Classification of Distinct Seismic Regions and Regional Temporal Modelling of Seismicity in the Vicinity of the Hellenic Seismic Arc

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Abstract—This paper investigates the presence and potential discrimination of distinct seismic regions in the vicinity of the Hellenic seismic arc focusing on its southern front. Seismological maps indicate the presence of several seismic swarms forming within the region of the Hellenic arc, which appear to be either distinct or interacting together in groups of two or more. The identification of the number of possibly individual seismic clusters in a seismological area is a very challenging task by itself, which becomes even more complicated when investigating their outer boundaries especially in the case of multiple interacting clusters. Complementary to that, the paper also investigates the possible temporal correlation of mid-intervals of consecutive large earthquakes and patterns in seismic activity during their preparation process in the vicinity of the southern Hellenic arc which is shown to be a possible distinct seismic region.

Index Terms—Long-term earthquake precursors, neuro-fuzzy models, pattern recognition, seismic epicentral clustering, spatio-temporal clustering, temporal seismic analysis.

I. INTRODUCTION

CONSTANT monitoring of the seismic activity of a particular area over long time periods unveils the emergence of multiple topical earthquake assemblies, which, as time progresses, tend to grow into compact neighbouring seismic clusters. Earthquake cluster discrimination is of outmost importance in seismology [1]–[5] as it can provide valuable information regarding the topology of the seismic phenomenon in relation with underlying faults [6]–[9]. In most cases, little detailed information is readily available regarding the underground structure of a seismogenic region of interest [9]–[11], which in terms of epicenter depth extends from a few meters to several tens of kilometers bellow sea level [10], [11]. What is made apparent is a distorted reflection of the underlying faults’ network on the surface of the planet painted by numerous compact seismic swarms [5], [12] that extend all the way across all active tectonic regions [7]–[9]. The fact that underground faults are rarely distinct and in most cases they tend to form large topical or extent interacting networks [9] complicates the process of surface seismic cluster discrimination as it is very difficult to identify discrete cluster boundaries. To make matters even more complex interacting seismic clusters can penetrate well into the stronghold vicinity of their companions and vice versa which can result in faulty allocations of seismic events to a particular cluster.

To evaluate this problem this paper introduces a new self-developed spatio-temporal clustering algorithm that enables the processing of either all recorder earthquakes or main seismic events alone, excluding foreshocks and aftershocks. This is achieved with the incorporation of dynamic filters in space and time which are encompassing empirical formulae [13]–[15] for the computation of the total earthquake preparation time, aftershocks duration, and radius of the sphere of earthquakes’ preparation and relief region, addressing that way the concept of topical seismic cluster formation.

Acting complementary to the above the paper also investigates the possible temporal correlation of mid-intervals of consecutive large earthquakes and patterns in seismic activity during the preparation process of large earthquakes in the vicinity of the Southern Hellenic arc, which is shown by the spatio-temporal clustering algorithm to be a distinct seismic region by itself. Several state-of-the-art applications in that area focus upon earthquake recurrence times [16]–[19] while others have been investigating for possible long term earthquake precursors such as particular changes in seismic activity patterns, which might occur during the preparation stages of large seismic events [19]–[21]. Despite, though, some sporadic cases of successful real-time predictions [22] and further attempts to support possible identified long-term earthquake precursors with laboratory-developed mechanical models [16], [21], [23]–[25], approaches based on the interpretation of long-term earthquake precursors have the downfall that the observed changes in seismic activity deemed as long-term earthquake precursors vary considerably among various seismological regions [17], [18], [21]. This by itself highlights further the importance for distinct seismic regions classification where applicable.

The uncertainty of the underlying physics regarding the earthquake generation mechanism along with the lack of causal relations associating seismicity patterns and related crustal environments led to the development of a number of recent methods incorporating neural networks [26]–[28]. These methods exploit the capability of neural networks to act as global approximators in an attempt to simulate the behaviour of a system governed by unknown non linear multivariate interconnections within a noisy physical crustal background, such as the seismic phenomenon. Neural networks allow for a ‘black-box’ targeted to-
wards mapping input to output data, such as possible long term earthquake precursors, e.g. changes in seismicity patterns, to time intervals between subsequent large seismic events [26], [27]. However, beside some previous successful applications of neural networks upon various seismic-related problems [29], [30], no consistent relations were identified bonding possible long-term earthquake precursors to the time of the occurrence of the next forthcoming large earthquake.

