An Assessment of the Impact of Natural and Technological Disasters Using a DEA Approach

Fuad Aleskerov and Sergey Demin

Abstract We consider a model of regions' ranking in terms of their vulnerability to natural and technological disasters. Regions are different in terms of their resistance to different disasters, by their population, by the distribution of the sources of potential disasters, etc. We consider different models of a data envelopment analysis (DEA) approach taking into account the risks of the implementation of different measures, their cost as well as the heterogeneity of regions. The numerical examples demonstrate the application of the constructed model for the regions of Russian Federation.

Keywords Technological and natural disasters • DEA • Ranking of regions

1 Introduction

Nowadays natural and man-made disasters occur and threaten people more and more often and with increasing impact, and cause a great amount of damage in terms of the numbers of killed and affected and the economic losses (Makhutov 2006; Guha-Sapir and Hoyols 2012; Kates et al. 2001).

The average damage, as well as the average number of killed and injured people, rose during the period from 1970 to 2010. Meanwhile, it is proved statistically that prevention of disasters can not only save people's lives, but also is cost-efficient (The World Bank 2010).

In these studies, pre-disaster spendings include expenditures on identifying risks, risk reduction by invention of new technologies and their implementation, risk transfer by using insurance, upgrading early warning systems, and educating the

F. Aleskerov (✉)
National Research University Higher School of Economics, Institute of Control Sciences of Russian Academy of Sciences, Moscow, Russia
e-mail: alesk@hse.ru

S. Demin
National Research University Higher School of Economics, Moscow, Russia
e-mail: ssdemin@edu.hse.ru

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public. In turn, post-disaster expenditures consist of expenditures on restoring resources, liquidating pollution and other ecological consequences, search and rescue operations, and rehabilitation and reconstruction.

Above all, in almost all countries, except Colombia, post-disaster expenditures are generally higher than pre-disaster expenditures (The World Bank 2010). In addition, the fluctuations in post-disaster spendings also have larger range, which can be explained by the fact that pre-disaster spendings are planned not only for 1 year, but also for a long period of time, which makes it more balanced and removes any significant fluctuations.

While analyzing the consequences of devastating disasters, certain systems of preventive measures, which can help to reduce disaster risk, were developed. It is convenient to divide all preventive measures into three groups: the first one—risk assessment and measures that reduce vulnerability of potentially dangerous objects; the second—monitoring, which can give indicators of impending disaster, and the last is early warning systems and educating the public.

It is important to point out that all types of precautionary measures play great role and none can be underestimated. This fact is supported by many studies. For instance, some researches give the list of factors that must be observed in order to prevent any negative consequences (Modoi et al. 2009). In turn, Coldewey (2009) studied parameters, which play great role in tailing security provision, and highlighted the following attributes: water level in reservoirs, potential precipitation, which can raise the water level, seismological activity, which can damage the reservoir, etc. Tracking of these parameters may detect potential threats in advance and, as a result, prevent disaster or at least mitigate its repercussions.

Meanwhile, some other studies pay more attention to early warning systems and educating the public (Akimov et al. 2004).

At the same time it is important to know what actions should be implemented because there may be a financial shortfall to fund all possible safety measures. There are several models, which can represent the results of precautionary measures and, as a result, will help in choosing the best strategy for disaster prevention or at least mitigation of its consequences.

Li et al. (2013) categorized the evaluation methods of disaster vulnerability by highlighting quantitative and qualitative approaches. The first is based on the relationship between preventive measures and consequences of potential disaster and, as a result, can show the best list of precautionary measures. These models can provide a great amount of information about a potential disaster; however, they require a great volume of input data with lots of details.

In turn, qualitative methods are based on expert assessments, and here lies the main problem of this approach—it makes assessment subjective. However, these methods help to solve the problem of data shortage. Moreover, some qualitative methods may become semi-quantitative. For instance, Wang et al. (2011a, b) applied a fuzzy analytic hierarchy process for assessment of flood risk.

