Deep Learning and Explainable AI for spatio-temporal drought monitoring

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Contents

1. Motivation and objectives

- Challenge in climate change: **Anticipation and detection of extreme events**
- **Machine learning** approaches…
  - have excelled in the detection of anomalies in **Earth data cubes**,
  - but are typically both computationally costly and supervised
- **Objectives**
  - Develop an **unsupervised**, **generic**, **efficient**, **generative** approach for **extreme event detection**
  - The **model not only detects extreme events, but also explains** why they were produced

2. Case study: Drought monitoring

- Objective: **Europe, severe Russian heat-wave** between **April-August 2010**

- Databases:
  1. **International Disaster Database (EM-DAT, 2008)**
     - Drought annotations at spatio-temporal location-level
     - Only used for evaluation

  2. **Earth System Data Lab (ESDL) (Mahecha et al., 2020)**
     - Essential Climate Variables (ECVs)
     - ECVs for droughts in 2003-2015
     - 3 different time periods for training, validation (non-drought periods) and test (drought+non-drought period) stages.

Russia counts the cost of drought and wildfires. Credit: BBC

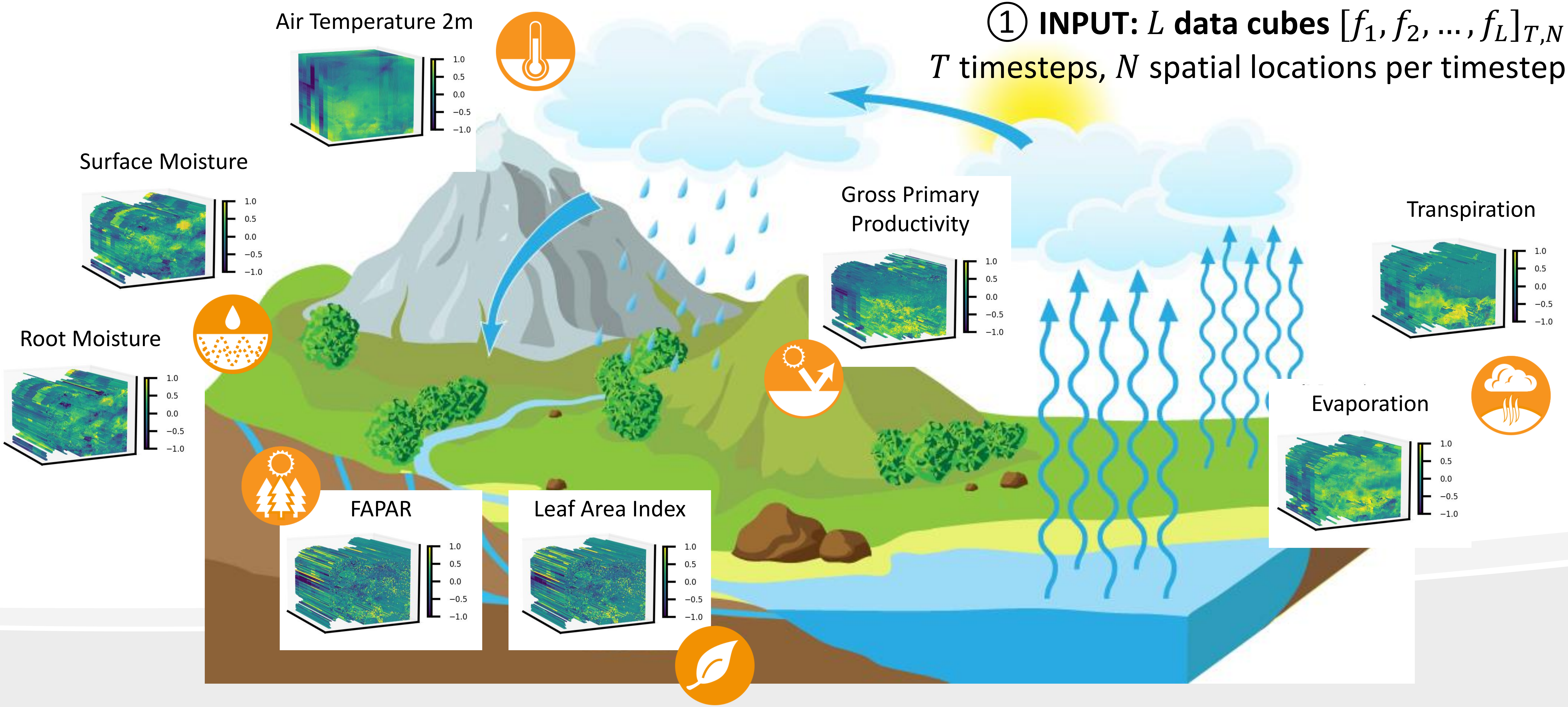
Mirny, a Russian village ravaged by wildfires during the drought in 2010. Credit: Yuri Kochetkov/European Pressphoto Agency

A fire near the village of Golovanovo, in the Ryazan region of Russia, during the heat-wave in 2010. Credit: Natalia Kolesnikova/Agence France-Presse — Getty Images

