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Performance of Prediction Algorithms

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Performance of the earthquake prediction algorithm CN in 21 regions of the world

I. Rotwain and O. Novikova

Abstract

We evaluate performance of intermediate term earthquake prediction algorithm CN in 21 region of the world. Prediction is completely reproducible, since the parameters of the algorithm were defined and published in advance. Current estimation of statistical significance of predictions is low, about 83%. It would reach at least 95% after few more earthquakes are predicted with about the same success-to-failure score. Results of the test imply that prediction by this algorithm should be continued and provide a point of departure for further improvement of prediction methods.

Introduction.

Algorithm CN (Allen et al., 1984; Keilis-Borok and Rotwain, 1990; introduction to this volume) was designed by retrospective analysis of seismicity patterns preceding the earthquakes with $M \geq 6.4$ in California and adjacent parts of Nevada, hence its name. The algorithm includes normalization of seismicity, so that it can be applied for different regions without a change of adjustable parameters. However for each region we have to specify the following "region-specific" conditions: the boundary of the territory, covered by prediction; the earthquake catalog which will be used for prediction; and the magnitude range of the earthquakes to be predicted. The latter is defined as $M \geq M_0$. These conditions are chosen by unformalized retrospective data analysis, so that some freedom of choice remains. After these conditions are set up, prediction becomes completely reproducible. Here, we sum up performance of algorithm CN in 21 regions of the world. Predictions cover the periods after the region-specific-conditions were set up (and published). References and results of prediction are given in Table 1. As we see, the test periods vary from a year in the Southern Dead Sea rift zone to 14.5 years in Southern California. Termination date given in Table 1 is the end of the earthquakes catalog we used. For several regions the test came to an end because routine determination of catalogs was terminated.

The results of prediction are summarized in Table 1 and plotted for some regions in Fig. 1. Altogether 21 strong earthquakes have occurred in all the regions during the test periods. Of these, 9 (43%) have been predicted and 12 were not. Total time of all alarms was 24% of the sum of the periods considered.

Statistical significance.

So far, the statistical significance of advance predictions was rigorously investigated (Molchan et al, 1990) only for one of several premonitory patterns, considered in the algorithm CN. This is "pattern B" or "burst of aftershocks" (Keilis-Borok et al., 1980); its statistical significance happens to be above 99.6%. However, this pattern is used in CN algorithm in a simplified form, for which statistical significance can be different.

Let us estimate now statistical significance of predictions considered here. A simple estimate of significance is usually based on the value

$$\vartheta = (n_\Sigma - N_\Sigma \tau_\Sigma) / \sqrt{N_\Sigma \tau_\Sigma (1- \tau_\Sigma)}; \qquad (1)$$

here N_Σ is total number of strong earthquakes, n_Σ is the total number of predicted ones, and τ_Σ is the total duration of alarms, divided by the sum of time-periods considered in each region (Molchan, 1990). In our case

$$\vartheta = (9-21\cdot 0.24)/\sqrt{21\cdot 0.24\cdot 0.76} = 2.02.$$

When alarms are declared randomly (hypothesis H_0), the distribution of ϑ is approximately a standard gaussian one. We will define the level of significance as $(1-\varepsilon)$,

$$1 - \varepsilon = 1 - P(\vartheta \geq 2.02 \,|\, H_0) = 95\% \qquad (2)$$

This is an upper estimation since it does not allow for the fact, that we deal with a set of time intervals T_i in different regions, and not with a single time interval $T = \Sigma T_i$ in one region. We shall describe now a more
accurate estimation. Let us consider only those regions where at least one strong earthquake has occurred during the test period (Table 1a). Let (N_i, n_i, τ_i) be the characteristics of prediction in region labeled i, so that results of the test are defined by information $A = \{(N_i, n_i, \tau_i), i = 1,\ldots,k\}$. Here, as before, N_i is the total number of strong eathquakes and n_i is the number of predicted ones, τ_i is total duration of alarms in % to the time period considered. By definition, significance of prediction results under A and H_0 is:

$$1 - \varepsilon = 1 - P\{ n_\Sigma \geq n_\Sigma^{obs} \mid A , H_0\} \qquad (3)$$

where n_Σ^{obs} are observed values of n_Σ.

