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Analysing Rice Productivity in India using a Fuzzy Logic Model based on Soil Quality Parameters

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ABSTRACT

This study integrates fuzzy logic modelling to evaluate the nonlinear interactions of soil quality parameters (i.e., soil pH, organic matter, moisture, and nutrient levels) on rice productivity across diverse agro-climatic regions of India, offering improved accuracy over conventional yield prediction models. Membership functions are developed using empirical field data and expert knowledge. The fuzzy inference system, including fuzzification and rule bases, is implemented using MATLAB. Fuzzy surface analyses identify optimal productivity ranges, particularly at pH levels of 5.0–7.5 and organic matter between 0.5% and 2.5%, supporting the application of sustainable soil management practices. Additional surface analyses involving interactions (such as soil pH–moisture and nutrient–moisture) confirm the model's validity, with predicted yields aligning closely with actual agricultural data. Sensitivity analysis indicates that soil pH and nutrient levels have the greatest impact on rice yields, while organic matter has more influence when considered in combination with other factors. The model identifies critical soil factors and provides practical guidance for applying sustainable interventions (such as organic fertilization, efficient irrigation, and crop rotation). It serves as a decision-support tool for policymakers, agricultural planners, and farmers, enabling data-driven, ecologically sound strategies to improve rice productivity and support long-term food security.

1. Introduction

India is the second-largest producer of rice in the world, and rice is the staple food crop of the country. According to the Food and Agriculture Organization (FAO), India produced 116.42 million tonnes of rice in 2020. However, the yield of rice in India is still low compared to other countries due to several factors, including soil quality. Soil pH is a critical factor that affects the availability of nutrients for rice plants. The optimum soil pH for rice cultivation is around 6.5. In India, the soil pH varies from state to state, with some states having acidic soils and others having alkaline soils. Soil organic matter (SOM) is another essential factor that influences rice productivity. SOM is the organic

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material in the soil that results from the decomposition of plant and animal residues. It plays a crucial role in maintaining soil health and fertility, as it improves soil structure, water-holding capacity, and nutrient availability. The SOM content in Indian soils ranges from less than 0.5% in some states to more than 2% in others. Soil moisture is an essential factor that affects rice productivity as it influences nutrient availability and plant growth. The availability of soil moisture depends on several factors, including rainfall, irrigation, and soil properties. In India, the distribution of rainfall varies significantly from state to state, with some states receiving high rainfall, while others receive low rainfall. Nutrient levels, including nitrogen, phosphorus, and potassium, are also critical factors that influence rice productivity. The availability of nutrients in the soil depends on various factors, including soil pH, SOM, and soil moisture. In India, the nutrient levels in the soil vary significantly from state to state, with some states having high nutrient levels and others having low nutrient levels.

Numerous studies have explored the integration of fuzzy logic in agricultural forecasting to manage uncertainty and improve predictive accuracy. Singh [1] introduced a simplified fuzzy time series method that addressed data imprecision while reducing computational complexity, demonstrating effectiveness in applications such as university enrollments and rice production. Duru *et al.* [2] applied fuzzy logic to soil productivity assessment, achieving high accuracy by focusing on critical parameters such as pH and organic matter content. In the domain of crop yield forecasting, Kumar [3] employed the adaptive neuro-fuzzy inference system (ANFIS) to relate climatic variables to rice yields, while Jayaram *et al.* [4] used fuzzy inference systems to predict sorghum yield, emphasizing the importance of granular membership functions. Kumar & Kumar [5] enhanced fuzzy time series techniques for agricultural forecasting and inventory management, addressing uncertainty in rice yield estimation through innovative methods. Garg & Garg [6] improved forecasting accuracy by incorporating percentage change and regression-based defuzzification, and suggested future integration with multidimensional datasets and genetic algorithms. Rana [7,8] reaffirmed the reliability of fuzzy models for rice production forecasting, proposing refined defuzzification methods. Similarly, Garg & Sah [9] as well as Garg *et al.* [10] applied hybrid fuzzy-ANN models to address challenges related to global food demand. Concurrently, Kumar and Sanyal [11], Daniel *et al.* [12], and Senthamarai *et al.* [13] highlighted the synergy between fuzzy logic, neural networks, and regression techniques in enhancing crop yield predictions and supporting farm management decisions. In broader agricultural productivity research, Das [14] proposed a fuzzy-based algorithm for solving geometric programming problems. Several foundational works collectively inform the present study, particularly the contributions of Mondal & Dolai [15], Dolai & Mondal [16-18], which offer critical insights into agricultural dynamics and support the development of a localized, adaptive fuzzy logic-based solution for managing the nonlinearities and uncertainties inherent in agricultural systems.

This study aims to assess the impact of soil quality factors on rice productivity in India, develop a fuzzy logic-based model to analyze these relationships, and recommend sustainable soil management practices to enhance productivity and food security.

2. Membership Formulation

The relationship between soil quality factors and rice productivity is assessed using fuzzy set theory, formulated as a fuzzy inference system. In this system, each soil quality factor (e.g., soil pH, SOM, soil moisture, and nutrient levels) is represented as a fuzzy set, enabling the incorporation of uncertainty and imprecision. Membership functions, derived from field measurements or expert knowledge, define the inputs for each soil quality factor. By applying fuzzy logic-based rules, the system processes these inputs to generate predictions or decisions regarding rice productivity, offering a robust framework for handling complex, imprecise data.

