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ORIGINAL PAPER

# Hybrid intelligent modeling of wild fires risk

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**Abstract** Forest fires are one of the most serious natural disasters for the countries of the Mediterranean basin and especially for Greece. Studying the climate change effect on the maximization of the problem is a constant objective of the scientific community. This research initially proposes an innovative hybrid version of the statistical Chi-Square test that employs Soft Computing methods. More specifically it introduces the Fuzzy Chi Square Independence test that fuzzifies p values using proper Risk Linguistics, based on Fuzzy Membership functions. In the second stage, it proposes a new Hybrid approach that models the evolution of burned areas in Greece. First it analyzes the parameters and determines the way they affect the problem, by constructing Fuzzy cognitive maps. The system projects into the future and forecasts the evolution of the problem through the years till 2100, based on the variance of average monthly temperature and average rain height (due to climate change) for the months May–October based on various climate models. Historical data for the period 1984–2004 were used to test the system for the areas of *Chania* and *Ilia*.

**Keywords** Fuzzy Chi Square test · Fuzzy cognitive maps · Correlation analysis · Forest fires · Climate change models

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## 1 Introduction

### 1.1 The evolving nature of the proposed system

Greece has a very important forest capital, as 50% of its 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. Based on historical data of the Greek Ministry of Environment and Energy for the years 1980–2008, the average annual burned areas in the country are more than 48,000 acres as a result of 1600 forest fires (http://www.ypeka.gr).

The precise quantification of future burnt areas using climate change models primarily requires a detailed spatiotemporal analysis of historical data of the study area and the search for correlations between the involved parameters that create and maximize the problem.

This research effort proposes an innovative forest fire modeling system, based on hybrid Soft Computing and Statistical methods. The system's core is built on the dynamic assessment of the dependences between the parameters associated with the burned areas, through the employment of Fuzzy cognitive maps (FCM). The evolutionary nature of the model is due to the dynamic nature of the climate change phenomenon. Modeling the constant temporal variation of climatic factors through the years, presupposes the development and adoption of an Evolving approach and a respective Information System, capable to evaluate all kinds of effects on the burned area problem over time. The produced FCM manage to dynamically capture the extent of the problem and the degrees of dependences through sliding spatiotemporal windows.

### 1.2 Literature review

The contribution of the meteorological parameters, drought, topography and vegetation in forest fire risk assessment has been widely studied and supported by many research efforts (Fang et al. 2015; Stagl and Weidinger 2016; Jellouli et al. 2016; Scasta et al. 2016; Holsinger et al. 2016; Fidanova and Marinov 2016; Armenteras et al. 2016; Eberle et al. 2015; Calviño-Cancela et al. 2017).

Correlation analysis is a common approach for the determination of the feature vectors that determine and maximize forest fire risk (Hamadeh et al. 2017; Shan et al. 2017). More specifically, Hamadeh et al. 2017 used correlation methods such as statistical regression, Pearson, Spearman and Kendall's Tau correlation to identify the most affecting parameters on fire ignition during the last 6 years in north Lebanon. The correlations of these attributes with fire occurrence were studied in order to develop the fire danger index. Shan et al. (2017) used a linear regression model to analyze linear trends between climate and fire weather indices with time treated as an independent variable. Moreover correlation analysis was used to detect correlations between fire frequency, areas burned, and fire weather indices. Dugan and Baker (2015) reconstructed and compared tree recruitment pulses evident in forest age structures within plots with tree ring reconstructions of pluvials, drought, forest fires and fire quiescence (longer fire-free periods). They used Chi Square (ChiSq) analysis to test for sequential contingency of combinations and permutations of pulse influences. Pasquet et al. (2015) evaluated changes in species composition using the Sørensen dissimilarity index in species frequency, with Chi Square goodness-of-fit tests and in species cover using one-sample t-tests. Schoennagel et al. (2011) argued that the proportion of total tree and sapling establishment was significantly different among equal time periods based on a Chi Square test, with highest tree and sapling establishment during the pre-fire-suppression period (1835–1919).

Anezakis et al. (2016a) proposed an Intelligent Soft Computing multivariable analysis system, to determine effective wild fire risk indices. More specifically they employed a Takagi–Sugeno–Kang rule based fuzzy inference system that produced partial risk indices (PRI) per factor and per subject category. These PRI were unified by using fuzzy conjunction operations (T-Norms) (Iliadis 2007; Iliadis and Papaleonidas 2016) in order to develop pairs of risk indices (PARI). The system determined which PARI were closely related to the actual burned areas. Through Chi Square hypothesis testing, plus classification of the PARI and forest fire burned areas (in three classes).

Many research efforts have employed climate change models produced by the CMIP5 and CORDEX programs, in an effort to perform short term forest fire risk and burned areas forecast (Miao and Tian 2016; Kerr et al. 2016; Wang et al. 2017). Meteorological and topographic data related to historical periods, have been used for this purpose.

Also Davis et al. (2017) modeled the normal fire environment for occurrence of large forest wildfires for the Pacific Northwest Region of the US. Large forest wildfire occurrence data from the recent climate normal period (1971–2000) was used as the response variable and fire season precipitation, maximum temperature, slope, and elevation were used as predictor variables. A projection of their model onto the 2001–2030 climate normal period showed strong agreement between model predictions and the area of forest burned by large wildfires from 2001 to 2015 (independent fire data). They then used downscaled climate projections for two greenhouse gas concentration scenarios and over 30 climate models to project changes in environmental suitability for large forest fires over the twenty-first century.

Moreover Tian et al. (2016) established a forest fire risk assessment model and index system based on the classic natural disaster risk model and available data, and the model was used to assess the forest fire risks in past and future. The future climate scenario data included outputs from five global climate models for RCPs respectively. Each component index of Fire Weather Index (FWI) system was calculated daily for each grid in 1987–2050 for the historical observations and future climate scenarios according to the maximum temperature, minimum relative humidity, wind speed and daily precipitation.

According to the literature, there is a serious gap in the use of FCM for the determination of the parameters influencing forest fire risk.

Štula et al. (2011) developed a FCM providing aid in image post-processing decision support, aiming towards the false alarm reduction in a forest fire monitoring system. It has been shown that FCM based post processing decision support, can greatly improve the overall system performance and diminish the false alarms rate. Carvalho et al. (2006) focused on the modeling and simulation of forest fire propagation using Dynamic Cognitive Map Cellular

Automata. Rule Based Fuzzy cognitive maps were used to represent the evolution of burning areas in Voronoi region.

Taheri et al. (2016) extended the classical methods of analysis of a two-way contingency table to the fuzzy environment. The α-cuts approach was used to extend the usual concepts of the test statistic, resulting in the use of fuzzy test statistic and fuzzy p values. In addition, some measures of association were extended to the fuzzy version in order to evaluate the dependence in such contingency tables.

Lin et al. (2012) used a Chi Square test of homogeneity to determine whether the cell probabilities of a multinomial are equal. This process of testing hypotheses was based on the assumption of two-valued logic. Huang (2012) compared ethnic majority and ethnic minority students' perception in secondary school. This research used fuzzy statistical analysis as a research tool. Taheri and Hesamian (2011) tested the hypothesis of independence using a novel method of decision making based on the concept of fuzzy p value. Grzegorzewski and Szymanowski (2015) proposed a method for constructing a generalized version of the Chi Square test of homogeneity on fuzzy data. According to Gil et al. (1988) if the hypothetical distribution involved unknown parameters, the extension of the Chi Square test required the estimation of those parameters from fuzzy data. Moreover, they proved that under certain assumptions the minimum inaccuracy principle of estimation from fuzzy observations provides a suitable method.

The above review clearly shows that there are efforts in the literature towards the fuzzification of the statistical Chi Square test. However to the best of our knowledge, such hybrid approaches have not been used in environmental risk modeling and more specifically for the case of forest fire risk.

