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Wind aggregation for storm clusters improves the design of vulnerability curves for insurance companies

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Abstract

Extra-tropical cyclones are a major source of insured losses in Western Europe, particularly when they occur in rapid succession. Although storm clustering can amplify cumulative impacts, most catastrophe models still estimate losses using vulnerability relationships calibrated on isolated storms. Such approaches neglect the potential change in vulnerability following successive storm impacts, as well as the enhanced damage potential associated with the succession of intense wind gusts. This may lead to biased estimates of risk and insured losses.

Here, we investigate the temporal compounding of winter windstorms, also called storm clustering, over France and its implications for impact modelling. Using atmospheric reanalysis and insurance loss data, we characterise the spatial and temporal properties of storm clustering and evaluate how storm succession influences observed damages. We show that, when their footprints overlap, clustered storms exhibit different damage responses compared to isolated storms, indicating that maximum wind intensity alone is insufficient to explain losses during such temporally-compounded events.

To address this limitation, we propose a wind aggregation framework that explicitly accounts for storm succession within clustered sequences. This aggregated hazard metric improves the representation of cumulative impacts and enhances the ability of vulnerability relationships to reproduce observed damages. Our

047 results demonstrate that storm clustering should be treated explicitly in catas-
048 trophe modelling frameworks to obtain more realistic estimates of windstorm risk
049 and cumulative losses.

050 **Keywords:** Storm, Impact, Insurance, France, Compound-Event, Storm clustering
051

052 1 Introduction

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056 Winter windstorms are among the costliest natural hazards affecting France and West-
057 ern Europe. Major storms that have affected France in recent decades, such as Lothar
058 and Martin in December 1999 [1–3], Klaus in January 2009 [4], and, more recently, Cia-
059 ran and Domingos in November 2023 [5], have highlighted the wide range of impacts
060 associated with such events. Consequently, improving the understanding and quantifi-
061 cation of windstorm risk has become a key priority for both the scientific community
062 and the insurance sector.

063 Risk can be represented through the interplay between three key components:
064 hazard, exposure, and vulnerability [6, 7]. In the case of windstorm risk, the hazard
065 describes the occurrence and intensity of damaging winter windstorms; the exposure
066 represents the people and assets located in areas affected by these storms; and the
067 vulnerability characterises the propensity of those exposed assets to sustain damage
068 when the hazard occurs. While the exposure is prescribed by the assets, infrastructure
069 or populations considered, the hazard depends on methodological choices, including
070 the meteorological input [8], the definition of storm events, and the temporal and
071 spatial aggregation used to characterise them. Importantly, vulnerability is not directly
072 observed but inferred from the relationship between a selected hazard metric and
073 observed damage [9]. Consequently, changing the representation of the hazard can
074 modify the estimated vulnerability and ultimately alter the resulting risk assessment.

075 Traditional risk assessments often assume hazards can be represented as indepen-
076 dent events [7]. However, compound events, defined as the combination of multiple
077 hazards contributing to societal risk [10, 11], challenge this assumption [12, 13]. In fact,
078 compound events can alter damage responses through mechanisms such as repeated
079 loading, persistence of adverse conditions, or incomplete recovery between successive
080 events, which can leave exposed systems in a more vulnerable state [14]. As a result, the
081 vulnerability inferred from isolated events may differ from the vulnerability observed
082 during sequences of events [15–17]. Studies have shown that damages associated with
083 multi-event or compound situations can exceed those expected from independent haz-
084 ards [18, 19]. Therefore, accurately representing the temporal structure of hazards is
085 essential for reliable risk estimation.

086 In the North Atlantic, extra-tropical cyclones (ETCs) provide a relevant exam-
087 ple of temporally compounding hazards. ETC activity exhibits substantial seasonal
088 and decadal variability, partly driven by fluctuations in large-scale atmospheric cir-
089 culation patterns [20, 21]. Over shorter periods, such as days to weeks, ETCs can
090 also arrive in rapid succession, affecting similar regions. This phenomenon, known as
091 storm serial clustering, describes the tendency of storms to occur in sequences rather
092

than independently [22–24]. Such clustering is favoured by persistent atmospheric circulation regimes, including jet-stream configurations promoting repeated cyclogenesis along similar North Atlantic trajectories [24, 25]. Storm clustering is particularly pronounced for intense storms [26, 27] and can lead to substantial cumulative losses when regions are repeatedly affected within short periods [28, 29].

Accurately quantifying the influence of storm clustering on damages requires careful attention to the representation of the underlying hazard. Different methodological choices can lead to substantially different representations of storm events and their associated footprints. At the event-definition level, storms can be characterised either from aggregated wind fields [30–32] or from dynamical information such as storm tracks combined with spatial constraints [31, 33]. This methodological choice becomes particularly important for sequences of ETCs, for which successive storms may overlap spatially and temporally. In such situations, aggregated hazard definitions may merge individual events, making it difficult to identify the contribution of each storm to the resulting impacts. Conversely, physically based definitions relying on a too-large footprint radius may assign the same wind gust to multiple storms, creating ambiguities in impact attribution [31]. More generally, spatially and temporally aggregated hazard metrics can obscure the structure of compound events by treating multiple interacting events as a single hazard footprint.

Within the risk assessment framework, such aggregation choices implicitly assume that vulnerability remains independent of the temporal structure of the hazard, which is of particular importance given that the hazard represents the greatest source of uncertainty in risk assessment [34, 35]. However, vulnerability may evolve during clustered storm sequences. Repeated hazards can modify damage susceptibility through cumulative structural weakening, incomplete recovery processes, emergency response limitations, and behavioural adaptation [36]. Structures affected by an initial storm may become more vulnerable to subsequent impacts, potentially leading to non-linear amplification of losses [37]. Furthermore, when storms occur in close succession, insurance claims may overlap spatially and temporally, complicating the attribution of damages to individual events and challenging the application of single-event vulnerability functions [28].

Despite the potential importance of storm clustering, this temporal compounding remains only partially represented in catastrophe modelling frameworks [31]. Most catastrophe models estimate damage by applying vulnerability relationships independently to individual storm events. These vulnerability functions are generally calibrated using isolated events and implicitly assume that each storm occurs independently, without influence from previous impacts [34, 38–41]. Such assumptions may be inadequate when multiple storms affect the same exposed regions within short time periods.

In this study, we investigate the role of storm clusters in windstorm risk in France. We quantify the proportion of claims occurring during sequences of storms (*clustered-storm* damage) and identify the subset of claims occurring within overlapping storm footprints, and therefore potentially exposed to wind gusts from multiple physical

events (*multiple-wind* damage). Based on these observations, we propose a representation of clustered windstorm hazards for damage estimation within catastrophe modelling frameworks. Specifically, we address the following questions:

- What is the proportion of *clustered-storm* and *multiple-wind* damage in France ?
- Can vulnerability relationships calibrated from isolated storm events accurately reproduce damage from temporally clustered storms?
- How should wind hazard be aggregated within storm sequences to better represent cumulative damage and evolving vulnerability?

Therefore, although hazard and vulnerability are commonly treated as separate components of risk assessment [42], this study investigates how the temporal structure of hazards can influence vulnerability and damage response. In particular, this work aims to improve the representation of storm clustering in windstorm risk assessment and contribute to the development of catastrophe modelling approaches that are better suited for temporally compound hazards. This is illustrated on the Generali France insurance portfolio.

2 Results

2.1 Spatial and temporal distribution of compounded events

Throughout this article, a *damage grid* refers to the combination of an ERA5 grid cell and an event at which at least one claim was recorded. The term "event" is defined in section 4.4. To investigate damage associated with storm clusters, we classify damage grids into three categories: *single-storm*, *clustered-storm* and *multiple-wind* damage. *Single-storm* damage refers to damage grids for which the damaging storm is a single storm. *Clustered-storm* damage refers to aggregated damage corresponding to a cluster of storms. Finally, *multiple-wind* damage refers to damage grids corresponding to a storm within a cluster and located in the intersection of the footprints of several storms of a cluster (see section 4.3). Thus, *multiple-wind* damage corresponds to locations affected by at least two wind gusts from multiple successive storms, whereas *clustered-storm* damage may result from the impact of only one of the storms in the cluster. The proportion of *clustered-storm* and *multiple-wind* damage varies and increases with the length of the clustering windows (see Section 4.4). Figure 1 shows, for different clustering windows, the proportion of *clustered-storm* and *multiple-wind* damage within Generali's portfolio.

