NEURAL INFORMATION PROCESSING SYSTEMS

LAMARR INSTITUTE FOR MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

UNIVERSITÄT BONN

CRC 1502 DETECT

Identifying Spatio-Temporal Drivers of Extreme Events

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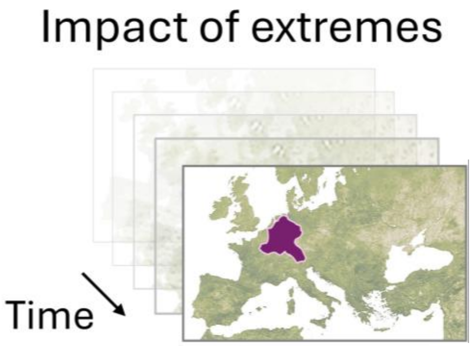
https://hakamshams.github.io/IDE

Overview:



Task: Identifying spatio-temporal **drivers** of measurable **impacts of extreme events.**

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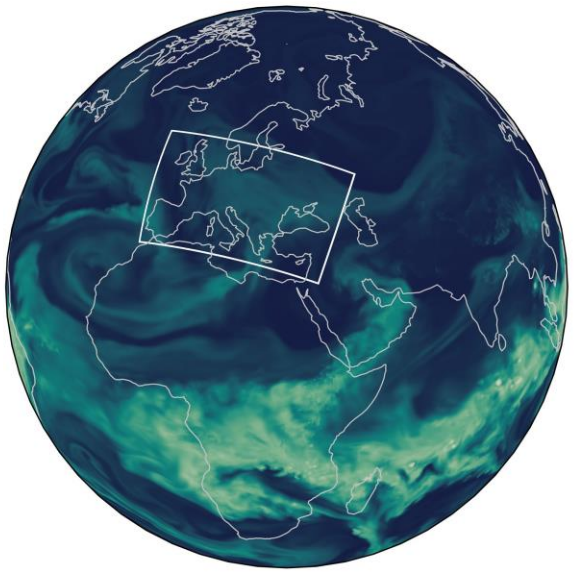
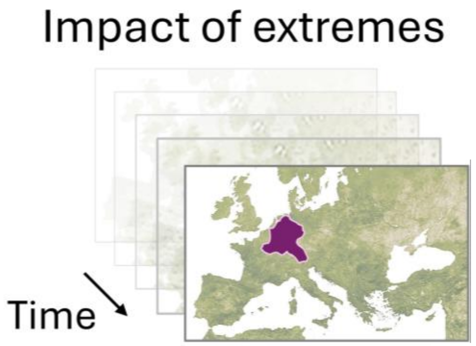


Atmospheric and land state variables

Which variables are associated with the impacts?



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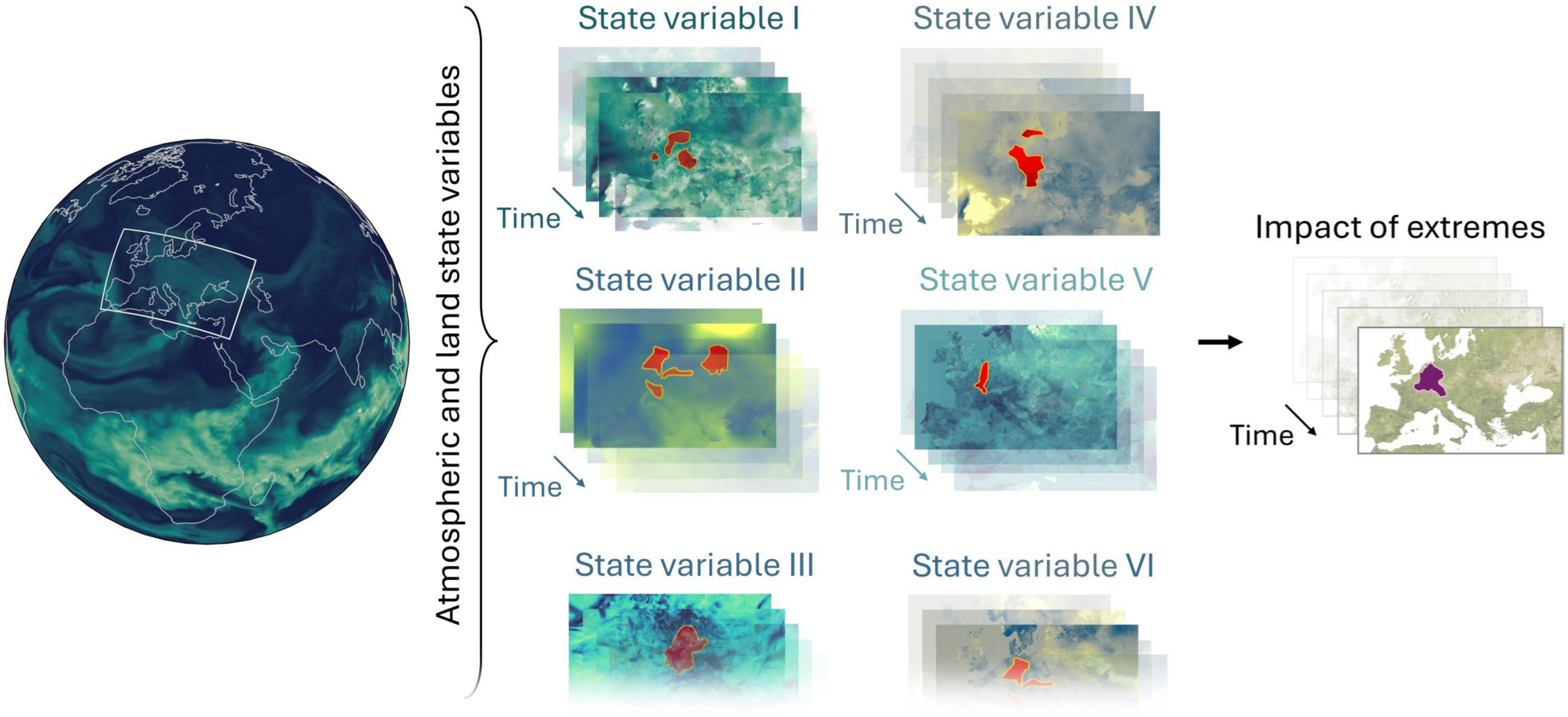

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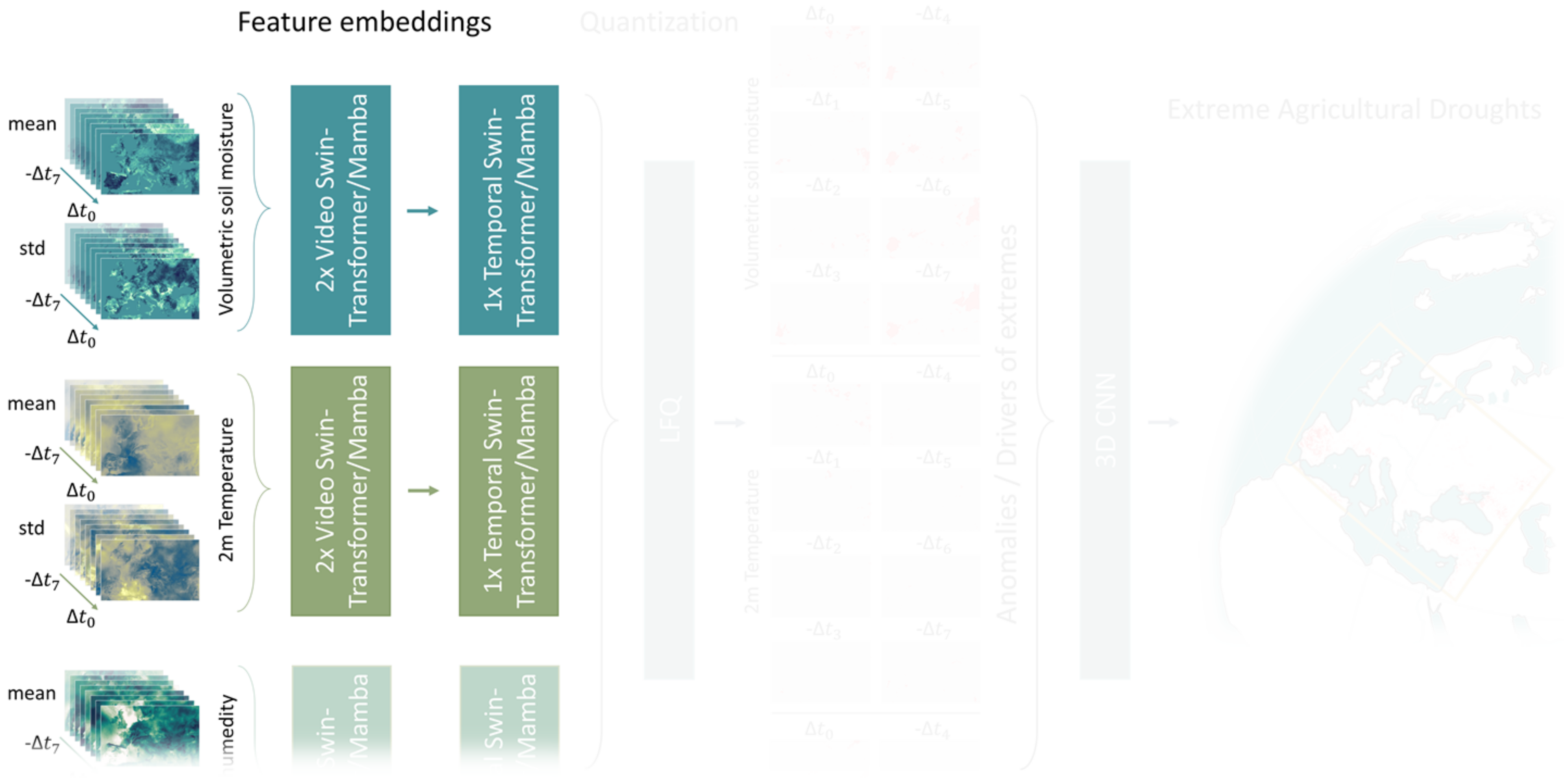

Feature embedding ⟶ Quantization ⟶ Predicting extreme events impacts from drivers