We determine ε by the method of generating functions. Specifically, when

$$\Pi(x\tau_i + \bar{\tau}_i)^{N_i} = p_0 + p_1 x + p_2 x^2 + \ldots, \text{ where } \bar{\tau}_i = 1 - \tau_i \text{, then}$$

$$\varepsilon = 1 - \Sigma\, p_i \cdot \chi(i < n_\Sigma^{obs}), \qquad (4)$$

where χ is a logical function equal to 0 or 1.

Application of formula (4) to the data in Table 1a gives statistical significance 1-ε = 83% This estimation is obviously low. One should note, however, that it would reach at least 93% after one more earthquake is predicted with about the same success-to-failure score. Statistics (N_i, n_i, τ_i) so far accumulated are yet insufficient for stable estimation of ε. This is illustrated by the following table showing variation of (1 - ε) with small variations of n_Σ^{obs} around the observed value, printed in bold.

n_Σ^{obs}	8	**9**	10	11
1-ε,%	76	**83**	93	98

Such a sensitivity is due to the discreteness of the distribution of ε and to the small size of samples so far accumulated. For this reason continuation of the test is necessary to decide on statistical significance of the algorithm.

Few more comments about the estimation of ε. Our method may exaggerate statistical significance, if we account for the regions where no strong earthquakes happened during the test period (Table 1b); to be on safe side we excluded such regions in calculating a conditional significance level. Note also that, we exclude also the Brabant - Ardennes region for which no alarm has been declared. Our estimation would not change, if we disregard the regions where the monitoring periods T_i are smaller than the return time Δt_i of strong earthquakes (Table 1a, # 3,4,7,10).

Discussion.

Performance of a prediction algorithm is characterized (Molchan, 1990) by the value $e = (1 - \nu_\Sigma - \tau_\Sigma)$, were ν_Σ is the relative number of earthquakes, missed by prediction, and τ_Σ is defined above. For random prediction $e = 0$; the larger is e, the better is prediction. In our case $\nu_\Sigma = 0.57$, $\tau_\Sigma = 0.24$ and $e = 0.29$. The quality of retrospective prediction was twice higher: we had $\nu_\Sigma = 0.17$, $\tau_\Sigma = 0.28$ and $e = 0.55$ (Arieh et al., 1992; De Becker et al., 1989; Bhatia et al., 1990; Gabrielov et al., 1986; Keilis-Borok et al., 1989; Keilis-Borok and Rotwain, 1989; Keilis-Borok and Rotwain, 1990; Novikova et al., 1996; Rundkvist and Rotwain, 1994). Although some reduction of performance is always expected after transfer from retrospection to forward prediction, such a twofold reduction is larger, than we expected.

Even with such a limited accuracy the prediction considered can be used for partial prevention of damage (Kantorovich and Keilis-Borok, 1977) and as a first approximation for more accurate second one; for example, territorial accuracy of some predictions considered could be improved by subsequent application of the algorithm Mendocino Scenario (Kossobokov et al., 1990).

Let us discuss now the implications for the further improvement of prediction methodology. The algorithm CN and other algorithms of this family (Keilis-Borok, 1990) is taking advantage of partial similarity of premonitory phenomena in different regions and time-periods. This allows to accumulate in reasonable time at least marginally sufficient sample of observations on premonitory phenomena; in each separate region this would be impossible, since strong earthquakes are by definition too rare for this purpose; in case of CN they are defined by condition, that their average return time in a region is 5 to 7 years. Therefore the retrospective analysis and the further monitoring in each region separately are based on a small sample (typically there are 4-5 events during the retrospection period and 1-2 events during the monitoring period in a region). To get larger numbers inevitably involves uniform analysis of many regions. However, this is achieved at a cost. Expanding the number of regions considered we increase the sample of strong earthquakes, but at the same time we make the population of the regions more inhomogeneous and introduce a "noise", caused by yet unformalized choice of the region-specific conditions, indicated above.

For the students of this Workshop specific examples of such a kind deserve attention.

