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MULTI-LAYER INFERENCE *FUZZY TSUKAMOTO* DETERMINING LAND SUITABILITY CLASS OF COCOA PLANTS

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ABSTRACT

Determining the land suitability class of plants specifically cocoa (Theobroma cacao) is significant to do because each plant has a different characteristic of growth. This research aims at implementing the algorithm to determine the land suitability class of cocoa plants using the Multi-Layer Inference *Fuzzy Tsukamoto* (MLIFT). This research uses 18 input variables including 15 non-linguistic variables or crisp and the rest are linguistic ones or fuzzy as the data of growth requirements of cocoa plants. Generally, the algorithm used consists of three main steps those are fuzzification, Tsukamoto inference machine, and defuzzification consisting of three layers. The first layer covers seven inference engines, while each of the second and the third ones only consists of one inference engine. The concept of inference process in *Fuzzy Tsukamoto* is calculating the weighted average of each result of the inference process. Based on the testing result, it can be concluded that the multi-layer inference *Fuzzy Tsukamoto* for determining the land suitability class of cocoa plants has an accuracy level amounted 97%.

Keywords: *Multi-Layer,* Tsukamoto *Fuzzy Inference System, Suitability Class, Cocoa Plant*

ABSTRAK

Penentuan kelas kesesuaian lahan pada tanaman khususnya kakao (*Theobroma cacao*) penting dilakukan karena setiap tanaman memiliki karakteristik pertumbuhan yang berbeda. Penelitian ini bertujuan untuk mengimplementasikan algoritma untuk penentuan kelas kesesuaian lahan tanaman kakao dengan *multi-layer inference Fuzzy Tsukamoto*. Variabel input yang digunakan pada penelitian ini terdiri dari 18 variabel input dengan 15 diantaranya merupakan variabel *nonlinguistic* atau *crisp* dan sisanya merupakan variabel linguistik atau *fuzzy* yang merupakan data persyaratan tumbuh tanaman kakao. Secara umum algoritma yang digunakan terdiri dari tiga tahapan utama, yaitu fuzzifikasi, mesin inferensi Tsukamoto dan defuzzifikasi yang terdiri dari tiga *layer*. *Layer* pertama terdiri dari tujuh mesin inferensi, sedangkan untuk *layer* kedua dan ketiga masing-masing hanya terdiri dari satu mesin inferensi. Konsep proses inferensi pada *Fuzzy Tsukamoto* adalah dengan menghitung rata-rata terbobot dari masing masing hasil proses inferensi. Berdasarkan hasil pengujian, dapat disimpulkan bahwa *multi-layer inference Fuzzy Tsukamoto* untuk penentuan kelas kesesuaian tanaman kakao memiliki tingkat akurasi sebesar 97%.

Kata Kunci: *Multi-Layer, Sistem Inferensi Fuzzy Tsukamoto, Kelas Kesesuaian, Tanaman Kakao*

I. INTRODUCTION

Cocoa Plant (Theobroma cacao) is a tree of commodity cultivation of plantation that originated from South America, and today the cocoa plant has been planted in various tropical areas including Indonesia. Indonesia is one of the third greatest countries of cocoa producers after Ghana with the production result amounted 17% with a land area of 1,774,303.97 ha [1]. One effort to increase either the quality or the quantity of cocoa production is by observing the aspect of cultivation and the cocoa plant itself [2] [3]. One of the efforts in selecting the suitable land to plant the cocoa plant, considering that there are a lot of factors of the growth requirements of the cocoa plant and the varied characteristics of land [4]. Evaluating the land to optimize the potential planting land is by conducting a classification of the certain land use. The land quality and characteristics are functioned to find out any factors affecting the land suitability on the cocoa plant to grow well with the qualified production result because each plant requires different needs. According to Djaenudi et.al, in [5], there are some parameters of the land characteristics that determine the land quality. Twelve parameters determining the land quality are: the temperature, the water availability, the drainage, the oxygen availability, the rooting state, the land texture, the nutrient availability, the toxicity, the sulfidic material, the erosion hazard, the flood, and the land supply. The land used to plant the cocoa is classified into four groups based on its physical and chemical characteristics as follows: the suitable land (S1), the very suitable land (S2), the less suitable land (S3), and the unsuitable land (N). By determining the distribution of the level parapet of the physical and chemical characteristics of the land, the application of the land criteria can be a guide for the planting plan of an area whether it is suitable or not for the cocoa plant. Generally, some parameters need to be observed in determining the land suitability class based on the land characteristics, among others are the temperature, the rainfall, the number of dry months, the relative humidity, the coarse fraction, the land depth, the CEC clay, the base saturation, PH H2O, C-organic, the salinity, the sulfidic depth, the surface rocks, the outcrop rocks, the drainage, the flood hazard, the land texture, and the erosion hazard level.

