

On the monitoring of seismic activity using the algorithms of discrete mathematical analysis

B. A. Dzeboev^{1,2} and R. I. Krasnoperov¹

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The paper presents a new mathematical approach, entitled Seismic Activity monitoring by Discrete mathematical analysis (SARD) and aimed at seismic level assessment. It is based on application of well-proven algorithms of Discrete Mathematical Analysis (DMA) for the study of earthquake catalogs. The possibility of applying the proposed method for the territory of California, Kamchatka Peninsula and the Caucasus is shown. Evaluation of efficiency of the developed method is carried out using an error diagram. **KEYWORDS:** Seismic activity monitoring; discrete mathematical analysis (DMA); fuzzy measure; error diagram; Seismic Activity monitoring by Discrete mathematical analysis (SARD); earthquake catalog.

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Introduction

The problem of reliable estimation of seismic hazard is an important task not only for seismology, but for all geophysical studies. Its solution is of great social and economic importance. The urgency of the problem rapidly increases with the vigorous growth of urban territories. According to the UN statistics, seismic catastrophes account for more than 50% of the total number of natural disasters and dominate all types of catastrophes. Earthquakes are the most complex natural phenomena associated with the dynamics of lithospheric plates, the accumulation of tectonic stresses and their drops. Strongest earthquakes lead to serious economic and financial loss and numerous casualties. A significant part of the territory of the

Russian Federation (about 25%), which resides 27 Russian regions with a population of more than 20 million people, is situated in seismic zones. Here, recreational facilities are developing rapidly.

Over the past 35 years in many countries, which are characterized by significant seismic activity, including occurrence of strongest earthquakes, scientific research on the creation of methods for earthquake prediction has been significantly developed. The experience amassed in international geophysics testifies that the creation of systems of complex observations, providing for the required sampling rate in space and time, a continuous collection of prognostic data with the leading role of seismological observations, is of fundamental importance for the successful solution of the problem of determining the place, time and strength of the expected earthquake [Laverov *et al.*, 2008]. The countries that have reached the highest level of methods and techniques for seismic risk assessment and earthquake prediction are Japan, the USA and China. China has the most powerful system of seismological monitoring, oriented on earthquake prediction. Several thousand seismic stations operate in the USA. In most earthquake-prone areas, for example in Cal-

¹Geophysical Center of the Russian Academy of Sciences, Moscow, Russia

²Geophysical Institute, Affiliate of Vladikavkaz Science Center, Russian Academy of Sciences, Vladikavkaz, Russia

ifornia, the density of the seismic network is such that the average distance between stations is about 10 km. Seismological monitoring of the territory of USA is carried out by the US Geological Survey (<http://www.usgs.gov/>). High density of networks of seismological and geophysical observations is typical for the territory of Japan. However, in comparison to China, research on earthquake prediction in Japan is coordinated to a much lesser extent.

The state of seismological observations in Russia is characterized by departmental disunity of the conducted work, decrease in the level of financial support of observational networks, and technical deterioration of equipment [Laverov *et al.*, 2008]. Currently there are no sufficiently developed observational networks for monitoring within seismically active regions of Russia. All these factors significantly reduce the provision of seismic safety for the population over the territory of this country. In this regard, the development of a mathematical approach for monitoring the rate of seismic regime in the regions of Russia on the basis of discrete mathematical analysis (DMA) is certainly topical.

To predict an earthquake means to determine with sufficient reliability its location, time and magnitude. Hence, it is necessary to know how and where the earthquake source is being prepared and to monitor the successive stages of its development.

The physical and geological basis and the principal possibility of forecasting earthquakes are determined by two conditions. First, the strength of the rocks composing the Earth's crust is heterogeneous: the stronger sections alternate with the weak ones. Secondly, the stresses accumulate slowly, for hundreds of years. Under these conditions, the preparation of a large rupture is preceded by successive acts of destruction of many less durable sites, each of which causes a small earthquake. Observing the weak seismicity, it is possible to identify the place and estimate the strength of a future strong earthquake.

