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1864-9

Ninth Workshop on Non-linear Dynamics and Earthquake Predictions

1 - 13 October 2007

Application of the Pattern Recognition Techniques to Earthquake-prone Areas Determination

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I. INTRODUCTION

The problem under consideration is to determine in the region the areas where strong (with magnitude $M \geq M_0$ where M_0 is a threshold specified) earthquakes are possible. The detailed description of this problem, approaches to its solving, and a review of the results obtained for several regions are given by *Gorshkov et al.* (2003). The basic assumption is that strong earthquakes associate with morphostructural nodes, specific structures that are formed about intersections of fault zones. This gives possibility to apply the pattern recognition approach.

The nodes are considered as objects of recognition. They are identified by means of the morphostructural zoning and described by characteristics determined on the basis of the topographical, geological, geomorphological and geophysical data. When these characteristics are measured, the objects are represented by vectors with components, which are values of the characteristics.

The problem as the pattern recognition one is to divide the vectors into two classes: vectors D (Dangerous) and vectors N, which represent correspondingly the nodes where earthquakes with $M \geq M_0$ may occur and the nodes where only earthquakes with $M < M_0$ may occur. Application of the pattern recognition algorithms requires a training set of vectors, for which we know *a priori* the class they belong to. The training set is formed on the basis of the data on seismicity observed in the region. It consists of vectors D_0 and N_0 representing correspondingly the nodes where strong earthquakes occurred and the nodes, which are far from the known epicenters of such earthquakes.

II. FORMULATION OF THE PROBLEM AND THE MAIN STAGES OF ITS INVESTIGATION

Consider a selected magnitude cutoff M_0 that defines large earthquakes in the region under study. Roughly speaking, the problem of determining earthquake-prone areas aims at separating places of potential earthquakes into two parts, D where earthquakes with magnitude $M \geq M_0$ can happen and N where earthquakes with magnitude $M \geq M_0$ are impossible.

The first question arising in a strict formulation of the pattern recognition problem is how to select the region and the magnitude cutoff M_0. The experience accumulated in *Gelfand et al.* (1972, 1973, 1974a, 1974b, 1976), *Zhidkov et al.* (1975), *Gvishiani et al.* (1978, 1987), *Caputo et al.* (1980), *Zhidkov and Kossobokov* (1980), *Gvishiani and Kossobokov* (1981), *Kossobokov* (1983), *Gvishiani and Soloviev* (1984), *Cisternas et al.* (1985), and *Gorshkov et al.* (1987) suggests the following heuristic criteria.

- The number of large earthquakes with $M \geq M_0$ in the region should be at least 10-20.
- The circles centered at epicenters of reported earthquakes with $M \geq M_0$ that have radii about the size of their source should not cover the entire region (otherwise, the problem has a trivial solution where the whole region is D).
- The region has to be tectonically uniform in sense of the similarity of possible causes of earthquakes with $M \geq M_0$.

These criteria establish certain limitations on the size of the region and the threshold M_0. For instance, M_0 = 5.0-6.0 implies the linear size of a region of the order of hundreds kilometers, whereas for M_0 = 7.0-7.5 this size should be larger than a thousand kilometers. M_0 = 8.0 requires a region tens of thousands kilometers long. These limitations were met in practice, for example, in Italy, M_0 = 6.0 (*Caputo et al.*, 1980); in California, M_0 = 6.5 (*Gelfand et al.*, 1976); in South America and Kamchatka, M_0 = 7.75 (*Gvishiani and Soloviev*, 1984), and in the whole Circumpacific, M_0 = 8.0 (*Gvishiani et al.*, 1978). The experience accumulated in a decade confirmed that pattern recognition methods might reliably distinguish earthquake-prone areas on different scales of lithospheric block hierarchy and in different seismic and tectonic environments (*Gelfand et al.*, 1972, 1973, 1974a, 1974b, 1976; *Zhidkov et al.*, 1975; *Gvishiani et al.*, 1978, 1987; *Caputo et al.*, 1980; *Zhidkov and Kossobokov*, 1980; *Gvishiani and Kossobokov*, 1981; *Kossobokov*, 1983; *Gvishiani and Soloviev*, 1984; *Cisternas et al.*, 1985; *Gorshkov et al.*, 1987).