It is not an easy job for the agricultural countries with a very wide land area to map the land suitability on certain kinds of plants. If the land is planted by a kind of plant that is suitable for its land characteristic, it will give the optimal result, and vice versa. Determining the kinds of plants incorrectly will bring a very big loss. There are also some factors affecting the process of land mapping which are the physical, social, and economic environment with a very quick level of change. Some previous researches have improved some concepts and or algorithms that aim at assisting in mapping the land suitability. The utilization of geographic information system, which later is called GIS, is for the evaluation of land suitability and the management of land optimization, one of which is by integrating GIS and AHP using the multi-criteria concept by conducting the weighing first [7], while [8] by adding the fuzzy concept on the system of GIS and AHP.

The fuzzy concept is much more used in some cases and applications because it is close to the real data. Many researchers develop the concept of inference fuzzy system on some

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varied scientific studies, among others are: elaborating with ANP (Analytic Network Process) in the risk assessment on the e-procurement system [9], the category of breast cancer [10], determining the toddler's nutrition with the fuzzy Sugeno [11], multi-mode driving [12], for diagnosing the tuberculosis disease on children by comparing the three models of fuzzy system (Mamdani-Sugeno-Tsukamoto) [13] and improved model using genetic neuro-fuzzy [14]. Determining the land suitability class of cocoa plant requires several times of interrelated inference steps, so this research is suggested to implement the algorithm of inference fuzzy system using the Tsukamoto model having the multi-layer architecture design. It is initiated by determining the class parapet for each land characteristic, determining the land evaluation class, and last determining the land suitability class for the cocoa plant. This paper consists of four parts those are: introduction, method of research, result and analysis, and the conclusion.

II. METHOD OF RESEARCH

Generally, there are three main steps in this research those are: fuzzification, inference engine Tsukamoto, and defuzzification. Besides the three main steps, there is a fuzzy rule database for each inference engine covering some rules of the extraction result of the expert knowledge in determining the land suitability class of cocoa plants. The method of research suggested in this research later is called the multi-layer inference *Fuzzy Tsukamoto*, which in details can be seen in Figure 1.

