

# Extended Fuzzy Decision Support Model for Cropland Recommendation of Food Cropping in Indonesia

Lucky Christopher Chen, Nurcahyo Wibowo and Ditdit Nugeraha Utama

Computer Science Department, BINUS Graduate Program - Master of Computer Science,  
Bina Nusantara University, Jakarta, Indonesia 11480

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## Corresponding Author:

Lucky Christopher Chen  
Computer Science Department,  
BINUS Graduate Program -  
Master of Computer Science,  
Bina Nusantara University,  
Jakarta, Indonesia 11480  
Email: lucky.chen@binus.ac.id

**Abstract:** Food crops are the preferred crops to be cultivated on agricultural land in Indonesia, which has a wide area available for use as agricultural land. Each region's agricultural lands in Indonesia have distinct features (e.g., water capacity, land porosity, land height, etc.). Rice, maize, red beans and green beans are significant food crops that are commonly cultivated in Indonesia. The goal of this research is to develop an extended Fuzzy logic-based Decision Support Model (FDSM). The model is able to propose the best food crops to plant on a certain plot of land or location. These suggestions are based on the worth of the distance between the plants as well as the unique worth of the land or location. These suggestions are based on the worth of the distance between the plants as well as the unique worth of the land or location. The primary methods employed in this study are fuzzy logic and Euclidean distance measuring. The fuzzy logic method is used on purpose to prevent confusing values and to consider parameter values based on human linguistics. The fitness value is then calculated using the Euclidean distance value as a basic value for choice suggestions. In this follow-up study, three parameters from previous research were included, for a total of eleven factors (water availability, temperature, humidity, land height, land slope, rainfall, land porosity, rocks on the surface, flood potential and water acidity level). biological food plants in search of the best value based on eight different types of food crops, the model generates simulation suggestions for 514 administrative areas in 34 districts or cities in Indonesia (rice, maize, peanuts, soybeans, green beans, sweet potatoes, cassava and wheat).

**Keywords:** Fuzzy Logic, Decision Support Model, Euclidean Distance, Food Crop, Indonesia

## Introduction

Food crop productivity is determined by the quality of the land used. If unproductive regions are not put aside while picking land at the start of plant growth, significant (financial) losses will occur later (Azis *et al.*, 2006). Climate and weather are the two most important factors influencing food security in Indonesia. Simply defined, if a land's climate and weather conditions are favourable, farmers may develop food crops with optimum yields and enough food supply. In contrast, if the land conditions have poor weather and environment for plants, production and food security would undoubtedly suffer.

Land management must be in accordance with plant characteristics so that plants do not wither and may develop to their maximum potential. Farmers were unaware of many of the causes that contributed to crop

loss. This study is a continuation of Utama *et al.* (2020) research on the suggestions of food plants that are best suited to be planted rationally in certain places using a decision support model based on fuzzy logic. There are twelve geographical characteristics in this follow-up study, including water availability, temperature, humidity, land height, land slope, rainfall, land porosity, rocks on the surface, possibility for floods and water acidity.

Using the Monte Carlo approach, more than 80% of the empirical data is utilized to perform model simulations and produce dummy data. The figures for plant combination similarity and for 514 districts and cities in Indonesia are shown. As a result, the competent authorities can make objective judgments on food crop planting methods for future food security in Indonesia.

Azis *et al.* (2006) applied the Artificial Neural Network (ANN) and the Learning Vector Quantization

(LVQ) approach to create a computer software that may be utilized as an acceptable tool in delivering information on acceptable plants for planting conveniently, swiftly and precisely. The training data were generated by combining land characteristic values from the S1 and S2 suitability classes. The test results reveal that the values of Eps (minimum expected error) = 0.005,  $\alpha = 0.05$ , maximum value of epoch = 10 and learning rate reduction value of  $0.1 * \alpha$  are highly successful and efficient in predicting the varieties of food plants. This is suited for planting in specific places since the forecast accuracy of 22 test data is 100%.

Nganji *et al.* (2018) also performed study in January-March 2017 to assess the suitability of food land in Umbu Ratu Nggay Barat Subdistrict, Central Sumba Regency. The LQ (Location Quotient) technique, the matching technique and the overlay technique are the analytical approaches applied. According to the findings of the investigation, the top three food commodities in the District of West Umbu Ratu Nggay are green beans, lowland rice and corn.

Mukminin *et al.* (2017) introduced a system to identify soil fertility in food crop kinds using fuzzy logic in this study, which is intended to assist farmers in selecting the proper type of plant with the suitable soil fertility level. This study's variables included oxygen, texture, humidity, temperature and acidity. Apples, oranges, corn, peanuts, tomatoes and chilies were among the plants studied. Using a fuzzy model in the research process can offer suggestions for plant kinds based on soil fertility levels.

Susilawati Rizal and Jamaludin (2019) also studied the suitability of paddy soil depending on soil pH and temperature. The purpose of this research is to look at the viability of paddy soil conditions for rice growing. The process of determining soil conditions is carried out with the aid of microcontroller and sensor technologies, namely the DS18B20 sensor to measure temperature and soil pH sensors, to provide reliable analysis findings.

The acquired temperature and pH data were then combined and computed utilizing the fuzzy logic approach to evaluate soil conditions. The findings of this investigation show that the applied sensor can interpret the temperature and pH conditions of the soil based on real-world settings, with a temperature sensor accuracy rate of 96.67% and a pH sensor accuracy rate of 97.00%. Furthermore, the applied fuzzy logic may be utilized to categorize lowland soil conditions as terrible, unfavourable, or favourable.

Nidomudin *et al.* (2017) conducted research on the construction of an expert system for detecting soil fertility levels for plant kinds using the fuzzy logic approach, which is intended to assist farmers in selecting the proper type of plant with a given amount of soil fertility. Before beginning any work on the farmer's farm, expert systems in agriculture may assist farmers in making judgments by picking the suitable sort of crop. This study's variables included oxygen, texture, humidity, temperature and acidity. Chili, maize, rice, peanuts,

soybeans and watermelon were among the plants studied. The resulting measurement findings are consistent with the land calculations and criteria that have been performed in a specific location.

Furthermore, Tai and Martin (2017) created a statistical model to assess agricultural production sensitivity to ozone air pollution and temperature extremes. The outcomes of the study highlight the significance of estimating ozone control as a feasible technique for practically boosting future food security. It is also predicted that wheat, soybean and maize output in the United States will plummet by 13, 28 and 43%, respectively.

Thompson and Meyer (2013) also investigated the influence of second-generation biofuels on food security. Thompson and Meyer created an economic model for this aim. The model indicates that the biofuel market has an impact on food costs; however, this is dependent on policy procedures and the market environment, where biofuels derived from agricultural leftovers are expected to decrease food costs. Abid *et al.* (2016), for example, investigated the relationship between climate change and food productivity in Pakistan. It intends to investigate wheat producers' adaptability to climate change, as well as the consequences on food output and revenue. The logistic regression analysis approach is employed consistently in this case. According to the findings of the study, farmers are acutely aware of climate change. They have changed plant varieties, fertilizer kinds and planting dates, among other things.

Santoso (2016) research intends to examine the influence of climate change on food crop production in Maluku Province using climatological data from 1995 to 2012, as well as plant commodities that can adapt to climate change. Maize, soybeans, rice and sweet potatoes are among the food crops most vulnerable to climate change. This study employs four trend analysis models: Linear least squares, quadratic, exponential and moving averages. The quadratic model is regarded acceptable for calculating the predicted value of lowland rice production in the 1995-2012 period based on the MSD value and the determination reached. The moving average trend model is appropriate for assessing the predicted value of maize, soybean and sweet potato output.

