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Windstorm losses in Europe – What to gain from damage datasets

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ABSTRACT

Windstorms are among the most impacting natural hazards affecting Western and Central Europe. Information on the associated impacts and losses are essential for risk assessment and the development of adaptation and mitigation strategies. In this study, we compare reported and estimated windstorm losses from five datasets belonging to three categories: Indices combining meteorological and insurance aspects, natural hazard databases, and loss reports from insurance companies. We analyse the similarities and differences between the datasets in terms of reported events, the number of storms per dataset and the ranking of specific storm events for the period October 1999 to March 2022 across 21 European countries. A total of 94 individual windstorms were documented. Only 11 of them were reported in all five datasets, while the large majority (roughly 60%) was solely recorded in single datasets. Results show that the total number of storms is different in the various datasets, although for the meteorological indices such number is fixed a priori. Additionally, the datasets often disagree on the storm frequency per winter season. Moreover, the ranking of storms based on reported/estimated losses varies in the datasets. However, these differences are reduced when the ranking is calculated relative to storm events that are common in the various datasets. The results generally hold for losses aggregated at European and at country level. Overall, the datasets provide different views on windstorm impacts. Thus, to avoid misleading conclusions, we use no dataset as "ground truth" but treat all of them as equal. We suggest that these different views can be used to test which features are relevant for calibrating windstorm models in specific regions. Furthermore, it could enable users to assign an uncertainty range to windstorm losses. We conclude that a combination of different datasets is crucial to obtain a representative picture of windstorm associated impacts.

1. Introduction

Windstorms are one of the major natural hazards affecting Western and Central Europe, causing serious damage to the natural environment, buildings and infrastructure (Mitchell-Wallace et al., 2017; Pinto et al., 2019; Walz and Leckebusch, 2019), and often having a significant impact on the total insured losses worldwide (Munich Re, 2022). For example, windstorm Kyrill[1] (Fink et al., 2009; Ludwig et al., 2015) was one of the most damaging storms in recent decades and affected large parts of Europe in January 2007. Kyrill was the strongest of a series of extratropical cyclones over the North Atlantic in the winter season 2006/2007 (Pinto et al., 2014) and swept with strong winds over many regions in Western, Central and Eastern Europe (Fink et al., 2009, their Fig.1), leading to significant disruptions in electricity and transportation services (Deutsche Rück, 2008). In total, 54 fatalities were reported and the insured (economic) losses in Germany, the United Kingdom, Belgium, and the Netherlands amounted to 4.6 billion (7.6 billion) Euro (Swiss Re, 2008). Kyrill was the costliest winter storm in Europe after Lothar and Martin in December 1999 (Deutsche Rück, 2005, 2008). Unlike Lothar, Kyrill was well-predicted in advance and warnings were issued by the National Meteorological Services (Deutsche Rück, 2008), which very likely prevented worse damage and a higher number of fatalities. For example, regional and long-range trains were halted nationwide for the first time across Germany. Regarding future decades, several studies provide evidence of a potential increase in losses associated with windstorms in Europe (e.g. Pinto et al., 2012; Catto et al.,

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[1] Storm names in this study are 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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Table 1
Overview of used datasets, including information on name, abbreviation, type of dataset and available time period.

NAME	ABBREVIATION	TYPE	TIME
Extreme Wind Storms Catalogue	**XWS**	Meteorological index	1979–2014
Copernicus Climate Change Service (Winter windstorm indicators)	**C3S**	Meteorological index	1979–2021
Loss Index	**LI3D**	Meteorological index	1999–2022
EM-DAT		Disaster database	1900 – present
PERILS		Insurance data	1999 – present

2019; Manning et al., 2022).

Storms like Kyrill highlight that a wind-related risk assessment and the forecasting of impacts is essential for the preparation for and mitigation of windstorm losses (Pinto et al., 2019; Merz et al., 2020; Gliksman et al., 2023). Various types/categories of datasets provide information on windstorm losses under present and future climate conditions from different perspectives. The first type includes indices that combine meteorological variables and insurance aspects, like storm severity indices or storm loss models (e.g. Klawa and Ulbrich, 2003). The second category covers natural hazard/disaster databases that collect information on disaster impacts, often from a humanitarian perspective (e.g. Kron et al., 2012). Another type is insurance data based on actual loss reports from insurance companies (e.g. Munich Re, Deutsche Rück). We examine the similarities and differences in loss reports/estimates in these types of damage datasets considering five examples, namely the Extreme Windstorm Catalogue (XWS; Roberts et al., 2014), windstorm indicators provided by the Copernicus Climate Change Service (C3S), the Loss Index (Pinto et al., 2012), EM-DAT and PERILS. We want to answer the following research questions:

- Which windstorm events are documented in the different datasets?
- How comparable are the different datasets in terms of the number of reported storms and the associated losses?
- What needs/ways forward for research on windstorm losses does this comparison highlight?

The paper is structured as follows: The datasets are introduced in Chapter 2, the results are presented in Chapter 3, and a summary and discussion conclude this paper in Chapter 4.

2. Loss data

In this study, we consider five different datasets that cover three types of windstorm impact data: meteorological indices, natural hazard or disaster databases, and insurance data. All chosen datasets are described in detail in the following sections. Since the datasets all cover different time periods and countries, we focus on the period October 1999–March 2022, during which data from at least three of the datasets is always available, and 21 European countries (see Sect. 2.1.2) to ensure comparability. Table 1 summarises the five datasets. For the comparison of the datasets, we use the original loss reports/estimates as well as normalized losses. The normalisation is done via a min-max scaling approach that scales the loss values between 0.0 and 1.0. Here, 1.0 corresponds to the impact of the top storm in a given dataset and all other storms range relative to this storm.

2.1. Meteorological indices

A large variety of storm severity indices and storm loss models can be employed to identify severe windstorms, estimate the associated losses/damage and analyse their likelihood, magnitude and trends (see Gliksman et al. (2023) for a detailed overview). They are often built from daily maximum wind speed or peak wind gust as these are assumed to be the most influential factors for storm losses (e.g. Klawa and Ulbrich, 2003; Leckebusch et al., 2008; Pardowitz et al., 2016; Welker et al., 2021). Many indices are actually based on the cube of wind speed, following the assumption that the damage is proportional to the wind power or to the wind kinetic energy flux. One of the first storm severity indices by Lamb (1991) incorporated the highest observed wind speed over land, the affected area and the overall duration. In the early 2000s, Klawa and Ulbrich (2003) developed a storm loss model based on station data where the maximum daily wind speeds are scaled with the local 98th percentile. This is based on the assumption that damaging winds (beaufort 8, circa 20 m/s) are reached in 2% of the days over Germany (Klawa and Ulbrich, 2003), and that infrastructure and other sensitive assets are generally adapted to local wind conditions. The scaling is applied in order to eliminate the effect of different wind climates at

Table 2
Extract of the list of all reported storms, including information on storm name, date and affected countries. Countries covered by PERILS are marked with *. Datasets are abbreviated as follows: PERILS (P), EM-DAT (E), C3S (C), XWS (X), LI3D (L). Colouring denotes the agreement between the datasets: white – no dataset reported storm, green – all available datasets reported storm, red – single dataset reported storm, yellow – all other cases (please see Sect. 3.1 for more details). See Supplementary Table S1 for full list.

