Synergetic management of water-energy-food nexus system and GHG emissions under multiple uncertainties: An inexact fractional fuzzy chance constraint programming method

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Abstract

Management of water-food-energy nexus (WEFN) is of great importance to achieve the Sustainable Development Goals. The development of WEFN management strategies is challenged by extensive uncertainties in different system components. Also, agricultural activities would contribute a large portion of the total GHG emissions in many countries, which are affecting the promised carbon neutrality in future. In this study, an inexact fractional fuzzy chance constraint programming method was developed towards planning the water-food-energy nexus system under consideration of both uncertainties and greenhouse gases (GHG) emission. An inexact fractional fuzzy chance constraint programming-based water-energy-food nexus (IFFCCP-WEFN) model has been established under consideration of various restrictions and GHG emissions. Solutions of the planting areas for different crops in different periods have been generated. These results imply that the corn cultivation would be prioritized to satisfy cereal demand due to its relatively lower GHG emission intensity. But the residual resources, after satisfying cereal demand, would tend to be allocated to vegetable planting. Comparison has been conducted among the IFFCCP-WEFN model and WEFN models based the inexact fuzzy chance constraint programming approach with and without GHG emissions. The results indicate that, the results from IFFCCP-WEFN model would achieve a highest unit benefit and lowest total GHG emissions. The total GHG emissions can be 11% less at most than GHG emissions from the resulting crop structures of the other two comparable models. Consequently, the developed IFFCCP-WEFN model can help decision-makers identify the desirable planting structure for crops with a priority of low GHG emission rate. The major contributions in this study include (i) the inexact fractional fuzzy chance constraint programming method to deal with interval and fuzzy parameters, reflect decision makers’ preferences and handle conflicts among contradictory objectives, (ii) the IFFCCP-WEFN model to achieve a maximized unit benefit with respect GHG emissions

Keywords: inexact fractional programming; fuzzy chance constraint, uncertainty; water-energy-food nexus system; decision making; GHG emission

1. Introduction

Consumptions of water, energy and food are accelerating due to rapid socio-economic development, booming population, and increasing living standard. Such an issue cannot only be deemed as a general problem of administration but also come into a large number of intricacies among water, energy and food (Liu et al., 2015). Moreover, water, food and energy have been involved in the 17 Sustainable Development Goals (SDGs) for 2030 to tackle global challenges (United Nations, 2015). However, water, energy and food systems are highly correlated. On the one hand irrigation is required for agricultural planting and at the same time, the effluents from farming will lead to pollution issues for the water systems. On the other hand, energy is required to sustain food transport, water treatment, farming, irrigation and water supply, while water resources can ensure stabilized energy generation, normal crops growth, processing and food production (Liu et al., 2015; Shang et al., 2018). Consequently, it is challenging to ensure water, food and energy demands accompanied with the urbanization process due to the complicated interactions among water, energy and food systems (Das et al., 2015; Yu et al., 2018). The deterioration of one factor in one system may spread to other components and cause serious consequences. The policy measure and security of water, energy or food may break the fragile balance among the three resources through critical demand and supply mechanism (Keskinen et al., 2016; Owen et al., 2018). Thus, integrated management strategies are desired for the water-energy-food nexus (WEFN) in order to address the above issue.

WEF has complex interactions, in which the water, energy and food systems are not only interdependent but also competitive among each other (Cai et al., 2018). Water and energy are the key factors for agricultural production, whilst agriculture would produce basic food and raw materials to other sectors (e.g., life, manufacturing, service) and support mankind's survival and economic development (Fernández et al., 2020; Guan et al., 2020; Zuo et al., 2021). Nevertheless, intensive contradiction among food demand and agricultural supply has been observed in many regions especially in water-scare areas. A recent report from FAO stated that 70% of the world's freshwater resources are used for agricultural irrigation and even up to 95% in low-income countries (FAO, 2017). Moreover, the water depletion would significantly affect crop yield, which has been experienced in many countries (Daher et al., 2019; Bhattarai et al., 2021).

In addition, a number of studies have demonstrated the high dependence of agriculture production and energy supply (e.g., Arizpe et al., 2011; Ghisellini et al., 2016; Buko et al., 2021), even through agriculture accounts for only a relatively small proportion of total final energy demand. Consequently, energy supply would also play a key role in agriculture production especially for farm machinery and irrigation. Many research works were conducted to explore management strategies of water-energy nexus (WEN), water-food nexus (WFN) and water-energy-food nexus (WEFN) (Perrone et al., 2011; Yu et al., 2019). For example, Tsolas et al. (2018) and Liu et al. (2019) employed a graphical and systematic program with the purpose of identifying and eliminating surplus from consumption and production of WEN system. Salmoral and Yan (2018) used the theory of virtual water and embedded energy to explore water and energy allocations in the economic system. Nevertheless, there are still some issues to be addressed to develop effective management strategies for the WEFN system.

Firstly, extensive uncertainties may exist in the WEFN system, which are embedded in different system components and also present different formats such as fuzzy, interval and random variables (Yu et al., 2020a; Ji et al., 2020a, b). This leads to challenges to reflect those uncertainties in developing the management policies for WEFN system. Recently, a number of studies have been proposed deal with various uncertainties in the WEFN system through inexact optimization techniques (Perrone et al., 2011; Georgiou et al., 2018; Tsolas et al., 2018; Liu et al., 2019; Yu et al., 2019; Zhang et al., 2018). Interval mathematical programming (IMP), stochastic programming (SP) and fuzzy programming (FP) are the three major approaches to reflect uncertainties in the WEFN systems, and each technique would have its unique feature and shortcomings in dealing with uncertainties. For instance, the stochastic programming (SP) approach can effectively tackle random variables quantified with probability distributions, whilst a large number of samples are required to formulate those probability distributions and thus this method is not applicable when only limited data are available (Gholizadeh et al., 2020). In comparison, the FP methods are able to deal with ambiguity in knowledge or information and vagueness in decision makers' aspirations, and the IMP methods can tackle uncertainties only having the lower and upper bounds which are useful when available data are insufficient (Li et al., 2017). These approaches have been widely used for management issues related to water, energy and food. For instance, Lv et al. (2018) proposed an interval-fuzzy chance-constraint programming method towards planning the energy-water nexus system in Hebei province, China. Ma et al. (2020) developed a multi-preference based interval fuzzy-credibility constrained programming (MIFCP)approach for planning the regional-scale water-resources management system (RWMS) of Henan Province. Zuo et al. (2021) developed a scenario-based type-2 fuzzy interval programming (STFIP) approach for planning agricultural water, energy and food (WEF) as well as crop area management for the Henan province. Nevertheless, due to the complexities of the WEFN system and also data availability, those uncertain parameters in WEFN may present in different formats (e.g., fuzzy and interval) and even subjective/linguistic uncertainties (preferences of decision makers). Consequently, advanced inexact optimization methods are still desired to reflect complex uncertainties in a WEFN system.

Secondly, a WEFN system is associated with different sectors/stakeholders such as energy, water and agriculture, and each sector may have their own prioritized concerns or objectives. This may lead to contradictions among different decision makers. Some studies have been proposed to deal with those contradictory issues in management of the WEFN system. For instance, Yu et al. (2020a) developed a copula-based interval two-level programming (CITP) method for optimizing energy-water nexus system management for Henan Province, in which the two-level programming method was adopted to balance the goals and preferences among different decision-making levels. Yu et al. (2020b) also developed multi-level interval fuzzy credibility-constrained programming (MIFCP) method for planning the regional-scale water-energy-food nexus (WEFN) system, in which a multi-level programming was used to handle conflicts and hierarchical relationships among multiple decision departments. Zhang et al., (2020) advanced a multi-level multi-objective stochastic approach to deal with main conflicting objectives of each decision-making level in water allocation in an arid agricultural region. The studies on dealing with contradictory goals in WEFN are still limited and more studies may be desired to explore the trade-offs among those conflicting concerns from different decision makers.

Moreover, carbon neutrality is becoming one of the most critical issues all over the world to mitigate the climate change effect. Agricultural activities and related farming operations constitute a large portion of the total GHG emissions in many countries, in which the main agricultural GHG emissions-CH_4 and N_2O-account for 10 - 12% of anthropogenic emissions globally (Robertson et al., 2000; Smith et al., 2008; Yang et al., 2014). In China, the agricultural carbon emissions have been accounted for 16 - 17% of the total carbon emissions, making up 50% and 92% of the CH_4 and N_2O emissions. Consequently, WEFN management also needs to consider both direct and indirect greenhouse gas (GHG) emissions in relevant activities. Therefore, it is desired to formulate effective strategies for water, energy and food management to coordinate rapid development of various relevant departments in a sustainable pathway under various uncertain conditions (Martinez et al., 2018; Wang et al., 2018).

Therefore, this paper aims to propose an inexact fractional fuzzy chance constraint programming (IFFCCP) method through coordinating interval programming (IP), fuzzy chance constraint programming (FCCP), and fractional programming (FP) into one framework. The developed inexact fractional fuzzy chance constraint programming method integrates the unique contribution of each individual technique, in which the IP would be adopted to deal with uncertain parameters presented in interval numbers, FCCP is employed to tackle fuzzy variables and also reflect preferences from decision makers, and the FP would be employed to reflect conflicting objectives of the studied problem. Moreover, an inexact fractional fuzzy chance constraint programming-based water-energy-food nexus (IFCCP-WEFN) model is developed for planning the water-energy-food nexus system for the City of Jinan, in which both the system benefit and the GHG emissions are to be considered subject to restrictions related to food requirements, water availability, energy supply and other environmental protection constraints. There are different modelling formulations for WEFN planning such as land-use optimization (e.g. Zuo et al., 2021), resource technology network optimization (e.g., Bieber et al., 2018), water and energy resources allocation (e.g., Li et al., 2019), and so on. In this study, the IFFCCP-WEFN model would be developed for planning the crop cultivation areas under consideration of energy and water requirements, as well as GHG emissions. In addition, both interval and fuzzy variables are employed to reflect extensive uncertainties existing in a WEFN system. In detail, interval numbers are adopted for some economic parameters (e.g., unit price for crops, unit cost of fertilizer), resources availability (total cultivation areas, availabilities for water resources, energy consumption, fertilizers and pesticides). The interval parameters are used since their lower and upper bounds can be easily specified with only limited data, and also help decision makers make trade-offs between lower and upper bound conditions. Also, some parameters, such as local population, food loss rate, irrigation reliability, are presented as triangular fuzzy numbers in order to explore their impacts on the resulting solutions for crop cultivation patterns. Particularly, one major unique feature for this study is that the direct and indirect GHG emissions from WEFN system would be considered in the IFFCCP-WEFN model. Those GHG emissions be used as the denominator in the objective function in order to generate maximized unit benefit with respect to GHG emissions for the WEFN system. The obtained solutions can help the local governor generate reliable planting schemes for different crops to achieve desirable system benefits and at the same time alleviate GHG emissions.

2. Overview of the Study Area

As the capital city, the City of Jinan is located in the north-western part of Shandong Province, with the latitude ranging between $36^0$01' and $37^0$32' N, and the longitude varying between $116^0$11' and $117^0$44' E. After absorbing the City of Laiwu, Jinan is now covering a terrain of 10244 km^2 and having a population of 8.91 million. The total Gross domestic product (GDP) in 2019 is about RMB 944.34 billion with an increase rate of 7.0%, ranked as the second largest city in Shandong Province (Jinan Municipal Bureau of Statistics, 2020). the Mount Tai is in the south of Jinan and Yellow River plain is located in the north part, leading to higher land in the south than that in the north. There are two major river systems, namely the Yellow River and Xiaoqing River, flowing across the city, with other small rivers such as North-South Dasha River and Yufuhe River, etc. Jinan has the warm temperate continental climate, with hot and rainy in Summer, and dry and rainless in other seasons. The annual average temperature is 13.5℃-15.5℃, the frost-free period all year round is about 230 days and the amount of precipitation is 600~900 mm.

As one of the major agricultural provinces, Shandong province is an important production area for a number of agricultural products such as wheat, corn, peanuts, which accounts for 8.4%, 11% and 16% respectively for food, vegetables and peanuts production in China in 2020. For the City of Jinan, the total output of grain was 2.855 million tons and the output of vegetables was 6.72 million tons in 2019. There are several crops sown in Jinan, but wheat, corn and vegetables are the three major crops. In 2019, the total sown areas for wheat, corn and vegetables are 2.19×10^6, 2.32×10^6, and 1.00×10^6 ha respectively, making a respective contribution of 35%, 37% and 16% to the total sown area (Jinan Municipal Bureau of Statistics, 2020). Even though there has been a prosperous growth for food and vegetable production in the City of Jinan, several issues need to be addressed to enhance the sustainability of the agriculture system in response to increasing food requirement, environmental protection and also climate change

a) The amount of water resources for irrigation is abundant, while its utilization efficiency is low and leads to serious waste of water. For instance, the total water demand in the city is about 1.542×10^9 m^3 in 2017, in which water demands for agricultural, industrial, municipal and environmental sectors are respectively 8.67×10^8, 1.99×10^8, 2.85×10^8, and 1.93×10^8 m^3 (Jinan Municipal Bureau of Statistics, 2018). For the water demand in agriculture, about 6.54×10^8 of water were supplied for irrigation, which made a contribution of 42% for the total water demand (Jinan Municipal Bureau of Statistics, 2018).

