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How are cumulative storm losses related?

A framework for understanding the correlation between aggregated losses of compound events

Toby P Jones, David B Stephenson & Matthew Priestley

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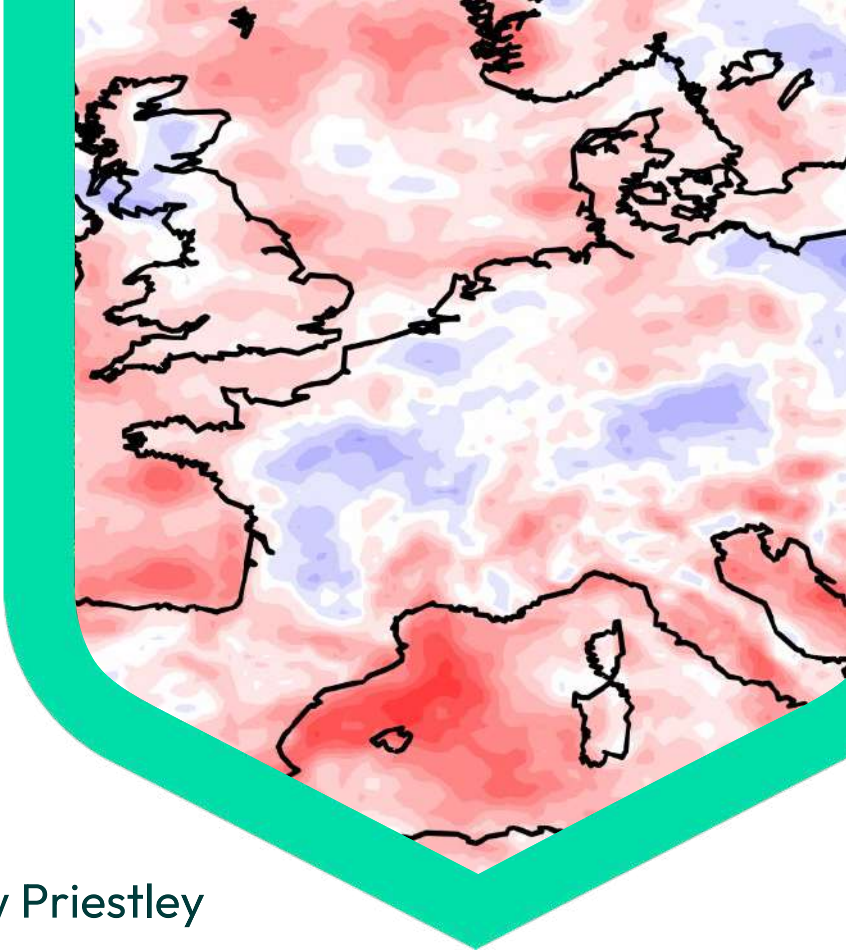

Motivation

- Storm losses from individual events large, particularly aggregated over a winter / calendar year

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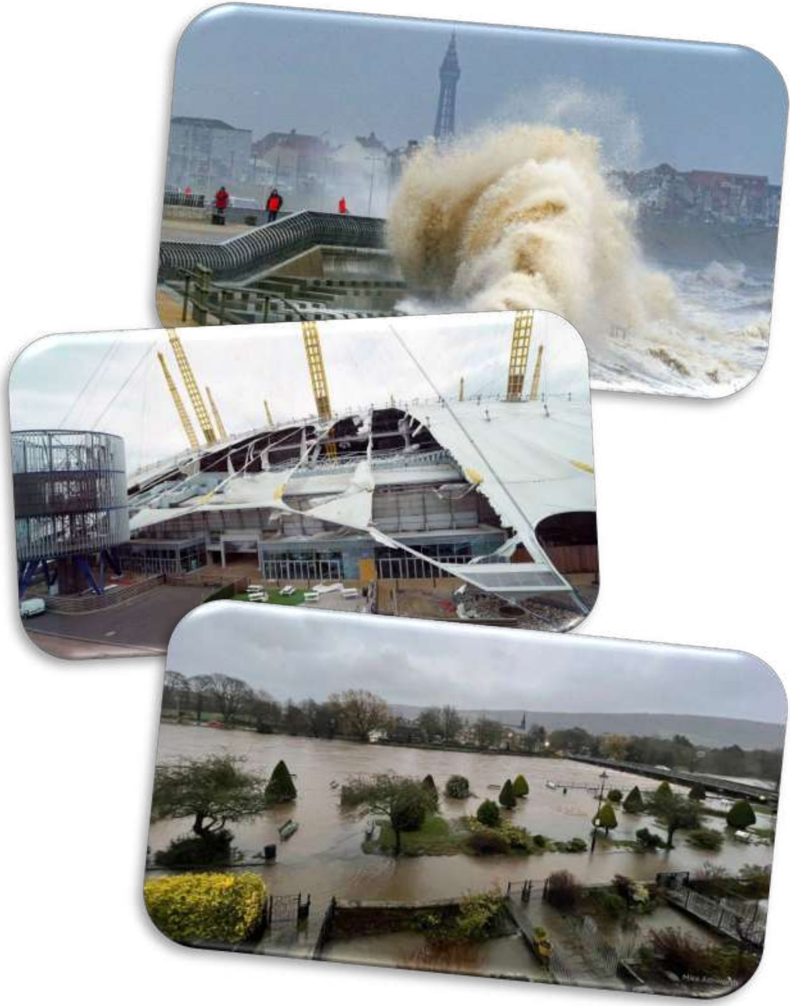
- Can we model the relationship between these aggregate risks?



Storms Dudley, Eunice and Franklin. Source: BBC

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Motivation

- Storm losses from individual events large, particularly aggregated over a winter / calendar year.
- Compound events are multi hazard: wind damage and rain causing flooding.
- Can we model the relationship between these aggregate risks?
- If so, what drives the relationship? Based on current knowledge, how may it change in the future?

