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Research Article

OPTIMIZING AGRICULTURAL DECISION-MAKING WITH INTEGRATED MCDM-MCDA METHODS: A CASE STUDY ON CROP ECONOMICS

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Abstract: Because of the quantitative and qualitative uncertainty and complexity, it is not sufficient to use just Multicriteria Decision Making (MCDM), but also Multi-Criteria Decision Analysis (MCDA). The MCDM relates to the methods by which decisions are taken (i.e., selection of alternatives, ranked or ordered, and for what is analyzed being objective values. While MCDA offers a comprehensive approach for systematic assessment of criteria considering its impact on decision outcomes. Given that both methods have their own strengths, it is necessary to apply both MCDM and MCDA in agricultural economics which has a lot of uncertainty because of market price variability, increasing input costs and changing weather patterns. In this paper, Fuzzy Hypersoft Sets (FHSs), is used to model this problem and a case study is solved with Stable Preference

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Ordering Towards Ideal Solution (SPOTIS), Random Forest (RF), and Multi-Objective Optimization by Ratio Analysis (MULTIMOORA) to identify the most favorable crop for Jane's farm in terms of weather, costs required during agricultural production process like water or land usage, pesticide resistance against pests as well as market demand. Maize as an alternative $A_7 = 0.526$ was identified as the best choice by all three methods with Tomatoes and Rice scoring second, based on calculated score values. Thus, it enables us to study both quantitative and qualitative data, making it extremely able for agriculture uncertainties. This unique usage of sophisticated mathematics integrated with machine learning allows the decision-makers to find more accurate results, meaning it can manage economic risks better and allocate resources intelligently in agriculture. The comparative analysis with existing studies highlights the superiority of proposed work. Thus, it is significantly superior in accuracy. Hence farmers can harness farm economics to address these challenges by managing economic risks using mathematical decision-making tool, thereby leading them towards sustainability of livelihoods, food security and a resilient agricultural sector.

Keywords: Uncertainty, agriculture economics, fuzzy hypersoft set theory, aggregate operators (AO), MCDM and MCDA techniques.

MSC: 03E72, 90B50.

1. INTRODUCTION

Crop economics, a branch of agricultural economics, applies economic principles to the production, distribution, and consumption of crops. It includes several factors that impact the financial aspects around crop production like input costs, sale prices, market trends, guidelines issued by federal bodies and overall profitability. Also, the costs of seed, fertilizer and pesticides and the labor used to harvest crops can all affect how farming is economically feasible. Crop production economics and risk might be crucial components of agriculture decision-making (DM) which can influence farmers in addition to stability for food corresponding security around the globe. This is because agriculture is a highly dynamic enterprise characterized by several different changes in price levels and demand patterns [1]. Again, climate variability makes crop output much more uncertain. As weather patterns have become more variable and less predictable, extreme weather events like droughts, floods, heat waves and storms are becoming more frequent [2]. These weather changes can either damage crops, lower yields or result in complete loss of crops. As a result, farmers must manage their resources prudently as well as invest on technologies that can reduce the impacts of ad-verse climatic conditions. Farmers and other stakeholders require support to maneuver the intricacies of agricultural production coupled with changing dynamics of the markets where decision-making and optimization in crop economics under uncertainty play a pivot role [3]. Several studies underline these as important issues towards sustainable and more profitable agriculture. Rastogi et al.'s paper states that data analytics, IoT devices [4], satellite imagery allows farmers to make right decisions about resource allocation, irrigation schedules and pest management. In this way agricultural productivity goes up while input use declines leading to improved financial outcomes eventually. Crop diversity on the other hand has been deeply analyzed in literature as one approach used in managing risk in case of unpredictable events [5]. It also helps protect farm income through spreading risks over multiple commodities. Moreover, there are models for optimization designed for decision-making (DM) purposes particularly when faced with ambiguity [6, 7, 8]. Optimizing cropping patterns to come up with best responses is proposed by Wani et al.'s article which uses stochastic optimization model incorporated with climate variability [9]. This way, farmers can identify the best crops and cropping patterns that will have minimum losses and maximum revenues by considering different climatic situations. Also, they suggest that the calculation of numerous climate scenarios gives rise to probabilities for decision-making. Government support as well as policy changes also affect how crop economists make their decisions and optimize their strategies [10]. Kumar and Chandel's study investigates the impact of agricultural policies on financial choices made by farmers [11].

