Article

Hybrid Economic-Environment-Ecology Land Planning Model under Uncertainty—A Case Study in Mekong Delta

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Abstract: The research on land natural resources as the leading factor in the Mekong Delta (MD) is insufficient. Facing the fragile and sensitive ecological environment of MD, how to allocate limited land resources to different land use types to obtain more economic benefits is a challenge that local land managers need to face. Three uncertainties in land use system, interval uncertainty, fuzzy uncertainty, and random uncertainty, are fully considered and an interval probabilistic fuzzy land use allocation (IPF-LUA) model is proposed and applied to multiple planning periods for MD. IPF-LUA considers not only the crucial socio-economic factors (food security, output of wood products, etc.) but also the ecological/environmental constraints in agricultural production (COD discharge, BOD5 discharge, antibiotic consumption, etc.). Therefore, it can effectively reflect the interaction among different aspects of MD land use system. The degree of environmental subordination is between 0.51 and 0.73, the net benefit of land system is between USD 23.31×10^9 and USD 24.24×10^9 in period 1, and USD 25.44×10^9 to 25.68×10^9 in period 2. The results show that the IPF-LUA model can help the decision-makers weigh the economic and ecological benefits under different objectives and work out an optimized land use allocation scheme.

Keywords: land planning; uncertainty; interval probabilistic fuzzy; land use allocation; Mekong Delta

1. Introduction

Land use planning is a comprehensive economic and technical measure for the development, utilization, governance and protection of land resources in time and space according to the requirements of economic development in the future and regional development conditions. Its purpose is to promote sustainable land use. Among them, land use allocation (LUA) is the core content and key component of land use planning [1,2]. LUA has great significance under the background of a growing economy and population [3]. On the one hand, LUA is an effective means of ensuring the sustainable development of regional land resources [4–7]. LUA can not only maintain the coordinated development of the regional economy and ecological protection [2,8,9] but also provides a healthy and comfortable living environment for residents [10–12]. On the other hand, there must be conflicts of interest among farmers, developers, government, and other stakeholders. Thus, LUA faces the challenge of balancing the interests of all parties as much as possible [13–17]. A reasonable LUA can effectively alleviate the conflicts between cultivated land production and urban construction land, and coordinate the conflicts between economic development and ecological protection [18–20]. Therefore, in order to maximize the benefits of the land system, managers should take various factors into consideration and obtain as many economic and ecological benefits of the system as possible when they conduct LUA [21–23].

In the past decades, many models, which are mainly divided into four types, have been used to solve LUA problems. (1) mathematical programming models [7,24–29], like the following: Kumar et al. [24] established a mixed-integer linear programming (MILP) model, which can analyze various factors affecting land use and sprawl measures; Turk

and Zwick [27]. developed an inquired land assignment model (ILAM) which combines binary integer planning with the geographic information system (GIS); Medeiros et al. [7] used a multi-objective linear programming to analyze the environmental and economic benefits of forest land production systems, and optimized the LUA of forest land; (2) spatial optimization models [30–35], for example, Sante et al. [31] proposed a parallel simulated annealing algorithm for land use spatial allocation based on irregular spatial structure, which optimizes the allocation of land use classification on the cadastral parcel map; Rall et al. [33] proposed the consumption of public participation geographic information system (PPGIS) to urban green infrastructure (UGI) planning, which can support multifunctional assessment; Ramya and Devadas [34] built a geographic information system-multi-criteria decision making (GIS-MCDM) model, which considered natural resource conditions, labor, urban location and other cost factors into consideration to solve the problems of industrial land planning; (3) simulative prediction models [36–42], for example, Liu et al. [39] put forward a future land use simulation (FLUS) model with full consideration of various climatic and social-economic factors, which can be applied to simulate land use change in different scenarios in the future; Wang et al. [41] proposed a land use prediction model that integrates the geographic information system (GIS) and the artificial neural network (ANNs), which is conducive to improving the accuracy and timeliness of decision-makers in formulating LUA policies; Liang et al. [38] incorporated planning policies into the future land use simulation model (FLUS) based on cellular automata (CA) to accurately predict and explain the development trend of cities; Xu et al. [42] proposed an artificial neural network–cellular automata–Markov chain (ANN–CA–MC) model to analyze the limitation of the traditional CA-MC model, and verified that the result of this model of accurately simulating and forecasting urban expansion was better than that of other CA-MC coupled models; (4) intelligent algorithm models [3,43–47], for example, Masoomi et al. [3] used multi-objective particle swarm optimization algorithm considering multiple objectives and constraints and tried to optimize multiple objectives at the same time; Mi et al. [43] combined the advantages of the genetic algorithm (GA) with the ant colony algorithm (ACA) and put forward the genetic ant colony algorithm (GACA), which was applied to determine the optimal space use allocation of the limited development ecological zone (LDEZ); Li and Parrott [45] proposed an improved genetic algorithm (GA) for multi-site land use allocation that could meet the different management objectives of decision-makers; Huang and Song [47] developed the LUA model based on a multi-agent system— "Multi-agent shuffled frog leaping algorithm" (MASFLA), which can effectively solve the optimized allocation problems of spatial structure and quantity of regional land use under the conditions of multi-agent, multi-objective and multi-constraints.

We can see from existing models that researchers are constantly improving and developing the LUA model from single-objective programming to multi-objective programming, from developing a single structural or spatial optimization model to developing multiple model couplings of structural and spatial models. These models can effectively deal with the LUA problems, such as location, urban expansion in the process of urban and agricultural land use.

However, the above models still have some shortcomings: (1) The uncertainties in the land system should be more fully considered. There are many uncertain factors in the actual land use system, such as policy uncertainty: the government's development, construction, and investment in land are random; economic uncertainty: the demand for land with different uses is uncertain in the regional economic development; social uncertainty: the change of population, the demand for food increase and the uncertainty of land use allocation; environmental uncertainty: there is uncertainty in the change of climatic and hydrological conditions, which will have an uncertain impact on agricultural production and industrial construction, as well as the uncertain external environmental impacts of excessive consumption of water resources on the land use allocation structure; ecological uncertainty: wetlands, soil erosion and the consumption of chemical fertilizers will bring uncertain impacts to LUA [22,48–50]. These uncertain factors may greatly

affect the accuracy of the calculation results of the above-mentioned land use allocation models [22]; (2) in studying land use systems, the above models mainly consider policies and economic factors, and there is still a lack of consideration for some important ecological and environmental factors, including the consumption of chemical fertilizers in agricultural land, the discharge of waste-water and solid waste in construction land [46], etc. How to integrate the uncertain factors in many land systems, such as policy, economy, society, ecology, and environment into a more complete model system for comprehensive analysis will be the focus of this study.

In addition, most of the world's deltas have become major economic development zones of various regions due to their unique natural resource conditions. At the same time, in the process of land use, these regions have caused acute environmental problems, such as urban sewage and solid waste discharge, water quality decline, and climate change [51–54].

However, the current research on LUA in the Mekong Delta region is relatively few. Therefore, this study proposes an interval probabilistic fuzzy programming model to simulate the LUA of the MD. Compared with previous LUA models, this model has advantages as follows: (1) A systematic and scientific quantitative analysis is conducted by comprehensively considering various uncertain factors in the land use system. (2) The proposed model supplements and improves existing LUA models in terms of constraints and modeling methods. (3) This study will analyze land use issues of the MD, such as constraints on water product output from aquaculture land, COD and BOD5 emissions, and wood product output from forest land. MD's LUA is quantitatively analyzed by the IPF-LUA model, which provides a reliable basis for managers to make planning decisions. At the same time, it can also provide theoretical and technical support for managers in other countries of the world to solve LUA problems in the delta regions.

2. Study Area

The Mekong Delta (MD) is located in southwestern Vietnam from 8°33′ N~11°01′ N and 103°50′ E~106°50′ E (Figure 1). There are 13 provinces and cities in the region, with an area of over 40,500 km^2, covering part of southwestern Vietnam. With a population of about 21 million (2019) and a population density of 530 people/km^2, the MD is one of the most densely populated delta regions in the world. Based on the geographical and climatic characteristics of the MD and considering MD's development strategy and regional development planning, the study area is divided into three sub-zones (Figure 1): The deep-water flood disaster sub-zone, the central sub-zone, the coastal and island sub-zone. Deep-water flood disaster sub-zone: the main uses of the region are flood management and freshwater storage, freshwater aquaculture, and watershed establishment; central sub-zone: this is a shallow water area with favorable soil conditions, so it is mainly used for developing diversified and specialized agricultural production areas; coastal and island sub-zone: the coastal areas of the region are vulnerable to seawater erosion and used to shift conventional agricultural production and aquaculture towards sustainable woodland (mangrove) ecosystems and to build and develop a sustainable tourism and service center.

