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# Multi-stage stochastic fuzzy random programming for food-water-energy nexus management under uncertainties

Ling Ji[a,*], Beibei Zhang[a], Guohe Huang[b], Yan Lu[c]

[a] Research Base of Beijing Modern Manufacturing Development, College of Economics and Management, Beijing University of Technology, Beijing, 100124, China
[b] Environmental Systems Engineering Program, Faculty of Engineering, University of Regina, Regina, Sask., S4S 0A2, Canada
[c] State Grid Jibei Electric Economic Research Institute, Beijing, 100045, China

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ABSTRACT

A hybrid inexact optimization model is developed for food-water-energy nexus system management with the consideration of complex uncertainties and decision makers' risk tolerance. A multi-stage stochastic fuzzy random programming (MSFRP) model is tailored to tackle variables with deeper uncertainties, a mixture of fuzzy and random fuzzy characteristics. Allowing to reflect decision makers' subjective opinion and risk preference, it can provide decision makers the tradeoff information between system benefit and risk attitude. The proposed model was applied to an agricultural area Shandong Province, China with the aim of maximum total system benefits. The valuable managerial insights on optimal cultivated land distribution, water resource allocation, and energy supply strategies are provided for decision makers under uncertainties. Meanwhile, the pesticide and fertilizer consumption for crop planting, and the carbon emission embodied in per unit crop supply are also quantitatively estimated. Moreover, by setting different water resource availability scenarios, the impacts of future water resource conditions on optimal management strategies under climate change are evaluated and discussed. The results suggested that rice would be the critical crop with the largest planting area for food security during the planning horizon. Under scarcer water resource conditions, the system benefits would reduce due to more desalination water consumption and planting strategy adjustment. However, it would lead to less carbon emission embodied in per unit crop supply and relieve local carbon emission control pressure. Compared to the conventional multi-stage stochastic programming, the developed MSFRP can be more effective to reflect the optimistic and pessimistic attitude of decision makers and deal with future scenario information with deeper uncertainties.

## 1. Introduction

Food, energy, and water resources are the basic necessaries for human survival and development. Due to climate change, population growth, and urbanization process, the sustainable development of human society faces enormous pressure from food safety, energy security, and water resource protection (Zhang et al., 2019a,b; Arthur et al., 2019). However, there are close and complex relationships among food-water-energy (FWE), which brings great challenges for policymakers to achieve sustainable goals. For example, food production requires sufficient irrigation; electricity is consumed in the collection, treatment, and transmission of irrigation water, and food processing; electricity generation also requires water withdrawals and consumption for cooling purpose (Ren et al., 2018; Zhang et al., 2018). Management on a single subsystem in an isolated way would lead to conflicts among different objectives and low efficiency. Therefore, integrated planning and management from the FWE nexus perspective is desired to formulate water resource allocation, energy consumption, and cultivated land use in a joint and efficient way.

Recently, a number of studies on FWE nexus have been carried out from different perspectives. Among them, a range of recent research have focused on building an integrated analytical framework of FWE nexus, quantifying the impacts of climate change and policies, and revealing the correlations and feedback mechanism among them (Salmoral and Yan, 2018; Nair et al., 2014), with wide practical application at different scales from global (Sušnik, 2018), national (Xiao et al., 2019), river basin (Basheer et al., 2018), region (Mroue et al., 2019; Lin et al., 2019), to city (Sherwood et al., 2017). Furthermore,

*Abbreviations:* FEW, food-water-energy; MFSP, multi-stage fuzzy stochastic programming; MSFRP, multi-stage stochastic fuzzy random programming; MSP, multi-stage stochastic programming; LAM, lower approximation model; UAM, upper approximation model

* Corresponding author at: School of Economics and Management, Beijing University of Technology, 100 Ping Le Yuan, Chaoyang District, Beijing, 100124, China.
*E-mail addresses:* hdjiling@126.com (L. Ji), zhangbb@emails.bjut.edu (B. Zhang), gordon.huang@uregina.ca (G. Huang), hdluyan@163.com (Y. Lu).

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efforts have also been made in the simulation and optimization methodologies of the FWE nexus system (Hang et al., 2016; Bergendahl et al., 2018; Khan et al., 2018). Due to various components and conflicts among economic, social, natural resources, and ecological environment, optimization for the FWE nexus system is even more complex under such an integrated framework than a simple subsystem. Various optimization models of FWE nexus have been conducted for different goals, such as water security, food safety, minimizing system cost, maximizing annual net incomes, and maximizing actual crop yield (Karan et al., 2018; Mortada et al., 2018; Zhang et al., 2018; Si et al., 2019; Zeng et al., 2019a). In addition, in a real FWE nexus system, decision makers have to face numbers of uncertainties caused by variations of natural conditions, social-economic environment, and internal relationships, such as fluctuations of water resource availability (flood or drought), variations of crop yield, changes in land use, improvement in power generation technologies, and agriculture irrigation types (Ethan Yang and Wi, 2018; Hussien et al., 2018; Walsh et al., 2018). These uncertain factors in the FWE nexus system would bring more risk in achieving optimal objectives and make considerable more complicated in decision-making. So far, there are few studies focusing on dealing with uncertainties in optimizing decision making for the FWE nexus system (Li et al., 2019; Zeng et al., 2019b).

Although few studies on FWE nexus management under uncertainties have been proposed, uncertain optimization methods have been extensively studied in energy system planning (Ji et al., 2018), water resources management (Chen et al., 2019), and many other fields (Tan et al., 2017). Various methods have been developed to handle uncertainties with various characteristics, such as stochastic mathematical programming (Simic, 2016), fuzzy mathematical programming (Yu et al., 2019), interval-parameter programming (Xie et al., 2018a), robust optimization (Ji et al., 2014), and hybrid inexact programming approaches (Xie et al., 2018b). Among them, multi-stage stochastic fuzzy random programming (MSFRP) is an effective tool for decision making under the integrated framework of multistage stochastic programming and fuzzy theory (Abdelazi and Masri, 2009; Zahiri et al., 2017). Inherent to the advantages of multi-stage stochastic programming (MSP), MSFRP could model the future uncertain information through a multi-layer scenario tree, and permit revised decisions at each time stage with future sequential realized uncertain events, which makes the decision-making process more flexible (Guan and Philpott, 2011). In addition, in traditional stochastic programming, the probability of scenarios is usually determined based on prediction model and special expertise, and described as deterministic value, which is relatively subjective and may change over the planning horizon (Vafa Arani and Torabi, 2018). By incorporating fuzzy theory, MSFRP can address deeper uncertainties with incomplete and imprecise information, and reflect the risk attitude of decision makers.

Therefore, under the framework of the MSFRP approach, the aim of this study is to develop a comprehensive agricultural food production management model from a food-water-energy nexus perspective under uncertainty. The FWE nexus concept adopted in this work mainly refers to the irrigation water for crop production, energy requirements for irrigation water supply and treatment, energy used in crop production activities. The main contributions of this study can be expressed as follows:

(a) A hybrid uncertain optimization model with the consideration of decision maker's risk attitude is proposed for FWE nexus management under uncertainties.
(b) The proposed MSFRP model can handle uncertainties with different information accuracy and subjective risk attitude by expressing them as probability and possibility distribution. Meanwhile, it also can guarantee the robustness and reliability of decision making and avoid system risk violations under a certain confidence level.
(c) The developed model is applied to a practical application of a comprehensive agricultural issue with FWE nexus in Shandong Province, China, which can provide reasonable allocation strategies on water resources supply and land use with the purpose of maximizing system profits, ensuring food security, as well as allowing decision makers to choose their own risk tolerance and risk preference.
(d) The impacts of fluctuating water resource conditions caused by climate change on optimal strategies are estimated to provide more managerial insight under uncertainties. Besides, the carbon emission embodied in crop production is quantitatively assessed for environmental concern.

The rest of this paper is organized as follows. The overview of the case study is described in Section 2. Model development with the mathematical formulation and main assumptions are presented in Section 3. The important results and discussion are provided in Section 4. The main conclusions are drawn in Section 5.

## 2. Overview of the study area

Shandong Province (34°22.9′-38°24.01′N, 114°47.5′-122°42.3′E) is located on the eastern coast of China and belongs to the lower reaches of the Yellow River. Shandong Province has the second-largest population (98.47 million), which still keeps increasing with a 0.58 % annual population growth rate. Such a massive population leads to numerous food demand and natural resource consumption. Meanwhile, it is one of the important agriculture production provinces in China. Shandong Province contributes 7.57 % of the total grain production with 1.63 % of land area, 6.17 % of cultivated land, and 0.54 % of water resources in the country (Shandong Statistical Bureau, 2016). The main food crops include cereals (*i.e.* rice, wheat, and corn), beans, and potatoes. In recent years, with the variation in the natural conditions, adjustment in national grain production policies, and fluctuation in food demand at home and abroad, the planting structure in Shandong Province is constantly changing. Especially, the proportion of wheat and corn keeps increasing and accounted for 92.52 % of the total production in 2014. Sustainable development of the agricultural sector requires greater water consumption, and water resources demand was $14.33 \times 10^9\,m^3$ in 2015, which was about 67.34 % of the total water consumption (Shandong Statistical Bureau, 2016).

