

A Hybrid Soft Computing Approach Producing Robust Forest Fire Risk Indices

Vardis-Dimitris Anezakis¹, Konstantinos Demertzis^{1(✉)},
Lazaros Iliadis¹, and Stefanos Spartalis²

¹ Lab of Forest-Environmental Informatics and Computational Intelligence,
Democritus University of Thrace, 193 Pandazidou st., 68200 Orestiada, Greece
{danezaki, kdemertz, liliadis}@fmenr.duth.gr

² Laboratory of Computational Mathematics, School of Engineering,
Department of Production and Management Engineering,
Democritus University of Thrace,
V.Sofias 12, Prokat, Building A1, 67100 Xanthi, Greece
sspart@pme.duth.gr

Abstract. Forest fires are one of the major natural disaster problems of the Mediterranean countries. Their prevention - effective fighting and especially the local prediction of the forest fire risk, requires the rational determination of the related factors and the development of a flexible system incorporating an intelligent inference mechanism. This is an enduring goal of the scientific community. This paper proposes an Intelligent Soft Computing Multivariable Analysis system (ISOCOMA) to determine effective wild fire risk indices. More specifically it involves a Takagi-Sugeno-Kang rule based fuzzy inference approach, that produces partial risk indices (PRI) per factor and per subject category. These PRI are unified by employing fuzzy conjunction T-Norms in order to develop pairs of risk indices (PARI). Through Chi Squared hypothesis testing, plus classification of the PARI and forest fire burned areas (in three classes) it was determined which PARI are closely related to the actual burned areas. Actually we have managed to determine which pairs of risk indices are able to determine the actual burned area for each case under study. Wild fire data related to specific features of each area in Greece were considered. The Soft computing approach proposed herein, was applied for the cases of Chania, and Iliia areas in Southern Greece and for Kefalonia island in the Ionian Sea, for the temporal period 1984–2004.

Keywords: Takagi-Sugeno-Kang · Fuzzy inference system · T-Norms · Chi-Square test · Individual indices · Unified index · Forest fires

1 Introduction

Greece has a very important forest capital, as 50 % of the territory is covered by woodland. About 25 % of it is characterized by high vegetation coniferous and broadleaf high biodiversity, the remaining of low trees and shrubs near inhabited areas. Also there are approximately 2 million acres of rangelands. During the last 20 years, the average annual burned areas in the country are higher than 45,000 acres as a result

of 1500 forest fires. The determination of the factors that favor ignition and contribute to the spread of wild fires (WF) requires a detailed spatiotemporal analysis of the historical data for each area under study. Moreover, the specification of the correlations between these parameters is absolutely necessary. This research paper proposes an innovative hybrid forest fire modeling system operating on a local basis. The reasoning of the ISOCOMA employs Computational Intelligence approaches in order to produce an overall fire risk index.

1.1 Literature Review

Iliadis and Betsidou [9] have implemented an intelligent rule based fuzzy inference system (FIS) evaluating wild fire risk for the forest departments of Greece. The estimation of the risk indices was done by using fuzzy triangular membership functions and Einstein fuzzy conjunction T-Norms. Iliadis and Zigkrika [11] have also developed a FIS that performs and evaluates scenarios (by assigning weights to the involved features) towards the estimation of a characteristic overall forest fire risk index in Greece. Papakonstantinou et al. [17] have proposed a fuzzy rule based system to produce the drought risk indices vectors for the forest regions of Cyprus under study. Iliadis et al. [10] have developed a fuzzy inference system under the MATLAB platform. The system uses three distinct Gaussian distribution fuzzy membership functions in order to estimate the partial and the overall risk indices due to wild fires in the southern part of Greece. Özbayoğlu and Bozer [16] estimated the potential burned areas using geographical and meteorological data. Several computational intelligence approaches were used namely: Multilayer Perceptron (MLP), Radial Basis Function Networks (RBFN), Support Vector Machines (SVM) and fuzzy logic. Shidik and Mustofa [18] used a Back-Propagation Neural Network which was trained based on meteorological and forest weather indices, so as to classify the burned area in three categories. Aldrich et al. [1] investigated the effect of variations in land use and climate in the occurrence of forest fires. Catry et al. [6] used logistic regression models to predict the relative probability of ignition occurrence, as a function of the resulting fire size.

