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bedartha@Precision-5540:projects$ csvlook -d , presentation_schedule.csv
| Date | Time | Team | Topic
|-----|-----|-----|-----
| 2021-07-21 | 10.00 | Carmen & Michael | Spatial pattern of West European surface temperatures from CNNs
| 2021-07-21 | 10.15 | Stefan & Alexander | Spatial pattern of average wind speeds over West Europe using CNNs
| 2021-07-21 | 10.30 | Johannes & Adrian | Regions of similar behaviour for West European rainfall from climate network communities
| 2021-07-21 | 10.45 | Dorothee & Frieder | Latent factors underlying West European surface temperatures from EOFs
| 2021-07-21 | 11.00 | Leonard & Rosanna | Prediction of West Europe surface temperatures using LSTMs
| 2021-07-21 | 11.15 | Ludwig & Christian | Rainfall over West Europe as a correlate of North Atlantic Oscillation (NAO)
| 2021-07-21 | 11.30 | Merle & Mara | Predicting spatial pattern of West European rainfall using CNNs
| 2021-07-28 | 10.00 | Felix & Moritz | Causal maps between NAO and WE precipitation
| 2021-07-28 | 10.15 | Kari & Naman | Mortality rates in West Europe modeled using cold / warm extremes
| 2021-07-28 | 10.30 | Tim & Shiaw-Shiuan | Predicting West European surface temperatures using Gaussian processes
| 2021-07-28 | 10.45 | Effi & Ricarda | Economic indicators of West European countries modeled using climatic observables
| 2021-07-28 | 11.00 | Jolanda & Robert | Predicting West European rainfall using LSTMs
| 2021-07-28 | 11.15 | Gereon & Josua | Regions of similar behaviour for average wind speeds over WE from climate network communities
| 2021-07-28 | 11.30 | Julian & Dexter | Latent factors underlying West European surface temperatures using VAEs
|-----|-----|-----|-----|
```

bedartha@Precision-5540:projects\$ █

LECTURE 8: Climate networks

ML-4430: Machine learning approaches in climate science

16 June 2021

What are climate networks

1

- How do we estimate climate networks?
- What do they tell us?

Avoiding potential pitfalls

2

- Autocorrelation (Palus et al., 2009)
- Boundary effects (Rheinwalt et al., 2011)
- Spatial embedding (Boers et al., 2019)

Networks from Graphical Models

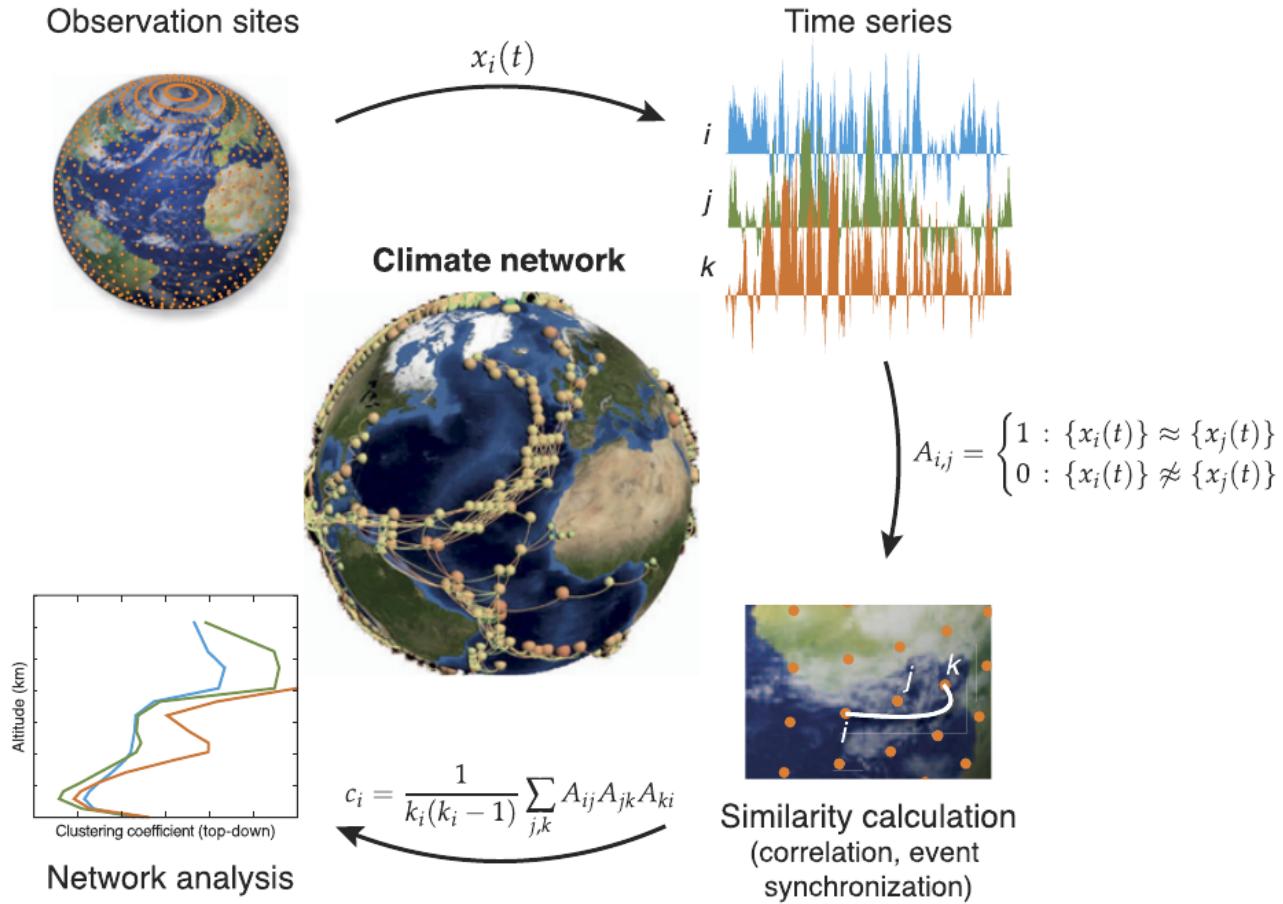
3

- Ebert-Uphoff & Deng, 2012
- Runge et al., 2015
- ~~Zerenner et al., 2012~~

Climate Networks with ML

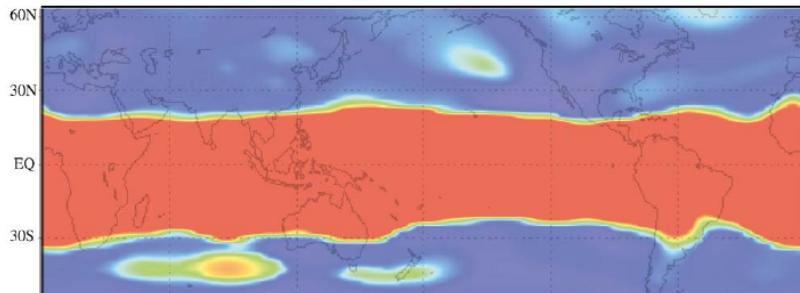
4

- Noteboom et al., 2018
- ~~Santos et al., 2020~~