However, in fact, Shandong Province faces a serious water crisis. The annual average water resource is only $30.00 \times 10^9\,m^3$, and the water resource per capita is $334\,m^3$, less than 1/6 of the national average. Regional water resources are mainly dependent on atmospheric precipitation, and the average precipitation in recent years is 680 mm, with more than 61 % of annual precipitation concentrated in summer (Shandong Statistical Bureau, 2016). In 2015, the total water supply amount in Shandong Province was $21.28 \times 10^9\,m^3$, where water resources from surface water source were $12.20 \times 10^9\,m^3$, and $8.31 \times 10^9\,m^3$ were from groundwater. As a big agricultural province, more than 67 % of the total water resources were consumed by the agricultural sector, and the local water resource in 2015 was only $16.84 \times 10^9\,m^3$, which could not satisfy the total water demand (Shandong Water Resources Department, 2016).

In the future, population increase and economy development will exacerbate its water shortage problems and lead to serious ecological degradation. Besides, the possible large variations in precipitation and extreme situations in runoff would bring great uncertainties in water resource supply, and become the main restriction and threat for social development. Meanwhile, due to advanced agricultural machinery, high-efficiency fertilization, and new food processing techniques, the energy demand and greenhouse gas emission associated with modern agriculture sector will also be considered in achieving sustainable development. Therefore, efficient agricultural management with the consideration of the interaction among crop planting, water, and energy resources under uncertainties to guarantee food security and alleviate the resource conflicts is of great importance for local decision

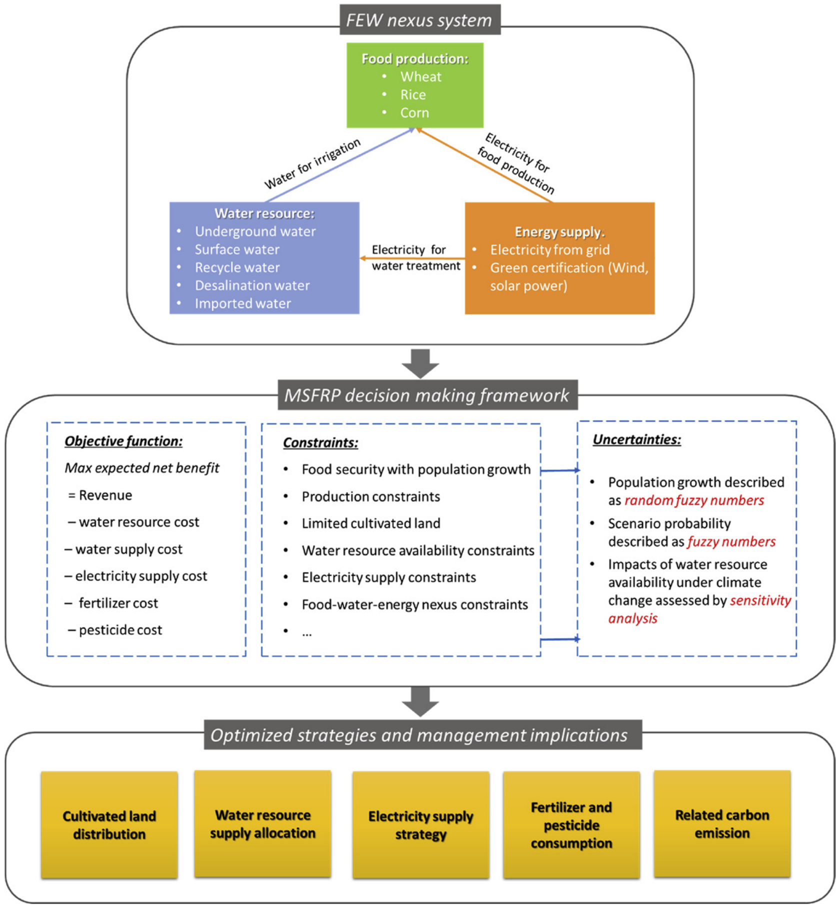


**Fig. 1.** Framework of a hybrid food-water-energy nexus management model with MSFRP method.

makers.

## 3. Model development

### 3.1. Modeling formulation

Fig. 1 presents the framework of a hybrid FWE nexus management model with the MSFRP method. In this study, the system boundary of FWE nexus only focuses on irrigation water and energy consumption for food production, and electricity for irrigation water treatment. The main purpose of the FWE nexus system is to maximize the economic benefits from food production under the constraints imposed by food security with population growth, limited cultivated land, and water resource, and the complex relationships among different subsystems. Meanwhile, the uncertainties in the nexus system are considered and addressed by the MSFRP method (the detail methodology seen in SI). In specific, the uncertain population growth estimated by decision makers can be addressed as fuzzy random numbers and its scenario probability with subjective judgment expressed as fuzzy numbers. The impacts of water resource availability under climate change are assessed by sensitivity analysis. The hybrid optimization model could provide the optimal strategies for cultivated land planning, water resource allocation, and electricity supply strategies with the consideration of different risk preferences of decision makers. In addition, the associated fertilizer and pesticide consumption, and carbon emission for optimal solutions could also be evaluated.

In the agricultural system, the system profit is the primary concern of decision makers, and the revenues are the benefit of food production, which can be calculated as crop yield multiply market price. The total costs mainly include the resource and supply cost of irrigation water, the cost of electricity used in food production and irrigation water processing, the cost of fertilizers and pesticides for food production. The objective function of system profit can be expressed as:

$$\max f = \sum_s \tilde{p}_s \cdot \Bigg( \sum_m \sum_t MP_{m,t} FP_{m,t,s} - \sum_i \sum_t WSR_{i,t} \cdot WS_{i,t,s} - \sum_i \sum_t WSC_{i,t} \cdot WS_{i,t,s} - \sum_t TF_t \cdot EP_{t,s} - \sum_j \sum_t GEC_{j,t} \cdot GEP_{j,t,s} - \sum_m \sum_t FC_t \cdot FA_{m,t} \cdot AVL_{m,t,s} - \sum_m \sum_t PC_t \cdot PA_{m,t} \cdot AVL_{m,t,s} \Bigg) \tag{1a}$$

where, $t$ is the index for the planning period ($t$ = 1, 2). $i$ denotes the types of water source (1 for underground water, 2 for surface water, 3 for recycle water, 4 for desalination water, 5 for imported water). $j$ is the index for renewable energy generation (1 for wind, 2 for solar). $m$ represents the type of crops (1 for wheat, 2 for rice, 3 for corn). $\tilde{p}_s$ is the probability of scenario $s$ (1 for low, 2 for medium, 3 for high) and expressed as the triangular fuzzy number ($p_s^l$, $p_s^m$, $p_s^u$). $MP_{m,t}$ represents the market price of crop $m$ (\$/kg). $FP_{m,t,s}$ is the production of crop $m$ in period $t$ (kg). $WSR_{i,t}$ and $WSC_{i,t}$ are the water resource cost and treatment cost (\$/ton), respectively. $WS_{i,t}$ is the amount of water supply (m$^3$). $TF_t$ is the electricity tariff (\$/MWh). $EP_t$ represents electricity supply from traditional thermal power generation (MWh). $GEP_{j,t}$ and $GEC_{j,t}$ are the power consumption amount (MWh) and electricity price (\$/MWh) of purchased green certificates. $FC_t$ and $PC_t$ denote the cost of fertilizer and pesticide utilization per unit area (\$/m$^2$). $FA_{m,t}$ and $PA_{m,t}$ denote the amount of fertilizer and pesticide utilization per unit area for crop $m$ (kg/m$^2$). $AVL_{m,t,s}$ represents the cultivated area of crop $m$ (m$^2$).

The constraints of the food-water-energy nexus optimization model can be divided into constraints from food, water, and energy three subsystems. The constraints can be expressed as follows:

### 3.1.1. Food system

*3.1.1.1. Food balance constraint.* The crop yield should satisfy local basic food requirements to guarantee food security. The local basic food requirement is estimated as the product of per capita food demand standard and population.

$$\sum_m FP_{m,t,s} \geq FD \cdot \tilde{\tilde{P}}_{t,s}, \forall\ t,\ s \tag{1b}$$

where, $FD$ is per capital food demand standard (kg per capital), $\tilde{\tilde{P}}_{t,s}$ denotes the number of population in planning horizon, which is expressed as fuzzy random number.

