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MULTIATTRIBUTE EVALUATION OF ORGANIC AND INORGANIC AGRICULTURAL FOOD INVESTMENTS USING FUZZY TOPSIS

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Abstract. Since people well know the threats of inorganic agriculture to their health, they are more interested in organic agriculture than ever. Organic agriculture is expected to play a major role for a healthy world in the future whereas inorganic agriculture nowadays increases the volume of agricultural production and presents lower priced foods but causes health problems. The agricultural investments are generally evaluated by using linguistic terms since most of the evaluation criteria are intangible and inherently require imprecise data to be used. In this paper, we analyze six types of agricultural investment alternatives using eight different criteria based on linguistic data. One of the most-used multi-criteria decision-making methods, TOPSIS is used under fuzziness for the solution of this problem. A sensitivity analysis is also given to examine the robustness of the decision.

Keywords: multiattribute, organic food, inorganic food, investment, fuzzy set, TOPSIS.

JEL Classification: C65, Q18.

Introduction

Organic agriculture produces fruits and vegetables using environmentally- and animal-friendly farming methods. The food from organic agriculture is high quality, nutritious and contributes to a healthy life. There are various definitions of organic agriculture. For instance, organic agriculture produces food without artificial chemicals but with organic-based chemicals (Legg, Viatte 2001).

Sustainable agriculture uses farming techniques protecting the environment, public health, and animal welfare. Sustainable farming systems should provide a long-term welfare through economical, environmentally friendly and socially acceptable food and other goods and services (Parris 2004).

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In these days, while a significant increase in inorganic agricultural production is observed, a meaningful increase in demand for organic food appears as well. The growth in demand and consumption of organic foods are mainly because of the increasing number of consumers demanding food quality and safety benefits with organic foods and/or food production systems. Since organic production systems frequently produce lower yields and higher costs, consumers have to pay higher prices for organic food (Leifert 2007).

The benefits of organic farming are now widely accepted in the world. This is the main reason for government support of organic farming. These benefits are (a) lower levels of pollution of surface and ground water (b) reduced energy use and (c) increased density and diversity (Niggli 2007).

Yields generally are lower on organic farms than the conventional farms. Both labor costs and profitability are generally higher due to price premiums and support payments in a lot of countries. Economic comparisons between organic and conventional farms may not be meaningful. The various environmental externalities arising from different farming systems should clearly be taken into account. Thus farmers can make decisions as to the most appropriate system to adopt (OECD 2003).

Decisions for organic or inorganic food farming investments include multi-criteria and multi-experts evaluations. Besides, these criteria may be conflicting and most of them can be evaluated by linguistic terms rather than numerical evaluations. For instance, a possible criterion effects on flora and fauna can be evaluated using linguistic terms such as very poor, poor, good, and very good. These kinds of evaluations can be better handled by the fuzzy set theory based methodologies. For this aim, many fuzzy multi-criteria decision-making methods have been developed in the literature. Fuzzy Analytic Hierarchy Process (AHP), fuzzy TOPSIS, fuzzy VIKOR, fuzzy ELECTRE, fuzzy PROMETHEE, and fuzzy DEMATEL are among these methods.

Little research exists on multi-criteria organic and inorganic food or farming investments. Hayashi (2000) gives a literature review and future perspectives on multiple criteria decision analysis for agricultural resource management. Girardin *et al.* (2000) propose a multi-criteria decision-making method for the evaluation of arable farming systems. Rozman *et al.* (2006) present a multi-criteria analysis for the evaluation of spelt food processing alternatives in small organic farms. Parra-Lopez *et al.* (2007) make a multi-criteria environmental comparison of conventional, organic and integrated olive-growing systems in Spain. Parra-López *et al.* (2008) use AHP for comparing performances of alternative olive growing systems in Andalusia. Latinopoulos (2009) uses multi-criteria decision analysis for the allocation of land and water resources in irrigated agriculture. Siciliano (2009) studies a multi-criteria evaluation of farming practices under soil degradation in Southern Tuscany, Italy. Masuda *et al.* (2010) present an application for organic coffee production in Kona, Hawaii by multi-criteria decision-making. Castellini *et al.* (2012) analyze the sustainability of different poultry production systems. The sustainability of the conventional, organic and organic-plus poultry production systems is compared by a multi-criteria decision analysis (MCDA) including the dimensions economic, social, environmental and quality. The examined farming systems show different results with respect to scientists, consumers and producers. Læssøe *et al.* (2014) discuss how the economic, psychosocial, and relational perspectives converge and diverge regarding the purpose of using a multicriteria assessment tool (MCA). Through this multiple-perspective approach, the general idea of MCA is expanded and elaborated to refine the design of an MCA tool for organic food systems. Kastberg (2015) presents a critical discussion of the promises and pitfalls of how multicriteria assessments may be communicated and coconstructed on a coactional, web-based platform for organic foods. As it is clearly seen from the literature review, there is no research on fuzzy multi-criteria decision analysis for organic/inorganic food investments.

