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RESEARCH ARTICLE

A Neutrosophic DEMATEL Framework with MSM Aggregation for Evaluating Food Security Factors

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Abstract Multi-criteria decision-making (MCDM) methods for evaluating complex systems often face challenges in effectively addressing uncertainty, indeterminacy and interdependencies among factors, particularly in decision-makers (DMs) based assessments. To overcome these limitations, this study proposes a hybrid framework that integrates the Neutrosophic Set (NS) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) method with the Maclaurin Symmetric Mean (MSM) aggregation operator. The MSM operator accounts for the symmetric interrelationships among expert evaluations, enabling more robust and consistent aggregation compared to traditional techniques. The proposed method is applied to a case study on food security (FdS) which is a study characterized by multidimensional and interrelated factors. By combining the strengths of NS and MSM aggregation within the DEMATEL framework, the model yields clearer causal structures and more reliable prioritisation of influencing factors. This facilitates improved strategic planning and policy development in complex and uncertain environments. The integration of MSM into NS-DEMATEL represents a methodological enhancement in MCDM under uncertainty, offering practical value for enhancing FdS strategies and supporting broader sustainable development objectives.

Keywords: Neutrosophic; Maclaurin Symmetric Mean; DEMATEL; Food Security; MCDM.

Introduction

Decision-making in complex systems often involves evaluating multiple interrelated factors under conditions of uncertainty and ambiguity. Multi-criteria decision-making (MCDM) techniques have been widely used to support such evaluations, with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method being particularly effective in identifying cause-effect relationships among factors [1]. DEMATEL enables decision-maker (DM) to model interdependencies within systems, offering clear visual representations of influence levels among criteria through directed graphs and matrix-based structures. However, traditional DEMATEL methods frequently rely on crisp or fuzzy data, which may not adequately capture the inherent vagueness and indeterminacy of human judgment.

To address this limitation, the Neutrosophic Set (NS) theory has emerged as a generalization of classical and fuzzy set theories. It allows for more broad representations of uncertainty through three independent membership degrees: truth (T), falsity (F), and indeterminacy (I) with each ranging independently from 0 to 1 [2]. NS has proven useful in various domains, including decision analysis [3], stability assessment [4], and distribution management systems [5] as it accommodates incomplete, inconsistent, or conflicting information more effectively than conventional frameworks. When integrated with DEMATEL, NS enhances the reliability of expert input representation in uncertain environments.

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In addition to uncertainty, aggregating expert evaluations remains a critical step in MCDM applications. Traditional aggregation methods, such as the arithmetic mean often neglects the interactions among criteria, which may lead to biased or imprecise outcomes. To improve this process, the Maclaurin Symmetric Mean (MSM) operator has been introduced as a more robust aggregation approach. MSM is capable of capturing the interrelationships among multiple inputs by considering the combined effects of variables symmetrically [6]. This makes it particularly suitable in environments where criteria are not independent and interaction effects influence decision outcomes. Compared to arithmetic means, MSM provides more consistent and representative aggregation, especially in systems with high complexity or data variability.

The MSM operator has been effectively utilized in various fuzzy environments. For instance, Hussain *et al*. [6] applied the MSM operator within the framework of intuitionistic fuzzy sets (IFS) for MCDM. Mu *et al*. [7] extended its application to Pythagorean fuzzy sets, while Liu *et al*. [8] employed it under the orthopair fuzzy set context. Additionally, Yang *et al*. [9] integrated the MSM operator into the neutrosophic environment. However, while previous studies have explored the integration of MSM with various fuzzy logic models, there is still a notable gap in the literature regarding the combination of the neutrosophic MSM operator with the DEMATEL method. This integration is particularly important, as DEMATEL is well-suited for analyzing and modeling complex interrelationships among criteria.

Extending the previous methodological work, this study proposes an integrated approach combining the NS-MSM operator with the DEMATEL method to address a real-world, complex decision problem which is food security (FdS). This integration aims to better capture both the uncertainty and the intricate interrelationships among the factors influencing FdS. FdS is a multidimensional issue closely tied to sustainability, public health, and economic development. The World Food Summit [10] defines food security as a state in which all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life. FdS is generally assessed across four key dimensions: availability, access, utilization, and stability. These dimensions are influenced by a range of factors including natural resources, population dynamics, governance, infrastructure, education, and resilience to crises such as climate change or pandemics.

Despite the increasing number of studies evaluating factors affecting FdS using MCDM tools, certain methodological gaps exist. Prior works, such as those by Dubey and Tanksale [11] and Liu *et al*. [12] have applied fuzzy DEMATEL to study food-related systems, yet most rely on conventional fuzzy set and simple averaging techniques for data aggregation. These methods do not adequately capture the uncertainty or interdependencies inherent in food security assessments. The use of NS in this field remains limited and the application of MSM aggregation operator is virtually absent in the literature. Consequently, reliance on arithmetic mean-based aggregation may yield oversimplified or inaccurate results, particularly in the presence of interrelated variables or expert disagreement.

To address these research gaps, this study proposes an integrated decision-making method that combines NS, the MSM aggregation operator and the DEMATEL method. The primary objective is to manage uncertainty in expert evaluations using NS, enhance aggregation precision through MSM and analyze the causal relationships among key FdS factors using DEMATEL. A case study is conducted involving eight core factors relevant to FdS, including land and water resources, population growth, governance, education and awareness, and resilience to shocks and crises. Through this study, an extended DEMATEL framework has contributed to enhanced decision-making accuracy in complex MCDM problems.

Preliminaries

Neutrosophic Set (NS)

NS, introduced by Florentin Smarandache in 1995 [13], emphasizes the study of neutralities, their nature, origins and the interactions across domains. The word “Neutrosophy” is a combination of word “neutral” and the Greek word “sophia” (wisdom), which gives the meaning of “the knowledge of neutral thought”. The simplest form of a NS can be defined as the following section.

Definition of NS [14]

NS, A in the universe U is of the form

$$A = \{(x, T_A(x), I_A(x), F_A(x)) : x \in U, T_A(x), I_A(x), F_A(x) \in [0,1]\} \quad (1)$$

In the equation (1), $T(x)$, $I(x)$, and $F(x)$ are the degree of Truth, Indeterminacy and Falsity of x in A respectively, which can be called as neutrosophic components of x. If the sum of $T(x)$, $I(x)$, and $F(x)$ is between 0 and 3, the set can be called a single-valued neutrosophic set (SVNS). For simplicity, a single-valued neutrosophic number (SVNN) $(\alpha, T_A(\alpha), I_A(\alpha), F_A(\alpha))$ in A can be denoted as $\alpha = (\alpha_T, \alpha_I, \alpha_F)$, where $\alpha_T, \alpha_I, \alpha_F \in [0,1]$ and $0 \leq \alpha_T + \alpha_I + \alpha_F \leq 3$.