*3.1.1.2. Production constraints.* The available cultivated area and yield rate are the main factors impact the production of a certain crop. According to the prevailing cropping practice, the lower and upper limits of cultivated area for different crops should be considered to ensure local food requirement diversity. In addition, the sum of cultivated area for different crops is restricted by the total available cultivated area.

$$FP_{m,t,s} \leq AVL_{m,t,s} \cdot PR_{m,t}, \forall\ m,\ t,\ s \tag{1c}$$

$$AVL_{m,t}^{\min} \leq AVL_{m,t,s} \leq AVL_{m,t}^{\max}, \forall\ m,\ t,\ s \tag{1d}$$

$$\sum_m AVL_{m,t,s} \leq TAVL_t, \forall\ t,\ s \tag{1e}$$

where, $PR_{m,t}$ is the crop yield per unit area (ton/m$^2$); $AVL_{m,t}^{\min}$ and $AVL_{m,t}^{\max}$ are the minimum and maximum cultivated area for crop $m$ (m$^2$), and $TAVL_t$ represents the total arable land area (m$^2$).

### 3.1.2. Water system

*3.1.2.1. Water balance.* Sufficient total water supply from various sources, including traditional (*i.e.* underground water, surface water) and unconventional (*i.e.* recycle water, desalination, and imported water) water resources, are required to guarantee crop growth.

$$\sum_m IWR_{m,t} \cdot FP_{m,t,s} \leq \sum_i WS_{i,t,s}, \forall\ t,\ s \tag{1f}$$

where, $i$ represents the type of water (1 for underground water, 2 for surface water, 3 for recycle water, 4 for desalination, 5 for imported water), and $IWR_{m,t}$ denotes the irrigation water requirements for crop $m$ (m$^3$/ton).

*3.1.2.2. Water resource availability constraints.* The water resource supply should not exceed the maximum available amount.

$$WS_{i,t,s} \leq AVW_{i,t}, \forall\ i,\ t,\ s \tag{1 g}$$

where, $AVW_{i,t}$ represents the available amount of water resource $i$ during period $t$ (m$^3$).

### 3.1.3. Energy system

*3.1.3.1. Electricity balance.* In this study, electricity consumption associated with food production mainly consists of two parts, that is, electricity consumption in crop production and water treatment process. Except for fossil power generation, green certificates are also encouraged to be considered as electricity supply to facilitate renewable energy generation and realize carbon emission mitigation.

$$\sum_m FER_{m,t} \cdot FP_{m,t,s} + \sum_i WER_{i,t} \cdot WS_{i,t,s} \leq (1-\beta)(P_{t,s} + \sum_j GEP_{j,t,s}), \forall\ t,\ s \tag{1 h}$$

where, $\beta$ is the loss factor, $FER_{m,t}$ and $WER_{i,t}$ denote the power requirement for per unit crop irrigation (MWh/ton) and water treatment and delivery (MWh/ton), respectively.

*3.1.3.2. Electricity consumption constraints.* The clean energy from green certificates is encouraged to make sure minimum renewable energy penetration. Besides, the green certificates of wind power and solar should not be larger than the allowable quantity.

$$\sum_j GEP_{j,t,s}/(P_{t,s} + \sum_j GEP_{j,t,s}) \geq \theta, \forall\ t,\ s \tag{1i}$$

$$GEP_{j,t,s} \leq AVGEP_{j,t}, \forall\ j,\ t,\ s \tag{1j}$$

where, $\theta$ represents the minimum percentage of renewable energy generation. $AVGEP_{j,t}$ is the maximum available tradable green certificates (MWh).

The above MSFRP model could be transferred into two deterministic linear submodels (Seen in SI.).

In addition, $CO_2$ emission in the food-water-energy nexus system is also measured to evaluate the environmental impacts. $CO_2$ emissions associated with food production are mainly generated from fossil power generation, fertilizer and pesticide utilization, which is formulated as:

$$TCE = \sum_m CEE_t \cdot EP_{t,s} + CEF_t \cdot FA_{m,t} \cdot VAL_{m,t,s} + CEP_t \cdot PA_{m,t} \cdot VAL_{m,t,s} \tag{2}$$

where, $CEE_t$ is the carbon emission coefficient of electricity (kg $CO_2$/kWh); $CEF_t$ is the carbon emission coefficient of fertilizer utilization (kg $CO_2$/kg); $CEP_t$ is the carbon emission coefficient of pesticide utilization (kg $CO_2$/kg).

## 3.2. Data collection and the main assumption

The whole planning horizon covers 10 years (2016–2025), which can be divided into two planning periods with 5 years for each period. In the comprehensive system with food-water-energy nexus, there are many parameters associated with food production, agricultural irrigation, cultivated area, and electricity consumption. These data for this case study are mainly collected from statistic yearbooks (Shandong Statistical Bureau, 2016), local development planning reports (Shandong Development and Reform Commission, 2016; Shandong Government, 2016), and relevant literatures (Su et al., 2014; Wang et al., 2017; Li et al., 2017, 2019; Dong et al., 2019), where some main technical and economic parameters are listed in Table 1. According to historical data and planning reports, future population with great uncertainty can be captured by possibility theory and expressed as there levels (*e.g.* low, medium, and high level). The uncertain population increase trend is estimated relying on subjective opinions and experts' knowledge through deeply analyzing of economy development, urbanization, ecological conditions, and policy. Thus, the forecasted population is assumed to be imprecise and formulated as a possibility distribution in the form of triangle fuzzy numbers. Fig. 2 presents the forecasted population with associated occurrence probabilities for each planning period.

Since water resource is a significant factor for crop growth and easily affected by climate change, the impacts of water resource availability on the objective value and optimal solutions would also be analyzed. Three scenarios with different water resource conditions are designed and described as following:

- Base: the normal water resource condition;
- W1: the available water resource amount is 10 % less than that in the Base scenario;
- W2: the available water resource amount is 20 % less than that in the Base scenario.

**Table 1**
Main economic and technical parameters in the case study.

***Food subsystem*** (Su, et al., 2014; Shandong Statistical Bureau, 2016; F. Zhang et al., 2019)

| Crop types | Irrigation requirement ($m^3$/ton) | | Fertilization consumption (ton/$km^2$) | | Pesticide consumption (ton/$km^2$) | |
|---|---|---|---|---|---|---|
| | $t$ = 1 | $t$ = 2 | $t$ = 1 | $t$ = 2 | $t$ = 1 | $t$ = 2 |
| Wheat | 388 | 388 | 19.8 | 19.5 | 0.0510 | 0.0500 |
| Rice | 732 | 732 | 31.6 | 30.0 | 0.1097 | 0.0960 |
| Corn | 116 | 116 | 22.5 | 21.5 | 0.0540 | 0.0520 |

| Crop types | Market price ($/ton) | | Maximum cultivated area ($km^2$) | | Minimum cultivated area ($km^2$) | |
|---|---|---|---|---|---|---|
| | $t$ = 1 | $t$ = 2 | $t$ = 1 | $t$ = 2 | $t$ = 1 | $t$ = 2 |
| Wheat | 360 | 380 | 220,000 | 200,000 | 112,500 | 116,700 |
| Rice | 450 | 470 | 7,500 | 6,600 | 4,150 | 3,850 |
| Corn | 330 | 350 | 195,000 | 190,000 | 102,500 | 100,500 |

***Water resource subsystem*** (Shandong Water Resources Department, 2016; Li, et al., 2017)

| Water sources | Maximum availability ($10^6$ $m^3$) | | Water supply cost ($/$10^3$ $m^3$) | | Water resource cost ($/$10^3$ $m^3$) | |
|---|---|---|---|---|---|---|
| | $t$ = 1 | $t$ = 2 | $t$ = 1 | $t$ = 2 | $t$ = 1 | $t$ = 2 |
| Underground water | 19,310.40 | 18,115.20 | 18.0 | 20.0 | 5.25 | 5.85 |
| Surface water | 13,906.80 | 12,585.60 | 13.5 | 14.6 | 4.15 | 4.75 |
| Recycle water | 1,929.60 | 2,563.20 | 8.0 | 7.0 | 4.11 | 4.50 |
| desalination water | 14,234.40 | 16,113.60 | 17.0 | 16.0 | 1.95 | 2.15 |
| Imported water | 17,586.00 | 16,394.40 | 16.2 | 15.6 | 2.49 | 2.70 |

