esa

AI for drought

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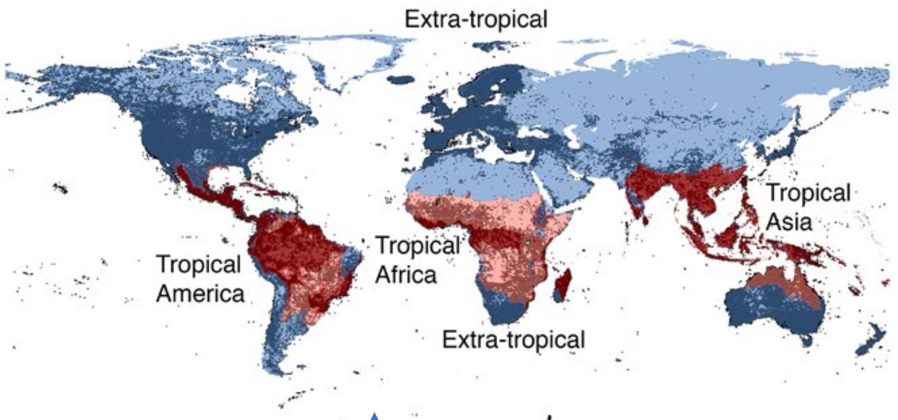
A crucial need:
Drought management in a changing climate.

Seasonal Context

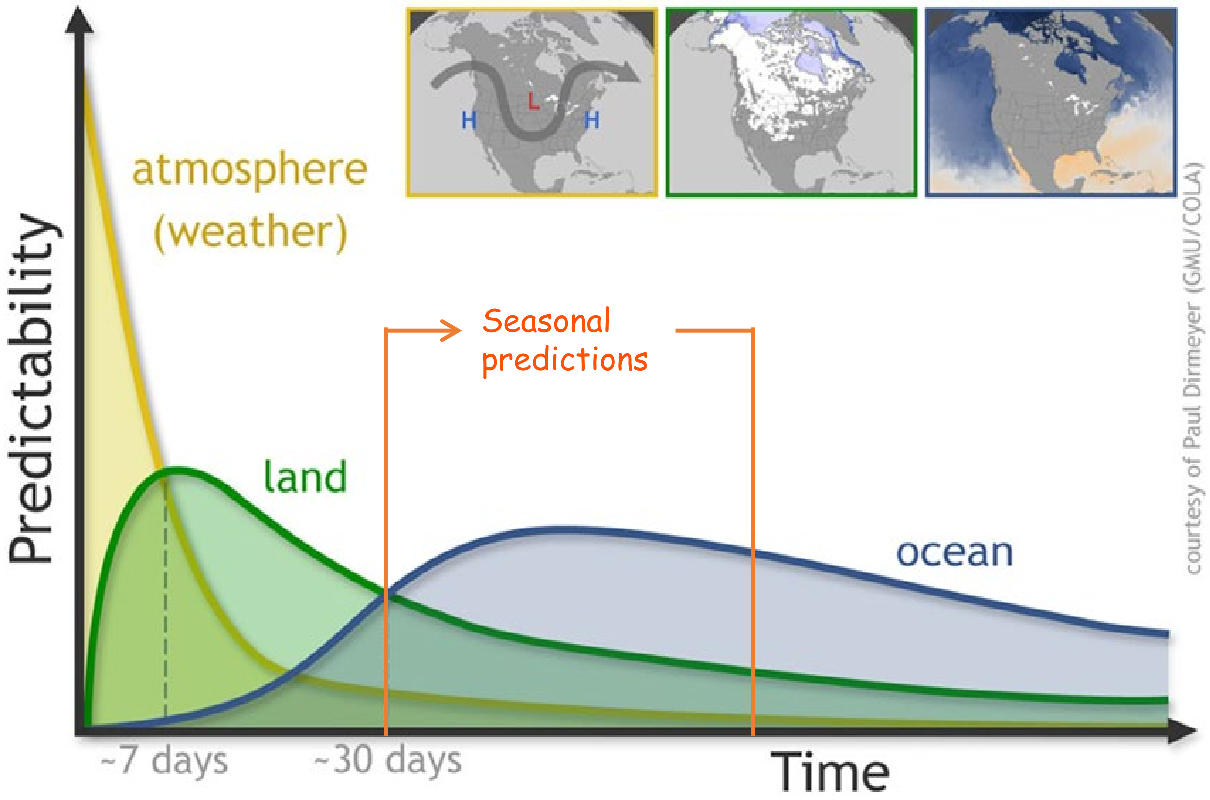


BLUE → Low skill

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

- 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

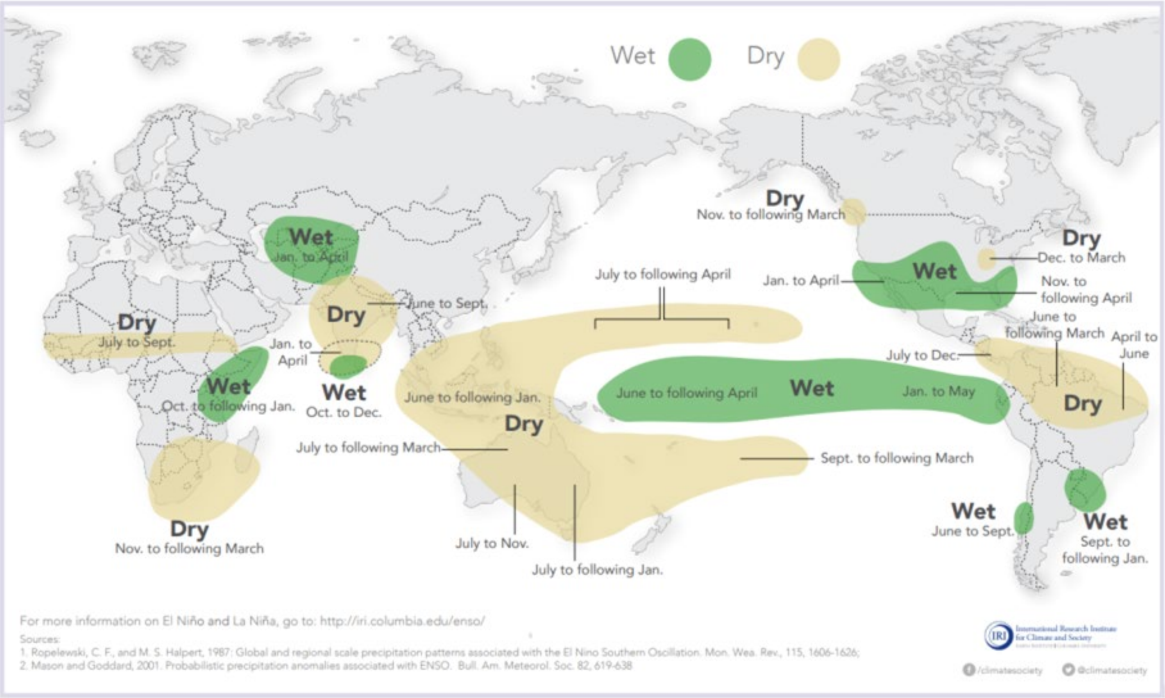
How can we predict next season conditions if we cannot predict the weather next week ?



- **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

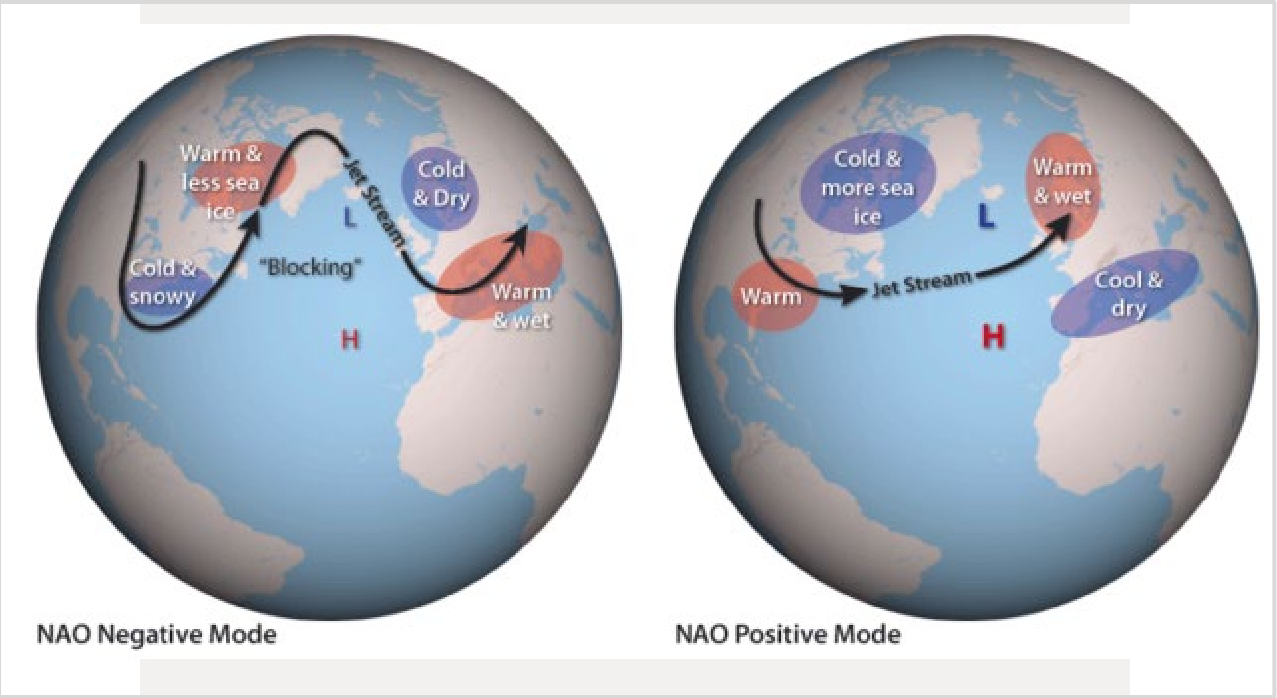
El Niño (ENSO)



