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# Empirical Baseline Seasonality Curves for Four Major Catastrophe Perils


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# Introduction

This paper provides baseline seasonality curves for four seasonal natural catastrophe perils relevant to insurance-linked securities (ILS) and catastrophe bond pricing models: U.S. Convective Storm, U.S. Hurricane, Japan Typhoon, and European Windstorm. The goal is to supply a simple starting point for seasonality adjustments in early-stage modeling and pricing.

The approach uses periodic regression with Fourier functions in a Poisson or Negative Binomial Generalized Linear Model (GLM), selecting the number of harmonics by the Akaike Information Criterion (AIC). Results are preliminary and intended as an initial baseline.

# 1 Methodological Overview

For each peril we apply the same framework, with peril-specific datasets and severity filters. The overall idea of using periodic functions is documented and has been used, for example, in [1] where the seasonal cycle for mid-Atlantic storm count (modeled as a Poisson process) is estimated with Fourier harmonics.

**Data preparation** Historical records are filtered to retain *severe* events (e.g., for U.S. Convective Storm: tornadoes above an EF threshold, thunderstorm wind above a speed threshold or percentile, and hail above a size threshold or percentile). We aggregate across full calendar years to form daily event counts by day-of-year and remove February 29 so the period length is $T = 365$. Exposure per day is equal by construction (full years), so no offset is required.

Let $Y_t$ denote the total number of severe events observed on calendar day $t \in \{1, \dots, 365\}$, summed over all years (optionally: normalize within year and average across years to reduce interannual variability).

**Model selection and inference** We first fit a Poisson GLM with a periodic Fourier basis:

$$Y_t \sim \text{Poisson}(\mu_t), \qquad \log \mu_t = \beta_0 + \sum_{k=1}^{K} \left[ \alpha_k \cos\left(\frac{2\pi kt}{T}\right) + \gamma_k \sin\left(\frac{2\pi kt}{T}\right) \right],$$

with $T = 365$ and $K \in \{1, \dots, 6\}$ chosen by the Akaike Information Criterion (AIC). We cap $K \leq 6$ to avoid spurious high-frequency wiggles in sparse settings. The Fourier basis enforces periodicity and continuity at the year boundary. For a given $K$, the number of estimated regression coefficients is $p = 1 + 2K$.

We assess overdispersion using the Pearson chi-square dispersion test for Poisson GLMs. Compute

$$X^2 = \sum_{t=1}^{365} \frac{(Y_t - \hat{\mu}_t)^2}{\hat{\mu}_t}, \qquad \hat{\phi} = \frac{X^2}{\mathrm{df}}, \quad \mathrm{df} = 365 - p,$$

and compare $X^2$ to $\chi^2_{\mathrm{df}}$. A large $\hat{\phi}$ with a small $p$-value indicates variance (or mean) misspecification relative to $\mathrm{Var}(Y_t) = \mu_t$. As a likelihood check, we also compare Poisson and Negative Binomial by AIC.

If overdispersion is detected and a Negative Binomial model materially reduces AIC (counting the dispersion parameter), we replace Poisson with the NB2 GLM and *reselect* $K$ within that family:

$$Y_t \sim \mathrm{NB}(\mu_t, \alpha), \qquad \mathrm{Var}(Y_t) = \mu_t + \alpha\, \mu_t^2, \quad \alpha \geq 0,$$
$$\log \mu_t = \beta_0 + \sum_{k=1}^{K} \left[ \alpha_k \cos\left(\frac{2\pi k t}{T}\right) + \gamma_k \sin\left(\frac{2\pi k t}{T}\right) \right].$$

This NB2 specification is likelihood-equivalent to a Poisson–Gamma mixture with multiplicative heterogeneity and typically downweights peak-season bins relative to Poisson, improving fit when outbreak clustering inflates variance. When comparing AIC, we count $\alpha$ as an additional parameter ($p_{\mathrm{NB}} = 1 + 2K + 1$).

**Seasonality extraction** The pricing seasonality curve is the normalized mean

$$p_t = \frac{\mu_t}{\sum_{u=1}^{365} \mu_u},$$

which integrates to one and can be reported daily or aggregated to weeks or months. Using counts rather than frequencies is convenient for likelihood-based fitting; both yield the same $p_t$ after normalization.

**Assumptions and scope** The target is the average seasonal distribution of severe activity, not day-level prediction. Key assumptions: (i) the seasonal *shape* is approximately stationary over the analysis window; (ii) reporting practices are sufficiently stable; and (iii) event dependence affects variance more than the mean seasonal structure. These curves are best interpreted as priors for seasonality in ILS pricing.