Energy subsystem (China National Energy Administration, 2019)

| Types of renewable energy | Price of green certification ($/MWh) | | Maximum available amount (GWh) | |
|---|---|---|---|---|
| | t = 1 | t = 2 | t = 1 | t = 2 |
| Wind | 31.77 | 18.76 | 600 | 1000 |
| Solar | 86.58 | 73.50 | 320 | 500 |

| | Electricity price ($/MWh) | | Emission factor (ton/MWh) | |
|---|---|---|---|---|
| | t = 1 | t = 2 | t = 1 | t = 2 |
| Electricity from grid | 37.8 | 34.5 | 1.010 | 0.976 |

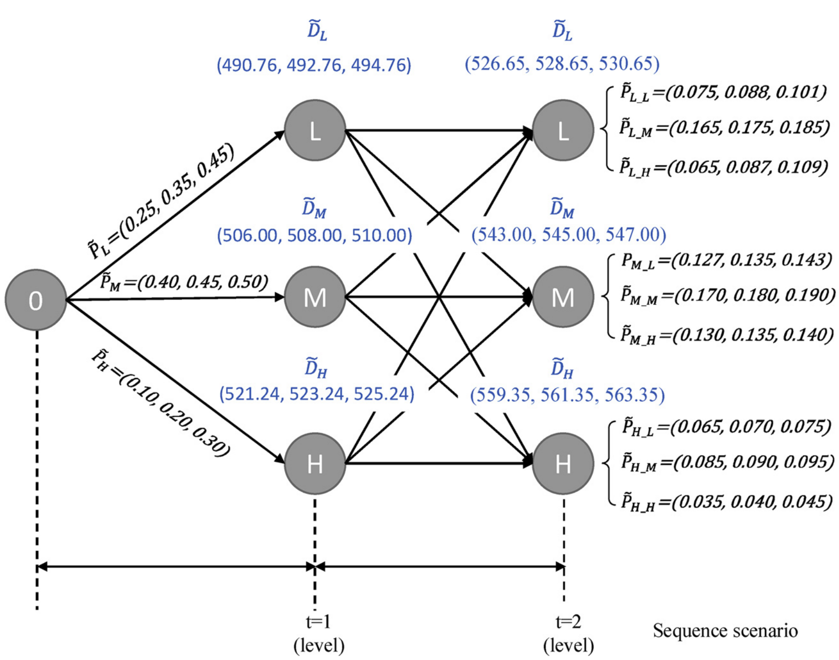


**Fig. 2.** Forecasted population with associated occurrence probabilities for each planning period.

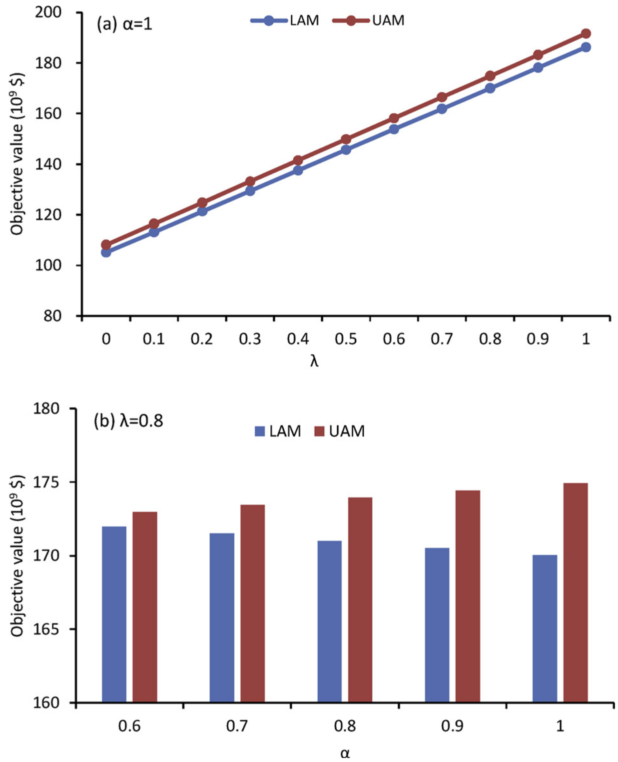


**Fig. 3.** Optimal objective value under different λ and α values.

## 4. Result analysis

### 4.1. Optimal objective value

Since α and λ are two critical parameters of the proposed MSFRP model to reflect the subjective risk attitude of decision makers under uncertainties, sensitivity analysis is conducted to track the impact of α and λ change on the optimal objective value. Fig. 3(a) shows the impact of the optimistic and pessimistic view on the objective value, where λ is various from 0 to 1 with 0.1 interval and α is fixed as 1. It is found that with λ value increasing, the objective function for both LAM and UAM would increase, which indicates that more optimistic decision maker would expect to gain greater benefits. Meanwhile, the differentiation value between UAM and LAM model also has a gently increasing trend as λ values increasing. For example, when λ = 0.1 and 0.9, the differentiation between UAM and LAM model would be $3.24 \times 10^9$ $ and $5.11 \times 10^9$ $, respectively. Fig. 3(b) illustrates the sensitivity analysis of another important uncertain parameter α, where α is various from 0.6 to 1 with 0.1 interval and λ is fixed as 0.8. As α value increasing, the objective function of the LAM and UAM model would behave in the opposite way. The objective value of the LAM model would decrease, and the value from the UAM model would increase. In addition, the differentiation between UAM and LAM would be further broadened under higher α value. From the results, it can be indicated that the confidence level would have an impact on constraints for rebalancing the interaction between subsystems, and that would directly lead to different variations of the LAM and UAM model.

### 4.2. Optimized solutions under different risk preferences

Table 2 summarizes the optimal cultivated land distribution among different crops under various demand levels and risk preferences with λ = 0.8. In general, the cultivated land distribution would change during the whole planning horizon. Due to its high market price and crop yield per unit area, rice planting area would reach its upper limitation in order to achieve the goal of maximizing total benefit. For example, the rice planting area would be $7.50 \times 10^3\,m^2$ in period 1, and $6.60 \times 10^3\,m^2$ in period 2, which would not be affected by the demand level or the risk attitude. The wheat planting area would take account for a large proportion in period 1, which is much more than corn and rice planting. However, the planting area of rice would greatly increase, and the land for wheat planting would reduce simultaneously during period 2. As a result, both rice and wheat would be important crops for cultivating in the planning horizon. To be more specific, the cultivated area of wheat, corn, and rice would be 64 %, 34 %, and 2 % in period 1, and that would be adjusted to 51 %, 47 %, and 2 % in period 2, respectively. In period 1, the cultivated land for wheat planting would also reach its maximum available area (*i.e.* $220 \times 10^3\,m^2$), which would not be affected by demand levels and risk attitudes. As the demand level increasing, the cultivated area for corn would increase to ensure food security. In addition, with higher α value or more conservative attitude, the optimal strategy for corn planting area would increase for the UAM model but decrease for the LAM model. For example, as α fixed with the value of 0.6 and 1 under medium demand level, the optimized corn planting area for the UAM model would be $111.36 \times 10^3\,m^2$ and $119.26 \times 10^3\,m^2$ in period 1, respectively. In period 2, as demand level increasing, the cultivated land for wheat would reduce, whereas that for corn would increase. For example, with α = 0.8 and λ = 0.8 under low-low and high_low scenario, the cultivated area for wheat would be $190.63 \times 10^3\,m^2$ and $189.46 \times 10^3\,m^2$ for LAM model, and the planting area for corn would be $162.59 \times 10^3\,m^2$ and $166.29 \times 10^3\,m^2$. In addition, the decision maker's risk attitude would also bring different effects on cultivated land distribution during period 2. For the conservative risk attitude, the cultivated area of wheat would increase, and that for corn would reduce in the LAM model. The optimal strategy would be converse in the UAM model.

Fig. 4 presents the optimized production of different crops under various demand levels and risk preferences. As expected, the production of different crops is proportional to their cultivated area. In period 1, the wheat production would be $136.18 \times 10^6$ ton, which becomes the main crop supply source and followed by corn. Rice production would be up to its maximum $6.30 \times 10^6$ ton due to the limited cultivated area. In addition, the yield of corn would vary under different demand levels and risk preferences. With α = 0.8 and λ = 0.8, the corn production for LAM model would be $71.32 \times 10^6$ ton, $72.16 \times 10^6$ ton, and $73.00 \times 10^6$ ton under low, medium, and high demand level, which is consistent with the fact that more food would be required for population increase. Besides, for the UAM model, the corn production would also increase to make sure system reliability under conservative attitude. In period 2, the corn production would increase under higher demand level, and the yield of wheat would decrease accordingly. For example, with α = 0.8 and λ = 0.8, under low_medium and high_medium demand level, the yield of wheat would be $118.19 \times 10^6$ ton and $117.47 \times 10^6$ ton in the LAM model, and the output of corn would be $105.68 \times 10^6$ ton and $108.09 \times 10^6$ ton, respectively.

