Machine Learning and Linguistic Neutrosophic Hypersoft based Techniques Integration in Smart Farming in the Context of Weather Uncertainty

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Abstract

This paper proposes a novel smart farming decision-making framework that integrates machine learning (ML) techniques Support Vector Machine (SVM), Fuzzy C-Means (FCM) clustering, with the generalized distance and similarity measures in a linguistic neutrosophic hypersoft set environment. ML processes real-time sensor data to predict weather patterns, while linguistic neutrosophic terms capture uncertainty, indeterminacy, and falsity, allowing for a more precise analysis of imprecise information. Through the application of generalized similarity measures, the framework ranks the cities suitable for farming strategies based on multiple criteria such as temperature, wind speed, and humidity. The use of linguistic neutrosophic terms offer enhanced flexibility in managing weather-related uncertainty compared to existing methods. The outcomes demonstrate that this integrated approach optimizes decision-making under uncertain environmental conditions, enabling more efficient resource management and improving resilience in farming practices. Future research will further explore the inclusion of additional environmental factors and improve similarity measures to increase decision accuracy among broader agricultural contexts. This model also has the potential to be applied to other domains where uncertainty management is crucial, such as climate resilience and environmental sustainability.

Keywords: Decision-making; Fuzzy Set; Neutrosophic Set; Hypersoft set; Machine learning; Weather uncertainty; Agriculture farming; MCDM

1. Introduction

The real-time data is critical for agricultural decision-making, especially in the challenge of uncertain and highly variable weather conditions. Field-based sensors are important to measure environmental parameters e.g. (temperature, humidity, soil moisture, or wind speed) [1]. However, weather is stochastic, and many conventional processing methods of data collection have uncertainty. In this case, the utilization of fuzzy numbers e.g. neutrosophic numbers on real-time sensor information allows decision-makers to model ambiguous and incomplete information in a more effective way, which results in better forecasts and more resilient farming strategies [2]. Precision farming, also known as smart agriculture, is considered as one of the most advanced means to mitigate current unresolved problems in agriculture like resource constraint and environmentally sustainable food production objectives [3]. Decision-making in agriculture involves competing demands (e.g., for crop yield, resource use efficiency, economic returns and environmental impact), all against an uncertain future. The integration of machine learning (ML) algorithms with multi-criteria decision-making (MCDM) frameworks has gained importance because it allows dealing effectively with large data and support farmers for making informed decisions, so that they can adapt their sustainability practices in a timely manner while mitigating the economic risk [4-6].

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The application of Fuzzy C-Means (FCM) and Support Vector Machines (SVM) in agriculture has become increasingly important due to their ability to handle complex, relationships in agriculture. FCM is particularly useful for modelling uncertain and dynamic systems, such as soil-plant interactions, and pest management by considering the relationships between key agricultural factors. It facilitates qualitative modelling, helping farmers make informed decisions [8]. On the other hand, SVM excels in classification and regression tasks, enabling precise predictions related to crop diseases, soil moisture levels, and yield estimations by analysing large datasets. In crop disease prediction, for instance, SVM has been utilized effectively for detecting diseases in various crops based on image data [9]. Together, FCM and SVM provide a comprehensive decision-support system that enhances the efficiency and sustainability of agricultural practices, particularly in precision farming, where the optimization of resource usage, such as water, fertilizer, and pesticides, is critical [10-11].

Crops are largely dependent on external factors such as market price between harvest and marketing, variation in input costs, weather conditions and similar other unpredictable situations; all this leads to crop economics being fraught with uncertainties. For farmers who need to allocate resources to optimize productivity and sustainability, these uncertainties create complicated decision-making problems. Fuzzy set (FS) [12] theory is a powerful mathematical framework over the imprecise and ambiguous data, which arises quite often within agricultural scenario where uncertainties need to be modelled, represented & managed. This is very different from traditional discrete logic that relies on clear-cut distinctions, standard truth-values of 0 or 1. FS theory avoids this problem by permitting an object to belong in a certain available set with the membership degree between operating limits full and void. This is especially useful in the sort of crop economics, where definitive information is less or incomplete and mostly decisions will be based on global knowledge.

Smarandache proposed the concept of neutrosophic sets (NS) characterized by uncertainty, inconsistency and indeterminacy in 1998 [13]. In the logical systems, which involve indeterminacy values added to the membership and non-membership values (T, I, and F) each one being independent. NS have been extended to single valued by [14], interval valued by [15] and multi-valued linguistic neutrosophic sets (MVLNS) by [16]. The applications of these extensions and multi-criteria decision-making (MCDM) approaches have been proposed by [17-19].

Smarandache [20] presented the theory of hypersoft set (HSS) is a mapping from cartesian product of sub-divided sets of alternatives to the power set. The extensions: fuzzy hypersoft sets (FHSs), intuitionistic hypersoft sets (IHSs), and neutrosophic hypersoft sets (NHSs) were also proposed in the same work to deal with uncertainty, and indeterminacy. Single-valued neutrosophic hypersoft sets (SVNHSs) [21] with their aggregate operators [22], multi-valued neutrosophic hypersoft sets (m-VNHSs), interval-valued neutrosophic hypersoft sets (IVNHSs), and [23] have introduced multi-valued interval neutrosophic hypersoft sets (m-IVNHSs). The matrix notions of HSS have been proposed by [24] along with MCDM algorithms to solve problems. NHSS-TOPSIS using distance and similarity measures were proposed by [25-26]. The concept of linguistic hypersoft set (LHSs) and linguistic neutrosophic hypersoft set (LNHSs) has been proposed by [27-28]. Other optimization methodologies, as well [29-30], are employed to address the same kind of optimization issues.