	AUT*	BEL*	CHE*	CZE	DEU*	DNK*	ESP	EST	FIN	FRA*	GBR*	IRL*	ITA	LTU	LUX*	LVA	NLD*	NOR*	POL	PRT	SWE*
Zubin (Dec 1999)		L		L	L	L		L	L		L			L		L		L	L		L
Anatol (Dec 1999)		L		L	PECXL	PECXL			L	C	ECL	CL	L	ECL	L	ECL	CL		ECL		ECXL
Lothar (Dec 1999)	CL	PEL	PECXL	CL	PECXL		CL		C	PECXL	ECL	EC	CL		PCL		CL	CL			
Martin (Dec 1999)	C	L	PCXL	CL	CL		ECL			PECXL	C		CXL		CL		L			L	
Afra (Jan 2000)											C	C						C			
Kerstin (Jan 2000)	L	L	L	L	L	L		L	L		L					L	L	L	L		L
Nicole (Oct 2000)		L			L	L				L	L				L		L	L			
Oratia (Oct 2000)		L			CXL	CL	C		L	CXL	CXL	C			C		CXL	CL			L
Yamura (Nov 2000)											C	C									
Elke (Dec 2000)							E													E	
Quendula-Romy (Dec 2000)							E				E										
Torsten (Nov 2001)							E														
Ginger-Heike (Jan 2002)		L	L	L	L	L		L	L	L	L	L		L	L	L	L		L		L
Jennifer (Jan 2002)		L	L	CL	ECL	CXL		CL		CL	ECXL	CL		CL	L	CL	L	CL	ECL		CL
Anna (Feb 2002)		L	L	L	CL	CL		L	L	CL	CL	CL		L	L	L	CL		C		C
Jeanett (Oct 2002)	ECXL	PECL	PEL	ECXL	PECXL	XL				PECXL	PECXL	CXL			CL		PECXL		ECXL		X
Tamara-Uschi (Nov 2002)	E									E											
Calvann (Jan 2003)			E		E					E											
Gerda (Jan 2004)					E																
Pia-Queenie (Jan 2004)		L			L			L		L	L				L		L				
Nina-Oralie (Mar 2004)		L		L	L	L				L	L	L		L	L		L		L		
Carolin (Oct 2004)												E									
Pia-Quimburga (Nov 2004)	L	L	L	L	L	L				L			L	L	L				L		L
Christian-Dimitri (Jan 2005)					L	L		L		L	L	L		L		L		L			L
Erwin (Jan 2005)		L			ECL	ECXL		ECL		CL	ECXL	ECXL		ECL		ECL	ECL	ECXL	ECL		ECXL
Gero (Jan 2005)											ECX	CX						C			
Lutz (Nov 2005)											C	C									
Nino (Nov 2005)											C	C						C			
Lotte (Dec 2006)		L	L		CL	CL				CL	CL	CL	L	L	L	L	CL		CL		L
Franz (Jan 2007)	L	L	L	L	L	L		L	L		L	L		L	L	L	L	L	L		L
Kyrill (Jan 2007)	ECXL	PECXL	PEL	ECL	PECXL	EL		L	L	PECXL	PECXL	PCXL		L	PCL	L	PECXL		ECL		L

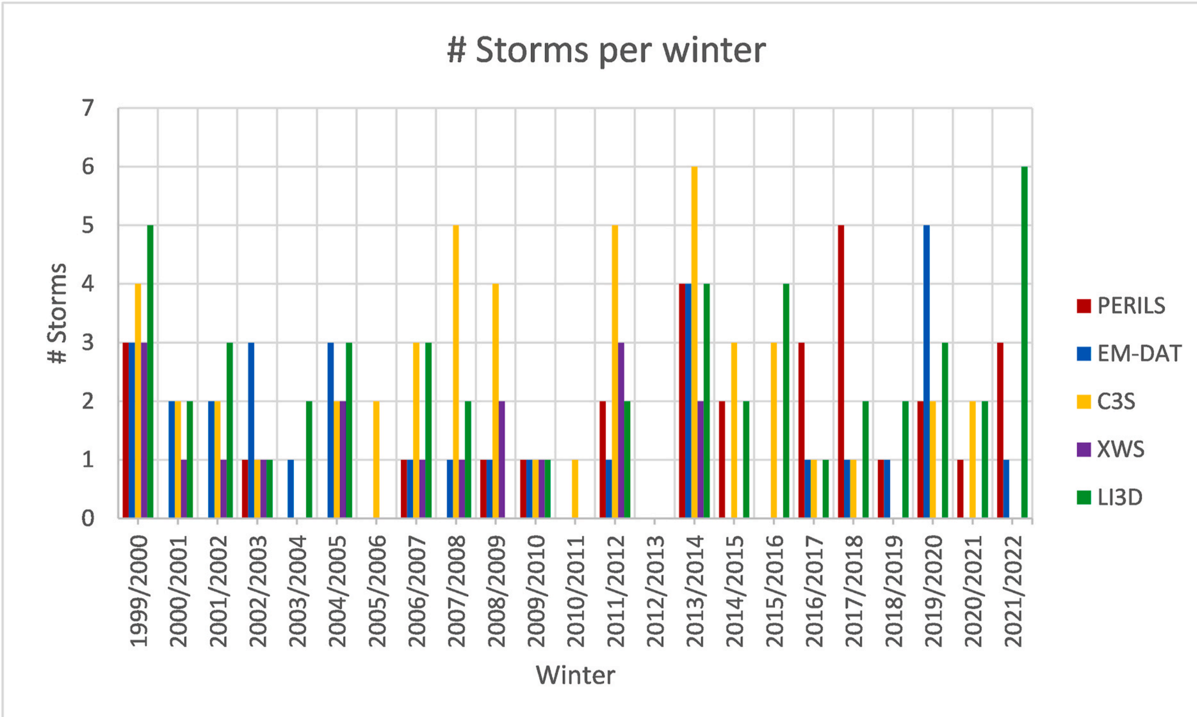

Fig. 1. Number of storms per winter half year (October–March) for the period 1999/2000–2021/2022 for PERILS (red), EM-DAT (blue), C3S (yellow), XWS (purple), and LI3D (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Averaged storm frequency per year for all five datasets for the period 1999/2000–2021/2022 as well as the common period 1999/2000–2013/2014. The last row gives the standard deviation.

	1999/2000–2021/2022	1999/2000–2013/2014
PERILS	1.30	0.87
EM-DAT	1.39	1.53
C3S	2.17	2.53
XWS	0.78	1.2
LI3D	2.17	1.87
Standard deviation	**0.6**	**0.64**

different locations and for building characteristics. A similar approach but adapted to gridded data was used by Leckebusch et al. (2007) to identify windstorms and to quantify their potential impact. The method was extended further by Pinto et al. (2012), who additionally considered the exposure and local population levels as proxies for insurance data in their Loss Index (see also Sect. 2.1.3). We analyse three different storm severity indices/storm loss models that are described in detail in the following sections.

2.1.1. Extreme Wind Storms catalogue (XWS)

The eXtreme Wind Storms (XWS) catalogue is a publicly available event set of the 50 most extreme European winter windstorms during the period October 1979–March 2014 (Roberts et al., 2014). The catalogue provides windstorm tracks, storm footprints and loss estimates and can be accessed at *www.europeanwindstorms.org*. The storm tracks were derived from ERA-Interim (Dee et al., 2011) following the method by Hoskins and Hodges (2002) that uses 850 hPa relative vorticity based on the algorithm of Hodges (1995, 1999). For the storm footprints, the ERA-Interim data was dynamically downscaled to 0.22° with the Met Office Unified Model (MetUM; Davies et al., 2005). The storm footprint is then defined as the maximum 3-second wind gust at each grid point over a 72 h period. In total, 5 730 storms were identified. The final event set consists of 23 storms highlighted by the insurance industry, which were chosen after consultation with Willis Research Network. The other 27 storms were selected based on the ranking of a meteorological storm severity index. This index (S_{ft}) relies on the maximum intensity (U_{max}) and the size of the storm (N), where U_{max} is defined as the maximum 925 hPa wind speed within a 3° radius of the vorticity maximum and N is defined as the area of the footprint that exceeds 25 m/s: $S_{ft} = U_{max}^3 * N$. For this study, we use the storm date, the affected countries, and the storm loss estimates based on the storm severity index.

2.1.2. Copernicus Climate Change Service (C3S)

The Copernicus Climate Change Service (C3S) provides a dataset of indicators for European winter windstorms in the period 1979–2021 derived from ERA5 reanalysis (Hersbach et al., 2020). The dataset is available at *https://cds.climate.copernicus.eu/* and includes climatological indicators like storm tracks and storm footprints, as well as loss and risk indicators to describe socio-economic impacts (C3S Climate Data Store, 2022), for a total of 148 storms. The dataset covers the following 21 European countries, which form the basis for our study (sorted by ISO country code): Austria (AUT), Belgium (BEL), Switzerland (CHE), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), Great Britain (GBR), Ireland (IRL), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), and Sweden (SWE). We focus on the loss indicators, where a high-resolution damage model is employed to estimate the financial loss at each building location for a particular storm event (Koks and Haer, 2020). This model uses publicly available hazard, exposure and vulnerability data. The hazard component is based on the storm footprints derived from ERA5 reanalysis. For the exposure component, building footprint data for 2018 are obtained from OpenStreetMap (OSM). The vulnerability data is based on the fragility curves (relation between wind speed and damage) by Feuerstein et al. (2011) for six different building types. These curves use a nonlinear scaling with an empirical exponent of 3/2 inherited from the Beaufort scale (Feuerstein et al., 2011; their Fig. 2). In the final step,

Table 4
Storm ranking based on reported/estimated losses at European level for those 37 storms that are reported in at least two of the five datasets. The different ranks are highlighted in colour: green for ranks 1–5, yellow for ranks 6–10, blue for ranks 11–15, red for ranks 16–20, white for ranks above 20, and grey for storms that are not reported in the dataset or not within the Top50 events (both marked with an "X").

