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Improving Europe-wide windstorm damage modeling using insurance loss data

Aditya N. Mishra[1,2], Gabriele Messori[1,2], Lukas Riedel[3,4], Athul Rasheeda Satheesh[5], and Joaquim G. Pinto[5]

[1]Department of Earth Sciences, Uppsala University, Uppsala, Sweden
[2]Swedish Centre for Impacts of Climate Extremes (climes), Uppsala University, Uppsala, Sweden
[3]Institute for Environmental Decisions (IED), ETH Zurich, Zurich, Switzerland
[4]Federal Office of Meteorology and Climatology MeteoSwiss, Zurich Airport, Switzerland
[5]Institute of Meteorology and Climate Research – Troposphere Research (IMK-TRO), Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany

Correspondence: Aditya N. Mishra (aditya.mishra@geo.uu.se)

Abstract.

Winter windstorms are among Europe's deadliest and most damaging natural hazards. In a changing climate, reliably estimating and projecting their impacts is essential for effective risk management. Such risk is often modeled as the intersection between hazard, exposure, and vulnerability, which are linked through functional relationships known as vulnerability curves (or damage models). The Schwierz et al. (2010) damage model is a widely used open-source standard for European windstorms, but its original calibration is based on a limited set of historical UK storms. In this study, this model is calibrated against recent loss data from the PERILS database (1999–2024) within the CLIMADA open-source framework, across 12 European countries. Calibration is conducted independently using two cost functions: Root Mean Squared Error (RMSE) and Root Mean Squared Logarithmic Error (RMSLE), enabling a systematic comparison of their influence on the optimised damage parameter and derived risk metrics. The default model is found to systematically underestimate losses across Europe, and a single pan-European model cannot capture the distinct vulnerability profiles of individual countries. By calibrating the model against PERILS losses, a new set of country-specific damage functions is developed, which reflect spatial heterogeneities in vulnerability. In addition, the analysis demonstrates that the chosen loss function (RMSE versus RMSLE) fundamentally shapes the calibrated curves and the resulting risk profile, underscoring that calibration metric is itself a key modeling decision. The results offer practical guidance for calibrating damage models and support more rigorous climate risk assessment.

1 Introduction

Winter windstorms are among Europe's most damaging natural hazards, producing extreme winds that cause widespread damage to physical assets, as well as lead to human fatalities (Schwierz et al., 2010; Pinto et al., 2019; Severino et al., 2024). These storms primarily travel easterly-northeasterly along the North Atlantic storm track, whose associated jet stream channels the intense cyclonic systems towards the European continent (Hoskins and Hodges, 2002; Ulbrich et al., 2009; Zappa et al., 2013). Even though regions as south as the Iberian Peninsula and Italy are also occasionally affected (e.g. storm "Klaus";

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Liberato et al. (2011)), this study focuses on the primary corridor of winterstorm activity - the British Isles, France, the Benelux countries, Germany, and Scandinavia (Pinto et al., 2012). These regions host major economic centres with high financial stakes for the insurance and reinsurance sector with approximately EUR 64.8 trillion (2022) worth of total insured value exposed to windstorms (PERILS AG, 2025). Infact, in recent years these regions have witnessed multiple billion-euro catastrophe events, including the February 2022 European windstorm series (Dudley, Eunice, Franklin) (Mühr et al., 2022; Williams et al., 2025), which generated estimated insured losses of EUR 3.8 billion (PERILS AG, 2023).

Cyclonic activity over the North Atlantic basin and Europe has undergone strong decadal variability recently, with relatively low activity in the 1960s, a peak in the 1990s, and a decline in the early twenty-first century, without a clear anthropogenic trend (Ulbrich et al., 2009; Feser et al., 2015). Under future climate conditions, projections from multi-model climate ensembles indicate that in spite of a general decrease in cyclone activity in global terms (Ulbrich et al., 2009) that the parts of western and central northwestern and northcentral Europe are set to experience an increase in both frequency and magnitude of windstorm-induced damages (Pinto et al., 2012; Severino et al., 2024) driven by an eastward extension of North Atlantic storm track in wintertime (Ulbrich et al., 2009; Zappa et al., 2013; Harvey et al., 2020). However, these projected changes in terms of storm frequencies, magnitude and impact pathways are subject to high uncertainties (Shaw et al., 2016; Catto et al., 2019; Severino et al., 2024; Alifdini et al., 2025). As multifaceted impacts of climate change compound on top of these projection uncertainties, robust risk quantification in the form of reliable estimation and projection of windstorm damage becomes imperative to accurately inform insurance pricing, and climate adaptation planning (Pinto et al., 2007; Donat et al., 2011; Pinto et al., 2019).

Within the established catastrophe risk framework - wherein total risk emerges from the intersection of hazard, exposure, and vulnerability - the vulnerability function (or damage model henceforth) constitutes the critical bridge between physical hazard intensities and economic losses (Field et al., 2014; Aznar-Siguan and Bresch, 2019). Windstorm risk is quantified using these damage models, which mathematically map maximum wind gust speeds (the hazard intensity metric) to damage ratios (bounded between 0 and 1, representing the fraction of asset value lost), enabling the translation of spatially resolved, event-level wind fields into estimates of economic impact (Khanduri and Morrow, 2003; Schwierz et al., 2010). The quality of these damage models directly determine the credibility of loss estimates, along with risk metrics such as average annual impact (AAI) and scenario-based loss projections - quantities routinely used by insurers to set reserves, price products, and manage portfolios (Watson and Johnson, 2004; Smith and Matthews, 2015). The fact that many of these models are proprietary, complicates the comparability between datasets and approaches (Schwierz et al., 2010; Roberts et al., 2014; Pinto et al., 2019; Moemken et al., 2024a).

The Schwierz et al. (2010) damage model represents a widely adopted open-source formulation for European windstorms that has been employed in numerous climate risk studies (Prahl et al., 2015; Aznar-Siguan and Bresch, 2019; Koks and Haer, 2020; Welker et al., 2020; Gliksman et al., 2023; Severino et al., 2024). The damage model is originally derived through calibration against reported losses from UK windstorms and has since been cross-validated with other European countries. The model expresses damage as a function of 10-metre wind gust speed and fraction of the asset value lost. Even though the model is popular in literature, the limited temporal and spatial basis of the original calibration - restricted to a narrow

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geography and historical window - raises legitimate concerns about the representativeness of the model for usage in current European exposure distributions and windstorm loss scenarios (Donat et al., 2011; Pinto et al., 2012; Severino et al., 2024; Alifdini et al., 2025). Therefore, the need for its robust calibration and validation is paramount, particularly because outdated parameterizations can lead to significant biases in risk assessment (Smith and Matthews, 2015; Kropf et al., 2022; Hu et al., 2023). These considerations motivate a rigorous, data-driven recalibration of the model using modern industry loss records to ensure its continued reliability for climate risk applications.

When fitting damage models to observed event losses, practitioners must specify a loss function to quantify the discrepancy between modeled and reported damages. The choice of this loss function influences the calibration as different loss functions emphasize different parts of the loss distribution, potentially affecting the resulting derived risk estimates. Two common choices for such applications are RMSE and RMSLE loss functions (Jadon et al., 2022). While RMSE applies quadratic penalties and is sensitive to large errors, RMSLE applies a logarithmic transformation that reduces the relative influence of outliers (Jadon et al., 2022). For windstorm applications, where loss distributions are highly skewed and individual catastrophic events can dominate aggregate statistics, the choice of loss function influences which portions of the loss distribution receive emphasis during calibration, and consequently, which risk metrics are well-reproduced and which may exhibit larger residuals (Prahl et al., 2015).

