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Multi Attribute Neutrosophic Optimization Technique forOptimal Crop Selection in Ariyalur District

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Abstract. Ranking crops is a vital part of sustainable farming practices. A deliberate strategy that incorporates multi-criteria decision-making is essential for achieving sustainability in agriculture. The process of choosing crops involves a lot of unknowns and unpredictable elements. The neutrosophic set, characterized by the three independent degrees of truth (T), falsity (F), and indeterminacy (I), is more adept at handling incomplete data. The current study combines single-valued multi-criteria neutrosophic programming with the TOPSIS approach to examine the crop selection process in the Ariyalur district. This study incorporated expert advice and a thorough literature analysis to identify the fundamental criteria for developing sustainable crop planning for important crops in the Ariyalur area. In order to rate the crops and achieve sustainability for agricultural production, eleven significant criteria were selected based on environmental, social, economic, and soil nutrient concerns. In this study, the relative importance of criteria and alternatives is assessed by consolidating the views of different decision-makers into a unified opinion through a single-valued neutrosophic set-based weighted averaging operator. The current approach will greatly enhance the self-sufficiency of the agricultural sector and boost the country's GDP. Additionally, it will support the Ministry of Agriculture and other stakeholders in formulating regulations related to crop harvesting methods.

Keywords: Crop selection; TOPSIS approach; Neutrosophic set; Multi criteria optimization; Group Decision. ———-

1. Introduction

Agriculture is an essential part of the global economy, providing food, feed, and fibre for an expanding population. Undoubtedly, the primary source of livelihood in India is agriculture and its related sectors, especially in the country's vast rural areas. It also makes a substantial contribution to the GDP. Some countries around the world, especially India, are encountering heightened difficulties in meeting their food demands due to population growth. Food

consumption often rises annually in tandem with a country's population growth; as a result, sufficient crop production that meets sustainability standards and yield rates is necessary. Sustainable agriculture is crucial for comprehensive rural development because it promotes rural employment, ensures food security, and supports environmentally friendly practices such as sustainable management of natural resources, soil conservation, and biodiversity preservation. Crop selection is important in agriculture because it influences the sustainability, profitability and productivity of farming operations. Because of fluctuating socioeconomic conditions and limited resources that differ from state to state and region to region in India, choosing crop patterns is even more difficult. The minimum support price (MSP) of crops is just insufficient to support farmers' economically viable growth, which presents another challenge for them in realising crop value. This study employs a multi-attribute decision-making (MADM) approach to examine the crop selection system in Ariyalur district, Tamil Nadu, India, with the aim of achieving sustainable and profitable agriculture. Numerous fields, including operation research, urban planning, natural science, and management science, have used MADM technique with either numerical or descriptive attribute values. When it comes to crop selection, it entails assessing and choosing the optimal crops to plant based on a variety of attributes, including yield, cost, environmental effect, climatic resilience, market demand, etc.

Classical MADM techniques, such as TOPSIS [\[1\]](#page-14-0), VIKOR [\[2\]](#page-14-1), PROMETHEE [\[3\]](#page-14-2), and ELECTRE [\[4\]](#page-14-3), use crisp numbers to represent the weights of each attribute and alternative ratings. However, due to attribute complexity and ambiguity, MADM problems' attribute values are not always described with precise numerical values. To overcome such an issue, Zadeh [\[5\]](#page-14-4) introduced fuzzy set theory. It is highly effective for decision-making in MADM scenarios where information is imprecise. To determine the most suitable crop for the land, F. Sari and F. Koyunch [\[6\]](#page-14-5) integrated AHP and TOPSIS with GIS (geographical information systems). AHP and fuzzy TOPSIS techniques were employed by Weilun Huanga and Qi Zhang [\[7\]](#page-14-6) to determine the best economic crop in the minority region. The fuzzy TOPSIS approach was proposed by Singh, R.K., and Mallick, J. [\[8\]](#page-14-7) as a means of selecting the vegetable cash crop for sustainable agriculture within the green chamber. To select the optimal biomass crop type for bio-energy production, Cobuloglu H. I. and Buyuktahtak I. E. [\[9\]](#page-14-8) introduced a new stochastic analytical hierarchy process (AHP) capable of managing ambiguous data and discovering the relative importance of criteria in the MCDM process. Various authors have created fuzzy-MCDM techniques for addressing the plant location selection (PLS) problem, drawing on principles from fuzzy set theory. For the PLS problem in a linguistic environment, Yong [\[10\]](#page-14-9) suggested the TOPSIS method. The location of the facility was chosen by Ertugrul and Karakasoglu [\[11\]](#page-14-10) using the fuzzy TOPSIS and fuzzy AHP approaches. The degree of belonging constitutes the only element in the fuzzy set. The most effective way to solve the

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MADM problem requires keeping in mind that membership and non-membership functions are equally important. Therefore, Atanassov [\[12\]](#page-14-11) proposed the intuitionistic fuzzy set (IFS), defined by belongings and non-belongings degrees simultaneously. To solve the PLS problem, Pankaj Gupta et al. [\[13\]](#page-14-12) suggested an expanded VIKOR technique using intuitionistic trapezoidal fuzzy parameters. To address the challenge of choosing $R \& D$ projects, Wan et al. [\[14\]](#page-14-13) created a novel approach for handling multi-attribute group decision-making (MAGDM) problems, including incomplete attribute weight information and Atanassov's interval-valued intuitionistic fuzzy values. Abbas Mardani et al. [\[15\]](#page-15-1) introduced an innovative combined approach that applies the step-wise weight assessment ratio analysis (SWARA) and the complex proportional assessment (COPRAS) method within the context of IFSs to determine the optimal biomass crop type for sustainable production of bio-fuel. In IFSs, the sum of a vague parameter's degrees of belonging and non-belonging does not amount to one. Consequently, an intuitionistic fuzzy set has some degree of incompleteness or indeterminacy. It is unable to effectively handle every kind of uncertainty in various real-world physical challenges, including those with indeterminate data.

