Since 2001 ajfand AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT

SCHOLARLY, PEER REVIEWED

Volume 25 No. 5
June 2025

PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

Afr. J. Food Agric. Nutr. Dev. 2025; 25(5): 26600-26628 https://doi.org/10.18697/ajfand.142.24495

Date	Submitted	Accepted	Published
	17th January 2024	14th May 2025	7th July 2025

PRICE PREDICTIONS ON RED CHILI (*CAPSICUM ANNUUM*) COMMODITIES IN INDONESIA

Andayani SA[1]*, Ismail AY[2], Permana NS[3], Nainggolan MF[4] and SA Sembiring[4]

Sri Ayu Andayani

Corresponding author email: sriayuandayani@unma.ac.id
ORCID: https://orcid.org/0000-0002-9807-3034

[1]Department of Agribusiness, Faculty of Agriculture, Universitas Majalengka, Majalengka, West Java, Indonesia

[2]Department of Master of Biology Education, Postgraduate School, Universitas Kuningan, Kuningan, West Java, Indonesia

[3]Department of Agribusiness, Faculty of Agriculture, Universitas Winaya Mukti, Sumedang, West Java, Indonesia

[4]Department of Agribusiness, Faculty of Agriculture, University of Santo Thomas, Medan, North Sumatera, Indonesia

ABSTRACT

Red chili peppers are a high-value crop, widely used for industrial needs and household consumption, leading to a continuous increase in demand. However, the instability in the availability of red chili peppers causes price and consumption fluctuations. Therefore, it is essential to evaluate not only the production aspects but also the consumption patterns of red chili peppers to enable more accurate price predictions and anticipate unexpected price changes. This study aimed to analyze the price prediction of red chili peppers based on consumption and production patterns, linked to variations in community consumption needs. The findings of this analysis are expected to serve as recommendations for balancing the demand and supply of red chili peppers. The research was conducted in Majalengka Regency, West Java Province, which was selected as the study area due to its status as one of the horticultural centers. Data were collected through direct interviews and questionnaires to farmers and red chili business actors in Majalengka Regency. The sample was determined to be 156 respondents. The analytical methods used in this study were the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Matrix Impact Cross-Reference Multiplication Applied to Classification (MICMAC) analysis, where both methods complement and reinforce each other's results. The findings indicate that price determination for red chili peppers in Majalengka is influenced by various variables analyzed using the ANFIS and MICMAC methods. The production variable is the most dominant factor in determining red chili pepper prices, with ANFIS achieving a prediction accuracy rate of 97.5%. Additionally, MICMAC analysis revealed that household needs, the hotel and restaurant industry, catering services, and production factors significantly influence future price predictions of red chili peppers. The implications of this study suggest that farmers can design production patterns aligned with consumption trends to improve the accuracy of red chili pepper price predictions. Furthermore, the findings can serve as policy recommendations for policymakers in developing production mapping strategies and planting patterns to maintain a stable supply of red chili peppers in the market. Through this approach, a balance between production and demand can be achieved, ultimately improving farmers' welfare and preventing detrimental price fluctuations.

Key words: Red Chili, Consumption Pattern, Farmer, ANFIS, MICMAC, Production, Price Prediction

Citation: **Andayani SA, Ismail AY, Permana NS, Nainggolan MF and SA Sembiring** Price predictions on red chili (*Capsicum annuum*) commodities in Indonesia. *Afr. J. Food Agric. Nutr. Dev.* 2025; **25(5):** 26600-26628 https://doi.org/10.18697/ajfand.142.24495

INTRODUCTION

Red chili is a horticultural and spice commodity that is widely produced in Indonesia [1]. Indonesia contributes 32% of the world's red chili production or around 4.1 million tons of the world's red chili production of around 12.8 million tons [2]. In Southeast Asia, red chili is popular as a food flavor enhancer [3]. Red chili is one of the crops characterized by production and price uncertainty [4]. Variations on supply and demand for red chili have always existed but there is unpredictable production due to variations in weather conditions [5], which have a negative impact on this sector [6].

Red chili is one of the strategic commodities; however, there are still many problems in farming related to uncertainty and climate and the long chain of marketing actors [7] often experiencing production risks [8]. Many factors affect red chili production including environmental factors, pests and diseases, lack of water, lack of superior varieties and soil fertility as experienced in Pakistan, quality is still low as well as low exports, and red chili farmers still have limited access to modern agriculture [9,10,11].

Red chili is one of the agricultural commodities that is in great demand in the world to be cultivated by farmers. Countries that produce red chili are Pakistan, Ethiopia, Myanmar, Mexico, Vietnam, Peru, Ghana, and Bangladesh as well as India [12]. Under current conditions, red chili has the potential to be developed because it has high economic value and very high benefits for household consumption and the food industry [13]. However, production is still not optimal and fluctuates, so it impacts prices.

Red chili is produced in the Americas, Europe and Asia including Indonesia , and has high economic value [14]. The price of red chili tends to fluctuate with changes in supply and demand, therefore, it has an impact on the unstable income of farmers, so predictions of red chili prices are needed. Price prediction is required to find out the condition of red chili prices in the future so that it helps farmers make decisions to carry out further cultivation [15]. Forecasting analysis is also needed to predict future red chili production so that it can help policymakers in improving chili production and export policies [16]. This will also help in expanding the chili trade to importing countries and is supported by paying attention to the rupiah exchange rate [1].

Red chili consumption also fluctuates but relatively increases by 3.29% every year [17] and the average consumption of red chili in Indonesia is 5 kg/capita/year and 90% of it is consumed fresh [18]. The growth of chili consumption will have an impact on the demand for chili and subsequently result in price disturbances, hence fluctuations [19].

Based on this phenomenon, production management efforts are needed to maintain the sustainability of red chili production and assess its sustainability by considering consumption patterns and needs. Therefore, this study aims to analyze price predictions and consumption patterns of red chili in relation to various consumption needs of the community in order to compile a red chili price prediction model.

MATERIALS AND METHODS

This research was conducted in Majalengka Regency, West Java Province, Indonesia, which is a red chili-producing area. The research time frame was from mid-2022 to 2023. The data used in this study were primary data and secondary data. The primary data used were data on red chili production, demand, consumption of red chili, and the price of red chili. Primary data were obtained by conducting direct observation, interviews, and also filling out questionnaires. Secondary data used included geographical position data and literature reviews from various references such as scientific journals and other supporting sources. Secondary data were obtained from the Majalengka district government data archive, books, previous research journals, and internet sources.

This study uses a cross-sectional research design, which means that data are collected at a certain point in time. Respondents consist of red chili farmers and the surrounding community who play a role in the development of red chili horticulture in Majalengka Regency. In this case, respondents are determined using purposive sampling, which is a sampling technique that is carried out intentionally based on certain criteria. In the context of this study, the respondents selected are red chili farmers and the surrounding community who are involved in the development of red chili horticulture. By using Slovin, 156 respondents were obtained from the total population of this study.

The study used a quantitative descriptive data analysis method using the ANFIS method and the MicMac method. Adaptive Neuro-Fuzzy Inference System (ANFIS) and Matrix Impact Cross-Reference Multiplication Applied to Classification (MICMAC) have a close relationship in complex system analysis, especially in decision-making and dynamic system modelling. Adaptive Neuro-Fuzzy Inference System (ANFIS) combines artificial neural network techniques with fuzzy logic, resulting in an adaptive model that can handle uncertainty or non-linearity in the data. Matrix Impact Cross-Reference Multiplication Applied to Classification (MICMAC) is a mapping method that analyzes the relationship between factors in a system through an impact matrix, thus helping to identify the main factors that most influence or are influenced in a system.

The combination of ANFIS and MICMAC is useful in complex modeling and analysis, where MICMAC can help identify key variables that can be incorporated into the ANFIS model. Thus, these two methods complement each other to produce more in-depth and accurate predictive models and analyses in complex systems. Several previous studies that used ANFIS as a system for making predictions, applied design of experiments (DOE) techniques to identify significant parameters in the design of adaptive neuro-fuzzy inference system (ANFIS) for stock price prediction. To estimate the price of agricultural commodities, a hybrid intelligence system called the Adaptive Neuro-Fuzzy Inference System (ANFIS) is used [40].

Data Preparation

The data used in this study were time series data obtained from direct observation from 2022 to 2023 in the Majalengka district. The data recorded were weekly red chili prices in Majalengka Regency. Based on observations and recording of weekly data, time series data of red chili prices for a year of observation were obtained, which was used to predict red chili prices in Majalengka Regency. Data analysis was done in two stages: the data preparation stage and the analysis stage. The data preparation stage included determining the part of the data to be measured, determining the criteria used for analysis, and data analysis tools. In the analysis stage, observation data were compared with prediction data that were issued by the artificial neural network. The data preparation stage of analysis starts with determining the index. All the indexes that are set must be supported by criteria as a determinant of good or bad performance. The scale determination uses a continuous line criterion that divides the basic response into 5 levels (very good, good, sufficient, less good, and bad).

