SPACETIME: Causal Discovery from Non-stationary Time Series

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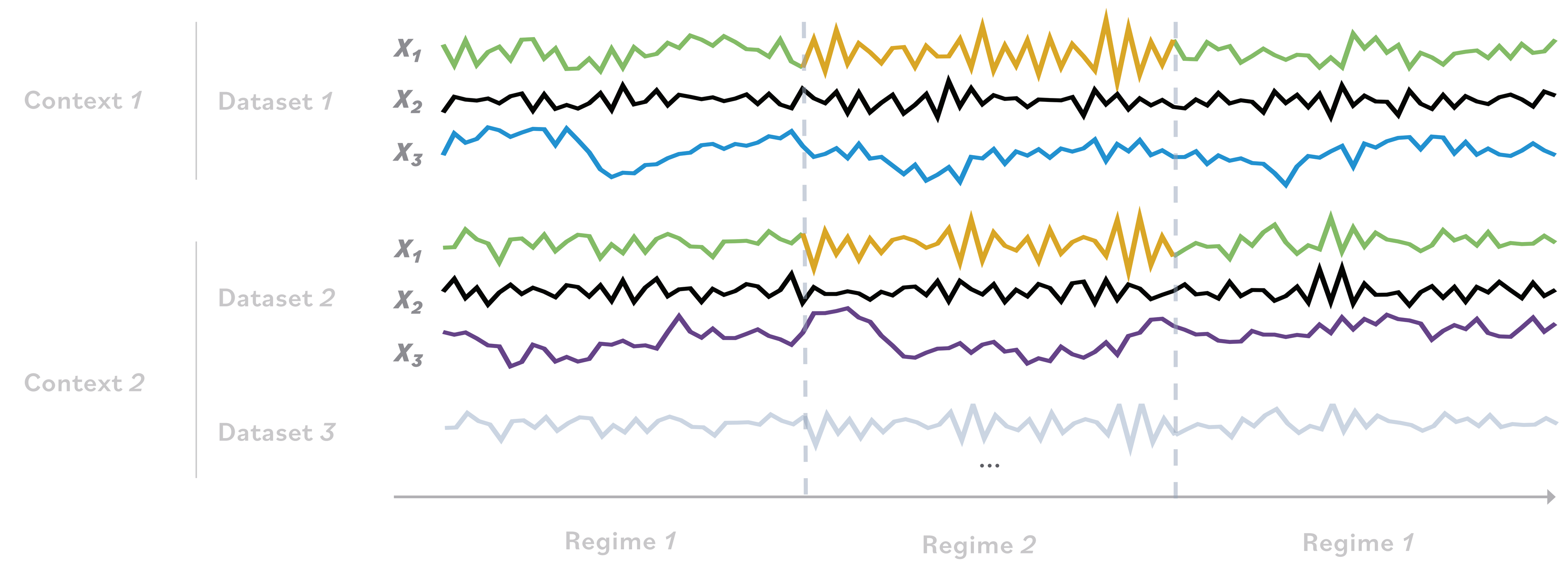
TLDR We discover causal graphs, temporal changepoints, and repeating regimes from multiple time series datasets

Setting

Non-Stationary Time Series



Assumptions

SCM with Contexts & Regimes

Context (k)
Group of datasets (d) where the same causal mechanisms apply.

Regime (r)
Time periods (t) across which the causal mechanisms remains the same. The time indices at which a causal mechanism shifts are called regime **changepoints**.

Non-stationarity only affects the causal mechanisms, the causal structure (graph) doesn't change.

Structural causal model for each variable

$$X_t^d = f^{k,r}(\mathrm{pa}(X_t^d), N_t^d)$$

Additional assumptions: independant mechanism changes, faithfulness, consistency

Approach

Iterative procedure using kernelized methods and MDL principle

Edge-Greedy Search We discover causal edges over all contexts and regimes based on the Algorithmic Algorithmic Model of Causation (AMC) and its MDL practical solution
→ *The true causal model has the lowest description length*

Causal functional mechanism modeling Non-parametric regression (Gaussian processes) with the identified causal parents

Changepoint Detection Kernelized changepoint detection on the prediction error using the fitted functions
→ *Higher prediction error means that the true function is different from the fitted one*

