Applying support vector machine and genetic algorithm in critical rainfall line for debris flows

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Abstract

The Chi-Chi earthquake in 1999 caused tremendous landslides which triggered many debris flows and resulted in significant loss of public lives and property. *Therefore, the critical rainfall line of several debris flow streams have been reduced caused Chi-Chi earthquake*. *To help preventing* the *damage* of debris flow, setting a critical rainfall line for each debris-flow stream is necessary. *In order to comprehend the critical rainfall line changes, this study utilizes first four years dataset, however, the occurrence of debris flow damges are not enough for analysis. Hence, this study adopts FCGA as clutering method to solve lack of data problem, in addtion,* 8 predisposing factors *for* debris flow were used to cluster 377 streams which have similar *geo-factors* into 7 groups via the genetic algorithm. Then, support vector machines (SVM) were applied to setup the critical rainfall line for debris flows. SVM is a machine learning approach proposed based on statistical learning theory and has been widely used on pattern recognition and regression. This theory raises the generalized ability of learning mechanisms according to the minimum *disaster* risk. Therefore, the advantage of using SVM can obtain results of minimized error rates without many training samples. Finally, the experimental results confirm that SVM method performs well in setting a critical rainfall line for each group of debris-flow streams.

1 Introduction

Taiwan is a mountainous island with very steep terrain and fragile geology. The extremely heavy rainfall caused by typhoon and Mei-Yu often lead to large-scale debris flow damages in mountains of Taiwan *every year*. Especially after the Chi-Chi earthquake in 1999, a lot of landslides have occurred in the center of Taiwan (*Lin et al., 2004; Chiou et al., 2007*). These *serious* landslides often *brought sediment material into the streambed,* in the initiation area of debris flow. These sediment materials will *be mobilized* by the rainfall and cause numerous debris flow *damages* which result in significant loss of public lives and property in the following rainy or typhoon seasons. Furthermore, the landslides triggered by the Chi-Chi Earthquake will have a significantly upward trend in scale and frequency (*Lin et al., 2006*). *This* means that the debris flow *damages* have been more unpredictable and destructive with the amount of sediment materials (*Lin and Tung, 2004*). *The numerous landslides* triggered by Chi-Chi Earthquake caused a lot of debris-flows (*Shieh et al., 2009*). *Lowered their* rainfall threshold of these debris-flows in subsequent years. Nakamura et al. (2000) *also reported a huge* number of landslides for about 42 years after the Kanto earthquake in Japan. *Almost* every landslides during that time induced server debris-flow *damages*.

Thus, in order to prevent the damage of debris flow, setting a critical rainfall line for each debris-flow stream is necessary *for defining potential region and avoiding diaster(Zhuang et al.,2015)*. In this research, we *aim* to setting a critical rainfall line for each debris-flow stream *of each group from clustering analysis*. Firstly, 377 debris-flow streams in the center of Taiwan affected by Chi-Chi earthquake *are* considered (*Lin et al., 2004; Liu et al., 2013; Huang and Li, 2014*). Then, 8 predisposing factors for debris flow were used to cluster streams into 7 groups via the genetic algorithm. *Streams with similar characteristics were then clustered together support vector machines (SVMs) applied to setup the critical rainfall line for each debris-flow clusters. The experimental result shows that SVM method performs well in setting a critical rainfall line for each group of debris-flow (Yuan et al., 2006).*

2 Study Area

The Chi-Chi earthquake occurred in 1999 in *Taiwan and caused* numerous landslides, *the locations of these landslides were up to 2365 and the total area were approximate 14347 hectares*, represented as Fig. 1(a). These landslides *are mostly located* in the mountains of central Taiwan. The debris flow streams *are* triggered by the landslides *affected* seriously by the Chi-Chi earthquake in the experiments *of previous study (Yu et al., 2014)*. 377 debris flow streams were chosen from 7 counties included Nan-Tou county, Maio-Li county, Taichung City, Taichung county, Chun-Chua county, Yun-Lin county and Chia-Yi county, represented as *(Fig. 1b)*.

According to Shieh and Tsai (2001), 8 important characteristics of the 377 debris-flow streams including rock type (R), watershed area (A), effective watershed area (A_{15})(15^o is the potential degree of slope for debris flow damages), landslide area (A_s), landslide ratio(A_s/A), length of channel in the effective watershed area (L), mean surface slope of the effective watershed area (S_s) and mean channel slope of the effective watershed area (S_c).Table 1. shows the eight characteristics of the 377 streams(*Yuan et al., 2006; Wan and Lei, 2009; Bui et al., 2012*).

3 Data Processing

In order to cluster the 377 debris flow streams into different groups, the statistical data *of first four years (1999-2002) data after Chi-Chi* earthquake including *geographical information from central geological survey MOEA, hydrological information from central weather bureau in Taiwan, historical data of damage from internet-based news* and statistical tables of eight predisposing factors *have to be* preprocessed. The preprocessing involved presentation of the data, normalization of the data and the measurement of the distance between two debris-flow streams. Eq. 1 represents the normalization of the data (Z-score).

$$Z_{ij} = \frac{x_{ij} - \overline{x_i}}{\sigma_i}, \qquad where\ 1 \le j \le K, 1 \le i \le M \tag{1}$$

Where *M* represents the 377 debris-flow streams and *K* is the eight attributes of *each stream*. Let F_i represent the i^{th} debris flow where $1 \le j \le K$, and F_j represent the j^{th} attribute of 8 predisposing factors where $1 \le i \le M$. The corresponding attribute vector for the debris flow F_i is represented as X_{ij}. The $\overline{X}$ and σ_i are the mean and mean absolute deviation of X_{ij} respectively.

After data normalization, the distance between two debris-flows *can be* calculated. The centered Person correlation was used to define the distance $D(F_i, F_j)$. Let $F_i = (X_{i1}, X_{i2},...X_{ik})$ and $F_j = (X_{j1}, X_{j2},...X_{jk})$ be normalized attribute vectors of two flows over a series of *K* attributes.

The distance between flows F_i and F_j was defined as Eq. 2 *where $\bar{X}_i$ and σ_{X_i} are refered to Eq.3 and Eq.4.*

$$S_{i,j} = \frac{1}{K}\sum_{l=1}^{k}\left[\frac{X_{il}-\overline{X_i}}{\sigma_{X_i}}\right]\left[\frac{X_{jl}-\overline{X_j}}{\sigma_{X_i}}\right], \qquad where\ -1 \leq S_{i,j} \leq 1 \tag{2}$$

$$\overline{X_\iota} = \frac{\sum_{l=1}^{k} F_{il}}{k} \tag{3}$$

$$\sigma_{x_i} = \sqrt{\frac{1}{k}\sum_{l=1}^{k}\left(X_{il}-\overline{X_i}\right)^2} \tag{4}$$

Since this term measures distance, the following was defined as Eq. 5

$$D(F_i, F_j) = 1 - S_{i,j}, \qquad where - 1 \leq D(F_i, F_j) \leq 1 \tag{5}$$

4 Clustering analysis of debris-flow steam

This section aims to cluster 377 debris-flow streams into seven groups, via clustering analysis such that streams in each group have similar characteristics. This study collects the first four years data after 921 earthquake to analyze the critical rainfall threshold of debris flow streams, however, there is not enough occurrence data for analyzing critical rainfall thresholds. Therefore, this study combines debris flow streams into one group with same patterns through clustering method to increase the numbers of debris flow occurrence data. An efficient clustering algorithm was considered for describing debris flows in order to illustrate the relationships by constructing a binary hierarchical tree (*Yang and Kao, 2000*). This approach was employed to group 377 debris flow streams into seven groups such that the critical rainfall line in the same group could be set. Many approaches to constructing binary hierarchical trees have been proposed. For example, Ward's method (Ward, 1963), the single-linkage method (Sibson, 1973), the average-linkage method (Defays, 1977), and the average-linkage(Voorhees, 1986) hierarchical clustering approach have been extensively applied in various fields to approximate such trees, including the fields of document clustering (Willet, 1988) and bioinformatics (Eisen et al., 1998; Alizadeh et al., 2000).