Change in the clustering of strong earthquakes. The algorithm CN declares an alarm (a "TIP") under several conditions including the following one:

$$\Sigma S(M_i) < S(M_0+dm), \quad t - 3years \le t_i \le t. \qquad (5)$$

Here t is beginning of the TIP, S(M) is the area of a fault-break unlocked by an earthquake with magnitude M; a uniform coarse estimation is used, $lgS \approx 10^{\,bM_i}$. Standard value *dm* = 0.7 is used in the algorithm. This condition reduces the possibility of false alarms, caused by a raise of seismicity after a strong earthquake. At the same time it increases the possibility that in a series of strong earthquakes all but the first one are missed.

This tradeoff is illustrated by Fig.2. It shows for Southern and Northern California together an error diagram (Molchan, 1990), as a function of the threshold *dm* set to cancel the alarms; the values of the threshold are listed in Table 2. We see, that raising *dm* to 0.8 we would predict 3 more earthquakes at the cost of some increase of duration of alarms.

The failure to predict these earthquakes is due to the increase of the clustering of strong earthquakes as they are reported in the catalogs after 1983. Such errors possibly can be better reduced not by change of *dm*, but by application of other algorithms, suggested by Knopoff et al. (1996) and Vorobieva and Levshina (1994).

Change in completeness of the catalog. Particularly sensitive to such a change is the count of the aftershocks after the each main shock (functional *Bmax,* defined by Keilis-Borok and Rotwain (1990)). High number of aftershocks may trigger an alarm; it will be a false one, if the rise of this number is due to the change in the way, by which the catalog is compiled. An example is a catalog for Nepal region. Table 3 gives cumulative distribution of the number of earthquakes over magnitude for two time periods: 1964-1984 and 1984-1997 After retrospective analysis all aftershocks reported were included in the count. However to equalize the average annual number of earthquakes in both periods will be about the same, if we assume, that actual magnitude cutoff in the first period was 4; other obvious explanations are less obvious. Counting only the aftershocks with M $\geq$4 in the second period will reduce alarm time from 7 to 4 years.

Incompleteness of a local catalog for adjacent territories. Local catalogs are necessary for prediction in low seismicity areas, where the magnitude cutoff of global catalogs is too high. However, these catalogs usually sample the territory of a single country, while premonitory seismicity patterns may be within much wider territory. As an example, Fig. 3 shows for the Brabant-Ardennes region the epicenters, given in the local catalog (by the Royal Observatory of Belgium) and in the global one (by the US National Earthquake Information Center NEIC). The strong earthquake, missed by prediction, occurred near the boundary the area, well covered by the local catalog.

Note, that the above observations are *by no means sufficient to change prediction algorithm.*

Current alarms.

When this is being written, the algorithm CN gives two current alarms, one in S. California and another in N. Appalachians (region 1). They are shown in Figure 1. The credibility of these alarms is increased by the fact, that 2 out of 3 false alarms in each region follow immediately a strong earthquake, while the current alarms are separated in time from a last strong earthquake.

Both alarms are due to increased seismicity rate in each of the regions. Figures 4 and 5 show main functionals that are used in the algorithm. We see clear similarity with their behavior before previous strong earthquakes.

No current alarms are identified in other regions. It is interesting to note, that the current alarm would be identified for Northern California too, if condition (5) is disregarded. This condition was the cause of two last failures-to-predict.

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Table 1a. Results of monitoring in the regions where strong earthquakes have occurred

Regions	References	Period	T, yrs	I_0	Δt, yrs	n/N	τ, yrs	τ,%
1. Cocos plate	Gabrielov et al.,1986	1984.1-1997.1	13.0	6.5	4.0	1/1	1.8	14
2. Caucasus	-"-	1988.6-1997.1	8.5	6.4	7.6	2/4	1.7	20
3. Assam	Bhatia et al., 1990	1988.8-1997.1	8.3	6.4	18.7	1/2	1.8	22
4. Nepal	-"-	1988.8-1997.1	8.3	6.4	9.3	1/1	7.0	84
5. N. California	Allen et al., 1984	1983.1-1997.1	14.0	6.4	6.4	1/3	3.5	25
6. S. California	-"-	1983.1-1997.6	14.5	6.4	4.1	2/5	5.6	39
7. South Dead See Rift	Rundkvist & Rotwain, 1996	1993.1-1994.1	1.0	5.5	20	1/1	1.0	100
8. Brabant -Ardennes	De Becker et al., 1989	1987.1-1995.1	8.0	4.5	7.0	0/1	0.0	0
9. Pamir	Gabrielov et al.,1986	1987.8-1991.3	3.3	6.5	4.3	0/1	0.7	21
10. Kangra	Bhatia et al., 1990	1988.8-1997.1	8.3	6.4	18.7	0/1	2	24
11. Baja California	Gabrielov et al.,1986	1984.1-1997.1	13.0	6.6	5.3	0/1	4.2	32
Total			**100.2**			**9/21**	**29.3**	