The increase in the fraction of *clustered-storm* damage with clustering period reflects the progressively less restrictive definition of a storm cluster. As the clustering window increases, an increasing number of storms are grouped into clusters. Because damage grids are defined by aggregating damage either over individual storms or over the cluster to which a storm belongs, this also affects the total number of damage grids. In particular, storms that were classified as single storms for shorter clustering windows may become part of a cluster when the window is extended, causing their damage to be aggregated with that of other storms and thereby reducing the overall number of damage grids. Despite this reduction, the proportion of damage grids associated with storm clusters increases with the clustering period.

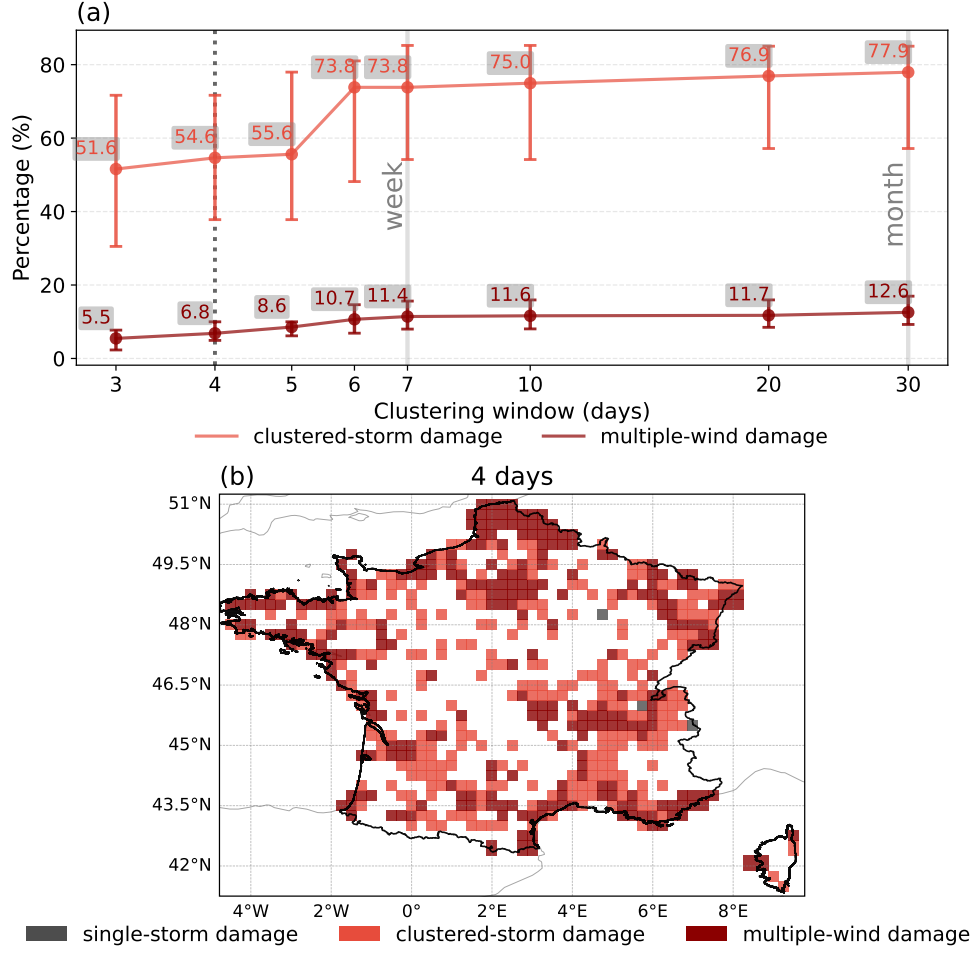


Fig. 1 (a) Percentage of *clustered-storm* (light red curve) and *multiple-wind* (dark red curve) damage grids as a function of the clustering window. Error bars correspond to the 1st and 3rd quantiles, computed over individual winter seasons. (b) Spatial distribution of *single-storm*, *clustered-storm*, and *multiple-wind* damage for the specific case of a 4d-cluster. Grid cells are coloured according to the type of damage experienced across all storms in all winters. A grid cell is shown in dark red if it experienced *multiple-wind* damage during at least one storm cluster, in light red if it experienced *clustered-storm* damage at least once but no *multiple-wind* damage, and in grey if it experienced only *single-storm* damage.

For example, with a 10-days (10d) clustering window, storms occurring within 10 days of one another can be assigned to the same cluster. Given the high frequency of winter windstorms over France, extending the clustering window progressively incorporates a larger fraction of storms into clusters and, consequently, a larger fraction of damage grids are classified as *clustered-storm* damage. For a 30-days clustering window, approximately 78% of the damage grids are associated with a storm cluster,

231 leaving only 22% associated with single storms. In this case, a single storm corresponds
232 to an event that is not connected to another storm within the 30-day clustering crite-
233 rion. Extending the clustering window would progressively connect more storms into
234 clusters, such that, at sufficiently large windows, virtually all damage grids would be
235 associated with storm clusters.

236 For clustering windows shorter than 7 days, at least 50% of damage grids are asso-
237 ciated with clustered storms. This highlights that a larger proportion of insured wind
238 damage in France is generated during periods of strong storm activity, with successive
239 storm events following each other. In contrast, *single-storm* damage characterised by
240 storms isolated from other events by more than 7 days accounts for only 25% of the
241 damage grids.

242 Regarding the *multiple-wind* damage, we also observe an increase in the percentage
243 with the widening of the clustering window. However, this percentage remains rela-
244 tively low. For cluster periods shorter than 7 days, *multiple-wind* damage represents
245 at most 11% of the damage grids. Even for the 30d-clusters, for which *clustered-storm*
246 damage represents 78% of the damage grids, only 12% are *multiple-wind* damage. This
247 indicates that within storm clusters, the spatial overlap of footprints between succes-
248 sive storm remains limited. Even at the seasonal scale (clustering window greater than
249 30 days), the succession of storms over a given impacted location remains uncommon.

250 Across all clustering windows, the fraction of *clustered-storm* damage exhibits sub-
251 stantial inter-seasonal variability. For example, the contribution of *clustered-storm*
252 damage varies substantially between seasons, ranging from 0% in Winter 1998/1999
253 to 95% in Winters 1999/2000 and 2020/2021, with similar values observed for both 4d
254 and longer clustering windows such as 30 days. This variability, previously highlighted
255 in [28, 32, 43], likely reflects the combined influence of seasonal differences in storm
256 frequency and intensity. Moreover, because the analysis relies on observed impacts
257 rather than storm occurrence alone, variations in the damage produced by successive
258 storms may also contribute to the observed range. The inter-seasonal variability is also
259 present in the fraction of *multiple-wind* damage. We observe a range of 0.8% (Winter
260 2002/2003) to 44% (Winter 2008/2009) for 30d-clusters and 0% (Winter 1998/1999,
261 2001/2002 and 2014/2015) to 29% (Winter 2018/2019) for the 4d-clusters.

262 Figure 1b shows the spatial distribution of the three types of damage for the special
263 case of the 4d-clusters. The figure shows that not all grid cells are coloured. This
264 reflects the spatial distribution of Generali's portfolio and, more broadly, the density of
265 insured buildings across France, where the centre of France concentrates less exposure
266 compared to coastal areas and major cities (Section 4.2 and Supplementary). Among
267 the coloured grid cells, only 3 damage grids experience exclusively *single-storm damage*
268 throughout all the winters, indicating that most locations experience *clustered-storm*
269 *damage* at least once. This is consistent with the mean proportion of 55% of damage
270 grids classified as *clustered-storm* for the 4d-cluster (Figure 1). *Multiple-wind* damage
271 grids are distributed across the entire territory, with a higher concentration in northern
272 France. This spatial pattern may reflect both the geographic distribution of Generali's
273 portfolio, which has a particularly high concentration of exposed buildings in the north
274 (see Supplementary), and the greater frequency of windstorms in this region.

