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Research article

Optimizing Farmer Selection Through Neutrosophic Soft Matrix-Based Decision Making

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Abstract

Complex decisions in varying domains necessitate making sense of information that is uncertain, deficient, or internally contradictory. The Neutrosophic Soft Set (NSS) theory fulfills this need by physically modeling truth, indeterminacy, and falsity. This research investigates NSS and their representation via a matrix, Neutrosophic Soft Matrices (NSM), with emphasis on the operations and comparatives indices of score, certainty, and accuracy. A series of aggregation operators are developed to combine neutrosophic evidence, which support the development of a Neutrosophic Multi-Criteria Decision-Making (MCDM) method based upon traditional decision rules. Academic experience is used to illustrate the methodology applied to an agricultural context for evaluating farmers based upon attributes like crop yield, soil condition, use of fertilizers, and pest control. Analysis shows that use of NSM facilitates systematic evaluation and selection of a best alternative in the presence of imprecision and uncertainty. In summary, this research supports the idea that neutrosophic models can be useful methods for decision analysis in complicated realworld situations.

Keywords: Soft set, Neutrosophic Soft Set Matrix, Multi-Criteria decision-making, Operators.

Mathematics Subject Classification (2020): 03E72, 68T37, 90B50

1 Introduction

Multiple mathematical paradigms (for example, FS, IFS, and SS) have been utilized to investigate decision problems in uncertain and imprecise settings. To model parameterized uncertainty, Molodtsov published results that advanced the field of soft set theory [1]. In a similar vein, Smarandache proposed the concept of neutrosophic sets, in which T, I, and F are independent propositions of information [2]. An amalgamation of these concepts led to the notion of NSS, and subsequently NSM, which offer a matrix-based medium for certainty weighting. Deli [3] undertook a formalization of NSMs and viably applied scoring functions and matrix operators into decision functions. Subsequently, Bera and Mahapatra [4] furthered scholarship by concerning algebraic properties of NSM and applying NSMs in MCDM. Das [5] extended the NSM framework in group decision scenarios by way of expert weights and aggregation operators.

Subsequent articles developed different variants of the NSM framework. For example, complex neutrosophic soft matrices [6] and metric-based neutrosophic soft matrices [7] were presented to aid the flexibility of modelling. Zhang et al. [8] presented an arrangement calculus with parameter reduction for IVNSS, for computational feasibility in decision contexts. Most recently, Boobalan and Mathivadhana [9] presented neutrosophic hyper-soft rough matrices, which incorporate rough set theory within neutrosophic constructs. Applications of NSM-based methods have been utilised in diverse domains, including medical diagnosis [10], disease control strategies [11], supplier and personnel selection [12], and resource allocation under uncertainty. Recent works have also extended NSM into emerging areas such as security modelling [13] and evaluation frameworks like QUALIFLEX [14]. Theoretical advancements include spectral analysis and matrix "energy" concepts for multi-valued neutrosophic matrices [15].

Three gaps motivate this work: (i) operator ambiguity (arithmetic vs. geometric vs. harmonic fusions), (ii) opacity in mapping (T,I,F) to a single value, and (iii) sensitivity to the decision makers risk stance. We address these issues via range-preserving operators, an explicit indeterminacy-penalised value mapping, and reporting under the Laplace, Maximin/Maximax, and Hurwicz models with sensitivity in α. Figure 1 summarises the workflow used throughout this process.

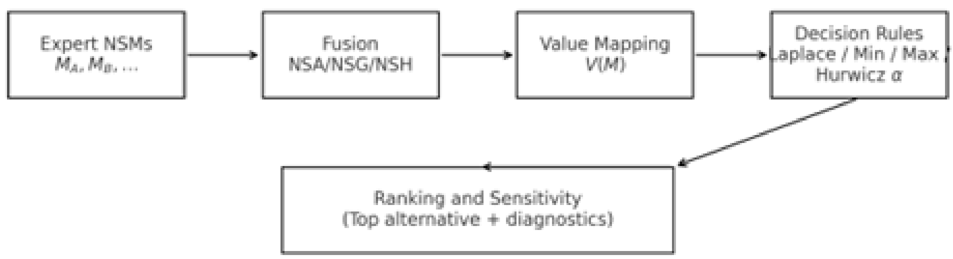


Figure 1. NSM–MCDM workflow: fusion → scoring → rules → ranking.

