Clustering of Extreme Storms

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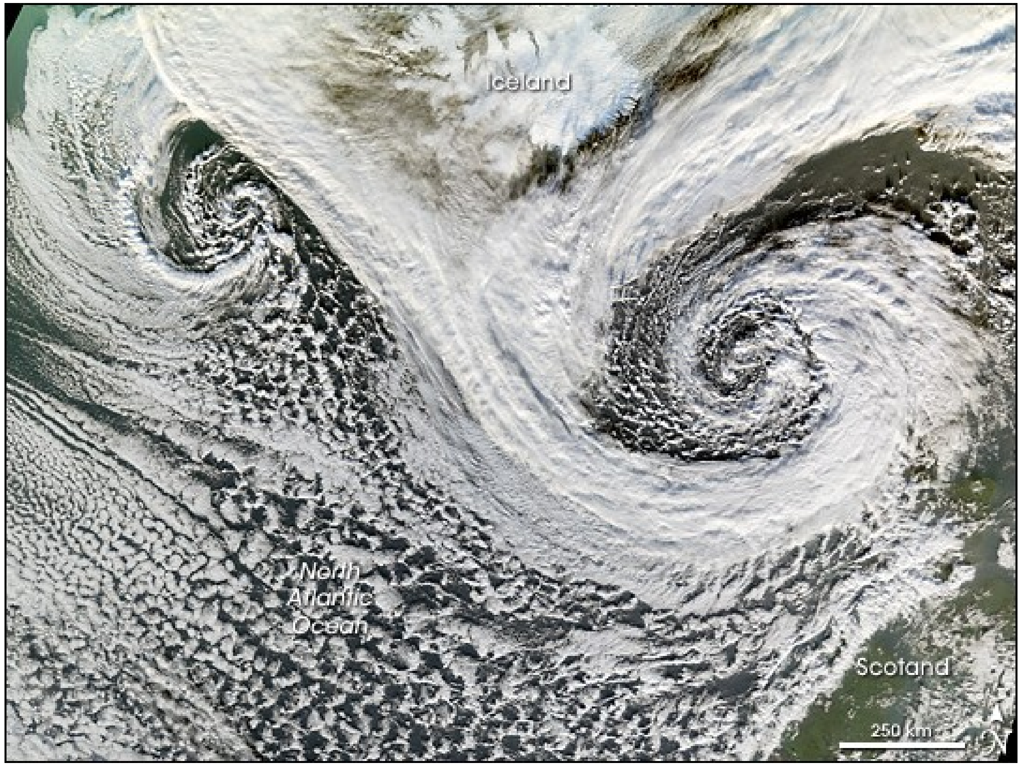
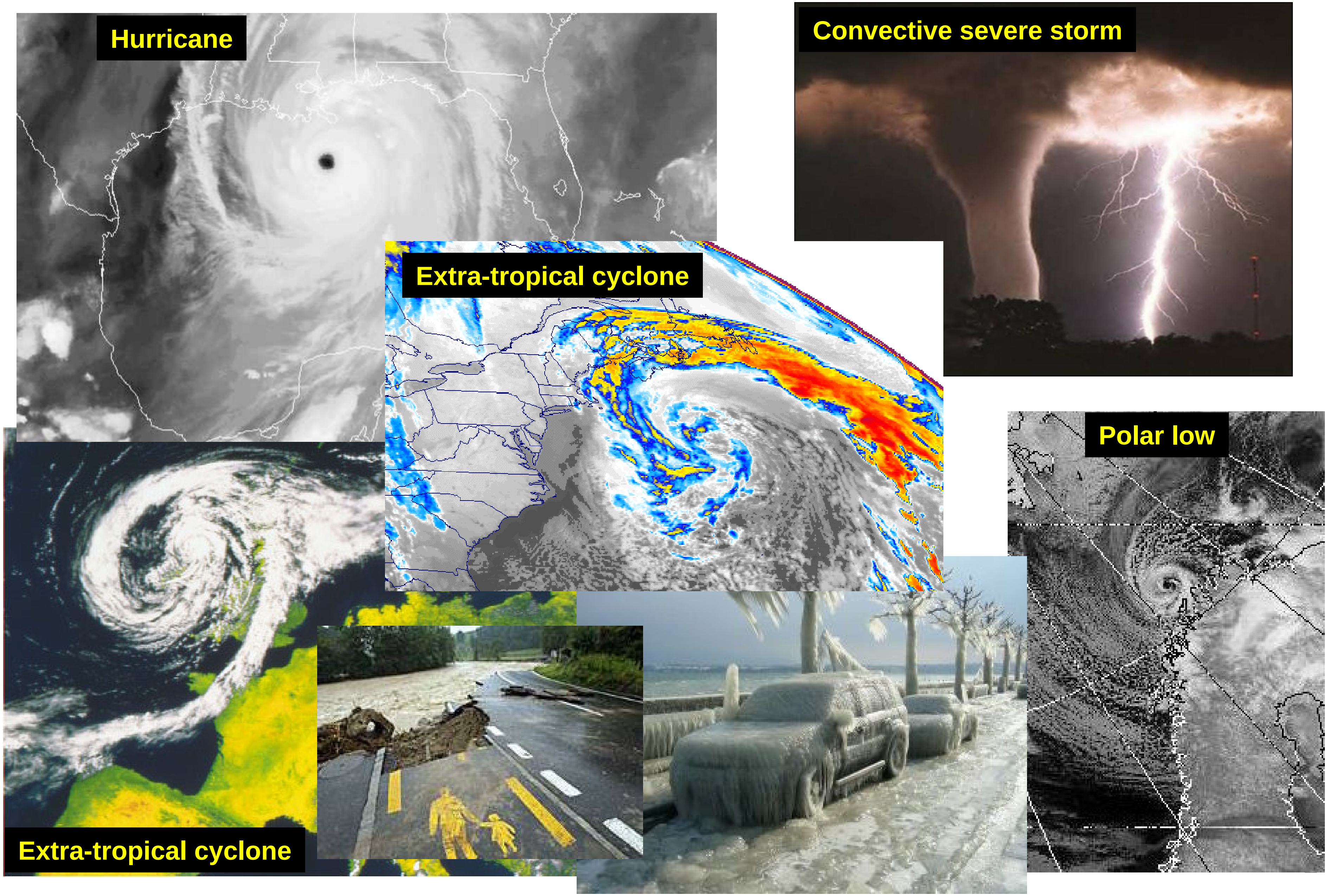
UNIVERSITY OF EXETER



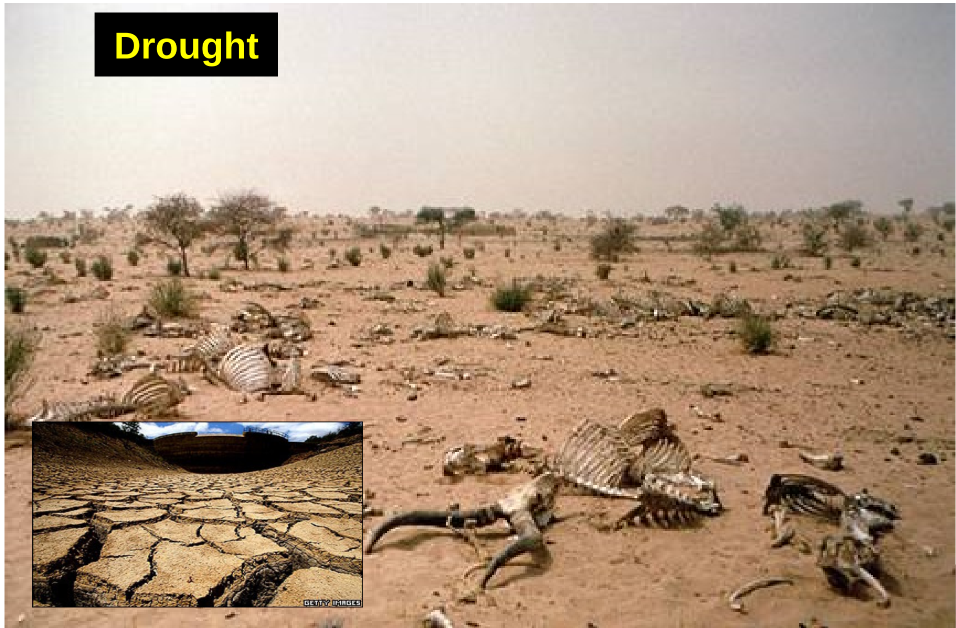
KNMI/EURANDOM workshop "Climate change and EVT", May 11-13 2009, Eindhoven

Willis Research Network

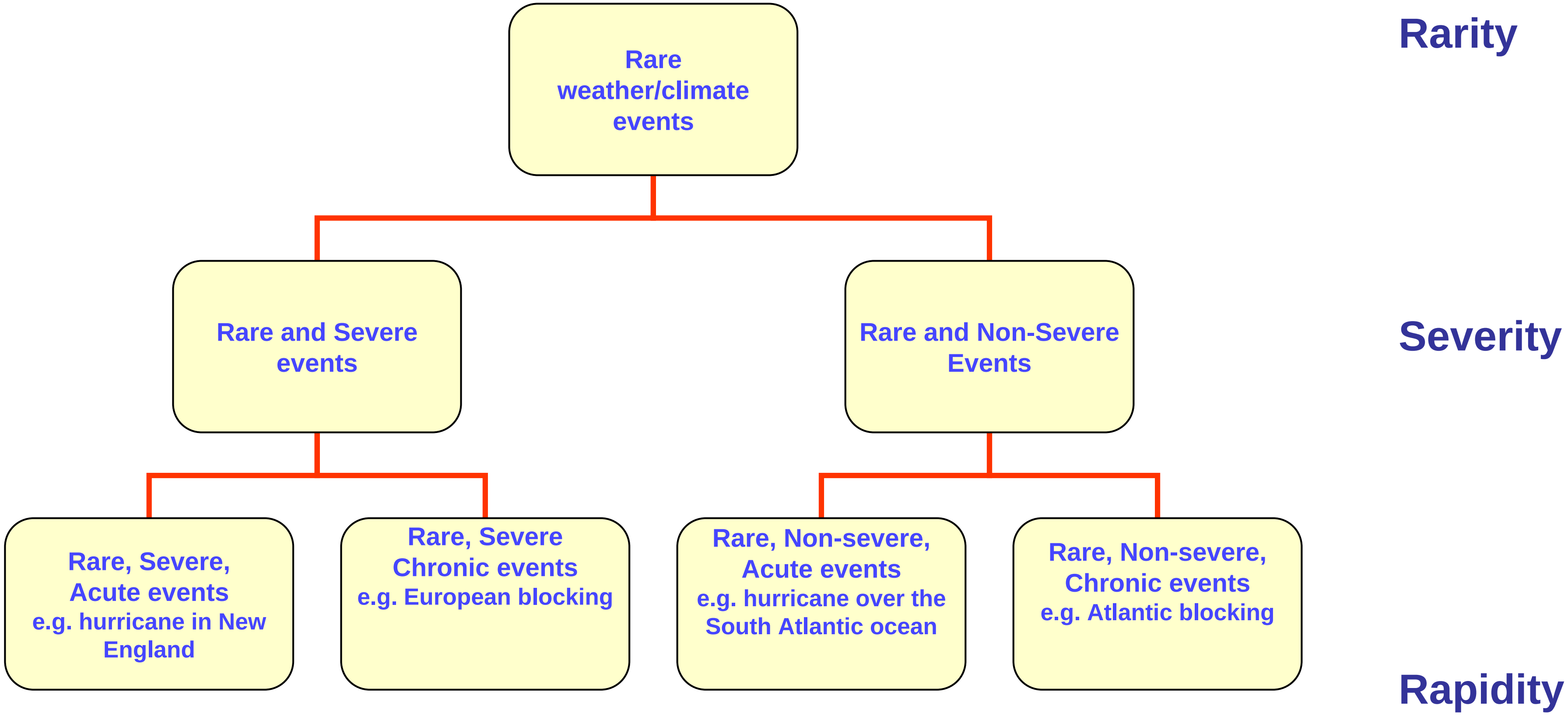
Examples of wet and windy extremes



Examples of dry and hot extremes



Simple taxonomy



Acute: Having a rapid onset and following a short but severe course.

Chronic: Lasting for a long period of time or marked by frequent recurrence

What do we mean by “extreme”?

Large meteorological values

- Maximum value (i.e. a local extremum)
- Exceedance above a high threshold
- Record breaker (threshold=max of past values)

Rare event

(e.g. less than 1 in 100 years – p=0.01)

Large losses (*severe* or *high-impact*)

(e.g. $200 billion if hurricane hits Miami)

RISK = Expected loss due to the event

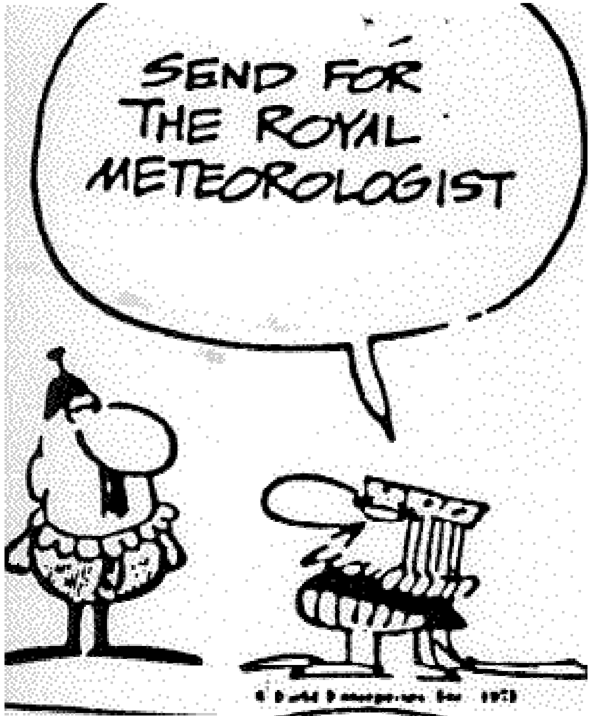
= Pr(event) x loss(event)

where loss = vulnerability x exposure

Definition of “extreme” event is:

- context-dependent;
- not a binary property (it’s a relative concept!)

