NEUTROSOPHIC KNOWLEDGE-BASED FRAMEWORKS FOR INTELLIGENT DECISION SUPPORT UNDER DEEP UNCERTAINTY: APPLICATIONS IN SMART AGRICULTURE

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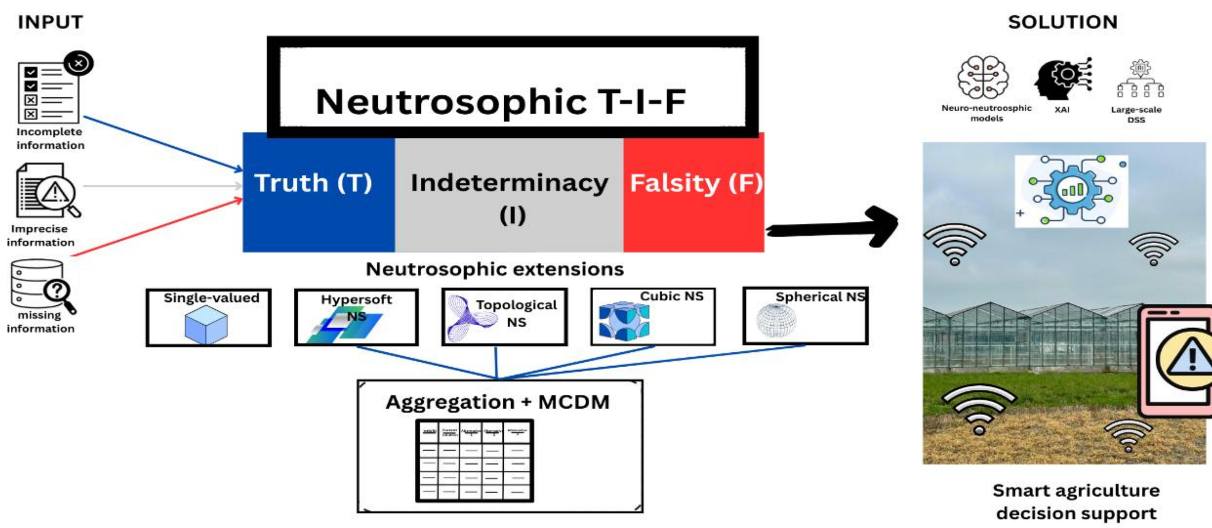
ABSTRACT
Neutrosophic statistics and logic are generalized Fuzzy logic models of uncertainty via an explicit account of terms of truth, indeterminacy and falsity, as extensions of classical probability, fuzzy sets and intuitionistic fuzzy sets. Over recent years, many neutrosophic extensions and hybrid models have been suggested in response to complex decision-making problems involving incomplete, imprecise, and conflicting information. This paper provides a summary of neutrosophic statistical and logical methods, focus on high-level structures, including single-valued, hypersoft, topological, cubic and spherical neutrosophic sets. Mathematical foundations, aggregation operators, and multi-criteria decision-making (MCDM) mechanisms within these frameworks are critically analysed and comparatively discussed. Rapidly evolving formulations in applications, such as multi-criteria and hybrid neutrosophic-learning models are overviewed to demonstrate the ability of neutrosophic models to model hierarchical, multi-attribute, and indeterminate information systems. Smart agriculture has been taken as a representative area of application to illustrate real-world modelling situations without limiting the generality of the offered frameworks. This study proposes a unified conceptual framework integrating neutrosophic theory and multi-criteria decision-making for intelligent decision support under deep uncertainty. The review also presents the major implementation and methodological issues such as parameterization based on experts, absence of standard benchmarks, insufficient software chains, and complexity. Future research directions are provided, including scalable neuro-neutrosophic models, explainable artificial intelligence (XAI) integration, and large-scale decision-support systems.

Graphical abstract



KEYWORDS: Neutrosophic sets, Multi-criteria Decision Making (MCDM), Uncertainty modelling, Computational intelligence, Decision support systems (DSS), Smart agriculture.

1. INTRODUCTION

The global population is projected to reach 9.7 billion by 2050, which means that food production efficiency and security will have to be increased by 60% above their existing levels primarily to fulfil the demand. As a result, the agricultural sector has seen a significant shift, and the idea of smart agriculture and Agriculture 4.0 have emerged [1]. Smart agriculture is an interdisciplinary subfield of agricultural science, technology, data science, and environmental science, aimed at increasing the efficiency of farming and solving problems like land shortage, climate change, and resource depletion. This transformation shifts farm management toward data-driven decisions that optimize labour, water and fertilizer use while at the same time lowering environmental damage [2, 3]. This transformation creates a cyber-physical farm management system, which unites the network infrastructure, powerful hardware, and advanced analytics [4]. IoT, artificial intelligence, robotics, big data analytics, and remote sensing are some of the key enabling technologies in smart agriculture. [4-8].

Core technologies

Primarily among these technologies is the Internet of Things (IoT), which enables real-time data acquisition and connectivity in real-time. Sensors commonly employed in smart farming include those used for monitoring soil moisture, plant disease detection, pH, temperature. These technologies make possible AI-powered decision tools that leverage the combination of IoT, sensor networks, climate analytics, and machine learning for the provision of climate-informed guidance on crop management. Wireless communication like LoRa, NB-IoT are extensively used in precision agriculture to transfer data to processing systems, thereby improving crop quality and agricultural production [9]. Machine learning and deep learning models are used to analyse the acquired data for time-series forecasting [10], yield prediction [11], disease detection [12], and resource optimization using spatial data [13].

Data uncertainties

While these are promising technologies with vast benefits, there is often a limitation to their performance because of the uncertainties inherently existing in the data [14]. Research indicates global crop models, has shown that models trained using historical data could be susceptible to biased responses in extreme climatic conditions, highlighting the systematic difficulty regarding uncertainty in crop growth data due to drought conditions, warming, rainfall, and seasonality [15]. Field sensors often suffer from calibration drift, communication loss, and physical damage, leading to biased and missing readings in IoT networks [16]. Power connectivity problems and lack of historical records make its datasets incomplete and diverse [17], and issues in integrating diverse agricultural datasets such as weather data, soil, and market data into multiple scales and resolutions also increase heterogeneity in datasets [18]. Qualitative insights provided through linguistic terms, such as qualitative classifications and rankings, can be heavily influenced by uncertainty and incomplete information [19].

Furthermore, classical probability struggles to capture the nuanced thresholds and risk levels that agronomists and policy experts often face. Classical statistics usually assumes that observations are realized around a single true value, and uncertainty is mainly due to sampling variability [20]. However, alternative uncertainty frameworks are motivated by the chance that these representations fail to adequately capture epistemic and internal uncertainty [21,22].

To better understand these limitations, distinguishing between aleatory and epistemic types of uncertainty in agricultural data is essential [23]. Aleatory uncertainty is caused by inherent randomness in the world, while epistemic uncertainty is due to a lack of knowledge [24]. Both types affect predictions and forecasting in agriculture datasets, but they are conceptually different, one is irreducible randomness, and the other is ignorance. Indeterminacy caused by incomplete and vague data specifically challenges Bayesian statistics, classical statistics, probability and fuzzy or intuitionistic fuzzy sets (IFS) [25]. Even Bayesian methods tend to give only one predictive distribution, which restricts the explicit modelling of indeterminacy ($p(Y \mid \text{data})$). Classical sets and probability only consider aleatory uncertainty, mainly as random variation around true value and treat data as precise value. Zadeh et al. [26] implemented fuzzy sets to represent vagueness by the use degree of membership values. While fuzzy sets represent graded truth ($\mu \in 0,1$) and can handle vague terms, they do not distinguish between partial truth and lack of knowledge [27]. Atanassov et al. [28] further extended the FSs theory to Intuitionistic fuzzy sets (IFS) introduced a hesitation based on both the degree of membership (T) and non-membership (F), expressed as 1-T-F, they restrict the sum ($T + I + F = 1$); however, it is often diluted because different kinds of indeterminacy are combined into the same residual term. This makes these frameworks unable to capture the indeterminacy as an independent, first-class component.