Based on the above context, the relevance of food crops for life and the relevance of appropriate land for human food production in Indonesia, the study came to fruition. This is an expanded version of Utama *et al.* (2020) study on agricultural acreage suitable for food crops in Indonesia. Seven characteristics (water availability, temperature, humidity, land height, land slope, rainfall and land porosity) were utilized in the research by Utama *et al.* (2020) to generate recommendations for optimal land areas for rice, maize, green beans, peanuts and soybeans.

The addition of three topography parameters (pH H<sub>2</sub>O, potential flooding and rock on the surface) and three crops (sweet potato, cassava and wheat) to the model to maximize yields on land suitable for eight crops

commonly consumed in Indonesia was one of the developments we made from the research of (Utama *et al.*, 2020). The fuzzy logic approach and Euclidean distance are used to create this model. The model is documented using three object-oriented diagrams (class, use case and activity diagram). The following diagram best explains the relationship between the entities or classes in each model. This academically designed model will offer suggestions for 514 district/city administrative areas in 34 provinces (in Indonesia) for appropriate food crops to be grown in the appropriate areas.

In this study, we will go through the Decision Support Model, the Model for Food Crops, the Research Methods and the Research Results in general. The Decision Support Model section addresses crop land research utilizing the DSM model. Furthermore, the Model for Food Crops addresses various agricultural research models. The Research Method then goes into depth on the stages of research and the methodologies employed. Finally, the Results section is separated into two sections: Parameterization (which covers the definition of what parameters are used and the data for each parameter) and Data (which covers the data for each parameter). The Constructed Model, which explains the creation of a model that is detailed with three diagrams (class, use case and activity diagram). This study's findings are depicted in the form of a bar chart.

## Literature Review

### *Decision Support Model*

According to Utama *et al.* (2020) study, the Decision Support Model (DSM) is a model that may assist decision makers in making objective decisions. Zhai *et al.* (2020) in the agricultural sector, this research intends to explore the impending issues of deploying agricultural decision support systems in Agriculture 4.0. By addressing the identified problems, future researchers may be able to develop decision assistance systems. The systematic literature review methodology is employed in this study to assess thirteen typical decision support systems and their applications for agricultural mission planning, water resource management, climate change adaptation and food waste reduction. Each decision support system is subjected to a thorough examination. A thorough examination is carried out in terms of interoperability, scalability, accessibility, usability, etc. Based on the evaluation results, emerging difficulties are identified and presented, as well as development patterns and proposed enhancements for future study.

In another study, Wall *et al.* (2020) created DSM to analyse the potential for water control and soil purification. The goals of this research were to build a qualitative decision support model to assess the water regulation and purification capability of agricultural soils

at the field level, perform sensitivity analysis on the model and verify the model with independent empirical data.

It is a DSM that can aid decision makers in making strategic or tactical crop production decisions. It was created to interpret climatic data into agricultural and commercial concepts. The model recommends decisions such as planting timing, crop and cultivar selection and so on. Wadhwa *et al.* (2019) also created a mathematical model for investment decision making in the building of a domestic grain production container station. The research was carried out for the instance of soybean shipping containers in the Minnesota region.

### *Model for Food Crops*

Many models or technological techniques have been created by researchers throughout the world to assist improve the process of growing crops, particularly food crops (Zhao *et al.*, 2019). For example, provided a basic generic crop model (SIMPLE) that may be simply adjusted for any crop to simulate crop development, growth and yield. SIMPLE's crop model has 13 parameters for specifying a crop type, four of which are for cultivar characteristics. Daily meteorological data, crop management and soil water holding characteristics are all commonly available inputs for the SIMPLE crop model.

Chen *et al.* (2018) presented a new technique to mapping large-scale agricultural land, cropping patterns and plant type planting areas in Brazil in their study. In this investigation, three types of plants were used: Soybeans, cotton and corn. This study makes use of time series data from the Moderate Imaging Spectroradiometer's (MODIS) resolution from 2015 to 2016.

Pacetti *et al.* (2017) also created a novel approach for assessing the effects of floods on food supply. (Pacetti *et al.* (2017) integrate agricultural statistics, water footprint databases and remote sensing data in this study. This technique is used in two case studies: Bangladesh (2007) and Pakistan (2010). According to the results of this study, flooding (as the most severe natural catastrophe affecting agriculture) causes a 5 to 8% decline in food supply.

Yu *et al.* (2016) created a novel assessment model, the fulfilled degree of crop water need, to evaluate the effects of water resources on the production of six major food crops in China. The findings indicate that: There are substantial dangers of water scarcity in China, including in south China, despite its plentiful precipitation; and the fulfilled degree of agricultural water demand implies significant temporal - geographical fluctuations. The hazards of spatial dispersion are considerable in large food production bases due to cropping system and crop-combination impact. Northwest China is a particularly intriguing situation. Water scarcity is severe in March and September due to seasonal fluctuations. These dangers severely limit China's food output. The findings also demonstrate that strategic water

resource management strategies must be carefully considered to address food security and regional sustainable development in China.

### *Fuzzy Logic*

Fuzzy Logic (FL) is a type of logic in which the degree of vagueness or fuzziness between true and false is a variable. The notion of fuzzy sets was proposed by Lotfi A. Zadeh, which opened a fresh perspective on systems, logic and reasoning models (Zadeh, 1965). FL accepts membership values ranging from 0 to 1, as well as grey, black and white and in linguistic form. "a little," "moderately," and "very" are all ambiguous terms.

FL is commonly employed in situations including uncertainty, imprecision and other factors. FL is a language that combines precise machine language with human language that stresses meaning. FL was created using natural language from humans. Zadeh coined the term "Notion of Linguistic Variables" to describe a concept (Zadeh, 1975).

There is a name, a defined domain, a set of values and an interpretation for linguistic variables. Variable names may be whatever you like, although it's a good idea to name them after the variable they'll be representing. The definition domain comprises a collection of Linguistic Terms that indicate possible values by varying the intensity of Linguistic Variables.

Linguistic words are fuzzy labelled sets, which are generally trapezoidal or bell-shaped in form. (In this example, the triangle is a trapeze with one point on the top side.) The supporters (the set of items with membership  $>0$ ) overlap across neighbours, but the core of this fuzzy set (the set of elements with 1st degree of membership) is sorted.

### *Euclidean Distance*

The length of a line segment between two locations in Euclidean space is known as the Euclidean distance in mathematics. It is also referred to as the Pythagorean distance since it can be computed from the Cartesian coordinates of the locations using the Pythagorean theorem, as a result, the Pythagorean distance is sometimes referred to. Although Euclid did not express distances as numbers and the relationship between the Pythagorean theorem and distance computation was not discovered until the 18th century, these names are derived from the ancient Greek mathematicians Euclid and Pythagoras.

The lowest distance between pairs of points from two things is generally described as the distance between two items that are not points. Distances between different sorts of objects, such as the distance between a point and a line, may be calculated using formulas. Distance has been expanded to abstract metric spaces in advanced mathematics and other distances beyond Euclidean have been investigated. The square of the Euclidean distance is used instead of the distance itself in several statistics and optimization applications.

