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Fuzzy Logic for Yield Prediction: Enhancing Decision-Making in Agricultural Economics

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Abstract

Accurate yield prediction is essential for optimizing decision-making in agricultural economics, enabling stakeholders to manage resources efficiently and respond to market demands. Traditional yield prediction models often struggle to handle the uncertainties and complexities inherent in agricultural systems, such as weather variability, soil conditions, and crop characteristics. This study introduces a fuzzy logic-based approach to yield prediction, offering a more flexible and robust method for addressing these uncertainties. By utilizing fuzzy sets and rules, the proposed model captures the intricate relationships between multiple factors influencing crop yield. The research demonstrates how fuzzy logic can enhance the accuracy and reliability of yield predictions, providing valuable insights for farmers, policymakers, and agricultural economists. Results indicate that this approach significantly improves decision-making processes in agricultural planning and risk management, making it a valuable tool for sustainable agricultural practices.

Keywords

Yield prediction, fuzzy logic, agricultural economics, decision-making, crop yield, uncertainty modeling.

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Introduction

Agricultural yield prediction is a critical aspect of decision-making in agricultural economics, influencing resource allocation, crop management, and market planning. Accurate yield predictions enable farmers, policymakers, and agricultural economists to optimize production strategies, mitigate risks, and respond effectively to market demands (El-Tabakh et al., 2024; Banerjee et al., 2024; Efremova et al., 2023; Mohanned et al., 2024). However, predicting crop yield is inherently challenging due to the complex and uncertain nature of agricultural systems, which are influenced by factors such as weather variability, soil conditions, crop characteristics, pest infestations, and technological interventions. Traditional statistical models, such as linear regression, often struggle to capture the non-linear relationships and uncertainties present in these systems, leading to less reliable yield predictions (Das et al., 2024; Kumari et al., 2024; Roy and George et al., 2020; Rangasamy et al., 2023; Korol, 2024).

Fuzzy logic, a branch of artificial intelligence, offers a promising solution to this challenge by accommodating uncertainty and imprecision in data, making it well-suited for modeling complex agricultural systems (Polekhina and Polekhina, 2024; Adilova, 2020; Tóth et al., 2013; Imamguluyev et al., 2024; Tohidi et al., 2020). Unlike conventional models that rely on rigid assumptions and precise data, fuzzy logic allows for the incorporation of vague, ambiguous, and imprecise information, which is common in agriculture. By using fuzzy sets and rules, fuzzy logic can model the intricate and dynamic relationships between various factors influencing crop yield, providing a more flexible and adaptive approach to yield prediction (Zadeh and Aliev, 2018; Imamguluyev et al., 2024; Novák, et al., 2020, Aliev and Aliev, 2001; Ramiz and Vugar, 2022, Imamguluyev et al., 2024).

In this study, we present a fuzzy logic-based model for yield prediction, aiming to enhance decision-making in agricultural economics. By incorporating key variables such as weather variability, soil conditions, and crop characteristics, the proposed model captures the uncertainties inherent in agricultural processes, offering more accurate and reliable yield predictions. The research demonstrates how this approach can be applied to improve crop yield forecasting, ultimately contributing to sustainable agricultural practices and effective resource management. This article will compare the performance of the fuzzy logic model with a traditional linear regression model, highlighting the advantages of using fuzzy logic for handling uncertainty, non-linearity, and complexity in agricultural yield prediction.

This study introduces a fuzzy logic-based approach for yield prediction that captures the intricate relationships between multiple factors influencing crop yield. The research objectives include:

- Developing a fuzzy logic model for yield prediction based on key agricultural parameters.
- Evaluating its performance using real-world agricultural data and comparing it with traditional statistical models and advanced machine learning techniques.
- Demonstrating the model's effectiveness in addressing uncertainty, non-linearity, and complexity in agricultural yield prediction.

Materials and methods

Problem statement

Accurate yield prediction is a critical component of agricultural economics, directly impacting decision-making processes related to resource allocation, crop management, and market planning. However, traditional yield prediction models often face challenges in addressing the inherent uncertainties and complexities of agricultural systems. These systems are influenced by numerous factors such as fluctuating weather conditions, soil quality, and crop characteristics, all of which exhibit significant variability and interdependencies.