2 Preliminaries

This section provides a review of fundamental definitions essential for the development of this paper.

2.1 Definition: (Molodtsov 1999)

Let U be a universe of items and E be a set of limitations. For $B \subseteq E$, a pair (G,B) is a soft set over U, where $G : B \to P(U)$.

Example 1. Consider the universal set of laptops $U = \{L1, L2, L3, L4\}$ with parameters $E = \{$cheap, lightweight, high battery, gaming$\}$ and parameters $B = \{$cheap, lightweight, high battery$\}$. Then the soft set can be written as

$$F = \{(\text{cheap}, \{L1, L2, L3\}), (\text{lightweight}, \{L2, L4\}), (\text{high battery}, \{L1, L4\})\}.$$

2.2 Definition: (Smarandache 2005)

A neutrosophic set A on the universe of discourse X is defined as $N = \{X, (T_A(x), I_A(x), F_A(x)) \mid x \in X\}$, where $T_A, I_A, F_A : X \to [0,1]$ and $-0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3+$; T, I, F are called neutrosophic components.

2.3 Definition: (Deli 2015)

Let U be a universe, $N(U)$ be the set of all neutrosophic sets on U, B be a set of parameters that describes the elements of U & $A \subseteq B$. Then, an NSS N over U is an approximate function, $f_N : A \to N(U)$.

Example 2. Let the universe be $U = \{r1, r2, r3\}$, representing three cities, and the parameters be $B = \{b1, b2, b3\}$, where $b1$ denotes clean,

$b2$ denotes green, and $b3$ denotes developed. Assume that

$$F(\text{clean}) = \{< r_1, .5, .6, .3 >,\ < r_2, .4, .7, .6 >,\ < r_3, .6, .2, .2 >\},$$
$$F(\text{green}) = \{< r_1, .6, .3, .5 >,\ < r_2, .7, .4, .3 >,\ < r_3, .8, .1, .2 >\},$$
$$F(\text{developed}) = \{< r_1, .7, .4, .3 >,\ < r_2, .6, .7, .3 >,\ < r_3 .7, .2, .5 >\}.$$

The NSS (F,B) is defined as follows:

$$(F,B) = \Big\{ \text{clean city} = \{< r_1, 0.5, 0.6, 0.3 >,\ < r_2, 0.4, 0.7, 0.6 >,\ < r_3, 0.6, 0.2, 0.2 >\},$$
$$\text{green city} = \{< r_1, 0.6, 0.3, 0.5 >,\ < r_2, 0.7, 0.4, 0.3 >,\ < r_3, 0.8, 0.1, 0.2 >\},$$
$$\text{developed city} = \{< r_1, 0.7, 0.4, 0.3 >,\ < r_2, 0.6, 0.7, 0.3 >,\ < r_3, 0.7, 0.2, 0.5 >\} \Big\}.$$

The tabular representation is given by

U	Clean	Green	Developed
r_1	(0.5, 0.6, 0.3)	(0.6, 0.3, 0.5)	(0.7, 0.4, 0.3)
r_2	(0.4, 0.7, 0.6)	(0.7, 0.4, 0.3)	(0.6, 0.7, 0.3)
r_3	(0.6, 0.2, 0.2)	(0.8, 0.1, 0.2)	(0.7, 0.2, 0.5)

2.4 Definition: (Tanushree 2015)

Let (F_A, E) be an NSS over U, where $F_A : B \to N^U$ such that $F_A(b) = \phi$, if $b \notin A$, where N^U is the set of all NS over U, & ϕ is a null NS. If $[(T_{ij}, I_{ij}, F_{ij})] = [T_{ij}(f_i, b_j),\ I_{ij}(f_i, b_j),\ F_{ij}(f_i, b_j)]$, then