(b) Due to rapid urbanization and industrialization, there has been a fierce competition for land use among municipal, industrial and agricultural sectors. The planting area of grain was 0.48×10^7 ha, decreased by 1.0% in 2019, whilst the sown area of vegetables was 0.1×10^7 ha decreased by 2.2% (Jinan Municipal Bureau of Statistics, 2020).

(c) There are growing electricity consumption in the city especially after 2019 while the city of Laiwu was merged into Jinan, especially for industrial and household power consumptions. For instance, the industrial and household consumption for electricity respectively increased from 121.5×10^8 and 66.8×10^8 kWh to 221.5×10^8 and 77.6×10^8 kWh in 2019. Nevertheless, the electricity production only increased from 152.9×10^8 to 295.1×10^8 kWh, which implied a remarkable power deficit and also serious competition for electricity consumption between agriculture and other sectors.

(d) In order to mitigate climate change, China has promised to reach carbon neutrality by 2060, which indicates remarkable carbon reduction pressures for all socio-economic sectors including agricultural production. The greenhouse gas emission from agricultural production accounts for

16-17% of the total emission in China (Huang et al., 2019). The agricultural greenhouse gas emissions are from various sources including both the direct and indirect emissions caused by utilization of fertilizers, pesticides, electricity and fossil fuels. As one of the major provinces for agricultural production, Shandong Province, including the City of Jinan, are facing a noticeable pressure for reducing carbon emissions in agricultural production process.

Due to the above issues, the sustainability of the agricultural system is being challenged in terms of food production, water availability, energy/electricity utilization and greenhouse gas emissions. Consequently, it is desired to develop effective management strategies for the water-energy-food nexus at the City of Jinan in order to achieve the coordination among planting agricultural planting, environmental protection and carbon reduction to promote the sustainable development of agriculture.

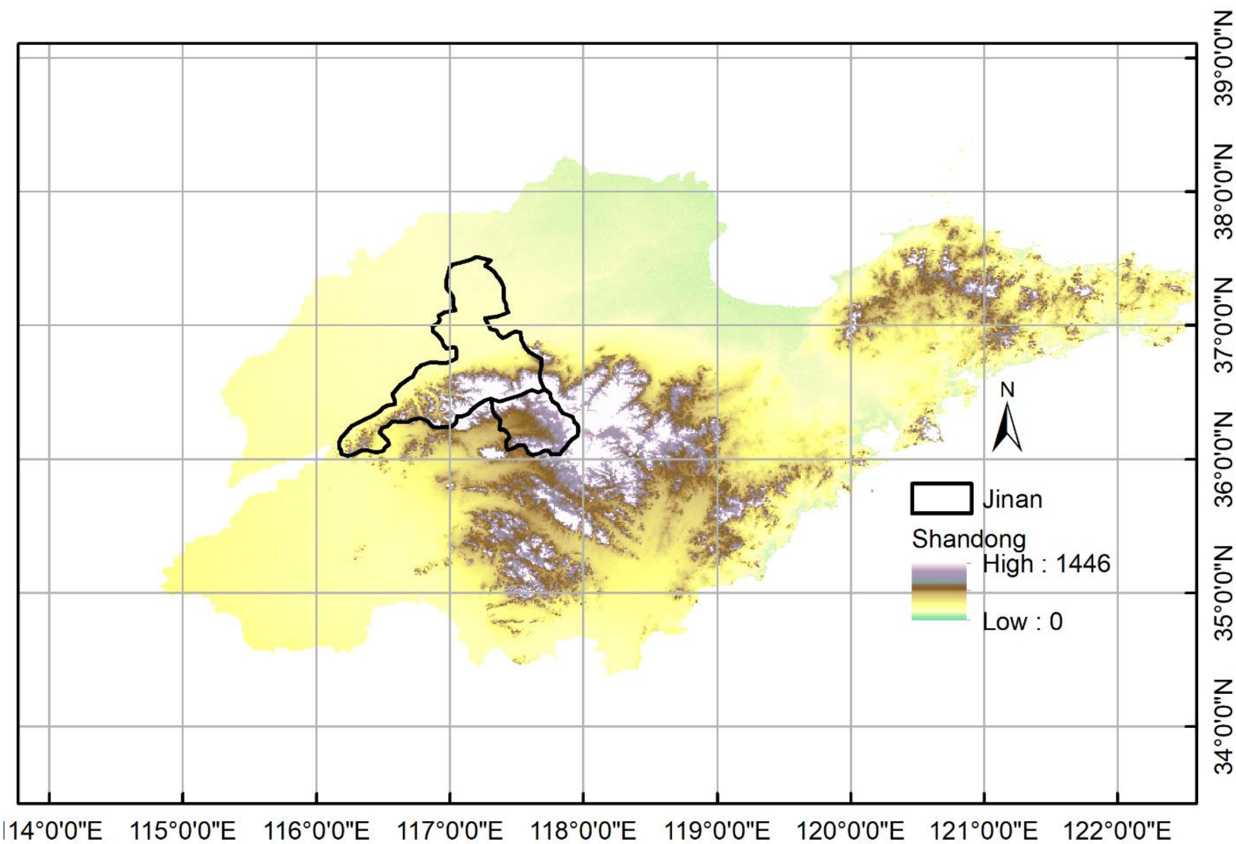

Figure 1. The location of the City of Jinan at Shandong Province

3. Model Development

3.1. Modeling formulation

For a real-world water-energy-food nexus system, there are multiple components and multiple uncertainties in association with different decision makers' preferences. There are many uncertain technical and economic parameters in the production and processing of agriculture. Besides, the management of water-energy-food nexus system does not only consider the profit of the entire system but also balances the contradiction among agricultural, water and energy resources managers according to different decision-making priorities. Consequently, a WEFN model need to be established for planning the water-energy-food nexus system for the City of Jinan, China, in which the agriculture activities (i.e. crop cultivation, crop processing, food generation, food transportation) and available resources control (i.e. fertilizer utilization, pesticide utilization, energy consumption for farming, water consumption for irrigation) are considered to achieve a desirable trade-off between system benefit and greenhouse gas emissions. Moreover, in order to reflect uncertain future in the planning horizon, inexact parameters are to be included in the WEFN model, which are denoted as either interval or fuzzy numbers.

Therefore, the objective of the WEFN model is to maximize unit benefits between agriculture profits and carbon emission. The agriculture profits include revenue of crops, and the cost used for the consumption of various resources (e.g., water, fertilizer, electricity and seed). In addition, the labor cost has not been taken into account.

$$\text{Max } f^{\pm} = (f_1 - f_2 - f_3 - f_4 - f_5 - f_6)/f_7 \quad (1a)$$

(1) Revenues of agricultural products

$$f_1 = \sum_{t=1}^{T}\sum_{v=1}^{V} SA_{t,v}^{\pm} \times UW_{t,v}^{\pm} \times UP_{t,v}^{\pm} \quad (1b)$$

(2) Costs for irrigation and discharge

$$f_2 = \sum_{t=1}^{T}\sum_{v=1}^{V} SA_{t,v}^{\pm} \times UIC_{t,v}^{\pm} \quad (1c)$$

(3) Costs for fertilizer utilization

$$f_3 = \sum_{t=1}^{T}\sum_{v=1}^{V} SA_{t,v}^{\pm} \times FC_{t}^{\pm} \times FA_{t,v}^{\pm} \quad (1d)$$

(4) Costs for pesticide utilization

$$f_4 = \sum_{t=1}^{T}\sum_{v=1}^{V} SA_{t,v}^{\pm}\times PC_t^{\pm}\times PA_{t,v}^{\pm} \tag{1e}$$

(5) Costs for energy consumption

$$f_5 = \sum_{t=1}^{T}\sum_{v=1}^{V} SA_{t,v}^{\pm}\times UOP_t^{\pm}\times UOC_{t,v}^{\pm} \tag{1f}$$

(6) Costs for seeds

$$f_6 = \sum_{t=1}^{T}\sum_{v=1}^{V} SA_{t,v}^{\pm} \times SEDP_{t,v}^{\pm} \tag{1g}$$

(7) Total greenhouse gas emissions

$$f_7 = \sum_{t=1}^{T}\sum TCE_t^{\pm} \tag{1h}$$

Here, GHG emission in the food-water-energy nexus system is also measured to evaluate the environmental impacts. GHG emissions associated with food production are mainly generated from electricity for irrigation, diesel for machinery, fertilizer and pesticide utilization. which is formulated as:

$$TCE_t^{\pm} = \sum_{v=1}^{V} SA_{t,v}^{\pm} \times (EF_{diesel}\times UOC_{t,v}^{\pm} + EF_{electricity}\times UEC_{t,v}^{\pm} + EF_{fertilizer,\ v}\times FA_{t,v}^{\pm} + EF_{pesticide,v}\times PA_{t,v}^{\pm}) \tag{1i}$$

Based on the current situation and future development strategy, the WEFN model would consider multifaceted and comprehensive constraints (e.g., limited utilization amount of land and electricity), which could be clearly seen as follows. The constraints can help plan the agricultural development, alleviate the contradictions among the development of socio-economic, environmental protection and other aspects at the City of Jinan, which will ultimately realize the sustainable development.

(1) Land availability for cultivation: The excessive exploitation of land for agriculture may lead to negative effects (e.g., ecological environment deterioration and soil erosion), which means cultivated area should be restricted. Also, there has been significant competition for land use between agricultural cultivation and other sectors, which lead to limited land availability for crop

cultivation. Constraint (2a) limited the minimum and maximum planting area of crops, so as to avoid large fluctuations of the market price of agricultural products. Meanwhile, the total planting area of crops should not exceed the available arable land in planning periods, as shown in constraint (2b).

$$SA_{t,v}^{min\pm} \leq SA_{t,v}^{\pm} \leq SA_{t,v}^{max\pm} \tag{2a}$$

$$\sum_{v=1}^{V} SA_{t,v}^{\pm} \leq TSA_t^{\pm} \tag{2b}$$

(2) 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.

$$\sum_{v=1}^{V} SA_{t,v}^{\pm} \times UW_{t,v}^{\pm} \times (1 - \tilde{u}_v) \geq \lambda \times FD_t^{\pm} \times \tilde{N}_t \tag{3}$$

where, $FD^{\pm}$ is per capital food demand standard (kg/person); $\tilde{N}_t$ denotes the number of population in planning horizon, which is expressed as fuzzy number; $\tilde{u}_v$ is the loss rate in production, transportation and other processes for crop v, which are also denoted as fuzzy numbers; λ denotes the food self-sufficiency rate for the study area.

(3) Water availability: Constraint (4) indicates that the total consumption of water should not exceed the available amount for agriculture in study area. Furthermore, this constraint can optimize the water use structure of crops under a certain amount of water resources, coordinate the contradictions among water-using departments, and obtain higher economic benefits.

$$\sum_{v=1}^{V} SA_{t,v}^{\pm} \times AWQ_{t,v}^{\pm} \times \tilde{o} \leq AWS_t^{\pm} \tag{4}$$

where $\tilde{o}$ is the reliability of irrigation, expressed as a fuzzy number, $AWQ_{t,v}^{\pm}$ is the irrigation quota for crop v in period t, and $AWS_t^{\pm}$ is the total water availability in period t.

(4) Energy system:

(a) Electricity constraint. In this study, electricity consumption associated with food production mainly consists of the electricity used for irrigation.

$$\sum_{v=1}^{V} SA_{t,v}^{\pm} \times UEC_{t,v}^{\pm} \leq PME_t^{\pm} \tag{5a}$$

where $PME_t^{\pm}$ is the total electricity availability for agricultural production.

(b) Fossil consumption constraints (here only the diesel is considered). The plowing machines are required in the food production process, which will consume diesel for their operation. In general, there are also certain limitations for fossil availability in different planning periods.

$$\sum_{v=1}^{V} SA_{t,v}^{\pm} \times UOC_{t,v}^{\pm} \leq PMO_t^{\pm} \tag{5b}$$

where $UOC_{t,v}^{\pm}$ is the unit diesel consumption (kg/ha) for crop v in period t, and $PMO_t^{\pm}$ is the total diesel availability for agricultural production.

(5) As the major sources of agricultural pollution and greenhouse gas emission, the utilization amounts of chemical fertilizers, pesticides would be restricted in constraints (6a), and (6b), respectively.

$$\sum_{v=1}^{V} SA_{t,v}^{\pm} \times FA_{t,v}^{\pm} \leq TCF_t^{\pm} \tag{6a}$$

$$\sum_{v=1}^{V} SA_{t,v}^{\pm} \times PA_{t,v}^{\pm} \leq TEP_t^{\pm} \tag{6b}$$

where $TCF_t^{\pm}$ and $TEP_t^{\pm}$ is respectively the total fertilizer and pesticide availability for agricultural production.