The open-source CLIMADA platform is a modular framework that integrates the hazard, exposure, and vulnerability components for impact assessment (Aznar-Siguan and Bresch, 2019). In this study, CLIMADA is used to recalibrate the Schwierz et al. (2010) damage model using recent, high-quality insurance loss data from the PERILS database (1999–2024) (PERILS AG, 2025), producing a new set of optimized windstorm damage models for 12 European countries. The calibration is conducted independently using RMSE and RMSLE, enabling a systematic comparison of how the choice of loss function influences the calibrated model and the derived risk metrics (Smith and Matthews, 2015; Hu et al., 2023). The study aims to provide a useful insight for practitioners and researchers tasked with calibrating damage models, with the aim of contributing to a broader scientific effort that advances climate risk assessment in a rigorous manner (Higuera Roa et al., 2025)

2 Data & Methods

2.1 Data

To calibrate the model, primarily event-level insurance loss data provided by PERILS (PERILS AG, 2025) is used, through an annual subscription database license. The PERILS dataset is compiled exclusively from information provided by insurance companies conducting business in covered territories, with strict protocols ensuring data provider anonymity. Neither the identity of participating insurance companies nor information that could lead to their disclosure (such as total market coverage) is made publicly available.

The database provides extratropical windstorm loss information across 12 European countries: Austria, Belgium, Denmark, France, Germany, Ireland, Luxembourg, the Netherlands, Norway, Sweden, Switzerland, and the United Kingdom. Loss data are available in national currencies, Euros (EUR), and US Dollars (USD). A windstorm event qualifies for inclusion if the total

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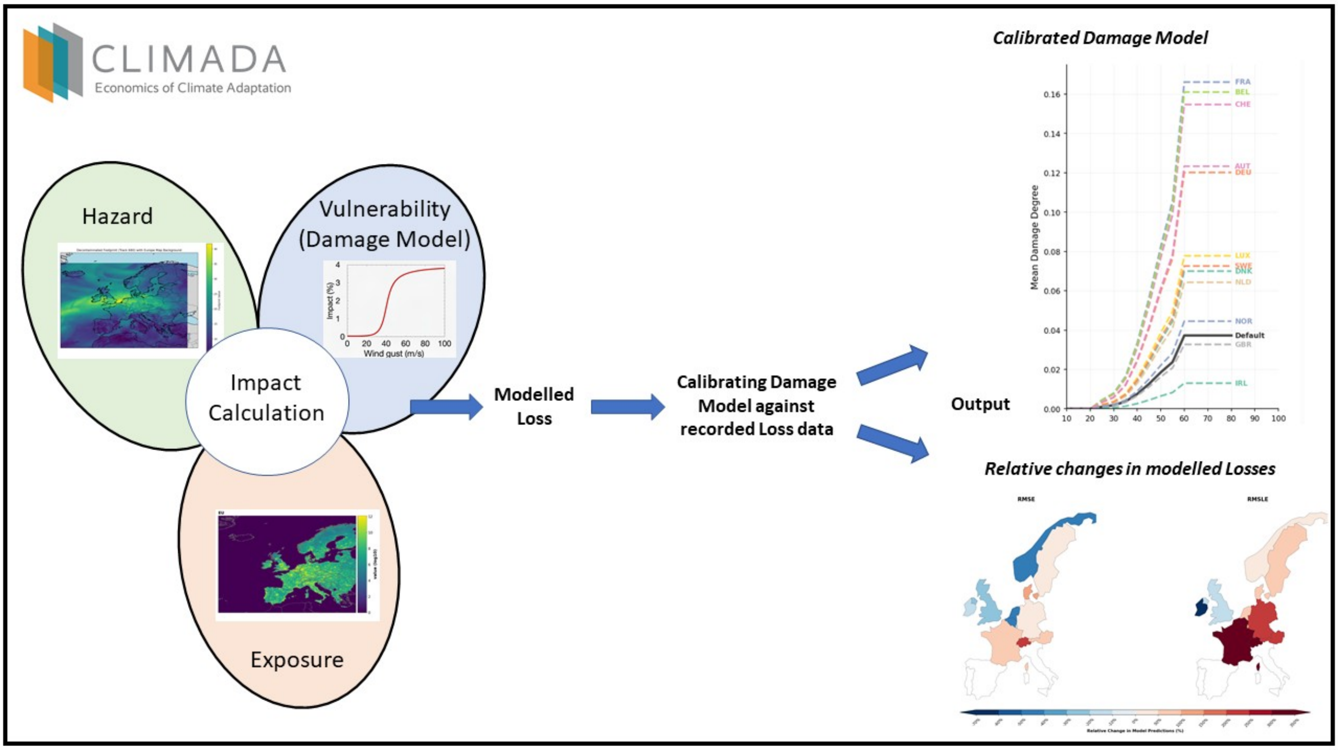

Figure 1. Schematic workflow of the windstorm damage model calibration framework. The core CLIMADA impact calculation integrates three components: Hazard footprints (wind gust), Exposure (asset distribution and value), and Vulnerability (damage model linking wind speed to proportion of asset value lost). Modeled losses are calculated and the vulnerability component is calibrated by minimizing the difference between modeled and reported losses.

insured loss exceeds 200 million EUR. This threshold was revised in September 2022 to 500 million EUR for pan-European events and 300 million EUR for country-specific events. The database contains windstorm losses for all qualifying events since 2009. In 2011, the dataset was retrospectively expanded to include loss estimates for five major European storm events from 1999 onwards: Anatol, Lothar, Martin, Jeanett, and Kyrill (Ulbrich et al., 2001; Fink et al., 2009).

Loss data for windstorms is also used from the Emergency Events Database (EM-DAT) (Delforge et al., 2025), a freely available disaster database launched in 1988 by the Centre for Research on the Epidemiology of Disasters (CRED) at UCLouvain in Brussels, Belgium. The database contains records of more than 22,000 disasters worldwide spanning from 1900 to the present, categorized into two primary types: natural and technological disasters. EM-DAT aggregates information from multiple sources, including UN agencies, non-governmental organizations (NGOs), the World Bank, research institutes, insurance and reinsurance companies, and news agencies. While the specific source for each disaster entry is not disclosed, events are typically included only if reported by at least two independent sources. The database compiles geographical, temporal, human,

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and economic impact data at the country-aggregated level. Moemken et al. (2024b) compared EM-DAT and PERILS datasets and concluded that they provide a complementary view of the losses.

The hazard component of the model is based on windstorm footprints from the Copernicus Climate Change Service (C3S) Enhanced Windstorm Service (EWS) dataset (van den Brink, 2019; Copernicus Climate Change Service, 2025), which provides the maximum 10 m wind gust over a 72-hour window for each event, derived from the ERA5 global reanalysis (Hersbach et al., 2020) using the TRACK cyclone tracking algorithm (Hodges, 1995, 1999). Asset exposure is represented using LitPop (Eberenz et al., 2020), a globally consistent dataset that disaggregates national asset values to a gridded resolution of 30 arcsec (∼1 km) proportional to a combination of nightlight intensity and population data, and is available through the CLIMADA platform (Aznar-Siguan and Bresch, 2019).

Several filtering steps are applied before the calibration and validation of the model (see Section 2.3).