This paper aims at selecting the best farming investment decision under multi-criteria and fuzzy environment. The originality of this paper comes from the first time application of a fuzzy multi-criteria decision-making method for organic or inorganic farming investment decisions. Our paper is constructed as follows. Section 1 gives the possible investment criteria and alternatives for agricultural farming investments. Section 2 presents a fuzzy multi-criteria decision-making method, namely fuzzy TOPSIS. Section 3 includes a multi-criteria investment analysis for agricultural farming. Final section gives the conclusions and suggestions for further research.

1. Investment criteria and alternatives in agricultural farming

Investment in agriculture is a popular problem of our day. Organic or inorganic farming investments involve many criteria those must be considered before an investment decision is given. Most of these criteria have to be evaluated by linguistic terms rather than numerical values. The considered criteria after a wide literature review have been listed as follows:

***Previously applied productions systems and technologies (PAPT)*:** This criterion tries to answer which production technologies have been used in the past for the considered arable field. It is known that an inorganic farming method would make use of pesticide or insecticides to get rid of pests and weeds. This may cause to exterminate the aliveness of the soil. Genetically modified organisms (GMO) change the chemical structure of soil and do not let the original natural structure to be recovered.

***Annual average net income (AAI)*:** Inorganic farming generally increases the amount of agricultural production since it uses chemicals and genetically modified organisms (GMO). Besides, the cost of inorganic farming is slightly higher than organic farming as it is illustrated in Figure 1 (Royte 2013). As a result, this causes organic foods be more expensive than inorganic foods.

***Increase in labor requirement (ILR)*:** In Turkey, inorganic farming needs more labor requirement when compared with organic farming. The literature provides evidence that labor use changes with respect to the climate conditions and technological requirements. When climate conditions and technological facilities become worse, inorganic farming needs more expenses.

***Effects on human health (EHH)*:** Organic food usually contains fewer contaminants, more nutrients less cause food poisoning and it is useful for the environment and human health (Givens *et al.* 2008).

***Effects on flora and fauna (EFF)*:** Suitable habitats for wildlife are only possible with the continuous maintenance of natural areas within and around organic fields and absence of chemical inputs (FAO.org).

***Need for alternation (NA)*:** Alteration is often the physical modification of a site usually to improve or allow agricultural production. Alteration in farming causes the agricultural production level to increase since the chemical components which same plants need decrease in the soil year by year.

***Soil characteristics (SC)*:** Soil characteristics have importance from the viewpoint of the type of the agricultural production, e.g. organic and inorganic production. In most applications of inorganic production, minimum level of natural soil is needed; instead, some chemicals are used, which accelerate the growth of plants.

***Farmer motivation (FM)*:** The motivational factors which affect a farmer's motivation can be listed as seasonality, community, social interactions, location and distances, economic reasons, environmental concerns, production methods, consumer and producer/vendor connection. Nowadays farmers generally prefer inorganic farming since the economic benefits from this kind of production are relatively larger than organic farming.

In this study, six possible farming investment alternatives have been considered:

***Organic field farming (A1)*:** It uses organic manures, and bio-pesticides without inorganic chemicals and pesticides.

***Organic farming in greenhouses with soil (A2)*:** This type of farming is applied in greenhouses using organic soil. This type costs more but provides the stable weather conditions.