There are five dimensional criteria set, these criteria were adjusted to field observation data in the form of production data, needs, household consumption, raw material consumption, hospital needs, cafes and catering (Horeca), and price data. These variables are important in predicting the price of red chili because each of these factors affects the balance between supply and demand in the market [21].

Red chili production data provides information about the amount of red chili available on the market. When chili production increases, supply will be abundant and tend to depress prices. Conversely, if there is a decrease in production (for example due to bad weather, pest attacks, or distribution problems), supply will decrease and potentially increase prices [22]. Red chili demand needs to include estimates of how much chili is needed overall on the market. The higher the demand (for example, during a certain season or increasing demand due to the spicy food trend), the price tends to increase. Conversely, if demand decreases, the price has the potential to be stable or even decrease [23].

Household consumption reflects demand at the end consumer level. This consumption is affected when households buy chilies in a lot of quantities, such as during the holiday season or in certain traditions, when demand increases, thus affecting market prices [24]. In addition, red chilies are also widely used as raw materials in the food processing industry, such as the production of sauces and various spicy foods. If the industry increases production, demand for red chilies as raw materials will also increase, which in turn can affect market price increases [25].

Red chili demand in the Horeca sector (hospitals, cafes, and catering) uses large amounts of red chili to meet customer needs. If the demand for red chili in Horeca increases (for example, due to certain culinary trends), then demand will increase which will have an impact on prices [26]. Red chili price data provide a basis for predicting future price trends. By analyzing historical price patterns, one can identify recurring trends and seasonal patterns. These data are also useful for projecting prices based on current supply and demand factors [27]. Overall, the combination of these variables allows to map the interaction between supply and demand, identify trends, and create more accurate predictive models.

The data that became the observation data were taken from the results of daily data collection from each variable that was set for 56 weeks from 2022 to 2023 in the Majalengka District area. The average compliance was converted into category data by determining the interval as determined above. This is done to be able to adjust to the factual conditions in the field and adjust to the vaccination cases that will be input into the ANFIS and MICMAC artificial neural networks. Table 1 shows the order of intervals that were adjusted based on direct observation data in the Majalengka District area.

Adaptive Neuro Fuzzy Inference System (ANFIS) analysis method

Adaptive Neuro Fuzzy Inference System (ANFIS) is a network based on a fuzzy inference system. Neuro-fuzzy is a combination of two systems, namely a fuzzy logic system and artificial neural networks [28]. Neuro-fuzzy systems are based on fuzzy inference systems that are trained using learning algorithms derived from artificial neural network systems. Thus, neuro-fuzzy systems have all the advantages possessed by fuzzy inference systems and artificial neural network systems. From their ability to learn, neuro-fuzzy systems are often referred to as ANFIS. Based on this, ANFIS is suitable for predicting the price of red chilies because of its ability to handle non-linear and fluctuating data, such as production variables, needs, consumption and historical price data. This method can integrate various variables that affect the price of red chilies and produce a model that is adaptive to changes in variables that are often uncertain, resulting in more accurate and reliable price predictions. One form of structure that is well-known is shown in Figure 1. In this structure, the fuzzy inference system applied is the Takagi-Sugeno-Kang fuzzy inference model.

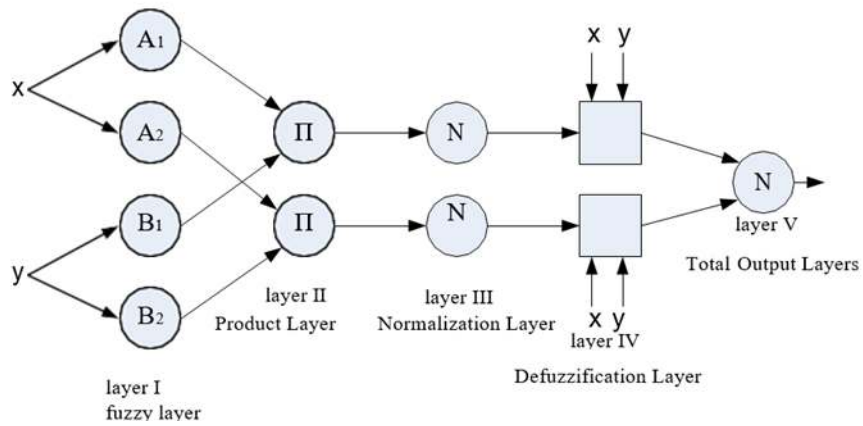


Figure 1: ANFIS Model Structure [28]

In the Neuro-Fuzzy system, there are five process layers where the functions and similarities of each layer are explained as follows: layer 1 is input data consisting of production, household consumption needs, industrial consumption, and consumption of hotels, restaurants, and catering businesses. The second layer is the formation of the model by ANFIS, layer 3 is the process of testing data by the ANFIS application, layer 4 is testing predictions based on training data and real data that have been entered into the application, and layer 5 is the process of model formation by ANFIS.

Layer 1: Fuzzification Layer

Make O1, i the output of each node in layer 1. Each node i in this layer is an adaptive node with node function O1, i = μAi(x) for i = 1, 2; or O1, i = μBi(y) for i = 1, 2, where x is the input to node i and Ai is the linguistic label (small, large, medium) corresponding to this node function. Elsewhere O1, i is the membership function of A1 and its membership degree is specific to x given sufficient quantization of Ai. Commonly used membership functions are Bell and Gaussian.
The Bell form membership function is expressed as:

https://doi.org/10.18697/ajfand.142.24495

ajfand Since 2001
AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

$$f\ x; a_i, b_i, c_i = \frac{1}{1 + \frac{x - c_i}{a_i}^{2b_i}} \tag{1}$$

With parameter b usually positive. Parameter c is located in the middle of the curve. The Gaussian membership function is expressed as:

$$\mu_A(x_t) = e^{\frac{-(x_t - c)^2}{2\sigma^2}} \tag{2}$$

Layer 2: Product layer

Each node in this layer consists of a prod t-norm operator as a node function. This layer synthesizes the transmission of information with layer 1 and multiplication of all incoming signals and sends the product out. The output of the product layer is expressed as:

$$O_{2,i} = w_i = \mu A_i(x). \mu B_i(y); i = 1,2 \tag{3}$$

Each node in this layer serves as a measure of the strength of the rule. The output of this layer acts as a weight function.

Layer 3: Normalization Layer

Each node in this layer normalizes the weight function obtained from the previous product layer. The normalized output is calculated by:

$$O_{3,1} = w_t \frac{w_i}{w_1 + w_2}, and\ i = 1,2 \tag{4}$$

The function can be expanded if there are more than two rules by dividing it by the total number w for all rules.

Layer 4: Defuzzification Layer

The nodes in this layer are naturally adaptive. The defuzzification output of this layer is calculated by the formula:

$$O_{4,1t} = w_{1t}^{*} Z_t^{(1)} = w_{1t}^{*}(\alpha_1 Z_{t-1} + \beta_1 Z_{t-2} + \gamma_1), \tag{5}$$

$$O_{4,2t} = w_{2t}^{*} Z_t^{(2)} = w_2^{*}(\alpha_2 Z_{t-1} + \beta_2 Z_{t-2} + \gamma_2) \tag{6}$$

where α_i, β_i, γ_i are the set of node parameters and are called consequence parameters.

Since 2001 ajfand AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

Layer 5: Total output layer

A single node at this layer synthesizes the information sent to layer 4 and returns the overall output using the following fixed function:

$$O_{5t} = \hat{Z}_t = w_{1t}^{*} Z_t^{(1)} + w_{2t}^{*} Z_t^{(2)} \quad (7)$$

MICMAC Analysis

Matrix of Crossed Impact Multiplications Applied to a Classification (MICMAC) method is one of the structural analysis methods. This method can provide solutions to the complexity of data on the influence of a variable by systematically and structurey sorting the elements of a system and through the form of relationships that occur between variables. The MICMAC method is often used to identify key factors [29].

Matrix Impact Cross-Reference Multiplication Applied to Classification (MICMAC) analysis can provide a more convincing and reliable basis for consideration in addressing the proposed problem. Through the use of this method, the main variables of a system can also be identified and analyzed [30]. Furthermore, the MICMAC method in its analysis is based on the depiction of two axis values, namely driver power (DP) and dependent variables so that the variables can be categorized or grouped into each sector/cluster/quadrant [31,32]. There are three basic steps in the MICMAC method, namely: identifying variables, explaining the relationship between variables and identifying key variables [33].