	PERILS	C3S	XWS	LI3D
Anatol (Dec 1999)	4	5	3	15
Lothar (Dec 1999)	1	1	13	3
Martin (Dec 1999)	3	2	11	6
Oratia (Oct 2000)	X	6	4	21
Jennifer (Jan 2002)	X	8	9	11
Anna (Feb 2002)	X	17	X	34
Jeanett (Oct 2002)	6	9	1	2
Erwin (Jan 2005)	X	3	5	28
Gero (Jan 2005)	X	24	14	X
Lotte (Dec 2006)	X	27	X	37
Kyrill (Jan 2007)	2	4	2	1
Emma (Feb 2008)	X	28	16	8
Kirsten (Mar 2008)	X	23	X	24
Klaus (Jan 2009)	7	7	7	X
Quinten (Feb 2009)	X	36	15	X
Xynthia (Feb 2010)	8	19	8	22
Joachim (Dec 2011)	22	14	10	42
Patrick (Dec 2011)	X	26	18	X
Andrea (Jan 2012)	17	18	12	9
Christian (Oct 2013)	11	15	17	47
Xaver (Dec 2013)	12	11	6	18
Dirk (Dec 2013)	16	22	X	27
Tini (Feb 2014)	20	10	X	X
Elon-Felix (Jan 2015)	18	20	X	23
Mike-Niklas (Mar 2015)	13	X	X	14
Ruzica (Feb 2016)	X	39	X	33
Thomas (Feb 2017)	27	X	X	30
ex-Ophelia (Oct 2017)	30	12	X	X
Burglind (Jan 2018)	14	X	X	36
Friederike (Jan 2018)	9	X	X	10
Dragi-Eberhard (Mar 2019)	15	X	X	13
Sabine (Feb 2020)	10	13	X	5
Victoria (Feb 2020)	21	30	X	29
Klaus-Luis (Mar 2021)	29	X	X	41
Hendrik-Ignatz (Oct 2021)	23	X	X	25
Nadia (Jan 2022)	28	X	X	46
Ylenia-Zeynep-Antonia (Feb 2022)	5	X	X	4
	PERILS	C3S	XWS	LI3D

damages are estimated by translating the fragility curves into vulnerability curves using reconstruction costs per building type. The loss estimates per storm are aggregated for each NUTS3 region (Nomenclature des Unités Territoriales Statistiques) and each country. To compare the C3S dataset to the others in this study, we only use the Top50 events in the period 1999–2021 and the country-aggregated loss estimates.

2.1.3. Loss Index (LI3D)

The third meteorological index used in the present study is the Loss Index (LI) developed by Pinto et al. (2012) and developed further by Karremann et al., (2014a). The index estimates potential losses for each calendar day, by adapting the storm loss model by Klawa and Ulbrich (2003) and making the following assumptions:

- Storm damage occurs only for the highest 2% of wind speeds, thus for daily maximum wind speeds above the local 98th percentile.
- The exposure of buildings to high wind speeds depends on the local wind climate. This is taken into account by scaling the wind values at every grid point with the local 98th percentile.

Table 5
Same as Table 4, but for (a) common "PCXL-storms" and (b) common "PCL-storms". Ranking is highlighted in colour: green for ranks 1–3, yellow for ranks 4–6, blue for ranks 7–10, red for ranks above 10.

a)	PERILS	C3S	XWS	LI3D
Anatol (Dec 1999)	4	4	3	6
Lothar (Dec 1999)	1	1	9	3
Martin (Dec 1999)	3	2	7	4
Jeanett (Oct 2002)	5	5	1	2
Kyrill (Jan 2007)	2	3	2	1
Xynthia (Feb 2010)	6	10	5	8
Joachim (Dec 2011)	10	7	6	9
Andrea (Jan 2012)	9	9	8	5
Christian (Oct 2013)	7	8	10	10
Xaver (Dec 2013)	8	6	4	7
	PERILS	C3S	XWS	LI3D

b)	PERILS	C3S	LI3D
Anatol (Dec 1999)	4	4	7
Lothar (Dec 1999)	1	1	3
Martin (Dec 1999)	3	2	5
Jeanett (Oct 2002)	5	5	2
Kyrill (Jan 2007)	2	3	1
Xynthia (Feb 2010)	6	11	9
Joachim (Dec 2011)	14	8	13
Andrea (Jan 2012)	11	10	6
Christian (Oct 2013)	8	9	14
Xaver (Dec 2013)	9	6	8
Dirk (Dec 2013)	10	13	11
Elon-Felix (Jan 2015)	12	12	10
Sabine (Feb 2020)	7	7	4
Victoria (Feb 2020)	13	14	12
	PERILS	C3S	LI3D

- The potential loss increases with the cube of the maximum wind speed, being proportional to the wind kinetic energy flux.
- Insured losses depend on the insurance coverage in the affected area. If the required insurance data is not available, population density is used as proxy.

Hence, the potential loss per calendar day (LI_{raw}) is defined as:

$$LI_{raw} = \sum_{ij}\left(\frac{v_{ij}}{v_{98_{ij}}}\right)^3 * POP_{ij} * I(v_{ij}, v_{98_{ij}})$$

with $I(v_{ij}, v_{98_{ij}}) = \begin{cases} 0\ for\ v_{ij} < v_{98_{ij}} \\ 1\ for\ v_{ij} > v_{98_{ij}} \end{cases}$, daily maximum wind speed v at grid point ij, local 98th percentile v_{98}, and population density POP. To clearly separate individual events of high LI_{raw}, overlapping 3-day sliding time windows are used and the temporal local maximum of each 3-day time window is analysed (Karremann et al., 2014b):

$$LI_{3D} = \sum_{ij}\left[max_{3D}\left(\frac{v_{ij}}{v_{98_{ij}}}\right)\right]^3 * POP_{ij} * I\left(v_{ij}, v_{98_{ij}}\right)$$

LI_{3D} is derived from ERA5 reanalysis at 0.25° spatial resolution using hourly 10 m wind speeds for the 23 winters 1999/2000 to 2021/2022. Gridded population density data for the year 2020 was taken from the Centre for International Earth Science Information Network (CIESIN) at Columbia University. It has a spatial resolution of 0.04° and was remapped onto the ERA5 grid. As we are only interested in extreme windstorm events, we focus on the Top50 events for the same 21 countries as in the C3S dataset.

2.2. Natural hazard/disaster database (EM-DAT)

There is a collection of global, multi-peril databases that compile information on losses from natural hazards, including Sigma from Swiss Re, NatCatSERVICE from Munich Re and EM-DAT from CRED (Kron et al., 2012; Wirtz et al., 2014; Gall, 2015). Additionally, numerous databases focussing on the national/regional scale or specific hazards are available worldwide.

In this study, we use the freely available Emergency Events Database EM-DAT that was launched in 1988 by the Centre for Research on the Epidemiology of Disasters (CRED, UCLouvain Brussels, Belgium). EM-DAT contains data on the occurrence and impacts of more than 22,000 disasters in the world from 1900 to today and is available at *https://www.emdat.be*. It differentiates between two types of disasters: natural and technological. Data is collected from various sources including UN agencies, NGOs, World Bank, research institutes, insurance/reinsurance companies and news/press agencies. The exact source of information for each disaster is not available, but an event is generally only included if at least two sources report it. A disaster enters the database if one of the following criteria is met (Below et al., 2009):

- 10 or more people dead, and/or
- 100 or more people affected, and/or
- Declaration of state of emergency, and/or
- Call for international assistance.

EM-DAT compiles geographical, temporal, human and economic information on a disaster at country-aggregated level. The data usually includes the event type, date of event and affected region, but for windstorms, information on affected population and loss is often missing. We consider all reported windstorm events in the period October 1999–March 2022.

