This article can be cited as A. M. Irawan, H. A. Nugroho, O. W. Purbo, S. T. Gustono, D. P. O. Veanti, Munawar and R. R. Mahmudiah, Real-time Landslide Early Warning System Based on Fuzzy Ad Hoc Data Covering Methods Using Empirically-based Model, International Journal of Artificial Intelligence, vol. 18, no. 2, pp. 74-100, 2020.

Real-time Landslide Early Warning System Based on Fuzzy Ad Hoc Data Covering Methods Using Empirically-based Model

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ABSTRACT

In this research, we take a different approach to build a new landslide warning system by using the fuzzy rule-based system (FRBS) model rather than either satellite remote sensing or dynamical approach that was employed in most landslides warning studies. This fuzzy model was developed based on ad hoc data covering methods and empirically-based model. In this case, fuzzy rules were set by learning from numerical data. We found the model satisfactorily simulated the occurrence of landslide with values of area under the Fuzzy Receiver Operating Characteristic (ROC) curve at 0.825 (range: 0 to 1, perfect score: 1) resulting in a good agreement with the occurrence of landslide data obtained from the Indonesian National Agency for Disaster Management (BNPB). For the domain research, this warning system is developed at Banjarnegara, Central Java, Indonesia, which chosen as an example of a populated highland that is highly vulnerable to landslides. In this system, Soil Moisture Index (SMI) was calculated based on a regolith-moisture model to represent the soil moisture conditions. Besides, the empirical intensity-duration (ID) threshold and cumulative rainfall threshold (CT) have been calculated as an empirically-based model. They were derived on a numerical basis, starting from a database of 141 shallow landslides from 2011 to 2017. Fuzzy ROC analysis was employed to validate an FRBS based on continuous time series of newest rainfall and evapotranspiration data and landslide database from 2018 to 2019. Ultimately, the Fuzzy model could simulate the gold standard of the landslide alert system with small error measures.

Keywords: landslides, early warning, fuzzy rule-based system, roc curve.

Mathematics Subject Classification: 03B52, 68T27, 94D05

Computing Classification System: Computing methodologies~Artificial intelligence~Knowledge representation and reasoning~Vagueness and fuzzy logic

1. INTRODUCTION

Landslides are induced either by earthquakes or by excessive rainfall (Ayalew et al., 2005; Huang, 2015; Keefer, 2002; Wati et al., 2010). It mostly occurs within minutes after a high-intensity earthquake, and several hours to weeks after intense, prolonged rainfalls (Malamud et al., 2004). The Emergency Events Database (EM-DAT), www.emdat.be, from the Centre for Research on the Epidemiology of Disasters (CRED), reported that at least 650 landslides occurred worldwide caused 49,707 casualties during the period 1900-2017. In Indonesia, Landslides occur almost every year during the wet season in many areas due to monsoonal precipitation (Ophiyandri et al., 2009). Aside from rainfall, road constructions, building excavations, deforestation, and mining might lead to slope instabilities which can cause landslides (Gill and Malamud, 2017).

It is well understood that Banjarnegara, Central Java Provine, Indonesia, is prone to landslides due to its geological conditions, topography, and climate. Historical records reported that Banjarnegara experienced many landslides induced rainfall during the wet seasons, resulting in many deaths and considerable economic losses (Priyono and Priyana, 2006; Warnadi, 2014). With the frequent and destructive landslides that had occurred throughout history in Banjarnegara, the area is an ideal site to research how to mitigate landslide damage and how to decrease the economic losses from landslides.

The concern on improving the estimation of landslides can be found in several studies. Liao et al. (2010) established the prototype of an experimental early warning system for rainfall-induced landslides in Indonesia using satellite remote sensing and geospatial datasets. Notably, Capparelli and Versace (2011) developed two mathematical models for early warning of landslides induced by rainfall in Italy by analysing the lag time from rainfall as a gamma function that triggers landslide. An integrated methodology for landslide early warning systems to reduce the risk from the disaster, including risk assessment, mapping, and mitigation strategy was established by Fathani et al. (2016) to decrease the negative social and economic impacts of the landslide in Central Java. Despite much promising development of landslide early warning system, Frattini et al. (2010) insist that there is a need to assess the accuracy of landslide model. In this case, simple statistics such as Threat score, Gilbert Skill Score, or Receiver Operating Characteristic (ROC) curve can be used.

For the fuzzy applications, many scientists have utilised the Fuzzy Logic (FL) algorithm for meteorology and hydrology problems (Alvisi et al., 2006; Chang and Chang, 2006; Tayfur and Singh, 2006; Xiong et al., 2001). In addition, fuzzy models proved to be successful in various fields. Gil et al. (2018) developed a fuzzy model to analyse the determination of the optimal green period ratio and traffic light cycle time in case of given traffic flow values. Notably, Devasenapati and Ramachandran (2011) developed a tool for misfire detection based on fuzzy unordered rule induction algorithm (FURIA) with correlation-based feature selection. The stability and sensitivity analysis on the use of Popov’s hyperstability theory was established by Precup and Preitl (2006) to provide useful information to the development of fuzzy control systems. For a novel mix of two data-driven algorithms, Roman et al. (2019) combined data-driven Virtual Reference Feedback Tuning (VRFT) algorithm and Compact Form Dynamic Linearization (CFDL) version of the authors’ Model-Free

Adaptive Control Takagi-Sugeno Fuzzy Algorithm (CFDLPDTSFA) to explore the main advantage of those methods and the experiential results then plotted to the arm angular position of the non-linear crane system. Recent fuzzy implementation was developed by Kviesis et al. (2020) to identify any abnormalities inside the honey bee colony employing temperature data as an input parameter and fuzzy logic. In addition, previous scientists have used fuzzy logic to model the landslide susceptibility mapping or forecast the landslide hazard zonation (Chung and Fabbri, 2001; Pradhan, 2010a; Pradhan, 2010b).

Specifically, most studies about the implementation of fuzzy model are focused on the landslide susceptibility maps, even though a landslide formation alerts also were developed. This paper takes a new approach to explore and ideally combine both the use of Fuzzy Rule-Based System (FRBS) and empirically-based model to build R-LEWS. We employed the use of empirical rainfall thresholds and soil moisture index (SMI) as an input parameter of FRBS model. Those input parameters were applied since they are one of the most critical parameters to trigger landslide in complex terrain areas, especially regions that routinely experience heavy rainfall (Liao et al., 2010). Ultimately, the first goal of the paper is to create the threshold of rainfall and SMI that induced landslides (especially for shallow landslides and debris flows), while earthquake-induced acceleration and human activities are neglected. The second goal of this paper is to develop R-LEWS utilising FRBS based on ad hoc data covering methods by using with an empirically-based model from that rainfall threshold and SMI. For the FRBS input parameters, we shall transform empirical rainfall thresholds and moisture indexes to be the possible outcome represented by the degree of membership.

1.1. Previous applications of fuzzy approach in landslide studies

Several studies have used a Fuzzy model to determine landslide susceptibility with several modifications on the algorithm. Landslide susceptibility is determined generally in three stages; landslide inventory, susceptibility analysis, and validation (Pradhan, 2013). The fuzzy approach has several advantages compared to other statistical methods, such as straightforward to apply, and the weighting of the supporting factors can be controlled (Shahabi et al., 2015). Identification and mapping of a suitable set of instability factors having a relationship with slope failures require a priori knowledge of the leading causes of landslides (Guzzetti et al., 1999). This instability factor then becomes the input of the fuzzification process in determining susceptibility.

Shahabi et al. (2015) tried to map landslide susceptibility in Iran using three statistical approaches such as Logistic Regression, Frequency Ratio, and Fuzzy Logic (FL). A central Zab basin located in the mountain areas in the southwest West Azerbaijan province in Iran was used for the study domain in that research. The result shows that Logistic regression has the best result in determining the area affected by landslide and the factor maps (slope, elevation, distance to road, distance to drainage network, distance to fault, NDVI, land cover, precipitation, and lithology). However, FL approach is modified, one can find that FL Gamma (lambda = 0.975) produce nearly similar prediction accuracy to Frequency Ratio Method (FL Gamma (0.975) = 94.64% and Frequency Ratio = 94.62%). Therefore, the modification of FL can bring completely different results and prediction accuracy. It shows the importance of choosing the right operator in each study area for maximising output quality.