Arithmetic Operations of NS [14]

The basic operations of two SVNN, $A = (\alpha_T, \alpha_I, \alpha_F)$ and $B = (\beta_T, \beta_I, \beta_F)$ are defined as follows:

(i) Arithmetic Operations of NS

$$A^c = (\alpha_T, 1 - \alpha_I, \alpha_F) \quad (2)$$

(ii) Addition of A and B

$$A \oplus B = (\alpha_T + \beta_T - \alpha_T\beta_T, \alpha_I\beta_I, \alpha_F\beta_F) \quad (3)$$

(iii) Multiplication of A and B

$$A \otimes B = (\alpha_T\beta_T, \alpha_I + \beta_I - \alpha_I\beta_I, \alpha_F + \beta_F - \alpha_F\beta_F) \quad (4)$$

(iv) Scalar Multiplication of A, $\lambda \in \mathbb{R}$

$$\lambda A = (1 - (1 - \alpha_T)^\lambda, \alpha_I^\lambda, \alpha_F^\lambda) \quad (5)$$

(v) Power of A, $k \in \mathbb{R}$

$$A^k = (\alpha_T^k, 1 - (1 - \alpha_I)^k, 1 - (1 - \alpha_F)^k) \quad (6)$$

The linguistic variables of Neutrosophic Set

Let h_i represents a fuzzy linguistic term. Let $H = \{h_0, h_1, \ldots, h_{2n}\}$ is a set of linguistic terms (LTS). The length of H is 2n+1 [14] and the fuzzy linguistic scale of NS was tabulated as Table 1 [15]. For instance, an LTS with five terms is given as below:

$$H = \{h_0 = Extreme\ Low, h_1 = Low, h_2 = Moderate, h_3 = High, h_4 = Extreme\ High\}$$

Table 1. Linguistic variables for Neutrosophic numbers

Influence Score	Linguistic Variable	Neutrosophic Numbers (T, I, F)
0	No Influence	(0.10,0.90,1.00)
1	Very Low Influence	(0.30,0.70,0.75)
2	Low Influence	(0.50,0.50,0.50)
3	High Influence	(0.80,0.20,0.25)
4	Very High Influence	(1.00,0.10,0.00)

DMs evaluate the influence of the studied factors by assigning a linguistic score, typically 0 - 4 where 0 = no influence and 4 = very high influence. The linguistic score will be fuzzified based on Table 1 and aggregated using MSM operator.

Maclaurin Symmetric Mean (MSM)

The MSM operator is a mathematical operator used to aggregate a set of non-negative real numbers in a way that reflects their symmetrical importance. Given a collection of numbers u_r (r=1,2,3…,m) and a chosen parameter k (k=1,2…,m) the MSM is defined by Deli & Öztürk [16].

$$MSM_k(u_1, u_2, \dots, u_m) = \frac{\sum_{1 \le r_1 < \dots < r_k \le m} \left(\prod_{i=1}^{k} u_{r_i}\right)^{\frac{1}{k}}}{C_m^k} \tag{8}$$

MSM$^{(k)}$ is the MSM, where $(r_1, r_2, \dots, r_k)$ traverses every k-tuple combination of (1, 2,…,m) and $C_m^k = \frac{m!}{k!(m-k)!}$ is the binomial coefficient. By implementing the MSM formula with the arithmetic operations of NS in (2) to (6), the Single Value Neutrosophic Number Maclaurin Symmetric Mean (SVNNMSM) are as follows [17]:

When $k = 1$, the SVNNMSM operator reduces to the average operator.

$$SVNNMSM_{(1)}(S_1, S_2, \dots S_n) = \langle \left(1 - \prod_{k=1}^{n}(1 - T_k)^{\frac{1}{n}}\right), \prod_{k=1}^{n}(I_k)^{\frac{1}{n}}, \prod_{k=1}^{n}(F_k)^{\frac{1}{n}} \rangle \tag{9}$$

When $k = 2$, the SVNNMSM operator reduces to the Bonferroni Mean (BM) operator.

$$SVNNMSM_{(2)}(S_1, S_2, \dots, S_n) = \left[1 - \prod_{k=2}^{C_n^2}\left(\{1 - T_{i1(k)} T_{i2(k)}\}^{\frac{1}{C_n^2}}\right)^{\frac{1}{2}}\right],$$
$$\langle \left[1 - \left\{1 - \prod_{k=2}^{C_2^n}\left(1 - \left[1 - I_{i1(k)}\left\{1 - I_{i2(k)}\right\}\right]^{\frac{1}{C_n^2}}\right)^{\frac{1}{2}}\right\}\right], \rangle \tag{10}$$
$$\left[1 - \left\{1 - \prod_{k=2}^{C_2^n}\left(1 - \left[1 - F_{i1(k)}\left\{1 - F_{i2(k)}\right\}\right]^{\frac{1}{C_n^2}}\right)^{\frac{1}{2}}\right\}\right]$$

When $k = n$, the SVNNMSM operator reduces to the geometric mean operator.

$$SVNNMSM_{(n)}(S_1, S_2, \dots, S_n) = \langle \prod_{k=2}^{n} (T_k)^{\frac{1}{n}}, 1 - (\prod_{k=2}^{n}(1 - I_k))^{\frac{1}{n}}, 1 - (\prod_{k=2}^{n}(1 - F_k))^{\frac{1}{n}} \rangle \tag{11}$$

Decision-Making Trial and Evaluation Laboratory (DEMATEL)

DEMATEL is a structured methodology used to visualize and analyse complex decision-making problems, particularly when addressing interrelationships between factors.