To begin with, for soil pH, the linguistic variables are categorized as "acidic," "neutral," and "alkaline," corresponding to the membership functions: "Low" for acidic, "Normal" for neutral, and "High" for alkaline. In Figure 1, x represents the input value for soil pH, while $\mu(x)$signifies the degree of membership of x within a specific linguistic category. This membership degree ranges from 0 to 1, indicating the extent to which the input value belongs to a particular fuzzy set. The trapezoidal membership functions for soil pH are classified into three categories: Low, Normal, and High, spanning pH values from 0 to 9. Notably, the "Normal" category reaches full membership between pH values of 4.5 and 7, which is widely recognized as optimal for rice cultivation.

$$\mu_{Low}(x) = \begin{cases} 0, & x \leq 3 \\ \frac{x-3}{3.5-3}, & 3 < x < 3.5 \\ 1, & 3.5 \leq x \leq 4.5 \\ \frac{5-x}{5-4.5}, & 4.5 < x < 5 \\ 0, & x \geq 5 \end{cases}$$

$$\mu_{Normal}(x) = \begin{cases} 0, & x \leq 4.5 \\ \frac{x-4.5}{5.5-4.5}, & 4.5 < x < 5.5 \\ 1, & 5.5 \leq x \leq 6.5 \\ \frac{7-x}{7-6.5}, & 6.5 < x < 7 \\ 0, & x \geq 7 \end{cases}$$

$$\mu_{High}(x) = \begin{cases} 0, & x \leq 6.5 \\ \frac{x-6.5}{7.5-6.5}, & 6.5 < x < 7.5 \\ 1, & 7.5 \leq x \leq 8 \\ \frac{8.5-x}{8.5-8}, & 8 < x < 8.5 \\ 0, & x \geq 8.5 \end{cases}$$

Fig. 1. Trapezoidal membership functions for input soil pH

Furthermore, in Figure 2, x represents the input value for SOM content (percentage), and $\mu(x)$denotes the degree of membership of x within a particular linguistic category. This degree ranges from 0 to 1, reflecting how strongly the input value aligns with the respective fuzzy set. The trapezoidal membership functions for SOM are divided into three categories: Low, Medium, and High, spanning values from 0 to 4. Importantly, the "Medium" category achieves full membership between SOM values of 1 and 2.5, signifying the ideal range for preserving soil fertility and supporting optimal crop growth under Indian agricultural conditions.

$$\mu_{Low}(x) = \begin{cases} 0, & x \geq 1.5 \\ \frac{x-0}{0.5-0}, & 0 < x < 0.5 \\ 1, & 0.5 \leq x \leq 1 \\ \frac{1.5-x}{1.5-1}, & 1 < x < 1.5 \end{cases}$$

$$\mu_{Medium}(x) = \begin{cases} 0, & x \leq 1 \text{ or } x \geq 2.5 \\ \frac{x-1}{1.5-1}, & 1 < x < 1.5 \\ 1, & 1.5 \leq x \leq 2 \\ \frac{2.5-x}{2.5-2}, & 2 < x < 2.5 \end{cases}$$

$$\mu_{High}(x) = \begin{cases} 0, & x \leq 2 \\ \frac{x-2}{2.5-2}, & 2 < x < 2.5 \\ 1, & 2.5 \leq x \leq 3 \\ \frac{3.5-x}{3.5-3}, & 3 < x < 3.5 \\ 0, & x \geq 3.5 \end{cases}$$

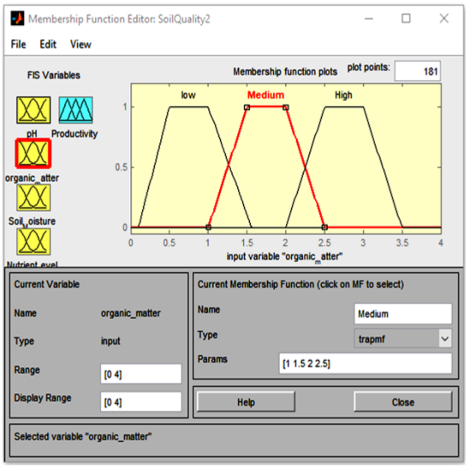

Fig. 2. Trapezoidal membership functions for input soil organic matter

In addition, Figure 3 illustrates the membership functions for Soil Moisture, where x denotes the input value (percentage), and $\mu(x)$ reflects the degree of membership within a defined fuzzy set. This membership degree, ranging from 0 to 1, indicates how well the input value fits into each linguistic category. The trapezoidal membership functions for soil moisture are divided into Low, Medium, and High categories, covering values from 0 to 60. Significantly, the "Medium" category reaches full membership between soil moisture levels of 30 and 45, representing the optimal moisture range essential for healthy rice growth in Indian farming environments.

$$\mu_{Low}(x) = \begin{cases} 0, & x \geq 35 \\ \dfrac{x - 10}{20 - 10}, & 10 < x < 20 \\ 1, & 20 \leq x \leq 30 \\ \dfrac{35 - x}{35 - 30}, & 30 < x < 35 \end{cases}$$

$$\mu_{Medium}(x) = \begin{cases} 0, & x \leq 30 \; or \; x \geq 45 \\ \dfrac{x - 30}{35 - 30}, & 30 < x < 35 \\ 1, & 35 \leq x \leq 40 \\ \dfrac{45 - x}{45 - 40}, & 40 < x < 45 \end{cases}$$

$$\mu_{High}(x) = \begin{cases} 0, & x \leq 40 \\ \dfrac{x - 40}{45 - 40}, & 40 < x < 45 \\ 1, & 45 \leq x \leq 50 \\ \dfrac{55 - x}{55 - 50}, & 50 < x < 55 \\ 0, & x \geq 55 \end{cases}$$

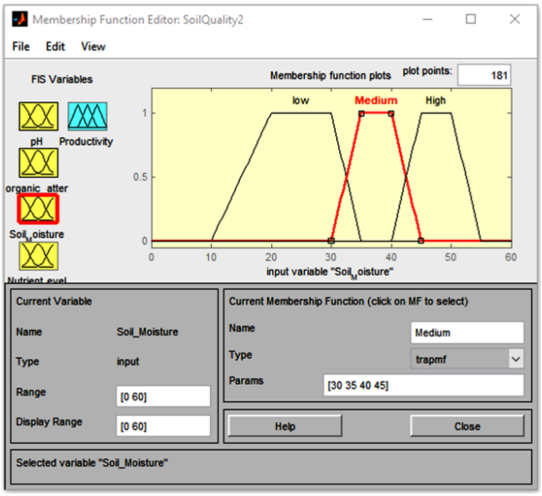

Fig. 3. Trapezoidal membership functions for input soil moisture

Moreover, in Figure 4, x signifies the input value for Nutrient Level (measured in appropriate units), and $\mu(x)$ represents the degree of membership of x within a given linguistic category. This degree ranges from 0 to 1, indicating how closely the input value matches a specific fuzzy set. The trapezoidal membership functions for nutrient levels are classified into Low Nutrient Level, Medium Nutrient Level, and High Nutrient Level, spanning values from 0 to 475. Specifically, the "Medium Nutrient Level" category achieves full membership between nutrient values of 275 and 400, highlighting the optimal nutrient range for balanced soil fertility, which is vital for improving crop yields in Indian agricultural practices.

