26 November 2024
Virtual Exchange on Artificial Intelligence for Integrated Drought Risk Management

AI for drought

Laia Romero[1], Jesús Peña-Izquierdo[1] , David Civantos[1], Maria José Escorihuela[1]

Lluis Palma[2] , Markus Donat[2] , Albert Soret[2]

Gonzalo Vilella[3] , Mihnea Tufis[3], Arjit Nandi[3]

[1] Lobelia.

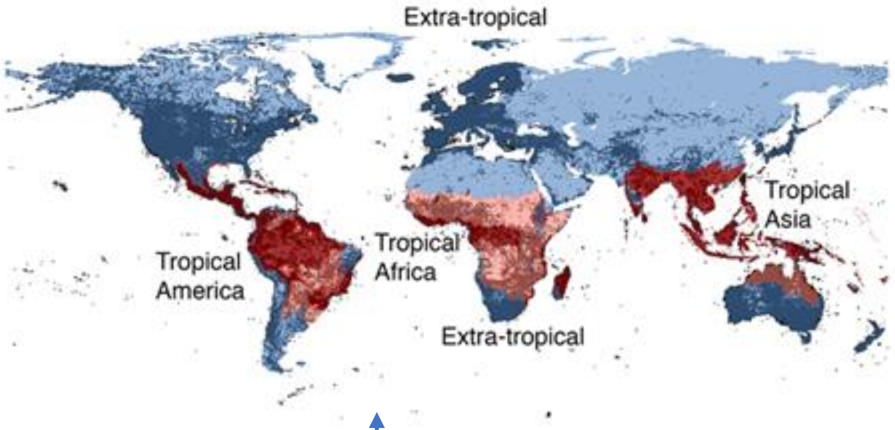
[2] Barcelona Supercomputing Center – Centro Nacional de Supercomputación

[3] eurecat – Centre Tecnològic de Catalunya

A crucial need:
Drought management in a changing climate.

Seasonal Context

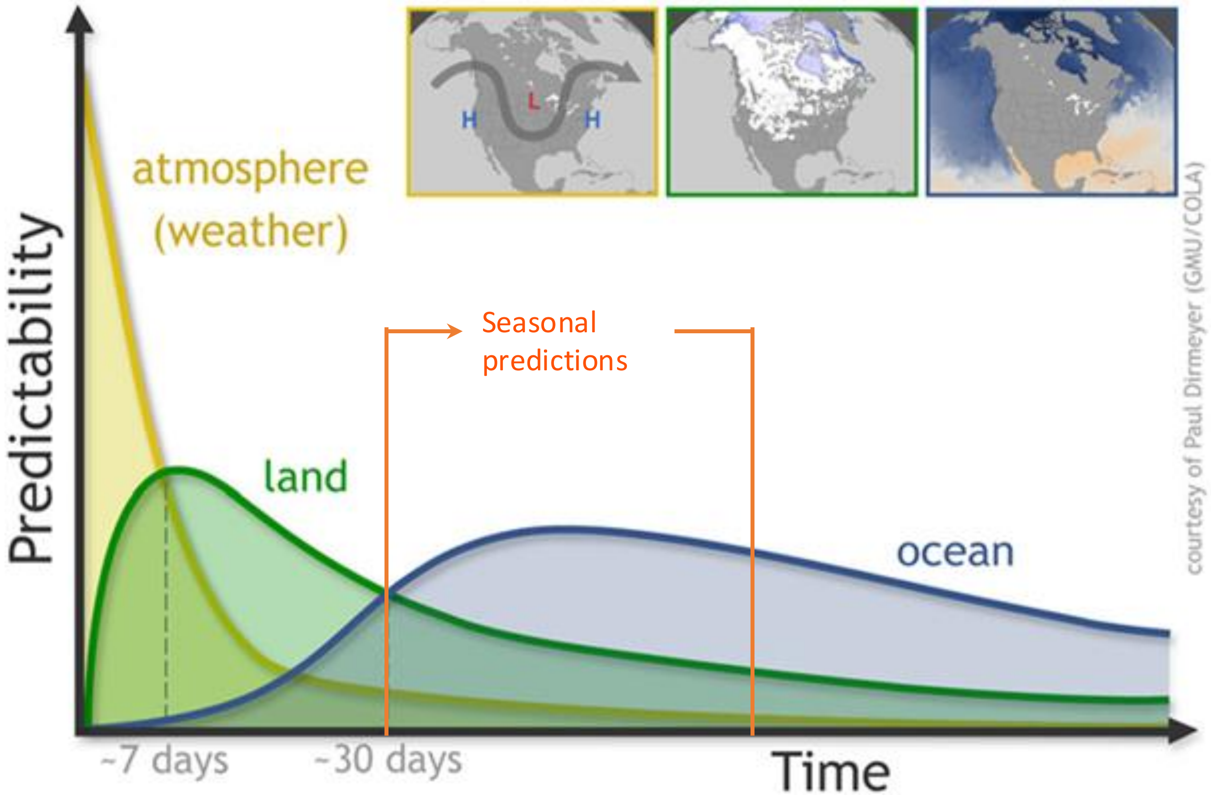
Seasonal climate predictions cover the gap between weather forecasts and climate projections