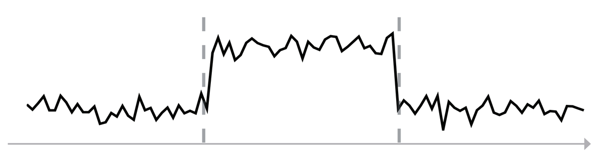
Regime- & Context Partitioning Partitioning of the time interval and datasets into regimes and contexts using kernelized independance (KCI) test
→ *Data from two subsets (two datasets or time periods), with same causal mechanisms, are independent of their subset assignment*

Algorithm

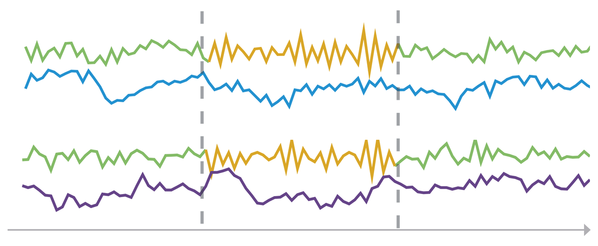
SPACETIME

Initialization
empty causal graph

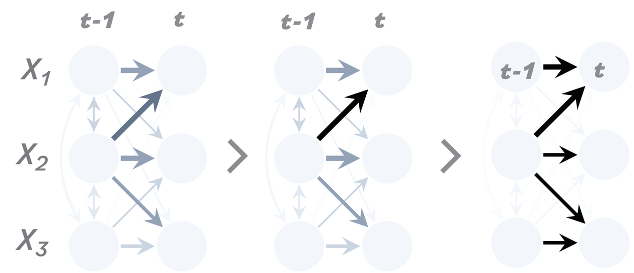
1 **Detect causal changepoints** over the residual distributions of effects given causes in the current causal graph



2 **Identify regimes & contexts** with similar causal mechanisms using hypothesis testing



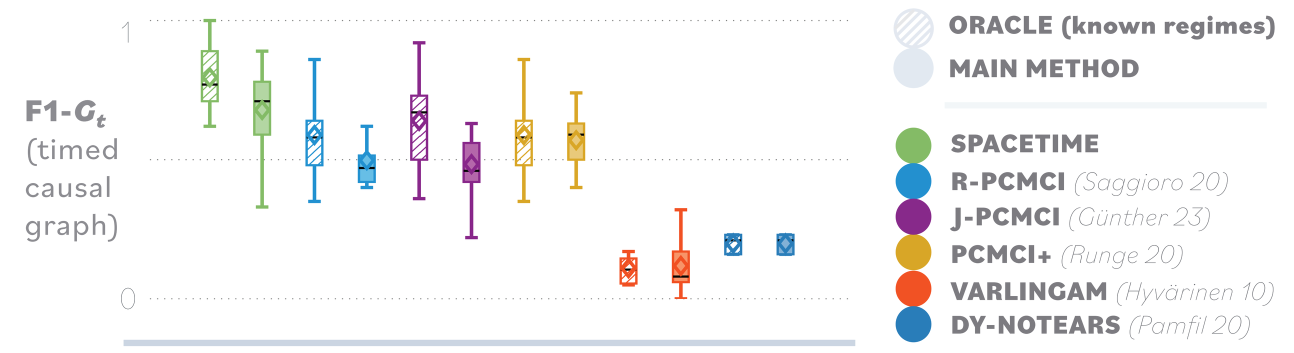
3 **Discover timed causal graph** by greedily adding edges in order of their strength, given the current changepoints



