A high-resolution compound vulnerability function for European winter storm losses

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Abstract

Economic losses from European winter storms impose a significant burden on society and are expected to increase due to exposure growth and climate change. Vulnerability functions play a key role in estimating such losses as they describe the relationship between a natural hazard's intensity and damage to the exposed asset. This study fills an important gap in the literature by providing a vulnerability function for residential buildings which, for the first time, is able to account for damage from both the wind and the precipitation that winter storms produce. This compound vulnerability function is estimated using truncated beta regressions, and based on a large number of object-level insurance claims from The Netherlands and ultra-high resolution meteorological observations. Comparing our vulnerability function to the conventional specification, which only considers damage from wind, shows that the latter underestimates the damage by 5% [21%] {57%} for winter storms with 24-hour cumulative precipitation levels of 50 mm [75 mm] {100 mm}. Given that climate change is projected to further increase the frequency and intensity of such precipitation extremes in Europe, our study provides evidence in favor of using compound vulnerability functions to estimate future winter storm losses more accurately. Our vulnerability function can be used in natural catastrophe models to accurately estimate damage to residential buildings from European winter storms.

1. Introduction

Windstorms are one of the most impactful natural catastrophes in Europe as their large scale strong winds and heavy precipitation cause, on average, dozens of fatalities and billions in economic and insured losses each year (EEA, 2023; Swiss Re, 2024). European windstorms are strong extratropical cyclones that originate either through cyclogenesis in the extratropical region (Stankovic et al., 2024) or by the extratropical transitioning of tropical cyclones (Haarsma, 2021). As the most powerful windstorms in Europe frequently occur during the winter months, they are also often referred to as European winter storms.

Insights into the potential losses of such influential natural catastrophes is important for, amongst others, disaster risk prevention and preparedness policies, effective and efficient (re)insurance arrangements and climate (change) impact studies. The state-of-the-art method for estimating these losses are natural catastrophe models (Reinders et al., 2023). These consist of three modules: (1) the hazard module, specifying the type, frequency and intensity of the natural hazard; (2) the exposure module, identifying the type and location of exposed assets; and (3) the vulnerability module, consisting of functions that describe the relationship between the natural hazard's intensity and its associated damage to a variety of exposed assets (Grossi and Kunreuther, 2005). Loss estimations are highly sensitive towards the vulnerability functions, because damage to an exposed asset is commonly expressed as a ratio of the total asset value and the functions apply to all exposed assets.[1] As such, the construction of accurate vulnerability functions is of instrumental importance to the accurate estimation of natural catastrophe losses (Endendijk et al., 2023).

Vulnerability functions (for winter storms) can be derived analytically by simulating the response of the built environment to natural hazards of various intensities (Alduse et al., 2022), heuristically by using expert judgment (Feuerstein et al., 2011), empirically by calibrating statistical models on post-disaster damage data (Khanduri and Morrow, 2001) or in a hybrid form (Heneka and Ruck, 2008). Although vulnerability functions are most often constructed empirically in the academic literature (Foote et al., 2017), few empirical European winter storm vulnerability functions for residential buildings are available, mainly due to a lack of damage data. Most studies that did construct these functions based on empirical data solely had access to highly aggregated damage data (Dorland et al., 1999; Klawa and Ulbrich, 2003). The resulting shortcoming is that those vulnerability functions are less accurate on higher resolutions as essential variation in both the hazard and exposure characteristics are not captured at higher levels of aggregation. The only European winter storm vulnerability function which is calibrated on residential building damage observations at the object-level stems from Schwierz et al. (2010)[2]. Theirs is a simplified version of the proprietary vulnerability function of an insurance company which solely describes the expected or mean damage ratio for the average residential building. Moreover, as Schwierz et al. (2010) do not provide information on the modelling methodology nor on the estimation outcomes, it is challenging to evaluate the reliability and/or the uncertainties of the vulnerability function's outcomes.

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[1] This sensitivity becomes apparent when one considers a seemingly small and easily conceivable adjustment of relatively low outputs of a vulnerability function. For instance, recalibrating a previously anticipated damage ratio that occurs at a certain storm intensity of 1% to a 2% damage ratio would double the loss estimation of a natural catastrophe model.

[2] This European winter storm vulnerability function is available on the open-source weather and climate risk modelling platform CLIMADA (Aznar-Siguan and Bresch, 2019).

This study aims to fill this gap by estimating European winter storm vulnerability functions for residential buildings. Based on a large sample of insurance claims at ultra-high spatial resolution (204,118 damage observations at the object-level over the period 2008-2021) from winter storms in the Netherlands, and on an ultra-high resolution dataset of their meteorological drivers, conditional vulnerabilities functions[3] (hereafter vulnerability functions) are estimated with truncated beta regressions (Ferrari and Cribari-Neto, 2004). There are four main advantages of using beta regressions to construct empirical vulnerability functions. First, they assume the dependent variable to be distributed on the unit interval (0, 1), which makes them more suitable to model damage ratios as compared to the (partially) unbounded distributions which are most often used in the empirical vulnerability function literature[4] (Wesson et al. 2004; Heneka and Ruck, 2008). Second, aligning the theoretical dependent variable distribution with the empirical distribution also enables the end-user to simulate a loss distribution by repeatedly drawing (simulating) random potential damage ratios from the conditional beta distribution of the vulnerability function. In addition to an expected loss estimate, such loss distributions also describe the range of plausible losses, often referred to as the risk. Considering a loss distribution is important when losses are estimated for small sample sizes and the variance of the damage ratio estimates is large i.e. when the damage ratio estimate is relatively uncertain. Under these circumstances, the sum of the expected individual losses (stemming from the expected damage ratio estimates) might deviate substantially from the materialized loss. Third, the beta regression is relatively flexible as it accommodates the heteroskedasticity and distributional asymmetries that are often found in regressions on fractional data (Ferrari and Cribari-Neto, 2004). Fourth, this parametric approach makes it possible to account for the non-observed losses below the imposed insurance deductibles, which is a common characteristic of insurance claims data, through truncation adjustments in the model estimation process.

