# Influence of Membership Function and Degree on Sorghum Growth Prediction Models in Machine Learning

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***Abstract*—Rapid advances in science and technology have significantly changed plant growth modeling. The main contribution to this transformation lies in using Machine Learning (ML) techniques. This study focuses on sorghum, an important agricultural crop with significant economic implications. Crop yield studies include temperature, humidity, climate, rainfall, and soil nutrition. This research has a novelty: the input factors for predicting sorghum plant growth, namely the treatment of applying organic fertilizer and dolomite lime to sorghum planting land. The three predicted sorghum plant growth factors, namely Height, Biomass, and Panicle weight, are the reasons for using the Multiple Adaptive Neural Fuzzy Inference System (MANFIS) model. This research investigates the impact of Membership Function and Degree on the MANFIS model. A comprehensive comparison of various membership functions, including Gaussian, Triangular, Bell, and Trapezoidal functions, along with various degrees of membership, has been carried out. The dataset used includes data related to sorghum growth obtained from field experiments. The main objective was to assess the effectiveness of membership and degree functions in accurately predicting sorghum growth parameters, consisting of height, biomass, and panicle weight. This assessment uses metrics such as MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), and RMSE (Root Mean Square Error) to evaluate the predictive performance of the MANFIS model when using four different types of membership functions and degrees. The results obtained the best level of accuracy in predicting panicle weight (ANFIS-3) with chicken manure treatment using the Trapezoidal membership function type and degree of membership function [3,3] with MAPE results of 5.77%, MAE of 0.2994, and RMSE of 0.395.***

***Keywords*—Prediction; MANFIS; membership function; organic fertilizer; sorghum**

## I. Introduction

Rice is the staple food of the Indonesian population; rice production in Indonesia in the last five years (2018-2022) has continued to decline, from 59.2 million tons in 2018 to 54.74 million tons in 2022, as well as the harvested area which in 2018 reached 11.37 million ha to 10.45 million ha in 2022[1]. Therefore, alternative food is needed to replace rice to ensure food security in Indonesia. *Sorghum* is an alternative crop suitable for planting in less fertile areas, such as tidal land. Suboptimal tidal swamp land has low fertility, an acidic pH, and low nutrients [2]. Sorghum plants can also be used for food diversification other than rice to maintain food security in Indonesia. Sorghum is more drought tolerant than similar crops such as corn and wheat [3]. Sorghum is suitable for cultivation in Indonesia because of its drought tolerance and adaptability to tropical areas [4].

The main problems of plant growth in tidal land are the level of water saturation and anaerobic conditions in the rhizosphere, pyrite or sulfide materials found in the soil, toxicity of Al, Fe, and Mn; highly acidic soil reaction, and low content of N, P, K, Ca, and Mg [5] [6] [7] [8]. Enhancing soil fertility in tidal land areas can be achieved through the application of fertilizers [9]. In such regions, leveraging local resources for sustainable agricultural practices is essential. One viable option is the utilization of organic fertilizers, such as chicken manure, cow manure, and vermicompost [10]. These locally available resources provide essential nutrients to the soil and promote soil health and microbial activity. By adopting a strategy that combines the application of these organic fertilizers with tidal land management practices, farmers can effectively improve soil fertility while minimizing the environmental impact, contributing to both agricultural productivity and environmental sustainability [11].

Many further research studies within the sorghum domain utilize machine learning techniques. These encompass efforts to predict sorghum biomass [12], detect and measure sorghum head counts [13], and make estimations of sorghum crop yields through machine learning algorithms [14] [15]. In combination, these investigations underscore the versatility and potential of machine learning in advancing various aspects of sorghum farming and administration, promoting more effective and sustainable agricultural practices.

Recent research on crop yield predictions utilizing machine learning techniques has emphasized the incorporation of several key input parameters. Rainfall has been identified as a significant factor in crop yield prediction, with multiple studies exploring its impact [16] [17] [18] [19], Temperature, humidity, and climate have also emerged as primary concerns, with some studies employing multiple linear regression to analyze weather forecasts by considering these parameters [16] [20] [18] [19] [21]. Moreover, soil pH and irrigation, as determinants of soil quality and optimal irrigation, are integral components of crop yield prediction models [19] [22] [21]. Wind speed, an external factor affecting plant growth, is considered in several research endeavors [20] [21]. Additionally, the location of crops is recognized as a crucial parameter in crop yield prediction, with crop location data serving as a variable in predictive analyses [18] [23]. These recent studies combine machine learning technology with a deep understanding of these diverse factors to enhance the accuracy of crop yield predictions. In this research, we introduce novelty by utilizing input parameters that include doses of organic fertilizers (chicken manure, cow manure, and vermicompost) and dolomite. Interestingly, these parameters have not been explored in previous studies related to predicting plant growth using machine learning technology.

Research conducted on predicting sorghum crop yields involve the use of various techniques, including the development of machine learning-based models. Several approaches have been employed, such as using TensorFlow with Convolutional Neural Networks (CNN) and Linear Regression to detect and estimate the weight of sorghum heads in images [24]. Additionally, a neuro-fuzzy model has been developed to predict the production rate of colorant extract from sorghum bicolor [25]. There has also been the development of image segmentation algorithms using deep learning CNN to detect and count sorghum heads[26]. Furthermore, frameworks and models have been created to detect leafhopper infestations in sorghum plants using deep learning technology and the YOLOv5m model [27]. Moreover, a performance evaluation of three deep learning methods, namely EfficientDet, SSD, and YOLOv4, has been conducted for the detection of sorghum heads in UAV RGB image [28].

