Causality for Climate (C4C)

Jakob Runge, Jordi Munoz-Mari

M. Bruhns, X. Tibau, C. Kaeding, A. Gerhardus, P. Nowack, G. Camps-Valls, V. Eyring

Support: Cameron Peron and Rebecca Wolff (Amazon), Neha Goel (Mathworks)

Knowledge for Tomorrow

December 15, 2019

Causality 4 Climate

- Real experiments

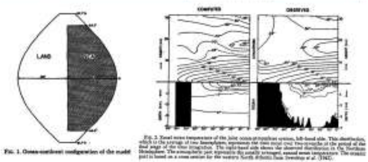
Bertini fresco of Galileo Galilei and Doge of Venice

Svante Arrhenius, 1909.
Print Collector/Getty Images / Getty Images

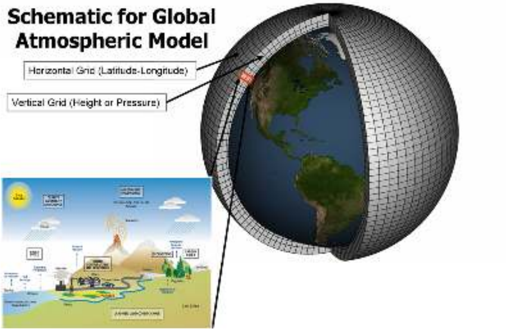
Earth Science Experiments Class Kit

Causality 4 Climate

- Real experiments
- Earth system simulation models



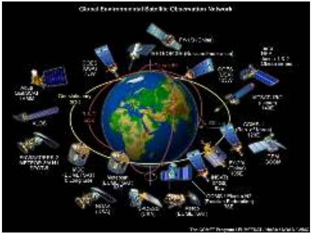
First coupled climate model: Manabe, S., and K. Bryan, 1969: Climate calculations with a combined ocean-atmosphere model. J. Atmos. Sci., 26, 786–789

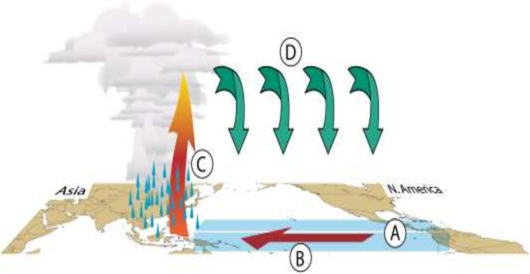


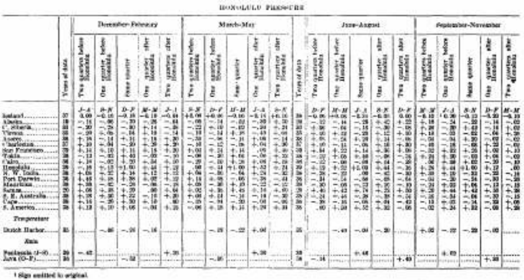
Causality 4 Climate

- Real experiments
- Earth system simulation models
- Observational data analysis

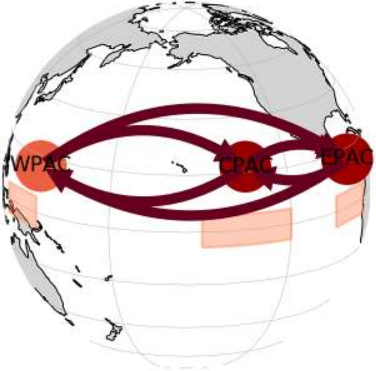
Walker, G T. 1924. “Correlations in Seasonal Variations of Weather.” IX. Mem. Ind. Metorol. Dept. 24: 53–84.



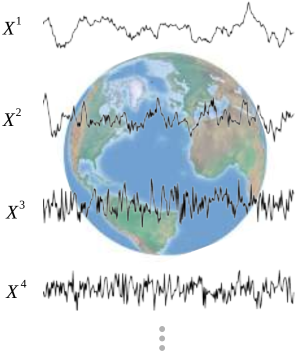

D
C
Asia
N.America
A
B


HONOLULU PRESSURE
December–February
March–May
June–August
September–November
Years of data
Two quarters before Honolulu
One quarter before Honolulu
Same quarter
One quarter after Honolulu
Two quarters after Honolulu
Iceland[1]
Alaska
C. Siberia
Vienna
Azores
Charleston
San Francisco
Tokio
Cairo
Honolulu
N. W. India
Port Darwin
Mauritius
Samoa
S. E. Australia
Cape
S. America
Temperature
Dutch Harbor
Rain
Peninsula (J–S)
Java (O–F)
[1] Sign omitted in original.

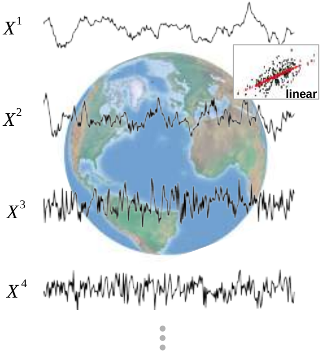
Correlation



Large-scale time series dataset



Large-scale time series dataset



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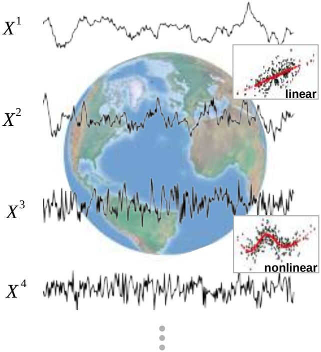
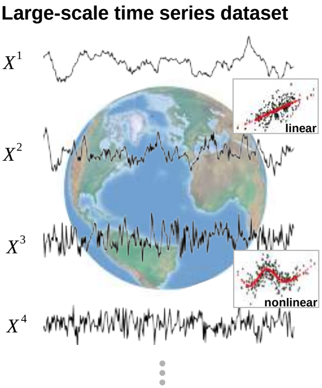
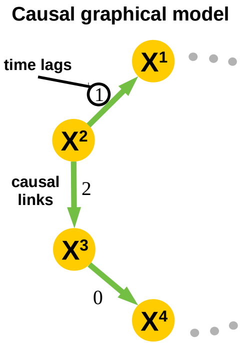
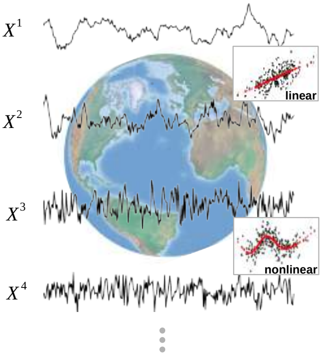
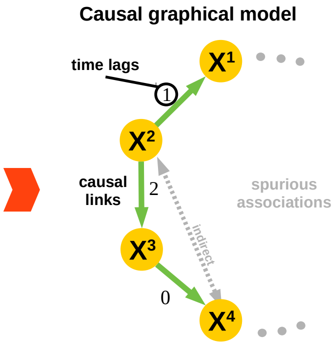


