Expert Systems With Applications 236 (2024) 121238

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Integration of strategic and operational attributes to calculate the optimal cultivation of crops

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ARTICLE INFO

Keywords:
Optimal cultivation
Multi-attribute optimization model (MAOM)
Sustainability
Risk-averse UTA (UTilité Additive)
Linear optimization model

ABSTRACT

Determining the optimal quantity of crops is crucial for establishing a sustainable cultivation pattern when multiple potential crops are available. To address this issue, we propose a novel hybrid multi-attribute optimization model (MAOM) based on two steps. Firstly, we calculate the sustainability score of candidate crops by taking into account strategic criteria categorized in terms of sustainability, including economic, social, and environmental dimensions. To ensure a more reliable choice, we develop a risk-averse UTA (UTilité Additive) to adjust the trade-off among the criteria of alternatives in multi-criteria decision-making (MCDM) problems. Secondly, we develop a linear optimization model to calculate the optimal amount of candidate crops based on the sustainability score and operational criteria. We employ this framework to determine the optimal cultivation pattern in Khorasan Razavi, Iran. The results suggest that Dried Garlic, Turnip, Forage, Millet, and Khasil are suitable crops for the six-month period of spring and summer, while Potato, Fodder Beet, Shah Seed, and Mung Bean are the optimal alternatives for the six-month period of autumn and winter among the 46 candidate crops. Finally, a conclusion is drawn and recommendations for further research are proposed.

1. Introduction

In recent years, agriculture's contribution to the global economy has been increasing, with its share in the gross domestic product (GDP) rising from 17.8% in 2019–20 to 19.9% in 2020–21 (Kapil, 2021). Agriculture has the potential to benefit the economy, society, and environment, but it can also have negative impacts on these areas if the wrong cultivation methods are used (Chen, Li, & Jin, 2016). Previous research on optimal cultivation patterns has mainly focused on operational criteria such as resource utilization optimization. However, there is growing awareness that sustainable agriculture requires the consideration of strategic criteria, including economic, social, and environmental factors (W. Chen et al., 2016).

Two main challenges make it difficult to include these strategic criteria in the agricultural decision-making process. Firstly, it requires the development of new models that can effectively balance multiple dimensions. Historically, decisions in agriculture have been based on operational criteria, such as the availability of workers and water. However, when strategic criteria such as environmental sustainability, social impact, and economic viability are added, a more comprehensive approach is needed to help decision-makers find a good balance between these different factors. Additionally, different stakeholders may have different priorities and trade-offs between these dimensions, making it difficult to agree on the best way to grow crops. Farmers may prioritize maximizing their profits, while environmentalists may focus on reducing agriculture's impact on natural ecosystems. Consumers may prioritize the accessibility and affordability of certain crops, while government officials may be interested in promoting certain crops for their economic benefits. Achieving a harmonious balance between these various priorities and compromises requires a comprehensive strategy that considers the requirements and concerns of all stakeholders involved. Therefore, there is a dilemma in which the criteria associated with the two levels must be addressed.

As the first contribution, this study proposes a multi-attribute optimization model (MAOM) to consider both the strategic and operational levels. The proposed model can take into account a broad spectrum of criteria that have a significant impact on the selection process and incorporate experts' perspectives.

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https://doi.org/10.1016/j.eswa.2023.121238
Received 8 November 2022; Received in revised form 21 June 2023; Accepted 16 August 2023
Available online 25 August 2023

Although multi-criteria decision-making (MCDM) methods have the potential to simplify decision-making, the trade-offs inherent in these methods may not result in appropriate choices in the long run, as the current literature suggests. MCDM methods may lead to the selection of an option with a higher weight in certain criteria, which may not be better in terms of other criteria. In other words, an alternative with strong performance in a few criteria may hide its weaknesses in other criteria (Wang, 2012). The allowance of unrestricted trade-offs between the criteria of each alternative, which is permissible in compensatory MCDM methods, may lead to the overlooking of a better alternative that aligns with decision-makers' preferences (Kheybari, 2021; Kheybari & Ishizaka, 2022). Therefore, in MCDM problems, it is essential to consider decision-makers' preferences while avoiding being excessively swayed by higher-weighted preferences. Reducing the risks associated with trade-offs in MCDM methods is of utmost importance. A sophisticated method to achieve this objective is to emphasize the shortcomings of each option during the assessment process. For this purpose, this paper proposes a risk-averse UTA (UTilité Additive) model in a two-level framework to determine the optimal cultivation pattern, which is the second contribution of this paper. The proposed model is used to compare different crops at the strategic level, and the optimal level of cultivation for each crop is calculated based on operational constraints using the score of each crop as a parameter of the objective function. Finally, the developed model is applied to a real case in Iran.

Taking into account the reasons discussed and the literature reviewed, this investigation seeks to:

- propose a more comprehensive framework of criteria classified as economic, social, and environmental dimensions;
- propose a risk-averse UTA method to calculate the weights of criteria at the strategic level that applies to multi-criteria problems;
- propose an MAOM using the output of a risk-averse UTA and considering operational criteria to determine the optimal cultivation pattern; and
- evaluate the proposed framework in a real-world case study.

The structure of this study is as follows: Section 2 reviews the literature on the cultivation pattern problem and identifies research gaps. Section 3 outlines the methodology employed in this investigation. Section 4 details the case study. Section 5 presents the results of applying the proposed methodology to the case study. Section 6 provides managerial implications for the proposed methodology. Finally, Section 7 offers conclusions and suggestions for future research.

2. Literature review

In order to develop the proposed framework, we conducted an investigation of studies attempting to address and solve the problem of optimal cultivation patterns. As we aimed to identify criteria at both the strategic and operational levels, we reviewed papers that employed Multi-Attribute Decision-Making (MADM) methods as methodologies. It is noteworthy that the text and tables of the studies were used to identify criteria at the two levels employed in the text.

Studies on the selection of optimal cultivation patterns using MCDM techniques can be classified into two main categories: Multi-Objective Decision Making (MODM) and MADM. Most studies have focused on two primary objectives: maximizing net returns from the proposed cultivation pattern and minimizing costs associated with the selected cultivation pattern. However, depending on the case being studied, individual scholars may have adopted other objectives (Sarker & Quaddus, 2002). MODM is the most commonly employed method in the literature, and it can be divided into two classes: Class A, which comprises studies that have employed multi-objective programming, and Class B, which encompasses those that have utilized single-objective programming.

As an example of the studies in class A Mainuddin, Gupta, and Onta (1997) proposed an optimal cropping plan with a multi-objective analysis using the Analytic Hierarchy Process (AHP) in Thailand, with the aim of maximizing both economic net benefit and irrigated area while taking into account the preferences of the decision makers. Ren et al. (2019) proposed a multi-objective stochastic fuzzy programming and AHP method for agricultural water and land optimization allocation in China, considering multiple uncertainties. The objectives of the model were to maximize net benefit, agricultural water productivity, and minimize irrigation area. The model was tested under multiple uncertainties related to a water shortage, and the results provided decision makers with the optimal water irrigation level and land resources. Regulwar and Gurav (2011) proposed a multi-objective fuzzy linear programming (MOFLP) approach to irrigation planning under uncertainty in India, with the objectives of net benefits, crop/yield production, employment generation/labor requirement, and manure utilization. The fuzzy concept was employed to account for uncertainty in the proposed model. Daghighi, Nahvi, and Kim (2017) proposed a multi-objective linear programming model for the purpose of locating an optimal cultivation pattern in Fars Province, Iran. This water resources planning model was designed to assist decision-makers in selecting an appropriate cultivation pattern, optimizing the exploitation of surface water resources, and determining the method of allocating water across different farm crops while minimizing the negative impacts of water scarcity.

As an example of the studies falling into class B, O. Heady (1954) employed a simplified linear programming approach to identify an optimal crop pattern, with the aim of determining the most profitable crop within the confines of land, capital, cultivation capacity, and labor. Itoh, Ishii, and Nanseki (2003) developed a linear model that accounted for the fuzziness and randomness of land and labor resources. Abedi, Peykani, and Kalashami (2011) employed a linear programming (LP) approach to assess the comparative advantage of corn in comparison to other competitor crops in optimal cultivation patterns in Kermanshah province, Iran. The performance of eight different crops was evaluated under two scenarios (with and without rotation) in eight states of Kermanshah. The results indicated that corn had a comparative advantage in all the states. Abedi et al. (2011) employed a LP approach to assess the comparative advantage of corn in comparison to other competitor crops in optimal cultivation patterns in Kermanshah province, Iran. The performance of eight different crops was evaluated under two scenarios (the existence and lack of rotation) in eight states of Kermanshah. The results indicated that corn had a comparative advantage in all the states.

Singh, Jaiswal, Reddy, Singh, and Bhandarkar (2001) developed a linear programming model to determine an optimal cropping pattern with respect to different water availability levels in India, with the objective of maximizing net return. The results indicated that wheat provided the most consistent profit among the eight crops. Garg and Dadhich (2014) conducted an investigation into an integrated non-linear single-objective mathematical model for optimal cropping pattern and irrigation scheduling under deficit irrigation. Variables such as deficit levels were incorporated into the model in order to maximize the net return. The results indicated that the optimal net financial return was increased by 92.5%, and the total optimal cropped area was enhanced by 109.7%. Additionally, there have been a few studies that have considered both single and multi-object. For example, Amini Fasakhodi, Nouri, and Amini (2010) proposed a Multi-Objective Fractional Goal Programming (MOFGP) approach to identify an optimal crop pattern in agricultural systems, with the aim of maximizing two ratios concurrently: net return/water consumption and labor employment/water consumption. The results indicated that the MOFGP solution was more advantageous than both Fuzzy Programming (FP) and LP models. Sarker and Quaddus (2002) conducted a study to explore the application of both single- and multi-objective models to address a nationwide crop-planning problem. They demonstrated how the information obtained from LP models can be incorporated into its goal programming (GP) counterpart to provide enhanced insights and decision support in a

Table 1
A comparison between our study to the most relevant ones in literature.

