

Assessing and mitigating natural hazards in a very uncertain world

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Earthquake risk is a game of chance of which we do not know all the rules.

It is true that we gamble against our will, but this doesn't make it less of a game.

(Lomnitz, 1989: 1662)

Introduction

Humans have to live with natural hazards. Natural hazard scientists describe this challenge in terms of *hazards* – the occurrence of earthquakes, floods or other dangerous phenomena – and the *risks*, or dangers they pose to lives and property. In this formulation, the risk is the product of hazard and *vulnerability*. We want to *assess* the hazards – estimate how significant they are – and develop methods to *mitigate* or reduce the resulting losses. This paper is drawn largely from Stein and Stein (2014), which provides detailed references and gives a brief overview of some key issues involved.

Hazards are geological facts not under human control that we assess as best we can. In contrast, risks are affected by human actions that increase or decrease vulnerability, like where people live and how they build. Areas with high hazard can have low risk because few people live there. Areas of modest hazard can have high risk due to large population and poor construction. A disaster occurs when – owing to high vulnerability – a natural event has major consequences for society.

On average, about 100,000 people per year are killed by natural disasters, with some disasters, such as the 2004 Indian Ocean tsunami, causing many more deaths. Although the actual numbers of deaths in many events, such as the 2010 Haiti earthquake, are poorly known, they are very large.

Economic impacts are even harder to quantify and various measures are used. Disasters cause losses, which are the total negative economic impact. These include direct losses due to destruction of physical assets such as buildings, farmland, forests, etc. and indirect losses that result from the direct losses. Losses due to natural disasters in 2012 worldwide were estimated as exceeding US\$170 billion. Disaster losses are increasing because more people live in hazardous areas. For example, the population of hurricane-prone Florida has grown from 3 million in 1950 to 19 million today.

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Society can thus be viewed as playing a high-stakes game of chance against nature. We know that we will lose in two ways. If disaster strikes, direct and indirect losses result. In addition, the resources used for measures that we hope will mitigate the hazards and thus reduce losses in the future are also lost to society because they cannot be used for other purposes.

Current status

Minimizing the combined losses from disasters themselves and also the efforts to mitigate them involves developing methods to better assess future hazards and mitigate their effects, but because this is difficult, our records are mixed. Sometimes we do well and sometimes not.

Often nature surprises us, such as when an earthquake, hurricane or flood is bigger or has greater effects than expected from hazard assessments. In other cases, nature outsmarts us, doing great damage despite expensive mitigation measures, or making us divert resources to address a minor hazard. We keep learning the hard way to maintain humility before the complexity of nature.

When natural hazard planning works well, hazards are successfully assessed and mitigated, and damage is minor. Conversely, disasters happen because a hazard was inadequately mitigated because it was not assessed adequately or the assessment was not effectively used. Disasters regularly remind us of how hard it is to assess natural hazards and make effective mitigation policies. This paper discusses these issues, mostly using earthquakes as examples, but they arise for all natural hazards.

The great earthquake that struck Japan's Tohoku coast in March 2011 was the 'perfect storm,' illustrating the limits of both hazard assessment and mitigation, and the challenges involved in doing better. The earthquake was much larger than predicted by sophisticated hazard models, and so caused a larger-than-expected tsunami. Because Japan has a major earthquake problem, scientists have studied the Japanese subduction zone extensively for many years using sophisticated equipment and methods, and engineers used the results to develop expensive mitigation measures. However, although some mitigation measures significantly reduced losses of life and property, more than 15,000 deaths and US\$210 billion damage occurred. The earthquake and tsunami catalyzed discussions amongst seismologists and earthquake engineers about the fact that highly destructive earthquakes often occur in areas that earthquake hazard maps predict to be relatively safe (Geller, 2011; Stein *et al.*, 2012; Stirling, 2012; Gulkan, 2013). As Kerr (2011: 912) noted, 'The seismic crystal ball is proving mostly cloudy around the world.'

Challenges

Events like the Tohoku earthquake are prompting interest in how to improve natural hazard assessment and mitigation. Among the key questions are:

Why are good hazard assessments often underutilized?

