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An Analysis of Flood Forecasting Criteria

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ABSTRACT

Damage caused by floods in some parts of the world, especially in Asia and the Pacific, accounted for the highest rate among the damage resulting from other natural disasters such as landslides, earthquake and tsunamis. Due to this factor, has motivated us to study further on flood forecasting. In previous studies, researchers focus on separate three criteria which are reliability groups, time complexity and error rate to forecast flood. In this paper, we study and analyze the three mentioned criteria in order to identify the highest criteria utilized in flood forecasting. The number of references studied and analyzed is in the year 2010 until 2019. From our findings, the highest criteria identified are under the reliability group, with highest accuracy index of 90%.

Key words: analysis, criteria, flood forecasting, reliability, accuracy.

1. INTRODUCTION

Natural disasters such as flood, landslides, earthquake and tsunamis bring irrecoverable losses to human beings. According to [1] around 200 million people were affected by floods in the years 2011 and 2012 throughout the world, with a total loss reaching $95 billion. Southeast Asia is the region considered to be most frequently affected by flood due to monsoonal rainfalls [2]. Malaysia is among the most vulnerable countries in the world to be hit by flood, for instance, the Kelantan River has been hit by flood in December 2014 [3].

In Malaysia, there have been few attempts to evaluate the overall adequacy of institutional arrangements for forecast flood, the exceptions being Leigh and Low. Too much criteria which is not necessary is focused on flood forecasting. To find the most popular criteria is important which review flood forecasting research. Therefore, three indicators including reliability, time complexity and error rate were investigated in this paper, and it was shown that accuracy index for evaluating and detecting criteria in real time was one of the most important indicators to forecast flood.

The rest of this paper is structured based on the following sections: Section 2 presents the related research. In this section, some previous work on flood forecasting has been reviewed. Analysis and discussion for criteria evaluation are presented in section 3. Finally, conclusions and future works in section 4.

2. RELATED RESEARCH

A unique method of hybrid artificial intelligence to determine flood susceptibility has been proposed [4]. The assessment of the model was done through precision, sensitivity, specificity, accuracy, root-mean-square error, mean absolute error, kappa curve, and area under the Receiver Operating Characteristic (ROC) curve criteria. Meanwhile, a comprehensive description on the data availability was introduced via geological observatories (e.g., seismological, hydrological), satellites, remote sensing and more recent sources, such as the social networking platform, Twitter [5]. Apart from that, the depth estimation of snow coming from the terrain parameters in Sakhvid Basin, Iran through the use of Artificial Neural Networks (ANNs) and M5 decision tree algorithm has been implemented [6]. In [7] has been developed hydrological models that can represent a different geo-climatic system, namely: humid, semi-humid and semi-arid systems, in China. In [8] forecasted the flow stream of River Nile at the Dongola station in Sudan via an ANN model, thus confirming the efficiency of the model with respect to the actual flow. River, South Korea [9]. Considering the effects of backwater of this river, the improved method of tributary water level forecasting is suggested. This is done by adding various water level data on the central river as input variables in the typical ANN structure, where rainfall and upstream water level data are often utilised.

According to [10] the main concern in many practical applications of monthly streamflow forecasting models is the accuracy and reliability of the forecasts; therefore, in such situations, statistical forecasting maybe more suitable. Authors applied an extreme learning machine to produce rapid forecasts of tsunami waveforms in coastal areas [11]. As discussed in [12], in monthly stream-flow forecasting, two sources of predictability are typically exploited: catchment conditions (wetness) at the time of the forecast and the effect of climate over the forecast period. Research work by [13] utilizes fuzzy logic approach to model the Kelantan River basin in Malaysia in real-time flood forecasting using the minimum implication function type which is the Mamdani fuzzy inference system. Three basic criteria are listed for a reliable forecast: accuracy, reliability, and timeliness [14], [8]. Evaluation and real-time detection criteria are divided into two categories, where the research on each of these indices is time consuming [15]. Our findings from these research works identified three important indicators for evaluating and detecting criteria in real time to forecast flood which are reliability, time complexity and error rate which are analyzed in this paper.

2.1 Benchmarking

Evaluation and real-time detection criteria are divided into two categories, shown in Figure 1 [15]. This study has been focus on the first craiteria (i).

i. Criteria of evaluation - consist of reliability, time complexity and error rate.
ii. Benchmarking techniques – e.g. ANN, fuzzy, Genetic Algorithm (GA), etc.

