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Shallow Versus Deep Uncertainties in Natural Hazard Assessments

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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 issue. They can make detailed hazard assessments, but the Earth often acts differently. Insight into why this occurs comes from a recent approach in risk analysis, which separates uncertainties in predicting future events into shallow versus deep uncertainties [*Cox*, 2012; *Hallegatte et al.*, 2012]. Shallow uncertainties arise when the probabilities of outcomes are reasonably well known. In such cases, past events are good predictors of future ones. For example, a baseball player's batting average is a good predictor of the chance that he will get a hit.

In contrast, deep uncertainties arise when the probabilities of outcomes are poorly known, unknown, or unknowable. This occurs when we have multiple possible models with poorly known parameters because we inadequately understand the system or it has inherently unpredictable elements. In such situations, past events may give little insight into future ones. An example would be trying to predict the winner of the World Series in the next baseball season. The teams' past performances provide only limited insight into the future of a complicated process. Various models could be developed based on past performance, but people would place little confidence in them.

The issues of shallow and deep uncertainties in assessing natural hazards can be illustrated by a simple example using a classic probability model.

Drawing Balls From an Urn

Imagine an urn containing balls (Figure 1a), in which *e* balls are labeled "E" for event and *n* balls are labeled "N" for no event. In mathematics, events and nonevents are called "successes" and "failures," but for hurricanes, volcanoes, floods, and earthquakes, these may be poor terms because "failure" is the preferred outcome. The probability of an event is that of drawing an E ball, which is the ratio of the number of E balls to the total number of balls.

Two models describe how the probability of an event changes with time. One is sampling with replacement—after drawing a ball, it is replaced. In successive draws, the probability of an event is constant or time independent and can be calculated using binomial or Poisson distributions [*Taylor*, 1997]. Events are independent because one happening does not change the probability of another happening. Thus, an event is never "overdue" just because one has not happened recently, and the fact that one happened recently does not make another less likely.

An alternative is sampling such that the fraction of E balls and the probability of another event change with time. One can add a number *a* of E balls after a draw when an event does not occur and remove *r* E balls when an event occurs. This makes the probability of an event increase with time until one happens, after which it decreases and then grows again. Events are not independent because one happening changes the probability of another.

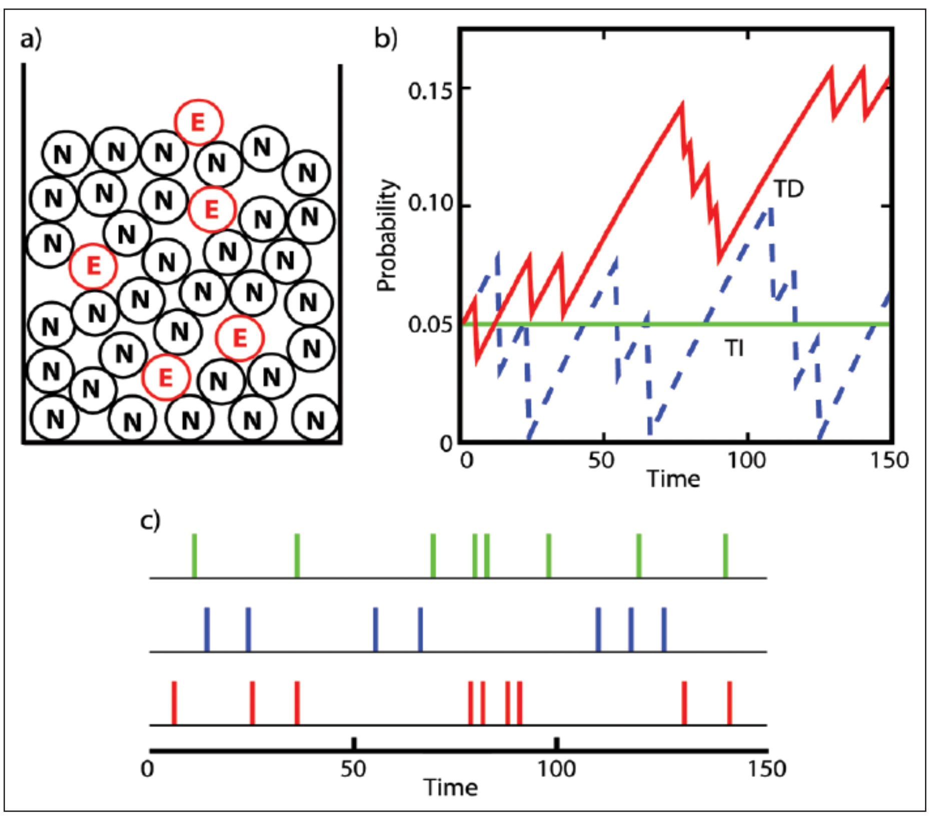

Fig. 1. (a) Model for the probability of an event: A ball is drawn every year from an urn containing balls labeled "E" for event and "N" for no event. (b) Comparison of the probability of an event as a function of time for time-independent (TI; green line) and time-dependent (TD; red and blue lines) models. (c) Sequence of events as a function of time for the three models in Figure 1b.