Since crops are largely dependent on external factors such as market price between harvest and marketing, variation in input costs, weather phenomena and similar other unpredictable situations; all this leads to crop economics being fraught with uncertainties. For farmers who need to allocate resources to optimize productivity and sustainability, these uncertainties create complicated decision-making problems. Fuzzy set (FS) [12] theory is a powerful mathematical framework over the imprecise and ambiguous data, which arises quite often within agricultural scenario where uncertainties need to be modeled represented & managed. This is very different from traditional discrete logic that relies on clear-cut distinctions, standard truth values of 0 or 1. FS theory avoids this problem by permitting an object to belong in a certain available set with the membership degree between operating limits full and void. This is especially useful in the sort of crop economics, where definitive information is less or incomplete and mostly decisions will be based on global knowledge. This theory is further extended to various set structures like: Single-valued fuzzy sets, multiple-valued fuzzy sets [13, 14], bipolar fuzzy sets [15], interval-valued fuzzy sets [16], m-polar interval-valued fuzzy sets [17], and hesitant fuzzy sets [18]. Many applications of fuzzy sets in real-life has been proposed by [19, 20]. Then, Atanassov extended the FS theory to intuitionistic fuzzy sets (IFS) [21] in 1986 which include the values of membership and non-membership. Through this foundation, it was generalized to Pythagorean fuzzy (PF) sets by [22] and applied with the rules of PF sets for solving multiple-criteria decision-making problems [23, 24], Indeterminacy in uncertain environments was introduced by Smarandache [25] in 1998 through a new theory known as neutrosophic set. The concept of the soft set is mapping at-tributes to the power set of a universal set, but it showed the significant bifurcation of attributes [26]. The theory of fuzzy soft set and its applications in MCDM were proposed by Maji [27, 28]. Smarandache [29] proposed the hypersoft set in 2018, which is a new set structure and anew from the product of divided attributes to the set on a universal set of attributes. It also retains fuzzy hypersoft sets, intuitionistic hypersoft sets, and neutrosophic hypersoft sets with considering truthiness, incertitude, and in-determinacy. Later, the definition of fuzzy hypersoft sets FHSs, the aggregate operators with similarity measures, and distance measures was proposed by [30, 31, 32] along with matrix notations and algorithms in case studies. The hybrid structures with applications in our daily life were also presented [33, 34], and with the integration of machine learning was proposed by [35].

Recent advances in smart agriculture and digitalization strategies have revolutionized the agricultural sector, especially for small-scale farmers, who are burdened with various economic and environmental issues. One of the example studies, by Bagherzadeh [36] that presented a study of smart technologies through wireless sensor networks and the potential they could help in improving crop productivity and the sustainability of resource management in agriculture. The authors partially suggest that resource monitoring technology can be optimized to a more significant extent. The work of Panda et al. [37] in a similar field could be observed with appropriate analysis. The potential of smart agriculture is further explored in the study by Zhou [38] and Nourkhah et al. [39], which describe an integrated technique for improving soil suitability through soil quality prediction and technological monitoring capacity. The studies of Yongyi Gu et al. [40] and Debnath [41] explain the opportunities to increase the economic capacity of farmers and develop efficient strategies in a market of uncertainty. Antifragility analyses, such as the one by Li et al. [42], could be an appropriate example of monitoring the progress in digital agriculture that has an integral role in ensuring the economy is stable. Overall, these sources give a more updated view of how future digitalization will look in agriculture, the study [43] presents the importance of smart technology in agriculture.

Recent advances in mathematical models and machine learning have varied implications across different research areas. El-Douh et al. [44] provide new insights into the predictivity problem by using machine-learning techniques and association rules within a neutrosophic background. In healthcare applications, uncertain management can provide an even higher result. The operation of fuzzy logic systems is presented in a study by Khaliq et al. [45] which explains the dynamics of tumor growth in a fuzzy situation using the generalized Hukuhara derivative system. Such an integrative system is presented in the work of Rahman [46] which operates in a hypersoft setting. Some other theoretical works are represented by Smarandache [47] studies about the SuperHyperSoft Set and its fuzzy representation and the examination of hypersoft and indeterm hypersoft sets [48]. Additionally, Imran and Ali [49] discuss the interplay between tourism and economic development in Pakistan, utilizing systemic analytics to uncover the synergistic relationships that drive economic growth. These sources cumulatively showcase a high integrative potential of fuzzy systems in multiple areas, from theoretical mathematics to data analysis and applied sciences.

