

Article

Geo-Information Driven Multi-Criteria Decision Analysis for Precision Agriculture Technologies Using Neutrosophic Entropy-DEMATEL and Hybrid TOPSIS

Venkata Prasanna Nagari *  and Vinoth Subbiah

Department of Mathematics & Statistics, Vignan's Foundation for Science, Technology & Research,
Vadlamudi 522213, Andhra Pradesh, India; drsv_sh@vignan.ac.in

* Correspondence: prasannakumarnagari@gmail.com

Abstract

Precision agriculture employs advanced technologies to enhance farm productivity and sustainability; however, selecting the most appropriate tools can be challenging for small and medium-sized farms. This study conducts a comparative analysis of ten key precision agriculture technologies (PATs): remote sensing, GPS, GIS, VRT, soil & crop sensors, DSS, UAVs/Drones, AI & ML-based precision farming, autonomous agricultural machinery, and IoT-based smart farming. The analysis employs a neutrosophic set-based multi-criteria decision-making (MCDM) framework. Domain experts evaluated ten representative technologies using a structured questionnaire based on ten critical criteria, including spatial-temporal accuracy, data acquisition latency, scalability, robustness, interoperability, environmental resilience, economic feasibility, and agro-ecological impact. A hybrid MCDM methodology was employed, integrating neutrosophic entropy and DEMATEL to construct criterion weights. Furthermore, we utilized neutrosophic DEMATEL to identify inter-criterion causal relationships. Neutrosophic TOPSIS, enhanced by a newly proposed hybrid Cosine-Jaccard similarity measure, was introduced to rank the alternatives under conditions of uncertainty. The findings reveal that IoT-based smart farming solutions achieved the highest overall score, followed by remote sensing and decision-support system (DSS) platforms. At the same time, variable-rate technology and sensor networks received lower rankings. The findings underscore the appropriateness of particular PATs for small and medium-scale farming contexts and illustrate the effectiveness of neutrosophic MCDM in addressing ambiguity and indeterminacy. The comparative insights provide direction for researchers, policymakers, and practitioners in prioritizing precision agriculture technologies and strategies to enhance sustainable practices in small and medium-scale farming.

Keywords: precision agriculture technologies; neutrosophic MCDM; entropy; DEMATEL; hybrid similarity measure; TOPSIS



Academic Editors: Wolfgang Kainz
and Jamal Jokar Arsanjani

Received: 27 October 2025

Revised: 6 December 2025

Accepted: 9 December 2025

Published: 11 March 2026

Copyright: © 2026 by the authors.

Published by MDPI on behalf of the

International Society for

Photogrammetry and Remote Sensing.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Precision agriculture (PA) has arisen as a revolutionary approach to augmenting agricultural productivity and resource efficiency through site-specific field management. Technologies such as GPS, GIS, sensors, UAV photography, and data analytics enhance decision-making and significantly impact profitability and sustainability, particularly in extensive agricultural systems [1]. The UNDP report “Precision Agriculture for Smallholder

Farmers” (2021) indicates that digital instruments such as mobile phones, satellites, drones, and sensors can significantly enhance productivity, decrease input costs, and foster environmental sustainability in smallholder systems. The paper emphasizes increasing accessibility in developing regions while also acknowledging enduring systemic and implementation obstacles [2].

Recent technological advancements are increasingly broadening the relevance of precision agriculture across various farming scenarios. Autonomous agricultural vehicles employing nonlinear model predictive control (NMPC) have demonstrated resilient navigation and real-time performance in unpredictable field settings [3]. In contrast, distributed NMPC has enabled efficient trajectory tracking in intricate tractor-trailer systems [4]. Unmanned aerial vehicles (UAVs) outfitted with multispectral and thermal imaging systems are indispensable for evaluating crop vitality, soil heterogeneity, and nutrient levels. Moreover, GIS and GPS technologies are fundamental to site-specific management and informed decision-making [5,6]. Advancements in economical GNSS systems, optical odometry, and UAV-based imaging have significantly increased accessibility for small and medium-sized farms [7–10]. Agriculture 4.0, driven by decision support systems (DSS), IoT, GNSS, and wireless sensor networks, enhances resource optimization at the system level, though persistent usability issues remain [11]. Multi-GNSS PPP provides a cost-effective alternative for high-precision positioning, particularly in obstructed environments [12].

The integration of IoT-based sensor networks, UAV imaging, and remote sensing has transformed precision agriculture by facilitating real-time monitoring, site-specific management, and energy-efficient irrigation practices [13–15]. Integration of sensor and UAV data facilitates automated assessment of crop health. In contrast, hyperspectral and multispectral imaging enhance the precision of disease detection, nutrient estimation, and biomass evaluation across various crops [16–18]. UAV enabled IoT systems have been widely used in irrigation, pest detection, and phenotyping, demonstrating high accuracy and enabling timely decision-making [19–21]. Machine learning models applied to UAV and sensor data have improved early pest management, yield prediction, and soil moisture estimation, underscoring the importance of intelligent, data-driven systems in commercial agriculture.

Recent advancements in smart farming integrate UAV platforms, deep learning, geoinformatics, blockchain-enhanced IoT, and cloud-based analytics to improve disease detection, plant management, and resource optimization [22–26]. Machine learning integrated with IoT sensors enables accurate irrigation, crop health assessment, and disease forecasting, while variable-rate technologies (VRT), including NDVI-based fertilizer applicators, minimize input waste and promote sustainability [27–30]. Innovations such as GPS-based navigation, soil-sensing technologies, intelligent UAV sprayers, cost-effective multirotor systems, and RTK-enhanced mapping are enhancing the efficiency of small- and medium-scale farming operations [31–38]. Smart agriculture solutions that incorporate GIS-deep learning models, IoT-enabled aeroponics, AI-based advisory systems, and UAV-assisted chemical application underscore the growing transition towards intelligent, scalable, and environmentally sustainable farming practices [39–43].

Despite technological advancements, decision-making in precision agriculture remains complex due to uncertain environmental conditions, incomplete data, conflicting expert opinions, and diverse evaluation criteria. Multi-criteria decision-making (MCDM) methods have been widely employed to address these challenges since the 1960s, concentrating on the analysis of competing objectives with varying weights and dimensions. MCDM has evolved into structured methodologies such as AHP and TOPSIS, and is now widely utilized in sustainability, engineering, and management contexts [44]. Classical and fuzzy MCDM techniques often struggle to capture indeterminacy in expert judgements effectively.

Neutrosophic sets, introduced by Smarandache [45] extend fuzzy and intuitionistic fuzzy sets by integrating three independent membership components: truth, indeterminacy, and falsity. This framework provides a more robust mathematical structure for representing uncertain and inconsistent information.

Despite significant progress in precision agriculture, current research remains fragmented, mainly focusing on individual technologies such as drones, sensors, and GPS tools in isolation. There has been no previous research that provides a comprehensive, multi-criteria, neutrosophic assessment of a wide range of ten critical PATs, particularly in the context of small and medium-sized farms. Furthermore, current decision-making frameworks predominantly rely on classical or fuzzy MCDM methods, which fail to adequately capture indeterminacy, conflicting expert judgments, and inherent uncertainty in real-world agricultural environments. Although individual neutrosophic methods, such as neutrosophic entropy, DEMATEL, and TOPSIS, have been applied independently in other domains, the literature lacks an integrated hybrid framework that simultaneously incorporates objective entropy weights, causal interdependencies (as in DEMATEL), and robust ranking mechanisms (as in TOPSIS) for comprehensive PAT assessment. This clear methodological and practical gap underscores the need for a holistic, uncertainty-resilient, neutrosophic MCDM framework capable of comparing multiple PATs and guiding technology selection tailored to the needs of small and medium-scale farms.

This study has been assembled around essential investigation objectives.

1. To explore and evaluate the core types of ten precision agriculture technologies based on insights from academic research and real-world applications.
2. To define ten key assessment criteria for the practical evaluation of these technologies.
3. To conduct a comparative study that identifies the advantages, drawbacks, and real-world applicability of various technologies across different agricultural settings.
4. To focus on recognizing technologies that are particularly suitable for the needs and constraints of small and medium-scale farming sectors.
5. To develop practical recommendations that can assist farmers, researchers, and policy-makers in making informed decisions about adopting precision agriculture technologies.

We established a specialist-oriented assessment methodology to prioritize essential PATs based on factors including accuracy, operational sustainability, economic feasibility, and scalability. We evaluated technologies such as UAVs, IoT, DSS, ML, and VRT using expert ratings and categorized them by performance. This methodology helps identify the most efficient solutions for contemporary, data-driven agriculture.

This research enhances the existing body of knowledge on precision agriculture through several significant avenues. Currently, there is a paucity of research systematically evaluating PATs against essential criteria, including accuracy, environmental resilience, ease of adoption, and scalability. This study identifies and analyses the most pertinent evaluation criteria for selecting PAT. Secondly, it evaluates key technologies such as UAVs, IoT systems, DSS, ML, and VRT according to their performance against these criteria. This study represents one of the initial comparative assessments of PATs designed explicitly for small to medium-scale farming contexts, providing significant insights for researchers, policymakers, and practitioners focused on improving sustainable, data-driven agricultural practices.

Note that these PATs are often used in combination rather than as isolated tools; for example, GPS data and satellite/drone imagery are typically integrated within a GIS framework to generate precise farm maps [46].

2. Materials and Methods

2.1. Description of Existing Methods

Existing literature extensively employs MCDM and neutrosophic methods to address complex decision-making problems under uncertainty. Prior research in agriculture has extensively employed MCDM methodologies, including fuzzy logic [47,48] and fuzzy-TOPSIS [49]. Similarly, neutrosophic sets have been extensively used in MCDM techniques, such as neutrosophic entropy [50–55], neutrosophic DEMATEL [56–58], neutrosophic TOPSIS [59,60], and neutrosophic MCDM [61–70].

Recent studies emphasize the growing importance of neutrosophic sets, MCDM techniques, and similarity measures in enabling sustainable, data-driven decision-making across sectors. Advanced hybrid MCDM frameworks have enhanced financial and strategic evaluations, as shown by Liew et al. [71], who integrated entropy, DEMATEL, and TOPSIS to evaluate the financial health of Dow Jones Industrial Average firms by identifying key indicators such as ROE, CR, and DER. Nabeeh et al. [72] formulated a neutrosophic AHP model for IoT-driven enterprises, assessing criteria such as safety, interactivity, and value, and adeptly addressing ambiguity, validated through case studies from Egypt, the UK, and China. Salam et al. [73] introduced a neutrosophic MABAC-entropy framework for UAV selection in agriculture under uncertain conditions, highlighting payload, endurance, and size as critical factors, and determining the YAMAHA FAZER R as the optimal choice. These studies collectively indicate that hybrid neutrosophic MCDM approaches are increasingly vital for precise evaluation, forecasting, and technology adoption in uncertain and complex environments.

2.2. Collection of Data and Data Preprocessing

The current study used a structured questionnaire to collect opinions from specialists on the scrutiny of 10 precision agriculture technologies (PATs), each constructed in accordance with the 10 fundamental requirements. The ten alternative PATs considered in the study for evaluation are denoted by symbols $(\tilde{A}_1 - \tilde{A}_{10})$ for consistency in the neutrosophic MCDM analysis, as shown in Table 1.

It is difficult to make direct comparisons across precision agriculture technologies because they each have different advantages, limitations, and purposes. For instance, GIS is usually used to analyze spatial patterns, GPS is used to locate things precisely, and remote sensing is used to learn about land and crops. In the real world, these technologies are commonly used together to achieve specific management goals rather than alone. It is crucial to compare PATs, even though they differ. This will help you choose the ideal technologies for your farm and make decisions when you do not know what will happen. These comparisons help people interested in a project find the best solutions by evaluating options based on factors such as cost, effectiveness, and ease of use.

Table 2 summarizes the ten criteria used to evaluate the performance of PATs in the study. Each criterion is denoted by a symbol $(\tilde{C}_1 - \tilde{C}_{10})$ and classified as either a benefit or a cost attribute. The descriptions clarify what each criterion measures, ensuring consistency in the neutrosophic MCDM analysis.

Table 1. Investigated precision agriculture technologies (PATs).

S.no	Types of PATs	Symbol	Description
1	Remote Sensing	$\tilde{A}_1$	Collects information about crops and soil from a distance using satellites or aerial imagery.
2	Global Positioning System (GPS)	$\tilde{A}_2$	Provides precise location data for field operations and mapping.
3	Geographic Information System (GIS)	$\tilde{A}_3$	Manages and analyses spatial and geographic data for farm planning.
4	Variable Rate Technology (VRT)	$\tilde{A}_4$	Adjusts the application of inputs, such as fertilizers and seeds, based on field variability.
5	Soil and Crop Sensors	$\tilde{A}_5$	Measures soil properties and crop conditions in real time to support decision-making.
6	Decision Support Systems (DSS)	$\tilde{A}_6$	Software tools that integrate data to recommend optimal farming practices.
7	Drones/UAVs (Unmanned Aerial Vehicles)	$\tilde{A}_7$	Captures high-resolution imagery and monitor crop health efficiently.
8	AI (Artificial Intelligence) and ML (Machine Learning)-based Precision Farming	$\tilde{A}_8$	Uses predictive models to optimize farming operations and yields.
9	Autonomous Agricultural Machinery	$\tilde{A}_9$	Self-operating equipment for planting, harvesting, and field management.
10	IoT (Internet of Things)-based Smart Farming	$\tilde{A}_{10}$	Connects sensors, devices, and systems to enable real-time farm monitoring and automation

Table 2. Evaluation criteria for PATs.

S.no	Criteria	Symbol	Attribute Type	Description
1	Spatial-temporal accuracy	$\tilde{C}_1$	Benefit	Measures the precision and timeliness of information collected by technology, including location accuracy and frequency of updates.
2	Data acquisition latency	$\tilde{C}_2$	Cost	Captures the delay between data collection and decision-making availability; lower latency is preferable.
3	Scalability and deployability	$\tilde{C}_3$	Benefit	Reflects how easily technology can be expanded or implemented across different farm sizes and locations.
4	Algorithmic robustness and AI integration	$\tilde{C}_4$	Benefit	Assesses the reliability and adaptability of the underlying algorithms, including integration with AI/ML models.
5	System interoperability and data integration	$\tilde{C}_5$	Benefit	Evaluates the technology's ability to integrate with other systems and datasets for seamless operations.
6	Environmental resilience	$\tilde{C}_6$	Benefit	Measures the technology's robustness to environmental conditions, including weather, soil variability, and climate.
7	Economic feasibility and ROI (return on investment)	$\tilde{C}_7$	Benefit	Reflects cost-effectiveness, initial investment, operational costs, and expected return on investment.
8	Automation and cognitive ergonomics	$\tilde{C}_8$	Benefit	Evaluates the level of automation and ease of use for operators, reducing human effort and cognitive load.
9	Operational sustainability	$\tilde{C}_9$	Benefit	Assesses long-term maintainability, reliability, and efficiency of the technology in farm operations
10	Agro-ecological impact	$\tilde{C}_{10}$	Benefit	Measures the positive or negative effects on soil health, biodiversity, and overall ecosystem sustainability.

While there are ten evaluation criteria, nine of them, $(\tilde{C}_1, \tilde{C}_3 - \tilde{C}_{10})$, are regarded as benefit criteria. Higher values demonstrate better performance. Only the data acquisition latency $(\tilde{C}_2)$ is considered a cost criterion, as it is considered more desirable to have a shorter latency. In the construction of positive and negative ideal solutions in the neutrosophic TOPSIS analysis, this classification ensures consistency. These criteria were chosen to

conduct an all-encompassing evaluation of PATs across their technological, operational, economic, and environmental aspects. These models capture the significant aspects that determine performance, adoption feasibility, and sustainability in real-world farming contexts. The research survey was communicated to five domain-qualified professionals: four in precision agriculture and one in environmental science. Their insights provide an exhaustive review, enabling an accurate comparison of several technologies according to the established standards of conduct. The study uses assessments from five experts, a number consistent with standard practices in neutrosophic and fuzzy MCDM research, where 3–7 experts are generally adequate given the cognitively demanding nature of uncertainty driven linguistic evaluations. The experts were intentionally selected for their expertise in precision agriculture and environmental systems, resulting in a small yet highly specialized and representative panel. We recognize that the small sample size may heighten sensitivity to individual judgments; thus, we implemented expert-importance weighting and robustness checks, including consistency assessments, to address this limitation. The remaining steps of the research procedure are illustrated in detail in the flowchart presented in Figure 1.

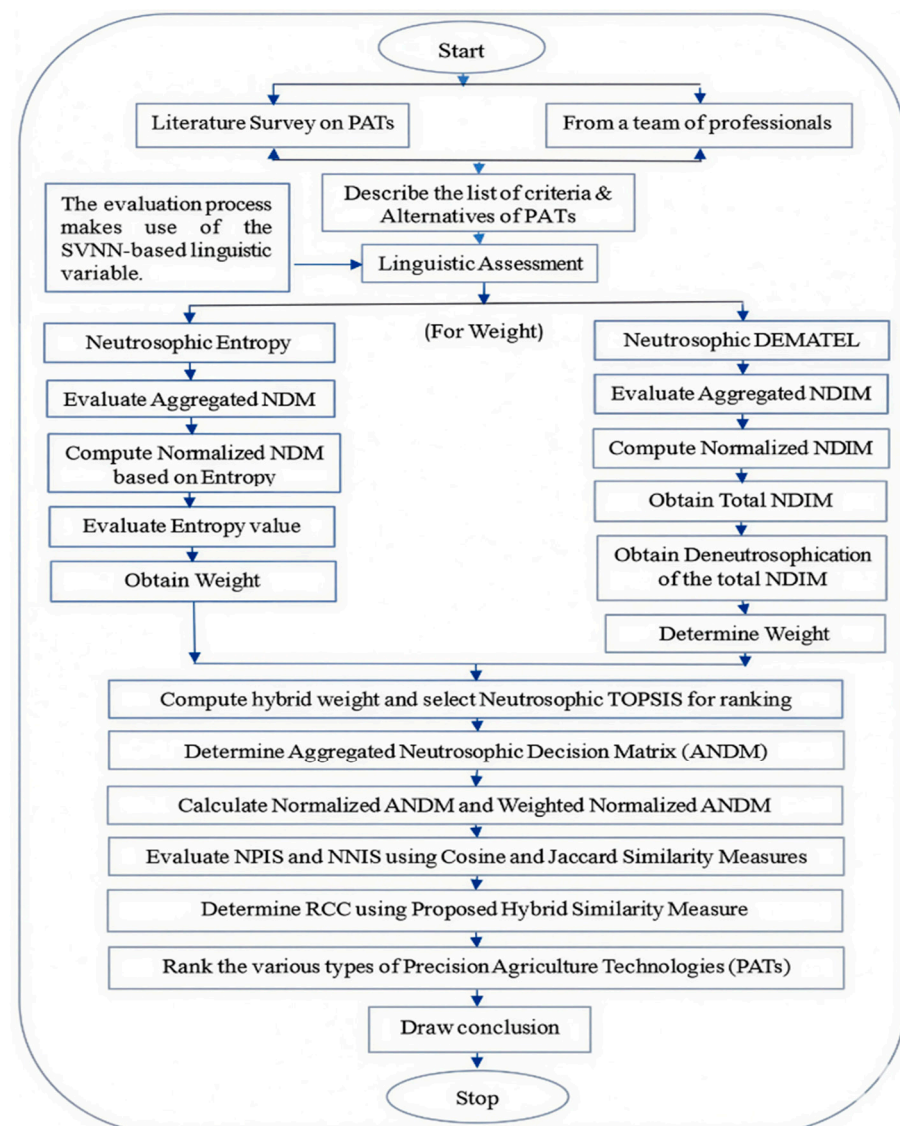


Figure 1. Flow of research.

Questionnaire Structure and Expert Evaluation Procedure

A standardized questionnaire was distributed to five domain experts, who responded independently to prevent group influence or mutual adjustment. The questionnaire included comprehensive descriptions of the ten evaluation criteria. It required experts to assess PAT using the single-valued neutrosophic linguistic scale (Table 3), which comprises eleven ordered terms ranging from ‘Extremely Bad’ to ‘Extremely Good’, each denoted by predefined (T, I, F) membership triplets.

Prior to undertaking the survey, experts received a succinct orientation on the interpretation of neutrosophic truth, indeterminacy, and falsity values, thereby ensuring uniform application of the scale. Upon collecting replies, fundamental consistency checks were performed to detect contradictory or ambiguous judgements; only authentic inconsistencies were referred back to experts for explanation. The residual fluctuations across experts were addressed objectively with the neutrosophic aggregation operator in Equation (4), which incorporates uncertainty and variations in confidence via the expert-importance weighting system.

2.3. Preliminaries

Some fundamental definitions of neutrosophic sets (NSs), single-valued neutrosophic sets (SVNSs), decision maker weights, the deneutrosophication of single-valued neutrosophic numbers (SVNNs), and arithmetic operations of SVNNs are given in this section.