Studies	Eco.	Soc.	Env.	Technique(s) used	Risk of Decision Maker's (DM's) attitude
Huang and Zhang (2020)	✓	✓	×	AHP, Fuzzy TOPSIS	Not considered
Honar et al. (2021)	×	✓	✓	AHP, TOPSIS, PROMETHEE, ELimination and ChoiceExpressingREality (ELECTRE)	Not considered
Mainuddin et al. (1997)	×	×	✓	AHP	Not considered
Amini Fasakhodi et al. (2010)	×	×	✓	Multi-objective Fractional Goal Programming	Not considered
Ren, Li, and Zhang (2019)	×	×	✓	Multi-objective Fuzzy Stochastic Programming	Not considered
Devatha and Thalla (2019)	×	×	✓	SAW, WPM, TOPSIS, PROMETHEE	Not considered
Agha et al. (2012)	×	×	✓	AHP, PROMETHEE	Not considered
Mohammadian and Heydari (2019)	×	×	✓	Fuzzy Goal Programming	Not considered
Daghighi et al. (2017)	×	×	✓	Linear Programming	Not considered
Singh et al. (2001)	✓	✓	✓	Linear programming	Not considered
Chen et al. (2021)	×	×	✓	Two-way ANOVA and optimization	Not considered
Sedighkia et al. (2023)	×	×	✓	Regression and Genetic Algorithm	Not considered
Hasanzadeh Saray et al. (2022)	×	×	✓	Regression Analysis and Mixed Integer Linear Programming	Not considered
Tofighy et al. (2005)	✓	×	×	Bayesian information criterion and smooth filters	Not considered
This study	✓	✓	✓	UTA, risk-averse UTA, Linear Programming	Considered

third-world country.

Despite the fact that MADM methods consider both quantitative and qualitative criteria in the decision-making process, including the selection of optimal cultivation patterns, there are fewer studies that address this problem using MADM methods. Furthermore, MADM techniques encompass a wide range of criteria compared to mathematical programming models, as the latter are more likely to result in a lack of feasible regions for the problem when a high number of variables and constraints are present. This constraint does not exist in. As a result, the utilization of MADM methods has been found to provide a more diverse and widespread set of criteria than those offered by mathematical programming models. Studies concerning cultivation patterns with a MADM approach have taken into account criteria that are closely related to economic, social, psychological, and cultural factors. For instance, Devatha and Thalla (2019) employed four MADM methods, namely Simple Additive Weighting (SAW), Weighted Product Method (WPM), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), to prioritize cropping alternatives in India. The results obtained by the MADM methods were compared to those of a non-linear optimization model, with wheat identified as the most profitable crop. Agha, Nofal, and Nassar (2012) used AHP and PROMPTEE to address the cultivation pattern problem for government lands in the Gaza Strip under both normal and resistant economic conditions. Their objective was to rank crops based on economic, financial, marketing, environmental, technical, political, and social criteria. Huang and Zhang

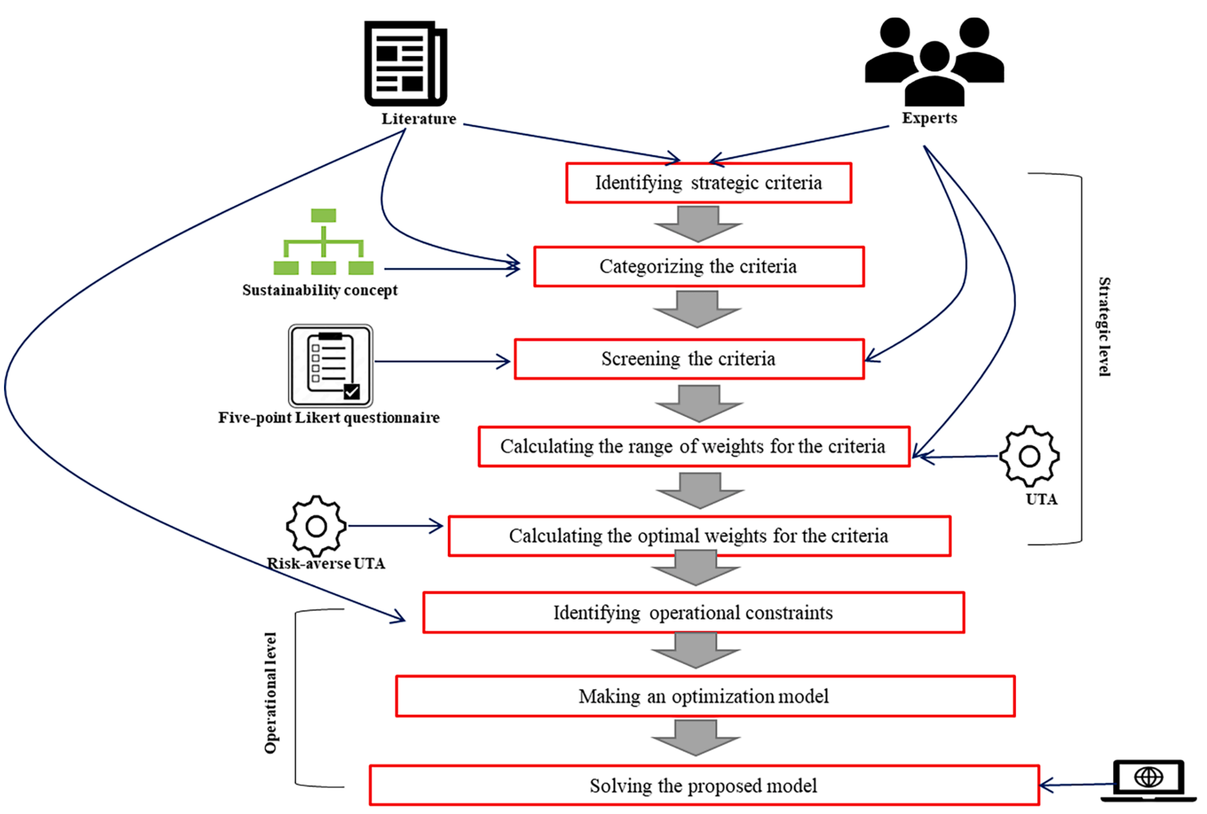

Fig. 1. Research Steps.

(2020) proposed an optimal economic crop model that combined AHP for generating criteria weights and Fuzzy TOPSIS for ranking crops to improve farmers' income and soil and water conservation in Taiwan. The study found that palm was the optimal crop.

Additionally, there is a body of research that examines the use of Statistical Analysis for the purpose of optimizing cultivation. An overview of this stream was conducted by Wu et al. (2022). Furthermore, Sedighkia et al. (2022) proposed an integrated optimization framework for agricultural planning that links an environmental flow model, drought analysis, a cropping pattern model, and deficit irrigation functions using regression models. The framework incorporates a genetic algorithm to generate an optimal plan for cropping patterns and irrigation supply that minimizes ecological impacts on the river ecosystem. The model is capable of minimizing ecological impacts on the river ecosystem in all hydrological conditions while also providing a sustainable plan for agricultural and environmental management.

Contemplating the studies in the literature, we found the following research gaps:

- Research conducted to date has largely been quantitative in nature, utilizing MCDM methods and not taking into account qualitative criteria, which require MADM techniques. Additionally, while some studies have employed statistical analysis to assess quantitative criteria, few have considered qualitative criteria, and none have considered both quantitative and qualitative criteria simultaneously. Previous research has addressed the economic, social, and environmental dimensions associated with the strategic level but has not utilized the output of the strategic level at the operational level or has simply considered the operational level while disregarding the strategic level. However, our study has not only implemented the strategic level but has also employed its output for the operational level, which has been demonstrated by a MAOM. Consequently, it encompasses a greater number of criteria. Additionally, several studies that have incorporated environmental criteria into their statistical analysis have neglected to consider the risk factor in their optimization problem ((J.-H. Chen et al., 2021), (Sedighkia, Fathi, Razavi, & Abdoli, 2023), (Saray et al., 2022)).
- According to the sustainability framework, although a long-lasting cultivation should be beneficial in terms of economy, society, and environment, there is a lack of research in the literature that comprises sustainability with detailed criteria for optimal cultivation selection. For example, Huang and Zhang (2020) considered soil and water conservation as two elements of sustainability for social and economic aspects, while Honar, Ghazali, and Nikoo (2021) examined the social and economic aspects of cultivation patterns from the perspective of stockholders. Additionally, Mainuddin et al. (1997) and Amini Fasakhodi et al. (2010) have both studied water management as an environmental criterion in sustainability. As a result, the effective criteria have been divided into three categories: those associated with human beings, society, and governmental regulations are categorized as society factors; those that either improve or worsen the environment are categorized as environmental factors; and the remaining criteria are considered economic criteria.
- As presented in Table 1, Singh et al. (2001) is the only work in the literature that considers all three dimensions of the cultivation pattern problem. However, this work does not consider the risk involved in weighing criteria or the opinions of decision-makers. Our study has addressed this shortcoming by including all sustainable dimensions, demonstrating the comprehensiveness of our investigation.

3. Methodology

The research depicted in Fig. 1 comprises eight steps. The first four steps, which concern the introduction and literature sections, are related to the strategic level. The modeling step, which is based on the output of a risk-averse UTA and optimization model, is associated with the operational level. Consequently, the proposed framework, MAOM, encompasses both the strategic and operational levels.

At the strategic level, relevant criteria were initially extracted from previous studies in the literature. Subsequently, experts were asked to provide their preferred criteria using a five-point Likert scale. Criteria were screened based on a threshold for the coefficient of variation (CV) of the scored criteria. After experimenting with a range of threshold values, a threshold of 3.2 was chosen as it ensured the number of subcriteria within each dimension was balanced in comparison to other dimensions (Salamirad, Kheybari, Ishizaka, & Farazmand, 2023). After the screening of criteria, the same experts were asked to select their top five crops and rank them among all those cultivable in Khorasan Razavi province. The number five was selected to provide the experts with an appropriate level of discrimination power. A high number of chosen crops can make it difficult for the experts to differentiate between them, while a low number may lead to an inadequate level of accuracy. In the subsequent step, the experts' priorities were provided to the UTA to obtain a range for the weight of each criterion. A risk-averse UTA was developed to identify the optimal weights of the criteria. These weights were then used to calculate the sustainability score of the candidate crops. Finally, after reviewing the literature on optimal cultivation selection, operational constraints were extracted.

In the operational step, a linear optimization problem was formulated to identify the optimal amount of cultivation for each crop, utilizing the output of the risk-averse UTA as coefficients of the objective function. This step was crucial, as operational constraints such as water, area, and human or machine resources had to be taken into account when cultivating crops that had been identified as sustainable at the strategic level. The mathematical model was solved using LINGO. In the following subsections, we provide a detailed account of each step.

