Challenges in KDD and ML for Sustainable Development

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ML-based climate data analytics

PART III

Bedartha Goswami


SUSTAINABLE DEVELOPMENT GOALS
1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
4 QUALITY EDUCATION
5 GENDER EQUALITY
6 CLEAN WATER AND SANITATION
7 AFFORDABLE AND CLEAN ENERGY
8 DECENT WORK AND ECONOMIC GROWTH
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
12 RESPONSIBLE CONSUMPTION AND PRODUCTION
13 CLIMATE ACTION
14 LIFE BELOW WATER
15 LIFE ON LAND
16 PEACE, JUSTICE AND STRONG INSTITUTIONS
17 PARTNERSHIPS FOR THE GOALS
SUSTAINABLE DEVELOPMENT GOALS

machine learning in climate science

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

ML

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Outline

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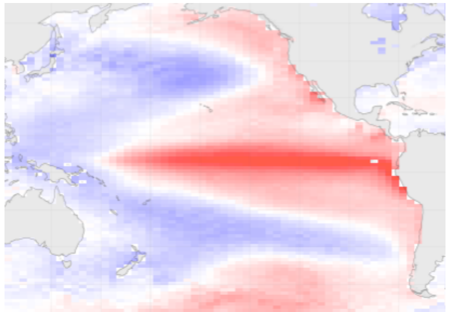
Part I Empirical orthogonal function analysis
→ principal components of the covariances in climate data



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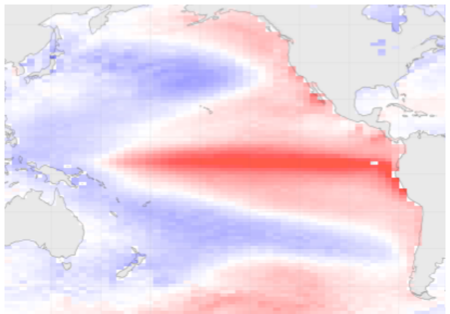
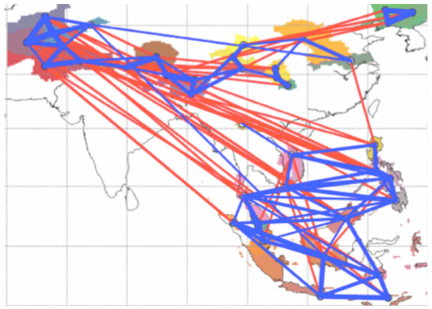
→ interactions between climate data represented as graphs





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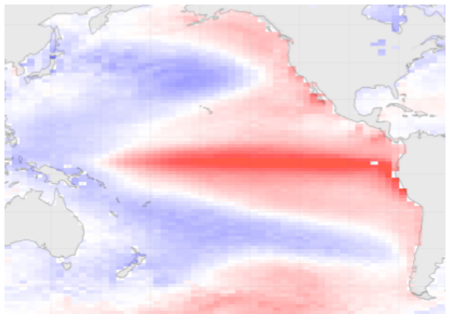
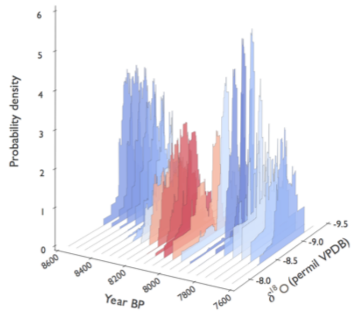
Climate data with uncertainties

→ detecting abrupt transitions in time series with uncertainties





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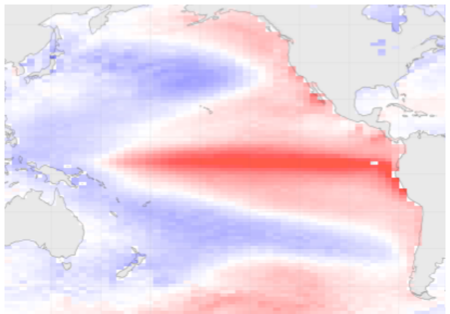
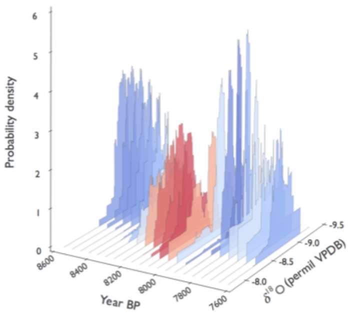
Outlook Deep learning for uncovering climate patterns
→ graph neural networks to reveal climate interations





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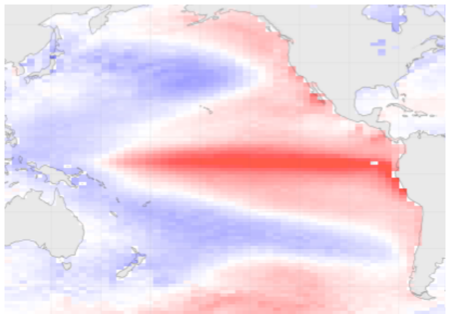
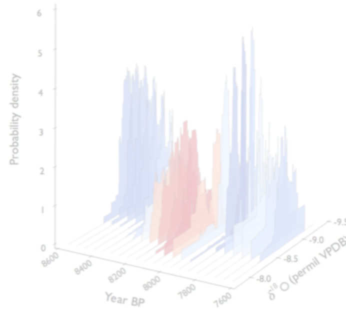




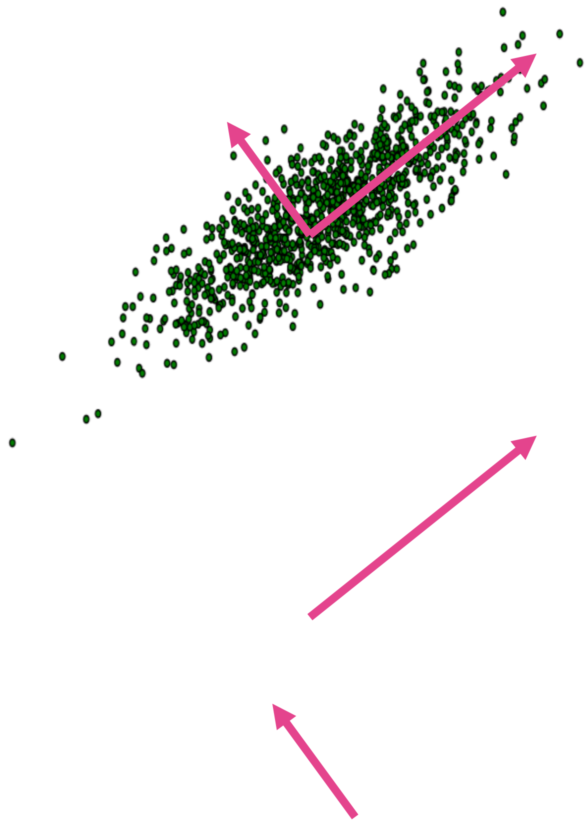
Empirical Orthogonal Functions (EOFs)

- Consider the data matrix
$$X = (\ x_1, x_2, \dots, x_p\ ),$$
- where p is the number of locations and
$$x_j = (x_{1j}, x_{2j}, \dots, x_{nj})^T$$
is the time series of length n at location j

- Esimate the covariance matrix of size p x p
$$C = X^T X$$

- Empirical orthogonal functions are the eigenvectors of C → allowing a change of basis

- It identifies the dominant directions of variability in the data



Empirical Orthogonal Functions (EOFs)

- Projecting the data onto each eigen direction reveals the different dominant "modes" of variability

- For a single time instant,

- $y^1_t = \boldsymbol{X}_t \rightarrow \boldsymbol{e}_1 = [x_{t1}, x_{t2}, \dots , x_{tp}]\ [e_{11}, e_{12}, \dots , e_{p1}]^{\mathbf{T}}$

- That is, for the entire time series

- $\boldsymbol{y}^1 = \mathbf{X}\ \boldsymbol{e}_1$

- gives the EOF time series for the first eigen direction

Considerations in estimating EOFs

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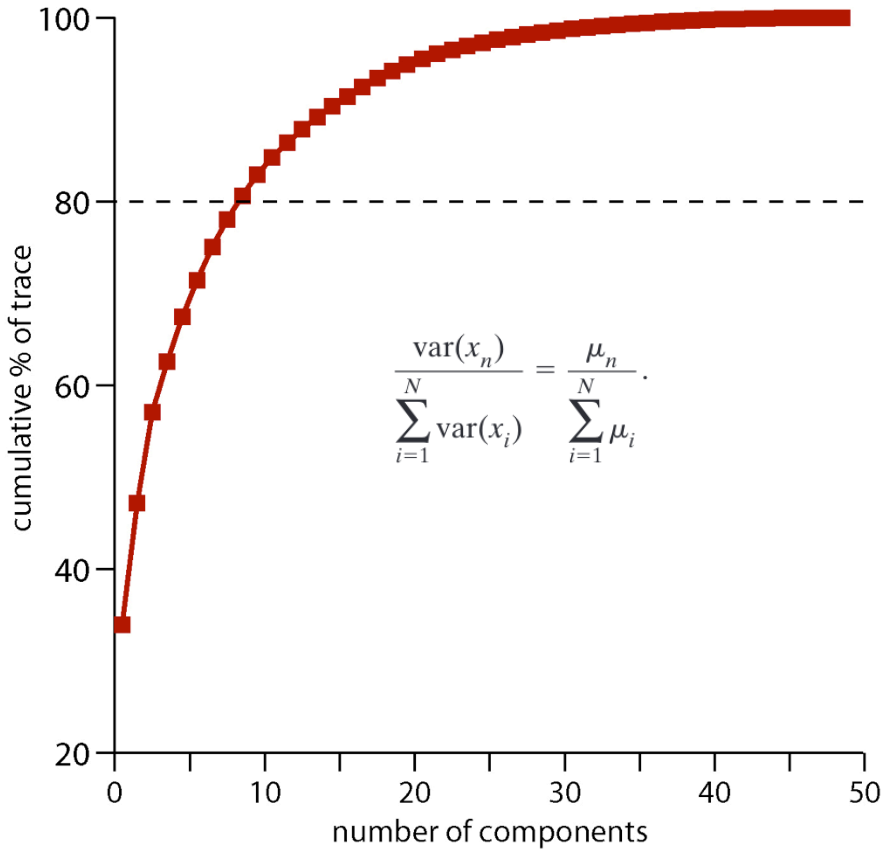
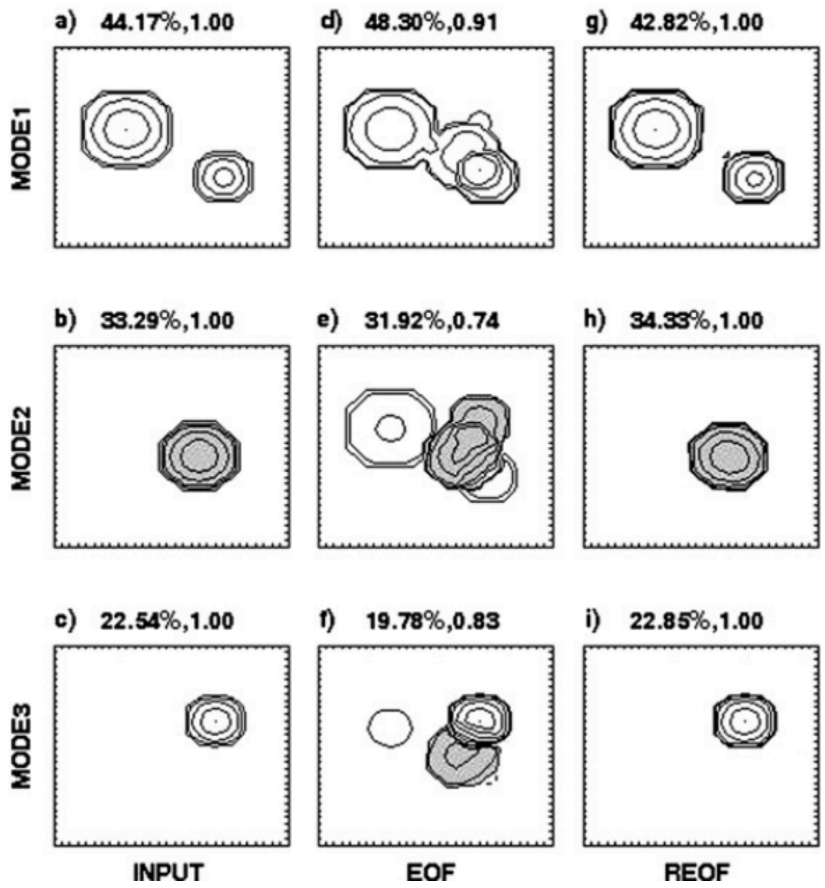
- **Truncation:**
  - Use only $k << p$ leading eigenvalues



Considerations in estimating EOFs

- **Truncation:**
  - Use only $k << p$ leading eigenvalues
- **Rotation:**
  - Obtain 'simple' structures
  - Minimally overlapping EOFs
  - Ease of interpretation



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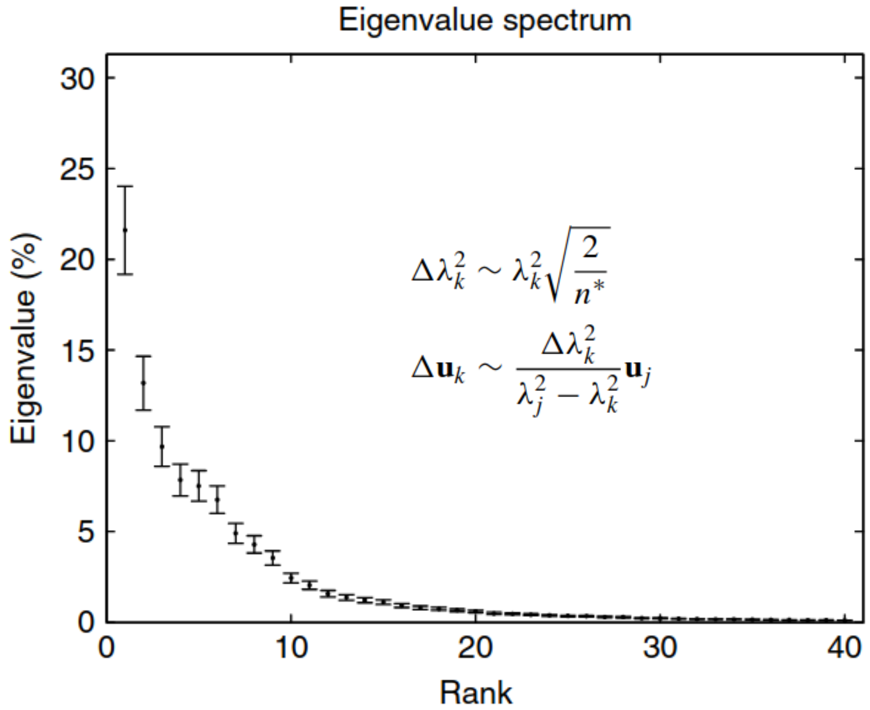
- **Uncertainty:**
  - North's rule of thumb (North et al., 1982)
  - Monte Carlo sampling