In addition to these methodological innovations, this study is first to incorporate multiple damage-driving mechanisms of European winter storms in the vulnerability function. Whereas conventional European winter storm vulnerability functions solely account for damaging wind speeds (Alduse et al., 2022; Dorland et al., 1999; Feuerstein et al., 2011; Heneka and Ruck, 2008; Khanduri and Morrow, 2001; Klawa and Ulbrich, 2003; Schwierz et al. 2010), the function produced by this study also represents the damaging effects of precipitation. Thus, in addition to describing the damaging effects from either wind or precipitation, the function also allows for damage estimations from their combined presence. The vulnerability function can therefore be considered as a compound vulnerability function for European winter storms (Zscheischler et al., 2020).

In general, the new vulnerability function can serve as input for private, academic and open-source natural catastrophe models to estimate damage to residential buildings from European winter storms more accurately. The compound vulnerability function is particularly suited for climate change impact analyses as precipitation levels in winter storms, next to their frequencies, are projected to increase over Europe, pronouncing its role in the damage process (Hawcroft et al., 2018; Kodama et al., 2019; Li et al., 2024; Little et al., 2023; Yettella et al., 2017).

[3] Conditional vulnerability functions describe the relationship between a natural hazard's intensity and damage to the exposed assets, conditional upon the building being damaged (Foote et al., 2017). Being exposed to a certain natural hazard intensity does not guarantee that the building will be damaged. Consequently, to estimate the losses from multiple assets using conditional vulnerability functions, one also needs to incorporate the chances of being damaged at different intensity levels.

[4] One-inflated beta regressions (Ospina and Ferrari, 2012) were considered by us to accommodate the inclusion of "complete loss" observations as these assume the dependent variable to be distributed on the half-open unit interval (0, 1]. However, the number of "complete loss" observations was deemed too low in our sample to model separately.

Comparing the expected damage ratio estimates from the compound vulnerability function with those from a vulnerability function that solely accounts for wind speeds shows that the latter underestimates the damage to residential buildings for high precipitation events. For an average residential building, the expected damage ratio will be underestimated by 6% [21%] {57%} for winter storms that produce wind gusts of 20 m/s and 50 mm [75 mm] {100 mm} of precipitation in 24-hours[5]. This 24-hour cumulative precipitation level only occurs once every 50 years [500 years] {~1000 years} at a specified location in the Netherlands (STOWA, 2019). In addition, the regression results also highlight that building characteristics such as the reconstruction value should be considered in vulnerability functions as they influence the damage ratio estimate: for a given set of damaging meteorological conditions, residential buildings with higher reconstruction values have less damage relative towards their reconstruction value as compared to those with lower reconstruction values. Furthermore, the results suggest that winter storm loss estimates for samples of limited size should be informed by a loss distribution as the variance of the damage ratio estimates is large. The large variance of the damage ratio estimates might stem from the unexplained variability in vulnerability characteristics and the randomness inherent to the damage process. Lastly, comparisons with a European winter storm vulnerability function for residential buildings from the literature point out that there is considerable uncertainty around the wind gust speed threshold from which damage starts to occur (Schwierz et al., 2010). Having this threshold wrong will lead to either under- or overestimations of damage to residential buildings from European winter storms.

The remainder of this paper is structured as follows. Section 2 introduces the data and methods, and section 3 presents and discusses the regression results. Section 4 compares the vulnerability functions with the literature and provides guidance on their use. Section 5 concludes.

[5] In terms of the gridded and partially model based meteorological observations used in this study.

2. Data and Methods

Data

The vulnerability functions are developed by using insurance data from a Dutch financial conglomerate. The insurance data is matched with meteorological data from the Royal Netherlands Meteorological Institute (KNMI), which is the Dutch national weather service.

Damage data

The insurance dataset provides weather-related residential building claims and policy holder information (e.g. building location) in the Netherlands at the object-level from 2008 up to and including 2021. Only the claims from October up to and including March are retained as this period represents the European winter storm season. Section S1 in the Supplementary Information discusses the additional filters used to isolate winter storm related claims. The claim amounts in the insurance dataset represent the insured's compensated damage net of any deductibles imposed by the insurance policies. To reflect the total damage to a building from a winter storm, i.e. the ground-up damage, the average deductible over this period of €200.- is added to claims from policyholders subjected to a deductible.

The dependent variable of interest is the damage ratio which represents the ground-up damage of a residential building as a ratio of its reconstruction value. The reconstruction value is an approximation of the costs of rebuilding a residential building according to the latest building codes, in case the building is completely damaged. Its calculation is based on a methodology provided by the Dutch Association of Insurers and mainly depends on the building type (e.g. an apartment or terraced housed), the building year, the building volume and characteristics of building structures such as the foundation or roof (Verbond van Verzekeraars, 2024). Section S2 in the Supplementary Information elaborates on the calculation of these reconstruction values. This normalization allows for a more accurate comparison between the dependent variable's observations because it partially corrects for the reconstruction value's effect on the ground-up damage: buildings with higher reconstruction values (originating from characteristics such as building size and materials) have more potential for damage simply because there is more value that can be damaged. However, as the damage does not rise proportionally with the reconstruction value, the effect of the reconstruction value on the ground-up damage differs for differing reconstruction values. Therefore, in order to normalize the damage ratios more comprehensively, this study includes the reconstruction value (Rv) as regressor in the models. Accordingly, the reconstruction value can be considered as a parsimonious proxy for relevant building characteristics. Both the ground-up damage and the reconstruction value are denoted in 2024 price levels. Section S3 in the Supplementary Information contains the index that is used to adjust the price levels in which the damage data was originally denoted, along with a description of the methodology employed to construct the index.

Meteorological data

The daily maximum 3-second wind gust in a 10-minute period at 10 m height (*W*) is used as one of the proxies for the damage-driving mechanisms of winter storms (Koninklijk Nederlands Meteorologisch Instituut [KNMI], 2018; KNMI, 2019; KNMI, 2022). The wind gusts are based on regional climate reanalysis, and are provided in hourly time series per grid at a horizontal resolution of 2.5 km. Academic literature suggests that these wind gusts are a suitable proxy, compared to other winter storm characteristics such as the maximum hourly average wind speed (Dorland et al., 1999). The other proxy is a precipitation intensity metric which aims to capture the damage resulting from the precipitation of winter storms. There is less consensus on which precipitation metric reflects its damage-driving process best (Spekkers et al., 2013). This is why two different precipitation accumulation intervals were considered: the daily maximum one-hour cumulative precipitation (*P1*) and the daily 24-hour cumulative precipitation (*P24*) (KNMI, 2017) [6]. The precipitation measurements are radar-based, adjusted by rain gauge observations and provided in hourly time series per grid at a horizontal resolution of 1 km. Section S4 in the Supplementary Information provides further detail on the measurement methodologies of the meteorological data.