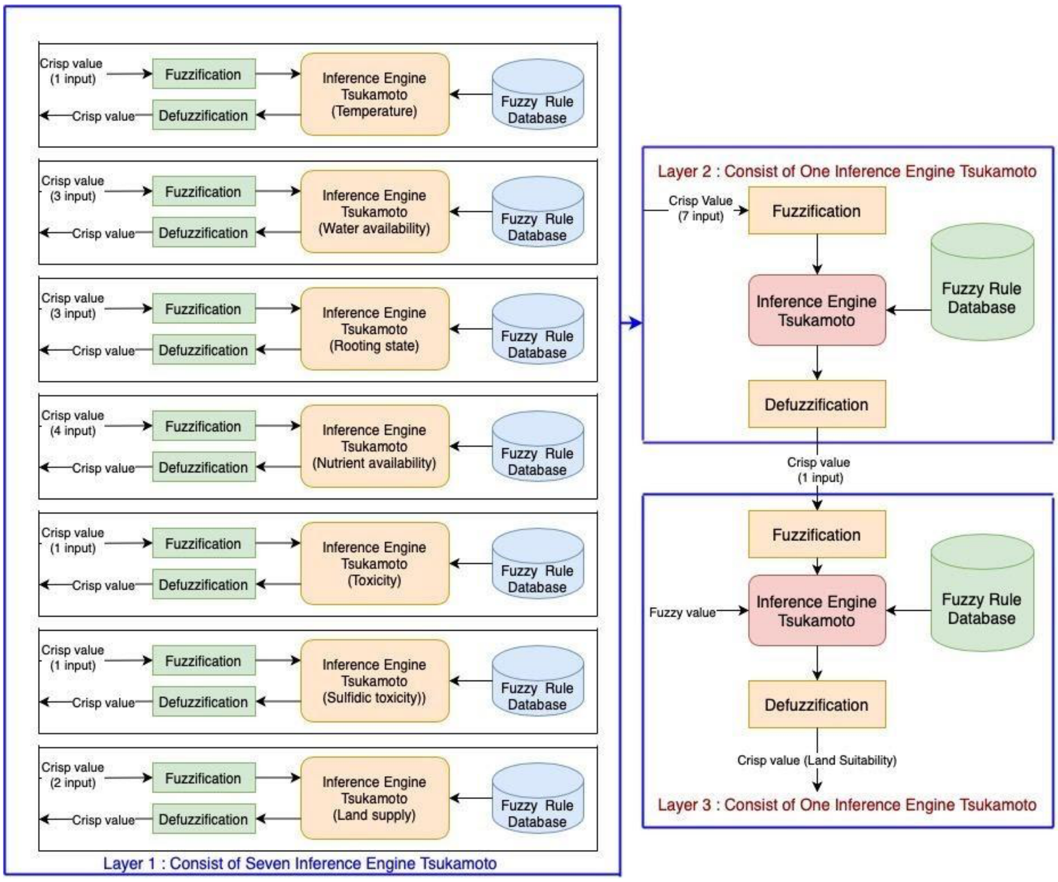

Figure 1. General description of research steps

2.1 Fuzzification

Generally, there are two kinds of inputs used in the fuzzification step those are the crisp and fuzzy data input. The fuzzification step is only for the crisp data. For determining the land suitability class of cocoa plants, it requires 18 data inputs with 15 crisp data inputs and the rest is the fuzzy data. The crisp data consists of the average annual temperature, the rainfall, the number of dry months, the relative

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humidity, the coarse fraction, the land depth, the CEC clay, the base saturation, PH H2O, C-organic, the salinity, the sulfidic depth, the surface rocks, the outcrop rocks, the drainage, the flood hazard, the land texture, and the erosion hazard level.

2.2 Inference Tsukamoto

Layer 1 consists of seven inference engines Tsukamoto those are: temperature, water availability, rooting state, nutrient availability, toxicity, sulfidic toxicity and land supply. Layer 1 will become the input for the inference engine Tsukamoto on the second layer. While layer 2 and 3 only consist of 1 inference engine Tsukamoto to determine the evaluation class and the land suitability class of cocoa plant. Each inference engine Tsukamoto has a fuzzy rule database that consists of the input and output variables for each inference engine by the subject universe. The fuzzy set, the membership function, and the domain are determined for each input variable. The detail of the data can be seen in Table 1. For example, the temperature as the input variable has seven fuzzy sets with each domain determined. While land suitability class as the output variable has five as fuzzy sets.

2.3 Defuzzification

In this step, there is a process of the values changing from fuzzy to crisp format. The output for all inference engine Tsukamoto on the first

Table I. Variables, fuzzy set, membership function, domain, and level of actual class for MLIFT

