https://doi.org/10.5194/nhess-2024-16
Preprint. Discussion started: 28 February 2024

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Insurance loss model vs meteorological loss index – How comparable are their loss estimates for European windstorms?

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Abstract. Windstorms affecting Europe are among the natural hazards with the largest socio-economic impacts. Therefore, many sectors like society, economy or the insurance industry are highly interested in reliable information on associated impacts and losses. There are different metrics to quantify windstorm-related losses, ranging from simple natural hazard databases over loss indices based on meteorological variables to more complex insurance loss (catastrophe) models. In this study, we compare estimated windstorm losses using the meteorological Loss Index (LI) with losses obtained from the European Windstorm Model of Aon Impact Forecasting. To test the sensitivity of LI to different meteorological input data, we furthermore contrast LI based on the reanalysis dataset ERA5 and its predecessor ERA-Interim. We focus on similarities and differences between the datasets in terms of loss values and storm rank for specific storm events in the common reanalysis period across 11 European countries.

Our results reveal higher LI values for ERA5 than for ERA-Interim for all of Europe, coming mostly from a higher spatial resolution in ERA5. The storm ranking is comparable for Western and Central European countries for both reanalyses. Compared to Aon's Impact Forecasting model, LI ERA5 shows comparable storm ranks. However, LI seems to have difficulties in distinguishing between extreme windstorms with high losses and those with only moderate losses. The loss distribution in LI is thus not steep enough and the tail is probably on the short side, yet it is an effective index, precisely because of its simplicity, suitable for estimating the impacts and ranking storm events.

1 Introduction

In Central and Western Europe, windstorms are among the major natural hazards. They regularly lead to high economic and insured losses (Munich Re, 2022), causing damage to natural and human-made environments like infrastructure, buildings, forestry and agriculture (Mitchell-Wallace et al., 2017; Pinto et al., 2019; Gliksman et al., 2023). In 2022, losses from European windstorms were well above average, with insured losses of \$5.7 billion and economic losses of \$7.5 billion, respectively (Aon, 2023a). In fact, European windstorms were among the five largest weather-related perils in 2022 (Swiss Re, 2023). The high losses were mainly caused by the windstorm series Ylenia-Zeynep-Antonia[1] (international: Dudley-Eunice-Franklin) in February 2022, which resulted in insured losses of $4.7 billion (Aon, 2023a). The storm series affected the British Isles and continental Europe (Mühr et al., 2022), with highest losses in Germany, the Benelux countries, the UK and France (PERILS, 2023).

For the insurance industry, but also for society and economy, it is crucial to assess the wind-related risk and to forecast the impacts of extreme storms in order to adapt to and mitigate windstorm losses (Pinto et al., 2019; Merz et al., 2020; Gliksman et al., 2023). In this context, risk is usually defined as the interaction of hazard, exposure and vulnerability (e.g. IPCC, 2022). The hazard component is defined as the occurrence of a natural event (in our case a windstorm), the exposure component represents the presence of people/livelihoods/ecosystems or economic/social assets, and the vulnerability component describes the disposition to be affected (IPCC, 2022). The information on windstorm risk and associated losses is provided by various types of datasets (Gliksman et al., 2023; Moemken et al., 2023), both for present and future climate conditions. These datasets do not always account for all three risk components. On one hand, several databases collect information worldwide on different natural hazard/disaster, thus providing a direct view on the impacts. This includes EM-DAT, NatCatSERVICE from Munich Re or Sigma from Swiss Re (Kron et al., 2012; Wirtz et al., 2014; Lee et al., 2024). Another type of loss datasets are indices combining meteorological variables and insurance aspects, like storm severity indices (Klawa and Ulbrich, 2003). These meteorological indices give a more hazard driven view on windstorm losses/impacts. A more complex way to estimate windstorm losses is provided by storm loss models developed, among others, by the insurance industry (catastrophe modelling). These models relate meteorological wind data to actual building damage data, using so-called damage functions that define the relationship between wind and damage (Prahl et al., 2015; Gliksman et al., 2023). Actual loss reports from insurance companies like Munich Re or Deutsche Rück are usually not publicly available.

Moemken et al. (2023) recently compared several examples of these loss datasets for windstorms across Europe, including a natural hazard database, insurance loss reports and various meteorological indices. Focusing on storm numbers and the ranking of specific storm events, they conclude that the datasets provide different perspectives on windstorm impacts and suggest that a combination of different types of datasets might be used to assign an uncertainty range to windstorm losses. A recent review paper by Gliksman et al. (2023) discusses open research questions related to damage from European windstorms. One raised issue is the lack of a clear methodology to select the most suitable index to assess windstorm losses for both present and future climate conditions. This is also important to address the question how windstorm-related losses will change in a changing climate. Moreover, loss calculations are affected by uncertainties, for example related to the used (meteorological) input data. They further point out that there is a need for a thorough comparison between meteorological loss indices and catastrophe models (used in insurance) to better understand loss estimates from different perspectives.

In our study, we try to answer two of these questions, namely:

- How sensitive are the loss estimates of a meteorological index to the meteorological input data?

[1] Storm names as given by the Freie Universität Berlin (https://www.wetterpate.de/namenslisten/tiefdruckgebiete/index.html; in German) and used by the German Weather Service (DWD).

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- How comparable are windstorm loss estimates from this meteorological index and an insurance loss model?

With this aim, we first calculate the Loss Index (LI) by Pinto et al. (2012) in the adaptation of Karremann et al. (2014a) using ERA5 (Hersbach et al., 2020) and its predecessor ERA-Interim (Dee et al., 2011). In a second step, we compare the loss estimates from LI to the output of an insurance loss (catastrophe) model for a set of historical European windstorms. Here, we use, for the first time in a scientific study, the European Windstorm Model of Aon Impact Forecasting (in the following Aon's IF Euro WS model). We analyse the differences and similarities, focusing on loss values and storm ranks of individual events. The study is restricted to 11 European countries covered by the model (see Sect. 2.2) and the extended winter season October – March (ONDJFM).

