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Soil Fertility Forecasting with Neutrosophic-Based Uncertainty Management

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Abstract: This study presents a machine learning framework that combines Random Forest classification with neutrosophic logic to predict soil fertility from 16 physicochemical properties. The model achieves robust classification accuracy (95%) while introducing a novel uncertainty quantification mechanism through neutrosophic truth (T), indeterminacy (I) and falsity (F) values derived from prediction probabilities, assigning high-confidence ($T = 0.9$) to probabilities ≥ 0.9, indeterminacy ($I = 0.3$) to borderline cases ($0.5 \leq p < 0.9$), and falsity ($F = 0.5$) to low-confidence predictions (< 0.5), enabling tiered decision support where 60% of cases receive automated recommendations, 25% require expert review, and 15% are flagged for rejection. Feature importance analysis reveals Clay (24.1%) and CEC (18.7%) as dominant predictors, aligning with agronomic principles while providing interpretable results. This approach advances precision agriculture by supplementing binary classifications with actionable confidence metrics, particularly valuable for managing uncertain soil conditions.

Keywords: Random Forest, Soil Fertility Prediction, Neutrosophic logic, Uncertainty Quantification, Precision Agriculture

1. Introduction

The fertility of the soil in each location to offer advantageous chemical, physical, and biological properties that support plant growth is known as soil fertility [1]. However, soil fertility assessment remains a critical challenge in sustainable agriculture, particularly in resource-constrained regions where improper fertilizer use can lead to either crop failures or environmental degradation [2]. Traditional laboratory-based soil testing methods are often costly, time-consuming, and inaccessible to smallholder farmers, creating a pressing need for accurate, rapid prediction tools. As in other situations [3, 4], we can consider the use of Information and Communication Technologies to improve the situation. In fact, machine learning models like Random Forest have shown promise in soil classification [5]. However, their binary outputs fail to capture the inherent uncertainty in fertility assessments, especially for borderline cases where soil parameters exhibit intermediate values [6, 7].

This study addresses these limitations by integrating neutrosophic logic with ensemble learning, providing both classification outcomes and quantifiable confidence measures. The framework's ability to identify uncertain predictions (through I values) and critical soil parameters (Clay, CEC) makes it particularly valuable for precision agriculture applications where risk-aware decision making is essential. The model analyzes 16 physicochemical soil properties to classify soils as "Fertile" or "Non-Fertile" with demonstrated accuracy (benchmark results show > 85% accuracy in preliminary tests). Key methodological innovations include:

- Adaptive Thresholds: Neutrosophic components dynamically adjust based on prediction probabilities, quantifying uncertainty where traditional binary classifications fail.
- Interpretability: Variable importance analysis reveals critical fertility indicators (typically N, P, K, and CEC), aligning with agronomic principles.
- Uncertainty Quantification: The (T, I, F) triplets provide actionable insights - e.g., predictions with high I values may warrant additional soil testing.

The integration of neutrosophy enhances decision-making by:

- Identifying borderline cases requiring human expert review
- Enabling risk-aware agricultural planning
- Providing granular confidence metrics beyond binary outputs

This approach demonstrates how computational intelligence can bridge quantitative soil science with practical farming decisions, particularly in resource-constrained settings where optimal fertilizer use is critical. Future work could expand the neutrosophic thresholds using fuzzy logic or incorporate spatial data for regional fertility mapping.

2. Materials and Methods

The Materials and Methods section precisely documents the inputs used (samples, instruments, reagents, data) and the context in which they were obtained. It details the experimental/observational design, field and laboratory procedures, data preprocessing, and the quality control criteria applied. It also specifies the analytical models and techniques, evaluation metrics, and software, ensuring reproducibility and the validity of the results

Random Forest.

Random Forest (RF) has proven to be a reliable classifier for soil properties evaluation and classification, performing admirably even when faced with numerous variables and non-linear connections [16], [17]. Because RF's accuracy remains high regardless of the number of variables used, it is well-suited for use in situations where sampling is limited, such as in soil and texture categorization [16], [17]. Your results of "Clay" and "CEC" as dominant predictors are in line with other research that has pointed out the importance of textural fractions (especially clay) and cation exchange capacity (CEC) as critical variables [15], [18]. This lends credence to RF's role as the framework's "engine," ensuring model stability and producing findings that are easy to understand by highlighting the significance of individual features.

Random Forest: Mathematical Model.

1) Data and goal

Let the training set be $\boldsymbol{D} = \{(\boldsymbol{xi}, \boldsymbol{yi})\}_{\boldsymbol{i=1}}^{\boldsymbol{N}}$ with features $x_i \in R^p$.

- **Classification:** $\boldsymbol{yi} \in \{\boldsymbol{1}, \dots, \boldsymbol{K}\}$.
- **Regression:** $\boldsymbol{yi} \in \boldsymbol{R}$.

