Supplement of Nat. Hazards Earth Syst. Sci., 26, 2817–2839, 2026
https://doi.org/10.5194/nhess-26-2817-2026-supplement

Natural Hazards and Earth System Sciences
Open Access

Supplement of

Unravelling wind-driven impact of storm clusters, a case study for the insurer Generali France

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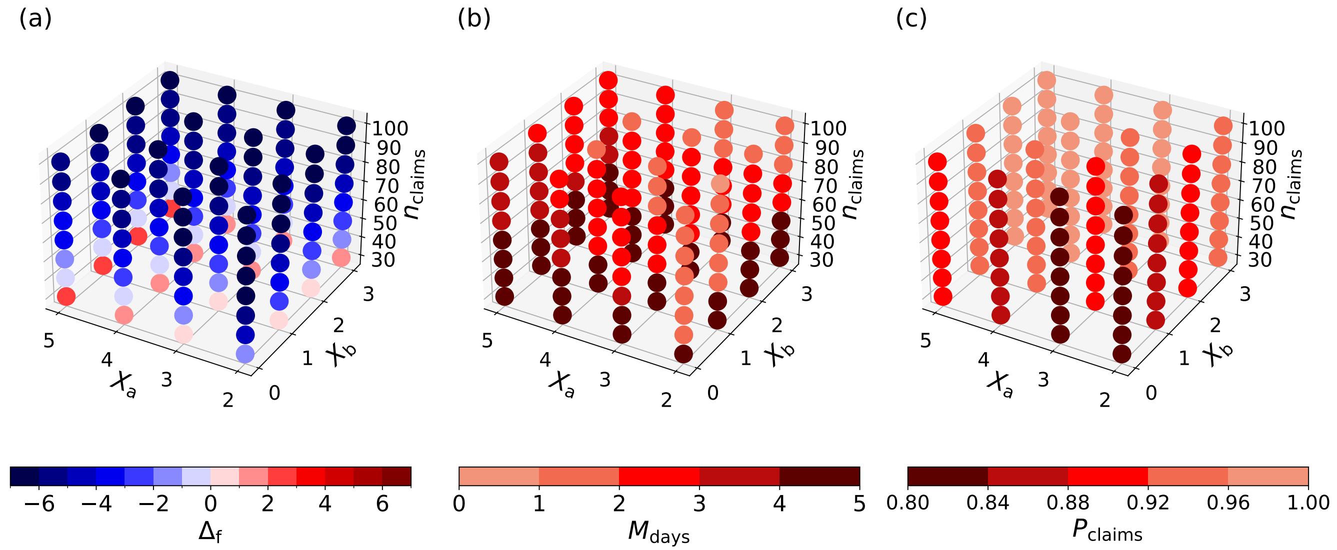

Figure S1. Frequency (Δ_f) in number of events (a), precision (M_{days}) in number of days (b) and completeness (P_{claims}) in percent (c) as a function of X_a (horizontal x), X_b (horizontal y) and n_{claims} (vertical z). The optimal set of parameters(X_a, X_b, n_{claims}) is obtained when the difference is null.

S1 Sensitivity to tuning parameters

This subsection inspects the evolution of the performance metrics (M_{days}, Δ_f and P_{claims}) as a function of the tuning parameters (X_b, X_a, n_{claims}. The performance metrics are computed independently for each winter and for X_b in $\{0,1,2,3\}$, X_a in $\{2,3,4,5\}$ and n_{claims} between 30 and 100 with 10 claims steps. The metrics are then averaged over all the winters. Figure S1 shows the variation of the frequency, precision and completeness metrics as a function of the tuning parameters. Lighter colours indicate better results in all the subfigures.

The impact of the association windows can first be evaluated. When X_a is too large, the precision decreases, as shown by the increased minimal difference between storm date and the nearest local maxima date (Fig. S1b). This indicates a degradation of the temporal alignment between identified storms and peaks in the claim time series. Conversely, increasing X_a enables the capture of more claims, thus being more representative of the global dataset (Fig. S1c). In terms of performance, this improves the completeness metric. Nonetheless, we see that the variation in the completeness varies less than the precision metric. The behaviour of X_b is similar to that of X_a, as it also enlarges the temporal window around d_{storm} within which claims are accepted. A greater value would allow for more completeness, but would also decrease the precision of the association. In contrast, the parameter n_{claims} does not alter the completeness performances. This parameter defines the threshold under which claims should be shifted; it thus does not influence the number of claims associated with storms. Regarding precision (Fig.S1b), shifting claims reduces the maximal difference between storm dates and the nearest peaks, suggesting that the adjusted claims are primarily those furthest from the peak dates. This confirms that Step 3 of the association method (Sec.**??**) improves the temporal alignment between storms and local maxima in claim counts.