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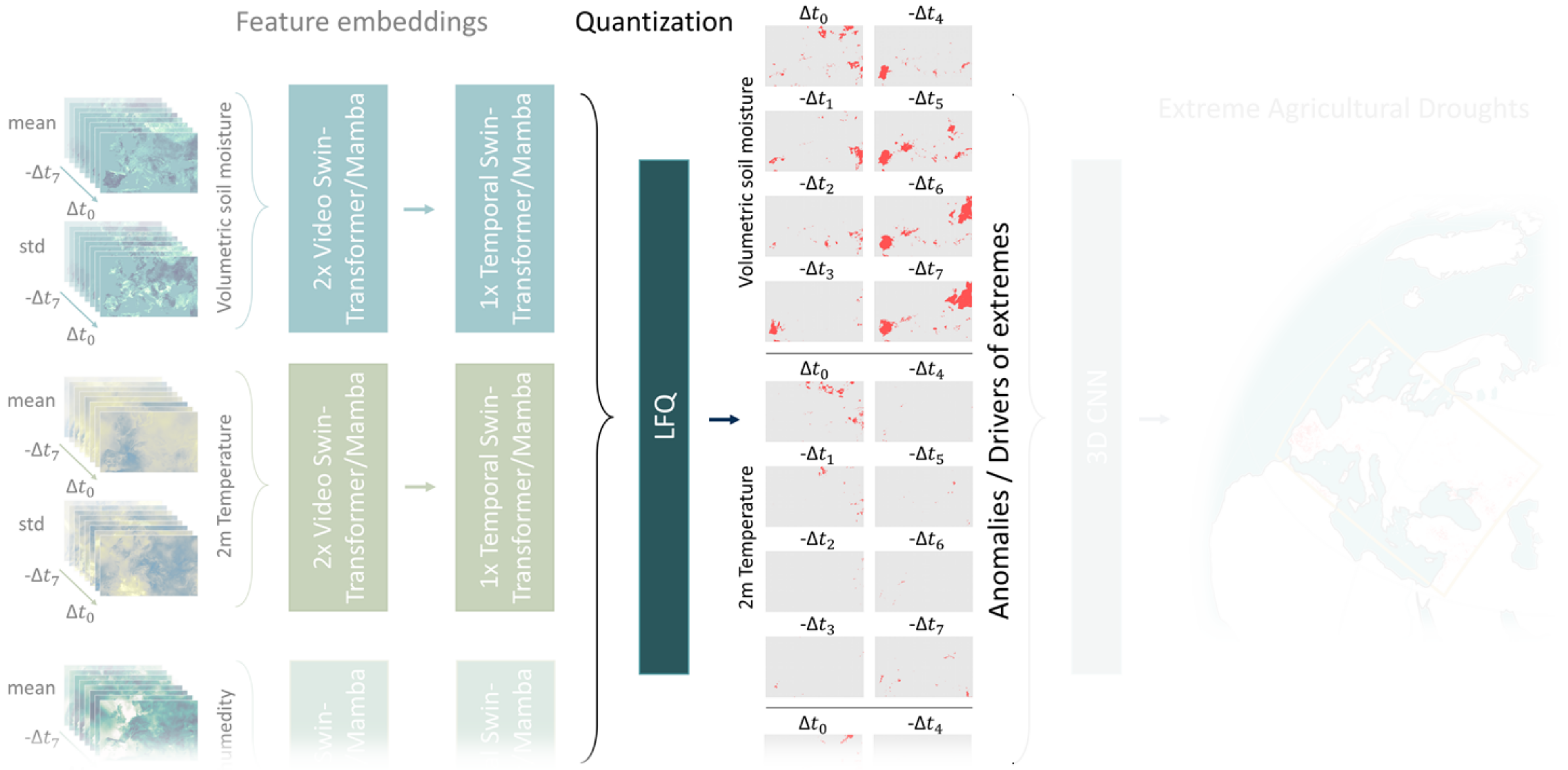

Feature embedding → Quantization → Predicting extreme events impacts from drivers

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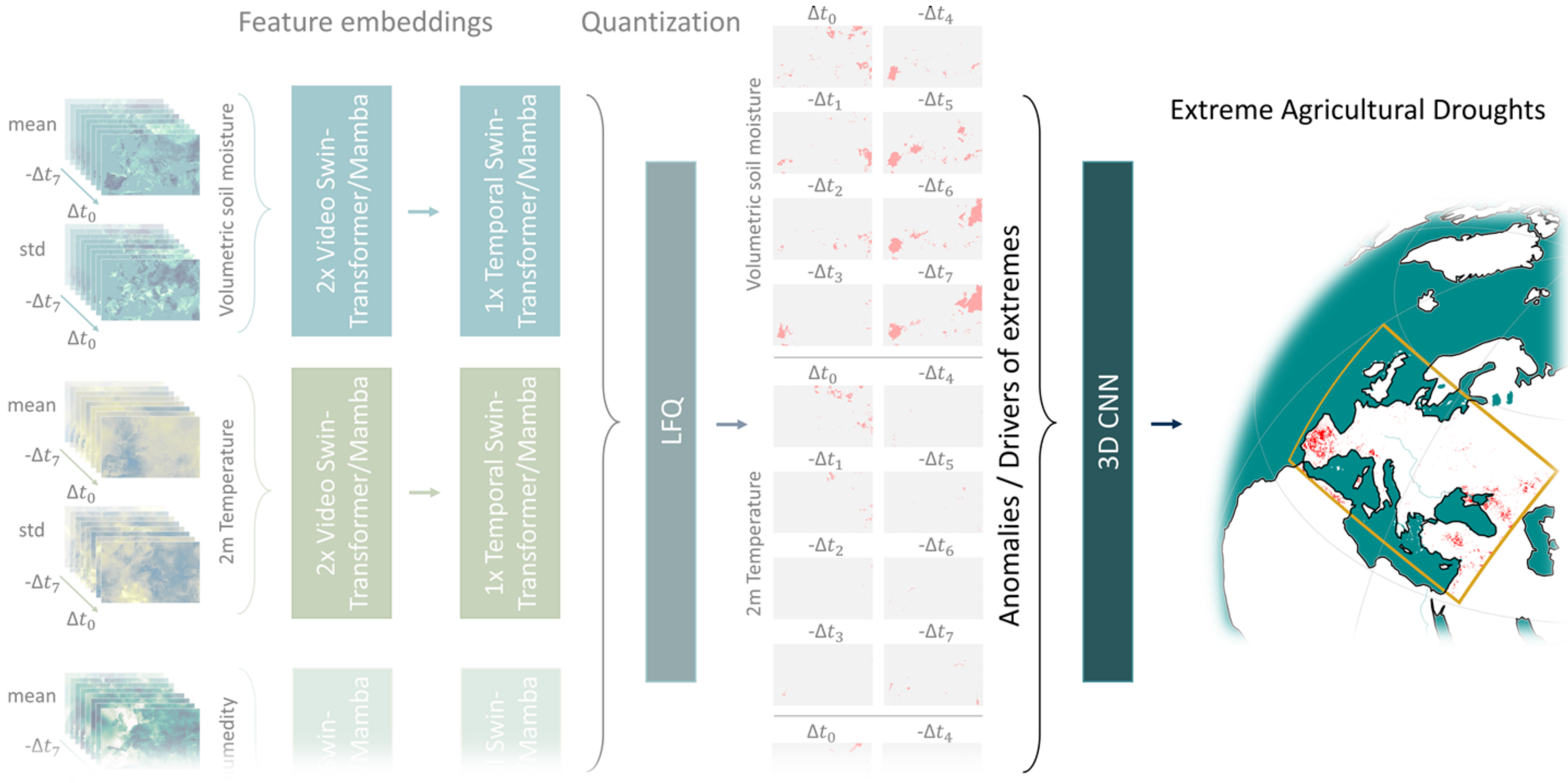

Feature embedding → Quantization → Predicting extreme events impacts from drivers

Method:

Objective Function:

$$\min_{\theta, \phi, \psi} \underbrace{\mathcal{L}_{(extreme)}\left(\mathbf{E}_v, \hat{\mathbf{E}}, \mathbf{S}\right)}_{\text{predicts extremes from drivers}} + \underbrace{\mathcal{L}_{(quantize)}(\mathbf{Z}_{\mathbf{l}})}_{\text{encourages confident quantization}} + \underbrace{\mathcal{L}_{(driver)}\left(\mathbf{Z}_q\ \hat{\mathbf{E}}_t, \mathbf{S}, \mathbf{Z}_{q=\mathbf{0}}\right)}_{\text{assigns drivers to the same code in the codebook}}$$

Method:

$$\mathcal{L}_{(extreme)}\left(\mathbf{E}_v, \hat{\mathbf{E}}, \mathbf{S}\right) = -\sum_{v}^{V+1} \left(\hat{\mathbf{E}} \log(\mathbf{E}_v) + \left(1 - \hat{\mathbf{E}}\right) \log(1 - \mathbf{E}_v)\right) \mathbf{S}$$

mask of valid pixels

ground truth

predicted extremes from variable v,
where $\mathbf{E}_{v=0}$ is the multivariate prediction

$\hat{\mathbf{E}}$

$\mathbf{E}_v$

$\mathbf{S}$

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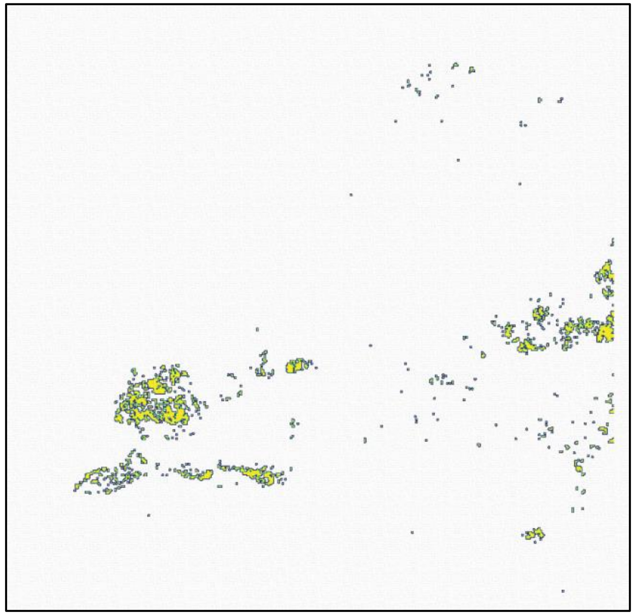

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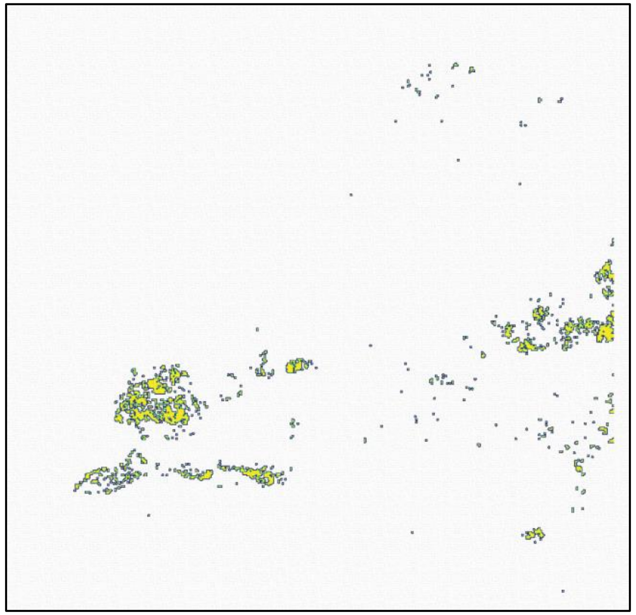

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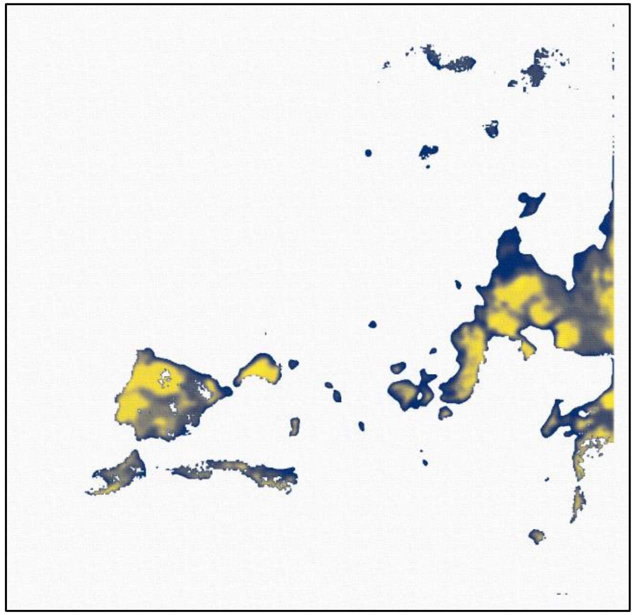

