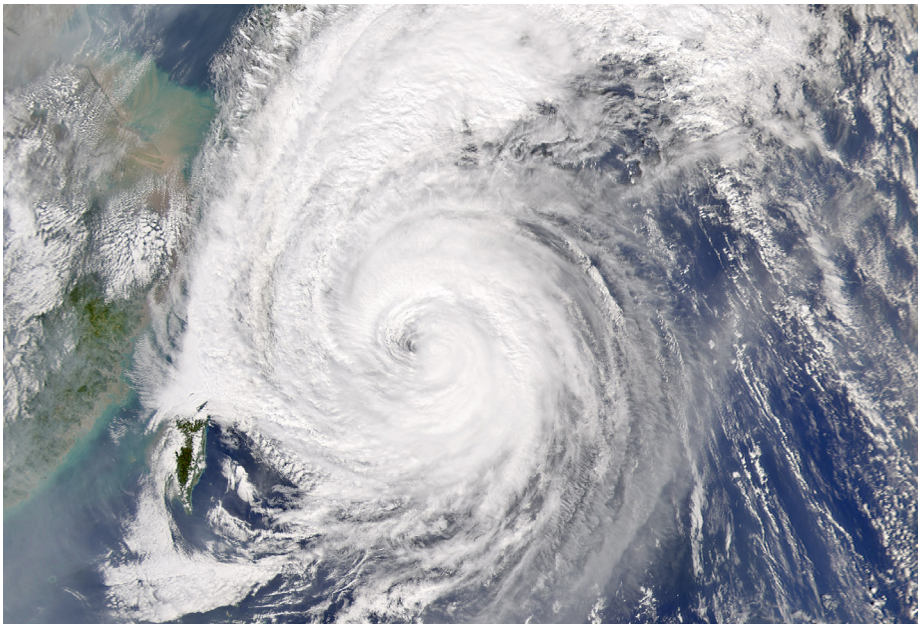
PartnerReviews

The Same Storms, Multiple Views of Risk

Ever wondered why a 'view of risk' can vary so much between experts, or why your risk assessments based on loss experience don't match those of catastrophe models?

A good angle to explore these differences from is the Exceedance Probability (EP) curve, a combined view of loss-frequency and severity. How these curves are built and what they're built of varies enormously. As a result, EP curve risk estimations can vary, sometimes, as in this comparative study, by over 100%.

Here we take the example of Japan Typhoon, examining the specific impact of different hazard data sources to highlight what's going on. We show you hidden aspects of EP curves, clarify why every curve needs some time and attention, and give advice on best practice for storm model validation.



One Japan Typhoon, multiple recordings of the hazard, multiple resulting wind fields

The most common hazard data for historical typhoons comes in the form of best track data (BTD), an approximation of an event's track, size and intensity over time. For Japan Typhoon, two meteorological agencies, JMA and JTWC, provide BTD, each reporting two distinct, but related, intensity metrics, vmax and cpres (see **table 1** for definitions).

Typhoon	A regionally adopted name given to the weather phenomenon scientifically known as a 'tropical cyclone'; a rapidly rotating low-pressure system that produces intense surface wind speeds, rainfall and storm surge.
BTD	Best track data; a record of tropical cyclone track, intensity and spatial extent information, provided by meteorological agencies.
JMA	Japan Meteorological Agency
JTWC	Joint Typhoon Warning Center
EP	Exceedance probability
TIV	Total Insured Value
cpres	central pressure (millibars)
vmax	maximum sustained wind speed (knots)

Table 1: Definitions and abbreviations relevant to Japan Typhoon risk assessment

Summary: Multiple 'views of risk'

Catastrophe risk assessment and pricing is based either on loss experience and actuarial techniques, or on hazard data that is combined with exposure and vulnerability information in a catastrophe model to generate modelled loss estimates. Exceedance Probability (EP) curves of 'expected loss' against 'return period' are a common perspective from which to compare the resulting 'views of risk'.

Knowing how a specific EP curve is built and understanding the variability in the loss experience and hazard data can explain why one 'view of risk' is not the same as another. With this knowledge, well-informed risk assessment, model validation and pricing decisions can be made.

