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Research article

Theory and Application of Variable Fuzzy Sets to Flood Loss Evaluation in Disaster Risk Analysis

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Abstract

Floods are increasing alarmingly worldwide. However natural disaster management is a typical issue with imprecision, uncertainty and partial truth. But the traditional probability statistical method ignores fuzziness with incomplete data sets and requires a large sample size of data. To improve the probability estimation, the fuzzy set methodology is introduced into the area of disaster risk analysis. In order to test the grade criterions of flood disaster loss and resolve the non-uniformity problem of evaluation results of disaster loss indexes, and to raise the grade resolution of flood disaster loss, a new method—variable fuzzy sets(VFS) is suggested for evaluating the grade model of flood disaster, where the disaster loss grade is continuous real number. The method can scientifically and reasonably determine the relative membership functions of disquisitive indexes at level interval that relating to flood, also it can fully use one’s experience and knowledge, qualitative and quantitative information of index system to obtain weights of indexes for operating comprehensive evaluation. The numerical example of floods in China has shown that the proposed method is feasible and effective, and it provides a new theory for flood loss evaluation with incomplete data sets.

Keywords: variable fuzzy sets; flood disaster; loss; evaluation.

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1 Introduction

Water as a special resource, which sustains all life, is the substance of sustainable development society. With the rapid development of economy and growth of population recently, the problem of flood、drought、water resources shortage and water environment deterioration becomes more and more acute. And in particular recent flooding disasters have shown the vulnerability of the so called developed and developing countries to such events. In China, flood disasters occur frequently, and about two-thirds of its area are facing the threat of different types and degrees of floods, they are the result of natural and unnatural reasons such as social, economic factors. As severe floods occurring frequently, flood risk management plays an important role in guiding the government take timely and correct decision for flood rescue and relief.

It is well known that constructing disaster control engineering system is a synthesis of muti-dimensional factors, so its evaluation shall be operated from single factor to multi factors, which means that routine evaluation method often omit important information and can not obtain integrated risk evaluation for engineering system. Accordingly, under global view of system, the variable fuzzy sets(VFS) is presented to evaluate the synthetic loss of disaster control engineering system in the risk management. The method can scientifically and reasonably determine membership degrees and relative membership functions of disquisitive objectives (or indicators) at level interval that relating to the disaster, also it can fully use one's experience and knowledge, qualitative and quantitative information of indicator system to obtain weights of objectives (or indicators) for operating comprehensive evaluation of flood (Wang et al., 2011; Zhang et al., 2011).

In this study we establish a new disaster loss assessment model based on variable fuzzy sets and it is then applied to the flood risk analysis in China successfully. In the second section we briefly describe some basic concepts and the principle of variable fuzzy sets. This is a new attempt at applying variable fuzzy sets in flood loss analysis. Computations based on this analytical flood loss assessment VFS-AHP model can yield an estimated flood damage value that is relatively accurate(Section 3). An example is carried out and indicates that the aforementioned model exhibits fairly stable analytical results, even when using a small set of sample data. The results also indicate that the method is highly capable of extracting useful information and therefore improves system recognition accuracy. These are shown by an example in Section 4. Finally, some discussion and conclusions are presented in Section 5.

2 Model Introduction

The theory of variable fuzzy sets (VFS) was established by author Chen (Chen SY,1998). Comprehensive evaluation of variable fuzzy sets (VFS) can effectively solve influence of border fuzzy and monitor error of estimation standard to evaluation result. The method can scientifically and reasonably determine membership degrees and relative membership functions of disquisitive objectives (or indexes) at level interval that relating to flood, also it can fully use one's experience and knowledge, qualitative and quantitative information of index system to obtain weights of objectives(or indexes) (Chen SY, 1998; Chen SY, 2002; Chen SY, 2005) for operating comprehensive evaluation of flood.

In this study we propose a loss evaluation model based on variable fuzzy sets and it is then applied to the flood loss evaluation in China successfully.

2.1 Variable Fuzzy Sets

To define the concept, let us suppose that U is a fuzzy concept, A express characteristic of attactability and

A^c states repellency. Hence, to any elements u ($u \in U$), $\mu_A(u)$ and $\mu_{A^c}(u)$ are relative membership degree (RMD) function that express degrees of attractability and repellency respectively. We have $\mu_A(u) + \mu_{A^c}(u)$ =1.Here $0 \le \mu_A(u) \le 1$, $0 \le \mu_{A^c}(u) \le 1$.