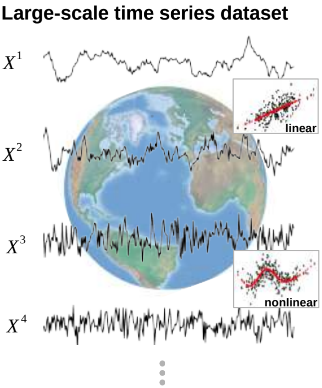

Large-scale time series dataset
X^1
X^2
X^3
X^4
linear
nonlinear


Causal graphical model
time lags
causal links
X1
X2
X3
X4
1
2
0

Causality 4 Climate



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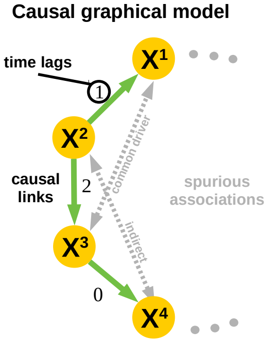
Causal graphical model
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causal
links
1
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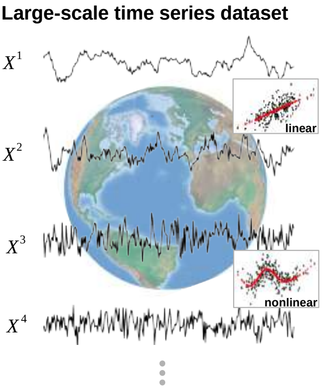
X1
X2
X3
X4
common driver
indirect
spurious
associations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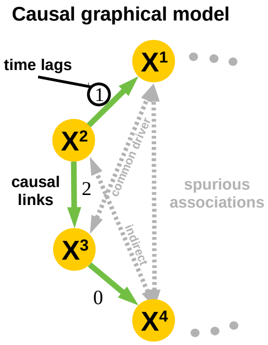
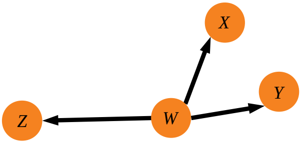
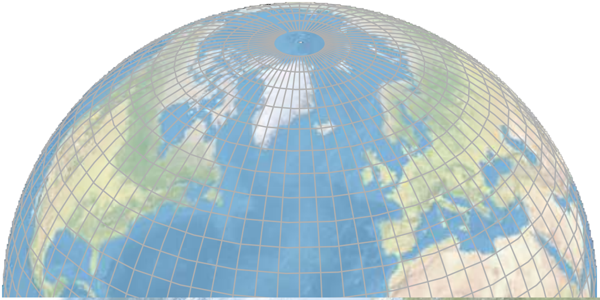

Causal graphical model
time lags
causal links
spurious associations
common driver
indirect
X1
X2
X3
X4
1
2
0

Challenges for causal discovery in Earth sciences

Challenges for causal discovery in the Earth sciences

Challenges

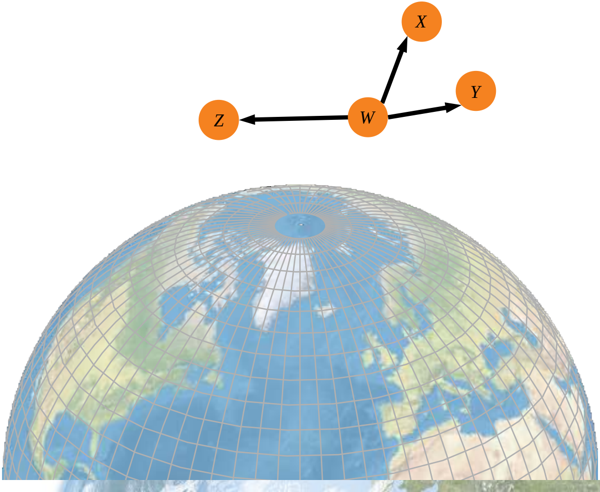




Challenges for causal discovery in the Earth sciences

Challenges

Process:

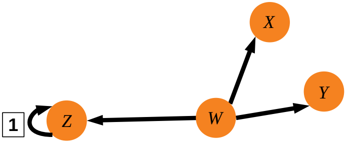


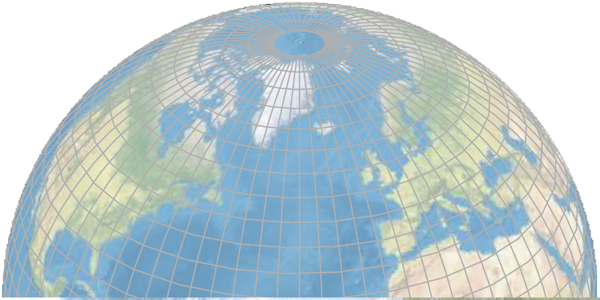
Challenges for causal discovery in the Earth sciences

Challenges

Process:

1 Autocorrelation

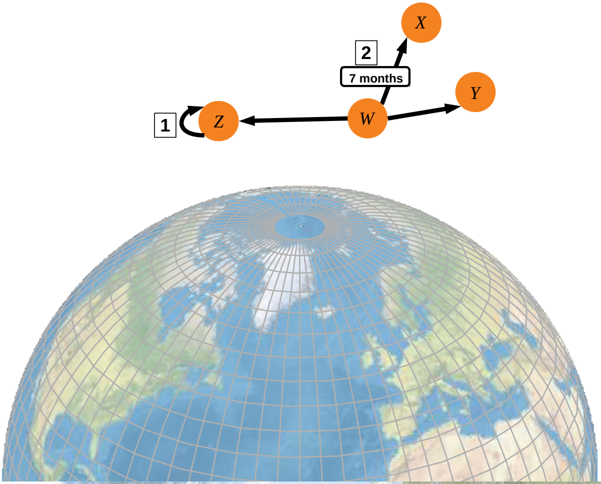




Challenges

Process:

1. Autocorrelation
2. Time delays

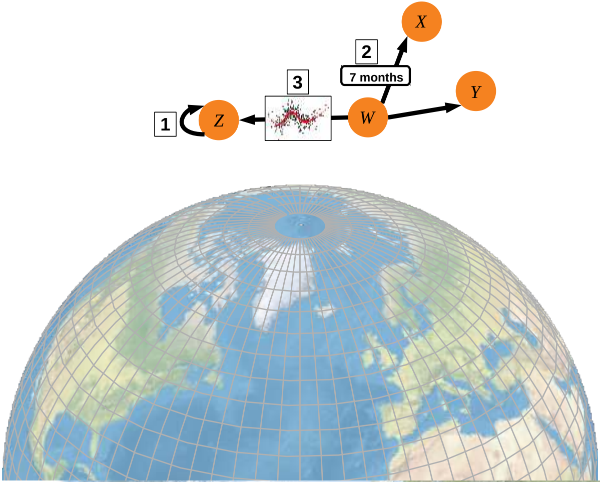


Challenges for causal discovery in the Earth sciences

Challenges

Process:

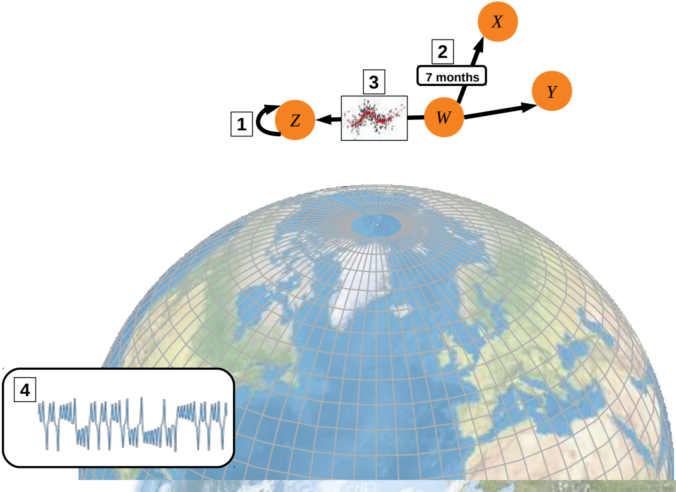
1 Autocorrelation
2 Time delays
3 Nonlinear dependencies



Challenges

Process:

1 Autocorrelation
2 Time delays
3 Nonlinear dependencies
4 Chaotic state-dependence

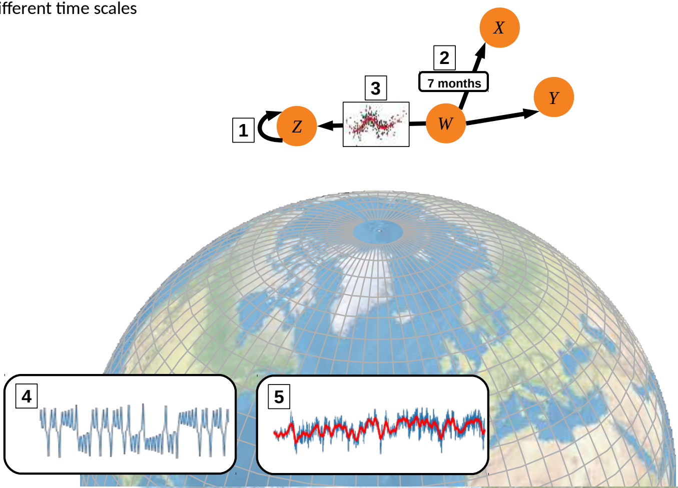


Challenges for causal discovery in the Earth sciences

Challenges

Process:

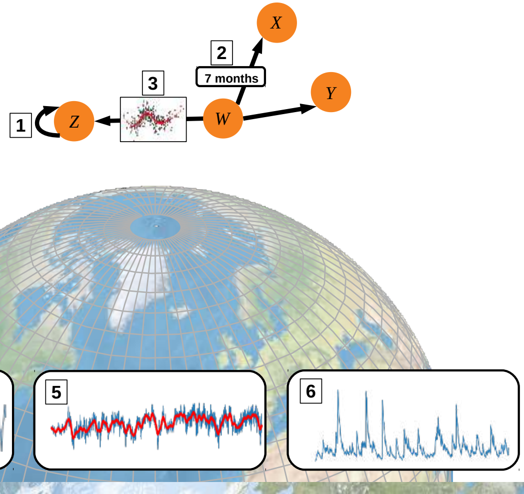
1 Autocorrelation
2 Time delays
3 Nonlinear dependencies
4 Chaotic state-dependence
5 Different time scales



Challenges

Process:

1 Autocorrelation
2 Time delays
3 Nonlinear dependencies
4 Chaotic state-dependence
5 Different time scales
6 Noise distributions



Challenges for causal discovery in the Earth sciences

Challenges

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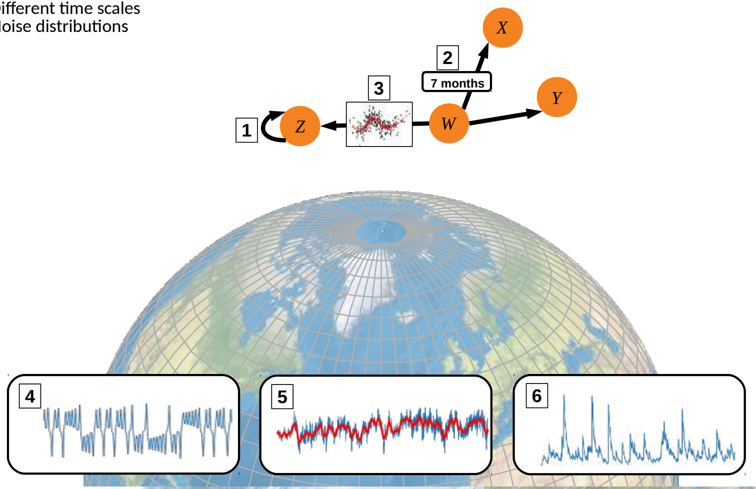

Challenges for causal discovery in the Earth sciences

Challenges

Process:

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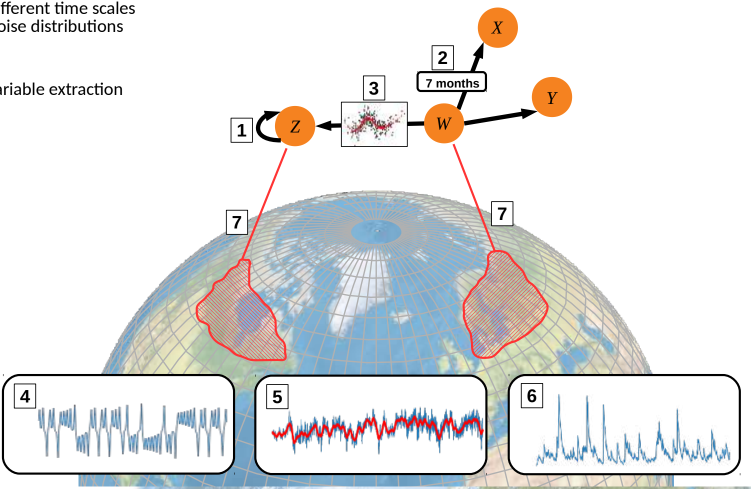
Data:

7 Variable extraction



Challenges for causal discovery in the Earth sciences

Challenges

Process:

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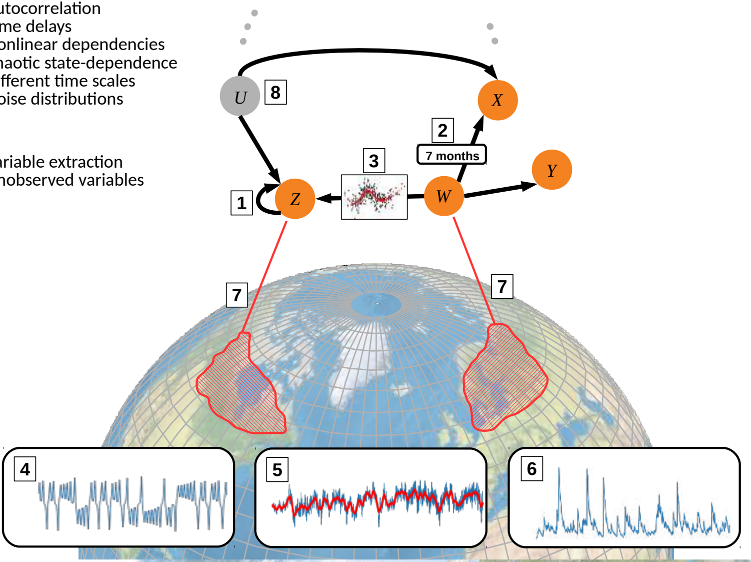
8 Unobserved variables



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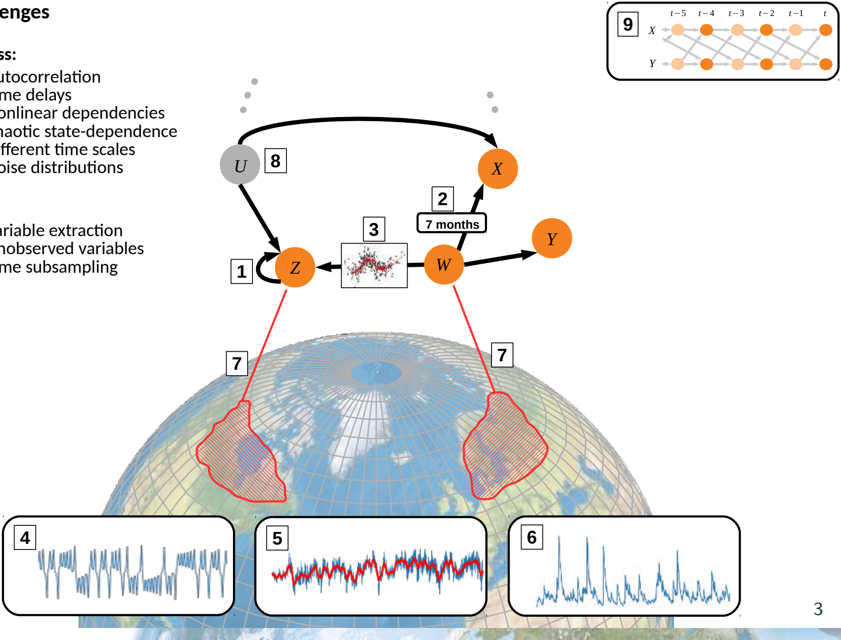