## **Research Methods**

The research begins with a review of the literature and an analysis of the data utilizing a table-based study technique. A lot of analysis and learning is done at this stage from a variety of associated publications and books with rigorously researched decision support models, agricultural land and food crops. Following the literature review, there were various challenges in choosing the most acceptable food crops to be planted in one place (Indonesia), because acceptable food plants grown on acceptable agricultural land were predicted to produce optimal outcomes. This type of circumstance will improve and increase the profitability of Indonesia's agricultural circumstances.

Following that, include the parameters or criteria that will be employed in the research. Data for each metric is gathered from the official government website (BMKG), as well as various publications and books. The data is then processed utilizing the Fuzzy Logic and Monte Carlo methods.

The fuzzy logic method is used to avoid bias in parameter value determination. Then, observation is utilized to collect the necessary data; however, little data makes doing research difficult. The approved institution did not provide all the needed information. For model simulation, we used about 80% empirical data (from the [bmkg.go.id](http://bmkg.go.id) website) to create 5,491 dummy data using the Monte Carlo method. In general, the Monte Carlo approach is a sort of methodology for getting numerical results (based on repeated random sampling) that is used for three purposes: Optimization, numerical integration and number generator (Kroese *et al.*, 2014). The dummy data was then verified by altering the empirical data as an edge for each resulting parameter value. Validation is performed to ensure that the data utilized in simulation are realistic and representative. This is beneficial for boosting the model's validity.

In general, fuzzy logic is not fuzzy. It is an accurate logic of ambiguity and approximation (Zadeh, 2008). Its fundamental contribution is to lay the groundwork for a transition from binarization to graduation, from binarism to pluralism (Zadeh, 2015). It is critical for it to be able to appropriately reason with imperfect knowledge that is unclear, incomplete, ambiguous, or only partially true owing to one unique situation (Zadeh, 2009). Subjective opinion is used to obtain information at some point. In practice, the fuzzy logic method has been used by Utama *et al.* (2017) in various research on the issue of smart and intelligent systems.

The design process of the model is the next stage of this research. The object-oriented approach is the primary strategy that benefits here (Mathiassen *et al.*, 2000). Several tools, such as class diagrams, use case diagrams, activity diagrams and so on, are officially operational. The class diagram depicts the model's interrelated entities. Academically, one entity is represented by a class configuration that consists of three components: Name, attributes and operations. The use case diagram depicts the high-level design of the built model, depicting the

communication pattern between models and actors (both human and non-human/system actors). The activity diagram follows as a full description of the use case diagram. The use case as a series of operations is attempted to be discussed in further depth below. The activity diagram clearly depicts the process's state and state.

Furthermore, the Euclidean distance calculation technique Utama *et al.* (2020) is used to determine the fitness value between ideal circumstances for food crop development and land features. The shortest distance value represents the closest distance, it suggests the most suited and it indicates that the alleged food crop is extremely suited to be grown in the alleged area:

$$d(p, q) = d(q, p) = \sqrt{\sum_{i=1}^n (q_i - p_i)^2} \quad (1)$$

$$d(p, q) = \sqrt{(q_1 - p_1)^2 + \dots + (q_n - p_n)^2} \quad (2)$$

The fundamental formula for calculating a distance between two points in Euclidean n-space is expressed in Eq. (1), where  $d$  represents Euclidean distance,  $p$  is point  $p$  and  $q$  is point  $q$ . The Pythagorean formula refers to the mathematical equation in Eq. (1). Anton (1994). It may be described mathematically in greater depth, as seen in Eq. (2). Because the greatest value is often shown by the greatest value, the minimum relative value of distance Utama *et al.* (2016) is also used here. It is the difference in value between the most minimal distance value and the present distance value calculated from compassion. The mathematical formula is clearly described in Eq. (3), where  $RV_{\min}$  represents a minimal relative value and  $VC$  represents a current value:

$$RV_{\min} = \frac{\min(V_1 \dots V_n)}{V_c} \quad (3)$$

## Results

### Parameterization

In this study, 10 topographical factors were used to assess the state of an agricultural region in 514 districts/cities throughout Indonesia. The impact diagram depicts the link between each parameter in the model that was created (Fig. 1 and 2). Rainfall, land porosity, land slope, land height, water availability, temperature, humidity, pH, rock on the surface and potential flooding are all characteristics that must work together in the created model. In this situation, the model developed will recommend the ideal combination of agricultural area and food crops to grow.

The Influence Diagram (Fig. 2) also depicts the sub-models that are engaged in the major created models. Mathematical models and fitness models are the two sub-models. Mathematical models are unavoidable in the development of this computer model; thus, the sub-model is incorporated into the main model. There is also a fitness

sub-model that is built using two fundamental approaches: Fuzzy logic and the Euclidean distance notion. Finally, influence diagrams highlight the core model's aims. The goal of developing the model in this study is to optimize crop yields in Indonesia.

Fuzzy logic ideas are applied to determine all parameters. The fuzzy triangular membership function with specified linguistic variable limitations is used to specify the bounds of each parameter. The rainfall parameter ( $\text{mm}^3$ ) is divided into three linguistic categories: Low (L), Medium (M) and High (H). With triangular bounds of (0,0,1800), (1200, 2400, 3600) and (3000, 4800, 4800). Figure 3 depicts the Rainfall parameter's membership function.

The triangular fuzzy membership function with three linguistic variables, Small (S), Medium (M) and Large (L), also classifies the Land Porosity parameter (%). S, M and L have triangle boundaries of (10, 10, 15), (10, 20, 30) and (25, 30, 30), respectively. Figure 4 depicts the fuzzy triangular membership function for the Land Porosity parameter.

Then, in Fig. 5, a triangular fuzzy membership function is used to characterize the Land Slope ( $\circ$ ) parameter. There are additional three linguistic variables created with triangular membership values: Flat (F), Slope (Sl) and steep (St): (8, 8, 15), (10, 20, 30) and (10, 20, 30). (25, 35, 35).

A fuzzy triangular membership function is also used to define the parameters of Land Height (m) (Fig. 6). There are three categories of linguistic variables that can be used: Low (L), middle (M) and High (H). They are theoretically constrained by the triangular bounds (200, 200, 550), (350, 700, 1100) and (350, 700, 1100). (900, 1200, 1200).

The criteria for Water Availability (mm) are Little (L), Middle (Mi) and Much (Mu). They are represented by the triangular points (110, 110, 130), (120, 140, 160) and (150, 170, 170), respectively. Figure 7 depicts the configuration of its fuzzy triangular membership function.

Furthermore, three language factors influence the humidity parameter (%): Little (L), Middle (Mi) and Much (Mu). Where the variable is defined by triangle points (60, 60, 70), (65, 75, 85) and (80, 90, 90). Figure 8 depicts the fuzzy triangular membership function of the humidity parameter.

Similarly, the temperature ( $^{\circ}\text{C}$ ) parameter is defined by three linguistic variables: Low (L), Middle (M) and High (H). The fuzzy triangle bounds used to characterize the variables are (5, 5, 15), (10, 17.5, 25) and (10, 17.5, 25). (20, 30, 30). The fuzzy triangular membership function for the Temperature parameter is seen in Fig. 9.

Further study has revealed that the pH parameter, which is likewise specified by the fuzzy triangular membership function, is an extra parameter (Fig. 10). Acid (Ac), Neutral (N) and Alkaline (Al) are three sorts of linguistic variables that work. The limits of the fuzzy triangular points (3, 3, 7), (6.5, 7, 7.5) and (6.5, 7, 7.5) potentially restrict them (7, 11, 11).