### 1.3 General description and innovation elements

Given that the Chi Square test offers a bivalent logic estimate regarding Independence or Dependence (InD/Dep) between the examined variables and it is unable to give the exact degree of dependence or independence, we propose a novel method to cover this gap and go one step further. As it has already been mentioned the proposed Fuzzy Chi Square test (FChiSq) fuzzifies the p values by producing proper Linguistics which express Low Medium or High degree of InD/Dep. In this way we go much further than binary results in a wider spectrum of outcomes. This is a big improvement in the approach which becomes more flexible and rational.

This research proposes an innovative system for the recording, analysis and study of the features related to forest fires. In this way it achieves a medium and long term forecasting of the extent of burned areas. More specifically, the system performs a symbolic descriptive representation and visualization of complex positive or negative correlations between meteorological, topographic and vegetation data to the severity of forest fires, with the development of Fuzzy cognitive maps. This is achieved by using historical data of the Ilia and Chania prefectures for the period 1984–2004.

Moreover, the output degree of positive or negative influence of the involved features is used to determine the *fuzzy weights* during the design of the FCM.

The model introduces a sophisticated method for the forecasting of burnt areas. This is done by considering the fluctuation of *the average–minimum–maximum monthly temperature* and average *monthly rainfall* values, as they are estimated by the climate models of the late project Coupled Model Inter-comparison Project Phase5 (*CMIP5*) in the four climate change scenarios. The temporal window was the long period up to the year 2100.

All of the data features included in the following Table 1 regarding the season (May–October 1984–2004) were introduced to obtain the FCM. More specifically, the data used to be connected, included the meteorological, topographic and vegetation values recorded at the site of each forest fire incident and additionally the monthly average values of the meteorological parameters. The aim was the determination of the relative changes in the connected features (reflecting changes in the values of the burned areas) caused by the differentiation of the meteorological parameters' values.

The examination of various change scenarios related to the monthly meteorological parameters using climate models, contributed to the calculation of the burned areas extent for each climate change scenario applied. In this way we can estimate the future relative changes in all of the parameters affecting forest fire spread. This projection can be done based on monthly meteorological values till the year 2099. Thus, we can have a clear assessment of the changes in parameter values and burned areas every 6 months (May–October) for each application scenario, based on the historical recorded fire incidents.

**Table 1** Factors affecting fire behavior on a daily basis

| Flammability of vegetation | Monthly rainfall until the record of the rainfall day |
|---|---|
| Canopy density | Previous month rainfall |
| Vegetation density | Altitude |
| Air temperature | Slope |
| Relative humidity | Ground orientation |
| Wind speed | Exposure |
| Daily rainfall | Minimum monthly temperature |
| Average monthly temperature<br>Monthly rainfall | Maximum monthly temperature |

An investigation of all interactions between the factors affecting the behavior of forest fires was performed, in order to assess the association of them with the level of destructiveness of such incidents.

Initially, correlation analysis was employed for the determination of all potential positive and negative relations between the involved parameters. Moreover, Fuzzy $\chi^2$ test was used to estimate real numbers corresponding to the degree of dependences among the independent features and the burned forest areas.

Additionally, previous research efforts of our team (Anezakis et al. 2016a) have introduced four partial risk indices (PRI) derived from the fuzzy aggregation of 12 parameters and leading to meaningful relationships and rules of correlations between them. 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. Our research has discovered correlations between the four above indices and the actual burned areas. Anezakis et al. (2016a) has used data, originating from the period 1984 to 2004 from the prefectures of Chania, Ilia and Kefalonia. The data related to the period 1984–2004 were collected from the forest inspections and from the Hellenic National Meteorological service. According to our research efforts (Anezakis et al. 2016a) the following factors have been identified as playing a key role in the problem of forest fires in Greece.

It is quite supportive to mention that the work of Kailidis (Kailidis 1990) one of the most important scientists regarding the forest fire problem in Greece is in total agreement with our feature model. Utilizing and analyzing in-depth studies in the raw meteorological, topographical and vegetative data of the areas concerned, the following categories were obtained (Bougoudis et al. 2015, 2016a, b). The results can be seen in the following Table 2.

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, Chania is 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 Ilia, and 857 in Chania.

We have employed fuzzy sets (*Linguistics*) for most of the involved features to properly determine their classes. This is a flexible, rational and effective way of representing real world concepts. However this approach was not possible for the parameters *wind, slope and ground orientation exposure*, due to the fact that they were classified and stored by using crisp boundaries in the initial database of the Greek Ministry of Environment and Energy. Thus it was not possible to obtain fuzzy sets. This particularity did not have a serious impact on the research carried out since

**Table 2** Classification of the involved parameters

| | Parameters | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 | Class 6 |
|---|---|---|---|---|---|---|---|
| Unified meteorological index | Wind (bf) | 0–1 | 1.1–4 | 4.1–7 | 7.1–9 | >9.1 | |
| | Air temperature | | | | | | |
| | Relative humidity | | | | | | |
| | Minimum monthly temperature | Low risk | Medium risk | High risk | | | |
| | Maximum monthly temperature | | | | | | |
| | Monthly rainfall | | | | | | |
| Unified Topographic index | Slope (%) | 0–20 | 21–40 | 41–60 | 61–80 | 81–100 | >100 |
| | Ground orientation exposure | Unspecified | North | South | East | West | |
| | Altitude | Low | Medium | High | | | |
| | Canopy density | Absent | Rare | Full | | | |
| Vegetation index | Vegetation density | Absent | Rare canopy <0.4 | Dense canopy >0.4 | | | |
| | Flammability of vegetation | Low risk | Medium risk | High risk | | | |
| Drought index | Rainfall (daily, monthly. previous month) | | | | | | |
| | Monthly rainfall until the record of the | Low | Medium | High | | | |

each class contains different boundary values and distinct characteristics. For example, class 1 contains the smallest wind intensity values and class 5 the highest ones. The form of these classes does not pose a problem as we assign the Linguistic very low risk to Class 1 and very high risk to class 5.

Each class related to the Ground Orientation Exposure feature, indicates a different degree of forest fire risk where southern exposures being considered as the most dangerous one.

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 Anezakis and Iliadis (2015) 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.

than the value of the Chi Square distribution then we accept $H_0$ otherwise we reject it Greenwood and Nikulin (1996).

The calculated p value prices include the possibility of error in the range [0–1]. Each error value is multiplied by 10, raised to the negative sixth power $\left(pvalue \times 10^{-6}\right)$. The p value equal to a is considered as boundary and it cannot determine the dependence or independence between the variables. The dependence is defined with p values < a, whereas the independence with p values > a.

In the next step the p values are fuzzified by the use of Fuzzy Chi Square test, according to the specified confidence interval and to the significance level. This process of course requires proper Fuzzy Membership functions (FMF) which were developed for the dependence (p value < a) in the closed interval [0–0.049999] and for the independence (p value > a) in the closed interval [0.050001–1]. This was done to produce the proper Linguistics. The following MATLAB commands were used to enhance the above for the Linguistics Low, Medium and High (Table 3).

$$\begin{aligned}
HighDependence &= trimf(dependence, [-0.020000\ 0.000000\ 0.020000]) \\
MediumDependence &= trimf(dependence, [0.005000\ 0.025000\ 0.045000]) \\
LowDependence &= trimf(dependence, [0.030000\ 0.049999\ 0.070000]) \\
\mathrm{LowIndependence} &= \mathrm{trimf(independence}, [-0.329900\ 0.050001\ 0.430001]) \\
\mathrm{MediumIndependence} &= \mathrm{trimf(independence}, [0.145100\ 0.525100\ 0.905000]) \\
\mathrm{HighIndependence} &= \mathrm{trimf(independence}, [0.620000\ 1.000000\ 1.380000]),
\end{aligned}$$

## 2 Theoretical frameworks and methodology

### 2.1 Chi Square Test and Fuzzy 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 (Corder and Foreman 2014; Greenwood and Nikulin 1996). The statistical control index used for this assessment is the test statistic $\chi^2$.

$$\chi^2 = \sum \frac{(f_o - f_e)^2}{f_e}, \tag{1}$$

where $f_e$ is the expected frequency and $f_o$ the observed one. The degrees of freedom are estimated as follows (based on the rXc table of labeled categories):

$$df = (r - 1)(c - 1), \tag{2}$$

For the $H_0$ the critical values for the test statistic $\chi^2$ are estimated by the $\chi^2$ distribution after considering the degrees of freedom. If the result of the test statistic is less

It should be specified that trimf is the MATLAB command for the Triangular fuzzy membership function (Table 4).