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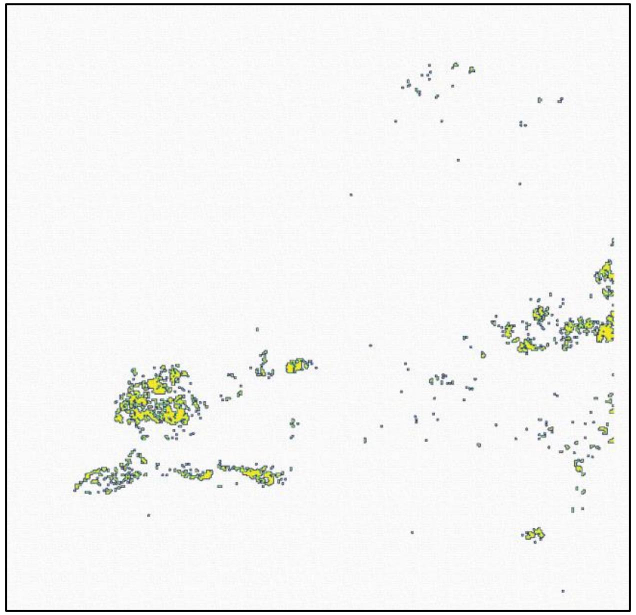

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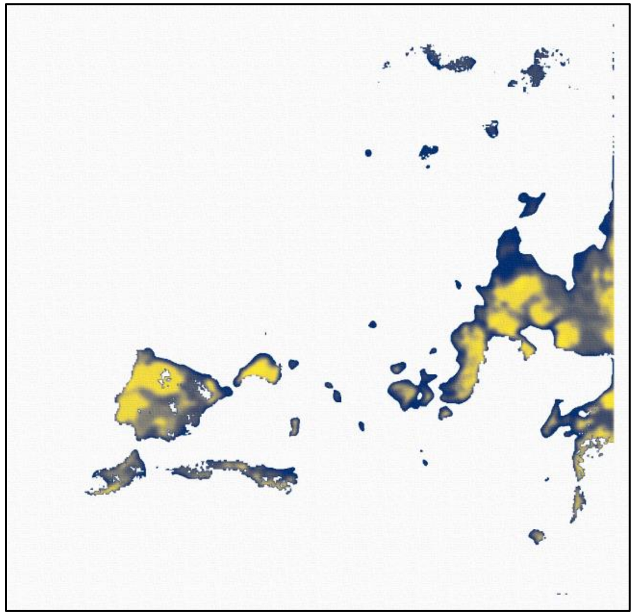

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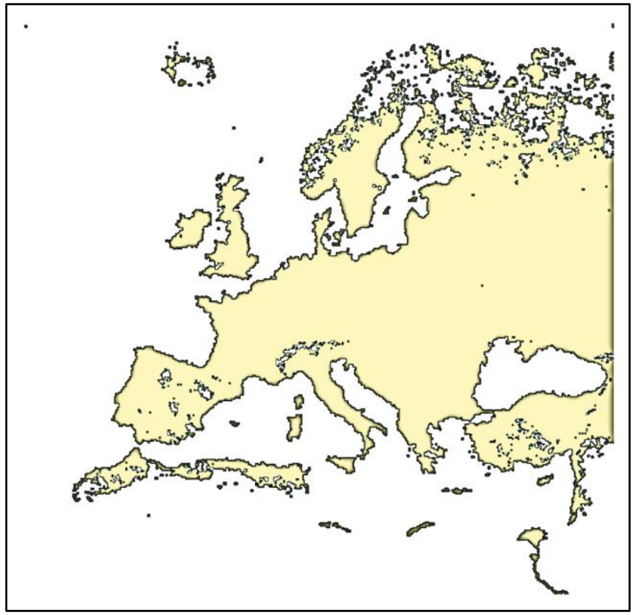

Method:

$$\mathcal{L}_{(quantize)}(\mathbf{Z}_l) = \lambda_c \, \|\mathbf{Z}_l - \mathrm{sg}(\mathrm{sign}(\mathbf{Z}_l))\|_2^2 + \lambda_e \, \mathbb{E}\big[H\big(\mathrm{sign}(\mathbf{Z}_l)\big)\big] - \lambda_d \, H[\mathbb{E}(\mathrm{sign}(\mathbf{Z}_l))]$$

weight stop gradient entropy

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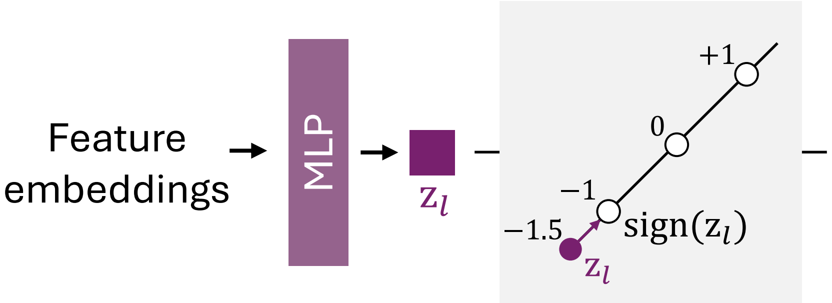
weight stop gradient entropy

Commitment loss



Entropy per Sample

Codebook entropy

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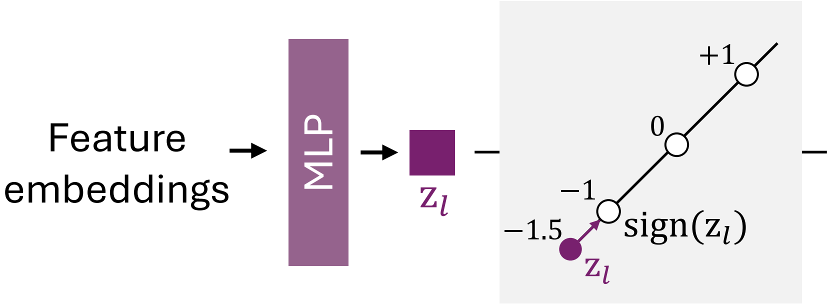

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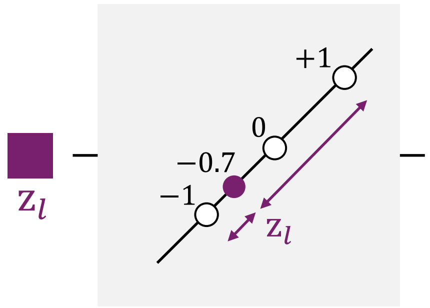

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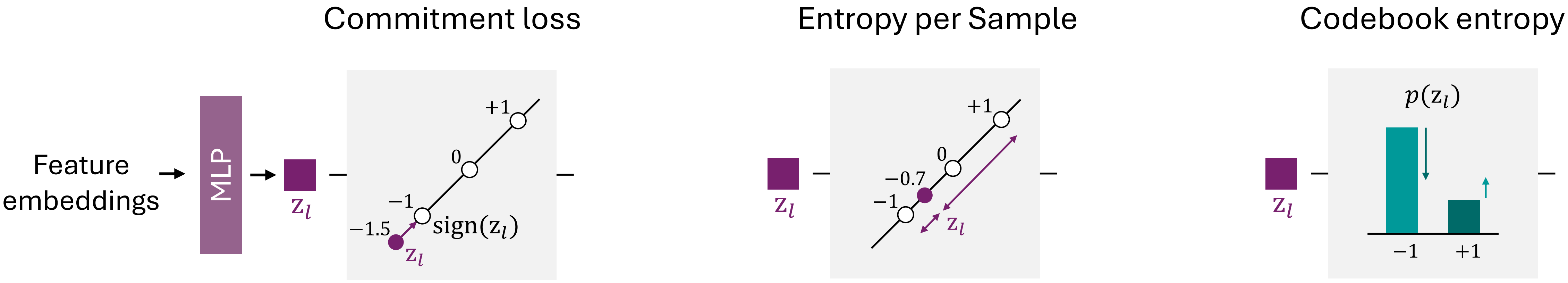

Method:

$$\mathcal{L}_{(driver)}\left(\mathbf{Z}_q\ \hat{\mathbf{E}}_t, \mathbf{S}, \mathbf{Z}_{q=\mathbf{0}}\right) \ = \lambda_a \left|\mathbf{Z}_q - \mathrm{sg}(\mathbf{Z}_{q=0}))\right| \left(1 - \hat{\mathbf{E}}_t\right) \mathbf{S}$$

quantization code of
the normal data

union of extremes
at all time steps

$\hat{\mathbf{E}}_t$

$(1 - \hat{\mathbf{E}}_t)$

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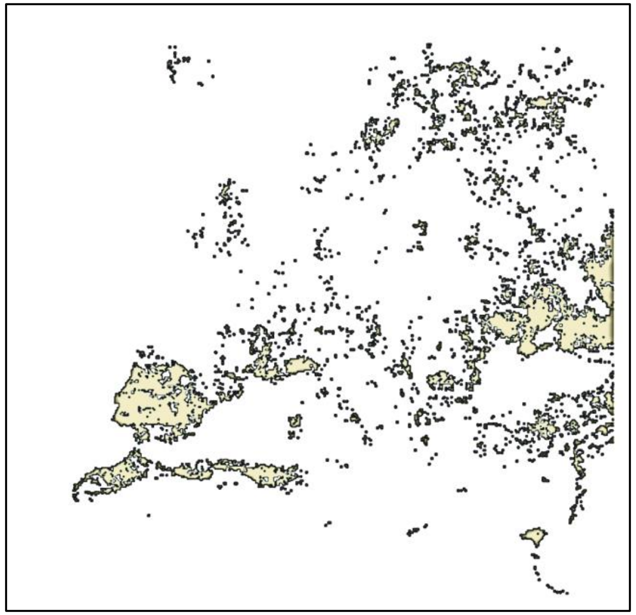

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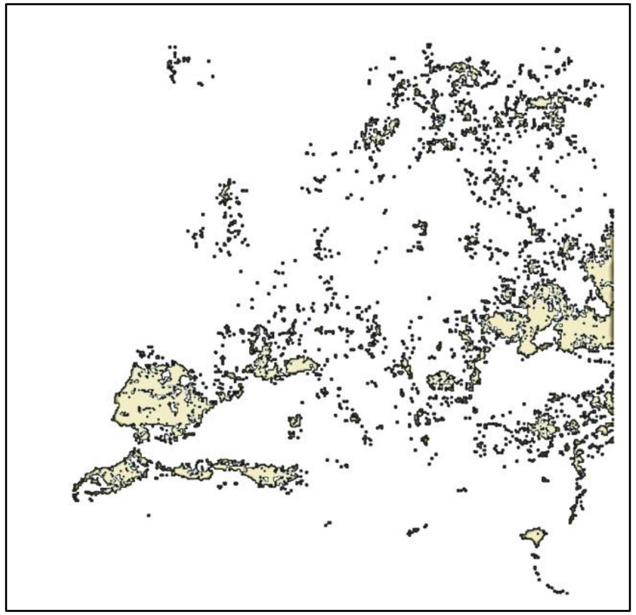