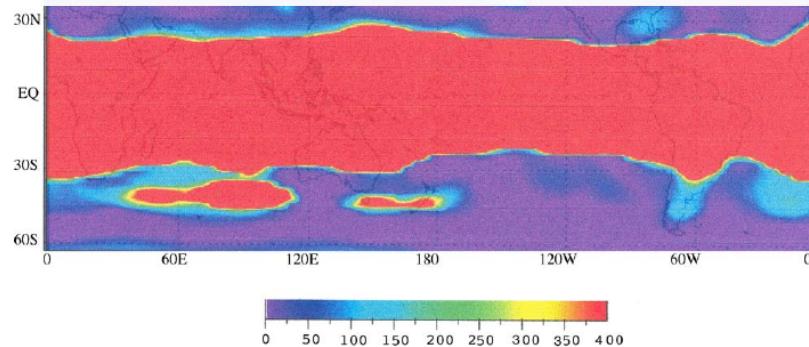
1. What are climate networks → How do we estimate climate networks?

Monthly Z500, 5 deg lat-lon grid, correlation coeff., 1% significance (threshold rho = 0.5)



Degree

"The physical interpretation [...] is that the climate system exhibits properties of stable networks [...] where information is transferred efficiently [...] 'information' should be regarded as 'fluctuations' from any source ([e.g.] the tropics, El Niño, etc.)."

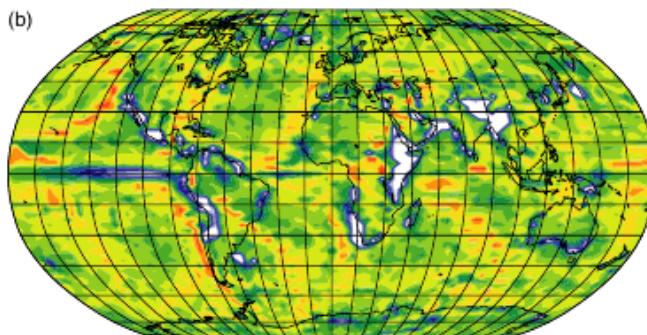


Degree > 5000 km

1. What are climate networks → What do they tell us?

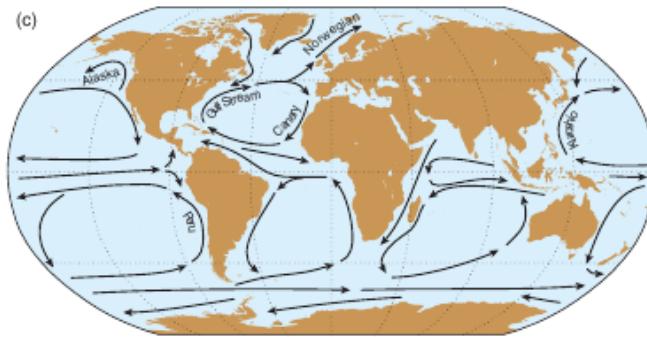


Monthly SAT, 2.5 deg lat-lon grid, Mutual Info., link density 0.5 %



Shortest path betweenness

"In analogy with the internet, we call the network of these channels of high-energy flow the backbone of the climate network."

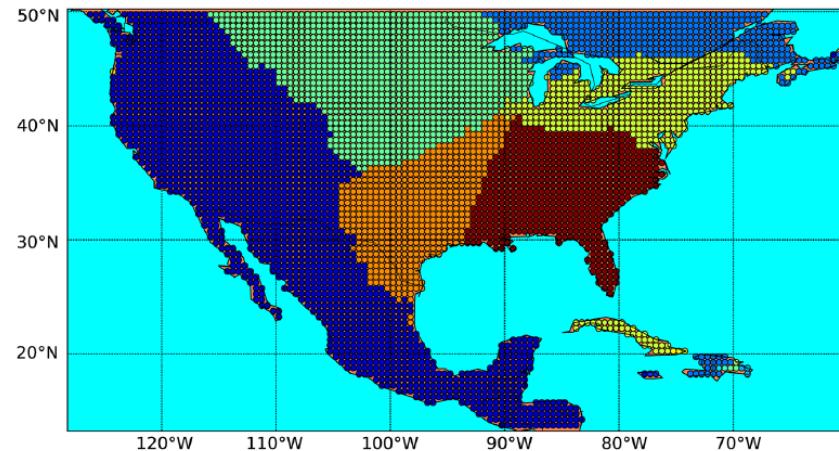


Ocean currents (schematic)

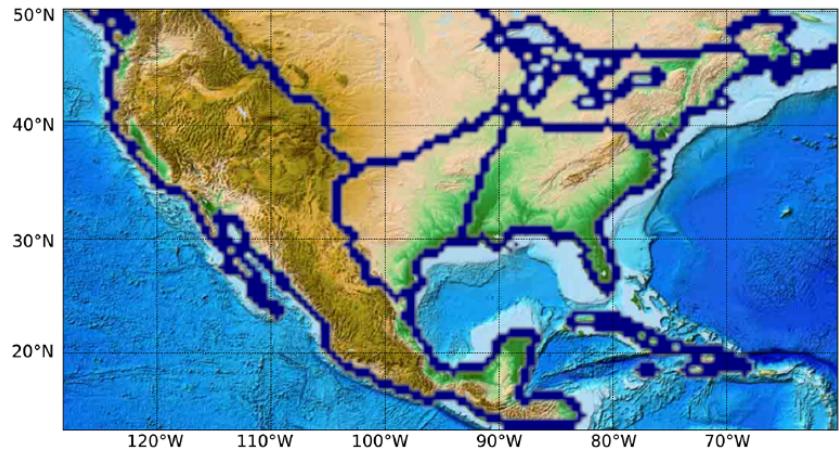
1. What are climate networks → What do they tell us?



Monthly Surface T, 0.5 deg lat-lon grid, Cross correlation, link density 5 %



Network communities



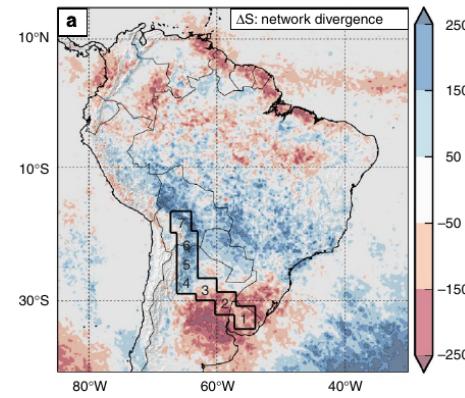
Underlying topography