For socio-political reasons, even good hazard assessments sometimes do not prevent disaster. Hurricane Katrina, which struck the US Gulf coast in August 2005, had been anticipated. Mitigation measures including levees and floodwalls were in place, but recognized to be inadequate to withstand a major hurricane. It was also recognized that many residents who did not have cars would likely not be able to evacuate unless procedures were established. Thus despite accurate and timely warning by the National Weather Service as the storm approached, about 1,800 people died. The total damage is estimated at US\$108 billion, making Katrina the costliest hurricane in US history.

An American Society of Civil Engineers (2006) report assessing the failure of the New Orleans' hurricane protection system described systemic problems:

A large portion of the destruction was caused not only by the storm itself, but by the storm's exposure of engineering and engineering-related policy failures. The levees and floodwalls breached because of a combination of unfortunate choices and decisions, made over many years, at almost all levels of responsibility.

Responsibility for the maintenance and operation of the levees and pump stations was spread over many federal, state, parish, and local agencies. This lack of inter-agency coordination led to many adverse consequences.

The hurricane protection system was constructed as individual pieces – not as an interconnected system – with strong portions built adjacent to weak portions, some pump stations that could not withstand the hurricane forces, and many penetrations through the levees for roads, railroads, and utilities. Furthermore, the levees were not designed to withstand overtopping.

The hurricane protection system was designed for meteorological conditions (barometric pressure and wind speed, for example) that were not as severe as the Weather Bureau and National Weather Service listed as being characteristic of a major Gulf Coast hurricane.

American Society of Civil Engineers (2006: v)

Other disasters reveal similar difficulties in mitigation efforts, many of which had been previously recognized but not addressed. As Warren Buffett said, 'You don't know who's swimming naked until the tide goes out' (Berkshire Hathaway, n.d.). Much needs to be done in this area.

Why are hazard assessments often poor?

In Shakespeare's *Henry IV*, Glendower says, 'I can call spirits from the vasty deep' and Hotspur replies, 'Why, so can I, or so can any man; but will they come when you do call for them?'. Scientists assessing natural hazards face the same challenge: they can make detailed assessments, but the earth often does not obey.

The Japanese seismic hazard map prior to the March 2011 Tohoku earthquake (Figure 10.1) illustrates the problem. The map was produced with the commonly used probabilistic seismic hazard assessment algorithm, which uses estimates of the probability of different future earthquakes and the resulting shaking to predict the maximum shaking expected with a certain probability over a given time. Larger than expected shaking corresponds to a higher than predicted hazard. A similar approach was used to forecast the largest expected tsunami.

The mappers used the historic earthquake record to divide the trench, along which the Pacific Plate subducts beneath Japan, into segments about 150 km long and infer how large an earthquake to expect on each segment. The resulting map predicted less than 0.1 percent probability of shaking with intensity '6-lower' on the Japan Meteorological Agency scale in the next 30 years off Tohoku. Thus such shaking was expected on average only once in the next 30/0.001 or 30,000 years; however, within 2 years, such shaking occurred. Five segments broke causing a magnitude (M) 9.1 earthquake, which was much larger than expected and the resulting tsunami was larger than anticipated. The mapping process significantly under-predicted what happened (Stein and Okal, 2011).

Similar discrepancies have occurred around the world (Stein *et al.*, 2012). The 2008 M7.9 Wenchuan, China, earthquake caused more 65,000 deaths and occurred on a fault system assessed as low hazard. The 2010 M7.1 Haiti earthquake, which caused more than 100,000 deaths,

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REALITY CHECK

The Japanese government publishes a national seismic hazard map like this every year. But since 1979, earthquakes that have caused 10 or more fatalities in Japan have occurred in places it designates low risk.