IRI

- Weak **influence** on Europe

North Atlantic Oscillation (NAO)



Climate.gov

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

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

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

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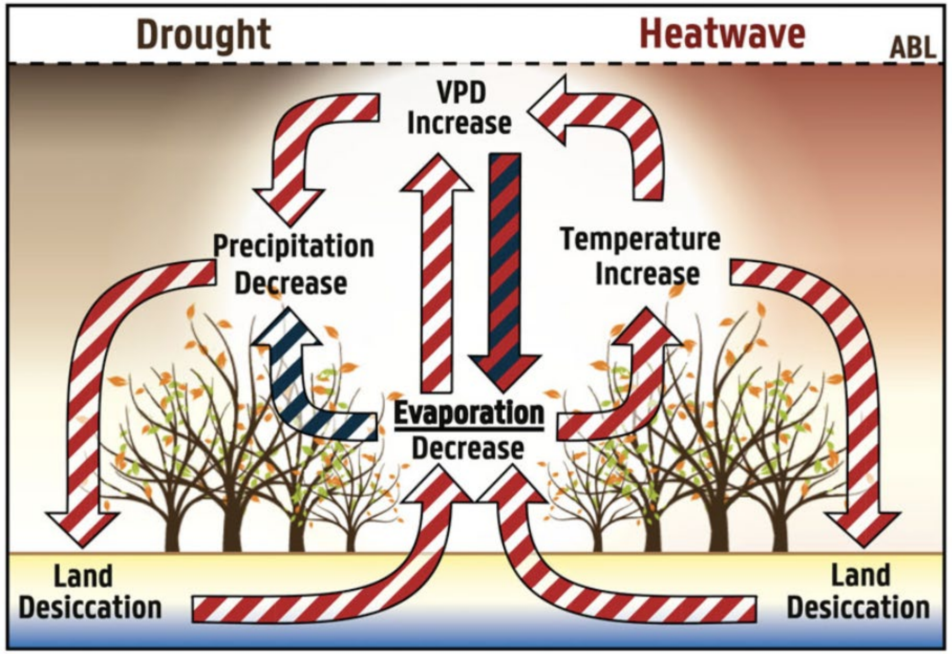
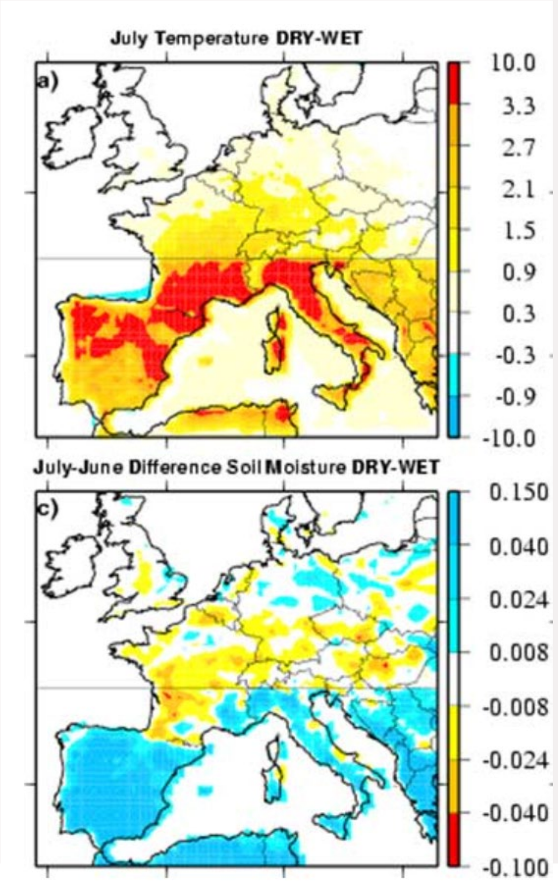
Local-scale predictors for Europe

- 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

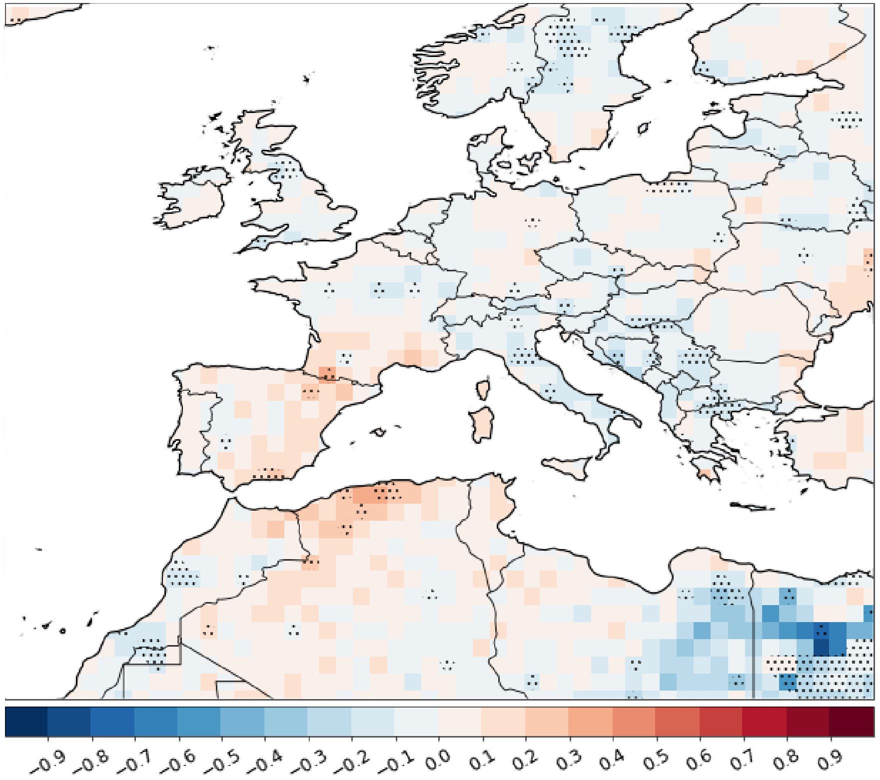
→ **Initialization** of soil conditions for predicting extremes

→ **Feedbacks** not captured in climate models

Can seasonal prediction be enhanced with data-driven methods?

Verification of summer prediction
for **precipitation prediction**

fairRPSS - prlr - ECMWF SEAS5 vs ERA5 - Seasonal Mean
Start date: 20200501 - Forecast period: months 1 to 3 - Reference period: 1993-2016



worse than climatology

better than climatology

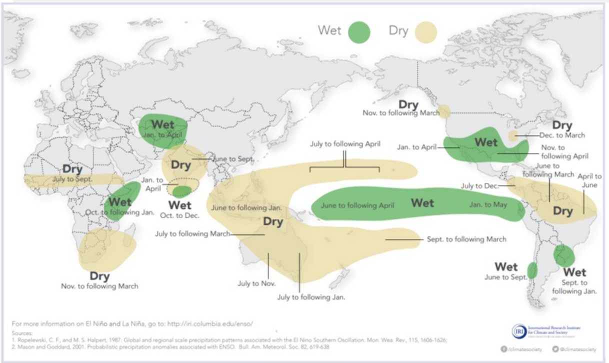
ML-based predictions

+

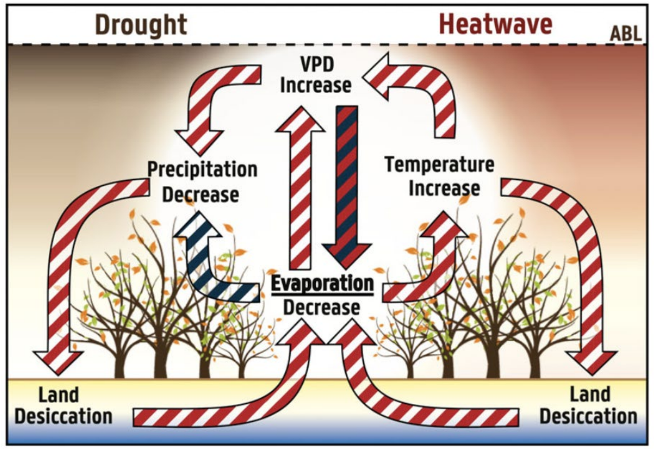
BUT we only have **10s of years** of **satellite data**