Integrated Organic Farming Systems (A3): In integrated organic farming, local resources are effectively recycled by involving other components. It includes integrated nutrient and pest management.

Inorganic farming in greenhouses with soil (A4): It is a type of farming using modern technologies aiming optimal nutrition for plants. Greenhouse farming may use crop protection materials to control pests. It is sustainable. Water use is reduced.

Inorganic field farming (A5): This type of farming is an agriculture production method including the use of manmade products such as pesticides, herbicides, etc. It requires less land and water use. It is sustainable.

Inorganic soilless farming in greenhouses (A6): Soilless farming is an artificial production of plants with support and a reservoir for nutrients and water. Inorganic chemicals are dissolved in water and supply all of the nutrients necessary for plants.

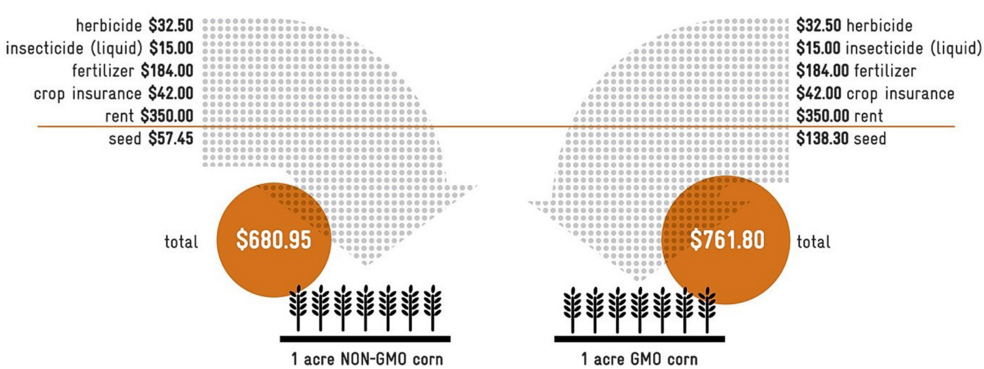

Fig. 1. Costs of 1 acre GMO and Non-GMO corn

2. Fuzzy multi-criteria evaluation: fuzzy TOPSIS

TOPSIS which is one of the most-used classical multi-criteria decision-making methods was developed by Hwang and Yoon (1981). Fuzzy extensions of TOPSIS have been developed by recently used in the analysis of various problems.

Ekmekçioğlu *et al.* (2010) used a modified fuzzy TOPSIS for the selection of the best municipal solid waste disposal method and site. Chen and Lee (2010) proposed an interval type-2 fuzzy TOPSIS method for the solution of fuzzy multiple criteria decision-making problems. Kutlu and Ekmekçioğlu (2012) used an integrated method including fuzzy TOPSIS and fuzzy AHP to develop a new FMEA which removes the shortcomings of traditional FMEA. Sun (2010) developed an evaluation model based on fuzzy AHP and fuzzy TOPSIS for performance evaluation in a fuzzy environment. Kaya and Kahraman (2011) proposed a fuzzy TOPSIS method for the selection of the best energy technology alternative. Paksoy *et al.* (2012) used fuzzy AHP and hierarchical fuzzy TOPSIS for prioritizing the organization strategies of distribution channel management in a firm. Kim *et al.* (2013) developed a fuzzy TOPSIS method for prioritizing the best sites for treated wastewater usage. Roshandel *et al.* (2013) evaluated four suppliers using the hierarchical fuzzy TOPSIS approach. Kahraman *et al.* (2013) evaluated possible higher education investment alternatives using an integrated method of fuzzy AHP and Fuzzy TOPSIS. Taylan *et al.* (2014) categorized the construction projects by fuzzy AHP and TOPSIS methods. Kannan *et al.* (2014) proposed a Fuzzy TOPSIS method for the selection among green suppliers for a Brazilian electronics company. Lee *et al.* (2014) used a fuzzy TOPSIS method based on α-cut level sets, aiming at improving the general flood vulnerability approach.

TOPSIS selects the alternative with the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS). It can consider various criteria, which might be conflicting and have different units simultaneously.

Consider the decision matrix with n attributes and m alternatives given in Eq. (1). TOPSIS chooses the alternative with the largest value of C_i^* in Eq. (2) and with the least value of C_i^- in Eq. (3) by using the vector normalization.

