A NOVEL EARLY WARNING SYSTEM USING FUZZY MULTIPLE ATTRIBUTE DECISION MAKING ALGORITHM AND METEOROLOGICAL DATA

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ABSTRACT

An early warning system (EWS) has the possibility to predict data accurately in the limited positions of units using sensors and additional data input. But in reality it is not easy, requires a lot of system, cross platform and field of science. This applies tries to realize the EWS, so it is necessary to configure the addition of input data, where data from sensors and meteorological data is required to predict floods accurately. The purpose of this system is to make decisions and determine the flooding area. In order to achieve this goal, Decision Support System (DSS) techniques with primary and secondary data are applied. Primary and secondary data as input of Fuzzy Multiple Attribute Decision Making (FMADM) algorithm. The expectation is based on weight, normalized model to get optimal prediction result. The EWS equipped by sirens, short messages, websites, and also Android apps to provide monitoring and prediction information. The experiment was carried out using EWS hardware mounted on streams and the results indicated the good performance of the system with fulfill errors.

Keywords: *flood area predicting, FMADM, DSS, meteorological data, early warning system*.

1. INTRODUCTION

In the last decades, early warning system (EWS) is become an important role as alerting system for the human life, particularly who live near the river or the coastal area. To obtain a better alerting system, it has to be equipped with prediction facility and decision support system (DSS) to improve the capability. However, the existing system does not have those facilities, so the alerting information has delay time. Due to this, a lot of damage will occur and the disaster cannot be avoided. According to [2], [3], several types of prediction methods have been employed on the EWS. One of the popular prediction methods uses monitoring and sensor network due to more secure and more accuracy. In fact, those prediction methods are very expensive and cannot be applied [4].

One of the ways to do predictions can be done through the DSS. The DSS is a decision search technique for optimal decision based on variable factors with selected algorithms [6], [7]. This has been applied in the previous study in monitoring system to determine the cause of floods [8], [9]. This technique makes EWS more flexible in the ability to predict flood time through the addition of geo-social media data input [10] but data obtained from the public is sometimes inaccurate. One important advantage of DSS and secondary data is the non-invasive technique associated with the environment because it does not require a large number of EWS units [11]. Another advantage of this system is a smaller data error than sensor networks.

In order to apply the DSS to the desired EWS application, it is often necessary to criteria, ratings, matrix norms, weighting and ranking results. Determining the criterion aims to analyze factors and look for alternatives [12]. However, the determination of these criteria is difficult to choose because of relationships that are subjectivity [13]. Previous researchers have used a secondary data approach; geo-social media to determine weather forecasts [14] and methods of smart adaptation activities [15] this technique is limited by the expensive cost. In today's work, many researchers have used artificial intelligence (AI) approaches such as fuzzy logic, artificial neural networks, and heuristic algorithms that adopt the behavior of the human brain [16].

The artificial intelligence is the parent of the DSS. In flood prediction the utilization of DSS requires additional data. The field data (main), meteorological data and old data (secondary) can be used as EWS input [17]. The use of DSS and secondary data does not require data training like some other algorithms. In contrast, sensor and meteorological retrieval opens more and more input variables and correlates with decision accuracy [18]. These variables are likely to be solved by DSS through a usable alternative algorithm; FL, TOPSISS, IRR, AHP, FMADM, ELECTRE, and the like so as to have their respective weaknesses and advantages [19]. Work that needs to be realized is to connect between EWS, prediction using DSS, and algorithm web processing information system in one system.

This paper presents a method for integrating it; DSS functions, meteorological data, and water level sensor data into the EWS system to predict the impact of flood areas in the watershed. We assume the DSS structure with the FMADM algorithm with simple additive weighting (SAW) completion is sufficient to implement. Criteria (Cj) and alternative functions (Ai) are divided into 7 and 4 respectively. Next to adjust the match rating table is made, followed by normalization of the matrix. Weights based on the analysis of the variables are given, then the end result can be presented [20]. The given DSS output is sent to EWS hardware and the result will be divided into Normal, Standby-3, Standby-2, and Standby-1 decisions. Each level has its own actions that will trigger the siren and SMS gateway.

The rest of this paper is structured as follows. The second section part of the summary of the EWS, determining the type of weight and calculation is also elaborated. The third section describes the results and experimental discussions. Finally, a conclusion is presented in section 4.

2. PREDICTION USING FMADM AND METEOROGICAL DATA

In this study, the EWS is done using the FMADM algorithm shown in Fig. 1. The water level sensor is connected to the embedded system through the ADC port as the main data input. While secondary data from meteorology agency inputted through the website. The website serves to run the FMADM algorithm, displays data, and sends it back to the EWS via a GPRS connection. Surface water sensor uses Sharp-GP2Y0A02YK0F with buoys shielded by 4-inch diameter pipe mounted perpendicularly. Other input data sourced from Indonesian Meteorological Agency [21] is used as FMADM input through various variables, for example; relative humidity, wind speed, wind direction, rain duration, and rainfall intensity. Then all variables are combined including the river level; conducted matching criteria and alternatives to obtain decision option using FMADM algorithm.

Data from the website is feedback to the EWS which will translate into the status category Standby-1, Standby-2, Standby-3, and Normal. The Android app is called to facilitate access to public information through the concept of mirror website. Each status by the embedded system is translated to execute commands such as; sending SMS and turning on the siren hazard.

Therefore, EWS works on three lines of communication; 1) sending raw data for processing with additional meteorological data to the website, 2) then sent back to EWS, and 3) finally sending SMS and/or siren hazard commands. In this paper, EWS with meteorological data is solved by FMADM with detailed descriptions of each section of the system described in the following sections.