Table S1 in SI lists the optimized water supply strategy under different demand levels under α = 1 and λ = 0.8. For more intuitionistic, Fig. 5 presents the optimized water supply proportion for the LAM model as supplementary. It could be found that imported water and groundwater would be the main water supply sources during the whole planning horizon, followed by surface water and desalination water. Recycle water would take a relatively small fraction of the total water supply. In general, the water supply structure among various sources would have little changes under different demand levels. In fact, the water resources supply from groundwater, surface water, recycle water, and imported water would all reach their maximum availability. Desalination water with more expensive total cost (water resource cost, water supply cost, and electricity cost for water treatment), would be considered as a flexible supplementary resource to guarantee water safety for crop production under uncertain demand level and ambiguous risk attitude. As demand level increasing, more desalination water

**Table 2**
Optimized cultivated land distribution strategies under various demand levels and risk preferences (λ = 0.8) Unit: $10^3$ $m^3$.

| | | | t = 1 | | | t = 2 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | L | M | H | L_L | L_M | L_H | M_L | M_M | M_H | H_L | H_M | H_H |
| Wheat | LAM | α = 0.6 | 220.00 | 220.00 | 220.00 | 189.68 | 189.68 | 189.68 | 189.09 | 189.09 | 189.09 | 188.51 | 188.51 | 188.51 |
| | | α = 0.8 | 220.00 | 220.00 | 220.00 | 190.63 | 190.63 | 190.63 | 190.05 | 190.05 | 190.05 | 189.46 | 189.46 | 189.46 |
| | | α = 1 | 220.00 | 220.00 | 220.00 | 191.59 | 191.59 | 191.59 | 191.00 | 191.00 | 191.00 | 190.42 | 190.42 | 190.42 |
| | UAM | α = 0.6 | 220.00 | 220.00 | 220.00 | 188.72 | 188.72 | 188.72 | 188.14 | 188.14 | 188.14 | 187.56 | 187.56 | 187.56 |
| | | α = 0.8 | 220.00 | 220.00 | 220.00 | 187.77 | 187.77 | 187.77 | 187.18 | 187.18 | 187.18 | 186.60 | 186.60 | 186.60 |
| | | α = 1 | 220.00 | 220.00 | 220.00 | 186.81 | 186.81 | 186.81 | 186.23 | 186.23 | 186.23 | 185.65 | 185.65 | 185.65 |
| Rice | LAM | α = 0.6 | 7.50 | 7.50 | 7.50 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 |
| | | α = 0.8 | 7.50 | 7.50 | 7.50 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 |
| | | α = 1 | 7.50 | 7.50 | 7.50 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 |
| | UAM | α = 0.6 | 7.50 | 7.50 | 7.50 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 |
| | | α = 0.8 | 7.50 | 7.50 | 7.50 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 |
| | | α = 1 | 7.50 | 7.50 | 7.50 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 | 6.60 |
| Corn | LAM | α = 0.6 | 112.04 | 113.33 | 114.63 | 165.61 | 165.61 | 165.61 | 167.46 | 167.46 | 167.46 | 169.31 | 169.31 | 169.31 |
| | | α = 0.8 | 110.06 | 111.36 | 112.65 | 162.59 | 162.59 | 162.59 | 164.44 | 164.44 | 164.44 | 166.29 | 166.29 | 166.29 |
| | | α = 1 | 108.09 | 109.38 | 110.68 | 159.57 | 159.57 | 159.57 | 161.42 | 161.42 | 161.42 | 163.27 | 163.27 | 163.27 |
| | UAM | α = 0.6 | 114.01 | 115.31 | 116.61 | 168.64 | 168.64 | 168.64 | 170.49 | 170.49 | 170.49 | 172.34 | 172.34 | 172.34 |
| | | α = 0.8 | 115.99 | 117.28 | 118.58 | 171.66 | 171.66 | 171.66 | 173.51 | 173.51 | 173.51 | 175.36 | 175.36 | 175.36 |
| | | α = 1 | 117.96 | 119.26 | 120.56 | 174.69 | 174.69 | 174.69 | 176.53 | 176.53 | 176.53 | 178.38 | 178.38 | 178.38 |

would be used for agricultural irrigation. For example, in period 1, the desalination water supply for the LAM model would be $12.84 \times 10^9$ $m^3$, $12.94 \times 10^9$ $m^3$, and $13.04 \times 10^9$ $m^3$ under low, medium, and high demand level, respectively. Since the other water resources would not be affected by demand levels and risk attitudes, Fig. 6 focuses on the variation of desalination water supply under different risk attitudes. As α value increasing, the optimal desalination water supply would increase in the UAM model, but decrease in the LAM model. For example, with α = 0.6 and 0.9, under medium demand level in period 1, the desalination water supply in the LAM would be $13.24 \times 10^9$ $m^3$and $13.01 \times 10^9$ $m^3$, and that in the UAM model would be $13.38 \times 10^9$ $m^3$and $13.62 \times 10^9$ $m^3$, respectively.

Fig. 7 shows the optimized electricity supply strategies under different demand levels and risk attitudes. It indicates that electricity purchased from the power grid would be the main energy source. The green certifications would be bought only to satisfy the minimum renewable energy penetration for low-carbon purpose. In period 1, electricity purchased from the power grid would increase as demand level from low to high, due to more crop production and water treatment. For example, with α = 0.6 and λ = 0.8, the purchased electricity would be $68.96 \times 10^6$ MWh, $69.09 \times 10^6$ MWh, and $69.23 \times 10^6$ MWh for low, medium, and high demand level in LAM model. As α value increasing, the optimal purchased electricity would increase in the UAM model, but decrease in LAM model, which is consistent with crop production and land allocation strategies. In addition, the green certificates for wind power would get priority due to its relatively low price. The amount of purchased wind power green certificates would reach its maximum availability and the value would be $0.60 \times 10^6$ MWh and $1.00 \times 10^6$ MWh in periods 1 and 2. The solar power green certificates would have a similar strategy with electricity from the power grid, although it is few in number. Moreover, the electricity supply during period 2 would not be affected by demand levels and risk attitudes. The optimal electricity supply would be $63.72 \times 10^6$ MWh from power grid, $1.00 \times 10^6$ MWh from wind power green certificates, and $0.50 \times 10^6$ MWh from solar power green certificates.

The corresponding pesticide and fertilizer consumption would have a positive correlation with crop planting, which could be found in SI. Seen from Fig. S1, in period 1, wheat with the largest cultivated area would consume the most pesticide and fertilizer, followed by corn. In period 2, due to the adjustment of planting structure, both wheat and corn would be the big consumers of pesticide and fertilizer. The pesticide and fertilizer consumption of rice would keep a very small proportion during the whole planning horizon, only about 3 %. Fig. S2 focuses on the pesticide consumption of wheat and corn under different levels and risk attitudes. The pesticide requirement of wheat would keep $11.22 \times 10^3$ ton regardless of demand level and risk attitude in period 1. Corn planting would require more pesticide under high demand level due to the increasing planning area. When α is fixed as 0.8, the pesticide consumption of corn in LAM model would be $5.94 \times 10^3$ ton, $6.01 \times 10^3$ ton, and $6.08 \times 10^3$ ton respectively. In addition, with a more conservative risk attitude, more pesticides would be required. In the UAM model, when α is fixed as 0.6, 0.8 and 1, its pesticide consumption would be $6.23 \times 10^3$ ton, $6.33 \times 10^3$ ton and $6.44 \times 10^3$ ton under medium demand level. In period 2, the pesticide consumption of wheat would decrease as demand level increasing, meanwhile, that of corn would increase accordingly. This is due to the fact that corn would become the main crop supplier gradually. Similarly, Fig. S3 depicts the fertilizer consumption of various crops under different demand levels and risk attitudes, which has the same variation trend with pesticide consumption.