The proposed WEFN model is established based on some recent studies (e.g., Yu et al., 2020a; Ji et al., 2020b; Zuo et al., 2021). However, there are some inherent assumptions in the establishment of the WEFN model. Firstly, the availabilities for some resources, especially for water and energy, are those can be allocated to agricultural production whilst those resources used by other sectors would be excluded. This assumption would be validated in the availability predictions for these resources, in which the relevant availabilities are projected through regression methods based on historical resources allocated to agricultural production. Secondly, there are GHG emissions in food production process but also carbon sinks in crop cultivation through soil organic carbon storage and cover carbon sequestration. Studies have argued that the major crops production showed as carbon sinks in general (e.g., She et al., 2017). However, in the developed WEFN model, the carbon sinks in crop planting are not considered. This assumption would be accepted since, without considering carbon sink, the developed WEFN model would generate crop cultivation structures with low GHG emission intensities. Finally, product prices, including crop products (e.g., wheat, corn, vegetables) and raw materials (e.g., fertilizers, energy), would have complex relationship with their supply-demand curves. In this study, those prices are simply projected through add an inflation rate based on historical product prices. Moreover, certain fluctuation ranges are added to those projected prices in order the reflect the price volatility. This is one of the main reasons to introduce uncertain parameters in the developed WEFN model.

Table 1 provides the definitions of the symbols used in the WEFN model as well as their uncertainty formats. The developed WEFN model expressed as Equations (1) - (6) is a nonlinear programming model since it has a fractional objective function. Here the fractional programming (FP) is introduced to deal with the benefit and GHG emission objectives in the WEFN system since it is an effective tool to deal with optimization of ratio, where the objective is quotient of system benefit and GHG emission. The FP method can compare objectives of different aspects directly through their original magnitudes and provide an unprejudiced measure of system efficiency (Zhu et al., 2014). It has been proved to be a natural way of approaching both economic and environmental criteria related to the systems' sustainability (Zhu and Huang, 2011). In the real WEFN system, parameters may be affected by a series of factors (e.g., limited data availability, inaccuracy of statistical data, subjective experience), which would result in system errors and multiple uncertainties (Si et al., 2019). For example, during the entire planning horizon, prices of agricultural products and costs of agricultural production conditions may fluctuate under the influence of demand-supply relationship and policies (Hoolohan et al., 2019). In general, the economic coefficients such as prices for crops, costs for utilization of energy, fertilizers and pesticides are uncertain in natures since they are closely related to the volatility of interest rates, inflation rates and other factors (i.e., energy price, labor fee, and operation condition) (Yu et al., 2020c). In this study, these parameters are denoted as interval variables due to limited data availability. Moreover, the future resources availabilities for the WEFN system such as water resources, electricity availability, fertilizer and pesticides availabilities are projected through regression methods based on historical data. However, these parameters would also be affected by a number of factors such as hydrometeorological conditions and would present uncertain features. Therefore, some variation ranges are added to those forecasting results and thus lead to interval parameters. In addition, the prioritized objective for WEFN system is to satisfy the food demand from local population, and the food loss rate in production, transportation and other processes are also quite crucial affecting the food availabilities to local people. Thus, these two parameters are presented as fuzzy numbers. Also, the fuzzy number would be used to express the uncertainty in irrigation reliability. The purpose of using fuzzy numbers was to explore the impacts of changes in population, food loss rates and irrigation reliabilities on the resulting crop cultivation patterns.

Table 1. Definitions of symbols used in the WEFN model

	Definition
Indices	
t	index of time period
v	index of crop (1 for wheat, 2 for corn, 3 for vegetables)
Decision variables	
$SA_{t,v}^{\pm}$	interval variables for sown areas of crop v in period t (ha)
Objective functions	
$f^{\pm}$	interval objective function for unit benefit of WEFN system with respect to GHG emissions
Parameters	
$UW_{t,v}^{\pm}$	interval parameters for the unit output of crop v in period t (kg/ha)
$UP_{t,v}^{\pm}$	interval parameters for the unit price of crop v in period t (RMB ¥/ha)
$UIC_{t,v}^{\pm}$	interval parameters for the unit cost of irrigation and drainage for crop v in period t (RMB ¥/ha)
$FC_{t}^{\pm}$	interval parameters for the unit cost of fertilizer (RMB ¥/ha)
$FA_{t,v}^{\pm}$	interval parameters for the amount of fertilizer utilization per unit area for crop v (kg/ha)
$PC_{t}^{\pm}$	interval parameters for the cost of pesticide (RMB ¥/ha)
$PA_{t,v}^{\pm}$	interval parameters for the amount of pesticide utilization per unit area for crop v (kg/ha)
$UOC_{t,v}^{\pm}$	interval parameters for the unit oil (i.e. diesel) consumption per unit area for crop v (kg/ha)
$UEC_{t,v}^{\pm}$	interval parameters for the unit electricity consumption (kWh/ha) for crop v in period t
$UOP_{t}^{\pm}$	interval parameters for the oil price in time period t (RMB ¥/kg)
$SEDP_{t,v}^{\pm}$	interval parameters the unit cost for seeds (RMB ¥/ha)
EF_{diesel}	the carbon emission factor for diesel (kg CO_2-eq/kg)
$EF_{electricity}$	the carbon emission factor for electricity (kg CO_2-eq/kg)
$EF_{fertilizer,\ v}$	the carbon emission factor for fertilizer utilization for crop v (kg CO_2-eq/kg)
$EF_{pesticide,v}$	the carbon emission factor for pesticide utilization for crop v (kg CO_2-eq/kg)
$SA_{t,v}^{min\pm}$	interval parameters for minimum planting areas for crop v in time period t (ha)
$SA_{t,v}^{max\pm}$	interval parameters for maximum planting areas for crop v in time period t (ha)
$TSA_{t}^{\pm}$	interval parameters for the total the available arable land (ha)
$\tilde{u}_v$	fuzzy parameters for the loss rate in production, transportation and other processes for crop v
$\tilde{N}_t$	fuzzy parameters for the total population in time period t
$FD_{t}^{\pm}$	the interval parameter for per capital food demand standard (kg/person) in period t
λ	parameter for food self-sufficiency rate
$AWQ_{t,v}^{\pm}$	interval parameters for the irrigation quota for crop v in period t (m^3/ha)

$AWS_t^{\pm}$	interval parameters for the total water availability in period t (m^3)
$PME_t^{\pm}$	interval parameters for the total electricity availability for agricultural production (kWh)
$PMO_t^{\pm}$	interval parameters for total diesel availability for agricultural production (kg)
$TCF_t^{\pm}$	interval parameters for the total fertilizer availability for agricultural production (kg)
$TEP_t^{\pm}$	interval parameters for the total pesticide availability for agricultural production (kg)

3.2. Solution Method

In order to reflect uncertain conditions in the future planning horizon, uncertain parameter, expressed either by interval or fuzzy numbers are introduced into the developed water-energy-food nexus (WEFN) model expressed as Equations (1) – (6). Consequently, an inexact fractional fuzzy chance constraint programming (IFFCCP) method will be developed to solve the proposed WEFN model, which will finally lead to an IFFCCP-WEFN model in this study. The proposed IFFCCP approach integrates the inexact fractional programming and fuzzy chance constraint programming approaches to deal with contradictory objectives and also multiple uncertainties in the water-energy-food nexus planning practices.

Consider a generic inexact fuzzy fractional programming with fractional objective function, and uncertain parameters expressed as interval and fuzzy numbers as follows:

$$\text{Max } f^{\pm} = (\textstyle\sum_{j=1}^{n} c_j^{\pm} x_j^{\pm} + \alpha^{\pm})/(\sum_{j=1}^{n} d_j^{\pm} x_j^{\pm} + \beta^{\pm}) \quad (7a)$$

Subject to

$$\textstyle\sum_{j=1}^{n} a_{ij}^{\pm} x_j^{\pm} \leq b_i^{\pm},\ i = 1, 2, \ldots, l \quad (7b)$$

$$\textstyle\sum_{j=1}^{n} \tilde{a}_{ij} x_j^{\pm} \leq \tilde{b}_i,\ i = l+1, \ldots, m \quad (7c)$$

$$x_j^{\pm} \geq 0 \quad (7d)$$

Based on the interactive transform algorithm proposed by Zhu et al. (2014), an inexact fractional programming (i.e. Equations (7a), (7b) and (7d)) can be converted into two conventional fractional programming submodels corresponding to the lower (i.e. pessimistic) and upper (i.e. optimistic) bound of the objectives. However, for the constraints with fuzzy parameters (i.e. Equations (7c)), a number of approaches have been proposed such as the α-cut method (e.g., Ammar, 2008), Lexicographic criteria (e.g., Pérez-Cañedo, 2020), possibility and necessity measures (Inuiguchi and Ramik, 2000; Xu et al., 2011). In this study, the measures of possibility and necessity will be adopted to deal with the constraints with fuzzy parameters. The necessity and possibility constraints are introduced by Dubois and Prade (1987), which are considered to be very relevant to the real life decision problems (Maity, 2011). These two measures have been used for many practical management problems with fuzzy uncertainties such as portfolio selection problem (Inuiguchi and Ramik, 2000), production-inventory control problem (Maity and Maiti, 2007), and so on. Consequently, based on the integration of the interactive transform algorithm and the measures of possibility and necessity, the IFFCCP model can be transformed into two conventional fractional programming submodels corresponding to the low and upper bound of the objective.

The first submodel corresponding to the lower bound (i.e. f^-) of the objective, which is formulated as follows (i.e. Submodel (I)):

$$\text{Max } f^- = (\sum_{j=1}^{k} c_j^- x_j^- + \sum_{j=k+1}^{n} c_j^- x_j^+ + \alpha^-)/(\sum_{j=1}^{k} d_j^+ x_j^- + \sum_{j=k+1}^{n} d_j^+ x_j^+ + \beta^+) \tag{8a}$$

Subject to

$$\sum_{j=1}^{k} |a_{ij}^{\pm}|^+ Sign(a_{ij}^{\pm}) x_j^- + \sum_{j=k+1}^{n} |a_{ij}^{\pm}|^- Sign(a_{ij}^{\pm}) x_j^+ \leq b_i^-,\ i = 1, 2, \ldots, l \tag{8b}$$

$$Nes\{\sum_{j=1}^{k} \tilde{a}_{ij} x_j^- + \sum_{j=k+1}^{n} \tilde{a}_{ij} x_j^+ \leq \tilde{b}_i\} \geq \alpha,\ i = l+1, \ldots, m \tag{8c}$$

$$x_j^- \geq 0,\ j = 1, 2, \ldots, k \tag{8d}$$

$$x_j^+ \geq 0,\ j = k+1, \ldots, n \tag{8e}$$

The second submodel corresponds to the upper bound (f^+) of the objective function, which is formulated as (i.e. Submodel (II)):

$$\text{Max } f^+ = (\sum_{j=1}^{k} c_j^+ x_j^+ + \sum_{j=k+1}^{n} c_j^+ x_j^- + \alpha^+)/(\sum_{j=1}^{k} d_j^- x_j^+ + \sum_{j=k+1}^{n} d_j^- x_j^- + \beta^-) \tag{9a}$$

Subject to

$$\sum_{j=1}^{k} |a_{ij}^{\pm}|^- Sign(a_{ij}^{\pm}) x_j^+ + \sum_{j=k+1}^{n} |a_{ij}^{\pm}|^+ Sign(a_{ij}^{\pm}) x_j^- \leq b_i^+,\ i = 1, 2, \ldots, l \tag{9b}$$

$$\sum_{j=1}^{r_i} a_{ij}^- x_j^+ + \sum_{j=r_i+1}^{k} a_{ij}^- x_{jopt}^- + \sum_{j=k+1}^{k+t_i} a_{ij}^- x_{jopt}^+ + \sum_{j=k+t_i+1}^{n} a_{ij}^- x_j^- \leq b_i^+ \quad i = 1, 2, \ldots, l \tag{9c}$$

$$Pos\{\sum_{j=1}^{k} \tilde{a}_{ij} x_j^+ + \sum_{j=k+1}^{n} \tilde{a}_{ij} x_j^- \leq \tilde{b}_i\} \geq \alpha,\ i = l+1, \ldots, m \tag{9d}$$

$$x_j^+ \geq 0,\ j = 1, 2, \ldots, k \tag{9e}$$

$x_j^+ \geq x_{jopt}^-, j = 1, 2, \ldots, k$ (9f)

$x_j^- \geq 0, j = k+1, \ldots, n$ (9g)

$x_j^- \leq x_{jopt}^+, j = k+1, \ldots, n$ (9h)

In the solution procedures denoted as Models (8) and (9), the former k ($k \leq n$) coefficients get their lower bounds for Submodel (I) and upper bounds for Submodel (II), which are determined by the criteria proposed by Zhu et al. (2014). The later $n - k$ coefficients get their upper bounds and lower bounds respectively corresponding to Submodel (I) and (II). x_{jopt}^- ($j = 1, 2, \ldots, k$) and x_{jopt}^+, ($j = k+1, \ldots, n$) are the optimal solutions obtained from Submodel (I). r_i and t_i stands for the numbers of $a_{ij}^\pm \geq 0$ associated with decision variables $x_j^\pm$ ($j = 1, 2, \ldots, k$) and $x_j^\pm$ ($j = k+1, \ldots, n$) for constraint i. Nes{.}in Equation (8c) is the measure of necessity for fuzzy numbers and Pos{.} in Equation (9d) indicates the measure of possibility for two fuzzy numbers. Consider two fuzzy numbers $\tilde{a}$ and $\tilde{b}$ with their membership functions being $\mu_{\tilde{a}}(x)$ and $\mu_{\tilde{b}}(y)$. For a confidence level $\alpha \in [0,1]$, we can have (Inuiguchi and Ramik, 2000; Xu et al., 2011):

$$Pos(\tilde{a} \leq \tilde{b}) = \sup\{\min(\mu_{\tilde{a}}(x), \mu_{\tilde{b}}(y)) \mid x \geq y\} \leq \alpha \Leftrightarrow a_\alpha^- \leq b_\alpha^+ \quad (10a)$$

$$Nes(\tilde{a} \leq \tilde{b}) = \inf\{\max(1-\mu_{\tilde{a}}(x), 1-\mu_{\tilde{b}}(y)) \mid x \leq y\} \geq \alpha \Leftrightarrow a_{1-\alpha}^+ \leq b_\alpha^- \quad (10b)$$

where $a_\alpha^- = \inf(x \mid x = \mu_{\tilde{a}}^{-1}(\alpha))$ and $a_\alpha^+ = \sup(x \mid x = \mu_{\tilde{a}}^{-1}(\alpha))$ are the lower and upper bounds for the α-cut of fuzzy number $\tilde{a}$, and $b_\alpha^- = \inf(y \mid y = \mu_{\tilde{b}}^{-1}(\alpha))$ and $b_\alpha^+ = \sup(y \mid y = \mu_{\tilde{b}}^{-1}(\alpha))$ are the lower and upper bounds for the α-cut for fuzzy number $\tilde{b}$.