2.1 Essential Climate Variables (ECVs) for droughts

① **INPUT:** L **data cubes** $[f_1, f_2, \ldots, f_L]_{T,N}$

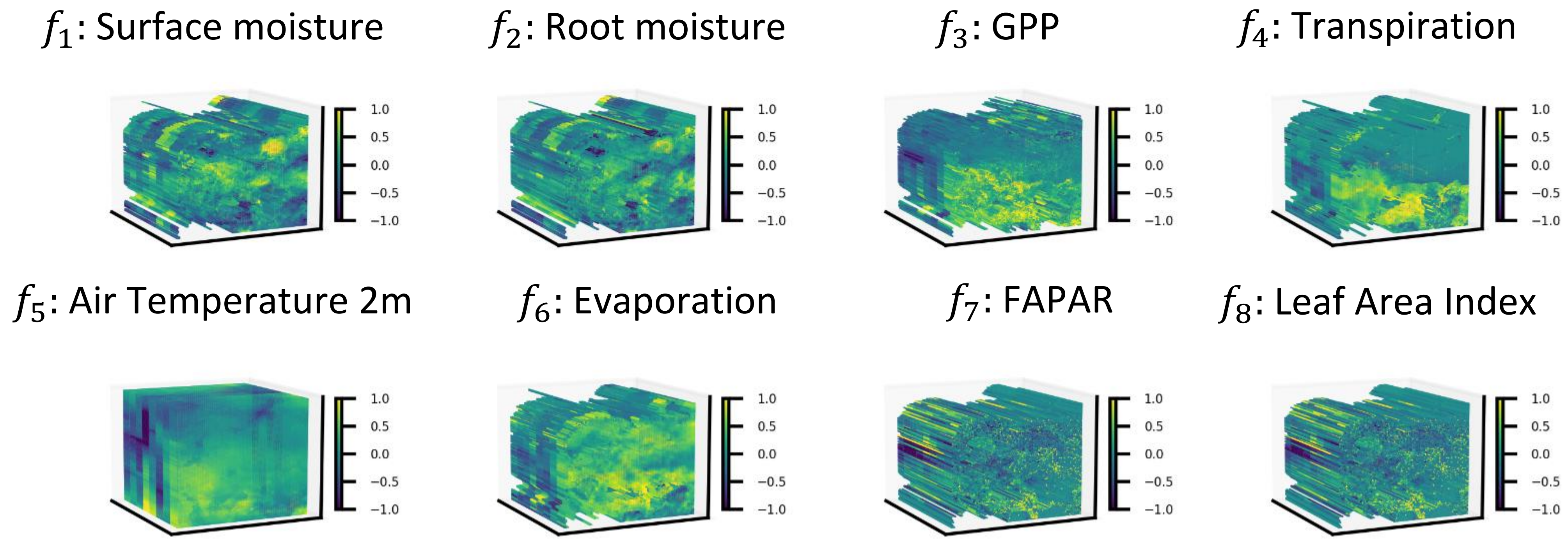
T timesteps, N spatial locations per timestep



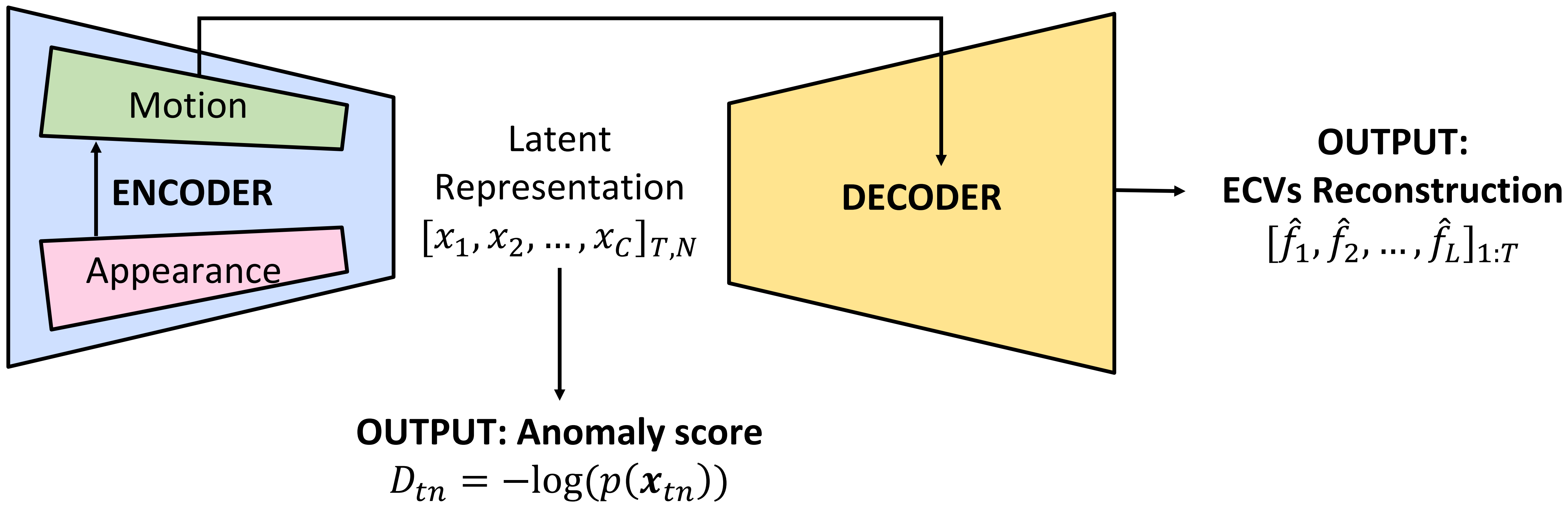
2.2 Deep Learning for drought detection

① **INPUT:** L **Essential Climate Variables** (ECVs) $[f_1, f_2, \dots, f_L]_{T,N}$