Another research that uses an entirely expert opinion-based approach is conducted by Akgun et al. (2012) for Sinop (Northern Turkey). The model is called MamLand, which uses a Mamdani fuzzy inference system (FIS) in MATLAB environment. The model used seven conditioning parameters (altitude, lithology, slope gradient, curvature, normalise difference vegetation index, stream power index, and topographical wetness index) to determine landslide susceptibility degrees. FIS is constructed using IF-THEN rules which are described using expert opinion. A total of 192 rules were applied for classifying the degree of susceptibility into five classes. Then the result is exported to GIS to produce maps. Validation using Area Under Curve (AUC) obtained from ROC shows that this model is successful in mapping the susceptibility of the study area, Sinop (Northern Turkey), and allows it to be applied in other regions with some adjustments needed.

The performance of the FL model is evaluated by comparing it against other models or fellow fuzzy models with variations. For example, Shahabi et al. (2015) compared FL with other two statistical methods and several modifications in the FL approach. Another study from Pradhan (2013) examined the predictive ability among three statistical purposes; Decision tree (DT), Support Vector Machine (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The three develop different landslide susceptibility mapping (Pradhan, 2013). The model used five variations in the number of input parameters. As a result, a total of fifteen models was obtained, and the resultant maps were validated using the landslide locations. ROC checked the prediction performances of these maps by using both the success rate curve and the prediction rate curve. The best predictive ability among all models was generated from ANFIS. It shows that the FL approach is quite reliable as a method for landslide susceptibility mapping.

However, rather than following most of the landslide studies to explore the use of the fuzzy model in landslide mapping or susceptibility, we employed the application of the FRBS to build a landslide warning system. Thus, the development of landslide warning system can be applied to mitigate the landslide impact and decrease the physical and economic loss, especially in the complex terrain areas.

2. GENERATION OF THE DATA

2.1. Study site

To develop R-LEWS, finding a suitable study site is important. In this case, Banjarnegara, Central Java, Indonesia, is chosen as the study site (Figure 1).

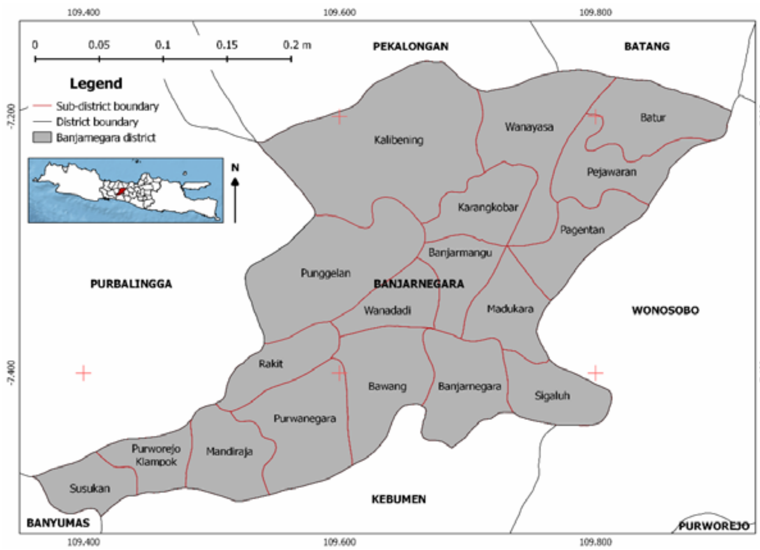

Figure 1. Domain location.

Banjarnegara regency is located in Central Java. Parts of Banjarnegara, especially in the west and north, are barely showed higher precipitation than other areas in Central Java. The location on the northern side of Banjarnegara experienced high annual rainfall up to 4000 mm/year. In addition to industrial forest, dryland agriculture, and shrubs spread in some locations (Figure 2).

This location is an instance of a populated highland that is highly susceptible to debris landslide, which is mainly caused by intense precipitation. In 2014, as reported by Haryono and Widjaja (2015), the landslide forced Karangkobar district at Banjarnegara on Friday evening. At least 93 people were believed to have been buried in the disaster. Then, Quiano and McKirdy contested that in 2016, approximately 35 people died after heavy rains and floods triggered landslides in Banjarnegara, the Indonesian province of Central Java.

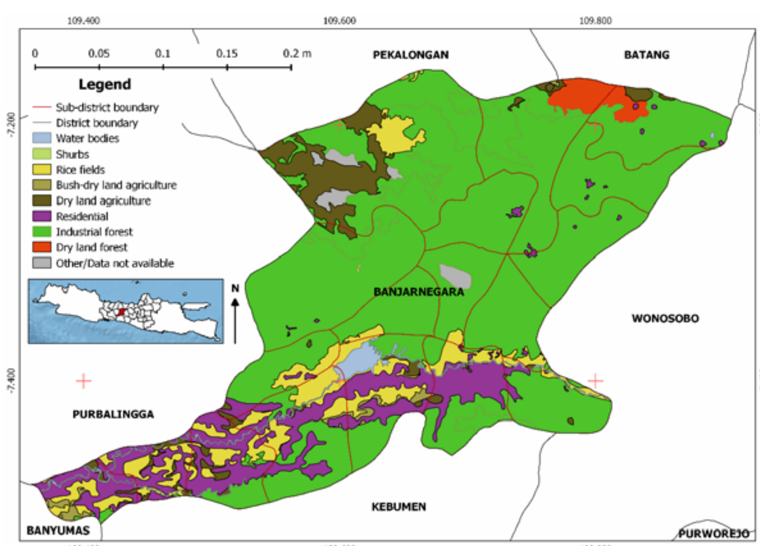

Figure 2. Land use in the model domain.

As illustrated in Figure 2, Banjarnegara shows a big contrast in land use. Most of the areas are industrial forests (green). The southern region is the dominant residential area (purple) surrounded by rice fields (yellow) and bush-dry land agriculture (seaweed colour). This condition is supported by the presence of water bodies that are more commonly found in this area. Bush-dry land agriculture and some part of ricefield can be seen in the north-west region, and dryland forests occupy the north-eastern area. Banjarnegara can be divided into three parts; northern zone, middle zone, and southern zone, based on its topography (Figure 3). The middle zone is a depression area called Serayu Depression, where the residential area surrounded by ricefield. Northern zone and the most southern zone are mountains with steep slopes. Those areas are prone to landslides and mostly covered by industrial forests.

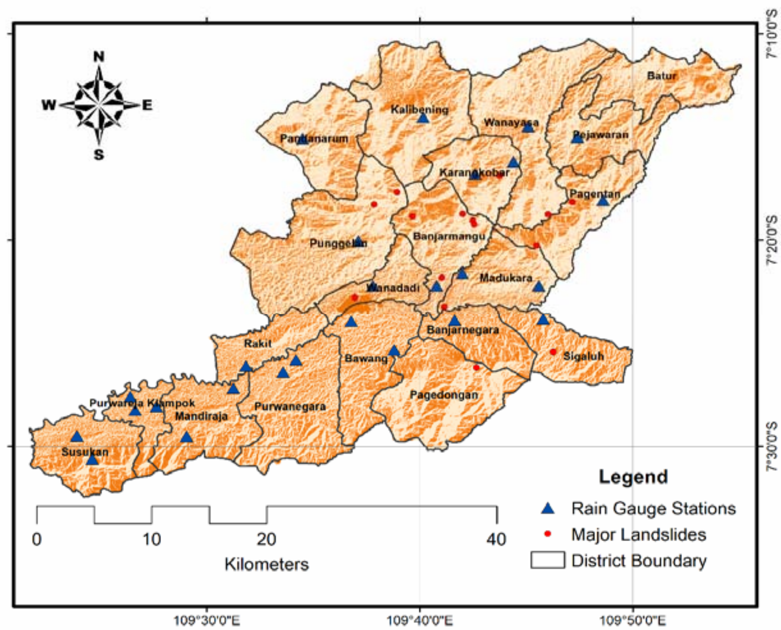

Figure 3. Map exhibiting regions of Banjarnegara rain gages and 15 major landslides in the database used to evaluate the thresholds. Landslides that shown in the maps are included major landslides because those landslides could be detected in google earth. The remaining 246 landslides have only address locations (Table 1).