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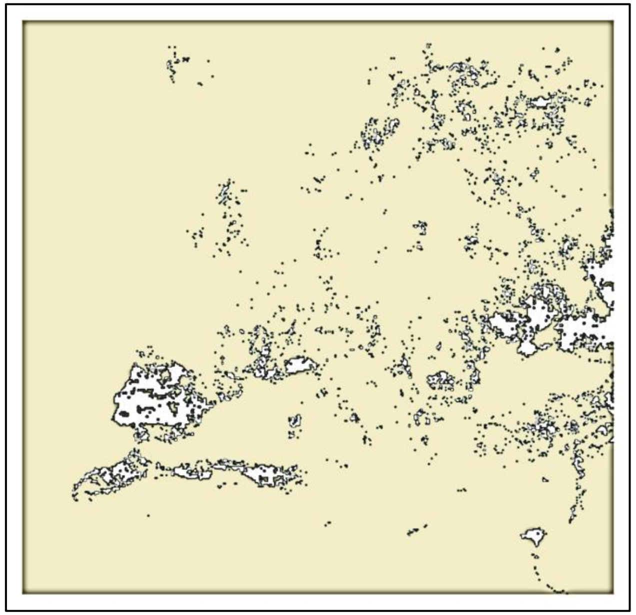

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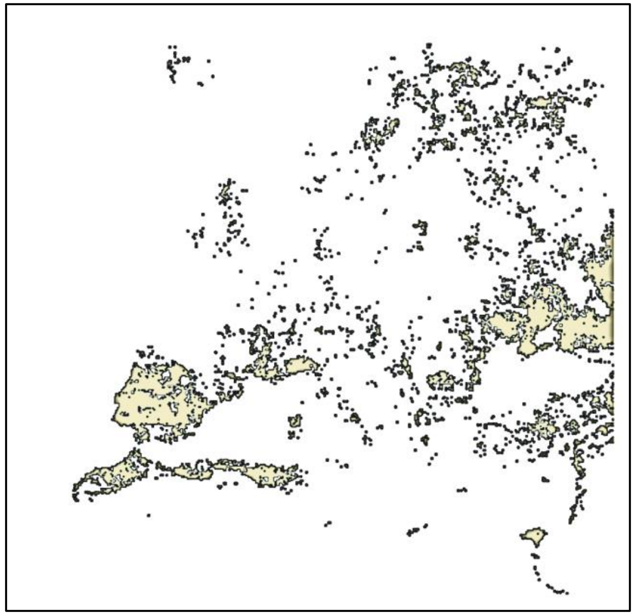

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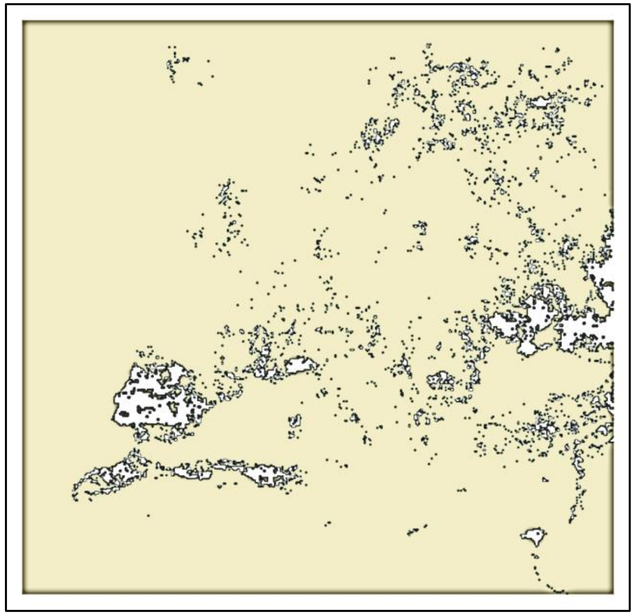

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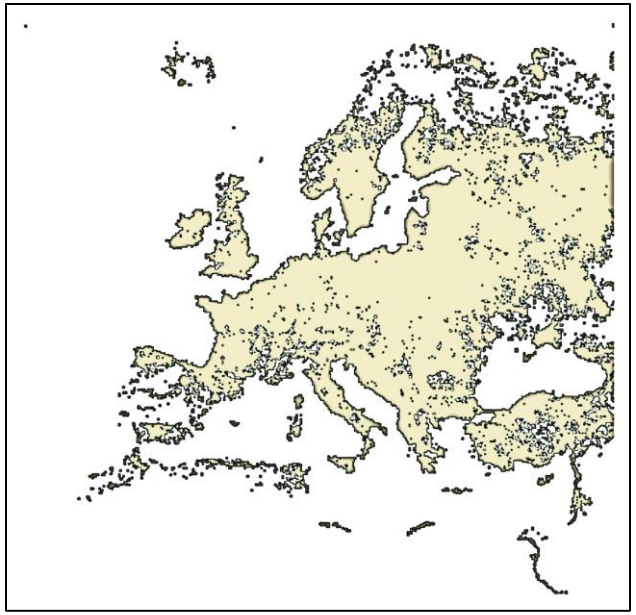
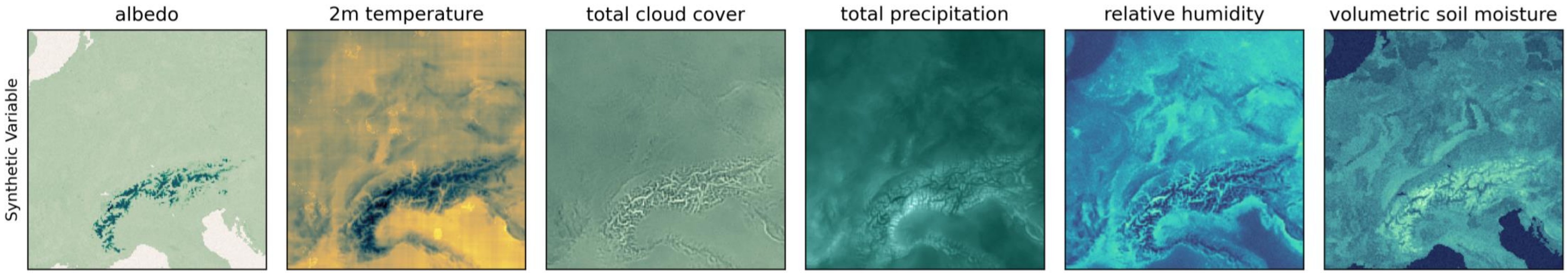


Synthetic data:

- How to reliably measure the accuracy of identifying drivers?

  → We introduce a new synthetic dataset

- The synthetic data are based on real-world climate signals (i.e., mean value at specific time and location).



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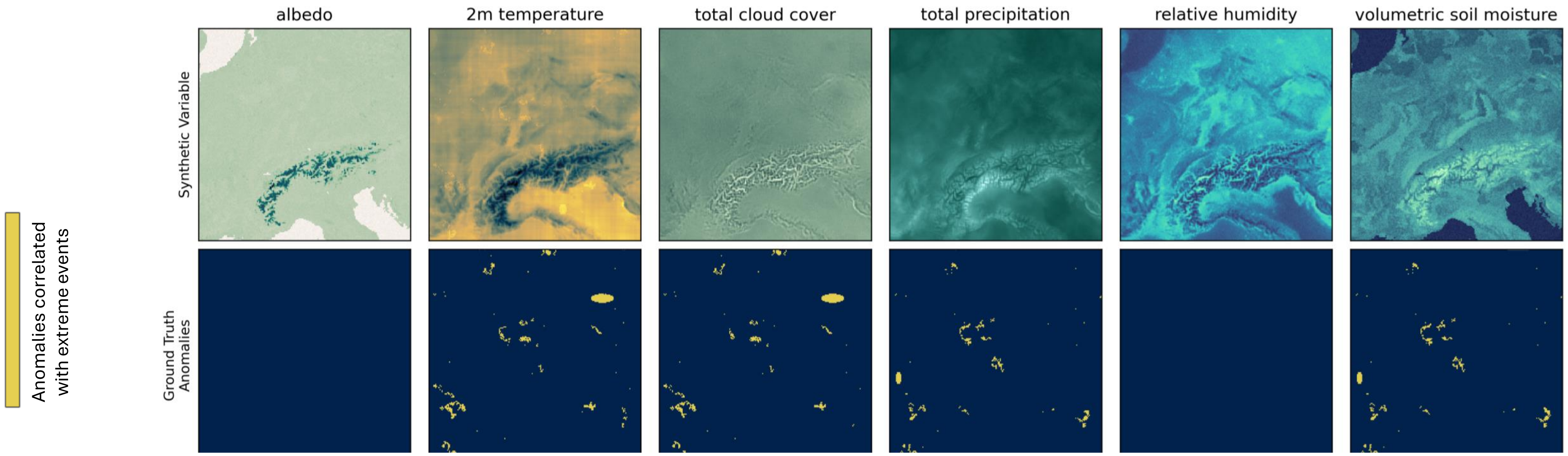