T timesteps, N spatial locations per timestep



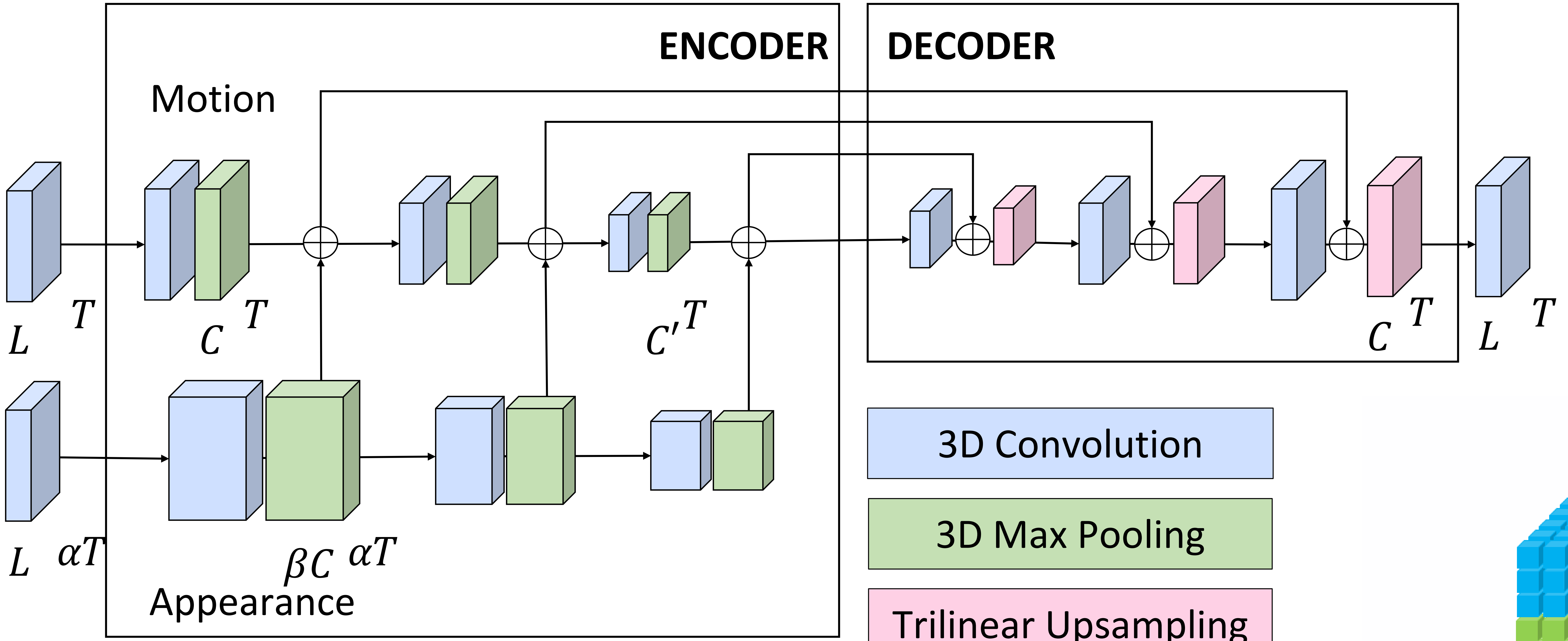
② SlowFast Convolutional Autoencoder



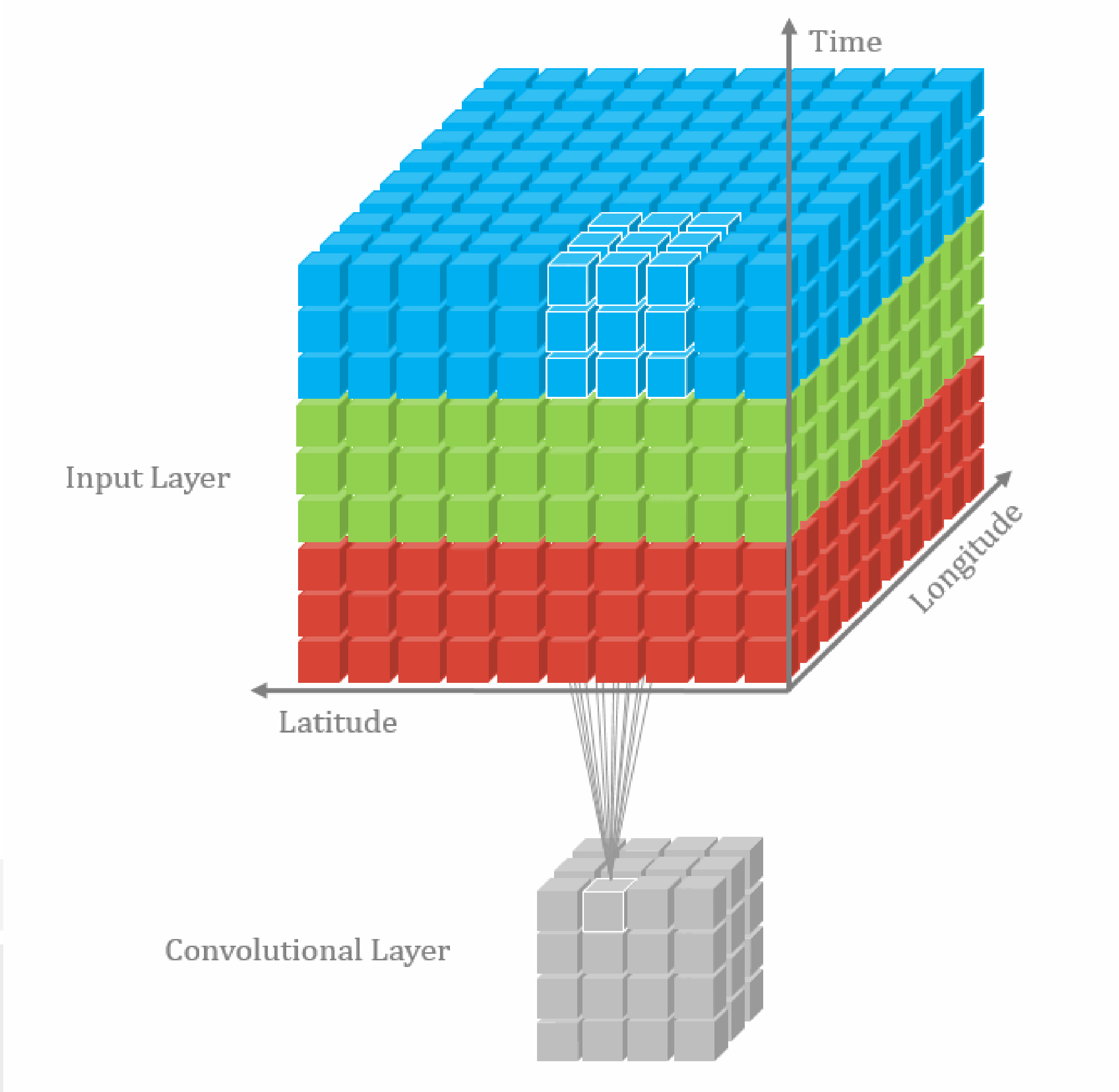
③ Gaussianization Flows (Unsupervised Deep Generative Model)