Challenges for causal discovery in the Earth sciences

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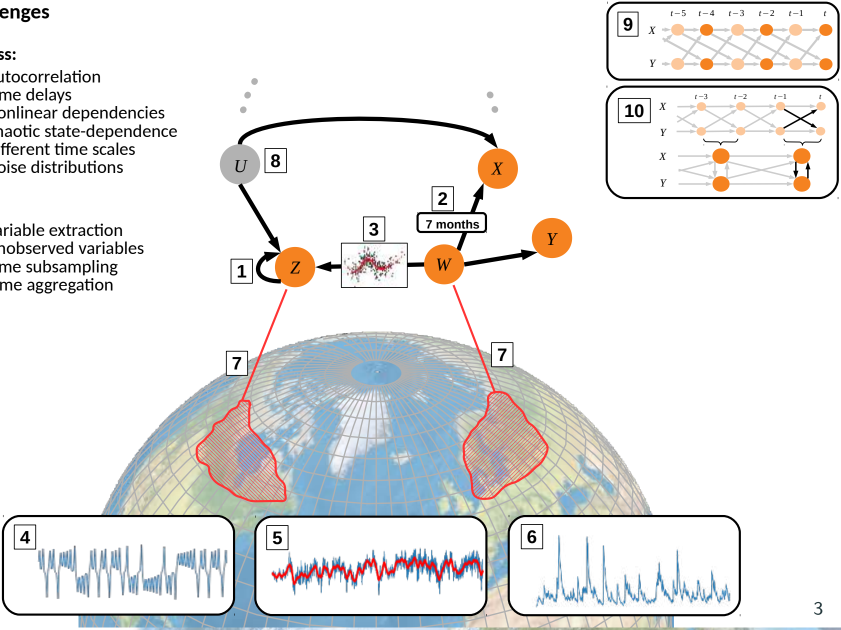
10 Time aggregation



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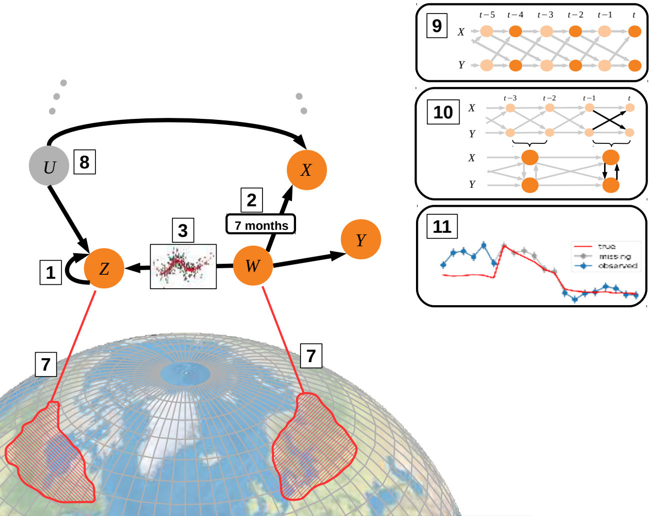
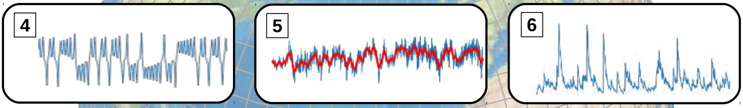
11 Measurement errors





Challenges for causal discovery in the Earth sciences

Challenges

Process:

1. Autocorrelation
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4. Chaotic state-dependence
5. Different time scales
6. Noise distributions

Data:

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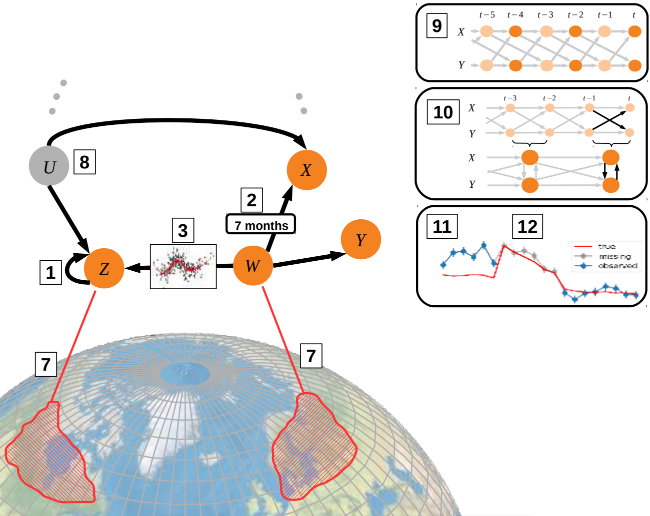
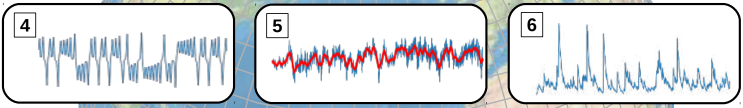
8. Unobserved variables
9. Time subsampling
10. Time aggregation
11. Measurement errors
12. Selection bias





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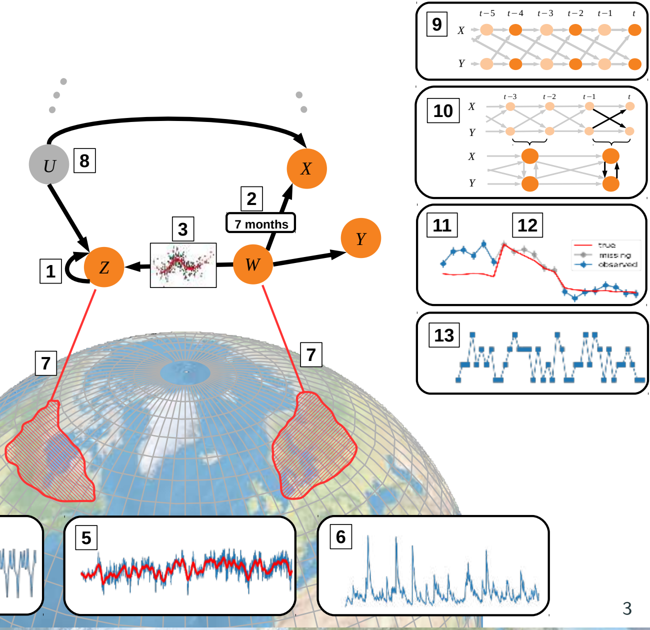

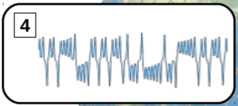

Challenges for causal discovery in the Earth sciences

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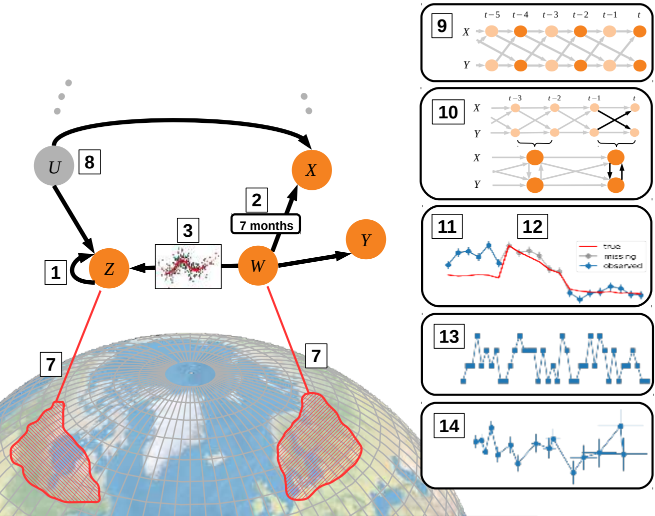
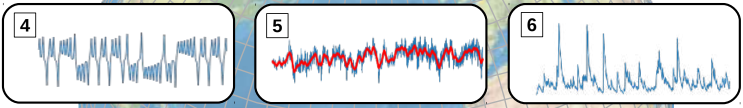
12 Selection bias
13 Discrete data
14 Dating uncertainties