Figure 3 shows the map of historical major landslides and rain gauge stations located in Banjarnegara overlaid with its topography. Daily rainfall data has been collected from two different national agencies, Semarang Climatological Station and Regional Agency of Water Resources Management (PSDA) Banjarnegara form 2011-2019 (9 years). It was taken from 23 rain gauges located in the study area (blue triangle). The historical landslide database is obtained from the Indonesian National Agency for Disaster Management (BNPB) contained the date, location, and impacts of the landslides. Furthermore, Google Earth software is used to detect landslide events from reported inventory. From the trails left by landslides, Google Earth can identify the major landslides events but the minor ones. It also can be used to find landslide events that are not reported but can be observed on google earth satellite images (Yamagishi and Moncada, 2018).

2.2. Input Data

Data from various sources have been collected based on the availability and relevance of the Banjarnegara regency. Table 1 employs the data used to develop R-LEWS of the study area. Parameters needed to build landslide warning using the FL model are obtained from several institutions, as summarised in Table 1.

Table 1. Input data sources and their date of acquisition used for landslide susceptibility analysis of the study area.

Data	Source	Date Acquisition
Daily rainfall data	Indonesia Agency for Meteorology, Climatology, and Geophysics (http://bmkgsoft.database.bmkg.go.id/)	2011-2019
Evapotranspiration data	the United States Geological Survey (USGS), (https://lpdaacsvc.cr.usgs.gov/appeears/)	2011-2019
Map of the earth face of Indonesia	Geospatial Information Agency, (1:25,000 scale map), (https://tanahair.indonesia.go.id/).	2000
Google Earth	www.google.com/earth/desktop/	
Historical landslides database	BNPB (http://geospasial.bnpb.go.id/pantauanbencana/data/datalongsorall.php)	2011-2019 (261 landslide)

2.3. Determination of rainfall Intensity-Duration (ID) and Cumulative Rainfall (CT) threshold

Caine (1980) depicts a rainfall intensity – duration (ID) threshold for the landslides that occurred on a global scale to measure the triggering influence of rainfall in producing shallow (less than 2 to 3 m deep) landslides and debris activity. A rainfall threshold may define the rainfall conditions that are likely to trigger landslides when exceeded or reached. Rainfall thresholds can be portrayed on physical (conceptual, process-based) or empirically-based models (Glade, 2001). Since the work of Caine (1980), many studies attempt to calculate the ID thresholds from the global to local scales (Glade, 2001; Guzzetti et al., 2007; Guzzetti et al., 2008). One of the most complete and comprehensive studies which continue the work of Caine (1980) is the study by Guzzetti et al. (2007).

The rainfall threshold for the initiation of landslides may define how much rainfall is likely to cause landslides when reached or exceeded. Guzzetti et al. (2007) proposed the rainfall ID threshold by measuring lower-bound lines to the plotted rainfall intensities on the y-axis and the duration on the x-axis that yielded in landslides in Cartesian, semi-log, or logarithmic coordinates. In this research, the empirically-based model derived from landslide historical data was used to calculate a rainfall ID threshold for the initiation of landslides. As the domain research is a small regency (1.204 km^2), it can be grouped as a local scale. Most studies describe that local and regional rainfall thresholds demonstrate good results in the area where the models were built. However, it cannot be handily used to other locations (Crosta, 1998). Based on Guzzetti et al. (2007), the general formula to calculate the rainfall ID threshold is:

$$I = c + \alpha D^{\beta} \quad (1)$$

where I is hourly rainfall, which is obtained from the 24-h average of daily rainfall data (mm per hour), D is rainfall duration, c is a constant with $c > 0, \alpha$ and β are empirical parameters. In addition, we used local empirical rainfall thresholds proposed by several researchers in many areas compiled by Guzzetti et al. (2007) to be plotted in a graph to compare the ID threshold in this paper.

Furthermore, the formula of Cumulative Rainfall Threshold (CT) is derived from the sum of rainfall three days and fifteen days before the three days (in mm) when a landslide occurs (Chleborad, 2000). Antecedent precipitation amounts were obtained using data records from stations closest to the individual landslide locations. Detail information on location and time of landslide occurrence was captured in the Indonesian National Agency for Disaster Management (BNPB) reports. Most of the landslides in the reports of 261 landslides from 2011 to 2019 are debris flows, slides, or shallow slumps (estimated failure depths equal or less than to 2 m); however, the landslide report also contains more deep-seated landslides.

2.4. Calculation of soil moisture indice

Aside from rainfall ID and CT, antecedent soil wetness is an essential factor for the initiation of landslides (Baum et al., 2005; Chleborad, 2000; Tubbs, 1974). Specifically, during the rainy season, the landslides mostly occurred when the soil is relatively wet. It shows that soil moisture indexes must be exceeded before the ID and CT can be employed. In addition, the soil moisture index is a significant factor in developing a hydrological model related to the occurrence of the landslide (including to determine the interception of rainfall by vegetation) (Crozier, 1999).

Based on Crozier (1999), This paper calculates groundwater system and soil moisture index that initiate a landslide with the following schemas: (i) positive pore pressures (one of the physical soil wetness factors that causing landslides) do not rise until the groundwater exceeds the soil field capacity, and (ii) moisture above field capacity is drained fast. We determine the initial magnitude of soil moisture index (M_0; mm) as the negative value of the soil field capacity (F_c; mm) and started at the end of the dry season. The general form to calculate soil moisture index (Gabet et al., 2004) are:

$$M_0 = F_c \quad (2)$$

the value F_c is determined as:

$$F_c = H(n - n_d) \quad (3)$$

Where n is total porosity, n_d is drained porosity, and H is regolith depth (mm) measured vertically. Furthermore, the effective rainfall that assists water to the hillslope is calculated as follow:

$$R_t = P_t - I \quad (4)$$

Where R_t is effective rainfall and P_t is total daily rainfall (mm) at time t. The intensity of rainfall (mm) intercepted by vegetation indicated by I. Then, daily moisture values (M_t) are calculated as:

$$M_t = M_{t-1} + R_t - D_t - E_t \tag{5}$$

Where M_{t-1} is the value of the moisture index on the previous day, D_t suggests the drainage and E_t depicts the daily evapotranspiration (mm). In this study, daily evapotranspiration data were downloaded from the United States Geological Survey (USGS) agency. Furthermore, the drainage D_t schema is determined as follow:

$$D_t \begin{cases} 0 & if \quad M_{t-1} \leq 0 \\ kM_{t-1} & if \quad M_{t-1} > 0 \end{cases} \tag{6}$$

Where k is a constant of dimensionless $(k = 0.9)$ (Gabet et al., 2004). The drainage calculates for water that drains rapidly from the soil after the field capacity has been surpassed.

2.5. Fuzzy Rule-Based System (FRBS) Construction

The benefit of the fuzzy method is that output is resulted by a combination of the degree of membership from each rule. In the development of the FRBS algorithm in forecast and control, there are mainly two methods: the first one is the Takagi-Sugeno, and the other is Mamdani approach. The theory of fuzzy sets strongly supports the Mamdani fuzzy system (Pereira et al., 2015). For Takagi-Sugeno algorithm (Tagaki and Sugeno, 1985), they do not have a precise defuzzification method. In contrast, the Mamdani method depicts clear steps, i.e. fuzzification, inference, and defuzzification schema. In addition, Mamdani method is easy to use and provide good performances (Dhar et al., 2015). Therefore, this research employs the Mamdani approach to construct FL rules. Thus, a Mamdani-type FRBS is composed of the following components (Figure 4):

- A Knowledge Base, that comprises the linguistic rules and membership function which introduce the fuzzy system behaviour.
- A Fuzzification Interface, that maintains the transformation of the crisp input data in values that may be treated in the fuzzy reasoning process.
- An Inference System, that uses these values and information kept in the base to include the effect of the inference process.
- A Defuzzification Interface, that is responsible for transforming the fuzzy action resulted from the inference process in a crisp work that makes up the global output of FRBS.