Multiple 'views of risk' can arise for many reasons; in this paper we explore two areas that can lead to differences in Japan Typhoon risk assessment:

1. How a catastrophe model sources and processes hazard data

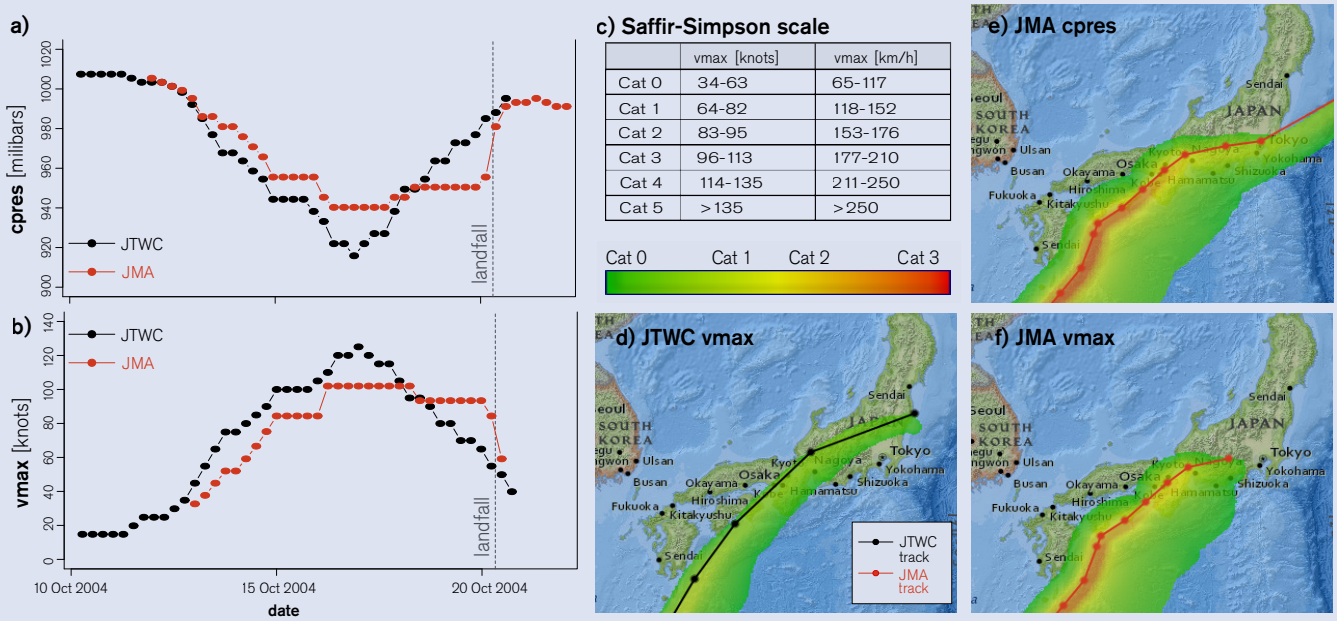
Wind. For the same past Japan Typhoon events, catastrophe models can select from different tropical cyclone best track data (BTD), leading to notably diverse wind fields in terms of storm intensity and spatial extent (**figure 1**) and different landfall climatologies, i.e. the annual number of storms making landfall (**figure 2**). PartnerRe's in-house tropical cyclone catastrophe model, CatFocus®, shows that parts of the resulting EP curves can vary by over 100% (**figure 4**).

The BTD selection also impacts EP curves derived from stochastic (model-generated) event sets, as these are based on historic event sets.

Storm surge and flood. A complete typhoon model will also include explicit storm surge and flood components. These aspects are not included in our example as we focus here on the wind component, but they are equally a source of EP curve variations.

