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Temporal dynamic vulnerability - Impact of antecedent events on residential building losses to wind storm events in Germany

Andreas Trojand[1], Henning W. Rust[1,2], and Uwe Ulbrich[1]

[1]Institute for Meteorology, Freie Universität Berlin, Carl-Heinrich-Becker Weg 6-10, 12165 Berlin
[2]Hans Ertel Centre for Weather Research, Carl-Heinrich-Becker Weg 6-10, 12165 Berlin

Correspondence: Andreas Trojand (andreas.trojand@fu-berlin.de)

Abstract.

Severe winter storm events are one of Central Europe's most damaging natural hazards, therefore particularly in focus for disaster risk management. One key factor for risk is vulnerability. Risk assessments often assume vulnerability as constant. This is, however, not always a justifiable assumption. This work seeks and quantifies a potential dynamic of vulnerability for residential buildings in Germany. A likely factor affecting the dynamics of vulnerability is the hazard itself. As an extreme events may destroy the most vulnerable elements, it is likely that the subsequent rebuilding or repair will reduce their vulnerability for following events. Therefore, the intensity of the previous events and the resulting damage can be assumed to be a decisive factor in changing vulnerability. A second important factor is the time period between the previous and current event. If the next event occurs during the reconstruction phase, vulnerability might be higher than when the reconstruction phase is completed.

We analyze the role of previous storm events for the vulnerability of residential buildings. For this purpose, generalized additive models are implemented to estimate vulnerability as a function of the intensity of the previous event and the time interval between the events. The damage is extracted from a 23-year-long data set of the daily storm and hail losses for insured residential buildings in Germany on the administrative district level provided by the German Insurance Association, and the hazard component is described by the daily maximum wind load calculated from the ERA5 reanalysis. The results show a negative relationship between the previous event's intensity and the current event's damage. The duration between two events shows a significant reduction of the damage for events occurring one or more winter seasons ago compared to events occurring within the same season. On a daily scale, the first five to ten days are especially crucial for vulnerability reduction.

1 Introduction

Severe windstorm events resulting from extratropical cyclones significantly impact economic losses in Central Europe. Although individual natural disasters, such as the flash flood that occurred in western Germany in July 2021 or the Elbe flood in 2002, are the most devastating single events, the accumulated damage from storm events caused three times more damage to residential buildings than other natural disasters between the years 2002 and 2021 (GDV, 2023). The impact on human life is relatively small, and the damage to individual buildings is generally moderate. Nevertheless, the frequency of windstorm

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events coupled with spatial expansion leading to a significant number of insurance claims and results in overall high losses (Sparks et al., 1994; MunichRe, 2023). Therefore, risk assessment plays a crucial role in the analyses of recent and predicting the impact of future events. Here we define risk as a function of hazard, exposure, and vulnerability (e.g. UNDRO, 1980; UNDRR, 2021; IPCC, 2022).

Extensive research has been conducted on storm events in Western European countries due to their significant impact. Klawa and Ulbrich (2003) developed a storm loss index based on the assumption that the loss grow with the cube of normalised gust intensity in excess of the 98th percentile threshold, which was adapted among others by Pardowitz et al. (2016) for probabilistic prediction of wind storm damages. Röösli et al. (2021) utilized ensemble weather predictions for forecasting winter storm impacts in Switzerland. The scale for the damage models ranges from regional (Donat et al., 2010) over federal states (Heneka et al., 2006) to Europe-wide models (Koks and Haer, 2020). In several publications return periods have been calculated (e.g. Heneka and Hofherr, 2011; Donat et al., 2011a) and expected future changes due to climate change have been investigated (e.g. Dorland et al., 1999; Schwierz et al., 2009; Donat et al., 2011b).

While all of these studies use different approaches to model recent and future impacts, they all assume vulnerability being constant in time, which has been critized among others by Aerts et al. (2018); Cremen et al. (2022). To improve disaster risk assessments, understanding vulnerability and its potential changes remains a critical point (Formetta and Feyen, 2019). Vulnerability is defined as the condition determined by physical, social, economic, and environmental factors or processes that increase the susceptibility of an individual, a community, assets, or systems to the impacts of hazards (UNDRR, 2021). All these conditions change over time and thereby change the vulnerability. Assuming static vulnerability may lead to over- or underestimation of risk (Aerts et al., 2018; de Ruiter and van Loon, 2022). After an event, existing risk assessments rapidly become outdated as the vulnerability changes due to the event itself (Gill and Malamud, 2016). Therefore, many studies advocate for a dynamic approach (e.g. Papathoma-Köhle et al., 2012; Di Baldassarre et al., 2018). This study aims to detect and quantify the temporal dynamics of the physical vulnerability of residential buildings in Germany due to windstorm events. The physical vulnerability is derived by vulnerability curves describing the relationship between intensity of the windstorm event and the resulting damage.