The paper is organized as follows: Section 2 describes the datasets and methods/models. Section 3 focuses on the sensitivity of LI to different reanalysis datasets, while Sect. 4 presents the comparison between LI and Aon's IF Euro WS model. Section 5 concludes this paper with a summary and discussion of results.

2 Data and methods

2.1 Meteorological loss index

Meteorological indices, also referred to as storm severity indices, are typically used to identify severe windstorms, study their magnitude and likelihood of occurrence, and estimate the associated losses. There exists a wide variety of indices, ranging from more general ones to those targeting specific sectors like forestry, agriculture or transport (see Gliksman et al. (2023) for a detailed overview). The key variable for many of these indices is the daily maximum wind speed or peak wind gust, which are considered as relevant for storm losses (Lamb, 1991; Klawa and Ulbrich, 2003; Leckebusch et al., 2008; Pardowitz et al., 2016). The assumption behind this is that the loss can be primarily attributed to the maximum gust, which corresponds to the maximum "pressure" on infrastructure (Klawa and Ulbrich, 2003).

In our study, we use the Loss Index (LI) by Pinto et al. (2012) in the adaptation of Karremann et al. (2014a). LI is built from the widely used storm loss model by Klawa and Ulbrich (2003) and is based on the following assumptions:

- Losses are proportional to the wind power or the wind kinetic energy flux, and thereby to the cube of wind speed/gust.
- Infrastructure and other assets are adapted to the local wind conditions. Therefore, it can be assumed that only the top 2% of wind gusts (corresponding to beaufort 8, circa 17-20 m/s) cause damage. This is taken into account by scaling the daily peak gust with the local 98th percentile.
- In the case that no insurance data is available, population density can be used as a proxy for the exposure component.
- The insurance clause for natural hazards is typically 72 hours. This also corresponds to the period during which an average storm crosses Europe and produces damaging winds (Hewson and Neu, 2015).

Hence, LI is calculated as:

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$$LI = \sum_{i=1}^{N}\sum_{j=1}^{M}\left(\frac{v_{ij}}{v_{98_{ij}}}\right)^3 * I\left(v_{ij}, v_{98_{ij}}\right) * P_{ij} * L_{ij} \quad (1)$$

with $I\left(v_{ij}, v_{98_{ij}}\right) = \begin{cases} 0 \; for \; v_{ij} < v_{98_{ij}} \\ 1 \; for \; v_{ij} > v_{98_{ij}} \end{cases}$,

$L_{ij} = \begin{cases} 0 \; over \; sea \\ 1 \; over \; land \end{cases}$,

maximum wind gust v in 72 hours at grid point ij, local 98th percentile v_{98}, and population density P. To separate individual events per extended winter season (October – March, ONDJFM), overlapping 72 hour sliding time windows (shifted every 6 hours) are used and the temporal local maximum of each 72 hour time window is analysed (Karremann et al., 2014a). We are particularly interested in extreme storm events. Therefore, we only consider events with LI values above a certain threshold, which corresponds to the selection of an average of five events per season (Pinto et al., 2012; Karremann et al., 2014a).

Any gridded dataset can be used to calculate LI. Here, we use reanalysis data – namely ERA5 (Hersbach et al., 2020) and its predecessor ERA-Interim (Dee et al., 2011). ERA5 is the latest reanalysis product of the European Centre for Medium-Range Weather Forecast (ECMWF). We use post-processed wind gusts at 10 m height at hourly temporal and 30 km (0.25°) horizontal resolution for the period 1959-2021. From ERA-Interim, we use 10 m post-processed wind gust data with 3-hourly temporal and 83 km (0.75°) horizontal resolution for the period 1979-2019. In both datasets, wind gusts are defined as the maximum 3-second wind at 10 m height following the definition of the World Meteorological Organisation (WMO). The post-processed wind gust is the maximum gust computed in every time step using the standard deviation of the horizontal wind based on the similarity relation by Panofsky et al. (1977). We use the datasets in their native resolutions in order to test the sensitivity of LI to the resolution of the input data. As proxy for the exposure, gridded population density data for the year 2020 at a spatial resolution of 0.25° (see Figure 1a) was downloaded from the Centre for International Earth Science Information Network (CIESIN) at Columbia University, USA. We assign a name to each storm event referring to those given by the Freie Universität Berlin and used by the German Weather Service (DWD): https://www.wetterpate.de/namenslisten/tiefdruckgebiete/index.html (in German). For events prior to 1999, we also refer to the Extreme Windstorms Catalogue (XWS) described in Roberts et al. (2014).

For the hazard component, windstorm footprints are required. Following the WMO and Haylock (2011), the footprint is defined as the percentage of wind gust values that exceed the local 98th percentile per 72-hour period:

$$wind\ gust\ footprint = \frac{(v_{max} - v_{98})}{v_{98}} * 100\% \quad (2)$$

With maximum wind gust in 72 hours at each grid point v_{max}, and local 98th percentile v_{98}. We use the same 72-hour periods as for the LI calculation. The corresponding cyclone tracks were derived following the tracking algorithm by Murray and Simmonds (1991) and Pinto et al. (2005). As an example, Figure 1b shows the footprint and cyclone track for windstorm Kyrill in January 2007 (Fink et al., 2009).

For the comparison between LI ERA5 and LI ERA-Interim, we use both original loss estimates as well as normalized losses. The normalization is done with a min-max scaling approach, which scales the loss values between 0.0 and 1.0. The top storm

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event corresponds to the value 1.0 and the event with the lowest impact to the value 0.0. The normalized losses of all other events relate to the top event. We only focus on losses aggregated at country level.