Typically, medium-term precursors appear several years or months before the main strong earthquake [Novikova and Rotvain, 1996]. They are based on the following characteristics of the seismic flow: the level of seismic activity, its variations over time, and the spatiotemporal grouping of earthquakes [Keilis-Borok *et al.*, 2001].

A new approach to the analysis of geophysical

data (discrete mathematical analysis, DMA), created and developed at the Geophysical Center of the Russian Academy of Sciences, is based on fuzzy mathematics and provides efficient monitoring of dynamic geophysical processes irregular in time and space, highlighting the background or normal component of the behavior of these processes and the anomalous component. At the same time, during such monitoring, the researcher himself determines the "virtual" nodes of the grid. They may not coincide with the nodes of real observations and there may be more of them than nodes of real observations.

DMA makes it possible to monitor the time- and space-dependent finite dynamic process. The essence of monitoring includes digitization, topological filtration, association with monitoring nodes, the aggregation of time series, and finally recognition of quiet/anomalous structures.

DMA-Monitoring of Seismic Level

Discrete mathematical analysis is a new approach to data analysis, developed at the Geophysical Center of the Russian Academy of Sciences. DMA is a series of algorithms aimed at solving the main tasks of data analysis: clustering and tracing in multi-dimensional arrays [Agayan *et al.*, 2014; Agayan and Soloviev, 2004; Gvishiani *et al.*, 2017b, 2017c; Mikhailov *et al.*, 2003; Soloviev *et al.*, 2016; etc.], morphological analysis of surface [Gvishiani *et al.*, 1994, 2008d; etc.], search for anomalies and trends in records [Gvishiani *et al.*, 2003, 2004, 2008a, 2008b, 2008c; Soloviev *et al.*, 2012a, 2012b; etc.]. All DMA algorithms are united by a common formal basis, based on fuzzy comparisons of numbers and proximity measures in discrete spaces. The idea of DMA is to create discrete analogues of the concepts of classical mathematical analysis: limit, continuity, smoothness, connectivity, monotonicity, extremum etc. DMA algorithms and their combinations provide a way to monitor the seismic process, irregular both in time and in space.

Let's consider an example: X is any seismic catalog in the domain Ω . The essence of monitoring:

0. The beginning is digitization. In time it is division into equal intervals $\{\delta t_i\}$. In space it is selection of monitoring nodes $\{\omega_j\}$ in the domain Ω .

1. Clustering (topological filtration – allocation of a reference dense subset Y_i in the image $X(\delta t_i)$ of the process X in the interval δt_i by means of the algorithm discrete perfect sets (DPS) [Gvishiani et al., 2013a, 2013b, 2013c]: $Y_i = \text{DPS}(X(\delta t_i))$.

2. Transfer of clustering to the monitoring nodes (the spatial grid of interest) is the construction of the fuzzy activity measure $\mu(\omega_j)(i) \in [0, 1]$ [Soloviev et al., 2013] by the DMA methods for each node ω_j relative to the process X for the period δt_i through the proximity ω_j to Y_i .

3. Postulation – monitoring $\text{Mon}(X)$ is the aggregation of time series in the monitoring nodes $\{\mu(\omega_j)(i)\}$.

4. Statistical, wavelet and DMA-analysis $\text{Mon}(X)$ with subsequent conclusions on the grid ω_j . In particular, recognition of quiet/anomalous structures within a grid.

SARD (Seismic Activity monitoRing by Discrete mathematical analysis) [Dzeboev, 2017], a method we apply here, continues a series of the DMA methods successfully applied to the analysis of earthquake catalogs. The seismic process is analyzed by studying its behavior at the nodes of the coordinate grid with a given interval (reference points) and constructing measures of activity. As a measure of activity, we use the value μ , determined by the algorithm of topological filtration (clustering) DPS [Agayan et al., 2014; Gvishiani and Dzeboev, 2015; Gvishiani et al., 2013a, 2013b, 2016, 2017c] or its adaptive version A-DPS (adaptive discrete perfect set).