2. Availability and treatment of loss experience

EP curves based on typhoon loss experience and actuarial methods also differ depending on the chosen indexation method and loss experience reporting period (**figure 4**).



	vmax [knots]	vmax [km/h]
Cat 0	34-63	65-117
Cat 1	64-82	118-152
Cat 2	83-95	153-176
Cat 3	96-113	177-210
Cat 4	114-135	211-250
Cat 5	>135	>250

Figure 1: Comparison of original JTWC and JMA BTD and the resulting wind fields for Typhoon Tokage 2004, which caused approximately USD 1.3 billion of insurance losses[1]. **Panels a) & b)** illustrate the time evolution of the intensity metrics cpres **a)** and vmax **b)**, reported by JMA (red) and JTWC (black). Distinct differences are observed. Over most of the lifecycle of Tokage, JTWC estimates higher intensities than JMA, i.e. lower cpres and higher vmax values. However, during the landfall phase, JMA reported a substantially higher intensity (cpres = 955 millibars, vmax = 75 knots) compared to the JTWC estimates (cpres = 984 millibars, vmax = 55 knots). **Panel c)** The Saffir-Simpson scale intensity categorization according to vmax values. **Panels d) – f)** Using the PartnerRe CatFocus® tropical cyclone model to compute the wind field for Tokage illustrates the sensitivity of the hazard component of catastrophe models to different BTD intensity metrics. JTWC vmax-, JMA vmax- and JMA cpres-based wind fields show distinct differences with respect to spatial extent and maximum wind speeds.

Figure 1a and b show the extent to which these intensity metrics can differ for a single typhoon event. The availability of the intensity metrics over time is also not consistent (see box, section "Agency approaches vary"). Our comparative study here uses 1977–2015 historical storms which are covered by the three different intensity metrics JMA vmax, JMA cpres and JTWC vmax; JTWC cpres has only been reported since 2001 and is therefore excluded.

Using BTD track, size and intensity information, catastrophe models employ the physical understanding of typhoons to produce a 'wind field' for each storm. Essentially, the model fills in the gaps to give each storm a full associated picture of intensity and movement over time.

Different catastrophe risk experts and vendor modeling companies select one or other or a combination of the three available BTD sources to create their Japan Typhoon wind fields. This BTD choice can have a substantial impact on the resulting wind fields (see **figure 1d–f**).

And multiple 'landfall climatologies' (number of Cat 0-5 landfalls per year)

A historical typhoon 'event set' for Japan comprises all the historical storms that made landfall[2] (hereafter 'landfalls'), together with their intensity and landfall location data, according to the chosen BTD source. From this, it's a simple step to compute a 'landfall climatology', a summary of the number of Cat 0–5 (i.e. tropical storm and stronger) landfalls per year. Of course, with three possible BTD sources reporting different storm intensities, there are three possible Japan Typhoon landfall climatologies.

Estimating the wind intensities of historical Japan Typhoons

Surface wind measurements using anemometers are not available for many areas in the world, particularly not over vast oceans like the Pacific where typhoons are active. This makes it difficult to get a full picture of a typhoon's evolving intensity. Reported typhoon intensity metrics therefore rely heavily on indirect methods, such as the Dvorak technique (Dvorak, 1984), which infers a typhoon's intensity from cloud characteristics based on visible and infrared satellite imagery.

Agency approaches vary

JMA BTD typhoon reports for the North West Pacific are available since 1951 and include cpres as the main intensity metric, with complementing vmax data since 1977. In contrast, JTWC BTD typhoon reports for the North West Pacific are available since 1945 and refer to vmax as the intensity metric, with complementing cpres data since 2001. Besides the partial overlap in the reporting timeframe of cpres and vmax, both JMA and JTWC data require careful handling/corrections to become useful and comparable, e.g. the application of a bias correction for JTWC 1945–1973 vmax data (Emmanuel, 2005) or a specific method to convert the reported JMA (10-min estimate) vmax values into the more common (and JTWC-like) 1-min vmax values (Mei and Xie, 2016). In **figure 1b**, for example, the original JMA vmax values for Tokage (2004) have been converted in our CatFocus® model to 1-min sustained wind using the KOBA table, as recommended by Mei and Xie (2016), so that they are comparable with the JTWC vmax values for the same storm.

Even after such corrections, JMA and JTWC BTDs differ systematically, and the magnitude of these variations is nonstationary over the historic period (Knapp and Kruk, 2010). The BTD differences between the two agencies relate to different interpretations of satellite imaginary (e.g. independent Dvorak techniques), how they incorporate *in situ* measurements and the evolution in the scientific understanding of the physics of tropical cyclones.

[1] Munich Re, NatCatSERVICE, 2014

[2] The landfall counts provided in this study also include typhoons that did not make landfall in mainland Japan according to their best track position, but which came within 100 km of the coastline and hence still had the power and reach to cause significant losses from wind, rain and storm surge.