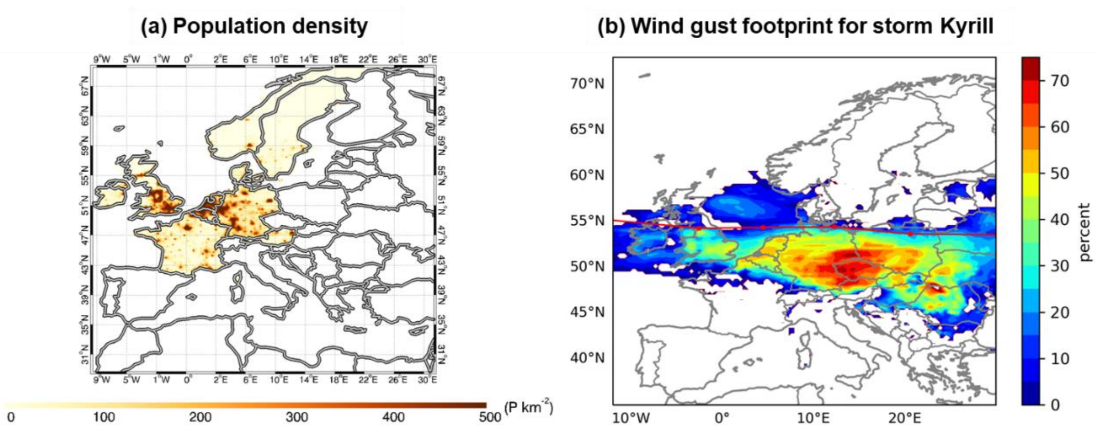

Figure 1: (a) Population density for 2020 derived from CIESIN for the 11 countries covered in this study. (b) Wind gust footprint for storm Kyrill in January 2007 based on ERA5. Shown is the percentage of the maximum wind gust in 72 hours that exceed the local 98th percentile of daily maximum wind gust. The red line and dots denote the cyclone track derived from ERA5 using the tracking algorithm of Pinto et al. (2005). Please refer to Sect. 2 for detailed information on the methods.

2.2 Aon Impact Forecasting European Windstorm Model and PERILS data

Storm loss (catastrophe) models determine the windstorm risk to residential and commercial buildings by relating wind speed to building damage (Palutikof and Skellern, 1991; Dorland et al., 1999; Gliksman et al., 2023), usually by implementing statistical modelling. Like for storm severity indices, the maximum daily wind gust speed is assumed to be the most relevant factor in these models (Dorland et al., 1999; Klawa and Ulbrich, 2003; Donat et al., 2011; Koks and Haer, 2020) and is used as the basis for the hazard component. The building damage data is usually represented using so-called loss ratios, which is the amount of insured loss occurring per district, divided by the corresponding sum of insured value (Klawa and Ulbrich, 2003; Prahl et al., 2015). For the relationship between wind and damage, also referred to as damage functions, various formulations exist in literature (see Prahl et al. (2015) for a detailed overview). Commonly used damage functions assume either a power law or an exponential form.

In our study, we use the European Windstorm Model of Aon Impact Forecasting (Aon's IF Euro WS model; Aon Impact Forecasting, 2023), which is implemented in ELEMENTS, Aon's loss modelling platform (Aon, 2023b). The model covers 22 countries in Western, Northern and Central Europe. The aim of this catastrophe model is to provide a quantification of financial losses from windstorm risk in Europe. The model consists of three components: hazard, vulnerability and exposure. The hazard component consists of 26 historical events (see Supplementary Table S1; Born et al., 2012) and a stochastic event set covering 4,731 years of simulated events (Karremann et al., 2014a). The stochastic events represent physically consistent

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storm events and are based on outputs of the ECHAM 5 global climate model (Jungclaus et al., 2006). The vulnerability component is divided into Chance of Loss (COL) and Conditional Mean Damage Ratio (CMDR), thereby giving a more realistic view of loss than a single mean damage ratio. The COL is applied first, rating the probability of loss for a certain wind speed and a given building. If the building is determined to have suffered a loss, then the conditional damage ratio (CMDR) is applied. The exposure component uses a combination of Aon's client data and the PERILS industry exposure database. The component comprises five lines of business: residential, commercial, industrial, agricultural, motor and forestry (only Norway, Sweden and Finland). Here, we only use the PERILS data for 2022 for the exposure. PERILS (https://www.perils.org) is a joint stock company, owned by ten shareholders from the insurance industry. It prepares and provides aggregated anonymized insurance data for different weather-related perils. The data provides, for selected events with a sizable financial footprint, a market estimation for the loss per country and CRESTA zone (a geographical data aggregation standard used by global insurance industry; www.cresta.org), property premium data per country, and the exposure (total sum of insured property) per country and CRESTA zone. For extratropical windstorms in Europe, PERILS provides data for 12 countries, 11 of which are also covered by Aon: Belgium, Denmark, France, Germany, Ireland, Luxembourg, the Netherlands, and the United Kingdom (in the following grouped to Core Europe; Pinto et al., 2012), Austria, Norway, and Sweden. The vulnerability component of the model applies IF's proprietary damage curves to calculate the physical loss for each event at each insured location. Original limits and other policy conditions are then applied per event to calculate the Gross loss and the Net loss, thus obtaining the value of insured loss (Aon Impact Forecasting, 2023). For the comparison to LI, we aggregate losses at country level and use normalized loss values.

3 Comparison between ERA5 and ERA-Interim

We first analysed the sensitivity of LI to the meteorological input data. To this end, we compared ERA5 and ERA-Interim in terms of wind gust as the relevant input variable for LI. We then used both datasets to derive LI for our study domain and compared the results with respect to storm loss and storm rank.