BLUE ⍰ Low skill

- Probabilistic forecasts of drought 6 months ahead
- Skill in the extra-tropics is very limited
- Multidimensional implications: drought – heatwaves – wildfires
- Adaptation need: skillful predictions months in advance

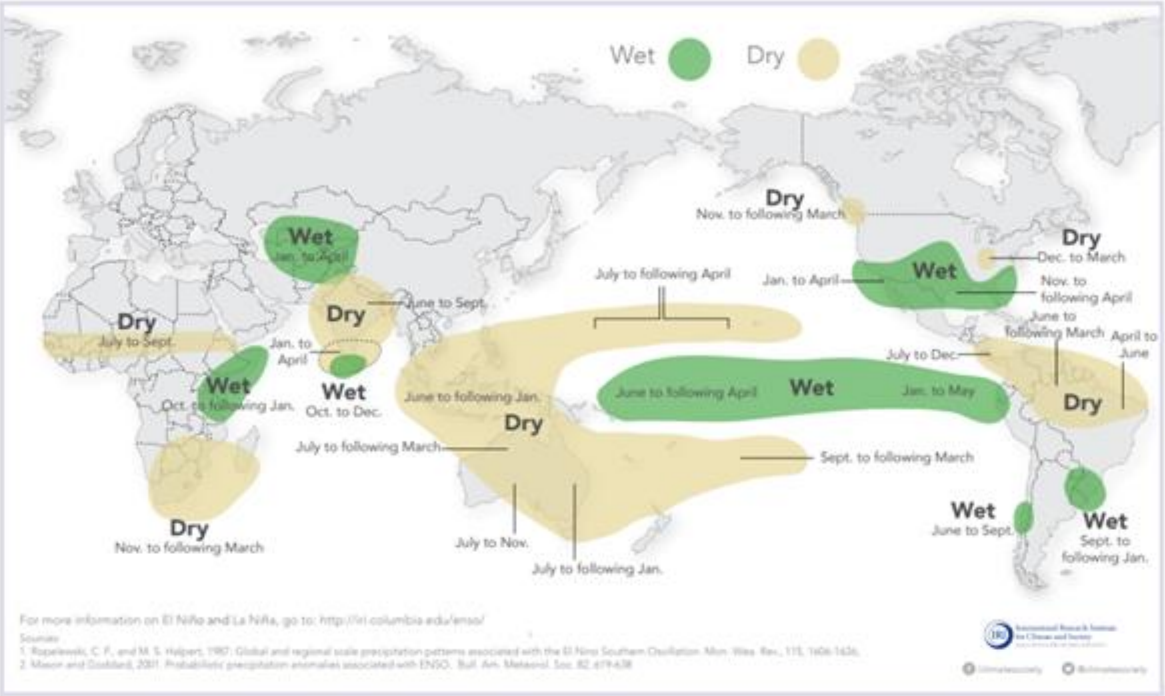
How can we predict next season conditions if we cannot predict the weather next week ?



- **Ocean** holds most of the **large-scale** predictability signal at seasonal and interannual scales
- **Land** holds predictability mostly at **local-scale** for amplifying large-scale variability

Large-scale predictors for Europe

El Niño (ENSO)