2.2 Criteria

Real-time detection needs a strong and reliable assessment instruments in a variety of conditions. Several criteria are presented for evaluating detectors in real-time. A real-time skin detector consist of reliability have been proposed which discussed their parameters and their relationship tested on skin dataset [16].

Reliability and real-time detection of data and the relationship between them are discussed [16], [17]. Calculation of reliability based on a large dataset with a specific area on the land is manually tested using a specific operator receiver of the dependent Receiver Operator Characteristic (ROC) curve.

2.3 Reliability Group

The correlation between the reliability groups and the importance of analyzing the criteria and the standard point of reference are reviewed in this section. The reliability group consists of three main parts, namely: relationship parameters (e.g., precision, recall, accuracy, and specificity), matrix parameters (e.g., confusion matrix), and behavioural parameters (e.g., G-measure and F-measure), as in Table 1. Numerous methods and employment have been assessed for real-time evaluation using reliability groups, which include three stages as follows:

A. Relationship Parameters

The steps of the parameter matrix (e.g., probabilistic models) and its relationship were emphasised.

The relationship parameters are comprised of four: precision, accuracy, recall, and specificity. The precision of the limiting factor is shown as TP when the prediction of the sample is true or positive, while TNI indicates true negative estimation if the sample is negative. Precision is intended as a vital benchmark in the assessment analysis. The measurements show the proximity of compliance between the estimated value and the established value. Apart from that, precision is a measure of weighted calculation among precision and recall.

In [20] explained that precision is referred as the precision of analytical modelling or the proximity of compliance between the estimated value and the established value, or similarly, as a positive predictive value or an acknowledged reference value. Hence, the structures of this measurement must be determined depending on the process of different inputs assessment.

The precision calculates the numerical accuracy of a binary classification test in recognising or removing a particular setting. In [21] measured the correct proportion of outcomes (TN and TP) across the number of samples studied. Moreover, precision could be referred to the closeness to the intended target and the accuracy of its closeness to the specified target. Therefore, this assessment represents an average accurate calculation for precision and reverse precision (priority based on prejudice) and an average weighted calculation for recall and reverse recall (priority based on popularity). Nevertheless, these characteristics do not convert this measurement to an evaluation parameter that can be generalised for each sample.

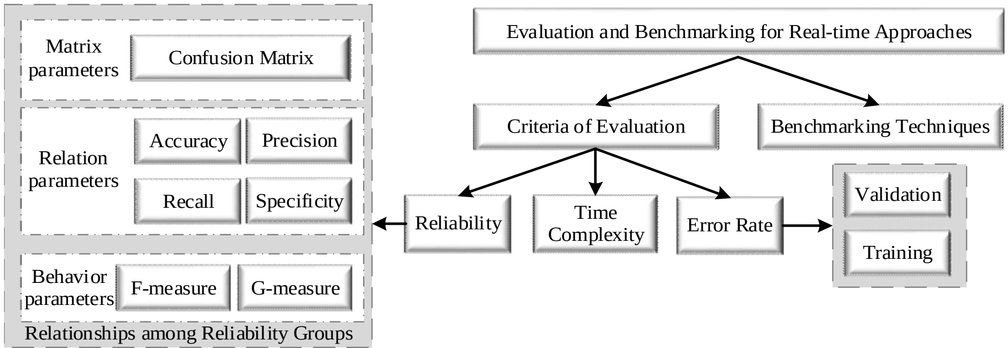

Figure 1: Evaluation and benchmarking framework [15].

B. Matrix of Parameters

The matrix of parameters reveals that the confusion matrix includes False Negative (FN) and True Negative (TN) models, which are completed with False Positive (FP) and True Positive (TP), respectively. The confusion matrix is a crucial criterion for all cases in the taxonomy model which are intended as a strong spine in numerical and mathematical estimations for all parameters in an evaluation matrix.

Table 1 indicates changes in the use of this benchmark in various investigations. The characteristics and methods of the confusion matrix are crucial to differentiate between negative and positive areas. Consequently, this benchmark must be measured in the initial criteria of the evaluation process and the benchmark.

C. Behavior Parameters

Behaviour parameters consist of F-measure and G-measure. F-measure signifies the weighted average precision and obtains precision and recall if the ideal value is close to 1. The poorest rating of the F-measure is the value of 0.

It should be noted that F-measure is the prevalent criterion, as it is created concerning caution and precision. On the other hand, Powers (2011) announced that the G-measure signifies an accurate normalised form of precision. As such, it is considered as a TP for geometric dimensions of true positive predictions along with facts.