$$\big[(T_{ij}, I_{ij}, F_{ij})\big]_{m\times n} = \begin{bmatrix} < \hat{T}_{11}, \hat{I}_{11}, \hat{F}_{11} > & < \hat{T}_{12}, \hat{I}_{12}, \hat{F}_{12} > & \cdots & < \hat{T}_{1n}, \hat{I}_{1n}, \hat{F}_{1n} > \\ < \hat{T}_{21}, \hat{I}_{21}, \hat{F}_{21} > & < \hat{T}_{22}, \hat{I}_{22}, \hat{F}_{22} > & \cdots & < \hat{T}_{2n}, \hat{I}_{2n}, \hat{F}_{2n} > \\ \vdots & \vdots & \ddots & \vdots \\ < \hat{T}_{m1}, \hat{I}_{m1}, \hat{F}_{m1} > & < \hat{T}_{m2}, \hat{I}_{m2}, \hat{F}_{m2} > & \cdots & < \hat{T}_{mn}, \hat{I}_{mn}, \hat{F}_{mn} > \end{bmatrix}$$

is termed a Neutrosophic Soft Matrix (NSM).

Example 3. Let $F = \{f_1, f_2, f_3, f_4\}$ denote the universal set and $D = \{d_1, d_2, d_3\}$ denote the set of attributes. Let $A = \{d_1, d_2\} \subseteq D$. Then the soft set (F_D, A) is

$$(F_D, A) = \{F_D(d_1), F_D(d_2)\},$$

where

$$F_D(d_1) = \{(f_1, .5, .2, .2),\ (f_2, .3, .4, .1),\ (f_3, .1, .6, .3),\ (f_4, .2, .3, .5)\}.$$

$$F_D(d_2) = \{(f_1, .3, .5, .1),\ (f_2, .6, .2, .2),\ (f_3, .4, .3, .3),\ (f_4, .3, .1, .5)\}.$$

Then, the NSM is given by

$$[(T_{ij}, I_{ij}, F_{ij})] = \begin{bmatrix} (0.5, 0.2, 0.2) & (0.3, 0.5, 0.1) \\ (0.3, 0.4, 0.1) & (0.6, 0.2, 0.2) \\ (0.1, 0.6, 0.3) & (0.4, 0.3, 0.3) \\ (0.2, 0.3, 0.5) & (0.3, 0.1, 0.5) \end{bmatrix}.$$

3 Operators on NSM

If $A = ([T^A_{ij}, I^A_{ij}, F^A_{ij}])$ & $B = ([T^B_{ij}, I^B_{ij}, F^B_{ij}])$ be two NSM of order $m \times n$, then the defuzzification value of

a) Neutrosophic Arithmetic operator (NSA)

$$NA^C = ([T_{ij}^c, I_{ij}^c, F_{ij}^c]) \quad \text{where} \quad T_{ij}^c = \frac{T_{ij}^A + T_{ij}^B}{2},\ I_{ij}^c = \frac{I_{ij}^A + I_{ij}^B}{2},\ F_{ij}^c = \frac{F_{ij}^A + F_{ij}^B}{2}.$$

b) Neutrosophic Geometric operator (NSG)

$$NG^C = ([T_{ij}^c, I_{ij}^c, F_{ij}^c]) \quad \text{where} \quad T_{ij}^c = \sqrt{(T_{ij}^A * T_{ij}^B)},\ I_{ij}^c = \sqrt{(I_{ij}^A * I_{ij}^B)},\ F_{ij}^c = \sqrt{(F_{ij}^A * F_{ij}^B)}.$$

c) Neutrosophic Harmonic operator (NSH)

$$NH^C = ([T_{ij}^c, I_{ij}^c, F_{ij}^c]) \quad \text{where} \quad T_{ij}^c = \sqrt{\frac{2 * T_{ij}^A * T_{ij}^B}{T_{ij}^A + T_{ij}^B}},\ I_{ij}^c = \sqrt{\frac{2 * I_{ij}^A * I_{ij}^B}{I_{ij}^A + I_{ij}^B}},\ F_{ij}^c = \sqrt{\frac{2 * F_{ij}^A * F_{ij}^B}{F_{ij}^A + F_{ij}^B}}.$$

3.1 Value-Matrix Mapping

Suppose $M = [T_{ij}^m, I_{ij}^m, F_{ij}^m] \in NSM$, then M is converted to a scalar matrix $V(M) = [v_{ij}]$, where

$$v_{ij} = \frac{(T_{ij}^m + F_{ij}^m)/2 + 2I_{ij}^m}{3} \quad \text{for all } i \text{ and } j.$$

4 Methodology

Step 1: Define NSM A1 and A2 representing the alternatives under consideration.
Step 2: Derive the resultant matrix by applying the appropriate operators of NSS to NSM.
Step 3: Transform the matrix M into its corresponding value matrix V(M) using the selected score function.
Step 4: Determine the most suitable alternative by applying decision-making criteria.