SlowFast Convolutional Autoencoder

INPUT: ECVs
$[f_1, f_2, \dots, f_L]_{T,N}$
T timesteps,
N spatial
locations per
timestep



OUTPUT:
ECVs Reconstruction
$[\hat{f}_1, \hat{f}_2, \dots, \hat{f}_L]_{1:T}$



Credit: Resuly's Blog, http://resuly.me/

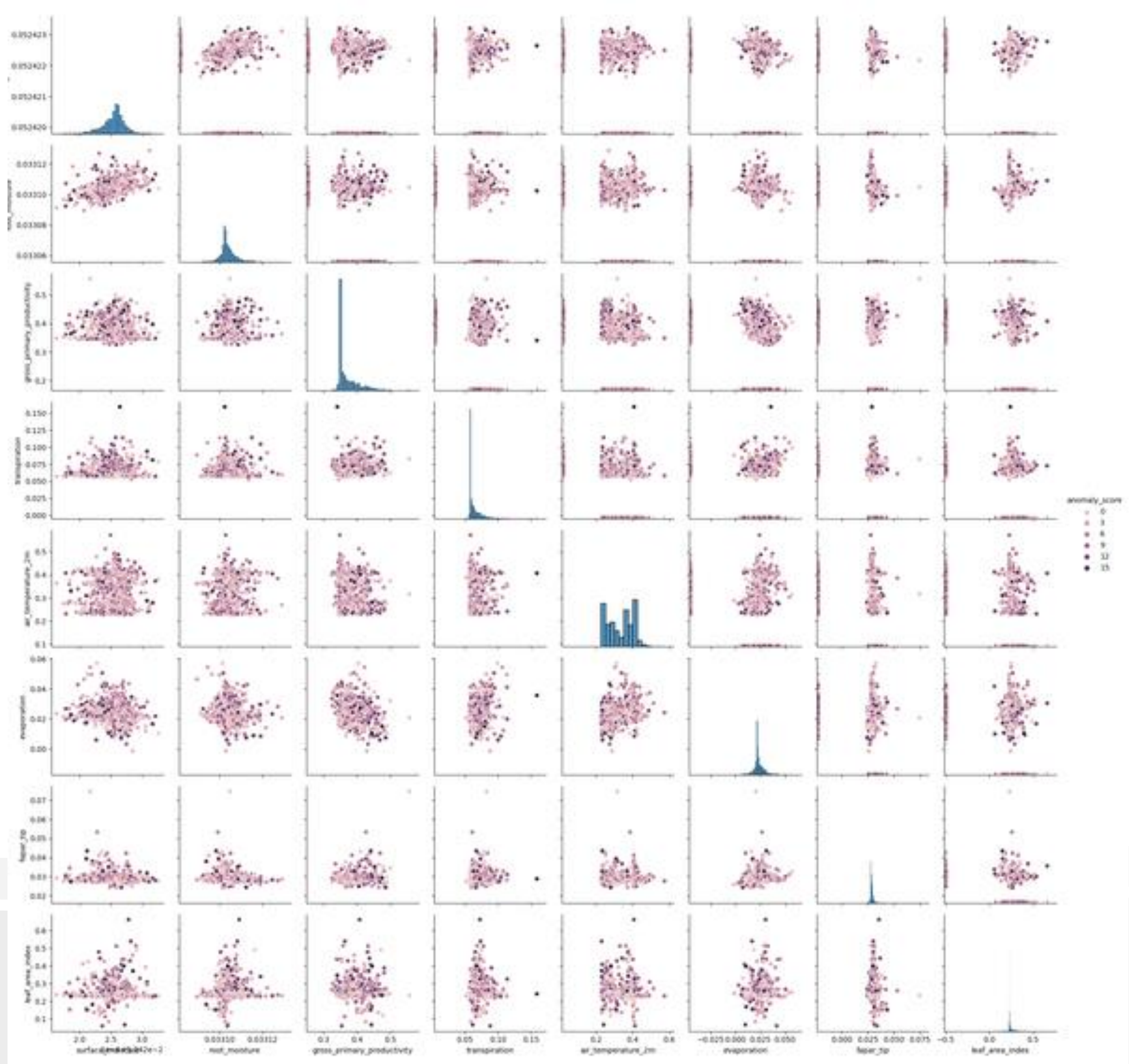
SlowFast Networks for Video Recognition (Feichtenhofer et al., 2019)

- *Slow* or appearance pathway: Low frame rate and temporal resolution αT, $\alpha < 1$; high number of channels (spatial resolution) βC, $\beta > 1$
- *Fast* or motion pathway: High frame rate and temporal resolution T; C channels
- Lateral connections between *Slow* and *Fast* pathways
- Skip connections between the encoder and the decoder

Gaussianization Flows (Meng et al., 2020)