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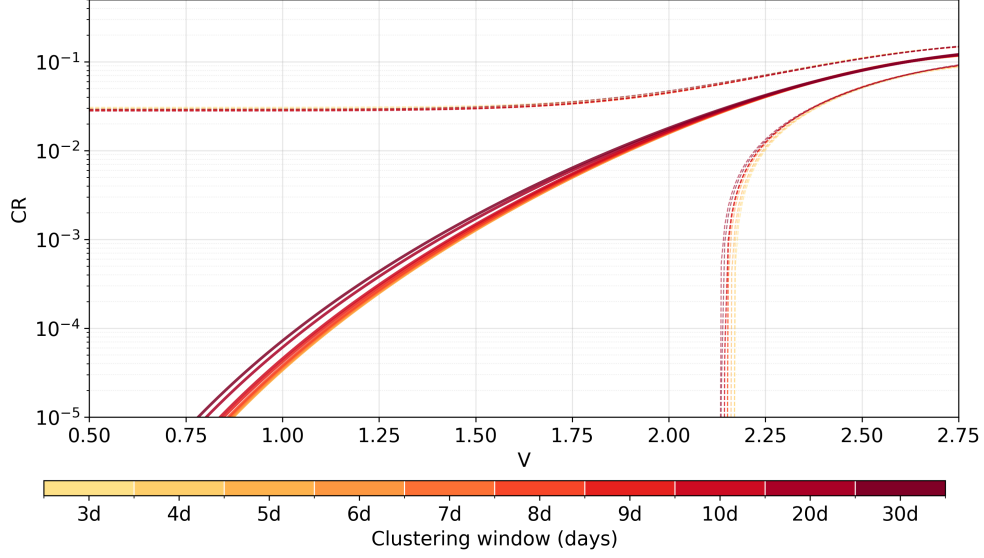


Fig. 2 Vulnerability curves, expressed as the claim ratio (CR) as a function of the maximum normalised wind V (see Section 4.5), obtained with the Weibull vulnerability model for clustering windows ranging from 3 to 30 days. Colours indicate the different clustering windows. Continuous lines represent the mean claim ratio, while dashed lines indicate the 95% confidence interval.

This section shows that storm clusters are over-represented relative to single storms among the damage grids. However, *multiple-wind* damage accounts for only a small fraction of all damage grids. The observed frequency pattern is influenced by both the spatial distribution of the storm hazard and the spatial distribution of Generali's insured portfolio. Their respective contributions are difficult to disentangle from the spatial distribution of damage types alone, as no clear spatial pattern emerges for *multiple-wind* damage (Figure 1b). We determine whether *multiple-wind* damage exhibits a distinct vulnerability response. In particular, we investigate whether damage at a given grid is primarily controlled by the maximum wind gust experienced, or whether successive storm events within a cluster provide additional explanatory power. This distinction is important because it determines whether vulnerability can be characterised solely as a function of peak hazard intensity or whether it should also account for the temporal accumulation of wind impacts. To address this question, the following section introduces temporally compounded wind vulnerability curves, which explicitly account for the intensity of the successive storms over different clustering periods.

2.2 Vulnerability curves

Vulnerability curves describe how damage varies with local hazard intensity and are therefore expressed here as the claim ratio (CR) as a function of the local wind intensity, defined as the maximum normalised wind (V) or aggregated wind (V_{agg}) (see

Section 4.5 and 4.6). The claim ratio is defined as the ratio of the number of claims to the number of contracts in the portfolio for each damage grid (see Section 4.2). Expressing damage in terms of claim ratio removes the influence of variations in the size and spatial distribution of the Generali portfolio. The vulnerability curves are calibrated through global optimisation of the historical damage grids (see Section 4.5). For short cluster periods such as 3d- or 4d-clusters, this corresponds exactly to what is done in usual catastrophe models for the estimation of event loss [30, 32, 39, 41]. For longer clustering windows, as most storms are aggregated into clusters, the claim ratio is estimated using the hazard intensity of the strongest storm event, which is more similar to an average annual damage estimation.

Figure 2 shows the vulnerability curves obtained for the different clustering windows (from 3 to 30 days). For all clustering windows, the expected claim ratio increases with the normalised wind, with all curves exhibiting a similar rate of increase. The vulnerability curves obtained for the different clustering windows also show similar performance, with a mean R^2 of 0.41. This indicates that the clustering window primarily affects the magnitude of the expected damage rather than the overall shape of the vulnerability relationship. Nonetheless, for a given maximum normalised wind, the expected claim ratio increases with the length of the clustering window. As explained previously, from a conceptual point of view, estimating the claim ratio using a 30d clustering window is closer to estimating the total damage accumulated over a substantial fraction of the winter season based on the strongest event, rather than the damage associated with an individual storm. The expected claim ratio is therefore higher because it accounts for damage accumulated over a longer period and potentially across several successive storms.

All curves present relatively wide 95% confidence intervals, particularly for low normalised wind values, while the width of the intervals decreases as normalised wind increases. This large variability reflects the heterogeneity of the damage grids included in the calibration dataset, which is further discussed in Section 2.3. Although damage is aggregated to reduce the influence of local-scale features (Section 4.5), differences in both exposure and hazard characteristics may still contribute to the observed variability. When considering exposure level, differences in building characteristics, such as construction type, roof geometry and orientation, surrounding vegetation, or other local features, may affect the response to a given wind intensity. Similarly, differences in wind direction and its temporal evolution may contribute to variations in damage for comparable maximum gusts. Finally, although the claim ratio is normalised by the number of insured contracts, damage grids with a small number of insured contracts cannot resolve very small claim ratios, which may contribute to the observed dispersion, particularly at low damage levels.

Given the behaviour and uncertainties of the vulnerability curves, we may question whether the maximum normalised wind is sufficient to capture *multiple-wind damage*. In the following section, we focus on the 4-day clustering window to investigate the relationship between claim ratio and normalised wind intensity for *multiple-wind damage*, and assess whether accounting for the intensity of successive storms explains more of the variability in claim ratio than using the maximum normalised wind gust alone.

2.3 Case study: 4–days clustering window

The 4–days temporal window is a particularly relevant case study, as it corresponds to the 96-hour event definition used for windstorm claim aggregation in Generali France’s reinsurance contracts. More generally, reinsurance contracts for windstorms commonly rely on temporal aggregation windows of around 72–96 hours [44]. Over such periods, insurance companies typically assume that all claims originate from a single event with a unique spatial footprint [44]. Using the clustering definition defined in Section 4.4, we identify 197 storms grouped into 76 clusters, representing 85% of the total claims [28] and 55% of the damage grids (see Figure 1).

Figure 3 shows the vulnerability curves obtained over all and *multiple-wind* damage grids. The global fit exhibits moderate performance ($R^2 = 0.41$, $p_{value} \approx 0$), with a large confidence interval reflecting the substantial dispersion in the observed claim ratio (see Section 2.2). When restricting the analysis to *multiple-wind* damage grids, the performance of the fit done using all damage grids decreases ($R^2 = 0.28$, $p_{value} \approx 0$). This decrease indicates that the vulnerability relationship fitted to all damage grids does not capture well the relationship between normalised wind and claim ratio for *multiple-wind* damage grids. Although improved fits can be obtained by calibrating exclusively on the subset of *multiple-wind* damage grids ($R^2 = 0.38$, $p_{value} \approx 0$), the resulting vulnerability curves display distinct behaviour (see Figure 3b).

In particular, the curve fitted exclusively to *multiple-wind* damage grids exhibits a higher expected claim ratio across the full range of normalised wind. For $V = 1.5$, corresponding to a wind gust equal to the 1.5 times the local 90th percentile, the fit based on all damage grids predicts a mean claim ratio of 1.3×10^{-3} , with a confidence interval of $[0; 3.1 \times 10^{-2}]$, compared with 3.7×10^{-3} , with a confidence interval of $[0; 4.5 \times 10^{-2}]$, for the fit based exclusively on *multiple-wind* damage grids. This difference suggests that, for a given normalised wind intensity, locations exposed to successive storms within overlapping footprints may experience greater damage than locations exposed to a comparable wind intensity from a single storm. The difference between the two curves becomes more pronounced at higher wind intensity. For $V = 2.5$, corresponding to a wind gust substantially greater than the local 90th percentile, the fit based exclusively on *multiple-wind* damage grids predicts a claim ratio of 1.2×10^{-1} , with a confidence interval of $[8.1 \times 10^{-2}; 1.6 \times 10^{-1}]$. This value is higher than the 8.1×10^{-2} predicted by the fit based on all damage grids, whose confidence interval is $[5.1 \times 10^{-2}; 1.1 \times 10^{-1}]$. The increasing divergence between the two curves with wind intensity indicates that the global vulnerability curve does not fully capture the higher claim ratios associated with *multiple-wind* damage. Conversely, for a given claim ratio, the *multiple-wind* vulnerability curve associates the observed damage with a lower wind than the global curve, suggesting an additional contribution of successive wind exposures to the observed damage.