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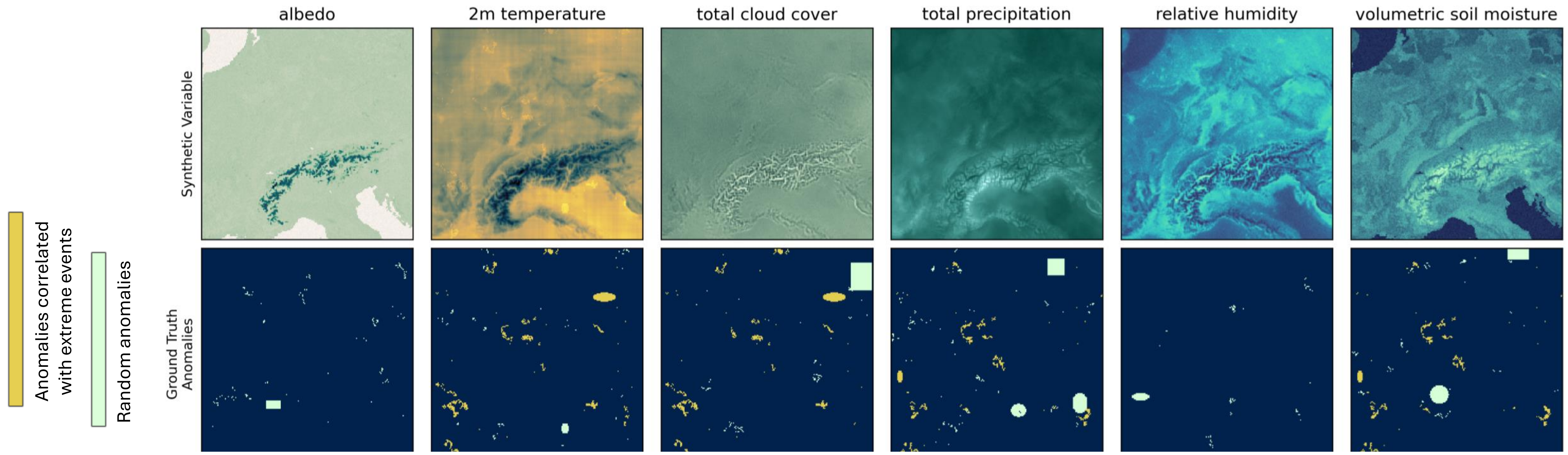
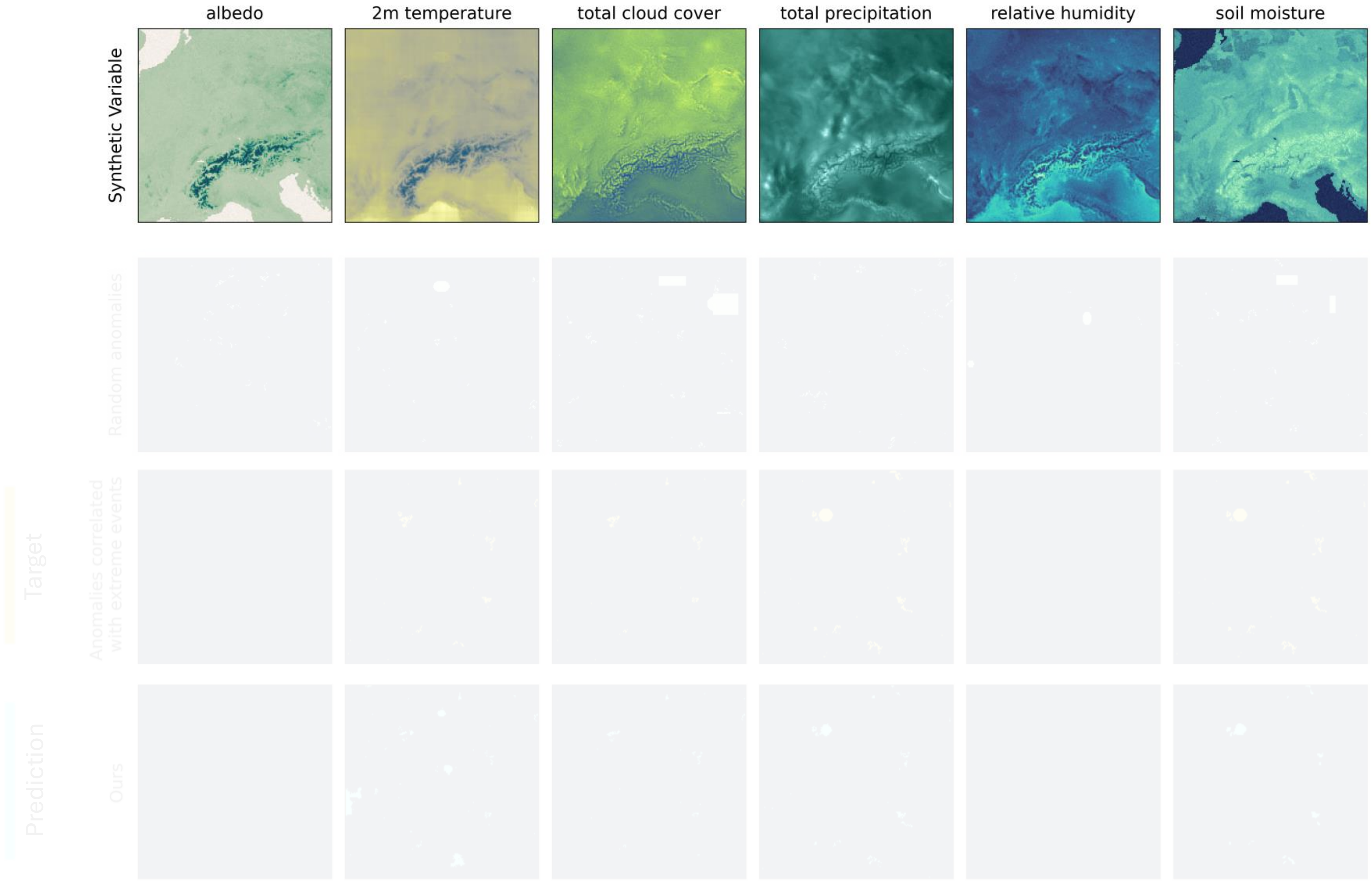


Qualitative results on the synthetic CERRA reanalysis:



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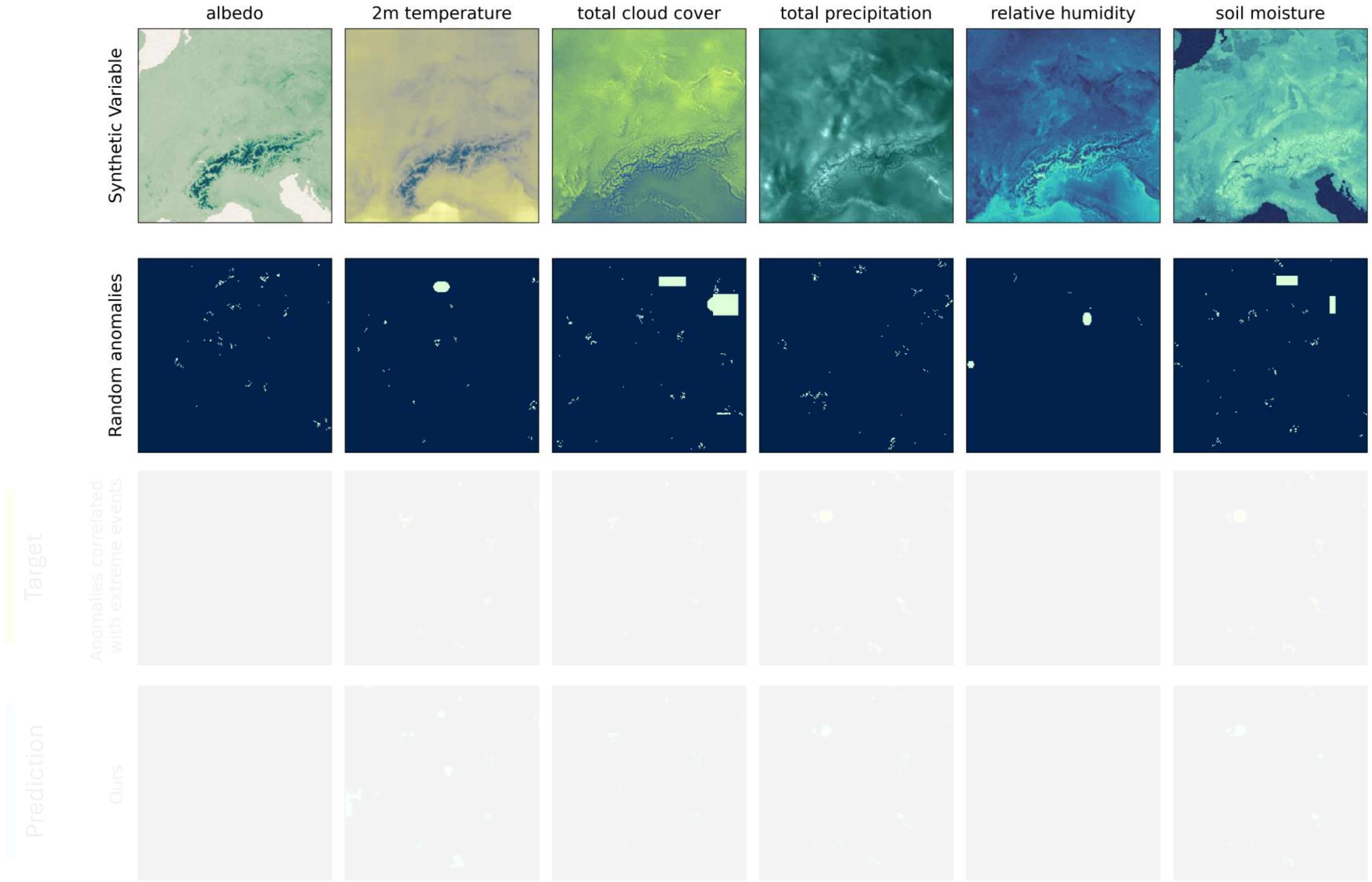

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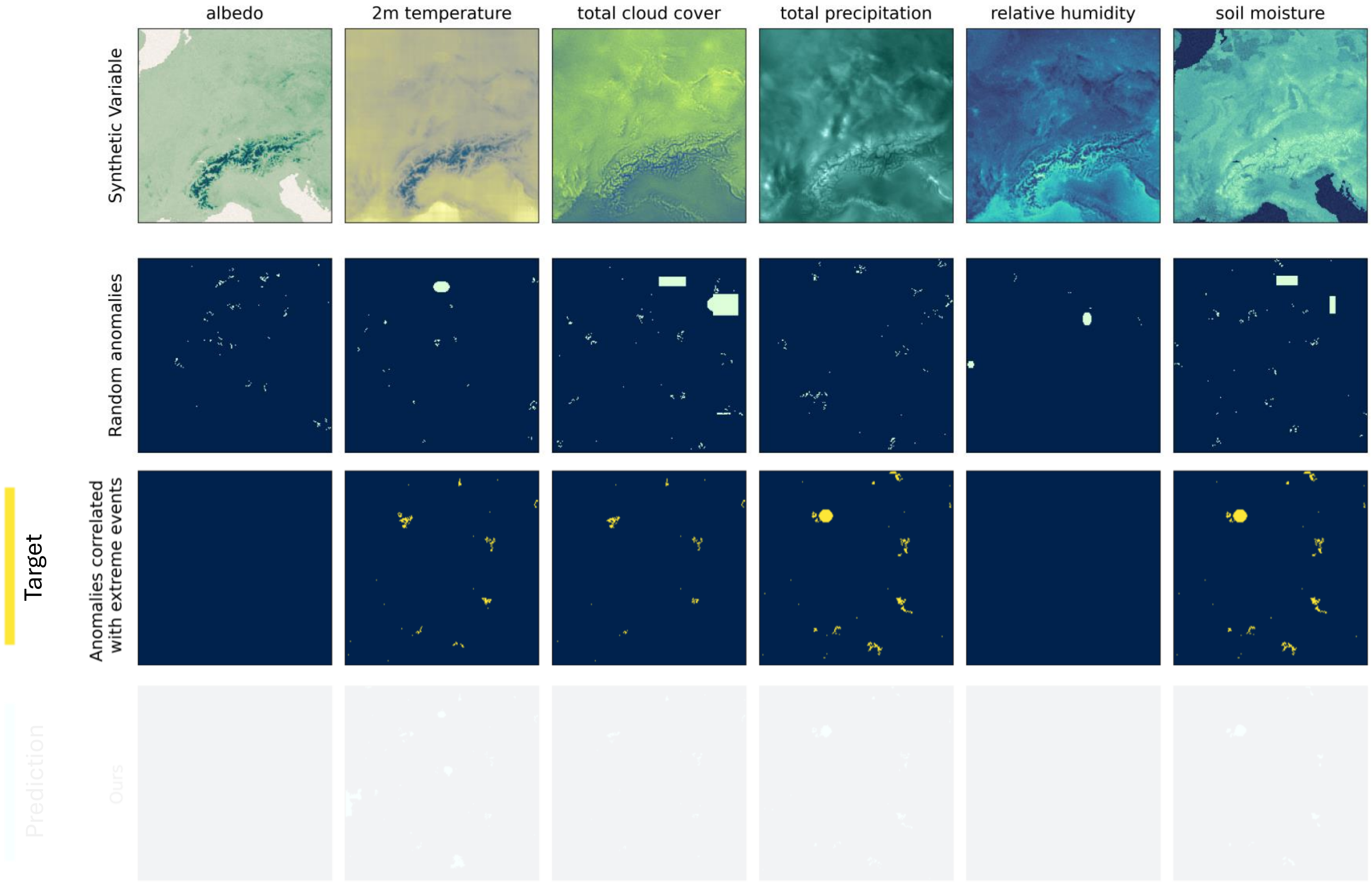

