Learning Granger Causal Feature Representations

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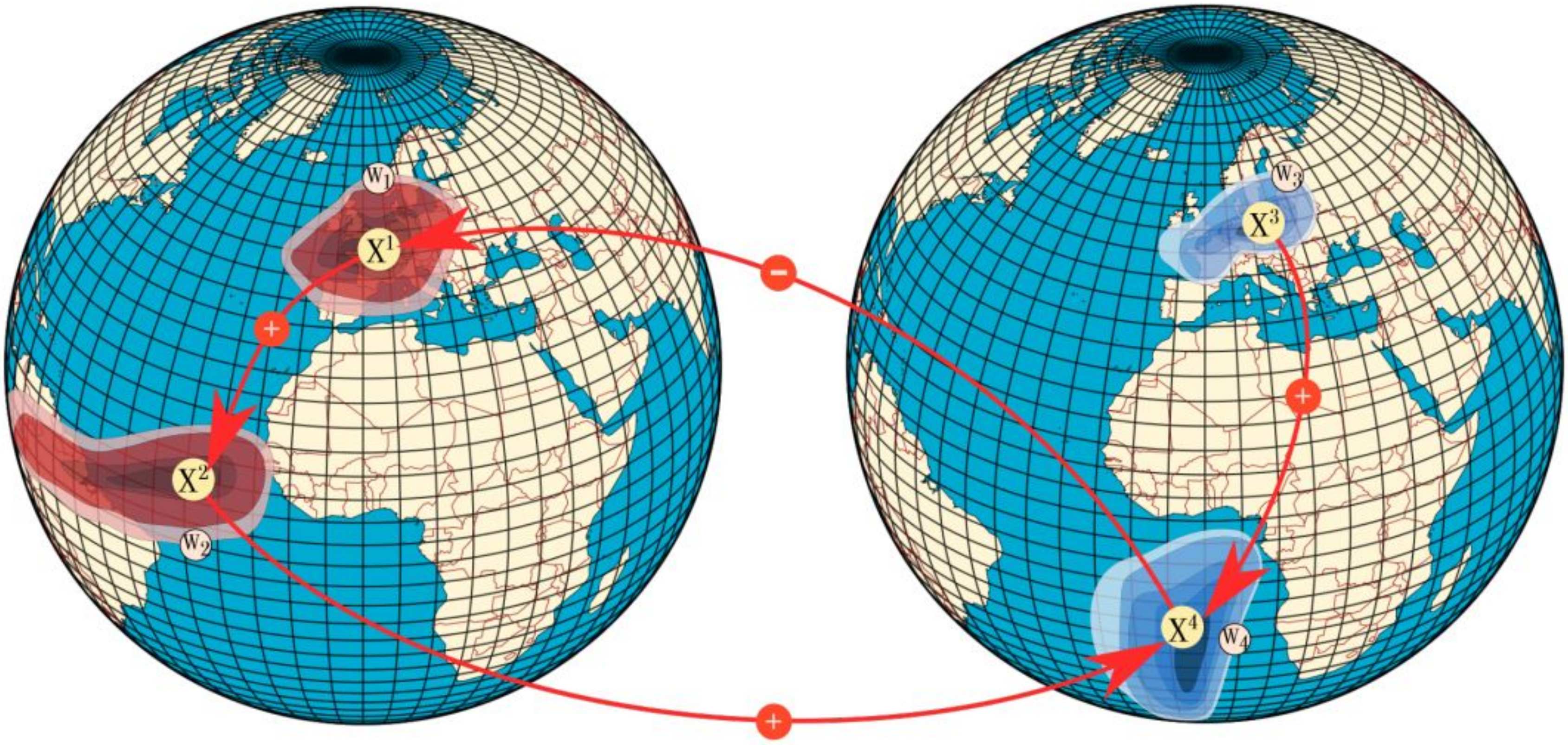
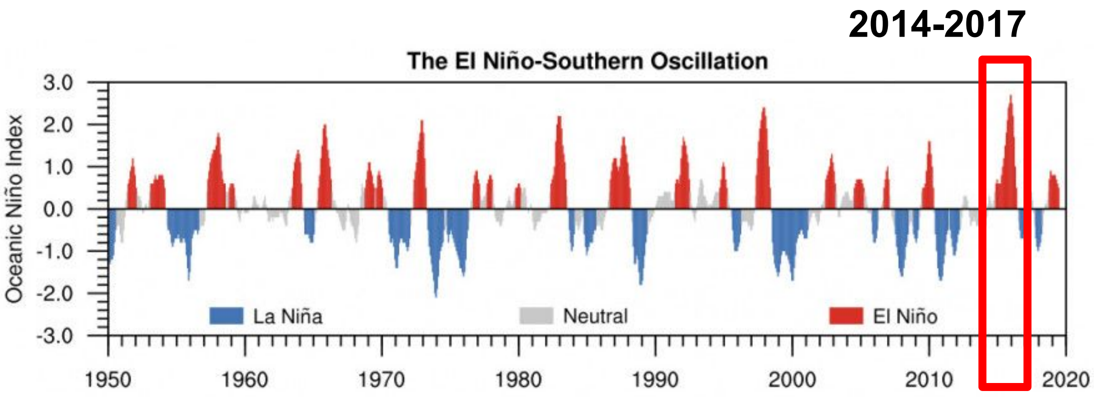
Climate Change AI