### 2.2 Correlation analysis

In order to test the level of linear relationship between meteorological parameters and air pollutants, the typical

**Table 3** Indicative degrees of membership of the dependency linguistics (Interval [0–0.049999])

| p value | Linguistics | High | Medium | Low |
|---|---|---|---|---|
| 0 | High | 1 | 0 | 0 |
| 0.00001 | High | 0.99945 | 0 | 0 |
| 0.012499 | High | 0.37505 | 0.37495 | 0 |
| 0.0125 | High/medium | 0.375 | 0.375 | 0 |
| 0.012501 | Medium | 0.37495 | 0.37505 | 0 |
| 0.03 | Medium | 0 | 0.75 | 0 |
| 0.035 | Medium | 0 | 0.5 | 0.2500125 |
| 0.037499 | Medium | 0 | 0.37505 | 0.374968 |
| 0.0375 | Low | 0 | 0.375 | 0.3750187 |
| 0.049999 | Low | 0 | 0 | 1 |

**Table 4** Indicative degrees of membership of the independency linguistics (Interval [0.050001–1])

| p value | Linguistics | Low degree of membership | Medium degree of membership | High degree of membership |
|---|---|---|---|---|
| 0.050001 | Low | 1 | 0 | 0 |
| 0.05001 | Low | 0.99997 | 0 | 0 |
| 0.287550 | Low | 0.374871 | 0.374868 | 0 |
| 0.287551 | Medium | 0.374868 | 0.374871 | 0 |
| 0.4301 | Medium | 0 | 0.75 | 0 |
| 0.71505 | Medium | 0 | 0.5 | 0.25013157 |
| 0.762518 | Medium | 0 | 0.375051 | 0.375047 |
| 0.762519 | High | 0 | 0.375048 | 0.375050 |
| 1 | High | 0 | 0 | 1 |

relativity analysis was performed, using the parametric correlation coefficient of Pearson (r). The Pearson linear correlation coefficient between two parameters X and Y is defined based on a sample of n pairs of observations $(x_i, y_i)$ $i=1,2,\ldots,n$, and it is denoted as $r\ (X, Y)$ or more briefly as $r$. The variables $\bar{x}$ and $\bar{y}$ are the averages of $(x_i, y_i)$. The $r$ is the covariance (CovX,Y) of the two variables divided by the product of their standard deviations (sx,sy). It is given by the following Eq. (1):

$$r = \frac{s_{xy}}{s_x s_y} = \frac{\sum_{i=1}^{v}\left(x_i-\bar{x}\right)\left(y_i-\bar{y}\right)}{\sqrt{\sum_{i=1}^{v}\left(x_i-\bar{x}\right)^2}\sqrt{\sum_{i=1}^{v}\left(y_i-\bar{y}\right)^2}} = \frac{\sum_{i=1}^{v} x_i y_i - v\bar{x}\bar{y}}{\sqrt{\sum_{i=1}^{v} x_i^2 - v\bar{x}^2}\sqrt{\sum_{i=1}^{v} y_i^2 - v\bar{y}^2}}. \tag{3}$$

The correlation coefficient (Rodgers and Nicewander 1988) is a pure number in the interval [−1, 1]. More specifically, when $0 < r \leqslant 1$,then $X, Y$ are linearly positively correlated and when $-1 < r < 0$, then $X, Y$ are negatively correlated. When $r=0$ or close to zero there is no correlation between them.

### 2.3 Fuzzy cognitive maps

FCM are fuzzy-graph structures. In the model of a fuzzy cognitive map, the nodes are linked together by edges and each edge connecting two nodes describes the change in the activation value. The direction of the edge implies which node affects the other. The sign of the causality relationship is positive if there is a direct influence, negative if there is an inverse influence relation and zero if the two nodes are uncorrelated. The causal relationships are described by the use of fuzzy linguistics and they are fuzzified by using membership functions taking values in the closed interval [−1, 1] (Papageorgiou and Salmeron 2013; Salmeron and Froelich 2016; Vidal et al. 2015).

Unlike the majority of complex dynamic systems, characterized by nonlinearity and high uncertainty, the Fuzzy cognitive maps use advanced learning techniques in order to choose appropriate weights for the causal connections between the examined variables. This is done in order to reflect the examined problem with absolute realism.

Combining the theoretical background of fuzzy logic, FCM cover the comparison and characterization purpose of the reference sets, towards modeling and solving complex problems for which there is no structured mathematical model. The FCM constitute a very strong tool towards modeling multi-parametric environmental risk cases like air pollution or even climate change (Anezakis et al. 2016b; Anezakis 2015).

### 2.4 Climate change scenarios used

Climate change is the most important environmental risk globally. Our team has already modeled complex systems related to climate change and its direct impacts including increased air pollutants concentrations in the atmosphere (Bougoudis et al. 2014, 2015, 2016a, b; Anezakis et al. 2016b; Anezakis 2015; Iliadis et al. 2014). The Intergovernmental named “Committee International Panel on Climate Change” (IPCC) which deals with the assessment of climate change is an international scientific body which until today has published five reports. The aim of the program (CMIP5) that was defined in the Fifth Assessment Report on Climate Change (IPCC-AR5, Assessment Report 5) was the design of climate models, aiming to estimate future climatic changes both in the short and in the long range. This objective is achieved by using Earth System Models (ESM) and global climate ocean–atmosphere coupling models “Atmospheric-Ocean General Circulation Models” (AOGCMs).

The latest report (AR5) finds significant improvement in the models to analyze mechanisms of temperature and precipitation, in the study of anthropogenic impact on the environment and in the study of the biochemical cycles. According to the report, four future scenarios of *Green-House* Gases (GHGs) concentration in the atmosphere have been developed. These scenarios are known in the literature under the RCPs acronym (Representative Concentration Pathways).

In the RCP2.6 scenario, a small increase in the emissions of greenhouse gases till the mid of the decade, would result in an increase of the solar radiation (SR) as high as 3 $W/m^2$ by 2050 and then in a decrease to the level of 2.6 $W/m^2$ by 2100.

In the scenarios RCP4.5 and RCP6.0, a moderate increase in the greenhouse gases emissions, would result in the increase of SR. In RCP4.5 the solar radiation values stabilize at about 4.5 $W/m^2$ before 2100 and respectively in the RCP6.0 they are stabilized at 6.0 $W/m^2$ after 2100.

Finally, in the most extreme scenario (RCP8.5) with rapid and continuous increase of the GHGs the SR rises as high as 8.5 $W/m^2$ and continues to rise after 2100. The climate models *bcc_csm1_1, bcc_ csm1_1_m, ccsm4, cesm1_cam5, csiro_mk3_6_0, fio_esm, gfdl_cm3, gfdl_esm2m, giss_e2_h, giss_e2_r, ipsl_cm5a_mr, miroc_esm, miroc_esm_chem, miroc5, mri_cgcm3, noresm1_m* of the CMIP5 project were employed in this research, as the most modern and reliable for finding changes in temperature and precipitation for the time period 2020–2099 Scafetta and Wilson (2014).

