

How much can we clear the crystal ball?

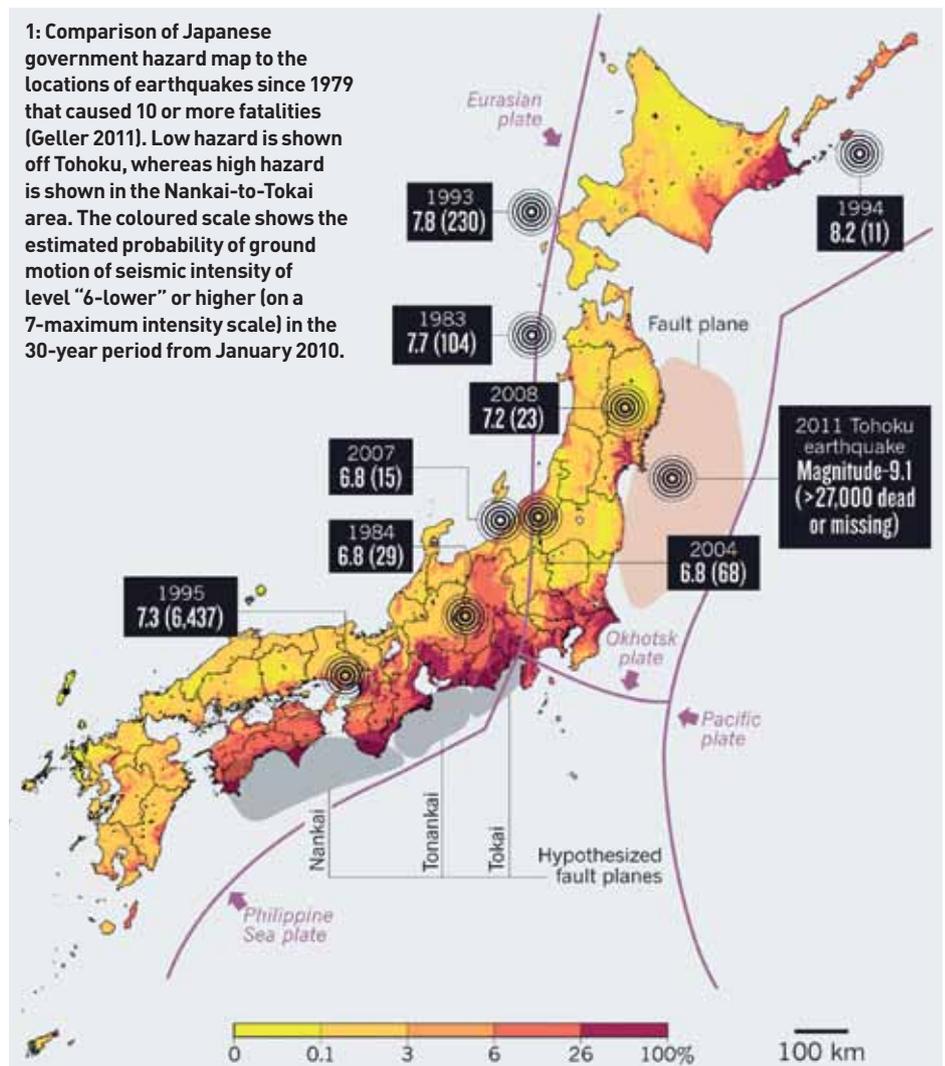
Earthquake forecasts often prove cloudy. Seth Stein and Anke Friedrich peer through the mist to examine the challenges and prospects for earthquake hazard mapping and how we should decide how much to spend on mitigation.

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

The problem is illustrated by images of the tsunami from the giant 2011 Tohoku earthquake pouring over 10 m seawalls, which catalysed discussions among seismologists and earthquake engineers about the fact that highly destructive earthquakes often occur in areas that earthquake hazard maps predict to be relatively safe. As *Science* magazine (Kerr 2011) explained, "The seismic crystal ball is proving mostly cloudy around the world." This cloudiness is a problem for the high-stakes game of chance that society plays in preparing for earthquakes and other natural disasters. We want to assess the hazard – how often dangerous events happen – and use this assessment to mitigate or reduce the risk – the resulting losses. Often Nature surprises us, 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.

Estimating probability

The Japanese seismic hazard map (figure 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 expected shaking corresponds to higher predicted hazard.