Let $D(u) = \mu_A(u) - \mu_{A^c}(u)$, Where $D(u)$ is defined as relative difference degree of u to A. Mapping $D: u \to D(u) \in [-1,1]$ is defined as relative difference function of u to A.Then $D(u) = 2\mu_A(u) - 1$,or $\mu_A(u) = [1 + D(u)]/2$. Let

$$V_0 = \{(u, D) | u \in U, D(u) = \mu_A(u) - \mu_{A^c}(u), D \in [-1,1]\}$$

$$A_+ = \{u | u \in U, 0 < D(u) < 1\}$$

$$A_- = \{u | u \in U, -1 < D(u) < 0\}$$

$$A_0 = \{u | u \in U, D(u) = 0\}$$

Here V_0 is defined as variable fuzzy sets(VFS), A_+, A_-, and A_0 are defined as attracting sets, repelling sets and balance boundary or qualitative change boundary of VFS V_0.

2.2 Methods of Relative Difference Function

We suppose that X_0 = [a, b] are attracting sets of VFS V on real axis, i.e. interval of $\mu_A(u) > \mu_{A^c}(u)$, X' = [c, d] is a certain interval containing X_0, i.e. $X_0 \subset X'$.(see Fig.1)

According to definition of VFS we know that interval [c, a]and [b, d] are all repelling sets of VFS, i.e. interval of $\mu_A(u) < \mu_{A^c}(u)$. Suppose that M is point value of D(u)=1 in attracting sets [a, b]. x is a random value in interval X', then if x locates at left side of M, its difference function is

$$\begin{cases} D(x) = \left(\dfrac{x-a}{M-a}\right)^{\beta} & x \in [a, M] \\ D(x) = -\left(\dfrac{x-a}{c-a}\right)^{\beta} & x \in [c, a] \end{cases} \tag{1}$$

or
$$\begin{cases} \mu(x) = 0.5[1 + (\dfrac{x-a}{M-a})^{\beta}] & x \in [a, M] \\ \mu(x) = 0.5[1 - (\dfrac{x-a}{c-a})^{\beta}] & x \in [c, a] \end{cases} \tag{2}$$

And if x locates at right side of M, its difference function is

$$\begin{cases} D(x) = (\frac{x-b}{M-b})^{\beta} & x \in [M,b] \\ D(x) = -(\frac{x-b}{d-b})^{\beta} & x \in [b,d] \end{cases} \quad (3)$$

or $$\begin{cases} \mu(x) = 0.5[1+(\frac{x-b}{M-b})^{\beta}] & x \in [M,b] \\ \mu(x) = 0.5[1-(\frac{x-b}{d-b})^{\beta}] & x \in [b,d] \end{cases} \quad (4)$$

Where β is index bigger than 0, usually we take it as β=1, viz. (1) and (3) become linear functions which equal Equations (2) and (4) .

3. VFS-AHP process to evaluate the synthetical degree value

Suppose the sample set is $\{x_1, x_2, \cdots, x_n\}$ and every sample with m indicators, so the sample indicator matrix is

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix} = (x_{ij}) \quad (5)$$

where x_{ij} is the ith indicator of sample j, and i=1,2,…m; j=1,2,…n.

And each indicator can be evaluated by c levels, so the indicator criteria interval matrices of each level is:

$$I_{ab} = \begin{pmatrix} [a_{11},b_{11}] & [a_{12},b_{12}] & \cdots & [a_{1c},b_{1c}] \\ [a_{21},b_{21}] & [a_{22},b_{22}] & \cdots & [a_{2c},b_{2c}] \\ \vdots & \vdots & \vdots & \vdots \\ [a_{m1},b_{m1}] & [a_{m2},b_{m2}] & \cdots & [a_{mc},b_{mc}] \end{pmatrix} = ([a_{ih},b_{ih}])$$

where i=1,2,…m; h=1,2,…c. Level 1 is the superior leval, leval c is the inferior leval. For every $[a_{ih},b_{ih}]$,we can determine its range of inteval $[c_{ih},d_{ih}]$ according the lower and upper limit of its adjacent intevals and the point M of each interval as follows:

$$I_{cd} = \begin{pmatrix} [c_{11},d_{11}] & [c_{12},d_{12}] & \cdots & [c_{1c},d_{1c}] \\ [c_{21},d_{21}] & [c_{22},d_{22}] & \cdots & [c_{2c},d_{2c}] \\ \vdots & \vdots & \vdots & \vdots \\ [c_{m1},d_{m1}] & [c_{m2},d_{m2}] & \cdots & [c_{mc},d_{mc}] \end{pmatrix} = ([c_{ih},d_{ih}])$$

$$M = \begin{pmatrix} M_{11} & M_{12} & \cdots & M_{1c} \\ M_{21} & M_{22} & \cdots & M_{2c} \\ \vdots & \vdots & \vdots & \vdots \\ M_{m1} & M_{m2} & \cdots & M_{mc} \end{pmatrix} = (M_{ih})$$

Based on matrixes $I_{[a,b]}, I_{[c,d]}$ and M, we judge that evaluating indicator x locates at left side or right side of point M, and according these to select (2) or (4) for calculating difference function $\mu_h(u_{ij})$ of indicators to standards. Here h is grade number; i is indicators number; j is the sample number.

Thus we get the the relative degree of membership matrix of the indicator values of the sample to each level according Eq.(2) and Eq.(4) as follows.

$$_jU = (\mu(x_{ij})_h) \tag{6}$$

And according to the Analytical Hierarchy Process (AHP), The two-level hierarchy that has been constructed to obtain the weights of the evaluation indicators and we obtain normalized weights of the evaluation indicators as w.

To get synthetic degree value of each indicator, we use variable fuzzy recognition model presented by Wu et al.(Wu et al., 2006) as follows,

$$u_h'(x_j) = \left\{ 1 + \left[\frac{\sum_{i=1}^{m} [w_i(1-\mu(x_{ij})_h]^p}{\sum_{i=1}^{m} [w_i\mu(x_{ij})_h]^p} \right]^{\frac{\alpha}{p}} \right\}^{-1} \tag{7}$$

$$H = (1, 2, 3, 4) * u_h(x_j) \tag{8}$$

Here h is the degree number and h=1, 2, 3, 4, x_j represent sample j, x_{ij} is the i-th indicator value of sample j. So H is the synthetic degree value vector of every sample.

4 An example of the method to the flood loss degree assessment

According to the above model, we can calculated the flood risk estimation of various degree in China based on the historical data from 1950 to 2009 collected by the Ministry of Water Resources of the People's Republic of China. (see Table 1) We select the set of 60 records as the large sample, and then 30 records are randomly chosen to form a small sample in order to compare the results of them by the method. Damage area, inundated area, dead population, and collapsed houses have been chosen as the disaster indicators in flood risk analysis. By frequency analysis the floods are classified into four levels: small, medium, large and extreme (see Table 2).

Table 1: Values of flood indicators during 60 years

year	disaster area (thousand hectares)	inundated area (thousand hectares)	Dead Population (persons)	collapsed houses (ten thousand)
195 0	6559.00	4710.00	1982	130.50
195	4173.00	1476.00	7819	31.80

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year	disaster area (thousand hectares)	inundated area (thousand hectares)	Dead Population (persons)	collapsed houses (ten thousand)
1				
1952	2794.00	1547.00	4162	14.50
1953	7187.00	3285.00	3308	322.00
1954	16131.00	11305.00	42447	900.90
1955	5247.00	3067.00	2718	49.20
1956	14377.00	10905.00	10676	465.90
1957	8083.00	6032.00	4415	371.20
1958	4279.00	1441.00	3642	77.10
1959	4813.00	1817.00	4540	42.10
1960	10155.00	4975.00	6033	74.70
1961	8910.00	5356.00	5074	146.30
1962	9810.00	6318.00	4350	247.70
1963	14071.00	10479.00	10441	1435.30
1964	14933.00	10038.00	4288	246.50
1965	5587.00	2813.00	1906	95.60
1966	2508.00	950.00	1901	26.80
1967	2599.00	1407.00	1095	10.80
1968	2670.00	1659.00	1159	63.00
1969	5443.00	3265.00	4667	164.60
1970	3129.00	1234.00	2444	25.20
197	3989.00	1481.00	2323	30.20

