J Seismol (2013) 17:1125–1137
DOI 10.1007/s10950-013-9381-4

ORIGINAL ARTICLE

Designing efficient earthquake early warning systems: case study of Almaty, Kazakhstan

J. Stankiewicz · D. Bindi · A. Oth · S. Parolai

Received: 28 November 2012 / Accepted: 1 July 2013 / Published online: 12 July 2013

Abstract Rapidly expanding urban areas in Central Asia are increasingly vulnerable to seismic risk; but at present, no earthquake early warning (EEW) systems exist in the region despite their successful implementation in other earthquake-prone areas. Such systems aim to provide short (seconds to tens of seconds) warnings of impending disaster, enabling the first risk mitigation and damage control steps to be taken. This study presents the feasibility of such a system for Almaty, Kazakhstan. Genetic algorithms are used to design efficient EEW networks, computing optimal station locations and trigger thresholds in recorded ground acceleration. Factors like the possibility of station failure, elevation and access difficulty to a potential site, and the potential usefulness of existing stations in the region are considered. We present a large set of possible efficient networks, to which further selection criteria can be applied by both the installation teams and the end user, such as authorities in Almaty.

Keywords Earthquake early warning · Seismic risk · Central Asia · Genetic algorithms

D. Bindi · S. Parolai
Deutsches GeoForschungsZentrum GFZ,
Helmholtzstrasse 7,
Potsdam, Germany

J. Stankiewicz (✉) · A. Oth
European Center for Geodynamics and Seismology,
Walferdange, Luxembourg
e-mail: jacek@ecgs.lu

J. Stankiewicz
e-mail: jacek@gfz-potsdam.de

1 Introduction

Central Asia faces a significant earthquake hazard and risk. In particular, rapid urbanization of the major cities in the region, such as Bishkek and Almaty, makes society increasingly vulnerable to natural disasters (e.g., Abdrakhmatov et al. 2003; Torizin et al. 2009; Bindi et al. 2011). Almaty in particular has repeatedly been severely damaged by earthquakes of magnitude 7 and higher (e.g., Delvaux et al. 2001), and continues to face high earthquake risk. This risk was one of the reasons for moving the capital of Kazakhstan to Astana in 1998. Some fault systems in the region are expected to generate a magnitude 7.5 earthquake (Erdik et al. 2005) with a risk scenario study of Bishkek showing that such an event could lead to 90,000 people requiring hospitalization (Bindi et al. 2011).

Worldwide, the proximity of many large cities (e.g., Tokyo, Mexico City, and Istanbul) to seismically active regions and the associated earthquake risk led to the development of earthquake early warning (EEW) systems (e.g., Doi 2011; Espinosa-Aranda et al. 2011; Sesetyan et al. 2011, respectively, for the aforementioned). These systems operate continuously, and aim to issue warnings after the earthquake has occurred, aiming to provide short-term (order of seconds or tens of seconds) warning of the impending disaster to the city. In this time, even in a few seconds, several steps can be taken to reduce and mitigate damage and risk. These include orderly shut-offs of electricity and gas supply, deceleration of rapid-transit vehicles, and controlled suspension of activity in hospitals (e.g., Allen et al. 2009; Nakamura et al. 2011). No such systems exist in Central Asia, though Picozzi et al. (2013) recently presented a feasibility study for designing such a system for Bishkek.

Several EEWs have been developed, differing in the type of input they use (single station or a seismic network) and the level of information they provide (e.g., Erdik et al. 2003; Doi 2011). A key issue of all the systems, however, is taking advantage of information being transmitted electronically at much higher speeds than those of seismic waves. Thus, the signals recorded at one or multiple stations can be transmitted to a central gateway, analyzed, and a warning can be issued while the most damaging seismic waves, the S- and surface waves, are still progressing to the target site. This warning can be updated with time, for instance every second, until these waves reach the target site.

The key parameter in all EEW systems is the lead time. The exact definition of this time depends on the configuration of the EEW system used (see Satriano et al. 2011, for a review) but it is usually defined as the time difference between the arrival of the destructive S-waves at the city and the time the first warning is available. This corresponds to the maximum possible warning time that can be given. Here, we define this time as the difference between the ground acceleration reaching a predefined threshold (most likely during the arrival of the S-wave) at the city, and the earthquake being reliably detected by ground acceleration thresholds being exceeded at different stations of the network. In all the calculations, we also assume the signal transmitted between individual stations and the central datacenter system to be instantaneous. This is clearly idealized and, as such, represents the optimum case. The networks used by the Japan Meteorological Agency require at least 2 s of processing time, though some systems in Japan have reduced this to 0.1 s (Nakamura et al. 2011). As a processing time in the order of seconds would significantly affect the possible warning time in the case of Almaty, any network would need to be accompanied by a high quality and efficient telecommunications system.

An important aspect in developing an EEW system is the geometry of the network. Evaluations of existing networks and suggestions for their improvement have already been performed (e.g., Zollo et al. 2009; Oth et al. 2010). The work presented in this article builds on the genetic algorithms developed by Oth et al. (2010) to show how an optimal network for a trigger-based warning system can be designed, addressing questions such as how many stations are necessary and sufficient, as well as their locations. The focus of our study is the city of Almaty in Kazakhstan, exposed to seismic risk from the Issyk-Kul and Chon-Kemin fault systems (Fig. 1).

2 Stochastic seismogram database

The optimization approach used here requires a representative sample of relevant seismic recordings. In the design of an EEW network, it is critical that all potential earthquake sources are considered. Due to the sparsity of large earthquake recordings in the region, stochastic simulations of scenario earthquakes were performed using the finite-source ground motion simulation code EXSIM (Boore 2009). Overall, 100 scenario earthquakes were considered. Sixty-four locations were randomly chosen along active segments of the Issyk-Kul and Chon-Kemin fault systems (provided by the Kyrgyz Institute of Seismology, digitized by the Arizona State University[1]), with moment magnitudes between 5.5 and 8.0. Furthermore, approximate locations of 11 large historical earthquakes, including the 1911 Kemin and the 1885 Belovodosk earthquakes, were considered (e.g., Delvaux et al. 2001). These had moment magnitudes between 5.1 and 8.3. Finally, 25 earthquakes randomly distributed in the study area, with magnitudes not exceeding 5.5, were considered (Fig. 1). For all scenarios, reverse faults were assumed with depths not exceeding 5 km.