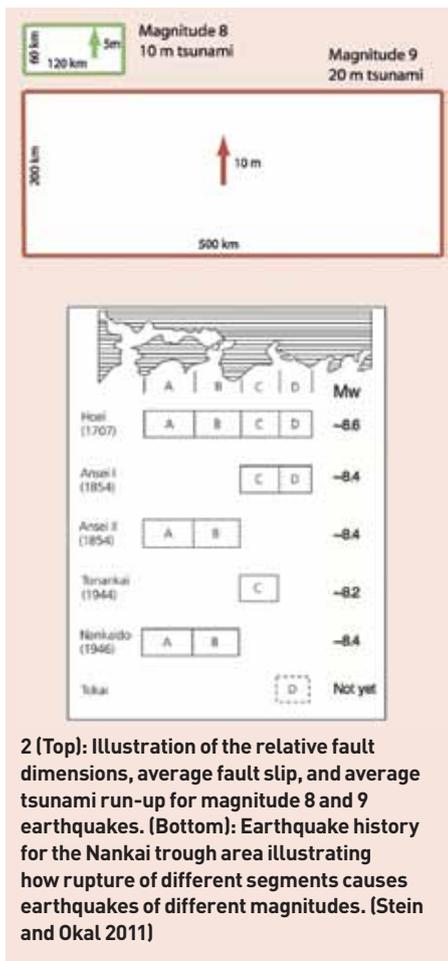
A similar approach was used to forecast the largest expected tsunami. Engineers used the results to design tsunami defences and build structures to survive earthquake shaking.

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. The resulting map predicted less than 0.1% 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 two years, such shaking occurred. On 11 March 2011, five segments

broke, causing a magnitude 9.1 earthquake, much larger than expected, and a tsunami, larger than anticipated (figure 2). The mapping process significantly underpredicted what happened.

Similar discrepancies have occurred around the world. The 2008 M7.9 Wenchuan, China, earthquake, which caused more than 65 000 deaths, occurred on a fault system assessed as low hazard. Another example is the plate boundary between Africa and Eurasia in North Africa. The 1999 Global Seismic Hazard Map, showing shaking expected at 10% probability in 50 years, features a prominent "bull's-eye" at the site of the 1980 M7.3 El Asnam earthquake. The largest subsequent earthquakes to date, the 2003 M6.8 Algeria and 2004 M6.4 Morocco events, did not occur in the regions designated



2 (Top): Illustration of the relative fault dimensions, average fault slip, and average tsunami run-up for magnitude 8 and 9 earthquakes. (Bottom): Earthquake history for the Nankai trough area illustrating how rupture of different segments causes earthquakes of different magnitudes. (Stein and Okal 2011)

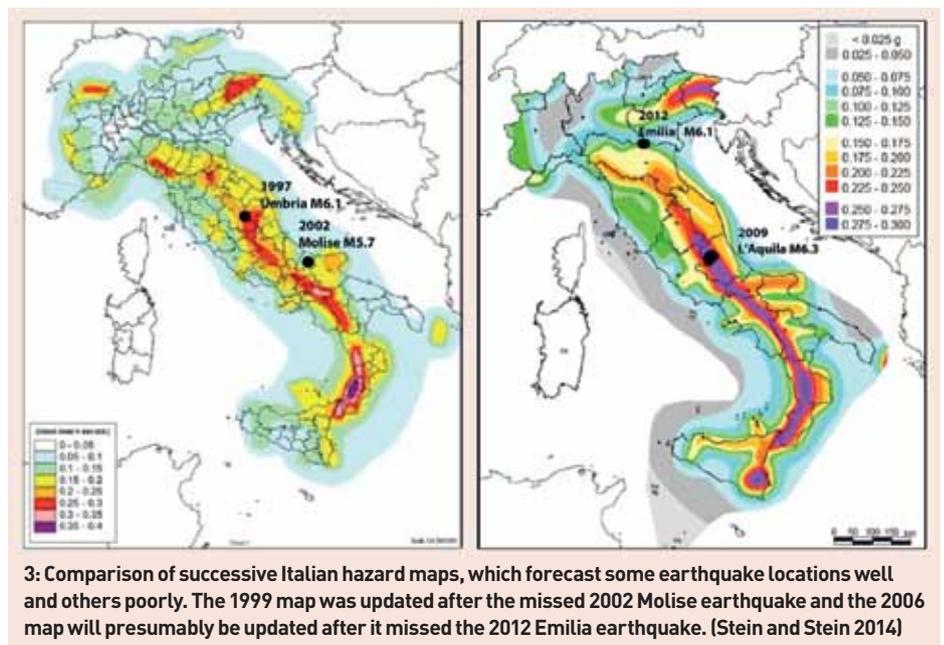
as high hazard. The 2010 M7.1 Haiti earthquake that caused more than 100 000 deaths occurred on a fault mapped in 2001 as having low hazard; it produced shaking far greater than predicted. The 2011 M6.3 earthquake, which did considerable damage in Christchurch, New Zealand, caused much stronger ground motion than predicted for the next 10 000 years.

This situation brought home the fact that although such maps are used to make costly policy decisions, their predictions have never been objectively tested. We have no real idea of their uncertainties or how well they predict what actually happens; the fact that they sometimes do poorly is not surprising.

Extensive discussions of what is going wrong and how to do better are underway (Geller 2011, Stein *et al.* 2012, Gulkan 2013). Some have taken place at the US Geological Survey's John Wesley Powell Center for Analysis and Synthesis, in a working group convened by the Global Earthquake Model project. Although most participants are involved with national or international earthquake hazard mapping programmes, we were invited as academics to offer external perspectives, which are summarized here.

Black swans or bad maps?