2.1 FMADM based Predicting

FMADM tries to make decisions in a manner similar to the human brain. Therefore, FMADM is weighted and compared to each other and will eventually form a sorting pattern. No longer ordering according to the number of attributes, but already based on matching criteria (C_j) and alternative (A_i) that were first normalized [22], [23]. The alternatives are A_1 = Standby-1, A_2 = Standby-2, A_3 = Standby-3, and Normal.

In order to use many attributes it is necessary to draft a decision that meets FMADM algorithm. Please note the completion steps. Determine the criteria that will be used as a reference in the decision decision in an alternative disaster decision [24]. Criteria are derived from an empirical environmental analysis. The criteria used in the determination of flood decisions, among others; C_1= river level, C_2 = relative humidity, C_3 = wind speed, C_4 = wind direction, C_5 = rain duration, and C_6 = rainfall intensity.

The above conditions have 4 alternatives and 9 criteria related to the prediction of potential floods. Criteria value grouped into primary and secondary data; C_1 as primary data while data C_2-C_6 as secondary data. Each criteria is assigned a different weight (W) based on empirical analysis, calculations and mathematical patterns according to geophysical studies [25], [26].

In theory, FMADM can be solved with simple weighting. A simple addictive weighting (SAW) is used to complete the algorithm. The basis of the SAW method is to find a weighted sum of performance ratings on each alternative on all attributes [27]. The SAW method requires the process of normalizing the decision matrix (X) into a scale comparable to all existing alternative values in Eq. 1.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{Max\ x_{ij}}\ if\ j\ as\ benefit \\ \\ \frac{Min_{ij}}{x_{ij}}\ if\ j\ as\ cost \end{cases} \quad \text{....(1)}$$

where r_{ij} is the normalized performance rating of the alternative Ai on the attribute C_j; i = 1,2, ..., m and j = 1,2, ..., n. The index j will be worth a profit if the value of j increases and the profit increases, and vice versa j will be worth the loss when the value j rises but the profit is reduced [28]. The preference value for each alternative (V_i) is written like in Eq. 2.

$$V_i = \sum_{j=1}^{n} w_j r_{ij} \quad \text{....(2)}$$

Continued match rating of each alternative on each criteria (X). The normalization matrix (R) is based on the equation adjusted to the attribute type (attribute gain or cost) to obtain a normalized matrix based on Eq. 2. Furthermore, after obtaining an alternative-criterion matrix rating (X), then normalized the matrix (R) based on the equation adjusted to the type of attribute (profit or cost) so as to obtain a normalized matrix [29] following Eq.3.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots\ r_{1n} \\ r_{21} & r_{22} & \cdots\ r_{2n} \\ r_{31} & r_{33} & \cdots\ r_{3n} \end{bmatrix} \quad \text{.... (3)}$$

If the value of R has been obtained, then followed with the weighting process (W). The W is given by the decision maker through the previous analysis, as in Eq. 4. The value of T for C_1 and so on until C_6 in this condition the magnitude of fuzzy weighted value will serve as a multiplier.

$$W = [T1_{C1} \quad T2_{C2} \quad T3_{C3} \quad T4_{C4} \quad Tn_{Cn}] \quad \text{.... (4)}$$

The value of W acquired at weighting is used as a numeratorial factor for the final result (V_n). The V_n is equaried from the summing process of the matrix multiplier (R) multiplied by weight. Consider the following Eq. 5.

$$\begin{aligned} V_1 &= r_{11} \times W_{c1} + r_{12} \times W_{c2} + \cdots r_{1n} \times W_{cn} \\ V_2 &= r_{21} \times W_{c1} + r_{22} \times W_{c2} + \cdots r_{2n} \times W_{cn} \\ &\ldots \\ V_n &= r_{n1} \times W_{c1} + r_{n2} \times W_{c2} + \cdots r_{nn} \times W_{cn} \end{aligned} \quad \text{.... (5)}$$

Looking for the greatest value of the final result (V_i) from Eq. 5, the maximum value obtained is the best alternative (A_i) and as a solution as a solution [30]. For example the maximum value obtained is V_3, then the appropriate decision alternative is A_3.

Table 1: Classification of All Criterions for Each Variable.

Variables	***Categories***							
C_1 (river level)	low (< 200 cm)	middle (210 – 400 cm)	high (> 400 cm)					
C_2 (relative humidity)	low (0-33%)	moderate (34-66%)	high (67-100%)	extreme (>100%)				
C_3 (wind speed)	low	moderate	high	extreme				
C_4 (wind direction)	N 337,5°-22,5°	NE 22,5°-67,5°	E 67,5° - 112,5°	SE 112,5°-157,5°	S 157,5°-202,5°	SW 202,5° -247,5°	W 247,5°-292,5°	NW 292,5°-337,5°
C_5 (rain duration)	short (≤ 60 min.)	middle (61-120 min.)	long (>120 min.)					
C_6 (rainfall intensity)	light (≤ 2 mm/h)	moderate (2-14 mm/h)	heavy (15-59 mm/h)	very heavy (30-60 mm/h)	torrential (> 60 mm/h)			

2.2 Meteorological Data based Predicting

In Indonesia, official meteorological data are issued by the government through the Meteorology, Climatology and Geophysics Agency (BMKG) - Indonesia. Based on meteorological parameters, observed data include C_2 = relative humidity, C_3 = wind speed, C_4 = wind direction, C_5 = rain duration, and C_6 = rainfall intensity are as secondary data. In order to predict the flood properly, all variables in C_1-C_6 must be set to the degree of fuzzy memberships. To do so, apply Eq. 6 to determine the fuzzy membership of each variable C.

$$\mu[x,a,b] = \begin{cases} 0; & x \le b \\ \left(\frac{(b-x)}{(b-a)}\right); & a \le x \le b \\ 1; & x \ge a \\ 0; & x \le b \\ \left(\frac{(x-a)}{(b-a)}\right); & a \le x \le b \\ 1; & x \ge b \end{cases} \qquad \text{....(6)}$$

Before Eq. 6 is applied, each variable C will be searched for categories based on BMKG-Indonesia standard with modifications with various standards and other scientific considerations. There are several categories after being grouped as in Table 1.

