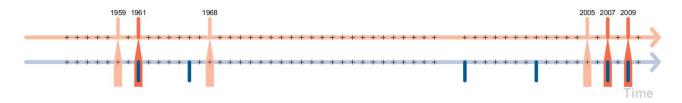


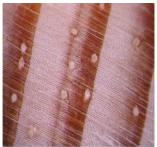
Event Coincidence Analysis

A simultaneity measure for event time series















Outline

Motivation

Conceptual Idea and Definition

Examples

• The R Package CoinCalc





Motivation

1. (Binary) event time series

storms, bushfires, volcanoes, floods, droughts,



2. Nonlinear relationships

Possibly nonlinear and nonstationary relationship between climate drivers and ecosystem responses

(e.g. impacts only appear after threshold exceedance)

IMSC Canmore, 2016

siegmund@pik-potsdam.de





Motivation

- Climate impact studies so far mostly use linear methods (correlation, linear regression models)
- Few results on properties of extreme responses to climate extremes (existence, conditions, strength of interrelationships, etc.)
- Impact studies often call for establishing possible cause-effect relationships

Need for a method that

- (i) can deal with event-like data
- (ii) can distinguish between differently directed relations
- (iii) is flexible and therefore suitable for various applications
- (iv) is (conceptually) easy to understand





- 1. Two binary event sequences with N events
- 2. Count "coincidences" (K)
- 3. Calculate coincidence rate r = K/N





- 1. Two binary event sequences with N events
- 2. Count "coincidences" (K)
- 3. Calculate coincidence rate r = K/N

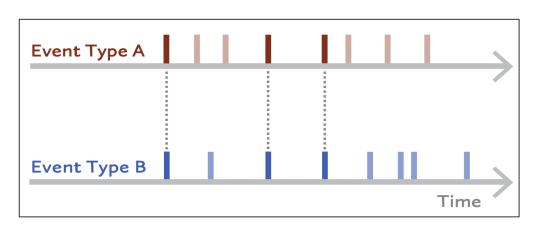
Case 1:

$$N_A = N_B$$
, $\tau = 0$, $\Delta T = 0$

$$K = 3$$

$$N = 8$$

$$r = 0.375$$



Event B causes Event A





Case 2:

$$N_A != N_B$$
, $\tau != 0$, $\Delta T != 0$



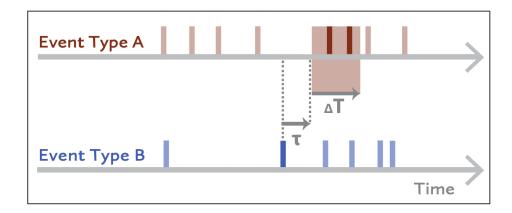


Case 2:

$$N_A != N_B$$
, $\tau != 0$, $\Delta T != 0$

trigger coincidence rate

$$r_t(\Delta T, \tau) = \frac{1}{N_B} \sum_{j=1}^{N_B} \Theta[\sum_{i=1}^{N_A} 1_{[0, \Delta T[}((t_i^A - \tau) - t_j^B)]$$







Case 2:

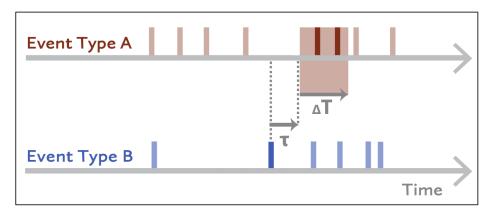
$$N_A != N_B$$
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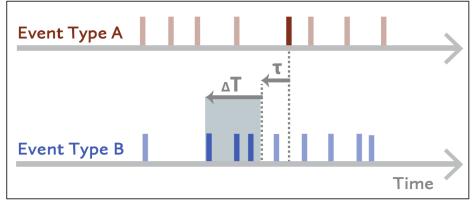
trigger coincidence rate

$$r_t(\Delta T, \tau) = \frac{1}{N_B} \sum_{j=1}^{N_B} \Theta[\sum_{i=1}^{N_A} 1_{[0, \Delta T[}((t_i^A - \tau) - t_j^B)]]$$

precursor coincidence rate

$$r_p(\Delta T, \tau) = \frac{1}{N_A} \sum_{i=1}^{N_A} \Theta[\sum_{j=1}^{N_B} 1_{[0, \Delta T[}((t_i^A - \tau) - t_j^B)],$$