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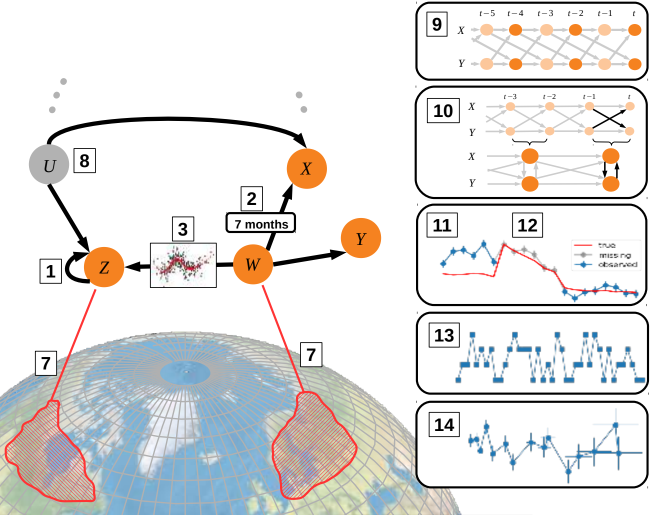
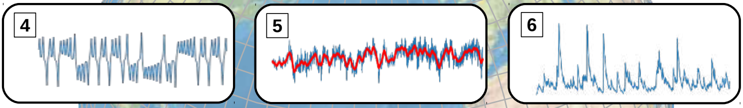
Computational / statistical:





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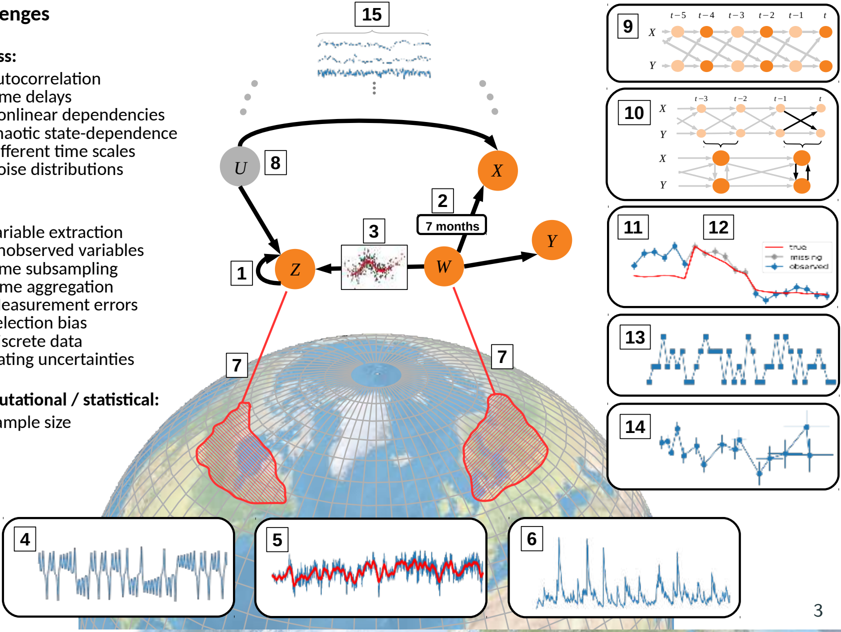
Computational / statistical:

15 Sample size



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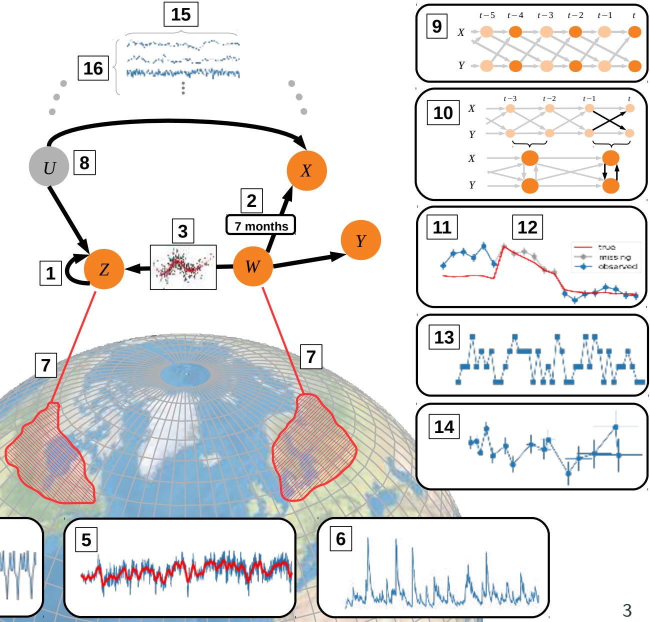
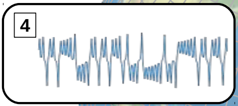
Computational / statistical:

15 Sample size
16 High dimensionality





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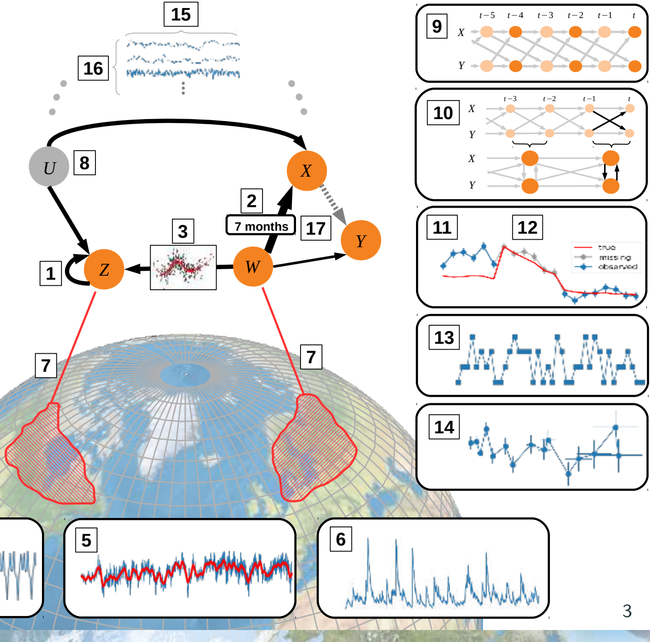
17 Uncertainty estimation



Challenges for causal discovery in the Earth sciences

Challenges

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6 Noise

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Computat
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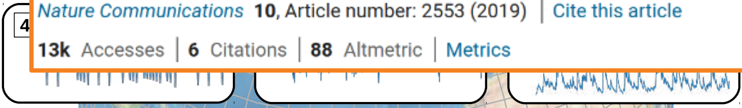
nature communications

Perspective | Open Access | Published: 14 June 2019

Inferring causation from time series in Earth system sciences

Jakob Runge, Sebastian Bathiany, Erik Bollt, Gustau Camps-Valls, Dim Coumou, Ethan Deyle, Clark Glymour, Marlene Kretschmer, Miguel D. Mahecha, Jordi Muñoz-Marí, Egbert H. van Nes, Jonas Peters, Rick Quax, Markus Reichstein, Marten Scheffer, Bernhard Schölkopf, Peter Spirtes, George Sugihara, Jie Sun, Kun Zhang & Jakob Zscheischler

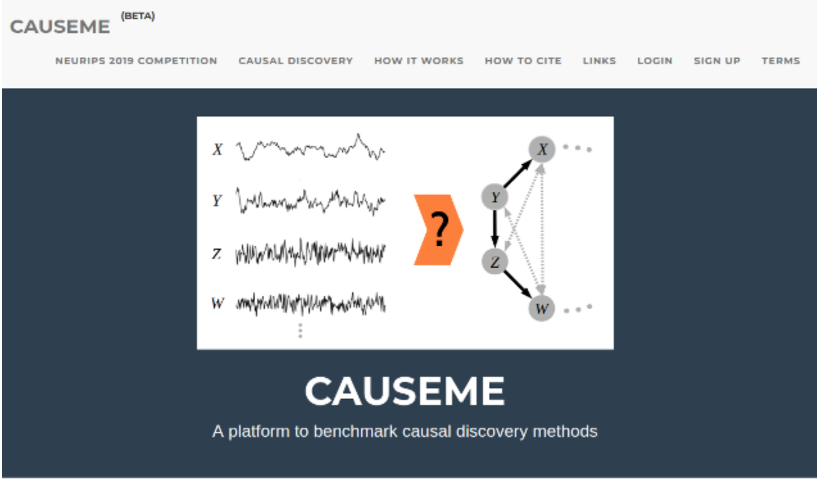
Nature Communications **10**, Article number: 2553 (2019) | Cite this article