Instead of addressing changes in seismicity patterns, this research paper introduces mean seismicity rates as a tool for monitoring the strain accumulation and release process in the distinct seismic region of the southern Hellenic seismic arc, which in effect acts as an energy storage and release management mechanism inside the Earth’s crust. It is widely accepted in the geophysical community that long quiet periods of low seismic-activity result in a significant build up of energy stored in a seismogenic area [17], [19] possibly due to the potentially constant import of energy because of the motion of the Eurasian and African plates where the latter moves by approximately 3 mm per year towards the former [31]. Eventually, a vast amount of that energy is released to the surface causing large magnitude earthquakes. The limited knowledge regarding the underlying physics of the energy storage and release mechanism, and the uncertainty of the boundaries of the involved parameters, prompted the author to incorporate to standard neural network models a certain degree of fuzziness for the simulation of the system’s behaviour. The resulting neuro-fuzzy model uses mean seismicity rates as inputs to provide it with information regarding the energy stored in the seismogenic area, whilst catalogued time-intervals between subsequent large earthquakes are imported as the required output. After successful training the resulting neuro-fuzzy model is then capable of estimating the time-interval from the last to the next sizeable seismic event by monitoring monthly mean seismicity rates of the seismogenic area.

II. EPICENTRAL SPATIO-TEMPORAL CLUSTERING ALGORITHM

In order to identify and discriminate potential distinct seismic regions within the vicinity of the Hellenic seismic arc a spatio-temporal clustering algorithm has been developed. Since all spatial clustering algorithms rely on distance calculations between points, the developed software incorporates an ellipsoidal Earth projected to a plane formula to estimate distance between earthquake events based on their geographical coordinates [32]. The data presented throughout the paper have been obtained by the National Observatory of Athens Institute of Geodynamics seismicity catalogue [33] for the entire Greek vicinity during the year 2011.

The self-developed spatio-temporal clustering algorithm clusters datasets of earthquake events spatiotemporally by calculating a strain radius and time window for each event and grouping events with overlapping strain radii and time windows into clusters. The event with the highest magnitude in each cluster is characterized as the cluster’s main event and thus cluster foreshock and aftershock events are evident by their time of occurrence in relation to the main event.

For the calculation of the strain radius the following formula has been implemented into the clustering algorithm based on event magnitude:

\[ \rho = 10^{0.414M - 1.696} \text{ (km)} \]

where \( M \) is the event magnitude [14]. The time window has been dynamically calculated for the time intervals before \( (t_{before}) \) [34] and after \( (t_{after}) \) [15] the main earthquake using the following formulae, respectively:

\[ t_{before} = 10^{0.51M - 1.151} \text{ (years)} \]
\[ t_{after} = 10^{0.51M - 1.151} \text{ (years)} \]

where \( t_{after} \) applies specifically to the current seismological region under investigation [15].

Besides their obvious use for main seismic events identification the aforementioned formulae are also being deployed by the proposed spatiotemporal algorithm, an iterative agglomerative clustering algorithm for seismic cluster identification displayed in Fig. 1. Initially, strain radius and time-window values are calculated for every event on the dataset and events are ordered by their time of occurrence and processed in the following manner: an unclustered event becomes the centre of a new cluster and all events within its strain radius and time-window become cluster members. At this point a competitive process begins where we look for the event with the highest magnitude within the newly-formed cluster. If that event is not the current cluster centre, a new cluster is formed and the aforementioned competitive process is repeated recursively. With the formation of a new
cluster seismic events spatially and temporally located towards the far outer region of the initial cluster with respect to the new spatio-temporal cluster centre might not fall within the strain radius and/or the time window of the new cluster; therefore they remain as members of the initial cluster. Consequently, the spatio-temporal algorithm forms irregularly-shaped seismic clusters allowing cluster interaction by enabling multiple clusters to occupy the same geographical area by exploiting time as an additional physical layer.

Characteristic results of the spatio-temporal clustering algorithm applied on the National Observatory of Athens Institute of Geodynamics seismicity catalogue throughout the Greek vicinity during 2011 can be examined in Fig. 2.

The spatio-temporal clustering algorithm clearly identifies, among others, the south Cretan (southern Hellenic seismic arc) and the Ionian region as individual seismic regions in accordance with empirical results on distinctive seismic zones [2], [15].