Names of Variables	Names of Sets	Membership Function	Domain	Level of actual class
		Input		
Temperature (^{0}C)	Cold	Trapmf	0-6.5	Unsuitable (N)
	Rather Cold	Trimf	5.5-20.5	Unsuitable (N)
	Cool	Trimf	19.5-25.5	Suitable Enough (S2)
	Medium	Trimf	24.5-28.5	Very Suitable (S1)
	Warm	Trimf	27.5-32.5	Suitable Enough (S2)
	Rather Hot	Trimf	31.5-35.5	Fit with Marginal (S3)
	Hot	Trapmf	>34.5	Unsuitable (N)
Rainfall (mm)	Very Light	Trapmf	0-1050	Unsuitable (N)
	Light	Trimf	950-1300	Unsuitable (N)
	Rather Light	Trimf	1200-1550	Fit with Marginal (S3)
	Moderate	Trimf	1450-2550	Very Suitable (S1)
	Rather Heavy	Trimf	2450-2950	Suitable Enough (S2)
	Heavy	Trimf	2950-3950	Fit with Marginal (S3)
	Very Heavy	Trapmf	>3950	Unsuitable (N)
The amounts of dry months (month)	Quick	Trapmf	1-2	Very Suitable (S1)
	Moderate	Trimf	2-3	Suitable Enough (S2)
	Rather Long	Trimf	3-4	Fit with Marginal (S3)
	Long	Trapmf	>4	Unsuitable (N)
Relative Humidity (%)	Very Moist	Trapmf	<30.5	Unsuitable (N)
	Moist	Trimf	29.5-35.5	Fit with Marginal (S3)
	Rather Moist	Trimf	34.5-40.5	Suitable Enough (S2)
	Medium	Trimf	39.5-64.5	Very Suitable (S1)
	Rather Dry	Trimf	64.5-75.5	Suitable Enough (S2)
	Dry	Trimf	74.5-85.5	Fit with Marginal (S3)
	Very Dry	Trapmf	>84.5	Unsuitable (N)
Coarse Fraction (%)	Little	Trapmf	<20	Very Suitable (S1)
	Medium	Trimf	10-40	Suitable Enough (S2)

	Many	Trimf	30-60	Suitable to Marginal (S3)
	A lot	Trapmf	>50	Unsuitable (N)
Land Depth (cm)	Very Shallow	Trapmf	<55	Unsuitable (N)
	Shallow	Trimf	45-80	Fit with Marginal (S3)
	Moderate	Trimf	70-105	Suitable Enough (S2)
	Deep	Trapmf	>95	Very Suitable (S1)
CEC Clay (cmol/kg)	Low	Trapmf	≤ 16	Suitable Enough (S2)
	High	Trapmf	>14	Very Suitable (S1)
Base Saturation (%)	Low	Trapmf	<25	Fit with Marginal (S3)
	Moderate	Trimf	15-40	Suitable Enough (S2)
	High	Trapmf	>30	Very Suitable (S1)
PH H2O	Very Acid	Trapmf	<5.6	Fit with Marginal (S3)
	Rather Acid	Trimf	5.4-6.1	Suitable Enough (S2)
	Neutral	Trimf	5.9-7.1	Very Suitable (S1)
	Rather Acid	Trimf	6.9-7.7	Suitable Enough (S2)
	Very AcId	Trapmf	>7.4	Fit with Marginal (S3)
C-Organic (%)	Low	Trapmf	<1	Fit with Marginal (S3)
	Moderate	Trimf	0.6-1.7	Suitable Enough (S2)
	High	Trapmf	>1.3	Very Suitable (S1)
Salinity (ds/m)	Low	Trapmf	<1.6	Very Suitable (S1)
	Rather Low	Trimf	.0.5-2.3	Suitable Enough (S2)
	Rather High	Trimf	1.3-2.7	Fit with Marginal (S3)
	High	Trapmf	>1.7	Unsuitable (N)
Sulfidic Depth (cm)	Low	Trapmf	<65	Unsuitable (N)
	Rather Low	Trimf	55-105	Fit with Marginal (S3)
	Rather High	Trimf	95-130	Suitable Enough (S2)
	High	Trapmf	>120	Very Suitable (S1)
Slope (%)	Flat	Trapmf	<9	Very Suitable (S1)
	Sloping	Trimf	7-17	Suitable Enough (S2)
	Rather Scarp	Trimf	15-31	Fit with Marginal (S3)
	Scarp	Trapmf	>29	Unsuitable (N)
Surface Rocks (%)	Low	Trapmf	<7	Very Suitable (S1)
	Rather Low	Trimf	3-17	Suitable Enough (S2)
	Rather High	Trimf	13-42	Fit with Marginal (S3)
	High	Trapmf	>38	Unsuitable (N)
Outcrop Rocks (%)	Low	Trapmf	<7	Very Suitable (S1)
	Rather Low	Trimf	3-17	Suitable Enough (S2)
	Rather High	Trimf	13-27	Fit with Marginal (S3)
	High	Trapmf	>23	Unsuitable (N)
Output				
Land Suitability Class	None	Trapmf	90-105	Very Suitable (S1)
	Light	Trimf	80-90	Very Suitable (S1)
	Moderate	Trimf	70-85	Suitable Enough (S2)
	Heavy	Trimf	60-75	Fit with Marginal (S3)
	Very Heavy	Trapmf	0-65	Unsuitable (N)

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Similarly, the third layer uses the data of the output result of the inference Tsukamoto engine on the second layer.

