

# Impact-based drought detection via interpretable machine learning and causal discovery

Paolo Bonetti, Matteo Giuliani, Teo Bucci, Veronica Cardigliano,  
Alberto Maria Metelli, Marcello Restelli, Andrea Castelletti

European Geosciences Union General Assembly 2026



**POLITECNICO**  
MILANO 1863



**ENVIRONMENTAL**  
INTELLIGENCE LAB

Why do we need better drought indicators?

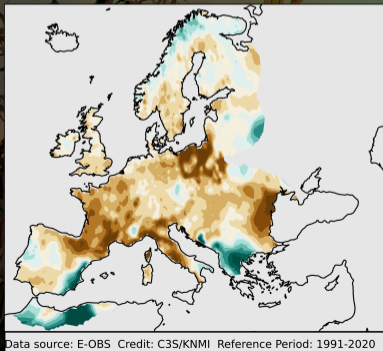


# Why do we need better drought indicators?

## Climate change

- ★ Increasing frequency, duration, severity of droughts

2022 Precipitation Anomaly

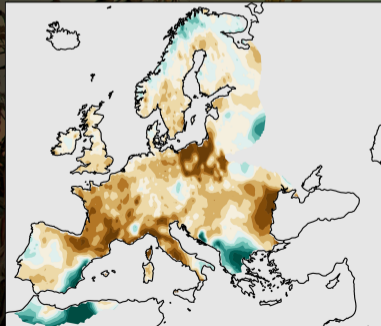


# Why do we need better drought indicators?

## Climate change

- ★ Increasing frequency, duration, severity of droughts
- ★ Major impacts on agriculture, energy, ecosystems