Data preparations

The damage data are spatially matched to the meteorological data by retaining the values from the meteorological grid cell with the centroid nearest to the centroid of the postal code 5 area associated with each claim. Regarding temporal matching, it is noted that the claim dates in the insurance dataset occasionally do not coincide with the dates of the winter storms. For instance, it is observed that a small portion of the claims from a large storm are reported one day after the storm. To correct for these discrepancies, the highest daily wind gust speed and highest daily 1-hour/24-hour cumulative precipitation level are selected over the four days leading up to the claim date, the claim date itself and the day after.

Because the above-average claim frequencies sharply decline in the days after large storms, it is reasonable to assume that this procedure corrects most of the targeted discrepancies. Nevertheless, the procedure cannot account for discrepancies between the reporting and the storm dates that are larger than the specified buffer. To address the potentially remaining matching errors, 940 observations were removed with damage ratios larger than the 97.5th quantile (damage ratios > 2.1%) at relatively modest meteorological intensities.[7] Here, modest meteorological intensities are defined as jointly observing maximum wind gusts below 15 m/s, and with 24-hour cumulative precipitation levels below 15 mm. This procedure also treats outliers resulting from inaccurate meteorological values. These originate, for instance, from the inability of the meteorological observations to capture very local damaging meteorological conditions such as whirlwinds. After removing the outliers, the sample consists of 203,401 claims and their associated damaging meteorological conditions. The sample includes three "complete loss" observations (i.e. having a damage ratio of one). As the beta regression cannot capture a probability mass at one, their damage ratios were set to 0.99.

[6] The daily 24-hour cumulative precipitation is defined as the cumulative precipitation measured between 00:00 AM and 23:59 PM UTC whereas the daily maximum one-hour cumulative precipitation is defined as the largest cumulative precipitation measured between each full hour of a specified day.

[7] The 97.5th quantile is measured over the subset with the relatively modest meteorological intensities.

Table 1. Descriptive statistics of the dependent variable, its components and regressors

	Ground-up damage	Reconstruction value	Damage ratio	Maximum wind gust	Maximum one-hour cumulative precipitation	24-hour cumulative precipitation
mean	€2054.-	€369,761.-	0.583 %	21.11 m/s	3.63 mm	12.41 mm
std	€4592.-	€126,477.-	1.086 %	5.85 m/s	2.19 mm	8.46 mm
min	€17.-	€22,708.-	0.004 %	6.35 m/s	0.00 mm	0.00 mm
Q25	€722.-	€301,280.-	0.204 %	16.04 m/s	2.26 mm	7.11 mm
Q50	€1264.-	€350,080.-	0.360 %	21.49 m/s	3.41 mm	11.60 mm
Q75	€2253.-	€404,355.-	0.648 %	25.82 m/s	4.62 mm	16.15 mm
max	€1,115,652.-	€3,156,547.-	99.000 %	37.32 m/s	32.46 mm	108.40 mm

Table 1 provides the descriptive statistics of the dependent variable, its components and the model regressors. Among the winter storm events that are covered by this sample are six events that are classified as "major storms" by the KNMI. An event is classified as "major storm" when average hourly wind speeds of at least 24.5 m/s (10 on the Beaufort scale) are transgressed. The sample also contains 8,048 observations with 24-hour cumulative precipitation levels between 25 and 35 mm, reflecting events with return periods between one and five years, respectively (STOWA, 2019). There are 1,609 observations between 35 and 50 mm, with the latter only occurring once in every 50 years. At the extreme, there are 81 observations with 24-hour cumulative precipitation levels between 75 (~500 year return period) and 100 mm (~1,000 year return period) and 14 observations exceeding 100 mm. Figure S1 in the Supplementary Information shows a heatmap of the observed mean damage ratios, per binned range of meteorological observations. The figure indicates that both high wind gust speeds and high 24-hour cumulative precipitation levels are associated with higher mean damage ratios. This finding suggests that damage ratios can be modelled along these two dimensions using statistical methods such as the beta regression. Figure S2 shows a two dimensional histogram of the observed combination of meteorological conditions. The figure indicates that the highest wind gust speeds do not cooccur with the highest 24-hour cumulative precipitation levels.

Methods

The development of the vulnerability functions is inspired by the data-driven procedure proposed by Rossetto et al. (2014) for estimating vulnerability functions. In search of the most appropriate vulnerability functions, multiple beta regressions, as introduced by Ferrari and Cribari-Neto (2004), were estimated by alternating the model specification. The Bayesian information criterion (BIC) is used to select the model with the best fit (Schwarz, 1978).

Beta regressions

Beta regressions assume that the dependent variable, Y, is beta distributed on the open unit interval (0, 1). Amongst other favorable characteristics, the open unit interval restriction of the dependent variable makes these regressions suitable for modelling continuous fractional data, such as damage ratios.

To facilitate the beta regressions, Ferrari and Cribari-Neto (2004) proposed to reparametrize the indexes of the original beta distribution. The alternative parameterization of the beta distribution $\mathcal{B}(\mu, \phi)$, where μ $(0 < \mu < 1)$ represents the distributional mean and ϕ $(\phi > 0)$ functions as a precision parameter, has the following density function

$$b(y;\, \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1}, \quad y \in (0,1) \tag{1}$$

where $\Gamma(\cdot)$ is the gamma function. When $Y \sim \mathcal{B}(\mu, \phi)$, then $\mathrm{E}(Y) = \mu$ and $Var(Y) = \mu(1-\mu)/(\phi + 1)$. The parameter ϕ can be interpreted as a precision parameter since a larger ϕ will result in a smaller variance of Y, provided that μ stays fixed. Moreover, as the variance of Y is a function of μ, a beta regression model can, by construction, account for heteroskedasticity. For $Y_i \sim \mathcal{B}(\mu_i, \phi), i = 1, \ldots, n$, the beta regression model can be defined as

$$g_1(\mu_i) = f_1(x_i, \beta) = \eta_{1i} \tag{2}$$

where $\beta = (\beta_1, \ldots \beta_k)^T$ is a $k \times 1$ vector of unknown regression parameters ($k < n$), $x_i = (x_{i1,}, \ldots, x_{ik})$ the vector of k regressors and $\eta_1 = (\eta_{11}, \ldots, \eta_{1n})^T$ being a predictor vector for the mean parameter. Lastly, $f_1(\cdot, \cdot)$ is a linear or nonlinear twice continuously differentiable function in the second argument and $g_1(\cdot)$ is a strictly monotonic and twice differentiable link function mapping $(0,1) \longmapsto \mathbb{R}$.