Algorithm of DEMATEL

Step 1: Construction of an Initial Direct-Relation Matrix, $\boldsymbol{D}$

Table 2. Initial Direct-Relation Matrix, $\boldsymbol{D}$

Factors	**F1**	**F2**	**….**	**F8**
F1				
F2				
…				
F8				

Step 2: Normalize the matrix $\boldsymbol{D}$

The Normalized Initial Direct-Relation Matrix, $\boldsymbol{D_N}$ is calculated using the formula:

$$\boldsymbol{D_N} = \frac{\boldsymbol{D}}{\max(\sum \boldsymbol{D_{row}})} \tag{12}$$

Step 3: Calculation of the Total-Relation Matrix, $\boldsymbol{T}$
The Total-Relation Matrix, $\boldsymbol{T}$ is calculated using the formula

$$\boldsymbol{T} = \boldsymbol{D_N} \times (\boldsymbol{I_8} - \boldsymbol{D_N})^{-1}, \text{where } \boldsymbol{I_8} \text{ is the } 8 \times 8 \text{ Identity Matrix} \tag{13}$$

Step 4: Interpretation of the results from the Total-Relation Matrix, $\boldsymbol{T}$
Two key indicators, the significance indicator, s and the relation indicator, r will be calculated using the formula:

$$s_i = Row\ Sum_i + Column\ Sum_i \tag{14}$$
$$r_i = Row\ Sum_i - Column\ Sum_i \tag{15}$$

A positive r value indicates a causal factor, while a negative r suggests an effect. The most positive r values signify the most influential factors, whereas the most negative r values represent factors most influenced by others in the system.

Integration of NS-MSM-DEMATEL in Food Security

FdS ensures a continued focus on FdS corresponding to the growth of the population and increasing nutritional demands, as what was embedded in the second Sustainable Development Goal (SDG) of Zero Hunger [18]. The growing of the human population or urbanization has gradually impacted on FdS, which demands various dietary and nutrition, in order to provide balanced diet to the community. Moreover, climate change [19] and the outbreak of viruses [20] are some of the verified challenges and factors that affect the balance of FdS. Therefore, it is important to identify more potential factors that can affect the stability of FdS.

These global challenges also manifest at the national and local levels, particularly in countries like Malaysia. While relatively food-secure at the national level, Malaysia faces rising concerns about sustainability due to rapid urbanization, heavy dependence on food imports and climate-related disruptions. The Covid-19 pandemic further exposed the vulnerability of food supply chains, particularly in highly populated urban areas like Kuala Lumpur and Selangor. Urban households, especially in low-income communities, experienced reduced food access due to rising prices, supply interruptions and unemployment during lockdowns. Limited space and lack of awareness restricted local food production, while over-reliance on imported products raised concerns about long-term FdS. The integration of NS-MSM-DEMATEL enables a more precise and accurate analysis of the interdependencies among FdS factors under uncertainty, where NS captures vagueness, MSM ensures stable aggregation of DMs' evaluations and DEMATEL reveals the structural influence pattern among the variables. The key factors or criteria relevant to the FdS problem in this study were defined in Table 3 [21 – 26].

Table 3. The eight factors studied in this study

No.	Factors	Description
F1	Climate patterns	How changing weather patterns impact crop yield, water availability, and agricultural productivity.
F2	Land and Water Resources	How changing weather patterns impact crop yield, water availability, and agricultural productivity.
F3	Seed and Fertilizer Availability	Access to quality seeds, fertilizers, and agricultural inputs.
F4	Economic Access	Household income, employment, and purchasing power to afford food.
F5	Population Growth	Rising population and urbanization trends affect food demand.
F6	Food Distribution Network	Proximity to food markets and transportation.
F7	Education and Awareness	Knowledge of healthy eating practices, food safety, nutrition education, food preparation knowledge.
F8	Resilience to Shocks and Crises	Investigating how resilient communities are to sudden shocks and the effectiveness of food security safety nets, such as emergency food reserves (adaptive strategies)

The criteria are evaluated by three decision-makers (DMs) consisted of a food staller, a chef and a lecturer. The selection of DMs was based on expertise, practical experience, and representativeness of different dimensions of the food security system. The food staller represents the grassroots and market-level perspective, offering direct insight into food availability, supply chain disruptions, pricing dynamics, and consumer access. The chef contributes expertise related to food utilization, nutrition, food safety, and preparation practices, which are critical components of food security. The lecturer provides an academic and policy-oriented viewpoint, with a systems-level understanding of governance, education, resilience, and sustainability issues affecting food security. By combining these complementary perspectives, the study ensures balanced representation across the practical, operational, and analytical dimensions of food security.

Procedure

Step 1: Data Collection from DMs

The influence scores from the three DMs were evaluated using neutrosophic numbers based on Table 1. For example, the data from DM1 is given as in Table 4.

Table 4. The data from DM1

Factors/ Factors	F1	F2	F3	F4	F5	F6	F7	F8
F1	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)
F2	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(1.00, 0.10, 0.00)	(0.10 , 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)
F3	(0.80, 0.20, 0.25)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)
F4	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)
F5	(0.30, 0.70, 0.75)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)
F6	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)
F7	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.30, 0.70, 0.75)
F8	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.50, 0.50, 0.50)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.50, 0.50, 0.50)	(0.10, 0.90, 1.00)

Step 2: Aggregation by MSM.

The evaluations are aggregated using MSM operator based on the equation (9) - (11).

Step 2.1: The $SVNNMSM_{(1)}$ for the influence score of each of the factors to other factors respectively from DM1, DM2 and DM3 were calculated by using the formula 3.9.

For instance, the fuzzified data for the influence score of F5 to F2, a_{52} from each of the DMs are given as follows:

$$DM_1(a_{52}) = \left(T_1(a_{52}), I_1(a_{52}), F_1(a_{52})\right) = (0.10,0.90,1.00)$$
$$DM_2(a_{52}) = \left(T_2(a_{52}), I_2(a_{52}), F_2(a_{52})\right) = (0.50,0.50,0.50)$$
$$DM_3(a_{52}) = \left(T_3(a_{52}), I_3(a_{52}), F_3(a_{52})\right) = (0.80,0.30,0.25)$$

where a_{52} represents the influence of F5 to F2.

Therefore, the $SVNNMSM_{(1)}(a_{52})$ is calculated by using the equation (9), as follows:

$$SVNNMSM_{(1)}(a_{52}) = \left\langle \begin{array}{c} \left[1-\left\{(1-T_1(a_{52}))^{\frac{1}{n}} \times (1-T_2(a_{52}))^{\frac{1}{n}} \times (1-T_3(a_{52}))^{\frac{1}{n}}\right\}\right], \\ \left[I_1(a_{52})^{\frac{1}{n}}\right] \times \left[I_2(a_{52})^{\frac{1}{n}}\right] \times \left[I_3(a_{52})^{\frac{1}{n}}\right], \\ \left[F_1(a_{52})^{\frac{1}{n}}\right] \times \left[F_2(a_{52})^{\frac{1}{n}}\right] \times \left[F_3(a_{52})^{\frac{1}{n}}\right] \end{array} \right\rangle$$

where $n = 3$ as there are 3 DMs involved in this survey.

