\pm}$ (ha)	[105850, 108214]	[106260, 110040]	[105253, 117882]	[105230, 114020]	122659
$x_6^{\pm}$ (ha)	[47422, 49229]	[44556, 47294]	[39520, 45943]	[42711, 48943]	36889
$x_7^{\pm}$ (ha)	[29199, 30028]	[29159, 29810]	[28974, 30400]	[28979, 30537]	64405
$x_8^{\pm}$ (ha)	[29094, 31184]	[26182, 28823]	[23002, 28294]	[24829, 30420]	21695
$x_9^{\pm}$ (ha)	[2262, 2624]	[2332, 2614]	[1928, 2756]	[2008, 2759]	1867
$x_{10}^{\pm}$ (ha)	[97030, 97750]	[97337, 97825]	[96877, 97969]	[96768, 97965]	97400
$x_{11}^{\pm}$ (ha)	[11116, 11148]	[11130, 11151]	[11111, 11157]	[11107, 11156]	11158
$x_{12}^{\pm}$ (ha)	[661, 731]	[661, 730]	[633, 760]	[633, 761]	770
$f_1^{\pm}$ (10^{11} yuan(RMB))	[8.234, 8.886]	[7.741, 8.382]	[6.819, 8.254]	[7.335, 8.803]	6.555
$f_2^{\pm}$ (10^{10} yuan(RMB))	[3.351, 3.557]	[3.370, 3.576]	[3.245, 3.733]	[3.228, 3.714]	3.397

effective policy will be formulated to regulate and control this process; to add arable land, approximately 17% of the other agricultural land will be consolidated and relevant capital should be prepared; due to with rich natural capital value, the quantities of water, beach and moor remain unchanged in planning period, implying much attention should be paid for protection of these land uses from urban growth encroachment and disturbance of human activities; the garden land should be reduced, while forest land is supposed to be increased, as in the most cases it has larger output ability for ecological benefit.

With this approach Yangzhou could get flexible LUSO for land use planning under uncertainties, where scheme is not a series of fixed values, but some interval numbers. Because uncertainties are considered in advance, flexible land use planning suffering not so much disturbances, and thus has strong vitality to achieve the target. So we think flexibility is the necessary guarantee to achieve optimized objectives and to improve effectiveness of land use planning. Also, with this approach stakeholders can get LUSO scheme with respect to preferences on trade-offs between economic and ecological benefits and to attitudes towards uncertainties, after that participants compare and weight alternatives, from which the informed one will be finally decided for land use planning. E.g., at first planning makers may set α=0.5 and w=2 to get solution, but they find ecological benefit of corresponding result is not obviously improved, so they change w=2 to w=5; this time they think trade-offs between economic and ecological benefits is acceptable while interval size of LUSO is a little wide, so they change α=0.5 to α=0.1, narrowing interval band to raise control effect of land use planning. Repeat this interactive process until they get the ideal scheme, and this transparent decision process based on our proposed model obviously enhances the effectiveness of land use planning of Yangzhou.

It was observed from Fig. 4 that, when significance level becomes smaller, interval of LUSO result became wider, e.g., when α=0.5 and w=2, the interval of urban land is [44 556, 47 294] to accommodate 50% of land use uncertainties, while when α=0.1, it expanded to [42 711, 48 943], accommodating for 90% of uncertainties. However, this does not necessarily mean that the wider interval will be better; actually it is a double-edged sword, one side accommodating more uncertainties, the other side weakening the restraint effect of land use planning. Reconciliation of this contradiction depends on attitudes of decision maker where if it is risk preferred style, α will be set with high value to narrow the interval, and thus tighten for land use planning control, then failure risk rises, and vice-versa. As w value enlarges, the solution with more relative ecological benefit in non-dominated set is likely to be selected. Comparing circumstance 1 and 2, of which w values are 2 and 5 respectively, the areas of land uses that have more natural capital value in circumstance 2 are larger than that in circumstance 1, e.g., the arable land is [318 230, 323 120] versus [315 654, 318 528], and garden land is [6638, 8288] versus [6593, 8214]. Fig. 4 depicts the distributions of LUSO objectives which fit the normal distribution approximatively. When α=0.5 and w=2, indicating 50% of uncertainties considered, the interval of economic and ecological objectives for Yangzhou are [8.234, 8.886] × 10^{11} and [3.351, 3.557] × 10^{10} yuan respectively, while when w=5, the ecological objective rises to [3.370, 3.576] × 10^{10} yuan and economic objective reduces to [7.741, 8.382] × 10^{11} yuan accordingly, and when significance level becoming 0.1, implying 90% of uncertainties considered, intervals of proposed objectives enlarge to [7.335, 8.803] × 10^{11} and [3.228, 3.714] × 10^{10} yuan respectively.