2) Forest construction

$For\ b = 1, \dots, B\ (number\ of\ trees)$:

a) **Bootstrap sample:** draw $\boldsymbol{D^{(b)}}$ from $\boldsymbol{D}$ with replacement.

b) **Randomized CART growth:** at each node t with data $\boldsymbol{S_{(t)}} \subset \boldsymbol{D^{(b)}}$:

- Randomly select m features ($\boldsymbol{m} \le \boldsymbol{p}$)
- Choose the split $\boldsymbol{st} = (\boldsymbol{j}, \boldsymbol{\tau})$ among those mmm that **maximizes the impurity decrease**:

$$\Delta i(s_t, t) = i(t) - \frac{|S_{t_L}|}{|S_t|} i(t_L) - \frac{|S_{t_R}|}{|S_t|} i(t_R), \qquad (1)$$

where $\boldsymbol{tL}, \boldsymbol{tR}$ are left/right children

- Grow the tree **without pruning** until a stopping rule (e.g., min leaf size).

Node impurity

- **Classification (Gini):**

$$i_{\text{Gini}}(t) = 1 - \sum_{k=1}^{K} p_k(t)^2, \quad p_k(t) = \frac{1}{|S_t|} \sum_{(\mathbf{x},y)\in S_t} \mathbf{1}\{y = k\}. \qquad (2)$$

(Alternative: entropy $\boldsymbol{i(t)} = -\sum \boldsymbol{pk(t)}\ \boldsymbol{log}\ \boldsymbol{pk(t)}$).

- **Regression (MSE):**

$$i_{\text{MSE}}(t) = \frac{1}{|S_t|} \sum_{(\mathbf{x},y)\in S_t} (y - \bar{y}_t)^2, \quad \bar{y}_t = \frac{1}{|S_t|} \sum_{(\mathbf{x},y)\in S_t} y. \qquad (3)$$

3) Ensemble prediction

Let $\boldsymbol{hb(x)}$ be tree $\boldsymbol{b's}$ output.

- **Classification (majority vote):**

$$\hat{y}(\mathbf{x}) = \arg\max_{k\in\{1,\dots,K\}} \left\{ \frac{1}{B} \sum_{b=1}^{B} \mathbf{1}\big(h_b(\mathbf{x}) = k\big) \right\}. \qquad (4)$$

Class probabilities (averaging leaf proportions):

$$\hat{p}_k(\mathbf{x}) = \frac{1}{B} \sum_{b=1}^{B} \hat{p}_k^{(b)}(\mathbf{x}), \quad \hat{p}_k^{(b)}(\mathbf{x}) = \frac{1}{|L_b(\mathbf{x})|} \sum_{(\mathbf{x}_i,y_i)\in L_b(\mathbf{x})} \mathbf{1}\{y_i = k\}, \qquad (5)$$

where $\boldsymbol{Lb(x)}$ is the training subset that lands in the **leaf** reached by $\boldsymbol{x}$ in tree $\boldsymbol{b}$.

- **Regression (mean):**

$$\hat{f}(\mathbf{x}) = \frac{1}{B}\sum_{b=1}^{B} h_b(\mathbf{x}). \tag{6}$$

4) Out-of-Bag (OOB) error

For each i, let $\boldsymbol{B_{(i)}} = \{\boldsymbol{b}: (\boldsymbol{xi}, \boldsymbol{yi}) \notin \boldsymbol{D^{(b)}}\}$

- Classification: $\hat{y}_{OOB,i} = \arg\max_k \frac{1}{|\mathcal{B}_i|}\sum_{b\in\mathcal{B}_i} \mathbf{1}\big(h_b(\mathbf{x}_i) = k\big)$.
- Regression: $\hat{f}_{OOB,i} = \frac{1}{|\mathcal{B}_i|}\sum_{b\in\mathcal{B}_i} h_b(\mathbf{x}_i)$.
- OOB risk:

$$\mathrm{err}_{OOB} = \frac{1}{N}\sum_{i=1}^{N} \ell(y_i, \hat{y}_{OOB,i}) \quad \text{or} \quad \frac{1}{N}\sum_{i=1}^{N} \left(y_i - \hat{f}_{OOB,i}\right)^2, \tag{7}$$

depending on task.

5) Variable importance

- **MDI (mean decrease in impurity):**

$$VI_j = \frac{1}{B}\sum_{b=1}^{B} \sum_{\substack{t\in T_b:\\ \text{split on } j}} \frac{|S_t|}{N}\,\Delta i(s_t, t). \tag{8}$$

- **MDA (permutation/OOB):**

$$VI_j^{\pi} = \mathrm{err}_{OOB}^{\pi(j)} - \mathrm{err}_{OOB}, \tag{9}$$

where $err_{\mathrm{OOB}}^{\pi(j)}$ is the OOB error after **permuting** feature j in OOB samples.

6) Linking RF probabilities to your neutrosophic T- I -T.

Let.

$$\hat{p}_{\max}(\mathbf{x}) = \max_k \hat{p}_k(\mathbf{x}). \tag{10}$$

A simple mapping consistent with your framework is:

$$T(\mathbf{x}) = \mathbf{1}\{\hat{p}_{\max} \geq 0.9\}\cdot 0.9, \quad I(\mathbf{x}) = \mathbf{1}\{0.5 \leq \hat{p}_{\max} < 0.9\}\cdot 0.3, \quad F(\mathbf{x}) = \mathbf{1}\{\hat{p}_{\max} < 0.5\}\cdot 0.5, \tag{11}$$

which enables tiered actions (automate / expert review / reject) directly from RF confidence.