To address ambiguous or indeterminate data often encountered in practical situations, Smarandache [\[16\]](#page-15-2) introduced the idea of a neutrosophic set (NS) within a philosophical context. However, applying NS directly in scientific and engineering fields proves to be challenging. Wang et al. [\[17\]](#page-15-3) created the single-valued neutrosophic set (SVNS), a subclass of NS, to address challenges. SVNSs have been utilised by neumorous academics to create decision-making models. [\[18–](#page-15-4)[21\]](#page-15-5). Using the weighted correlation coefficient of SVNSs, Ye [\[22\]](#page-15-6) investigated the MCDM problem. MCDM problem under interval neutrosophic set information were examined by Zhang et al. [\[23\]](#page-15-7). Chi and Liu [\[24\]](#page-15-8) developed an enhanced TOPSIS method for addressing multi-attribute decision-making (MADM) problems involving interval neutrosophic sets. A TOPSIS model was introduced by Nancy and Grag [\[25\]](#page-15-9) to evaluate the MCDM when there was insufficient weight data available for SVNSs. An innovative weighted aggregated sum product assessment (WASPAS) framework using SVNS was developed by Arunodaya Raj Misra et al. [\[26\]](#page-15-10) to identify the biomass crop option that is most optimal for producing biofuel. For professional selection, Abdel-Basset M. et al. [\[27\]](#page-15-11) introduced a novel hybrid neutrosophic MCDM framework that combines neutrosophic analytical network processes (ANP) and TOP-SIS using bipolar neutrosophic numbers. To manage uncertainty in SVNS data, Shahzaib et al. [\[28\]](#page-15-12) created a hybrid averaging and geometric aggregation operator utilising a sine trignometric function. Additionally, the approach is used for agricultural land selection in order to demonstrate its efficacy. In order to define the available water resources in the agricultural sector based on possibility measurements in a generalised single-valued non-linear bipolar neutrosophic environment, Garai T., and Garg H. [\[29\]](#page-15-13) devised a multi-criterion water resource

management technique. To address multi-attribute decision-making issues in a multi-valued neutrosophic environment, Dongsheng Xu and Lijuan Peng [\[30\]](#page-15-14) suggested a novel approach based on TOPSIS and TODIM. The benefits of TOPSIS include being simpler, easier to understand, and more computationally efficient, according to an assessment of the literature. Consequently, choosing agricultural crops may benefit from the current study's combination of the TOPSIS technique with SVNSs. The primary goal of this research is to evaluate and rank the most suitable crops grown in the Ariyalur district using a TOPSIS-based (MAGDM) approach.

This study is structured as follows: Section 2 reviews preliminary research on SVNSs; Section 3 covers the study area; Section 4 details the methodology employed; Section 5 illustrates the application of the methodology; and Section 6 summarizes the conclusions drawn from the study.

2. Preliminary

To advance the paper, certain fundamental definitions of a single valued neutrosophic set are given in this section.

2.1. Single Valued Neutrosophic Set

A single valued neutrosophic set (SVNS) P, over the universe of discourse U is represented as

$$
P = \{(u, T_P(u), I_P(u), F_P(u))/u \in U\}
$$

where $T_P(u)$, $I_P(u)$, $F_P(u)$ are values in the range [0,1], and the sum $T_P(u) + I_P(u) + F_P(u)$ satisfies $0 \le T_P(u) + I_P(u) + F_P(u) \le 3$.

2.2. Complement

The complement of a SVNS P, represented as $c(P)$, is defined by: $T_{c(P)}(u) = F_P(u)$, $I_{c(P)}(u) = 1-I_P(u), F_{c(P)}(u) = T_P(u)$, for all u in U.

2.3. Neutrosophic Operators

If P and Q be two SVNSs then

(i) $P \oplus Q = (T_P(u) + T_Q(u) - T_P(u) \cdot T_Q(u), I_P(u) + I_Q(u), F_P(u) + F_Q(u))$ (ii) $P \otimes B = (T_P(u).T_Q(u), I_P(u) + I_Q(u) - I_P(u).I_Q(u), F_P(u) + F_Q(u) - F_P(u).F_Q(u))$ (iii) $P \cup Q = (\max(T_P(u), T_Q(u)), \max(T_P(u), I_Q(u)), \min(F_P(u), F_Q(u)))$ or $P \cup Q = (\max(T_P(u), T_Q(u)), \min(T_P(u), I_Q(u)), \min(F_P(u), F_Q(u)))$ (iv) $P \cap B = (\min(T_P(u), T_Q(u)), \min(T_P(u), I_Q(u)), \max(F_P(u), F_Q(u)))$ or $P \cap Q = (\min(T_P(u), T_Q(u)), \max(T_P(u), I_Q(u)), \max(F_P(u), F_Q(u)))$

Study Area

Appropriate crop selection is crucial to establishing sustainable agriculture and increasing agricultural profitability. This paper presents a TOPSIS-based neutrosophic programming approach to crop planning in the Ariyalur district, one of the Cauvery Delta regions. The Ariyalur District covers a total area of 193,338 hectares. 94,725 hectares are the net area that has been planted. Of which, 58441 ha are rainfed and 36284 ha are under irrigation. Rainfall averages 954 mm per year. This district grows a variety of crops, and the majority of its residents work in agriculture. Since 70% of the population makes their living from agriculture and related industries, agriculture remains the most important component of the district's economy. In order to increase production, the Agriculture Department has implemented several development schemes and disseminated pertinent technology, stepping up its efforts to attain a higher growth rate in the sector. The department's objectives and policies focus on sustaining agricultural production stability and promoting sustainable growth to meet the food demands of a growing population, while also providing raw materials for agro-based industries, thereby generating employment for the rural population. The Ariyalur district's soil is made up of ferruginous red clay and limestone. The colour typically varies from red at the top to yellow at the lower horizon, with a loamy texture. These soils are of medium depth with good drainage, characterized by low levels of organic content, nitrogen, and phosphorus, yet generally containing ample amounts of potash and lime. The pH range is 6.5 to 8.0, and they are free from salt and calcium carbonate formation. This district is used to develop sugarcane, groundnuts, maize, cotton, and paddy crops. The primary irrigation sources in this district include open wells, canals, tanks, and tube wells. Bore wells and tube wells contribute significantly to irrigation. The alternatives that were examined in this study were sugarcane, maize, groundnut, cotton, brinjal, tomato, chilli, and onion.

4. Multi Attribute TOPSIS Based Neutrosophic Technique

Hwang and Yoon introduced the TOPSIS method in 1981. This technique determines the optimal solution as the one that is closest to the positive ideal solution and farthest from the negative ideal solution. In terms of determining the ideal response, the negative approach maximizes the cost criterion while decreasing the benefit criteria, and the positive approach maximises the benefit criteria while minimising the cost criteria. Numerous studies have used TOPSIS to address MCDM problems in research. The next set of steps presents the computing procedures for the TOPSIS-based neutrosophic technique.