In this research, a machine learning prediction model was developed using the Multiple Adaptive Fuzzy Inference System (MANFIS) model. ANFIS harnesses the strengths of neural networks and fuzzy logic, collectively enhancing its predictive capabilities [29]. This fusion of Neural Network and Fuzzy Logic equips ANFIS with a robust framework for precise predictions. Additionally, ANFIS possesses the unique capability to integrate both numerical and linguistic knowledge, making it adaptable and valuable across a broad spectrum of domains [30]. Its capacity to handle diverse types of information is a substantial asset, enabling it to efficiently address a multitude of real-world situations. However, integrating ANFIS models into soil remediation offers a promising avenue for restoring contaminated land to a fertile state, enabling sustainable agricultural practices. Many have widely implemented the ANFIS for prediction, classification, and clustering [31] [32] [33]. In this study, the input parameters and output parameters have more than one parameter. Hence, the prediction model in this study uses nine ANFIS models to predict three output parameters (height, biomass, and panicle weight) of sorghum plants with three different organic fertilizer treatment datasets.

The connection between membership functions and the degree of membership in ANFIS is essential for fuzzy logic-based inference. Here, the functions establish fuzzy sets, and the degree of membership measures how closely input values align with these sets. This association is vital for the fuzzy reasoning and decision-making procedures in the ANFIS framework. In the selection of membership functions and degrees of membership in the ANFIS model, research has highlighted the importance of choosing appropriate membership functions. Studies have explored various forms of membership functions, such as triangular, trapezoidal, shape-bell, and Gaussian, as well as the selection of the correct number of membership functions [34]. The choice of appropriate membership functions can have a significant impact on the performance of the ANFIS model [35]. Experiments are often employed to determine the optimal membership functions, allowing precise adjustments to the system's performance [36]. Over time, research continues to develop best practices in the selection of membership functions and degrees of membership to enhance the performance of ANFIS-based systems. Therefore, in this study, to optimize the accuracy of prediction results using the MANFIS model, the selection of membership function types and degrees of membership is conducted on nine ANFIS models. Four membership functions and four combinations of degrees of membership will be evaluated for each input and output parameter of the MANFIS model designed to obtain the best prediction results for sorghum plant growth.

This research advances the field of plant growth prediction through machine learning by introducing new input factors, such as organic fertilizer dosage and dolomite, which previous studies have not explored. In this study, we present novelty by including input variables such as the amount of organic fertilizer (chicken manure, cow manure, and vermicompost) and dolomite. Previous studies on predicting plant growth using machine learning technology did not investigate these variables. Additionally, it emphasizes the importance of carefully choosing appropriate membership functions for the ANFIS model and conducting experiments to improve its performance. These efforts contribute to developing best practices in this domain, enhancing the accuracy and effectiveness of predicting crop yields.

## II. Related Works

The choice of membership function significantly influences the prediction model's accuracy when using ANFIS. One study compared eight different ANFIS membership functions to optimize ERP satisfaction values, ultimately revealing that the triangular membership function yielded the best prediction results [37]. To guarantee reliable and accurate predictions, the research prioritized two crucial factors: the number of inputs within the training dataset and the selection of the membership function within the ANFIS model. This optimization procedure included comparing outcomes with techniques like Particle Swarm Optimization and Genetic Algorithms [36]. Furthermore, researchers conducted performance evaluations to assess how effectively the ANFIS model addressed various classification problems by investigating four popular forms of membership functions: triangular, bell-shaped, trapezoidal, and Gaussian [35]. Another study delved into the impact of different membership function types, specifically triangular, trapezoidal, and Gaussian, on the performance of a fuzzy logic controller [38]. In a different context, researchers employed two approaches to generate Gaussian and triangular fuzzy membership functions using fuzzy c-means for predicting sunspots [39]. These various investigations collectively contribute to our understanding of the significance of membership functions and their impact on ANFIS model performance in different applications. In this research, a comparison was carried out among four types of membership functions and four combinations of membership degree functions across nine ANFIS models employed in a machine learning framework for predicting the growth of sorghum. This comparison aims to determine the most accurate prediction results within the constructed model.

The ANFIS model utilizes the Takagi-Sugeno rule set for its fuzzy inference system. Eq. (1) and Eq. (2) present a standard rule set for the commonly used first-order Takagi-Sugeno fuzzy model, which includes two fuzzy if-then rules [40].

Rule 1: If ($x$ is $A_1$) and ($y$ is $B_1$), then: $Z_1 = p_1x + q_1y + r_1$ (1)

Rule 2: If ($x$ is $A_2$) and ($y$ is $B_2$), then: $Z_2 = p_2x + q_2y + r_2$ (2)

where, $p_1$, $p_2$, $q_1$, $q_2$, $r_1$, and $r_2$ are linear, and $A_1$, $A_2$, $B_1$, and $B_2$ are non-linear parameters.

In Fig. 1 shows the structure of ANFIS, which consists of five layers [41]. The framework of the ANFIS method has 5 (five) layers, namely the fuzzification layer, the rule layer, the normalization layer, the defuzzification layer, and a single neuro result [42] [43].

- Layer 1: This layer serves as the fuzzification layer, where each neuron's output corresponds to the degree of membership determined by the input membership function. The fundamental categories of membership functions include four types: triangular, trapezoidal, bell-shaped, and Gaussian [35].