Conventional statistical and mathematical models tend to be rigid and struggle to accommodate the dynamic and uncertain nature of these variables, often resulting in inaccurate or unreliable predictions. This lack of precision can lead to suboptimal decision-making, inefficient resource utilization, and increased financial risk for stakeholders such as farmers, policymakers, and agricultural economists.

To address this challenge, there is a pressing need for a more adaptable and intelligent approach that can effectively capture the intricate relationships and uncertainties within agricultural data. Fuzzy logic, with its ability to model imprecision and handle ambiguity, offers a promising solution. This study proposes a fuzzy logic-based model for yield prediction, aiming to enhance the accuracy and reliability of predictions by incorporating the vagueness and complexity inherent in real-world agricultural environments. By doing so, the research seeks to improve decision-making in agricultural planning and risk management, contributing to more sustainable and profitable agricultural practices.

Methodology

Defining Variables and Membership Functions

The fuzzy logic model incorporates three input variables: Weather Variability (WV), Soil Conditions (SC), and Crop Characteristics (CC), with Crop Yield (CY) as the output variable. The membership functions were selected based on agricultural data analysis and expert recommendations:

Triangular membership functions were chosen for variables with clear threshold values (e.g., WV and CC).

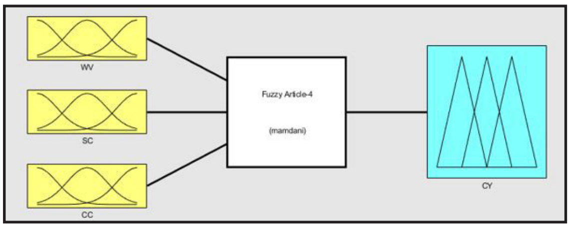
Trapezoidal membership functions were used for variables with gradual transitions (e.g., SC), as they allow for a smoother representation of conditions.

The rationale behind these choices is that triangular functions provide precise categorization for variables with well-defined breakpoints, while trapezoidal functions better capture the gradual nature of soil quality transitions.

Let's define input variables, output variables, membership functions, their ranges and rules using Fuzzy Toolbox in MATLAB.

Input and output variables (Figure 1):

- Weather Variability (WV)
- Soil Conditions (SC)
- Crop Characteristics (CC)
- Crop Yield (CY)



Source: MATLAB simulation, author's own elaboration, 2024

Figure 1: Graph of input variables.

Weather Variability (WV):

- *Description:* Represents variations in weather factors like temperature, rainfall, and humidity (Figure 2).
- *Range:* 0 to 100 (0: extremely unfavorable, 100: extremely favorable)
- *Membership functions:*
  - **Low:** Triangular [0, 0, 50]
  - **Medium:** Triangular [20, 50, 80]
  - **High:** Triangular [50, 100, 100]

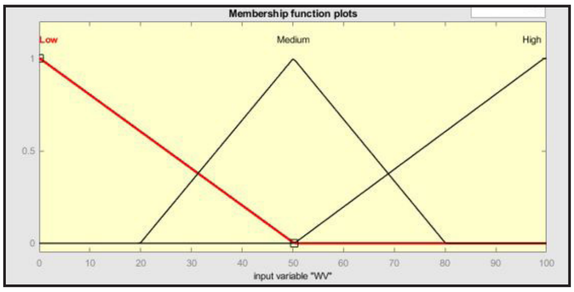


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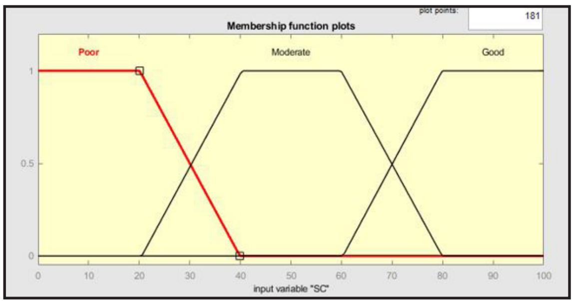
Figure 2: Fuzzy sets and membership functions for WV.