Neutrosophic statistics as a solution

To address these limitations, neutrosophic statistics (NS) emerge as a powerful generalization of Intuitionistic fuzzy sets (IFS), specifically designed to handle uncertain, indeterminate, and inconsistent information [22, 29-35]. Neutrosophic set is a mathematical framework developed by Smarandache, designed to handle uncertain, unclear, vague, and incomplete data, addressing the constraints of classical probability and fuzzy sets, the sum can range up to 3 ($0 \leq T + I + F \leq 3$). The idea of neutrosophic sets is a broader platform, building upon the principles of the fuzzy and classical sets [36]. It differs from previous approaches because neutrosophic sets maintain distinct categories of truth, indeterminacy, and falsity. It can represent the real-world agricultural data where data is often conflicting or vague. Soil moisture, pH, temperature and humidity sensors may fail, drift or transmit inconsistent readings, whereas neutrosophic logic distinguishes each value into T (how believable), F (evidence against it) and I (how uncertain it is), rather than depending on a single crisp or fuzzy value. In the precision agriculture mechanism model, neutrosophic logic is integrated with IoT and cloud computing to automate geometric soil analysis and environmental monitoring while directly using uncertainty in calculation. Neutrosophic logic expands to other forms of neutrosophic statistical techniques, many of which have been proposed, including multiple regression analysis [37], analysis of variance [38], forecasting [39], and acceptance sampling plans [40]. Moreover, neutrosophic techniques have been applied to unsupervised learning tasks including cluster analysis along distance and similarity metrics [41].

This review synthesizes a wide range of previous studies, with an emphasis on how neutrosophic sets improve Multi-Criteria Decision-Making (MCDM) frameworks for resolving conflicting agricultural parameters. It highlights how neutrosophic approaches to decision-making are enhanced by addressing uncertainties inherent in agricultural data, including those from soil conditions to market dynamics. Furthermore, the efficiency of neutrosophic models in handling ambiguous or contradictory situations is compared with classical statistical methods and represents an advanced computational intelligence paradigm extending fuzzy reasoning for intelligent decision-making under deep uncertainty.. Finally, the article examines the current challenges of applying neutrosophic statistics in agriculture, paving the way for future research in this interdisciplinary field.

2. Bibliometric Overview of Neutrosophic Research in Smart Agriculture

2.1 Data Source and Analysis Tools

This review used the Scopus database as its bibliometric source due to its comprehensive coverage of peer-reviewed sources in all fields of engineering, agricultural sciences, and interdisciplinary studies. TITLE-ABS-KEY field was used to conduct the search to achieve high topical relevance. A search was made with TITLE-ABS-KEY (("neutrosophic" OR "neutrosophic logic" OR "neutrosophic set" OR "indeterminacy") AND ("agriculture" OR "farming" OR "crop" OR "soil" OR "irrigation" OR "smart agriculture" OR "precision agriculture")). The initial searched yielded 223 records. There were no restrictions on the publication year so as to fully encompass the temporal development of neutrosophic research in the agricultural sector. The records recovered were directly exported out of Scopus in CSV format and imported into the biblioshiny web interface of the bibliometrix R package to analyse. Descriptive statistics and annual scientific production trends and source dynamics were generated with the help of Biblioshiny, whereas network analyses, such as country collaboration and keyword co-occurrence, were used to study the intellectual and thematic structure of the area. The combination of these tools made it possible to conduct a systematic and reproducible bibliometric evaluation of neutrosophic logic applications in smart agriculture.

2.2. Publication Trends

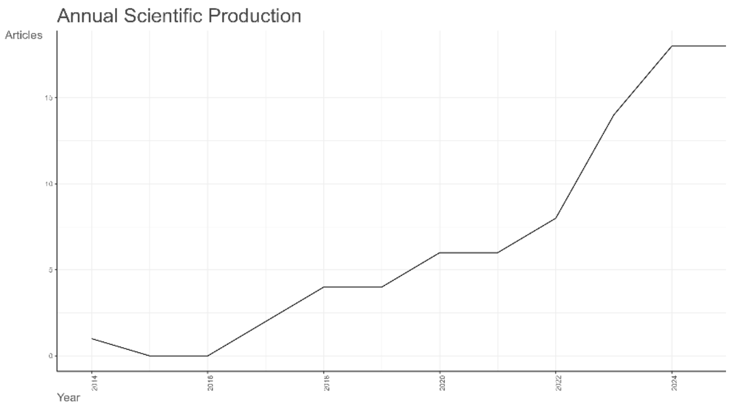


Figure 1. Annual Scientific Production

Figure 1. shows the scientific output concerning neutrosophic research in the field of agriculture annually. These findings suggest that the publication activity was very low before 2017 and since then, it has gradually risen between 2018 and 2021. There is a sharp growth peak after 2022 and the highest number of publications are found between 2024-2025. The apparent decline in 2026 is attributed to the indexing lag typical of real-time database access, rather than a reduction in scholarly interest. In general, the identified tendency defines neutrosophic applications in agriculture as a research area with a swift rise in academic interest.

2.3. Country-wise Collaboration

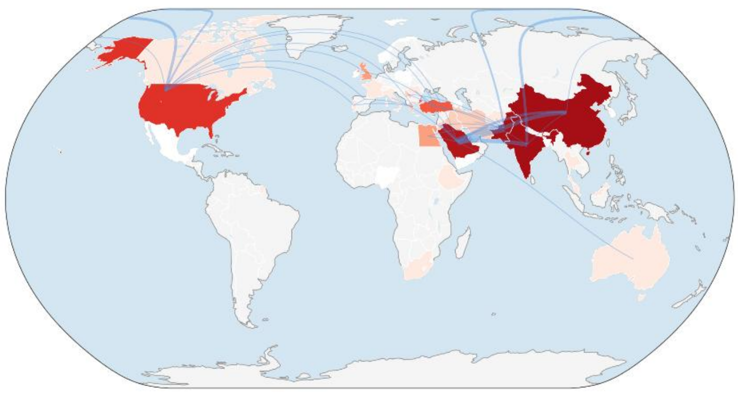


Figure 2. Global collaboration

Figure 2. shows the network of international co-authorship of countries participating in the research of neutrosophic in smart agriculture. The network also emphasizes the geographical dispersion of research output and the strength of the

collaborative links. India and China are significant contributors, which means the active research in the area of neutrosophic decision-making and uncertainty modelling of agricultural systems. Such countries also share a wide range of collaborative relationships with scholars in the Middle East, Europe and North America. The United States and some European nations show a moderate yet steady involvement which suggests increasing interdisciplinary involvement. Contrastingly, the low representation of Africa and South America indicates research gaps in the region. In general, the collaboration network demonstrates a skewed yet growing international research environment with the necessity to collaborate on a larger international level. This regional concentration in Asia reflects the high priority given to Agriculture 4.0 and computational intelligence in these developing countries.

2.4. Keyword Co-occurrence and Research Themes

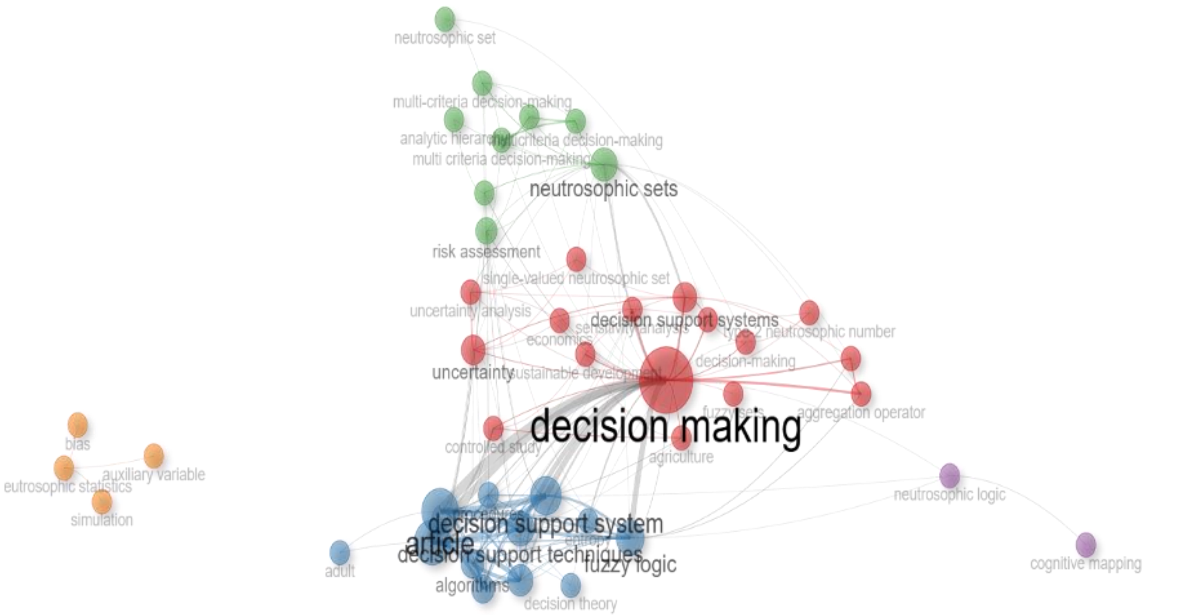


Figure 3. Keyword Co-occurrence Network

The thematic form of neutrosophic research in agriculture is captured by the keyword co-occurrence network in Figure 3. The main focus of the methodological approach of the field is represented by a dominant central cluster around neutrosophic decision-support systems and uncertainty-aware modelling. The keywords closely related are those that involve decision-making, optimization and handling of indeterminacy, as applied in the agricultural environment. Secondary clusters are related to application-based themes, such as crop management, soil assessment, irrigation planning, and decision models related to sustainability. Peripheral clusters are new or niche areas of research, which mean that it is at an initial stage of diversification with respect to application areas. The inter-cluster connectivity is rather low, which indicates an emerging field of research where theoretic and practical contributions are still in their early stages of integration. This shows the necessity of the enhanced methodological integration between sophisticated neutrosophic models and practical smart agriculture infrastructures. Notably, the keywords co-occurrence network reveals a significant green cluster dedicated specifically to multi-criteria-decision-making (MCDM) and the Analytic Hierarchy Process (AHP), validation the selection of MCDM as the primary analytical lens for this review.