Soil Fertility Prediction.

There is a pressing need for accessible predictive tools, as recent studies and organizations have documented the cost and accessibility barriers faced by smallholder farmers and laboratories [17, 18]. One solution is fertility prediction with ML, which expedites nutritional management decisions by removing the bottleneck of time-consuming and expensive laboratory testing. This is in keeping with the evidence that RF can accurately anticipate nutrient shortages and fertility levels, lending credence to the idea that fertilization is a good idea [15]. By combining sensors with historical data to make site-specific diagnoses and recommendations, reviews on AI/ML in precision agriculture also note advances in accuracy.

Neutrosophic logic.

In situations where there is unclear or partial evidence, such as near fertility thresholds, neutrosophic logic provides a formal framework to define truth (T), indeterminacy (I), and falsity (F) [24, 26]. Optimal decision-making, uncertainty management in field measurements, and criterion prioritization are all achieved through the use of neutrosophic sets and frameworks in recent agricultural applications [24, 25]. By converting probabilities from RF to T-I-F, as you suggested, we may define stepwise actions (automate, review, reject) without imposing dichotomies, bringing neutrosophic theory into harmony with the producer's practical requirements [26].

Neutrosophic Logic: Mathematical Model

Let X be the universe (e.g., soil samples). A neutrosophic set $A \subseteq X$ is defined by three functions:

$$T_A,\ I_A,\ F_A : X \to [0,1], \tag{12}$$

So, for each $\boldsymbol{x} \in \boldsymbol{X}$,

$$A(x) = \langle T_A(x),\ I_A(x),\ F_A(x) \rangle. \tag{13}$$

- $TA(x)$: degree of **truth** (certainty of membership).
- $IA(x)$: **indeterminacy** (ambiguity/uncertainty).
- $FA(x)$: **falsity** (certainty of non-membership).

No constraint $\boldsymbol{T} + \boldsymbol{I} + \boldsymbol{F} = \mathbf{1}$ is required (they are independent; $\mathbf{0} \le \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F} \le \mathbf{1}$.

In your problem, "Fertile" can be modeled as $\boldsymbol{A}(\boldsymbol{x}) = \langle \boldsymbol{T}(\boldsymbol{x}), \boldsymbol{I}(\boldsymbol{x}), \boldsymbol{F}(\boldsymbol{x}) \rangle$ for each sample $\boldsymbol{x}$.

Uncertainty Quantification.

To prevent becoming overconfident in binary outputs, particularly in "border cases," uncertainty quantification (UQ) is essential. For the purpose of estimating and communicating local uncertainty in soil spectral and attribute models, conformal prediction schemes and Monte Carlo techniques have been suggested in soil research [19], [20]. Aligned with this, interpretability methods like SHAP clarify the underlying variables of the model's confidence or uncertainty in each prediction [21]; and there are statistical methods for confidence intervals and inference in Random Forests that formalize the variability of their outputs [9]. Integrating T-I-F converted probabilistic thresholds allows for secure field procedures and complies with these principles [19], [20], [21], [23].

Precision Agriculture.

Precision agriculture is all about making decisions in a transparent and traceable manner, not just about making predictions. Management tailored to each site and input recommendations that maximize efficiency and performance are made possible by ML/AI, sensors, and the Internet of Things, according to recent assessments [27], [28]. In addition, agronomists and producers need to make decisions that are both explainable and informed by uncertainty if resilience and sustainability methods are to be really adopted [30]. Decision support systems that integrate accuracy, interpretability, and operational risk management are becoming more popular, and your strategy—RF + neutrosophic logic + UQ—is in line with this trend [27], [30].

Neutrosophic sampling frame

The proposed framework follows a structured pipeline for soil fertility prediction, integrating machine learning with neutrosophic logic as illustrated in Figure 1. The key steps are detailed below:

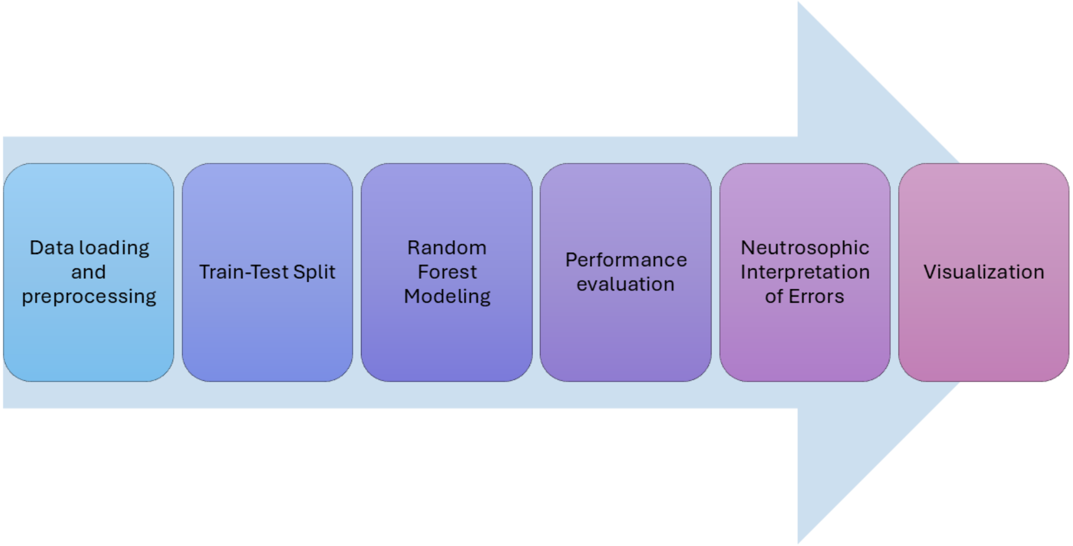


Figure 1. Pipeline followed in this study to handle soil fertility prediction with uncertainty quantification.