Case 2:

$$N_A != N_B$$
, $\tau != 0$, $\Delta T != 0$

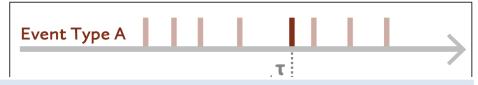
trigger coincidence rate

$$r_t(\Delta T, \tau) = \frac{1}{N_B} \sum_{j=1}^{N_B} \Theta[\sum_{i=1}^{N_A} 1_{[0, \Delta T[}((t_i^A - \tau) - t_j^B)]$$

Event Type A Event Type B Time

precursor coincidence rate

$$r_p(\Delta T, au) = rac{1}{N_A} \sum_{i=1}^{N_A} \Theta[\sum_{j=1}^{N_B} 1_{[0, \Delta T[}((t_i^A - au) - au)])$$



Note: Tolerance window can also be defined symmetrically (Siegmund et al. 2016, under rev.)



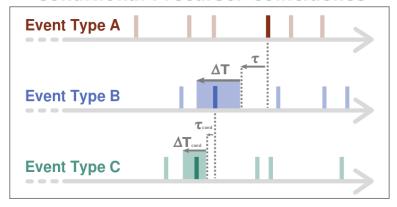


Case 3: Conditional Event Coincidence

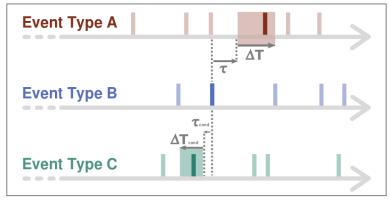
Possible conditioning of events in B by events in C

For $\Delta T_{cond} = 0$ and $\tau_{cond} = 0$: Joint Event Coincidence

Conditional Precursor Coincidence



Conditional Trigger Coincidence







- 4. Testing for significance of the coincidence rate $(r_t \text{ and } r_p)$
- a) Analytical test: independent Poisson processes as null model

$$P(K \ge K_e) = \sum_{K^* = K_e}^{N_A} P(K^*; N_A, 1 - (1 - p)^{N_B})$$

with

$$P(K; N_A, 1 - (1 - p)^{N_B}) = \binom{N_A}{K} \left(1 - \left(1 - \frac{\Delta T}{T - \tau} \right)^{N_B} \right)^K \left(\left(1 - \frac{\Delta T}{T - \tau} \right)^{N_B} \right)^{N_A - K}$$

If conditions (events are rare and distributed independently and uniformly) for this approximation do not hold: numerical approximation of test statistics → surrogate tests





- 4. Testing for significance of the coincidence rate $(r_t \text{ and } r_p)$
- b) Shuffling/Resampling Test

create a large ensemble of artificial time series

- → perform ECA on the ensemble
- → distribution of r for independent event sequences





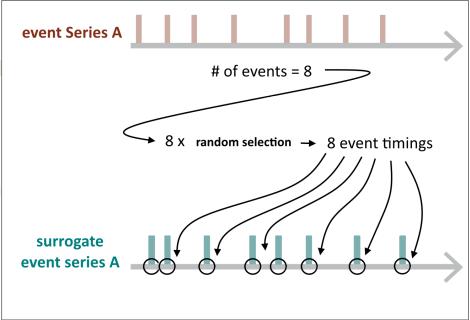
4. Testing for significance of the coincidence rate $(r_t \text{ and } r_p)$

b) Shuffling/Resampling Test

Creates e.g. 1000 surrogate

- \rightarrow 1000x ECA
- \rightarrow distribution of 1000 r
- → "normal" r under random

Monte Carlo Surrogates







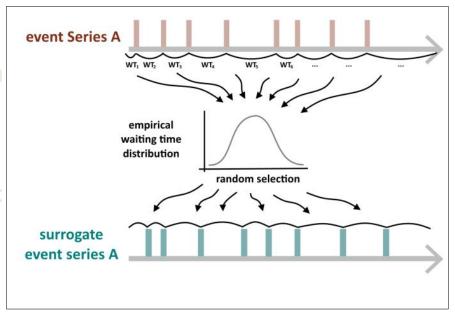
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b) Shuffling/Resampling Test