Recent advances in smart agriculture and digitalization strategies have revolutionized the agricultural sector, especially for small-scale farmers, who are burdened with various economic and environmental issues [31-32]. Zhou [33] and Nourkhah et al. [34], which describe an integrated technique for improving soil suitability through soil quality prediction and technological monitoring capacity, further explore the potential of smart agriculture in the study. The studies of Yongyi Gu et al. [35] and Debnath [36] explain the opportunities to increase the economic capacity of farmers and develop efficient strategies in a market of uncertainty. Li et al. [37] have studied the role of stable digital agriculture. The study [38-39] presents the importance of smart technology in agriculture. Overall, these sources give a more updated view of how future digitalization will examine in agriculture.

Research Gap: Smart farming and decision-making frameworks have progressed considerably, this methodology usually does not cope well with real-time (data assimilation) agricultural data because of the uncertainty often caused by unpredictable weather conditions. The tools to deal with imprecise information, traditional decision-making models are incapable of incorporating complex nature like (indeterminacy-uncertainty-falsity). Furthermore, most existing methods just consider small number of criteria like crop yield or economic performance, and they inadequately integrate real time environmental sensor data for the better decision provisioning. Though machine learning (ML) is extended to deal with large-sized data (simply agricultural database), however, the convergence of MCDM and indeterminacy management tools like neutrosophic sets and ML has been fewer considered. This gap emphasizes the need for more powerful, adaptable models that can bridge the insights in making data-driven decisions provided by ML and facilitate rigorous decision-making under environmental uncertainty and indeterminacy.

Contribution: We propose a new distance and similarity measures approach under the linguistic neutrosophic hypersoft set (NLHSs) and by integrating it with machine learning (ML) Fuzzy C-Means (FCM) and Support Vector Machines (SVM) methods. ML-based real-time sensor data processing for predicting weather patterns and

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key environmental factors, and the other one is an application of linguistic neutrosophic sets to address uncertainty, indeterminacy and falsity in decision-making. We do this by applying similarity measures that rank farming strategies in terms of crop yield, resource efficiency and economic viability across multiple criteria to enable optimized decisions under highly variable conditions.

Significance: The importance of this study is that it can greatly increase the strength and efficiency in agriculture farming practices when dealing with unexpected environmental issues such as weather and land fertility changes. The method introduces measured sensor data in real-time to facilitate intelligent decision-making. This helps to increase the food security and sustainability of climate-sensitive regions. Moreover, the approach applied in this work is extendable to industries other than agriculture e.g., environmental sustainability, climate resilience, and disaster management. Thus, this study is of significance for agricultural decision-making and the larger context of dealing with uncertainty in complex systems.

The paper originality, it integrates FCM, SVM and proposed distance and similarity measures for NLHSs based framework to tackle the weather uncertainty in agriculture. Through the application of similarity measures, the framework ranks farming approaches based on multiple criteria such as crop yield, resource efficiency, and economic sustainability. The use of linguistic neutrosophic terms offer better flexibility in managing weather-related uncertainty compared to existing methods. This unique usage of sophisticated mathematics integrated with machine learning allows the decision-makers to find more accurate results, meaning it can manage economic risks better and allocate resources intelligently in agriculture.

The following indicates that how the work is organized:

Section2: Material and method.

Section3: Proposed distance and similarity measures for NLHSs.

Section4: Numerical illustration using FCM, SVM, and Distance and Similarity Measures.

Section5: Results discussion, comparison and limitations.

Section6: Concluded with future directions.

2. Material and Methods

The section we discuss the importance of selected methods i.e. distance and similarity measures, Fuzzy C-Means (FCM) and Support Vector Machines (SVM).

2.1 Linguistic Neutrosophic Hypersoft Set (LNHSs) [28]

Smarandache extended soft sets (SS's) to hypersoft set and deal with the further bifurcations of attributes. Let $\mathcal{Y} = \{\mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \dots \mathrm{p}_s\}$ be the set of alternatives and $\mathcal{A}$ be the set of attributes. Let $P(\mathcal{Y})$ denote the power set of $\mathcal{Y}$. Let $\xi^1, \xi^2, \xi^3 \dots \xi^n$ for $n \geq 1$ be different attributive features, whose corresponding attributive values are the sets $\varsigma^1, \varsigma^2, \varsigma^3, \dots \varsigma^n$ with $\varsigma^{m_i} \cap \varsigma^{n_i} = \emptyset$ for $m \neq n, m_i, n_i = 1,2 \dots n$ respectively. Then, the pair $(\mathcal{G}, \xi^1, \xi^2, \xi^3 \dots \xi^n)$ is said to be hypersoft set over $\mathcal{Y}$,

$$\mathcal{G}: \xi^1 \times \xi^2 \times \xi^3 \dots \times \xi^n \rightarrow P(\mathcal{Y})$$

Then the neutrosophic-linguistic valued hypersoft set will be,

$$\Gamma(\alpha(k)) = \{M(\alpha(T, I, \mathcal{F})) \mid T, I, \mathcal{F} \in k = \{\kappa^1, \kappa^2, \kappa^3, \dots, \kappa^t\}\}$$

$$where\ k\ is\ the\ set\ of\ lingusitic\ quantifiers\ in\ ascending\ order\ i.e. None - Perfect.$$

2.2 Distance and Similarity Measures [40]: Distance measures play an important role in studies where the similarity between objects or alternatives is crucial when handling uncertainty, or indeterminacy. This especially applies in the context of multi-criteria decision-making (MCDM) where such measures can enable evaluation within linguistic terms to capture different kinds of errors like vagueness or indeterminacy. The distance and similarity measures of the attributes that are further subdivided can be studied using the proposed distance and similarity measures under LNHSs.