$$\mu_{Low}(x) = \begin{cases} 0, & x \geq 300 \\ \dfrac{x - 150}{200 - 150}, & 150 < x < 200 \\ 1, & 200 \leq x \leq 275 \\ \dfrac{300 - x}{300 - 275}, & 275 < x < 300 \end{cases}$$

$$\mu_{Medium}(x) = \begin{cases} 0, & x \leq 275 \; or \; x \geq 400 \\ \dfrac{x - 275}{300 - 275}, & 275 < x < 300 \\ 1, & 300 \leq x \leq 375 \\ \dfrac{400 - x}{400 - 375}, & 375 < x < 400 \end{cases}$$

$$\mu_{High}(x) = \begin{cases} 0, & x \leq 375 \\ \dfrac{x - 375}{400 - 375}, & 375 < x < 400 \\ 1, & 400 \leq x \leq 450 \\ \dfrac{475 - x}{475 - 450}, & 450 < x < 475 \\ 0, & x \geq 475 \end{cases}$$

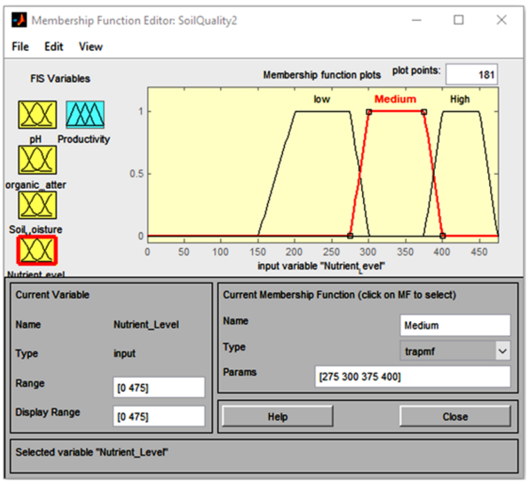

Fig. 4. Trapezoidal membership functions for input nutrient level

Lastly, in Figure 5, x denotes the input value for Rice Productivity (measured in kg/ha), while $\mu(x)$ expresses the degree of membership of x within the corresponding linguistic category. This degree ranges from 0 to 1, showing how strongly the input value belongs to the respective fuzzy set. The trapezoidal membership functions for rice productivity are divided into three fuzzy sets: Low Rice Productivity, Medium Rice Productivity, and High Rice Productivity, spanning values from 0 to 5000 kg/ha. Notably, the "Medium Rice Productivity" category reaches full membership between 2000 and 4000 kg/ha, reflecting the optimal yield range for sustainable rice cultivation in Indian agricultural systems.

$$\mu_{Low}(x) = \begin{cases} 0, & x \geq 2000 \\ \dfrac{x - 1000}{1500 - 1000}, & 1000 < x < 1500 \\ 1, & 1500 \leq x \leq 2000 \\ \dfrac{2500 - x}{2500 - 2000}, & 2000 < x < 2500 \end{cases}$$

$$\mu_{Medium}(x) = \begin{cases} 0, & x \leq 2000 \; or \; x \geq 4000 \\ \dfrac{x - 2000}{2500 - 2000}, & 2000 < x < 2500 \\ 1, & 2500 \leq x \leq 3500 \\ \dfrac{4000 - x}{4000 - 3500}, & 3500 < x < 4000 \end{cases}$$

$$\mu_{High}(x) = \begin{cases} 0, & x \leq 3500 \\ \dfrac{x - 3500}{4000 - 3500}, & 3500 < x < 4000 \\ 1, & 4000 \leq x \leq 4500 \\ \dfrac{5000 - x}{5000 - 4500}, & 4500 < x < 5000 \\ 0, & x \geq 5000 \end{cases}$$

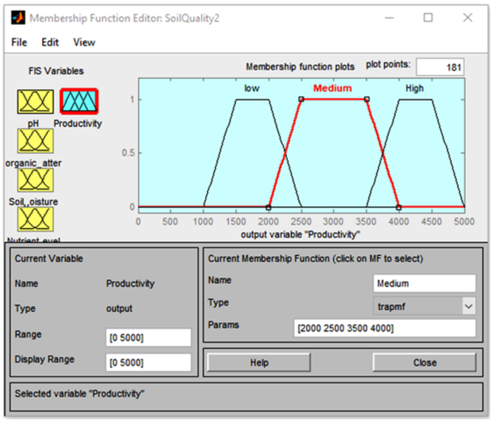

Fig. 5. Trapezoidal membership functions for output rice productivity

3. Methodology

The methodology for building a fuzzy logic system for prediction involves several key steps. First, the input variables and their corresponding fuzzy sets are defined. Let $X = \{X_1, X_2, \ldots, X_n\}$ represent the set of input variables, and $A_i = \{a_{i1}, a_{i2}, \ldots, a_{in}\}$ denote the fuzzy set for each input variable X_i, where p_i is the number of membership grades for X_i. Next, the output variable and its fuzzy set are established, with Y as the output variable and $B = \{b_1, b_2, \ldots, b_q\}$ as its fuzzy set, where q is the number of membership grades for Y. Subsequently, a set of fuzzy rules is formulated to relate the input variables to the output variable. This rule set $R = \{R_1, R_2, \ldots, R_m\}$ consists of rules in the form: "If X_1 is A_{i1} and X_2 is A_{i2} and ... and X_n is A_{in}, then Y *is* B_j", where $A_{i1}, A_{i2}, \ldots, A_{in}$ and B_j are the fuzzy sets for X_i and Y, respectively.

Fuzzy logic inference is then used to combine the fuzzy sets of the input variables and apply the fuzzy rules to derive a fuzzy set for the output variable. The degree of support for each rule R_i is calculated as:

$$\boldsymbol{\alpha_{i,j} = \min(u_{i,j})}, \tag{1}$$

where $u_{i,j}$ is the degree of membership of X_i in A_i. The degree of support for the output fuzzy set B_j is calculated as:

$$\boldsymbol{\beta j = max(\alpha_{i,j})}, \tag{2}$$

and the degree of membership of Y in B_j is then calculated as:

$$\boldsymbol{\mu_Y(B_j) = \beta_j}. \tag{3}$$

Finally, defuzzification is performed to obtain a crisp output value. This is achieved by calculating $\frac{(\Sigma j \mu_Y(B_j) * z_j)}{\Sigma j \; \mu Y(B_j)}$, where z_j is the representative value for the *j*-th membership grade of Y in B.

