AN INTELLIGENT INFORMATION SYSTEM FOR FUZZY ADDITIVE MODELLING (HYDROLOGICAL RISK APPLICATION)

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Abstract. In this paper we propose and construct Fuzzy Algebraic Additive Model, for the estimation of risk in various fields of human activities or nature's behavior. Though the proposed model is useful in a wide range of scientific fields, it was designed for to torrential risk evaluation in the area of river Evros. Clearly the model's performance improves when the number of parameters and the actual data increases. A Fuzzy Decision Support System was designed and implemented to incorporate the model's risk estimation capacity and the risk estimation output of the system was compared with the output of other existing methods with very interesting results.

1. **Introduction**

Fuzzy logic models are universal approximators as they can model an arbitrary multivariate function to a given degree of accuracy. The higher the accuracy required, the more variables (with more linguistic values) and more rules are needed [10]. Actually a mapping of the form $R^n \rightarrow R^m$ takes place in an inference fuzzy model. Successful fuzzy modelling research efforts have been published recently in Bio and Earth Sciences [14],[16].

Risk evaluation is extremely important, because it can be very useful towards the design of prevention and protection measures and integrated policies. In this research effort, a risk estimation Fuzzy Additive Model (FAM) has been designed and applied to the Torrential Risk Estimation (TRE) in the mountainous watersheds of the river Evros, which is the natural border between Greece and Turkey; a part of its basin is also located in Bulgaria. This is a very crucial task, considering the great flood problems that were caused in 2005 in the wider area of the river basin and the hundreds of millions of Euros lost.

An effective Decision Support System (DSS) named FARIESYS (Fuzzy Additive Risk Evaluation System) was designed and implemented as a smart relational fuzzy database containing not only data but also fuzzy rules and facts.

Although the application of the FAM has a specific scope and orientation, its framework can be easily adjusted for other cases of risk management. Thus the FAM has a very wide potential significance and role, in the sense that it can be re-adjusted to act as a universal risk approximator with a very small effort.

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1.1. **Existing Methods and Necessity for a New Torrential Risk Model.** The equation of Gavrilovic, developed in 1972, is a very well established and effective means of indirect measuring the torrential risk of mountainous watersheds mainly by estimating the levels of erosion [13], [5] [6]. More specifically, it estimates the torrential risk based on the average annual load of sediments in m3/year. It is a popular and quite old statistical torrential risk estimation model which is still applied today [3] [4] [23]. Though it was slightly improved in 1998 [6] its nature remains deterministic and its philosophy has not changed much either. Another similar model, developed by Stiny in 1938 was still in use until recently [19]. However, modern mathematical and artificial intelligence tools offer more flexible and intelligent approaches towards natural hazards risk estimation.

In a completely dynamic system like a mountainous watershed, several properties and characteristics can change and this may cause a severe differentiation in the degree of torrential risk. For example, serious forest fire incidents may result in a heavily deforested watershed, which increases the level of torrential risk dramatically. This problem would not be considered by the equation of Gavrilovic [13] [5] for several years, and until the average recorded load of sediments starts increasing significantly on an annual basis. Existing models have a pure deterministic nature and they tend to adopt crucial changes in the values of significant environmental factors *very slowly.*

Four years ago, our research team developed a Decision Support System using fuzzy sets and fuzzy relations for the estimation of long-term torrential risk of mountainous watersheds [7][15]. This is not a rule based system. It evaluates partial degrees of risk due to different parameters and then unifies them by applying fuzzy T-norms. It is an innovative method with interesting results.

The research effort described here, introduces a rule based FAM approach that is implemented as a fuzzy database. It also compares this approach with other methods with regard to efficiency.

2. Materials and Methods

2.1. **Fuzzy Modelling.** There exist two types of sets: crisp and fuzzy. An element either belongs to a crisp set or it does not. We say that the membership function of a crisp set is a "*characteristic function*" wihich has only two values, 1 and 0. Crisp sets use specific boundaries and this is a serious disadvantage. Fuzzy sets can be used to produce rational and sensible clustering [26] [9] and elements of the real world belong to them with differing degrees of membership [25]. For every fuzzy set there exists a degree of membership $\mu_s(X)$ that is mapped onto [0,1] [26] [9] [8] [27]. A curve or triangle-like fuzzy set might define what the user or engineer means by the term "*cool air*". Each measured air temperature is both "*cool*" to a degree and partly "*not cool*". Hence fuzzy systems are "fuzzy" or vague. Human judgment or statistical learning must pick the shape of these sets. Figure 1 shows a fuzzy set, that models the term "*temperature*" as closest to the human thinking as possible.