Convergence
temporal causal graph, changepoints, regimes and contexts

Evaluation

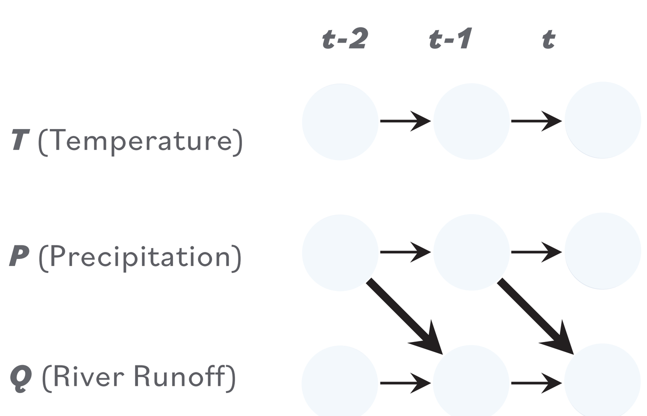
Temporal Graph Discovery



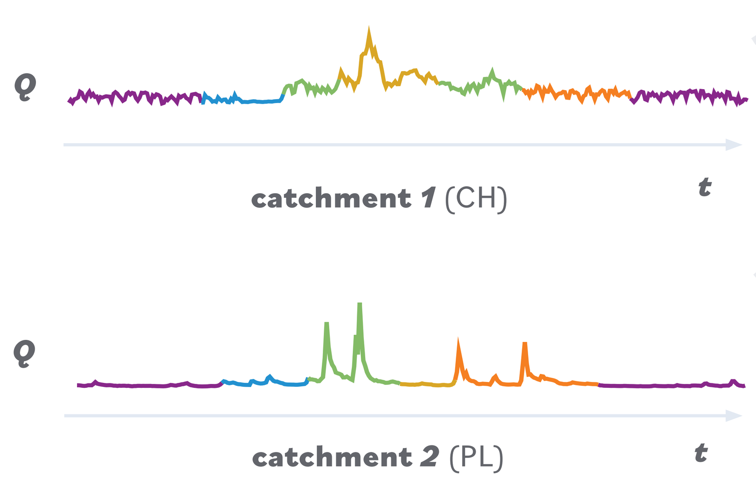
Case Study A

River Discharge in European Catchments

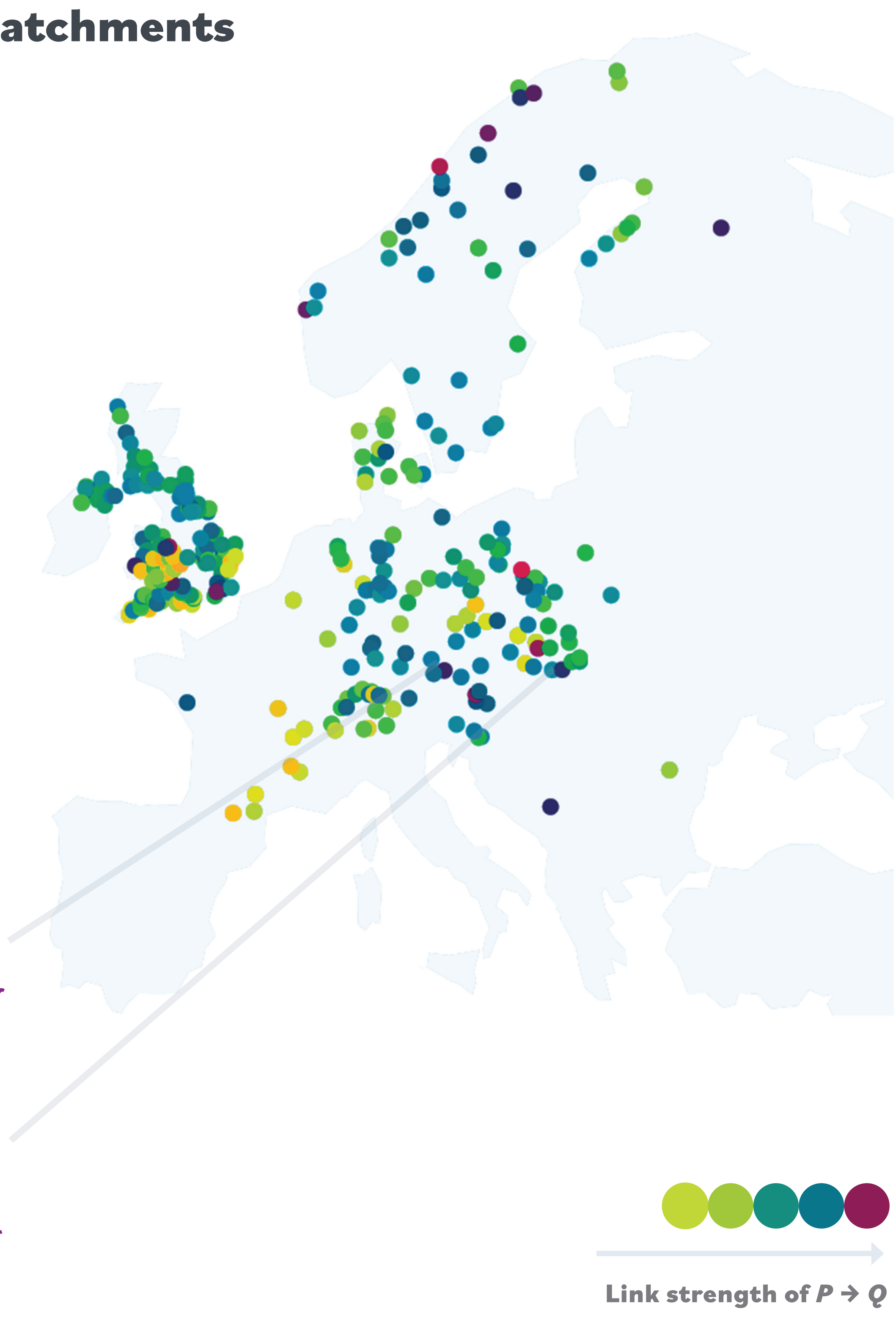
GRDC dataset, Cornes et al. 18; Günther et al. 23