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}; \qquad (1)$$

$$\text{Weights} \quad w_1 \quad \cdots \quad w_j \quad \cdots \quad w_n$$

$$C_i^* = \frac{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^-\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^*\right)^2} + \sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^-\right)^2}}, \quad i = 1, 2, \ldots, m; \tag{2}$$

$$C_i^- = \frac{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^*\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^*\right)^2} + \sqrt{\sum_{j=1}^{n}\left(w_j \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} - v_j^-\right)^2}}, \quad i = 1, 2, \ldots, m. \tag{3}$$

where i represents the number of alternatives ($i = 1, \ldots, m$) and j represents the number of attributes ($j = 1, \ldots, n$); w_j is the jth attribute's weight; x_{ij} is the value of jth attribute for ith alternative in the decision matrix; v_j^* is the positive-ideal value of jth attribute; v_j^- is the jth attribute's negative-ideal value.

The steps of fuzzy TOPSIS are given in the following (Yoon, Hwang 1995):

Step 1. Determination of criteria weights and construction of decision matrix: The fuzzy scales given in Tables 1 and 2 are used in the construction of decision matrix.

Table 1. Fuzzy evaluation scale for the weights of criteria

Linguistic terms	Fuzzy scale
Absolutely Strong (AS)	(2, 5/2, 3)
Very Strong (VS)	(3/2, 2, 5/2)
Fairly Strong (FS)	(1, 3/2, 2)
Slightly Strong (SS)	(1, 1, 3/2)
Equal (E)	(1, 1, 1)
Slightly Weak (SW)	(2/3, 1, 1)
Fairly Weak (FW)	(1/2, 2/3, 1)
Very Weak (VW)	(2/5, 1/2, 2/3)
Absolutely Weak (AW)	(1/3, 2/5, 1/2)

Table 2. Fuzzy evaluation scale for the alternatives

Linguistic terms	Fuzzy scale
Very Poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium Poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium Good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very Good (VG)	(9, 10, 10)

Step 2. Normalization of the obtained scores.

The linear scale transformation is given in Eq. (4):

$$r_{ij} = \begin{cases} x_{ij} / x_j^*, \ \forall j, \ \text{for benefit attributes} \\ x_j^- / x_{ij}, \ \forall j, \ \text{forcost attributes.} \end{cases} \tag{4}$$

By applying Eq. (4), we can write the normalized decision matrix (D) as:

$$D = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{i1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix}. \tag{5}$$

In the fuzzy case, the normalized decision matrix is obtained as follows.

Let the minimum value be $\tilde{x}_j^- = \left(a_i^-, b_i^-, c_i^-, d_i^-\right)$ for cost attributes and the maximum value be $\tilde{x}_j^* = \left(a_j^*, b_j^*, c_j^*, d_j^*\right)$ for benefit attributes in the decision matrix, then we have

$$r_{ij} = \begin{cases} x_{ij}(\div)x_j^* = \left(\dfrac{a_{ij}}{d_j^*}, \dfrac{b_{ij}}{c_j^*}, \dfrac{c_{ij}}{b_j^*}, \dfrac{d_{ij}}{a_j^*}\right), \text{ for benefit attributes} \\ x_j^-(\div)x_{ij} = \left(\dfrac{a_j^-}{d_{ij}}, \dfrac{b_i^-}{c_{ij}}, \dfrac{c_i^-}{b_{ij}}, \dfrac{d_i^-}{F_{ij}}\right), \text{ for cost attributes.} \end{cases} \tag{6}$$

Step 3. Construction of the weighted normalized fuzzy decision matrix.