Crop economics, as a subject, is just immensely complex and uncertain. And that certainty has lots of uncertainty around it too because farmers must make decisions on not only resource allocation but also how to behave in an ever more unpredictable world. These uncertainties can come in the shape of rising input costs, unpredictable weather patterns, pest incursion, or changes to government policy which may also have further sub-divided values. If these factors are ignored in crop economics, they may have the potential to significantly impact yield and profit margins and create unique barriers as farmers consider economically viable adaptation strategies that can also be unsustainable. The existing Decision-making models do not allow us to address the quantitative and qualitative uncertainty together. Also, the existing models are unable to address the uncertainty of further bi-furcated attributes and due to nature of the agriculture problems.

Integrating techniques of MCDM and MCDA to solve the crop economic uncertainties would result in more accurate solutions of the issues together. The MCDM technique, MULTIMOORA, and the Random Forest model under fuzzy hypersoft set theory have been proposed to address the uncertainty of further bifurcation of attributes. While MCDA technique SPOTIS have been applied to address the quantitative and qualitative nature of the problem together. By leveraging the complementary strengths of MCDM and MCDA, decision-makers can achieve greater precision and adaptability in agricultural planning, ultimately improving risk management and fostering sustainable agricultural practices.

This paper originality, it integrates MCDM technique (namely MULTIMOORA method and Random Forest model) proposed under FHSs based framework and MCDA technique SPOTIS is used for tackling agriculture decision making issues combining complexities and uncertainties. The studies in the past were carried out by using either one method at a time or only considered quantitative approaches, so this paper is beneficial as all the methods are used together and it can be used to solve crop production economics. This unique usage of sophisticated mathematics integrated with machine learning allows the decision-makers to find more accurate results, meaning it can manage economic risks better and allocate resources intelligently in agriculture.

The following indicates that how the work is organized:

- Section 2: Preliminaries are presented.
- Section 3: Definition, and mathematical notions of MULTIMOORA method, Random Forest Model and MCDA technique SPOTIS.
- Section 4: The proposed case study that shows the applicability of the algorithm.
- Section 5: Result discussion, comparison and limitations.
- Section 6: Concluded with future directions.

2. PRELIMINARIES

In this section, we will cover some fundamental definitions essential to building the framework of this paper: hypersoft sets (HSS), and fuzzy hypersoft sets (FHSs).

Definition 1. [29] *Let,* $\alpha^1,\ \alpha^2,\ \alpha^3,\ \ldots,\ \alpha^t\ for\ t\ \geq 1$ *be* t *distinct parameters, whose corresponding parametric values are respectively the sets* $\Upsilon^1, \Upsilon^2, \Upsilon^3, \ldots, \Upsilon^t$ *with* $\Upsilon^i \cap \Upsilon^j = \emptyset$, *for* $\neq j$, *and* $i,\ j\ \in \{1, 2, \ldots, t\}$. *Then the pair (*$\Gamma,\ \Lambda$*) where* $\Lambda = \{\Upsilon^1 \times \Upsilon^2 \times \Upsilon^3 \times \ldots \times \Upsilon^t$ *: t is finite and real valued} is known as hypersoft set over* Ω *with mapping.*

$$\Gamma : \Lambda = \Upsilon^1 \times \Upsilon^2 \times \Upsilon^3 \times \ldots \times \Upsilon^t \longrightarrow P(\Omega). \tag{1}$$

Definition 2. [30, 31, 32] *In equation (1), if we assign the values to each attribute in the form of truthiness* $< T >$ *where* $\Gamma : T \rightarrow [0,1]$. *then the pair* (Γ, Λ) *is called a fuzzy hypersoft set.*

Definition 3. [50] *Multi-Criteria Decision Making (MCDM) is a branch of operations research that evaluates and rank multiple complex criteria in decision-making processes. It involves various methods and tools designed to help decision-makers choose the best option among alternatives based on different criteria and preferences.*

3. MATHEMATICAL METHODS

Mathematical modeling is important for study real-world complex problems. It helps to make decisions, inspires advances in technology and science, assesses and manage risks facing society, and builds the knowledge needed to ensure that transformation.

3.1. MCDM Technique MULTIMOORA in Term of Hypersoft Set

Multi-Objective Optimization by Ratio Analysis (MULTIMOORA) [51] is an established Multi-Criteria Decision-Making (MCDM) technique that has been applied to solve complex decision-making problems under various conflicting and sometimes competing criteria. MULTIMOORA is unique in that it provides a full overview by merging three different methods to assess alternatives with respect to performance over various criteria. The Ratio System, the Reference Point Approach and the Full Multiplicative Form enable these methods to rank all possible alternatives.