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year	disaster area (thousand hectares)	inundated area (thousand hectares)	Dead Population (persons)	collapsed houses (ten thousand)
1				
197 2	4083.00	1259.00	1910	22.80
197 3	6235.00	2577.00	3413	72.30
197 4	6431.00	2737.00	1849	120.00
197 5	6817.00	3467.00	29653	754.30
197 6	4197.00	1329.00	1817	81.90
197 7	9095.00	4989.00	3163	50.60
197 8	2820.00	924.00	1796	28.00
197 9	6775.00	2870.00	3446	48.80
198 0	9146.00	5025.00	3705	138.30
198 1	8625.00	3973.00	5832	155.10
198 2	8361.00	4463.00	5323	341.50
198 3	12162.00	5747.00	7238	218.90
198 4	10632.00	5361.00	3941	112.10
198 5	14197.00	8949.00	3578	142.00
198 6	9155.00	5601.00	2761	150.90
198 7	8686.00	4104.00	3749	92.10
198 8	11949.00	6128.00	4094	91.00
198 9	11328.00	5917.00	3270	100.10
199 0	11804.00	5605.00	3589	96.60
199	24596.00	14614.00	5113	497.90

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year	disaster area (thousand hectares)	inundated area (thousand hectares)	Dead Population (persons)	collapsed houses (ten thousand)
1				
1992	9423.30	4464.00	3012	98.95
1993	16387.30	8610.40	3499	148.91
1994	18858.90	11489.50	5340	349.37
1995	14366.70	8000.80	3852	245.58
1996	20388.10	11823.30	5840	547.70
1997	13134.80	6514.60	2799	101.06
1998	22291.80	13785.00	4150	685.03
1999	9605.20	5389.12	1896	160.50
2000	9045.01	5396.03	1942	112.61
2001	7137.78	4253.39	1605	63.49
2002	12384.21	7439.01	1819	146.23
2003	20365.70	12999.80	1551	245.42
2004	7781.90	4017.10	1282	93.31
2005	14967.48	8216.68	1660	153.29
2006	10521.86	5592.42	2276	105.82
2007	12548.92	5969.02	1230	102.97
2008	8867.82	4537.58	633	44.70
2009	8748.16	3795.79	538	55.59

Table 2: Flood disaster rating standard

Disaster level	Damage area (thousand hectares)	Inundated area (thousand hectares)	Dead population (persons)	Collapsed houses (ten thousand)	Recurrence interval (years)	Grade number
Small flood	0~9045	0~4989	0~3446	0~112.1	<2	1
Medium flood	9045~14197	4989~8216.7	3446~5113	112.1~247.7	2~5	2
Large flood	14197~20388	8216.7~13000	5113~10676	247.7~754.3	5~20	3
Extreme flood	20388~80000	13000~50000	10676~100000	754.3~5000	>20	4

The two-level hierarchy that has been constructed to obtain the weights of the evaluation indicator is presented. In the figure, the goal is “the weights of the evaluation indicators”. All evaluation indicators (attributes) are listed under the goal. These are damage area, inundated area, dead population, and collapsed houses.

The pairwise comparison is made using a scale based on Saaty (Saaty, 1980) proposal , detailed in Table 3. To illustrate the kind of results obtained, Table 4 presents a pairwise comparison matrix drawn from the information provided from the expert for the evaluation of the importance of the factors. Then the consistency of the comparison matrix was tested and the relative weight of the elements was computed along with the consistency ratio as presented in Table 5. Since the consistency ratio (CR) is below 10%, then the judgments are considered consistent.

Table 3: Scale preferences used in the pairwise comparison process

Range	Category	Score
Superior	Absolutely superior	9
	Very strongly superior	7
	Strongly superior	5
	Moderately superior	3
Equal	Equal	1
Inferior	Absolutely inferior	1/9
	Very strongly inferior	1/7
	Strongly inferior	1/5
	Moderately inferior	1/3

Table 4: Pairwise comparison of the alternatives with respect to flood disasters

	damage area	inundated area	dead population	collapsed houses
damage area	1	1/3	1/7	1/5
inundated area	3	1	3/7	3/5

dead population	7	7/3	1	7/5
collapsed houses	5	5/3	5/7	1

Table 5: Vector of weights of the alternatives with respect to flood disasters

	Flood impact
damage area	0.0625
inundated area	0.1875
dead population	0.4375
collapsed houses	0.3125

And according to the Analytical Hierarchy Process (AHP) we obtain normalized weights of the evaluation indicators as: w = [0.0625 0.1875 0.4375 0.3125] = (w_i).