The original beta regression model can be extended by considering a variable precision parameter ϕ_i (Smithson and Verkuilen, 2006; Simas et al., 2010), which can be modelled similarly as the mean parameter

$$g_2(\phi_i) = f_2(z_i, \gamma) = \eta_{2i} \tag{3}$$

where $\gamma = (\gamma_1, \ldots \gamma_h)^T$ is a $h \times 1$ vector of unknown regression parameters ($k + h < n$), $z_i = (z_{i1,}, \ldots, z_{ih})$ the vector of h regressors, $\eta_2 = (\eta_{21}, \ldots, \eta_{2n})^T$ being a predictor vector for the precision parameter, $f_2(\cdot, \cdot)$ a function as specified above and $g_2(\cdot)$ the link function.

For additional information on the maximum likelihood estimation of the beta regression parameters, their inference, diagnostic measures and model selection tools, the reader is referred to Ferrari and Cribari-Neto (2004).

Modelling procedure

The candidate vulnerability functions were constructed by modelling the predictor for μ_i as linear functions of its parameters and regressors. Inspired by the data driven procedure proposed by Rossetto et al. (2014) for estimating vulnerability functions, multiple combinations of regressors (*Rv*, *W*, *P1 & P24*), interactions of the meteorological variables (*W*P1/P24*) and their potential non-linearities ($\sqrt{x_i}, {x_i}^2, {x_i}^3, {x_i}^4$ & ${x_i}^5$) were considered. As such, approximately 400 candidate model specifications were estimated. Moreover, ϕ_i is assumed to be constant and the logit link function, $g(\chi) = \log(\chi/(1-\chi))$, is used for μ_i and ϕ throughout.

As damage to residential buildings below the insurance policy's deductible is not present in the insurance claims dataset, the dependent variable is truncated from the left. Without explicitly accounting for the part of the dependent variable's distribution that is below the deductible, one might overestimate the damage. All beta regressions are therefore estimated with truncated beta density functions that are conditioned upon the damage being larger than the deductible[8].

The BIC is used to select the model with the highest probability of being the true model out of all candidate models. Given the size of our sample, the BIC favors parsimonious models and, therefore, promotes a fairer comparison between models with different numbers of regressors. Goodness-of-fit is assessed by two pseudo R^2 indices: R_p^2 defined as the square of the Pearson correlation coefficient between the dependent variable and the fitted values for the dependent variable and R_{CS}^2 as proposed by Cox and Snell (1989). Additionally, the root mean squared error (RMSE) is calculated. Lastly, 99%

[8] All parameters were estimated by maximum likelihood through a Newton-Raphson algorithm (Rigby and Stasinopoulos, 2005) using the **GAMLSS** package version **5.4-22** in R (Stasinopoulos et al., 2004).

confidence intervals for the expected dependent variable were constructed as discussed in *Appendix B* in Ferrari and Cribari-Neto (2004).

3. Results

Table 2. Regression results

	Compound vulnerability function	*Univariate vulnerability function*
$\boldsymbol{\mu}$		
Intercept	-4.314	-4.310
	(1.269e-02)	(1.267e-02)
	[2e-16]	[2e-16]
$\sqrt{Rv}$	-1.536e-03	-1.537e-03
	(2.100e-05)	(2.099e-05)
	[2e-16]	[2e-16]
W^3	8.587e-06	8.533e-06
	(1.957e-07)	(1.952e-07)
	[2e-16]	[2e-16]
$P24^3$	4.558e-07	
	(5.445e-08)	
	[2e-16]	
$\boldsymbol{\sigma}$[9]		
Intercept	-2.596	-2.596
	(1.908e-03)	(1.909e-03)
	[2e-16]	[2e-16]
N	203,401	203,401
Degrees of freedom	5	4
R_p^2	0.0166	0.0165
R_{CS}^2	0.0368	0.0365
Global Deviance	-1,691,833	-1,691,776
AIC	-1,691,823	-1,691,768
BIC	-1,691,772	-1,691,727
RMSE	0.0108	0.0108

This table contains the estimated coefficients, (standard errors) and [p-values] for the *compound vulnerability function* and *univariate vulnerability function* for both their predictors for μ_i and their precision parameters ϕ. The table also reports on the R_p^2, R_{CS}^2, Global Deviance, AIC, BIC and RMSE as goodness-of-fit measures.

[9] In accordance with the estimation output from the GAMLSS package, the precision parameter is reported as σ, a reparameterization of ϕ which was proposed by Rigby et al. (2019). Here, $\sigma = \frac{1}{(\phi+1)^{1/2}}$ or $\phi = \frac{1}{\sigma^2} - 1$, with $0 < \sigma < 1$ and $Var(Y) = \sigma^2\mu(1-\mu)$. Hence, a lower σ results in a smaller variance of Y.

Table 3 Average marginal effects

	Compound vulnerability function	*Univariate vulnerability function*
$\boldsymbol{\mu}$		
$\sqrt{Rv}$	-9.04e-06	-9.04e-06
	(1.25e-07)	(1.25e-07)
	[2e-16]	[2e-16]
W^3	5.05e-08	5.02e-08
	(1.15e-09)	(1.15e-09)
	[2e-16]	[2e-16]
$P24^3$	2.68e-09	
	(3.28e-10)	
	[2e-16]	

This table contains the average marginal effects (standard errors) [p-values] of the regressors in the predictor function of μ_i on the dependent variable. The average marginal effects are denoted in damage ratios.