The MICMAC analysis stage is based on two main stages. The first stage is understanding the scope of the problem and the system to be studied [34]. The flow of analysis using MICMAC can be seen in Figure 2.

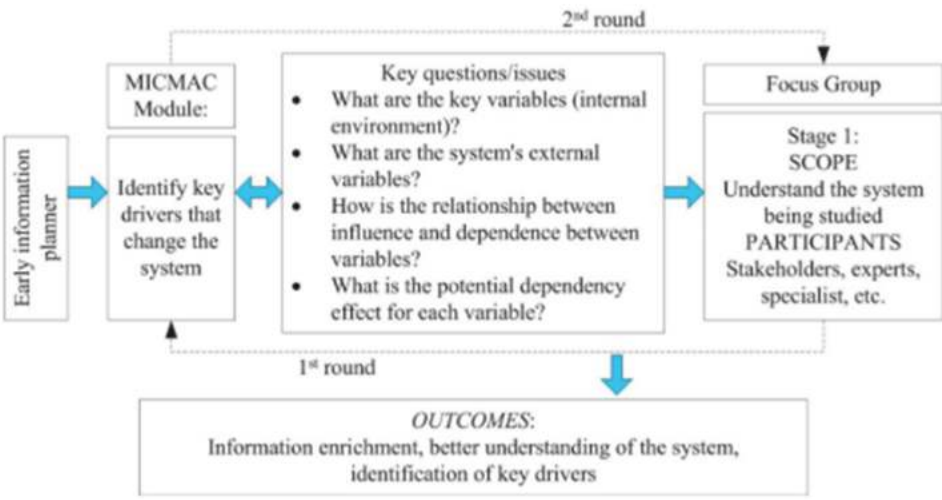


Figure 2: MICMAC Framework [34]

MICMAC Analysis Design

The data collected are the data that are used as a reference in building attributes or variables of red chili production, red chili needs, red chili consumption, and red chili prices. Data from each variable were collected based on the results obtained from direct observations around the Majalengka Regency. Implementation in filling in time series observation data is transformed into scale data that describes the direct relationship between variables by quantifying the use of a scale of 0 to 3 and P: 0 = no relationship (non-existent) 1 = weak relationship (low direct influence) 2 = equal relationship (medium direct influence) 3 = strong relationship (high direct influence) P = potential (potential influence).

RESULTS AND DISCUSSION

Based on the results of the distribution of questionnaires and FGDs, some variables have been determined, and the relationship between variables has been built so that a direct influence matrix is obtained as shown in Table 1. Through the MICMAC application, Figure 3 in the form of a Matrix of Data Influence (MDI) is converted into a variable map, which reflects or illustrates the position of the influence dependence chart into four sectors (quadrants).

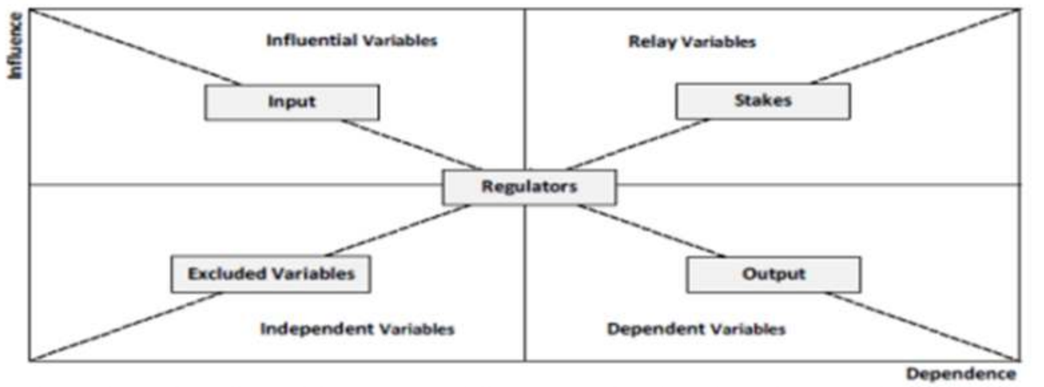


Figure 3: Illustration of MICMAC Analysis Results [34]

In Indonesia, red chili is a food crop with high economic value because it is widely used in household consumption and the food industry [35]. Average consumption is 5 kg/capita/year and around 90% is consumed fresh [36]. The growth of red chili consumption, although fluctuating, is relatively high at around 3.29% each year [37]. The key variables in determining the price of red chili consist of the state of the commodity in the market (Product), market needs, and consumption (Household, industry, (hotel, restaurant, and catering/horeca business)). The application of prospective analysis in decision-making considers the position and intensity of the influence of variables, both directly and indirectly, without any causal relationship.

Since 2001 ajfand AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

This approach has proven its validity and effectiveness in identifying the most influential variables. One of the main developments in this analysis is the understanding of the dynamics of influence in determining prices, where stock variables play a key role. In addition, this approach also contributes to projecting expected future profits. An important component in looking at prices is the determination of variables that are key factors. The condition of the strength relationship between the variables depicted in the influence-dependence quadrant is presented in Figure 4.

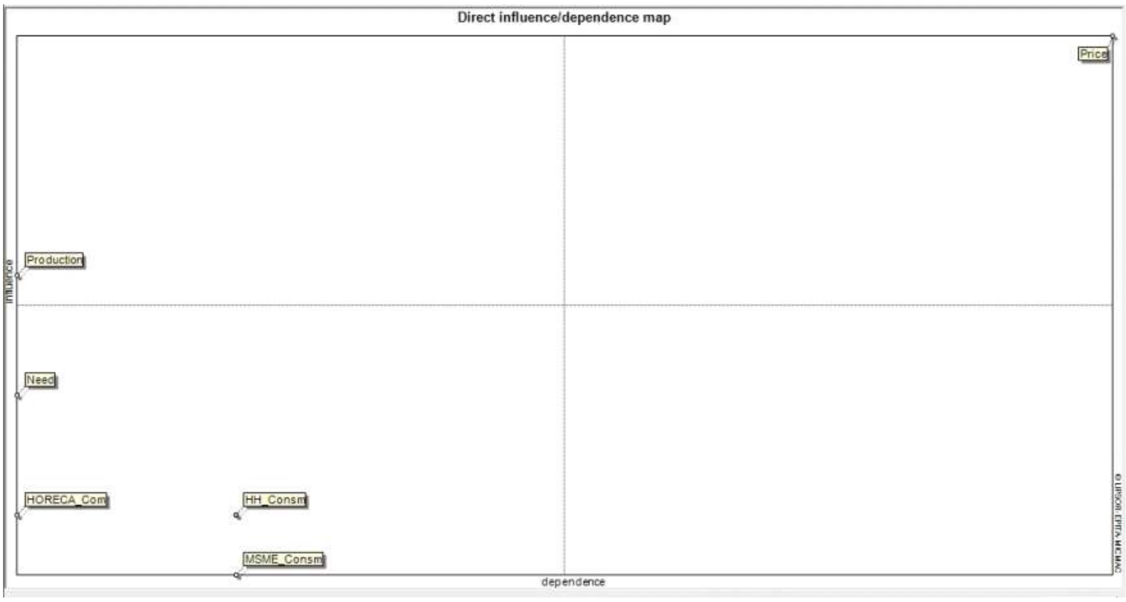


Figure 4: The position of a system variable in the direct influence-dependence map

Based on the results of the MICMAC analysis in Figure 4, it can be seen that the influence variables are in the left quadrant while the variables for receiving benefits or influenced variables are in the right quadrant. It is obtained that the variable in the first quadrant (determinant variables) is the production of red chili pepper farmers in the Majalengka area (Production). The first quadrant's characteristics are variables with a high level of influence and low dependence. Variables that have a high influence and a high level of dependency, but show an unstable relationship between variables, are located in the second quadrant (key variables). These variables include market needs (Need), household consumption (HH_Consm), industrial consumption (MSME_Consm), and consumption for hotel, restaurant, and catering businesses (HORECA_Com). Furthermore, the variables in quadrant three (outcome variables) have a low influence but a high level of dependency. This variable can be occupied by variables that are influenced by the independent variable, in this case the price of red chili (price). Quadrant four (Autonomous variables) variables have low influence and dependence there are no variables that have a low influence on prices.

Furthermore, the shape of the relationship between variables is expressed in the graph shown in Figure 5.