5 Case Study: Farmer Selection under Uncertainty

A rural development committee seeks to allocate a special agricultural subsidy package, comprising improved seeds and irrigation facilities, to one of four farmers. To guarantee that the candidate who deserves to be selected is picked, the allocation must be based on multiple criteria. Because of the uncertainty embedded within hesitancy within expert judgment, we have taken on the Neutrosophic Soft Matrix (NSM) model to represent the evaluations.

For this purpose, two neutrosophic soft sets, (M_A, D) and (N_B, D), are constructed by experts E_1 and E_2, respectively, over the universal set of farmers

$$U = \{\hat{F}_1, \hat{F}_2, \hat{F}_3, \hat{F}_4\}.$$

The attribute set is defined as

$$D = \{\hat{d}_1, \hat{d}_2, \hat{d}_3, \hat{d}_4, \hat{d}_5\},$$

where the criteria correspond to soil fertility $(\hat{d}_1)$, water availability $(\hat{d}_2)$, seed-handling skill $(\hat{d}_3)$, pest and disease resistance $(\hat{d}_4)$, and market access $(\hat{d}_5)$. Accordingly, the NSM-based MCDM methodology provides a structured evaluation and ranking process that assists the committee in selecting the farmer best suited to receive the subsidy package. Given NSS

$(M_A, D) = \{M_A(\hat{d}_1), M_A(\hat{d}_2), M_A(\hat{d}_3), M_A(\hat{d}_4), M_A(\hat{d}_5)\}$
$M_A(\hat{d}_1) = \{\tilde{F}_1(.9, .6, .3),\ \tilde{F}_2(.4, .1, .1),\ \tilde{F}_3(.7, .3, .2),\ \tilde{F}_4(.5, .3, .3)\}$
$M_A(\hat{d}_2) = \{\tilde{F}_1(.8, .7, .6),\ \tilde{F}_2(.6, .4, .4),\ \tilde{F}_3(.7, .7, .3),\ \tilde{F}_4(.3, .3, .1)\}$
$M_A(\hat{d}_3) = \{\tilde{F}_1(.8, .8, .6),\ \tilde{F}_2(.6, .3, .1),\ \tilde{F}_3(.7, .5, .5),\ \tilde{F}_4(.3, .2, .1)\}$
$M_A(\hat{d}_4) = \{\tilde{F}_1(.6, .5, .5),\ \tilde{F}_2(.4, .3, .2),\ \tilde{F}_3(.7, .6, .5),\ \tilde{F}_4(.6, .6, .3)\}$
$M_A(\hat{d}_5) = \{\tilde{F}_1(.7, .6, .6),\ \tilde{F}_2(.4, .3, .2),\ \tilde{F}_3(.4, .4, .1),\ \tilde{F}_4(.6, .5, .3)\}$

and

$(N_B,D)=\{N_B(\hat{d}_1),N_B(\hat{d}_2),N_B(\hat{d}_3),N_B(\hat{d}_4),N_B(\hat{d}_5)\}$

$N_B(\hat{d}_1)=\{\tilde{F}_1(.7,.4,.1),\ \tilde{F}_2(.6,.3,.3),\ \tilde{F}_3(.7,.5,.4),\ \tilde{F}_4(.7,.5,.3)\}$

$N_B(\hat{d}_2)=\{\tilde{F}_1(.8,.5,.4),\ \tilde{F}_2(.6,.6,.2),\ \tilde{F}_3(.7,.5,.3),\ \tilde{F}_4(.6,.3,.3)\}$

$N_B(\hat{d}_3)=\{\tilde{F}_1(.8,.6,.4),\ \tilde{F}_2(.4,.3,.1),\ \tilde{F}_3(.7,.3,.3),\ \tilde{F}_4(.5,.4,.1)\}$

$N_B(\hat{d}_4)=\{\tilde{F}_1(.8,.7,.5),\ \tilde{F}_2(.5,.5,.4),\ \tilde{F}_3(.9,.4,.3),\ \tilde{F}_4(.8,.6,.3)\}$