2.2 CLIMADA Framework

CLIMADA (CLIMate ADAptation) is an open-source, modular software platform for probabilistic assessment of socioeconomic impacts from natural hazards, implementing the IPCC risk framework wherein risk emerges from the interaction of three components: hazard, exposure, and vulnerability (Aznar-Siguan and Bresch, 2019). The platform architecture consists of three main modules: (i) a hazard module defining the spatiotemporal probability distribution and intensity of extreme events; (ii) an exposure module that can store user-provided information on the spatial distribution, asset values, and asset characteristics (e.g., building types, occupancy) of elements at risk; and (iii) a vulnerability module containing impact functions that map hazard intensities to damage ratios for specific asset types and geographic regions. These modules are integrated through a centroid-based spatial framework, wherein each centroid represents a geographic point (typically on a regular grid) linked to both hazard intensity time series and exposure values. Wind gust intensity at each centroid is converted into a mean damage degree (MDD), representing the fraction of the exposed asset value damaged at that wind intensity, which CLIMADA then combines with the exposure data to compute event-level damage. The event-level modeled loss is the sum of these centroid-level damage estimates and aggregating across events yields total loss estimates for a given country or region. Within CLIMADA's implementation, the Schwierz model is represented as an empirically-derived nonlinear function, originally calibrated against historical insurance losses from UK windstorms (1987–1990 period) and subsequently validated across multiple European countries. The model maps wind gust speed to an MDD value at a set of fixed intensity nodes. The model exhibits negligible damage below approximately 15 m/s (below which wind impacts are typically insurable at minimal loss), reaches approximately 50% of maximum damage at moderate gust speeds (35–40 m/s), and approaches saturation at MDD's maximum value ($\mathrm{MDD}_{\max}$) at extreme wind speeds (>60 m/s)(see Fig. 2a). This nonlinear relationship is crucial: small changes in wind gust magnitude can produce large changes in damage, particularly in the transition region between 30–50 m/s where the slope is steepest. This differs from Vmax/V98-type approaches, which relate losses to exceedances above a local high-percentile threshold (Klawa and Ulbrich, 2003; Pinto et al., 2007).

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2.3 Calibration Methodology

The calibration problem is posed as a single-parameter optimisation task. Given a set of historical windstorm events with reported insured losses and corresponding modeled hazard footprints (wind gust fields from C3S-EWS) and exposure layers (LitPop), the goal is to determine the optimal value of $\mathrm{MDD}_{\max}$ that minimises the discrepancy between modeled and reported losses. The ratio of $\mathrm{MDD}_{\max}/\mathrm{MDD}_{\max}^{\mathrm{default}}$ rescales the entire MDD curve proportionally i.e., all MDD values at every intensity node are multiplied by a common factor.

The calibrated MDD at wind speed v is

$$\mathrm{MDD}(v;\theta) = \frac{\theta}{\mathrm{MDD}_{\max}^{\mathrm{default}}} \times \mathrm{MDD}^{\mathrm{default}}(v) \tag{1}$$

where $\mathrm{MDD}^{\mathrm{default}}(v)$ is the default MDD array of the model, $\mathrm{MDD}_{\max}^{\mathrm{default}} = 0.0373$ is its saturation value, and $\theta = \mathrm{MDD}_{\max}$ is the calibrated parameter. This calibration strategy is consistent with the approach applied by Severino et al. (2024).

For this analysis, all reported windstorm events occurring between 1999 and 2024 are considered. First, only events that can be reliably matched to a corresponding EWS hazard footprint (via event name, date, and affected country) are retained. Events for which either the loss record or the associated hazard field is incomplete, missing, or clearly inconsistent (e.g. grossly mismatched spatial footprint versus reported affected countries) are discarded. This ensures that the calibration uses only events for which the hazard–loss linkage is trustworthy. The resulting subset of well-matched events for a given country forms the training dataset for calibration.

Calibration is undertaken separately for each country using two alternative cost functions Root Mean Squared Error (RMSE) and Root Mean Squared Logarithmic Error (RMSLE), yielding paired calibrations that enable systematic comparison of how loss function choice influences the calibrated $\mathrm{MDD}_{\max}$ and resulting risk estimates.

RMSE is defined as

$$\mathrm{RMSE}(\theta) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(L_i^{\mathrm{rep}} - L_i^{\mathrm{model}}(\theta)\right)^2} \tag{2}$$

where L_i^{rep} is the reported loss for event i, $L_i^{\mathrm{model}}(\boldsymbol{\theta})$ is the modeled loss as a function of parameters $\boldsymbol{\theta}$, and n is the number of events in the training set. RMSE penalizes prediction errors quadratically, meaning that large errors incur disproportionately high penalties.

RMSLE applies a logarithmic transformation prior to error calculation:

$$\mathrm{RMSLE}(\theta) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\log(L_i^{\mathrm{rep}}+1) - \log(L_i^{\mathrm{model}}(\theta)+1)\right)^2} \tag{3}$$

The logarithmic transformation effectively reduces the relative magnitude of large absolute errors, particularly for high values.

Formally, the optimal parameter $\theta^* = \mathrm{MDD}_{\max}^*$ is sought such that

$$\theta^* = \underset{\theta \in (0,1]}{\arg\min}\ \mathrm{Cost}\big(L^{\mathrm{model}}(\theta), L^{\mathrm{rep}}\big), \tag{4}$$

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where the 'Cost' denotes loss function of either RMSE (Eq. 2) or RMSLE (Eq. 3), and the bound $\theta \in (0,1]$ ensures that the calibrated $\mathrm{MDD_{max}}$ remains physically plausible.

For each event in the training set, the full CLIMADA impact calculation chain is executed: (1) exposure centroids are linked to corresponding hazard centroid locations via nearest-neighbor assignment within a 20-km distance threshold; (2) hazard intensities (wind gust speeds) at each centroid are extracted from the C3S-EWS wind footprint for the event date; (3) modeled losses are computed as $\text{Impact} = \text{Exposure} \times \text{Damage Model}(v_{c,i})$ where $v_{c,i}$ is the wind gust speed at centroid c during event i and is aggregated across all centroids; (4) the modeled loss is compared to the recorded loss via the selected loss function.

The Limited-memory Broyden–Fletcher–Goldfarb–Shanno with box constraints algorithm (L-BFGS-B) (Byrd et al., 1995; Zhu et al., 1997) is used to iteratively adjust the $\mathrm{MDD_{max}}$ to minimize the specified cost function. This quasi-Newton optimizer is well-suited for this application because it: (i) requires only gradient approximations, reducing computational cost; (ii) enforces parameter bounds (e.g., threshold wind speed > 0, maximum damage ≤ 1); and (iii) converges reliably for smooth, nonlinear cost landscapes typical of impact function calibration. The optimization terminates when relative improvement between iterations falls below a specified tolerance (typically 10^{-4}), indicating convergence to a local minimum.

Calibration is performed independently for RMSE and RMSLE, using identical training data, event sets, and parameter bounds, ensuring that differences in fitted parameters arise solely from the loss function choice rather than from differences in data or optimization setup. Both calibrations are firstly conducted for the whole of Europe and thereafter conducted per country, yielding a 12-country $\times$ 2-cost-function matrix of calibrated damage models.

2.4 Leave-one-out cross validation & Uncertainty quantification

Leave-one-out cross-validation (LOOCV) is used to assess out-of-sample predictive performance of the calibrated windstorm impact model by iteratively withholding each event record and predicting its loss from a model re-fitted on the remaining data. Specifically, for each event i among n event - country observations, a training set of size $n-1$ is formed by excluding i, re-optimizing the calibration parameter ($\mathrm{MDD_{max}}$) on this reduced set, and then computing the predicted loss for the held-out event i using its fixed hazard footprint and exposure representation. Repeating this procedure for all n events yields n LOO predictions that can be compared to recorded losses using error metrics; in this implementation RMSE and RMSLE are reported. LOOCV was executed separately for two cost functions - RMSLE-calibrated and RMSE-calibrated - so that their out-of-sample predictive skill could be compared directly under identical LOO splits. The results showed remarkable stability in the calibrated model with the LOO predictions being very close to in-sample fits (correlation 0.97), indicating that the single-parameter calibration is robust and not driven by individual extreme events. It could also be inferred that any calibrated $\mathrm{MDD_{max}}$ value is a generalized parameter suitable for future event prediction, rather than an artifact of the specific training catalog.