3. Neutrosophic Theory and Modelling Basics

3.1.Neutrosophic set (NS): core concept

A neutrosophic set on a universe X is typically written as

NS = $\{(x, T(x), I(x), F(x)) \mid x \in X\}$, (1)

T-I-F triplet; T(x) - level of truth/membership, I(x) - level of indeterminacy, F(x) - level of falsity or membership, with the range of $0 \leq T(x), I(x), F(x) \leq 1$ and $0 \leq T+I+F \leq 3$. These functions return values in the open interval of (0, 1), without restrictive sum constraint found in fuzzy or intuitionistic sets (T + I + F = 1). This generality allows NS to capture inconsistencies commonly found in real datasets [22]. This tricomponent setup allows for a more nuanced representation of real-world agricultural data compared to traditional binary and even fuzzy logic systems [42].

3.2.Single-valued neutrosophic sets (SVNS)

For real-world application, single-valued neutrosophic sets restrict T(x), I(x) and F(x) to the unit interval [0,1], while maintaining their independence. Due to the balance expressive power with computational simplicity, SVNS has become widely adopted in MCDM, predictive modelling, and sustainable agriculture assessments. Typical notation is,

A = $[x, u(x), r(x), v(x)): x \in X]$. (2)

where, u(x) – Single-valued truth, r(x) – Indeterminacy, v(x) – Level of falsity, with respect to a mild condition such as $0 \leq u(x), r(x), v(x) \leq 3$. In the case of decision-making processes, neutrosophic logic is a system that allows the inclusion of more dimensions for the analysis. It finds great application in fields such as smart agriculture, where choices have to be derived from sensor data that might be influenced by the noise, be incomplete, or changed by the environment [30]. For instance, a smart agriculture mechanism model integrated with neutrosophic theory, IoT, and cloud computing has been demonstrated to perform more detailed calculations by considering uncertain situations inherent in neutrosophic numbers and log [30]. This integration allows for better decision-making in irrigation, pest control, and nutrient management by incorporating the degrees of truth, indeterminacy, and falsity associated with various environmental parameters and crop responses

3.3. Soft, hypersoft and extended neutrosophic sets

Let X be a universe and E a set of parameters. A neutrosophic soft set (NSS) is a parameterized family of neutrosophic sets defined as a mapping:

$$F: E \rightarrow \mathcal{NS}(X), \quad (3)$$

where each parameter e∈Eis associated with a neutrosophic set over X. Each object–parameter pair is described by a triplet TIF, enabling flexible modelling of uncertain multi-attribute decision problems [43].

Neutrosophic logic, when combined with a soft set theory, offered by Molodtsov et al. [44] improves decision-support systems by handling uncertain and imprecise parameters. Within the context of neutrosophic soft sets, suggested by Maji et al. [43], every pair of an object-parameter is described as a neutrosophic triplet (T, I, F). Where T, I and F are the degrees of truth, indeterminacy, and falsity, respectively. In this method, the emphasis is laid on the attribution of neutrosophic membership values to the objects of the universal set to the attribution of the same to parameters, thus providing additional flexibility in modelling uncertainty. As a result, soft neutrosophic sets offer a powerful framework to multi-criteria decision-making (MCDM) issues. An example is when determining the best variety of crop to grow, the yield potential, resistance to disease, and irrigation needs are among the factors that may be weighted with uncertainty, and with this method, a more realistic approach to this problem can be obtained.

Neutrosophic hypersoft sets extend neutrosophic soft sets by allowing tuples of sub-parameters. Let

$$E = E_1 \times E_2 \times \cdots \times E_n, \quad (4)$$

where each Eirepresents a sub-attribute (e.g., soil fertility, climatic zone, irrigation availability). An NHSS maps each parameter tuple to a neutrosophic set on X. The neutrosophic hypersoft sets (NHSS) and neutrosophic hypersoft topological structures extend existing from neutrosophic soft and hypersoft models, allowing tuples of sub-parameters, including climatic zone, soil fertility, and water availability, and specifying neutrosophic structures on their Cartesian products. This feature of modelling has been effectively applied to use in advanced agricultural multi-criteria decision-making (MCDM) problems, such as farm site selection. NHSS is able to reflect complex interdependencies of the agricultural decision processes, including choosing the crop depending on the interaction between the climate zone, soil fertility, and availability of irrigation as can be observed in recent research [45, 46]. This degree of complexity is particularly vital within the agricultural sector, where the decision factors are commonly of a nested and hierarchical nature. For instance, soil quality which is a critical agricultural parameter that may be sub-divided into sub-attributes like pH, nitrogen content, phosphorus content, and organic matter, each having a neutrosophic measure attached to it. NHSS consequently enables the finer modelling of multi-level hierarchical uncertainty, which promotes the more accurate agricultural planning and optimizes resource allocation. Figure 4. Schematically illustrates the structural shift from soft neutrosophic sets to neutrosophic hypersofts and further to extended neutrosophic models to manage deep layers of agricultural uncertainty.

Extended neutrosophic sets are a generalization of standard neutrosophic sets where T, I, and F can be expressed as intervals and multiple values instead of being expressed as single numerical values. This generalization leads to some forms such as interval-valued neutrosophic sets, multi-valued neutrosophic sets and n-valued neutrosophic sets, that provide broader frameworks for uncertainty. They are useful especially when more specific numerical estimates cannot be made, as is prevalent within agricultural decision problems that require crop yield estimation, price forecasts, and effects of fertilizer in uncertain situations. Consequently, extended neutrosophic models have been successfully integrated into advanced decision-support frameworks, including neutrosophic goal programming and bio-inspired optimization algorithms, to address complex multi-criteria decision-making problems frameworks is in crop land allocation problems that typically maximize profit and output and minimize costs in conditions of uncertainty of yield, market price, and the effectiveness of applied fertilizer [47]. Such extended sets can be substituted with a neutrosophic goal programming method that may include bio-inspired algorithms to optimize land distribution, and as an effective approach to indeterminate criteria e.g. seed growth response and fertilizer suitability. These enhanced neutrosophic models enable a more detailed computation, through an explicit consideration of subtle uncertainty in agricultural data to enhance the accuracy and reliability of agriculture decision-making in smart agriculture applications, such as IoT-based monitoring systems, predictive modelling, and risk assessment [30, 48].

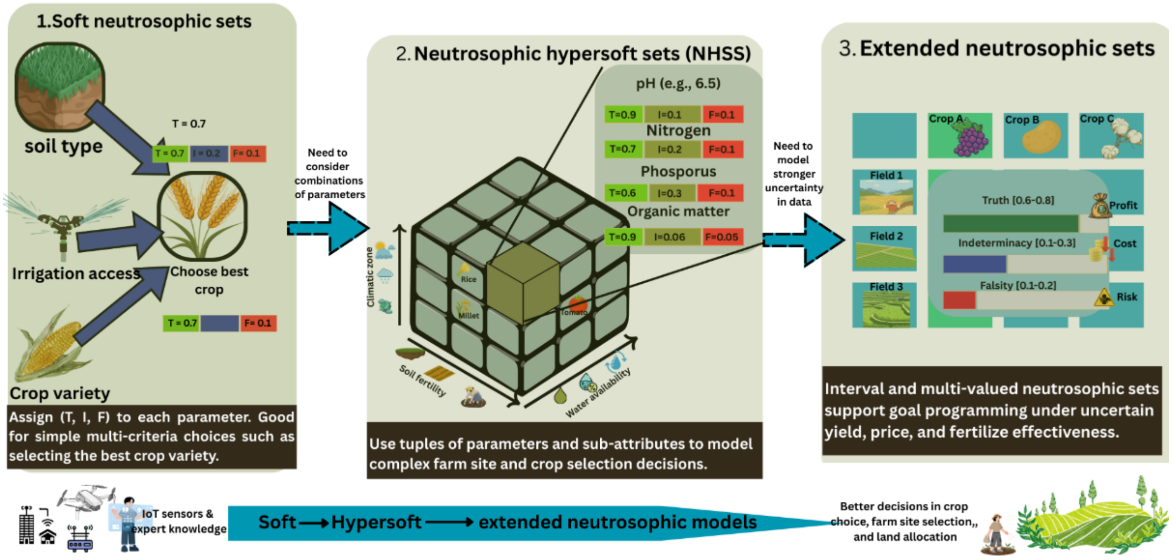


Figure 4. Soft, hypersoft and extended neutrosophic sets in smart agriculture.

