

Reading the Tea Leaves: When Risk Models Fail to Predict Disaster Impacts

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Risk models are built on the best available data—but the best data are often less than ideal. It is only when a disaster occurs that we can retrospectively assess how accurately a risk model predicted the extent and magnitude of disaster impacts. Models sometimes surprise us with their accuracy, but more often, they over- or underestimate the scale of the disaster. Postdisaster forensics offers an opportunity for determining why a risk model has failed, but in our experience this information is not being effectively utilized to improve risk models.

The effort to understand model efficacy raises several key issues.

First, model results are often not well understood by decision makers. The failure of a perfect prediction of loss is often viewed as a failure of the whole model. Once a disaster has occurred, it is

too late to highlight the aphorism that “all models are wrong but some are useful.”¹ If decision makers are not well versed in the purpose and scope of model results, they will not be able to use them to prioritize critical response activities or to guide longer-term recovery operations such as “building back better.” Thus, the effective communication of loss modeling results is paramount to practical implementation.

Second, the dimensions of catastrophe loss modeling have evolved considerably since modeling was introduced in the early 1980s (Steinbrugge 1982). Where early estimates of loss were essentially limited to reports of building damage caused by a single peril, assessments now consider an array of secondary and higher-order effects that

often require more sophisticated modeling—and that when not considered will underestimate the true impact of a disaster.

Third, technological advances such as remote sensing and emerging approaches such as crowdsourcing have not had the expected transformative impact on modeling. This is in large part due to lack of experience and validation. Remote sensing has the potential to improve loss modeling through developing exposure data—i.e., generating inventory models of buildings and critical infrastructure using moderate- and high-resolution imagery. But advances in this area will depend on robust sensor deployments and detailed validation studies using imagery at all spatial resolutions and inventory data sets collected from field surveys.

Fourth, the technological advances that have accelerated

¹ This saying is commonly credited to George Box. See for example Box and Draper (1987, 424).

improvement in many areas of loss estimation modeling have not been equal across all constitutive models. To ensure the most robust estimates of risk and loss, a balanced investment in the development of the constitutive hazard, vulnerability, and exposure models is needed. That is, the reliability of an overall loss estimate is often modulated by the reliability of the least understood component of the model. With unlimited resources, exposure and vulnerability could be accurately quantified, but substantial fundamental research is still required to better constrain the physics of perils such as earthquakes, volcanic eruptions, storm surge, etc. This is especially true in developing countries, where long-term investment in fundamental science and research is particularly limited.

Finally, loss modeling has been dominated by proprietary models often used for quantifying insured losses after major disasters. That situation seems to be changing, however, and efforts are under way to develop open source models that provide transparent access to hazard, vulnerability, and exposure data for many developing regions that go beyond insured losses to include social and full economic impact. Developing these newer models entails some expense because the framework for accepting, sharing, updating, and disseminating information must be developed and must be robust enough to work with constitutive models that may be disparate in resolution and data

formats (a problem that is also critical in proprietary models).

The discussion below examines each of these issues and suggests specific steps for improving our ability to accurately estimate the impacts of future disasters.

Effectively Communicating the Results of Loss Modeling

Although loss modeling for natural disasters has been around for decades, its application during the actual response to an event is fairly new and poses a particular challenge for communication of model results. With the rapid development of loss modeling and the emergence of large-scale sensor networks, including ubiquitous monitoring (satellites), researchers have pushed the notion of near real-time loss estimation as a key tool in the disaster responder's toolbox (Eguchi et al. 1997). Loss estimates for recent disasters, including earthquakes in Haiti (2010), Tohoku, Japan (2011), and Nepal (2015), have demonstrated that this type of information can aid in the physical planning for the recovery process. For decision makers to use the outputs appropriately, however, they need to better understand the development and reliability of this information; in addition, they need to adapt response protocols so that this information becomes an integral part of the postevent workflow process.