According to Table 2 and Chen (Chen, 1997), we set up values matrix of parameters for calculating difference function of VFS：

$$I_{[a,b]} = \begin{bmatrix} [0,9045] & [9045,14197] & [14197,20388] & [20388,80000] \\ [0,4989] & [4989,8216.7] & [8216.7,13000] & [13000,50000] \\ [0,3446] & [3446,5113] & [5113,10676] & [10676,100000] \\ [0,112.1] & [112.1,247.7] & [247.7,754.3] & [754.3,5000] \end{bmatrix}$$

$$I_{[c,d]} = \begin{bmatrix} [0,14197] & [0,20388] & [9045,80000] & [14197,80000] \\ [0,8216.7] & [0,13000] & [4989,50000] & [8216.7,50000] \\ [0,5113] & [0,10676] & [3446,100000] & [5113,100000] \\ [0,247.7] & [0,754.3] & [112.1,5000] & [247.7,5000] \end{bmatrix}$$

$$M = \begin{bmatrix} 0 & 10762 & 18324 & 80000 \\ 0 & 6064 & 11406 & 50000 \\ 0 & 4002 & 8822 & 100000 \\ 0 & 157 & 585 & 5000 \end{bmatrix}$$

Based on matrixes $I_{[a,b]}, I_{[c,d]}$ and M, we judge that evaluating indicator x locates at left side or right side of point M, and according these to select (1) or (2) for calculating difference function $\mu_h(u_{ij})$ of indicators to standards. Here h is grade number and h = 1, 2, 3, 4; i is indicators number and i = 1, 2,3,4; j is the sample number and $j = 1, 2 \cdots 32$,…60.

For example, for sample 1 and its 4th indicator-collapsed houses, i.e. i = 4, its attracting matrix [a, b], interval matrix [c, d] and point values matrix M respectively are

[a, b] = ([0, 112.1] [112.1, 247.7] [247.7, 754.3] [754.3, 5000]);

[c, d] = ([0, 247.7] [0, 754.3] [112.1, 5000] [247.7, 5000]);

M = (0 157 585 5000);

When i = 4, the value of collapsed houses of sample 1 is x_{41} = 130.50. First we calculate the relative membership degree (RMD) of x_{41} to the first degree, because of c_{41} = 0, a_{41} = 0, b_{41} = 112.1, d_{41}=247.7, M_{41} = 0, we can see that indicator value (130.50) locates at right side of point b_{41} and belongs to interval [b_{41}, d_{41}], so we select equation

$$\mu_A(u_{41}) = 0.5[1-(\frac{x_{41}-b_{41}}{d_{41}-b_{41}})^{\beta}] \quad \text{in Eq. (4).}$$

Substituting β=1 and other relevant parameters into this equation then we obtain $\mu_A(u_{41})$ = 0.4322. Analogously, we get relative membership function $\mu_A(u_{ih})$ of each single indicator under i = 1, 2, 3, 4 to degrees h = 1, 2, 3, 4 as:

$$u_A(x_1) = \begin{bmatrix} 0.6374 & 0.3626 & 0 & 0 \\ 0.5280 & 0.4720 & 0 & 0 \\ 0.7124 & 0.2876 & 0 & 0 \\ 0.4322 & 0.7035 & 0.0678 & 0 \end{bmatrix} \quad (9)$$