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

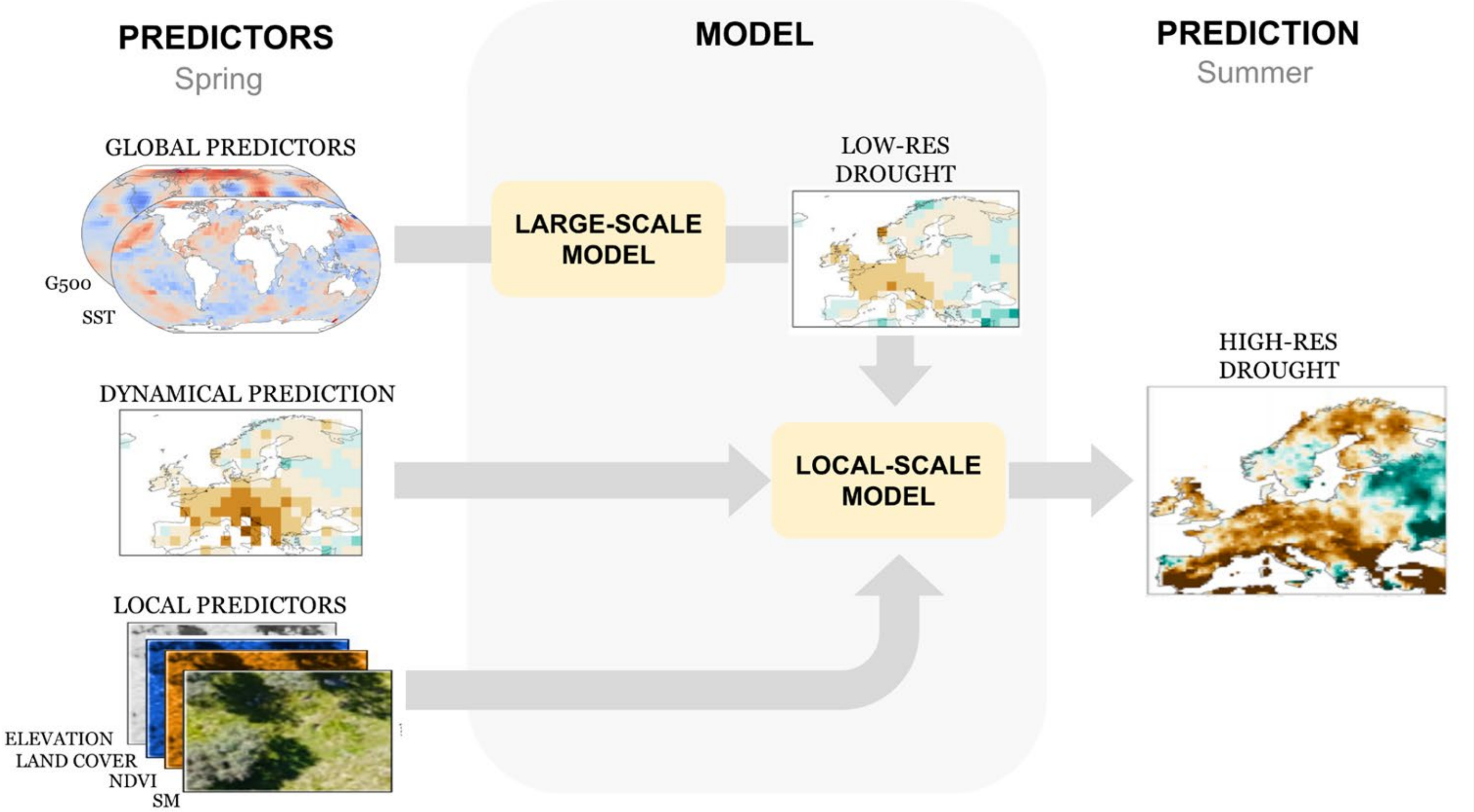
Large-scale drivers



Local-scale drivers



An hybrid approach to predict summer conditions



→ **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**

An hybrid approach to predict summer conditions

PREDICTORS (SPRING)

Large-scale

SPEI prediction from large-scale model

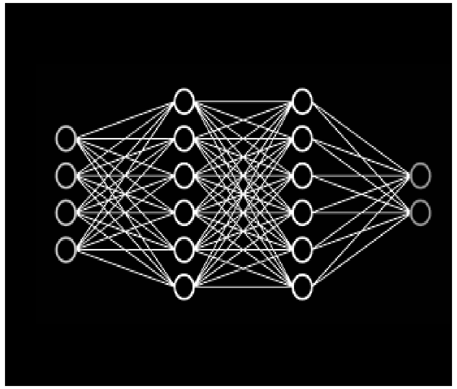
Dynamical Prediction

SPEI from ECMWF SEAS5

Local-scale

- Initial local conditions (Spring)
    - Remote sensing observations for soil mositure, vegetation etc.

PREDICTION (SUMMER)



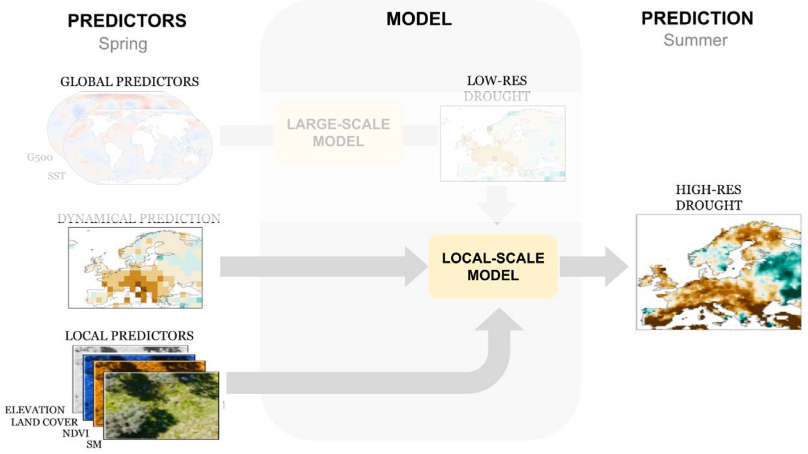
Summer Soil Moisture Anomaly

- Pixel-based model (Tree-based model)
- Period 2000-2020 (4-year fold cross-validation)
- 0.25º spatial resolution
- Europe domain
- Target: Summer (SM standardized anomaly)
- **Benchmark:** Persistence (Spring' SM st anomaly)

Inputs

- SEAS5 SPEI3 prediction (Summer)
- SPEI3 future (Summer)
- Initial local conditions (Spring):
  - SPEI1
  - SPEI3
  - Elevation
  - Soil Moisture
  - Land cover
  - Temperature
  - NDVI
  - Potential Evapotranspiration standardized anomaly

Metrics

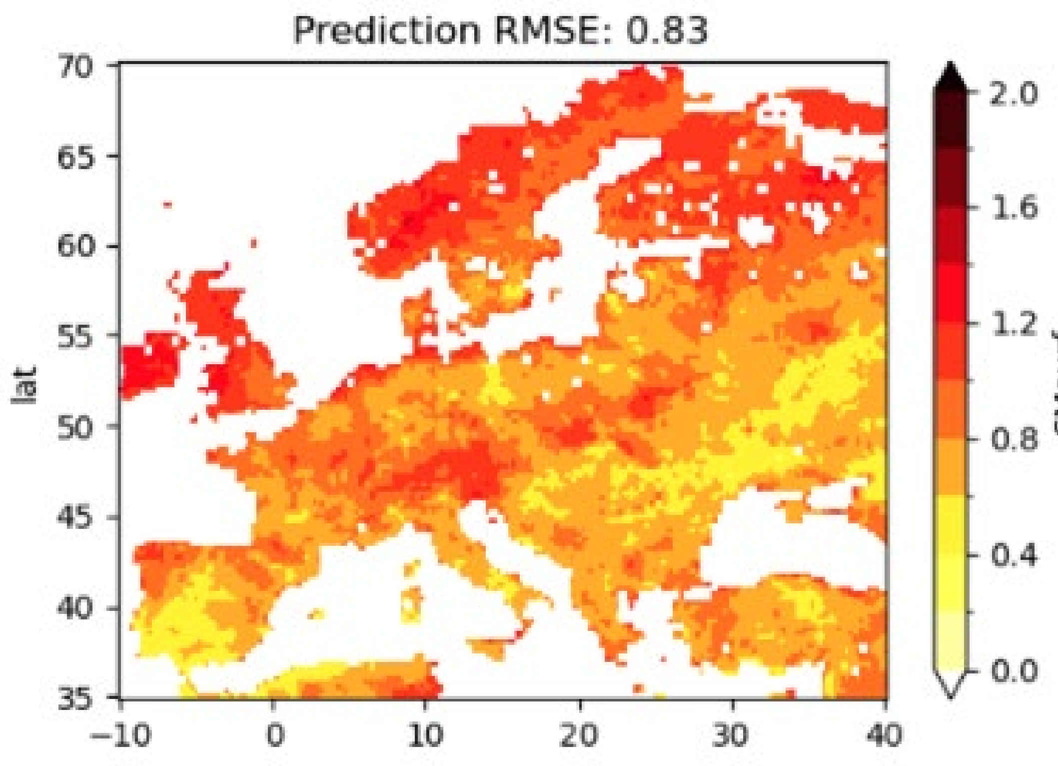


- RMSE
- R-square
- MSSS: **Mean Square Skill Score**
  - 1 for perfect prediction
  - 0=persistence
  - <0 persistence is better than the prediction

