TerraDT

WEBINAR SERIES - TECH TALKS

Machine learning in TerraDT:

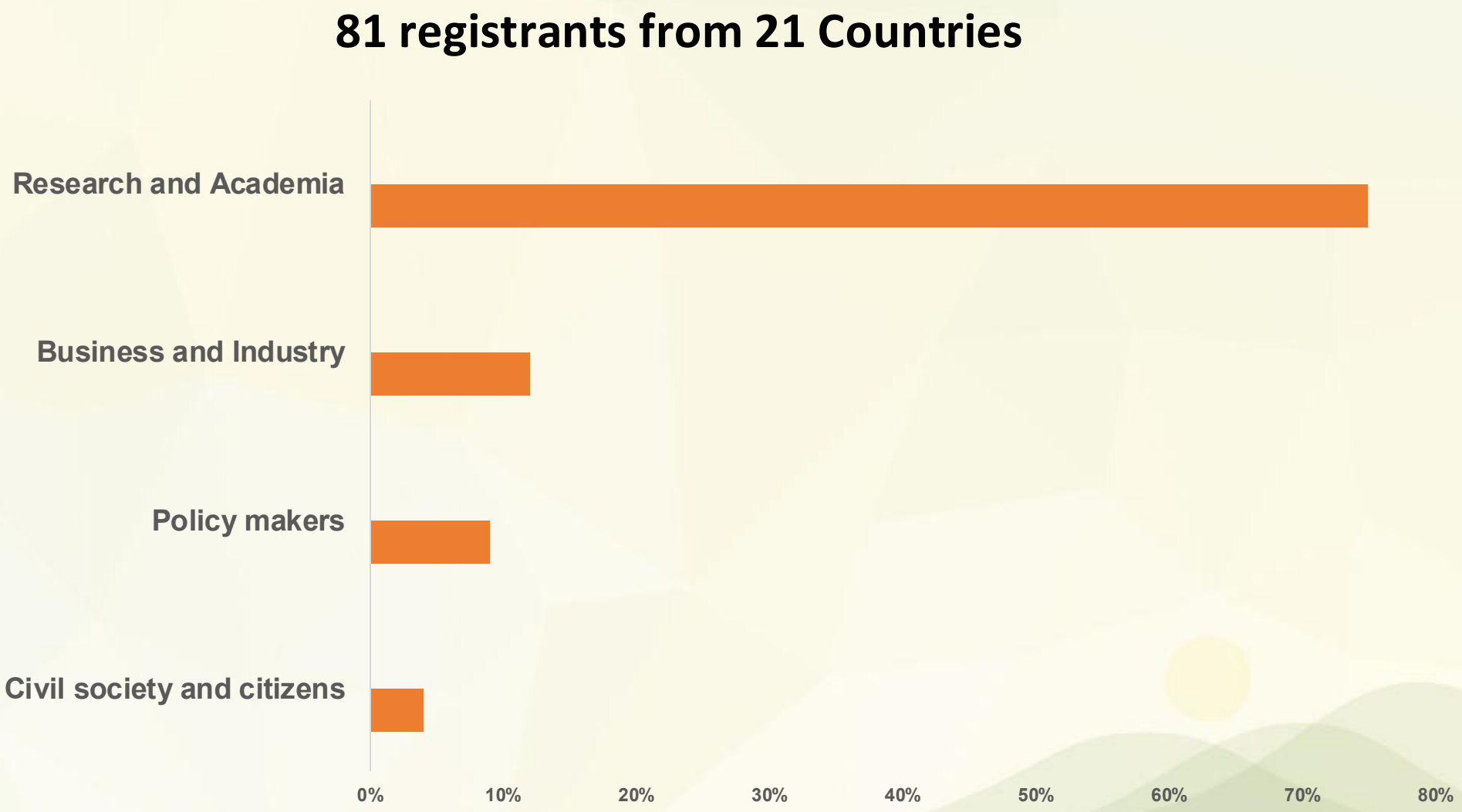
from emulators to impact models for the cryosphere and land surface



Register now Sep 17th | 11:00

Funded by the European Union

Who is here today



Agenda

- **11:00 - 11:05 | Welcome and housekeeping** *Maria Giuffrida (Trust-IT Services)*
- **11:05 - 11:15 | Introduction: the role of machine learning in TerraDT-** *Devaraju Narayanappa (CSC)*
- **11:15 - 11:25 | Machine learning for urban impact assessment: carbon sequestration and climate extremes**, *Inês Girão, (CoLAB +ATLANTIC)*
- **11:25 - 11:35 | Constructing the high-resolution, time-varying land-use dataset with machine learning**, Amirpasha Mozaffari *(BSC)*
- **11:35 - 11:45 | Coupling AI-driven and physics-based digital twin components** *Benjamin Rodenberg (DKRZ)*
- **11:45 - 11:55 | Machine learning approaches in WeatherGenerator** *Peter Dueben, ECMWF*
- **11:55 - 12:15 | Q&A and closing**

Housekeeping



The event will be recorded and will be made available on the TerraDT.eu website after the event (including the presentations of each speaker)

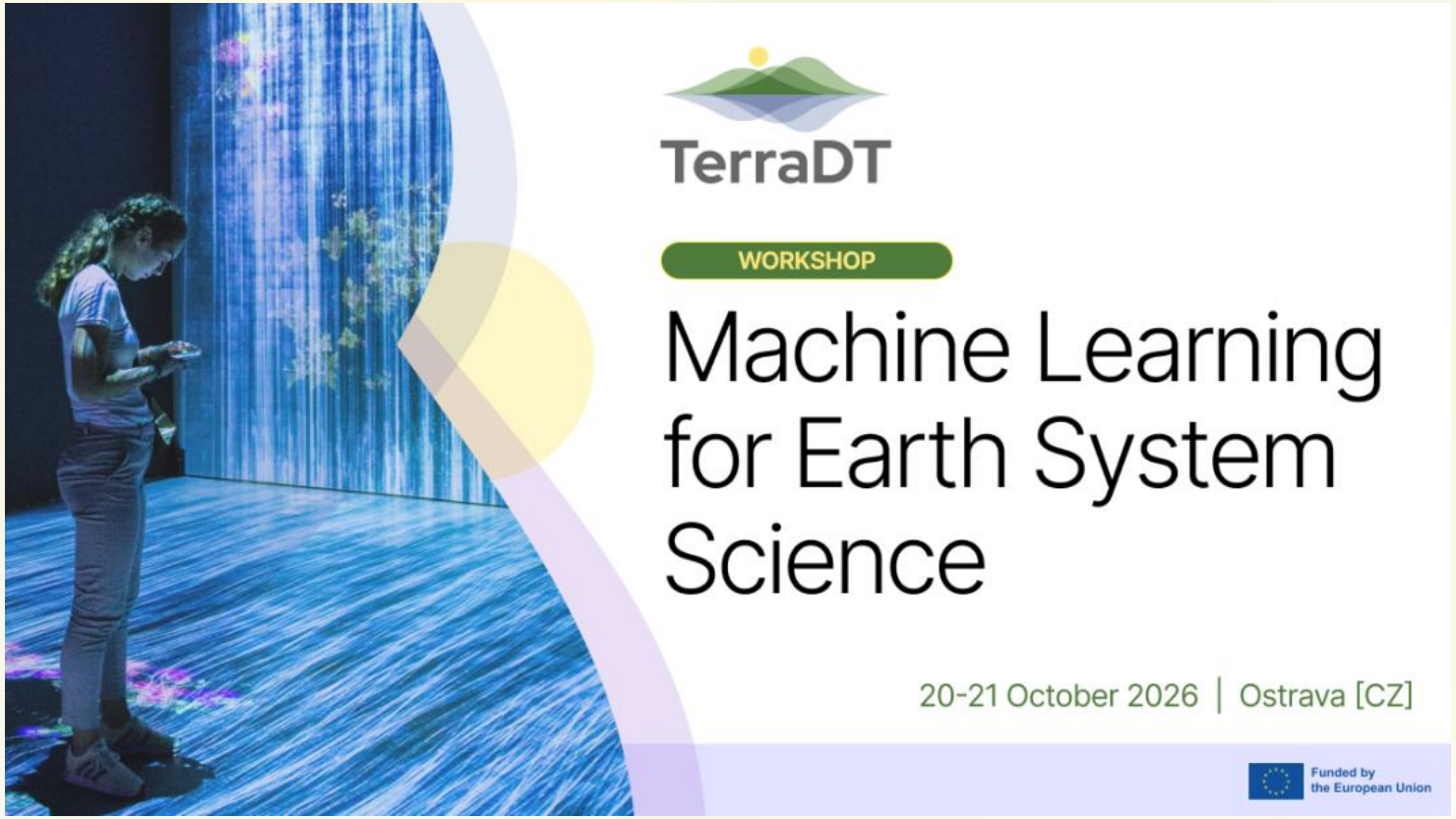
We do encourage you to enter any question in the dedicated Q/A box placed in the lower toolbar. The speakers will be pleased to answer back your questions during the event





You can follow the chat to be informed and receive links on the main activities of TerraDT and Weather Generator.

Our upcoming events



https://terradt.eu/events/workshop-machine-learning-earth-system-science

Our upcoming events



https://terradt.eu/events/digital-twins-land-ice-connecting-users-across-projects

AI-based digital twin platform for climate: CLAIMA



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DTO apps for policy, industry and civil society: OCEANITY



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TerraDT

Digital Twin of Earth system for Cryosphere, Land surface and related interactions

Role of Machine Learning in TerraDT

Devaraju Narayanappa
CSC-IT Center for Science, Espoo, Finland.

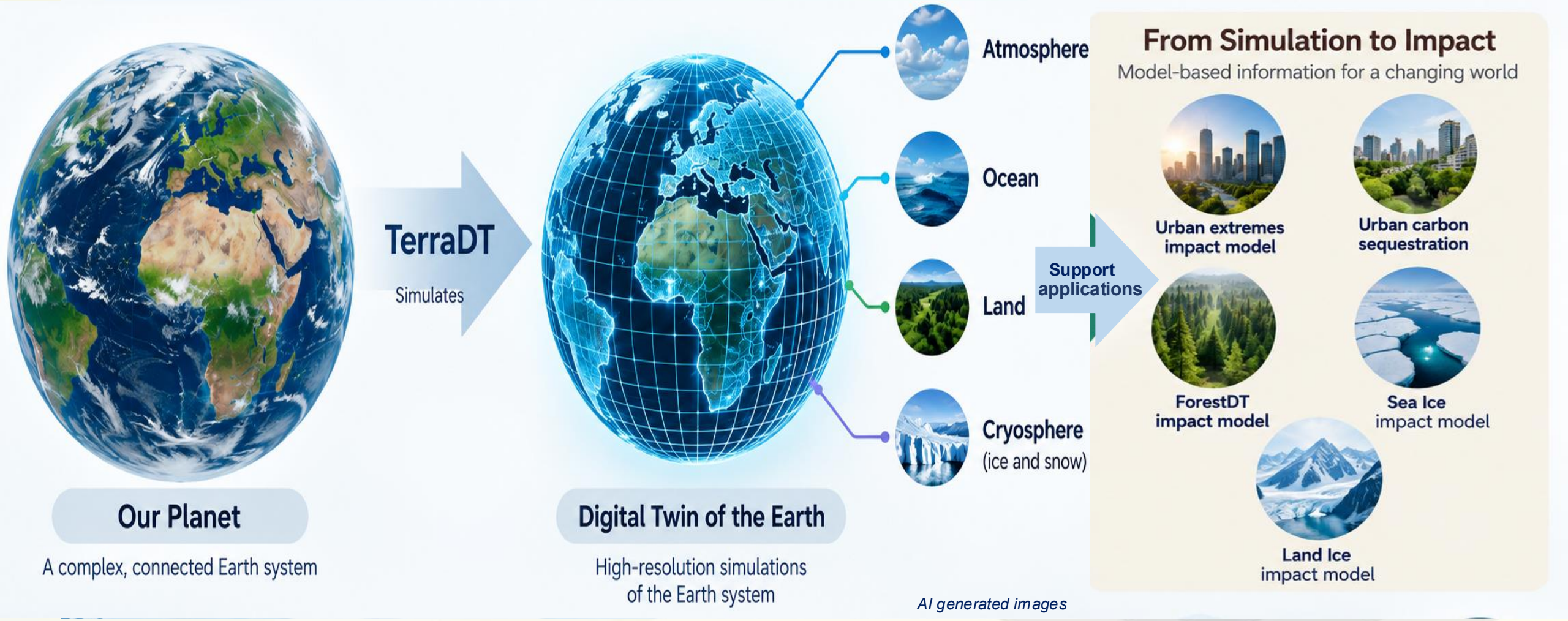
ML Webinar 17 September 2026



Funded by the European Union

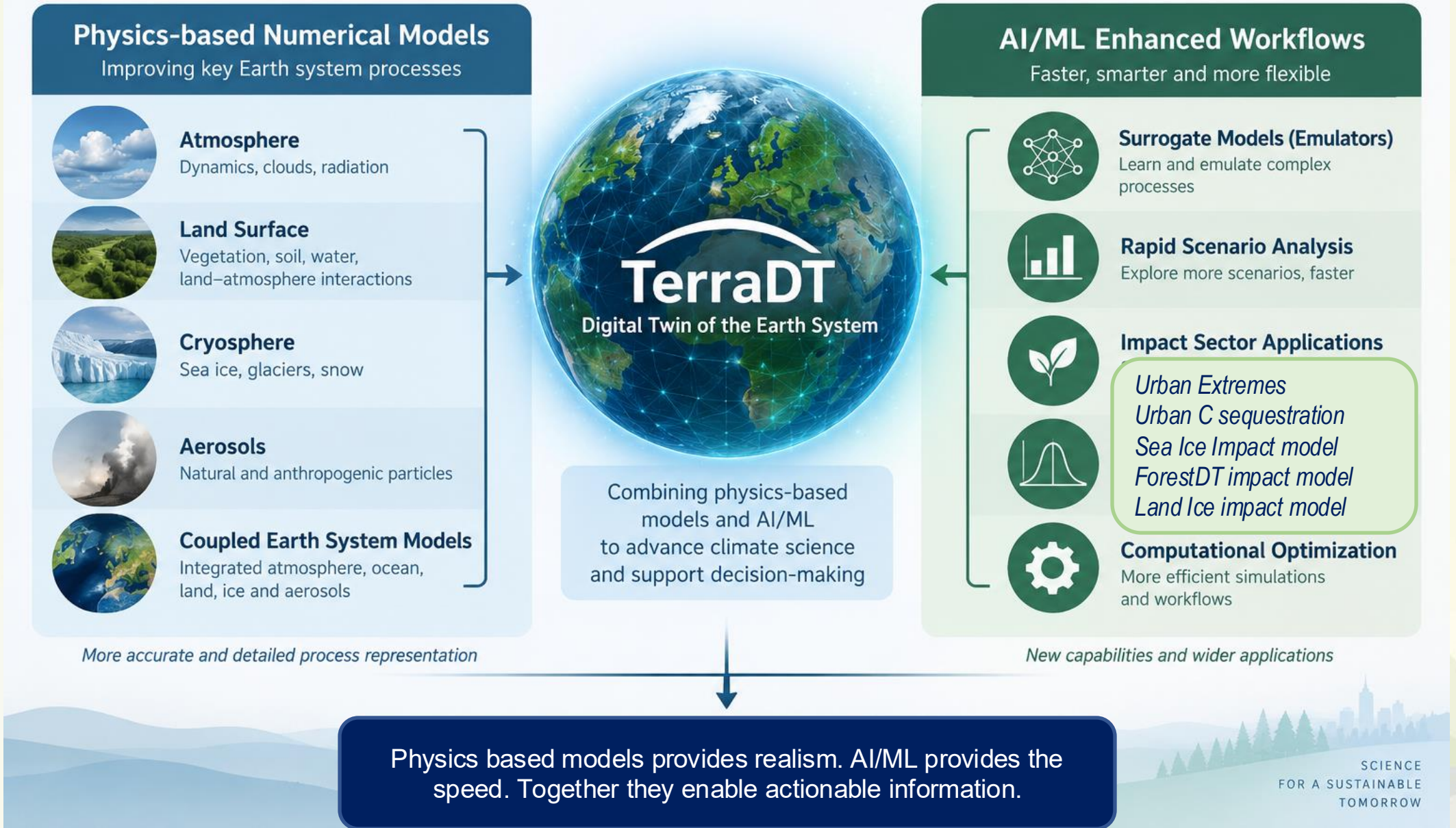
Numerical Simulation of Earth system

- A digital replica of the Earth system to understand and support decisions



AI generated images

How are we using Machine Learning in TerraDT?

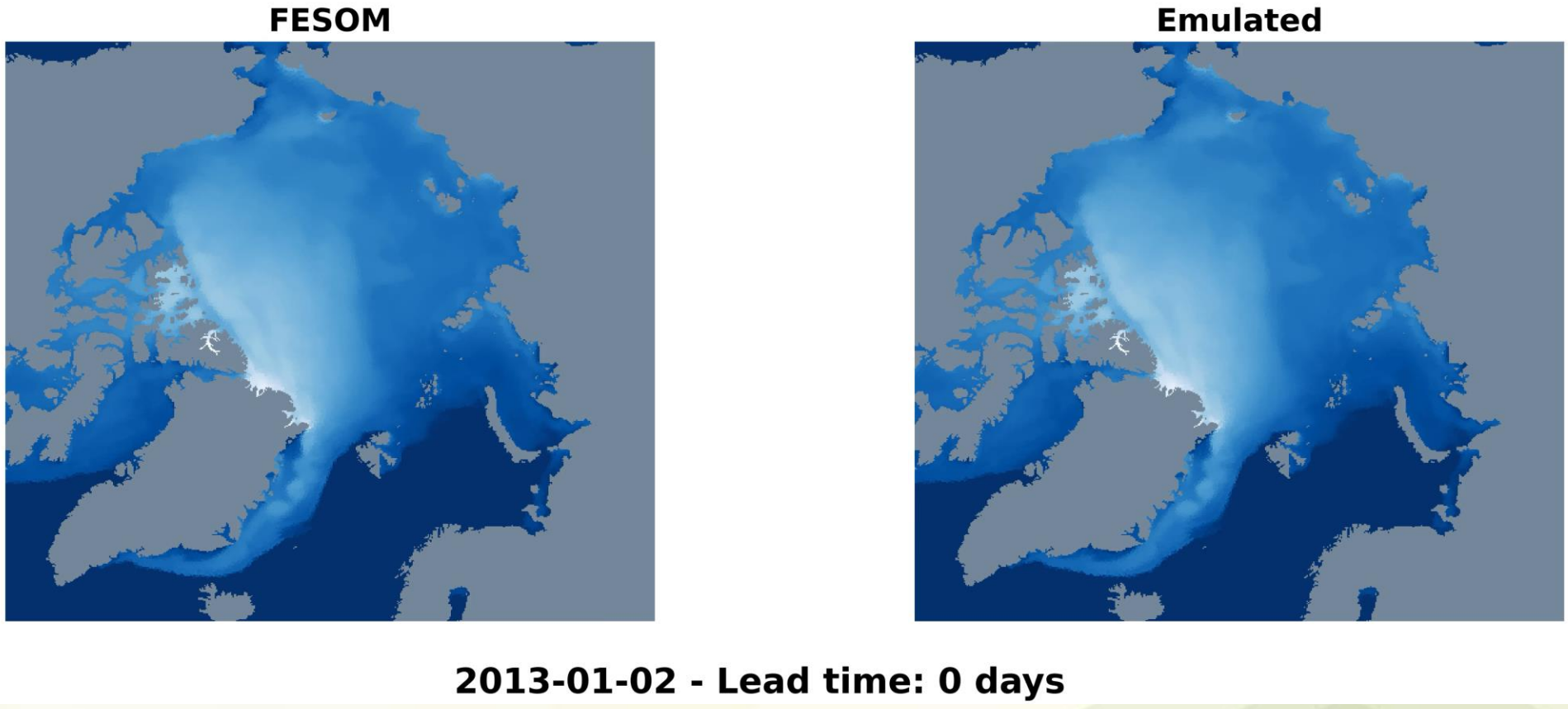


Key applications of AI/ML methods in TerraDT

- AI based sea ice emulator
  - Goal
    - Emulate physics-based sea ice model at fraction of the computational cost
    - Enable reliable predictions from **seasonal to decadal timescales**
    - Advance toward **hybrid Physics - AI modeling**
  - Why it matters?
    - Sea ice numerical modeling can account for up to 20% of total simulation time
    - AI emulators significantly reduce computational burden while preserving predictive skill
- AI approach
  - ConvNeXt U-Net architecture

Can we achieve stable and realistic predictions at seasonal to multi-annual timescales?

Yes, for sea ice thickness and concentration



Credits to: Florent, Nils & Nikolay AWI

Key applications of AI/ML methods in TerraDT

- Sea Ice Impact Model
  - Goal – Fast prediction of sea-ice conditions and drift
  - Application – Offshore wind farm impact assessment
  - Method – U-Net emulator

- Aerosol DTC
  - Goal – Efficient aerosol simulations at high resolution
  - Application – aerosol-climate model acceleration
  - Method – Vision transformer based approach

Key applications of AI/ML methods in TerraDT

- ForestDT impact model
  - Goal:
    - High-resolution forest impact assessment and efficient forest growth emulation
  - Application:
    - Downscaling of coarse land surface data to forest pixel scale,
    - Consistent and coherence forest impact models
  - AI approach:
    - RNN-based forest growth emulator
    - Multiscale, multistage downscaling framework combining empirical constraints and deep learning.