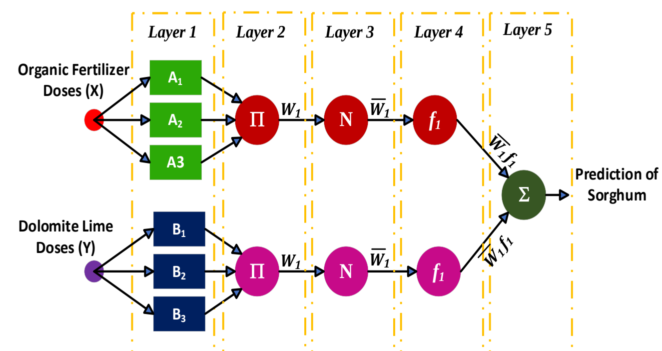


Fig. 1. A schematic of an ANFIS structure.

The triangular membership function (Trimf) stands out as the most straightforward among the various membership functions. It requires three parameters to define the three points, as illustrated in Eq. (3).

$$Trimf(x,a,b,c) = max\left(min\left(\frac{x-a}{b-a},\frac{c-x}{c-b},0\right)\right) \quad (3)$$

where the value a < b < c which represents the coordinates of the Trimf on the x-axis.

Eq. (4) illustrates how four scalar parameters define the curve of the trapezoidal membership function (Trapmf).

$$Trapmf(x,a,b,c,d) = max\left(min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-b},0\right)\right) \quad (4)$$

where the value a < b < c < d which represents the coordinates of the Trapmf on the x-axis

The general bell-shaped membership function (Gbellmf) features a symmetric shape resembling a bell, as illustrated in Eq. (5).

$$Gbellmf(x,a,b,c) = \frac{1}{1+\left[\frac{x-c}{a}\right]^{2b}} \quad (5)$$

where, c is the center of the curve in the universe of speech, a determines the width of the bell-shaped curve, and b is a positive integer.

The Gaussian membership function (Gaussmf) relies on two parameters: c to locate the center and σ to specify the curve's width, as shown in Eq. (6).

$$Gaussmf(c,\sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (6)$$

where, c is the center of the cluster and width value σ are used to describe the Gaussmf.

- Layer 2: This layer comprises a constant neuron (represented by the symbol Π), which computes the product of all input values, as indicated in Eq. (7).

$$\boldsymbol{wk = \mu Ak \, . \, \mu Bk} \quad (7)$$

Typically, practitioners use the AND operator and refer to the result of this computation as the firing strength of a rule. Each neuron corresponds to a specific rule indexed ask.

- Layer 3: Each neuron in this layer is a constant neuron, represented by the *N*. The calculation takes the *k* firing strength (*wk*) ratio to the total sum of firing strengths in the second layer, as shown in Eq. (8).

$$\overline{w}_k = w_k w_1 + w_2, \quad i = 1, 2 \quad (8)$$

The result obtained from this calculation is termed the normalized firing strength.

- Layer 4: This layer consists of neurons that adapt to an output, as shown in Eq. (9).

$$\overline{w}_k f_k = \overline{w}_k \langle q_k Z_{t-1} + r_k Z_{t-2} + s_k \rangle \quad (9)$$

where, $\overline{w}_k$ is the normalized firing strength in the third layer and qk, rk, and sk are the parameters of the neuron. These parameters are commonly called consequent parameters.

- Layer 5: This layer comprises a solitary neuron (represented by a symbol) that results from summating all outputs from the fourth layer, as depicted in Eq. (10).

$$\sum \overline{w}_k f_k = \frac{\sum_k w_k f_k}{\sum_k w_k} \quad (10)$$

*A. Proposed Method*

The research methodology aims to predict Sorghum growth using MANFIS (Multiple Adaptive Neuro-Fuzzy Inference System) models, emphasizing optimizing the selection of membership functions and membership degrees to achieve the highest accuracy, as depicted in Fig. 2. Data collection involved conducting experiments that utilized three types of organic fertilizers: chicken manure, cow manure, and vermicompost, in combination with dolomite lime on tidal soil. The experimental design employed a two-factor factorial design. The data obtained from these experiments served as the MANFIS model's dataset to predict three sorghum growth parameters: height, biomass weight, and panicle weight. The dosage of organic fertilizers and dolomite lime forms the basis for these predictions.

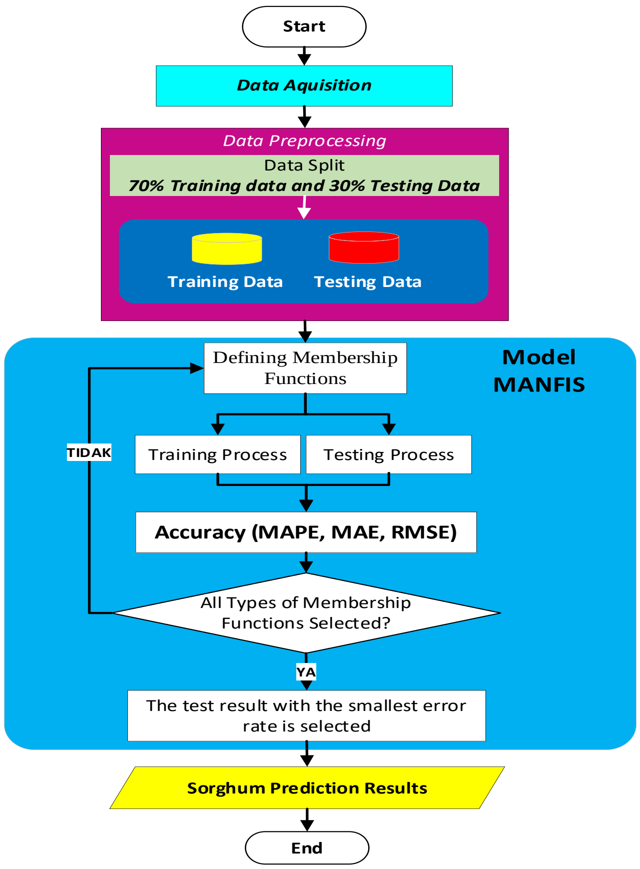


Fig. 2. Research methodology.