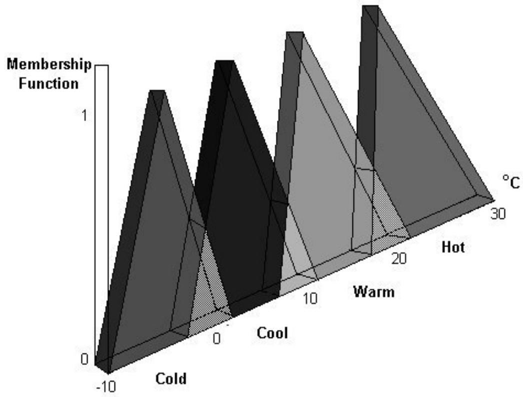

FIGURE 1. A Fuzzy Set Model for the Term "Temperature"

Effective fuzzy inference models require the use of "*If-Then*" fuzzy rules that capture knowledge in the same way as humans. "Humanlike" linguistics are used to describe situations closer to human intuition. For example, the "linguistic" terms "*Low rain-height*", "*Moderate rain-height*", "*High rain-height*", can be used to describe actual situations considering the rain-height in a specific area. When dealing with typical real life problems, many parameters are involved, each one of which can take many "linguistic" values. The more the parameters a model incorporates, the closer it is to the actual situation. The corresponding rules in such cases can take the following form R1:

R1: IF X1=low AND X2=moderate AND X3=low,..., AND Xi=very_high THEN Y=high

where i is the number of parameters involved.

Rule 1: Example of a potential multifactor Rule

In a hypothetical fuzzy model with three input variables using two, four and three linguistics respectively, the number of rules required is $N_R = 2*3*4 = 24$. It is important to note that these rules together form a union of rules. In other words, rules are implicitly connected by an OR operator, which can be represented by S-Norms in fuzzy algebra. Equation 1 calculates the number of the rules required by a fuzzy DSS (FDSS) [10].

Equation 1: Determining the number of rules required

$$N_S = n_{FS_1} * n_{FS_2} * ... * n_{FS_u} \tag{1}$$

where n_{FS_i} is the number of fuzzy sets (linguistics) for the ith input variable x_i and u is the number of input variables.

Fuzzy sets use membership functions $\mu_s(x)$ which are mappings of the universe of discourse X on the closed interval [0,1]. That is, the degree of belonging of some element x to the universe X, can be any number $\mu_s(x)$, where $0 \leq \mu_s(x) \leq 1$. The following Table 1 shows the five major steps that should be followed when designing fuzzy models [10].

Step#	Description of actions in each step
Step 1:	Define the Universe of discourse (e.g. domains, input and output parameters)
Step 2:	Specify the Fuzzy Membership Functions
Step 3:	Define the Fuzzy Rules
Step 4:	Perform the numerical part, like T-Norms, S-Norms or other custom inference
Step 5:	If not-Normal Fuzzy sets exist, perform Defuzzification

TABLE 1. Design Steps in Fuzzy Modeling

2.2. **Fuzzy Additive Modeling.** Fuzzy inference systems usually apply fuzzy "*If-Then*" rules to produce consequents. FAM are very powerful fuzzy modeling tools and they add the "*Then*" parts of all active rules, that is, they use the SUM operator. An Additive Fuzzy System (AFS) [10] [11] [12] is a mapping of the general form $F : R^n \to R^m$,that stores m rules of the form "*IF* $X = A_j$ *Then* $Y = B_j$," and adds the "fired" "*Then*" parts $B'_j(x)$ to give the output set $B(x)$ as shown in Equation 2.