The amount of information conveyed from the G-measure is related to the average computing information with precision and recall. Commonly, the G-measure signifies the geometric mean of recall and precision for evaluating the algorithm efficiency. Computational intelligence algorithms utilised for forecasting are Artificial Neural Network (ANN), Support Vector Machine (SVM), Wavelet Artificial Neural Fuzzy Inference System (WANFIS), Artificial Neural Fuzzy Inference System (ANFIS), Internet of Things (IT), Genetic Algorithm (GA), Wavelet Artificial Neural Network (WANN), Wireless Sensor Network (WSN), Expert System (ES), Neural Network (NN), Discrete Wavelet Transform (DWT), and Early Warning System (EWS).

2.4 Time Parameter

The intricacy of time is a crucial factor or study for many findings. The time index for evaluating and detecting criteria in real time is one of the most important indicators to forecast flood. Various forms of segmentation algorithms are provided through the expansion of computer and information technology (CIT) [22].

These algorithms are used in various systems of information. The use of segmentation or division method requires the establishment of proper complexity algorithm with the implemented model conclude if the algorithm is relevant for use [23], [24]. Correspondingly, the intricacy of time to measure in processing is critical [24].

2.5 Error Rate

The frequency of errors denotes the smallest possible error for each classification of an irregular result pattern that is similar to the unrelated error.

This group or faction is a fundamental measure in the process of estimating and benchmarking (as reference point) in real-time tracking, constructed using soft computing techniques of distinct datasets. The number of references studied and analysed in this paper is in the year 2010 until 2019. Table 1 shows the literature review of the evaluation criteria. The table presents various studies on flood forecasting. An extensive analysis of the reliability group was also explored throughout forecasting and discrete sub-criteria. In Table 1, seven criteria have been investigated, including the model parameters, precision, specificity, recall, accuracy, F-measure, and G-measure.

$$p = \frac{N}{30}.100 \qquad (1)$$

Where, N is the number of usage in articles, P is the percentage of usage and 30 is the total number of articles.

3. ANALYSIS AND DISCUSSION

Flood forecasting model design is performed in both analytical and geological forms, which often complement each other. The factors that are considered for analytical forecasting of the flood includes the following:

- Topographical study of the part of watershed that provides water flow to the studied area.
- Determining the type of land cover (rock, soil, plants) to estimate the proportion of running water to permeating and evaporated water
- Determining the largest storm and rainfall given the available data.
- Attention to the season, because conditions such as the saturation of the land with water or covering its surface with snow have a direct impact on the water surface flow.
- Determining the storage capacity of the main river bed and its surrounding floodplain and possible changes in the storage capacity of the downstream regions.

Table 1: Comparison of previous research

No	References	Category of Natural Disaster	Method	Criteria												
				Reliability										Time	Error Rate	
				Matrix of Parameters (Confusion Matrix)				Accuracy	Precision	Recall	Specificity	F-measure	G-measure		Training	Validation
				TP	TN	FP	FN									
1	[4]	flood	**LMT**	√	√	√	√	√	√	√	√	×	×	√	×	×
2	[25]	Natural disasters	**DATA MINING**	×	×	×	×	×	×	×	×	×	×	×	×	×
3	[6]	flood	**ANN**	×	×	×	×	√	√	×	×	√	×	√	√	×
4	[26]	Daily water	**WANN / WANFIS**	×	×	×	×	√	×	×	×	√	×	√	√	√
5	[27]	flood	**SVM/ ANN**	×	×	×	×	√	×	×	×	×	√	√	√	×
6	[28]	flood	**GA**	×	×	×	×	×	×	×	×	×	×	√	√	√
7	[29]	flood	**EWS**	×	×	×	×	√	×	×	×	×	×	√	√	√
8	[30]		**SVM/ FUZZY**	×	×	×	×	√	×	×	×	√	×	×	√	√
9	[31]	River stage	**WPANN /ANFIS**	×	×	×	×	√	√	×	×	×	×	√	√	√
10	[32]	flood	**WGEP**	×	×	×	×	√	×	×	×	√	√	√	×	√
11	[33]	Sediment transport	**ANN/ SVM/ FL**	×	×	×	×	√	×	×	×	×	×	√	√	√
12	[8]	flood	**ANN**	×	×	×	×	√	×	×	×	×	×	√	√	×
13	[34]	flood	**IOT (WSN)**	×	×	×	×	√	×	×	√	×	×	×	×	√
14	[35]	Earthquake	**ES**	×	×	×	×	√	√	×	×	×	×	√	√	√
15	[36]	flood	**SVM**	×	×	×	×	√	×	×	×	×	×	√	√	√
16	[37]	flood	**WNN**	×	×	×	×	√	×	×	×	√	√	×	√	√
17	[38]	flood	**NN/ANN/ WANN**	×	×	×	×	√	×	×	×	×	×	√	√	√
18	[39]	flood	**NN**	×	×	×	×	√	×	×	×	×	×	×	√	√