1.2 Innovations of the Proposed Methodology

The main innovation of the ISOCOMA is the development of four partial risk indices (PRI), which are derived from the respective analysis of separate parameters, creating and analyzing meaningful relationships and rules of correlations between them. This raises the problem of wild fires (WF) on an absolutely realistic basis. In addition, it is for the first time that an intelligent system combines the use of an adaptive fuzzy inference Takagi-Sugeno-Kang (AFITS) system with the wide use of fuzzy conjunction T-Norms in order to obtain higher fitting rates between PRI and TPRI with the actual burned areas.

1.3 Data

The first step towards the development of an overall wild fire risk index model was the determination of all factors that affect the behavior of a forest fire. The data collected from the forest inspections and from the Hellenic national meteorological service. According to [12] the following factors have been identified as playing a key role (Table 1).

Table 1. Factors affecting fire behavior

Flammability of vegetation	Monthly rainfall
Canopy density	Previous month rainfall
Vegetation density	Altitude
Air temperature	Slope
Relative humidity	Ground orientation
Wind speed, daily rainfall	Exposure

Utilizing and analyzing in-depth studies in the raw meteorological, topographical and vegetative data of the areas concerned [3, 4] the following categories were obtained (Table 2).

Table 2. Classification of the fire parameters

	Parameters	Class1	Class2	Class3	Class4	Class5	Class6
Meteorological	Wind	0–1 bf	1.1–4 bf	4.1–7 bf	7.1–9 bf	>9.1 bf	
	Air temperature/relative humidity	Low risk	Medium risk	High risk			
Topographic	Slope	0–20 %	21–40 %	41–60 %	61–80 %	81–100 %	>100 %
	Ground Orientation Exposure	Unspecified	North	South	East	West	
	Altitude	Low	Medium	High			
Vegetation	Canopy Density	Absent	Rare	Full			
	Vegetation Density	Absent	Rare canopy < 0.4	Dense canopy > 0.4			
	Flammability of vegetation	Low risk	Medium risk	High risk			
Drought	Rainfall (Daily, Monthly, Previous Month)	Low	Medium	High			

1.4 Areas of Study

Kefalonia (island in the Ionian Sea) Ilia (prefecture in Peloponnese) and Chania (prefecture in Crete island) have been chosen as the areas of interest. They have rich vegetation, they have protected areas (under Natura network) and their climate is dry and hot with low rain height. Also both Chania and Kefalonia are characterized by high touristic development and growth with high land value. On the other hand ancient Olympia is located in Ilia prefecture. Thus, it is an area of high cultural and touristic

value. During the period 1984–2014, totally 1397 wild fires occurred in Iliia, 857 in Chania and 1298 in Kefalonia.

The Fire Ignition Indicator (FIGI) which emerges by combining the effect of temperature and humidity and the Spread Index which considers the effect of wind and slope (SPRI) have been used to produce significant evidence of forest fire risk. In a previous research effort of our team [2] have found that the SPRI is “High” in the 30–50 % of the cases, whereas the FIGI has shown smaller high and medium hazard rates.

2 Theoretical Framework and Methodology

2.1 Fuzzy Inference Systems

The Sugeno Fuzzy implication is the basic modeling approach used by the ISOCOMA. Introduced in 1985 [19], it is similar to the Mamdani method. While Mamdani FIS uses the technique of defuzzification of a fuzzy output, Sugeno FIS uses weighted average to compute the crisp output. The fuzzy membership functions (FMF) of the output are either linear (first order polynomials or constant crisp values). A typical rule in a Sugeno fuzzy model if the outputs are first-order linear has the form:

$$\text{If Input 1} = x \text{ and Input 2} = y \text{ then Output is } z = ax + by + c \quad (1)$$

For a zero-order Sugeno model, the output level z is a constant crisp value c ($a = b=0$).