4. Dataset

Various research studies, government reports, and soil survey databases were used to construct the model and develop the membership functions. Key sources include the Soil Fertility Maps of India published by the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP), Nagpur, India; the Soil Health Card Portal maintained by the Ministry of Agriculture and Farmers' Welfare, Government of India; State-wise Soil Health Status Reports published by the Indian Council of Agricultural Research (ICAR); the Indian Institute of Soil Science (IISS) in Bhopal, India; and the Directorate of Rice Development, Government of India. Additionally, real data is required to validate and refine the model. For this purpose, data has also been obtained from various websites such as www.drought.gov, bhuvan-app3.nrsc.gov.in, www.gsi.gov.in, www.fao.org, and soilgrids.org.

5. Results and Discussion

This proposed model is highly organized, optimized, and precise. Using MATLAB, it incorporates five key soil quality parameters—soil pH, organic matter, moisture, and nutrient levels—offering a more comprehensive approach compared to other models that utilize different parameters. Designed to establish a reliable data framework based on a Fuzzy Inference System, the model effectively analyzes complex relationships. The fuzzy surface provides a clear visual representation of the interactions between the input variables (soil pH, soil organic matter, soil moisture, and nutrient levels) and the output variable (rice productivity). By examining this surface, critical zones—such as peak regions where rice productivity is maximized—can be identified, leading to a deeper understanding of system behavior and enabling more accurate predictions of future rice productivity.

The color gradients on the fuzzy surface enhance the visualization by distinguishing different productivity levels, making it easier to interpret the impact of each soil factor on rice yield. Warmer colors (such as yellow and red) typically highlight regions of higher productivity, while cooler colors (such as blue and green) indicate lower productivity zones. This multidimensional representation allows for a more intuitive analysis of how the interaction between soil pH, organic matter, moisture, and nutrient levels collectively influences rice production.

In Figure 6(a), the relationship "$f(soil\ pH\ \&\ soil\ moisture) \rightarrow rice\ productivity$" illustrates how variations in soil pH and soil moisture significantly influence rice productivity. For optimal rice cultivation in India, the preferred soil pH typically ranges from 5.0 to 7.5, favoring slightly acidic to neutral conditions, which support nutrient availability and root development. Additionally, soil moisture plays a crucial role, as rice is commonly cultivated in flooded or saturated soils that can effectively retain water. This consistent moisture is especially vital during the germination and early growth stages, ensuring steady nutrient uptake and healthy plant growth. The fuzzy surface plot indicates that rice productivity tends to improve when the soil pH is maintained between 5.0 and 7.0, coupled with soil moisture levels exceeding 35%. These conditions create an optimal environment for rice plants, enhancing yield potential. However, it is important to recognize that these ideal parameters may vary depending on the specific rice variety, regional climate variations, and local soil characteristics. Tailoring soil management practices to these dynamic factors can further optimize rice production, ensuring sustainable and efficient agricultural outcomes.