Eq. (7) is used for the crisp case:

$$v_{ij} = r_{ij} w_j, \forall i, j. \tag{7}$$

In the fuzzy case, Eq. (8) is used:

$$\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot)\tilde{w}_j = \begin{cases} \left(\dfrac{a_{ij}}{d_j^*}\alpha_j, \dfrac{b_{ij}}{c_j^*}\beta_j, \dfrac{c_{ij}}{b_j^*}\gamma_j, \dfrac{d_{ij}}{a_j^*}\delta_j\right), \text{ for benefit attributes} \\ \left(\dfrac{a_i^-}{d_{ij}}\alpha_j, \dfrac{b_i^-}{c_{ij}}\beta_j, \dfrac{c_i^-}{b_{ij}}\gamma_j, \dfrac{d_i^-}{a_{ij}}\delta_j\right), \text{ for cost attributes.} \end{cases} \tag{8}$$

The result of Eq. (8) can be summarized as:

$$\tilde{V} = \begin{bmatrix} \tilde{v}_{11} & \cdots & \tilde{v}_{1j} & \cdots & \tilde{v}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{v}_{i1} & \cdots & \tilde{v}_{ij} & \cdots & \tilde{v}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{v}_{m1} & \cdots & \tilde{v}_{mj} & \cdots & \tilde{v}_{mn} \end{bmatrix}. \tag{9}$$

Step 4. Calculation of the distances from fuzzy PIS and fuzzy NIS for each alternative:

$$A^* = \left[\tilde{v}_1^*, \ldots, \tilde{v}_n^*\right]; \quad (10)$$

$$A^- = \left[\tilde{v}_1^-, \ldots, \tilde{v}_n^-\right], \quad (11)$$

where $\tilde{v}_j^* = \max \tilde{v}_{ij}$ and $\tilde{v}_j^- = \min \tilde{v}_{ij}$.

For fuzzy data, $\tilde{v}_j^*$ and $\tilde{v}_j^-$ may be obtained through some ranking procedures. Chen (2000) proposed that $\tilde{v}_j^* = (1,1,1)$ and $\tilde{v}_j^- = (0,0,0)$, which very much simplifies the calculations. We will prefer Chen's (2000) approach in this paper.

Step 5. Calculation of closeness coefficients (CC_i).

To calculate these coefficients, the separation measures S_i^* and S_i^- are calculated by Eq. (12) and Eq. (13).

$$S_i^* = \sum_{j=1}^{n} D_{ij}^*,\ i = 1, \ldots, m \quad (12)$$

and

$$S_i^- = \sum_{j=1}^{n} D_{ij}^-,\ i = 1, \ldots, m. \quad (13)$$

In the crisp case, the difference measures D_{ij}^* and D_{ij}^- are given in Eq. (14) and Eq. (15):

$$D_{ij}^* = \left| v_{ij} - v_j^* \right|; \quad (14)$$

$$D_{ij}^- = \left| v_{ij} - v_j^- \right|. \quad (15)$$

For fuzzy data:

$$D_{ij}^* = 1 - \left\{ sup_x \left[\mu_{v_{ij}}(x) \wedge \mu_{v_j^*}(x) \right] \right\} = 1 - L_{ij}, \forall j, i, \quad (16)$$

where the highest degree of similarity of v_{ij} and v_j^* is L_{ij}.

The difference between $\mu_{v_{ij}}(x)$ and $\mu_{v_{ij}^-}(x)$ is defined in Eq. (17):

$$D_{ij}^- = 1 - \left\{ sup_x \left[\mu_{v_{ij}}(x) \wedge \mu_{v_j^-}(x) \right] \right\} = 1 - L_{ij}, \forall j, i. \quad (17)$$

Note that D_{ij}^* and D_{ij}^- are crisp numbers.

Thus S_i^* and S_i^- are obtained as crisp numbers. They are used for the calculation of closeness coefficients as in Eq. (18):

$$CC_i = \frac{S_i^-}{S_i^* + S_i^-}. \quad (18)$$

The alternative with the largest CC_i index is selected.

3. A multi-criteria investment analysis for agricultural farming

A farmer in Sakarya, a city in Marmara region of Turkey, who has an arable field of 23,500 m^2, wants to decide which food production method he should select. He is confused among many criteria and alternatives. A team of five experts from Republic of Turkey Ministry of Food, Agriculture and Livestock helps farmers giving this kind of decisions by multi-criteria approaches. The team decided to use the criteria and alternatives given in Section 1. Table 3 shows the evaluations of these experts for the criteria, based on the scale in Table 1.