The output level z_i of each rule is weighted by the firing strength w_i of the rule. For an AND rule with Input 1 = x and Input 2 = y , the firing strength is

$$w_i = \text{AndMethod} (F_1(x), F_2(y)) \quad (2)$$

where $F_{1,2}$ are the membership functions for Inputs 1 and 2. The final output of the system is the weighted average of all rule outputs, computed as in (3).

$$\text{Final output} = \frac{\sum_{i=1}^N w_i z_i}{\sum_{i=1}^N w_i} \quad (3)$$

where N is the number of rules.

2.2 T-Norms

This paper attempts to calculate the Unique Overall Risk Index (UORI), resulting from the cumulative effect of all the related factors, after performing integration operations on all individual fuzzy sets. This task is carried out, by the use of specific fuzzy conjunction “AND” operators (CONO) known as T-Norms in the literature. The Min, the Algebraic, the Drastic, the Einstein and the Hamacher Products act as T-Norms [5, 7, 13–15]. The T-Norms are the unifiers of partial risk indices and they are quite optimistic as they are assigning the minimum risk value to the overall index [8].

2.3 Chi-Square Test

The Chi-Squared hypothesis-testing is a non-parametric statistical test in which the sampling distribution of the test statistic is a chi-square distribution when the null hypothesis is true. The null hypothesis H_0 usually refers to a general statement or default position that there is no relationship between two measured phenomena, or no difference among groups. The H_0 is assumed to be true until evidence suggest otherwise [20]. The statistical control index used for this assessment is the test statistic X^2 .

$$X^2 = \sum \frac{(f_o - f_e)^2}{f_e} \quad (4)$$

Where f_e is the expected frequency and f_o the observed one. The degrees of freedom are estimated as follows (based on the $r \times c$ table of labeled categories):

$$df = (r - 1)(c - 1) \quad (5)$$

For the H_0 the critical values for the test statistic X^2 are estimated by the X^2 distribution after considering the degrees of freedom. If the result of the test statistic is less than the value of the Chi-Square distribution, then we accept H_0 otherwise we reject it.

3 Description of the Proposed Methodology

The core of the modeling approach proposed herein was based on the grouping of twelve initial fire risk indices in four classes of partial risk indices and subsequently their integration into a unique overall one, the Conceptual Risk Index (CRI), for each fire incident and for each area of study. Then based on the burned area, the Actually Burned Surfaces Index (ACBUS) was determined. Moreover, we performed fuzzy conjunction (with T-Norms) of the four CRI $_i$ indices ($i = 1 \dots 4$) selecting all combinations of pairs in order to find those that belong to the same Linguistics with the ones of ACBUS. For example, we tried to estimate the forest fire incidents that were assigned “High Risk” pairs of indices and at the same time “High Risk” ACBUS ones.

3.1 The Algorithm

The proposed algorithmic process involves 9 distinct steps, which are discussed below:

1. Evaluating the twelve initial features influencing the phenomenon of forest fires and subsequently grouping them conceptually, in four thematic areas (feature categories). A distinct Conceptual Risk Index (CRI) has been developed for each feature category, totally four of them CRI $_i$ ($i = 1 \dots 4$). More specifically, the Weather Risk Index (WRI) was constructed from the contribution of temperature, humidity and wind speed. Correspondingly the drought index (DRI) comprises of the daily plus the monthly precipitation and of the precipitation in the previous month.

The topographic Risk index (TRI) is related to the slope to the altitude and to the exposure. The vegetation Risk index (VRI) is defined by the flammability of forest species, the canopy density and the vegetation density. The same methodology has been followed for all three areas under study.