The DPS algorithm is the part of DMA [Gvishiani et al., 2008a], an algorithmic approach that is being developed in the Geophysical Center of RAS under the leadership of A. D. Gvishiani. It is included in its DMA-clustering block [Agayan and Soloviev, 2004; Gvishiani et al., 2008d]. DMA-clustering algorithms solve the problems of topological filtering of multidimensional data sets, highlighting in these arrays the most significant parts and cutting off the non-essential ones. DPS is the result of further development of ideas presented in [Agayan et al., 2014]. As the results of the research showed [Gvishiani et al., 2013a, 2016; etc.], it can be used for recognizing the locations of strong earthquakes' possible occurrence along with the classical EPA method (Earthquake-Prone Areas recognition) [Gvishiani and Dubois, 2002, Gvishiani et al., 2017a; Soloviev et al., 2014].

The calculated measure μ varies within the interval $[-1, 1]$. In contrast to the classical measure of seismic activity [Riznichenko, 1967], the measure μ reflects the relative density of epicenters that varies over time in comparison with the spatial environment. A local increase in time of the parameter μ may reflect an increase in the activity of weak earthquakes, often accompanying the final stage of the preparation of a strong earthquake [Keilis-Borok et al., 2001; Kossobokov and Shebalin, 2003]. Thus, the variation of μ in time can be also used for diagnosis of periods of seismic hazard level increase and for estimating the forthcoming earthquake location.

By the monitoring of seismic activity, we mean the analysis and study of the behavior of the set of time series for measure μ at the reference points. Time series are constructed with a constant step. At each step, the time interval t_i is considered. For each interval, with the use of the DPS or A-DPS algorithm, a dense subset of epicenters of earthquakes (clusters) is allocated. The idea of application of the DPS algorithm (β, q) for solving the task of seismic activity monitoring is to use its free input parameter β – the level of the maximum density of the determined dense clusters of epicenters of earthquakes (we used the input parameter q to calculate the localization radius). Parameter $\beta \in [-1, 1]$ allows the results of the DPS analysis of the earthquake catalog for a certain period of time t_i to be transferred to the nodes of the regular geographic grid covering the investigated region by constructing for each node the measure $\mu(t_i)$ of the activity of the seismic process in its vicinity for the period of time t_i . For this purpose, the earthquake catalog is preliminarily divided into time intervals t_i . For each t_i , a DPS clustering of the earthquake catalog with discretely varying values of parameter β is carried out and a measure $\mu(t_i)$ corresponding to the maximum parameter $\beta^* \in [-1, 1]$ is assigned to each grid node, at which the node is close to the distinguished $\text{DPS}(\beta^*, q)$ -clusters of earthquake epicenters. If the node is not close to any of the subsets selected by the DPS algorithm, then its measure of activity is -1 .

Since the seismic process in a certain spatial neighborhood is irregular in time, and the change in the level of its activity, often indicating an increase or decrease in potential seismic risk, occurs over a certain time interval, when assessing seismic

activity at time t_i , it is necessary to take into account its time memory. For this, at each instant of time t_i , the value of measure μ is recalculated with respect to the memory in the time interval $[t_{i-\Delta}, t_{i-1}]$ in the form of power averaging with weighting coefficients:

$$\mu_{\Delta}(t_i) = \left(\frac{\sum_{k=1}^{\Delta} a_k \mu(t_{i-k})^p}{\sum_{k=1}^{\Delta} a_k} \right)^{1/p} \in [0, 1],$$

$$a_k = \frac{1}{k}, \quad k = 1, \dots, \Delta$$

The measure μ_{Δ} varies on the interval $[0, 1]$. It should be noted that the calculation of the measure μ_{Δ} over a period of time t_i is performed without the involvement of $\mu(t_i)$, and the values of measure μ for Δ of the preceding time periods are used. Thus, we get that the value of $\mu_{\Delta}(t_i)$ is a kind of forecast for a period of time t_i . In the future, under the monitoring of seismic activity, we mean the analysis and study of the behavior of a set of time series of the measure μ_{Δ} at the grid nodes.