2022 Precipitation Anomaly



Data source: E-OBS Credit: C3S/KNMI Reference Period: 1991-2020



BBC

Recent droughts are 'slow-moving global catastrophe' - UN report

# Why do we need better drought indicators?

## Traditional drought indices

e.g., SPI, SPEI

- 👍 Components of hydrological cycle
- 🗨️ Impacts and consequences

# Why do we need better drought indicators?

## Traditional drought indices

e.g., SPI, SPEI

- 👍 Components of hydrological cycle
- 🗨️ Impacts and consequences

## Satellite-based indices

e.g., NDVI, VHI

- 👍 Real-time observed impacts
- 🗨️ No future projections

# Why do we need better drought indicators?

## Traditional drought indices

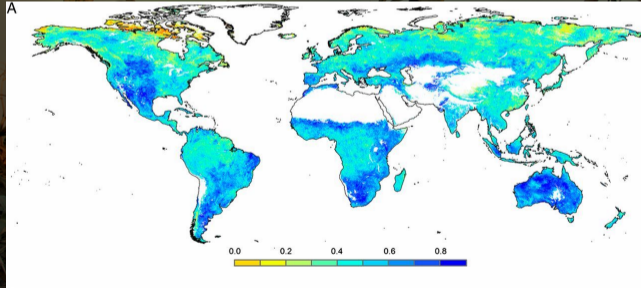
e.g., SPI, SPEI

- 👍 Components of hydrological cycle
- 🗨️ Impacts and consequences

## Satellite-based indices

e.g., NDVI, VHI

- 👍 Real-time observed impacts
- 🗨️ No future projections



# Contribution: Toward impact-based drought indicators

**Solution #1:** empirical indicators

👍 Physics aware, human interpretable

👎 Ad hoc expert-based formulations

## Contribution: Toward impact-based drought indicators

### **Solution #1:** empirical indicators

👍 Physics aware, human interpretable

👎 Ad hoc expert-based formulations

### **Solution #2:** data-driven ML indicators

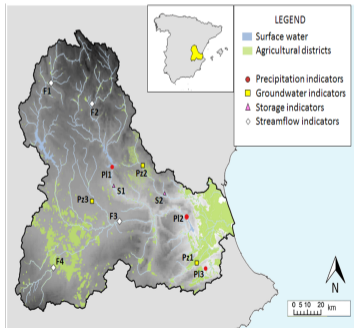
👍 Generalizable, flexible, automated

👎 Lack of interpretability and causality

# Contribution: Toward impact-based drought indicators

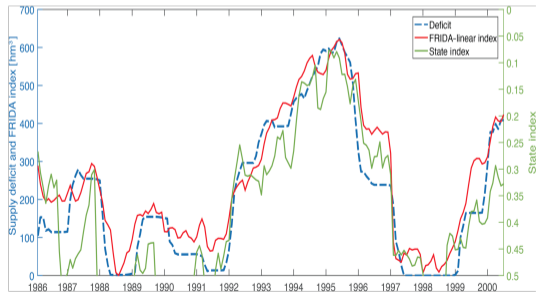
## Solution #1: empirical indicators

- 👍 Physics aware, human interpretable
- 👎 Ad hoc expert-based formulations



## Solution #2: data-driven ML indicators

- 👍 Generalizable, flexible, automated
- 👎 Lack of interpretability and causality



➔ Bridging empirical indicators interpretability/causality and black-box ML

**1. Interpret**  
every stage of  
the pipeline

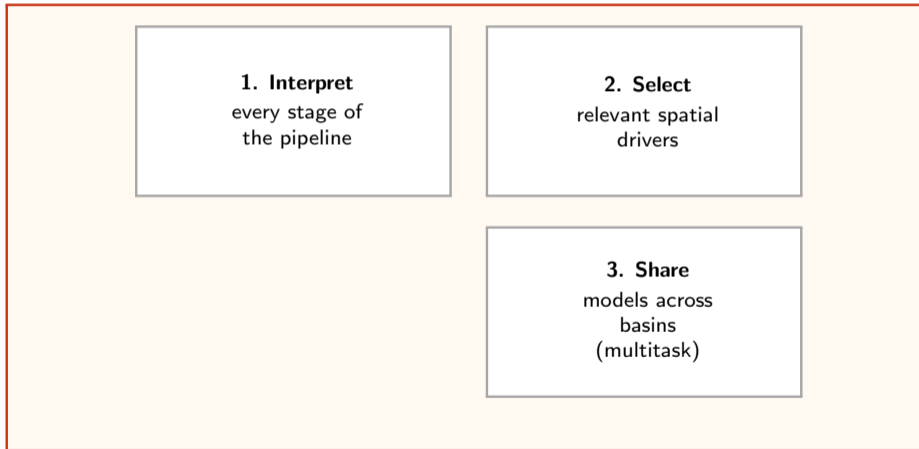
➔ Bridging empirical indicators interpretability/causality and black-box ML

**1. Interpret**  
every stage of  
the pipeline

**2. Select**  
relevant spatial  
drivers

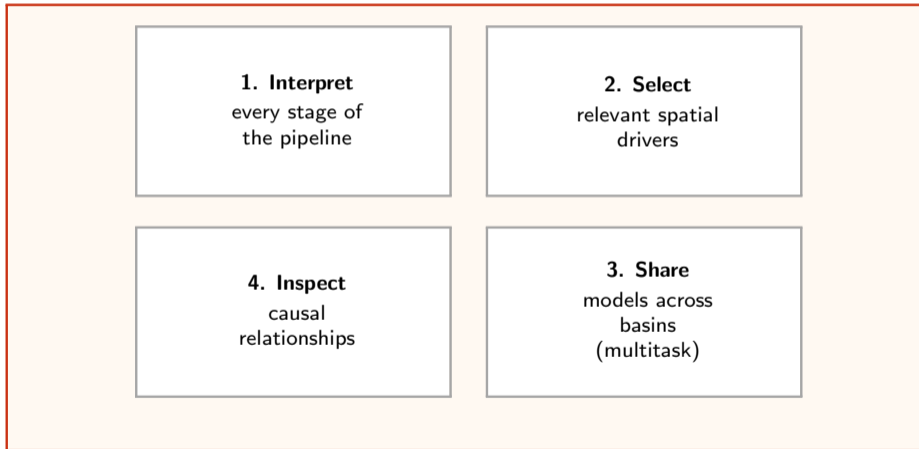
# Contribution: Toward impact-based drought indicators