To address this discrepancy, we introduce a wind aggregation metric that accounts for the contribution of successive storms rather than relying solely on the maximum normalised wind (see Section 4.6). The metric is constructed from the full wind footprints of each storm within a cluster, rather than considering only the maximum normalised wind. For *single-storm* damage grids, the normalised wind value of V

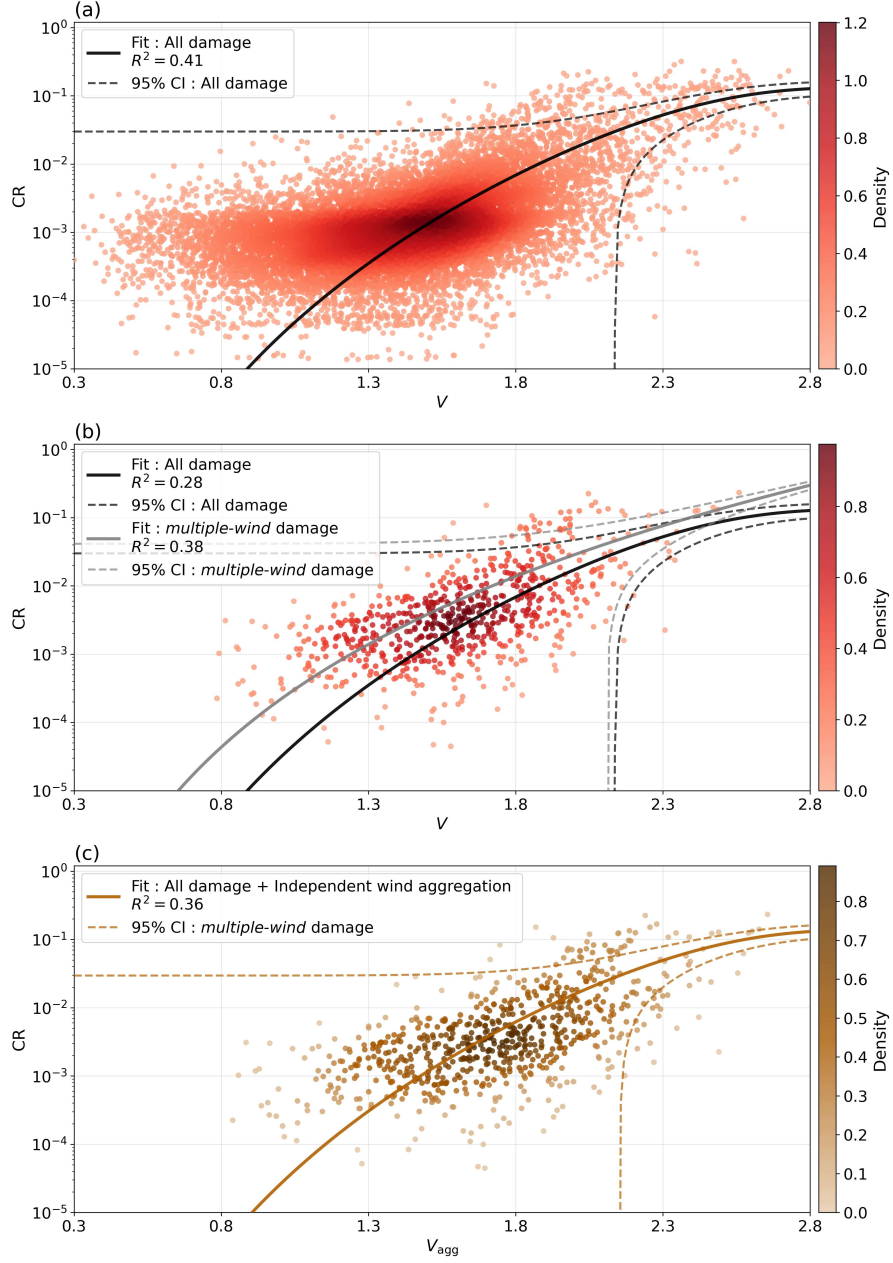


Fig. 3 Claim ratio (CR) as a function of the maximum normalised wind (V) and aggregated wind (V_{agg}), together with fitted vulnerability curves obtained using all damage grids (black lines) or *multiple-wind* damage grids (grey lines). Panel (a) shows all damage grids; panel (b) focuses on *multiple-wind* damage grids. Scatter-point colours indicate point density, with darker colours corresponding to higher densities. Panel (c) shows *multiple-wind* damage intensity as a function of the aggregated wind, together with the corresponding vulnerability curves fitted using the optimal aggregated wind (Independent model, see section 4.6).

remains unchanged. Figure 3c presents the vulnerability curve obtained using the optimal wind aggregation method, namely the Independent wind model (see Section 4.6), for the 4d-cluster case study. This aggregation improves the fit, increasing the R^2 to 0.36.

With the aggregated wind metric, *multiple-wind* damage grids are associated with an aggregated wind value greater than the maximum wind gust produced by any individual storm (see Figure 3c). This can be interpreted in a counterfactual framework: for a given amount of damage, the aggregated wind represents the wind intensity that would be required from a single storm to produce an equivalent claim ratio. In other words, the additional contribution of successive wind exposures is expressed as an equivalent increase in wind intensity. This interpretation is consistent with the results presented in Figure 3b, where *multiple-wind* damage grids exhibit higher claim ratios than single-storm damage grids for the same maximum wind gust. Together, these results indicate that damage resulting from compounded wind events is not fully explained by the peak wind gust alone, but also reflects the cumulative effect of successive wind exposures.

To further quantify the role of the aggregation process, we analyse the optimal coefficients associated with each wind aggregation model (see Section 4.6). Figure 4 presents these coefficients as a function of wind intensity (or rank), together with the relationship between the aggregated wind and the maximum normalised wind. The max wind aggregation model provides the baseline approach, assigning a weight of 1 to the maximum normalised wind value and zero weight to all other normalised wind values. Consequently, the aggregated wind is, by definition, equal to the maximum normalised wind.

For the Independent wind aggregation model, the coefficients depend solely on the rank of the wind intensity, without imposing any constraint on the relationship between the coefficients. Consequently, two wind sequences such as $[20, 5]$ m.s⁻¹ and $[20, 19]$ m.s⁻¹ are assigned the same coefficients to their respective wind values, despite resulting in different V_{agg} values. The optimal aggregation assigns decreasing weights to successive wind events: the locally strongest wind gust receives a weight of one, the second strongest a weight of approximately 0.1, while the weakest wind gust receives a weight close to zero and therefore doesn't contribute much to the aggregated intensity. This weighting indicates that, within the optimal aggregation, the second strongest wind gust contributes approximately 10% as much as the strongest gust. The optimal power parameter of 1.04 is also close to one, suggesting that the power coefficient doesn't improve the results. Figure 4f shows that the resulting V_{agg} is systematically greater than V_{max} . This is consistent with the previous analysis, which showed that *multiple-wind* damage grids exhibit higher claim ratios than single-storm damage grids for the same maximum wind gust. The aggregation therefore effectively increases the wind intensity associated with *multiple-wind* damage, providing a way to account for the additional contribution of successive wind exposures. For the 4d-cluster case study, this aggregation model yields the highest R^2 score, suggesting that, over this clustering period, the relative ordering of wind intensities across successive storms provides more information for explaining the observed claim ratios than their absolute values alone.