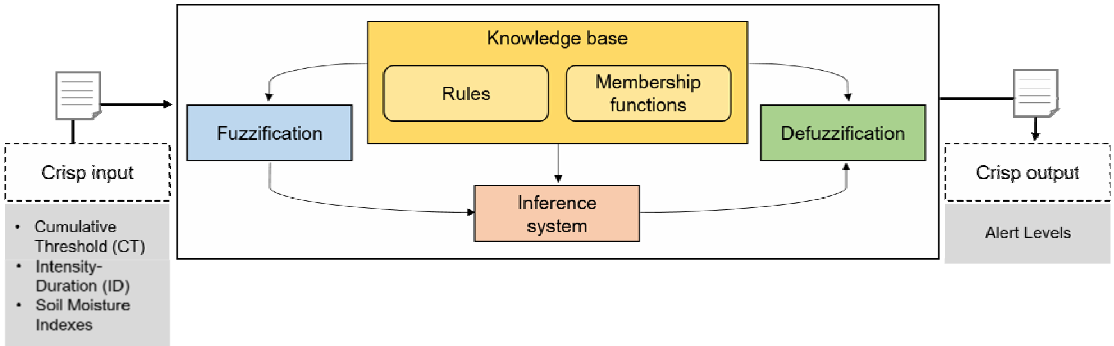

Figure 4. Flow chart to the show of methodology obtained from Mehran (2008).

Further analysis will be described in the next subsections.

2.5.1 The Knowledge Base

Knowledge base saves several rules that enclose two different parts:

- RB: Built by a set of IF-THEN operators while there are multiple inputs but single output FRBS. The structure is explained by equation (7)

$$IF\ X_1\ is\ A_1\ and \dots and\ X_n\ is\ A_n\ THEN\ Y\ is\ B \tag{7}$$

  with X_i and Y being input and output linguistic variables, respectively, and with A_i and B being linguistic labels.

- DB: Consisting of the descriptions of the fuzzy sets connected to the operators used in the rules associated with RB.

2.5.2 Fuzzification interface

The management of real inputs and outputs in Mamdani-type FRBSs is handled by the Fuzzification Interface. This component creates a structured mapping of the correspondence between each value in the crisp input space and fuzzy set. It defined the universe of discourse of the input, securing membership function related to each one of the system inputs.

Symbolically, this component is calculated as follows:

$$A' = F(x_0) \tag{8}$$

with x_0 being a crisp input value for the FRBS defined in the universe of discourse $\cup$, A' being a fuzzy set defined in the same domain, and F being a fuzzification operator. We can choose the operator F with these following possibilities:

1. Punctual fuzzification: A' is generated as a punctual fuzzy set (singleton) with the aid of x_0. It is declared as membership function

$$A'(x) = \begin{cases} 1, & if\ x = x_0 \\ 0, & otherwise \end{cases} \tag{9}$$

2. Non-punctual or approximate fuzzification: Based on equation (9), The value of $A'(x_0)$ starting from 0 (the furthest from x_0), as it is closer to x_0, the values climb up to the value of 1. The second operator is used to deal with other types of membership functions. For instance, the triangular membership functions can be described by

$$A'(x) = \begin{cases} 1 - \dfrac{|x - x_0|}{\sigma}, & if\ |x - x_0| \le \sigma \\ 0, & otherwise \end{cases} \tag{10}$$

The former is the one most used due to its simplicity.

2.5.3 The inference system

The following fuzzy rule approach characterises the inference system of the Mamdani approach:

$$IF\ x\, is\ A\, then\ y\, is\ B \tag{11}$$

From a functional viewpoint, a Mamdani schema is a non-linear mapping from an input domain $X \in R^n$ to an output domain $Y \in R^m$. Without loss of generality, we presume that both the input and the output domain are defined as hyper-intervals:

$$X \times Y = Z = Z_1 \times \ldots \times Z_n \times Z_{n+1} \times \ldots \times Z_{n+m} \tag{12}$$

where $z_i = [m_i, M_i], i = 1, 2, \ldots, n + m$

This input/output mapping is created by averages of R rules of the following approach:

$$IF\ X\ is\ A^{(r)}\ Then\, Y\ is\ B^{(r)} \tag{13}$$

where $r = 1,2,\ldots,R$ is the index of the rule, while $A^{(r)}$ and $B^{(r)}$ are fuzzy relations over X and Y serially. When an input vector x is presented to the schema, a fuzzy set B is inferred according to the following approach:

$$B(y) = \bigvee_{r+1}^{R} \left(A^{(r)}(x) \wedge B^{(r)}(y) \right) \tag{14}$$

where the formalism $A(.)$ indicates the membership function of a fuzzy set A, and $\wedge, \vee$ are $T - norm$ and $T - conorm$ respectively (generally the min and the max functions are employed).

2.5.4 The defuzzification interface

Since the system must give a crisp output, the Defuzzification Interface has to develop the task of aggregating the information provided by each one of the fuzzy sets and transform it into a single crisp value. The fuzzy set output can be defuzzified by averages of several approaches, among which the most frequently depicted is the centroid or centre of gravity (COG) of the area under the membership function, defined as:

$$\tilde{Y} = \frac{\int_y B(y).y.dy}{\int_y B(y).dy} \quad (15)$$

Mamdani methods can be acquired with different schemas of defuzzification, as well as different awareness of $T-norm$ and $T-conorm$. The detail of Mamdani forms is described in (Jang and Sun, 1995).

2.6. Evaluate the model using fuzzy Receiver Operating Characteristic (ROC) curve

The Receiver Operating Characteristic (ROC) approach calculates the likelihood to recognise the true identity of each individual. This identification is acquired by a criterion that is impartial of the tests being analysed, generally stated as the “gold standard”. However, in the medical study, for instance, the gold standard is also a deficient evaluation, and for this reason, Langlotz (2003) addresses it as a “reference standard” The gold standard commonly separates parameters in two groups, and in this study, we determine it as (i) Warning (W) and (ii) Outlook $(\overline{W})$ to evaluate the model. Thus, a membership function of fuzzy set Warning can depict the gold standard into a set with a possibility that varies from 0 to 1. For the test result, it described by a membership function of a fuzzy set determined as a “fuzzy test result”. This means that the cut-off threshold ceases to be a constant value (k) and becomes a membership function of the Positive (P) or Negative $(\overline{P})$ set.

For an individual to be classified correctly by the test based on the gold standard, it must be included in both sets W and P. Should the parameter belong to one of the sets but does not belong to the other, it is classified as False Positive (FP) or False Negative (FN). For the fuzzy set, if I be a set of individuals and $X = \{x_1, x_2, ..., x_n\}$ the set of test results to the n individuals should include setting I. The fuzzy subset (Positive P) X indicated by a membership function $\mu_p : X \rightarrow [0,1]$ where $\mu_p(x)$ shows the possibility (degree of membership) of the individual with the test result x in the Positive set. Regarding the fuzzy subset, Negative $\overline{P}$ is its complement, the membership function of $\mu_{\overline{p}}(x) = 1 - \mu_p(x)$. The same form also applied for the gold standard of the Warning set $\mu_w : X \rightarrow [0,1]$, and its complement has $\mu_{\overline{w}}(x) = 1 - \mu_w(x)$.

Furthermore, to calculate fuzzy ROC, Parasuraman et al. (2000) determine the fuzzy membership with a degree of membership in a range [0,1] for each response category as follow:

$$TP = P \cap W$$
$$TP = \overline{P} \cap \overline{W}$$
$$FP = P - TP = P - (P \cap W)$$
$$FN = \overline{P} - TN = \overline{P} - (\overline{P} \cap \overline{W})$$

For calculating ROC, two necessary performance skills (sensitivity and specificity) must be calculated for each cut-off point. As this point shifts, the sensitivity increases during the specificity decline or vice versa. In addition, for the fuzzy method, they are calculated by the following form:

$$Sensitivity(\mu_p) = \frac{p(TP)}{p(W)} = \frac{\sum_{i=1}^{n} \mu TP(x_i)}{\sum_{i=1}^{n} \mu TP(x_i) + \sum_{i=1}^{n} \mu FN(x_i)} \quad (16)$$

$$Specificity(\mu_p) = \frac{p(TN)}{p(W)} = \frac{\sum_{i=1}^{n} \mu TN(x_i)}{\sum_{i=1}^{n} \mu TN(x_i) + \sum_{i=1}^{n} \mu FP(x_i)} \quad (17)$$

where x_i is the test result for the $i\,th$ individual, and n is the total number of individuals in the population studied. The ROC curve is developed by drawing the true positive fraction $(sensitivity)$ (sensitivity) on the ordinate as a function of the false positive fraction $(1 - specificity)$ for all cut-off values of the test. Further details of fuzzy ROC forms and example of its applications can be found in (Castanho et al., 2007; de Paula Castanho et al., 2008; DeLeo and Campbell, 1990; Gomez and Dasgupta, 2002; Orfila et al., 2003; Zadeh, 1965).