Neutrosophic Set (NS): The neutrosophic set has its roots in neutrosophy, a relatively recent area of philosophy that examines the nature, origin, and extent of neutralities, and their interactions with various ideational spectra.

Definition 1 ([59]). Let X denote the universe of discourse. The NS M in X has the following form.

$$M = \{ \langle x, T_M(x), I_M(x), F_M(x) \rangle \mid x \in X \} \quad (1)$$

where $T_M(x)$ denotes the truth-membership function; $T_M \in]0^-, 1^+[$; $I_M(x)$ denotes the indeterminacy-membership function; $I_M \in]0^-, 1^+[$; and $F_M(x)$ denotes the falsity-membership function; $F_M \in]0^-, 1^+[$. These membership functions must satisfy the following constraints:

$$0^- \leq T_M(x) + I_M(x) + F_M(x) \leq 3^+$$

Definition 2 ([45]). The complement of NS M is denoted by M^c and defined as $T_M^c(x) = 1^+ - T_M(x)$, $I_M^c(x) = 1^+ - I_M(x)$, and $F_M^c(x) = 1^+ - F_M(x)$ for all $x \in X$.

Definition 3 ([45]). A neutrosophic set M is contained in another neutrosophic set N , i.e., if and only if $\inf T_M(x) \leq \inf T_N(x)$, $\sup T_M(x) \leq \sup T_N(x)$, $\inf I_M(x) \geq \inf I_N(x)$, $\sup I_M(x) \geq \sup I_N(x)$, $\inf F_M(x) \geq \inf F_N(x)$, $\sup F_M(x) \geq \sup F_N(x)$ for all x in X .

Single-Valued Neutrosophic Set (SVNS): SVNS is a special case of neutrosophic sets. There are practical, scientific, and engineering uses for it. Some fundamental definitions, operations, and characteristics of SVNS are presented in the sections that follow.

Definition 4 ([59]). Let X be a nonempty set. The SVNS M in X has the following form:

$$M = \{ \langle x, T_M(x), I_M(x), F_M(x) \rangle \mid x \in X \}$$

where membership functions T_M , I_M , and $F_M \in]0^-, 1^+[$ and satisfy the following constraint:

$$0^- \leq T_M(x) + I_M(x) + F_M(x) \leq 3^+ \quad (2)$$

Definition 5 ([59]). A SVN $m = \langle t_m(x), i_m(x), f_m(x) \rangle$ is a special case of an SVNS on the real numbers $\mathcal{R}$, where $t_m(x), i_m(x), f_m(x) \in [0, 1]$ and $0 \leq t_m(x) + i_m(x) + f_m(x) \leq 3$.

Definition 6 ([62]). Decision makers' relative relevance might fluctuate in a decision-making situation. The important weight should be calculated to represent the significance of decision makers in the decision-making process. In these circumstances, SVNNS can be used to rate the relevance of decision makers; the important weight of the k^{th} decision maker can be written as follows:

$$w_k = \frac{1 - \sqrt{\{(1 - T_k)^2 + (I_k)^2 + (F_k)^2\}/3}}{\sum_{k=1}^q \left(1 - \sqrt{\{(1 - T_k)^2 + (I_k)^2 + (F_k)^2\}/3}\right)} \quad (3)$$

Definition 7 ([56]). The criteria and options in an MCDM challenge may be viewed differently by each decision maker. The majority of MCDM methods, including neutrosophic DEMATEL, require combining decision makers' opinions with varying relevance weights. In light of this instance, let $A^k = (a_{ij}^k)_{n \times n}$ represent the k^{th} decision makers' decision matrix and $w = (w_1, w_2, \dots, w_q)^U$ represent the decision makers' importance vector. The evaluation aggregate of several decision makers with varying importance weights can then be computed as shown in Equation (4).

$$\begin{aligned} \text{SVNWA}_w(a_{ij}^{(1)}, a_{ij}^{(2)}, \dots, a_{ij}^{(q)}) &= \prod_{k=1}^q w_k a_{ij}^k \\ &= 1 - \prod_{k=1}^q \left(1 - T_{ij}^{(k)}\right)^{w_k}, \prod_{k=1}^q \left(I_{ij}^{(k)}\right)^{w_k}, \prod_{k=1}^q \left(F_{ij}^{(k)}\right)^{w_k} \end{aligned} \quad (4)$$

The process of converting any neutrosophic number into a single actual number is known as deneutrosophication. The Definition of SVN denotification is as follows:

Definition 8 ([65]). Let $M = \{\langle x, T_M(x), I_M(x), F_M(x) \rangle \mid x \in X\}$ be an SVN; then the denotification of M is the process of the set M mapping into a real number $Y \in X$, i.e., $f: M \rightarrow Y$ for $x \in X$. The set M is reduced to a crisp number $Y \in X$. Therefore, the denotification can be computed as Equation (5).

$$Y_M = 1 - \sqrt{\{(1 - T_M(x))^2 + (I_M(x))^2 + (F_M(x))^2\}/3} \quad (5)$$

Definition 9 ([45,74]). Let $\tilde{\mathcal{M}} = \langle \mathcal{T}_{\tilde{\mathcal{M}}}(x), \mathcal{I}_{\tilde{\mathcal{M}}}(x), \mathcal{F}_{\tilde{\mathcal{M}}}(x) \rangle$ and $\tilde{\mathcal{N}} = \langle \mathcal{T}_{\tilde{\mathcal{N}}}(x), \mathcal{I}_{\tilde{\mathcal{N}}}(x), \mathcal{F}_{\tilde{\mathcal{N}}}(x) \rangle$ be any two SVNNS; then the following definitions of arithmetic operations are given.

- (i) $\tilde{\mathcal{M}} + \tilde{\mathcal{N}} = \langle \mathcal{T}_{\tilde{\mathcal{M}}}(x) + \mathcal{T}_{\tilde{\mathcal{N}}}(x) - \mathcal{T}_{\tilde{\mathcal{M}}}(x) \cdot \mathcal{T}_{\tilde{\mathcal{N}}}(x), \mathcal{I}_{\tilde{\mathcal{M}}}(x) \cdot \mathcal{I}_{\tilde{\mathcal{N}}}(x), \mathcal{F}_{\tilde{\mathcal{M}}}(x) \cdot \mathcal{F}_{\tilde{\mathcal{N}}}(x) \rangle$
- (ii) $\tilde{\mathcal{M}} \times \tilde{\mathcal{N}} = \langle \mathcal{T}_{\tilde{\mathcal{M}}}(x) \cdot \mathcal{T}_{\tilde{\mathcal{N}}}(x), \mathcal{I}_{\tilde{\mathcal{M}}}(x) + \mathcal{I}_{\tilde{\mathcal{N}}}(x) - \mathcal{I}_{\tilde{\mathcal{M}}}(x) \cdot \mathcal{I}_{\tilde{\mathcal{N}}}(x), \mathcal{F}_{\tilde{\mathcal{M}}}(x) + \mathcal{F}_{\tilde{\mathcal{N}}}(x) - \mathcal{F}_{\tilde{\mathcal{M}}}(x) \cdot \mathcal{F}_{\tilde{\mathcal{N}}}(x) \rangle$
- (iii) $\tilde{\mathcal{M}} \cup \tilde{\mathcal{N}} = \{\max(\mathcal{T}_{\tilde{\mathcal{M}}}(x), \mathcal{T}_{\tilde{\mathcal{N}}}(x)), \max(\mathcal{I}_{\tilde{\mathcal{M}}}(x), \mathcal{I}_{\tilde{\mathcal{N}}}(x)), \min(\mathcal{F}_{\tilde{\mathcal{M}}}(x), \mathcal{F}_{\tilde{\mathcal{N}}}(x))\}$
- (iv) $\tilde{\mathcal{M}} \cap \tilde{\mathcal{N}} = \{\min(\mathcal{T}_{\tilde{\mathcal{M}}}(x), \mathcal{T}_{\tilde{\mathcal{N}}}(x)), \max(\mathcal{I}_{\tilde{\mathcal{M}}}(x), \mathcal{I}_{\tilde{\mathcal{N}}}(x)), \max(\mathcal{F}_{\tilde{\mathcal{M}}}(x), \mathcal{F}_{\tilde{\mathcal{N}}}(x))\}$
- (v) $\lambda \tilde{\mathcal{M}} = \{1 - (1 - \mathcal{T}_{\tilde{\mathcal{M}}}(x))^\lambda, (\mathcal{I}_{\tilde{\mathcal{M}}}(x))^\lambda, (\mathcal{F}_{\tilde{\mathcal{M}}}(x))^\lambda\}$
- (vi) $(\tilde{\mathcal{M}})^\lambda = \{(\mathcal{T}_{\tilde{\mathcal{M}}}(x))^\lambda, (1 - (1 - \mathcal{I}_{\tilde{\mathcal{M}}}(x))^\lambda), (1 - (1 - \mathcal{F}_{\tilde{\mathcal{M}}}(x))^\lambda)\}$

2.4. Similarity Measure

In multi-criteria decision-making (MCDM) involving neutrosophic sets, a similarity measure is a vital mathematical function used to quantify the degree of resemblance between two alternatives or between an alternative and the ideal solution. The similarity measure helps in determining how close a given alternative is to the positive ideal solution (PIS) and how far it is from the negative ideal solution (NIS), which is crucial for effective ranking.

3. Proposed Method for Weight Determination and Ranking Utilizing Neutrosophic Entropy-DEMATEL and Neutrosophic TOPSIS with a Hybrid Similarity Measure

Given the uncertainty inherent in expert judgments and data incompleteness, this study uses a hybrid similarity measure that combines the Cosine and Jaccard indices, each weighted to reflect their contributions to decision-making. The Cosine similarity focuses on vector orientations and is suitable for high-dimensional data. In contrast, the Jaccard similarity measures the shared attributes between sets, making it effective for capturing feature overlap. By integrating these two measures, the hybrid metric balances geometric interpretation and commonality-based assessment, improving robustness.

3.1. Proposed Similarity Measure Formula [75]: Hybrid Weighted Cosine-Jaccard Neutrosophic Similarity Measure

$$Hyb_{CJS}(\mathcal{P}, \mathcal{Q}) = \Psi \mathcal{S}_{CS} + (1 - \Psi) \mathcal{S}_{JS} \text{ where } 0 \leq \Psi \leq 1 \quad (6)$$

$$\begin{aligned} \text{Cos}_w(\mathcal{P}, \mathcal{Q}) &= \mathcal{S}_{CS} \\ &= \sum_{i=1}^n w_i \frac{(\mathcal{T}_{\mathcal{P}}(x_i) \cdot \mathcal{T}_{\mathcal{Q}}(x_i) + \mathcal{I}_{\mathcal{P}}(x_i) \cdot \mathcal{I}_{\mathcal{Q}}(x_i) + \mathcal{F}_{\mathcal{P}}(x_i) \cdot \mathcal{F}_{\mathcal{Q}}(x_i))}{\sqrt{(\mathcal{T}_{\mathcal{P}}^2(x_i) + \mathcal{I}_{\mathcal{P}}^2(x_i) + \mathcal{F}_{\mathcal{P}}^2(x_i))} \sqrt{(\mathcal{T}_{\mathcal{Q}}^2(x_i) + \mathcal{I}_{\mathcal{Q}}^2(x_i) + \mathcal{F}_{\mathcal{Q}}^2(x_i))}} \end{aligned} \quad (7)$$

$$\begin{aligned} \text{Jac}_w(\mathcal{P}, \mathcal{Q}) &= \mathcal{S}_{JS} = \sum_{i=1}^n w_i * \\ &\frac{(\mathcal{T}_{\mathcal{P}}(x_i) \cdot \mathcal{T}_{\mathcal{Q}}(x_i) + \mathcal{I}_{\mathcal{P}}(x_i) \cdot \mathcal{I}_{\mathcal{Q}}(x_i) + \mathcal{F}_{\mathcal{P}}(x_i) \cdot \mathcal{F}_{\mathcal{Q}}(x_i))}{[(\mathcal{T}_{\mathcal{P}}^2(x_i) + \mathcal{I}_{\mathcal{P}}^2(x_i) + \mathcal{F}_{\mathcal{P}}^2(x_i)) + (\mathcal{T}_{\mathcal{Q}}^2(x_i) + \mathcal{I}_{\mathcal{Q}}^2(x_i) + \mathcal{F}_{\mathcal{Q}}^2(x_i)) - (\mathcal{T}_{\mathcal{P}}(x_i) \cdot \mathcal{T}_{\mathcal{Q}}(x_i) + \mathcal{I}_{\mathcal{P}}(x_i) \cdot \mathcal{I}_{\mathcal{Q}}(x_i) + \mathcal{F}_{\mathcal{P}}(x_i) \cdot \mathcal{F}_{\mathcal{Q}}(x_i))]} \end{aligned} \quad (8)$$

where $\sum_{i=1}^n w_i = 1$

Validity checking for hybrid weighted Cosine-Jaccard neutrosophic similarity measure.

Property 1: $0 \leq Hyb_{CJS}(\mathcal{P}, \mathcal{Q}) \leq 1$

Proof. Since both Cosine and Jaccard similarity measures satisfy the condition.

$$\begin{aligned} 0 &\leq \text{Cos}_w(\mathcal{P}, \mathcal{Q}) \leq 1 \text{ and } 0 \leq \text{Jac}_w(\mathcal{P}, \mathcal{Q}) \leq 1, \\ \Rightarrow \text{The weighted combination } 0 &\leq \Psi \text{Cos}_w(\mathcal{P}, \mathcal{Q}) + (1 - \Psi) \text{Jac}_w(\mathcal{P}, \mathcal{Q}) \leq 1 \\ \Rightarrow 0 &\leq Hyb_{CJS}(\mathcal{P}, \mathcal{Q}) \leq 1. \end{aligned}$$

Property 2: symmetry condition: $Hyb_{CJS}(\mathcal{P}, \mathcal{Q}) = Hyb_{CJS}(\mathcal{Q}, \mathcal{P}) \quad \square$

Proof. Since both Cosine and Jaccard similarity measures are symmetric, meaning that interchanging A and B does not affect their values,

$$\Rightarrow Hyb_{CJS}(\mathcal{P}, \mathcal{Q}) = \Psi \mathcal{S}_{CS} + (1 - \Psi) \mathcal{S}_{JS} = Hyb_{CJS}(\mathcal{Q}, \mathcal{P})$$

Property 3: identity condition

If $\mathcal{P}$ and $\mathcal{Q}$ are identical

That is if $\mathcal{T}_{\mathcal{P}}(x_i) = \mathcal{T}_{\mathcal{Q}}(x_i)$, $i_{\mathcal{P}}(x_i) = i_{\mathcal{Q}}(x_i)$, $\mathcal{F}_{\mathcal{P}}(x_i) = \mathcal{F}_{\mathcal{Q}}(x_i)$

$$\begin{aligned} \text{Then } \mathcal{S}_{\mathcal{CS}} = 1 \ \& \ \mathcal{S}_{\mathcal{JS}} = 1 \Rightarrow \text{Hyb}_{\mathcal{CJS}}(\mathcal{P}, \mathcal{Q}) = \Psi(1) + (1 - \Psi)(1) = \theta + 1 - \theta = 1 \\ \Rightarrow \text{Hyb}_{\mathcal{CJS}}(\mathcal{P}, \mathcal{Q}) &= 1 \end{aligned}$$

□

The proposed hybrid measure satisfies the fundamental properties of boundedness (Property 1), symmetry (Property 2), and identity (Property 3). While the triangle inequality is a key property for distance metrics, it is not a standard requirement for similarity measures. The focus of the proposed $\text{Hyb}_{\mathcal{CJS}}$ is to effectively quantify the resemblance between neutrosophic sets for ranking purposes within the MCDM framework, for which the established properties are sufficient and appropriate.

3.2. Proposed Methodology

MCDM is a method for ranking alternatives to identify the highest-quality quantitative feedback. In this research, we used neutrosophic entropy and DEMATEL because of their high accuracy in estimating the combined weight and reliability of product feature attributes. Matrix representation of the MCDM problem:

$$\tilde{\mathcal{H}} = \begin{matrix} & \tilde{\mathcal{C}}_1 & \tilde{\mathcal{C}}_2 & \dots & \tilde{\mathcal{C}}_q \\ \begin{matrix} \tilde{\mathcal{A}}_1 \\ \tilde{\mathcal{A}}_2 \\ \vdots \\ \tilde{\mathcal{A}}_p \end{matrix} & \begin{bmatrix} \acute{a}_{11} & \acute{a}_{12} & \dots & \acute{a}_{1q} \\ \acute{a}_{21} & \acute{a}_{22} & \dots & \acute{a}_{2q} \\ \vdots & \vdots & \vdots & \vdots \\ \acute{a}_{p1} & \acute{a}_{p2} & \dots & \acute{a}_{pq} \end{bmatrix} \end{matrix}$$

where $\tilde{\mathcal{C}}_1, \tilde{\mathcal{C}}_2, \dots, \tilde{\mathcal{C}}_q$ are the criteria on which the available alternatives are to be rated, and $\tilde{\mathcal{A}}_1, \tilde{\mathcal{A}}_2, \dots, \tilde{\mathcal{A}}_p$ are the available alternatives that the decision maker is to rank. Based on the criterion $\tilde{\mathcal{C}}_j$, $\acute{a}_{ij}$ represents the performance of the value of alternative $\tilde{\mathcal{A}}_i$, and w_j represents the weight of the criterion $\tilde{\mathcal{C}}_j$.

3.2.1. Application of Entropy Method

Claude Shannon pioneered the entropy approach to evaluate data uncertainty and unpredictability through information theory in 1948. Subsequently, it was updated to support MCDM in impartially assigning weights to criteria based on their informational value, where greater variability indicates greater importance. Neutrosophic set theory (NST), which incorporates memberships of truth, indeterminacy, and falsity to address data uncertainty, indeterminacy, and inconsistency, enhances the conventional Entropy method; hence, we implement it. This renders it optimal for intricate decision-making with limited data.

Neutrosophic entropy (NEntropy) is advantageous for weight determination in risk assessment, supplier selection, PATs evaluation, environmental management, and portfolio optimization, as it effectively addresses ambiguous and disparate data.

3.2.2. Neutrosophic Entropy Method [73]

Neutrosophic entropy helps investigate ambiguity and indeterminacy in data that is confusing, inconsistent, or imprecise. Entropy with truth, indeterminacy, and falsity memberships is the best for complex decision-making. Drawing on many experts' opinions

can help this technique overcome uncertainty and blend diverse perspectives. Follow these procedures to compute the weights for the decision matrix $\tilde{\mathcal{H}}$ using the entropy approach: Step 1. A brief overview of the investigation factors was constructed.

The initial stage of the PATs evaluation process involves analyzing existing standards and establishing decision-making criteria. The parameters are categorized and examined by a group of experts in the field for further investigation.

Step 2. Participants in the survey were experts or decision makers.

To evaluate key characteristics employing an SVNS, I collected data independently from five experts in PATs with diverse backgrounds. Utilizing this scale, expert linguistic phrases ranging from ‘EB’ to ‘EG’ were converted into numerical values for decision matrices, as illustrated in Table 3. The truth, indeterminacy, and falsity of each term (collectively referred to as SVNS) were subsequently converted into a unique value for the proposed model. The scoring function (Equation (9)) builds data-driven decision-making by transforming the neutrosophic matrix into a crisp matrix.

$$\text{Score function} = \frac{2 + (T - F - I)}{3} \quad (9)$$

In this case, T , F , and I stand for truth, falsity, and indeterminacy, respectively. This allows decision makers to rank and objectively evaluate criteria, removing less important ones to produce a final, prioritized list.

Table 3. Single-valued neutrosophic scale [76].

Linguistic Term	Abbreviation	SVNNs		
		T	I	F
Extremely Bad	EB	0.00	1.00	1.00
Very Very Bad	VVB	0.10	0.90	0.90
Very Bad	VB	0.20	0.85	0.80
Bad	B	0.30	0.75	0.70
Medium Bad	MB	0.40	0.65	0.60
Medium	M	0.50	0.50	0.50
Medium Good	MG	0.60	0.35	0.40
Good	G	0.70	0.25	0.30
Very Good	VG	0.80	0.15	0.20
Very Very Good	VVG	0.90	0.10	0.10
Extremely Good	EG	1.00	0.00	0.00

Step 3. Aggregated and normalized decision matrix.

We use Equation (10) to combine these matrices into the aggregated decision matrix, and Equation (11) normalizes this combined decision framework using an entropy-based technique.

$$\mathcal{Y}_{ij} = \frac{\sum_{j=1}^n \mathcal{Z}_{ij}}{n} \quad (10)$$

$$\text{Norm}_{ij} = \frac{\mathcal{Y}_{ij}}{\sum_{j=1}^m \mathcal{Y}_{ij}} \quad (11)$$

Here, $\mathcal{Z}_{ij}$ represents the value of the i^{th} alternative with respect to the j^{th} criterion in the decision matrix, n denotes the number of experts, and m is the number of alternatives. The term $\sum_{j=1}^m \mathcal{Y}_{ij}$ indicates the total value of the j^{th} column (criterion) in the aggregated decision matrix.