1. What are climate networks → What do they tell us?

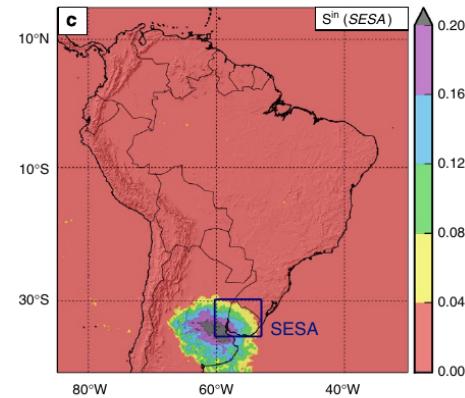


3-hourly extreme rainfall, 0.25 deg lat-lon grid, Event Synchronisation, link density 2 %

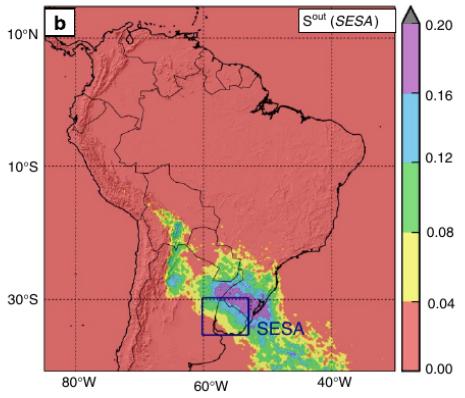
Network divergence



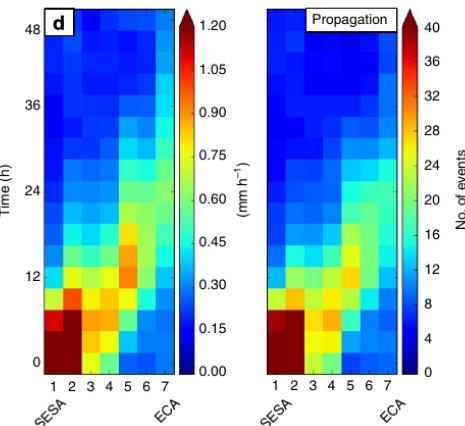
Incoming links to SESA



Outgoing links from SESA



Propagation of events



1. What are climate networks → What do they tell us?



What are climate networks

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- How do we estimate climate networks?
- What do they tell us?

Avoiding potential pitfalls

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- Autocorrelation
(Palus et al., 2009)
- Boundary effects
(Rheinwalt et al., 2011)
- Spatial embedding
(Boers et al., 2019)

Networks from Graphical Models

3

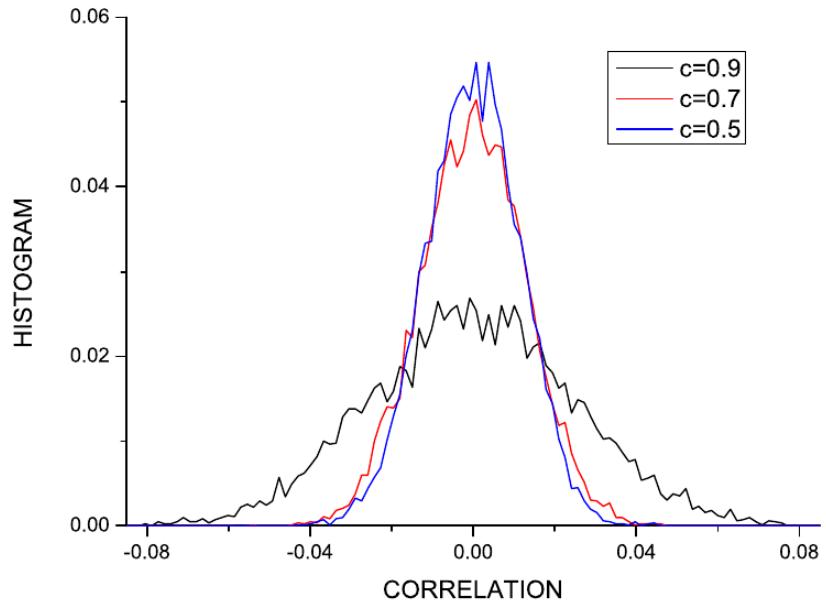
- Ebert-Uphoff & Deng, 2012
- Runge et al., 2015
- ~~Zerenner et al., 2012~~