One of the quantitative methods is introduced by Yanenko et al. (2008). This model, which evaluates the probability of a disaster occurrence for a nuclear power reactor, is based on the assumption that the progress of every disaster can be described as a model with three steady states. The first state conforms to a common situation at the object. The second one corresponds to extreme situations (for example, an electricity blackout) that can cause a disaster. And the third state is an occurrence of a disaster with devastating consequences.

Then, all parameters characterizing the condition of the reactor were divided into four groups. Subsequently, taking into account the safety values of parameters and their weights, the authors evaluate the risk assessment of the reactor. Moreover, they also obtain the vulnerabilities connected to different features of a reactor, such as the efficiency of the protective system, the activity of radioactive waste, or the human factor (e.g., staff qualification).

In that paper, an open system with intake means and resources, and outside—products and contaminations—is studied. This mathematical model represents the dynamics of many parameters connected to the disaster, including money flows for different aims, the power of the pollution, the speed of distribution of the contamination, the speed of resource depreciation, and many other indicators. Moreover, taking into account that this is a dynamic model, we can know not only the final consequences of the disaster, but also the details of the process.

Another study, connected to the technological disasters, describes the mathematical model that helps to fix the size of taxation for the level of air pollution by enterprises (Aleskerov 1990). For this aim, we simulate the contamination from a group of polluters, taking into account the geographical situation in the region and the location of the factories and find the value of tax on each polluter. Moreover, afterwards, considering limited resources and opportunities of the single enterprise, this study discusses preventive measures for contamination reduction.

The next model explains how to estimate the damage and the casualties (Aleskerov et al. 2005). In this study, the authors at the first step divide the region in question into the clusters according to the features of the buildings (the construction, number of stories, and the construction year). Afterwards they estimate the potential damage to the buildings in case of earthquakes of different intensity, according to the statistics. Subsequently, this data helps to estimate the casualties.

Finally, the model that helps to choose the best list of precautionary measures for the region with application to the Yaroslavl region is given in Aleskerov et al. (1988). In this study, all measures were divided into several classes according to two main characteristics (value of prevented damage per one cost unit and reduction of the acuteness value for the implementation area) by highlighting Pareto-optimal alternatives. Subsequently, the decision-maker should just chooses the measures, and the computer program will show the features of the selected choice, such as the percentage of the prevented damage and cost of measures.

However, Huang et al. (2011) denoted that many methods of quantitative assessment are very sensitive to the weight indices. The authors mentioned that the main shortcoming is the relative contribution of variables used for assessment, and the variables should be weighted differently, while some other scientists, on the contrary, prefer to neglect these mutual contributions (Cutter et al. 2000). This is why we apply a method based on another approach to the problem—data envelopment analysis (DEA).

We use DEA as a mathematical tool to compare different decision-making units (DMUs). For this purpose, all objects get some input and output parameters, which describe these objects. Subsequently, based on the efficiency, which is represented as the comparison of parameters, we find the best bound, where the efficiency is equal to 100 %. Afterwards, we rank the objects according to the position regarding the efficiency frontier and choose the best alternative taking into account constructed ranging scale.

The main advantage of this method is the fact that DEA does not only show the efficiency of all DMUs, but also identifies the benchmark elements for inefficient DMUs. For this reason, DEA has been used in many fields. For instance, Abankina et al. (2012) used this method for ranking universities. Further applications of this method include analysis of national innovation systems efficiency (Shao and Lin 2002; Kotsemir 2013), bank efficiency and productivity growth (Andries 2010), etc.

One more advantage is the fact that efficiency value is independent of the measuring unit (Wang and Tsai 2009). Therefore, it is not necessary to assess inputs and output in one scale.

However, turning back to the main aim of our research, it is crucial to examine applications of DEA in the sphere of disaster prevention.

Furthermore, this method can be combined with other approaches that can improve the model. For instance, Saein and Saen (2012) used an improved DEA model for the assessment of the region vulnerability to earthquakes. This model, introduced by Saen (2011), is based on cross-efficiency approach. The main idea of this method implies the use of DMUs cross-comparison instead of self-evaluation. For this purpose, each time one determines the highest efficiency of a certain DMU one should take into account all other DMUs' efficiency. Finally, the result for every concrete DMU is calculated as the mean of all cross-efficiencies.