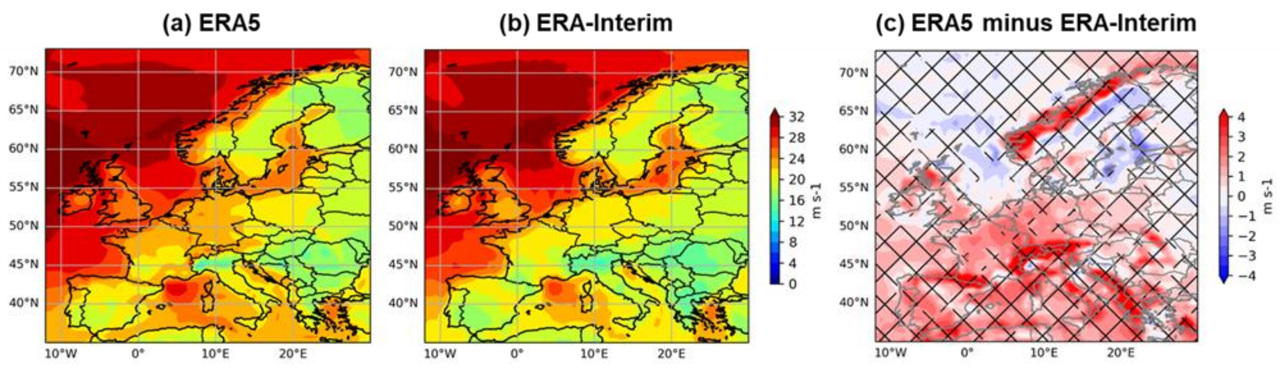

Figure 2: 98th percentile of daily maximum wind gust for the winter half year (October – March, ONDJFM) for the period 1979-2019 derived from (a) ERA5, and (b) ERA-Interim. (c) Difference between (a) minus (b), with crossed lines indicating significant differences at the 95% confidence interval (t-test).

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3.1 Wind gust climatology

We use the 98th percentile of daily maximum wind gust, which is the relevant threshold for LI, to compare ERA5 and ERA-Interim. The percentile is calculated for the winter half year ONDJFM for 1979-2019, the period common to both datasets. Figure 2 shows the 98th percentile for ERA5 (Fig. 2a) and ERA-Interim (Fig. 2b), as well as the absolute difference between the datasets (Fig. 2c). Both datasets show a similar spatial pattern: For most of Europe, the 98th percentile ranges between 16 and 30 m/s, with highest values over the North and Baltic Sea, and the British Isles. Except for Sweden and the Baltic region, values are in general higher for ERA5 compared to ERA-Interim. Differences are statistically significant for large parts of Europe (Fig. 2c), reaching highest values (over 4 m/s) over mountainous regions like the Alps, the Pyrenees and the Scandinavian mountains. For Core Europe, differences are in the range of 2 m/s, but often not significant. Differences result most likely from the different ECMWF model version used for the reanalysis and the overall better representation of resolution and physical processes in the ERA5 setup.

3.2 Storm losses and storm ranking

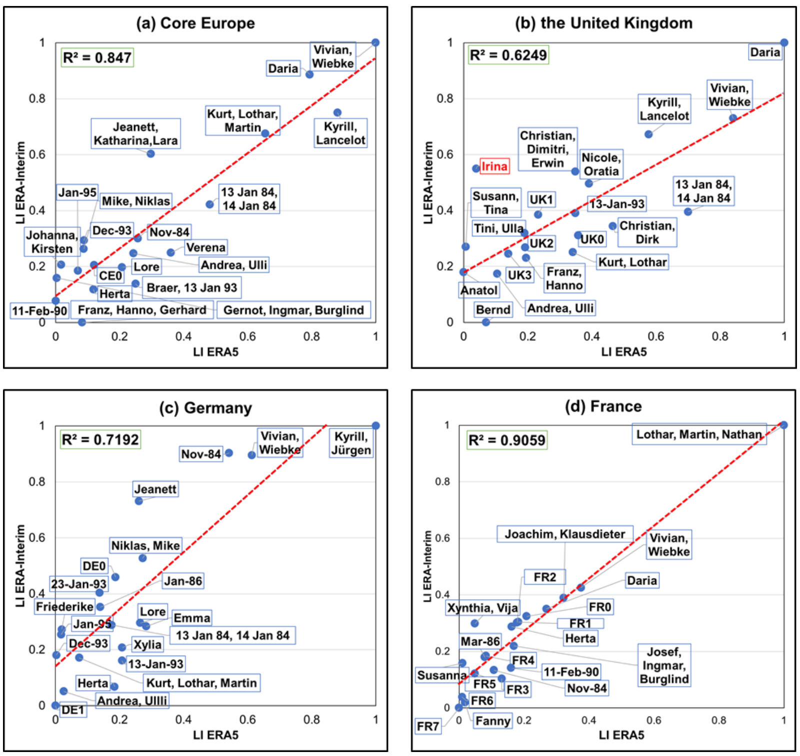

Figure 3: Comparison of normalized loss values based on LI ERA5 (x-axis) and LI ERA-Interim (y-axis). Depicted are the common 20 most extreme storms in the period 1979-2019 for (a) Core Europe, (b) the United Kingdom, (c) Germany, and (d) France. Corresponding storm names to each data point are marked with a blue line. Storms without a formal name are named based on the region (e.g. CE for Core Europe) and the loss value (starting from zero for storm with highest loss). The red dashed line denotes the linear regression line. The correlation between the datasets is given in the upper left corner (R^2 value). Outlier storms based on the IQR method (see Sect. 3.2) are marked in red.

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In the next step, we compare the loss values and the storm ranking for the 20 common most extreme storms (Top20) in the period 1979-2019. The Top20 storms are derived separately for each country as well as for Core Europe. The storm list for Core Europe can be found in Supplementary Tables 2 and 3. Figure 3 presents the comparison of normalized loss values derived from LI ERA5 (x-axis) and LI ERA-Interim (y-axis) for four different regions/countries, namely Core Europe, the United Kingdom, Germany, and France. For most events and countries, the datasets show comparable normalized losses. Moreover, the ratio between extreme storms with high losses to extreme storms with moderate losses is similar in both datasets. This is confirmed when looking at the correlation between the datasets (see R^2 values in Figure 3). It ranges from about 0.6 for the UK to about 0.9 for France. The correlation for the other countries can be found in Table 1. One reason for the lower correlation in the UK is the inclusion of storm Irina (October 2002) in the Top20. This storm is classified as an outlier, i.e. that the difference in loss value is large based on the Inter-Quartile Range (IQR; Dodge, 2008). The large difference between ERA5 and ERA-Interim for storm Irina is easily explained by looking at the storm footprint (Fig. S1): Unlike ERA-Interim, ERA5 shows a broader area of high wind gusts, especially over the UK and Western continental Europe. Overall, differences in normalized loss values between ERA5 and ERA-Interim are significant for five out of 11 countries, namely Austria, Belgium, France, Germany and Norway (Table 1). The other countries as well as Core Europe show non-significant differences based on a paired Wilcoxon Signed-Rank test (Wilcoxon, 1945).