Step 4. Determine each criterion's entropy value in the decision matrix.

$$\mathcal{E}_j = -\mathcal{H} \sum_{i=1}^m \text{Norm}_{ij} * \ln \text{Norm}_{ij}, \text{ where } \mathcal{H} = \frac{1}{\ln(m)} \quad (12)$$

Step 5. Compute the entropy's weight for each criterion.

$$\mathcal{W}_{e_j} = \frac{1 - \mathcal{E}_j}{\sum_{j=1}^n (1 - \mathcal{E}_j)} \quad (13)$$

The weights assigned to each criterion are determined at the conclusion of this step, aiding in the PATs evaluation process.

3.2.3. Application of DEMATEL Method

DEMATEL (Decision Making Trial and Evaluation Laboratory) was invented by the Battelle Memorial Institute in Geneva in the early 1970s to study complex cause-and-effect relationships in decision-making problems. The criteria interdependencies are outlined using matrix operations and directed graphs. Neutrosophic DEMATEL improves on traditional DEMATEL by integrating neutrosophic set theory, which incorporates truth, indeterminacy, and falsity memberships to manage expert judgment, ambiguity, vagueness, and uncertainties. In complicated systems with confusing or contradictory relationships and data, it works well.

Neutrosophic DEMATEL (NDEMATEL) enhances modeling of uncertain and interdependent features and the identification of causal relationships in supply chain management, sustainable development, risk management, PATs assessment, and healthcare systems.

3.2.4. Neutrosophic DEMATEL Method [62]

To determine the causal relationships among PATs, this study proposes the following NDEMATEL approach.

Step 1. Determine the neutrosophic aggregated direct-influence matrix (DIM), denoted as $\tilde{\mathcal{H}}^A$.

Each expert's evaluation of how one element affects another is collected using the scale shown in Table 4.

Table 4. [62]. Linguistic variables and their associated single-valued neutrosophic numbers.

Linguistic Variables	Single-Valued Neutrosophic Numbers (SVNNs)
Very unimportant (VU)	(0.10, 0.80, 0.90)
Unimportant (U)	(0.35, 0.60, 0.70)
Medium Important (MI)	(0.50, 0.40, 0.45)
Important (I)	(0.80, 0.20, 0.15)
Absolutely Important (AI)	(0.90, 0.10, 0.10)

Once the important weight of each expert has been determined using Equation (3), the aggregation is performed using Equation (4), yielding the aggregated DIM, or $\tilde{\mathcal{H}}^A$, as illustrated below.

$$\tilde{\mathcal{H}}^A = \begin{bmatrix} \hat{a}_{11} & \cdots & \hat{a}_{1q} \\ \vdots & \ddots & \vdots \\ \hat{a}_{p1} & \cdots & \hat{a}_{pq} \end{bmatrix}$$

In the matrix, the degree to which factor i influences factor j is represented by an SVNN, a_{ij} , which is written as $\langle T_{ij}(x), I_{ij}(x), F_{ij}(x) \rangle$. Previously, these terms were defined as the truth, indeterminacy, and falsity-membership values, respectively.

Step 2. Normalize the neutrosophic aggregated DIM to obtain a matrix $\mathcal{U}$, as shown in Equations (4) and (5).

$$\mathcal{U} = \mathcal{K} \times \mathcal{H}^{\sim A} \text{ Where } \mathcal{K} = \text{Min} \left(\frac{1}{\text{Max}_{1 \leq i \leq n} \sum_{j=1}^n T_{ij}}, \frac{1}{\text{Max}_{1 \leq j \leq n} \sum_{i=1}^n T_{ij}} \right) \quad (14)$$

Thus, it is important to note that the value of $\mathcal{K}$ is obtained from the truth-membership values of the aggregated DIM during the normalization procedure. The normalized matrix is then obtained through multiplication.

Step 3. Evaluate the total DIM $\mathcal{S}$ by using the following formula:

$$\mathcal{S} = \mathcal{U} + \mathcal{U}^2 + \mathcal{U}^3 + \dots + \mathcal{U}^{\mathcal{K}} = \mathcal{U}(\mathcal{I} - \mathcal{U})^{-1} \quad (15)$$

$$\text{where } \mathcal{S} = (\mathcal{S}_{ij})_{n \times n} = \begin{bmatrix} \mathcal{S}_{11} & \dots & \mathcal{S}_{1q} \\ \vdots & \ddots & \vdots \\ \mathcal{S}_{p1} & \dots & \mathcal{S}_{pq} \end{bmatrix}, \text{ and } \mathcal{S}_{ij} = \langle T_{ij}(x), I_{ij}(x), F_{ij}(x) \rangle$$

In Equation (15), $\mathcal{I}$ represent the neutrosophic identity matrix.

The truth, indeterminacy, and falsity-membership functions, among other comparable operations, are carried out independently for every element in the neutrosophic set using Equations (16)–(18).

$$\text{Matrix } [T_{ij}] = \mathcal{U}_T(1 - \mathcal{U}_T)^{-1} \quad (16)$$

$$\text{Matrix } [I_{ij}] = \mathcal{U}_I(1 - \mathcal{U}_I)^{-1} \quad (17)$$

$$\text{Matrix } [F_{ij}] = \mathcal{U}_F(1 - \mathcal{U}_F)^{-1} \quad (18)$$

The values of truth, indeterminacy, and falsity memberships are determined independently, then combined to create the total DIM, $\mathcal{S}$, prior to the deneutrosophication step.

Step 4. Determine the deneutrosophication of the total DIM, $\mathcal{S}$.

To get precise numbers, the elements in matrix $\mathcal{S}$ are deneutrosophied. The deneutrosophication can be calculated using Equation (5). Equations (19) and (20) can be used to determine the importance and relationship of each criterion from the deneutrosophied matrix $\mathcal{S}$.

$$\tilde{a} = (\tilde{a}_i)_{n \times 1} = \left[\sum_{j=1}^n \mathcal{S}_{ij} \right]_{n \times 1} \quad (19)$$

$$\tilde{\mathcal{C}} = (\tilde{\mathcal{C}}_i)_{1 \times n} = \left[\sum_{i=1}^n \mathcal{S}_{ij} \right]_{1 \times n} \quad (20)$$

In the matrix $\mathcal{S}$, $\tilde{a}_i$ represents the sum of row i , and $\tilde{\mathcal{C}}_i$ represents the sum of column j . The values $(\tilde{a}_i + \tilde{\mathcal{C}}_i)$ reflect the importance of each criterion. The values $(\tilde{a}_i - \tilde{\mathcal{C}}_i)$ can be divided into two categories: cause and effect. A positive $(\tilde{a}_i - \tilde{\mathcal{C}}_i)$ value indicates that criterion i influences other criteria, whereas a negative $(\tilde{a}_i - \tilde{\mathcal{C}}_i)$ value shows that criterion i is influenced by other criteria.

Step 5. Determine the weights of the criteria

The $(\tilde{a}_i + \tilde{\mathcal{C}}_i)$ values of the factors can be normalized to obtain their significance values. The proportion of the associated value relative to the total is calculated using the classic distance-based normalization type.

3.2.5. Hybrid Weighting Approach [77]

The hybrid weight approach thoroughly considers and evaluates both objective and subjective weights. The weight assigned to the criterion significantly affects the selection of the scheme in the MCDM assessment process, as it can alter the evaluation outcome. The application of the mixed-weight approach in the selection strategy can mitigate deviations arising from a single objective or subjective weights, assuming that the quantity of assessment index items is ‘ n ’ at a specific facet or evaluation level.

The weights determined by the neutrosophic entropy and DEMATEL weight methods are denoted as $\mathcal{W}_{ej} = (w_{e1}, w_{e2}, \dots, w_{en})$ and $\mathcal{W}_{dj} = (w_{d1}, w_{d2}, \dots, w_{dn})$, respectively. To integrate the weight values derived from both methods, the hybrid weight vector for each criterion is calculated as follows:

$$\mathcal{W}_{hj} = \frac{\mathcal{W}_{ej} \times \mathcal{W}_{dj}}{\sum_{j=1}^n \mathcal{W}_{ej} \times \mathcal{W}_{dj}}, \text{ for } j = 1, 2, \dots, n \quad (21)$$

Hybrid weights $\mathcal{W}_{hj}$ are normalized prior to weighting: $\sum_{j=1}^n \mathcal{W}_{hj} = 1$.

3.2.6. Application of TOPSIS Method

Hwang and Yoon invented the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), an MCDM method, in 1981. It examines solutions based on their deviation from a negative ideal solution (NIS) (which lowers costs) and their closeness to an ideal solution (which maximizes benefits). We nominate Neutrosophic TOPSIS (NTOPSIS) as classical TOPSIS that integrates neutrosophic set theory, which more effectively addresses uncertainty, indeterminacy, and incomplete information by employing truth, indeterminacy, and falsity memberships. NTOPSIS is proficient at addressing real-world issues characterized by confusing or erroneous data.

NTOPSIS has improved decision-making in ambiguous and contentious domains, such as supply chain management, renewable energy selection, PATs assessment, healthcare resource distribution, and project risk appraisal.

3.2.7. Neutrosophic TOPSIS Method [62]

NTOPSIS facilitates the assessment and prioritization of multiple externally provided alternatives using distance metrics. The identified options are presumed to be the ones nearest to the PIS and the farthest from the NIS. The ideal solution is defined as one that optimizes benefit criteria while decreasing cost criteria. The procedure for implementing a neutrosophic TOPSIS approach includes the following steps:

Step 1. Aggregated neutrosophic decision matrix (NDM) [45].

Equation (3) determines the weight assigned to each expert, and Equation (4) aggregates the data, yielding the aggregated NDM.

Step 2. Normalized aggregated NDM.

$$\mathcal{R}_{ij} = \frac{\tilde{a}_{ij}}{\sqrt{\sum_{i=1}^q (\tilde{a}_{ij})^2}} \quad (22)$$

where q is the number of alternatives.

The process of normalization is essential to the TOPSIS methodology. PATs exhibit considerable variation by type; normalization improves fair, consistent comparisons across these diverse technologies.

Step 3. Weighted normalized aggregated NDM.

The weighted matrix is calculated by multiplying the normalized decision matrix by the criteria hybrid weights ($\mathcal{W}_{hj}$), which are obtained from the hybrid weight of neutrosophic entropy and DEMATEL, as explained.

$$\vartheta_{ij} = \mathcal{W}_{hj} \times \mathcal{R}_{ij} \quad (23)$$

Step 4. Obtain neutrosophic PIS and NIS.

The normalization in Equation (22) standardizes all criterion values onto a comparable scale via vector normalization, ensuring unit independence across the 10 PAT criteria. This step itself does not account for the direction of preference. Therefore, in this step, the benefit and cost attributes (as summarized in Table 2) are explicitly treated as cost-type criteria, such as data acquisition latency, and inverted so that higher normalized values uniformly represent better performance. This treatment guarantees consistency when constructing positive and negative ideal solutions (PIS and NIS). Calculate the relative neutrosophic PIS S_i^+ and NIS S_i^- for the benefit and cost characteristics listed below.

$$S_i^+ = \left\{ \begin{array}{l} < \max(T_{ij}), \min(I_{ij}), \min(F_{ij}) | i = 1, 2, \dots, m | j \in j^+ >, \\ < \min(T_{ij}), \max(I_{ij}), \max(F_{ij}) | i = 1, 2, \dots, m | j \in j^- >, \end{array} \right\} \quad (24)$$

$$S_i^- = \left\{ \begin{array}{l} < \min(T_{ij}), \max(I_{ij}), \max(F_{ij}) | i = 1, 2, \dots, m | j \in j^+ >, \\ < \max(T_{ij}), \min(I_{ij}), \min(F_{ij}) | i = 1, 2, \dots, m | j \in j^- >, \end{array} \right\} \quad (25)$$

where j^+ refers to the benefit impact, while j^- indicates non-benefit (cost) impact.

Step 5. Compute the hybrid similarity measure of each alternative from the neutrosophic PIS and NIS.

The hybrid weighted Cosine-Jaccard similarity measure for each alternative relative to the neutrosophic PIS and NIS is calculated using Equations (6)–(8) to obtain the results.

Step 6. Calculation of the relative closeness coefficient ($\mathcal{Rcc}_i$) with respect to the neutrosophic ideal solution.

$$\mathcal{Rcc}_i = \frac{S_i^+}{S_i^+ + S_i^-} \quad (26)$$

where $0 \leq \mathcal{Rcc}_i \leq 1$.

Step 7. Compute the rank of each alternative.

According to the $\mathcal{Rcc}_i$ values, a higher $\mathcal{Rcc}_i$ indicates better performance of alternative $\tilde{\mathcal{A}}_i$, for $i = 1, 2, \dots, p$.

4. Real Life Application and Results

To validate the proposed neutrosophic MCDM framework, a real-life application was conducted to evaluate the performance of ten prominent precision agriculture technologies (PATs) under realistic conditions. A key limitation of this study is the small number of experts ($n = 5$). Although such panel sizes are standard in neutrosophic and fuzzy MCDM applications due to the intensive nature of linguistic and uncertainty-based evaluations, a smaller group may increase sensitivity to individual expert judgments. This limitation is acknowledged, and robustness was strengthened through expert-importance weighting, inter-rater agreement assessment, and jackknife leave-one-expert-out analysis. Each technology was evaluated using ten carefully selected criteria that capture technical, economic, and ecological aspects such as spatial-temporal accuracy, system interoperability, environmental resilience, and operational sustainability. By combining the weights derived

from the neutrosophic entropy and DEMATEL methods and ranking the alternatives using neutrosophic TOPSIS enhanced with a hybrid similarity measure, the study delivers a comprehensive, real-world comparison of these technologies. This application demonstrates the practicality and robustness of the proposed model in supporting data-driven decision-making for sustainable agricultural innovation. The categories of advanced technologies in precision agriculture are comprehensively depicted in the flowchart shown in Figure 2.

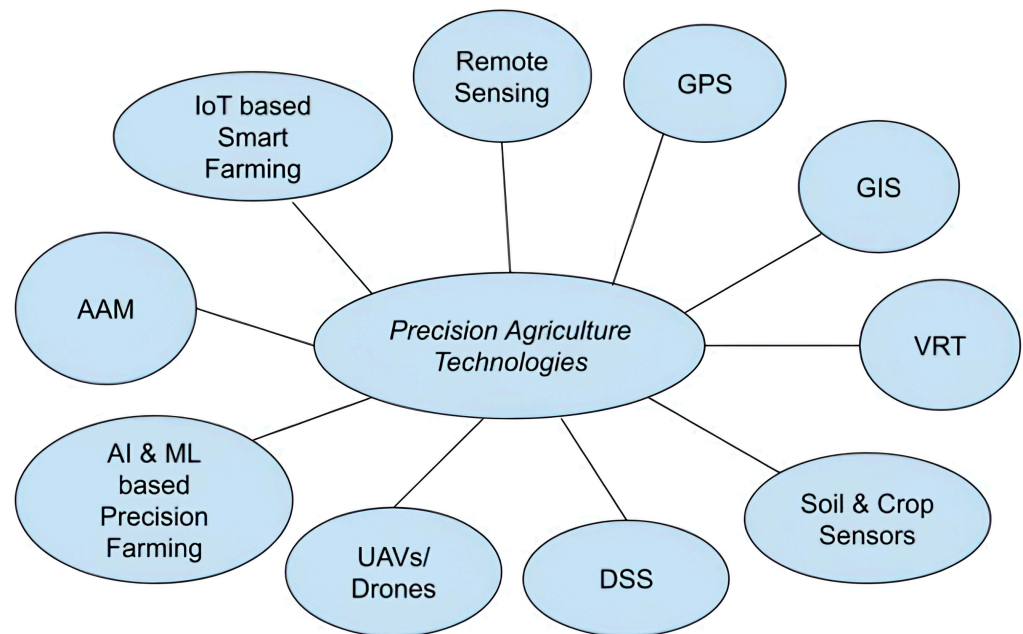


Figure 2. Categories of advanced technologies in precision agriculture.

4.1. Empirical Results

4.1.1. Calculations of Neutrosophic Entropy Values

In NEntropy, initially, after developing the experts' linguistic factors into a neutrosophic SVN scale, precise values are derived using the score function [Equation (9)]. The aggregated values are presented in Table A1 (Appendix A).

$$\text{i.e., } \acute{e}_{11}(\text{Remote sensing to Spatial} - \text{Temporal Accuracy}) = \frac{0.82+0.72+0.82+0.38+0.90}{5} = 0.73$$

The aggregated numbers are normalized, using Equation (11). $\acute{e}_{11} = \frac{0.73}{7.20} = 0.10$. The resulting normalized neutrosophic decision matrix (NDM) is presented in Table A2 (Appendix A). The entropy values and corresponding entropy weights for each criterion within the decision matrix are generated.

$$\acute{e}_{11} = 0.10 \times \ln(0.10) = -0.23$$

Following normalization, the entropy values are computed by evaluating the expression ' $Norm_{ij} \times \ln Norm'_{ij}$ ' for each element. These calculations are detailed in Table A3 (Appendix A). Using Equations (12) and (13), the entropy value for each criterion is calculated, and the corresponding weights are derived. These results are summarized in Table 5.

Table 5. Entropy value for each criterion, and its weight.

	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
Entropy value (E_j)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Weight ($\mathcal{W}_{ej}$)	0.09	0.12	0.14	0.16	0.11	0.05	0.13	0.05	0.11	0.06

4.1.2. Calculations of Neutrosophic DEMATEL Values

In NDEMATEL, we initially obtain the importance of weight using Equation (3). i.e.,

$$w_{\mathcal{DM}_1} = \frac{0.82}{\{0.82 + 0.55 + 0.55 + 0.82 + 0.82\}} = 0.23$$

The complete set of importance weights represented using SVNns is shown in Table 6.

Table 6. Importance of decision makers with SVNns.

	$\mathcal{DM}_1$	$\mathcal{DM}_2$	$\mathcal{DM}_3$	$\mathcal{DM}_4$	$\mathcal{DM}_5$
Linguistic variable	High important	Medium important	High important	High important	High important
Weight in SVN Scale	(0.80, 0.20, 0.15)	(0.50, 0.40, 0.45)	(0.50, 0.40, 0.45)	(0.80, 0.20, 0.15)	(0.80, 0.20, 0.15)
Decision makers-Weight	0.23	0.16	0.16	0.23	0.23

The aggregated neutrosophic DIM is derived utilizing Equation (4). Shown as Table A4 (Appendix A), i.e.,

$$\begin{aligned} \acute{e}_{11} = & \langle (1 - ((1 - 0.1)^{0.23} * (1 - 0.1)^{0.16} * (1 - 0.1)^{0.16} * (1 - 0.1)^{0.23} \\ & * (1 - 0.1)^{0.23}), (0.8)^{0.23} * (0.8)^{0.16} * (0.8)^{0.16} * (0.8)^{0.23} \\ & * (0.8)^{0.23}, (0.8)^{0.23} * (0.8)^{0.16} * (0.8)^{0.16} * (0.8)^{0.23} \\ & * (0.8)^{0.23} \rangle = (0.10, 0.80, 0.90) \end{aligned}$$

Normalize the neutrosophic aggregated DIM, utilizing Equation (14). Shown as Table A5 (Appendix A). i.e., here, $\acute{e} = 0.15$

$$\acute{e}_{11} = (0.15 * 0.10, 0.15 * 0.80, 0.15 * 0.90) = (0.01, 0.12, 0.13)$$

The Total DIM is calculated by applying Equations (16)–(18) within Microsoft Excel (MINVERSE tool). The computation of truth, indeterminacy, and falsity values is performed independently, followed by their integration to represent the values as SVNns, as demonstrated in Table A6 (Appendix A). During the deneutrosophication step, the total DIM is transformed into precise numerical values, using Equation (3). As shown in Table A7 (Appendix A).

$$\acute{e}_{11} = 1 - \sqrt{\left(\left((1 - 0.64)^2 + (0.19)^2 + (0.22)^2 \right) / 3 \right)} = 0.73$$

In Table 7, $\tilde{a}_i$ represents the sum of rows, i.e., firstrow $(0.73 + 0.83 + 0.79 + 0.82 + 0.80 + 0.82 + 0.69 + 0.84 + 0.79 + 0.77) = 7.90$

$$\begin{aligned} \tilde{e}_i \text{ represents the sum of columns, i.e., firstcolumn } & (0.73 + 0.79 + 0.89 \\ & + 0.82 + 0.87 + 0.81 + 0.74 + 0.87 + 0.88 + 0.81) = 8.24 \end{aligned}$$

Table 7. Using Equations (19) and (20), obtain the cause-and-effect criteria.