Spectrum, in percentage, of the covariance matrix of wintermonthly (DJF) SLP as per North's rule of thumb

Considerations in estimating EOFs

- **Truncation:**
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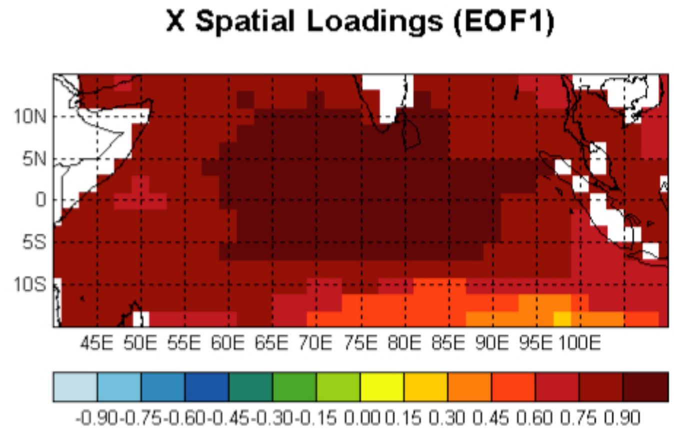
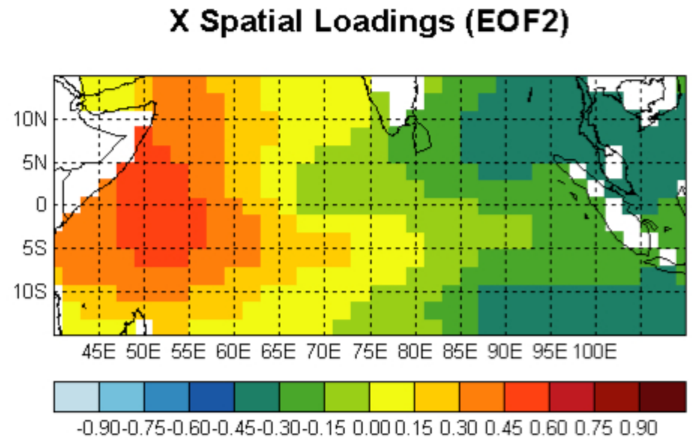
- **Rotation:**
  - Obtain 'simple' structures
  - Minimally overlapping EOFs
  - Ease of interpretation
- **Uncertainty:**
  - North's rule of thumb (North et al., 1982)
  - Monte Carlo sampling
- **Spatial effects:**
  - For a rectangular grid, scale (co)variances by latitudes
  - Buell Patterns





EOF example: Sea surface temperatures in the Pacific

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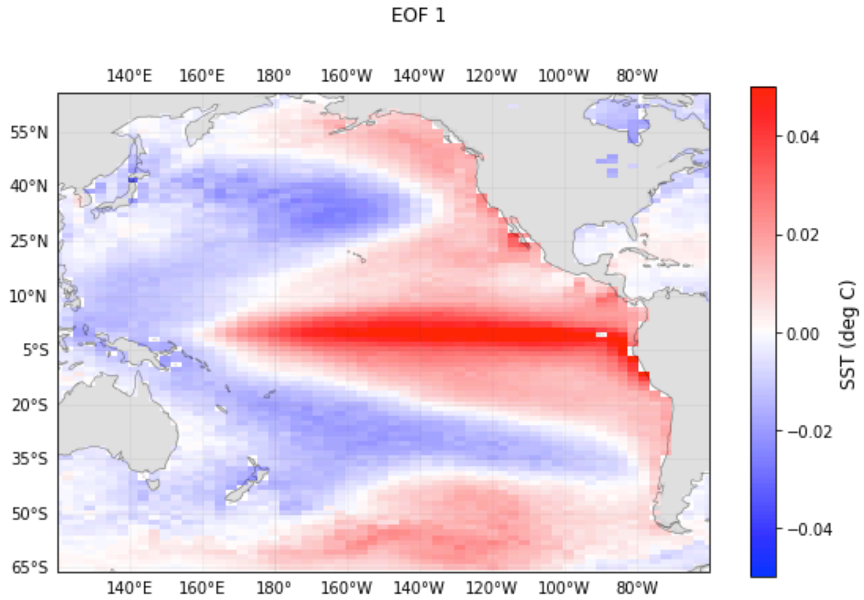
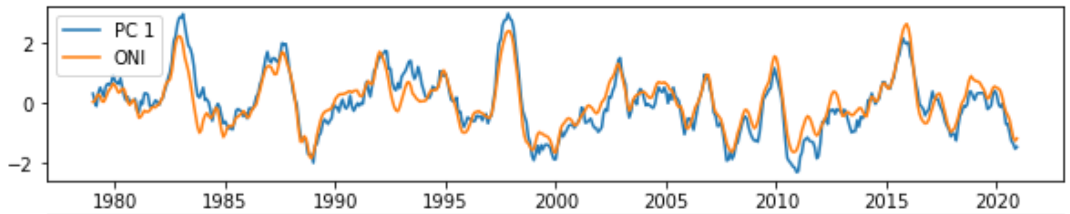
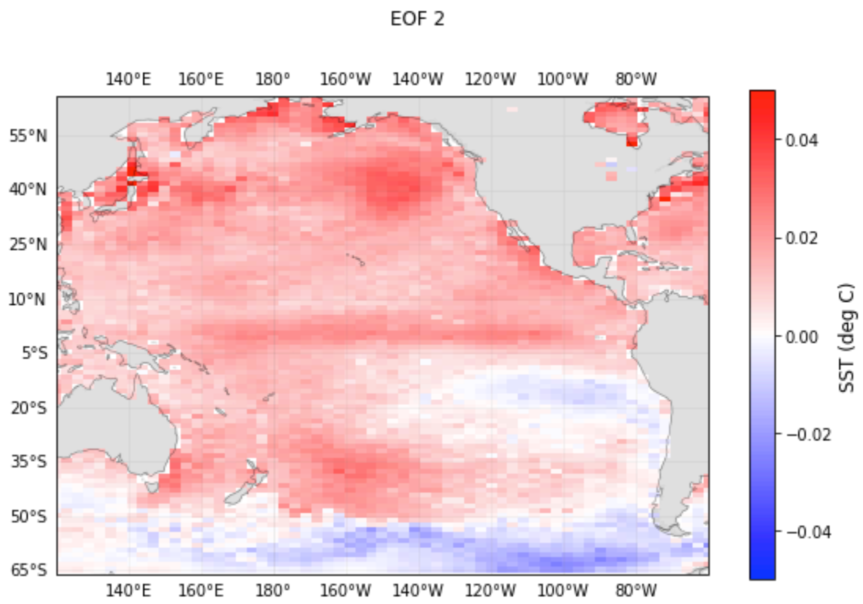
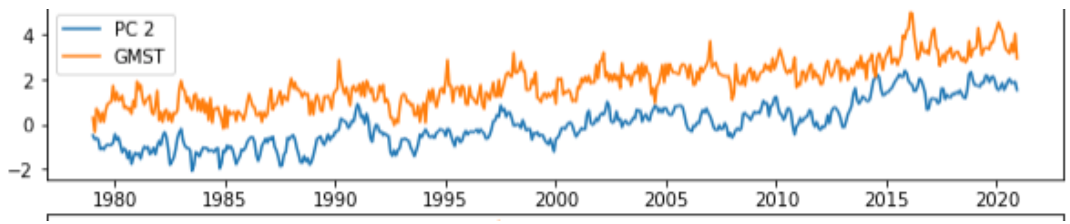




https://github.com/mlcs/mlcs.github.io/blob/master/files/sose2021/tutorial/pca_pacific.ipynb

EOF example: Sea surface temperatures in the Pacific





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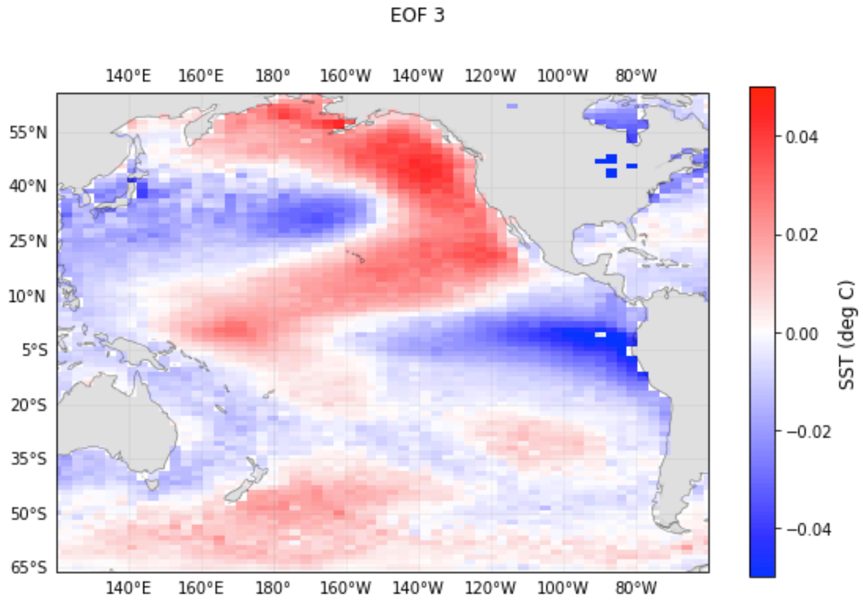

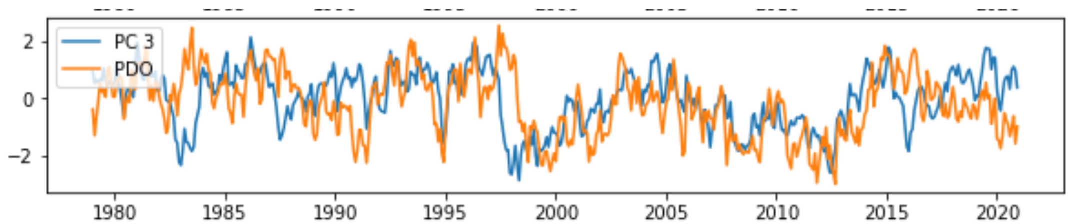

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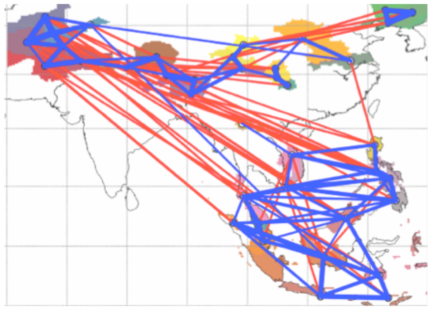
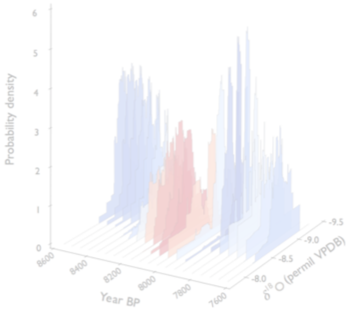
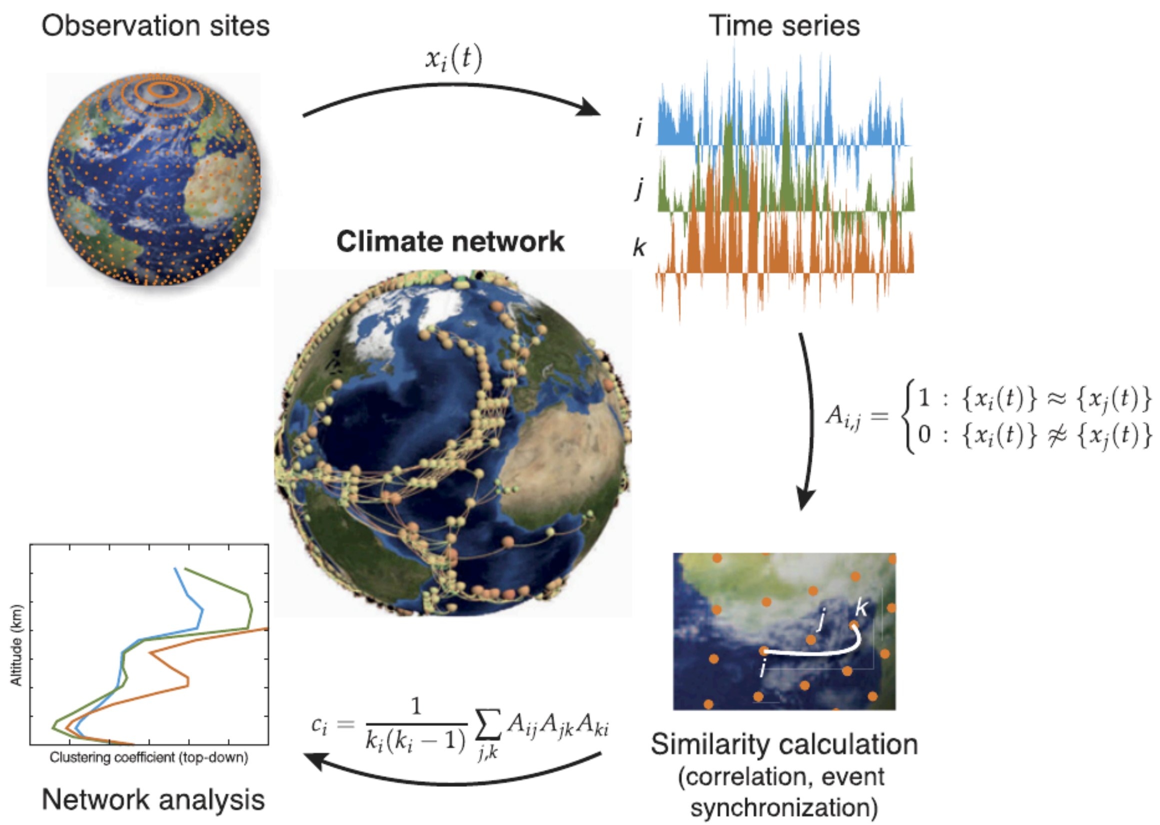




Boers et al., J. Phys. Complex., 2021

What are climate networks?