In the field of disaster risk management, temporal dynamic vulnerabilities can be categorized into two groups. The first group pertains to underlying dynamics such as an increase in gross national product, technical progress, long-term deterioration of buildings (Stewart et al., 2011, 2012) or lack of maintenance (Orlandini et al., 2015). These general changes also arise even if no hazard occurs and therefore can be described as non-hazard specific dynamics (de Ruiter and van Loon, 2022; Fuchs and Glade, 2016). Non-hazard specific dynamics are in general not included in risk assessments (Simpson et al., 2021; Drakes and Tate, 2022). The second group involves dynamics due to the hazard itself, which can be further divided into two subgroups. The most common idea is “build back better” (UNISDR, 2017), which refers to the recovery phase in the aftermath of an event. During this phase, there is the opportunity to not just restore the pre-event status, but to reduce vulnerability by improving the construction to future events. Nikkanen et al. (2021) found that people who suffered from experience of earlier storm impacts were more likely to prepare and thereby reduced the risk. After very severe events, there have been cases of an imposed change in building standards (Stewart, 2003; Walker, 2011; Stewart, 2013). Stewart and Li (2010) investigated changes in vulnerability

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due to a new home building code for Queensland, Australia, showing a decrease in vulnerability due to enhanced building standards. In different case studies reduction in vulnerability due to previous events could be shown for other hazard types (e.g. Kreibich et al., 2017; Becker et al., 2017; Kreibich et al., 2023). These studies lack, however, the inclusion of the intensity of previous events and a more holistic approach, even though the intensity of the previous event is likely to substantially effect the amount of reduction in physical vulnerability. The assumption is that most vulnerable buildings get damaged, as a consequence reconstructed better and thereby are less vulnerable to the next event. Therefore the first research objective of this study is to quantify the effect of the intensity of antecedent events on the changes of vulnerability.

The second type of dynamics of vulnerability due to hazard impacts is the changes in vulnerability during consecutive or compound events (Clark-Ginsberg et al., 2018). Latter is outside of the study's scope as we are restricting ourselves to effects of one hazard type. Consecutive events can lead to more significant damage than isolated events (Marzocchi et al., 2012; Gill and Malamud, 2014; Aerts et al., 2018; de Ruiter et al., 2020), whereas the time between two events can substantially change the vulnerability to the second event (Gill and Malamud, 2014; de Ruiter et al., 2020). The time between two events is crucial for winter storm events in Germany as these occur in a short amount of time more often than other hazards. For example, wind storm series Ylenia, Zeynap, and Antonia occurred within a few days in February 2022 (Mühr et al., 2022). In cases where significant time is between the two events, the vulnerability might decrease due to preparedness (Gill and Malamud, 2016). Rathfon et al. (2012) state that the speed of housing recovery processes after an event has not been described quantitatively, but as the recovery of the housing sector is crucial to the overall post-disaster community recovery, an in-depth analysis is necessary. Therefore, the second research objective of this study is to quantify the impact of the time between two events on the dynamics of vulnerability.

The data used for both research objectives are described in detail in section 2, before in section 3 the definition of the events and previous events is explained. The subsequent section on methods describes generalized additive models used to quantify the effects. In section 4 the results from the different models are shown and discussed in section 5, followed by the conclusion in section 6.

2 Data

Two data sets are used to quantify the temporal dynamic vulnerability of residential buildings in Germany due to windstorm events. The first data set, provided by the German Insurance Association (Gesamtverband der deutschen Versicherungswirtschaft - GDV), contains information about the loss and the exposure of residential buildings. The ERA5 data from the European Centre for Medium-Range Weather Forecasts (ECMWF) is used for the meteorological part of the analysis.

2.1 Insurance Data

The GDV provided a 23-year-long data set on insured losses for residential buildings in Germany. These records contain losses, the number of claims on a daily basis, the insured sum, and the number of contracts accumulated on the administrative district level from 1997 to 2019. The dataset comprises losses incurred solely from storm and hail events. To exclude hail events,

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the study limits its scope to the winter half year, spanning October through March. In these months, the damage is almost exclusively caused by windstorm events. Furthermore we define the loss ratio as

$$\text{loss ratio} = \frac{\text{total loss in €}}{\text{insured sum in } 10^3\text{€}}. \tag{1}$$

Using the loss ratio has three advantages: First, with the total insured sum, the exposure and its temporal changes is included in the modelling approach. Second, division by the insured sum adjusts for inflation. Last, with the standardization, the administrative districts, which have different sizes from about $35\mathrm{km}^2$ for urban municipalities ("Kreisefreie Städte") up to about $4500\mathrm{km}^2$ for rural districts ("Landkreise") and different building densities are comparable.

2.2 Meteorological Data

For the hazard component of the model, the ERA5 Reanalysis data, produced by the ECMWF, are employed, which is based on 4D-data assimilation and the model forecasts in CY41R2 Integrated Forcast System (ECMWF, 2016). The ERA5 data has a spatial resolution of $31\mathrm{km}$ for the hourly realization of analysis and short forecasts (18 hours).

Most studies working on impacts of wind storm events use the maximum wind gust (e.g. Dorland et al., 1999; Heneka and Hofherr, 2011; Pardowitz, 2015) as the hazard component. In this study however the daily maximum wind load

$$q = \frac{\rho}{2} v_{\text{gust}}^2 , \tag{2}$$

is used, including v_{gust} being the maximum daily wind gust and the air density ρ at the hour of the daily maximum wind gust. As the air density is not included in the ERA5 data, it is calculated based on the surface pressure and temperature in $2\mathrm{m}$ height. The wind load was chosen over the wind gust, as the wind load also takes the orography due to the air density in account. The conversion from wind speed to wind load under physical standard condition for the classification of the Beaufort scale is shown in table 1.

Table 1. Wind load according to the Beaufort scale (WMO, 1970) and corresponding wind speed under physical standard conditions of 0C and $1013.25\mathrm{hPa}$ air pressure.