Table 3. Linguistic evaluation scores for the weights of criteria

Expert No	Criteria							
	FM	PAPT	AAI	ILR	NA	EHH	EFF	SC
1	FS	FS	VS	E	SS	VS	VS	SW
2	VS	VS	FS	E	FS	AS	VS	AW
3	FS	SS	VS	SS	SS	VS	FS	FW
4	VS	FS	VS	FS	FS	FS	VS	E
5	SS	FS	FS	E	SS	AS	VS	VW

Table 4. Evaluation of alternatives with respect to the criteria

Alternatives	Criteria							
	FM	PAPT	AAI	ILR	NA	EHH	EFF	SC
A1. Organic field farming	G	VG	MG	VG	MP	VG	VG	MG
A2. Organic farming in greenhouses with soil	MG	G	F	MG	MP	VG	VG	MG
A3. Integrated Organic Farming System	G	G	F	G	P	MG	VG	G
A4. Inorganic farming in greenhouses with soil	F	FS	G	MG	G	P	MG	MG
A5. Inorganic field farming	MG	MG	VG	G	MG	P	P	MG
A6. Inorganic soilless farming in greenhouses	MP	VP	MG	MP	G	VP	F	G

Table 4 gives the decision matrix including the experts compromised lingusitic evaluations for the alternatives with respect to the criteria.

Table 5 presents the corresponding numerical values of the linguistic evaluations in Table 4. Table 6 shows the normalized decision matrix. All the criteria are assumed to be benefit criteria and scored with respect to this assumption. For the criterion FM, since the largest possible value is 7, all the values of FM are divided by 7.

The criteria weights are determined by averaging the linguistic evaluations made by the five experts in Table 3. For instance, the weight of the criterion FM is calculated as follows (FS+VS+FS+VS+SS)/5 = [(1, 3/2, 2)+(3/2, 2, 5/2) + (1, 3/2, 2)+((3/2, 2, 5/2)+(1, 1, 3/2)]/5 = (6, 8, 10.5)/5 = (1.2, 1.6, 2.1). These values for the other criteria PAPT, AAI, ILR, NA, EHH, EFF, and SC are (1.1, 1.5, 2.0), (1.0, 1.2, 1.7), (1.3, 1.8, 2.3), (1.0, 1.1, 1.3), (1.6, 2.1, 2.6), (1.4, 1.9, 2.4), and (0.58, 0.71, 0.83), respectively. Later, defuzzification of these fuzzy numbers by averaging the triple values of each number and then normalizing the defuzzified values gives us the weights 0.135, 0.127, 0.107, 0.149, 0.094, 0.173, 0.157, and 0.059 for FM, PAPT, AAI, ILR, NA, EHH, EFF, and SC, respectively.

Table 7 gives the weighted normalized decision matrix. Tables 8 and 9 present the distances to the positive and negative ideal solutions for each alternative, respectively.

Table 10 gives the similarity coefficient to ideal solution of each alternative.

Table 5. Fuzzy decision matrix and criteria weights

Alternatives	Criteria																							
	FM			PAPT			AAI			ILR			NA			EHH			EFF			SC		
A1. Organic field farming	5	6	7	6	7	7	5	6	7	4	5	6	5	6	7	5	6	7	4	5	6	5	6	7
A2. Organic farming in greenhouses with soil	1	2	3	4	5	6	4	5	6	4	5	6	1	2	3	4	5	6	5	6	7	4	5	6
A3. Integrated Organic Farming System	4	5	6	5	6	7	4	5	6	5	6	7	4	5	6	4	5	6	5	6	7	4	5	6
A4. Inorganic farming in greenhouses with soil	1	2	3	4	5	6	3	4	5	2	3	4	2	3	4	3	4	5	4	5	6	2	3	4
A5. Inorganic field farming	4	5	6	4	5	6	4	5	6	2	3	4	2	3	4	3	4	5	3	4	5	3	4	5
A6. Inorganic soilless farming in greenhouses	5	6	7	4	5	6	2	3	4	2	3	4	5	6	7	3	4	5	2	3	4	3	4	5
Criteria weights (w)	0.135			0.127			0.107			0.149			0.094			0.173			0.157			0.059		