3. RESULTS

3.1. Cumulative Rainfall Thresholds (CT) for Banjarnegara

We employed the mean of daily rainfall, historical landslide database, and soil wetness conditions to define the initiation of landslides. We used these thresholds as input parameters to the FRBS model for developing the R-LEWS at Banjarnegara area. To improve the CT condition, we compare the amount of rainfall in the last three days (72 hours) to the rainfall in the previous 15 days. We used historical rainfall data associated with landslide events from 2011 to 2017, and we calculated the formula regarding the linear trend characteristic.

As can be seen in Figure 5, the CT formula for Banjarnegara area is $P_3 = 110.62 - 0.443 P_{15}$. The solid red line is a lower-bound value that is probably triggering landslide for the intensity of 15-day antecedent rainfall is lower than 250 mm. In addition, as demonstrated in Figure 5(A), we determine a lower-bound threshold formula when a 15-day antecedent rainfall less than 250 mm. An estimation for lower-bound CT is defined as $P_3 = 110.62 - 0.443 P_{15}$. For the 15-day antecedent rainfall below 250, the lower-bound threshold depicts the downward trend of 3-day rainfall, taking a minimum value of previous 15-day rainfall from 57.9 mm to 230 mm.

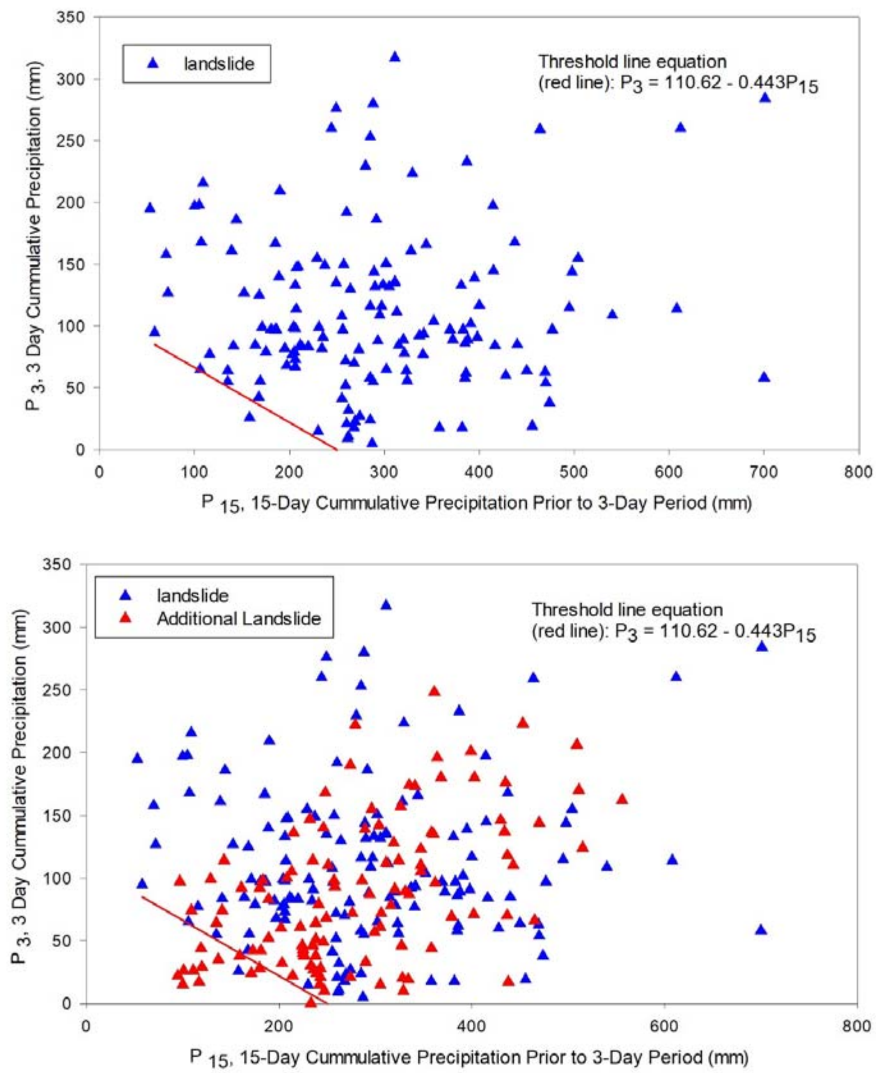

Figure 5. Cumulative 3-day and previous 15-day rainfall threshold (CT) associated with historical landslides at Banjarnegara. (A) CT plot showing cumulative 3-day and last 15-day rainfall from 2011 to 2017, and (B) CT plot exhibiting antecedent rainfall associated with an expanded landslide database from 2019 to 2019 period (filled red circles).

Furthermore, as illustrated on that downward trend plot, the cumulative 3-day rainfall shows its highest value of 3 days cumulative precipitation of 216 mm when a 15-day antecedent rainfall value is up to 109 mm. Then, we determine the threshold of 3-day cumulative rainfall at 0 mm as a minimum rainfall that probably to initiate landslide should exceed the previous 15-day cumulative rainfall greater than 250 mm. This clarifies that, for 15-day cumulative rainfall excess 100 hours, a slightly lower cumulative 3-day rainfall after that could affect slope failures that initiate debris landslide in the Banjarnegara.

Furthermore, as illustrated in Figure 5(B), we compared cumulative 3-day and previous 15-day rainfall threshold (CT) from 2011 to 2017 with additional landslide events from 2018 to 2019 to see the performance of this CT. The new data from 2018 to 2019 are consistent with the previously established CT threshold; approximately 90% of the added data points (red triangles) fall on or over the CT. In addition, the landslide events that rarely occur were not included in this threshold. For instance, some landslides event below the solid red line in figure 4 is included as an infrequent condition because it falls outside from the dominant landslide cluster. In addition, based on this fact, we employ the FRBS model to manipulate the data and transform a conclusion as fuzzy logic rather than classical logic to develop R-LEWS.

3.2. Rainfall Intensity Duration (ID) thresholds

For developing ID thresholds, the rainfall intensity that occurred during and before the landslide events have been checked with the landslide known date that accessed from the BNPB database. The landslide database collected for this analysis be composed of information on 141 reported landslides that occurred in the regency of Banjarnegara from 2011 to 2017. We compiled the daily rainfall data from the nearest rain gauge to the landslide event. It was taken from 15 rainfall stations located in the study domain (Figure 6).

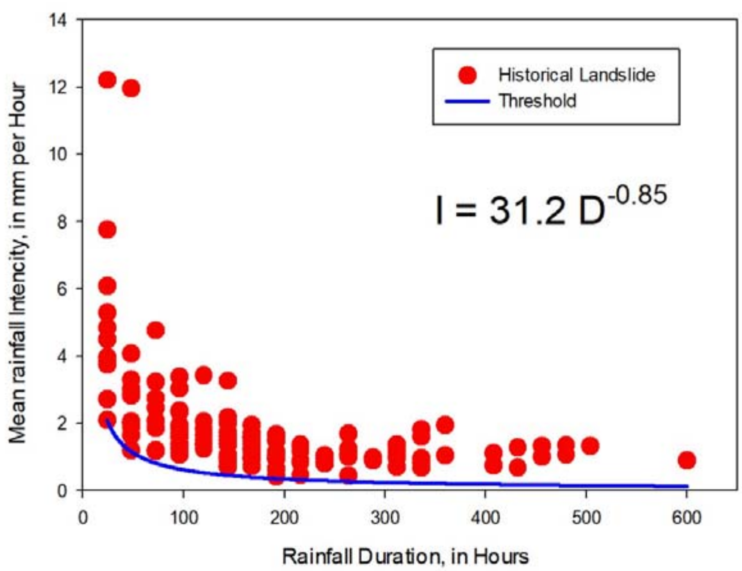

Figure 6. Rainfall intensity and duration threshold (ID) for Banjarnegara regency, Central Java, Indonesia.