Criteria	$\tilde{a}_i$	$\tilde{\theta}_i$	$\tilde{a}_i + \tilde{\theta}_i$	$\tilde{a}_i - \tilde{\theta}_i$
$\tilde{C}_1$	7.90	8.24	16.13	−0.34
$\tilde{C}_2$	7.59	8.29	15.89	−0.70
$\tilde{C}_3$	8.59	8.31	16.90	0.29
$\tilde{C}_4$	7.80	8.23	16.02	−0.43
$\tilde{C}_5$	8.47	8.12	16.59	0.35
$\tilde{C}_6$	8.19	8.45	16.64	−0.26
$\tilde{C}_7$	7.68	7.56	15.24	0.12
$\tilde{C}_8$	8.48	8.40	16.88	0.08
$\tilde{C}_9$	8.74	8.00	16.74	0.74
$\tilde{C}_{10}$	8.04	7.89	15.92	0.15

Finally, calculate the weight (%) for each criterion. Here, $\sum(\tilde{a}_i + \tilde{\theta}_i) = 162.94$

$$\text{weight for } \tilde{C}_1 = \frac{16.13}{162.94} = 0.10$$

The final importance weights of the PAT criteria using N-DEMATEL are summarized in Table 8.

Table 8. Importance weights of PAT criteria of NDEMATEL.

Criteria (C_i)	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
Weight (W_{di})	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.10	0.10	0.10

The hybrid weights obtained using NEntropy and NDEMATEL methods are presented in Table 9.

Table 9. Hybrid weight from NEntropy and NDEMATEL, using Equation (21).

Criteria's	Weight (NEntropy)	Weight (NDEMATEL)	Hybrid Weight
$\tilde{C}_1$	0.09	0.10	0.09
$\tilde{C}_2$	0.12	0.10	0.12
$\tilde{C}_3$	0.14	0.10	0.14
$\tilde{C}_4$	0.16	0.10	0.16
$\tilde{C}_5$	0.11	0.10	0.12
$\tilde{C}_6$	0.05	0.10	0.05
$\tilde{C}_7$	0.13	0.09	0.12
$\tilde{C}_8$	0.05	0.10	0.05
$\tilde{C}_9$	0.11	0.10	0.11
$\tilde{C}_{10}$	0.06	0.10	0.06

Figure 3 presents a comparison of the criteria weights for key decision-making variables derived using NEntropy, NDEMATEL, and the proposed hybrid approach.

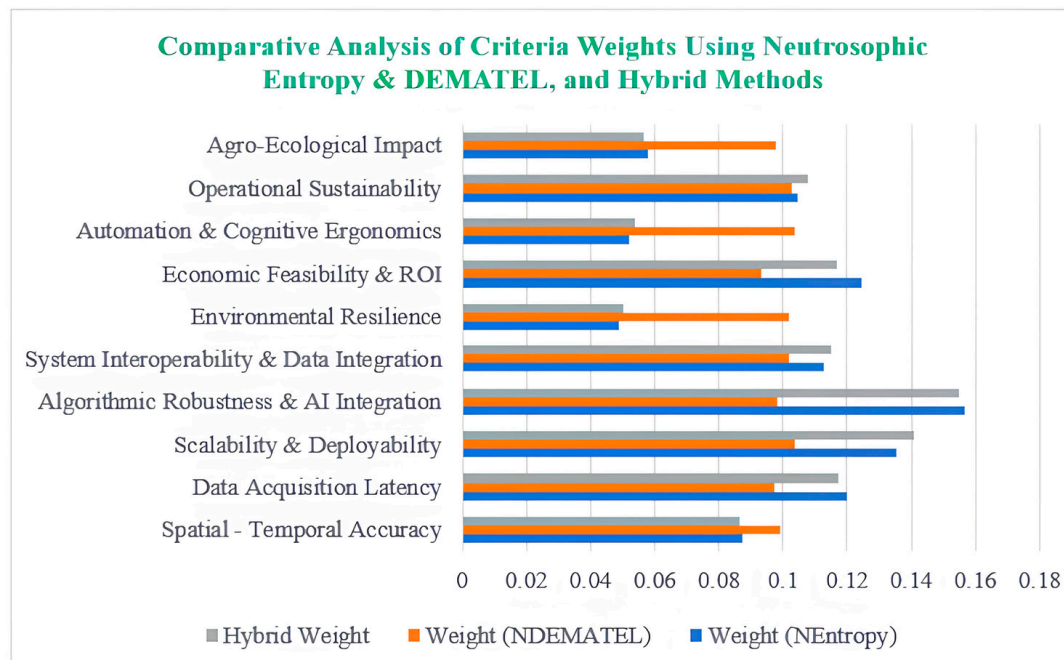


Figure 3. Comparing criteria weights for significant decision-making variables based on NEntropy, NDEMATEL, and hybrid approaches.

4.1.3. Calculations of Neutrosophic TOPSIS

In NTOPSIS, the neutrosophic aggregated NDM is initially obtained by using Equation (4). Presented as below, i.e.,

$$\hat{a}_{11} = \langle 1 - ((1 - 0.80)^{0.23} * (1 - 0.70)^{0.16} * (1 - 0.80)^{0.16} * (1 - 0.40)^{0.23} * (1 - 0.90)^{0.23}), (0.15)^{0.23} * (0.25)^{0.16} * (0.15)^{0.16} * (0.65)^{0.23} * (0.10)^{0.23}, (0.20)^{0.23} * (0.30)^{0.16} * (0.20)^{0.16} * (0.60)^{0.23} * (0.10)^{0.23} \rangle = (0.77, 0.21, 0.23).$$

Similarly, the aggregated neutrosophic decision matrix (NDM) has been calculated and is presented in Table A8 (Appendix A). In the normalization step, using Equation (22).

$$\hat{a}_{11} = \langle \frac{0.77}{2.69}, \frac{0.21}{0.59}, \frac{0.23}{0.66} \rangle = (0.28, 0.37, 0.36)$$

The normalized form of the aggregated NDM has been computed and is presented in Table A9 (Appendix A). During the weighted normalization phase, each element of the SVNNS is multiplied by its respective criterion weight, as specified in Equation (23).

$$\hat{a}_{11} = \langle 0.28 * 0.09, 0.37 * 0.09, 0.36 * 0.09 \rangle = (0.02, 0.03, 0.03)$$

Similarly, the weighted normalized aggregated NDM has been calculated and is presented in Table A10 (Appendix A). The neutrosophic PIS and NIS are derived from Equations (24) and (25), respectively. As shown in Table A11 (Appendix A). The similarity associated with the neutrosophic PIS is determined by using the cosine similarity measure as summarized in Equation (7) and as presented in Table A12 (Appendix A). i.e.,

$$\hat{a}_{11} = \langle 0.09 \times \frac{0.02*0.03+0.03*0+0.03*0}{\sqrt{\{(0.02)^2+(0.03)^2+(0.03)^2\}} \sqrt{\{(0.03)^2+(0)^2+(0)^2\}}} \rangle = 0.04$$

And $\mathbb{S}_i^+$ = sum of rows.

The evaluation of cosine similarity concerning the neutrosophic NIS is performed in the same manner as shown in Table A13 (Appendix A), and $\mathbb{S}_i^- = \text{sum of rows}$.

The similarity associated with the neutrosophic PIS is determined using the Jaccard similarity measure as summarized in Equation (8) and as presented in Table A14 (Appendix A). i.e.,

$$\begin{aligned} & \phi_{11} \\ &= \langle 0.09 \times \frac{0.02*0.03+0.03*0+0.03*0}{\{((0.02)^2+(0.03)^2+(0.03)^2)+((0.03)^2+(0)^2+(0)^2)-(0.02*0.03+0.03*0+0.03*0)\}} \rangle \\ &= 0.02 \end{aligned}$$

The subsequent steps adhere to the same methodology outlined previously. The Jaccard similarity values calculated from NPIS and NNIS are presented in Table A14 and Table A15, respectively (Appendix A). The RCC and resulting rankings, computed from both the Cosine and Jaccard similarity measures using Equation (26), are displayed in Table 10.

$$\text{Cosine similarity rank for } \tilde{\mathcal{A}}_1 = \frac{0.78}{(0.78 + 0.75)} = 0.51$$

In the same way, calculate the RCC of the Jaccard similarity measure and its ranks. The RCC values and rankings based on the Cosine and Jaccard similarity measures are presented in Table 10.

Table 10. RCC and Ranking from Cosine and Jaccard Similarity Measures.

Alternatives	Cosine Similarity Measure		Jaccard Similarity Measure	
	RCC	Rank	RCC	Rank
$\tilde{\mathcal{A}}_1$	0.51	2	0.51	2
$\tilde{\mathcal{A}}_2$	0.48	5	0.47	5
$\tilde{\mathcal{A}}_3$	0.48	6	0.47	4
$\tilde{\mathcal{A}}_4$	0.37	10	0.30	10
$\tilde{\mathcal{A}}_5$	0.40	9	0.35	9
$\tilde{\mathcal{A}}_6$	0.50	3	0.49	3
$\tilde{\mathcal{A}}_7$	0.43	8	0.40	8
$\tilde{\mathcal{A}}_8$	0.49	4	0.47	6
$\tilde{\mathcal{A}}_9$	0.46	7	0.43	7
$\tilde{\mathcal{A}}_{10}$	0.54	1	0.55	1

A comparative ranking of alternatives using the Cosine and Jaccard similarity measures is presented in Figure 4, highlighting the consistency between the two methods.

The RCC and the correlated rankings, derived from the hybrid Cosine–Jaccard similarity measure as listed in Equation (6), are provided.

$$\tilde{\mathcal{A}}_1 = \frac{(0.25 * 0.78 + 0.75 * 0.68)}{\{(0.25 * 0.78 + 0.75 * 0.68) + (0.25 * 0.75 + 0.75 * 0.65)\}} = 0.58$$

Similarly, the RCC and rankings derived from the hybrid Cosine–Jaccard similarity measure have been calculated and are presented in Table 11.

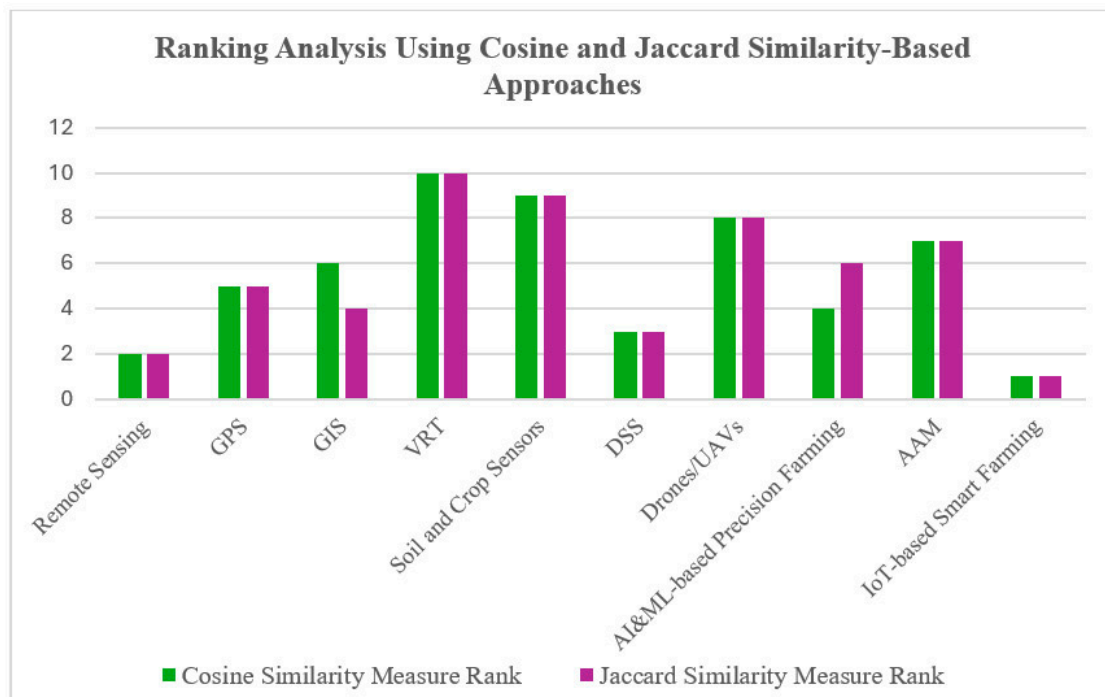


Figure 4. Comparative ranking of alternatives using Cosine and Jaccard similarity measures, demonstrating consistency between the two approaches.

Table 11. RCC and ranking from the hybrid Cosine-Jaccard similarity measure.

Alternatives	$\Psi = 0$		$\Psi = 0.25$		$\Psi = 0.50$		$\Psi = 0.75$		$\Psi = 1$	
	RCC	Rank	RCC	Rank	RCC	Rank	RCC	Rank	RCC	Rank
$\tilde{A}_1$	0.51	2	0.51	2	0.51	2	0.51	2	0.51	2
$\tilde{A}_2$	0.47	5	0.47	6	0.48	5	0.48	5	0.48	5
$\tilde{A}_3$	0.47	4	0.47	4	0.48	6	0.48	6	0.48	6
$\tilde{A}_4$	0.30	10	0.32	10	0.34	10	0.35	10	0.37	10
$\tilde{A}_5$	0.35	9	0.36	9	0.38	9	0.39	9	0.40	9
$\tilde{A}_6$	0.49	3	0.49	3	0.49	3	0.50	3	0.50	3
$\tilde{A}_7$	0.40	8	0.41	8	0.42	8	0.43	8	0.43	8
$\tilde{A}_8$	0.47	6	0.47	5	0.48	4	0.48	4	0.49	4
$\tilde{A}_9$	0.43	7	0.44	7	0.44	7	0.45	7	0.46	7
$\tilde{A}_{10}$	0.55	1	0.54	1	0.54	1	0.54	1	0.54	1

The mixing parameter (Ψ) regulates the equilibrium between cosine similarity, which measures directional alignment in continuous, normalized performance data, and Jaccard similarity, which indicates overlap in attribute performance. A sensitivity analysis was conducted to assess the impact of Ψ , varying Ψ within the range $[0, 1]$ at intervals of 0.25. The rankings presented in Table 11 showed strong consistency, with Spearman's rank correlation coefficients between the baseline ($\Psi = 0$) and subsequent scenarios of 0.99 ($\Psi = 0.25$), 0.95 ($\Psi = 0.50$), 0.95 ($\Psi = 0.75$), and 0.95 ($\Psi = 1$). These high correlations (>0.95) demonstrate the stability of the proposed hybrid similarity measure across changes in Ψ . The observed robustness demonstrates that the hybrid approach successfully combines the orientation-based strength of cosine similarity with the overlap-based contribution of Jaccard similarity, yielding a balanced and dependable similarity assessment across all parameter settings.

4.1.4. Sensitivity Analysis of Weight Selection

The sensitivity analysis confirms the robustness of the proposed model under varying degrees of parameter influence. The comparison of rankings across three Ψ values, representing different priority levels for truth, indeterminacy, and falsity shows only minor fluctuations in the rankings of the alternatives. As illustrated in Figure 5, key alternatives such as $\tilde{A}_4$, $\tilde{A}_5$, and $\tilde{A}_7$ consistently maintained high positions across all Ψ settings, indicating stable performance across different weighting scenarios. Although some alternatives, such as $\tilde{A}_2$, $\tilde{A}_3$, and $\tilde{A}_8$, showed slight variations in ranking, these changes did not significantly alter the overall interpretation of the results. The consistency observed across $\Psi = 0, 0.25, 0.50, 0.75$, and 1 suggests that the method is not overly sensitive to changes in the neutrosophic parameters, reinforcing the reliability of the model. This outcome highlights the framework's ability to deliver reliable and meaningful rankings even when subject to perturbations in weights.

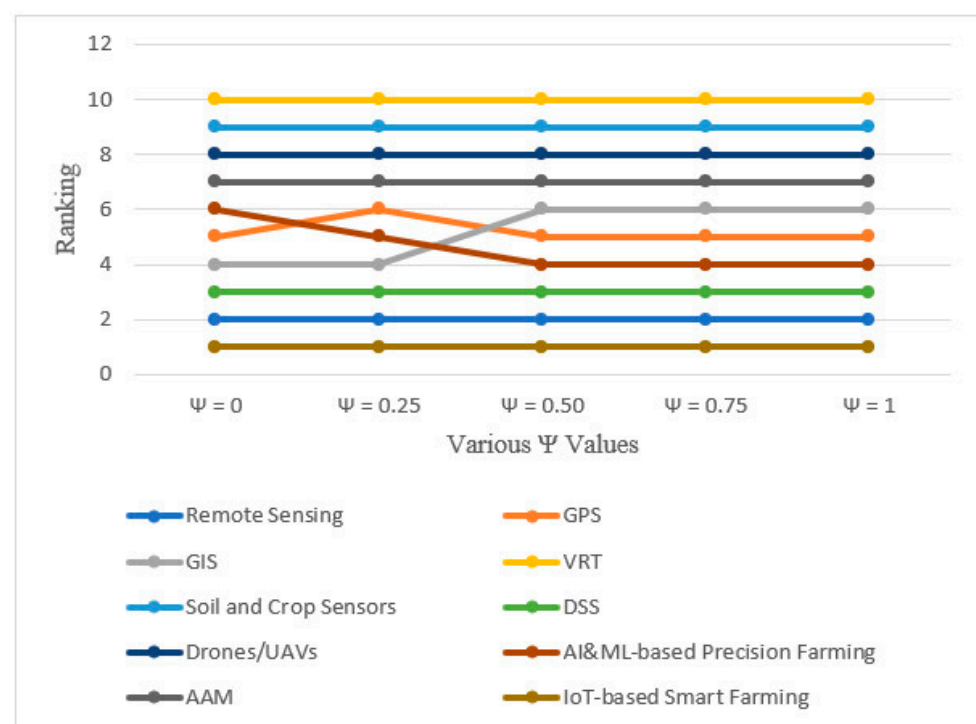


Figure 5. Comparative ranking of alternatives based on Cosine and Jaccard similarity measures through various scenarios.

Furthermore, it indicates that the method is adaptable and can maintain its validity across different decision-making contexts, data characteristics, and expert judgment profiles. Figure 5 presents the comparative stability of rankings across different Ψ values, highlighting the resilience and practical applicability of the proposed approach. A comparative ranking of alternatives based on the Cosine and Jaccard similarity measures across different scenarios is presented in Figure 5.

The cause-and-effect analysis, conducted using the DEMATEL method, provides critical insights into the interdependencies among the evaluation criteria for precision agriculture technologies. The analysis identifies which criteria act as “cause” factors, exerting influence on other indicators, and which are “effect” factors, influenced by others. In this study, criteria such as spatial-temporal accuracy, system robustness, and technological adaptability emerged as prominent causal factors. These criteria not only drive the overall performance of PATs but also significantly affect downstream variables like economic

feasibility, ease of implementation, and agro-ecological impact. For example, a high level of data collection accuracy can improve input efficiency, thereby enhancing both economic feasibility and environmental sustainability.

On the other hand, criteria such as user-friendliness and maintenance costs were identified as effect factors, meaning the underlying performance and complexity of the technology largely shape them. This structural mapping helps decision makers understand the root drivers of technological success and failure. By focusing on improving the influential (cause) criteria, such as enhancing spatial accuracy or system resilience, policymakers and developers can indirectly improve several dependent (effect) outcomes. Ultimately, this analysis reinforces the strategic value of investing in foundational technological attributes that create a ripple effect across other performance dimensions, leading to more effective adoption and a longer-term impact for PATs. The cause-and-effect diagram is presented in Figure 6.

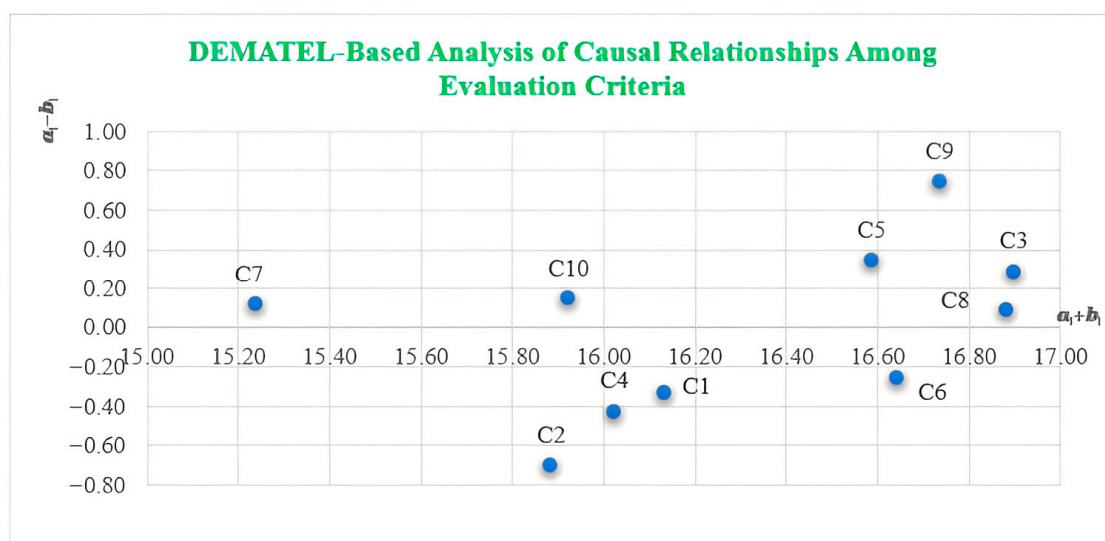


Figure 6. Cause and effect diagram.