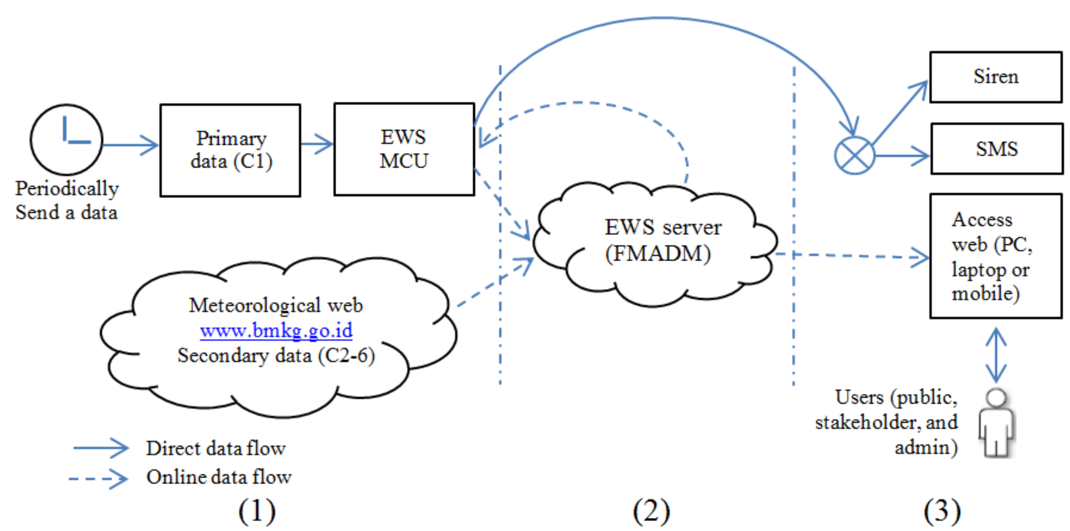

Figure 2: Block diagram layers on EWS with FMADM

After we knew the number of classification as in Table 1, it can be determined fuzzy memberships for each criterion. Each criterion has different fuzzy memberships. In this experiment membership is at least three categories and a maximum of eight categories.

The process of making fuzzy memberships are used as the basis of FMADM which will be solved using Eq. 1 and 2. So it can be asserted that the result of Table 1 is not used for the prediction process, either Fuzzy Mamdani or Fuzzy Sugeno. The flood prediction is done by weighting process as in Eq. 4 [31].

2.3 Early Warning System

Early warning systems can use the following methods to assess stability assessments: data-driven methods for anomaly detection, machine learning, statistical methods, [32] empirical data failure analysis and so on. Therefore, not common enough to be relied upon on the design of EWS in general [33]. Similarity, once EWS is generated and applied; a series of actions taken e.g. village headman send SMS manually. This pattern is the old way while the more advanced way is applied to this EWS. As in the flow diagram in Fig. 2, that all work is done automatically by the system.

According to Fig. 2, primary and secondary data are very important in the flood prediction process. The reception of data from the web server to the EWS consists of the following steps: First, when powered on, the EWS initializes the water level sensor and GPRS module and then sends the water level sensor data to the web server. Second, the calculated data with secondary data via FMADM is sent to the EWS as an input. The incoming data is matched to find one of four conditions. Third, the condition results will execute the automatic sending back to webserver, message delivery command and/or turn on hazard siren. Finally, the repetition is done from the first step to the third to get the data continuously, in order to take real time data. In this study the secondary data obtained from BMKG Indonesia which is forwarded to the website system.

3. EXPERIMENTAL RESULTS

In this section, several experiments were conducted in the FMADM method for flood prediction. Flood prediction is calculated from primary and secondary data. Primary data delivery interval (C_1) and secondary data (C_2-C_6). Primary data is sent every 15-25 second interval, while secondary data is sent every 60 minutes. Then the calculation process based on FMADM is done on the website and the results are sent back to the EWS hardware. Fig. 3 illustrates the experimental area of the EWS.

3.1 Experiment 1: Calculate FMADM to Making Decisions

Before the system is implemented, it is necessary to experiment by entering Equation 4. Although categorization has been established by BMKG-Indonesia standard and geophysical study, test still required. The test is done in 3 times, based on Eq.4 to find the most appropriate weighting composition before program is written into Hypertext Preprocessor (PHP) for the web server.

Performed a calibration process to find the proper weighting of some weighting options. This calibration process is done by taking data on website [34] and meteorological data and then check the condition of the field to ensure the empirical conditions in real location. For calibration data is used on December 20th, 2017.

Table 2: Match between Alternatives and Criteria.