Notations: T - duration of the period considered; M_0 - minimal magnitude of strong earthquake to be predicted; Δt - average return time of strong earthquakes, in retrospection; N - number of strong earthquakes; n - number of predicted earthquakes; τ -

total duration of alarms; τ, % = τ:T

Table 1b. Results of monitoring in the regions where no strong earthquakes have occurred

Regions	Ref.	Period	T, yrs	I_0	Δt, yrs	τ, yrs	τ,%
1. Tan-Shan	Gabrielov et al.,1986	1987.8-1991.3	3.3	6.4	4.3	0	0
2. Baikal	-"-	1984.1-1992.1	8	6.4	?	0	0
3. E. Carpatians	Novikova et al., 1996	1994.1-1997.4	3.3	6.4	9.4	0	0
4. N. Appalachians (region 1)	Keilis-Borok& Rotwain,1989	1985.1-1997.1	12	5.0	10.5	1.8	15
5. N. Appalachians (region 2)	-"-	1985.1-1997.1	12	5.0	?	0	0
6. Krasnovodsk	Gabrielov et al.,1986	1984.1-1991.1	7	6.4	?	4.5	64
7. Kopetdag	-"-	1984.1-1991.1	7	6.4	18	0	0
8. Elburs	-"-	1984.1-1991.1	7	6.4	?	2.5	36
9. Jordan-Dead Sea rift zone	Arieh et al.,1992	1990.1-1994.1	4	5.0	7.5	1.7	42
10. Central Italy	Keilis-Borok et al.,1989	1986.1-1997.1	11	5.6	6	4.2	38
Total			**74.6**			**14.8**	

Notations are the same, as in table 1. Question mark means that there was no strong earthquake in retrospection period either.

Table 2. Results of prediction with different thresholds *dm* for cancellation of alarms in California.

#	Σ	*dm*	*n*	η,%	τ,%
1	20	1.3	26	7	58.6
2	15.8	1.2	25	11	55.6
3	12.6	1.1	25	11	52.8
4	10	1.0	25	11	51.4
5	7.9	.9	25	11	48.5
6	6.3	.8	25	11	45.8
7	4.9	.7	22	21	36.5
8	4.0	.6	19	32	35.7
9	3.2	.5	15	46	30.8
10	2.5	.4	11	61	22.8
11	2.0	.3	8	71	16

Notations: *dm* is the threshold defined in (5); n - number predicted earthquakes; η - rate of failures to predict; τ,- total duration of alarms in % to time-period considered. In previous publications the value $\Sigma = \Sigma S(M_i)$ was used instead of *dm*; line 7 corresponds to standard value *dm*.

Table 3. Annual average number of earthquakes in Nepal, data of the US National Earthquake Information Center

Period	magnitude ≥								
	0	**3.0**	**3.5**	**4.0**	**4.5**	**5.0**	**5.5**	**6.0**	**6.5**
1966-1984	9.2	9.0	8.7	6.8	4.1	2.3	0.8	0.6	0.17
1984-1997	16.5	16.5	14.5	9.4	3.3	1.1	0.4	0.2	0

Figure captions:

Fig.1. Time of Increased Probability of strong earthquakes in four regions.

Fig.2. The error diagram by Molchan (1990).
$\nu = \nu_\Sigma / N_\Sigma$ is the relative number of earthquakes, missed by prediction;
$\tau = \tau_\Sigma / T$, here τ_Σ is the total duration of alarms and T is the total time considered.
Different dots correspond to different values of parameter *dm* listed in Table 2.

Fig. 3. Epicenters of the earthquakes in Brabant-Ardennes.
Top is the map according to local catalog by Royal Observatory of Belgium;
bottom is the map according to NEIC.
Small circles $M < 4.5$; large circles - "strong" earthquakes, $M \geq 4.5$;
star - earthquake of April 13, 1992 , M=5.8, missed by prediction.