## 3 Description of the proposed methodology

The basic proposed modeling methodology of the forest fires problem is based on the determination of the correlations between the independent and depended variables that influence the break and favor the spread of forest fires. It employs and proposes a hybrid Fuzzy Chi Square test approach, which calculates the degree of correlation of two variables, based on the fuzzy membership grades of the p values to properly designed fuzzy sets.

Moreover, various climate models obtained by the project (CMIP5) were used for the forecasting of the burned areas values till 2100. This projection is performed by using Fuzzy cognitive maps. The entire algorithmic process involves seven distinct stages in each study area (Ilia and Chania), which are discussed below. In all of the following steps data for the period May–October 1984–2004 were used.

Step 1: Initially, 16 parameters related to wildfires are evaluated. It should be clarified that each distinct parameter has a significant influence in the extent of the burned areas. A hybrid fuzzy Chi Square statistical approach is employed, aiming to determine the actual degree of dependence or degree of independence of the features, by fuzzifying the p value values in the closed interval [0, 1].

The fuzzification of the p values is performed after the statistical test (Test Statistic). The hybrid Fuzzy Chi Square test indicates the degree membership of the p values to the Linguistics *Low, Medium, High*. In this flexible way, we can obtain a more accurate judgment of the degree of dependence or independence.

Correlation analysis has been performed between the variables under consideration: humidity (H), air temperature (AT), wind (W), daily rainfall (DR), previous month rainfall (PMR), monthly rainfall until the record of the rainfall day (MRRRD), altitude (A), slope (S), ground orientation exposure (GOE), canopy density (CD), vegetation density (VD), flammability of vegetation (FV), burned areas (BA), minimum monthly temperature (MINMT), maximum monthly temperature (MAXMT), average monthly temperature (AMT), monthly rainfall (MR). https://ams.confex.com/ams/7firenortheast/webprogram/Paper126829.html.

Through this fuzzy process, we have managed not only to model the Linguistics of Positive or Negative correlation but we have obtained the level of correlation as well. This approach determines the level of influence between the involved parameters. Finally, the correlation values (positive or negative) were used as fuzzy weights in the design of the FCM.

Step 2: Partitioning of the variables with negative correlation from the ones with positive correlation is performed with the use of the assigned Linguistics over the initial crisp values. Three successive and overlapping triangular membership functions are employed in order to classify the correlations to the corresponding fuzzy sets (Linguistics) "*Low*", "*Medium*" and "*High*". The following Table 5 presents clearly the fuzzification of the correlation results (assignment of the corresponding Linguistics).

Step 3: All of the associated parameters are added and named and then they are interconnected by synapses to create the causal positive or negative correlations. The design of the FCM following the input and the interconnection of all correlated variables, based on the Linguistics that emerged after the fuzzification of the crisp numerical values.

The fuzzification of the correlations, i.e. the description of each interface in verbal common terms was accomplished by selecting six Linguistics namely: three positive scales [low positive (+), middle positive (++), high positive (+++)]. Three negative scales [low negative (−), middle negative (−−), high negative (−−−)] corresponding to fuzzy weights (Table 6).

The algorithm simulating the interactions between two nodes of the FCM was implemented by performing a repetitive calculation of the new link value corresponding to each node. This value depends on the weight of the node from which an edge begins and also on the weight of the edge joining the two nodes. The transfer function estimates the new value of each node and the weight of each connection. The negative type of influence is depicted with an orange color and the positive with a blue color. The degree of influence depends on the thickness of each line (Table 7). The higher the influence the thicker the line, as you can see in the Fig. 1.

The degree of influence between some variables depicted in the Fig. 1.

**Table 5** Fuzzification of the parameters correlation for the prefecture of Ilia

| | H | AT | W | DR | PMR | MRRRD | A | S | GOE | CD | VD | FV | BA | MINMT | MAXMT | AMT | MR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| H | 1 | −− | − | + | + | + | − | + | − | + | + | + | − | − | − | − | + |
| AT | −− | 1 | + | − | −− | − | − | + | − | + | − | − | + | ++ | ++ | ++ | − |
| W | − | + | 1 | + | − | + | + | + | − | − | + | − | + | − | − | − | + |
| DR | + | − | + | 1 | + | + | + | − | − | + | − | + | − | − | − | − | + |
| PMR | + | −− | − | + | 1 | + | + | + | + | + | + | + | − | −− | −− | −− | + |
| MRRRD | + | − | + | + | + | 1 | − | − | + | + | + | − | − | − | − | − | + |
| A | − | − | + | + | + | + | 1 | + | + | − | − | − | + | − | − | − | + |
| S | + | + | + | − | + | − | + | 1 | + | + | + | + | + | + | + | + | − |
| GOE | − | − | − | − | + | + | + | + | 1 | + | + | + | + | − | + | − | + |
| CD | + | + | − | + | + | + | − | + | + | 1 | ++ | + | + | + | − | + | − |
| VD | + | − | + | − | + | + | − | + | + | ++ | 1 | + | + | − | − | − | − |
| FV | + | − | − | + | + | − | − | + | + | + | + | 1 | + | − | − | - | − |
| BA | − | + | + | − | − | − | + | + | + | + | + | + | 1 | + | + | + | − |
| MINMT | − | ++ | − | − | −− | − | − | + | − | + | − | − | + | 1 | +++ | +++ | −− |
| MAXMT | − | ++ | − | − | −− | − | − | + | + | − | − | − | + | +++ | 1 | +++ | −− |
| AMT | − | ++ | − | − | −− | − | − | + | − | + | − | − | + | +++ | +++ | 1 | −− |
| MR | + | − | + | + | + | + | + | − | + | − | − | − | − | −− | −− | −− | 1 |

**Table 6** Effect and value of six linguistics which corresponding to fuzzy weights

| Effect | Value |
|---|---|
| High positive (+++) | 1 |
| Middle positive (++) | 0.5 |
| Low positive (+) | 0.25 |
| Low negative (−) | −0.25 |
| Middle negative (−−) | −0.5 |
| High negative (−−−) | −1 |

Step 4: The changes in the values of temperature and precipitation due to climate change (CC) for the period 2020 till 2099 are fuzzified in order to obtain the corresponding linguistics. The whole process includes extended testing of various scenarios (RCP2.6, RCP4.5, RCP6.0, RCP8.5) for the months May to October for the period 1984 till 2004.

Step 5: Partitioning of the scenarios variables, based on the changes in minimum-average-maximum monthly temperature and monthly precipitation, according to the 16 climate models. Moreover, the obtained crisp numerical values are fuzzified, with the use of eight triangular fuzzy membership functions (FMF) and 16 semi-triangular fuzzy membership functions (S-FMF). Two of FMF and four of S-FMF are related to Average Monthly temperature changes in the closed interval [−1.79, +9.83] °C. The first S-FMF, the FMF and the last S-FMF cover the reduction in the interval [−1.79, 0]. These FMF correspond to the fuzzy sets: low negative (−), middle negative (−−), high negative (−−−), whereas the linguistic high negative (−−−) contains values close to the highest estimated change. The next S-FMF, the FMF and the last S-FMF were used for the increase of the average monthly temperature. These FMF correspond to the low positive (+), middle positive (++), high positive (+++), with the high positive (+++) being close to the maximum temperature change. In the same way, two FMF and four S-FMF were developed for the other parameters (Tables 8, 9, 10, 11, 12, 13).