2.3 Fuzzy C-Means (FCM) [41]: Fuzzy C-Means is a clustering algorithm, which can quickly cluster datasets with uncertainty. Traditional clustering methods assign each data point to a one-and-only-one cluster whereas in FCM, a given data point can be part of multiple clusters and with different degrees of memberships. FCM minimizes an objective function that takes the distance of data points from centroid of clusters with weighted by the membership values. For our study, Fuzzy C-Mean algorithm is used to cluster the weather conditions with proposed distance measures in a linguistic neutrosophic hypersoft set LNHSs environment.

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2.4 Support Vector Machines (SVM) [42-43]: SVM is the most popular supervised learning algorithm, which can also perform classification and regression tasks. It is suitable for small as well as large datasets, capable of handling high dimensional data. SVM works on the principle of categorizing data into small parts with a maximum clear gap among classes. The SVM can classify uncertain weather conditions with attributes such as distance and similarity measures that are described in the linguistic neutrosophic hypersoft set. The SVM model learns the patterns of uncertainty in these input attributes and hence it can be used to predict any indeterminacy in weather data.

3. Proposed Distance and Similarity Measures for LNHSs

In this section, we propose some distance measures especially built for the linguistic neutrosophic hypersoft set (LNHSs) environment. This method will allow us to measure the qualitative differences between alternatives by interpreting how much truth, indeterminacy and falseness is contained in linguistic expressions. In other words, our proposed measures will describe the natural indeterminacy and imprecision of data which occurs in all the real-world multi-criteria decision-making problems. The distances proposed in this paper are aimed to add a more robust tool for evaluating alternatives within complex environments.

Definition 3.1 Let $\mathbb{A} = \mathcal{A}_i$ and $\mathbb{B} = \mathcal{B}_i$ be the two LNHSs where $\mathcal{A}_i = \left(T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}}\right)$ and $\mathcal{B}_i = \left(T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}}\right)$ for $i = \{1,2,3,\ldots,n\}$, then Normalized Hamming distance (NHD) between $\mathbb{A}$ & $\mathbb{B}$ LNHSs is defined as;
$\mathcal{D}(\mathbb{A},\mathbb{B}) = \frac{1}{3n}\sum_i^n \langle \left|T_i^{\mathbb{A}} - T_i^{\mathbb{B}}\right| + \left|I_i^{\mathbb{A}} - I_i^{\mathbb{B}}\right| + \left|F_i^{\mathbb{A}} - F_i^{\mathbb{B}}\right| \rangle$

Example 3.2 Let us say we have 2 cities $\mathcal{C}^1$, $\mathcal{C}^2$ that need to be evaluated using the criteria / attribute: Temperature ($\mathbb{T}$), wind speed ($\mathbb{W}$), and humidity ($\mathbb{H}$). The linguistic terms for each attribute can be taken from [28], which are none to perfect. Moreover, to model the data each of these attributes will have a degree of $(T, I, \mathcal{F})$ in the form of linguistic variables.
Let $\mathbb{A} = \langle \mathcal{C}^1, \mathbb{T}(medium, low, high), \mathbb{W}(high, low, none), \mathbb{H}(none, high, v.v.high)\rangle$, and
$\mathbb{B} = \langle \mathcal{C}^2, \mathbb{T}(low, medium, high), \mathbb{W}(v.high, low, low), \mathbb{H}(v.v.high, high, low)\ \rangle\}$ be two LNHSs. Then, the NHD can be calculated as:

$$\mathcal{D}(\mathbb{A},\mathbb{B}) = \frac{1}{3(3)}(|medium - low| + |high - v.high| + |none - v.v.high| + |low - medium| + |low - low| + |high - high| + |high - high| + |none - low| + |v.v, high - low|)$$

To solve this, we consider the fuzzy values from [28].

$$\mathcal{D}(\mathbb{A},\mathbb{B}) = \frac{1}{3(3)}(|0.5 - 0.4| + |0.6 - 0.7| + |0.0 - 0.8| + |0.4 - 0.5| + |0.4 - 0.4| + |0.6 - 0.6| + |0.6 - 0.6| + |0.0 - 0.4| + |0.8 - 0.4|)$$

$$\mathcal{D}(\mathbb{A},\mathbb{B}) = \frac{1}{3(3)}(1.9) = 0.211 = v.v.low$$

Proposition 3.3 Let $\mathbb{A} = \mathcal{A}_i$, $\mathbb{B} = \mathcal{B}_i$ and $\mathbb{C} = C_i$ be three LNHSs where $\mathcal{A}_i = \left(T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}}\right)$, $\mathcal{B}_i = \left(T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}}\right)$ and $C_i = \left(T_i^{\mathbb{C}}, I_i^{\mathbb{C}}, F_i^{\mathbb{C}}\right)$ for $i = \{1,2,3,\ldots,n\}$, Then, it satisfies the following axioms:

1. $\mathcal{D}(\mathbb{A},\mathbb{B}) \geq 0$, non-negativity
2. $\mathcal{D}(\mathbb{A},\mathbb{B}) = \mathcal{D}(\mathbb{B}, \mathbb{A})$ Associativity
3. $\mathcal{D}(\mathbb{A},\mathbb{B}) = 0\ if\ and\ only\ if\ (\mathbb{A} = \mathbb{B})$ Invertible
4. $\mathcal{D}(\mathbb{A},\mathbb{B}) + \mathcal{D}(\mathbb{B},\mathbb{C}) \geq \mathbb{D}(\mathbb{A},\mathbb{C})$

The axioms validation is done using python code (find in Appendix section) See the Figure 1, with above stated results.

```
Non-negativity (D(A, B) ≥ 0): Satisfied
Associativity (D(A, B) = D(B, A)): Satisfied
Invertibility (D(A, B) = 0 if A = B): Satisfied
Triangle Inequality (D(A, B) + D(B, C) ≥ D(A, C)): Satisfied
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Figure 1. The distance measure axioms validation result

Definition 3.4 Let $\mathbb{A} = \mathcal{A}_i$ and $\mathbb{B} = \mathcal{B}_i$ be the two LNHSs where $\mathcal{A}_i = \left(T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}}\right)$ and $\mathcal{B}_i = \left(T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}}\right)$ for $i = \{1,2,3,\ldots,n\}$, then Normalized Euclidean distance (NED) between $\mathbb{A}$ & $\mathbb{B}$ LNHSs is defined as:

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$$\mathcal{D}\,(\mathbb{A}\,,\mathbb{B}) = \sqrt{\frac{\sum_i^n \langle |T_i^{\mathbb{A}} - T_i^{\mathbb{B}}| + |\,I_i^{\mathbb{A}} - \,I_i^{\mathbb{B}}| + |\,F_i^{\mathbb{A}} - \,F_i^{\mathbb{B}}|\rangle}{3n}}$$

NED between $A\ and\ B\ =\ 0.331 = v.low$

Definition 3.5 Let $\mathbb{A} = \mathcal{A}_i$ and $\mathbb{B} = \mathcal{B}_i$ be the two LNHSs where $\mathcal{A}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$ and $\mathcal{B}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$ for $i = \{1,2,3, \dots, n\}$, then for $\lambda > 0\ and\ \sum_{i=1}^n \omega_i = 1$ the generalized weighted Euclidean distance (GWD) for between $\mathbb{A}$ & $\mathbb{B}$ LNHSs is defined as;

$$\mathcal{D}_\lambda\,(\mathbb{A}\,,\mathbb{B}) = \frac{1}{3n}\sum_i^n \omega_i \left[\langle |T_i^{\mathbb{A}} - T_i^{\mathbb{B}}|^\lambda + |\,I_i^{\mathbb{A}} - \,I_i^{\mathbb{B}}|^\lambda + |\,F_i^{\mathbb{A}} - \,F_i^{\mathbb{B}}|^\lambda\rangle\right]^{\frac{1}{\lambda}}$$

For the $weights\ =\ [0.4, 0.3, 0.3]$ the GWD between $A\ and\ B =\ 0.089 = v.v.v.low$

The comparison for all the three distances is presented below in figure 2.

Distance Measure	Value	Linguistic Quantifier
Normalized Hamming Distance	0.211111	V.V-Low
Normalized Euclidean Distance	0.331662	Very Low
Generalized Weighted Euclidean Distance	0.089464	V.V.V Low

Figure 2. Different distance measures result with linguistic quantifiers

Definition 3.6 Let $\mathbb{A} = \mathcal{A}_i$ and $\mathbb{B} = \mathcal{B}_i$ be the two LNHSs where $\mathcal{A}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$ and $\mathcal{B}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$ for $i = \{1,2,3, \dots, n\}$, then Similarity measure (SM) between $\mathbb{A}$ & $\mathbb{B}$ LNHSs is defined as:

$$\mathcal{S}\,(\mathbb{A}\,,\mathbb{B}) = 1 - \frac{1}{3n}\sum_i^n \langle |T_i^{\mathbb{A}} - T_i^{\mathbb{B}}| + |\,I_i^{\mathbb{A}} - \,I_i^{\mathbb{B}}| + |\,F_i^{\mathbb{A}} - \,F_i^{\mathbb{B}}|\rangle$$

Example 3.7 Consider data from example 3.2

$$\mathcal{S}\,(\mathbb{A}\,,\mathbb{B}) = 1 - \frac{1}{3n}\sum_i^n \langle |T_i^{\mathbb{A}} - T_i^{\mathbb{B}}| + |\,I_i^{\mathbb{A}} - \,I_i^{\mathbb{B}}| + |\,F_i^{\mathbb{A}} - \,F_i^{\mathbb{B}}|\rangle$$

$$\begin{aligned}\mathcal{S}\,(\mathbb{A}\,,\mathbb{B})\ &= 1 - \frac{1}{3(3)}(|medium - low| + |high - v.high| + |none - v.v.high| + |low - medium| \\ &\quad + |low - low| + |high - high| + |high - high| + |none - low| + |v.v,high - low|)\end{aligned}$$

To solve this, we consider the fuzzy values from [28].

$$\begin{aligned}\mathcal{S}\,(\mathbb{A}\,,\mathbb{B})\ &= 1 - \frac{1}{3(3)}(|0.5 - 0.4| + |0.6 - 0.7| + |0.0 - 0.8| + |0.4 - 0.5| + |0.4 - 0.4| + |0.6 - 0.6| \\ &\quad + |0.6 - 0.6| + |0.0 - 0.4| + |0.8 - 0.4|)\end{aligned}$$

$\mathcal{S}\,(\mathbb{A}\,,\mathbb{B}) = 0.788 = v.v.high$

Proposition 3.8 Let $\mathbb{A} = \mathcal{A}_i$, $\mathbb{B} = \mathcal{B}_i$ and $\mathbb{C} = C_i$ be three LNHSs where $\mathcal{A}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$, $\mathcal{B}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$ and $C_i = (T_i^{\mathbb{C}}, I_i^{\mathbb{C}}, F_i^{\mathbb{C}})$ for $i = \{1,2,3, \dots, n\}$, Then, it satisfies the following axioms:

1. $0 \le \mathcal{S}\,(\mathbb{A}\,,\mathbb{B})\ \le 1$.
2. $\mathcal{S}\,(\mathbb{A}\,,\mathbb{B}) = 1\ iff\ \mathbb{A} =\ \mathbb{B}$;
3. $\mathcal{S}\,(\mathbb{A}\,,\mathbb{B}) = \mathcal{S}\,(\mathbb{B}, \mathbb{A}\,)$.
4. If $\mathbb{A}\ \subset\ \mathbb{B} \subset \mathbb{C}$. then $\mathcal{S}\,(\mathbb{A}\,,\mathbb{C})\ \le\ \ \mathcal{S}\,(\mathbb{A}\,,\mathbb{B}).\ \ and\ \mathcal{S}\,(\mathbb{A}\,,\mathbb{C})\ \le\ \mathcal{S}\,(\mathbb{B}, \mathbb{C})$

The axioms validation is done using python code (find in Appendix section) See the Figure 3, with above stated results.