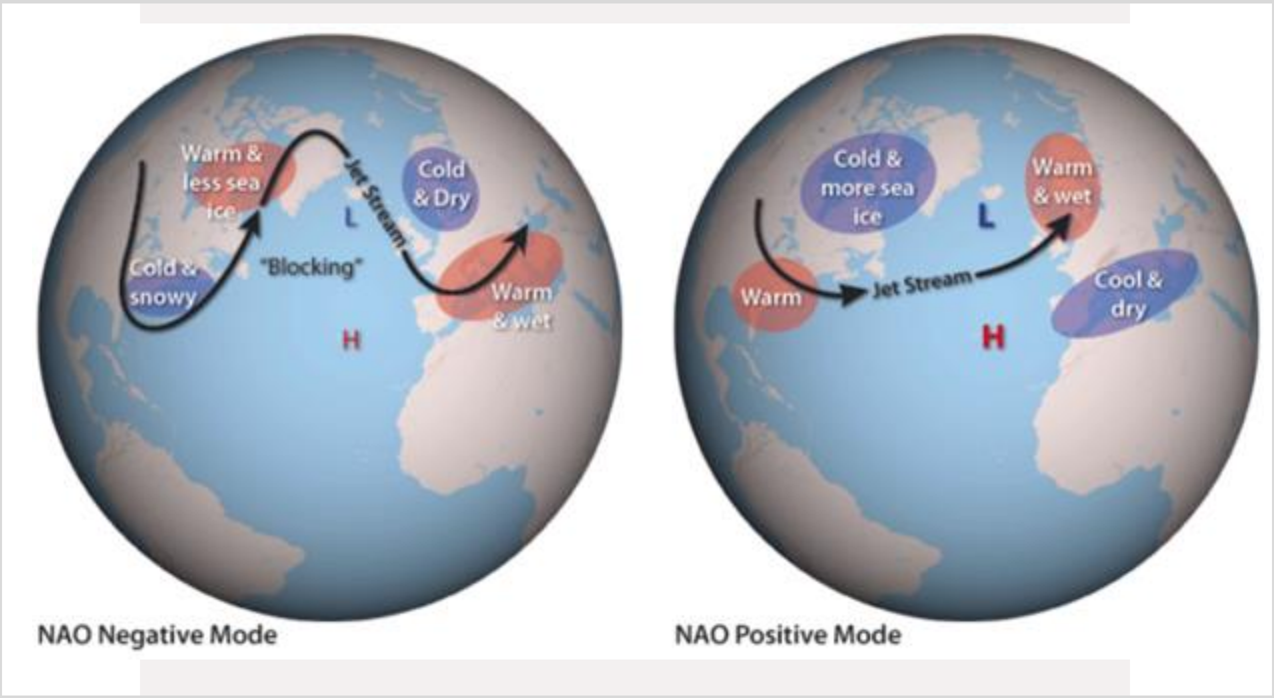


IRI

- Weak **influence** on Europe

→ Need of **additional sources** of large-scale predictability

North Atlantic Oscillation (NAO)



Climate.gov

- **Weak** summer **predictability**

A global empirical system for probabilistic seasonal climate prediction based on generative AI and CMIP6 models

Lluís Palma[1], Alejandro Peraza[1], Amanda Duarte[1], David Civantos[2], Stefano Materia[1], Arijit Nandi[3], Jesús Peña-Izquierdo[2], Mihnea Tufis[3], Gonzalo Vilella[3], Laia Romero[2], Albert Soret[1], and Markus Donat[1]

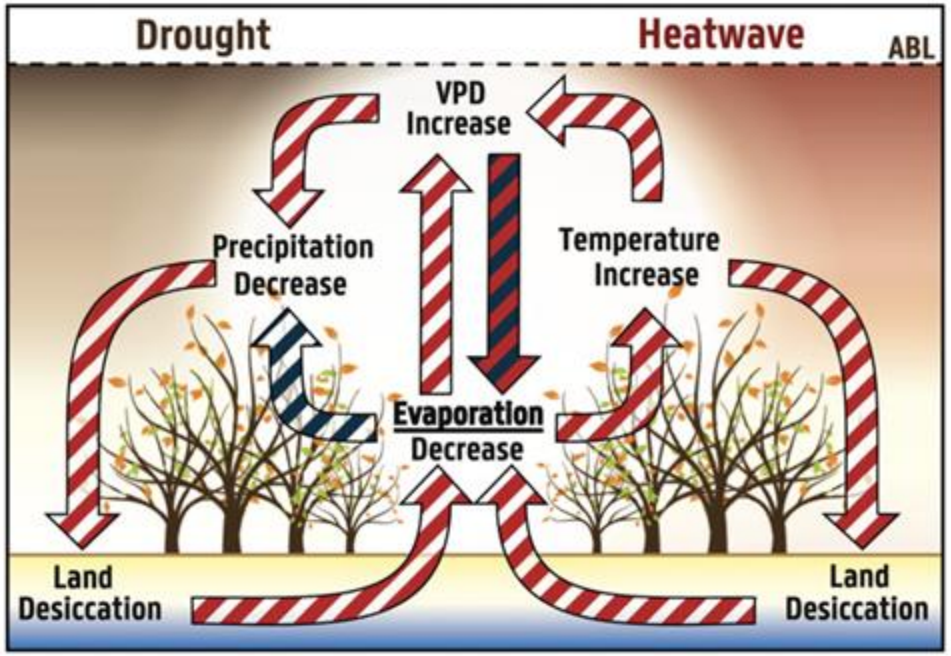
[1] Barcelona Supercomputing Center, Earth Sciences Department, Spain | [2] Lobelia Earth, Barcelona, 08005, Spain | [3] Eurecat Technology Center of Catalunya, Barcelona, 08005, Spain