Table 1: Correlation (R^2) between LI ERA5 and LI ERA-Interim for storm loss and storm rank. Bold numbers denote statistically significant differences between LI ERA5 and LI ERA-Interim, using a paired Wilcoxon Signed-Rank Test at a significance level of 0.05.

	Loss	Rank
Core Europe	0.84	0.64
Austria	**0.35**	0.43
Belgium	**0.62**	0.61
Denmark	0.51	0.18
France	**0.62**	0.76
Germany	**0.72**	0.50
Ireland	0.27	0.30
Luxembourg	0.65	0.64
Netherlands	0.56	0.20
Norway	**0.31**	0.28
Sweden	0.72	0.51
United Kingdom	0.64	0.49

When comparing the original loss values (Fig. S2), the values based on ERA5 are approximately 10 times larger than those for ERA-Interim for all regions. The most obvious reason is the higher spatial resolution of ERA5 compared to ERA-Interim

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(roughly 3 times higher): As LI sums over all grid points with wind gusts above the 98th percentile, a higher number of grid points results in an overall higher value of LI. Another reason is a slight shift towards higher gust speeds in the wind gust distribution of ERA5 compared to ERA-Interim (not shown) for large parts of Central Europe.

The comparison of storm ranks between LI ERA5 and LI ERA-Interim is presented in Figure 4. Differences are generally larger than for the loss values, although not significant (Table 1). This is confirmed both by a higher number of outlier storms in individual countries such as France, and by overall lower correlation values ranging between 0.18 and 0.76 (see Table 1). In the following chapter, we focus only on LI ERA5, in order to benefit from the higher spatial and temporal resolution and the more recent data.

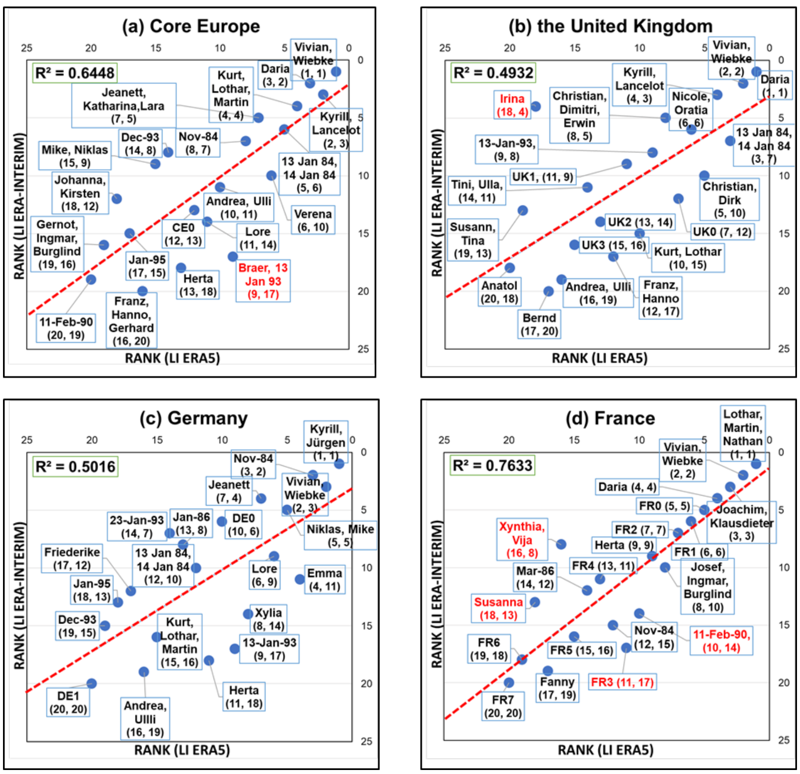

Figure 4: Same as Figure 3, but for the comparison of storm ranks. The values in brackets indicate the rank (first value ERA5, second value ERA-Interim).

4 Comparison of loss estimates from LI ERA5 and Aon's IF Euro WS model

In the second part of our study, we compared LI ERA5 to the output from Aon's IF Euro WS model, focusing on normalized losses and storm ranks at country level. The analysis is based on Aon's historical event set of insured storms in the period 1990-2020 (see Table S1). Thus, the number of common storms between the Aon model and LI ERA5 can differ in the individual countries (see Table 2). Please note that some events cannot be clearly separated based on the LI (e.g. Lothar and

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Martin, see Fig. 3 and Table S2), while they are single events in Aon's WS model. In these cases, we assign the same LI value to both storm events for the comparison between LI and the Aon model.

Table 2: Same as Table 1, but for the comparison between LI ERA5 and Aon's IF Euro WS model. The number of common storms per country is given in the last column (#).