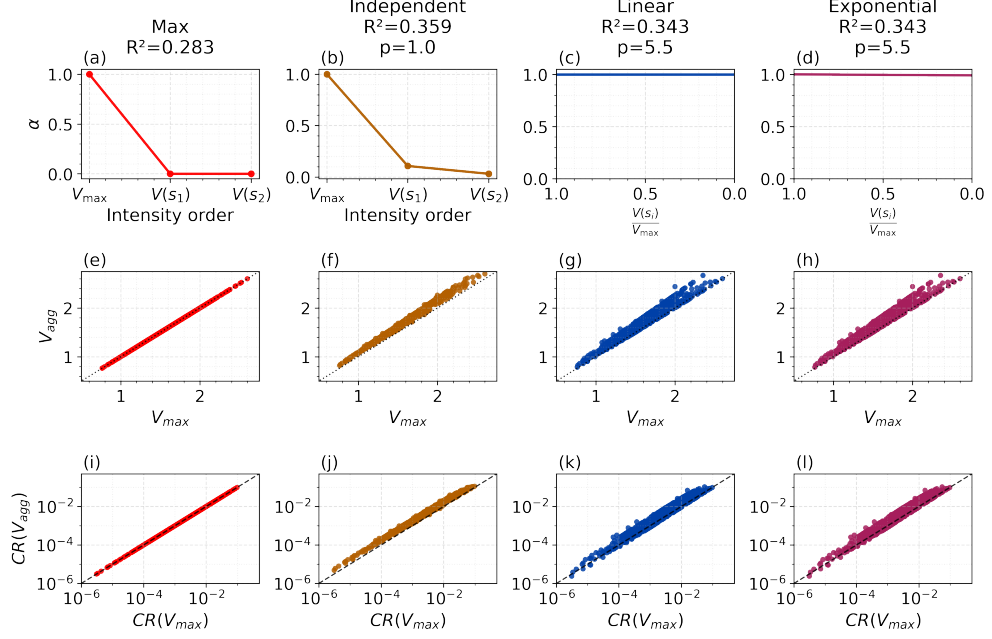


Fig. 4 Parameters of the wind aggregations (a,b,c,d), V_{agg} as a function of V_{max} (e,f,g,h), and claim ratio predicted with the aggregated wind as a function of the occurrence ratio predicted using the maximal wind (i,j,k,l). Panels (a,e,i) show results obtained using the V_{max} wind metric, while panels (b,f,j), (c,g,k), and (d,h,l) show results obtained using the aggregated wind V_{agg} with the independent, linear, and exponential aggregation methods, respectively (see Section 4.6). Colours indicate the corresponding wind metric used in the analysis. The R^2 values are obtained by fitting the model using all points based on the aggregated wind and evaluating the resulting fit only on the *multiple-wind* damage points. The p value corresponds to the power parameter introduced in the aggregated wind formulation (see Section 4.6).

The Powered Linear and Powered Exponential models yield similar aggregated wind estimates (Figures 4c,d,g,h). Unlike the rank-based aggregation models, these approaches depend directly on the magnitude of each wind gust relative to the maximum observed value. In both models, the optimal coefficients remain approximately constant across wind intensities, indicating that the relative contribution assigned to each storm does not vary substantially with the magnitude of its wind gust. The resulting aggregation therefore accounts for the magnitude of all successive wind events, rather than assigning weights primarily according to their rank. The optimal power parameter is 5.51 for both models, which is higher than the value obtained for the Independent wind aggregation model (1.04). This results in slightly larger V_{agg} values than those obtained with the Independent model, particularly when successive storms produce relatively intense wind gusts.

In practice, all three aggregation models produce V_{agg} values greater than the corresponding V_{max} of the cluster. For example, in the observed damage grids, a cluster with $V_{max} = 1.5$ can correspond to an aggregated wind of approximately 1.7 under

the Independent model and 1.8 under the Powered Linear and Powered Exponential models. Thus, the aggregation translates the additional contribution of successive wind exposures into an equivalent increase in wind intensity. From a counterfactual perspective, damage associated with a cluster reaching a maximum wind intensity of 1.5 could correspond to the damage that would have been produced by a single storm with a wind intensity of approximately 1.7–1.8.

Panels (i)–(l) of Figure 4 show the claim ratio predicted using V_{agg} as a function of that predicted using V_{max} , illustrating how the aggregation modifies the effective wind intensity. As expected, the claim ratio predicted using the aggregated wind is generally higher than that predicted from the maximum wind alone. The relationship between the two claim ratios is nonlinear, as the magnitude of the adjustment depends on the number and intensity of successive wind gusts within the cluster. For the Independent model, this adjustment is primarily determined by the number and rank of the successive wind events, whereas for the Powered Linear and Powered Exponential models it depends on their relative intensities. The higher claim ratios obtained after aggregation are consistent with the vulnerability curves presented in Figure 3, which show that *multiple-wind* damage grids exhibit higher claim ratios than single-storm damage grids for the same maximum wind intensity.

For the 4-day clustering case study, the results indicate that damage is not explained solely by the most extreme wind gust. Wind gusts from successive storms also contribute to the observed damage, even when their individual intensities are small compared to the maximum gust within the cluster. Using the optimal aggregation model therefore results in a higher effective wind intensity for clustered events and, consequently, higher expected damage than would be inferred from the maximum wind gust alone. This provides further evidence that successive wind exposures contribute to the occurrence and magnitude of damage during storm clusters.

Although the aggregation models improve the performance of the vulnerability curve over the *multiple-wind* damage grids, this raises the question of whether introducing an additional aggregation mechanism might reduce the overall performance of the vulnerability model. Indeed, when wind aggregation is included, the parameters of both the damage model and the wind aggregation model are optimised simultaneously (see Section 4.5 and 4.6). The results show, however, that introducing wind aggregation improves the fit over the full dataset, with a particularly marked improvement for *multiple-wind* damage grids. This indicates that the improved representation of compounded wind exposure does not come at the expense of the model’s ability to reproduce the overall relationship between wind intensity and damage.

2.4 Added value of the wind aggregation for all the cluster periods

Beyond the 4d-cluster case study, we assess the performance of the vulnerability model across different clustering periods and evaluate the added value of wind aggregation. Figure 5 compares the R^2 scores obtained using the maximum normalised wind (V_{max}) and the three wind aggregation methods, both for the full set of damage grids and for *multiple-wind* damage grids.

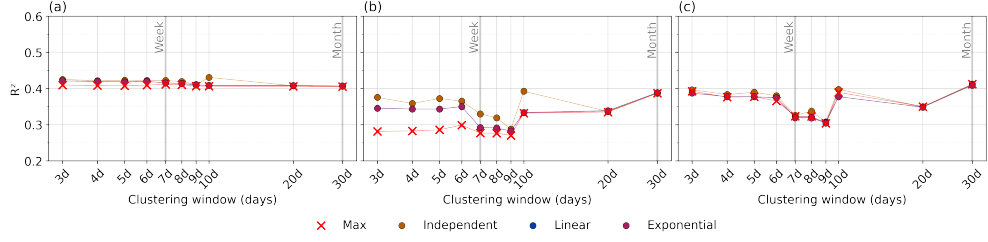


Fig. 5 R^2 scores as a function of the clustering period for different wind aggregation methods, shown by different colours. (a) R^2 obtained for all damage grids and evaluated over the same set of grids; (b) R^2 obtained for all damage grids and evaluated over the *multiple-wind* damage grids; and (c) R^2 obtained from curves fitted to and evaluated over the *multiple-wind* damage grids only.

Without wind aggregation, the performance of the vulnerability model over all damage grids remains relatively stable across clustering periods (Figure 5a). However, its performance when evaluated specifically on *multiple-wind* damage grids is consistently lower (Figure 5b). Importantly, Figure 5c shows that substantially higher R^2 scores can be obtained when the vulnerability model is fitted exclusively to *multiple-wind* damage grids. This indicates that the maximum normalised wind intensity remains a relevant predictor of damage, but that the relationship between wind intensity and claim ratio differs between *multiple-wind* and the other damage grids. In other words, the lower performance observed when applying the global vulnerability curve to *multiple-wind* damage does not necessarily result from a poor wind metric, but rather from a different damage response to a given wind intensity. This difference becomes less pronounced for longer clustering periods, partly because an increasing proportion of damage grids are classified as *multiple-wind* damage. Nevertheless, the persistently lower R^2 obtained when evaluating the global fit on *multiple-wind* damage confirms that $V_{\max}$ alone does not fully capture the damage response to successive wind exposures.

Introducing wind aggregation substantially improves the representation of *multiple-wind* damage (Figure 5b). Because the aggregated wind is identical to $V_{\max}$ for all damage grids that are not classified as *multiple-wind*, any improvement in the global R^2 results from a better representation of *multiple-wind* damage, without degrading the fit for the remaining points. Importantly, wind aggregation increases the R^2 for *multiple-wind* damage grids to values comparable to those obtained when the model is fitted specifically to these points (Figure 5c). This indicates that wind aggregation can largely account for the difference in damage response without requiring a separate damage model for *multiple-wind* events. The improvement is particularly pronounced for short clustering periods, for which the aggregated wind substantially increases the R^2 over *multiple-wind* damage. For clustering periods of up to approximately 6 days, the three aggregation approaches improve the performance of the fit, suggesting that accounting for successive wind exposures largely reconciles the difference in the damage response between *multiple-wind* and single-storm events.