3.1. UTAa

The UTilité Additive (UTA) was initially proposed by Acquet-Lagreze and Siskos (Jacquet-Lagreze & Siskos, 1982) in 1981. UTA can be used to prioritize different performance metrics that are important for the nonlinear service system, such as customer satisfaction, service quality, and efficiency. The weights of these metrics can be determined based on expert judgment or through a survey of system users. UTA can then be used to rank different control strategies based on their performance on these metrics, which can be used to select the best strategy for the nonlinear service system. The purpose of UTA is to identify the decision maker's preference model within the criteria involved in decision making, so that the output generated by its application is most similar to the actual decisions made. The utilization of the summability utility model as a methodology for MADM problems has been demonstrated in several studies. This model requires the decision-maker to prioritize a reference set of options according to their preferences (Beuthe & Scannella, 2001). This has been demonstrated to be effective in addressing the issue of dependent criteria when estimating a utility function. This model is able to solve the problem of having dependent criteria while estimating the utility function. Providing sensitivity analysis on the optimal answer is another advantage of this method. This method has many applications for ranking alternatives in many areas, such as selection material in engineering (Athawale, Kumar, & Chakraborty, 2011) and road building (Rezaeinia, 2022).

There are several studies extending the UTA method. For example, Angilella, Greco, Lamantia, and Matarazzo (2004) developed a non-additive utility function in the framework of the so-called fuzzy integrals, which permits modeling preference structures of Decision Makers (DMs) with interaction between criteria. Or Chhipi-Shrestha, Kaur, Hewage, and Sadiq (2018) proposed a UTA where conflicting criteria can be considered. However, there is no study about UTA extension where the risk attitude of DMs during their ranking process is considered. We explain in the next sub-section how we extend UTA such that it can consider risk in the evaluation process. We extended the UTA method proposed and applied in the literature (Angilella et al., 2004; Chhipi-Shrestha et al., 2018; Rezaeinia, 2022) by considering the risk-averseness of DMs in the weighting process, as explained in the next sub-section. Moreover, we discuss the details of the UTA model in Appendix A.

3.2. Risk-averse UTA

In the evaluation process, decision makers often seek to minimize the weaknesses of alternatives. To this end, the developed risk-averse UTA model highlights the weaknesses of each alternative by seeking the best weight in the possible range for each criterion. To further emphasize the weaknesses of alternatives, the concept of Data Envelopment Analysis (DEA) is utilized in the risk-averse UTA model. The optimization model (1) is conducted to obtain weights that emphasize the shortcomings of the alternatives, thus avoiding the application of a single set of weights to all alternatives.

$$\underset{i}{\text{Minimize}}\sum_j w_{ij}u_{ij}$$

Subject to:

$$\sum_j w_{ij} = 1\forall i$$

$$w_j^{*l} \leq w_{ij} \leq w_j^{*u}\forall j \tag{1}$$

Model 1 presents the risk-aversion rationale as a method of selecting the optimal weight point by minimizing the output of alternatives. The proposed model ensures that the chosen alternative surpasses any criterion whose weight is set to the lowest possible value. In other words, by controlling the trade-off, the risk of the evaluation is reduced. w_{ij} is the weight of criterion j for the alternative i, and w_j^{*u} and w_j^{*l} are the upper and lower bounds of criterion j (c_j) calculated by the UTA. u_{ij} is the normalized value of alternative i for criterion j which are calculated by Eqs. (2) and (3).

$$u_{ij} = \frac{x_{ij} - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})}\forall i \text{and positive} j \tag{2}$$

$$u_{ij} = \frac{\max_i(x_{ij}) - x_{ij}}{\max_i(x_{ij}) - \min_i(x_{ij})}\forall i \text{and negative} j \tag{3}$$

where x_{ij} indicates the score of alternative i in criterion j.

Finally, the candidate alternatives were ranked by calculating the overall score of the alternative using the simple weighted sum function presented in Eq. (4).

$$s_i = \sum_j u_{ij}w_{ji}\forall i \tag{4}$$

3.3. Optimal cultivation model

In this section, the aim is to identify an optimal set of crops. To achieve this aim, the year of cultivation is divided into two six-month periods. Based on the experts' opinion, potential crops for each season are grouped and considered as candidates for cultivation. Prior to presenting the linear mathematical model, the parameters and decision variables are defined.

Notations

There are two groups of crops to be cultivated because warmness and coolness of weather directly affect the behavior of crops. This classification has been recognized by the experts.

Indices

i: Set of crops for cultivation ($i \in I$)

j: Set of cities ($j \in J$)

Parameters.

D_i: A vector showing the upper level of demand for crop i *(measured by kilogram per square meter).*

a_i: A vector illustrating the area required to cultivate one unite of crop i (measured by *square meter per kilogram*).

AT_j: A vector showing the available area in city j *(measured by square meter).*

p_i: A vector showing the required power supplied by human and machine resources to cultivate one unite of crop i *(measured by horse power per hour).*

PT_j: A vector illustrating the available power supplied by human and machine resources in city j *(measured by horse power per hour).*

wt_i: A vector illustrating shows the water amount required to cultivate one unite of crop i *(measured by cubic meter per kilogram).*

WT_j: A vector illustrating the available amount of water in city j *(measured by cubic meter).*

s_i: A vector showing the suitability index obtained by cultivating one unit of crop i.

Decision Variables

x_{ij}: A matrix illustrating the amount of crop i that is cultivated in city j.

Objective function.

We consider a single-objective function. Equation (5) calculates the total sustainability obtained by cultivated crops.

$$Maximize\sum_i\sum_j s_i x_{ij} \tag{5}$$

Constraints.

To consider limitations of the cultivation pattern, we have the following constrains:

The set of constraints (6) expresses upper bound demand for each crop. The constraints guarantee that at most how much from each crop should be cultivated.

$$\sum_j x_{ij} \leq D_i\forall i \tag{6}$$

The set of constrains (7) states the available power supplied by human and machine resources in each city. These constraints guarantee that the consumed machine and human resources do not exceed their available counterparts in each city. In fact, each city has a limited number of machine and human resources that must be considered when a crop is to be cultivated.

$$\sum_i p_i x_{ij} \leq PT_j\forall j \tag{7}$$

The set of constraints (8) denotes the amount of available water in each city. These constraints guarantee that the consumed machine resources do not exceed their available counterpart resources.

$$\sum_i wt_i x_{ij} \leq WT_j\forall j \tag{8}$$

The set of constraints (9) expresses the available area in each city. These constraints guarantee that the available land limit for each city has been considered.

$$\sum_i a_i x_{ij} \leq AT_j\forall j \tag{9}$$

4. Case study

According to the report of the World Bank in 2017, the labor

Table 2
Experts information.

Respondents	Faculty member	Experienced farmer	Average years of work experience
Screening criteria	12	8	12.6
Filling questionnaire	6	2	15.5

proportion of the agriculture sector to the total number of employed people in the world is equal to 26.5% while this proportion has been estimated at 17.6% in Iran based on Iran Statistics Center (The World Bank (2021), 2021). Specifically, our case study has been conducted in Khorasan Razavi, which is one of the top five provinces in Iran when it comes to talking about the most arable area. Khorasan Razavi is a province located in northeastern Iran. Mashhad is the center and capital of the province. This province has a population of 6,434,501 and has 33 cities. It is also the second-largest province in Iran. The area of the province is 118,854 square kilometers, which makes it the fifth largest province in Iran and occupies seven percent of the area of Iran.

Even though the province has numerous advantages, its agriculture industry has faced some difficulties in choosing which crops to cultivate because of the water shortage crisis and environmental challenges over the last decade. In addition, according to the Mashhad University of Medical Sciences statistics, this province has been tremendously involved in the COVID-19 outbreak from 2020 to 2022. Hence, its human resource availability has become a serious concern for the agriculture industry in this province. As a result, a sustainable cultivation pattern would be extremely advantageous for this province. It goes without saying that similar provinces can be benefited by our proposed sustainable framework. The potential crops for cultivation are collected by using an online questionnaire, and then experts give the score of each crop with respect to the criteria. Subsequently, the optimal weights are calculated, and then the optimal amount of crops is determined.

4.1. Data collection

Generally speaking, data sources in our paper are divided into two classes. Data of the UTA method that is gathered by experts' opinions as mentioned in Table 2. The data enables us to calculate the weight of each criteria. In the second group of data, which is considered the strategic level of our investigation, we have used data from the Statistical Center of Iran (2022) and Ministry of Agriculture (2022). To run the optimization model, which is actually the operational level of our study, we obtained the data for the model's parameters by using the Statistical Center of Iran and the Ministry of Agriculture of Jihad.

We regarded the opinion of Khorasan Razavi Agricultural Jihad experts and researchers of the department of agriculture, Ferdowsi University of Mashhad. The number of experts is 20, all of whom are adept, as detailed information provided in Table 2 about their expertise and work experience attests. To have access to and exchange information with the experts, we have utilized their online profiles. We asked the