Table 2 presents the beta regression results of the vulnerability function specification with the lowest BIC (highest probability of being the true model), which is called the *compound vulnerability function*. Additionally, Table 3 provides the average marginal effects of the regressors in the predictor function of μ_i on the expected damage ratio. Next to $\sqrt{Rv}$, the predictor function of μ_i includes W^3 and $P24^3$ as proxies for the damage-driving mechanism of winter storms[10]. Cubic relationships between wind speeds and economic losses are often found in the literature, for instance in Klawa and Ulbrich (2003). Interestingly, the cube of a wind speed is proportional to wind power (i.e. the wind's kinetic energy flux), suggesting that the power of wind is a better determinant of the damage ratio than wind speed itself. To compare, Table 2 also reports the results of the vulnerability function specification with the lowest BIC that does not contain a regressor to represent precipitation damage from winter storms, which is called the *univariate vulnerability function*. It turns out that the variables that were selected, their sign and transformations coincide with those from the *compound vulnerability function*. The regression parameters of both models differ from zero at any conventional critical value. Figure 1 displays the c*ompound vulnerability function'*s output evaluated at the sample's mean observed reconstruction value (~€370,000.-) and for differing wind gust speeds and precipitation levels.

[10] Note that this also implies that the 24-hour cumulative precipitation was preferred over the one-hour cumulative precipitation to describe the damage-driving mechanisms of precipitation in winter storms. A potential explanation for the underperformance of the one-hour cumulative precipitation metric is that its measurement boundaries (i.e. between each full hour) were somewhat arbitrarily set. Consequently, the measurement period might have been misaligned to properly capture the damaging effect of short but intense precipitation events as the cumulative precipitation measurement could have "stopped too early", "started too late" or both.

The reconstruction value

In both models, the reconstruction value is negatively related to μ_i[11]. This indicates that, for a given set of damaging meteorological conditions, residential buildings with higher reconstruction values have a smaller fraction of damage as compared to those with lower reconstruction values. Put differently, although the ground-up damage from winter storms increases for residential buildings with higher reconstruction values, it increases less than proportionally to the increase in the reconstruction value[12]. Moreover, the selected transformation of the reconstruction value (i.e. the square root) indicates that this effect diminishes for higher reconstruction values. The average marginal effect of the reconstruction value equals -9.04e-06 in both models.

This finding also implies that vulnerability functions that do not account for differences in reconstruction values (or more generally, other relevant building characteristics) will reflect an "averaged out" effect of the omitted regressor, and produce less accurate damage ratios for residential buildings at either end of the reconstruction values range, underestimating damage to buildings with low reconstruction values, and vice versa.

The consequence of omitting precipitation

Comparing the *compound vulnerability function* results with those from the *univariate vulnerability function*, it becomes clear that there is a role for both wind gusts and the 24-hour cumulative precipitation in explaining the damage-driving mechanisms of winter storms. This follows from the positive association that both regressors have towards μ_i and from the BIC of the former being significantly lower than that of the latter vulnerability function according to the guidelines provided by Neath and Cavanaugh (2012). For the *compound vulnerability function*, the average marginal effect of the wind gusts equals 5.05e-08. For the 24-hour cumulative precipitation, the average marginal effect equals 2.68e-09. Considering their average marginal effects in the context of their observed regressor values, the contribution of the 24-hour cumulative precipitation to the damage ratio is approximately 30% larger than that of the wind gusts[13]. Consequently, not accounting for the damaging effects of precipitation from winter storms will lead to underestimations of the expected damage ratio.

Nevertheless, conventional winter storm vulnerability functions only consider wind gusts as proxy for the damage-driving mechanisms of winter storms, thereby departing from this study's presumed true model: the *compound vulnerability function*. Assessing the regression results from this type of specification, i.e. those from the *univariate vulnerability function*, shows that the parameters from a conventional model cannot (erroneously) compensate for an omitted precipitation regressor.

[11] Contrary to the damage ratio, the ground-up damage increases for residential buildings with higher reconstruction values. For instance, the *compound vulnerability function* estimates a damage ratio of 0.65% and a ground-up damage of €1950.- for a residential building with a reconstruction value of €300,000.-, wind gusts of 20 m/s and a 24-hour cumulative precipitation level of 50 mm. The residential building with a reconstruction value of €370,000.- in turn has a lower damage ratio: 0.59% but a higher ground-up damage: €2119.-.

[12] A proportional change would imply that a residential building with, for example, twice the reconstruction value of another, would also have a ground-up damage that is two times larger, all else equal.

[13] For instance, evaluating their contributions at the (maximum) {$\frac{Maximum}{2}$} observed 24-hour precipitation level (108.40 mm) {54.20 mm} and wind gust (37.32 m/s) {18.66 m/s} using their average marginal effects shows that the former contributes (0.341% points) {0.043% points} to the damage ratio and the latter (0.262% points) {0.033% points}.

These underestimations will be relatively pronounced for winter storms that produce low wind gust speeds and high precipitation levels as the damage estimations can solely account for the (minor) impact of wind. For instance, considering a residential building with an average reconstruction value of €370,000.-, wind gusts of 20 m/s and a 24-hour cumulative precipitation level of 50 mm [75 mm] {100 mm}, the *compound vulnerability function* estimates an expected damage ratio of 0.59% [0.68%] {0.88%} and the *univariate vulnerability function* 0.56%. This amounts to an underestimation of the latter function of 5% [21%] {57%}. The underestimation in the expected damage ratio can reach up to 7% [28%] {80%} when the parameter uncertainty of the 24-hour cumulative precipitation is considered at the 99% confidence interval level[14].

The goodness-of-fit measures

Table 2 also reports the RMSE and two pseudo R^2 indices as goodness-of-fit measures. The similarity of the RMSE and pseudo R^2 values between the *compound vulnerability function* and the *univariate vulnerability function* are attributed to two factors. First, as the variances of the prediction errors are relatively large compared to the expected predictions, relative improvements in the prediction accuracy in terms of the RMSE become less noticeable. Second, there is a relatively limited amount of claims in the estimation sample that are induced by high precipitation levels (> 50 mm of precipitation in 24-hours) as compared to those that are mainly driven by wind gusts. Consequently, the *univariate vulnerability function*'s prediction errors on damage driven by high precipitation levels have relatively less weight in the RMSE calculations. The same explanations apply for the obtained pseudo R^2 values as these indices aim to approach the R^2 metric and this metric, in turn, depends on the (large) prediction errors.