III. TEMPORAL ANALYSIS OF SEISMICITY IN THE DISTINCT SEISMIC REGION OF THE SOUTHERN HELLENIC SEISMIC ARC

The subduction of the African plate beneath the Eurasian plate casts the area of the southern Hellenic seismic arc as one of the most seismically active regions in the world [7]. Beside the fact that this area has experienced several large earthquakes it remains home to over a million people. The focal area for this work, in accordance to the distinct seismic region outer boundaries depicted by the spatio-temporal clustering algorithm, ranges between 33.2°–37.1°N in latitude and 22.4°–30°E in longitude with data being retrieved by the Geodynamic Institute of the National Observatory of Athens (GI-NOA) catalogue from 1988 until 2010, with our analysis being restricted to shallow seismic events [33].

In order to investigate the possible temporal correlation of mid-intervals of consecutive large earthquakes and patterns in seismic activity during their preparation process in that particular distinct seismic region a hybrid model involving the incorporation and mergence of neural networks and fuzzy logic bonded together in a hybrid adaptive neuro-fuzzy inference system is proposed. Neuro-fuzzy models are adaptive artificial neural networks with intrinsic fuzzy logic abilities [35], i.e. the synaptic weights of the artificial neurons in the network define the premise and consequent parameters of a fuzzy inference system. Premise parameters characterize the shape and size of the input membership functions, while consequent parameters determine the characteristics of the equivalent output membership functions and define the rules guiding the fuzzy inference system.

Monthly mean seismicity rates are imported to the neuro-fuzzy model acting on behalf of the latter as a monitoring mechanism of the energy storage and release process of the pre-defined seismogenic area of the southern Hellenic arc. This information along with measured time-intervals between subsequent seismic events of magnitudes greater than or equal to MS 5.9 [26], [27] form the training data set applied to the neuro-fuzzy model along with a hybrid training algorithm. Every training pattern in the training data set consists of four inputs and a required output. The four inputs have been allocated to the mean seismicity rates between subsequent large (MS > 5.9) earthquakes at time intervals n and n – 1, respectively, calculated from the cumulative activity curves for two magnitude bands, 3.5 ≤ MS < 4 and MS ≥ 4, by regression line fitting. This particular configuration of the input data set introduces recursion to the network [36], and allows for some information to be fed to the neuro-fuzzy model regarding foreshocks and aftershocks that accompany large earthquakes. The required output is the time interval (n+1) between the latest and the next subsequent large (MS ≥ 5.9) seismic event.

In order to generate an initial fuzzy inference system subtractive clustering has been applied upon the input data of the training data set using a radius of 0.5 [37], [38] aiming to produce an initial set of premise and consequent parameters. The structure of the neuro-fuzzy model depends upon the overall number of inputs and the number of input membership functions per input. Each rule and each membership function is being assimilated by a single neuron. The number of rules driving the fuzzy inference system equals the membership functions’ number per input to the power of the total number of inputs of the neuro-fuzzy model. A single neuron is used as bias to allow for variable importance among the rules of the neuro-fuzzy model. Each rule is linked to a single output membership function. Finally, a single neuron is used for defuzzification in order to produce a crisp output. The architectural structure of the neuro-fuzzy model for this particular application composes of six distinct layers (Fig. 3) operating according to the following equations:

**Layer 1:** Mean seismicity rates as defined above are used as inputs \((A \text{ to } D)\) to the neuro-fuzzy model.
Layer 2: Every node $i$ in this layer is an adaptive node obeying the following node functions: $O_{1,i} = \mu A_i(x)$, for $i = 1,2$; $O_{1,i} = \mu B_i(y)$, for $i = 3,4$; $O_{1,i} = \mu C_i(z)$, for $i = 5,6$ and $O_{1,i} = \mu D_i(k)$, for $i = 7,8$, where $x$, $y$, $z$ and $k$ are the inputs to each node $i$, respectively, and $A_i$, $B_i$, $C_i$ and $D_i$ are the equivalent membership functions, respectively. The type of membership functions $A$, $B$, $C$ and $D$ is that of the generalised bell function: $\mu A(x) = 1/(1 + (x - c_i)/a_i)^2$, where $a_i$, $b_i$, $c_i$ are the premise parameters of the network which determine the shape and size of each membership function.

Layer 3: All nodes $i$ in this layer are fixed nodes used to calculate the normalised firing strength of every rule, respectively, according to the following node function: $O_{2,i} = \overline{w}_i = \frac{w_i}{\sum_i w_i}$, where $w_i = \mu A_i(x)\mu B_i(y)\mu C_i(z)\mu D_i(k)$.