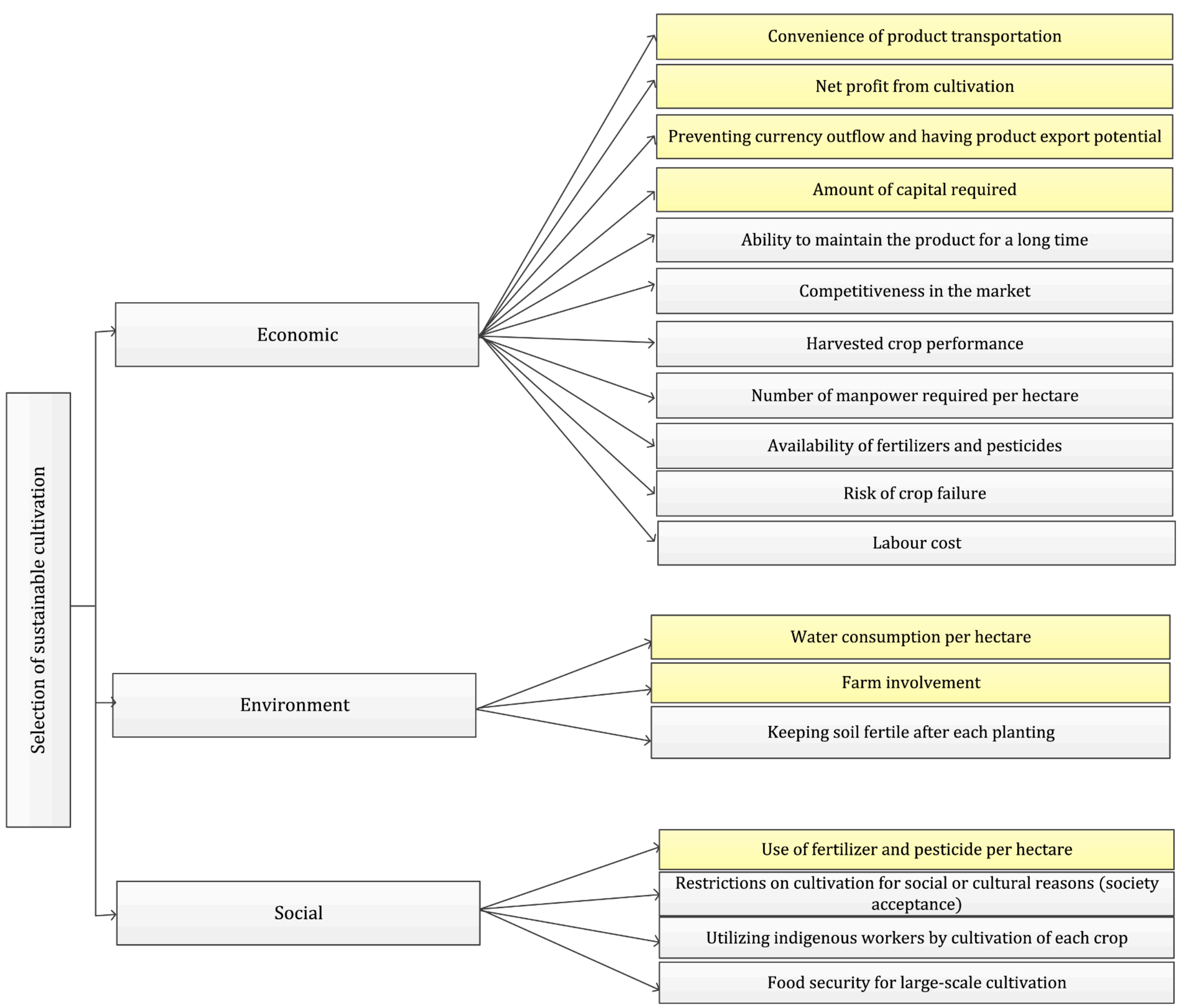

Fig. 2. Screened criteria in terms of sustainable cultivation.

Table 3
Upper and lower bounds of criteria.

Criterion	Lower bound	Upper bound	Weight (middle)	Rank
Net profit from cultivation (C_1)	0	0.7243	0.3621	3
Amount of capital required (C_2)	0	0.4438	0.2219	6
Usage of fertilizer and pesticide per hectare (C_3)	0	0.4440	0.2220	5
Convenience of crop cultivation (C_4)	0	0.9034	0.4517	1
Farm involvement(C_5)	0	0.4356	0.2178	7
Water consumption per hectare (C_6)	0	0.9020	0.4510	2
Preventing currency outflow and having crop export potential (C_7)	0	0.4918	0.2459	4

Table 4
Weight of each dimension.

Main Level	Weight	Rank
Economic dimension	0.5899	1
Social dimension	0.1022	3
Environment dimension	0.3079	2

experts to identify any missing criteria that we had not covered in the literature. In this step, we gave the criteria in the three dimensions (economy, society, and environment) as mentioned in Section 2. Then, we asked the experts to score the criteria by filling out a questionnaire based on a five-point Likert scale, with 1 being the lowest and 5 being the highest.

4.2. Criteria screening

Following data collection, criteria screening was conducted to optimize the reliability of comparisons between criteria (Kheybari, Ishizaka, & Salamirad, 2021; Kheybari, 2023) and to enhance the discrimination power of the experts (Wanke, Barros, & Emrouznejad, 2016). Using a threshold of 3.2 for the coefficient of variation (CV) measure, we selected seven criteria (out of 19), which are highlighted in yellow in Fig. 2.

5. Results and discussion

In this section, the local weights of the criteria at each main level are calculated. The UTA stipulates the optimal range of the weights for any criterion by averaging the intervals obtained from the experts' opinions. To analyze the experts' opinions, we selected the middle of the optimal ranges as the local weight of their corresponding criteria. In order to determine the optimal weight, the output of the risk-averse UTA is utilized as the objective function coefficients of the mathematical model proposed in Section 3.2. For more detailed investigation, the codes related to original UTA, risk-averse UTA, and MAOM can be seen in Online Appendix, respectively.

5.1. Local weight of criteria

After the UTA model has been used, the lower and upper limits of each criterion are found by taking the minimum and maximum weights from the UTA. Subsequently, the mean of the lower and upper bounds is calculated (Table 3). As mentioned, the mean value of the lower and upper bounds is utilized to analyze the weights.

Table 4 presents the weights of the three sustainability dimensions. The weight of each main dimensions is determined by summing its corresponding sub-level weights. For instance, the *economic* dimension score is calculated by summing the weights of its respective components. As C_1 (*net profit from cultivation*), C_2 (*amount of capital required*), C_4 (*convenience of crop cultivation*), and C_7 (*preventing currency outflow and having crop export potential*) are associated with the economic dimension, the score is equal to 0.5899. The *economic* dimension has been given the highest priority out of the three. This may be because of the sanctions put on Iran, which have stopped agricultural centers from using modern technology. It may also be because of a lack of investment, traditional farming, and a weak economy, which has made it much harder to take risks.

Table 3 demonstrates that C_4 (*convenience of crop cultivation*) is of the highest importance among the economic sub-criteria due to the fact that transportation cost is a major factor for crop cultivation in Khorasan Razavi. Furthermore, the quality of crops for export necessitates that suppliers pay the utmost attention to the appearance of the crop. Since C_5 (*farm involvement*) and C_6 (*water consumption per hectare*) are both components of the *environment* dimension, its score is equal to 0.3079. As shown in Table 3, C_6 (*Water consumption per hectare*) has more weight than C_5 (*farm involvement*) mainly because Khorasan Razavi is considered to have a cold semi-arid climate, meaning that it has a low rate of rain. On the other hand, since it is a wide province, C_5 (*farm involvement*) is not a big issue. Finally, since only C_3 (*usage of fertilizer and pesticide per hectare*) belongs to the social dimension, its score is equal to 0.1022.

5.2. Optimal weight of criteria and alternative assessment

In this section, the crops are evaluated using the optimal weight of criteria obtained from risk-averse UTA. The optimal weight of the criteria can be calculated using the risk-averse UTA by utilizing the optimal range of weight of criteria (Table 3) and the normalized decision matrix (Table A in Appendix B). Examination of Table 5 reveals that the opinions of experts are most consistent in C_2 compared to the other criteria. In fact, sample standard deviations for C_1 to C_7 are 0.0357, 0.0024, 0.0218, 0.0702, 0.0062, 0.0519, and 0.0155, respectively.

Table 6 presents the overall score of the risk-averse UTA, which is obtained by the summation of the resulting weights for each crop (Equation (4). Additionally, the overall score of the original UTA for each crop is calculated by taking the average score of eight experts. Upon examining Table 6, it can be seen that A_7, A_{35}, and A_{11} are the top three crops in terms of risk-averse UTA overall scores, while A_5, A_1, and A_{46} are the bottom three among the 46 crops.

5.3. Analyzing the results of risk-averse UTA and original UTA

Discussion of the rankings of A_{29} and A_{32} is conducted in order to analyze the outcomes of the suggested methodology. When the risk-averse UTA was applied, the rank of A_{29} shifted from 8 to 15, while the rank of A_{32} moved from 20 to 14. This suggests that, when the risk-averse factor is taken into account in the initial ranking, criteria with weaker performance in the original UTA can outperform in the risk-averse condition. As illustrated in Fig. 3, A29 outperforms A_{32} for more than half of the criteria (five out of seven; C_1, C_3, C_5, C_6, and C_7); however, A_{29} performs significantly weaker in C_2 and C_4.

The results presented in Table 6 demonstrate that the weaknesses of A_{29} were not taken into account in the assessment process with the original UTA, resulting in A_{29} obtaining a higher rank than A_{32} (rank 8 versus rank 20). To address this issue and prevent any irreversible consequences, the risk-averse UTA emphasizes the weaknesses of alternatives in the optimal range of weights determined by the original UTA. To put it in other words, the risk-averse UTA model gives the upper bound of the weight to the criteria where the crops do not outperform and underrates the other criteria. In this vein, as depicted in Fig. 4, by lowering the weight of the criteria where the alternatives (crops) outperform (i.e. C_1, C_3, C_5, C_6, and C_7 for A_{29} and C_2 and C_4 for A_{32}) and adding it to the criteria where the crops perform poorly (i.e. C_2 and C_4 for A_{29} and C_1, C_3, C_5, C_6, and C_7 for A_{32}), we are able to magnify the weaknesses of alternatives in the weight range determined by the

Table 5
Optimal weights obtained by using risk-averse UTA.