$$MSSS_j = 1 - \frac{MSE_j}{MSE_{cj}}$$

A. Local model with only local factors as input

Input=local factors



☹

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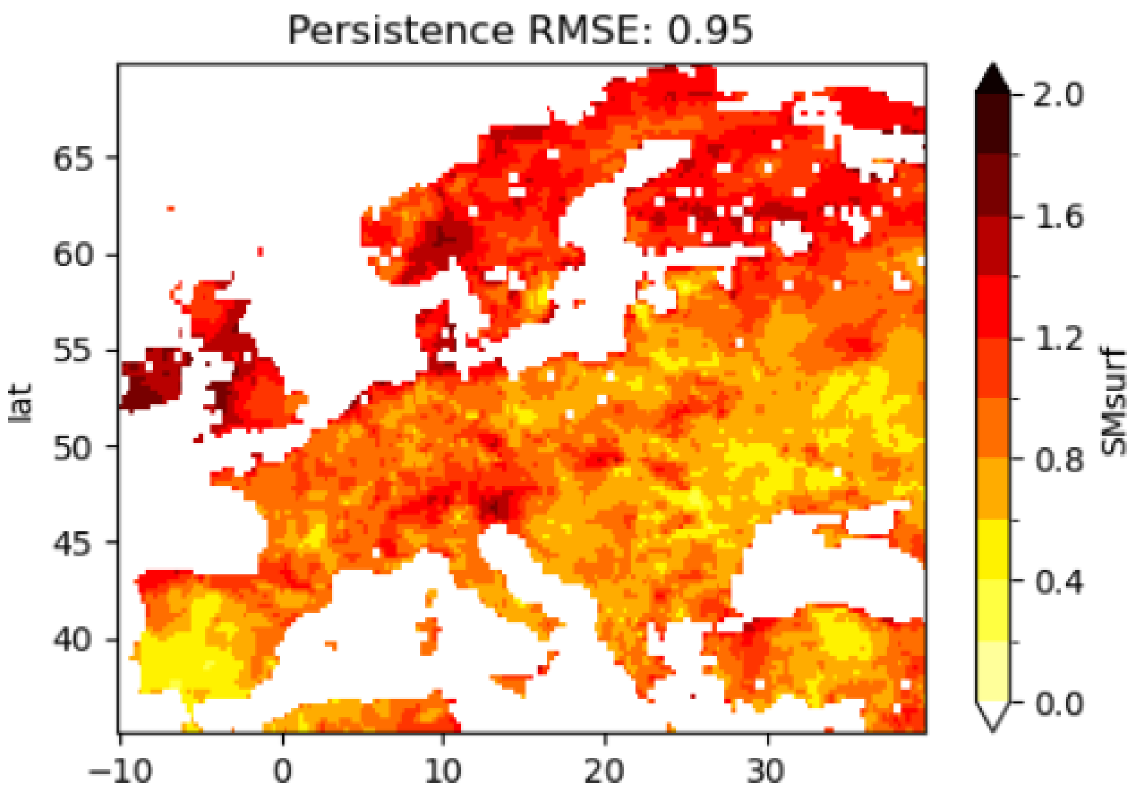
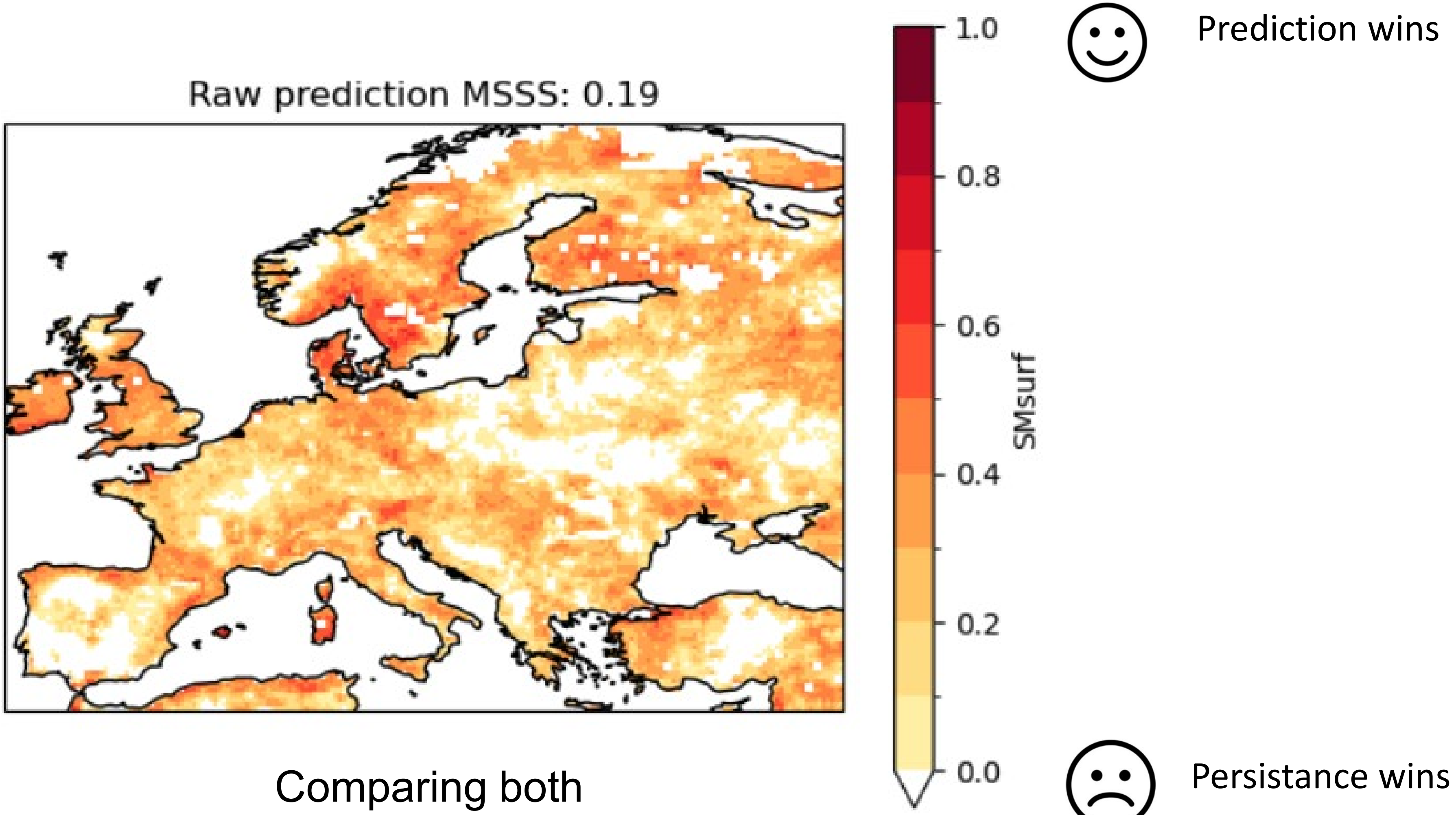
Persistence as predictions



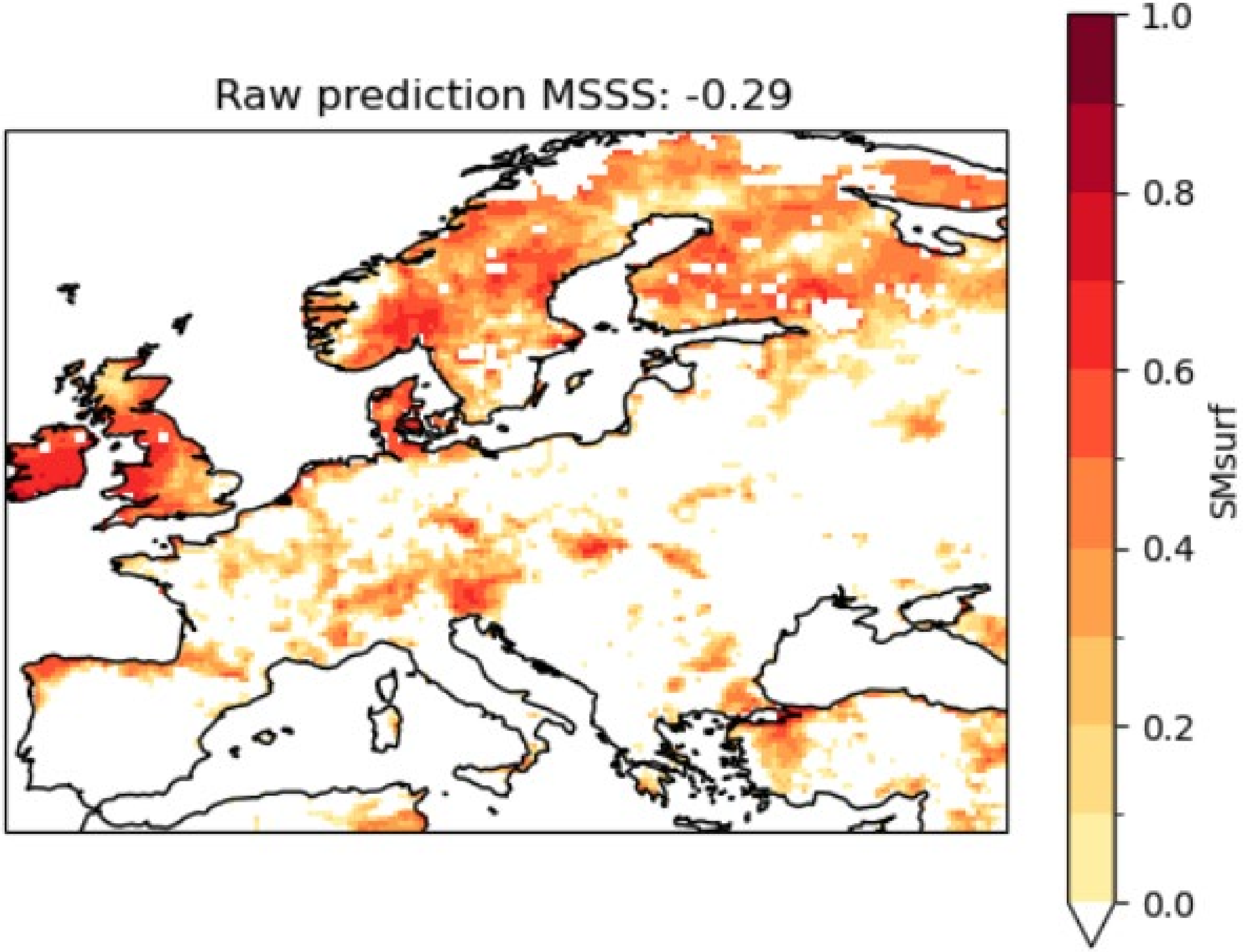
A. Local model with only **Spring initial conditions = local factors** as input



Comparing both

Lobelia.