Key applications of AI/ML methods in TerraDT

- Urban Impact model
  - Downscale regional climate information into sub-kilometre.
  - AI approach – ETR (Extra Trees Regressor) – more details in the following presentation by:

Inês Girão,
CoLAB +ATLANTIC



Key applications of AI/ML methods in TerraDT

- Land Surface DTC
  - Goal – High resolution land use change datasets, ML emulator for time varying land cover, LAI
  - AI approach – more details in the following presentation by:

Amirpasha Mozaffari, BSC



Takeaway message

- Physics based numerical models are the core climate models of TerraDT
- AI/ML methods are applied to accelerate computation and enable scalable impact assessments

TerraDT

Digital Twin of Earth system for Cryosphere, Land surface and related interactions

COORDINATOR

CSC

Partners

ALFRED-WEGENER-INSTITUT HELMHOLTZ-ZENTRUM FÜR POLAR- UND MEERESFORSCHUNG

Barcelona Supercomputing Center Centro Nacional de Supercomputación

CoLAB +ATLANTIC

COMMpla Communication Platforms and Online Solutions

DKRZ DEUTSCHES KLIMARECHENZENTRUM

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

CSCS Centro Svizzero di Calcolo Scientifico Swiss National Supercomputing Centre

ILMATIETEEN LAITOS METEOROLOGISKA INSTITUTET FINNISH METEOROLOGICAL INSTITUTE

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TAL TECH

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UPPSALA UNIVERSITET

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THANK YOU

TerraDT

Digital Twin of Earth system for Cryosphere, Land surface and related interactions

CoLAB +ATLANTIC

MAPPING OF HEAT- EXTREME EXPOSURE IN CITIES

Inês Girão

+ATLANTIC CoLAB



Funded by the European Union

TerraDT

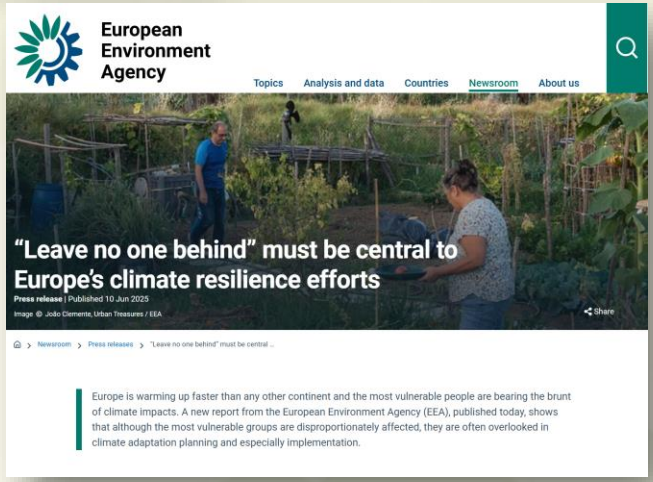
THE PROBLEM

Climate and Environmental Hazards are LOCAL
Their monitoring and forecast IS NOT

Currently, weather, climate and environmental monitoring lacks spatial detail





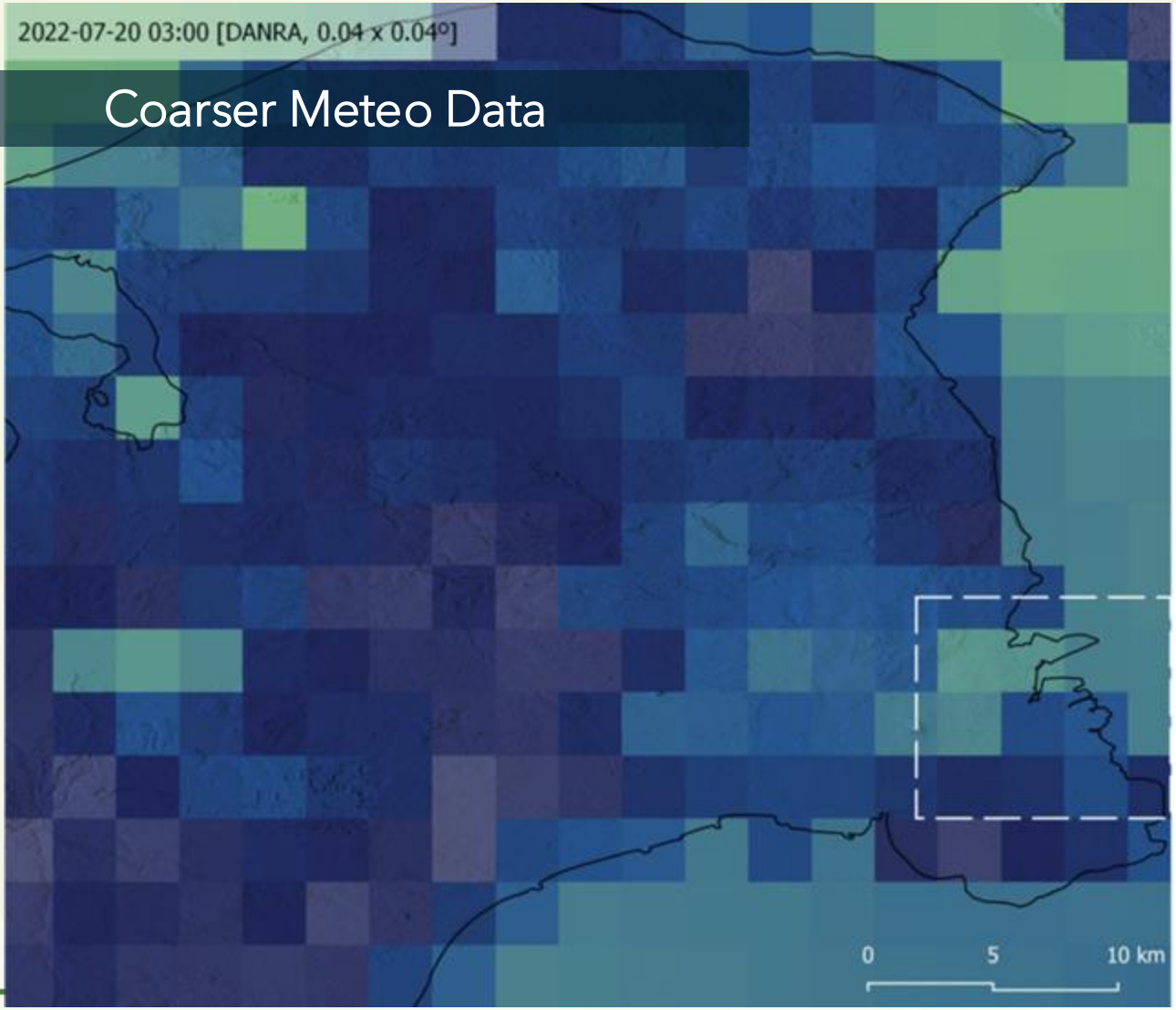


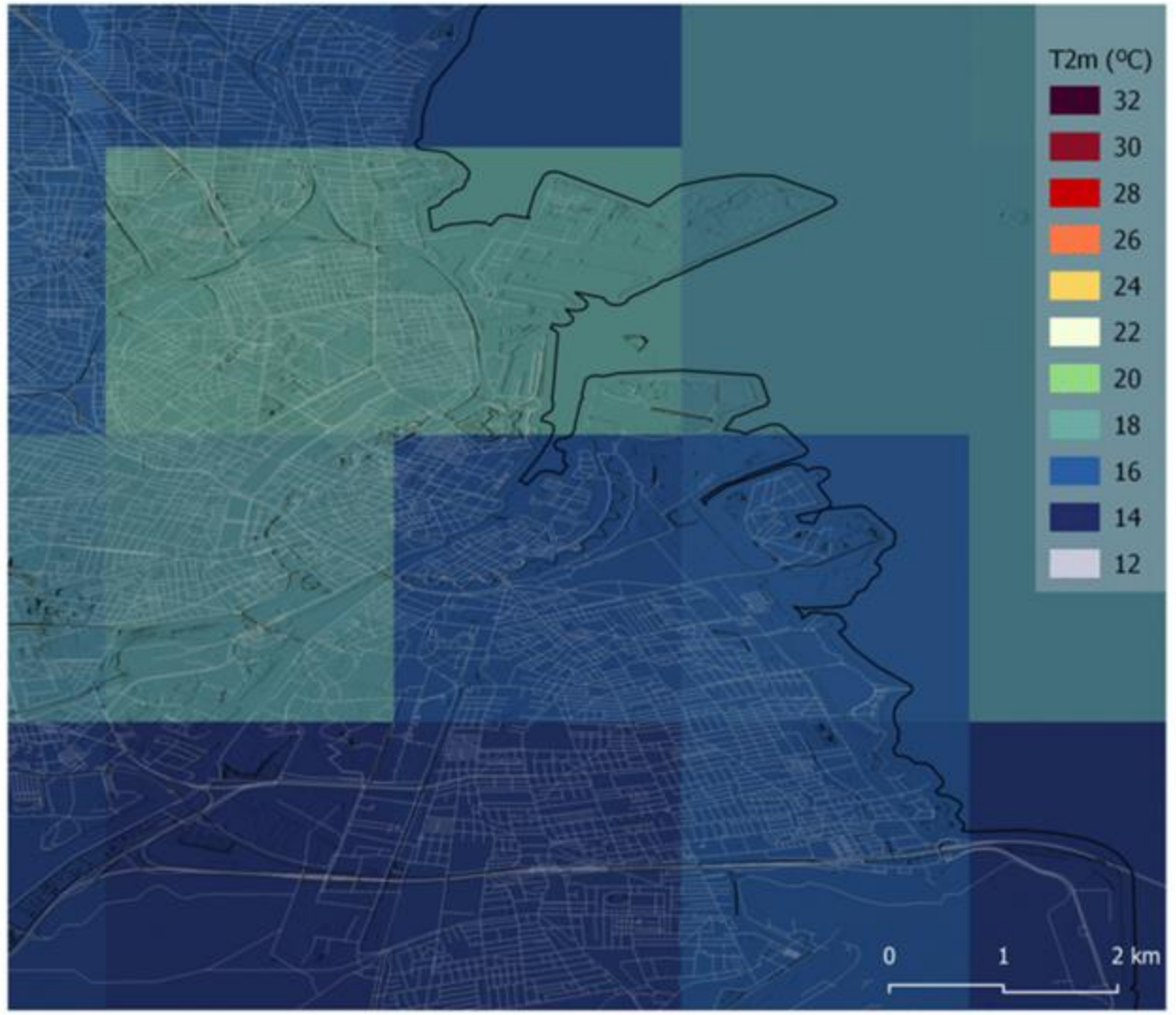
✓ **OK** regarding **WHEN**
! **NOK** regarding **DETAIL**

TerraDT

THE SOLUTION

CLIM4 CITIES

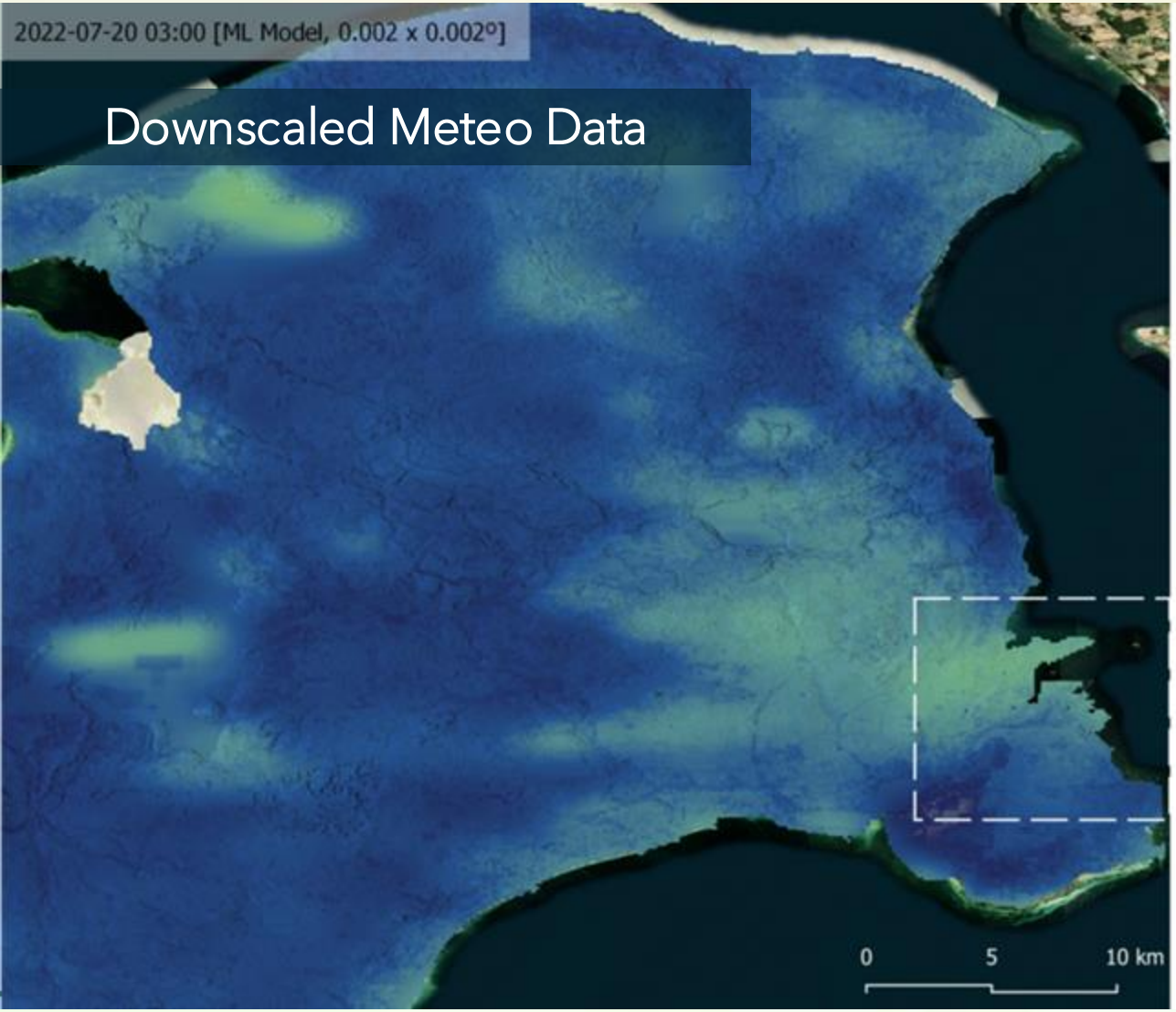


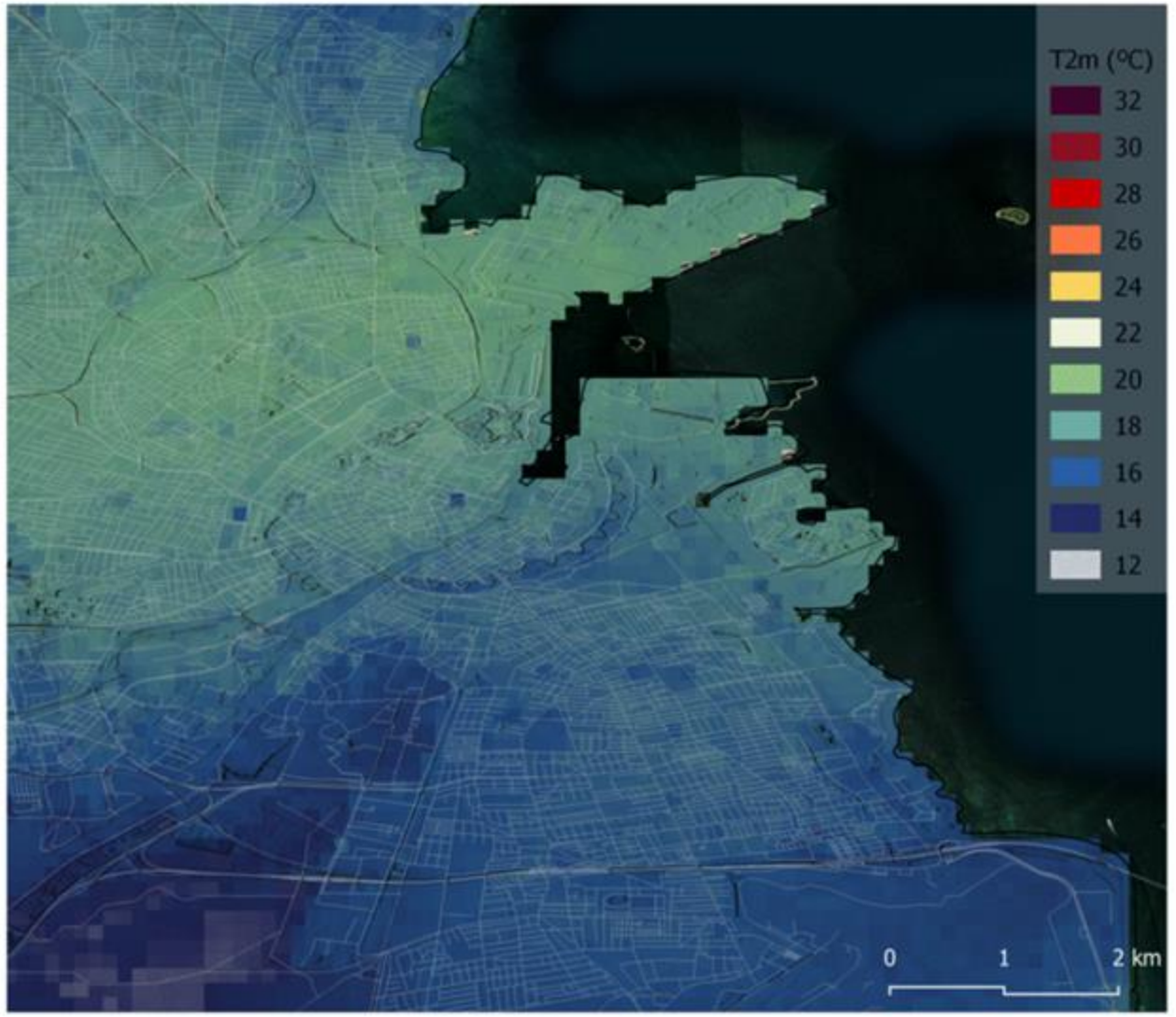


TerraDT

THE SOLUTION

CLIM4 CITIES





TerraDT

THE SOLUTION

Observations

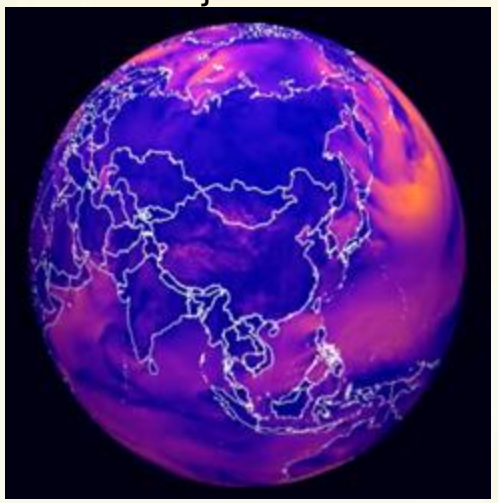
Sensors, IoT, Crowdsourcing



=

Synoptic (Background) Weather

Reanalysis, Forecast and Climate Projections



+

Local (Time-Fixed) Predictors

Landscape and Urban Features

Topography

Terrain, Topographic Wind Exposure

Green Features

Vegetation Density and Type, Phenology

+

Urban Features

Urban Density, Imperviousness, Sky View Factor

Blue Features

Proximity to the Coast or Large Water Bodies

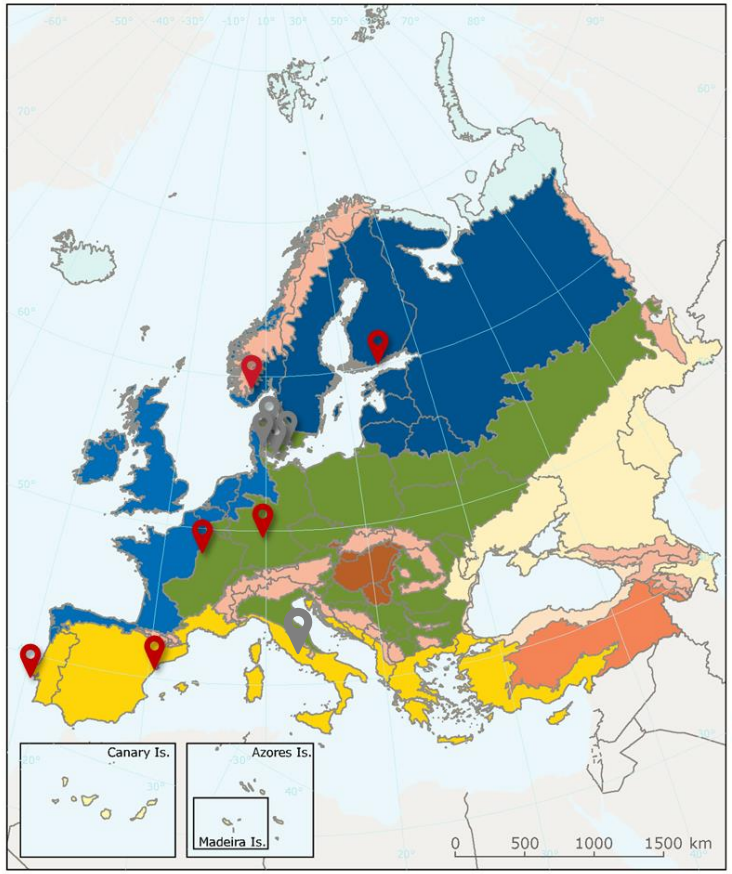
+

Machine Learning

Domain-Informed Data-driven Downscaling



THE SOLUTION

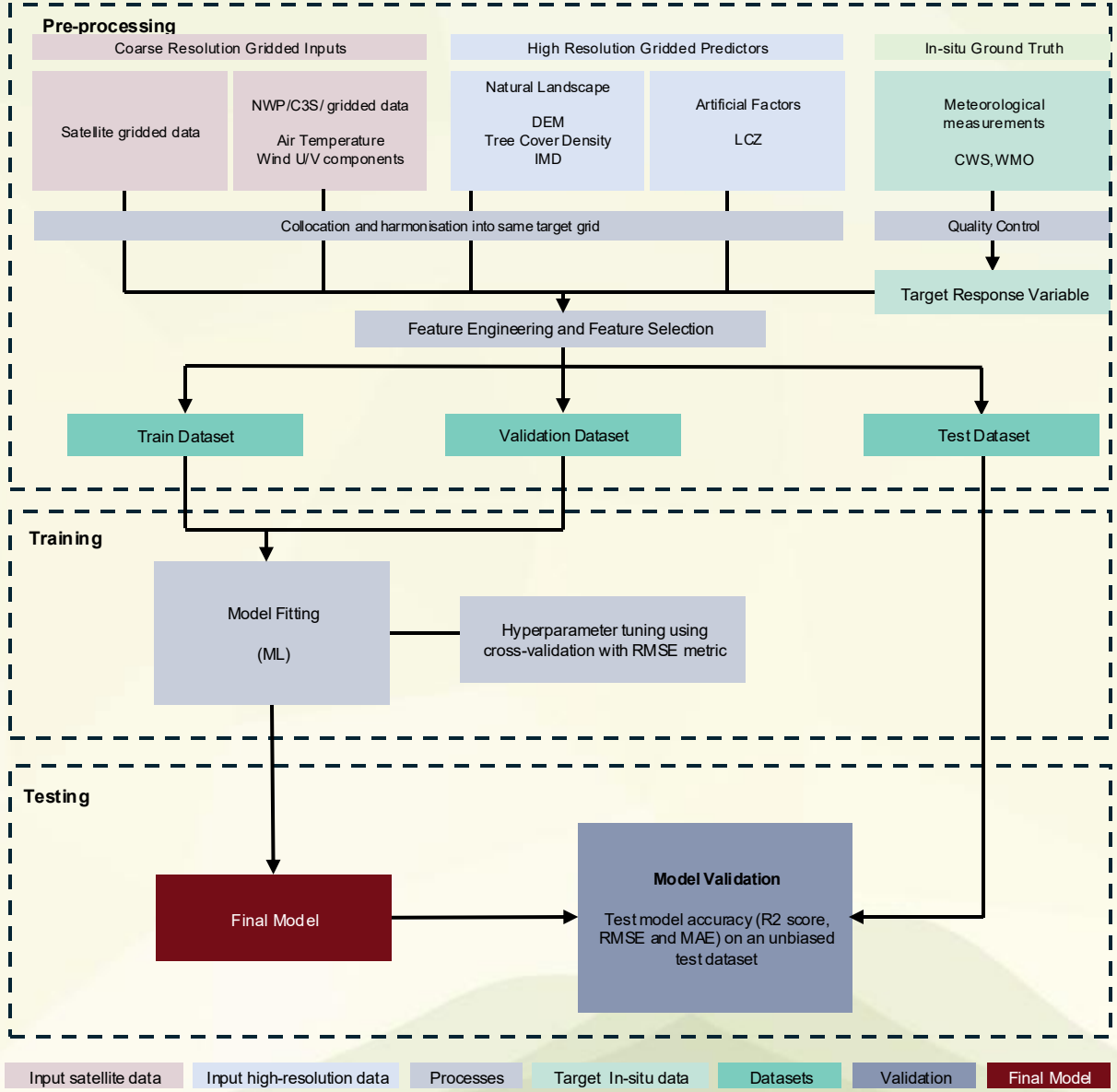


Biogeographical regions in Europe, 2016

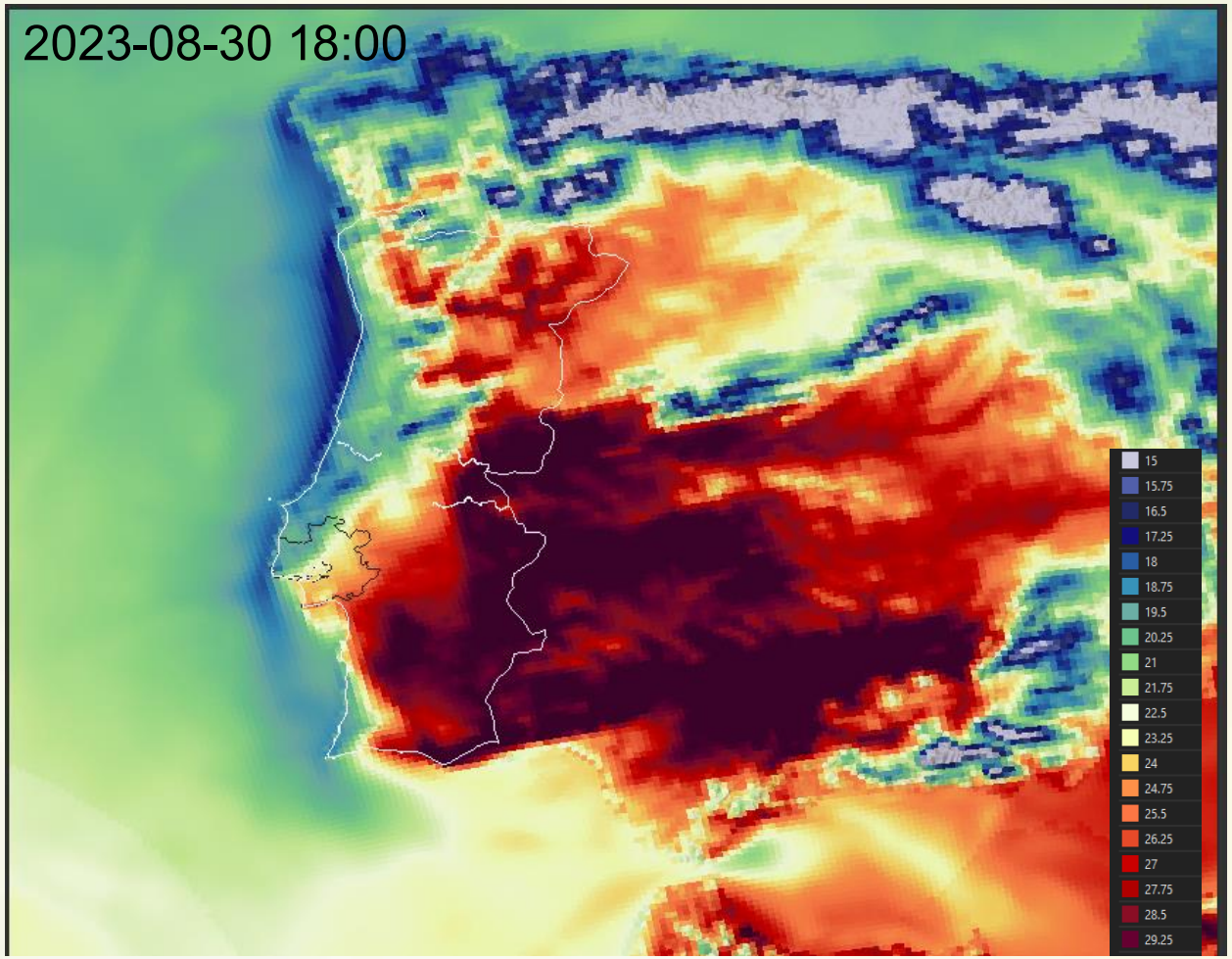
- Alpine
- Anatolian
- Arctic
- Atlantic
- Black Sea
- Boreal
- Continental
- Macaronesia
- Mediterranean
- Pannonian
- Steppic
- Outside data coverage