# 2 Peril-Specific Results

## 2.1 U.S. Convective Storm (SCS)

### 2.1.1 Filters and Data

- **Intensity filter:** Tornado rating greater than EF2, hail size greater than 2 inches, and wind speed greater than 75 mph. These thresholds are based on the classifications of the National Weather Service [2] and represent strong or severe convective events.
- **Historical range:** 2007–2024. The starting year reflects the change in tornado classification methodology (implementation of the Enhanced Fujita scale) in 2007, ensuring consistency across the dataset.
- **Source:** NCEI NOAA database.

### 2.1.2 Seasonality curve

The retained model is the Negative Binomial NB2 with periodic Fourier functions. The dispersion test rejected the Poisson GLM and the improvement $\Delta AIC$ between models is important.

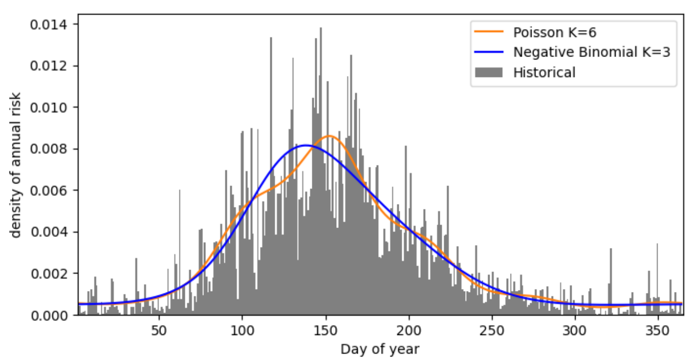


Figure 1: Baseline seasonality curve for U.S. Convective Storm.

It is important to note that the number of Fourier harmonics is not the same for the two models. As a consequence, the Negative Binomial GLM seasonality curve is smoother and the slight bumps (in May and August) are now traded for a more homogeneous peak.

## 2.2 U.S. Hurricane

### 2.2.1 Filters and Data

- **Intensity filter:** Saffir–Simpson Category 2 or higher (Category 2–5), based on internal decision to focus on damaging hurricane events.
- **Geographical filter:** Landfalls or close approaches within a 150 km buffer around the U.S. coastline.
- **Historical range:** 1925–2024. Pre-1920 records are excluded due to increased measurement uncertainty; the 100-year range is rounded for practicality.
- **Source:** IBTrACS dataset [3], [4], [8], [9]

### 2.2.2 Seasonality curve

The retained model is the Poisson with periodic Fourier functions. The dispersion test showed no evidence of overdispersion and no statistical improvement has been observed with the Negative Binomial NB2 GLM. The retained number of harmonics is $K = 2$.

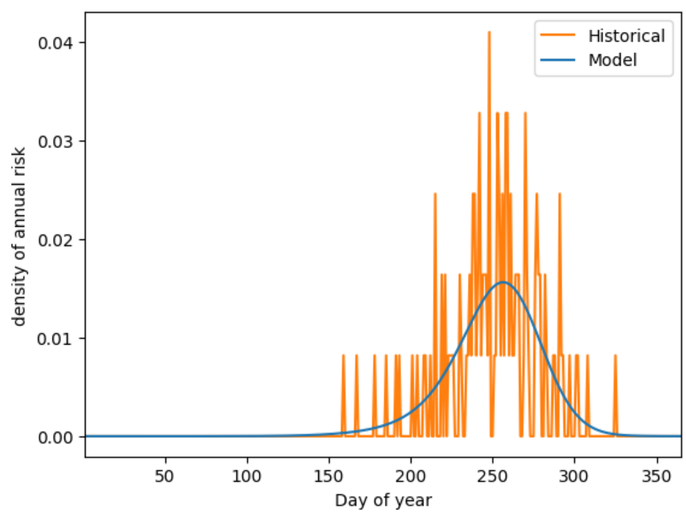


Figure 2: Baseline seasonality curve for U.S. Hurricane.

