Climate-KIC / Lighthill Risk Network Project Report

This report summarises the work done between January and April as part of the Lighthill Risk Network / Climate-KIC funded research project on high resolution climate modelling of European Windstorms.

1) Project Plan

This project, which was funded by Climate-KIC with co-funding from the Lighthill Risk Network. The key research aims as dictated in the project specification document are shown in section 2) below. Red areas are where work hasn’t been completed pending commercial restrictions and interactions with re/insurers who license commercial cat model datasets.

1) Acquiring and reformatting GCM data, converting to peak gusts and creating an insurance exposure data layer to convert this data to losses and loss-checking. Output is insured loss by storm and a methodology document.

a) Downloading a large amount of model data and convert this to a NetCDF format
b) Converting the wind output into an appropriate gust by either using modelled roughness length or derived values
c) Building an insurance exposure database that exists on the model data grid using available online risk data
d) Perform some iterations on the output loss data to ensure dataset is sensible. Also check wind frequency for no peculiar biases.

2) Creation of a dataset of extreme windstorm footprints. Analysis of these footprints, how they effect risk and research into interdecadal variability. Committing to further requests from funding partners.

a) Create a dataset (lat, long, windspeed, loss return period, loss, SSI) of all storm footprints
b) Perform analysis into size and shape (latitudinal, longitudinal extent) of footprints and how they vary with return period
c) Perform some analysis on the loss data to create EP curves, EP curves by decade, by region and by territory to understand decadal variability
d) Loss exceedance probability curves for each of the 100 ensembles to create some "alternative histories" of the dataset to understand counterfactual analysis and variability around alternative histories
e) Obtain - if possible - a lower-resolution dataset to be able to compare the statistics from item b) and understand the impact of resolution

3) Creation of project analysis document and final presentation for key stakeholders

The two sub-points in red are those areas outstanding. We would like to work with a reinsurer to perform item 2e): we have approached two, currently without success.

In addition to the project work, we have also taken the opportunity above and beyond this to look into the role of NAO, how this impacts losses and frequency of events and event clustering across the dataset and over time, as well as identifying some potential tail events that may not be evident in the historical record, but may be worth considering in risk analysis (essentially “grey swan” events).
2) Project Dataset

The data behind the project comes from the **d4PDF** dataset. To quote from their website: “The d4PDF consists of outputs from global warming simulations by a global atmospheric model….with horizontal grid spacing of 60 km. The climate of the latter half of the 20th century is simulated for 6000 years”.

The data is most useful for risk studies because of the number of years modelled, meaning we can start to look at changes in tail risk, potentially. Again to quote from their website: “From large ensemble simulations, probabilistic future changes in extreme events are available directly without using any statistical models. In addition, the results enable the assessment of probabilistic change in localized severe events that have large uncertainty from internal variability.”

The 6100 years of simulation in the model are from 1951-2011, simulated 100 times over. The dataset includes a warming trend in keeping with history: “The sea-surface temperature (SST), sea-ice concentration (SIC), and sea-ice thickness (SIT) are prescribed as the lower boundary conditions, and global-mean concentrations of greenhouse gases and three-dimensional distributions of ozone and aerosols as the external forcing. Each set of experiments has 90-100 ensemble members, for which the initial conditions and the lower boundary conditions are perturbed.” The SST averaged from 60S to 60N is shown in the chart below.

![SST chart](image)

Given the size of the dataset (2PB for all data) we have, for practicality, taken a subset of this data across Europe, downloading only the maximum daily 10-metre windspeed: more about this variable later.