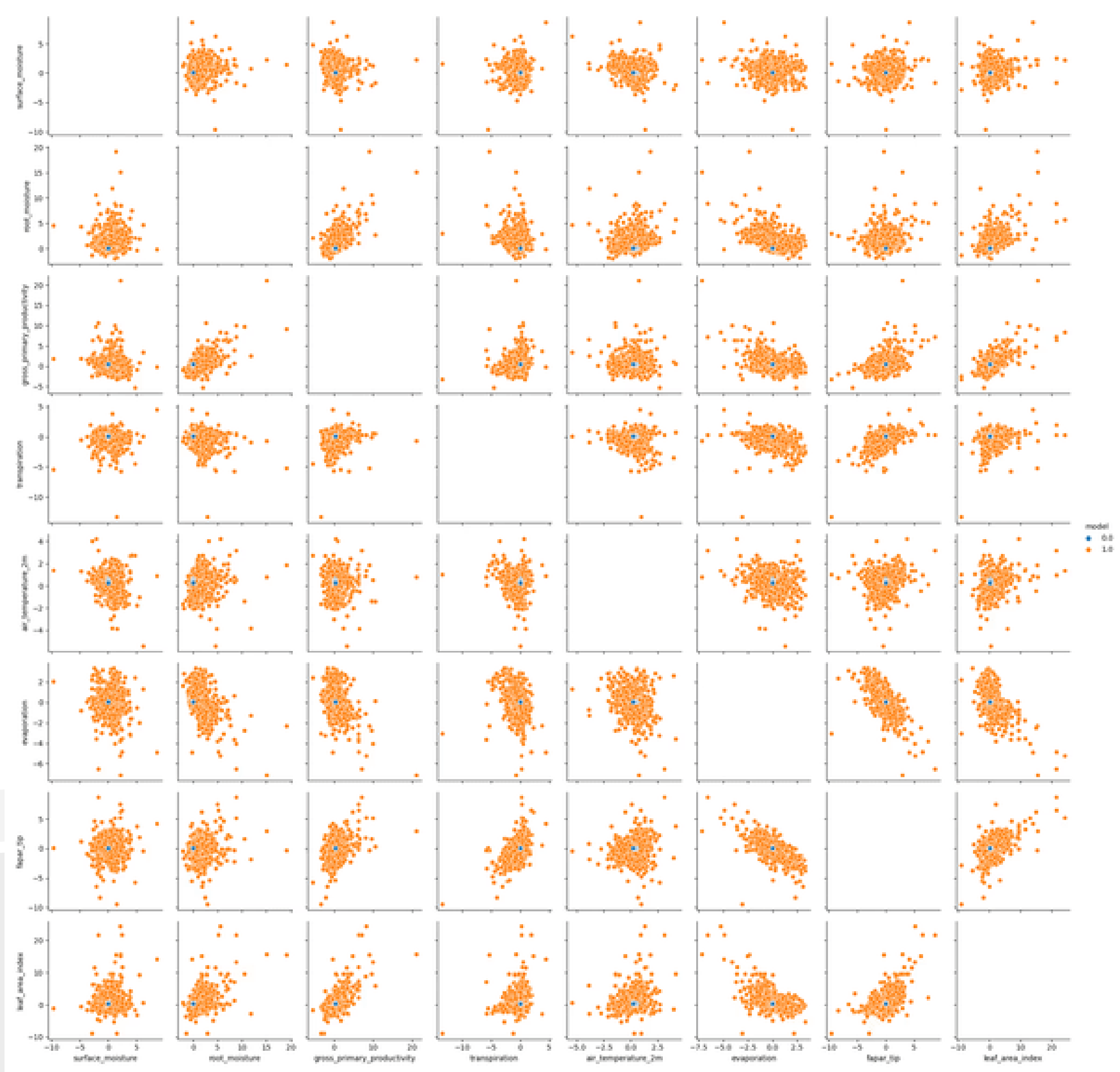
- Deep generative, trainable model: **Efficient PDF estimation via maximum likelihood + sample generation**
- **Bijective, invertible mapping** from data distribution to a standard Gaussian distribution (target)
- **Anomaly score**: **Negative Log-Likelihood (NLL)** → $D_{tn} = -\log(p(\boldsymbol{x}_{tn}))$
- Visualization of training phase through epochs:

Input samples $\boldsymbol{x}$

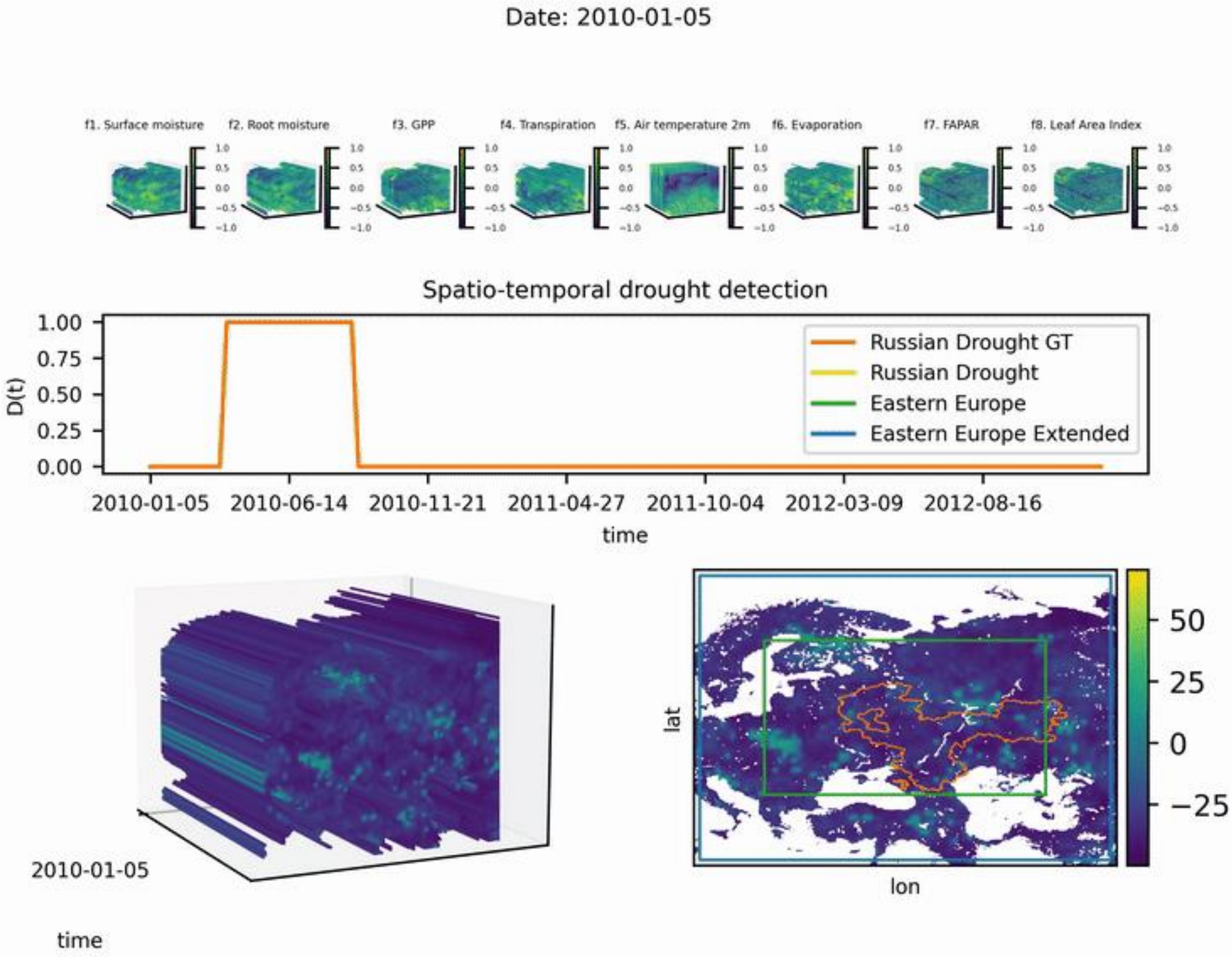


Gaussianized PDF $p(\boldsymbol{z})$

Real (blue) vs. estimated (orange) PDF $p(\mathbf{x})$



Drought detection

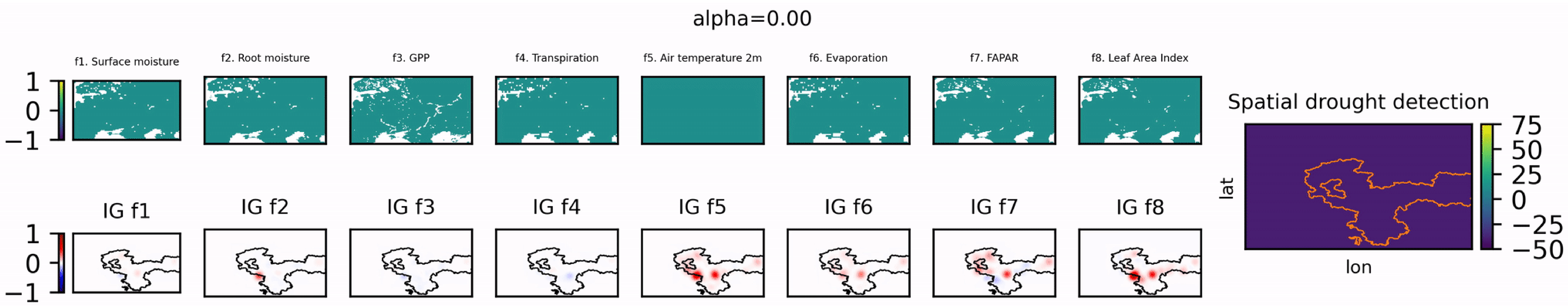


2.3 EXplainable AI (XAI) for drought monitoring

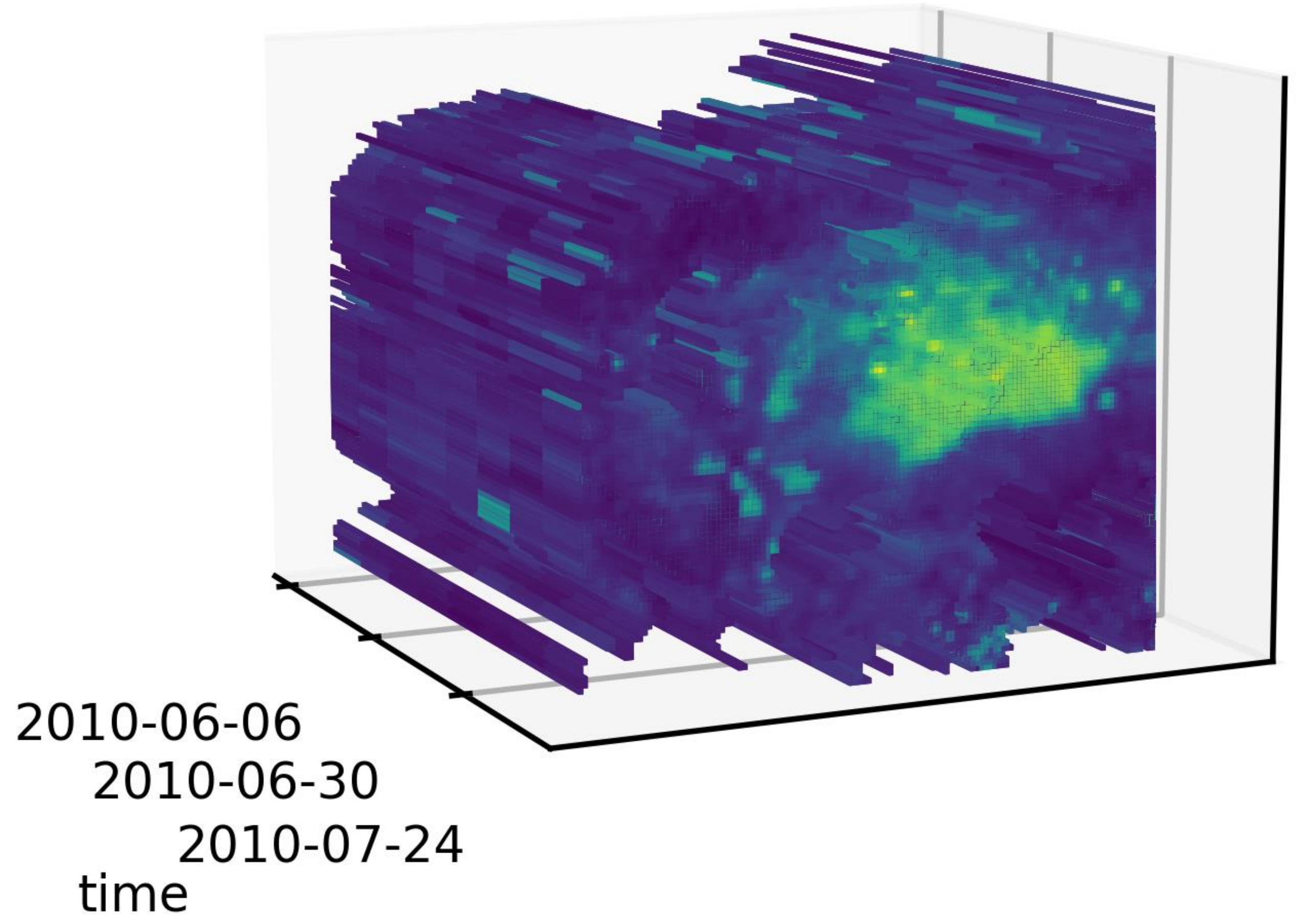
- **Integrated Gradients (IG) (Sundararajan et al., 2017)**: Integral of gradients of the output D with respect to inputs along the path from a given baseline $f'_{1:L}$ to input $f_{1:L}$.