When selecting the region and threshold magnitude M_0, it is necessary to define the objects of recognition.

Gelfand et al. (1972) were the first who applied pattern recognition methods to determine earthquake-prone areas in the Pamirs and Tien Shan. Since then, several important improvements in such a determination have been developed, including a broader choice of natural objects for recognition. In general, one may consider three types of objects in a study of earthquake-prone areas: planar areas, segments of linear structures, and points.

Gelfand et al. (1972) used planar morphostructural nodes of the Pamirs and Tien Shan as candidates for earthquake-prone areas. At that time, even a formal definition of this structure that permits reproducible identification did not exist and was subject of further analysis by gemorphologists and mathematicians (*Alekseevskaya et al.*, 1977). However, because most fractional areas are characterized by multidirectional intensive tectonic movements, nodes essentially attract epicenters of large earthquakes. The fact that most earthquakes with $M \geq M_0$ in a region originate within nodes is a necessary precondition for using them as objects of recognition. *Ranzman* (1979) formulated the geomorphological basis that favors this precondition. *Gvishiani and Soloviev* (1981) suggested a statistical method for testing it in practice, even when the boundaries of nodes are not defined precisely.

In planar nodes, pattern recognition algorithms classify morphostructural node in the region either as a D node, which is prone to earthquakes with $M \geq M_0$, or as a N node, where strong earthquakes are not possible. Such a classification determines the area D as the union of all D nodes and the area N as the union of all N nodes. The remaining territories of the region complementary to the nodes are not assumed to be dangerous (they are rejected with a certain level of confidence by preconditioning strong earthquake – node association).

This natural choice of objects entails a difficult problem outlining the boundaries of morphostructural nodes. When the difficulty is overwhelming, one may try substituting the nodes with intersections of morphostructural lineaments as done by *Gelfand et al.* (1974b). Tracing lineaments and their intersections is much easier task for a geomorphologist that essentially delivers similar (though less complete) information on the most fractured places of multidirectional intensive tectonic movements. That is why intersections of morphostructural lineaments were commonly used for determining of earthquake-prone areas (*Gelfand et al.*, 1974b, 1976; *Zhidkov et al.*, 1975; *Caputo et al.*, 1980; *Zhidkov and Kossobokov*, 1980; *Gvishiani and Soloviev*, 1984; *Cisternas et al.*, 1985; *Gorshkov et al.*, 1987; *Gvishiani et al.*, 1987). The necessary precondition of using nodes as recognition objects is transformed to a hypothesis that epicenters of strong earthquakes originate near intersections of morphostructural lineaments (*Gelfand et al.*, 1974b). This hypothesis is likely to be confirmed in a region if the following two conditions are valid: (1) the distance from all accuratelly determined epicenters of earthquakes with $M \geq M_0$ to the nearest intersection does not exceed a predefined distance r; (2) the area covered by circles of radius r centered in all intersections is a small part of the total area of the region. A statistical justification of the hypothesis can be obtained by using the algorithm developed by *Gvishiani and Soloviev* (1981).

Pattern recognition algorithms assign the vectors that describe intersections of lineaments to two classes: class D of intersections having vicinities prone to earthquakes with $M \geq M_0$ (D intersections) and class N. The classification of vectors determines the preimage of area D as the union of all vicinities of D intersections. The area N is the complement of area D in the union all vicinities of intersections. It is assumed that the remaining territories of the region complementary to all vicinities of intersections are not dangerous.

Usually, earthquakes are associated with segments of faults that they rapture. Therefore linear objects of recognition, like segments of active faults or fault zones, may seem most natural to many seismologists (*Gelfand et al.* (1976) give an excellent demonstration of how the problem is viewed differently). Pattern recognition algorithms divide linked linear objects into two classes: D segments capable of originating earthquakes with $M \geq M_0$ and N segments that are not.