The possible station locations were considered on a grid with 0.1° spacing, from 42.1° to 43.3° north and from 76.0° to 78.7° west. With some locations not considered due to coinciding with Lake Issyk-Kul, 293 possible locations were considered. For each location, stochastic seismograms were computed for all scenario earthquakes resulting in a database consisting of 29,300 traces representing ground acceleration. One of the possible station locations coincided with the city of Almaty—the seismograms computed for this site are particularly important regarding the timing and level of a warning that is to be issued and for using these ground motions to provide macroseismic intensity estimates (e.g., Sokolov and Chernov 1998). The

[1] http://activetectonics.asu.edu/N_tien_shan/N_tien_shan_data.html

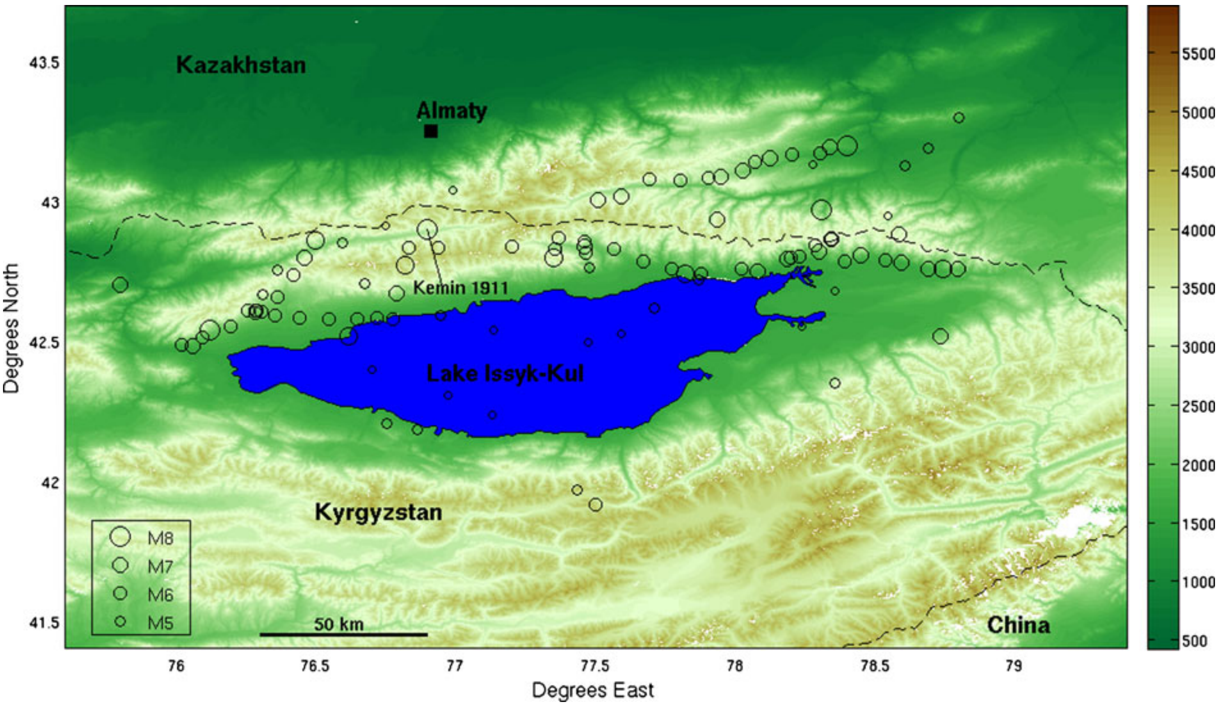

Fig. 1 Topographic map of the study area. Elevation given in meters. *Black square* Almaty, *dashed line* international borders. One hundred scenario epicenters considered in the study are marked with *circles* of size corresponding to the magnitude. Epicenter of the 1911 Kemin earthquake (M=8.2) was indicated

velocity models and most other EXSIM parameters used were similar to those used by Picozzi et al. (2013). Site amplification effects were estimated from the topographic slope, which can be considered a proxy for shear wave velocity of the uppermost 30 m, V_{S30} (Wald and Allen 2007). Following Böse (2006), the P- and S-wave contributions were computed separately using appropriate velocities, source terms, and attenuation parameters, and then added with the respective time delays.

3 Network evaluation and optimization

3.1 Determining the quality of a network

The methodology for evaluating and optimizing network performance used in this study has mostly been developed by Oth et al. (2010) for the Istanbul EEW system, and only an overview will be presented here. An important aspect of an EEW system's performance is its ability to give not only timely, but also reliable warnings with respect to the shaking that needs to be expected at the target site. In the work of Oth et al. (2010) for the case of Istanbul, the expected degree of shaking is expressed in terms of warning classes. Four classes of events are thus defined with respect to the peak ground acceleration (PGA) that arises for a given event at the target site. Class 0 means that the expected PGA at the target, in our case Almaty, will not exceed 0.02 g. Class I events are defined as those with PGA between 0.02 and 0.07 g, class II between 0.07 and 0.12 g, and for class III exceeding 0.12 g. These are the same values as used by Oth et al. (2010), who followed the estimate that ground motions with PGA>~0.1 g are considered as potentially seriously damaging (Anderson 2003) and used warning classes equally wide in terms of PGA range. While the chosen values are to a degree arbitrary, they nonetheless give an indication of scale of the expected ground motion. We use the parameter PGA and the ranges given above for demonstration purposes, yet depending on the target site and application to be carried out in case of a warning, other parameters (providing for instance a better representation of long-period ground motions) and ranges might be more appropriate.

For each hypothetical network, as well as specifying the locations of all the stations, three ground acceleration trigger thresholds need to be defined for event class identification—if during a 5-s window a given trigger threshold is exceeded at any set of three stations of the network, a warning of the class associated with this trigger threshold is declared. While these trigger thresholds thus correspond to the warning classes, their values do not necessarily correspond to the class boundaries defined above, with the former quantifying the ground motion at the section of the network closest to the epicenter, and the latter providing bounds for the expected ground motions at the target site.

Thus, each network consisting of n stations is defined by n+3df—the station locations and trigger thresholds. The optimal network is the one that can give the correct level warning (i.e., correct class of expected ground motion at the target) at a sufficiently long lead time for the highest number of scenario earthquakes.