As illustrated in **figure 2**, both the overall number of Cat 0-5 landfalls per year and their Saffir-Simpson Scale intensity categorization can differ substantially depending on the BTD source. For example, in 2013, JTWC vmax results in four Cat 0 landfall events, JMA vmax results in two Cat 0 and two Cat 1 landfall events, and JMA cpres leads to three Cat 0 and two Cat 2 and above landfall events.

Looking at the observed landfall values over time for Japan, **figure 2** shows a long-term average of around 3.5 landfalls per year. Variability is also observed on a decadal time-scale, whereby the most recent decade showed about average activity, in contrast to more heightened activity in the 1990s.

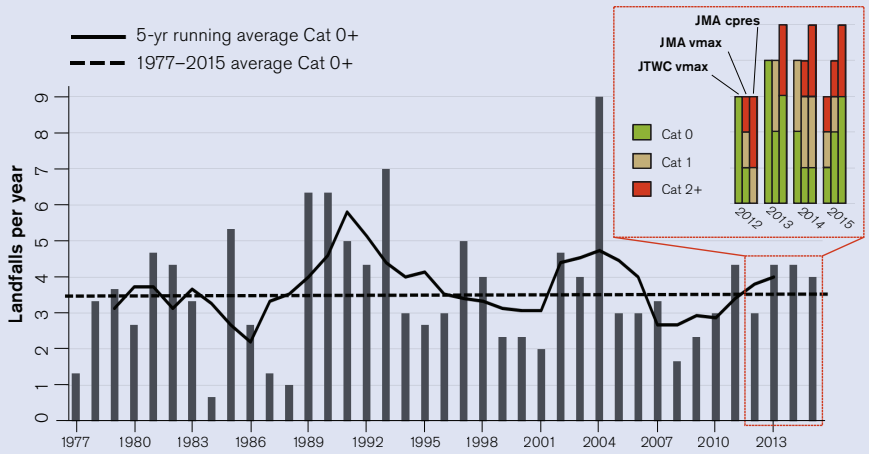


Figure 2: Landfall climatology for typhoons (Cat 0 and above) making landfall in mainland Japan from 1977 to 2015 (average values for the three BTD sources; JMA vmax, JMA cpres and JTWC vmax). The climatology exhibits distinct year-to-year variability and decadal cycles. As separately illustrated for 2012 to 2015, the climatologies can differ substantially by BTD source as regards the annual number and intensity categorization at landfall. For example, JMA cpres shows more high-intensity (Cat 2 and above) events than the other two sources, when using the Brown and Franklin (2002) wind-pressure conversion to convert the cpres values into vmax and then to categorize according to the SaffirSimpson scale (shown in **Figure 1c**).

Historical loss experience is equally a source of variation

Typhoon risk assessment based on loss experience, whereby actuarial methods are applied to the data for direct risk assessment and/or for validation of catastrophe model outputs, requires the loss experience to be complete and homogeneous.

An indication of completeness would be verification against the hazard-based landfall climatology. A perfect match would not be expected, however, due to the risk portfolio's specific exposure and factors including the extent, location and intensity of the typhoons. However, the differences for Japan Typhoon are particularly notable (**figure 3**) and rather reflect a change in approach, whereby smaller magnitude events are only included in the more recent loss experience years (2004 to 2015). For the risk assessment of such smaller magnitude events, the loss experience record is therefore only complete for the years 2004–2015.

In terms of homogenization, the loss experience must be re-evaluated for current-day conditions. This process, termed indexation, consists of an adjustment for possible changes in the monetary value of the loss amount (i.e. inflation/deflation), and a normalization in terms of other economic developments in the insurance portfolio, such as changes in the insurance penetration.

Some aspects are more difficult, if not impossible, to homogenize to current-day conditions. These include distinct changes in the geographical concentration of the risk portfolio (e.g. after mergers and acquisitions) or systematic or gradual changes to the underlying policy terms and conditions (e.g. market accepted changes in deductible and limit structures).