Step 6: It includes extended testing of various scenarios based on the potential changes in the temperature and precipitation and moreover its influence in the burned areas of Ilia and Chania. The fuzzy Linguistics produced by the use of climate change scenarios are defuzzified in

**Table 7** The degree of influence between some variables for *Chania* area (Crete)

| | BA | MINMT | MAXMT | AMT | MR |
|---|---|---|---|---|---|
| Burned areas (BA) | 1 | + | + | + | + |
| Minimum monthly temperature (MINMT) | + | 1 | +++ | +++ | −− |
| Maximum monthly temperature (MAXMT) | + | +++ | 1 | +++ | −− |
| Average monthly temperature (AMT) | + | +++ | +++ | 1 | −− |
| Monthly rainfall (MR) | + | −− | −− | −− | 1 |

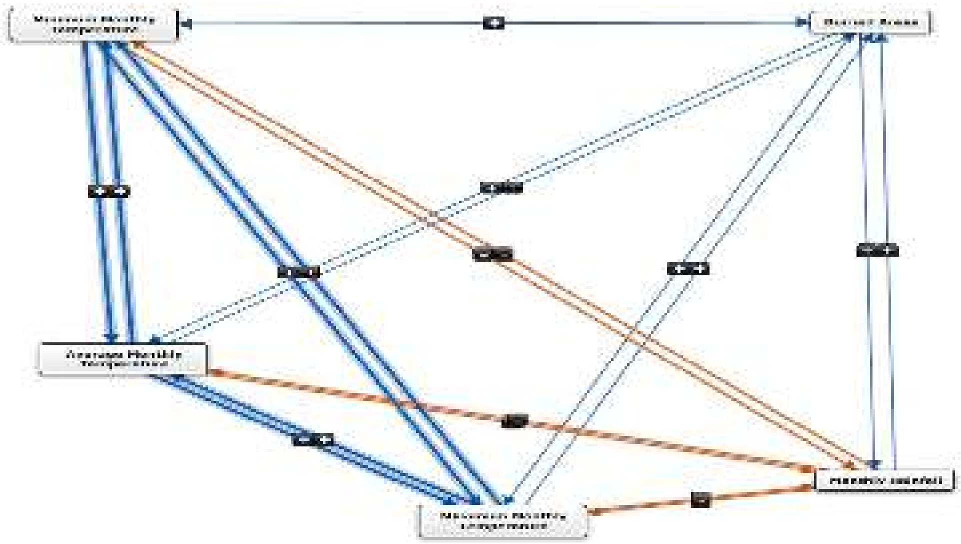

**Fig. 1** A FCM between average monthly temperature, monthly rainfall, minimum monthly temperature, maximum monthly temperature and burned areas for Chania Prefecture

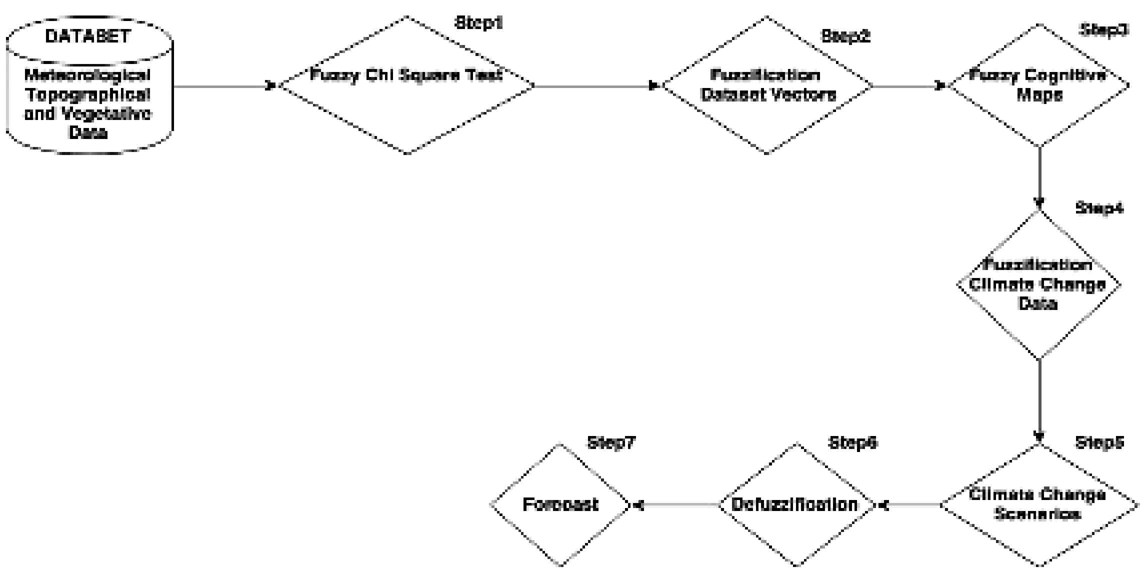


**Fig. 2** Flowchart of proposed methodology

**Table 8** FMF and S-FMF boundaries of average monthly temperature, and monthly rainfall for Ilia area

| Fuzzy sets corresponding to average monthly temperature and monthly rainfall changes | FMF and S-FMF boundaries in the closed interval [−1.79, +9.83] °C | FMF and S-FMF boundaries in the closed interval [−12.68, +33.71] mm |
|---|---|---|
| −−− (S-FMF) | −1.79 −1.074 | −12.68 −7.608 |
| −− (FMF) | −1.611 −0.895 −0.179 | −11.41 −6.34 −1.268 |
| − (S-FMF) | −0.716 0 | −5.072 0 |
| + (S-FMF) | 0 3.932 | 0 13.48 |
| ++ (FMF) | 0.983 4.915 8.847 | 3.376 16.86 30.34 |
| +++ (S-FMF) | 5.898 9.83 | 20.23 33.71 |

**Table 9** FMF and S-FMF boundaries of Minimum monthly temperature and Maximum monthly temperature for Ilia area

| Fuzzy sets corresponding to minimum monthly temperature and maximum monthly temperature changes | FMF and S-FMF boundaries in the closed interval [−2.66, +14.99] °C | FMF and S-FMF boundaries in the closed interval [−6.04, +8.85] °C |
|---|---|---|
| −−− (S-FMF) | −2.66 −1.596 | −6.04 −3.624 |
| −− (FMF) | −2.394 −1.33 −0.2652 | −5.436 −3.02 −0.6004 |
| − (S-FMF) | −1.064 0 | −2.416 0 |
| + (S-FMF) | 0 5.996 | 0 3.54 |
| ++ (FMF) | 1.499 7.495 13.5 | 0.885 4.425 7.97 |
| +++ (S-FMF) | 8.994 14.99 | 5.31 8.85 |

**Table 10** FMF and S-FMF boundaries of average monthly temperature, and monthly rainfall for Chania area

| Fuzzy sets corresponding to average monthly temperature and monthly rainfall changes | FMF and S-FMF boundaries in the closed interval [−2.05, +6.97] °C | FMF and S-FMF boundaries in the closed interval [−4.37, +13.66] mm |
|---|---|---|
| −−− (S-FMF) | −2.05 −1.23 | −4.37 −2.622 |
| −− (FMF) | −1.845 −1.025 −0.2038 | −3.933 −2.185 −0.4345 |
| − (S-FMF) | −0.82 0 | −1.748 0 |
| + (S-FMF) | 0 2.788 | 0 5.464 |
| ++ (FMF) | 0.697 3.485 6.277 | 1.366 6.83 12.3 |
| +++ (S-FMF) | 4.182 6.97 | 8.196 13.66 |

**Table 11** FMF and S-FMF boundaries of minimum monthly temperature and maximum monthly temperature of Chania area

| Fuzzy sets corresponding to minimum monthly temperature and maximum monthly temperature changes | FMF and S-FMF boundaries in the closed interval [−0.69, +9.93] °C | FMF and S-FMF boundaries in the closed interval [−6.28, +4.00] °C |
|---|---|---|
| −−− (S-FMF) | −0.69 −0.414 | −6.28 −3.768 |
| −− (FMF) | −0.621 −0.345 −0.0687 | −5.652 −3.14 −0.6255 |
| − (S-FMF) | −0.276 0 | −2.512 0 |
| + (S-FMF) | 0 3.972 | 0 1.6 |
| ++ (FMF) | 0.993 4.965 8.941 | 0.4 2 3.602 |
| +++ (S-FMF) | 5.958 9.93 | 2.4 4 |

order to obtain the forecast of the potential future crisp values of the burned areas. In this way we perform a projection in the distant future for the problem of environmental degradation due to forest fires.