For longer clustering periods, the benefit of wind aggregation becomes progressively smaller. Although aggregation continues to improve the representation of *multiple-wind* damage, the increase in R^2 is more limited for clustering periods of 10 days and longer. In particular, the Linear and Exponential wind aggregation models provide little or no improvement for clustering periods of 10–30 days. This suggests that, as the clustering window increases, the damage response becomes increasingly dominated by the most intense wind event within the cluster, reducing the additional explanatory value of weaker wind resulting from the successive storms.

The relative performance of the aggregation methods also changes with the clustering period. While the three approaches perform similarly for short clustering windows, the Independent wind aggregation increasingly outperforms the Linear and Exponential formulations for periods of 10 days and longer. This result, also observed in the 4d-cluster case study, suggests that the relative ordering of successive wind intensities provides relevant information for characterising compounded damage, particularly as the number of storms included within a cluster increases.

Overall, these results demonstrate that wind aggregation provides a consistent improvement in the representation of damage from successive storm events. The effect is strongest for short clustering periods, when the contribution of successive storms is most clearly expressed in the observed damage, while the diminishing improvement for longer periods indicates an increasing dominance of the most intense wind event.

3 Discussion

In this study, we explored the effects of temporally clustered windstorms on vulnerability curves. When several storms affect the same area, the damage caused by a subsequent event depends not only on its wind intensity but also on the damage produced by antecedent events and the time elapsed between successive storms [37]. Therefore, the effects of storm clustering depend on the intensity of individual events and the time elapsed between them.

To account for the effects of successive intense winds within clustered events, we introduced a metric that aggregates wind gusts from successive storms and evaluated its ability to predict the claim ratio. Our results show that, at a given location, successive storms are associated with greater damage than would be expected from the maximum wind gust alone. This finding is consistent with previous studies showing that serial clustering can amplify cumulative seasonal losses and affect insurance and reinsurance risk estimates [24, 29, 45].

The increase in expected damage is particularly pronounced for short clustering periods, with the strongest effect observed for periods shorter than 7 days. This interval is consistent with the timescale over which buildings may recover from damage caused by an initial windstorm. A limited recovery period between successive events could therefore contribute to the larger number of buildings affected by closely spaced windstorms compared with what would be expected from the maximum wind gust alone. Conversely, we find little further improvement in damage prediction when the clustering period exceeds approximately 10 days. This is consistent with the 8–10-day period over which storm vulnerability was found to stabilise in Germany [37].

691 Together, these results suggest that recovery processes may help explain the temporal
692 window over which successive windstorms influence observed vulnerability.

693 Results also suggest that the prediction of claim ratio is improved when using an
694 aggregated wind metric rather than relying solely on the maximum gust across suc-
695 cessive storms. The proposed metric is identical to the maximum gust for isolated
696 events, thereby retaining the conventional interpretation of single-event hazard mea-
697 sures, while also capturing the cumulative intensity and persistence of wind exposure
698 during clustered events. It therefore provides a simple extension of existing windstorm
699 metrics for representing additional damage potential associated with storm clustering.

700 Nonetheless, these improvements should be interpreted in light of the challenges
701 associated with calibrating windstorm vulnerability curves. Claim ratios reconstructed
702 from wind-gust information alone remain highly variable, reflecting several intrinsic
703 characteristics of insured windstorm losses.

704 First, the damage distribution is strongly skewed: a small number of severe events
705 account for a disproportionate share of total damage [34, 39, 40]. Consequently, no
706 single vulnerability curve is optimal for all applications; the appropriate calibration
707 depends on the intended use of the model. Optimising the RMSE on the original claim
708 ratio scale, as done in this study, assigns greater weight to large absolute errors and
709 consequently gives more influence to events with the highest damage levels [15, 34, 41].
710 This is appropriate when the primary objective is to reproduce extreme damage levels,
711 but it can result in curves that overestimate damage or poorly represent more fre-
712 quent moderate claim ratios. Alternative approaches optimise a probabilistic damage
713 model and explicitly represent the conditional distribution of claims [46, 47]. Another
714 possibility is to minimise the RMSE after logarithmic transformation, which reduces
715 the influence of extreme observations and gives greater weight to the bulk of the claim
716 ratio distribution [41]. Such a transformation must nevertheless be handled carefully
717 in the presence of zero or very small claim ratios and may under-represent the upper
718 tail. The choice of calibration criterion should therefore reflect the intended applica-
719 tion, whether the objective is to estimate average damage, reproduce moderate claim
720 ratios, or quantify extreme damage.

721 Second, claim ratios depend not only on peak wind intensity but also on the spatial
722 footprint of the storm, the characteristics of the exposed buildings, and the composi-
723 tion of the insured portfolio [48, 49]. In this study, claims are aggregated to the ERA5
724 grid to reduce sampling noise and smooth local variations in exposure. Neverthe-
725 less, building characteristics are spatially heterogeneous across France and remain an
726 important source of variability in observed losses [50, 51]. Future work could stratify
727 the analysis according to vulnerability-related attributes (e.g. roof type, wall mate-
728 rial, floor area, elevation or vegetation) to assess whether the influence of successive
729 storms varies across different categories of buildings.

730 Finally, the vulnerability curves derived in this study are calibrated using claims
731 from the Generali France portfolio and should therefore be interpreted within this spe-
732 cific exposure context. Although Generali France insures properties throughout the
733 country, its portfolio represents only a subset of the national building stock. Applying
734 the same methodology to other insurers or countries would likely yield different vulner-
735 ability curves because of differences in exposure, building characteristics, and claims
736

management practices. Furthermore, even over the 27-year study period, only a limited number of locations experienced successive high-intensity wind gusts at the ERA5 resolution. This limited sample restricts our ability to robustly constrain vulnerability changes associated with repeated storm impacts. Future work using larger insurance portfolios, higher-resolution hazard datasets, or multi-country analyses could help determine whether this scarcity primarily reflects the limited observational sample or stems from physical dynamics of successive storms.

Despite these limitations, the proposed framework modifies the representation of the hazard rather than relying solely on adjustments to the vulnerability curve. By accounting for the cumulative effects of successive storms within the hazard metric itself, the approach is not tied to a specific vulnerability curve and could therefore be applied to other portfolios or countries following appropriate calibration.

More broadly, these results suggest that temporal compounding can be incorporated directly into catastrophe models, providing a physically interpretable framework that remains compatible with existing vulnerability modelling approaches. This could improve the estimation of extreme losses from successive storms, particularly when multiple events affect the same exposure within a short period. More accurate estimates of these losses could, in turn, inform reinsurance decisions by distinguishing the coverage needed for isolated extreme storms from that required for temporally clustered events and storm sequences. Accounting for these temporal dependencies at the portfolio level could therefore support more consistent loss aggregation, event definitions, and the design of reinsurance coverage.

4 Methods

4.1 Claim Data

All analyses are conducted on the Generali IARD (Property and Casualty) portfolio, with a focus on property insurance and, more specifically, multi-risk home insurance (MRH). Only claims declared between the 1st October and the 31st March are retained, as these correspond to the extended winter season. Commercial and industrial risks are excluded, as residential insurance constitutes the largest share of Generali's damage portfolio and provides a more representative and comprehensive loss record. All monetary values are detrended using the FFB construction cost index [52]. This indicator, specific to France, monitors the variation of different factors that can influence building cost (materials, labour, taxes, etc.). This index is used in the insurance sector to adjust premiums and claim reimbursements, and thus appropriately captures temporal changes in both exposure and losses.

Generali France's property and casualty claims portfolio over the period 1998–2026 is used as the impact dataset. Generali's market share in the French residential insurance sector is estimated at approximately 4% [53], corresponding to about one million contracts. Given that residential property insurance coverage in France approaches 99% [54], this dataset provides a representative sample of storm-related residential losses (see Supplementary). The analysis focuses on windstorm claims occurring during the extended winter season (October–March). Each claim includes the location of the insured property, the claim declaration date, and the reported date of damage. The

reported date of damage is used as the claim date (d_{claim}), acknowledging that it may differ from the actual occurrence date of the hazard [32, 55]. Loss severity is quantified using the net insured loss after application of deductibles and coverage limits. Claims with zero or negative insured losses are excluded. At the time of extraction, claims are classified according to their processing status as *closed*, *open*, or *out of order*. Closed claims correspond to losses that have been validated as resulting from the insured hazard and which have been reimbursed. Open claims are claims for which the damage assessment process is still ongoing, either because the cause of damage has not yet been confirmed or because the repair costs have not been fully assessed. Claims classified as *out of order*, which are unrelated to the hazard of interest, are excluded from the analysis. The dataset was extracted on May 1st, 2026 and contains approximately 4% open claims, primarily associated with events occurring during March–April 2026. After filtering, the final dataset contains approximately 130 000 entries.