Equation 2: The output of a typical FAM

$$B(x) = \sum_{j=1}^{m} w_j B'_j(x) = \sum_{j=1}^{m} w_j a_j(x) B_j(x) \text{ for scalar rule weights } w_j \neq 0 \quad (2)$$

The system described here is "fuzzy" [21],[22] or "vague" because the m rules correlate multivalued subsets of the input and output spaces. A fuzzy or multivalued set $A \subset R^n$ has a multivalued indicator function $a : R^n \to [0, 1]$. We call this map a set function or a "membership" function [15], because $a(x)$ measures the degree to which the object $x \in R^n$ belongs to the set $A : a(x) = Degree(x \in A)$. The "*Then-part*" set $B_j \subset R^p$ has a similar set function $b_j : R^p \to [0\ ,\ 1]$.

A finite discrete space $X = \{x_1, ..., x_n\}$ has a continuum of fuzzy subsets $A \in X$ in the form of fuzzy unit or *fit* vectors $A = (A_1, ..., A_n)$. We can write $a_i = a(x_i)$ for the discrete set function $a : X \to [0, 1]$ and hence each fuzzy set or fit vector defines a unique point in the unit hypercube $[0, 1]^n$[9] [10] [11]. This cube or sets-as-points framework extends to countable spaces X [11]. A rule patch $A_j X B_j \subset R^n X R^n$ has a set function $R_{A_j X B_j} : R^n X R^p \to [0, 1]$. This defines a fuzzy matrix in the finite case. The value of a rule patch most often equals a simple product of fit values at each point in the I/O state space: $R_{A_j} X B_j(x, y) = a_j(x).b_j(y)$[11].

The second sum in the above equation 2, states that the additive model is *standard* because it expands the fired "Then-part" set $B'_j(x)$with product scaling or correlation-product encoding: $B'_j(x) = a_j(x).B_j(x)$ for the "Then-part" set $B'_j(x)$[11].

Equation 3 shows the simplest form of a FAM also known as a Standard Additive Model. (SAM) [10].

Equation 3: A typical SAM model

$$Y = B(x) = \frac{\sum_{i=1}^{N} \mu(x, c_i) r_i}{\sum_{i=1}^{N} \mu(x, c_i)} \tag{3}$$

Here μ is the corresponding membership function (degree of belonging), N is the number of rules, and r_i stands for the center of the area (or center of gravity, centroid) of the ith output singleton.

When modeling an $R^1 \rightarrow R^1$ mapping, the equation 3 describes a standard fuzzy "*If-Then*" rule where $Y = B(x)$ is the consequent membership function [9]. Another, less general, SAM case is the so called TSK case. Sugeno and Terano [21], [22] call this the "third inference method" for how a fuzzy system f maps an input x to an output $f(x)$. Equation 4 below describes a typical TSK model.

Equation 4: A typical TSK model

$$f(x) = \frac{\sum_{j=1}^{m} a_j(x)[b_0^j + b_1^j * x_1 + ... + b_m^j * x_m]}{\sum_{j=1}^{m} a_j(x)} \tag{4}$$

In this case the ith rule will have the following form:

$$\textit{IF X=Aj THEN}\ Y = b_0^j + b_1^j * x_1 + ... + b_n^j * x_n$$

where the consequent "*Then*" part term describes a linear set function (a triangular [18] or a trapezoidal [9], [17]). The FAM given by equation 3 is valid when the output membership functions are singletons (the case when they have a single output value).

When the mapping is in the form of $R^n \rightarrow R^1$ the FAM function is as shown in Equation 5.

Equation 5: A FAM mapping $R^n \rightarrow R^1$

$$y = B(x) = \frac{\sum_{i=1}^{N} w_i \mu(x, c_i) A_i r_i}{\sum_{i=1}^{N} w_i \mu(x, c_i) A_i} \tag{5}$$

Again, N is the number of rules, w_i is the rule-weight which shows the degree of relevance of each r_i rule to the problem studied, A_i is the area of the corresponding ith (membership function) and r_i is the center of area, or center of gravity of the ith output fuzzy set. When the mapping is in the form of $R^n \rightarrow R^m$, a FAM is given by equation 6 below.