III. RESULT AND ANALYSIS

To conduct the process of testing the suggested algorithm, the data used in one of the lands have been validated by three experts in the land science on the land suitability class of the crisp or fuzzy characteristic. The number of rules used in the multi-layer Tsukamoto fuzzy inference is 258 rules: average annual temperature (7 rules), water availability (113 rules), root state (16 rules), nutrient availability (90 rules), toxicity (4 rules).), sulfidic toxicity (4 rules), erosion hazard (4 rules), flood hazard (4 rules), and soil preparation (16 rules). The example of crisp data is that the average annual temperature is 260 and so on, while the fuzzy data is that the land texture on the surface is rather soft, and so on. Furthermore, based on the result of observation and assessment of the

experts related to the land condition in Table 2, it can be concluded that it has the land suitability class for the cocoa plant S3 which means it fits with the marginal.

Table 2. Data sample for determining land suitability class for the cocoa plant

Requirements of Land Use	Data Values	Class Parapet
Temperature (tc)		**S1**
Average annual temperature (^{0}C)	26	
Water Availability (wa)		**S2**
Average annual rainfall (mm)	2500	
The amounts of dry months (month)	1	
Relative humidity (%)	40	
Oxygen Availability (oa)		**S1**
Drainage	Good	
Rooting State (rc)		**S3**
Surface land texture	Rather Soft	
Coarse fraction (%)	16	
Land depth (cm)	76	
Nutrient availability(nr)		**S2**
CEC clay (cmol/kg)	17	
Base saturation (%)	25	
PH H2O	7	
C-organic (%)	1.7	
Toxicity (xc)		**S2**
Salinity	1.2	
Sulfidic Toxicity (xs)		**S2**
Sulfidic depth (cm)	105	
Erosion Hazard (eh)		**S2**
Erosion Hazard Level (eh)	Very Low	
Flood Hazard (fh)		**S1**
Flood	F0	
Land Supply (lp)		**S3**
Surface Rocks (%)	6	
Outcrop Rocks (%)	17	
Land Suitability Class		**S3**

The solution of the case example in Table 2 is suggesting the use of several inference engines Tsukamoto that are divided into three layers of the inference engine. The first layer consists of seven inference engines with the output variable of 'class parapet' with four fuzzy sets those are: very heavy, heavy, medium, and light. While the function of membership and domain used is as shown in Figure 2.

The inference engine for the first layer consists of seven kinds of inference engines with various input variables.

3.1 The inference engine of temperature with the input variable of average annual temperature

If the average temperature is 26°C, the rule formed is :

```
[R4]IF the average annual temperature is medium THEN the average annual temperature class parapet is light
```

The result of the defuzzification process is 97.5 with the light category.

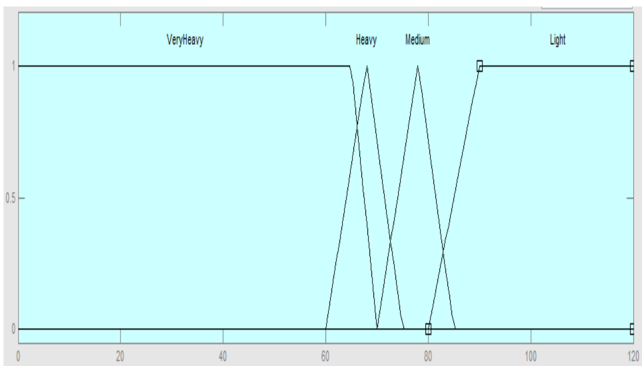

Figure 2. Graph of fuzzy membership for output variable of 'class parapet', axis x indicates subject universe of a class parapet with value 0-120, while axis y indicates a value of fuzzy membership

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3.2 The inference engine of water availability has 3 input variables (rainfall, the amounts of dry months, and relative humidity)