Alt.	Criterions					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	30	10	40	80	30	50
A_2	24	20	30	60	25	40
A_3	17	30	20	40	20	30
A_4	11	40	10	20	15	20

Look at the Table 2; if the value assigned to each alternative and criteria as a match value, then the greatest value is best. Through the analysis and consideration of the process of giving preference weight (W) to C_1-C_6. In this experiment we performed five weights, where the weighting with good predictions will be used in experiments 2 and 3.

$$W_1 = [8, 2, 2, 5, 8, 9]$$
$$W_2 = [8, 2, 3, 6, 9, 9]$$
$$W_3 = [7, 3, 2, 5, 9, 7]$$
$$W_4 = [7, 3, 2, 5, 8, 7]$$
$$W_5 = [8, 3, 2, 5, 9, 9]$$

The result of decision matrix is formed from match table as follows;

$$X = \begin{bmatrix} 30 & 10 & 40 & 80 & 30 & 50 \\ 24 & 20 & 30 & 60 & 25 & 40 \\ 17 & 30 & 20 & 40 & 20 & 30 \\ 11 & 40 & 10 & 20 & 15 & 20 \end{bmatrix}$$

Furthermore, the matrix normalization result (R) based on the alternative-criterion matching rating table (X) is adjusted to the attribute type of r_{11} to r_{46};

$$r_{11} = \frac{30}{max\{30; 24; 17; 11\}} = \frac{30}{30} = 1$$
$$r_{21} = \frac{24}{max\{30; 24; 17; 11\}} = \frac{24}{30} = 0.8$$
$$r_{31} = \frac{17}{max\{30; 24; 17; 11\}} = \frac{17}{30} = 0.56$$
$$r_{41} = \frac{11}{max\{30; 24; 17; 11\}} =$$

$$r_{12} = \frac{10}{max\{10; 20; 30; 40\}} =$$
$$r_{22} = \frac{20}{max\{10; 20; 30; 40\}} =$$
$$r_{32} = \frac{30}{max\{10; 20; 30; 40\}} =$$
$$r_{42} = \frac{40}{max\{10; 20; 30; 40\}} =$$

$$r_{13} = \frac{40}{max\{40; 30; 20; 10\}} =$$
$$r_{23} = \frac{30}{max\{40; 30; 20; 10\}} =$$
$$r_{33} = \frac{20}{max\{40; 30; 20; 10\}} =$$
$$r_{43} = \frac{10}{max\{40; 30; 20; 10\}} =$$

$$r_{14} = \frac{80}{max\{80; 60; 40; 20\}} =$$
$$r_{24} = \frac{60}{max\{80; 60; 40; 20\}} =$$
$$r_{24} = \frac{40}{max\{80; 60; 40; 20\}} =$$
$$r_{44} = \frac{20}{max\{80; 60; 40; 20\}} =$$

$$r_{15} = \frac{30}{max\{30; 25; 20; 15\}} =$$
$$r_{25} = \frac{25}{max\{30; 25; 20; 15\}} =$$
$$r_{35} = \frac{20}{max\{30; 25; 20; 15\}} =$$
$$r_{45} = \frac{15}{max\{30; 25; 20; 15\}} = \frac{15}{30} = 0.5$$
$$r_{16} = \frac{50}{max\{50; 40; 30; 20\}} = \frac{50}{30} = 1$$
$$r_{26} = \frac{40}{max\{50; 40; 30; 20\}} = \frac{25}{30} = 0.8$$
$$r_{36} = \frac{30}{max\{50; 40; 30; 20\}} = \frac{30}{50} = 0.6$$
$$r_{46} = \frac{20}{max\{50; 40; 30; 20\}} = \frac{20}{50} = 0.4$$

Then get the normalized matrix (R):

$$R = \begin{bmatrix} 1 & 0.25 & 1 & 1 & 1 & 1 \\ 0.8 & 0.5 & 0.75 & 0.75 & 0.83 & 0.8 \\ 0.56 & 0.75 & 0.5 & 0.5 & 0.66 & 0.6 \\ 0.36 & 1 & 0.25 & 0.25 & 0.5 & 0.4 \end{bmatrix}$$

Continued by ranking the final result (V) by summing the first line V_1 to V_4 of the heavy product (W_1) with R as follows;

$$V_1 = (1 \times 8) + (0.25 \times 2) + (1 \times 2) + (1 \times 5) + (1 \times 8) + (1 \times 9) = 32.5$$

$$V_2 = (0.8 \times 8) + (0.5 \times 2) + (0.75 \times 2) + (0.75 \times 5) + (0.83 \times 8) + (0.8 \times 9) = 26.49$$
$$V_3 = (0.56 \times 8) + (0.75 \times 2) + (0.5 \times 2) + (0.5 \times 5) + (0.66 \times 8) + (0.6 \times 9) = 20.16$$
$$V_4 = (0.36 \times 8) + (1 \times 2) + (0.25 \times 2) + (0.25 \times 6) + (0.5 \times 8) + (0.4 \times 9) = 14.23$$

In the same way, rate W_2 to W_5, with the following results.