3.4. Neutrosophic Relations and Cognitive Maps

Neutrosophic Cognitive Maps (NCMs) are extension of fuzzy cognitive maps by including indeterminate relationship represented by the value I. Vertex in NCM may have states; 1 (active), 0 (inactive), I (indeterminate). Each vertex (nodes) in NCM indicate a factor, variable or indicator that influence in agriculture. Edges are weighted from the set {-1, 0, 1, I}, that shows the possibility of positive, negative, neutral or uncertain influence, NCMs represent a powerful tool to model agricultural sustainability, especially when the interactions between variables are not completely known. Figure 5. Shows a neutrosophic cognitive map of agricultural decision variables as state nodes {1, 0, 1} interconnected by directed edges of weight {-1, 0, 1, I} to characterize positive, negative, neutral and indeterminate casual relationships.

Zulqarnain et al. [49] introduce generalized aggregate operators on NHSS, including extended union, extended intersection, AND/OR operations, and necessity operators, and study their properties for multi-criteria decision making (MCDM). These operators are designed to aggregate evaluations from multiple experts and multiple sub-attributes, supporting selection and planning in complex decision problems. In a smart-agriculture context, the same operators can be interpreted as neutrosophic logic operators that fuse heterogeneous sensor readings and expert assessments such as combining soil, crop and weather sub-criteria into a single neutrosophic decision score for tasks such as crop variety selection, irrigation scheduling, fertilizer recommendation, or disease risk assessment.

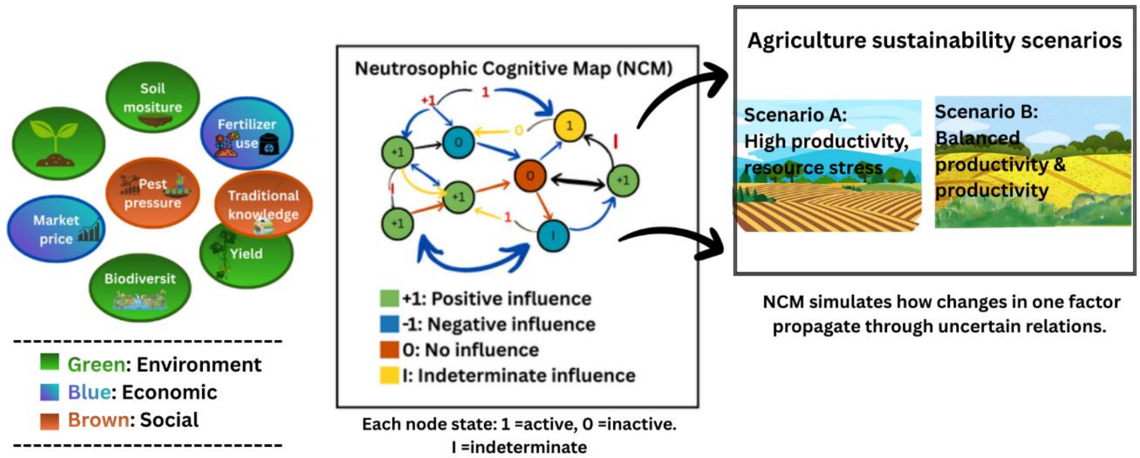


Figure 5. Neutrosophic Cognitive Map (NCM)

3.5. Neutrosophic Logic operators

Neutrosophic logic extends classical logic operators AND, OR, and NOT to represent three-dimensional uncertainty. These operators have been applied effectively in anomaly detection for smart farming to handle ambiguous sensor data [50].

Neutrosophic AND:

$$A \wedge_N B = (\min(T_A, T_B), \max(I_A, I_B), \max(F_A, F_B)) \quad (5)$$

In the case of two neutrosophic sets A and B, the truth value of A AND B is given by the minimum of the truth values, the indeterminacy value is given by the maximum of the indeterminacy values, while the falsity value is given by the maximum of the two falsity values. This operator represents a model of situations where multiple conditions have to be simultaneously met, and the uncertainty in one condition raises the overall uncertainty.

Neutrosophic OR:

$A \vee_N B = (\max(T_A, T_B), \min(I_A, I_B), \min(F_A, F_B))$ (6)

The truth degree of A OR B is the maximum of their truth degrees, the indeterminacy degree is the least of their indeterminacy degrees, and the falsity degree is the minimum of their falsity degrees. This operator is used when any one of several conditions can fulfil a requirement.

Neutrosophic NOT:

$\neg_N A = (F_A, I_A, T_A)$ (7)

The complement of a neutrosophic set A changes its truth and falsity degrees and keeps the indeterminacy. This operator stands for the negation of a proposition. Figure 6. demonstrates the operational workflow of netrosophic logic in agricultural decision support, where sensor inputs are transformed into (T, I. F) triplets and synthesized using AND, OR, and NOT operators. These operators are very essential to decision support systems that are used in agriculture. As an example, in a smart irrigation system, decisions might be influenced by several factors such as soil moisture (T1, I1, F1), weather forecast (T2, I2, F2), and crop growth stage (T3, I3, F3) [30]. Neutrosophic operators may merge these uncertain sensor readings and expert knowledge to find out the best irrigation action while at the same time they recognize the environmental data indeterminacy [30]. In the case of crop yield prediction, they have the capability of integrating various uncertain inputs such as rainfall, temperature, and soil nutrient levels in order to forecast future yields while also being very clear about the indeterminacy for each factor [48].

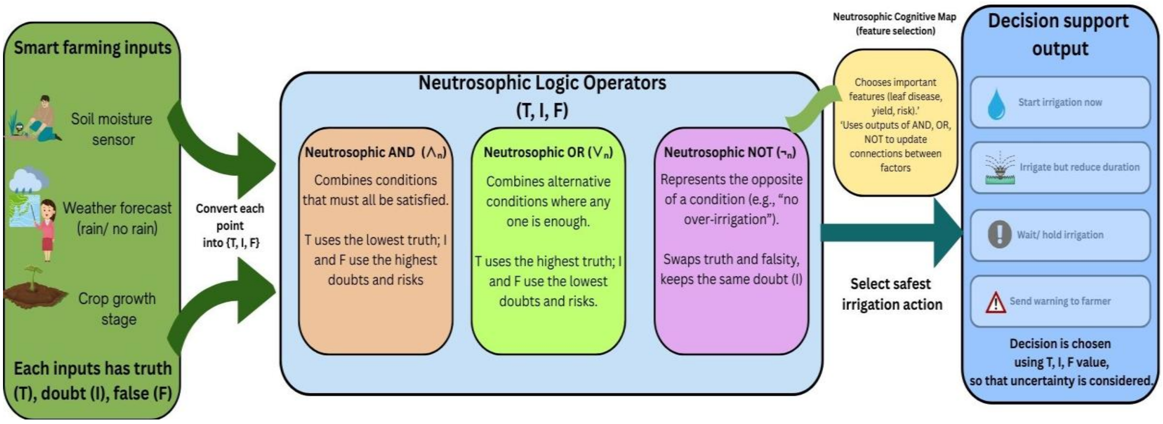


Figure 6. Neutrosophic operators logic-based in irrigation.