Project Acronym [Expected ML availability]:
Country: Functional Urban Area

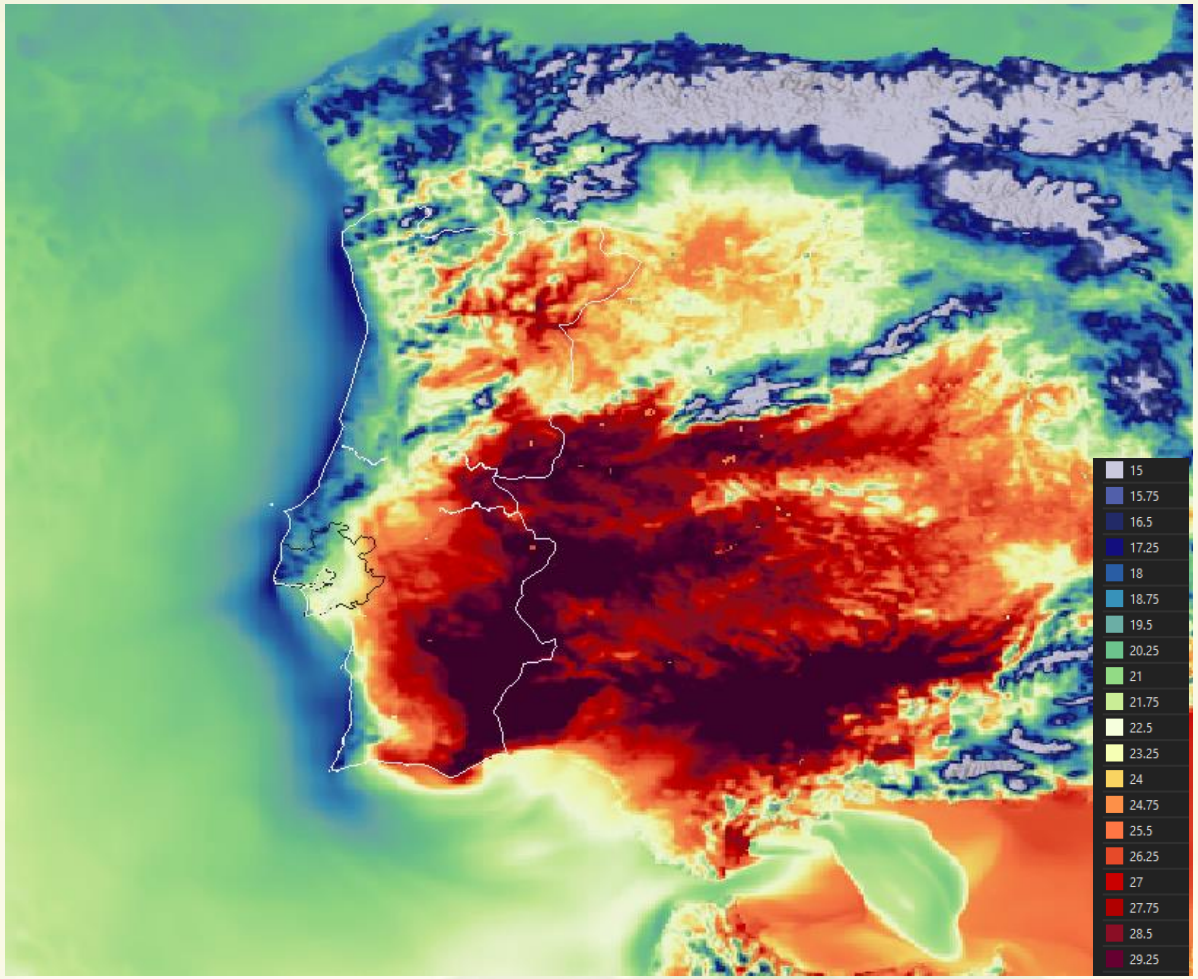
HORIZON EU Terra DT [Mar 2026]:
ES: Barcelona
PT: Lisbon
FI: Helsinki
DE: Munich
FR: Paris



TerraDT

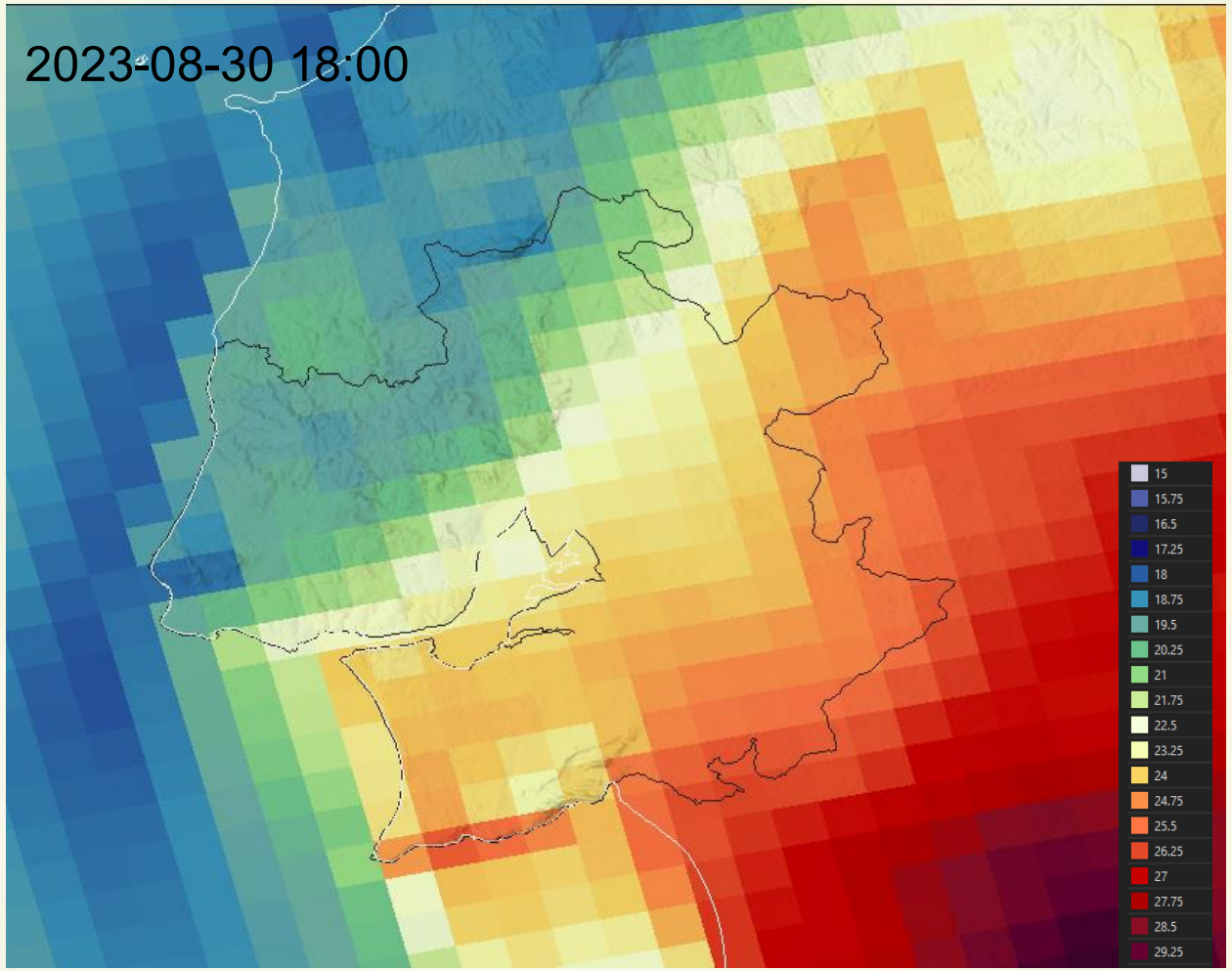


CERRA (0.05x0.05º)

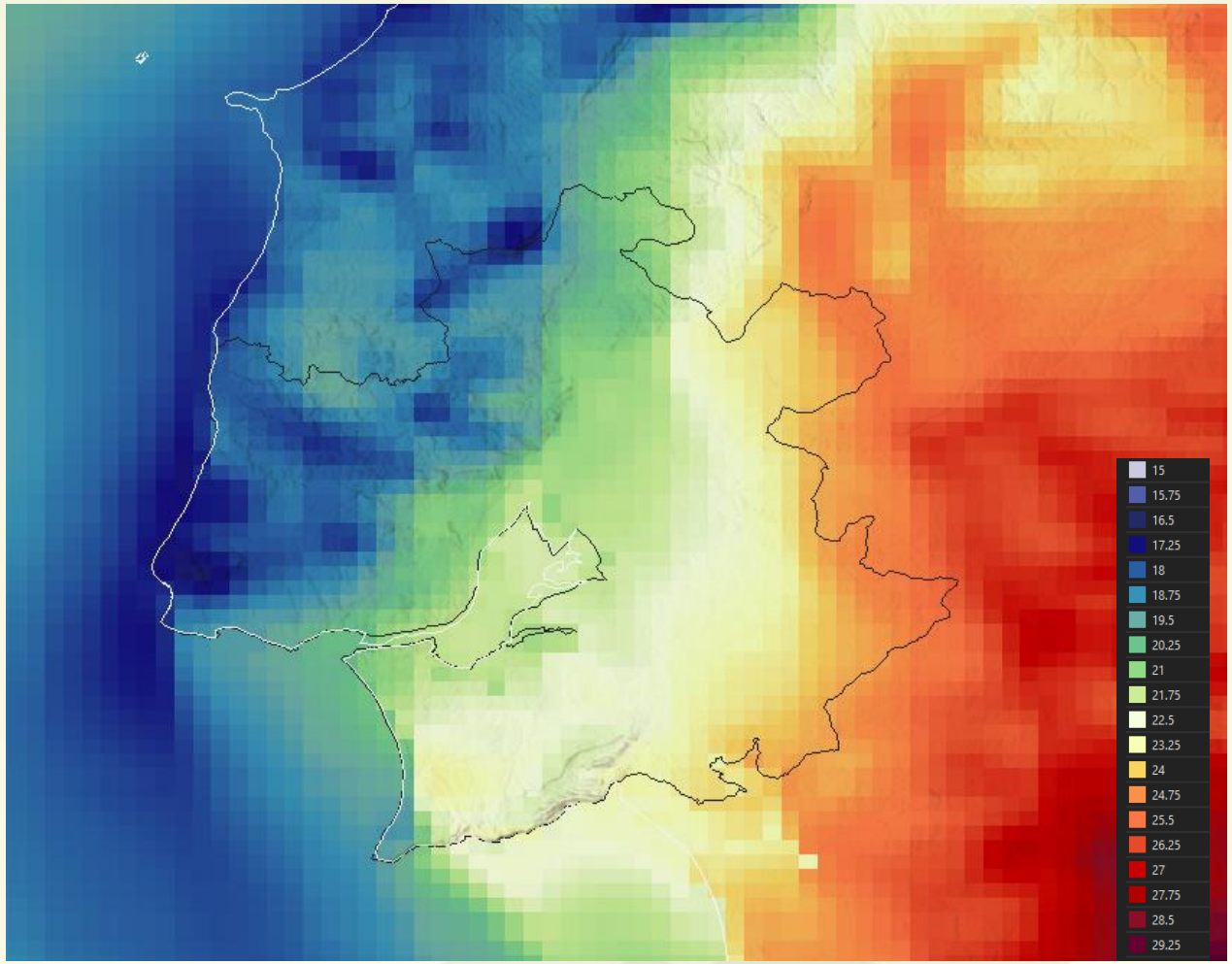


AROME - IBI (0.025x0.025º)

TerraDT



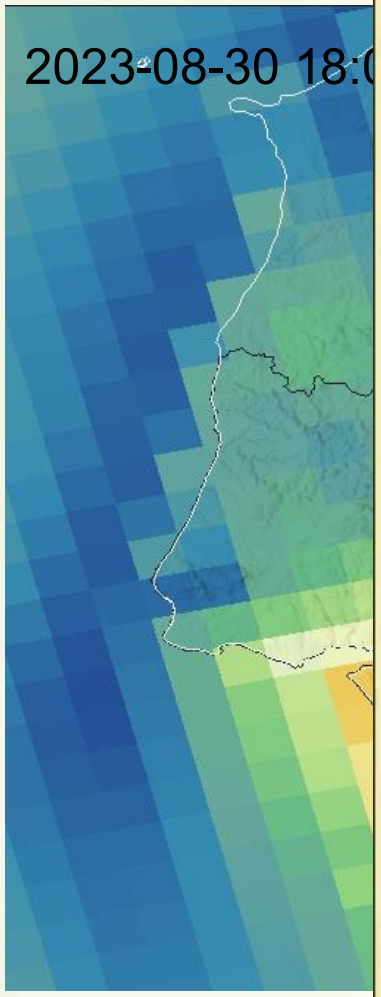
CERRA (0.05x0.05º)



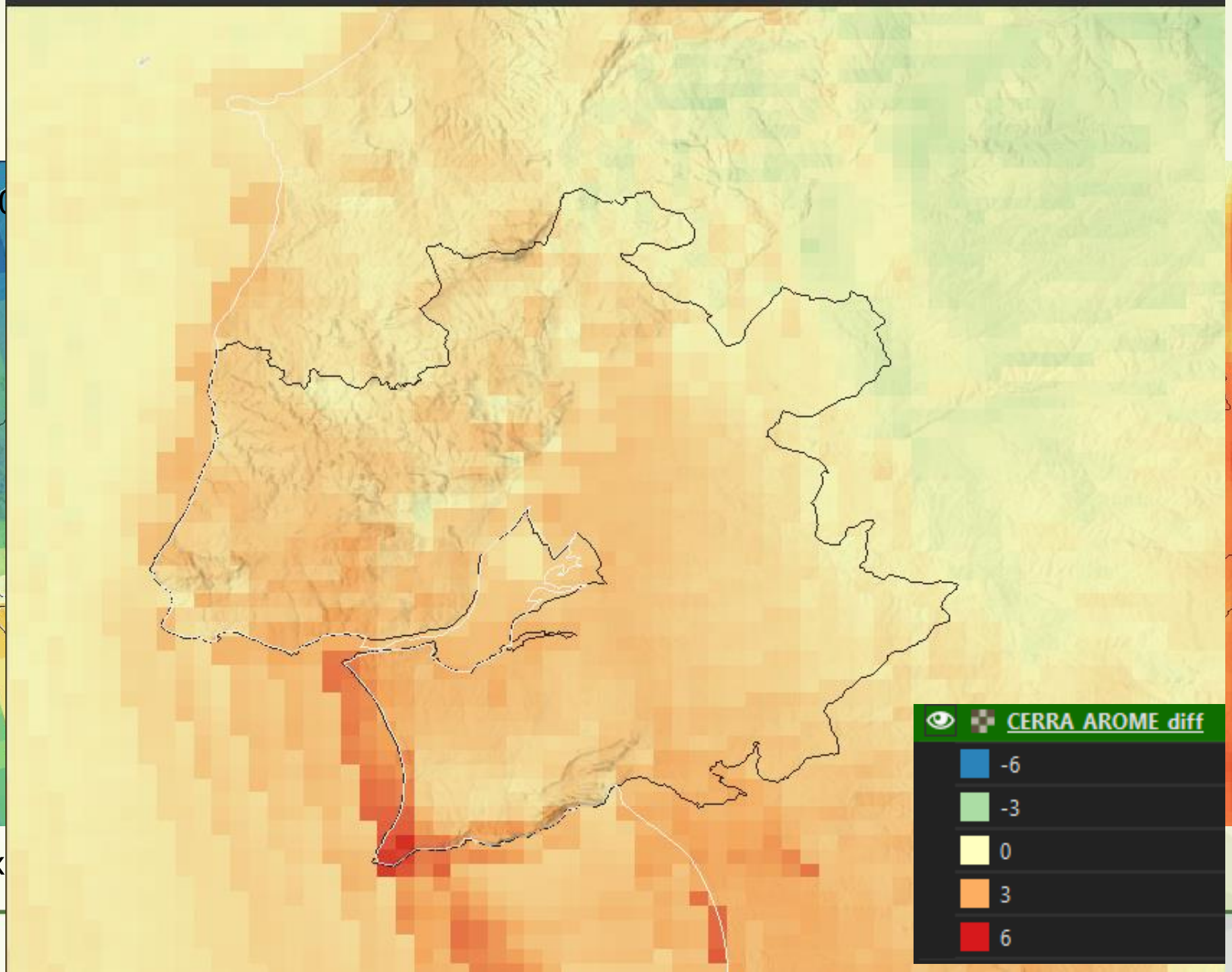
AROME - IBI (0.025x0.025º)

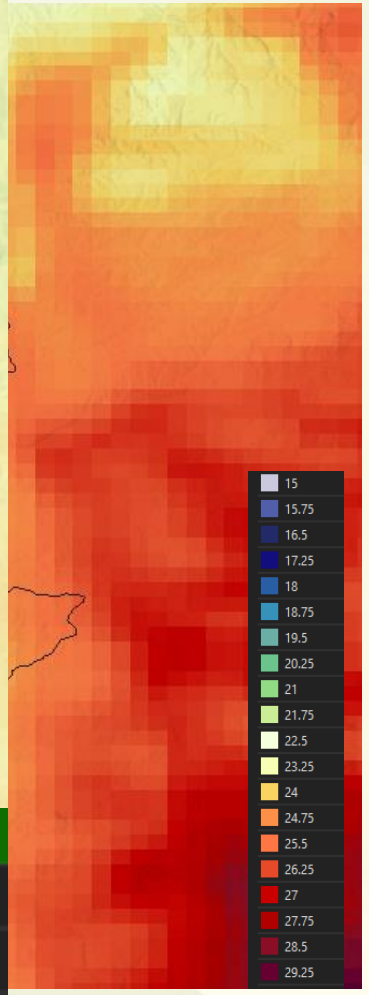
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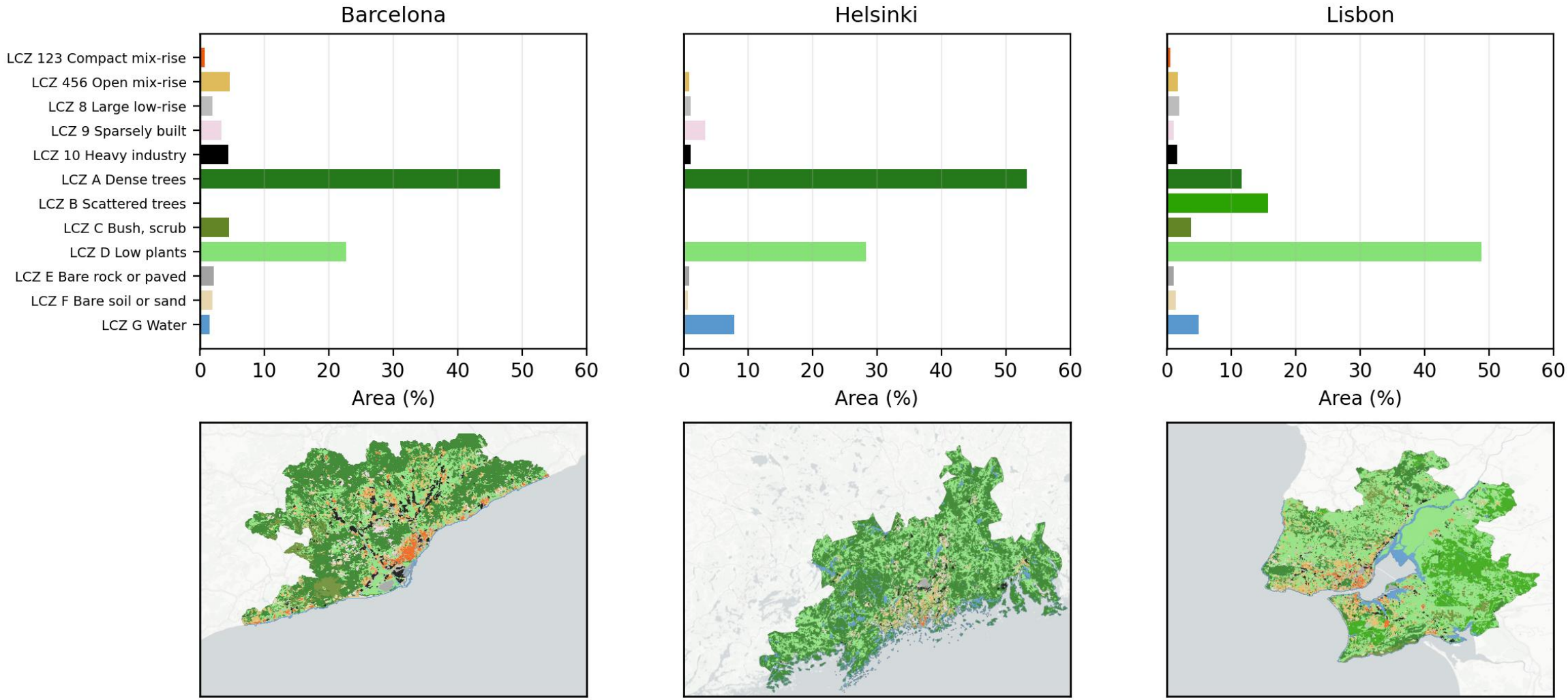
2023-08-30 18:0