In turn, De Almada Garcia Adriano et al. (2013) used DEA for the assessment of the security level at a nuclear power plant. For this purpose, the authors offered to use the improved and more realistic DEA model. They took into consideration the effect of weight indices restriction. For instance, taking into account the expert assessments, it was assumed that the severity of the failure mode is more important than other criteria (occurrence and detectability). As a result, there was added one more restriction (v_S, v_D, v_O—weight coefficients of severity, occurrence, and detectability accordingly):

$$v_S - (v_D + v_O) \geq 0$$

This approach allows constructing of a more realistic and more precise method, which will pay attention to the ratio of importance of different criteria.

Another application of DEA is offered by Zhang and Fu (2012), who introduced a model for the evaluation of emergency logistics performance. The main idea of this method is the combination of two basic approaches—DEA and analytical hierarchy process (AHP). At the first stage, AHP calculates the weight of each part of the emergency logistics system (Zhang and Fu 2012). Subsequently, the relative efficiency of different parts is developed by the DEA method. Finally, one should calculate the overall efficiency of the emergency logistics system by summarizing the results of different parts.

In addition, it is important to point out that in this work we provide a new approach to the application of DEA method to an assessment of natural and technological disasters based on the new model of DEA with sequential exclusion of alternatives.

2 Framework

As was mentioned above, the main method that will be used in our research is DEA, specifically the CCR approach, named by first letters of the authors' surnames: Charnes, Cooper, and Rhodes (Charnes et al. 1978). The key idea of this model is presentation of the efficiency of preventive measures as a fraction over resources spent. We will analyze the following goal functions:

$$\max_{u_i, v_j}\left(e_k = \frac{\sum_{i=1}^{M} u_{ik}x_{ik}}{\sum_{j=1}^{N} v_{jk}y_{jk}}\right), \tag{1}$$

under the constraints:

$$\begin{cases} \dfrac{\sum_{i=1}^{M} u_{ik}x_{ik}}{\sum_{j=1}^{N} v_{jk}y_{jk}} \leq 1,\ k = 1, \ldots, R \\ \forall i\ u_i > 0 \\ \forall j\ v_j > 0 \end{cases} \tag{2}$$

In these inequalities we introduced the following variables: e_k—efficiency of k-th safety measures; u_{ik}, v_{jk}—weight coefficients, that illustrate the importance of appropriate parameters; x_{ik}—output parameters, which show achieved results; y_{jk}—input parameters, which show spent resources; M—the number of output parameters; N—the number of input parameters; and R—the number of preventive measures.

The main advantage of this technique is automatic selection of u_{ik}, v_{jk}, based on criterion (1). In addition, this model can be transformed to the linear programming task by the conversion proposed by Charnes and Cooper (1962):

$$\min_{\theta_k, \lambda} \theta_k \tag{3}$$

In this way, the restrictions will also change:

$$\begin{cases} -q_k + Q * \lambda \geq 0, \\ \theta_k x_k - X * \lambda \geq 0, \\ \lambda \geq 0, \end{cases} \tag{4}$$

where θ_k is a scalar, indicative the efficiency of k-th safety measures, λ—vector of constants ($R * 1$), Q—matrix of output indices of all preventive measures ($M * R$), X—matrix of input indices of all precautionary measures ($N * R$). $\theta_k \in [0; 1]$, $\theta_k = 1$ shows the 100 % efficiency of k-th safety measure relative to others.

We will analyze now all available precautionary measures and construct the efficiency frontier, which shows us the best possible result. Subsequently, we rank all variants of preventive measures taking into account that the closer to the borderline the alternative is, the more efficient it is.

Another method, which will be used for an assessment, was introduced by Aleskerov and Petrushchenko (2015). The main improvement of this model is a less strict assessment of the inefficient DMUs. It is achieved by exchanging the benchmark for inefficient alternatives taking into account the heterogeneity of the evaluated sample.