Gare Montparnasse, 22 Oct 1895



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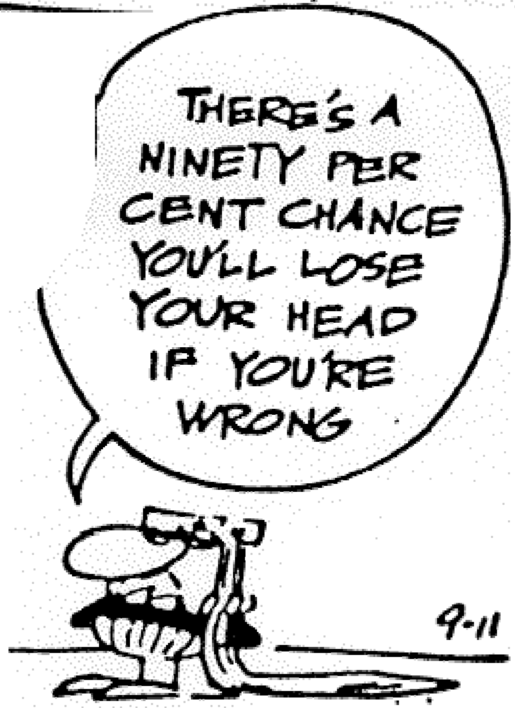

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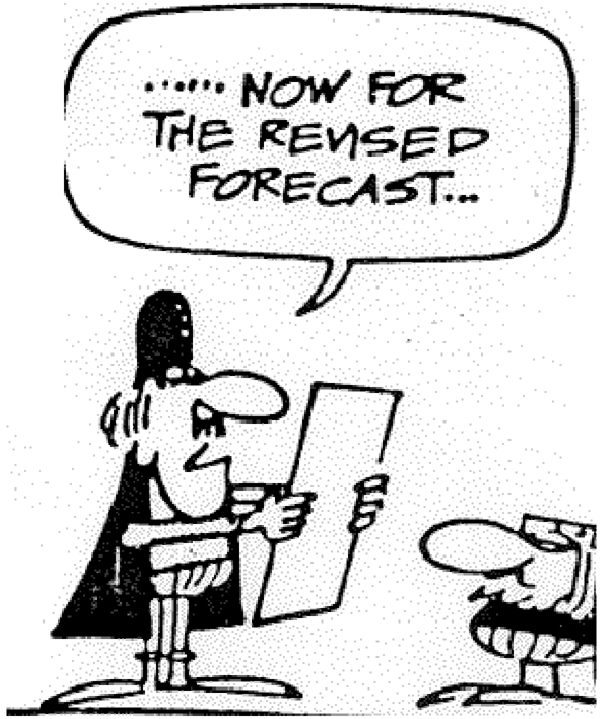

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Societal relevance of storm clustering

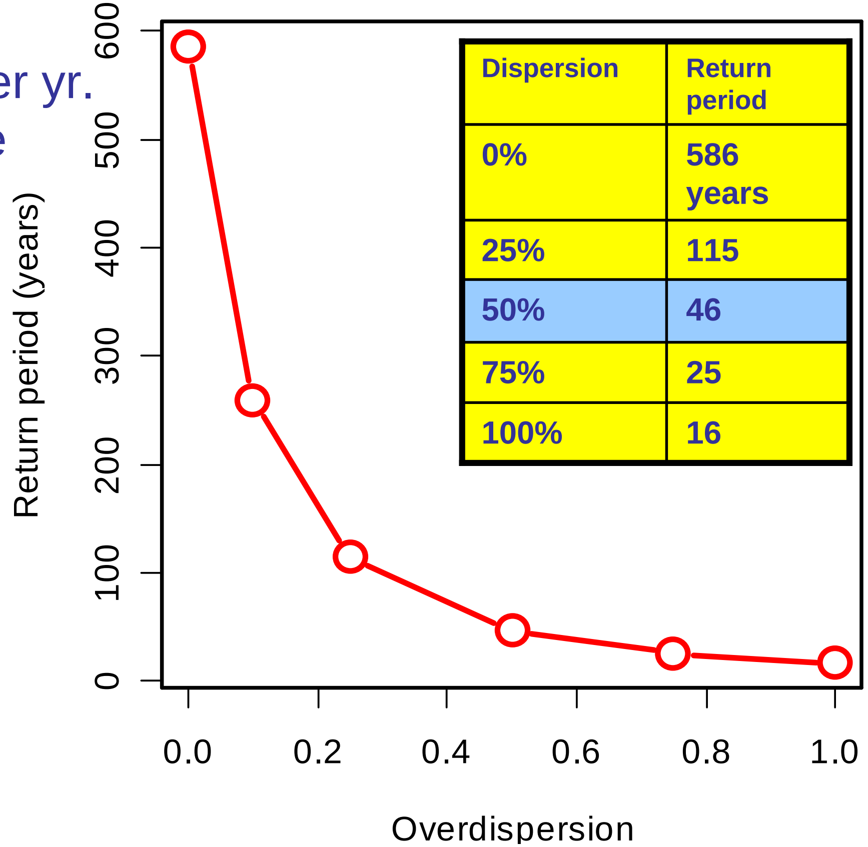
Clustering of European winter storms leads to cumulative insurance losses comparable to those from a catastrophic hurricane:

- Dec 1999: 3 consecutive storms (loss $7.5 bn)
- Dec 1989/Jan 1990: 8 consecutive storms (loss $10.5 bn)

Example 2:Return periods for >15 storms/month estimated using negative binomial with a mean rate of 5.7 cyclones/month

Example 1:
Reinsurance typically bought for 2 events per yr.
Assume to buy cover from 15% exceedance probability level:

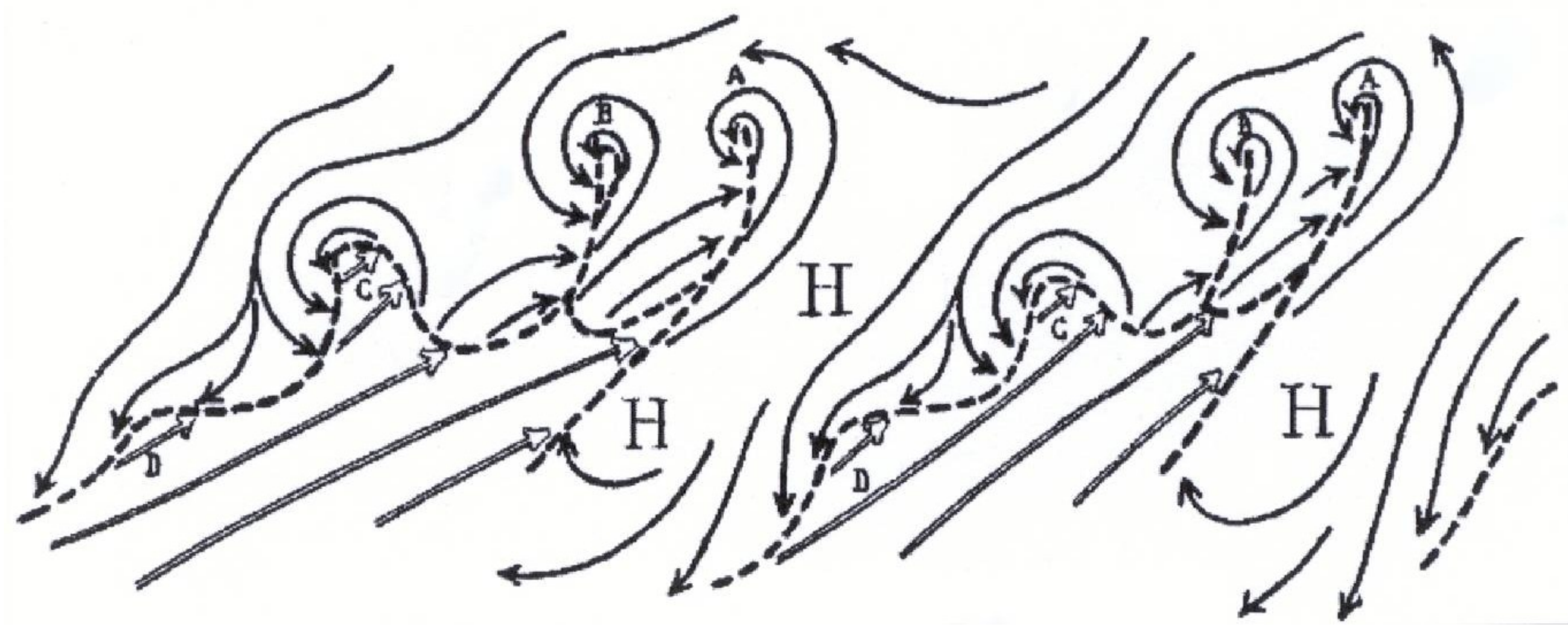
Dispersion =	0	0.5
Prob[2 events/yr]	0.011	0.021
Prob[>2 events/yr]	0.001	0.008



Dispersion	Return period
0%	586 years
25%	115
50%	46
75%	25
100%	16

Some key scientific questions

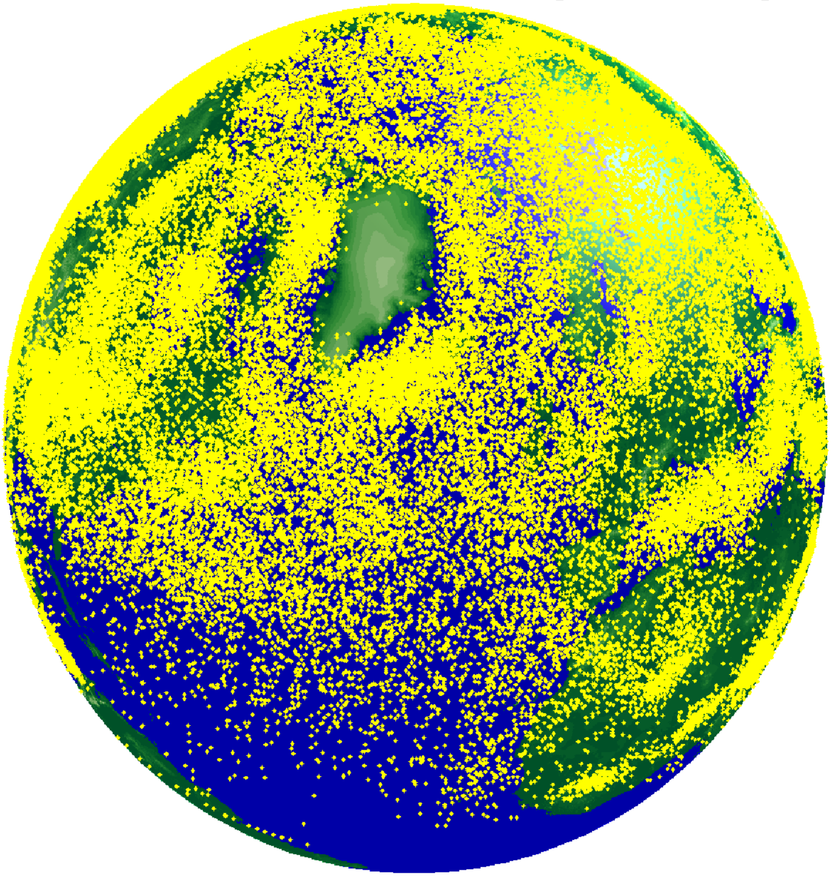
- How much do extratropical wintertime storms cluster?
- How does clustering depend on storm intensity?
- Can large-scale flow be used to explain the clustering?
- What are the implications of this for estimating return periods?



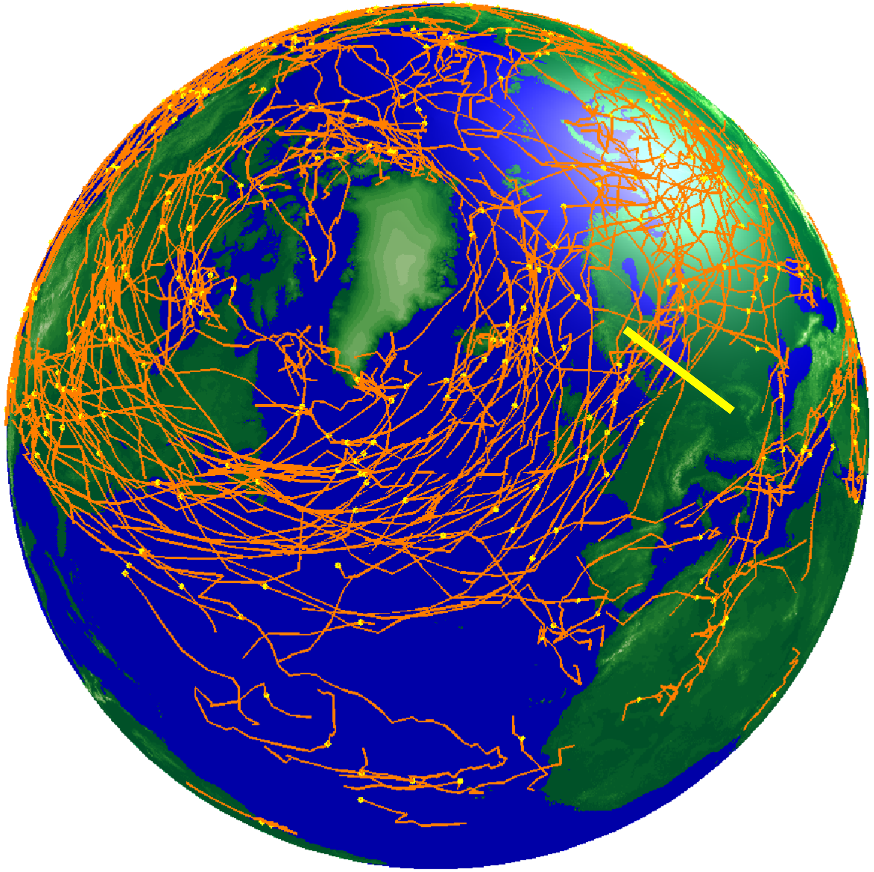
Storm feature tracking 1948-2003

- Eastward cyclone tracks identified objectively using TRACK software
- Extended winters (1 Oct-31 Mar)
- 6 hourly NCAR/NCEP reanalyses from 1948-2003

355,460 VOR zeniths (maxima)