The initial phase of our research began with problem identification, focusing on utilizing organic fertilizer comprising chicken manure, cow manure, and vermicompost, which was applied to tidal lands to nurture sorghum plants. Subsequently, we collected data, drawing information from the growth records of sorghum plants cultivated on tidal lands subjected to three different organic fertilizer treatments or doses.

*1) Vermicompost fertilizer:* The treatment parameter for vermicompost fertilizer used four doses, namely: 0, 2.5, 5, and 7.5 tons/ha, combined with two doses of dolomite lime (0 and 0.404 tons/ha) and repeated three times.

*2) Chicken manure:* The treatment parameters of chicken manure used four doses, namely: 0, 5, 6.5, and 8.5 tons/ha, combined with two doses of dolomite lime (0 and 0.404 tons/ha), and repeated three times.

*3) Cow manure:* The treatment parameter for cow manure used four doses, namely: 0, 5, 10, and 15 tons/ha, combined with two doses of dolomite lime (0 and 1.84 tons/ha), and repeated three times.

The researchers obtained the dataset by conducting experimental sorghum cultivation in a greenhouse. We applied organic fertilizer to the cultivated land two weeks before planting sorghum. After 105 days, we harvested the sorghum plants and measured three growth parameters: height, biomass, and panicle weight.

In the subsequent phase, we conducted data training using four different membership functions, namely triangular, trapezoidal, bell-shaped, and gaussian, to achieve the highest level of accuracy. We utilized 70% of the entire dataset in the training phase and executed the training process on nine ANFIS models. Fig. 3 illustrates the configuration of the MANFIS model designed for chicken manure fertilizer treatment. This model comprises three ANFIS components, denoted ANFIS-1, ANFIS-2, and ANFIS-3. The input variables for their membership functions are characterized by degrees of membership, specifically (4, 2). In particular, the dosage of chicken manure fertilizer has four membership degrees, while dolomite lime has two membership degrees.

In this process, the training data, randomly selected from a dataset, is employed to train individual ANFIS models using distinct types and degrees of membership functions. There are four distinct types of membership functions and four combinations of membership function degrees applied during this training phase. The ANFIS model training utilizes these combinations of membership function types and degrees, including Triangular, Trapezoidal, Generalized bell-shaped, and Gaussian functions, along with four degrees of membership functions: {3,2}, {3,3}, {2,2}, and {4,2}.

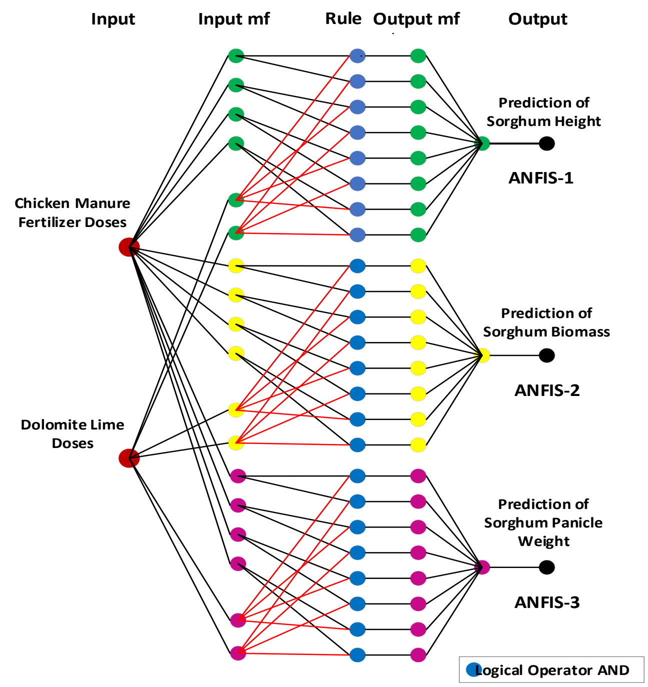


Fig. 3. Model structure for chicken manure treatment.

Using these diverse combinations of membership function types and degrees, we assess the accuracy of the prediction outcomes for each ANFIS model using three accuracy measurement indicators: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). We derive the formulas for calculating the accuracy of prediction results from Eq. (11), (12), and (13) as detailed in reference [44].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{A_t - P_t}{A_t}\right] x\ 100\% \tag{11}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}[P_t - A_t] \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_t - P_t)^2} \tag{13}$$

where, $A_t$ represents the target value, $P_t$ refers to the prediction value (the model's output), and $n$ is the number of data points.

## III. Result and Analysis

The results of the ANFIS model's accuracy evaluation, including three prediction accuracy metrics (MAPE, MAE, and RMSE), along with the utilization of four types of membership functions and four degrees of membership functions for each treatment related to the application of organic fertilizer and dolomite lime, have been recorded in Tables I, II, and III. These results specifically relate to three observed output variables: the sorghum plant's height, biomass weight, and panicle weight.

Table I presents the accuracy assessment results for MANFIS models (ANFIS-1, ANFIS-2, and ANFIS-3) using the metrics MAPE, MAE, and RMSE. These results stem from the training and testing processes conducted on data from the chicken manure treatment dataset. To streamline the process of identifying the membership function types and degrees that produce the most accurate results, we visually represent the accuracy measurements in Table I through Fig. 4, Fig. 5, and Fig. 6.

Fig. 4 visually depicts the accuracy outcomes in the context of chicken manure treatment, explicitly focusing on sorghum height (ANFIS-1) as the output parameter. It is evident from Fig. 4 that the highest accuracy values, as measured by the three accuracy assessment tools, are achieved when using the trapezoidal membership function type and membership function degrees {2, 2}. The corresponding accuracy values are MAPE of 13.23%, MAE of 11.1969, and RMSE of 14.7685.