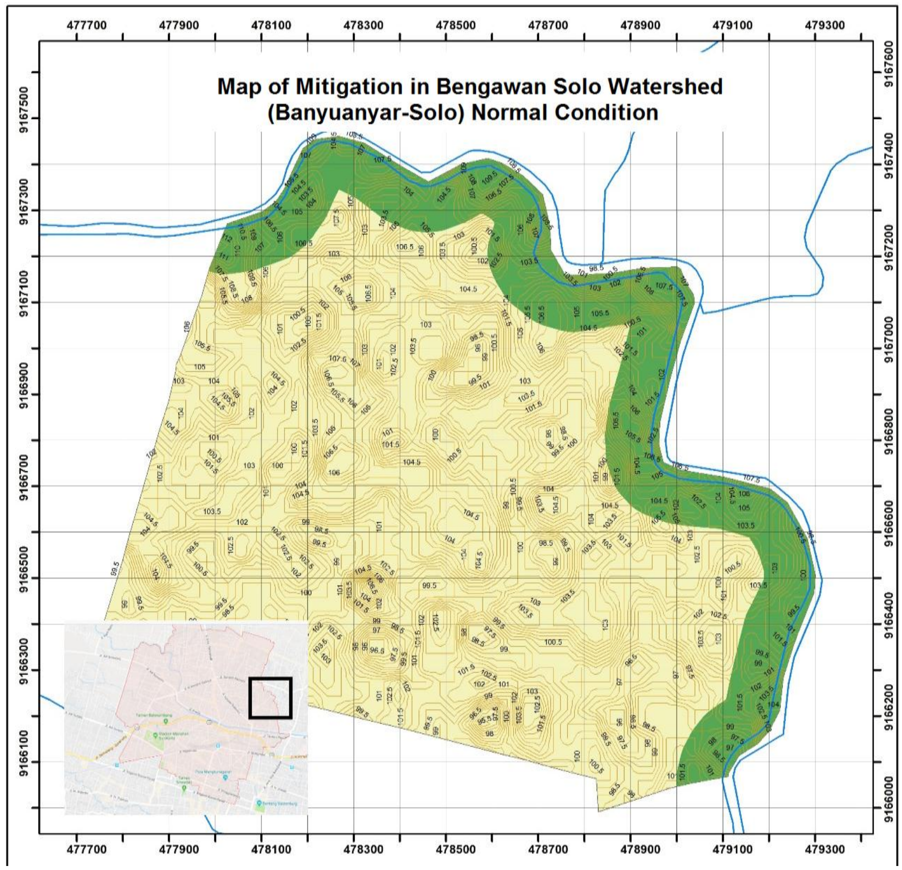

Figure 3. Area of the EWS in Bengawan Solo Watershed Surakarta

for W_2:
$V_1 = 35.5$
$V_2 = 28.82$
$V_3 = 21.82$
$V_4 = 15.23$

for W_3:
$V_1 = 30.75$
$V_2 = 26.49$
$V_3 = 20.16$
$V_4 = 14.23$

for W_4:
$V_1 = 29.75$
$V_2 = 24.59$
$V_3 = 19.15$
$V_4 = 14.07$

for W_5:
$V_1 = 33.75$
$V_2 = 27.82$
$V_3 = 21.57$
$V_4 = 15.73$

The decision result of V_1 to V_4 is found that each W will have proximity to the disaster level map that has been plotted according to Stanby-1, Stanby-2, Stanby-3, and Normal status. Based on Figure 3, the weighted calibration (W) is very close to the real condition of W_2 with a tolerance of 15%.

3.2 Experiment 2: Implementation of FMADM on EWS

After obtaining calibration by matching the result of weighting with empirical parameters. The EWS will interpret any data sent from the server to the hardware as in Figure 2. First, take the primary data from the water level conditions on the riverbanks and at the same time take secondary data from the BMKG site. Furthermore, primary data and secondary data are processed using FMADM algorithm. Delivery of data at 25-second intervals for sending via TCP/IP to remain valid. Finally, the received data is sequenced to determine the condition of the status level of the Bengawan Solo watershed.

Detailed implementation of FMADM algorithm applied to EWS can be illustrated as Figure 4. Gradually work, hardware developed with the FMADM algorithm is divided into three parts. First, the reading of data input, starting from the system initialization followed by displaying information to the secondary data summing process of the web server and the primary water level sensor. The second stage is the filtration stage in which the

```
    input: sensor water level (buoy) as C1, and data meteorological from www.bmkg.go.id as C2-6
    output: Identified pattern index, prediction, and risk of upcoming floods
1   void setup()
2   {
      Start the serial communication with the computer host;
      Start communication with the SIM800L in 9600;
3   }
4   void loop(){
5   Reading a buoy sensor as primary data (C1);
6   Data C1 sent to web server;
7   Received feedback data C1 + C2...6 (Vn) or FMADM data result;
8   If FMADM data result  >= 150 then go to lene 15;
9   else if FMADM data result is >= 100 or <= 149 then go to line 15;
10  else if FMADM data result is >= 50 or <= 99 then go to line 15 and 34;
11  else if FMADM data result is >= 30 or <= 49 then 15 and turn on go to line also 34;
12  else sent data to host (go line 15) turn on a siren (line 30), sent a message go to line 34 (1), and
             34(2);
13  Delay in between reads for stability;
14  }
15  void senthost() {
16  Read the buoy sensor;
17  Start IP stack;
18  Open GPRS connection;
19  Delay in between reads for stability;
20  Start GPRS;
21  Delay in between reads for stability;
22  HTTP initiation;
23  Delay in between reads for stability;
24  HTTP parameter;
25  Delay in between reads for stability;
26  Sent URL and data;
27  Delay in between reads for stability;
28  Close GPRS connection;
29  }
30  void sirine() {
31  Turn on a siren;
32  Turn off a siren;
33  }
34  void sms () {
35  Setting type SMS;
36  Setting SMS configuration;
37  Input the receiver number;
38  Compose a massage (content 1,2,3,4);
39  Sent a SMS;
40  }
```

Figure 5. Algorithm of EWS after received data from webserver (FMADM)

incoming data (secondary and primary) are classified into which parts correspond to the four specified statuses. The last stage is the execution of the screening process, each decision data will be accompanied by execution for example; sending reply data to the web server, flood status, sending SMS to the listed number (stakeholder), and or activating flood siren. Inside the hardware needs to be underlined. The purpose of setting this interval for data sent successfully received by server. Because in principle there is an echo received every time the data is sent. Figure 5 shows the appropriate algorithm and pseudo code flow diagram. On the website data is received from hardware, executed by the line 7. Because the communication is built using GPRS through access TCP/IP then selected open-close method. Selected this method to ensure that data sent up into database, although this method is at risk slightly slower. The total time it takes to execute a send subroutine to a host is at an