2. The Fuzzy Inference Engine Takagi-Sugeno-Kang (FIETS) has been used. According to it, each feature is fuzzified based on properly designed fuzzy Trapezoidal membership functions. In this way each parameter of each incident has been assigned fuzzy risk linguistics.
3. This process determines the corresponding fuzzy set (linguistic) for each wild fire incident.
4. Proper fuzzy weighted rule sets have been designed and implemented. The number of the trapezoidal fuzzy membership functions used for the determination of each partial risk index related to each one of the 12 parameters, was determined by the number of its corresponding classes in Table 2. The number of fuzzy sets created for each feature, were exactly as many as its corresponding classes in Table 2. For the topographic parameter “Ground Orientation Exposure” the first class was removed because it was declared officially as unspecified (Tables 3 and 4).

Table 3. Fuzzy Sets and the corresponding Linguistics of each feature

	Kefalonia	Chania	Ilia
Air temperature	3 Low(L), Medium (M), High(H)	3 L, M, H	3 L, M, H
Relative humidity,	3 L, M, H	3 L, M, H	3 L, M, H
Daily rainfall	3 L, M, H	3 L, M, H	3 L, M, H
Monthly rainfall	2 M, H	3 L, M, H	3 L, M, H
Previous month rainfall	3 L, M, H	3 L, M, H	3 L, M, H
Altitude	3 L, M, H	3 L, M, H	3 L, M, H
Flammability of vegetation	3 L, M, H	3 L, M, H	3 L, M, H
Canopy density, vegetation density	3 Very Low(VL), L, H	3 VL, L, H	3 VL, L, H
Wind speed	4 L, M, H, Very High(VH)	5 L, M, H, VH, Ultra High(UH)	5 L, M, H, VH, UH
Slope	5 VL, L, M, H, VH,	6 VL, L, M, H, VH, UH	6 VL, L, M, H, VH, UH
Ground orientation exposure	4 VL, L, M, H	4 VL, L, M, H	4 VL, L, M, H

It should be clarified that in the following Table 5, the fuzzy values of the involved features are connected with the Min T-Norm (Table 6).

5. Each of the four CRIs has been calculated. The output of the Sugeno-type FIS takes values in the closed interval [0, 1] (Table 7).

Table 4. Conceptual Fuzzy Sets and the Linguistics of the (CRI)

	WRI	DRI	TRI	VRI	UORI
Kefalonia	5L, M, H, VH, UH	3L, M, H	4L, M, H, VH	4 L, M, H, VH	5 L, M, H, VH, UH
Chania	5L, M, H, VH, UH	3L, M, H	4L, M, H, VH	4 L, M, H, VH	5 L, M, H, VH, UH
Iliia	4L, M, H, VH	3L, M, H	4L, M, H, VH	4 L, M, H, VH	5 L, M, H, VH, UH

Table 5. Fuzzy rule set (T-Norms Fuzzy-AND) for the determination of the WRI

Humidity	Air temperature	Wind speed	WRI
H	L	L	L
H	L	M	L
H	M	L	L
H	M	M	M
H	M	H	M
H	M	VH	M
H	H	H	H
H	H	VH	UH
M	L	L	L
M	L	M	L
M	L	H	L
M	M	L	L
M	M	M	M
M	M	H	L
M	M	VH	H
M	M	UH	H
M	H	L	L
M	H	M	M
M	H	H	H
M	H	VH	VH
M	H	UH	VH
L	L	L	L
L	L	M	L
L	L	H	L
L	M	L	L
L	M	M	L
L	M	H	L
L	M	VH	L
L	M	UH	M
L	H	M	L
L	H	H	L

Table 6. Number of rules in the fuzzy rule sets use for the determination of each CRI and for the UORI for each area.

	WRI	DRI	TRI	VRI	UORI
Kefalonia	23	8	44	20	46
Chania	23	11	50	18	61
Iliia	33	12	47	21	68

Table 7. Four CRIs and UORI membership functions

Linguistics of CRIs and UORI	Constant values
Low	0
Medium	0.5
High	0.9
Very High	0.95
Ultra High	1

6. The UORI has been produced by adjustment of the weights of the fuzzy rules (Table 7).
7. The actual burned area for each area under study has been fuzzified by obtaining four fuzzy Linguistics representing the Actually Burned Surfaces (ACBUS_{ij}) $i = 1 \dots 4$ and $j = 1 \dots N$ (N is the number of examined cases) namely: Low Burned (LBUR), Average Burned (ABUR), High Burned (HBUR) and Extremely Burned (ExBUR). Subsequently, a comparative analysis has been performed between the four CRIs and the UORI with the ACBUS for each case (Table 8).