For the defuzzification the centroid function was used which estimates the center of gravity of the fuzzy set distribution (Van Leekwijck and Kerre 1999; Madau and Feldkamp 1996).

$$x = \frac{\int x \cdot \mu(x)dx}{\int \mu(x)dx}. \tag{4}$$

Step 7: The index of the magnitude of change in the burned areas is calculated based on the amount of relative change of each parameters value (Bennett and Briggs 2005; Törnqvist et al. 1985) (Fig. 2).

$$\frac{FinalValue - InitialValue}{InitialValue}. \tag{5}$$

## 4 Results and discussion

For the *Ilia* prefecture, it was discovered that the burned areas (BUAR) have a clear dependence from the temperature and the Ground Orientation exposure. On the other hand, they were highly independent from the moisture, daily and monthly rain height (till the exact rainy day) and flammability. The highest dependence with degree of membership (DOM) equal to 1 was recorded between BUAR, wind and exposition. The highest independence with DOM equal to 0.998326 was found between BUAR and daily rainfall.

For the *Chania* prefecture, there has proven to be a high dependence between the BUAR and moisture, wind, slope and exposition, whereas burned areas were highly independent from daily rain height (till the day of the rainfall) monthly rain height, rain height of the previous month, altitude and flammability of vegetation.

**Table 12** Fuzzy Chi Square test application between burned areas and involved features in Ilia area

| | Statistic test | p value | Linguistics of p value | Degree of membership of linguistics |
|---|---|---|---|---|
| Burned areas—humidity | 2.7615 | 0.838125 | High independence | 0.574013 |
| Burned areas—air temperature | 22.2546 | 0.001089 | High dependence | 0.94555 |
| Burned areas—wind | 33.1424 | <0.00001 | High dependence | 1 |
| Burned areas—daily rainfall | 0.3255 | 0.999364 | High independence | 0.998326 |
| Burned areas—monthly rainfall until the record of the rainfall day | 0.3491 | 0.999222 | High independence | 0.997953 |
| Burned areas—previous month rainfall | 1.2839 | 0.732965 | Medium independence | 0.452843 |
| Burned areas—altitude | 6.1051 | 0.411521 | Medium independence | 0.701108 |
| Burned areas—slope | 7.7055 | 0.260484 | Low independence | 0.446097 |
| Burned areas—ground orientation exposure | 47.606 | <0.00001 | High dependence | 1 |
| Burned areas—canopy density | 5.8013 | 0.121691 | Low independence | 0.811342 |
| Burned areas—vegetation density | 6.39 | 0.094105 | Low independence | 0.883937 |
| Burned areas—flammability of vegetation | 2.3163 | 0.888439 | High independence | 0.706418 |
| Burned areas—minimum monthly temperature | 7.7063 | 0.26042 | Low independence | 0.446266 |
| Burned areas—maximum monthly temperature | 9.6061 | 0.142251 | Low independence | 0.757237 |
| Burned areas—monthly rainfall | 1.2592 | 0.97386 | High independence | 0.931211 |
| Burned areas—average monthly | | | | |
| Temperature | 9.2173 | 0.161722 | Low independence | 0.705997 |

**Table 13** Fuzzy Chi Square test application between burned areas and involved features in Chania area

| | Statistic test | p value | Linguistics of p value | Degree of membership of linguistics |
|---|---|---|---|---|
| Burned areas—humidity | 31.267 | 0.000023 | High dependence | 0.99885 |
| Burned areas—air temperature | 15.8513 | 0.014575 | Medium dependence | 0.47875 |
| Burned areas—wind | 38.7908 | <0.00001 | High dependence | 1 |
| Burned areas—daily rainfall | 0.1347 | 0.999952 | High independence | 0.999874 |
| Burned areas—monthly rainfall until the record of the rainfall day | 0.3615 | 0.948081 | High independence | 0.863371 |
| Burned areas—previous month rainfall | 0.1798 | 0.980783 | High independence | 0.949429 |
| Burned areas—altitude | 1.2228 | 0.975746 | High independence | 0.936174 |
| Burned areas—slope | 17.5168 | 0.00756 | High dependence | 0.622 |
| Burned areas—ground orientation exposure | 80.7685 | <0.00001 | High dependence | 1 |
| Burned areas—canopy density | 2.8219 | 0.419915 | Medium independence | 0.723197 |
| Burned areas—vegetation density | 3.5055 | 0.320046 | Medium independence | 0.460384 |
| Burned areas—flammability of vegetation | 2.9897 | 0.810144 | High independence | 0.500379 |
| Burned areas—minimum monthly temperature | 5.0471 | 0.537781 | Medium independence | 0.96662 |
| Burned areas—maximum monthly temperature | 4.0712 | 0.667042 | Medium independence | 0.62637 |
| Burned areas—monthly rainfall | 11.4782 | 0.074674 | Low independence | 0.935071 |
| Burned areas—average monthly temperature | 7.012 | 0.319735 | Medium independence | 0.459566 |

The highest dependency with DOM equal to 1 was obtained for wind and Ground Orientation exposure. The highest independency with DOM as high as 0.999874, was obtained between BUAR and daily rainfall.

It is worth mentioning that in both areas the burned areas were mostly related to the wind and to the slope.

### 4.1 Future climate projections in the examined areas

After applying various CC scenarios (including various potential changes in minimum–average–maximum monthly temperature and monthly rainfall) under the 16 climate models for Ilia and Chania, the forecasted Relative

Changes (RC) in the burned areas were obtained. Finally, 512 scenarios were developed by the combination of minimum–average–maximum monthly temperature and monthly rainfall for Ilia and Chania. In addition, a number of scenarios have been used to reduce the uncertainties due to the different configurations used by the distinct climatic models and to the uncertainty of greenhouse gas concentrations in the future.

The results of a set of simulations of different climate models combined with various scenarios of greenhouse gas emissions were used to verify the reliability of temperature and rainfall changes.

The climate models of the CMIP5 program provide a specific set of simulations aiming in the following:

1. The assessment of the results of the various established models, for the estimation of the present climate conditions.
2. The short term or long term future climate changes estimations.
3. Understanding the factors responsible for the differences between the models' results.

The experiments used are related to long term simulations which cover periods of centuries and they accept results of coupled ocean–atmosphere models (AOGCMs) as input. In this way they reach safe and reliable conclusions.

The relative change in the values of the burnt areas and other interconnected parameters was calculated based on historical data for the years 1984–2004, which were used as the *initial values* required by Eq. (5). The application of various climate models and scenarios helped in finding the variations of monthly climatic parameters (MCLIP) for the period 1984–2100. These changing values of the MCLIP were the *final ones* used by Eq. (5). Knowing the initial and the final values of the MCLIP we have obtained the fraction of Eq. (5) which represents the degree of the relative change. All relative changes of the involved features were calculated based on the positive or negative causal links in the Fuzzy Cognitive Map modeling process and also by the final output of Eq. (5) which produces the positive or negative variation of each feature from its initial value.

Attempting a thorough presentation of the most significant changes observed in the prefecture of Ilia from May to October to 2100 (Table 14), it is evident that a high increase of the maximum (+8.85 °C), minimum (+14.99 °C) and average (+9.83 °C) monthly temperature, in combination with a middle reduction (−6.34 mm) of the monthly rainfall, contributes significantly to the increase of the burned areas (ID12).