Crops	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Baghala (A_1)	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Onion (A_2)	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Tomato (A_3)	0.1037	0.0148	0.0122	0.5038	0.0670	0.1407	0.1577
Red pepper (A_4)	0.1704	0.0102	0.0122	0.3499	0.0670	0.2265	0.1637
Leafy vegetables (A_5)	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Glandular vegetables (A_6)	0.1704	0.0102	0.0122	0.4357	0.0670	0.1407	0.1637
Potato (A_7)	0.1704	0.0148	0.0323	0.3224	0.0744	0.2219	0.1637
Dried garlic (A_8)	0.0649	0.0102	0.0122	0.5034	0.0674	0.2196	0.1222
Sangolak (A_9)	0.1083	0.0102	0.0511	0.5038	0.0740	0.0948	0.1577
Clover (A_{10})	0.1365	0.0102	0.0122	0.3499	0.0670	0.2627	0.1615
Turnip and forage (A_{11})	0.1704	0.0079	0.0511	0.4357	0.0740	0.0971	0.1637
Carrots (A_{12})	0.1083	0.0079	0.0511	0.5038	0.0740	0.0971	0.1577
Millet (A_{13})	0.1704	0.0079	0.0122	0.3499	0.0693	0.2265	0.1637
Khasil (A_{14})	0.1960	0.0079	0.0122	0.4357	0.0693	0.1407	0.1381
Fodder beet (A_{15})	0.1704	0.0079	0.0122	0.3499	0.0693	0.2265	0.1637
Fodder Corn (A_{16})	0.1704	0.0148	0.0122	0.3499	0.0670	0.2219	0.1637
Cluster Corn (A_{17})	0.1195	0.0079	0.1342	0.3751	0.1030	0.0971	0.1631
Alfalfa (A_{18})	0.1704	0.0148	0.0122	0.3499	0.0670	0.2219	0.1637
Corn (A_{19})	0.1037	0.0148	0.0122	0.5038	0.0670	0.1407	0.1577
Khakshir (A_{20})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Watermelon seed (A_{21})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Sunflower (A_{22})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Broom (A_{23})	0.1488	0.0148	0.0122	0.5038	0.0670	0.1407	0.1126
Pumpkin seed (A_{24})	0.1704	0.0102	0.0122	0.3499	0.0670	0.2265	0.1637
Jo (A_{25})	0.1704	0.0102	0.0122	0.3499	0.0670	0.2265	0.1637
Maize (A_{26})	0.1704	0.0102	0.0122	0.3499	0.0670	0.2265	0.1637
Shaltook (A_{27})	0.1704	0.0102	0.0122	0.3499	0.0670	0.2265	0.1637
Wheat (A_{28})	0.1365	0.0102	0.0122	0.3499	0.0670	0.2627	0.1615
Canola (A_{29})	0.0630	0.0148	0.0122	0.5038	0.0690	0.1796	0.1577
Sesame (A_{30})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Golrang (A_{31})	0.0921	0.0148	0.0511	0.5038	0.0856	0.0948	0.1577
Shah seed (A_{32})	0.1704	0.0102	0.0122	0.3499	0.0670	0.2265	0.1637
Sugar beet (A_{33})	0.1037	0.0148	0.0122	0.5038	0.0670	0.1407	0.1577
Cotton (A_{34})	0.1037	0.0148	0.0511	0.5038	0.0740	0.0948	0.1577
Tobacco (A_{35})	0.0649	0.0079	0.0122	0.4215	0.0693	0.2627	0.1615
Mendab (A_{36})	0.1083	0.0102	0.0122	0.5038	0.0740	0.1337	0.1577
Pea (A_{37})	0.0649	0.0102	0.0122	0.5038	0.0670	0.2196	0.1222
Dried baghala (A_{38})	0.1083	0.0102	0.0122	0.5038	0.0740	0.1337	0.1577
Lentils (A_{39})	0.1488	0.0102	0.0122	0.5038	0.0700	0.1722	0.0828
Bean (A_{40})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Mung bean (A_{41})	0.1704	0.0148	0.0122	0.4311	0.0670	0.1407	0.1637
Cucumber (A_{42})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Melon (A_{43})	0.1083	0.0079	0.0122	0.5038	0.0693	0.1407	0.1577
Pumpkin family (A_{44})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577
Watermelon family (A_{45})	0.1083	0.0102	0.0511	0.5038	0.0740	0.0948	0.1577
Eggplant (A_{46})	0.1083	0.0102	0.0122	0.5038	0.0670	0.1407	0.1577

experts to the extent that is feasible. Hence, the proposed model demonstrates that after underscoring the criteria in which the alternatives have higher risks, we should select A_{32} as a more suitable alternative than A_{29} because it has fewer weaknesses and a more uniform performance score compared with A_{29}.

5.4. Analyzing the results of optimization cultivation model

In this case study, 46 crops are divided into two groups, Group A and Group B, based on their climatic features. Group A consists of 16 crops that can be cultivated during the warm period (the first six months of a year), while Group B consists of 30 crops that can be cultivated during the semi-cold or cold period (the second six months of a year). The values of parameters for the linear optimization problem for Groups A and B are presented in Appendix B (Table B for Group A and Table C for Group B). The optimal cultivation magnitudes for crops in Groups A and B are detailed in Tables D-F in Appendix B, respectively.

As demonstrated in Table 7, the optimal cultivation pattern model was applied to crops in Group A, resulting in the selection of Crops 8, 13, 11, and 14 as the optimal solution, with respective ranks of 43, 3, 7, and 6. Notably, Crops 11, 13, and 14 achieved the highest possible value of their respective demands, indicating the strategic dimension of the MAOM. It is noteworthy that Crop 8 has achieved approximately half of its maximum demand due to its low rank (43) and its ability to satisfy operational constraints, as evidenced by the values of its respective parameters in the model.

As demonstrated in Table 8, the same reasoning applies to crops in Group B. Specifically, the demand constraint is the primary factor, provided that the other constraints are satisfied. From the 30 crops, those with sustainability ranks of 1, 10, 14, and 5 (i.e., crops 7, 15, 32, and 41, respectively) were chosen. If the selection of only four crops from Group B was to be made without taking operational-level criteria into account, then it would be reasonable to select the four crops with the highest rankings. However, our linear mathematical model suggests otherwise, as we are confronted with certain constraints in the real-world environment that are taken into consideration in our cultivation model (operational level). It is observed that crops with ranks 7, 15, and 32 have achieved their highest levels of demand, whereas crop number 41 has not yet reached its peak demand. An intriguing outcome is related to the fact that crops with ranks 4, 8, 9, and 11 have not been chosen. This is likely due to the fact that these crops have significantly lower demand in comparison to crops with ranks 1, 10, 14, and 5. In our objective function, the decision variable is maximized, thus the model seeks to identify crops that satisfy the constraints while also having a high potential value of cultivation. For instance, Crop 2 has a high demand, however, due to its low rank, the model will not select it as the

Table 6
Ranking result of risk-averse UTA and original UTA.

Alternatives	Risk-averse UTA		Original UTA	
	Overall score	Rank	Overall score	Rank
A_1	0.1459	45	0.2139	45
A_2	0.2074	36	0.2953	35
A_3	0.1917	40	0.2731	42
A_4	0.2509	30	0.2846	37
A_5	0.1414	46	0.2113	46
A_6	0.3606	17	0.3797	25
A_7	0.6215	1	0.5906	1
A_8	0.1859	43	0.2544	44
A_9	0.3257	25	0.4215	17
A_{10}	0.3130	26	0.3274	29
A_{11}	0.5256	3	0.5433	2
A_{12}	0.2331	32	0.3527	27
A_{13}	0.4730	7	0.4652	7
A_{14}	0.4913	6	0.4991	4
A_{15}	0.4526	10	0.4507	9
A_{16}	0.4445	11	0.4285	15
A_{17}	0.3505	20	0.3868	24
A_{18}	0.4598	9	0.4380	13
A_{19}	0.3574	18	0.4329	14
A_{20}	0.2011	38	0.2938	36
A_{21}	0.2541	29	0.3318	28
A_{22}	0.2008	39	0.2752	40
A_{23}	0.2332	31	0.3041	34
A_{24}	0.4242	12	0.4192	18
A_{25}	0.4644	8	0.4490	10
A_{26}	0.5117	4	0.4801	6
A_{27}	0.4240	13	0.4189	19
A_{28}	0.3564	19	0.3601	26
A_{29}	0.3929	15	0.4608	8
A_{30}	0.2273	33	0.3174	32
A_{31}	0.2908	27	0.3872	23
A_{32}	0.4069	14	0.4087	20
A_{33}	0.2615	28	0.3194	31
A_{34}	0.3621	16	0.4408	11
A_{35}	0.5699	2	0.5421	3
A_{36}	0.3312	24	0.4271	16
A_{37}	0.2058	37	0.2743	41
A_{38}	0.3452	21	0.4385	12
A_{39}	0.3370	22	0.4004	22
A_{40}	0.3329	23	0.4066	21
A_{41}	0.4984	5	0.4814	5
A_{42}	0.1910	41	0.2783	38
A_{43}	0.2104	35	0.3131	33
A_{44}	0.1905	42	0.2778	39
A_{45}	0.2211	34	0.3235	30
A_{46}	0.1787	44	0.2586	43

optimal set of solutions.

Considering the practical constraints in the province investigated in our case study, we observe that even top crops in terms of risk-averse UTA output may not be selected, proving how realistic our optimal cultivation model is. For example, as shown in Table 6, according to risk-averse overall score, A_7, A_{35}, A_{11}, A_{26}, and A_{41} are among the top 5 with respect to the risk-averse overall score; however, according to Table 7, A_8, A_{11}, A_{13}, and A_{14} for group A and A_7, A_{15}, A_{32}, and A_{41} for group B are selected when we consider operational constraints. As it can be seen, A_7, A_{11}, and A_{41} are common between what the risk-averse overall score and our optimization problem choose. This result reveals that our MAOM appropriately captures the strategic and operational dimensions of the proposed framework. Moreover, currently in the province, A_8, A_{13}, A_1, and A_{17} in group A and A_7, A_{15}, A_{43}, and A_{44} in group B are cultivated. According to Tables 7 and 8, we observe some differences between what actually happens and our suggested optimization model. To be more specific, for group A, our optimization problem choses A_{11} and A_{14} instead of A_1 and A_{17} and for group B, A_{32} and A_{41} instead of A_6 and A_{43}. There is an important note behind this difference signifying why our optimal cultivation pattern is better than what happens in the real case. To prove this fact, it suffices to refer to the objective function value for the two cases:

For group A, in the real situation, A_1 and A_{17} have respective values of 9000 and 9624, and given their risk-averse overall scores of 0.1459 and 0.3505, the objective function is 4686.3120 (according to Eq. (5); however, according to our model's suggestion, A_{11} and A_{14} have respective values of 47,619 and 55,248 and considering their respective risk-averse overall scores of 0.5256 and 0.4913, the objective function, according to Eq. (5), is equal to 52171.8888. Hence, since our model presents a higher objective function, it is better (remember that the objective function is the sustainability score of the cultivation pattern). Our inference is that the reason for satisfying upper demand for crops with a not-that-high rank in risk-averse UTA is having decent performance in operational constraints (the constraints of our optimization model); i.e., the entire focus on the cultivation of these crops over the long-term is not justifiable.

Similarly, for group B, the similar reasoning is valid. To sum up, since our optimization model's output both is similar to the output of risk-averse overall scores and considers operational constraints, it results in a more sustainable cultivation pattern. We also reported time execution for the optimization models in Table G of Appendix B.

