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Three variables are better than one: detection of European winter windstorms causing important damages

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Abstract

In this paper, we present a flexible methodology aimed at detecting European winter windstorms with high damage potential, using only meteorological variables. We start by analysing ten events known by the insurance industry to have caused extreme damages. Looking at their surface signature in three fields: the relative vorticity at 850 hPa, the sea-level pressure anomaly, and the ratio of the 10 m wind speed to its 98th percentile, we find that those ten major events share an intense signature in all three fields. They were therefore extreme extra-tropical cyclones that became major economic events by crossing high-populated areas. These ten major events are however not the most intense ones of any of the three variables considered; so while using only one variable cannot select the targeted events very well, the combination of the three variables proves to be more efficient.

We further test this method based on the combination of variables on different reanalysis datasets, and find that it can consistently isolate a small set of events containing the ten major events as well as other events with damage potential. It thus seems ready to be applied to climate model simulations, for example to extract potentially damaging events in future climate projections.

1 Introduction

Extra-Tropical Cyclones (ETCs) are an important component of the mid-latitude atmospheric circulation. The North Atlantic ETCs regularly reach Europe, where they are responsible for strong wind and rainfall episodes. During the winter season, some of them, usually referred to as European windstorms, can be particularly intense and generate important wind-related damages. Munich Reinsurance Company (Munich Re) recently released a ranking of the ten costliest European windstorms over the last thirty years (Table 1). Each of them generated more than 2 thousand million USD (United States Dollar) of economic losses. European insurers are highly exposed to these extreme events, leading them to buy significant reinsurance covers in order to mitigate their risks. Therefore, and especially in a context of climate change, there is a need to characterize ETCs leading to important damages and to measure the potential evolution of their surface signature (in terms of intensity and frequency) in the next decades.

The study of ETCs in current and future climate has been along two main lines. The most common one is to compute statistics of ETCs such as areas of genesis and lysis, cyclones density and cyclones intensity. In this first kind of analysis, all ETCs are detected and tracked thanks to automated algorithms. Ulbrich et al. (2009) provide a review of the existing approaches of cyclone definition, leading to different detection and tracking schemes; more inter-comparison and insights on their performance can be found in Neu et al. (2013). These automated algorithms are based on the two-dimensional field of the following variables: the mean sea-level pressure (MSLP), the relative vorticity at 850 hPa (RV850) or the Laplacian of the MSLP. The detection of features is done by looking for either simple maxima of RV850 or minima of MSLP, or more complex features such as opened or closed isobars. Feature tracking is then performed by linking features at successive time steps thanks to probabilistic prediction of feature movement. All the choices and assumptions made to develop a scheme offer an analysis of the ETC characteristics from different angles but also introduce uncertainties (Neu et al., 2013). Once ETCs are detected their intensity is measured by the value of the detection variable over the ETC lifetime. Extreme ETCs are defined as a particular class of cyclones, i.e. the ones with the highest intensity, but are not necessarily associated with strong winds or losses.

The second type of approach aims at evaluating the losses associated with European winter windstorms (Leckebusch et al., 2007; Pinto et al., 2007, 2012; Della-Marta et al., 2009; Schwierz et al., 2010; Donat et al., 2011). In all these studies, the 10 m wind speed is used as a basis meteorological variable, together with some model of associated losses. The studies of Leckebusch et al. (2007), Pinto et al. (2007), Donat et al. (2011) and Pinto et al. (2012) compute a loss function from the daily maximum

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10 m wind speed and the population density; in addition Pinto et al. (2012) separate the two driving loss factors of event severity, measured by a “meteorological index”, from the economic exposure. Della-Marta et al. (2009) also derive several indices, based either on the mean or on percentiles of the wind speed field, and compute return periods of extreme wind events using extreme value theory. Schwierz et al. (2010) use the ratio of the 10 m wind speed over its local 98th percentile to detect events with criteria on intensity and spatial extension. The catalogue of events obtained is then used as input for an insurance loss model.

The approach we present in this paper mixes both types of analysis: we aim to detect the events with the highest damage potential, but using only meteorological variables and no loss model to remain flexible. Our methodology is designed from the characteristics of the ten major events known for having caused important losses (Table 1), and we not only use the 10 m wind speed (variable used in the second type of analysis), but also the 850-hPa relative vorticity and the mean sea-level pressure (variables used in the first type of analysis). Indeed, the ten major events were primarily extreme extra-tropical cyclones, with an intense signature in the three variables, and became major economic events when crossing high-populated areas. Looking for similar intense meteorological signatures should thus lead to the detection of events with a potential for similarly high damage. Since the methodology is meant to be applied to the output of varied models, another key aspect is the adaptability of the detection and tracking criteria.

The paper is structured as follows: in Sect. 2, an overview of the data and the variables is given. In Sect. 3, we present the methodology and the choice of detection parameters. Finally, in Sect. 4, we compare the results in different reanalysis datasets. Conclusions are drawn in Sect. 5. All acronyms used in the text are listed in Table A1 in the Appendix.

2 Data and variables

2.1 Data

Three datasets are used in this paper. The detection methodology (Sect. 3) is developed with the ERA Interim (ERAI) reanalysis dataset (Dee et al., 2011). ERAI is a 6 hourly dataset at a $0.75^{\circ} \times 0.75^{\circ}$ spatial resolution covering the period from 1979 to 2011, provided by the European Centre for Medium-Range Weather Forecasts. In Sect. 4, two other datasets are used along with ERAI to complete the analysis and validate the methodology. First, we use the NCEP-DOE (NCEP2) reanalysis from NCEP/NCAR, a 6 hourly data from 1979 to 2011 with a $2.5 \times 2.5^{\circ}$ spatial resolution (Kanamitsu et al., 2002). Second, we compute a spatial average of ERA Interim on the NCEP2 2.5° resolution (ERAI-2.5).