3.6. Cubic Spherical Neutrosophic Sets (CSNS)

Cubic Spherical Neutrosophic sets represents a high-level extension of classical neutrosophic sets. Their purpose is to enhance the modelling of multi-level and geometrically structured uncertainty. Correspondingly, each element in CSNS is represented not only by the neutrosophic membership degree of truth (T), indeterminacy (I), and falsity (F) but also by the additional radius parameter (r) describing the spatial interpretation of uncertainty. It expressed as,

$A = \{(x, [T^L(x), T^U(x)], [I^L(x), I^U(x)], [F^L(x), F^U(x)], (T(x), I(x), F(x)))\}$ (8)

Where the membership values are subject to the following constraints:

$\{T(x), I(x), F(x), r(x)\}, 0 \leq T^2 + I^2 + F^2 \leq 1$ (8a)

$r(x) = \sqrt{1 - (T^2(x) + I^2(x) + F^2(x))}$ (8b)

CSNS would generally extend this concept by integrating cubic sets with spherical neutrosophic sets. Spherical neutrosophic sets enable decision-makers to separately assign grades for truth, indeterminacy, and falsity such that their total is less than or equal to one. The term "cubic" usually refers to the combination of interval-valued information with fuzzy numbers, thus allowing a more detailed depiction of uncertain data. In the case of agriculture, where sensor data might be inaccurate for instance, soil moisture levels varying within a certain range and expert opinions might be unclear like "the crop is moderately healthy", CSNS could provide a high-level technique for the aggregation and data analysis. As an example, determining the health of the crop might mean that not only single values for truth, indeterminacy, and falsity are considered, but also intervals for these values, thus indicating a deeper level of imprecision in diagnosis or prediction. This would, therefore, enable more dependable decision, making in precision agriculture areas, such as the detection of the earliest symptoms of disease or the efficient use of irrigation when it is difficult to establish exact thresholds. In particular, this improvement adds to geometric robustness and considers multi-level uncertainty. The CSNS has broad applicability in agriculture, especially for crop ranking under climatic variability, risk evaluation in crop planning, assessing risk under fluctuating climatic conditions and resource allocation and sustainability assessment [51].

4.Current neutrosophic application in smart agriculture

The wide range of application of neutrosophic logic to smart agriculture are summarised in Figure 7, illustrating its incorporation into decision-support systems for land allocation, soil assessment, yield forecasting, and intelligent anomaly detection under uncertainty.

4.1.IoT- Enabled Smart Farming

The combination of neutrosophic logic and IoT smart farming systems provides a reliable way to deal with uncertainty in real-time farming systems. Sensor data regarding soil analysis, climate, GPS farming, and crop analysis coordinates are often incomplete or noisy. Neutrosophic-IoT systems can effectively overcome this problem by representing raw data as neutrosophic triplets before processing. The core components of the Neutrosophic Inference Engine (NIED) and the corresponding smart agriculture applications are summarized in Table 1.

Table 1. Core Neutrosophic Inference Engine (NIED) Components and Their Smart Agriculture application

Component	Core Technique	Key Innovation	Smart Agriculture Application	Reference
NIED	Neutrosophication and de-neutrosophication	Transformation of pentagonal and trapezoidal neutrosophic numbers using area-based and mean-based methods	IoT data acquisition and pre-processing	[52]
NIED	Neutrosophic clustering and analysis	Outlier and boundary handling using Lagrange multipliers and G-metrics on single-valued neutrosophic set	Data classification and big data analytics	[53]
NIED	Neutrosophic IF-THEN rules	Rule-based inference under indeterminate conditions	Real-time decision support in smart farming	[30]

Recently, studies have shown that cloud-assisted and edge-enabled IoT systems in which neutrosophic inferences are incorporated enhance reliability of irrigational decision, nutrient scheduling as well as environmental monitoring. These platforms are capable of increasing the flexibility and scalability of a precision agriculture system to dynamic field conditions through the explicit modelling of indeterminacy of data.

4.2.Decision support and Crop recommendation systems

Kaviyarasu et al. [54] have proposed “Algorithm 1”, using neutrosophic hypersoft sets (NFHSs) for farm site selection, define variables with double sets (S1, Γ1) and S2Γ2, their combination through “resultant union,” and ranking sites based on the final score ($O_i=r_i-c_i$), which is obtained through summation of rows(r_i) and columns (c_i), selecting the one with highest score ($y_j=\arg\max_i\{O_i\}$) to handle uncertainty.

Kaviyarasu et al. [54] continued to advance the usage of neutrosophic hypersoft sets in “Algorithm 2”, incorporating topology with the integration of open sets based on the location and decision parameters, along with integration of data based on advanced operations, and site selection based on net scores ($O_i=r_i-c_i$)- achieving consistent results like identifying site y_2 optimal across more than 12 parameters for robust uncertainty management. The effectiveness of hypersoft and cubic neutrosophic models for capturing interdependencies among multiple criteria and expert assessments. Neutrosophic DSS offer greater robustness, and their outcomes are more explainable compared to traditional MCDM approaches, particularly for regions facing climatic uncertainty and resource constraints [51, 54].

Angammal and Grace. [55] model crop selection for medium farm holders in Ariyalur as a multi-objective, multi-attribute neutrosophic optimization problem, where truth, indeterminacy and falsity membership functions explicitly represent uncertainty in yield, prices, seed growth, fertilizer suitability and other agri-inputs. By minimizing under-deviation in truth and over-deviation in indeterminacy and falsity, the neutrosophic goal programming models simultaneously optimize production, profit and expenditure under constraints of land, labour, water and food requirements. This demonstrates that neutrosophic decision-support systems can provide practical, field-validated crop allocation and crop choice recommendations for specific regions such as Ariyalur district.

4.3.Soil, Water, and Land Suitability assessment

Soils and land evaluation processes are based on a set of physical, chemical, and biological indicators showing spatial variability, which are often measured with a certain degree of imprecision. To overcome these challenges, the Neutrosophic Fuzzy–Analytic Hierarchy Process (NF-AHP) and similar hybrid models have been applied in soil quality indexing and land suitability analysis.

By incorporating neutrosophic judgments into pairwise comparisons, these approaches explicit model expert uncertainty and conflicting assessments. From a methodological perspective, the criteria for soil and land evaluation are first hierarchically organized, and expert judgments are elicited through linguistic terms that are converted to neutrosophic numbers. Neutrosophic pairwise comparison matrices are then set up for each criterion relationship, capturing the truth, indeterminacy, and falsity. Criterion weights are determined via neutrosophic aggregation and normalization processes, continuing with consistency analysis adapted to the neutrosophic format. Weighted criteria are eventually combined with spatial or quantitative indicators of soil to calculate the composite soil quality or land suitability indices. Empirical results show that neutrosophic-enhanced soil and land evaluation models outperform classical AHP and fuzzy-AHP in selecting suitable zones for cultivation and determining land degradation risk, especially in the case of climate-sensitive agricultural systems [56].

4.4. Yield Prediction and agriculture risk assessment

Neutrosophic logic has emerged as a vital tool for modelling yield and risk under climate variability, incomplete data, and expert vagueness, where classical probability and even fuzzy logic struggle. Recent literature integrates neutrosophic logic with statistical and deep learning models for crop-yield prediction under climate stress. A recent framework combines neutrosophic logic with least squares regression and an independence test to estimate crop-loss functions and classify crops by profitability and environmental risk, focus specifically on extreme-weather events. Deep learning, particularly restricted Boltzmann machines (RBM), is used to capture complex nonlinear relations between climate, management variables, and yield, while neutrosophic representations encode truth, falsity, and indeterminacy in expert and sensor inputs [48]. The model is demonstrated gains in estimation of yield damage and provides farmers with functional risk indicators to support adaptation decisions such as diversification and input adjustment [48].

At the planning level, multi-objective neutrosophic fuzzy linear programming has been applied to optimize seasonal crop portfolios such as wheat and rice in canal-irrigated systems under uncertain water availability and climate shocks. Here, yield, water requirements, storage limits, and canal capacities are modelled as neutrosophic–fuzzy parameters so that both randomness and imprecision like expert scenarios rather than hard data are reflected. The optimization aims to maximize net profit and total production while addressing to hydrological and infrastructural limitations, demonstrating that neutrosophic fuzzy algorithms can handle yield uncertainty more effectively than conventional fuzzy models when parameters are susceptible to sudden, climate-driven changes [57].

Neutrosophic approaches are also being embedded in probabilistic sequence models for yield forecasting. A single-valued neutrosophic hidden Markov model (HMM) has been proposed to represent long-run weather regimes and their transitions, with neutrosophic probability capturing indeterminate states. This model is used to forecast crop yields and notify farmers about likely favourable and unfavourable yield states under evolving weather conditions [58]. In addition to forecasting, neutrosophic logic supports risk assessment in crop selection. Quadripartitioned single-valued neutrosophic sets and associated entropy/similarity measures have been used to transform expert linguistic assessments of multiple risks (climate, soil, pest, market) into interpretable risk levels for alternative crops. A case study on mustard and paddy shows how final risk levels such as "absolutely high" vs "very low" can be robustly derived from imprecise, multi-expert inputs, improving strategic crop choice under uncertainty [59]. Neutrosophic goal programming has likewise been used to determine optimal land allocation under uncertain yields, prices, and agronomic factors, leveraging separate truth, indeterminacy, and falsity membership functions and bio-inspired optimization to maximize profit and production under resource constraints [47].