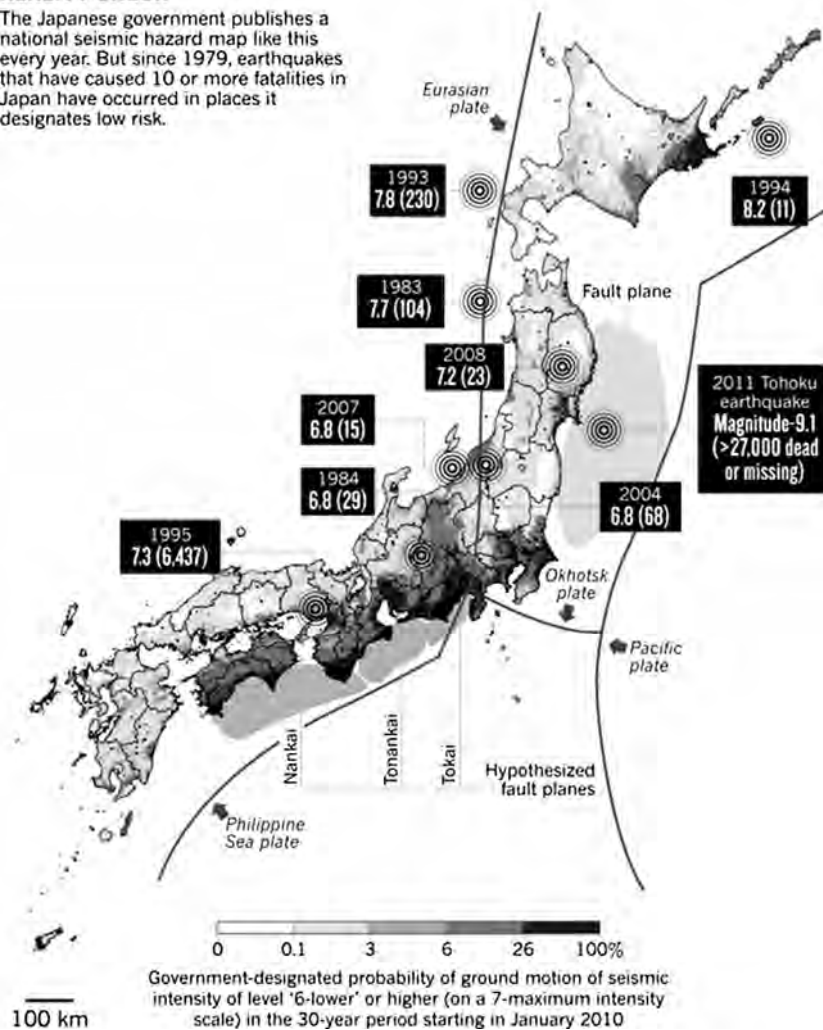


Figure 10.1 Comparison of Japanese hazard map to the locations of earthquakes since 1979 that caused ten or more fatalities

occurred on a fault mapped in 2001 as having low hazard, but produced shaking far greater than predicted. The 2011 M6.3 earthquake, which did considerable damage in Christchurch, New Zealand, caused much stronger ground motion than was predicted for the next 10,000 years.

Our ability to forecast natural hazard events is improving due to new data and methods; however, some key parameters are poorly known, unknown or unknowable. A major challenge, therefore, is to improve what we can, in many cases by looking at what has gone wrong.

Why are supposedly rare events relatively common?

When hazard assessments do poorly, a common explanation is that the events are low-probability events. These are termed 'black swans' because before Europeans reached Australia all swans were

thought to be white. After Hurricane Sandy in 2012 caused more than US\$60 billion damage, New York governor Cuomo said, 'we have a 100-year flood every two years . . . the frequency of extreme weather is going way up' (Dwyer, 2012). Less than a year later, major floods in Central Europe did enormous damage. A German café owner, who was trying to keep the highest floodwater in five centuries out of his café, complained, 'The flood of a century is supposed to happen once in a lifetime, not once every 10 years' (Eddy, 2013).

Such supposedly rare events illustrate the need to improve models. In many cases, the hazard was modelled as time-independent events, assuming that their history gives a reasonable estimate of their future probability. However, long-term meteorological hazard forecasts face uncertainties associated with possible effects of climate change because rainfall patterns and storm frequencies or intensities may change. For example, the European floods reflect winter storms from the Atlantic shifting northward, causing increased rain and flooding in northern Europe and increasing drought in southern Europe.

How much can forecasts be improved?

Although our ability to forecast natural hazard events is improving, some key parameters are poorly known, unknown or unknowable. For example, where and when large earthquakes happen is more variable than assumed in hazard maps. Some earthquakes appear where and when they were not expected and others are much larger than expected. Part of the problem is that because large earthquakes on a given fault segment occur hundreds or thousands of years apart on average, the short records from seismology (about a hundred years) and historical accounts (hundreds to thousands of years) are often inadequate to show what is going on.