To quantify this network quality, we use the cost function developed by Oth et al. (2010):

$$\text{cost} = \sum_{i=1}^{N} W_i\left(L(1-\text{K}) \times S\left(t_{\text{warn},i}\right) + K\right) \qquad (1)$$

where N is the number of events (100 in this case) and $t_{\text{warn},i}$ represents the warning (lead) time for each event. K is 0 if the event class has been identified correctly and 1 otherwise, L is 0 for class 0 events and 1 otherwise, and W is the weight associated with each event. $S(t_{\text{warn},i})$ is a continuous function with values between 0 and 1 comparing the lead time to a predefined time being considered as a sufficient warning time, $t_{\text{sufficient}}$. This function tends to 1 for small, insufficient lead times, and to 0 for large lead times. Oth et al. (2010) used a sigmoid function centered at $t_{\text{sufficient}}$ (Fig. 2). The exact value of the lead time considered to be sufficient depends on factors such as proximity to the seismogenic zone and the measures expected to take place once the warning has been issued. Satriano et al. (2011) used a value of 10 s when illustrating the principles of early warning. While a 10-s warning time can be considered sufficient, this is not always possible for Almaty. Figure 3 shows the distribution of S-wave travel times of the 100 scenario earthquakes. Two of these times are under 10 s, and a further six between 10 and 15 s. Given that the detection and location of the earthquake is not instantaneous but will take at least a few seconds, a 10-s lead time for these events is not possible and any network optimization algorithm requiring a sufficient warning time of 10 s would ignore these events. As these include the Kemin earthquake, this would not be an appropriate approach. We thus use an asymmetrical sigmoid as cost function (Fig. 2). With this function, lead times above 10 s are considered sufficient in a similar way to a standard sigmoid,

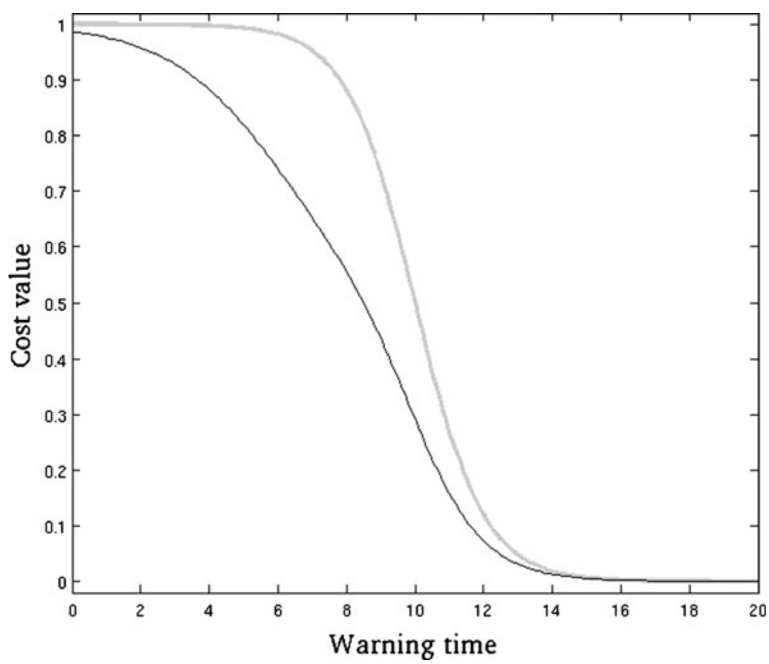

Fig. 2 Two possibilities for function S in Eq. (1) used in the study. The standard sigmoid centered at 10 s marked as a *thick gray line*, the asymmetric function more tolerant of lower lead times as a *thin black line*

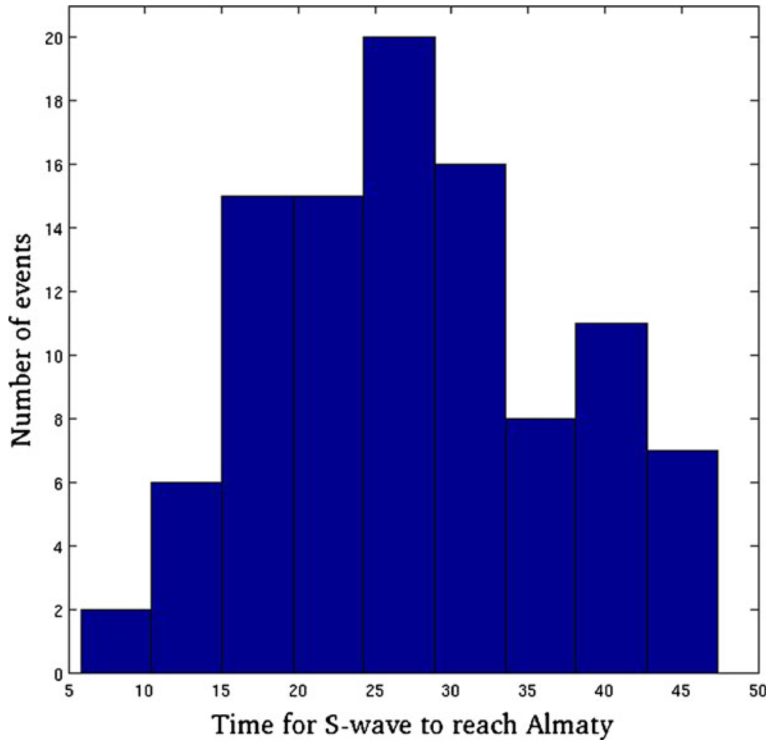

Fig. 3 Histogram of S-wave travel times from the 100 epicenters to Almaty

but lower lead times are treated with more leniency. This way, the optimization approach will nonetheless attempt to maximize the warning time for events where a 10-s warning is impossible.

3.2 Minimizing the cost function

To minimize the cost function and thus find the optimal station locations and trigger thresholds, a microgenetic algorithm (MGA; Krishnakumar 1989) was used. MGAs are a specific subset of genetic algorithms (GAs), which are guided search techniques based on evolutionary principles to find optimal models with respect to a given objective function (i.e., cost function). Typically, a random set of starting models, termed the population, is generated at the start of such an algorithm. Each model, termed the chromosome, consists of parameters termed genes. In our case, the genes are the positions of the n stations within the grid and 3 is the trigger threshold values. Each chromosome, made up of n+3 genes, represents a possible network. For each chromosome, the cost function is computed, and the fittest chromosomes (networks with the lowest cost function) are allowed to mate and exchange genetic information via a predefined crossover operator and possibly random mutations. Over a large number of iterations (termed generations), the algorithm will converge to a minimum cost value representing the optimal network. Given the random input to start the algorithm and the non-uniqueness of such an optimization problem, the solution is likely to be a local, rather than absolute, minimum. It is therefore important to perform a number of independent runs to obtain an overview of the range of best solutions.