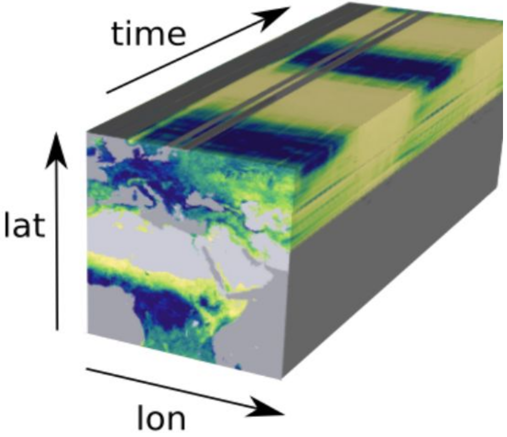
Climate teleconnections



Learning climate teleconnections with machine learning

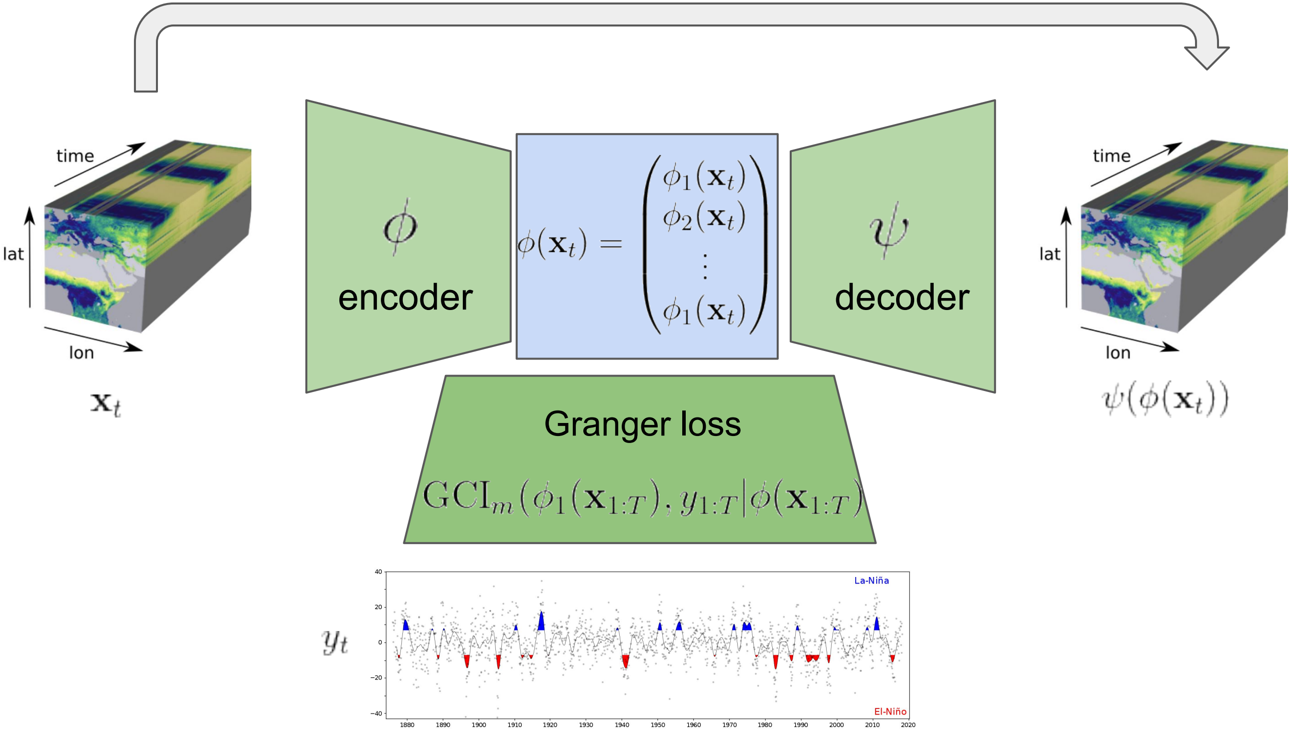
- **ENSO** changes patterns of essential variables like **moisture, greenness & precipitation**
- **Goal:** Learn causal impact teleconnections of ENSO on greenness
  - NDVI from MODIS in Africa, linear interp, anomalies
  - ENSO3.4 index, focus on 2014-2017





