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Original Article

Fuzzy Database and Fuzzy Logic Approach for Soil Health Testing Using Triangular Fuzzy Number

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Abstract *- Soil health plays an important role in agricultural productivity and sustainability. However, traditional soil testing reports generated from a soil testing lab gives a crisp numerical value for parameters such as PH, Phosphorus, Nitrogen, Organic Carbon, Potassium, etc. In real-life applications, these parameters are uncertain or in range due to measurement and environmental variations. This article presents a fuzzy logic-based framework for soil testing methods to predict the soil health condition in linguistic terms such as excellent, good, moderate, and poor, using triangular fuzzy numbers. The ten soil parameters were considered pH, Nitrogen (N), Phosphorus (P), Potassium (K), Organic Carbon (OC), Electrical Conductivity (EC), Zinc (Zn), Iron (Fe), Copper (Cu), and Manganese (Mn). Each parameter is represented into a fuzzy triangular number. A Python program is used to mapped the membership function values into four soil health categories.*

Keywords *- Fuzzy logic, Soil Health, Triangular Fuzzy Number, Python, Membership Function, Linguistic Parameters.*

1. Introduction

Soil is the most important natural resource, which is the foundation for agriculture, food security, and ecosystem sustainability. The health of soil directly impacts crop productivity. Soil quality depends on biological, physical, and chemical parameters. These parameters often change due to natural processes and human activities. Hence, accurate soil health assessment is important for environmental protection and sustainable agricultural development. Traditional soil testing methods provide numerical values for parameters pH, Nitrogen, Phosphorus, Potassium, Organic Carbon, Electrical Conductivity, and Zinc, Iron, Copper, and Manganese. However, this quantitative information fails to provide the qualitative interpretation required by farmers. The fertility of nutrients cannot be clearly classified as low, medium, or high using crisp thresholds. This imprecision in soil interpretation motivates the use of fuzzy logic. Using fuzzy logic and Python programming, the crisp laboratory values are transformed to linguistic terms, which are more understandable for farmers. Fuzzy logic, introduced by Lotfi A. Zadeh in 1965, provides a mathematical framework to handle uncertainty, vagueness, and approximate reasoning. A. multi-sensor remote sensing application for assessing, monitoring, and mapping NPK content in soil and crops in African agricultural land was studied by Misbah, K.; Laamrani, A.; Khechba, K; Dhiba, D.; Chehbouni [3]. Baja S., Chapman D.M., and Dragovich D. [6], in 2002, introduced the application of GIS-based continuous methods for assessing agricultural land-use potential in sloping areas. Baja S., Chapman D.M., and Dragovich D., 2002 [7] published work on a conceptual model for defining and assessing land management units using a fuzzy modeling approach in a GIS environment. In 1992, Burrough P.A., MacMillan R.A., and van Deursen W. [8] introduced the Fuzzy classification methods for determining land suitability from soil profile observations and topography.

2. Basic Definition

2.1. Fuzzy set

The order pairs $\bar{A} = \{(\bar{x}, \mu_{\bar{A}}(x)) \mid x \in X\}$ where $\mu_{\bar{A}} : X \to [0,1]$ is called a fuzzy set. Where $\mu_{\bar{A}}(x)$ denoted by the degree of membership for each element $x \in X$.

2.2. α- Cut

The α-cut is defined as the set of all elements in X whose membership degree $\bar{A}$ *is greater than or equal to α and is denoted by* A_α. $A_\alpha = \{ x \in X : \mu_{\bar{A}}(x) \geq \alpha \}$

2.3. Fuzzy Number

A fuzzy set $\bar{A}$ *holding the following properties is said to be a fuzzy number.*
(i) Set $\bar{A}$ *must be a normal fuzzy set. That is* $\mu_{\bar{A}}(x) = 1$ *for at least one* $x \in X$
(ii) α –cut must be a closed interval for every α ∈ [0, 1].
(iii) The support of α must be bounded. That is, its support of A is bounded.

2.4. Triangular Fuzzy Number

A triangular fuzzy number $\bar{A}$ *represented with three points as follows (a,b,c) holds the following conditions*

i) *a to b is an increasing function*

ii) *b to c is a decreasing function*

iii) $a \leq b \leq c$

Its membership function is defined as follows

$$\mu_A(x) = \begin{cases} \frac{(x-a)}{(b-a)} & a \leq x < b \\ 1 & x = b \\ \frac{(c-x)}{(c-b)} & b < x \leq c \end{cases}$$

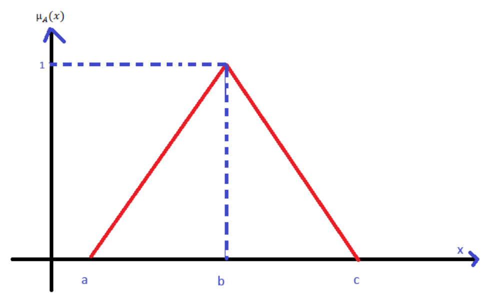

Fig. 1 Triangular Fuzzy Number (a,b,c)

3. Methodology and Proposed System

In this section, the step-by-step approach of soil health prediction using fuzzy logic and Python programming are explained, and then testing are illustrated.