Fig. 5 provides a visual representation of the accuracy results in the context of chicken manure treatment, explicitly highlighting the Biomass weight (ANFIS-2) of sorghum as the output parameter. The figure demonstrates that the highest accuracy values, as assessed by the three accuracy measurement tools, are attained when employing the Bell-shaped membership function type with membership function degrees {4, 2}. The corresponding accuracy values are MAPE of 20.89%, MAE of 2.5163, and RMSE of 3.2552.

TABLE I. ACCURACY MEASUREMENT RESULTS OF ANFIS FOR CHICKEN MANURE TREATMENT

| Membership Function | | Output Parameters | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Type | Degree | Sorghum Height (ANFIS-1) | | | Sorghum Biomass Weight (ANFIS-2) | | | Sorghum Panicle Weight (ANFIS-3) | | |
| | | MAPE | MAE | RMSE | MAPE | MAE | RMSE | MAPE | MAE | RMSE |
| Triangular | [3 3] | 7.57 | 7.6624 | 9.6971 | 24.77 | 3.8184 | 4.7042 | 7.07 | 0.3216 | 0.4717 |
| | [3 2] | 7.11 | 7.0251 | 9.5958 | 27.68 | 4.0041 | 4.8796 | 6.59 | 0.3109 | 0.4947 |
| | [2 2] | 8.05 | 8.0693 | 10.3974 | 26.63 | 3.7491 | 4.9433 | 6.31 | 0.2929 | 0.4766 |
| | [4 2] | 7.44 | 7.33 | 9.9284 | 21.68 | 3.6174 | 5.1553 | 6.8 | 0.3148 | 0.4809 |
| Trapezoidal | [3 3] | 7.34 | 7.3734 | 9.4516 | 25.43 | 3.64 | 4.8043 | 7.25 | 0.3321 | 0.4718 |
| | [3 2] | 7.64 | 7.6231 | 9.6295 | 25.12 | 3.7713 | 4.6919 | 6.61 | 0.3146 | 0.4957 |
| | [2 2] | 7.29 | 7.2511 | 9.5181 | 21.62 | 3.6038 | 5.0974 | 6.49 | 0.3076 | 0.4847 |
| | [4 2] | 7.32 | 7.3311 | 9.5143 | 22 | 3.6717 | 5.2302 | 7.45 | 0.3784 | 0.6374 |
| Bell-shaped | [3 3] | 8.25 | 8.9019 | 13.2622 | 30.17 | 4.2531 | 5.4302 | 15.93 | 0.6813 | 0.8268 |
| | [3 2] | 7.38 | 7.1854 | 10.9684 | 26.87 | 3.9804 | 5.0931 | 13.7 | 0.5578 | 0.6737 |
| | [2 2] | 8.16 | 8.2203 | 10.2186 | 28.69 | 4.1439 | 5.2805 | 13.42 | 0.5579 | 0.6636 |
| | [4 2] | 7.14 | 6.9103 | 9.9857 | 27.93 | 4.2529 | 5.4921 | 14.06 | 0.5899 | 0.6771 |
| Gaussian | [3 3] | 7.22 | 7.0862 | 9.8436 | 35.13 | 5.34 | 6.9752 | 6.34 | 0.2997 | 0.4798 |
| | [3 2] | 7.55 | 7.5134 | 9.5617 | 25.51 | 3.7674 | 4.785 | 6.66 | 0.3145 | 0.4511 |
| | [2 2] | 7.8 | 7.8058 | 9.933 | 35.28 | 5.5481 | 7.1964 | 6.55 | 0.3087 | 0.4533 |
| | [4 2] | 7.37 | 7.3733 | 10.1953 | 27.44 | 4.0184 | 4.8416 | 14.11 | 0.5176 | 0.7754 |

TABLE II. ACCURACY MEASUREMENT RESULTS OF ANFIS FOR COW MANURE TREATMENT

| Membership Function | | Output Parameters | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Type | Degree | Sorghum Height (ANFIS-4) | | | Sorghum Biomass Weight (ANFIS-5) | | | Sorghum Panicle Weight (ANFIS-6) | | |
| | | MAPE | MAE | RMSE | MAPE | MAE | RMSE | MAPE | MAE | RMSE |
| Triangular | [3 3] | 7.57 | 7.6624 | 9.6971 | 24.77 | 3.8184 | 4.7042 | 7.07 | 0.3216 | 0.4717 |
| | [3 2] | 7.11 | 7.0251 | 9.5958 | 27.68 | 4.0041 | 4.8796 | 6.59 | 0.3109 | 0.4947 |
| | [2 2] | 8.05 | 8.0693 | 10.3974 | 26.63 | 3.7491 | 4.9433 | 6.31 | 0.2929 | 0.4766 |
| | [4 2] | 7.44 | 7.33 | 9.9284 | 21.68 | 3.6174 | 5.1553 | 6.8 | 0.3148 | 0.4809 |
| Trapezoidal | [3 3] | 7.34 | 7.3734 | 9.4516 | 25.43 | 3.64 | 4.8043 | 7.25 | 0.3321 | 0.4718 |
| | [3 2] | 7.64 | 7.6231 | 9.6295 | 25.12 | 3.7713 | 4.6919 | 6.61 | 0.3146 | 0.4957 |
| | [2 2] | 7.29 | 7.2511 | 9.5181 | 21.62 | 3.6038 | 5.0974 | 6.49 | 0.3076 | 0.4847 |
| | [4 2] | 7.32 | 7.3311 | 9.5143 | 22 | 3.6717 | 5.2302 | 7.45 | 0.3784 | 0.6374 |
| Bell-shaped | [3 3] | 8.25 | 8.9019 | 13.2622 | 30.17 | 4.2531 | 5.4302 | 15.93 | 0.6813 | 0.8268 |
| | [3 2] | 7.38 | 7.1854 | 10.9684 | 26.87 | 3.9804 | 5.0931 | 13.7 | 0.5578 | 0.6737 |
| | [2 2] | 8.16 | 8.2203 | 10.2186 | 28.69 | 4.1439 | 5.2805 | 13.42 | 0.5579 | 0.6636 |
| | [4 2] | 7.14 | 6.9103 | 9.9857 | 27.93 | 4.2529 | 5.4921 | 14.06 | 0.5899 | 0.6771 |
| Gaussian | [3 3] | 7.22 | 7.0862 | 9.8436 | 35.13 | 5.34 | 6.9752 | 6.34 | 0.2997 | 0.4798 |
| | [3 2] | 7.55 | 7.5134 | 9.5617 | 25.51 | 3.7674 | 4.785 | 6.66 | 0.3145 | 0.4511 |
| | [2 2] | 7.8 | 7.8058 | 9.933 | 35.28 | 5.5481 | 7.1964 | 6.55 | 0.3087 | 0.4533 |
| | [4 2] | 7.37 | 7.3733 | 10.1953 | 27.44 | 4.0184 | 4.8416 | 14.11 | 0.5176 | 0.7754 |