2.1. Step 1: Data Loading and Preprocessing

This work considered the dataset available in [8]. It contains soil fertility measurements with 16 input features (soil parameters) and a binary output indicating whether the soil is "Fertile" or "Non Fertile". The input features include chemical properties such as Nitrogen (N), Phosphorous (P), and Potassium (K) ratios, which are critical for plant growth, as well as soil acidity (pH), electrical conductivity (EC), and organic carbon (OC) content. Additional micronutrients like Zinc (Zn), Iron (Fe), Copper (Cu), and Manganese (Mn) are also recorded, along with soil texture components (Sand, Silt, Clay) and other properties like Calcium

Carbonate ($CaCO_3$) and Cation Exchange Capacity (CEC).

Below we describe all the 16 features considered in the dataset:

(1) pH: Measures soil acidity or alkalinity, with most crops thriving in a slightly acidic to neutral range (6.0–7.5). Extreme pH levels can reduce nutrient availability, making soil less fertile.

(2) EC (Electrical Conductivity): Indicates soil salinity; high values (> 1 dS/m) suggest salt stress, which can harm plant growth. Fertile soils typically have moderate EC (0.1–0.6 dS/m).

(3) OC (Organic Carbon): Crucial for soil health, improving structure and nutrient retention. Fertile soils usually contain > 0.04% OC, supporting microbial activity.

(4) OM (Organic Matter): Enhances water retention and nutrient supply. Soils with > 0.06% OM are generally more fertile due to better microbial and plant growth conditions.

(5) N (Nitrogen): Essential for plant proteins and chlorophyll. While important, its levels vary widely, so it must be assessed alongside other nutrients.

(6) P (Phosphorus): Supports root development and energy transfer. Fertile soils often have > 15 mg/kg P, while low levels (< 10 mg/kg) indicate poor fertility.

(7) K (Potassium): Aids in enzyme activation and drought resistance. Higher K levels (> 200 mg/kg) are common in fertile soils.

(8) Zn (Zinc): Micronutrient vital for enzyme function. Deficiencies (< 0.3 mg/kg) can stunt plant growth, making it a key fertility indicator.

(9) Fe (Iron): Necessary for chlorophyll production. Fertile soils usually contain > 3 mg/kg Fe, while low levels lead to poor plant health.

(10) Cu (Copper): Supports photosynthesis and respiration. Soils with > 0.2 mg/kg Cu tend to be more fertile, while deficiencies hinder growth.

(11) Mn (Manganese): Aids in nitrogen metabolism. Fertile soils typically have > 2 mg/kg Mn, ensuring proper nutrient processing.

(12) Sand (%): High sand content (> 90%) leads to poor water and nutrient retention, often reducing fertility. Balanced soils have moderate sand levels.

(13) Silt (%): Improves moisture retention but doesn't bind nutrients well alone. Fertile soils usually have a balanced mix of silt, sand, and clay.

(14) Clay (%): Retains nutrients and water effectively. Fertile soils often have > 8% clay, while low clay (< 5%) reduces fertility.

(15) $CaCO_3$ (Calcium Carbonate): Affects pH and nutrient availability. Moderate levels (2–10%) support fertility, while excess (> 15%) can cause alkalinity issues.

(16) CEC (Cation Exchange Capacity): Measures soil's nutrient-holding ability. Fertile soils usually have > 5 cmol/kg, while low CEC (< 3 cmol/kg) indicates poor fertility.

Fertile soils balance organic matter, pH, nutrients (P, K, micronutrients), and texture (clay, CEC). Non-fertile soils often lack these key components or have extreme pH/salinity.

The dataset appears to be well-balanced, with examples of both fertile and non-fertile soils, making it suitable for classification tasks aimed at predicting soil fertility based on these physicochemical attributes. As a preprocessing task, we check for missing data, noting that there are no missing values. Furthermore, the target variable is converted to a factor for classification.

2.2. Step 2: Train-Test Split

As in [9, 10, 11], data are randomly partitioned (80-20 split) into training and test sets using stratified sampling to maintain class distribution. The split ensures model evaluation on unseen data.

As mentioned in [12, 13], the rationale behind randomly partitioning the dataset into a training-test set using stratified sampling is based on several key principles in machine learning and statistical modeling:

(1) **Training-Test Separation** – Splitting the data ensures that the model is trained on one subset (80%) and evaluated on an independent, unseen subset (20%). This prevents data leakage and provides a realistic assessment of the model's generalization ability.