Segments of linear structures were used as objects for recognition of earthquake-prone areas in California (*Gelfand et al.*, 1976), where the basic linear structure was San-Andreas fault, in the whole linear structure of Circumpacific seismic belt (*Gvishiani et al.*, 1978), and in the Western Alps (*Cisternas et al.*, 1985), where the segments of linear structures, forming a neotectonic scheme of the region were considered.

The usage of pattern recognition algorithms with learning necessitates an a priori selection of the training set W_0, which is the union of two subjects that do not overlap: the training set D_0 from class D and the training set N_0 from class N. Such a selection of $W_0 = D_0 \cup N_0$ depends on the types of the objects for recognition. In the case of planar objects, all of those, including known epicenters of earthquake with $M \geq M_0$, form D_0, whereas the subset N_0 consists of all remaining objects from W, $N_0 = W \setminus D_0$, or those of such objects that do not contain known epicenters of earthquakes with $M \geq M_0 - \delta$ (where $\delta > 0$ is usually 0.5 or about this value). It is necessary to emphasize that N_0 is not "pure" training set in the sense that some of its members belong to class D. In the first case, where $N_0 = W \setminus D_0$, the problem consists of distinguishing samples that spoil the purity of N_0. Such a fussy type of learning highlights a specific difficulty in locating possible earthquake-prone areas by pattern recognition techniques.

It is natural to require the condition $D_0 \subseteq D$, where D denotes the vectors classified as belonging to class D. In other words, all places of strong earthquakes that are known should be recognized. When D_0 many vectors a part of it can be excluded from the training set and reserved to verify the reliability of the decision rule obtained.

When recognition objects are points, the training set D_0 is assembled from those that are situated at a distance not exceeded a certain fixed value r from the reported epicenters of earthquakes with $M \geq M_0$. The choice of r must satisfy the condition that the distance from most (practically all) of the well located epicenters of strong earthquakes in the region to the nearest recognition point is less than r. Naturally r scales with M_0. For instance, *Zhidkov and Kossobokov* (1980) used $r = 40$ km for $M_0 = 6.5$ in the eastern part of Central Asia; *Gvishiani and Soloviev* (1984) chose $r = 100$ km for $M_0 = 7.75$ on the Pacific coast of South America. The training set N_0 consists of either all remaining points or those of them that are at a distance r_1 ($r_1 \geq r$) or longer from the epicenters of earthquakes with $M \geq M_0 - \delta$ ($\delta > 0$). In this case the training set N_0 also can contain points that are potentially from class D.

There is a certain difficulty when recognition objects are points; one epicenter can be attributed to several objects if its distance to each of them is r or less. In such case the training set D_0 may have some objects from class N. Algorithm CLUSTERS, which takes into account this specific feature of the training set D_0 is used to overcome this difficulty. In case of ambiguity, the condition that $D_0 \subseteq D$ is changed by another natural one: each epicenter of an earthquake with $M \geq M_0$ has a point D object at a distance r or less.

When recognition objects are linear segments, the training set D_0 assembles those containing a projection of an epicenter of a strong earthquake. The training set N_0 is either $N_0 = W \setminus D_0$ or contains segments from W that are not neighbors of D_0. Another way to form N_0 is to exclude those segments from $W \setminus D_0$ that contain a projection of an epicenter of an earthquake with $M \geq M_0 - \delta$ (where $\delta > 0$ is a parameter). As a rule, there is a unique projection of an epicenter that does not create ambiguity in selecting D_0: therefore, it is natural to require that $D_0 \subseteq D$.