The intensity of rainfall that caused the landslide is explained as the sum of rainfall that occurred during consecutive rainy days immediately during and before the landslide. As illustrated in Figure 6, we plotted the intensity of precipitation on the y-axis against rainfall duration on the x-axis. In this research, the duration of rainfall (D) is in the range of from 24 hours to 600 hours (25 days). Specifically, based on figure 6, the intensities of rainfall are considered in the field of 0.4 mm/hours to 12.2 mm/hours. The ID threshold is drawn as a power function on the rainfall lower-bound data in the scatter plot. Based on this lower-bound threshold line, we determine the ID formula as a power function of $I = 31.2D^{-0.85}$. As demonstrated by Figure 6, the hourly rainfall intensity presents a downward trend over the given time. This rainfall intensity has a downward trend until it reaches a consistent value at 0.4 mm after 196 hours.

In addition, we plotted the logarithmic function of local rainfall ID thresholds from many local regions obtained from Guzzetti et al. (2007) and newly threshold (green line) from Banjarmangu area, the sub-district part of Banjarnegara regency, proposed by Irawan et al. (2019) and compared them to the ID threshold for Banjarnegara. As demonstrated in Figure 7, the ID thresholds from other areas in the world extend a substantial range of precipitation amounts intensities and their durations. In addition, as described in Figure 7, most of the thresholds comprise the range of intensities between 1 and 100 mm per hour and the variety of durations under 200 hours. All of the local ID thresholds employ a simple power formula indicated by $c = 0$ at equation (1). For Figure 6, all the listed ID thresholds have a negative scaling exponent (Guzzetti et al., 2007), where the ID formula in this study at Banjarnegara showed the highest negative scaling exponent at -0.85. This negative exponent of power-law shows the decrease of rainfall needed to initiate slope failures against rainfall duration. Meaning, the longer the rainfall duration, the less rainfall intensity is required to cause landslides. In addition, they show the range of α operators from 1.7 to 85.58 (Guzzetti et al., 2007).

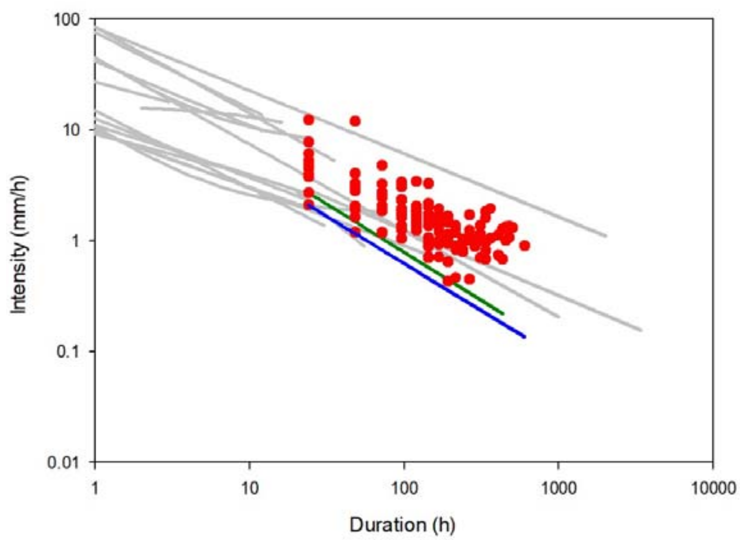

Figure 7. ID thresholds on a logarithmic scale. Legend: The grey lines depict other local ID thresholds obtained from Guzzetti et al. (2007); thick blue line is the local threshold for Banjarnegara regency; the thick green line represents a local threshold for Banjarmangu sub-district proposed by Irawan et al. (2019) that visually also has a similar pattern compared to ID threshold at Banjarnegara regency; the solid red dots show Banjarnegara historical landslides from 2011-2017.

The analysis of Figure 7 reveals that ID relationships for Banjarnegara are generally lower than other areas in duration above 100 hours. This means rainfall duration excess 100 hours; a slightly lower average rainfall could affect slope failures that initiate debris landslide in the Banjarnegara areas. Generally, local thresholds that potentially trigger landslide are affected by varied topography so that lead for more varied ranges of rainfall duration, especially when compared to the global and regional thresholds (Guzzetti et al., 2007).

3.3. Soil moisture index

For the third FRBS inputs, the antecedent rain that falls over the soil and exceeds its regolith field capacity was estimated by moisture index regarding equation (4). This moisture above regolith capacity is rapidly drained. It should be noted, this moisture index calculation for R-LEWS in this study ignored any physical factor. In addition, we neglected the impact of bedrock topography on subsurface drainage convergence (Anderson and Burt, 1978). As an impact, we presume that the highly weathered bedrock and the soil possess identical hydrologic and hillslope properties. However, this regolith-moisture index can estimate the interception of rainfall by vegetation and consider the impact of the hillslope hydrology (Gabet et al., 2004).

As is demonstrated in Figure 8, when the wet season started, the soil moisture index increases rapidly during storms when field capacity is reached. The analysis of Figure 8 shows that when soil moisture index depicts negative value, its shape decreases slightly as an impact of evapotranspiration. In contrast, the rapid decrease shape occurred in the positive pore pressure, when moisture index depicts positive value, regarding the combination of evapotranspiration and drainage. In addition, this soil moisture index shows a similar pattern compared to the observation data that not always the cumulative rain that falls within the domain area leads a landslide. Furthermore, based on figure 8, landslide phenomena generally occur should the pore pressure indicating the value exceeds 0 mm in this moisture index.

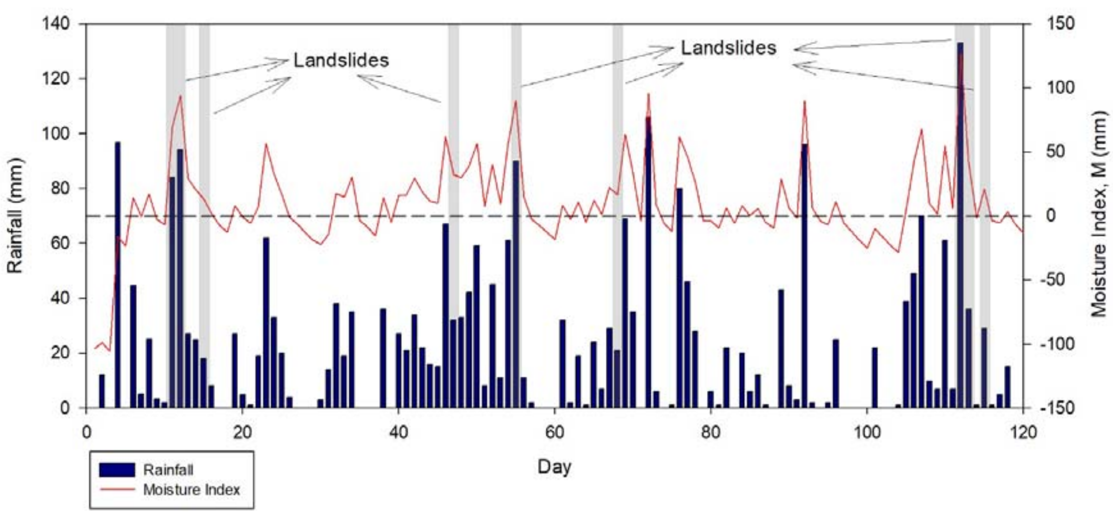

Figure 8. The example of shifts in the soil moisture index started from the end of the dry season from 01 December 2018 to 30 March 2019. We choose Banjarmangu as an example of the sub-district area in Banjarnegara. Columns bar represents daily precipitation, and the red line indicates soil moisture index (M). Positive pore pressures (above dashed line area) show the soil moisture index exceeds the regolith field capacity. In this soil moisture model, we defined the interception = 2 mm/day, k = 0.9, and field capacity = 150 mm.

In 2019, during the wet period, there were nine landslides occur at Banjarmangu. All of the landslide events were detected greatly with this soil model, indicated by high rainfall and moisture index that fall on the positive pore pressure during landslide events. For instance, based on the BNPB report dataset, there were two landslides occur in Banjarmangu sub-district on 21 and 22 March 2019 (days 112 and 113), as illustrated in Figure 8. This landslide occurrence can be detected when this soil moisture index shows positive value exceeds 0 mm and a peak of rainfall during that month. However, as employed in figure 8, many soil moisture indexes show positive values without coupled with the landslide. Based on this fact, we applied this soil moisture index as an indicator for soil wetness and used it together with ID and CT as rainfall thresholds for developing an R-LEWS.