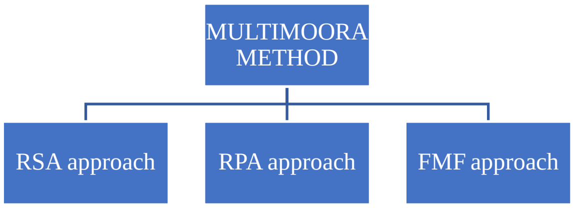

Figure 1: The graphical form of MULTIMOORA MCDM method

Figure 1 shows the graphical representation of the algorithm. Table 1 shows the mathematical form of the algorithm.

Table 1: The Mathematical representation of MULTIMOORA method

Input Goal, Criteria's $\boldsymbol{\mathcal{C}_i}$, and Alternative's $\boldsymbol{\mathcal{A}_j}$ **Output Ranking and final prioritization**	
RSA	In this approach, optimal alternative can be selected as: $\mathcal{Y}_i = \mathcal{Y}_i^+ - \mathcal{Y}_i^-$ Where, $\mathcal{Y}_i^+ = \sum_{j\in\Omega_{max}} \omega_i r_{ij}$, $\mathcal{Y}_i^- = \sum_{j\in\Omega_{min}} \omega_i r_{ij}$, $and \quad r_{ij} = \frac{x_{ij}}{\sum_{i=1} x_{ij}}$
RPA	In this approach, optimal alternative can be selected as: $\eth_i^{max} = \max_j(\omega_j \lvert r_j^* - r_{ij} \rvert)$ Where, $r_j^* = \begin{cases} \max_i r_{ij} \ , & j \in \Omega_{max} \\ \min_i r_{ij} \ , & j \in \Omega_{min} \end{cases}$
FMF	In this approach, optimal alternative can be selected as: $u_i = \frac{a_i}{b_i}$ Where, $a_i = \prod_{j\in\Omega_{max}} \omega_i r_{ij}$, $b_i = \prod_{j\in\Omega_{min}} \omega_i r_{ij}$
As it is known, after determining the alternatives to be evaluated with respect to certain criteria using MULTIMOORA method, 3 different ranking lists are built. By applying dominance theory, the alternative that seems first on all ranking lists is considered the optimally ranked eligible variant.	

From crop economic point of view, MULTIMOORA uses several quantitative criteria such productivity parameters and target specific input expenses or price over market return to rank various crops scenario directly. It can also blend with qualitative results from soil health, environmental impact, farmer preference. Therefore, in this traditional framework, farmers can both rank alternatives objectively and choose the best alternative under various scenarios even when levels of correction are uncertain through presenting a simple value-based decision rule that could be applied to any dataset relevant information.

3.2. Random Forest (RF) Model

Random Forests (RF) is an ensemble learning method for classification and regression, that operates by constructing multiple decision trees at training time and developing a consensus based on predictions made by some or all the individual constituent classifiers. Introduced by Leo [52], it works by creating decision trees using bootstrap optimization and random subsets of features to produce tree diversity. It is an ensemble method (regressor or classifier), the predictions of all trees are averaged (in case of regression) and majority voting done in (case classification), which helps to improve performance on noisy dataset, also its more powerful & accurate than single decision tree.

Crop economists can use the Random Forest (RF) model as a practical approach to improve decision making amidst uncertainty. Up to the point of Jane, a small-scale farmer trying to figure out what crop she is going to plant in her limited land; RF can process all this data with historical weather patterns, soil conditions, market prices and input costs. Building several numbers of decision trees with a large variety of datasets, the RF model bundles greater accuracy and resilience in making decisions than single decision tree. This ensemble model helps to reduce any error in individual prediction and ultimately be beneficial in the case of complexities and uncertainties occur at crop agriculture.

3.3. MCDA technique - Stable Preference Ordering towards Ideal Solution (SPOTIS)

Stable Preference Ordering Towards Ideal Solution (SPOTIS) [53] is one of these several Multi-Criteria Decision Analysis (MCDA) techniques. As mentioned in the introduction, SPOTIS investigates ranking and selecting alternatives based on how well each aligns with an ideal solution across many criteria. This is especially useful in decision making cases, where multiple conflicting criteria need to be considered simultaneously such as crop economics (yield vs cost), or market demand and environmental impacts etc. SPOTIS will assess the distance of each action from an ideal solution and hence guide DMs to select a best alternative in due consideration, ensuring structured complexity and uncertainty of multi-criteria decision-analysis situations. Readers are referred to the actual paper [53] for an in-depth mathematical formulation and comprehensive explanation.