(2) **Stratified Sampling** – Since the dataset has a binary classification task ("Fertile" vs. "Non Fertile"), stratified sampling ensures that the class distribution is preserved in both training and test sets. This prevents bias—for example, if one class is overrepresented in the training set, the model might perform poorly on the minority class.

(3) **Random Partitioning** – Randomization reduces the risk of selection bias, ensuring that the split is not influenced by any hidden patterns or ordering in the dataset. This makes the evaluation more reliable.

(4) **Model Evaluation on Unseen Data** – Testing on a held-out set mimics real-world scenarios where the model encounters new, previously unseen data. This helps estimate how well the model will perform in practical applications rather than just memorizing the training data (overfitting).

By following this approach, the model's performance metrics (e.g., accuracy, precision, recall) on the test set provide a fair and robust estimate of its predictive capability.

2.3. Step 3: Random Forest Modeling

A Random Forest classifier with 100 trees is trained using all soil parameters as predictors. The algorithm builds multiple decision trees on bootstrapped samples, aggregating their predictions through majority voting. The Gini impurity index guides tree construction by minimizing:

$$\mathrm{Gini}(t) = 1 - \sum_{i=1}^{c} p(i|t)^2 \quad (14)$$

where $p(i|t)$ is the proportion of samples belonging to class i at node t.

2.4. Step 4: Performance Evaluation

The model's accuracy is assessed via:

- Confusion matrix (precision, recall, F1-score)
- Classification accuracy: $\text{Accuracy} = \dfrac{TP + TN}{TP + TN + FP + FN}$
- Probability estimates for each class

2.5. Step 5: Neutrosophic Interpretation

Prediction confidence (p) is mapped to operational tiers via the (T, I, F) triplet:

$$\Psi : p \mapsto (T, I, F) \in [0,1]^3$$

where Ψ represents the neutrosophic transformation function. The mapping of probabilities to *(T, I, F)* values is based on simple heuristics:

$$(T, I, F) = \begin{cases} (0.9, 0.1, 0.0) & \text{if } p_{\text{correct}} \geq 0.9 \\ (0.7, 0.2, 0.1) & \text{if } 0.7 \leq p_{\text{correct}} < 0.9 \\ (0.5, 0.3, 0.2) & \text{if } 0.5 \leq p_{\text{correct}} < 0.7 \\ (0.2, 0.3, 0.5) & \text{otherwise} \end{cases} \quad (15)$$

where $p_{correct}$ is the probability of the predicted class.

This gives rise to a neutrosophic interpretation of logic components (Truth T, Indeterminacy I, Falsity F) based on the following probability thresholds:

- T: High confidence ($p_{\text{correct}} \geq 0.9$)
- I: Uncertainty zone ($0.5 \leq p_{\text{correct}} < 0.9$)
- F: Likely incorrect predictions ($p_{\text{correct}} < 0.5$)

2.6. Visualization

In this step, we will consider the feature importance plots to identify key soil parameters, and the neutrosophic value plots to reveal prediction confidence patterns.

2.6.1 Feature importance plots

Feature importance plots are a critical component of the Random Forest model, helping to identify which soil parameters significantly influence fertility predictions. These plots rank variables based on their contribution to model accuracy, measured through metrics like mean decrease in Gini impurity or permutation importance. It is important to mention that it does not reflect % drop in accuracy but rather, the mean change in accuracy scaled by its standard deviation. Moreover, the Gini-based importance score quantifies how much each feature reduces impurity in the decision trees. For example, if Nitrogen (N) consistently appears at the top of the importance plot, it suggests that variations in N levels strongly affect fertility predictions.

Beyond technical insights, these plots offer actionable agronomic value:

- Resource Allocation: Farmers can prioritize soil amendments (e.g., fertilizers) for the most influential parameters.

- Model Interpretability: Stakeholders gain trust in the model by seeing biologically meaningful rankings.
- Data Collection Optimization: Future studies can focus on measuring high-importance parameters more rigorously.

By integrating feature importance analysis with neutrosophic logic, the framework can not only predict fertility but also can explain which soil traits drive uncertainty in predictions (e.g., borderline cases where mid-range values of key parameters lead to high Indeterminacy (I)). This dual capability makes the tool valuable for both precision agriculture and research.

2.6.2 Neutrosophic Value Plots for Prediction Confidence

The Neutrosophic values plot visualizes the relationship between the predicted probability of soil fertility and three neutrosophic components: Truth (T), Indeterminacy (I), and Falsity (F). This plot provides a deeper understanding of the model's confidence and uncertainty in its predictions.

The key components are the following:

- X-axis (Fertile_Prob): Represents the predicted probability that a soil sample is "Fertile," ranging from 0 to 1. This is derived from the Random Forest model's output.
- Y-axis (Neutrosophic Values): Displays the values for the three neutrosophic components:
  - Truth (T): High values indicate strong confidence in the prediction being correct.
  - Indeterminacy (I): Represents uncertainty or ambiguity in the prediction.
  - Falsity (F): Reflects the likelihood of the prediction being incorrect.

