SPACETIME: Causal Discovery from Non-Stationary Time Series

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

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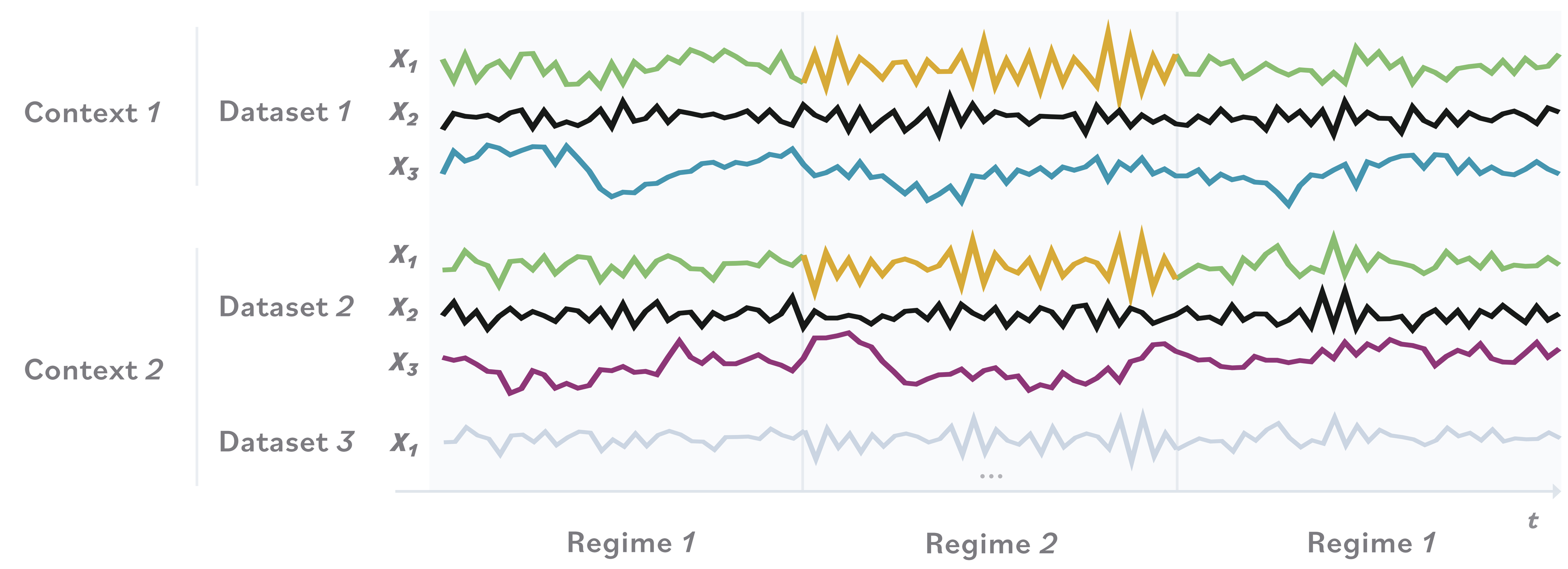
Setting
Non-Stationary Time Series



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 remain 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 (temporal causal graph) does not change

Structural causal model for each variable

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

Additional assumptions: causal Markov condition, faithfulness, sufficiency, independence of causal mechanism changes

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 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*

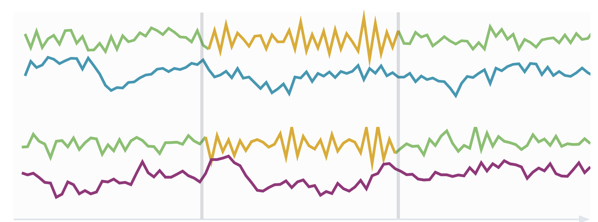
Regime- & context partitioning Partitioning of the time interval and datasets into regimes and contexts using kernelized independence (KCI) test
→ *Data from two subsets (two datasets or time periods), with the same causal mechanisms, are independent of their subset assignment*