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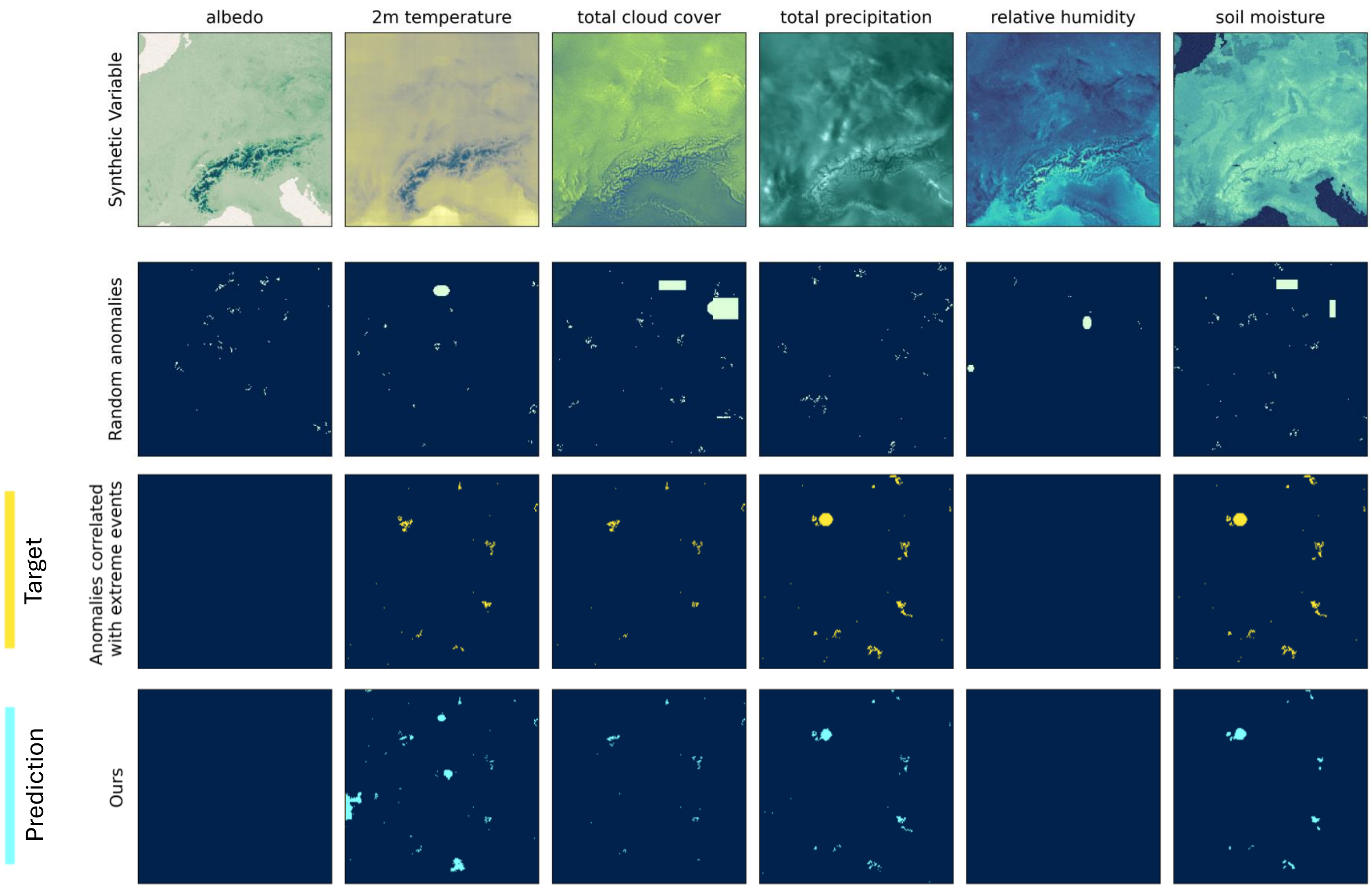
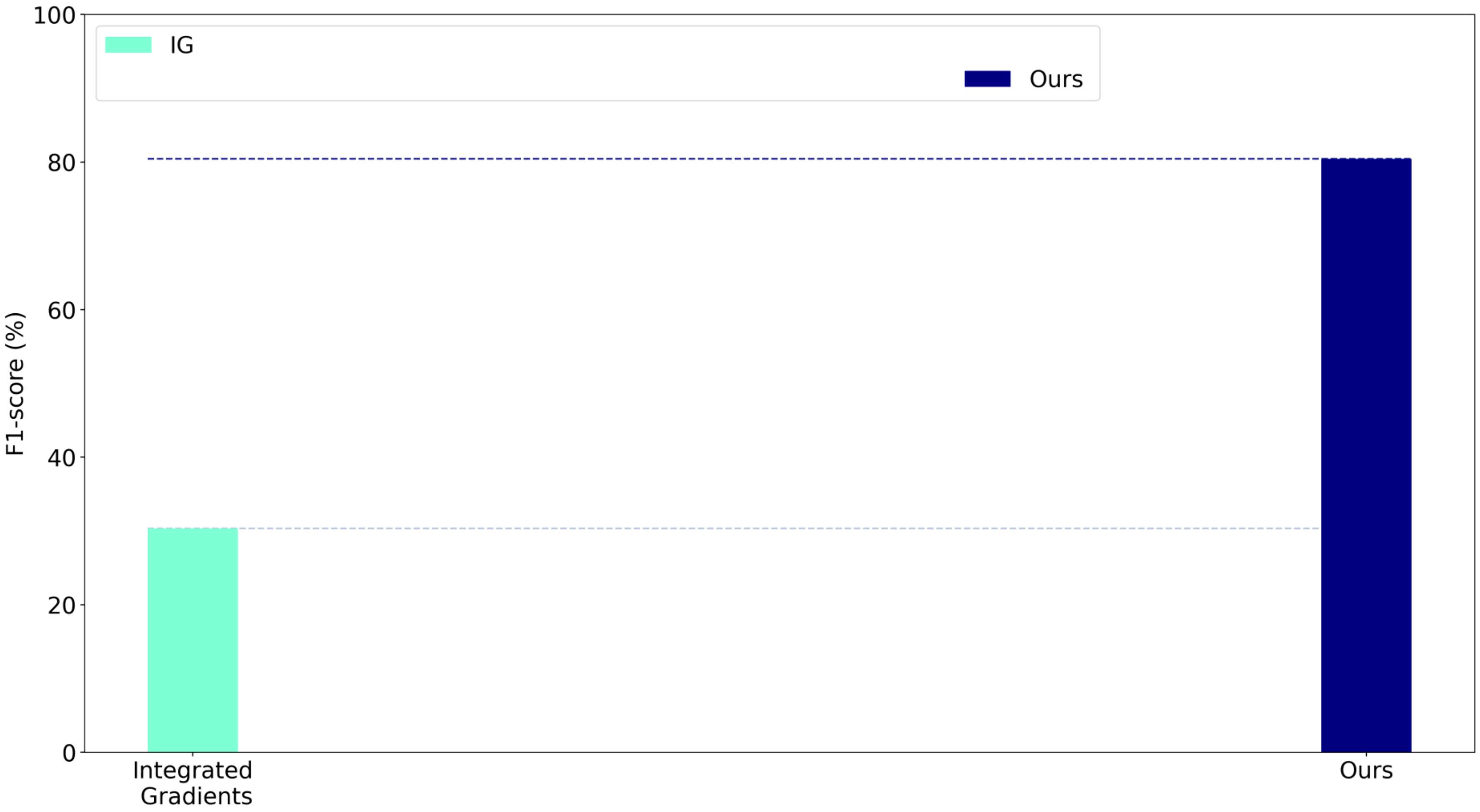


Comparison to baselines:

Baselines: interpretable forecasting, one-class unsupervised, reconstruction-based, and multiple instance learning.

Anomaly detection results on the synthetic CERRA reanalysis.



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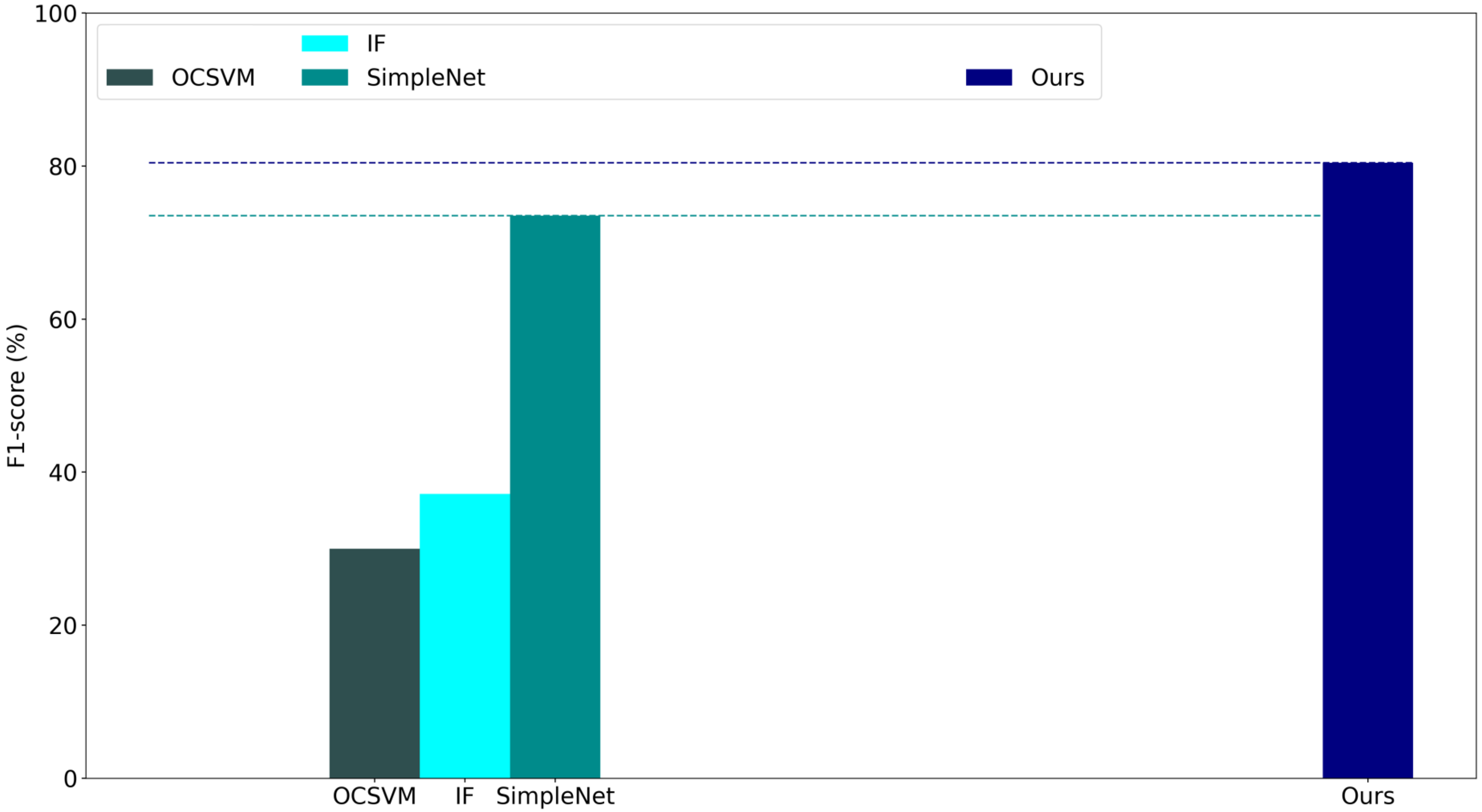