Fig. 4. Functionals of the CN algorithm in S.California
Vertical line is the moment of strong earthquake.

Fig. 5. Functionals of the CN algorithm in N.Appalachians
Vertical line is the moment of strong earthquake.

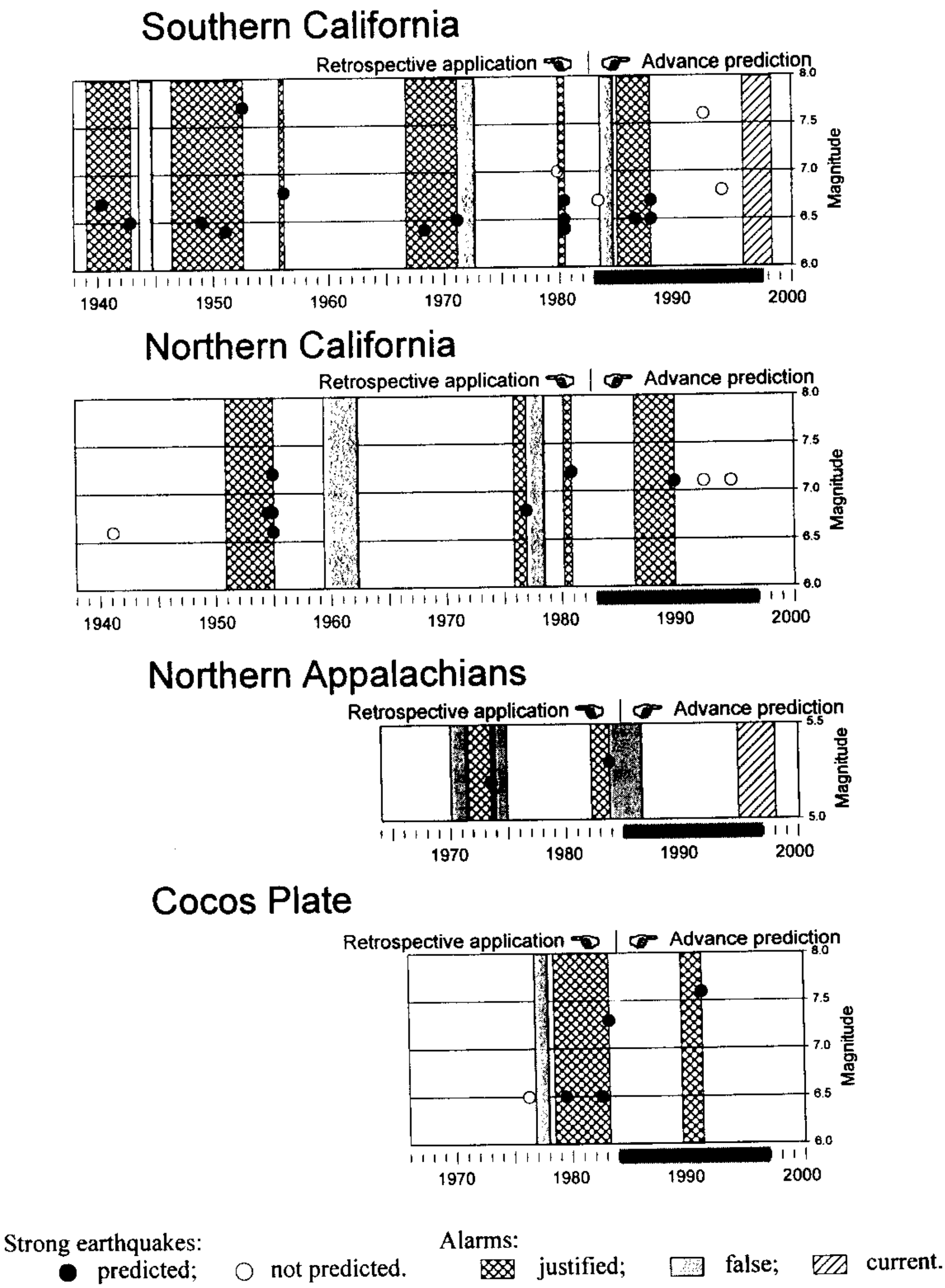
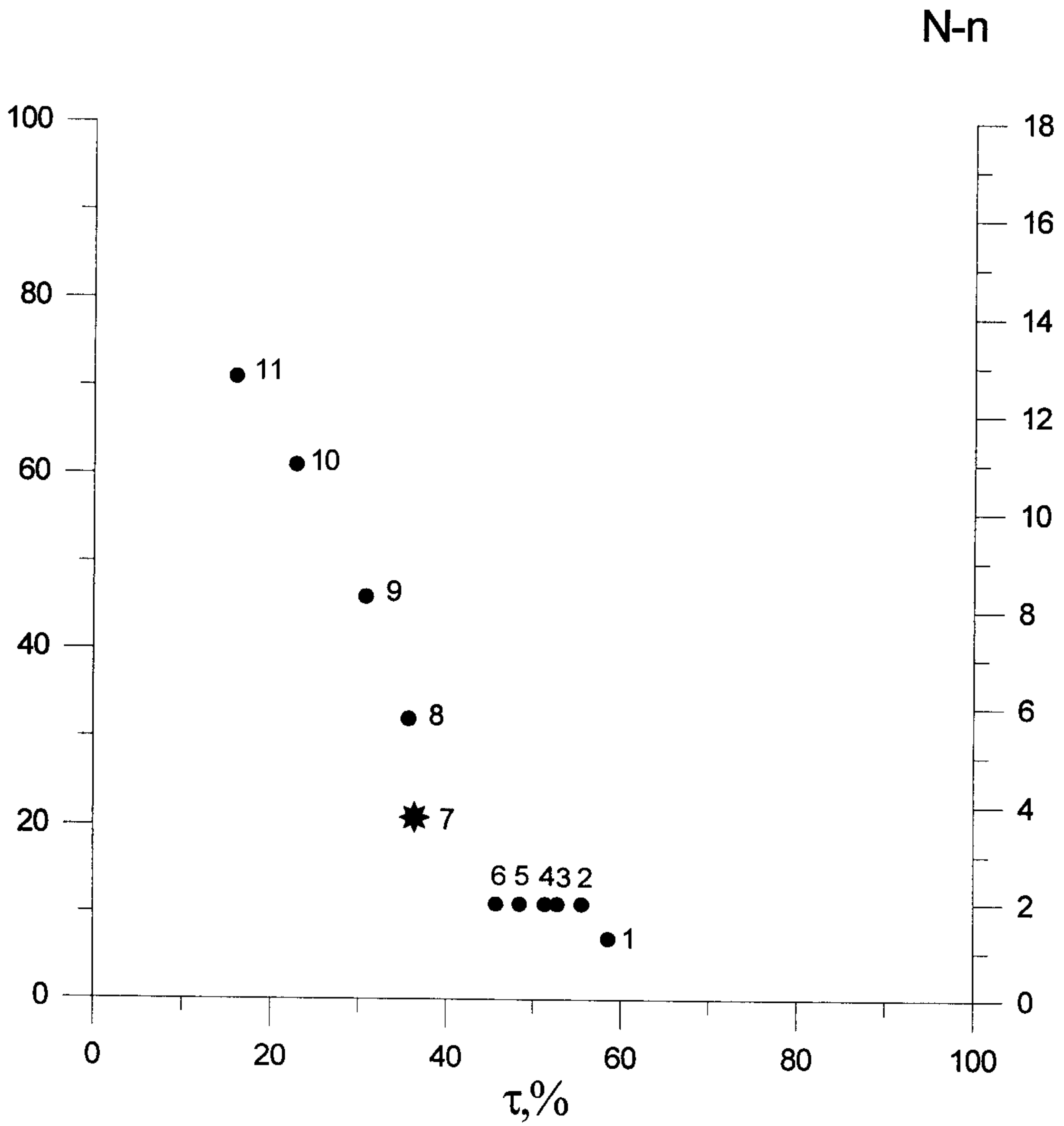