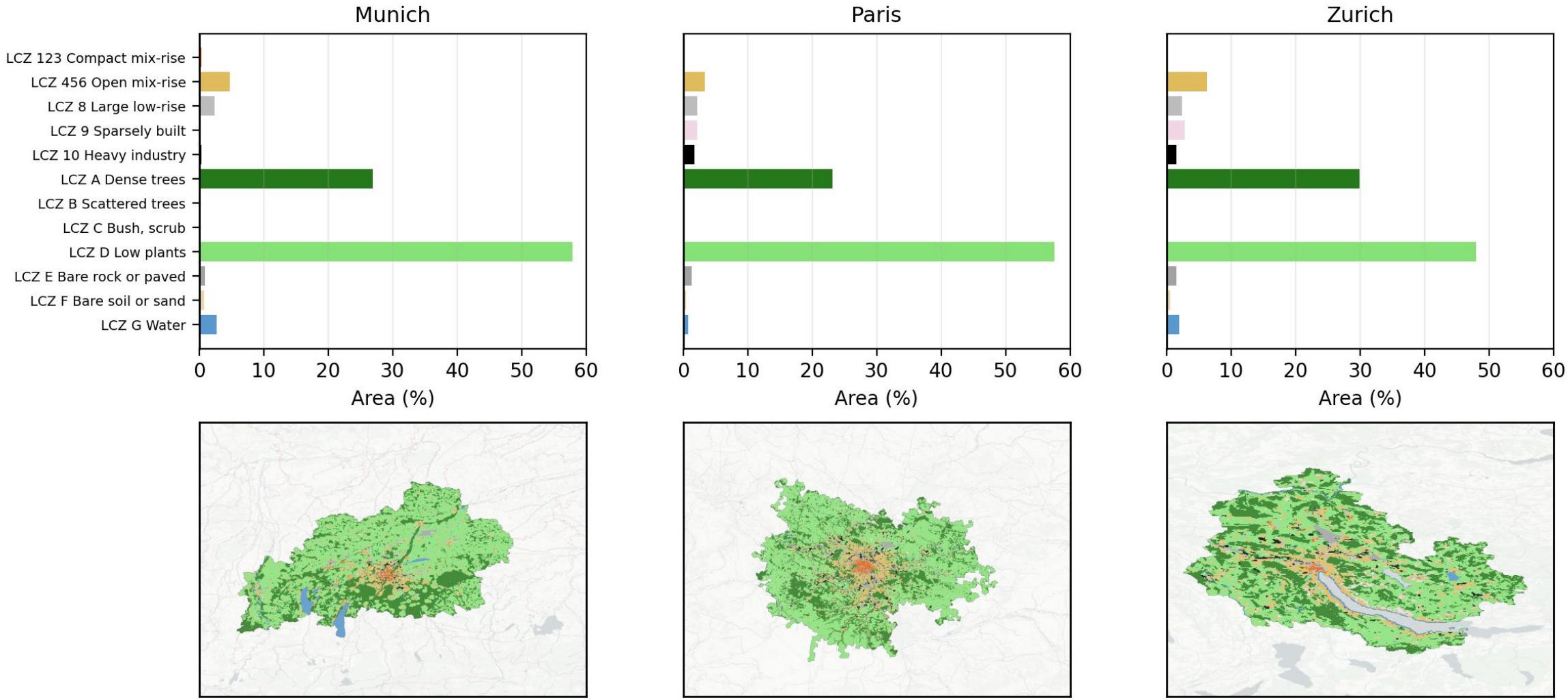
CERRA (0.05x





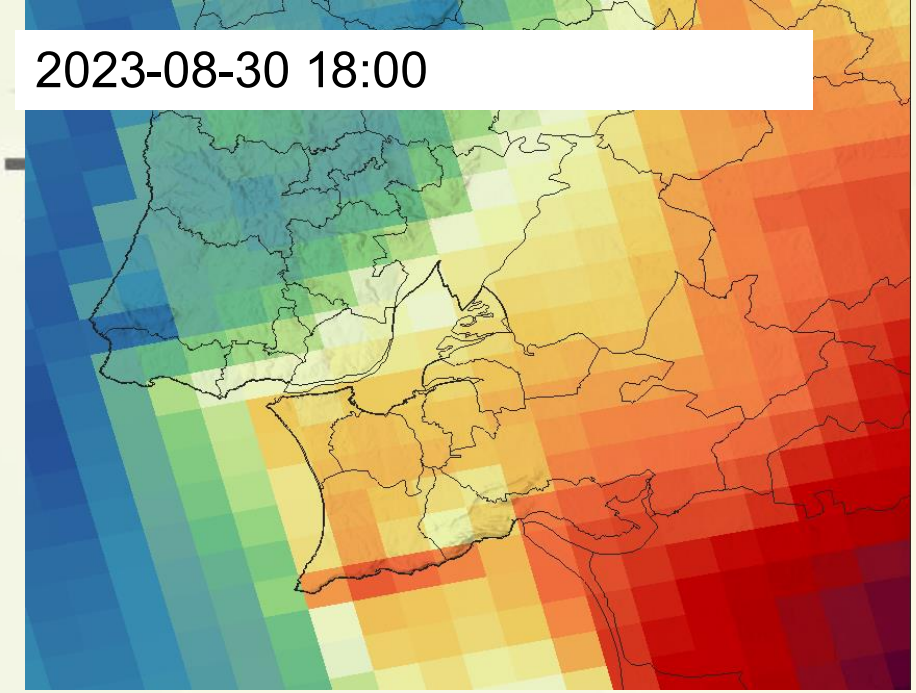


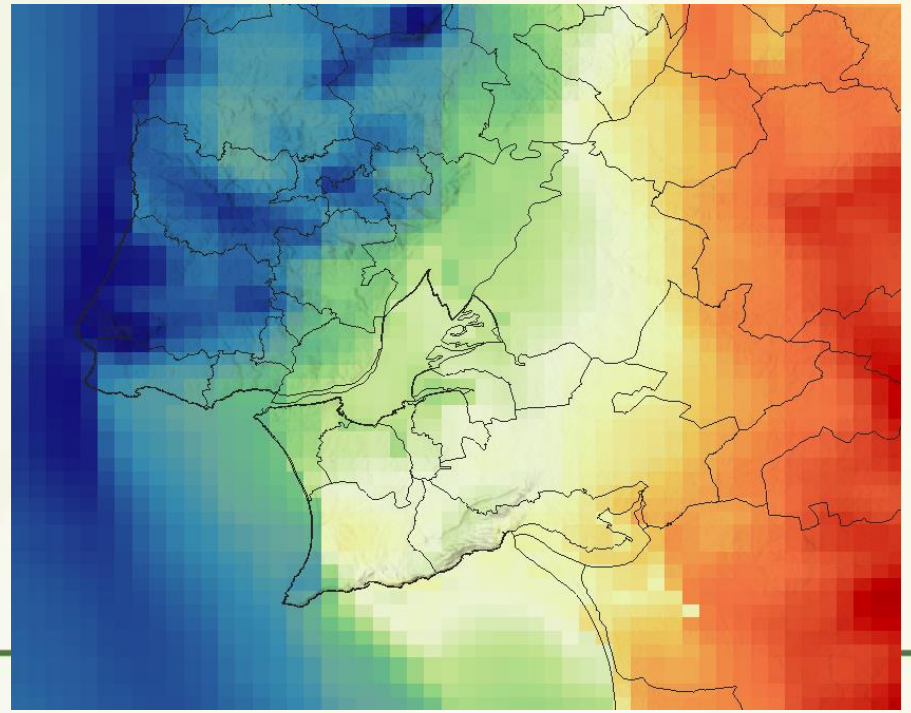
Oliveira et al., 2020

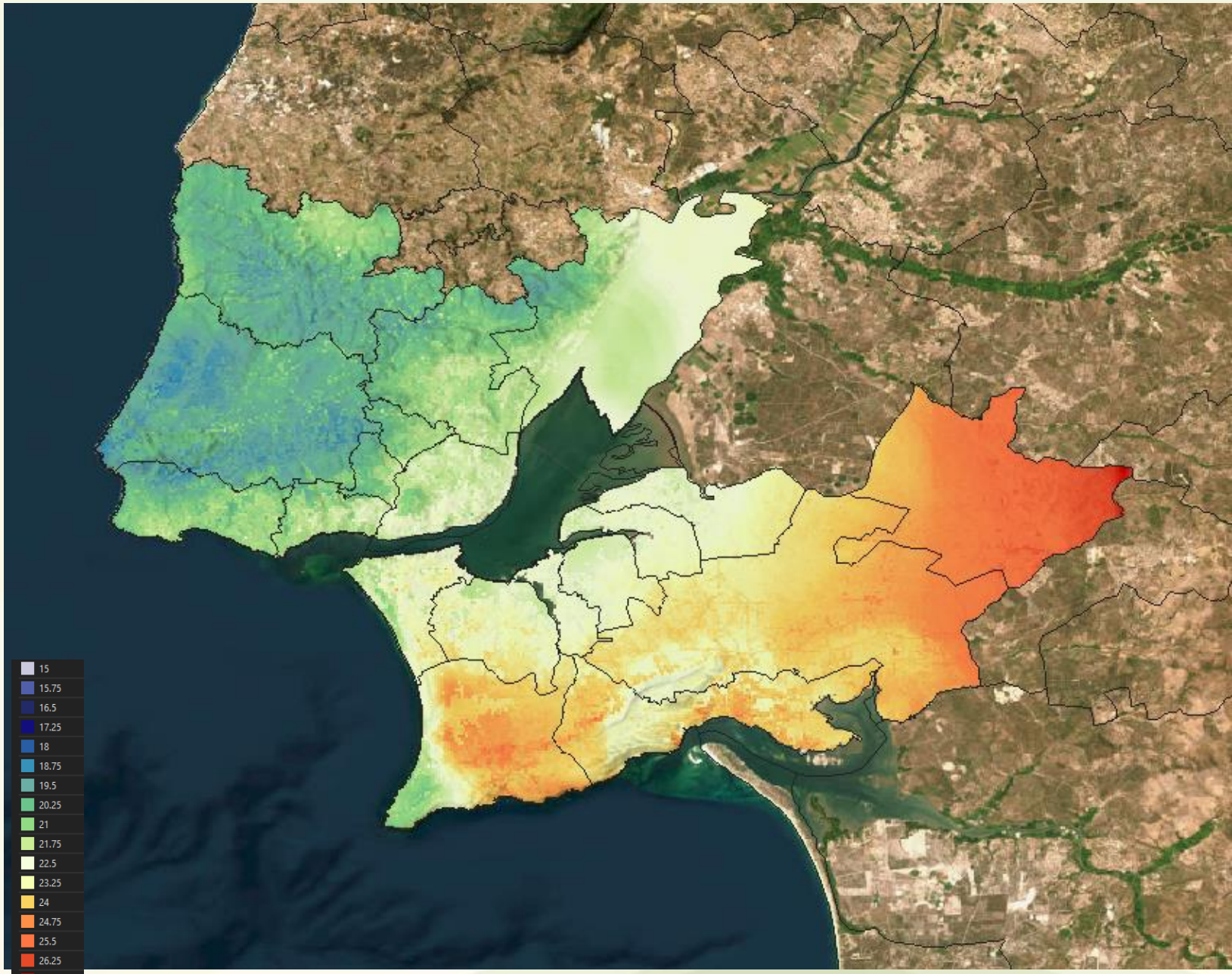


Oliveira et al., 2020

2023-08-30 18:00

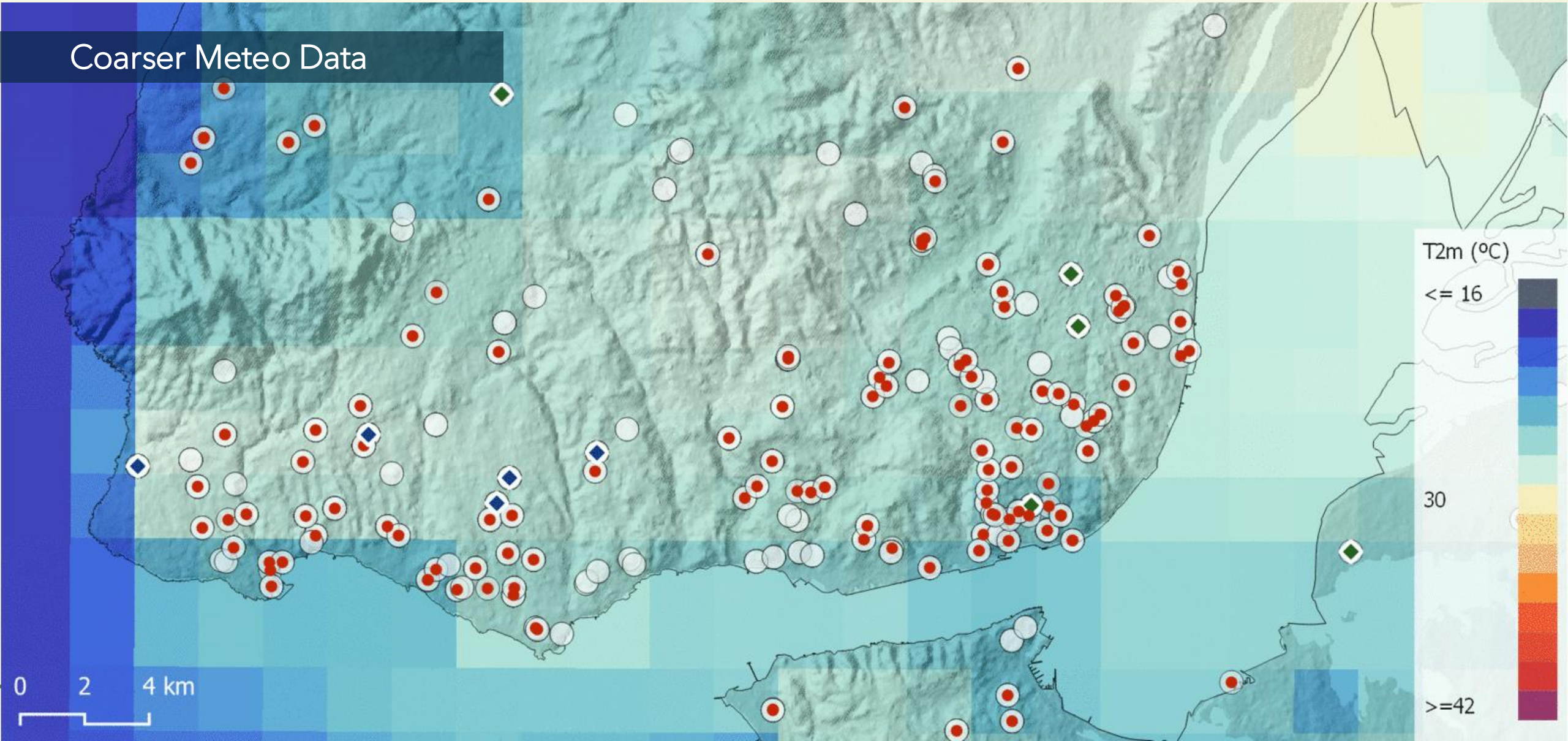




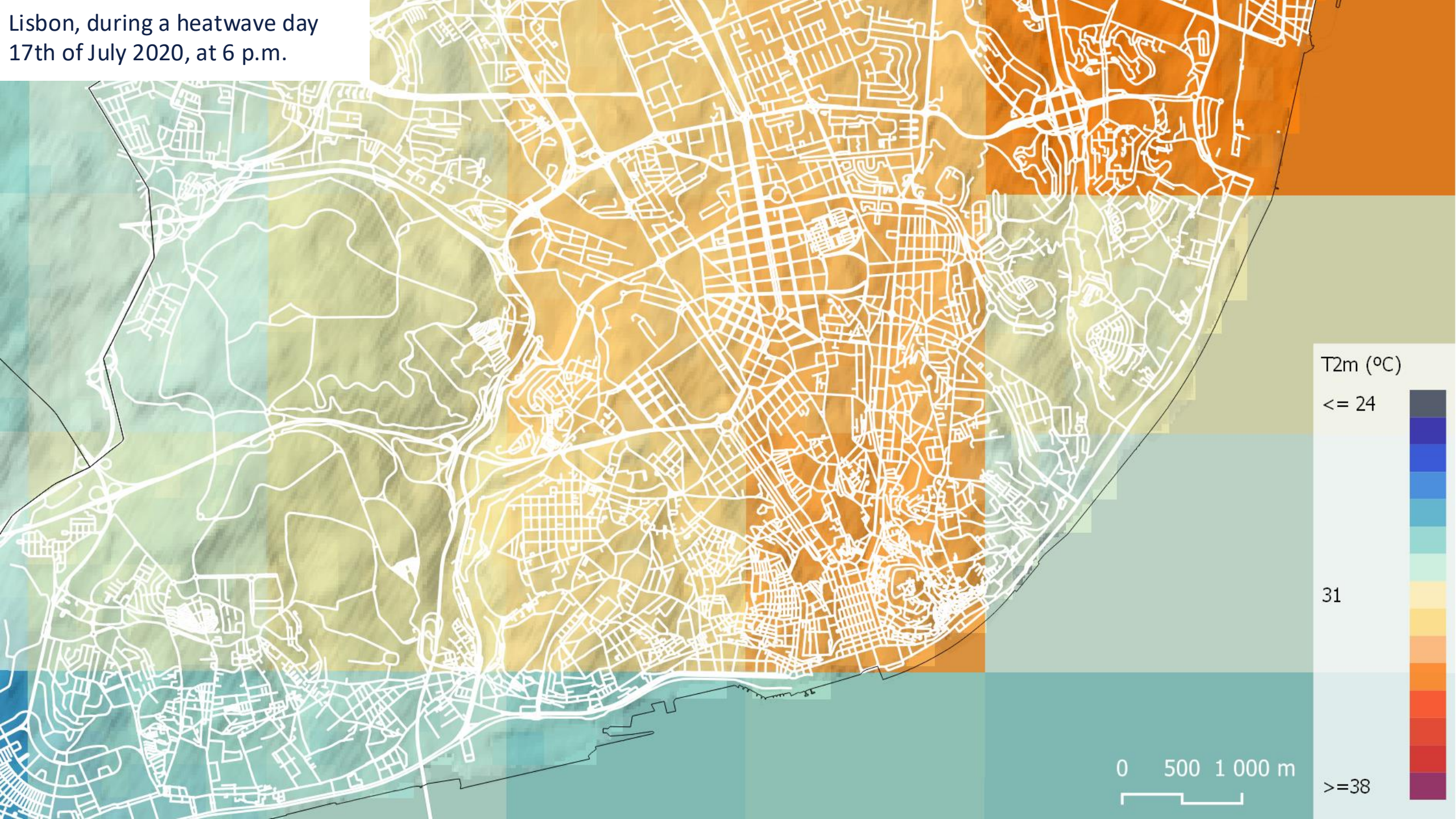


TerraDT

Coarser Meteo Data

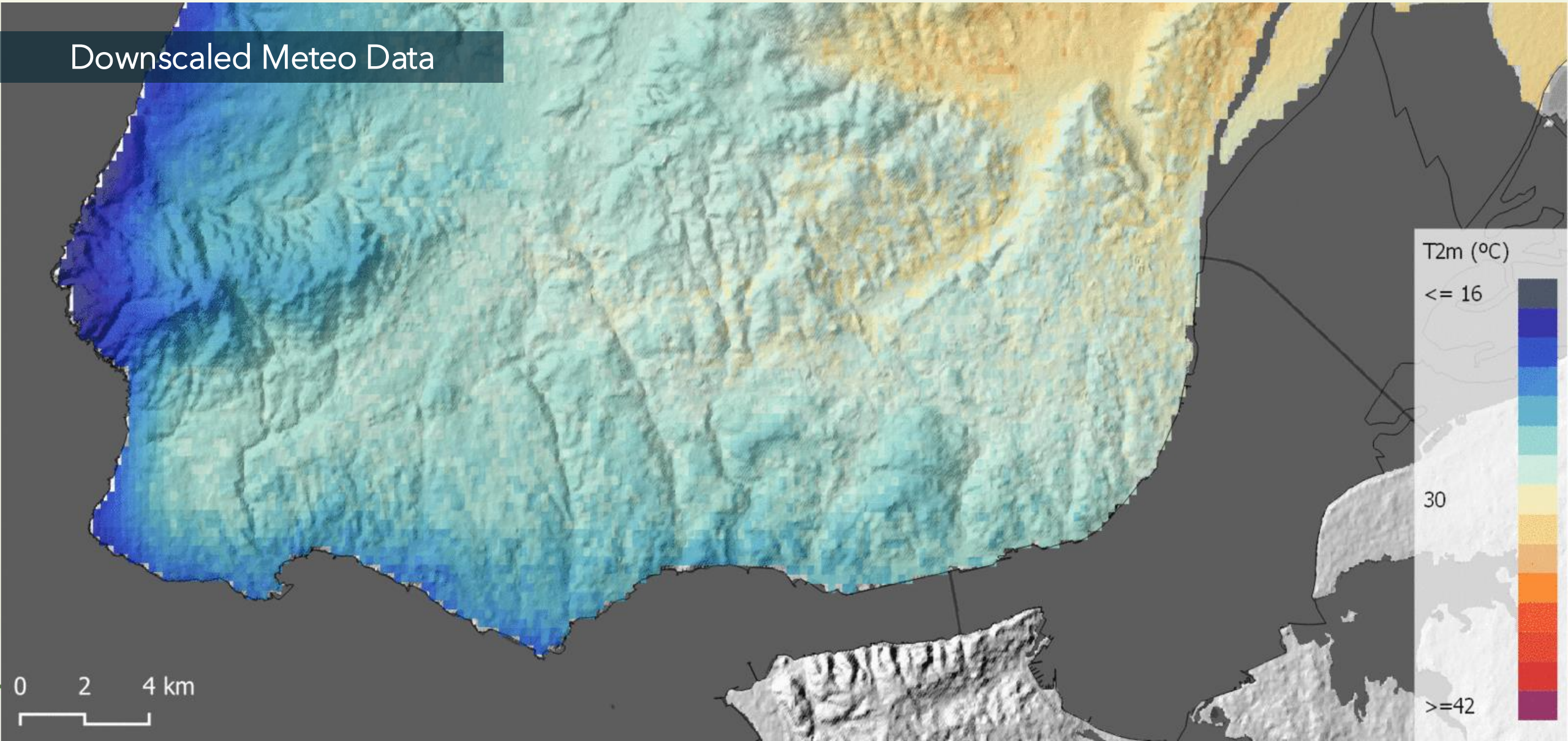


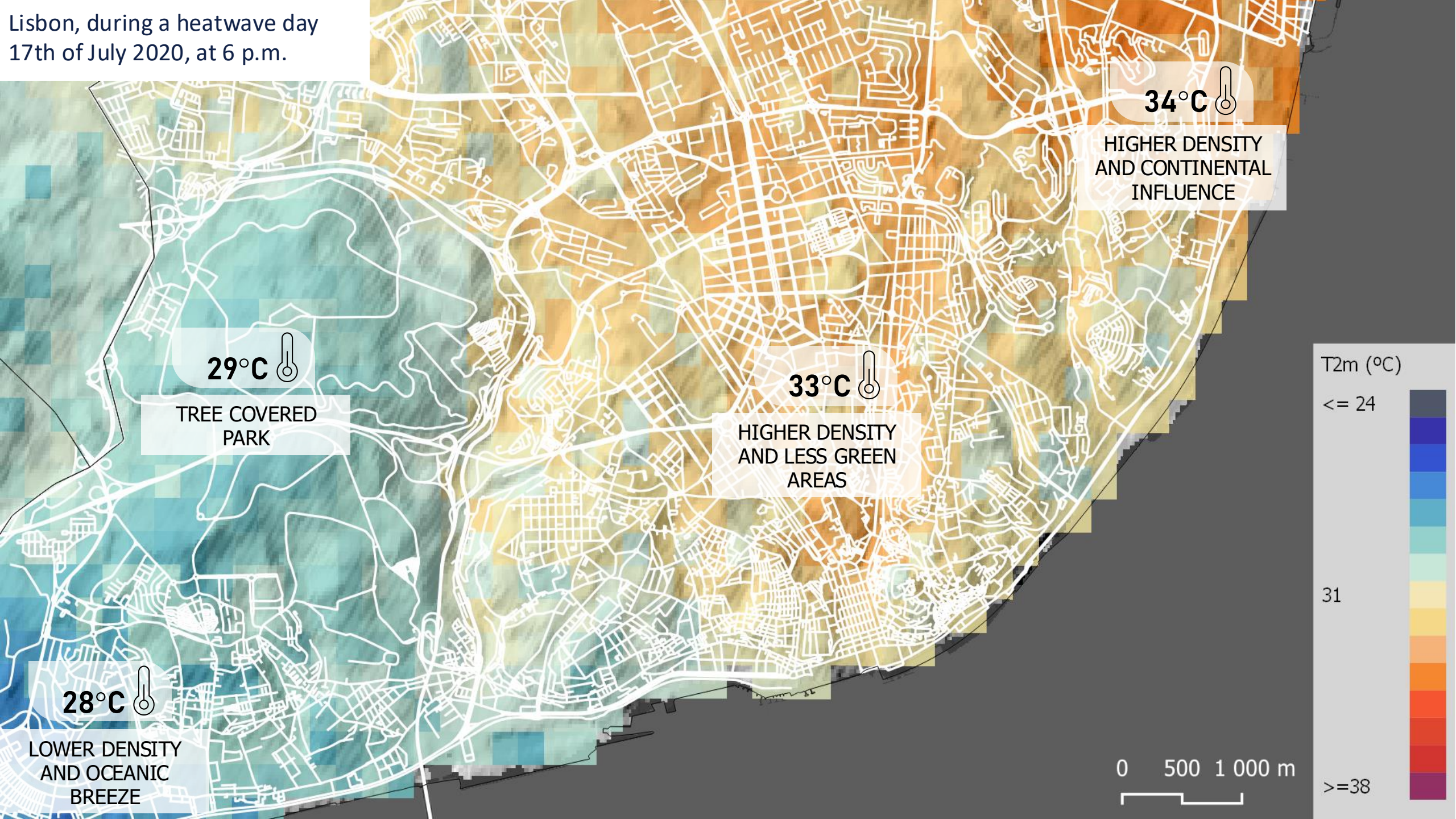
Lisbon, during a heatwave day
17th of July 2020, at 6 p.m.



