Ecosystem Insights through Extreme Values: A Fresh Look at Meteorological Drivers

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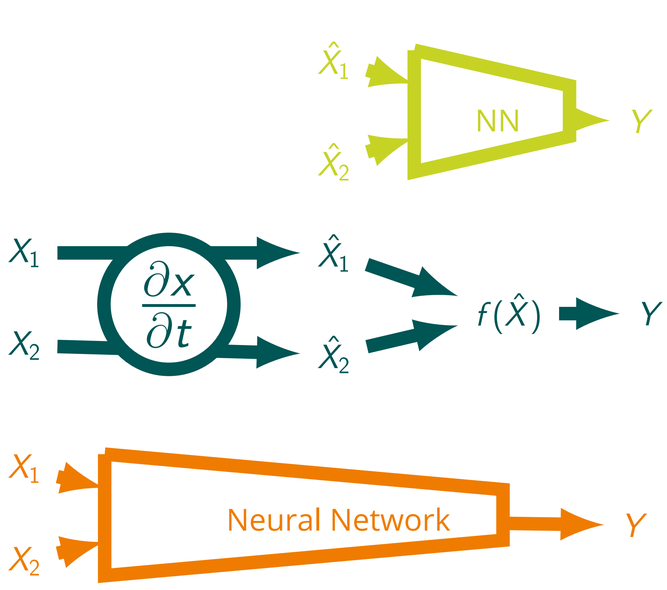
Research Gap



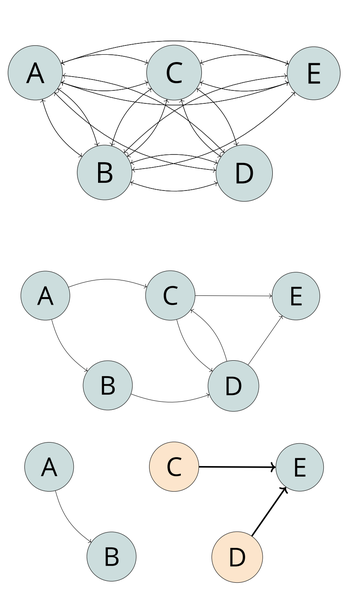
- In many scientific disciplines, the target of machine learning is to **identify** a mechanism instead of **imitating** it.
- Measured values often do not directly enter the mechanism, they interact via a dynamical system.
- We want to learn the mechanism itself, not the surrounding dynamics.
- Simulating the mechanism and the dynamical system together leads to biases.

▶ We propose to train on the extreme values only

Main Result

- ▶ Training on extreme values recovers the true mechanism.
- ▶ We present an analytical proof and empirical evidence for a simple example.
- ▶ Next: more realistic models and real data.

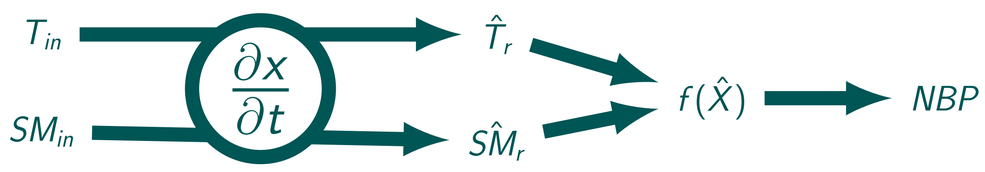
Causal View



- Causal graphs often almost fully connected.
- simplify by ignoring less important links
- Extreme values increase the signal-to-noise ratio.
- The causal graph becomes simpler.

Simple Model

▶ Evaluate this using a simple example.



Dynamics:

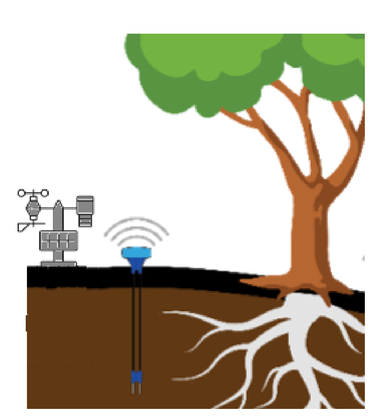
$$T_r = T_{in} - \frac{C_T}{1 + e^{-(SM_{in} T_{in} - C_0)}}$$

$$SM_r = SM_{in} - \frac{C_{SM}}{1 + e^{-(SM_{in} T_{in} - C_0)}}$$

Mechanism:

$$NBP = \alpha T_r + \beta SM_r + \gamma + \epsilon$$

Example



- When measuring temperature and soil moisture, we do not measure at the tree roots but some distance away.
- The same is true temporally.