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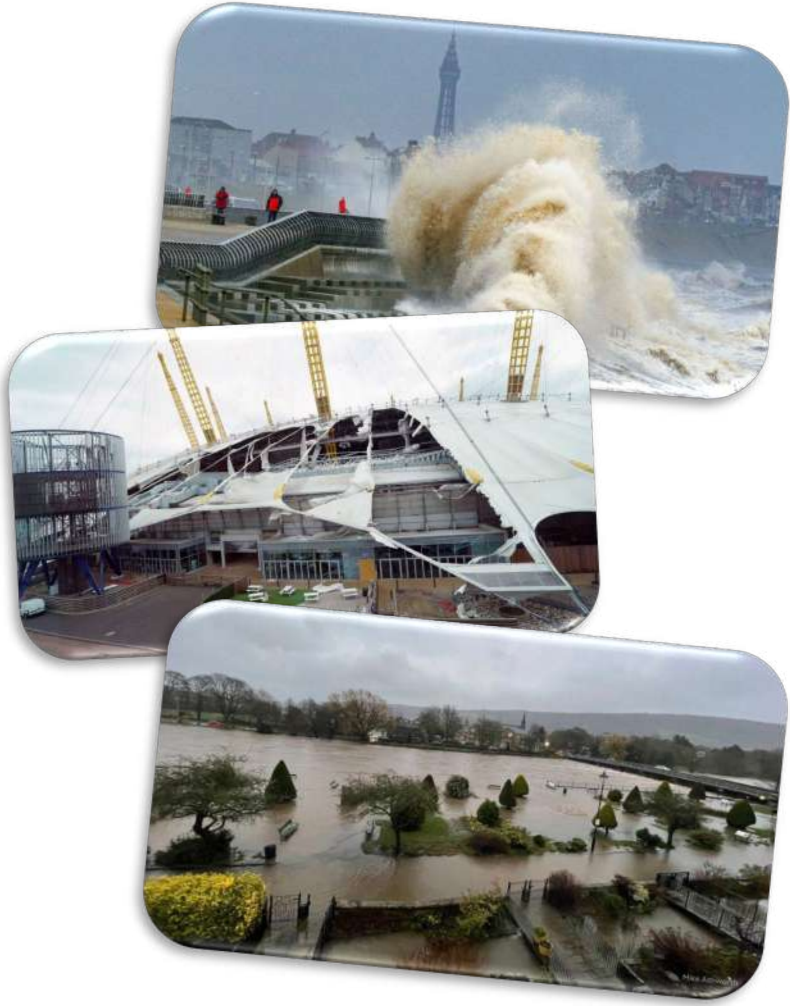

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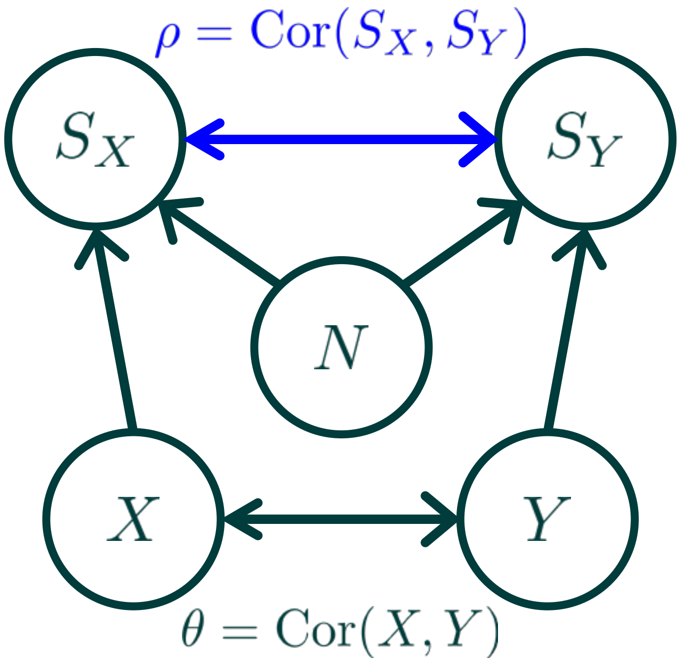
Framework



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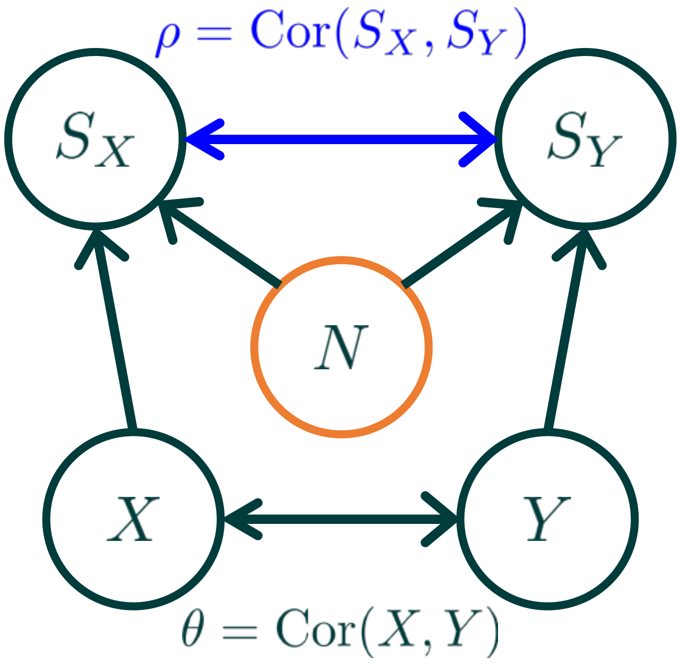
Framework

- We observe N events in a given time period (e.g year)



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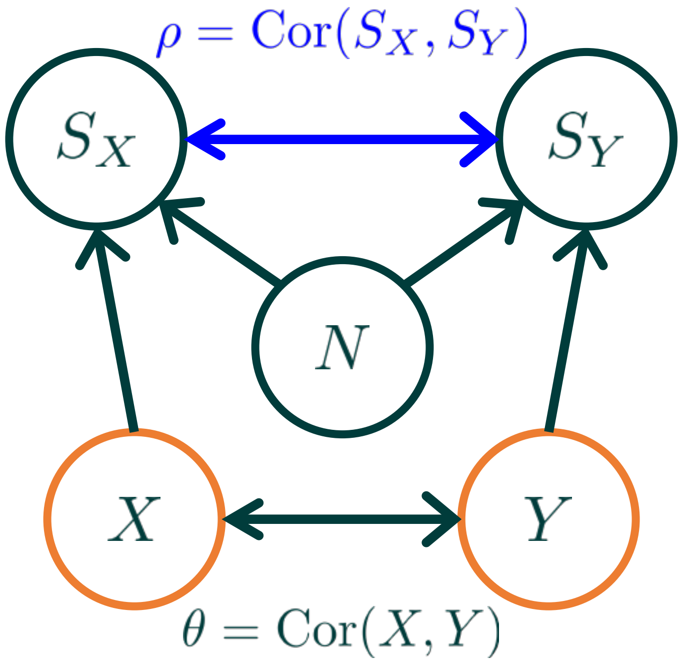
- We observe N events in a given time period (e.g year)