→ Bridging empirical indicators interpretability/causality and black-box ML



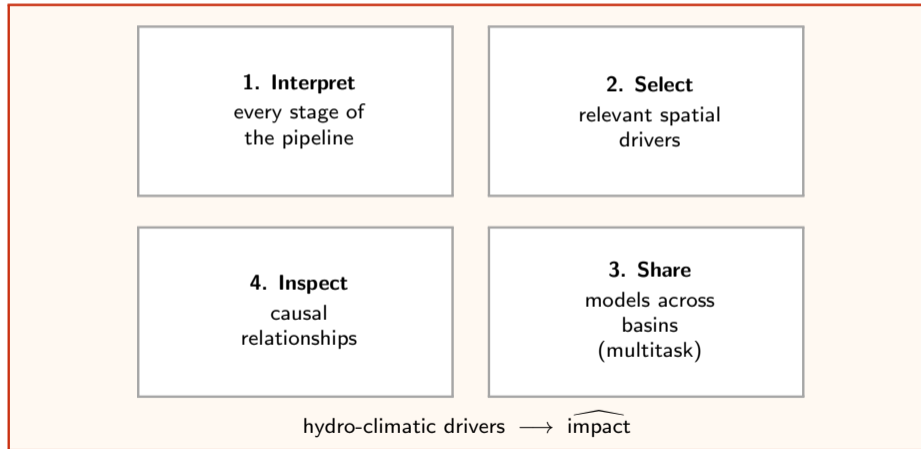
# Contribution: Toward impact-based drought indicators

➔ Bridging empirical indicators interpretability/causality and black-box ML



# Contribution: Toward impact-based drought indicators

→ Bridging empirical indicators interpretability/causality and black-box ML



# Data: Po River Case Study

Target: state of vegetation

**Vegetation Health Index** of cultivated pixels (8-day aggregation)

Candidate drivers

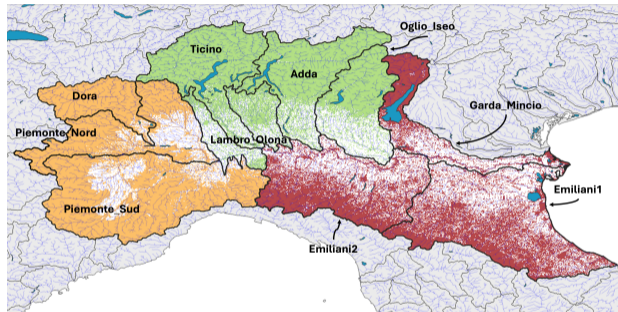
7 temporal aggregations: 8D to 24W

Temperature 991 pixels

Precipitation 991 pixels

Snow depth 53 pixels

Lake water levels 4 lakes

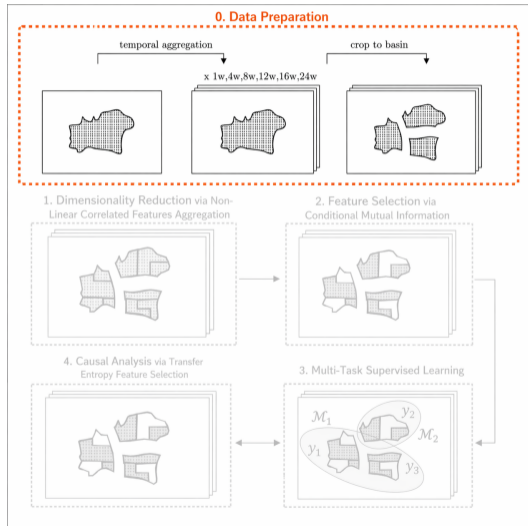
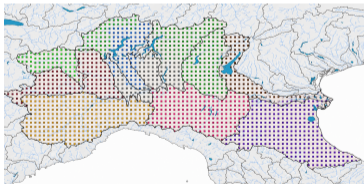


- Tasks: 10 sub-basins, 3 clusters
- Samples: 411 train (2001–2009), 228 validation (2010–2014), 228 test (2015–2019)