4.1.5. Comparative Analysis of Weighting Schemes

The rankings of alternatives based on entropy-only, DEMATEL-only, and hybrid (entropy-DEMATEL) weights, highlighting consistent top and bottom positions and minor variations among mid-ranked alternatives, demonstrate the robustness of the hybrid weighting model, as presented in Table 12.

A comparative ranking analysis was conducted to validate the robustness of the proposed hybrid weighting model in Equation (21), utilizing entropy-only, DEMATEL-only, and hybrid (entropy $\times$ DEMATEL) weights. The findings demonstrate significant consistency among the three approaches. The highest and lowest ranked alternatives remain constant, with alternative $\tilde{A}_{10}$ consistently attaining the highest relative closeness coefficient ($RCC \approx 0.54$) and alternative $\tilde{A}_4$ attaining the lowest ($RCC \approx 0.33$). Minor differences are observed solely among mid-ranked alternatives (e.g., $\tilde{A}_2$ and $\tilde{A}_3$ alternating between 5th and sixth positions), suggesting limited sensitivity to the weighting method. The high rank concordance indicates that the multiplicative fusion approach preserves outcome stability while successfully incorporating data variability (entropy) and causal influence (DEMATEL), thereby demonstrating the robustness of the hybrid weighting model.

Table 12. Comparative rankings of alternatives using different weighting schemes.

Alternatives	Neutrosophic Entropy-TOPSIS Method		Neutrosophic DEMATEL-TOPSIS Method		Neutrosophic (Hybrid) Entropy-DEMATEL-TOPSIS Method	
	RCC	Rank	RCC	Rank	RCC	Rank
$\tilde{A}_1$	0.51	2	0.51	2	0.51	2
$\tilde{A}_2$	0.47	5	0.47	6	0.48	5
$\tilde{A}_3$	0.47	6	0.47	5	0.48	6
$\tilde{A}_4$	0.33	10	0.33	10	0.34	10
$\tilde{A}_5$	0.38	9	0.37	9	0.38	9
$\tilde{A}_6$	0.49	3	0.50	3	0.49	3
$\tilde{A}_7$	0.42	8	0.41	8	0.42	8
$\tilde{A}_8$	0.48	4	0.48	4	0.48	4
$\tilde{A}_9$	0.44	7	0.45	7	0.44	7
$\tilde{A}_{10}$	0.54	1	0.54	1	0.54	1

4.2. Robustness and Sensitivity Analysis of Expert Evaluations

The outcomes of a jackknife sensitivity analysis, in which each scenario reflects the omission of one expert's analysis from the overall aggregation, are detailed in Table 13. The baseline shows rankings derived from the collective opinions of all five experts, while Scenarios 1–5 show rankings obtained by sequentially excluding the data of each expert (from Expert 1 to Expert 5). Spearman's rank correlation coefficients measure the consistency between each reduced-expert scenario and the baseline rankings.

Table 13. Jackknife sensitivity analysis and corresponding Spearman's rank correlations.

Alternatives	Base Line		Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	RCC	Rank	RCC	Rank	RCC	Rank	RCC	Rank	RCC	Rank	RCC	Rank
$\tilde{A}_1$	0.51	2	0.47	5	0.45	3	0.35	8	0.47	4	0.54	1
$\tilde{A}_2$	0.48	5	0.58	1	0.61	1	0.60	1	0.48	1	0.51	3
$\tilde{A}_3$	0.48	6	0.50	2	0.48	2	0.47	2	0.43	8	0.53	2
$\tilde{A}_4$	0.34	10	0.37	10	0.31	10	0.31	10	0.39	10	0.44	10
$\tilde{A}_5$	0.38	9	0.38	9	0.34	9	0.39	6	0.41	9	0.44	9
$\tilde{A}_6$	0.49	3	0.47	4	0.43	5	0.36	7	0.45	6	0.46	7
$\tilde{A}_7$	0.42	8	0.39	8	0.37	7	0.44	4	0.44	7	0.50	4
$\tilde{A}_8$	0.48	4	0.44	7	0.38	6	0.42	5	0.46	5	0.47	6
$\tilde{A}_9$	0.44	7	0.44	6	0.37	8	0.31	9	0.48	2	0.44	8
$\tilde{A}_{10}$	0.54	1	0.49	3	0.44	4	0.46	3	0.47	3	0.47	5

The significance of decision makers was assessed using the single-valued neutrosophic number (SVNN) weighting scheme outlined in Equation (3), which measures each expert's contribution based on their truth-membership (T_k), indeterminacy (I_k) and falsity (F_k) degrees. This formulation guarantees that experts exhibiting increased certainty and diminished hesitation or error exert a proportionately larger impact on the aggregated outcomes. Thus, the calculated weights represent each decision makers' perceived reliability and decisiveness in assessing the criteria. To evaluate the influence of this weighting structure on the final results, experts' ratings were consolidated using their calculated SVNN-based important weights, and robustness was additionally examined by jackknife resampling. The jackknife analysis (Scenarios 1–5) demonstrated Spearman's rank correlations between

the baseline (all experts) and reduced-expert scenarios, ranging from 0.29 to 0.69, indicating partial stability of the rankings and underscoring that Experts 3 and 5 exerted greater influence on the composite scores. Kendall's W coefficients across the ten criteria (0.12–0.39) demonstrated low to moderate inter-rater agreement, signifying variability in expert evaluations. The findings indicate that the SVNN-based expert importance scheme identifies significant variations in expert reliability; yet, the ultimate outcomes are still slightly influenced by individual expert contributions. To improve robustness and interpretability, future studies should stratify specialists by domain (e.g., growers, service providers, economic assessors) to produce subgroup-specific rankings and more accurately reflect sectoral perspectives within the multi-criteria evaluation framework.

Although no previous study has comprehensively compared all 10 PATs within a unified MCDM framework, the present work constitutes the first integrated assessment using expert-based evaluations and a neutrosophic entropy-DEMATEL-TOPSIS approach tailored for small and medium-scale farming contexts. To strengthen the plausibility of the results, cross-validation was conducted using recent systematic reviews and case-based studies reported in the literature. The top-ranked technologies in this study, particularly IoT-based smart farming, remote sensing, and decision support systems (DSS), also exhibit high adoption potential and performance benefits in real-world agricultural applications. Getahun et al. [78] demonstrated that IoT, drones, and variable-rate technology (VRT) significantly enhance resource efficiency, yields, and environmental sustainability in empirical field contexts. Likewise, Mamabolo et al. [79] reported that IoT sensors, GIS, and UAVs are among the most widely adopted tools for soil health monitoring and crop protection. Padhiary et al. [80] further highlighted the increasing integration of IoT, artificial intelligence (AI), machine learning (ML), and automation in precision agriculture, which yielded measurable gains in cost-effectiveness and operational efficiency. Collectively, these findings provide partial cross-validation of the present ranking outcomes, supporting the external consistency and practical relevance of the expert-derived prioritization.

5. Discussion of Results

IoT-based smart farming emerged as the highest-ranked technology in the neutrosophic MCDM analysis, owing to its superior performance across multiple critical criteria, including spatial-temporal accuracy, automation, and system interoperability. Its integration of sensors, connectivity, and real-time analytics enables precise, site-specific decision-making, helping farmers optimize water, fertilizer, and pesticide use. This aligns with the existing literature, which emphasizes the transformative potential of IoT to improve farm productivity and environmental resilience, particularly for small and medium-scale farming operations [81]. While the TOPSIS rankings identify technically high-performing PATs in terms of spatial-temporal accuracy, scalability, and sustainability, these results must be interpreted alongside real-world adoption constraints. Many small and medium-scale farmers face high initial investment costs, inadequate rural infrastructure, and weak policy/financial support [82], as well as connectivity/IoT implementation barriers such as unreliable power and limited maintenance services [83]. Consequently, even technologies that score highly in our model (e.g., UAVs, IoT-based irrigation) may be infeasible for broad uptake without complementary measures, notably targeted financing/subsidies, accessible training and extension services, and improvements to rural connectivity. Future work should validate the model's recommendations through pilot field trials and stakeholder engagement before large-scale policy or procurement decisions are made.

Remote sensing was the second-best performer, driven by its ability to provide high-resolution, wide-area imagery that facilitates efficient monitoring of crop health, moisture

levels, and pest activity. The accessibility of satellite and UAV-based imaging technologies further enhances their applicability across diverse agricultural zones (Sishodia et al., [21]). Decision support systems (DSS) ranked third, reflecting their strength in aggregating complex datasets and delivering actionable recommendations to improve decision-making and resource efficiency (Zhai et al., [84]).

GPS and GIS technologies were placed in the mid-tier, valued for their foundational roles in geospatial mapping and field variability analysis but limited in analytical depth. UAVs, or drones, also demonstrated moderate performance. Their effectiveness in field-level imaging and disease detection is acknowledged; however, regulatory constraints, operator training requirements, and data-processing demands affect their ease of adoption. AI- and ML-based precision agriculture platforms showed considerable potential for predictive analytics and yield forecasting, yet their practical deployment remains limited by data availability and computational complexity. Autonomous agricultural machinery faces similar challenges despite reducing labor dependency and enhancing precision; their high cost and maintenance requirements hinder widespread adoption in smaller operations.

In contrast, variable-rate technology (VRT) and standalone soil and crop sensors received the lowest rankings. VRT, although theoretically effective at reducing input waste, was constrained by substantial capital requirements, calibration complexity, and underutilization in fragmented landholdings (Späti et al., [85]). Similarly, soil and crop sensors, when not embedded within broader IoT frameworks, suffer from high hardware costs, limited interoperability, and maintenance issues, which diminish their viability for resource-constrained farmers (Testa et al., [86]). These findings reinforce that the real-world utility of precision agriculture tools depends not only on their technical potential but also on factors such as economic feasibility, system integration, training availability, and infrastructural readiness. The neutrosophic MCDM approach, by incorporating both weighted criteria and uncertainty handling, offers a more flexible and realistic evaluation of technologies, allowing for context-sensitive recommendations.

It should be noted that PATs evolve rapidly. For example, recent reports highlight emerging platforms (drones, ground robots, AI-driven sensors, etc.). Thus, our rankings reflect the current set of PATs, and future analyses should incorporate innovations and updated field data as they arise.

We note that the proposed neutrosophic entropy-DEMATEL-TOPSIS framework is computationally intensive (requiring multiple matrix operations and iterative similarity calculations) and relies on a small panel of experts. This may limit scalability and introduce subjective bias. Consistent with best practice [47], future work should validate the rankings with diverse field data, stakeholder surveys, or case studies to complement expert judgments.

6. Conclusions

This study introduced a novel weighted neutrosophic TOPSIS framework that integrates entropy weighting, DEMATEL, and a Cosine-Jaccard similarity measure to evaluate and rank precision agriculture technologies (PATs). The neutrosophic approach models each criterion with degrees of truth, indeterminacy, and falsity, making it particularly suitable for handling uncertainty and imprecision in expert assessments [87]. By combining entropy-derived objective weights with DEMATEL-based relational weights, the framework balances data-driven analysis with expert judgment. The incorporation of a Cosine-Jaccard similarity measure enhances robustness in handling mixed-scale criteria. The application of this hybrid MCDM method to ten PATs revealed substantial performance differences. Among the evaluated technologies, IoT-based sensor networks rank first, followed by remote sensing platforms (including drones and satellites), and

decision support systems, highlighting their ability to collect and process real-time data, thereby improving both productivity and resource efficiency [88]. Conversely, tools such as variable-rate fertilization systems and standalone soil or crop sensors ranked lower, reflecting broader challenges associated with high capital investment, technical complexity, and limited accessibility for smallholder farmers [89].

However, these technical rankings should be interpreted in light of adoption barriers (cost, infrastructure, training and financing); targeted policy support and pilot testing are required to translate rankings into equitable, scalable implementations [82].

The results of this evaluation hold valuable implications for farmers, policymakers, and agricultural development agencies. By identifying high-performing technologies under conditions typical of small- and medium-scale farming, this study supports more targeted deployment of PATs. For instance, promoting affordable IoT sensor packages or mobile-based monitoring solutions could provide quick returns on efficiency, particularly in regions with limited infrastructure. More advanced tools, such as VRT, could be introduced gradually in better-resourced areas, with support in the form of financing and training. Policymakers can use these insights to inform subsidy programs, credit facilities, and rural connectivity projects, ensuring that high-impact technologies become accessible where they are most needed. As highlighted in recent studies, improving the adoption rate of PATs requires a nuanced understanding of local challenges, such as resource limitations and digital literacy. Practical implementation must align with regional capacities, with foundational tools prioritized in underdeveloped regions and more sophisticated systems piloted in areas with better infrastructure. Across all contexts, complementary investment in training, technical support, and extension services is essential to bridge the gap between technological potential and actual use [88].

Despite this approach's strengths, several limitations must be acknowledged. The analysis was built on expert-driven linguistic data and focused on a limited set of 10 technologies and selected criteria, primarily economic, technical, and environmental. As a result, important dimensions such as labor efficiency, long-term soil health, and user acceptance were not included. Furthermore, the expert input was region-specific, which may limit the generalizability of the findings. Future research should expand the set of performance indicators to include social inclusion, sustainability metrics, and resilience indicators.

Additionally, incorporating more technologies, including smartphone advisory tools, robotics, and cloud-based analytics, would enrich the analysis. Real-world adoption data, including time-series usage records, farm-level performance outcomes, and user feedback, would strengthen the model by validating its rankings against practical experience. Accordingly, we recommend implementing pilot studies and stakeholder co-design (farmers, extension agents, policymakers) in representative agro-ecological zones to test feasibility, assess financing mechanisms, and refine deployment strategies before recommending large-scale adoption [82]. Moreover, testing this framework in diverse agro-ecological and socio-economic settings, particularly in Africa and Latin America, would help to assess its adaptability and global relevance.

Going forward, expanding the indicator scope to capture labor-related and sustainability concerns will enhance the comprehensiveness of PATs evaluations. Incorporating empirical data from actual field deployments, such as sensor logs and farmer surveys, can increase the model's predictive accuracy and reliability. Application of the model across a broader geographic spectrum will provide comparative insights that inform tailored strategies for different regions. Further, integrating machine learning and AI-based analytics can help process large datasets and identify performance trends that are not easily discernible through traditional methods. In conclusion, this study provides a practical, theoretically

sound foundation for evaluating PATs, particularly in data-limited, uncertainty-prone contexts. By building on these insights, stakeholders, including governments, research institutions, and development organizations can craft evidence-based policies and adaptive frameworks that promote equitable, sustainable precision agriculture. Collaborative efforts in data collection, contextualization of adoption strategies, and farmer education will be instrumental in translating technological innovations into measurable agricultural development.

Author Contributions: Conceptualization, Venkata Prasanna Nagari and Vinoth Subbiah; methodology, Venkata Prasanna Nagari; software, Venkata Prasanna Nagari; validation, Venkata Prasanna Nagari and Vinoth Subbiah; formal analysis, Venkata Prasanna Nagari; investigation, Venkata Prasanna Nagari; resources, Venkata Prasanna Nagari data curation, Venkata Prasanna Nagari; writing—original draft preparation, Venkata Prasanna Nagari; writing—review and editing, Venkata Prasanna Nagari and Vinoth Subbiah; visualization, Venkata Prasanna Nagari; supervision, Vinoth Subbiah; project administration, Venkata Prasanna Nagari and Vinoth Subbiah; funding acquisition, Vinoth Subbiah. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The raw data supporting this study are available at PAT (Raw Data).csv.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. Aggregated neutrosophic decision matrix (NDM) is determined by applying Equation (10).

$\tilde{A}_i/\tilde{C}_i$	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
$\tilde{A}_1$	0.73	0.71	0.73	0.75	0.75	0.67	0.60	0.60	0.65	0.77
$\tilde{A}_2$	0.77	0.83	0.79	0.70	0.71	0.67	0.77	0.65	0.73	0.73
$\tilde{A}_3$	0.76	0.78	0.77	0.80	0.83	0.74	0.71	0.67	0.75	0.73
$\tilde{A}_4$	0.70	0.69	0.67	0.63	0.65	0.71	0.57	0.61	0.59	0.67
$\tilde{A}_5$	0.60	0.65	0.61	0.56	0.63	0.61	0.61	0.63	0.61	0.63
$\tilde{A}_6$	0.69	0.61	0.69	0.71	0.75	0.70	0.61	0.57	0.63	0.65
$\tilde{A}_7$	0.77	0.65	0.69	0.67	0.68	0.63	0.63	0.70	0.74	0.67
$\tilde{A}_8$	0.74	0.71	0.63	0.77	0.74	0.70	0.61	0.67	0.67	0.70
$\tilde{A}_9$	0.67	0.67	0.59	0.67	0.65	0.68	0.61	0.65	0.61	0.65
$\tilde{A}_{10}$	0.77	0.74	0.74	0.77	0.77	0.72	0.63	0.65	0.67	0.69

Table A2. Normalized NDM based on Entropy.

$\tilde{A}_i/\tilde{C}_i$	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
$\tilde{A}_1$	0.10	0.10	0.11	0.11	0.11	0.10	0.10	0.09	0.10	0.11
$\tilde{A}_2$	0.11	0.12	0.11	0.10	0.10	0.10	0.12	0.10	0.11	0.11
$\tilde{A}_3$	0.11	0.11	0.11	0.11	0.12	0.11	0.11	0.11	0.11	0.11
$\tilde{A}_4$	0.10	0.10	0.10	0.09	0.09	0.11	0.09	0.10	0.09	0.10
$\tilde{A}_5$	0.08	0.09	0.09	0.08	0.09	0.09	0.10	0.10	0.09	0.09
$\tilde{A}_6$	0.10	0.09	0.10	0.10	0.11	0.10	0.10	0.09	0.10	0.10
$\tilde{A}_7$	0.11	0.09	0.10	0.10	0.09	0.09	0.10	0.11	0.11	0.10
$\tilde{A}_8$	0.10	0.10	0.09	0.11	0.10	0.10	0.10	0.11	0.10	0.10
$\tilde{A}_9$	0.09	0.10	0.09	0.10	0.09	0.10	0.10	0.10	0.09	0.10
$\tilde{A}_{10}$	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.10	0.10	0.10

Table A3. Calculations of ' $Norm_{ij} \times \ln Norm'_{ij}$ ' values.

$\tilde{\mathcal{A}}_i/\tilde{\mathcal{C}}_i$	$\tilde{\mathcal{C}}_1$	$\tilde{\mathcal{C}}_2$	$\tilde{\mathcal{C}}_3$	$\tilde{\mathcal{C}}_4$	$\tilde{\mathcal{C}}_5$	$\tilde{\mathcal{C}}_6$	$\tilde{\mathcal{C}}_7$	$\tilde{\mathcal{C}}_8$	$\tilde{\mathcal{C}}_9$	$\tilde{\mathcal{C}}_{10}$
$\tilde{\mathcal{A}}_1$	−0.23	−0.23	−0.24	−0.24	−0.24	−0.23	−0.22	−0.22	−0.23	−0.25
$\tilde{\mathcal{A}}_2$	−0.24	−0.25	−0.25	−0.23	−0.23	−0.23	−0.26	−0.23	−0.24	−0.24
$\tilde{\mathcal{A}}_3$	−0.24	−0.24	−0.25	−0.25	−0.25	−0.24	−0.25	−0.24	−0.25	−0.24
$\tilde{\mathcal{A}}_4$	−0.23	−0.23	−0.23	−0.22	−0.22	−0.24	−0.22	−0.22	−0.22	−0.23
$\tilde{\mathcal{A}}_5$	−0.21	−0.22	−0.21	−0.20	−0.21	−0.22	−0.22	−0.23	−0.22	−0.22
$\tilde{\mathcal{A}}_6$	−0.22	−0.21	−0.23	−0.23	−0.24	−0.23	−0.22	−0.22	−0.22	−0.22
$\tilde{\mathcal{A}}_7$	−0.24	−0.22	−0.23	−0.23	−0.22	−0.22	−0.23	−0.24	−0.24	−0.23
$\tilde{\mathcal{A}}_8$	−0.23	−0.23	−0.22	−0.24	−0.23	−0.23	−0.23	−0.24	−0.23	−0.23
$\tilde{\mathcal{A}}_9$	−0.22	−0.22	−0.21	−0.22	−0.22	−0.23	−0.23	−0.23	−0.22	−0.22
$\tilde{\mathcal{A}}_{10}$	−0.24	−0.24	−0.24	−0.24	−0.24	−0.24	−0.23	−0.23	−0.23	−0.23
Total	−0.23	−0.23	−0.24	−0.24	−0.24	−0.23	−0.22	−0.22	−0.23	−0.25

Table A4. Neutrosophic aggregated direct influence matrix (DIM).