4.5.Anomaly Detection and edge intelligence in smart farming

Anomaly detection has grown in importance in the agricultural field with sensors networks and edge or fog computing systems being installed to assist in smart farming. The sensor measurements are prone to noise, missing values, and variation in the environment making traditional anomaly detectors to have missed detection or false alarm [60]. In reaction, edge-based deep learning systems, including CNN-LSTM based and LSTM (Convolutional Neural Network- Long Short-Term Memory) autoencoders, have shown that intelligence pushed to sensors can be highly detected and low latency in smart farms settings [50, 61]. The neutrosophic logic provides a complementary model in that it explicitly models truth, falsity, and indeterminacy in both data and decisions. Neutrosophic multivariate time-series models together with graph learning have been applied in the context of Industrial IoT to improve the performance of the anomaly detector when the dimensionality is high and the sensor data is distorted [62]. Likewise, neutrosophic-enhanced ensemble methods to detect intrusion in the IoT break down prediction confidence into truth, falsity, and indeterminacy and allow systems to avoid making uncertain decisions, which is a valuable feature of edge deployments that demand trust in autonomous actions [63]. Even though the majority of anomaly detection methods in smart agriculture still utilize probabilistic or deep learning models like GANs (Generative Adversarial Network), autoencoders, CNN-LSTM models, and ensemble outlier detectors instead of neutrosophic logic [50, 60, 64, 65], neutrosophic modelling has already been used in agricultural decision-support systems to operate with uncertain soil and environmental data [30]. This suggests a potential future direction of research: namely, the incorporation of neutrosophic representations into edge-based anomaly detection in smart farming, wherein edge nodes should be able to distinguish sensor behaviour as normal or abnormal, but should in addition be able to describe indeterminate states that humans may choose to inspect or conserve via conservative control. This can improve the reliability of systems, minimize unnecessary alarms, and facilitate the open human-in-the-loop decision-making at the network edge [30, 62, 63]. Table 2. Provides a consolidated comparative overview of recent neutroosphic methodological applied across various smart agriculture domains, highlighting the modelling approaches, evaluation criteria, and practical outcomes.

4.6.Implication of agriculture statistics and practice

The neutrosophic approaches fill a significant interface between agricultural statistics and decision science by looking at indeterminacy as a first-class statistical object instead of noise to be discarded or pushed to traditional probabilistic models [33]. Neutrosophic statistics is based on classical methodologies by breaking down the observations into determinate and indeterminate parts, thus allowing the analysis of experimental data, soil measurements, and yield records that naturally incorporate vagueness and does not arbitrarily treat these as completely precise. Furthermore, model output is not limited to single point estimates or confidence interval, but instead can be presented as neutrosophic triplets (T, I, F) which are naturally related to action-based decision criteria like accept, review, or intervene. This model resembles the decisions made by agronomists and farmers in a real situation when they are uncertain [66]. Although regression analysis, geostatistical modelling, and machine learning are crucial in large-scale agriculture prediction processes, neutrosophic logic improves the trustworthiness of decisions in scenarios where data is incomplete, measurement uncertainty, or expert judgments are deployed [56]. Neutrosophic methods are typically best applied in conjunction with conventional statistical and machine learning predictors, working at the decision-support and interpretation tiers of smart agriculture systems rather than substituting existing predictive pipelines [67].

Design and analysis: Neutrosophic analysis of experimental data enables the expression of treatment effects that demonstrate indeterminacy components. It is especially useful in cases where field replicas are few, measurement errors are large, and expert-based assessments, including disease severity scales or visual soil ratings, are subjective or ambiguous in nature [68].

Risk-sensitive advisory: Neutrosophic yield and soil fertility models should be used to detect borderline cases with high indeterminacy, and hence provide advice to do further sampling or expert evaluation instead of making overconfident advisories. This knowledge-based risk management guidance increases the safety and reliability of agricultural advisory services particularly in climate-sensitive areas [66].

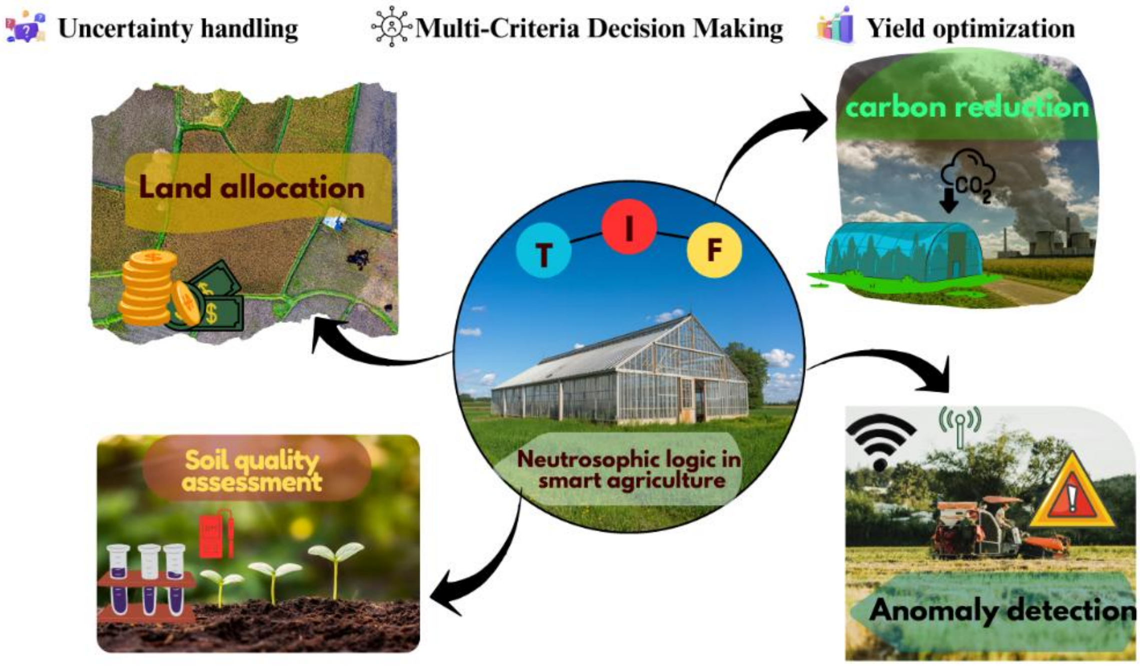


Figure 7. A schematic figure of decision support of neutrosophic logic-based smart agriculture.

Table 2. Key neutrosophic logic in smart-agriculture studies

Application domain	Neutrosophic method	Factors considered	Main outcome for smart agriculture	Reference
Crop land allocation and optimal crop mix	Neutrosophic Goal Programming + bio-inspired algorithms (GWO, SGO, PSO)	Yield, prices, seed growth, fertilizer suitability; land, labour, water, food demand	Maximizes profit and production, minimizes expenditure; neutrosophic–bio-inspired solution outperforms fuzzy methods	[47]
Land allocation & resource planning	Neutrosophic linear programming	Regions A_j (60,150,20,10 ha), demands b_i (800,200,600,1000,2500 tons), productivity Na_ij [wheat A1= {4,6} tons/ha], profit Np_i [wheat={1400,1600}/ton]	Maximizes neutrosophic profit under constraints, robust to yield/price uncertainty	[69]
Carbon emission reduction policy	Fermatean neutrosophic using WINGS with AHP-EWM	9 factors (τ4=carbon policy, τ6=tech adoption, τ8=sustainable management)	Policy prioritization tool (τ_4=carbon policy 0.220 top)	[70]
Maize silage soil quality	NF-AHP weights using MLR and RFR prediction	89 samples, 28 indicators (slope 0.0746, MBC 0.0787)	MLR > RFR (R^2=0.99), precision soil assessment	[56]