3.4. The application of ad hoc data covering methods by using the empirically-based model

Wang and Mendel (1992) developed the ad hoc data covering methods which is simple and has high performance. It analyses the behaviour of the problem being worked on, in a represented input-output data set. This Wang and Mendel method is relevant to the Mamdani approach, which is designed in term of described input and output (Moallem et al., 2015). The ad hoc data covering method is applied to the following provisions (Alcalá et al., 2000):

1. Decide a fuzzy partition of the input parameter spaces. It can be obtained from the available expert information or the numerical examples of the used datasets. In our study, we work with non-symmetric fuzzy partitions of trapezoidal membership functions, as illustrated in Figure 9.

This fuzzy class interval (Figure 9) is specified based on lower bound of the plotted ID, CT, and soil moisture index and will be written as non-punctual fuzzification system. For instance, the following is the moisture index (M) fuzzification interface based on Figure 9:

$$\mu(x_i)_{M\ Low} = \begin{cases} 1, & x_i < 20 \\ \dfrac{(-5 - x_i)}{(-5-(-20))}, & -20 \le x_i < -5 \\ 0, & x_i \ge -5 \end{cases}$$

$$\mu(x_i)_{M\ Mod} = \begin{cases} 0, & x_i \le -10\ or\ x_i \ge 35 \\ \dfrac{(x_i - (-10))}{(0-(-10))}, & -10 < x_i \le 0 \\ 1, & 0 < x_i \le 25 \\ \dfrac{(35 - x_i)}{(35-20)}, & 25 < x_i < 35 \end{cases}$$

$$\mu(x_i)_{M\ High} = \begin{cases} 0, & x_i \le 25 \\ \dfrac{(x_i - 25)}{(45-25)}, & 25 < x_i \le 45 \\ 1, & x > 45 \end{cases}$$

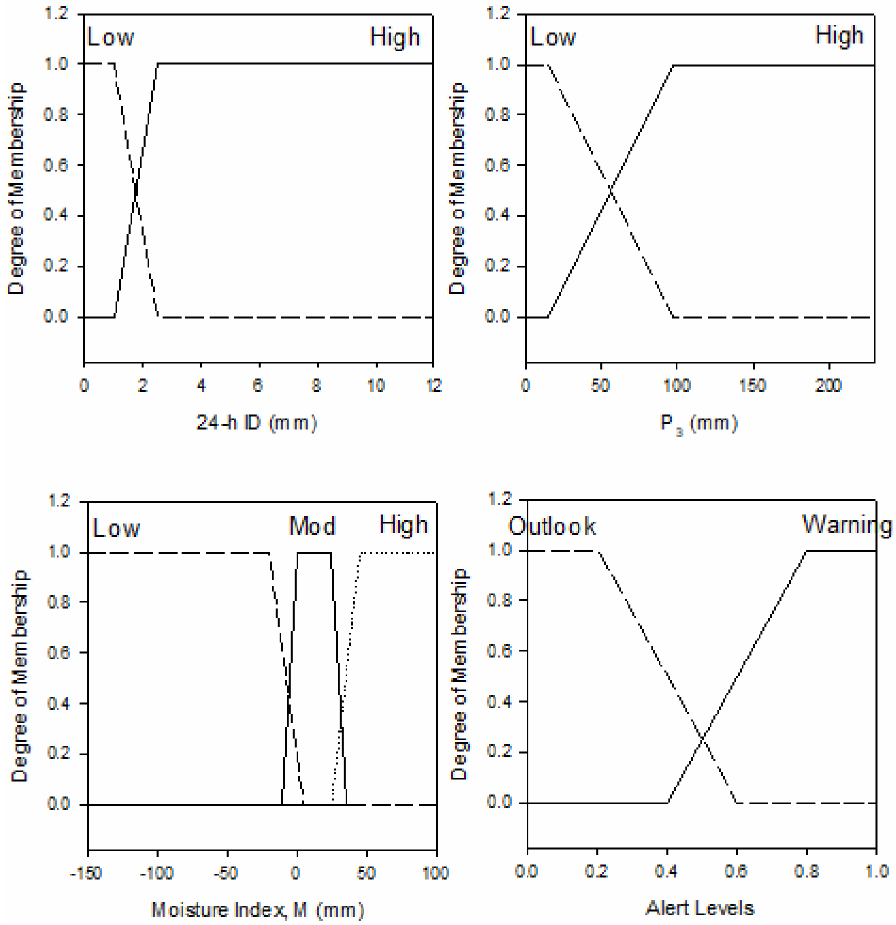

Figure 9. Assignment of FRBS value to empirical rainfall thresholds and soil moisture index and output variable representation. Those membership functions were developed using 2011-2017 dataset as training data.

2. Construct a preliminary linguistic rule set, best covered each input-output data pair contained in the input-output dataset. It may be obtained by analysing a specific case, i.e., an n+1-dimensional real array (n input and 1 output values), then assign each variable to the linguistic labels (associated fuzzy set) for every array component.
3. Choose an importance degree to each rule: Let $R_l = IF\ x_1\ is\ A_1\ and\ ...and\ x_n\ is\ A_n\ THEN\ y\ is\ C$ be the linguistic rule created from the example $e_l = (x_1^l, ..., x_n^l, y^l)$. The importance degree associated with it has resulted as follows:

$$G(R_l) = \mu_{A_1}(x_1^l) \cdot ... \cdot \mu_{A_n}(x_n^l) \cdot \mu_B(y^l) \qquad (18)$$

4. Obtain an RB from the preliminary fuzzy ruleset: The rule that has maximum importance degree is selected for each antecedent combination. For the case considered in this study, i.e., generating fuzzy rules from numerical data, only “and” rules are chosen since the antecedents are different components of a single input vector. The results of fuzzy rules and defuzzification were illustrated in Table 2.

Table 2. R-LEWS Fuzzy rules use ad hoc data covering method to develop FRBS inference system. These rules have chosen by considering both the rule that has a maximum degree and empirical threshold formula of rainfall and SMI. The first column is the rule numbers, and the last column is the output of each rule.

Number	$24-h\ ID$	P_3	Moisture Index (M)	Alert Level
1	Low	Low	Low	Outlook
2	Low	Low	Mod	Outlook
3	Low	Low	High	Outlook
4	High	Low	Low	Outlook
5	High	Low	Mod	Outlook
6	High	Low	High	Outlook
7	Low	High	Low	Outlook
8	Low	High	Mod	Warning
9	Low	High	High	Warning
10	High	High	Low	Outlook
11	High	High	Mod	Warning
12	High	High	High	Warning

The following labels were used to the output variables alert level: (i) Outlook, if rainfall threshold and soil moisture index shows the range from low to moderate class categories; (ii) Warning, if all input variables met the criterion for landslides. We used the equation (15) as a defuzzification method to model FRBS. The output of the alert levels exhibits a real number. Therefore, in this study, for landslide warning level where the system output is developed from input variables, we have $\mu_p(x)$ in the range [0,1] shows that the closer to 1, the bigger the occurrence of the landslide. The input values were obtained from a historical dataset of each variable. The following is an example of our FRBS calculation from input parameters that contains two rules (rule number 5 and 11):

$$Rule\,5: IF\ 24-h\ ID\ is\ High\ and\ P_3\ is\ Low\ and\ M\ is\ Mod\ THEN\ Alert\ Level\ is\ Outlook$$

$$Rule\,11: IF\ 24-h\ ID\ is\ High\ and\ P_3\ is\ High\ and\ M\ is\ Mod\ THEN\ Alert\ Level\ is\ Warning$$

the Defuzzification Interface has to develop the task of aggregating the information provided by each one of the fuzzy sets and transform it into a single crisp value. For the previous instance, if the value of the parameter $24-h\ ID$ is set as high (6.25 mm), the value of the parameter P_3 is set in the two classes as low and high (79 mm), and the value of the parameter M is placed in the two criteria as Mod and High (24.9 mm), then the results of defuzzification (Centroid) regarding rule number 5 and 11 is 0.64. This defuzzification value $(\tilde{Y})$ was obtained by calculating the aggregation from rule number 5 and 11 using the centroid method following equation (15). Furthermore, $\mu_p(x_i)$ that showing the possibility (degree of membership) of each alert level will be used for calculating ROC as the validation method of the R-LEWS.

