Learning Biosphere Responses to Climate Drivers Using Echo State Observers

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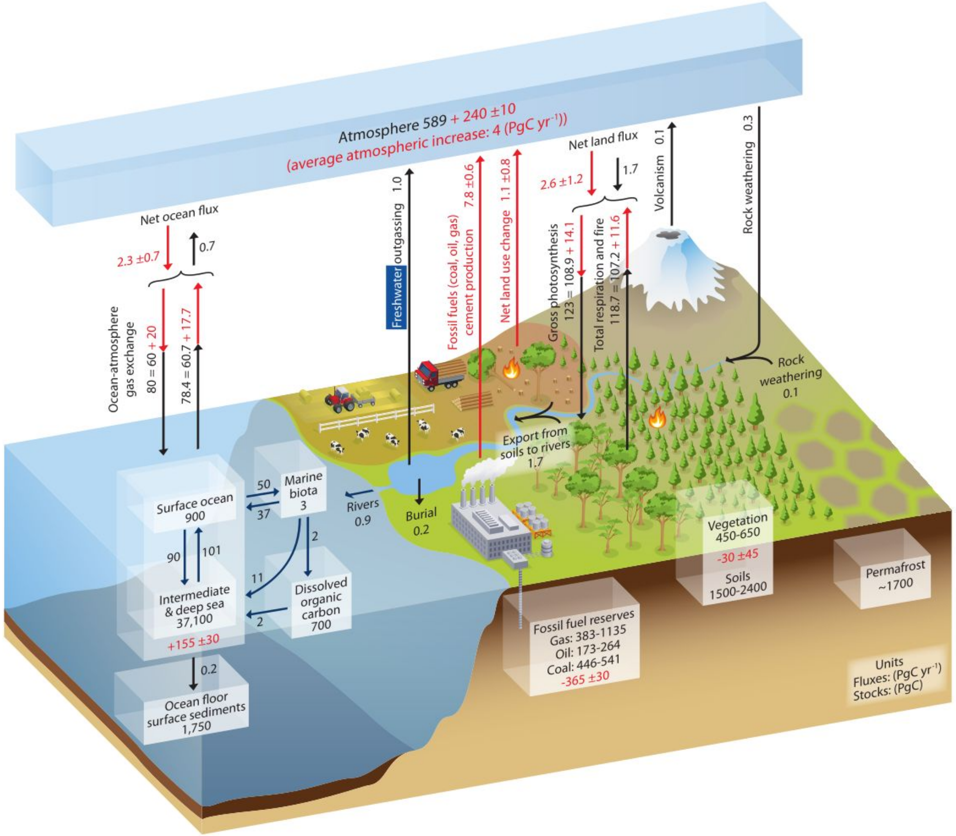
Vegetation and the Carbon Cycle

- Vegetation plays an essential part in the carbon cycle
- Extreme events can disrupt carbon sinks with negative consequences
- Vegetation dynamics are hard to model, showing long term trends, seasonality, and an immediate response to atmospheric drivers



https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_Chapter06_FINAL.pdf
Corinne Le Quéré et al. "Trends in the sources and sinks of carbon dioxide"
Markus Reichstein et al. "Climate extremes and the carbon cycle"

Question

Atmospheric observables

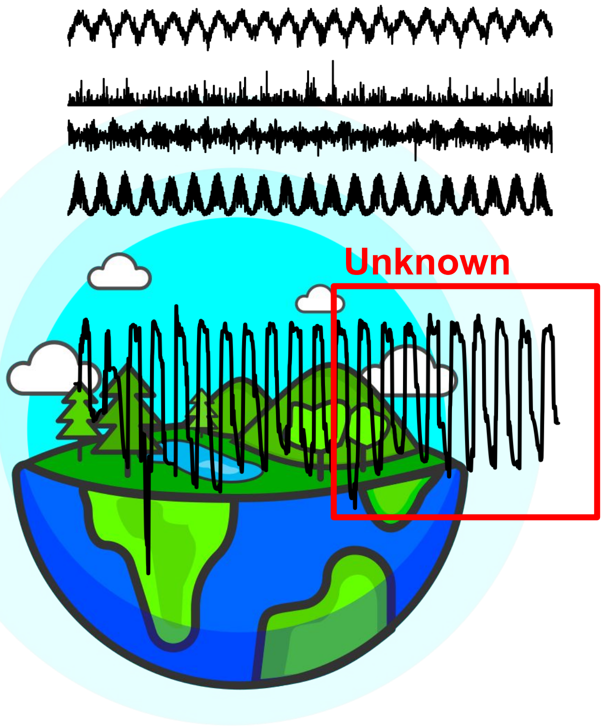
- Precipitation sum (rr)
- Mean temperature (tg)
- Averaged sea level pressure (pp)
- Mean global radiation (qq)

Vegetation: normalized difference vegetation index (ndvi)

Can we model the unknown part of **v**(t)?