5.5. Sensitivity analysis of the optimal cultivation model

After consulting with experts, it was determined that the only parameter in the optimal cultivation model that can be considered uncertain is demand. The experts provided four plausible scenarios based on their past experience. To this end, in order to assess the sensitivity of our primary results presented in Sections 7 and 8 for Groups A and B of products, four scenarios were considered in which the demand for the products was increased by 10%, 20%, 40%, and 60%, respectively. It was found that the selection of products for cultivation remained the same after implementing new scenarios, suggesting that the proposed optimal cultivation model is approximately robust with respect to demand changes of up to 60%. This result was presented for both Group A and Group B of products in Table 9. It was observed from the preceding sub-sections that A_7, A_8, A_{11}, A_{13}, A_{14}, A_{15}, A_{32}, and A_{41} were selected as optimal crops (for group A and B) to be cultivated. An example of the effects of a 10% increase in demand, as seen in Table 9, is that A_{32} and A_{41} are no longer selected as the optimal products in the new scenario

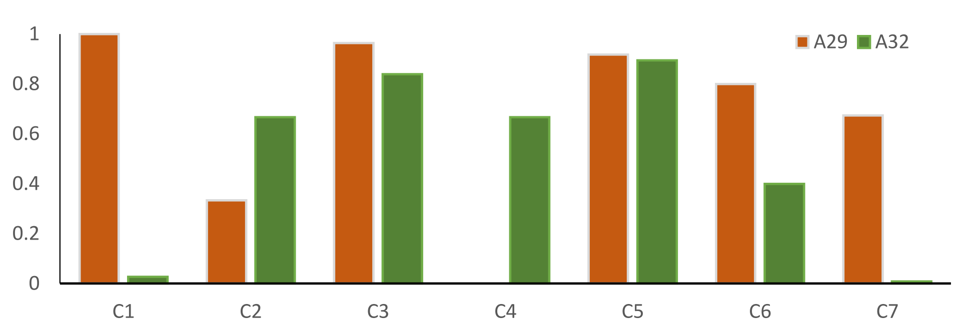

Fig. 3. Normalized value of A_{29} and A_{32}.

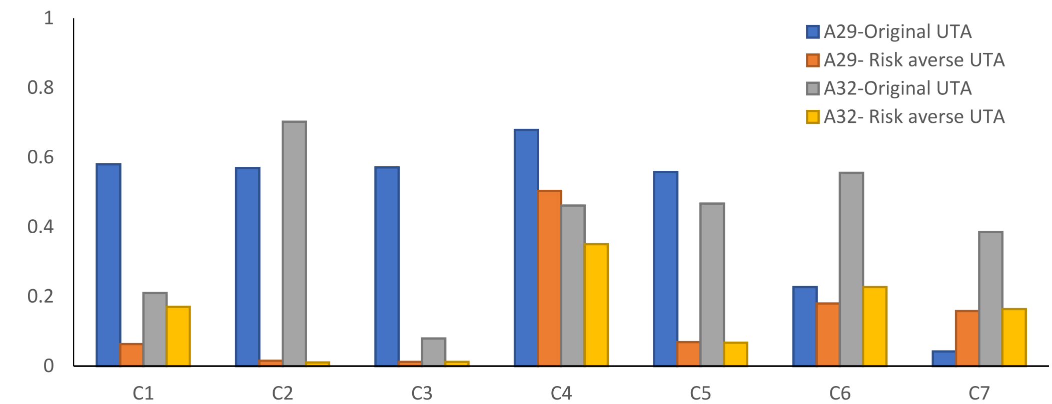

Fig. 4. The respective performance of A_{29} and A_{32} on criteria in which they practice within the evaluation process based on the original and risk-averse UTA.

Table 7
Optimal set of solution for crops in group A.

Crop	Rank	Optimal Cultivation	D_i
A_1	45	0	9000
A_8	43	20483.8105	41,666
A_9	25	0	1170
A_{11}	3	47,619	47,619
A_{13}	7	17,857	17,857
A_{14}	6	55,248	55,248
A_{17}	20	0	9624
A_{19}	18	0	600
A_{24}	12	0	2702
A_{27}	13	0	4000
A_{28}	19	0	1751
A_{35}	2	0	2481
A_{36}	24	0	1175
A_{37}	37	0	2500
A_{38}	21	0	1004
A_{40}	23	0	1169

Table 8
Optimal set of solution for crops in group B.

Crop	Rank	Optimal Cultivation	D_i
A_2	36	0	45,454
A_3	40	0	38,461
A_4	30	0	20,000
A_5	46	0	23,255
A_6	17	0	26,315
A_7	1	32,786	32,786
A_{10}	26	0	7032
A_{12}	32	0	6024
A_{15}	10	50,505	50,505
A_{16}	11	0	6896
A_{18}	9	0	3508
A_{20}	38	0	700
A_{21}	29	0	1533
A_{22}	39	0	3003
A_{23}	31	0	800
A_{25}	8	0	6301
A_{26}	4	0	3974
A_{29}	15	0	925
A_{30}	33	0	1388
A_{31}	27	0	3484
A_{32}	14	51,020	51,020
A_{33}	28	0	2403
A_{34}	16	0	2617
A_{35}	22	0	1404
A_{41}	5	3792.4602	20,325
A_{42}	41	0	19,880
A_{43}	35	0	35,714
A_{44}	42	0	28,328
A_{45}	34	0	23,809
A_{46}	44	0	31,250

Table 9
Outcomes of the optimal cultivation model following an increase in demand.

Scenario	Product Number	Rank	Optimal Cultivation	Demand
	7	1	36064.6	36064.6
	8	43	45832.6	45832.6
	11	3	52380.9	52380.9
	13	7	19642.7	19642.7
Demand + 10% Demand	14	6	60772.8	60772.8
	15	10	29738.7	55555.5
	17	20	6800.3	10586.4
Demand + 20% Demand	7	1	39343.2	39343.2
	8	43	49999.2	49999.2
	11	3	57142.8	57142.8
	13	7	21428.4	21428.4
	14	6	66297.6	66297.6
	15	10	17954.1	60,606
	17	20	4105.6	11548.8
Demand + 40% Demand	7	1	41526.5	45900.4
	8	43	54858.3	58332.4
	11	3	66666.6	66666.6
	13	7	24999.8	24999.8
	14	6	77347.2	77347.2
Demand + 60% Demand	7	1	29723.5	52457.6
	8	43	48608.4	66665.6
	11	3	76190.4	76190.4
	13	7	28571.2	28571.2
	14	6	88396.8	88396.8

compared to the before-change state. Furthermore, in all four scenarios, A_7, A_8, A_{11}, A_{13} and A_{14} remain optimal, indicating that these products are the most reliable ones in terms of dealing with demand uncertainty.

6. Managerial implications

The study suggests a framework that combines qualitative and quantitative criteria with an optimization approach to address both short-term and long-term concerns in MCDA contexts. The research introduces a risk-averse UTA method that considers both experts' opinions and the information in the decision matrix to avoid anchoring bias in the weighting process. The proposed methodology eliminates the complexity associated with the application of probabilistic or fuzzy methods in decision-making. Moreover, the MAOM can reduce the dimensions of complex problems, making them feasible to solve. The framework can be used in various areas, including multi-level supply chain management, healthcare system optimization, and financial markets, where the complexity of the situation can be overwhelming. The proposed methodology can suggest alternatives with the fewest weaknesses, leading to satisfaction in the long term, even in crises such as the emergent need for hospital location. The current weighting methods that rely solely on experts' opinions can lead to a preference for certain criteria, ultimately resulting in suboptimal alternatives. The proposed method can consider both experts' opinions and the information in the decision matrix, ensuring a comprehensive evaluation and weighting of criteria. The proposed method yields the following insights:

- Organizations can effectively consider both short-term and long-term concerns in their decision-making process by utilizing strategic and operational criteria.
- The proposed MAOM reduces the risk of the decision-making process.
- When there is a lack of information regarding potential alternatives, when the alternatives are only known to experts, or when a crisis situation necessitates the selection of alternatives, current methods may be effective in the short-term, but they may not take into account the long-term implications of the alternatives as the MAOM can.

7. Conclusions and future studies

This study proposed a Multi-Attribute Optimization Model (MAOM) to determine the optimal amount of cultivation of crops considering both strategic and operational criteria in order to promote sustainable agricultural development. The framework of strategic criteria was divided into economy, society, and environment dimensions and used to calculate the sustainability score of candidate crops in the first step. In order to reduce the risk of low-scoring criteria, a risk-averse UTA was developed in this step. In the second step, a linear mathematical model was developed to calculate the optimal amount of candidate crops, taking into account the results of risk-averse UTA as the parameter of the objective function and operational criteria as constraints.

We employed the MAOM in Khorasan Razavi, Iran. An analysis of the local weight of strategic criteria revealed that the three dimensions had varying levels of importance, with the economic dimension being the most significant. An analysis of the local weight of sub-criteria in the three dimensions revealed that *convenience of crop cultivation, water consumption per hectare, and usage of fertilizer and pesticide per hectare* are the most significant factors from *economic*, *social*, and *environmental* perspectives.

In this study, the risk-averse UTA was used to figure out the sustainability scores of 49 candidate crops, and the crops were then ranked according to their scores. The highest and lowest scores were achieved by Potato and Leafy vegetables, respectively. Furthermore, a comparison between the original UTA and the risk-averse UTA revealed that the latter was able to effectively adjust the trade-off between decision-making criteria by determining the optimal weight for each. Finally, the optimization problem yielded the result that Dried garlic, Turnip and forage, Millet, and Khasil should be cultivated during the spring and summer months, while Potato, Fodder beet, Shah seed, and Mung bean are recommended for the autumn and winter months. Moreover, sensitivity analysis on the proposed model showed that our results are approximately robust with respect to demand uncertainty. This outcome can be valuable for policymakers by helping them to formulate policies, allocate resources, and promote economic stability in the agricultural sector. For example, policymakers can use the proposed framework to design policies that incentivize farmers to cultivate that particular crop. This can help ensure a stable supply of the crop even if demand fluctuates.

In this study, we used multi-criteria decision-making (MCDM) methods to come up with a hierarchical structure of criteria to figure out how sustainable crops are. This suggested structure provides valuable insights for both scholars and policymakers. Scholars can use the criteria to enhance and create agricultural machinery and seeds for sustainable production, while policymakers can use the framework of criteria to rank farmers' concerns and devise sustainable strategies to address them.