$\mathcal{C}_i \backslash \mathcal{C}_i$	$\tilde{\mathcal{C}}_1$	$\tilde{\mathcal{C}}_2$	$\tilde{\mathcal{C}}_3$	$\tilde{\mathcal{C}}_4$	$\tilde{\mathcal{C}}_5$
$\tilde{\mathcal{C}}_1$	(0.10, 0.80, 0.90)	(0.77, 0.21, 0.21)	(0.47, 0.44, 0.50)	(0.78, 0.21, 0.22)	(0.68, 0.30, 0.33)
$\tilde{\mathcal{C}}_2$	(0.72, 0.25, 0.25)	(0.10, 0.80, 0.90)	(0.86, 0.14, 0.14)	(0.83, 0.17, 0.14)	(0.47, 0.44, 0.50)
$\tilde{\mathcal{C}}_3$	(0.87, 0.13, 0.12)	(0.88, 0.12, 0.11)	(0.10, 0.80, 0.90)	(0.88, 0.12, 0.11)	(0.83, 0.17, 0.14)
$\tilde{\mathcal{C}}_4$	(0.84, 0.16, 0.15)	(0.72, 0.26, 0.23)	(0.88, 0.12, 0.11)	(0.10, 0.80, 0.90)	(0.78, 0.20, 0.20)
$\tilde{\mathcal{C}}_5$	(0.76, 0.23, 0.23)	(0.81, 0.17, 0.18)	(0.75, 0.24, 0.19)	(0.73, 0.24, 0.25)	(0.10, 0.80, 0.90)
$\tilde{\mathcal{C}}_6$	(0.50, 0.47, 0.45)	(0.50, 0.47, 0.45)	(0.73, 0.24, 0.25)	(0.65, 0.31, 0.30)	(0.74, 0.26, 0.21)
$\tilde{\mathcal{C}}_7$	(0.29, 0.65, 0.68)	(0.46, 0.47, 0.50)	(0.69, 0.29, 0.26)	(0.29, 0.65, 0.68)	(0.26, 0.67, 0.77)
$\tilde{\mathcal{C}}_8$	(0.78, 0.20, 0.20)	(0.81, 0.17, 0.18)	(0.74, 0.26, 0.21)	(0.83, 0.17, 0.14)	(0.61, 0.32, 0.36)
$\tilde{\mathcal{C}}_9$	(0.65, 0.31, 0.30)	(0.65, 0.31, 0.30)	(0.74, 0.26, 0.21)	(0.43, 0.47, 0.53)	(0.88, 0.12, 0.11)
$\tilde{\mathcal{C}}_{10}$	(0.61, 0.36, 0.39)	(0.50, 0.47, 0.45)	(0.28, 0.61, 0.69)	(0.57, 0.37, 0.39)	(0.61, 0.36, 0.39)
	$\tilde{\mathcal{C}}_6$	$\tilde{\mathcal{C}}_7$	$\tilde{\mathcal{C}}_8$	$\tilde{\mathcal{C}}_9$	$\tilde{\mathcal{C}}_{10}$
$\tilde{\mathcal{C}}_1$	(0.65, 0.32, 0.33)	(0.17, 0.75, 0.85)	(0.78, 0.20, 0.20)	(0.65, 0.31, 0.30)	(0.62, 0.36, 0.39)
$\tilde{\mathcal{C}}_2$	(0.50, 0.47, 0.45)	(0.31, 0.61, 0.70)	(0.81, 0.17, 0.70)	(0.21, 0.72, 0.82)	(0.50, 0.47, 0.45)
$\tilde{\mathcal{C}}_3$	(0.86, 0.14, 0.14)	(0.59, 0.38, 0.35)	(0.89, 0.12, 0.11)	(0.52, 0.42, 0.45)	(0.28, 0.61, 0.69)
$\tilde{\mathcal{C}}_4$	(0.50, 0.47, 0.45)	(0.21, 0.68, 0.77)	(0.85, 0.15, 0.13)	(0.17, 0.75, 0.85)	(0.47, 0.44, 0.50)
$\tilde{\mathcal{C}}_5$	(0.72, 0.28, 0.23)	(0.62, 0.36, 0.35)	(0.66, 0.29, 0.32)	(0.73, 0.26, 0.26)	(0.61, 0.36, 0.36)
$\tilde{\mathcal{C}}_6$	(0.10, 0.80, 0.90)	(0.85, 0.15, 0.13)	(0.28, 0.61, 0.69)	(0.90, 0.10, 0.10)	(0.85, 0.15, 0.13)
$\tilde{\mathcal{C}}_7$	(0.85, 0.15, 0.13)	(0.10, 0.80, 0.90)	(0.60, 0.34, 0.35)	(0.89, 0.11, 0.11))	(0.90, 0.10, 0.10)
$\tilde{\mathcal{C}}_8$	(0.57, 0.36, 0.38)	(0.60, 0.34, 0.35)	(0.10, 0.80, 0.90)	(0.87, 0.13, 0.12)	(0.60, 0.34, 0.35)
$\tilde{\mathcal{C}}_9$	(0.87, 0.13, 0.12)	(0.90, 0.10, 0.10)	(0.90, 0.10, 0.10)	(0.10, 0.80, 0.90)	(0.75, 0.24, 0.19)
$\tilde{\mathcal{C}}_{10}$	(0.90, 0.10, 0.10)	(0.87, 0.13, 0.12)	(0.60, 0.34, 0.35)	(0.83, 0.17, 0.14)	(0.10, 0.80, 0.90)

Table A5. Neutrosophic normalized aggregated DIM.

	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$
$\tilde{C}_1$	(0.01, 0.12, 0.13)	(0.11, 0.03, 0.03)	(0.07, 0.06, 0.07)	(0.11, 0.03, 0.03)	(0.10, 0.04, 0.05)
$\tilde{C}_2$	(0.10, 0.04, 0.04)	(0.02, 0.12, 0.13)	(0.12, 0.02, 0.02)	(0.12, 0.02, 0.02)	(0.07, 0.06, 0.07)
$\tilde{C}_3$	(0.13, 0.02, 0.02)	(0.13, 0.02, 0.02)	(0.01, 0.12, 0.13)	(0.13, 0.02, 0.02)	(0.12, 0.02, 0.02)
$\tilde{C}_4$	(0.12, 0.02, 0.02)	(0.10, 0.04, 0.03)	(0.13, 0.02, 0.02)	(0.01, 0.12, 0.13)	(0.11, 0.03, 0.03)
$\tilde{C}_5$	(0.11, 0.03, 0.03)	(0.12, 0.03, 0.03)	(0.11, 0.03, 0.03)	(0.11, 0.03, 0.04)	(0.01, 0.12, 0.13)
$\tilde{C}_6$	(0.07, 0.07, 0.07)	(0.07, 0.07, 0.07)	(0.11, 0.03, 0.04)	(0.09, 0.04, 0.04)	(0.11, 0.04, 0.03)
$\tilde{C}_7$	(0.04, 0.09, 0.10)	(0.07, 0.07, 0.07)	(0.10, 0.04, 0.04)	(0.04, 0.09, 0.10)	(0.04, 0.10, 0.11)
$\tilde{C}_8$	(0.11, 0.03, 0.03)	(0.12, 0.03, 0.03)	(0.11, 0.04, 0.03)	(0.12, 0.02, 0.02)	(0.09, 0.05, 0.05)
$\tilde{C}_9$	(0.09, 0.05, 0.04)	(0.09, 0.05, 0.04)	(0.11, 0.04, 0.03)	(0.06, 0.07, 0.08)	(0.13, 0.02, 0.02)
$\tilde{C}_{10}$	(0.09, 0.05, 0.06)	(0.07, 0.07, 0.07)	(0.04, 0.09, 0.10)	(0.08, 0.05, 0.06)	(0.09, 0.05, 0.06)
	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
$\tilde{C}_1$	(0.09, 0.05, 0.05)	(0.02, 0.11, 0.12)	(0.11, 0.03, 0.03)	(0.09, 0.04, 0.04)	(0.09, 0.05, 0.06)
$\tilde{C}_2$	(0.07, 0.07, 0.07)	(0.04, 0.09, 0.10)	(0.12, 0.02, 0.10)	(0.03, 0.10, 0.12)	(0.07, 0.07, 0.07)
$\tilde{C}_3$	(0.12, 0.02, 0.02)	(0.09, 0.06, 0.05)	(0.13, 0.02, 0.02)	(0.08, 0.06, 0.07)	(0.04, 0.09, 0.10)
$\tilde{C}_4$	(0.07, 0.07, 0.07)	(0.03, 0.10, 0.11)	(0.12, 0.02, 0.02)	(0.02, 0.11, 0.12)	(0.07, 0.06, 0.07)
$\tilde{C}_5$	(0.10, 0.04, 0.03)	(0.09, 0.05, 0.05)	(0.10, 0.04, 0.05)	(0.11, 0.04, 0.04)	(0.09, 0.05, 0.05)
$\tilde{C}_6$	(0.01, 0.12, 0.13)	(0.12, 0.02, 0.02)	(0.04, 0.09, 0.10)	(0.13, 0.01, 0.01)	(0.12, 0.02, 0.02)
$\tilde{C}_7$	(0.12, 0.02, 0.02)	(0.01, 0.12, 0.13)	(0.09, 0.05, 0.05)	(0.13, 0.02, 0.02)	(0.13, 0.01, 0.01)
$\tilde{C}_8$	(0.08, 0.05, 0.06)	(0.09, 0.05, 0.05)	(0.01, 0.12, 0.13)	(0.13, 0.02, 0.02)	(0.09, 0.05, 0.05)
$\tilde{C}_9$	(0.13, 0.02, 0.02)	(0.13, 0.01, 0.01)	(0.13, 0.01, 0.01)	(0.01, 0.12, 0.13)	(0.11, 0.03, 0.03)
$\tilde{C}_{10}$	(0.13, 0.01, 0.01)	(0.13, 0.02, 0.02)	(0.09, 0.05, 0.05)	(0.12, 0.02, 0.02)	(0.01, 0.12, 0.13)

Table A6. Total DIM.

$C_i \setminus C_i$	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$
$\tilde{C}_1$	(0.64, 0.19, 0.22)	(0.73, 0.09, 0.10)	(0.70, 0.13, 0.15)	(0.73, 0.09, 0.11)	(0.70, 0.11, 0.13)
$\tilde{C}_2$	(0.68, 0.11, 0.12)	(0.60, 0.19, 0.22)	(0.70, 0.08, 0.09)	(0.70, 0.09, 0.11)	(0.63, 0.14, 0.17)
$\tilde{C}_3$	(0.84, 0.06, 0.07)	(0.85, 0.06, 0.06)	(0.75, 0.17, 0.19)	(0.84, 0.06, 0.07)	(0.82, 0.07, 0.07)
$\tilde{C}_4$	(0.72, 0.09, 0.10)	(0.71, 0.10, 0.11)	(0.73, 0.07, 0.08)	(0.63, 0.19, 0.22)	(0.70, 0.09, 0.11)
$\tilde{C}_5$	(0.81, 0.08, 0.09)	(0.82, 0.07, 0.08)	(0.82, 0.08, 0.08)	(0.80, 0.08, 0.09)	(0.70, 0.17, 0.20)
$\tilde{C}_6$	(0.73, 0.13, 0.13)	(0.74, 0.12, 0.13)	(0.77, 0.08, 0.09)	(0.75, 0.10, 0.10)	(0.75, 0.09, 0.10)
$\tilde{C}_7$	(0.63, 0.17, 0.19)	(0.66, 0.13, 0.15)	(0.69, 0.10, 0.11)	(0.63, 0.17, 0.19)	(0.62, 0.18, 0.21)
$\tilde{C}_8$	(0.81, 0.08, 0.08)	(0.82, 0.07, 0.08)	(0.82, 0.08, 0.08)	(0.82, 0.07, 0.07)	(0.77, 0.10, 0.11)
$\tilde{C}_9$	(0.83, 0.09, 0.09)	(0.84, 0.09, 0.09)	(0.85, 0.08, 0.07)	(0.80, 0.12, 0.13)	(0.84, 0.06, 0.06)
$\tilde{C}_{10}$	(0.72, 0.11, 0.12)	(0.71, 0.13, 0.13)	(0.69, 0.15, 0.17)	(0.71, 0.11, 0.12)	(0.71, 0.11, 0.13)
	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
$\tilde{C}_1$	(0.73, 0.10, 0.11)	(0.55, 0.19, 0.23)	(0.75, 0.08, 0.10)	(0.67, 0.11, 0.12)	(0.65, 0.12, 0.14)
$\tilde{C}_2$	(0.67, 0.13, 0.14)	(0.53, 0.17, 0.21)	(0.72, 0.08, 0.20)	(0.58, 0.18, 0.22)	(0.60, 0.14, 0.16)
$\tilde{C}_3$	(0.86, 0.05, 0.06)	(0.69, 0.11, 0.11)	(0.87, 0.05, 0.06)	(0.75, 0.11, 0.12)	(0.70, 0.15, 0.17)
$\tilde{C}_4$	(0.70, 0.13, 0.13)	(0.54, 0.18, 0.21)	(0.75, 0.07, 0.09)	(0.60, 0.18, 0.22)	(0.62, 0.13, 0.15)
$\tilde{C}_5$	(0.83, 0.08, 0.08)	(0.68, 0.11, 0.12)	(0.82, 0.09, 0.10)	(0.76, 0.09, 0.09)	(0.73, 0.11, 0.11)
$\tilde{C}_6$	(0.71, 0.18, 0.20)	(0.68, 0.09, 0.10)	(0.74, 0.15, 0.18)	(0.75, 0.07, 0.08)	(0.73, 0.08, 0.08)
$\tilde{C}_7$	(0.73, 0.08, 0.09)	(0.53, 0.21, 0.25)	(0.70, 0.11, 0.13)	(0.68, 0.09, 0.10)	(0.67, 0.08, 0.10)
$\tilde{C}_8$	(0.81, 0.10, 0.10)	(0.68, 0.11, 0.12)	(0.75, 0.17, 0.20)	(0.78, 0.06, 0.06)	(0.73, 0.10, 0.11)
$\tilde{C}_9$	(0.89, 0.06, 0.06)	(0.76, 0.07, 0.07)	(0.89, 0.05, 0.06)	(0.73, 0.17, 0.20)	(0.79, 0.08, 0.08)
$\tilde{C}_{10}$	(0.79, 0.06, 0.07)	(0.66, 0.09, 0.10)	(0.75, 0.10, 0.12)	(0.72, 0.09, 0.09)	(0.61, 0.19, 0.22)

Table A7. Deneutrosophication of the total DIM, using Equation (5).

$\tilde{C}_i \backslash \tilde{C}_j$	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
$\tilde{C}_1$	0.73	0.83	0.79	0.82	0.80	0.82	0.69	0.84	0.79	0.73
$\tilde{C}_2$	0.79	0.72	0.82	0.81	0.75	0.78	0.69	0.79	0.71	0.79
$\tilde{C}_3$	0.89	0.90	0.79	0.90	0.88	0.91	0.80	0.91	0.83	0.89
$\tilde{C}_4$	0.82	0.81	0.83	0.73	0.81	0.80	0.69	0.84	0.72	0.82
$\tilde{C}_5$	0.87	0.88	0.88	0.87	0.77	0.88	0.79	0.87	0.84	0.87
$\tilde{C}_6$	0.81	0.82	0.85	0.83	0.84	0.77	0.80	0.80	0.84	0.81
$\tilde{C}_7$	0.74	0.77	0.80	0.74	0.73	0.83	0.67	0.80	0.80	0.74
$\tilde{C}_8$	0.87	0.88	0.87	0.88	0.84	0.86	0.79	0.79	0.86	0.87
$\tilde{C}_9$	0.88	0.88	0.90	0.85	0.90	0.92	0.85	0.93	0.78	0.88
$\tilde{C}_{10}$	0.81	0.80	0.78	0.81	0.81	0.87	0.79	0.83	0.82	0.81

Table A8. Aggregated neutrosophic decision matrix (NDM).

$\tilde{A}_i \backslash \tilde{C}_j$	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$
$\tilde{A}_1$	(0.77, 0.21, 0.23)	(0.72, 0.24, 0.28)	(0.75, 0.21, 0.25)	(1.00, 0.00, 0.00)	(1.00, 0.00, 0.00)
$\tilde{A}_2$	(0.79, 0.18, 0.21)	(1.00, 0.00, 0.00)	(1.00, 0.00, 0.00)	(0.69, 0.25, 0.31)	(0.74, 0.21, 0.26)
$\tilde{A}_3$	(0.76, 0.19, 0.24)	(0.77, 0.18, 0.23)	(0.80, 0.17, 0.20)	(0.79, 0.16, 0.21)	(1.00, 0.00, 0.00)
$\tilde{A}_4$	(0.69, 0.25, 0.31)	(0.69, 0.26, 0.31)	(0.69, 0.26, 0.31)	(0.65, 0.31, 0.35)	(0.67, 0.29, 0.33)
$\tilde{A}_5$	(1.00, 0.00, 0.00)	(0.68, 0.27, 0.32)	(0.64, 0.32, 0.36)	(0.61, 0.36, 0.39)	(0.67, 0.29, 0.33)
$\tilde{A}_6$	(0.72, 0.25, 0.28)	(0.62, 0.35, 0.38)	(0.71, 0.24, 0.29)	(1.00, 0.00, 0.00)	(1.00, 0.00, 0.00)
$\tilde{A}_7$	(1.00, 0.00, 0.00)	(0.66, 0.29, 0.34)	(0.71, 0.24, 0.29)	(0.70, 0.25, 0.30)	(0.67, 0.27, 0.33)
$\tilde{A}_8$	(1.00, 0.00, 0.00)	(0.73, 0.23, 0.27)	(0.65, 0.30, 0.35)	(1.00, 0.00, 0.00)	(0.74, 0.21, 0.26)
$\tilde{A}_9$	(0.68, 0.27, 0.32)	(0.70, 0.25, 0.30)	(0.63, 0.33, 0.37)	(1.00, 0.00, 0.00)	(0.67, 0.28, 0.33)
$\tilde{A}_{10}$	(1.00, 0.00, 0.00)	(0.72, 0.22, 0.28)	(0.73, 0.22, 0.27)	(1.00, 0.00, 0.00)	(1.00, 0.00, 0.00)
	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
$\tilde{A}_1$	(0.69, 0.27, 0.31)	(0.66, 0.31, 0.34)	(0.68, 0.31, 0.32)	(0.70, 0.26, 0.30)	(0.79, 0.18, 0.21)
$\tilde{A}_2$	(0.69, 0.26, 0.31)	(1.00, 0.00, 0.00)	(0.67, 0.28, 0.33)	(1.00, 0.00, 0.00)	(0.75, 0.20, 0.25)
$\tilde{A}_3$	(0.75, 0.19, 0.25)	(0.74, 0.21, 0.26)	(0.70, 0.26, 0.30)	(0.79, 0.18, 0.21)	(0.75, 0.20, 0.25)
$\tilde{A}_4$	(0.72, 0.23, 0.28)	(0.60, 0.36, 0.40)	(0.64, 0.32, 0.36)	(0.61, 0.34, 0.39)	(0.68, 0.27, 0.32)
$\tilde{A}_5$	(0.64, 0.32, 0.36)	(0.64, 0.32, 0.36)	(0.65, 0.31, 0.35)	(0.64, 0.32, 0.36)	(0.67, 0.29, 0.33)
$\tilde{A}_6$	(0.69, 0.25, 0.31)	(0.64, 0.32, 0.36)	(0.57, 0.40, 0.43)	(0.65, 0.31, 0.35)	(0.66, 0.29, 0.34)
$\tilde{A}_7$	(0.68, 0.30, 0.32)	(0.68, 0.30, 0.32)	(0.71, 0.24, 0.29)	(0.73, 0.21, 0.27)	(0.69, 0.26, 0.31)
$\tilde{A}_8$	(0.69, 0.25, 0.31)	(0.64, 0.31, 0.36)	(0.68, 0.28, 0.32)	(0.68, 0.28, 0.32)	(0.69, 0.25, 0.31)
$\tilde{A}_9$	(0.68, 0.27, 0.32)	(0.63, 0.33, 0.37)	(1.00, 0.00, 0.00)	(0.64, 0.32, 0.36)	(0.66, 0.30, 0.34)
$\tilde{A}_{10}$	(0.71, 0.23, 0.29)	(0.65, 0.31, 0.35)	(0.66, 0.29, 0.34)	(0.69, 0.27, 0.31)	(0.70, 0.25, 0.30)

Table A9. Normalized Aggregated NDM.