What do climate networks tell us?

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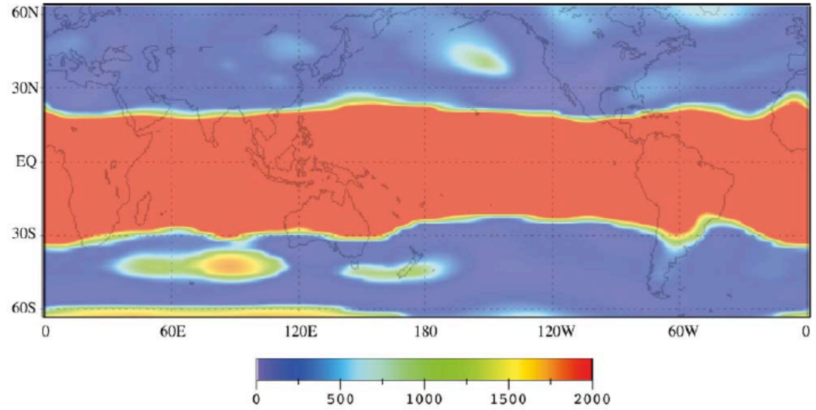
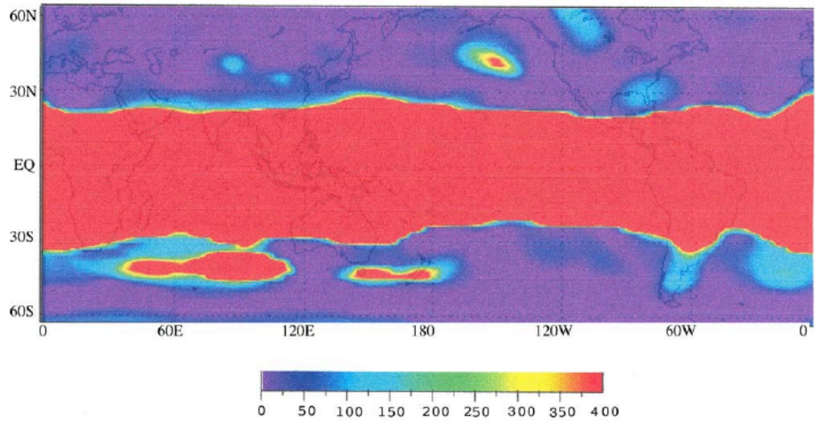
Monthly Z500, 5 deg lat-lon grid, correlation coeff., 1% significance (threshold rho = 0.5)



Degree



Degree > 5000 km

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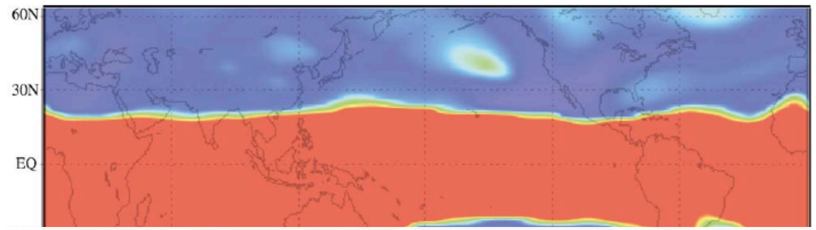
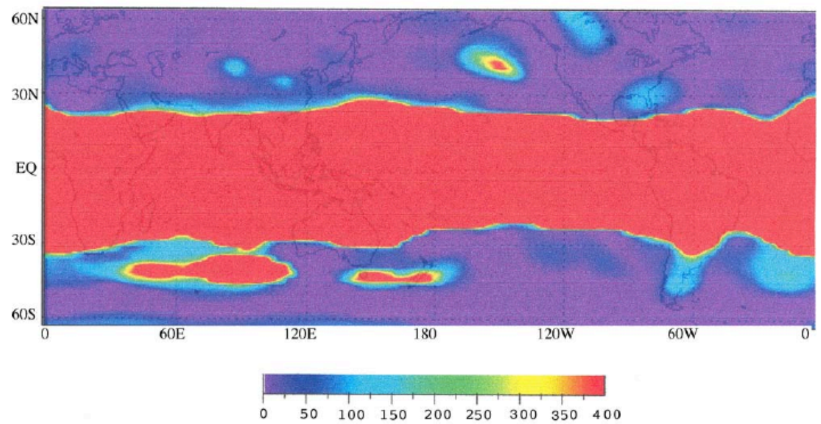


Degree

"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.). "

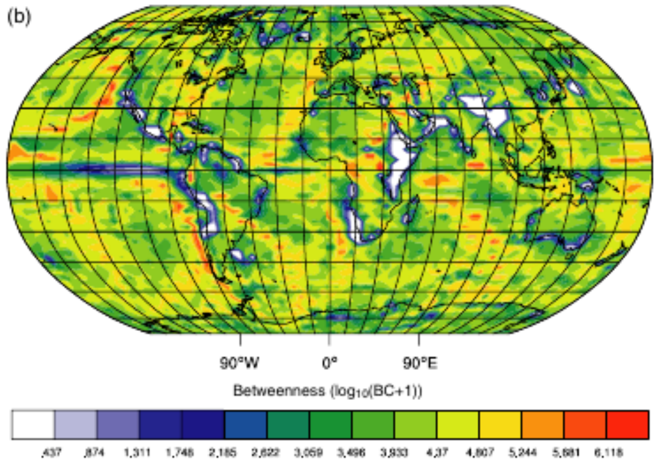


Degree > 5000 km

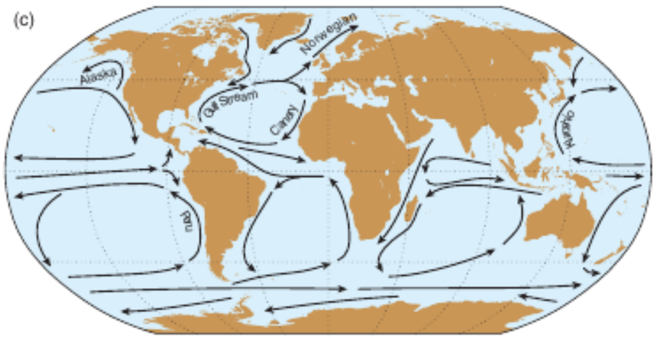
Donges et al., Europhys Lett, 2009

What do climate networks tell us?

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



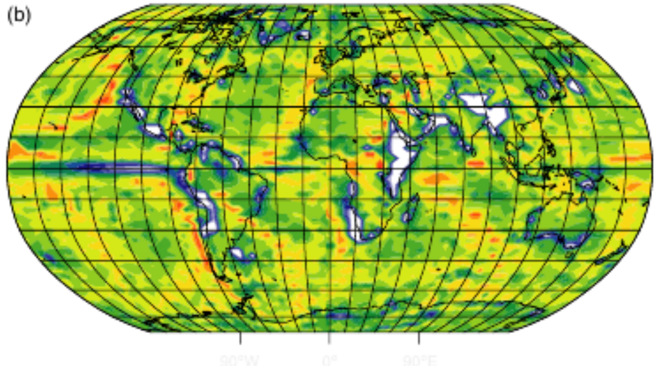
Shortest path betweenness



Ocean currents (schematic)

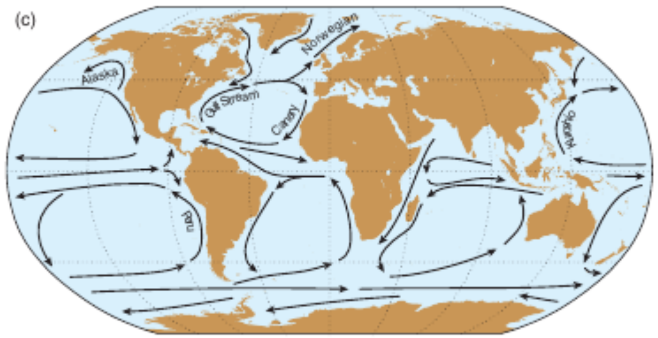
What do climate networks tell us?

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."

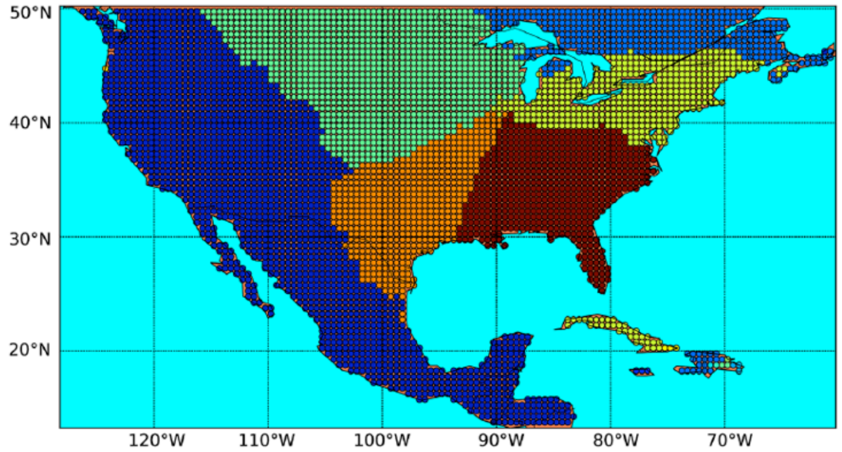


Ocean currents (schematic)

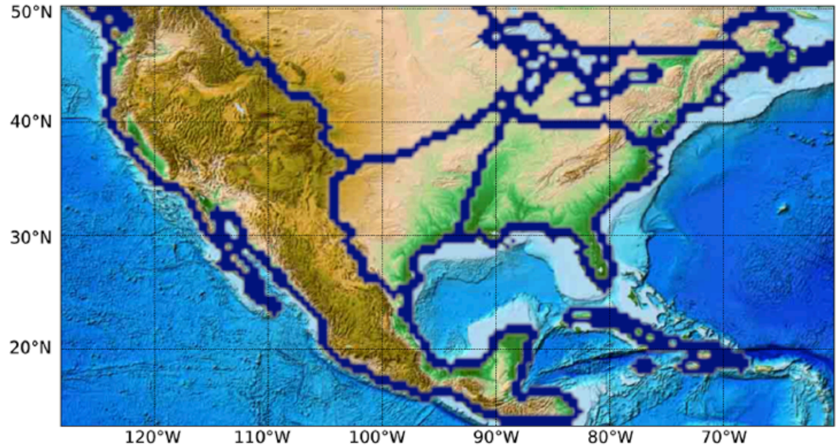
Peron et al., Nonlin. Proc. Geophys., 2014

What do climate networks tell us?

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



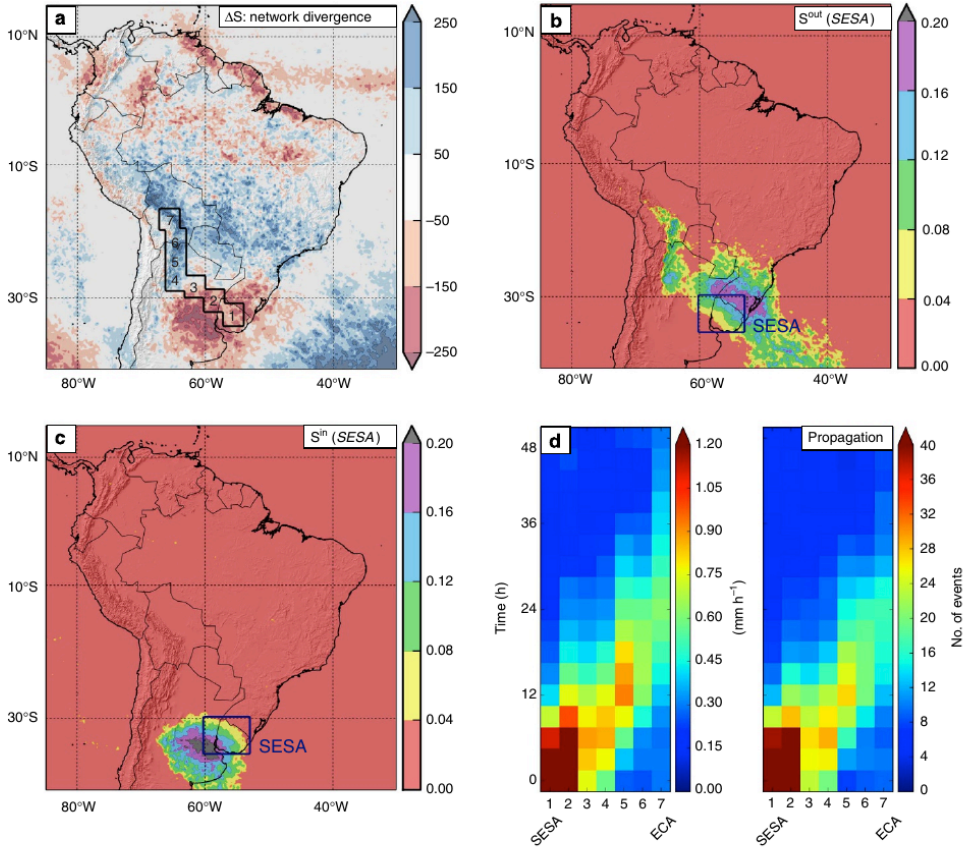
Network communities



Underlying topography

What do climate networks tell us?