Beaufort	Description	Wind speed	Wind load
8	Gale	17.2 - $20.7\mathrm{m/s}$	191 - $278\mathrm{N/m}^2$
9	Strong gale	20.8 - $24.4\mathrm{m/s}$	279 - $386\mathrm{N/m}^2$
10	Storm	24.5 - $28.4\mathrm{m/s}$	387 - $523\mathrm{N/m}^2$
11	Violent storm	28.5 - $32.6\mathrm{m/s}$	524 - $688\mathrm{N/m}^2$
12	Hurricaneforce	$\geq 32.7\mathrm{m/s}$	$\geq 689\mathrm{N/m}^2$

For the assignment of the meteorological data to the insurance data, a $31\mathrm{km}$ buffer was calculated around each district in a first step. In the second step, all grid points of the ERA5 grid that were located within the calculated area were assigned to this

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district and the maximum of the grid points was selected for each day and assigned to the district for further evaluation. The buffer of $31\mathrm{km}$ was selected so that at least four ERA5 grid points could be assigned to each district.

115 3 Methods

Events and previous events are defined in 3.1, followed by the regression approach using generalized additive models and the resulting model setups.

3.1 Definition of Event and Pre-Event

We follow the rules of homeowner insurance in Germany (Wohngebäudeversicherung (GDV, 2022)): An event is defined by
120 wind speeds of at least $17.2\mathrm{m/s}$ (Beaufort scale 8 (WMO, 1970)). For this study, we use this threshold for the daily maximum ERA5 wind gust data. If consecutive days exceed this threshold, these days are considered as belonging to one event with the maximum wind load of these days assigned to it; the associated damage is accumulated over the event days. As a consequence there is always at least one full day between events on which the threshold value is not exceeded. Figure 1 shows the distribution of the events with an exponential increase of loss ratio with increasing wind load.

125 The definition of a pre-event is different: It is assumed that minor damage will not have a significant impact on the entire administrative district for the next event, as loss ratio is accumulated over the entire area. Therefore, a threshold of loss ratio is used instead of an excess wind speed threshold. A prior event is defined as a loss ratio exceedance of 0.01‰ (Figure 1 - red line) in the same administrative district as the occurrence of the event.

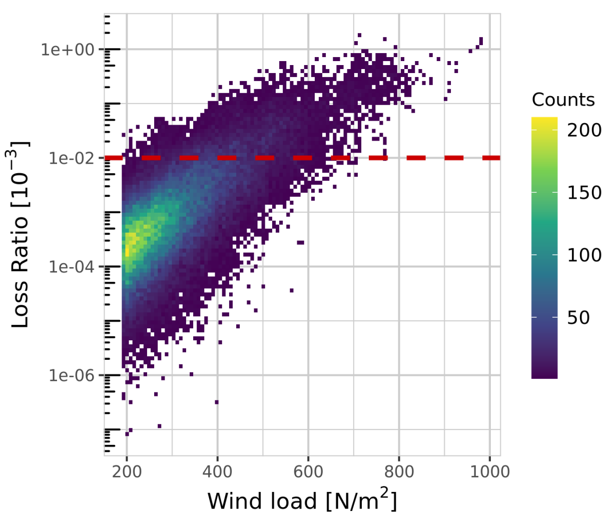

Figure 1. Counts of events with wind loads and the related loss ratio on logarithmic scale. Threshold for previous events (dashed red line) = 0.01‰.

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3.2 Generalized additive models

The expected loss ratio $\mathbb{E}[LR]$ for a certain event can be described by a generalized linear model

$$\mathbb{E}[L] = g^{-1}(\boldsymbol{X_i}\boldsymbol{\beta}) \tag{3}$$

with inverse link function $g^{-1}(.)$, j covariates $\boldsymbol{X_i} = (X_{i1}, ..., (X_{ij})$, where $\boldsymbol{\beta} = (\beta_1, ..., \beta_j)$ are the corresponding model parameters to be estimated. As the variance of observed loss ratio increases with the expected value (Figure 1), we assume loss ratio being a random variable with a Gamma distribution and a logarithmic link function $g(x) = \log(x)$ (e.g. de Jong and Heller, 2008; Laudagé et al., 2019; Garrido et al., 2016).

We use generalized *additive* models to allow for more flexibility than it is the case for generalized *linear* models which is a typical choice (e.g. Donat et al., 2011b; Pardowitz et al., 2016). Generalized additive models (Hastie and Tibshirani, 1986; Wood, 2017) are an extension of generalized linear models using smooth instead of linear functions of covariates . This leads to

$$\mathbb{E}[L] = g^{-1}\left(\beta_0 + \sum_{j=1}^{J} f_j(x_j)\right) \tag{4}$$

where f_i are the smooth functions of the covariate x_j and β_0 is the intercept. Each smooth function f_i is represented by a sum of K simpler, fixed basis function ($b_{j,k}$) multiplied by corresponding coefficients ($\beta_{j,k}$), which need to be estimated

$$f_j(x_j) = \sum_{k=1}^{K} \beta_{j,k} b_{j,k}(x_j) \tag{5}$$

with the basis size K determines the maximum complexity of each smoother.

3.3 Model Setup

Recent studies include only the hazard component and a parameter for exposure as covariates into the damage model approach (e.g. Heneka et al., 2006; Pardowitz et al., 2016; Welker et al., 2021). To quantify the temporal dynamics of vulnerability due to previous events, additional predictors are implemented in this study to account for these changes. The dynamics of vulnerability can be quantified by analysing the influence of additional covariates on the impact of the hazard on the loss ratio.