```
Axiom 1: 0 ≤ S(A, B) ≤ 1: Satisfied
Axiom 2: S(A, B) = 1 iff A = B: Satisfied
Axiom 3: S(A, B) = S(B, A): Satisfied
Axiom 4: If A ⊂ B ⊂ C then S(A, C) ≤ S(A, B) and S(A, C) ≤ S(B, C): Satisfied
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Figure 3: The similarity axioms validation result

Definition 3.9 Let $\mathbb{A} = \mathcal{A}_i$ and $\mathbb{B} = \mathcal{B}_i$ be the two LNHSs where $\mathcal{A}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$ and $\mathcal{B}_i = (T_i^{\mathbb{A}}, I_i^{\mathbb{A}}, F_i^{\mathbb{A}})$ for $i = \{1,2,3, \dots, n\}$, then for $\lambda > 0\ and\ \sum_{i=1}^n \omega_i = 1$ the generalized weighted similarity measure (GWSM) for between $\mathbb{A}$ & $\mathbb{B}$ LNHSs is defined as;

$$\mathcal{S}_\lambda\,(\mathbb{A}\,,\mathbb{B})\ \ = 1 - \frac{1}{3n}\sum_i^n \omega_i \left[\langle |T_i^{\mathbb{A}} - T_i^{\mathbb{B}}|^\lambda + |\,I_i^{\mathbb{A}} - \,I_i^{\mathbb{B}}|^\lambda + |\,F_i^{\mathbb{A}} - \,F_i^{\mathbb{B}}|^\lambda\rangle\right]^{\frac{1}{\lambda}}$$

For the $weights\ =\ [0.4, 0.3, 0.3]$ the GWS between $A\ and\ B\ =\ 0.9105 = v.v.v.high$

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4. Numerical illustration

In this study, we integrate machine-learning techniques to analyze weather uncertainty using the proposed distance and similarity measures within the linguistic neutrosophic hypersoft set environment. First, historical weather data, including parameters such as temperature, wind speed, and precipitation, is transformed into linguistic terms to handle the inherent uncertainty in weather patterns. These linguistic values are then modeled using a linguistic neutrosophic hypersoft set, assigning degrees of truth, indeterminacy, and falsity to each criterion. To analyze the data, we apply the proposed distance and similarity measures to quantify the relationship between different weather conditions. To classify weather patterns, Fuzzy C-Means (FCM) clustering is used, which help us detect uncertain weather conditions. The distances and similarities have been calculated to use them to train Support Vector Machines (SVM) and to classify weather conditions into "uncertain" or "stable". By combining these methods, one can analyze weather uncertainty more flexibly, incorporating both machine learning and mathematical modeling approaches that may enhance the decision-making ability in weather prediction.