4. NUMERICAL ILLUSTRATION

4.1. Calculations Using MULTIMOORA Method Based on FHSs

Jane, who is a small-scale farmer operating a small family business in agriculture faces the dilemma of which crop to plant in this next planting season due to her limited land and resources. With so many economic considerations for the farmer, it makes her decision difficult as to when and which crop she should plant. Jane must put these options in the context of what crops will be most profitable, grower friendly to adverse weather conditions and conversely costs that are associated with accumulating yield. To deal with these complexities, Jane can combine MCDM (MULTIMOORA) and MCDA technique SPOTIS for providing her decision-making results. By applying the MULTIMOORA technique, Jane can measure different crop options against one another according to a set of preferences defined by various quantitative criteria (crop yield estimates vs. costs including for seeds, fertilizers and labor, market prices) This helps to determine what the best economic choice for crops are with conditions. Jane could also apply MCDA technique to evaluate non-quantifiable attributes (e.g., the risk of extreme weather events; match between soil and crop; pest susceptibility) For example, some MCDA techniques would allow Jane to decide critically how much one criterion is more important than another given her risk aversion and the long-run game she wants for a farm. MCDA considers expert opinions, weather forecasts and local knowledge among others when making decisions allowing for a robust model that fully encompasses the natural ambiguities of agricultural decision-making.

With the integration of MCDM and MCDA techniques, Jane can make a better choice with regards to crop selection covering both quantitative and qualitative dimensions. Having a combined approach makes it easier for her to choose the crop that will get maximum profit and very less risk, enabling her smallholder farming business more sustainable and resilient. The flowchart of proposed problem is presented in Figure 2.

The task of getting enough information before making up a mind involves watching market trends that can tell what customers around are interested in purchasing and discussing this matter with other farmers as well as agricultural consultants among others so that these choices can be made with some accuracy regards yields per hectare etc., according to media reports about sales happening currently across countries, Table 2, presents the attributes and alternatives of this case study.

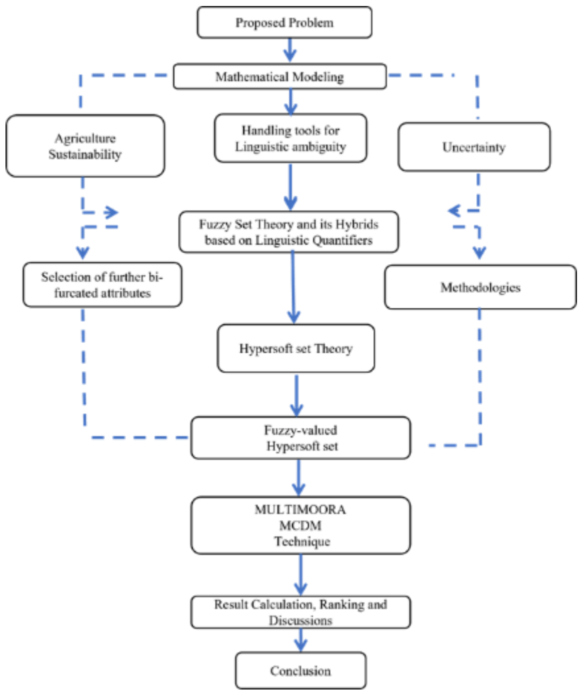

Figure 2: The algorithm for proposed case study and modelling

Table 2: The proposed alternatives and attributes in case study

Alternative		Criteria	
$\mathbf{A_1}$	Rice	C_1	Demand
$\mathbf{A_2}$	Soybeans	C_2	Sale Price (Expected)
$\mathbf{A_3}$	Wheat	C_3	Weather (Flood, high temp etc.)
$\mathbf{A_4}$	Oats	C_4	Harvest cost
$\mathbf{A_5}$	Potato	C_5	Soil fertility
$\mathbf{A_6}$	Sugarcane	C_6	Seeds cost
$\mathbf{A_7}$	Maize	C_7	Irrigation facility
$\mathbf{A_8}$	Tomatoes		

Assume that the relation for the function $\mathcal{F}: C_1 \times C_2 \times C_3 \times C_4 \times C_5 \times C_6 \times C_7 \rightarrow P(A)$ as $\mathcal{F}(C_1 \times C_2 \times C_3 \times C_4 \times C_5 \times C_6 \times C_7)$ and we get hypersoft sets are presented in Table 3. In this case, plainly a decision-maker with $\{\mathbb{M}^1 = Jane\}$ who wants to choose the best crop on her farm should consider most of characteristics related to farming facilities and conditions at least available. Jane decides based on a lot of parameters such as expected yield, cost to cultivate it, resistant against pests and diseases, and market demand. Jane applies Fuzzy Hypersoft Sets (FHSs) (presented in Table 3) to reveal her preferences/opinions concerning each potential crop. FHSs enable her to take a mix from qualitative and quantitative data, which captures the nature of uncertainty and ambiguity in decision making. The data used in this study can be retrieved from [55].