4 Discussion

Comparing to existing uncertain programming models, our modeling is considered to have three important advantages. Firstly, interval number is used to represent LUSO uncertainties, particularly grey prediction plus

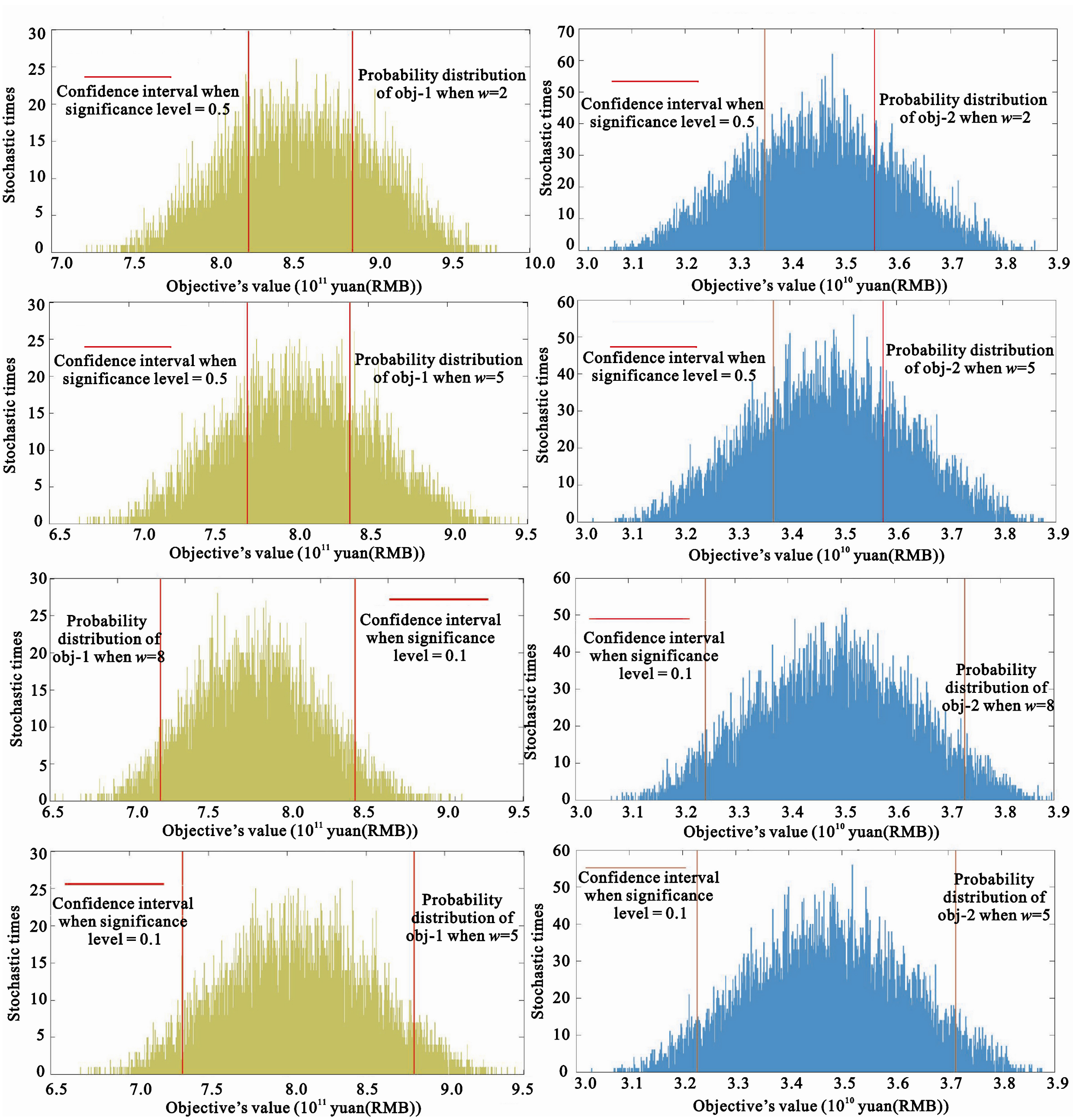

Fig. 4 Probability distribution of objectives for Land use structure optimization (LUSO) of Yangzhou City, China