And this all translates into substantial spread in the resulting EP curves

To translate hazard data into a measure of loss for the insurance industry, catastrophe models combine the wind fields and landfall climatology data with exposure and vulnerability information. The resulting modeled losses can be expressed as an EP curve, the model's best estimation of 'expected loss' against 'return period'.

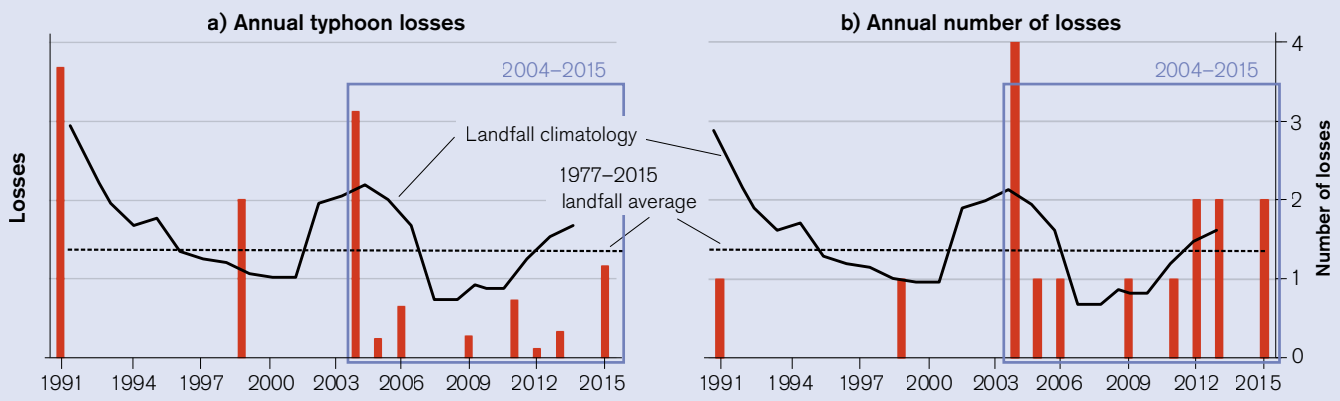


Figure 3: 1991–2015 record (red bars) of **a)** annual Japan Typhoon losses and **b)** annual number of losses, based on loss experience for a synthetic portfolio. The loss experience shows only a few losses in the 1990s, namely Mireille (1991) and Bart (1999), the first and third costliest typhoons since 1980[1]. From 2004 onward, the loss experience also includes lower severity events. At first glance this indicates an increased typhoon risk (particularly of smaller magnitude, frequency events). However, Japan's landfall climatology (black line, based on **figure 2**) tells a different story; 1991–2003 in fact experienced a similar number of landfalls as 2004–2015.

Adopting a single BTD source as the basis of both the wind fields and landfall climatology for each EP curve, and using fixed exposure and vulnerability data, **figure 4a** shows how each of the three BTD sources for Japan delivers a very different curve. For example, assuming a synthetic, representative portfolio, the estimated 2-year return period loss in **figure 4a** would be 0.02% of total insured value (TIV) based on JMA vmax, 0.04% of TIV based on JTWC vmax and 0.06% of TIV based on JMA cpres.

The EP curves in **figure 4b** are based on historical loss experience from the same synthetic portfolio modeled in **figure 4a**. The number of losses and loss amounts (shown in **figure 3**) are combined to determine a direct loss-frequency estimation. The observed spread among the (current-day condition) loss-frequency estimations relates to the chosen indexation method (e.g. subject loss, subject premium, inflation, consumer price index or wage index; impact indicated by the length of the vertical bars) and the reporting period. As discussed in the previous section, earlier years in the reported loss experience record often exclude higher frequency, smaller magnitude events. The impact of reporting period is shown by the blue and grey curves; the grey curve uses the full loss experience going back to 1991, whilst the blue curve only uses losses from 2004 (and is therefore not representative of tail[3] events). For example, the estimated 2-year return period loss in **figure 4b** based on the 1991–2015 record is 0.05% of TIV, compared to 0.1% of TIV using the 2004–2015 record. Using only the more recent, and complete, reporting period therefore results in a 100% increase in the estimated loss for 1 to 10-year return period events.