TerraDT

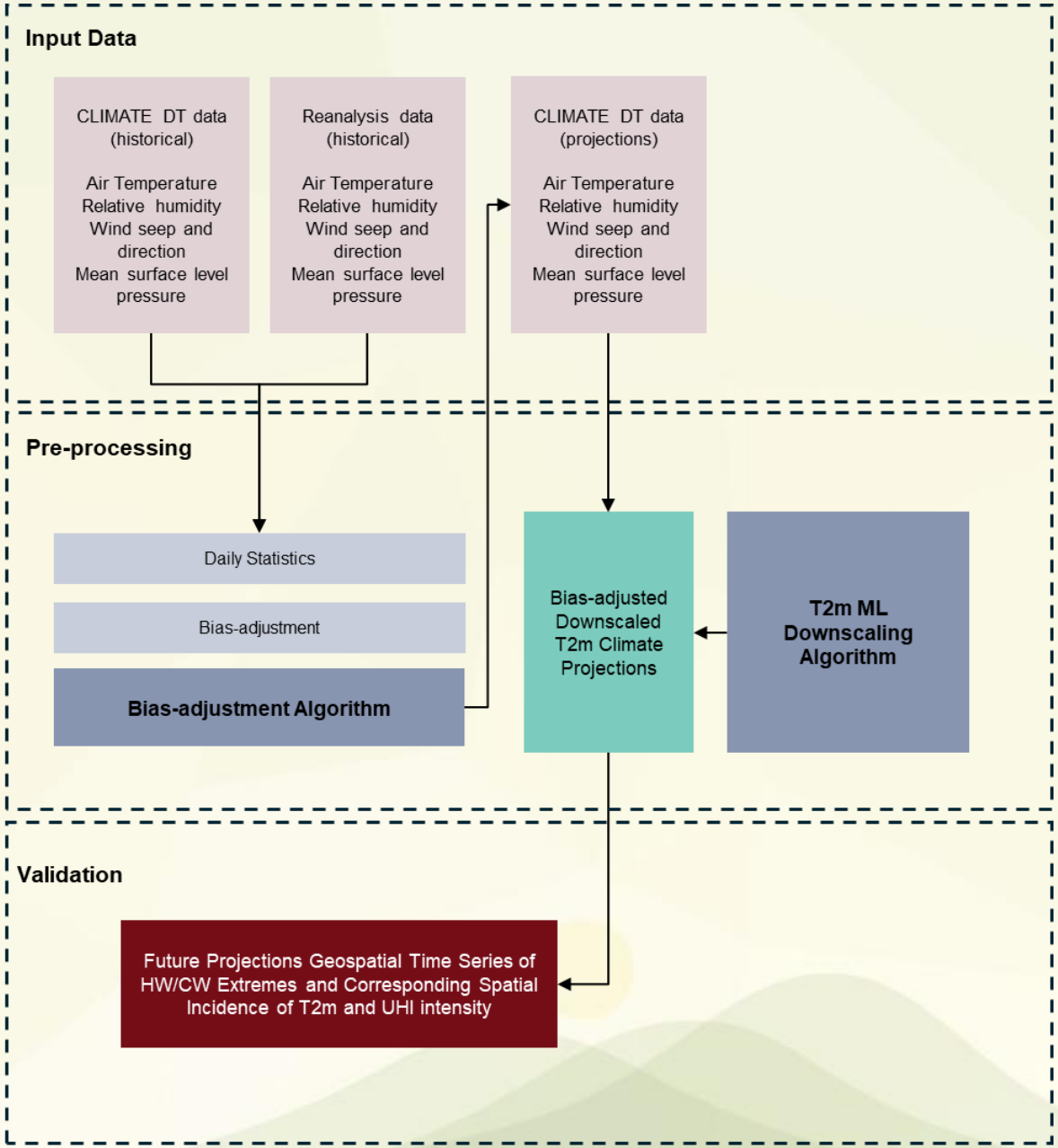
Downscaled Meteo Data




Lisbon, during a heatwave day
17th of July 2020, at 6 p.m.
34°C
HIGHER DENSITY AND CONTINENTAL INFLUENCE
29°C
TREE COVERED PARK
33°C
HIGHER DENSITY AND LESS GREEN AREAS
28°C
LOWER DENSITY AND OCEANIC BREEZE
T2m (°C)
<= 24
31
>=38
0 500 1 000 m

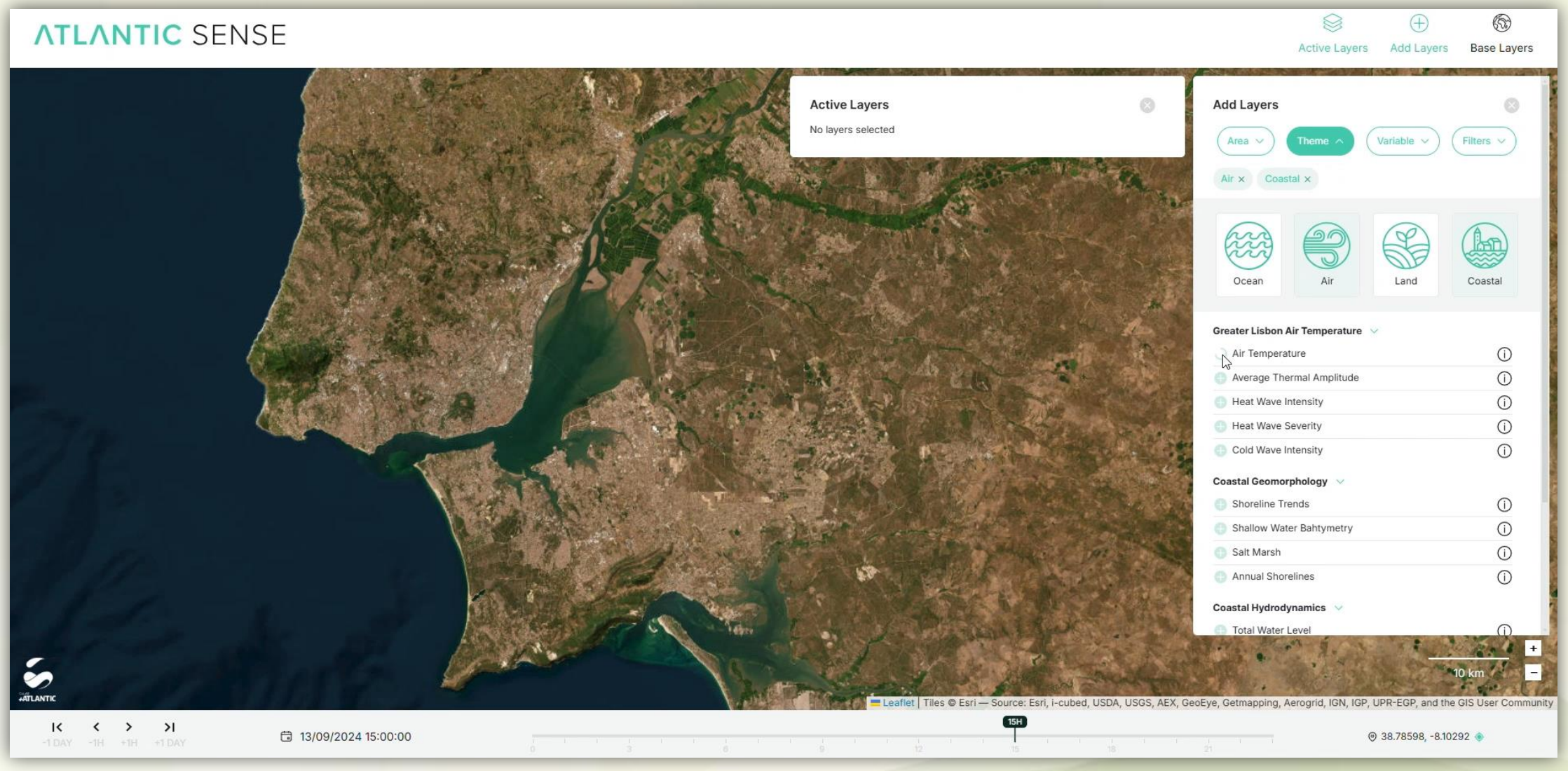
TerraDT

What about the future?



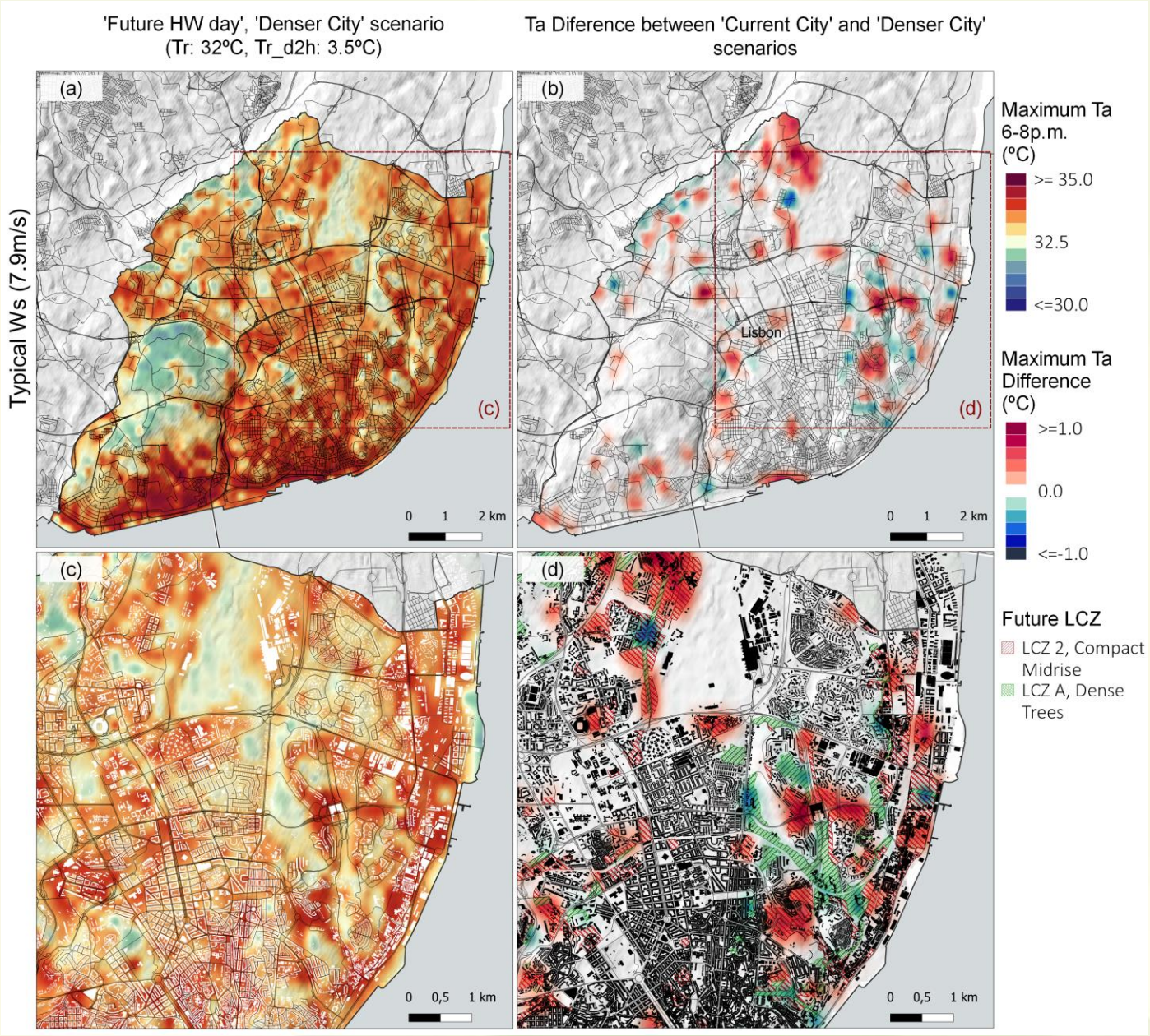
Input data | Processes | Datasets | Models | Results

TerraDT


ATLANTIC SENSE
Active Layers
Add Layers
Base Layers
Active Layers
No layers selected
Add Layers
Area
Theme
Variable
Filters
Air ×
Coastal ×
Ocean
Air
Land
Coastal
Greater Lisbon Air Temperature
Air Temperature
Average Thermal Amplitude
Heat Wave Intensity
Heat Wave Severity
Cold Wave Intensity
Coastal Geomorphology
Shoreline Trends
Shallow Water Bahtymetry
Salt Marsh
Annual Shorelines
Coastal Hydrodynamics
Total Water Level
10 km
Leaflet | Tiles © Esri — Source: Esri, i-cubed, USDA, USGS, AEX, GeoEye, Getmapping, Aerogrid, IGN, IGP, UPR-EGP, and the GIS User Community
-1 DAY
-1H
+1H
+1 DAY
13/09/2024 15:00:00
15H
38.78598, -8.10292

TerraDT

- How much cooler/warmer a neighbourhood is, compared to the long-term average climate?
- How extreme is the heat (cold) in a given neighbourhood, compared to the local temperature range?
- Which are the cooling (heating) acclimatization needs, in each neighbourhood?



TerraDT

Digital Twin of Earth system for Cryosphere, Land surface and related interactions

THANK YOU

CoLAB +ATLANTIC



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TerraDT

Digital Twin of Earth system for Cryosphere, Land surface and related interactions

Constructing the high-resolution, time-varying land-use dataset with machine learning

Machine learning in TerraDT: from emulators to impact models for the cryosphere and land surface



Amirpasha Mozaffari, Marina Castaño, Stefano Materia, Etienne Tourigny, Oscar Molina-Sedano, Jordi Varela-Agrelo, Dario Garcia-Gasulla, Miguel Castrillo Melguizo, Mario Acosta, Amanda Duarte

Funded by the European Union

The team behind this work



Amanda Duarte[1]



Amirpasha Mozaffari[1]



Marina Castaño[1]



Ferran Mirabent Rubinat[1]



Joan Vedri Casino[1]



Miguel Castrillo Melguizo[1]



Stefano Materia[1]



Etienne Tourign[1]



Junyan Ding[1]



Dario Gracia Gasulla[2]



Oscar Molina-Sedano[2]



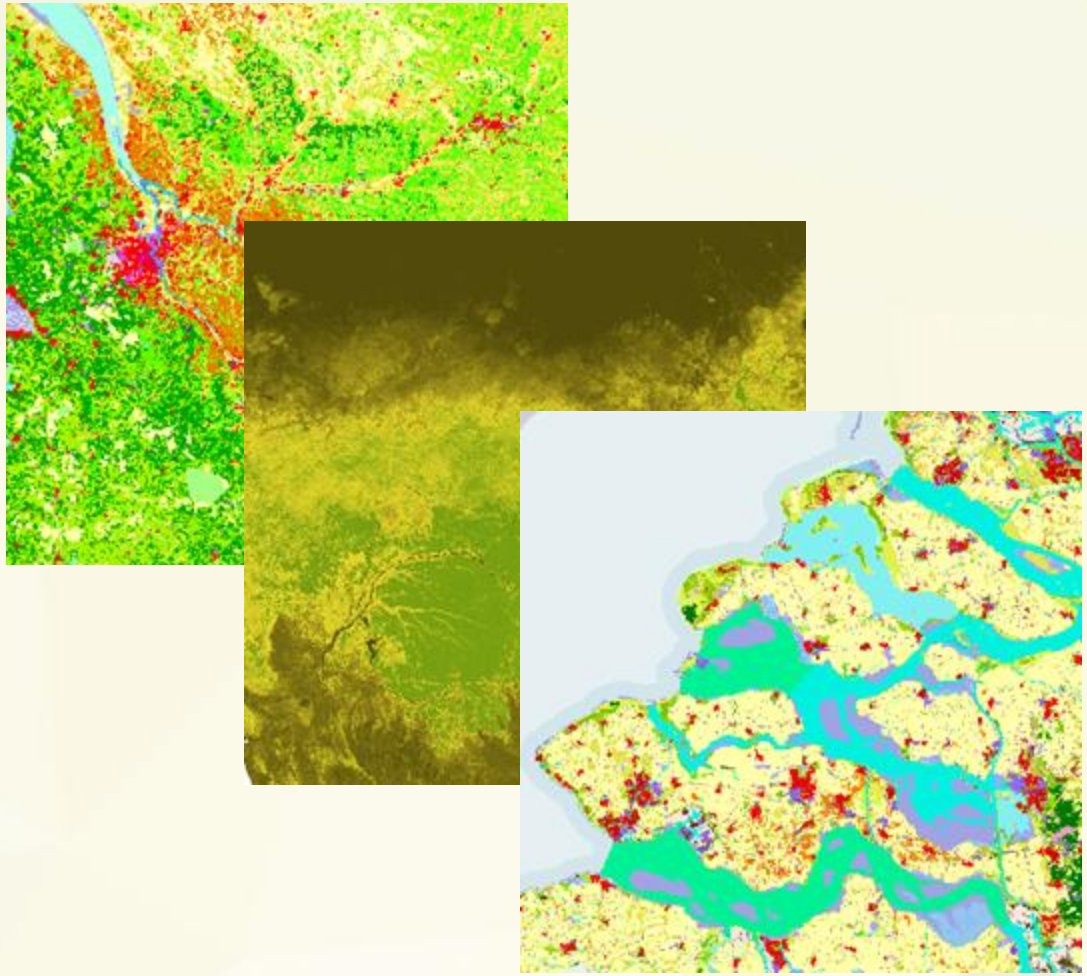
Jordi Varela Agrelo[2]

1: Earth Department, BSC
2: AI Institute, BSC

Motivation

Lack consistent, **high-resolution datasets** for historical periods (pre-EO) and future projections.

We aim at Improving the representation of **land surface parameters** to ensure more realistic fluxes of water, energy, and carbon towards the atmosphere.



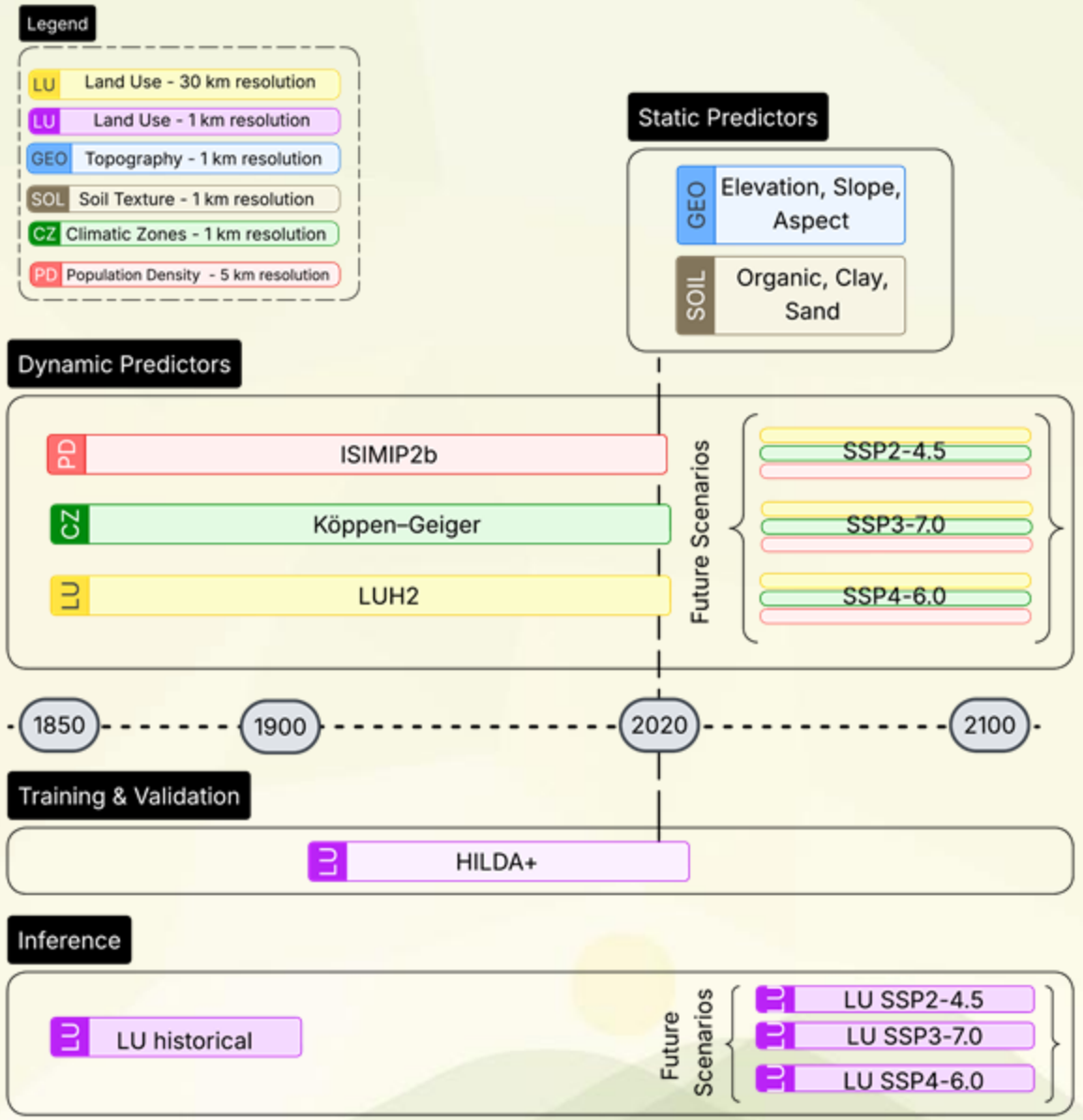
Goals

To produce:

- High-resolution global map of **land use** change (LU) covering the historical and the future scenario period (1850-2100)
- High-resolution dataset of annually-varying **land cover** (LC)
- High-resolution dataset of weekly-varying **leaf area index** (LAI)
- And couple the produced models into weather-climate frameworks to serve as **real-time land surface emulators** for Digital Twins of the Earth

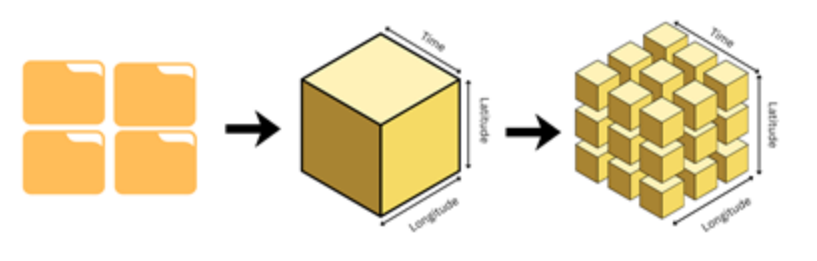
Land Use

- **Dynamic Predictors**: coarse-resolution ~30km LU data (LUH2h), and high-resolution 1km data for population (ISIMIP2b) and climatic zones (Köppen-Geiger)
- **Static Predictors**: high-resolution 1km data for topography and soil (GEBCO, PNNL)
- **Training Target**: high-resolution 1km LU data (HILDA+)
- **Final Output**: 1km resolution LU dataset spanning 1850-2100



Data structure

In collaboration with AI Factory, we already have a working prototype pipeline to generate a unified ARCO* Zarr store for LU reconstruction task.