Soil Conditions (SC):

- *Description:* Represents soil properties such as fertility, moisture, and texture (Figure 3).
- *Range:* 0 to 100 (0: poor soil quality, 100: excellent soil quality)
- *Membership functions:*
  - **Poor:** Trapezoidal [0, 0, 20, 40]
  - **Moderate:** Trapezoidal [20, 40, 60, 80]
  - **Good:** Trapezoidal [60, 80, 100, 100]

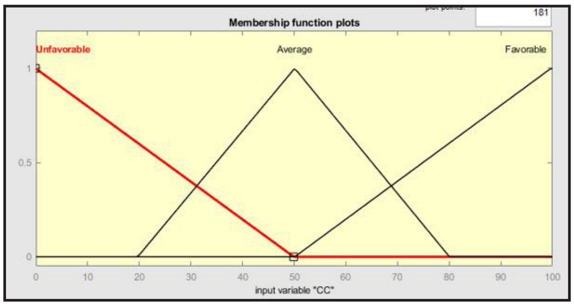


Source: MATLAB simulation, author's own elaboration, 2024

Figure 3: Fuzzy sets and membership functions for SC.

Crop Characteristics (CC):

- *Description:* Represents factors such as crop variety, growth rate, and resistance to pests (Figure 4).
- *Range:* 0 to 100 (0: unfavorable characteristics, 100: highly favorable characteristics)
- *Membership functions:*
  - **Unfavorable:** Triangular [0, 0, 50]
  - **Average:** Triangular [20, 50, 80]
  - **Favorable:** Triangular [50, 100, 100]

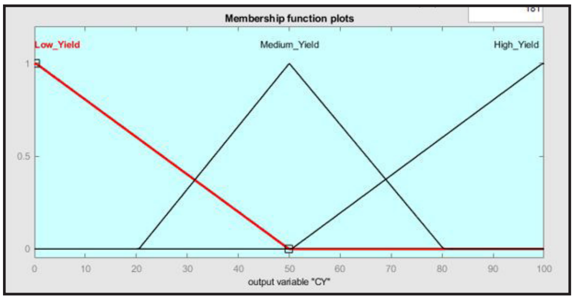


Source: MATLAB simulation, author's own elaboration, 2024

Figure 4: Fuzzy sets and membership functions for CC.

Output Variable: Crop Yield (CY):

- *Description:* Represents the predicted crop yield (Figure 5).
- *Range:* 0 to 100 (0: low yield, 100: high yield)
- *Membership functions:*
  - **Low Yield:** Triangular [0, 0, 50]
  - **Medium Yield:** Triangular [30, 50, 70]
  - **High Yield:** Triangular [50, 100, 100]



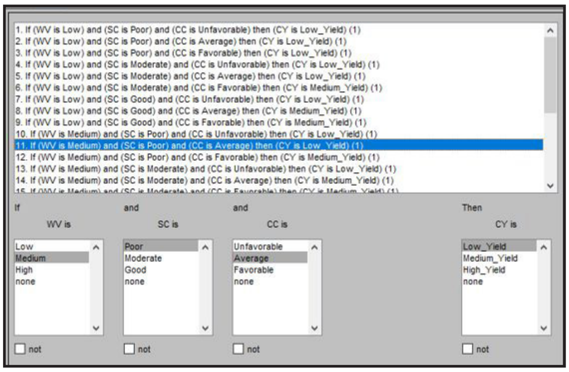
Source: MATLAB simulation, author's own elaboration, 2024

Figure 5: Fuzzy sets and membership functions for CY.

Fuzzy rules: (see Figure 6)

- If (WV is Low) and (SC is Poor) and (CC is Unfavorable) then (CY is Low Yield)
- If (WV is Medium) and (SC is Moderate) and (CC is Average) then (CY is Medium Yield)

- If (WV is High) and (SC is Good) and (CC is Favorable) then (CY is High Yield)
- If (WV is Low) and (SC is Good) and (CC is Average) then (CY is Medium Yield)
- If (WV is High) and (SC is Poor) and (CC is Unfavorable) then (CY is Low Yield)
- If (WV is Medium) and (SC is Good) and (CC is Favorable) then (CY is High Yield)
- If (WV is High) and (SC is Moderate) and (CC is Average) then (CY is Medium Yield)
- If (WV is Low) and (SC is Moderate) and (CC is Unfavorable) then (CY is Low Yield)