Pattern recognition algorithms operate with vectors of characteristics representing natural recognition objects. As far as the earthquake-prone areas are considered, it appears natural to use the characteristics describing, either directly or indirectly, the intensity of recent tectonic activity at the locality of each object. The accumulated experience in recognizing earthquake-prone areas has established the following characteristics as typical:

- a multitude of characteristics describing topography: maximum (H_{max}) and minimum (H_{min}) altitudes above sea level inside the object area, altitude range ΔH; dominating combination of geomorphological structures in the object's vicinities, percentage of the object's area with existing Paleogene Quaternary sediments, etc.;
- characteristics describing the complexity of geomorphological and neotectonic network of structures: number of lineaments forming the object, the highest rank of lineament among those which form the object, etc.;
- characteristics describing gravitational field anomalies.

In case of planar objects the sense of "area" is obvious. When objects are points the area is a circle of the same radius for all objects centered at an object. When objects are linear segments the area is a circle of the same radius for all objects centered at the middle of a segment. Planar objects may have various areas and the area of an object may be used as one of characteristics.

In principle, all available information related directly or indirectly to the level of seismic activity can be used to characterize objects. The only necessary precondition for a characteristic is availability of uniform measurements across the entire region under consideration. After measuring selected characteristics for all the objects, they are converted to vectors $\mathbf{w}^i = \{w_1^i, w_2^i, ..., w_m^i,\}$, $i = 1, 2, ..., n$, where m is the total number of characteristics, n is the total number of objects in W, and w_k^i is the value of the k-th characteristic measured for the i-th object.

The pattern recognition algorithms, which are used to investigate the problem, work in a binary vectors space. Their application requires a transformation of vectors that describe natural recognition objects into binary ones.

Given the training set of vectors $W_0 = D_0 \cup N_0$, a pattern recognition algorithm determinates a classification $W = D \cup N$ where D and N are sets of vectors of classes D and N, respectively. As pointed above, the resulting classification should satisfy certain conditions, like $D_0 \subseteq D$ for planar objects. To avoid a trivial solution when all places considered belong to D, the following condition is usually introduced:

$$|D| \leq \beta\ |W|,$$

where $|D|$ and $|W|$ stand for the numbers of objects in sets D and W, respectively; and β, $0 < \beta < 1$, is a real constant, which sets an a priori upper bound for the fraction of D vectors in W. The value and justification of β must result from an expert evaluation of geological, seismological, and other available information on the region.

The quality and reliability of a classification can be verified by control tests. If successful, such test favors the classification that actually divides the region into earthquake-prone areas and areas where earthquakes with $M \geq M_0$ are not likely. Usually, pattern recognition of earthquake-prone areas involves a small sample of natural objects whose size does not allow reserving a control set for verification. Nevertheless, certain verification of the classification can be achieved by the comprehensive analysis of the result and additional information that was not used initially, of which the most important are data on epicenters of large earthquakes, e.g., noninstrumental, either historical or paleoseismological.

Classifications that are not satisfactory and have no meaningful interpretation are usually not reported. To get a satisfactory classification, a researcher can perform several cycles of trial and error through the following stages of recognition:

- definition of the region under study and the magnitude cutoff attributed to earthquake-prone areas;
- choice of the natural recognition objects;
- selection of the training set $W_0 = D_0 \cup N_0$;
- description of objects as vectors;
- discretization and coding of the characteristics;
- classification of vector space $W = D \cup N$ by a pattern recognition algorithm;
- evaluation of the reliability of classification from control tests;
- interpretation of the classification $W = D \cup N$ as a division of the region into earthquake-prone and other areas;
- generalization of geological and geomorphological interpretation of classification and the rules used to obtain it.

After the definition of D and N areas in the region territory it is advisable to do a statistical analysis of the locations of the known epicenters of earthquakes with $M < M_0$ relative to the located areas (as, e.g., in *Kossobokov and Soloviev*, 1983). The result of such comparison can lead, in principle, to the conclusion that the obtained D and N areas are actually earthquake-prone areas for earthquakes with $M \geq M'_0$ where M'_0 is a smaller magnitude threshold than M_0.