$\mathcal{A}_i \setminus \mathcal{C}_i$	$\tilde{\mathcal{C}}_1$	$\tilde{\mathcal{C}}_2$	$\tilde{\mathcal{C}}_3$	$\tilde{\mathcal{C}}_4$	$\tilde{\mathcal{C}}_5$
$\tilde{\mathcal{A}}_1$	(0.28, 0.37, 0.36)	(0.31, 0.31, 0.30)	(0.32, 0.27, 0.27)	(0.37, 0.00, 0.00)	(0.38, 0.00, 0.00)
$\tilde{\mathcal{A}}_2$	(0.29, 0.32, 0.32)	(0.43, 0.00, 0.00)	(0.43, 0.00, 0.00)	(0.26, 0.41, 0.43)	(0.28, 0.32, 0.34)
$\tilde{\mathcal{A}}_3$	(0.28, 0.34, 0.37)	(0.33, 0.24, 0.26)	(0.34, 0.22, 0.22)	(0.29, 0.26, 0.30)	(0.38, 0.00, 0.00)
$\tilde{\mathcal{A}}_4$	(0.26, 0.45, 0.46)	(0.30, 0.34, 0.34)	(0.30, 0.33, 0.34)	(0.24, 0.50, 0.49)	(0.25, 0.45, 0.44)
$\tilde{\mathcal{A}}_5$	(0.37, 0.00, 0.00)	(0.29, 0.35, 0.35)	(0.27, 0.42, 0.40)	(0.23, 0.58, 0.55)	(0.26, 0.45, 0.44)
$\tilde{\mathcal{A}}_6$	(0.27, 0.45, 0.43)	(0.27, 0.45, 0.42)	(0.30, 0.31, 0.32)	(0.37, 0.00, 0.00)	(0.38, 0.00, 0.00)
$\tilde{\mathcal{A}}_7$	(0.37, 0.00, 0.00)	(0.28, 0.37, 0.37)	(0.31, 0.30, 0.32)	(0.26, 0.41, 0.43)	(0.26, 0.43, 0.43)
$\tilde{\mathcal{A}}_8$	(0.37, 0.00, 0.00)	(0.31, 0.29, 0.30)	(0.28, 0.39, 0.38)	(0.37, 0.00, 0.00)	(0.28, 0.33, 0.35)
$\tilde{\mathcal{A}}_9$	(0.25, 0.48, 0.48)	(0.30, 0.32, 0.33)	(0.27, 0.42, 0.41)	(0.37, 0.00, 0.00)	(0.26, 0.44, 0.44)
$\tilde{\mathcal{A}}_{10}$	(0.37, 0.00, 0.00)	(0.31, 0.29, 0.30)	(0.31, 0.28, 0.30)	(0.37, 0.00, 0.00)	(0.38, 0.00, 0.00)
	$\tilde{\mathcal{C}}_6$	$\tilde{\mathcal{C}}_7$	$\tilde{\mathcal{C}}_8$	$\tilde{\mathcal{C}}_9$	$\tilde{\mathcal{C}}_{10}$
$\tilde{\mathcal{A}}_1$	(0.31, 0.32, 0.32)	(0.30, 0.33, 0.33)	(0.31, 0.34, 0.31)	(0.31, 0.31, 0.31)	(0.35, 0.22, 0.22)
$\tilde{\mathcal{A}}_2$	(0.31, 0.32, 0.32)	(0.45, 0.00, 0.00)	(0.30, 0.31, 0.32)	(0.44, 0.00, 0.00)	(0.33, 0.26, 0.27)
$\tilde{\mathcal{A}}_3$	(0.34, 0.24, 0.26)	(0.34, 0.22, 0.25)	(0.31, 0.28, 0.30)	(0.35, 0.21, 0.22)	(0.34, 0.25, 0.26)
$\tilde{\mathcal{A}}_4$	(0.33, 0.28, 0.29)	(0.27, 0.39, 0.38)	(0.29, 0.36, 0.36)	(0.27, 0.41, 0.40)	(0.30, 0.35, 0.34)
$\tilde{\mathcal{A}}_5$	(0.29, 0.39, 0.38)	(0.29, 0.35, 0.35)	(0.29, 0.34, 0.34)	(0.28, 0.39, 0.37)	(0.30, 0.36, 0.35)
$\tilde{\mathcal{A}}_6$	(0.32, 0.31, 0.32)	(0.29, 0.35, 0.34)	(0.26, 0.45, 0.42)	(0.29, 0.36, 0.36)	(0.30, 0.36, 0.36)
$\tilde{\mathcal{A}}_7$	(0.31, 0.36, 0.33)	(0.31, 0.32, 0.30)	(0.32, 0.26, 0.29)	(0.32, 0.25, 0.27)	(0.31, 0.33, 0.32)
$\tilde{\mathcal{A}}_8$	(0.32, 0.31, 0.32)	(0.29, 0.33, 0.34)	(0.31, 0.31, 0.31)	(0.30, 0.33, 0.33)	(0.31, 0.32, 0.32)
$\tilde{\mathcal{A}}_9$	(0.31, 0.32, 0.33)	(0.29, 0.35, 0.35)	(0.45, 0.00, 0.00)	(0.28, 0.38, 0.37)	(0.29, 0.37, 0.36)
$\tilde{\mathcal{A}}_{10}$	(0.32, 0.28, 0.30)	(0.30, 0.33, 0.33)	(0.30, 0.32, 0.33)	(0.30, 0.32, 0.32)	(0.31, 0.31, 0.32)

Table A10. Weighted normalized aggregated NDM.

$\mathcal{A}_i \setminus \mathcal{C}_i$	$\tilde{\mathcal{C}}_1$	$\tilde{\mathcal{C}}_2$	$\tilde{\mathcal{C}}_3$	$\tilde{\mathcal{C}}_4$	$\tilde{\mathcal{C}}_5$
$\tilde{\mathcal{A}}_1$	(0.02, 0.03, 0.03)	(0.04, 0.04, 0.04)	(0.05, 0.04, 0.04)	(0.06, 0.00, 0.00)	(0.04, 0.00, 0.00)
$\tilde{\mathcal{A}}_2$	(0.03, 0.03, 0.03)	(0.05, 0.00, 0.00)	(0.06, 0.00, 0.00)	(0.04, 0.06, 0.07)	(0.03, 0.04, 0.04)
$\tilde{\mathcal{A}}_3$	(0.02, 0.03, 0.03)	(0.04, 0.03, 0.03)	(0.05, 0.03, 0.03)	(0.04, 0.04, 0.05)	(0.04, 0.00, 0.00)
$\tilde{\mathcal{A}}_4$	(0.02, 0.04, 0.04)	(0.03, 0.04, 0.04)	(0.04, 0.05, 0.05)	(0.04, 0.08, 0.08)	(0.03, 0.05, 0.05)
$\tilde{\mathcal{A}}_5$	(0.03, 0.00, 0.00)	(0.03, 0.04, 0.04)	(0.04, 0.06, 0.06)	(0.03, 0.09, 0.08)	(0.03, 0.05, 0.05)
$\tilde{\mathcal{A}}_6$	(0.02, 0.04, 0.04)	(0.03, 0.05, 0.05)	(0.04, 0.04, 0.05)	(0.06, 0.00, 0.00)	(0.04, 0.00, 0.00)
$\tilde{\mathcal{A}}_7$	(0.03, 0.00, 0.00)	(0.03, 0.04, 0.04)	(0.04, 0.04, 0.04)	(0.04, 0.06, 0.07)	(0.03, 0.05, 0.05)
$\tilde{\mathcal{A}}_8$	(0.03, 0.00, 0.00)	(0.04, 0.03, 0.04)	(0.04, 0.05, 0.05)	(0.06, 0.00, 0.00)	(0.03, 0.04, 0.04)
$\tilde{\mathcal{A}}_9$	(0.02, 0.04, 0.04)	(0.04, 0.04, 0.04)	(0.04, 0.06, 0.06)	(0.06, 0.00, 0.00)	(0.03, 0.05, 0.05)
$\tilde{\mathcal{A}}_{10}$	(0.03, 0.00, 0.00)	(0.04, 0.03, 0.04)	(0.04, 0.04, 0.04)	(0.06, 0.00, 0.00)	(0.04, 0.00, 0.00)
	$\tilde{\mathcal{C}}_6$	$\tilde{\mathcal{C}}_7$	$\tilde{\mathcal{C}}_8$	$\tilde{\mathcal{C}}_9$	$\tilde{\mathcal{C}}_{10}$
$\tilde{\mathcal{A}}_1$	(0.02, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)	(0.03, 0.03, 0.03)	(0.02, 0.01, 0.01)
$\tilde{\mathcal{A}}_2$	(0.02, 0.02, 0.02)	(0.05, 0.00, 0.00)	(0.02, 0.02, 0.02)	(0.05, 0.00, 0.00)	(0.02, 0.01, 0.02)
$\tilde{\mathcal{A}}_3$	(0.02, 0.01, 0.01)	(0.04, 0.03, 0.03)	(0.02, 0.02, 0.02)	(0.04, 0.02, 0.02)	(0.02, 0.01, 0.01)
$\tilde{\mathcal{A}}_4$	(0.02, 0.01, 0.01)	(0.03, 0.05, 0.04)	(0.02, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)
$\tilde{\mathcal{A}}_5$	(0.01, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)
$\tilde{\mathcal{A}}_6$	(0.02, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.01, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)
$\tilde{\mathcal{A}}_7$	(0.02, 0.02, 0.02)	(0.04, 0.04, 0.04)	(0.02, 0.01, 0.02)	(0.03, 0.03, 0.03)	(0.02, 0.02, 0.02)
$\tilde{\mathcal{A}}_8$	(0.02, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)
$\tilde{\mathcal{A}}_9$	(0.02, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.00, 0.00)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)
$\tilde{\mathcal{A}}_{10}$	(0.02, 0.01, 0.01)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)	(0.03, 0.03, 0.03)	(0.02, 0.02, 0.02)

Table A11. Neutrosophic PIS and NIS.

Criteria	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$
V^+	(0.03, 0.00, 0.00)	(0.03, 0.05, 0.05)	(0.06, 0.00, 0.00)	(0.06, 0.00, 0.00)	(0.04, 0.00, 0.00)
V^-	(0.02, 0.04, 0.04)	(0.05, 0.00, 0.00)	(0.04, 0.06, 0.06)	(0.03, 0.09, 0.08)	(0.03, 0.05, 0.05)
Criteria	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$
V^+	(0.02, 0.01, 0.01)	(0.05, 0.00, 0.00)	(0.02, 0.00, 0.00)	(0.05, 0.00, 0.00)	(0.02, 0.01, 0.01)
V^-	(0.01, 0.02, 0.02)	(0.03, 0.05, 0.04)	(0.01, 0.02, 0.02)	(0.03, 0.04, 0.04)	(0.02, 0.02, 0.02)

Table A12. Cosine Similarity from NPIS.

	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$	S_i^+
$\tilde{A}_1$	0.04	0.12	0.09	0.16	0.12	0.05	0.06	0.03	0.06	0.06	0.04
$\tilde{A}_2$	0.05	0.05	0.14	0.06	0.06	0.05	0.12	0.03	0.11	0.06	0.05
$\tilde{A}_3$	0.04	0.11	0.10	0.09	0.12	0.05	0.08	0.03	0.08	0.06	0.04
$\tilde{A}_4$	0.03	0.12	0.08	0.05	0.04	0.05	0.05	0.03	0.05	0.06	0.03
$\tilde{A}_5$	0.09	0.12	0.06	0.04	0.04	0.05	0.06	0.03	0.05	0.05	0.09
$\tilde{A}_6$	0.03	0.12	0.08	0.16	0.12	0.05	0.06	0.02	0.05	0.05	0.03
$\tilde{A}_7$	0.09	0.12	0.08	0.06	0.05	0.05	0.07	0.03	0.07	0.06	0.09
$\tilde{A}_8$	0.09	0.11	0.07	0.16	0.06	0.05	0.06	0.03	0.06	0.06	0.09
$\tilde{A}_9$	0.03	0.12	0.06	0.16	0.04	0.05	0.06	0.05	0.05	0.05	0.03
$\tilde{A}_{10}$	0.09	0.11	0.09	0.16	0.12	0.05	0.06	0.03	0.06	0.06	0.09

Table A13. Cosine Similarity from NNIS.

$\mathcal{A}_i \setminus \mathcal{C}_i$	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$	S_i^-
$\tilde{A}_1$	0.09	0.07	0.14	0.04	0.04	0.05	0.12	0.05	0.11	0.05	0.09
$\tilde{A}_2$	0.09	0.12	0.06	0.15	0.11	0.05	0.05	0.05	0.05	0.06	0.09
$\tilde{A}_3$	0.09	0.08	0.13	0.15	0.04	0.05	0.11	0.05	0.10	0.06	0.09
$\tilde{A}_4$	0.09	0.06	0.14	0.15	0.12	0.05	0.12	0.05	0.11	0.06	0.09
$\tilde{A}_5$	0.03	0.06	0.14	0.16	0.12	0.05	0.12	0.05	0.11	0.06	0.03
$\tilde{A}_6$	0.09	0.05	0.14	0.04	0.04	0.05	0.12	0.05	0.11	0.06	0.09
$\tilde{A}_7$	0.03	0.06	0.14	0.15	0.12	0.05	0.12	0.05	0.10	0.06	0.03
$\tilde{A}_8$	0.03	0.07	0.14	0.04	0.11	0.05	0.12	0.05	0.11	0.06	0.03
$\tilde{A}_9$	0.09	0.06	0.14	0.04	0.12	0.05	0.12	0.02	0.11	0.06	0.09
$\tilde{A}_{10}$	0.03	0.07	0.138	0.042	0.043	0.049	0.116	0.053	0.107	0.057	0.03

Table A14. Jaccard Similarity from NPIS.

$\tilde{A}_i \setminus \tilde{C}_i$	$\tilde{C}_1$	$\tilde{C}_2$	$\tilde{C}_3$	$\tilde{C}_4$	$\tilde{C}_5$	$\tilde{C}_6$	$\tilde{C}_7$	$\tilde{C}_8$	$\tilde{C}_9$	$\tilde{C}_{10}$	S_i^+
$\tilde{A}_1$	0.02	0.11	0.07	0.16	0.12	0.05	0.04	0.02	0.04	0.06	0.02
$\tilde{A}_2$	0.03	0.03	0.14	0.03	0.04	0.05	0.12	0.02	0.11	0.06	0.03
$\tilde{A}_3$	0.02	0.09	0.08	0.06	0.12	0.05	0.07	0.02	0.07	0.06	0.02
$\tilde{A}_4$	0.02	0.11	0.05	0.02	0.02	0.05	0.03	0.02	0.03	0.05	0.02
$\tilde{A}_5$	0.09	0.11	0.04	0.02	0.02	0.04	0.04	0.02	0.03	0.05	0.09
$\tilde{A}_6$	0.02	0.12	0.05	0.16	0.12	0.05	0.04	0.01	0.03	0.05	0.02
$\tilde{A}_7$	0.09	0.12	0.05	0.03	0.02	0.05	0.05	0.03	0.05	0.05	0.09
$\tilde{A}_8$	0.09	0.11	0.04	0.16	0.04	0.05	0.04	0.02	0.04	0.05	0.09
$\tilde{A}_9$	0.01	0.11	0.03	0.16	0.02	0.05	0.04	0.05	0.03	0.05	0.01
$\tilde{A}_{10}$	0.09	0.10	0.06	0.16	0.12	0.05	0.04	0.02	0.04	0.05	0.09

Table A15. Jaccard Similarity from NNIS.

$\mathcal{A}_i \setminus \mathcal{C}_i$	$\tilde{\mathcal{C}}_1$	$\tilde{\mathcal{C}}_2$	$\tilde{\mathcal{C}}_3$	$\tilde{\mathcal{C}}_4$	$\tilde{\mathcal{C}}_5$	$\tilde{\mathcal{C}}_6$	$\tilde{\mathcal{C}}_7$	$\tilde{\mathcal{C}}_8$	$\tilde{\mathcal{C}}_9$	$\tilde{\mathcal{C}}_{10}$	$\mathbb{S}_i^-$
$\tilde{\mathcal{A}}_1$	0.08	0.05	0.12	0.02	0.02	0.05	0.11	0.05	0.10	0.05	0.08
$\tilde{\mathcal{A}}_2$	0.08	0.12	0.03	0.14	0.11	0.05	0.03	0.05	0.03	0.05	0.08
$\tilde{\mathcal{A}}_3$	0.08	0.06	0.11	0.11	0.02	0.04	0.10	0.05	0.08	0.05	0.08
$\tilde{\mathcal{A}}_4$	0.09	0.04	0.14	0.15	0.12	0.05	0.12	0.05	0.11	0.06	0.09
$\tilde{\mathcal{A}}_5$	0.01	0.04	0.14	0.16	0.12	0.05	0.12	0.05	0.11	0.06	0.01
$\tilde{\mathcal{A}}_6$	0.09	0.03	0.13	0.02	0.02	0.05	0.12	0.05	0.11	0.06	0.09
$\tilde{\mathcal{A}}_7$	0.01	0.03	0.13	0.14	0.12	0.05	0.11	0.05	0.10	0.06	0.01
$\tilde{\mathcal{A}}_8$	0.01	0.05	0.14	0.02	0.11	0.05	0.12	0.05	0.10	0.06	0.01
$\tilde{\mathcal{A}}_9$	0.09	0.04	0.14	0.02	0.12	0.05	0.12	0.01	0.11	0.06	0.09
$\tilde{\mathcal{A}}_{10}$	0.01	0.05	0.13	0.02	0.02	0.05	0.11	0.05	0.10	0.06	0.01

Table A16. Symbol domains and dimensions.

Symbol	Meaning	Dimension
x_{ij}	Expert rating of alternative a_i under criterion $\mathcal{C}_j$	Linguistic term–SVNN–[0, 1]
T_{ij}, I_{ij}, F_{ij}	Truth, indeterminacy, falsity of x_{ij}	$T, I, F \in [0, 1],$ $0 \leq T + I + F \leq 3$
$\mathcal{W}_{ej}, \mathcal{W}_{dj}$	Weight by Entropy and DEMATEL	[0, 1]
$\mathcal{W}_{hj}$	Hybrid weight	[0, 1]
$\tilde{a}_{ij}$	Aggregated values (T_{ij}, I_{ij}, F_{ij}) in NTOPSIS	[0, 1]
a_i^+, a_i^-	PIS & NIS under Neutrosophic environment	Triples (T, I, F)
$\mathcal{S}_{CS}, \mathcal{S}_{JS}$	Cosine and Jaccard Similarity measures	[0, 1]
Ψ	weighting parameter	[0, 1]
$\mathbb{S}_i^+, \mathbb{S}_i^-$	PIS and NIS under Neutrosophic Cosine and Jaccard Similarity measures	[0, 1]
$\mathcal{R}cc_i$	Relative closeness coefficient	[0, 1]

References

1. Sanyaolu, M.; Sadowski, A. The role of precision agriculture technologies in enhancing sustainable agriculture. *Sustainability* **2024**, *16*, 6668. [CrossRef]
2. United Nations Development Programme. *Precision Agriculture for Smallholder Farmers*; UNDP Global Centre for Technology, Innovation and Sustainable Development: Singapore, 2021. Available online: <https://www.undp.org/sites/g/files/zskgke326/files/2021-10/UNDP-Precision-Agriculture-for-Smallholder-Farmers.pdf> (accessed on 1 March 2024).
3. Kraus, T.; Ferreau, H.; Kayacan, E.; Ramon, H.; De Baerdemaeker, J.; Diehl, M.; Saeys, W. Moving horizon estimation and nonlinear model predictive control for autonomous agricultural vehicles. *Comput. Electron. Agric.* **2013**, *98*, 25–33. [CrossRef]
4. Kayacan, E.; Kayacan, E.; Ramon, H.; Saeys, W. Distributed nonlinear model predictive control of an autonomous tractor-trailer system. *Mechatronics* **2014**, *24*, 926–933. [CrossRef]
5. Raeva, P.L.; Šedina, J.; Dlesk, A. Monitoring of crop fields using multispectral and thermal imagery from UAV. *Eur. J. Remote Sens.* **2018**, *52*, 192–201. [CrossRef]
6. Néményi, M.; Mesterházi, P.Á.; Pecze, Z.; Stépan, Z. The role of GIS and GPS in precision farming. *Comput. Electron. Agric.* **2003**, *40*, 45–55. [CrossRef]
7. Nijak, M.; Skrzypczyński, P.; Ćwian, K.; Zawada, M.; Szymczyk, S.; Wojciechowski, J. On the Importance of Precise Positioning in Robotised Agriculture. *Remote Sens.* **2024**, *16*, 985. [CrossRef]
8. Mazzia, V.; Comba, L.; Khaliq, A.; Chiaberge, M.; Gay, P. UAV and Machine Learning Based Refinement of a Satellite-Driven Vegetation Index for Precision Agriculture. *Sensors* **2020**, *20*, 2530. [CrossRef]
9. Zhang, M.; Zhou, J.; Sudduth, K.A.; Kitchen, N.R. Estimation of maize yield and effects of variable-rate nitrogen application using UAV-based RGB imagery. *Biosyst. Eng.* **2020**, *189*, 24–35. [CrossRef]