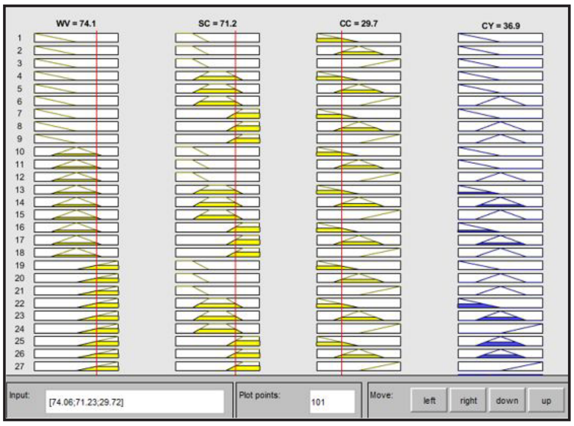
Source: MATLAB simulation, author's own elaboration, 2024

Figure 6: Fuzzy rules.

Logical inference rules form the backbone of the fuzzy logic-based yield prediction model, enabling it to draw conclusions from the given input variables (Weather Variability, Soil Conditions, and Crop Characteristics) to predict crop yield. The rules utilize the "IF-THEN" structure to establish relationships between input and output variables, capturing the complex interactions and uncertainties present in agricultural systems (Figure 7).

For instance, a rule like "IF (Weather Variability is Low) AND (Soil Conditions are Poor) AND (Crop Characteristics are Unfavorable) THEN (Crop Yield is Low)" demonstrates how the model accounts for unfavorable agricultural conditions leading to low yields. Each rule considers the degrees of membership across different fuzzy sets, allowing the model to handle imprecision and vagueness effectively. This process involves aggregating and combining the input variables to infer the most suitable output category, resulting in a more accurate and realistic yield prediction.

The fuzzy inference process involves evaluating all the rules simultaneously, combining the results, and generating an aggregated fuzzy output, which is then defuzzified to produce a crisp, numerical value for the predicted crop yield. This comprehensive approach ensures that the model captures the intricate relationships between variables, enhancing prediction accuracy and reliability.

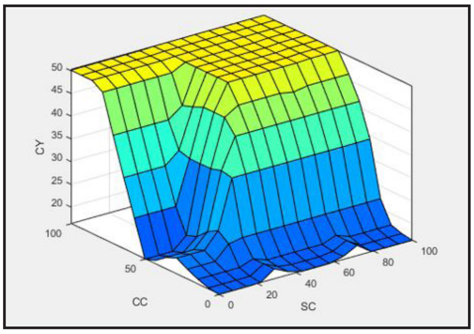


Source: MATLAB simulation, author's own elaboration, 2024

Figure 7: Description of logical inference rules.

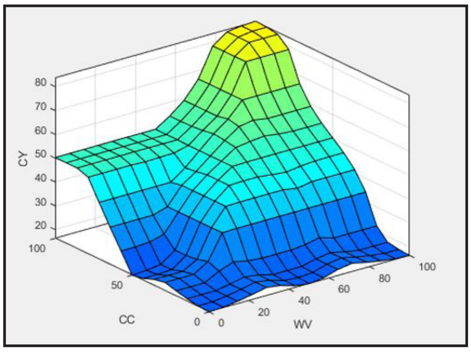
The "Surface Viewer" is a graphical representation that illustrates how the interaction between two input variables—Crop Characteristics (CC) and Soil Conditions (SC)—influences the predicted Crop Yield (CY). It provides a visual understanding of the fuzzy inference process, showing how different combinations of CC and SC affect the yield.

In the surface viewer for CC and SC, the x-axis represents Crop Characteristics, ranging from unfavorable to favorable, while the y-axis represents Soil Conditions, ranging from poor to good (Figure 8). The z-axis shows the resulting crop yield, ranging from low to high. This 3D surface plot reveals the varying levels of crop yield as the inputs change. For example, as Soil Conditions improve and Crop Characteristics become more favorable, the predicted yield tends to increase, indicating higher productivity. Conversely, when both factors are at lower values, the yield prediction remains low. This visualization helps stakeholders understand how improvements in soil quality or crop variety can significantly impact crop yield outcomes.