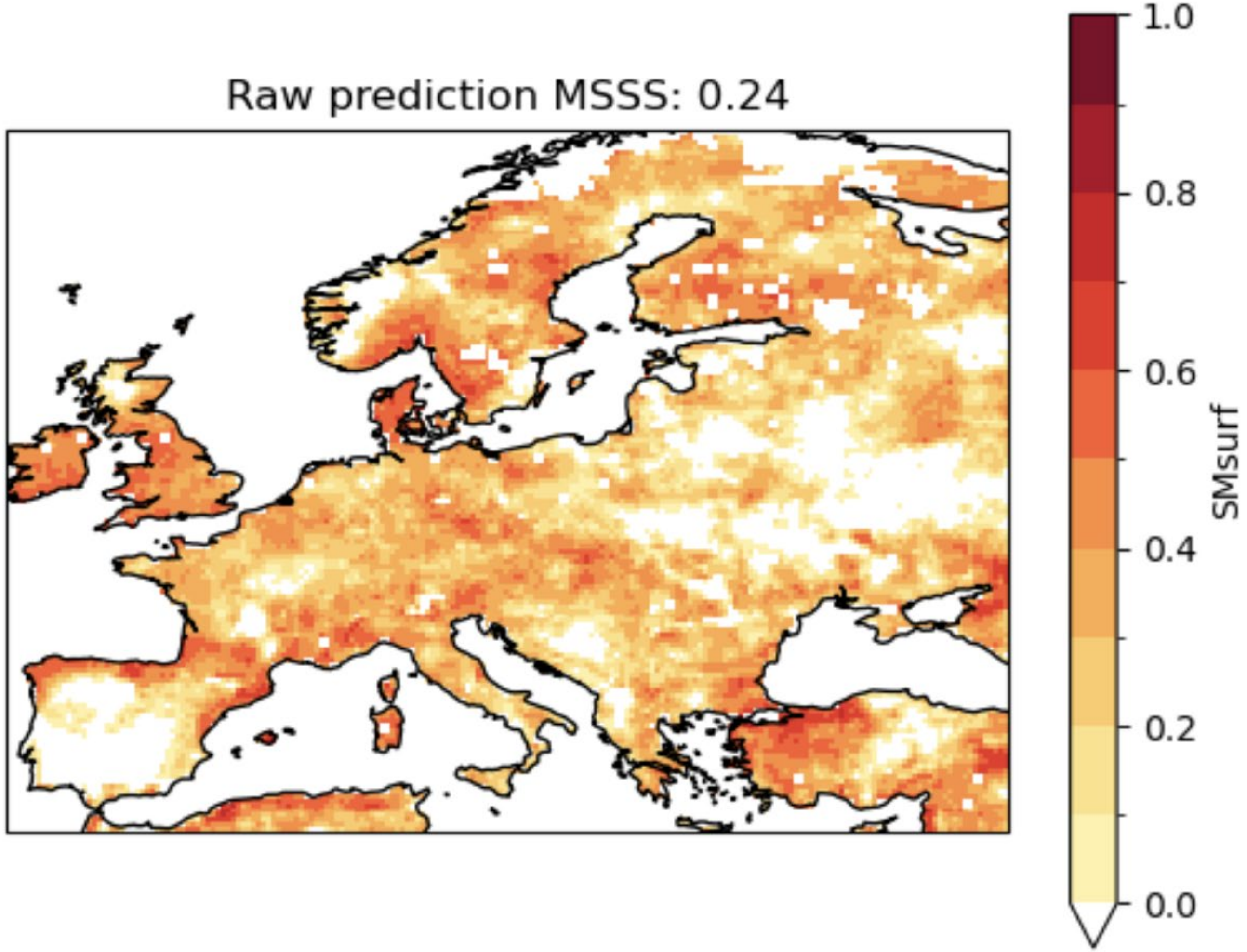
B. Local model with only **Summer SEAS5 SPEI3** (prediction)



Prediction wins

Persistance wins

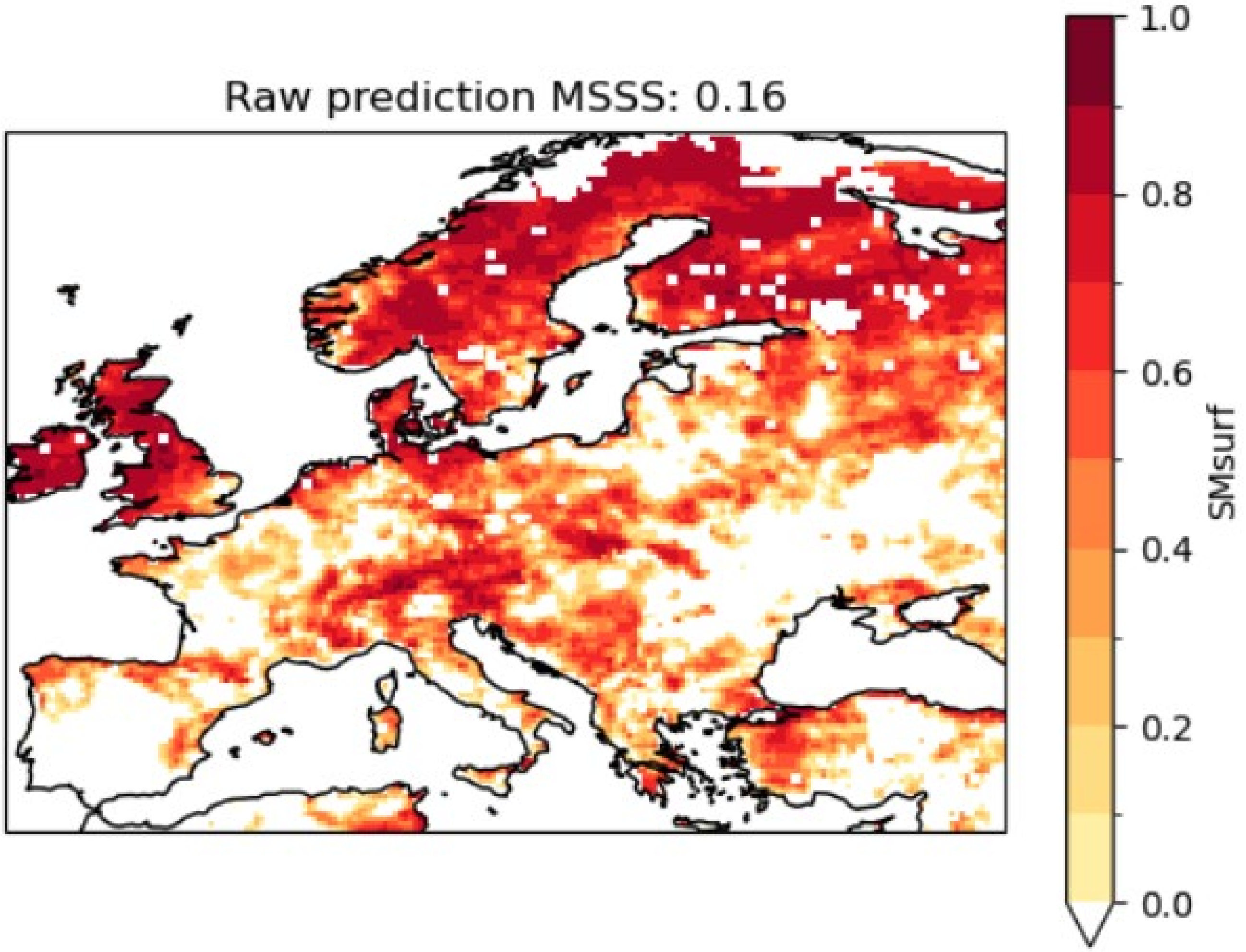
C. Local model with **Summer SEAS5 SPEI3 + initial conditions**