The MD benefits from natural geographical conditions: the terrain is flat, with rich water resources, fertile land, and a dense river network, turning the region into veritable a "land of fish and rice" from an almost uninhabited jungle. Moreover, the MD is the largest agricultural production center in Vietnam's agricultural land, accounting for 25% of the total agricultural land. Rice, aquaculture, and fruit accounts for 54%, 65%, and 70% of the country's total, respectively, with about 95% of rice and 60% of aquaculture exported. Furthermore, the MD is called a "biological treasure house", since thousands of creatures live there.
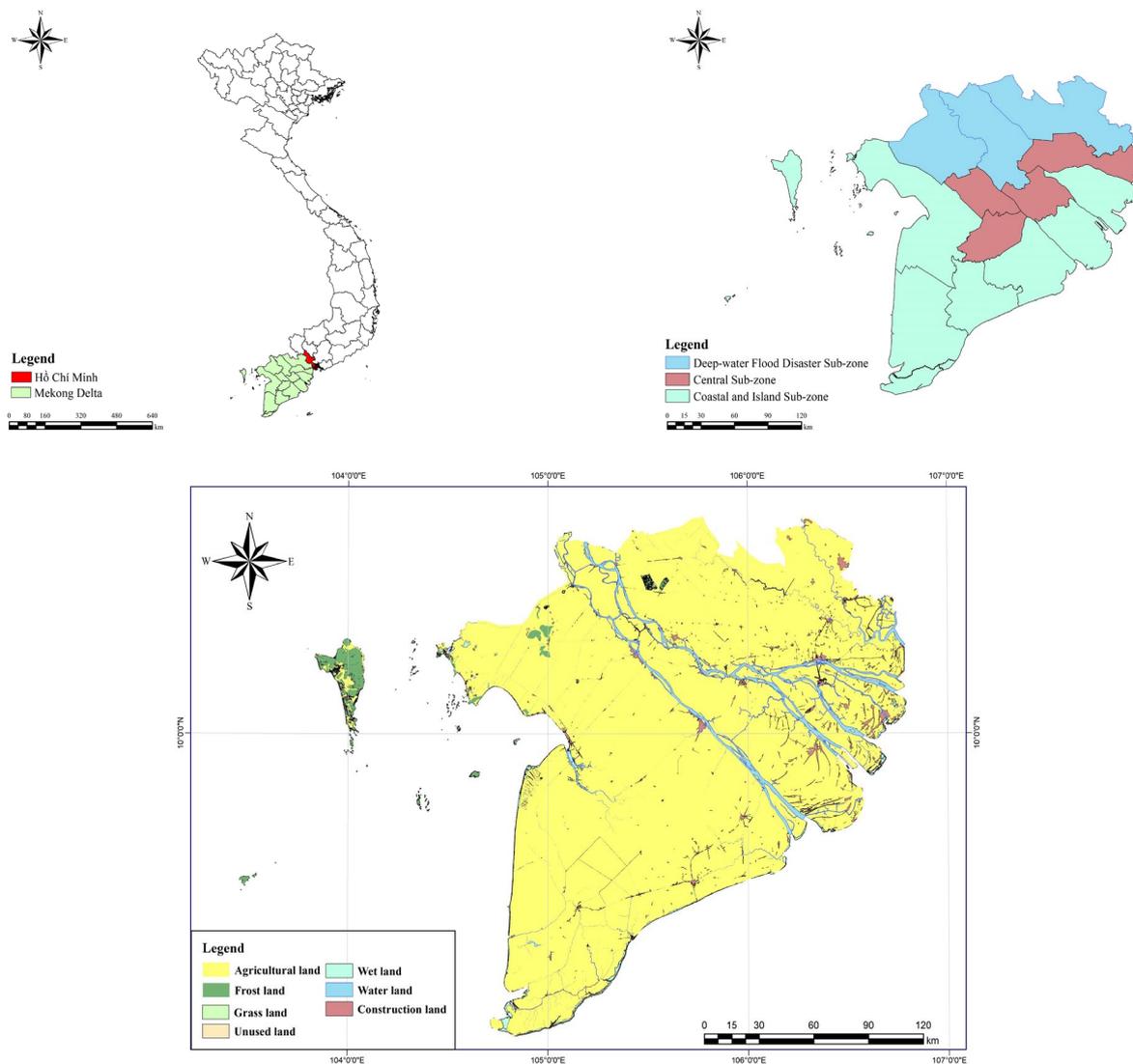
Figure 1. The study area.

However, the rapid pace of industrialization and urbanization has made MD's already sensitive natural conditions more fragile. According to the environmental management report of the MD provinces, enterprises in industrial zones and industrial clusters directly discharge about 220,000 tons of solid waste into the environment every year. Meanwhile, the amount of solid waste brought directly into rivers and canals day and night by livestock is about 22,500 tons. In recent years, while the agricultural land of the MD is estimated at 22,500 tons. In recent years, while the agricultural land of the MD has been reduced, the agricultural productivity has been steadily increasing, which is related to the use of a large quantity of pesticides, fertilizers, and aquaculture antibiotics. Relevant studies have shown that in the two largest rice-producing provinces of the MD, An Giang Province and Kien Giang Province, rice farmers used 20–30% more fertilizers than recommended. These behaviors are also one of the important causes for the deterioration of surface water quality in this region. These problems have led to the low level of ecological environment in the MD, threatening the life quality of the local people and the sustainable development of the region.

In summary, the regional characteristics of the MD can be summarized as follows: obvious advantages in agricultural economic development conditions, serious environmental pollutions, and ecological deterioration, which need to be solved urgently. The region needs effective land-use allocation plans to solve the problem. In view of the above

challenges, the corresponding land use allocation model will be proposed in the next part of this study.

3. IPF-LUA for MD

The land use system of the MD in the study area of this paper is defined as an uncertain system. Based on the factors analyzed by typical land use allocation system and taking the land use characteristics of the MD region into full consideration, this paper analyzes the following uncertain factors in the MD land use system: (1) Economic factors: MD's development requirements of agriculture, forestry, and fishery industries, such as grain and aquatic product demand, investment and other factors; (2) social factors: The development of the MD industry is affected by water supply and labor force, for example, agricultural water supply and labor force supply; (3) environmental factors: MD mainly focuses on agriculture, forestry, and fishery industries, accompanied by the production of sewage, solid waste, and other pollutants, such as wastewater, COD and BOD5 factors; (4) ecological factors: The biochemical substances used by farmers in the production process of MD paddy and aquaculture, such as antibiotics, pesticides and fertilizers. Based on the MD land use characteristics and the above factors, we applied this IPF-LUA model to land-use allocation in the MD which leads to an IPF-LUA (interval probabilistic fuzzy land-use allocation model).

3.1. Objective Function

The objective function is the net benefit from land-use system of the MD, and it equals all benefits from cultivated land, forest land, aquaculture land, and construction land minus cost from all types of land uses. Specifically, the benefits come from industries in the land use system. For example, the benefit of industries such as grain comes from cultivated land; the benefit of industries such as timber and furniture comes from forest land; the benefit of industries such as fish, shrimp, and aquatic products comes from aquaculture land; the benefit of industries such as coal, petroleum, and rubber come from construction land. Cost is from maintenance fees of all types of land uses. For example, we must provide cultivated land and aquaculture land with water; furthermore, these two land uses will generate wastewater and solid waste which are needed to handle. Based on the above settings, our objective function can be expressed as:

$$
\begin{aligned}
\text{MaxNBL}^{\pm} \cong{}& \sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{CLB}_{i,j=1,t}^{\pm}\times x_{i,j=1,t}^{\pm}\right)+\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{FLB}_{i,j=2,t}^{\pm}\times x_{i,j=2,t}^{\pm}\right)\\
&+\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{ALB}_{i,j=3,t}^{\pm}\times x_{i,j=3,t}^{\pm}\right)+\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{CLP}_{i,j=4,t}^{\pm}\times x_{i,j=4,t}^{\pm}\right)\\
&-\sum_{i=1}^{3}\sum_{t=1}^{2}\left[\left(\text{UWTC}_{i,j=1,t}^{\pm}+\text{USTC}_{i,j=1,t}^{\pm}\right)\times x_{i,j=1,t}^{\pm}\right]\\
&-\sum_{i=1}^{3}\sum_{t=1}^{2}\left[\left(\text{UWTC}_{i,j=3,t}^{\pm}\right)\times x_{i,j=3,t}^{\pm}\right]\\
&-\sum_{i=1}^{3}\sum_{t=1}^{2}\left[\left(\text{UWTC}_{i,j=4,t}^{\pm}+\text{USTC}_{i,j=4,t}^{\pm}\right)\times x_{i,j=4,t}^{\pm}\right]\\
&-\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{UWMC}_{i,j=5,t}^{\pm}\times x_{i,j=5,t}^{\pm}\right)\\
&-\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{UUDC}_{i,j=6,t}^{\pm}\times x_{i,j=6,t}^{\pm}\right)
\end{aligned}
$$

where NBL is objective function which means the net benefit from land-use system (USD); "$\pm$" = interval values; "@" = fuzzy equal; x is the decision variable; i represents the name of district, where $i = 1$ for Deep-water flood disaster sub-zone, $i = 2$ for central sub-zone, and $i = 3$ for coastal and island sub-zone; j represents type of land use, where $j = 1$ for cultivated land, $j = 2$ for forest land, $j = 3$ for aquaculture land, $j = 4$ for construction land, $j = 5$ for water land, $j = 6$ for unused land; t represents time of planning, where $t = 1$ for period 1 (2021), $t = 2$ for period 2 (2022); $\text{CLB}_{i,j=1,t}$ = unit benefit of cultivated land (USD/ha),

FLB$_{i,j=2,t}$ = unit benefit of forest land (USD/ha); ALB$_{i,j=3,t}$ = unit benefit of aquaculture land (USD/ha); CLP$_{i,j=4,t}$ = unit benefit of construction land (USD/ha); UWTC$_{i,t}$ = unit waste-water-tackling cost; USTCi,t = unit solid waste-tackling cost; UWMC$_{i,j=5,t}$ = unit maintenance costs of water land; UUDC$_{i,j=6,t}$ = unit developing costs of unused land.