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



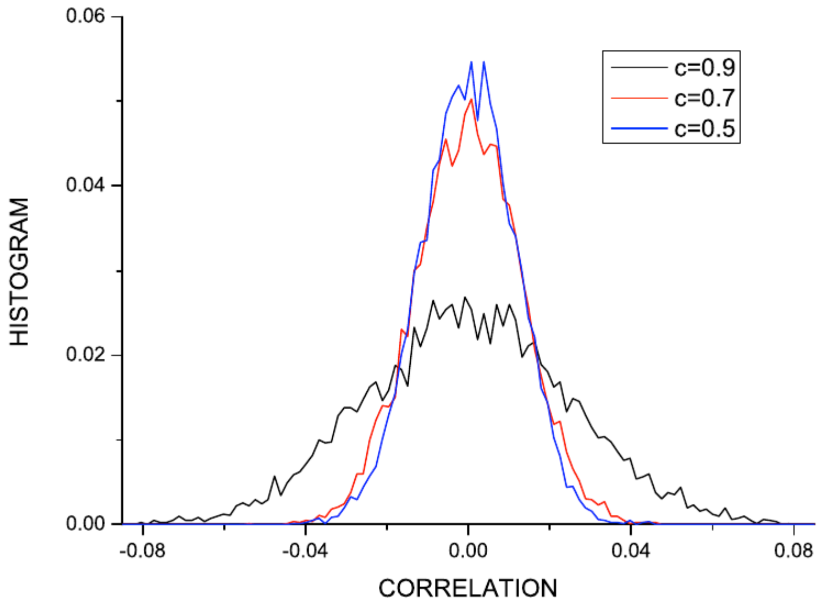
Outgoing links from SESA

Propagation of events

Potential pitfalls in climate networks

Palus et al., Nonlin. Proc. Geophys., 2011

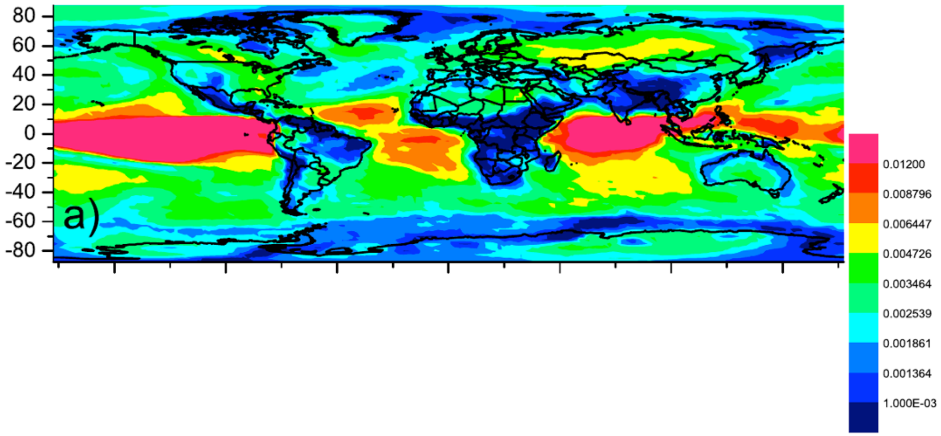
Potential pitfalls in climate networks: *Autocorrelation*



Potential pitfalls in climate networks: *Autocorrelation*

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

Area-weighted degree (original data)



Palus et al., Nonlin. Proc. Geophys., 2011

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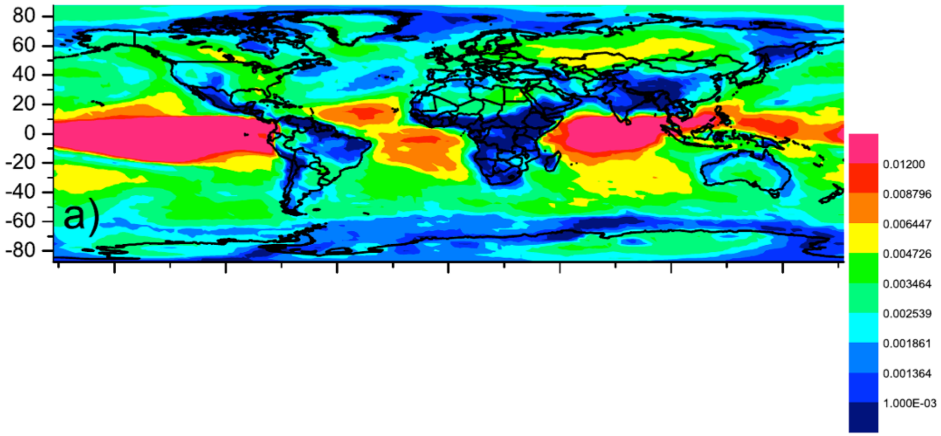

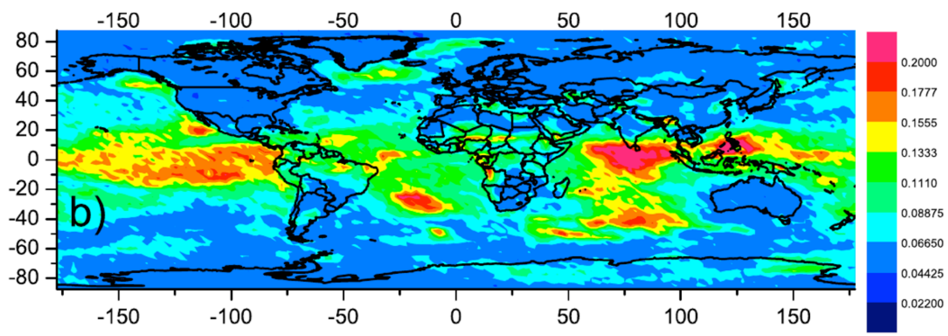

Area-weighted degree (randomised data)

Palus et al., Nonlin. Proc. Geophys., 2011

Potential pitfalls in climate networks: *Autocorrelation*

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

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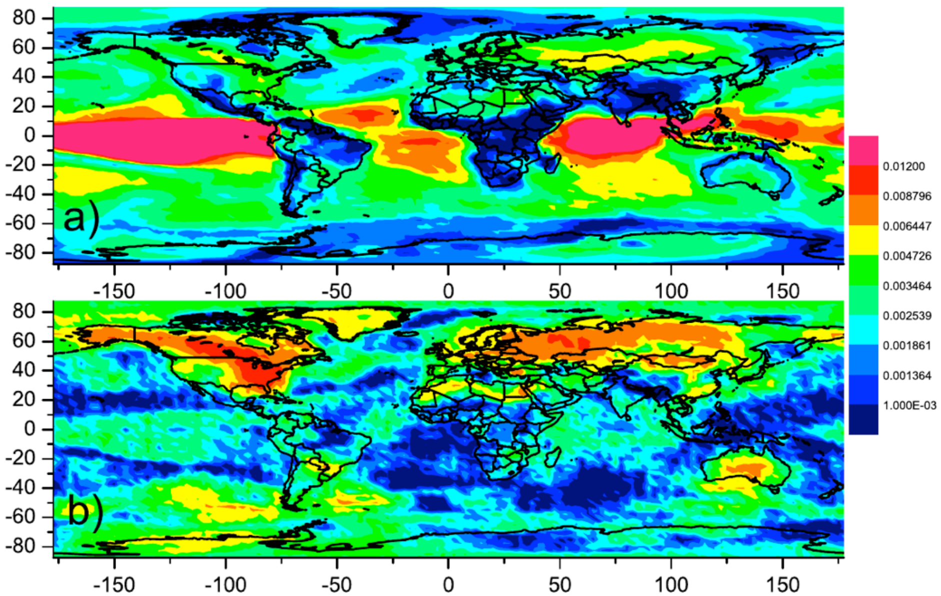
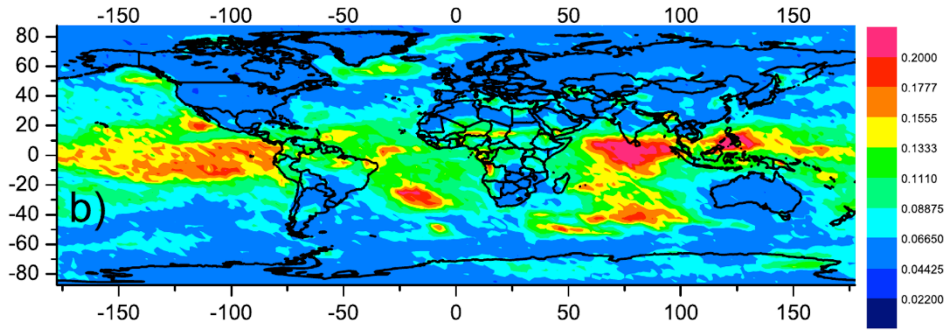


Z-score of area-weighted degree (original data)
(w.r.t. the distribution from randomised data)



Area-weighted degree (randomised data)

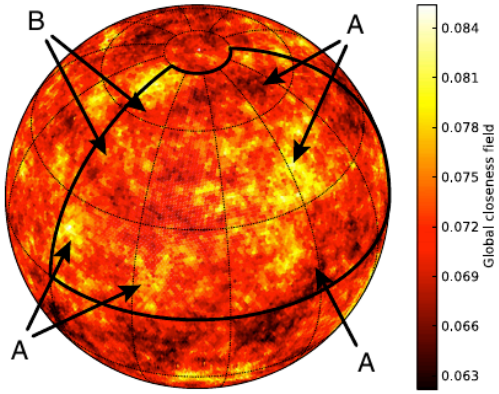
Potential pitfalls in climate network: *Boundary effects*

Rheinwalt et al., Europhys Lett., 2012

Potential pitfalls in climate network: *Boundary effects*

Closeness centrality on a random network on a sphere

Closeness centrality
(Full data)



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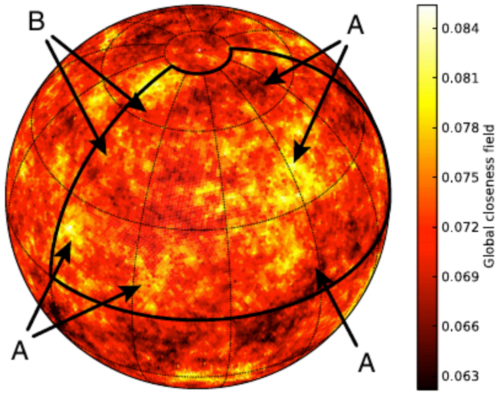
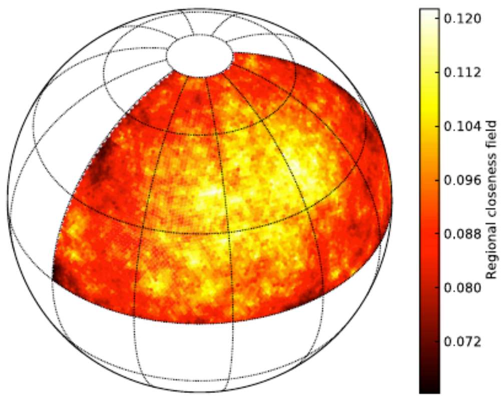




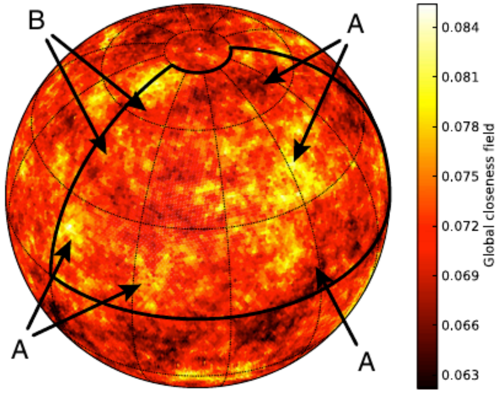
Closeness centrality
(boxed data)

Rheinwalt et al., Europhys Lett., 2012

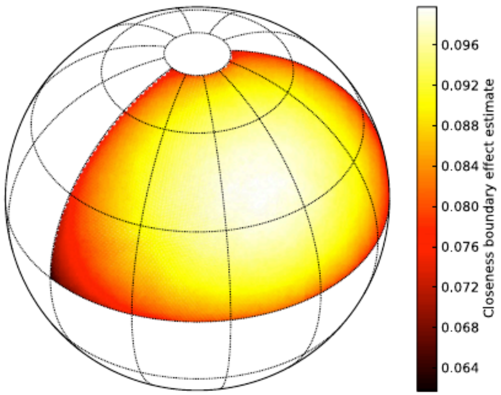
Potential pitfalls in climate network: *Boundary effects*

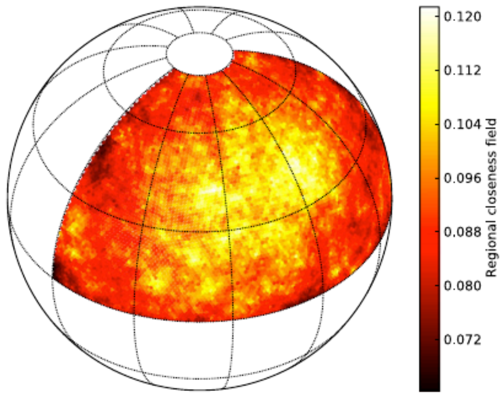
Closeness centrality on a random network on a sphere

Closeness centrality
(Full data)



Closeness centrality
(random model preserving link
length distribution)





Closeness centrality
(boxed data)

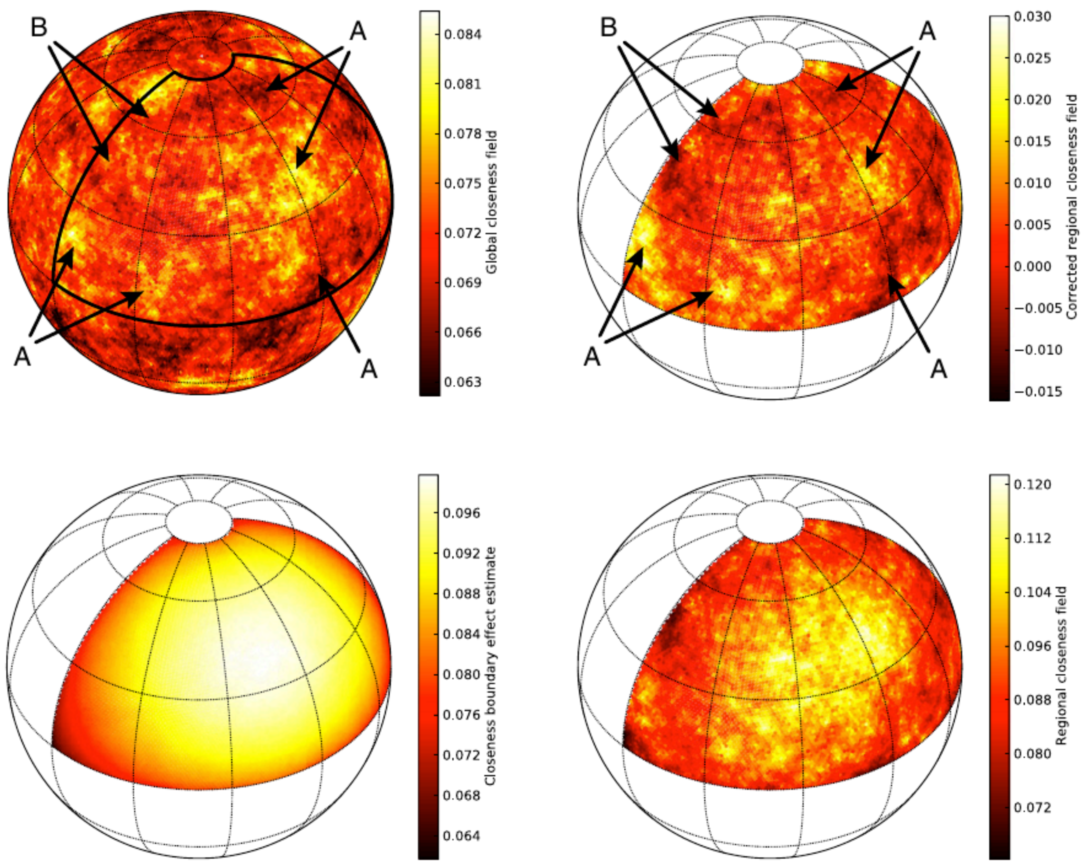
Rheinwalt et al., Europhys Lett., 2012

Potential pitfalls in climate network: *Boundary effects*

Closeness centrality on a random network on a sphere

Closeness centrality
(Full data)