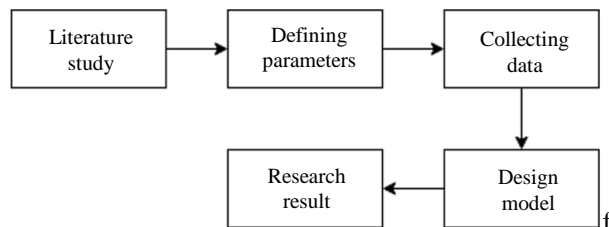
Furthermore, the flood potential characteristics (%)

were characterized using three linguistic variables: Low (L), Medium (M) and High (H). With the triangular bounds (0,0,15), (20, 50, 80) and (70, 80, 80). Figure 11 depicts the function parameters of potential flooding.

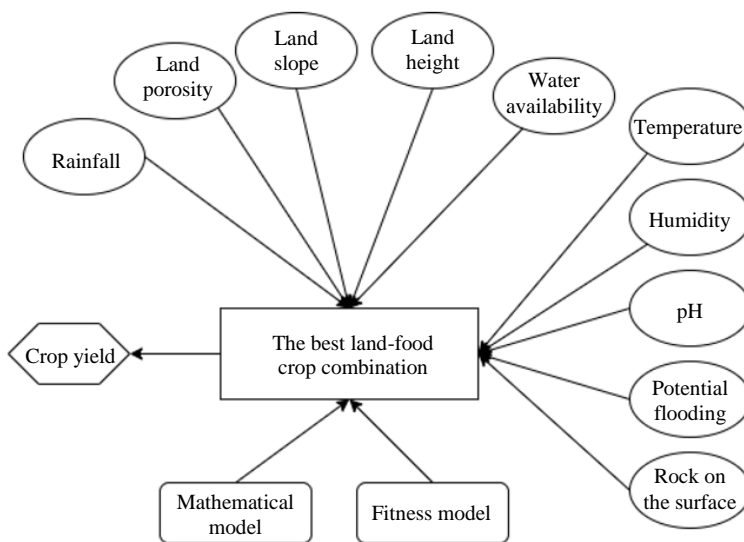
The last element is the number of rocks on the surface, which may be described by three linguistic variables: Little (L), Middle (Mi) and Much (Mu). They are represented by the matching triangular fuzzy points (0, 0, 10), (5, 15, 25) and (20, 30, 30). Figure 12 shows the setup of its triangular fuzzy membership function.

Table 1 and 2 exhibit examples of dummy data used in model simulations. They all detail the geographical parameters of 514 districts/cities in 34 Indonesia provinces. Table 1 displays data from the first five factors, which are rainfall, land Porosity (P), land Slope (S), land Height (H) and Water Availability (WA). Table 2 displays

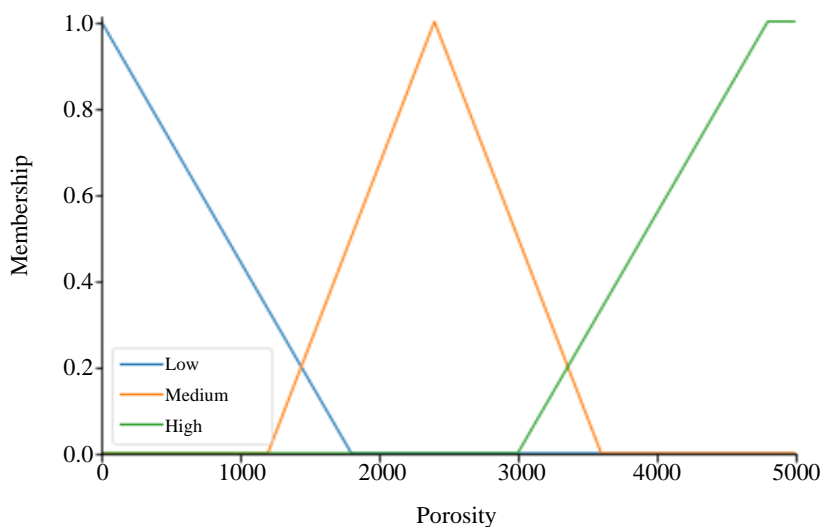
data from five more parameters: Humidity (Hu), Temperature (T), acidity of water (pH), potential Flooding (F) and rock on the surface. It can be observed that the values of all these parameters are theoretically presented in terms of fuzzy values, exemplifying the degree of truth value for each parameter value.



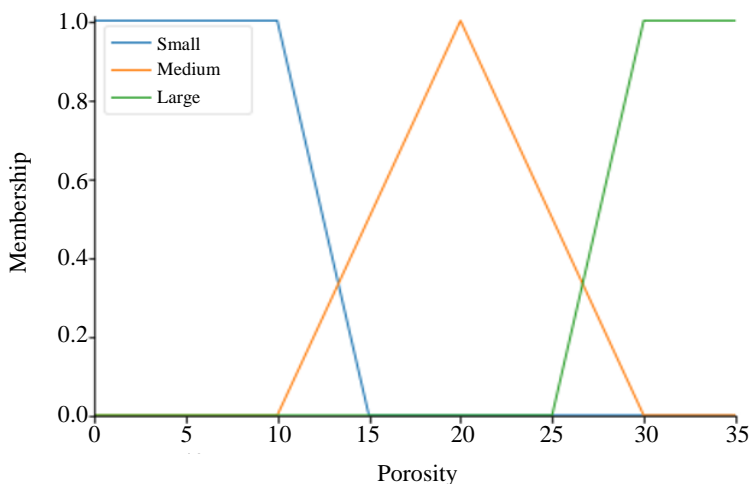
**Fig. 1:** Research method



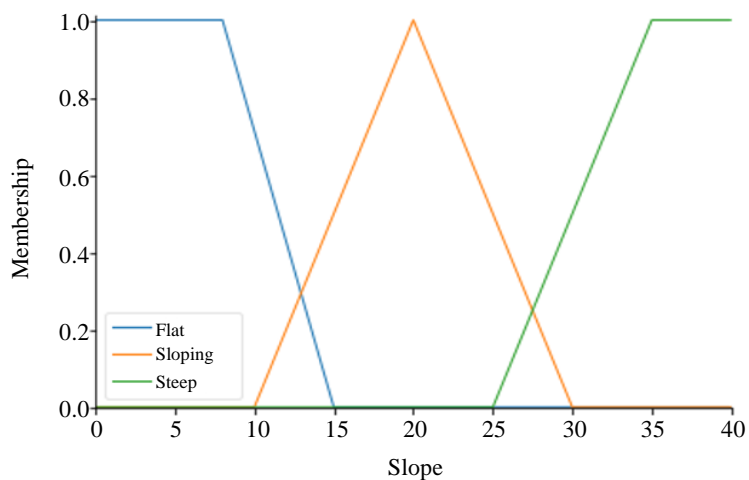
**Fig. 2:** Influence diagram to connect parameters, sub-models and the constructed model’s objective