As such, the similarities in goodness-of-fit measures between the two models should not be considered as evidence for equal prediction accuracy for winter storms with high precipitation levels. Graphical comparisons between the mean observed damage ratios for such winter storms and the corresponding mean damage ratio predictions from either the *compound vulnerability function* or the *univariate vulnerability function* clearly show that the latter is, on average, less accurate as it tends to underestimate these damage ratios more severely and more often (Figures S3 and S4 in the Supplementary Information). In numerical terms, comparing the mean prediction error of the *compound vulnerability function* with that of the *univariate vulnerability function* on recorded claims with 24-hour cumulative precipitation levels of 50 mm [75 mm] and above, demonstrates that the *univariate vulnerability function* has a 249% [265%] higher mean prediction error.

The consequence of large prediction errors

The relatively high RMSE and low pseudo R^2 values are partly driven by the underestimation of several large damage ratios[15]. Foremost, they could be indicative of the sizable variation in vulnerability characteristics that is left unexplained and the randomness inherent to the damage process. Accordingly, these factors have also manifested themselves in a large variance of the damage ratio estimates.

The sizable degree of uncertainty encompassing the damage ratio estimates also implies that winter storm losses for small samples cannot accurately be predicted by summing all expected individual losses (stemming from the expected damage ratio estimates). This follows from the law of large numbers, which prescribes that the chance of a considerable discrepancy between the expected

[14] The uncertainty in the expected damage ratio estimate, stemming from the parameter uncertainty of the 24-hour cumulative precipitation, is isolated as the difference in expected damage ratio estimate from the *compound vulnerability function* and the *univariate vulnerability function* at their 99% confidence interval levels (in excess over the damage ratio estimates from the mean parameters), evaluated at the stated meteorological conditions.

[15] For instance, omitting 1167 observations with damage ratios larger than the 99.5th quantile reduces (increases) the RMSE (the pseudo R^2 values) for the *compound vulnerability function* with almost 50%.

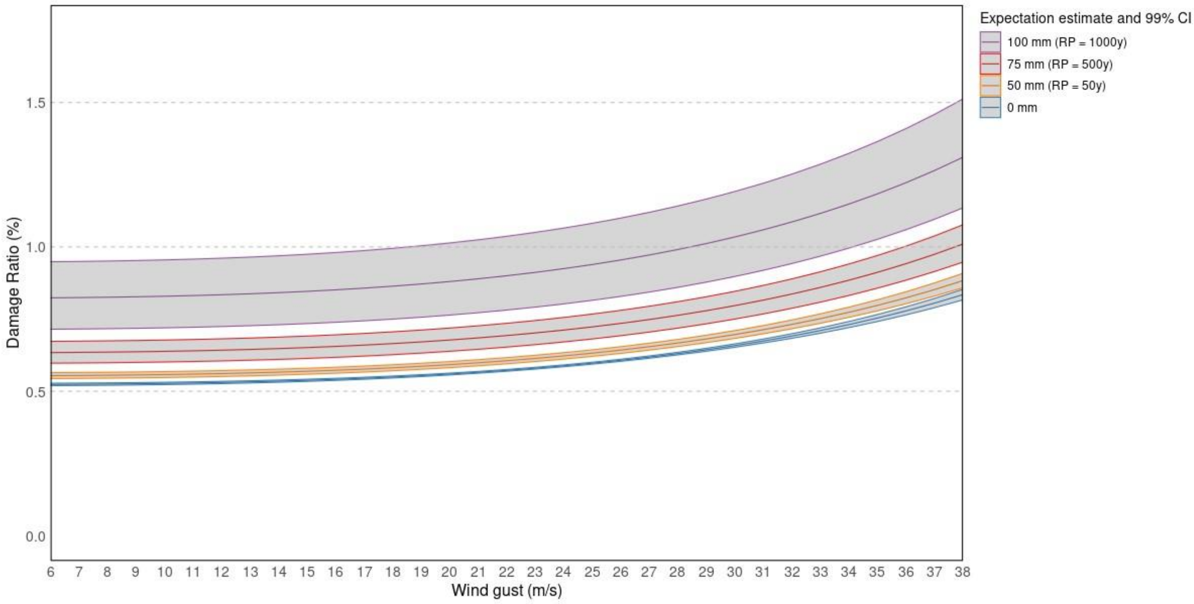
damage ratio and the average of the materialized damage ratios increases for smaller sample sizes. Instead of solely relying on the sum of expected losses (a point estimate), it is advised to consider a probabilistic range of loss estimates, also known as a loss distribution, for smaller sample sizes. A loss distribution informs the end-user on both the expected loss estimate and the range of plausible losses also known as risk. Having knowledge on the latter makes it possible to (probabilistically) account for potential deviations from this expected loss estimate by also considering alternative loss materializations. The loss distribution can be generated by repeatedly drawing (simulating) random potential damage ratios from a conditional beta distribution and assigning them to the damaged residential buildings. Accordingly, the beta distribution is conditioned on the reconstruction value and meteorological conditions of interest.

Lastly, the need to establish a loss distribution for smaller samples also reiterates the relevance of incorporating a precipitation regressor in the vulnerability functions. That is, omitting the precipitation regressor limits the chances of randomly drawing the relatively large damage ratios from the conditional beta distribution which are observed at higher precipitation levels. To illustrate, evaluating the *compound vulnerability function'*s beta distribution at the 99th quantile, conditional upon the inputs from the previous example and using the mean parameters, shows that 1% of these damage ratios are predicted to be larger than 2.44% [2.63%] {3.02%}. For the univariate vulnerability function, we can also calculate the quantiles that correspond to these damage ratios, which results in the exceedance probabilities 0.9% [0.62%] {0.28%} rather than 1%. As such, the chance of randomly drawing damage ratios larger than 2.44% [2.63%] {3.02%} from the conditional beta distribution of the latter model is 11% [61%] {257%} smaller than in the former.