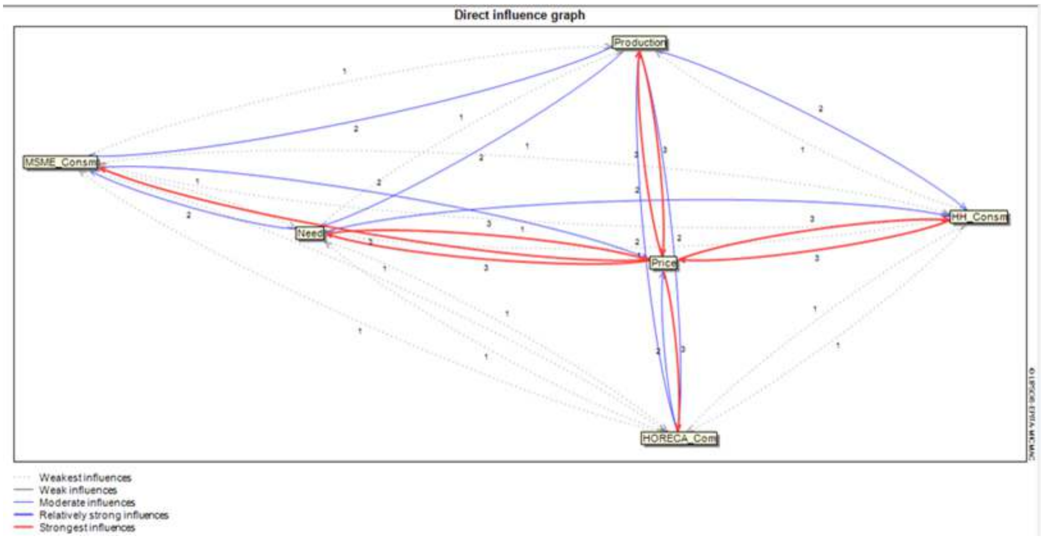


Figure 5: Graphic illustration of influence-dependence variable (Graphic illustration of influence-dependence

Based on Figure 5, the relationship expressed by the dotted line means Weak influences, the blue line means Moderate influences, and blue line means Relatively strong influences, and the red line means Strongest influences. The determination of the price of red chili peppers is sequentially influenced by various variables, namely the production of red chili farmers in the Majalengka area (Production), price determination based on agreements according to market needs (Need), household consumption (HH_Consm), consumption for hotel, restaurant, and catering businesses (HORECA_Com), and industrial consumption (MSME_Consm). These variables have a significant influence on the results shown in Figure 5. In contrast, the lowest value is the industrial consumption variable (MSME_Consm). Based on this, it can be concluded that the variables of production of red chili, needs, household consumption, and consumption for HoReCa, are variables that determine the fluctuation of chili prices in the Majalengka area.

Matrix of Indirect Influence

Apart from being based on MDI, the position of variables in the influence-dependence chart quadrant is also based on MII (Matrix of indirect Influence) so that changes in their position can be seen through the displacement map. Based on the MII, each system variable is reclassified into four sectors (quadrants) based on its position on the influence-dependence chart, as presented in Figure 6. There is no movement in the position of the variable, which indicates that the variables set are determinant factors in determining the price of chili in the Majalengka area.

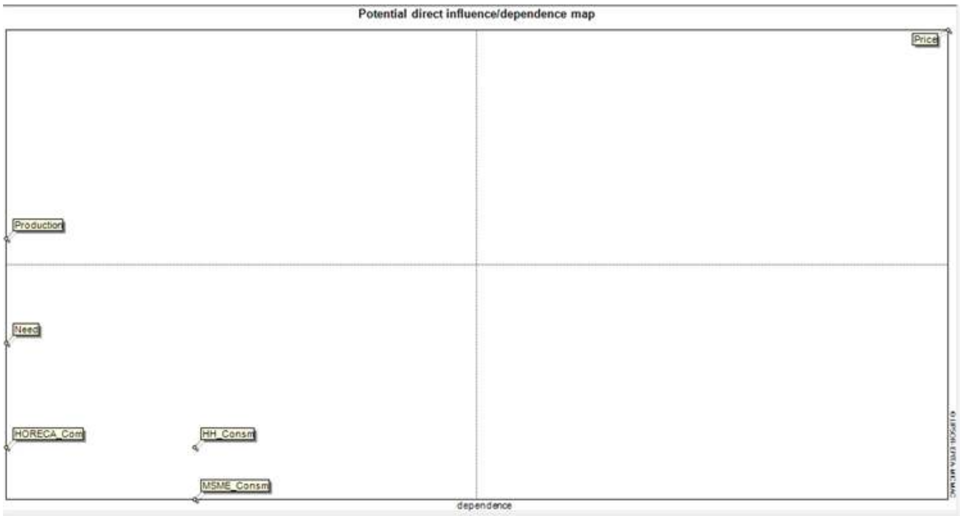


Figure 6: Matrix of Indirect Influence

A visual representation of the complexity of interactions between system variables related to the level of influence and dependence indirectly (indirect influence) on other variables is shown in Figure 7. It can be seen that visually the production variable of chili farmers in the Majalengka region (Production) is the strongest variable in influencing the determination of chili prices in the Majalengka region. In addition, it is also seen that Household consumption (HH_Consm) and Market Needs (Need) influence price determination. The number on each arrow indicates the degree or rating of influence obtained through the iteration of the Boolean matrix. In contrast to direct influence, most variables have a strong dependent influence on other variables (marked by many red lines).

ajfand Since 2001
AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

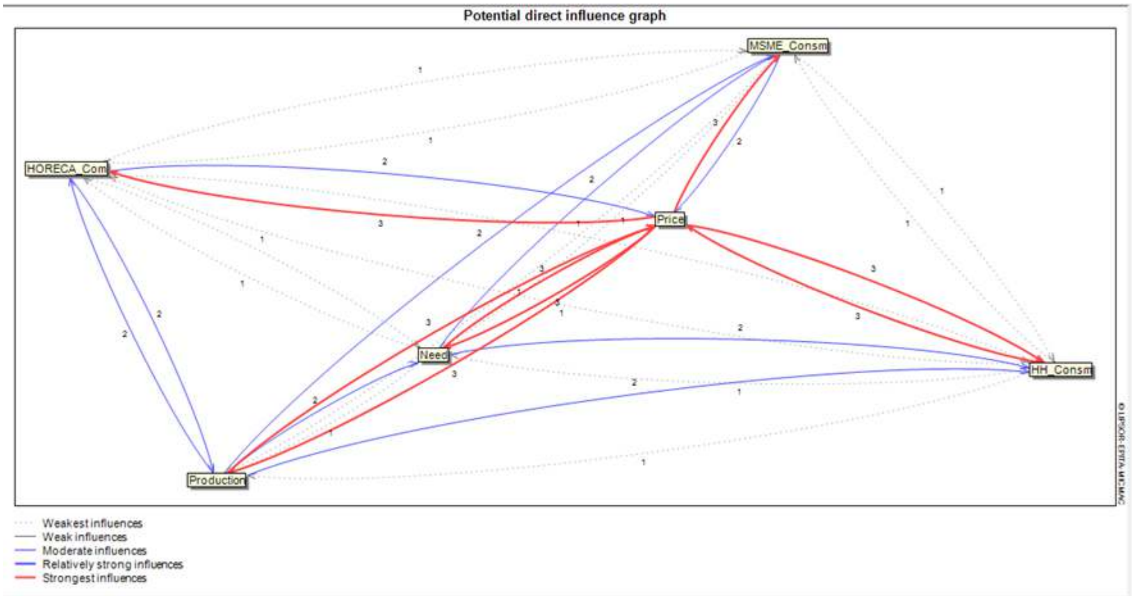


Figure 7: Potential Indirect Influence Graph

Implementation of Neuro-Fuzzy- ANFIS

In this study, the design of the development model was carried out using observation data that had been set on a scale that was in accordance with the scale provisions in the research method. There are 6 input data such as production variables, needs, household consumption, industrial consumption, and HORECA business consumption while price observation data. Data from these input variables are used as training data for predictors against ANFIS then ANFIS automatically develops an input data model that forms a rule as a reference in prediction.