	Loss	Rank	#
Core Europe	**0.60**	0.52	23
Austria	**0.74**	0.73	15
Belgium	**0.08**	0.22	21
Denmark	**0.51**	0.41	15
France	**0.70**	0.60	17
Germany	**0.51**	0.57	23
Ireland	**0.12**	0.20	19
Luxembourg	**0.15**	0.26	15
Netherlands	**0.55**	0.64	21
Norway	**0.30**	0.40	9
Sweden	**0.26**	0.23	13
United Kingdom	**0.30**	0.35	20

4.1 Windstorm loss

First, we analyse the normalized losses of individual storm events at country level. Figure 5 presents this comparison for two representative case studies: Storm Daria in January 1990 (Fig. 5a/b) as an example for a "high impact" event, and storm Isaias in February 2019 (Fig. 5c/d) as example for a rather "moderate impact" event. For Daria, the datasets agree with regard to the region affected by the storm, which closely follows Daria's cyclone track (black line and dots in Figure 5a). However, the normalized loss values in the countries can differ significantly in the two datasets. In Germany, for example, LI ERA5 has a value of 1, while it is around 0.3 for the Aon model. On the other hand, both datasets show comparable loss values for the UK and the Netherlands. The differences between LI ERA5 and Aon's IF Euro WS model are less pronounced for storm Isaias. One exception is the UK, where LI ERA5 features high loss values around 0.6, while the value is close to zero for Aon. In general, the agreement/disagreement between the datasets is different for each event and systematic differences are not apparent.

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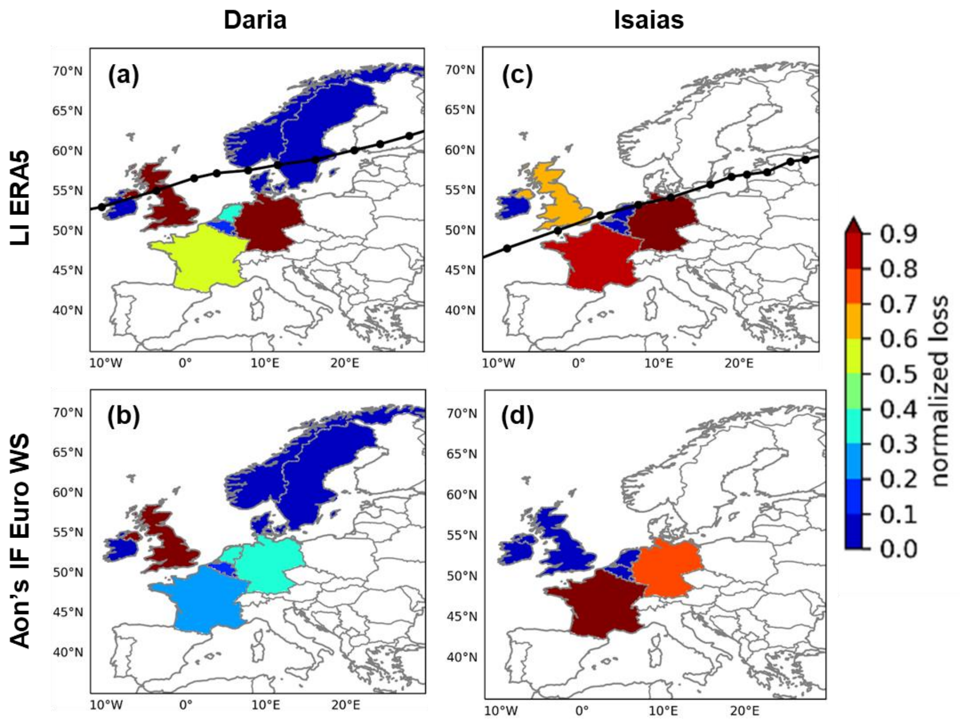

Figure 5: Normalized losses at country level for storm Daria in January 1990 (a, b), and storm Isaias in February 2019 (c, d). Losses are derived from LI ERA5 (upper row) and Aon's IF Euro WS model (lower row). The black line and dots in the upper row denote the cyclone track derived from ERA5 using the tracking algorithm of Pinto et al. (2005). Losses are only shown for the 11 countries covered by Aon.

Similar results are found when comparing the normalized loss values derived from Aon's IF Euro WS model (x-axis) and LI ERA5 (y-axis) for all storms for four different regions/countries: Core Europe, the United Kingdom, Germany, and France (Fig. 6). The two datasets reveal large differences, which are significant in all countries (Table 2). Only individual storm events like Daria in January 1990 or Kyrill in January 2007 show comparable normalized losses. This is supported by rather low correlations, ranging between 0.08 for Belgium and 0.74 for Austria (Table 2). Nevertheless, only a small number of storms is identified as outliers based on the IQR method – for example Sabine in Core Europe or Martin in France. The range of LI values is quite similar between larger regions like Core Europe and smaller regions (individual countries). On the other hand, Aon's IF Euro WS model reveals a different range of loss values for different regions. Overall, Aon's IF Euro WS model shows a clear distinction between extreme "high loss" storm events such as Daria and those events with "moderate" losses (e.g. Isaias). This distinction is less pronounced in LI ERA5 (see e.g. Fig. 6b).

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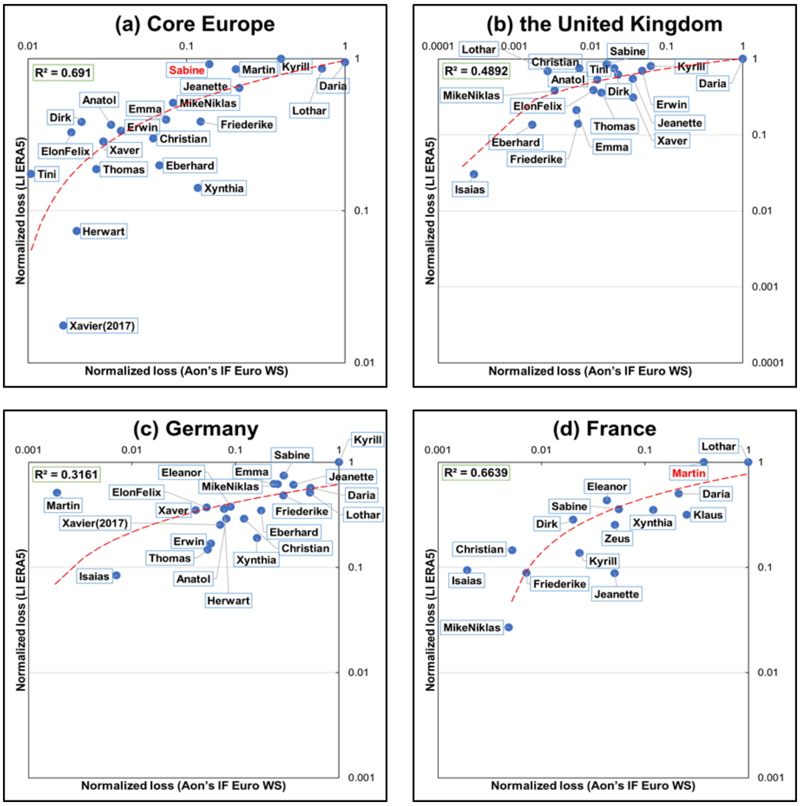