2.3. Insurance data (PERILS)

In this study, we use insurance data provided by PERILS on an annual subscription basis in accordance with a database license. PERILS (*https://www.perils.org*) was founded in early 2009, as a joint stock company. It is owned by ten shareholders: Allianz, Axa, Generali, Groupama, Guy Carpenter, Insurance Australia Group, Munich Re, Partner Re, Swiss Re and Zurich Insurance. The main aim of PERILS is to prepare aggregated anonymised insurance data and make them available to interested parties. The data are based on information exclusively received from insurance companies writing business in the territories covered by PERILS. The identity of the insurance companies providing data or any other information that might lead to the disclosure of their identity (e.g. total market coverage) are not made public. However, PERILS confirms that it has sufficient market coverage (defined as more than 40% of market property premium) to be able to produce robust industry level loss estimates. Upon receipt, the data are quality controlled, anonymised, aggregated, and extrapolated to market level. To subscribers, PERILS provides the following data:

- Ultimate gross event loss per country and CRESTA zone
- Property premium data per country
- Exposure (total sums of property insured) per country and CRESTA zone.

CRESTA is a geographical data aggregation standard used by the global insurance industry (*www.cresta.org*). PERILS uses the low resolution CRESTA zones that follow administrative boundaries (e.g. province/county) or merged postal code areas (e.g. first two digits).

Information on extratropical windstorm losses is provided for 12 European countries (Austria, Belgium, Denmark, France, Germany, Ireland, Luxembourg, Netherlands, Norway, Sweden, Switzerland, and United Kingdom) and, where feasible, four lines of business (residential

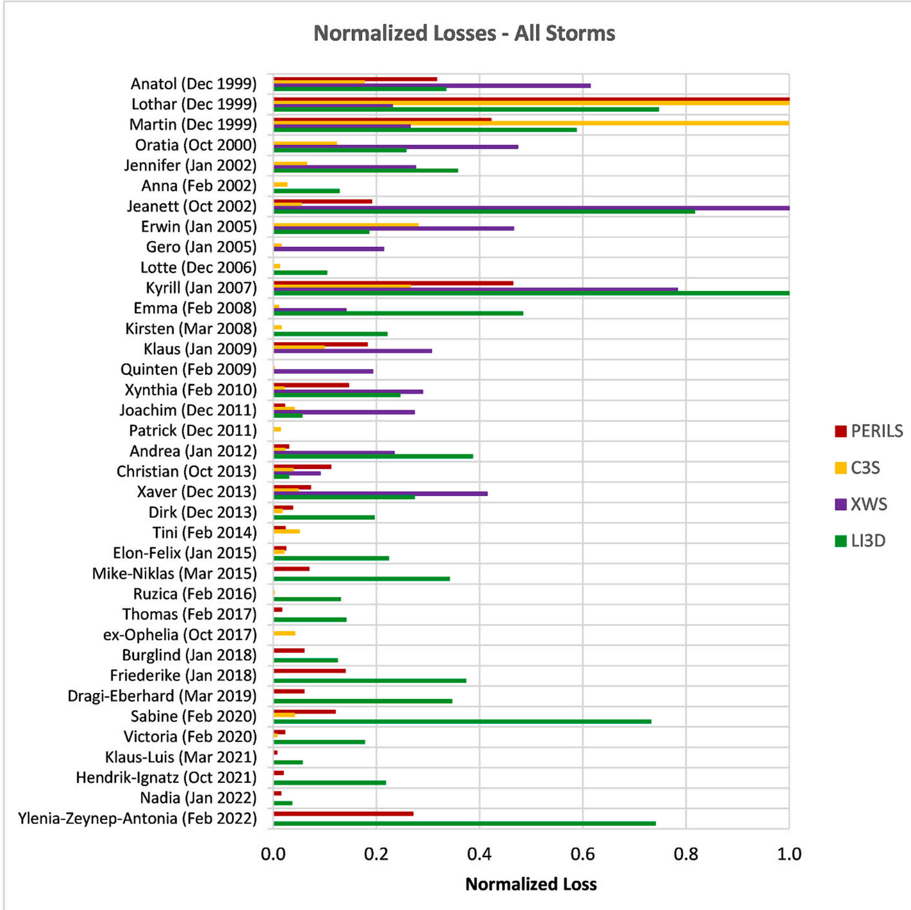

Fig. 2. Normalized losses (via min-max scaling) at the European level for those 37 storms that are reported in at least two of the five datasets for PERILS (red), C3S (yellow), XWS (purple), and LI3D (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

property, commercial property, industrial property, agricultural property). Data are available in national currencies, Euros (EUR) and US Dollars (USD). A windstorm event is reported if the total insured loss is larger than 200 Million EUR. This threshold was adapted in September 2022 to 500 Million EUR for pan-European events and 300 Million EUR for events affecting individual countries. Windstorm losses are available for all events that have exceeded this threshold since 2009. In 2011, the event set was extended to include loss estimates for five major European storm events since 1999, namely Anatol, Lothar, Martin, Jeanett and Kyrill.

For the comparison with the other datasets in this study, we have decided to use country-aggregated loss ratios, calculated as ultimate event loss divided by exposure (e.g. Prahl et al., 2015). In PERILS, exposure data are only available for 2013–2022. There are several ways to estimate the exposure for years prior to 2013: applying the trend, using inflation, or using the consumer price index. Here, we decided to use the trend, i.e. we calculated the linear trend in exposure for 2013–2022 and applied it backwards to estimate the exposure for the missing years 1999–2012.

3. Results

3.1. Reported storms

In a first step, we compiled a list of all storms that were reported in at least one of the five datasets. Only storms in the wintertime period 1999/2000 to 2021/2022 were considered, from October to March. Based on the event date, each storm is assigned a name employing those given by the Freie Universität Berlin and used by the German Weather Service (DWD). The list of storm names is available at *https://www.wetterpate.de/namenslisten/tiefdruckgebiete/index.html* (in German). Besides the storm name and date, the compiled list includes information on the affected countries. A sample of the storm list is given in Table 2. The whole list can be found in Supplementary Table S1. The datasets are abbreviated as follows: PERILS (P), EM-DAT (E), XWS (X), C3S (C), and LI3D (L). For easier comparison, the individual entries are coloured:

- White means that either the storm was not reported in any of the datasets or that the country was not affected.
- Red represents storms that are only present in a single dataset.
- Green denotes storms that are documented in all available datasets. As the datasets cover different countries and periods (see Chapter 2 and Table 1), this corresponds to:
  - o PECXL for the 12 countries covered by PERILS (marked by *) for 1999/2000–2013/2014
  - o PECL for the 12 countries covered by PERILS for 2014/2015–2021/2022
  - o ECXL for the 9 remaining countries for 1999/2000–2013/2014
  - o ECL for the 9 remaining countries for 2014/2015–2021/2022.
- Yellow represents all other cases.

In total, 94 storms were identified in the different datasets. Only 11 of these storms (less than 15%) are recorded in all datasets. On the other hand, 56 storms (roughly 60%) are only reported by single datasets, usually by either C3S or LI3D. Furthermore, the datasets show a large disagreement regarding the countries affected by a storm event. Even for