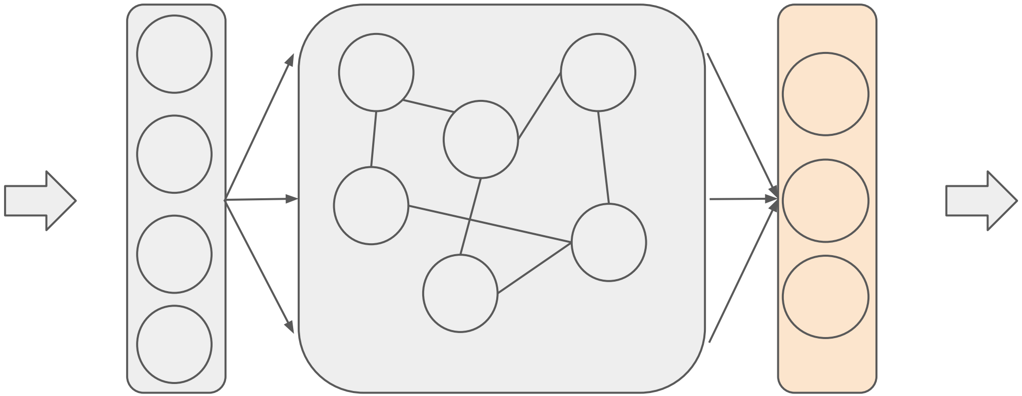
$$\mathbf{u}(t) = \begin{pmatrix} rr(t) \\ tg(t) \\ pp(t) \\ qq(t) \end{pmatrix}$$

$$\mathbf{v}(t) = ndvi(t)$$



https://www.ecobricks.org/bare-biosphere-1000px-2/

Echo State Networks



$$\mathbf{W}_{in}$$

$$\mathbf{W}$$

$$\mathbf{W}_{out} = \mathbf{Y}^{target}\mathbf{X}^{T}(\mathbf{X}\mathbf{X}^{T} + \beta\mathbf{I})^{-1}$$

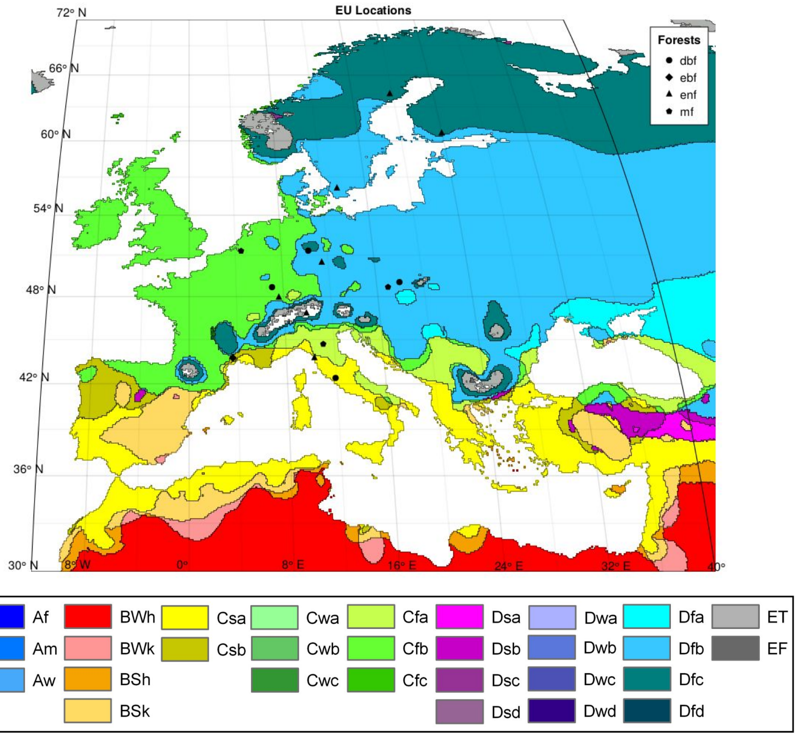
input $\mathbf{u}(t)$ → output $\mathbf{v}(t)$