4.2 Exposure Data

Exposure is estimated from Generali France’s residential insurance (MRH) portfolio. Policy-level information is disaggregated to the site level, acknowledging that a single policy may cover multiple properties (e.g., a primary residence and outbuildings) located at different addresses. This disaggregation provides a more precise spatial representation of the insured portfolio. Over the period 1998–2026, the portfolio contains approximately 5.6 billion policy records. However, the quality of the recorded address information varies across sites. Among these, 245,788 sites ($\approx 0.9\%$) have neither an address nor a postal code and are therefore excluded from the analysis.

The site-level exposure is subsequently aggregated per year onto the ERA5 grid, providing a common spatial framework for the exposure and hazard fields. For each year, the mean number of insured sites is estimated by accounting for the duration of each policy’s activity during the year. For a given site, the number of insured days is equivalent to the period during which the corresponding policy is active. These durations are summed over ERA5 grid and divided by the mean number of days in a year ($= 365.25$), yielding the equivalent number of insured buildings. This approach accounts for policies that are active for only part of a year and provides an estimate of the mean number of insured sites at each ERA5 grid cell and for each year. The temporal and spatial evolution of the exposure is further illustrated in the Supplementary.

The claim ratio (CR) at the ERA5 grid-cell level is defined as the ratio between the number of claims (n_{claims}) and the number of insured buildings (n_{insured}). For a storm event s at location x , it is given by $\text{CR}(x, s) = \frac{n_{\text{claims}}(x, s)}{n_{\text{insured}}(x, s)}$. Few studies have reported CR at such a fine spatial resolution. At national scales, typical values range from 10^{-8} to 10^{-2} [34, 39, 41], whereas policy-level studies report loss ratios ranging from 10^{-6} to 10^{-2} [15, 32, 37]. At the ERA5 grid-cell scale, the observable range of CR is strongly constrained by the local exposure. In particular, a grid cell containing fewer than 1,000 insured buildings cannot exhibit a non-zero CR smaller than 5×10^{-2} , as a single claim already corresponds to a CR of 1/500.

To avoid over-representing grid cells with limited exposure, while retaining most of the available damage observations, we exclude grid cells containing fewer than 500

insured buildings from the analysis. This filtering removes about 7000($\approx 35\%$) of damage grids, corresponding to a total of 25 000($\approx 21\%$) claims.

4.3 Storm catalog

Storm events are identified over the period 1997–2026 using the ERA5 dataset [56]. ETC tracks are detected using the TRACK algorithm [57, 58], which identifies local maxima of the 850 hPa vorticity field (ζ_{850}) truncated at the spectral resolution T42. Detected ETCs are further filtered by requiring a maximal vorticity exceeding 10^{-5} s^{-1} , a minimum track length of 1000 km and a minimum lifetime of 24 h. We define the storm date (d_{storm}) as the date at which the location of ζ_{850} is closest to the 7.5°W meridian. This date, together with the coordinates of this point of closest approach, is used to uniquely define storm events. For example, a storm for which the ζ_{850} track point is the closest to the 7.5°W meridian on 26 December 1999 at 12:00 UTC, at the coordinate ($-10.8^\circ\text{W}; 51.6^\circ\text{N}$), will be labelled as “1999-12-26 12h [-4.2; 51.5]”. This naming convention uniquely identifies storms, even when multiple storms crossed the 7.5°W longitude on the same date. Storm footprints are defined using the maximum 10 m wind gust field expressed in m s^{-1} , masked within a radius of 1300 km around each cyclone centre identified from the vorticity tracks. For each tracked position, retained values correspond to the maximum wind gust occurring within a temporal window of ± 12 h. This temporal window accounts for delayed wind gusts relative to the cyclone centre, while the spatial masking captures damaging winds occurring far from the vorticity maximum, notably along frontal structures, and limits the inclusion of wind gusts associated with other storm systems. The temporal windows, smaller than the 72 h window commonly used for defining storm footprints [8, 30, 31, 41] together with the spatial mask, enable wind footprints from closely successive storms to be distinguished.

We associate the insurance claims with windstorm events using storm trajectories and footprints [28]. This approach corrects potentially erroneous claim dates and assigns each claim to the storm producing the strongest local wind gust at the affected location. We apply the same parameter configuration, while restricting the analysis to the subset of MRH policies described in Section 4.1 [28]. We additionally perform a reassignment procedure to ensure that claim locations are effectively located within the corresponding storm footprints. Over the period 1997–2026, we identify 339 storms associated with at least one impact.

4.4 Clusters of storms and temporal compounding

We define storm clusters as sequences of at least two ETCs associated with observed damage and for which the storm dates (d_{storm}) are separated by less than a given sliding temporal window. We consider a range of clustering windows spanning synoptic to seasonal timescales, from a few days to a month. Specifically, we analyse windows of 3, 4, 5, 6, 7, 10, 20, and 30 days. This captures both short-duration clustering with successive storms possibly interacting and longer periods mainly dominated by a major event. For notation, we write Dd -cluster for a cluster of storms which has been

875 computed using the temporal window of D days. A cluster defined with a $D = 3$ days
876 clustering period will thus be referenced as a $3d$ -cluster.

877 To ensure physical separation between ETC events, footprints are spatially decon-
878 taminated using a circular radius of influence centred on each storm track, thereby
879 isolating the wind gusts associated with individual storms, as described in Sec. 4.3.
880 Decontamination ensures that the intense wind gusts within a given storm footprint
881 are attributed exclusively to that storm and are not contaminated by gusts gener-
882 ated by other ETCs occurring nearby in space and/or time [31]. Although each claim
883 is attributed to the storm producing the maximum local wind gust, other storms
884 within the same cluster may also generate substantial winds, potentially increasing
885 the likelihood of damage at the same location.

886 By concatenating the decontaminated footprints of all storms belonging to the
887 same cluster, we reconstruct, for each location, the sequence of maximum wind gusts
888 associated with successive storms. Duplicate wind gust values and missing values, cor-
889 responding to locations lying outside the footprint of a given storm, are removed. For
890 example, during the cluster of December 1999, the location of Paris (2.25°W ; 48.75°N)
891 is associated with the wind-gust sequence $[30, 37, 21] \text{ m s}^{-1}$, where the value corre-
892 sponds respectively to the maximum wind gust generated by storm Kurt[59], storm
893 Lothar[1, 3] and storm Martin. In such cases, each storm event produced intense wind
894 gusts in Paris locations, but this is not always the case. For example, Perpignan
895 (2.75°W ; 42.5°N) is associated with the wind-gust sequence $[19, 0, 0] \text{ m s}^{-1}$ during
896 the same cluster, indicating that only one of the storms produced intense winds at
897 this location, while the storm tracks of the other events were too distant to affect the
898 location.

899 We define *multiple-wind* damage grids as damage grids located within the overlap-
900 ping footprints of successive storms and therefore associated with a sequence of wind
901 gusts from multiple storms. This distinction is important because clusters are defined
902 purely according to the temporal proximity of storms and do not necessarily imply
903 that the same location is affected by all storms within the cluster. Consequently, the
904 occurrence of a storm cluster does not necessarily result in *multiple-wind* damage. This
905 framework allows us to quantify the extent to which individual locations are repeat-
906 edly affected by successive windstorms within clusters of different durations and to
907 assess the contribution of temporal compounding to overall damage.

908 The term "event" refers either to a single storm occurring independently or to a
909 cluster considered as a single aggregated event, encompassing all of its constituent
910 storms.

911

912 4.5 Vulnerability curves

913

914 Vulnerability curves quantify expected damage by relating either the number of claims
915 or the intensity of the losses to the hazard intensity. We use the CR introduced in 4.1
916 as the proxy for damage.

917 For ETCs, the intensity of the wind gust represents the major threat for the
918 infrastructure. Hence, windstorm vulnerability curves are typically derived from local
919 maximum wind gusts, from wind gusts normalised by local climatological quantiles
920 [34, 60] or aggregation as broader scale with the Storm Severity Index (SSI)[38]. The

SSI accounts for the local climatology by normalising wind gusts with a high percentile of the wind distribution. For a storm s at location x , the SSI is defined as

$$\left(\frac{v(x, s)}{v_{98}(x)} - 1\right)^3 \quad \text{if } v(x, s) \geq v_{98}(x), \quad (1)$$

where $v_{98}(x)$ denotes the 98th percentile of the daily maximum wind gust at location x .