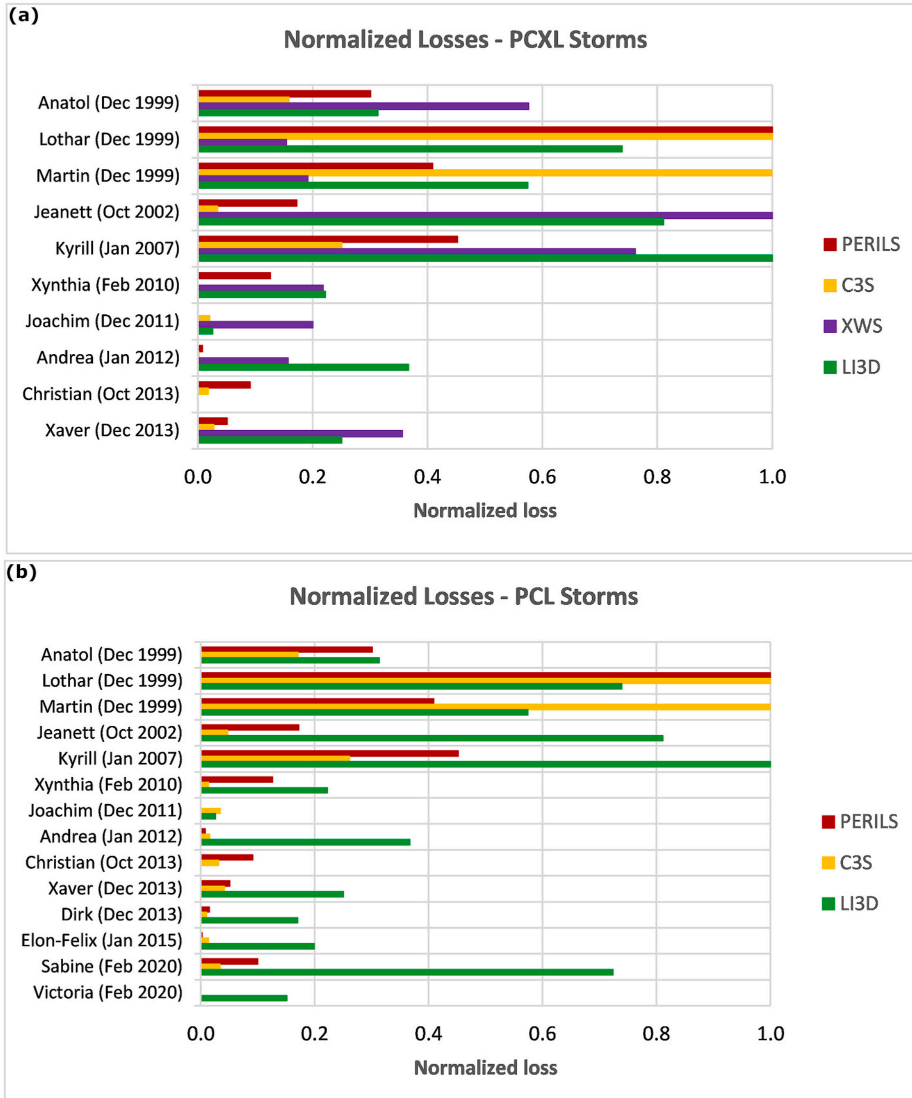

Fig. 3. Same as Fig. 2, but for (a) common "PCXL-storms" and (b) common "PCL-storms".

storms like Jeanett in 2002 or Kyrill in 2007 (see also Sect. 3.4), where large parts of Europe were impacted, only some countries are documented in all datasets. In the case of Kyrill, for instance, losses are reported in all datasets for only five of the possible 21 countries (namely BEL, DEU, FRA, GBR, and NLD). Five different countries, on the other hand, are only documented in LI3D. Even datasets like C3S and LI3D, which belong to the same category and use the same reanalysis data, do not necessarily agree on the reported windstorm events and affected countries (see e.g. Anatol in 1999).

3.2. Comparison of storm numbers

In the next step, we compared the datasets regarding the total number of storm events, the number of storms per winter half year, and the average storm frequency per year. This is done for the extended period 1999/2000 to 2021/2022 as well as for the period common to all datasets, namely 1999/2000 to 2013/2014. Note that even if the total number of storms or the number of storms in one winter season is the same in different datasets, it does not necessarily mean that those datasets identified the same storm events. Again, we see large differences between the datasets. For the extended period (Fig. 1 and Supplementary Table S2), C3S and LI3D have a total of 50 events (per definition, see Sect. 2.1). The total number in XWS is 18, namely roughly a third, while PERILS and EM-DAT reported a comparable number of storms (30 vs 32). The agreement is a little better when looking at the total number of storms in the common period only (Fig. 1 and Supplementary Table S3). C3S with 38 storms still includes the highest number of documented events. PERILS and XWS identify less than half as many: 13 and 18 respectively, but are now much closer to each other. EM-DAT and LI3D report 23 and 28 storms, respectively.

The number of storms per winter can also deviate strongly in the individual datasets (Fig. 1). For example, the winters of 2007/2008 and 2008/2009 are striking: For 2007/2008, 5 storms were documented for C3S, 2 storms in LI3D, while EM-DAT and XWS reported only a single event and no storm at all is included in PERILS. On the other hand, the datasets show a good agreement for winter seasons like 1999/2000, 2013/2014 (3-6 storm events), 2009/2010 (single storm event) or 2012/2013 (no storm).

The mismatch between the datasets is also evident when looking at the average storm frequency per year (Table 3). In agreement with the number of storms, the frequency is highest for C3S and LI3D. Somewhat surprisingly, the differences do not necessarily decrease when only common years are considered (see higher standard deviation), unlike for the total number of storm events.

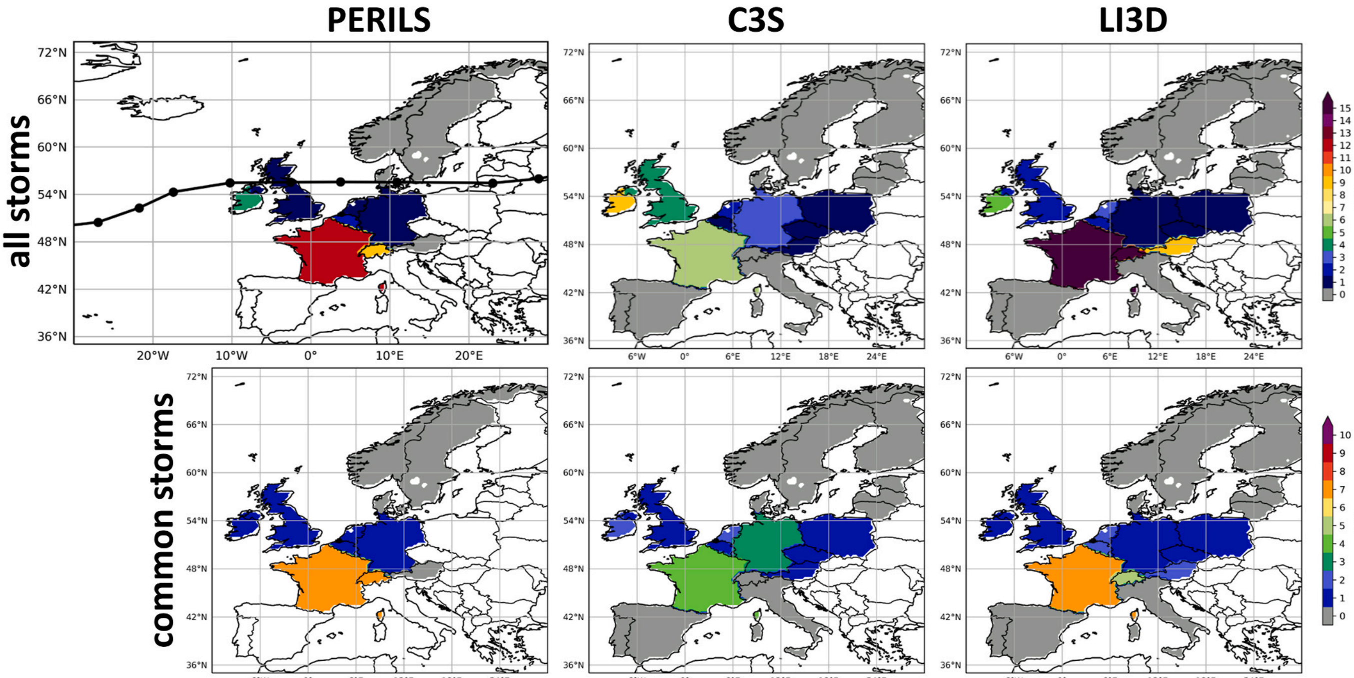

Fig. 4. Storm ranking based on reported/estimated losses at country level for storm Kyrill in January 2007. The ranks are highlighted in colour, grey denotes storms that are not reported in the dataset or not within the Top50 events, and white marks regions not covered by the dataset. Upper row: ranking based on all reported storms per dataset; lower row: ranking based on common "PCL-storms". Please note the different colour scales. The black line and dots in the upper left panel denote the cyclone track derived from ERA5 using the tracking algorithm of Pinto et al. (2005). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

