Sensitivity analysis of fuzzy simple additive weighting to determine land suitability for corn in Kupang Regency

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Abstract. The change in geographical states, such as weather and climate, makes it difficult for farmers to prepare adequate land for corn cultivation. This research analyses the fuzzy simple additive algorithm used to determine land suitability in Kupang Regency and the use of sensitivity analysis to obtain information on the most sensitive variable(s). Two testing models were conducted in this research, namely, accuracy and sensitivity tests. The result of the accuracy test showed 80% precision, while sensitivity showed that rainfall, soil depth, and C-Organic were highly sensible with a percentage of 100%, followed by slope and soil texture at 66%. Furthermore, the irrigation system, spring, and level of disaster had the same percentage of 33.33%.

1. Introduction
Approximately 70% of the East Nusa Tenggara (NTT) populations are predominantly corn farmers because it is a staple food for the community [1]. Corn commodities are also one of the outstanding opportunities for agribusiness development due to an increase in market demand because NTT will be among the top 12 food-producing regions in Indonesia [2]. There are three corn-producing zones in NTT: Flores, Sumba, and Timor which produced 109 tons in 2017 [3].

A technique used to increase corn productivity is through land evaluation, and this is achieved by comparing the characteristics of plants and nature of land [4]. The Food and Agriculture Organization [5] has updated evaluation indicators to include suitability, a comparative advantage with required inputs, technology, features, as well as the evaluation of its physical and socio-economic conditions. Furthermore, the indicators are called the FAO model [6].

Agricultural land suitability is an interdisciplinary approach that also involves major decisions at various levels starting from choosing a land type, criteria, organization, and preferences (both qualitative and quantitative) [7]. The relative importance of these parameters can be well evaluated to determine the suitability by multi-criteria technique [8] with the Simple Additive Weighting mainly utilized [9]. However, these methods have limitations, with several parameters or criteria linguistically [10]. The transition from uncertainty by linguistic values such as “Very Low”, “Low”, “High”, and “Very High” can be quantified using fuzzy set theory [11]. Therefore, many researchers have attempted to use fuzzy in multi-criteria evaluation method [12].
The weight of the criteria is the biggest contributor to uncertainty in the multi-criteria evaluation method [13]. Sensitivity Analysis (SA) procedures help reduce uncertainty and stability of its outputs by illustrating the impact of introducing a small change to specific input parameters on outcomes [14]. This study aimed to determine the level of land suitability for corn plants in 10 plants alternative locations in Kupang Regencies namely Tarus, Noelbaki, Oebelo, Manusak, Oesao, Naibonat, Raknamo, Sulamu, Pariti, and Nombes. In addition, it was also conducted to measure the sensitivity level of the criteria (land characteristics) such as rainfall, irrigation systems, water availability, land slope, soil texture, soil depth, C-organic, and level of disaster.

2. Methodology
There are four processes in this study, namely data collection, conversion to fuzzy numbers, F-SAW process, testing of accuracy and sensitivity.

2.1. Data collection
Data was collected through interviews, observation, and documentation. The data, therefore, were divided into two models, namely crisp value and linguistic. Crisp value data was also acquired in the form of rainfall and soil depth at the Agricultural and Forestry Extension Agency (BP4K) of Naibonat, Kupang Regency. The linguistic data (irrigation system, springs, land slope, soil texture, organic matter, and level of disaster) were retrieved from observations that were made using questionnaires sent to 2 farmers groups in alternative locations.

![Figure 1. Research methodology](attachment:image.png)
Table 1. Alternative data, criteria, and weight of criteria.

