Catastrophe Model Implementation Uncertainty - China Typhoon Case Study

To understand all the causes of catastrophe model uncertainty, external factors such as data completeness must be included.

As regulators demand an increased understanding of the catastrophe modelling process, there is a solid appreciation across analytical, underwriting and senior management functions of the main sources of scientific uncertainty in catastrophe models. Less understood, however, are the uncertainties arising from external factors such as the completeness and accuracy of the input exposure data and the appropriateness of model option settings used. Uncertainties or inaccuracies in risk characteristics such as occupancy or construction type may propagate dramatically into the estimates of losses. This impact can be at least as sizable as the aleatoric or epistemic uncertainty.

Impact of Risk Characteristics Assumptions

Using a TransRe province level property exposure database for China, Figure 1 shows the range of exceedance probability losses that arise from using the differing construction and number of stories assumptions provided by 10 large Chinese insurers (+80% of the market). Across the entire curve, the losses at the top of this range are over double those at the bottom. These are all large national books which are not likely to have that level of variability in their underlying exposure. From a reinsurance perspective this impact cannot be ignored: on a typical non-proportional structure the technical rate on line is significantly impacted. Using the range of losses produced in Figure 1, the technical rate on line produced for a per occurrence mid-program layer ranges from 5-14%.

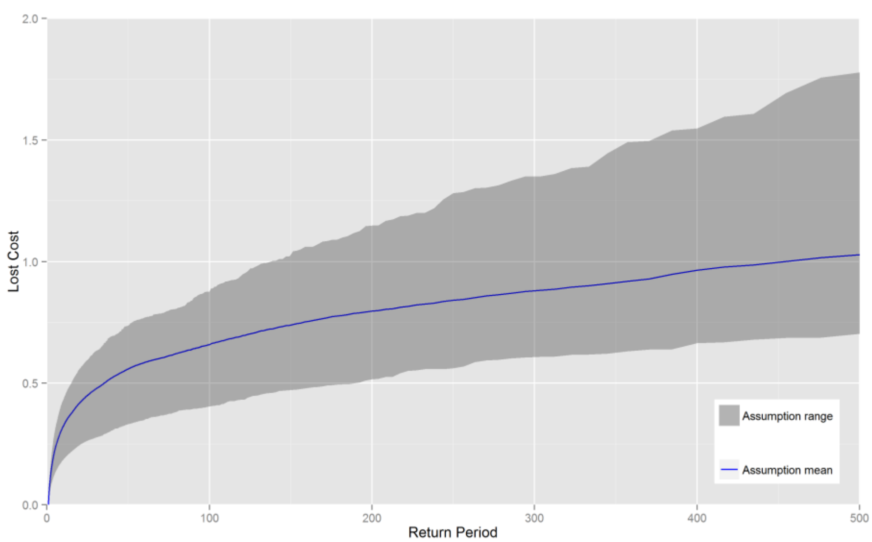

Figure 1 China Typhoon - Impact of construction and number of stories on modeled losses.

Recap: uncertainty types

Aleatoric uncertainty (aka statistical uncertainty) arises from the inherent randomness associated with natural hazard events.

Epistemic (or systematic) uncertainty can be due to lack of information or knowledge of the hazard (physical phenomena underlying catastrophic behavior), inaccuracy due to a limited available data, changes in the environment which interfere with the measurement process and sometimes imperfect methods of observation.

Implementation uncertainty is introduced from external factors including the quality of the data being fed into the model and the appropriateness of model option settings used.

Impact of Location Information

Aggregating data to a certain geographical level (such as county) will add to implementation and epistemic uncertainties. Epistemic uncertainties would arise if the model attempts to disaggregate the data. Disaggregation techniques depend on an internal view of the built environment, a view that is often out of date in China both in terms of geographic spread and construction practices. Figure 2a shows the rapid expansion around Guangdong over 10 years from 2000; the gray areas were developed in 2000, the red areas are new urban areas added by 2010. In a rapidly changing urban environment, having up-to-date disaggregation is key.

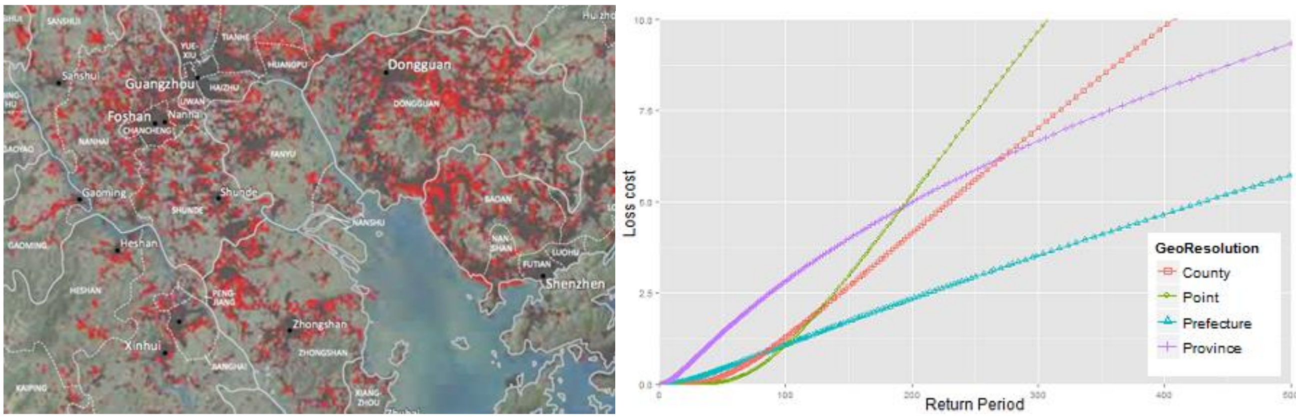

Figure 2a (left) 10 years of development in the Pearl River Delta Region (red = new urban area), 2b (right) Impact of geographic resolution (single location - China typhoon)

Implementation uncertainty arises from the geographical level of the input data. Figure 2b illustrates the impact of geographical resolution on an individual location on modelled losses (in this example a commercial risk close to the coast in Guangzhou).

Impact of Model Parameter Options

Lastly, implementation uncertainty will also arise from the modelling options selected by the user. These include whether to disaggregate, select demand surge, rely on the vendor's 'average properties' assumptions for vulnerability and so on.

The influence that implementation uncertainty has on modelled losses should not be underestimated. A key strength of catastrophe modelling has always been relative comparisons (e.g., year on year or between portfolios) rather than absolute ones. Having good quality input data will reduce the uncertainty in these relative comparisons.

Whilst there will always be (aleatoric, epistemic and implementation) uncertainty in catastrophe modelling, a good understanding of the key sources of uncertainty, and clear communication of the impacts on loss estimates, will help reduce the adverse impact of uncertainty on key decisions.

"Essentially, all models are wrong, but some are useful"… if used correctly

-With apologies to George E.P. Box

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