3.2. Social-Economic Constraints

(i) Government investment constraints:

In the MD, all costs are paid by government investment, so the government investment constraints can be expressed as:

$$
\begin{aligned}
&\sum_{i=1}^{3} \sum_{t=1}^{2} \left[\left(\text{UWTC}_{i,j=1,t}^{\pm} + \text{USTC}_{i,j=1,t}^{\pm} \right) \times x_{i,j=1,t}^{\pm} \right] \\
&- \sum_{i=1}^{3} \sum_{t=1}^{2} \left[\left(\text{UWTC}_{i,j=3,t}^{\pm} \right) \times x_{i,j=3,t}^{\pm} \right] \\
&- \sum_{i=1}^{3} \sum_{t=1}^{2} \left[\left(\text{UWTC}_{i,j=4,t}^{\pm} + \text{USTC}_{i,j=4,t}^{\pm} \right) \times x_{i,j=4,t}^{\pm} \right] \\
&- \sum_{i=1}^{3} \sum_{t=1}^{2} \left(\text{UWMC}_{i,j=5,t}^{\pm} \times x_{i,j=5,t}^{\pm} \right) - \sum_{i=1}^{3} \sum_{t=1}^{2} \left(\text{UUDC}_{i,j=6,t}^{\pm} \times x_{i,j=6,t}^{\pm} \right) \lesssim \text{MGI}^{\pm}
\end{aligned}
$$

where MGI = maximum government investment (USD).

(ii) Grain input-output constraints:

In the MD, the core industry in food production is the main pillar of local economic development. In our model, the food supply is aimed at meeting the needs of both local residents and economic development (export of food products), food products are mainly produced by paddy cultivated land:

$$
\sum_{i=1}^{3} \sum_{t=1}^{2} \left(\text{UGP}_{i,t}^{\pm} \times x_{i,j=1,t}^{\pm} \right) \gtrsim \text{GD}^{\pm}
$$

where UGP$_{i,t}$ = unit grain production from cultivated land (ton/ha); GD = demand grain production (ton).

(iii) Water production input-output constraints:

In the MD, aquaculture is an important pillar of local economic development. Therefore, in this model, the supply of aquatic products should not only meet the living needs of local residents but meet the needs of economic development (export of aquatic products). Aquatic products are mainly produced by aquaculture land:

$$
\sum_{i=1}^{3} \sum_{t=1}^{2} \left(\text{UWP}_{i,t}^{\pm} \times x_{i,j=3,t}^{\pm} \right) \gtrsim \text{WD}^{\pm}
$$

where UWP$_{i,t}$ = unit water production from aquaculture land (ton/ha); WD = demand water production (ton).

(iv) Wooden production input-output constraints:

Vietnam is the largest exporter of wood and wood products in Southeast Asia. The wooden production industry not only brings economic benefits but provides a large number of jobs. Therefore, wooden production should meet the economic development needs of the MD:

$$
\sum_{i=1}^{3} \sum_{t=1}^{2} \left(\text{UWOP}_{i,t}^{\pm} \times x_{i,j=3,t}^{\pm} \right) \gtrsim \text{WOD}^{\pm}
$$

where UWOP$_{i,t}$ = unit wooden production from forest land (m^3/ha); WOD = demand wooden production (m^3).

(v) Agricultural water consumption constraints:

MD's main water sources are from the Mekong River Basin and rainfall; MD's 70% of regional water supply is used for agricultural production. Effective water supply has a decisive impact on MD's most important industry, food production, and aquaculture. Therefore, the total agricultural water consumption should not exceed the total regional agricultural water supply capacity:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{WCC}_{i,t}^{\pm}\times x_{i,j=1,t}^{\pm}\right) + \sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{WCA}_{i,t}^{\pm}\times x_{i,j=3,t}^{\pm}\right) \lesssim \text{RWSA}_{t}^{\pm}$$

where $\text{WCC}_{i,t}$ = Water consumption per unit of cultivated land (m^3/ha); $\text{WCA}_{i,t}$ = Water consumption per unit of aquaculture land (m^3/ha); RWSA_{t} = regional water supply planning for agriculture in the MD (ton).

(vi) Available labor constraints:

Similarly, all land industries require labor, however, available labor is limited in the MD:

$$\sum_{i=1}^{3}\sum_{j=1}^{6}\sum_{t=1}^{2}\left(\text{LC}_{i,t}^{\pm}\times x_{i,j,t}^{\pm}\right) \lesssim \text{AL}^{\pm}$$

where $\text{LC}_{i,t}$ = labor in a unit land area (person/ha); AL = available labor (person).

3.3. Environmental Constraints

(i)   BOD5 emissions constraints:

The intensive and industrialized aquaculture of the MD has brought rich aquatic benefits, but at the same time, it has also brought a large amount of aquatic wastewater, which contains BOD5, COD, and other substances. In order to ensure the continuous growth of the quality and quantity of MD fish, shrimp, and other aquatic products, the emissions of BOD5 in MD aquaculture wastewater should not exceed the emissions allowed by the MD environment:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{DB}_{i,t}^{\pm}\times x_{i,j=3,t}^{\pm}\right) \leq \text{MTDB}^{p}$$

where $\text{DB}_{i,t}$ = discharge amount of BOD5 for unit aquaculture land (ton/ha); MTDB = maximum total BOD5 discharge (ton); p = probability of violating the constraints of environmental capacities, and $p \in [0,1]$.

(ii) COD emissions constraints

Similarly, the discharge of COD in the MD aquaculture wastewater should not exceed the allowable discharge in the MD environment:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{DC}_{i,t}^{\pm}\times x_{i,j=3,t}^{\pm}\right) \leq \text{MTDC}^{p}$$

where $\text{DC}_{i,t}$ = discharge amount of COD for unit aquaculture land (ton/ha); MTDC = maximum total COD discharge (ton).

(iii) Wastewater treatment capacity constraints

In the model, the wastewater generated from aquaculture land and construction land should not exceed the wastewater treatment capacity of the MD:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{WDA}_{i,t}^{\pm}\times x_{i,j=3,t}^{\pm}\right) + \sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{WDB}_{i,t}^{\pm}\times x_{i,j=4,t}^{\pm}\right) \leq \text{WTPC}^{p}$$

where $\text{WDA}_{i,t}$ = wastewater discharging factor of aquaculture land (ton/ha); $\text{WDB}_{i,t}$ = wastewater discharging factor of construction land (ton/ha); WTPC = wastewater treatment capacity in the MD (ton).

(iv)   Solid-waste treatment capacity constraints

The discharge of solid waste should not exceed the solid waste treatment capacity of the MD:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{SDC}_{i,t}^{\pm} \times x_{i,j=1,t}^{\pm}\right) + \sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{SDB}_{i,t}^{\pm} \times x_{i,j=4,t}^{\pm}\right) \leq \text{STC}^{p}$$

where $\text{SDC}_{i,t}$ = solid-waste discharging factor of cultivated land (ton/ha); $\text{SDB}_{i,t}$ = solid-waste discharging factor of construction land (ton/ha); STC = solid-waste treatment capacity in the MD (ton).

3.4. Ecological Constraints

(i)   Antibiotic consumption constraints

In the past ten years, the MD has vigorously developed industrialized aquaculture and constructed a large amount of industrial aquaculture land. In the production process, the fishermen did not use antibiotics scientifically and reasonably, which led to the destruction of the ecosystem. The extensive use of antibiotics pollutes the water land of the MD and has a toxic effect on most aquatic organisms. Therefore, the consumption of antibiotics should not exceed the maximum consumption amount:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{AC}_{i,t}^{\pm} \times x_{i,j=3,t}^{\pm}\right) \leq \text{MAC}^{p}$$

where $\text{AC}_{i,t}$ = antibiotics consumption for unit aquaculture land (ton/ha); MAC = maximum antibiotics consumption (ton).