Algorithm
SPACETIME

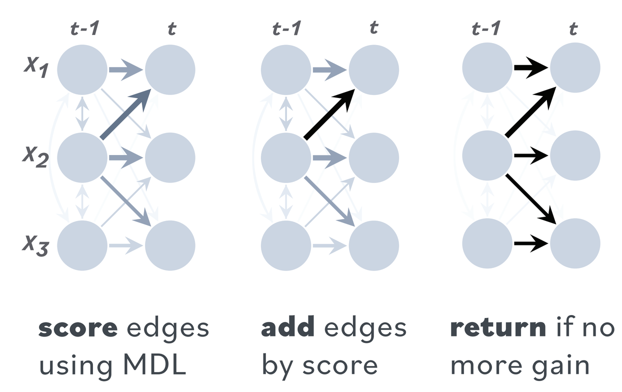
Initialization
empty causal graph

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

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

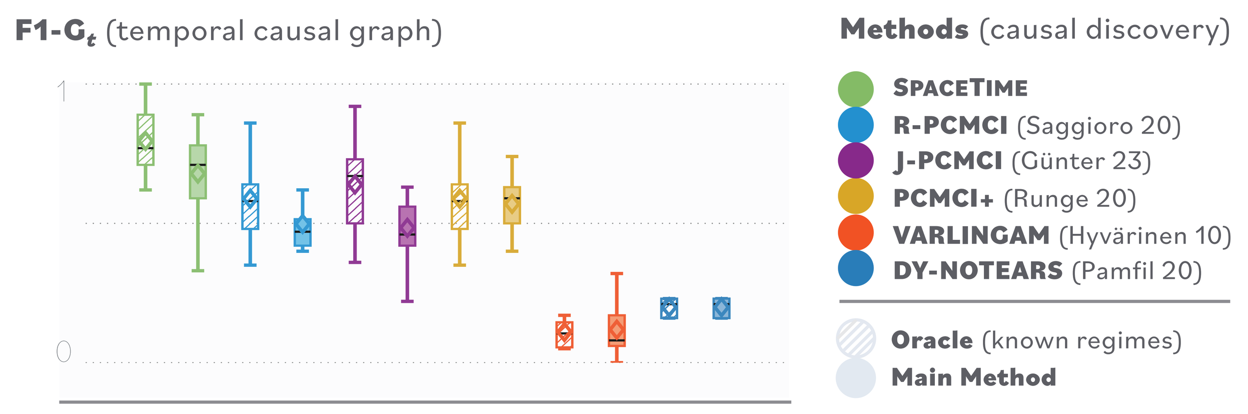


3 **Discover timed causal graph** under current changepoints using greedy search for edges



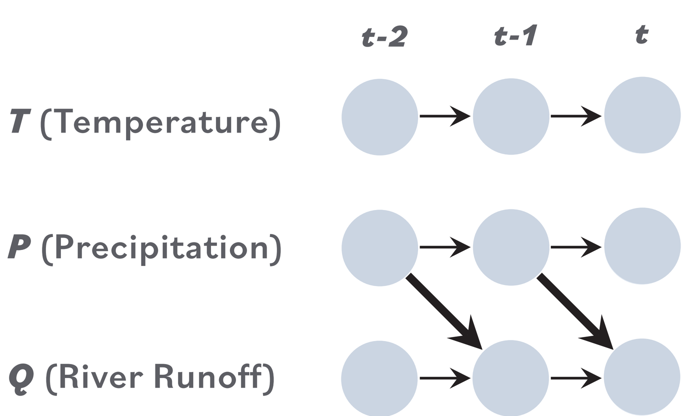
Convergence
temporal causal graph, changepoints, regimes and contexts