In total, four different models are developed (Table 2). All four models have in common: the loss ratio as the response variable, and the wind load as covariate in the predictor for the hazard. In model $M_{preEvent}$ only the loss ratio of the previous event within the same administrative district is implemented to quantify the effect of the previous events in general without taking the time between two events into account. The three models M_{Season}, M_{Weeks} and M_{Days} additionally include time as a covariate distinguishing a seasonal, weekly and a diurnal time scale. Within these three models, model M_{Season} uses the binary information if a previous event happened in the same or previous winter seasons. For model M_{Weeks} all pre-events that happened within the same season as the event are taken into account to analyze the impacts of previous event on a finer temporal scale.In model M_{Days} the temporal scale is refined further to a diurnal time scale and only pre-events happened within four weeks (28 days) before the event are included in the model.

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These different temporal resolutions are chosen because shortly after the event occurrence, we expect the daily scale being essential and around one seventh of all previous events fall in this time span. In contrast, on longer terms, an accumulation over a more extended period seems appropriate, as the amount of pre-events with longer time spans to the event decreases.

An additional covariate is included to describe the overall development of buildings within one district, to ensure that the models results for the covariate describing the intensity of the previous event does not include general trends in vulnerability. The trends, like higher buildings standards for new buildings could lead to a decrease of the overall vulnerability in a district, without an event occurring. Therefore we use with the mean value 1914 (mV_{1914}), a covariate that represents the non-hazard specific changes of the vulnerability and is used as a baseline of variation. The value 1914 ("Wert 1914") is a fictive value for insurance companies in Germany, reflecting the value a building would have cost in gold mark in 1914 (GDV, 2024). For better comparability residential buildings are valued in 1914 values, as in this year, construction costs were not subject to any significant fluctuations. The value 1914 is divided by the number of contracts to derive mV_{1914}. It is assumed that an increase in mV_{1914}, leads to a decrease in vulnerability. It should be noted that the value 1914 includes not only the building quality, but also the building type (e.g. detached house or apartment building).

Table 2. Covariates used in the four different generalized additive models

Modelname	Hazard	Vulnerability		
		Pre Event	Time Between Events	Baseline
$M_{preEvent}$	Wind Load	Pre-Event Loss Ratio	-	mV_{1914}
M_{Season}	"	"	Season Between	"
M_{Weeks}	"	"	Weeks Between	"
M_{Days}	"	"	Days Between	"

4 Results

We identified 70703 events in the 23-year-long data set for the 401 administrative district in Germany based on the definitions described in subsection 3.1. Nearly 60% of all events have a wind load lower than $300\mathrm{N/m^2}$ (Beaufort scale 8) and nearly 40% of all previous events loss ratio are lower than 0.02‰ (Figure 2). The number of events decreases with higher wind loads and more damaging previous events. Especially events with wind loads larger $700\mathrm{N/m^2}$ (Beaufort scale 12) and previous event loss ratios of more than 0.1‰ occur rarely.

4.1 Intensity of previous events

First, we compute the effect of previous event loss ratios on the vulnerability without taking the time between two events into account. In Figure 3, the results for three different for the model $M_{preEvent}$. The predominant factor on the loss ratio is the

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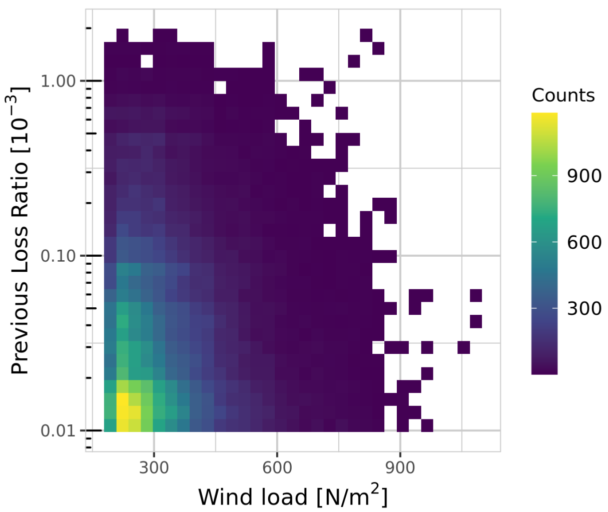

Figure 2. Counts of events with wind loads and the related previous loss ratio.

wind load. With higher wind load the loss ratio increases. The expected loss ratio for an event does not only depend on the wind load occurring, but also on the loss ratio occurring in the previous previous event. For a given wind load, the expected loss ratio for the event is lower if the previous event had a higher loss ratio. Thus the vulnerability describing the loss ratio for a certain wind load is lower in cases with higher previous event loss ratios.

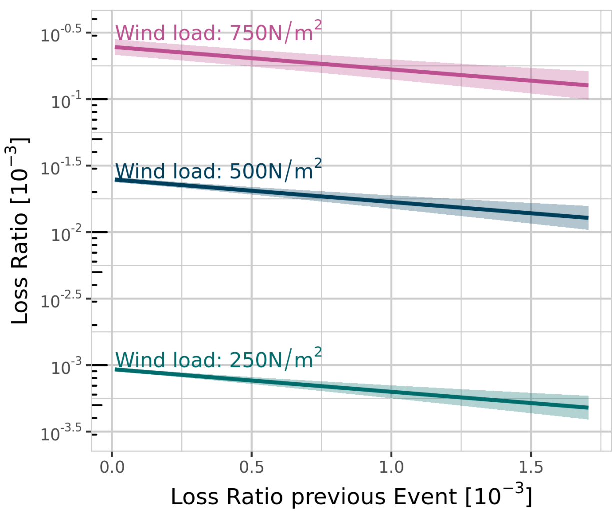

Figure 3. Results of Model $M_{preEvent}$ showing the relationship between loss ratio of an event and the intensity of the loss ratio of the previous event for three different wind loads with the 95% confidence interval (shaded areas).