MGAs differ from classic GAs in using small population sizes. Each time the algorithm has converged (which, in this study, is considered to be the case if less than 5 % of the genes differ from one chromosome to another in the population), the population is resized to random, except for the fittest chromosome, which is kept in the population. Oth et al. (2010) found MGAs to be appropriate for computing optimal networks for Istanbul, and we apply their approach in our study. Population size was set at 15 for all simulations, the cross-over operator was set at 0.95, and no mutations were used. Each algorithm was allowed to run for 5,000 generations. These values were deemed appropriate following trial-and-error simulations with different values for these parameters. Networks with between 5 and 12 stations were considered. For computing the cost function, both the standard sigmoid and the asymmetrical one (Fig. 2) were considered in independent simulations. For each number of stations–sigmoid combinations, 20 independent runs of the MGA, each using random input, were performed. The output of each MGA run is not just the network with the lowest cost function but a number of networks with marginally higher cost functions.

3.3 Pre-existing stations

While no EEW systems exist in Central Asia, a number of stations are maintained by the Kazakhstan National Data Centre. In particular, 10 stations located between Almaty and the seismogenic zone considered in this study could potentially aid the EEW system (Table 1). For our calculations, we projected each of these stations to the nearest grid point used in our stochastic database and MGA. Using one or more of the pre-existing stations would reduce the costs and logistical issues during the installation and management of an EEW network. However, we do not want to force any of these stations into a network as their positions might not be optimal for EEW purposes. By trial and error, we found that reducing the cost function of a network calculated in Eq. 1 by 2 % for each pre-existing station used provides a balance between prioritizing pre-existing stations and finding efficient networks.

3.4 Dealing with station failures

An important, and perhaps dangerous, assumption in the approach described above is that all stations remain operational. Failure of a strategically placed station would seriously jeopardize the performance of the EEW system. It would therefore be advisable to design a network whose efficiency is not dependent on a single, critical, station.

Two approaches to deal with station failures were considered here. The first is to incorporate the possibility of such failure into the MGA. For each considered network of n stations, each station in turn is ignored and the cost function of the resulting $n-1$ station networks is computed using Eq. 1. The cost function of the full network is then taken as the highest cost of the n networks of $n-1$ stations (the worst case scenario). The MGA then attempts to minimize this value.

The problem with the aforementioned approach is the significant increase of computational time. Considering a 10-station network, incorporating the possibility of a single station failure increases the run time of the optimization algorithm 10 times. Should the possibility of two stations failing be considered, the run time would increase 45 times. We thus present a second approach, where the MGA is run as described earlier, assuming all stations being operational. As mentioned previously, the output is a large number of possible networks. For these, or a number of the best of these, the effect of any single station failing can be evaluated by calculating the cost function for all $n-1$ station networks, and, as before, taking the worst case scenario. Networks can then be sorted according to this worst case cost function. The result is a network which is efficient as a whole and remains efficient when any single station fails. While this approach might not be as strictly mathematically correct as the first one, it has an advantage of significantly lower computational times. Tests were performed to compare the quality of the two approaches and differences in the results were small. We therefore proceed with the second, less computation intensive, approach.

Table 1 Existing stations in the study area

Station code	Latitude north	Longitude east	Network
KNDC	43.217	76.966	KNDC
BOOM	42.490	75.940	IS RK
ANO	42.783	77.667	IS RK
PRJ	42.474	78.406	IS RK
MTB	43.130	76.430	SEME RK
TNS	43.050	76.933	SEME RK
AAA	43.267	76.950	SEME RK
TRG	43.307	77.637	SEME RK
SAT	43.057	78.407	SEME RK
KST	43.043	75.963	SEME RK

4 Results and discussion

An important question in designing a network is how many stations are necessary. To establish this, we look at the lowest cost function found by 20 independent MGA runs for networks between 5 and 12 stations, using both sigmoid functions discussed earlier. The results are shown in Fig. 4. It should be pointed out that while here, and throughout this study, lower values are obtained for cost function using the asymmetric sigmoid, this does not imply the networks computed

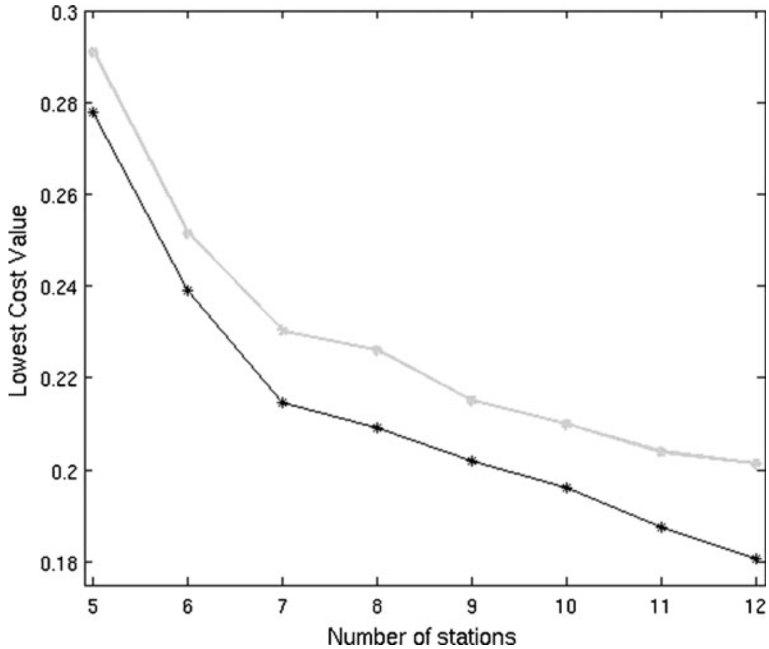

Fig. 4 Lowest cost values obtained for different numbers of stations used. Two curves correspond to the sigmoids in Fig. 2

using it are superior. This is merely the effect of lesser costs associated with not providing a 10-s warning. Figure 4 shows that with few (five or six) stations, adding one station can make a significant improvement to the cost function. While the cost function always decreases with an increasing number of stations, this decrease becomes gradual once more than seven stations exist in a network. Given the risk of station failure is being considered, we thus propose that 10 stations are necessary for an efficient network.