### *4.3. Impacts of water resource availability*

To evaluate the impact of water resource availability, the parameters reflecting risk preference are fixed for convenient, *i.e.* α = 0.9, λ = 0.8. Under Base, W1, and W2 scenarios, the optimal objective value would be $170.53 \times 10^9$ \$, $170.27 \times 10^9$ \$, and $169.91 \times 10^9$ \$ for LAM model, respectively. It would be $174.42 \times 10^9$ \$, $174.14 \times 10^9$ \$, and $173.77 \times 10^9$ \$ for UAM model. It demonstrates that the optimal objective value would decrease under the scarcer water resource scenario, indicating worse water resource conditions would shrink total benefits. The changes in water resource conditions would bring great effects on crop planting strategies and yield. Since there are close synchronous changes among crop cultivated area, production, pesticide, and fertilizer consumption, the comparison only focuses the changes of crop production under different water resource scenarios and demand levels, shown in Fig. 8. When facing scarcer water resource conditions, the yield of wheat would reduce, that of corn would increase. While the yield of rice would still keep full production with the maximum available cultivated area, which indicates rice planting always gain the priority due to its high market price. For example, in LAM model for medium demand level, the optimized wheat production would be $136.18 \times 10^6$ ton, $128.46 \times 10^6$ ton, and $116.25 \times 10^6$ ton under Base, W1 and W2 scenario. The corn production would be $71.52 \times 10^6$ ton, $79.24 \times 10^6$ ton and $91.45 \times 10^6$ ton accordingly, and rice production would be $6.30 \times 10^6$ ton regardless of water

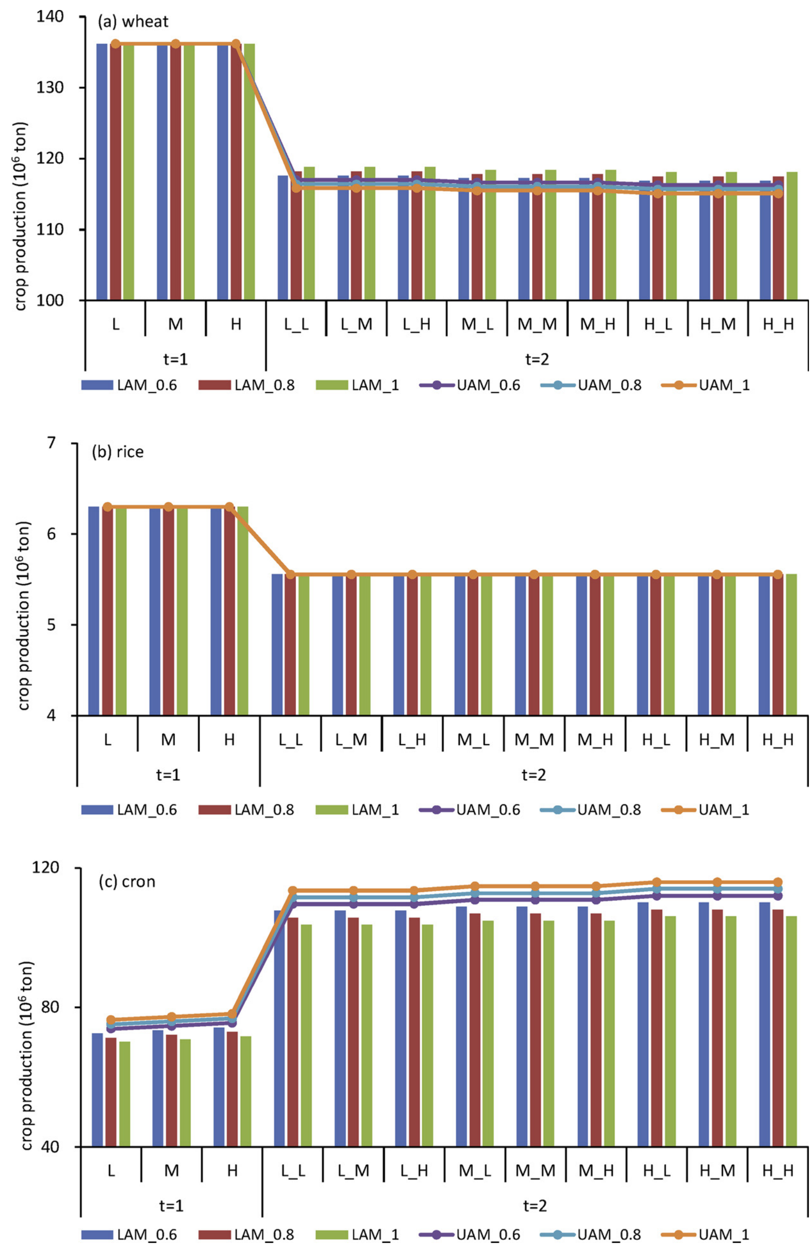


**Fig. 4.** Optimized crop production under different demand levels and α value (λ = 0.8).

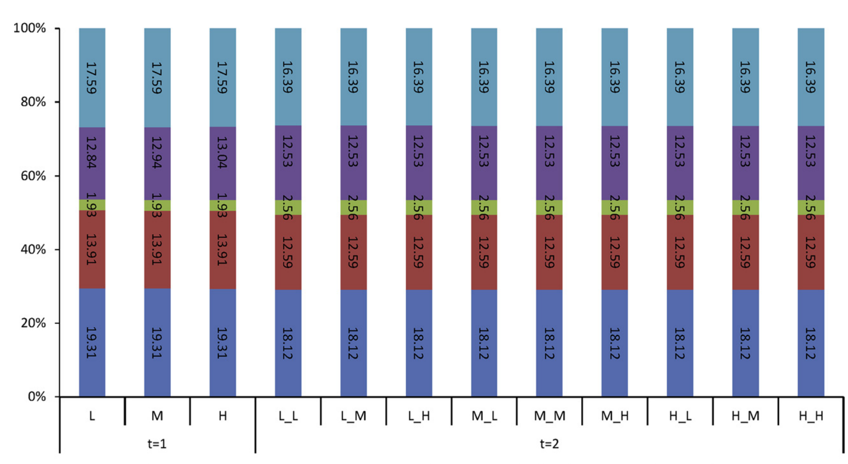


**Fig. 5.** Optimized water supply proportion for LAM model (α = 1, λ = 0.8).

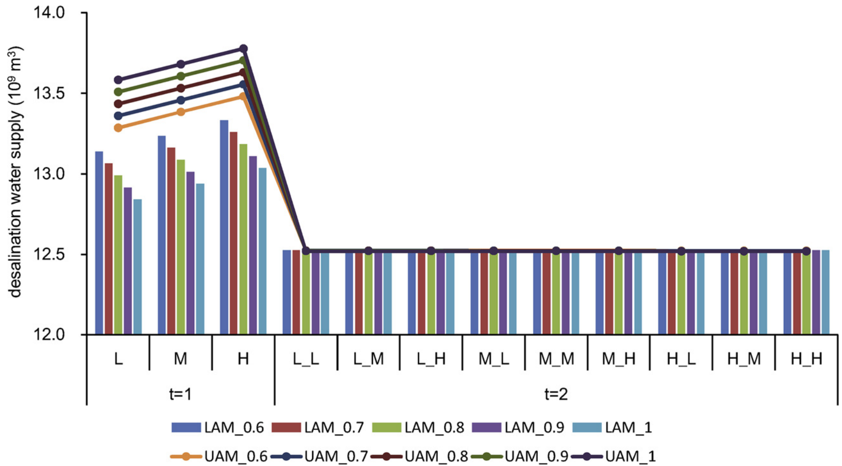


**Fig. 6.** Optimized desalination water supply under different α values (λ = 0.8).

resource conditions. Moreover, the production of wheat and corn would have a positive relationship with demand level as expected. However, under scarcer water resource conditions, rice production would decrease under high demand level in period 2. That is, under W2 scenario, the optimized rice production would be $5.56 \times 10^6$ ton, $5.56 \times 10^6$ ton, and $4.90 \times 10^6$ ton for low_medium, medium_medium, and high_medium demand level.

Table 3 presents the optimized water supply strategies under different water resource scenarios for the UAM model with α = 0.9 and λ = 0.8. As irrigation amount from groundwater and surface water decreasing, the desalination water amount would increase as supplementary regardless of its high total cost. For example, for the low_low demand level, irrigation amount from desalination water would be $12.52 \times 10^9$ m$^3$, $14.67 \times 10^9$ m$^3$, and $16.11 \times 10^9$ m$^3$ under Base, W1, and W2 scenario, respectively. Moreover, the supply amount of other water resources except desalination water would still reach up to their maximum availability. The supply amount of desalination water would reach up to the upper limitation only under desperately scarce water available situations. For example, the supply amount of desalination water would reach its upper limitation, $14.23 \times 10^9$ m$^3$ under the W1 scenario in period 1 and $16.11 \times 10^9$ m$^3$ under W2 scenario in period 2.