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4.2 Temporal Impacts

4.2.1 Seasons

On a seasonal scale, we distinguish between *same-season pre-events* and *pre-season pre-events*. In case of *same-season pre-events* the previous event occurred within the same season as the event, which means, that at least one event with a loss ratio larger than 0.01‰ happened before the event we are looking at, but still within the same winter half year. If several pre-events occur within the same winter half, only the immediately preceding pre-event is assigned as the same-season pre-event to the event. If there is no same-season pre-event, the most damaging event of the previous season is assigned to the event and categorized as pre-season pre-events.

For quantifying the effect of time between two events on the dynamics of vulnerability, Figure 4 shows the vulnerability curves for the same-season and pre-season pre-events with two different fixed previous loss ratios.

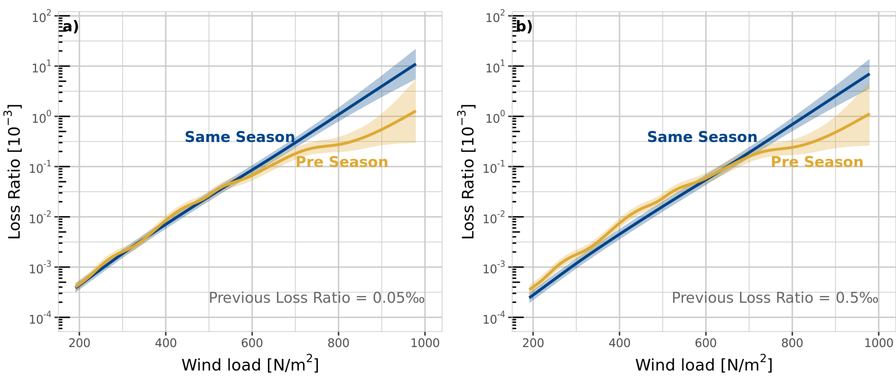

Figure 4. Comparison of events happening with same-season pre-events(blue) or with pre-season pre-events (yellow) for a fixed previous event of **a)** 0.05‰ and **b)** 0.5‰. Shaded area the 95% confidence interval.

For an event with a loss ratio of the pre-event of 0.05‰, wind loads higher than about $550\mathrm{N/m^2}$ (Beaufort Scale 11 - “violent storm”) lead to a significantly lower vulnerability for events with a pre-season event than with a same-season event as for the same wind load the loss ratio is lower. This significant difference for a previous loss of 0.5‰ begins at $650\mathrm{N/m^2}$. The differences as the uncertainties increase in both cases with increasing wind load.

There is no clear trend visible for wind loads below $550\mathrm{N/m^2}$ for previous loss ratios of 0.05‰. For previous loss ratios of 0.5‰ and wind loads lower than $650\mathrm{N/m^2}$, the vulnerability is higher for events wit pre-season pre-events compared to those with same-season pre-events.

A detailed analysis of the differences for the whole range of previous intensities is shown in Figure 5. For events with a wind load lower than $550\mathrm{N/m^2}$ the loss ratio is in general higher for events with pre-events occuring at least one winter season before, than events happening within the same season as the pre-event.

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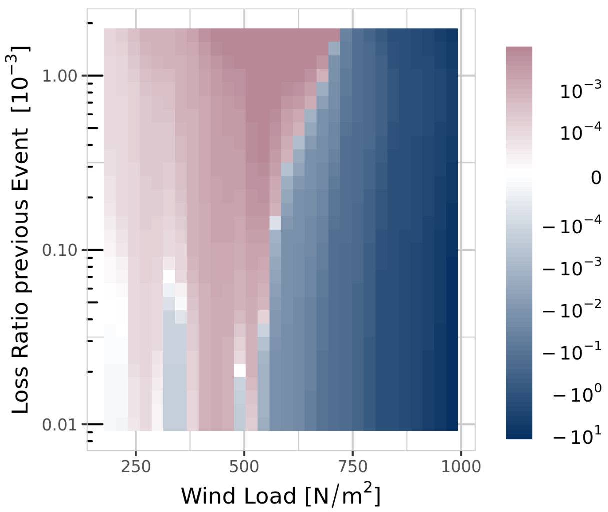

Figure 5. Absolute loss ratio difference between events with same season pre-events and events with pre-season pre-events. Bluish colours indicate a higher loss ratio for same season events, reddish colour a higher loss ratios for events with pre-season pre-events.

Events between $500\mathrm{N/m^2}$ and $700\mathrm{N/m^2}$ (12 Beaufort) with very intense previous events also show lower loss ratios for cases where event and pre-event happened within the same winter season rather than with one or more seasons in between. With decreasing loss ratios of the previous event the events' loss ratio with pre-events within one season lead to a higher loss ratio than with previous events more than one season in between.