investigation methods employed to determinate interval size, making that strongly evidential; i.e., we illustrate why interval number is selected and how the size of it is obtained, which is crucial to final result. Secondly, it provides two adjustable parameters for decision makers to manage trade-offs between economic and ecological benefits and uncertainties to be accommodated correspondingly, which is useful for achievement of informed and agreeable LUSO interactively to improve effectiveness of land use planning. Thirdly, a heuristics similar to Monte Carlo based on Genetic Algorithm is developed to solve this uncertain model rather than directly reducing it to common programming model, which reestablishes uncertain environment for LUSO and no doubt enhance optimization results level.

The significant policy implication of this research includes two aspects. The first is that uncertainties management during land use planning is supposed to receive great attentions from government and academic. Land use planning in China would shift from blindly high-pressure control to flexible management, which is the inevitable choice corresponding to the complex uncertainties of future; otherwise, even a lot of regulatory cost is input, effectiveness of land use planning still not satisfied. The second is that informed decision is generated by comparing and weighting the alternatives involved by various stakeholders rather than decided by political leader; because benefits provided by land resources is to meet public demands that is difficult to be fully perceived only by governments. People have no confidence on planning decision made in a non-transparent process with less of public participation. Providing an interactive platform regarding on trade-offs of incompatible interests and uncertainties management for stakeholders to make planning decision is critical to improve its effectiveness.

Uncertain programming is the innovative theme in operational research, and new uncertain variable types are always put forward, from stochastic, fuzzy, and rough to a comprehensive uncertain variable to describe different uncertainties, also there are more and more literatures about uncertain resources and environmental optimization to improve policy effects. However, for uncertain LUSO, not only various uncertain variables are applied to substitute into programming model, but more attention should be paid to research the external performances and mathematical personalities of LUSO uncertainties, e.g., how to obtain membership function of fuzzy variable or interval number size for LUSO uncertainties. As a complicated system, different aspects of land use may have mutual relationships, making identification and quantification of LUSO uncertainties harder, so uncertain LUSO from a system point of view is worth to be pursued, as well due to with spatial character, uncertain land-use spatial optimization should be researched urgently.

5 Conclusions

Based on a comprehensive analysis of uncertainties for land use structure optimization (LUSO), an uncertain programming model with interval number as uncertain variable was established. Although all steps of LUSO suffer from uncertainties, only uncertainties in variables input and result representation stages could be tackled with mathematical model. Interval numbers were adopted to describe uncertainties in this manuscript, of which size was determinate by the combination of grey prediction and expert investigation methods. To solve this uncertain model, a heuristic algorithm with Pareto evolutionary rule was developed based on Genetic Algorithm (GA), by which the interval of LUSO result under given significance level was calculated. The main conclusions of this research are as follows:

(1) There are different types of uncertainties from certainty to indeterminacy in the five steps of LUSO due to inherent variability of land use and imperfect knowledge for design-makers. As posing serious challenges for land use planning, these uncertainties should be quantified into LUSO programming model. However, because of complexity of uncertainties, it is not appropriate to adopt single mathematical variable to describe them; yet interval number was proved to have the ability of expressing comprehensive uncertainties in this paper.

(2) Our proposed model was proved with good potential for flexible land use planning making with respect to trade-offs of conflicted objectives and attitudes towards uncertainties, thus making planning decision process transparent. Two parameters were provided to regulate levels of uncertainties and trade-offs of conflicted objectives in this manuscript by which alternatives were generated according to different stakeholders' preferences, and informed scheme can be obtained only if these alternatives are carefully weighted and compared.

(3) Due to advanced perception and acceptance for uncertainties with already reserved space, flexible management could enhance land use planning effectiveness primarily. Uncertain environment with high complexity is the real case of future, so rigid planning is no longer appropriate, otherwise efficiency loss or implementation failure will happen, because reasonable demand is not satisfied by rigid land use planning that finally becomes invalid under frequent disturbances of uncertainties.