The geographical window used for the detection of events is restricted to Western Europe. The Mediterranean region is excluded because of the high regional cyclonic activity occurring there (Lionello et al., 2002; Campins et al., 2010; Nissen et al., 2010) independently, which is out of the scope of our study.

We finally use the ten most damaging events since 1987 ranked by Munich Re (Table 1). These events, called reference storms hereafter, are used as case studies in order to develop the methodology (Sect. 3). They cover a time period from 1987 to 2010, and are concentrated in the winter season from October to March. As a result, we choose to work with the 6 month winters (October–March) from 1987 to 2010 and not the whole period covered by ERA Interim or NCEP2.

2.2 Variables

We consider three (near-) surface variables: the relative vorticity at 850 hPa, the mean sea-level pressure and the 10 m wind speed. These variables are commonly used either to detect and track ETCs (Ulbrich et al., 2009; Neu et al., 2013) or to assess potential impacts of ETCs (Leckebusch et al., 2008; Pinto et al., 2012). We briefly illustrate

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in Fig. 1 the spatial patterns of these three variables in the case of the major storm Lothar (December 1999).

The relative vorticity at 850 hPa (RV850) is either directly provided or computed as the curl of the velocity field at 850 hPa. The vorticity field is very sensitive to the spatial resolution; it becomes noisy at finer resolutions, leading to the detection of numerous and intense local-scale features (Hoskins and Hodges, 2002; Ulbrich et al., 2009). Studies looking at cyclones over extended areas therefore apply a spatial smoothing of RV850, which also accounts for the poleward decrease of the grid size (Murray and Simmonds, 1991; Hodges, 1996; Sinclair et al., 1997; Hoskins and Hodges, 2002). In our study, since we consider a small geographical window over Europe, the grid size is roughly uniform and we do not use any spatial smoothing. Features detected with the relative vorticity are also not necessarily associated with an ETC in the classical meaning of a pressure minimum. Hence, most of the detection schemes look for a minimum of mean sea-level pressure in the vicinity of the maximum of relative vorticity to define the centre of an ETC (e.g. Murray and Simmonds, 1991; Blender et al., 1997; Gulev et al., 2001; Pinto et al., 2005). We instead start by detecting intense events independently with the relative vorticity at 850 hPa, the mean sea-level pressure and the 10 m wind speed.

We next use the anomaly of the mean sea-level pressure defined, at each time step, as the difference between the MSLP and its running average over eight days ($\overline{\mathrm{MSLP}^{8\,\mathrm{days}}}$):

$$\mathrm{MSLP}_{\mathrm{anom}}(i,j,t) = -\left[\mathrm{MSLP}(i,j,t) - \overline{\mathrm{MSLP}^{8\,\mathrm{days}}}(i,j,t)\right] \tag{1}$$

$$\overline{\mathrm{MSLP}^{8\,\mathrm{days}}}(i,j,t) = \frac{1}{32} \cdot \sum_{t-16}^{t+16} \mathrm{MSLP}(i,j,t) \tag{2}$$

where (i,j) are the grid points coordinates and t the 4-time daily time steps.

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The mean sea-level pressure is a large-scale field, so it is better resolved than the vorticity. It is also strongly constrained in reanalysis datasets thanks to the great number and quality of observation data, especially over continents. When developing a detection scheme with this variable, it is important to account for two characteristics of the MSLP field. First, over high orography, MSLP values are extrapolated and may not be meaningful. Most of the approaches based on the MSLP field therefore ignore lows detected in areas higher than a predefined threshold, usually 1000 m or 1500 m (Murray and Simmonds, 1991; Pinto et al., 2005; Hanley and Caballero, 2012). Second, the ETCs evolve on a more slowly varying background flow that also has large MSLP gradients. A spatial or temporal filter is often used to bring out the small-scale features and remove the biases due to variations of the background MSLP (Hoskins and Hodges, 2002). A simple temporal filter is used in our study. We first tried removing the climatology of MSLP but it was not enough to bring out some of the targeted events. We thus chose to work with the running average of MSLP over eight days, which represents the signature of the weather regime surrounding the occurrence of ETCs (Feldstein, 2000) and has also been used by Rivière and Joly (2006). $\overline{\text{MSLP}^{\text{8days}}}$ is computed at a given time step t as the average of the MSLP over sixteen time steps preceding time step t and sixteen time steps following it (i.e. over 32 time steps or 8 days), see Eq. (2).

The third variable we use is the ratio of the 10 m wind speed to its 98th percentile (WND10_{98}), computed for continental grid points only:

$$\text{WND10}_{\text{ratio}}(i,j,t) = \frac{\text{WND10}(i,j,t)}{\text{WND10}_{98}(i,j)} \tag{3}$$

The 10 m wind speed is strongly dependent on the modelling of boundary layer processes, even in the reanalyses, as well as on the time and space resolution of the outputs. Using the ratio over the 98th percentile alleviates some of these biases. This specific ratio is also often used in ETC impact studies, not to detect features but rather as a measure of potential damages, the 98th percentile being the threshold above which a building is at risk of being partially or totally destroyed. In addition to the 10 m wind speed ratio, indices of ETC impacts usually integrate the population density, duration and spatial extension of the event (Klawa and Ulbrich, 2003; Leckebusch et al., 2007; Pinto et al., 2007; Donat et al., 2011). In this paper, the 10 m wind speed ratio is used as a detection variable, similar to the Schwierz et al. (2010) one or to the "Meteorological Index" from Pinto et al. (2012).