- *Regridded data from several sources (7.6 TB)*
- *NetCDF files*
- *Fixed variables and yearly variables (23 variables)*
- *2D variables*

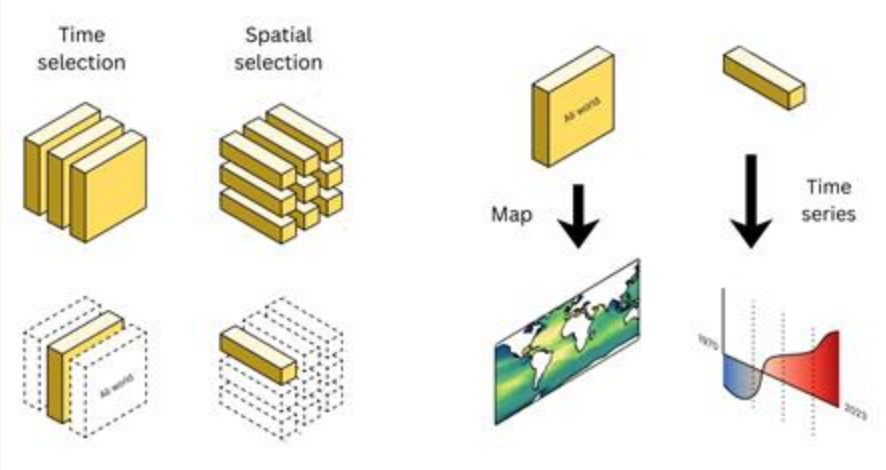
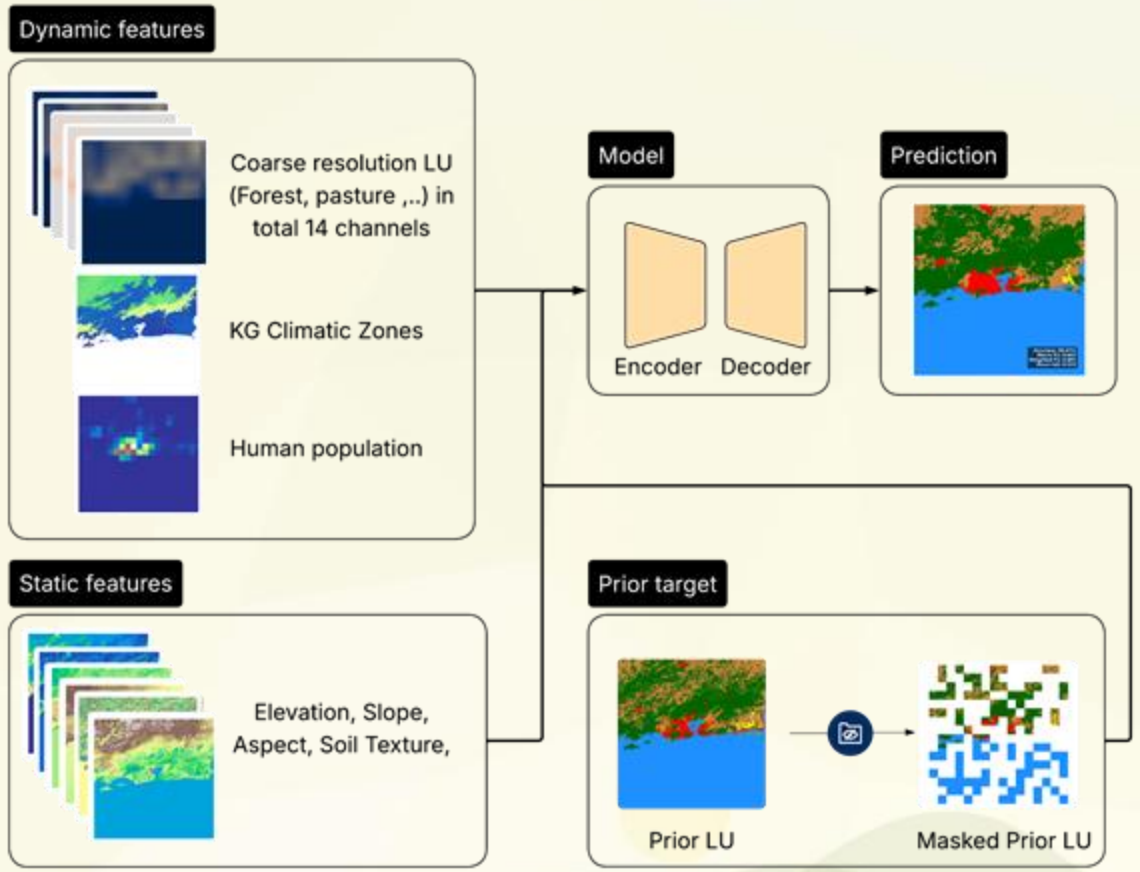


Image: Lobelia.earth

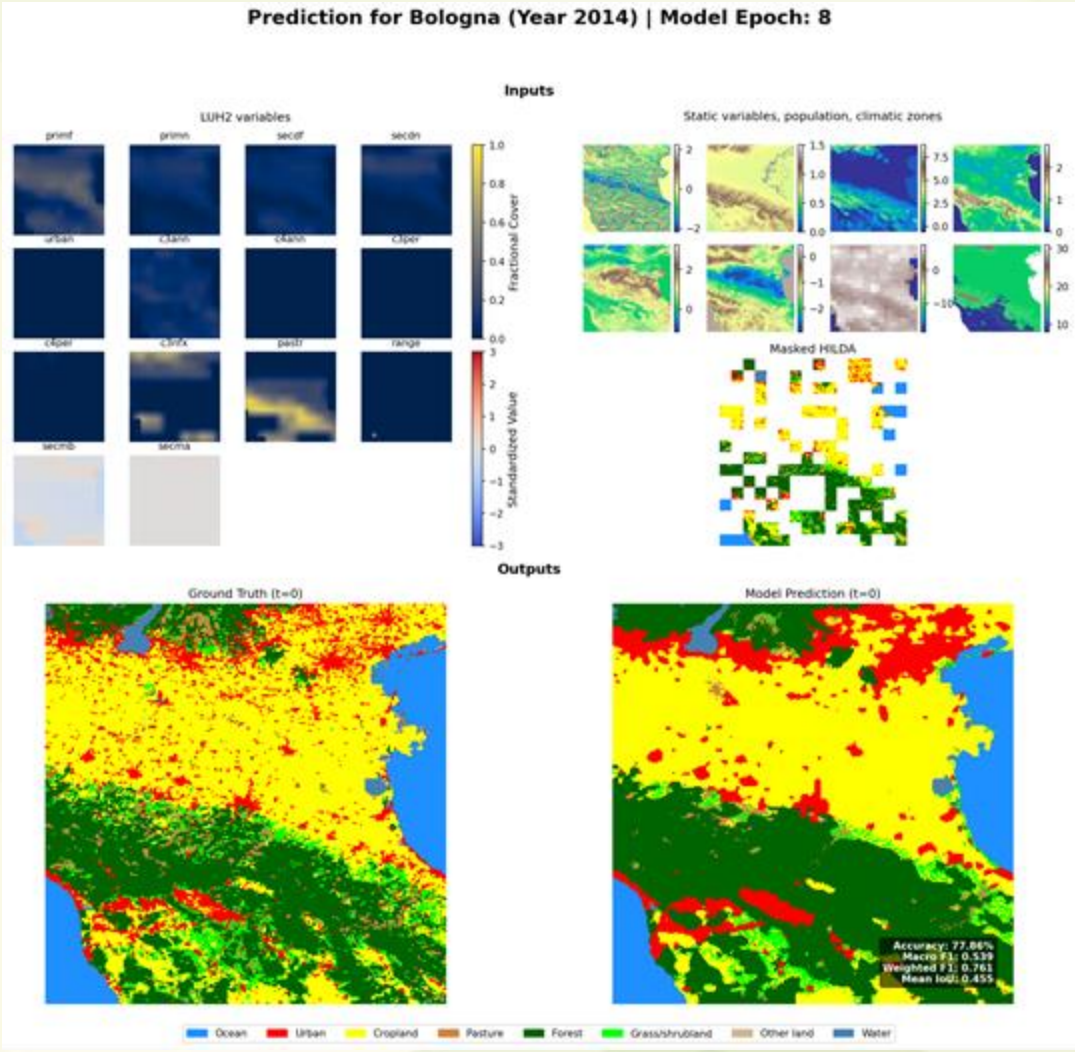
Model design

- **UNet & ViTt** with 256 x 256 pixel images
- **Inputs**
  - Coarse-resolution Land Use
  - Elevation
  - Climatic zones
  - Population
  - Soil texture
  - Masked prior
- **Embeddings**
  - Categorical variables: climatic zones, prior
- **Target**
  - High-resolution Land Use



Task 1: Downscaling

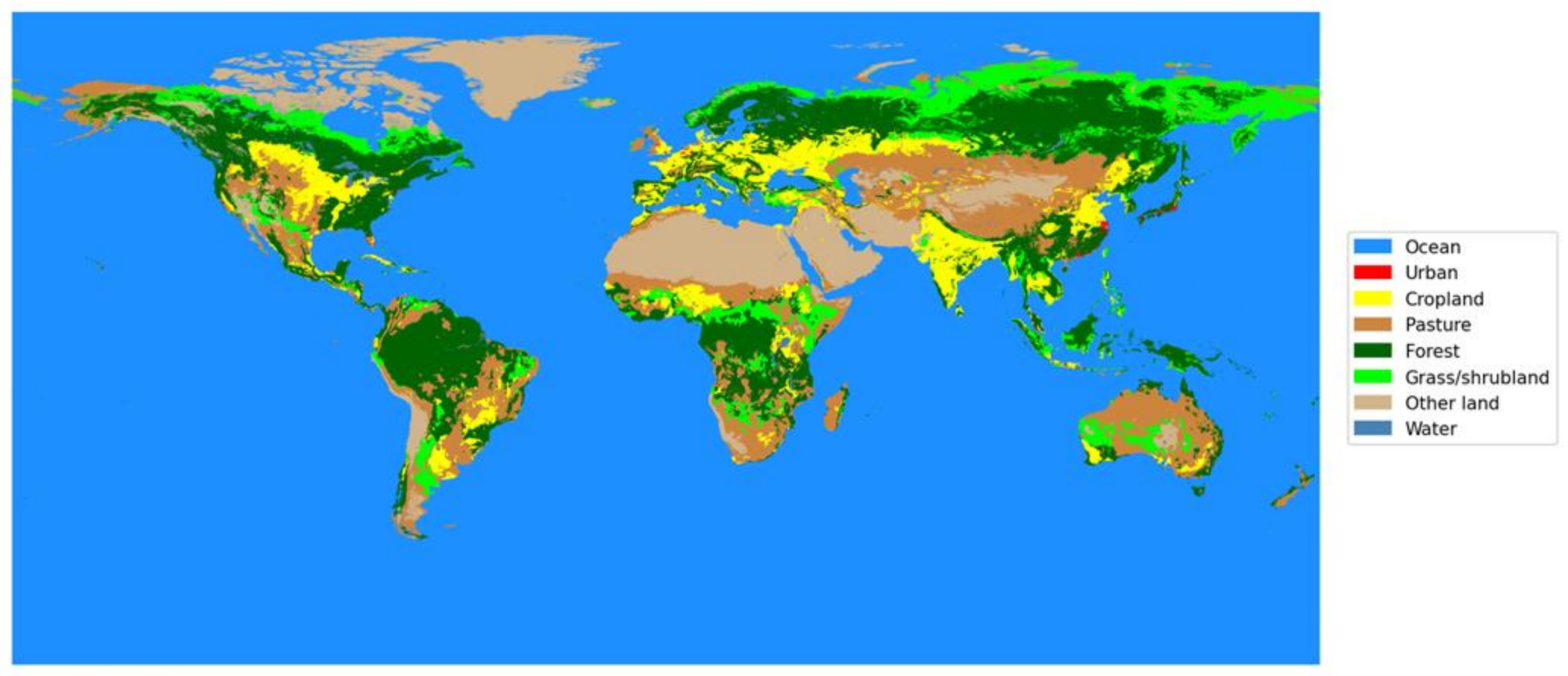
Metric	First Year		15-Year Average	
	Overall	LU Change	Overall	LU Change
Accuracy	0.8826	0.4796	0.8270	0.4513
Macro F1	0.8072	0.3182	0.7110	0.2661
Weighted F1	0.8802	0.4818	0.8156	0.4175
Mean IoU	0.6983	0.2089	0.5894	0.1748



"Machine Learning-Based Reconstruction and Projection of Global Land Use at High Resolution" Castaño et al., ECMWF-ESA ML workshop
"AI4Land: A Scalable Deep Learning Framework on MareNostrum5 for Global High-Resolution Land Use Reconstruction," Mozaffari et al., Procedia Computer Science, 2026

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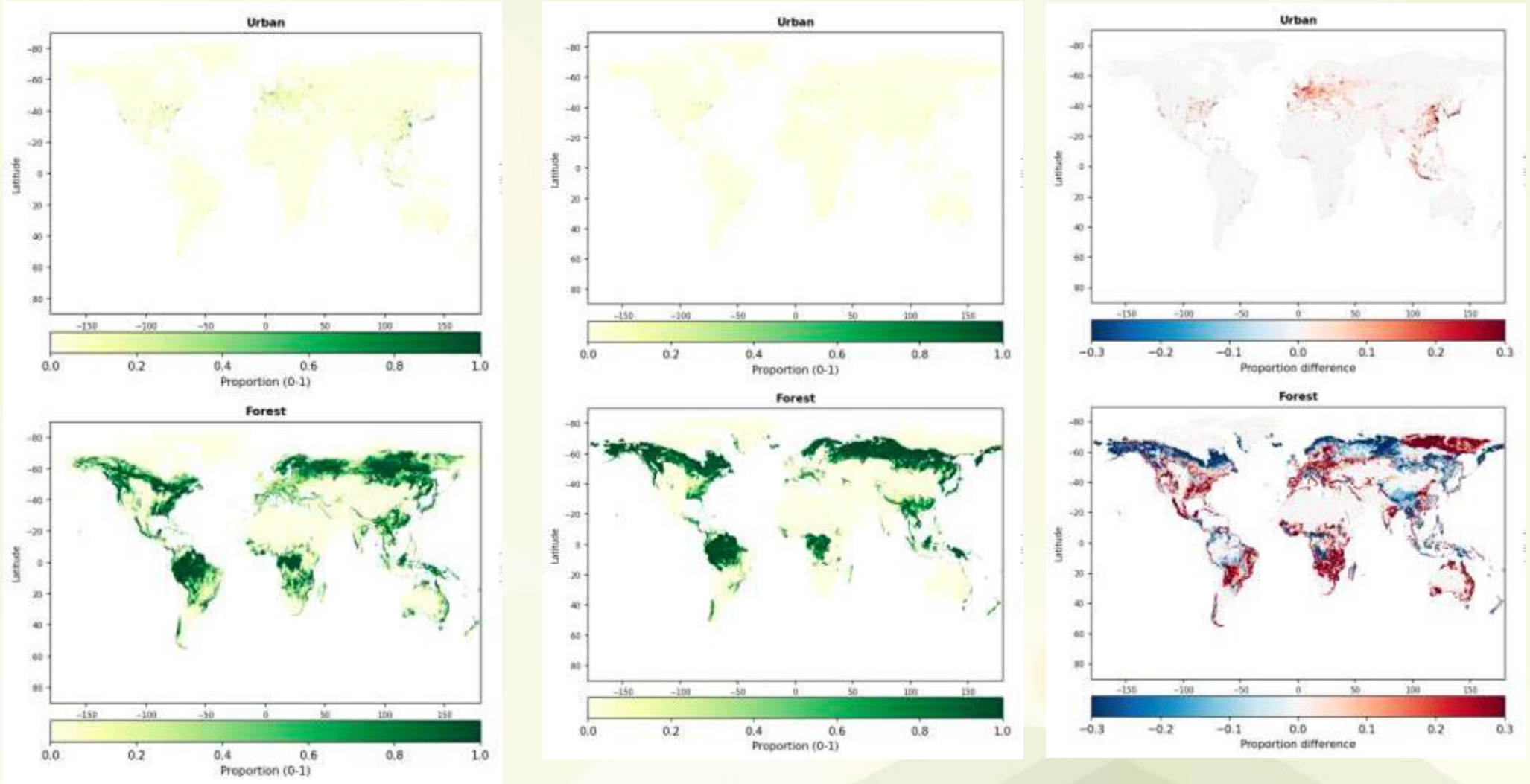
Inference



“AI4Land: A Scalable Deep Learning Framework on MareNostrum5 for Global High-Resolution Land Use Reconstruction," Mozaffari et al., Procedia Computer Science, 2026

Comparison to current standard

Comparison of upscaled LU data and LUH2 (0.25º), which is the current standard for ESMs' land use boundary conditions.



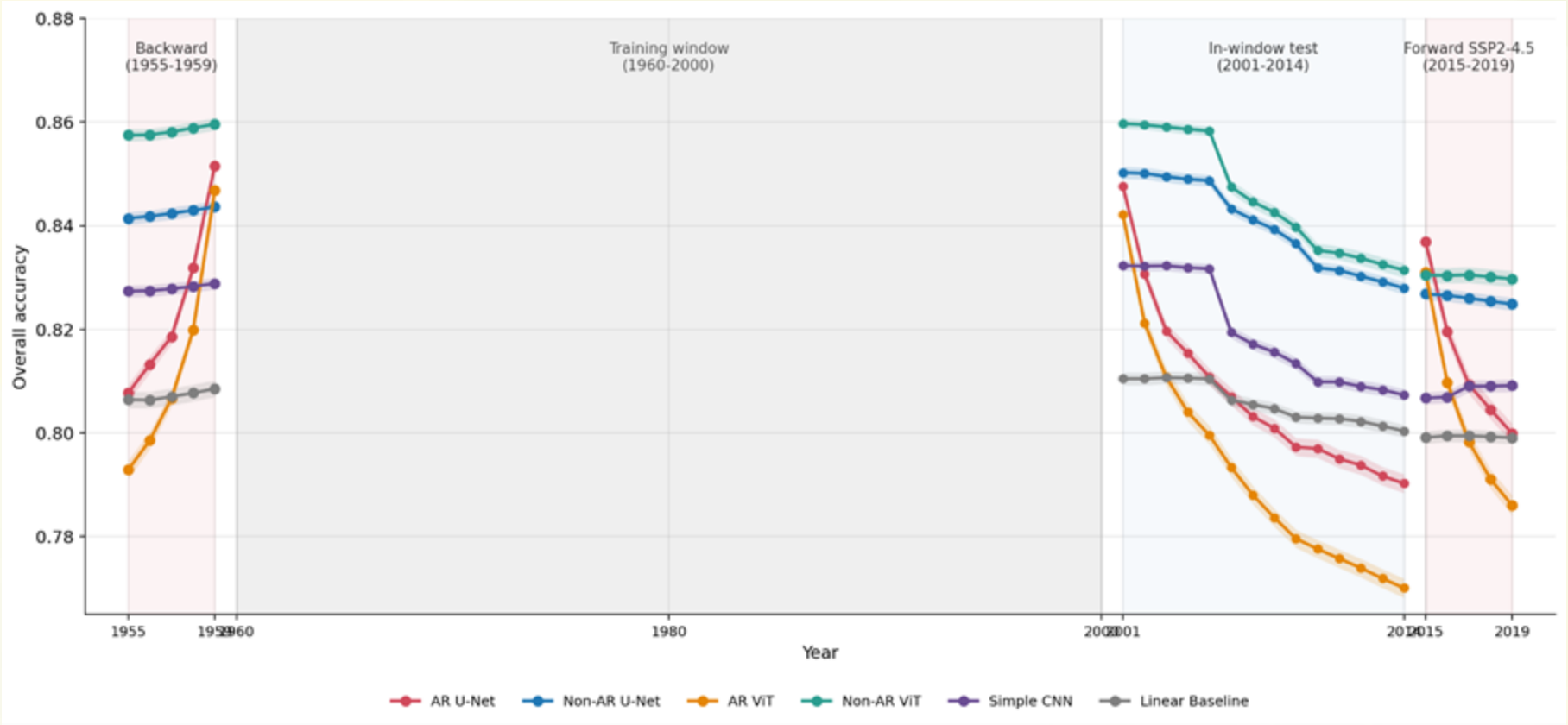
Fraction of urban (top) and forest (bottom) land in each gridbox

Task 2: Temporal consistency

TerraNostra - Bench
Benchmark dataset for consistent high-resolution long-term land use reconstruction and projection

Model	Overall		Land-use change	
	Acc.	mIoU	Acc.	mIoU
Rolling persistence	0.9947	0.9890	0.0000	0.0000
Frozen persistence	0.9704	0.9419	0.1630	0.0883
Linear	0.8115	0.3994	0.4388	0.1904
Simple CNN	0.8302	0.4938	0.4594	0.2006
AR U-Net	0.8083	0.4216	**0.5046**	**0.2385**
non-AR U-Net	0.8464	0.5333	0.4815	0.2264
AR Swin-ViT	0.7968	0.4532	0.5030	0.2380
non-AR Swin-ViT	**0.8607**	**0.5480**	0.4143	0.1893

Model	Backward (1955–1959)		Forward (2015–2019)	
	Overall Acc.	Change Acc.	Overall Acc.	Change Acc.
AR U-Net	0.8246	0.3207	0.8140	0.4212
non-AR U-Net	0.8425	**0.3559**	0.8259	0.3923
AR Swin-ViT	0.8130	0.3010	0.8032	**0.4452**
non-AR Swin-ViT	**0.8583**	0.3312	**0.8303**	0.4131
Simple CNN	0.8280	0.2987	0.8082	0.4188
Linear	0.8072	0.3361	0.7993	0.3663



TerraNostra-Bench: Deep-Learning Models and a Benchmark Dataset for High-Resolution Land-Use Reconstruction and Projection , in prep. IOP ML Earth

Summary and Future Steps

We have build a deep learning framework to generate high-resolution land surface boundary conditions for Land Use, Land Cover, Leaf Area Index.

- Releasing the TerraNostra - LU benchmark dataset and paper
- Complete LC and LAI emulators and datasets

- Historical Reconstruction and Future Projection of Land Surface Boundary Conditions, NeurIPS workshop, tackling climate change with AI, 2025
- A Unified Data-Driven Framework for High-Resolution Land Surface Boundary Conditions, EGU, 2026
- Global 1 km Reconstruction of Historical and Future Land Use with Machine Learning, EGU, 2026
- AI4Land: A Scalable Deep Learning Framework on MareNostrum5 for Global High-Resolution Land Use Reconstruction, Procedia Computer Science, 2026

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Digital Twin of Earth system for Cryosphere, Land surface and related interactions

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Digital Twin of Earth system for Cryosphere, Land surface and related interactions

Coupling AI-driven and physics-based digital twin components

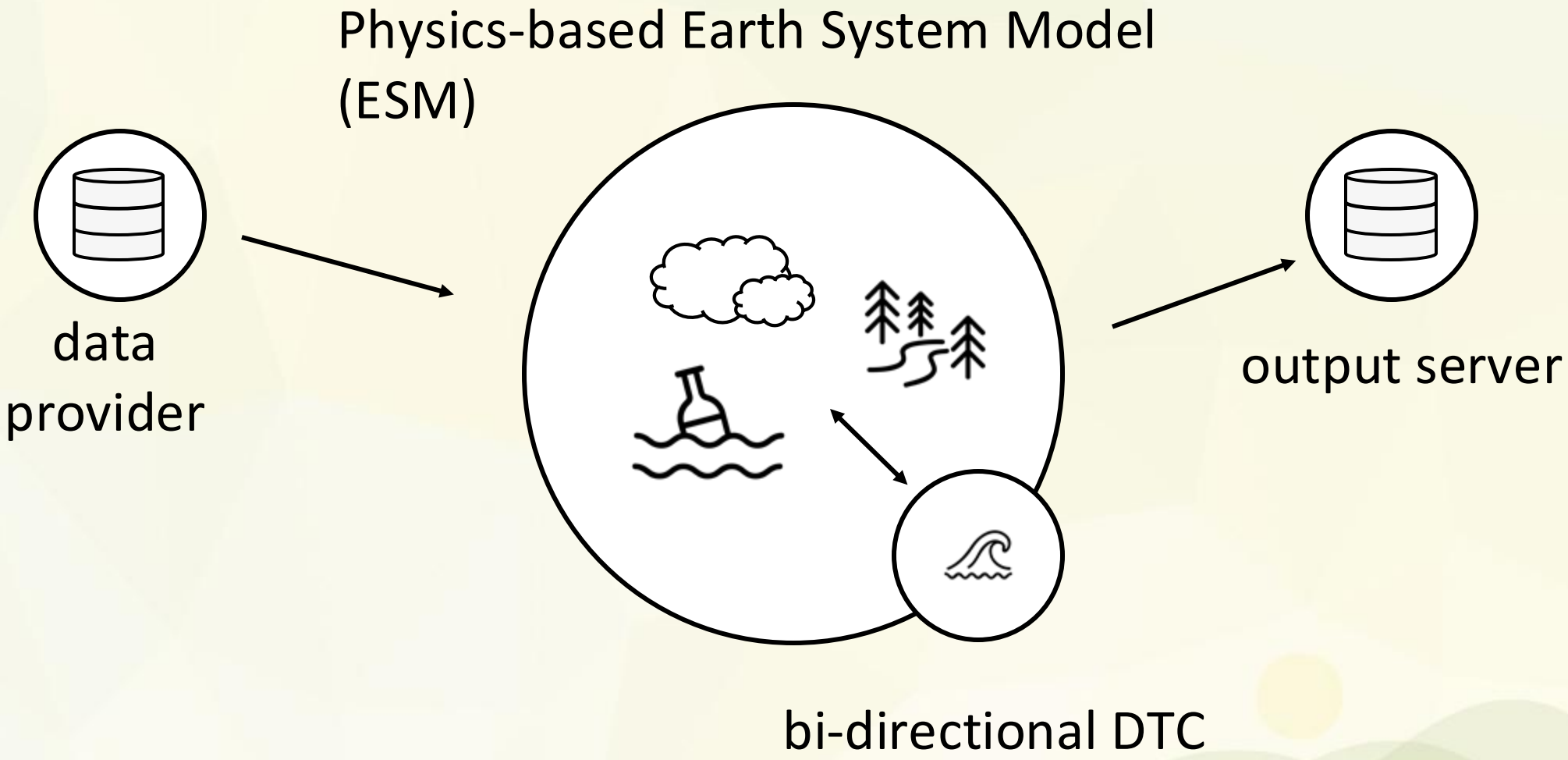
Benjamin Rodenberg (DKRZ)