Since 2001
ajfand
AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

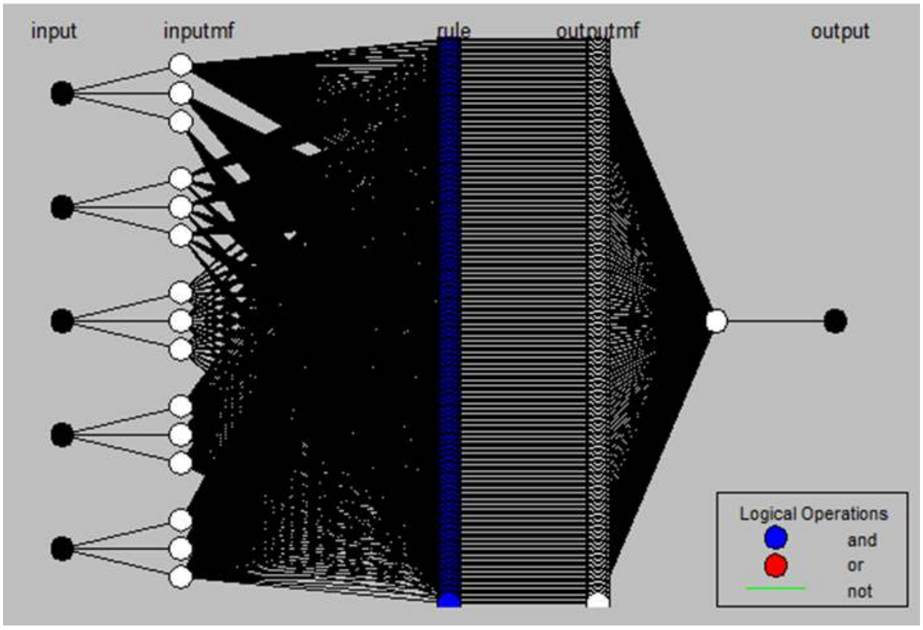


Figure 8: Data input and model development in Neuro-Fuzzy- ANFIS

Adaptive Neuro-Fuzzy Inference System (ANFIS) input data must be tested by determining the training error on ANFIS. To perform error training, it is necessary to determine the number of epochs. The epoch used is 100 with an Error Tolerance value of 0. The results of the ANFIS error training can be seen in the main graph in Figure 9. The error value is 0.192. Based on the error value which is close to 0, it can be concluded that the input data will be read by the ANFIS program accurately.

Since 2001 ajfand AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

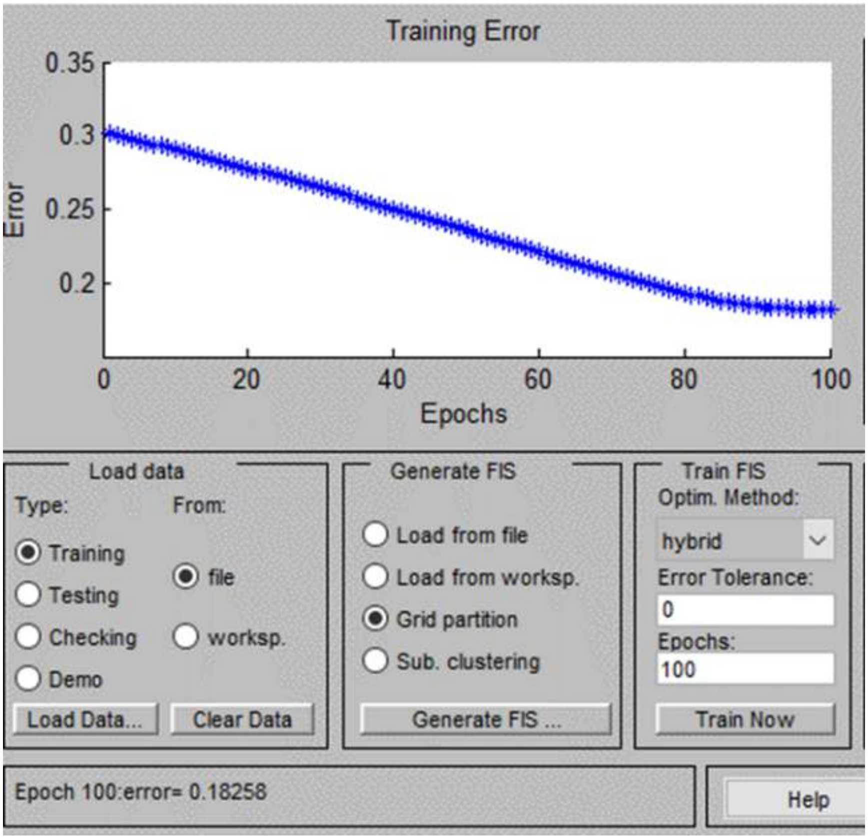


Figure 9: Training data and determination of ANFIS programming tolerance errors

Adaptive Neuro-Fuzzy Inference System (ANFIS) will display a visualization of the accuracy of training data on the ANFIS Editor graph. Based on the ANFIS visualization in Figure 10, the blue circle is symbolized by the training data, while the red dot indicates the results of ANFIS training. The more precise the red dot on the blue circle, the more precise ANFIS trains the training data, the smaller the average training error, the closer to the error tolerance, and the better the quality of the system designed in the accuracy of producing output data as prediction data. Figure 10 shows that the red dot is almost entirely on the blue circle, indicating that the input data has an error value close to 0, so it can be concluded that the input data as a variable of production, needs, household consumption, industrial consumption and HORECA business consumption can represent the chili price prediction model that will be issued by the ANFIS program.

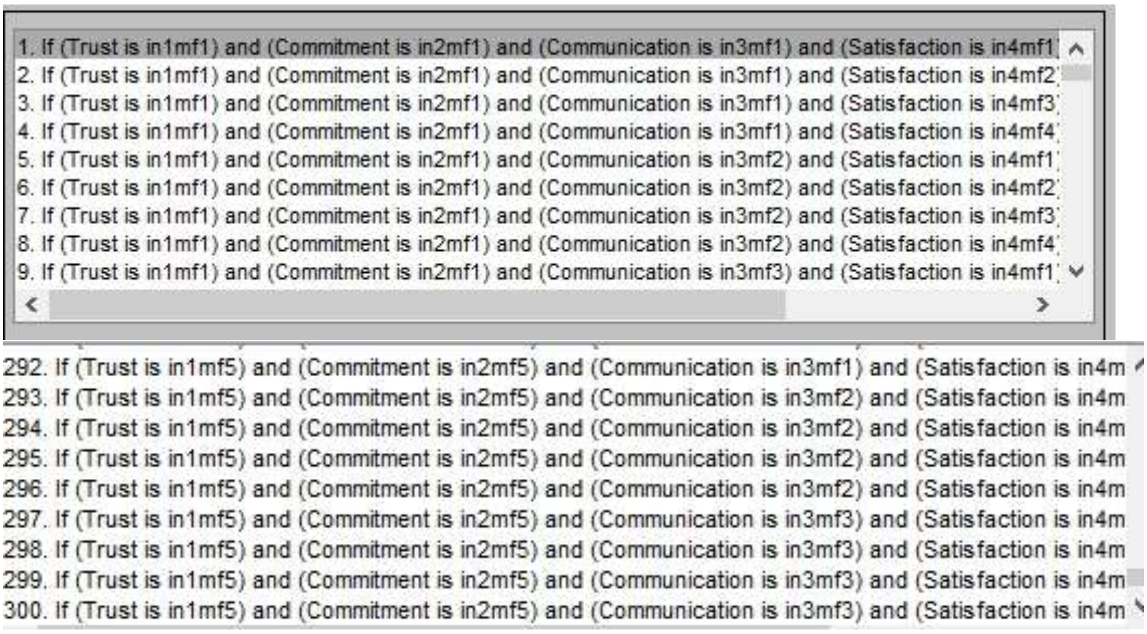
Since 2001
ajfand
AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