To assess the robustness of the calibrated ($\mathrm{MDD_{max}}$) derived from the RMSE and RMSLE calibration strategies, the uncertainty and sensitivity quantification module (Unsequa) is employed within the CLIMADA framework (Kropf et al., 2022). While deterministic calibration provides a single optimal parameter set, it does not account for the inherent uncertainties in the input components i.e., hazard intensity, exposure value, and the damage model itself. Therefore a probabilistic analysis

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is conducted to compare how the choice of loss function (RMSE vs. RMSLE) influences the stability and accuracy of the modeled output through AAI (relative to reported PERILS losses). The model sensitivity to input uncertainties is quantified using Latin Hypercube Sampling (LHS), a stratified Monte Carlo method, to generate N=300 samples per country. Uniform uncertainty distributions are defined for the three primary model components. For hazard intensity, a $\pm 10\%$ range is adopted because ERA5 wind fields have been shown to represent strong extratropical winds comparatively well, with systematic underestimation of the order of 8–10% at the 95th–99th percentiles in the North Atlantic (Campos et al., 2022; Cheshm Siyahi et al., 2024; Cornér et al., 2025). For exposure total value, a $\pm 20\%$ range accounts for uncertainties in the national total asset value and in the subnational spatial disaggregation of the LitPop exposure model (Eberenz et al., 2020). A $\pm 20\%$ range is sampled around the optimal calibrated ($\mathrm{MDD_{max}}$), following Prahl et al. (2012) and Severino et al. (2024) who estimate this range to be a reasonable bound on the error in European windstorm damage modeling, reflecting the larger and less directly constrained uncertainties inherent in the vulnerability component. This stratified sampling approach ensures efficient coverage of the multidimensional parameter space, capturing the combined effects of exposure, hazard, and calibration uncertainty.

Model performance is evaluated using the normalized AAI calculated over the full 1999–2024 catalog, defined as $\mathrm{AAI_{norm}} = \mathrm{AAI_{model}}/\mathrm{AAI_{rep}}$, where $\mathrm{AAI_{model}}$ is the simulated average annual impact and $\mathrm{AAI_{rep}}$ is the corresponding baseline reported by PERILS. In this framework, probability density functions (PDFs) of $\mathrm{AAI_{norm}}$ centered at 1.0 indicate unbiased accuracy, while narrower distributions signify greater robustness against input perturbations. Comparing these PDFs allows us to determine which optimization objective yields a risk model that is both accurate and robust.

3 Results

Initially, the windstorm damage model is calibrated using two independent loss datasets: the high-resolution PERILS insurance database and the EM-DAT disaster database. As shown in Fig. 2, substantial differences emerge in both the optimal damage model parameter ($\mathrm{MDD_{max}}$) and overall model performance. The model's default state has $\mathrm{MDD_{max}}$ of 0.0387, which upon calibrating against the PERILS dataset, by minimizing the RMSLE loss function, increases to a higher $\mathrm{MDD_{max}}$ of 0.0757. In contrast, the $\mathrm{MDD_{max}}$ is 0.0379 when the minimized loss function is RMSE. When calibrated against EM-DAT, however, the results diverge substantially depending on the choice of loss function. While the RMSE-optimized $\mathrm{MDD_{max}}$ of 0.0445 remains comparable to PERILS, using RMSLE produces a stark contrast, driving the $\mathrm{MDD_{max}}$ up to 0.1796. To quantify the uncertainty introduced by a much smaller sample size in EM-DAT (24), a bootstrap resampling with 24 subsamples each containing 80% of the original PERILS storm events is conducted (Fig. 2a). While the RMSE parameter is within the uncertainty band, the calibrated RMSLE parameter is found to lie substantially outside the PERILS uncertainty band. Given this deviation and far fewer events available in EM-DAT, PERILS is used exclusively for all further calibration and analysis. The EM-DAT calibration performance is shown in Fig. 2d-e nonetheless, for completeness.

To evaluate calibration effectiveness, modeled damages for individual storm events calculated using the default and calibrated versions of the Schwierz et al. (2010) model are compared to the reported storm losses. Scatter plots illustrate model performance separately for the PERILS (Fig. 2b–c) and EM-DAT (Fig. 2d–e) loss datasets, using RMSLE and RMSE loss

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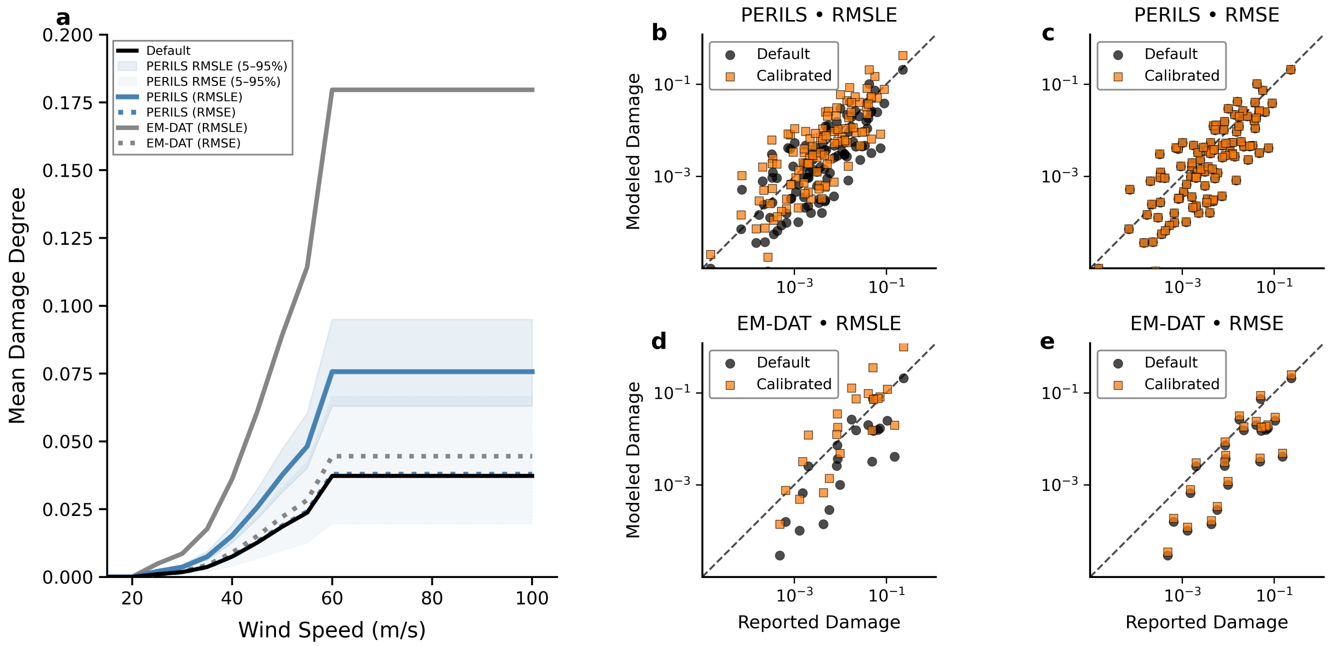

Figure 2. Calibration of windstorm damage model using PERILS and EM-DAT damage databases (a) Damage models showing mean damage degree (MDD) as a function of wind speed. The default Schwierz et al. (2010) damage model (black), with calibrated versions of the model against loss datasets: PERILS (blue) and EM-DAT (grey), optimized using RMSLE (solid lines) and RMSE (dotted lines) loss functions. Shaded bands indicate 5th–95th percentile ranges of calibrated model obtained from bootstrap resampling (N = 24, B=300) of PERILS data. (b–e) Scatter plot representing model performance for each calibration configuration. Black circles represent default model estimates; orange squares represent calibrated model estimates. All losses are normalized by the maximum PERILS-reported loss.

function respectively. The default model (black circles) systematically underestimates losses for events as modeled damages frequently fall short of reported damages, clustering along a trajectory below the 1:1 line. For PERILS RMSLE calibration (Fig. 2b), model-data agreement is markedly improved as modeled damages (orange squares) shift upward, substantially reducing bias and achieving better alignment with the 1:1 reference line, especially for mid-magnitude events where insurance loss data are most reliable. In the case of RMSE calibration (Fig. 2c), model-data agreement is improved slightly at high-magnitude damage events, pulling down modeled damages towards reported values. However, mid-range event predictions are penalized by this optimization, as the steeper curvature required to fit extreme losses degrades performance for moderate events. The choice of loss function substantially influences the calibrated damage model here. RMSLE's emphasis on relative errors yields improved performance across low-to-mid-damage events, whereas RMSE optimization prioritizes absolute error reduction, particularly for high-impact events. This metric-dependent trade-off reflects fundamentally different optimization priorities in catastrophe modeling applications.