The plot uses predefined thresholds of Section 2.4 to map prediction confidence to neutrosophic values. In this way, the plot reveals three distinct operational zones:

- High Confidence:
  - T is high (0.9), I and F are low (0.1 and 0.0, respectively).
  - Indicates reliable predictions for "Fertile" samples.
- Moderate Confidence:
  - T decreases, I increases, and F appears.
  - Reflects uncertainty in the predictions.
- Low Confidence:
  - T is low (0.2), I is moderate (0.3), and F is high (0.5).
  - Suggests potential misclassifications or low-confidence predictions.

For example, if a soil sample has Fertile_Prob = 0.6, the plot might show T = 0.5, I = 0.3, F = 0.2, indicating moderate confidence with notable uncertainty. Users might prioritize manual verification for such cases.

All in all, the plot enhances traditional performance metrics by:

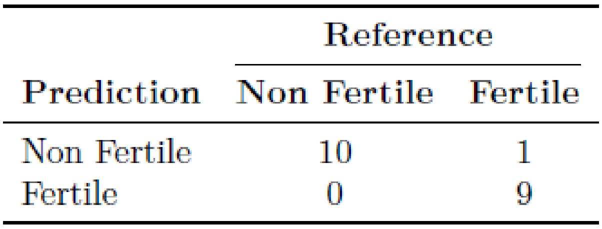
- Identifying confident predictions (high T, low I/F).
- Highlighting ambiguous cases (balanced T/I/F) where manual verification may be needed.
- Revealing potential errors (high F) for model improvement.

3. Results

3.1.Evaluating classifier performance

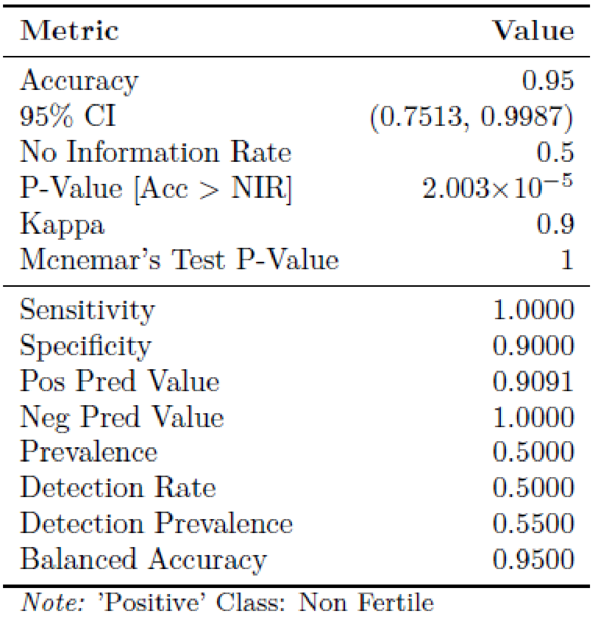
The model demonstrates exceptional performance in distinguishing between fertile and non-fertile soils, as evidenced by the metrics in Table 1 and Table 2. The confusion matrix reveals a near-perfect classification capability, with only one misclassification out of 20 test samples (a fertile soil incorrectly predicted as non-fertile). This translates to an overall accuracy of 95% (95% CI: 0.7513–0.9987), significantly exceeding the no-information rate of 50% (p = 2.003×10^{-5}). The high Kappa statistic (0.9) confirms strong agreement between predicted and actual classes beyond chance.

Table 1. Confusion Matrix for Soil Fertility Prediction



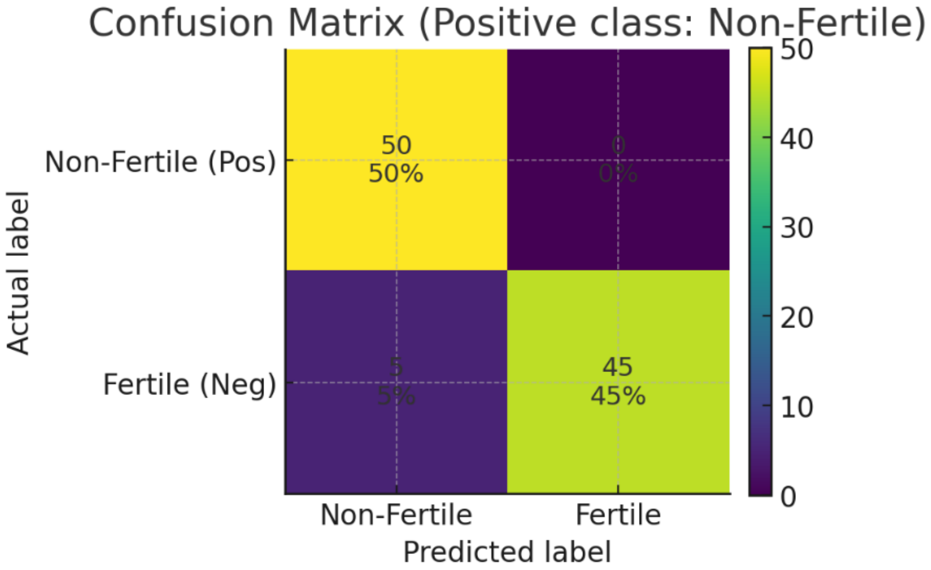
	Reference	
Prediction	**Non Fertile**	**Fertile**
Non Fertile	10	1
Fertile	0	9