Prediction wins

Persistance wins

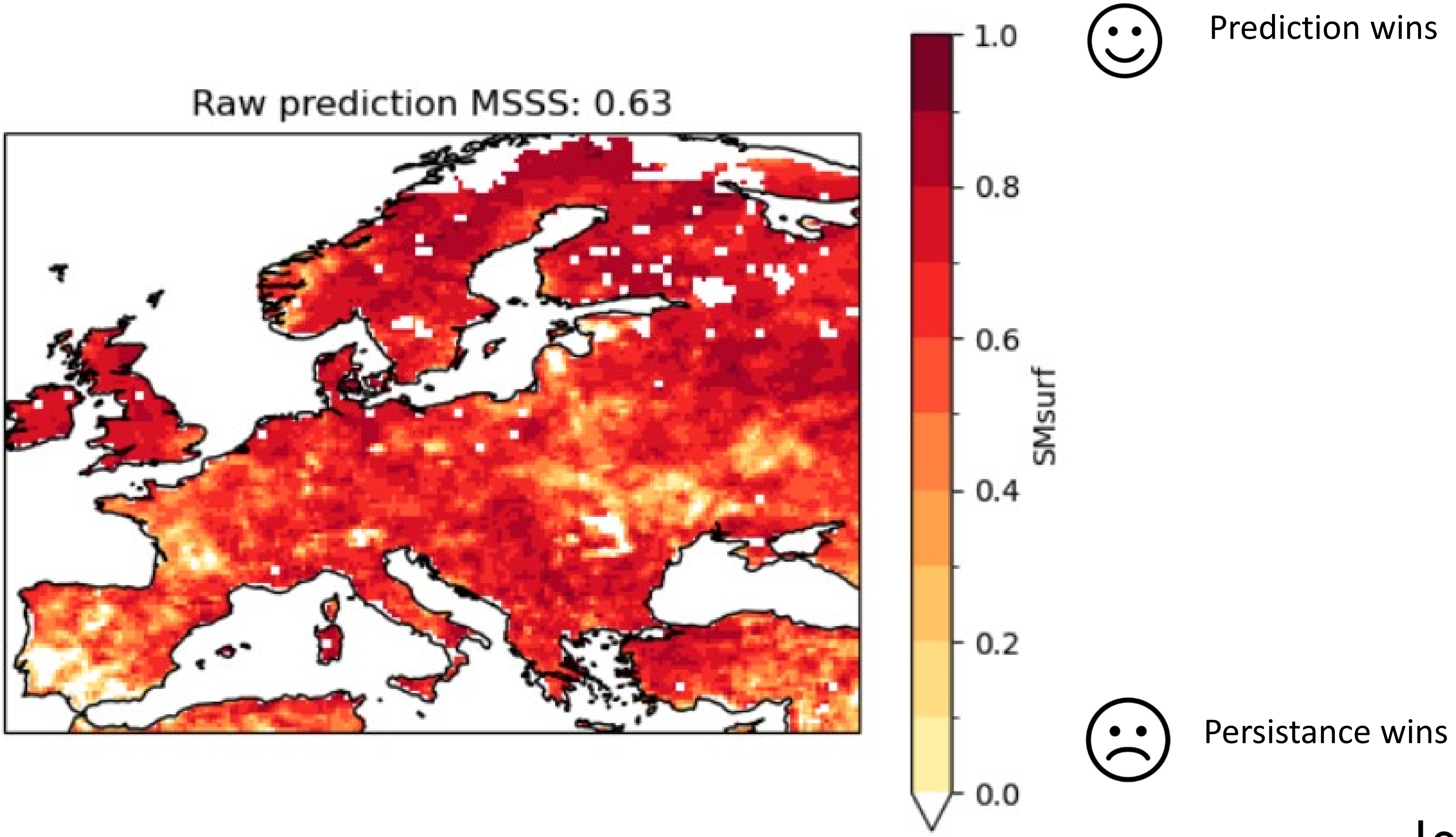
D. Local model with only the **actual Summer's SPEI3** (perfect)



Prediction wins

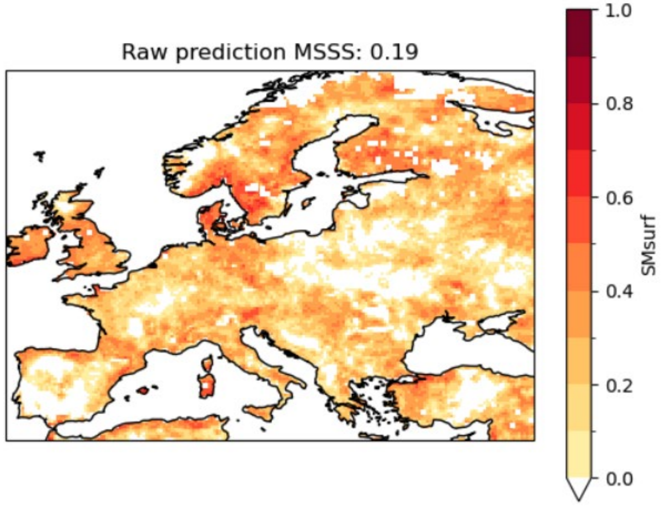
Persistance wins

E. Local model with **Actual Summer's SPEI3 + initial conditions**

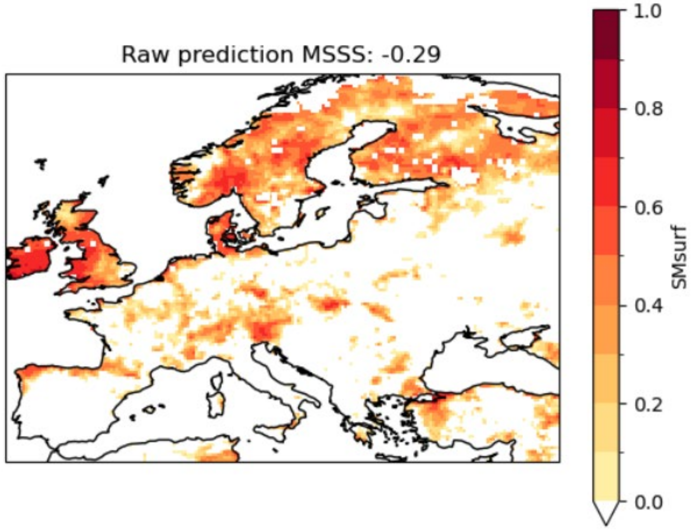


Case studies (different sources of information for the model)

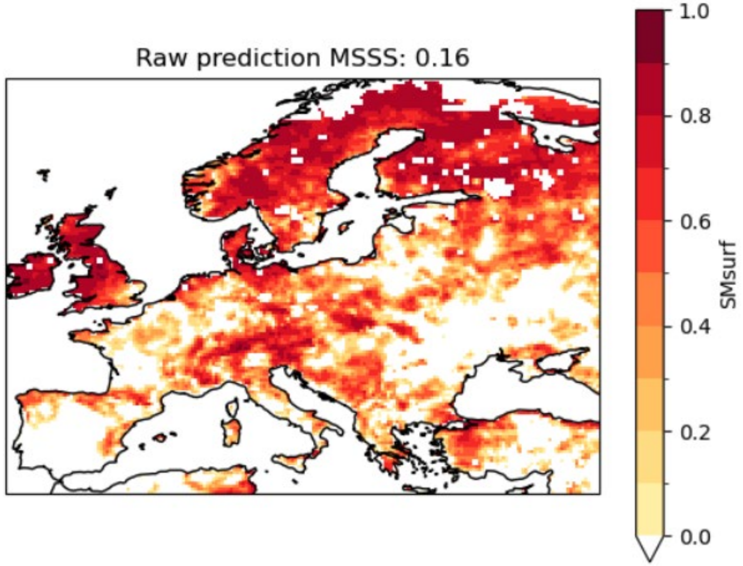
Spring Initial Conditions



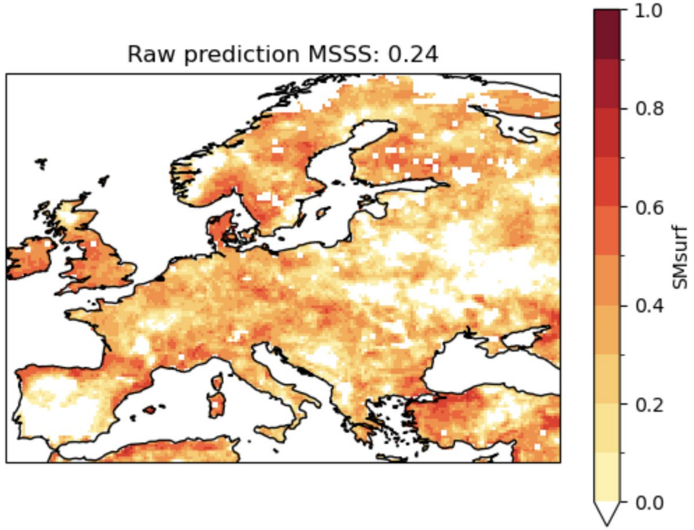
Summer SEAS5 SPEI3 (prediction)