Moreover, earthquake occurrence seems at least partly chaotic. It seems likely that all earthquakes start off as tiny earthquakes, which happen frequently, but only a few cascade through random failure into successively larger earthquakes. This hypothesis draws on ideas from nonlinear dynamics or chaos theory, in which some small perturbations grow to have unpredictable large consequences.

A useful analogy is a thought experiment (Lorenz, 1995). If weather was not chaotic, it would be controlled only by the seasons, and every year storms would follow the same tracks. In reality, storm tracks differ significantly from year to year. Thus, 'the difficulty in planning things in the real world, and the occasional disastrous effects of hurricanes and other storms, must be attributed to chaos' (Lorenz, 1995: 109).

By analogy, without chaos steady motion between plates would produce earthquakes that repeat in space and time. In contrast, the chaos view predicts that the locations of big earthquakes on a plate boundary and intervals between them should be highly variable, placing fundamental limitations on how well we can forecast earthquake hazards.

A similar situation arises for volcanoes. Volcano prediction is sometimes very successful. The area around Mount St. Helens, Washington, was evacuated before the 1980 eruption, reducing the loss of life to only 60 people, including a geologist studying the volcano and citizens who refused to leave. The 1991 eruption of Mount Pinatubo in the Philippines destroyed over 100,000 houses and a nearby US Air Force base, and yet only 281 people died because of evacuations. In other cases, however, a volcano may seem to be preparing to erupt, but does not. In 1982, uplift and other activity near Mammoth Lakes, California, suggested that an eruption might be imminent. A volcano alert was issued, causing significant problems. Housing prices fell 40 percent. Businesses closed, new shopping centers stood empty and townspeople left to seek jobs elsewhere. Angry residents called the US Geological Survey the 'US Guessing Society,' and the county supervisor who arranged for a new road providing an escape route in the event of

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an eruption was recalled in a special election. Even in hindsight, however, the alert seems sensible given the data then available, illustrating the challenge involved. The incident provided the basis for the film *Dante's Peak*, in which the volcano actually erupts. Volcanologists thus accept that 'volcanoes are really difficult to predict because they are so nonlinear – they suddenly decide to do something very different' (Fountain, 2015).

How can forecast performance be measured?

In some applications, although hazard assessments are used to make costly policy decisions, their predictions have never been objectively tested. For example, earthquake hazard mapping is used to make major decisions but without careful assessment of the uncertainties in these maps or objective testing of how well they predict future shaking. We have no real idea of how well they predict what actually happens, and the fact that they sometimes do poorly is not surprising.

In contrast, weather forecasts are routinely evaluated to assess how well their predictions matched what actually occurred (Stephenson, 2000). This assessment involves adopting metrics. Murphy (1993: 281) notes that 'it is difficult to establish well-defined goals for any project designed to enhance forecasting performance without an unambiguous definition of what constitutes a good forecast.'

Recent large earthquakes have catalyzed interest for earthquakes using various approaches (Stirling and Petersen, 2006; Miyazawa and Mori, 2009; Stirling and Gerstenberger, 2010; Stein *et al.*, 2012; Wyss *et al.*, 2012; Nekrasova *et al.*, 2014; Mak *et al.*, 2014) and are being developed under auspices of the Global Earthquake Model project (www.globalquakemodel.org).

An important point is that no single metric alone fully characterizes what we would like forecasts to do. For example, how good a baseball player Babe Ruth was depends on the metric used. In many seasons Ruth led the league in both home runs and in the number of times he struck out. By one metric he did very well, and by another, very poorly. Similarly, using several metrics can provide useful insight for comparing and improving hazard assessments (Stein *et al.*, 2015a).

How can forecast uncertainties be quantified and presented?

Many natural hazard forecasts involve subjective assessments and choices amongst many poorly known or unknown parameters. Such models are sometimes termed BOGSATs, from 'Bunch Of Guys Sitting Around a Table' (Kurowicka and Cooke, 2006). As a result, their uncertainties are hard to quantify.