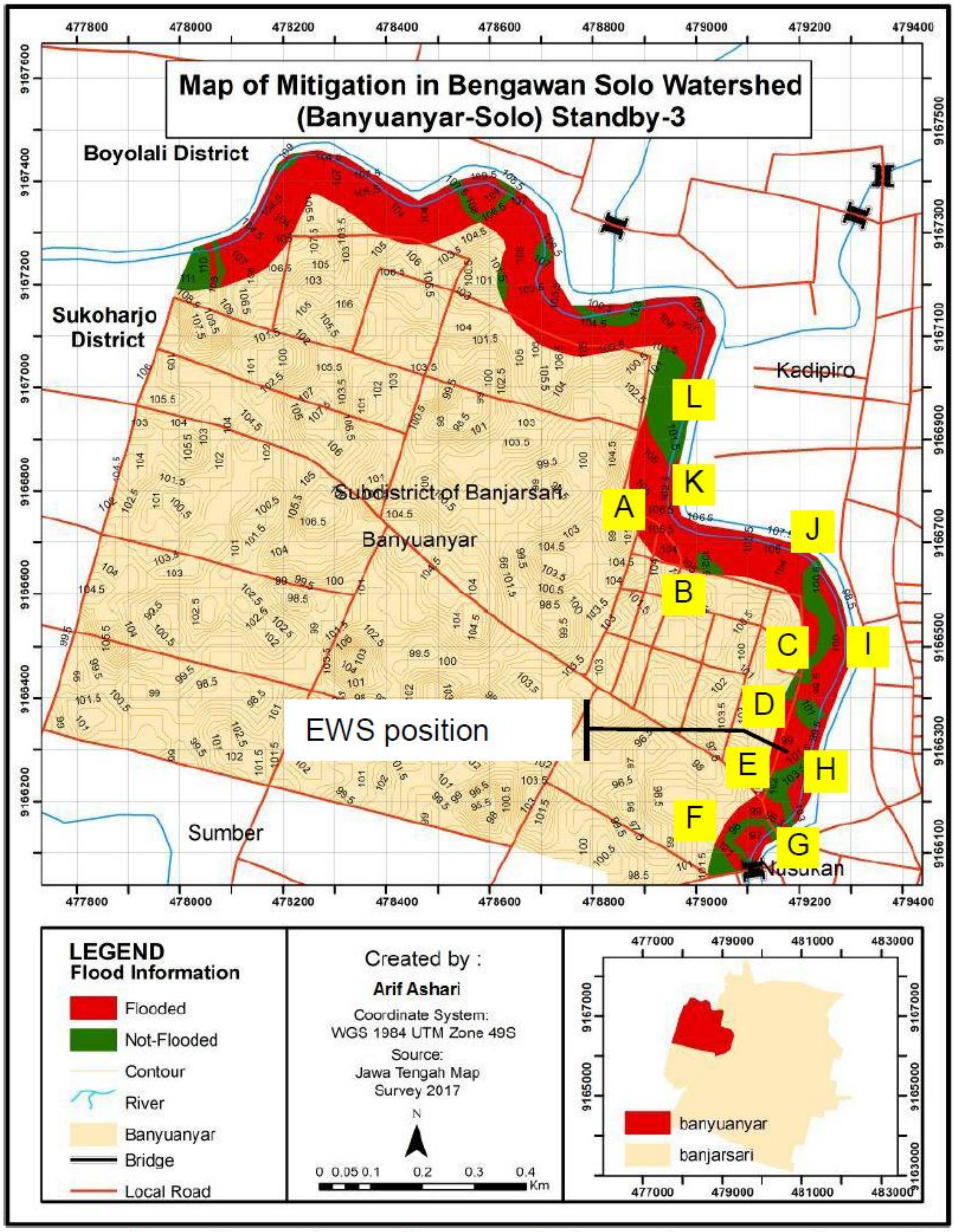

Figure 7: The Standby-3 Status and 12 Points of Reference of Bengawan Solo Watershed.

interval of 12-60 seconds. As shown in Fig. 6, the data is displayed in gauge, graphic, table, and image of the areas affected by flooding. The data displayed on the graph can be traced by time. As for the gauge is used to represent the incoming data at that time or the latest. Last data in the table also has the same function with the graph, but emphasis on readability by the user.

3.3 Experiment 3: FMADM Based Prediction

The dataset of the real weather detection and forecasting process is used to test the proposed algorithm. The tools used in the process include the EWS and website. The general description of the dataset can be found in Table 3. The total period for 271 days is applied continuously with a total of 8126 tags. The 778 cm water detection rate occurs on 31/10/2017 at approximately 3:37 pm. This paper will test the prediction accuracy but not test the efficiency of the algorithm, because it will be done in the next study.

Table 3: Statistics of the Dataset

Description	Number
Total time period	271 days
Total number of tags	8126
Highest peak alarm rate	778 cm
Num. Standby 1 status	2
Num. Standby 2 status	101
Num. Standby 3 status	1862
Num. Normal status	6161

Accuracy of the proposed algorithm detection has been praised from the aspect of detection rate. Here is the weighing process chosen based on the experiment 1. The accuracy value can be searched by comparing the prediction result on the map according to real field conditions. In order to know the value of accuracy then marked on the map by giving the node as a measuring point. The difference in the distance on each node to the outside is the basis for the assessment of the accuracy of each status. The dataset as shown by the red shading in Fig. 7 is the FMADM result data in Bengawan Solo watershed.