4.1 Data Collection and Preprocessing

Gathering historical data of 50 different cities of Pakistan. The data has been retrieved from *https://www.kaggle.com/datasets/ahmddbilall/pakistan-weather?resource=download* Only temperature, wind speed, and precipitation has been considered as a potential attribute to model the weather uncertainty problem. The data is then converted into linguistic neutrosophic quantifiers from (None - Perfect) by assigning, degrees of truth, indeterminacy, and falsity to each attribute. Consider $C = \{C^1, C^2, \ldots, C^{50}\}$ *be* fifty cites as alternatives, and DM wants to find the weather similarities. The goal should be to identify the cities with the same weather conditions, while minimizing any unintended negative consequences. Consider the parameters be: $\alpha^1 = temperature$, $\alpha^2 =$ wind speed, and $\alpha^3 =$ precipitation. Then the function.

$$\Gamma : \Lambda = \Upsilon^1 \times \Upsilon^2 \times \Upsilon^3 \longrightarrow P(\Omega)$$

and assume the hypersoft set $C = \{C^1, C^2, \ldots, C^{50}\} \subset \Omega$ where $\Omega = \{C^1, C^2, \ldots, C^{50}\}$ be the universal set.

Step1: Construction of neutrosophic linguistic preference table for alternatives

Table 1: DM interaction and information gathering in neutrosophic linguistic form.

Cities	Temperature	Wind Speed	Precipitation
C1	$(high, low, v.low)$	$(v.v.high, v.v.low, none)$	$(high, medium, low)$
C2	$(low, v.low, high)$	$(high, medium, low)$	$(v.high, low, medium)$
C3	$(perfect, none, none)$	$(none, v.low, none)$	$(low, low, high)$
C4	$(v.high, none, v.low)$	$(low, v.low, high)$	$(medium, medium, low)$
C5	$(low, high, medium)$	$(v.low, high, medium)$	$(v.low, low, high)$
C6	$(high, medium, high)$	$(medium, high, low)$	$(none, high, v.high)$
C7	$(medium, low, none)$	$(high, high, low)$	$(low, none, low)$
C8	$(v.v.high, none, high)$	$(medium, low, none)$	$(high, medium, none)$
C9	$(high, low, low)$	$(high, none, none)$	$(none, low, low)$
⋮	⋮	⋮	⋮
C50	$(v.v.high, low, v.low)$	$(v.high, medium, none)$	$(medium, high, low)$

Step2: Construction of neutrosophic linguistic valued hypersoft weighted geometric averaging operator (NLV-HSWGAO) based matrix.

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$$\begin{array}{c} Cities \\ C^1 \\ C^2 \\ C^3 \\ C^4 \\ C^5 \\ C^6 \\ C^7 \\ C^8 \\ C^9 \\ \vdots \\ C^{50} \end{array} = \begin{bmatrix} NLV - HSWGAO\ values \\ (v.high, low, v.low) \\ (medium, low, none) \\ (high, medium, none) \\ (medium, low, medium) \\ (medium, low, low) \\ (high, high, low) \\ (high, medium, high) \\ (perfect, none, none) \\ (v.high, low, medium) \\ \vdots \\ (low, v.low, high) \end{bmatrix}$$

Step3: List the aggregated values of all the alternatives $\sigma_i^t(T, I, \mathcal{F})$.

$$\begin{array}{c} Cities \\ C^1 \\ C^2 \\ C^3 \\ C^4 \\ C^5 \\ C^6 \\ C^7 \\ C^8 \\ C^9 \\ \vdots \\ C^{50} \end{array} = \begin{bmatrix} aggregated\ values \\ high \\ medium \\ high \\ medium \\ medium \\ v.v.v.high \\ high \\ perfect \\ v.high \\ \vdots \\ low \end{bmatrix}$$

Step4: Rank the alternative with highest truthiness (T) value, that shows C^6 as the best alternative.

4.2 Calculation of Distance and Similarity Measures

We calculate the distance and similarity measures (presented in Table 2) proposed in section 3, to measure the uncertainty of weather data. The data is then quantified through the linguistic neutrosophic representations of temperature, wind speed and precipitation (as we will see later) and applied to each city to capture how much uncertainty they can introduce to weather forecasts. The distance measure indicates the degree of variation between different weather conditions, how far they are from each other. In contrast, the similarity measure evaluates just how similar (equivalent) are the weather states with respect to some patterns or correlations. When we evaluate the data from these calculations, it helps us understand the heterogeneity and complexity of conditions in these cities. This analysis is crucial for decision-making processes that rely on accurate and nuanced weather predictions.

Table 2: Calculated distance and similarity measures

City	GWED	GWS	City	GWED	GWS
C1	0.02304049	0.97695951	C26	0.014444444	0.985555556
C2	0.019180752	0.980819248	C27	0.033240612	0.966759388
C3	0.027261876	0.972738124	C28	0.023908261	0.976091739
C4	0.02662033	0.97337967	C29	0.02304049	0.97695951
C5	0.02116951	0.97883049	C30	0.052363874	0.947636126
C6	0.006382847	0.993617153	C31	0.02116951	0.97883049