Equation 6: A FAM mapping Rn → Rm

$$y = B(x) = \frac{\sum_{i=1}^{N} w_i \mu(x, c_i) V_i r_i}{\sum_{i=1}^{N} w_i \mu(x, c_i) V_i} \tag{6}$$

We note that V_i is the volume of the corresponding membership function and w_i is the weight assigned to the ith rule.

3. The Torrential Risk Modelling

3.1. Parameters Used as Input-limitations of Data. It is well known that the river Evros basin and its mountainous watersheds are shared by Greece, Bulgaria and Turkey. The fact that the data we have at our disposal are only from the Greek part, makes this research effort a pilot one. However, considering that the major part of the river is located on the Greek side reduces the potential consequences of this problem.

For every research area and for each torrential stream the morphometric characteristics used as input to the system were specified. The morphometric characteristics were produced after the process of maps (scale 1:100.000) of the Greek Geographic Army Service (GAS) and the accuracy of the data was confirmed by visits of our research teams in the areas of interest. According to Kotoulas [13] and Stefanidis [20], the following morphometric characteristics of the watersheds that influence the torrential risk of an area most: The area, the perimeter, the shape of the watershed, the degree of the round shape of the watershed, the maximum altitude, the minimum altitude, the average altitude, the average slope of the watershed, and its maximum altitude.

Most of the proposed morphometric characteristics were applied based on the existing surveys. Surface characteristics like the percentage of forest cover and the compact geological forms of the ground surface were also considered and rain height, a very crucial torrential factor, was used as an input to the system [13] [20]. Of course, we do not claim that this model has considered all causal parameters or that it is better than the existing ones. What is for sure is that after 30 years a new method for estimating torrential risk is proposed and applied on a pilot basis.

It is important that this system considers most of the factors suggested in the watersheds management literature and all of the existing data from the Greek surveys. No model is perfect, but a model is good when it is useful and from this point of view, the approach described here is interesting. A real advantage of this approach is the fact that it views the problem as multiparametric and that any serious change in the characteristics of the area under study which have a real and direct effect in the produced degree of risk is taken into serious consideration.

3.2. Design of the FAM. Fuzzy approximate reasoning often makes use of linguistic variables [19]. The model was designed in so that each of the parameters involved in the problem of Torrential Risk Estimation can have three potential linguistic values, "*Low*", "*Moderate*" and "*High*". This means that the model can be divided in four separate sub-FAM, each one of them performing a mapping in the form of $R^2 \rightarrow R^1$.

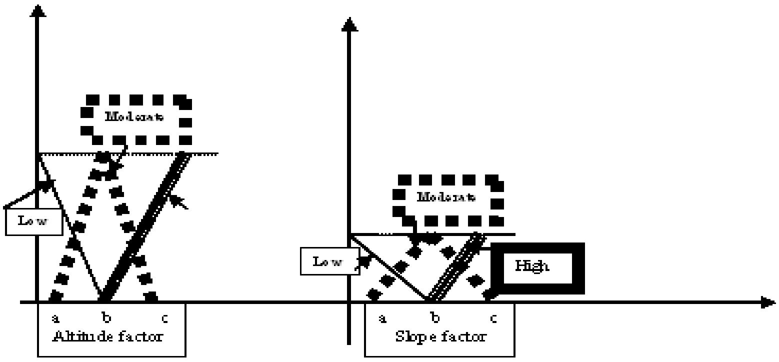

FIGURE 2. Graphical Representations of Altitude and Slope Membership Functions

The most serious problem in applying FAM is the rule explosion phenomenon [10]. The following Table 2 shows the input and the output of each sub-FAM.

	INPUT	OUTPUT
SUB-FAM 1	1. Slope 2. Altitude	Spatial_Risk
SUB-FAM 2	1.Forest_Cover 2.Compact_Geological _Forms	Surface_Risk
SUB-FAM 3	1. Spatial_Risk 2. Surface_Risk	Potential_Risk1
SUB-FAM 4	1. Potential_Risk1 2. Rain_Height	Overall_Torrential_Risk

TABLE 2. Structure of the FAM Incorporated

The total number of rules for such a model is:

$$N_R = \sum_{i=1}^{4} NR_i = NR_1 + NR_2 + NR_3 + NR_4$$

$$NR_1 = NR_2 = NR_3 = NR_4 = 3 * 3 = 9$$

Consequently there are 4*9=**36** rules in a potential DSS using this model. If we do not divide the rules into categories we would have 35=**243** rules. This means that the design of the model is very effective and it produces significant rule reduction and the constructed model deals with the problem of combinatorial explosion successfully. Figure 2 shows the five subsets (membership functions) that contribute their values as input to the FAM.