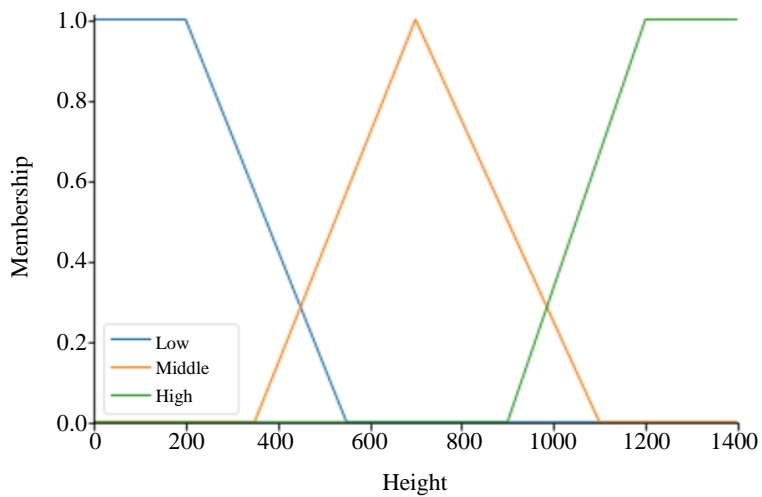
**Fig. 3:** The graph of fuzzy triangular membership function for rainfall



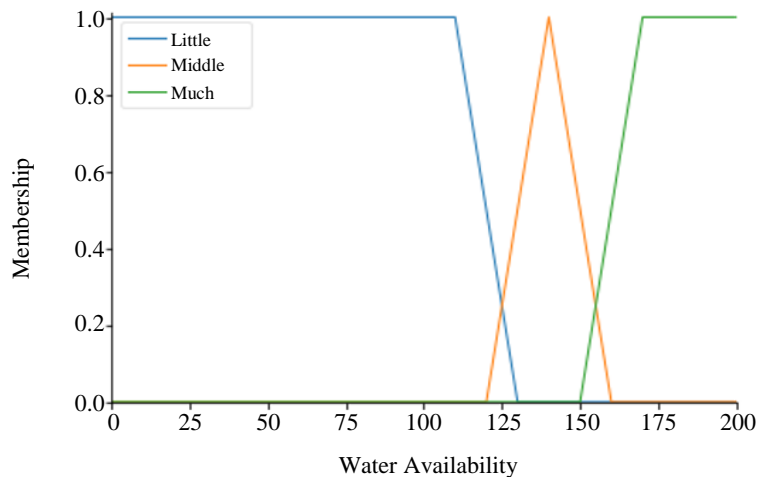
**Fig. 4:** The graph of fuzzy triangular membership function for porosity



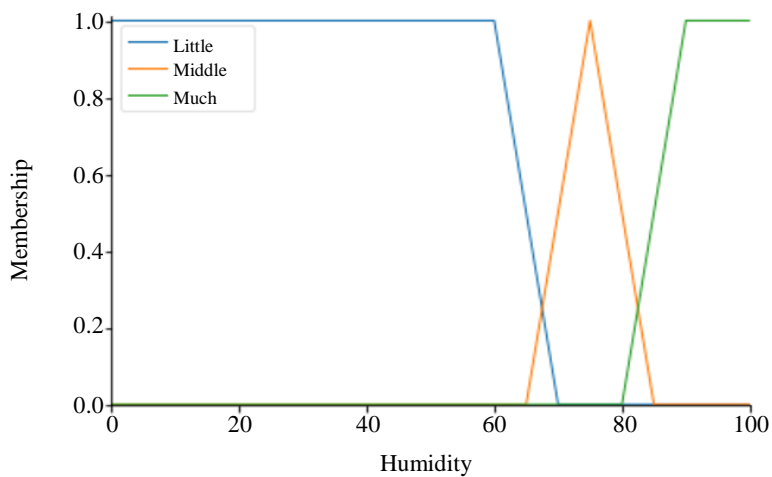
**Fig. 5:** The graph of fuzzy triangular membership function for slope



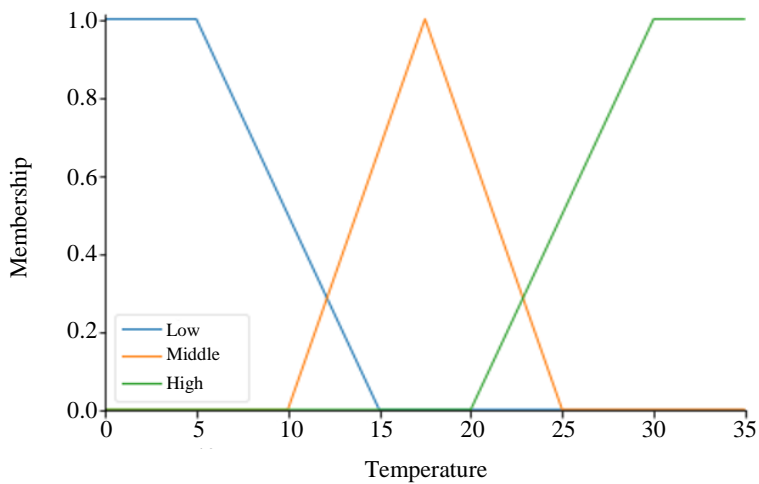
**Fig. 6:** The graph of fuzzy triangular membership function for height