Table 3: Fuzzy hypersoft set decision matrix proposed by decision-maker.

Alternative / Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.080	0.021	0.125	0.341	0.112	0.234	0.123
A_2	0.176	0.558	0.511	0.281	0.550	0.390	0.713
A_3	0.136	0.675	0.326	0.309	0.197	0.650	0.891
A_4	0.020	0.425	0.262	0.216	0.420	0.530	0.507
A_5	0.040	0.312	0.388	0.267	0.266	0.631	0.298
A_6	0.005	0.338	0.382	0.161	0.159	0.660	0.116
A_7	0.010	0.520	0.311	0.171	0.840	0.970	0.781
A_8	0.012	0.210	0.257	0.367	0.280	0.540	0.213

The weights are calculated using the entropy method. $w_{c1} = 0.254$; $w_{c2} = 0.045$; $w_{c3} = 0.062$, $w_{c4} = 0.287$, $w_{c5} = 0.141$, $w_{c6} = 0.170$; $w_{c7} = 0.039$.

Solution:
Step 1. Construction of decision matrix.
Step 2-4. Calculations using *RSA, RPA, FMF methods of MULTIMOORA* are presented in Table 4.

The MULTIMOORA method was employed for evaluating a set of crop alternatives having similar attributes as given in Table 2. Here, the three individual approaches including Ratio System; Reference Point Approach and Full Multiplicative Form are used to calculate ranking. Using dominance theory [51], the alternative with top ranked positions in all the ordered rankings as most preferred alternative. Figure 3 shows that

$\boldsymbol{A_7 = Maize}$ is the best-ranked alternative, whereas $\boldsymbol{A_8 = Tomatos}$ *and* $\boldsymbol{A_1 = Rice}$ are the second and third ranked in crop selection for her farm.

Table 4: The calculated results using proposed MULTIMOORA method based on FHSs

Alternatives	RSA	RPA	FMF
$\boldsymbol{A_1}$	0.0215792	0.0576	741551.718
$\boldsymbol{A_2}$	0.0039243	0.0103	127856.161
$\boldsymbol{A_3}$	0.0018103	0.0209	113208.766
$\boldsymbol{A_4}$	0.0116689	0.0219	236248.732
$\boldsymbol{A_5}$	0.0131453	0.0445	401864.397
$\boldsymbol{A_6}$	0.0211727	0.0479	370002.167
$\boldsymbol{A_7}$	0.0359856	0.0911	773951.525
$\boldsymbol{A_8}$	0.0261933	0.0675	870021.246

Step 5. The optimal choice for the Jane to harvest is calculated and presented below in Table 5.

Table 5: Crop production economics ranking

Method	**Alternative Scores ranking**
RSA	$\mathcal{Y}_7 > \mathcal{Y}_8 > \mathcal{Y}_1 > \mathcal{Y}_6 > \mathcal{Y}_5 > \mathcal{Y}_4 > \mathcal{Y}_2 > \mathcal{Y}_3$
RPA	$\eth_7^{max} < \eth_8^{max} < \eth_1^{max} < \eth_6^{max} < \eth_5^{max} < \eth_4^{max} < \eth_3^{max} < \eth_2^{max}$
FMF	$u_8 > u_7 > u_1 > u_5 > u_6 > u_4 > u_2 > u_3$

4.2. Calculations Using Random Forest (RF) Model

Implementing the Random-Forest model to represent how decision is made. The code below (Appendix A) is designed to solve a case study on how the decision-maker can use the model built from data in Table 3 and that includes Jane motivations over each of her potential crops, this explanation corresponds with Figure 3. An RF model then is applied to the dataset of multiple crops (alternatives) and their characteristics (criteria).

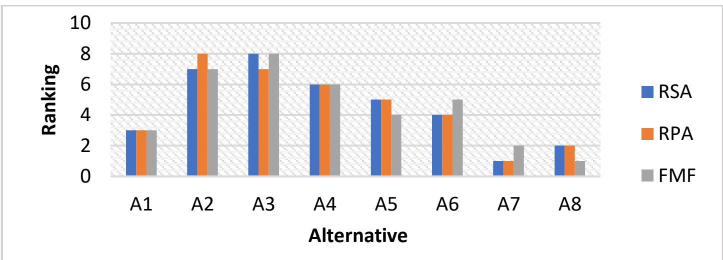

Figure 3: MULTIMOORA method based on FHSs calculated results

Implementation Steps:

- **Pre-process Data:** Information provided in Table 3 (containing Jane's preferences represented through Fuzzy Hypersoft Sets, i.e., FHSs), needs to be converted from linguistic terms into data that can undergo analysis. FHSs assign a grade of membership to every crop within the different attributes, corresponding to uncertainty and vagueness in Jane's adores.