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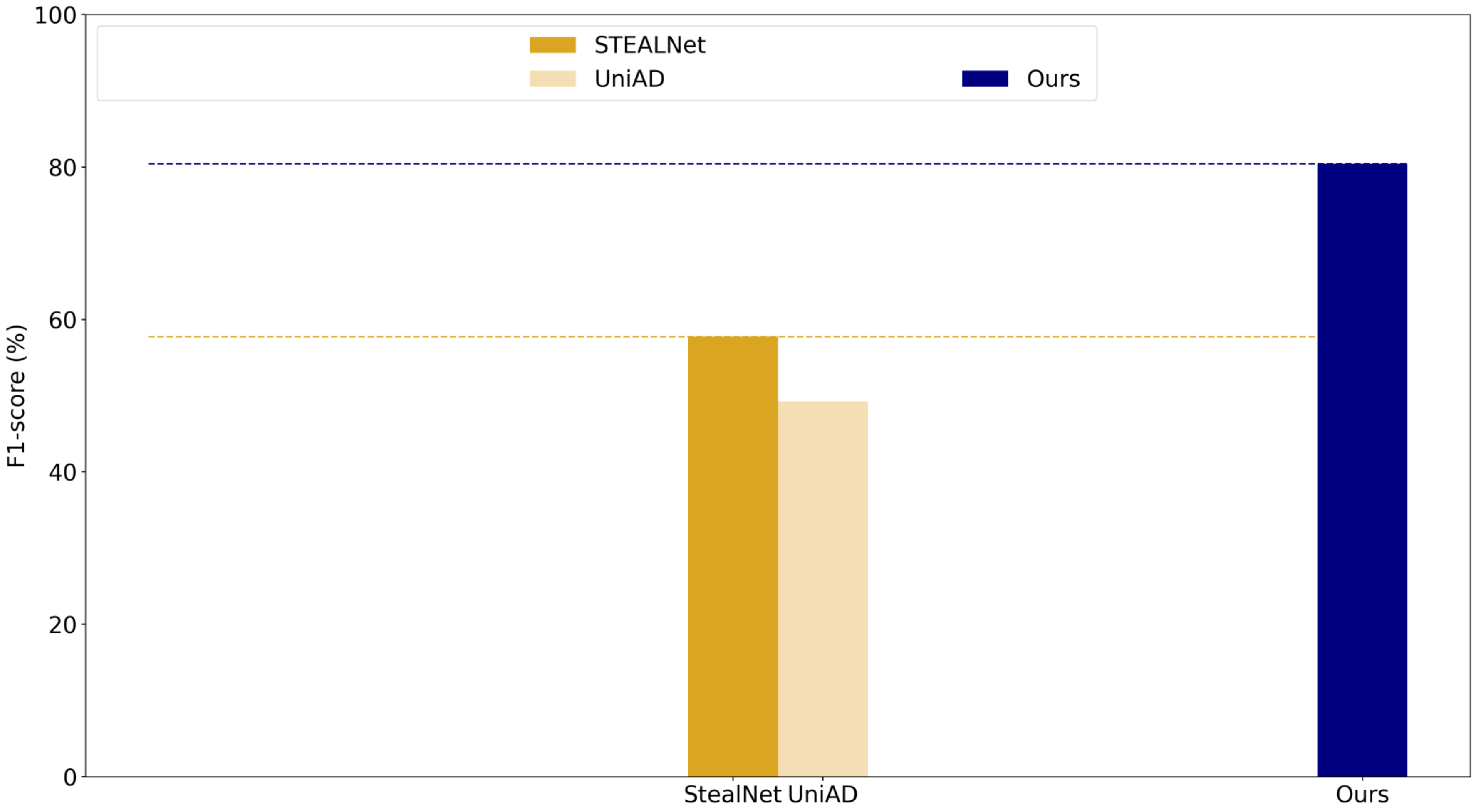

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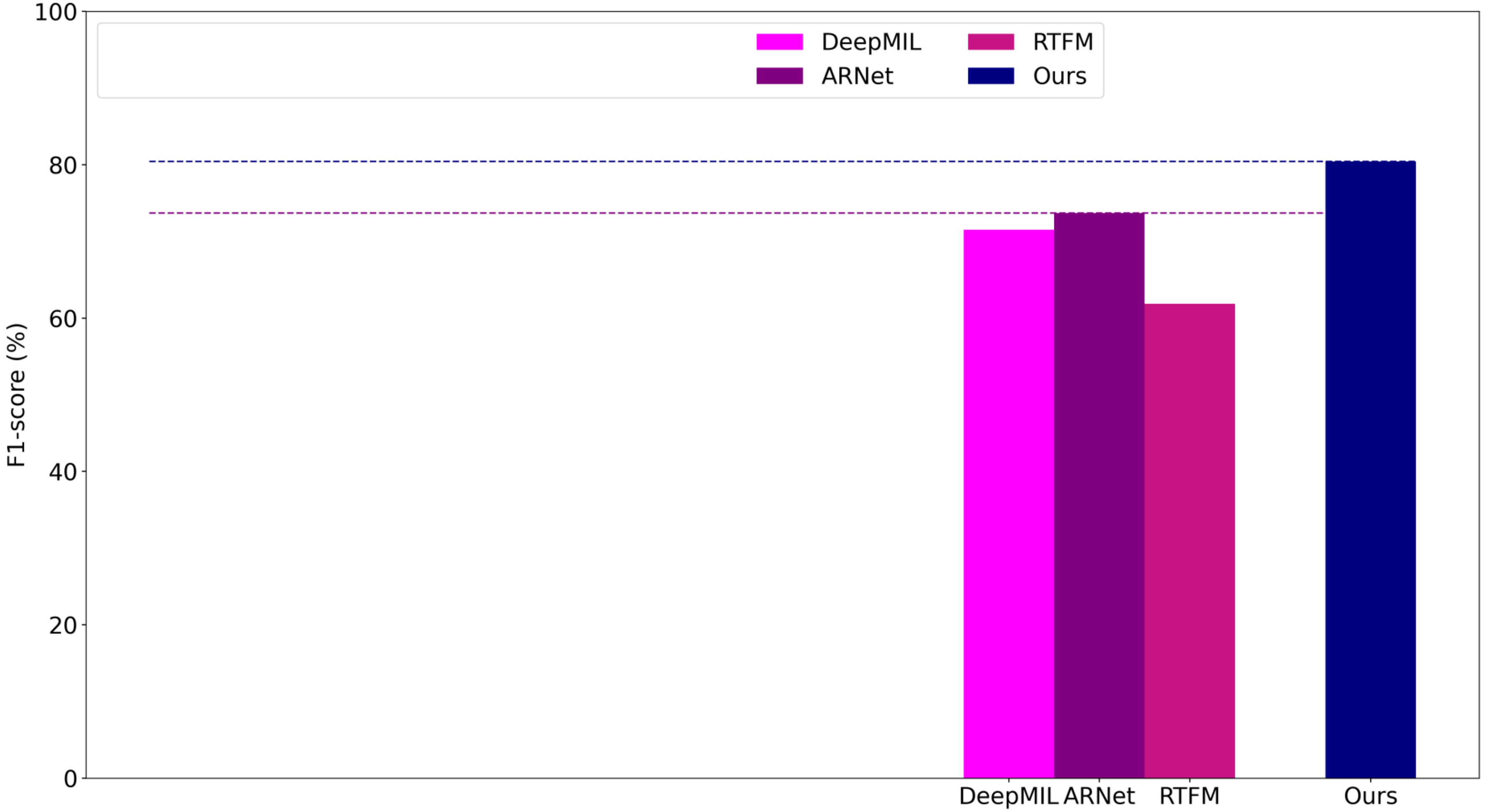

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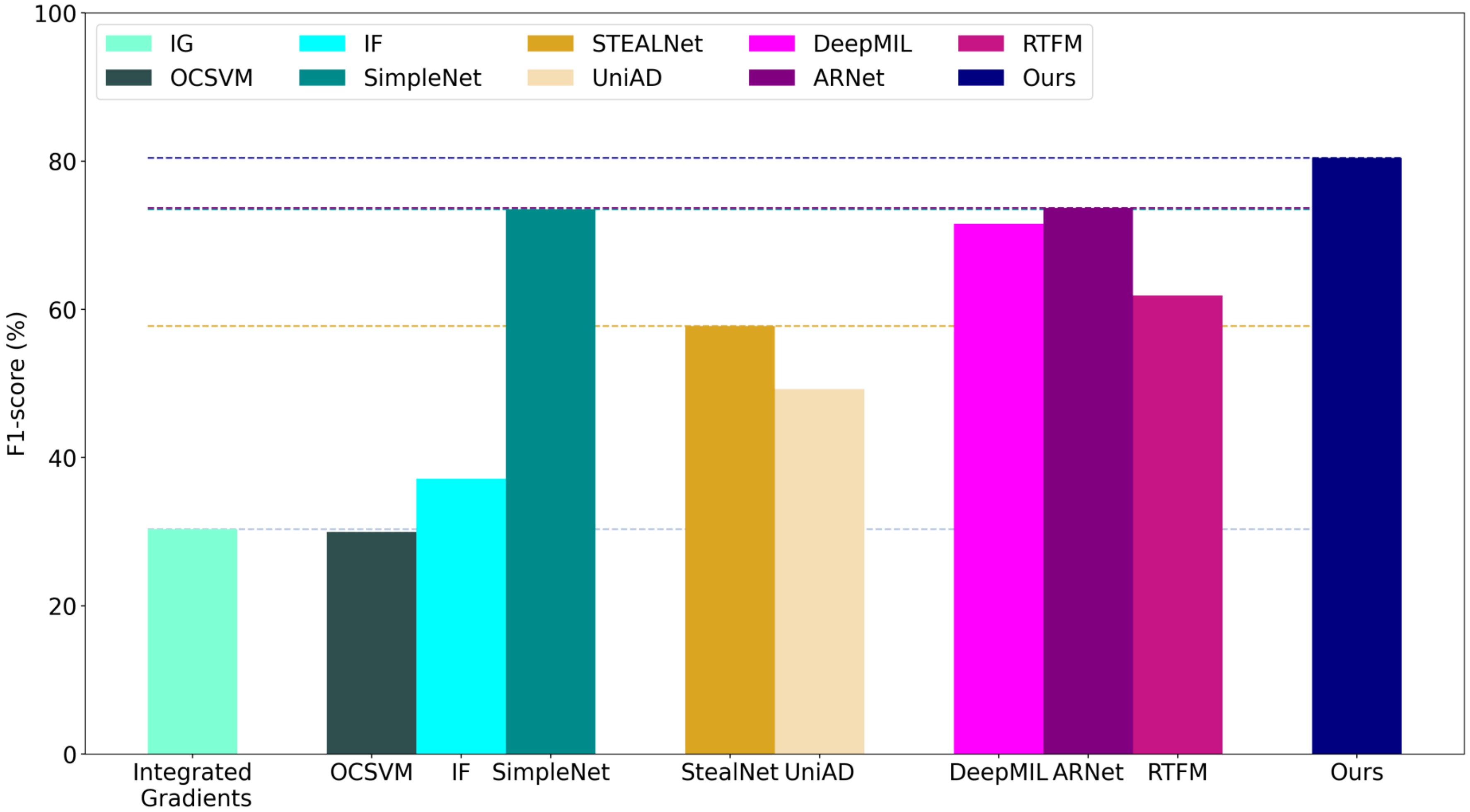


Real-world data:

- We conducted experiments on two real-world reanalysis (ERA5-Land and CERRA) including data from five continents.