The overall question is whether the apparent failures of earthquake hazard maps indicate bad maps or simply bad luck. Several explanations



3: Comparison of successive Italian hazard maps, which forecast some earthquake locations well and others poorly. The 1999 map was updated after the missed 2002 Molise earthquake and the 2006 map will presumably be updated after it missed the 2012 Emilia earthquake. (Stein and Stein 2014)

have been offered.

One end member explanation is that these earthquakes are low-probability events allowed by probabilistic maps, termed “black swans” because before Europeans reached Australia, all swans were thought to be white. However, current practice in which maps are remade after “unexpected” earthquakes (figure 3; Peresan and Panza 2012) illustrates that mapmakers recognize that these are not simply low-probability events. If they were, there would be no reason to change the maps. Lottery commissions expect a few winners, and do not change their odds when these rare events occur. Statisticians refer to such *a posteriori* changes to a model as “Texas sharpshooting”, in which one shoots at the barn and draws circles around the bullet holes.

The other end member explanation is that the probabilistic approach is fundamentally flawed (Wang 2011), for several possible reasons. One is that earthquake probabilities cannot be usefully defined. Freedman and Stark (2003) argue that “Probability is a property of a model ... the models, unlike models for coin-tossing, have not been tested against relevant data. Indeed, the models cannot be tested on a human time-scale, so there is little reason to believe the probability estimates.” Thus deriving reliable probability estimates from earthquake histories is very difficult (Savage 1994, Parsons 2008, Stein and Stein 2014).

Another criticism is that the expected value of shaking in a given time period is a mathematical quantity inappropriate for designing earthquake-resistant structures, especially for rare large events that critical facilities like nuclear power plants should withstand.

Because the expected value is the predicted value times the assumed probability that it will occur, it is likely to be less than the shaking that actually occurs if such an event happens. Hence

in this view, it is better to specify the largest earthquakes expected in a deterministic seismic hazard assessment (Peresan and Panza 2012), avoiding assumptions about earthquake probabilities. However, this approach still requires assuming the magnitude of the largest earthquakes, and designing for these events without considering their rarity can be uneconomic.

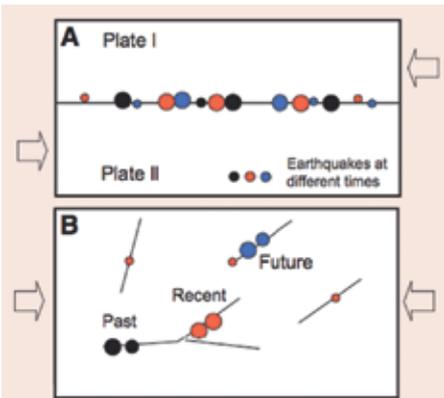
Most recent discussions take a view intermediate between the end members. In this view, the probabilistic algorithm is reasonable in principle, but in many cases key parameters required are poorly known, unknown, or unknowable. This situation results in maps with large uncertainties and some failures. If so, maps can be improved somewhat by improving those parameter estimates that can be improved, while recognizing that others cannot.

Similar analysis also applies to deterministic algorithms, which require assuming the same parameters except for an earthquake probability.

The underlying problem: chaos

Fundamentally, the problem is that where and when large earthquakes happen is more variable than assumed in hazard maps. The conceptual model on which they are based comes from boundaries between plates, where steady motion between plates loads a major fault rapidly at constant rate. In this case, the largest earthquakes should ideally be spatially focused, temporally quasi-periodic, and have similar magnitudes (figure 4).

However, maps made under these assumptions often do poorly. 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