Causal Graph Discovered temporal causal graph over time and all measurement sites



Changepoints over time of the link $P \to Q$, at selected sites (Martinsbruck, CH; Dunajec, Nowy Sacz, PL)

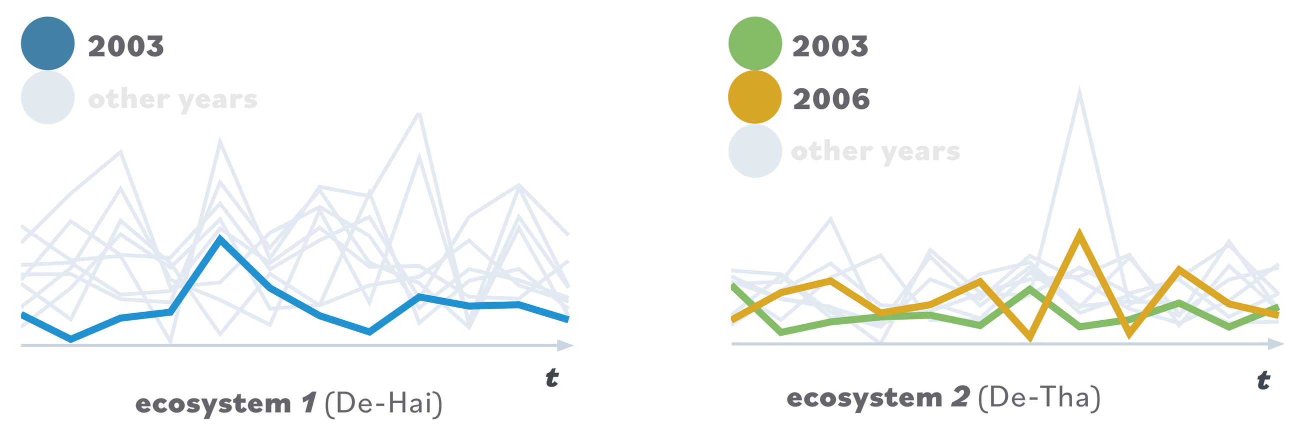


Variability across space of the interaction strength between $P \to Q$ due to individual geographical characteristics at the catchment sites