A small sample of a part of the rule-base has the following form:

If average slope is high and altitude is high then spatial risk is high
If forest cover is high and compact geological forms is high then surface risk is high
If spatial risk is high and surface risk is high then potential risk is high
If potential risk is high and rain height is high then total risk is high

The materialization of the FAM model requires the choice of three singletons (because three linguistics were used) for each parameter ; for each factor i used as input as shown in Table 2 and for each linguistic value corresponding to a code number j, a singleton membership function is chosen having the value of the centers of gravity of the corresponding triangle membership functions for river Evros, according to equation 7 [10].

Equation 7: Center of gravity calculation function is taken into serious consideration

$$r_{i\,j} = \frac{\sum_{j=1}^{N} \mu_j(x) X_j}{\sum_{j=1}^{N} \mu_j(x)_j}, \tag{7}$$

where μ_j are the membership values and x_j the input crisp values.

Triangular membership functions were used. In fact, they were Semi-Triangular, because after the point of the highest membership value, its reduction had no meaning. The formulation of the membership functions was based on the minimum and maximum values ever recorded in the area, for each parameter. The singleton values that were chosen for the parameters were defined based on data coming from Greece, and are shown in Table 3. If a higher maximum or a smaller minimum value is ever recorded, the membership function is adjusted automatically.

Parameter	MIN	A	C	B	MAX
Average Rain-Height (mm)	0	200	400	600	2000
Average Slope (%)	0	10	30	50	100
Average Altitude m	0	200	500	800	2900
Forest Cover (%)	0	10	19	30	100
Compact Geological Forms (%)	0	10	32	50	100

Table 3. Singletons Chosen for All Parameters

The values r_{11}, r_{12}, r_{13}, are the centers of gravity that correspond to the linguistics "low" "moderate" and "high" respectively, for the factor of slope. Also r_{21}, r_{22}, r_{23}, are centers of gravity that correspond to the linguistics "low" "moderate" and "high" respectively, for the factor of altitude and so on.

A weighted version of equation 3 has been used in this research effort as the SAM function.

For a crisp input, for example an altitude of 1200m and a slope of 15%, the FAM value representing the Spatial Risk will be as shown in Equation 8.

Equation 8: Estimation of the spatial risk

B=f(1200,15)=

$$\frac{w_1 * [(\mu_{L_1} * r_{11}) + (\mu_{M_1} * r_{12}) + (\mu_{H_1} * r_{13})] + ... + w_i * [(\mu_{L_i} * r_{i1}) + (\mu_{M_i} * r_{i2}) + (\mu_{H_i} * r_{i3})]}{(\mu_{L_1} + \mu_{M_1} + \mu_{H_1}) + ... + (\mu_{L_i} + \mu_{M_i} + \mu_{H_i})} \tag{8}$$

Again, μ_{L_i} is the membership value of a watershed for factor i for the linguistic “low” μ_{M_i} for the linguistic “moderate” and μ_{H_i} for the linguistic “high”. The value of i varies from one to eight as it equals to the number of input parameters evolved. Of course, the weights w_i can be also assigned depending on expert opinion regarding the influence of the i compared with that of j.

3.3. **The Software.** FARIESYS was implemented as a relational fuzzy database that comprises of tables following the three main normal forms [2]. The proper relations of the form “1 to 1” and “1 to many” were defined between the tables.

The software was developed using Microsoft Access, because its reasoning requires the proper retrieval and use of a vast amount of data, which have to be organized and used in a fast and accurate way to ensure their integrity. Various composite SQL (**S**tructured **Q**uery **L**anguage) and fuzzy SQL [1] statements are applied every time the system is executed in order to materialize all of the membership functions and the FAM functions and of course to retrieve the proper data when necessary.