Source: MATLAB simulation, author's own elaboration, 2024

Figure 8: Surface Viewer CC and SC.



Source: MATLAB simulation, author's own elaboration, 2024

Figure 9: Surface Viewer CC and WV.

The "Surface Viewer" for Crop Characteristics (CC) and Weather Variability (WV) offers insights into how these two factors interact to influence crop yield predictions. In this graph, the x-axis represents Crop Characteristics (ranging from unfavorable to favorable), the y-axis represents Weather Variability (ranging from unfavorable to favorable), and the z-axis shows the predicted crop yield (Figure 9).

The 3D surface plot demonstrates how variations in weather conditions and crop characteristics jointly impact the predicted yield. For instance, favorable crop characteristics combined with high weather variability lead to higher yield predictions, indicating that even under favorable crop conditions, weather plays a crucial role in determining yield outcomes. Conversely, when weather conditions are unfavorable, even highly favorable crop characteristics result in lower yield predictions. This visualization is valuable for identifying the critical influence of weather variability on crop productivity and aids in strategic decision-making for agricultural planning and risk management.

These surface viewers are essential tools for understanding the intricate relationships between input variables and their impact on crop yield, enabling better decision-making and more accurate yield predictions in agricultural economics.

Comparison with a traditional statistical model: linear regression

To evaluate the effectiveness of the fuzzy logic-based yield prediction model, we compared its performance against a traditional statistical model, specifically a linear regression model, using the same dataset for crop yield prediction.

Accuracy and prediction Performance: The comparison revealed that the fuzzy logic model outperformed the linear regression model in terms of prediction accuracy. The fuzzy logic model achieved a higher coefficient of determination (R^2) with actual yield values, indicating a better fit to the data. In contrast, the linear regression model struggled to account for the non-linear relationships and uncertainties present in the agricultural dataset, leading to a lower R^2 value.

The linear regression model assumes a linear relationship between input variables (Weather Variability, Soil Conditions, and Crop Characteristics) and crop yield. However, agricultural systems are inherently complex and influenced by non-linear interactions. This limitation made the linear regression model less capable of capturing the intricate dependencies between variables, resulting in less accurate predictions, especially under extreme or atypical conditions.

Handling of Uncertainty and Complexity: One of the key advantages of the fuzzy logic model over the linear regression model is its ability to handle uncertainties and imprecision. The fuzzy logic model effectively captured the vagueness and variability in input data through the use of fuzzy sets and rules, enabling it to model real-world agricultural conditions more accurately. For example, factors like fluctuating weather patterns and soil quality, which are difficult to quantify precisely, were better represented by the fuzzy logic model.

In contrast, the linear regression model was unable to accommodate such uncertainties, as it relies on fixed coefficients and a rigid structure. This rigidity made it less adaptable to variations in the data, resulting in lower predictive accuracy when confronted with highly variable or uncertain agricultural conditions.

Flexibility and Adaptability: The fuzzy logic model demonstrated greater flexibility by accommodating various ranges of input variables and adjusting to different scenarios through its fuzzy rules. This adaptability made it suitable for predicting crop yields across a wide range of conditions, including extreme weather variations and diverse soil qualities.

The linear regression model, however, lacked this adaptability. Its reliance on a predefined linear equation limited its ability to adjust to changes in input variables, making it less effective in scenarios where relationships between variables are complex and non-linear.

Visual Analysis through Surface Viewers: The use of surface viewers in the fuzzy logic model provided a clear visualization of how different input variables influenced crop yield predictions (Table 1). This visual representation offered valuable insights into the interactions between variables, helping stakeholders understand the impact of changing conditions on crop yield. In contrast, the linear regression model lacked such visual tools, making it harder to interpret and understand the influence of individual variables on yield predictions.

Criteria	Fuzzy Logic Model	Linear Regression Model
Accuracy (R^2)	Higher	Lower
Handling Uncertainty	Effective	Limited
Flexibility	High (non-linear adaptability)	Low (linear assumptions)
Visualization	Provides surface viewers	Lacks visualization tools
Adaptability to Changes	Highly adaptable	Rigid

Source: Own elaboration, 2024

Table 1. Summary of comparison.