Step 1: Assume the alternatives A_i and the criteria C_j , where $i = 1, 2, ..., m$ and $j =$ 1, 2, ..., n. Additionally, assume that the decision makers have provided $w = \{w_1, w_2, \ldots, w_n\}$ as the weight vector for the criteria C_1, C_2, \ldots, C_n . Also, create the decision matrix that

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follows, which shows the values corresponding to the alternatives and criteria for MADM problems.

$$
D = [d_{ij}]_{m \times n} = \begin{array}{c} A_1 & C_1 & C_2 & \cdots & C_n \\ A_1 & d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_m & d_{m1} & d_{m2} & \cdots & d_{mn} \end{array}
$$

Step 2: Use professional advice or another technically sound method to determine which criteria are most important.

Step 3: Convert each value assigned to the alternatives according to the attributes in the decision matrix, as defined in step one, into a single-valued neutrosophic number. Following such conversion, the resulting matrix is defined as follows:

$$
(d_{ij})_{m \times n} = (T_{ij}, I_{ij}, F_{ij})_{m \times n}
$$

\n
$$
C_1 \t C_2 \t \cdots \t C_n
$$

\n
$$
A_1 \t \begin{bmatrix} (T_{11}, I_{11}, F_{11}) & (T_{12}, I_{12}, F_{12}) & \cdots & (T_{1n}, I_{1n}, F_{1n}) \\ (T_{21}, I_{21}, F_{21}) & (T_{22}, I_{22}, F_{22}) & \cdots & (T_{2n}, I_{2n}, F_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (T_{m1}, I_{m1}, F_{m1}) & (T_{m2}, I_{m2}, F_{m2}) & \cdots & (T_{mn}, I_{mn}, F_{mn}) \end{bmatrix}
$$

Step 4: Convert the decision matrix mentioned in step 3 into the normalized single valued neutrosophic decision matrix $(\tilde{d}_{ij})_{m \times n}$, where $(\tilde{d}_{ij}) = d_{ij}$ for benefit criteria C_j and $(\tilde{d}_{ij}) = d_{ij}$ for cost criteria.

Step 5: In a collective decision-making scenario, decision-makers are not of equal importance. Therefore, at this stage, the weight of the decision-maker is established. Assume that there exist r decision makers and that the linguistic word mentions their importance and expresses it in terms of neutrosophic numbers. Then, the weight of t^{th} decision-maker is specified by:

$$
\varphi_t = \frac{1 - \sqrt{\frac{\{(1 - T_s(u))^2 + (F_s(u))^2 + (F_s(u))^2\}}{3}}}{\sum_{t=1}^r \left(1 - \sqrt{\frac{\{(1 - T_s(u))^2 + (F_s(u))^2 + (F_s(u))^2\}}{3}}\right)}, \text{and} \sum_{t=1}^r \varphi_t = 1
$$
\n(1)

Step 6: Create an aggregated neutrosophic decision matrix by applying the single-value neutrosophic weighted averaging (SVNWA) operator as described:

1 \mathbf{I} \vert \parallel \vert \vert \vert

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$$
C_1 \hspace{1cm} C_2 \hspace{1cm} \cdots \hspace{1cm} C_n
$$

$$
[d_{ij}]_{m \times n} = \begin{bmatrix} A_1 & (AT_{11}, AI_{11}, AF_{11}) & (AT_{12}, AI_{12}, AF_{12}) & \cdots & (AT_{1n}, AI_{1n}, AF_{1n}) \\ (AT_{21}, AI_{21}, AF_{21}) & (AT_{22}, AI_{22}, AF_{22}) & \cdots & (AT_{2n}, AI_{2n}, AF_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (AT_{m1}, AI_{m1}, AF_{m1}) & (AT_{m2}, AI_{m2}, AF_{m2}) & \cdots & (AT_{mn}, AI_{mn}, AF_{mn}) \end{bmatrix}
$$
\n
$$
(2)
$$

where $AT_{ij} = 1 - \prod_{t=1}^{r} (1 - T_{ij}^{(t)})^{\varphi_t}$, $AI_{ij} = \prod_{t=1}^{r} (I_{ij}^{(t)})^{\varphi_t}$ and $AF_{ij} = \prod_{t=1}^{r} (F_{ij}^{(t)})^{\varphi_t}$, $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

Step 7: Every decision-maker in a group setting has a different viewpoint on every criterion. Gathering a thorough assessment of each attribute's significance from all decision-makers is necessary to obtain the grouped opinion on the chosen attribute. Consequently, the SVNWA operator is used to determine the aggregated weights for the criteria at this phase as follows: $w_j = \left(1 - \prod_{t=1}^r \left(1 - T_j^{(t)}\right)\right)$ $\left(\begin{matrix}I(t)\end{matrix}\right)^{\varphi_t}, \prod_{t=1}^r \left(\begin{matrix}I_j^{(t)}\end{matrix}\right)$ $\left(\begin{matrix}t\\j\end{matrix}\right)^{\varphi_t}, \prod_{t=1}^r \left(F_j^{(t)}\right)$ $\binom{p(t)}{j}^{\varphi_t}$, where $j = 1, 2, \ldots, n$. Step 8: Compute the weighted aggregated neutrosophic decision matrix using the two neutrosophic sets multiplication approach as follows:

$$
(d_{ij})_{m \times n} \qquad \times \qquad w_j \qquad = \qquad (AT_{ij} \cdot w_j, AI_{ij} \cdot w_j, AF_{ij} \cdot w_j) \qquad \dots \qquad C_n
$$

$$
= \begin{bmatrix}\n(AT_{11} \cdot w_1, AI_{11} \cdot w_1, AF_{11} \cdot w_1) & (A T_{12} \cdot w_2, A I_{12} \cdot w_2, AF_{12} \cdot w_2) & \cdots & (A T_{1n} \cdot w_n, A I_{1n} \cdot w_n, AF_{1n} \cdot w_n) \\
(A T_{21} \cdot w_1, A I_{21} \cdot w_1, AF_{21} \cdot w_1) & (A T_{22} \cdot w_2, A I_{22} \cdot w_2, AF_{22} \cdot w_2) & \cdots & (A T_{2n} \cdot w_n, A I_{2n} \cdot w_n, AF_{2n} \cdot w_n) \\
\vdots & \vdots & \ddots & \vdots \\
(A T_{m1} \cdot w_1, A I_{m1} \cdot w_1, A F_{m1} \cdot w_1) & (A T_{m2} \cdot w_2, A I_{m2} \cdot w_2, A F_{m2} \cdot w_2) & \cdots & (A T_{mn} \cdot w_n, A I_{mn} \cdot w_n, A F_{mn} \cdot w_n)\n\end{bmatrix}
$$
\n(3)