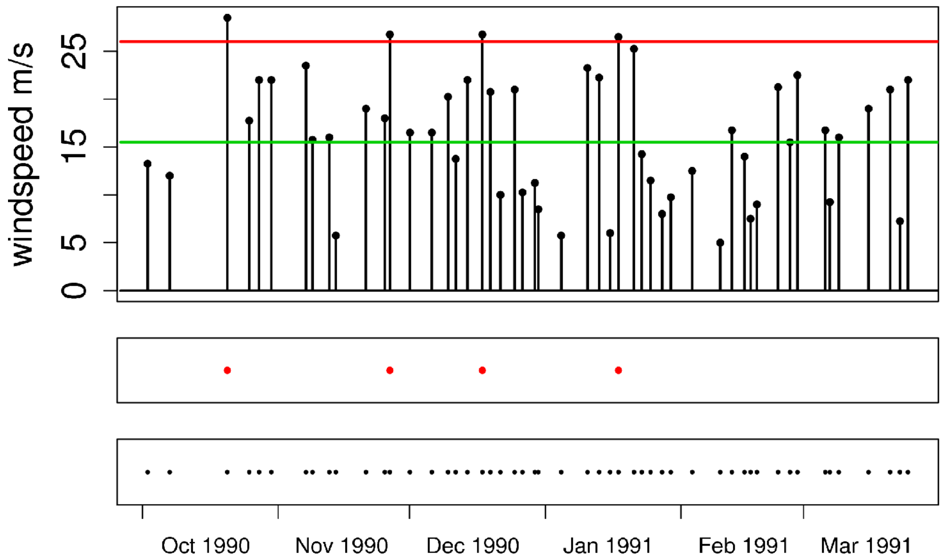


The Storms of Dec 1989-Feb1990

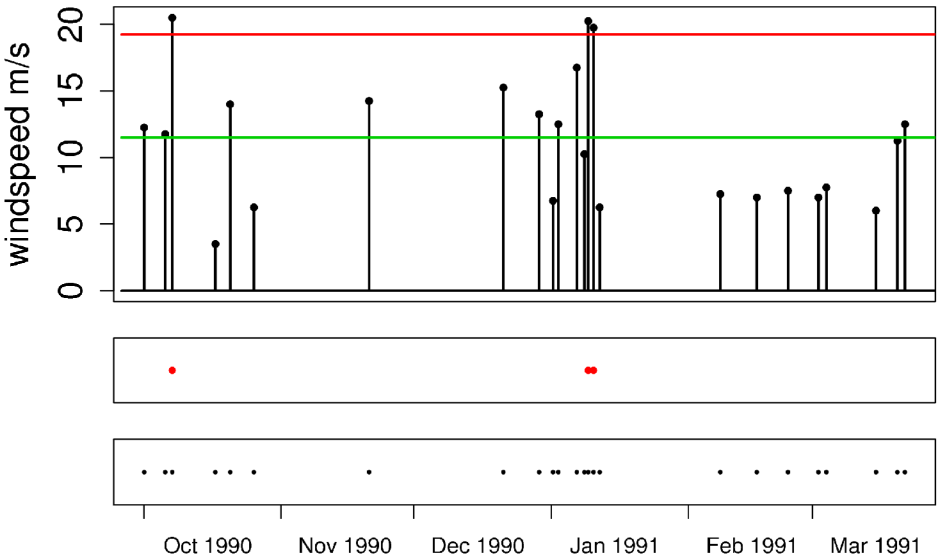


Clustering of storms

Transits +/-10⁰ of Nova Scotia (45°N, 60°W)



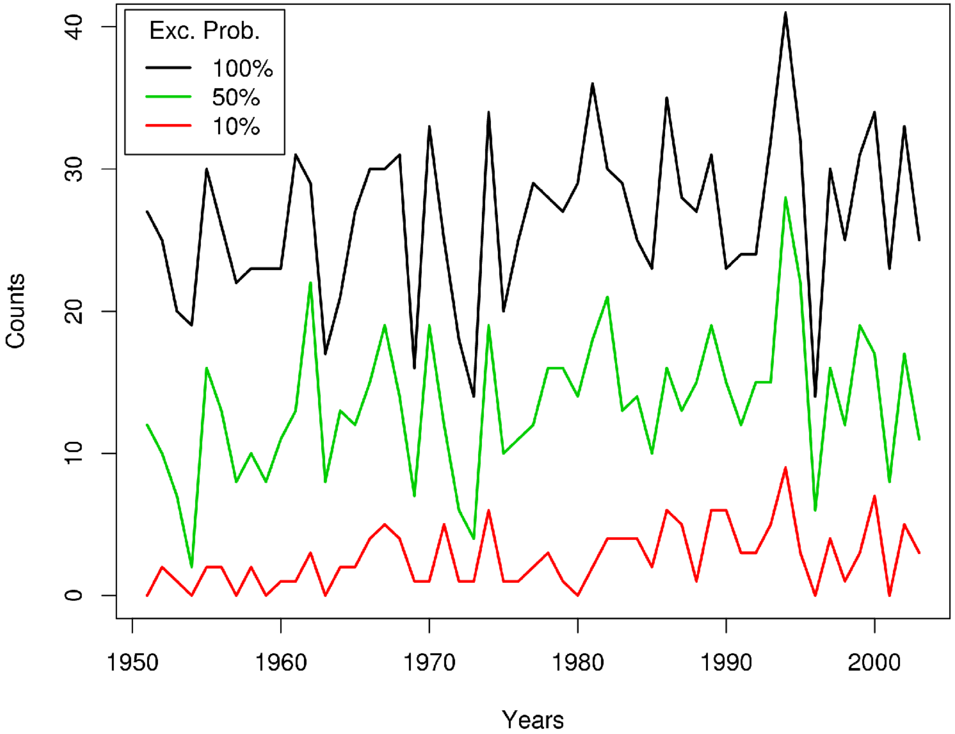
Transits +/-10⁰ of Berlin (52°N,12.5°E)

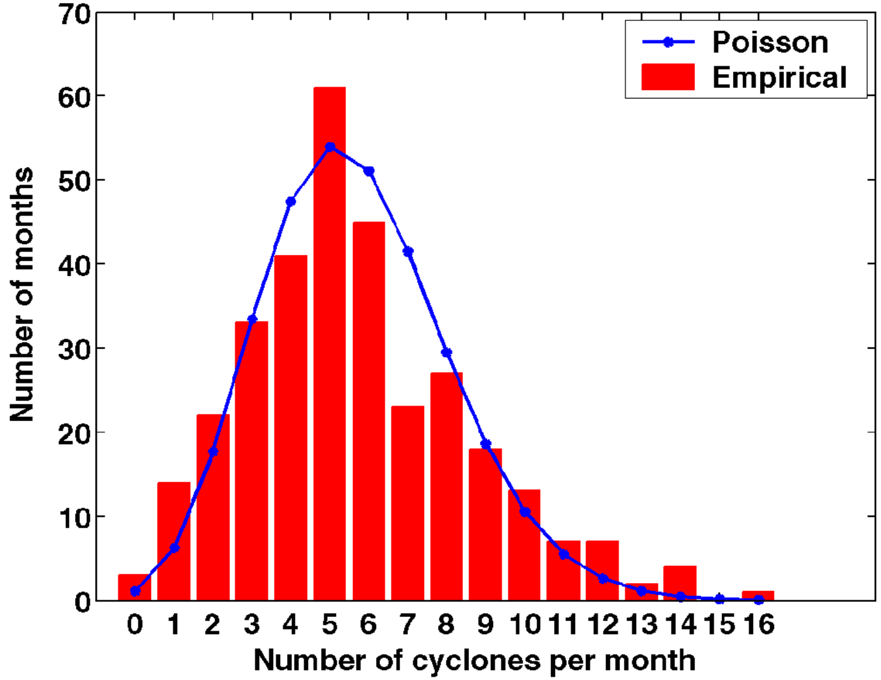


→ Clustered over Europe but not over western Atlantic

Dispersion of storm counts

Oct-Mar counts near Berlin





Dispersion statistic:

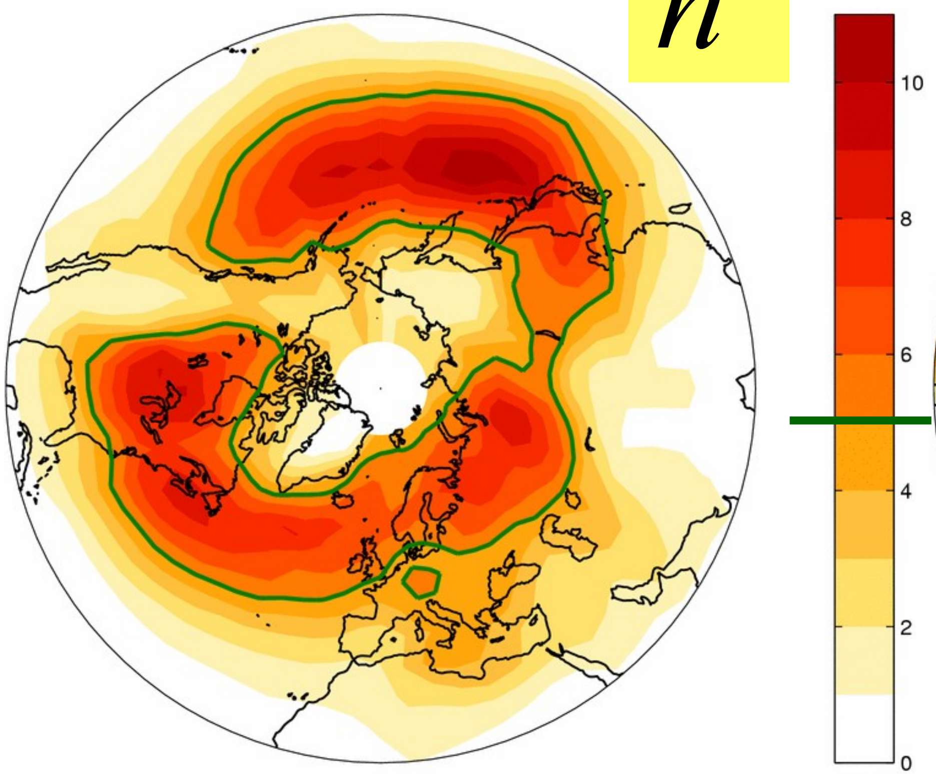
$$\psi = \frac{Var(n)}{mean(n)} - 1$$

=0 when Var(n)=Mean(n) e.g. Poisson distributed counts

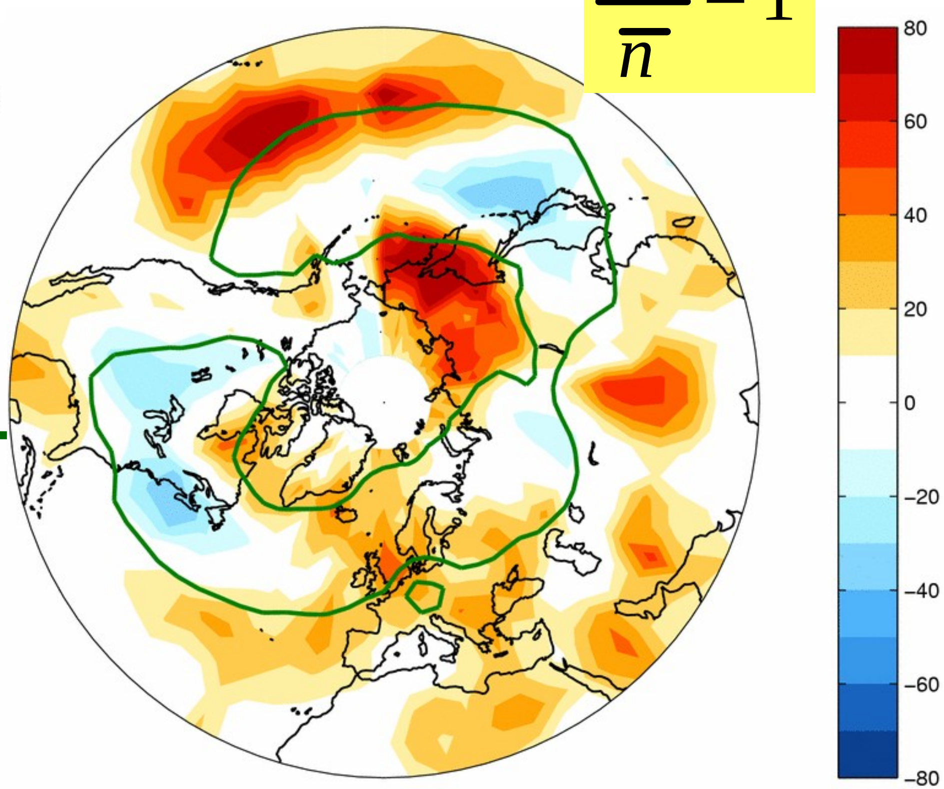
>0 when Var(n)>Mean(n)