3) Project Design: From Windspeed to Loss

In order to make the data into an analysable format, a number of steps have been taken given the data format and type and also given some issues with the model itself.

i) **Conversion of data to an analysable format**

Unfortunately, the data was split about the meridian, and also the data came in monthly chunks for each ensemble. Therefore, for each month/ensemble member chunk (there were 73200) we had to download separate files east and west of the Meridian and join these together. The data was then converted into netcdf files for each ensemble, with daily maximum windspeed from Jan 1st 1951 to Dec 31st 2011. Each ensemble file is about 350mb.
ii) **Conversion of wind data owing to roughness issues**

Upon checking the model winds, it was evident that some parts of Europe had significantly lower winds than others, such that no loss was produced and, upon closer inspection, much of Europe had a roughness length of around 0.066m (including the major cities) – not far off that expected for basic open terrain. This meant that overly strong winds were felt in populated areas where winds are expected to be attenuated by surface roughness.

In order to create a new wind dataset, we had to apply some boundary layer theory to adjust the windspeed to more realistic numbers commensurate with the actual underlying roughness lengths. We were very grateful to the DMI for allowing us to use their Global Wind Atlas dataset that included roughness length estimates.

We simply calculated the mean roughness length within the model grid cell and converted the wind from the model's roughness to a new roughness using boundary layer theory based around this equation:

\[
S = \frac{U_p}{U_m} = \frac{\ln z_b/z_0}{\ln z_m/z_0} = \frac{\ln z_b/z_{ref}}{\ln z_m/z_{ref}}.
\]

Where \(z_m\), \(z_{ref}\) are 10m, \(x_b\) is 60m typically and \(z_{ref}\) is 0.03. The ratio of the correction factor calculated for the model and the observed roughness gives us a factor by which we can change the windspeed.

iii) **Calculation of an industry exposure database**

In order that we can produce meaningful results, we wanted to create a simple representation of the industry loss through exposure and a simple one-size-fits-all vulnerability curve. We are very grateful to PERILS for providing us with their total industry exposure per country. We simply used population density data to calculate the population percentage in each grid-box in each country and then multiplied this by the total industry exposure in that country to get exposure by grid cell.

iv) **Calculation of a vulnerability curve**

The over-arching aim here was to build a vulnerability curve that produced sensible loss outputs from the model: we were not building a cat model here, just wanting to obtain sensible results from which we could then do some analysis.

When building the vulnerability curve, it was important to consider the actual hazard going into the curve. Our model output is simply the daily maximum 10m windspeed: it was not a peak gust, however and is likely (we cannot find detailed in the documentation) the maximum modelled windspeed output at the model’s timestep.
We considered converting the modelled windspeed into a gust, but this we felt was adding an extra level of complexity to the process, so we stick with a base wind speed that is the modelled output wind. It’s not a gust, but equally not a sustained windspeed value, and thus makes it difficult to contrast this dataset with others given we’re not using a peak gust, which we appreciate is a drawback for direct comparison maybe with catastrophe models.

There was a simple validation performed to ensure we had sensible loss numbers. The European Windstorm model comparison gave us targets for the vulnerability curve, and we simply ensured that our 30-, 200-year AEP and AAL losses were within the bounds of the vendor models for European Windstorm Loss.

For reference, the vulnerability curve that is pictured below is the one used in the model. US Hurricane categories are referenced in the background just to give it some grounding (although the model’s wind isn’t strictly a sustained wind).

4) Project Results

Before we present any results, it is worth comparing the country-by-country breakdown of results versus key vendor catastrophe models as this is a key result.
The countries have been grouped into regions for simplification, but comparing our DIAS output with mean of the vendor models, the limitations of taking data “out of the box” are very simply exposed. France is low, Germany is low, UK and Ireland are probably too high – and Austria/Switzerland and Scandinavia could well suffer from issues in the model due to roughness length which seems to decrease the wind speeds to values too low to produce losses. However this shouldn’t prevent us from being able to use the model for some of the project goals.

i) Dataset of all footprints

We have produced image files of the top ranked 1000 footprints for Europe. For further investigation, this code can be altered to produce values for individual countries. This dataset can only be used within the academic restriction of the original data.

ii) Size and shape of footprints

Although we have not defined a simple algorithm to define shape and size of footprints, we have done some basic inspection of the events at various return periods. As well as the fairly standard, broad wind footprints, one thing that is evident is there are narrow storms across many return periods that one might not expect to find in catastrophe modelling output. We have put a selection of footprints from various return periods in the Appendix.