Theoretical Result

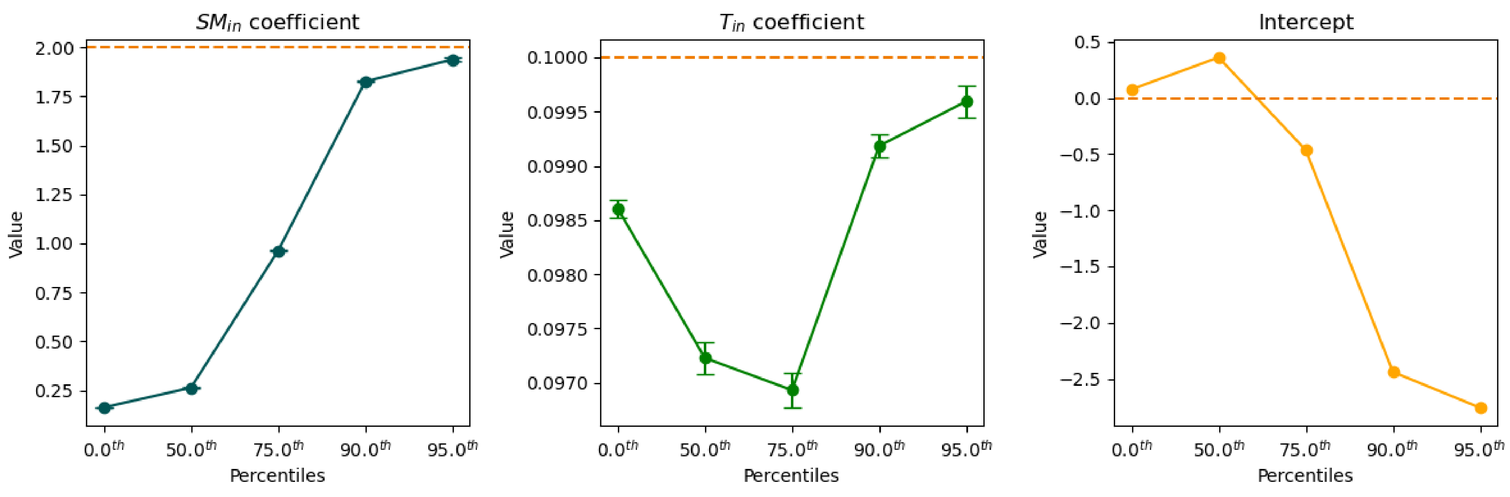
Corollary 1: *If we make reasonable assumptions, a linear regression on T_{in} and SM_{in} does not return the correct values α and β, but*

$$\alpha^* = \frac{\alpha}{1 - C_T SM_{in}} \quad \text{and} \quad \beta^* = \frac{\beta}{1 - C_{SM} T_{in}}. \tag{1}$$

However, if we train only on extreme values, we find

$$\alpha^* = \alpha \quad \text{and} \quad \beta^* = \beta. \tag{2}$$

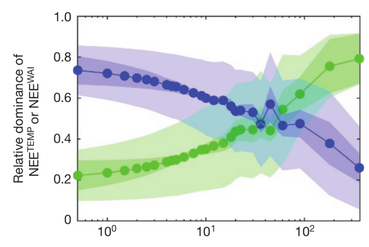
Empirical Results



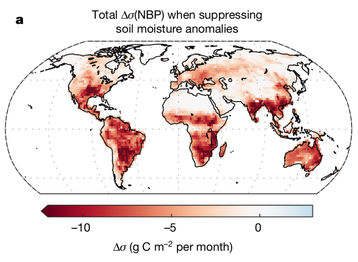
Relevance

▶ For example, the effects of soil water and temperature on plant productivity are still unclear.

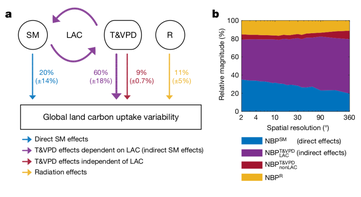
- Jung et al. (2017) find that plant productivity is locally mostly influenced by water availability but globally by temperature.



- Seneviratne et al. (2013) find that global models lose more than 80% of the variability in plant productivity when removing the variability in soil moisture.



- Humphrey et al. (2021) claim that this difference is due to land–atmosphere feedback.



Jung, Martin, et al. "Compensatory water effects link yearly global land CO2 sink changes to temperature." Nature 541.7638 (2017): 516-520.

Seneviratne, Sonia I., et al. "Impact of soil moisture-climate feedbacks on CMIP5 projections: First results from the GLACE-CMIP5 experiment." Geophysical Research Letters 40.19 (2013): 5212-5217.

Humphrey, Vincent, et al. "Soil moisture–atmosphere feedback dominates land carbon uptake variability." Nature 592.7852 (2021): 65–69.