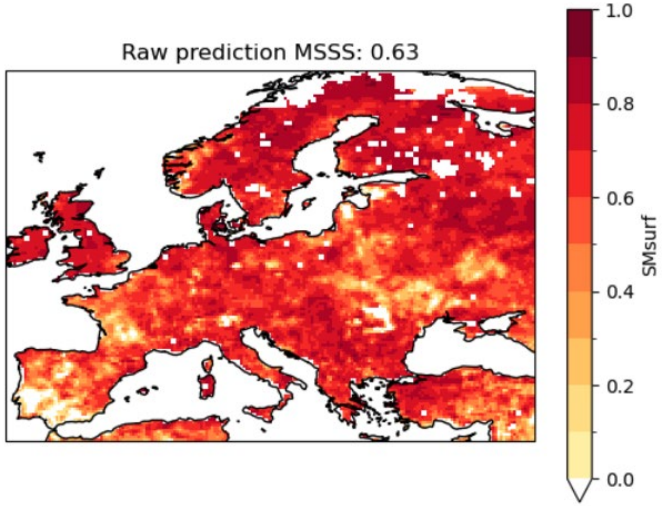


Actual Summer's SPEI3



Summer SEAS5 SPEI3 + initial conditions

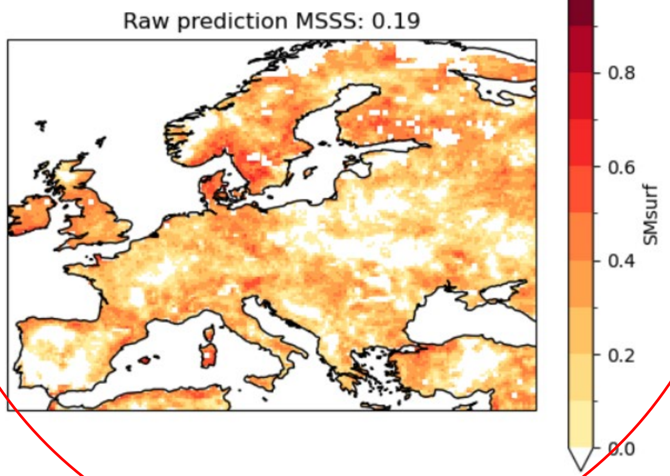




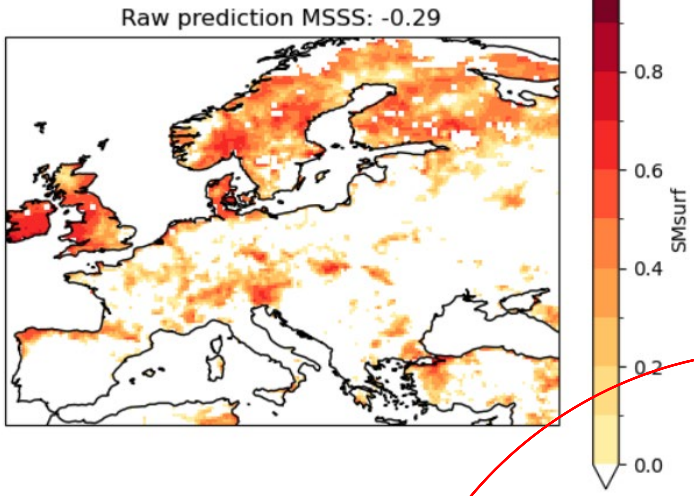
Actual Summer's SPEI3 + initial conditions

Case studies (different sources of information for the model)

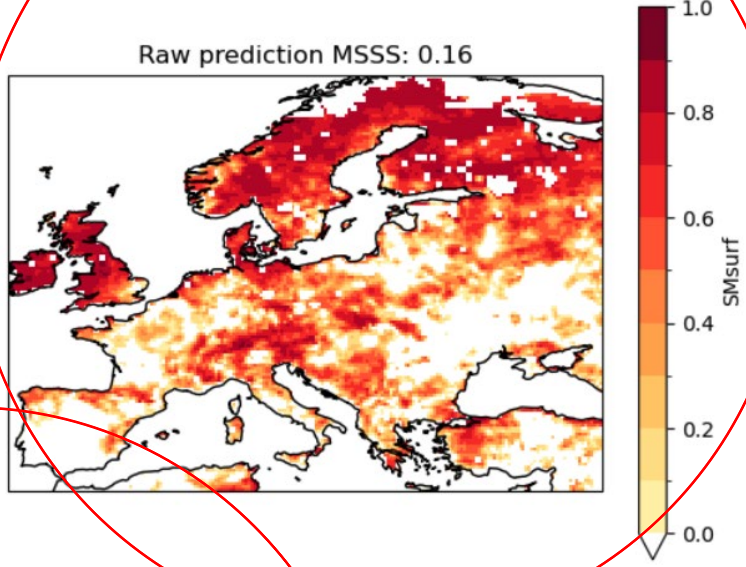
Spring Initial Conditions



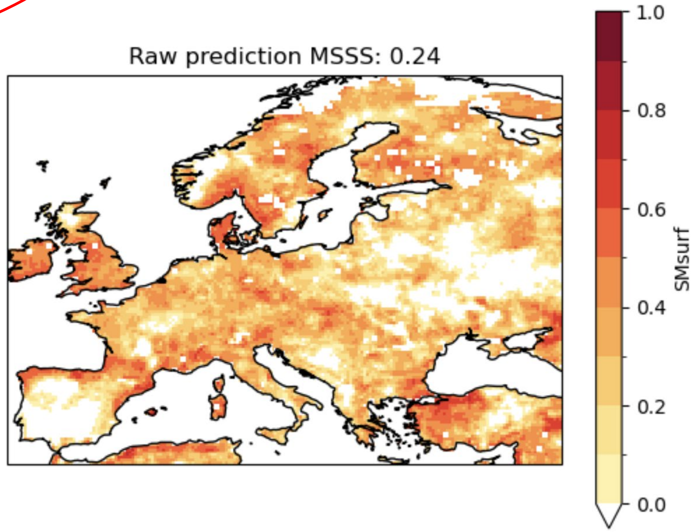
Summer SEAS5 SPEI3 (prediction)