Granger Autoencoder

Reconstruction error $||\mathbf{x}_t - \psi(\phi(\mathbf{x}_t))||_2^2$



$$\frac{1}{T}\sum_{t=1}^{T} \|\mathbf{x}_t - \psi(\phi(\mathbf{x}_t))\|_2^2 - \beta\, \mathrm{GCI}_m(\phi_1(\mathbf{x}_{1:T}), y_{1:T}|\phi(\mathbf{x}_{1:T}))$$

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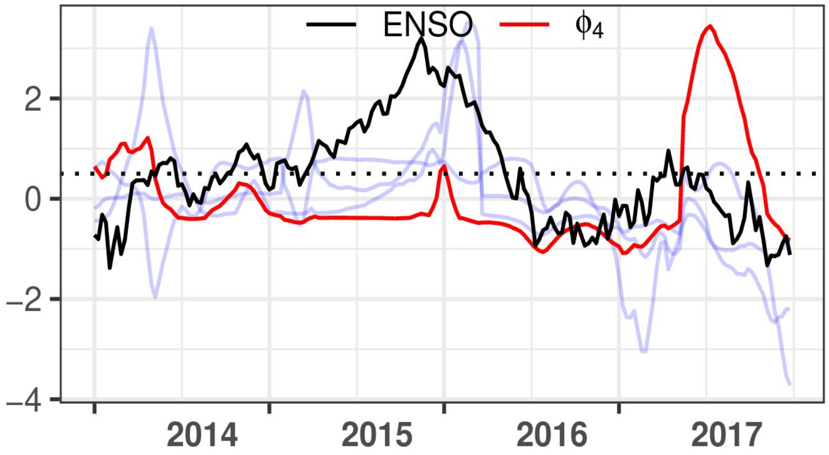
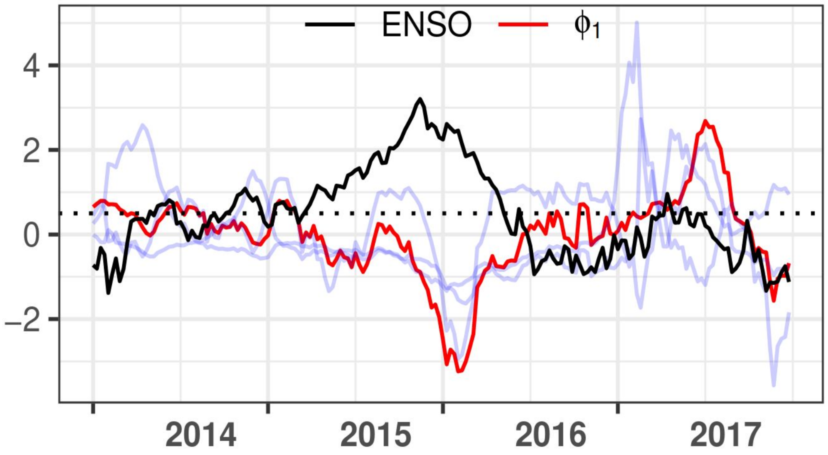
Learning Granger causal features