19	[13]	flood	**FUZZY LOGIC MAMDANI**	×	×	×	×	√	×	√	×	×	×	×	×	√
20	[14]	flood	**FUZZY INFERENCE SYSTEM (T-S)**	×	×	×	×	√	×	×	√	×	√	√	×	√
21	[40]	flood	**SANN/ FUZZY LOGIC/NAM**	×	×	×	×	√	×	√	×	×	×	×	×	√
22	[41]	Stream flow	**DWT-SVR**	×	×	×	×	√	×	×	×	×	×	√	×	×
23	[42]	Rainfall-runoff	**WANN**	×	×	×	×	√	×	×	√	×	√	×	√	×
24	[43]	flood	**ANN/ANFIS/ANN/WNF**	×	×	×	×	×	√	×	×	×	×	√	√	√
25	[44]	Flood	**NN/EWS**	×	×	×	×	×	×	√	×	×	×	×	√	×
26	[45]	flood	**ML**	×	×	×	×	√	√	×	×	×	×	√	×	√
27	[46]	Water level	**ANN**	×	×	×	×	√	×	×	×	×	×	√	√	√
29	[47]	River flow	**SAM-PSO**	×	×	×	×	√	√	×	×	×	×	√	×	×
20	[48]	Stream flow	**GA**	×	×	×	×	√	×	×	×	×	×	√	×	√
30	[7]	flood	**SVM/ ANN**	×	×	×	×	√	×	×	√	×	×	√	×	×
	Average			1	1	1	1	27	7	4	5	5	5	21	18	20
	Percentage			4%	4%	4%	4%	90%	23%	16%	17%	20%	20%	70%	60%	67%

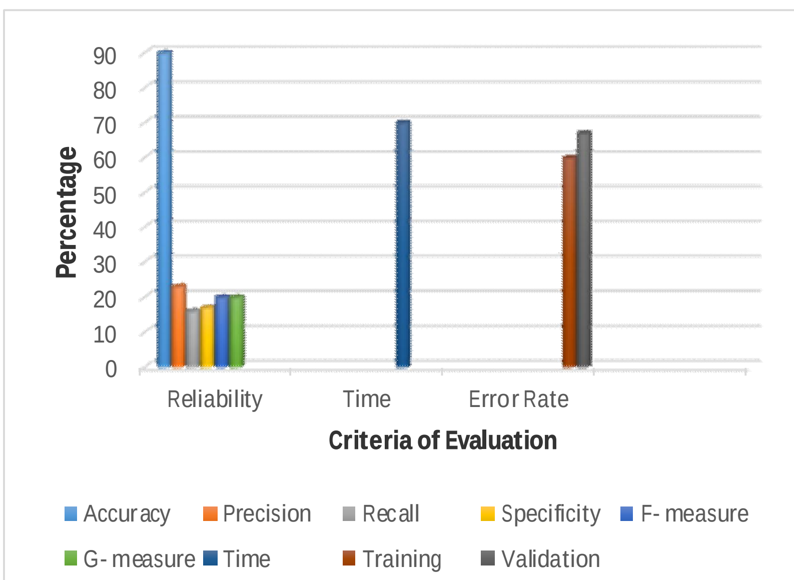

Figure 2: Overview of the criteria of evaluation

Three basic criteria are listed for a reliable forecast: accuracy, reliability, and timeliness. Evaluation and real-time detection criteria are divided into two categories that the research oneach of these indices have been time consuming. The highest criteria identified under the reliability groups are the accuracy and time with percentage of 90% and 70%, respectively. Furthermore, ANN is the most popular method used.

4. CONCLUSION AND FUTURE WORKS

There have been many efforts to forecast natural disasters

based on the accuracy and time. Three criteria for evaluation consist of reliability, error rate, and time which have been reviewed from previous research from 2010 to 2019. The result produced 90% for accuracy and 70% for time.
For future works, ANN will be analysed to identify the limitations of ANN in terms of accuracy and time. Combination of ANN with other techniques will also be investigated.

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