Mean and dispersion of monthly counts

$\overline{n}$



$\dfrac{s_n^2}{\overline{n}} - 1$



Green lines outline area with
>5 storms/month passing 20° N-S line

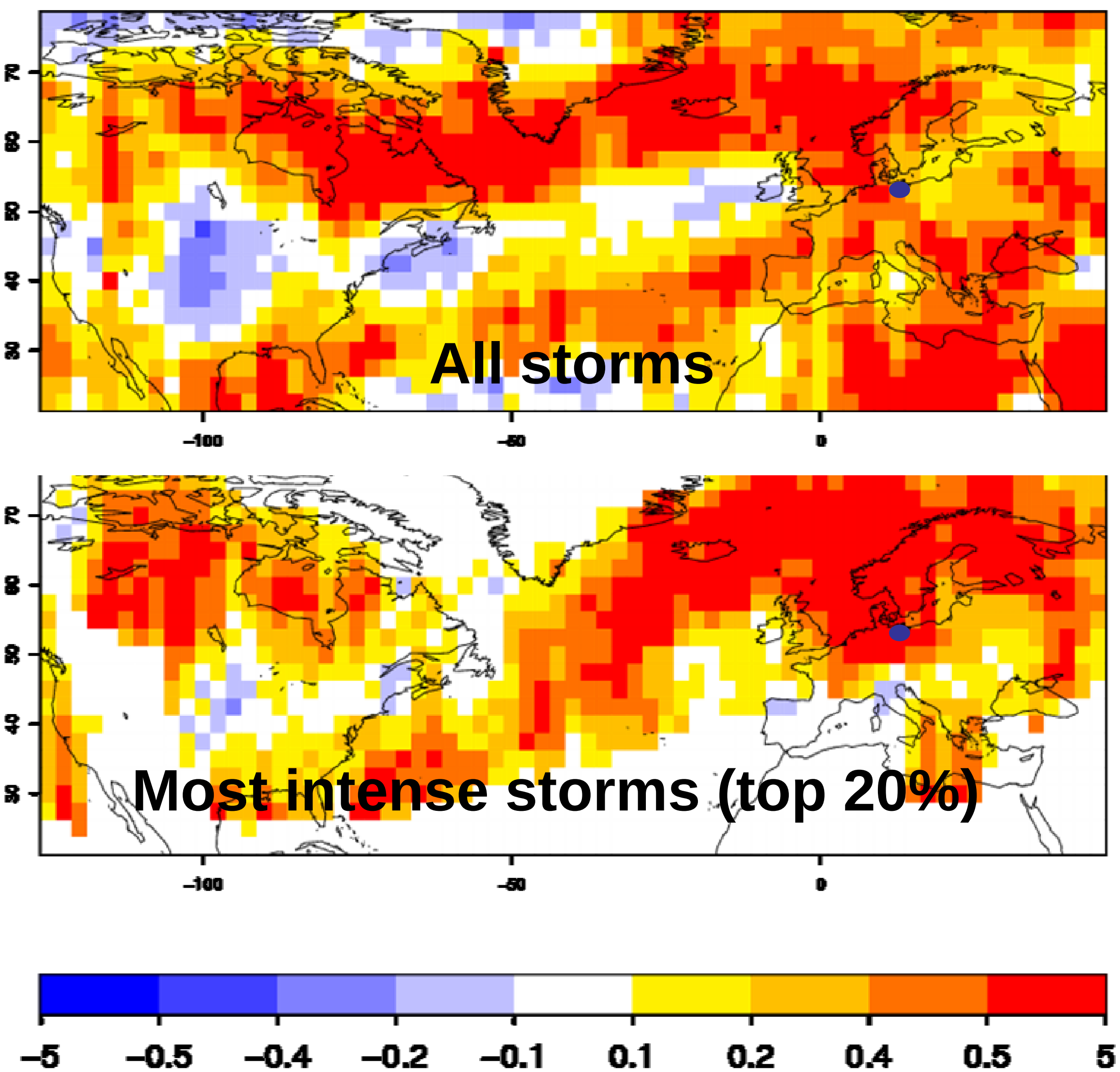
Units: counts/month

Units: %

→Regions of overdispersion (reds) and underdispersion (blues)

Mailier, P.J., Stephenson, D.B., Ferro, C.A.T. and Hodges, K.I. (2006):
Serial clustering of extratropical cyclones, Monthly Weather Review, 134, pp 2224-2240

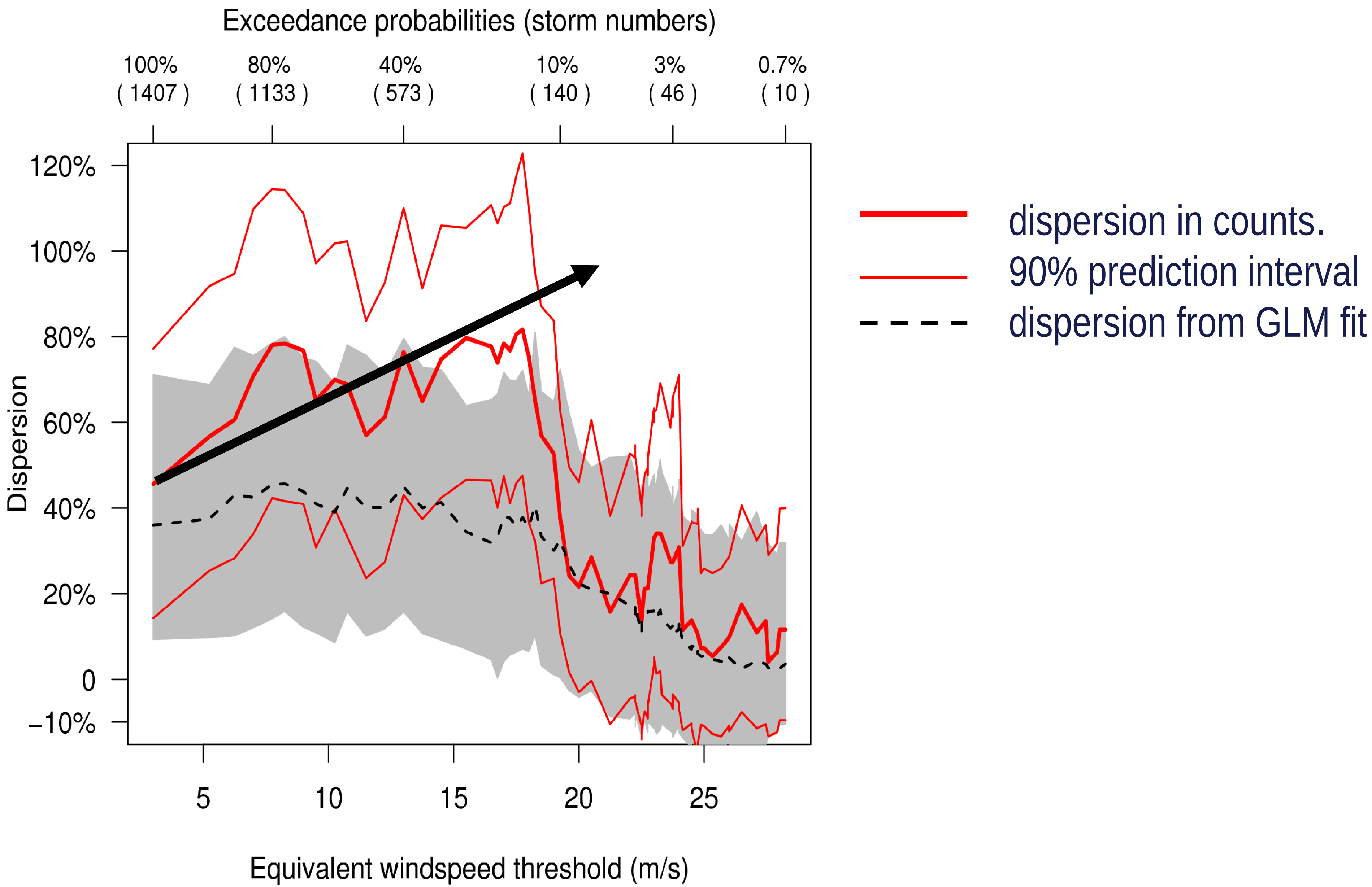
Dispersion increases for intense storms



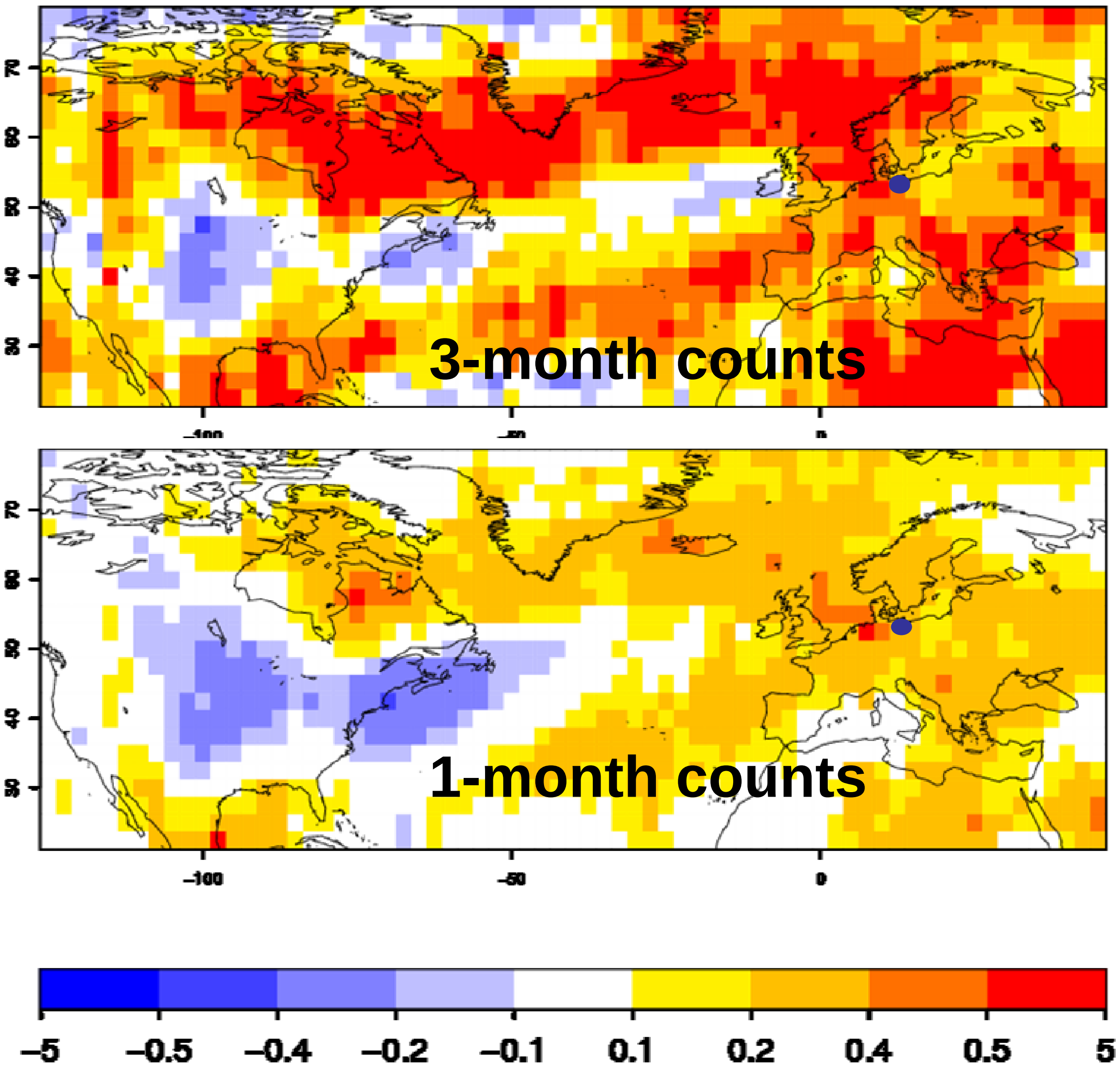
Dispersion of
3-month counts:

$$\frac{s_n^2}{\overline{n}} - 1$$

Dispersion versus intensity for Berlin



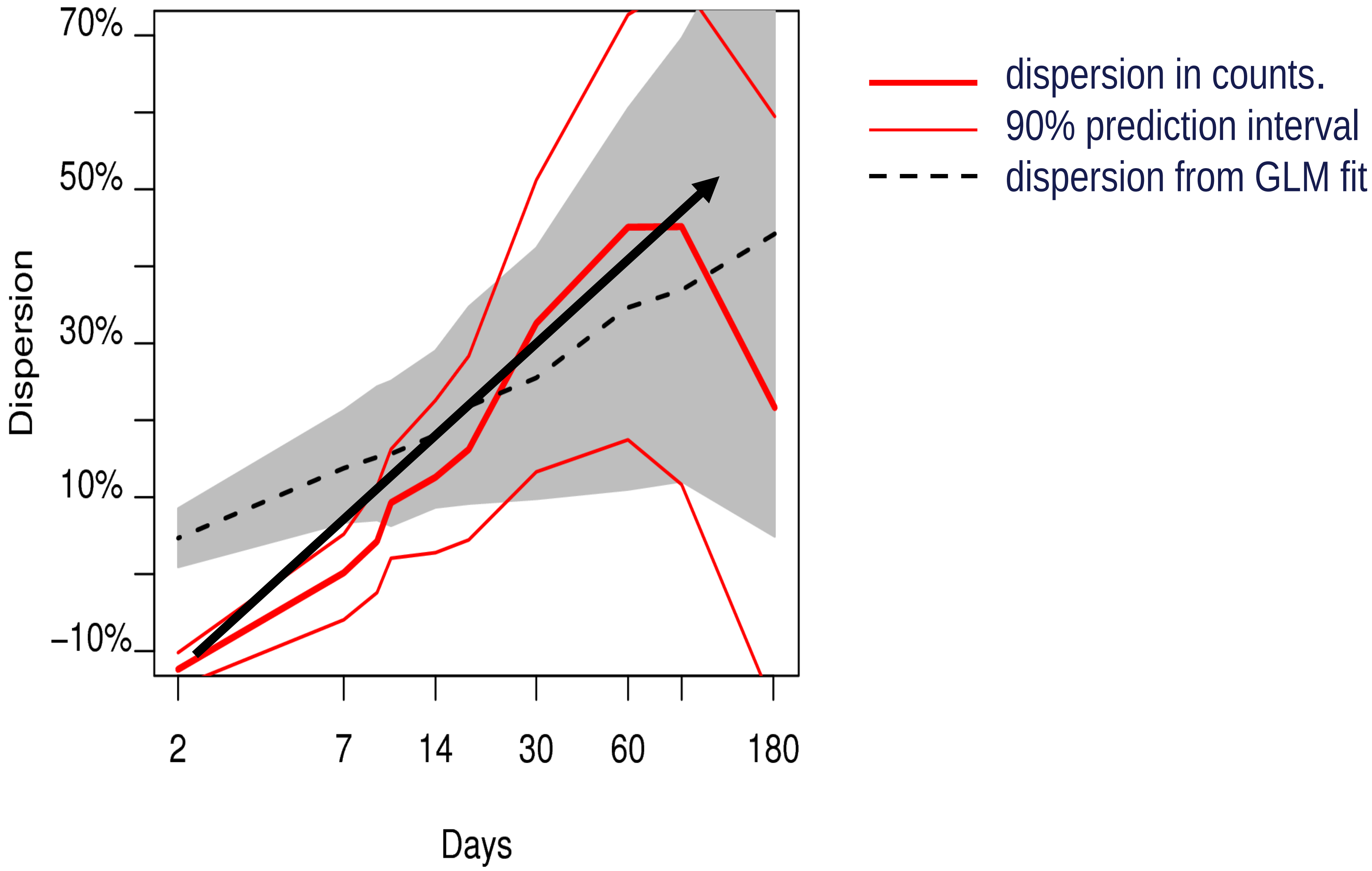
Dispersion increases for longer periods



Dispersion of
counts for all storms:

$$\frac{s_n^2}{\overline{n}} - 1$$

Dispersion versus aggregation period for Berlin



Flow-dependent clustering (e.g. UK buses)

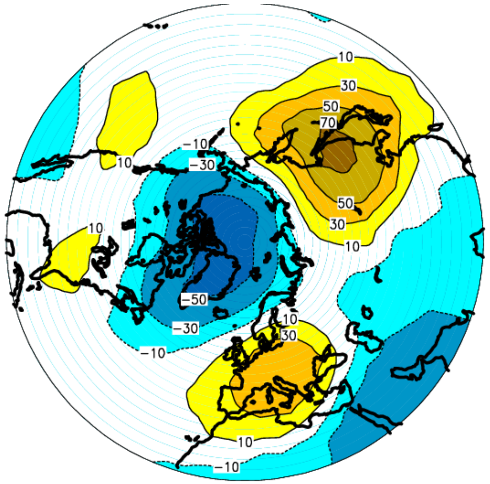
Is this because bus drivers really love each other?