Each of the three variables described captures specific spatio-temporal scales and thus accounts for different aspects of extra-tropical cyclones. The relative vorticity at 850 hPa captures local and fast meso-scale structures whereas the MSLP anomaly captures larger and slower systems. The ratio of the 10 m wind speed measures, at a local scale, a wind intensity that is strongly correlated with the damage potential.

3 Case study and methodology

This section presents a method for detecting and tracking events with a high damage potential in Europe. The method itself and the choice of parameters are based on the case study of the ten reference storms (Sect. 3.1), using the ERA Interim dataset. The case study aims at answering the following questions: do major events with important economic losses share some meteorological characteristics? How extreme is their signature? Is there a variable that isolates them better than another one? The answers to these questions lead us to the definition of the appropriate criteria for the detection of potentially damageable events within a given meteorological dataset (Sect. 3.2).

3.1 Case study

A preliminary examination of maps of the three variables at the time of occurrence of the ten reference storms reveals that all ten events display a strong signature in each of the three considered variables, which singles them out from their surrounding environment when they pass across the Western Europe geographical window (the example of Lothar is shown in Fig. 1). Usually, detection methods select all the local maxima above a specified threshold because several cyclones can exist at a given time step within a wide region (Hoskins and Hodges, 2002). Here, since the considered area is small and since there are no other significant local maxima during the time each reference storm crossed this area (see Fig. 1), we choose to only retain the global maximum of each variable at each 6 h time step.

The intensity of the ten reference storms is compared to the distribution of the global maxima in Fig. 2. In the first row, time series of the maxima of the three variables are shown together with their respective 95th percentile (red dashed line) and 98th percentile (blue line). The maximum values reached at the time of occurrence of the ten reference storms, coloured in green, are mainly located in the upper part of the plot. This demonstrates that in ERAI the ten reference storms (major events in terms of economic losses) all have a particularly intense surface signature at the same time in each of the three variables. This signature is now used to define detection thresholds: the second row of Fig. 2 shows again the maximum values of each variable, but only during the occurrence of the ten reference storms. Most are above the 95th percentile of their respective distributions. Furthermore, there is for each case and each variable at least one value above the 98th percentile. These two percentiles are therefore chosen for the methodology, as detection and selection thresholds respectively. Different combinations of detection and selection thresholds have been tested and sensitivity tests have been performed on the intensity of these thresholds. Raising the detection threshold proves to be inefficient since some reference storms would not be detected afterwards. The combination of 95th and 98th percentiles is retained because it ensures the detection of the ten reference storms while minimizing the total number of selected events.

3.2 Methodology

We gather the previous findings to design a specific method for the detection of events with potentially high economic impacts. The method is illustrated in Fig. 3 and described hereafter. First, the time series of the maxima at each time step is computed for each variable, and the 95th percentile of the time series' distribution is used as a detection threshold. Second, a simple tracking is performed, that gathers into one "event" consecutive detected maxima above the 95th percentile if there is an eastward shift and if the distance between the two consecutive maxima is lower than 900 km. Third, we restrict our events set to events having at least one value above the 98th percentile and lasting at least two time steps. Fourth, we compare the events selected by using the three different variables, and retain the ones that are present for all three (i.e. selected events that share at least at one time step above the 95th percentile for the three variables).

The rationale for the last step is that applying the selection process to ERAI produces 149 events with the relative vorticity, 117 events with the pressure anomaly and 91 events with the 10 m wind speed. The ten reference storms are included in each set of events, but the number of events obtained exceeds the initial objective. Additionally, the intensity ranking of events within the three sets (Table 2) indicates that the reference storms are not top-ranked for any of the three variables. This leads to the conclusion that the reference storms cannot be isolated through the use of a single variable and high detection thresholds. However, even though the ten reference storms are not the top-ranked events of any variable, they are selected with each of them. This may not be the case for the other events of the catalogues.

The complementarity of the three variables is further analysed in the first panel of Fig. 4 that shows the number of events common to sets built with different variables. Two events selected either using two different variables or in two different datasets are considered as common if they share at least one 6 h time step. In ERAI, the number of events common between pair-wise variables is less than half the number of events detected with each variable separately; and taking events common to the three variables further reduces that number to 24 (see Fig. 4, first panel): the ten reference storms, a few other smaller but known events (such as Wiebke, Lili, Oratio...) and unnamed events that did cause important electricity shortcuts or broke wind speed records. This result demonstrates that the events that caused great damages over the last thirty years belong to a particular group of meteorological systems that exhibit an intense surface signature in every field considered. Taking the intersection of event sets for three separate variables therefore gives more satisfying results than the use of a single one, in terms of global event intensity or potential for major impacts. Indeed, the number of 24 events finally selected over the last thirty years is consistent with records from insurance companies of major damages over the area considered. Trying to isolate the same number of events using one variable only would leave aside several of the 10 that actually led to major losses. The complementarity of the three variables is therefore a powerful tool to further restrict our events selection and to constitute the last step of the procedure.