The Results of Applying the SARD Method

California

Testing of the SARD method was carried out for the territory of California and the adjoining states of the USA within $30\text{--}44^{\circ}$ N, $113\text{--}126^{\circ}$ W. The ANSS catalog (Advanced National Seismic System) for the period 1962–2015 was used. Earthquake epicenters with magnitude $M \geq 2.9$ were chosen, because their representativeness in the catalog during the considered period was sufficient. We used the following values for the input parameters: $q = -2.0$, time period $t_i - 1$ month, latitude-longitude grid spacing -0.5° , spacing by $\beta - 0.05$, $\Delta - 12$ months, $p = 2$.

The analysis of the results of seismic activity monitoring obtained with the help of the developed method was carried out for the period 1980–2015. Since 1980, the catalog is fairly complete for the entire studied area.

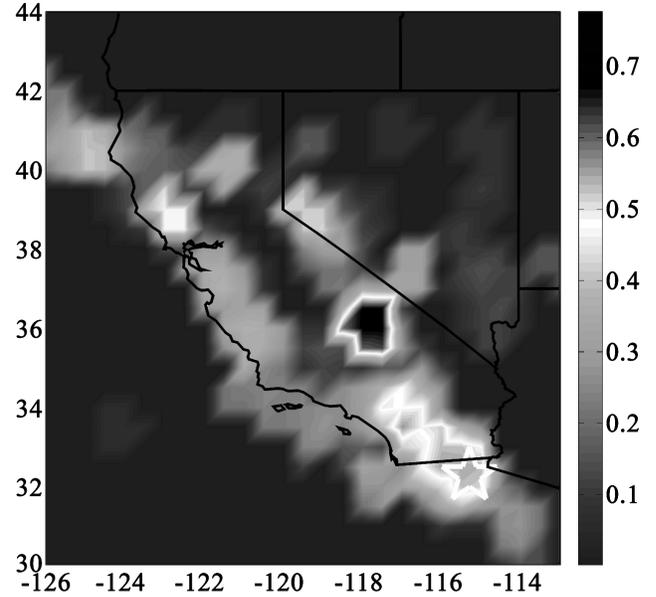


Figure 1. Value of the measure μ_{Δ} on April 1, 2010. The $M = 7.24$ earthquake epicenter on April 4, 2010 is shown with white asterisks.

As an example, Figure 1 shows the spatial distribution of the measure μ_{Δ} on April 1, 2010. It is easy to see two zones with large values of μ_{Δ} . This is the zone in the south of central California near the border with the state of Nevada and the zone on the border with Mexico. Inside the second zone falls the epicenter of the $M = 7.2$ earthquake on April 4, 2010, located in the north of Mexico. Slightly smaller values of μ_{Δ} are fixed in two zones: the coast of central California and the ocean near the coast in northern California. In April 2010, earthquakes with $M = 4.0 - 4.5$ occurred in these zones.

Within the considered period 258 seismic events with $M \geq 5$ occurred in the studied area including the aftershocks and 146 main shocks. A significant part of them occurred with the activity measure μ_{Δ} exceeding the level of 0.45.

We evaluated the effectiveness of the method using an error diagram [Molchan, 1991; Shebalin, 2006]. The considered space and time are divided into cells of $1 \text{ month} \times 0.5^{\circ}$. If we introduce the threshold μ_0 for the measure μ_{Δ} , then exceeding this threshold can be considered as a prediction of an earthquake with $M \geq 5$ in a given spatial cell during the subsequent time interval. We specified earthquakes with $M \geq 5$ with epicenters outside the cells with prediction as missed targets. Their