(ii)   Fertilizer consumption constraints

Due to the favorable natural conditions of the MD, its crops such as rice are planted twice or three times a year, which makes farmers need to continuously apply fertilizers to maintain and improve the soil quality as much as possible. However, the use of large amounts of fertilizers will seriously damage MD's fragile environment. Therefore, the consumption of fertilizers should not exceed the maximum consumption amount:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{FC}_{i,t}^{\pm} \times x_{i,j=1,t}^{\pm}\right) \leq \text{MFC}^{p}$$

where $\text{FC}_{i,t}$ = fertilizer consumption for unit cultivated land (ton/ha); MFC = maximum fertilizer consumption (ton).

(iii)   Pesticide consumption constraints

Similarly, the pesticide consumption in cultivated land should not exceed the maximum consumption amount:

$$\sum_{i=1}^{3}\sum_{t=1}^{2}\left(\text{PC}_{i,t}^{\pm} \times x_{i,j=1,t}^{\pm}\right) \leq \text{MPC}^{p}$$

where $\text{PC}_{i,t}$ = pesticide consumption for unit cultivated land (ton/ha); MPC = maximum pesticide consumption (ton).

3.5. Technical Constrains

(i) Total land areas constraints:

$$\sum_{i=1}^{3}\sum_{j=1}^{6}\sum_{t=1}^{2} x_{i,j,t}^{\pm} = \text{TLA}_{i,j,t}^{\pm}$$

where TLA is total land areas constrain in period t.

(ii) Non-negative constraints:

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

3.6. Data Collection

The parameters of the IPF-LUA model include four types: beneficial and cost parameters (Table 1); economic and social parameters (Table 2); environmental and ecological parameters (Table 3). Beneficial and cost parameters can be obtained from land evaluation. Economic and social parameters can be obtained through index forecasting models. Environmental and ecological parameters can be obtained through stochastic models.

Table 1. Benefits and cost for different land-use types (USD/ha).

Land-Use Type	Symbol	Period			
		$t = 1$		$t = 2$	
		Lower	Upper	Lower	Upper
Benefits of land use	$\text{CLB}_{i=1,j=1}\ (10^3)$	4.74	6.42	4.89	6.61
	$\text{CLB}_{i=2,j=1}\ (10^3)$	3.69	4.99	3.80	5.14
	$\text{CLB}_{i=3,j=1}\ (10^3)$	2.87	3.88	2.95	3.99
	$\text{FLB}_{i=1,j=2}\ (10^3)$	3.02	4.09	3.12	4.21
	$\text{FLB}_{i=2,j=2}\ (10^3)$	6.76	9.15	6.96	9.42
	$\text{FLB}_{i=3,j=2}\ (10^3)$	2.16	2.93	2.23	3.01
	$\text{ALB}_{i=1,j=3}\ (10^3)$	9.83	13.30	10.13	13.70
	$\text{ALB}_{i=2,j=3}\ (10^3)$	10.73	14.51	11.05	14.95
	$\text{ALB}_{i=3,j=3}\ (10^3)$	8.94	12.10	9.21	12.46
	$\text{CLP}_{i=1,j=4}\ (10^3)$	14.85	20.09	15.89	21.50
	$\text{CLP}_{i=2,j=4}\ (10^3)$	25.68	34.75	27.48	37.18
	$\text{CLP}_{i=3,j=4}\ (10^3)$	12.70	17.19	13.59	18.39
Costs of land use	$\text{UWTC}_{i=1,j=1}$	0.76	1.14	0.93	1.29
	$\text{USTC}_{i=1,j=1}$	95.71	103.05	104.03	117.25
	$\text{UWTC}_{i=1,j=3}$	1.02	1.51	1.24	1.71
	$\text{UWTC}_{i=1,j=4}$	77.68	83.99	86.00	93.81
	$\text{USTC}_{i=1,j=4}$	707.60	747.47	877.03	956.76
	$\text{UWMC}_{i=1,j=5}$	398.65	428.55	508.28	538.18
	$\text{UUDC}_{i=1,j=6}$	847.13	896.96	976.69	1245.78

3.7. Model Solving

According to the algorithm of the IPF-LUA model which is introduced in Appendix A, the IPF-LUA model can be transformed into two definite sub-models, which correspond to the upper and lower limits of the expected objective function values at different p levels. Then, we can calculate these two linear models in Lingo 12 software. The framework of the IPF-LUA model is shown in Figure 2.

Table 2. Economic, social, environmental, and technical parameters.

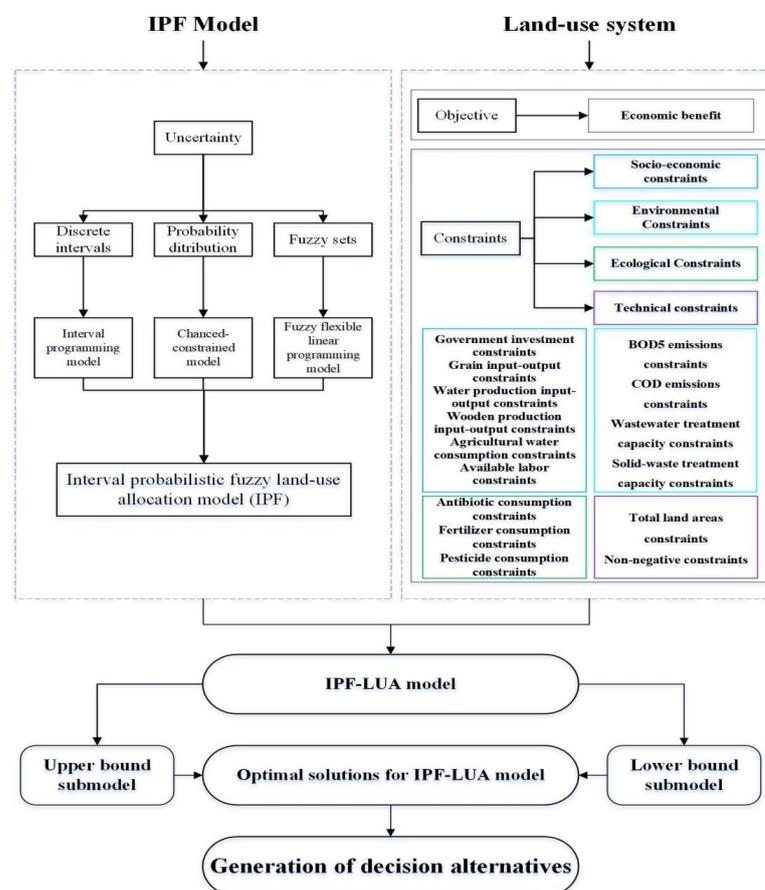| Symbol	Period			
	$t = 1$		$t = 2$	
	Lower	Upper	Lower	Upper
MGI_t (10^6USD)	23.9	32.3	28.0	37.8
$UGP_{i=1}$ (ton/ha)	9.84	13.32	9.76	13.20
GD (10^6ton)	1.50	2.03	1.51	2.05
$UWP_{i=1}$ (ton/ha)	57.54	77.84	59.14	80.02
WD (10^3ton)	494.52	669.05	499.46	675.74
$UWOP_{i=1}$ (m^3/ha)	4.70	6.36	4.68	6.34
WOD ($10^3 m^3$)	872.78	1180.82	898.96	1216.25
$WCC_{i=1}$ (10^3/ha)	1.79	2.42	1.89	2.56
$WCA_{i=1}$ ($10^3 m^3$/ha)	8.50	11.50	9.01	12.19
RWSA ($10^9 m^3$)	0.45	0.61	0.48	0.65
$LC_{i=1}$ (people/ha)	2.29	3.09	2.29	3.09
AL (10^6people)	8.65	11.71	8.64	11.69
$DB_{i=1,j=3}$ (ton/ha)	0.23	0.31	0.24	0.33
$DC_{i=1,j=3}$ (ton/ha)	0.41	0.56	0.43	0.59
$WDA_{i=1,j=3}$ (10^3ton/ha)	5.15	6.97	5.41	7.32
$WDB_{i=1,j=4}$ (10^3ton/ha)	0.14	0.19	0.15	0.20
$SDC_{i=1,j=1}$ (ton/ha)	9.86	13.34	9.73	13.16
$SDB_{i=1,j=4}$ (ton/ha)	8.14	11.01	8.95	12.11
$AC_{i=1}$ (kg/ha)	13.02	17.62	13.28	17.97
$FC_{i=1}$ (kg/ha)	663.00	897.00	595.00	805.00
$PC_{i=1}$ (kg/ha)	5.60	7.60	5.10	6.90

Figure 2. Framework of the IPF-LUA model.

Table 3. Eco-environmental capacity under different *p* levels.