Layer 4: Every node $i$ in this layer is an adaptive node assimilating the role of an output membership function in order to compute the weighted output of each equivalent rule, according to the following node function: $O_{3,i} = \overline{w}_i f_i$, where $f_i = p_i + q_i + m_i + n_i + r_i$ and $\{p_i, q_i, m_i, n_i, r_i\}$ are the consequent parameters of the neuro-fuzzy model that specify the rules of its inherent fuzzy inference system.

Layer 5: The only node in this layer is a fixed node used to convert the weighted fuzzy outputs of each rule of the neuro-fuzzy model into a single crisp output, as described by the following node function: $O_{4,1} = \sum_i \overline{w}_i f_i$.

Layer 6: The node holds the actual output of the neuro-fuzzy model for a given input data set.

A hybrid algorithm [39] combining the backpropagation algorithm [37] and the least squares estimator [39] enables supervised learning to be performed upon the neuro-fuzzy model, training it to map the input data set to the output data set by adjusting accordingly its membership functions’ and rules’ parameters. In a similar way to artificial feed-forward neural networks [40], the neuro-fuzzy model generates an output signal during its “forward pass” [39], based on the initial set of membership functions. The consequent parameters [41] are specified during the “forward pass” using the least squares method [37]. This allows the neuro-fuzzy model to produce a first crisp output, which is then compared to the required output (i.e. known time intervals among consecutive large earthquakes) and their difference in the form of an error signal is fed back to the neuro-fuzzy model to be used during the “backward pass” [39] to readjust the premise parameters [41] using the backpropagation algorithm. This process repeats itself for as many epochs, twenty seven epochs in this particular application, until the error signal becomes sufficiently small (ideally zero) [42]. A separate checking data set is run in parallel to the training data set to prevent over-fitting [36], [39] the training data.

IV. Temporal Analysis Results

The time periods from January 1988 to December 2004, 2006, 2008, and 2010, respectively, were used to form four different training data sets in the distinct seismogenic area of the southern Hellenic arc as described in the previous section. Having applied a threshold magnitude to ensure homogeneity of the training data set [27], the overall number of seismic events with $MS > 3.5$ for the four time intervals are 7423, 10413, 15824, and 22135, respectively, with the large increment from 2008 onwards coinciding with a significant expansion of the seismological recording network in the vicinity of the southern Hellenic arc [33]. During the considered time-interval eighteen seismic events with magnitudes $MS \geq 5.9$ have occurred, fourteen of which were main earthquakes with a mean recurrence time of 1.8 years excluding the year 2008 when five large earthquakes occurred out of which two were main earthquakes. Foreshocks and aftershocks of magnitudes greater or equal to $MS 5.9$ have been excluded from the training data sets as the training purpose of the neuro-fuzzy model is to estimate the time intervals between consecutive main earthquakes and the not the evolution of the topical seismic sequence, i.e. foreshocks and aftershocks, accompanying any particular main earthquake.

Looking in greater detail, the first training data set (1988–2004) is feeding the neuro-fuzzy model with mean seismicity rates and time-intervals between subsequent large earthquakes until the 17th of March, 2004 earthquake of $MS 6.5.$ After completion of the training process the neuro-fuzzy model was operated using as inputs mean seismicity rates only, for the time intervals $n$ and $n - 1$, corresponding to the time periods between the last two large earthquakes, i.e. between the 22nd of January, 2002, earthquake of $MS 6.6$ and the 17th of March, 2004 earthquake of $MS 6.5$; and between the 24th of May, 2000 earthquake of $MS 5.9$ and the 22nd of January, 2002 earthquake of $MS 6.6$, respectively. The neuro-fuzzy model then aims to estimate the time interval to the next upcoming large earthquake, falling outside the original training data set. The neuro-fuzzy model’s output was shown to be 706, which when added to the date of occurrence of the last sizeable earthquake, i.e. 17th of March, 2004, corresponds to the calendar date of the 21st of February, 2006. This date strays by 44 days from the actual date of the next large ($MS \geq 5.9$) earthquake observed after the 17th of March, 2004 $MS 6.5$ earthquake in the aforementioned seismogenic area of the southern Hellenic arc. The actual earthquake occurred, as recorded by GI-NOA [33], on the 8th of January, 2006 measuring a magnitude of $MS 6.9$. 