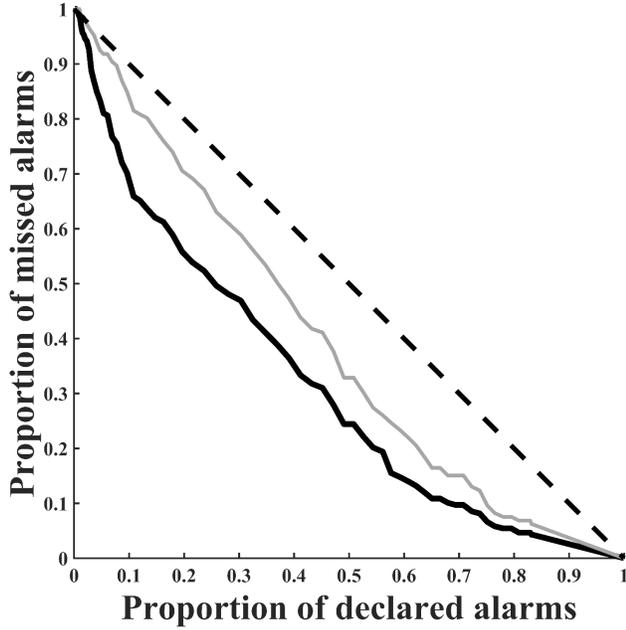


Figure 2. Error diagram for California. Thick dark line shows the relationship between the percentage of missed targets and the percentage of declared alarms for all earthquakes with $M \geq 5$ in the studied area, thin light line shows only major shocks with $M \geq 5$.

proportion is shown in the error diagram along the ordinate axis (Figure 2). The abscissa shows the probability of an accidental earthquake $M \geq 5$ in a cell with a prediction in accordance with a given model of seismicity [Shebalin et al., 2014]. As a rule, the simplest model of seismicity is used, in which the probability of an earthquake is proportional to the number of earthquakes registered in a given cell, with a magnitude, for example, $M \geq 4$. Therefore, the probability of accidental entry is often interpreted as the proportion of space-time of alarms weighted by seismicity [Kossobokov and Shebalin, 2003]. The greater the deviation of the error diagram from the diagonal (the diagonal corresponds to random guessing), the more effective the algorithm is [Shebalin, 2006]. It can be seen from the diagram that the effectiveness of the developed method of monitoring the level of the seismic regime is considerably high. The results obtained are significantly different from random guessing.

Kamchatka

The SARD approach has been implemented for the seismically active region of the Kamchatka Peninsula. The catalog of earthquakes of Kamchatka and the Commander Islands (Kamchatka branch of the Geophysical Service of Russian Academy of Sciences. Earthquake catalog of the Kamchatka Peninsula and the Commander Islands, <http://www.emsd.ru/sdis/earthquake/catalogue/catalogue.php>) for the period 1962–2015 was used with a depth of hypocenters not exceeding 70 km [Fedotov and Solomatina, 2015; Levina et al., 2013]. The catalog contains earthquakes with $M_L \geq 3.5$, where M_L is the Kamchatka regional magnitude [Abubakirov et al., 2018]. We used the following values for the input parameters: $q = -2.5$, time period $t_i = 1$ month, latitude-longitude grid spacing -0.5° , spacing by $\beta = 0.05$, $\Delta = 12$ months, $p = 2$.

The analysis of the results of the monitoring of the level of seismic activity in Kamchatka, obtained with the SARD method, was carried out according to earthquake data since 1980, due to the fact that from that time the catalog is sufficiently complete for the entire studied area.

For the period 1980–2015 in Kamchatka, according to the catalog (Kamchatka branch of the Geophysical Service of Russian Academy of Sciences. Earthquake catalog of the Kamchatka Peninsula and the Commander Islands. (<http://www.emsd.ru/sdis/earthquake/catalogue/catalogue.php>)), there were 6 earthquakes with $M_L \geq 6.5$ without excluding the aftershocks. Five of them occurred when measure μ_Δ exceeded the level of 0.45, three of them occurred with $\mu_\Delta > 0.55$.

Figure 3 provides an example of the spatial distribution of the values of measure μ_Δ on March 1, 1992 (Figure 3a) and December 1, 1997 (Figure 3b), white asterisks show epicenters of earthquakes with $M_L \geq 6.5$, that occurred on March 2, 1992 and on December 5, 1997, respectively.