No Granger penalization $\beta = 0$



Granger penalization $\beta = 0.01$



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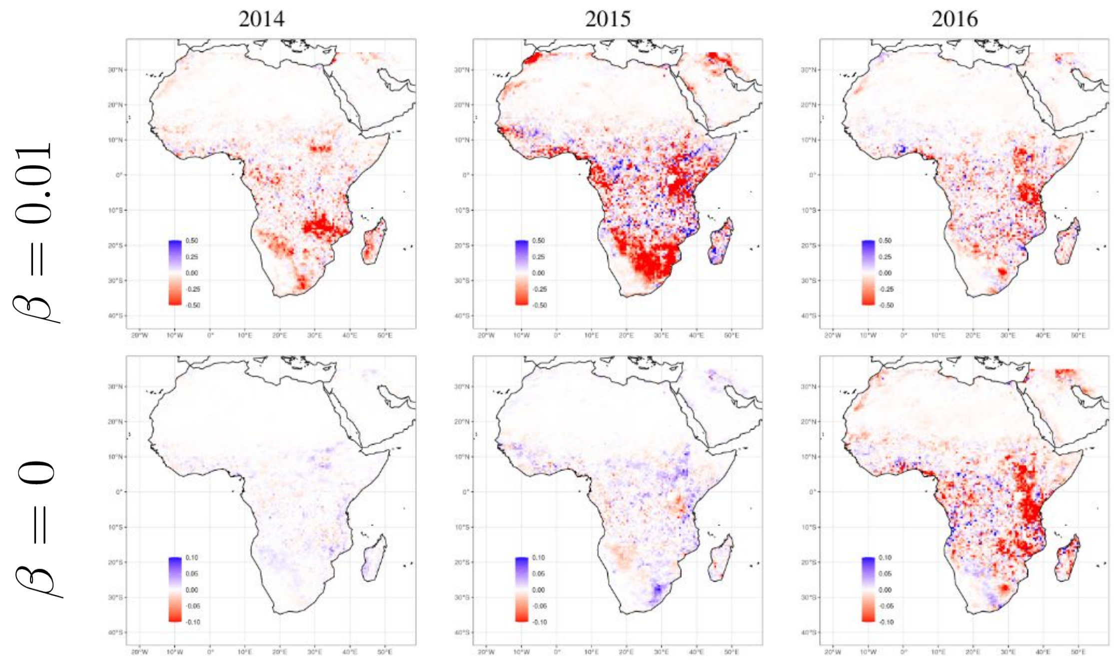
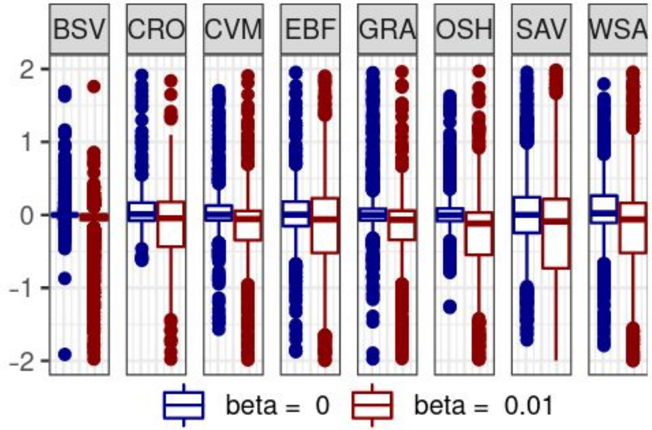
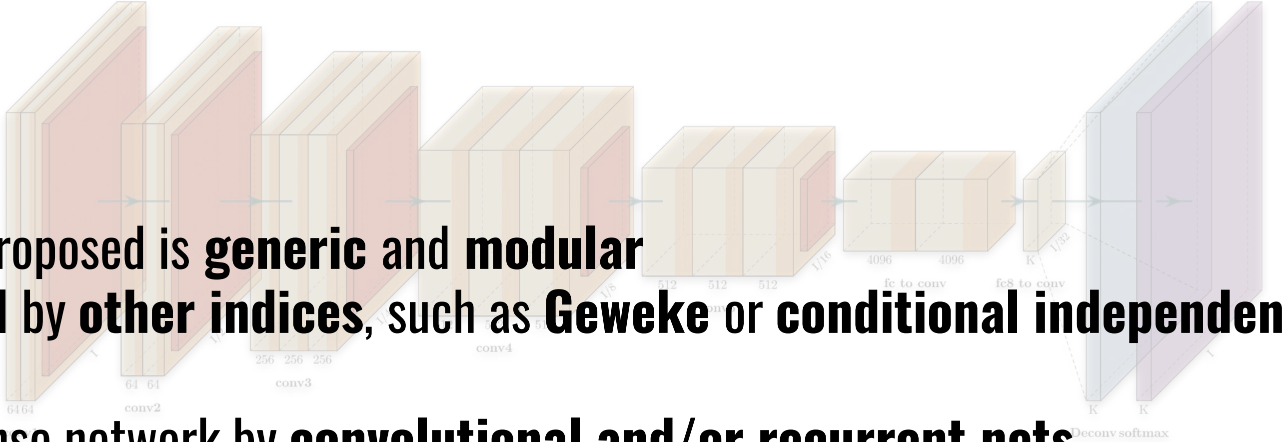
Explaining representations

- XAI → Neuron Integrated Gradients (NIG) over the Granger Autoencoder
- Spatially-explicit and temporally resolved activation maps per biome





Conclusions and future work



- **Methodology** proposed is **generic** and **modular**
  - Replace GCI by **other indices**, such as **Geweke** or **conditional independence tests**
  - Replace dense network by **convolutional and/or recurrent nets**

- Study generalization and robustness of causal representations

- Way to gain **insights on physical processes from Earth data**

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github.com/IPL-UV/LatentGranger

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