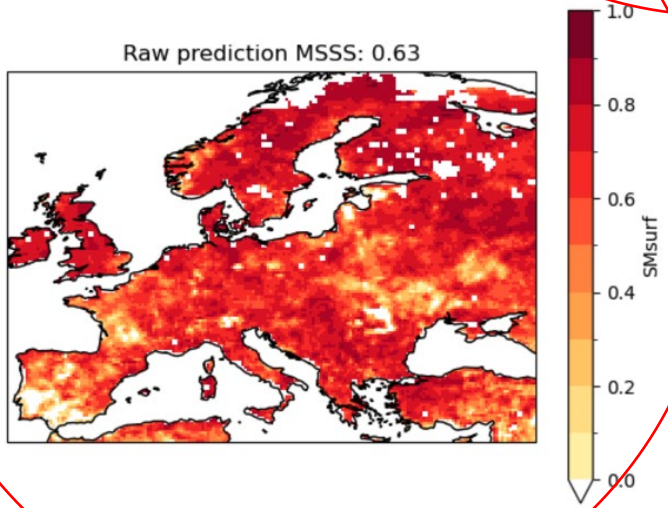


Actual Summer’s SPEI3



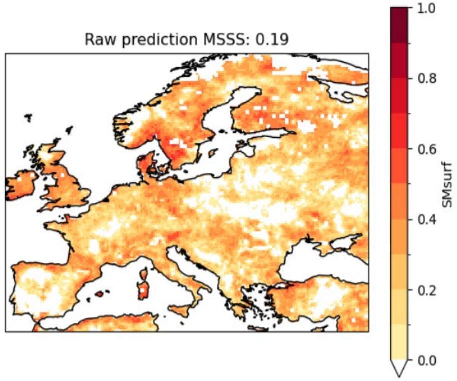
Summer SEAS5 SPEI3 + initial conditions



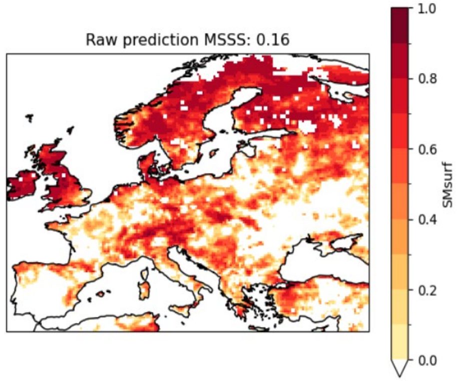


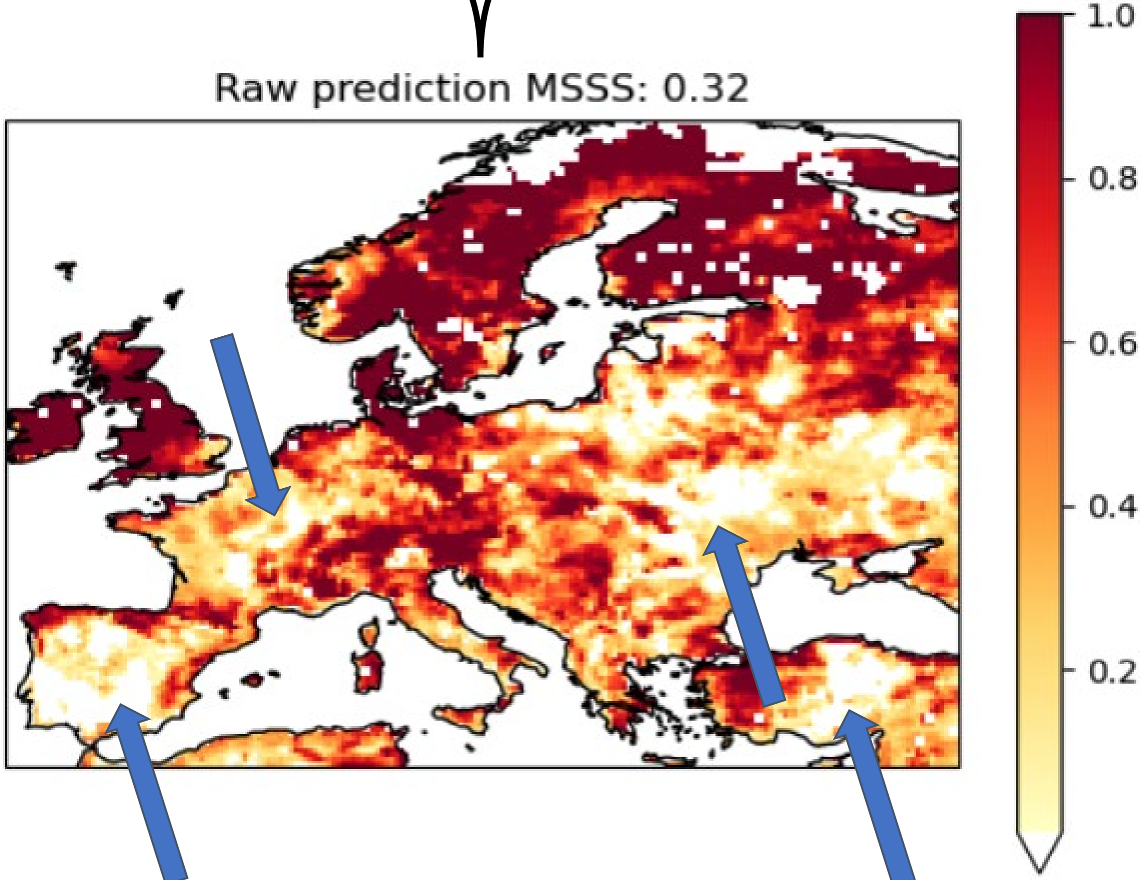
Actual Summer’s SPEI3 + initial conditions

Spring Local Factors

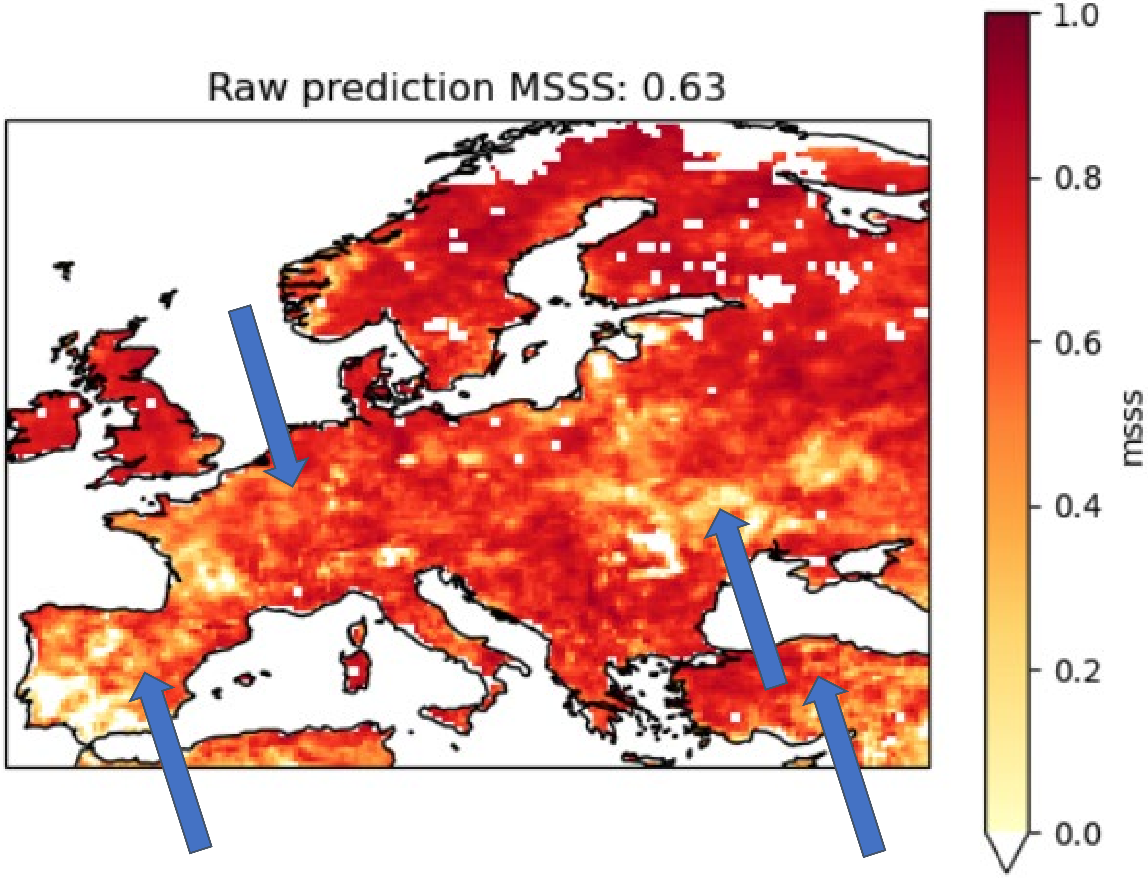


Summer’s ERA5 SPEI3 (perfect)

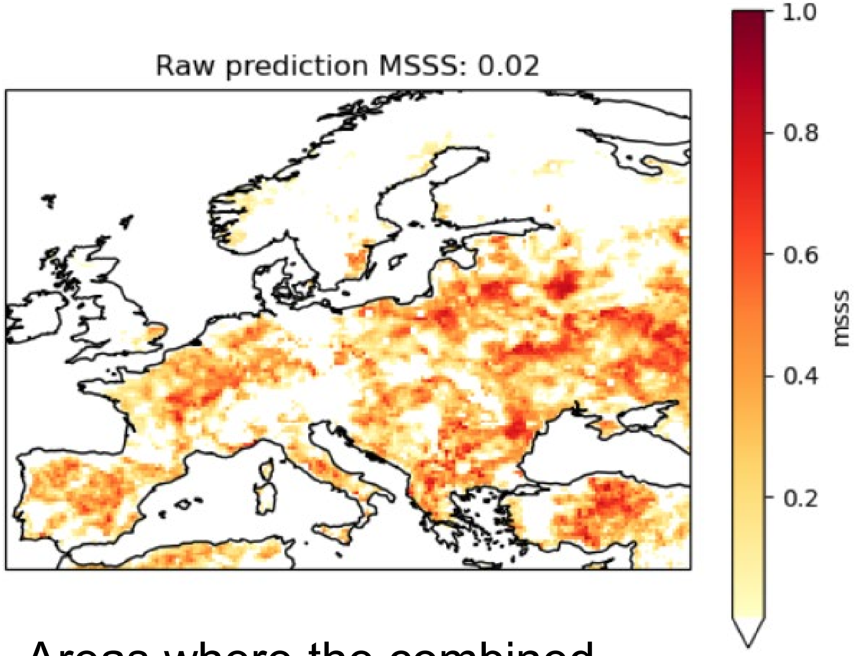




Local model results using Summer’s ERA5 SPEI3 + local initial factors as input features:



Comparison with land-atmosphere feedback theory



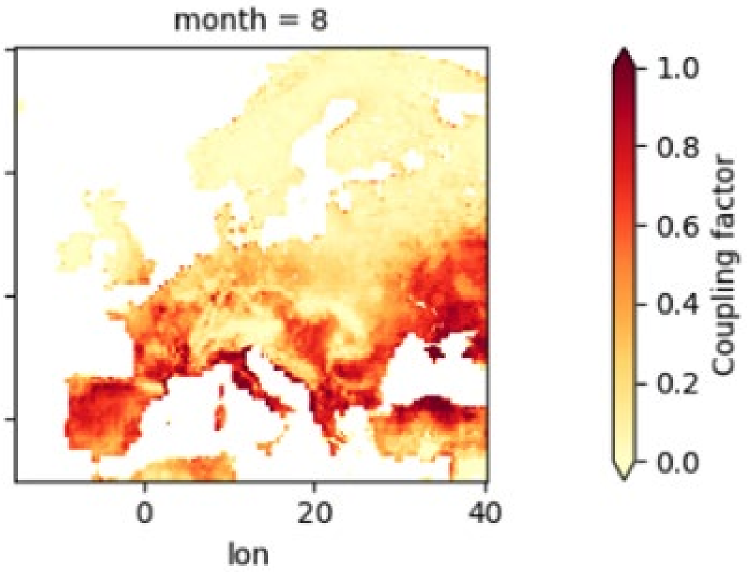
Areas where the combined ML model outperforms the linear combination of independent input models

Let's see if has some relationship with land-atmosphere feedbacks (soil moisture-temperature coupling factor)

$$\pi = \left(H' - Hp'\right)T'|$$

Miralles et al. 2012

coupling factor



Conclusions

- Seasonal forecasting is complex
- Observations of initial conditions are crucial for the improvement of seasonal forecasts in Europe
- Local conditions represented by satellite observations provide with valuable predictability information not captured in climate models and not captured by persistence
- Machine learning is an efficient method for integrating initial conditions in the prediction and mapping non-linear interactions with the atmospheric forcing

Thank you!

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

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www.aifordrought.com