Closeness centrality
(boxed data, corrected)



Closeness centrality
(random model preserving link
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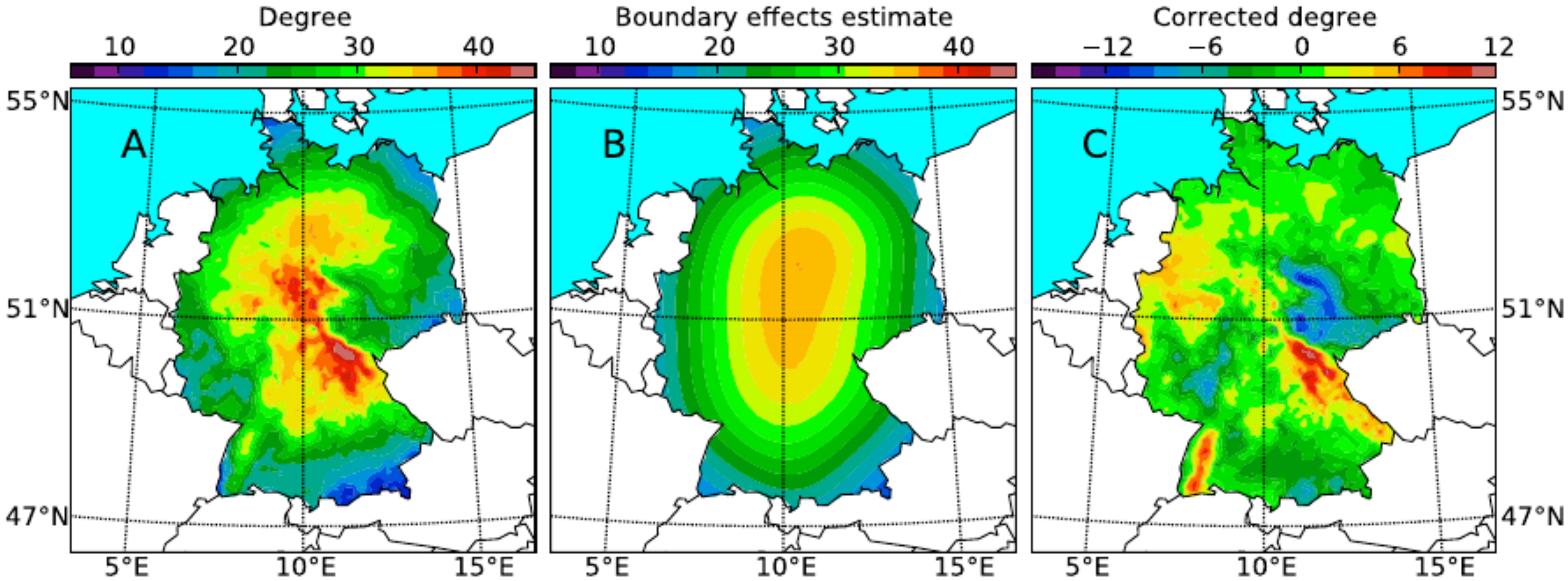
Closeness centrality
(boxed data)

Rheinwalt et al., Europhys Lett., 2012

Potential pitfalls in climate network: *Boundary effects*

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

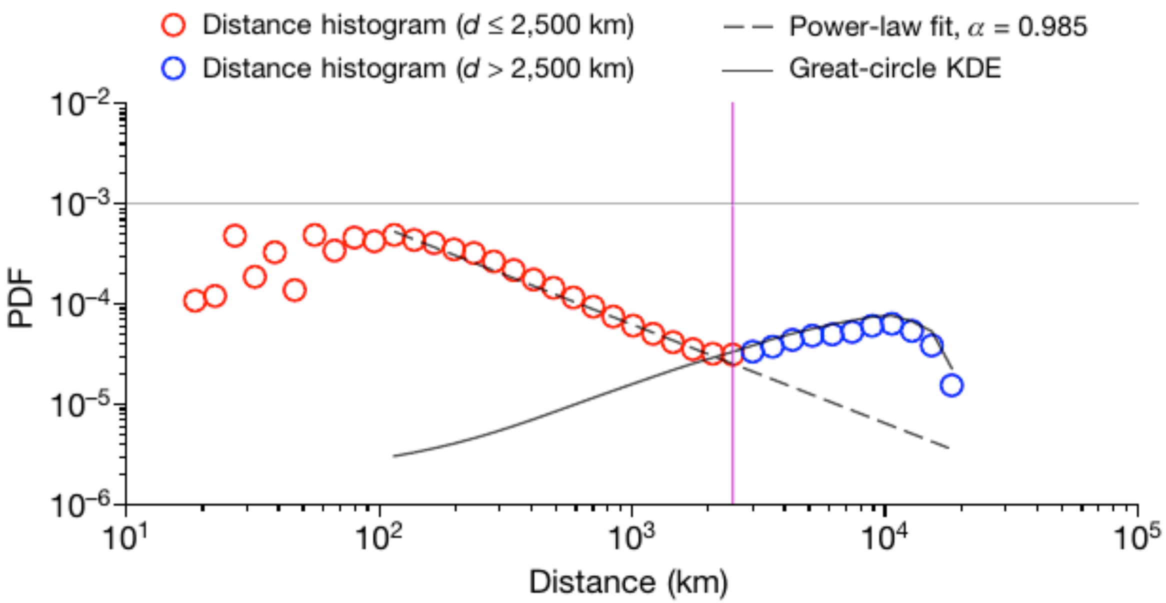


Potential pitfalls in climate network: *Spatial embedding*

Boers et al., Nature, 2019

Potential pitfalls in climate network: *Spatial embedding*

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



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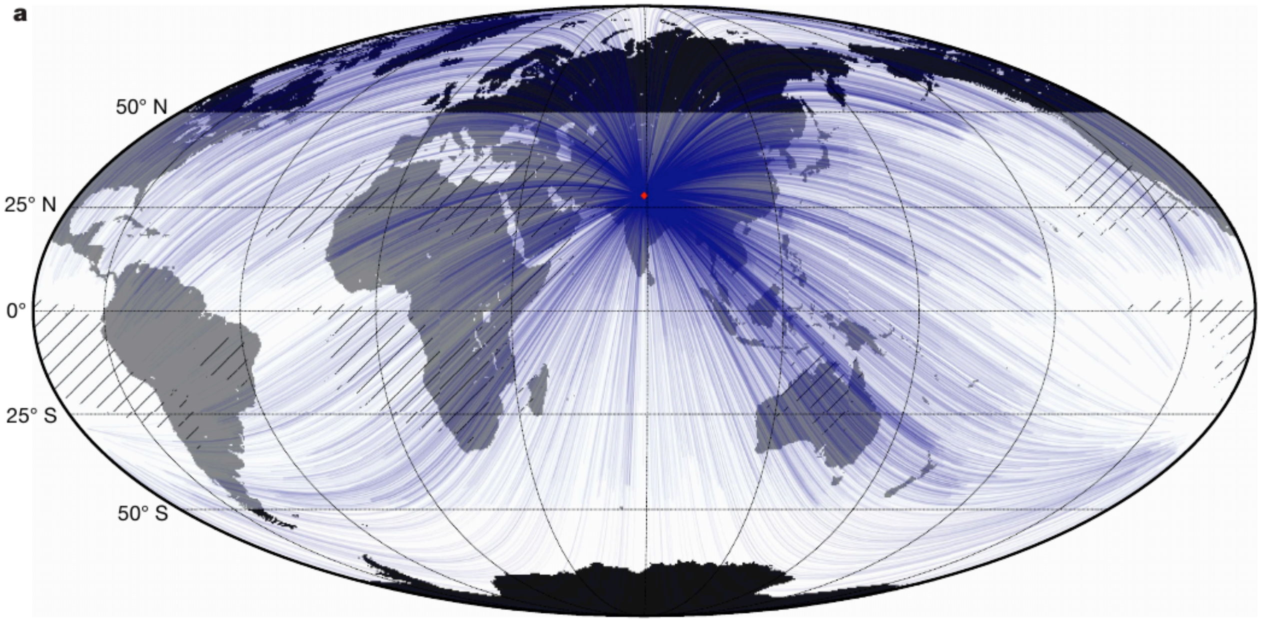
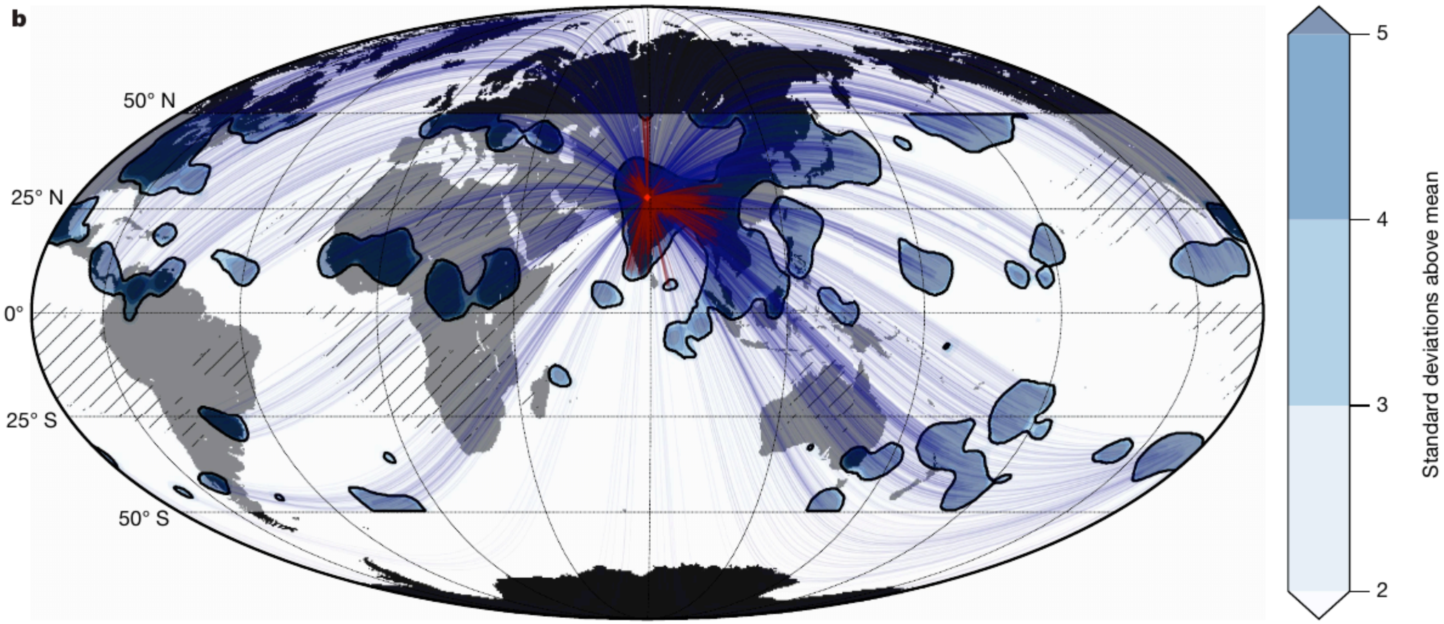
Daily extreme rainfall, 0.25 deg lat-lon grid, Event Synchronisation, 0.5% significance



Boers et al., Nature, 2019

Potential pitfalls in climate network: *Spatial embedding*

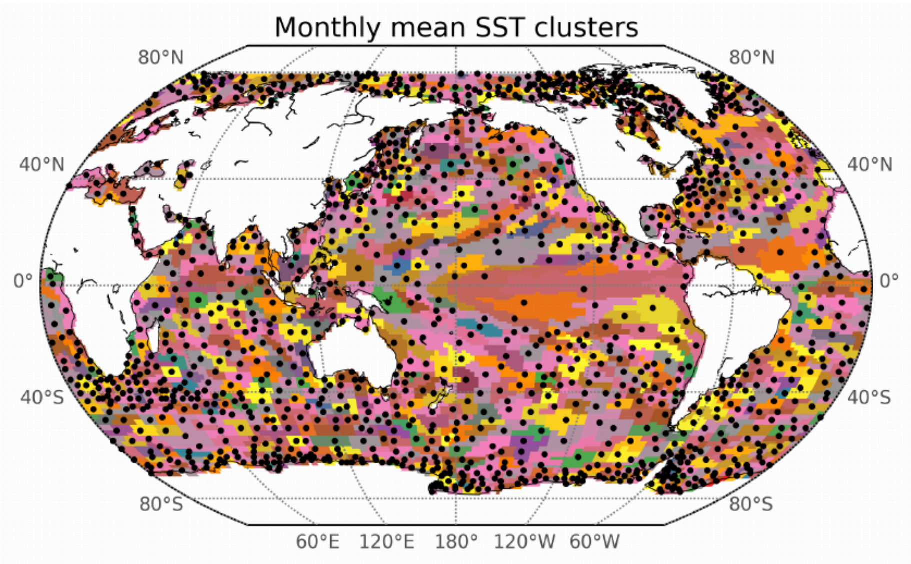
Daily extreme rainfall, 0.25 deg lat-lon grid, Event Synchronisation, 0.5% significance