To evaluate the sensitivity of the vulnerability model to the choice of hazard predictor, we compare models based on the local maximum wind gust with models using normalized wind gusts computed relative to the 90th, 95th, and 98th percentiles of the local wind climatology. The best-performing model is obtained using the ratio with respect to the 90th percentile (see Supplementary). We consequently denote the new wind vector by V and refer to it as the *normalised wind*, defined as

$$V(x, s) = \frac{v(x, s)}{v_{90}(x)}. \quad (2)$$

Several formulations of the vulnerability function are evaluated (see Supplementary), based on functional forms commonly used in the literature [34, 38, 61]. Among the formulations tested, the function providing the best regression performance is retained for the remainder of the analysis. This formulation is inspired by the Weibull function [62, 63] and is defined as

$$\text{CR}(x, s) = L_{max} \left(1 - e^{-\left(\frac{V(x, s)}{l}\right)^k}\right). \quad (3)$$

The selected formulation follows a Weibull-type function, which describes the progressive increase in the claim ratio with wind speed. The function is bounded by L_{max} and approaches this value asymptotically as wind speed increases. The scale parameter l controls the wind-speed range over which the claim ratio increases, while the shape parameter k determines the rate and curvature of this increase. At low wind speeds, the function remains close to zero, before increasing progressively and eventually approaching L_{max} at high wind speeds. To avoid attributing damage to very low wind speeds, the function is thresholded below a minimum wind-speed value.

4.6 Wind aggregation methods

During storm clusters, a given location may experience strong wind gusts from multiple successive storms, potentially resulting in *multiple-wind* damage. Standard vulnerability curves typically consider only the maximum wind gust observed over the full duration of a cluster and do not account for the other storms which have affected this location during the cluster of storms. We introduce a wind aggregation that considers not only the maximum gust but also all the wind gusts occurring from the several storm events of the cluster.

967 We define the aggregated wind at location x for a cluster of storms $\mathcal{C}$, denoted
 968 $V_{\text{agg}}(x, \mathcal{C})$, as:

$$969 \quad V_{\text{agg}}(x, \mathcal{C}) = \left(\sum_{s \in \mathcal{C}} \alpha(s) V(x, s)^p \right)^{1/p} \quad (4)$$

970 where $V(x, s)$ denotes the wind vector intensity of the s storm, part of the cluster $\mathcal{C}$,
 971 at location x and $\alpha(s)$ are weighting coefficients representing the relative contribution
 972 of each gust. The coefficient p is introduced to mimic the power usually introduced
 973 in the computation of the SSI. The coefficients α_s together with the power p are
 974 optimised at the same time as the optimisation of the coefficients of the vulnerability
 975 curve (L_{max}, k, l) introduced in section 4.5

976 The coefficients α_s quantify the contribution of wind gusts from storm events other
 977 than the event associated with the locally maximum wind gust to the total claim ratio.
 978 They are estimated jointly across all temporally compounded points, together with
 979 the optimisation of the vulnerability curve parameters. Depending on the selected
 980 aggregation method, the weights may be defined either as a function of the event rank,
 981 ordered by decreasing local maximum wind gust intensity, or as a function of the ratio
 982 between the local maximum wind gust of each event and the maximum local wind
 983 gust reached over the entire cluster. During the optimisation of the coefficients α_s , we
 984 impose the constraint that the most intense wind gust within each cluster is assigned a
 985 weight of one, while the weights associated with less intense events decrease according
 986 to their intensity rank or their ratio to the cluster maximum wind gust.

987 We consider several aggregation schemes for the decay of the weights:

- 988 • Linear decay :

989 The coefficients are defined as:

$$990 \quad \alpha(x, s) = 1 - m \left(1 - \frac{v(x, s)}{v_{\text{max}}(x, \mathcal{C})} \right), \quad (5)$$

991 where m is a slope parameter controlling the rate of decrease. Negative coefficients
 992 are not permitted and are set to zero. Larger values of m lead to a steeper decline in
 993 weights. In the limit $m \rightarrow \infty$, the formulation converges towards a maximum-only
 994 wind representation.

- 995 • Exponential decay.

996 The coefficients are given by:

$$997 \quad \alpha(x, s) = \exp \left(-d \left(1 - \frac{v(x, s)}{v_{\text{max}}(x, \mathcal{C})} \right) \right), \quad (6)$$

998 where d controls the rate of exponential decay. This formulation yields a smooth,
 999 nonlinear down-weighting of sub-maximal gusts, where contributions decrease as
 1000 wind intensity departs from the cluster maximum. For wind gusts close to the
 1001 maximum intensity, i.e. $v(x, s) \approx v_{\text{max}}(x, \mathcal{C})$, a first-order Taylor expansion of the
 1002 exponential term leads to a linear decay, recovering the formulation introduced in
 1003 5. The parameter d controls the sensitivity to weaker gusts, with larger values of d
 1004 increasingly isolating the dominant events.

- Independent scheme. n parameters $(\alpha(s_1), \dots, \alpha(s_1))$ depending on the maximum number of storms in the cluster $\mathcal{C}$.

In this approach, the coefficients $\alpha(s)$ are estimated independently for each event rank, without assuming a predefined functional relationship between the weight and the wind intensity. The number of coefficients to optimise thus depends on the maximum number of storms that can be present in an Dd -cluster. For short durations, such as the $3d$ -cluster, this will correspond to 3 coefficients, while for longer periods, such as the $30d$ -cluster, it can increase to 6 coefficients. The coefficients are constrained to $[0, 1]$, with the most intense windgust, ranked first locally, assigned a weight of one. Unlike the linear and exponential decay schemes, this formulation does not impose any assumption on how the contribution of sub-maximal gusts decreases with intensity. It therefore provides a flexible framework to assess whether the relative contribution of successive gusts is governed by intensity alone or by additional effects such as repeated exposure to multiple wind events.

The coefficients of the aggregated wind models are optimised simultaneously with the parameters of the vulnerability curves. The optimisation aims to minimise the Root Mean Square Error (RMSE) between the observed and predicted CR. In practice, this involves jointly estimating the 3 parameters of the vulnerability curves (Section 4.5) together with the aggregation coefficients described in Section 4.6. The choice of optimisation metric strongly influences the interpretation of the resulting model [34, 41]. By minimising the RMSE, larger prediction errors are penalised more heavily, giving greater weight to accurately representing the most damaging events. This is particularly appropriate in the present context, as the largest insurance losses are typically associated with storm clusters [28].

Simultaneous optimisation of the wind aggregation and vulnerability model parameters accounts for the behaviour of temporally compound damage through two mechanisms. First, the relationship between the claim ratio and the maximum normalised wind alone may not adequately represent locations affected by multiple storms. The aggregated wind models address this limitation by incorporating the contribution of successive wind events into a single hazard metric. Second, even after aggregation, the functional relationship between the aggregated wind and the expected claim ratio may differ from that of the maximum-wind model. Joint optimisation of the vulnerability curve parameters allows this relationship to adapt accordingly, ensuring that both the hazard metric and the damage function are calibrated consistently.

All model fits are performed using a bootstrap procedure with 1,000 runs. The confidence intervals reported throughout the analysis are derived from the resulting bootstrap distributions.

Supplementary information

The article contains supplementary files.

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1066

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1068

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1072

1073

1074 Conflict of interest

1075 The authors declare no conflicts of interest.
1076

1077

1078 Ethics approval and consent to participate

1079

1080 Not applicable

1081

1082 Data availability

1083 ETC tracks were provided by Matthew Priestley. ERA5 data is openly available in
1084 Copernicus Climate Change Service Climate Data Store at [10.24381/cds.bd0915c6](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels)
1085 (Copernicus Climate Change Service, 2026). Generali claims datasets analysed in the
1086 current study are not publicly available as they are proprietary to the company.

1087

1088 Materials availability

1089

1090 Not applicable

1091

1092 Code availability

1093

1094 Code and scripts are available at the following link: [10.5281/zenodo.23009348](https://zenodo.org/record/23009348).

1095

1096 Author contribution

1097

1098 LH: Conceptualisation, Methodology, Software, Validation, Formal analysis, Data
1099 Curation, Writing – Original Draft; Visualisation; PY: Conceptualisation, Supervision,
1100 Writing – Review and Editing; QH: Conceptualisation, Supervision, Data Curation

1101

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