Don’t think so! More to do with rate of arrival depending on time varying background traffic flow.

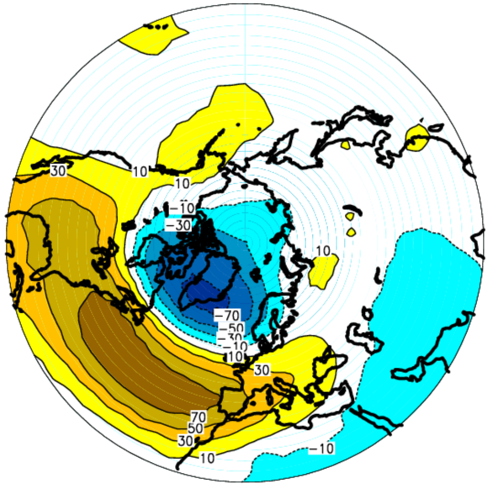
Teleconnection patterns

Leading rotated EOFs of 700mb geopotential height

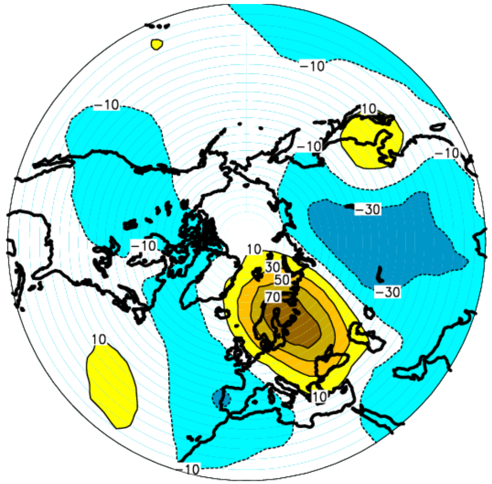
Polar-Eurasian



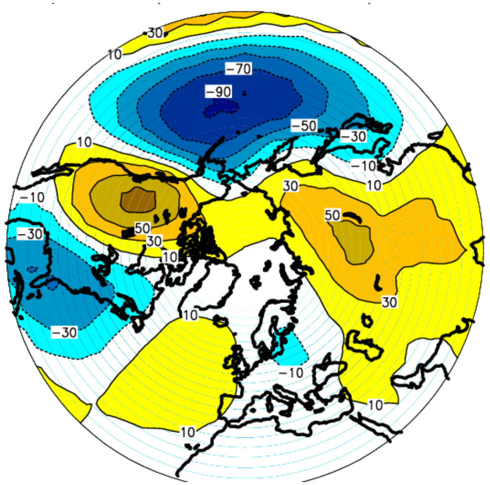
NAO



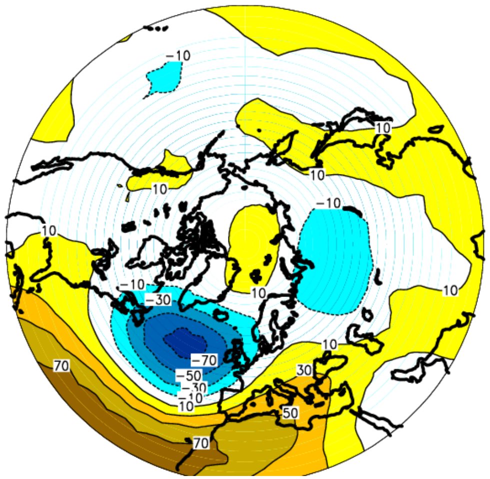
Scandinavian



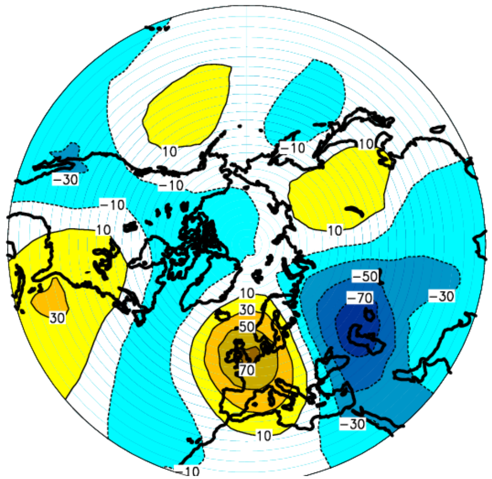
PNA



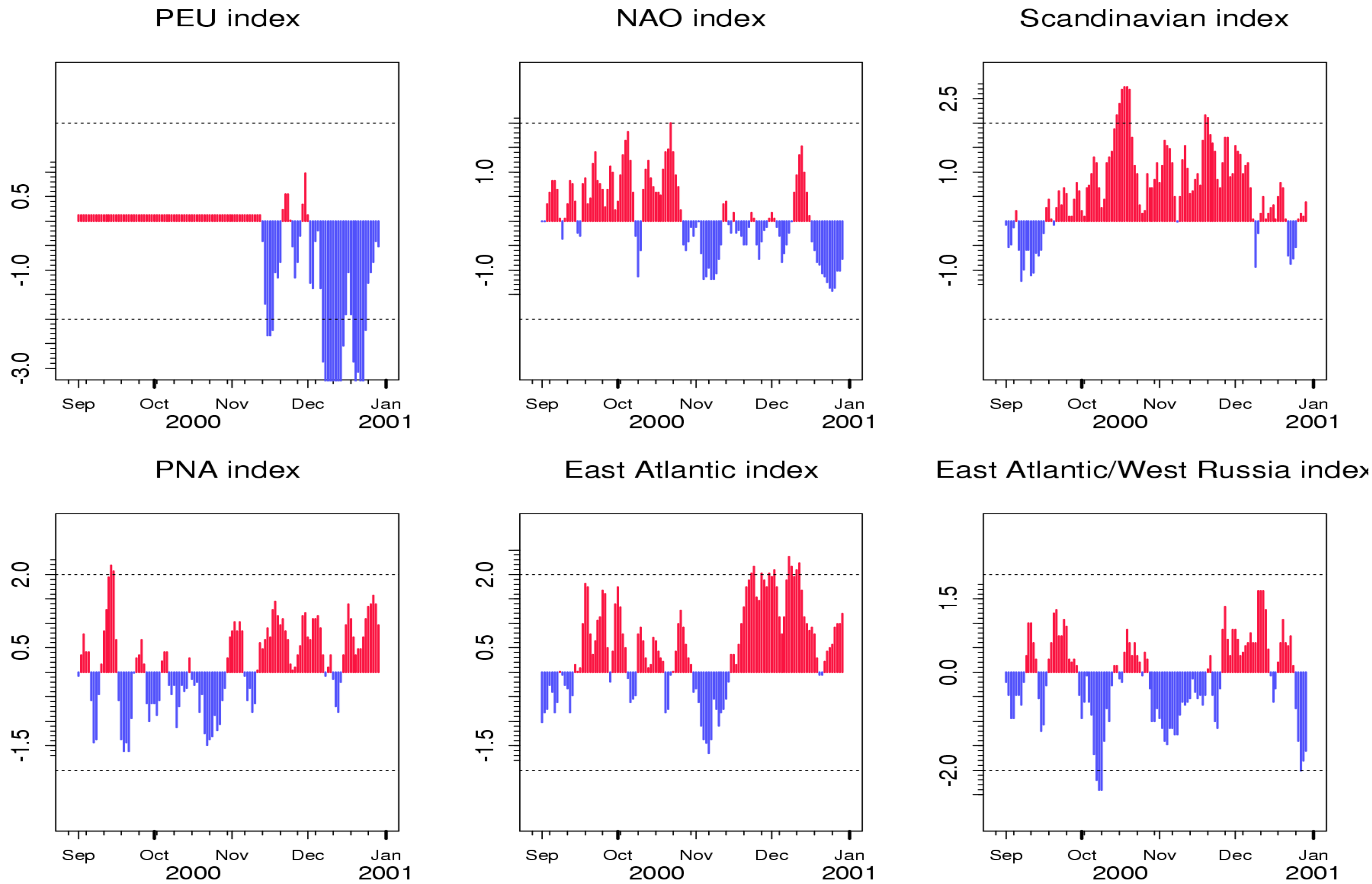
East Atlantic



E. Atl/W. Russian



Daily teleconnection indices x_k

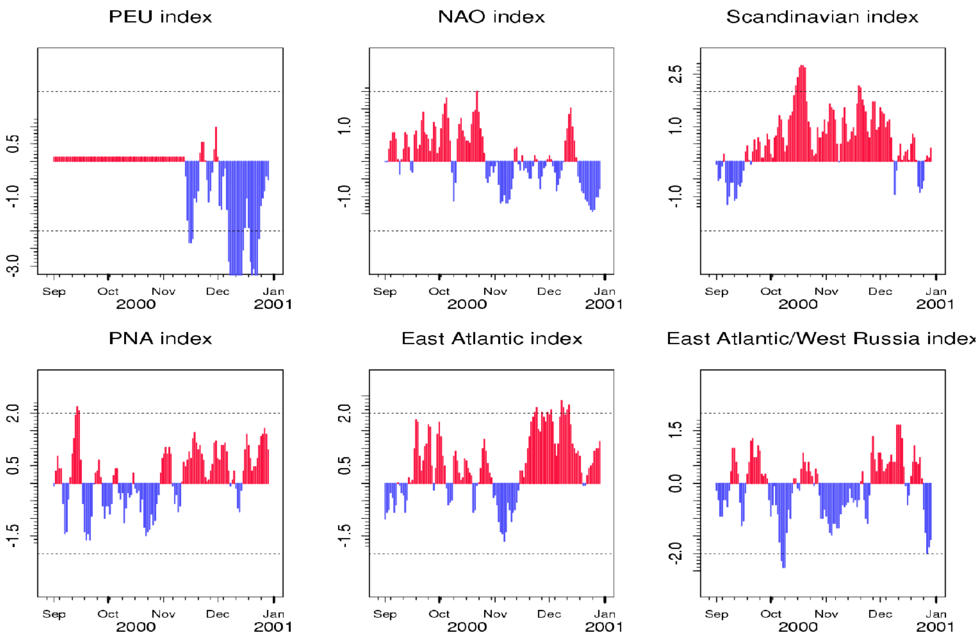


Regression of counts on teleconnections: rate depends on large-scale flow

Poisson regression

$$n \mid x \sim Poisson(\mu)$$

$$\log \mu = \beta_0 + \sum_{k=1}^{K} \beta_k x_k$$



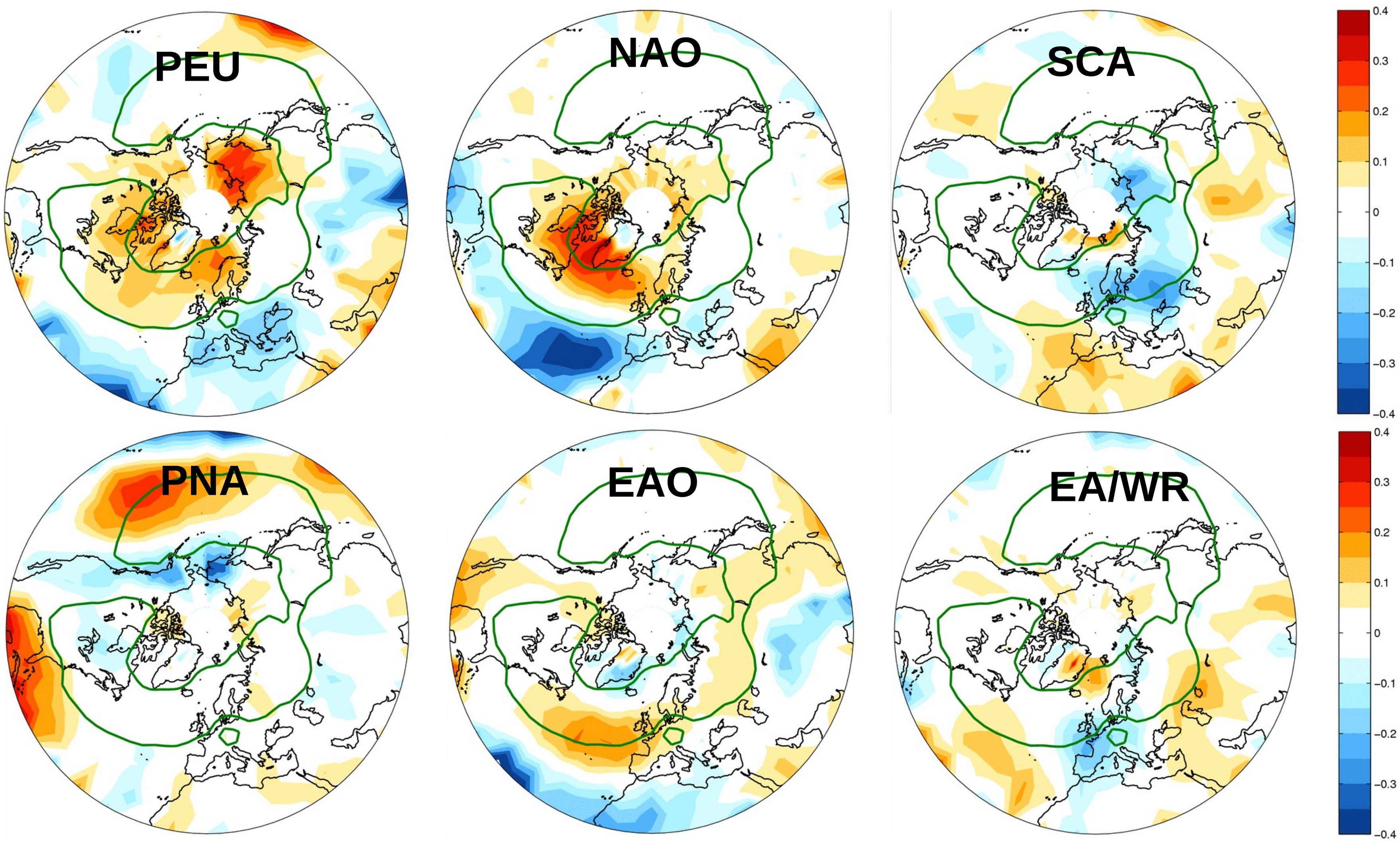
n = number of storms, e.g. monthly counts of windstorms.