Table 8. ACBUS is a two dimensional matrix as it is shown below. N is the number of the areas under study

$\mu_{11} = \text{LBUR}_{11}$	$\mu_{12} = \text{ABUR}_{12}$	$\mu_{13} = \text{HBUR}_{13}$	$\mu_{14} = \text{ExBUR}_{14}$
$\mu_{21} = \text{LBUR}_{21}$	$\mu_{22} = \text{ABUR}_{22}$	$\mu_{23} = \text{HBUR}_{23}$	$\mu_{24} = \text{ExBUR}_{24}$
....
$\mu_{N1} = \text{LBUR}_{N1}$	$\mu_{N2} = \text{ABUR}_{N2}$	$\mu_{N3} = \text{HBUR}_{N3}$	$\mu_{N4} = \text{ExBUR}_{N4}$

8. The fuzzy T/Norms (Algebraic, Drastic, Einstein, Hamacher - products, Min relation) have been applied through the combination of all four (4) ACBUS membership values (in pairs) in order to perform three distinct risk scenarios.

Totally six Pair Risk Indices (PARI) have been developed by considering the partial indices in pairs.

a. Conjunction between the:

- (i) Meteorological Indices (MI) AND the Drought indices (DRI) which produces the (MIDRI)

- (ii) The Topographic indices (TI) AND the Vegetation indices (VEGI) that produces the (TIVEGI). Thus, two Pair Risk Indices (PARI) have been developed namely: the MIDRI and the TIVEGI.
 - b. Conjunction between the:
 - (i) MI AND the TI which produces the (MITI)
 - (ii) The DRI AND the VEGI which produces the (DRIVEGI). Also two Pair Risk Indices have been developed the MITI and the DRIVEGI.
 - c. Conjunction between the:
 - (i) MI AND the VEGI which produces the (MIVEGI)
 - (ii) DRI AND the TI that produces the (DRITI). Moreover two Pair Risk Indices have been designed MIVEGI and DRITI.

Totally for each research area 5 (the number of T-Norms) * 6 (the number of PARI) = 30 cases were obtained.

9. Use of the Chi-Square Statistical Test at significance level of $\alpha = 0.05$ in order to obtain the PARI where the three Linguistics (low, medium, high risk) are depended on the three corresponding linguistics (low, medium, high Burned) of the ACBUS. The tables used were $3 * 3$ and the degrees of freedom $df_4 = 9,488$ (Fig. 1).