Figure 3 shows the zones with high values of the measure of seismic activity μ_Δ along the coast of central Kamchatka. It can be seen in Figure 3a that the epicenter of the earthquake that occurred on March 2, 1992 with $M_L = 6.6$ ($M_w^{\text{GCMT}} = 6.8$), is located in the northeast of Avacha Bay in the zone for which the values $\mu_\Delta > 0.64$ were the maximum

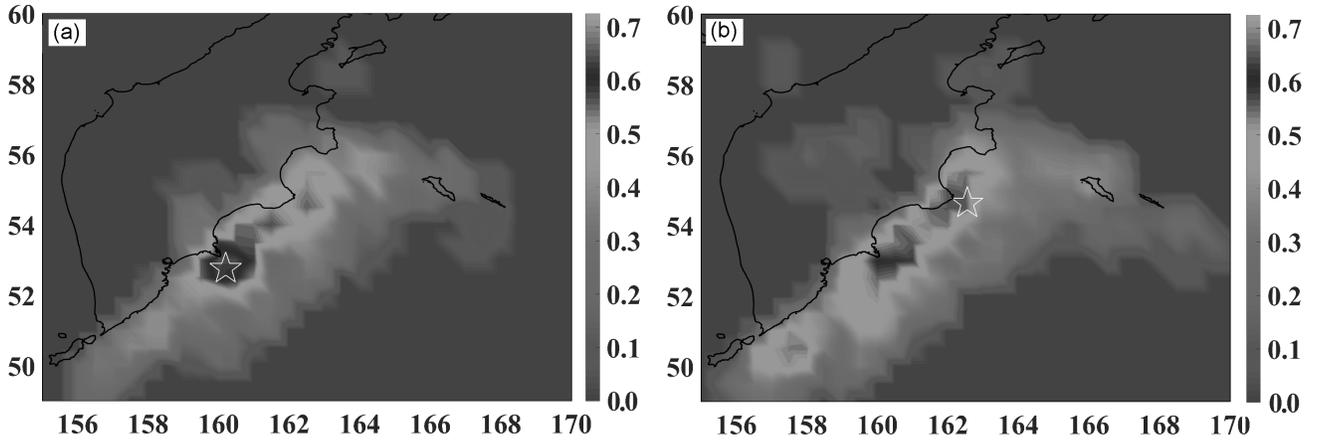


Figure 3. a) the value of the measure μ_{Δ} on March 1, 1992, white asterisk shows the epicenter of the earthquake on March 2, 1992 with $M_L = 6.6$ ($M_w^{GCMT} = 6.8$); b) the values of the measure μ_{Δ} on December 1, 1997, white asterisk shows the epicenter of the earthquake on December 5, 1997 with $M_L = 7.0$ ($M_w^{GCMT} = 7.8$).

for the entire region in the figure at the beginning of the corresponding month. The epicenter of the earthquake on December 5, 1997 with $M_L = 7.0$ ($M_w^{GCMT} = 7.8$) is located in the southeast of the Kamchatka Gulf in the zone with values $\mu_{\Delta} > 0.56$ and is shown in Figure 3b with white asterisk.

We evaluated the effectiveness of the developed method using error diagram [Shebalin et al., 2014] (Figure 4). For this purpose, the considered time and space were divided into cells. The earthquake forecast with $M_L \geq 6.5$ was estimated as exceeding a certain threshold by measure μ_{Δ} . Errors such as “missed targets” were the earthquakes with $M_L \geq 6.5$, falling beyond the cells with accurate prediction. In the error diagram (Figure 4), the abscissa shows the probability of an accidental earthquake with $M_L \geq 6.5$ in the cell with a prediction, the ordinate shows the fraction of errors such as “missed targets”, the diagonal corresponds to random guessing [Dzeboev, 2017; Shebalin et al., 2011]. To estimate an accidental entry of a strong earthquake in a cell with a prediction, the simplest model of seismicity was used in which the probability of an earthquake is proportional to the number of earthquakes with $M_L \geq 5.5$ recorded in a given spatial cell [Kossobokov and Shebalin, 2003; Shebalin et al., 2014]. The greater the deviation of the error diagram from the diagonal, the more effective the algorithm is [Shebalin et al., 2011]. Figure 4 shows that the proposed method is effective. The presented results differ from random guessing.