The behaviour of the frequency metric is more complex as it depends on the interaction of the three parameters (Fig. S1a). For a given temporal window (X_a and X_b fixed), increasing the minimal number of claims (n_{claims}) reduces the number of storms associated with claims and consequently decreases the Δ_f. This reduction is needed when a positive frequency is observed, i.e. when more storms are detected than local maxima in the claim time series. However, decreasing n_{claims} excessively leads to a negative Δ_f, corresponding to an over-concentration of claims around the major storm events, with more local maxima than the number of storms. The situation when too many storms are captured (positive Δ_f) is mostly observed when n_{claims} is small.

A trade-off should be found between the width of the association windows (X_a and X_b) and the strength of the concentration over the major events (n_{claims}). The optimal association should not only be complete but also correctly attribute claims to the relevant storms. Fig. S1c shows that the smallest percentage of claims that can be linked to storm events is 80%. As this is already satisfactory, the optimisation therefore focuses on frequency consistency and temporal alignment between storm dates and local maxima.

The optimal tuning parameters X_b, X_a and n_{claims} are obtained by minimizing the cost function defined as :

$$f_{cost}(w_{freq}) = \sqrt{w_{freq} \times \Delta_f^2 + (1 - w_{freq}) \times M_{\text{days}}^2}. \tag{S1}$$

The frequency and precision metrics are normalized between 0 and 1, w_{freq} is a weight attributed to the frequency metric, which can vary between 0 and 1. This weight is used to quantify the sensitivity of the optimal parameters found. Optimisation is performed over f_{cost} using global minimization search for $(X_a, X_b, N_{\text{min\_claims}}) \in \{0,3\} \times \{2,5\} \times \{30,100\}$. The robustness of the results to w_{freq} is discussed in Sect. 2.

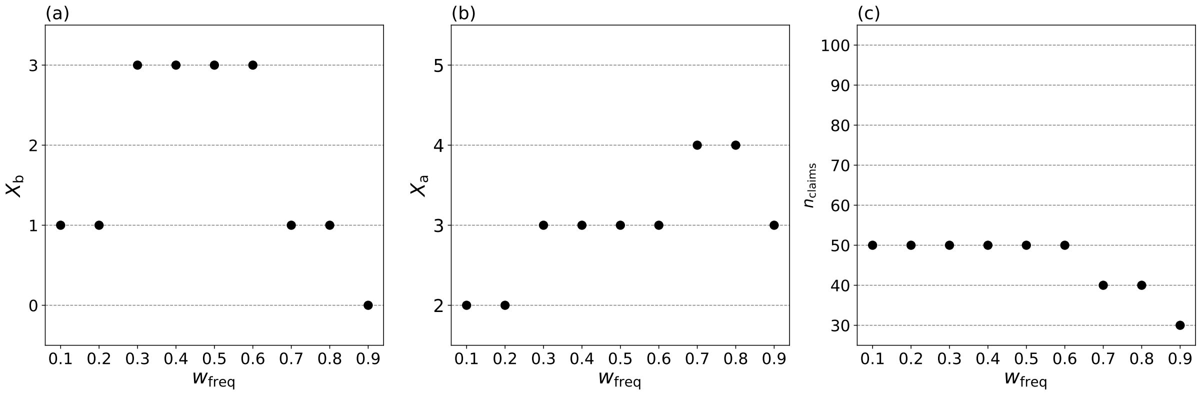

Figure S2. Optimal value of X_b (a), X_a (b) and n_{claims} (c) as a function of the weight of the frequency metric w_{freq}

S2 Sensitivity to cost function

The cost function f_{cost} defined in Sect.1 varies as a function of the weight assigned to the frequency metric (w_{freq}). Fig. S2 shows the optimal values of the parameters X_b, X_a and n_{claims} as a function of the varying weight. It can be underlined that the optimal values of all the parameters are identical for the weight varying between 0.3 and 0.6. This means that, with a balanced penalty between the precision and frequency metrics, the optimal parameters are identical.