where $AT_{ij} \cdot w_j = \left(1 - \prod_{t=1}^r \left(1 - T_{ij}^{(t)}\right)^{\varphi_t}\right) \times \left(1 - \prod_{t=1}^r \left(1 - T_j^{(t)}\right)\right)$ $\left(\begin{matrix}t\end{matrix}\right)^{\varphi_t}$ $AI_{ij} \cdot w_j = \prod_{t=1}^r \left(\hat{I}_{ij}^{(t)}\right)^{\varphi_t} + \prod_{t=1}^r \left(I_j^{(t)}\right)$ $\left(I^{(t)}_j\right)^{\varphi_t} - \prod_{t=1}^r \left(I^{(t)}_{ij}\right)^{\varphi_t} \cdot \prod_{t=1}^r \left(I^{(t)}_j\right)^{\varphi_t}$ $\binom{t}{j}$ ^{φ_t} $AF_{ij}\cdot w_j= \prod_{t=1}^r \left(F_{ij}^{(t)}\right)^{\varphi_t}+ \prod_{t=1}^r \left(F_{j}^{(t)}\right)$ j φ^t − Q^r ^t=1 F (t) ij φ^t · Q^r ^t=1 F (t) $\left(\begin{matrix} p_i(t) \\ j \end{matrix}\right)^{\varphi_t}$ $\forall i = 1, 2, \ldots, m$ and $j = 1, 2, ..., n$.

Step 9: Determine the relative neutrosophic positive ideal solution A_N^+ $_N^+$ and negative ideal solution $A_N^ N_N$ for the attributes of benefit and cost as described below:

$$
A_N^+ = \left(d_{1,w}^+, d_{2,w}^+, \dots, d_{j,w}^+\right); \quad A_N^- = \left(d_{1,w}^-, d_{2,w}^-, \dots, d_{j,w}^-\right)
$$

where $d_{j,w}^+ = \left((AT_j.w)^+, (AI_j.w)^+, (AF_j.w)^+\right); \quad d_{j,w}^- = \left((AT_j.w)^-, (AI_j.w)^-, (AF_j.w)^-\right)$

$$
(AT_j.w)^+ = \left\{\left(\max_i \{(AT_{ij}.w_j) \mid j \in j_1\}\right), \left(\min_i \{(AT_{ij}.w_j) \mid j \in j_2\}\right)\right\}
$$

$$
(AI_j.w)^+ = \left\{\left(\min_i \{(AI_{ij}.w_j) \mid j \in j_1\}\right), \left(\max_i \{(AI_{ij}.w_j) \mid j \in j_2\}\right)\right\}
$$

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$$
(AF_j.w)^+ = \left\{ \left(\min_i \left\{ (AF_{ij}.w_j) \mid j \in j_1 \right\} \right), \left(\max_i \left\{ (AF_{ij}.w_j) \mid j \in j_2 \right\} \right) \right\}
$$

$$
(AT_j.w)^- = \left\{ \left(\min_i \left\{ (AT_{ij}.w_j) \mid j \in j_1 \right\} \right), \left(\max_i \left\{ (AT_{ij}.w_j) \mid j \in j_2 \right\} \right) \right\}
$$

$$
(AI_{j.w})^- = \left\{ \left(\max_i \left\{ (AI_{ij.w_j}) \mid j \in j_1 \right\} \right), \left(\min_i \left\{ (AI_{ij.w_j}) \mid j \in j_2 \right\} \right) \right\}
$$

$$
(AF_{j.w})^- = \left\{ \left(\max_i \left\{ (AF_{ij.w_j}) \mid j \in j_1 \right\} \right), \left(\min_i \left\{ (AF_{ij.w_j}) \mid j \in j_2 \right\} \right) \right\}
$$

Step 10: Calculate the closeness coefficient for each alternative based on its distance from the relative neutrosophic positive and negative ideal solutions.

$$
C_i^* = \frac{D_i^-}{D_i^+ + D_i^-}
$$

where,

$$
D_i^+\n\frac{\sqrt{\frac{1}{3n}\left\{\sum_{j=1}^n\left[\left(A_{ij}.w_j - \left(A_{ij}.w_j\right)^+\right)^2 + \left(A_{ij}.w_j - \left(A_{ij}.w\right)^+\right)^2 + \left(A_{ij}.w_j - \left(A_{ij}.w\right)^+\right)^2\right]\right\}}}}{D_i^-}\n= \n\sqrt{\frac{1}{3n}\left\{\sum_{j=1}^n\left[\left(A_{ij}.w_j - \left(A_{ij}.w\right)^-\right)^2 + \left(A_{ij}.w_j - \left(A_{ij}.w\right)^-\right)^2 + \left(A_{ij}.w_j - \left(A_{ij}.w\right)^-\right)^2\right]\right\}}}{\text{Step 11: Rank the alternatives according to their closeness coefficients from highest to lowest.}
$$

Step 12: Identify the best alternatives in accordance with the closeness coefficients. The best alternative is the one with the maximum closeness coefficient.

5. Model Implementation

Crop selection has a significant role in creating sustainable agriculture. In this study, to improve the sustainable agriculture of Ariyalur district, which plays a major role in the agriculture sector, the above-mentioned method is used to rank the crops (sugarcane, paddy, cotton, groundnut, maize, brinjal, tomato, chilli, onion) cultivated there on the basis of criteria (production, profitability, water availability, seed growth, soil texture, precipitation, irrigation, crop demand, price of crop, expenditure and fertilizer). Based on the advice of agriculture field specialists and a comprehensive assessment of the literature, these criteria were developed. An alternative and attribute-based questionnaire is used to gather data for the current study from the agriculture experts in the Ariyalur district. The agriculture experts provided the complete data in the predetermined format. The weight of the attributes and the weight of the alternatives based on the attributes are collected from the four-decision maker in the form of linguistic terms. The linguistic terms' rates are expressed as a single-valued neutrosophic set. The linguistic terms for attributes and importance of decision-makers are shown in Table 1. Also, the linguistic terms of alternatives are mentioned in Table 2 in SVNS rating

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Linguistics Term	SVNN
Very important (VI)	(0.95, 0.05, 0.05)
Important (I)	(0.85, 0.15, 0.15)
Median(M)	(0.50, 0.40, 0.45)
Unimportant (UI)	(0.30, 0.60, 0.70)
Very unimportant (VUI)	(0.05, 0.85, 0.95)

TABLE 1. Linguistic terms of decision maker and Attributes.

Table 2. Alternatives' Linguistic Terms.