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C7	0.024113927	0.975886073	C32	0.015634719	0.984365281
C8	0.021430335	0.978569665	C33	0.016887427	0.983112573
C9	0.018087578	0.981912422	C34	0.009094836	0.990905164
C10	0.060929022	0.939070978	C35	0.030651365	0.969348635
C11	0.018087578	0.981912422	C36	0.025603819	0.974396181
C12	0.021285827	0.978714173	C37	0.01435872	0.98564128
C13	0.012813958	0.987186042	C38	0.020214895	0.979785105
C14	0.01692394	0.98307606	C39	0.023908261	0.976091739
C15	0.02116951	0.97883049	C40	0.031289173	0.968710827
C16	0.020306297	0.979693703	C41	0.012813958	0.987186042
C17	0.011055416	0.988944584	C42	0.011111111	0.988888889
C18	0.019277057	0.980722943	C43	0.014315665	0.985684335
C19	0.02116951	0.97883049	C44	0.009026709	0.990973291
C20	0.031308895	0.968691105	C45	0.016887427	0.983112573
C21	0.029439203	0.970560797	C46	0.006382847	0.993617153
C22	0.023985592	0.976014408	C47	0.015674151	0.984325849
C23	0.01692394	0.98307606	C48	0.011111111	0.988888889
C24	0.015791856	0.984208144	C49	0.011111111	0.988888889
C25	0.024820342	0.975179658	C50	None	None

4.3 Clustering with Fuzzy C-Means (FCM)

FCM is used to classify similar weather patterns with LNHSs distance and similarity measures. We can identify the weather conditions (patterns leading to storms, clouds etc.) despite the uncertainty and complexity of dataset. The results and the cluster formation within the data are shown in Figure 4 and Figure 5 and are calculated using Python programming.

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```
Accuracy: 0.7333333333333333
FCM Results - Clusters: 2, Fuzziness: 1.5
Cluster Labels: [0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0]
FCM Results - Clusters: 2, Fuzziness: 2
Cluster Labels: [0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0]
FCM Results - Clusters: 2, Fuzziness: 2.5
Cluster Labels: [1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1]
FCM Results - Clusters: 3, Fuzziness: 1.5
Cluster Labels: [1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 1 1 1 1 1 0
 0 1 1 0 0 0 0 0 0 0 0 0 0]
FCM Results - Clusters: 3, Fuzziness: 2
Cluster Labels: [1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 1 1 1 1 1 2
 2 1 1 2 2 2 2 2 2 2 2 2 2]
FCM Results - Clusters: 3, Fuzziness: 2.5
Cluster Labels: [1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 1 1 1 1 1 2
 2 1 1 2 2 2 2 2 2 2 2 2 2]
FCM Results - Clusters: 4, Fuzziness: 1.5
Cluster Labels: [0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 2 2 2 2 2 3 3 2 2 2 1 0 0 0 0 0 1
 1 0 0 1 1 1 1 1 1 1 1 1 1]
FCM Results - Clusters: 4, Fuzziness: 2
Cluster Labels: [0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 1 2 2 2 2 3 0 0 0 0 0 3
 3 0 0 3 3 3 3 3 3 3 3 3 3]
FCM Results - Clusters: 4, Fuzziness: 2.5
Cluster Labels: [2 2 2 2 2 2 2 1 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 2 2 2 2 1 1
 1 2 2 0 0 0 0 0 0 0 0 0 0]
```

Figure 4. FCM Results for the proposed case study

Results obtained from the Fuzzy C-Means (FCM) analysis showed that this method is efficient in classifying and clustering cities according to their weather attributes. The FCM clustering results present a more nuanced perspective by assigning degrees of membership for cities within different climate groups. This methodology suggests that climate conditions are not fit and do not fall purely into one category.

Figure 5. FCM Results for the proposed case study

4.4 Classification with Support Vector Machines (SVM)

The SVM technique is used to classify weather conditions as “uncertain” or “stable” based on the LNHSs based similarity measures. The distance measures can serve as input features for SVM, which will then predict the likelihood of uncertain weather. The results (presented in Figure 6) of SVM successfully categorized cities into distinct climate classes, providing a clear framework for understanding and comparing different climatic zones.

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```
Best SVM Parameters: {'C': 10, 'gamma': 0.001, 'kernel': 'linear'}
SVM Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.86      0.75         7
           1       0.83      0.62      0.71         8

    accuracy                           0.73        15
   macro avg       0.75      0.74      0.73        15
weighted avg       0.76      0.73      0.73        15
```

Figure 6. FCM Results for the proposed case study

4.5 Sensitivity Analysis:

The sensitivity analysis of the SVM, FCM, GWDM and WSM is carried out to see how different values of attributes affect the performance and results output by each method. For SVM, adjusting with the regularization parameters: C, kernel type and gamma showed how the model accuracy changes when having a simple or a more complex data. The FCM analysis, considering the number of clusters and the fuzziness parameter (m), demonstrates how cities are grouped based on weather patterns, emphasizing the balance between distinct clustering and recognizing overlap in data.