Then the formula can be simplified to

$$SVNNMSM_{(1)}(a_{52}) = \left\langle \begin{array}{c} 1-\sqrt[3]{[1-T_1(a_{52})] \times [1-T_2(a_{52})] \times [1-T_3(a_{52})]}, \\ \sqrt[3]{I_1(a_{52}) \times I_2(a_{52}) \times I_3(a_{52})}, \\ \sqrt[3]{F_1(a_{52}) \times F_2(a_{52}) \times F_3(a_{52})} \end{array} \right\rangle$$

By substituting the respective values into the equation, the calculation is as follows:

$$SVNNMSM_{(1)}(a_{52}) = \left\langle \begin{array}{c} 1-\sqrt[3]{[1-0.1] \times [1-0.5] \times [1-0.8]}, \\ \sqrt[3]{0.9 \times 0.5 \times 0.3}, \\ \sqrt[3]{1 \times 0.5 \times 0.25} \end{array} \right\rangle$$
$$= \langle 0.5519, 0.5130, 0.5000 \rangle \ (4\ DP)$$

Thus, this is the $SVNNMSM_{(1)}$ of the influence score of F5 to F2.
The same calculation process was applied to the others' influence scores. By implementing equation (9). the $SVNNMSM_{(1)}$ data from DM1, DM2 and DM3 are presented in Table 5.

Table 5. The $SVNNMSM_{(1)}$ data

Factors/ Factors	F1	F2	F3	F4	F5	F6	F7	F8
F1	(0.10, 0.90, 1.00)	(1.00, 0.21, 0.00)	(1.00, 0.25, 0.00)	(1.00, 0.30, 0.00)	(1.00, 0.30, 0.00)	(1.00, 0.36, 0.00)	(0.55, 0.51, 0.50)	(1.00, 0.21, 0.00)
F2	(1.00, 0.25, 0.00)	(0.10, 0.90, 1.00)	(0.10, 0.90, 1.00)	(0.55, 0.51, 0.50)	(1.00, 0.10, 0.00)	(1.00, 0.30, 0.00)	(1.00, 0.30, 0.00)	(1.00, 0.25, 0.00)
F3	(1.00, 0.14, 0.00)	(1.00, 0.30, 0.00)	(0.10, 0.90, 1.00)	(0.55, 0.51, 0.50)	(1.00, 0.30, 0.00)	(1.00, 0.21, 0.00)	(1.00, 0.30, 0.00)	(1.00, 0.30, 0.00)
F4	(0.67, 0.43, 0.40)	(1.00, 0.36, 0.00)	(1.00, 0.29, 0.00)	(0.10, 0.90, 1.00)	(1.00, 0.21, 0.00)	(1.00, 0.36, 0.00)	(1.00, 0.25, 0.00)	(1.00, 0.30, 0.00)
F5	(1.00, 0.33, 0.00)	(0.55, 0.51, 0.50)	(1.00, 0.30, 0.00)	(1.00, 0.36, 0.00)	(0.10, 0.90, 1.00)	(1.00, 0.36, 0.00)	(0.59, 0.47, 0.45)	(1.00, 0.30, 0.00)
F6	(0.39, 0.61, 0.63)	(1.00, 0.30, 0.00)	(1.00, 0.21, 0.00)	(1.00, 0.29, 0.00)	(1.00, 0.43, 0.00)	(0.10, 0.90, 1.00)	(1.00, 0.21, 0.00)	(0.55, 0.51, 0.50)
F7	(1.00, 0.17, 0.00)	(1.00, 0.30, 0.00)	(1.00, 0.14, 0.00)	(1.00, 0.30, 0.00)	(0.67, 0.43, 0.40)	(0.55, 0.10, 0.50)	(0.10, 0.90, 1.00)	(0.59, 0.47, 0.45)
F8	(1.00, 0.21, 0.00)	(1.00, 0.29, 0.00)	(1.00, 0.21, 0.00)	(1.00, 0.14, 0.,00)	(1.00, 0.21, 0.00)	(0.67, 0.43, 0.40)	(0.73, 0.36, 0.31)	(0.10, 0.90, 1.00)

Step 2.2: the $SVNNMSM_{(2)}$ of the influence score for each of the factors to other factors for the combination of DM1 DM2, DM1 DM3 and DM2 DM3 were calculated by using equation (10).

For example, by considering the same data set from the previous part, that is the influence score of F5 to F2 from each of the DMs, the formula of $SVNNMSM_{(2)}$ for the combination of DM1 and DM2 from formula 3.10, is given as follows:

$$SVNNMSM_{(2)}(DM1(a_{52}), DM2(a_{52})) = \begin{matrix} \left[1 - \prod_{k=1}^{C_n^2}\left(\left\{1 - T_{1(k)}(a_{52})T_{2(k)}(a_{52})\right\}^{\frac{1}{C_n^2}}\right)^{\frac{1}{2}}\right], \\ \langle\left[1 - \left\{1 - \prod_{k=1}^{C_n^2}\left(1 - \left\{1 - I_{1(k)}(a_{52})\left[1 - I_{2(k)}(a_{52})\right]\right\}^{\frac{1}{C_n^2}}\right)^{\frac{1}{2}}\right\}\right],\rangle \\ \left[1 - \left\{1 - \prod_{k=1}^{C_n^2}\left(1 - \left\{1 - F_{1(k)}(a_{52})\left[1 - F_{2(k)}(a_{52})\right]\right\}^{\frac{1}{C_n^2}}\right)^{\frac{1}{2}}\right\}\right] \end{matrix}$$

Now, take $n = 2$ as there are 2 DMs involved in this combination.