Using the MGA described above, we obtained tens of thousands network layouts. As these are impossible to present in their entirety, we attempt to identify patterns in the best stations. For this, for each of the two different sigmoid functions defining the cost, the 1,000 networks with lowest cost function values were considered. Figure 5 shows the locations of the stations appearing in at least 10 % of the 1,000 solutions. The stations are color coded according to how frequently they are selected. Pre-existing stations are labeled with their codes from Table 1. In Fig. 5a, the standard sigmoid centered at a lead time of 10 s was used. The cost values of the best 1,000 networks vary between 0.210 and 0.232. As expected, no new stations are present in proximity of the scenarios less than 50 km from Almaty (including the Kemin event)—only the pre-existing TNS station is used by more than 10 % of the solutions. As no network is capable of giving a 10-s warning for these near events, the MGA effectively ignored them. Figure 5b shows the most common stations in the solutions obtained using the asymmetric sigmoid more tolerant of lower warning times. Here, the cost values of the fittest 1,000 stations vary between 0.196 and 0.216. Several of the stations are the same as in Fig. 5a, but a crucial difference is that stations closer to the epicenters of the events close to the city appear more frequently. Station TNS, for example, which from a visual inspection is strategically well placed between the Kemin epicenter and Almaty, is used by more than 30 % of the solutions.

TNS is not the only pre-existing station to appear in the solutions, and it is interesting to note that stations far from Almaty are frequently used. Station SAT in the east appears prominently for both sigmoids, as does station KST in the west. Stations closer to Almaty are not as frequently selected as might have been expected. Station ANO appears in 6 and 17 % of the standard and asymmetric sigmoid solutions, respectively. However, both sets of solutions place strong emphasis (68 and 62 %) on a new station just 0.2° west of ANO. We thus postulate that while pre-existing stations can aid the network, there exist critical locations where new stations would need to be deployed, even if a station already exists nearby.

In the results presented so far, fully functional networks were assumed. We now consider the possibility

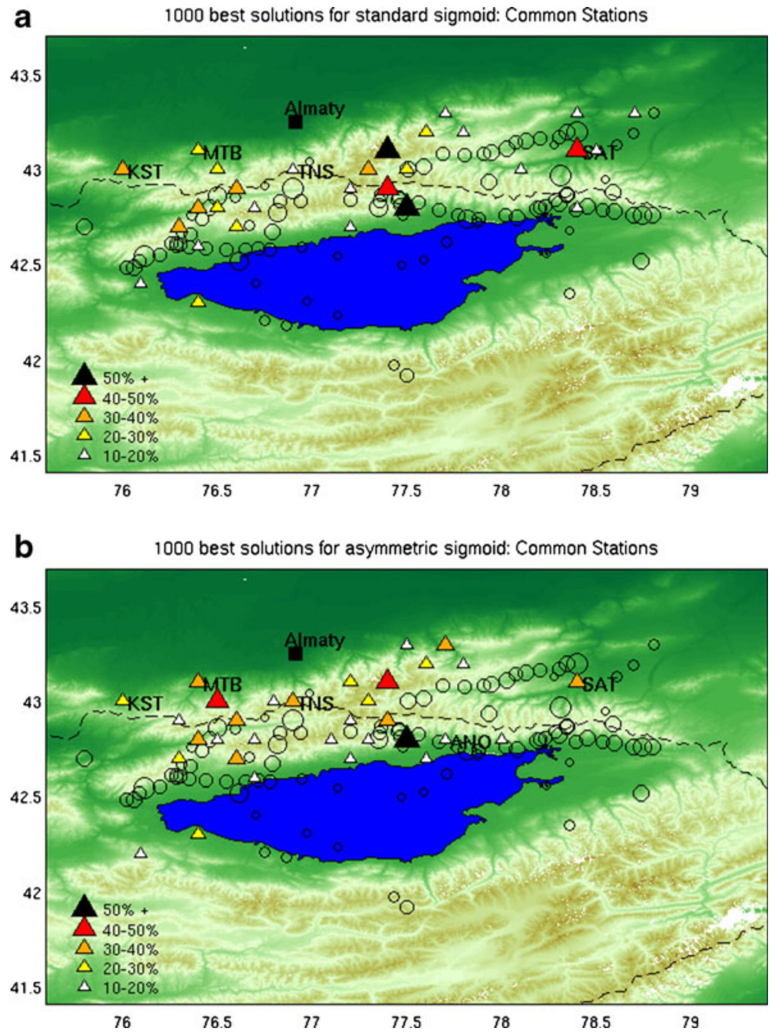

Fig. 5 Stations appearing most frequently in the 1,000 ten-station networks with the lowest cost values. Stations are color coded according to how frequently they appear in the best solutions. Pre-existing stations from KNDS networks are marked and labeled; **a** standard sigmoid and **b** asymmetric sigmoid. Elevation scale as in Fig. 1

of station failure. Only the networks computed using the asymmetric sigmoid will be used to present results of this. For the 1,000 networks with the lowest cost value, we consider the possibility of a single station failing. Thus for each network, we compute the cost of 10 nine-station networks effectively left after any single of the 10 stations ceases to be operational. Figure 6 presents a network not overly dependent on any single station. The top panel shows the location of the stations over a topographic map of the region, with pre-existing stations marked in yellow and station that would need to be deployed new in white. The middle left panel shows how many of the events in each class have been classified correctly or misclassified by 1 or 2 warning class levels (assuming full functionality of the network). An obvious weakness of this network would be the high number of incorrect warnings for class II events, though at least warnings would be issued for them. The middle right panel shows the histogram of lead times that could be provided for the scenario events. The bottom panels show the warning time that could be issued as a function of event magnitude and epicentral distance. The cost value of this network is 0.215, making it only 809th in the list of computed networks. However, with a single station failing, the cost value would go up to between 0.224 and 0.248 (depending on which station fails). By comparison, a single station failure of the most efficient network could make the cost value rise from 0.196 to 0.266.