This work is limited in that, although we have attempted to cover more criteria by taking into account a sustainability index, it may not be the most comprehensive in terms of sustainability. Future research should consider other operational issues such as workforce allocation, irrigation scheduling, transportation of raw materials, and produced crops to better proxy real-life situations in optimal cultivation patterns. Moreover, other mathematical programming, such as stochastic programming can model the uncertainty of parameters at operational level more appropriately. Such an extension for the proposed model will provide decision-makers with more accurate results. In addition, if our proposed model applies to a wider scope (country), the size of the problem gets bigger and needs meta-heuristic algorithms for providing efficient solutions. Therefore, devising a meta-heuristic algorithm for a large-scale version of our proposed framework is beneficial. Finally, even though this study extends UTA method by considering risk-averse factor in decision-making process, since uncertainty is intertwined with decision-making context (Chun-Yueh, 2022), a combination of reinforcement learning (Zamfirache, Precup, Roman, & Petriu, 2022) and UTA is appreciated to include both risk factor and uncertainty for multi-criteria decision-making problems.

CRediT authorship contribution statement

Mohammad Reza Mehrpour: Conceptualization, Investigation, Resources, Validation, Data curation, Formal analysis, Software, Visualization, Writing - original draft, Writing - review & editing. **Siamak Kheybari:** Conceptualization, Investigation, Methodology, Resources, Validation, Data curation, Formal analysis, Project administration, Software, Supervision, Visualization, Writing - original draft, Writing - review & editing. **Jagjit Singh Srai:** Validation, Conceptualization, Investigation, Writing - original draft, Writing - review & editing. **Abbas Rohani:** Resources, Validation, Conceptualization, Data curation, Funding acquisition, Investigation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A

Appling the UTA model entails the following assumptions:

- A set of criteria as $\{g_1, g_2, \cdots, g_n\}$ is defined in which n denotes the number of decision criteria.
- A_R includes the options that are ranked by the decision maker.
- Possible values for different options within criterion i in real interval is defined such that g_i^* and g_{i^*} denote the worst and best level of criterion i in a non-decreasing real interval.

- The value of option a in criterion i is equal to $g_i(a)$ and $g(a)$ that shows the performance of option a in n decision criteria.
- As the performance of an option increases, its preference increases. In other words, we have:

$$g_i(a) > g_i(b) \Leftrightarrow a\,P\,b \quad \forall i$$

$$g_i(a) = g_i(b) \Leftrightarrow a\,I\,b \;\forall i \tag{A1}$$

Where P is called the strict preference relation and I the indifference relation.

- Marginal utility function of alternative a for criterion i is denoted by $u_i(g_i(a))$, and global utility function of alternative a is denoted by $U(a)$. Both marginal utility and global utility functions are positive, non-decreasing, and one-to-one functions, and they belong to the set of real numbers. Global utility function lies within the interval [0,1] while marginal utility function is a fraction of this interval, and we have:

$$u_i : [g_{i^*}, g_i^*] \rightarrow [01] \forall i$$

$$U(g(a)) > U(g(b) \Leftrightarrow a > b$$

$$U(g(a)) = U(g(b)) \Leftrightarrow a \approx b \tag{A2}$$

- Assuming that Global utility function is an additive function, we have:

$$U(g(a)) = \sum_i^n u_i(g_i(a))$$

$$\sum_i^n u_i(g_i^*) = 1$$

$$u_i(g_{i^*}) = 0, \;\forall i = 1, 2, \cdots, n \tag{A3}$$

- As shown in Fig. A, any marginal utility function is regarded as a continuous piecewise linear function, meaning that it consists of a series of linear functions that are interconnected.
- We assume that $[g_{i^*}, g_i^*]$ can be divided into $(\alpha_i - 1)$ equal parts such that the ending point of each interval for criterion i and sub-interval j is equal to:

$$g_i^j = g_i + \frac{j-1}{\alpha_i - 1}(g_i^* - g_{i^*}) \forall i = 1, 2, \cdots, \alpha_i \tag{A4}$$

Where using linear interpolation, $u_i(g_i(a))$ is equal to:

$$\mathrm{u_i}(g_i(a)) = u_i(g_i^j) + \frac{g_i(a) - g_i^j}{g_i^{j+1} - g_i^j}\left(u_i(g_i^{j+1}) - u_i(g_i^j)\right) \tag{A5}$$

This method uses a linear programming to achieve utility functions such that the rankings obtained from these functions are as consistent as possible with the initial rankings performed on the A_R reference set. Since the answer obtained from the model may be exactly in accordance with the initial preferences of the decision maker, some errors are considered in the model such that the utility function defined in Equation (3) changes into Equation (6).

$$U'(g(a)) = \sum_i^n u_i(g_i(a)) + \sigma(a) \forall a \in A_R \tag{A6}$$

Where $\sigma(a)$ is potential error of $U(g(a))$.

Considering the ranking done in A_R and assuming that a_1 is at the highest rank and a_n is at the lowest the rank, in each pair of alternatives (a_k, a_{k+1}), it is possible (i) a_k takes precedence over a_{k+1} (($a_k > a_{k+1}$)) or (ii) the two alternatives are indifferent to each other (($a_k \approx a_{k+1}$)). In other words, we have:

$$\begin{aligned}&\Delta(a_k, a_{k+1}) = U[g(a_k)] - U[g(a_{k+1})] \geq \delta \text{ for } a_k > a_{k+1} \;\forall k\\ &\Delta(a_k, a_{k+1}) = U[g(a_k)] - U[g(a_{k+1})] = 0 \text{ for } a_k \approx a_{k+1} \;\forall k\end{aligned} \tag{A7}$$

Where δ is a very small value appropriately showing significant difference between two consecutive alternatives. Given the aforementioned explanations, marginal utility function is equal to:

$$Minimize\, F = \sum_{a \in A_R} \sigma(a)$$

Subject to:

$$\Delta(a_k, a_{k+1}) = U[g(a_k)] - U[g(a_{k+1})] \geq \delta \, for \, a_k > a_{k+1} \forall k$$

$$\Delta(a_k, a_{k+1}) = U[g(a_k)] - U[g(a_{k+1})] = 0 \, for \, a_k \approx a_{k+1} \forall k$$

Table A1
Normalized score of candidate crops across decision-making criteria.

Crops	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.059	0.334	0.84	0	0.948	0.4	0.039
A_2	0.096	0.334	0.875	0	0.918	0.8	0.056
A_3	0.071	0	0.858	0	0.823	0.8	0.039
A_4	0.046	0.667	0.929	0.334	0.888	0.2	0.022
A_5	0.096	0.334	0.858	0	0.777	0.4	0.056
A_6	0.31	0.667	0.822	0.334	0.896	0.6	0.009
A_7	0.059	0.667	0.893	1	0.915	0.8	0.031
A_8	0.41	0.667	0.911	0	0.955	0.2	0.271
A_9	0.561	0.667	0.947	0	0.758	1	0.374
A_{10}	0.065	0.667	0.786	0.667	0.731	0	0.035
A_{11}	0.052	1	0.875	0.667	0.976	1	0.026
A_{12}	0.071	1	0.911	0	0.916	1	0.039
A_{13}	0.076	1	0.786	0.667	0.963	0.6	0.042
A_{14}	0	1	0.875	0.667	0.967	0.8	0.019
A_{15}	0.015	1	0.768	0.667	0.919	0.6	0
A_{16}	0.015	0.334	0.768	0.667	0.916	0.6	0
A_{17}	0.071	1	0	0.667	0	0.8	0.039
A_{18}	0.069	0.334	0.768	0.667	0.916	0.6	0.037
A_{19}	0.749	0.667	0.983	0	0.986	0.8	0.503
A_{20}	0.052	0.334	0.929	0	0.956	0.8	0.026
A_{21}	0.423	0.667	0.947	0	0.919	0.6	0.279
A_{22}	0.31	0.667	0.965	0	0.904	0.4	0.202
A_{23}	0.052	0.334	0.929	0	0.873	0.6	0.588
A_{24}	0.075	0.667	0.822	0.667	0.956	0.4	0.042
A_{25}	0.069	0.667	0.768	0.667	0.916	0.6	0.037
A_{26}	0.247	0.667	0.804	0.667	0.864	0.6	0.159
A_{27}	0.077	0.667	0.822	0.667	0.943	0.4	0.043
A_{28}	0.184	0.667	0.786	0.667	0.939	0	0.116
A_{29}	1	0.334	0.965	0	0.918	0.8	0.674
A_{30}	0.184	0.334	0.965	0	0.916	0.8	0.116
A_{31}	0.561	0.334	0.911	0	0.397	1	0.374
A_{32}	0.027	0.667	0.84	0.667	0.895	0.4	0.009
A_{33}	0.486	0.334	0.786	0	0.917	0.6	0.322
A_{34}	0.687	0.334	0.875	0	1	1	0.46
A_{35}	0.875	1	0.947	0.667	0.941	0.2	0.588
A_{36}	0.498	0.667	1	0	0.978	1	0.331
A_{37}	0.561	0.667	0.84	0	0.937	0.2	0.374
A_{38}	0.561	0.667	1	0	0.985	1	0.374
A_{39}	0.473	0.667	0.911	0	0.896	0.6	1
A_{40}	0.661	0.667	0.893	0	0.915	0.8	0.443
A_{41}	0.096	0.334	0.822	0.667	0.866	0.8	0.056
A_{42}	0.04	0.334	0.822	0	0.866	0.8	0.018
A_{43}	0.096	1	0.858	0	0.87	0.8	0.056
A_{44}	0.037	0.334	0.822	0	0.866	0.8	0.016
A_{45}	0.077	0.334	0.822	0	0.889	1	0.043
A_{46}	0.109	0.334	0.893	0	0.866	0.6	0.065

$$\begin{aligned} \sum\nolimits_i^n u_i\left(g_i^*\right) &= 1 \\ u_i\left(g_i^{j+1}\right) - u_i\left(g_i^j\right) &\geq 0 \; \forall\, i, j \\ \sigma(a) &\geq 0 \end{aligned} \tag{A8}$$

If $F^* = 0$, then it means that we have found a solution set for the final utility such that the ranking resulted from the model perfectly matches the initial ranking presented by the reference set; otherwise, it means that there is no set of values to accurately create the same initial ranking of the A_R. Therefore, the ranking obtained from the model is created with some error in relation to the decision-maker's point of view.