Table 6. Normalized decision matrix

Alternatives	Criteria																							
	FM			PAPT			AAI			ILR			NA			EHH			EFF			SC		
A1	0.71	0.86	1.00	0.86	1.00	1.00	0.71	0.86	1.00	0.57	0.71	0.86	0.71	0.86	1.00	0.71	0.86	1.00	0.57	0.71	0.86	0.71	0.86	1.00
A2	0.14	0.29	0.43	0.57	0.71	0.86	0.57	0.71	0.86	0.57	0.71	0.86	0.14	0.29	0.43	0.57	0.71	0.86	0.71	0.86	1.00	0.57	0.71	0.86
A3	0.57	0.71	0.86	0.71	0.86	1.00	0.57	0.71	0.86	0.71	0.86	1.00	0.57	0.71	0.86	0.57	0.71	0.86	0.71	0.86	1.00	0.57	0.71	0.86
A4	0.14	0.29	0.43	0.57	0.71	0.86	0.43	0.57	0.71	0.29	0.43	0.57	0.29	0.43	0.57	0.43	0.57	0.71	0.57	0.71	0.86	0.29	0.43	0.57
A5	0.57	0.71	0.86	0.57	0.71	0.86	0.57	0.71	0.86	0.29	0.43	0.57	0.29	0.43	0.57	0.43	0.57	0.71	0.43	0.57	0.71	0.43	0.57	0.71
A6	0.71	0.86	1.00	0.57	0.71	0.86	0.29	0.43	0.57	0.29	0.43	0.57	0.71	0.86	1.00	0.43	0.57	0.71	0.29	0.43	0.57	0.43	0.57	0.71

Table 7. Fuzzy weighted normalized decision matrix

Alternatives	Criteria																							
	FM			PAPT			AAI			ILR			NA			EHH			EFF			SC		
A1	0.10	0.12	0.14	0.11	0.13	0.13	0.08	0.09	0.11	0.09	0.11	0.13	0.07	0.08	0.09	0.12	0.15	0.17	0.09	0.11	0.13	0.04	0.05	0.06
A2	0.02	0.04	0.06	0.07	0.09	0.11	0.06	0.08	0.09	0.09	0.11	0.13	0.01	0.03	0.04	0.10	0.12	0.15	0.11	0.13	0.16	0.03	0.04	0.05
A3	0.08	0.10	0.12	0.09	0.11	0.13	0.06	0.08	0.09	0.11	0.13	0.15	0.05	0.07	0.08	0.10	0.12	0.15	0.11	0.13	0.16	0.03	0.04	0.05
A4	0.02	0.04	0.06	0.07	0.09	0.11	0.05	0.06	0.08	0.04	0.06	0.09	0.03	0.04	0.05	0.07	0.10	0.12	0.09	0.11	0.13	0.02	0.03	0.03
A5	0.08	0.10	0.12	0.07	0.09	0.11	0.06	0.08	0.09	0.04	0.06	0.09	0.03	0.04	0.05	0.07	0.10	0.12	0.07	0.09	0.11	0.03	0.03	0.04
A6	0.10	0.12	0.14	0.07	0.09	0.11	0.03	0.05	0.06	0.04	0.06	0.09	0.07	0.08	0.09	0.07	0.10	0.12	0.04	0.07	0.09	0.03	0.03	0.04

Table 8. Distances to positive ideal solutions

Alternatives	Criteria								
	FM	PAPT	AAI	ILR	NA	EHH	EFF	SC	Total
A1	0.884	0.879	0.908	0.894	0.919	0.852	0.888	0.949	7.175
A2	0.962	0.909	0.924	0.894	0.973	0.877	0.866	0.958	7.362
A3	0.904	0.891	0.924	0.872	0.933	0.877	0.866	0.958	7.224
A4	0.962	0.909	0.939	0.936	0.960	0.901	0.888	0.975	7.470
A5	0.904	0.909	0.924	0.936	0.960	0.901	0.910	0.966	7.411
A6	0.884	0.909	0.954	0.936	0.919	0.901	0.933	0.966	7.404