Typically, scientists consider *shallow uncertainty*, recognizing they do not know the outcomes, but assuming they know a probability density function describing them. In this case, models based on a system's past are good predictors of the future. The alternative is *deep uncertainty* in which the probability density function is unknown, and models based on a system's past are therefore likely to be poor predictors of the future (Stein and Stein, 2013a). In sports terms, shallow uncertainty is like estimating the chance that a soccer player will score on a penalty kick. For this, his past average is a good predictor. Deep uncertainty is like trying to predict the champion in the next season because the team's past performance gives only limited insight into the future.

For example, earthquake hazard maps involve choosing hundreds or thousands of parameters to predict the answers to four questions over periods of 500–2,500 years: Where will large earthquakes occur? When will they occur? How large will they be? How strong will their shaking be? Some parameters are reasonably well known, some are somewhat known, some

are essentially unknown, and some may be unknowable (e.g. Stein *et al.*, 2012). Although some parameters could be better estimated, and knowledge of some will improve as new data and models become available, major uncertainties seem likely to remain (Stein and Friedrich, 2014).

One way to illustrate the uncertainties is to examine how hazard map predictions depend on the choice of poorly known parameters. Figure 10.2 compares the predicted hazard at two cities in the central US, which varies by a factor of more than three. At Memphis, close to the region's main faults, the primary effect is from the assumed maximum magnitude, with M8 models predicting the highest hazard. At St. Louis, the ground motion model has the largest effect and the 'Frankel' models predict the highest hazard. The uncertainty is even bigger than shown because the effect of choosing between time-independent and time-dependent models is shown for specific parameters and a specific combination of maximum magnitude and ground motion model.

Unfortunately, such uncertainties are not usually communicated to users of hazard maps; instead, mappers typically combine predictions for various parameters through a 'logic tree' in which they assign weights to the parameter choices. Adjusting the weights changes the predicted hazard. Because there is no objective way to assign weights, the result – which often will not be known for hundreds of years or longer – will be as good or as bad as the preconceptions that the mappers used to assign weights actually turn out to be. As we have seen, sometimes these prove to have been poor choices. Because showing the resulting single value does not convey the uncertainty, it would be better to communicate estimates of these uncertainties to potential users. Recognizing the uncertainties – even if they are poorly known and probably underestimated – would help users decide how much credence to place in maps and make them more useful in formulating cost-effective hazard mitigation policies.

A good example would be the meteorological community's goal (Hirschberg *et al.*, 2011: 1654) of 'routinely providing the nation with comprehensive, skillful, reliable, sharp, and useful information about the uncertainty of hydrometeorological forecasts.' Although researchers dealing with other hazards have different challenges and a longer way to go, it makes sense to try to do the same.

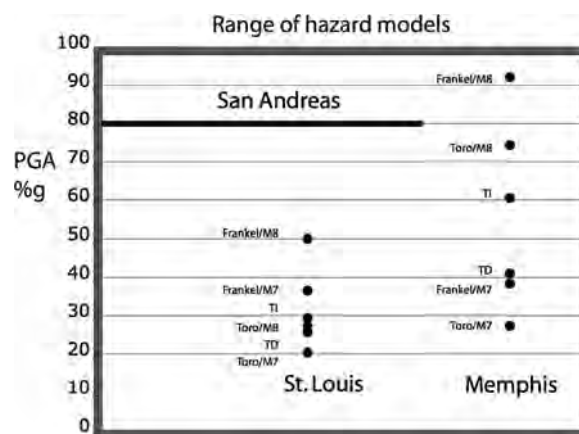


Figure 10.2 Comparison of earthquake hazard, described as peak ground acceleration (PGA) as a percentage of the acceleration of gravity expected with 2 percent risk in 50 years, predicted by various assumptions for two sites in the central US

When and how should hazard assessments be updated?

An important question is what to do after a hazardous event is much greater or has greater effects than predicted, such as an earthquake yielding shaking larger than anticipated. Hazard assessors have two choices. They can regard what occurred as a low-probability event consistent with the assessment or accept it as showing the need to revise the assessment.

Whether and how much to revise a hazard assessment is complicated because a new assessment that describes the past better may or may not predict the future better. The issue is like deciding after a coin has come up heads four times whether to continue assuming that the coin is fair and the run is a low-probability event, or to change to a model in which the coin is assumed to be biased. Either choice runs a risk. If the coin is severely biased, staying with the assumption that it is fair will continue to yield poor predictions; however, if the coin is fair and the four heads were just a low-probability event, changing to the assumption that the coin is biased does a better job of describing what happened in the past, but will make the prediction worse.