Causality benchmark platform

Causality benchmark platform `CauseMe.net`

Joint work with Jordi Munoz-Mari and Gustau Camps-Valls (U Valencia)



Causality benchmark platform CauseMe.net

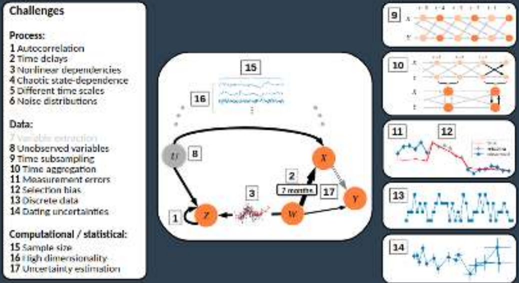
Joint work with Jordi Munoz-Mari and Gustau Camps-Valls (U Valencia)

CAUSEME (BETA)

NEURIPS 2019 COMPETITION | CAUSAL DISCOVERY | HOW IT WORKS | HOW TO CITE | LINKS | LOGIN | SIGN UP | TERMS

HOW IT WORKS

Causeme currently covers a wide range of synthetic model data mimicking a number of real world challenges. These cover time delays, autocorrelation, nonlinearity, chaotic dynamics, extreme events, measurement error, and will be extended by many more. Method developers can upload their predictions (matrices of causal connections) and the platform evaluates and ranks the methods according to different metrics of performance. After registering and logging in, more information, datasets, and example code snippets are given.



Causality benchmark platform `CauseMe.net`

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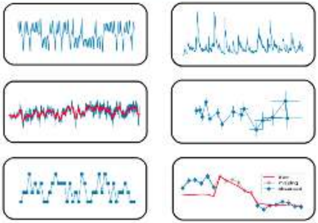
JAKOB RUNGE DATA AND MODELS METHODS RANKING HOWTO MY RESULTS LOGOUT

DATA AND MODELS



Below you find a list of available datasets. Currently, they come from dynamical model systems featuring different challenges for causal discovery from time series as discussed in the accompanying Nature Communications Perspective paper. At the end of this page you find information on how to contribute real world datasets or model systems. Clicking on the model name will bring you to a description of the model and a list of experimental datasets. Please see the CauseMe workflow description in HowTo on how to upload your results for these experiments.

You can search through the database by name, description or tags.

Filter models:

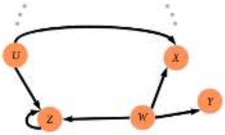
Name	Long name	Type	Tags

Causality benchmark platform `CauseMe.net`

Joint work with Jordi Munoz-Mari and Gustau Camps-Valls (U Valencia)

JAKOB RUNGE   DATA AND MODELS   METHODS   RANKING   HOWTO   MY RESULTS   LOGOUT

METHODS



Below you find a list of methods applied by users of this platform. Clicking on the name will bring you to a description of the method. You can search through the database by name, user, and tags. Register your own methods on My Results!

Show 10 entries

Filter methods:

Name	User	Tags
adaptive-lasso	Jakob runge	Linear, time delays, high-dimensional
correlation	Jakob runge	Linear, time series, non conditional
distance correlation	Jakob runge	Time delays, nonlinear, non-conditional
FullCI-CMIknn	Jakob runge	Time delays, nonlinear
FullCI-GPDC	Jakob runge	Time delays, nonlinear
FullCI-ParCorr	Jakob runge	Linear, time delays

Causality benchmark platform `CauseMe.net`

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JAKOB RUNGE — DATA AND MODELS — METHODS — RANKING — HOWTO — MY RESULTS — LOGOUT

RANKING

The table below presents a ranking of methods for different experiments and can be sorted according to the different metrics in columns. Optionally, the table can be filtered by metric values above or below a certain threshold. For example, one can display only methods with a FPR below 6% and sort these by TPR in decreasing order. In addition, the search field can be used on the whole table to select only particular experiments or particular methods (or both). For example, "varmodel N-10 T-150" will list all methods with 'varmodel' in the string and all experiments with N=10 variables and sample length T=150. See here for a description of metrics: AUC is based on scores, while F-measure, FPR, and TPR are based on binary link predictions by thresholding uploaded p-values at 0.05 (only available if p-values were uploaded). TLR requires lag predictions.

Filter: FPR < 0.06 Go Paper Code Validated

Show 100 entries — Search: linear-VAR_multirealizations_N-

Id	User	Experiment	Method (params)	Paper	Code	Valid.	Time	AUC	AUC-PR	F-measure	FPR	TPR	TLR	Boxplot FPR	Boxplot TPR
[illegible]	Jakob Runge	linear-VAR_multirealiz	PCMCI-ParCorr (tau_max=5,pc_	✔	✔	✔	2.97	0.98	0.89	0.56	0.05	0.92	0.98		
[illegible]	Jakob Runge	linear-VAR_multirealiz	adaptive-lasso (tau_max=5,)	✔	✖	✔	18.99	0.96	0.86	0.75	0.02	0.92	0.99		
[illegible]	Jakob Runge	linear-VAR_multirealiz	varmodel (maxlags=5,)	✔	✔	✔	0.48	0.95	0.69	0.50	0.05	0.76	0.98		
[illegible]	Jakob Runge	linear-VAR_multirealiz	FullCI-ParCorr (tau_max=5,)	✔	✔	✔	11.24	0.94	0.70	0.51	0.05	0.74	0.98		

Showing 1 to 4 of 4 entries (filtered from 1,604 total entries)

Previous 1 Next

DLR

Causality 4 Climate competition

Challenges

Process:

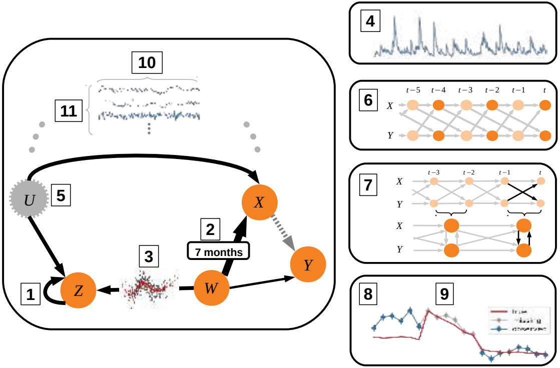
1 Autocorrelation
2 Time delays
3 Nonlinear dependencies
4 Non-gaussian noise

Data:

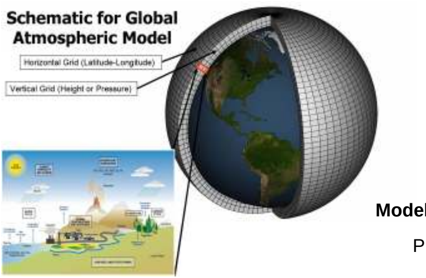
5 Non-stationarity due to unobserved drivers
6 Time subsampling
7 Time aggregation
8 Observational noise
9 Missing values

Computational / statistical:

10 Sample size
11 High dimensionality



Data generation



Source: NOAA

Steps

1. Select random CMIP5 model

Models used: IPSL-CM5A-MR and CanESM2

Pre-industrial control simulations

Data generation

Variable 1

Variable 2

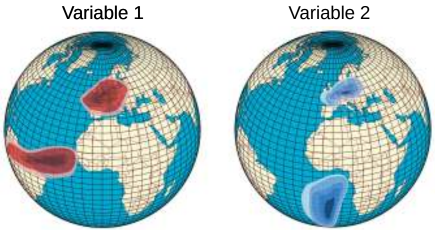
Steps

1. Select random CMIP5 model
2. Select random climate variables

At random height levels

Climate variables used: psl, hur, hus, huss, hfls, hfss, rlds, rlus, rlut, ta, tas, tasmax, tasmin, uas, va, vas, wap and zg