**Table 14** Relative changes of burned areas for Ilia based on the climate change scenarios

| ID | Average monthly temperature | Minimum monthly temperature | Maximum monthly temperature | Monthly rainfall | H | AT | W | DR | BA |
|---|---|---|---|---|---|---|---|---|---|
| 1 | High negative (−1.79 °C) | Low positive (0 °C) | High negative (−6.04 °C) | High positive (+33.71 mm) | 0.42 | −0.61 | 0.23 | 0.45 | −0.36 |
| 2 | Medium negative (−0.895 °C) | Low positive (0 °C) | High negative (−6.04 °C) | High positive (+33.71 mm) | 0.39 | −0.58 | 0.21 | 0.42 | −0.32 |
| 3 | Medium negative (−0.895 °C) | Low positive (0 °C) | Medium negative (−3.02 °C) | Medium positive (+16.86 mm) | 0.39 | −0.58 | 0.21 | 0.41 | −0.32 |
| 4 | High negative (−1.79 °C) | Low positive (0 °C) | Medium negative (−3.02 °C) | High positive (+33.71 mm) | 0.39 | −0.58 | 0.21 | 0.41 | −0.32 |
| 5 | High negative (−1.79 °C) | Low positive (0 °C) | High negative (−6.04 °C) | Medium positive (+16.86 mm) | 0.4 | −0.59 | 0.2 | 0.42 | −0.32 |
| 6 | High positive (+9.83 °C) | Medium positive (+7.49 °C) | Medium positive (4.425 °C) | Low negative (0 mm) | 0.01 | −0.02 | −0.01 | 0 | 0 |
| 7 | Medium positive (+4.915 °C) | Low positive (0 °C) | High positive (8.85 °C) | Medium negative (−6.34 mm) | 0.01 | −0.05 | −0.01 | 0 | 0.01 |
| 8 | Medium positive (+4.915 °C) | Medium positive (+7.495 °C) | Low positive (0 °C) | High negative (−12.68 mm) | 0.04 | −0.09 | −0.02 | 0.01 | 0.01 |
| 9 | High positive (+9.83 °C) | Medium positive (+7.495 °C) | Medium positive (4.425 °C) | Medium negative (−6.34 mm) | −0.01 | 0 | −0.02 | −0.02 | 0.02 |
| 10 | Medium positive (+4.915 °C) | Medium positive (+7.495 °C) | Medium positive (4.425 °C) | High negative (−12.68 mm) | 0.01 | −0.04 | −0.03 | −0.01 | 0.02 |
| 11 | Medium positive (+4.915 °C) | Low positive (0 °C) | High positive (8.85 °C) | High negative (−12.68 mm) | −0.02 | −0.01 | −0.04 | −0.04 | 0.03 |
| 12 | High positive (+9.83 °C) | High positive (+14.99 °C) | High positive (8.85 °C) | Medium negative (−6.34 mm) | −0.1 | 0.13 | −0.07 | −0.1 | 0.06 |

More specifically, the application of the most extreme scenario (ID12) for the period 2080–2099 produces an important increase of the daily maximum temperature by +0.13 a simultaneous decrease of the average moisture and rainfall by −0.1 and a monthly rainfall reduction till the day of the next rainy day by −0.11. The increase of the daily temperature by 0.13 is interpreted as the degree of the relative change of the daily temperature between the historical period 1984–2004 and the future one of 2080–2099.

The highest increase in the burned areas (ID12) was based in the application of two climate models namely, *miroc_esm* and *miroc_esm_chem* for the period 2080–2099 for the most extreme case (RCP8.5).

Based on the scenarios (ID7–ID12) the increase of the burned areas is produced by the following combinations:

C1: Moderate (+4.915 °C) or high (+9.83 °C) increase of the average monthly temperature.

C2: Low (0 °C), average (+7.495 °C) or high (+14.99 °C) increase of the minimum monthly temperature.

C3: Low (0 °C), average (4.425 °C) or high increase (+8.85 °C) of the maximum monthly temperature.

C4: Average (−6.34 mm) or high (−12.68 mm) decrease of the monthly rainfall.

On the other hand, a high decrease of the average and maximum monthly temperature by −1.79 C and −6.04 °C respectively, combined with a minor increase by (0.001 °C) of the minimum monthly temperature and with a high increase of the monthly rainfall by +33.71 mm would result in the highest reduction of the burned areas (ID1).

The highest reduction of the burned areas by (−0.36) is directly related to the important decrease of the daily average temperature by (−0.61) and it is also seriously connected to the moisture increase by (+0.42) and to the daily rainfall by (+0.45 giss_e2_h) climate model appeared to have the highest decrease of the burned areas for the period 2040–2059 and 2080–2099. The same thing also happened for the model giss_e2_r for the time interval 2060–2079. It should be mentioned that both models had the highest reduction, based on the most moderate climate change scenario which is the RCP2.6.

Based on the scenarios (ID1–ID5) the highest reduction of the burned areas is related to the following combinations:

C1: Medium (−0.895 °C) or high (−1.79 °C) decrease of the average monthly temperature.

C2: Low (0.001 °C) increase of the minimum monthly temperature.

C3 Medium (−3.02 °C) or high (−6.04 °C) decrease of the maximum monthly temperature

C4 Medium (+16.86 mm) or high (33.71 mm) increase of the monthly rainfall

Tables 14 and 15 presents the most important of the forecasted values which are Humidity (H), Air Temperature

**Table 15** Relative changes of burned areas for Chania based on the climate change scenarios

| ID | Average monthly temperature | Minimum monthly temperature | Maximum monthly temperature | Monthly rainfall | H | AT | W | DR | BA |
|---|---|---|---|---|---|---|---|---|---|
| 1 | High negative (−2.05 °C) | High negative (−0.69 °C) | Medium negative (−3.14 °C) | Low positive (0 mm) | 0.22 | −0.45 | 0.07 | 0.21 | −0.14 |
| 2 | High negative (−2.05 °C) | Low positive (0 °C) | High negative (−6.28 °C) | Low negative (0 mm) | 0.15 | −0.33 | 0.05 | 0.14 | −0.12 |
| 3 | High negative (−2.05 °C) | Medium negative (−0.345 °C) | Medium negative (−3.14 °C) | Low positive (0 mm) | 0.2 | −0.39 | 0.06 | 0.19 | −0.12 |
| 4 | Low positive (0 °C) | Medium positive (+4.965 °C) | Medium negative | High positive (+13.66 mm) | 0.1 | −0.15 | 0.04 | 0.09 | −0.01 |
| 5 | Medium positive (+3.485 °C) | Medium positive (+4.965 °C) | Low negative (0 °C) | Low positive (0 mm) | 0 | −0.03 | 0 | 0 | −0.01 |
| 6 | Medium positive (+3.485 °C) | Medium positive (+4.965 °C) | Low negative (0 °C) | Medium positive (+6.83 mm) | 0.02 | −0.04 | 0.01 | 0.02 | −0.01 |
| 7 | High positive (+6.97 °C) | High positive (+9.93 °C) | High positive (4 °C) | High negative (−4.37 mm) | −0.32 | 0.23 | −0.19 | −0.22 | −0.01 |
| 8 | medium positive (+3.485 °C) | Medium positive (+4.965 °C) | Medium negative (−3.14 °C) | Medium positive (+6.83 mm) | 0.04 | −0.08 | 0.02 | 0.04 | −0.01 |
| 9 | Medium positive (+3.485 °C) | Medium positive (+4.965 °C) | Low negative (0 °C) | Low positive (0 mm) | 0 | −0.03 | 0 | 0 | −0.01 |
| 10 | Medium positive (+3.485 °C) | High positive (+9.93 °C) | Low negative (0 °C) | Medium positive (+6.83 mm) | −0.02 | 0.02 | 0 | −0.02 | 0 |
| 11 | Medium positive (+3.485 °C) | High positive (+9.93 °C) | Medium positive (2 °C) | Low negative (0 mm) | −0.16 | 0.14 | −0.08 | −0.11 | 0 |

(AT), Wind (W), Daily Rainfall (DR) and Burned areas (BA).