Fig. 3. Neuro-fuzzy model’s architecture.
The second training data set (1988–2006) expands upon the first training data set thereby feeding the neuro-fuzzy model with mean seismicity rates and time-intervals between subsequent large earthquakes until the 8th of January, 2006 earthquake of MS 6.9. After completion of the training process the neuro-fuzzy model was operated using as inputs mean seismicity rates only, for the time intervals \( n \) and \( n - 1 \), corresponding to the time periods between the last two large earthquakes, i.e. between the 17th of March, 2004, earthquake of MS 6.5 and the 8th of January, 2006 earthquake of MS 6.9; and between the 22nd of January, 2002 earthquake of 6.6 and the 17th of March, 2004 earthquake of 6.5, respectively. The neuro-fuzzy model then aims to estimate the time interval to the next upcoming large earthquake, falling outside the original training data set. The neuro fuzzy model’s output was shown to be 906, which when added to the date of occurrence of the last sizeable earthquake, i.e. 8th of January, 2006, corresponds to the calendar date of the 3rd of July, 2008. Since the model is time-dependant mean seismicity rates have also been fed as inputs to the neuro-fuzzy model until the end of 2007 to account for the intermediate seismic activity. The calibrated neuro-fuzzy model’s output was 890 corresponding to the calendar date of the 16th of June, 2008 very close to the initial estimation. This is supported by the limited seismic activity recorded during 2007, which only effects by a margin the initially estimated calendar date. The long time interval since the last large earthquake accompanied with limited interim seismic activity, thus little release of energy to the surface, resulted in a great energy build up in the seismogenic area which gave in effect multiple large earthquakes in two packs as recorded by GI-NOA [33]; an MS 6.7 and with an aftershock of MS 6.6 on the 14th of February, 2008 closely followed by another aftershock of MS 6.5 on the 18th of February, 2008, a mere four months before the estimated date; and an MS 6.0 on the 21st of June, 2008 followed by an MS 6.7 on the 15th of July, 2008 almost co-insiding with the estimated dates. Fortunately, part of the accumulated energy was released slightly prematurely than the estimated date of occurrence preventing a very large catastrophic earthquake from occurring around that date.

The third training data set (1988–2008) expands upon the first two training data sets thereby feeding the neuro-fuzzy model with mean seismicity rates and time-intervals between subsequent large earthquakes until the 15th of July, 2008 earthquake of MS 6.7. After completion of the training process the neuro-fuzzy model was operated using as inputs mean seismicity rates only, for the time intervals \( n \) and \( n - 1 \), corresponding to the time periods between the last two large main earthquakes, i.e. between the 14th of February, 2008, earthquake of MS 6.7 and the 15th of July, 2008 earthquake of MS 6.7; and between the 8th of January, 2006 earthquake of 6.9 and the 15th of February, 2008 earthquake of MS 6.7, respectively. The neuro-fuzzy model then aims to estimate the time interval to the next upcoming large earthquake, falling outside the original training data set. The neuro fuzzy model’s output was shown to be 112, which when added to the date of occurrence of the last sizeable earthquake, i.e. 15th of July, 2008, corresponds to the calendar date of the 3rd of July, 2009. A significant earthquake of MS 5.7 was recorded shortly after, i.e. on the 13th of January, 2009, prolonging the required time interval for the underground energy build up to reach critical amounts. The actual earthquake, as recorded by GI-NOA [33], occurred on the 1st of July 2009 measuring a magnitude of MS 6.3.

The final training data set (1988–2010) expands upon all the previous training data sets thereby feeding the neuro-fuzzy model with mean seismicity rates and time-intervals between subsequent large earthquakes until the 1st of July, 2009 earthquake of MS 6.3. After completion of the training process the neuro-fuzzy model was operated using as inputs mean seismicity rates only, for the time intervals \( n \) and \( n - 1 \), corresponding to the time periods between the last two large earthquakes, i.e. between the 17th of July, 2007, earthquake of MS 6.7 and the 1st of July, 2009 earthquake of MS 6.3; and between the 14th of February, 2008 earthquake of 6.7 and the 15th of July, 2008 earthquake of 6.7, respectively. The neuro-fuzzy model then aims to estimate the time interval to the next upcoming large earthquake, falling outside the original training data set. The neuro fuzzy model’s output was shown to be 823, which when added to the date of occurrence of the last sizeable earthquake, i.e. 1st of July, 2009, corresponds to the calendar date of the 2nd of October, 2011. Since the model is time-dependant mean seismicity rates have also been fed as inputs to the neuro-fuzzy model until the end of 2010 to account for the intermediate seismic activity. The calibrated neuro-fuzzy model’s output was 815 corresponding to the calendar date of the 24th of September, 2011 very close to the initial estimation. This is supported by the limited seismic activity recorded during 2010, which only effects by a margin the initially estimated calendar date. The actual impending earthquake was fortunately broken down to two slightly smaller earthquakes which occurred, as recorded by GI-NOA [33], on the 26th of annuary, 2012 measuring a magnitude of MS 5.8 and one day later measuring a magnitude of MS 5.7.