It will be useful to develop also some simple algorithms for size of event footprint. One such simple one could be, for each event, “area covered that is within X% of the maximum wind in the footprint”. This could be a way of contrasting the modelled output with that of catastrophe models, too, without necessarily having to use the same hazard base.

iii) Time-varying EP curves

One of the benefits of this dataset is that there are 1000 years per decade (the data is 100 ensembles from 1951-2011). With this, we have been able to produce EP curves for each decade. The chart here shows the change in EP loss over time.

The main point of interest here obviously is how the 1980s-2000s decadal EP curves show a not insignificant uptick in losses.
This also brings into focus the importance around the question of "which historical timescale should we be using to calculate losses in catastrophe models?". The chart on the right shows the EP curve for using a 1981-2011 baseline for the "model" contrasting a longer timeline which has losses around 15-20% lower.

We can also split this analysis into countries rather than for the whole of Europe to further look at nuances between territories.

The chart below shows the 1951-1980 and 1981-2010 EP curves for France and the UK. Both territories show an increase in the EP curve between the earlier and later stages, but there are differences in the behaviour of the shift. The area below the 1-in-25 year RP is probably the most interesting. Here the UK data only shows a slight increase, whereas the France curve shows a marked increase of as much as 50%.

This difference is interesting in that we've seen the UK maybe have less activity since 1990, with an uptick in events in France, and it could be that we're seeing a manifestation of this in the model data, too. This will be touched upon later when we look at using this dataset for counterfactual analysis.

### iv) Variability in history and counterfactual analysis

Possibly the most interesting aspect of the project – that maybe was less of an expected end result – was using the 100 ensembles as a representative sets of "history" to understand variability and trends but also to question our use of history as a validation tool in modelling.
a) EP variability

The chart here shows the EP curve calculated from 100 versions of history. It’s a simple calculation for each 60 year history where, for example, the 10th ranked storm is the 60/10 = 6 year RP.

The surprise from this work is the extent of the variability around low return period losses. The 5-year return period value here ranges from 3.7bn to 6.6bn in the 10th-90th percentile range, which seems a surprisingly wide range for such a small RP. Event the 2 year RP has a range of 1.2-2.1bn.

The red lines on the chart are merely indicative. The issue here is that the history we see could be any of these 100 histories – so when models are validated against history, what does our history represent? It could be any of the lines on this chart.

A natural follow-up question to this is “How many years of data would we need before we can be comfortable the one history we have available is producing an accurate representation of a specific return period?”.

With this in mind, the chart here shows the 100 60-year ensemble members turned instead into 25 240-year pseudo-histories. We can see that the longer “historical” dataset means we have more certainty around the 5-year return period (around 3.9-5.2bn), but it still highlights the amount of historical data required, at least in this EUWS example, before you can be comfortable with historical data as a “target” for return losses when building your stochastic model.

b) Testing Short-Term views of risk

More recently in catastrophe modelling we tend to use recent trends in historical data to infer a change of risk. We can ask here: how does a mooted change in risk look like in the eyes of 100 re-runs of history? One development in windstorm modelling in the last few years is the recognition that windstorm activity has dropped away in recent years.

We can take a look at a simple test for this: there is a feeling that post-1990, losses have dropped away, which is certainly evident in our historical record. Is this, maybe, a sign of a trend that is maybe as a result of the warming globe – or maybe the North Atlantic Oscillations alleged longer term fluctuations.
The chart above shows the change in AAL from 1951-1990 versus 1991-2010, in AAL change “bins” indicated on the x-axis. The average AAL increase across the whole dataset is 9% - so broadly upward.

If we assume that the AAL recently has dropped, if the results above all showed a similar drop then maybe we’d have support for the recent drop in activity. However, it’s broadly a 50/50 split between increases and decreases. Yes, this is just one climate model, but the variability seen here around this 1990 pivot in time suggests that there is – potentially – a lot of variability around historical data for windstorms so selecting “our history” may not necessarily be representative of history.