Based on Models (8) and (9), the final solutions for Model (7) under any fuzzy confidence level α can be obtained as follows:

$f^\pm = [f_{opt}^-, f_{opt}^+]$ (11a)

$x_{opt}^\pm = [x_{jopt}^-, x_{jopt}^+]$ (11b)

3.3 Data collection

In this study, three planning period will be considered with each one having one year (i.e. 2022-2024). The parameters for the water-energy-food nexus system such as water availability, unit outputs for different crops and their sown area limits, unit consumptions for fertilizers, pesticides, electricity and fossils are collected from national, provincial, and local yearbooks (Shandong Statistical Bureau, 2017, Jinan Municipal Bureau of Statistics, 2017, 2018, 2019; National Development and Reform Commission, 2018) as well as relevant literatures (Hu et al., 2016; Zhu et al., 2017; Hu et al., 2019; Ji et al., 2020a,b; Ma et al., 2020, MARA, 2020). The irrigation quotas for different crops are obtained from the local irrigation policy (No. DB37/T 3772-2019) released by the Water Resources Department of Shandong Province. Table 2 presents the variation intervals for relevant agricultural and economic parameters. Here the interval values are adopted to reflect uncertainties in those parameters. Table 3 presents the availabilities for water resources, electricity, fertilizers and pesticides.

Table 2. Agricultural parameters. All these parameters are obtained as intervals based on local statistical yearbooks and relevant literatures (e.g. Jinan Municipal Bureau of Statistics, 2017, 2018, 2019; National Development and Reform Commission, 2018, 2019; MARA, 2020; Ji et al., 2020a,b; Ma et al., 2020; Hu et al., 2016; Zhu et al., 2017; Hu et al., 2019; Li et al., 2020))

Time Period	*t* =1	*t* = 2	*t* = 3
Unit weight of different crops (kg/ha)			
Wheat	[5696, 6182]	[5696, 6182]	[5696, 6182]
Corn	[5748, 6452]	[5748, 6452]	[5748, 6452]
Vegetables	[65475, 66918]	[65475, 66918]	[65475, 66918]
Unit price of different crop products (RMB/kg)			
Wheat	[2.52, 2.57]	[2.57, 2.62]	[2.62, 2.67]
Corn	[1.73, 1.89]	[1.76, 1.93]	[1.80, 1.97]
Vegetables	[1.75, 1.80]	[1.78, 1.84]	[1.82, 1.87]
Consumption of fertilizer (kg/ha)			
Wheat	[425, 470]	[404, 447]	[384, 424]
Corn	[375, 415]	[356, 394]	[339, 374]
Vegetables	[640, 687]	[608, 652]	[577, 620]
Price of the fertilizer (RMB/kg)			
	[5.34, 5.79]	[5.45, 5.90]	[5.56, 6.02]
Consumption of pesticide (kg/ha)			
Wheat	[9, 10.05]	[8.55, 9.55]	[8.12, 9.07]
Corn	[10.83, 11.37]	[10.29, 10.80]	[9.77, 10.26]
Vegetables	[37.84, 39.73]	[35.95, 37.75]	[34.15, 35.86]
Price of the pesticide (RMB/kg)			
	[30.47, 31.99]	[31.08, 32.63]	[31.70, 33.28]
Costs for irrigation and discharge (RMB/ha)			
Wheat	[636, 683]	[649, 697]	[662, 711]
Corn	[368, 389]	[375, 397]	[383, 405]
Vegetables	[700, 736]	[714, 750]	[728, 765]
Fossil consumption for machinery operation (kg/ha)			
Wheat	[207.1, 213.9]	[207.1, 213.9]	[207.1, 213.9]
Corn	[111.7, 115]	[111.7, 115]	[111.7, 115]

Vegetables	[46.3, 48.6	[46.3, 48.7	[46.3, 48.8
Fossil price (RMB/kg)			
	[7.68, 7.92]	[7.83, 8.08]	[7.99, 8.24]
Minimum sown areas for different crops (10^5 ha)			
Wheat	[1.68, 1.89]	[1.68, 1.89]	[1.68, 1.89]
Corn	[1.51, 1.69]	[1.51, 1.69]	[1.51, 1.69]
Vegetables	[0.64, 0.72]	[0.64, 0.72]	[0.64, 0.72]
Maximum sown areas for different crops (10^5 ha)			
Wheat	[2.20, 2.64]	[2.20, 2.64]	[2.20, 2.64]
Corn	[2.32, 2.78]	[2.32, 2.78]	[2.32, 2.78]
Vegetables	[1.0, 1.2]	[1.0, 1.2]	[1.0, 1.2]
Irrigation Quota (m^3/ha)			
Wheat	[3300, 3675]	[3300, 3675]	[3300, 3675]
Corn	[1155, 1545]	[1155, 1545]	[1155, 1545]
Vegetables	[2400, 3075]	[2400, 3075]	[2400, 3075]
Food demand (kg/person)			
Cereals (wheat and corn)	[285, 315]	[291, 322]	[294, 325]
Vegetables	[372, 411]	[379, 419]	[385, 426]

Table 3. Resources availability: The resource availabilities are projected linearly based on historical records from 2011-2019 collected from local statistical yearbooks (Jinan Municipal Bureau of Statistics, 2017, 2018, 2019)

Time Period	$t = 1$	$t = 2$	$t = 3$
Water availability (10^8 m^3)	[9.27, 9.67]	[9.24, 9.63]	[9.22, 9.61]
Fertilizer availability (10^8 kg)	[2.86, 3.22]	[2.77, 3.12]	[2.69, 3.03]
Pesticide availability (10^6 kg)	[7.73, 8.69]	[7.50, 8.43]	[7.26, 8.14]
Electricity availability (10^8 kWh)	[7.34, 8.97]	[6.96, 8.50]	[6.58, 8.04]

The GHG emissions associated with food production are mainly generated from electricity for irrigation, diesel for machinery, fertilizer and pesticide utilization. The emission coefficients for these sources are presented in Table 4. Here the emission coefficients for fertilizer utilization for different crops would be different duet to different combinations of nitrogen (N), phosphorus (P) and potassium (K) fertilizers for different crops. The emission coefficients for pesticide utilization are also different because of different usages of herbicide, pesticide and fungicide for different crops.

Table 4. The GHG emission coefficient from different sources. These emission coefficients are collected from relevant literatures (Hu et al., 2016; Zhu et al., 2017; Hu et al., 2019)

Source	Emission coefficients	Unit
Fertilizer		
Wheat	4.68	kg CO_2-eq/kg
Corn	3.93	kg CO_2-eq/kg
Vegetables	3.53	kg CO_2-eq/kg
Pesticide		

Wheat	12.73	kg CO_2-eq/kg
Corn	12.22	kg CO_2-eq/kg
Vegetables	12.3	kg CO_2-eq/kg
diesel	3.1	kg CO_2-eq/kg
electricity	0.8	kg CO_2-eq/kWh

In addition to the uncertain parameters presented as intervals, there are also some parameters estimated as fuzzy numbers such as the irrigation reliability, the loss rates for food and vegetables and also local population in the City of Jinan. There are several methods to express a fuzzy number. The triangular fuzzy number is adopted to present the fuzzy uncertainty since the membership function for a fuzzy number is easily established. This kind of fuzzy numbers has been wide used in a number of studies (e.g., Fan et al., 2009, 2012; Ma et al., 2020). The fuzzy parameters used in this study are presented in Table 5.

Table 5. Fuzzy parameters used in this study.

	t = 1	t = 2	t = 3
Local population (10^6)	(8.80, 8.98, 9.16)	(8.87, 9.05, 9.23)	(8.94, 9.12, 9.30)
Food loss rate	(0.03, 0.035, 0.04)	(0.03, 0.035, 0.04)	(0.03, 0.035, 0.04)
Vegetable loss rate	(0.28, 0.30, 0.32)	(0.28, 0.30, 0.32)	(0.28, 0.30, 0.32)
Irrigation reliability	(0.5, 0.625, 0.7)	(0.5, 0.625, 0.7)	(0.5, 0.625, 0.7)

4. Result Analysis

Based on the constraints (e.g., environmental protection and limited resource utilization) and the objective of maximum unit benefit, the planting areas of different crops as well as total CO_2 emission during the planning periods could be obtained by solving the inexact fractional fuzzy chance constraint programming-based water-energy-food nexus model. Particularly, three α-cut levels (i.e., α = 0.2, 0.5, 0.8) are chosen to deal with the fuzzy parameters in the developed model in order to reflect the preferences by the decision maker. Under each α-cut level, two submodels corresponding to the optimistic and pessimistic conditions are formulated based on the solution method presented in Section 3.2, leading to six submodels in total. Each submodel is a conventional fractional programming model with deterministic parameter values. In current study, the cultivation areas for corn, wheat and vegetables would be generated from the

IFFCCP-WEFN model in three planning periods. Therefore, the developed IFFCCP-WEFN as well as its corresponding submodels would have nine decision variables. The generated submodels were solved through LINGO 11.0 software packagewith a computational time less than 1 second and infeasibility tolerance less than 10^{-6}. Interval solutions are finally obtained, under each α-cut level, to reflect the potential farming pattern in different planning periods.

Table 6 clearly shows crops' planting area and the corresponding variation trend during the planning periods under different preferences (i.e. α-cut levels) from the decision maker, which would further help the decision makers to formulate and implement scientific planning schemes. It can be seen that the planting areas for different crops would vary in different planning periods due to the socioeconomic and environmental restrictions. In detail, the planting areas for corn and vegetables show a slightly increasing trend, while in comparison, the sown area for wheat tends to keep constant. For instance, the planting area for corn would be 1.784×10^5 ha in period 1 and 1.932×10^5 ha in period 3 under a fuzzy confidence level of 0.2, showing an increasing rate of 8.3%. In comparison, cultivation area for wheat would be 1.89×10^5 ha for all the planning periods, which is the upper bound of the minimum planting limit. The results imply that the corn seems to be prioritized between corn and wheat in the planting structure to satisfy the cereal demand from local population. More specifically, as the cereal demand increases in time periods 2 and 3, these demands would also be satisfied by corn, and thus lead to an increasing trend for corn cultivation over the planning horizon. In addition, the cultivation area for vegetables would slightly increase from $[0.956, 1.204]\times10^5$ ha in period 1 to $[0.996, 1.204]\times10^5$ ha in period 3 under this fuzzy confidence level, with an increasing rate of 4.2% for the lower bound. The increasing trend for vegetable cultivation under the demanding/pessimistic conditions (i.e. lower bound) may also be attributed to the increasing vegetable demand over the planning horizon. Moreover, compared with the cultivation structures for corns and wheat, there are certain fluctuations ranges for vegetable planting between demanding/pessimistic and advantageous conditions (e.g., $[0.956, 1.204]\times10^5$ ha in period 1). The advantageous/optimistic conditions generally correspond to more resource availabilities (e.g., water resources, electricity, fertilizers etc.) but less food demand (e.g., less population, less food loss rate etc.). The fluctuation ranges for vegetable cultivation indicate that, when more resources are available, these resources tend to be utilized to increase sown areas for vegetables. Furthermore, as the fuzzy confidence level changes, the detailed sown areas for corn and vegetables would be changed, whilst the variation pattern would not change significantly. Figure 2 presents the fluctuation of sown areas for the three crops in the planning horizon, which shows the variation trends under both advantageous and demanding conditions under different fuzzy confidence levels.

Table 6. The sown areas for different crops in different planning period (10^5 ha). Three fuzzy confidence levels are considered denoted as α.