The four-step methodology has been developed using the ERA Interim dataset. We have shown that it can isolate a group of events that can be defined as extremes in terms of meteorological signature and could lead to important damages if crossing areas with high exposure. However, the method is meant for easily analysing the outputs of various models over large periods of time so its robustness and flexibility need to be further tested.

4 Testing the robustness of the methodology

One initial objective was to apply the method to the outputs of general circulation models such as the ones participating to the Coupled Model Intercomparison Project (CMIP5). Most of these models have a coarser spatial resolution than ERAI (around 2.5°), especially when run over longer periods. In order to validate its robustness against spatial resolution, the methodology is thus applied to the coarser reanalysis datasets NCEP2 and ERAI downgraded to the 2.5° spatial resolution. This will partially separate the resolution effect (ERAI vs. ERAI-2.5) from the model effect (ERAI-2.5 vs. NCEP2), with the caveat that downgrading the output of a 0.75° run to 2.5° is different from using a 2.5° output run at 2.5°.

The results presented hereafter are obtained with the methodology presented in Sect. 3. We first present the distributions of the maxima of the three variables in order to analyse the differences and similarities between the reanalysis datasets that impact the detection of events (Sect. 4.1). We then focus on the events selected with each variable and compare the results between the reanalysis datasets (Sect. 4.2). Finally, we compare the final sets of events and conclude on the relevance of the multi-variables approach (Sect. 4.3).

4.1 Maxima distribution functions

The Probability Distribution Functions (PDFs) obtained from the maxima time-series defined in Sect. 3.1 are plotted in Fig. 5 for ERAI, ERAI-2.5 and NCEP2. While the distributions of MSLP anomaly and 10 m wind speed ratio are nearly identical from one dataset to the other, the relative vorticity distributions differ: a first shift towards lower values is observed when downgrading the resolution (from ERAI to ERAI-2.5), a second one when changing the model (from ERAI-2.5 to NCEP2). RV850 indeed greatly depends on the spatial resolution (Ulbrich et al., 2009; Hodges et al., 2011); when dealing with outputs at different spatial resolutions, it is thus important to keep in mind that its values (and particularly extreme values) might not be reproduced similarly from one dataset to the other. This stresses out the necessity of using intensity thresholds based on percentiles rather than absolute values, in order to ensure the adaptability of the detection to different kinds of datasets.

The second step of the procedure is the detection of the maxima above the 95th percentile of each PDF. Selected events are formed from these maxima; so a condition to have a common event in two datasets is that a maximum above the 95th percentile is detected at the same time step in both. Therefore, in order to measure the likelihood to get the same events from one dataset to the other, we compare the number of maxima above the 95th percentile in common between ERAI and ERAI-2.5, and ERAI-2.5 and NCEP2 (Fig. 6). A good agreement is achieved with the MSLP anomaly between ERAI and ERAI-2.5 (85 % of common maxima above the 95th percentile), as well as between

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ERAI-2.5 and NCEP2 (83 % of common maxima above the 95th percentile). It is thus very likely that the events detected in ERAI, ERAI-2.5 and NCEP2 with the MSLP anomaly will be the same. Results on the two other variables depend on the reanalysis datasets. For ERAI and ERAI-2.5, the high number of common maxima above the 95th percentile with the relative vorticity (62 %) and the 10 m wind speed (71 %) suggests that the events detected in both datasets will be the same. For ERAI-2.5 and NCEP2, the number of common maxima above the 95th percentile happening at the same time is smaller: around 42 % with both relative vorticity and 10 m wind speed ratio. It is therefore unlikely that the events detected with any of these two variables will be the same between ERAI-2.5 and NCEP2.

To conclude, the three reanalysis datasets display differences in some variables that could impact the detection of events. Differences in intensity (strongest with the relative vorticity at 850 hPa) do not impact the detection if they are a uniform change, as they would be offset by the definition of thresholds as percentiles of the PDFs derived from each dataset. However, differences in the ordering of the distribution, and in particular of its tail, greatly impact the events detection: events are formed from the maxima above the 95th percentile, so if they do not occur at the same times in two datasets, different events will detected. The variable least sensitive to the choice of dataset is the anomaly of mean sea-level pressure that has a comparable intensity in the three datasets and a high percentage of common maxima. As mentioned in Sect. 2, the mean sea-level pressure is a large-scale field (compared to the relative vorticity and the 10 m wind speed) with a large amount of assimilated observation data, which may explain the small differences between the three reanalysis datasets.

4.2 Generating the three events sets

Once the maxima above the 95th percentile are detected, events are formed for each variable and compared between the reanalysis datasets. Figure 7a shows the number of events for each reanalysis dataset and the number of common events between ERAI and ERAI-2.5, and between ERAI-2.5 and NCEP2. Many events are selected for each variable within the three datasets. This confirms one of the findings of the analysis with ERAI in Sect. 3: one variable is not enough to isolate satisfyingly the reference storms. As we did in Sect. 3 with ERAI only, we consider the ranking of the ten reference storms within the three variables and the three reanalysis datasets (Fig. 7b). We see that the ten reference storms are not the ten most extreme events in any pair of reanalysis datasets and variables, which generalizes the result obtained with ERAI only. Additionally, the ranks of the ten reference storms vary with the dataset. For example, in order to select the ten reference storms with the anomaly of mean sea-level pressure, we must take the 55 first events with ERAI, the 110 first ones with ERAI-2.5 and the 100 first ones with NCEP2. The rank is therefore not a robust criterion to select effectively the reference storms and other similar events in outputs from various models.