A possible problem associated with the deployment and maintenance with networks considered so far is the high altitude of some proposed station locations. In the

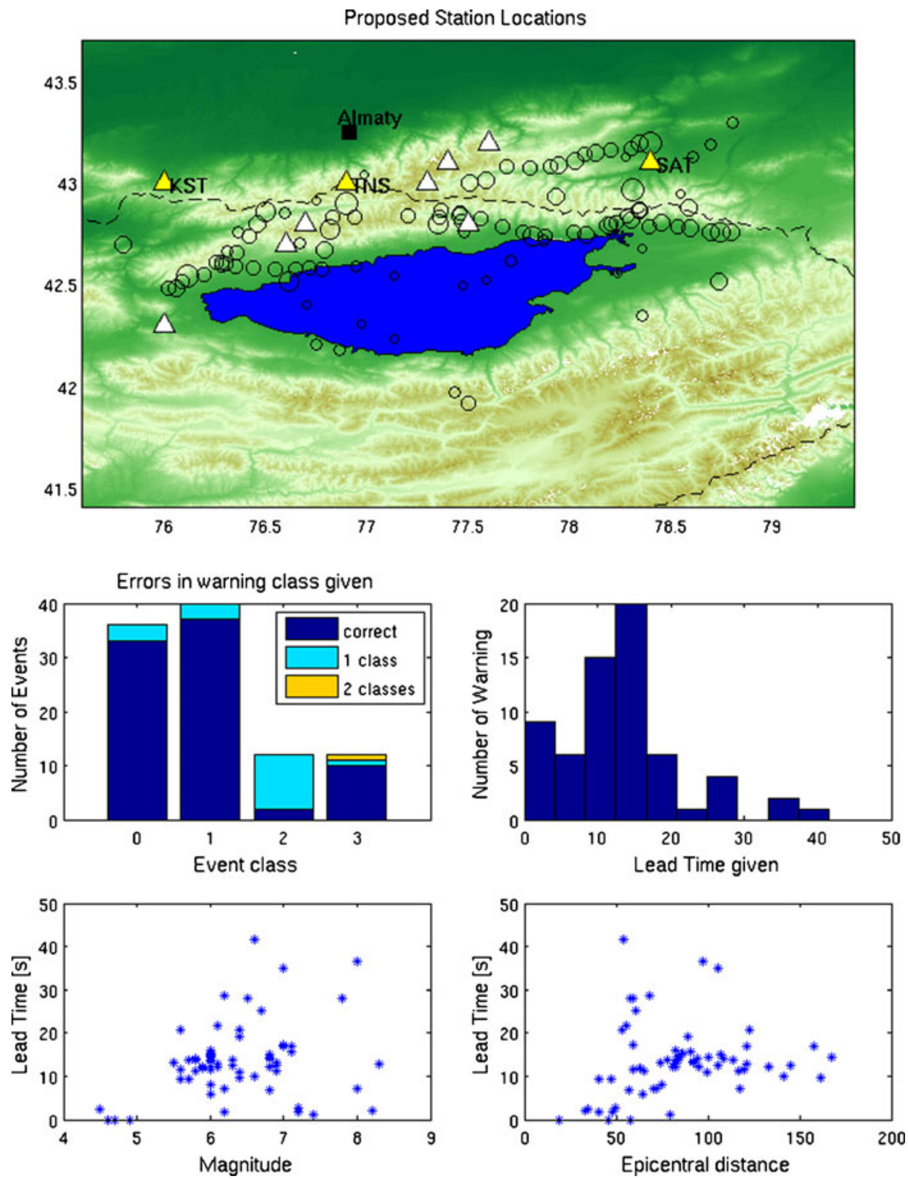

Fig. 6 A 10-station network which would be most efficient despite any single station failing. *Top panel* station distribution, with pre-existing stations that would be part of the network in *yellow* and new stations in *white*. *Middle left panel* number of correctly classified and misclassified events for each event class. *Middle right panel* Histogram of warning times. *Bottom panels* lead time available for the considered scenarios as a function of magnitude and epicentral distance. The trigger thresholds for the three warning classes are 0.03, 0.15, and 0.24 g

network shown in Fig. 6, six stations are at elevation higher than 3,000 m above sea level, two of them being above 4,000. To deal with this issue, a penalty function can be introduced to the cost value. For each station located above 3,000 m above sea level, the cost function is increased by 3 % of its value and by 10 % if the altitude is greater than 4,000 m. These values were chosen to provide a compromise between discouraging stations at altitude, but not excluding them if the location is indeed strategically beneficial. The MGA was run a further 20 times with this penalty function, using 10 stations and the asymmetric sigmoid.

The optimal network with this additional penalty incorporated into the cost value is shown in Fig. 7.