Fig.1. Time of Increased Probability of strong earthquakes in four regions

Note: Periods of advance prediction are shaded on the time scale.



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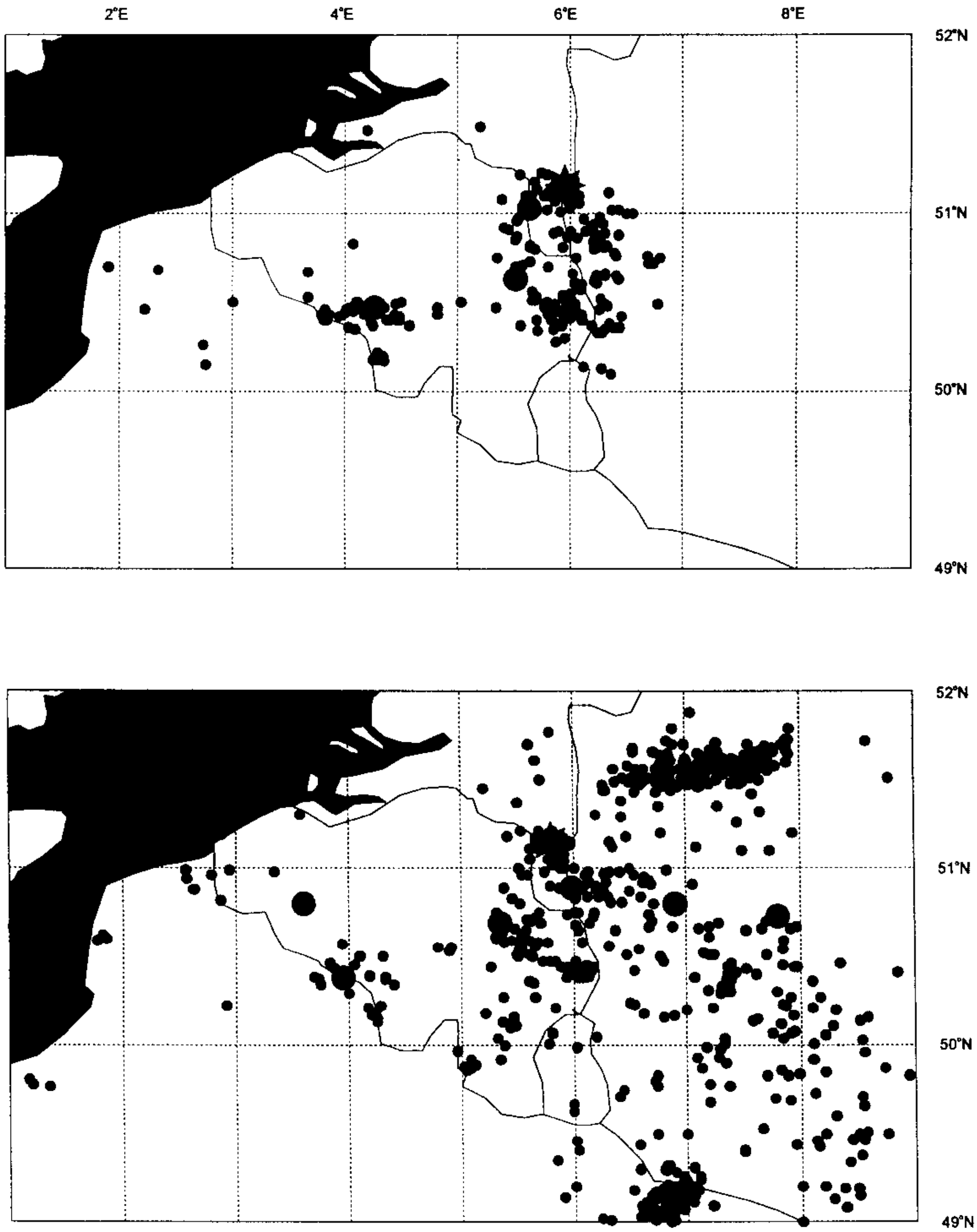