In this study, *a family competition genetic algorithm (FCGA) was used to construct a hierarchical tree of streams*. *The method used in this study combines family competition,* *neighbor-join mutation (NJ)* and edge assembly crossover (EAX)(Nagata & Kobayashi, 1997; Yang and Kao, 2000; *Tsai et al., 2001; Tsai et al., 2002*). The primary difference between the method in this study and that in our previous work is in the integration of these three mechanisms(Fig. 2).

The experimental results revealed that the FCGA is a promising method for constructing the optimal tree of streams. Figure 3 presents the seven groups of 377 debris-flow streams *on the basis of their patterns among 8 factors mentioned them in previous section*. In Fig. 3(a)-(g), the x-axis represents the eight important characteristics and the y-axis is the normalized values of each characteristics *each group* include 39, 58, 61, 42, 67, 47 and 63 streams respectively. Each groups all exhibited different trends in their characteristics and the characteristics in the same group were similar. Additionally, it should be noted that Fig. 3(f) and 3(g) use different scales. The clustering results showed that the proposed method was able to cluster streams into separate groups with similar characteristics. As a result, this method represents *a possible mean* of establishing a critical rainfall line for debris flow streams in each group. The critical rainfall lines of each groups could be set according to the characteristics.

5 Establishing the critical rainfall line for debris flows

When the streams with similar characteristics have clustered together, the critical rainfall line of debris flow could be set via SVM. SVM is a new machine learning approach proposed by Vapnic(1998) based on statistical learning theory *and structural risk minimization (SVM)*. The advantage of SVM is that this theory raises the generalized ability of learning mechanisms according to minimize the *risk and reduces the probability of overfitting probelm under lack of data condition*. Therefore, we can obtain the results with minimum error rates and without many training samples. Otherwise, SVM is an optimized algorithm which can *be performed* by a standard programming algorithm and obtained the global optima. The SVM has been widely applied in many disciplines to solve the problems of classification and regression in the field of hydrological engineering(Yu et al., 2011; Lin and Chen, 2011; Shen et al., 2011; *Liang et al., 2012). This study intends to establish the critical rainfall line of debris flow via SVM*.

Each data of debris flow stream were consider as a vector or a point in a multidimensional space. *The hyper-plane separating the vectors into two parts, is then search for, according to the occurrence of debris flow (Fig. 4). (Vapnik, 1995)*

However, two problems are frequently encountered during the process of classification. Figure 5 shows the two problems, it is possible that there are many hyper-planes existed in the multidimensional space exactly. (Tax and Duin, 2002)

Therefore, we switched these training data (Eq. 6) to a higher dimensional space called feature space via a non-linear function φ(x)(Eq. 7).

Training data : $[(x_1,y_1),(x_2,y_2),...,(x_l,y_l)]$ *(6)*

where $y_i \in \{+1,-1\}$ *as output data and* x_i *is input vector*

$$f(x) = sign[w^T \cdot \phi(x) + b] \quad (7)$$

where $\phi(x)$ *is non-linear function in feature space; w and b are the classifier parameters*

In the feature space, we could still find several hyper-planes can separate the training data into two groups.

$$\begin{aligned} &Minimize \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i x_j) \\ &Subject\ to \sum_{i=1}^{n} \alpha_i y_j = 0 \\ &0 \le \alpha_i \le C \end{aligned} \quad (8)$$

where αi, αj are Largrange multipliers, C is the penality

However, the method of SVM we applied can choose a particular plane from those hyper-planes named maximum margin hyper-plane (optimal hyper plane as Eq. 8). Fig. 6 shows that with the advantage of SVM, a maximum margin hyper-plane could be selected from several hyper-planes. This maximum margin hyper-plane represents the inner product of the vector in the feature space. This inner product generally *is* made by a kernel function, hence we can easily find the maximum margin hyper-plane with a suitable kernel function. Under the situation of maximum margin hyper-plane, the sum of distance from those training data closest to the plane would be maximum. The decision-making hyper-plane for classification could be illustrated with less training data near the hyper-plane called support vector. Therefore, these training data can classified easily and efficiently(Vapnik, 1998; Ballabio and Sterlacchini, 2012).

This section describes the result of the proposed method SVM to establish the critical rainfall line for each group of debris flows. When the debris flow streams with similar characteristics have clustered together into seven group, the critical rainfall line of each debris-flow group could be set via SVM. Fig. 7(a)-(g) shows the critical rainfall line of group A, group B, group C, group D, group E, group F and group G, respectively. In Fig. 7, the *yellow* dots represent the rainfall data with debris flow events and the *blue* dots symbolize the rainfall data without debris-flow event. The green zone represents a range of hazardous area with debris flow. In contrast, the black zone represents a range without debris flow. The boundary between the green area and black region stands for a critical rainfall line of each debris flow groups.

Compared with the critical rainfall lines of each groups respectively, it could find that the critical rainfall lines of group D and group F were lower than others, showed in Table 2. It is *possible* that the group F have a higher landslides ratio (A_s/A) and group D have a vulnerable rock type (R) and steep slope on mean channel of the effective watershed area (S_c) and mean surface of the effective watershed area (S_s)(Fig. 3). In contrast, group A and group E have higher critical rainfall lines with each characteristic lower than the average of other groups. *Overall, most of critical rainfall lines have a obviously decreasing pattern after Chi-Chi earthquake, especially for Gorup D and F, these two groups are influenced by high landslide ratio which is produced by Chi-Chi earthquake. Due to the results above, the original critical rainfall lines might be changed, and this is the reason why this study estableshes new crtical rainfall lines for debris flow streams because they are not suitable for them after large earthquake.* As a result, we can establish the critical rainfall lines of each debris flow groups clustered together with similar characteristic via support vector machine. The critical rainfall lines were set according to the characteristic of debris flow.

6 Conclusions

This study aims to set up the critical rainfall line of debris flows via a series of statistical methods *after Chi-Chi earthquake*. 377 debris-flow streams in the center of Taiwan affected by Chi-Chi earthquake and 8 predisposing factors *for* debris flow were considered. *Due to lack of data problem,* 377 debris flow streams were clustered into 7 groups with similar characteristic via family competition genetic algorithm, then support vector machine was used to set up the critical rainfall line of each debris flow groups. The results reveal that SVM can establish the critical rainfall lines of debris flow successfully and the critical rainfall lines were set according to the characteristic of each debris flow groups. *The significant changes of critical rainfall lines after Chi-Chi earthquake has found in Group D and F, and this phenomenon is caused by high* *landslide ratio.* Hence, the method proposed in this study can be an effective instrument for establishing critical rainfall lines. In the future, the weights and the interactions of the predisposing characteristics would be the focus of research.