For example, an earthquake that produced higher-than-expected shaking can be regarded as a low-probability event allowed by the hazard map. The usual choice, however, is to revise the map to show increased hazard in the heavily shaken area. This process can amount to ‘Texas sharpshooting,’ named because it is like first shooting at the barn and then drawing a target around the bullet holes. To make things worse, sometimes the new map does not predict future shaking well and soon requires further updating. Italy’s earthquake hazard map, intended to forecast hazards over the next 500 years, has required remaking every few years (Figure 10.3).

This decision could be addressed using Bayes’ Rule, in which how much to change a model after an event depends on one’s confidence in it prior to the event. The less confidence we have in the prior model, the more a new datum can change it. Stein *et al.* (2015b) suggest considering the BOGSAT process from a Bayesian perspective. This would recognize that the predicted hazard reflects mappers’ view of the world based on their assessment of diverse data and models, and that when and how maps are revised once new data become available depends on the mappers’ preconceptions.

How sensible policy be made given our limited forecasting skills?

On the hazard assessment side, the problem is that we lack full information. Geoscience tells us a lot about the natural processes that cause hazards, but not everything. We are learning more with new ideas, methods, and data, but still have a long way to go. For example, meteorologists are steadily improving forecasts of the tracks of hurricanes, but forecasting their strength is harder. We know a reasonable amount about why and where earthquakes will happen, some about how big they will be, but much less about when they will happen. Although learning more is a major research task, into which there is considerable amount of effort being put in, major advances will probably come slowly because of how complicated nature is and how much we do not yet understand. We therefore need to decide what to do given these uncertainties.

On the mitigation side, methods are getting better and cheaper. Still, choosing strategies is constrained because society has finite resources. There’s no free lunch – resources used for mitigating hazards are not available for other purposes. Funds that hospitals spend strengthening buildings to resist earthquake shaking cannot be used to treat patients. Money spent putting more steel in school buildings does not get used to hire teachers. Spending on seawalls and levees comes at the expense of other needs.

The challenge is deciding *how much mitigation is enough*. More mitigation can reduce losses in possible future disasters, at increased cost. In the extreme, too much mitigation could cost more

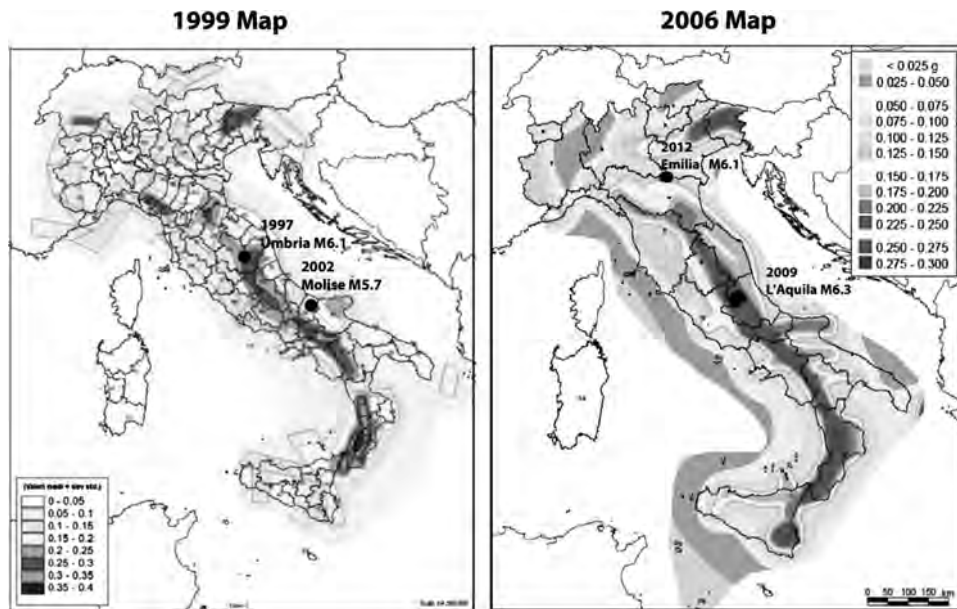


Figure 10.3 Comparison of successive Italian hazard maps, which forecast some earthquake locations well and others poorly

than the problem we want to mitigate. However, less mitigation reduces costs, but can increase potential losses and hence too little mitigation can cause losses that it would make more sense to avoid. We want to hit a ‘sweet spot’ – a sensible balance. This means being careful, thoughtful gamblers. Choosing priorities is always hard, but it is especially difficult in dealing with natural hazards because of our limited ability to forecast the future.