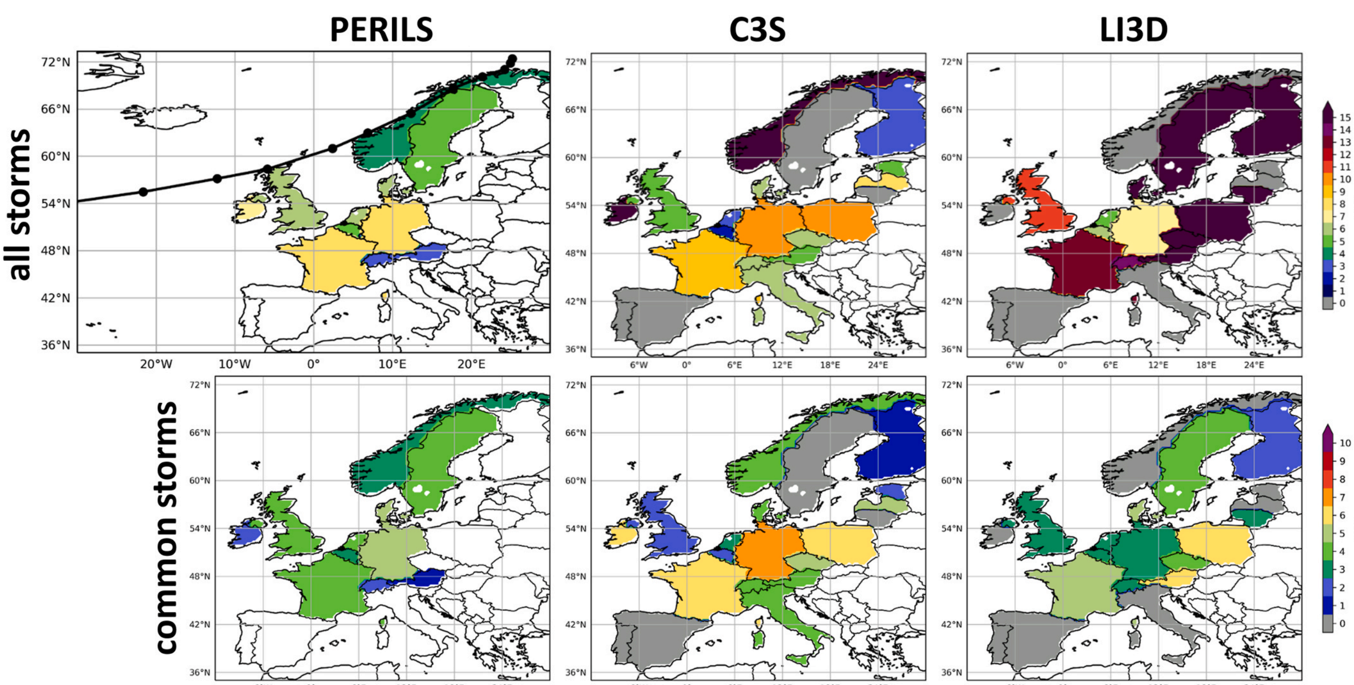

Fig. 5. Same as Fig. 4, but for storm Sabine in February 2020.

3.3. *Comparison of ordinal and relative storm ranking at European level*

We also compared the datasets in terms of the ranking (and therefore the impact) of specific storm events based on reported/estimated losses. This is done for losses aggregated at the European level. Additionally, we analysed the relative ranking of windstorm events based on normalized losses. EM-DAT is not part of this comparison as a ranking was not possible due to the amount of missing loss data.

3.3.1. *Ordinal storm ranking*

In a first step, we compared the ranking of all storm events that are reported in at least two of all five datasets (37 storms in total). The

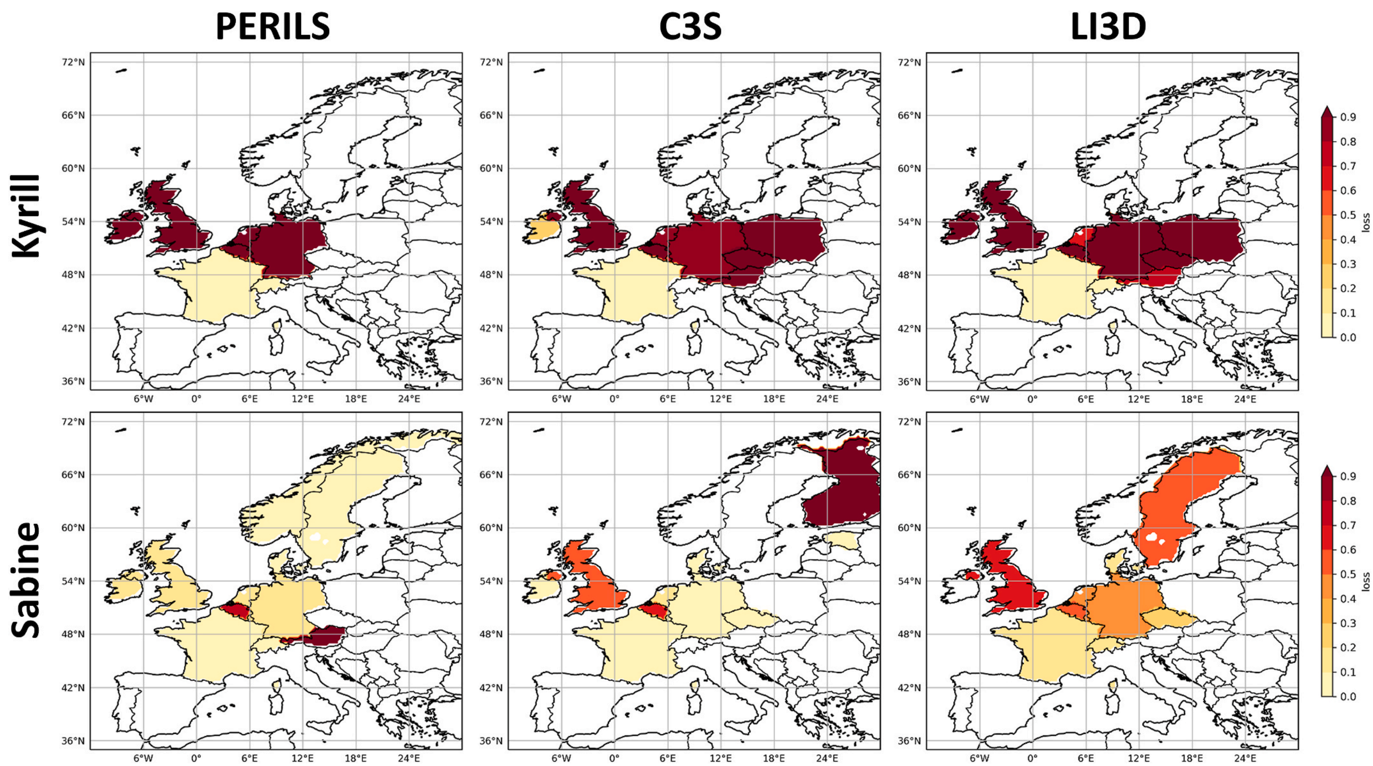

Fig. 6. Normalized losses at country level for storm Kyrill in January 2007 (upper row) and storm Sabine in February 2020 (lower row). The ranking is based on common "PCL-storms".

ranking in Table 4 is highlighted in colour to facilitate the comparison:

- Green: rank between 1 and 5
- Yellow: rank between 6 and 10
- Blue: rank between 11 and 15
- Red: rank between 16 and 20
- White: rank above 20
- Grey: Either rank not in Top50 or storm not recorded in dataset.

For the majority of storms, there are large differences between the datasets. Only for individual events does the ranking agree, e.g. for Kyrill (January 2007; among the Top5 in all datasets) or Klaus (January 2009; rank 7 in all datasets that recorded this event). For other storms (e. g. Lothar in December 1999) the ranking is at least comparable in three out of four datasets, while the fourth dataset is clearly different from the rest. Since the ranking is affected by the total number of storms per dataset, we repeated the analysis for the 10 storm events that are common in all four datasets ("PCXL-storms"). Again, the ranking is highlighted in colour (Table 5a):

- Green: rank between 1 and 3
- Yellow: rank between 4 and 6
- Blue: rank between 7 and 10.

The datasets show a higher level of agreement for the ranking of the common storms (cf. Tables 4 and 5). However, for some windstorms (e. g. Lothar, Martin), the ranking still clearly varies between the different datasets. Another example is Jeanett in October 2002, which is in the Top2 for XWS and LI3D and yet ranked 5 (6) for C3S (PERILS). As XWS is only available until 2014, we repeated the ranking, in a last step, for the common storms in PERILS, C3S and LI3D. This resulted in 14 "PCL-storms". The colour code in Table 5b is the same as in Table 5a, but with an additional red colour for ranks above 10. Like for the 10 "PCXL-storms", the ranking agrees better than when using all reported events.