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1

R		A_s/A (%)		S_c (°)		S_s (°)	
Type	Stream No.	Range	Stream No.	Range	Stream No.	Range	Stream No.
Alluvion	4	0~5	3	0~10	3	0~0.5	81
Conglomerate	30	5~10	9	10~15	11	0.5~1.0	35
Sand stone	35	10~15	67	15~20	42wq	1.0~2.0	65
Sand & shale	191	15~20	115	20~25	80	2.0~3.0	39
Shale	5	20~25	99	25~30	103	3.0~5.0	45
Slate	55	25~30	56	30~35	93	5.0~10.0	49
Metamorphic sand	57	＞30	28	＞35	45	＞10.0	63

A (hectare)		A_{15} (hectare)		A_s (hectare)		L (km)	
Range	Stream No.	Range	Stream No.	Range	Stream No.	Range	Stream No.
0~10	13	0~10	23	0~0.1	59	0~0.5	54
10~20	19	10~20	34	0.1~0.5	45	0.5~1.0	88
20~30	18	20~30	22	0.5~1.0	37	1.0~1.5	78
30~40	32	30~40	30	1.0~2.0	53	1.5~2.0	44
40~50	17	40~50	28	2.0~3.0	25	2.0~3.0	53
50~60	19	50~60	23	3.0~4.0	30	3.0~4.0	19
60~70	18	60~70	18	4.0~5.0	23	4.0~5.0	10
70~80	13	70~80	13	5.0~10.0	38	5.0~6.0	11
80~90	19	80~90	19	10.0~20.0	29	6.0~7.0	4
90~100	14	90~100	12	20.0~30.0	15	7.0~8.0	4
100~200	91	100~200	71	30.0~40.0	9	8.0~9.0	1
200~300	30	200~300	27	40.0~100.0	8	9.0~10.0	4
300~500	36	300~500	25	＞100.0	6	＞10.0	7
＞500	38	＞500	32				

A_{15}: The effective watershed area is the region where is located over 15° of riverbed.

1 Table 1. The statistical table of 8 characteristics with 377 streams.

Group	Group A	Group B	Group C	Group D	Group E	Group F	Group G
Rainfall Intensity	31.5	23	18	23.5	40.5	22.5	18.5
Rainfall Accumulation	235.5	195	195	70	218	50	280

Table 2. The value of critical rainfall line of each debris flow groups.

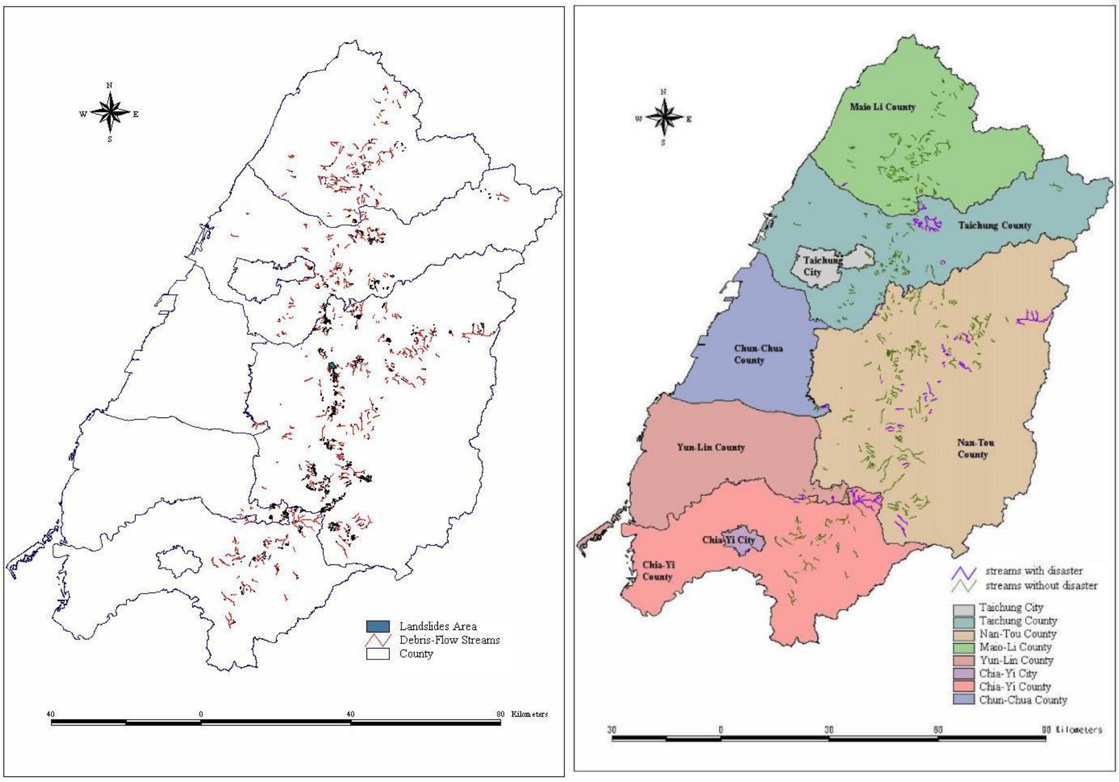


*Figure 1.(a)*The position and landslide area of 377 debris-flow streams in central Taiwan; *1.(b)*The historical *damage* and position of 377debris-flow streams in central Taiwan.