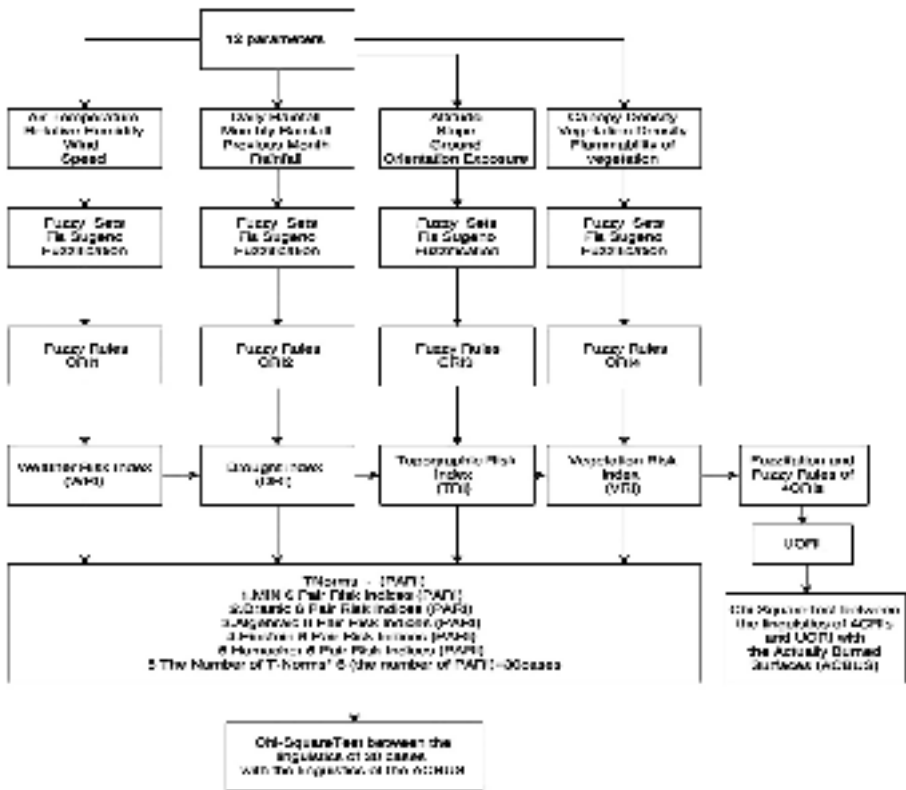


Fig. 1. Flowchart of the proposed methodology

4 Results and Discussion

After extensive testing on multiple scenarios and different methods for the examination of all possible coupling combinations of forest fire severity for Sites Kefallonia Chania and Iliia, important conclusions were drawn on what indicators determine the risk of burned areas. The best Linguistic fitting with the ACBUS indices was derived from the UORI and from the combination of MI-TI PARI for all areas. The DRI and other combinations like the DRIVEGI did not show high convergence with the actual burned areas (Table 9).

Table 9. Test statistic and P-Value between four CRIs and UORI with ACBUS

T-Norms	MI- ACBUS	DRI- ACBUS	TI- ACBUS	VEGI- ACBUS	UORI- ACBUS
<i>Ileia</i>					
Test statistic	27.58	0.82	31.37	15.45	180.18
P-Value	0.00001	0.9344	0.00001	0.0038	0.00001
<i>Kefalonia</i>					
Test statistic	105.22	0.316	1.4	3.34	716.04
P-Value	0.00001	0.988	0.843	0.5	0.00001
<i>Chania</i>					
Test statistic	42.45	0.68	67.67	7.76	258.07
P-Value	0.00001	0.9531	0.00001	0.1	0.00001

For the Iliia prefecture, the MI and the TI and all of their combinations have shown an important influence on the actual burned areas. According to the X squared test the null hypothesis was rejected which has proved the dependency. Moreover, the DRI-VEGI and the MIVEGI indices have shown a rather minor effect on the determination of the actual burned areas (small Test Statistic-higher P-Value). On the other hand, the burned area has proven to be independent from the MIDRI PARI.

In Kefalonia the MI index and all of its combinations have proved to have great influence in the burned areas. The result was the opposite for the other indices (TI, VEGI, DRI).

In Chania, the TI and MI indices and all of their combinations have shown a high correlation with the total burned areas (high Test Statistic values and Low P-Value). The DRIVEGI does not seem to be correlated to the burned areas (Tables 10 and 11).

Summarizing and evaluating the four indicators studied it was proved that the MI and the TI are the key factors that affect the severity of forest fires whereas beyond any expectation the DRI was not the catalyst or retarding factor in the spread of forest fires. Also from the examined pairs of indices, the combination of MI-TI has shown the highest test Statistic and the highest correlation with the ACBUS index.

Finally, it was observed that the fuzzy T-NORMS relations, constitute a highly reliable method for the development of a unified overall risk index (UORI) which is capable of modeling a very complex problem by combining several parameters or partial indices.