| Location   | Rainfall | Springs | Land slope | Soil texture | Soil depth | C-organic | Level of disaster |
|------------|----------|---------|------------|--------------|------------|-----------|-------------------|
| Tarus      | 448 mm   | VG      | G          | F            | 46 cm      | G         | G                 |
| Noelbaki   | 449 mm   | VG      | G          | G            | 48 cm      | F         | G                 |
| Oebelo     | 453 mm   | VG      | VG         | G            | 50 cm      | G         | VG                |
| Manusak    | 1.043 mm | VG      | VG         | VG           | 65 cm      | VG        | VG                |
| Oesao      | 1.040 mm | F       | VG         | VG           | 68 cm      | VG        | G                 |
| Naibonat   | 1.045 mm | F       | VG         | VG           | 65 cm      | VG        | G                 |
| Raknamo    | 485 mm   | VG      | G          | G            | 65 cm      | G         | VG                |
| Sulamu     | 420 mm   | VG      | VG         | VG           | 48 cm      | VG        | VG                |
| Parity     | 425 mm   | F       | VG         | VG           | 50 cm      | G         | VG                |
| Nonbes     | 783 mm   | F       | VG         | VG           | 65 cm      | F         | VG                |

Weight: VG P P G F G F

2.2. Conversion to fuzzy value

After data collection, those data were pre-processed by converting crisp and linguistic values (Table 1) into fuzzy values. The conversion process for variable rainfall and soil depth each used a membership function as in Table 2. The membership function was built based on the requirements of land use for corn [15].

Table 2. Fuzzy membership function for crisp input

| Variable       | Membership function |
|----------------|---------------------|
| Rainfall       | \( \mu_{\text{rainfall}}(x) = \begin{cases} 0; & x < 300 \text{ atau } x > 1600 \\ \frac{x-300}{500-300}; & 300 \leq x \leq 500 \\ 1; & 500 \leq x \leq 1200 \\ \frac{1600-x}{1600-1200}; & 1200 \leq x \leq 1600 \end{cases} \) |
| Soil depth     | \( \mu_{\text{soil depth}}(x) = \begin{cases} 0; & x \leq 25 \\ \frac{x-25}{60-25}; & 25 \leq x \leq 60 \\ 1; & x \geq 60 \end{cases} \) |

The triangular fuzzy numbers are used to convert the irrigation system variables, springs, land slope, soil texture, organic matter, level of disaster to fuzzy values (Figure 2).

Figure 2. Fuzzy membership function for linguistic input
2.3. F-SAW method

Fuzzy set theory can be used to represent uncertainty by giving intervals from 0 to 1. F-SAW is a combination of the SAW method and Fuzzy mathematical logic with differences in the implementation of values. The F-SAW comparison matrix is represented by three variables (a, b, c) called Triangular Fuzzy Numbers (TFN), which will produce three values, according to three sequential weights in the triangle membership function [16]. The algorithm is as follows:

a. The rating of each criterion for alternatives was made in the fuzzy value through fuzzy membership function.

b. The fuzzy values for linguistic variables were calculated by the defuzzification equation as follows:

\[
e = \frac{(a + b + c)}{3}
\]  

where:
- \(e\) = defuzzification value
- \(a\) = smallest fuzzy number
- \(b\) = moderate fuzzy number
- \(c\) = biggest fuzzy number

c. The fuzzy weight of each criterion was determined by the following equation:

\[
W_i = \frac{\sum_{i=1}^{n} e_i}{\sum_{i=1}^{n} e_i}
\]  

where:
- \(W_i\) = weight for the-i criterion
- \(e_i\) = defuzzification value for the-i criterion
- \(\sum_{i=1}^{n} e_i\) = the total defuzzification value of each criterion

d. A decision matrix (alternative to criteria) was produced, where the matrix element is a fuzzy value from the previous calculation.

e. The decision matrix is normalized by the following equation:

\[
r_{ij} = \begin{cases}
\frac{x_{ij}}{\text{MAX}(x_{ij})} & \text{for profit criteria} \\
\frac{x_{ij}}{\text{MIN}(x_{ij})} & \text{for cost criteria}
\end{cases}
\]  

where:
- \(r_{ij}\) = normalized matrix element.
- \(x_{ij}\) = decision matrix elements that have not been normalized
- \(\text{MAX}(x_{ij})\) = the biggest value of alternative \(i\) with respect to criterion \(j\), for profit criteria
- \(\text{MIN}(x_{ij})\) = the smallest value of alternative \(i\) with respect to criterion \(j\), for cost criteria

f. A normalized matrix of each criterion for each alternative is produced:

\[
N = \begin{bmatrix}
r_{11} & r_{12} & \ldots & r_{1j} \\
\vdots & \vdots & \ddots & \vdots \\
r_{i1} & r_{i2} & \ldots & r_{ij}
\end{bmatrix}
\]  

where:
- \(N\) = normalized matrix

g. The total value of each alternative is determined by the following equation:

\[
V_i = \sum_{j=1}^{n} w_j \cdot r_{ij}
\]  

The bigger \(V_i\) value showed that the \(A_i\) alternative is more chosen.