Moreover, the number of common events between pair-wise reanalysis datasets confirms the previous analysis on the number of common maxima above the 95th percentile (Fig. 7a). The mean sea-level pressure displays the highest percentage of common events between ERAI and ERAI-2.5 (93 %) as well as between ERAI-2.5 and NCEP2 (92 %). For the relative vorticity and the 10 m wind speed, many common events are found between ERAI and ERAI-2.5 (around 60 % of common events for both variables) but only a small percentage of common events is found between ERAI-2.5 and NCEP2 (around 35 % for both variables).

4.3 Generating the final events set

Fig. 4 presents for each reanalysis datasets the number of events detected with each of the variables, the number of common events to pair-wise variables and the number of events in the final set (i.e. events common to the three variables).

The number of events common to the three variables is always reduced compared to the number for individual variables: 24 events with ERAI, 21 with ERAI-2.5 and 33 with NCEP2. While the ten reference storms do belong to the final set for ERAI and ERAI-2.5, Lothar (December 1999) is missing from the NCEP2 final events set. In NCEP2 Lothar is only detected with the 10 m wind speed ratio, while maximum values of the relative vorticity and the anomaly of MSLP are lower than the 95th percentile. ERAI and ERAI-2.5 share 15 common final events, while ERAI-2.5 and NCEP2 have 16 (not shown in the figure). For each reanalysis dataset, the final set of events can thus be divided in two groups: one group with events common to the three reanalysis datasets (including the reference storms) and another one with events specific to the reanalysis dataset.

For each dataset, we are therefore able to isolate a small group of events sharing a similar meteorological surface-signature with the ten reference storms, with no need to modify the parameters of the method. The use of percentile-based thresholds leads to the detection of a similar number of extreme events with different resolutions; these events are however generally not the same or ranked differently, with the exception of the ones obtained from the MSLP anomaly. The multi-variables approach enables in each case to further restrict the number of selected events (roughly by a factor of 4), while retaining all the major ones.

5 Conclusions

The methodology presented in this paper enables a reliable detection of events with high damage potential, easily adaptable to different datasets or model outputs. Its robustness comes from two main factors. The use of thresholds based on percentiles of the distribution of the variables as only parameters ensures the adaptability to different datasets, especially with varying resolutions. More originally, we showed that an approach based on several variables of different scales was more efficient than trying to select extreme events in a single variable. Indeed, when only one variable is considered, a number of minor events need to be retained in order to get all the known major ones (e.g. the ten storms since 1987), thereby weakening the selectivity. Moreover, these weaker events largely differ according to the variable considered or the reanalysis dataset used. However, if the major damaging events are not the absolute most intense for any given meteorological variable, they remain strong for every one. Taking

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events that have a strong signature in several variables at once therefore proved to be a simple but efficient filter.

The method's novelty lies in its ability to target extreme events having a great impact on insurance policies while using exclusively meteorological variables. Previous research on ETCs usually consists either in analysis of their physical properties or in loss models applied to the European insurance market, each of these analyses addressing specific questions. Our method instead uses a simple combination of relevant physical parameters to detect potential high-loss events. This will be of particular interest for the construction of event catalogues in current and future climates, contributing to improve the monitoring of European winter windstorms, by the insurance companies for example.

The next step of the project will be to apply the methodology to the outputs of the CMIP5 model ensemble in order to create catalogues of extra tropical storms in the North Atlantic–Western Europe region and to compare the events detected in historical and scenario runs.

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Table 1. List of the European winter windstorm that caused more than 1 thousand million US Dollar over the last 30 yr. In bold are the ten reference storms used in our study (Source: Compiled by Earth Policy Institute from Munich Re, "Natural Disasters: Billion-$ Insurance Losses", in Louis Perroy, "Impacts of Climate Change on Financial Institutions' Medium to Long Term Assets and Liabilities", presented to the Staple Inn Actuarial Society, 14 June 2005; Munich Re, Topics Geo: Natural Catastrophes 2004, 2005, 2006, 2007, 2008, and 2009, Munich: 2005, 2006, 2007, 2008, 2009, and 2010).

Year	Winter storm name	Insured Losses	Economic Losses
		US$ m, original values	
Oct 1987	**87J**	**3100**	**3700**
Jan 1990	**Daria**	**5100**	**6800**
Feb 1990	Herta	1300	1950
Feb 1990	**Vivian**	**2100**	**3200**
Feb 1990	Wiebke	1300	2250
Dec 1999	**Anatol**	**2350**	**2900**
Dec 1999	**Lothar**	**5900**	**11 500**
Dec 1999	**Martin**	**2500**	**4100**
Oct 2002	Jeanett	1500	2300
Jan 2005	**Erwin**	**2500**	**5800**
Jan 2007	**Kyrill**	**5800**	**10 000**
Feb 2008	Emma	1500	2000
Jan 2009	**Klaus**	**3000**	**5100**
Feb 2010	**Xynthia**	**3100**	**6100**

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Table 2. The ten reference storm events are ranked: in the second row according the insured losses (Munich Re), from the third to the fifth column according to the maximum value they reach as ERA Interim events of relative vorticity at 850 hPa (RV850), anomaly of the mean sea-level pressure (MSLP ANOM) and 10 m wind speed ratio (WND10 RATIO). For example, with the relative vorticity at 850 hPa (RV850), we detect 149 events that we ranked according the maximum of RV850 reached during their period they are detected over the window. Here we present the rank for the ten reference storms only.