Table S2 in SI shows the optimized electricity supply schemes under different water resource scenarios with α = 0.9 and λ = 0.8. Since the crop production decrease under scarcer water resource scenario, the requirement of electricity supply would also reduce accordingly. The decline in electricity purchased from the main grid would be significant. For example, for medium demand level in LAM model, the amount of purchased electricity from power grid would be 68,782.66 GW h, 67,774.15 GW h, and 65,099.51 GW h under Base, W1, and W2 scenario, respectively. The amount of purchased green certificates would also decrease due to the fixed percentage requirement of renewable energy. The amount of purchased wind power certificates would keep its maximum availability no matter how the water resource situation and demand level would be. However, as the demand level increasing, the amount of purchased solar power certificates would increase. Meanwhile, as the water resource declining, the amount of purchased solar power certificates would decrease. For example, for medium demand level, the purchased solar power certificates in the UAM model would be 174.17 GW h, 153.94 GW h, and 124.19 GW h under Base, W1, and W2 scenario. Under W1 scenario, the purchased green certificates of solar power in the UAM model would be 153.92 GW h, 153.94 GW h, and 153.96 GW h for low, medium, and high demand level, respectively.

Fig. 9 evaluated the carbon emission embodied in per unit crop under different water resource scenarios and demand levels with α = 0.9 and λ = 0.8. The carbon emission embodied in per unit crop would decrease as the demand level increased due to the adjustment of crop planting structure. For example, under the Base scenario in the LAM model, the carbon emission embodied in per unit crop would be 0.4017 kg $CO_2$/kg, 0.4011 kg $CO_2$/kg, and 0.4005 kg $CO_2$/kg for low, medium, and high demand level, respectively. Moreover, under the scarcer water resource situation, the carbon emission embodied in per unit crop would also decline. For example, for medium demand level in the UAM model, the carbon emission embodied in per unit crop would be 0.3974 kg $CO_2$/kg, 0.3893 kg $CO_2$/kg, and 0.3773 kg $CO_2$/kg for Base, W1, and W2 scenarios. From the results, it can be seen that the embodied carbon emission per unit crop production is calculated with the consideration of energy consumption in water resources supply and crop planting, as well as fertilizer and pesticide utilization, which could help to evaluate the carbon emission from the resource consumption perspective. The total carbon emission during the agricultural production process, including both carbon fixed by the crop during the growth period and carbon emission associated with energy and water resource consumption, should be further analyzed to achieve low-carbon agricultural structure adjustment.

## 5. Discussion

This study could be formulated as multi-stage fuzzy stochastic programming (MFSP) if the deeper uncertainties in scenarios are not considered. In the MFSP approach, the scenarios of the population in the planning horizon are estimated as low, middle, and high with fuzzy numbers ($\tilde{\tilde{P}}_{t,s}$), while the corresponding probabilities are estimated as deterministic values ($p_s$). As a result, the confidence level α (0.5 ≤ α ≤ 1) is still used to considered to reflect the uncertain levels of parameters, and the optimistic and pessimistic attitude of decision makers is not considered (*i.e.* neutral attitude with λ = 0.5). Furthermore, the study could be turned into a classic multi-stage stochastic programming (MSP) problem, when the scenarios of population ($P_{t,s}$) and the corresponding probabilities ($p_s$) are both simplified into deterministic values rather than fuzzy numbers. As a result, the expected system profit and optimal solutions for each scenario would be deterministic values. If the probabilities and scenario levels are set as the prominent points of fuzzy numbers, the optimal system benefit of the MSP model would be the 157.47 $10^9$ $, which is in the range of objective value obtained from MSFRP model. It is mainly because the MSFRP model considers more uncertain information and optimistic and pessimistic attitude of decision makers. Summarily, compared to MFSP and MSP, the proposed MSFRP method allows reflecting the subjective probabilities setting and possible perturbation in their values. The obtained solutions of MSFRP model could provide an in-depth analysis of the tradeoff among system benefits and supply security risk according to the optimistic and

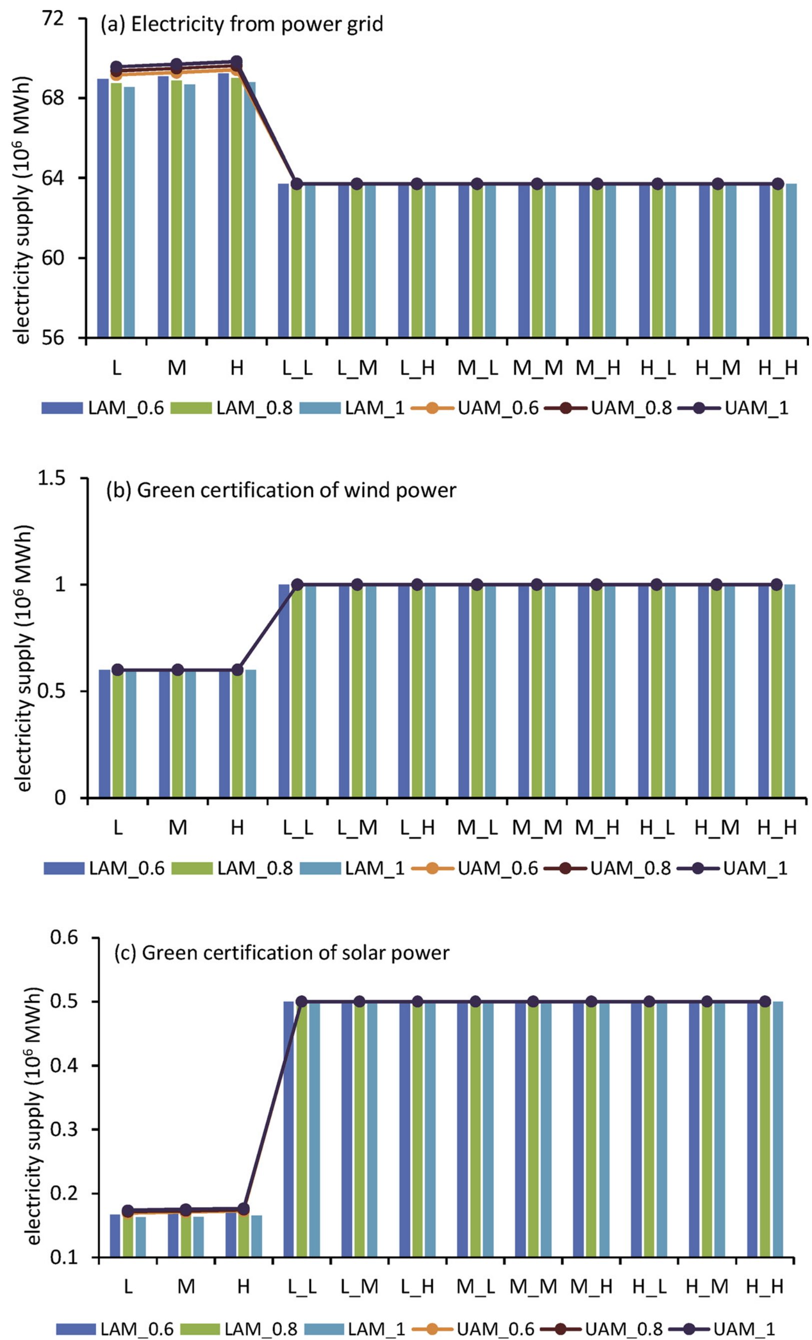


**Fig. 7.** Optimized electricity supply strategies under different α values (λ = 0.8).

pessimistic attitude of decision makers, and the confidence level of uncertain parameters.

## 6. Conclusions

In this study, a multi-stage stochastic fuzzy random programming is developed to deal with uncertainties with mixed characters of fuzzy and random fuzzy, and tailored to a practical study of a comprehensive agricultural issue with FWE nexus in Shandong, China. The proposed model provides the optimal optimistic-pessimistic tradeoff strategies of cultivated land planning, food production arrangement, irrigation water allocation, and energy supply in an efficient and sustainable way. Various results can be obtained as follows:

(a) The hybrid inexact optimization model for FWE nexus management could provide tradeoff information between system benefit and risk attitude, which can help decision makers to choose optimal strategies according to risk tolerance and subjective opinion. (b) In the study area, rice would gain the priority to grow regardless of demand level, risk attitude, or water resource condition. Wheat would be the main food supply during period one, while corn planting would increase in period two and become the important grain as wheat for food security. (c) Considering both the regular water supply cost and energy cost for water treatment, desalination water with the highest total cost would be considered as a flexible supplementary water resource to satisfy agricultural irrigation under different demand levels and risk attitudes. The other water resources would be used as much as their maximum availability. (d) In spite of encouraging green certificates purchasing, the electricity consumption for the FWE nexus system is mainly from the traditional coal-fired dominated power grid due to the relatively cheap electricity price. With the compulsory requirement of