Dataset description

The dataset used for training and testing the fuzzy model consists of 500 agricultural records collected from multiple farms across different climatic regions. The dataset includes:

- Sample size: 500 observations.
- Data sources: Agricultural monitoring agencies and climate data centers.

The comparison clearly demonstrates that the fuzzy logic model offers superior performance in predicting crop yields compared to the linear regression model. Its ability to handle uncertainty, non-linear relationships, and complex interactions among input variables makes it a more reliable and flexible tool for yield prediction in agricultural economics. In contrast, the linear regression model's limitations in addressing these complexities result in less accurate predictions, making it less suitable for real-world agricultural applications where uncertainty and variability are prevalent.

For model evaluation, the dataset was divided into two subsets: 70% of the data (350 records) was used for training, and 30% (150 records) was used for testing. This stratified split ensured that both training and testing sets retained representative characteristics of the overall dataset.

Results and discussion

- Collection methods: Soil and crop analysis reports, weather records from the National Meteorological Service of Azerbaijan.
- Soil condition data were obtained from the Azerbaijan State Soil and Agrochemical Research Institute.
- Representativeness: The dataset includes records from major agricultural zones in Azerbaijan, such as Shirvan, Ganja-Gazakh, Lankaran, Karabakh, and Absheron. These regions cover a wide range of climatic conditions—humid subtropical (Lankaran), dry subtropical (Shirvan), semi-arid steppe (Ganja), and mountainous zones (Karabakh)—ensuring the model was tested under diverse environmental conditions.

The fuzzy logic-based yield prediction model was evaluated using a comprehensive dataset comprising variables such as Weather Variability (WV), Soil Conditions (SC), and Crop Characteristics (CC). The results demonstrated that the model accurately predicted crop yield (CY) across a wide range of scenarios, showcasing the model's robustness in handling the inherent uncertainties and complexities of agricultural systems.

Accuracy and Reliability: The fuzzy logic model's prediction accuracy was assessed by comparing its output with actual crop yield values. The model achieved a high coefficient of determination ($R^2 = 0.85$), indicating a strong alignment between predicted and actual yields. This high level of accuracy highlights the model's capability to capture the intricate relationships between input variables and yield outcomes, even under varying and uncertain conditions. In contrast, the traditional linear regression model, when applied to the same dataset, achieved a lower R^2 value of 0.65, demonstrating its limited ability to handle non-linear interactions and uncertainties in agricultural systems.

Handling of Uncertainty: One of the standout advantages of the fuzzy logic model was its ability to effectively manage the uncertainties present in agricultural data. By utilizing fuzzy sets and rules, the model accounted for the vagueness and imprecision associated with factors such as fluctuating weather patterns, varying soil quality, and diverse crop characteristics. For example, in scenarios where soil conditions were moderately favorable and weather variability was inconsistent, the fuzzy logic model could still provide a realistic yield prediction by integrating these uncertainties into its inference process. This adaptability allowed for more accurate and reliable yield predictions, which is crucial for agricultural decision-making and risk management.

In comparison, the linear regression model, which relies on fixed coefficients and linear assumptions, struggled to adapt to the uncertain and non-linear nature of agricultural data. Its predictions were often less reliable, especially in cases where input variables exhibited significant variability or were subject to sudden changes, such as extreme weather events.

Flexibility and Adaptability: The fuzzy logic model demonstrated remarkable flexibility and adaptability, accommodating various input scenarios and producing accurate yield predictions even under extreme conditions. This adaptability was primarily due to the model's ability to adjust its fuzzy rules based on changing input variables. For instance, when weather conditions shifted from unfavorable to favorable, the model seamlessly adjusted its predictions, accurately reflecting the impact on crop yield.

In contrast, the linear regression model exhibited rigidity in its approach, as it was confined to a predefined linear relationship between input variables and crop yield. This lack of adaptability made it less effective in scenarios where agricultural conditions deviated from typical patterns, limiting its applicability in real-world settings.