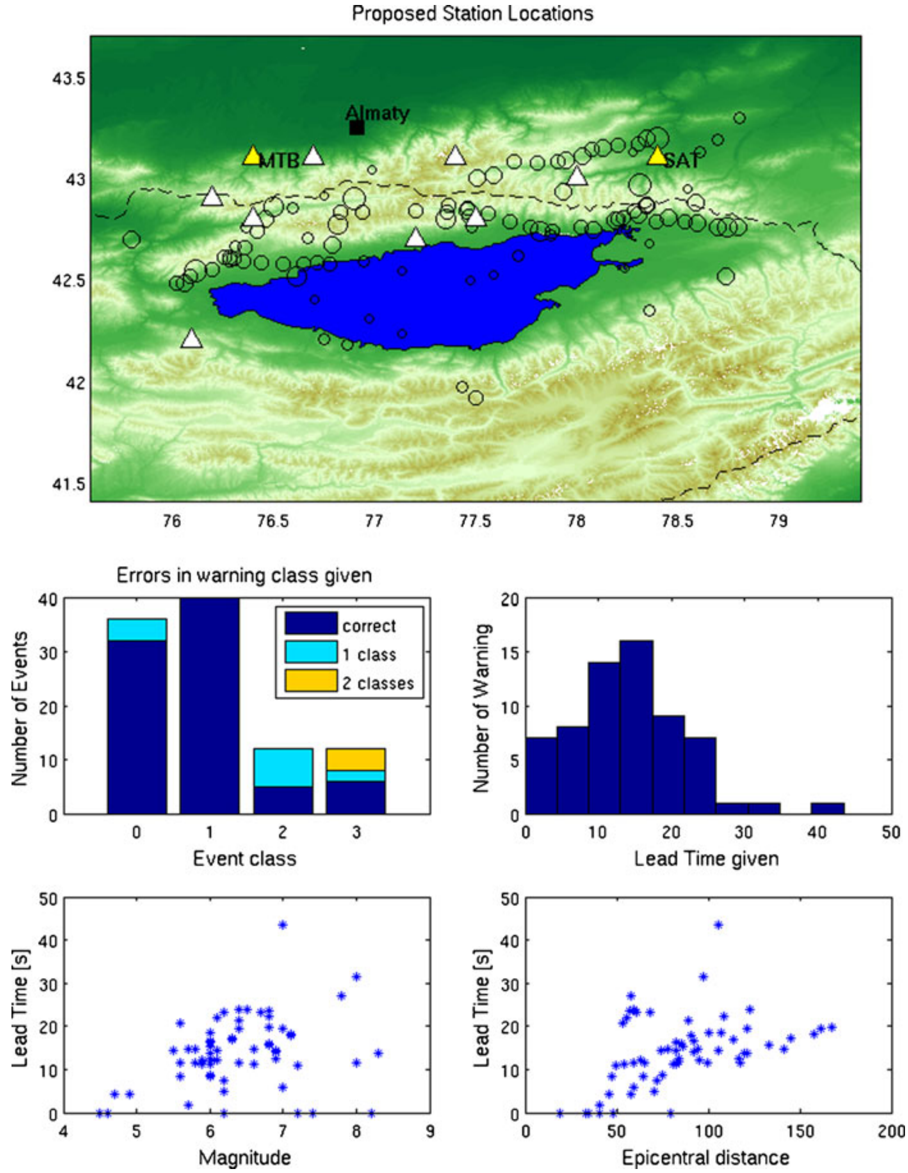

Fig. 7 The most efficient network when a penalty is imposed for stations above 3,000 m altitude. Panels as in Fig. 6. The trigger thresholds for the three warning classes are 0.02, 0.16, and 0.30 g

Only one of the stations is above 3,000 m altitude. The cost value of this network is 0.207, which includes the 3 % penalty—without it, the cost value would be 0.201. This network would only function efficiently if all stations remain operational. A single station failure could make the cost value rise to 0.273 (not including the 3 % penalty). To find a network which is least dependent on any single station, we use the same technique as previously, evaluating effective nine-station networks following any station failure among the 1,000 most efficient networks. The result is presented in Fig. 8. Two of the stations are above 3,000 m and the cost value of the network is 0.227 (real cost 0.215 and a 6 % elevation penalty). The worst case station failure scenario would raise the cost value to 0.265 (real cost 0.250 and a 6 % penalty). These values are almost the same as those for the network shown in Fig. 6 (where station elevation was not considered). However, important differences in network performances can be seen when studying the lower panels of

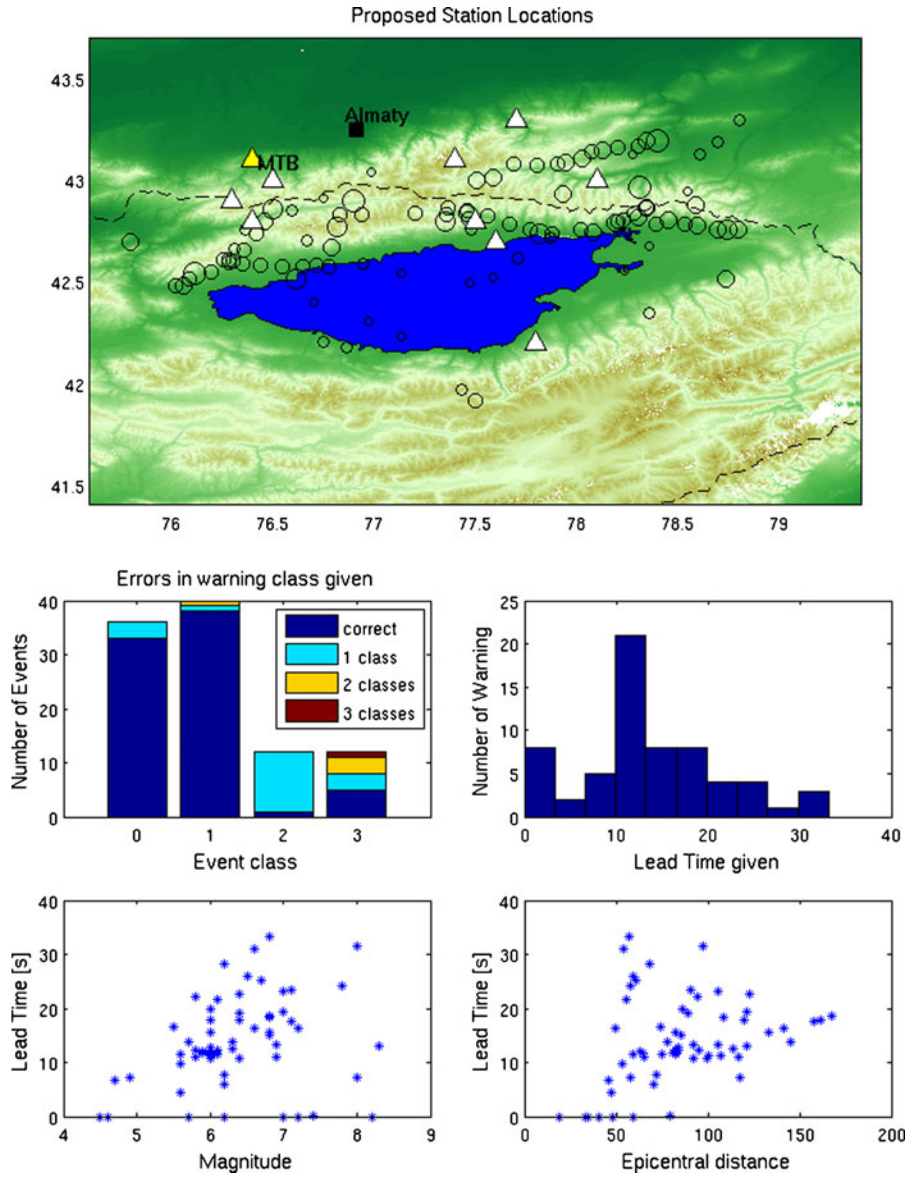

Fig. 8 Network which would be most efficient following any single station failure, with a penalty imposed of stations above 3,000 m altitude. Panels as in Fig. 6. The trigger thresholds for the three warning classes are 0.03, 0.23, and 0.28 g

Figs. 6 and 8. The network in Fig. 8 misclassifies more events than the one in Fig. 6, one class III event is even completely missed. It does, on the other hand, give more lead times over 10 s. This illustrates the difficulty associated with finding the balance between warnings being timely and accurate. While the quality of a network can be mathematically expressed with a single cost value, it is important to carefully analyze the network performance, as important information can potentially be lost in the averaging process defined in Eq. (1).

The results presented here are still open to input from the end users, i.e., the authorities in Almaty, who need to decide what is to be done once a warning has been issued. Should they consider a warning time of less than 10 s insufficient for any practical purposes, the results obtained using the standard sigmoid in the cost function (e.g., Fig. 5a) can be used. If this is the case, it is possible that no warning at all will be given for an event close to the city, and more reliable and timely warnings will be possible for earthquakes farther away.