The scatter diagram on Fig. 4 outlines the performance of the developed neuro-fuzzy model for the checking data set, and plots the estimated times of origin against the observed occurrence times of large (MS ≥ 5.9) earthquakes in the seismogenic area of the southern Hellenic arc. The ‘*’ indicates actual occurrence times. The ‘\( \angle \)’ indicates pure attempts for temporal prediction by the neuro-fuzzy model with the predicted earthquakes having remained unseen by the neuro-fuzzy model during its training process. The leftmost square indicates the actual time of occurrence of the premature MS 6.7 earthquake on the 14th of February, 2008 while the ‘\( \angle \)’ above it (almost coinciding with the ‘*’) indicates the estimated date of the 16th of June, 2008, which almost coincides with the actual earthquake eventually occurring on the 21st of June, 2008. The rightmost square indicates the actual time of occurrence of the MS 5.7 earthquake on the 13th of January, 2009, which prolonged the initial estimated time of occurrence (4th of November, 2008, indicated by the ‘\( \angle \)’ bellow it) by almost six months.

Table 1 provides a list of all the MS ≥ 5.9 main earthquakes recorded from 1988 to 2010. The first column displays the earthquake number whilst the second column holds the actual occurrence date and the third column outlines the predicted occurrence date measuring a mean precision error of approximately ±2 months (the ‘+’ symbol indicates events shown to
the neuro-fuzzy model during training and thus are not being accounted towards evaluating its performance). Column four shows the earthquakes’ magnitude (MS). The single ‘*’ symbol is to highlight early partial energy release four months before the estimated date that resulted in two main large earthquakes instead of a single catastrophic one, with the second earthquake occurring only few days apart from the estimated date of occurrence. The double ‘**’ symbol highlights an MS 5.7 earthquake occurred just over a month after the estimated date of occurrence which prolonged the time interval to the expected large earthquake by almost another six months. The ‘***’ symbol highlights the breaking down of an >MS 5.9 earthquake into two large earthquakes with the second earthquake occurring the following day. These results indicate that it takes about a year and a half to two years for enough seismic energy to be stored in underground faults for a large main earthquake to occur. It also appears that it takes one or two closely-timed together large earthquakes to decongest the amount of the underground stored energy by releasing a substantial part of it towards the planet’s surface.

V. CONCLUSIONS

This paper demonstrates that there is a temporal pattern of the seismic phenomenon in the possibly distinct seismic region of the southern Hellenic arc and also presents novel information on what happens when the accumulation of underground stored energy approaches a threshold point after which a large earthquake is eminent:

a) A delay on the time of occurrence of a large earthquake is likely to emerge if medium-sized earthquakes occur in the meantime; in that case retraining the neuro-fuzzy model correctly estimates the new time interval.

b) Very close estimations on the time of occurrence of a large earthquake are achieved by the neuro-fuzzy model when there is little if none premature energy release.

c) A breakdown, at the estimated time of occurrence, of the large earthquake into multiple (typically two or three) slightly weaker large earthquakes is possible.

It is important to emphasize that after training the neuro-fuzzy system gives an estimate of the time period to the next large earthquake. When that is considerably large (typically over a year) it is possible to retrain the neuro-fuzzy system including the additional recorded data. In that case providing the mid-seismic activity is quite low, with few if any medium-sized earthquakes, the neuro-fuzzy model’s new estimated time-period to the next large earthquake points to the almost exactly the same date as in the first case.

The possible existence of a temporal pattern in seismic activity in the potentially distinct seismic region of the southern Hellenic arc works vice-versa providing additional complementary value to both observations.

REFERENCES