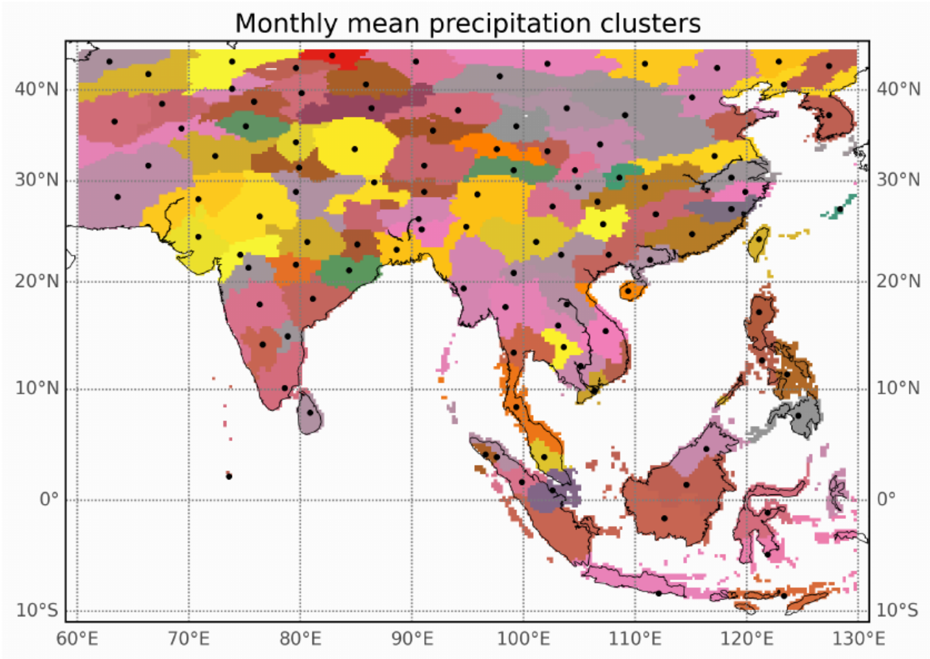


Teleconnection networks, or: a climate network of networks

Rheinwalt et a., Machine Learning and Data Mining Approaches to Climate Science (2015)

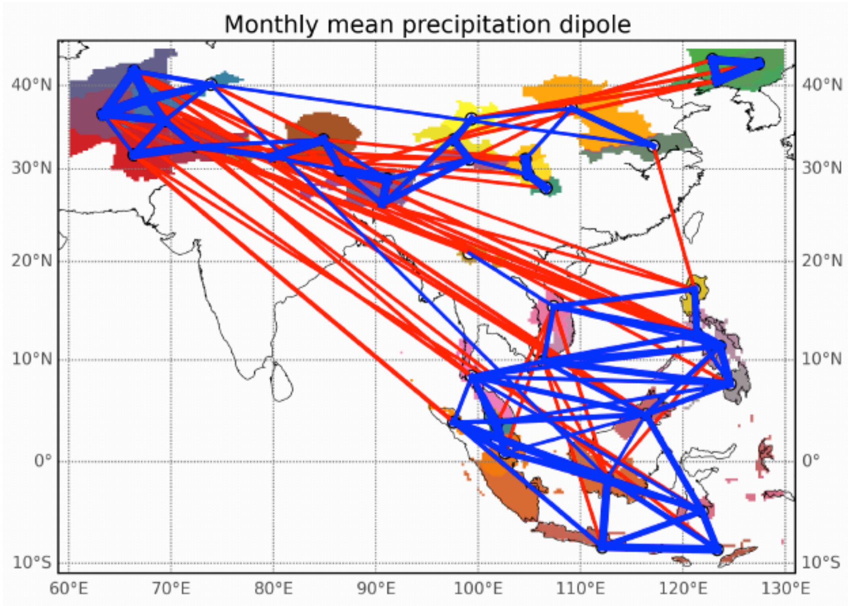
Teleconnection networks, or: a climate network of networks





Monthly mean data, arccos distance metric based on Spearman's correlation, complete linkage clustering

Teleconnection networks, or: a climate network of networks



Monthly mean data, arccos distance metric based on Spearman's correlation, complete linkage clustering

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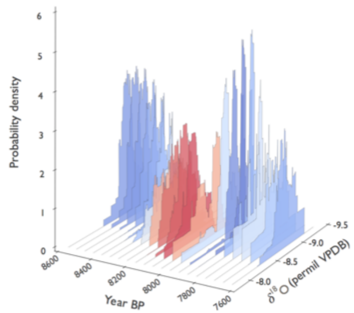

Uncertainties in paleoclimate proxy time series

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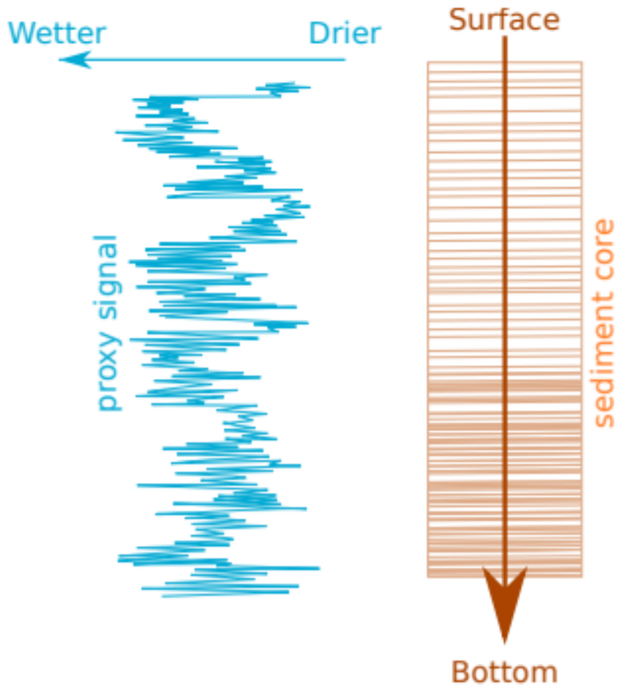

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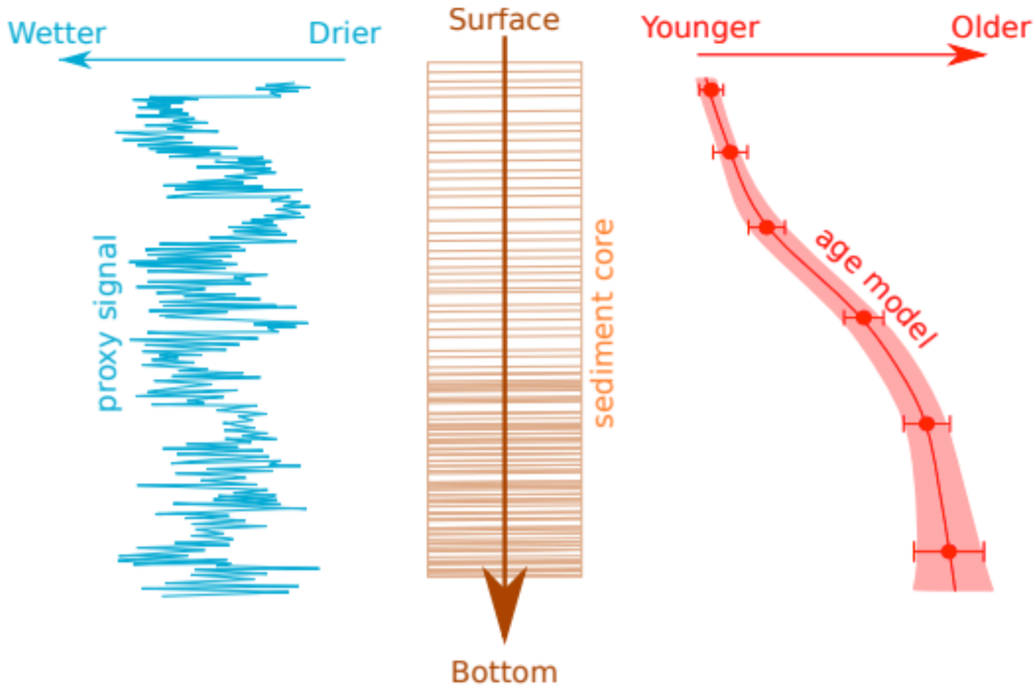

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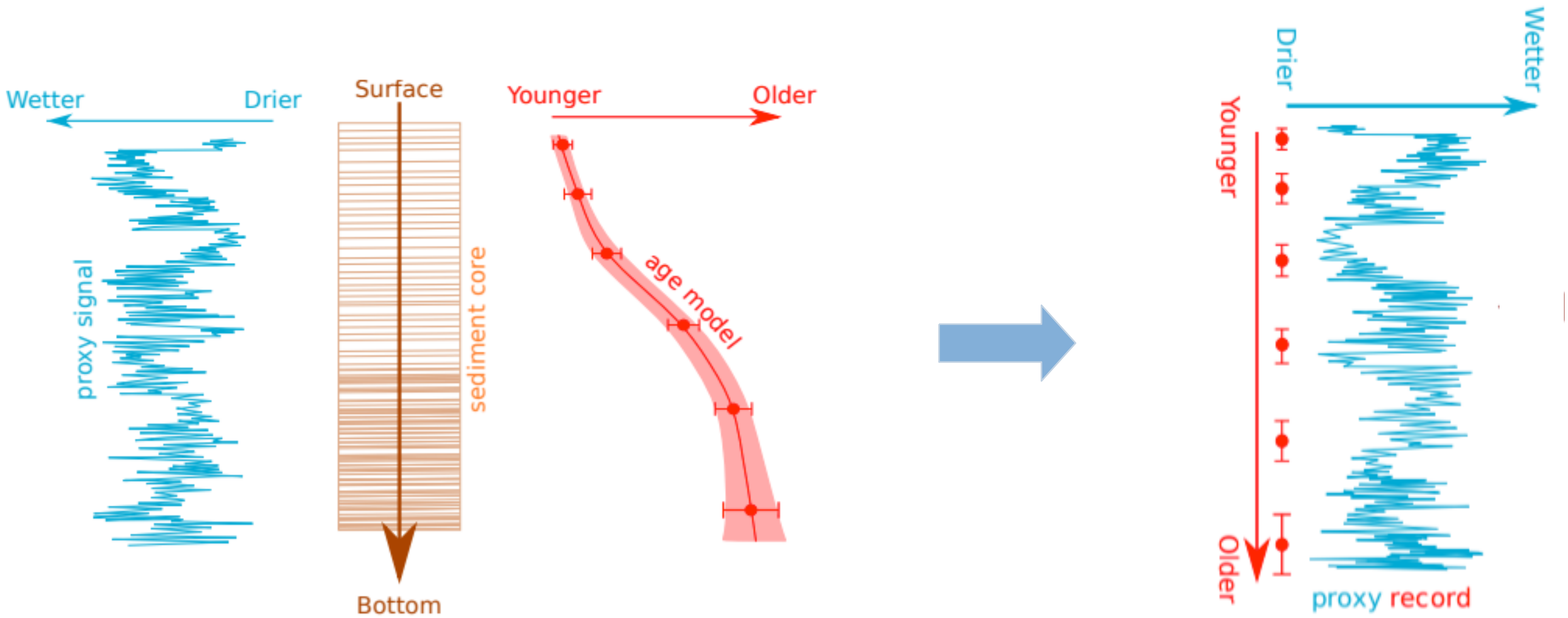

Breitenbach et al., *Clim. Past*, 2012

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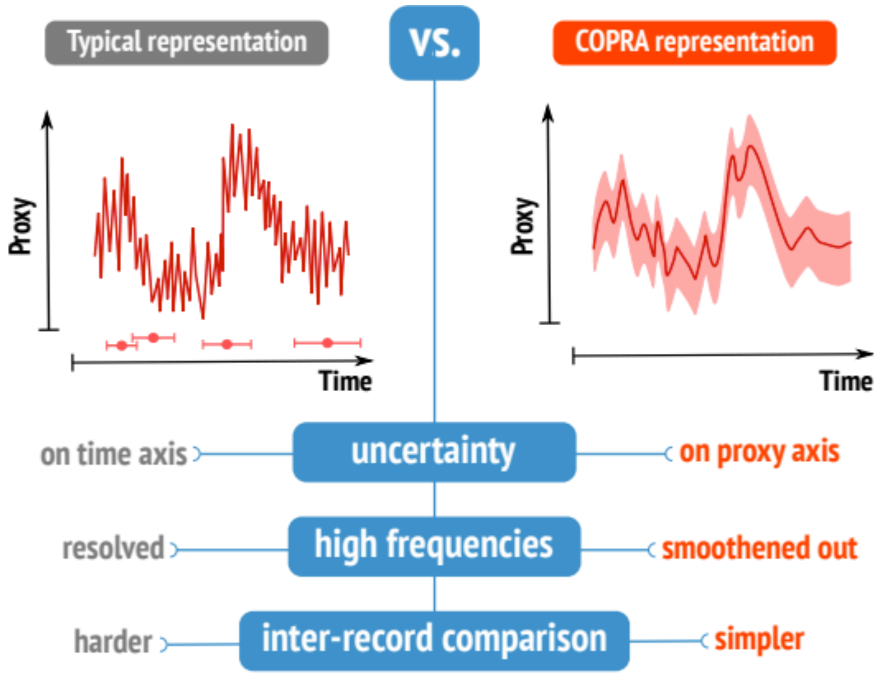

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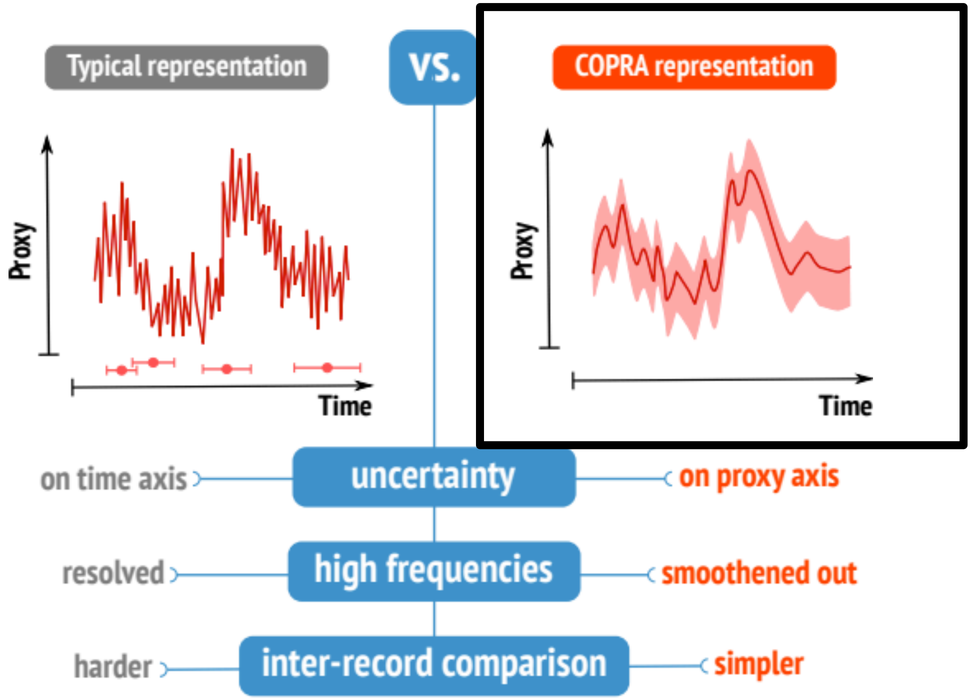