State $\mathbf{x}(t)$

$$\mathbf{x}(t + \Delta t) = (1 - \alpha)\mathbf{x}(t) + \alpha f(\mathbf{W}\mathbf{x}(t) + \mathbf{W}_{in}\mathbf{u}(t))$$

Jaeger, Herbert (2001)
Pathak, Jaideep, et al. (2018)
Chattopadhyay, Ashesh, et al. (2020)

Chosen locations



Selected locations:

- different climate zones
- diverse vegetation cover

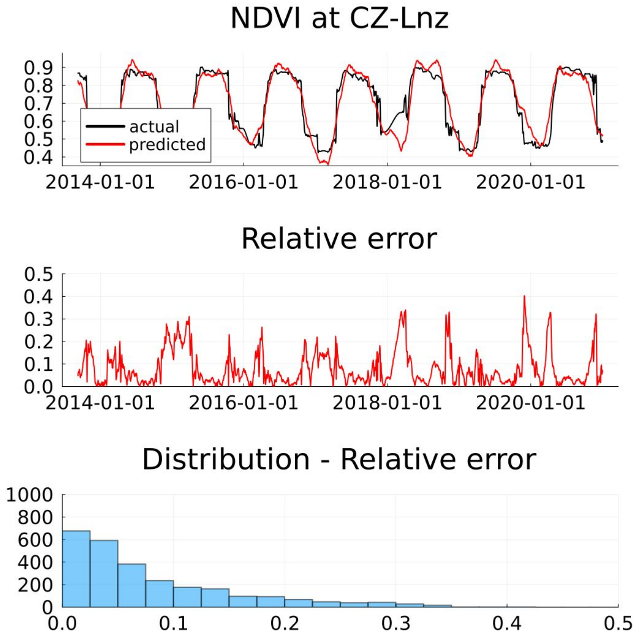
We chose to focus on forest sites to minimize the imperfections in the data due to human activity

Data from E-OBS and FluxnetEO datasets

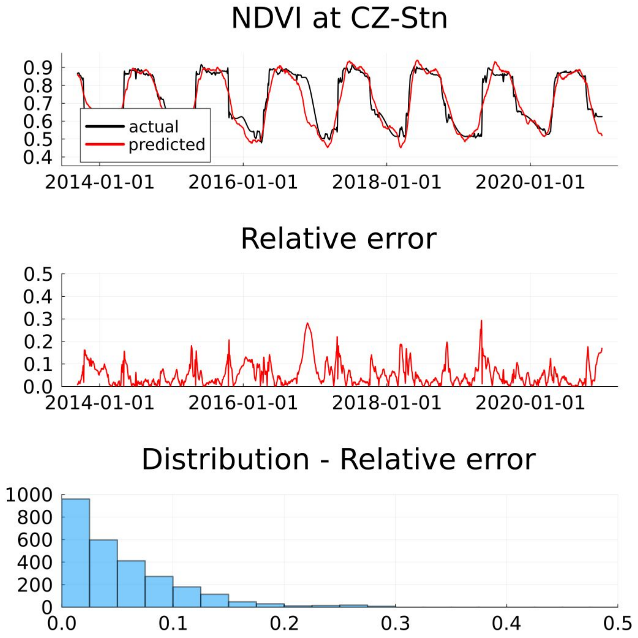
https://staging.igrac.kartoza.com/layers/igrac:other_climate_2007_koppen_geiger
M. C. Peel, B. L. Finlayson, and T. A. McMahon. Updated world map of the Koppen-Geiger climate classification
R. C. Cornes et al. "An ensemble version of the e-obs temperature and precipitation data sets"
S. Walther, S. Besnard et al. A view from space on global flux towers by modis and landsat: the fluxneteo data set.