Figure 10: Training data input ANFIS programming

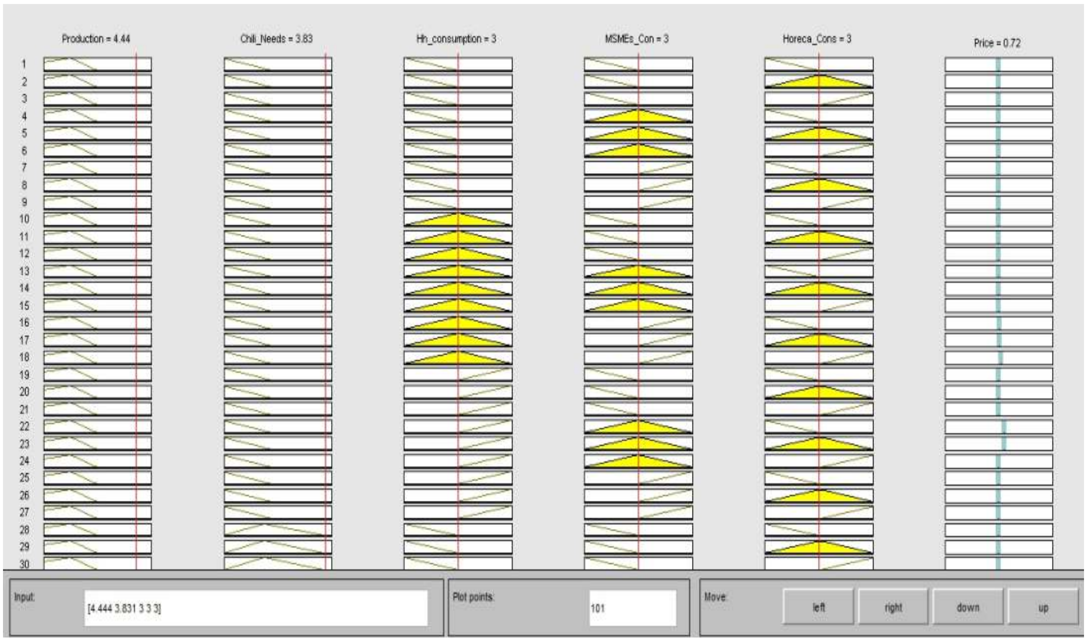
Based on the training data input into the ANFIS program, ANFIS automatically develops rules based on the data. From the input data of 6 variables to see the prediction of the price of red chili, a total of 300 rules were obtained that were suggested by ANFIS (Figure 11a). As one example of a rule developed by ANFIS, it can be seen that if the parameters in the rule viewer are moved manually, changes to the model will be immediately visible. Of the 300 rules formed by ANFIS, examples of rules are taken in Figure 11b and Figure 11c. In Figure 11b, an example of rules is taken at the input value of the production variable, needs, household consumption, industrial consumption, and HORECA business consumption, respectively [4.4 3.8 3 3 3 3] then the price is at a value of 0.72. In Figure 11c the input value of the production variable, needs, household consumption, industrial consumption, and HORECA business consumption are respectively, [1.05 3.83 3 3 3] then the price is at a value of 3.15. From the results of the visualization of the rules built by ANFIS, it is considered that the variable production of red chili peppers by farmers has a very significant impact on influencing the price of red chili peppers in the Majalengka area. If adjusted to the observation data, it will show real fluctuations in the price of chili based on the rules issued by ANFIS.

ajfand Since 2001
AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

a



b



c

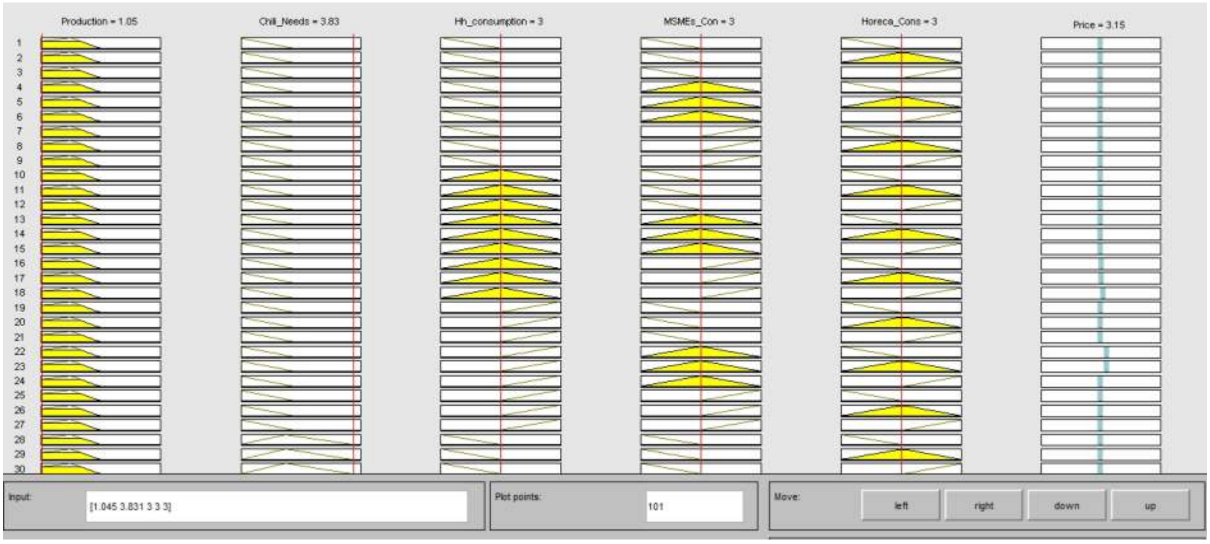


Figure 11: (a) Rules built by ANFIS programming, (b) ANFIS Rule viewer, (c) ANFIS Rule viewer

Figure 12 shows the result of 3d surface visualization built by ANFIS programming. Figure 12(a) presents a visualization of the relationship between production variables and chili demand on the price of red chili. Figure 12a shows that the highest price of chili is created when production by farmers is low (scale 1) and market demand is high (Scale 4). Figure 12(b) presents a visualization of the relationship between household production and consumption variables on chili prices. The results of the analysis show that the highest chili prices occur when farmer production is low (scale 1) and household consumption is high (scale 5). Figure 12c is a visualization of production variables and industry consumption of red chili prices. From the surface visualization, it can be seen that the highest price of chili is created when production on medium farmers (scale 3) and industry consumption is high (Scale 5). There is a uniqueness in the case of industrial needs, namely, entrepreneurs will import chili from outside the region to maintain the stability of business production when it is known that production for farmers is low. When the industry decides to buy local products when production in farmers is stable, of course, this greatly affects market prices considering the quantity of chili shopping for industrial needs is relatively large. Figure 12d is a visualization of the production and consumption variables of the HORECA business on the price of red chili. Based on the visualization, it can be seen that the highest chili price occurs when farmer production is at a low level (Scale 1) and consumption by the Horeca sector is at a high level (Scale 3). This condition is caused by stable demand from the Horeca

ajfand Since 2001 AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

sector, which relies on local resources. As a result, when local chili production decreases, prices increase significantly.

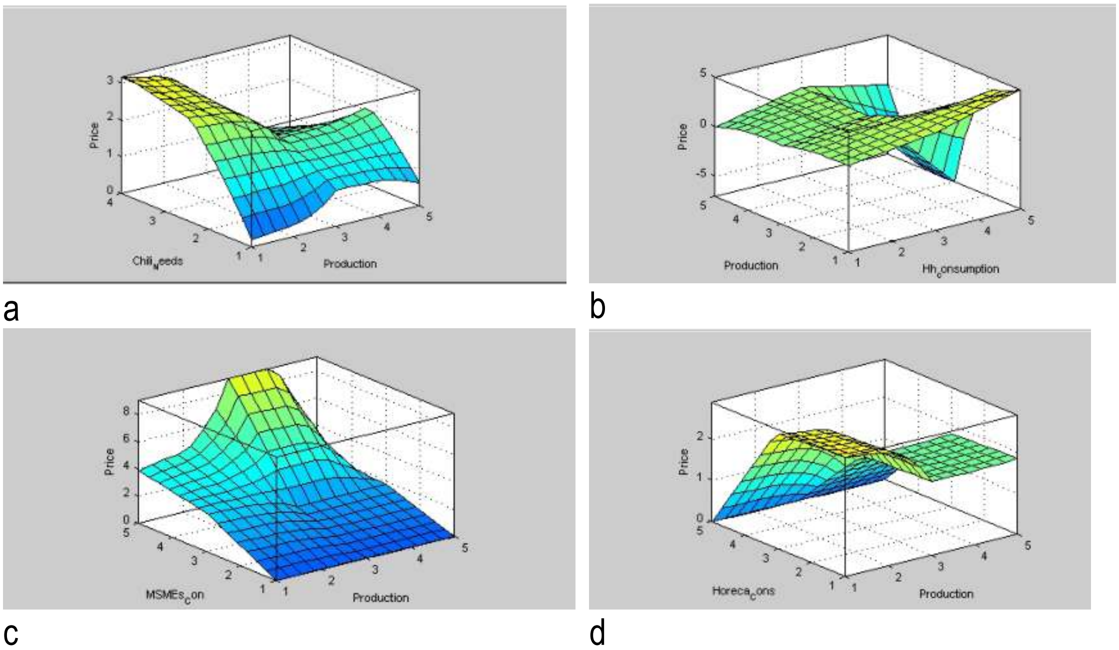


Figure 12: Visualization of surface images of ANFIS programming results in (a) a visualization of production variables, and the need for chili (b) a visualization of production variables and household consumption (c) a visualization of production variables, and industrial consumption (d) a visualization of production variables, and consumption of HORECA businesses

The accuracy of the model produced by the ANFIS program is assessed based on the RMSE value when performing Training Error and also based on the comparison of input training data to observation data or actual data. In this study, it can be seen in Figure 13 that an accuracy of 97.5% was obtained, indicating that the input data in the model can represent real data at the research location. Based on this accuracy, it can be concluded that decisions in predicting chili prices can refer to the rules formed by ANFIS.