Diagnostics
Figures S5-9 in the Supplementary Information present various (residual) diagnostic plots for the *compound vulnerability function* to further examine its fit. Figures S5 and S6 show the Pearson residuals against the fitted values (i.e. the expected damage ratio estimates) and the indices of the observations. No significant patterns are observed in these figures, which implies that the model adequately captures the non-linear relationship between the dependent variable and regressors. Figure S7 depicts a normal quantile-quantile plot where the residuals are quantile residuals as proposed by Dunn and Smyth (1996). This plot highlights that the *compound vulnerability function* has difficulties in describing both tails of the empirical damage ratio distribution. In particular, it underestimates the right tail of the empirical damage ratio distribution (i.e. there are more large damage ratios than the fitted beta distribution anticipates) whereas it overestimates the left tail of the empirical damage ratio distribution (i.e. there are less small damage ratios than the fitted beta distribution anticipates). In addition, the densities of the quantile residuals and standard normal distribution in Figure S8 also reveal discrepancies between the central regions of the empirical damage ratio distribution and the fitted beta distribution. These observations are confirmed by the descriptive statistics of both the Pearson and quantile residuals in tables S18-19 in the Supplementary Information, as they show that these residuals are on average right-skewed and leptokurtic. Nonetheless, both mean residuals are close to zero indicating that the *compound vulnerability function* can safely be applied to large samples as it turns out that, under these circumstances, the inaccuracies of the fitted beta distribution have been averaged out. If, however, the sample is small and simulation methods have to be performed, it is important to point out that the loss distribution will resemble the characteristics of the theoretical damage ratio distribution (i.e. the fitted beta distribution). Consequently, this loss distribution will differ from one simulated according to the empirical damage ratio distribution, in the same manner as their underlying damage ratio distributions differ. The magnitude of these differences can decrease to a certain extent for simulations from larger samples. Lastly, Figure S9 displays the leverage values of all observations against their indices to examine their influence on the regression parameters. Although there are many high leverage observations (i.e. having a substantially higher leverage than the mean leverage), they appear not to be of influence as the regression parameters are at

least robust to removing the top 0.5% observations (~1000 observations), ranked according to their leverage.

Figure 1.



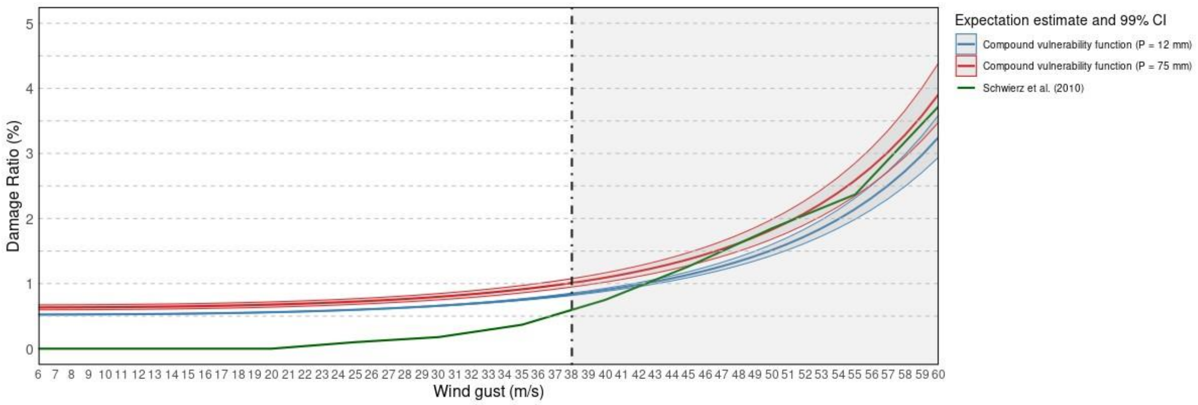
This figure shows the c*ompound vulnerability function'*s output for differing wind gust speeds and 24-hour cumulative precipitation levels. In this figure, RP refers to the return period and CI to the confidence interval. The return periods are derived from STOWA (2019).

4. Discussion

Comparison with the literature

Due to a lack of (granular) damage data, few empirical European winter storm vulnerability functions for residential buildings are reported in the literature. Figure 2 compares the *compound vulnerability function* with the only available European winter storm vulnerability function that we are aware of. This function was provided by Schwierz et al. (2010) and hereafter referred to as the *Sw vulnerability function*. Before their outputs are compared, it is important to describe how the *compound vulnerability function's* specification distinguishes itself from that of the *Sw vulnerability function*. Firstly, by including a regressor reflecting the effect of a reconstruction value and one for the damaging effects of precipitation. The inclusion of these regressors enables to adequately differentiate between the vulnerabilities of different types of residential buildings and improves the accuracy of damage ratio estimations for winter storms with heavy precipitation levels. Secondly, the *compound vulnerability function*'s parameters, their uncertainties and the 99% confidence intervals of the expected damage ratio estimates are reported. This allows for model reliability assessments and ensures that simulations can be performed by conditioning the beta distribution on the reconstruction value and meteorological conditions of interest. In contrast, the *Sw vulnerability function* solely provides an expected damage ratio estimate, which, according to our results, should restrict its usage to large samples only. As a result, it also does not provide parameter uncertainty ranges (for the expected damage ratio estimates) nor is a distribution specified around the expectation to represent variation.

Figure 2.



This figure shows the *compound vulnerability function's* output and that from the vulnerability function of Schwierz et al. (2010). In this figure, RP refers to the return period and CI to the confidence interval. The return periods are derived from STOWA (2019). The *compound vulnerability function* performs out of sample damage ratio predictions after wind gust speeds of 38 m/s. The out of sample boundary is marked by the dotted vertical line.

The *compound vulnerability function's* output evaluated at the sample's mean reconstruction value (~€370,000.-) and 24-hour cumulative precipitation level (~12 mm) most closely resembles the output from the *Sw vulnerability function*, as the latter's output reflects the "averaged out" effects of these omitted regressors. Comparing those expected damage ratio estimates reveals that there are notable output differences at virtually all wind gust speeds.

The biggest difference revolves around the assumed wind gust speed from which damage starts to occur. Similar to numerous studies (see for example Donat et al. (2010) and Pinto et al. (2012)), Schwierz et al. (2010) set this boundary at the 98th quantile of the local daily maximum wind gust distribution. In the context of their study, and (coincidentally) also that of ours, this boundary approximately equals wind gusts of 20 m/s. However, the lower wind gusts speeds found to be associated with the claims in this study indicate that damage to residential buildings might start earlier. Moreover, the large variance of the damage ratio estimates suggests that there is likely not a universal "damage threshold" for all types of residential buildings. It is more plausible that these boundaries will depend on building vulnerability characteristics and the randomness inherent to the damage process. Nonetheless, our best estimate for such a damage threshold would be for wind gusts between 9 and 10 m/s as this is the threshold from which large numbers of claims are observed. Consequently, this inference implies that winter storm losses will be underestimated if higher boundary speeds are assumed because damage arising from lower wind gust speeds will be overlooked. Note however that these boundary values are only suitable for use cases where the incorporated meteorological observations are alike to those in this study. That is, empirically validated and reanalyses based wind gusts reported per grid at a horizontal resolution of 2.5 km. These boundary values might not apply to for example, vulnerability functions that are calibrated on meteorological observations with different characteristics (e.g. with differing horizontal resolutions).