III. RECOGNITION OF EARTHQUAKE-PRONE AREAS FOR THE WESTERN ALPS

The problem of recognition of places in the Western Alps where earthquakes with $M \geq 5.0$ may occur (*Cisternas et al.*, 1985) is briefly considered below.

The intersections of the morphostructural lineaments obtained as the result of the morphostructural zoning of the Western Alps are objects of pattern recognition. The scheme of the morphostructural zoning of the Western Alps and the objects are shown in Fig. 7. The total number of objects in the set W is 62. The problem is to classify these objects into two classes: objects where earthquakes with $M \geq 5.0$ may occur (class D) and objects where earthquakes with $M \geq 5.0$ are impossible (class N).

Table 1 contains the list of characteristics, which describe the objects. The components of vectors $\mathbf{w}^i$ are the values of these characteristics.

The epicenters of earthquakes with $M \geq 5.0$ or $I \geq 7$ (I is maximum macroseismic intensity) are shown in Fig. 7 by dark circles with years of occurrence. The training set D_0 includes intersections located near epicenters of earthquakes with $M \geq 5.0$, 1900-1980. If an epicenter is at a distance less than 25 km from two intersections, both them are included in D_0. As a result, 14 intersections (3, 12, 13, 14, 20, 30, 31, 35, 40, 41, 42, 44, 51, and 57) constitute D_0. Intersections 1, 5, 6, 8, 53, 55, 56, 58, 60, and 61 hosting historic earthquake with $I \geq 7$ are not included both in D_0 and N_0 training sets as well as intersections 18 and 19. The latter are near the 1905 epicenter represented in D_0 by the nearest intersection 20. The remaining 36 intersections compose the training set N_0.