The experience of the 2010 Haiti earthquake is instructive. Decision makers reported feeling that the data (loss results) were just "parachuted in" and that they had no time to change existing protocols to effectively include them (World Bank, GFDRR, and ImageCat 2013). Appropriate and effective use of the data would require (1) creating an umbrella framework to unite multilateral agencies in a crisis and to allow materials to be combined and collectively used by all; (2) establishing response protocols that specifically include satellite-derived loss estimates; and (3) training first responders to use the loss estimate data sets. A disaster or crisis is the worst time to introduce new analytics and tools, as people will inevitably rely on the tested and trusted approaches of their standard operating procedures. To ensure that decision makers use information from risk models and real-time analysis during a crisis, we need to build capacity and trust in this information long before a disaster strikes.

Modeling Secondary Effects

Differences in modeled versus actual damage are in some cases due to limitations and uncertainties in the data. In other cases, however, they are due to more fundamental issues, such as the failure to model secondary effects. Experience from the 2010-2011 Canterbury earthquake sequence and the 2011 Tohoku earthquake

indicates that loss models underestimated damage and economic losses principally because secondary perils and consequential effects were not modeled. In Canterbury, damage associated with liquefaction and rockfall was not included in loss models; and the loss models associated with subduction earthquakes in Tohoku omitted a larger-than-expected tsunami and the consequential nuclear accident at Fukushima. This same discrepancy exists for major flood or cyclone events, where models capture the impact from fluvial events relatively well, but fail to include the pluvial events (e.g., landslides or flash floods).

and actionable recommendations.

During the earthquake response in both Haiti and Christchurch, a large international community of engineers and scientists was mobilized to perform near real-time damage assessments through crowdsourcing. This approach gave hundreds of individuals access to thousands of satellite and aerial images so they could identify collapsed or damaged structures. These experiences taught two important lessons: given the many volunteers who want to help in the response to a large disaster, damage assessment protocols must be simple, clear, and easily implemented;

Balancing Model Accuracies in Overall Loss Estimates

Currently, there is little guidance for determining the right level of detail or accuracy for the three constitutive models in the loss estimation process—that is, the hazard model, which defines the severity and frequency of the hazard (e.g., flood heights and frequencies); the exposure model, which quantifies the number or value of assets exposed to the hazard (e.g., number of residential buildings); and the vulnerability model, which relates the exposed assets' susceptibility to damage or

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Enabling Disaster Response through Technology

There is no question that technology can help provide situational awareness during the response to a disaster, and decision makers often indicate that any information is better than no information at all. But there is also no question that uncoordinated, repetitive, and nonvalidated information is confusing; it cannot be helpful, for example, to receive 400 maps per day at the height of a crisis. Adoption and use of information technologies in disaster response requires a thorough postdisaster review of the success and failure of these technologies, including extraction of key lessons

and those using crowdsourced results to make critical response decisions must fully understand their limitations. Two other lessons emerged through postevent analysis:² (1) the assignment of damage grades of 4 or 5 (EMS-98 damage scale) has high reliability (greater than 70 percent), but “false negatives” are relatively common; and (2) to extrapolate the results of crowdsourced damage assessments to lower damage grades, extensive field calibration is necessary using the same damage states and descriptions. These lessons point to the importance of using postevent forensics that helps to validate and calibrate the models and procedures used to estimate disaster losses.

loss to specific hazard intensities. In practice, these constitutive models are convolved to estimate loss parameters (such as average annual loss or maximum probable loss) or scenario-based losses. In most cases, data sets reflecting mean values or algorithms that assume average trends are used to calculate resulting losses. However, the level of uncertainty in each model can vary widely; and these uncertainties can greatly affect the reliability or “believability” of the final results. Thus loss estimates with large bands of uncertainty, where the drivers of those uncertainties are largely unknown, are common.

Recently, there has been an attempt to quantitatively

² See Booth et al. (2011); Ghosh et al. (2011); and Foulser-Piggott et al. (2016).

estimate the contribution that constitutive model uncertainties have on an overall loss estimate (Taylor 2015). “Robust simulation” allows analysts to use simulation methods to (1) quantitatively account for model uncertainties in complex convolutions of loss, (2) identify where individual model uncertainties drive the reliability of the overall results, and most importantly, (3) determine where model improvements can help drive down the overall uncertainty of a loss result. This type of approach can facilitate a more balanced investment in model development and enhancement.