ajfand Since 2001
AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

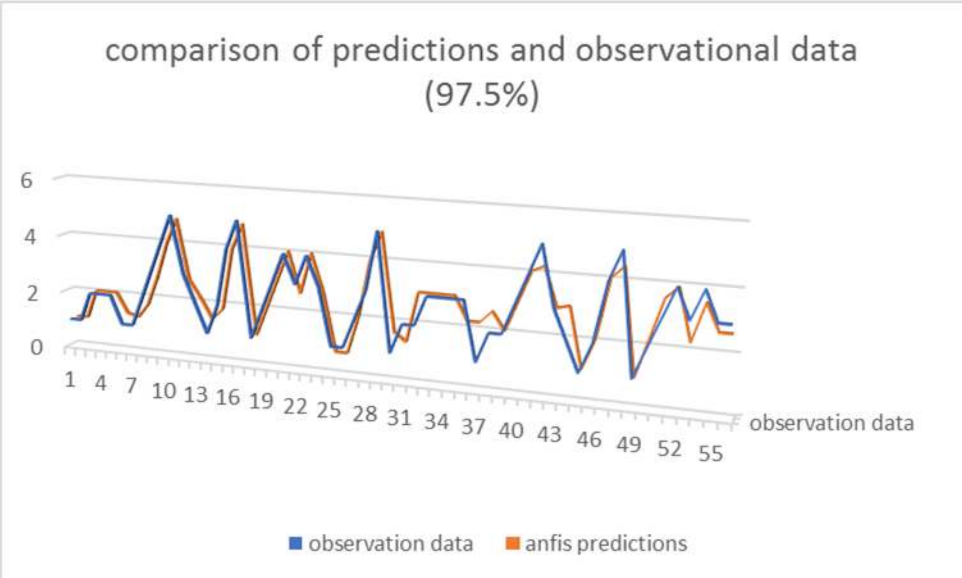


Figure 13: Prediction accuracy of the ANFIS program

Determination of the price of red chili is influenced by the main variable, namely the production of farmers, then followed by market needs, household needs, and industrial needs that increased consumption of red chilies can affect the demand for red chilies, which ultimately has an impact on market prices [37]. Price fluctuations also occur due to the demand for red chili which does not match the volume of production. Production fluctuations and consumption fluctuations have an impact on price fluctuations [38]. The results of ANFIS and MicMac analysis can be explained together showing that the production variable has a strong effect on prices. Decreasing and increasing production can predict the price of red chili in the future and consumption patterns of both household needs, industry, and hotel restaurant catering are not so strong influences on price predictions. This is reinforced by research, that there must be a policy in developing production and encouraging farmers' interest in increasing production so that the supply of red chili peppers can be stable and sustainable [40].

MICMAC and ANFIS Correlation Output

Micmac and ANFIS (Adaptive Neuro-Fuzzy Inference System) analysis provide important insights into the determinants of chili prices in the Majalengka region.

Chili Production by Farmers: The results of the Micmac analysis identify chili production by farmers as the main variable influencing prices. When chili production is high, prices generally decrease because supply is greater than demand. Conversely, if production is low, prices tend to increase due to scarcity of supply.

Market Demand and Household Needs: The second and third factors influencing prices are market demand and household needs. If market demand is high, prices will tend to increase, especially when supply is limited. Likewise, household needs also play a role in determining prices because they reflect specific local demands.
Adaptive Neuro-Fuzzy Inference System (ANFIS) approach: The ANFIS model strengthens the results of the Micmac analysis. Adaptive Neuro-Fuzzy Inference System (ANFIS) shows that high farmer production is inversely proportional to prices, so a decrease in farmer production will directly increase chili prices in the market.

Overall, these results highlight the importance of maintaining production stability and responding to demand fluctuations to control chili prices in the region.

By looking at the results of the analysis of these two methods, there is a correlation between the results of the Micmac and ANFIS analysis. In the Micmac analysis, it was found that the main variables that determine prices in the Majalengka region are chili production by farmers, followed by market demand variables and household needs. This finding is in line with the results obtained from the rules built by the Adaptive Neuro-Fuzzy Inference System (ANFIS), which show that the level of farmer production significantly affects price determination, as shown in Figure 12a–d.

CONCLUSION AND RECOMMENDATIONS FOR DEVELOPMENT

The determination of the price of red chili in the Majalengka region seen from the results of ANFIS and Micmac is influenced by each variable observed. The variable that most influences price determination is the production variable. The ANFIS prediction accuracy value can be used as a reference in determining the price of red chili in the Majalengka region, namely 97.5%. The prediction of the price of red chili can be significantly influenced by the pattern of household needs, the hotel restaurant industry, catering, and production. Where based on the results of MICMAC, the variables of household needs, the hotel restaurant industry, catering, and production significantly affect the prediction of the price of red chili in the future. The results of this study imply that farmers can make production patterns that are adjusted to consumption patterns so that they can predict future chili prices and can also provide recommendations for policymakers in making policies with mapping and production planting patterns to ensure the supply of red chili.

ajfand Since 2001
AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

ACKNOWLEDGEMENTS

Many thanks to Majalengka University for their support for this research as well as the collaboration and participation of Kuningan University, and Santo. Thomas University Medan.

Author Contributions

Conceptualization, SAA, Methodology MFN, Validation AYI, Data curation NSP, Writing the original draft preparation SAS, and Supervision SAA and MFN. All authors have read and agreed to the published version of the manuscript.

ajfand Since 2001 AFRICAN JOURNAL OF FOOD, AGRICULTURE, NUTRITION AND DEVELOPMENT
SCHOLARLY, PEER REVIEWED
Volume 25 No. 5
June 2025
PUBLISHED BY AFRICAN SCHOLARLY SCIENCE COMMUNICATIONS TRUST
ISSN 1684 5374

Table 1: Adjustment of average field observation data to data transformation Scale

Scale	Farmer Production (kg)	Chili needs (kg)	Household consumption (kg)	Industry consumption (kg)	Horeca consumption (kg)	Red chili price (Rp)
1	2130 - 2700	2560 – 3205	2067 - 2611	686 - 746	560 – 624	41250 - 50500
2	2701 - 3271	3206 – 3850	2612 - 3155	74 7- 806	625 – 688	50501 - 59750
3	3272 - 3841	3851 – 4495	3156 - 3699	807 - 866	689 - 752	59751- 69000
4	3842 - 4411	4496 – 5140	3700 - 4243	867 - 926	753 - 816	69001 - 78250
5	4412 - 4890	5141 - 5789	4244 - 4789	927 - 987	817 - 880	78250 - 87500

Source: Directly Processed Data on Weekly Average

Table 2: Identification of Dimensions and Direct Influence Variables on Red Chili Commodities

Dimensions	Variable/Attribute	
	Long Label	Short Label
Production	Red chili production data of farmers in Majalengka district in the weekly period.	Production
Needs	Market demand for red chili in the Majalengka region	Need
Household Consumption	Red chili consumption at the household level in the Majalengka region	HH_Consm
Industry consumption	Red chili consumption in industry coverage in the Majalengka region	MSME_Consm
Horeca Business Consumption	Red chili consumption at Horeca coverage in the Majalengka region	HORECA_COM
Price	The price of red chili peppers in the Majalengka region in the weekly period	Price

REFERENCES

1. **Sundari MT, Darsono JS and A Ernoiz** Analysis of Trade Potential and Factors Influencing Chilli Export in Indonesia. *The Journal Open Agriculture*. 2023; **8(1):** 20220205. https://doi.org/10.1515/opag-2022-0205

2. **Shimelis T** Spices production and marketing in Ethiopia: A review. *Cogent Food Agriculture*. 2021; **7(1):**1–17. https://doi.org/10.1080/23311932.2021.1915558

3. **Asidawati, Yetty O and PS Fifian** The Relation of Price and Red Chili Production in Baturaja Ogan Komering Ulu Regency. *International Journal of Social Science*. 2022; **2(2):** 1367-1374. https://doi.org/10.53625/ijss.v.2i2.2739

4. **Nining H** The Risk Level of Production and Price of Red Chili Farming in Kediri Regency, East Java Province. Indonesia. *AGRISE*. 2017; **17(2):** 81. https://doi.org/10.21776/ub.agrise.2017.017.2

5. **Yilong D** Article of The Risk Pricing Mechanism of Order Agriculture Supply Chain, *Management and Engineering Brighton East*, 2018; **31:** 61-67. https://doi.org/10.5503 JME 201831.009

6. **Tinashe M** Adapting to Climate Change: Reflections of Peasant Farmers In Mashonaland West Province Of Zimbabwe. *JAMBA Journal of Disaster Risk Studies.* 2019; **7(1)**. https://doi.org/10.4102/jamba.v11i1.571

7. **Sriyadi S and A Yekti** Farmers' behavior towards risks of shallot farming: a case study in Kalisoro village, Tawangmangu district, Karanganyar regency, Central Java. *In E3S Web of Conferences.* 2021; **316:** 02043. https://doi.org/10.1051/e3sconf/202131602043