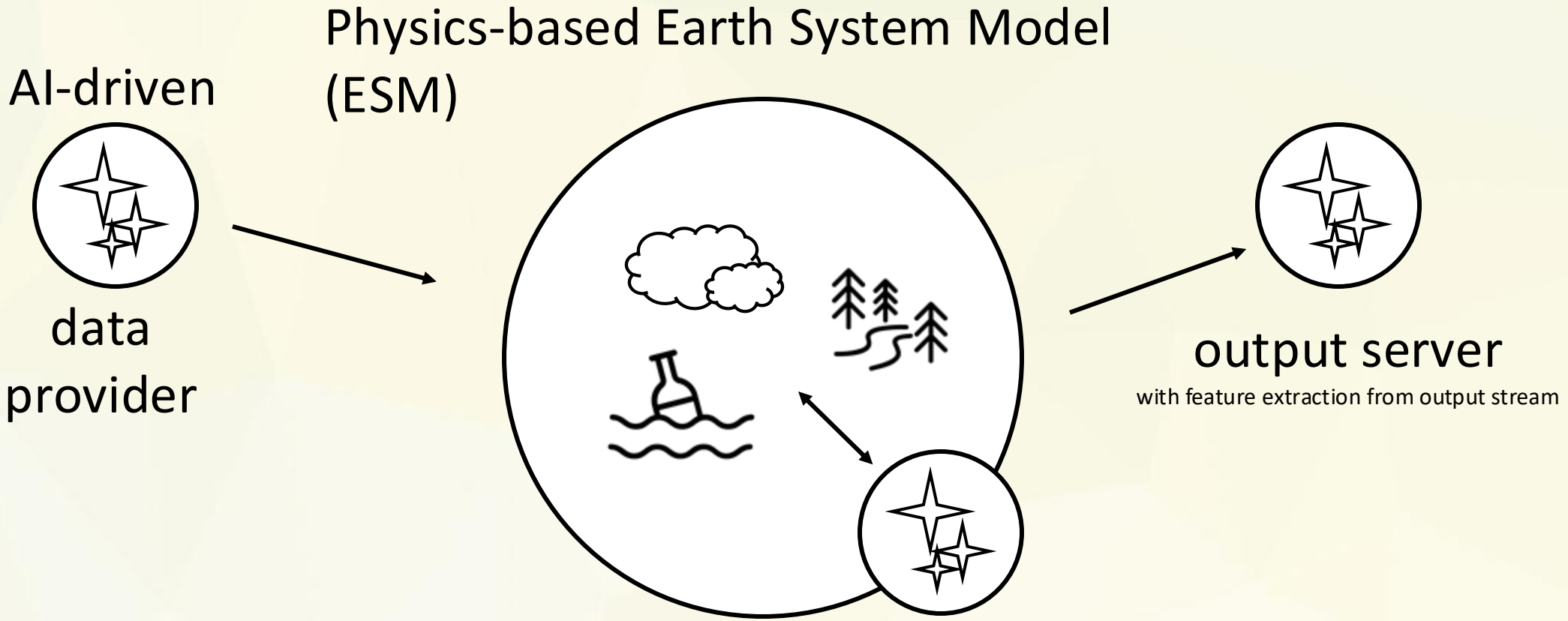
Funded by the European Union

TerraDT

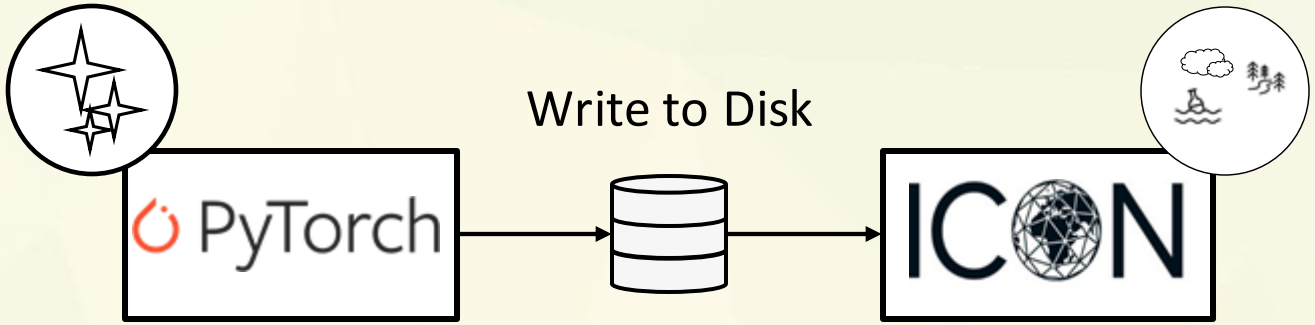
Physics-based Digital Twin Components



Add AI-driven Digital Twin Components



Overview of Coupling Approaches



+ simple
- needs IO

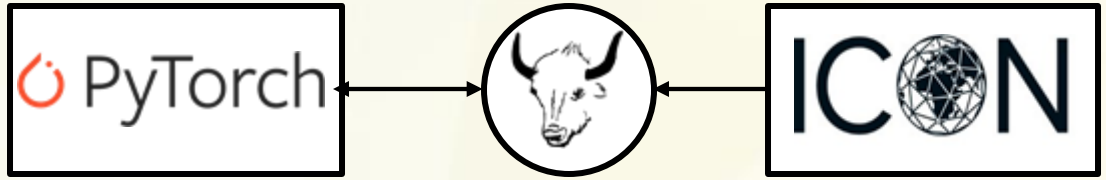
Rewrite: Monolithic Code



+ robust
- expensive

(FTorch potentially needs to be developed)

Use coupler: Partitioned approach



+ code reuse, flexible
  hides impl. details
- relatively complex

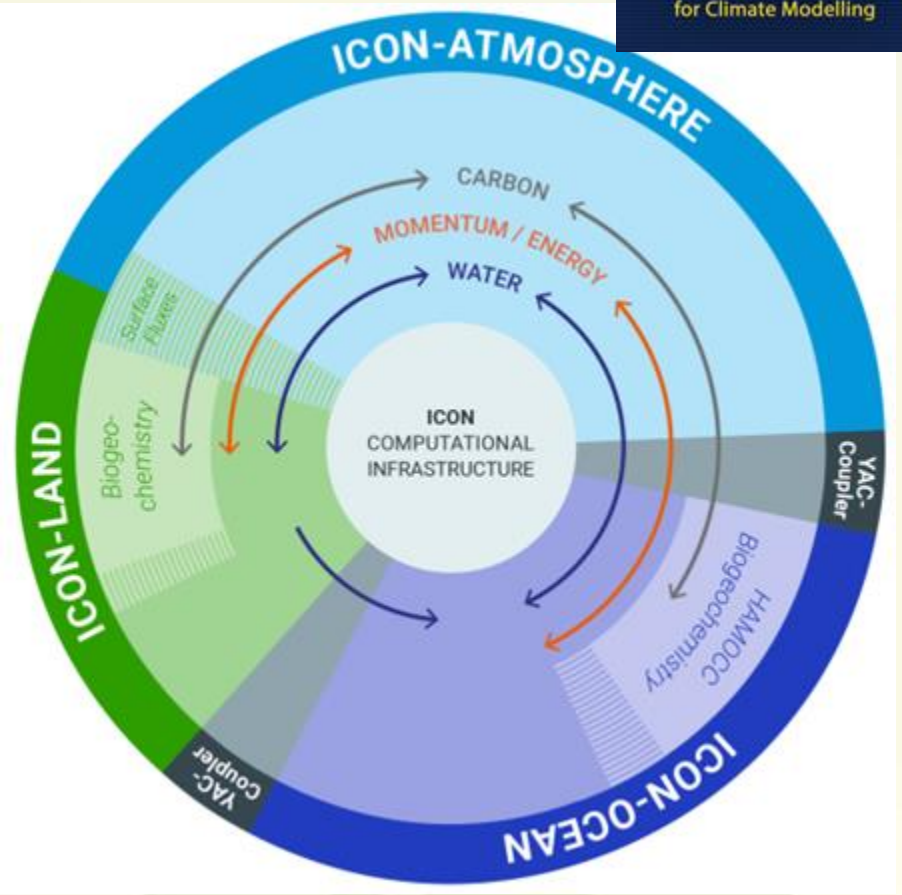
YAC = Yet Another Coupler

- Coupling library
- Open source
- Developed @ DKRZ

https://gitlab.dkrz.de/dkrz-sw/yac

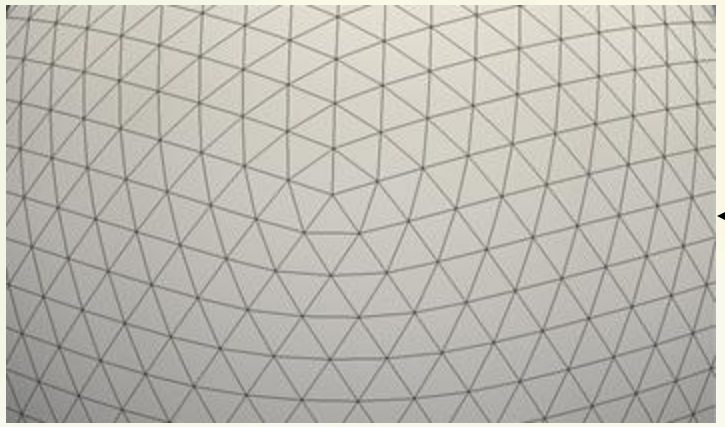
Main use-case of YAC:

ACM Gordon Bell Prize for Climate Modelling

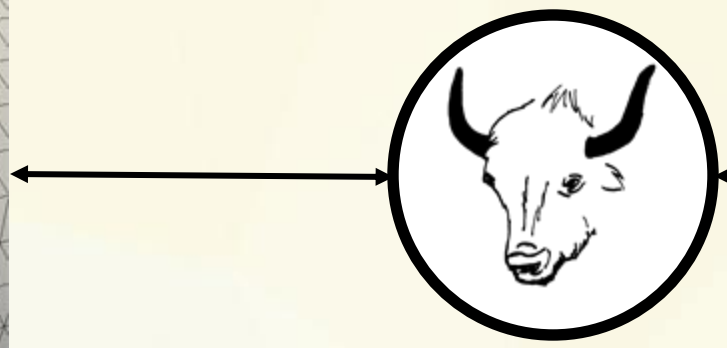


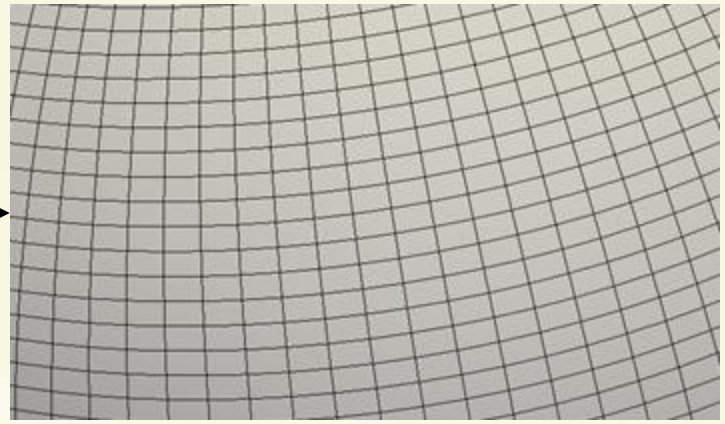
From Klocke, D., Frauen, C., Engels, J. F., et al. (2025). Computing the Full Earth System at 1km Resolution. In SC '25: https://doi.org/10.1145/3712285.3771789

Coupling Library Features: Mapping



unstructured



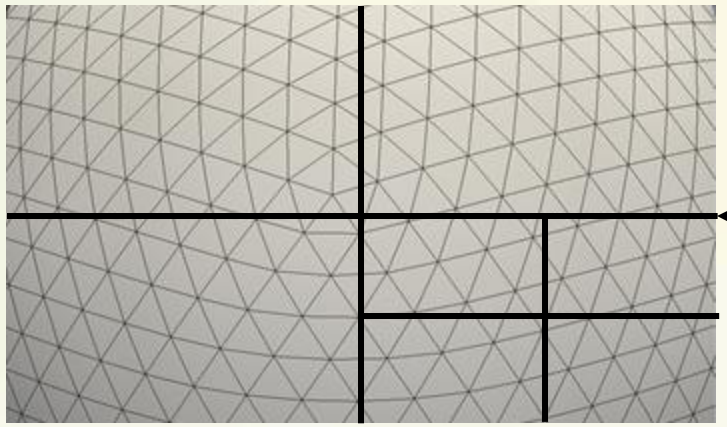


lon/lat

Coupling Library Features: P2P & MPI

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ICON



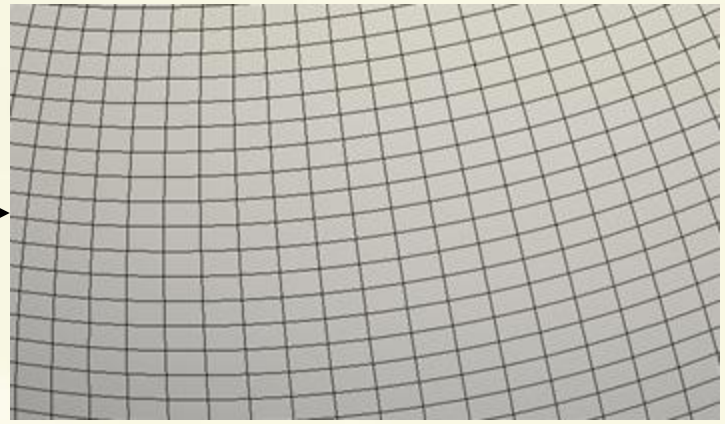


ICON runs on Levante @ DKRZ



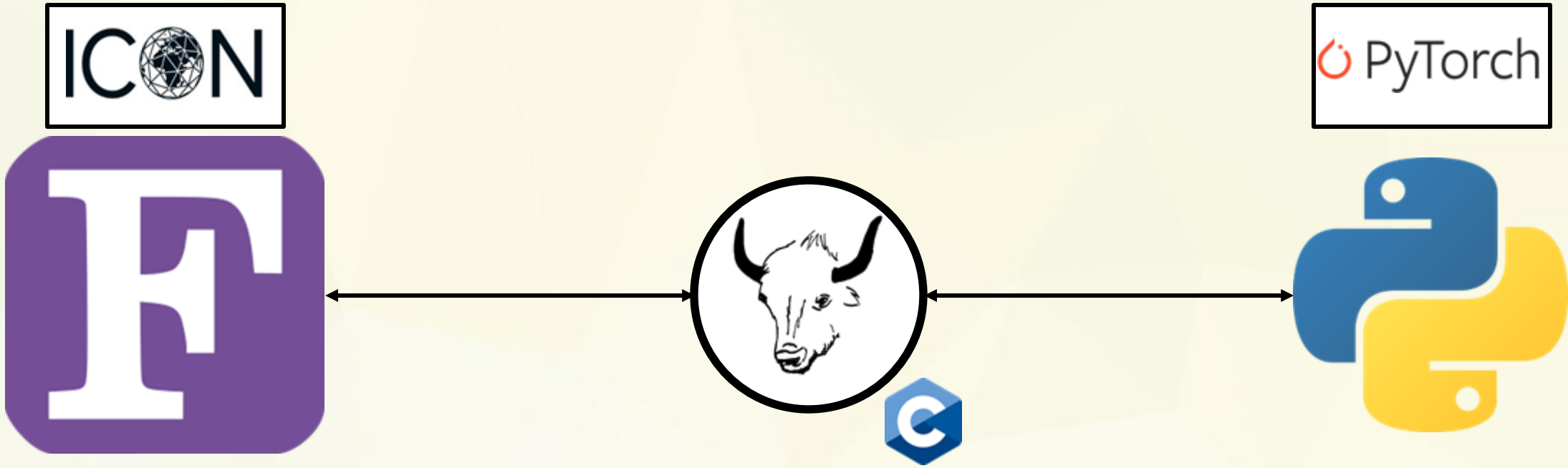
MPI is not trivial!

PyTorch

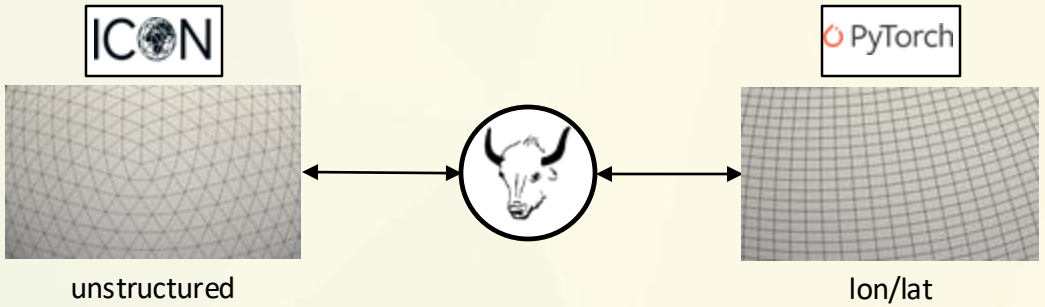


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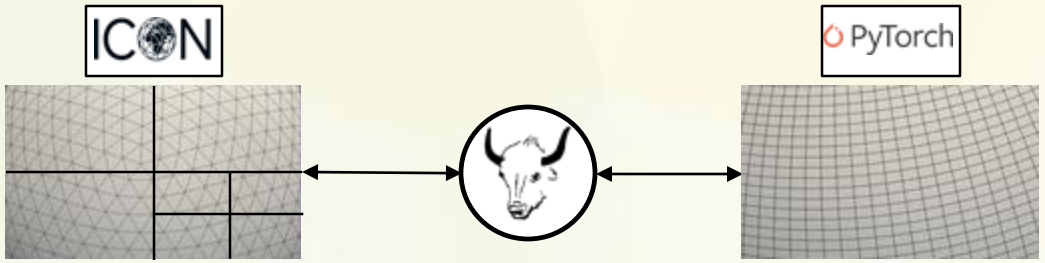
Coupling Library Features: Language Bindings



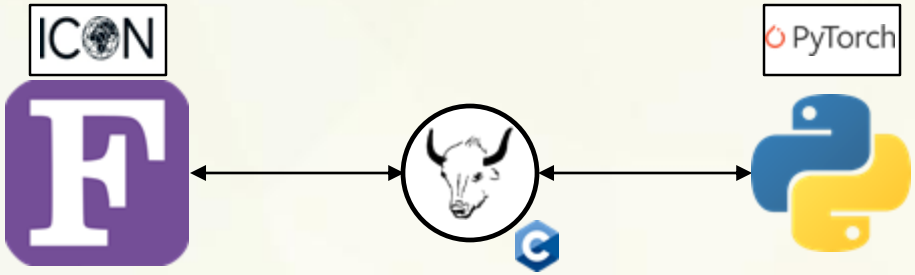
Summary: What you need to couple ESM to ML



mapping

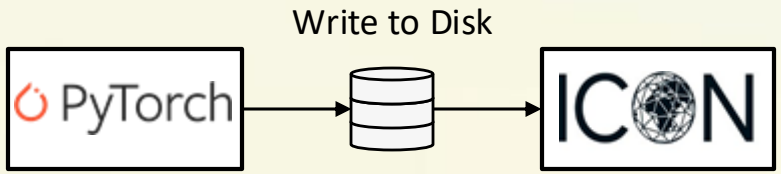


parallelization



Fortran

Alternatives:



Rewrite: Monolithic Code

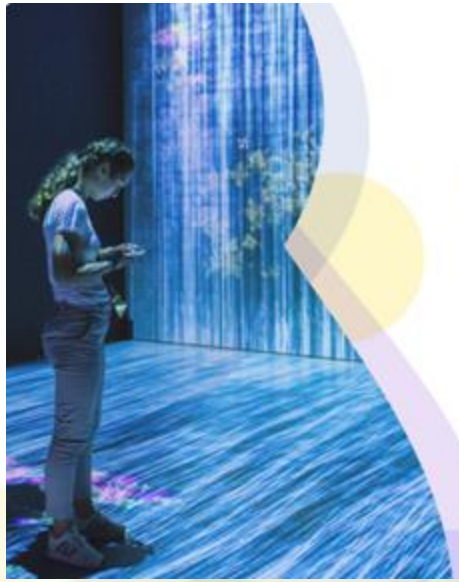


… many more

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Digital Twin of Earth system for Cryosphere, Land surface and related interactions

REGISTER NOW →



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WORKSHOP

Machine Learning for Earth System Science

20-21 October 2026 | Ostrava [CZ]

rodenberg@dkrz.de



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Norwegian Meteorological Institute

ECMWF

JÜLICH Forschungszentrum

buluttan Weather Intelligence

MAX PLANCK INSTITUTE FOR BIOGEOCHEMISTRY

LT

Met Office

Statkraft

METEO FRANCE
À VOS CÔTÉS, DANS UN CLIMAT QUI CHANGE

cmcc Centro Euro-Mediterraneo sui Cambiamenti Climatici

ETH zürich

netherlands eScience center

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Confederation

Federal Department of Home Affairs FDHA
Federal Office of Meteorology and Climatology MeteoSwiss

MeteoSwiss

Royal Netherlands Meteorological Institute
Ministry of Infrastructure and Water Management

SMHI

KAJO www.kajoservices.com

What's next for machine learning in Earth sciences?

Weather Generator

Task specific training for languages:
Input: English text → Output: Spanish text
Inference for task specific training for languages:
Input: English text → Output: Spanish text → Translate English to Spanish

Large Language Models (LLMs) based on self-supervised training:
Input: All text available → Output: Gapfill all text available

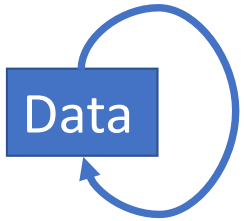
Training on all text is helping the neural network to learn a general model of natural language.

LLMs inference for languages:
Input: I want a recipe for a vegan lasagne in Spanish → Output: Spanish recipe
Input: Translate this English text into Chinese → Output: Chinese text
Input: How would Shakespeare have written this letter? → Output: Letter in Tudor style
…

Fine-tuning and model distillation can help to calibrate LLMs for a specific application to make them more accurate, faster and cheaper.

What's next?

1. Self-supervised training:



machine learning

2. Use all data available in a single model:
Model forecasts, (re-)analysis, and observations from the past, present and future and across a wide range of scales

3. Build a meaningful latent space representation for general applications in the field of Earth system science, including timestepping and uncertainty representation

4. Scale to the big machines and distill the core:
100 million degrees of freedom → 10 billion degrees of freedom

The new ambition:
A foundation model for Earth system modelling

reanalysis data
- ERA5
- CERRES
- ...

simulation data
- DestinE DT
- IFS
- ...

observations
- satellite
- ground-based
- unconventional
- ...