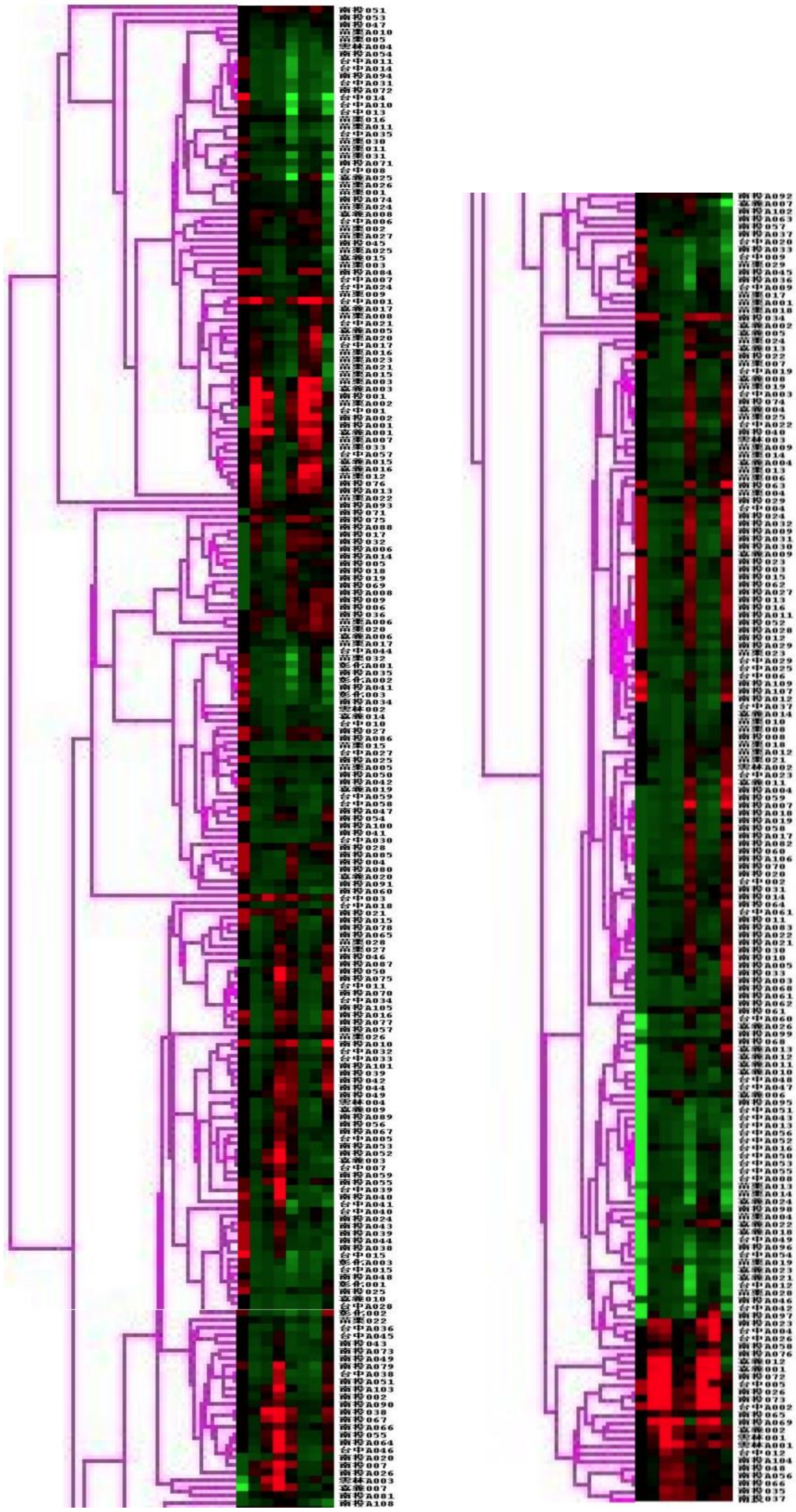


Figure 2. FCGA and hirachical tree analysis results

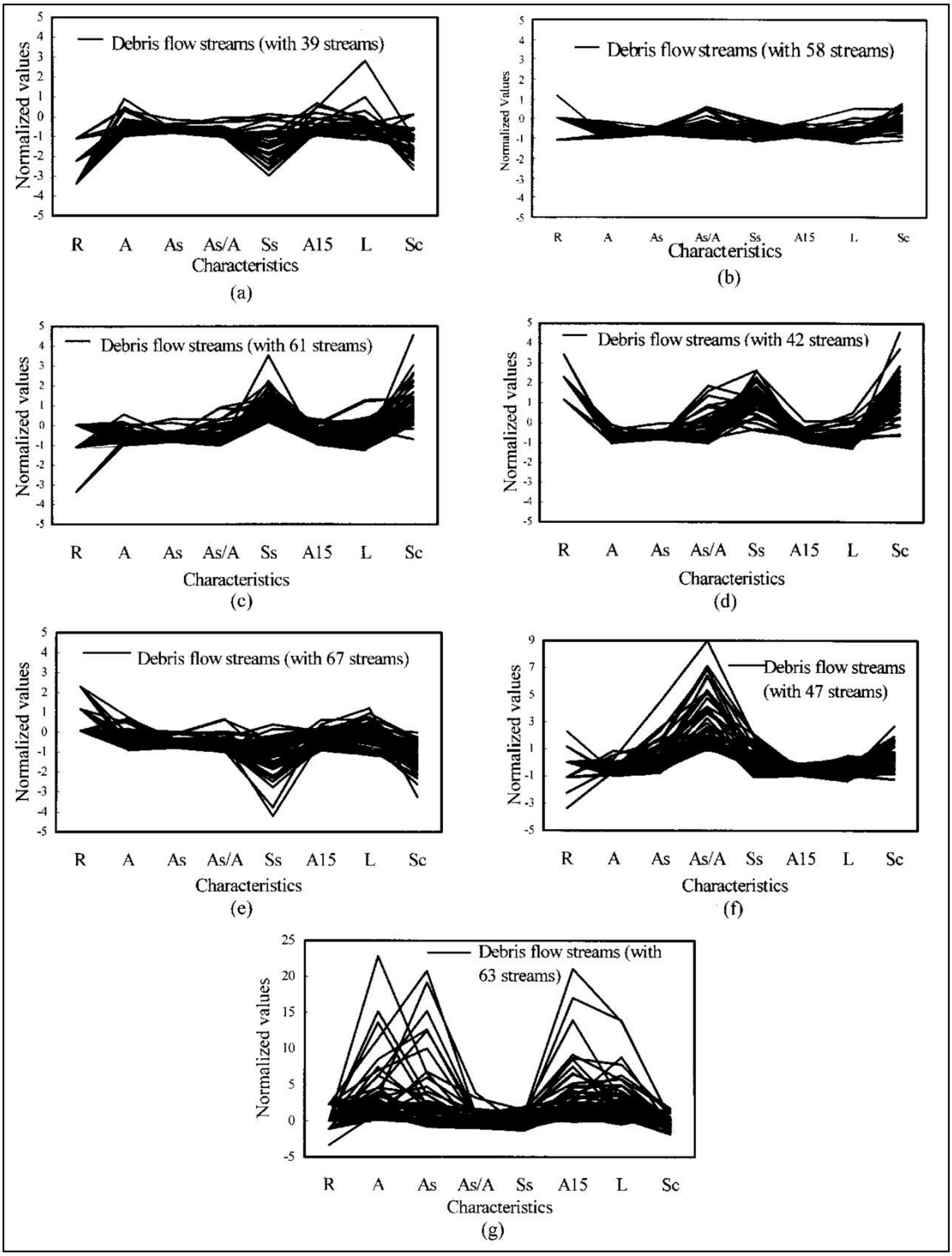


Figure 3. The results of clustering analysis on 377 debris-flow streams.

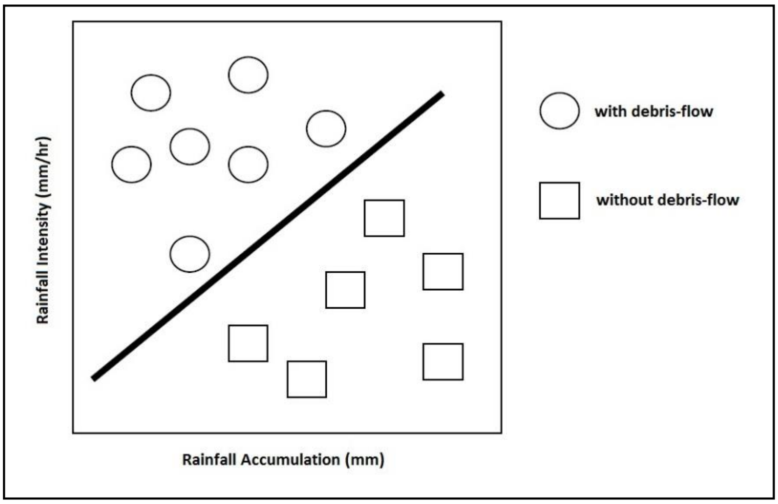


Figure 4. The multidimensional space with vector of debris-flow.

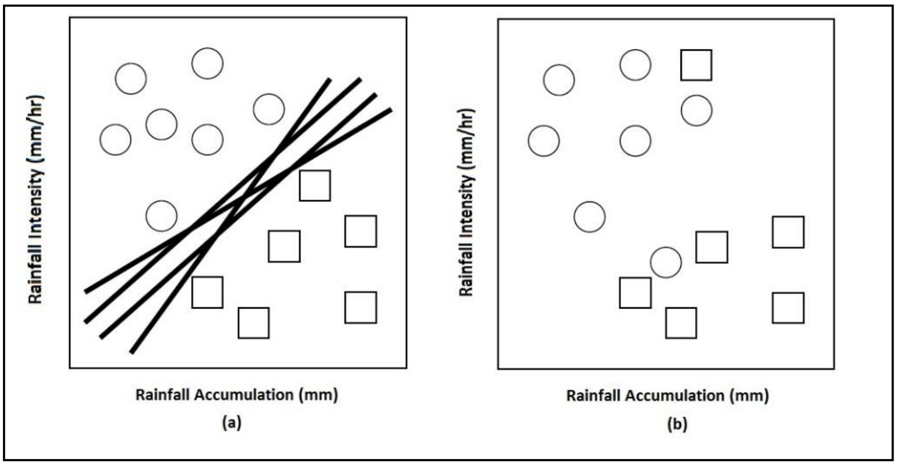


Figure 5. The examples of problems encountered in most cases.