$$C_2^2 = \frac{2!}{2!\,(2-2)!} = 1$$

Then, the formula is simplified to

$$SVNNMSM_{(2)}(DM1(a_{52}), DM2(a_{52})) = \langle \begin{matrix} \left[1 - \prod_{k=1}^{1}\left(\left\{1 - T_{1(k)}(a_{52})T_{2(k)}(a_{52})\right\}^{1}\right)^{\frac{1}{2}}\right], \\ \left[1 - \left\{1 - \prod_{k=1}^{1}\left(1 - \left\{1 - I_{1(k)}(a_{52})\left[1 - I_{2(k)}(a_{52})\right]\right\}^{1}\right)^{\frac{1}{2}}\right\}\right], \\ \left[1 - \left\{1 - \prod_{k=1}^{1}\left(1 - \left\{1 - F_{1(k)}(a_{52})\left[1 - F_{2(k)}(a_{52})\right]\right\}^{1}\right)^{\frac{1}{2}}\right\}\right] \end{matrix} \rangle$$

$$SVNNMSM_{(2)}(DM1(a_{52}), DM2(a_{52})) = \langle \begin{matrix} \left[1 - \sqrt{1 - T_1(a_{52})T_2(a_{52})}\right], \\ \left[1 - \left(1 - \sqrt{1 - I_1(a_{52})\{1 - I_2(a_{52})\}}\right)\right], \\ \left[1 - \left(1 - \sqrt{1 - F_1(a_{52})\{1 - F_2(a_{52})\}}\right)\right] \end{matrix} \rangle$$

$$SVNNMSM_{(2)}(DM1(a_{52}), DM2(a_{52})) = \langle \begin{matrix} \left[1 - \sqrt{1 - T_1(a_{52})T_2(a_{52})}\right], \\ \sqrt{1 - I_1(a_{52})\{1 - I_2(a_{52})\}}, \\ \sqrt{1 - F_1(a_{52})\{1 - F_2(a_{52})\}} \end{matrix} \rangle$$

By substituting the respective data of the influence score of F5 to F2 from DM1 and DM2, the $SVNNMSM_{(2)}(DM1, DM2)$ is calculated as follows:

$$SVNNMSM_{(2)}(DM1(a_{52}), DM2(a_{52})) = \langle\left[1 - \sqrt{1 - 0.1 \times 0.5}\right], \sqrt{1 - 0.9\{1 - 0.5\}}, \sqrt{1 - 1\{1 - 0.5\}}\rangle$$

$$SVNNMSM_{(2)}(DM1(a_{52}), DM2(a_{52})) = \langle 0.0253, 0.7416, 0.7071\rangle \ (4\ DP)$$

Step 2.3: The process is repeated for the combination of DM1 with DM3, $SVNNMSM_{(2)}(DM1, DM3)$ and DM2 with DM3, $SVNNMSM_{(2)}(DM2, DM3)$ respectively.

Step 2.4: The MSM aggregation operator is calculated from the three sets of $SVNNMSM_{(2)}$ data obtained in Step 2.1 to 2.3, using equation (11), as follows:

$$SVNNMSM_{(n)}(DM1, DM2, DM3) = \left\langle \begin{array}{c} \prod_{k=1}^{n} (T_k)^{\frac{1}{n}}, \\ \left[1 - \left(\prod_{k=1}^{n} (1 - I_k)\right)^{\frac{1}{n}}\right], \\ \left[1 - \left(\prod_{k=1}^{n} (1 - F_k)\right)^{\frac{1}{n}}\right] \end{array} \right\rangle$$

where $m = n = 3$, as there are 3 sets of $SVNNMSM_{(2)}$ to be aggregated.

Thus, the formula can be simplified to

$$SVNNMSM_{(3)}(DM1, DM2, DM3) = \left\langle \begin{array}{c} \prod_{k=1}^{3} (T_k)^{\frac{1}{3}}, \\ \left[1 - \left(\prod_{k=1}^{3} (1 - I_k)\right)^{\frac{1}{3}}\right], \\ \left[1 - \left(\prod_{k=1}^{3} (1 - F_k)\right)^{\frac{1}{3}}\right] \end{array} \right\rangle$$

$$SVNNMSM_{(3)}(DM1, DM2, DM3) = \left\langle \begin{array}{c} \sqrt[3]{T_1 \times T_2 \times T_3}, \\ \left[1 - \sqrt[3]{(1 - I_1)(1 - I_2)(1 - I_3)}\right], \\ \left[1 - \sqrt[3]{(1 - F_1)(1 - F_2)(1 - F_3)}\right] \end{array} \right\rangle$$

where

$SVNNMSM_{(2)}(DM1, DM2) = (T_1, I_1, F_1)$
$SVNNMSM_{(2)}(DM1, DM3) = (T_2, I_2, F_2)$
$SVNNMSM_{(2)}(DM2, DM3) = (T_3, I_3, F_3)$

For example, all the $SVNNMSM_{(2)}$ values for a_{52} are given as:

$$SVNNMSM_{(2)}(DM1(a_{52}), DM2(a_{52})) = (0.0253, 0.7416, 0.7071)$$
$$SVNNMSM_{(2)}(DM1(a_{52}), DM3(a_{52})) = (0.0408, 0.6083, 0.5000)$$
$$SVNNMSM_{(2)}(DM2(a_{52}), DM3(a_{52})) = (0.2254, 0.8062, 0.7906)$$

Thus, the value of $SVNNMSM_{(3)}(DM1(a_{52}), DM2(a_{52}), DM3(a_{52}))$ is calculated as follows:

$$SVNNMSM_{(3)}(DM1(a_{52}), DM2(a_{52}), DM3(a_{52})) = \left\langle \begin{array}{c} \sqrt[3]{0.0253 \times 0.0408 \times 0.2254}, \\ 1 - \sqrt[3]{(1 - 0.7416)(1 - 0.6083)(1 - 0.8062)}, \\ 1 - \sqrt[3]{(1 - 0.7071)(1 - 0.500)(1 - 0.7906)} \end{array} \right\rangle$$

$$SVNNMSM_{(3)}(DM1(a_{52}), DM2(a_{52}), DM3(a_{52})) = \langle 0.0615, 0.7303, 0.6870 \rangle$$

The output of the aggregation is presented in Table 6.