Climate Networks with ML

4

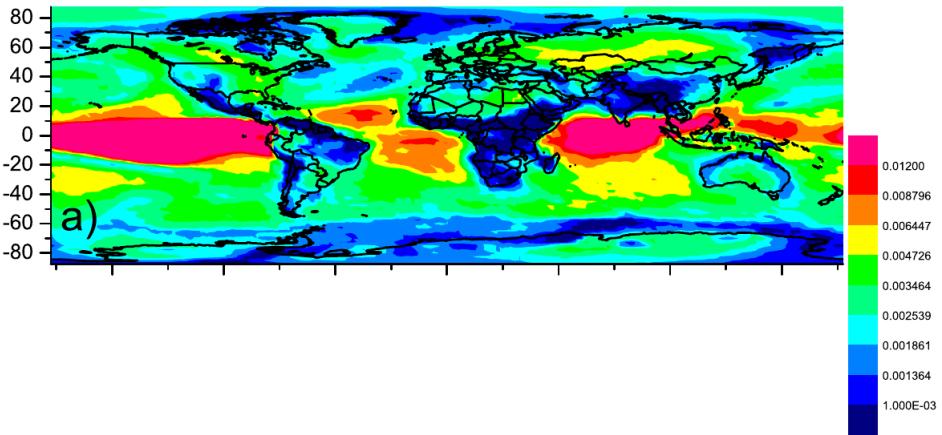
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- ~~Santos et al., 2020~~

Correlations between 8192 independent AR(10) processes for different AR coefficients



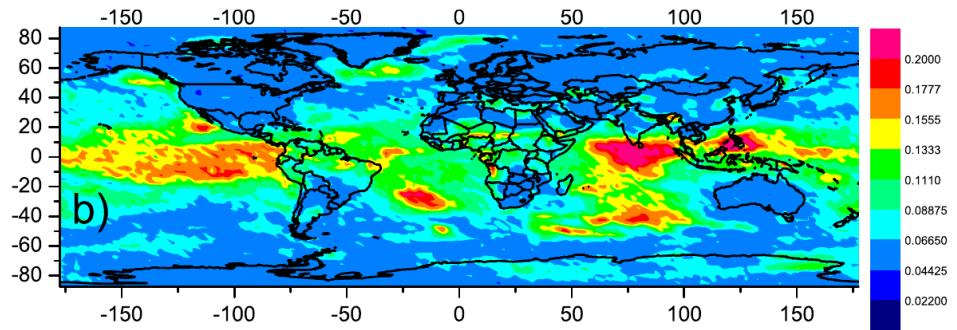
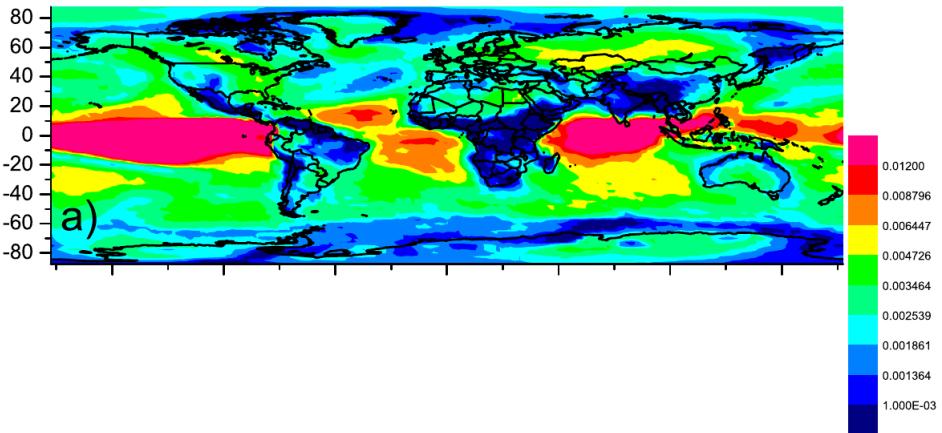
Monthly SAT, 2.5 deg lat-lon grid, absolute correlation coeff., link density 0.5 %

Area-weighted degree (original data)



Monthly SAT, 2.5 deg lat-lon grid, absolute correlation coeff., link density 0.5 %

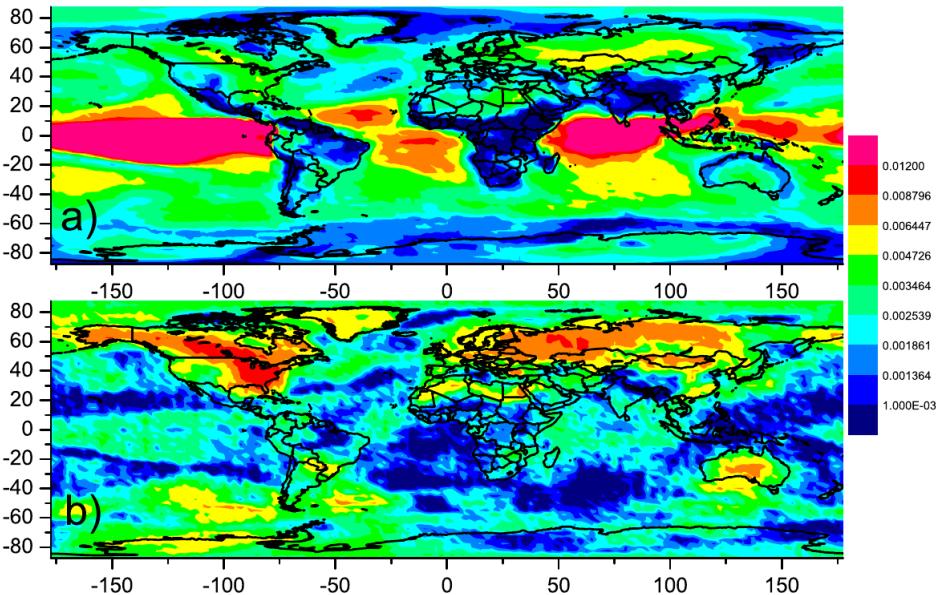
Area-weighted degree (original data)



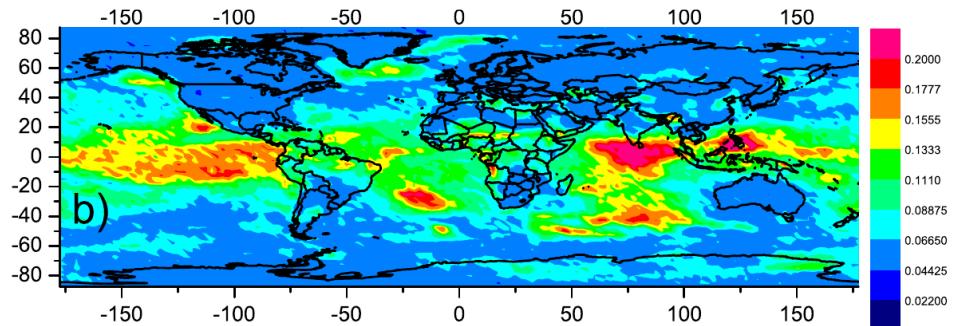
Area-weighted degree (randomised data)

Monthly SAT, 2.5 deg lat-lon grid, absolute correlation coeff., link density 0.5 %

Area-weighted degree (original data)

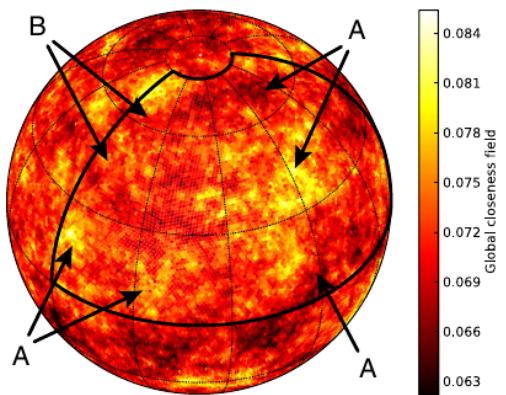


Z-score of area-weighted degree (original data)
(w.r.t. the distribution from randomised data)