Self-supervised training

Meaningful latent space including use for time stepping

WeatherGenerator

$p_\theta(x, y)$

Input and output can be global/local, 100m/100km resolution, past/present/future

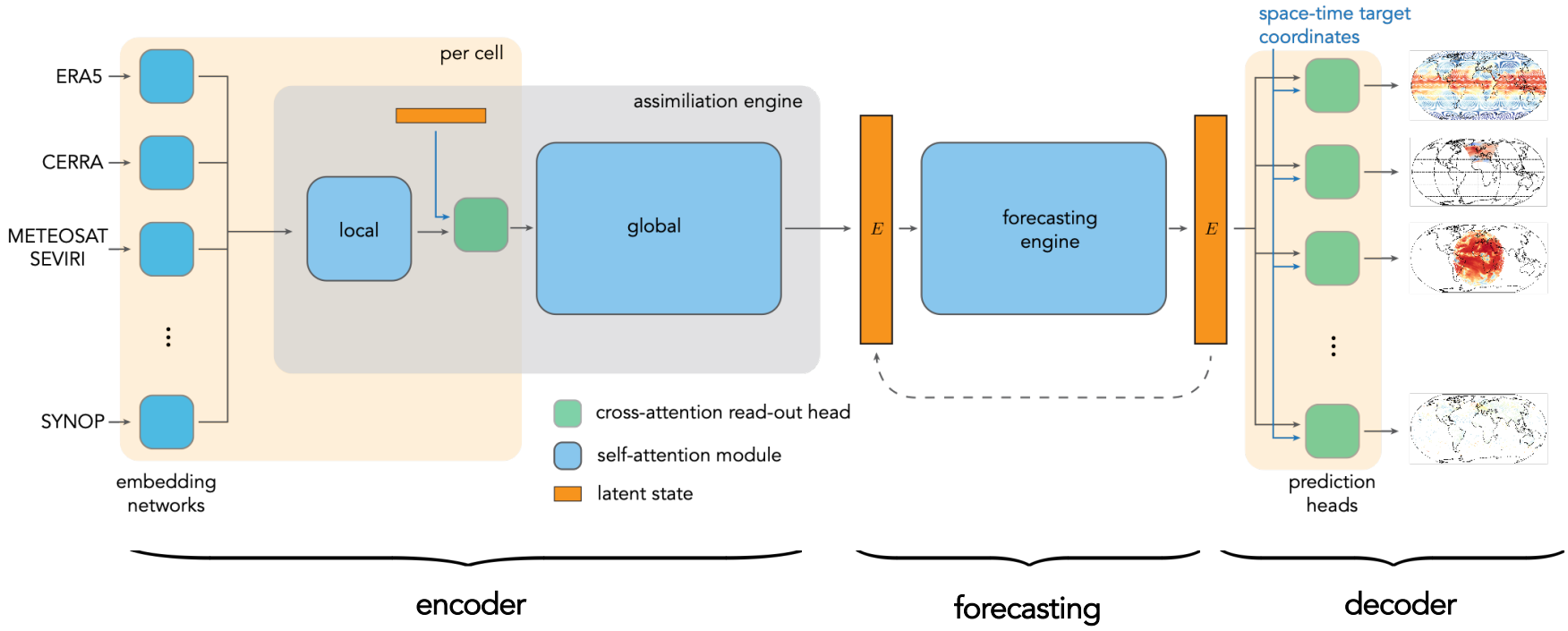
The models may have 100b DOFs

seamless prediction
- nowcasting
- medium-range
- decadal projections

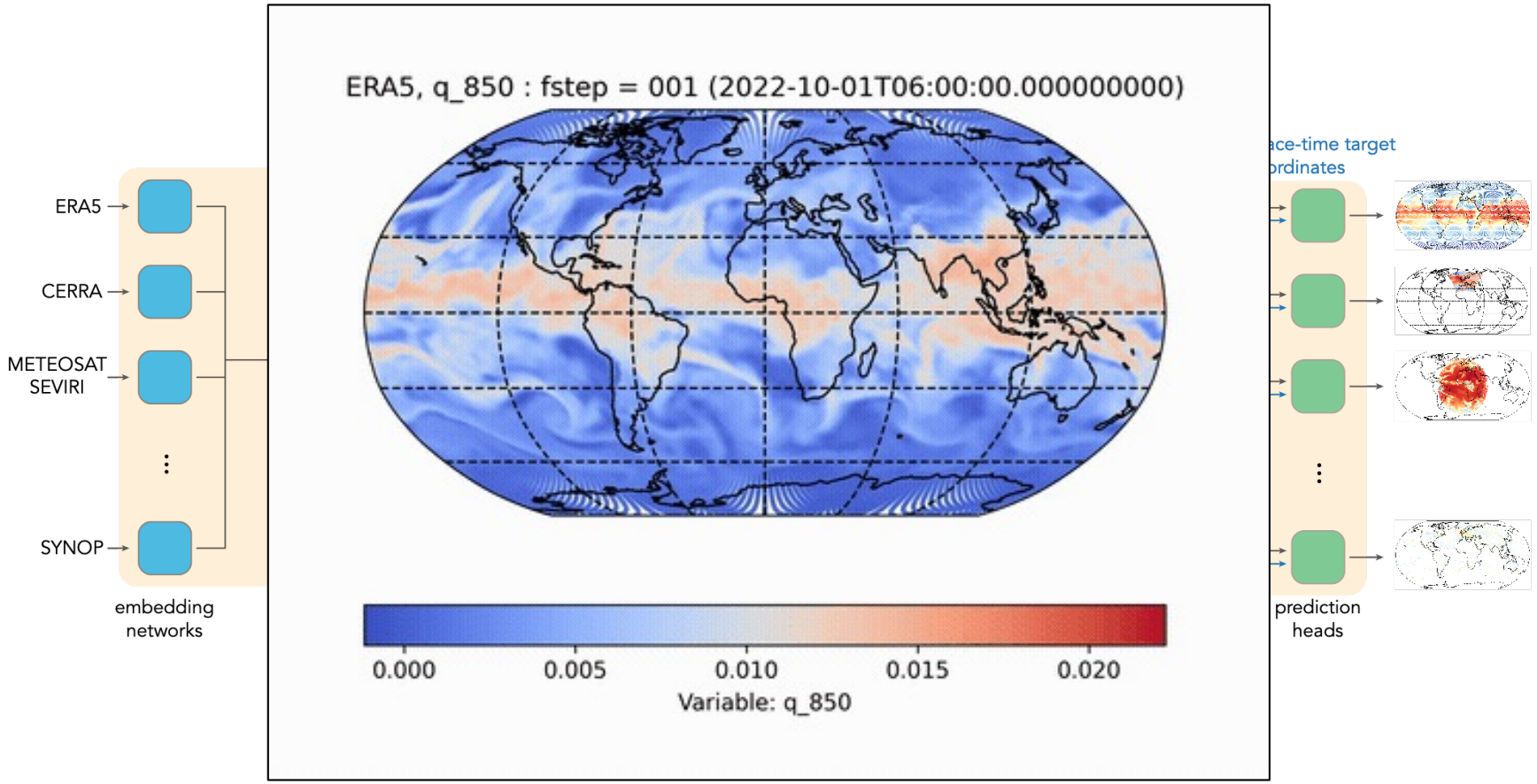


WeatherGenerator.eu

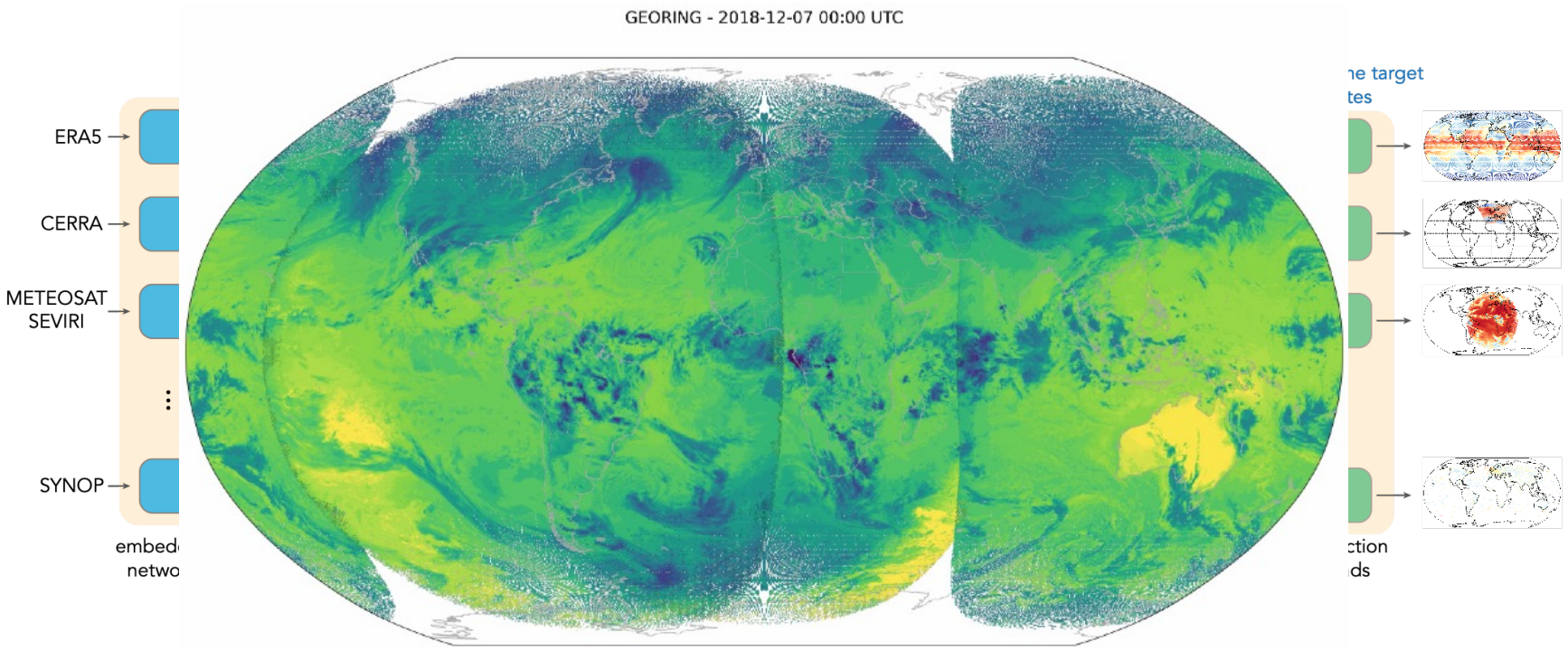
Use all available data and build a meaningful latent space



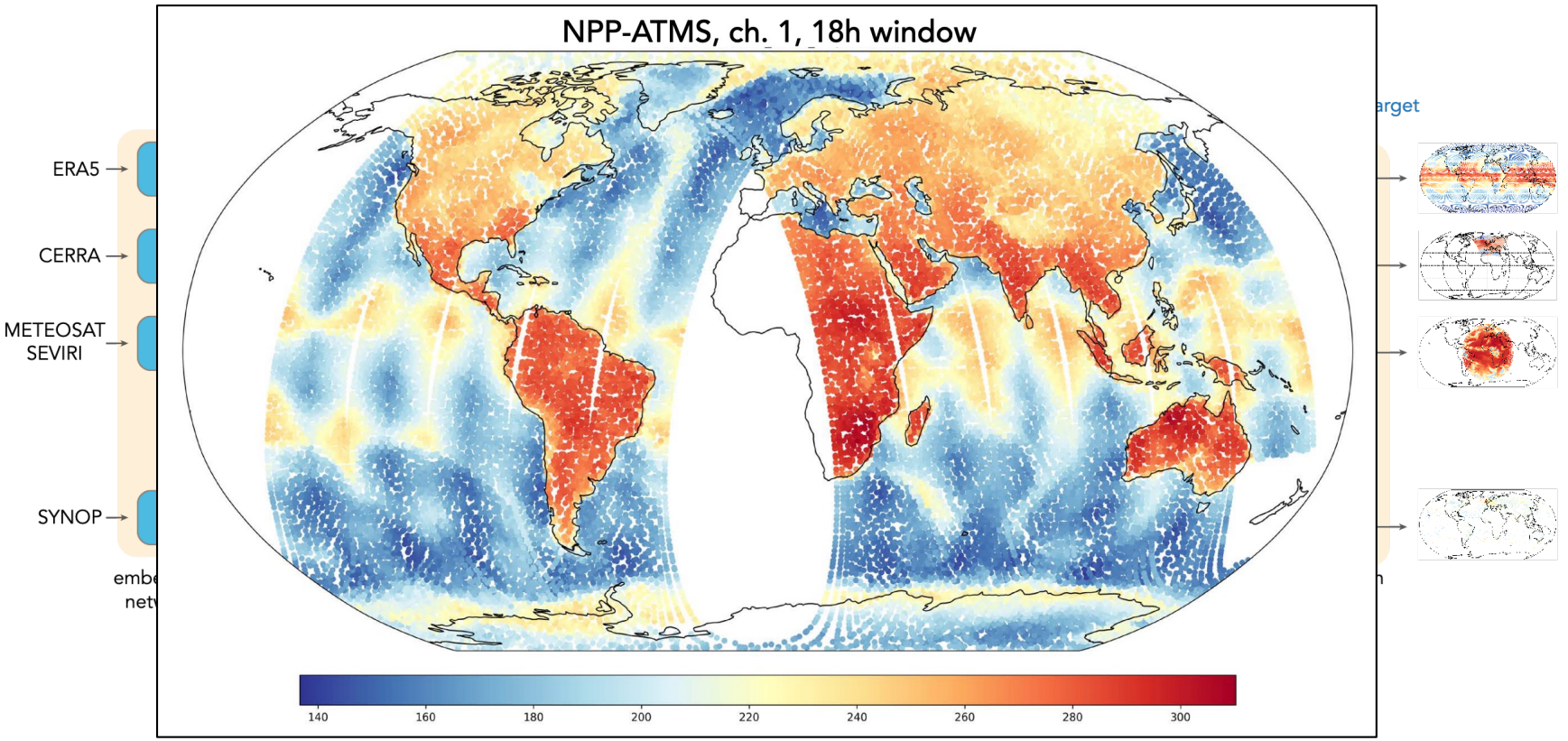
Use all available data and build a meaningful latent space



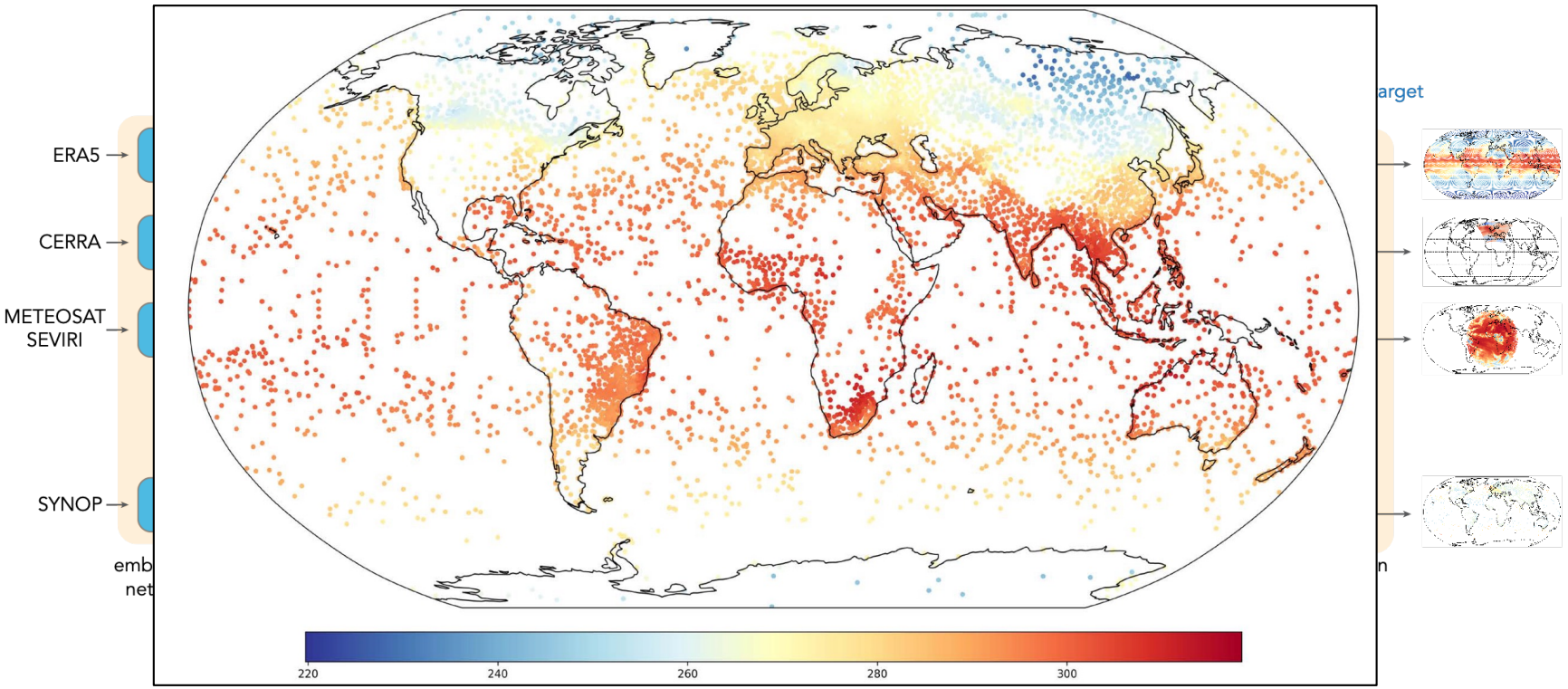
Use all available data and build a meaningful latent space



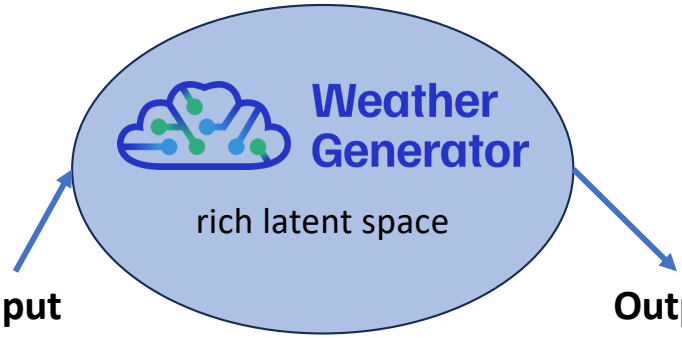
Use all available data and build a meaningful latent space

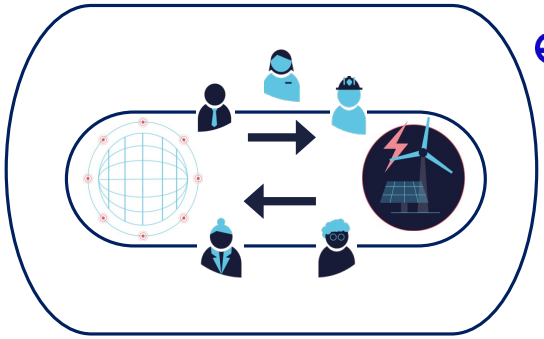


Use all available data and build a meaningful latent space



How to use the WeatherGenerator?

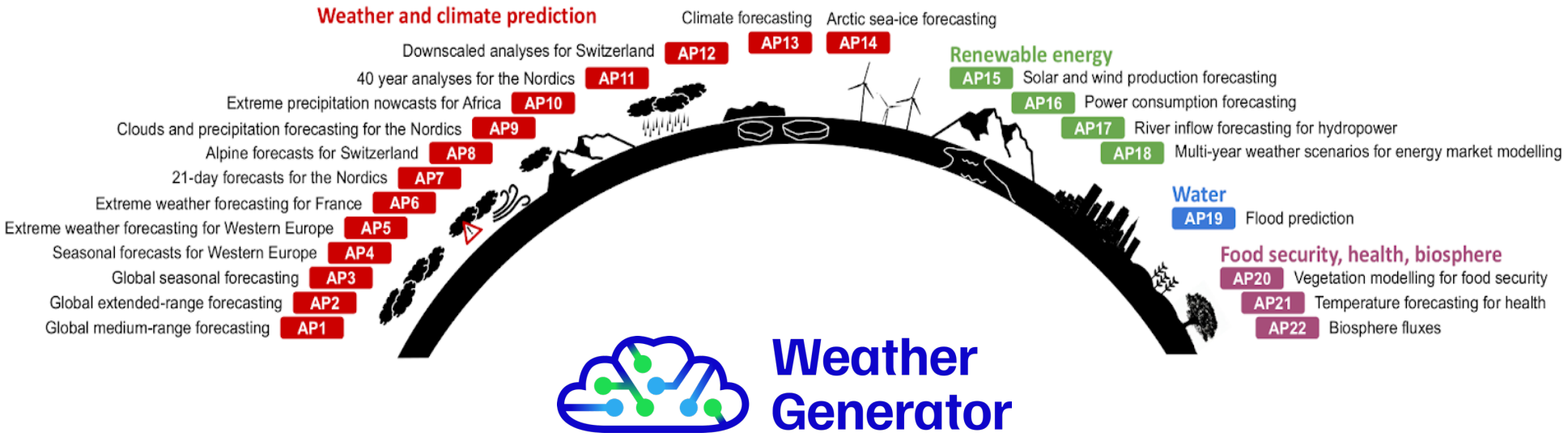




Weather Generator

Input		Output		Application
Satellite and synoptic observation	→	ERA (35km) and CERRA (5km)	→	Data assimilation
IFS initial conditions (9km)	→	IFS state in the future (9km)	→	Global weather forecast
IFS forecast (9km)	→	OPERA (2km)	→	Model downscaling
DestinE Extremes Twin (4km)	→	synoptic observations	→	Post-processing
Sentinel-1	→	AROME (2km)	→	Observation operator
DestinE Climate Twin (4km)	→	ECOSTRESS (100m)	→	Vegetational water stress predictor
A date	→	IFS state	→	A climate emulator
…				

The aim of the WeatherGenerator



Aim: This project will build the machine-learned WeatherGenerator – the world's best generative Foundation Model of the Earth system – that will serve as a Digital Twin in Destination Earth (DestinE).

https://www.ecmwf.int/en/about/media-centre/news/2024/weathergenerator-project-aims-recast-machine-learning-earth-system

Registration now open for the WeatherGenerator Community Hackathon



https://weathergenerator.eu/news/weathergenerator-community-hackathon-news/

WeatherGenerator Service Call 2026



https://weathergenerator.eu/news/service-call-2026/



Funded by the European Union

Coordinated by ECMWF



Weather Generator

www. weathergenerator.eu

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Norwegian Meteorological Institute

MAX PLANCK INSTITUTE FOR BIOGEOCHEMISTRY

Royal Netherlands Meteorological Institute
Ministry of Infrastructure and Water Management

METEO FRANCE
À VOS CÔTÉS, DANS UN CLIMAT QUI CHANGE

SMHI

Met Office

cmcc Centro Euro-Mediterraneo sui Cambiamenti Climatici

netherlands eScience center

buluttan Weather Intelligence

www.kajoservices.com

LT

Statkraft

ETH zürich

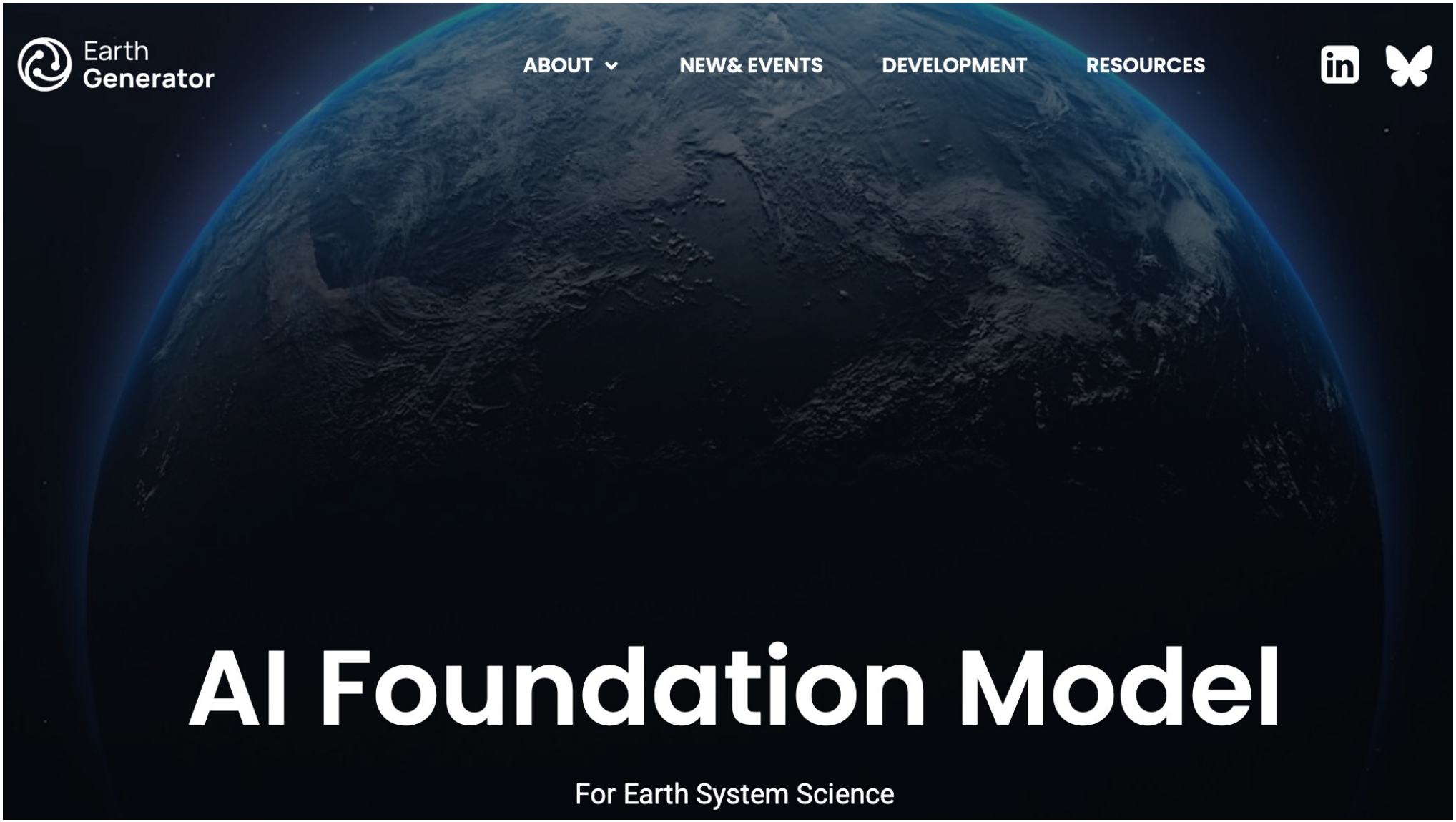
Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Confederation

Federal Department of Home Affairs FDHA
Federal Office of Meteorology and Climatology MeteoSwiss

MeteoSwiss

The WeatherGenerator project (grant agreement No101187947) is funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the Commission. Neither the European Union nor the granting authority can be held responsible for them.


Earth
Generator
ABOUT
NEW& EVENTS
DEVELOPMENT
RESOURCES
AI Foundation Model
For Earth System Science

CLAIMA

AI-based digital twin platform for climate

CLAIMA is a Horizon Europe project coordinated by the Alfred-Wegener-Institut, running from September 2026 to August 2030. It will develop an AI platform for European climate modelling, designed for deployment on European HPC and AI Factory infrastructures and aligned with initiatives such as Destination Earth.

COMING SOON