TABLE III. ACCURACY MEASUREMENT RESULTS OF ANFIS FOR VERMICOMPOST TREATMENT

| Membership Function | | Output Parameters | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Type | Degree | Sorghum Height (ANFIS-7) | | | Sorghum Biomass Weight (ANFIS-8) | | | Sorghum Panicle Weight (ANFIS-9) | | |
| | | MAPE | MAE | RMSE | MAPE | MAE | RMSE | MAPE | MAE | RMSE |
| Triangular | [3 3] | 6.05 | 5.8729 | 8.2177 | 21.72 | 4.9165 | 10.9312 | 7.49 | 0.4447 | 0.5465 |
| | [3 2] | 6.43 | 6.2208 | 8.1537 | 34.84 | 5.7267 | 9.8537 | 7.7 | 0.4538 | 0.5528 |
| | [2 2] | 6.48 | 6.4189 | 8.6914 | 23.26 | 4.8663 | 10.7253 | 8.09 | 0.4715 | 0.5574 |
| | [4 2] | 6.49 | 6.5281 | 8.6078 | 30.95 | 5.4974 | 9.5147 | 8.9 | 0.5109 | 0.6914 |
| Trapezoidal | [3 3] | 6.72 | 6.372 | 9.0279 | 25.45 | 5.1818 | 11.3331 | 7.46 | 0.4481 | 0.5494 |
| | [3 2] | 6.26 | 6.0985 | 7.8162 | 34.35 | 5.7109 | 9.8386 | 8.08 | 0.4779 | 0.5521 |
| | [2 2] | 6.35 | 6.3306 | 8.5164 | 34.48 | 5.7302 | 9.8525 | 7.75 | 0.4592 | 0.617 |
| | [4 2] | 6.15 | 5.9474 | 7.9856 | 50.26 | 6.9171 | 15.6322 | 7.25 | 0.4357 | 0.6138 |
| Bell-shaped | [3 3] | 6.34 | 6.3658 | 9.3784 | 36.13 | 6.5497 | 10.5085 | 7.79 | 0.4646 | 0.6032 |
| | [3 2] | 6.42 | 6.2479 | 7.9644 | 31.06 | 5.936 | 10.1495 | 7.74 | 0.4584 | 0.5958 |
| | [2 2] | 6.97 | 6.6223 | 8.85 | 23.91 | 4.9333 | 10.683 | 7.5 | 0.4429 | 0.6034 |
| | [4 2] | 6.44 | 6.2097 | 8.1773 | 22.62 | 4.8991 | 10.8324 | 7.97 | 0.47 | 0.6102 |
| Gaussian | [3 3] | 6.28 | 6.0763 | 7.8944 | 22.94 | 4.9947 | 11.3718 | 7.98 | 0.4676 | 0.5786 |
| | [3 2] | 6.18 | 5.9994 | 7.8711 | 32.32 | 5.6328 | 9.6765 | 7.73 | 0.4588 | 0.5605 |
| | [2 2] | 6.08 | 5.9147 | 7.7382 | 22.06 | 4.9958 | 11.3755 | 7.89 | 0.4641 | 0.5479 |
| | [4 2] | 6.43 | 6.2469 | 8.039 | 32.95 | 5.6962 | 9.6584 | 7.5 | 0.4522 | 0.5749 |

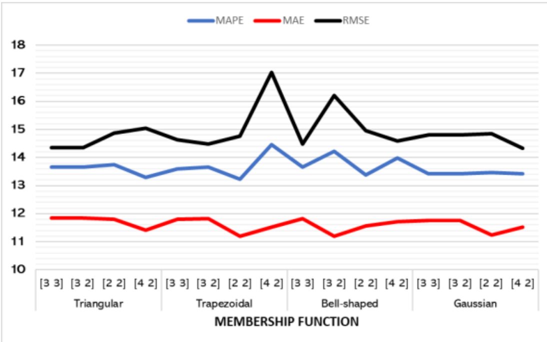


Fig. 4. The prediction accuracy level of sorghum height in chicken manure treatment.