## 2.3 Japan Typhoon

### 2.3.1 Filters and Data

- **Intensity filter:** JMA Intensity Scale of Typhoon or stronger (Typhoon, Very Strong Typhoon, and Violent Typhoon).
- **Geographical filter:** Landfalls or close approaches within a 150 km buffer around Japan.
- **Historical range:** 1951–2024, beginning with the availability of JMA best-track data.
- **Source:** IBTrACS dataset [3], [4], [8], [9]

### 2.3.2 Seasonality curve

The retained model is the Poisson with periodic Fourier functions. The dispersion test showed no evidence of overdispersion and no statistical improvement has been observed with the Negative Binomial NB2 GLM. The retained number of harmonics is $K = 2$.

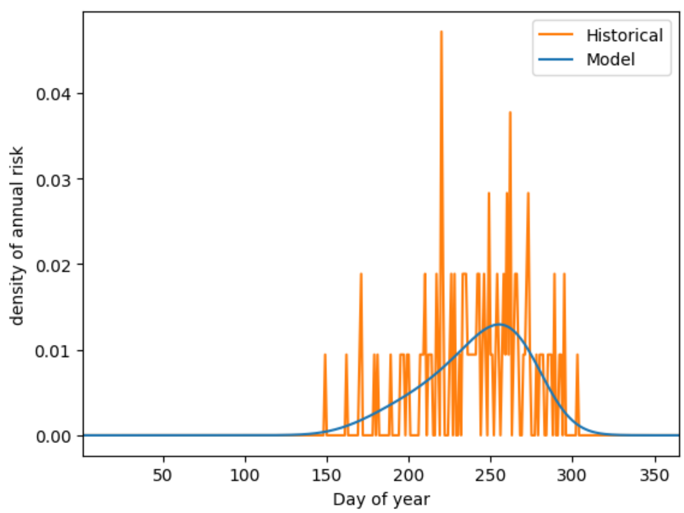


Figure 3: Baseline seasonality curve for Japan Typhoon.

## 2.4 European Windstorm

### 2.4.1 Filters and Data

- **Intensity filter:** Wind gusts exceeding 25 m/s over a contiguous land area greater than 150 km$^2$. The 25 m/s threshold is a commonly used severe wind benchmark, and the 150 km$^2$ area threshold is supported by prior research. [5][6]
- **Historical range:** 1940–2024, encompassing the entire available dataset.
- **Source:** Climate Data Store [7]

### 2.4.2 Seasonality curve

The retained model is the Poisson with periodic Fourier functions. The dispersion test showed no evidence of overdispersion and no statistical improvement has been observed with the Negative Binomial NB2 GLM. The retained number of harmonics is $K = 1$.

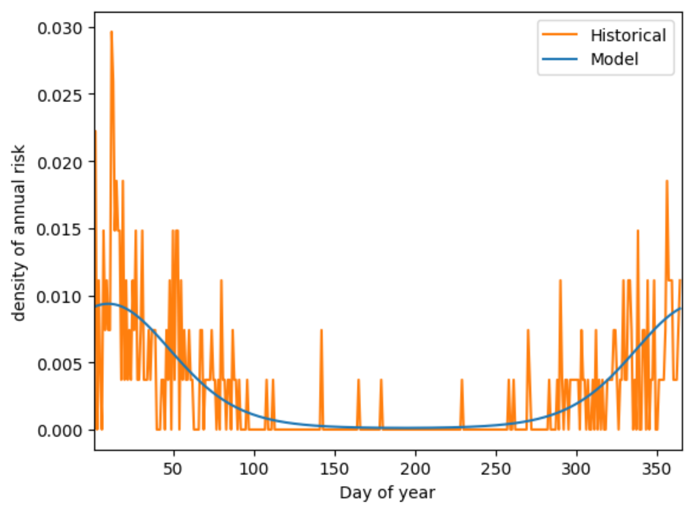


Figure 4: Baseline seasonality curve for European Windstorm.

# 3 Limitations and Next Steps

The baseline omits synoptic and climate covariates and does not model outbreak dependence explicitly, so pointwise error metrics are modest by design. This is acceptable for pricing seasonality, where smoothness and stability are preferred to overfitting. Next steps include testing alternative frameworks (e.g., GAMs, Bayesian harmonic regression), sensitivity to filter choices, integration of interannual climate drivers such as ENSO/AMO/PDO, and benchmarking against catastrophe model seasonal profiles.

## Disclaimer

These seasonality curves are provided as a baseline reference. They are intended for preliminary pricing adjustments and should be refined with further data, testing, and peer review.

## References


[1] Andrew R. Solow (1989): Statistical Modeling of Storm Counts, Bulletin of American Meteorological Society, doi:10.1175/1520-0442(1989)002¡0131:SMOSC¿2.0.CO;2

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