Figure 6: Comparison of normalized loss values between Aon's IF Euro WS model (x-axis) and LI ERA5 (y-axis). Depicted are the common most extreme storms for the period 1990-2020 for (a) Core Europe, (b) the United Kingdom, (c) Germany, and (d) France. A logarithmic scale is used for the axes. The red dashed line denotes the logarithmic regression. The correlation between the datasets is given in the upper left corner (R^2 value). Outlier storms based on the IQR method are marked in red. Please note the different scales.

4.2 Storm ranking

We also compare LI ERA5 and Aon's IF Euro WS model in terms of storm ranks for the common most extreme storms per country. Figure 7 shows this comparison for Core Europe, the UK, Germany and France. As for the normalized losses, we see rather large differences between the datasets. However, these differences are statistically not significant (Table 2). On average, correlations are slightly higher than for storm losses (Table 2), although some countries (e.g. France) show lower values.

Finally, we compute Spearman's rank correlation coefficients (Spearman, 1904; Dodge, 2008) to quantify and map the differences in storm ranks between the datasets across countries. Figure 8 displays the correlation coefficients for each country, providing a clear depiction on the agreement or disagreement between LI ERA5 and the Aon IF model. The two datasets show a high agreement for most parts of Central Europe, with correlation values reaching up to 0.86 for Austria. Lower correlations with values below 0.5 and therefore larger differences can be found for Ireland, Belgium and Sweden.

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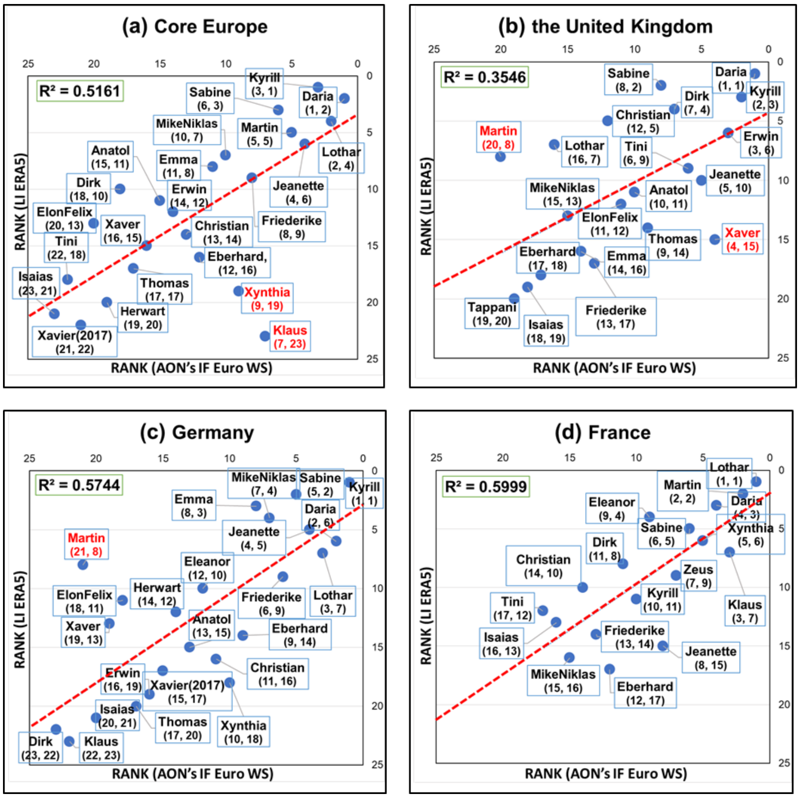

Figure 7: Same as Figure 6, but for the comparison of storm ranks. The values in brackets indicate the rank (first value Aon's model, second value LI ERA5)

5 Summary and discussion

In this study, we compared estimated windstorm losses over Europe from the meteorological Loss Index (LI) and the catastrophe windstorm model of Aon Impact Forecasting, used in insurance. Furthermore, we tested the sensitivity of LI to the meteorological input data by using both ERA5 and its predecessor ERA-Interim. The main results can be summarized as follows:

- For all of Europe, LI values are higher for ERA5 than for ERA-Interim. The main reason is the higher spatial resolution in ERA5. Additionally, the wind gust distribution in ERA5 is slightly shifted towards higher values. With regard to normalized losses and storm ranks, LI ERA5 and LI ERA-Interim show a comparable behaviour for Western and Central Europe.
- Compared to Aon's IF Euro WS model, LI ERA5 shows overall lower loss values, while the storm ranks are comparable for most of Central Europe. Moreover, the Aon model seems to better distinguish between high and moderate impact events. The difference between the highest and lowest insured loss, as given by Aon IF's wind model (e.g. Daria vs Isaias in UK, see Fig. 6b) is 3 orders of magnitude, while the corresponding LI ERA-5 difference is

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typically 1 to 1.5 orders of magnitude. In addition, the catastrophe model shows a clear regional dependency of loss values. This regional dependence is less pronounced in LI ERA5.