The Caucasus

We use the SARD method for the territory of the Caucasus within 40–44°N and 41–51°E. The

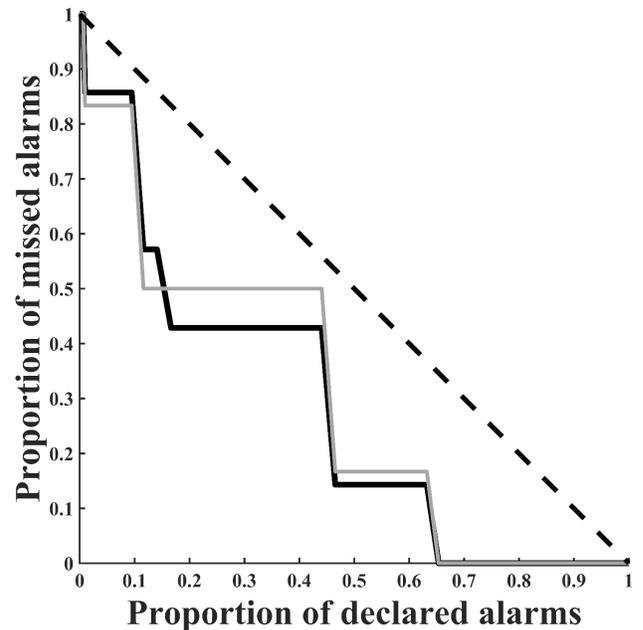


Figure 4. Error diagram for Kamchatka. Thick dark line shows the relationship between the proportion of missed targets and the proportion of declared alarms for all earthquakes with $M_L \geq 6.5$ in the studied area, thin light line shows only major shocks with $M_L \geq 6.5$.

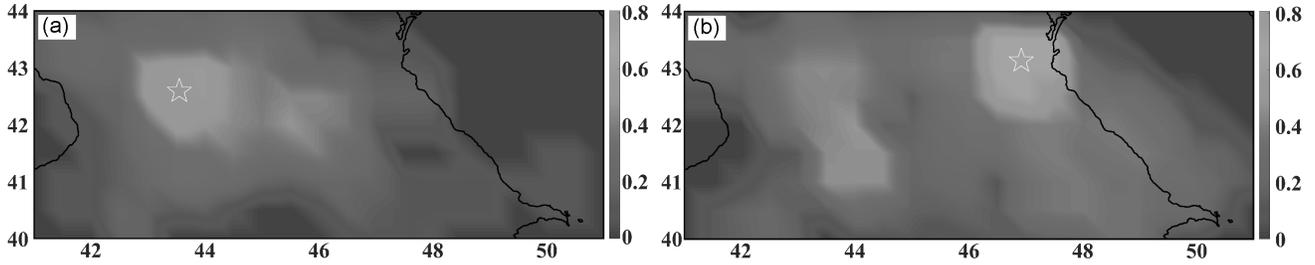


Figure 5. a) the values of the measure μ_{Δ} on December 1, 1994, white asterisk shows the epicenter of the earthquake on December 12, 1994 with $M = 5.1$; b) the values of the measure μ_{Δ} on September 1, 1999, white asterisk shows the epicenter of the earthquake on September 19, 1999 with $M = 5.4$.

catalog of earthquakes was compiled using the catalogs “Earthquakes in the USSR” (1962–1991) [Nauka, 1997] and “Earthquakes of Northern Eurasia” (1992–2008) [GS RAN, 2013] with depths of hypocenters not exceeding 70 km. To monitor the level of activity of the seismic process, we chose the epicenters of earthquakes with $M \geq 3.0$. It is worth noting that in connection with the absence of a homogeneous catalog of magnitudes for the considered region. The known correlation relationships between magnitudes were applied [Bormann, 2012; Rautian et al., 2007]. We used the following values for the input parameters: $q = -3.0$, time period $t_i - 1$ month, latitude-longitude grid spacing $- 0.5^\circ$, spacing by $\beta - 0.05$, $\Delta - 12$ months, $p = 2$.