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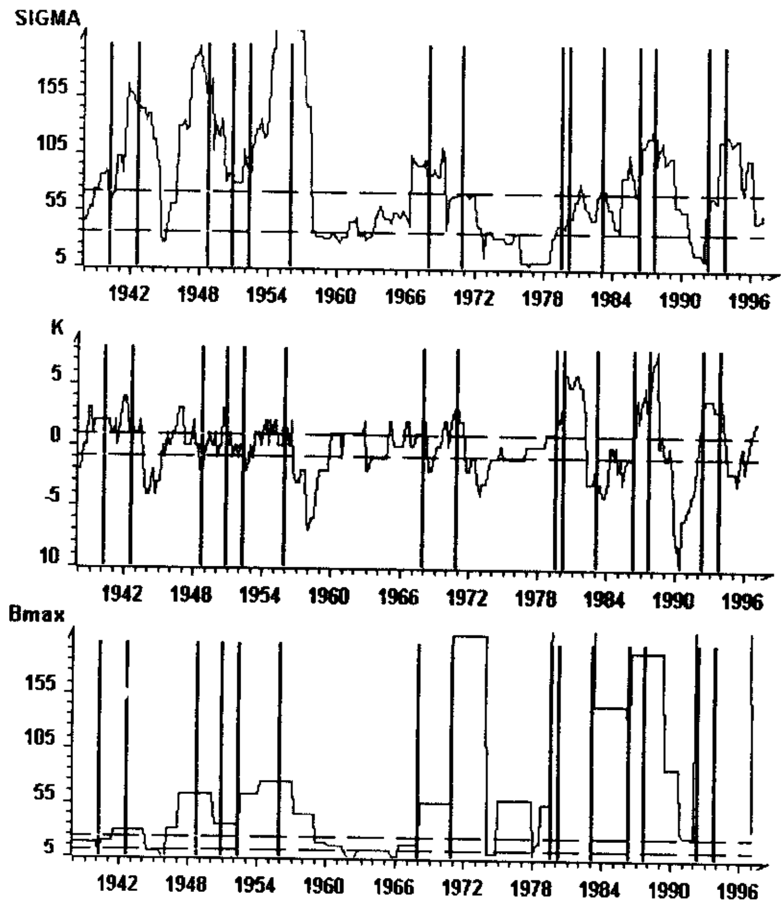

Fig. 4. Functionals of the CN algorithm in S.California
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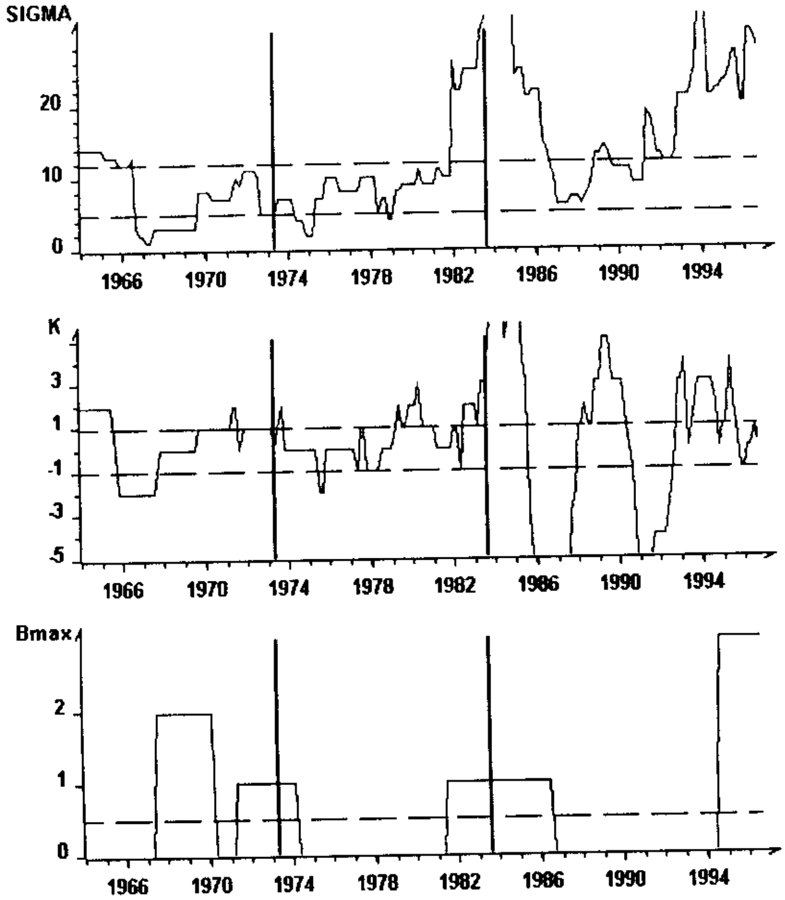

Fig. 5. Functionals of the CN algorithm in N.Appalachians
Vertical line is the moment of strong earthquake.