- Individual compound event i causes random losses X_i and Y_i



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- We observe N events in a given time period (e.g year)
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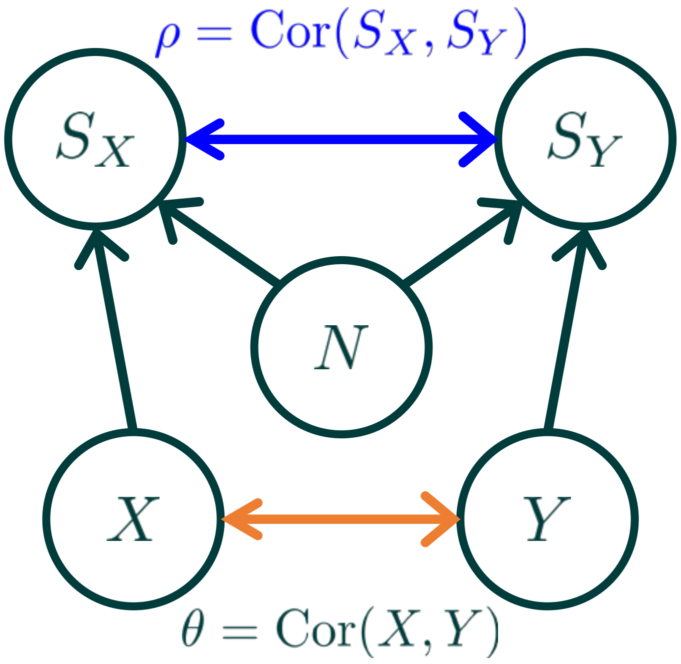
- Define relationship between X_i and Y_i to be $\theta = \mathrm{Cor}(X, Y)$.



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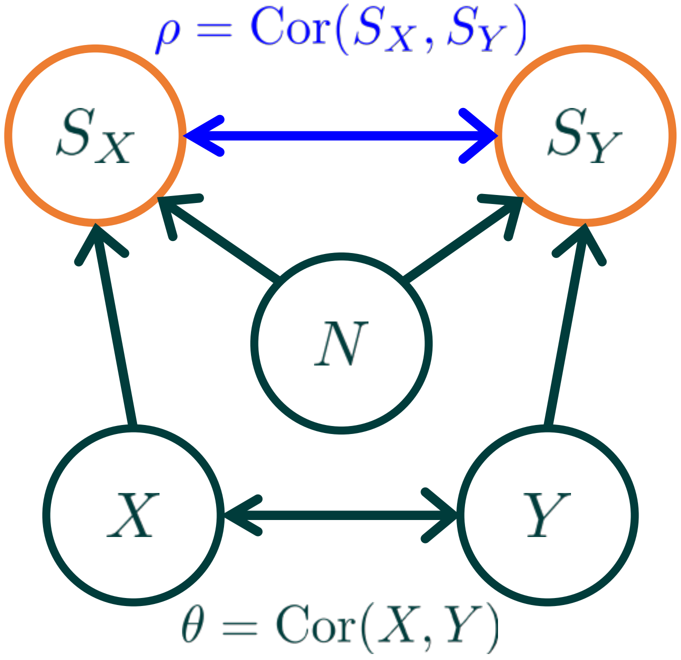
- Define aggregate losses over period:

$$S_X = X_1 + \ldots + X_N$$
$$S_Y = Y_1 + \ldots + Y_N$$



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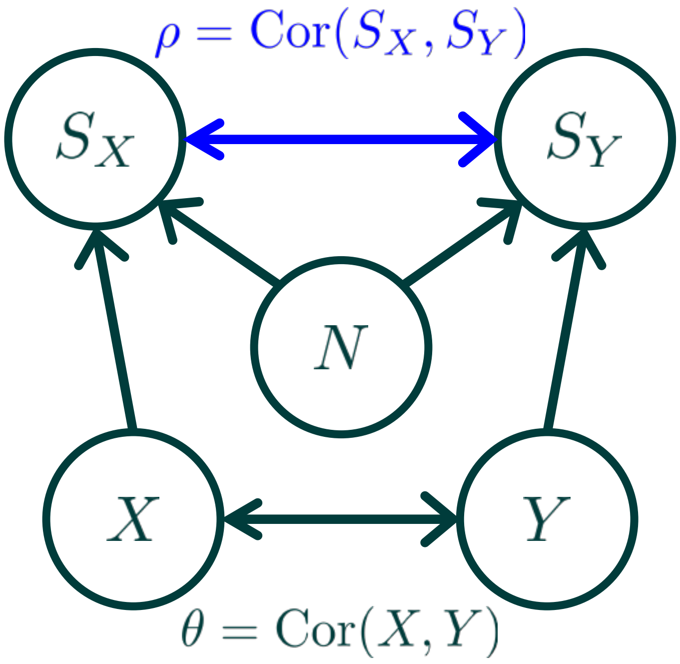
Framework

- Known results for the mean and variance of aggregate risk:



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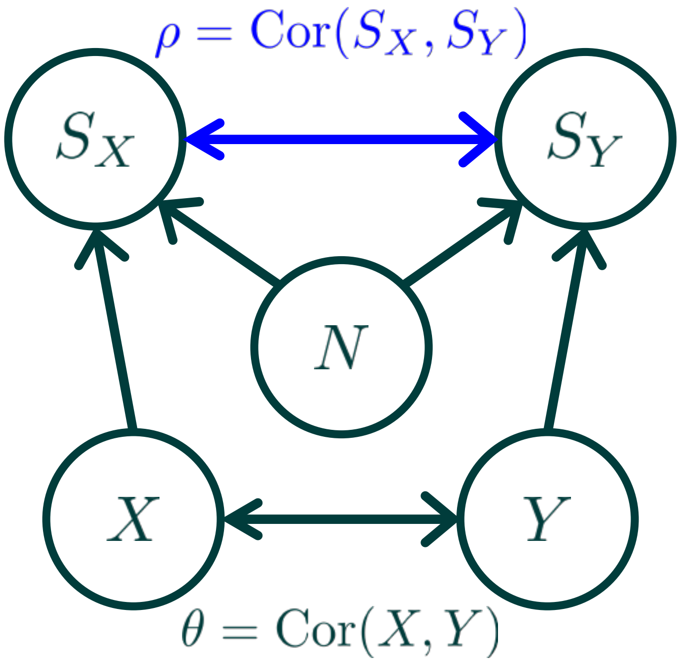
$$E[S_X] = E[N]E[X]$$