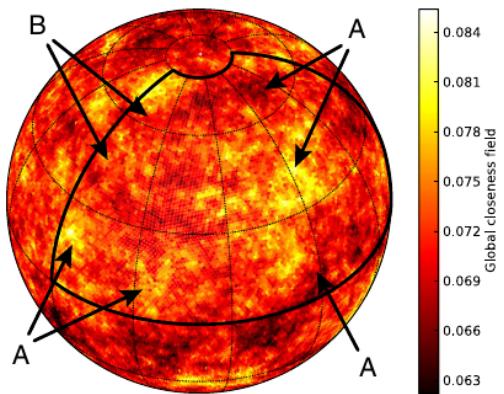
Area-weighted degree (randomised data)

Closeness centrality
(Full data)

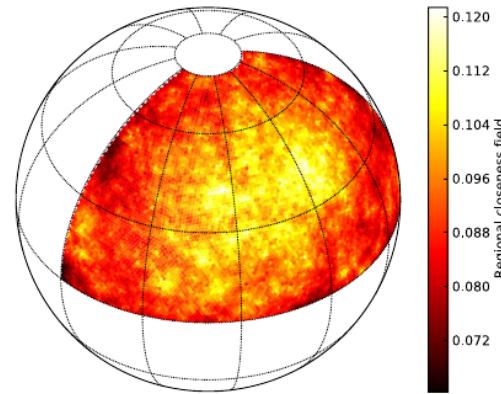


Closeness centrality on a random network on a sphere

Closeness centrality
(Full data)

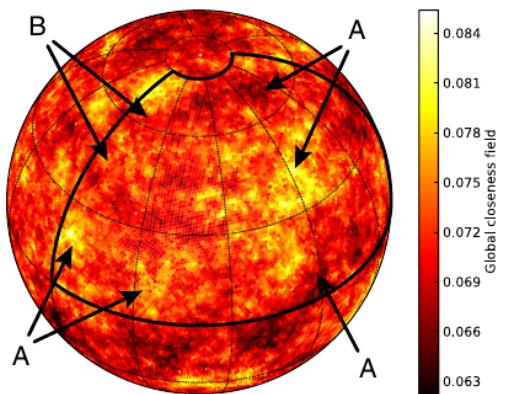


Closeness centrality on a random network on a sphere

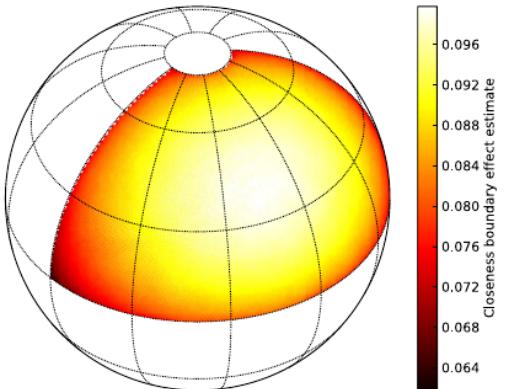


Closeness centrality
(boxed data)

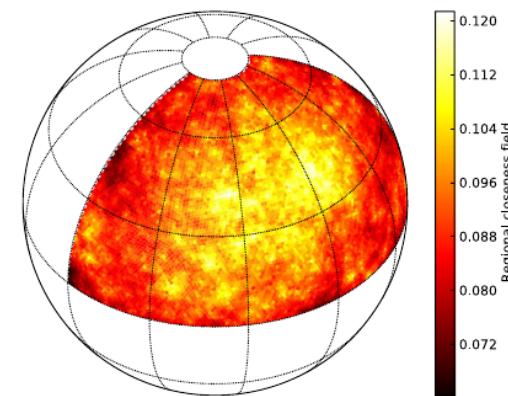
Closeness centrality
(Full data)



Closeness centrality
(random model
preserving link length
distribution)

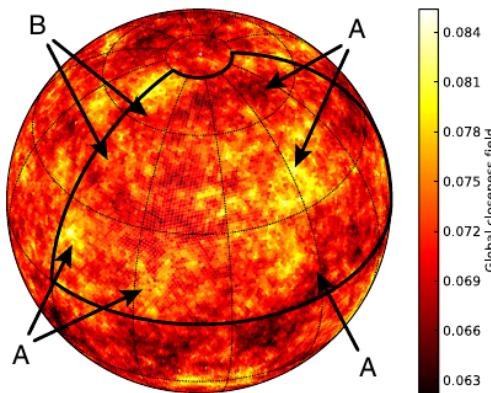


Closeness centrality on a random network on a sphere

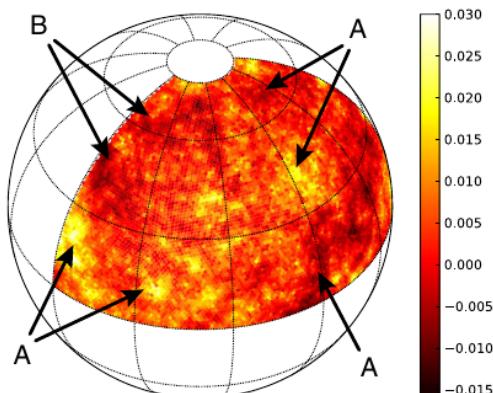


Closeness centrality
(boxed data)

Closeness centrality
(Full data)

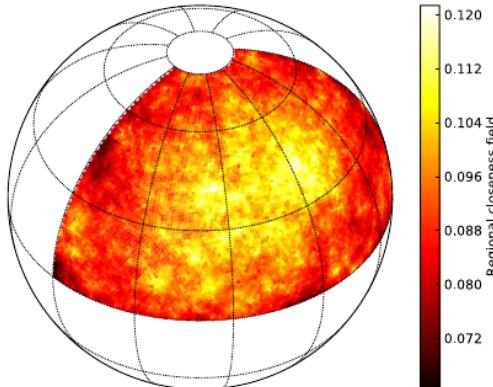
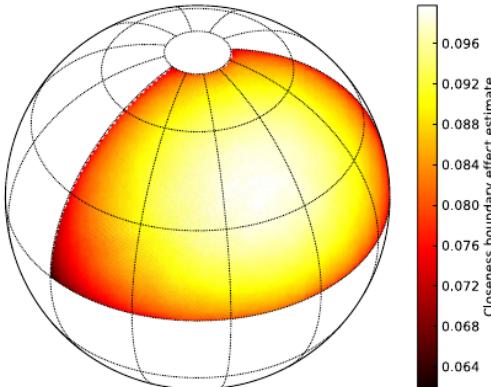


Closeness centrality on a random network on a sphere