$N_B(\hat{d}_5)=\{\tilde{F}_1(.7,.4,.2),\ \tilde{F}_2(.6,.5,.1),\ \tilde{F}_3(.8,.4,.3),\ \tilde{F}_4(.6,.3,.5)\}$

The payoff matrix A is

$$\begin{array}{c} \\ \tilde{F}_1\\ \tilde{F}_2\\ \tilde{F}_3\\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5\\ (.9,.6,.3) & (.8,.7,.6) & (.8,.8,.6) & (.6,.5,.5) & (.7,.6,.6)\\ (.4,.1,.1) & (.6,.4,.4) & (.6,.3,.1) & (.4,.3,.2) & (.4,.3,.2)\\ (.7,.3,.2) & (.7,.7,.3) & (.7,.5,.5) & (.7,.6,.5) & (.4,.4,.1)\\ (.5,.3,.3) & (.3,.3,.1) & (.3,.2,.1) & (.6,.6,.3) & (.6,.5,.3) \end{bmatrix}$$

The payoff matrix B is

$$\begin{array}{c} \\ \tilde{F}_1\\ \tilde{F}_2\\ \tilde{F}_3\\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5\\ (.7,.4,.1) & (.8,.5,.4) & (.8,.6,.4) & (.8,.7,.5) & (.7,.4,.2)\\ (.6,.3,.3) & (.6,.6,.2) & (.4,.3,.1) & (.5,.5,.4) & (.6,.5,.1)\\ (.7,.5,.4) & (.7,.5,.3) & (.7,.3,.3) & (.9,.4,.3) & (.8,.4,.3)\\ (.7,.5,.3) & (.6,.3,.3) & (.5,.4,.1) & (.8,.6,.3) & (.6,.3,.3) \end{bmatrix}$$

a) Crisp value by NSA

$$\begin{array}{c} \\ \tilde{F}_1\\ \tilde{F}_2\\ \tilde{F}_3\\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5\\ (.8,.5,.2) & (.8,.6,.5) & (.8,.7,.5) & (.7,.6,.5) & (.7,.5,.4)\\ (.5,.2,.2) & (.6,.5,.3) & (.5,.3,.1) & (.45,.4,.3) & (.5,.4,.15)\\ (.7,.4,.3) & (.7,.6,.3) & (.7,.4,.4) & (.8,.5,.4) & (.6,.4,.2)\\ (.6,.4,.3) & (.45,.3,.2) & (.4,.3,.1) & (.7,.6,.3) & (.6,.4,.3) \end{bmatrix}$$

The value matrix $V(\mathrm{M1})$ is

$$\begin{array}{c} \\ \tilde{F}_1\\ \tilde{F}_2\\ \tilde{F}_3\\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5\\ .5 & .62 & .68 & .6 & .52\\ .25 & .48 & .3 & .39 & .38\\ .43 & .57 & .45 & .53 & .4\\ .42 & .31 & .28 & .57 & .42 \end{bmatrix}$$

b) Crisp Value by *NSG*

$$\begin{array}{c} \\ \tilde{F}_1\\ \tilde{F}_2\\ \tilde{F}_3\\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5\\ (.79,.49,.17) & (.80,.59,.49) & (.80,.69,.49) & (.69,.59,.50) & (.70,.49,.35)\\ (.49,.17,.17) & (.60,.49,.28) & (.49,.30,.10) & (.45,.39,.28) & (.49,.39,.14)\\ (.70,.39,.28) & (.70,.59,.30) & (.70,.39,.39) & (.79,.49,.39) & (.57,.40,.17)\\ (.59,.39,.30) & (.42,.30,.17) & (.39,.28,.10) & (.69,.60,.30) & (.60,.39,.30) \end{bmatrix}$$