Creates e.g. 1000 surrogate ti

- \rightarrow 1000x ECA
- → distribution of 1000 r
- ightarrow "normal" r under random ϵ

Waiting Time Surrogates







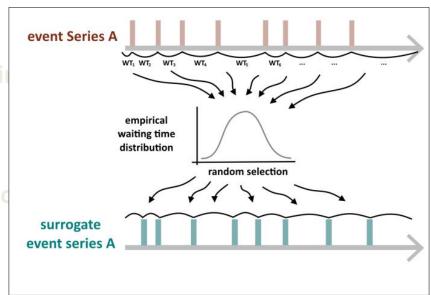
4. Testing for significance of the coincidence rate $(r_t \text{ and } r_p)$

b) Shuffling/Resampling Test

Creates e.g. 1000 surrogate ti

- \rightarrow 1000x ECA
- \rightarrow distribution of 1000 r
- → "normal" r under random

Waiting Time Surrogates



ECA Output: r_t, r_p, p_t, p_p



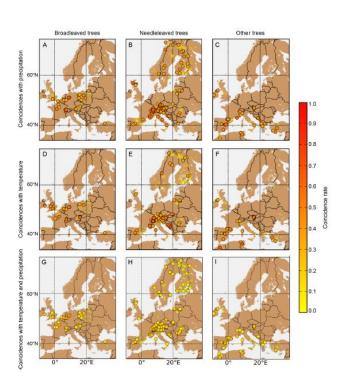


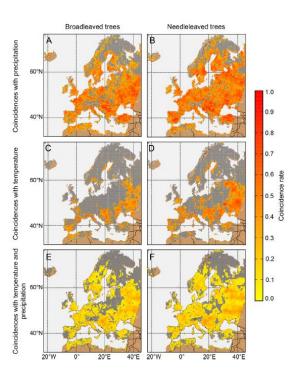




Tree Ring widths and model output

Rammig, A. et al. (2015)



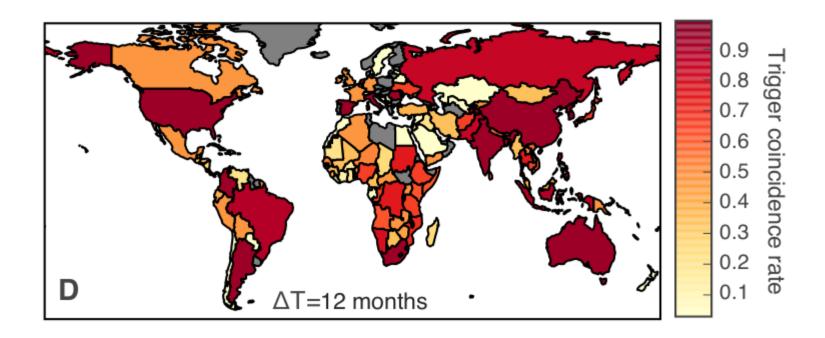






Flood events vs. epidemics

Donges, J. et al. (2016)

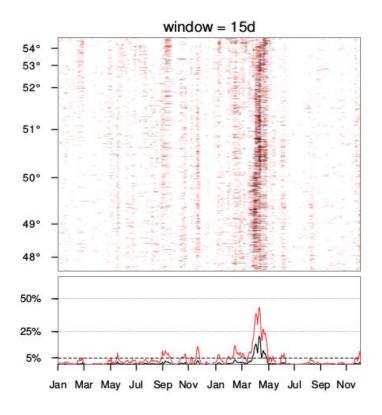






Flowering dates vs. extreme temperature

Siegmund, J. et al. (2015)

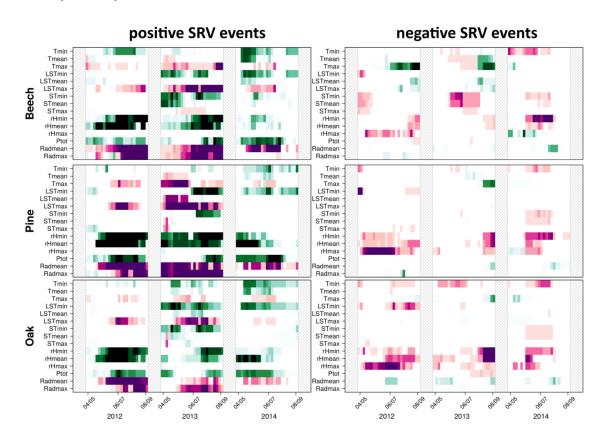






Extreme tree stem radius changes vs. climate extremes

Siegmund, J. et al. (2016)