The authors propose to generate a new efficiency frontier using the best alternative and the barycenter of all DMUs. For this purpose, they introduce a heterogeneity coefficient μ, which is equal to the ratio of the mean value of the distance between the alternative and the barycenter to the maximum value. Then the benchmark is constructed by combining the best alternative and the barycenter with weights $(1 - \mu)$ and μ, respectively. Afterwards, the efficiency of inefficient DMUs is evaluated. Then all alternatives, which has an efficiency less than 1, are excluded from the sample, and the assessment continues for inefficient alternatives, which get an efficiency equal to 1.

It is important to choose which elements will be compared. There might be two approaches to this task. In the first one, different regions (including all enterprises in them) are compared. In the second one, the elements are enterprises themselves.

3 Input and Output Parameters

In many DEA studies, it is mentioned that the selection of input and output parameters is one of the most important stages in this method (e.g., Golan and Roll 1989). Moreover, at this stage some problems with evaluation of parameters could take place, because sometimes it is very difficult to estimate the value of a parameter (Saein and Saen 2012). The authors point out that the best solution in such cases is to use the value of a parameter with respect to some classes on a scale.

We will apply our model for both types of disasters: technological and natural. For more accurate results, in each case, we will examine a certain source of danger, because different catastrophes require different input and output parameters. Thus, we will consider industrial accidents at a chemical or nuclear plant as an example of technological disaster and earthquakes as an example of a natural one.

3.1 Parameters for Technological Disasters

The main target of our project is to rank different safety measures according to their efficiency. Any precautionary measures demand financial funds, and it is one of the most crucial input parameters. In addition, it is important to divide all expenditures into money flows according to the aims.

As a result, we will identify the following money flows:

1. Expenditures on equipment upgrading. This is the main use of financial funds, because it helps us to keep the object in a steady state. For instance, in 2011 the Fukushima disaster caused a great amount of damage (Lipscy et al. 2013). One of the main reasons for enormous negative consequences is the unavailability of qualitative protective equipment.
2. Expenditures on a disaster alert system and educating the public. It is important to point out that in many cases the number of victims could be much less if the population would be warned in time and made aware of disaster-safe behavior. For instance, in 1984 in Bhopal (Dutta 2002), residents were not warned, and, as a result, about 18,000 people died and more than 150,000 affected. Therefore, this money flow plays an important role in reducing the number of victims from a disaster.
3. Expenditures on scientific research. This part of financial funds influences the efficiency of the first money flow (updating equipment) because by using new technologies we can decrease certain hazards.

However, there is a great difference between two cases: a technological disaster somewhere in the middle of a desert with nobody around the epicenter, and the same technological disaster, for instance, in the center of a big city. Thus, we use the number of people, not far from the epicenter of the disaster.

However, we should parameterize not only the source data, but also the results of precautionary measures. In this part, we will point out one parameter—the probability of a devastating consequence of the disaster. This parameter will depend on expenditures on updating equipment. Here we will use the assumption that all financial funds have decreasing returns to scale.

Therefore the probability is evaluated as $p = ae^{-be_1}$, where p is the probability of the occurrence of extreme situations with devastating consequences, e_1—expenditures on updating equipment, and a, b—rate-setting coefficients. These coefficients should be evaluated separately for each situation (possibly by expert assessment). We will use two assumptions. The first one is that with no expenditures on updating equipment p will be high (e.g., 90 %). And vice versa, huge expenditures will decrease p to 10 %.

Table 1 Input and output parameters of DEA model for technological disasters

Input parameters	Output parameters
e_1—expenditures on equipment upgrading	p—probability of devastating consequences of the disaster
e_2—expenditures on disaster alert system and educating the public	y_1—number of killed
	y_2—number of affected
e_3—expenditures on scientific research	y_3—economic losses in spite of production stoppage
x—the number of people, who live not far from the epicenter of the disaster	y_4—spendings on recovery from the disaster
	s—defeat area—area, wherein people have a probability of injury

However, in addition to the probability, we should highlight one more group of parameters, which will show the consequences of a potential disaster: the number of killed, the number of affected people, the economic losses, in spite of production stoppage, spendings on recovery from the disaster, and contamination of the territory. For the contamination of the territory, we have the same problems as with the population of the territory. So, the solution will be the same: we will use defeat area—area, wherein people have a probability of injury.