Table 9. Distances to negative ideal solution

Alternatives	Criteria								
	FM	PAPT	AAI	ILR	NA	EHH	EFF	SC	Total
A1	0.117	0.121	0.093	0.108	0.081	0.150	0.114	0.051	0.834
A2	0.042	0.092	0.077	0.108	0.029	0.125	0.136	0.043	0.652
A3	0.098	0.110	0.077	0.129	0.068	0.125	0.136	0.043	0.786
A4	0.042	0.092	0.062	0.066	0.042	0.101	0.114	0.026	0.545
A5	0.098	0.092	0.077	0.066	0.042	0.101	0.092	0.034	0.602
A6	0.117	0.092	0.048	0.066	0.081	0.101	0.070	0.034	0.609

Table 10. Similarity coefficients to ideal solution

Alternatives	Similarity coefficients to ideal solution	Rank
A1	0.104	1
A2	0.081	3
A3	0.098	2
A4	0.068	6
A5	0.075	5
A6	0.076	4

According to the results in Table 10, the order from the best to the worst is A1 > A3 > A2 > A6 > A5 > A4. Organic field farming is suggested to the farmer as the best alternative. Integrated organic farming system has the second order while organic farming in greenhouses with soil does the third order. Inorganic farming alternatives A6, A5, and A4 have the later orders.

A sensitivity analysis is needed to see the robustness of the decision. Table 11 shows the results of the sensitivity analysis for three additional cases. *Criteria weights-0* represents the present weights assigned by the experts. Organic field farming always takes the first order even significant changes in criteria weights occur. Even significant changes were made in the weights of the criteria, the order has not changed and it is still A1 > A3 > A2 > A6 > A5 > A4. This means that our decision is a robust decision.

Table 11. Sensitivity analysis

Cases	Criteria								Alternative rankings (from the best to the worst)					
	FM	PAPT	AAI	ILR	NA	EHH	EFF	SC						
Criteria Weights-0	0.135	0.127	0.107	0.149	0.094	0.173	0.157	0.059	1	3	2	6	5	4
Criteria Weights-1	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	1	3	2	6	5	4
Criteria Weights-2	0.145	0.127	0.107	0.139	0.094	0.163	0.167	0.059	1	3	2	6	5	4
Criteria Weights-3	0.125	0.127	0.107	0.159	0.094	0.183	0.147	0.059	1	3	2	6	5	4

A Comparative analysis using crisp TOPSIS is given below. In crisp analyses, the experts use their most expected values instead of fuzzy numbers. For instance, if it is FS in the fuzzy case, the corresponding value would be the most possible value, 1.5. Based on this assumption, the above analysis is repeated and the obtained results are given in Table 12.

Table 12. Similarity coefficients to ideal solution in the crisp case

Alternatives	Similarity coefficients to ideal solution	Rank
A1	0.118	1
A2	0.090	3
A3	0.112	2
A4	0.074	6
A5	0.08080	5
A6	0.08497	4

In the crisp case, even the similarity coefficients changed, the order of the alternatives has not changed and it is still A1 > A3 > A2 > A6 > A5 > A4. This may not be the case for every problem, especially in case the nonsymmetrical fuzzy numbers are used in the fuzzy analysis.

Conclusions

In these days, the products of organic farming are demanded much more than ever. Our multi-criteria decision-making model shows that organic field farming, organic farming in greenhouses with soil, and integrated organic farming system take the first three orders when they are compared with the alternatives of inorganic farming. If a single criterion analysis based on the criterion *annual average net income (AAI)* had been made, it is certain that the alternatives of inorganic farming would take the first three orders. Investors generally use the monetary criteria ignoring the nonmonetary issues and this causes short-term and nonstrategic decisions be given for agricultural investments.

Experts usually prefer making linguistic evaluations rather than making exact numerical assignments. For this reason we have selected a fuzzy multi-criteria decision-making method and the experts really enjoyed this method because of its appropriateness for their evaluations. We have not forced them for exact numerical evaluations whittling the ones in their minds.

For further study, we suggest more criteria to be added to our proposed model. There are also other possible multi-criteria methods which can be extended to use under fuzziness. These may be fuzzy analytic hierarchy process, fuzzy VIKOR, fuzzy ELECTRE, etc. The extensions of ordinary fuzzy sets such as hesitant fuzzy sets, intuitionistic fuzzy sets, and type-2 fuzzy sets can be used to expand this study.

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