There are 12 points that become a references in Standby-3, the point is determined by geographical location. Some points closer to the reference points (river bank) or coincide in the image represents a high similarity value between predictions compared to real conditions. Table 4 shows the flood hazard sequence information in each of the selected groups. The test is said to be accurate when measuring the size that should be measured or capable of measuring the actual number. The points A through F are on the south-west side while the points G to L are on the opposite. It should be noted that points G to L are administratively part of Karanganyar District, or in other words Bengawan Solo River is the geographical boundary.

Accuracy was obtained from comparing data of FMADM result with data on Bangawan Solo watershed condition. Measurement conditions are measured through GIS Analysis rules with buffering and query techniques as applied in Figure 3. Contrast between FMADM results with real conditions then can be calculated accuracy value as in Table 4. EWS installed for almost 11 months with each accuracy is different, the lowest is 69.7% when the sample is taken on 30/09/2017, while the highest accuracy when the sample is measured on 09/12/2017 is 80.1%. Of the total 8126 data entered in the database and taken random samples every month as table 4, the decision conditions that appear are Normal, Standby 2, and Standby 3 while Standby 1 does not appear in this sampling. The final assertiveness test results show that 76.3% is accurate.

Table 4: Results of Accuracy Tests.

Time	*Decision*	*Accuracy (%)*
25/04/2017 01:38	Normal	76.8
10/05/2017 07:22	Normal	78.2
11/06/2017 12:34	Normal	78.0
14/07/2017 10:45	Normal	77.6
10/08/2017 07:57	Normal	79.3
11/08/2017 08:27	Normal	73.5
30/09/2017 05:31	Normal	69.7
09/10/2017 12:20	Normal	75.4
13/11/2017 07:23	Normal	74.6
09/12/2017 16:48	Normal	80.1
04/01/2018 15:03	Normal	76.6
Total Accuracy (%)		76.3

Anything that appears on the web is the result of execution of information from hardware installed, it is necessary to perform the area of impact based on calculations with the FMADM algorithm. To illustrate the watershed impacted FMADM results still need to be verified map through buffering techniques and queries from geography, so it appears as in Figure 8 and 9. The picture shows the status of Standby-1, and Standby-2 (Appendix A and B).

The difference between standby-2 and standby-1 is the increment of puddles in standby-1. There is only one area that is not impacted within 100 meters from the river bank. Such conditions are interesting to be observed again. That the distance standard is 100 meters specified in disaster mitigation actually passes in general when the contours of the land are flat. An example of a decision result by FMADM shows that an algorithm applied works not only determining the outcome but also the process of adopting buffering and query techniques from the geographic discipline. The process of buffering and query obtained the contour of the ground is relatively uneven. There are 16 mainland points were not flooded for Standby-3 status, then increase in Standby-2 to 12 dots. Last is Standby-1 where there is only 1 point with height of 111 masl. The points A and K in figure Appendix 1 and 2 show a significant change from the non-submerged area to flood areas.

The coverage of predicted area is analyzed and adapted to the flow pattern. At points A, B, and C are factually lower land (90-98 masl) with altitude below the contours in that area, 97-110 masl Thus the flow pattern will always overflow to the mainland as in the yellow area image. The prediction process using the FMADM algorithm obtained from primary and secondary data can predict but the resulting pattern is still static.

4. CONCLUTIONS

In this work, the predicted impact and status of flood using primary data (sensor) combine with secondary data (meteorological data) was successfully developed and implemented in a EWS using the FMADM algorithm. Based on the experimental results, it is concluded that prediction using primary and secondary data with the FMADM algorithm can achieve a good performance and thus can be implemented for different applications such as landslide and bridge structure.