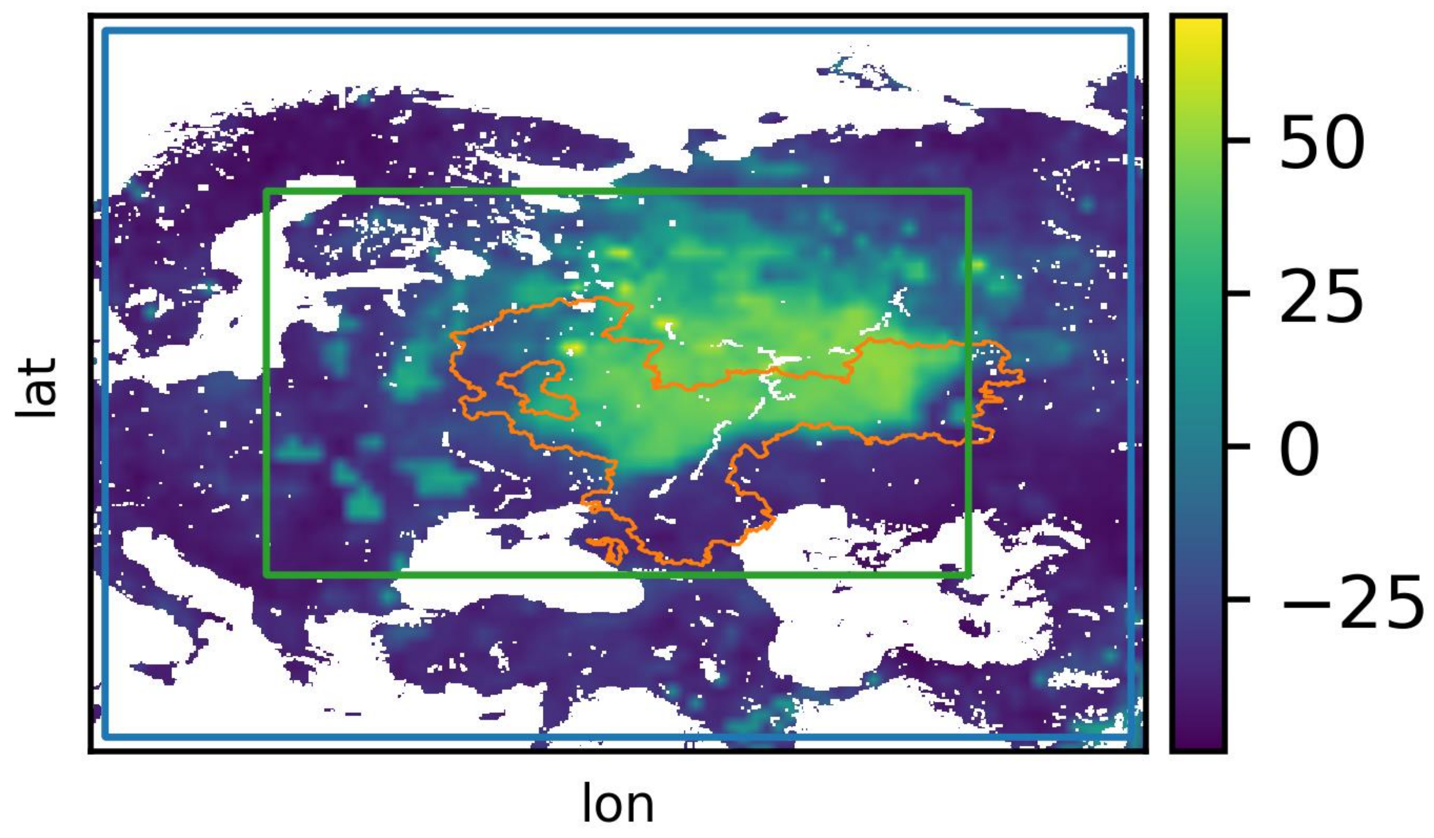
$$IG(f_{1:L}) \coloneqq (f_{1:L} - f'_{1:L}) \cdot \int_{\alpha=0}^{1} \frac{\partial D(f'_{1:L} + \alpha \times (f_{1:L} - f'_{1:L}))}{\partial f_{1:L}} d\alpha$$