Generally, fuzzy queries are applied combining many fuzzy sets. In the case of multiple fuzzy sets we search for cases that have, to some degree, characteristics of our combined concepts [1]. An example of a fuzzy query is shown in the statements below:

Select watershed_name
from watershed_table
where altitude is high
and rain_height is high
and forest_cover is high;

To answer this type of fuzzy queries, the computer system needs to know what constitutes a high altitude, a high rain_height and a high forest_cover area. Instead of using specific crisp boundaries, we use fuzzy relations. When the degree of membership of a watershed to a respective fuzzy set is greater than zero, there obviously exist cases with a positive degree of membership with respect to the fuzzy set D={watershed with high altitude and with high rain height and with high forest cover}. The conjunction degree of membership is determined by using

FAM [1]. For the purpose of demonstration, such a relation is shown in table 4 for hypothetical data.

watershed name	altitude	rain height	forest cover	(altitude)	(rain height)	(forest cover)
n1	980	200	0.55	0.7	0.7	0.6
n2	1200	500	0.40	0.8	0.9	0.5
n3	50	99	0.08	0	0	0
n4	780	89	0.12	0.65	0	0.1

Table 4. Example of the Fuzzy Meaning of Terms

For evaluating the fuzzy SQL statements, the watersheds *n1* and *n2* in table 4 will be characterized as having high rain height and high altitude and high forest cover.

Obviously, the database does not only contain primitive data but it also a large amount of rules and formulas. In general terms it can be considered as data-driven.

Finally, the user interface was designed to be operational, graphical and friendly. The user can not only perform a risk evaluation, but he can also store new sets of data by adding records to the tables.

4. **Area of Application**

The application area is located in the Northeastern part of Greece near the border of Greece Bulgaria and Turkey. This area contains the most important torrential streams of the Greek watershed of river Evros and was chosen due to its serious torrential phenomena. The testing area was divided into three main sub-areas based on hydrologic and geologic homogeneity criteria and according to the use of land.

The area of river Evros was divided into the sub-areas of Northern Evros, Central Evros and Southern Evros. Finally, these sub-areas were further were divided into numerous parts, each containing an important stream or river watershed. The watersheds were encoded using integer numbers. In the rest of the paper we will refer to the torrential watersheds by number.

The division of the river Evros area in the three sectors was carried out as follows:

a. The sector of Northern Evros, which includes the torrential streams of the northern part of the Evros prefecture and the torrential streams of the river Ardas.

b. The sub-area of Central Evros, which includes the torrential streams of the Erithro- potamos river and extends to the south to the Likertzotiko stream in the area of Lyras-Laginon.

c. The division of Southern Evros, which includes the remainder of the Evros prefecture.

Data was gathered from the Greek public services responsible for meteorological and map data storage. Maps of the Geographical Army Service (GAS) on a scale of 1:250.000 were used for this purpose. The most important elements of the relief were recorded and the most important rivers (*"Evros", "Filiouris", "Ardas", "Erythropotamos"*) were located. These rivers accept the main volume of the torrential streams of the area. Then the torrential streams of each sub-area were located from the maps (scale 1:100.000) of the GAS and their limits were defined. For this reason, we considered the largest streams that comply with the sub-areas of our study. The main river beds of the rivers *Evros, Filiouris, Ardas, Erythropotamos* and their secondary streams were defined. The upper and lower limits of the watershed areas are 300 and 2 km2 respectively [13].

5. **Results**

The FARIESYS system was applied using equal weights for all the factors affecting the problem. Of course, various scenarios can be considered by assigning different weights of to the parameters involved.

The system was applied to the 15 streams of Northern Evros, the 39 streams of Central Evros and the 24 streams of Southern Evros (totally 78 streams) in order to determine the most risky ones. The results for the fifteen most risky watersheds, a small part of the final results, are shown in Table 5.

From Table 5 one can see that the most risky streams are located in Central Evros, followed by the southern and by the northern sub-areas. This is an initial overall risk estimation approach. The three most risky watersheds are c40, c39 and c2 (all located in Central Evros) followed by s22, s9 of the Southern and by n1 of the Northern. The least dangerous streams are in the Northern and in the Southern divisions and the least risky stream of Central area is still ten times more risky than those of the other locations.