Symbol	Period							
	t = 1				*t* = 2			
	p = 0.01	*p* = 0.05	*p* = 0.10	*p* = 0.15	*p* = 0.01	*p* = 0.05	*p* = 0.10	*p* = 0.15
MTDB (10^3 ton)	296.92	304.72	314.48	324.24	306.76	314.96	325.21	335.45
MTDC (10^3 ton)	365.03	379.50	397.59	415.67	383.28	398.47	417.47	436.46
WTPC (10^9 ton)	4.90	5.09	5.33	5.58	5.14	5.35	5.60	5.86
STPC (10^6 ton)	4.52	4.70	4.92	5.15	4.97	5.17	5.42	5.66
MAC (10^3 ton)	8.04	8.36	8.76	9.16	8.20	8.53	8.93	9.34
MFC (10^6 ton)	2.06	2.14	2.24	2.34	2.06	2.14	2.24	2.34
MPC (10^3 ton)	174.42	181.33	189.93	198.52	174.56	181.47	190.06	198.78

4. Result and Discussion

4.1. Optimized Land-Use Patterns under Different p Levels during Two Periods

Figures 3–5 present the optimization solutions to land allocation for decision variables obtained through the IPF-LUA model under different *p* levels. The results show that any change of *p* will result in different environmental capacity which leads to different LUA modes. At the same time, in the land use system, economic development, environmental and ecological changes, and pollutant emissions will also lead to different LUA modes. In the case of excess waste, allotments to forest land for environmental protection should be assigned firstly and then to construction land, while allotments to cultivated land, aquaculture land, and unused land are mainly due to policy constraints. Analysis of the modeling solutions is provided below.
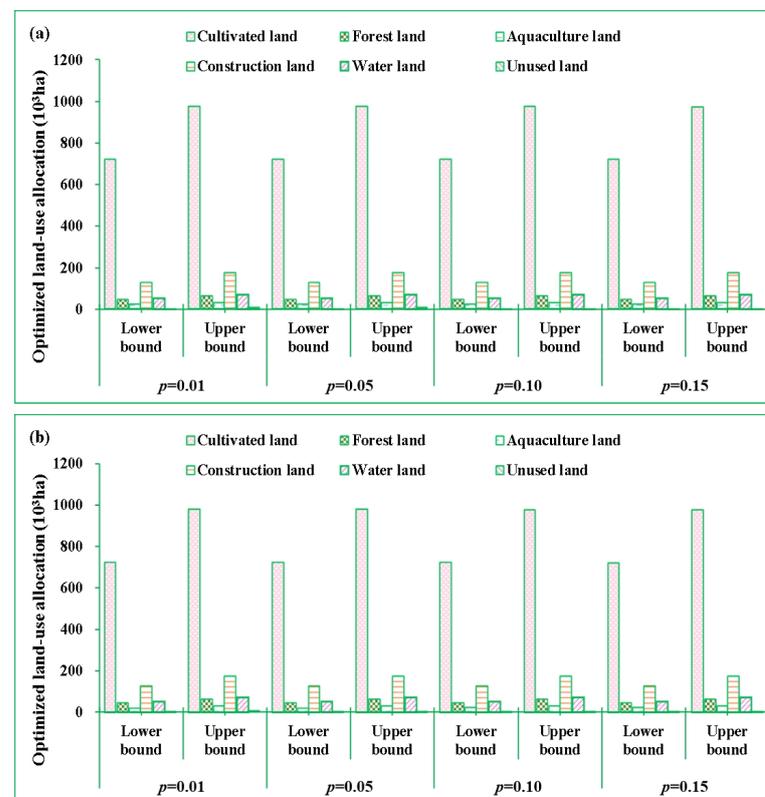

Figure 3. (**a**) *t* = 2021 and (**b**) *t* = 2022 Optimized land-use allocation in the Deep-water flood disaster sub-zone under *p*-levels during two periods.

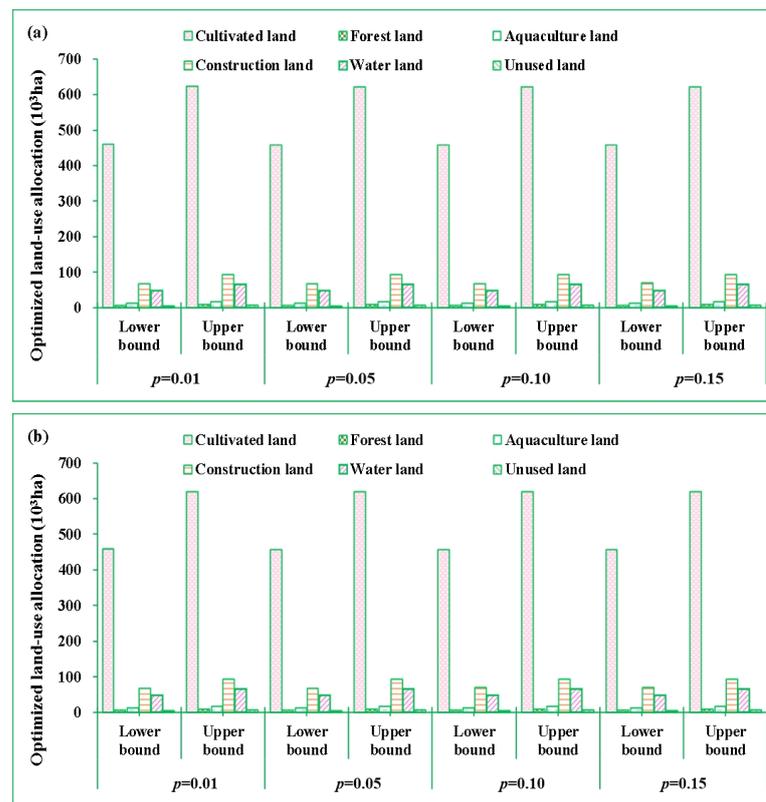**Figure 4.** (**a**) *t* = 2021 and (**b**) *t* = 2022 optimized land-use allocation in the central sub-zone under different *p*-levels during two periods.
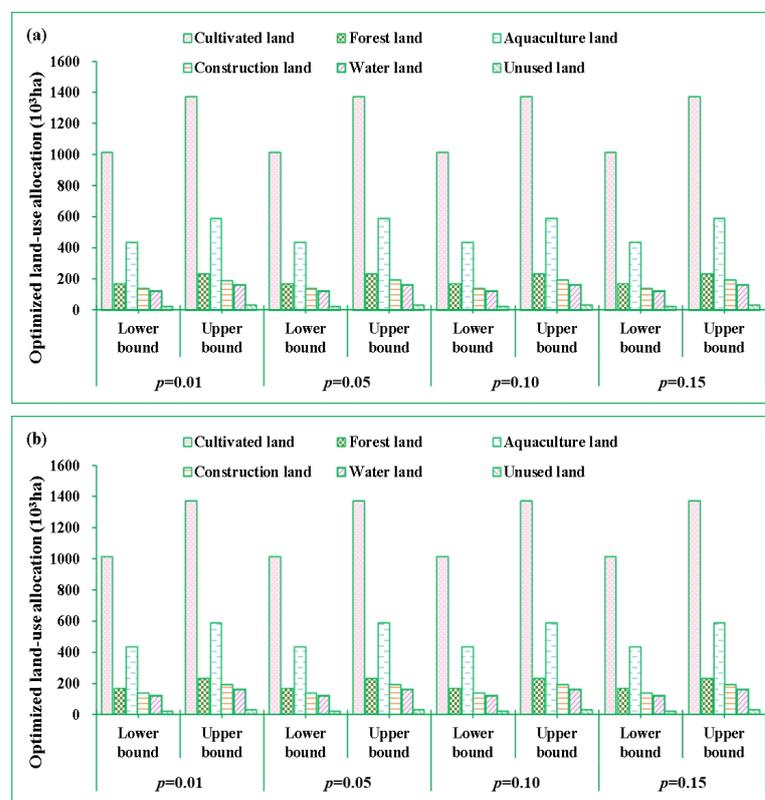

Figure 5. (**a**) *t* = 2021 and (**b**) *t* = 2022 optimized land-use allocation in the coastal and island sub-zone under different *p*-levels during two periods.

The optimized allocation in the deep-water flood disaster sub-zone under varied risk levels of violating environmental capacity constraints during two periods is presented in Figure 3 and Table 4. We can clearly see that in period 1, with the increase of p-value, the area of forest land, aquaculture land and construction land in the deep-water flood disaster sub-zone also increased. The p-level indicates the probability of environmental/ecological constraints being violated. When the p-value increases, the probability of violating environmental/ecological constraints will increase, but at the same time, the environmental/ecological capacity will expand. Therefore, the IPF-LUA model tends to allocate more land types with economic benefits, such as forest land, aquaculture land, and construction land. Based on this, in general, the cultivated land should also increase, but in the overall development plan of the MD, the cultivated land will turn to fruit planting and aquaculture. This feature of MD's regional development has been considered in the constraints of the IPF-LUA model. Therefore, in the land optimization results of the MD, the cultivated land area will be slightly decreased. This also shows that the IPF-LUA model has the characteristics of adjusting measures to local conditions. Compared with period 2, under the situation that MD's development planning policy remains unchanged, there is no obvious change in the way of land allocation in the deep-water flood disaster sub-zone. The agricultural industry represented by cultivated land is the regional leading industry of the MD. The model is based on MD's macro-policy planning. First, it is in order to meet the local people's food demand and food export plan. Second, it is constrained by MD's economic development requirements and natural ecological/environmental conditions. Cultivated land should be transferred to land types with more economic benefits, such as fruit, forest, and aquaculture land, to develop diversified agricultural industries. As a result, the cultivated land area continued to decrease, while the forest, aquaculture, and construction land area continued to increase.