μ = time-varying, flow dependent rate.

$x_k(t)$ = large-scale teleconnection indices (covariates).

GLM maximum likelihood estimation of $ß_0$, $ß_i$

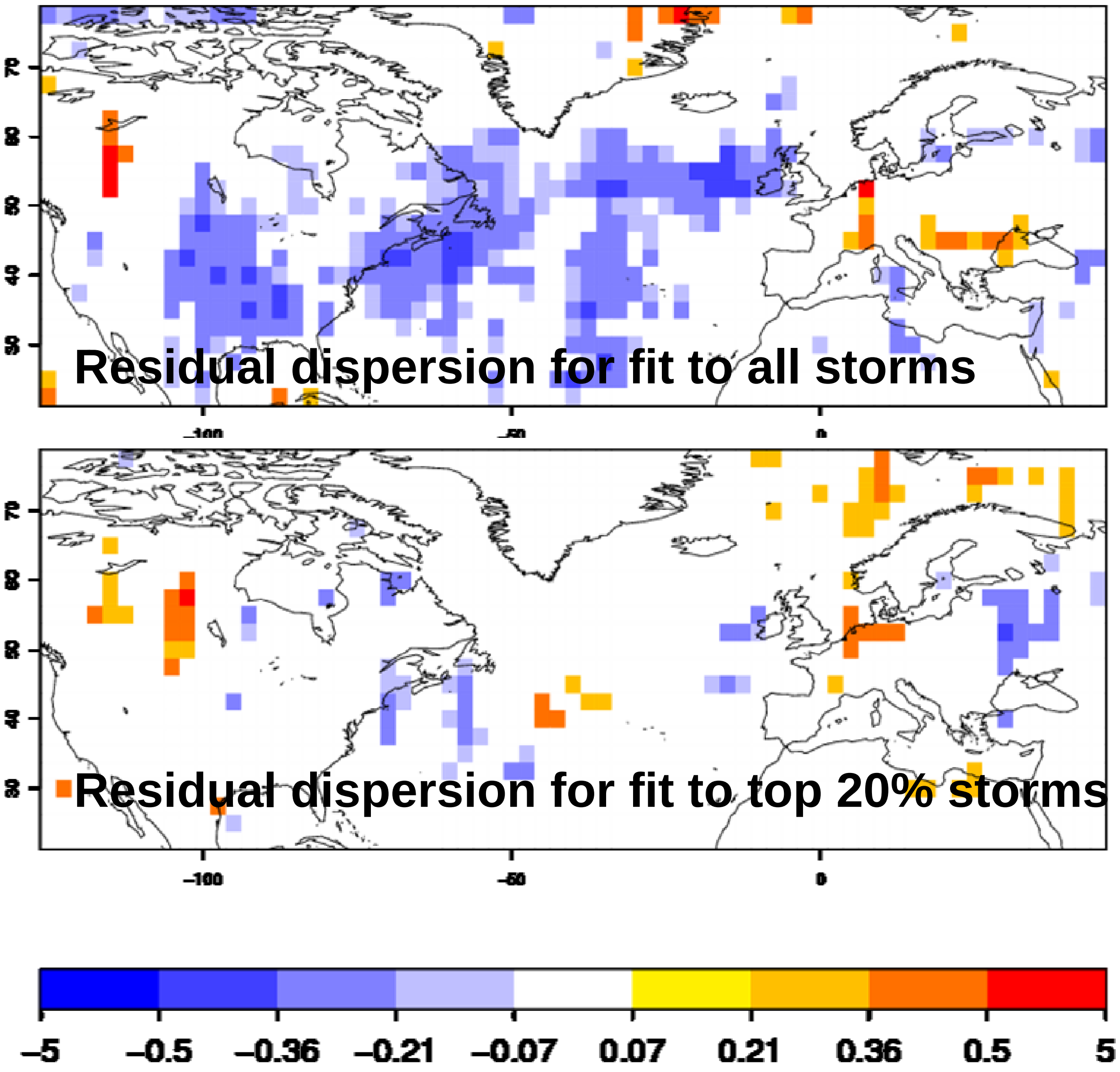
Estimated ß regression parameters



→all teleconnection patterns are important for European storms

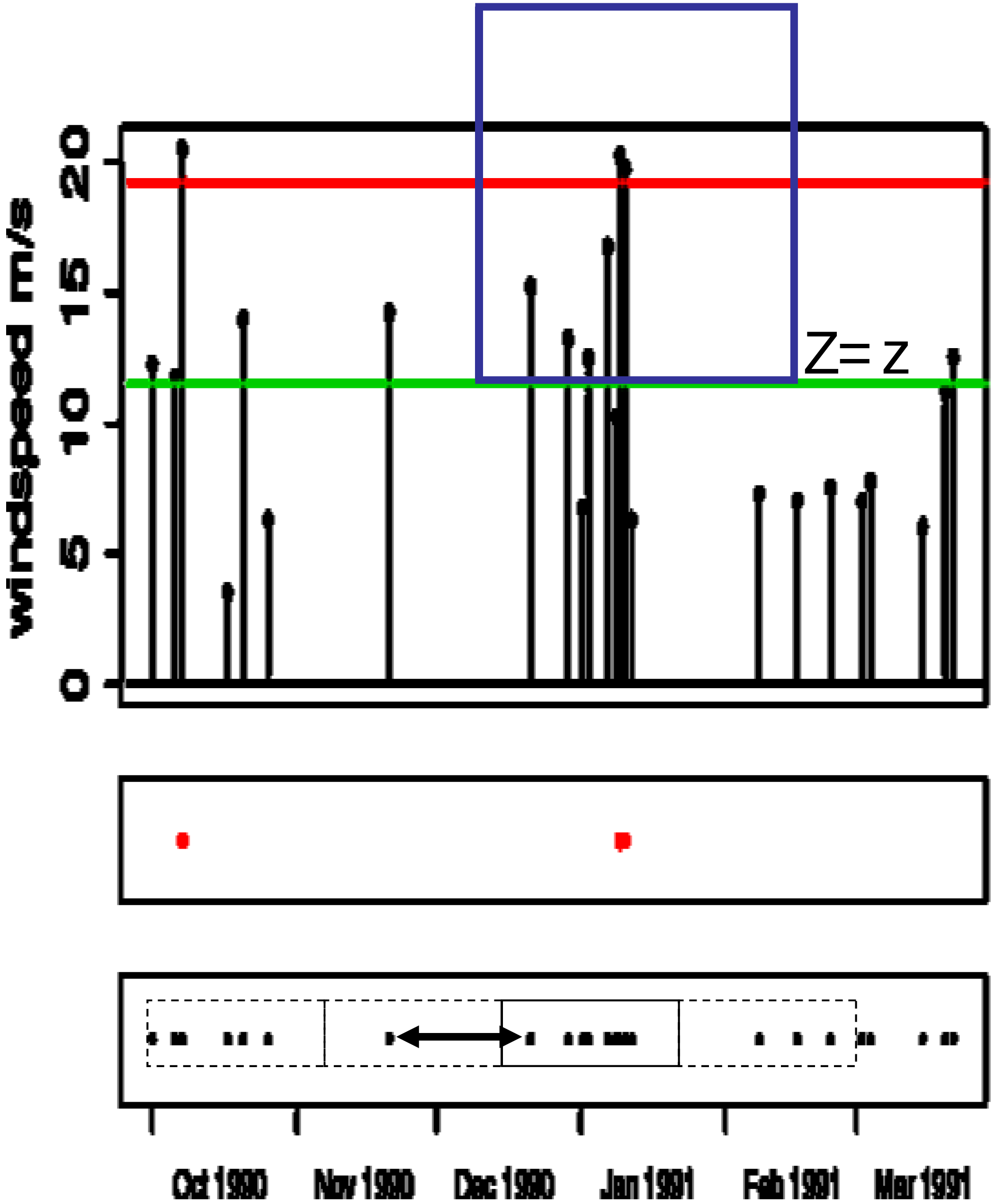
See Seierstad et al. (2007)

Teleconnections account for overdispersion



Residual dispersion of fits to 3-month counts

Stochastic modelling of the process



Consider the points $Z_i > z$

$(i/(n+1), Z_i = (Y_i - b_n)/a_n)$

$i = 1,2,\dots,n$

In the limit $n \to \infty$

$N \sim Poisson(\Lambda)$

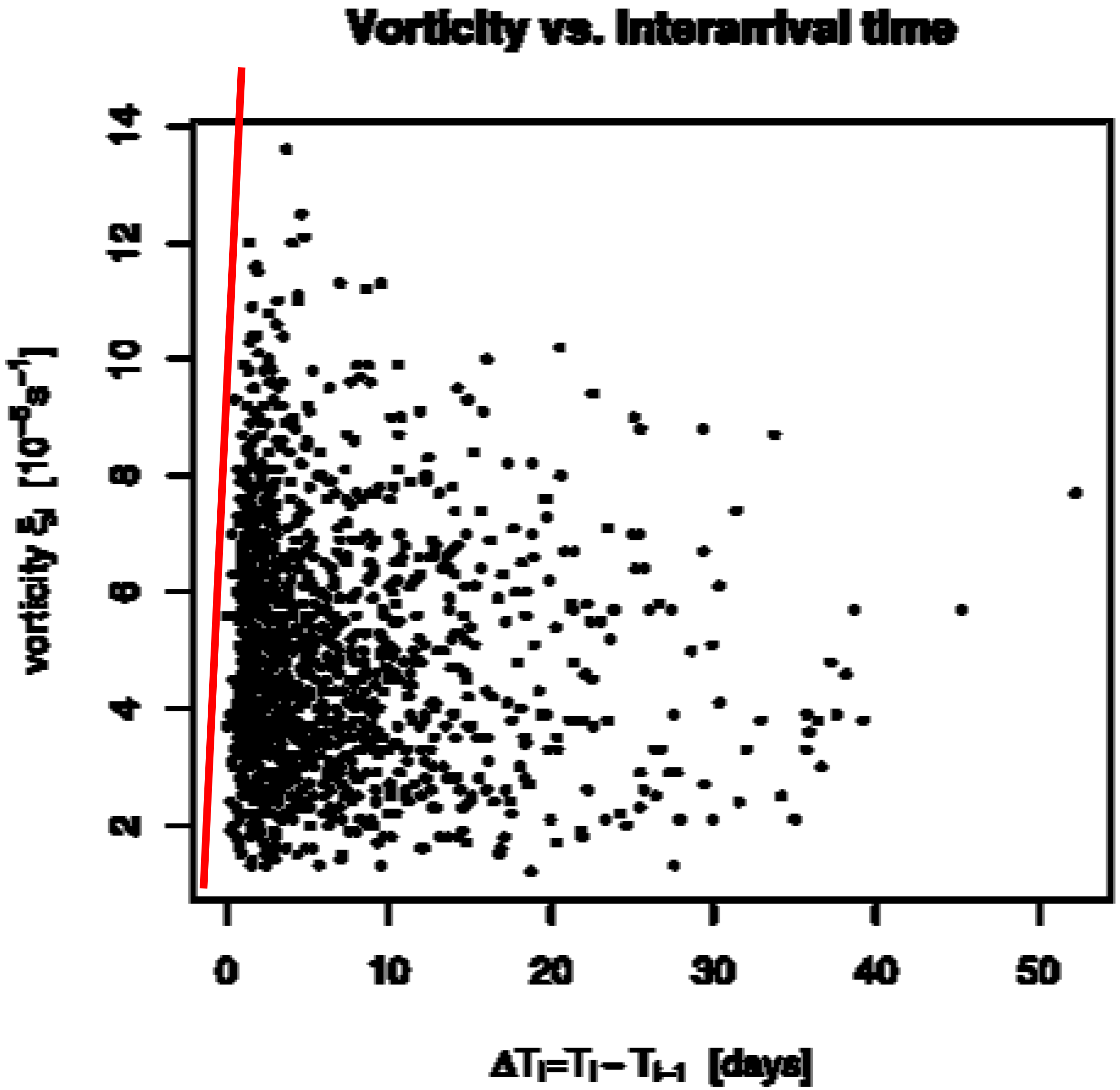
$$\Pr(N = n) = \frac{\Lambda^n e^{-\Lambda}}{n!}$$

$$\Lambda = (t_2 - t_1)\left\{1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right\}^{-1/\xi}$$