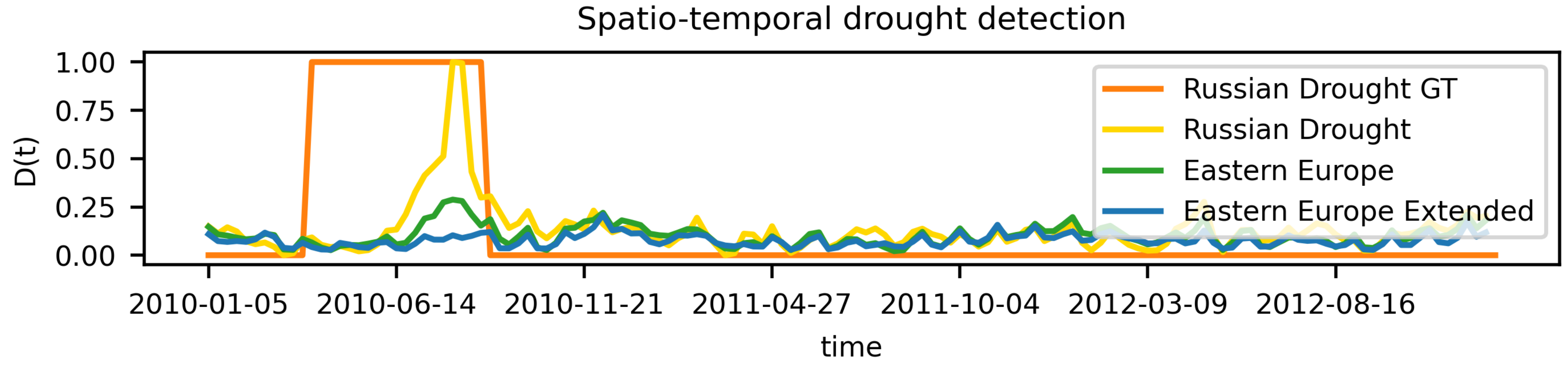
- Two **fundamental axioms of IG**:
    - **Sensitivity**: *"For every input and baseline that differ in one feature but have different predictions, the differing feature should be given a non-zero attribution"*
    - **Implementation invariance**: *"Attributions are always identical for two functionally equivalent networks (i.e. their outputs are equal for all inputs, despite having very different implementations)"*

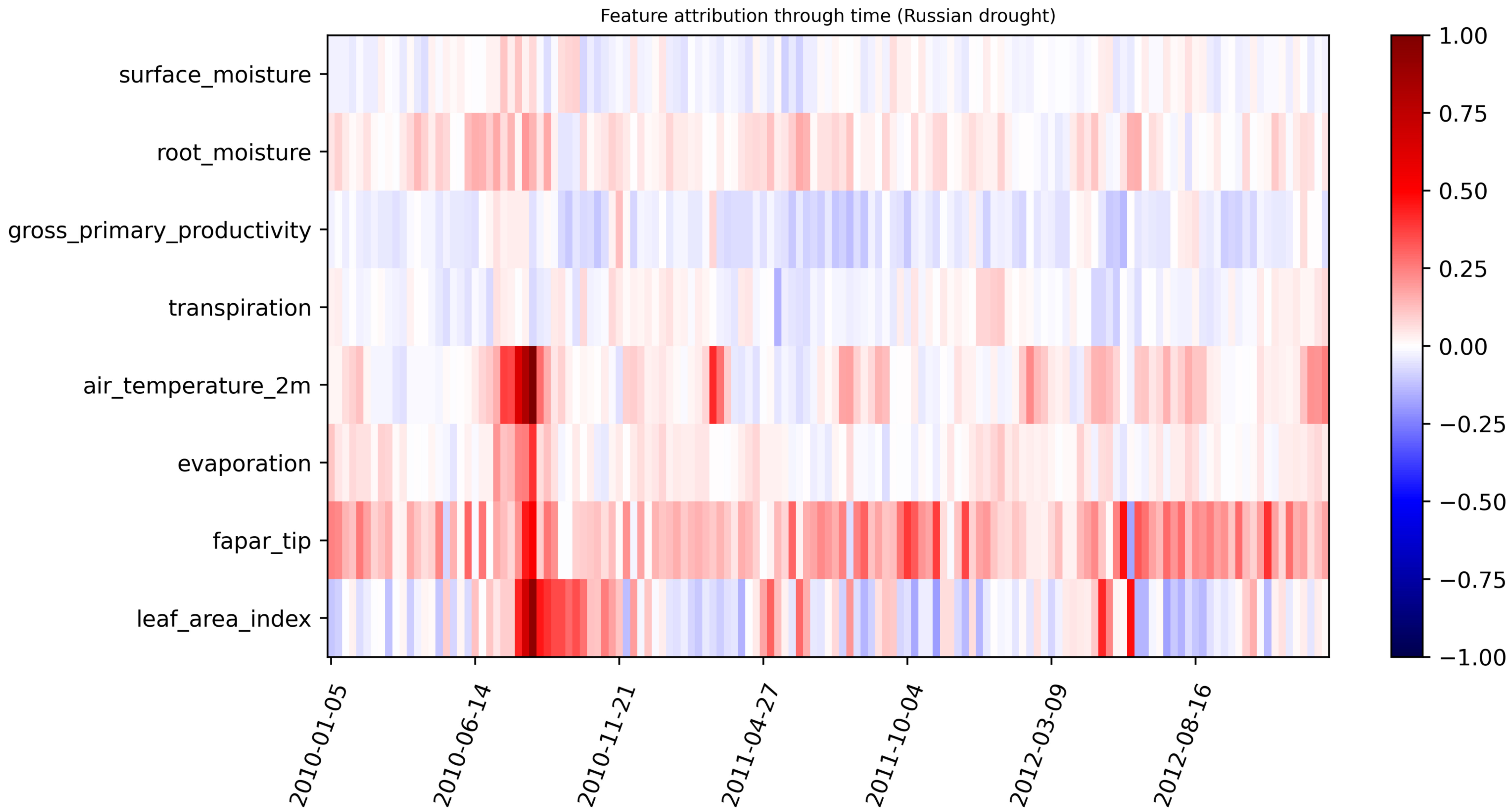


Drought monitoring









3. Take-home messages for the application of AI4NDM

1. **Fully unsupervised model**
   – Semi-supervised/supervised models: Annotations at spatio-temporal location-level might be inaccurate
2. **Generic vs. context-aware framework**
   – Should we use different models for drought detection in Russia/Europe/Worldwide?
3. **Generic model**
   – Extension to other extreme events
4. **XAI for the study and analysis of compound events**

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