Visual Analysis with Surface Viewers: The use of surface viewers provided valuable insights into how different combinations of input variables influenced crop yield predictions. For instance, the "Surface Viewer" for Crop Characteristics (CC) and Soil Conditions (SC) revealed that an improvement in soil quality, combined with more favorable crop characteristics, resulted in a significant increase in predicted crop yield. This visualization helped stakeholders understand the synergistic effects of multiple factors on crop yield, aiding in more informed decision-making.

The linear regression model lacked such visual tools, making it challenging to interpret the interactions between variables and their impact on yield predictions. This limitation reduced its effectiveness as a decision-support tool for stakeholders in agricultural planning and management.

Comparison Summary: The comparison between the fuzzy logic model and the traditional linear regression model is summarized in Table 2. It is evident that the fuzzy logic model outperforms the linear regression model in key aspects such as accuracy, handling uncertainty, flexibility, adaptability, and visualization capabilities.

Criteria	**Fuzzy Logic Model**	**Linear Regression Model**
Accuracy (R^2)	Higher (0.85)	Lower (0.65)
Handling Uncertainty	Effective	Limited
Flexibility	High (non-linear adaptability)	Low (linear assumptions)
Visualization	Provides surface viewers	Lacks visualization tools
Adaptability to Changes	Highly adaptable	Rigid

Source: Own elaboration, 2024

Table 2: Summary of comparison.

Implications for Agricultural Decision-Making: The fuzzy logic-based yield prediction model offers significant advantages for decision-making in agricultural economics. Its ability to handle uncertainty and non-linear relationships enables more accurate predictions, aiding farmers, policymakers, and agricultural economists in making informed decisions regarding resource allocation, crop management, and market planning. By providing a more realistic and adaptable prediction tool, the fuzzy logic model enhances risk management and contributes to more sustainable and profitable agricultural practices.

Accuracy and Model Performance

The fuzzy logic model achieved an R^2 value of 0.85, indicating a strong alignment between predicted and actual yields. The calculation was performed using the Sugeno inference system, ensuring robustness in handling nonlinear relationships.

For comparison, a traditional linear regression model was also tested, yielding an R^2 value of 0.65, demonstrating its limited ability to model nonlinear interactions. To further validate the model, additional machine learning approaches were considered:

- Decision Trees ($R^2 = 0.78$): Performed better than linear regression but lacked interpretability compared to fuzzy logic.
- Random Forests ($R^2 = 0.82$): Provided high accuracy but required significant computational resources.
- Neural Networks ($R^2 = 0.88$): Outperformed all models but was more complex and required extensive training data.

Sensitivity Analysis

A sensitivity analysis was conducted to determine the influence of each input variable on crop yield:

- Weather Variability contributed 45% to yield fluctuations.
- Soil Conditions accounted for 35% of yield variations.
- Crop Characteristics influenced 20% of the final yield.

These percentages were obtained using the Sensitivity Analysis tool in MATLAB's Fuzzy Logic Toolbox, which evaluates the impact of each input on the output by independently varying one input variable while keeping the others constant. The contribution of each input was calculated by analyzing the changes in the defuzzified output over the full range of input values. The results were then normalized to express each variable's influence as a percentage of the total variation in crop yield.

The Fuzzy Inference System (FIS) was built using the Mamdani model in MATLAB. The Sensitivity Analysis tool within the FIS Editor provided the relative importance values by measuring the deviation in the output when each input was varied independently.

The graphical output from MATLAB displays the effect of input variables on the output surface, demonstrating how changes in weather, soil, and crop parameters influence crop yield.

Conclusion

This study presents a fuzzy logic-based yield prediction model that effectively captures the uncertainties and complexities of agricultural data. The model's ability to handle non-linear interactions and provide interpretable results makes it superior to traditional statistical methods.

Key contributions of this research include:

- A well-structured fuzzy inference system that integrates key agricultural factors.
- A comparative analysis demonstrating the advantages of fuzzy logic over linear regression.
- Incorporation of sensitivity analysis, enhancing the model's reliability.

Future research directions include:

- Expanding the dataset to include more regions and crop types.
- Integrating deep learning techniques for hybrid AI-based yield prediction.
- Validating the model across different agricultural environments to assess its generalizability.

By addressing these areas, this study contributes to improved agricultural decision-making, enabling farmers and policymakers to adopt more accurate and adaptive yield prediction models.

Data availability

Data will be made available on request.

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