Wald (1945)



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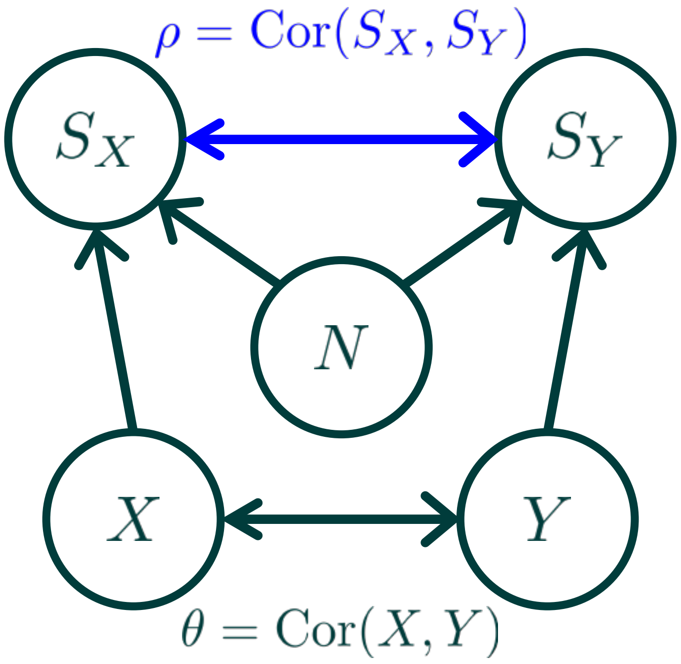
$$\mathrm{Var}(S_X) = \mathrm{E}[N]\mathrm{Var}(X) + \mathrm{E}[X]^2\mathrm{Var}(N)$$

Blackwell and Girschick (1947)



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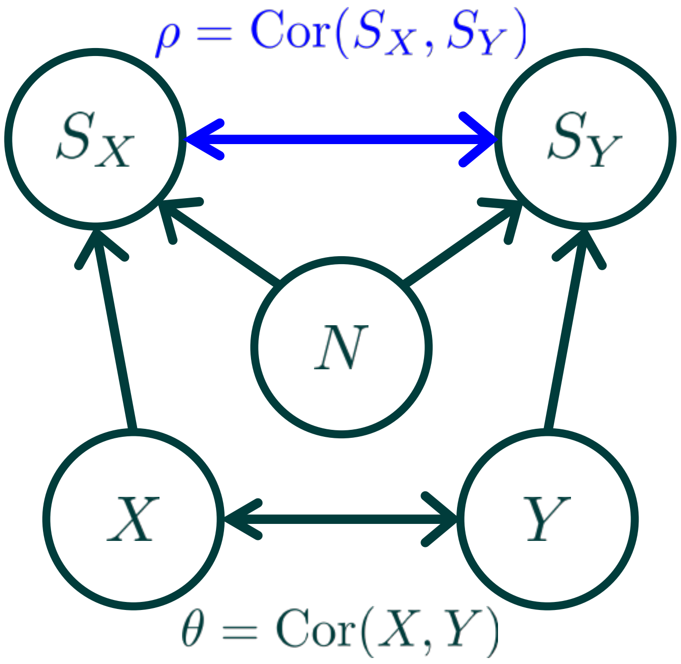
- Can then find the covariance:

$$\mathrm{Cov}(S_X, S_Y) = E[N]\mathrm{Cov}(X, Y) + \mathrm{Var}(N)E[X]E[Y]$$



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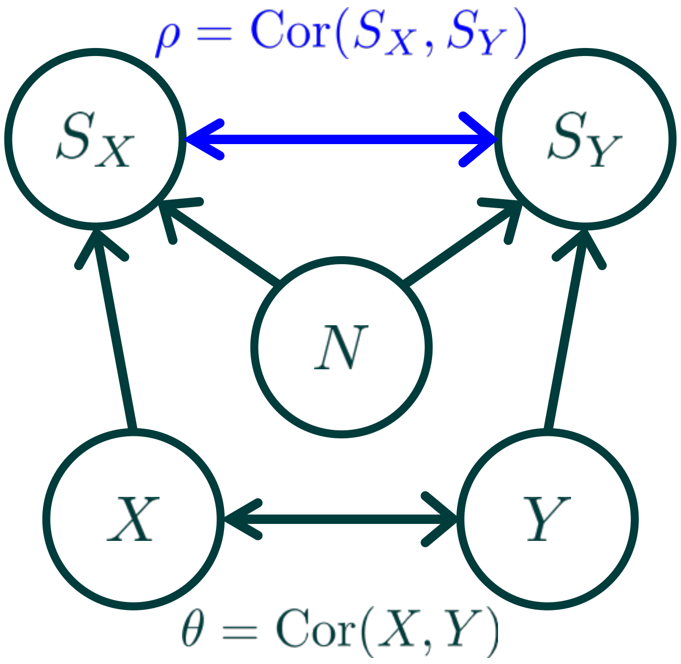
Framework

- With covariance easy to obtain expression for correlation:

$$\rho = \frac{\theta + \phi J_X J_Y}{\sqrt{(1 + \phi J_X^2)(1 + \phi J_Y^2)}}.$$



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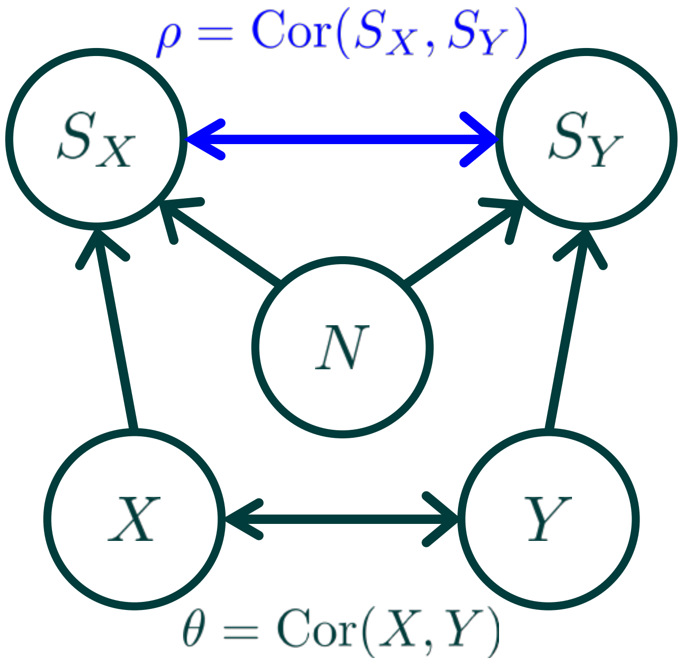