For events with hurricane force ($> 700\mathrm{N/m^2}$) the loss ratio and thereby the vulnerability is always smaller if the pre-event occurred at least one winter season in between and not within the same winter season independent from the intensity of the previous event.

Finally, we evaluate the impact of previous events on the vulnerability separately for events with a pre-event occurring within the same season as the event and the pre-event occuring at least one winter season before the event. Figure 6 shows the results for an event with a wind load of $750\mathrm{N/m^2}$ (Hurricane - 12 Beaufort). For pre-season pre-events, there is no significant effect with increase of previous events loss ratios. On the other hand, events with same-season pre-events show a decrease in loss ratios with increasing previous events' loss ratios up to around 0.8‰.

4.2.2 Weeks

While in the previous subsection the focus was on the impact of different winter half years, here only events happening within the same winter half as the previous event are taken into account and accumulated to a weekly temporal resolution. Most pre-events occur one week before the event (Figure 7). The longer the time period between the pre-event and the event the lower is the number of occurrences. Less than 0.5% pre-event – event observations occur with more than 20 weeks in between, i.e. the pre-event in October and the event in March. For the model M_{Weeks} we only take pre-event – event combinations into account

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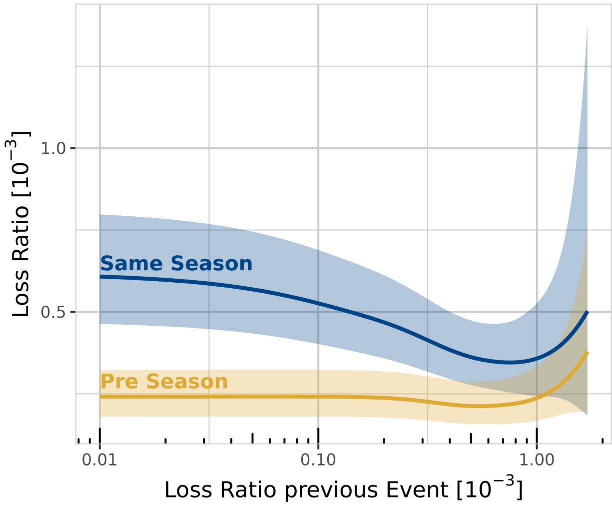

Figure 6. Comparison of events with a pre-event happening within the same season (blue) or with at least one summer season in between (yellow) for a fixed event of $750\mathrm{N/m^2}$. Dots indicate observations. Shaded area the 95% confidence interval.

with maximum 14 weeks in between. These make up 95% of all data within one season, reduces the influence of outliers of pre-event – event observations and still includes the most important time range of over three month after an event to recover.

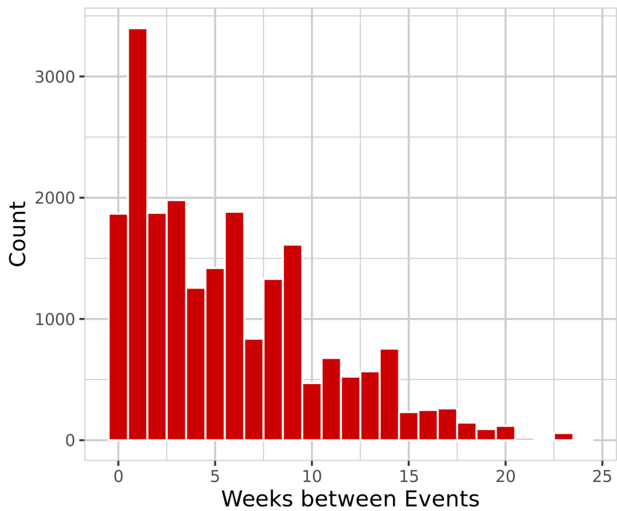

Figure 7. Histogram for pre-events occurring within the same season as the event accumulated to weekly basis.

225 Figure 8 shows the result of model M_{Weeks} for three different event types, a gale (Figure 8a – $250\mathrm{N/m^2}$), a storm (Figure 8b – $500\mathrm{N/m^2}$) and a hurricane event(Figure 8c – $750\mathrm{N/m^2}$). For each event type the different previous event loss ratios are shown with a minor previous event of 0.01‰ loss ratio, a medium pre-event of 0.1‰ and a major pre-event with 1‰.

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Each of the nine combinations show a decrease in vulnerability within the first two to three weeks as the loss ratio decreases with more weeks in between, while having a constant wind load for an event and a constant previous event loss ratio. In case of an storm event (Figure 8b) and hurricane event (Figure 8c) a more intense previous event lead to a higher vulnerability if the two events occur within a short amount of time.

With increasing time between gale and storm events, the vulnerability is lower if the previous event had a higher loss ratio. The high peaks of loss ratios in cases with 11 weeks between the previous and the current event resolved due two events (Niklas – 31.03.2015 and Friederike – 18.01.2018), which made up nearly half of all data for this amount of weeks between events. These were two events with major damages while the wind load mostly was in the range of a storm event around 500 to $600\mathrm{N/m^2}$.