As a result, we get the following list of input and output parameters for our DEA model (Table 1).

3.2 Parameters for Natural Disasters

As in the case of technological disasters, again the majority of input parameters of the model are different types of expenditures. We will identify the following flows of investment:

1. Expenditures on scientific research,
2. Expenditures on disaster alert system and educating the public,
3. Expenditures on construction of new earthquake-proof buildings and seismic improvement of those already existing.

Another input parameter is the construction typology of houses in regions because an earthquake can have varied influence on buildings with different types of structure. Four main groups of buildings in question are: masonry, reinforced concrete, wooden masonry composite, and steel frame.

Each type of construction has the unique rate of seismic resistance and an average number of people living in one house of this type (Aleskerov et al. 2005). We also assume that the population in the houses of the type is the same for all regions. This assumption is not applicable for more exact analysis, but we do not have access to this information from regions.

Table 2 Input and output parameters of DEA model for natural disasters

Input parameters	Output parameters
e_1—expenditures on scientific research	y_1—economic losses
e_2—expenditures on disaster alert system and educating the public	y_2—number of killed
	y_3—number of affected
e_3—expenditures on construction of new earthquake-proof buildings and seismic improvement of already existing construction typology of houses	y_4—number of homeless

As for output parameters to illustrate the consequences of a potential disaster in case of earthquake occurrence we will use expected economic losses, the number of deaths, the number of affected people, and the number of homeless.

As a result, we get the following list of input and output parameters for our DEA model (Table 2).

4 Application of the Model

We apply our method for comparing the efficiency of 27 Russian regions, which have the highest Seismic Risk Index (value more than 0.1). These regions constitute 65 % of Russia's territory. As it was mentioned by Li et al. (2013) there should be used at least twice the number of input and output parameters. Since the exact data on security expenditures are not open to the public, we had to use a simulation technique.

4.1 Application to Technological Disasters

We used main parameters of the chosen regions, such as population and gross domestic product (GDP). Then, we make a list of assumptions.

Firstly, the data about the number of killed and the number of affected have been obtained from the comparative analysis of losses and injures in some previous situations. Secondly, we believe that GDP shows the production volume, which influences the economic losses in spite of production stoppage and spendings on recovery from the disaster.

As a result, after application of our DEA model for assessment of efficiency in regions we get the following results (efficiency 1 is the efficiency according to the basic DEA approach, while efficiency 2 is the efficiency according to the improved DEA approach) (Table 3).

Table 3 Results of DEA model application for technological disasters

Region	Efficiency 1	Efficiency 2
Altai Krai	0.67	0.71
Altai Republic	0.64	0.77
Amur Oblast	1	1
Chechen Republic	1	1
Chukotka Autonomous Okrug	1	1
Irkutsk Oblast	0.84	0.87
Jewish Autonomous Oblast	1	1
Kabardino-Balkar Republic	0.6	0.67
Kamchatka Krai	1	1
Karachay-Cherkess Republic	0.41	0.63
Kemerovo Oblast	0.76	0.8
Khabarovsk Krai	0.77	0.93
Krasnodar Krai	1	1
Krasnoyarsk Krai	1	1
Magadan Oblast	0.6	0.69
Primorsky Krai	0.75	0.8
Sakha (Yakutia) Republic	0.76	0.9
Sakhalin Oblast	1	1
Stavropol Krai	0.71	0.74
The Republic of Adygea	0.41	0.69
The Republic of Buryatia	0.44	0.54
The Republic of Dagestan	0.83	0.86
The Republic of Ingushetia	0.97	1
The Republic of Khakassia	0.9	0.92
The Republic of Northern Ossetia—Alania	0.41	0.6
Tuva Republic	0.46	0.89
Zabaykalsky Krai	1	1

4.2 Application to Natural Disasters

In the case of natural disasters we used almost the same data and assumptions as in Sect. 4.1. The only important difference is the assessment of the number of killed, injured, and affected people.