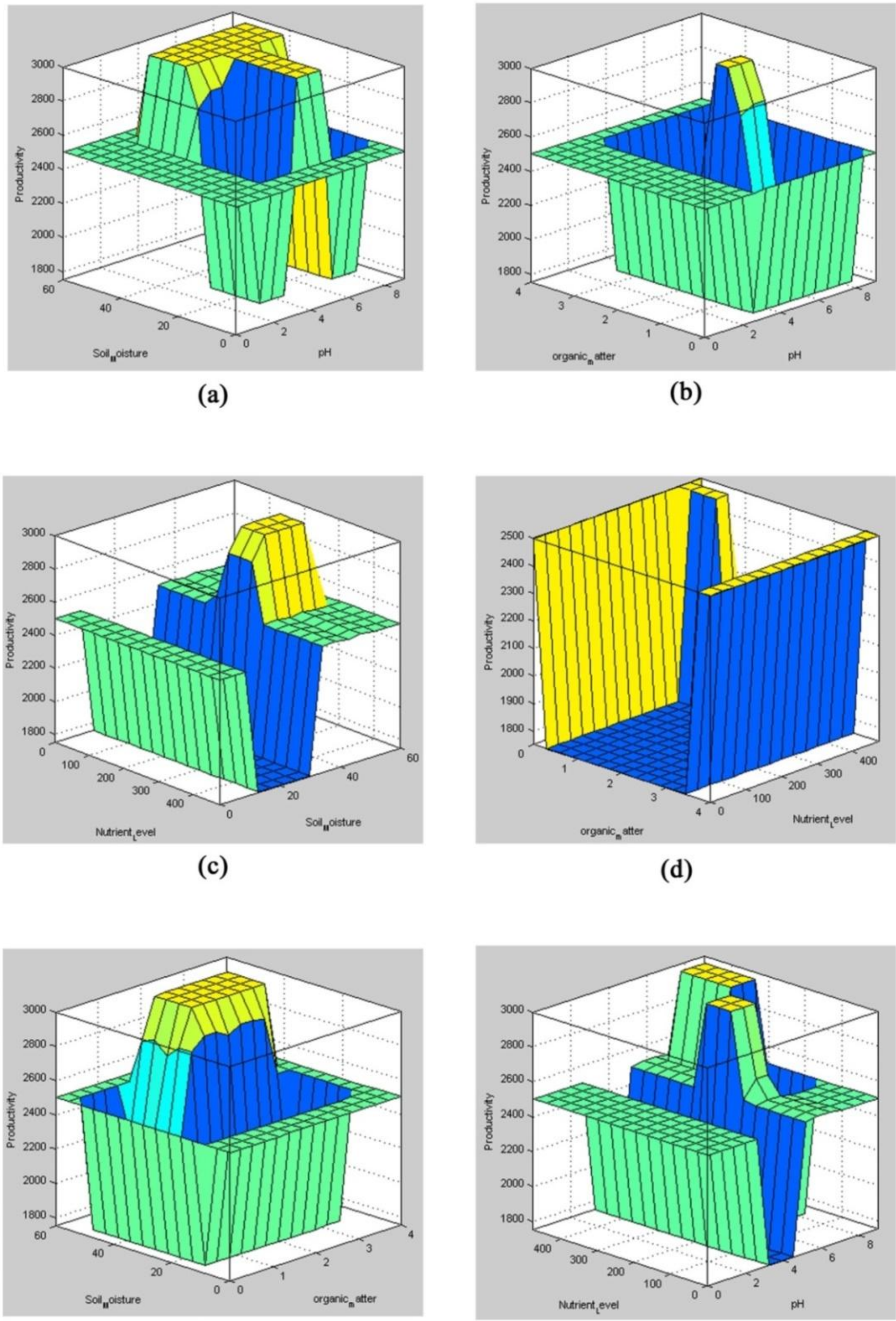

Fig. 6. Surface Plots of Rice Productivity based on various soil quality factors: (a) Soil pH and soil moisture, (b) Soil pH and soil organic matter, (c) Nutrient levels and soil moisture, (d) Soil organic matter and nutrient levels, (e) Soil moisture and soil organic matter, and (f) Nutrient levels and soil pH.

Figure 6(b) effectively captures the intricate relationship between soil pH, soil organic matter, and rice productivity, expressed through the function $f(soil\ pH\ \&\ soil\ organic\ matter) \rightarrow rice\ productivity$. Rice cultivation generally thrives in soils with a pH range of 5.0 to 7.5, where slightly acidic to neutral conditions enhance nutrient availability and microbial activity, although it can tolerate pH levels as low as 4.5, which are less favorable for optimal yield. Additionally, soil organic matter is a critical factor in maintaining soil fertility, with a recommended minimum content of 1–1.5% for productive rice growth in India; however, this is often difficult to achieve in regions with poor soil health or where intensive farming has led to degradation. The figure highlights that rice productivity remains favorable when soil organic matter ranges between 0.5% and 2.5%, a level commonly observed across major rice-growing regions in India. Variations in soil organic matter can result from differences in soil type, management practices, and land use history, emphasizing the need for sustainable agricultural practices such as organic amendments, crop rotation, and reduced soil disturbance to improve soil health and maximize rice productivity.

Figure 6(c) illustrates the dynamic relationship between nutrient levels and soil moisture and their combined impact on rice productivity, expressed through the function $f(nutrient\ levels\ \&\ soil\ moisture)\ \rightarrow\ rice\ productivity$. This figure provides valuable insights into how varying nutrient concentrations and soil moisture levels influence rice yield, offering practical guidance for optimizing fertilization and irrigation strategies. In general, the essential nutrient requirements for rice cultivation in India typically include 80–120 kg/ha of nitrogen (N), 30–40 kg/ha of phosphorus (P), and 20–30 kg/ha of potassium (K), although these values may vary based on soil type, climate, and rice variety. For optimal soil moisture, rice thrives in conditions where soil moisture is maintained at 35–40% field capacity, ensuring consistent water availability during critical growth stages. The figure highlights that rice productivity significantly improves when nutrient levels exceed 150 kg/ha and soil moisture remains above 30%, reflecting a positive correlation between these factors and yield. However, this relationship is not indefinite; while increased nutrient and moisture levels enhance productivity up to a threshold, excessive application may lead to diminishing returns or even adverse effects on crop health and environmental sustainability.

Furthermore, Figure 6(d) highlights the intricate relationship between soil organic matter and nutrient levels and their combined influence on rice productivity, represented by the function $f(soil\ organic\ matter\ \&\ nutrient\ levels)\ \rightarrow\ rice\ productivity$. This relationship emphasizes the critical role of soil organic matter in enhancing soil fertility and facilitating effective nutrient cycling, both of which are fundamental for sustaining healthy rice growth. Higher levels of organic matter enrich the soil with essential nutrients, improving its structure, water-holding capacity, and microbial activity, all of which contribute to increased nutrient availability for rice plants. Consequently, soils with elevated organic matter typically exhibit higher nutrient content, directly supporting optimal rice yields. To achieve and maintain this balance, farmers are encouraged to integrate organic amendments such as crop residues, animal manure, and compost into their soil management practices.

Additionally, Figure 6(e) illustrates the dynamic relationship between soil moisture and soil organic matter levels and their combined impact on rice productivity, represented by the function $f(soil\ moisture\ \&\ soil\ organic\ matter)\ \rightarrow\ rice\ productivity$. This relationship highlights the critical synergy between these two factors in supporting healthy rice growth. Soil organic matter significantly enhances the soil's water-holding capacity, improves soil structure, and increases nutrient availability, creating a more resilient environment for crop development. Simultaneously, adequate soil moisture is vital for the decomposition of organic matter and the subsequent release of nutrients essential for plant growth. A well-maintained balance between soil moisture and organic matter not only promotes optimal rice productivity but also contributes to the long-term sustainability of agricultural practices.

Finally, Figure 6(f) illustrates the critical relationship between nutrient levels and soil pH and their combined influence on rice productivity, represented by the function $f(nutrient\ levels\ \&\ pH)\ \rightarrow\ rice\ productivity$. This relationship highlights how variations in soil pH directly impact nutrient availability, while nutrient applications can, in turn, influence the soil's pH balance. For optimal rice growth, maintaining an appropriate pH range (typically 5.0 to 7.5) is essential, as extreme pH levels can hinder the uptake of key nutrients like nitrogen, phosphorus, and potassium. Similarly, imbalanced nutrient levels may alter soil pH, disrupting the soil's chemical equilibrium and reducing productivity. To address this, adopting integrated nutrient management (INM) strategies—blending organic amendments (such as compost and green manure) with inorganic fertilizers—is vital for sustaining soil health and achieving higher rice yields.

6. Validation and Refinement of the Model

To ensure the accuracy and reliability of the proposed model, it is essential to validate and refine it using real-world data collected from various states across India. However, given the country's vast geographical diversity and varying agricultural practices, gathering comprehensive data from all regions may not always be practical. In such instances, using averaged or representative data becomes a necessary approach. It is crucial to recognize that soil quality factors exhibit complex and dynamic interactions, where even minor changes in one factor can significantly influence others. Therefore, during the model validation process, it is assumed that all other influencing factors are maintained under standard conditions to accurately assess the model's performance.