We need to develop sensible approaches to evaluate alternative strategies. In addition to science, this process involves complicated economic, societal, and political factors. For example, after Hurricane Katrina breached coastal defenses in 2005 and flooded much of New Orleans, choosing to what level these defenses should be rebuilt became an issue. Should they be rebuilt to withstand a similar hurricane or a stronger one? Similarly, given the damage to New York City by the storm surge from Hurricane Sandy in 2012, options under consideration range from doing little, through intermediate strategies like providing doors to keep water out of vulnerable tunnels, to building up coastlines or installing barriers to keep the storm surge out of rivers.

Although our first instinct might be to protect ourselves as well as possible, reality sets in quickly because resources used for hazard mitigation are not available for other societal needs. Should we spend billions of dollars making buildings in the central US as earthquake-resistant as in California, or would these funds do more good if used otherwise? Should all hospitals in California be made earthquake-resistant or would it be wiser to use these resources caring for millions of people without health insurance? As a doctor mused, ‘we could treat a lot of people for \$50 billion.’ In the same spirit, a European Union official charged with hazard mitigation pointed out that plans for higher levees to reduce river flood damage compete for funds with ones to improve kindergartens.

Unfortunately – as the Tohoku sea walls showed – mitigation policies are often developed without careful consideration of their benefits and costs. Communities are often unclear about

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what they are buying and what they are paying. Because they are playing against nature without a clear strategy, it is not surprising that they sometimes do badly. Doing better requires selecting strategies to wisely use limited resources. This is not easy because the benefits of various strategies cannot be estimated precisely, given our limited ability to estimate the occurrence and effects of future events; however, even simple estimates of the costs and benefits of different strategies often show that some make much more sense than others.

Figure 10.4 illustrates a way to compare options (Stein and Stein, 2012, 2013b). The optimum level of mitigation n^* minimizes the total cost $K(n)$, the sum of the present value of expected loss in future earthquakes and the cost of mitigation. The U -shaped total cost curves illustrate the tradeoff between mitigation and loss. For no mitigation, $n = 0$, the total cost $K(0)$ equals the expected loss, $Q(0)$. Initial levels of mitigation reduce the expected loss by more than their cost, and so the curve decreases to a minimum at the optimum. $K(n)$ is steepest for $n = 0$ and flattens as it approaches the optimum, showing the decreasing marginal return on mitigation.

Relative to the optimum, less mitigation decreases construction costs but increases the expected damage and therefore the total cost. Consequently, it makes sense to invest more in mitigation. Conversely, more mitigation than the optimum gives less expected damage but at higher total cost, and so the additional resources required would do more good if invested otherwise.

The optimum can be viewed in terms of the derivatives of the functions (Figure 4B). Because increasingly high levels of mitigation are more costly, the marginal cost increases with n . Conversely, the reduced loss from additional mitigation decreases. The lines intersect at the optimum, n .