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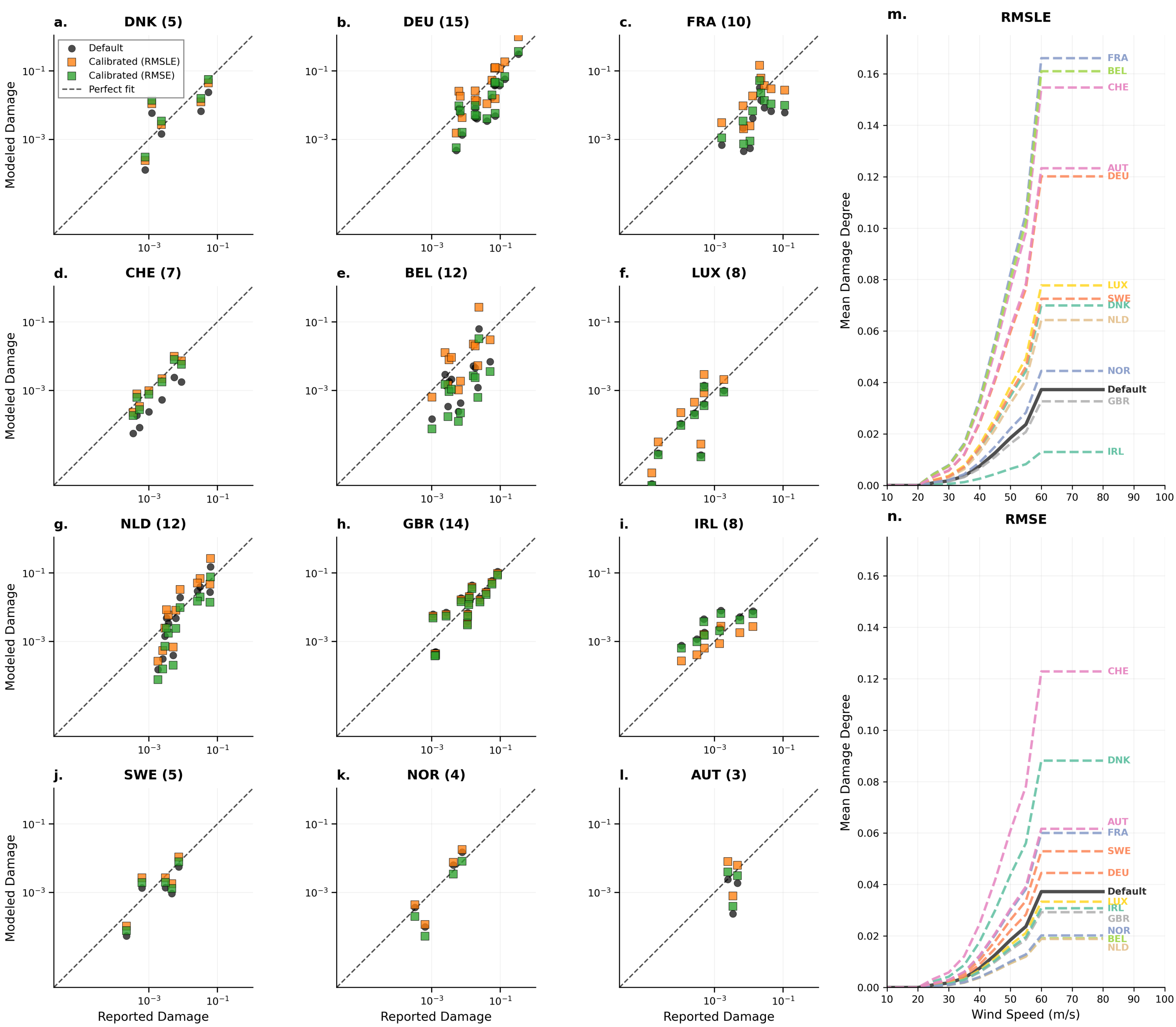

Figure 3. Calibration of windstorm damage model for individual countries using PERILS data (a–l) Scatter plot representing model performance for default and calibrated states. Black circles represent default model estimates; orange squares represent RMSLE-optimized calibrated model estimates; green squares represent RMSE-optimized estimates. Damage values are normalized due to license agreements. (m–n) Country-specific calibrated damage models in colours and the default model in solid grey for RMSLE (m) and RMSE (n) loss functions. Country abbreviations used: DNK (Denmark), DEU (Germany), FRA (France), CHE (Switzerland), BEL (Belgium), LUX (Luxembourg), NLD (Netherlands), GBR (United Kingdom), IRL (Ireland), SWE (Sweden), NOR (Norway), AUT (Austria).

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To capture spatial heterogeneity in reported damage patterns in the calibrated model, country-specific calibration is conducted for 12 European countries with loss data in PERILS dataset. Substantial variability in MDD parameter is observed across Europe (Fig. 3m & n). When RMSLE loss function is used (Fig. 3m), France, Belgium, and Switzerland exhibit the steepest damage models with $\mathrm{MDD}_{\mathrm{max}}$ values exceeding 0.15, followed by Austria and Germany at ≈ 0.12. Conversely, Ireland, Great Britain, and Norway yield substantially flatter curves with $\mathrm{MDD}_{\mathrm{max}} < 0.04$. The RMSE-calibrated damage models (Fig. 3n) exhibit a qualitatively different spatial pattern, where Switzerland ($\mathrm{MDD}_{\mathrm{max}} \approx 0.12$) and Denmark ($\mathrm{MDD}_{\mathrm{max}} \approx 0.09$) produce the steepest curves. In contrast, most other countries including France, Belgium, and Germany cluster in a lower range ($\mathrm{MDD}_{\mathrm{max}} \approx 0.02$–$0.06$), often near or below the default model. This metric-dependent spatial heterogeneity indicates that optimal damage model reflects the underlying wind-damage relationship observed in each country.

The default Schwierz et al. (2010) model (black circles) in Fig. 3a–l exhibits a systematic negative bias across most countries, with modeled damages clustering below the 1:1 line. Calibration using RMSLE (orange squares) effectively mitigates this underestimation, resulting in improved model-data concordance at mid-range magnitudes, particularly for Germany (Fig. 3b), France (Fig. 3c), Switzerland (Fig. 3d), Belgium (Fig. 3e) and the Netherlands (Fig. 3g). However, this proportional adjustment - inherent to the RMSLE loss function - can lead to overestimation at high-range magnitudes, as seen in Germany (Fig. 3b), France (Fig. 3c), Belgium (Fig. 3e) and the Netherlands (Fig. 3g). On the other hand, RMSE calibration (green squares) produces markedly negative adjustments for the majority of countries, most notably Belgium for (Fig. 3e), the Netherlands (Fig. 3g), and Ireland (Fig. 3i). An exception to this trend is observed in Denmark (Fig. 3a) and Switzerland (Fig. 3d), where RMSE calibration raises damage estimates susbtantially to match reported high-loss events. Through these results, the loss function's emphasis on different portions of the distribution is highlighted.