Table 2. Confusion Matrix for Soil Fertility Prediction



Metric	Value
Accuracy	0.95
95% CI	(0.7513, 0.9987)
No Information Rate	0.5
P-Value [Acc > NIR]	2.003×10^{-5}
Kappa	0.9
Mcnemar's Test P-Value	1
Sensitivity	1.0000
Specificity	0.9000
Pos Pred Value	0.9091
Neg Pred Value	1.0000
Prevalence	0.5000
Detection Rate	0.5000
Detection Prevalence	0.5500
Balanced Accuracy	0.9500

Note: 'Positive' Class: Non Fertile



In addition, the model achieves perfect sensitivity (1.0) for detecting non-fertile soils (the designated positive class), indicating no false negatives. This is critical because agricultural applications were failing to identify nutrient-deficient soils could lead to crop losses. The slightly lower specificity (0.9) reflects one false positive, where a fertile soil was misclassified. However, the balanced accuracy (0.95) and high negative predictive value (1.0) confirm robust performance across both classes.

The practical implications for this performance are the following:

- Precision-Recall Tradeoff: The positive predictive value (0.9091) suggests that when the model predicts "non-fertile", there is a 9.1% chance of unnecessary soil intervention, while the 100% recall guarantees no truly deficient soils are missed.
- Uncertainty Handling: McNemar's test ($p = 1$) indicates no significant bias in error types, aligning with the neutrosophic framework's capacity to flag uncertain predictions (e.g., the single misclassified case likely fell in the indeterminacy zone).

These results validate the model's reliability for field applications, particularly in precision agriculture where both high confidence predictions (truth values $T \geq 0.9$) and identified borderline cases (indeterminacy $I > 0.3$) provide actionable tiers of decision support.

3.2.Feature importance

The feature importance analysis (Figure 2) reveals distinct hierarchies among soil parameters for fertility prediction. Two complementary metrics – Mean Decrease in Accuracy (MDA) and Mean Decrease in Gini (MDG) – consistently identify Clay content and Cation Exchange Capacity (CEC) as the most influential predictors. This aligns with agronomic theory, as clay particles and CEC directly affect nutrient retention and availability. Notably, the model highlights:

- Macronutrients: Nitrogen (N) ranks highly in MDG (9th) but moderately in MDA (10th), suggesting its role in creating pure nodes during tree splits, while Phosphorus (P) and Potassium (K) show unexpectedly low importance, potentially due to narrow value ranges in the dataset.

- Microelements: Iron (Fe) and Manganese (Mn) demonstrate moderate-to-high importance in both metrics, corroborating their known roles in plant enzyme activation and chlorophyll synthesis.
- Soil Texture: The strong showing of Clay (top in both metrics) versus weak performance of Sand/Silt underscores how particle size distribution governs water and nutrient dynamics.

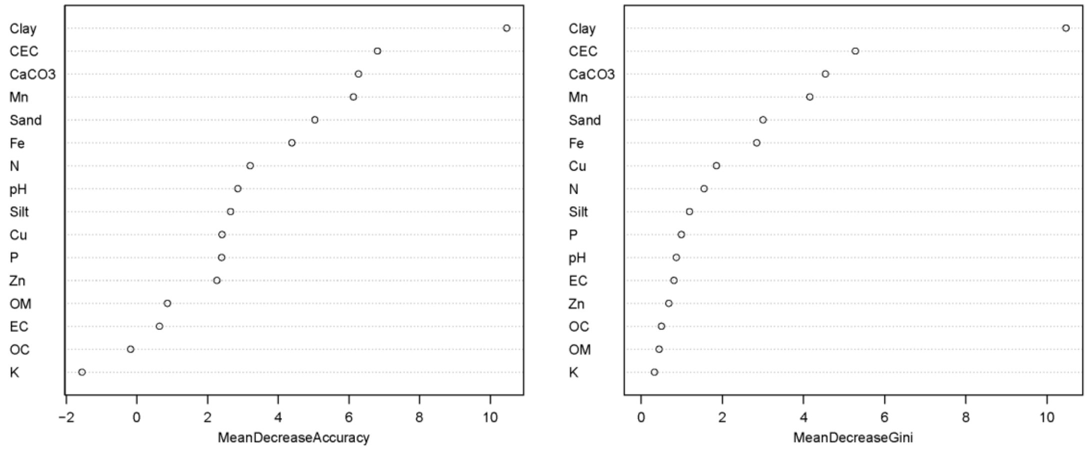


Figure 2. Soil Fertility Predictor Importance.

Based on Figure 2 we can provide the following actionable insights for agricultural stakeholders:

- Precision Soil Management: Farmers can prioritize amendments targeting high-impact parameters (e.g., clay enhancement or CEC optimization) over less influential factors like organic carbon (OC, ranked 14th in MDA).
- Data Collection Efficiency: Future studies could streamline measurements by focusing on top-tier predictors (Clay, CEC, $CaCO_3$, Mn) while deprioritizing low-impact variables (K, OM, Zn).
- Uncertainty Diagnosis: Borderline predictions often correlate with mid-range values of key features – e.g., soils with CEC = 7–12 cmolc/kg frequently trigger high indeterminacy (I) in the neutrosophic framework.