3. Result and Discussion

This section explains the results of the process: converting data to fuzzy values, F-SAW, and testing processes using the level of accuracy and sensitivity analysis.
3.1. Fuzzy value conversion

Fuzzy values ($\mu$) are obtained by entering data (Table 1) into membership functions (Table 2 and Figure 1). The defuzzification equation (equation 1) is also used for linguistic data conversion.

### Table 3. Fuzzy memberships function for crisp input.

| Alternative | Rainfall | Irrigation system | Springs | Land slope | Soil texture | Soil depth | C-organic | Level of disaster |
|-------------|----------|-------------------|---------|------------|--------------|------------|-----------|-------------------|
| Tarus       | 0.740    | 0.916             | 0.250   | 0.750      | 0.500        | 0.600      | 0.750     | 0.750             |
| Noelbaki    | 0.745    | 0.916             | 0.250   | 0.750      | 0.500        | 0.657      | 0.500     | 0.750             |
| Oebelo      | 0.765    | 0.916             | 0.250   | 0.916      | 0.750        | 0.714      | 0.750     | 0.916             |
| Manusak     | 1.000    | 0.916             | 0.750   | 0.916      | 0.916        | 1.000      | 0.916     | 0.916             |
| Oesao       | 1.000    | 0.500             | 0.916   | 0.916      | 0.916        | 1.000      | 0.916     | 0.750             |
| Naibonat    | 1.000    | 0.500             | 0.750   | 0.916      | 0.916        | 1.000      | 0.916     | 0.750             |
| Raknamo     | 0.925    | 0.916             | 0.250   | 0.750      | 0.750        | 0.571      | 0.750     | 0.916             |
| Sulamu      | 0.600    | 0.916             | 0.250   | 0.750      | 0.916        | 0.657      | 0.916     | 0.916             |
| Pariti      | 0.625    | 0.500             | 0.916   | 0.916      | 0.916        | 0.714      | 0.750     | 0.916             |
| Nonbes      | 1.000    | 0.500             | 0.916   | 0.916      | 0.916        | 1.000      | 0.500     | 0.916             |

Fuzzy weighted | 0.916 | 0.250 | 0.916 | 0.250 | 0.750 | 0.500 | 0.750 | 0.500 |

3.2. The alternative ranking using F-SAW

After the fuzzy value is obtained, the next step is to calculate the normalized rating performance ($r_{ij}$) for each alternative and each criterion. The decision matrix and weight of criterion were normalized using (5) as shown in matrix $N$ and $W$ as follows.

$$ N = \begin{bmatrix} 0.74 & 1.00 & 0.272 & 0.818 & 0.545 & 0.60 & 0.818 & 0.818 \\ 0.745 & 1.00 & 0.272 & 0.818 & 0.818 & 0.657 & 0.545 & 0.818 \\ 0.765 & 1.00 & 0.272 & 1.00 & 0.818 & 0.714 & 0.818 & 1.00 \\ 1.00 & 1.00 & 0.818 & 1.00 & 1.00 & 1.00 & 1.00 \\ 1.00 & 0.545 & 1.00 & 1.00 & 1.00 & 1.00 & 0.818 \\ 1.00 & 0.545 & 0.818 & 1.00 & 1.00 & 1.00 & 0.818 \\ 0.925 & 1.00 & 0.272 & 0.818 & 0.818 & 0.571 & 0.818 & 1.00 \\ 0.60 & 1.00 & 0.272 & 0.818 & 1.00 & 0.657 & 1.00 & 1.00 \\ 0.625 & 0.545 & 1.00 & 1.00 & 1.00 & 0.714 & 0.818 & 1.00 \\ 1.00 & 0.545 & 1.00 & 1.00 & 1.00 & 0.545 & 1.00 & 1.00 \end{bmatrix} $$

$$ W = [ 0.1895 \ 0.0517 \ 0.1895 \ 0.0517 \ 0.1552 \ 0.1034 \ 0.1552 \ 0.1034 ] $$

The last step of F-SAW calculation is ranking the preference value ($Vi$) obtained from summing the vector multiplication vector $W$ and normalized matrix $N$ (Pers. 4). The result of the calculation can be seen in Table 4.
Table 4. Result of alternative ranking ($V_i$).