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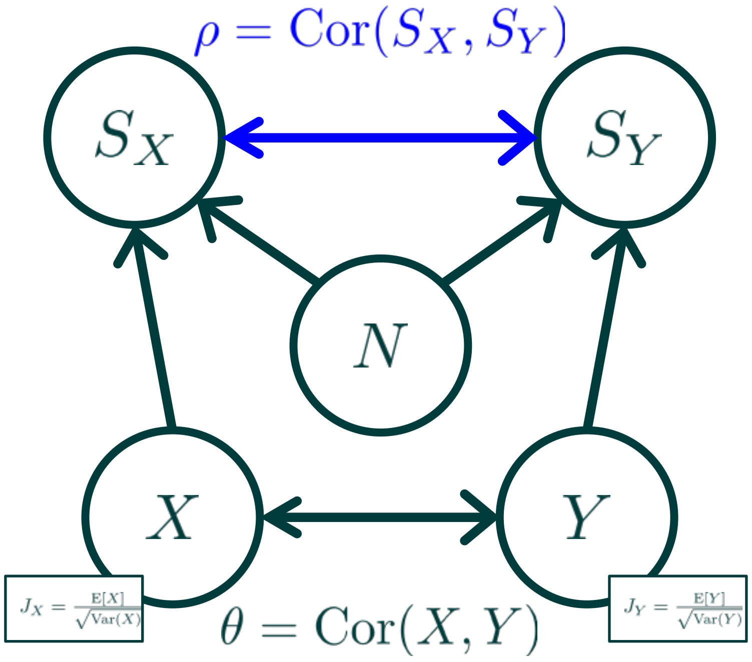

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Framework

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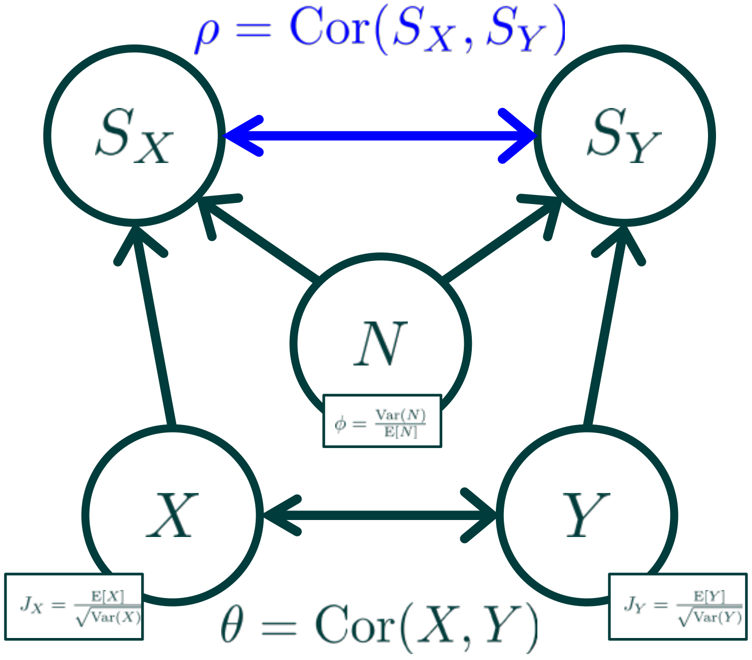
- θ – Correlation between X and Y
- $J_X = \frac{\mathrm{E}(X)}{\mathrm{sd}(X)}$ - ratio of mean to standard deviation of X (same for J_Y).
- $\phi = \frac{\mathrm{Var}(N)}{\mathrm{E}[N]}$ - dispersion statistic, measure of event clustering.



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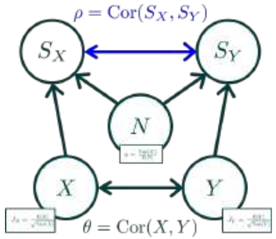
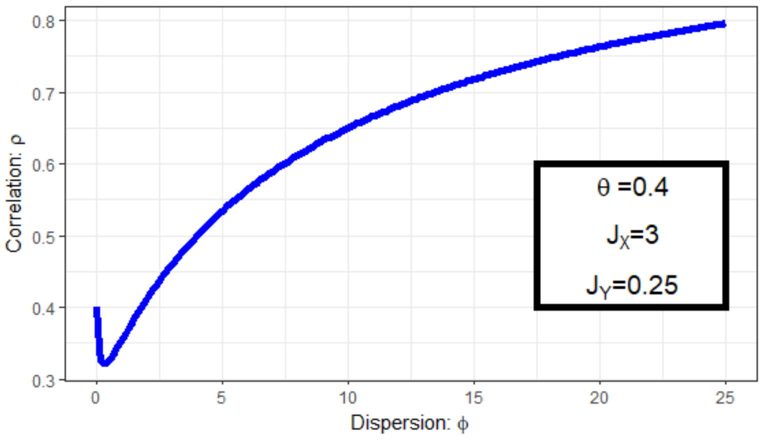
Theoretical Results

- Dispersion statistic influences correlation, with $\lim_{\phi \to \infty} \rho = 1$ and $\lim_{\phi \to 0} \rho = \theta$.

$$\rho = \frac{\theta + \phi J_X J_Y}{\sqrt{(1 + \phi J_X^2)(1 + \phi J_Y^2)}}.$$





Correlation increasing with clustering, showing ability to decrease first.