$$\to (t_2 - t_1)\exp\left\{-\left(\frac{z-\mu}{\sigma}\right)\right\}$$

when $\xi \to 0$

Distribution of marks & inter-arrival times

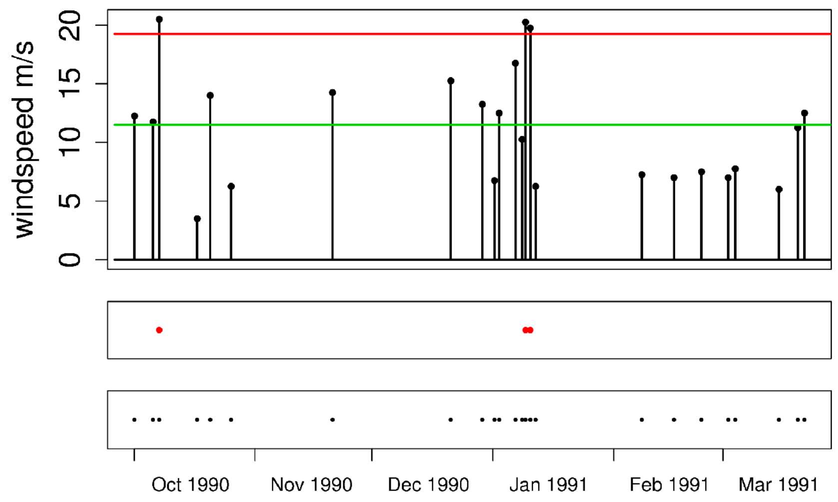


→ More time needed before more intense storms

Modelling times & intensities of extreme storms

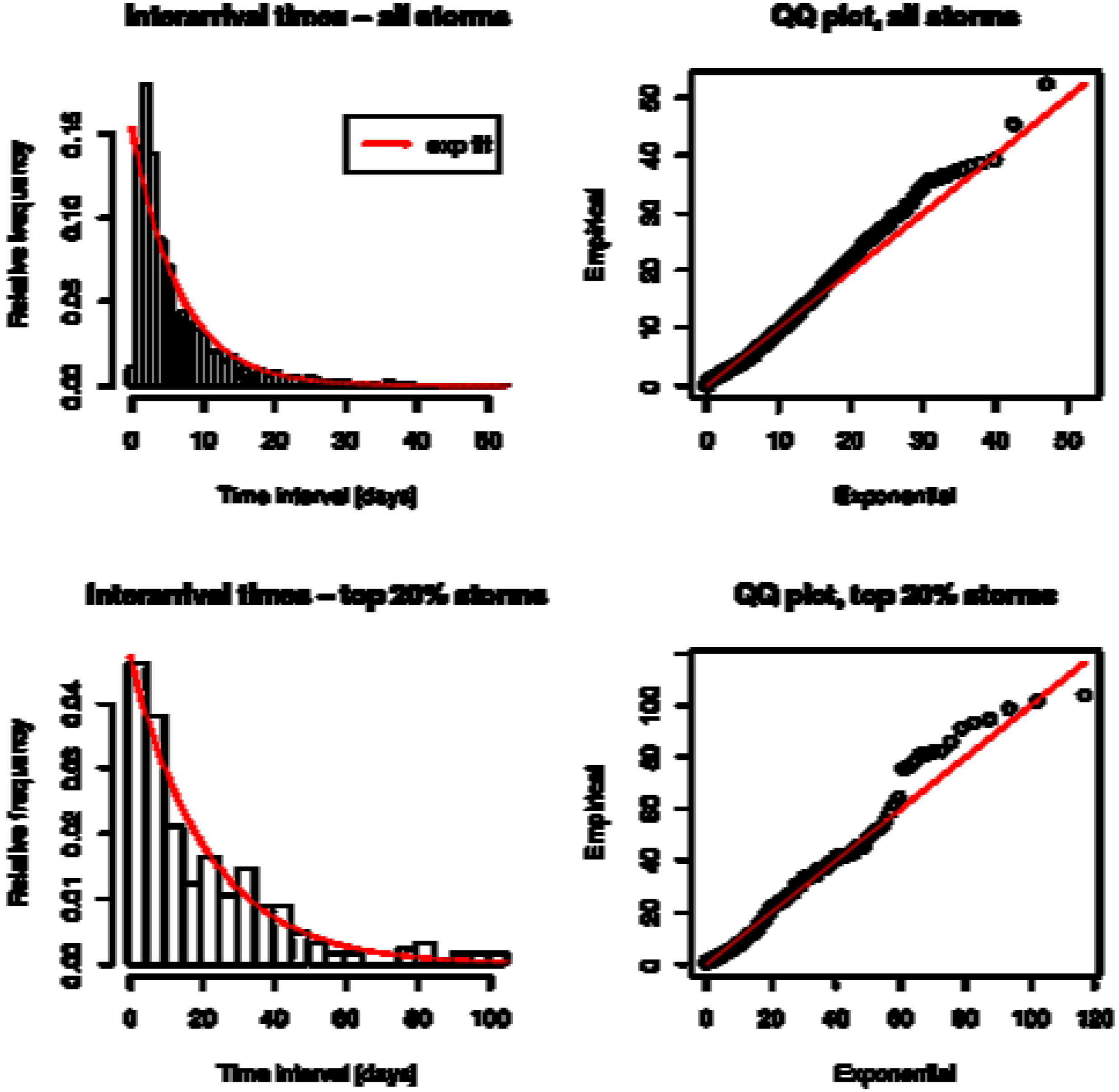
Large-scale flow patterns are known to influence
the growth rate of storms AND the path of the storms.

Hence, we try to capture both these processes by modelling extreme storms as a COMPOUND POISSON PROCESS - a marked point process where the arrival times are independent of the marks (the vorticities).



Start by trying a Poisson process with time-varying rate for the arrival times AND a GPD fit for the marks.
The arrival rate and GPD parameters are allowed to depend on the NAO, EAP, EWP and SCP teleconnection indices (covariates).

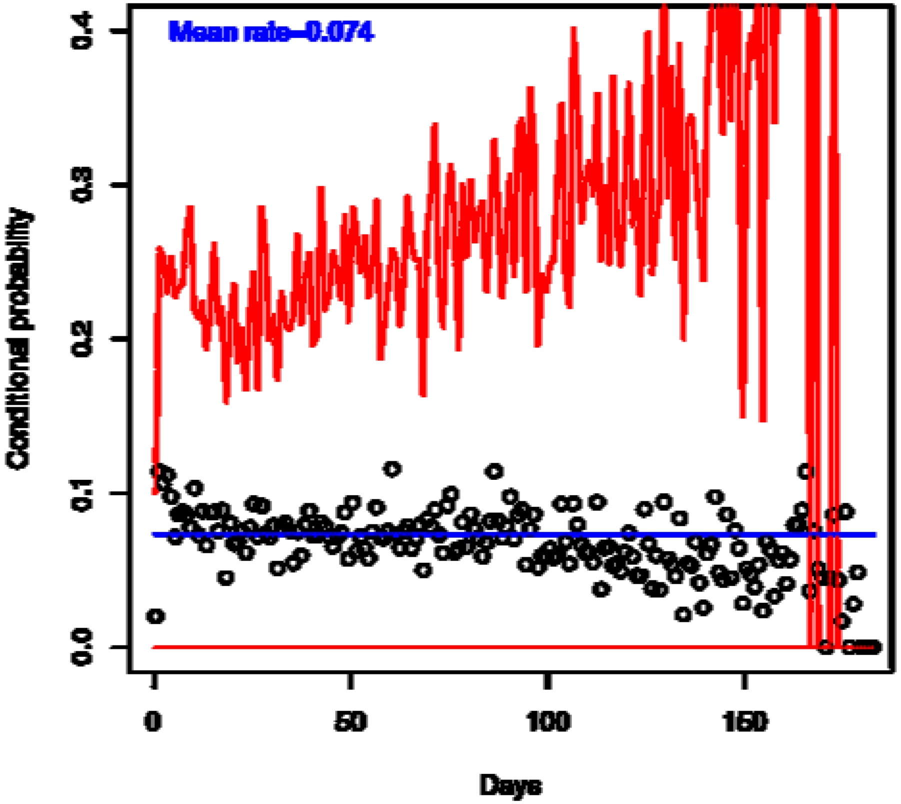
Distribution of inter-arrival times

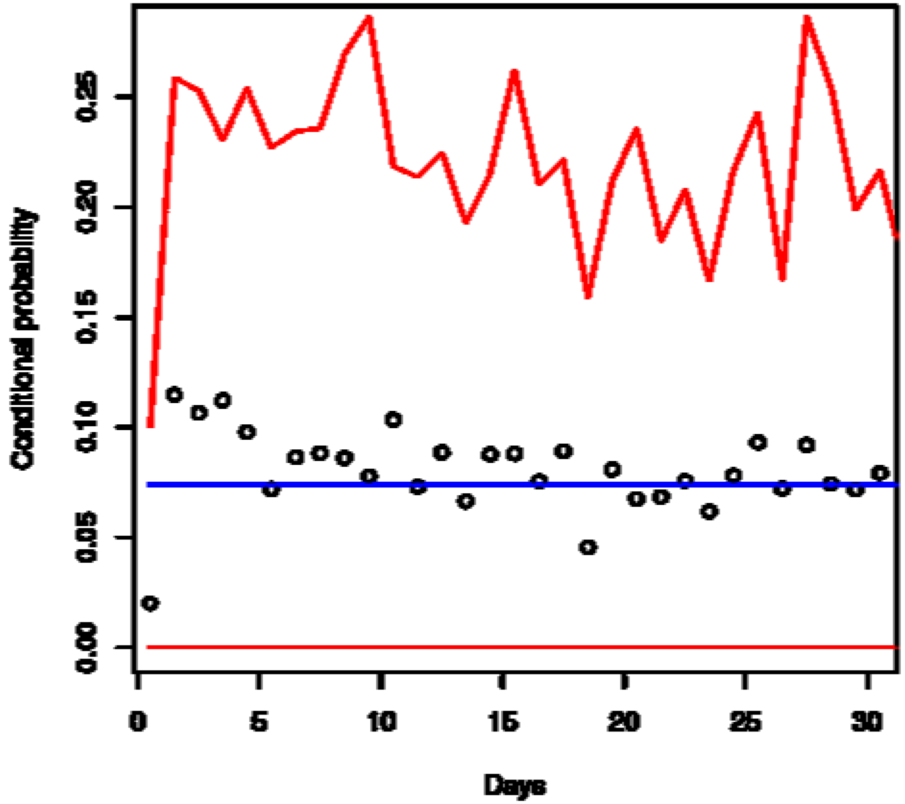


→ Interarrival times are more dispersed than exponential

Auto-intensity function for top 50% most intense storms

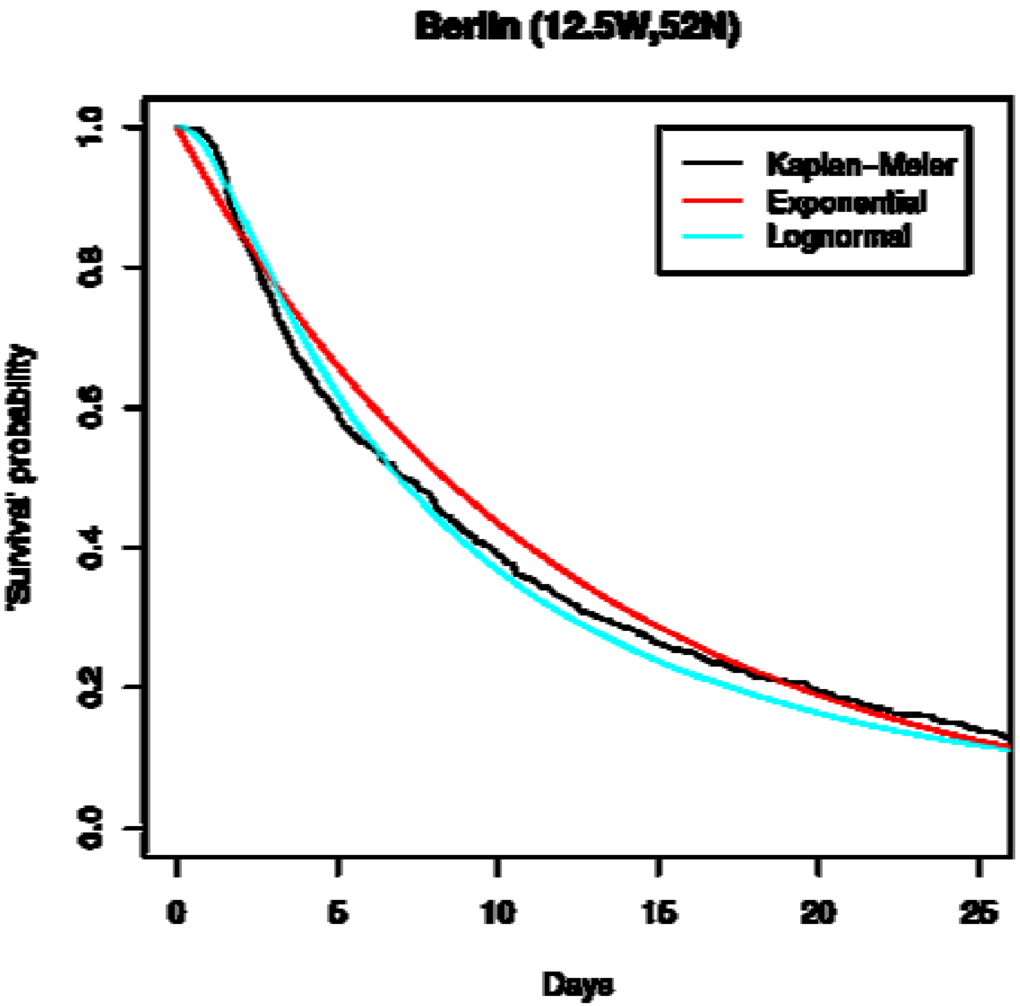
Conditional probability density that an event arrives at time T+ lag, given that an event arrived at time T.





Inhibition at lag=1day. Storms can't arrive too close (hard-core rejection)
Clustering at lag=2,3,4 days. Higher conditional probability of a 2nd storm.

Survival function for 50% most intense storms



→ Log-normal gives a much better fit than does Exponential (or Gamma & Weibull)

Rate-varying Poisson process for arrival times (*)

$$\Delta t \sim Exp(\lambda(t))$$

$$\log \lambda(t) = \beta_0 + \sum_k \beta_k X_k(t)$$

Maximum-likelihood estimates for storms passing Berlin:

	Rate	NAO	EAP	EA/WR	SCA
Beta	2.053	0.092	0.175	-0.25	-0.32
2*SE	0.061	0.067	0.064	0.064	0.062

Statistically significant non-zero effects of EAP, SCA and EA/WR patterns.