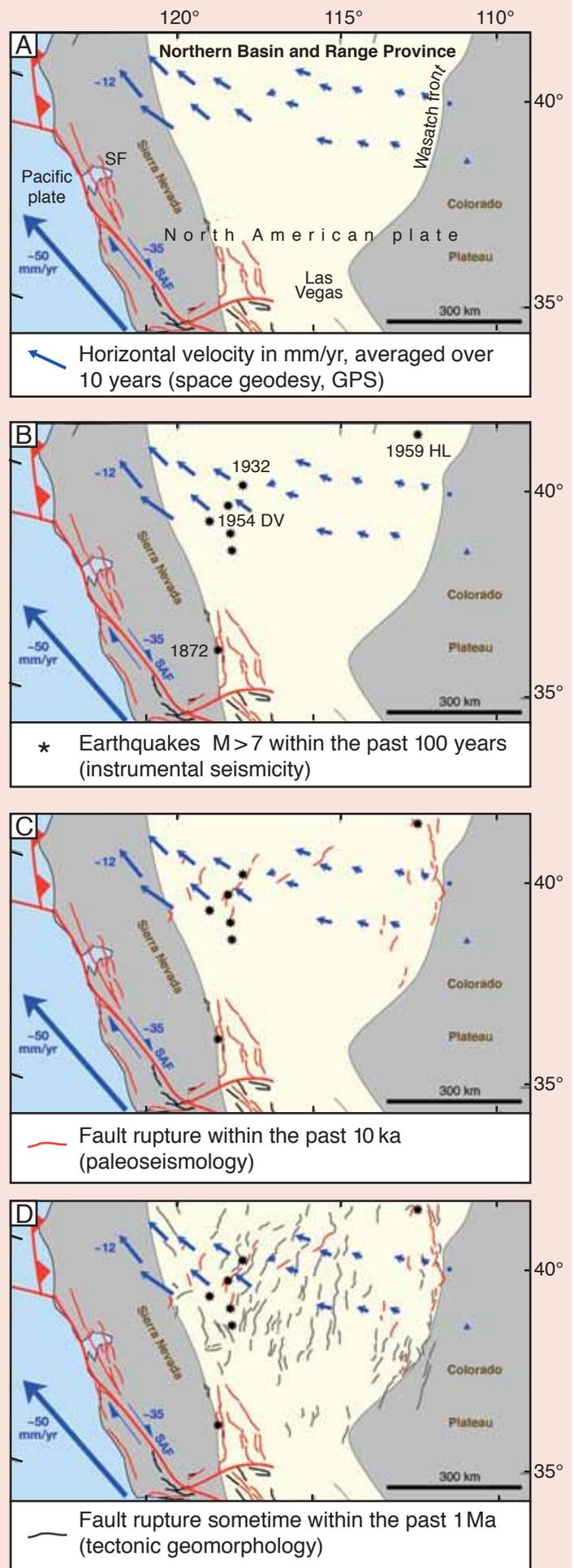
4: Cartoon showing the difference between earthquakes (A) at ideal plate boundary faults and (B) in mid-continents. The plate boundary fault is loaded at a constant rate by the steady relative plate motion, causing quasi-periodic earthquakes to concentrate along the plate boundary. The mid-continent is loaded from the far field and the loading is shared by a complex system of interacting faults. Hence the loading rate on each fault may be variable, and earthquakes may shut off on one fault and migrate to another. (Liu *et al.* 2011)

accounts (hundreds to thousands of years) are inadequate to show what is going on.

Moreover, the world is more complicated than the ideal, because 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 via a random failure process into successively larger earthquakes. This hypothesis draws on ideas from nonlinear dynamics (chaos theory), in which some small perturbations grow to have unpredictable large consequences.

A useful analogy is a thought experiment, after Lorenz (1995). If weather were not chaotic, it would be controlled only by the seasons so, every year, storms would follow the same tracks. In reality, storm tracks differ significantly from year to year. Thus, reasoned Lorenz, “the difficulty in planning things in the real world, and the occasional disastrous effects of hurricanes and other storms, must be attributed to chaos”. 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 interval between them should be highly variable (Kagan *et al.* 2012), as the geological record shows (figure 2). Hence even if the long-term earthquake hazard along a boundary is uniform, apparent gaps and concentrations in seismicity result (Swafford and Stein 2007). These artifacts can bias hazard assessment either to assume that areas with recent large events are more dangerous, or conversely that areas without recent large events are dangerous “gaps” “overdue” for earthquakes. Both biases are common (e.g. figure 1) and can cause map failures.

5: Deformation of the Basin and Range province shown by different datasets spanning different time windows.



The situation is even more challenging where there is a broad boundary zone between plates, or within plates (Stein *et al.* 2009, Leonard *et al.* 2013). In these situations, tectonic loading is collectively accommodated by a complex system of interacting faults, so the loading rate on a given fault is slow and may not be constant. As a result, earthquakes can cluster on a fault for a while then shift elsewhere (figure 4).

A striking example is a 2000-year record from North China showing migration of large earthquakes between fault systems across a broad region, such that no large earthquake ruptured the same fault segment twice (Liu *et al.* 2011). A map made from any short subset of the record would be biased. For example, one using the 1900 years prior to 1950 would miss recent activity including the 1976 Tangshan earthquake, which occurred on a previously unknown fault and killed nearly 240 000 people.

Combining data types to do better

The best prospects for improving the situation are to lengthen observational periods by integrating results from different methods (Friedrich *et al.* 2003). For example, the 2008 Wenchuan earthquake occurred on the Longmenshan fault, which was mapped as having low hazard because it had little instrumentally recorded seismicity. A different view would have arisen from considering the dramatic topographic transition between the Tibetan plateau and Sichuan plain and strain accumulation shown by global positioning system (GPS) measurements (Witze 2009). Similarly, the fault on which the 2010 Haiti earthquake occurred was mapped as low hazard because of its low recent seismicity, despite a historic record of large earthquakes and GPS data showing strain accumulation (Manaker *et al.* 2008). Moreover, digital elevation models and satellite imagery (including Google Earth) show sharp fault traces, implying long-term fault activity.

Understanding how deformation varies in space and time will require collecting more data and learning what they mean. The Basin and Range province in the Western US illustrates this possibility (figure 5). The most recent data, GPS measurements over a 10-year period, show the motion of sites relative to the stable interior of North America (Bennett *et al.* 2003). These rates increase steadily from 1–2 mm/yr across the Wasatch front to about 12 mm across the Sierra Nevada, showing the portion of the approximately 50 mm/yr motion between the Pacific and North American plates occurring in the diffuse boundary zone east of the San Andreas fault system.