Model 8 considers only positive errors, whereas since this error is not defined as an absolute value, it may have a negative value. For this purpose, an improved version of UTA was proposed by Siskos et al., (Siskos, Grigoroudis, & Matsatsinis, 2016)., called UTA STAR (Model 9).

$$MinimizeZ = \sum_{i=1}^{m} \sigma^+(a_k) + \sigma^-(a_k)$$

Subject to:

$$\begin{aligned} &\Delta(a_k, a_{k+1}) \geq \delta \quad \forall\, a_k > a_{k+1} \quad \forall k \\ &\Delta(a_k, a_{k+1}) = 0 \quad \forall\, a_k \approx a_{k+1} \quad \forall k \end{aligned}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{\alpha_i - 1} w_{ij} = 1 \; \forall\, i, j$$

Table B1
Parameters of linear optimization model for group A.

Crop	D_i	a_i	p_i	w_i
A_1	9000	11,000	0.1459	0.864
A_8	41,666	2400	0.1859	0.164
A_9	1170	85,400	0.3257	27.77
A_{11}	47,619	0.21	0.5256	0.086
A_{13}	17,857	5600	0.4730	0.32
A_{14}	55,248	0.181	0.4913	0.095
A_{17}	9624	10,398	0.3505	13.611
A_{19}	600	166,600	0.3574	4.83
A_{24}	2702	37,000	0.4242	2.51
A_{27}	4000	25,000	0.4240	2.125
A_{28}	1751	57,100	0.3564	5.139
A_{35}	2481	40,300	0.5699	3.52277
A_{36}	1175	85,100	0.3312	3.319
A_{37}	2500	40,000	0.2058	3.68
A_{38}	1004	99,600	0.3452	2.988
A_{40}	1169	85,500	0.3329	10.39

Table C1
Parameters of linear optimization model for group B.

Crop	D_i	a_i	p_i	w_i
A_2	45,454	0.22	0.2074	0.256
A_3	38,461	0.26	0.1917	0.26
A_4	20,000	0.5	0.2509	0.78
A_5	23,255	0.43	0.1414	1.29
A_6	26,315	0.38	0.3606	0.554
A_7	32,786	0.305	0.6215	0.786
A_{10}	7032	1.422	0.3130	5.119
A_{12}	6024	1.66	0.2331	1.99
A_{15}	50,505	0.198	0.4526	0.229
A_{16}	6896	1.45	0.4445	1.74
A_{18}	3508	2.85	0.4598	3.42
A_{20}	700	14.28	0.2011	9.71
A_{21}	1533	6.523	0.2541	7.56
A_{22}	3003	3.33	0.2008	4.49
A_{23}	800	12.5	0.2332	21.875
A_{25}	6301	1.587	0.4644	1.9
A_{26}	3974	2.516	0.5117	4.7
A_{29}	925	10.81	0.3929	12.648
A_{30}	1388	7.204	0.2273	8.64
A_{31}	3484	2.87	0.2908	22.81
A_{32}	51,020	0.196	0.4069	0.287
A_{33}	2403	4.16	0.2615	4.91
A_{34}	2617	3.82	0.3621	0.37
A_{35}	1404	7.12	0.3370	10.38
A_{41}	20,325	0.492	0.4984	0.91
A_{42}	19,880	0.503	0.1910	0.93
A_{43}	35,714	0.28	0.2104	0.5
A_{44}	28,328	0.353	0.1905	0.65
A_{45}	23,809	0.42	0.2211	0.65
A_{46}	31,250	0.32	0.1787	0.592

$$\begin{aligned} & w_{ij} \geq 0 \; \forall i,j \\ & \sigma^{+}(a_k) \geq 0 \; \forall k \\ & \sigma^{-}(a_k) \geq 0 \; \forall k \end{aligned} \tag{A9}$$

where

$$\Delta(a_k, a_{k+1}) = U[g(a_k)] - \sigma^{+}(a_k) - \sigma^{-}(a_k) - U[g(a_{k+1})] + \sigma^{+}(a_k) - \sigma^{-}(a_k) \tag{A10}$$

$$w_{ij} = u_i\left(g_i^{j+1}\right) - u_i\left(g_i^{j}\right) \geq 0 \; \forall i = 1, 2, \cdots, n, j = 1, 2, \cdots, \alpha_i - 1 \tag{A11}$$

Note that m in the objective function of model number 9 is equal to the number of alternatives of set A_R.

To calculate the optimal weigh of criteria contributed to decision making problems, we should solve optimization model 12 (Siskos et al., 2016).

$$\underset{i}{\text{Minimize}}\left(u_i\left(g_i^{*}\right)\right) = \sum_{j=1}^{\alpha_i - 1} w_{ij} \quad \forall i$$

Subject to:

Table D1
Parameters related to common parameters of crops.

City (j)	AT_j	PT_j	WT_j
1	67,721	4284	47129.2169
2	26,805	1695	18654.4596
3	57,862	3660	40268.0224
4	23,088	1460	16067.6800
5	16,275	1029	11326.2947
6	17,541	1109	12207.3447
7	1580	99	1099.5727
8	5581	353	3883.9970
9	16,249	1028	11308.2005
10	44,824	2835	31194.4599
11	16,267	1029	11320.7273
12	30,717	1943	21376.9459
13	15,622	988	10871.8511
14	15,631	988	10878.1145
15	20,831	1317	14496.9613
16	17,840	1128	12415.4284
17	17,128	1083	11919.9248
18	30,588	1935	21287.1707
19	96,603	6111	67229.1274
20	35,231	2228	24518.3834
21	48,330	3057	33634.3978
22	38,459	2433	26764.8521
23	25,026	1583	17416.3964
24	8729	552	6074.7912
25	6693	423	4657.8735
26	44,609	2822	31044.8345
27	20,026	1266	13936.7360
28	6275	396	4366.9738
29	18,176	1149	12649.2616

Table E1
Optimal cultivation magnitude in detail for crops in group A.

City (j)	A_7	A_{11}	A_{14}	A_{15}
1	10640.5473	0.0000	0.0000	0.0000
2	4210.0205	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.0000	11669.7159
4	3626.3303	0.0000	0.0000	0.0000
5	0.0000	4640.1469	0.0000	0.0000
6	2754.5208	0.0000	0.0000	0.0000
7	0.0000	0.0000	414.3600	0.0000
8	876.7771	0.0000	0.0000	0.0000
9	2553.3339	0.0000	0.0000	0.0000
10	0.0000	0.0000	11865.7636	0.0000
11	608.5280	3535.3500	0.0000	0.0000
12	4825.9998	0.0000	0.0000	0.0000
13	0.0000	0.0000	4135.2291	0.0000
14	0.0000	0.0000	0.0000	3150.1856
15	0.0000	0.0000	5512.2436	0.0000
16	0.0000	0.0000	4721.1927	0.0000
17	2689.9423	0.0000	0.0000	0.0000
18	0.0000	0.0000	8098.8545	0.0000
19	0.0000	0.0000	15691.2691	7531.1117
20	0.0000	10046.8875	0.0000	0.0000
21	0.0000	0.0000	0.0000	9747.0824
22	0.0000	0.0000	0.0000	7757.4915
23	0.0000	7138.3406	0.0000	0.0000
24	0.0000	130.7719	0.0000	1667.5578
25	0.0000	1907.4656	0.0000	0.0000
26	0.0000	12725.4563	0.0000	0.0000
27	0.0000	5708.8687	0.0000	0.0000
28	0.0000	1785.7125	0.0000	0.0000
29	0.0000	0.0000	4809.0873	0.0000

$$\begin{cases} \sum_{k=1}^{m} [\sigma^{+}(a_k) - \sigma^{-}(a_k)] \leq Z^{*} + \varepsilon \\ alltheconstraintsoflinearprogram(9) \end{cases} \tag{A12}$$

where Z^{*} is the optimal value of linear program 9 and ε is a very small positive number.

Table F1
Optimal cultivation magnitude in detail for crops in group B.

City (j)	A_8	A_{13}	A_{17}
1	0.0000	0.0000	3123.4255
2	0.0000	352.8561	1007.6036
3	0.0000	0.0000	2668.4727
4	0.0000	0.0000	1064.4727
5	0.0000	0.0000	750.2345
6	0.0000	0.0000	808.5618
7	0.0000	0.0000	72.1800
8	696.4062	0.0000	0.0000
9	2028.0610	0.0000	0.0000
10	5592.9503	0.0000	0.0000
11	2030.0338	0.0000	0.0000
12	3833.1931	0.0000	0.0000
13	1949.1481	0.0000	0.0000
14	0.0000	1113.8078	0.0000
15	0.0000	1484.7013	0.0000
16	0.0000	1271.6348	0.0000
17	0.0000	1220.9047	0.0000
18	3817.4105	0.0000	0.0000
19	0.0000	6889.1494	0.0000
20	0.0000	2511.7043	0.0000
21	6030.9168	0.0000	0.0000
22	4799.8759	0.0000	0.0000
23	0.0000	1784.5727	0.0000
24	1088.9977	0.0000	0.0000
25	834.5037	0.0000	0.0000
26	3418.9005	1227.6688	0.0000
27	2497.5926	0.0000	0.0000
28	781.2375	0.0000	0.0000
29	2266.7724	0.0000	0.0000

Table G1
Time complexity of the mathematical model presented in this research.

Model	Execution time (in seconds)
Calculating Range of Weights of Criteria	30.12
Calculating Optimal Weights of Criteria	42.34
Calculating Optimal Amount of Crops	71.04

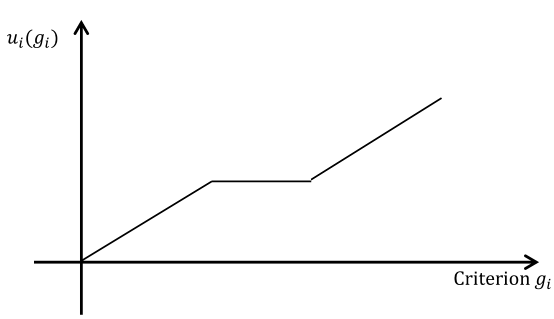

Fig. A1. Marginal utility function.

Appendix B

See Table A1-G1.
See Fig. A1.

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