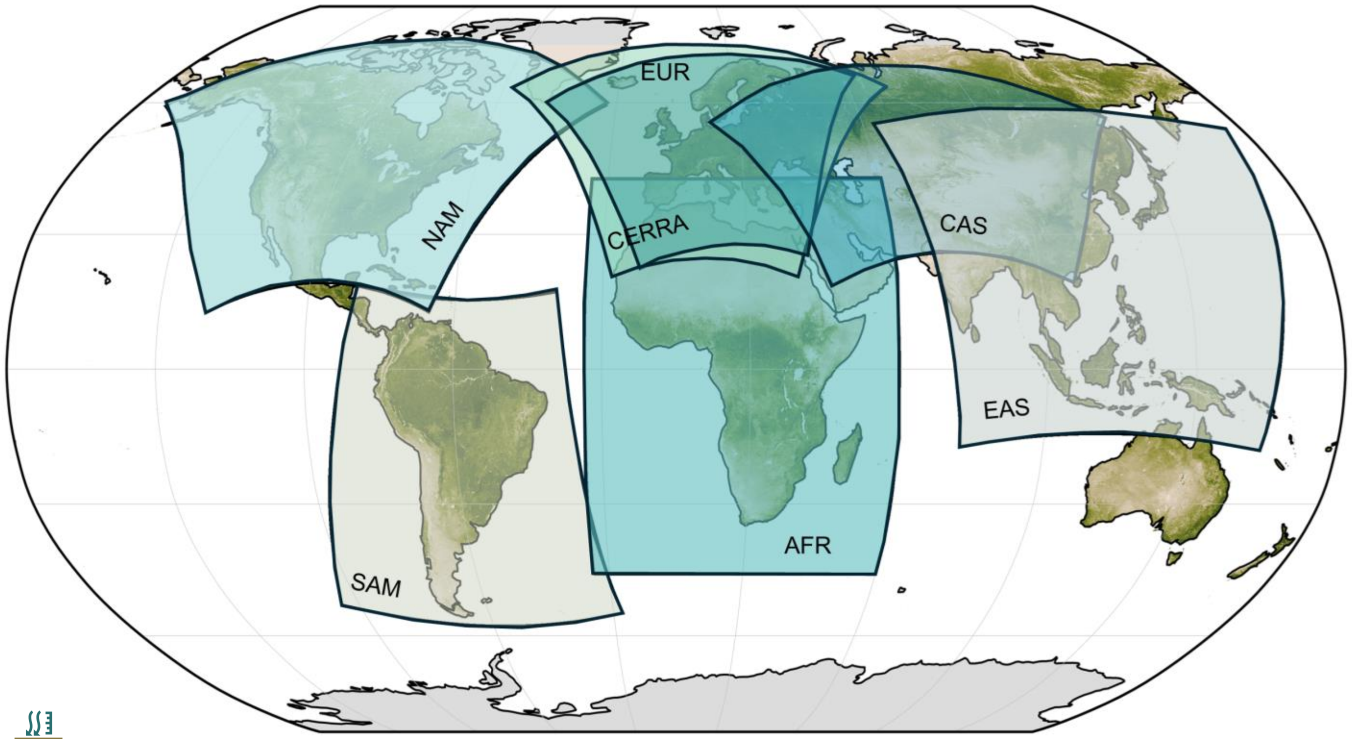
- Data:

    - ERA5-Land Reanalysis (1981 – 2024)

    - CERRA Reanalysis (1984 – 2021)

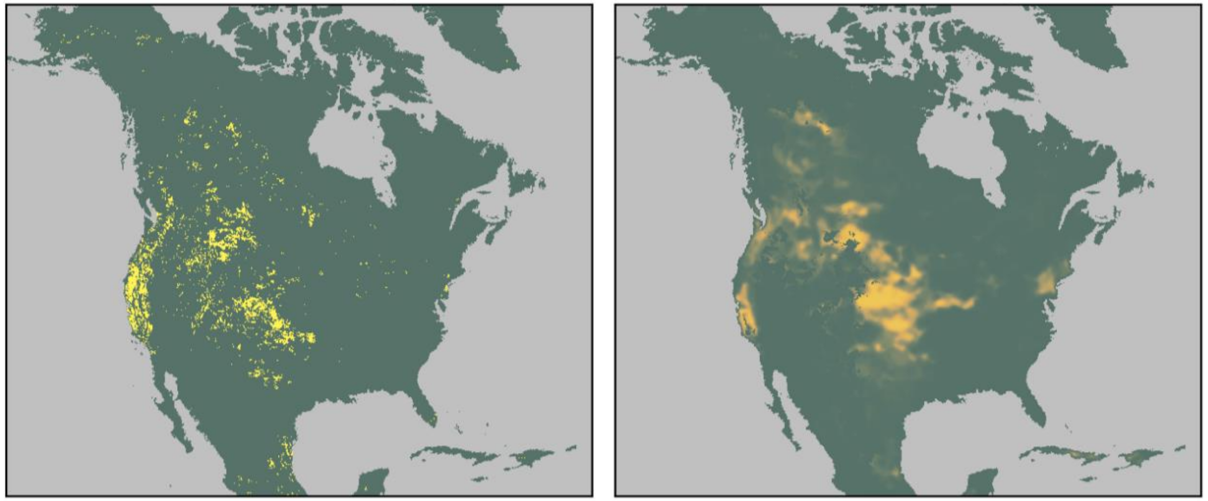
- Reanalysis data include variables such as:

  2-meter temperature (t2m)
  2-meter relative humidity (r2)
  2-meter dewpoint temperature (d2m)
  volumetric soil moisture (swv)
  skin temperature (skt)
  soil temperature (stl) | albedo (al)
  total cloud cover (tcc) | surface pressure (sp)
  total evaporation (e) | total precipitation (tp)



Qualitative results on real-world ERA5-Land reanalysis:

Observed extreme droughts at Δt_0 | Predicted extreme droughts at Δt_0



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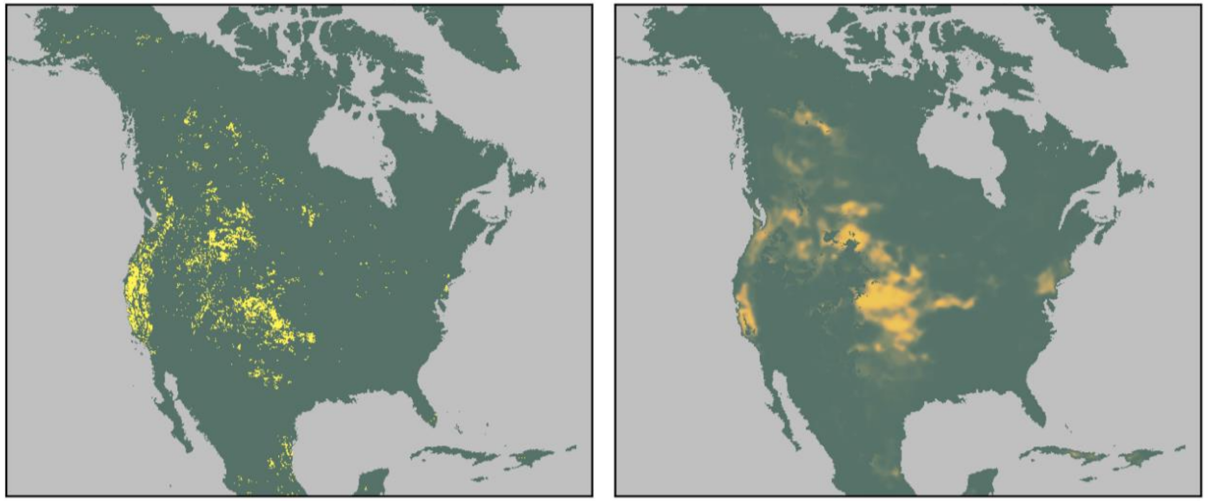


Δt_0 | $-\Delta t_1$ | $-\Delta t_2$ | $-\Delta t_3$ | $-\Delta t_4$ | $-\Delta t_5$ | $-\Delta t_6$ | $-\Delta t_7$

Soil moisture

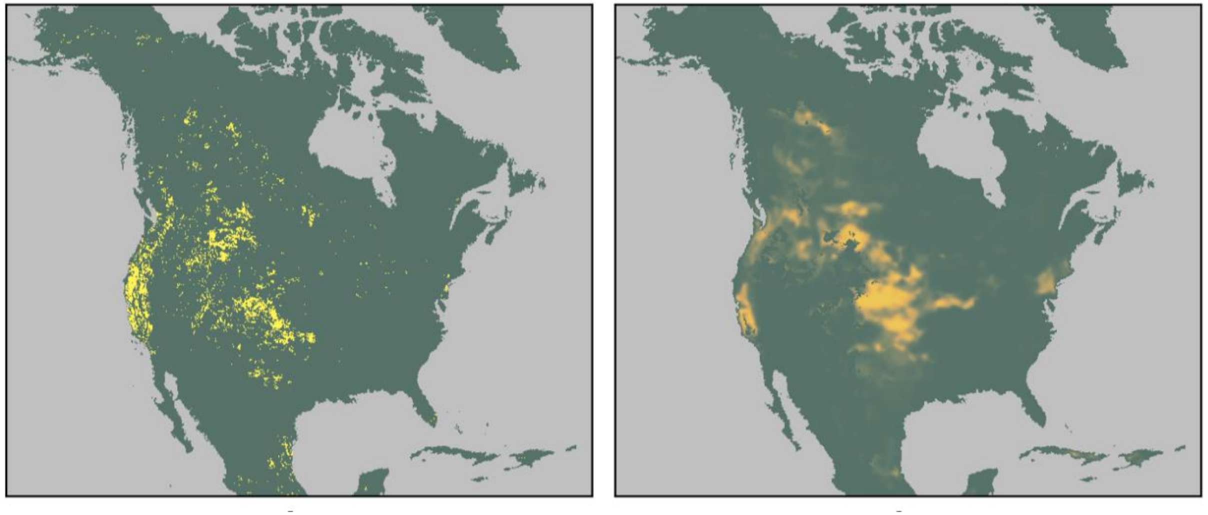
Total evaporation

Time

Qualitative results on real-world ERA5-Land reanalysis:

Observed extreme droughts at Δt_0

Predicted extreme droughts at Δt_0



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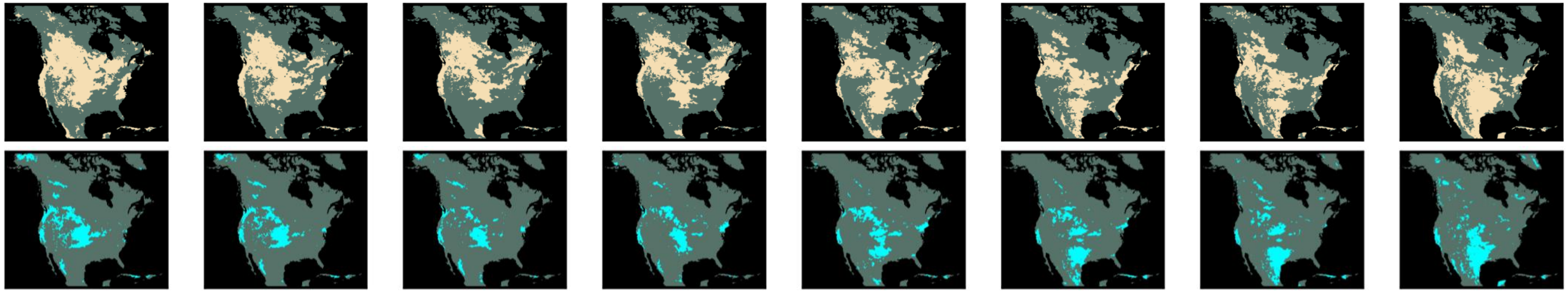

Soil moisture

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Thank you for your attention

https://hakamshams.github.io/IDE

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