Event	Munich Re	RV850	MSLP ANOM	WND10 RATIO
Lothar	1	32	57	2
Kyrill	2	43	15	30
Daria	3	19	12	25
87J	4	2	9	11
Xynthia	5	22	49	28
Klaus	6	51	59	1
Martin	7	6	6	3
Erwin	7	39	38	8
Anatol	8	1	7	19
Vivian	9	62	2	39

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Table A1. Table of variables and acronyms.

Variables:
MSLP: Mean Sea Level Pressure
$MSLP^{8\ days}$: Running Average over eight days of the mean sea level pressure $MSLP_{anom}$: Mean sea level pressure anomaly RV850: Relative Vorticity at 850 hPa (hectoPascal) WND10: 10 m wind speed $WND10_{98}$: 98th percentile of the 10 m wind speed, computed for each grid point over the whole given period $WND10_{ratio}$: Ratio of the 10 m wind speed over its 98th percentile
Datasets:
ERAI: ERA Interim ERAI-2.5: ERA Interim downgraded at 2.5° NCEP2: NCEP-DOE Reanalysis 2
Other:
CMIP5: Coupled Model Intercomparison Project Phase 5 ECMWF: European Centre for Medium-Range Weather Forecasts ETC: Extra-Tropical Cyclone NCEP/NCAR: National Centre for Environmental Prediction/National Centre for Atmospheric Research PDF: Probability Distribution Function

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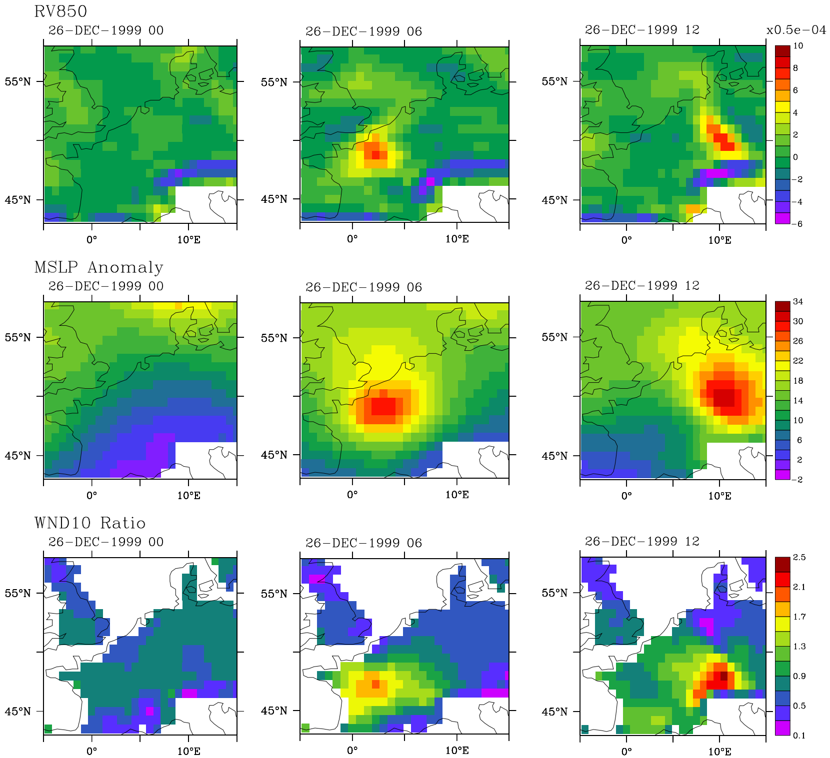

Fig. 1. Maps for the three variables' fields at the time of Lothar (from 26 December 1999, 00:00 UTC to 26 December 1999, 12:00 UTC) in ERA Interim: first row, relative vorticity at 850 hPa ($1\,s^{-1}$); second row the mean sea-level pressure anomaly (hPa); last row, the 10 m wind speed ratio (only grid points over land are considered). We masked the Mediterranean area of the domain.

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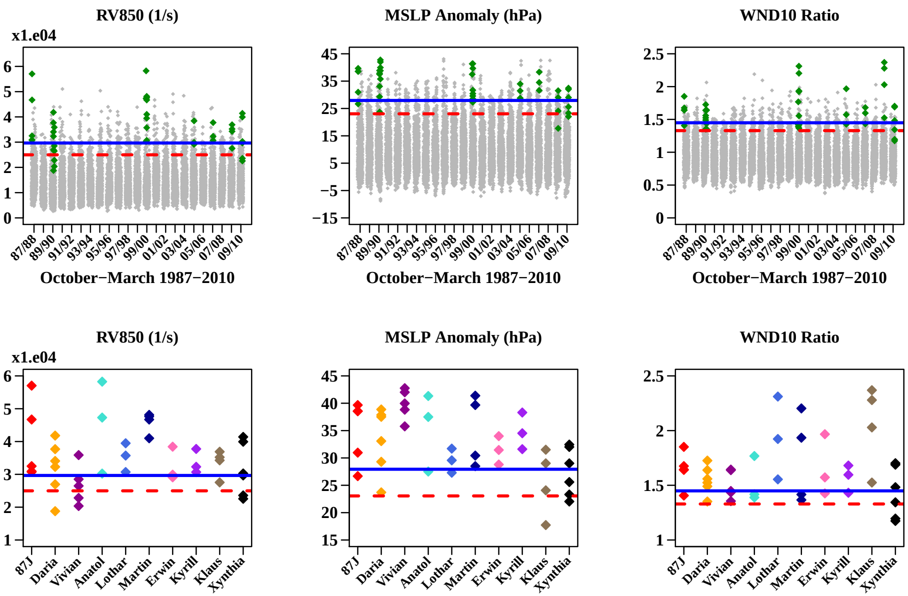

Fig. 2. The first row shows the time series of the detected maxima of each variable over the time period (six-hourly time steps over October–March from 1987 to 2010, i.e. 16 768 maxima) and geographical window. The horizontal lines are the 95th (dashed red line) and 98th (blue line) quantiles of the distribution of the maxima of each variable. The second row represents the values of the maxima of each variable at the time of occurrence of the ten reference storms. Each point for a given storm corresponds to a different 6 hourly time step during its passage.