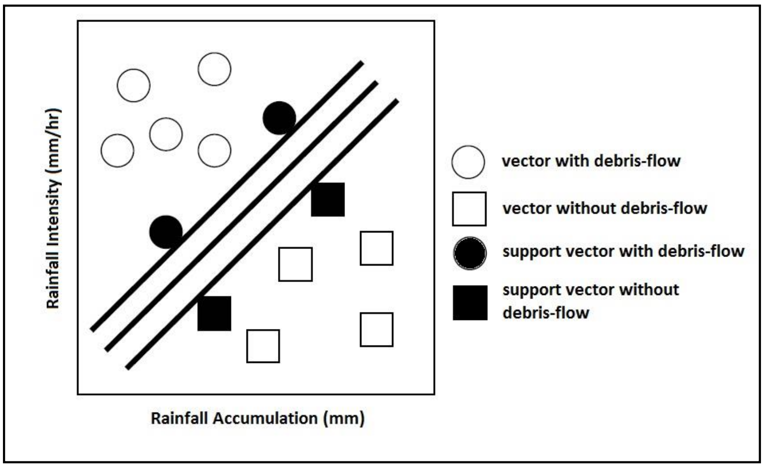
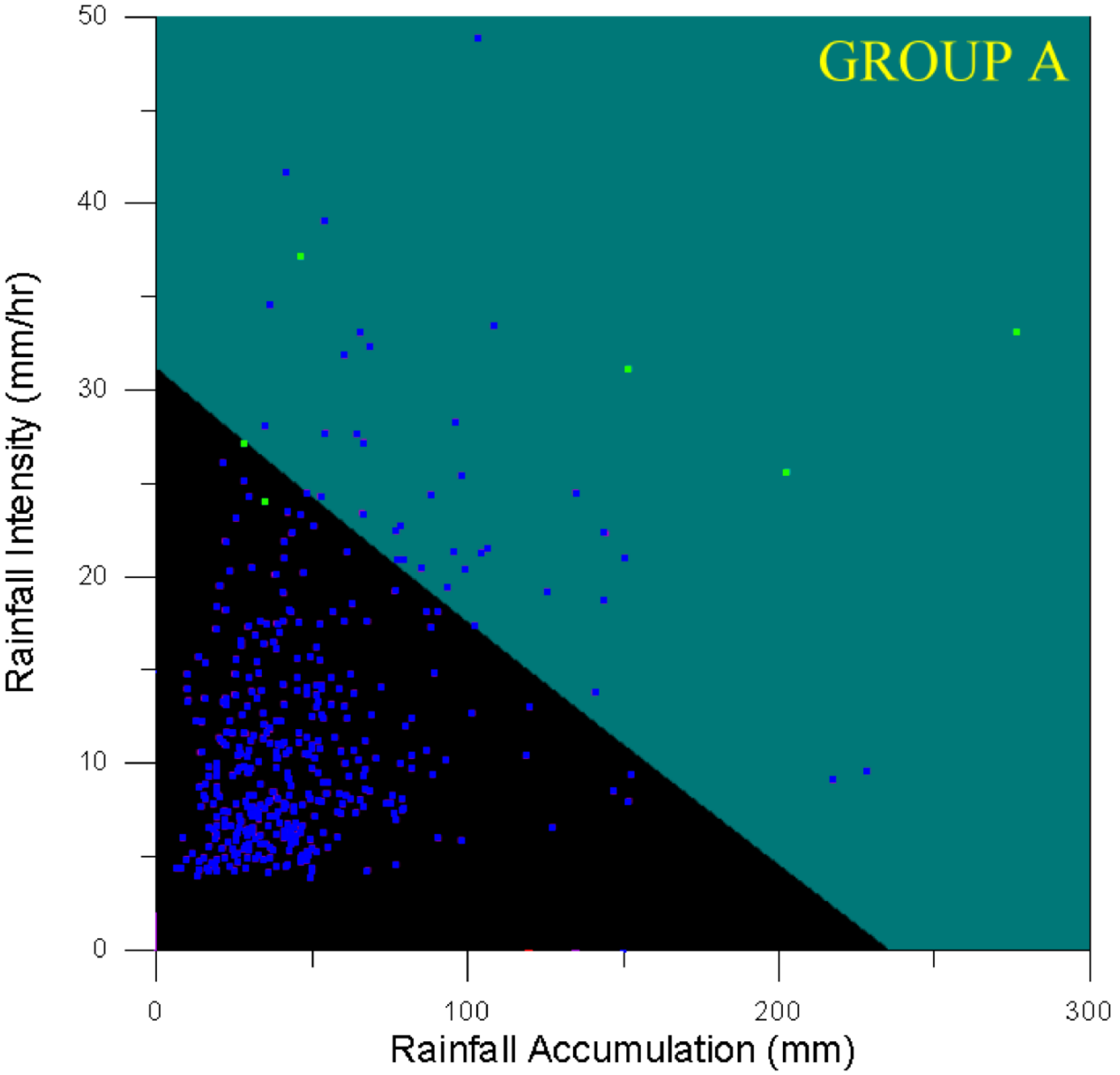
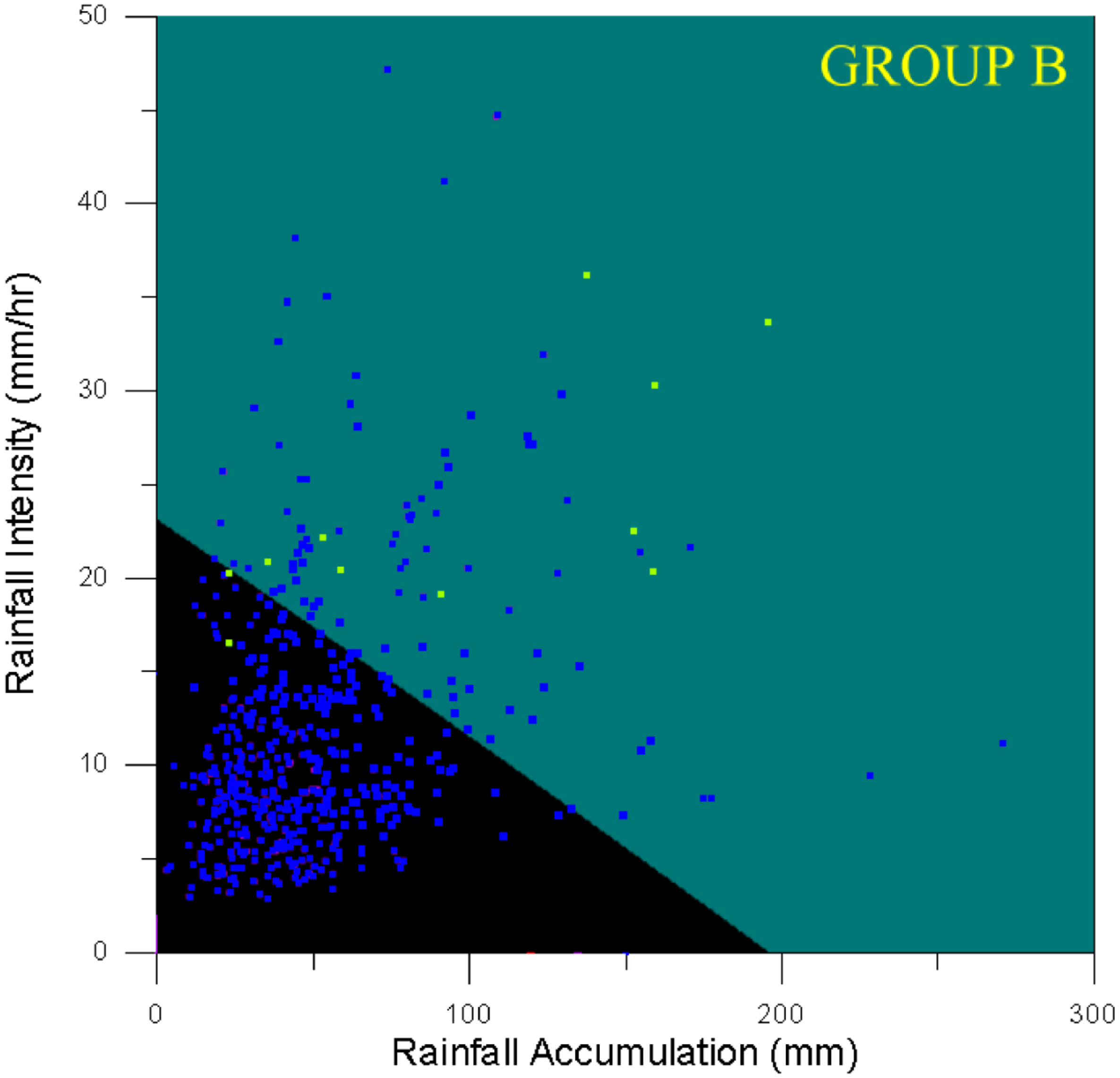