The spatial distribution of changes in modeled losses between calibrated and default models further highlights the divergent effects of the two loss functions (Fig. 4). Under RMSLE optimization (right panel), the systematic mitigation of negative bias translates into a broad amplification of modeled losses across much of continental Europe. The largest positive changes are concentrated over France and extend into neighboring Central European countries, including Germany, the Benelux region, and Switzerland, while the British Isles show small negative changes. In contrast, the RMSE optimization (left panel) produces a more heterogeneous spatial response, consistent with its negative adjustments of mid-range events. Strong negative corrections appear over Norway and parts of northwestern Europe, notably the Netherlands and the UK/Ireland, whereas Switzerland stands out with a pronounced positive change. This pronounced spatial variability underscores the critical necessity of regionally resolved damage models, as a single pan-European calibration would fail to capture the distinct vulnerability profiles inherent to each country.

Building on the country-level calibration diagnostics (Fig. 3) and their spatial translation (Fig. 4), the empirical loss exceedance frequency curves (Fig. 5) assess how the calibrated models compare to each other and to the recorded loss data in a 25-year catalog. Each panel ranks events by occurrence frequency (x-axis), with frequently occurring, lower-magnitude events on the left and progressively rarer, higher-magnitude events on the right. Across most countries, the default model (gray dotted line) consistently underestimates damage at all occurrence frequencies with some exceptions like Ireland (Fig. 5i). The RMSLE-calibrated model (blue dash-dot line) provides a good fit to the recorded losses across the full frequency range for

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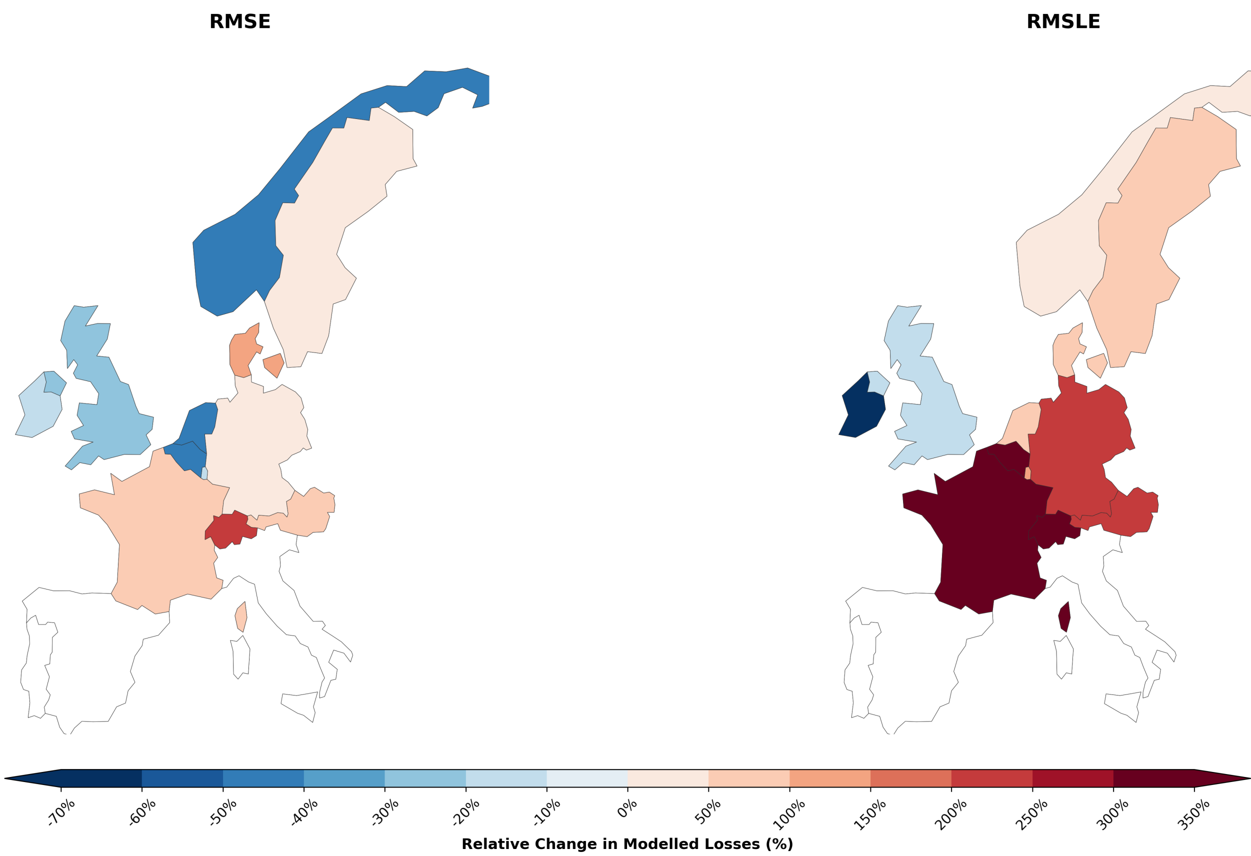

Figure 4. Spatial distribution of relative changes in modeled windstorm damage. Percentage change in total modeled losses (calibrated modeled minus default modeled) for each country using RMSE (left) loss function and RMSLE (right) loss function.

275 events in France (Fig. 3c), Switzerland (Fig. 3d), Great Britain (Fig. 3h) and lies almost parallel to the recorded loss dataset (green solid line). A particularly strong concordance is seen for frequently occurring events in Germany (Fig. 5b), Belgium (Fig. 5e), and the Netherlands (Fig. 5g). However, the lines diverge away from each other at the rare, high-magnitude end of the spectrum. An opposite behaviour is noticeable in the RMSE-calibrated model (orange dashed line) where there is clear gap between recorded and modeled losses for more frequent events but a convergence for high-loss, rarer events. For countries with sparse event catalogs, such as Denmark (Fig. 3a), Sweden (Fig. 3j), Norway (Fig. 3k) and Austria (Fig. 3l), both calibrations struggle to reproduce the PERILS curve, reflecting the limited event samples that constrain parameter estimation.

The UNSEQUA experiments extend this comparison by quantifying how metric choice propagates through exposure, hazard, and vulnerability uncertainties into average annual loss estimates (Fig. 6). A stratified Monte Carlo approach is employed to assess the robustness of the calibrated $\mathrm{MDD}_{\max}$ (see Methods for details). The resulting histograms display normalized average annual impact (AAI) distributions for RMSE (blue) and RMSLE (pink) calibrations relative to the PERILS benchmark (black