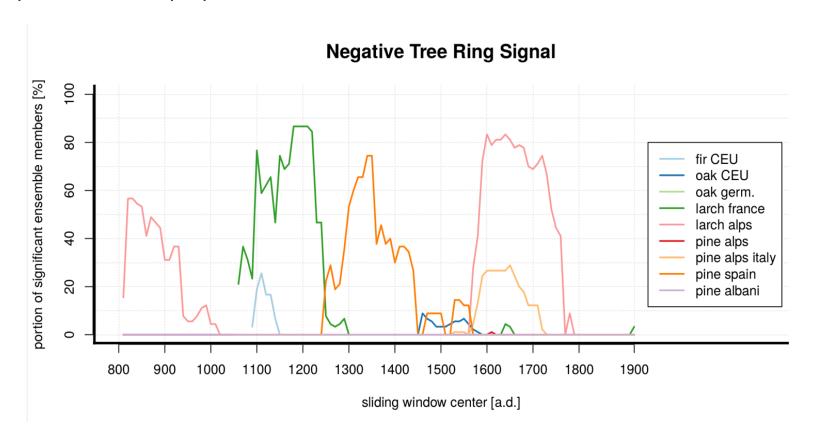






Volcanic eruptions vs. tree ring widths

Pieper, H. et al., in prep.

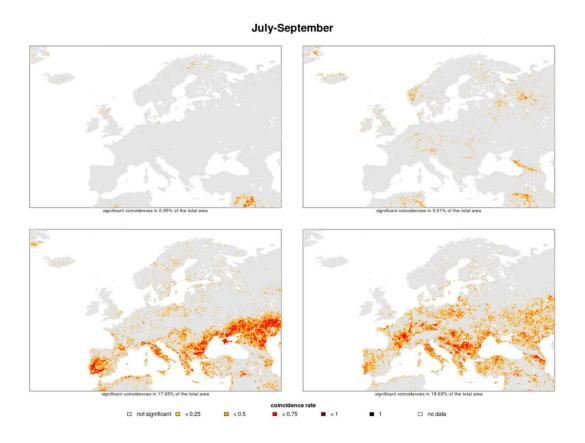






Remote sensing: terrestrial productivity and climate extremes

Baumbach, L. et al, in prep.







The R package CoinCalc

R implementation of event coincidence analysis

version 1.02 (available, beta-tested)

- variable ΔT , τ , tolerance window type, ...
- time series binarization
- plot function
- three different significance tests
- some small data sets with example calculations

version 1.4 (available upon request, not beta-tested)

- multivariate/conditional ECA
- ECA for spatial data sets

github.com/JonatanSiegmund/CoinCalc





Summary

Event Coincidence Analysis

Classical statistical methods are insufficient to quantify interdependencies between event sequences in a general context

- ECA is
 - a new tool to quantify simultaneities between event time series
 - important addition to classical linear methods (e.g. correlation, ...)
- ready-to-use R-package CoinCalc





Literature

- Donges, JF. Schleussner, C.F., Siegmund, JF. and Donner, RV. (2016):

 Event coincident analysis for quantifying statistical Interrelationships between event time series.

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- Donges, J., Donner, R., Trauth, M., Marwan, N., Schellnhuber, H.-J., and Kurths, J. (2011). Nonlinear detection of paleoclimate-variability transitions possibly related to human evolution. Proceedings of the National Academy of Sciences of the USA 108, 20422–20427
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 Biogeosciences 12, 373-385 (2015)
- Siegmund JF, Sanders TGM, Heinrich I, van der Maaten E, Simard S, Helle G and Donner RV (2016) Meteorological Drivers of Extremes in Daily Stem Radius Variations of Beech, Oak, and Pine in Northeastern Germany: An Event Coincidence Analysis. *Front. Plant Sci.* 7:733
- Siegmund, J. F., Wiedermann, M., Donges, J. F., and Donner, R. V. (2015): Impact of climate extremes on wildlife plant flowering over Germany. In: Biogeosciences Discuss., 12, 18389-18423