- **Feature Selection:** Table 3 shows each attribute as a feature for the Random Forest model. Features can be classifier-dependent attributes with numerical values (e.g. demand, weather, cost etc.) and the calculated means are presented in Figure 4.
- **Training the Model:** We train RF model on dataset described in Table 3. It builds more than one decision trees by randomly choosing subsets of data (crops) and features(attributes) to make sure that our model engagements the degenerate case, where it's too overfitted. Suited crops of a dataset are differentiated by recursively splitting the set on selected features each tree in forest is built from.
- **Testing the Model:** After training the RF model predicts how applicable each crop is through an aggregation of all decision trees hence determining the ranking So when Jane lists her attributes and preferences, these predictions are used to rank the crops by predicted score Figure 3, which is a measure of their overall suitability given any set of Jane's characteristics.
- **Model Validation:** The performance of the model is then evaluated by testing how well the RF models prediction outputs compare with any known outcomes or expert judgement. This step enables us to validate that the model accurately reflects Jane's preferences and delivers consistent recommendations.

Figure 4: RF Model for mean ranking calculations

Analysis of data from Table 3 was carried out to decide which crop is the best choice for Jane's farm using a power ensemble learning known as Random Forest (RF) model. The RF model used a range of traits including predicted mean, cultivation cost, pest tolerance, expected demand and weather uncertainty. The RF model captures uncertainties and variability in Jane's preferences as well as farming conditions by creating different decision tree-based models on multiple crops, attributes. This indicate that among all the potential benefits Maize was Jane's best alternative overall. Mixing both qualitative and quantitative features of the crops into RF model was able to provide a rich analysis that informed decision making. The consistency of these rankings on various decision tress within the RF model indicates that Maize is a preferred choice for Jane's farm.

4.3. Calculations using SPOTIS Method

Stable Preference Ordering Towards the Ideal Solution (SPOTIS) is a Multi-Criteria Decision Analysis (MCDA) technique designed to rank alternatives based on their proximity to an ideal solution. In the context of crop selection for Jane's farm, the SPOTIS method can be used to evaluate various crop alternatives considering multiple attributes, such as expected yield, cultivation costs, pest resistance, market demand, and environmental sustainability. The goal is to determine which crop is closest to the ideal solution across all criteria.

Step-by-Step Calculations for SPOTIS

- Construct the Decision Matrix (see Table 3)
- Determine Ideal and Anti-Ideal Solutions
- Calculate the Distances to the Ideal and Anti-Ideal Solutions
- Calculate the Relative Closeness C_i to the Ideal Solution
- Rank the Alternatives

The calculated C_i values for the alternatives are presented below in Table 6 and based the scores one can list the best alternative.

Table 6. Ranking of alternatives based on MCDA method SPOTIS

Alternatives	$\mathbf{C}_i$ values	Ranking
$\boldsymbol{A_1}$	0.478	3
$\boldsymbol{A_2}$	0.173	7
$\boldsymbol{A_3}$	0.169	8
$\boldsymbol{A_4}$	0.217	6
$\boldsymbol{A_5}$	0.399	5
$\boldsymbol{A_6}$	0.455	4
$\boldsymbol{A_7}$	0.526	1
$\boldsymbol{A_8}$	0.500	2

The SPOTIS method results indicate that $\boldsymbol{A_7 = 0.526}$ (Maize) is the most suitable crop for Jane's farm, followed by Rice and Tomatoes. The ranking reflects that Maize has the closest proximity to the ideal solution across the criteria, balancing high yield, moderate costs, and good market demand. Rice is the second best, offering a good compromise between cost and market demand but slightly lower yield performance.

5. RESULT DISCUSSION, COMPARISON AND LIMITATIONS

The authors adopted three methods SPOTIS, Random Forest (RF), and MULTIMOORA to identify the most favorable crop for Jane's farm in terms of weather, costs required during agricultural production process like water or land usage, pesticide resistance against pests as well as market demand. Maize was identified as the best choice by all three methods, with Tomatoes and Rice scoring second. The alternative ranking shows that SPOTIS results are depends on how much it resembles an ideal solution, effectively balancing both benefit and cost criteria. The most preferable alternative crop found as Maize. A machine learning Random Forest (RF) model is employed to assess crop rankings, accounting for the interactive nature of these attributes. Reasons: RF also ranks Maize the highest consumer-preference and it is best for use of production situations under uncertain conditions. MULTIMOORA is also applied, and Maize is the best alternative, further validating the findings. Jane is confident to choose Maize as the best crop so far. This study demonstrates the power of mixing decision-making tools to provide robust means for addressing uncertainties and assuring reliable agricultural decisions.