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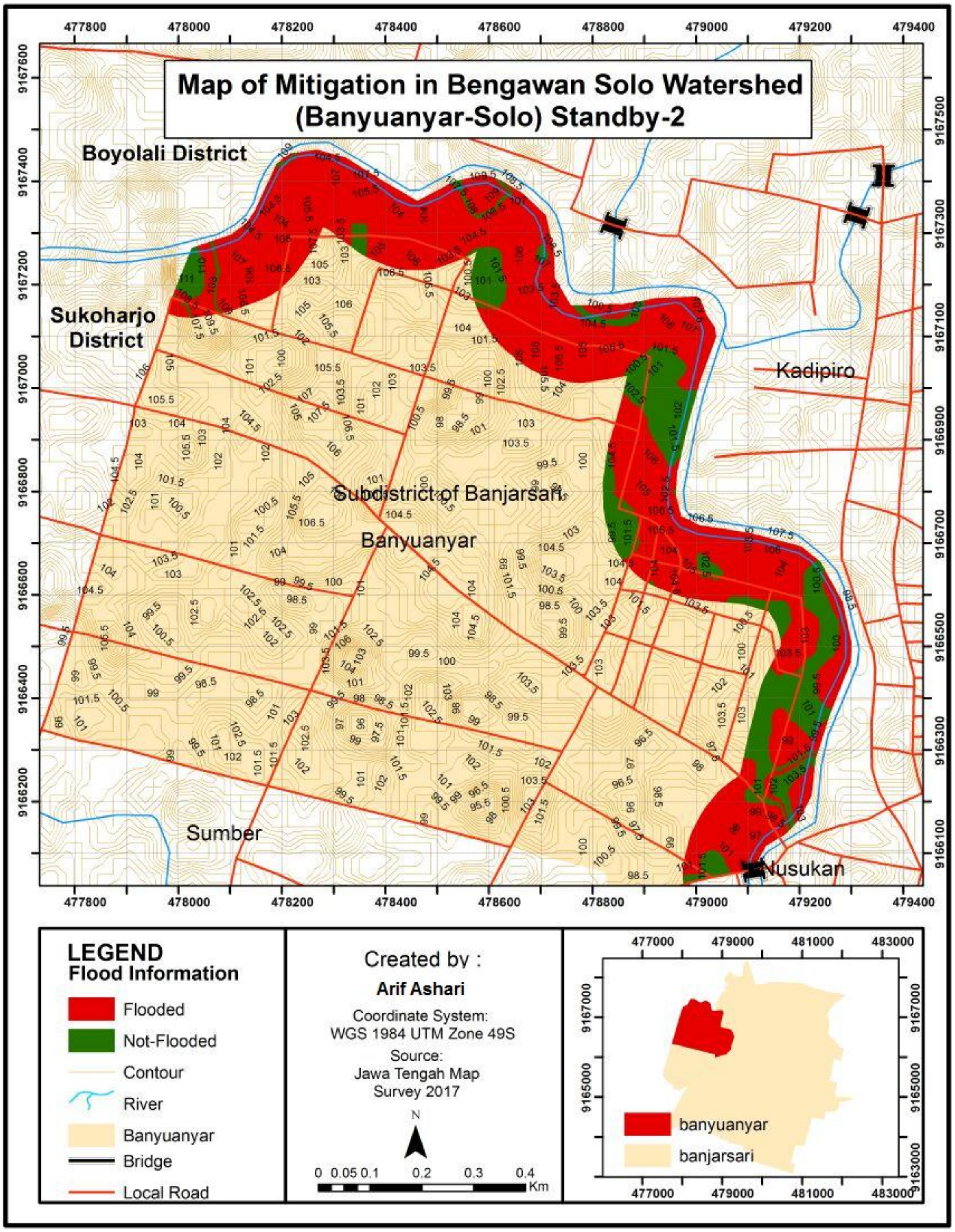
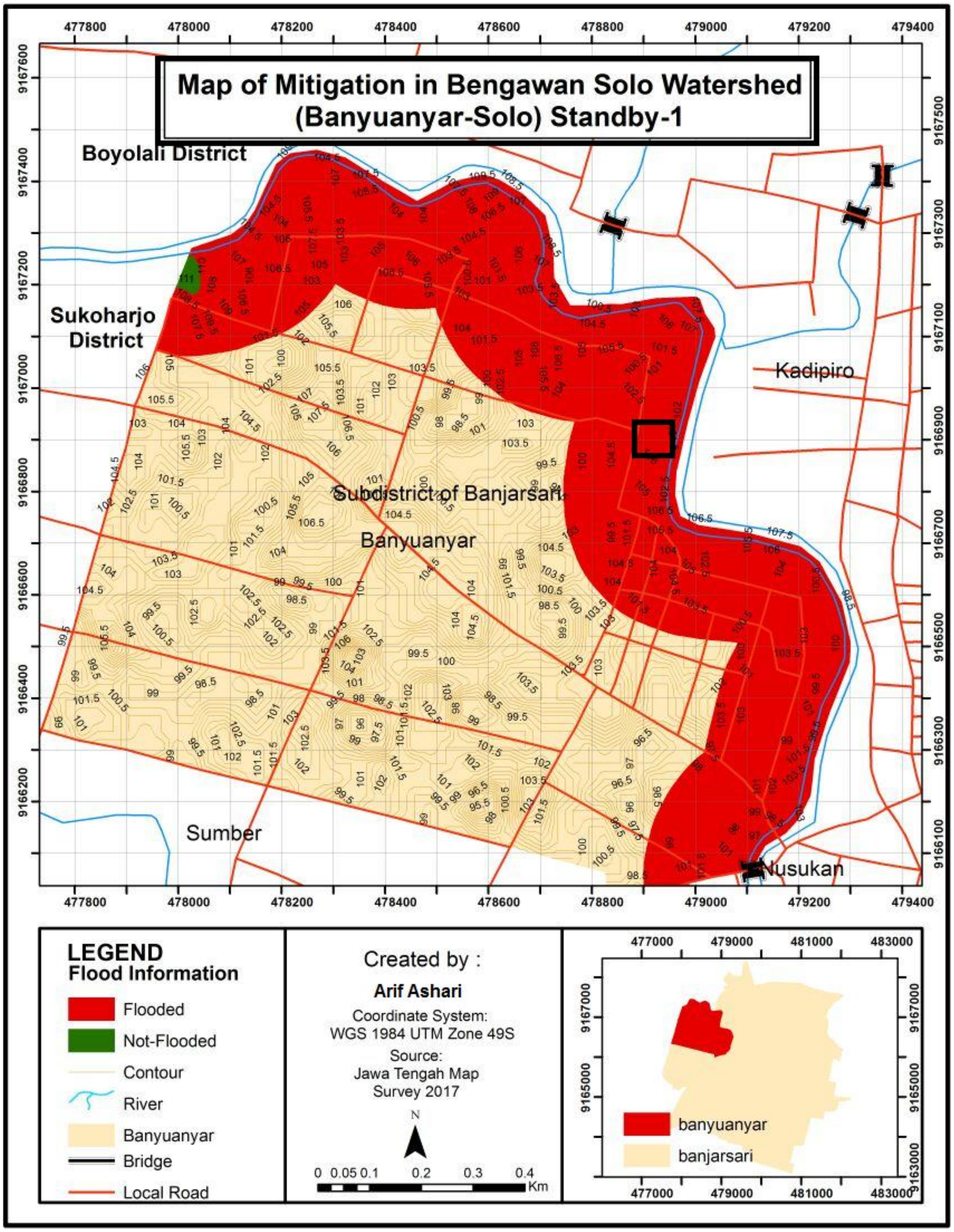
Appendix A: Standby-2



Appendix B: Standby-1.



Appendix C: Android Apps of the EWS.