Linguistics Term	SVNN
Extremely high (EH)	(1, 0, 0)
Very high (VH)	(0.95, 0.10, 0.05)
High(H)	(0.85, 0.15, 0.15)
Median (M)	(0.65, 0.40, 0.35)
Low (L)	(0.20, 0.75, 0.80)
Very low (VL)	(0.10, 0.85, 0.90)
Extremely low (EL)	(0.05, 0.90, 0.95)

format. In this present study, the linguistic term for (DM_1, DM_2, DM_3, DM_4) is (VI, I, VI, M) respectively.

Using Eq. (1), the decision makers' weights are ascertained as follows:

$$
\varphi_1 = \frac{1 - \sqrt{\frac{\{(1 - T_1(x))^2 + (I_1(x))^2 + (F_1(x))^2\}}{3}}}{\sum_{t=1}^4 \left(1 - \sqrt{\frac{\{(1 - T_s(x))^2 + (I_s(x))^2 + (F_s(x))^2\}}{3}}\right)}
$$

$$
= \frac{1 - \sqrt{\frac{\{(0.05^2 + 0.05^2 + 0.05^2\}}{3}}{4 - \sqrt{0.0025} - \sqrt{0.0025} - \sqrt{0.0025} - \sqrt{0.2042}}}
$$

$$
\varphi_1 = 0.2888
$$

Similarly, $\varphi_2 = 0.2577$, $\varphi_3 = 0.288$, $\varphi_4 = 0.1662$. Therefore (0.288, 0.2577, 0.288, 0.1662) is the four decision makers' weight vectors.

The linguistic term of every alternative $A_i(i = 1, 2, ..., 9)$ in relation to every criterion C_j (j = 1, 2, ..., 11), as well as the linguistic terms for the weights of the criteria provided by the four decision makers (DM_1, DM_2, DM_3, DM_4) are displayed in Table 3. Using Table 1 & Table 2, convert the linguistic terms of the alternatives and attributes in Table 3 into SVNNs. Then, as stated in Step 3, generate the single-valued neutrosophic decision matrix. Additionally, apply Step 4 to normalize the decision matrix. After these conversions, Step 6 is used to define the aggregated neutrosophic decision matrix in the following manner:

$d_{11} = \left(1 - \prod_{t=1}^4 \left(1 - T_{11}^{(t)}\right)^{\varphi_t}, \prod_{t=1}^4 \left(I_{11}^{(t)}\right)^{\varphi_t}, \prod_{t=1}^4 \left(F_{11}^{(t)}\right)^{\varphi_t}\right)$

Alter	D.M	Prod	Prof	W.A	S.G	S.T	Р	I.T	$_{\rm C.D}$	P.C	E	F
Sugarcane	$\mathbf 1$	Η	Η	Η	Η	VН	L	VH	VH	Η	М	VH
	$\overline{2}$	Н	М	М	Η	$\mathbf M$	Г	Η	Η	Г	$\rm H$	Η
	3	$\mathbf M$	М	М	H	VH	L	VH	М	L	H	H
	4	М	М	М	М	Η	$\mathbf M$	Η	М	М	М	VH
	$\mathbf{1}$	Η	М	VH	Η	VH	Г	VH	VH	Η	H	VH
	$\overline{2}$	M	М	М	М	\mathbf{M}	Г	М	М	Г	М	Н
Paddy	3	М	М	L	L	VH	L	М	Г	М	VH	М
	$\overline{4}$	VL	VL	VL	Η	M	VL	Η	VL	VL	VH	VH
	$\mathbf 1$	Η	Η	М	Η	VH	М	VH	VH	Η	М	Η
	$\boldsymbol{2}$	М	М	VL	Η	Η	Г	Η	М	Г	Η	Η
Cotton	3	VH	L	VL	Η	H	VL	Η	М	L	М	Η
	$\overline{4}$	L	М	М	М	L	VL	VН	VH	VL	VH	М
	$\mathbf{1}$	М	М	М	Η	VH	М	VH	Η	Η	H	VH
Groundnut	$\overline{2}$	M	М	М	$\mathbf H$	Η	L	Η	Η	M	М	Η
	3	М	$_{\rm M}$	М	М	М	VL	Η	Η	$\mathbf M$	Η	Η
	$\overline{4}$	M	М	М	М	Η	L	VH	Η	M	Η	VH
	$\mathbf 1$	М	Η	М	Η	VH	М	VH	М	$\mathbf H$	M	Η
Maize	$\overline{2}$	М	М	М	Η	VH	М	Η	М	М	М	Η
	3	H	М	Г	H	Η	VL	Η	Η	Г	М	Η
	4	М	М	VL	М	М	L	VН	VH	М	Η	Η
	$\mathbf{1}$	М	Η	М	Η	Η	М	Η	Η	Η	М	G
Brinjal	$\boldsymbol{2}$	$\mathbf M$	М	М	М	Η	M	Η	М	M	М	Η
	3	Η	L	М	М	Η	VL	Η	Η	Η	Η	Η
	$\overline{4}$	VL	Г	L	М	М	VL	Η	М	М	VH	М
	$\mathbf 1$	М	Η	М	Η	Η	М	М	VH	H	М	Η
Tomato	$\boldsymbol{2}$	Г	М	М	Η	Η	Г	Η	Η	Η	М	Η
	3	Н	М	М	H	Η	VL	М	Η	М	М	Η
	4	М	М	М	М	Η	VL	Η	М	VL	М	VH
	$\mathbf{1}$	VH	VH	М	Η	M	М	М	VH	Η	М	Η
Chilli	$\overline{2}$	Н	Η	H	Η	VH	Г	Η	Η	$\mathbf H$	М	Η
	3	М	М	М	М	Η	VL	Η	М	М	Η	Η
	$\overline{4}$	М	М	L	М	M	VL	VH	М	М	Η	М
	$\mathbf 1$	М	Η	М	М	Η	М	Η	VH	Η	$\mathbf H$	Η
Onion	$\overline{2}$	М	Η	М	Η	Η	$\rm H$	Η	Η	М	М	Η
	3	Η	М	М	М	Η	VL	М	H	H	М	Η
	$\overline{4}$	L	L	VL	L	М	VL	VН	L	М	М	Η
	$\mathbf{1}$	VI	I	VI	VI	VI	VI	VI	VI	I	I	VI
weight	$\boldsymbol{2}$	I	VI	I	I	I	I	I	I	VI	I	I
	$\sqrt{3}$	VI	VI	VI	VI	VI	VI	VI	VI	VI	I	I
	$\overline{4}$	VI	I	I	VI	VI	VI	VI	VI	I	I	VI

Table 3. Weight for alternatives and attributes in linguistic terms.