Table 10. P-Values between the linguistics of the PARI and the linguistics of the ACBUS

T-Norms	MIDRI	TIVEGI	MITI	DRIVEGI	MIVEGI	DRITI
<i>Ileia</i>						
MIN	0.33	0.00001	0.00001	0.004	0.01	0.00001
Algebraic	0.29	0.00001	0.00001	0.004	0.0029	0.00001
Drastic	0.51	0.00001	0.00001	0.02	0.01	0.00001
Einstein	0.289	0.00001	0.00001	0.0018	0.012	0.00001
Hamacher	0.33	0.00001	0.00001	0.004	0.011	0.00001
<i>Kefalonia</i>						
MIN	0.00001	0.63	0.00001	0.50	0.005	0.84
Algebraic	0.00001	0.52	0.00001	0.49	0.00001	0.84
Drastic	0.00001	0.83	0.00001	0.55	0.00001	0.78
Einstein	0.00001	0.93	0.00001	0.47	0.00001	0.84
Hamacher	0.00001	0.61	0.00001	0.50	0.00001	0.84
<i>Chania</i>						
MIN	0.00001	0.00001	0.00001	0.10	0.00001	0.00001
Algebraic	0.00001	0.00001	0.00001	0.09	0.47	0.37
Drastic	0.00001	0.00001	0.00001	0.09	0.00001	0.00001
Einstein	0.00001	0.00001	0.00001	0.09	0.00001	0.00001
Hamacher	0.00001	0.00001	0.00001	0.10	0.00001	0.00001

Table 11. Test statistic between the linguistics of the PARI and the linguistics of the ACBUS.

T-Norms	MIDRI	TIVEGI	MITI	DRIVEGI	MIVEGI	DRITI
<i>Ileia</i>						
MIN	4.6	59.06	291.5	15.01	12.55	35.6
Algebraic	4.91	265.12	484.55	15.05	16.05	40.67
Drastic	3.28	67.51	475.69	11.57	13.18	33.78
Einstein	4.97	35.82	468.27	11.88	12.8	40.97
Hamacher	4.6	60.78	329.19	15.01	12.97	41.58
<i>Kefalonia</i>						
MIN	71.89	2.57	646.13	3.33	14.55	1.4
Algebraic	71.93	3.19	646.62	3.39	215.76	1.4
Drastic	59.04	1.45	646.53	3.02	323.87	1.72
Einstein	78.19	0.79	649.64	3.53	215.81	1.4
Hamacher	78.15	2.65	646.28	3.3	217.39	1.4
<i>Chania</i>						
MIN	45.62	49.63	153.57	7.68	38.55	66.85
Algebraic	42.46	54.67	124.43	7.87	3.5	4.25
Drastic	42.98	39.86	113.23	7.87	34.88	70.65
Einstein	43.5	55.01	113.38	7.87	39.48	67.88
Hamacher	42.46	33.25	118.89	7.7	41.35	66.98

5 Conclusions and Future Work

This research proposes the use of an innovative method for the analysis and study of the main parameters related to forest fires. The proposed approach was developed towards the estimation of the UORI (forest fire severity index) which is based on advanced soft computing techniques. More specifically, a fuzzy inference system was developed. After the performance of extensive testing, the actual interrelationships between the involved parameters were discovered and hidden knowledge was revealed. This modeling research effort has yielded high rates of accurate classifications as a result of a comparative analysis between the obtained indices and the ACBUS. The function of the model was tested in consideration with various scenarios and presented important outcome regarding those indices or their pairs which directly determine the forest fires risk.

It is important to mention that it is the first time that so many parameters are used and combined to estimate the potential severity of wildfires, creating numerous individual indicators in order to construct a unified index that highly reflects the ACBUS.

As future directions that could improve the proposed model we suggest the potential use of more parameters directly related to forest fires in order to create more combinations of fuzzy rules and sub-indicators. In this way it will be possible to derive an even stronger final adaptive unified index compatible with the ACBUS.

Finally, we propose the future use of other machine learning methods (unsupervised - competitive learning) or hybrid soft computing approaches (fuzzy-neural networks) and optimization algorithms aimed at even higher rates of correct classification.

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