Future advancements can be made in the following directions [54, 55, 56] as well to enhance the literature broadness [57, 58]. It can be extended to explore fuzzy fixed-point results applied to fuzzy differential equations [59], fuzzy sampled-data stabilization for chaotic nonlinear systems [60] and focus on sliding mode control for semi-Markov jump T-S fuzzy systems with time delays [61]. Recent advancements in multi-criteria decision-making (MCDM) methods highlight their diverse applications using aggregation operators [62, 63, 64, 65]. The fuzzy model to use to analyze the impacts of smog mitigation through a comprehensive MCDM framework [66] and logistics specialist selection has been studied by [67]. The study can be extended to the concepts proposed in [68, 69] as well.

Study limitations and Recommendations: Listed results of this study are consistent among SPOTIS, Random Forest (RF), and MULTIMOORA methods however have some limitations. These techniques depend on the data entered to a high degree of condition and comprehensiveness, which means that any imperfect or obsolete information can easily yield incorrect decisions. Moreover, the models are largely based on static data and not equipped to consider real-time changes in markets or even developments related to weather. In summary, to mitigate these limitations it is imperative that future studies focus on the integration of real-time data, improve both quality and diversity in model inputs, and especially explore hybrid models combining different DM approaches. The development of user-friendly tools to make decisions and a deeper exploration into decision-making models could advance the practical usefulness that can work, like providing Jane with informed more sustainable choices.

Ethical Considerations: Getting informed consent is important when you are learning from farmers. All data should be securely stored and with strong access control to ensure no one is authorized to use the data outside what was already agreed upon by farmer. Must focus on privacy and security, in line with well-documented policies of all data consumption. It would also be good to recognize the wider social, economic and environmental impacts of any new farming practices or technologies that are introduced so as not only as contribute towards strong resilient sustainable communities but ensure benefits are equally shared.

Future directions: The new research should consider how to model a real-time data about weather and market conditions for more adaptable decision-making. Hybrid models that integrate machine learning methods with MCDM / MCDA can be used to improve the accuracy in dealing with decision problems. Additional studies could examine sub-divided criteria frameworks for strategic planning, improve data quality and variety, as well as develop farmers need based decision support systems. Also, in the broad-scale and cope social and economic implications of various agricultural technologies could become clearer to adopt models that can facilitate or assistant strategies with respect to each region leading sustainable adoption.

6. CONCLUSION

The paper presents an integrated decision-making model for agriculture using MCDM techniques: i.e. MULTIMOORA and Random Forest under Fuzzy Hypersoft Sets (FHSs), and MCDA technique Stable Preference Ordering Towards Ideal Solution (SPOTIS). This study identifies the quantitative as well as qualitative uncertainties and complexities prevailing in agricultural economics due to volatile market prices, constantly rising input costs, fluctuating weather conditions among several other factors. The framework, however, is a power tool for improving decision-making processes by bringing together MCDM and MCDA approaches allowing farmers to make well-informed decisions about the allocation of resources which gives them an additional edge over maximizing income.

The studies in the past were carried out by using either one method at a time or only considered quantitative approaches, so this paper is beneficial as all the methods are used together and it can be used to solve crop production economics. This unique usage of sophisticated mathematics integrated with machine learning allows DM to serve more accurate results. Application and validation of the model with case study demonstrate its advantage to deliver real-world benefits such as increased farm economics, improved risk management for individual farmers and resilience overall.

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APPENDIX

The source code used for the correlation calculation using RF Model for the proposed case study.

Python Code:

```
str_list = [] # empty list to contain columns with strings (words)
for colname, colvalue in data.iteritems():
if type(colvalue[1]) == str:
str_list.append(colname)
# Get to the numeric columns by inversion
num_list = data.columns.difference(str_list)
# Create Dataframe containing only numerical features
data_num = data[num_list]
f, ax = plt.subplots(figsize=(16, 12))
plt.title('Pearson Correlation of features')
# Draw the heatmap using seaborn
   #sns.heatmap(data_num.astype(float).corr(),linewidths=0.25,vmax=1.0,
   square=True, cmap="PuBuGn", linecolor='k', annot=True)
   sns.heatmap(data_num.astype(float).corr(),linewidths=0.25,vmax=1.0,
   square=True, cmap="cubehelix", linecolor='k', annot=True)
```