Data generation



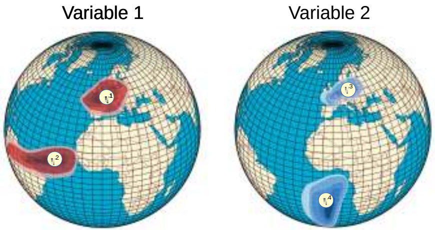
Steps

1. Select random CMIP5 model
2. Select random climate variables
3. Extract monthly modes of variability

Using PCA-Varimax rotation

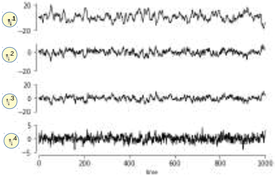
$$R_{varimax} = \arg\max_R \Big(\frac{1}{p}\sum_{j=1}^{k}\sum_{i=1}^{p}(\Lambda R)^4_{ij} - \sum_{j=1}^{k}\big(\frac{1}{p}\sum_{i=1}^{p}(\Lambda R)^2_{ij}\big)^2\Big)$$

Data generation



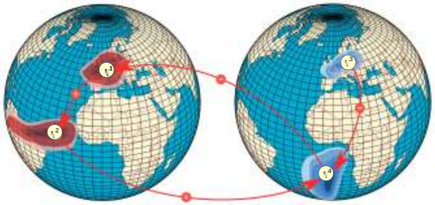
Steps

1. Select random CMIP5 model
2. Select random climate variables
3. Extract monthly modes of variability
4. Compute daily components



Data generation

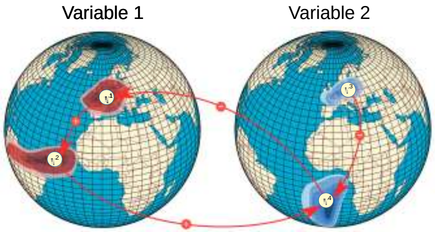
Variable 1 Variable 2



Steps

1. Select random CMIP5 model
2. Select random climate variables
3. Extract monthly modes of variability
4. Compute daily components
5. Fit VARmodel

Data generation

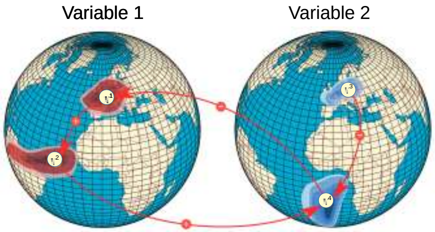


Steps

1. Select random CMIP5 model
2. Select random climate variables
3. Extract monthly modes of variability
4. Compute daily components
5. Fit VARmodel
6. Generate data

Use the residuals obtained from VARmodel as noise:
→ Non-gaussian climate/weather noise

Data generation



Steps

1. Select random CMIP5 model
2. Select random climate variables
3. Extract monthly modes of variability
4. Compute daily components
5. Fit VARmodel
6. Generate data
7. Further process data

Overview of experiments

Model	Process challenges (in addition to autocorrelation, time delays, non-Gaussian noise)	Data challenges	Number of variables	Sample size
CLIM		Time aggregation (30 days)	N = 5, 40	T= 100, 250
CLIMnoise		Time aggregation observational noise	N = 5, 40	T= 100, 250
CLIMnonstat	Nonstationarity	Time aggregation	N = 5, 40	T= 100, 250
WEATH	Nonlinearity		N = 5, 10	T= 1000, 2000
WEATHsub	Nonlinearity	Time-subsampling	N = 5, 10	T= 1000, 2000
WEATHnoise	Nonlinearty	Observational noise	N = 5, 10	T= 1000, 2000
WHEATmiss	Nonlinearty	Missing values	N = 5, 10	T= 1000, 2000

Overview of experiments

Linear model: climate data

$$X_t^j = \sum_{\tau=1}^{\tau_{max}} a_j^\tau X_{t-\tau}^j + \sum_{i=1}^{N} \sum_{\tau=1}^{\tau_{max}} c_{ji}^\tau X_{t-\tau}^i + \eta_t^j$$

$$\tilde{X}_t^j = \frac{1}{30} \sum_{t'=t-14}^{t'+15} X_{t'}^j$$

N = 5, 40
T = 100, 250

12 datasets

1. CLIM: Climate data
2. CLIMnoise: Climate data with Gaussian observational noise
3. CLIMnonstat: Climate data with non-stationary trend

Overview of experiments

Linear model: climate data

$$X_t^j = \sum_{\tau=1}^{\tau_{max}} a_j^\tau X_{t-\tau}^j + \sum_{i=1}^{N} \sum_{\tau=1}^{\tau_{max}} c_{ji}^\tau X_{t-\tau}^i + \eta_t^j + w_t^j$$

N = 5, 40
T = 100, 250

12 datasets

1. CLIM: Climate data
2. CLIMnoise: Climate data with Gaussian observational noise
3. **CLIMnonstat:** Climate data with non-stationary trend

w_t^j is a trend value coming from an Ornstein-Uhlenbeck stochastic process

Overview of experiments

Nonlinear model: weather data

$$X_t^j = \sum_{\tau=1}^{\tau_{max}} a_j^\tau X_{t-\tau}^j + \sum_{i=1}^{N} \sum_{\tau=1}^{\tau_{max}} c_{ji}^\tau f_{ji}^\tau(X_{t-\tau}^i) + \eta_t^j$$

N = 5, 10
T = 1000, 2000

16 datasets

1. WEATH: Weather data
2. WEATHsub: Weather data with observations every 3 time steps
3. WEATHnoise: Weather data with observational Gaussian noise
4. WEATHmiss: Weather data with 1% of missing values

f is smooth nonlinear function

Bonus experiments

LINEAR-VAR

$$X_t^j = aX_{t-1}^j + \sum_{i=1}^{N}\sum_{\tau=1}^{\tau_{max}} c_{ji}^{\tau} X_{t-\tau}^i + \eta_t^j$$

N = 10, 100
T = 150

L = *N* links are randomly drawn
a, c, tau are randomly drawn
eta is standard normal noise

2 datasets

Bonus experiments

NONLINEAR-VAR

$$X_t^j = aX_{t-1}^j + \sum_{i=1}^{N} \sum_{\tau=1}^{\tau_{max}} c_{ji}^{\tau} f_{ji}^{\tau}(X_{t-\tau}^i) + \eta_t^j$$

f are smooth nonlinear functions that still yield stationary processes

N = 20
T = 600

1 dataset

Bonus experiments

LOGISTIC

$$X_t^j = X_{t-1}^j (4 - 4X_{t-1}^j - \sum_{i=1}^{N} \sum_{\tau=1}^{\tau_{\max}} c_{ij}^{\tau} X_{t-\tau}^i + \sigma \eta_t^j) \quad mod \;\; 1$$

N = 5
T = 150

3 datasets

1. deterministic: σ = 0
2. low noise: σ = some nonzero value
3. high noise: σ = some higher nonzero value

eta is standard uniform noise

Setup and score metric

Setup and score metric

For both Test* and Final* datasets:

- *B = 200* time series realizations were generated for each dataset with aforementioned models (→ robust evaluation)
- Users upload a score entry *(i,j)* indicating confidence in a link *i* --> *j*

Setup and score metric

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Area Under the Receiver Operating Characteristic Curve (ROC AUC):

- Based on the score matrices
- The true label of a link is binary: 0 (missing) or 1 (causal link).
- Here AUC is computed by concatenating all *(N, N)* matrices (excluding self-links) of the *B* different datasets in an experiment *(B=200)* and provides a summary metric
- High AUC values (maximum is 1) indicate better performance

Some numbers...

- 190 total, 40 active participants

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- 146 different methods

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- 190 total, 40 active participants
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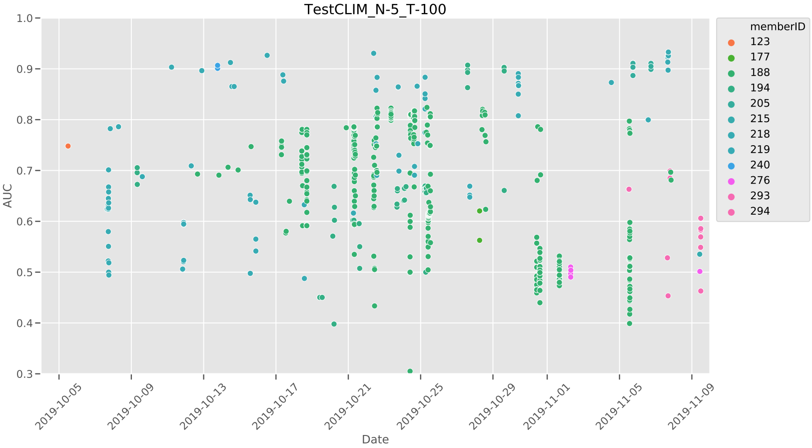
- Testing phase impressions...