References

Berke P, Kaiser E J, 2006. *Urban Land Use Planning* (*5th Edition*). Urbana, US: University of Illinois Press, 45–168.

Brown J D, 2004. Knowledge, uncertainty and physical geography: towards the development of methodologies for questioning belief. *Transactions of the Institute of British Geographers*, 29(3): 367–381. doi: 10.1111/j.0020-2754.2004.00342.x

Cao K, Huang B, Wang S W *et al*., 2012. Sustainable land use optimization using Boundary-based Fast Genetic Algorithm. *Computers Environment and Urban Systems*, 36(3): 257–269. doi: 10.1016/j.compenvurbsys.2011.08.001

Cheng S, Chan C W, Huang G H, 2003. An integrated multi- criteria decision analysis and inexact mixed integer linear programming approach for solid waste management. *Engineering Applications of Artificial Intelligence*, 16(5–6): 543–554. doi: 10.1016/s0952-1976(03)00069-1

Chuai X W, Huang X J, Lai L *et al*., 2013. Land use structure optimization based on carbon storage in several regional terrestrial ecosystems across China. *Environmental Science & Policy*, 25(25): 50–61. doi: 10.1016/j.envsci.2012.05.005

Costanza R, R D Groot, P Sutton *et al*., 2014. Changes in the global value of ecosystem services. *Global Environmental Change*, 26(1): 152–158. doi: 10.1016/j.gloenvcha.2014.04.002

Dong C, Huang G H, Tan Q *et al*., 2014. Coupled planning of water resources and agricultural landuse based on an inexact-stochastic programming model. *Frontiers of Earth Science*, 8(1): 70–80. doi: 10.1007/s11707-013-0388-5

Gao Q Z, Kang M Y, Xu H M *et al*., 2010. Optimization of land use structure and spatial pattern for the semi-arid loess hilly-gully region in China. *Catena*, 81(3): 196–202. doi: 10.1016/j.catena.2010.03.002

Jiangsu Statistics Bureau, 2007–2014. *Jiangsu Statistical Yearbook 2007–2014*. Beijing: China Statistics Press. (in Chinese)

Li M, Guo P, Fang S Q *et al*., 2013. An inexact fuzzy parameter two-stage stochastic programming model for irrigation water allocation under uncertainty. *Stochastic Environmental Research and Risk Assessment*, 27(6): 1441–1452. doi: 10.1007/s00477-012-0681-y

Li Xin, Ou Minghao, Liu Jiansheng *et al*., 2014. Regional land use structure optimization under uncertain theory. *Transactions of the Chinese Society of Agricultural Engineering*, 30(4): 176–184. (in Chinese)

Li Xin, Ou Minghao, Yan Siqi *et al*., 2013. Calculation of elastic interval of land use structure based on interval optimization model. *Transactions of the Chinese Society of Agricultural Engineering*, 29(17): 240–247. (in Chinese)

Li Y P, Huang G H, Chen X, 2011. Planning regional energy system in association with greenhouse gas mitigation under uncertainty. *Applied Energy*, 88(3): 599–611. doi: 10.1016/j.apenergy.2010.07.037

Linkov I, Satterstrom F K, Kiker G *et al*., 2006. From comparative risk assessment to multi-criteria decision analysis and adaptive management: recent developments and applications. *Environment International*, 32(8): 1072–1093. doi: 10.1016/j.envint.2006.06.013

Liu B D, 2015. *Uncertainty Theory* (*4th Edition*). Berlin, Heidelberg: Springer Berlin Heidelberg Press, 15–20.

Liu S F, Lin Y, 2006. *Grey Prediction*. London, UK: Springer London Press, 275–314.

Liu Y F, Ming D P, Yan J Y, 2002. Optimization of land use structure based on ecological GREEN equivalent. *Geo-spatial Information Science*, 5(4): 60–67. doi: 10.1007/BF02826478

Liu Y, Qin X, Guo H *et al*., 2007. ICCLP: an inexact chance-constrained linear programming model for land-use management of lake areas in urban fringes. *Environmental management*, 40(6): 966–980. doi: 10.1007/s00267-007-9013-2

Liu Y, Yu Y J, Guo H C *et al*., 2009. Optimal land-use management for surface source water protection under uncertainty: a case study of Songhuaba watershed (Southwestern China). *Water Resources Management*, 23(10): 2069–2083. doi: 10.1007/s11269-008-9370-5