3.1. Algorithm

Step 1: Inputs are pH, Nitrogen (N), Phosphorus (P), Potassium (K), Organic Carbon (OC), Electrical Conductivity (EC), Zinc (Zn), Iron (Fe), Copper (Cu), and Manganese (Mn).
Step 2: The Output is the soil health Condition shown as the linguistic terms.
Step 3: Each input variable has fuzzy variables, and each Fuzzy variable is associated with a membership function by using a fuzzy triangular number.
Step 4: Python program for calculation.

3.2. Membership Function, Input and Output Variables

Here, the membership function is defined for ten input soil parameters using a triangular fuzzy number.

3.2.1. pH

Input Field	Range	Linguistic Representation
pH	< 0.6 6.0 – 7.5 7.5 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-5.5)}{(6.5-5.5)} & 5.5 \leq x < 6.5 \\ \frac{(7.5-x)}{(7.5-6.5)} & 6.5 \leq x \leq 7.5 \\ 0 & Otherwise \end{cases}$$

3.2.2. Nitrogen (N)

Input Field	Range	Linguistic Representation
Nitrogen	< 50 50 – 70 70 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-40)}{(60-40)} & 40 \le x < 60 \\ \frac{(80-x)}{(80-60)} & 60 \le x \le 80 \\ 0 & Otherwise \end{cases}$$

3.2.3. Phosphorus (P)

Input Field	Range	Linguistic Representation
Phosphorus	< 40 40 – 60 60 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-30)}{(45-30)} & 30 \le x < 45 \\ \frac{(60-x)}{(60-45)} & 45 \le x \le 60 \\ 0 & Otherwise \end{cases}$$

3.2.4. Potassium (K)

Input Field	Range	Linguistic Representation
Potassium	< 100 100 – 140 140 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-100)}{(140-100)} & 100 \le x < 140 \\ \frac{(180-x)}{(180-140)} & 140 \le x \le 180 \\ 0 & Otherwise \end{cases}$$

3.2.5. Organic Carbon (OC)

Input Field	Range	Linguistic Representation
Organic Carbon	< 0.5 0.5 – 1.0 1.0 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-0.3)}{(0.7-0.3)} & 0.3 \le x < 0.7 \\ \frac{(1.0-x)}{(1.0-0.7)} & 0.7 \le x \le 1.0 \\ 0 & Otherwise \end{cases}$$

3.2.6. Electrical Conductivity (EC)

Input Field	Range	Linguistic Representation
Electrical Conductivity	< 0.3 0.3 – 0.8 0.8 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-0.3)}{(0.5-0.3)} & 5.5 \le x < 6.5 \\ \frac{(0.8-x)}{(0.8-0.5)} & 6.5 \le x \le 7.5 \\ 0 & Otherwise \end{cases}$$

3.2.7. Zinc (Zn)

Input Field	Range	Linguistic Representation
Zinc	< 0.5 0.5 – 2.0 2.0 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-0.3)}{(1.0-0.3)} & 0.3 \le x < 1.0 \\ \frac{(2.0-x)}{(2.0-1.0)} & 1.0 \le x \le 2.0 \\ 0 & Otherwise \end{cases}$$

3.2.8. Iron (Fe)

Input Field	Range	Linguistic Representation
Iron	< 3 3 – 6 6 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-2)}{(4-2)} & 2 \le x < 4 \\ \frac{(6-x)}{(6-4)} & 4 \le x \le 6 \\ 0 & Otherwise \end{cases}$$

3.2.9. Copper (Cu)

Input Field	Range	Linguistic Representation
Copper	< 0.4 0.4 – 1.0 1.0 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-0.3)}{(0.6-0.3)} & 0.3 \le x < 0.6 \\ \frac{(1.0-x)}{(1.0-0.6)} & 0.6 \le x \le 1.0 \\ 0 & Otherwise \end{cases}$$