3.3.2. Normalized losses

As the ordinal ranking does not say how different two storms are, we also analysed the relative ranking of the storm events based on normalized losses. Again, we first compared the 37 windstorms that are reported in at least two of all five datasets (Fig. 2). As before, there are large differences between the datasets for most events. For C3S (yellow bars), there is virtually no difference in the relative ranking of the Top2 storms (with 1.0 for Lothar and 0.99 for Martin), while all other events included in this dataset show only small losses with values below 0.2. In PERILS (red bars), normalized losses for Kyrill (rank 2 with 0.47) and Martin (rank 3 with 0.42) are less than half as high as for the top storm Lothar. The normalized losses for the Top5 storm events in LI3D (green bars) are much closer together, with values ranging between 0.73 (Sabine) and 1.0 (Kyrill). The relative ranking in XWS (purple bars) seems to be clustered, with, for instance, rank 1 and 2 as well as rank 4–6 forming a group of comparable normalized losses.

The differences between the datasets are largely preserved, albeit less pronounced, when looking at the relative ranking for the common "PCXL-storms" (Fig. 3a) and the common "PCL-storms" (Fig. 3b). The overall ranking pattern of the datasets remains mostly unchanged. Thus, the Top2 storms in C3S are still barely distinguishable, while the losses of the Top5 events in LI3D are close to one another. Similarly, in PERILS the normalized losses of the different events are less than half the size of the rank 1 storm Lothar. There is no clear relationship between the various datasets (see also the scatter plots in Supplementary Figure S1). Only for individual storm events, some datasets show a good agreement – such as PERILS and LI3D for Anatol in December 1999.

3.4. Comparison at country level

We conclude our analysis with comparing the ranking of storms in individual countries based on losses aggregated at country level. To quantify and map the differences between the datasets across countries, we additionally compute Spearman's rank correlation coefficients (Spearman, 1904; Dodge, 2008). As in the previous section, EM-DAT is

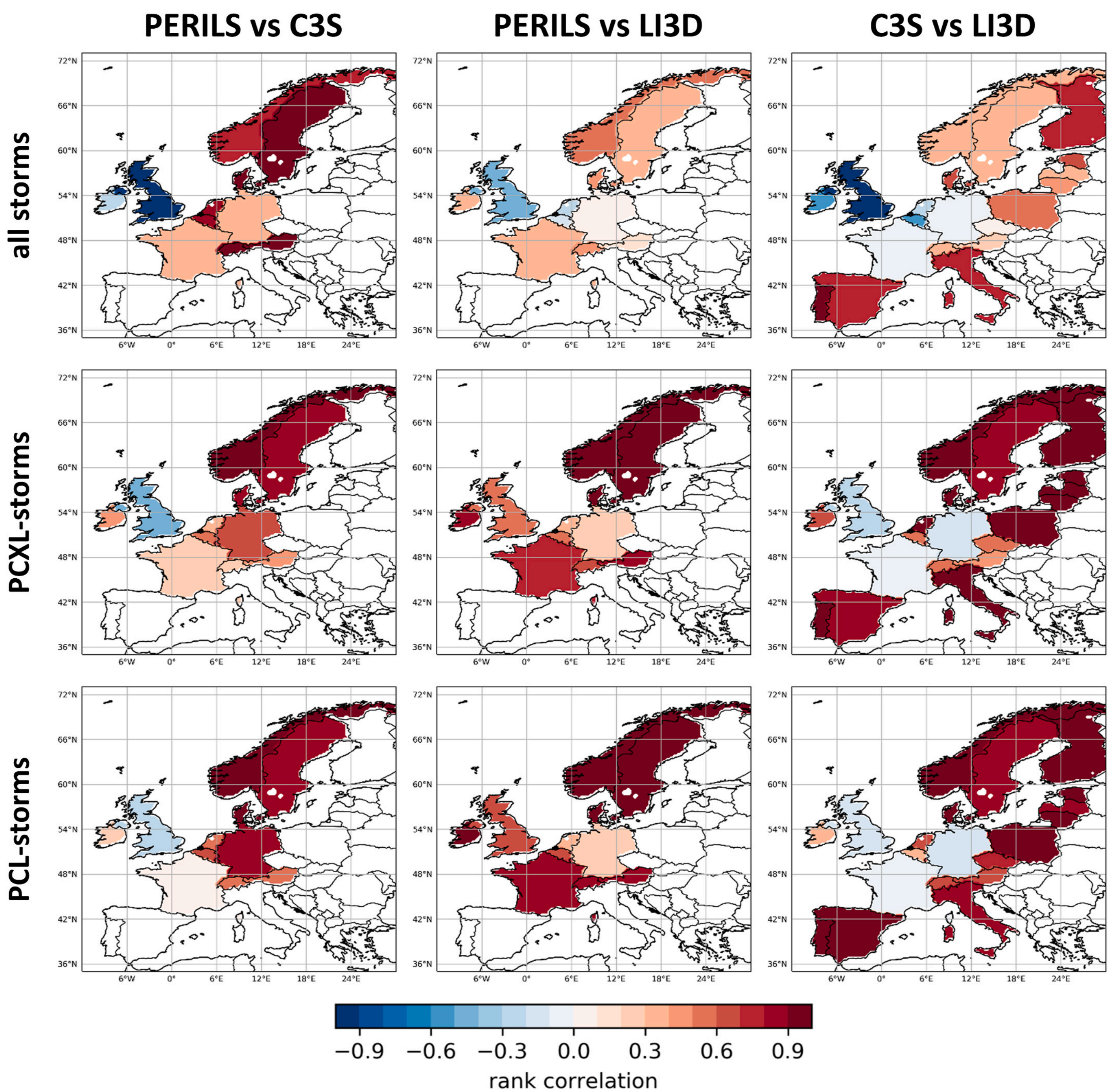

Fig. 7. Spearman's rank correlation coefficient at country level for PERILS vs C3S (left), PERILS vs LI3D (middle), and C3S vs LI3D (right). Upper row: ranking based on all storms per dataset; middle row: ranking based on common "PCXL-storms"; lower row: ranking based on common "PCL-storms".

not considered due to the amount of missing loss data. Furthermore, XWS is not included in this part of the analysis as it only provides loss information aggregated over all affected countries and no information beyond 2014.

3.4.1. *Case studies*

The rank comparison focuses on two representative case studies: Storm Kyrill in January 2007 (Fig. 4), which is among the Top5 events in all datasets (see Sect. 3.3), and storm Sabine in February 2020 (Fig. 5), for which the ranking at European level varies more in the different datasets. For both cases, we compare the ordinal ranking based on all recorded storm events per dataset to the ranking based on the common "PCL-storms". The different ranks are highlighted in colours, while grey means that either the rank is not in the Top50 or that the country is not affected by the storm event. White marks all regions/countries that are not covered by the dataset. The ordinal ranking at country level for the other "PCL-storms" is shown in Supplementary Figures S2-S4.

For Kyrill (Fig. 4), the three datasets largely agree on the region affected by the storm. Moreover, they all agree that some countries (e.g. UK, Germany) have been more severely impacted than others (e.g. France). Thereby, all datasets are consistent with Kyrill's storm track (Fig. 4, upper left panel) and its footprint (not shown). Nevertheless, the storm ranking in the countries can differ considerably in the single datasets. In France, for instance, Kyrill ranks 12th for PERILS, while it reaches rank 6 for C3S and above rank 15 for LI3D. The datasets show a better agreement when only common events are considered for the ranking (Fig. 4, lower row). The ranking then deviates by no more than one or two positions in the individual countries.

For Sabine (Fig. 5), the picture is somewhat different. The three datasets reveal discrepancies in the region affected by the event, which cannot be explained by the different data coverage alone. In some cases, the datasets even fail to report the storm in countries alongside Sabine's storm track (Fig. 5, upper left panel). In Sweden, for instance, Sabine ranks 5th in PERILS and above 15 in LI3D, while it is not documented in C3S. Another example is Norway, where Sabine reaches rank 4 in PERILS and above rank 15 in C3S, but is not in the Top50 events for LI3D. Furthermore, the rank differences in the individual countries are more pronounced than they were for the first case study Kyrill. Nonetheless, even for Sabine, the differences become smaller when focussing only on common storms. Then the ranking usually varies by just one or two positions, but can reach up to four for single countries like Germany or Ireland. Results are comparable for storm Lothar (Fig. S2) or storm Andrea (Fig. S3), where the datasets also do not agree on the region affected by the storm event.