# Workflow: The DRIER Framework

## Input example

Temperature  $t_g$ , 1-week aggregation  
1w, 10 sub-basins



# Workflow: The DRIER Framework

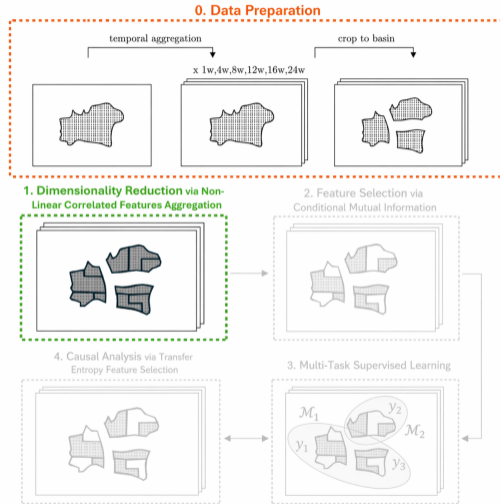
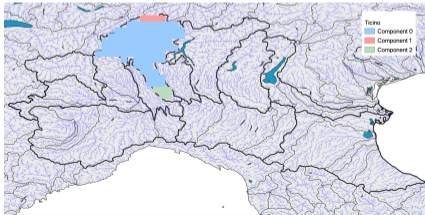
Dimensionality reduction:

**NonLinCFA** [Bonetti et al., 2023]

- Principled aggregation:

$$\frac{\sigma^2}{\sigma_f^2(n-1)} \geq R_{f,\phi_1\phi_2}^2 - R_{f,h(\phi_1,\phi_2)}^2$$

- Benchmark: PCA
- Example: **Ticino** weekly temp



# Workflow: The DRIER Framework

Feature Selection:

**Forward CMI** [Beraha et al., 2019]

■ Non-linear filter:

$$I(X; Y) := \mathbb{E}_{X, Y} \left[ \log \frac{p(X, Y)}{p(X)p(Y)} \right]$$

■ Benchmark: wrapper FS

■ **Ticino** selected drivers

Temp + Prec + Lake + Snow

tg\_1w\_0

tg\_1w\_0

rr\_4w\_0

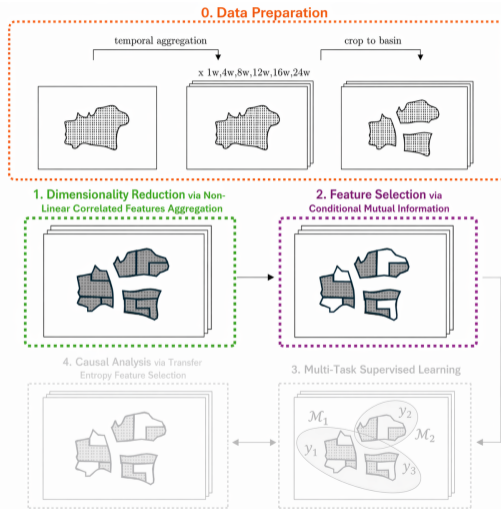
rr\_4w\_0

tg\_1w\_2

snow\_1w

Lugano\_1w

Maggiore\_16w



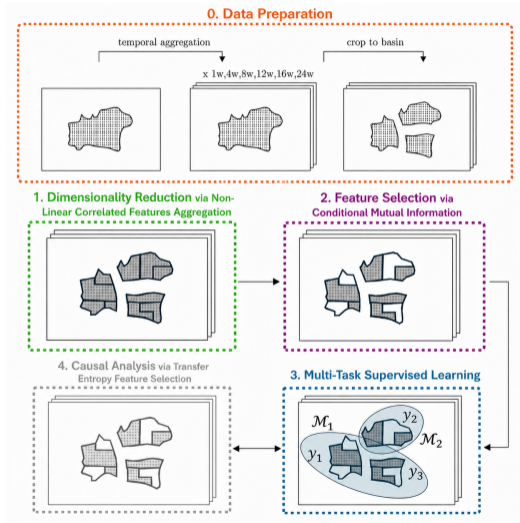
# Workflow: The DRIER Framework

## Multi-task linear regression

- Shared cluster-level features:

$$\begin{cases} \hat{y}_1 = \hat{w}_1 x_1 + \dots + \hat{w}_D x_D + \hat{\beta}_1, \\ \dots \\ \hat{y}_K = \hat{w}_1 x_1 + \dots + \hat{w}_D x_D + \hat{\beta}_K. \end{cases}$$