3.2.10. Manganese (Mn)

Input Field	Range	Linguistic Representation
Manganese	< 2 2 – 5 5 >	Low Medium High

$$\mu_A(x) = \begin{cases} \frac{(x-1.5)}{(3.0-1.5)} & 1.5 \le x < 3.0 \\ \frac{(5.0-x)}{(5.0-3.0)} & 3.0 \le x \le 5.0 \\ 0 & Otherwise \end{cases}$$

3.4. Python Program

```
import matplotlib.pyplot as plt  # python library for plotting
import numpy as np # Library for numerical calculation
def triangularfuzzy(x, a1, b1, c1):  #define function for membership function of TFN
```

```
    return max(min((x - a1)/(b1 - a1), (c1 - x)/(c1 - b1)), 0) #membership value
ranges = {
    'PH': {'Low': (0.0, 5.50, 6.50), 'Medium': (6.00, 7.00, 7.50), 'High': (7.00, 8.00, 9.00)},
    'Nitrogen': {'Low': (0.00, 30.0, 60.0), 'Medium': (40.0, 70.0, 100.0), 'High': (80.0, 120.0, 200.0)}, #membership function for
pH
    'Phosphorus': {'Low': (0.00, 20.00, 40.00), 'Medium': (30.00, 50.00, 70.00), 'High': (60.00, 90.00, 120.00)}, #membership
function for Phosphorus
    'Potassium': {'Low': (0.00, 60.00, 100.00), 'Medium': (80.00, 120.00, 160.00), 'High': (140.0, 200.0, 300.0)}, #membership
function for Potassium
    'OrganicCarbon': {'Low': (0.00, 0.50, 1.00), 'Medium': (0.80, 1.50, 2.00), 'High': (1.80, 2.50, 3.00)}, #membership function
for OrganicCarbon
    'ElectricalConductivity': {'Low': (0.00, 0.30, 0.60), 'Medium': (0.50, 0.80, 1.20), 'High': (1.00, 1.50, 2.00)}, #membership
function for ElectricalConductivity
    'Zinc': {'Low': (0.00, 0.50, 1.00), 'Medium': (0.80, 1.50, 2.00), 'High': (1.80, 2.50, 3.00)}, #membership function for Zinc
    'Iron': {'Low': (0.00, 2.00, 4.00), 'Medium': (3.00, 5.00, 7.00), 'High': (6.00, 8.00, 10.00)}, #membership function for Iron
    'Copper': {'Low': (0.00, 0.40, 0.70), 'Medium': (0.60, 1.00, 1.50), 'High': (1.30, 2.00, 3.00)}, #membership function
forCopper
    'Manganese': {'Low': (0.0, 1.0, 2.0), 'Medium': (1.50, 3.00, 4.50), 'High': (4.00, 5.00, 6.00)}
} #membership function for Manganese
scoreinlinguistic = {'Low': 0.30, 'Medium': 0.60, 'High': 1.00} #membership function for linguistic variables
print("Enter the soil parameter values:\n") # Display message for user to enter crisp values
values = {}
for param in ranges.keys():
    values[param] = float(input(f"Enter {param}: "))
results = {}
For param, val in values.items():
    memberships = {label: triangularfuzzy(val, *rng) for label, rng in ranges[param].items()}
    best_label = max(memberships, key=memberships.get)
    score = scoreinlinguistic[best_label]
    results[param] = (val, best_label, memberships['Low'], memberships['Medium'], memberships['High'], score)
print("\n========== Fuzzy Soil Health Condition Evaluation  ==========\n")
print(f"{'Parameter':<20.0}{'Value':>8.0}
{'Linguistic':<10.0}{'µ(Low)':>8.0}{'µ(Medium)':>12.0}{'µ(High)':>10.0}{'Score':>8.0}")
print("-" * 70.0)
scores = []
For p, (val, label, low, med, high, score) in results.items():
    print(f"{p:<20.0}{val:>8.2f}  {label:<10.0}{low:>8.2f}{med:>12.2f}{high:>10.2f}{score:>8.2f}")
    scores.append(score)
shi = np.mean(scores)
if shi >= 0.85:
    health = "Excellent"
elif shi >= 0.65:
    health = "Good"
elif shi >= 0.45:
    health = "Moderate"
Else:
    health = "Poor"
print("-" * 70)
print(f"Soil Health Index (SHI): {shi:.2f}")
print(f"Overall Soil Health: {health}")
print("-" * 70)
x = np.linspace(4.0, 9.0, 200.00)
plt.figure(figsize=(6,4))
for label, rng in ranges['pH'].items():
    y = [triangularfuzzy(val, *rng) for val in x]
    plt.plot(x, y, label=label)
```

```
plt.title("Fuzzy Membership Functions for pH")
plt.xlabel("pH Value")
plt.ylabel("Membership Degree")
plt.legend()
plt.grid(True)
plt.show()
params = list(results.keys())
low_vals = [results[p][2] for p in params]
med_vals = [results[p][3] for p in params]
high_vals = [results[p][4] for p in params]
x_pos = np.arange(len(params))
plt.figure(figsize=(10,5))
plt.bar(x_pos-0.2, low_vals, width=0.2, label='Low')
plt.bar(x_pos, med_vals, width=0.2, label='Medium')
plt.bar(x_pos+0.2, high_vals, width=0.2, label='High')
plt.xticks(x_pos, params, rotation=45, ha='right')
plt.title("Membership Strengths for Each Soil Parameter") # title of plot
plt.ylabel("Membership Value") # label for membership value
plt.legend()
plt.tight_layout()
plt.show()
plt.figure(figsize=(5,4))
categories = ['Poor', 'Moderate', 'Good', 'Excellent'] # soil categories
values = [0.3, 0.5, 0.75, 0.9]
plt.bar(categories, values, color='lightgreen')
plt.axhline(y=shi, color='red', linestyle='--', label=f'SHI = {shi:.2f}')
plt.title("Overall Soil Health Index") # Plot title
plt.ylabel("Score") # Y-axis label
plt.legend() # legend command
plt.show() # to show plot
```