Although these motions include transient effects after large earthquakes, their pattern shows deformation varying smoothly across the boundary zone when measured over less than 20 years.

Table 1: Earthquake hazard uncertainties and their potential for reduction

Cause of uncertainty	How much can the uncertainty be reduced?
Where will large earthquakes occur?	Significantly on plate boundaries, somewhat in interiors
When will large earthquakes occur?	Little if at all
How large will they be?	Significantly for lower bound (paleoseismology, GPS), not for upper (short sample)
How strong will the shaking be?	Significantly in seismically active areas, less so in less active ones

The seismological and historical record of earthquakes over the past 150 years show a quite different pattern, with most activity concentrated along two belts, as shown by the largest ($M > 7$) events. Deformation in the central Nevada seismic belt is shown by the 1954 Dixie Valley events and others, and the 1872 Owens Valley earthquake illustrates the eastern California shear zone. Deformation on the eastern edge is indicated by the Intermountain seismic belt, including the 1959 Hebgen Lake event, although no large earthquakes occurred in its southern part, the Wasatch fault zone.

A third view arises from paleoseismic data, geologic records of past earthquakes. Holocene surface ruptures (Friedrich *et al.* 2004, Koehler and Wesnousky 2011) record the locations of large earthquakes in the past 10 000 years, including the recent large ones. As well as indicating that large earthquakes occurred along the Wasatch fault zone, they show large earthquakes west and east of the central Nevada seismic belt, and east of the Owens Valley earthquake. Tectonic geomorphology, mapping the traces of faults that have been active at least in Quaternary times, provides a fourth view, showing that over the past million years, most faults ruptured at least once (Hecker 1993, Dohrenwendt *et al.* 1996).

Comparing the datasets illustrates apparent contradictions and how they can be reconciled. At face value, the GPS and seismicity data are inconsistent, with the first showing deformation across the entire region and the second showing deformation concentrated at its margins. Traditional seismic hazard estimation would ignore the GPS data, and assume high hazard along the margins and low hazard between them. However, the fault data show that the entire region has experienced large earthquakes in the past million years and is likely to experience them in the future. Thus the present broad regional deformation shown by the GPS data has been going on for this entire time period, and the recent concentration of seismicity reflects only the most recent episodes of fault motion in this slowly deforming region. Hence faults with apparent earthquake recurrence

times on order of thousands of years should be classified as potentially active and included in earthquake hazard mapping.

Shallow versus deep uncertainties

As this example showed, acquiring new data and developing better models of the dynamics of deformation and faulting should improve hazard maps. The question is how much.

Because the maps seek to describe unknown future events, characterizing the sources of uncertainty is crucial. Various formulations are available. To date, seismic hazard analysis follows engineering literature in distinguishing uncertainties by their sources: aleatory uncertainties are due to irreducible physical variability of a system, while epistemic uncertainties are due to lack of knowledge of the system, and so can be reduced by more knowledge.

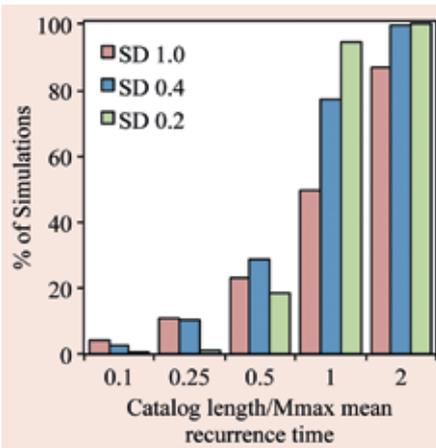
An alternative considers how well we can describe uncertainty. Typically, scientists consider shallow uncertainty, recognizing they do not know the outcomes, but assuming they know a probability density function describing them. In this case, models based on a system’s past are good predictors of the future. The alternative is deep uncertainty in which the probability density function is unknown, so models based on a system’s past are 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 teams’ past performance give only limited insight into the future.

How much better can we do?

Hazard mapping assumes that the uncertainties involved are shallow and characterized by probability density functions that can be inferred from the limited past data available. However, map failures indicate that some of the uncertainties are deep and underestimated. Table 1 gives our assessment of the near-term prospects for reducing the uncertainties.