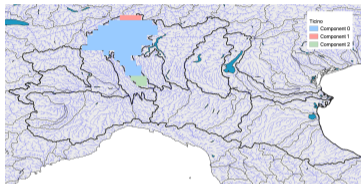
- Benchmark: FFNN, RF, SVR
- Coefficient of determination:





# Results Summary

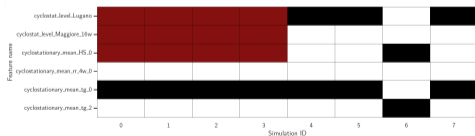
**Dimensionality Reduction:** from 991x7x2 to 549 features



**Feature Selection:** at most 5 features for each sub-basin

Ticino	Temp + Prec	+ Lake + Snow
	tg_0w_0	tg_0w_0
	rr_4w_0	rr_4w_0
	tg_0w_2	snow_0w
		Maggiore_16w
		Lugano_0w

## Causal Analysis:



## (Multi-task) linear regression:



# Results Summary

**Dimensionality Reduction:** from 991x7x2 to 549 features

**Feature Selection:** at most 5 features for each sub-basin

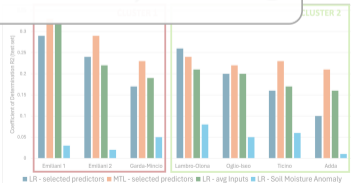
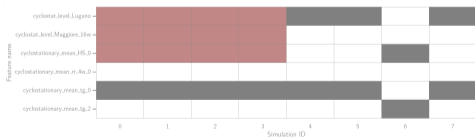
Temp + Prec + Lake + Snow



**Data-Driven Impact-Based Drought index (Ticino):**

$$\widehat{VHI} = -0.35 \cdot tg\_0w\_0 + 0.88 \cdot Lugano\_0w - 0.52$$

Causal Analysis:



- Impact based drought indices → 👍 Generalizable across sectors and spatial domains 👎 Need ML experts and users validation

# Take-home messages

- Impact based drought indices → 👍 Generalizable across sectors and spatial domains 👎 Need ML experts and users validation
- Reconstruction performances → 👍 interpretability of all the steps 👎 limits of linear regression

## Take-home messages

- Impact based drought indices → 👍 Generalizable across sectors and spatial domains 🗑️ Need ML experts and users validation
- Reconstruction performances → 👍 interpretability of all the steps 🗑️ limits of linear regression
- (Causal) Feature Importance → 👍 relevant information extracted 🗑️ more variables could be included for improvements

Thank you!








POLITECNICO  
MILANO 1863



ENVIRONMENTAL  
INTELLIGENCE LAB



# References

- 
- Beraha, M., Metelli, A. M., Papini, M., Tirinzoni, A., and Restelli, M. (2019). Feature selection via mutual information: New theoretical insights. In *2019 international joint conference on neural networks*, pages 1–9. IEEE.
- 
- Bonetti, P., Metelli, A. M., and Restelli, M. (2023). Nonlinear feature aggregation: Two algorithms driven by theory. *arXiv preprint arXiv:2306.11143*.
- 
- Bonetti, P., Metelli, A. M., and Restelli, M. (2024). Causal feature selection via transfer entropy. In *2024 International Joint Conference on Neural Networks (IJCNN)*, pages 1–10.
- 
- Runge, J., Nowack, P., Kretschmer, M., Flaxman, S., and Sejdinovic, D. (2019). Detecting and quantifying causal associations in large nonlinear time series datasets. *Science advances*, 5(11):eaau4996.
- 
- Vicente-Serrano, S. M., Gouveia, C., Camarero, J. J., Beguería, S., Trigo, R., López-Moreno, J. I., Azorín-Molina, C., Pasho, E., Lorenzo-Lacruz, J., Revuelto, J., et al. (2013). Response of vegetation to drought time-scales across global land biomes. *Proceedings of the National Academy of Sciences*, 110(1):52–57.



Zaniolo, M., Giuliani, M., Castelletti, A. F., and Pulido-Velazquez, M. (2018). Automatic design of basin-specific drought indexes for highly regulated water systems. *Hydrology and Earth System Sciences*, 22(4):2409–2424.