Lu S S, Guan X L, Zhou M *et al*., 2014. Land resources allocation strategies in an urban area involving uncertainty: a case study of Suzhou, in the Yangtze River Delta of China. *Environmental management*, 53(5): 894–912. doi: 10.1007/s00267-014-0247-5

Lu S S, Zhou M, Guan X L *et al*., 2015. An integrated GIS-based interval-probabilistic programming model for land-use planning management under uncertainty: a case study at Suzhou, China. *Environmental Science and Pollution Research International*, 22(6): 4281–4296. doi: 10.1007/s11356-014-3659-0

Luo B, Li J B, Huang G H *et al*., 2006. A simulation-based interval two-stage stochastic model for agricultural nonpoint source pollution control through land retirement. *Science of the Total Environment*, 361(1–3): 38–56. doi: 10.1016/j.scitotenv.2005.09.053

Matott L S, Babendreier J E, Purucker S T, 2009. Evaluating uncertainty in integrated environmental models: a review of concepts and tools. *Water Resources Research*, 45(6): 735–742. doi: 10.1029/2008wr007301

Messina V, Bosetti V, 2003. Uncertainty and option value in land allocation problems. *Annals of Operations Research*, 124(1): 165–181. doi: 10.1023/B:ANOR.0000004767.84402.b3

Nie X H, Huang G H, Wang D *et al*., 2008. Robust optimisation for inexact water quality management under uncertainty. *Civil Engineering and Environmental Systems*, 25(25): 167–184.

doi: 10.1080/10286600801908964

Polasky S, Carpenter S R, Folke C *et al.*, 2011. Decision-making under great uncertainty: environmental management in an era of global change. *Trends in Ecology & Evolution*, 26(8): 398–404. doi: 10.1016/j.tree.2011.04.007

Qiu B K, Lu S S, Zhou M *et al.,* 2015. A hybrid inexact optimization method for land-use allocation in association with environmental/ecological requirements at a watershed level. *Sustainability*, 7(4): 4643–4667. doi: 10.3390/su7044643

Refsgaard J C, van der Sluijs J P, Højberg A L *et al*., 2007. Uncertainty in the environmental modelling process: a framework and guidance. *Environmental Modelling and Software*, 22(11): 1543–1556. doi: 10.1016/j.envsoft.2007.02.004

Sadeghi S H R, Jalili K, Nikkami D, 2009. Land use optimization in watershed scale. *Land Use Policy*, 26(2): 186–193. doi: 10.1016/j.landusepol.2008.02.007

Singh K, 1999. Sustainable development: some reflections. *Indian Journal of Agricultural Economics*, 54: 6–41.

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 Europe. *Journal of Environmental Management*, 127(S3): 132–144. doi: 10.1016/j.jenvman.2012.08.038

Walker W E, Harremoës P, Rotmans J *et al*., 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment*, 4(1): 5–17. doi: 10.1076/iaij.4.1.5.16466

Wang Hongrui, Gao Yuanyuan, Liu Qiong *et al*., 2010. Land use allocation based on interval multi-objective linear programming model: A case study of Pi County in Sichuan Province. *Chinese Geographical Science*, 20(2): 176–183. doi: 10.1007/s11769-010- 0176-z

Wang W Y, Zeng W H, 2013. Optimizing the regional industrial structure based on the environmental carrying capacity: an inexact fuzzy multi-objective programming model. *Sustainability*, 5(12): 5391–5415. doi: 10.3390/su5125391

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(2): 61–74. doi: 10.1016/S0169-2046(03)00095-1

Yangzhou Statistics Bureau, 2007–2014. *Yangzhou Statistical Yearbook 2007–2014*. Beijing: China Statistics Press. (in Chinese)

Zhong T Y, Mitchell B, Huang X J, 2014. Success or failure: Evaluating the implementation of China's National General Land Use Plan (1997–2010). *Habitat International*, 44: 93–101. doi: 10.1016/j.habitatint.2014.05.003

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(42): 479–491. doi: 10.1016/j.landusepol.2014.09.002

Zhou Min, Cai Yunlong, Guan Xingliang *et al*., 2014. A hybrid inexact optimization model for land-use allocation of China. *Chinese Geographical Science*, 25(1): 62–73. doi: 10.1007/s11769-014-0708-z