$$
AT_{11} = 1 - \prod_{t=1}^{4} \left(1 - T_{11}^{(t)}\right)^{\varphi_t}
$$

= 1 - \left((1 - 0.85)^{0.288} \times (1 - 0.85)^{0.2577} \times (1 - 0.65)^{0.288} \times (1 - 0.65)^{0.1662}\right) = 0.7796

$$
AI_{11} = \prod_{t=1}^{4} \left(I_{11}^{(t)} \right)^{\varphi_t} = (0.15)^{0.288} \times (0.15)^{0.2577} \times (0.4)^{0.288} \times (0.4)^{0.1662} = 0.2342
$$

$$
AF_{11} = \prod_{t=1}^{4} \left(F_{11}^{(t)} \right)^{\varphi_t} = (0.15)^{0.288} \times (0.15)^{0.2577} \times (0.35)^{0.288} \times (0.35)^{0.1662} = 0.2204
$$

Similarly, all the values of $(AT_{ij}, AI_{ij}, AF_{ij})$ will be determined. Consequently, the following is the final aggregated neutrosophic decision matrix:

Now the aggregated weight of the attributes is defined by using Step7 as follows:

Alter	Prod	Prof	W.A	S.G	S.T	$\mathbf P$	I.T	C.D	P.C	E	$\mathbf F$
	(0.7796,	(0.7257,	(0.7257,	(0.8273,	(0.9009,	(0.3027,	(0.9203,	(0.8393,	(0.5694,	(0.4504,	(0.9089,
S	0.2342,	0.3016 ,	0.3016.	0.1766.	0.1529,	0.6756,	0.1188,	0.2084,	0.4250,	0.5637,	0.1247,
	0.2204)	0.2742)	0.2742)	0.1727)	0.0991)	0.6973)	0.0.0797)	0.1607	0.4306)	0.5495)	0.0911)
	(0.6791,	(0.5905,	(0.7033,	(0.6977,	(0.8859,	(0.1842,	(0.9203,	(0.8393,	(0.5694,	(0.4504,	0.9089
$\rm P$	0.3418.	0.4534.	0.3645,	0.3071,	0.18,	0.7658,	0.228,	0.3645.	0.402,	0.6613	0.1655
	0.3209)	0.4095)	0.2967)	0.3023)	0.1141)	0.8158)	0.1736)	0.2967)	0.397	0.6688	0.1162
	(0.8204,	(0.652,	(0.4139,	(0.8273,	(0.8556,	(0.3348,	(0.9089,	(0.8554,	(0.4962,	(0.4932,	(0.8273,
Co	0.2246,	0.3614,	0.6036,	0.1766,	0.1744,	0.6624,	0.1248,	0.2131,	0.4817,	0.5332,	0.1766,
	0.1796)	0.348)	0.5861)	0.1727)	0.1444)	0.6652)	0.0911)	0.1446)	0.5038)	0.5068)	0.1727)
	(0.65,	(0.65,	(0.65,	(0.7796,	(0.8604,	(0.3477,	(0.9089,	(0.85,	(0.7258,	(0.3535,	(0.9089,
GN	0.4,	0.4,	0.4,	0.2342,	0.1771,	0.6488,	0.1248,	0.15,	0.3016,	0.6379,	0.1248,
	(0.35)	(0.35)	(0.35)	0.2204)	0.1396)	0.6523)	0.0911)	0.15)	0.2742)	0.6465)	0.0911)
	(0.7258,	(0.7258,	(0.4803,	(0.8273,	(0.9052,	(0.4729,	(0.9089,	(0.8015,	(0.652,	(0.5984,	(0.85,
$\mathbf M$	0.3016,	0.3016,	0.5434,	0.1766,	0.1415,	0.5518,	0.1248,	0.2395,	0.3614,	0.4441,	0.15,
	0.2742)	0.2742	0.5095)	0.1727)	0.0948)	0.5271)	0.0911)	0.1985)	0.348)	0.4016)	0.15)
	(0.6791,	(0.6008,	(0.5984,	(0.7258,	(0.8273,	(0.4625,	(0.85,	(0.7851,	(0.7851,	(0.4804,	(0.8273,
\boldsymbol{B}	0.3418,	0.4013,	0.4441,	0.3016,	0.1766,	0.5634,	0.15,	0.2274,	0.2274,	0.5434,	0.1766,
	0.3209)	0.3992)	0.4016)	0.2742)	0.1727)	0.5375)	0.15)	0.2149)	0.2149)	0.5196)	0.1727)
	(0.6606,	(0.7258,	(0.65,	(0.8273,	(0.85,	(0.3348,	(0.7556,	(0.8741,	(0.7421,	(0.65,	(0.875,
$\mathbf T$	0.3546,	0.3016,	0.4,	0.1766,	0.15,	0.6624,	0.264,	0.1571,	0.2655,	0.4,	0.1403,
	0.3394)	0.2742)	(0.35)	0.1727)	0.15)	0.6652)	0.2444)	0.1259)	0.2579)	(0.35)	0.125)
	(0.8393,	(0.8393,	(0.6772,	(0.78,	(0.8339,	(0.3348,	(0.8405,	(0.8393,	(0.78,	(0.4905,	(0.8273,
$\rm Ch$	0.2084,	0.2084,	0.3449,	0.2342,	0.211,	0.6624,	0.186,	0.2084,	0.2342,	0.5322,	0.1766,
	0.1607)	0.1607)	0.3228	0.2204)	0.1661)	0.6652)	0.1595)	0.1607)	0.2204)	0.5095)	0.1727)
	(0.6854,	(0.7471,	(0.5905,	(0.6772,	(0.8273,	(0.5679,	(0.8405,	(0.8556,	(0.7851,	(0.5559,	(0.85,
Ω	0.3348,	0.26,	0.4534,	0.3449,	0.1766,	0.4375,	0.186,	0.1744,	0.2274,	0.4794,	0.15,
	0.3146)	0.2529)	0.4095)	0.3228	0.1727)	0.4321)	0.1595)	0.1444)	0.2149)	0.4441)	0.15)

Table 4. Aggregated neutrosophic decision matrix.

$$
w_1 = \left(1 - \prod_{t=1}^4 \left(1 - T_1^{(t)}\right)^{\varphi_t}, \prod_{t=1}^4 \left(I_1^{(t)}\right)^{\varphi_t}, \prod_{t=1}^4 \left(F_1^{(t)}\right)^{\varphi_t}\right)
$$

where

$$
1 - \prod_{t=1}^{4} \left(1 - T_1^{(t)}\right)^{\varphi_t} = 1 - (1 - 0.95)^{0.288} \times (1 - 0.85)^{0.2577} \times (1 - 0.95)^{0.288} \times (1 - 0.95)^{0.1662}
$$