	Wheat	Corn	Vegetables
alpha = 0.2			
t =1	1.889	1.784	[0.956, 1.20]
t = 2	1.889	1.868	[0.974, 1.20]
t = 3	1.889	1.932	[0.996, 1.20]
alpha = 0.5			
t =1	1.889	1.784	[0.956, 1.20]
t = 2	1.889	1.851	[0.978, 1.20]
t = 3	1.889	1.915	[1.000, 1.20]
alpha = 0.8			
t =1	1.889	1.784	[0.956, 1.20]
t = 2	1.889	1.835	[0.983, 1.20]
t = 3	1.889	1.899	[1.003, 1.20]

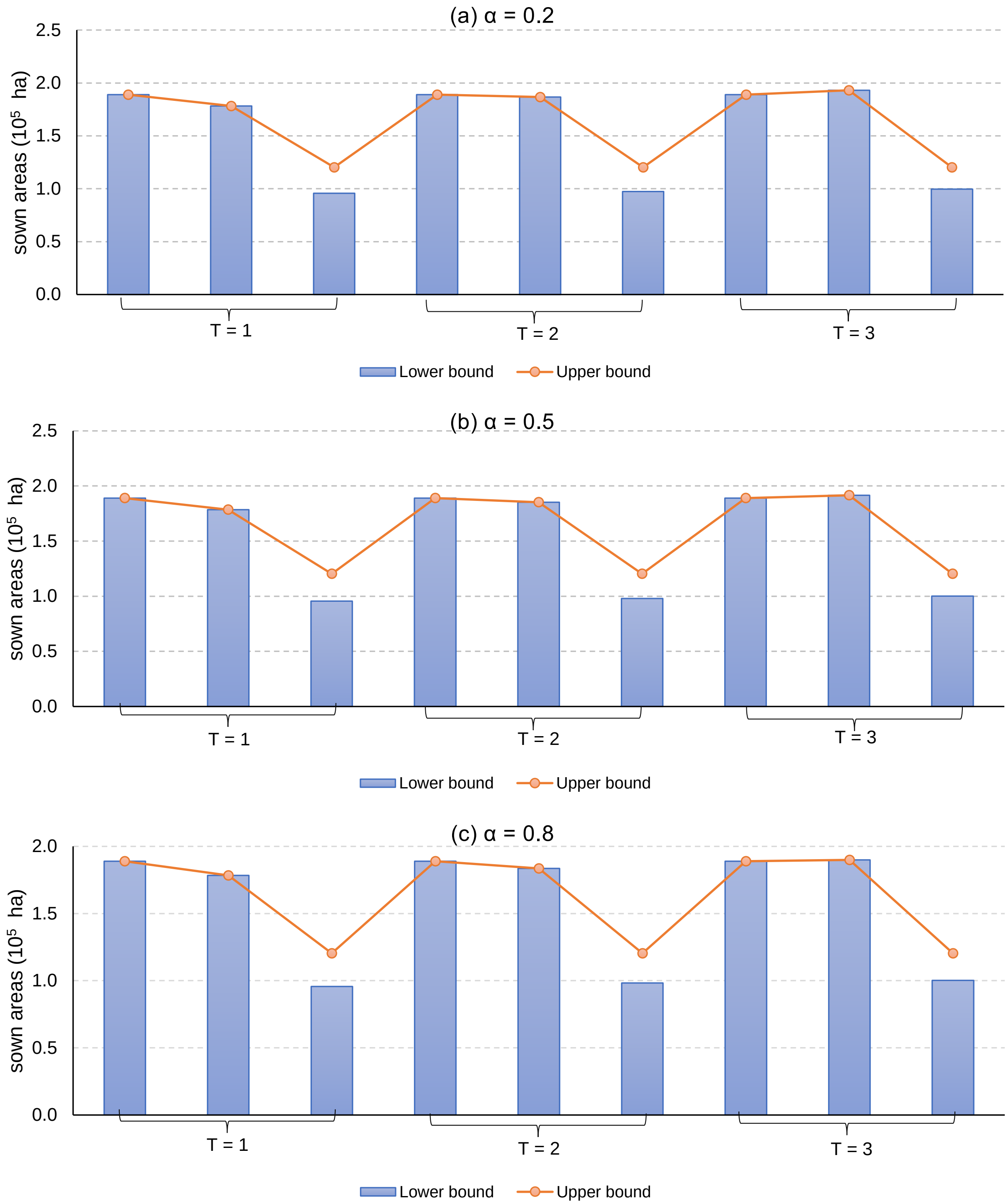

Figure 2. The planting patterns for wheat, corn, and vegetables over the planning horizon under different fuzzy confidence levels. Three fuzzy confidence levels, denoted as α, are considered in this study. The Grey bars denote the lower bound of cultivation areas for different crops and the angle dashed lines present the upper bounds of crop cultivation areas.

In this study, three fuzzy confidence levels are chosen to reflect the variations of the predefined triangular fuzzy parameters (i.e., α = 0.2, 0.5, and 0.8). Under each fuzzy confidence level, the α-cut method would be employed to convert the fuzzy numbers into corresponding interval numbers under this level. These three levels are selected since they can generally reflect the variations of fuzzy parameters under low, medium and high possibilities. The α-cut value of 0.2 indicates a low possibility for the corresponding parameter ranges (i.e., the intervals of fuzzy numbers under α-cut = 0.2), but such ranges can cover most possible values for the fuzzy parameters. In comparison, the α-cut value of 0.8 indicates a high possibility for the corresponding parameter ranges but such ranges may neglect some possible parameter values with low possibilities. Consequently, through choosing these three fuzzy confidence levels, the proposed IFFCCP-WEFN model would generate desired cultivation structures under different possibilities. Moreover, based on the solutions under multiple fuzzy confidence levels, the impacts of fuzzy parameters on the resulting solutions can be explored.

As stated in Table 6, it can be concluded that the change of fuzzy confidence levels may not pose significant effects on the resulting solutions under advantageous conditions since there would be less food demand but sufficient resource availabilities under these conditions. In comparison, the fuzzy confidence level would have some visible impacts on the detail sown areas for corn and vegetables. Under the demanding/pessimistic conditions, the necessity measure would be adopted as presented in Equation (11b). Figure 3 compared the local population and crop cultivation under different fuzzy confidence levels. As the increase of fuzzy confidence level, less population would be estimated (i.e., $(P_t)^+_{0.8} \leq (P_t)^+_{0.2}$), leading to less food demand. Nevertheless, more food loss rate may happen as the increase of fuzzy confidence level (i.e., $(1-\eta)^L_{1-0.8} \leq (1-\eta)^L_{1-0.2}$). Figures (3a) and (3b) present constant sown areas for corn and vegetables for all three fuzzy confidence levels at time period 1. This implies that the decreasing food demand, with the increase of fuzzy confidence level, would be balanced by the decreases of food loss rates. Thus, the fuzzy confidence level would not have explicit impacts on crop cultivation in this planning period. However, in time periods 2 and 3, more food demands (especially for cereal) are expected per person as presented in Table 2. Therefore, the decrease of local population, as a result of increasing fuzzy confidence level, would lead to more decrease of total food demand than that happened in period 1, which would not be balanced by the corresponding increases of food loss rates. Consequently, the food demand in both periods 2 and 3 would generally decrease as the increase of fuzzy confidence levels. This would lead to less sown area for corn as the fuzzy confidence level increases as presented in Figure (3c) and (3e). Besides, the reduction of corn cultivation would generally lead some residues for arable land. The remaining land would tend to be utilized for planting vegetables and thus lead to increasing sown areas for vegetables as presented in Figure (3d) and (3e). Such a conclusion is consistent with the changes of cultivation patterns under advantageous conditions where sufficient resources are available.

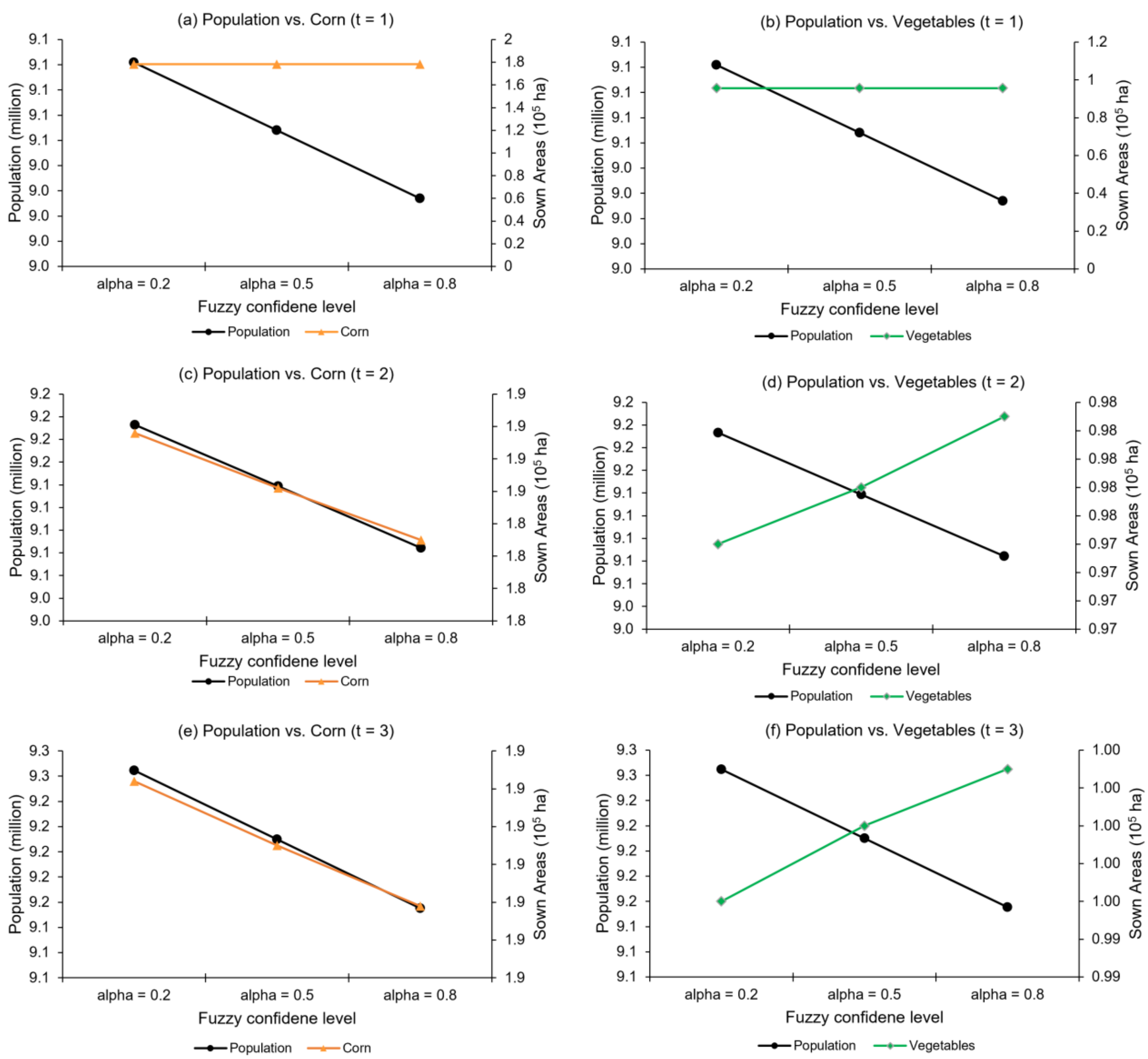

Figure 3. Comparison between local population and crop cultivation under different fuzzy confidence levels over the planning horizon for the demanding conditions.

As stated in Table 6 and Figure 2, different sown areas would be expected for wheat, corn and vegetables in different planning period under different fuzzy confidence levels. These planting structures would also lead to different GHG emissions from utilization of electricity, fossil, fertilizers and pesticides. Figure 4 presents the percentages of the cultivation areas for the three crops as well as the associated GHG emission contributions in the planning horizon under a fuzzy confidence level of 0.2. The results indicate that the proportion for wheat cultivation shows a decreasing trend due to the increasing proportion for corn. This can be attributed to the relatively high GHG emission rate from wheat. For instance, under the pessimistic conditions, the wheat cultivation has a planting proportion of 40.8% but it would make a contribution of 42.1% to the total GHG emission in time period 1. In comparison, the cultivation of corn would contribute 29.1% of GHG emission through a 38.5% planting proportion. However, it can be observed from Figure 4 that the cultivation of vegetables seems to have higher CO_2 emission intensity than the other two crops, which would contribute 20.7% to the total CO_2 emissions through a planting proportion of 28.9% in time period 1 for pessimistic conditions. Nevertheless, the sown areas for the vegetables would still show an increasing trend especially under the demanding/pessimistic condition as presented in Table 6 and Figure 2. This may be due to two possible reasons: i) the vegetables would generally have much higher unit production weight than corns and wheat, which may lead to more profits; ii) both corn and wheat belong to cereals and thus they are interchangeable, but the vegetables can hardly be replaced by cereals. Consequently, a large proportion of the sown areas should be allocated to vegetables to meet the vegetable demands in the local area. More importantly, as presented in Table 6 and Figure 3, after satisfying the cereal demands from local population, the residual resources (e.g., arable land, water resources, electricity, etc.) would be suggested to be used for vegetable cultivations. Figures 5 and 6 present the cultivation pattern for the three crops and the corresponding contributions of GHG emissions under the fuzzy confidence levels of 0.5 and 0.8. The results also reveal similar patterns for crop cultivation and GHG emissions with those under a fuzzy confidence level of 0.2. However, the GHG emissions from corn cultivation would likely decrease as the increase of the fuzzy confidence level especially in time periods 2 and 3. This would be due to the decreasing sown areas for corn as presented in Figure 3. In comparison, the GHG emissions from vegetables would slightly increase at the same time. For instance, under the pessimistic condition, the cultivation for corn and vegetables would respectively have proportions of 39.2%, 20.7% in time period 2 under a fuzzy confidence level of 0.5, and 39.0%, 20.9 % under a fuzzy confidence level of 0.8. Correspondingly, the GHG emissions from corn and vegetables would respectively make contributions of 29.6% and 29.1% under the fuzzy confidence level of 0.5, and 29.4% and 29.2% under the fuzzy confidence level of 0.8. These results also demonstrate the priority of corn cultivation to meet the cereal demand in the City of Jinan.