For this purpose, we used data, which was highlighted above—the unique rate of seismic resistance and the average number of people living in one house of this type (Aleskerov et al. 2005).

As a result, after application of our DEA model for assessment of efficiency in regions we get the following results (efficiency 1 is the efficiency according to the basic DEA approach, while efficiency 2 is the efficiency according to the improved DEA approach) (Table 4).

Table 4 Results of DEA model application for natural disasters

Region	Efficiency 1	Efficiency 2
Altai Krai	0.71	0.86
Altai Republic	0.81	0.83
Amur Oblast	0.84	0.94
Chechen Republic	1	1
Chukotka Autonomous Okrug	0.88	0.96
Irkutsk Oblast	0.81	0.91
Jewish Autonomous Oblast	0.7	0.75
Kabardino-Balkar Republic	0.83	0.91
Kamchatka Krai	1	1
Karachay-Cherkess Republic	0.75	0.82
Kemerovo Oblast	0.71	0.86
Khabarovsk Krai	0.71	0.75
Krasnodar Krai	1	1
Krasnoyarsk Krai	0.71	0.82
Magadan Oblast	0.87	0.96
Primorsky Krai	0.7	0.75
Sakha (Yakutia) Republic	0.69	0.75
Sakhalin Oblast	1	1
Stavropol Krai	0.71	0.76
The Republic of Adygea	1	1
The Republic of Buryatia	0.96	0.97
The Republic of Dagestan	0.96	0.98
The Republic of Ingushetia	0.84	0.94
The Republic of Khakassia	1	1
The Republic of Northern Ossetia—Alania	0.79	0.83
Tuva Republic	1	1
Zabaykalsky Krai	0.89	0.95

5 Analysis

As expected, the results of the two methods give us almost the same efficiency for the regions. The only difference is the fact that the DEA with sequential exclusion of alternatives shows better results (higher efficiency), because it uses the special alternative as a benchmark for inefficient DMUs instead of the best DMU as in the basic DEA approach.

5.1 Results for Technological Disasters

The results of our model highlight 9 regions with 100 % efficiency in disaster prevention. Good results of the majority of these regions can be explained by their specifics—all of them except Krasnodar Krai and Chechen Republic have a low density of population. In this case, it is not necessary to spend a great part of local budget on industrial security.

In turn, the efficiency of Krasnodar Krai can be explained by the occurrence of the Krasnodar Krai flood in 2012, which forced local authorities to raise industrial security and implement a vast range of precautionary measures.

Returning to general results for all regions, it is important to highlight the Republic of Northern Ossetia—Alania, which has the worst result—41 % (60 %). Some data force certain regions to take measures to improve their efficiency.

5.2 Results for Natural Disasters

In case of the assessment of earthquake mitigation efficiency, the model points out 7 regions with 100 % result. Some leaders, such as Krasnodar Krai, Sakhalin Oblast, Kamchatka Krai, and Chechen Republic, are the same. However, there are also some regions, for which results in technological disaster mitigation are not so good, the Republic of Adygea, the Republic of Khakassia, and Tuva Republic.

In turn, Sakha (Yakutia) Republic gets the worst result—just 69 % (75 %). Here we can detect one more fact, which should be highlighted. The range of result distribution is much less—just 31 % (59 % in technological disaster mitigation). However, the results of this application of the model also force certain regions to take measures to improve their efficiency.

6 Conclusion

In our work, we applied two methods based on DEA to the regions of the Russian Federation. The first method is the standard DEA approach, the second one is the new method based on sequential exclusion of alternatives. Both methods give reasonable rankings of regions in terms of preventive measures efficiency. However, the second method gives higher values of efficiency for regions. It can be explained by the fact that this method does not refer to the best practice in the whole sample, but rather takes into account compactness in terms of their evaluations subsamples.

These methods may be applied to similar problems.

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