Time series as a sequence of probability distributions

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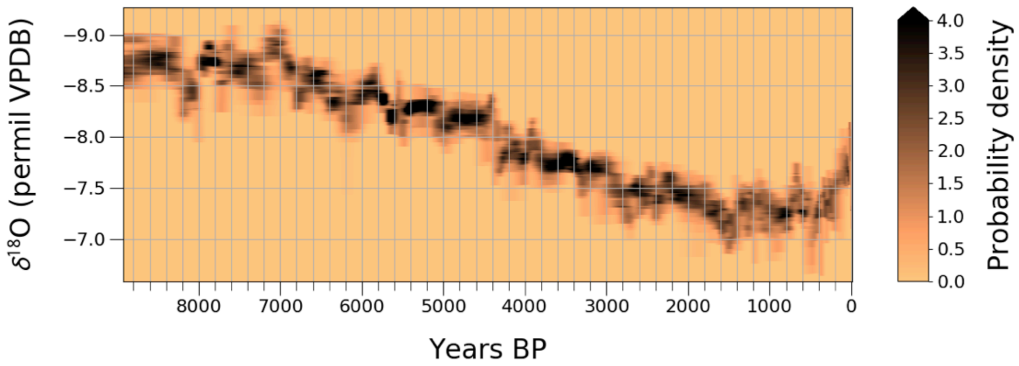

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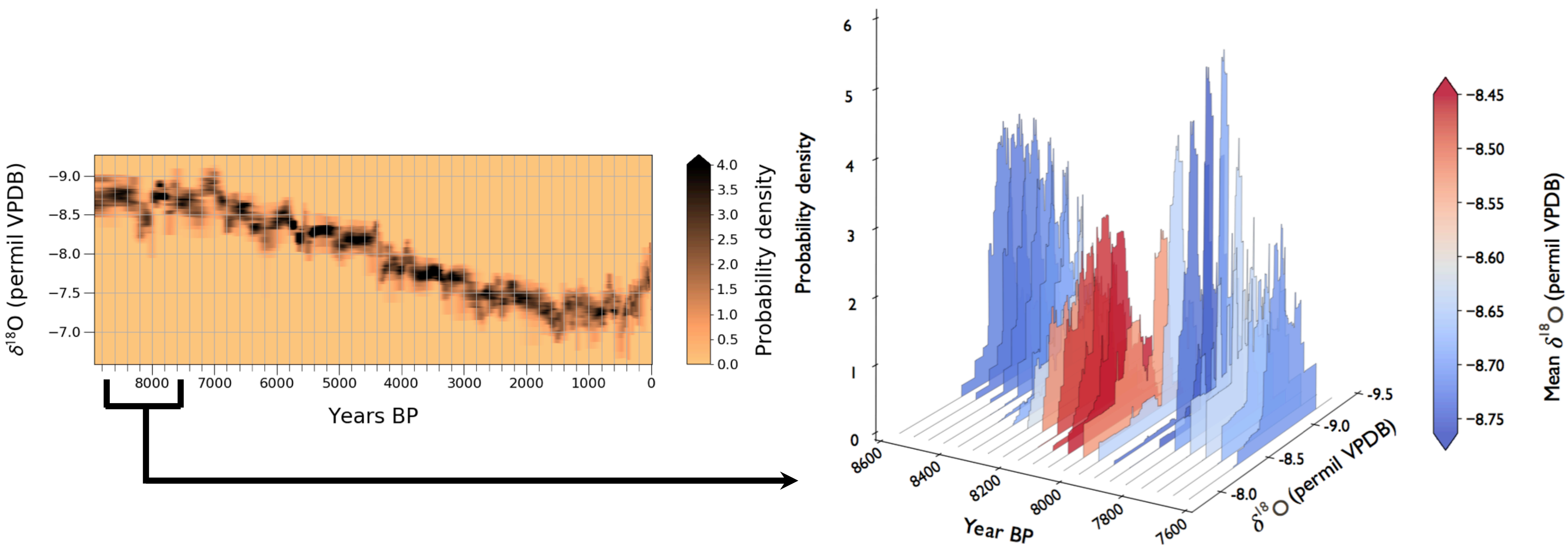
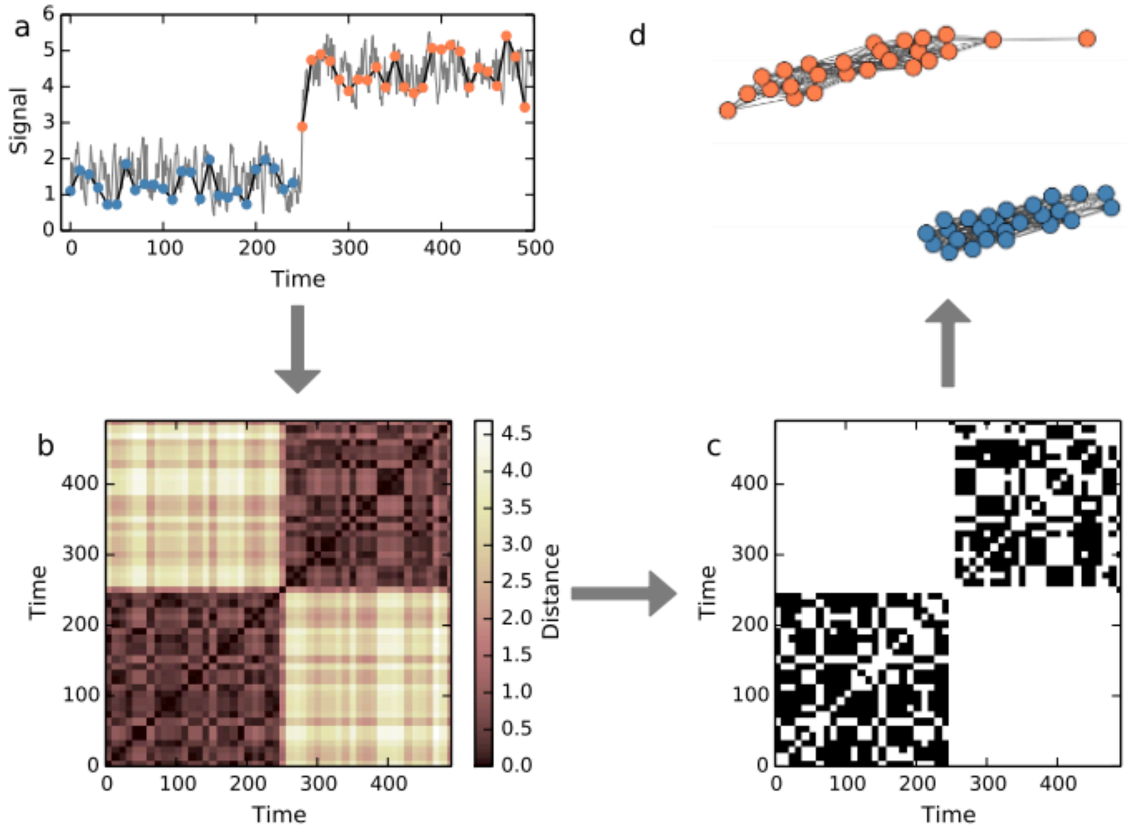


Abrupt transitions as a community detection problem

Abrupt transitions as a community detection problem



Put it together: Abrupt transitions in time series with uncertainties

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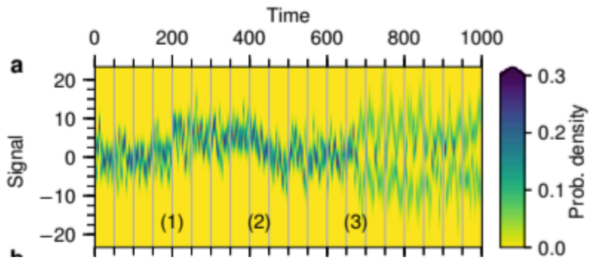
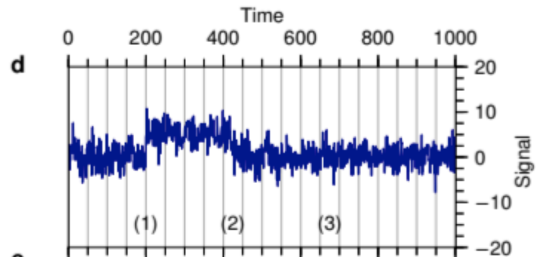
Time series as PDFs





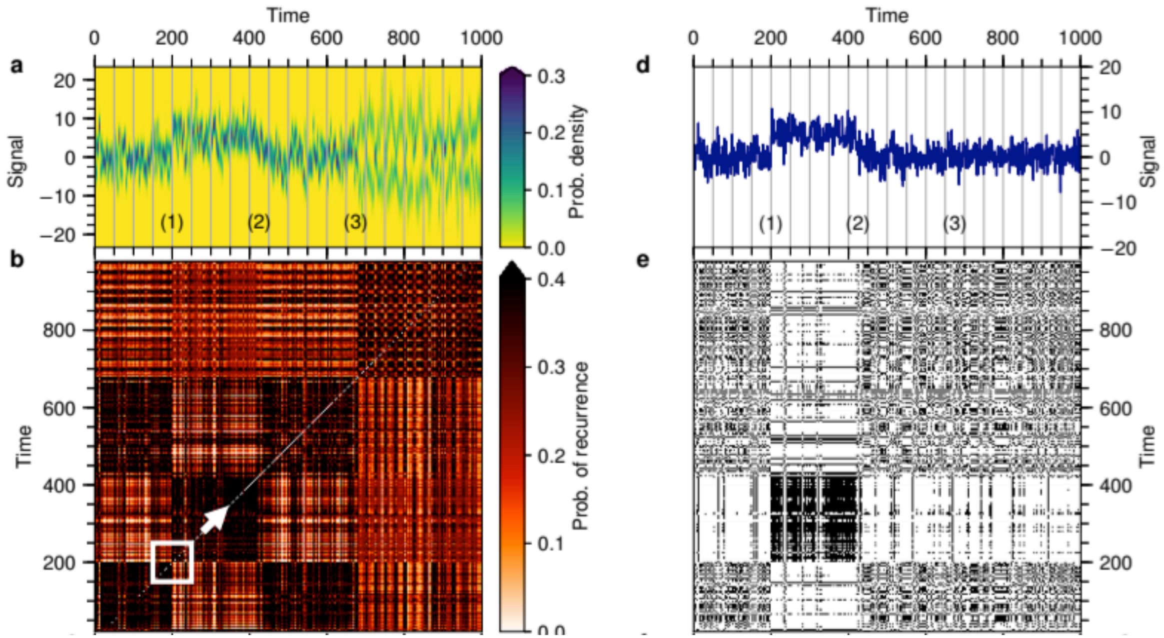
Classical tme series (mean)

Goswami et al., Nature Commnications, 2018

Put it together: Abrupt transitions in time series with uncertainties

Time series as PDFs

Probability of recurrence matrix



Classical tme series (mean)

Recurrence matrix

Goswami et al., Nature Commnications, 2018

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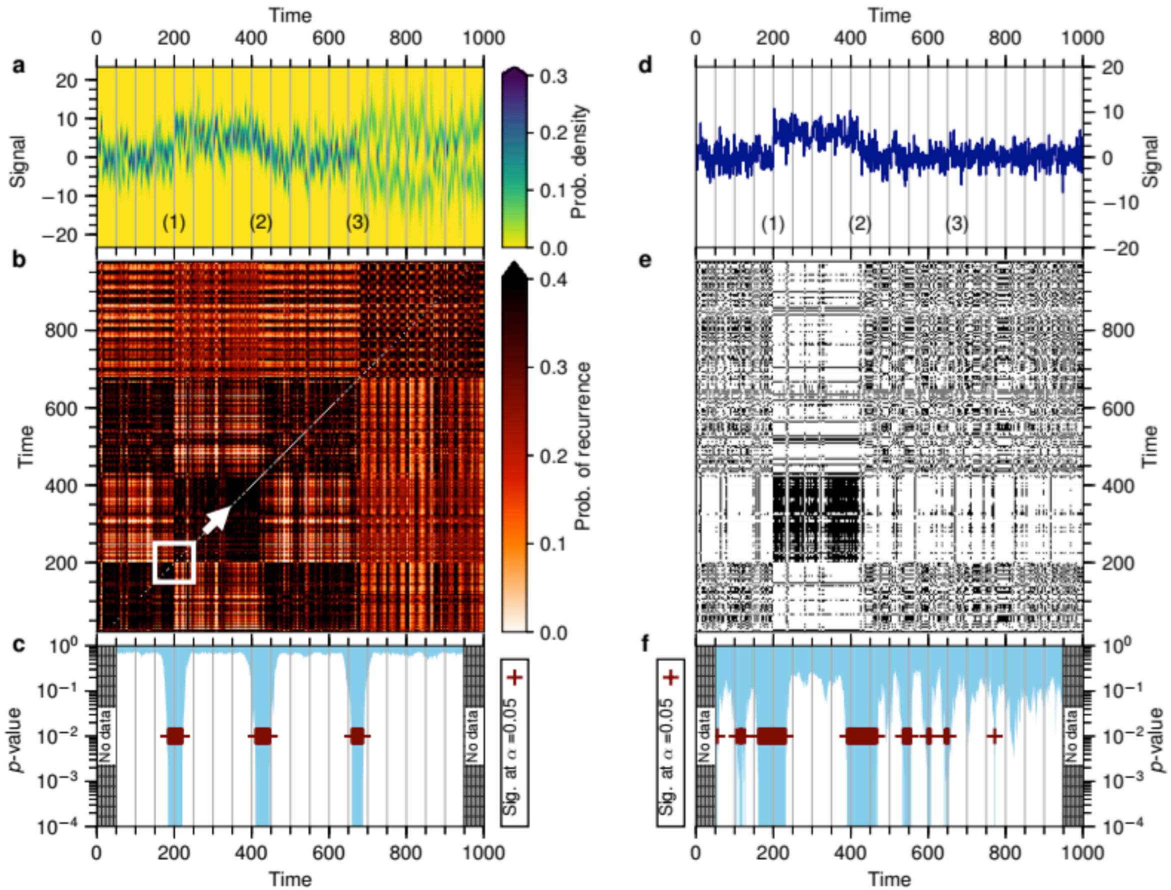
Probability of recurrence matrix

p-values of test in each window



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Transitions in the East Asian Summer Monsoon in the Holocene