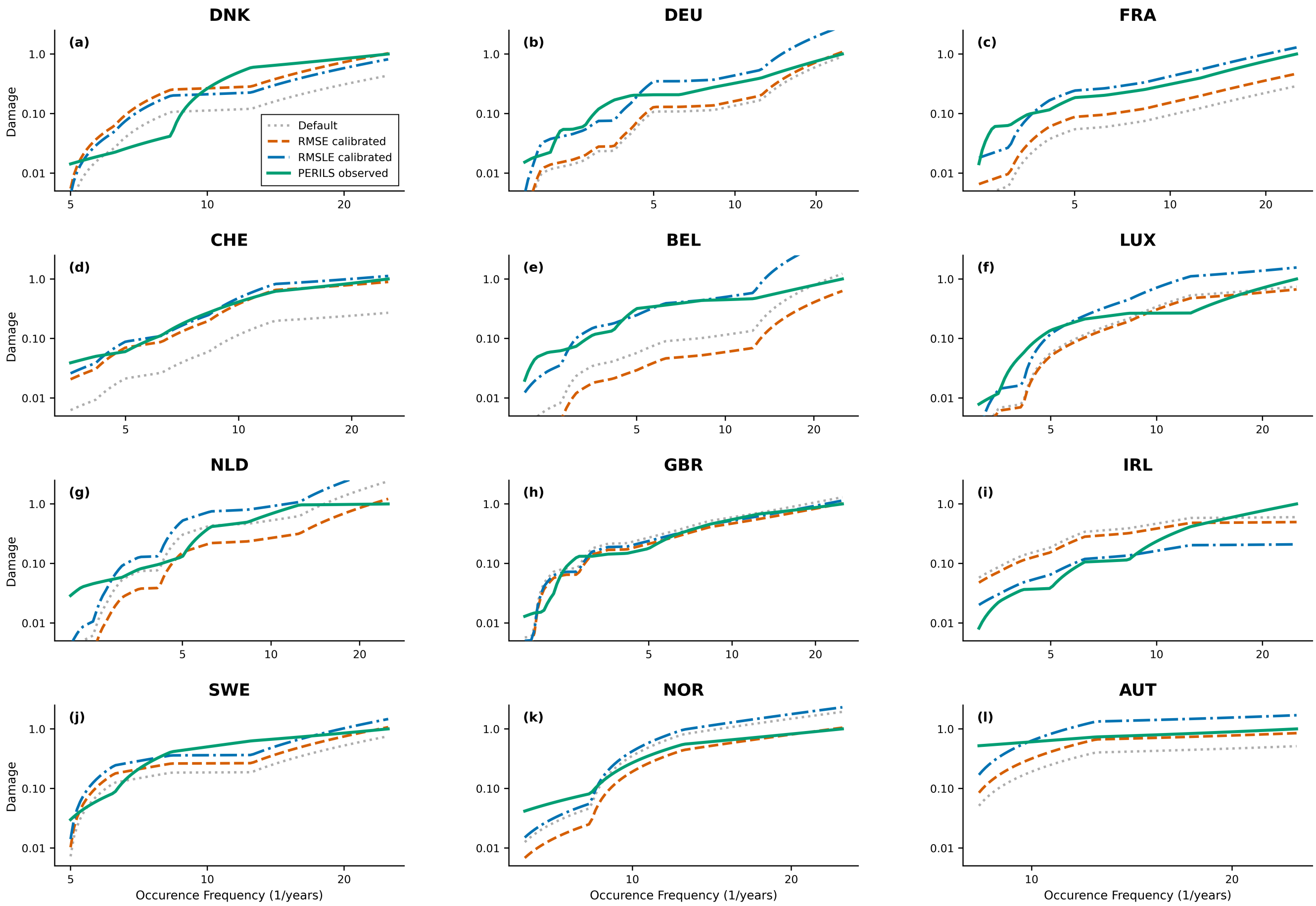

Figure 5. Country-specific loss exceedance frequency curves for windstorm losses. (a–l) Event loss exceedance frequency curves showing normalized damages as a function of occurence frequency for twelve European countries. Green solid lines represent PERILS-reported losses; blue dash-dotted lines show RMSLE-optimized model estimates; orange dashed lines show RMSE-optimized model estimates; gray dotted lines show default model estimates. All losses are normalized by the maximum PERILS-reported loss for each country. Occurence frequency is computed from the catalog period (1999–2024, 26 years).

dashed line). For RMSE calibration, the distributions typically exhibit narrower spreads and a tendency to cluster near or below the benchmark, reflecting a conservative bias. In countries like Germany (Fig. 6c), Switzerland (Fig. 6g), and Austria (Fig. 6w), the RMSE mean AAI is very close to recorded dataset (0.98, 0.95, and 1.06 respectively), providing a stable estimate of the expected annual loss. However, this conservative approach leads to significant underestimation in France (0.61) (Fig. 3e) and Belgium (0.60) (Fig. 3i), while paradoxically resulting in overestimation in Ireland (1.91) (Fig. 3q) and Norway (1.85) (Fig. 3u).

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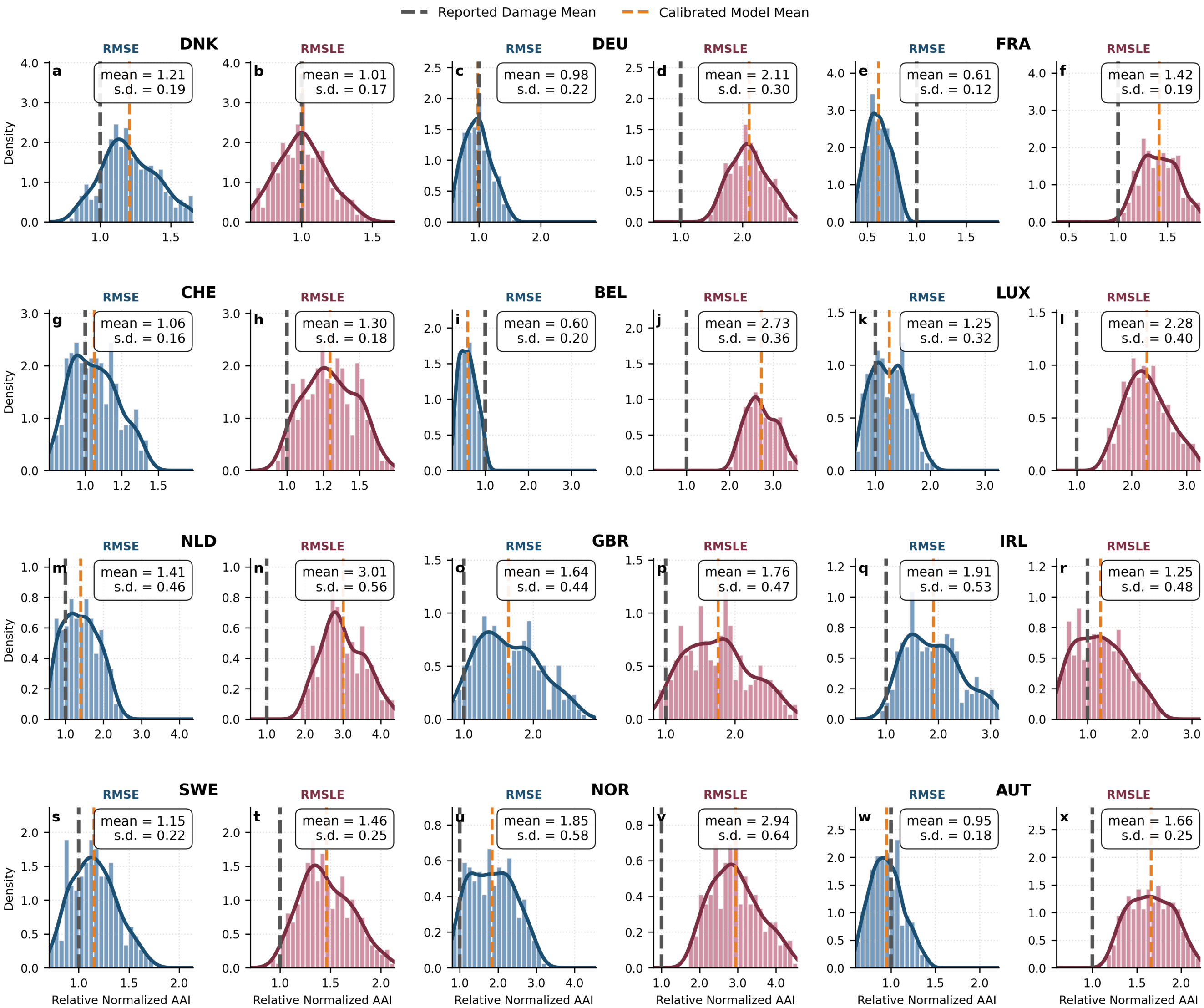

Figure 6. Uncertainty distributions of average annual impact from country-specific windstorm damage models. Paired histograms show probability density distributions of normalized average annual impact (AAI) for RMSE-optimized (left, blue) and RMSLE-optimized (right, pink) damage models across twelve European countries (a–x). Distributions derived from Latin hypercube sampling (N = 300) with simultaneous variation of exposure values (±20%), hazard intensity (±10%), and $\mathrm{MDD}_{\mathrm{max}}$ (±20% around calibrated value). All AAI values normalized by country-specific PERILS-reported average annual damage over catalog period (1999–2024, 26 years). Solid curves show kernel density estimates; histograms use 30 bins. Grey dashed vertical lines indicate normalized PERILS reference value (1.0); orange dashed lines show calibrated model mean.