Table 6. Aggregated Influence Scores from all DMs

Factors/ Factors	F1	F2	F3	F4	F5	F6	F7	F8
F1	(0.10, 0.95, 1.00)	(0.14, 0.76, 1.00)	(0.33, 0.81, 0.80)	(0.11, 0.80, 1.00)	(0.11, 0.80, 1.00)	(0.07, 0.66, 0.56)	(0.06, 0.73, 0.69)	(0.50, 0.87, 0.88)
F2	(0.33, 0.81, 0.80)	(0.01, 0.95, 1.00)	(0.14, 0.76, 1.00)	(0.06, 0.80, 0.79)	(1.00, 0.95, 0.00)	(0.11, 0.68, 0.59)	(0.11, 0.68, 0.59)	(0.33, 0.88, 1.00)
F3	(0.67, 0.90, 1.00)	(0.11, 0.68, 0.59)	(0.01, 0.95, 1.00)	(0.06, 0.80, 0.79)	(0.11, 0.80, 1.00)	(0.14, 0.76, 1.00)	(0.11, 0.68, 0.59)	(0.11, 0.80, 1.00)
F4	(0.09, 0.74, 0.71)	(0.07, 0.66, 0.56)	(0.23, 0.79, 0.77)	(0.10, 0.95, 1.00)	(0.14, 0.76, 1.00)	(0.07, 0.66, 0.56)	(0.33, 0.81, 0.80)	(0.11, 0.80, 1.00)
F5	(0.16, 0.73, 0.69)	(0.06, 0.73, 0.69)	(0.11, 0.80, 1.00)	(0.07, 0.66, 0.56)	(0.01, 0.95, 1.00)	(0.07, 0.66, 0.56)	(0.13, 0.84, 0.83)	(0.11, 0.68, 0.59)
F6	(0.04, 0.79, 0.77)	(0.11, 0.68, 0.59)	(0.14, 0.76, 1.00)	(0.23, 0.79, 0.77)	(0.02, 0.76, 1.00)	(0.10, 0.95, 1.00)	(0.14, 0.76, 1.00)	(0.06, 0.73, 0.69)
F7	(0.44, 0.85, 1.00)	(0.11, 0.68, 0.59)	(0.67, 0.90, 1.00)	(0.11, 0.68, 0.59)	(0.09, 0.74, 0.71)	(0.06, 0.73, 0.69)	(0.01, 0.95, 1.00)	(0.13, 0.78, 0.75)
F8	(0.14, 0.76, 1.00)	(0.23, 0.79, 0.77)	(0.50, 0.92, 1.00)	(0.67, 0.90, 1.00)	(0.14, 0.76, 1.00)	(0.09, 0.74, 0.71)	(0.27, 0.84, 0.84)	(0.10, 0.95, 1.00)

Step 4: Defuzzification of the neutrosophic numbers
In this study, the score function is employed for defuzzification due to its suitability for single valued neutrosophic numbers, as it simultaneously incorporates the degrees of truth, indeterminacy, and falsity into a single crisp value. This allows uncertainty and hesitation in expert judgments to be preserved during the defuzzification process. In contrast, other defuzzification approaches such as centroid method is primarily geometry-based and does not explicitly account for indeterminacy, while the max-membership method considers only the dominant membership degree and may result in information loss. Moreover, the DEMATEL method involves repeated matrix operations that require numerical stability and computational efficiency, both of which are effectively supported by the score function. Given these advantages and its widespread adoption in MCDM studies, the score function is selected as an appropriate and reliable defuzzification approach in this study.

The aggregated score are defuzzified using the score function defined by [16]:

$$\sigma_s(a) = \frac{T_x(a)+I_x(a)-F_x(a)+1}{3} \tag{7}$$

From the previous example, the aggregated neutrosophic score is:

$$SVNNMSM_{(3)}(DM1(a_{52}), DM2(a_{52}), DM3(a_{52})) = \langle 0.0615, 0.7303, 0.6870 \rangle$$

The defuzzified influence score for a_{52} is computed as follows:

$$\begin{aligned} \sigma_s(a_{52}) &= \frac{T_x(a_{52}) + I_x(a_{52}) - F_x(a_{52}) + 1}{3} \\ &= \frac{0.0615 + 0.7303 - 0.6870 + 1}{3} \\ &= 0.3683\ (4\ DP) \end{aligned}$$

The remaining influence scores are presented in Table 7.

Table 7. The defuzzied MSM of the data

	F1	F2	F3	F4	F5	F6	F7	F8	Total column
F1	0.3197	0.2978	0.4465	0.3020	0.3020	0.3928	0.3683	0.4947	2.9238
F2	0.4465	0.3197	0.2978	0.3580	0.6513	0.3977	0.3977	0.4035	**3.2721**
F3	0.5248	0.3977	0.3197	0.3580	0.3020	0.2978	0.3977	0.3020	2.8996
F4	0.3737	0.3928	0.4146	0.3197	0.2978	0.3928	0.4465	0.3020	2.9398
F5	0.3995	0.3683	0.3020	0.3928	0.3197	0.3928	0.3781	0.3977	2.9508
F6	0.3541	0.3977	0.2978	0.4146	0.2596	0.3197	0.2978	0.3683	2.7095
F7	0.4319	0.3977	0.5248	0.3977	0.3737	0.3683	0.3197	0.3855	3.1991
F8	0.2978	0.4146	0.4710	0.5248	0.2978	0.3737	0.4249	0.3197	3.1242
Total row	3.1479	2.9862	3.0742	3.0674	2.8039	2.9354	3.0307	2.9733	3.1479

Step 5: DEMATEL

The DEMATEL was integrated with the data in Table 7 to analyse the causal relationship among the eight factors studied. The Initial Direct-Relation Matrix, $\boldsymbol{D}$ is derived from the defuzzified $SVNNMSM_{(3)}$ values.

To normalize the matrix, all entries in $\boldsymbol{D}$ are divided by the highest value of the row and column sums (equation (12)) which is 3.2721. The Normalized Initial Direct-Relation Matrix is presented in Table 8.

Table 8. The Normalized, $\boldsymbol{D_N}$ matrix

	F1	F2	F3	F4	F5	F6	F7	F8
F1	0.0977	0.0910	0.1365	0.0923	0.0923	0.1200	0.1126	0.1512
F2	0.1365	0.0977	0.0910	0.1094	0.1990	0.1215	0.1215	0.1233
F3	0.1604	0.1215	0.0977	0.1094	0.0923	0.0910	0.1215	0.0923
F4	0.1142	0.1200	0.1267	0.0977	0.0910	0.1200	0.1365	0.0923
F5	0.1221	0.1126	0.0923	0.1200	0.0977	0.1200	0.1156	0.1215
F6	0.1082	0.1215	0.0910	0.1267	0.0793	0.0977	0.0910	0.1126
F7	0.1320	0.1215	0.1604	0.1215	0.1142	0.1126	0.0977	0.1178
F8	0.0910	0.1267	0.1439	0.1604	0.0910	0.1142	0.1299	0.0977

The Total-Influence Matrix, T, is then obtained using equation (13) and the results are provided in Table 9.