IoT anomaly detection	SVNS with decision matrices using correlation scoring	Sensor streams (uncertainty, missingness)	Real-time edge anomaly detection, fewer false alarms	[50]
Farm site selection	Neutrosophic hypersoft topological MCDM	Soil, climate, water, economics + sub-attributes	Robust farm selection despite contradictory judgments	[54]
Sugar beet soil quality assessment in semi-arid soils	Neutrosophic Fuzzy-AHP (NF-AHP) for SQI; predicted with multi-class logistic regression, random forest, one-against-all SVM	Physical, chemical, fertility, biological indicators under semi-arid conditions; linked to NDVI from Sentinel-2A	NF-AHP-based SQI framework with ML classifier accuracy for data-driven soil/crop management in semi-arid agriculture	[71]
Crop yield & risk assessment	Neutrosophic least squares with RBM (Restricted Boltzmann Machine)	Rice/banana yields, weather extremes, 160 farmers	Risk-aware yield prediction with damage categories under uncertainty	[48]
Soil quality assessment in sub-humid ecosystem	Neutrosophic fuzzy-AHP using support vector machine	Soil indicators scored via linear/nonlinear functions in sub-humid mountain areas	Hybrid SQI model for accurate soil quality evaluation aiding sustainable land management	[72]
Crop recommendation under uncertainty	Neutrosophic–paraconsistent uncertainty expert system with Butterfly Optimization Algorithm (UES-BOA)	Soil fertility and climate parameters: Nitrogen (N), Phosphorus (P), Potassium (K), temperature, relative humidity, soil pH, rainfall; 2200 instances, 22 crop classes; certainty degree (μ) and contradiction degree (λ) via neutrosophic and paraconsistent logic	Robust crop recommendation under uncertainty with optimized rules, achieving 95.8% accuracy and outperforming ANN, MLP, and SVM.	[73]
Multi-criteria decision-making in agriculture (farmer performance selection)	Neutrosophic Soft Matrices (NSM) with score and value functions	Farmer performance indicators including crop productivity, input use, and resource management, evaluated using truth, indeterminacy, and falsity degrees.	Reliable farmer selection under uncertainty using score-based neutrosophic soft matrices. .	[74]

5.Advanced neutrosophic frameworks for smart agriculture

Modern farmework evolve from classic neutrosophic methods by integrating complex mathematical structures capable of addressing complex agricultural decision-making defined by interacting criteria and deep uncertainty. Broadly, the literature on neutrosophic logic-based decision-making in agriculture is dominated by two primary branches: (i) neutrosophic hypersoft and topological models, (ii) hybrid neutrosophic-fuzzy MCDM frameworks.

5.1.Neutrosophic hypersoft and Topological frameworks

Advanced neutrosophic hypersoft and topological structures extend classical neutrosophic sets to represent multi-attribute, hierarchically structured, and highly uncertain information typical of smart agriculture. Neutrosophic hypersoft sets generalize soft and neutrosophic sets by allowing each parameter such as soil type, climate and input type to be partitioned into sub-parameters and handled as multi-argument tuples, enabling precision modelling of complex agronomic criteria under truth, indeterminacy and falsity membership degrees [75, 76, 77]. In a 2025 study Kaviyarasu et al. [54] proposed neutrosophic hypersoft topological framework for agricultural decision-making constructs a neutrosophic agricultural topology in which open sets are generated from a neutrosophic sub-base and standard topological notions like basis, subspace, interior and closure are adapted to hypersoft neutrosophic spaces [54]. The research introduces two algorithms, one directly on neutrosophic hypersoft sets and another operating on neutrosophic hypersoft topological spaces. Numerical case studies using real agricultural data included crop alternatives evaluated under multiple agronomic and economic factors show that this topology-based MCDM approach improves the efficiency and reliability of decision strategies when the number of variables is large and uncertainty is high.

Topological variants, such as neutrosophic semi-open and semi-closed hypersoft sets, further refine this framework. By defining semi-open and semi-closed neutrosophic hypersoft sets and constructing corresponding topologies, decision algorithms have been developed for multi-attribute group decision-making. Although these models were demonstrated using COVID-19 case studies, the authors explicitly indicate that similar MAGDM (Multi-Attribute Group Decision-Making) schemes can be adapted to agricultural yield optimization and related planning problems [78, 79].
Beyond pure topology, hypersoft hybrids extensions such as possibility neutrosophic hypersoft sets, interval-valued complex neutrosophic hypersoft sets, fermatean neutrosophic hypersoft provide enhanced decision- capabilities by incorporating possibility degrees, phase information and higher-order uncertainty [46,75, 79, 80]. These models have been applied to sustainable agriculture case studies in which environmental, social, and economic criteria and their sub-attributes are evaluated under indeterminate and conflicting evidence, demonstrating improved handling of ambiguity and trade-offs compared to conventional MCDM methods [46].

5.2.Hybrid Neutrosophic-Fuzzy and MCDM models

Hybrid neutrosophic–fuzzy and MCDM models provide structured decision support in smart agriculture by combining rich representations of uncertainty with powerful ranking and weighting procedures. Neutrosophic and advanced fuzzy sets such as fermatean, q-rung orthopair, t-spherical, hypersoft allow expert opinions, sensor data, and qualitative assessments to be expressed with degrees of truth, falsity, and indeterminacy rather than crisp numbers, capturing hesitation and conflicting evidence typical of climate, market- and soil-driven decisions [46, 81-83]. These uncertainty models are then embedded in MCDM frameworks such as AHP, TOPSIS, CODAS, GRA, SPOTIS, MACBETH, or new hybrid schemes to weigh criteria and rank alternatives, for example when comparing agricultural production techniques, smart farming modes, UAV platforms, or vertical-farm technologies under multiple economic, environmental and social criteria [84, 85].
In practice, such hybrid models have been used to analyse sustainable agriculture and water-demand strategies with fuzzy AHP–TOPSIS variants, to optimize green supplier selection using Z-numbers with fuzzy LMAW–CRADIS, to evaluate Agriculture 4.0 decision support systems with hyperbolic fuzzy weighting and CODAS, and to select smart farming or robotic agri-farming modes under (p, q)-rung or q-rung orthopair fuzzy environments [81, 84, 86, 87]. They also support specialized problems like designing sustainable weed-management strategies in a t-spherical probabilistic hesitant fuzzy setting or ranking agri-food waste-valorization solutions with fermatean fuzzy SWARA–DEMATEL–QFD [88, 89]. Across these applications, hybrid neutrosophic–fuzzy MCDM models consistently aim to improve realism of expert input, integrate heterogeneous criteria, and deliver stable rankings checked by sensitivity and comparative analyses, making them a core advanced framework for smart-agriculture decision-making under deep uncertainty. Table 3. is a summary of representative hybrid neutrosophic-fuzzy MCDM frameworks and their applications in agriculture.
The NF-AHP weighting of 28 soil indicators enabled more nuanced handling of ambiguous field measurements and expert judgments, and produced stable, interpretable importance scores for key physical, chemical, productivity, and biological indicators in a climate-sensitive region [56]. Complementary work on land allocation for medium farm holders proposed a bi-level TOPSIS-based neutrosophic programming technique, showing higher net profit and better risk handling than fuzzy and intuitionistic fuzzy optimization approaches under uncertain water supply, labour, and yield conditions [47]. In sustainable agriculture, fermatean neutrosophic hypersoft MCDM algorithms further demonstrate that integrating neutrosophic structures with soft sets yields more flexible and realistic evaluations of agricultural techniques and inputs than conventional fuzzy-only schemes [46].

Table 3. Neutrosophic–Based Hybrid MCDM Models Applied to Agricultural Planning and Sustainability

Hybrid model	Agricultural application	Reference
Neutrosophic–fuzzy AHP and TOPSIS	Soil quality indexing and suitability ranking under uncertain indicators	[56, 90]
Neutrosophic TOPSIS and programming (bi-level)	Land allocation and farm planning with profit–risk trade-offs	[47]
Fermatean neutrosophic hypersoft MCDM	Sustainable practice and input selection using environmental, social–economic criteria	[46]

6.Unified neutrosophic Intelligent Decision Framework for Smart Agriculture

To effectively incorporate neutrosophic intelligence in smart agricultural decision environments, this review proposes a Unified Neutrosophic Intelligent Decision Framework that incorporates five interconnected layers that provide deep uncertainty management and intelligent decision-making. The Data Layer will obtain real-time agricultural data via IoT-powered sensors installed in farming fields, where they will monitor soil, climatic, and crop-related data that are vital in precision agriculture [30]. The Uncertainty Representation Layer leverages neutrosophic modelling to explicitly describe truth, falsity, and indeterminacy related to heterogeneous agricultural data to facilitate the successful manipulation of incomplete, inconsistent and noisy data [30, 54]. In the Reasoning Layer, neutrosophic aggreagation operators combine multi-source uncertain data into analysable representations, which are robust to conflicting or partially missing data [54, 85]. The Decision Layer integrates neutrosophic Multi-Criteria Decision-Making (MCDM) models to evaluate the alternatives across economic, environmental, and operating criteria to assist in optimized agricultural planning and resource allocation [46]. Finally, the Application Layer translates the framework into the real world by implementing smart farming management with the help of intelligent Decision Support Systems (DSS), which transforms the results of analysis into recommendations and action. The proposed layered architecture defines a unified interface between IoT-based data acquisition, uncertainty-sensitive reasoning, and intelligent decision-making, hence presenting a conceptual foundation for next-generation smart agricultural systems working on deep uncertainty. In order to present a systematized understanding of uncertainty-aware decision-making in smart agriculture, Unified Neutrosophic Intelligent Decision Framework is proposed, consisting of interrelated layers such as data acquisition, uncertainty representation, reasoning, decision-making, and implementation deployment, as shown in Figure 8.