8. **Intan F, Koestiono D, Aprilia A and RA Febriana** Risk Control strategies for Red Chili seed Production, *AGRISOCIONOMICS.* 2020; **4(2):** 299-311. https://doi.org/10.14710/agrisocionomics.v4i2.5296

9. **Praveen KV, Agrawal N, Tamrakar S and RB Tiwari** Cost benefit analysis of vegetable crops at borsi farm of Bhatapara, and Chhattisgarh, India. *Int. J. Curr. Microbiol. App. Sci.* 2018; **7(2):** 1112-1115

10. **Channa M H, Sial M, Dahri GN, Jamro AS, Solangi T, Nasir A and A Aamir** Measuring profitability of chilli Pepper production in Sindh, Pakistan. *Journal. Econ. Sustainability Development*. 2020; **08(11):** 81-89. https://doi.org/10.7176/JESD/11-8-09

11. **Rais MUN, Mangan T, Sahito JGM and NA Qureshi** A trend analysis: Forecasting growth performance of production and export of chilli in Pakistan. *Sarhad J Agric,* 2021; **37(1):** 220–5. https://doi.org/10.17582/journal.sja/2021/37.1.220.225

12. **Singla S and M Sagar** Integrated Risk Management in Agriculture; an Inductive Research *The Journal of Risk Finance.* 2012; **13(3)**:199-214. https://doi.org/10.1108/15265941211229235

13. **Putri N, Fhira N and D Sae** Price Prediction of Chili Commodities in Bandung Regency Using Technology Bayesian Network. *International Journal on Information and Communication.* 2018; **4(2):**19-32, https://doi.org/10.21108/INDOjc-2018.42.204

14. **Mehar UINR, Tahmina M, Jam Ghulam MS and AQ Naeem** A Trend Analysis Forecasting Growth Performance of Production and Export of Chili in Pakistan. *Sarhad Journal of Agriculture.* 2020; **37(1):** 220-225, https://doi.org/1017582/journal.sja/2021/37.1.220.225

15. **Ministry of Agriculture**. Outlook for Chile - Horticulture sub-sector agricultural commodities. Jakarta: Ministry of Agriculture. 2020.

16. **Ministry of Agriculture.** Outlook for Chile - Horticulture sub-sector agricultural commodities. Jakarta: Ministry of Agriculture. 2021.

17. **Andayani SA, Lies S and P Tomy** The Development of Red Chili Agribusiness Cluster with Soft System Methodology Approach in Garut, *Journal Mimbar.* 2016; **32(2):** 302-310.

18. **Abraham A** Adaptation of Fuzzy Inference System Using Neural Learning. In: Nedjah, N., Macedo Mourelle, L. (eds) Fuzzy Systems Engineering. Studies in Fuzziness and Soft Computing. *Springer.* 2005; **181**. https://doi.org/10.1007/11339366_3

19. **Kennerley M and A Neely** A Framework of the Factors Affecting the Evolution of Performance Measurement Systems. *International Journal of Operations and Production Management.* 2020; **22:** 1222-1245. https://doi.org/10.1108/01443570210450293

20. **Bosma R, Kaymak U and J van den Berg** Using Fuzzy Logic Modelling to Simulate Farmers Decision -Making on Diversification and Integration in The Mekong Delta, Vietnam. *Soft Comput.* 2015; **15**: 295-310, https://doi.org/10.1007/s00500-010-06180-7

21. **Ayankoya K, Calitz AP and JH Greyling** Real-Time Grain Commodities Price Predictions in South Africa: A Big Data and Neural Networks Approach. *Agrekon.* 2016; ***55*(4):** 483–508. https://doi.org/10.1080/03031853.2016.1243060

22. **Mohanty MK, Thakurta PKG and S Kar** Agricultural commodity price prediction model: a machine learning framework. *Neural Comput and Applic.* 2023; **35:** 15109–15128. https://doi.org/10.1007/s00521-023-08528-7

23. **Sari M, Duran S and H Kutlu** Various optimized machine learning techniques to predict agricultural commodity prices. *Neural Comput and Applic.* 2023; **36:** 11439–11459. https://doi.org/10.1007/s00521-024-09679-x

24. **Wang Y** Agricultural product price prediction based on improved RBF neural network model. *Applied Artificial Intelligence.* 2023; **37(1).** https://doi.org/10.1080/08839514.2023.2204600

25. **Harba JN, Tigu G and AA Davidescu** Exploring Consumer Emotions in Pre-Pandemic and Pandemic Times. A Sentiment Analysis of Perceptions in the Fine-Dining Restaurant Industry in Bucharest, Romania. *Int. J. Environ. Res. Public Health.* 2021; **18:** 13300. https://doi.org/10.3390/ijerph182413300

26. **Zhao H** Futures price prediction of agricultural products based on machine learning. *Neural Comput and Applic*, 2023; **33:** 837–850. https://doi.org/10.1007/s00521-020-05250-6

27. **Tair F, Taib MN and F Ibrahim** Adaptive Neuro Fuzzy Infrerence System for Diagnosis Risk in Dengue Patients. *Expert System with Aplication.* 2012; **39**: 4483-4495.

28. **Santika GD, Mahmudy WF and A Naba** Electrical load forecasting using adaptive neuro-fuzzy inference system. *International Journal of Advances in Soft Computing and Its Applications.* 2017; **9(1):** 50-69.

29. **Majumdar R, Kapur PK and SK Khatri** Assessment of environmental factors affecting software development process using ISM & MICMAC analysis. *International Journal of Systems Assurance Engineering and Management.* 2016; **7(4):** 435-441. https://doi.org/10.1007/s13198-016-0477-4

30. **Ariyani N and A Fauzi** Analysis of Strategic Variables for Ecotourism Development; an Application of Micmac. *South Asian Journal of Social Studies and Economics.* 2019; **3(3):** 1-12. https://doi.org/10.9734/SAJSSE/2019/v3i330107

31. **Agung S, Chandra W, Kusrini N and S Gafur** Analysis of Factors Affecting the Supply of Used Cooking Oil for Restaurants Using ISM (interpretive structure modeling) and MICMAC (cross-impact matrix multiplication applied to the classification). *Journal of Social Economic of Agriculture.* 2018; **7(2):** 116-128.

32. **Khaba S and C Bhar** Analysing the barriers of lean in Indian coal mining industry using integrated ISM-MICMAC and SEM, *Benchmarking: An International Journal.* 2018; **25(7):** 2145-2168. https://doi.org/10.1108/BIJ-04-2017-0057

33. **Andayani SA, Prasetyo TF, Wijaya AA, Sukmasari MD, Umyati S and MF Nainggolan** Prediction Model of Sacha Inchi Crop Development Based on Technology and Farmers' Perception of Socio-Economic Factors. *Sustainability*. 2024; **16(7):** 2680. https://doi.org/10.3390/su16072680

34. **Fauzi A** Sustainability Analysis Techniques. Gramedia Pustaka Utama, Jakarta. Kompas Gramedia. 2019.

35. **Chatziioannou I and I Alvarez** Structural Analysis Method For The Management Of Urban Transportation Infrastructure And Its Urban Surroundings. *Cogent Engineering.* 2017; **4(1):** 1326548. https://doi.org/10.1080/23311916.2017.13 26548

36. **Lestari EP, Prajanti SDW, Wibawanto W and F Adzim** ARCH-GARCH analysis: An approach to determine the price volatility of red chili. *Agraris.* 2022; **8(1):** 90–105. https://doi.org/10.18196/agraris. v8i1.12060

37. **Siti MK, Maksum M and S Endy** Trend Analysis of Red Chili Price-Formation Models. *AgriTECH.* 2020; **40 (1):** 57-63. http://doi.org/10.22146/agritech.45946

38. **Heriz EW, Rihan I and F Ariffatchur** Comparison of Chilli Price Volatility in Crushing Province of Indonesia. *Journal of Agri Socio-Economics and Business JASEB.* 2023; **5(1):** 89-104, https://doi.org/10.31186/jaseb.05.1.89

39. **Meysam A, Mohsen G, Elnaz F and R Roy** Design and analysis of experiments in ANFIS modeling for stock price prediction. *International Journal of Industrial Engineering Computations.* 2011; **2 (2):** 409-418. https://doi.org/10.5267/j.ijiec.2011.01.001

40. **Atsalakis GS** Agriculture Commodity Prices Forecasting Using a Fuzzy Inference System. In: Zopounidis, C., Kalogeras, N., Mattas, K., van Dijk, G., Baourakis, G. (eds) Agricultural Cooperative Management and Policy. *Cooperative Management. Springer, Cham*, 2014. https://doi.org/10.1007/978-3-319-06635-6_19