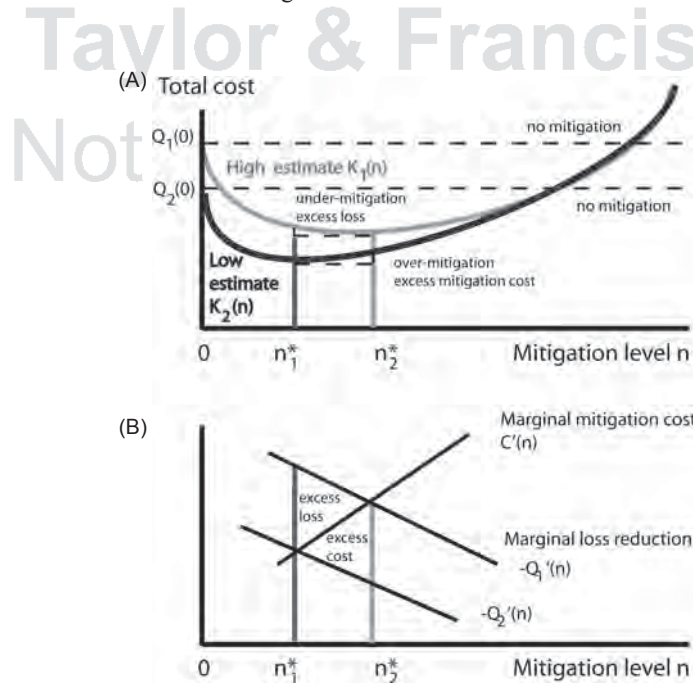


Figure 10.4 (A) Comparison of total cost curves for two estimated hazard levels. For each, the optimal mitigation level, n^* , minimizes the total cost, the sum of expected loss and mitigation cost. (B) In terms of derivatives, n^* occurs when the reduced loss $-Q'(n)$ equals the incremental mitigation cost $C'(n)$. If the hazard is assumed to be described by one curve but actually described by the other, the assumed optimal mitigation level causes nonoptimal mitigation, and thus excess expected loss or excess mitigation cost

Given our limited ability to assess hazards, we should formulate policies whilst accepting the uncertainties involved. To see how, consider cost curves between $K1(n)$ and $K2(n)$. These can correspond to high and low estimates of the hazard, high and low estimates of the loss, or, more realistically, a combination of the uncertainties in hazard and loss estimates. These start at different values, representing the expected loss without mitigation. They converge for high levels of mitigation because in the limit of enough mitigation there would be no loss.

In the limiting cases, the hazard is assumed to be described by one curve but is actually described by the other. As a result, the optimal mitigation level chosen as the minimum of the assumed curve gives rise to non-optimal mitigation, shown by the corresponding point on the other curve. Assuming too-low hazard causes under-mitigation and excess expected loss, as shown by the height of the U-curve above the dashed line for optimum mitigation. In terms of the derivatives, it is the triangular area between the marginal loss reduction and marginal mitigation cost lines. Conversely, assuming too-high hazard causes over-mitigation and excess mitigation cost; however, as long as this point is below the dashed line for the correct curve, the total cost is less than from doing no mitigation.

Given the range of hazard estimates, we should choose an estimate between them. The resulting curve will lie between the two curves, and thus probably have a minimum between n_1^* and n_2^* . Relative to the actual but unknown optimum, this mitigation is non-optimal, but perhaps not unduly so. As long as the total cost is below the loss for no mitigation, non-optimal mitigation is better than none.

This is a simple example of robust risk management – accepting the uncertainty and developing policies to give acceptable results for a range of possible hazard and loss scenarios. Such graphs are schematic guides rather than functions we can compute exactly. Given the uncertainties involved, it would be unrealistic to seek an optimum strategy; however, even simple estimates can show which strategies make more sense than others. Although in real cases such approaches cannot give an optimum strategy, they could identify sensible strategies.

How can we develop a new multidisciplinary ethos?

Mitigation policy decisions involve socio-cultural preferences beyond purely economic grounds. Society is sometimes overly concerned about relatively minor hazards and downplays other more significant ones. This situation often leads to policies that make little scientific or economic sense. Hazard assessments often underestimate the limits of scientific knowledge. Mitigation policies are often developed without considering their costs and benefits. The net result is that communities often over-prepare for some hazards and under-prepare for others.

For these and other reasons, no unique or right answers exist for a particular community, much less for all communities; however, new approaches like those discussed here can help communities make more informed and better decisions.

Part of the problem is that current approaches generally treat the relevant geoscience, engineering, economics, and policy formulation separately. Geoscientists generally focus on using science to assess hazards, engineers and planners focus on mitigation approaches, and economists focus on costs and benefits. Each group often focuses on its aspect of the problem, but does not fully appreciate how the others think, what they know, and what they do not know.

More effective natural hazards policy can be developed by advancing each of the relevant disciplines and integrating their knowledge and methods. Fortunately, there is an increasing awareness of this need, especially among young researchers who would like to do a better job of mitigating hazards.

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