lluis.palma@bsc.es

Local-scale predictors for Europe

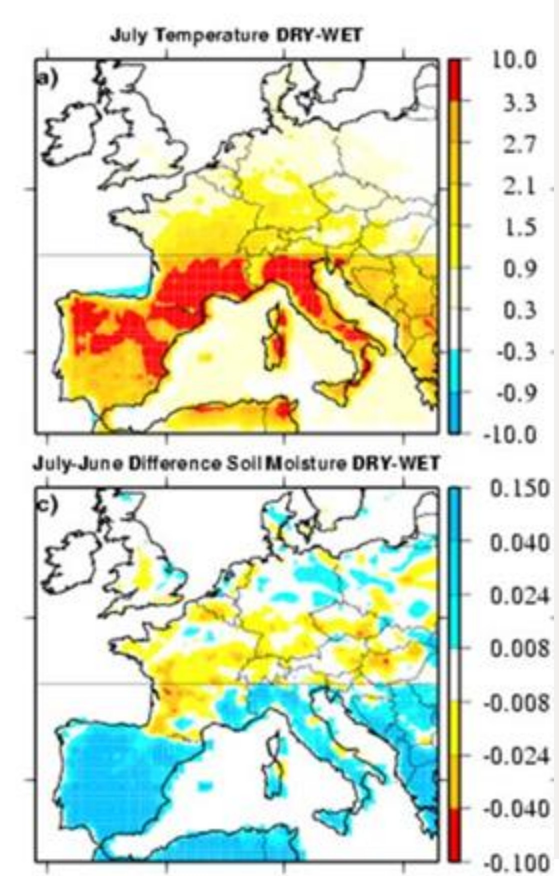
- Land-atmosphere feedbacks play a major role **amplifying** large-scale signal leading to **extremes**

- **Soil moisture** is the **key variable** here



Miralles et al. 2019

Only with **spring dry soil conditions** the historic **2003 summer heat-wave** can be reproduced



A much warmer summer

A drier summer

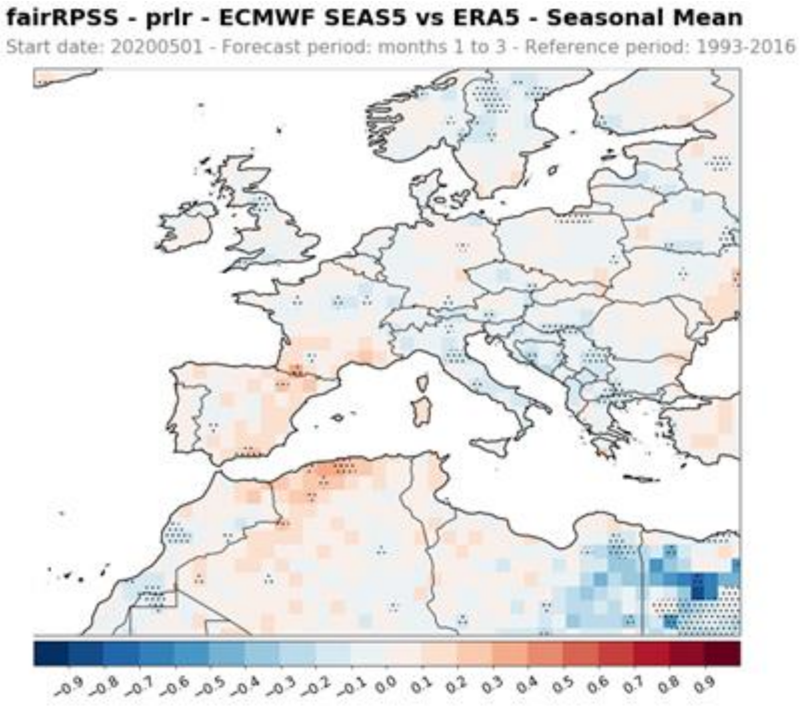
Vautard et al. 2007

→ **Initialization** of soil conditions for predicting extremes

→ **Feedbacks** not captured in climate models

Can seasonal prediction be enhanced with data-driven methods?