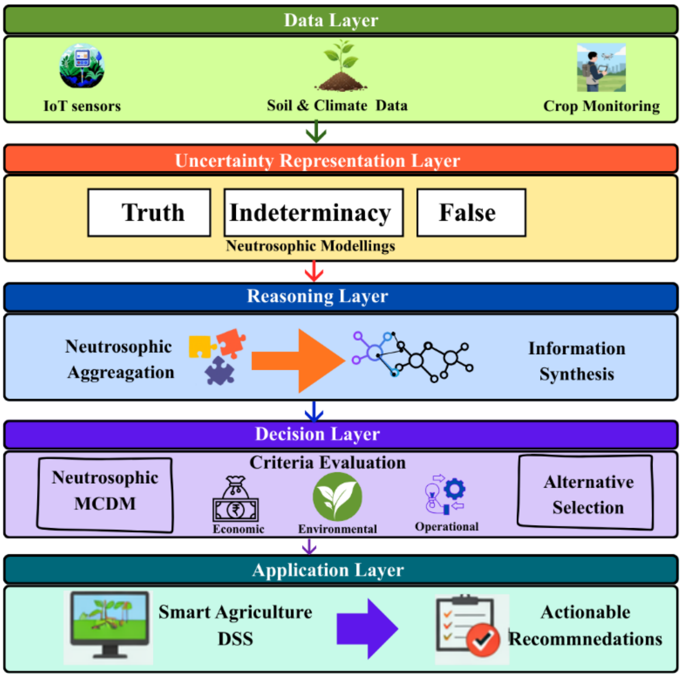


Figure 8. Unified Neutrosophic Intelligent Decision Framework for Smart agriculture

7.Limitations and critical assessment

7.1.Methodological limitations

7.1.1. Parameter selection and subjectivity: Defining the neutrosophic triple (T, I, F), mapping of linguistic terms to membership values and selection of aggregation operators remains predominantly expert-driven and usually ad hoc. These choices can directly influence outcomes crop ranking, land suitability, and yield risks estimation. As a result, decision outcomes shift significantly when alternative parametrization or mapping schemes are applied. Despite this sensitivity, systematic sensitivity analyses are reported in the existing literature, a limitation that has been consistently cited in both the application-based research and methodological reviews [91, 92].

7.1.2.Lack of standardized metrics and benchmarks: Currently, no standardized set of evaluation metrics exists that simultaneously accounts for predictive accuracy and uncertainty calibration for neutrosophic predictions. This lack of standardisation hinders comparative analysis comparison and meta-analysis across studies report only task-specific measures such as classification accuracy or MCDM ranking scores. According to recent surveys, it is necessary to have shared benchmark and standardized evaluation protocols to facilitate a fair comparison among neutrosophic, fuzzy, and ML-based approach, and XAI-driven models [67, 93].

7.2.Practical implementation limitations;

7.2.1.Limited software tools and packages: Software support for neutrosophic modelling lacks a unified framework contrast to the robust ecosystem of fuzzy logic and mainstream machine learning systems (scikit-learn, TensorFlow). Although prototype libraries such as PyIVNS (Python Interval-Valued Neutrosophic Set) prove the viability of inter-valued neutrosophic operations, they are not yet widely integrated into standard data-science work-flows. This limitation hinders reproducibility and slows the transition of neutrosophic methods into practical agricultural decision-support system [91].

7.2.2.Computational complexity of hypersoft and topological variants: Hypersoft sets and hypersoft topologies are advanced neutrosophic frameworks that offer significant expressive power for multi-subattribute MCDM by enabling robust topological operations and cartesian products of multiple sub-attributes. However, this increased modelling flexibility is paired with large computational complexity especially when applied to large-scale spatial or remote sensing datasets. Developers of hypersoft topologies model identify challenges related to dimensionality growth and algorithmic scalability, which may limit real-world utility in data-intensive agricultural applications [54, 78].

8.Research gaps

8.1.Few extensive field validations: Multi-site and multi-season experiments across a wide range of agro-ecological conditions are notably scarce, and most neutrosophic research studies in agriculture have been restricted to localized pilot projects, or on simulated data. Lack of field evaluation on a large scale fails to validate that these approaches are robust to real-world farming systems, in heterogenous climatic and management conditions [67, 93].

8.2.Scarce comparison with strong ML baselines: Most neutrosophic works are limited in their comparison with fuzzy or Intuitionistic fuzzy variants. Insufficient benchmarking against good machine learning baselines like Random forests, XGBoost and deep neural networks, is usually missing, undermining statements about performance improvements. Evidence suggests that tree-based ensembles and deep learning models are already very strong in predicting factors such as crop yield prediction and remote sensing. In the absence of systematic comparisons, it remains difficult to distinguish between the benefits of explicitly uncertainty modelling and the improvements due to more complex models or feature engineering [56, 94].

9.Future research direction for Smart agriculture

Future research directions in smart agriculture, particularly through the lens of neutrosophic sets, highlight the necessity of a methodological roadmap. Primary research must pivot to the systematic integration of neutrosophic intelligence with machine learning and deep learning models, emphasizing neutrosophic feature encoding for yield, price, and risk forecasting, and transforming sensor observations into (T, I, F) triplets prior to learning. Neutrosophic logic is well-positioned for widely adopted in noise-robust learning, yet it is not thoroughly explored within regression models and deep architectures [30]. Targeted efforts should focus on neuro-neutrosophic hybrid models, neutrosophic-based regularization strategies, and uncertainty-aware loss function designed to enhance generalization in the presence of missing, biased, or heterogeneous agricultural data [95]. Additionally, the development of neutrosophic explainable-AI (XAI) framework is critical, as interpretability remains a key challenge in data-driven agricultural decision-support systems. Hence, in the coming years, researchers should prioritize integrate neutrosophic logic theories along with other XAI techniques such as SHAP (SHapley Additive exPlanations) [96] and LIME (Local Interpretable Model-agnostic Explanations) [97] may enhance transparency and trust in decision-making processes. Furthermore, employing neutrosophic logic tasks in IoT-based edge clouds and cloud infrastructures for support real-time anomaly identification offers significant potential [30]. Future studies should also investigate scaling neutrosophic models to satellite, UAV (Unmanned Aerial Vehicle), hyperspectral, and other multi-source big-data platforms using cloud-edge collaborative architectures. On the other hand, normalization processes along with the development of common datasets should be executed to facilitate appropriate deployment in policy-focused tasks.

CONCLUSION

The integration of neutrosophic logic in smart agriculture is a critical evolution in the response to the complexities and uncertainties of agricultural decision-making. Neutrosophic techniques that incorporate neutrosophic linear programming, clustering and IF-THEN rule offers a resilient architecture in optimization of land allocation, resource planning and real-time farming decision. These approaches are effective in mitigating inherent uncertaunty in the agricultural variables, such as the yield, price and environmental factors. To illustrate, interval-valued complex neutrosophic hypersoft sets (IV-CNHS) have been developed, allowing labels to be partitioned into multi-sub parametric tuples, which offers a more detailed and mathematically adequate treatment of the complex, interdependent variables of agricultural systems.

Although these developments are encouraging, yet persistent several limitations in its methodology. The subjectivity involved in the selection of parameters based on expert judgment and the manipulation of linguistic words into a value based on membership compromise the integrity of outcomes which may include crop ranking and land suitability assessment. This variability explains why sensitivity analyses are essential, and it is not reported in existing studies often. Furthermore, the absence of standardized measures of assessing neutrosophic outputs makes it complicated to assess the predictive accuracy and uncertainty calibration, which needs for unified standards in this area.

The development of advanced neutrosophic systems, such as neutrosophic hypersoft sets also improves the ability to manage intricate interdependencies between decision parameters especially in areas with uncertain climatic conditions. These frameworks enable incorporation of various variables in the decision-making process like soil quality and climatic conditions thus enhancing the robustness of the agricultural practices.

In conclusion, the neutrosophic logic does propose to improve the decision-making in the smart farming, but it is important to address identified limitations to make it as effective as possible. The further studies and collaboration among experts are required to refining these approaches, establishing the metrics of the standard evaluation, and eventually enhance the productivity and sustainability in an increasingly uncertain climatic- agriculture.

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Authors Contribution

DevaDharshini: writing original draft, collection of literatures, conceptualization, Editing; Kalpana Muthuswamy: Supervision, review and editing; M Vijayabhama: Supervision; P Vasanthi: Supervision; R Parimalarangan: Supervision.

Ethical Approval

The article does not contain any studies involving human participants or animal performed by any of the authors.

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