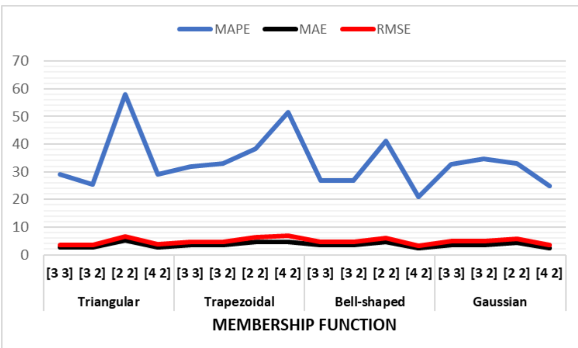


Fig. 5. The prediction accuracy level of sorghum biomass in chicken manure treatment.

Fig. 6 visually represents the accuracy outcomes in the context of chicken manure treatment, explicitly focusing on sorghum's Panicle weight (ANFIS-3) as the output parameter. Fig. 6 shows that the highest accuracy values, as measured by the three accuracy assessment tools, are achieved when using the Trapezoidal membership function type and membership function degrees {3, 3}. The corresponding accuracy values are MAPE of 5.77%, MAE of 0.2994, and RMSE of 0.395.

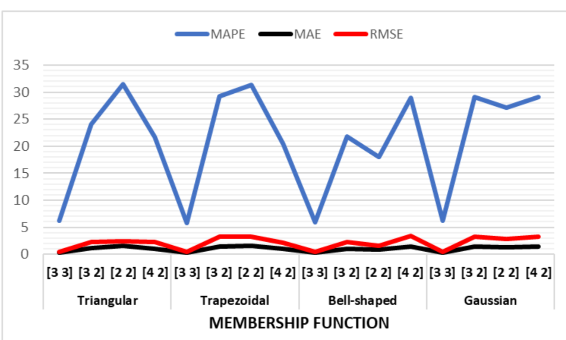


Fig. 6. The prediction accuracy level of sorghum panicle weight in chicken manure treatment.

To identify the membership function types and degrees that offer the highest accuracy in treatments involving cow manure and vermicompost, a similar methodology was applied to that used in the chicken manure treatment. By assessing the accuracy using MAPE, MAE, and RMSE for three distinct organic fertilizer dosages in a tidal swamp area for sorghum growth, the specific membership function types, and degrees for the MANFIS model predicting sorghum growth are determined and outlined in Table IV.

TABLE IV. RESULTS OF MEMBERSHIP FUNCTION TYPE AND DEGREE SELECTION

| MANFIS | Type Membership Function | Degree Membership Function |
|---|---|---|
| ANFIS-1 | Trapezoidal | {2,2} |
| ANFIS-2 | Bell-Shaped | {4,2} |
| ANFIS-3 | Trapezoidal | {3,3} |
| ANFIS-4 | Triangular | {3,2} |
| ANFIS-5 | Trapezoidal | {2,2} |
| ANFIS-6 | Triangular | {2,2} |
| ANFIS-7 | Triangular | {3,3} |
| ANFIS-8 | Triangular | {3,3} |
| ANFIS-9 | Trapezoidal | {4,2} |

Based on the accuracy testing results achieved through the utilization of four types of membership functions and four degrees of membership functions in the MANFIS model, as outlined in Table IV, we depict the schematic of the MANFIS model designed for predicting three sorghum plant growth parameters in tidal swamp land in Fig. 7.

Subsequently, the predefined MANFIS model, with the chosen membership function type and degree, is subjected to simulation using the Simulink tool. This simulation aims to predict sorghum plant growth based on input parameters related to organic fertilizer dosage and dolomite lime application. The MANFIS model is simulated in this study using the Matlab/Simulink tool, as shown in Fig. 8. The ANFIS simulation model loads the fuzzy inference system (fis) files, which are the result of the data training process on the ANFIS model. These files are the result of the data training process of the ANFIS model, according to the input parameters of organic fertilizer and the predicted output parameters. During this simulation, nine ANFIS models predict three output parameters, with three organic fertilizer treatments as inputs.

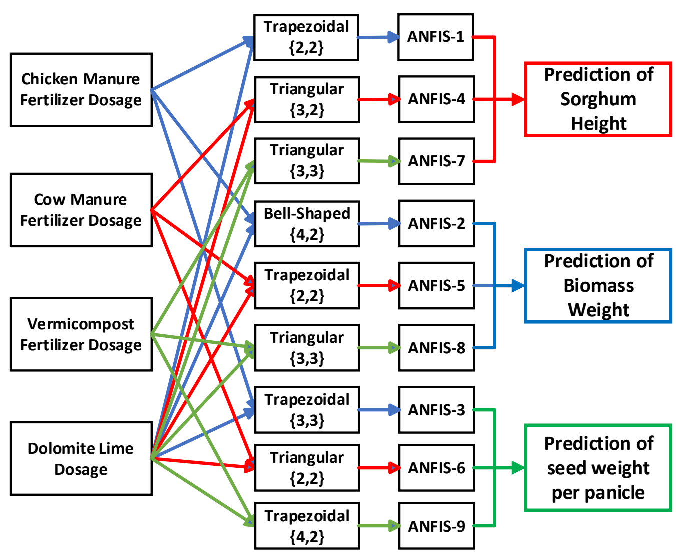


Fig. 7. MANFIS prediction model with selected membership function.