Additional noteworthy differences are identified between the wind gust speeds of the damage threshold of Schwierz et al. (2010) (20 m/s) and the maximum observed wind gust speed in this study's sample (~38 m/s): the *compound vulnerability function* predicts structurally higher expected damage ratios than the *Sw vulnerability function*. This pattern reverses itself however for the out-of-sample predictions (> 38 m/s) of the *compound vulnerability function*. Here, the expected damage ratio predictions of the *Sw vulnerability function* remain somewhat close to that of the *compound vulnerability function* at the 99% confidence interval level, but resembles the evaluation at 75 mm of 24-hour cumulative precipitation levels more closely. Conclusively, if the *compound vulnerability function's* calibration represents the true European winter storm vulnerability function for residential buildings, then the reference function in Schwierz et al. (2010) underestimates the damage ratio below wind gust speeds of ~42 m/s, where the underestimation becomes more pronounces for winter storms with higher levels of precipitation. Moreover, the *Sw vulnerability function* would overestimate the damage ratio above these wind gust speeds for winter storms with relatively low precipitation levels, but accurately estimate the damage ratio for those winter storms with extreme precipitation levels.

Applying the vulnerability functions
Given their limited availability in the literature, the main purpose of this study is to deliver vulnerability functions for residential buildings that can be implemented in private, academic and open-source natural catastrophe models for European winter storms. Well known use cases of the loss estimates of natural catastrophe models are to support the financial risk management of (re)insurers or to inform their premium pricing process. However, as natural catastrophe risks increase due to economic growth and climate change (O'Neill et al., 2022), such loss estimates become more relevant for the climate-related risk management and reporting of other (financial) organizations as well (Fiedler et al., 2021). The *compound vulnerability function* is especially appropriate to estimate future European winter storm losses as it explicitly accounts for the damaging effects of precipitation, which intensity and frequency is thought to be altered by climate change (Hawcroft et al., 2018; Kodama et al., 2019; Li et al., 2024; Little et al., 2023; Yettella et al., 2017). The vulnerability functions can, therefore, also be a suitable guide to cost-benefit analyses of climate risk reduction measures, as the functions give insight into their maximum potential benefits i.e. the (expected) damage before the adaptation measures.

Natural catastrophe modelers and other interested parties are encouraged to apply the *compound vulnerability function* from this study if the availability of 24-hour cumulative precipitation level data allows for it. When this is not the case, the users might resort to the *univariate vulnerability function* while keeping its outlined limitations in mind. The end-users of these vulnerabilities functions should be aware that their predictions are predominantly appropriate for residential buildings of a similar build quality as those found in the Netherlands and within the range of the meteorological conditions in this study which, furthermore, are of the same horizontal resolution and produced by alike methods[16]. To facilitate the usage of these vulnerability functions, section S5 in the Supplementary Information provides tables with damage ratio output from the *compound vulnerability function* for an average residential building (i.e. with a reconstruction value of €370,000.-) at differing wind gust speeds, 24-hour cumulative precipitation levels, quantiles of the conditional beta distribution and confidence intervals for the expected damage ratio.

Lastly, to estimate losses from multiple buildings, the end user also requires information on the chance of being damaged given certain meteorological conditions alongside these vulnerability functions. Empirical models that estimate the chance of being damaged can also be constructed from insurance data and provide opportunities for further research. Especially finding that precipitation levels are a significant contributor to residential building damage signals that such research endeavors could be worthwhile as it suggests that the chance of being damaged is also influenced by this factor.

[16] Note that the required reconstruction value is denoted in EUR in 2024 price levels.

5. Conclusion

Based on ultra-high resolution insurance claim observations in the Netherlands, we constructed winter storm vulnerability functions for residential buildings. By doing so, an important gap in the natural catastrophe modelling literature is filled as empirical European winter storm vulnerability functions for residential buildings are scarce. Moreover, our research innovates upon previous studies by using the truncated beta regression to estimate the vulnerability functions. In this regression model, the dependent variable distribution is fully aligned with the empirical distribution of the damage ratios. It also accommodates the heteroskedasticity and distributional asymmetries that are often found in regressions on fractional data and accounts for the non-observed losses below the imposed insurance deductibles through truncation adjustments. In addition, we are first to produce a compound vulnerability function for European winter storms that incorporates the damaging effects of both wind and precipitation, which makes the vulnerability function especially appropriate for climate change impact analyses.

By comparing this study's best model specification with alternative setups and a vulnerability function from the literature, four key conclusions can be drawn. First, accounting for reconstruction values in the vulnerability function provides means to differentiate between the vulnerabilities of different types of residential buildings, which improves the estimation accuracy of the damage ratio. Second, factoring in the damaging effects of precipitation in winter storm vulnerability functions prevents damage ratio underestimations for high precipitation level events. Third, it is recommended to simulate a loss distribution for samples of limited size as the variance of the damage ratio estimates is large. The damage ratios can be simulated with the vulnerability function parameters provided in this study by conditioning the beta distribution on the reconstruction value and meteorological conditions of interest. Fourth, there exists considerable uncertainty around the wind gust speed threshold from which residential building damage starts to occur. Foremost, this is due to the limited availability of winter storm vulnerability functions and likely exacerbated by differences in the horizontal resolution of the meteorological observations and their measurement methodologies.

Our vulnerability functions can serve as input for private, academic and open-source natural catastrophe models to accurately estimate damage to residential buildings from European winter storms which can be used for a variety of applications. Important use cases include financial risk management and premium pricing for (re)insurers, but increasingly also the climate-related (financial) risk management of other (non-) financial organizations as well.

Data availability
The datasets generated and/or analyzed during the current study are not publicly available as they are proprietary to the financial conglomerate.

Code availability
The underlying code for this study is not publicly available but may be made available to qualified researchers on reasonable request to the corresponding author.

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