Table 9. The Total-Influence Matrix, $\boldsymbol{T}$

	F1	F2	F3	F4	F5	F6	F7	F8
F1	1.4014	1.3278	1.4143	1.3616	1.2504	1.3339	1.3683	1.3813
F2	1.5913	1.4778	1.5172	1.5257	1.4929	1.4801	1.5239	1.5012
F3	1.4566	1.3487	1.3695	1.3676	1.2477	1.3003	1.3703	1.3198
F4	1.4285	1.3639	1.4127	1.3728	1.2605	1.3429	1.3998	1.3330
F5	1.4379	1.3606	1.3834	1.4002	1.2697	1.3479	1.3840	1.3662
F6	1.3190	1.2693	1.2781	1.3037	1.1592	1.2274	1.2589	1.2569
F7	1.5577	1.4711	1.5543	1.5049	1.3815	1.4395	1.4704	1.4632
F8	1.4881	1.4491	1.5098	1.5143	1.3333	1.4135	1.4739	1.4133

The structural correlation analysis was performed by computing the two key indicators, the significance indicator, s and the relation indicator, r using the equation (14) and (15) respectively and the results for the degree of prominence of the eight factors are tabulated in Table 10.

Table 10. The degree of prominence and causal relationship of the eight factors studied

Factors	Description	r_i	c_i	$r_i + c_i$	$r_i - c_i$	Causal Relationship
F1	Climate Patterns	10.8390	11.6805	22.5195	-0.8415	Net receiver
F2	Land and Water Resources	12.1102	11.0683	23.1786	1.0419	Net causer
F3	Seed and Fertilizer Availability	10.7806	11.4393	22.2199	-0.6588	Net receiver
F4	Economics Access	10.9140	11.3508	22.2648	-0.4368	Net receiver
F5	Population Growth	10.9499	10.3953	21.3451	0.5546	Net causer
F6	Food Distribution Network	10.0725	10.8856	20.9581	-0.8130	Net receiver
F7	Education and Awareness	11.8427	11.2495	23.0921	0.5932	Net causer
F8	Resilience to Shocks and Crises	11.5953	11.0350	22.6303	0.5604	Net causer

Results and Discussion

Causal Diagram

The causal diagram is constructed based on the values of $r_i + c_i$ as the horizontal axis while the values of $r_i - c_i$, as the vertical axis in the diagram, from Table 6. The causal diagram is plotted as follows:

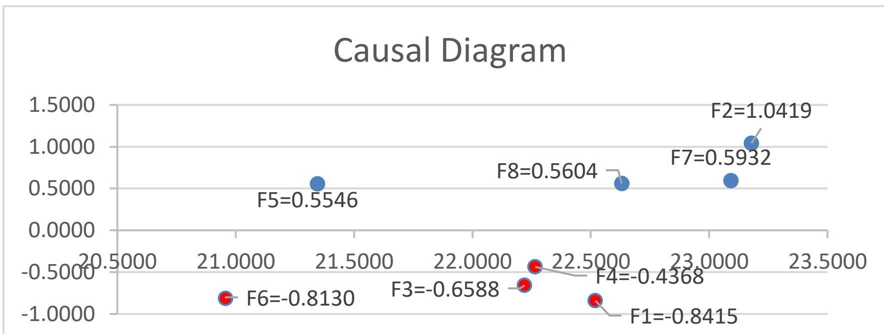

Figure 1. The Causal Diagram of eight FdS factors studied

Through the proposed Neutrosophic DEMATEL-MSM method, the causal diagram presented in Figure 1 effectively reveals the net causers and receivers within the food security system. It is observed that land and water resources (F2), population growth (F5), education and awareness (F7), and resilience to shocks and crises (F8) are identified as net causers, meaning they exert greater influence on other factors than they receive. Among these, land and water resources (F2) is the most significant influencing factor with the highest positive $r_i - c_i$ values among the other net causer. This directly supports the objective of using the model to uncover reliable causal relationships among interrelated FdS factors.

On the other hand, climate pattern (F1), seed and fertilizer availability (F3), economic access (F4) and food distribution network (F6) are categorized as net receivers in this study, which shows that these factors are more affected by other factors than they affect themselves. Climate Patterns (F1) have the most negative $r_i - c_i$ values, emerging as the most affected factor in the system. This distinction between causers and receivers demonstrates the model's effectiveness in prioritizing and categorizing factors based on their systemic influence, which is critical for strategic planning and policy development.

Network-Relationship Map (NRM)

The Total-Influence with Threshold Matrix, $\boldsymbol{TT}$ in Table 11 is computed by dividing all the entries in $\boldsymbol{T}$ matrix (Table 9) with the average of the entries and assign a value of 1 or 0 for the entries that are higher or lower than the average value respectively. Table 11 is used to construct NRM. Each value of 1 indicates an outgoing influence (arrow pointing from the row factor to the column factor), and a value of 0 indicates the factor receives influence (incoming arrow) from others.

Table 11. The Total-Influence with Threshold Matrix, $\boldsymbol{TT}$

Factors	F1	F2	F3	F4	F5	F6	F7	F8
F1	1	0	1	0	0	0	0	0
F2	1	1	1	1	1	1	1	1
F3	1	0	0	0	0	0	0	0
F4	1	0	1	0	0	0	1	0
F5	1	0	0	1	0	0	0	0
F6	0	0	0	0	0	0	0	0
F7	1	1	1	1	0	1	1	1
F8	1	1	1	1	0	1	1	1

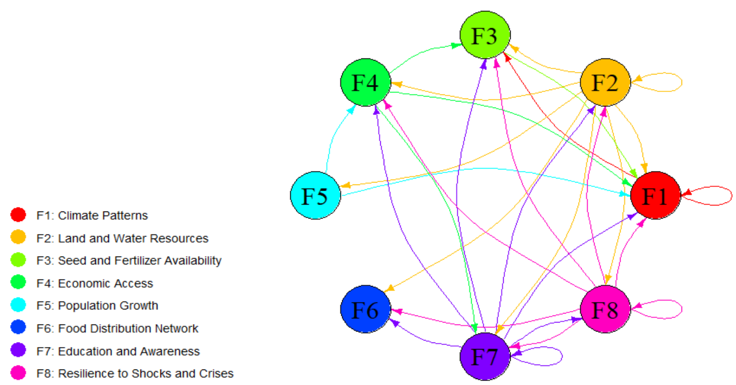

Figure 2. The NRM of eight FdS factors studied

The NRM illustrated in Figure 2 shows a complex web of interrelated factors influencing food system stability (FdS), with climate patterns (F1) playing a central role. Climate pattern (F1) occupies a central and vulnerable position which interacts in feedback loops with factors like Seed and fertilizer availability (F3) and land and water resources (F2). These interactions show how environmental degradation, unsustainable agricultural practices, and external shocks can compound, leading to cascading effects on food availability and distribution. This complexity underscores the value of using MSM aggregation which captures the symmetric interrelationships between expert evaluations and represents a methodological enhancement that addresses the study's objective of improving aggregation precision in uncertain and interconnected systems.