Closeness centrality
(boxed data, corrected)

Closeness centrality
(random model
preserving link length
distribution)

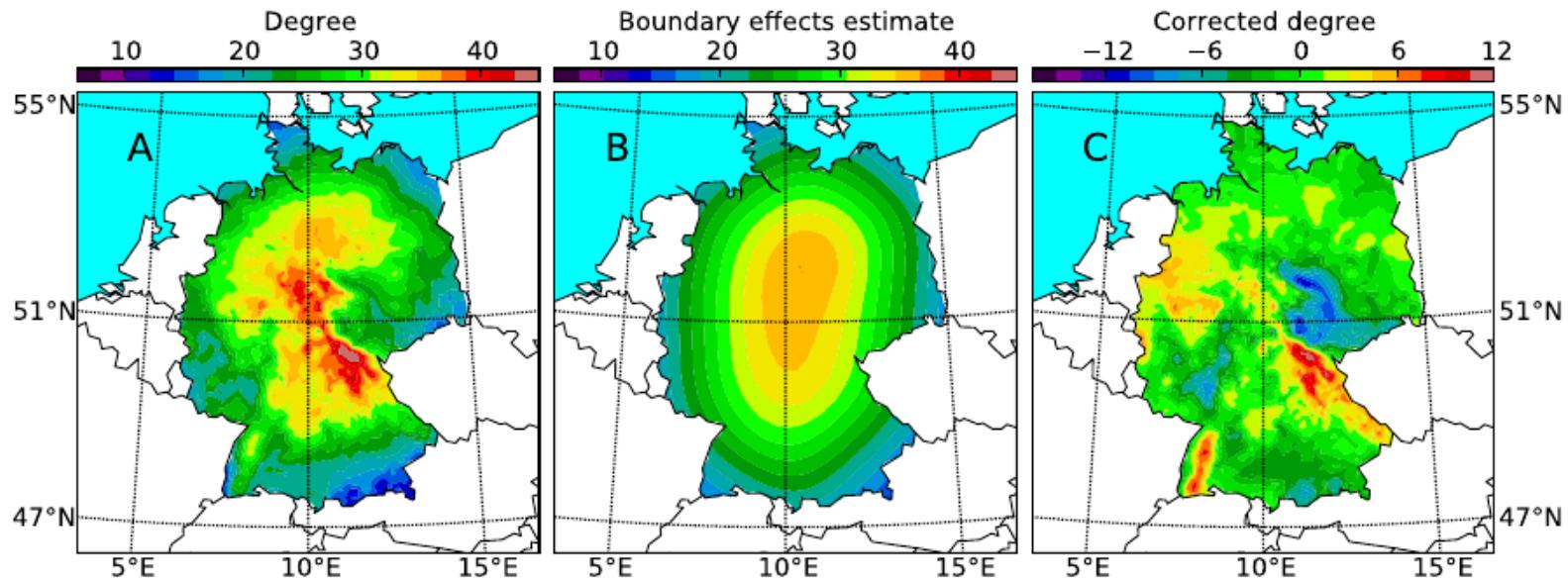


Closeness centrality
(boxed data)

2. Avoiding potential pitfalls → Boundary effects



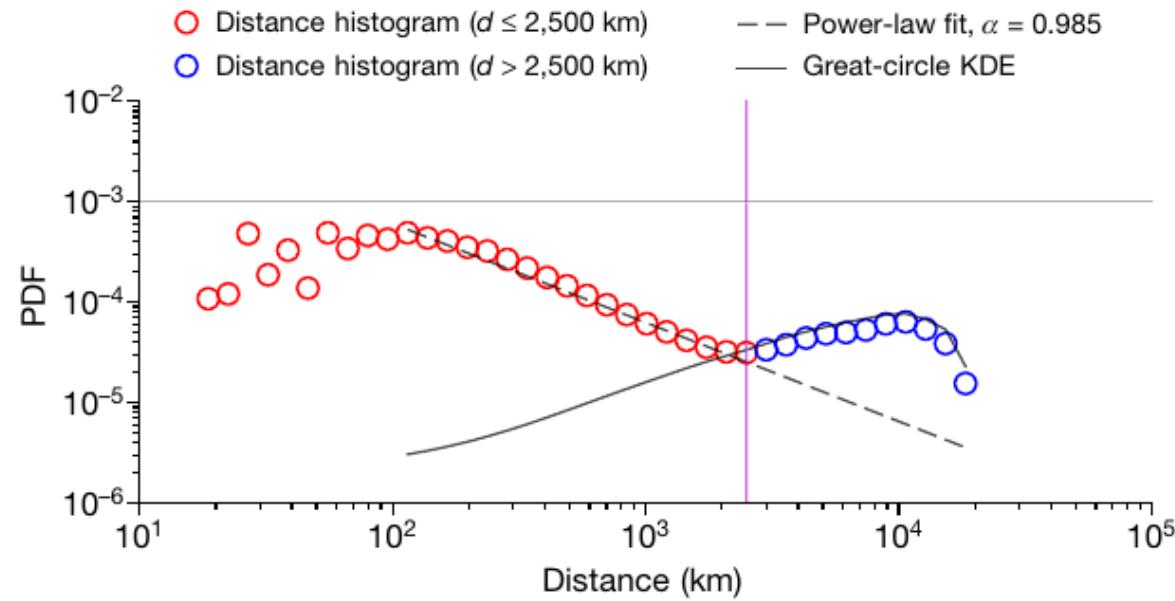
Daily extreme rainfall, 2000 weather stations, Event Synchronisation, 50 % link density



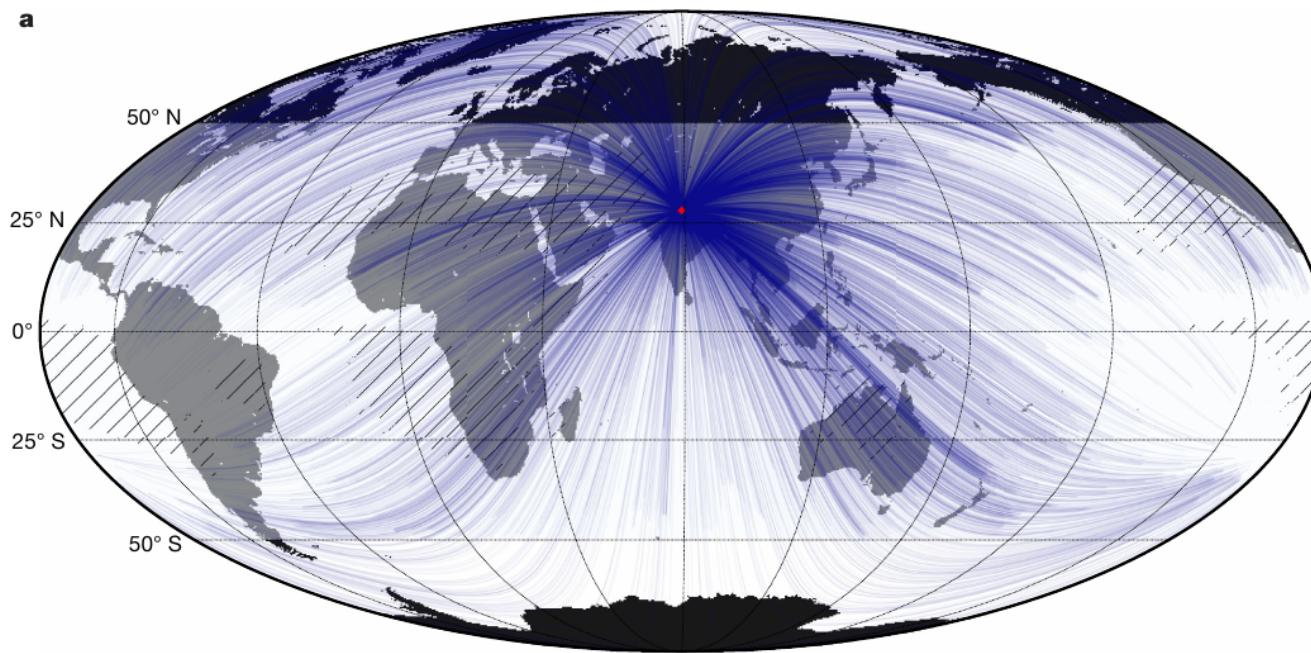
2. Avoiding potential pitfalls → Boundary effects



Daily extreme rainfall, 0.25 deg lat-lon grid, Event Synchronisation, 0.5 % significance



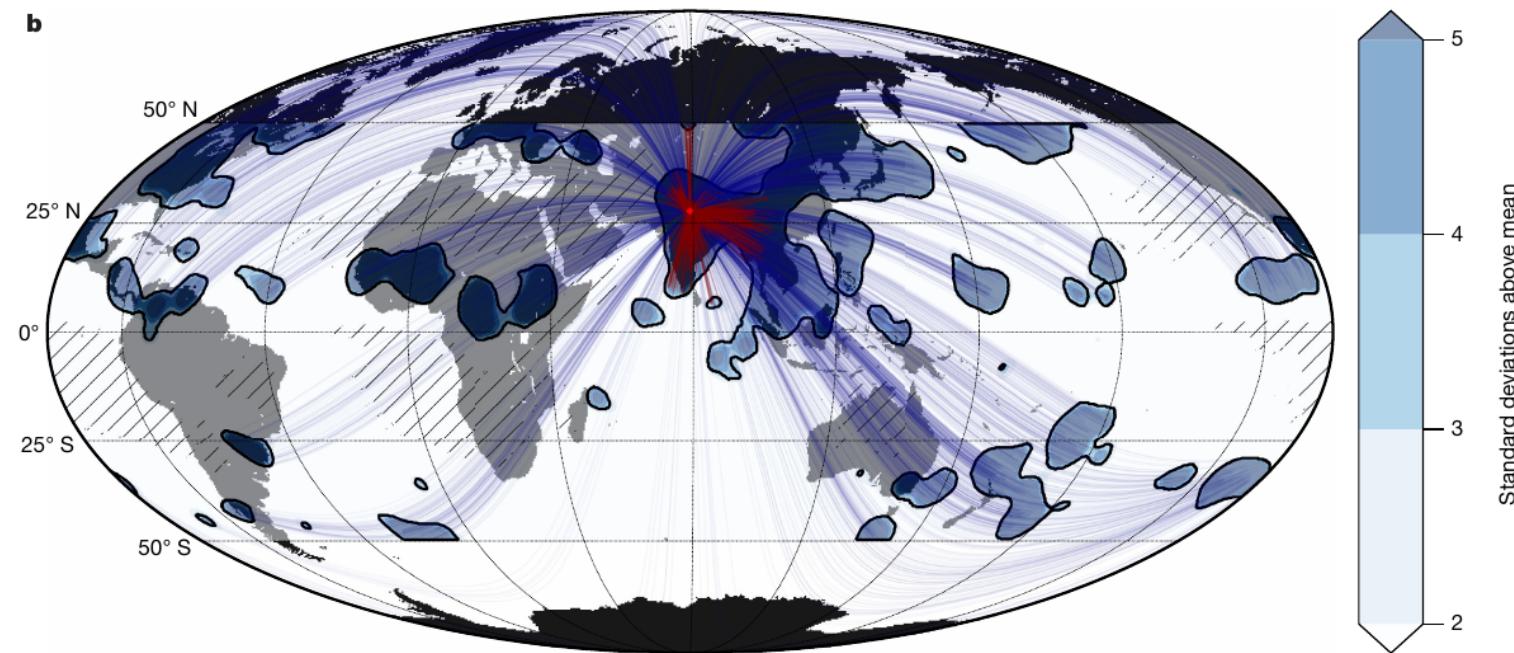
Daily extreme rainfall, 0.25 deg lat-lon grid, Event Synchronisation, 0.5 % significance



2. Avoiding potential pitfalls → Spatial embedding



Daily extreme rainfall, 0.25 deg lat-lon grid, Event Synchronisation, 0.5 % significance



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- How do we estimate climate networks?