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In contrast, RMSLE ensembles are systematically broader and centered significantly above the PERILS benchmark across most countries. This upward shift is most pronounced in the Belgium (Fig. 6j), Netherlands (Fig. 6n) and Norway (Fig. 6v), where the RMSLE mean AAI exceeds the recorded value by factors of 2.73, 3.01 and 2.94 respectively. This indicates that while RMSLE improves the fit for frequent events (as seen in Fig. 5), its emphasis on logarithmic error amplifies parameter sensitivity, leading to a substantial overestimation of the aggregated annual risk. A notable exception is Ireland (Fig. 6r), where RMSLE actually reduces the mean bias compared to RMSE (1.25 vs 1.91) and slightly tightens the distribution, suggesting that for certain loss profiles, the relative error metric may offer better stability. Overall, these uncertainty patterns demonstrate that metric choice fundamentally alters both the central estimate and the confidence bounds of the risk model: RMSE generally provides a more robust and conservative view of tail risk, whereas RMSLE offers a higher-sensitivity model that frequently overestimates in aggregate loss assessments.

4 Discussion and Conclusions

The study demonstrates that the widely used Schwierz et al. (2010) windstorm damage model systematically underestimates losses for historical events across Europe, and that a single pan-European model is inadequate to capture the distinct vulnerability profiles inherent to each country. To this end, a set of recalibrated, country-specific windstorm damage models is developed for 12 European countries (Fig. 3), derived by optimizing the default damage model against the high-resolution PERILS insurance loss database. These newly calibrated models enable a better representation of the spatial heterogeneity in vulnerability of the individual regions. Moreover, the study also shows that the choice of loss function minimized during the optimzation process fundamentally alters the resulting risk profile. For example, while the use of RMSLE produces highly sensitive damage models for France and Germany ($\mathrm{MDD}_{\max} \approx 0.12$–$0.16$) (Fig. 5m), RMSE optimization yields markedly more conservative parameters for the same countries ($\mathrm{MDD}_{\max} \approx 0.04$–$0.06$) (Fig. 3n).

Based on the above, it is argued that the spatial heterogeneity and loss-function dependence reflect genuine differences in regional risk profiles rather than merely optimization artifacts. The marked variability in country-specific parameters is consistent with regional differences in vulnerability, exposure characteristics, and market or claims conditions, which may result in higher wind resistance in storm-prone regions (Klawa and Ulbrich, 2003; Prahl et al., 2015; Koks and Haer, 2020; Moemken et al., 2024b). Simultaneously, the divergence between calibration results highlights that the definition of "best fit" is not neutral: RMSLE, by applying a logarithmic transformation before computing the squared error, implicitly assigns equal weight to proportional deviations across the full magnitude spectrum. This produces damage functions with elevated $\mathrm{MDD}_{\max}$ values that effectively correct the systematic negative bias of the default model across frequent and moderate events. RMSE, in contrast, penalizes errors in proportion to their absolute magnitude, causing the optimization to be disproportionately influenced by the few largest events in the catalogue. The resulting damage functions are thus more conservative, with lower $\mathrm{MDD}_{\max}$ values that sacrifice accuracy for common events to avoid overestimation in the tail. This divergence has direct consequences for derived risk metrics. The empirical loss execeedance frequency curves (Fig. 5) show that RMSLE-optimized models are able to better reproduce the observed loss-frequency relationship for frequently occurring events, while RMSE-

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optimized models converge toward recorded data only for the rare, high-magnitude end of the spectrum. When propagated through the UNSEQUA uncertainty framework (Fig. 6), RMSE calibrations yield narrower and more stable normalized AAI distributions that cluster near or below the PERILS benchmark, whereas RMSLE calibrations produce broader distributions that are often centered substantially above the benchmark. This indicates that RMSLE's proportional emphasis, while beneficial for event-level accuracy, can amplify parameter sensitivity and lead to overestimation of aggregate annual risk.

These results are consistent with the broader literature on the challenges of calibrating damage functions to heavily skewed loss distributions. For example, Prahl et al. (2015) noted that the wide and asymmetric distribution of insured storm losses poses fundamental difficulties for both the calibration and evaluation of damage models, and that different functional forms can yield substantially different loss estimates depending on which portion of the distribution they are optimized against. The current findings here extend this insight by demonstrating that even within a single functional form, the metric used to define the 'best fit' can produce qualitatively different risk profiles. This has practical implications for catastrophe modeling: applications focused on pricing attritional losses or estimating expected annual damages may benefit from RMSLE calibration, whereas applications concerned with solvency capital requirements or tail risk where conservative estimation of rare, high-impact events is paramount may favour RMSE-based calibration (Watson and Johnson, 2004; Moody's Analytics, 2025).

Inevitably, the performance of the calibration is conditioned by the scope and characteristics of the underlying hazard, exposure and loss data (Moemken et al., 2024b; Flynn et al., 2025). The PERILS database, although representing the high-quality industry loss record for European windstorms, imposes a reporting threshold of EUR 500 million for pan-European events (EUR 300 million for individual countries; (PERILS AG, 2025)). Accordingly, smaller but potentially informative storms are excluded from the optimization, which may bias the parameters toward the behaviour of moderate-to-large events. Moreover, the limited number of events available for the Nordic countries (4-5 storms) remains a specific constraint, reflected in the weaker model-observation agreement for Denmark, Sweden, Norway. The same is true for Austria. These data limitations highlight that while the recalibrated functions capture broad regional vulnerability differences, further improvement, particularly for small event performance can be improved with access to finer grained loss records.

Despite these challenges, the recalibrated country-specific damage models presented here represent a substantial improvement over the previous default version (Schwierz et al., 2010). The newly calibrated models are directly applicable within the CLIMADA framework for current-climate risk assessment (Moemken et al., 2024a) and can also serve as an updated baseline for climate change projection studies (Severino et al., 2024). The transparent comparison of RMSE and RMSLE calibration strategies provides practitioners with the information needed to select the appropriate loss function for their specific application context, whether that be portfolio-level expected loss estimation, regulatory capital calculations, or scenario-based climate impact assessments. The study contributes to the broader effort of making climate risk assessment more scientifically rigorous and adaptable to other regions (Aznar-Siguan and Bresch, 2019; Kropf et al., 2022; Riedel et al., 2024). When combined with the hazard uncertainty (Roberts et al., 2014; Flynn et al., 2025), this approach can provide an excellent pathway for a further improved and more transparent risk assessment of windstorms affecting Europe.

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Data Availability

CLIMADA is an open-source software available at https://doi.org/10.5281/zenodo.17233409 under a General Public Licence version 3 (GPL-3.0). Windstorm footprints data is taken from the Copernicus Climate Change Service (C3S) Enhanced Windstorm Service (EWS) (Copernicus Climate Change Service, 2025). LitPop is used for representing asset exposure data (Eberenz et al., 2020), available within the CLIMADA platform (Aznar-Siguan and Bresch, 2019). Loss data for windstorms is taken from PERILS (PERILS AG, 2025) and is granted via an annual subscription in accordance with the PERILS database license (www.perils.org). Loss data from the Emergency Events Database (EM-DAT) (Delforge et al., 2025) is also used and freely available at www.emdat.be.

Author Contributions

ANM contributed to conceptualization, data curation, formal analysis,visualization, and writing of the original manuscript draft. GM, LR, ARS and JPG contributed to conceptualization and writing - editing and review - of the manuscript. Supervision and project administration by GM.

Competing Interests

At least one of the (co-)authors is a member of the editorial board of Natural Hazards and Earth System Sciences. The authors declare that they have no other competing interests.

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