The uncertainty in where large earthquakes

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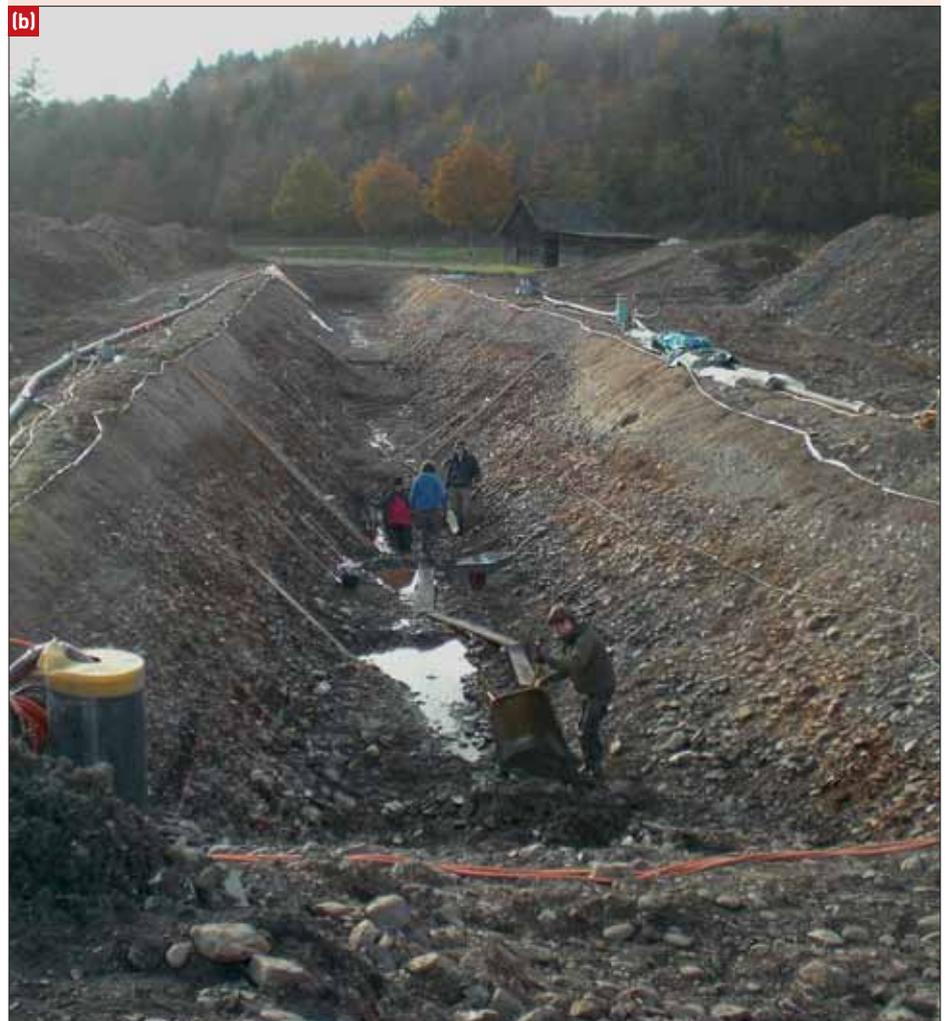
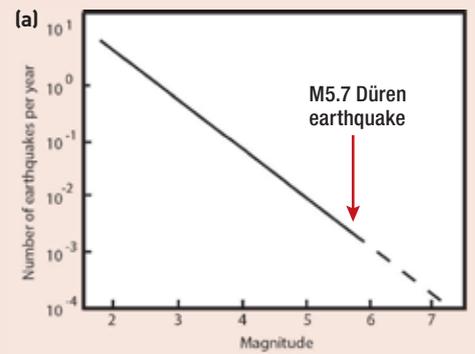
6: Numerical simulations assessing how often earthquake catalogues of different lengths recover the actual maximum magnitude M_{\max} of earthquakes in an area. Catalogue lengths are given as a fraction of the mean recurrence time for earthquakes with magnitude M_{\max} . Colours show results for Gaussian distributions of recurrence times with standard deviation equal to the indicated fraction of the mean. The largest earthquake observed probably reflects the length of the history used, even if larger earthquakes occur, so a catalogue shorter than an earthquake's mean recurrence time is unlikely to contain an event of that size. (Merino *et al.* 2014)

will occur is significantly reducible at plate boundaries. As the Haiti earthquake showed, using the historic earthquake record, GPS data or high-resolution topographic and satellite data (tectonic geomorphology) would have shown that a large earthquake was possible within a few hundred years. In plate boundary zones or plate interiors the problem is much harder, because seismicity migrates, so focusing on the locations of recent earthquakes can be misleading. Often, faults are identified only once an earthquake occurs.

Moreover, even if potentially active faults are identified, it is hard to tell which are likely to have earthquakes soon. GPS data can show which are accumulating strain and thus likely to have earthquakes. They can also show which are not accumulating strain, presumably implying that no large earthquakes are imminent. Similarly, tectonogeomorphologic records of the land surface may be mapped to reveal potentially active fault systems. However, until we understand the dynamics of such fault systems (Li *et al.* 2009) we will not know how to use the observations fully, so large deep uncertainties remain.

The uncertainty in when large earthquakes will occur is deep and appears irreducible with current knowledge. Despite many studies, we do not know how to best describe earthquake probabilities and have little confidence in the models used. To start, we do not even know whether to assume that the probability of a major earthquake on a fault is constant with time, or follows a seismic cycle with lower probability

7 (a): Earthquake frequency–magnitude data, Lower Rhine Graben (Vanneste *et al.* 2013). **(b)** Excavation of trench for paleoseismic studies in the area of the 1756 Düren earthquake. (Photo courtesy Simon Kübler). The fault rupture is visible mid-way up the trench where red/black strata step to higher levels. The recent excavation was conducted by Simon Kübler, Anke Friedrich, and Manfred Strecker with funding from the German Science Foundation (FR-1973/1-1).



shortly after the last major earthquake and higher probability later. Both assumptions are used, often inconsistently. Often workers show a hazard map computed with time-independent probabilities, and then speak of an “overdue” earthquake. The seismic cycle assumption is appealing and is why the Nankai area is predicted to have high hazard (figure 1). However, large earthquakes often fail to occur preferentially in the assumed gaps (Kagan and Jackson 1991). Thus we can estimate earthquake probabilities in different ways and get quite different numbers, making it difficult to talk except in generalities about “the” probability of an earthquake (Savage 1991).