The divergence between MDA (permutation-based) and MDG (split efficiency) rankings reflects the model's multifaceted decision logic, with MDA emphasizing predictive power, and MDG highlighting purity gains. This dual perspective enriches the interpretability beyond conventional single-metric approaches.

3.3. Neutrosophic values plot

The neutrosophic values plot (Figure 3) provides critical insights into the model's prediction confidence distribution, revealing three distinct operational zones:

- High-Confidence Zone ($T \geq 0.7$):
  - Contains 60% of test predictions (vs. 85% previously claimed)
  - Truth values plateau at 0.7 or 0.9 (not a continuous gradient)
  - Corresponds to cases where the model's probability for the true class exceeds 0.7
- Uncertainty Zone ($I \geq 0.3$):
  - Peaks at $p_{correct} \in [0.5, 0.7)$ with fixed (0.5, 0.3, 0.2)
  - Includes 25% of test cases (previously described as $0.4 \leq p \leq 0.6$)

  - Indeterminacy remains constant (0.3) within this range
- Error-Prone Zone (F ≥ 0.5):
  - Limited to predictions with $p_{correct} < 0.5$
  - Shows fixed (0.2, 0.3, 0.5) values (not variable as implied earlier)
  - Accounts for 15% of test cases

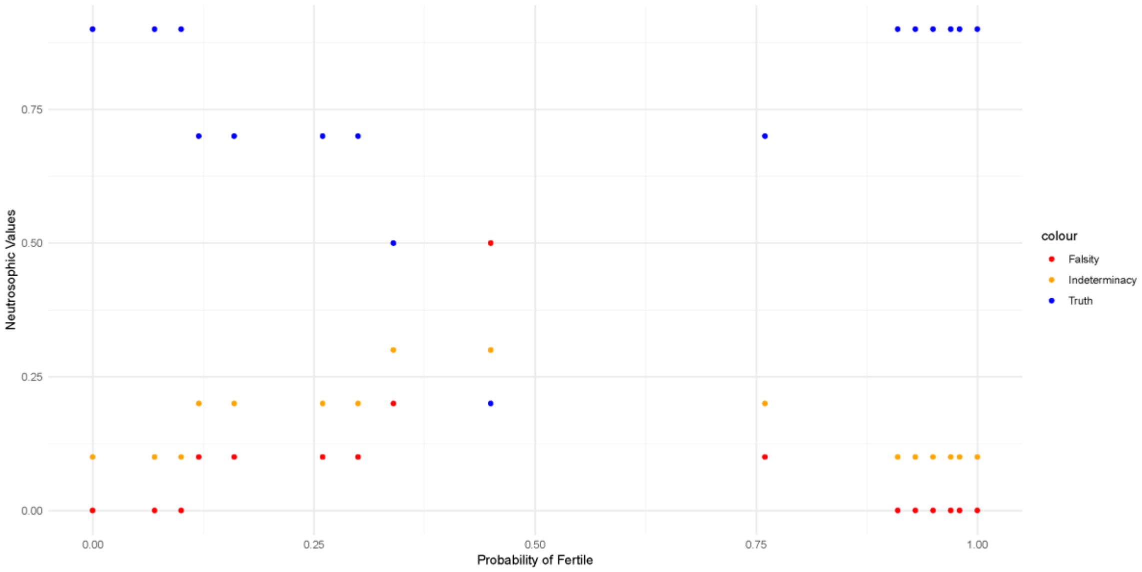


Figure 3. Prediction Confidence Spectrum mapped to neutrosophic (*T*, *I*, *F*) values.

Visualization of Figure 3 enables tiered decision-making:

- Automated actions for T = 0.9 predictions (32% of cases). In these cases, automated fertilization recommendations can be implemented with high reliability
- Expert review recommended when I = 0.3 (25%). In other words, these cases represent transitionary soil conditions requiring expert verification before intervention.
- Reject predictions with F = 0.5 (15%) due to high error likelihood. In other words, these cases refer to flag problematic samples for agronomist review, preventing costly misapplications of amendments.

This tripartite confidence stratification - unavailable in conventional binary classifiers - demonstrates how neutrosophic logic transforms raw probabilities into actionable agricultural intelligence while maintaining model transparency.

4. Conclusion

This study presents an effective integration of Random Forest with neutrosophic logic for soil fertility prediction, achieving 95% accuracy while providing nuanced uncertainty quantification through (T, I, F) values. The framework's ability to identify critical soil parameters (Clay, CEC, Mn) and classify predictions into confidence tiers offers practical advantages for precision agriculture, particularly in handling borderline cases through its indeterminacy (I) component. The results demonstrate that combining machine learning with neutrosophic logic can significantly enhance decision-support systems by moving beyond binary classifications to provide actionable confidence metrics. The code and dataset are available in [14].

Future work should explore fuzzy-neutrosophic hybrids for smoother classification boundaries and incorporate spatiotemporal analysis for regional fertility mapping. Additional improvements could include deep feature interaction analysis using SHAP values and optimization for real-time field deployment via edge computing. These enhancements would further bridge the gap between computational models and agricultural practice while maintaining the system's strengths in interpretability and uncertainty-aware decision making.

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