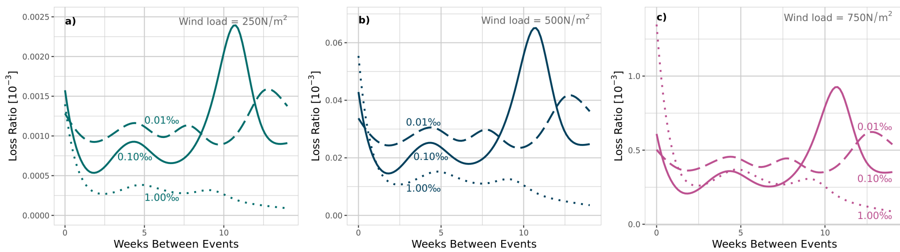

Figure 8. Results Model M_{Weeks} for a fixed event of a) $250\mathrm{N/m^2}$, b) $500\mathrm{N/m^2}$ and c) $750\mathrm{N/m^2}$ and three different loss ratio intensities of previous events (dotted lines 1‰, solid lines = 0.1‰, dashed lines = 0.01‰).

4.2.3 Days

A total of 9266 previous events occur within 28 days before the event. Out of these events, only 94 happen with only one full day between them. Most pre-events happen 10 days before the event and two-thirds of all the events within the first two weeks (Figure 9).

The results of model M_{Days} (Figure 10) confirm the model M_{Weeks} results of a steep decrease in vulnerability with increasing time between two events within the first weeks, and give the possibility to analyse the decrease in a higher temporal resolution.

For minor previous events (previous loss ratio of 0.01‰) the impact of increasing days between events is low within the first days and nearly constant after three to four days. For medium previous events (previous loss ratio of 0.1‰) and major previous events (previous loss ratio of 1‰) the decrease within the first days is stronger and it takes eight to ten days until the vulnerability remains constant with increasing time between the events.

In cases of a gale event (Figure 10a) or a storm event (Figure 10b) the vulnerability of residential buildings increases with the increase of previous loss ratio directly after the previous event. After around five days in between two events a turning point occurs and the more intense the previous event is, the less vulnerable is the affected administrative district.

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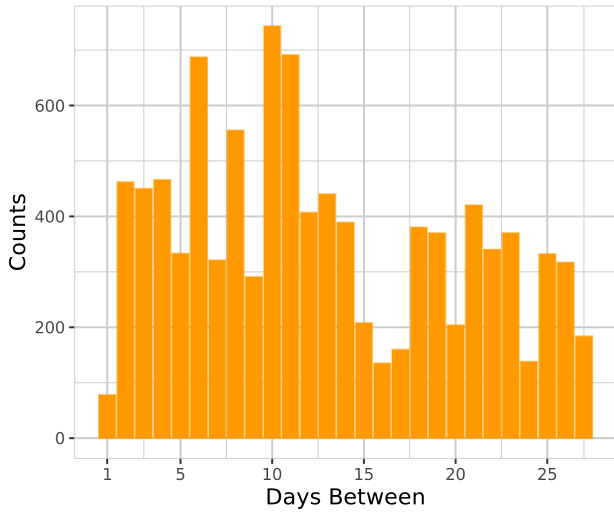

Figure 9. Histogram for pre-events occurring within 28 days before the event.

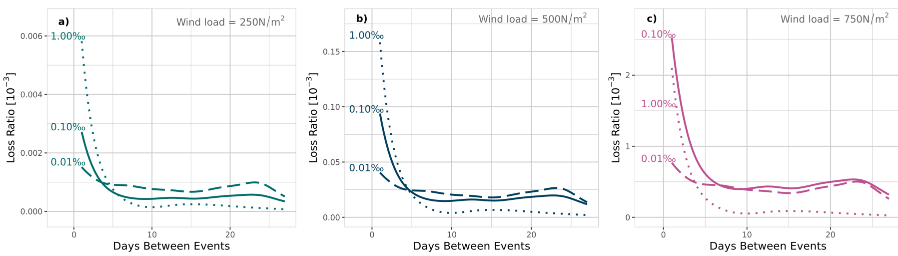

Figure 10. Results Model M_{Days} for a fixed event of a) $250\mathrm{N/m^2}$, b) $500\mathrm{N/m^2}$ and c) $750\mathrm{N/m^2}$ and three different loss ratio intensities of previous events (dotted lines = 1‰, solid lines = 0.1‰, dashed lines = 0.01‰).

5 Discussion

The results of our analysis are in line with theories from studies about temporal dynamic vulnerability (Aerts et al., 2018; de Ruiter and van Loon, 2022). A decrease in physical vulnerability, meaning a decrease in loss ratio of residential buildings to a certain winter storm intensity due to previous events, has been found. To our knowledge, an analysis of the influence of previous events on the vulnerability has not yet been conducted for storm events. Kreibich et al. (2023) focused on socio-hydrological data and used the Likert scale to estimate changes in the vulnerability, but, for example, did not quantify the impact of the time between two events.

The daily temporal resolution allows a detailed analysis of the time between events, which gives the possibility to evaluate consecutive storm events occurring within days or weeks. Note, however, that the report of damage to the insurance company does not always happen directly after the event, leading to possible misassignments of the reported damage to the wrong event that caused the damage. Late reported damages might get assigned to the more intense previous event, especially for weak

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events occurring within one season following a very intense event. This misassignment could increase the loss of the previous intense event and decrease the loss of the weak event. A misassignment is unlikely when there is a whole summer season in between, leading to lower vulnerability for minor events with very damaging previous events happening within the same season compared to events with pre-events in previous winter half years.

The spatial resolution of the insurance data, in general, leads to uncertainties in the results as the changes in vulnerability can only be quantified for a whole district. Especially for events with a weak previous loss ratio and wind load, the probability is lower that the same building gets hit twice. A finer spatial resolution is desirable and thereby being able to use different vulnerability curves for different building types (Smith and Henderson, 2016).