Verification of summer prediction
for **precipitation prediction**



worse than climatology

better than climatology

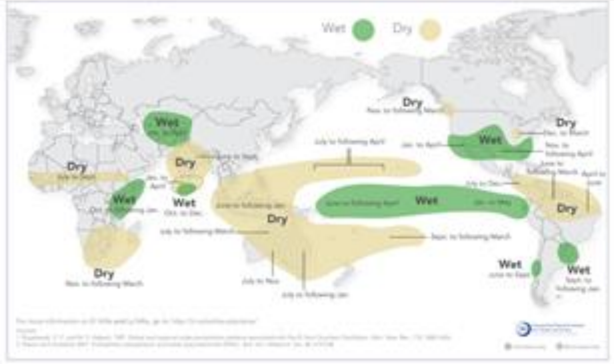
ML-based predictions

+

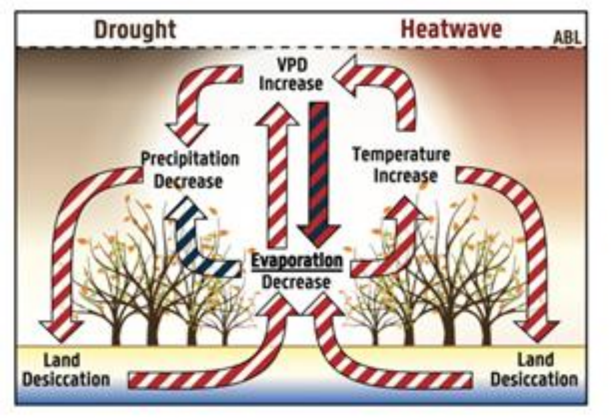
BUT we only have **10s of years** of **satellite data**

and need **1000s** of **observational** years **for training**!