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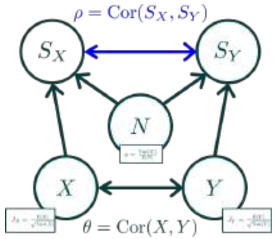
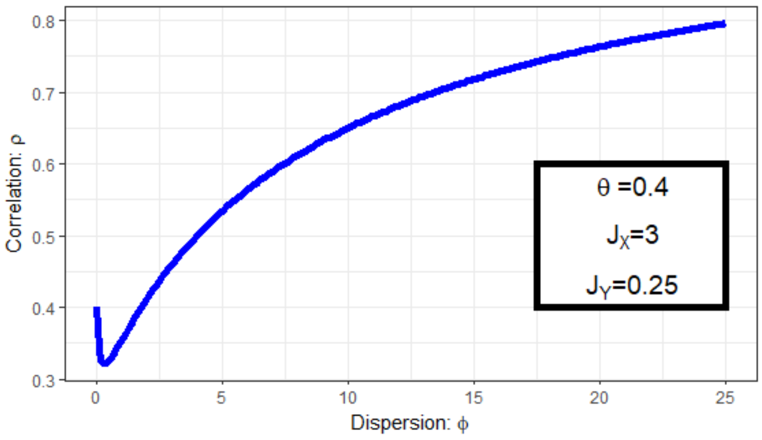
- Correlation increases with clustering (i.e $\frac{\partial \rho}{\partial \phi} > 0$) dependent on value of θ.
  - True for ~98% of the region we investigated.





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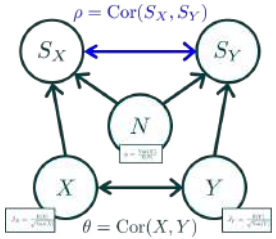
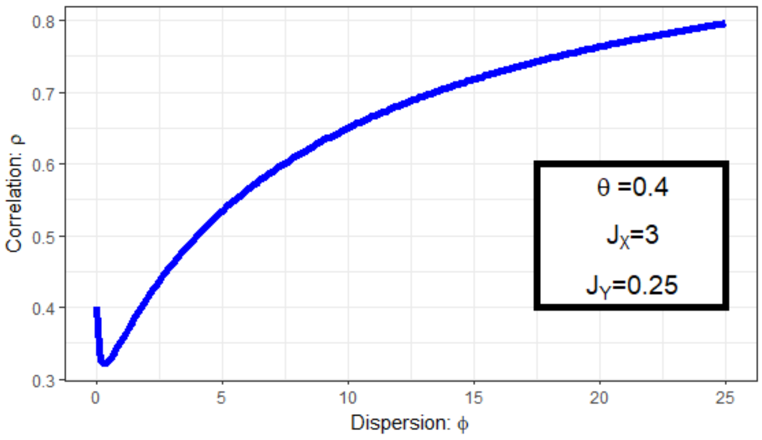
- Correlation increases with clustering (i.e $\frac{\partial\rho}{\partial\phi} > 0$) dependent on value of θ.
  - True for ~98% of the region we investigated.
- Economou et al. (2015) predicted an increase in clustering of extreme storms in Europe – greater correlation between aggregate risks?

$$\rho = \frac{\theta + \phi J_X J_Y}{\sqrt{(1+\phi J_X^2)(1+\phi J_Y^2)}}.$$





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Test case data

- "Test-case" using ERA5 data (1980-2020), hourly observations over a 0.25° grid.
- X_i is maximum value of 10m wind gusts exceedances above 20m/s from 5° radius of storm track's centre.
- Y_i is cumulative rainfall over 10mm from 10° radius of storm track's centre.
- N is number of tracks passing through grid point.

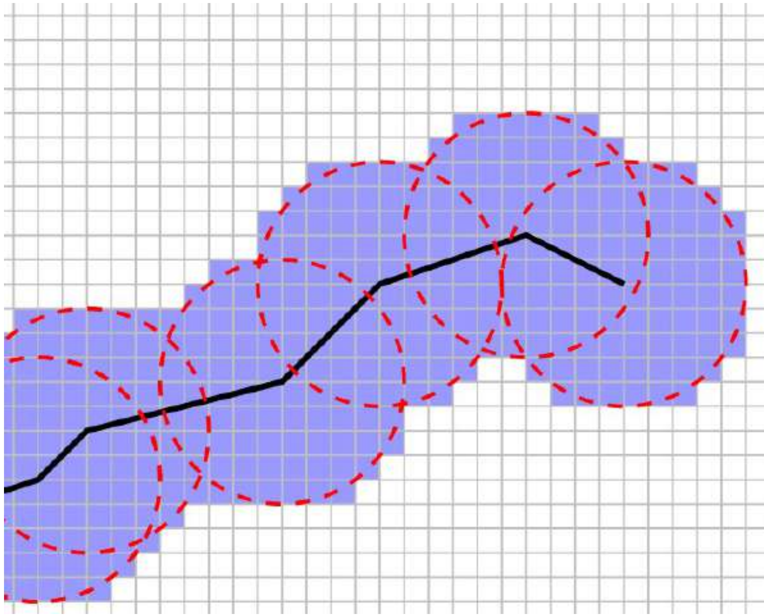

Illustration of storm track (black line) and it's radius of influence (red circle) with grid points affected by the storm in purple.

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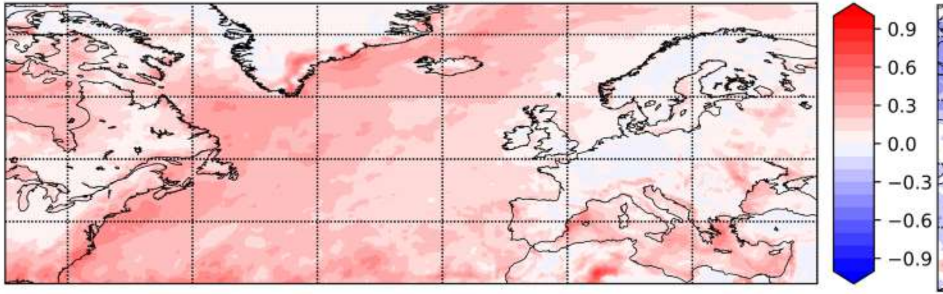
Test case results

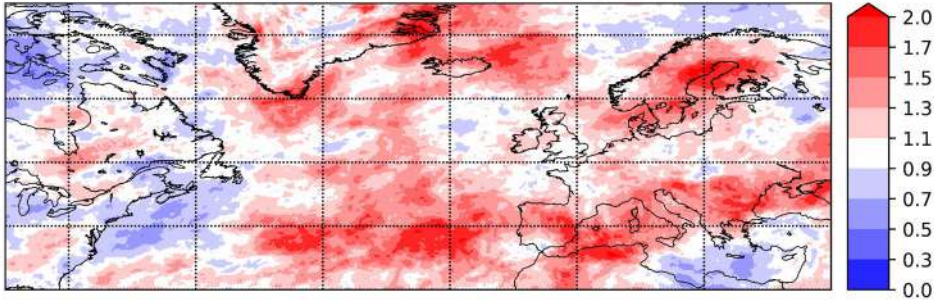
θ (Correlation between X and Y)

Exceedances above 20m/s & 10mm.