3.6. Evaluating the performance of the R-LEWS

To see how far the accuracy of the model, we use newly the landslide database from BNPB and daily rainfall data obtained from Indonesia Agency for Meteorology Climatology and Geophysics from 2018 to 2019. For the validation, we used the new data of daily rainfall, evapotranspiration, and landslide database from the beginning of the wet season in 2017 to the end of the wet season in 2019. Therefore, for a more realistic model, we build a membership function to explain the gold standard based on the frequency of landslide warning levels compared to the landslide database information. For this, 7904 individuals of the landslide database (when landslide occur and otherwise) were used for the validation. Thus, we construct the landslide frequency in which each output result exhibits the landslide warning level. The total population distribution is shown in Figure 10.

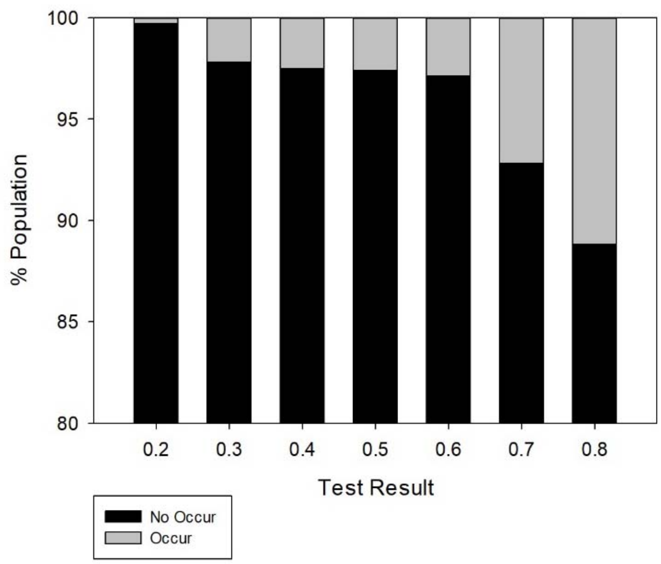

Figure 10. Population distribution with alert levels of outlook (No Occur), and with a warning (Occur).

Based on the distribution illustrated in Figure 11, we build the membership function only from the “Outlook” set to represent the fuzzy gold standard. In this study, the gold standard specifies the frequency in which the event of landslide did not occur. Furthermore, based on a fuzzy gold standard, we develop an ROC curve to evaluate the performance of this FRBS model (Figure 12).

Plotting the fuzzy ROC curve, as illustrated in Figure 12, we review a family of membership functions of the “Outlook” set as decision threshold, and we calculate the sensitivity and specificity using the equation of (12) and (13). To determine the ‘‘best” cut-o□ point, we calculate the test e□ciency defined as the arithmetic average between sensitivity and specificity. The highest values show the best cut-off point, both defined by the arithmetic average and the product of these measures. The cut-off point that exhibits the highest e□ciency is 0.88, where the test sensitivity is 0.646 and specificity is 0.882. Furthermore, we calculate the area under the fuzzy ROC curve using the trapezoidal numerical integration method. For the results, it shows the values at 0.825. This area under the fuzzy ROC curve can be analysed as the possibility that a randomly selected event with the landslide did not occur has a test result that is higher than the one for a randomly chosen event with landslide has occurred.

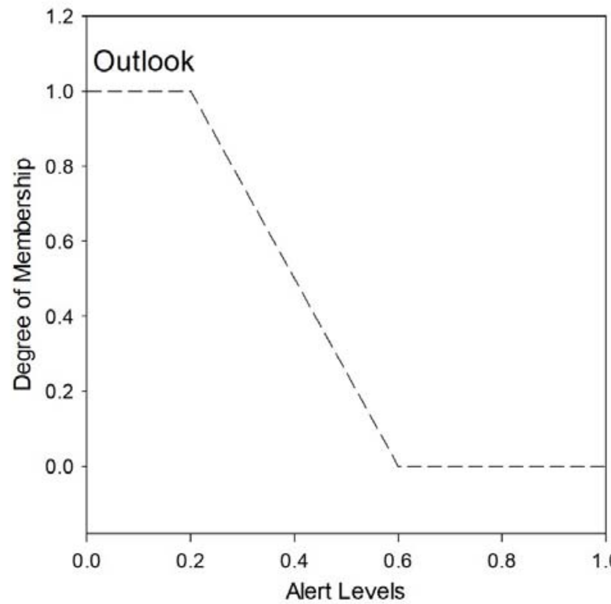

Figure 11. Membership function of the gold standard

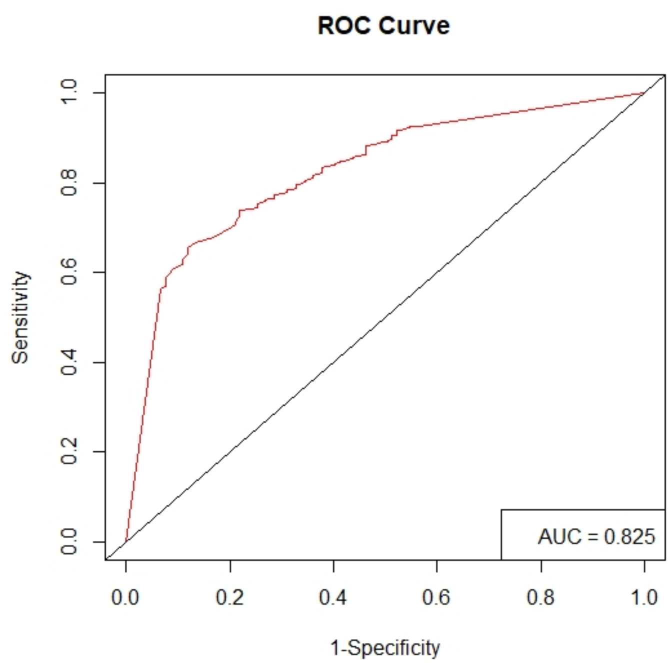

Figure 12. Fuzzy ROC curve calculated using both fuzzy test results and the gold standard.

4. DISCUSSION AND CONCLUSION

This contribution explored the extent to which the FRBS method can use as an approach to develop R-LEWS. We built the system input of FRBS by using empirical rainfall thresholds and soil moisture index to overcome the absence of soil-related variables. For the validation of the model, we employ a fuzzy ROC curve based on the chosen gold standard to stretch the limitation of dichotomous classification decided by the traditional ROC approach. The primary benefit of using the proposed methodology is to avoid the disadvantage of information and to analyse vague concepts. Using fuzzy sets, the error of classification can be almost totally abolished at the cost of many numbers of uncertain classifications. However, to develop FRBS, there are some limitations to this study. A small number of fuzzy sets cause unrepresentative predictions, whereas a large number of fuzzy sets lead to many calculations. In previous researches, many numbers of fuzzy sets are selected initially from 3 to 6 (Kucukali and Baris, 2010; Stuber et al., 2000). Therefore, it is difficult to determine the length of interval for FL methods. In this study, we set the number of fuzzy from 2 to 3 and labelled with, low, medium, and high regarding the highest accuracy of the training landslides dataset. Thus, we employed 3 number of fuzzy sets to save computational resources. For the FRBS, membership functions play a critical key in representing problems (Zadeh, 1996). Several authors documented the landslide behaviour from expert knowledge and training data. Furthermore, in this study, we selected importance degree to each rule based on ad hoc data covering methods. Besides, we used triangular and trapezoidal membership functions based on the functioning of the landslide that visually matched with its pattern criteria.

For the results, the model satisfactorily simulated the occurrence of landslide with values of area under the fuzzy ROC curve at 0.825 (range: 0 to 1, perfect score: 1), resulting in a good agreement with the occurrence of landslide data obtained from BNPB landslide database. However, if we construct an ROC curve based on the stage of warning (events of landslide occur), the area under the fuzzy ROC depicts value around 0.3. Therefore, we need to add other factors causing landslides, i.e. elevation, slope gradient, slope aspect, land cover type, or lithology, to increase the accuracy of the landslide at the warning stage. It is also possible to compare this FRBS approach with another method such as Logistic Regression, Frequency Ratio, or ANFIS to get the better skill of landslides prediction.

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