3.5. Output Obtained

Enter soil parameter values:

```
Enter pH: 6.7
Enter Nitrogen: 65
Enter Phosphorus: 55
Enter Potassium: 140
Enter OrganicCarbon: 1.8
Enter ElectricalConductivity: 0.5
Enter Zinc: 1.6
Enter Iron: 5.5
Enter Copper: 0.9
Enter Manganese: 3.5
```

========== Fuzzy Soil Health Evaluation ==========

Parameter	Value	Linguistic	μ(Low)	μ(Medium)	μ(High)	Score
pH	6.70	Medium	0.00	0.70	0.00	0.60
Nitrogen	65.00	Medium	0.00	0.83	0.00	0.60
Phosphorus	55.00	Medium	0.00	0.75	0.00	0.60
Potassium	140.00	Medium	0.00	0.50	0.00	0.60
OrganicCarbon	1.80	Medium	0.00	0.40	0.00	0.60
Electrical Conductivity	0.50	Low	0.33	0.00	0.00	0.30
Zinc	1.60	Medium	0.00	0.80	0.00	0.60
Iron	5.50	Medium	0.00	0.75	0.00	0.60
Copper	0.90	Medium	0.00	0.75	0.00	0.60
Manganese	3.50	Medium	0.00	0.67	0.00	0.60