If the data for the rainfall is 2500 mm, the amounts of dry months are one month, and the relative humidity is 40%, the rule formed is four types as follows:

```
[R87] IF the rainfall is moderate AND the amounts of dry months are quick AND the relative humidity is rather moist THEN the class parapet of water availability is medium

[R88] IF the rainfall is moderate AND the amounts of dry months are quick AND the relative humidity is moderate THEN the class parapet of water availability is light

[R115] IF the rainfall is rather heavy AND the amounts of dry months are quick AND the relative humidity is rather moist THEN the class parapet of water availability is medium

[R116] IF the rainfall is rather heavy AND the amounts of dry months is quick AND the relative humidity is moderate THEN the class parapet of water availability is medium
```

The result of the defuzzification process is 83.79 for the class parapet of water availability with a medium category.

3.3 The inference engine of the rooting state has two input variables (coarse fraction and land depth)

If the data for the coarse fraction and the land depth is 16% and 76 cm, the rule formed is two types as follows:

```
[R6] IF the coarse fraction is medium AND the land depth is shallow THEN the class parapet of the rooting state is heavy

[R7] IF the coarse fraction is medium AND the land depth is medium THEN the class parapet of rooting state is medium
```

The result of the defuzzification process is 72.5 for the class parapet of rooting state with a heavy category.

3.4 The inference engine of nutrient availability has four input variables (CEC clay, base saturation, PH H2O, and C-organic)

If the data for the CEC clay, the base saturation, PH H_2O, and C-organic is 17 cmol/kg; 25%, 7, and 1.7, the rule formed is two types as follows:

```
[R69] IF the CEC clay is high AND the base saturation is moderate AND PH H2O is neutral AND the C-organic is high THEN the class parapet of nutrient supply is medium

[R70] IF the CEC clay is high AND the base saturation is moderate AND PH H2O is rather alkali AND the C-organic is high THEN the class parapet of nutrient supply is medium
```

The result of the defuzzification process is 83.48 for the class parapet of nutrient supply with the medium category.

3.5 The inference engine of toxicity only has 1 input variable of salinity

If the data value is 1.2 ds/m, the rule formed is only one type.

```
[R1] IF the salinity is rather low THEN the class parapet of toxicity is medium.
```

The result of the defuzzification process is 83.88 for the class parapet of toxicity with the medium category.

3.6 The inference engine of sulfidic toxicity only has 1 input variable of sulfidic depth

If the data value is 105 ds/m, there will be one rule formed:

```
[R1] IF the sulfidic depth is rather high THEN the class parapet of sulfidic toxicity is medium.
```

The result of defuzzification process is 83.88 for the class parapet of sulfidic toxicity with the medium category.

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3.7 The inference engine of land supply has 2 input variables (surface rocks and outcrop rocks)

If the data value is 6% and 17%, there will be two rules formed as follows:

```
[R6] IF the surface rocks are rather low AND
the outcrop rocks are rather high THEN the
class parapet of land supply is heavy
```

The result of the defuzzification process is 72.49 for the class parapet of land supply with the heavy category.

The next step is that the output of the seven inference engines becomes the input data for the inference engine on the second layer with the variables of the following ones: temperature, water availability, rooting state, nutrient availability, toxicity, sulfidic toxicity, and land supply. The second layer consists of 1 inference engine with the output variable of 'land evaluation class' including four fuzzy sets those are: very suitable (S1), suitable enough (S2), fit with marginal (S3), and unsuitable (N) with the domain as shown in Figure 3.