For instance, the state of West Bengal, a key rice-producing region in India, exhibits diverse soil conditions across its districts, providing a comprehensive basis for validating the proposed model (see Figure 7).

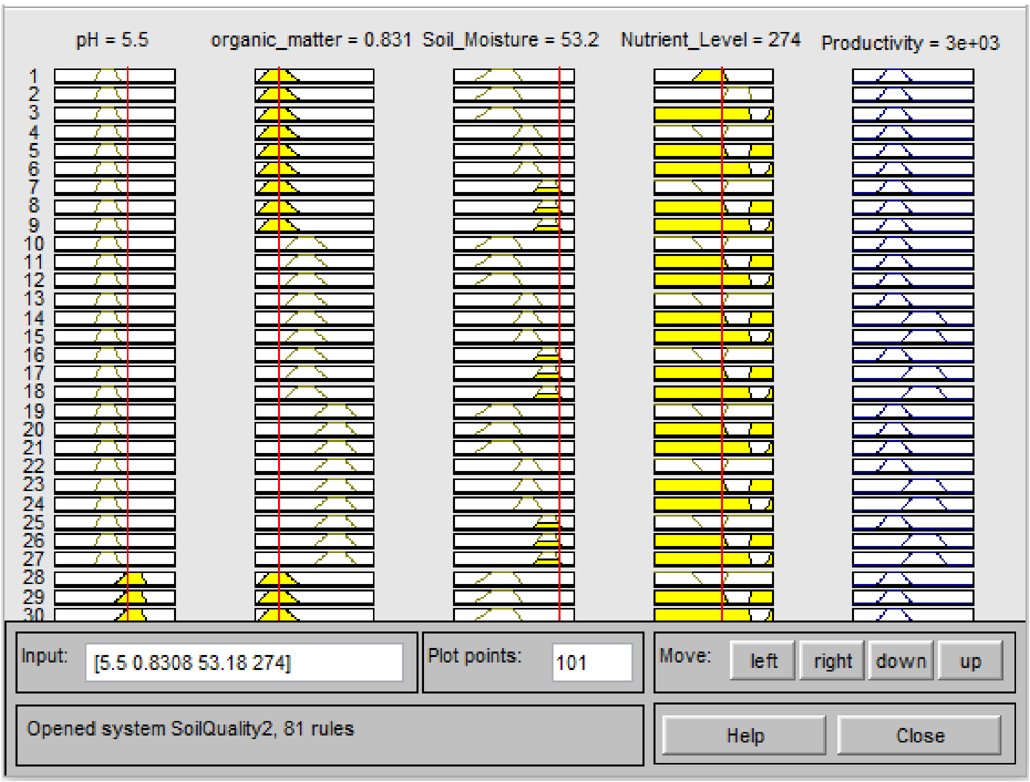

Fig. 7. Fuzzy inference system output for rice productivity with input parameters *soil pH* = 5.5, *organic matter* = 0.8308%, *soil moisture* = 53.18%, *nutrient level* = 274 kg/ha.

In Darjeeling, the average soil pH ranges from 4.32 to 5.28 [19], while in Medinipur, it varies from 5.32 to 6.91 [20]. The soil organic matter content spans from 0.63% to 0.72% in Darjeeling and 0.33% to 0.57% in Medinipur. Additionally, soil moisture levels range from 61.53% to 76.92% in Darjeeling and 55.5% to 61.5% in Medinipur [21]. The state's average nutrient level is approximately 274 kg/ha. In the year 2019–20, the recorded rice productivity in West Bengal was 2926 kg/ha. By inputting the average values—soil pH of 5.5, soil organic matter of 0.83%, soil moisture of 53.2%, and nutrient level of 274 kg/ha—into the proposed model, the predicted rice productivity is 3000 kg/ha. This close alignment with the actual productivity confirms the model's robustness and its applicability in accurately predicting rice yields under varying soil conditions in West Bengal (see Figure 7).

Furthermore, raising the soil organic matter by 10%, from 0.83% to 1.23%, while keeping other factors constant, maintains the predicted rice productivity at 3000 kg/ha. Although the model does not reflect a significant yield increase in this case, it emphasizes the need for integrated soil management practices that consider the complex interactions among soil properties.

Similarly, analyzing the state of Bihar provides further validation for the model. Bihar's agricultural landscape presents a diverse range of soil conditions, with soil pH varying from 5.5 to 9.5 [22] and soil organic matter content between 0.42% and 0.51% [23]. Soil moisture levels typically range from 25% to 35%, while nutrient levels fall between 90.97 to 159.16 kg/ha [23]. The average rice productivity in Bihar for the year 2019–20 was recorded at 2182 kg/ha. By inputting the average values—soil pH of 6.89, soil organic matter at 0.523%, soil moisture at 30.4%, and nutrient level at 157 kg/ha—into the proposed model, the predicted rice productivity is 2190 kg/ha. This close alignment with actual data validates the model's accuracy in predicting rice productivity under Bihar's prevailing soil conditions (see Figure 8).