Estimating the assumed magnitude of the largest future earthquakes expected on a fault or

in an area, termed M_{\max} , involves large deep uncertainties. The Tohoku, Haiti, and Wenchuan earthquakes were so damaging because they were much larger than the M_{\max} assumed. No theoretical basis exists to infer M_{\max} because even where we know the long-term rate of motion across a plate boundary fault, or the deformation rate across an intraplate zone, or the fault geometry of individual faults, none of these predict how strain will be released. As a result, quite different estimates can be made (Kagan and Jackson 2013).

All one can say with certainty is that M_{\max} is at least as large as the largest in the available record. However, the maximum magnitude appearing tends to be that of earthquakes with mean recurrence time equal to the catalogue

length. Because catalogues are often short relative to the average recurrence time of large earthquakes, larger earthquakes than anticipated often occur (figure 6).

Estimating M_{max} is particularly challenging within plates, where large earthquakes are infrequent compared to the length of the available earthquake history, vary in space and time, and sometimes occur on previously unrecognized faults. Figure 7a illustrates this for the Lower Rhine Graben seismic zone including portions of Belgium, Germany and the Netherlands. An earthquake catalogue compiled by the Royal Observatory of Belgium shows the classic Gutenberg–Richter frequency–magnitude relation, $\log_{10}N = a - bM$, where N is the annual number of earthquakes with magnitude $\geq M$, a defines the seismicity rate, and b is the slope of the line relating the rates of small and large earthquakes. The largest known earthquake, the 1756 Düren earthquake, has magnitude 5.7 and should recur on average about every 400 years.

An obvious question is whether this is the largest earthquake that can occur here, or simply the largest that has happened in the past 650 years spanned by the catalogue. This question matters, especially for critical facilities such as nuclear power plants that should be designed to withstand the maximum shaking in 10000 years. Extrapolating the line predicts that a M7.3 earthquake would occur on average about every 10000 years, but does not indicate whether such earthquakes actually take place. This question is being addressed by paleoseismic studies like one in Untermaubach, Germany near the Jülich nuclear reactor (figure 7b), which seek evidence of the rate and magnitude of paleoearthquakes. The excavation shows that at most two earthquakes occurred on this fault in the past 10000 years, so M5.7 events do not repeat regularly here.

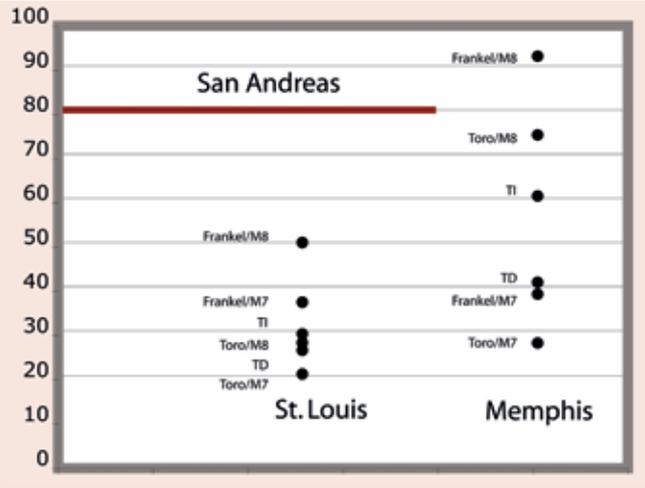
Such studies can improve estimates of the lower bound on M_{max} by finding larger past earthquakes. However, they cannot resolve the upper-bound issue either, because we have no way of knowing whether a bigger earthquake will occur, although inferences can be made from fault lengths.

The final source of uncertainty is in assuming how much shaking earthquakes will produce. In areas that are seismically active enough, seismological observations can be used to develop better ground-motion models. However, in less-active areas such as the central US, there are no seismological records of shaking from large earthquakes. In such cases, mappers choose relations derived using data from smaller earthquakes and from theoretical models, which predict quite different ground motion and thus hazard.

Dealing with the uncertainties

One way to illustrate the uncertainties is to examine how hazard map predictions depend

8: Comparison of the hazard at St Louis and Memphis predicted by hazard maps generated for different parameters. For example, Frankel/M8 indicates the Frankel *et al.* ground-motion model with a maximum magnitude of 8. TI and TD indicate time-independent and time-dependent models. (Stein *et al.* 2012)



on the choice of poorly known parameters. Figure 8 compares the predicted hazard at two cities in the central US which vary by a factor of more than three. At Memphis, close to the region’s main faults, the primary effect is from M_{max} , with “M8” models predicting the highest hazard. At St Louis, the ground-motion model has the largest effect, so 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. In reality, for each combination of M_{max} and ground-motion model, there would be a range of predicted hazard depending on whether one chose time-independent or time-dependent probability models and the parameters in each.