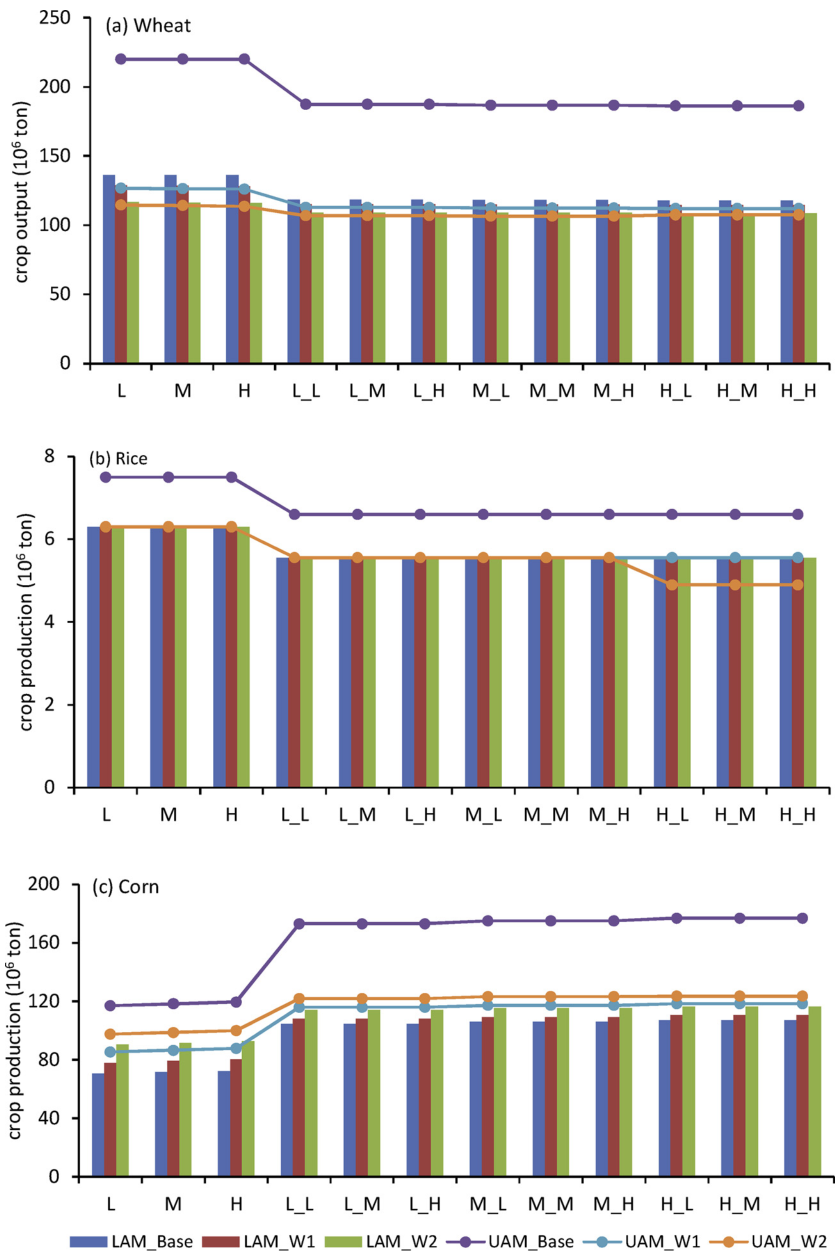


**Fig. 8.** Crop production under different water supply scenarios ($\alpha = 0.9$, $\lambda = 0.8$).

**Table 3**
Optimized water supply strategy under different water resource scenarios for the UAM model ($\alpha = 0.9$, $\lambda = 0.8$) Unit: $10^9$ $m^3$.

| Water source | Scenarios | L | M | H | L_L | L_M | L_H | M_L | M_M | M_H | H_L | H_M | H_H |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $i = 1$ | BASE | 19.31 | 19.31 | 19.31 | 18.12 | 18.12 | 18.12 | 18.12 | 18.12 | 18.12 | 18.12 | 18.12 | 18.12 |
| | W1 | 17.38 | 17.38 | 17.38 | 16.30 | 16.30 | 16.30 | 16.30 | 16.30 | 16.30 | 16.30 | 16.30 | 16.30 |
| | W2 | 15.45 | 15.45 | 15.45 | 14.49 | 14.49 | 14.49 | 14.49 | 14.49 | 14.49 | 14.49 | 14.49 | 14.49 |
| $i = 2$ | BASE | 13.91 | 13.91 | 13.91 | 12.59 | 12.59 | 12.59 | 12.59 | 12.59 | 12.59 | 12.59 | 12.59 | 12.59 |
| | W1 | 12.52 | 12.52 | 12.52 | 11.33 | 11.33 | 11.33 | 11.33 | 11.33 | 11.33 | 11.33 | 11.33 | 11.33 |
| | W2 | 11.13 | 11.13 | 11.13 | 10.07 | 10.07 | 10.07 | 10.07 | 10.07 | 10.07 | 10.07 | 10.07 | 10.07 |
| $i = 3$ | BASE | 1.93 | 1.93 | 1.93 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 |
| | W1 | 1.93 | 1.93 | 1.93 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 |
| | W2 | 1.93 | 1.93 | 1.93 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 | 2.56 |
| $i = 4$ | BASE | 13.51 | 13.61 | 13.70 | 12.52 | 12.52 | 12.52 | 12.52 | 12.52 | 12.52 | 12.52 | 12.52 | 12.52 |
| | W1 | 14.23 | 14.23 | 14.23 | 14.67 | 14.67 | 14.67 | 14.66 | 14.66 | 14.66 | 14.66 | 14.66 | 14.66 |
| | W2 | 14.23 | 14.23 | 14.23 | 16.11 | 16.11 | 16.11 | 16.11 | 16.11 | 16.11 | 16.11 | 16.11 | 16.11 |
| $i = 5$ | BASE | 17.59 | 17.59 | 17.59 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 |
| | W1 | 17.59 | 17.59 | 17.59 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 |
| | W2 | 17.59 | 17.59 | 17.59 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 | 16.39 |

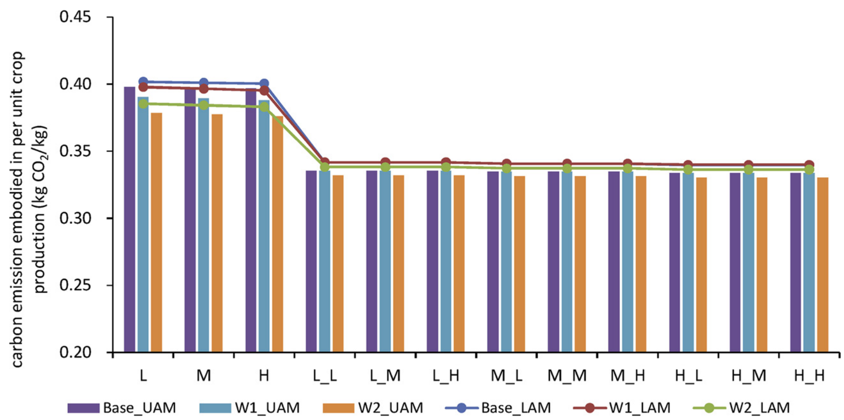


**Fig. 9.** Carbon emission embodied in per unit crop production under different water supply scenarios (α = 0.9, λ = 0.8).

renewable energy penetration, wind power green certificates would gain the priority rather than solar power. (e) Scarcer water resource conditions would bring economic losses for crop production due to higher water supply cost and crop planting structure adjustment, but it would lead to less carbon emission embodied in per unit crop supply and relieve local carbon emission control pressure. (f) The decision maker should adjust food-water-energy nexus management according to the population growth, water resource conditions as well as subjective cognition and risk attitude to maximize total benefit and guarantee system reliability.

The proposed MSFRP model for the integrated FWE nexus management under uncertainties could be applied to coordinate food production benefits, water resource allocation, and energy consumption in a sustainable manner at the national or regional scale. However, there are also forward improvements to be considered in future studies. For example, in a practical food-water-energy nexus management, more uncertain factors and their complex interactions should be elaborated to enhance system reliability. This study focuses on water consumption by crop planting, while ignores the water consumption in energy supply, therefore, the boundary of the FWE nexus system could be further broadened. In addition, although useful managerial insights have been provided under different water resource availability in the future, the impacts of other environmental policies such as carbon emission, pesticide and fertilizer pollutant control, should gain more concern.

## Author contributions

L. J. designed this research; L. J. and B. Z. developed the model and performed analysis; Y. L. collected data; All authors contributed to the results' interpretations and writing.

## Declaration of Competing Interest

We wish to draw the attention of the Editor to the following facts which may be considered as potential conflicts of interest and to significant financial contributions to this work. We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support of this work that could have influenced its outcome.

We confirm that all authors of this manuscript have directly participated in the planning, execution, and analysis of this study. We further confirm that the manuscript has been read and approved by all named authors.

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## Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.resconrec.2019.104665.

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