Dfb: Warm Summer Continental or Hemiboreal Climate

Mixed forest

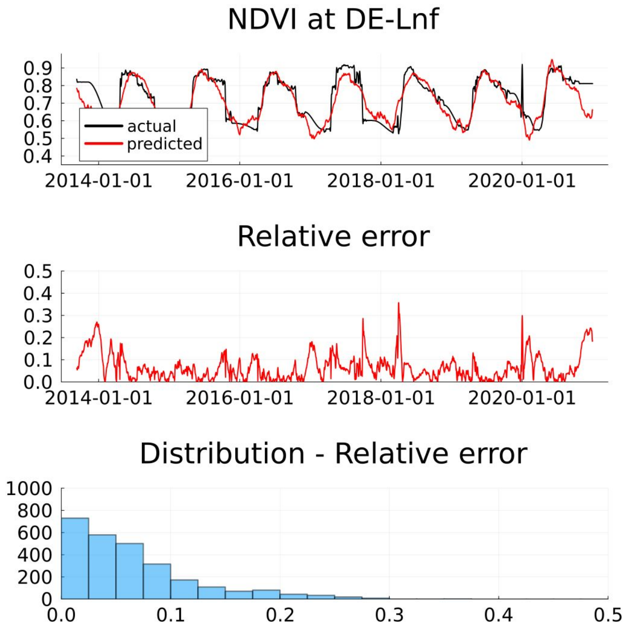


Deciduous broad-leaved forest

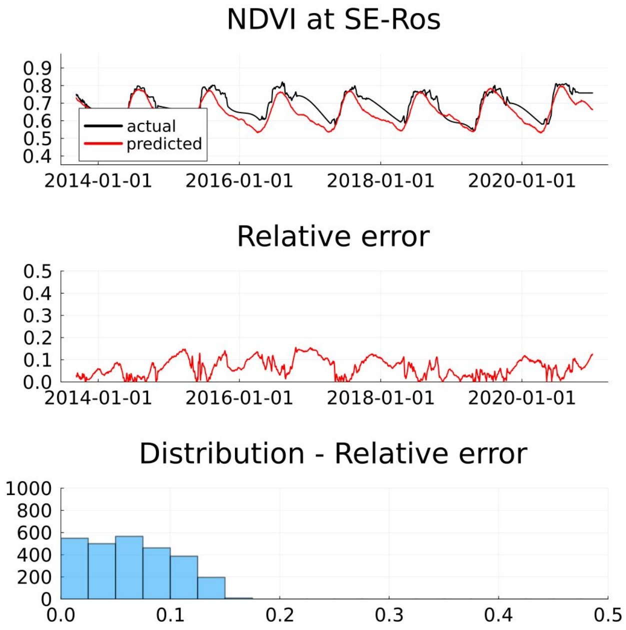


Dfc: Subartic or Boreal Climates

Deciduous broad-leaved forest

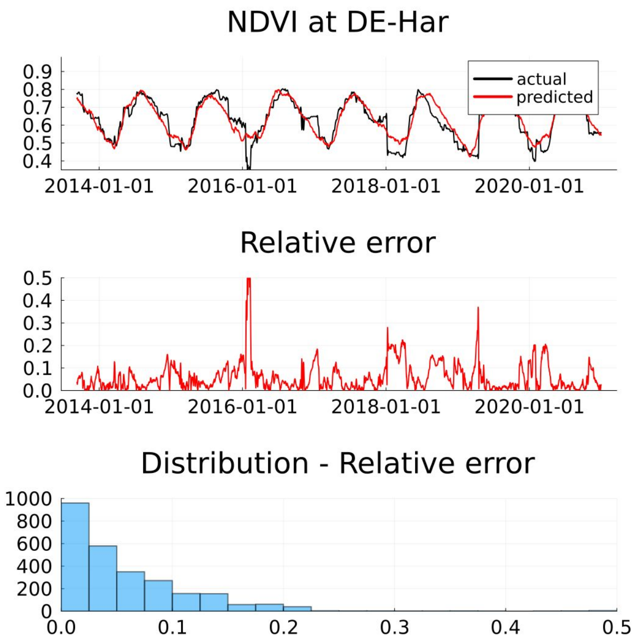


Evergreen needle-leaved forest

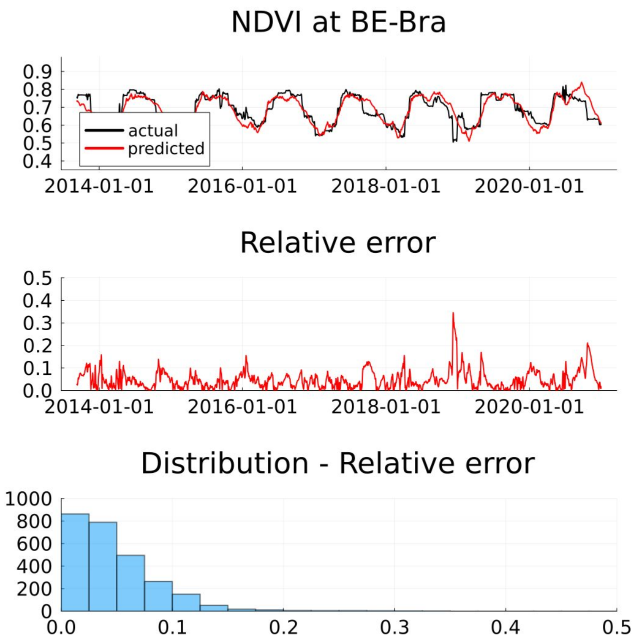


Cfb: Oceanic Climate

Evergreen needle-leaved forest

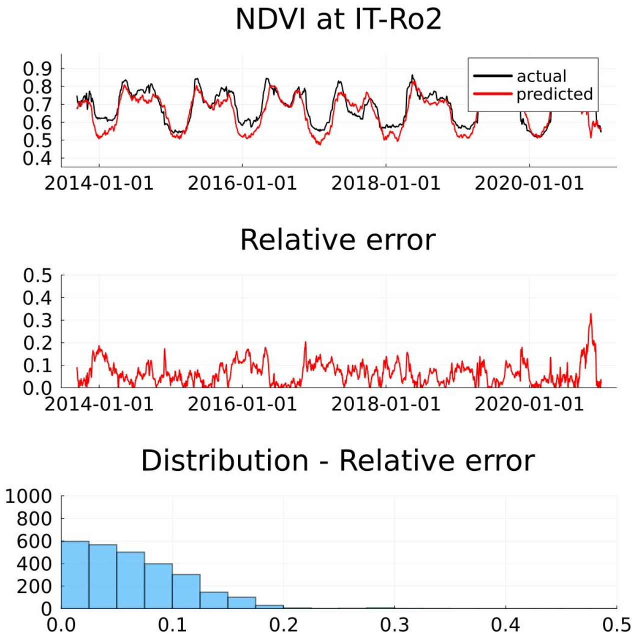


Mixed forest

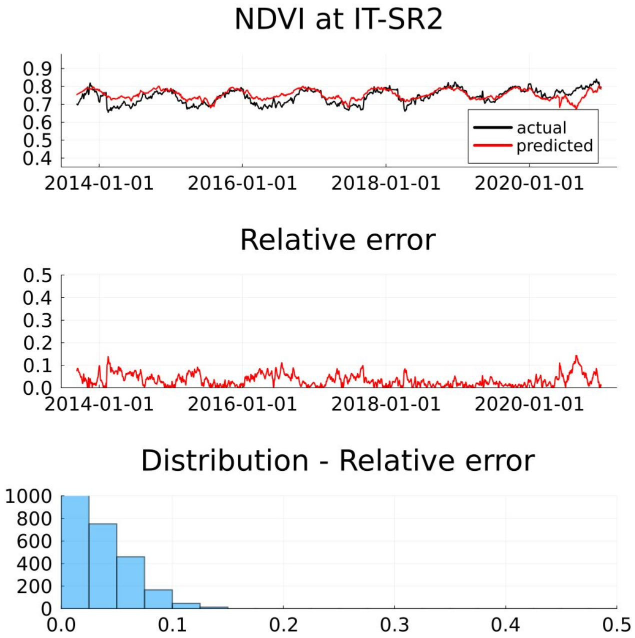


Csa: Mediterranean Hot Summer Climates

Deciduous broad-leaved forest



Evergreen needle-leaved forest



Conclusions and future directions

- We showed that the Echo State Networks can successfully learn the dynamics of ndvi in different settings, thus working as observers for the biosphere-atmosphere system

- Even if the data presented some strong artifacts in the training set the model was able to extrapolate the underlying dynamics

- The next step is an in depth comparison with other recurrent models (LSTM, GRU, and RNN)

Thanks for your attention

Echo State Networks

- Based on random and untrained (fixed) recurrent neural network

$$\mathbf{x}(t+\Delta t) = (1-\alpha)\mathbf{x}(t) + \alpha f(\mathbf{W}\mathbf{x}(t) + \mathbf{W}_{\text{in}}\mathbf{u}(t))$$

- The hidden states $\mathbf{x}(t)$ are collected in a states matrix $\mathbf{X}$
- The output layer ($\mathbf{W}_{\text{out}}$) is computed at the end as linear regression of the teacher output on the reservoir states.

$$\mathbf{W}_{\text{out}} = \mathbf{Y}^{\text{target}}\mathbf{X}^{\mathsf{T}}(\mathbf{X}\mathbf{X}^{\mathsf{T}} + \beta\mathbf{I})^{-1}$$

- The predictions leverage the same update equations to obtain the states, and the predicted state is obtained as

$$\mathbf{v}(t) = g(\mathbf{W}_{\text{out}}\mathbf{x}(t))$$