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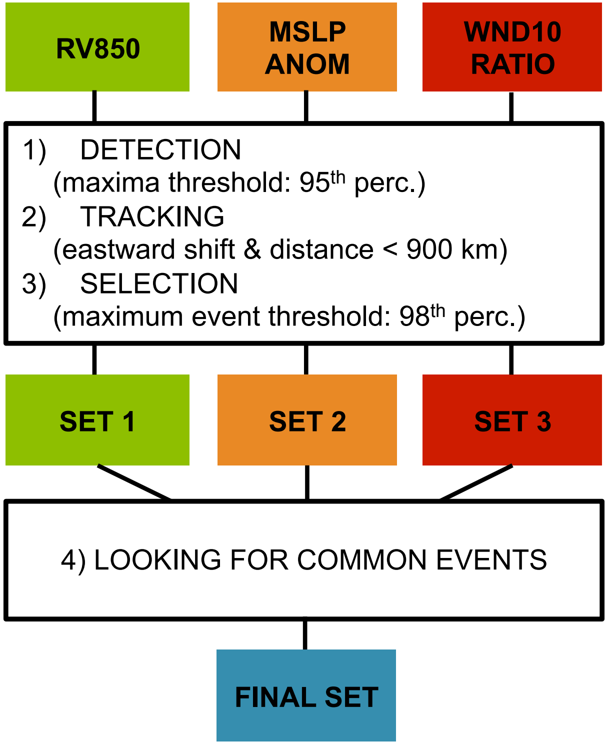

Fig. 3. Illustration of the procedure. Relative vorticity at 850 hPa (RV850), the mean sea-level pressure anomaly (MSLP ANOM) and the 10 m wind speed ratio (WND10 RATIO) are used separately to detect, track and select events. The final step consists in comparing the three sets and looking for common events. An event is defined as common to the three sets if it is detected simultaneously in the three sets during at least one time step. The final set contains events that we define as events with high damage potential.

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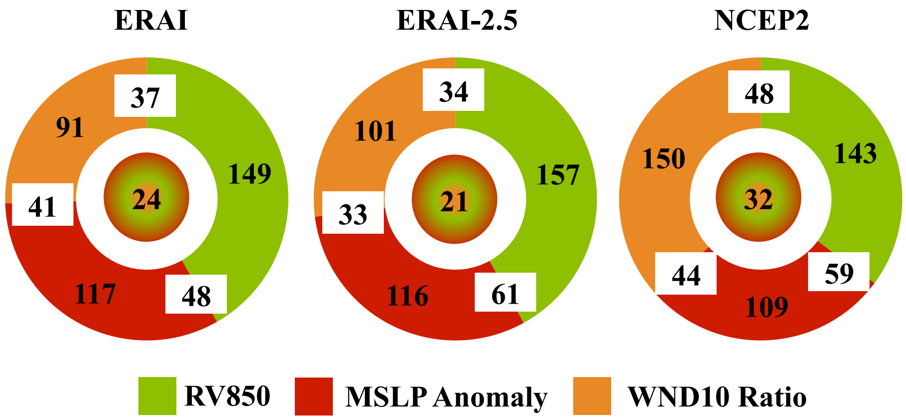

Fig. 4. Per reanalysis dataset: number of events detected with each variable, number of common events to two-by-two variables and number of common events to the three variables. For example, with ERAI, 149 events are detected with the relative vorticity at 850 hPa (RV850), 117 with the mean sea-level pressure anomaly (MSLP ANOM) and 91 with the 10 m wind speed ratio. 48 events are common to RV850 and MSLP ANOM, 41 to MSLP ANOM and WND10 RATIO, 37 to WND10 RATIO and RV850. Finally, 24 events are common to the three variables (i.e. they are detected simultaneously with the three variable during at least one time step).

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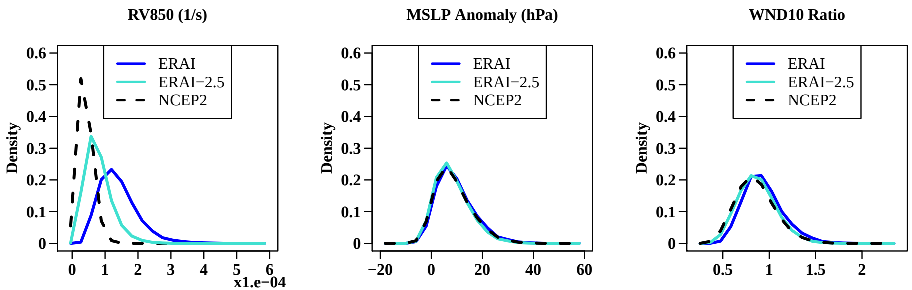

Fig. 5. Probability Distributions of the maxima of relative vorticity at 850 hPa (RV850), mean sea-level pressure anomaly (MSLP ANOM) and 10 m wind speed ratio (WND10 RATIO). ERA Interim distribution curves are represented by a dark blue line, ERAI-2.5 distribution curves by a light blue line and the black-dashed lines represent NCEP2 distributions.