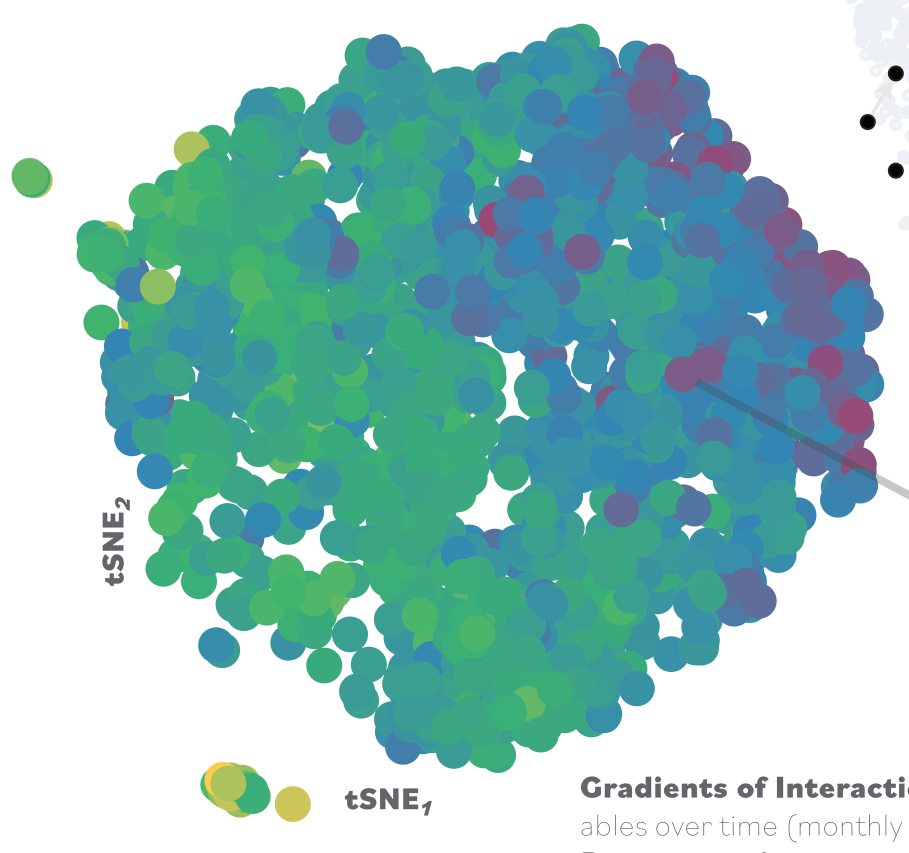
Case Study B

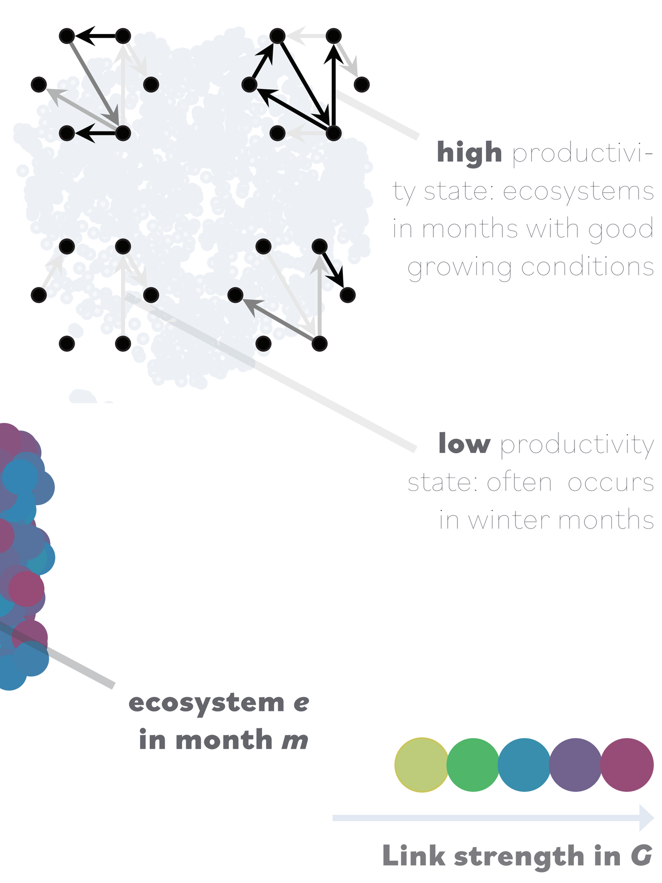
Biosphere-Atmosphere Interactions

FLUXNET database, Baldocci 14; Krich et al. 21



Partitioning by similarity of causal mechanisms shows years with abnormal weather trends - here due to the European heat wave in 2003





Gradients of Interaction Strength between meteorological variables over time (monthly intervals) and space (different ecosystems). Ecosystems often traverse different productivity states over the year