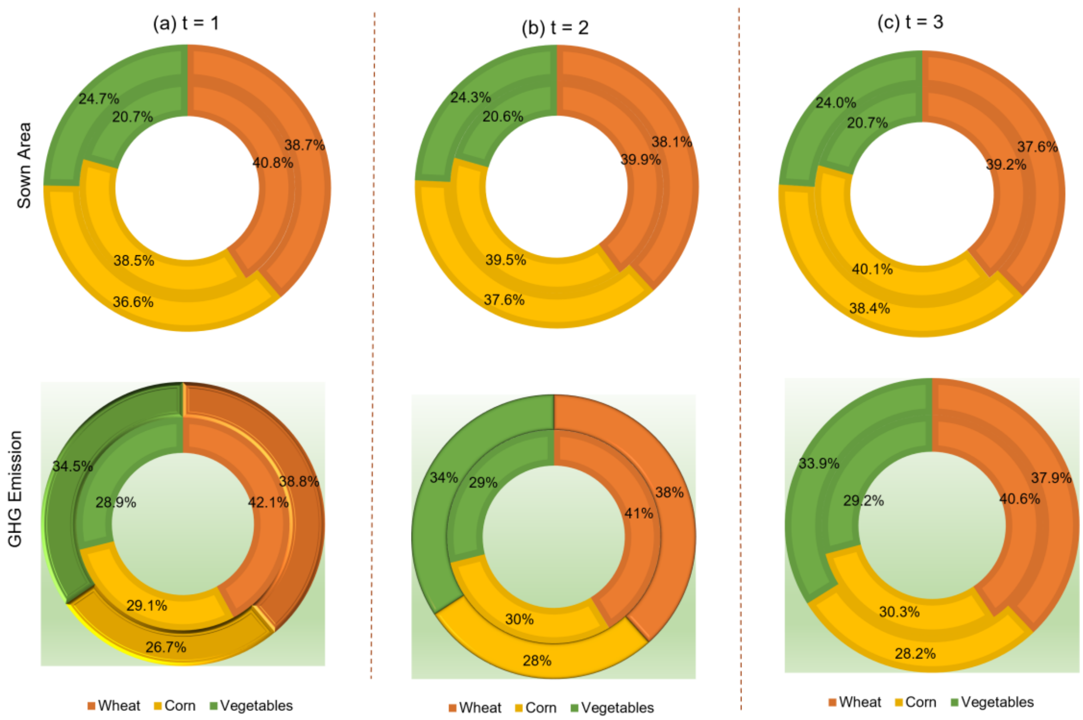

Figure 4. the percentages of sown areas and the associated CO_2 emissions under the fuzzy confidence level of 0.2. The inner doughnut corresponds to the demanding (or pessimistic) condition while the outer one corresponds to the optimistic condition. A larger percentage of corn cultivation would be preferred to meet the cereal demands since more than 40% of corn planting only leads to about 30% of CO_2 emissions.

Figure 5. the percentages of sown areas and the associated GHG emissions under the fuzzy confidence level of 0.5. The inner doughnut corresponds to the demanding (or pessimistic) condition while the outer one corresponds to the optimistic condition. A slight decrease for cultivation percentage would be expected in time periods 2 and 3 for corn under both pessimistic and optimistic conditions as the fuzzy confidence level increases from 0.3 to 0.5, which also lead to percentage increase for the other two crops.

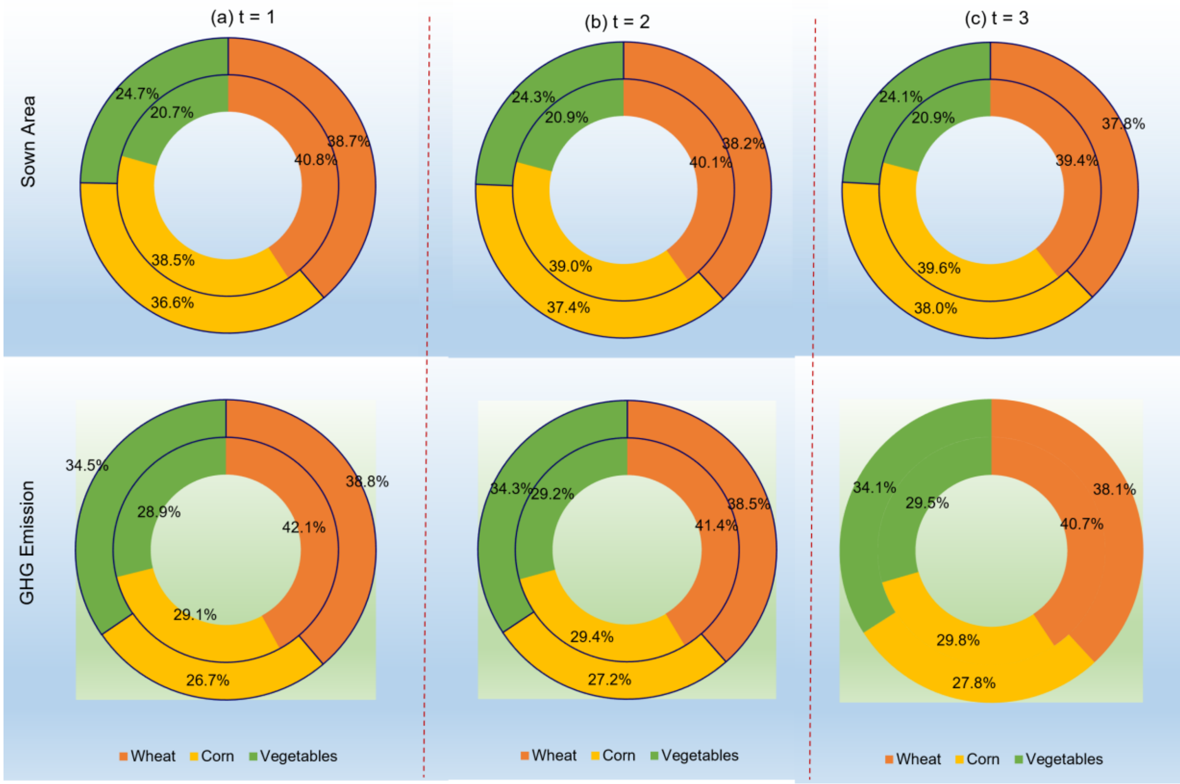

Figure 6. the percentages of sown areas and the associated GHG emissions under the fuzzy confidence level of 0.8. The inner doughnut corresponds to the demanding (or pessimistic) condition while the outer one corresponds to the optimistic condition. The cultivation percentage of corn will continue decrease as the fuzzy confidence level increases due to less food demand, while the residual resources tend to be allocated to vegetable cultivation.

Figure 7 presents both the unit benefits and total benefits obtained from the developed IFFCCP-WEFN model under different fuzzy confidence levels. Under the demanding conditions, which corresponding to more food demands, less resource availabilities and thus lower objective bounds, an increasing trend would be observed as the increase of fuzzy confidence level. For instance, the unit benefit would range between 8.410, 8.438 and 8.459 RMB/kg CO_2-eq respectively under the fuzzy confidence level being 0.2, 0.5 and 0.8. Correspondingly, the total benefits would be RMB 4.095×10^{10}, RMB 4.103×10^{10}, and RMB 4.109×10^{10}, respectively. This may be due to more sown areas for vegetables as presented in Table 6. For the advantageous conditions corresponding to the upper bound of the objective, an increasing trend would be still observed since, after satisfying cereal demands, the remaining resources tend to be allocated to vegetables. Nevertheless, the total benefit as presented in Figure (7b) tends to slightly decrease from RMB 5.379×10^{10} under α = 0.2 to RMB 5.373×10^{10} under α = 0.8. This would be mainly because that, under the advantageous conditions where the possibility measure is adopted, the increase of fuzzy confidence level would also lead to increase for the lower bound of irrigation reliability (i.e., $(\tilde{o})_{\alpha}^{-}$) in Constraint (4). Such an increase would lead to decrease for the total sown areas for the three crops as presented in Table 6 (i.e., sown area for corn decreases while the sown areas for the other two crops keep constant). Consequently, this would lead to a slight decrease in the total benefit under advantageous conditions.

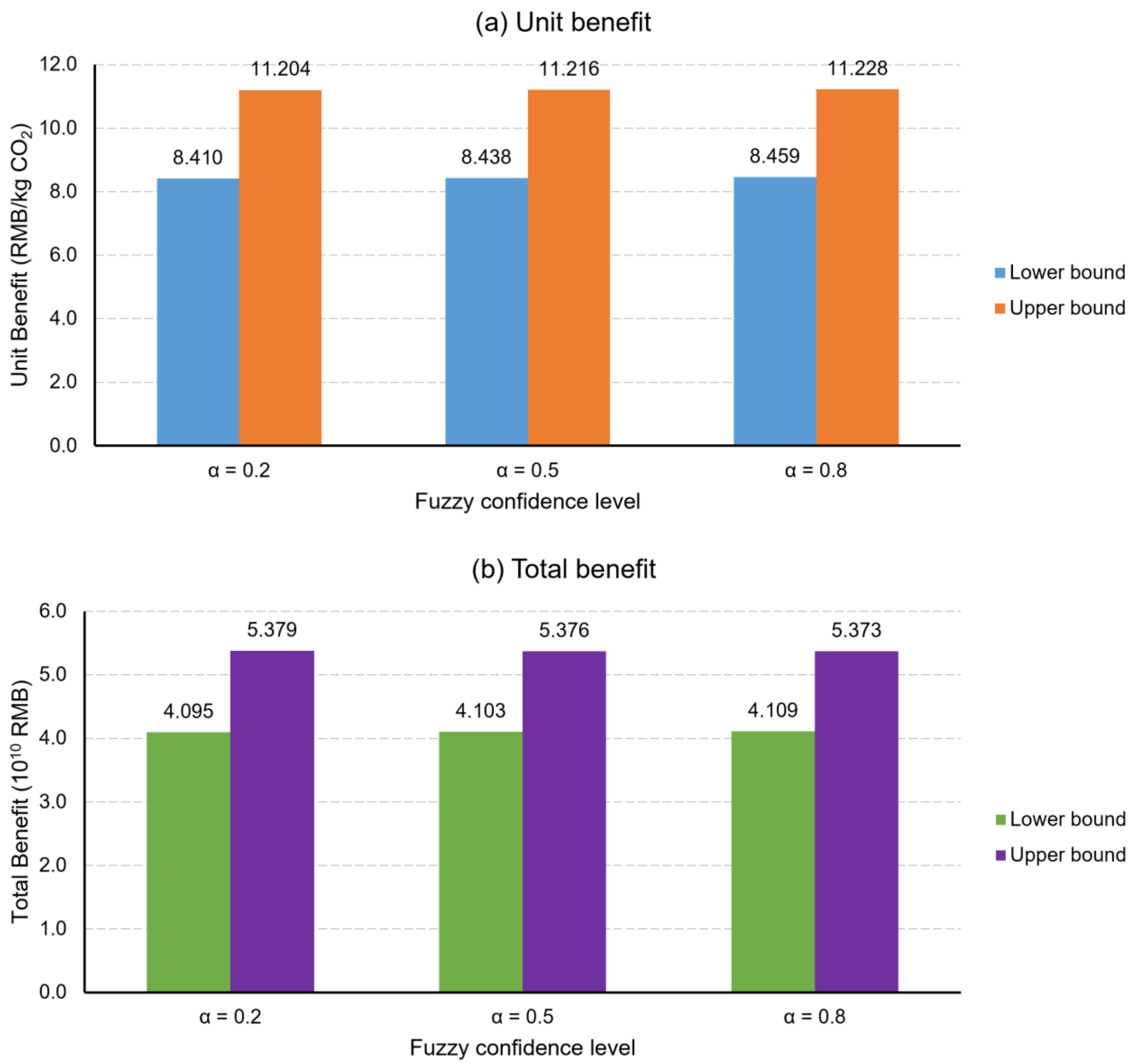

Figure 7. System benefits for the IFFCCP-WEFN model. A slightly increasing trend, under the demanding conditions, can be observed for both unit and total benefits as the increase of fuzzy confidence level (denoted as α). The unit benefit would also increase for advantageous conditions while the total benefit would decrease due to the decrease of total crop sown areas.