* - of top 50% most intense storms

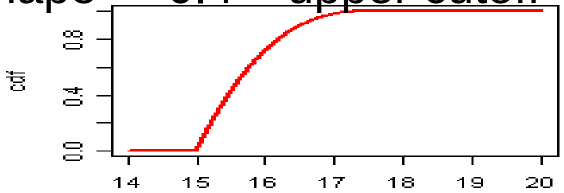
Generalized Pareto Distribution (GPD)

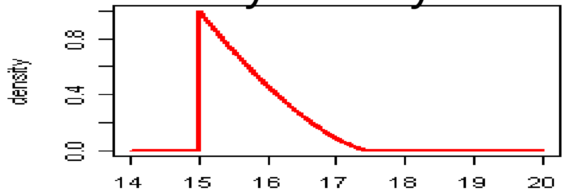
$$F(z) = \Pr\{Z \le z \mid Z > u\} = 1 - \left[1 + \xi\left(\frac{z-u}{\tilde{\sigma}}\right)\right]^{-1/\xi} \qquad \tilde{\sigma} = \sigma + \xi(u - \mu)$$

$$\Rightarrow f(z) = \frac{dF}{dz} = \frac{1}{\tilde{\sigma}}\left[1 + \xi\left(\frac{z-u}{\tilde{\sigma}}\right)\right]^{-1-1/\xi} \rightarrow \begin{cases} 0 & \text{when } z \ge u - \tilde{\sigma}/\xi = \mu - \sigma/\xi \\ \tilde{\sigma}^{-1}\exp(-z/\tilde{\sigma}) & \\ \frac{1}{\tilde{\sigma}}\left(\frac{\xi z}{\tilde{\sigma}}\right)^{-(1+1/\xi)} & \end{cases}$$

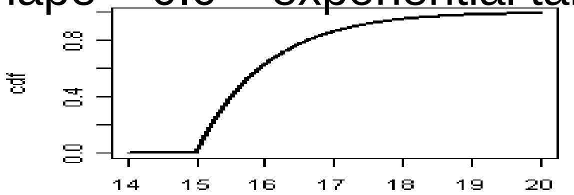
Shape = -0.4 – upper cutoff

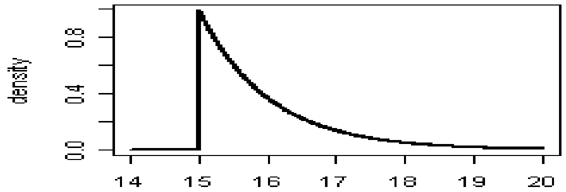
Probability density function



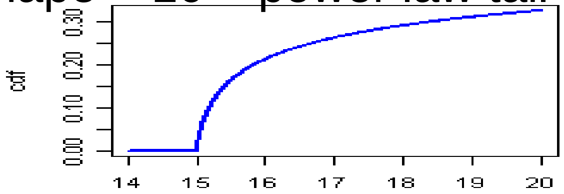


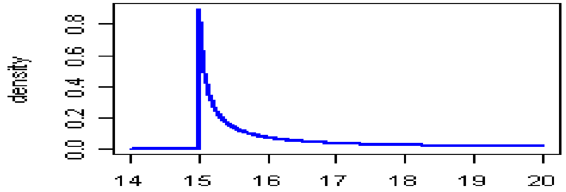
Shape = 0.0 – exponential tail



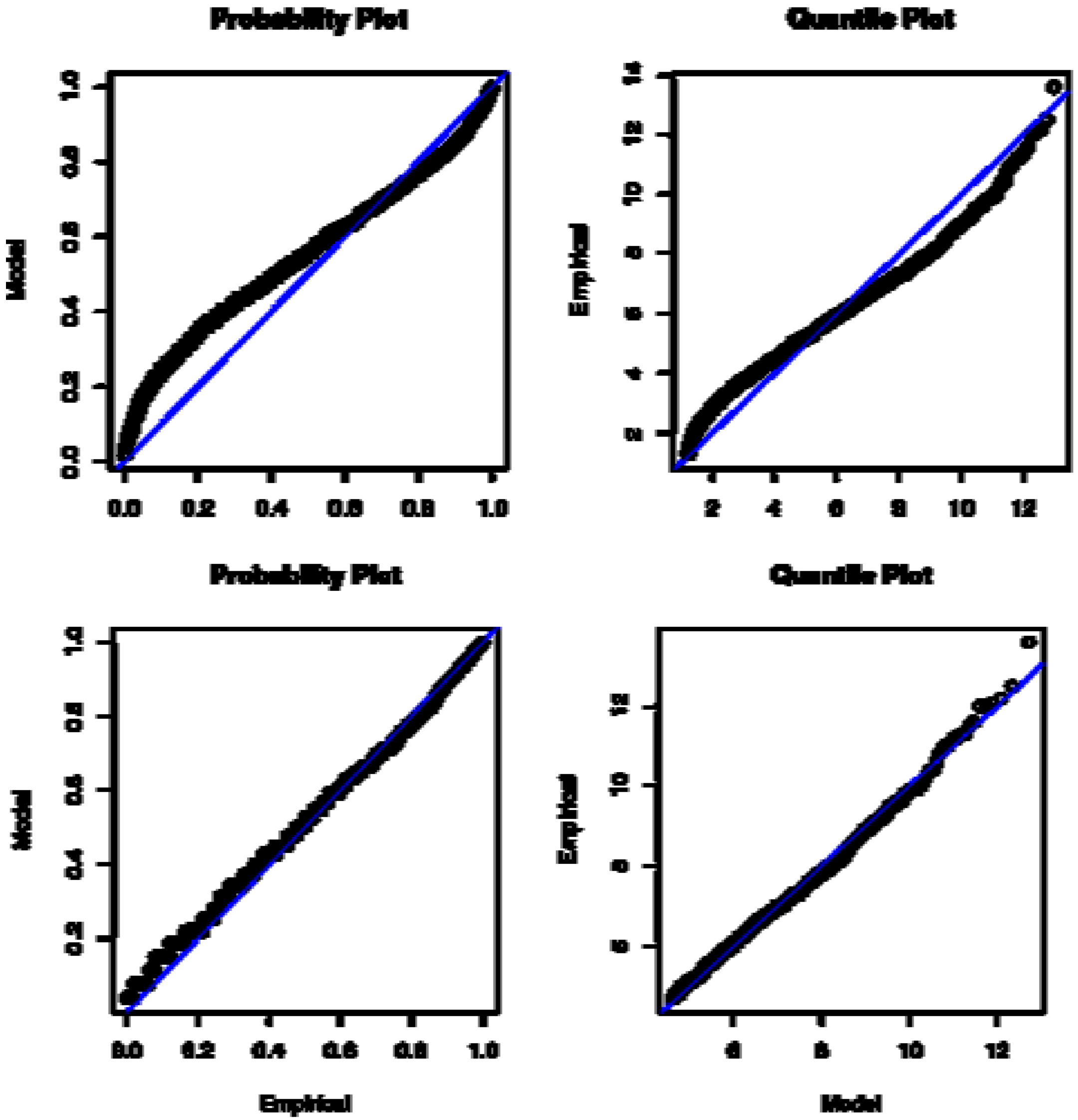


Shape = 10 – power law tail





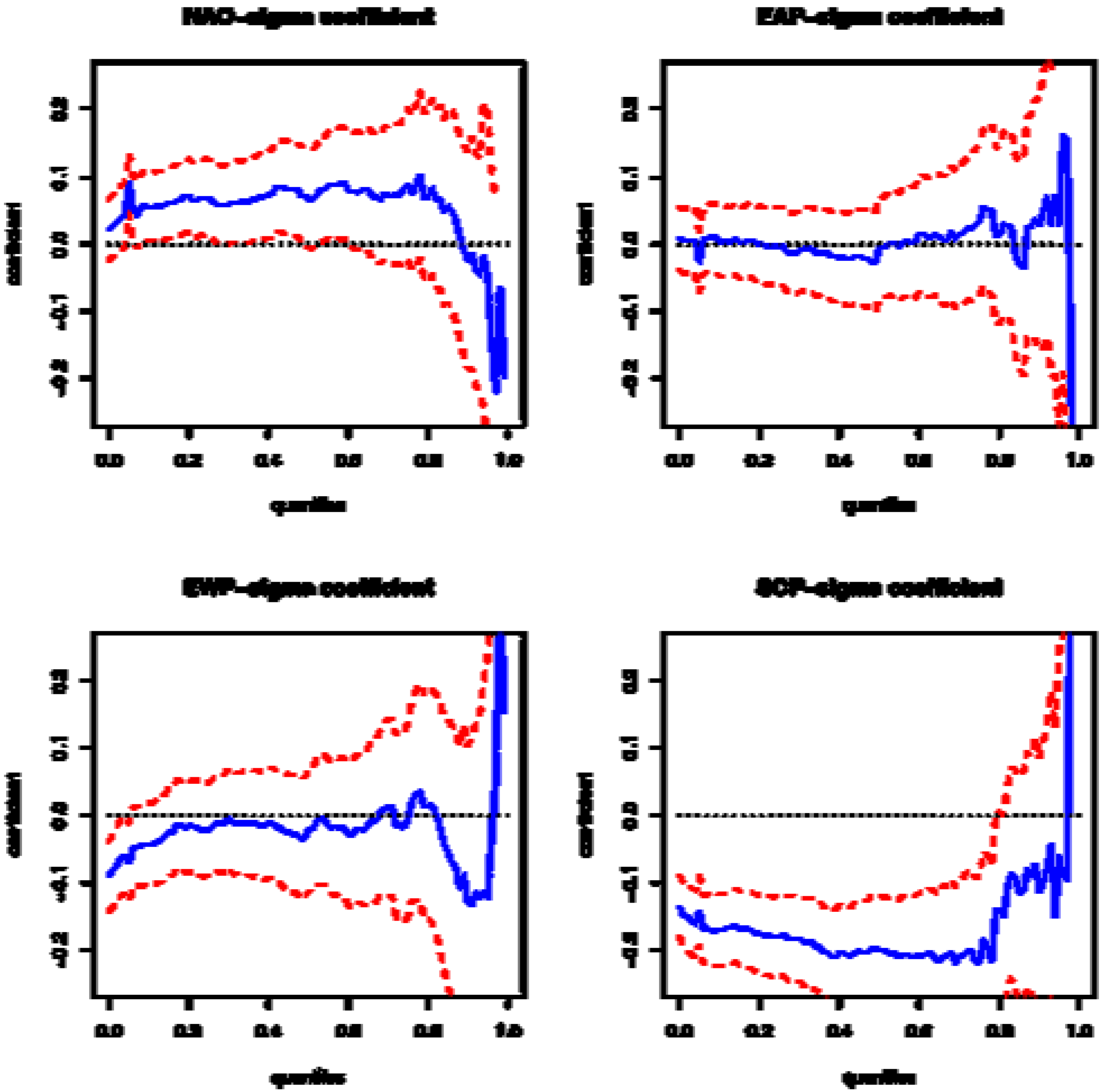
How well does Generalised Pareto Distribution fit the vorticity marks at Berlin?



All storms:
Not a good fit

Storms with vorticity > 50% quantile:
Much better fit

Including teleconnection covariates in the GPD



$$Y \sim GPD(\sigma, \xi)$$

$$\log \sigma = \alpha_0 + \sum_k \alpha_k X_k(t)$$

Blue: estimate of alpha
Red: estimate ± 2 s. error

Summary

- Extratropical wintertime storms cluster esp. over NW Europe;
- Dispersion of counts increases for more intense storms;
- Dispersion of counts increases for longer count periods;
- Large-scale teleconnection indices can account for this overdispersion;
- Interarrival times show clustering (and inhibition)
- Have started to use a compound Poisson-GPD process to model the extremes but may need a compound renewal-GPD process

References

Mailier, P.J., Stephenson, D.B., Ferro, C.A.T. and Hodges, K.I. (2006):
Serial clustering of extratropical cyclones
Monthly Weather Review, 134, pp 2224-2240

Vitolo, R., Stephenson, D.B., Cook, I.M. and Mitchell-Wallace, K. (2008):
Serial clustering of intense European storms
Meteorologische Zeitschrift (in press).

Seierstad, I.A., Stephenson, D.B., and Kvamsto, N.G. (2007):
How useful are teleconnection patterns for explaining variability in extratropical storminess?
Tellus A, 59 (2), pp 170–181

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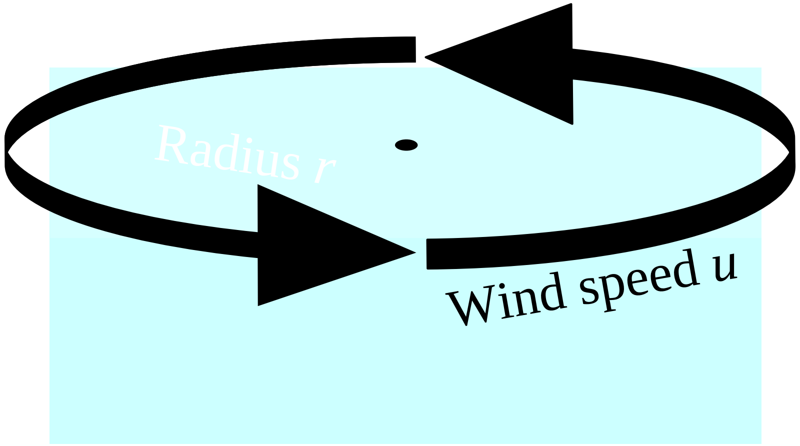
One small
step ...

Relative Vorticity : the "spin"



$$VORTICITY = \frac{CIRCULATION}{AREA} \approx \frac{u \; 2\pi r}{\pi r^2}$$

$$= 2\frac{u}{r}$$

$$= 2\,\Omega\,.$$

e.g.: wind speed of 15 m/s and radius of 500 km → vorticity of 6x10^-5 /s.

Why use relative vorticity instead of SLP?

- More prominent small-scale features allow earlier detection
- Much less sensitive to the background state
- Directly linked with low-level winds (through circulation) and precipitation (through vertical motion)