These deep uncertainties cannot be reduced by any knowledge we are likely to acquire soon, or adequately described by a probability density function. The best we can do is give a sense of about how large they likely are.

Unfortunately, such uncertainties are not usually communicated to users of hazard maps. Instead, mappers typically combine predictions for various parameters via 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 the mappers used to assign weights ultimately 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 – 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.

Testing maps

Beyond figuring how to assess and communicate the uncertainties of current maps, there is also the question of how to improve them. One approach is to improve the science. Learning more about earthquakes in specific areas and earthquake physics will improve hazard assessments, although there are probably limits to how well we can do.

The other approach is establishing how well maps work, which is crucial in deciding how much faith to put in them when making expensive policy decisions. A good analogy is weather forecasts, which are routinely evaluated to assess how well their predictions matched what occurred. This process involves agreed criteria for “good” and “bad” forecasts. Forecasts are tested against null hypotheses, including seeing if they do better than using the average of that date in previous years, or assuming that today’s weather will be the same as yesterday’s. Over the years, this process has significantly improved forecasts and estimates of their uncertainties.

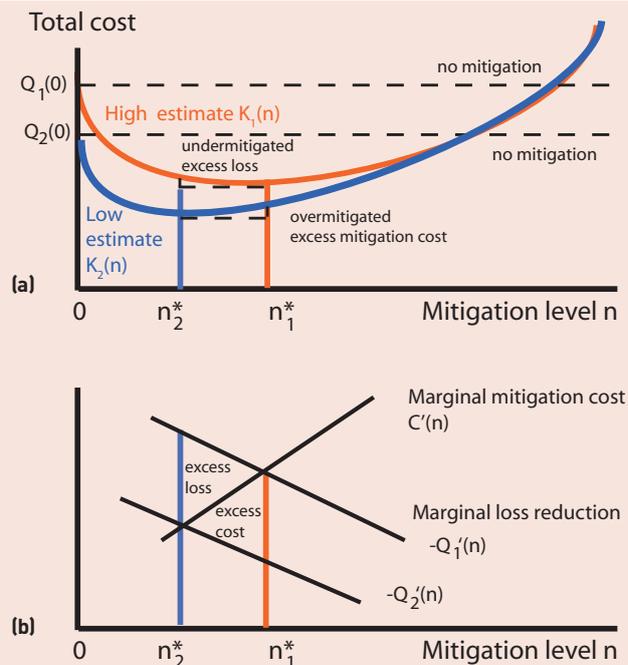
Similar testing of hazard maps requires criteria for comparing their predictions to shaking that occurred after they were published. Such testing would show how well the maps worked, better assess their true uncertainties, and indicate whether changes in map-making methods over time give better maps.

Hazard mitigation; deep uncertainty

Society has a range of mitigation options for natural hazards, but operates under major constraints. First, we have only inadequate estimates of the hazard. Second, we have limited resources to allocate between hazard mitigation and other needs. Third, we have a wide range of societal, political and economic considerations. Given these, we have to decide somehow how much mitigation is appropriate – how much mitigation is enough.

Figure 9 shows a way to compare options. 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

9 (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 non-optimal mitigation, and thus excess expected loss or excess mitigation cost. (Stein and Stein 2013b)



cost of mitigation. The U-shaped curve illustrates 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, so $K(n)$ 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 investment in mitigation.

Relative to the optimum, less mitigation decreases construction costs but increases the expected damage and thus increases the total cost; it makes sense to invest more in mitigation. Conversely, more mitigation than the optimum gives less expected damage but at higher total cost, 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 9b). 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 .

As we have seen, our ability to assess hazards is limited. Thus we need to formulate policies while accepting the uncertainties involved. To see how, consider a range of total cost curves between $K_1(n)$ and $K_2(n)$. These can correspond to high and low estimates of the hazard, high and low estimates of the loss, or – most 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 as the mitigation costs exceed the expected loss, 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 undermitigation 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 overmitigation and excess cost. However, so 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 somehow 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. So long as the total cost is below the loss for no mitigation, this 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. Thus, although in real cases such approaches cannot give an optimum strategy, they can identify sensible strategies.

Mitigation policy decisions are not made on purely economic grounds. Society is sometimes

overly concerned about relatively minor hazards and downplays other more significant ones. Hence in some cases we spend more than makes sense, and in others we spend less.

Even so, it is clear that we could do better using two approaches. First, we should try to better assess hazards, recognizing and understanding the uncertainties involved, and communicate these uncertainties to the public and planners formulating mitigation policies. Second, mitigation policies should be developed by considering the uncertainties in the hazard and loss estimates and the costs and benefits of alternative strategies. Both approaches are challenging, but could significantly improve our ability to deal with earthquakes and other natural hazards. ●

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