6. **Discussion-comparison with Other Existing Methods**

The complete lack of a survey recording the actual flood incidents in the area of river Evros, makes the comparison of the system's output to the actual flood cases impossible. However, a risk analysis was performed by using other methods and the outputs were compared.

The results of FARIESYS were compared with those obtained by using Gavrilovics equation [13], [6] in order to investigate their level of compatibility.

The compatibility between FARIESYS and Gavrilovics equation is as high as 55% for the Central Evros, 75% for Southern Evros and 62.5% for Northern Evros. However, it is inreresting that for the Central Evros area and for the first eleven most risky watersheds we have compatibility equal to 82% whereas for Southern Evros this compatibility is as high as 90% and for Northern 80%. This means that the developed system in several cases has a high level of compatibility with the Gavrilovic model, but, on the other hand, in many cases its results are different as it offers a new overall approach that considers many more independent parameters.

Northern Evros watershed code	Overall Risk	Central Evros watershed code	Overall Risk	Southern Evros watershed code	Overall Risk
n1	0.124334914	c40	0.174545322	s22	0.133222953
n5	0.118509904	c39	0.158531313	s9	0.128665567
n15	0.109608758	c2	0.136254026	s16	0.116176228
n13	0.104317223	c41	0.125909271	s6	0.112887851
n4	0.101655232	c37	0.119916846	s14	0.109847436
n14	0.101484425	c3	0.118374169	s8	0.109256207
n6	0.096112121	c38	0.11580816	s24	0.096519785
n2	0.085716643	c6	0.114584299	s23	0.096331258
n12	0.084940679	c1	0.114455195	s2	0.096276739
n11	0.084626054	c7	0.113442895	s21	0.09599664
n3	0.08419557	c4	0.112656116	s5	0.091967935
n7	0.081931824	c11	0.112075942	s1	0.088849006
n10	0.081849315	c8	0.111526155	s3	0.08822652
n8	0.081816231	c9	0.110908632	s10	0.087818135
n9	0.081326748	c10	0.110608491	s18	0.084678558

TABLE 5. The Fifteen Most Risky Watersheds in Each of the Three Sub-areas

There seems to be a high level of compatibility in several cases, which suggests that this is just an indicative comparative analysis with encouraging results. However, no certain validity conclusions can be drawn if we do not record torrential phenomena in the watersheds of Evros for several years.

The difference of the innovative proposed approach for some watersheds was expected because the developed FAM considers many more risk factors compared to the equation of Gavrilovic. Thus, when the history of the load of sediments manages to capture the actual degree of risk, the two models seem to agree. On the other hand when new incidents like deforestation or change in the rain high level occur, the FARIESYS seems to capture the actual degree of risk immediately whereas the existing approaches need time to do so.

Again, various scenarios can be considered by assigning different weights to the FAM input parameters which cannot be done by the Gavrilovic equation. This could be the subject of a future research effort.

Finally, the results of FARIESYS were compared with the results from another fuzzy risk evaluation system (using T-Norms) which was also developed by our research team [4]. This method uses conjunction operators to unify the torrential risk. It offers different T-Norm operators and thus different estimations of the torrential risk under various perspectives. For example when the Drastic Product norm is applied, it characterizes as areas of highest risk only the ones that have extreme values for one or more factors. Other T-Norms act as overall risk estimators.

The comparative study between the two fuzzy systems has proven that, in the case of the Algebraic Product T-Norm [24] and for the area of Southern Evros, regardless of the membership function (MF) used, the compatibility of the two systems was equal to 76.6%. On the other hand, in the case of the Trapezoidal MF and the Einstein T-Norm, the compatibility was at most 73.3%.

In the case of Northern Evros, the compatibility was equal to 80% regardless of the MF or the T-Norm applied. All of these comparisons were made for the first eleven most risky watersheds of each sub-area.

In the future, data concerning the load of sediments in each of the examined watersheds should be gathered, and actual serious torrential phenomena (marked on a scale 1-5) should be assigned to each torrential stream. In this way, the evaluation process will obtain the actual efficiency of the system and also to compare it with the actual efficiency of other accepted methodologies.

In addition, future extensions can include more parameters and, of course, more linguistics in the original model.

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