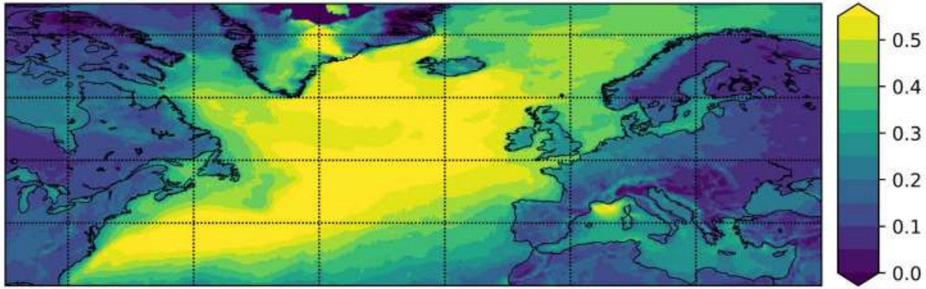
$\phi = Var(N)/E[N]$

Exceedances above 20m/s & 10mm.



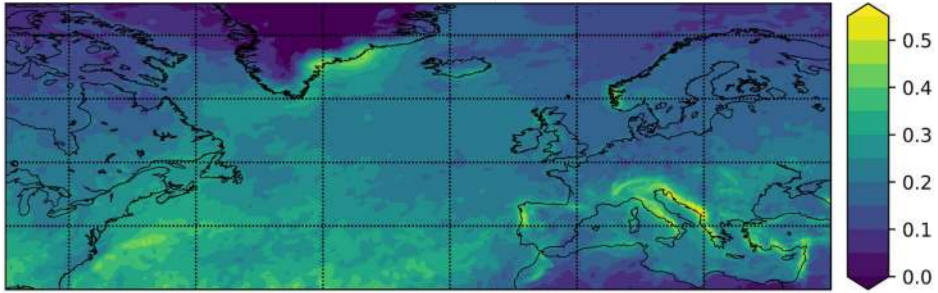
$J_X = E[X]/sd(X)$

Exceedances above 20m/s & 10mm.



$J_Y = E[Y]/sd(Y)$

Exceedances above 20m/s & 10mm.



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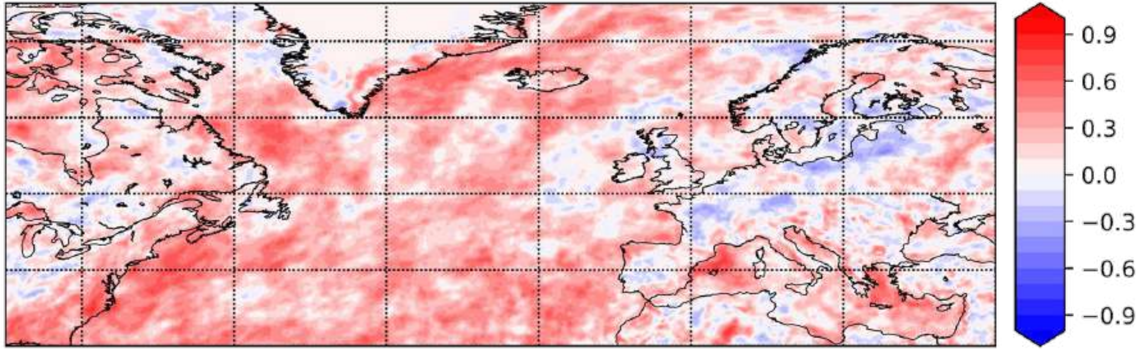
Test case results

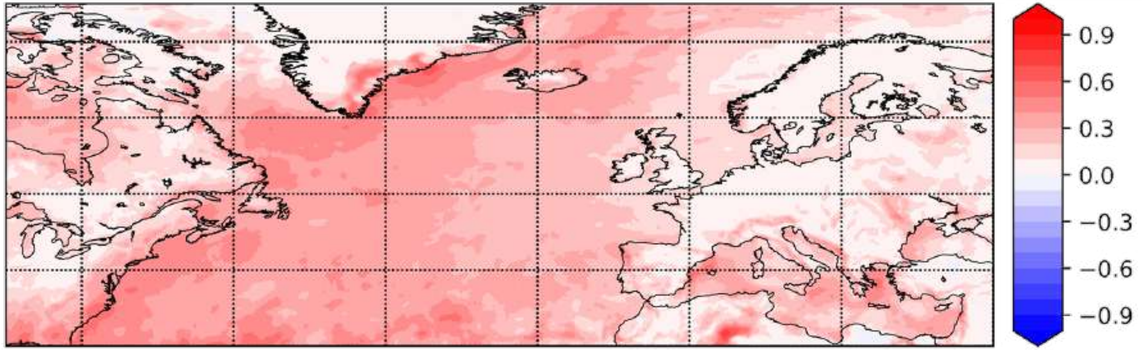
Sample correlation (top)

- Strong positive correlation over ocean
- Weaker and negative areas over land
- "Rough" with no distinct patterns



Predicted correlation (bottom)

- Captures positive ocean and weaker land correlation well
- Cannot reproduce negative values
- Picks up general trend in a smoothed way



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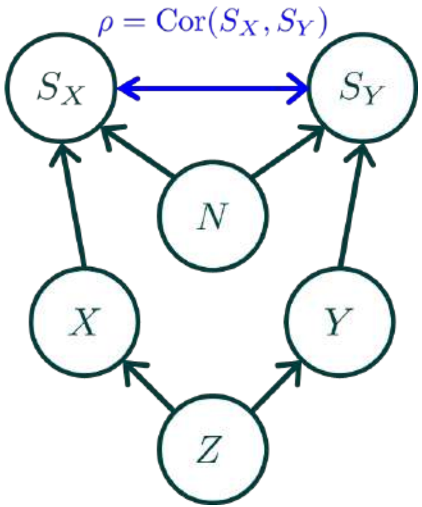
Next steps

- Extend the framework to include time-varying climate modulators.
  - e.g. dependency of storm intensity on teleconnection indices (Z).
  - Promising early work on this so far!