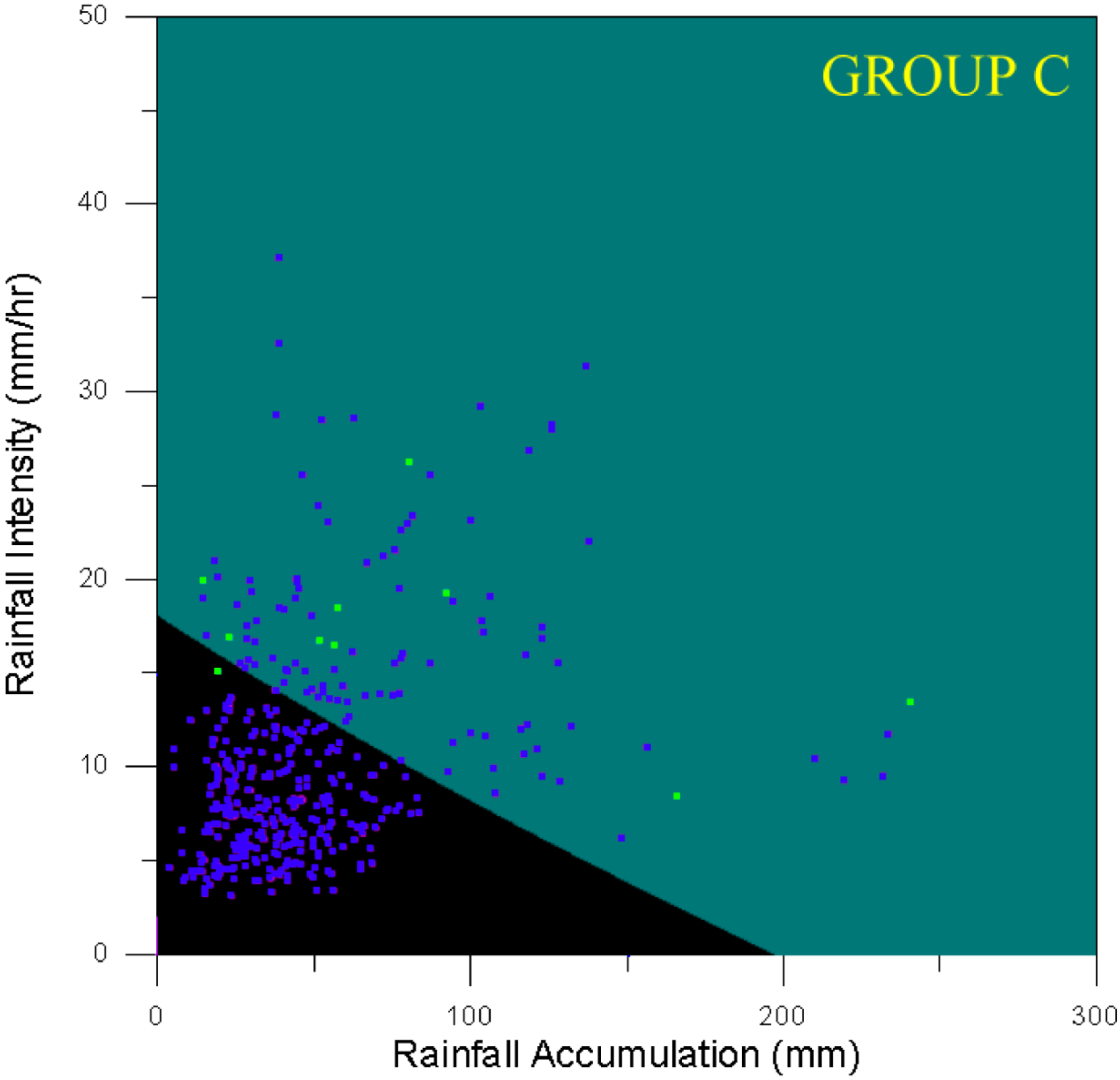
Figure 6. An example of maximum margin hyper-plane and support vector.


GROUP A
Rainfall Intensity (mm/hr)
Rainfall Accumulation (mm)
50
40
30
20
10
0
0
100
200
300