To get synthetic RMD of each indicator, we use variable fuzzy recognition model presented by Wu et al. (Wu et al., 2006)as follows,

$$u_h'(x_j) = \left\{ 1 + \left[\frac{\sum_{i=1}^{m} [w_i(1-\mu(x_{ij})_h]^p}{\sum_{i=1}^{m} [w_i \mu(x_{ij})_h]^p} \right]^{\frac{\alpha}{p}} \right\}^{-1} \quad (10)$$

$$H = (1, 2, 3, 4) * u_h(x_j) \quad (11)$$

Here h is the degree number and h=1, 2, 3, 4, x_j represent sample j, x_{ij} is the i-th indicator value of sample j. Firstly we may use variable fuzzy recognition model (10) to calculate synthetic relative membership degree of sample 1. With Formula (10) we obtain synthetic relative membership degree of each indicator for flood $u_h'(x_j)$, after normalizing them that we get normalized synthetic relative membership degree of each indicator $u_h(x_j)$. Here w_i is the above indicator weight; m is number of indicators and m=4; $\mu(x_{ij})_h$ is the above difference function of indicator i of the sample j to degree h; α is rule parameter of model optimization, α =1 is least single method and α =2 is least square method; p is distance parameter, p =1 is hamming distance and p =2 is Euclidean distance.

When taking rule parameter of model optimization α =2 and distance parameter p =2 and substituting relative data in (9) into model (10) we get synthetic relative membership degree $u_h'(x_j)$. After normalized it is $u_h(x_j)$ .Using Formula (11) we get disaster degree of sample 1 as H= 1.3571. In the same way, we can calculate the disaster degree values of all the 60 samples as shown in Table 6.

Table 6: The disaster degree values during the 60 years in China

Sample	Degree value	Degree	Sample	Degree value	Degree
1	1.3571	small	31	1.7174	medium
2	2.2648	medium	32	2.2289	medium
3	1.5536	medium	33	2.4889	medium
4	1.7778	medium	34	2.5849	large
5	3.3745	large	35	1.7503	medium
6	1.2042	small	36	1.7886	medium
7	3.2422	large	37	1.5728	medium
8	2.232	medium	38	1.6082	medium
9	1.4712	small	39	1.7737	medium
10	1.6809	medium	40	1.5097	medium
11	2.1472	medium	41	1.5923	medium
12	2.138	medium	42	2.7934	large
13	2.1344	medium	43	1.3841	small
14	3.5177	extreme	44	1.7698	medium
15	2.2334	medium	45	2.6973	large
16	1.1893	small	46	2.0392	medium
17	1.073	small	47	2.869	large
18	1.0226	small	48	1.4536	small
19	1.0632	small	49	2.4492	medium
20	2.0048	medium	50	1.4828	small
21	1.1223	small	51	1.305	small
22	1.1168	small	52	1.1254	small
23	1.0734	small	53	1.4897	small
24	1.3432	small	54	1.6739	medium
25	1.2588	small	55	1.1469	small
26	3.6992	extreme	56	1.517	medium
27	1.1365	small	57	1.3548	small
28	1.3071	small	58	1.2681	small
29	1.066	small	59	1.0558	small
30	1.3058	small	60	1.0536	small

Due to the standard of four grades(Chen SY, 2009), so we have :

(a) If $1.0 \leq H \leq 1.5$,then flood degree belongs to small.

(b) If $1.5 < H \leq 2.5$,then it belongs to medium.

(c) If $2.5 < H \leq 3.5$, then it belongs to large.

(d) If $3.5 < H \leq 4$, then it belongs to extreme.

Hence we judge that comprehensive flood loss evaluation (1.3571) belongs to small grade, the rest can be obtained in the same way. The results are showed in Table 6.

5 Conclusions

Floods occur frequently in China and cause great property losses and casualties. In order to implement a compensation and disaster reduction plan, the losses caused by flood disasters are among critically important information to flood disaster managers. The purpose of this study is to establish a fuzzy model to evaluate flood risk. This paper puts forward a method based on variable fuzzy sets (VFS) for disaster loss assessment. And the results indicates that the methodology is effective and practical so that it has the potentiality to be used to forecast the flood risk in flood risk management. It is also hoped that by conducting such risk analysis lessons can be learned so that the impact of flood disasters can be mitigated in the future.

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Figures:

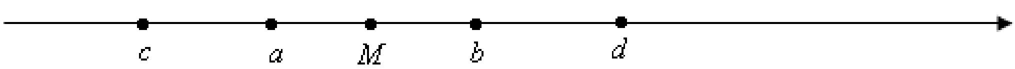

Figure 1 : Relationship between points X , M and internals [a, b], [c, d]