**Fig. 7:** The graph of fuzzy triangular membership function for water availability

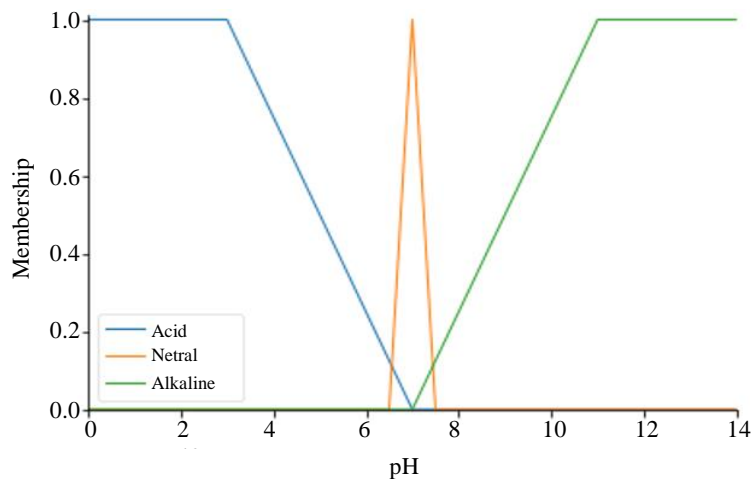


**Fig. 8:** The graph of fuzzy triangular membership function for humidity

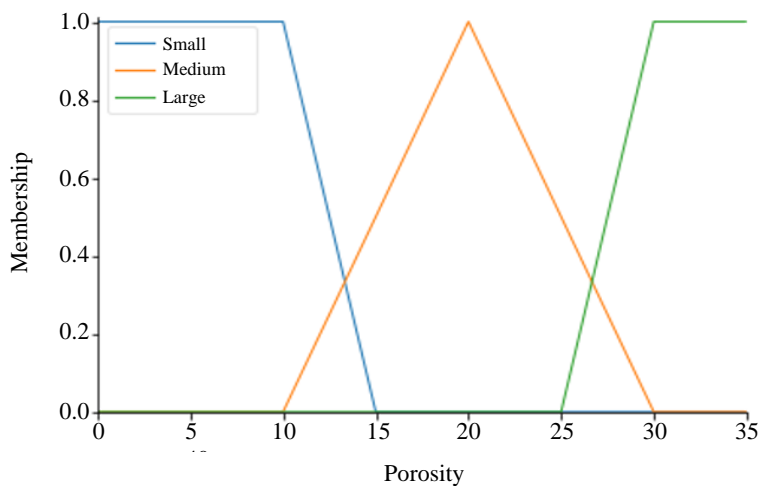


**Fig. 9:** The graph of fuzzy triangular membership function for temperature

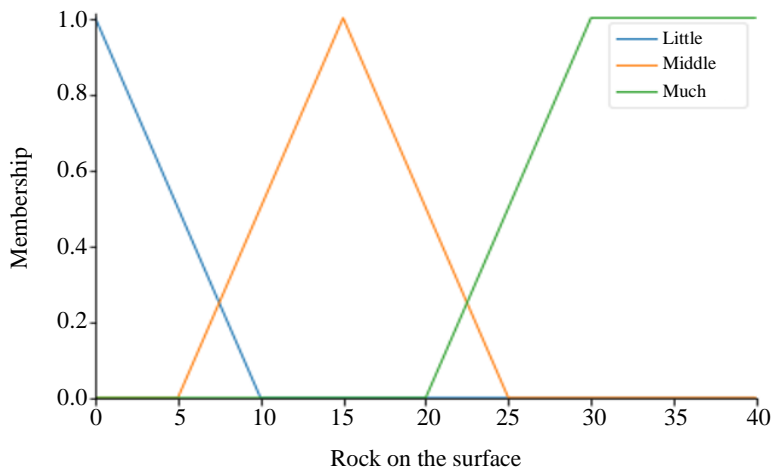




**Fig. 10:** The graph of fuzzy triangular membership function for pH H2O



**Fig. 11:** The graph of fuzzy triangular membership function for potential flooding



**Fig. 12:** The graph of fuzzy triangular membership function for rock on the surface

### *The Constructed Model*

The class diagram in Fig. 13 depicts the relationship between classes or entities. Several classes are required to construct this DSM model. The model is conceptually divided into six elements or classes: Land, Crop, Fuzzy Logic, Membership Functions, Euclidean Distance and Decisions. Land Class and Crop are qualities that indicate the evaluation or criteria of each land in 514 districts and cities, as well as eight food crops. The second layer determines all of the qualities of each class, where especially for the Crop class, this characteristic says that the plant is under perfect conditions for growth. The Crop class attributes will be compared to the Land class attributes so that they can subsequently indicate the fitness value of the distance desired.

Fuzzy logic is used as a primary class and it contains four sorts of processes: Extracting data(), Fuzzifying(), defuzzifying() and defining Parameters() (). More information on the four types of operations will be provided in the section that discusses the activity diagram seen in Fig. 14. The Membership Function class is excellent for processing all operations on the fuzzy logic class. All attributes in the Membership Function class describe the triangular membership function's attributes: MFID to represent the triangular membership function's identity, linguistic Variable to express linguistic variables, low bound to represent the lower bound value, mid bound to represent the middle value and up Bound to represent the upper bound value. The Membership Function class implementation has been discussed and shown in detail in Fig. 3 to 12.

The last class is the Euclidean Distance class, which represents the calculated value of the Euclidean distance, which is stored in the distance attribute. The Distance() attribute is used in the computation procedure. It was previously stated in the drafting of this study that the distance value symbolizes the value of the appropriateness of land and crops, so that it can be genuinely utilized to decide objective conclusions. The decision value indicated by the registered distance value is created by the attribute generating decision () and is reflected in the Decision class.

In Fig. 15, a use case diagram depicts the high-level composition of the developed model. The model is divided into four use cases: Fuzzy parameterization, similarity calculation, decision generation and reporting. Fuzzy Parameterizing is used to process the preset parameters through the fuzzy logic approach. The actor in the Fuzzy Parameterizing use case is a Ministry of Agriculture employee. In the use case Calculating Similarity, the similarity gap between land and crops is computed. The Meteorology, Climatology and Geophysics Agency (BMKG) as a system actor that delivers all the data and information needed to run the model and the Ministry of Agriculture as a human actor that operates the model compassionately are accountable for this use case.

The model that is developed directly and automatically

can generate judgments in the use case Generating Decision. Decisions based on suggestion forms for the most appropriate food crops for a certain location are offered in the use case Generating Decision. List the specific mix of regions and plants that have a match; the model will return the essential data and information via use case Reporting. The actor with control over both use cases is the Republic of Indonesia's Ministry of Agriculture.

After that, Fig. 14 depicts a process or operation using an activity diagram and three use cases: Fuzzy Parameterization, Calculating Similarities and Generating Decisions. The Data Extraction procedure extracts data from 514 districts and cities in Indonesia that have been gathered. The Fuzzifying Parameters procedure converts all values of each parameter into fuzzy values. Then, using the De-fuzzifying Parameters procedure, the value is turned back into a crisp value (crisp output value).

The Distance Calculation procedure computes the utilization of Euclidean distances for each land and crop combination. The distance value, in theory, reflects the similarity value. As a result, the process of calculating distances is included in the use case of computing similarities. Equation is also used to transform the value to a relative value (3). This is done to demonstrate that the best score is generally expressed and represented by the greatest score. Following that, in the process of selecting the Best, the model might recommend suitable plants for the land. The procedure is carried out in the use case Generating Decision.

All topographic parameters (such as rainfall, land porosity, land slope, land height, water availability, temperature, humidity, pH, rock on the surface and potential flooding) are evaluated when assessing the status of an agricultural field. The sub-model influences the connection between parameters in the generated model (mathematical model and fitness model). In this instance, the model will recommend the ideal combination of agricultural land and food crops to plant.

The relative Euclidean distance values for each district and for food crops have been obtained through calculations. The calculation's result or value indicates the value of appropriateness between districts and food crops. Table 3 and 4 clearly depict an example of a suitability value for the 15 districts. The highest score represents the food crop that is best suited to the district.

From Table 3 and 4 shows that districts of Bengkulu Tengah, Humbang Hasundutan, Pinrang, Sikka, Situbondo, Muara Enim, Bogor, Gunungkidul and Blitar are good for rice farming, whereas Bengkulu Tengah and Gunungkidul are good for maize production.

Green beans may be grown in the districts of Bengkulu Tengah, Pinrang and Gunungkidul; peanuts can be grown in the districts of Aceh Utara, Bengkulu Tengah, Humbang Hasundutan, Situbondo, Bogor and Gunungkidul.