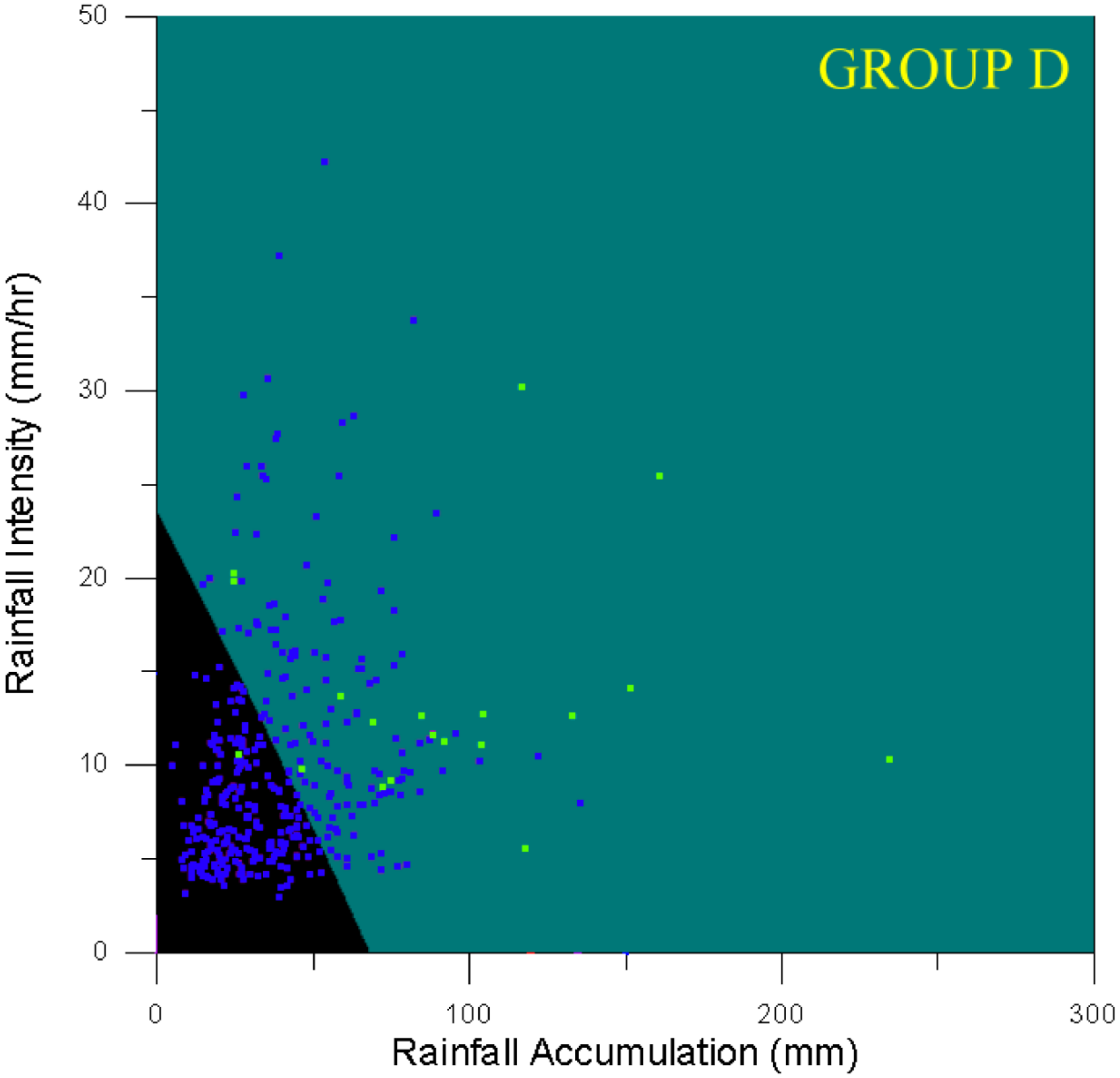
1

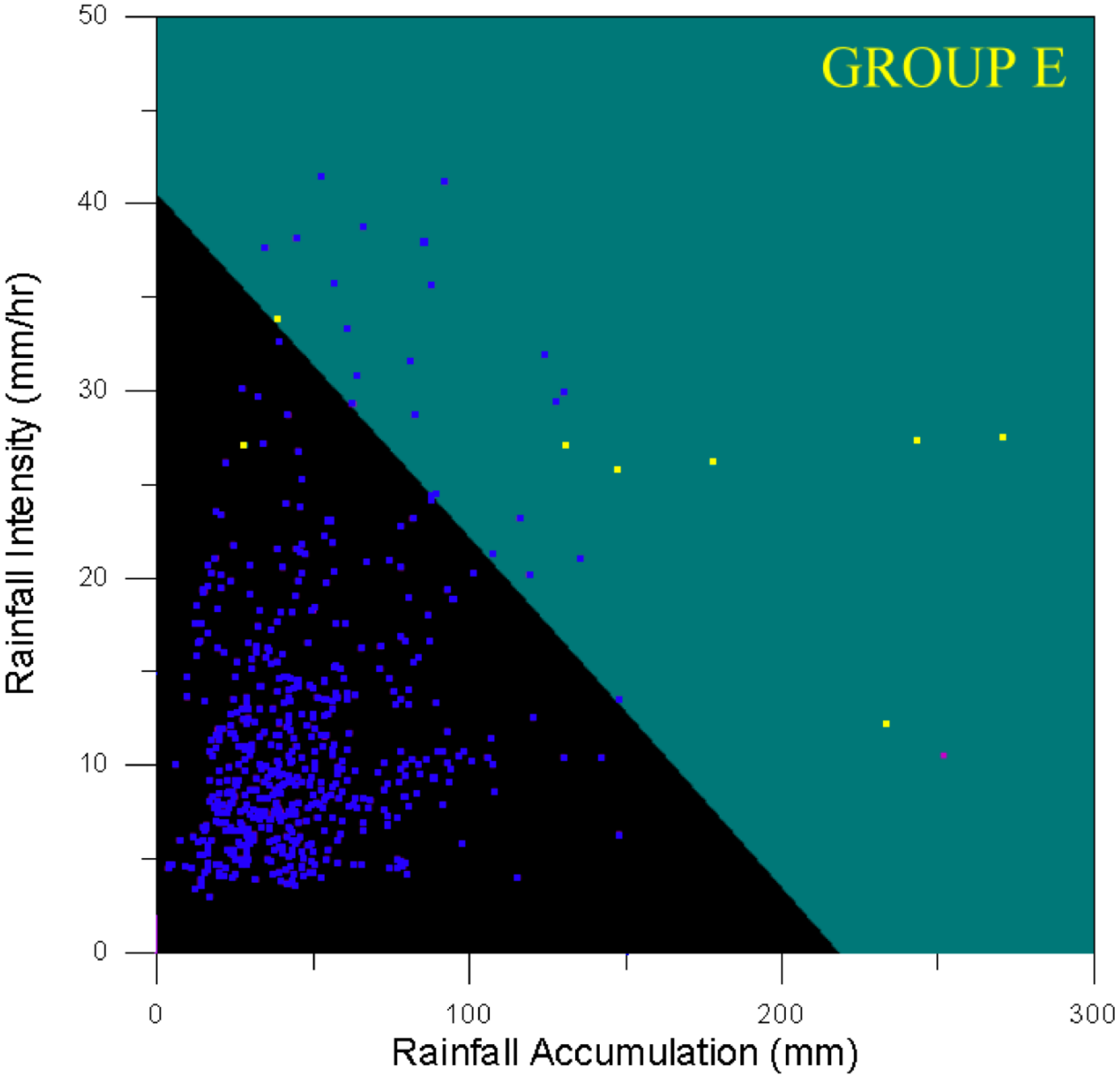

GROUP B
Rainfall Intensity (mm/hr)
Rainfall Accumulation (mm)
0
10
20
30
40
50
0
100
200
300