= 0.9336

$$
\prod_{t=1}^{4} \left(T_1^{(t)}\right)^{\varphi_t} = 0.05^{0.288} \times 0.15^{0.2577} \times 0.05^{0.288} \times 0.05^{0.1662} = 0.0664
$$

 $_{t=1}^{4}\left(F_{1}^{\left(t\right) }\right)$ $\prod_{t=1}^{4} \left(F_1^{(t)} \right)^{\varphi_t} = 0.05^{0.288} \times 0.15^{0.2577} \times 0.05^{0.288} \times 0.05^{0.1662} = 0.0664$ Thus, $w_1 = (0.9336, 0.0664, 0.0664)$. Similarly, the weights of the criteria (profitability, water availability, seed growth, soil texture, precipitation, irrigation, crop demand, price of crop,

expenditure and fertilize) will be determined, and the final aggregated weight of the criteria is as follows:

$$
W = \begin{bmatrix} (0.9336, 0.0664, 0.0664); & (0.9176, 0.0824, 0.0824) \\ (0.9203, 0.0797, 0.0797); & (0.9336, 0.0664, 0.0664) \\ (0.9336, 0.0664, 0.0664); & (0.9336, 0.0664, 0.0664) \\ (0.9336, 0.0664, 0.0664); & (0.9336, 0.0664, 0.0664) \\ (0.9176, 0.0824, 0.0824); & (0.85, 0.15, 0.15) \\ (0.9089, 0.0911, 0.0911) \end{bmatrix}
$$

The weighted aggregated neutrosophic decision matrix is computed using Step 8 in the following manner after locating the aggregated neutrosophic decision matrix and the attributes' aggregated weights:

 $d_{11} \times w_1 = (AT_{11} \cdot w_1, A_{11} \cdot w_1, AF_{11} \cdot w_1)$ where,

$$
AT_{11} \cdot w_1 = \left(1 - \prod_{t=1}^4 \left(1 - T_{11}^{(t)}\right)^{\varphi_t}\right) \times \left(1 - \prod_{t=1}^4 \left(1 - T_{1}^{(t)}\right)^{\varphi_t}\right)
$$

\n= 0.7796 × 0.9336 = 0.7278
\n
$$
AI_{11} \cdot w_1 = \prod_{t=1}^4 \left(I_{11}^{(t)}\right) + \prod_{t=1}^4 \left(I_{1}^{(t)}\right)^{\varphi_t} - \prod_{t=1}^4 \left(I_{11}^{(t)}\right) \times \prod_{t=1}^4 \left(I_{1}^{(t)}\right)^{\varphi_t}
$$

\n= 0.2342 + 0.0664 - 0.2342 × 0.0664 = 0.2851
\n
$$
AF_{11} \cdot w_1 = \prod_{t=1}^4 \left(F_{11}^{(t)}\right) + \prod_{t=1}^4 \left(F_{1}^{(t)}\right)^{\varphi_t} - \prod_{t=1}^4 \left(F_{11}^{(t)}\right) \times \prod_{t=1}^4 \left(F_{1}^{(t)}\right)^{\varphi_t}
$$

\n= 0.2204 + 0.0664 - 0.2204 × 0.0664 = 0.2722

Similarly, all the values of $(AT_{ij} \cdot w_j, AI_{ij} \cdot w_j, AF_{ij} \cdot w_j)$ will be determined, and the final weighted aggregated neutrosophic decision matrix is presented in Table 5.

Using Step 9, the relative positive and negative ideal solutions are generated from Table 5 as follows:

$$
A_{N}^{+} = \begin{bmatrix} (0.7836, 0.261, 0.2164); & (0.7702, 0.2736, 0.2298) \\ 0.6679, 0.3573, 0.3321); & (0.7724, 0.2313, 0.2276) \\ (0.8451, 0.1985, 0.1549); & (0.5302, 0.4749, 0.4698) \\ (0.8592, 0.1773, 0.1408); & (0.8161, 0.2065, 0.1839) \\ (0.7204, 0.2910, 0.2796); & (0.1408, 0.8279, 0.8592) \\ (0.8261, 0.2045, 0.1739) & (0.1408, 0.8279, 0.8592) \\ (0.7519, 0.2516, 0.2481) & (0.2975, 0.66, 0.7025) \\ (0.7519, 0.2516, 0.2481) & (0.2975, 0.66, 0.7025) \\ (0.7519, 0.2516, 0.2481) & (0.2975, 0.66, 0.7025) \\ (0.7519, 0.2516, 0.2481) & (0.2975, 0.66, 0.7025) \\ (0.2975, 0.66, 0.7025) & (0.2975, 0.66, 0.7025) \\ (0.2975, 0.66, 0.7025) & (0.2975, 0.66, 0.7025) \\ (0.2975, 0
$$

Using the above positive and negative ideal solutions, and Step 10 the distance measures are determined as follows:

$$
D_{1}^{+} = \sqrt{\frac{1}{33} (\sum_{j=1}^{n} [(AT_{1j} \cdot w_j - (AT_j \cdot w)^{+})^{2} + (AI_{1j} \cdot w_j - (AI_j \cdot w)^{+})^{2} + (AF_{1j} \cdot w_j - (AF_j \cdot w)^{+})^{2}])}
$$