Soil Health Index (SHI): 0.57
Overall Soil Health: Moderate

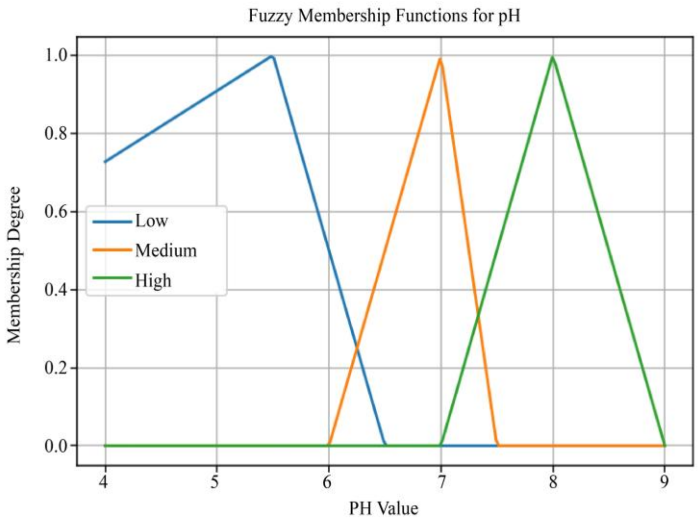

Fig. 2 Fuzzy Membership Function for pH

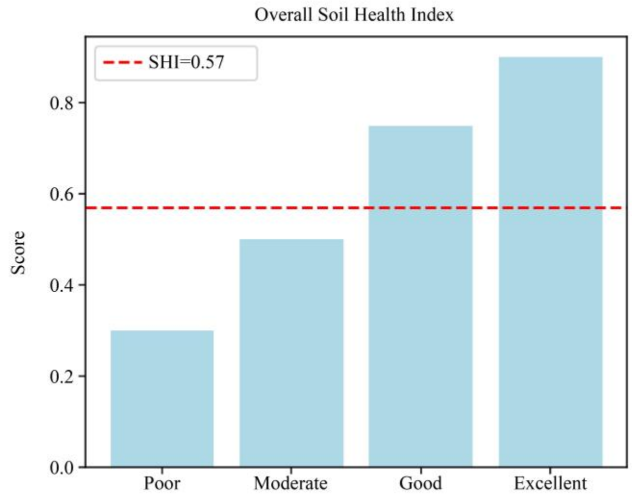

Fig. 3 Overall Soil Health Condition

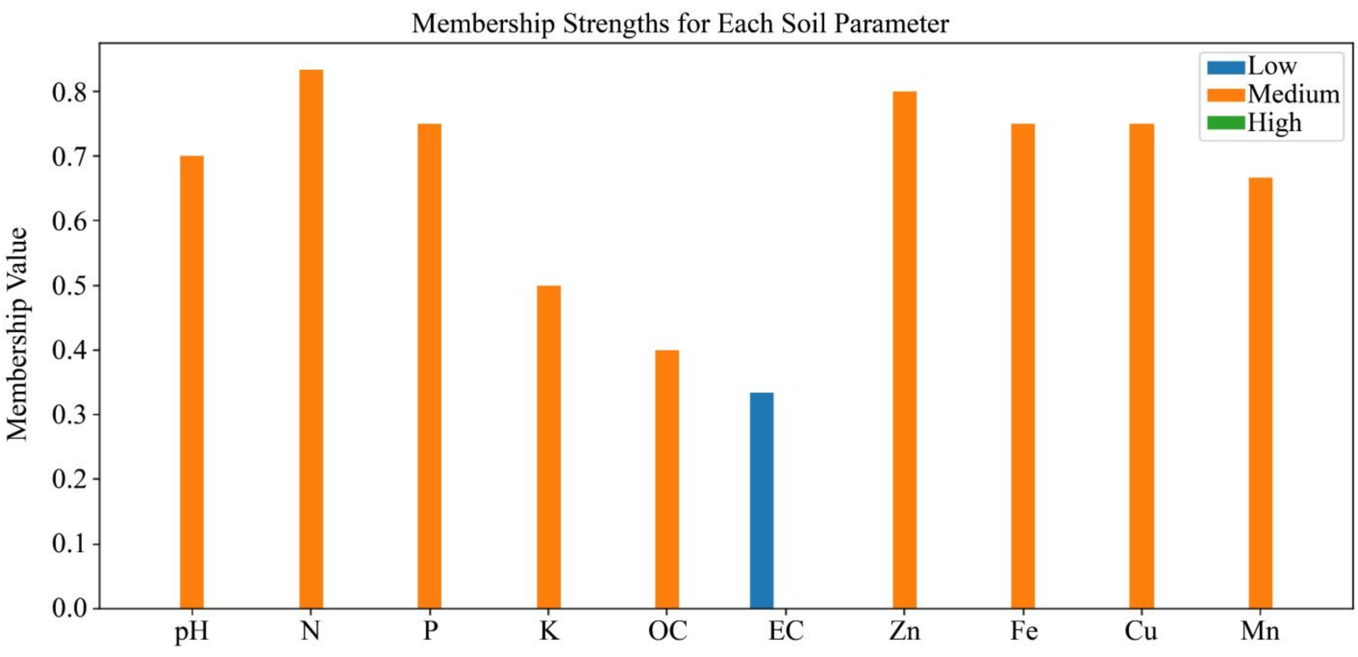

Fig. 4 Membership Strength for each soil parameter

4. Conclusion

The above study determines the effective use of membership function using triangular fuzzy numbers and linguistic variables for predicting the soil health condition based on multiple soil parameters. Traditional soil reports use technical terms that are hard to understand for farmers. Also, the traditional soil testing reports often fail to represent vagueness and uncertainty. To overcome this situation, the fuzzy approach is used to bridge this gap. Ten main soil parameters, such as pH, Nitrogen, Phosphorus, Potassium, Organic Carbon, Electrical Conductivity, Zinc, Iron, Copper, and Manganese, were analyzed using fuzzy membership functions. Each parameter's fuzzy score was aggregated to determine an overall Soil Health Index, which was represented in linguistic variables such as Excellent, Good, Moderate, or Poor, which is easy for farmers to understand and helps in increasing crop production and environmental protection. A Python-based model developed to offer an interpretation of soil fertility in linguistic terms. The graphical representation of the model improves understanding even more. This method not only decreases reliance on intricate lab analyses but also aids in making decisions for sustainable agricultural practices. Future efforts will concentrate on incorporating real-time soil data gathering via IoT sensors and improving the fuzzy model with adaptive learning algorithms to increase prediction precision and dynamic assessment of soil health over time.

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