1

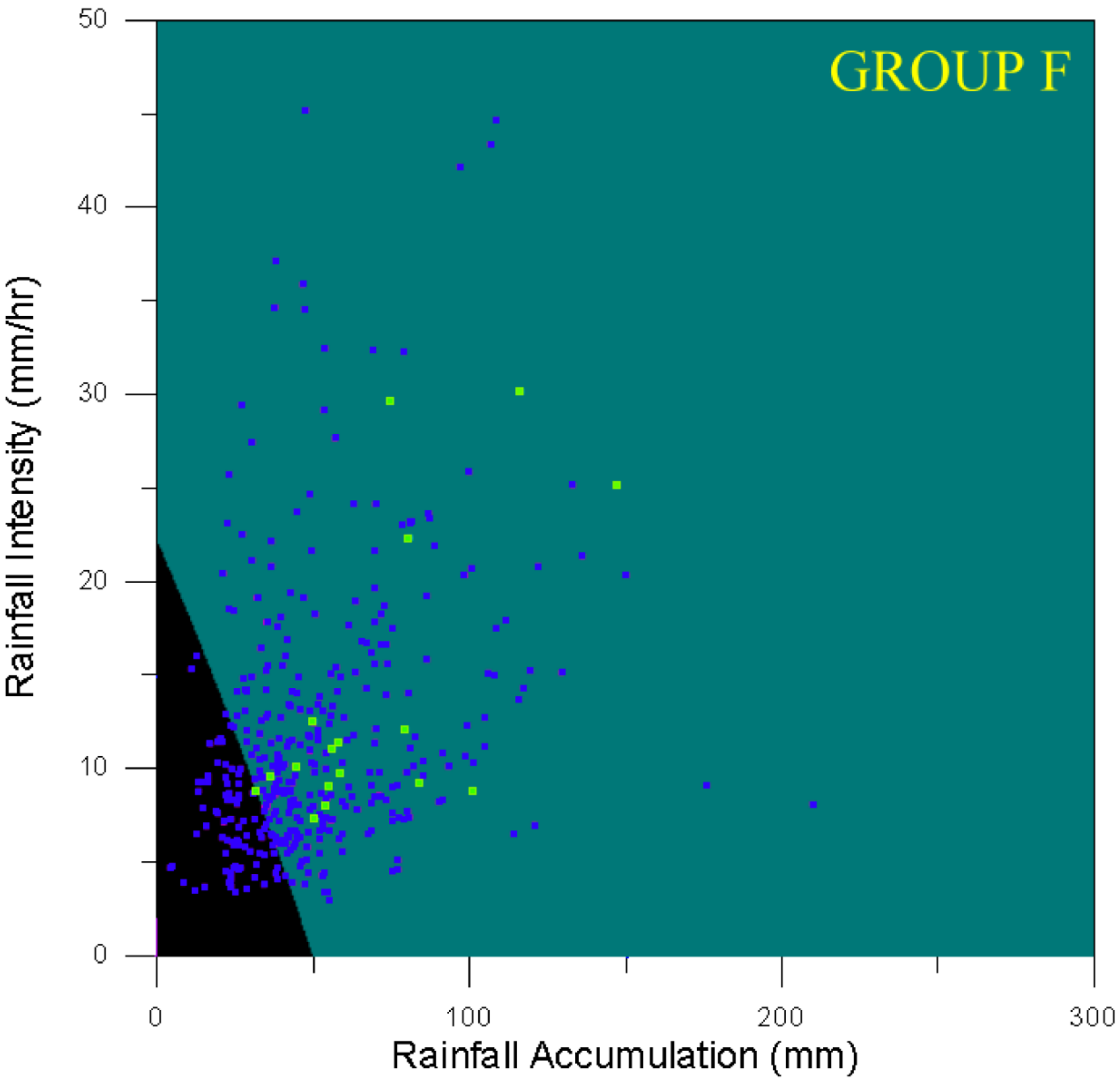

GROUP C
Rainfall Intensity (mm/hr)
Rainfall Accumulation (mm)
50
40
30
20
10
0
0
100
200
300

1


GROUP D
Rainfall Intensity (mm/hr)
Rainfall Accumulation (mm)
0
10
20
30
40
50
0
100
200
300


GROUP E
Rainfall Intensity (mm/hr)
Rainfall Accumulation (mm)
0
10
20
30
40
50
0
100
200
300

1


GROUP F
Rainfall Intensity (mm/hr)
50
40
30
20
10
0
0
100
200
300
Rainfall Accumulation (mm)

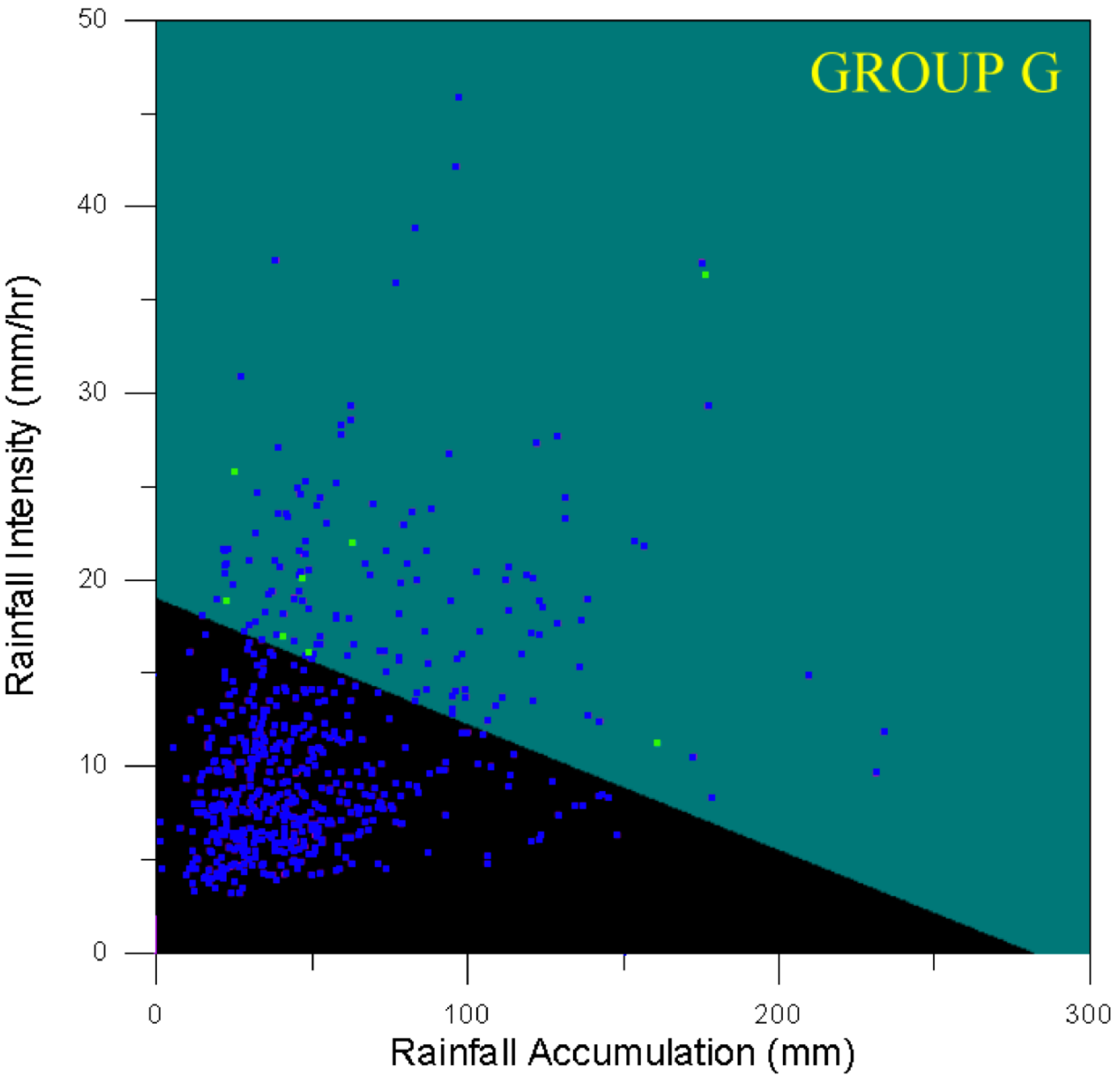


Figure 7. The result of our research tested on 7 groups.