5. Discussion

The objective of the developed IFFCCP-WEFN model is to achieve a maximized unit benefit for the agriculture department with respect to the GHG emissions. This is the reason to introduce a fractional objective function into the IFFCCP-WEFN model. If the objective function is to maximize the total benefit of the water-energy-food nexus system, this will lead to an inexact fuzzy chance constraint programming-based water-energy-food nexus (IFCCP-WEFN) model. More specifically, if the GHG emission target is not considered, the objective function in Equation (1) will be denoted as Max $f^{\pm} = f_1 - f_2 - f_3 - f_4 - f_5 - f_6$, which is denoted as IFCCP-Case1 in the following analyses. Moreover, the GHG emission can also be considered in the IFCCP-WEFN model through introducing a carbon trading objective, in which the function of f_7 can be revised as $f_7 = \sum_{t=1}{}^{T}\sum CTP_t^{\pm} * TCE_t^{\pm}$ and the objective function in Equation (1) will be denoted as Max $f^{\pm} = f_1 - f_2 - f_3 - f_4 - f_5 - f_6 - f_7$. Here $CTP_t^{\pm}$ denote the carbon trading price in time period t, which was set as [48, 60], [51.1, 65.4] and [54.5, 71.3] RMB/tonne for t = 1, 2 and 3 respectively. Such an IFCCP-WEFN model is denoted as IFCCP-Case2 in the following comparison analyses.

Compared with the developed IFFCCP-WEFN model, both IFCCP-Case1 and IFCCP-Case2 models can be converted into two conventional linear programming submodels under each fuzzy confidence level, which were solve by LINGO 11.0 software package in this study. Also, the submodels generated from the two IFCCP models would be solved with less computational time than those fractional submodels generated from the IFFCCP-WEFN model. However, due to the small model size for the studied WEFN system, all the submodels (including linear programming and fractional programming submodels) were solved by the LINGO 11.0 software package within 1 second. Therefore, there would be no computational burden in practical computation for the developed IFFCCP-WEFN model. In addition, since the fractional submodels would be generated from the IFFCCP-WEFN model, only local optimal solutions would be obtained from LINGO corresponding to both pessimistic and optimistic conditional. In comparison, the submodels for the IFCCP-WEFN model (both IFCCP-Case1 and IFCCP-Case2 models) would generate global optimal solutions since these submodels are linear programming models.

Figure 8 compares the low and upper bounds of the total benefits obtained through the IFFCCP and IFCCP models. The results indicate that the IFCCP-Case1 model would generate the highest total benefits for both demanding/pessimistic and advantageous/optimistic conditions since the GHG emissions from WEFN system is not considered. For instance, the total benefits would range between RMB[4.111, 5.574]$\times 10^{10}$ under a fuzzy confidence level of 0.2, compared with the total benefit of RMB[4.095, 5.379]$\times 10^{10}$ from IFFCCP-WEFN model, which leads to an slightly increase rate of 0.4% for the lower bound and 3.6% for the upper bound. In comparison, when the GHG emission is also consider in the IFCCP-WEFN model (i.e., IFCCP-Case2), the obtained total benefits would be lower than the benefit from IFFCCP-WEFN model under demanding conditions, but higher for the advantageous conditions where sufficient resources are available. For example, the total benefit from the IFCCP-Case2 model would be RMB[4.078, 5.546]$\times 10^{10}$ under a fuzzy confidence level of 0.2, leading to a decreasing rate of 0.4% for the benefit from IFFCCP-WEFN model under demanding conditions, but an increasing rate of 3.1% for the upper bound. Moreover, the lower bounds of the total benefit from all three models would present an increasing trend as the increase in fuzzy confidence level, implying the visible effect of the decision makers' preferences on the desired crop planting structures. Nevertheless, except the slightly decreasing trend for the upper bound objective from IFFCCP model, the upper bound benefits for the two IFCCP models would keep constant regardless of the changes in fuzzy confidence level. This suggest that the decision preferences would not have explicit impact on the desired WEFN management strategies under advantageous conditions.

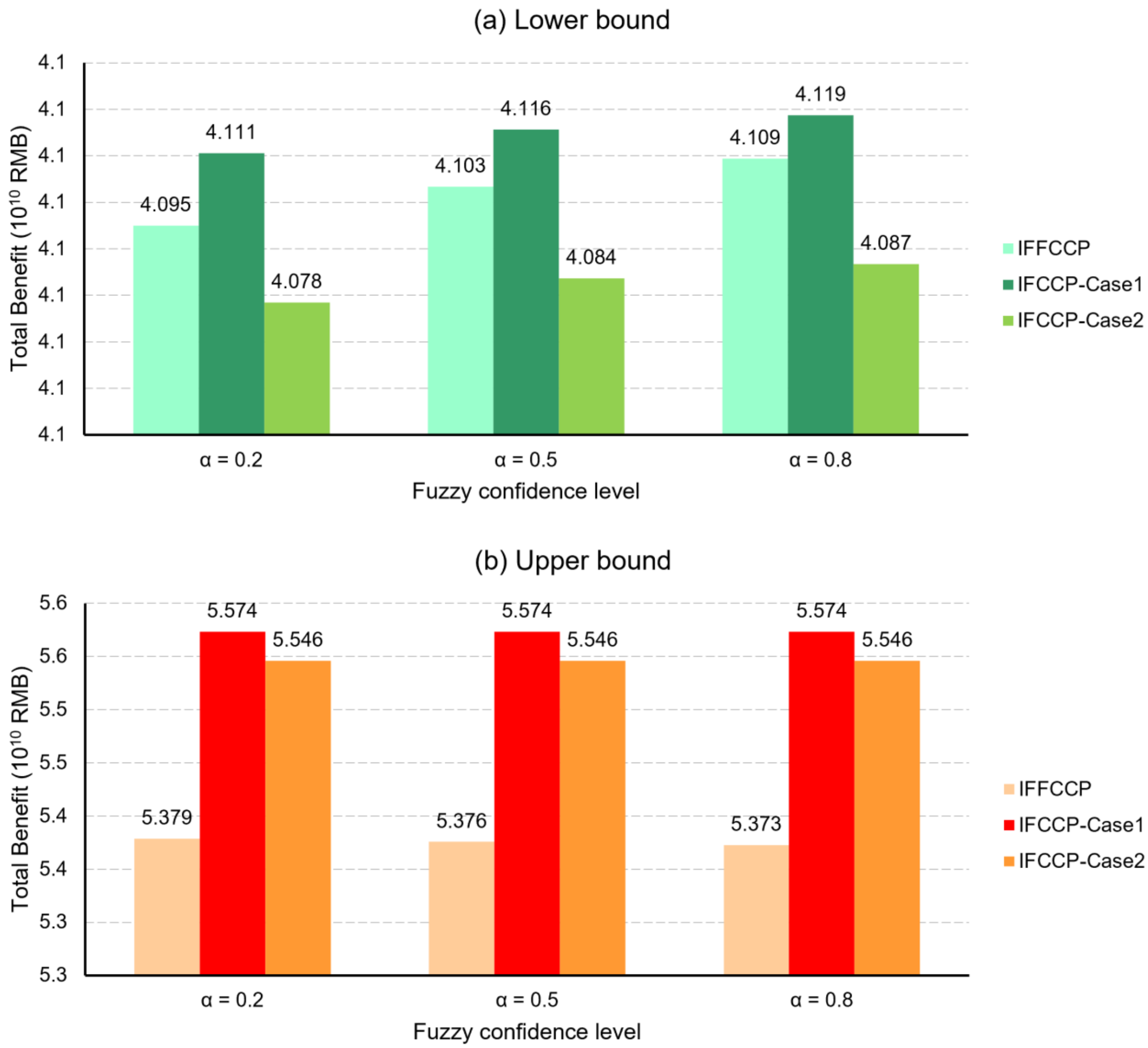

Figure 8. Comparison of the total benefits for the water-energy-food nexus system between the inexact fractional fuzzy chance constraint programming (IFFCCP) model and inexact fuzzy chance constraint programming (IFCCP) models.

Figure 9 presents the comparison of the unit benefits with respect to GHG emissions from the IFCCP-WEFN model and two IFCCP-WEFN models. Since the IFCCP-Case1 model did not consider the GHG emissions during the crop cultivation process, it is straightforward that the unit benefit with respect to GHG emissions would generally lower than that obtained from the developed IFFCCP-WEFN model. For instance, the unit benefit generated from the IFCCP-Case1 model would range within [8.401, 10.398] RMB/kg CO_2-eq under a fuzzy confidence level of 0.2, whilst the unit benefit from IFFCCP-WEFN model would vary within

[8.410, 11.204] RMB/kg CO_2-eq. A decreasing rate about 0.1% would be observed for the lower bound while the decreasing rate for the upper bound can increase to 7.2%. The results indicate that the planting structure for crops without consideration of GHG emission may not be as efficient as the solution from IFFCCP-WEFN model in response to GHG mitigation especially when sufficient resources are available for crop planting. It is noticeable that the introduction of carbon trading in the IFCCP model (i.e., IFCCP-Case2) would not enhance the efficiency of GHG mitigation as presented in Figure 9. The unit benefits from the IFCCP-Case2 model are the same as the unit benefits obtained from IFCCP-Case1 model for both demanding and advantageous conditions under all three fuzzy confidence levels. These results may be due to two possible reasons: i) both the IFCCP-Case1 and IFCCP-Case2 models were developed to maximize the total system benefit and thus the unit benefit with respect to GHG emission was not considered. ii) the GHG trading price, obtained from some open news report, would be too low (e.g., 0.07 RMB/kg CO_2-eq for the highest price), and such a price may not visibly affect the desired crop planting structure from the IFCCP models. This can be further demonstrated through comparing the total benefits from the two IFCCP models. The total cost for carbon trading (i.e., the benefit from IFCCP-Case1 model minus the benefit from IFCCP-Case2 model) would only have a proportion about 0.8% under demanding conditions and 0.5% under advantageous conditions in the total benefit.

Figure 10 presents the total GHG emissions in different planning periods under different fuzzy confidence levels. It indicates that the GHG emissions from the planting patterns obtained by the IFCCP-WEFN models (i.e., IFCCP-Case1 and IFCCP-Case2) are higher than those from the cultivation structure obtained by IFFCCP-WEFN model in all the planning periods under all the fuzzy confidence levels. This is because that the IFFCCP model would maximize the unit benefit with respect to GHG emissions while the IFCCP models only considered the total system benefits. In addition, the total GHG emissions, under each fuzzy confidence level, tend to decrease over the planning period for all the three WEFN models. This may be mainly because that the resources availabilities, especially for fertilizers and pesticides, would decrease due to more strict environmental restrictions. These results demonstrated the ineffectiveness of the planting structure obtained from the IFCCP-WEFN models for GHG emission control.

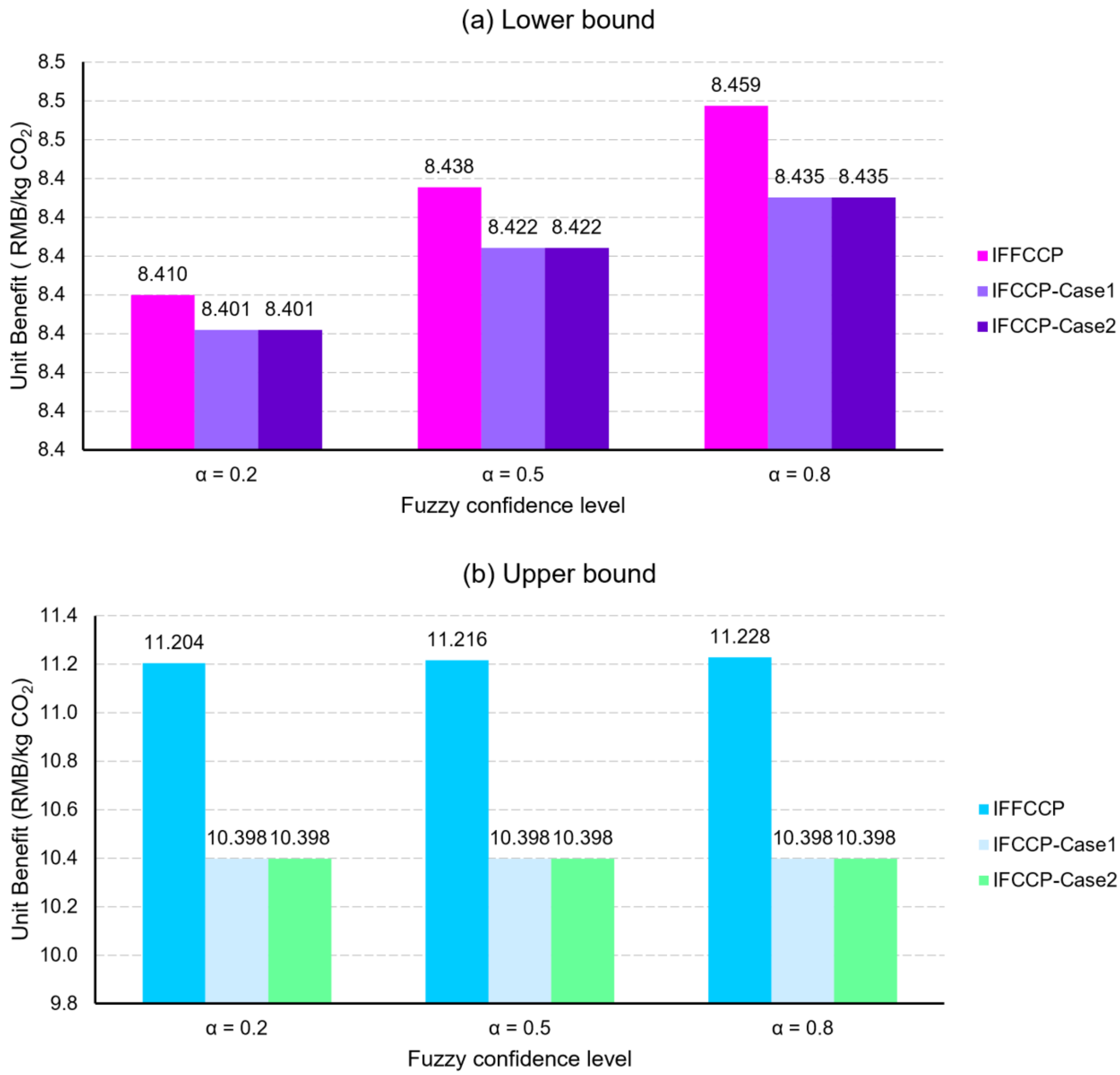

Figure 9. Comparison of the unit benefit for the water-energy-food nexus system between IFFCCP model and IFCCP models. Under all the fuzzy confidence levels, the IFFCCP model will lead to higher unit benefits with respect to CO_2 emissions than the IFCCP models, especially for the advantageous conditions.