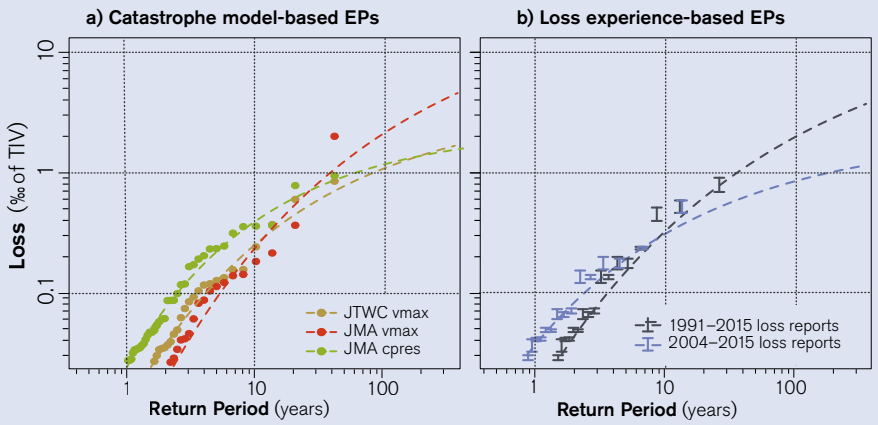


Figure 4: EP curves (log-log scale) for a synthetic portfolio based on **a)** historical 1977–2015 wind fields and landfall climatologies based on JTWC vmax, JMA vmax and JMA cpres BTD (presented in **figures 1 & 2**) implemented in PartnerRe's CatFocus® tropical cyclone model, and **b)** the loss experience for the same portfolio. Point markers denote single event losses. Dashed lines denote Generalized Pareto Distributions (GPD) fitted to the respective events. In **a)**, considerable differences in the typhoon estimated loss-frequency relationship are observed depending on the BTD metric. In **b)**, a similar level of variation is observed depending on the choice of indexation method (denoted by the vertical bars) and the loss experience period (1991–2015 vs. 2004–2015).

Which means: Know your EP curves – know your uncertainties – inform your 'view of risk'

Knowing your EP curves means:

- in general: knowing the data and assumptions behind the curves
- specific to catastrophe models: knowing the sensitivities of a catastrophe model output linked to the various aspects of model methodology and the choice of hazard data (in this study: the BTD source)
- specific to your loss experience: knowing the quality and representativeness of the reported loss record used for either direct risk estimation and/or model validation.

This knowledge enables better judgement of the uncertainties, and therefore determines the level of confidence in a specific 'view of risk'.

Translating this into best practice for typhoon (and all storm) model validation: When comparing catastrophe model and loss experience based EP curves for the purpose of model validation, we recommend the following key considerations:

1. Use an appropriate indexation method for your loss experience EP curves: select an indexation method that accurately accounts for the monetary developments of the covered insurance portfolio, thereby homogenizing the historical losses to create a meaningful loss sample referenced to today's exposure data.

2. Consider the long-term average landfall climatology: verify whether the chosen loss experience period is consistent with the long-term landfall climatology. For Japan Typhoon, this means determine whether or not your loss experience occurred during a period of typical typhoon activity by comparing the number of landfalls registered within your chosen loss experience reporting period with the long-term landfall climatology (**figure 2**). Take any difference from this comparison into account when using the loss experience EP curve to validate the model EP curve.

3. Compare like with like: compare equivalent parts of catastrophe model and loss experience EP curves (e.g. 1 to 10-year return period events) and assure that the loss experience used is complete with respect to those events.

4. Accept the limitations of model validation: validation based on losses is limited for tail events due to the insufficient loss experience for infrequent events. Other scientific methods are used to validate the frequency and severity of tail events.

5. Ensure internal consistency: a stochastic event set is ultimately used for pricing catastrophe risk, 'internal consistency' is achieved if the catastrophe model's historic and stochastic event set EP curves match for the shorter return period years[4].

Risk expertise and catastrophe research at PartnerRe

To find out more about our P&C solutions and catastrophe risk expertise, and to contact us, please go to www.partnerre.com/risk-solutions

Contributor: Dr. Niklaus Merz, Catastrophe Research, PartnerRe
Editor: Dr. Sara Thomas, PartnerRe

[3] Events with a return period of over 10 years.
[4] Cat Models "Get Real", PartnerRe (2010).