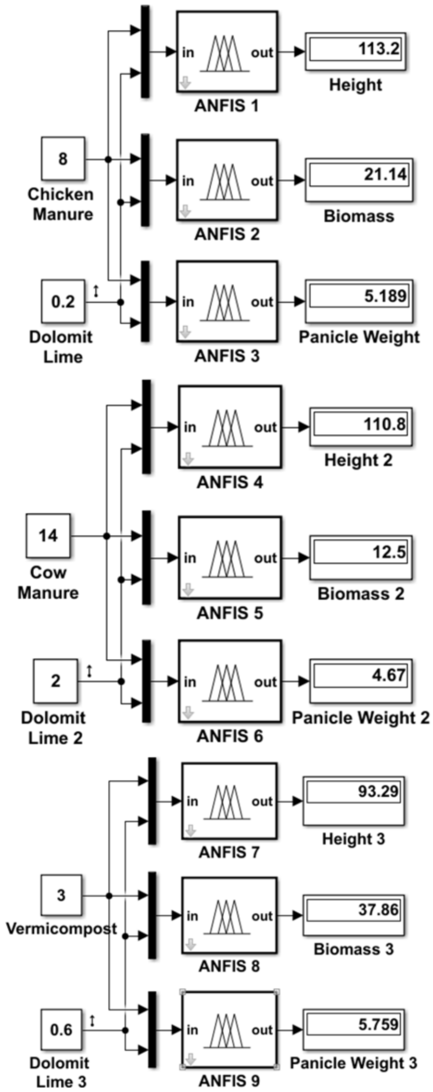


Fig. 8. Simulation of MANFIS prediction model.

In Fig. 8, for chicken manure fertilizer with a dose of 8 tons/ha and dolomite lime with a dose of 0.2 tons/ha, the predicted results are as follows: sorghum height (ANFIS-1) = 113.2 cm, sorghum biomass weight (ANFIS-2) = 21.14 tons/ha, and sorghum panicle weight (ANFIS-3) = 5.189 tons/ha. For cow manure fertilizer with a dose of 14 tons/ha and dolomite lime with a dose of 2 tons/ha, the predicted results are sorghum height (ANFIS-4) = 110.8 cm, sorghum biomass weight (ANFIS-5) = 12.5 tons/ha, and sorghum panicle weight (ANFIS-6) = 4.67 tons/ha. Similarly, for vermicompost fertilizer with a dose of 3 tons/ha and dolomite lime with a dose of 0.6 tons/ha, the predicted results are sorghum height (ANFIS-7) = 93.29 cm, sorghum biomass weight (ANFIS-8) = 37.86 tons/ha, and Sorghum panicle weight (ANFIS-9) = 5.759 tons/ha.

Table V presents the simulation results of predictions (height, biomass, and sorghum panicle weight) for various treatments with different doses of organic fertilizer and dolomite lime. In this Table V, each organic fertilizer is subjected to three combinations of organic fertilizer and dolomite lime doses, resulting in three predicted outcome parameters through the conducted simulations. This MANFIS model simulation (see Fig. 8) provides insights into the predicted outcomes obtained from applying various doses of organic fertilizer and dolomite lime on tidal land soil for sorghum plant growth prediction.

TABLE V. RESULTS OF MANFIS MODEL SIMULATION PREDICTION

| Fertilizer Dosage (ton/ha) | Dolomite Lime Dosage (ton/ha) | Prediction Results | | |
|---|---|---|---|---|
| | | Height (cm) | Biomass (ton/ha) | Panicle weight (ton/ha) |
| Chicken Manure | | | | |
| 5 | 0.404 | 109.6 | 22.76 | 6.3 |
| 2 | 0.6 | 98.34 | 19.58 | 6.331 |
| 8 | 0.2 | 113.2 | 21.14 | 5.189 |
| Cow Manure | | | | |
| 5 | 1.5 | 104.5 | 21 | 3.782 |
| 8 | 1 | 108.2 | 18.86 | 4.493 |
| 14 | 2 | 110.8 | 12.5 | 4.67 |
| Vermicompost | | | | |
| 5 | 0.404 | 101.1 | 17.4 | 5.595 |
| 8 | 0.1 | 50.23 | 10.11 | 3.1 |
| 3 | 0.6 | 93.29 | 37.86 | 5.759 |

## IV. CONCLUSION

The type of membership function used in this prediction model has a different type of membership function for each treatment of organic fertilizer on tidal soil for sorghum. The MANFIS model, using a dataset derived from observational data on sorghum plant height, biomass, and panicle weight with treatments of organic fertilizers (chicken manure, cow manure, vermicompost) in tidal soil, can be implemented to predict sorghum plant growth, including three predicted parameters: plant height, biomass, and panicle weight. The structure of the MANFIS model designed in this study consists of nine ANFIS models. The comparison of prediction accuracy results, utilizing three measurement tools - MAPE, MAE, and RMSE, demonstrates that the choice of membership function types and degrees influences the accuracy of prediction outcomes for each input data originating from the organic fertilizer treatment in tidal swamp land. This research achieved the highest prediction accuracy with the ANFIS-5 model for predicting the panicle weight of sorghum using Trapezoidal membership type and membership function parameters [3,3]. The model assessed the accuracy levels with a Mean Absolute Percentage Error (MAPE) of 5.77%, Mean Absolute Error (MAE) of 0.2994, and Root Mean Square Error (RMSE) of 0.395.

In conclusion, this research has successfully outlined a robust approach for predicting three sorghum plant growth parameters with high accuracy using the MANFIS model and optimal membership function selection. These findings hold significant potential for advancing agriculture and aiding stakeholders in making informed decisions in sorghum cultivation. Furthermore, this study also contributes to developing ANFIS modelling techniques in the agricultural context. The optimal membership function selection applied in this research can serve as a guideline for future similar studies in predicting sorghum plant growth and other agricultural research endeavours. In future research, researchers can incorporate additional environmental factors like climate and rainfall for predicting plant growth. Additionally, they can explore other machine learning models to compare their prediction accuracy.

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