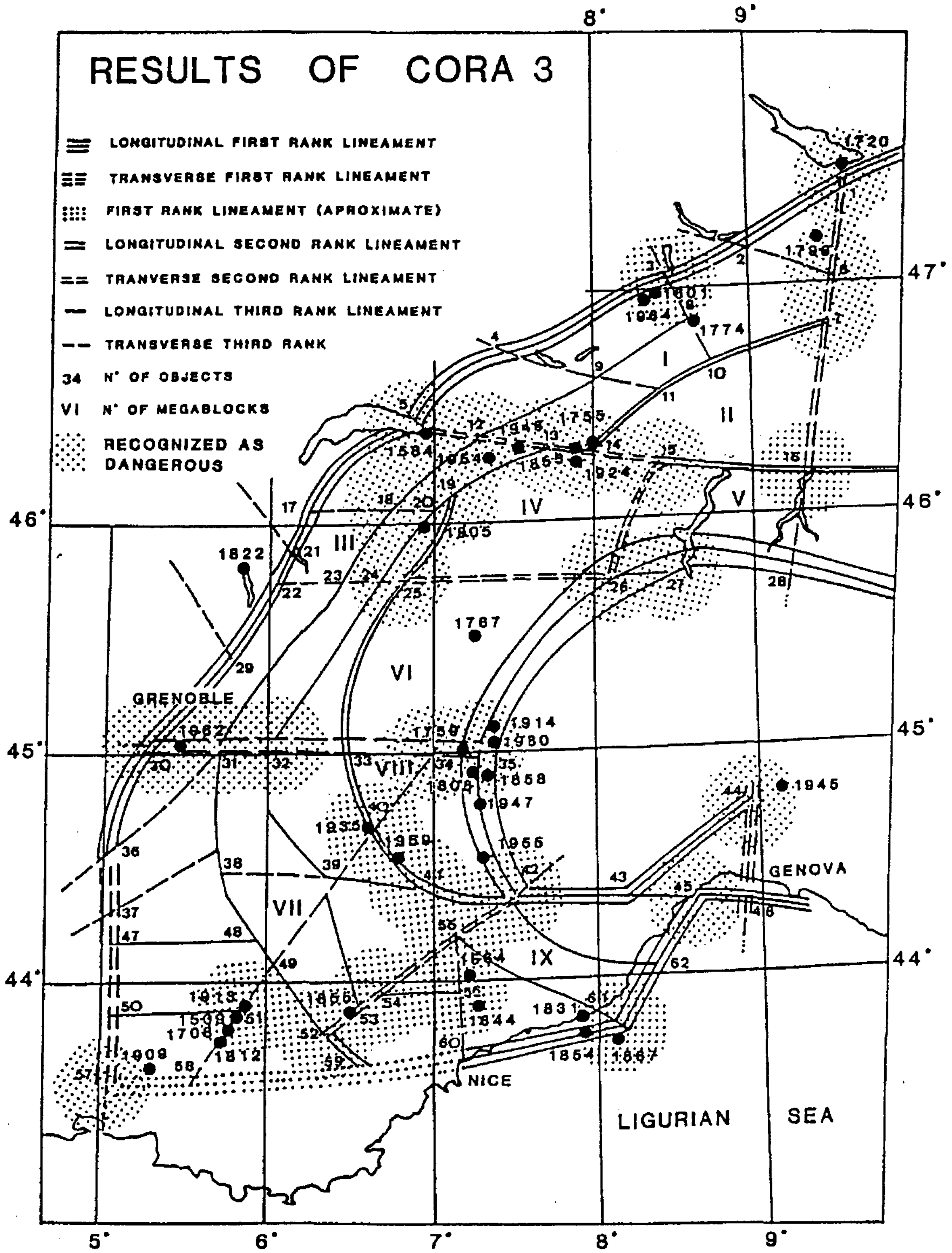

FIGURE 7 The morphostructural scheme of the Western Alps and the result of recognition.

Table 1 lists the characteristics and the discretization thresholds used for recognition. Except for the combination of topographic forms, their binary coding was S type. The most informative characteristics are: maximum altitude H_{max}, altitude gradient $\Delta H/l$, the percentage of Quaternary deposits Q, the highest rank of the lineament R_h, the distance to the nearest second rank lineament ρ_2. For all of them $P_{max} > 20\%$.

The value of β, which sets an a priori upper bound for the fraction of D vectors in W, was estimated as 0.6. Therefore classifications with $|D| \leq 0.6\ |W|$ were considered only.

The main case of classifying the 62 binary vectors was obtained through CORA-3 with $k_1 = 3$, $\bar{k}_1 = 2$, $k_2 = 11$, $\bar{k}_2 = 1$, and $\Delta = 0$. The main case resulted in the eleven D traits and eight N traits listed in Table 2. The traits are given in the table as conjunctions of inequalities in the values of the characteristics of the intersections. The classification of the intersections is shown in Fig. 7: 34 intersections are assigned to class D, and the remaining 28 to N. Class D includes all D_0, 11 intersections from N_0, and 9 intersections from outside the training sets.

TABLE 1 Characteristics of intersections in the Western Alps

Characteristics	Discretization thresholds	
	first	second
Maximum altitude H_{max}, *m*	2686	4807
Minimum altitude H_{min}, *m*	325	-
Altitude at the intersection H_0, *m*	490	900
Distance between points where H_{max} and H_{min} are measured *l*, *km*	32	42
$\Delta H = H_{max} - H_{min}$, *m*	2500	-
Altitude gradient $\Delta H/l$, *m/km*	51	91
Combinations of large topographic forms (yes, no)		
mountain ranges separated by a longitudinal valley (m/m)		
a mountain range and a piedmont plain (m/p)		
a mountain range and piedmont hills (m/pd)		
piedmont hills and piedmont plain (pd/p)		
The percentage of Quaternary deposits Q, %	10	-
The highest rank of the lineament R_h	1	2
The number of lineaments forming an intersection n_l	2	-
The number of lineaments in a circle of 25 *km* radius N_l (3 thresholds)	2	3, 4
The distance to the nearest intersection ρ_{int}, *km*	20	31
The distance to the nearest first rank lineament ρ_1, *km*	0	32
The distance to the nearest second rank lineament ρ_2, *km*	0	40
The maximum value of Bouguer anomaly B_{max}, *mGal*	-82	-8
The minimum value of Bouguer anomaly B_{min}, *mGal*	-145	-85
$\Delta B = B_{max} - B_{min}$, *mGal*	45	65
$\bar{B} = (B_{max} + B_{min})/2$, *mGal*	-110	-44
$HB = 0.1\ H_{max}\ [m] + B_{min}\ [mGal]$	153	-
The minimum distance between two Bouguer anomaly isolines spaced at 10 *mGal* $(\nabla B)^{-1}$, km	2	3