In the Chania prefecture (Crete) there were minor changes in the number of burned areas. (Table 15). The highest reduction (ID1) of the burned area by (−0.14) came from the application of the following conditions

C1: High reduction (−2.05 °C) of the average monthly temperature
C2: High reduction (−0.69 °C) of the minimum monthly temperature
C3: Moderate reduction (−3.14 °C) of the maximum monthly temperature
C4: Minor increase (0.001 mm) of the monthly rainfall

More specifically, the application of this scenario resulted in the significant increase of the daily moisture by (+0.22) in the increase of the daily and monthly rainfall till the next rainy day by (+0.21) and (+0.31) respectively, whereas the daily temperature dropped by (−0.45). The above relative changes were obtained by the application of the ipsl_cm5a_mr climate model under the RCP2.6 and RCP6 scenarios for the temporal period 2020–2039. It should be mentioned that there was not increase in the burned area for the period till 2100 and in both most extreme scenarios the wild fires were estimated to burn the same as for the period 1984–2004.

In this scenario (using two different climate models) the relative changes of the burned areas were equal to zero. In the first case, modeling was performed according to the climate model *miroc_esm_chem* on the most extreme climate change scenario (*RCP8.5*) for the time period 2060–2079.

More specifically, the burned areas were at the levels of the period 1984–2004, under the following conditions (ID10)

C1: Moderate increase (+3.485 °C) of the average monthly temperature
C2: High increase (+9.93 °C) of the minimum monthly temperature
C3: Small decrease (0 °C) of the highest monthly temperature
C4: Moderate increase (+6.83 mm) of the monthly rainfall

According to this scenario there was decrease of the daily moisture and rainfall, decrease of the monthly rainfall and increase of the daily temperature. This scenario had the smallest fluctuations for the involved parameters compared to the rest scenarios.

The zero relative change in the total burned areas was also obtained by the use of a second scenario based on the climate model *miroc5* applied on the most extreme climate change scenario (RCP8.5) for the period 2080–2099 (ID11). This application was based on the following changes in the monthly climatic parameters:

C1: Moderate increase (+3.485 °C) of the average monthly temperature
C2: High increase (+9.93 °C) of the minimum monthly temperature
C3: Moderate increase (+4 °C) of the maximum monthly temperature
C4: Minor decrease (0 mm) of the monthly rainfall

Specifically this scenario significantly changed the values of the meteorological parameters, highly contributing in the reduction of the daily moisture by (−0.11) and of the rainfall by (−0.24) and on the other hand in the increase of the temperature by (+0.14).

Table 16 refers to the most extreme scenario and it presents the estimated values of the following involved

**Table 16** Parameters forecasted values based on the more extreme scenarios

| Period | H | AT | W | DR | PMR | MRNRD | BA |
|---|---|---|---|---|---|---|---|
| 1984–2004 ILIA (INITIAL VALUES) | 48.99 | 27.07 | 2.7 | 0.29 | 13.48 | 3.7 | 402,515 |
| Extreme Scenario (ILIA)-(ID12) | −0.1 | +0.13 | −0.07 | −0.1 | −0.14 | −0.11 | +0.06 |
| 2080–2099 (FINAL VALUES) | 44.091 | 30.5891 °C | 2.511 | 0.261 | 11.5928 | 3,293 | 426,665.9 |
| Exterme Scenario (ILIA)-(ID1) | +0.42 | −0.61 | +0.23 | +0.45 | +0.56 | +0.42 | −0.36 |
| 2040–2059, 2080–2099 (FINAL VALUES) | 69.57 | 10.56 °C | 3.32 | 0.41 | 21.04 | 5.25 | 257,609.6 |
| 1984–2004 CHANIA(INITIAL VALUES) | 40.8768 | 25.9857 | 3.314 | 0.084 | 3.898 | 1.43 | 335,852 |
| Extreme Scenario (CHANIA) –(ID1) | +0.22 | −0.45 | +0.07 | +0.21 | +0.26 | +0.31 | −0.14 |
| 2020–2039 (FINAL VALUES) | 49.8697 | 14.2922 | 3.546 | 0.102 | 4.91 | 1.873 | 288,832.72 |
| Exterme Scenario (CHANIA)-(ID11) | −0.16 | +0.14 | −0.08 | −0.11 | −0.1 | −0.24 | 0 |
| 2080–2099 (FINAL VALUES) | 34.3365 | 29.6237 | 3.0493 | 0.075 | 3.508 | 1.087 | 335,852 |
| Exterme Scenario (CHANIA)-(ID10) | −0.02 | +0.02 | 0 | −0.02 | −0.02 | −0.02 | 0 |
| 2060–2079 (FINAL VALUES) | 40.0592 | 26.5054 | 3.314 | 0.082 | 3.82 | 1.401 | 335,852 |

meteorological parameters: humidity (H), air temperature (AT), wind (W), daily rainfall (DR), previous month rainfall (PMR), monthly rainfall until the next rainy day (MRNRD).

Since the projections are going far to the future (as far as 2100) and the feedback of the system is produced by climate change scenarios, there is no way to verify or reject the produced output. However this research is very important and innovative. Its aim is not to specify with accuracy the consequences of the forest fires in the next 100 years, but it is twofold. First it aims to offer the scientists a very strong and useful tool to make projection in the future regarding the consequences of natural disasters in the next century, as they will be influenced by the climate change that has already started. So depending on the scenario, this hybrid and intelligent model can accept climate change input and it is capable to output the flora destruction due to natural disasters in a scale of 100 years based on best, average and worst case scenarios. So the scientists and the societies will have a compass for the future that can define and influence current decisions and activities. The most important is that this model can be adjusted with minimum effort to operate under other natural disasters cases with new parameters. The areas of Ilia and Chania in Greece were chosen just to demonstrate the actual application of the model, its flexibility and its potentials.

## 5 Conclusions-future work

This research initially proposes an innovative approach for the analysis and modeling of the relationships between the main parameters that define the severity of a forest fire, under several climate change scenarios. It is a hybrid Soft Computing approach which employs Fuzzy cognitive maps (FCM) and the Fuzzy Chi Square test (FChiSq). Additionally this model uses feedback from the first part to forecast the fluctuation level of the total burned areas for specific pilot prefectures of Greece, based on climate change scenarios and climate models. The projection is done in a wide temporal scale.

This is achieved by the use of sophisticated Computational Intelligence hybrid methods. More specifically, Fuzzy cognitive maps are used to capture the correlation of meteorological, topographic and vegetation features that determine the extent of the wild fire burned area. Two prefectures that are considered as high risky in terms of wild fires namely Chania and Ilia were used as pilot case studies for the period 1984–2004. Various climate change scenarios were produced by choosing 16 climate models obtained by the CMIP5 project.

Moreover the model performed estimation of the increase/decrease of the burned areas based on the estimated fluctuation of various climate indicators as they are formed based on the chosen climate models for the period till 2100.

The obtained scenario presented significant forecasts not only on the future forest fire risk but also on the fluctuations of the rest parameters that specify the severity of wild fires (ignition and spread).

Based on the results it is clear that according to the most extreme scenario for the Ilia prefecture, the average daily temperature will significantly increase with a parallel reduction of the daily moisture and rainfall levels (ID12). This application estimated an increase of the burned areas by 24,151 Ha for the period 2080–2099 for the *Ilia* prefecture, compared to the period 1984–2004. This increase by (+0.06) corresponds to the degree of relative change (see Table 16). For the *Chania* prefecture the most extreme scenarios related to the periods 2060–2079 and 2080–2099 produced an increase of the average daily temperature and a decrease of the average daily moisture and rainfall. The total burned areas did not appear any fluctuations but they remained exactly in the same levels as for the historical period 1984–2004.

As future research the model can use different confidence levels for the Chi Square test. Additionally a significant step would be the monthly and seasonal application which can offer a much more clear consideration of the problem. Finally, evolutionary genetic algorithms can be applied to potentially enhance the efficiency of the model. Finally more climate models might be employed in more wider areas with high level of vulnerability to wild fires and moreover socioeconomic features can be inserted in the Fuzzy cognitive maps.

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