Table 4. Optimized land-use allocation in the deep-water flood disaster sub-zone under different p-levels during two periods.

Variable		x (j = 1)	x (j = 2)	x (j = 3)	x (j = 4)	x (j = 5)	x (j = 6)
	p = 0.01	[721,709, 976,430]	[44,985, 60,862]	[20,594, 27,862]	[127,872, 173,003]	[49,930, 67,552]	[899, 1216]
t = 1	p = 0.05	[721,114, 975,625]	[45,155, 61,092]	[20,849, 28,207]	[128,042, 173,233]	[50,015, 67,667]	[814, 1101]
	p = 0.10	[720,604, 974,935]	[45,325, 61,322]	[21,104, 28,552]	[128,212, 173,463]	[50,100, 67,782]	[729, 986]
	p = 0.15	[720,179, 974,360]	[45,495, 61,552]	[21,274, 28,782]	[128,297, 173578]	[50,185, 67,897]	[644, 871]
	p = 0.01	[721,284, 975,855]	[45,070, 60,977]	[20,764, 28,092]	[128,042, 173,233]	[50,015, 67,667]	[814, 1101]
t = 2	p = 0.05	[720,774, 975,165]	[45,240, 61,207]	[21,019, 28,437]	[128,127, 173,348]	[50,100, 67,782]	[729, 986]
	p = 0.10	[720,349, 974,590]	[45,410, 61,437]	[21,189, 28,667]	[128,297, 173,578]	[50,185, 67,897]	[644, 871]
	p = 0.15	[719,924, 974,015]	[45,580, 61,667]	[21,359, 28,897]	[128,382, 173,693]	[50,270, 68,012]	[559, 756]

The optimized allocation in the other two sub-zone under various p levels during two periods is presented in Figures 4 and 5. Figure 4 indicates that in the central sub-zone, the area of cultivated land and unused land decreases with the p-level and the area of other land types will decrease. Unlike the other two sub-zones affected by floods and coastal environment, the central sub-zone is less affected by adverse natural conditions. Therefore, the area of cultivated land in the region has diverted more towards other agricultural lands, aquaculture land and construction land, with a slight increase in forest land. Generally speaking, the area less restricted by adverse natural environmental conditions should allocate more land to the land types with higher economic benefits, and the central sub-zone should be allocated to construction land first, followed by aquaculture land. However, according to the development advantages and natural characteristics of the region, the model shows some constraints. For example, according to the construction land and labor population density, the labor force constraint is put forward; according to the characteristics of pollutant discharge during aquaculture, COD and BOD5 discharge constraints are established, along with other constraints. These constraints cause the model to fail when simply increasing the area of high-benefit land types in the process of land allocation.

For example, the benefits of construction land are higher than that of aquaculture land and other agricultural land. However, based on the above conditions, the area of other agricultural land and aquaculture land increases more than that of construction land in the central sub-zone. In Figure 5, the land allocation pattern of the coastal and island sub-zone is similar to that of the deep-water flood disaster sub-zone.

However, we can see that the aquaculture area in the three districts has increased more. The coastal and island sub-zone is close to the ocean, which is vulnerable to natural disasters such as coastal landslides. However, at the same time, the sub-zone is rich in water resources and has the largest woodland area in the entire MD. Considering these factors, the model allocates more land to aquaculture land and less land to forest land and construction land.

The optimization results in Figures 3–5 also show the interval solution generated by the IPF-LUA model. The interval solution can provide an effective scheme for regional land use allocation. For example, in the central sub-zone, combining the lower bound for cultivated land, construction land and aquaculture land with the upper bound for forest land, unused land and water land corresponds to lower land system economic benefits. However, this combined allocation pattern can meet the needs of people's lives and ensure a high-quality ecological environment. It is a trade-off between economic benefits and the quality of the ecological environment and is a relatively conservative land use management strategy. When the upper bound of cultivated land, construction land, and aquaculture land are combined with the lower bound of forest land, unused land, and water land, a higher economic benefit of the land system can be achieved. This kind of combined allocation pattern can obtain as many economic benefits as possible. At the same time, it also means that the probability of ecological and environmental damage increased. It represents a more radical economic strategy. The optimization results of the model provide a system benefit interval solution in the planning scheme. For example, when $p = 0.01$, the land system benefit of the whole MD is USD $[20.8, 28.1] \times 10^9$ in period 1. The net benefits of the land system in this region range from USD 20.8×10^9 to USD 28.1×10^9, which means that the actual net profits brought by different land use planning patterns change in the upper and lower bound. Generally speaking, the allocation with lower system benefits has a lower risk of violating system constraints, and this region has higher ecological environment quality.

4.2. Optimized Ecological/Environmental Pollutant Discharge and Eco-Environmental Policy Analysis under Different p Value Levels

Figures 6 and 7 show the BOD5 discharge and aquaculture antibiotic consumption after IPF-LUA optimization. The lower bound of BOD5 discharge and antibiotic consumption correspond to lower system benefits, but maintain a higher level of eco-environmental quality, implying a more conservative environmental protection strategy. The values of BOD5 and antibiotics increase correspondingly when the manager wants to obtain more net benefits from the system. For the whole system, the risks of water pollution and unhealthy aquatic products increase.

4.3. Trade-Off between Economic Objective and Eco-Environmental Constraints

The *p*-value level represents the probability of violating ecological/environmental capacity. Figures 6 and 7 also reflect that different levels of pollutants (such as BOD5 and antibiotics) will be produced under different *p*-values, thus the land system will produce different levels of economic benefits. For example, in period 1, when $p = 0.05$, the net profit of the land system is USD $[20.78, 28.11] \times 10^9$. In contrast, when $p = 0.15$, the net profit of the land system is USD $[20.82, 28.16] \times 10^9$. Obviously, the area of the land type that brings higher economic benefits will increase with an increase in the *p*-value. An increase in the value of the violation probability p means that the model tends to have a more relaxed environmental capacity. Based on this, the model will allocate more land area to the land with higher net profits. Accordingly, the area of land with low profits or costs will be

reduced. Figure 8 shows the relationship between violation probability *p* and economic profits of the land system.

4.4. Trade-Off between System Benefit and Membership λ and Constraints

Through calculation, the value of optimized membership λ is [0.51,0.73]. The value of membership λ represents the membership satisfying all objective functions and constraints. As shown in Figure 9, when λ value increases, the system profit increases corresponding to more aggressive land use policies, and each constraint condition of the model is more relaxed. When the value of λ decreases, the profit of the system decreases, and each constraint condition of the model is stricter corresponding to the more conservative land use policies. The value of λ represents the compromise between the objective function of the land system and all constraints and reflects the relationship between economic benefits and social benefits, ecological benefits, and environmental benefits. Through calculation, the value of optimized membership λ is [0.51,0.77]. The value of membership λ represents the membership satisfying all objective functions and constraints. As shown in Figure 9, when λ value increases, the system profit increases corresponding to more aggressive land use policies, and each constraint condition of the model is more relaxed. When the value of λ decreases, the profit of the system decreases, and each constraint condition of the model is stricter corresponding to the more conservative land use policies. The value of λ represents the compromise between the objective function of the land system and all constraints and reflects the relationship between economic benefits and social benefits, ecological benefits, and environmental benefits. For example, more water resources, more fertilizers, and antibiotics correspond to a larger λ, thus generating more systematic economic benefits, as shown in Figure 10.
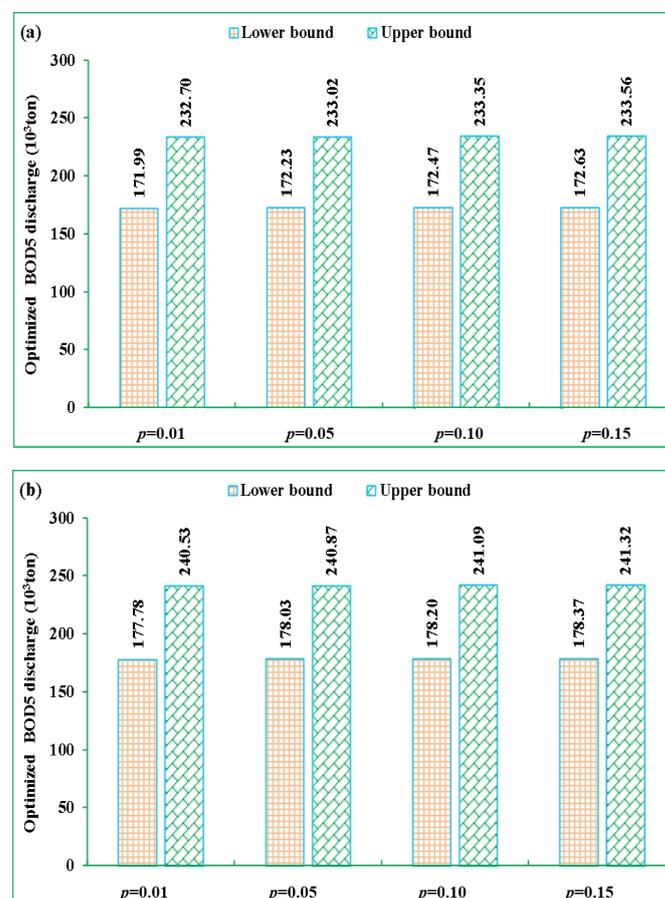