Meanwhile, seed and fertilizer availability (F3) impacted by climate and land conditions and contributes to environmental change. Unsustainable agricultural practices, such as overuse of fertilizers and water-intensive crops, intensify greenhouse gas emissions and resource depletion, feeding back into climate patterns (F1). Economic access (F4) emerges as another pivotal factor when limited, it restricts the ability of farmers to afford quality inputs and hinders access to education and sustainable practices, reinforcing poverty cycles. Additionally, population growth (F5) increases pressure on land and economic resources, contributing to deforestation and rising emissions, further destabilizing climate and food systems.

Education and awareness (F7) and resilience to shocks and crises (F8) are shown as critical enablers within this system. F7 promotes sustainable practices, efficient resource use and economic management, while also improving the effectiveness of food distribution networks (F6). Self-reinforcing (F8) plays a key role in stabilizing systems during environmental or economic shocks. It supports long-term sustainability by encouraging adaptive practices and infrastructure investment. Both F7 and F8 demonstrate extensive influence across the network, highlighting the importance of informed, proactive, and resilient communities in maintaining food system stability amidst ongoing environmental and socio-economic challenges.

Comparative Analysis

This study conducted a comparative analysis of FdS factors using four MCDM frameworks which are fundamental DEMATEL, NS-DEMATEL, MSM-DEMATEL and the proposed NS-MSM-DEMATEL to examine causal interrelationships and factor importance under different levels of uncertainty and aggregation strategies. The comparative analysis is presented in Table 12.

Table 12. Comparative Analysis

Methods	Net Impact	Importance Degree Ranking
DEMATEL	Net receiver: F1, F3, F5, F6 Net causer: F2, F4, F7, F8	F3 > F8 > F1 > F2 > F7 > F4 > F5 > F6
NS-DEMATEL	Net receiver: F1, F3, F5, F6 Net causer: F2, F4, F7, F8	F3 > F8 > F1 > F2 > F7 > F4 > F5 > F6
MSM-DEMATEL	Net receiver: F1, F3, F4 Net causer: F2, F5, F6, F7, F8	F8 > F1 > F3 > F7 > F2 > F4 > F5 > F6
NS-MSM-DEMATEL	Net receiver: F1, F3, F5, F6 Net causer: F2, F4, F7, F8	F3 > F8 > F1 > F2 > F7 > F4 > F5 > F6

Based on the comparative analysis in Table 12, it can be seen that across all methods except MSM-DEMATEL, the net causer and net receiver groups remained consistent with factors F2, F4, F7 and F8 categorized as net causers while F1, F3, F5 and F6 were primarily net receivers. This pattern reflects a stable underlying structure in the FdS system, suggesting that policy, governance, education (F2, F4, F7) and crisis response (F8) contribute to the performance of other factors like resource availability (F1), infrastructure (F3) and population dynamics (F6).

The importance degree rankings further highlight F3 (infrastructure) and F8 (resilience to crises) as the most influential across most methods, confirming their central role in supporting FdS. The consistency of these rankings particularly in DEMATEL, NS-DEMATEL and NS-MSM-DEMATEL method strengthens their credibility and emphasizes the robustness of infrastructure and resilience as pillars of food system stability.

The MSM-DEMATEL method yielded different causal groupings, placing F4 (governance) among receivers and F5 (natural resources) among causers. This variation may be attributed to the MSM operator's abality to capture interdependencies and interaction effects in a symmetrical manner, thereby revealing underlying relationships that may not be detected by traditional linear aggregation approaches. However, this variation also suggests that MSM alone, without neutrosophic representation might introduce sensitivity to expert input without effectively addressing vagueness or inconsistency.

Notably, NS-MSM-DEMATEL yielded similar factor rankings to traditional DEMATEL and NS-DEMATEL. This consistency serves to validate the robustness of the decision-making structure across various modeling assumptions. The incorporation of NS ensured that uncertainty and vagueness in expert input were appropriately accounted for, while the MSM operator captured underlying interdependencies in the aggregation process. Even when output similarity is observed, such integrative methods contribute significantly by strengthening decision reliability in complex systems like FdS.

Conclusions

This study proposed a novel hybrid decision-making framework by integrating NS, the MSM aggregation operator, and the DEMATEL method to address the complexities of MCDM in uncertain and interdependent systems. By applying the model to a case study on FdS, the framework demonstrated its capacity to manage uncertainty, capture expert opinion more reliably, and reveal the causal relationships among critical influencing factors.

The results show that land and water resources (F2), population growth (F5), education and awareness (F7) and resilience to shocks and crises (F8) are significant causal factors in the FdS system, exerting influence over other variables. In contrast, climate patterns (F1) is identified as the most impacted factor, serving as a net receiver in the system. The NRM further illustrated the dynamic interdependencies among the eight factors, providing deeper insight into how environmental, social and economic dimensions interact to shape FdS outcomes.

The incorporation of the MSM operator enhanced the aggregation process by accounting for the symmetric relationships among expert evaluations, thereby improving the consistency and robustness of the decision-making findings. Additionally, the use of NS enabled a more detailed representation of expert uncertainty, addressing one of the key limitations in traditional DEMATEL and fuzzy-based approaches.

Overall, the proposed NS-MSM-DEMATEL framework presents a methodological advancement in handling complex, uncertain decision environments. Its application to FdS demonstrates its practical relevance, particularly for policymaking and strategic planning in sustainable development strategies. Investments in education and public awareness programmes can further enhance food system resilience by promoting sustainable consumption practices, efficient resource use, and informed decision-making at the household and community levels. In addition, strengthening institutional preparedness and adaptive capacity, such as emergency food reserves, supply chain diversification, and crisis response mechanisms, can mitigate the impacts of external shocks including climate variability and economic disruptions. Future research is recommended to validate the proposed NS-MSM-DEMATEL framework across different fields and larger datasets, possibly incorporating real-time data, machine learning or participatory modeling techniques to enhance objectivity, scalability, and applicability in MCDM environments.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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