We consider only winter months for wind storm events and exclude summer months, as the damage data set includes storm and hail damages for residential buildings, but it is not possible to distinguish within the data between the causes for a certain loss. Similar to storm events, hail events mainly lead to roof and window damage of residential buildings. A hail event is likely to impact the vulnerability of residential buildings, which could not be included in this work due to the lack of hail data in the ERA5 data set and others. In general, extending the models to a multi-hazard approach is desirable.

On a seasonal scale, the differences between same-season and pre-season pre-events increase strongly with exceeding a wind load of around $600\mathrm{N/m^2}$ and thereby considerable structural damage according to the Beaufort scale. While on lower wind loads, only slight structural damages occur.

On the daily and weekly scale two findings should be noted: First, the strongest decrease of vulnerability within increasing days between the event up to 10 days, indicating that in Germany a huge amount of reconstruction is done within a short amount of time. Second, the vulnerability increases within the first days in between if the previous event had higher losses. One assumption for this relation might be that buildings damaged within the pre-event are more vulnerable (e.g. roof tiles become loose) and have not been repaired within this short time. The more damaged in the pre-event occurred the more buildings might be more vulnerable. Both findings should be investigated in more detail.

Additionally on daily and on weekly scale the vulnerability nearly stays constant with increasing time in between events, indicating that the time in between two events does not have an influence if we have a minor previous event. This results supports the choice of choosing the previous event threshold with 0.01‰ and assuming that previous event loss ratios below this threshold do not have an influence on the vulnerability.

The covariate mV_{1914} is used as a baseline for dynamics in vulnerability and represents changes in vulnerability due to non-hazard specific effects. In general the model results show a decrease in vulnerability with increasing mV_{1914} and thereby confirm the assumption Figure A1. It must be noted, that the value 1914 not just depend on the quality of the house, but also on the type of the house, with higher prices for apartment buildings than for detached houses. A more refined approximation for the changes in non-hazard specific vulnerability is desirable in general.

While having an nearly linear decrease in losses with increasing intensity of previous events, including the time between two events leads to non-linear relations in the statistical model, which justifies generalized additive models over generalized linear models.

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For the analyses of the changes in vulnerability, the use of empirical vulnerability curves allows quantifying the changes in depth, which might be more difficult using indices or other vulnerability descriptions. However, this approach cannot asses future changes in political decisions, materials, or construction standards (Konthesingha et al., 2015). The derived vulnerability curves allow learning from the past and expanding them in the future to analyse the effectiveness of future adaptation measures. This method of changes in vulnerability can be transferred to other factors like spatial differences comparing different countries or wind load zones or to other hazards to get a more holistic view of the dynamics in vulnerability.

6 Conclusions

The general approach of temporal dynamic vulnerability has been discussed in literature (e.g. Papathoma-Köhle et al., 2012; Di Baldassarre et al., 2018), this study is the first to quantify the dependencies of physical vulnerability due to wind storm events in Germany. The focus was on the impact of the intensity of previous events and the impact of the time between two events. By using generalized additive models, the detection of non-linear functional relationships between the loss ratio and the time between events was possible.

With increasing loss ratios of previous events, the vulnerability decreases for the next event; the longer the period between two events, the lower the vulnerability of the second event. Both findings are in line with theories by Aerts et al. (2018); de Ruiter and van Loon (2022). By quantifying these changes, the vulnerability in risk assessments could be adjusted, leading to the possibility of an improved understanding of past events and the resulting damage, more adequate loss or risk prediction and risk management for the future. These results show the necessity of considering vulnerability as a temporal dynamic and that previous events and the time between two events significantly impact the changes in vulnerability.

Data availability. Due to the data protection policies of the data provider German Insurance Association, the data cannot be made available.

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Appendix A

A1

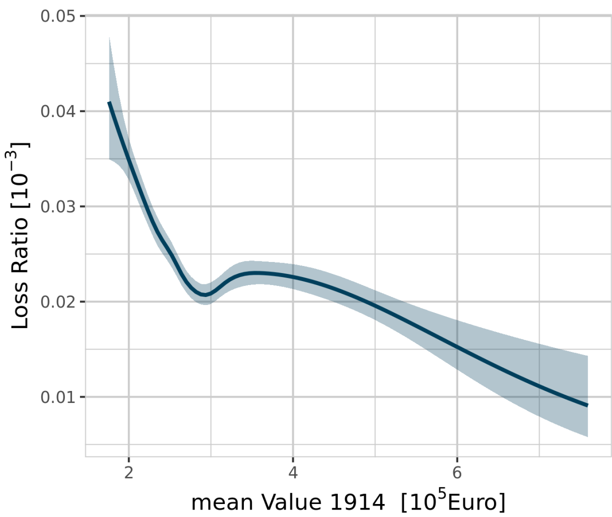

Figure A1. Results of $M_{preEvent}$ for mean value 1914 for an event with wind load = $500\mathrm{N/m^2}$ and a previous loss ratio of 0.05‰

Author contributions. Andreas Trojand: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft preparation, review & editing
Henning Rust: Conceptualization, Methodology, Supervision, Funding acquisition, Writing – review & editing
Uwe Ulbrich: Conceptualization, Supervision, Funding acquisition, Writing – review & editing

Competing interests. One of the co-author is a member of the editorial board of Natural Hazards and Earth System Sciences.

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