TestCLIM_N-5_T-100
AUC
Date
memberID
123
177
188
194
205
215
218
219
240
276
293
294
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
2019-10-05
2019-10-09
2019-10-13
2019-10-17
2019-10-21
2019-10-25
2019-10-29
2019-11-01
2019-11-05
2019-11-09

Talks by two of the winning teams

Prizes

Prizes

Mapefast

Best in 3 categories

Prizes

aws

Rookie

Best in 13 categories

Mapefast

Best in 3 categories

Prizes

aws

Copenhagen Causality Lab

Best in 18 categories + overall AUC score

Rookie

Best in 13 categories

Mapefast

Best in 3 categories

Overall average AUC results

User	average AUC across all datasets
Copenhagen Causality Lab	0.917
BCause	0.722
rookie	0.676
iggisv9t	0.660
SharifCausalAI	0.443
BJTU-INSIS	0.413
WenhuiZhang	0.310
joelonglin	0.286
Harikrishnan N B	0.250
fisehrwsy	0.236
Mapefast	0.156
Liting Huang	0.130
Aditi Kathpalia	0.122
n_causeme	0.096
causal_man	0.092
astroman	0.048
cheruk	0.042

Results for individual datasets

Dataset	User	AUC
FinalCLIM_N-5_T-100	Copenhagen Causality Lab	0.934
	SharifCausalAI	0.914
	rookie	0.905
FinalCLIM_N-5_T-250	Copenhagen Causality Lab	0.944
	SharifCausalAI	0.930
	rookie	0.928
FinalCLIM_N-40_T-100	Copenhagen Causality Lab	0.920
	rookie	0.858
	BCause	0.661
FinalCLIM_N-40_T-250	Copenhagen Causality Lab	0.947
	rookie	0.864
	BCause	0.755

NeurIPS C4C `CauseMe.net/neurips2019`

Dataset	User	AUC
FinalCLIMnoise_N-5_T-100	Copenhagen Causality Lab	0.901
	SharifCausalAI	0.879
	iggisv9t	0.752
FinalCLIMnoise_N-5_T-250	Copenhagen Causality Lab	0.921
	rookie	0.904
	SharifCausalAI	0.903
FinalCLIMnoise_N-40_T-100	Copenhagen Causality Lab	0.877
	BCause	0.615
	iggisv9t	0.586
FinalCLIMnoise_N-40_T-250	Copenhagen Causality Lab	0.907
	BCause	0.689
	iggisv9t	0.621

NeurIPS C4C `CauseMe.net/neurips2019`

Dataset	User	AUC
FinalCLIMnonstat_N-5_T-100	Copenhagen Causality Lab	0.923
	SharifCausalAI	0.913
	rookie	0.861
FinalCLIMnonstat_N-5_T-250	Copenhagen Causality Lab	0.942
	joelonglin	0.931
	SharifCausalAI	0.930
FinalCLIMnonstat_N-40_T-100	Copenhagen Causality Lab	0.907
	iggisv9t	0.568
	BCause	0.528
FinalCLIMnonstat_N-40_T-250	Copenhagen Causality Lab	0.908
	rookie	0.873
	BCause	0.624

NeurIPS C4C CauseMe.net/neurips2019

Dataset	User	AUC
FinalWEATH_N-5_T-1000	rookie	0.935
	Copenhagen Causality Lab	0.924
	SharifCausalAI	0.875
FinalWEATH_N-5_T-2000	Copenhagen Causality Lab	0.951
	rookie	0.950
	fisehrwsy	0.947
FinalWEATH_N-10_T-1000	rookie	0.940
	Copenhagen Causality Lab	0.937
	fisehrwsy	0.912
FinalWEATH_N-10_T-2000	rookie	0.951
	Copenhagen Causality Lab	0.946
	WenhuiZhang	0.919

NeurIPS C4C `CauseMe.net/neurips2019`

Dataset	User	AUC
FinalWEATHsub_N-5_T-1000	Copenhagen Causality Lab	0.898
	rookie	0.888
	WenhuiZhang	0.886
FinalWEATHsub_N-5_T-2000	Copenhagen Causality Lab	0.898
	rookie	0.895
	joelonglin	0.883
FinalWEATHsub_N-10_T-1000	rookie	0.884
	Copenhagen Causality Lab	0.883
	WenhuiZhang	0.815
FinalWEATHsub_N-10_T-2000	rookie	0.904
	Copenhagen Causality Lab	0.903
	joelonglin	0.884

NeurIPS C4C CauseMe.net/neurips2019

Dataset	User	AUC
FinalWEATHnoise_N-5_T-1000	rookie	0.834
	Copenhagen Causality Lab	0.831
	joelonglin	0.830
FinalWEATHnoise_N-5_T-2000	rookie	0.853
	Copenhagen Causality Lab	0.853
	WenhuiZhang	0.826
FinalWEATHnoise_N-10_T-1000	rookie	0.852
	Copenhagen Causality Lab	0.840
	iggisv9t	0.733
FinalWEATHnoise_N-10_T-2000	rookie	0.868
	Copenhagen Causality Lab	0.860
	joelonglin	0.849

NeurIPS C4C CauseMe.net/neurips2019

Dataset	User	AUC
FinalWEATHmiss_N-5_T-1000	rookie	0.927
	Copenhagen Causality Lab	0.925
	SharifCausalAI	0.878
FinalWEATHmiss_N-5_T-2000	rookie	0.939
	Copenhagen Causality Lab	0.935
	SharifCausalAI	0.881
FinalWEATHmiss_N-10_T-1000	rookie	0.934
	Copenhagen Causality Lab	0.926
	fisehrwsy	0.802
FinalWEATHmiss_N-10_T-2000	rookie	0.947
	Copenhagen Causality Lab	0.940
	BJTU-INSIS	0.718

NeurIPS C4C `CauseMe.net/neurips2019`

Dataset	User	AUC
Finallinear-VAR_N-10_T-150	Copenhagen Causality Lab	0.956
	BCause	0.850
	causal_man	0.848
Finallinear-VAR_N-100_T-150	Copenhagen Causality Lab	0.930
	BCause	0.855
	n_causeme	0.823
Finalnonlinear-VAR_N-20_T-600	Copenhagen Causality Lab	0.873
	astroman	0.869
	n_causeme	0.868

NeurIPS C4C CauseMe.net/neurips2019

Dataset	User	AUC
Finallogistic-lownoise_N-5_T-150_medium	Mapefast	0.999
	Copenhagen Causality Lab	0.984
	BJTU-INSIS	0.964
Finallogistic-largenoise_N-5_T-150_medium	Mapefast	0.992
	Copenhagen Causality Lab	0.982
	BJTU-INSIS	0.949
Finallogistic-deterministic_N-5_T-150_medium	Mapefast	0.987
	Copenhagen Causality Lab	0.975
	BJTU-INSIS	0.948

C4C carbon footprint

Winner teams present remotely which saved ~23.000 kg in CO2 emissions

… let's go for more virtual conferences !

Thank you !!!

Continue on www.CauseMe.net

Website

Jordi Munoz-Mari
Gustau Camps-Valls

Dataset generation

Xavier Tibau
Matthias Bruhns
Peer Nowack

Testing

Matthias Bruhns
Xavier Tibau
Christoph Kaeding
Andreas Gerhardus

Support
Cameron Peron
Rebecca Wolff
Bernhard Schölkopf