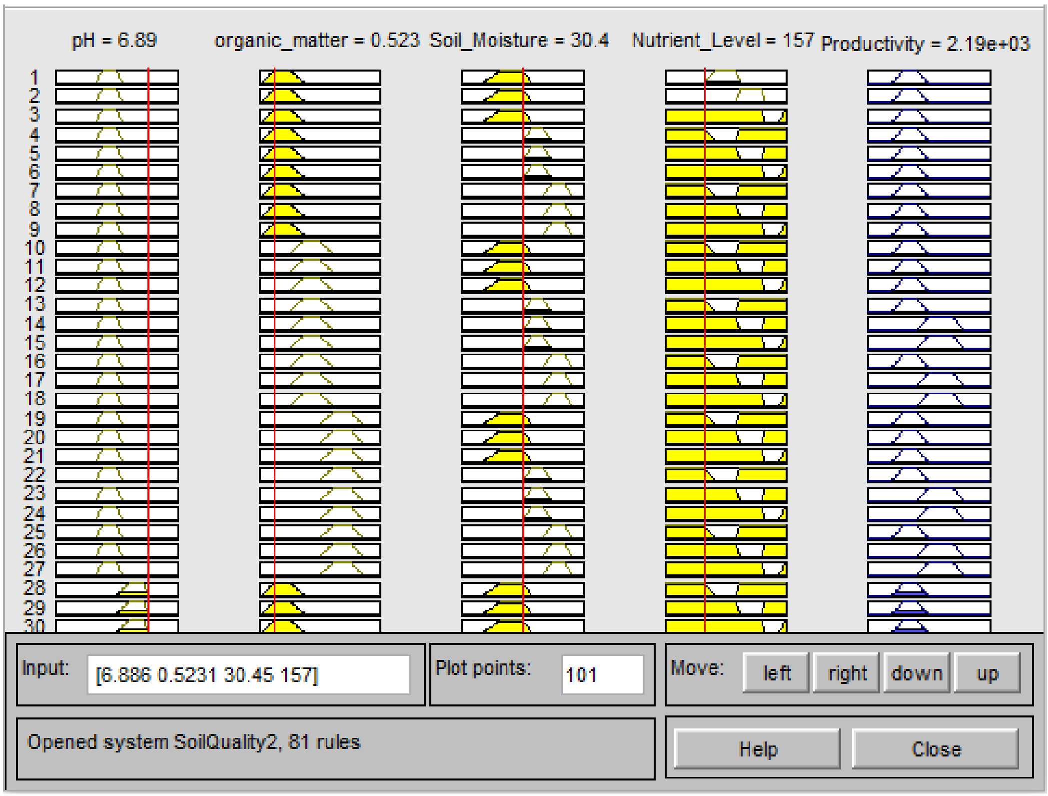

Fig. 8. Fuzzy inference system output for rice productivity with input parameters *soil pH* = 6.886, *organic matter* = 0.5231%, *soil moisture* = 30.45%, *nutrient level* = 157 kg/ha.

Further enhancement of soil conditions reveals significant potential for yield improvement. By increasing soil moisture by 5% (to 33.4%) and nutrient levels by 10% (to 204.5 kg/ha) while maintaining other factors constant, the model predicts an increase in rice productivity to 2,320 kg/ha. This outcome highlights the critical role of effective water management and balanced fertilization in improving crop yields.

Assam, a key rice-producing state in India, offers another practical scenario for validating the proposed model. The region's average soil pH ranges from 4.27 to 5.34 [24], with soil organic matter content between 2.33% and 3.04% [25,26]. The average soil moisture level is recorded at 29.3 ± 1%

[27], and the nutrient level averages 408 kg/ha [28]. In the year 2019–20, Assam's average rice productivity was 2176 kg/ha. By inputting the region's average values—soil pH of 4.8, soil organic matter of 2.69%, soil moisture of 29.8%, and nutrient level of 408 kg/ha—into the proposed model, the predicted rice productivity is 2420 kg/ha. This prediction closely aligns with the actual productivity, validating the model's reliability and accuracy in reflecting Assam's rice-growing conditions (see Figure 9).

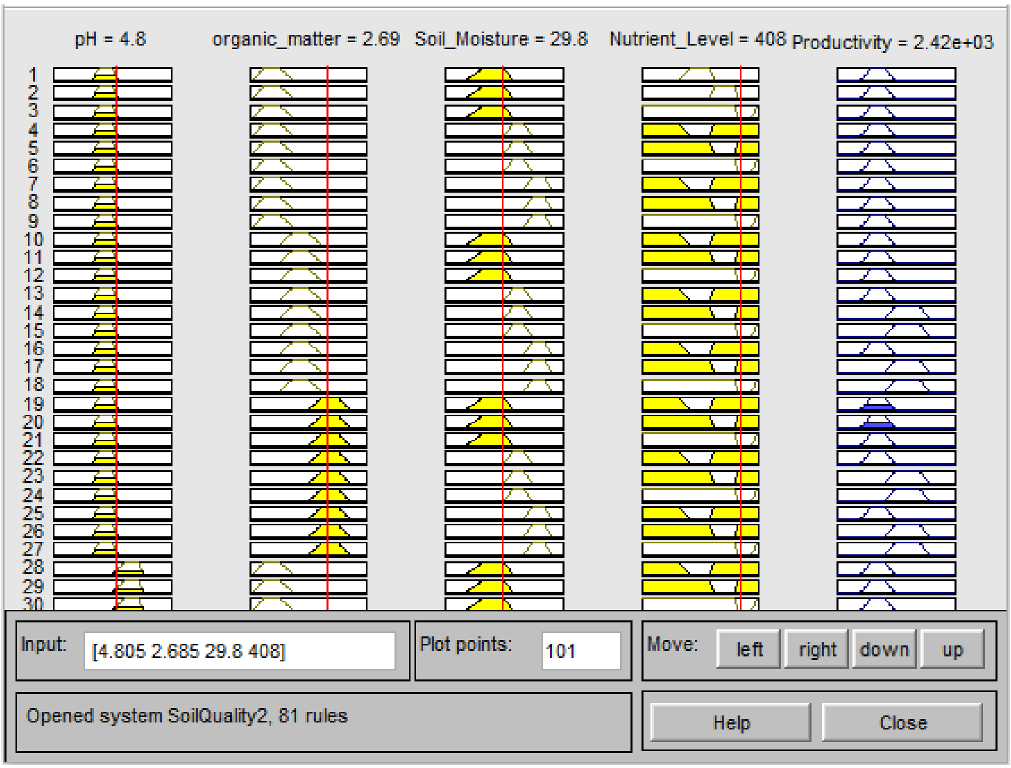

Fig. 9. Fuzzy inference system output for rice productivity with input parameters *soil pH* = 4.805, *organic matter* = 2.685%, *soil moisture* = 29.8%, *nutrient level* = 408kg/ha.

Furthermore, targeted improvements in soil management can significantly enhance rice yields in Assam. For instance, increasing the soil pH slightly from 4.8 to 5.25—while keeping other factors constant—leads to a notable rise in predicted rice productivity from 2,420 kg/ha to 3,000 kg/ha. This considerable improvement highlights the sensitivity of rice productivity to soil pH adjustments and emphasizes the importance of proper soil management.