Figure 6. (**a**) *t* = 2021 and (**b**) *t* = 2022 relationship between *p* and optimized BOD5 discharge in MD during two periods.
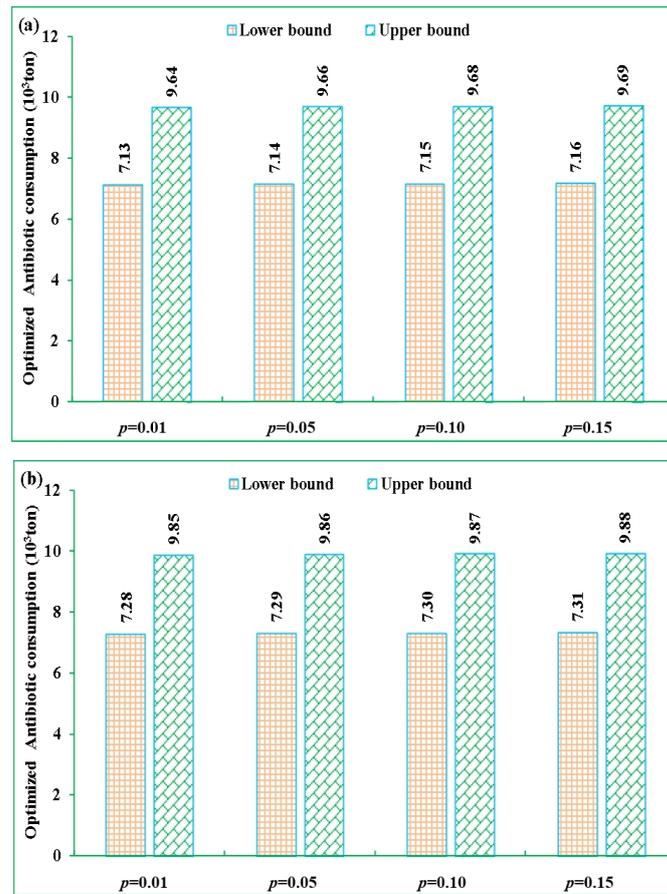
Figure 7. (**a**) *t* = 2021 and (**b**) *t* = 2022 relationship between *p* and optimized Antibiotic consumption in MD during two periods.
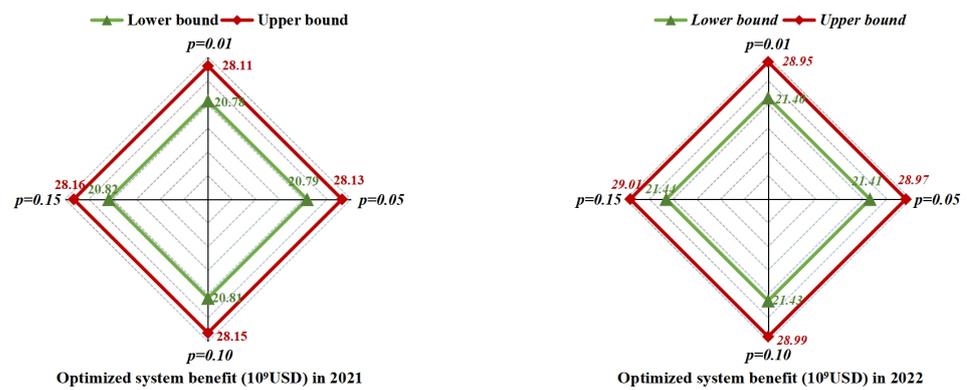

Figure 8. Relationship between *p* and optimized system benefit in MD during two periods.
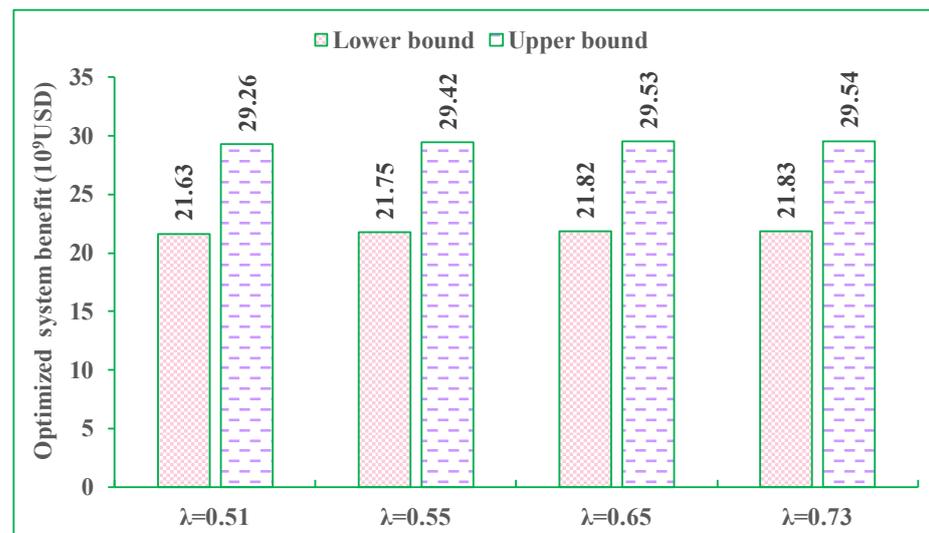
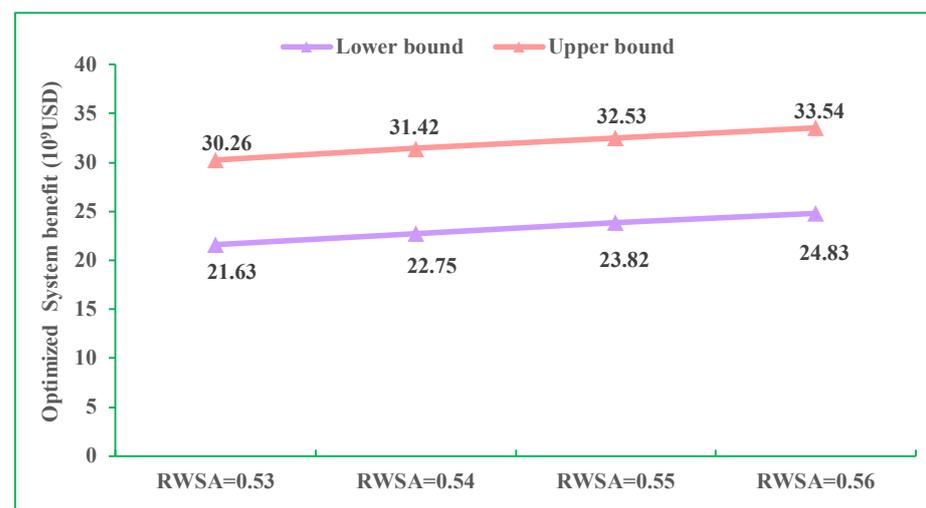**Figure 9.** Relationship between λ and optimized system benefit.

Figure 10. Relationship between regional water supply planning and optimized system benefit.

5. Conclusions

In this paper, the interval probabilistic fuzzy land-use allocation model (IPF-LUA) based on uncertainty is proposed and applied to the Mekong River Delta. The existing studies in this region mainly focus on water resources, and few studies focus on land. At the same time, the ecological environment of the MD is extremely fragile and sensitive. The IPF-LUA model proposed in this paper establishes a reasonable land use optimization model by combining interval parametric programming, probabilistic programming, and fuzzy linear programming, and fully considering the ecological and environmental factors of the MD. This method can help decision-makers to analyze the relationship among economic, ecological, and environmental benefits. By dismantling the model, calculating the upper and lower expectations, and choosing different land allocation methods, the decision-makers can keep the balance between economic and ecological benefits. The IPF-LUA model can solve the problem of allocation of land use quantity structure in an LUA: by analyzing the current land use situation, development conditions and objectives of the research area, and fully considering the uncertain factors in the regional land use system, the objective function and constraint conditions are constructed to make the optimization results more flexible. Moreover, combining the quantitative structure optimization results of IPF-LUA with the LUCC simulation model or spatial layout optimization model can

simultaneously provide support and help for land use planning from both quantitative structure and spatial layout.