Evaluation
Temporal Graph Discovery



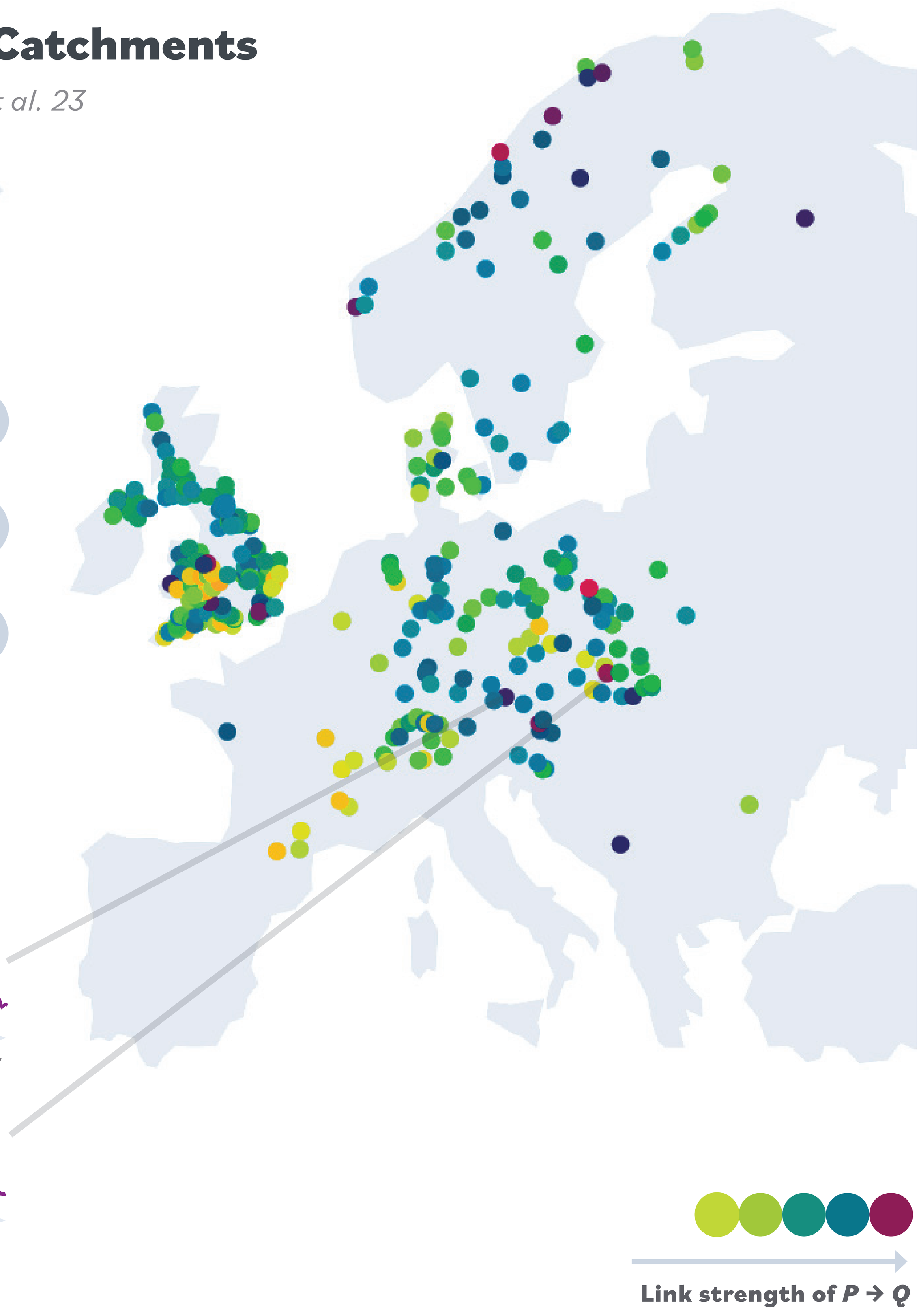
Case Study A
River Runoff in European Catchments

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



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

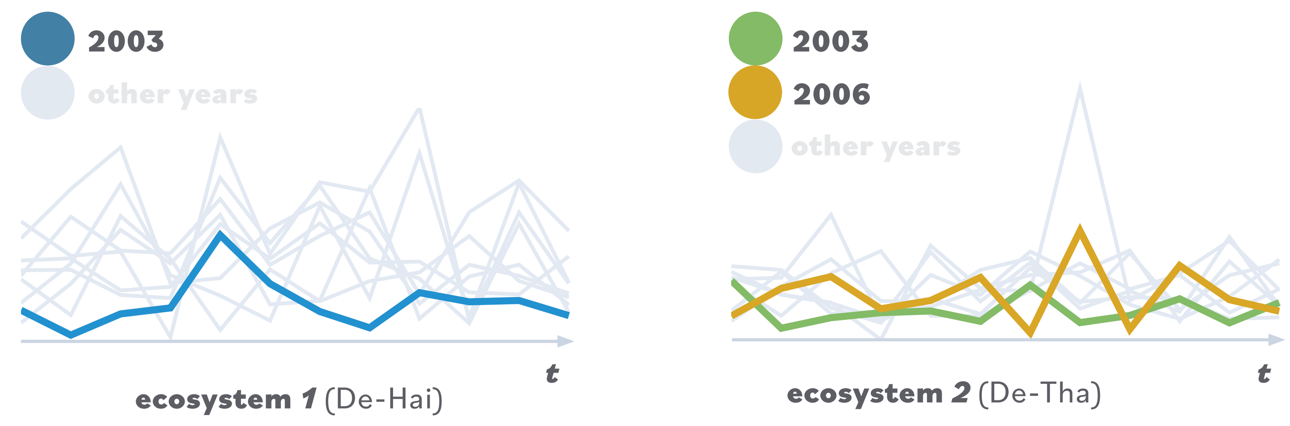
Changepoints over time for $P \to Q$, at selected sites (Martinsbruck, CH; Dunajec, Nowy Sacz, PL)