Andhra Pradesh, a major rice-producing state in India, provides another valuable case for validating the proposed model. The state's average soil pH ranges from 6.5 to 7.5 [29], with soil organic matter content between 0.49% and 1.84% [30]. The average soil moisture level is recorded at 32.31%, and the nutrient levels vary between 113 to 298 kg/ha [31]. In the year 2019–20, the average rice productivity in Andhra Pradesh was 3765 kg/ha. By inputting the average values—soil pH of 7, soil organic matter of 1.85%, soil moisture of 33.5%, and nutrient level of 298 kg/ha—into the proposed model, the predicted rice productivity is 3510 kg/ha. This prediction closely aligns with the actual recorded productivity, confirming the model's accuracy and reliability in reflecting the real-world agricultural conditions of Andhra Pradesh (see Figure 10).

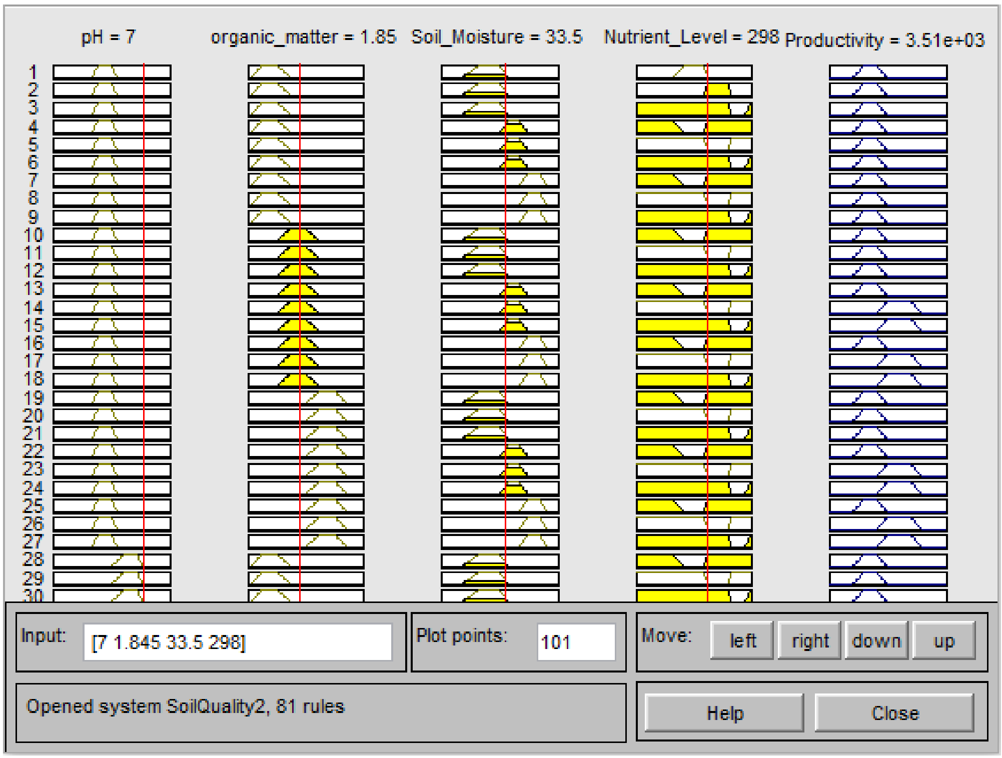

Fig. 10. Fuzzy inference system output for rice productivity with input parameters *soil pH* = 7, *organic matter* = 1.85%, *soil moisture* = 36.5%, *nutrient level* = 298 kg/ha.

Moreover, enhancing soil moisture levels can further improve rice yields in Andhra Pradesh. For example, increasing the soil moisture by 5%, from 33.5% to 36.5%, while keeping other factors constant, results in a significant increase in predicted rice productivity from 3,510 kg/ha to 4,010 kg/ha. This improvement shows the critical role of effective water management in boosting crop yields.

7. Conclusion

This study shows that integrating fuzzy logic modelling is a robust and accurate framework for evaluating the complex, nonlinear effects of key soil quality factors—soil pH, organic matter, moisture, and nutrient levels—on rice productivity across India, effectively managing uncertainty and improving yield predictions compared to conventional models. Membership functions for each input variable were defined using field data and expert knowledge, with all inputs represented by trapezoidal membership functions, while the fuzzy rule base, fuzzification, and inference were implemented using MATLAB. The fuzzy surface analysis reveals how soil pH and organic matter affect rice productivity, showing optimal yields at pH levels of 5.0–7.5 and organic matter between 0.5% and 2.5%, highlighting the need for sustainable practices to maintain soil health. Similar fuzzy surface analyses were conducted for other input combinations, such as Soil pH–Moisture, Nutrient–Moisture, Organic Matter–Nutrients, Organic Matter–Moisture, and Nutrients–Soil pH. For instance, when Bihar's average soil values—pH 6.89, soil organic matter 0.523%, soil moisture 30.4%, and nutrient level 157 kg/ha—were input into the fuzzy inference system, the model predicted a rice yield of 2,190 kg/ha, closely matching the actual recorded yield of 2,182 kg/ha in 2019–20, with similar validation for West Bengal, Assam, and Andhra Pradesh.

Importantly, the parameter sensitivity analysis reveals soil pH and nutrient levels as the most influential determinants of rice yield. Small yet strategic improvements in these parameters yielded substantial productivity gains—for instance, a slight increase in Assam's soil pH elevated predicted yield from 2,420 to 3,000 kg/ha. Similarly, targeted enhancements in nutrient content and moisture availability in Bihar and Andhra Pradesh led to marked yield improvements. Conversely, soil organic matter demonstrated lower individual impact, suggesting its effect may be amplified in combination with other factors. These findings highlight the critical importance of integrated soil and water management practices that are tailored to regional needs.

By incorporating localized soil characteristics, it not only forecasts rice productivity with high precision but also identifies leverage points for intervention. This enables the formulation of sustainable, data-driven agricultural practices—such as optimized fertilization, organic matter enhancement, and efficient irrigation—that bolster soil health, improve resilience to environmental variability, and ultimately secure food production for the future. In essence, this research paves the way for a more intelligent, adaptive, and ecologically sound approach to rice cultivation—one that harmonizes technology with traditional agricultural wisdom, and empowers stakeholders at every level to achieve enhanced productivity and long-term sustainability.

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Conflicts of Interest
The authors declare no conflicts of interest.

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