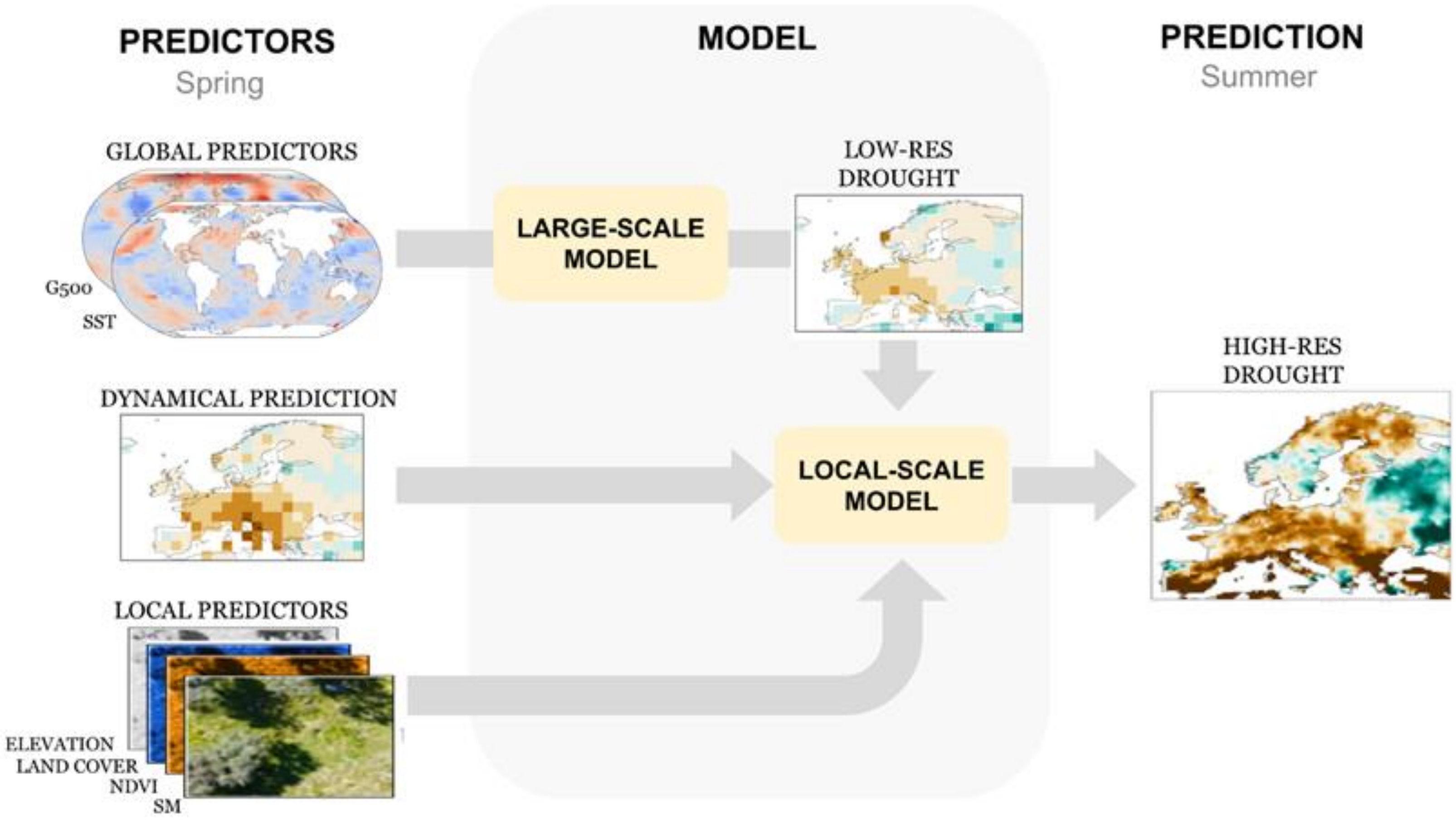
Large-scale drivers



Local-scale drivers



AI4DROUGHT System Architecture



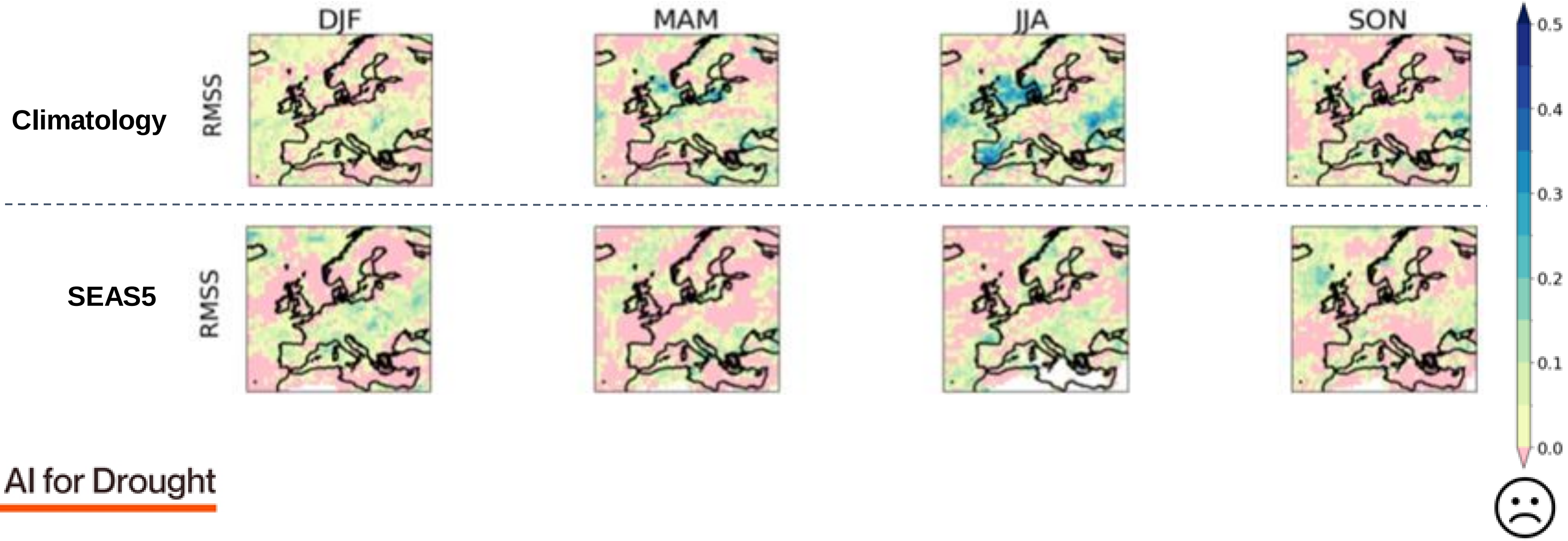
→ **Climate simulations** provide 1000s of year of **physically consistent** natural variability

→ A **pixel-based** model allows for 1000s of **spatially scattered** training samples within **10s of years of observational data**

Large-scale model results

- We measure our large-scale model accuracy against two benchmarks: climatology and SEAS5
- Results show skill improvement over SEAS5 in Europe, yet predictability at seasonal timescales remains very limited
- Generative approaches, including deep learning CVAEs, can improve data-driven seasonal predictions through non-linear and probabilistic modelling.

Precipitation - Skill Scores 2002-2022 [ref.1981-2001]