We can also look at the same chart, but for UK and France. Certainly in recent years, we’ve only seen Daria and Kyrill in the UK whilst France has seen Lothar, Martin, Xynthia and Klaus. Is there a suggestion of more activity in France?
The results here are quite interesting. The UK across all the ensembles shows a decrease in AAL, but France does show a slight increase. More interestingly, the France output shows 17 of the 100 simulations has a >100% increase in AAL, suggesting, potentially a notable increase in tail events that might be driving the shift in the AAL.

5) Additional Project Research Items

i) Clustering

The model gives us also an opportunity to look at the frequency of events in any season in a warming climate. In order to look at this we've taken a look at the return period of number of particular events in a season by decade (remember we have 1000 seasons per decade):

<table>
<thead>
<tr>
<th>RP of x 0.5bn events</th>
<th>&gt;=0</th>
<th>&gt;=1</th>
<th>&gt;=2</th>
<th>&gt;=3</th>
<th>&gt;=4</th>
<th>&gt;=5</th>
<th>&gt;=6</th>
<th>&gt;=7</th>
<th>&gt;=8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950</td>
<td>1.0</td>
<td>1.9</td>
<td>3.8</td>
<td>8.1</td>
<td>20</td>
<td>67</td>
<td>333</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1960</td>
<td>1.0</td>
<td>1.9</td>
<td>4.0</td>
<td>9.2</td>
<td>24</td>
<td>59</td>
<td>100</td>
<td>500</td>
<td>1000</td>
</tr>
<tr>
<td>1970</td>
<td>1.0</td>
<td>1.8</td>
<td>3.5</td>
<td>7.8</td>
<td>26</td>
<td>71</td>
<td>200</td>
<td>250</td>
<td>500</td>
</tr>
<tr>
<td>1980</td>
<td>1.0</td>
<td>1.7</td>
<td>3.2</td>
<td>6.1</td>
<td>12</td>
<td>29</td>
<td>67</td>
<td>200</td>
<td>500</td>
</tr>
<tr>
<td>1990</td>
<td>1.0</td>
<td>1.7</td>
<td>3.2</td>
<td>7.8</td>
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<td>45</td>
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<tr>
<td>2000</td>
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<td>1.6</td>
<td>3.0</td>
<td>6.5</td>
<td>14</td>
<td>32</td>
<td>83</td>
<td>500</td>
<td></td>
</tr>
</tbody>
</table>

The interesting aspect here is obviously the increase in the frequency (i.e. the lowering of the Return Period) of multiple event years in Europe as we head post-1980. For what it’s worth, the model’s main warming kicks in around 1980 (per the chart earlier in the introduction to the model), so maybe we are seeing a bi-product of this.

ii) NAO and Clustering

We have also taken the mean sea level pressure for each month from Iceland and the Azores in this model and used this to calculate a model NAO. This is simply done by taking the mean model pressure across all the ensembles for Iceland and the Azores and using this to calculate a winter-season (ONDJFM) NAO index by contrasting the mean pressure anomaly between Iceland and the Azores.
Across the whole dataset there is a broad trend towards more positive NAO over time. Looking broadly at the trend from a 5-yearly perspective in the chart below, we see that over time as the NAO broadly increases, we note an increase in the average number of storms.

We can also see the impact of NAO on the EP curve, which present interesting results should NAO predictability continue to improve:

The marked difference, say, in the 1-in-10 of 4.5bn versus 10.4bn clearly highlights how European windstorm risk is impacted by this NAO index and how its predictability could be useful for risk-takers.

iii) “Grey swans” within the dataset

Something else that dropped out of the study are interesting types of event which, as they haven't typically been seen in history, may not necessary be on the radar of risk-takers: the
“grey swans” that we know might physically be possible but just haven’t happened in our history.