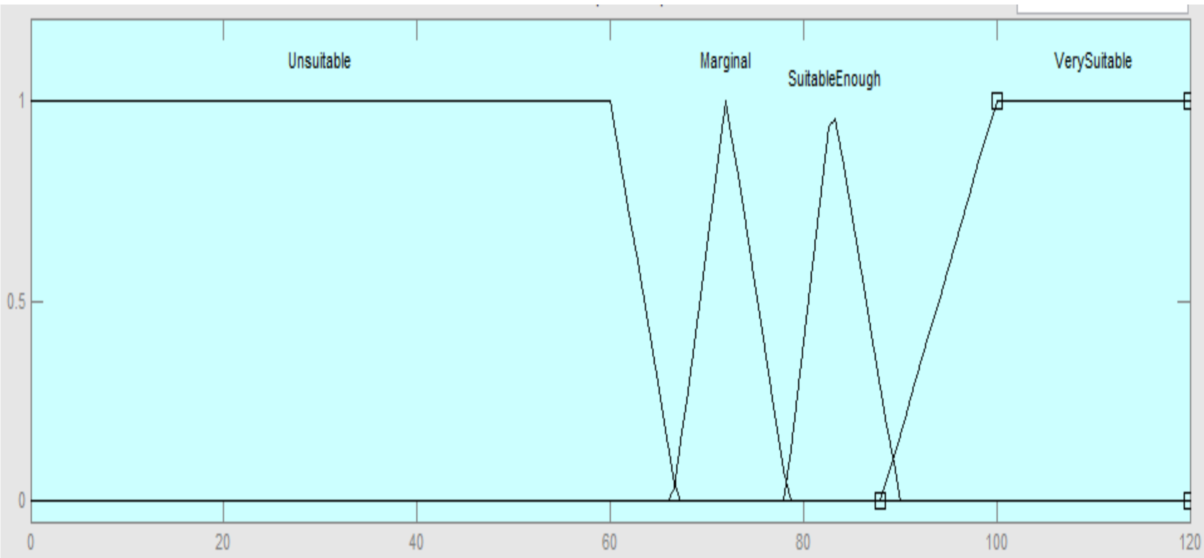

Figure 3. Graph of fuzzy membership for output variable of 'land evaluation class', axis x indicates subject universe of land evaluation class with values 0-120, while axis y indicates a value of fuzzy membership

The inference engine on the second layer has seven data inputs as the output result of the inference engine on the first layer. For this case, the rule used is:

```
[R1623] If there is no temperature or it
is   light AND the water availability is
medium AND the rooting state is heavy AND
the nutrient availability is medium AND the
toxicity is medium AND the sulfidic toxicity
is medium AND the land supply is heavy THEN
class parapet of land evaluation fits with
the marginal (S3)
```

The result of the defuzzification process is 72.5 for the land evaluation class with the category fit with the marginal (S3). While the third layer consists of one inference engine with the output variable of 'land suitability class' consisting of four fuzzy sets those are: very suitable (S1), suitable enough (S2), fit with marginal (S3), and unsuitable (N) by forming the inference engine by collaborating the two types of input, the crisp data input as the result of the inference engine on the second layer with the fuzzy data input using the IF–THEN rule. While the non-fuzzy parameters are: drainage, land texture, erosion hazard, and flood hazard, with the rule as follows:

```
[R3 drainage] IF the drainage is good THEN
there is no class parapet of drainage or it
is light

[R3 texture] IF the land texture is rather
soft THEN there is no class parapet of land
texture or it is light

[R4 erosion] IF the erosion hazard is very
light THEN there is no class parapet of
erosion or it is light
```

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```
[R3 flood] IF the flood hazard is FO THEN
there is no class parapet of flood or it is
light
```

The rule formed in this case in Table 2 is:

```
IF the fuzzy output evaluation class fits
with the marginal (S3) OR there is no
drainage or it is light (S1) OR there is no
land texture or it is light (S1) OR there is
no erosion hazard or it is light (S1) OR
there is no flood hazard or it is light (S1)
THEN the land suitability class fits with
the marginal (S3)
```

Table 3. Data Testing

No	Land Data	Land Data									
		I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**
1.	Temperature (^{0}C)	25 [S1]	33 [S3]	28 [S2]	28 [S2]	20 [S2]	28 [S2]	28 [S2]	27 [S1]	27 [S1]	19 [N]
	Average annual rainfall (mm)	2600 [S2]	1500 [S3]	2400 [S1]	2500 [S2]	2000 [S1]	2400 [S1]	1600 [S1]	1700 [S1]	2000 [S1]	3500 [S3]
2	The amounts of dry months (month)	2 [S2]	2 [S2]	1 [S1]	3 [S3]	2 [S2]	2 [S2]	1 [S1]	1 [S1]	1 [S1]	3 [S3]
	Relative humadity (%)	68 [S2]	30 [S3]	50 [S1]	60 [S1]	45 [S1]	40 [S1]	45 [S1]	50 [S1]	45 [S1]	76 [S3]
3	Drainage	[S3]	[S1]	[S1]	[S3]	[S1]	[S3]	[S3]	[S1]	[S1]	[S1]
4	Surface land texture	[S1]	[S3]	[S1]	[S2]	[S1]	[N]	[S1]	[S1]	[S1]	[S1]
	Coarse fraction (%)	17 [S2]	40 [S3]	12 [S1]	36 [S3]	30 [S2]	55 [N]	14 [S1]	12 [S1]	14 [S1]	15 [S2]
	Land depth (cm)	80 [S2]	70 [S3]	98 [S2]	52 [S3]	77 [S2]	60 [S3]	76 [S2]	150 [S1]	110 [S1]	80 [S2]
5	CEC clay (cmol/kg)	16 [S2]	7 [S2]	20 [S1]	10 [S2]	16 [S2]	7 [S2]	15 [S2]	40 [S1]	25 [S1]	30 [S1]
	Base saturation (%)	38 [S1]	20 [S2]	40 [S1]	24 [S2]	30 [S2]	25 [S2]	25 [S2]	40 [S1]	50 [S1]	44 [S1]
	PH H_2O	6 [S2]	8 [S3]	7 [S1]	8 [S3]	6 [S2]	8 [S3]	6 [S2]	6.8 [S1]	6.5 [S1]	8 [S3]
	C-organic	1.5 [S2]	1.5 [S2]	2 [S1]	1.5 [S2]	1 [S2]	0.8 [S3]	1 [S2]	4 [S1]	2 [S1]	0.8 [S3]
6	Salinitas (ds/m)	1.3 [S2]	1.9 [S3]	1 [S1]	0 [S1]	1.5 [S2]	3 [N]	1 [S1]	0.5 [S1]	0.6 [S1]	2 [N]
7	Sulfidic depth (cm)	115 [S2]	65 [S3]	130 [S1]	0 [S1]	122 [S2]	88 [S3]	120 [S2]	165 [S1]	160 [S1]	100 [S3]
8	Erosion hazard	[S2]	[S2]	[S1]	[S2]	[S2]	[S2]	[S2]	[S1]	[S1]	[S3]
9	Flood hazard	F0 [S1]	F2 [N]	F0 [S1]	F0 [S1]	F0 [S1]	F1 [S3]	F0 [S1]	F0 [S1]	F0 [S1]	F1 [S3]
10	Surface rocks (%)	5 [S2]	60 [N]	4 [S1]	30 [S3]	10 [S2]	40 [N]	13 [S2]	4 [S1]	3 [S1]	5 [S2]
	Outcrop rocks (%)	5 [S2]	40 [N]	4 [S1]	20 [S3]	15 [S2]	30 [N]	14 [S2]	4 [S1]	4 [S1]	10 [S2]
The experts		**S3**	**N**	**S2**	**N**	**S2**	**N**	**S3**	**S1**	**S1**	**N**
System		**S3**	**N**	**S2**	**N**	**S2**	**N**	**S3**	**S1**	**S1**	**N**
Accuracy		**90%**	**90%**	**100%**	**100%**	**100%**	**90%**	**100%**	**100%**	**100%**	**100%**

Based on the final result of the rule representation, the land output rule for the fuzzy output and the land suitability class of the non-fuzzy fit with the marginal (S3) with the range value of presentation amounted to 72.5%. To find out the accurate level of algorithm suggested, testing is conducted with 10 data as shown in Table 3.

For example, the first data in the third column with the land data with the temperature

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25%, the annual rainfall 2600 mm, and so on has the land suitability class for the cocoa plant S3, which means it fits with the marginal. In this case, the output produced by the expert and the system is similar to the percentage of suitability amounted 90%. A similar process is also conducted on the second data until the tenth. As a whole the system developed using the multi-layer inference fuzzy tsukamono has the percentage of suitability amounted 97%.

IV. CONCLUSION

The algorithm suggested with the multi-layer inference *Fuzzy Tsukamoto* can be used to determine the suitability class of land for the cocoa plant with the accurate level amounted 97%. Several types of plants either food, plantation, horticulture, forestry, and other commodities certainly have their characteristics. This affects the algorithm applied.

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