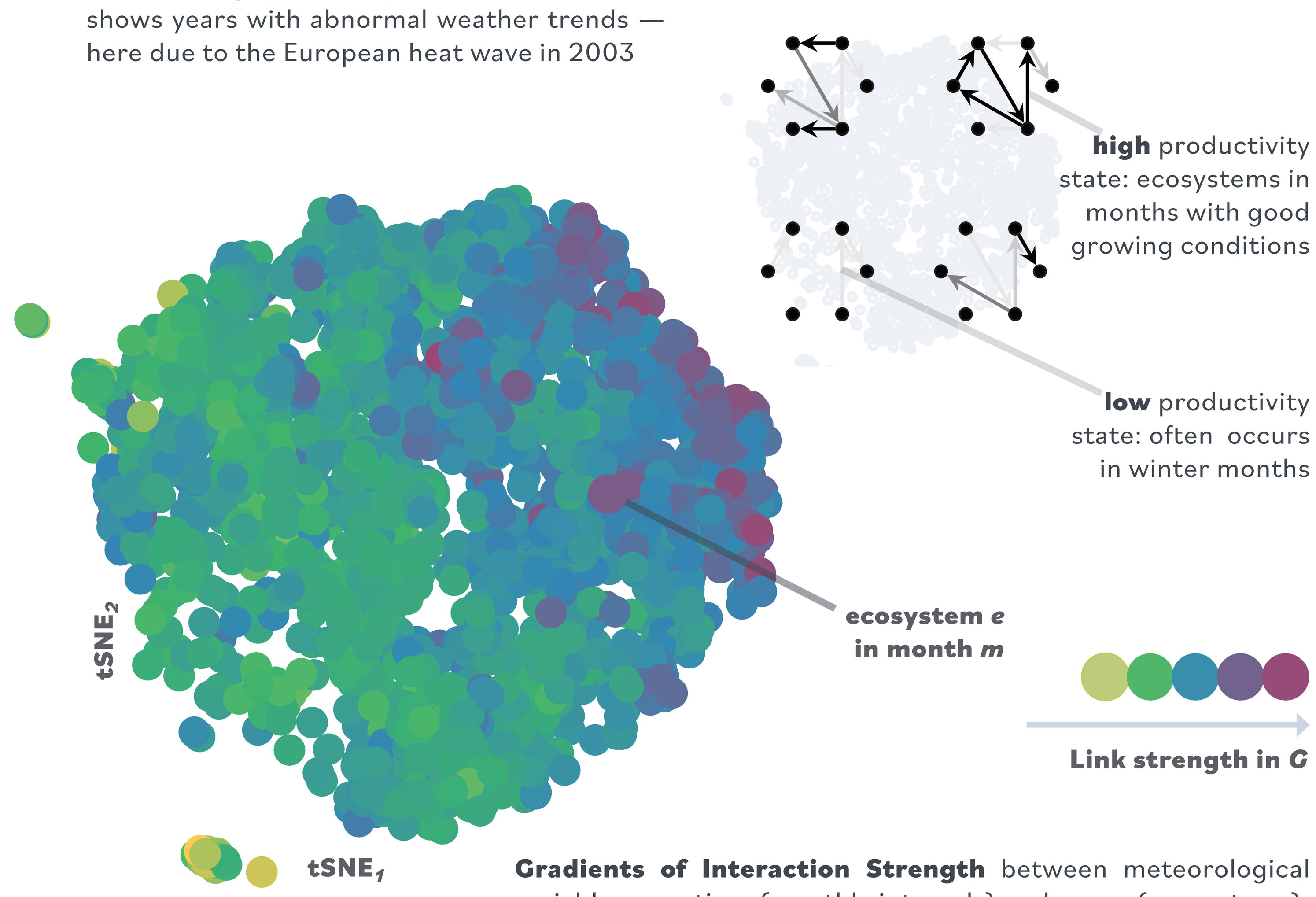
Variability across space of the response of runoff Q to precipitation P. The interaction is heterogeneous due to geographical characteristics, regional climate, and local hydrometeorological processes and events

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 (ecosystems). Ecosystems often traverse different productivity states over the year, as becomes visible in a TSNE embedding of all link strengths