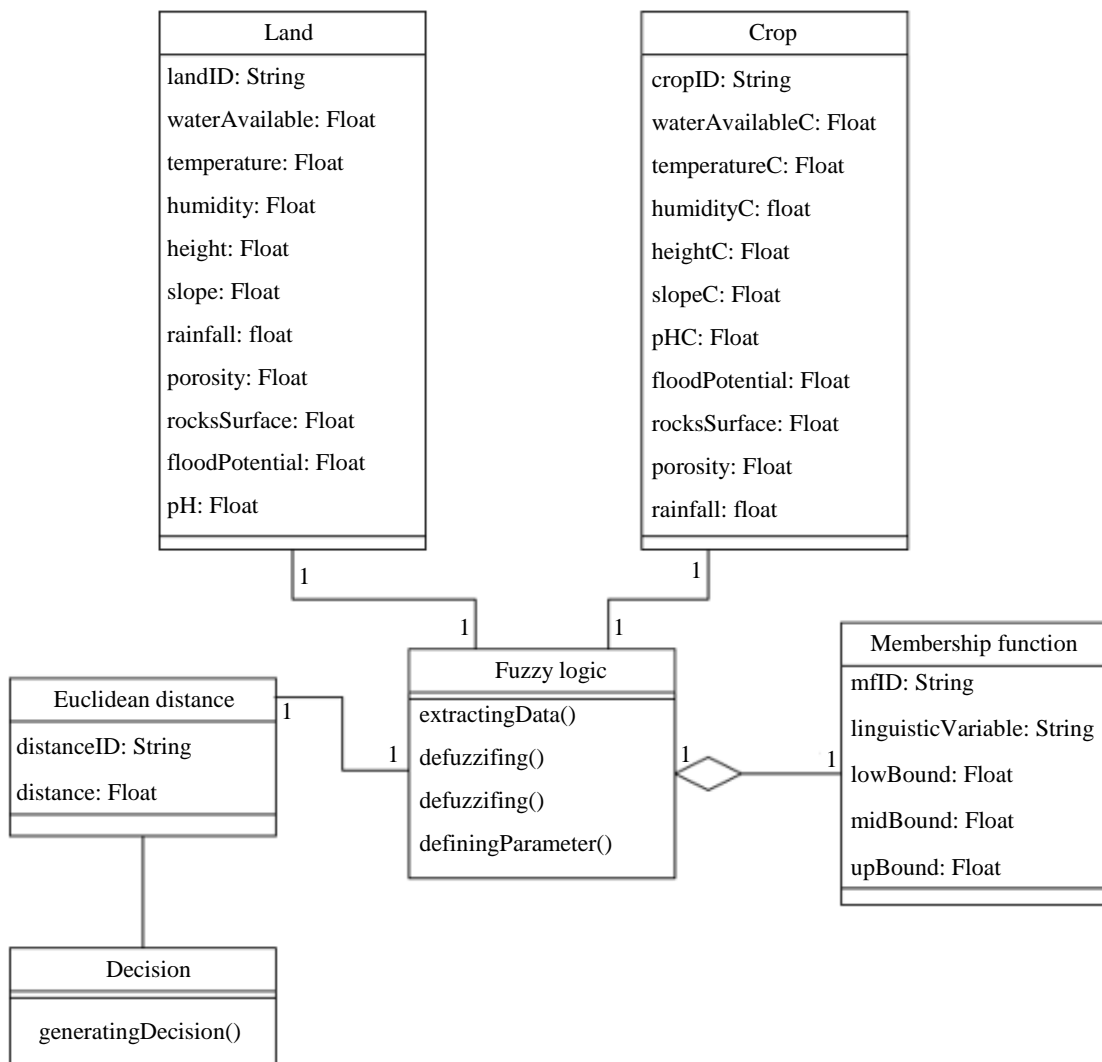


Fig. 13: The class diagram for the constructed model

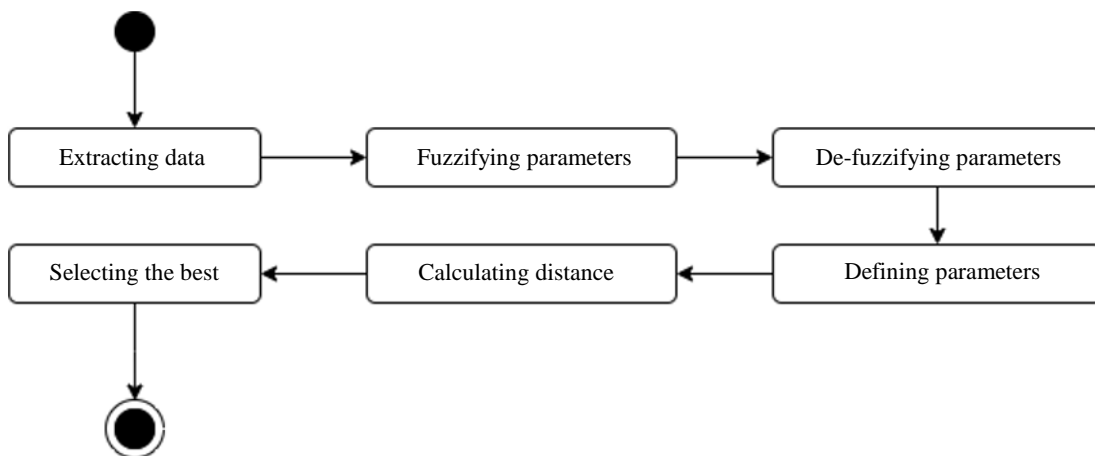
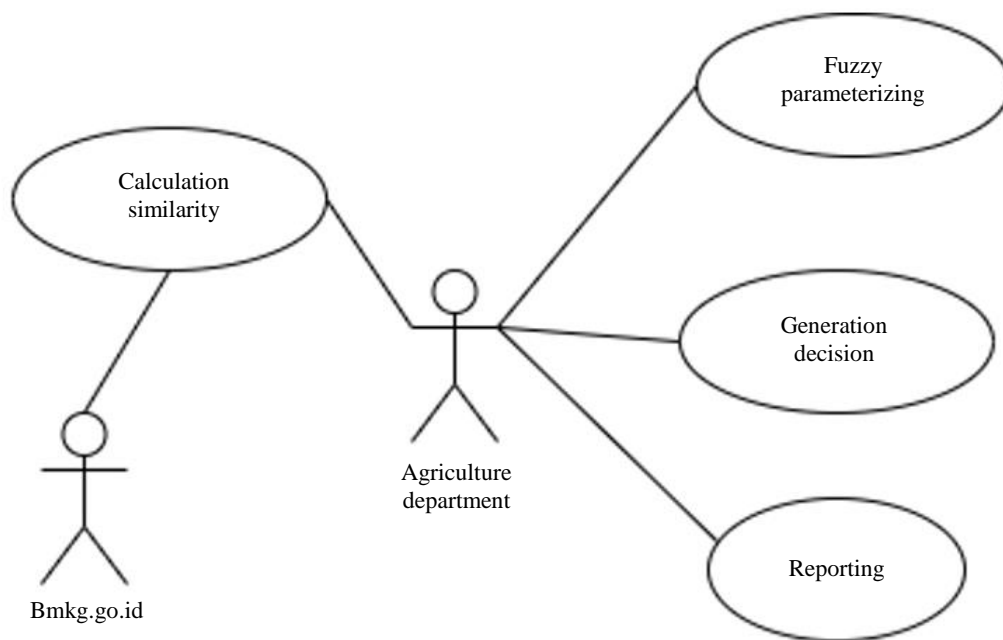


Fig. 14: The activity diagram for the constructed model



**Fig. 15:** The use case diagram for the constructed model

**Table 1:** Data example of rainfall, porosity, slope, height, water availability (in fuzzy value)

District	R	P	S	H	WA
Aceh utara	0.1M 0.47L	1S	1F	1L	1L
Bengkulu tengah	0.46M	1S	1F	1L	0.44M
Bima	0.68M	1M	1F	0.45L 0.11M	1L
Donggala	0.65M	0.13S 0.4M	0.83Si	L	1L
Humbang hasundutan	0.59L	0.99M	0.33Si 0.27F	0.49L 0.14M	1L
...	...	...	...	...	...
Poso	0.54L	1 S	0.54Si	1L	1L
Pinrang	0.88M	0.1S 0.41M	1F	1L	1M
Sikka	0.81L	0.21M 0.64S	0.36Si 0.2F	1L	1L
Situbondo	0.6M	1S	0.29Si 0.42F	1L	1M
Surabaya	0.84M	0.85M	1S	1L	1M
...	...	...	...	...	...