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Figure 1b illustrates the differences for an urn that initially has 20 E balls and 380 N balls, giving 1/20 initial probability of an event or, on average, one every 20 years for samples drawn yearly. For $a = r = 0$, the probability is time independent and does not change (green line). The situation differs for time-dependent models, as shown by two cases. For one with $a = 1$ and $r = 20$ (blue line), the probability growth between events is approximately offset by the decrease after events, so on average, the probability oscillates about the time-independent case. For one with $a = 1$ and $r = 10$ (red line), the probability decreases less after events and so tends to increase with time.

In mathematical applications, the model—how sampling is done—and model parameters—e, n, a, and r—are known. For natural hazards, these are inferred from the history of past events and scientists' ideas about the process involved. This is like inferring the contents of the urn and the sampling process from the samples that have already been drawn. As Figure 1c shows, this is very difficult. The resulting uncertainties in predicting when events will occur are shallow if we know the appropriate model and parameters reasonably well, and deep if we do not. In the time-independent scenario represented by the green line, the probability of a future event can be given with reasonable confidence, whereas in the time-dependent scenarios represented by the blue and red lines, it cannot. Thus, the best way of distinguishing between the scenarios is to examine how well models predict what occurs.

Application to Natural Hazards

Both shallow and deep uncertainties arise for natural hazards. The occurrences of floods and hurricanes in a given area are treated as involving shallow uncertainties. These are modeled as time-independent events [*Kirby*, 1969; *Klotzbach and Gray*, 2010], assuming that the history of events gives a reasonable estimate of their future probability, which improves as the history available gets longer. The resulting shallow uncertainties reflect a model that works reasonably well, with reasonably well estimated parameters. However, forecasts with a long timescale face deep uncertainties associated with possible effects of climate change because rainfall patterns and storm frequencies or intensities may change in ways that are hard to predict from climate models [*Morgan et al.*, 2009].

Earthquake hazard assessments involve multiple sources of deep uncertainty. This fact was brought to the fore by the great March 2011 earthquake off Japan's Tohoku coast, which was much larger than predicted by the map showing earthquake hazard for the area and produced a much higher tsunami than expected in hazard planning [*Geller*, 2011]. Such underestimates often occur [*Kerr*, 2011], illustrating the uncertainties involved in estimating future hazards from past events [*Stein et al.*, 2012]. As a result, hazard maps are often changed repeatedly as large earthquakes continue to occur in areas previously shown as having low hazard [*Peresan and Panza*, 2012].

One source of deep uncertainty is assessing earthquake recurrence in time. As in the urn example (Figure 1), neither the appropriate model nor the appropriate parameters is well constrained, despite decades of study. Many seismic hazard maps use time-independent models. Other studies favor models in which strain accumulates across a fault and is released in earthquakes, so the probability of a large earthquake decreases after one occurs and then rises. Using the limited historical record to infer which model, which probability distribution, and which parameters are most appropriate is challenging, especially because time-dependent models have additional parameters. By analogy to the urn example, it is unsurprising that studies find divergent results [*Parsons*, 2008; *Savage*, 1992; *Kagan et al.*, 2012].

The resulting deep uncertainty is illustrated by the Parkfield earthquake prediction in which, based on a 128-year period during which part of the San Andreas Fault had moderate (magnitude 6) earthquakes about every 22 years, the next such earthquake was predicted using a time-dependent model to occur at 95% confidence before 1993. However, such an earthquake did not occur until 2004, 11 years after the end of the prediction window [*Kerr*, 2004]. This event can be regarded as either occurring too late, consistent with a low-probability event, or as indicating that the recurrence is better described as time independent [*Jackson and Kagan*, 2006].

A second source of deep uncertainty involves where to expect earthquakes. On plate boundaries, although all parts of the boundary are expected to slip eventually, attempts to forecast the timing of major slip events have been unsuccessful. However, within plates it is hard to forecast even where large earthquakes will occur. A prime example is in northern China, where a 2000-year record shows migration of large earthquakes between fault systems spread over a broad region, such that no large earthquake ruptured the same fault segment twice in this time interval [*Liu et al.*, 2011]. A map based on any short subset of the record would be biased. For example, a map using the 2000-year earthquake record prior to 1950 would miss the subsequent activity in the northern China plain, including the 1976 Tangshan earthquake (moment magnitude 7.8), which occurred on a previously unknown fault and killed nearly 240,000 people.