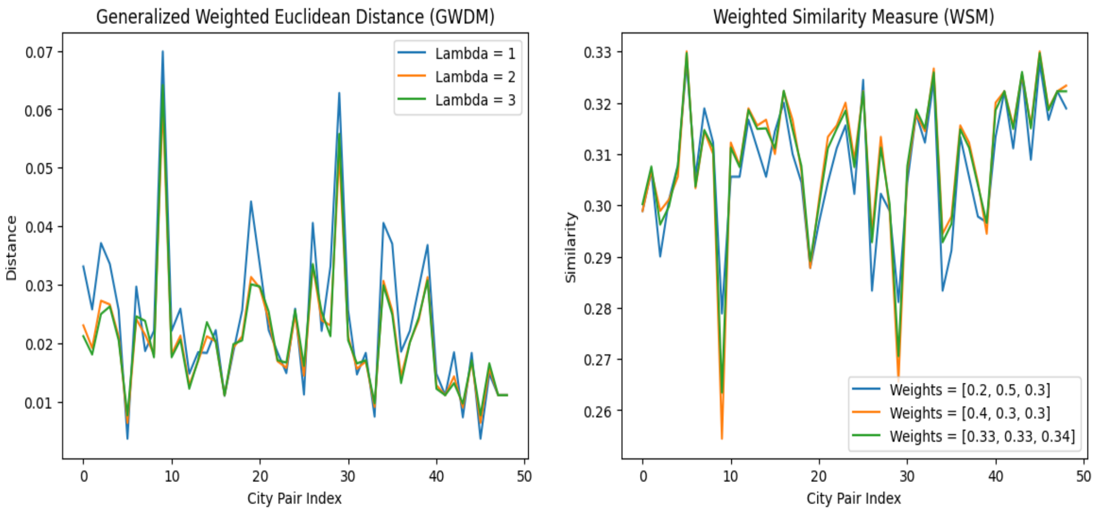

Figure 7. Sensitivity Analysis of proposed Distance and Similarity Measures

The effect of change in weather attributes in the GWDM model has been illustrated by changing parameter value `lambda` and attribute weights. It shows how changing values affect the distance between cities as well. Results show that DM must pay attention to select appropriate weights when calculating the similarities presented in Figure 7. Similarly, the WSM analysis is done by changing the weights of each weather parameter to study the impact in classification and results are calculated. The results show that the increase in attributes has a significant impact on the classification. The right selection of parameters provides robustness and helpfulness to study the different clustering within the data set.

5. Result Discussion and Effectiveness of the Methods

The study proposes a novel approach to evaluate cities in detail about explicit weather attributes, using Support Vector Machine (SVM), Fuzzy C-Means (FCM) Clustering, and LNHSs based Generalized Weighted Euclidean Distance, and finally LNHSs based Generalized Similarity Measures. By grouping cities into different meteorological categories, SVM becomes a powerful tool to deal with the complexity and non-linearity of the data. It is beneficial, for example, when there is a need to determine some regions, which are most suitable for different crops under certain conditions. FCM clustering is used to classify the land into distinct climate categories, which

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cannot be done physically. By doing this, it helps us find how real weather patterns have vagueness and how it is useful in resource allocation.

The use of LNHSs based Generalized Weighted Euclidean Distance (GWED) and LNHSs based Generalized Similarity Measures (GSM) calculate similarity between cities based on weather attributes. These results help us to understand the distinctions in different cities and to cluster the cities. Hence, this comparison in forecasting and strategic planning, especially in sectors like agriculture, energy management, or urban development will be very useful. Recent advancements in fuzzy systems and machine learning have tackled uncertainty across diverse fields [44-45]. It includes type-2 fuzzy system [46], T-S fuzzy in time delay [47], and robust decision-making methods using the concepts of [48-49]. Future advancements can be made in the following directions as well to enhance the literature broadness [50-52].

Limitations: The main limitation of the study is the errors caused by the quality and completeness of weather data. Secondly, the introduction of linguistic quantifiers introduces subjectivity, improbability, and simplification from dynamic weather conditions to limited attributes that may neglect interrelationships. Lastly, the static nature of SVM and FCM analysis creates only a historical view, thus requiring constant updates of data that would account for the dynamic behavior of climate.

Future directions: More attributes like air pressure, rainfall, dryness, air quality, and precipitation patterns can be used to study the interrelationship of weather. Consideration of dynamic clustering and data assimilation can be incorporated to enhance the adaptability to weather changes. This model could be improved with the integration of GIS data to include a spatial dimension. Advanced machine learning models (Neural Networks, Random Forests) can be used.

6. Conclusion

The paper presents a novel framework for smart farming decision-making problems. It integrates machine learning (ML) approaches such as Support Vector Machine (SVM) and Fuzzy C-Means (FCM) clustering with generalized distance and similarity measures in a linguistic neutrosophic hypersoft set environment. It uses Machine Learning for real sensor data analysis in the case of predicting weather patterns and Linguistic Neutrosophic terms to express indeterminacy, and falsity resulting in a more accurate evaluation of imprecise information. Cities are ranked using generalized similarity measures between the cities in order of their scores based on selected variables of interest, e.g. temperature, wind speed, or humidity. The results of this study show that, under uncertain and dynamic environmental conditions, an integrated approach helps to determine which options are fitter for the management of their land's potential resources while providing the rest of farming resilience.

The study allows us to deal with weather-related uncertainty in a more flexible aspect compared to existing methods, which is highly beneficial for smart farming. The addition of more environmental factors and enhanced definitions of distance and similarity measures can be useful in gaining more accuracy. This model could be a useful decision-support tool in problems where the study of uncertainty is vital, including climate resilience and environmental sustainability. Thus, proposed methods can be used in strategic planning and resource allocation for environmental sustainability.

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Author Contributions: Conceptualization, methodology, writing—Muhammad Saqlain does original draft; Poom Kumam does the Supervision and Wiyada Kumam does review of final draft, and the funding acquisition.

Data Availability Statement: The data and sources codes can be provided on demand.

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