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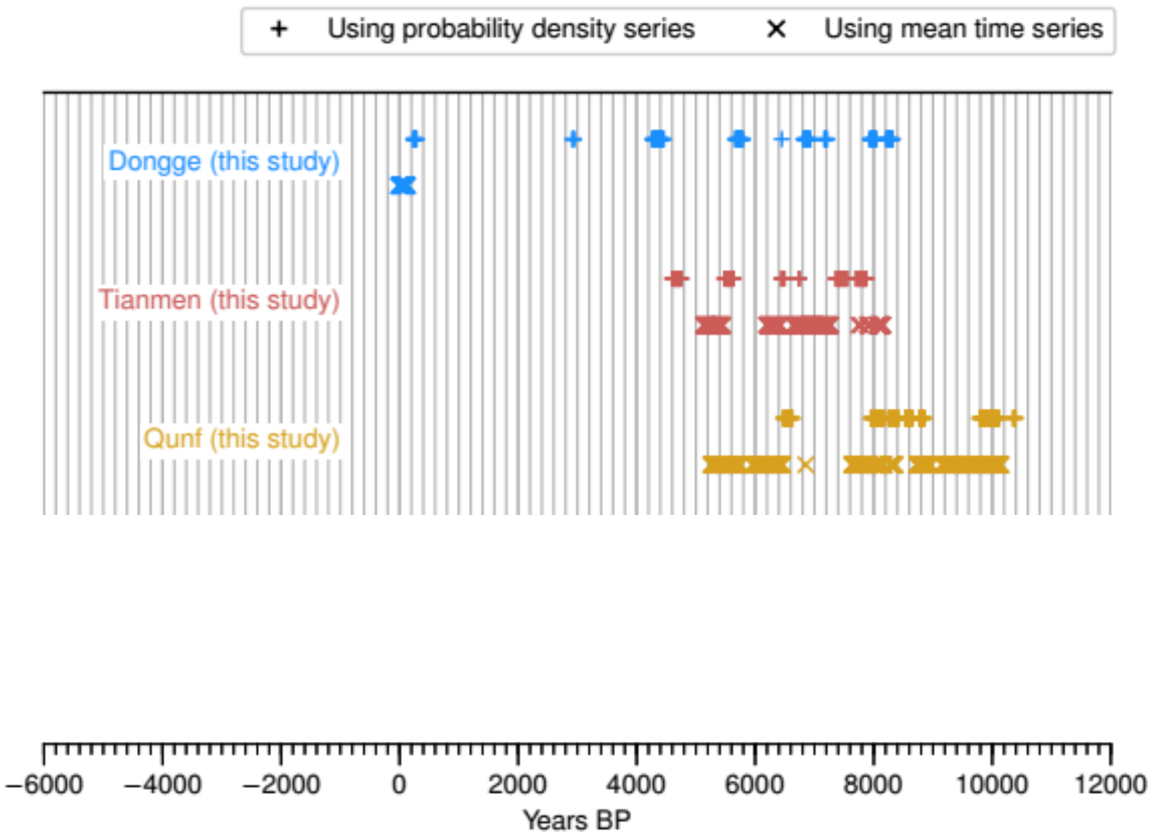
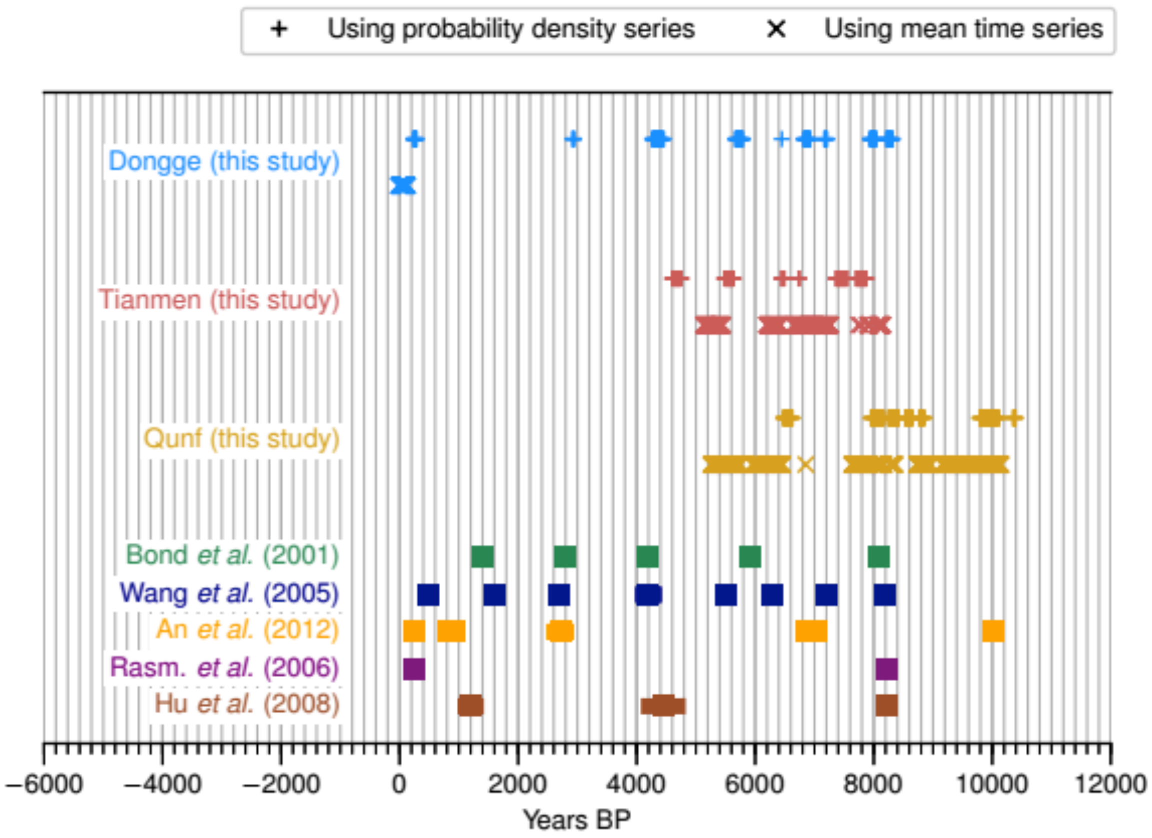


Goswami et al., *Nature Commnications*, 2018

Transitions in the East Asian Summer Monsoon in the Holocene



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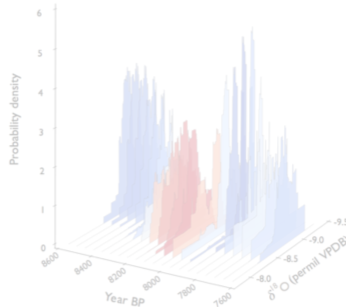

The world as graph: A Graph Neural Network for climate data

The World as a Graph: Improving El Niño Forecasts with Graph Neural Networks

Salva Rühling Cachay[1], Emma Erickson*[2],
Arthur Fender C. Bucker*[3, 4], Ernest Pokropek*[5], Willa Potosnak*[6],
Suyash Bire[8], Salomey Osei[7], and Björn Lütjens[8]

[1]Technical University of Darmstadt, [2]University of Illinois at Urbana-Champaign,
[3]University of São Paulo, [4] Technical University of Munich, [5]Warsaw University of Technology,
[6]Duquesne University, [7]African Institute for Mathematical Sciences, [8]Massachusetts Institute of Technology

Cachay et al., arXiv, 2021

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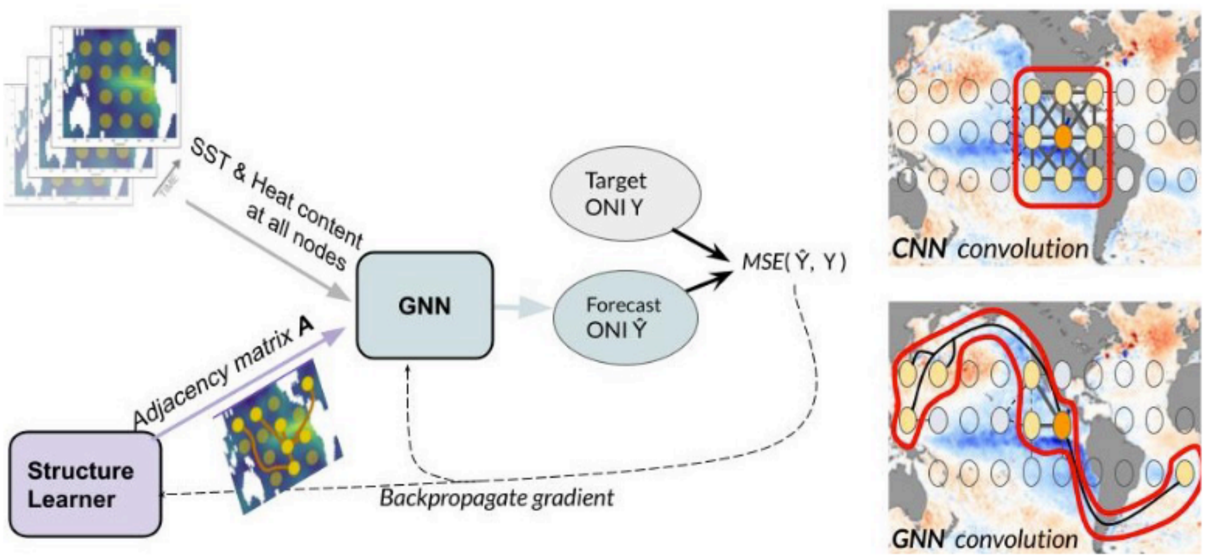

Cachay et al., arXiv, 2021

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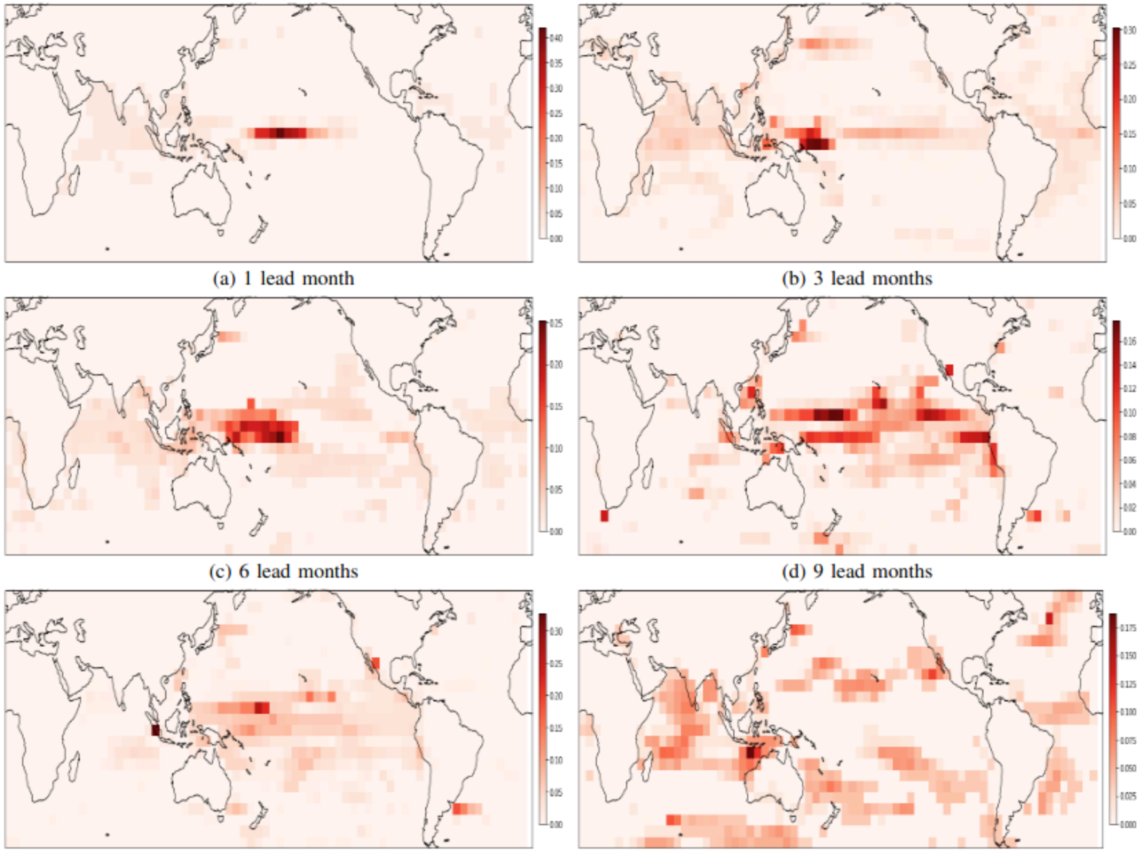

(a) 1 lead month (b) 3 lead months

(c) 6 lead months (d) 9 lead months

(e) 12 lead months (f) 23 lead months

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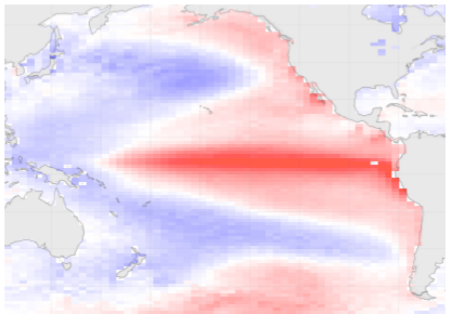

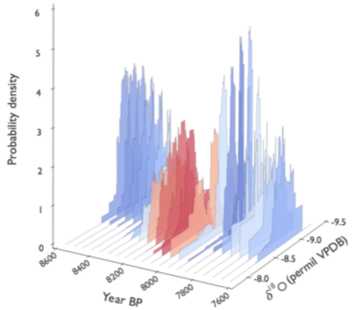

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