Similar results are also found for the normalized loss at country level for the two case studies (Fig. 6) and the other "PCL-storms" (Figs. S5-S7). For Kyrill, the three datasets show comparable normalized losses across countries. The only exception is Ireland, where the normalized loss in C3S is roughly half as high as in PERILS and LI3D. The mismatch between the datasets is again larger for Sabine. However, the differences in normalized losses are less pronounced than in the ordinal ranking. Overall, we see that the (dis-)agreement between the datasets is different for each storm, and no immediately identifiable systematic differences emerge.

3.4.2. Rank correlation

As final step, we analyse the differences between the datasets across countries using Spearman's rank correlation. Fig. 7 shows the correlation coefficients for each country for all three combinations of datasets: PERILS vs C3S, PERILS vs LI3D, and C3S vs LI3D. Again, we compare the ranking based on all storms, the common "PCXL-storms" and the common "PCL-storms". Fig. 7 gives a clear picture on the (dis-)agreement between the datasets. In general, the datasets show a high agreement for Scandinavia and small countries like Switzerland and Austria. On the other hand, differences are usually larger for Central Europe, including the UK, Germany and France. As before, for most countries, we see a higher correlation for common storm events than for all storm events. Interestingly, the correlations between PERILS and the individual meteorological indices are often higher than between the meteorological indices themselves, especially for Central Europe.

4. Summary and discussion

In the present study, we compared reported and estimated windstorm losses from five different damage datasets for the 23 winters 1999/2000 to 2021/2022. The datasets belong to one of the three categories: meteorological indices, natural hazard databases and insurance data. The main findings can be summarized as follows:

- In total, 94 storms were documented. Only 11 of them were reported in all five datasets, while a large majority (roughly 60%) was solely recorded in single datasets.
- The total number of storms is different in the various datasets. Highest numbers are usually reported in C3S and LI3D, while the number is lowest in PERILS and XWS. Moreover, the datasets often disagree on the average storm frequency per year as well as the actual number of damaging storms per winter season. An example is the winter 2007/2008, where 5 storms are documented for C3S but none for PERILS.
- The ranking of storms based on reported/estimated losses varies in the datasets. Only a few storms, like Kyrill, show a similar ranking in all datasets. The rank differences are reduced when computing the rankings relative to storm events that are common in the various datasets. The results hold for losses aggregated at both European and country level. In many cases, large discrepancies in ranking at country level translate into large differences at the European scale.

The different number of windstorms in the individual datasets is most likely primarily related to the different thresholds used for storm reporting. PERILS, for instance, uses a strict threshold of 200 Million EUR for the reporting of events. They adjusted this threshold to an even higher loss value of 500 Million EUR for pan-European events in September 2022. This will likely result in a smaller number of storm events in the future, making a comparison to other datasets with softer reporting criteria, like EM-DAT, even more difficult. Regarding the meteorological indices, the choice of 50 events in C3S and LI3D to capture extreme storm events is arbitrary, roughly corresponding to 2–3 events per year. These Top50 events probably include also smaller and less intense/impactful storms that are not documented in datasets with stricter reporting criteria. However, a sensitivity study using only the Top30 events in C3S and LI3D (and thereby the same number of events as in PERILS) revealed only marginal differences in terms of storm ranking (compare Fig. 2 and S8), and thus our conclusions remain unaltered.

The insurance data and the meteorological indices seem to derive more comparable results in some regions than in others. In general, the results reveal – somewhat surprisingly – a better agreement for Scandinavia and small countries like Switzerland, thus suggesting that complex topography has little impact on the performance of the meteorological indices. Hence, the (dis-)agreement might be more related to the insurance policy of the individual countries. In countries like France, Norway or Switzerland, extratropical cyclone coverage is by law included in natural hazard insurance (in PERILS under the property fire policy), while for example in Germany, this coverage is optional in most federal states but generally included. In addition, the countries distinguish between different property occupancy types – ranging from two types (personal and commercial lines, e.g. in Great Britain or Austria) to four types (residential, commercial, industrial and agricultural lines, e.g. in France or Belgium). Both factors influence the total insurance coverage for the individual nations and could therefore lead to differences in estimated losses. Moreover, political decisions/"regulations" in single countries can alter loss reports. For storm Klaus in January 2009, for instance, the Spanish government decided to pay for all damage incurred. Therefore, Klaus is not included in insured loss reports in Spain for 2009.

Our results also highlight the shortcomings of the datasets. EM-DAT, for instance, does not provide the exact source of its information. Additionally, regional differences in the reporting institutions may lead to a different quality and quantity of loss reports in the different countries (Harrington and Otto, 2020). Depending on the political situation, reports may even be biased or completely missing (Kron et al., 2012; Guha-Sapir and Checchi, 2018; Tschumi and Zscheischler, 2020), although this is likely more important in countries outside the European Union. Moreover, EM-DAT provides little information on windstorm impacts, due to the amount of missing/incomplete loss data. Insurance data, on the other hand, can be quite heterogeneous in both space and time, depending on the insurance policy and coverage in individual countries. PERILS, for example, provides only limited insights in the detailed origin and processing of its data, due to commercial reasons. Furthermore, given the different market coverage and total sums of insured property in individual countries, storm events affecting high insured exposure (e.g. Germany, France) might be overrepresented. This effect could intensify in the future, as PERILS has adjusted its reporting threshold to a higher value in September 2022. The meteorological indices in general depend on the reliability of the underlying wind data (from reanalyses, observations, climate models) and on the quality of the impact functions/fragility curves used for the loss calculations. The fragility curves used in C3S (Feuerstein et al., 2011) were originally developed for tornadoes in Central Europe. Nevertheless, Dotzek et al. (2009) could show that the underlying wind intensity distributions are similar to distributions from the USA, indicating a worldwide applicability. LI3D is based on the storm loss model by Klawa and Ulbrich (2003), which was originally developed and validated for Germany using insurance data from the "Gesamtverband der Deutschen Versicherer e.V." (German Insurance Association, GDV) and Munich Re. Karremann et al. (2014b) could show that the adopted 98th percentile is a reasonable threshold for the identification of storm events in Western and Central Europe. However, this threshold might be too low in Scandinavia, the Mediterranean and South Eastern Europe, where 9 m/s would be a more adequate threshold (Karremann et al., 2014b). XWS is based on ERA-Interim, which does not reflect well all storms of the last decades. Studies like Ulbrich et al. (2001) and Donat et al. (2011) suggest discrepancies especially for storms with small-scale meteorological features (e.g. Anatol and Martin in 1999). Based on our results, however, it is hard to say whether XWS (and therefore ERA-Interim) differs more from the other datasets for storms with small-scale features than for others. In addition, the meteorological indices might overestimate the loss values, as they only use present-day exposure levels (2018 for C3S, 2020 for LI3D) instead of taking trends in exposure over time into account (Koks and Haer, 2020). All of this hampers the comparison of the datasets – for which reason we decided not to use one of them as "ground truth". In our opinion, using a "non-representative" ground truth would lead to more misleading conclusions than treating all datasets as equal.

Overall, the datasets provide different views on windstorm impacts. PERILS and (to a certain extend) EM-DAT give a direct view on the impacts themselves. The meteorological indices, on the other hand, present a more hazard driven view, which depends on the assumed relation between certain wind speeds and damage. Still, indices like C3S and LI3D try to account for the exposure component by using building footprints or population density as proxies. In general, it is difficult to define which dataset is good or bad in providing information on windstorm losses as no single dataset can cover all aspects of windstorm impacts. To study specific (high impact) windstorm events, one should therefore consider/combine different types of datasets (e.g. meteorological indices and insurance data) in order to get a broader picture, and for example test which differences between datasets are relevant for calibrating loss models and which are not. This will presumably depend on the loss model, and thus the results would presumably be user-specific. Additional multi-dataset analyses, such as an attempt to use the different datasets to assign an uncertainty range to the windstorm losses, would require more publicly available and reliable data to be implemented in practice. Useful information to this end includes time-resolved details of insurance coverage at national or sub-national level, details of government pay-outs for wind-related damage and traceable information sources in databases such as EM-DAT. With regard to insurance data, this could be accomplished, for example, via an open access solution for scientific purposes. For international disaster databases on the other hand, a systematic, standardised and traceable procedure for data collection is needed, ideally at the local scale. Finally, methodological improvements in selecting the most suitable meteorological indices/storm models for the task at hand (Gliksman et al., 2023) would also benefit a future multi-dataset representation of storm losses.

CRediT authorship contribution statement

Julia Moemken: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Gabriele Messori:** Conceptualization, Methodology, Writing – review & editing. **Joaquim G. Pinto:** Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wace.2024.100661.

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