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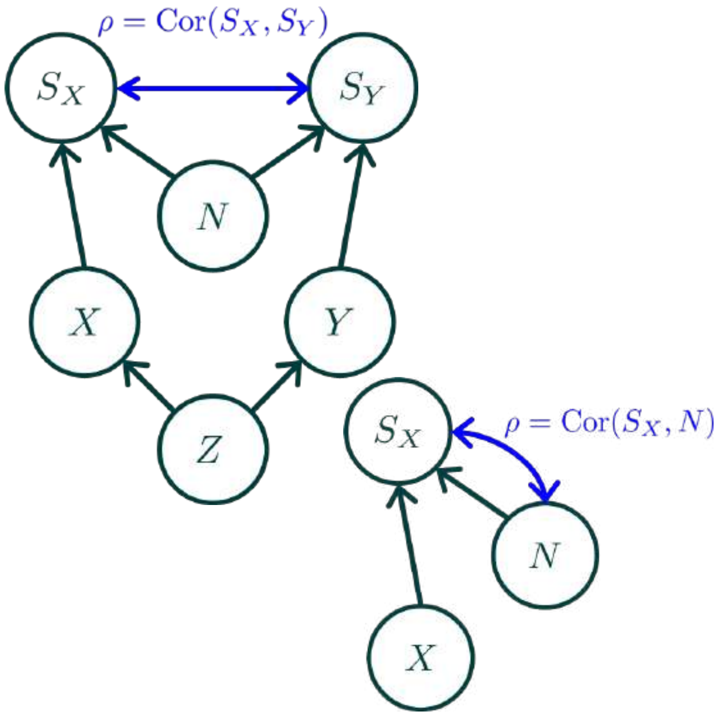
- Correlation between aggregate risk and storm frequency



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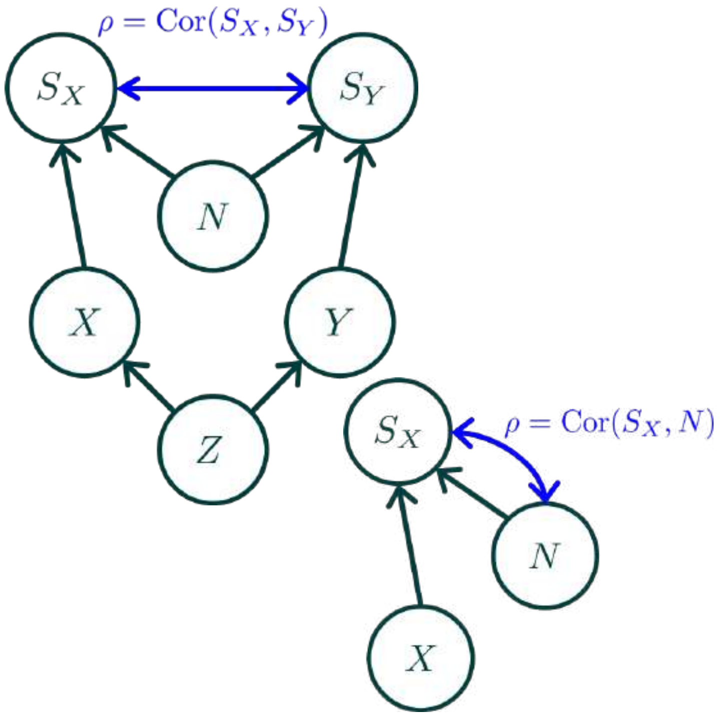
- Correlation between aggregate risk and storm frequency

- Adaptation to correlation between different non-gridded locations, e.g. cities or districts



$$\mathrm{Cor}(S_{X_i}, S_{X_j}) = ?$$

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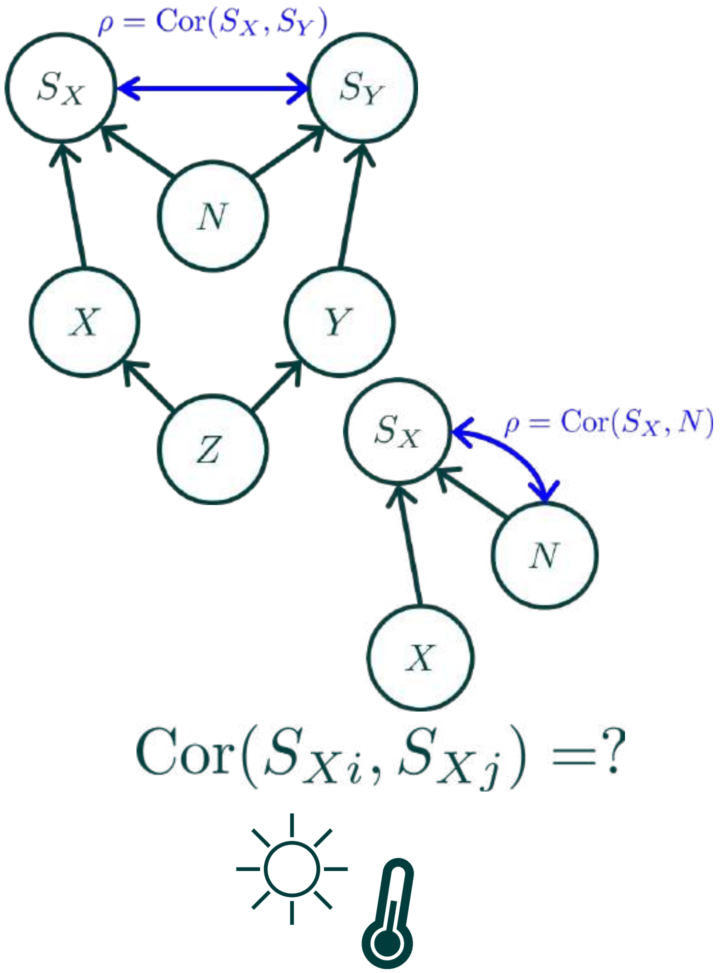
- Correlation between aggregate risk and storm frequency
- Adaptation to correlation between different non-gridded locations, e.g. cities or districts
- Extension to other compound extremes e.g. compound dry hot events.



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Summary

- More storm clustering (usually) increases correlation between aggregate risks.

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Summary

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- Simple framework captures general ocean/land trend.

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- More storm clustering (usually) increases correlation between aggregate risks.
- Simple framework captures general ocean/land trend.
- Future work involves changing dependency structure with promising work currently in progress.
- Adapt framework to correlation between locations and to other compound extremes.

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