The value matrix $V(M2)$ is

$$\begin{array}{c} \\ \tilde{F}_1\\ \tilde{F}_2\\ \tilde{F}_3\\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5\\ .49 & .61 & .68 & .59 & .50\\ .23 & .47 & .3 & .38 & .36\\ .42 & .56 & .44 & .52 & .39\\ .41 & .30 & .27 & .57 & .41 \end{bmatrix}$$

c) Crisp Value by *NSH*

$$\begin{array}{c} \\ \tilde{F}_1 \\ \tilde{F}_2 \\ \tilde{F}_3 \\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5 \\ (.79,.48,.15) & (.80,.58,.48) & (.80,.69,.48) & (.69,.58,.50) & (.70,.48,.30) \\ (.48,.15,.15) & (.60,.48,.27) & (.48,.30,.10) & (.44,.38,.27) & (.48,.38,.13) \\ (.70,.38,.27) & (.70,.58,.30) & (.70,.38,.38) & (.79,.48,.38) & (.53,.40,.15) \\ (.58,.38,.30) & (.40,.30,.15) & (.38,.27,.10) & (.69,.60,.30) & (.60,.38,.30) \end{bmatrix}$$

The value matrix $V(M3)$ is

$$\begin{array}{c} \\ \tilde{F}_1 \\ \tilde{F}_2 \\ \tilde{F}_3 \\ \tilde{F}_4 \end{array}\begin{bmatrix} \hat{d}_1 & \hat{d}_2 & \hat{d}_3 & \hat{d}_4 & \hat{d}_5 \\ .48 & .60 & .67 & .59 & .49 \\ .21 & .46 & .3 & .37 & .35 \\ .41 & .56 & .43 & .51 & .38 \\ .40 & .29 & .26 & .56 & .40 \end{bmatrix}$$

Decisions are made using the following analysis:

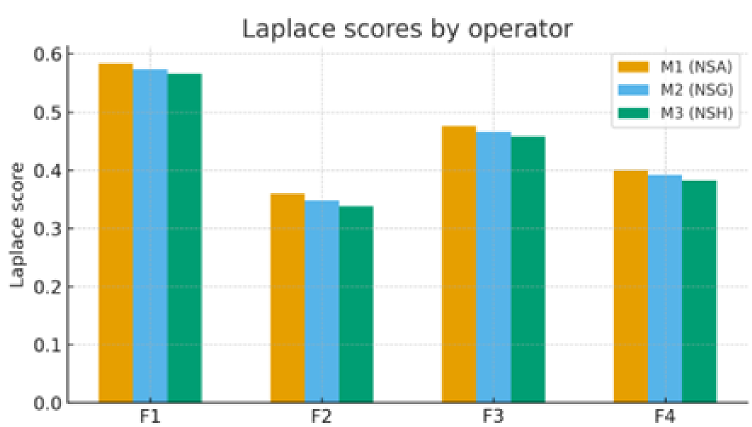
i) **Laplace criterion**

For $S_i = (v_{i1}, \ldots, v_{in})$

$$S_i^{Lap} = \frac{1}{n} \sum_{j=1}^{n} v_{ij}$$

Table 1. Laplace scores by operator

	Alternatives $(\tilde{F}_i)$				**Max value**
V(M1)	.584	.36	.476	.40	**.584**
V(M2)	.574	.348	.466	.392	**.574**
V(M3)	.566	.338	.458	.382	**.566**



We first compare Laplace scores across operators in Table 1. $\tilde{F}_1$ is consistently highest, indicating robustness of the top choice to the fusion rule. Figure 2 provides a compact visual of the same comparison.

ii) **Maximin criterion**

$$S_i^{\max} = \min_j v_{ij}, \qquad S_i^{\max} = \max_j v_{ij}$$

Table 2. Maximin / Maximax

alternative	Payoff matrix					
	1		2		3	
$\tilde{F}_1$	.50	.68	.49	.68	.48	.67
$\tilde{F}_2$	.25	.48	.23	.47	.21	.46
$\tilde{F}_3$	.40	.57	.39	.56	.38	.56
$\tilde{F}_4$	.28	.57	.27	.57	.26	.56
maximin	.5		.49		.48	
maximax	.68		.68		.67	