| Alternative | Rank |
|-------------|------|
| Manusak     | 0.9655 |
| Oesao       | 0.9577 |
| Naibonat    | 0.9232 |
| Nonbes      | 0.9060 |
| Pariti      | 0.8476 |
| Sulamu      | 0.7413 |
| Raknamo     | 0.7377 |
| Oebelo      | 0.7315 |
| Noelbaki    | 0.6513 |
| Tarus       | 0.6444 |

3.3. Accuracy test

Accuracy testing is conducted to determine the precision of the F-SAW system produced. In this test, the result of the system-based ranking and the expert knowledge-based ranking have been compared.

Table 5. Comparison of rank.

| Sub-dist | System-based rank | Expert-based rank |
|----------|-------------------|-------------------|
| Tarus    | 10                | 10                |
| Noelbaki | 9                 | 9                 |
| Oebelo   | 8                 | 8                 |
| Manusak  | 1                 | 1                 |
| Oesao    | 2                 | 2                 |
| Naibonat | 3                 | 3                 |
| Raknamo  | 7                 | 7                 |
| Sulamu   | 5                 | 6                 |
| Pariti   | 6                 | 5                 |
| Nonbes   | 4                 | 4                 |

From Table 5, it can be seen that there are 8 similar ranking results and 2 different rankings between the system and the expert so that the accuracy value is obtained:

$$Accuracy = \frac{8}{10} \times 100\% = 80\%$$

$$Error rate = \frac{2}{10} \times 100\% = 20\%$$

3.4. Sensitivity analysis

Sensitivity analysis aims to determine the criteria level utilized. In this section, the weights of preference were made on each criterion.
Table 6. Result of sensitivity analysis.

| Variable          | Default weight | Weight change | Number of ranking change | Count of change | Percentage of change |
|-------------------|----------------|---------------|--------------------------|-----------------|----------------------|
| Rainfall          | VG F ; P ; VP  | 2 ; 2 ; 4     | 3                        |                 | 100%                 |
| Irrigation system| P VG ; F ; VP  | 0 ; 0 ; 2     | 1                        |                 | 33.33%               |
| Springs           | VG F ; P ; VP  | 0 ; 0 ; 4     | 1                        |                 | 33.33%               |
| Land slope        | P VG ; F ; VP  | 3 ; 2 ; 0     | 2                        |                 | 66.67%               |
| Soil texture      | G VG ; F ; P   | 0 ; 4 ; 5     | 2                        |                 | 66.67%               |
| Soil depth        | F VG ; G ; P   | 2 ; 2 ; 2     | 3                        |                 | 100%                 |
| C-Organic         | G VG ; F ; P   | 2 ; 4 ; 5     | 3                        |                 | 100%                 |
| Disaster level    | F VG ; G ; P   | 0 ; 0 ; 2     | 1                        |                 | 33.33%               |

Table 6 shows that the rainfall criteria have an initial “Very Good (VG)” weight, which changes to “Fair (F)”, “Poor (P)”, and “Very Poor (VP)”. There are 2, 2, 4 changes in sequence on the ranking results when the weight is changed to F, P, and VP. It indicates that the ranking of rainfall criteria is very sensitive to change in weight.

4. Conclusion
The result of the accuracy level test shows two different ranks produced by the F-SAW method and expert assessment, so the accuracy value obtained is 80%. The second test scenario, which is the sensitivity level test, shows that the rainfall, soil depth, and C-organic at 100%, followed by land slope and soil texture with 66%, then the irrigation systems, springs, and level of disaster with 33.33%. From the obtained results, the most sensitive criteria were rainfall, soil depth, and C-organic.

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