TABLE 2 Characteristic traits selected by algorithm CORA-3 for the Western Alps

#	*Q*, %	n_l	N_l	ρ_1, *km*	ρ_2, *km*	ΔB, *mGal*	$(\nabla B)^{-1}$, km
	D traits						
1				≤32		≤65	≤2
2				>0		≤65	≤2
3				≤32	0	≤65	
4			>3		0	≤65	
5			>4			>45	≤3
6					>0; ≤40	>45	
7		2		>32		>45	
8		2		>32			≤3
9		>2	≤3				≤2
10	>10		>3		≤40		
	N traits						
1						≤45	>2
2					>0	≤45	
3		2				≤45	
4					>40	≤45	
5					>40		>2
6		2			>40		
7		2	≤3		>0		
8		2		0			

IV. REVIEW OF THE RESULTS ON RECOGNITION OF EARTHQUAKE-PRONE AREAS

Table 3 contains a list of regions where the earthquake-prone areas have been determined.

TABLE 3 Regions where the earthquake-prone areas have been determined

Region	M_0	Reference
The Western Alps	5.0	*Cisternas et al.* (1985)
The Pyrenees	5.0	*Gvishiani et al.* (1987)
The Greater Caucasus, *intersections*	5.0	*Gvishiani et al.* (1988)
The Greater Caucasus, *nodes*	5.5	*Gorshkov et al.* (2003)
Italy	6.0	*Caputo et al.* (1980); *Gorshkov et al.* (2002)
The Alps and Dinarides	6.0	*Gorshkov et al.* (2004)
Tien Shan and Pamirs	6.5	*Gelfand et al.* (1972)
Balkans, Asia Minor, Transcaucasia	6.5	*Gelfand et al.* (1974a)
California and Nevada	6.5	*Gelfand et al.* (1976)
Himalayas	6.5 7.0	*Bhatia et al.* (1992) *Bhatia et al.* (1994)
Andes of South America	7.75	*Gvishiani and Soloviev* (1984)
Circumpacific seismic belt	8.2	*Gvishiani et al.* (1978)

Table 4 summarizes up to 2003 the comparison between the location of epicenters of strong earthquakes occurred in these regions after completing the recognition and the results of the earthquake-prone areas determination (*Gorshkov et al.*, 2003). One can see from this table that only 4 of 71 strong earthquakes have occurred in N-objects and 8 strong earthquakes have occurred outside the objects of recognition. Note that 18 strong earthquakes have occurred in D-objects that did not belong to the training set D_0. Such D-objects are marked by *.

TABLE 4 Summary of the test of earthquake-prone areas determination

Region	M_0	Result obtained in	Total number of strong earthquakes	Occurred in		Out of recognition objects
				D (D*)-objects	N-objects	
The Western Alps	5.0	1985	5	4 (1)	1	-
The Pyrenees	5.0	1987	2	1	1	-
The Greater Caucasus	5.0	1988	14	11 (3)	1	2
Italy	6.0	1979	5	3 (1)	-	2
Tien Shan and Pamirs	6.5	1972	6	4 (1)	-	2
Balkans, Asia Minor, Transcaucasia	6.5	1974	20	19 (5)	1	-
California and Nevada	6.5	1976	15	13 (5)	-	2
Himalayas	6.5	1992	2	2 (1)	-	-
Andes of South America	7.75	1982	2	2 (1)	-	-
Total			71	59 (18)	4	8

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