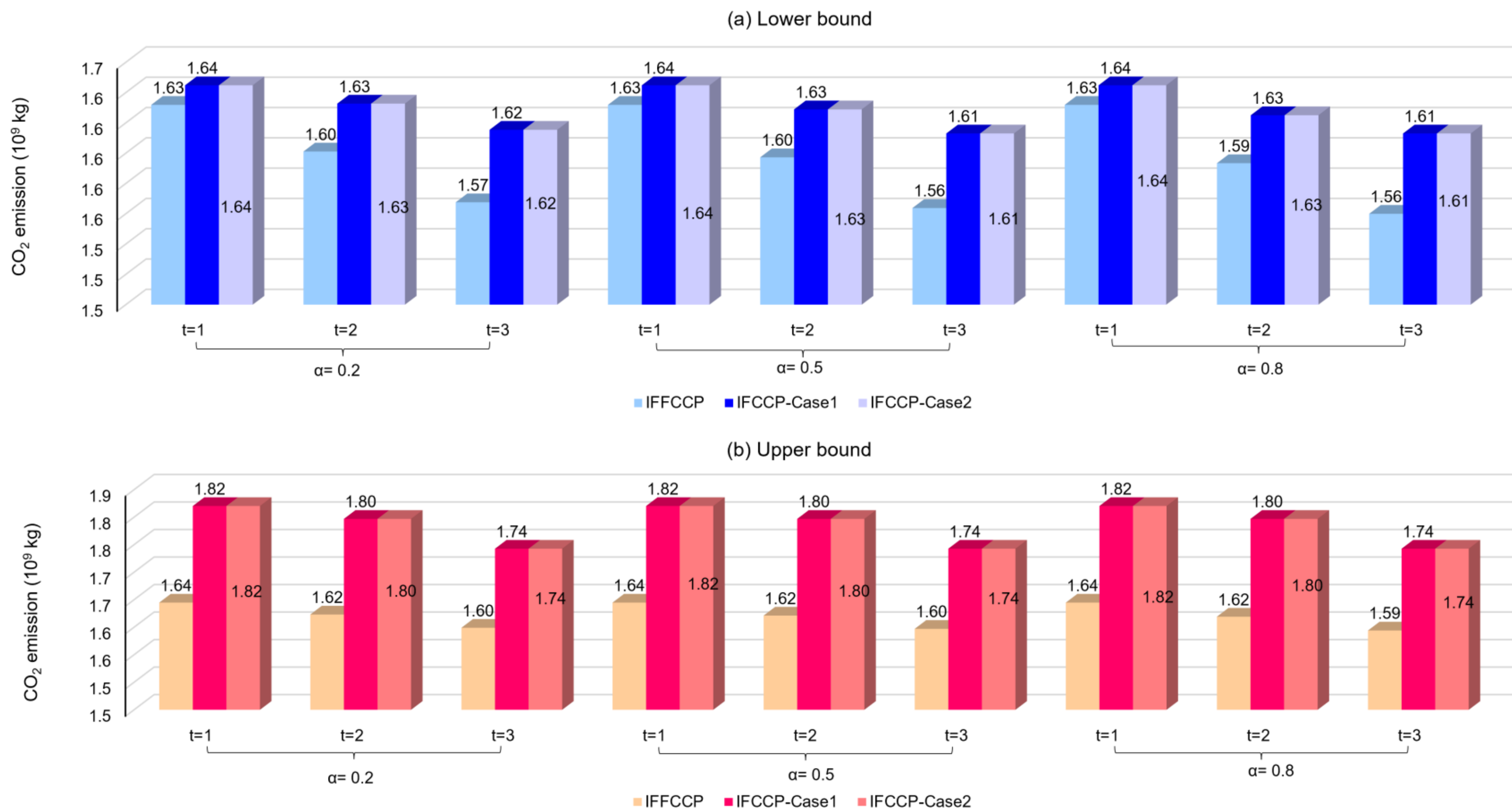

Figure 10. Comparison of GHG emissions from the water-energy-food nexus system in different time periods between the IFFCCP model and the IFCCP models. Visible decreases can be expected for the planting pattern obtained by the IFFCCP model since compromise between system benefits and GHG emissions would be considered in IFFCCP. In comparison, the IFCCP model would lead to significant increases of GHG emissions due to the low GHG mitigation efficiency.

In this study, the contradictory objectives between system benefits and GHG emissions for a WEFN system were reflected through introducing the fractional programming method into the developed IFFCCP approach in order to achieve a maximum unit benefit with respect to GHG emissions. However, such contradiction issues in the WEFN system would also be tackled through bi-level or multi-level programming methods as developed in Jin et al. (2018), Yu et al. (2020a), Zhang et al. (2020) and other relevant studies. Nevertheless, we argue that the developed IFFCCP approach would have some merit when compared with bi-level or multi-level methods in dealing with trade-offs among contradictor objectives. Firstly, the bi-level or multi-level methods would need to pre-define the hierarchical structure for the upper-level and lower-level models. For the same conflicting objectives (e.g., system benefit and GHG emissions), different hierarchical structures (e.g., the upper-level for system benefit or the upper-level for GHG emissions) would lead to significant discrepancies in the desired solutions. In comparison, the developed IFFCCP approach would reflect contradiction between system benefit and GHG emissions through maximizing the unit benefit with respect to GHG emission, without pre-specifying the priority among these two objectives. Moreover, the bi-level or multi-level models would be solved through some complex interactive algorithms (e.g., Jin et al. 2018), in which one model (either the upper-level or the lower-level model) would be solved firstly, and the other one would then be solved for decision variables around their solutions from the first model within a pre-defined tolerance (Jin et al. 2018). This may lead to two possible issues: i) the tolerance was commonly determined subjectively by the decision makers or model developers, in which different tolerance values would lead to different solutions. ii) Since the second model would be solved around the solutions of the decision variables obtained from the first model, this would also lead to local optimal solutions. Furthermore, we admit that the bi-level or multi-level models may generate crop planting structures with relatively higher unit benefits than the IFCCP models (IFCCP-Case1 and IFCCP-Case2). However, those models may hardly produce the crop planting structure with a higher unit benefit than the desired cultivation pattern generated by the developed IFCCP-WEFN model based on the shortcomings for the bi-level or multi-level models discussed above.

6. Conclusions

In this study, an inexact fractional fuzzy chance constraint programming (IFFCCP) method has been developed to provide management strategies for the complex water-energy-food nexus (WEFN) system. An IFFCCP-based water-energy-food nexus (IFFCCP-WEFN) model has been formulated for planning the WEFN system for the City of Jinan, Shandong province under consideration of both system benefits and GHG emissions. Solutions of the planting areas for different crops under different periods have been generated in order to achieve a maximized unit benefit with respect to the GHG emissions.

Based on the IFFCCP-WEFN model, results indicated that, the increase of cereal demand over the planning horizon would be mainly satisfied by the corn cultivation, while the cultivation area of wheat would maintain at it upper bound of minimum requirement to avoid noticeable fluctuation for wheat price. This is due to the relatively lower GHG emission intensity from corn, in which the proportion of GHG emissions from corn would approximately drop 10 percentage points compared with its proportion in the crop cultivation areas. In addition, the sown area for vegetables, under strict restrictions, would also increase to meet the vegetable demand over the planning area. However, the sown area of vegetables would reach its upper bound under the advantageous conditions whilst the corn and wheat cultivation would not change even though more resources would be available under advantageous conditions. This implies that, after satisfying the cereal demand, the residual resources (e.g., water, fertilizer, energy, etc.) would tend to be allocated to vegetable planting. Moreover, preferences of decision makers on fuzzy parameters, as denoted as fuzzy confidence level, would generally pose explicit impacts on the obtained crop planting structure under demanding conditions where strict constraints are adopted. In detail, the increase of fuzzy confidence level would generally lead to decreased planting area for corn but increased planting area of vegetables in the time periods 2 and 3. This is because that, under, the increase of fuzzy confidence level would lead to decreased population estimation and thus decreased food demand. Therefore, less corn planting is required whilst the residual resources would be allocated to vegetables and thus lead to increased vegetable planting. Conversely, the planting structure would keep constant regardless of changes of fuzzy confidence level since the decreased food demand, with the increase of fuzzy confidence level, would be balanced by the decreased food loss rates.

The objective of the IFFCCP-WEFN model is to achieve a maximized unit benefit with respect to GHG emission, and thus the obtained planting scheme is different from that generated by the inexact fuzzy chance constraint programming-based water-energy-food nexus (IFCCP-WEFN) models. The results suggest that the unit benefit from IFFCCP-WEFN model would higher than that from IFCCP-WEFN models both considering and not considering GHG emissions. Moreover, the total GHG emissions from the cultivation scheme obtained by IFFCCP-WEFN model would be less than the cultivation scheme generated by the IFCCP-WEFN models. This is particularly explicit under advantageous conditions where sufficient resources are available. The GHG emissions based on the IFFCCP-WEFN model can be reduced by about 11% at most than those from the IFCCP-WEFN models. Particularly, inclusion of GHG emission objective in the traditional IFCCP-WEFN model (i.e., IFCCP-Case2) would not produce distinguishable results with the IFCCP-WEFN model without GHE emission target (i.e., IFCCP-Case1) since the cost for carbon trading would only account for a small proportion in the total benefit (about 0.8% under demanding conditions and 0.5% under advantageous conditions). Consequently, these results indicate that the IFFCCP-WEFN model would generate more desirable support for sustainable WEFN management in response to climate change.

In this study, an inexact fractional fuzzy chance constraint programming (IFFCCP) approached have been developed for management of water-energy-food nexus system under consideration of GHG emissions. This study would have contributions in both methodology and model development for WEFN planning and management. Firstly, the proposed IFFCCP method is able to reflect uncertainties presented as both fuzzy and interval numbers. Particularly, the measures of necessity and possibility, which are considered to be very relevant to the real-life decision problems (Maity, 2011), are introduced to reflect decision preferences on fuzzy parameters. Secondly, the fractional programming is introduced into the IFFCCP approach to deal with contradictory targets in the WEFN system. The IFFCCP-based models can be solved more easily than those models based on bi-level or multi-level programming methods, in which subjective pre-specifications for hierarchical model structure and solution tolerance are required. Finally, the proposed IFFCCP-WEFN model has considered GHG emissions in food production in order to achieve a maximized unit benefit with respect GHG emission. The obtained solutions have been demonstrated to be more effective in GHG mitigation than the results from some traditional models even considering carbon trading. Moreover, such a model can be transferred to other areas to provide scientific support for carbon emission control in the water-energy-food nexus system.

Even though the proposed IFFCCP-WEFN model has been demonstrated to be effective for sustainable management of WEFN system, further studies are still required to address some potential issues in the present IFFCCP-WEFN model. Firstly, only the GHG emissions were considered in the current IFFCCP-WEFN model whilst the carbon sink from crop cultivation was not considered. In fact, some studies (i.e., She et al., 2017) has demonstrated that the major crops production showed as carbon sinks rather than carbon sources in general. Secondly, the uncertain parameters adopted in the proposed model are only expressed as fuzzy or interval variables, while some studies claimed that some parameter may present as multiple uncertain formats based on different data availability (e.g., Yu et al., 2020c, Yue et al., 2021). Therefore, further studies are required to improve the developed model to include carbon sink and also multiple uncertain parameters.

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