Analysis of the results of the monitoring of the level of seismic activity in the Caucasus obtained with the help of the SARD method has been carried out based on earthquake data since 1990. From that time the catalog is sufficiently complete for the entire studied area.

In 1990–2008, in the Caucasus, according to the compiled catalog, more than 100 earthquakes with $M \geq 5.0$ occurred excluding the aftershocks. Most of them occurred at the measure μ_{Δ} exceeding the level of 0.5.

Figure 5 provides an example of the spatial distribution of the values of measure μ_{Δ} on December 1, 1994 (Figure 3a) and September 1, 1999 (Figure 3b), white asterisks show epicenters of earthquakes with $M > 5.0$, that occurred on December 12, 1994 and September 19, 1999, respectively.

In Figure 5a the earthquake epicenter with $M = 5.1$ was located in the area, for which the values of $\mu_{\Delta} > 0.55$ were the maximum for the entire region in the figure at the beginning of the corre-

sponding month. The epicenter of the earthquake in Figure 5b with $M = 5.4$ is shown with white asterisk, located within the area with the values of $\mu_{\Delta} > 0.65$.

To evaluate the effectiveness of the SARD method we constructed an error diagram [Shebalin et al., 2011] (Figure 6). The earthquake forecast with $M \geq 5.0$ was estimated as exceeding a certain threshold by measure μ_{Δ} . Errors such as “missed targets” were the earthquakes with $M \geq 5.0$, falling

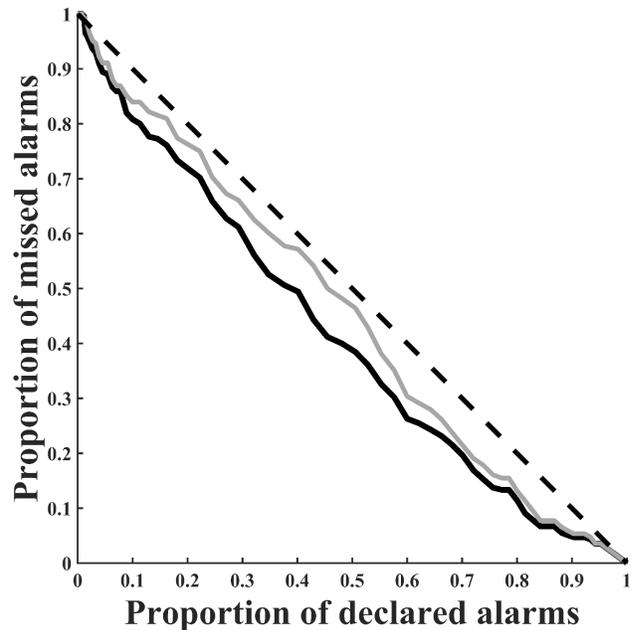


Figure 6. Error diagram for the Caucasus. Thick dark line shows the relationship between the proportion of missed targets and the proportion of declared alarms for all earthquakes with $M \geq 5.0$ in the studied area, thin light line shows only major shocks with $M \geq 5.0$.

beyond the cells with accurate prediction. To estimate an accidental entry of a strong earthquake in a cell with a prediction, the epicenters of the earthquakes with $M \geq 4.0$ were used. Figure 6 shows that the proposed method is effective. The presented results differ from random guessing.

It is worth noting that the results of applying the SARD method for the territory of the Caucasus are less representative than for Kamchatka and even more so for California [Dzeboev, 2017]. One of the possible reasons may be the known heterogeneity of the catalog.

Conclusions

- A new mathematical method SARD is proposed for monitoring the level of the seismic regime for estimating the probability of a strong earthquake.
- The possibility of using SARD for the territory of California, the Kamchatka Peninsula and the Caucasus is shown.
- To evaluate the effectiveness of SARD we constructed an error diagram which showed that the proposed method was effective. The obtained results differ from random guessing.

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B. A. Dzeboev and R. I. Krasnoperov, Geophysical Center of the Russian Academy of Sciences, 3 Molodezhnaya St., 119296 Moscow, Russia. (b.dzeboev@gcras.ru)