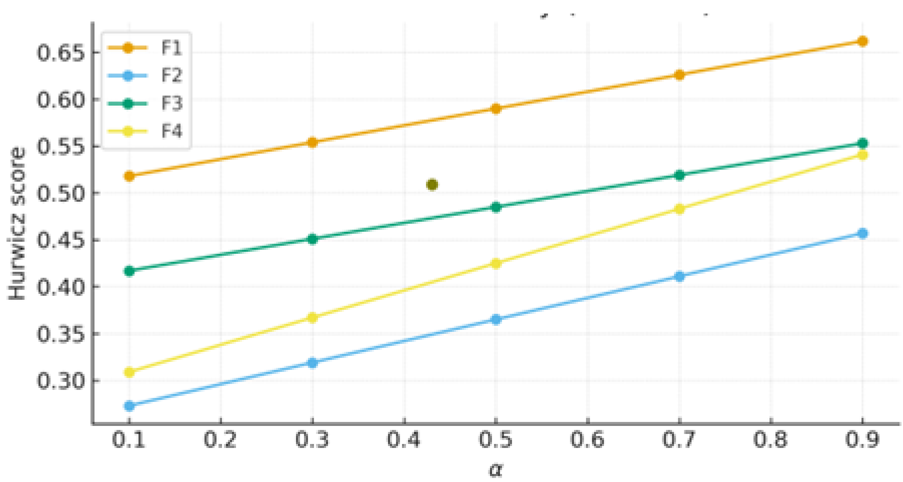
To assess pessimistic and optimistic stances, Table 2 reports per-alternative minima and maxima of the value entries under each operator. $\tilde{F}_1$ retains a competitive lower bound and the largest (or tied) upper bound.

iii) Hurwicz criterion

Weighted average, $h = \alpha\,(\text{max payoff}) + (1-\alpha)(\text{min payoff})$

Table 3. Hurwicz scores at $\alpha = 0.3$

Alternative	NSA operator			NSG operator			NSH operator		
	Max payoff	Min payoff	Wt avg ($\alpha = 0.3$)	Max payoff	Min payoff	Wt avg ($\alpha = 0.3$)	Max payoff	Min payoff	Wt avg ($\alpha = 0.3$)
$\tilde{F}_1$	.68	.5	**.554**	.68	.49	**.547**	.67	.48	**.537**
$\tilde{F}_2$	.48	.25	.319	.47	.23	.302	.46	.21	.285
F_3	.57	.4	.451	.56	.39	.441	.56	.38	.434
$\tilde{F}_4$	.57	.28	.367	.57	.27	.36	.56	.26	.35



Finally, Table 3 and Figure 3 evaluate Hurwicz scores. At $\alpha = 0.3$, the ranking remains $\tilde{F}_1 > \tilde{F}_3 > \tilde{F}_4 > \tilde{F}_2$, and the sensitivity curves are well-separated over α, indicating stability across risk attitudes.

6 Result

Collectively, all three criteria indicate that farmer $\tilde{F}_1$ consistently outperforms the others across decision environments. The results demonstrate the robustness of the NSM framework in capturing uncertainty & providing stable, evidence-based decisions.

7 Limitations

While the method recommended provides certain benefits, it does have some drawbacks. It is largely applied in the agricultural context and could require alterations for application in a different domain. The method of multiple aggregation operators can be computationally expensive for terms of larger datasets. In addition, the performance of various functions and aggregation operators may be sensitive to parameters, possibly impacting decisions. Examine data that can be very ambiguous or conflicting still could provide challenges, and the reliance on the Laplace, Optimism, and Hurwicz criteria could limit the applicability of the results.

8 Future Work

Future research could look to expand the neutrosophic soft set and MCDM framework to larger and more complicated datasets, possibly even in terms of elements with high-dimensional decision problems. This methodology might team up with machine learning, fuzzy systems, or artificial intelligence-based techniques to enhance predictive capability, automate decision making, etc. Also, extending the work further study could focus on examining new aggregation operators, hybrid approaches, and sensitivity analysis to make the framework more robust to extreme uncertainty. The framework could even be adapted potentially cross-domain application in sectors such as health care, finance, environmental management, smart cities, and industrial resource allocation to have an even greater practical effect.

9 Conclusion

This research offered a practical NSMMCDM pipeline included formal operators, value mapping, and formal rules of decision; it illustrated a robust outcome for farmer selection. This research highlights how neutrosophic modelling can transform complex, real-world decision-making problems; this is particularly evident in the context of agricultural decision-making. Future research could extend this work through advanced criterion-weighting (AHP/entropy), calibration of expert reliability, alternative scoring paradigms, and cross-domain applications to enhance both versatility and impact.

Authors' Contributions

All authors have the same contribution.

Data Availability

The manuscript has no associated data or the data will not be deposited.

Conflicts of Interest

The authors declare that there is no conflict of interest.

Ethical Considerations

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