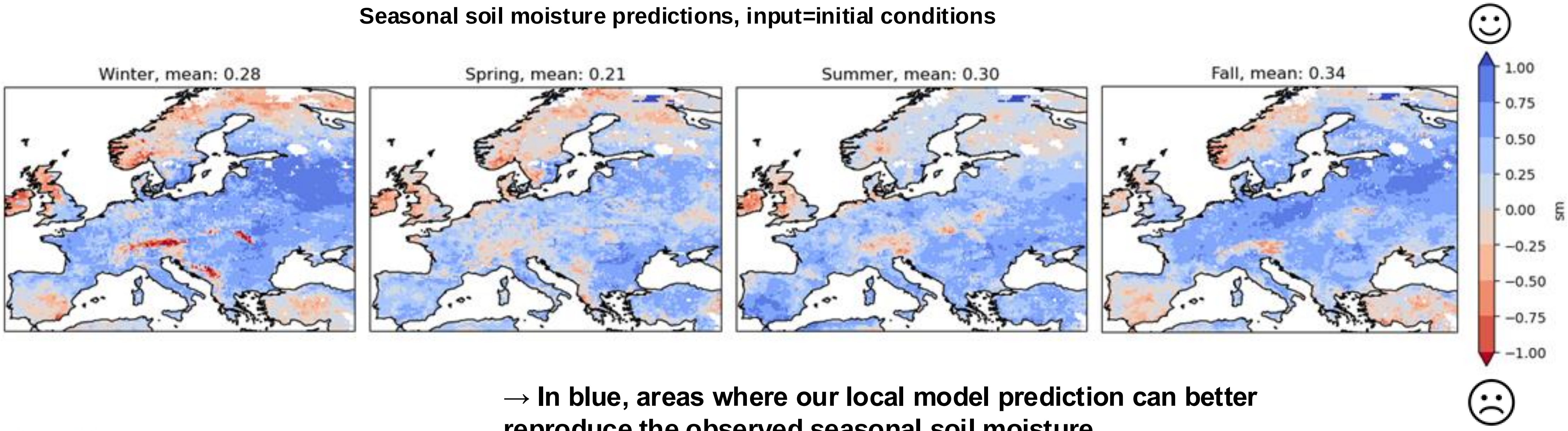
→ In blue, areas where our large scale model performs better than climatology

→ In blue, areas where our large scale model performs better than SEAS5 (ECMWF)

Local-scale model results

- We measure our local-scale model fit against observational soil moisture reanalysis
- Results show skillful seasonal predictions using only initial conditions → integrating soil moisture satellite observations from the past moth
- Soil moisture memory provides more predictability than actual precipitation and evapotranspiration (in blue)
- Soil Moisture initial conditions are essential to forecast drought anomalies at seasonal time-scales

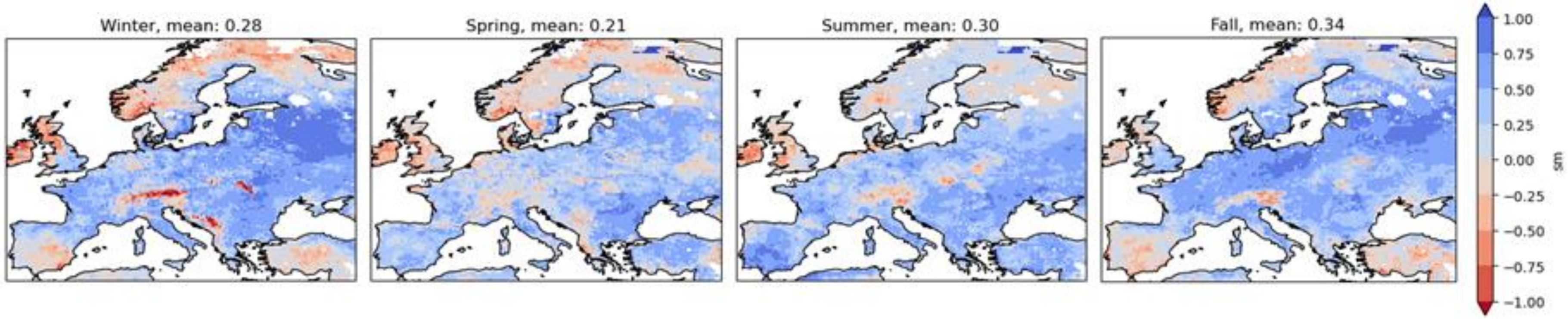
Seasonal soil moisture predictions, input=initial conditions



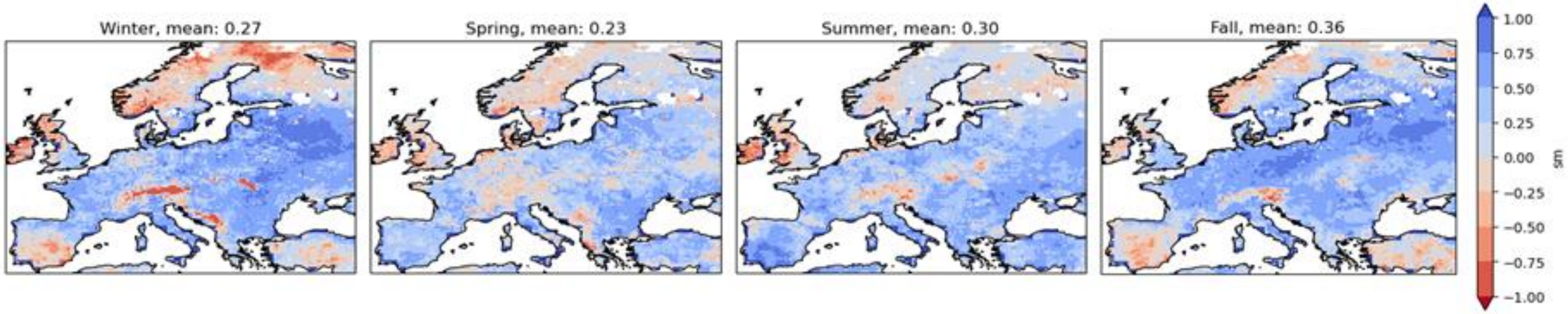
→ In blue, areas where our local model prediction can better reproduce the observed seasonal soil moisture