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Networks from Graphical Models

3

- Ebert-Uphoff & Deng, 2012
- Runge et al., 2015
- ~~Zerenner et al., 2012~~

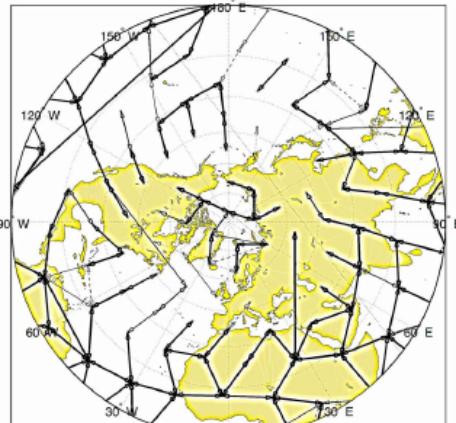
Climate Networks with ML

4

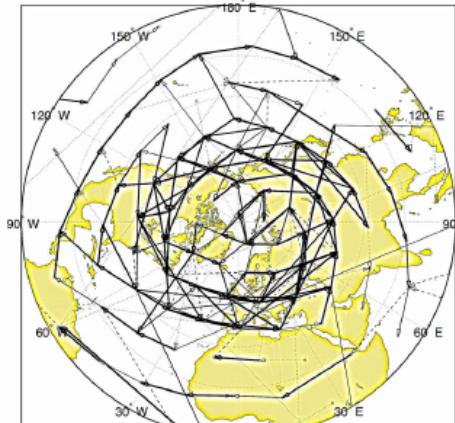
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Construction of the network ...

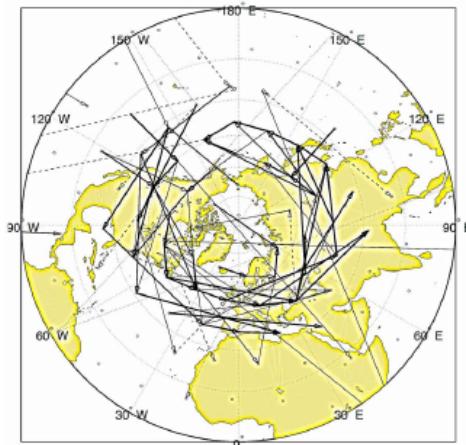
- Z500 geopotential height in the northern hemisphere from 1948 – 2011
 - 200 locations / time series
- PC algorithm (Spirtes & Glymour, 1991) to construct the graphical model
 - $S = 15$ time delays
 - Fischer's Z-test at 10 % confidence
- Data transformed to equidistant grid on the sphere using the Fekete algorithm (Bendito et al., 2007)
- Directed climate network of $15 \times 200 = 3000$ nodes



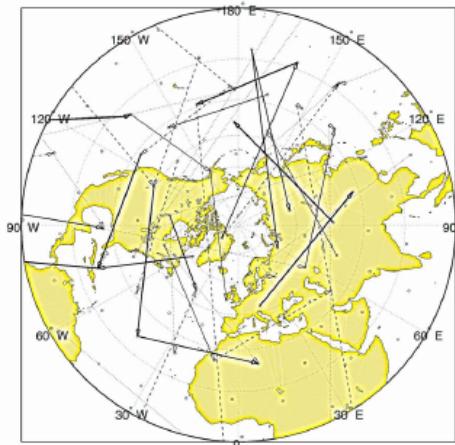
(a) 0-day-delay



(b) 1-day-delay



(c) 2-day-delay



(d) 3-day-delay

3. Networks from Graphical Models → Ebert-Uphoff & Deng, 2012

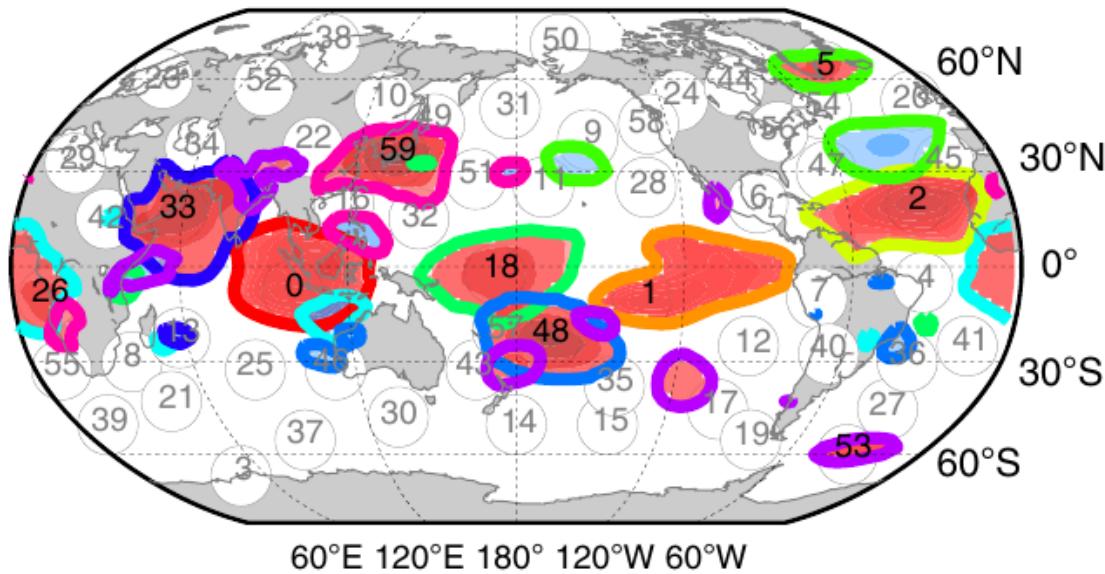


Construction of the network ...