In eyeballing some of the event footprints, we spotted a number of events that approach Europe from the south but also appear to have a fairly uniform windfield upon approach to Europe. A selection are shown in the plot below: you’ll notice that they are all early-season events that represent - potentially – the overlap between the hurricane and extratropical seasons.

Are these dying tropical events? This is probably the source of another piece of work entirely, but if this sort of very low frequency event exists in these models despite not occurring in history, it is something worth taking note: especially, but not exclusively, for risk-takers in Spain and Portugal. There was also an interesting corollary to this data in that the events chosen randomly here are all after the 1990.

As part of our model region, we developed a simple flat portfolio across the whole of the domain to help isolate storm severity rather than having exposure-weight storm valuations. The plot below shows how the influence of early-season losses has change hugely from 1951 to 2010 in the model, suggestive, potentially of tropical-extratropical input:
We’ve simply totalled the loss for each month across all the 100 ensembles in 20-year blocks. The actual loss value here is immaterial, it’s the relativity we want to look at. The Sept-Nov total loss is only about 21% of the year’s AAL in 1951-1970: this increases to 47% by 1991-2010 along with a general increase in storm activity throughout the year.

It is interesting that these early-season loss increases may be suggestive of tropical-extratropical overlap increasing as we’ve headed through the 20th century even though we don’t really have any historical evidence of this happening owing to the low frequency nature of such events.

6) Conclusions and Potential Future Work

a) Conclusions

The key points to have emerged from the work are:

- Building a simple risk model “out of the box” from climate model output leads to some notable biases when compared to existing model vendors.

- The higher resolution of the climate model used has highlighted the importance of resolution in resolving long-track, narrow, intense wind footprints.

- Time-varying EP curves have pointed to a slowly-increasing risk, broadly, over time and also raises the question of how far back in time we should be looking for informing the present-day view of risk in stochastic models.

- The huge variability between ensemble simulations raises a question around the accuracy of using historical data as a “target” for historical simulations and how much historical data we need to be comfortable of knowing what an accurate X-year return period loss might be.

- Given the wide-ranging ensemble variability, we’ve also shown how using historical data to develop short-term views of risk (e.g. the near-term drop in historical losses in EUWS) might be a dangerous assumption.

- We have shown however that the model potentially backs up the assertion of a slight decrease in risk for the UK, with an increase in risk for France.

- The model output has suggested increases in risk over time could be linked to the growth of more positive NAO states as the planet warm. We’ve also noted how there is an increase in multiple-event seasons in the data (i.e. an increase in clustering).

- The data also has been used to highlight the significant difference in risk between positive, neutral and negative NAO seasons, which could be a useful result if we are able to develop good predictive skill in NAO forecasting.

- The data has also shown a possible increase in the crossover between tropical and extratropical seasons over time, with a marked increase, for example in early-winter storm activity over Spain.

1 Further interrogation will be possible by insurers to contrast footprint size and shape with lower-resolution climate model driven catastrophe models to see if there is a potential consequence here.
b) Future Work

Given that the project threw up some unexpectedly interesting results, there are a number of possible threads that could be followed in the future:

- More digging into clustering from a more of a statistical perspective from the data that has been produced. Are we seeing more negative binomial distribution of storm arrivals with time/as the earth warms in the model simulation?

- Follow-up research work on the impact of global climate model resolution, storm sizes and shapes and how this affects may potentially affect EP curve shape.

- Investigating the role of ex-tropical storms and their frequency as a function of a warming climate: do we start to see an increase in the likelihood of tropical/extratropical interaction, albeit in increase in very small probabilities, but enough for it to be considered in the tail of our EUWS EP curves?

- Comparing other modelling work (e.g. the Met Office “UNSEEN” project) with this data to contrast results.
Appendix

The charts below show the 6 wind footprints with the RP closest to the RP shown. It’s largely used for eyeballing of footprints

250-year RP
100-year RP
Narrow footprints – various RPs

This is simply to demonstrate how narrow a number of the wind footprints are at different return periods. The hypothesis is that using low resolution GCMs to build event sets may mean this type of event is less prevalent in catastrophe models.