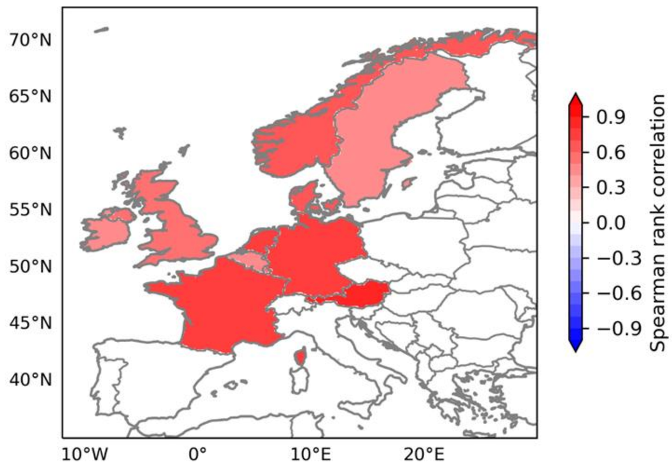

Figure 8: Spearman's rank correlation coefficient at country level for LI ERA5 vs Aon's IF Euro WS model. The ranking is based on the common storms in each country.

In previous studies, LI has been calculated and analysed for a variety of reanalysis datasets with different spatial and temporal resolutions: ERA-40 with 1.125° and 6-hourly resolution in Pinto et al. (2012), NCEP with 1.875° and 6-hourly resolution in Karremann et al. (2014a), or ERA-Interim with 0.75° and 6-hourly resolution in Priestley et al. (2018). In line with our results, these studies show that the magnitude of LI is sensitive to the spatial resolution of the underlying dataset. Nevertheless, they all agree on the general (regional) behaviour of LI. Another reason for the different LI values for ERA5 compared to ERA-Interim is a slight shift towards higher gust speeds in the wind gust distribution of ERA5. This is in line with Minola et al. (2020), who compared wind gust data from ERA-Interim and ERA5 with observational data across Sweden. They find an overall better agreement between observations and ERA5, although some discrepancies persist in regions with complex topography. We therefore conclude that it is adequate to use the recent ERA5 dataset for the comparison to the insurance model in the second part of our study.

One reason for the differences between the meteorological index and the catastrophe model of Aon Impact Forecasting is their different methodological design: First, Aon uses a 1-day window for the loss calculation, while LI is based on 72-hour windows. Thus, Aon is better able to separate storm events in short succession (like Lothar and Martin in December 1999). On the other hand, Aon's IF Euro WS model uses the same event date for all affected countries and might therefore lose information on the evolution of a storm event that travels over Europe. The 72-hour event definition in LI corresponds to a definition often used in reinsurance treaties (Klawa and Ulbrich, 2003; Karremann et al., 2014a). Second, LI only includes the hazard component and an estimate for the exposure component, while the Aon model additionally includes a sophisticated

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engineering-based vulnerability component that takes e.g. building resistance, loss frequency due to quasi-random effects and local societal adaptations into account.

Aside from that, our study reveals some shortcomings of the two approaches. As all meteorological indices, LI relies upon the quality of both the underlying wind data and the impact function used for the calculation of loss. In the specific case of LI, the initial index was developed and evaluated for Germany by Klawa and Ulbrich (2003), employing insurance data of Munich Re and GDV ("Gesamtverband der Deutschen Versicherer e.V."). In a follow-up study, Karremann et al. (2014b) were able to demonstrate that the chosen 98th percentile is an appropriate threshold to identify extreme storm events over Central and Western Europe. Nevertheless, they also point out that the 98th percentile might be too low for South Eastern Europe, the Mediterranean and Scandinavia. For these regions, Karremann et al. (2014b) suggest the use of a fixed, reasonable threshold below which losses are improbable. Moreover, the usage of present-day population density as proxy for exposure levels might lead to an overestimation of loss values (Koks and Haer, 2020). Finally, the LI index is missing a detailed damage component, thus it struggles to capture the non-linear response of the buildings at the tail of the gust spectrum for the high impact events. In some extreme cases, certain exposures (e.g. greenhouses, timber building or agricultural buildings) may have vulnerability functions approximating a step-function. The Aon catastrophe model on the other hand, includes no information on not-insured market loss. Additionally, insurance data in general depend on the insurance coverage and policy in single countries. Both factors might result in an overrepresentation of windstorms that hit countries with high market coverage (Moemken et al., 2023).

Overall, our results suggest that the loss distribution in LI is not steep enough and accordingly the tail is too short, leading to an underestimation of high impact windstorms compared to the insurance catastrophe model. Nonetheless, LI is an effective index precisely because of its simplicity. Although it cannot be used to price a storm (due to the missing vulnerability information), it is suitable for estimating the impacts and rank events. The first comparison between a meteorological index and a full commercial windstorm model could serve as a reference for future studies focussing on the development and improvement of both storm loss models and storm severity indices.

Data availability

The ERA5 and ERA-Interim reanalysis data (input for the loss index) can be downloaded from the Copernicus Climate Change Service (C3S) Climate Data Store (https://cds.climate.copernicus.eu/). Access to PERILS is granted via an annual subscription in accordance with a PERILS database license.

Author contribution

JM, AMR and JGP conceived and designed the study. IA performed the data analysis and made the figures with the help of AG, AB and LB. JM wrote the initial paper draft. All authors discussed the results and contributed with manuscript revisions.

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Competing interests

One of the authors (JGP) is member of the editorial board of Natural Hazards and Earth System Sciences.

Acknowledgements

IA was funded by European Union's Horizon 2020 research and innovation programme under Marie Skłodowska-Curie grant no. 956396 (EDIPI project). JM was funded by the Bundesministerium für Bildung und Forschung (BMBF; German Ministry for Education and Research) under project "RegIKlim-NUKLEUS" (01LR2002B and 01LR2002B1). JGP thanks the AXA Research Fund for support. AMR was supported by the Helmholtz 'Changing Earth' program. We thank the German Climate Computing Center (DKRZ, Hamburg) for computing and storage resources. IA thanks Petr Svoboda and the team of Aon Impact Forecasting for support during her stay in Prague. We thank Ting-Chen Chen for preparing the cyclone track data, Jisesh Sethunadh for help with LI calculations, and Federico Stainoh (all KIT) for help with statistical analysis methods.

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