Ensuring Effective Open Source Solutions

In the last several years, practitioners have promoted open source solutions in response to the limited access offered by proprietary and expensive loss models. Most existing models are embedded in proprietary platforms designed to address (re)insurance applications. Typical issues that arise in this environment are “black box” modeling (i.e., lack of transparency), proprietary data formats, inability to mix and match the best models, difficulty in comparing model outputs from different modeling vendors, and inability to apply these models to noninsurance situations.

Several international initiatives have been established that seek to make risk data and assessment tools openly available,³ although

they still face many technical challenges. For example, while access to individual models may be straightforward, ensuring that models are compatible is more difficult. Constitutive models are built on different data sets—some for different regions of the world, and some from different time periods—so integrating these models means checking model input-output requirements and in some cases developing translational interfaces. Once these obstacles are overcome—likely in the next several years—we will be able to evaluate firsthand the benefits, costs, and efficacies of open source modeling approaches.

Summary

Although risk or loss models sometimes fail to predict the impacts of large disasters, the progress made after each event has been noteworthy. In many cases, new and innovative technologies did indeed contribute to better response and recovery results. The next decade will see further advances in model development and data collection. With a prudent program of data archiving and a meaningful commitment to model enhancement, our ability to accurately predict the effects of disasters should rise exponentially.

References

- Booth, Edmund, Keiko Saito, Robin Spence, Gopal Madabhushi, and Ronald T. Eguchi. 2011. “Validating Assessments of Seismic Damage Made from Remote Sensing.” *Earthquake Spectra* 27, no. S1 (October): S157–S178.
- Box, George E. P., and Norman R. Draper. 1987. *Empirical Model-Building and Response Surfaces*. John Wiley and Sons.
- Eguchi, Ronald T., James D. Goltz, Hope A. Seligson, Paul J. Flores, Neil C. Blais, Thomas H. Heaton, and Edward Bortugno. 1997. “Real-Time Loss Estimation as an Emergency Response Decision Support System: The Early Post-Earthquake Damage Assessment Tool (EPEDAT).” *Earthquake Spectra* 13, no. 4 (November): 815–32.
- Foulser-Piggott, Roxane, Robin Spence, Ronald T. Eguchi, and Andrew King. 2016. “Using Remote Sensing for Building Damage Assessment: GEOCAN Study and Validation for 2011 Christchurch Earthquake.” *Earthquake Spectra* 32, no. 1 (February): 611–31.
- Ghosh, Shubharoop, Charles K. Huyck, Marjorie Greene, Stuart P. Gill, John Bevington, Walter Svekla, Reginald DesRoches, and Ronald T. Eguchi. 2011. “Crowdsourcing for Rapid Damage Assessment: The Global Earth Observation Catastrophe Assessment Network (GEOCAN).” *Earthquake Spectra* 27, no. S1 (October): S179–S198.
- Steinbrugge, Karl V. 1982. *Earthquakes, Volcanoes, and Tsunamis: An Anatomy of Hazards*. New York: Skandia America Group.
- Taylor, Craig E. 2015. *Robust Simulation for Mega-Risks: The Path from Single Solution to Competitive, Multi-Solution Methods for Mega-Risk Management*. Springer.
- World Bank, GFDRR (Global Facility for Disaster Reduction and Recovery), and ImageCat. 2013. “The 2010 Haiti Earthquake—Final Report: Post-Disaster Building Damage Assessment Using Satellite and Aerial Imagery Interpretation, Field Verification and Modeling Techniques.” <https://www.gfdrr.org/sites/gfdrr/files/publication/2010haitiearthquakepost-disasterbuildingdamageassessment.pdf>.

Model (GEM) Foundation (<https://www.globalquakemodel.org/>) and the Oasis Loss Modeling Platform (<http://www.oasislmf.org/>).

³ Examples include the Global Earthquake