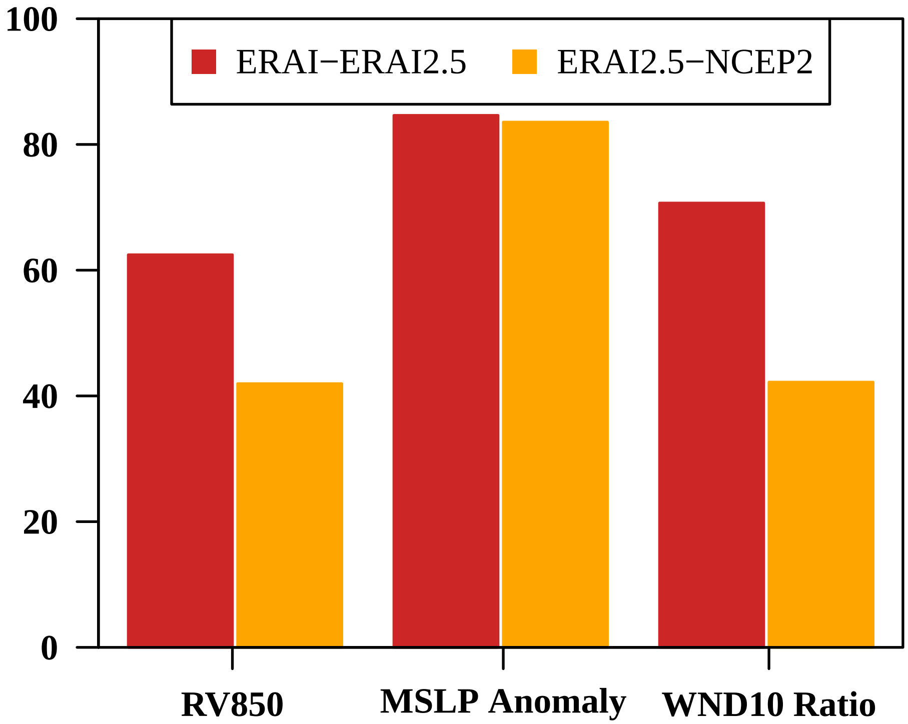

Fig. 6. Comparison of the percentage of common maxima above the 95th percentile between ERAI and ERAI-2.5 (red), between ERAI-2.5 and NCEP2 (orange).

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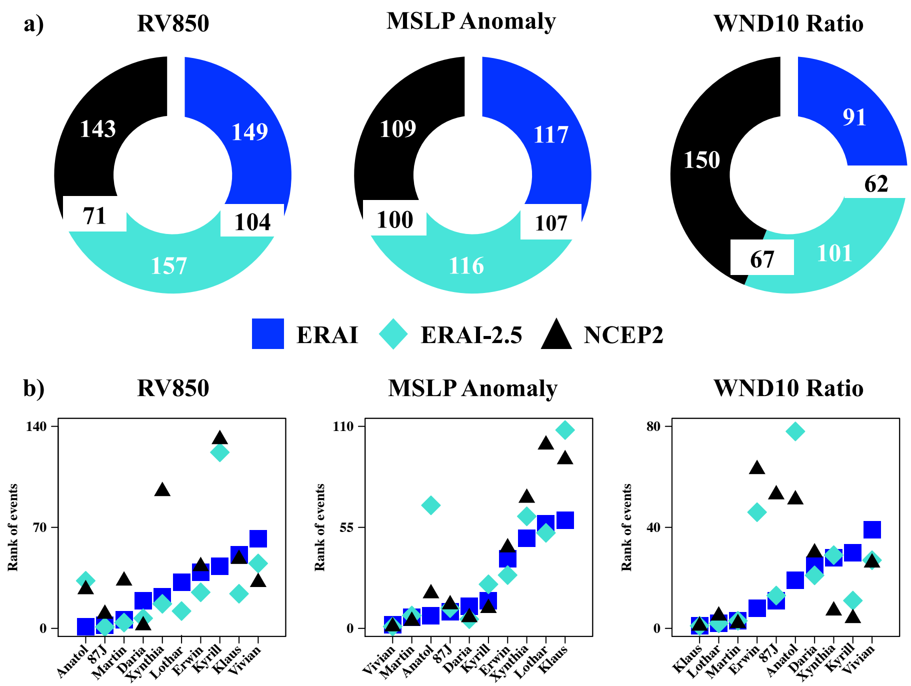

Fig. 7. (a): per variable, number of events detected within each reanalysis dataset and number of common events between ERAI (dark blue squares) and ERAI2.5 (light blue diamonds), between ERAI-2.5 and NCEP2 (black triangles). For example, with the relative vorticity (RV850), 149 events are detected within ERAI, 157 within ERAI-2.5 and 143 within NCEP2. 104 events are common to ERAI and ERAI-2.5 (i.e. 104 events have been detected simultaneously in ERAI and ERAI-2.5 during at least one time step) and 69 are common to ERAI-2.5 and NCEP2. **(b)**: per variable, ranking of the ten reference storms using respectively the relative vorticity at 850 hPa (RV850), the MSLP anomaly (MSLP ANOM) and the 10 m wind speed ratio (WND10 RATIO). Reference storms are ranked according to their rank in ERA Interim.

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