Large-scale + Local-scale models

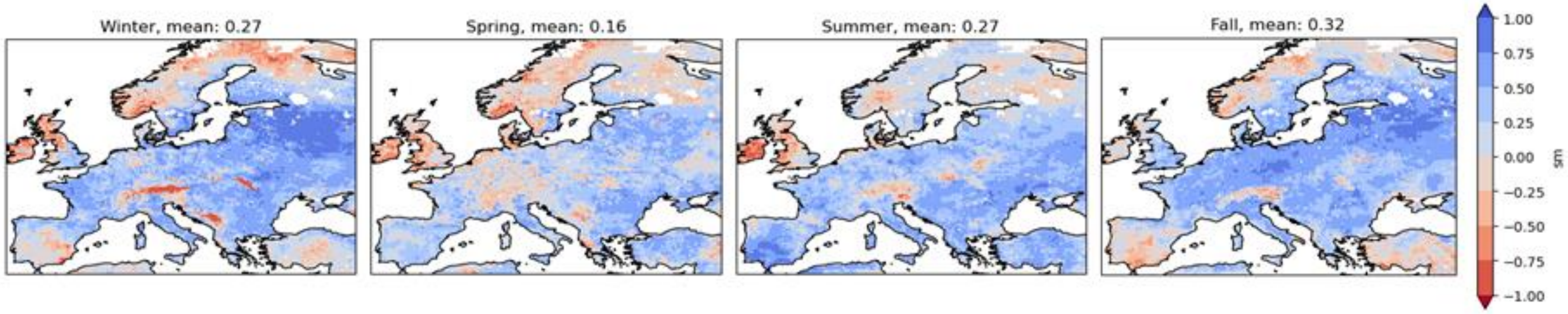
Not a significant improvement integrating precipitation!



Only initial conditions



Initial conditions + SEAS5 SPEI3

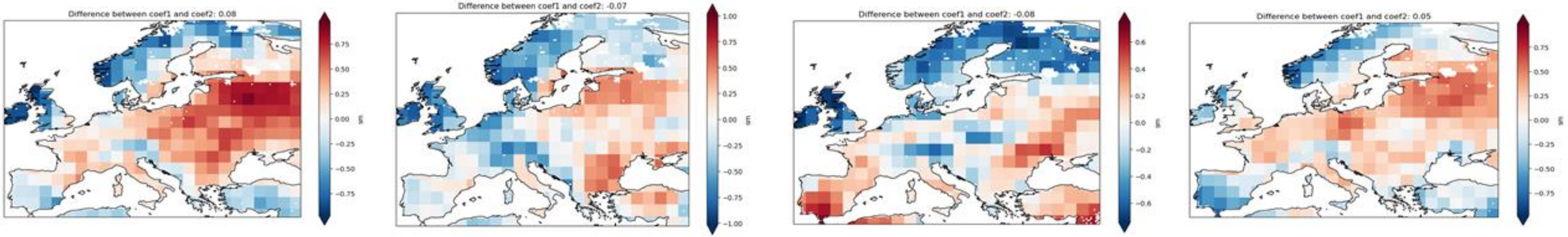


Initial conditions + Large-scale SPEI3

Lobelia.

Interpretability of results

Winter Spring Summer Autumn



Initial conditions more important than precipitation

Precipitation more important than initial conditions

→ **In red, areas where AI4DROUGHT satellite-based soil moisture provide seasonal drought predictability where traditional methods have no skill**

→ **Important input for an accurate soil moisture prediction product in different seasons and regions in Europe**

→ **Hybrid approaches are a promising way forward in seasonal forecasts**

Thank you!

Laia Romero, Jesús Peña Izquierdo
and David Civantos on behalf of the
AI for Drought team

laia@lobelia.earth

www.aifordrought.com

Lobelia.
Barcelona Supercomputing Center
Centro Nacional de Supercomputación
eurecat