A third source of deep uncertainty is how large an earthquake to expect. We do not know whether the largest known earthquake in an area is really the largest that happens there or just the largest observed to date. As the 2011 Tohoku and 2004 Sumatra earthquakes showed, a much bigger earthquake than expected often occurs [*McCaffery*, 2007; *Stein and Okal*, 2011]. This realization is a challenge for hazard planning. For example, Japanese authorities face the question of whether to invest in preparing communities along the Nankai Trough for much larger tsunamis than previously anticipated because their probability cannot be usefully estimated beyond saying such a tsunami would be rare, perhaps once in a millennium [*Cyranoski*, 2012].

These deep uncertainties result from scientists' limited understanding of how earthquakes vary in time, space, and size. Thus, although geologic and paleoseismic data can be used to study the past motion on individual faults and GPS data can show the present strain accumulation on each, there are probably fundamental limits as to what can be said about future strain release. Additional uncertainties are involved in choosing a relation to predict the ground motion expected at a given distance from earthquakes of a given size. These uncertainties should be recognized and communicated to users of hazard maps [*Stein et al.*, 2012; *Stein and Geller*, 2012].

Hazard Mitigation Strategies in the Face of Uncertainty

Ultimately, the goal of hazard assessments is to help develop mitigation policies. This step involves an additional uncertainty because formulating policies also involves comparing the costs and benefits of mitigation options [*Goda and Hong*, 2006; *Stein and Stein*, 2012, 2013]. More extensive mitigation measures cost more but are expected to produce increasing reduction of losses in future events. For example, given the damage to New York City by the storm surge from Hurricane Sandy, options under consideration range from doing nothing, through intermediate strategies like providing doors to keep water out of vulnerable tunnels, to building up coastlines and installing barriers to keep storm surges out of rivers [*Navarro*, 2012]. A challenge is that even for an assumed level of flooding—the estimation of which involves the deep uncertainties associated with climate change [e.g., *Bamber and Aspinall*, 2013]—there is uncertainty in estimating the expected losses for, and thus the benefits of, different mitigation options. Similar issues arise in mitigating volcanic risk, both via long-term land use planning and short-term evacuations [*Marzocchi and Woo*, 2009].

Such situations illustrate *Cox*'s [2012, p. 1607] description, "Some of the most troubling risk management challenges of our time are characterized by deep uncertainties. Well-validated, trustworthy risk models giving the probabilities of future consequences for alternative present decisions are not available; the relevance of past data for predicting future outcomes is in doubt;

experts disagree about the probable consequences of alternative policies."

The deep versus shallow uncertainty approach is one of several ways of attempting to characterize unknown future events. In a seminal paper, *Knight* [1921] proposed that to distinguish between "the measurable uncertainty and an unmeasurable one, we may use the term 'risk' to designate the former and the term 'uncertainty' for the latter." Since then, various nomenclatures and ways of classifying uncertainty have been used in different fields. For example, in the natural hazards literature, "hazard" denotes the natural occurrence of earthquakes or other phenomena, and "risk" denotes the dangers that hazards pose to lives and property.

Seismic hazard analysis follows the engineering literature in distinguishing uncertainties by their sources, in which aleatory (from the Latin word for dice, *aleae*) uncertainties are due to irreducible physical variability of a system and epistemic uncertainties are due to lack of knowledge of the system. The shallow versus deep distinction has similarities but focuses on the mathematical representation, in that shallow uncertainties can be usefully treated through probabilities but deep ones cannot.

The aleatory/epistemic versus shallow/deep approaches lead to different ways of choosing mitigation strategies. In seismic hazard analysis, a specific scenario is chosen by the logic tree process, in which weights are assigned to various possible scenarios [*Reiter*, 1990]. The deep uncertainty view leads to an approach called robust risk management—accepting that there is a large range of possible scenarios and developing policies that should give a reasonable outcome for a large range of the possible scenarios [*Manski*, 2010; *Cox*, 2012; *Stein and Stein*, 2013].

Although using the deep uncertainties approach in natural hazard policy decisions would be new, analogous approaches are being explored in the context of how to adapt to climate change [*Morgan et al.*, 2009; *Hallegatte et al.*, 2012]. In years to come, similar approaches can be used to improve natural hazard mitigation policies.

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—SETH STEIN, Earth and Planetary Sciences, Northwestern University, Evanston, Ill.; E-mail: seth@earth.northwestern.edu; and JEROME L. STEIN, Professor Emeritus of Economics, Brown University (deceased 8 February 2013)