This method has been applied to the LUA case study in the MD of Vietnam. The results of four different *p*-value scenarios in two planning periods show the quantitative relationship between economic benefits and the ecological environment. It provides decision-makers with a variety of planning schemes that give priority to economic benefits or conservation of the ecological environment. Collectively, the results show an optimization method that compromises the economic benefits of land system and ecological environment management.

The IPF-LUA model in this paper can effectively tackle the optimization problem in LUA. The results of model optimization would be more rational if other key ecological and environmental data, as well as stakeholder-related data, were available. In addition, the model has limitations: IPF-LUA is a method to optimize the quantitative structure of land use, which focuses on the optimization of the quantitative structure, but fails to provide help for land use planning in the aspect of spatial layout optimization. At the same time, the optimization of land use quantity structure in LUA is not only a linear programming problem, but also a nonlinear programming problem which is not considered in this study. Therefore, our next work is to couple IPF-LUA with the land use spatial layout optimization model and build a coupling model that can solve both quantitative and spatial optimization, so as to solve the more complex LUA optimization problem in reality. In addition, there are a large number of uncertain factors in the land use system. We will consider and design more constraints, such as climate change and policy constraints, to further improve the IPF-LUA model and make it more perfect.

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Appendix A

Introduction of the ICCF (interval chance-constrained fuzzy) model [48,55]:

$$Max f^{\pm} \cong C^{\pm} x^{\pm} \tag{A1}$$

Subject to:

$$C^{\pm} x^{\pm} \gtrsim b_{opt}^{\pm} \tag{A2}$$

$$A_i^{\pm} x^{\pm} \lesssim b_i^{\pm} \quad i = 1, 2, \ldots, m, i \neq s \tag{A3}$$

$$A_s^{\pm} x^{\pm} \lesssim b_s^{(p_s)} \quad s = 1, 2, \ldots, m, s \neq i \tag{A4}$$

where x is an $n \times 1$ alternative set; C is a $1 \times n$ coefficient of an objective function; A_i is an $m \times n$ matrix of coefficients of constraints and b_i is an $m \times 1$ matrix (right-hand sides, RHS). "$\pm$" express intervals; "$\cong$" represents fuzzy equality; "$\gtrsim$" and "$\lesssim$" represent fuzzy inequality. p_s denotes the probability that the constraints s are violated. $b_s^{(p_s)}$ represent

corresponding values given the cumulative distribution function of bs and the probability of violating constraint s (p_s).

On the basis of the principle of fuzzy flexible programming, let $l^{\pm}$ value corresponds to the membership grade of satisfaction for a fuzzy decision. Specifically, the flexibility in the constraints and fuzziness in the system objective, which are represented by fuzzy sets and denoted as "fuzzy constraints" and "fuzzy goal", are expressed as membership grades $l^{\pm}$ corresponding to the degrees of overall satisfaction for the constraints/objective. Thus, above model can be converted to:

$$Max \ l^{\pm} \tag{A5}$$

Subject to:

$$C^{\pm}x^{\pm} \lesssim f_{opt}^- + (1 - l^{\pm})(f_{opt}^+ - f_{opt}^-) \tag{A6}$$

$$A_i^{\pm}x^{\pm} \leq b_i^- + (1 - l^{\pm})(b_i^+ - b_i^-) \quad i = 1, 2, \dots, m, i \neq s \tag{A7}$$

$$A_s^{\pm}x^{\pm} \lesssim b_s^{(p_s)} \quad s = 1, 2, \dots, m, s \neq i \tag{A8}$$

$$x^{\pm} \geq 0 \tag{A9}$$

$$0 \leq l^{\pm} \leq 1 \tag{A10}$$

where f_{opt}^+ and f_{opt}^- denote the upper and lower bounds of the objective's aspiration level as designated by decision-makers; $l^{\pm}$ denotes the control decision variable corresponding to the degree (membership grade) to which $x^{\pm}$ solution fulfills the fuzzy objective or constraints. Model (A5) can be solved through a two-step method where a sub-model corresponding to l^- is first formulated and solved. In the second step, the other sub-model corresponding to l^+ can then be formulated supported by the solution of the first submodel. If $b_i^+ \geq 0$ and $f_i^+ \geq 0$, the sub-model corresponding to l^- can be formulated as follows:

$$Max \qquad l^- \tag{A11}$$

Subject to:

$$\sum_{j=1}^{k_1} C_j^+ x_j^+ + \sum_{j=k_1+1}^{n} C_j^+ x_j^- \leq f_{opt}^- + (1 - l^{\pm})(f_{opt}^+ - f_{opt}^-) \tag{A12}$$

$$\sum_{j=1}^{k_1} |a_{ij}|^- sign(a_{ij}^-)x_j^+ + \sum_{j=k_1+1}^{n} |a_{ij}|^+ sign(a_{ij}^+)x_j^- \leq b_i^- + (1 - l^-)(b_i^+ - b_i^-), \forall i \tag{A13}$$

$$\sum_{j=1}^{k_1} |a_{sj}|^- sign(a_{sj}^-)x_j^+ + \sum_{j=k_1+1}^{n} |a_{sj}|^+ sign(a_{sj}^+)x_j^- \leq b_s^{p_s}, \forall s, s \neq i \tag{A14}$$

$$x_j^- \geq 0, j = 1, 2, \dots, k_1 \tag{A15}$$

$$x_j^+ \geq 0, j = k_1 + 1, k_2 + 2, \dots, n \tag{A16}$$

$$0 \leq l^{\pm} \leq 1 \tag{A17}$$

where Sign is a signal function, which is defined as:

$$sign(x^{\pm}) = \left\{ \begin{array}{l} 1, \text{ if } x^{\pm} \geq 0 \\ -1, \text{ if } x^{\pm} \leq 0 \end{array} \right\}$$

Let x_{jopt}^+ ($j = 1, 2, \dots, k_1$) and x_{jopt}^- ($j = k_1 + 1, k_2 + 2, \dots, n$) be solutions of sub-model (3). Then, the second sub-model corresponding to l^+ can be formulated supported by the solution of sub-model (A18):

$$Max \qquad l^+ \tag{A18}$$

Subject to:

$$\sum_{j=1}^{k_1} C_j^- x_j^- + \sum_{j=k_1+1}^{n} C_j^- x_j^+ \leq f_{opt}^- + (1 - l^{\pm})(f_{opt}^+ - f_{opt}^-) \tag{A19}$$

$$\sum_{j=1}^{k_1} \left|a_{ij}\right|^+ sign(a_{ij}^+)x_j^- + \sum_{j=k_1+1}^{n} \left|a_{ij}\right|^- sign(a_{ij}^-)x_j^+ \leq b_i^- + (1 - l^+)(b_i^+ - b_i^-), \ \forall i \tag{A20}$$

$$\sum_{j=1}^{k_1} \left|a_{sj}\right|^+ sign(a_{sj}^+)x_j^- + \sum_{j=k_1+1}^{n} \left|a_{sj}\right|^- sign(a_{sj}^-)x_j^+ \leq b_s^{p_s}, \ \forall s, \ s \neq i \tag{A21}$$

$$x_{jopt}^+ \geq x_j^- \geq 0, \ j = 1, 2, \ldots, k_1 \tag{A22}$$

$$x_j^+ \geq x_{jopt'}^-, \ j = k_1 + 1, k_2 + 2, \ldots, n \tag{A23}$$

$$0 \leq l^{\pm} \leq 1 \tag{A24}$$

Let x_{jopt}^- $(j = 1, 2, \ldots, k_1)$ and x_{jopt}^+ $(j = k_1 + 1, k_2 + 2, \ldots, n)$ be solutions of sub-model (4). Thus, we can obtain the interval solutions as follows:

$$l_{opt}^{\pm} = \left[l_{opt}^-, l_{opt}^+\right] \tag{A25}$$

$$x_{jopt}^{\pm} = \left[x_{jopt}^-, x_{jopt}^+\right], \forall j \tag{A26}$$

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

$$f_{opt'}^- \sum_{j=1}^{k_1} C_j^- x_j^- + \sum_{j=k_1+1}^{n} C_j^- x_j^+ \tag{A27}$$

$$f_{opt'}^- \sum_{j=1}^{k_1} C_j^+ x_j^+ + \sum_{j=k_1+1}^{n} C_j^+ x_j^- \tag{A28}$$

Thus, we have:

$$f_{jopt}^{\pm} = \left[f_{jopt'}^-, f_{jopt}^+\right], \forall j \tag{A29}$$

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