- Global weekly surface pressure at 2.5 deg lat-lon grid from 1948 – 2012
 - 10512 time series, each 3339 points long
- Data dimensionality reduction using PCA with Varimax rotation
 - Top 60 components retained
- Modified PC algorithm (Runge et al., 2012) to construct the network based on graphical model
 - Delay considered = 4 (weeks)
- Quantifying causal effect:
 - Path coefficient: regression coefficient for the link $X_{t-\tau}^i \rightarrow X_t^j$



Top 60 components of Varimax rotated PCA, areas defined by 98% of loading

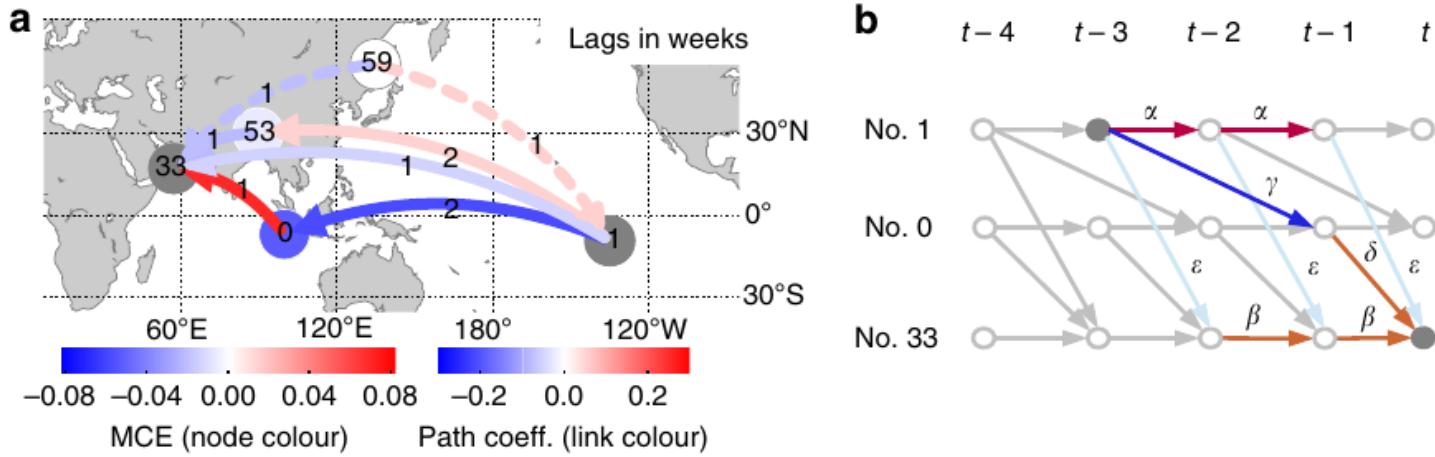


Quantifying causal effect ...

- Path coefficient:
 - Regression coefficient for the link $X^i_{t-\tau} \rightarrow X^i_t$
- Total causal effect:
 - Sum over the products of path coefficients along indirect causal paths, i.e., all paths between X^i and X^j at lag τ
- Mediated Causal Effect (MCE):
 - MCE of a node is the sum over products of path coefficients that pass through that node



MCE and path coefficients of nodes in the Indo-Pacific region



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Climate Networks with ML

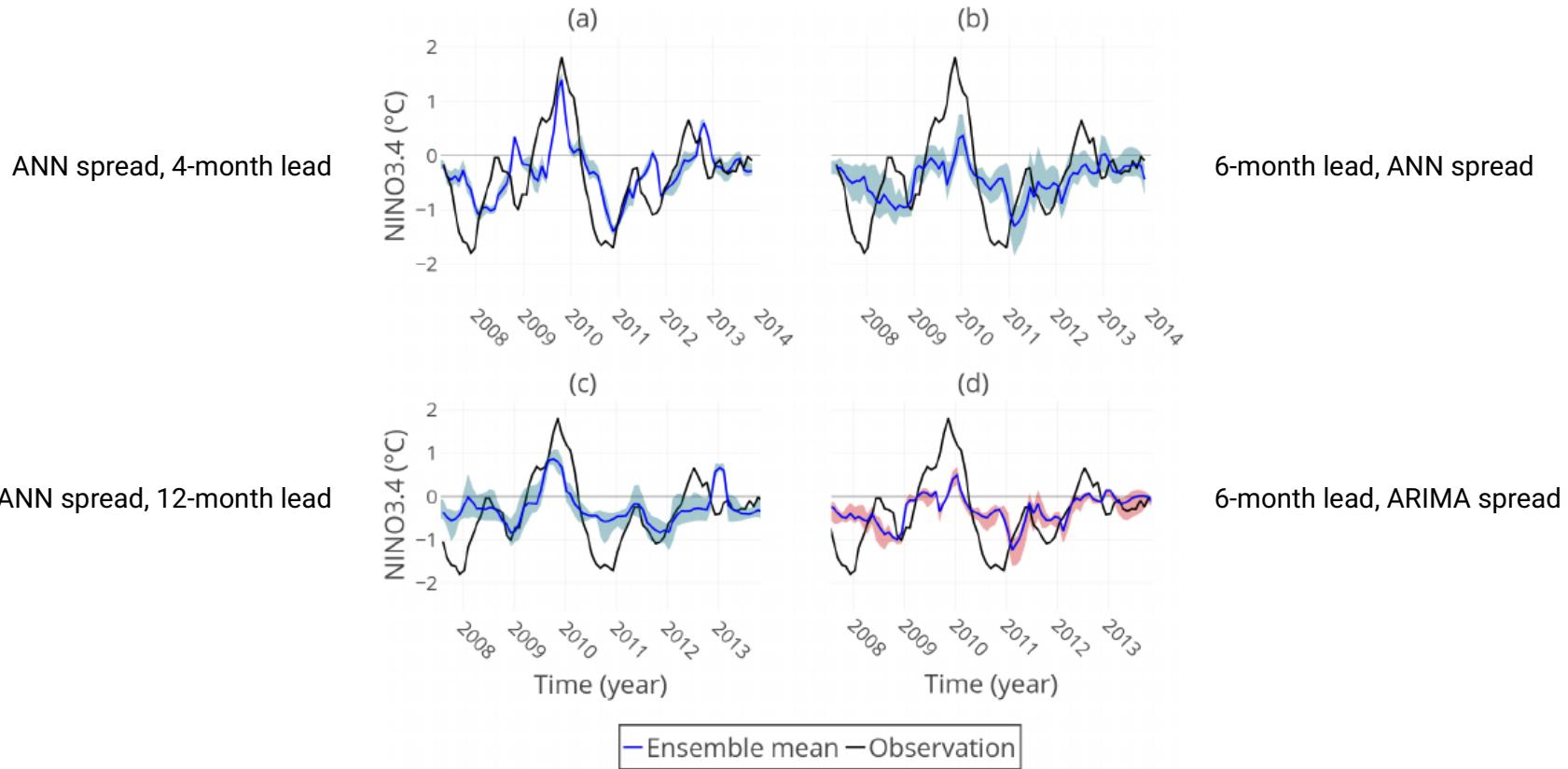
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Main idea ...

- Use climate networks + ANNs to forecast the Niño 3.4 index
- $Z_t = Y_t + N_t$
 - Z_t := Niño 3.4 index to be predicted
 - Y_t := ARIMA process
 - N_t := residual of the ARIMA fit, predicted with an ANN
- Simple ANN structure: 3 layers: 2 neurons x 1 neuron x 1 neuron
- Input features:
 - Warm water volume (WWV)
 - C_2 := fraction of components of size 2
 - Seasonal cycle
 - Second principal component of EOF analysis of wind stress
- Zebiak-Cane model used to test climate network features





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Q&A