**Table 2:** Data example of humidity, temperature, pH H<sub>2</sub>O, potential flooding, rock on the surface (in fuzzy value)

District	Hu	T	pH	F	R
Aceh utara	0.32Mu 0.13Mi	0.62H	0.57AC	1 L	0.86L
Bengkulu tengah	0.14Mu 0.45Mi	0.64H	0.80 AC	0.11M 0.58L	0.41M
Bima	0.51Mi	0.71H	0.50 AC	1L	0.51L
Donggala	0.63Mi	0.65H	0.68 AC	1L	0.97L
Humbang hasundutan	0.38Mu 0.11Mi	0.58H	0.72 AC	0.19 M 0.57L	1M
...	...	...	...	...	...
Poso	0.38Mu 0.18Mi	0.74H	0.53 AC	1L	0.58L
Pinrang	0.64Mi	0.38H 0.34M	0.80 AC	0.17H 0.31M	0.87L
Sikka	0.85Mi	0.74H	0.76 AC	0.71L	0.21L 0.24M
Situbondo	0.13Mu 0.44Mi	0.74H	0.6 AC	0.7L	0.6M
Surabaya	0.53Mi	0.88H	0.64 AC	1L	0.74M
...	...	...	...	...	...

**Table 3:** Value of four food crops for each district or city

District	Rice	Maize	Green Beans	Peanuts
Aceh utara	0.45	0.47	0.59	0.60
Bengkulu tengah	0.70	0.54	0.78	0.79
Bima	0.50	0.41	0.59	0.56
Donggala	0.58	0.46	0.59	0.37
Humbang hasundutan	0.76	0.45	0.59	0.83
...	...	...	...	...
Poso	0.49	0.44	0.40	0.57
Pinrang	0.73	0.50	0.76	0.56
Sikka	0.62	0.42	0.57	0.43
Situbondo	0.66	0.48	0.42	0.72
Surabaya	0.50	0.44	0.58	0.50
...	...	...	...	...
Muara Enim	0.60	0.41	0.59	0.58
Bogor	0.60	0.48	0.55	0.62
Gunungkidul	0.77	0.54	0.71	0.66
Blitar	0.65	0.46	0.41	0.52
Bone	0.38	0.46	0.43	0.48
...	...	...	...	...

**Table 4:** Value of four food crops for each district or city

District	Soy beans	Sweet potato	Cassava	Wheat
Aceh utara	0.53	0.47	0.63	0.34
Bengkulu tengah	0.75	0.70	0.79	0.56
Bima	0.51	0.45	0.57	0.33
Donggala	0.40	0.57	0.41	0.48
Humbang hasundutan	0.79	0.68	0.82	0.67
...	...	...	...	...
Poso	0.52	0.67	0.59	0.29
Pinrang	0.59	0.74	0.55	0.64
Sikka	0.46	0.53	0.46	0.56
Situbondo	0.68	0.54	0.73	0.45
Surabaya	0.47	0.44	0.52	0.30
...	...	...	...	...
Muara Enim	0.56	0.48	0.60	0.56
Bogor	0.60	0.59	0.59	0.43
Gunungkidul	0.67	0.75	0.66	0.53
Blitar	0.53	0.56	0.53	0.53
Bone	0.42	0.32	0.44	0.26
...	...	...	...	...

Soybean agriculture is appropriate in Bengkulu Tengah, Humbang Hasundutan, Situbondo, Bogor and Gunungkidul districts; sweet potato cultivation is appropriate in Bengkulu Tengah, Humbang Hasundutan, Pinrang and Gunungkidul.

Cassava may be grown in the districts of Aceh Utara, Bengkulu Tengah, Humbang Hasundutan, Situbondo, Muara Enim and Gunungkidul; wheat may be grown in the districts of Humbang Hasundutan and Pinrang.

## Discussion

We'd like to compare our work to that of others in this section. For instance, consider what Chen *et al.* (2018) accomplished. Chen *et al.* (2018) devised a method for calculating cropping patterns, croplands and crop planted area in Brazil, with a focus on soy, cotton and maize. It

was comparable to the outcome of our research. In this work, we also built a model to choose the best food crop to grow on a given piece of land. In all of Indonesia, we discovered the best crop-land combination (in 514 districts of 34 provinces).

Chen *et al.* (2018) used 2015-2016 time-series big data to perform the investigation, as well as about 93 percent (large number of) single data to give model data. However, we needed additional sorts of crops in practice, so we employed eight different types of food crops (i.e., rice, maize, peanuts, soybeans, green beans, sweet potatoes, cassava and wheat). Our suggested model can also read and accept various sorts of time-series data on a technological level.

To categorize cropping patterns, Chen *et al.* (2018) used a decision tree. It can successfully extract croplands, cropping pattern and crop kind, with 90, 73 and 86%

efficacy, respectively. Instead, we used the fuzzy logic approach for parameterizing, which was coupled with the Euclidean distance to get the similarity value. We also didn't calculate the effectiveness value; instead, we determined the optimal land-crop combination based on 80% empirical data. Nonetheless, depending on chosen geographic and biotic factors, the result indicated that the land-crop combination might provide the highest efficacy.

Additionally, Utama *et al.* (2020) studied the model which is able to recommend an appropriate food crop to be grown in a certain region in a reasonable manner. The suggestion is based on the plant's distance from the region characteristic value. This follow up study has similar way to create the model, but with more parameter to achieve the best outcomes. We handled parameters technically as if they were the most important climatic limitations in determining agricultural land.

## Conclusion and Further Works

This is a follow-up research to Utama *et al.* (2020), which discussed agricultural land recommendations for food crops in Indonesia. Seven characteristics (water availability, temperature, humidity, land height, land slope, rainfall and land porosity) were utilized in this study to indicate ideal land for rice, maize, green beans, peanuts and soybeans.

In this follow-up study, three topographic characteristics (pH H<sub>2</sub>O, possible floods and surface rock) and three crops (sweet potato, cassava and wheat) were included to the model to optimize production on suitable land for eight crops commonly consumed in Indonesia. The fuzzy logic method and Euclidean distance are the foundations of this approach. Based on object-oriented methods, the model was specified in three diagrams (class, use case and activity diagrams). These diagrams clearly show the relationship between entities or classes in each model.

The model's inability to run due to a lack of data sources is a big issue. Using the Monte Carlo method, we generated 5,491 dummy data from around 80% empirical data (based on [bmkg.go.id](http://bmkg.go.id)). The similarity values of land and food crop combinations for 514 districts or cities have been shown. As a result, the competent authorities can make objective judgments about food crop planting strategies for future food development in Indonesia.

More research is needed to determine the productivity of food crops. To achieve the best outcomes, we need more precise data (we can collaborate with the appropriate authorities). Other parameters, such as population size, nutrition, etc., can also be incorporated to enrich the model.

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## Author's Contributions

**Lucky Christopher Chen:** Analyzing all data, design the model and finalizing the manuscript

**Nurchahyo Wibowo:** Analyzing all data, design the model and finalizing the manuscript

**Ditdit Nugeraha Utama:** Reviewing and finalizing model and manuscript

## Ethics

This manuscript substance is the authors' own original work and has not been previously published somewhere else. Authors already read and approved the manuscript and no potential ethical issues immersed.

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