= 0.1012

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Alter	Prod	Prof	W.A	S.G	S.T	${\bf P}$	I.T	$\mathbf{C}.\mathbf{D}$	P.C	$\bf E$	$\mathbf F$
	(0.7278,	(0.666,	(0.6679,	(0.7724,	(0.8411,	(0.2826,	(0.8592,	(0.7836,	(0.5225,	(0.2104,	(0.8261,
S	0.2851,	0.3591,	0.3573,	0.2313,	0.2092,	0.6972,	0.1773,	0.261,	0.4724,	0.7668,	0.2045,
	0.2722)	(0.334)	0.3321)	0.2276)	0.1589)	0.7174)	0.1408)	0.2164)	0.4775)	0.7896)	0.1739)
	(0.6341,	(0.5418,	(0.6473,	(0.6514,	(0.8271,	(0.1719,	(0.7715,	(0.6566,	(0.5533,	(0.1408,	(0.8032,
$\mathbf P$	0.3855,	0.4985,	0.4152,	0.3531,	0.2345,	0.7813.	0.2792,	0.4067.	0.4512,	0.8279,	0.2415,
	0.3659)	0.4582)	0.3527)	0.3486)	0.1729)	0.8281)	0.2285)	0.3434)	0.4467)	0.8592)	0.1968)
	(0.7659,	(0.5983,	(0.3809,	(0.7724,	(0.7988,	(0.3126,	(0.8486,	(0.7986,	(0.4553,	(0.2309,	(0.7519,
Co	0.2761,	0.4141,	0.6352,	0.2313,	0.2293,	0.6848,	0.1829,	0.2654.	0.5244.	0.7468.	0.2516,
	0.2341)	0.4017)	0.619)	0.2276)	0.2012)	0.6874)	0.1514)	0.2014)	0.5447)	0.7806)	0.2481)
	(0.6068,	(0.5964,	(0.5982,	(0.7278,	(0.8033,	(0.3246,	(0.8486,	(0.7935,	(0.666,	(0.1757,	(0.8261,
GN	0.4399,	0.4495.	0.4479.	0.2851,	0.2317,	0.6721,	0.1829,	0.2065.	0.3591,	0.8105.	0.2045,
	0.3932)	0.4036)	0.4018)	0.2722)	0.1967)	0.6754)	0.1514)	0.2065)	0.3340)	0.8243)	0.1739)
	(0.6776,	(0.666,	(0.4421,	(0.7724,	(0.8451,	(0.4415,	(0.8486,	(0.7483,	(0.5983,	(0.2723,	(0.7723,
$\mathbf M$	0.348,	0.3591,	0.5798,	0.2313,	0.1985,	0.5815,	0.1829,	0.29,	0.4141,	0.6904,	0.2275,
	0.3224)	(0.3340)	0.5486)	0.2276)	0.1549)	0.5585)	0.1514)	0.2517)	0.4017)	0.7277)	0.2275)
	(0.6341,	(0.5513,	(0.5507,	(0.6776,	(0.7724,	(0.4317,	(0.7935,	(0.733,	(0.7204,	(0.2142,	(0.7519,
\boldsymbol{B}	0.3855,	0.4506.	0.4884.	0.348,	0.2313,	0.5924,	0.2065,	0.2787,	0.2910,	0.7531,	0.2516,
	0.3659	0.4487)	0.4493)	0.3224)	0.2276)	0.5683)	0.2065)	0.267)	0.2796)	0.7858	0.2481)
	(0.6168,	(0.666,	(0.5982,	(0.7724,	(0.7935,	(0.3126,	(0.7054,	(0.8161,	(0.6809,	(0.2975,	(0.7953,
$\mathbf T$	0.3975.	0.3591,	0.4479,	0.2313.	0.2065,	0.6848,	0.3128,	0.2131,	0.3260.	0.66,	0.2186,
	0.3832)	0.3340)	0.4018)	0.2276)	0.2065)	0.6874)	0.2946)	0.1839)	0.3191)	0.7025)	0.2047)
	(0.7836,	(0.7702,	(0.6232,	(0.7278,	(0.7785,	(0.3126,	(0.7847,	(0.7836,	(0.7153,	(0.2259,	(0.7519,
Ch	0.261,	0.2736,	0.3971,	0.2851,	0.2634,	0.6848,	0.2401,	0.261,	0.2973,	0.7474,	0.2516,
	0.2164)	0.2298)	0.3768	0.2722)	0.2215)	0.6874)	0.2153)	0.2164)	0.2847)	0.7741)	0.2481)
	(0.6399,	(0.6855,	(0.5434,	(0.6322,	(0.7724,	(0.5302,	(0.7847,	(0.7988,	(0.7204,	(0.2531,	(0.7725,
Ω	0.379,	0.321,	0.497,	0.3884,	0.2313,	0.4749,	0.2401,	0.2293.	0.2910,	0.7138,	0.2275,
	0.3601)	0.3145)	0.4566	0.3678)	0.2276)	0.4698)	0.2153)	0.2012)	0.2796)	0.7469	0.2275)

Table 5. Weighted aggregated neutrosophic decision matrix.

$$
D_1^- = \sqrt{\frac{1}{33} \left(\sum_{j=1}^n \left[\left(A T_{1j} \cdot w_j - (A T_j \cdot w)^{-} \right)^2 + \left(A I_{1j} \cdot w_j - (A I_j \cdot w)^{-} \right)^2 + \left(A F_{1j} \cdot w_j - (A F_j \cdot w)^{-} \right)^2 \right] \right)}
$$

= 0.1375

Similarly, all the relative neutrosophic distance measures will be calculated. After calculating all $D_i^+, D_i^-,$ the closeness coefficient is determined by using the formula mentioned in step 10 as follows:

$$
C_1^* = \frac{D_1^-}{D_1^+ + D_1^-} = \frac{0.1375}{0.1012 + 0.1375} = 0.576
$$

The distance measures and the closeness coefficients of all the alternatives are mentioned in the Table 6. Additionally, Figure 1 illustrates the graphical representation of alternatives versus the closeness coefficient. From Table 6, and Figure 1, it is clear that the closeness coefficient of the alternative chilli is greater than the other alternatives. Therefore, chilli is the most desirable crop. Also, the order preference of all the alternatives is Chilli $>$ Onion $>$ $Sugarcane > Groundnut > Brinial > Maize > Tomato > Cottom > Paddy.$

Figure 1. Alternatives vs Closeness coefficients

Alternatives	D^+	D	C^*
Sugarcane	0.1012	0.1375	0.576
Paddy	0.1573	0.0986	0.3853
Cotton	0.1456	0.1019	0.4117
Groundnut	0.1035	0.1286	0.5541
Maize	0.1037	0.1218	0.5401
Brinjal	0.1053	0.1276	0.5479
Tomato	0.1121	0.1271	0.5314
Chilli	0.0814	0.1535	0.6535
Onion	0.0885	0.1553	0.637

Table 6. Closeness Coefficients of the Alternatives.

6. Conclusion

Crop selection for sustainable agriculture is a complicated procedure. It presents a number of difficulties, particularly when it is accomplished while taking into consideration a wide range of sustainability-influencing criteria. The TOPSIS-based SVNS is used in this study for Ariyalur district farmers to rank the nine crops—sugarcane, paddy, cotton, groundnut, maize, brinjal, tomato, chilli, and onion—based on the criteria of production, profitability, water availability, seed growth, soil texture, precipitation, irrigation, crop demand, crop price, expenditure, and fertilizer. From the closeness coefficient of this study, it is concluded that

chilli is the most optimal crop to cultivate in Ariyalur district. A neutrosophic-based multicriteria approach is crucial because multiple uncertainties and instabilities frequently impact the crop selection process. This strategy can assist policymakers and farmers in creating allencompassing policies that support sustainable farming methods, which the world desperately needs. Subsequent studies could look into ways to mitigate and adapt to the consequences of climate change, which would eventually lead to more sustainable farming methods and better decision-making.

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