10. Li, B.; Xu, X.; Zhang, L.; Han, J.; Bian, C.; Li, G.; Liu, J.; Jin, L. Above-ground biomass estimation and yield prediction in potato by using UAV-based RGB and hyperspectral imaging. *ISPRS J. Photogramm. Remote Sens.* **2020**, *162*, 161–172. [\[CrossRef\]](#)
11. Zhai, Z.; Martínez, J.F.; Beltran, V.; Martínez, N.L. Decision support systems for agriculture 4.0: Survey and challenges. *Comput. Electron. Agric.* **2020**, *170*, 105256. [\[CrossRef\]](#)
12. Guo, J.; Li, X.; Li, Z.; Hu, L.; Yang, G.; Zhao, C.; Fairbairn, D.; Watson, D.; Ge, M. Multi-GNSS precise point positioning for precision agriculture. *Precis. Agric.* **2018**, *19*, 895–911. [\[CrossRef\]](#)
13. Sanjeevi, P.; Prasanna, S.; Kumar, B.S.; Gunasekaran, G.; Alagiri, I.; Anand, R.V. Precision agriculture and farming using Internet of Things based on wireless sensor network. *Trans. Emerg. Telecommun. Technol.* **2020**, *31*, e3978. [\[CrossRef\]](#)
14. Abiodun Emmanuel, A.; Zainal Abidin, M.S.; Mahmud, M.S.A.; Buyamin, S.; AbdRahman, M.K.I.; Otuoze, A.O.; Ramli, M.S.A.; Ijike, O.D. IoT monitoring and data-driven modelling of drip irrigation system for mustard leaf cultivation. *Inf. Process. Agric.* **2020**, *7*, 561–576. [\[CrossRef\]](#)
15. Ojha, T.; Misra, S.; Raghuwanshi, N.S. Internet of Things for Agricultural Applications: The State-of-the-art. *IEEE Internet Things J.* **2021**, *8*, 2966–2998. [\[CrossRef\]](#)
16. Shafi, U.; Mumtaz, R.; García-Nieto, J.; Hassan, S.A.; Zaidi, S.A.R.; Iqbal, N. Precision Agriculture Techniques and Practices: From Considerations to Applications. *Sensors* **2019**, *19*, 3796. [\[CrossRef\]](#)
17. Ampatzidis, Y.; Partel, V. UAV-based high throughput phenotyping in citrus utilizing multispectral imaging and artificial intelligence. *Remote Sens.* **2019**, *11*, 410. [\[CrossRef\]](#)
18. Lu, B.; Dao, P.D.; Liu, J.; He, Y.; Shang, J. Recent advances of hyperspectral imaging technology and applications in agriculture. *Remote Sens.* **2020**, *12*, 2659. [\[CrossRef\]](#)
19. Tsouros, D.C.; Bibi, S.; Sarigiannidis, P.G. A review on UAV-based applications for precision agriculture. *Information* **2019**, *10*, 349. [\[CrossRef\]](#)
20. Tetila, E.C.; Machado, B.B.; Astolfi, G.; Belete, N.A.d.S.; Amorim, W.P.; Roel, A.R.; Pistori, H. Detection and classification of soybean pests using deep learning with UAV images. *Comput. Electron. Agric.* **2020**, *179*, 105836. [\[CrossRef\]](#)
21. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of remote sensing in precision agriculture: A review. *Remote Sens.* **2020**, *12*, 3136. [\[CrossRef\]](#)
22. Zheng, J.; Fu, H.; Li, W.; Wu, W.; Yu, L.; Yuan, S.; Tao, W.Y.W.; Pang, T.K.; Kanniah, K.D. Growing status observation for oil palm trees using unmanned aerial vehicle (UAV) images. *ISPRS J. Photogramm. Remote Sens.* **2021**, *173*, 95–121. [\[CrossRef\]](#)
23. Roberts, D.P.; Short, N.M.; Sill, J.; Lakshman, D.K.; Hu, X.; Buser, M. Precision agriculture and geospatial techniques for sustainable disease control. *Indian Phytopathol.* **2021**, *74*, 287–305. [\[CrossRef\]](#)
24. Vangala, A.; Das, A.K.; Kumar, N.; Alazab, M. Smart secure sensing for IoT-based agriculture: Blockchain perspective. *IEEE Sens. J.* **2021**, *21*, 17591–17605. [\[CrossRef\]](#)
25. Raj, M.; Gupta, S.; Chamola, V.; Elhence, A.; Garg, T.; Atiquzzaman, M.; Niyato, D. A survey on the role of Internet of Things for adopting and promoting Agriculture 4.0. *J. Netw. Comput. Appl.* **2021**, *187*, 103107. [\[CrossRef\]](#)
26. Akhter, R.; Sofi, S.A. Precision agriculture using IoT data analytics and machine learning. *J. King Saud Univ. Comput. Inf. Sci.* **2022**, *34*, 5602–5618. [\[CrossRef\]](#)
27. Sharma, A.; Jain, A.; Gupta, P.; Chowdary, V. Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access* **2021**, *9*, 4843–4873. [\[CrossRef\]](#)
28. Yin, H.; Cao, Y.; Marelli, B.; Zeng, X.; Mason, A.J.; Cao, C. Soil sensors and plant wearables for smart and precision agriculture. *Adv. Mater.* **2021**, *33*, 2007764. [\[CrossRef\]](#)
29. Mirzakhani, H.; Singh, M.; Bector, V.; Gupta, O.P.; Singh, R. Design and development of a variable rate applicator for real-time application of fertilizer. *Sustainability* **2021**, *13*, 8694. [\[CrossRef\]](#)
30. Späti, K.; Huber, R.; Finger, R. Benefits of increasing information accuracy in variable rate technologies. *Ecol. Econ.* **2021**, *185*, 107047. [\[CrossRef\]](#)
31. Zualkernan, I.; Abuhani, D.A.; Hussain, M.H.; Khan, J.; ElMohandes, M. Machine learning for precision agriculture using imagery from UAVs: A survey. *Drones* **2023**, *7*, 382. [\[CrossRef\]](#)
32. Raptis, E.K.; Krestenitis, M.; Egglezos, K.; Kypris, O.; Ioannidis, K.; Doitsidis, L.; Kapoutsis, A.C.; Vrochidis, S.; Kompatsiaris, I.; Kosmatopoulos, E.B. End-to-end precision agriculture UAV-based functionalities tailored to field characteristics. *J. Intell. Robot. Syst.* **2023**, *107*, 23. [\[CrossRef\]](#)
33. Carvalho, G.S.; Silva, F.O.; Pacheco, M.V.O.; Campos, G.A.O. Performance analysis of relative GPS positioning for low-cost receiver-equipped agricultural rovers. *Sensors* **2023**, *23*, 8835. [\[CrossRef\]](#)
34. Elashmawy, R.; Uysal, I. Precision agriculture using soil sensor driven machine learning for smart strawberry production. *Sensors* **2023**, *23*, 2247. [\[CrossRef\]](#)

35. Catala-Roman, P.; Segura-Garcia, J.; Dura, E.; Navarro-Camba, E.A.; Alcaraz-Calero, J.M.; Garcia-Pineda, M. AI-based autonomous UAV swarm system for weed detection and treatment in organic farming. *Internet Things* **2024**, *28*, 101418. [\[CrossRef\]](#)
36. Toscano, F.; Fiorentino, C.; Capece, N.; Erra, U.; Travascia, D.; Scopa, A.; Drosos, M.; D'aNtonio, P. Unmanned aerial vehicle for precision agriculture: A review. *IEEE Access* **2024**, *12*, 69188–69195. [\[CrossRef\]](#)
37. Jayaram, D.K.; Raja, V.; Arputharaj, B.S.; AL-bonsrulah, H.A.Z. Design and performance analysis of a multirotor UAV for precision farming. *Int. J. Aerosp. Eng.* **2024**, *2024*, 8703004. [\[CrossRef\]](#)
38. Mehedi, I.M.; Hanif, M.S.; Bilal, M.; Vellingiri, M.T.; Palaniswamy, T. Remote sensing and decision support system applications in precision agriculture: Challenges and possibilities. *IEEE Access* **2024**, *12*, 44786–44794. [\[CrossRef\]](#)
39. Anitha Selvasofia, S.; SivaSankari, B.; Dinesh, R.; Muthukumaran, N. GINSER: GIS-based optimal route recommendation via optimized Faster R-CNN. *Int. J. Comput. Intell. Syst.* **2025**, *18*, 75. [\[CrossRef\]](#)
40. Dhanasekar, S. A comprehensive review on IoT issues and advancements in precision agriculture. *Comput. Sci. Rev.* **2025**, *55*, 100694. [\[CrossRef\]](#)
41. Shahab, H.; Naeem, M.; Iqbal, M.; Aqeel, M.; Ullah, S.S. IoT-driven smart agricultural technology for real-time soil and crop optimization. *Smart Agric. Technol.* **2025**, *10*, 100847. [\[CrossRef\]](#)
42. Mali, S.S.; Scobie, M.; Baillie, J.; Plant, C.; Shammi, S.; Das, A. Integrating UAV-based multispectral and thermal infrared imagery with ML for predicting wheat water stress. *Precis. Agric.* **2025**, *26*, 44. [\[CrossRef\]](#)
43. Testa, R.; Galati, A.; Schifani, G.; Migliore, G. Cost-effectiveness of conventional and precision agriculture sprayers in vineyards: A break-even point analysis. *Precis. Agric.* **2025**, *26*, 39. [\[CrossRef\]](#)
44. Erdogan, S.A.; Šaparauskas, J.; Turskis, Z. A multi-criteria decision-making model to choose the best option for sustainable construction management. *Sustainability* **2019**, *11*, 2239. [\[CrossRef\]](#)
45. Biswas, P.; Pramanik, S.; Giri, B.C. TOPSIS method for multi-attribute group decision-making under single-valued neutrosophic environment. *Neural Comput. Appl.* **2016**, *27*, 727–737. [\[CrossRef\]](#)
46. United States Government Accountability Office. *Precision Agriculture: Benefits and Challenges for Technology Adoption and Use*; GAO-24-105962; U.S. Government Accountability Office: Washington, DC, USA, 2024. Available online: <https://www.gao.gov/assets/d24105962.pdf> (accessed on 15 August 2023).
47. Banihabib, M.E.; Shabestari, M.H. Fuzzy hybrid MCDM model for ranking the agricultural water demand management strategies in arid areas. *Water Resour. Manag.* **2017**, *31*, 495–513. [\[CrossRef\]](#)
48. My, L.T.D.; Wang, C.-N.; Thanh, N.V. Fuzzy MCDM for improving the performance of agricultural supply chain. *Comput. Mater. Continua* **2022**, *73*, 4003–4025. [\[CrossRef\]](#)
49. Rouyendegh, B.D.; Savalan, Ş. An integrated fuzzy MCDM hybrid methodology to analyze agricultural production. *Sustainability* **2022**, *14*, 4835. [\[CrossRef\]](#)
50. Qin, K.; Wang, L. New similarity and entropy measures of single-valued neutrosophic sets with applications in multi-attribute decision making. *Soft Comput.* **2020**, *24*, 16165–16176. [\[CrossRef\]](#)
51. Bian, X.; Pan, H.; Zhang, K.; Chen, C.; Liu, P.; Shi, K. NeDSeM: Neutrosophy domain-based segmentation method for malignant melanoma images. *Entropy* **2022**, *24*, 783. [\[CrossRef\]](#) [\[PubMed\]](#)
52. Wu, H.; Yuan, Y.; Wei, L.; Pei, L. On entropy, similarity measure and cross-entropy of single-valued neutrosophic sets and their application in multi-attribute decision making. *Soft Comput.* **2018**, *22*, 7367–7376. [\[CrossRef\]](#)
53. Sharma, S.; Singh, S. A complementary dual of single-valued neutrosophic entropy with application to MAGDM. *Mathematics* **2022**, *10*, 3726. [\[CrossRef\]](#)
54. Ye, J.; Cui, W. Exponential entropy for simplified neutrosophic sets and its application in decision making. *Entropy* **2018**, *20*, 357. [\[CrossRef\]](#)
55. Majumdar, P.; Samanta, S.K. On similarity and entropy of neutrosophic sets. *J. Intell. Fuzzy Syst.* **2014**, *26*, 1245–1252. [\[CrossRef\]](#)
56. Awang, A.; Abdullah, L.; Ab Ghani, A.T.; Aizam, N.A.H.; Ahmad, M.F. A fusion of decision-making method and neutrosophic linguistic considering multiplicative inverse matrix for coastal erosion problem. *Soft Comput.* **2020**, *24*, 9595–9609. [\[CrossRef\]](#)
57. Tian, L.; Gu, H. Using the neutrosophic DEMATEL method to determine the effect of internet finance and big data risk control monitoring. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 9395567. [\[CrossRef\]](#)
58. Awang, A.; Ab Ghani, A.T.; Abdullah, L.; Ahmad, M.F. A DEMATEL method with single valued neutrosophic set (SVNS) in identifying the key contribution factors of Setiu Wetland's coastal erosion. *AIP Conf. Proc.* **2018**, *1974*, 020011. [\[CrossRef\]](#)
59. Karabasevic, D.; Stanujkić, D.; Zavadskas, E.K.; Stanimirović, P.; Popović, G.; Predić, B.; Ulutaş, A. A novel extension of the TOPSIS method adapted for the use of single-valued neutrosophic sets and Hamming distance for e-commerce development strategies selection. *Symmetry* **2020**, *12*, 1263. [\[CrossRef\]](#)
60. Angammal, S.; Grace, H.G. A new bi-level TOPSIS based neutrosophic programming technique for land allocation to medium farm holders. *Heliyon* **2024**, *10*, e36166. [\[CrossRef\]](#)
61. Long, X.; Liu, L.; Liu, Q. A selection model of compositions and proportions of additive lime mortars for restoration of ancient Chinese buildings based on TOPSIS. *Sustainability* **2024**, *16*, 9977. [\[CrossRef\]](#)

62. Kilic, H.; Yalcin, A.S. Comparison of municipalities considering environmental sustainability via neutrosophic DEMATEL based TOPSIS. *Socio-Econ. Plan. Sci.* **2020**, *27*, 1008. [CrossRef]
63. Abdel-Basset, M.; Atef, A.; Smarandache, F. A hybrid neutrosophic multiple criteria group decision making approach for project selection. *Cogn. Syst. Res.* **2019**, *57*, 216–227. [CrossRef]
64. Eldrandaly, K.A.; El Saber, N.; Mohamed, M.; Abdel-Basset, M. Sustainable manufacturing evaluation based on enterprise Industry 4.0 technologies. *Sustainability* **2022**, *14*, 7376. [CrossRef]
65. Awang, A.; Aizam, N.A.H.; Abdullah, L. An integrated decision-making method based on neutrosophic numbers for investigating factors of coastal erosion. *Symmetry* **2019**, *11*, 328. [CrossRef]
66. Nabeeh, N.A.; Smarandache, F.; Abdel-Basset, M.; El-Ghareeb, H.A.; Aboelfetouh, A. An integrated neutrosophic-TOPSIS approach and its application to personnel selection: A new trend in brain processing and analysis. *IEEE Access* **2019**, *7*, 29734–29746. [CrossRef]
67. Junaid, M.; Xue, Y.; Syed, M.W.; Li, J.Z.; Ziaullah, M. A neutrosophic AHP and TOPSIS framework for supply chain risk assessment in the automotive industry of Pakistan. *Sustainability* **2020**, *12*, 154. [CrossRef]
68. Wang, Z.L.; Kim, J.; Selvachandran, G.; Smarandache, F.; Son, L.H.; Abdel-Basset, M.; Thong, P.H.; Ismail, M. Decision making methods for evaluation of efficiency of general insurance companies in Malaysia: A comparative study. *IEEE Access* **2019**, *7*, 160638–160648. [CrossRef]
69. Abdel-Basset, M.; Mohamed, R.; Chang, V. A multi-criteria decision-making framework to evaluate the impact of Industry 5.0 technologies: Case study, lessons learned, challenges and future directions. *Inf. Syst. Front.* **2024**, *27*, 791–821. [CrossRef]
70. Alzahrani, F.A.; Ghorui, N.; Gazi, K.H.; Giri, B.C.; Ghosh, A.; Mondal, S.P. Optimal site selection for women university using neutrosophic multi-criteria decision-making approach. *Buildings* **2023**, *13*, 152. [CrossRef]
71. Liew, K.F.; Lam, W.S.; Lam, W.H. Financial network analysis on the performance of companies using integrated Entropy–DEMATEL–TOPSIS model. *Entropy* **2022**, *24*, 1056. [CrossRef]
72. Nabeeh, N.A.; Abdel-Basset, M.; El-Ghareeb, H.A.; Aboelfetouh, A. Neutrosophic multi-criteria decision-making approach for IoT-based enterprises. *IEEE Access* **2019**, *7*, 59559–59574. [CrossRef]
73. Salam, A.; Mohamed, M.; Venkatachalam, K. An efficient model for selection of unmanned aerial vehicles designed for precision agriculture. *Optim. Agric.* **2024**, *1*, 22–39. [CrossRef]
74. Abdullah, L.; Ong, Z.; Mohd Mahali, S. Single-Valued Neutrosophic DEMATEL for Segregating Types of Criteria: A Case of Subcontractors' Selection. *J. Math.* **2021**, *2021*, 6636029. [CrossRef]
75. Pramanik, S.; Biswas, P.; Giri, B.C. Hybrid vector similarity measures and their applications to multi-attribute decision making under neutrosophic environment. *Neural Comput. Appl.* **2017**, *28*, 1053–1064. [CrossRef]
76. Abdel-Basset, M.; Gamal, A.; Moustafa, N.; Abdel-Monem, A.; El-Saber, N. A security-by-design decision-making model for risk management in autonomous vehicles. *IEEE Access* **2021**, *9*, 107657–107679. [CrossRef]
77. Chen, C.-H. A hybrid multi-criteria decision-making approach based on ANP-entropy TOPSIS for building materials supplier selection. *Entropy* **2021**, *23*, 1597. [CrossRef]
78. Getahun, S.; Kefale, H.; Gelaye, Y. Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review. *Sci. World J.* **2024**, *2024*, 2126734. [CrossRef]
79. Mamabolo, E.; Mashala, M.J.; Mugari, E.; Mogale, T.E.; Mathebula, N.; Mabitsela, K.; Ayisi, K.K. Application of Precision Agriculture Technologies for Crop Protection and Soil Health. *Smart Agric. Technol.* **2025**, *12*, 101270. [CrossRef]
80. Padhiary, M.; Kumar, A.; Sethi, L.N. Emerging Technologies for Smart and Sustainable Precision Agriculture. *Discov. Robot.* **2025**, *1*, 6. [CrossRef]
81. Mansoor, S.; Iqbal, S.; Popescu, S.M.; Kim, S.L.; Chung, Y.S.; Baek, J.-H. Integration of smart sensors and IoT in precision agriculture: Trends, challenges and future perspectives. *Front. Plant Sci.* **2025**, *16*, 1587869. [CrossRef] [PubMed]
82. McFadden, J.R. *Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms*; EIB-248; U.S. Department of Agriculture, Economic Research Service: Washington, DC, USA, 2023. Available online: https://ers.usda.gov/sites/default/files/_laserfiche/publications/105894/EIB-248.pdf?utm_source=chatgpt.com (accessed on 10 August 2023).
83. Rejeb, A.; Keogh, J.G.; Abdollahi, A.; Treiblmaier, H. The Interplay between the Internet of Things and Agriculture: A Bibliometric Analysis and Research Agenda. *Internet Things* **2022**, *19*, 100580. [CrossRef]
84. Zhai, X.; Cheng, W.; Huang, Y. Decision support systems in precision agriculture: Trends and challenges. *Comput. Electron. Agric.* **2021**, *187*, 106253.
85. Späti, B.; Ehlert, D.; Rothmund, M. Economic analysis of variable rate nitrogen application using drone technologies. *Precis. Agric.* **2021**, *22*, 1354–1371.
86. Testa, R.; Schifani, G.; Migliore, G. Integrating VRT sprayers and UAVs for cost-effective pest management in vineyards. *Sustain. Agric. Rev.* **2022**, *50*, 201–218.
87. fs.unm.edu. Neutrosophic Logic and Applications. Available online: <https://fs.unm.edu> (accessed on 10 August 2025).

88. SpringerLink. Precision Agriculture and the Future of Farming: Smart Technologies and IoT Applications. Available online: <https://link.springer.com> (accessed on 20 September 2025).
89. Government Accountability Office. Precision Agriculture: USDA Should Improve Efforts to Identify and Meet the Needs of Small Farms. Available online: <https://www.gao.gov> (accessed on 15 April 2024).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.