5 Conclusions

In this manuscript, we present a tool for designing an optimal EEW network, using the city of Almaty as a case study. By simulating the ground acceleration resulting from 100 scenario earthquakes at 293 prospective sites, as well as Almaty, we use genetic algorithms to identify station locations and acceleration trigger thresholds that would make up a network capable of giving timely and reliable warnings. We estimate that 10 stations is an appropriate number for an efficient network. The networks are only considered to be acceptable if they remain efficient after any single station fails. We also demonstrate that while some stations already existing in the region can be used to aid the network, there nonetheless exist critical locations where further stations are necessary.

While we have presented examples of highly efficient networks, we stress that these are not the only solutions we have computed. With thousands of networks of similar quality available, it is possible to introduce further constraints on the optimal network. This can be done by excluding networks not meeting new criteria from the list of solutions or introducing a penalty into the cost function and rerunning the MGA. For example, if prior to the installation, a certain area becomes politically unstable, networks containing stations there can be removed from the list of solutions and the network with the lowest cost among those remaining can be installed. Similarly, it might be considered impractical to install, or maintain, stations above a certain altitude or more than a specified distance from a road or settlement. The presented feasibility study remains open to input from the end users, i.e., the authorities in Almaty.

The EEW systems presented here are aimed at regional earthquakes. For an earthquake close to the city, it is not possible to give a timely warning. It is thus recommended that a regional EEW system is complemented by a single station on-site system (Satriano et al. 2011). Lastly, we note that the balance between networks being fast and reliable is very delicate and the performance of any prospective network should not simply be assigned a single value, but be carefully evaluated.

Acknowledgments The research presented here is funded by the Potsdam Research Cluster for Georisk Analysis, Environmental Change and Sustainability (PROGRESS) in collaboration with the REAKT project (Towards Real Time Earthquake Risk Reduction) of the European Seventh Framework Programme. Support was also provided by the Fonds National de la Recherche, Luxembourg cofunded by the Marie Curie Actions of the European Commission (FP7-COFUND) (AFR project 4817114). The article benefited from constructive feedback by two anonymous reviewers.

References

Abdrakhmatov K, Havenith H-B, Delvaux D, Jongmans D, Trefois P (2003) Probabilistic PGA and arias intensity maps of Kyrgyzstan (Central Asia). J Seismol 7:203–220

Allen RM, Gasparini P, Kamigaichi O, Böse M (2009) The status of earthquake warning around the world: an introductory overview. Seismol Res Lett 80(5):682–693

Anderson J (2003) Strong motion seismology. In: Lee WHK, Kanamori H, Jennings PC, Kissling C (eds) International handbook of earthquake engineering and seismology. International Association for Earthquake Engineering, San Diego, USA, pp 937–966

Bindi D, Mayfield M, Parolai S, Tyagunov S, Begaliev UT, Abdrakhmatov K (2011) Towards an improved seismic risk scenario for Bishkek, Kyrgyz Republic. Soil Dyn Earthq Eng 31:521–525

Boore DM (2009) Comparing stochastic point-source and finite-source ground-motion simulations: SMSIM and EXSIM. Bull Seismol Soc Am 99(6):3202–3216

Böse M (2006) Earthquake early warning for Istanbul using artificial neural networks. PhD thesis, University of Karlsruhe, Karlsruhe, Germany

Delvaux D, Abdrakhmatov K, Lemzin I, Strom A (2001) Landslides and surface breaks of the 1911 Ms 8.2 Kemin earthquake (Kyrgyzstan). Russ Geol Geophys 42(10):1583–1592

Doi K (2011) The operation and performance of earthquake early warnings by the Japan Meteorological Agency. Soil Dyn Earthq Eng 31:119–126

Erdik M, Fahjan Y, Ozel O, Alcik H, Mert A, Gul M (2003) Istanbul earthquake rapid response and the early warning system. Bull Earthq Eng 1:157–163

Erdik M, Rashidov T, Safak E, Turdukulov A (2005) Assessment of seismic risk in Tashkent, Uzbekistan and Bishkek, Kyrgyz Republic. Soil Dyn Earthq Eng 25:473–486

Espinosa-Aranda JM, Cuellar A, Rodriguez FH, Frontana B, Ibarrola G, Islas R, Garcia A (2011) The seismic alert system of Mexico (SASMEX): progress and its current applications. Soil Dyn Earthq Eng 31:154–162

Krishnakumar K (1989) Micro-genetic algorithms for stationary and non-stationary function optimization. In: Proceedings of SPIE: Intelligent Control and Adaptive Systems, vol 1196, Philadelphia, pp. 289–296

Nakamura Y, Saita J, Sato T (2011) On an earthquake early warning system (EEW) and its applications. Soil Dyn Earthq Eng 31:127–136

Oth A, Böse M, Wenzel F, Köhler N, Erdik M (2010) Evaluation and optimization of seismic networks and algorithms for earthquake early warning—the case of Istanbul (Turkey). J Geophys Res 115, B10311

Picozzi M, Bindi D, Pittore M, Kieling K, Parolai S (2013) Real-time risk assessment in seismic early warning and rapid response: a feasibility study in Bishkek (Kyrgyzstan). J Seismol 17:485–505

Satriano C, Wu Y-M, Zollo A, Kanamori H (2011) Earthquake early warning: concepts, methods and physical grounds. Soil Dyn Earthq Eng 31:106–118

Sesetyan K, Zulfikar C, Demircioglu M, Hancilar U, Kamer Y, Erdik M (2011) Istanbul earthquake rapid response: methods and practices. Soil Dyn Earthq Eng 31:170–180

Sokolov VY, Chernov YK (1998) On the correlation of seismic intensity with Fourier amplitude spectra. Earthq Spectra 14(4):679–694

Torizin J, Jentzch G, Malischewsky P, Kley J, Abakanov N, Kurskeev A (2009) Rating of seismicity and reconstruction of the fault geometries in northern Tien Shan within the project “Seismic Hazard Assessment for Almaty”. J Geodyn 48:269–278

Wald DJ, Allen TI (2007) Topographic slope as a proxy for seismic site conditions and amplification. Bull Seismol Soc Am 97:1379–1395

Zollo A, Iannaccone G, Lancieri M, Cantore L, Convertito V, Emolo A, Festa G, Gallovic F, Vassallo M, Martino C, Satriano C, Gasparini P (2009) Earthquake early warning system in southern Italy: methodologies and performance evaluation. Geophys Res Lett 36:L00B07