WCRP CORDEX

25-29 SEPTEMBER 2023 TRIESTE, ITALY

ICRC-CORDEX 2023

International Conference On Regional Climate

Session A3: Statistical downscaling and machine learning.

A brief overview to warm up

José M. Gutiérrez

Instituto de Física de Cantabria (IFCA)

Santander, Spain

UNIVERSIDAD DE CANTABRIA CSIC

IFCA Instituto de Física de Cantabria

ICRC2023

CORDEX Conference

Trieste/Pune,

25-29 September

The Future scientific challenges for CORDEX: Empirical Statistical Downscaling (ESD)

José M. Gutiérrez, Tereza Cavazos, Jason Evans, Grigory Nikulin, Samuel Somot, Douglas Maraun, Rasmus E. Benestad, Bruce Hewitson, Maria L. Bettolli

Draft version v1 (initial draft from SAT members): 25 November 2021.
v2 version – including comments from POCs until 11 February 2022.
v3 version – final version (21 June 2022)

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- **Current state and achievements of CORDEX ESD activities**
- **Future Challenges**
    1. **Methodological advances (e.g. multivariate)**
    2. **Machine Learning for ESD**
    3. Intercomparison/validation experiments
    4. Data and infrastructure
    5. Distillation of actionable information
- Last mile on bridging climate science with society needs

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CORDEX experiment design for statistical downscaling of CMIP6

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  5. **Distillation of actionable information (sessions B and C)**
- **Last mile on bridging climate science with society needs (sessions B and C)**

The downscaling ecosystem

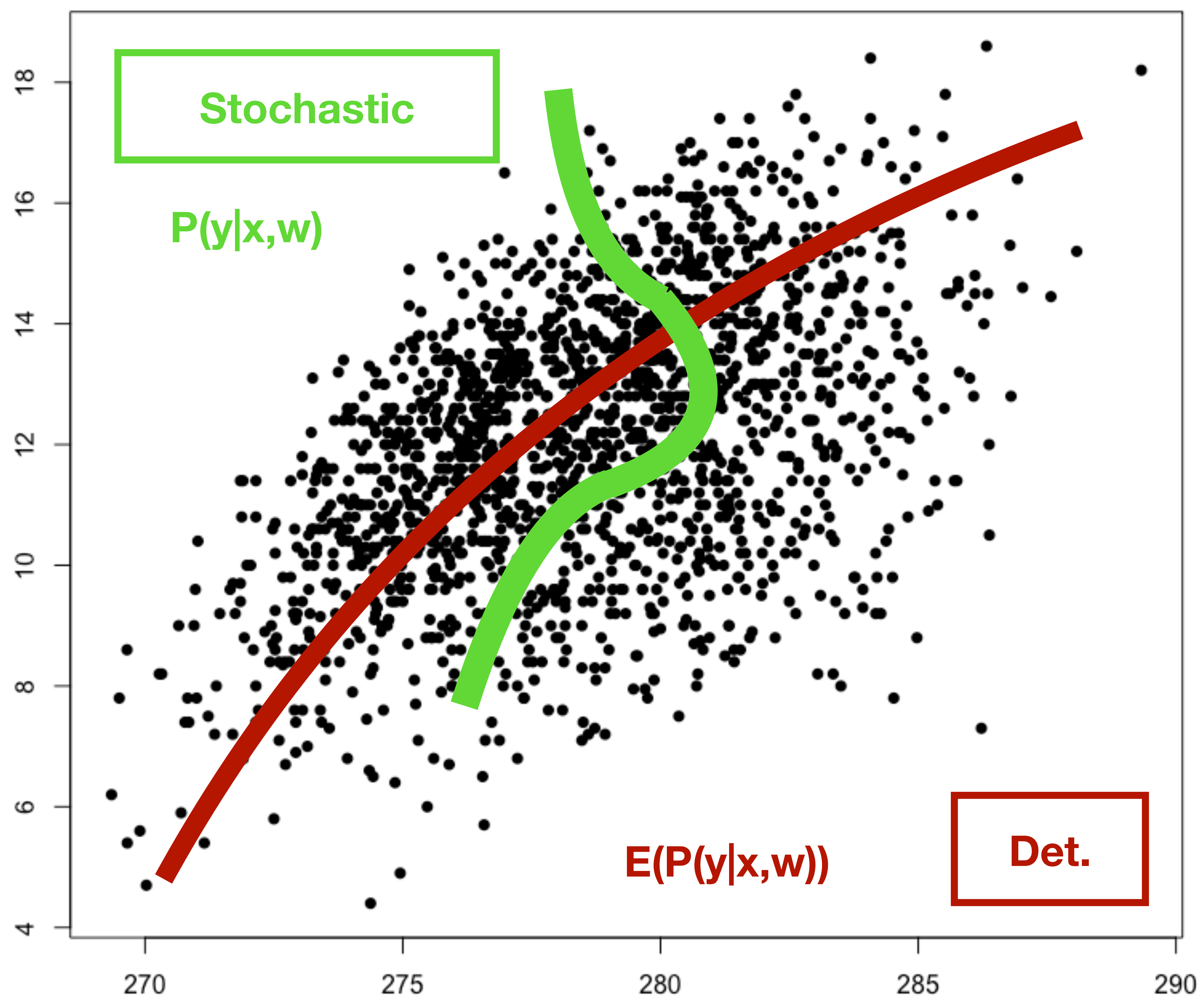
Dynamical Downscaling: Regional Climate Models (RCM) driven by a GCM at the boundaries (CP, 3km)

OBSERVATIONS

Statistical Downscaling (ESD): Data-driven models linking large-scale predictors and observed predictands

Perfect prognosis	**MOS (bias adjustment)**	**Weather Generator**

Hybrid: Combining them



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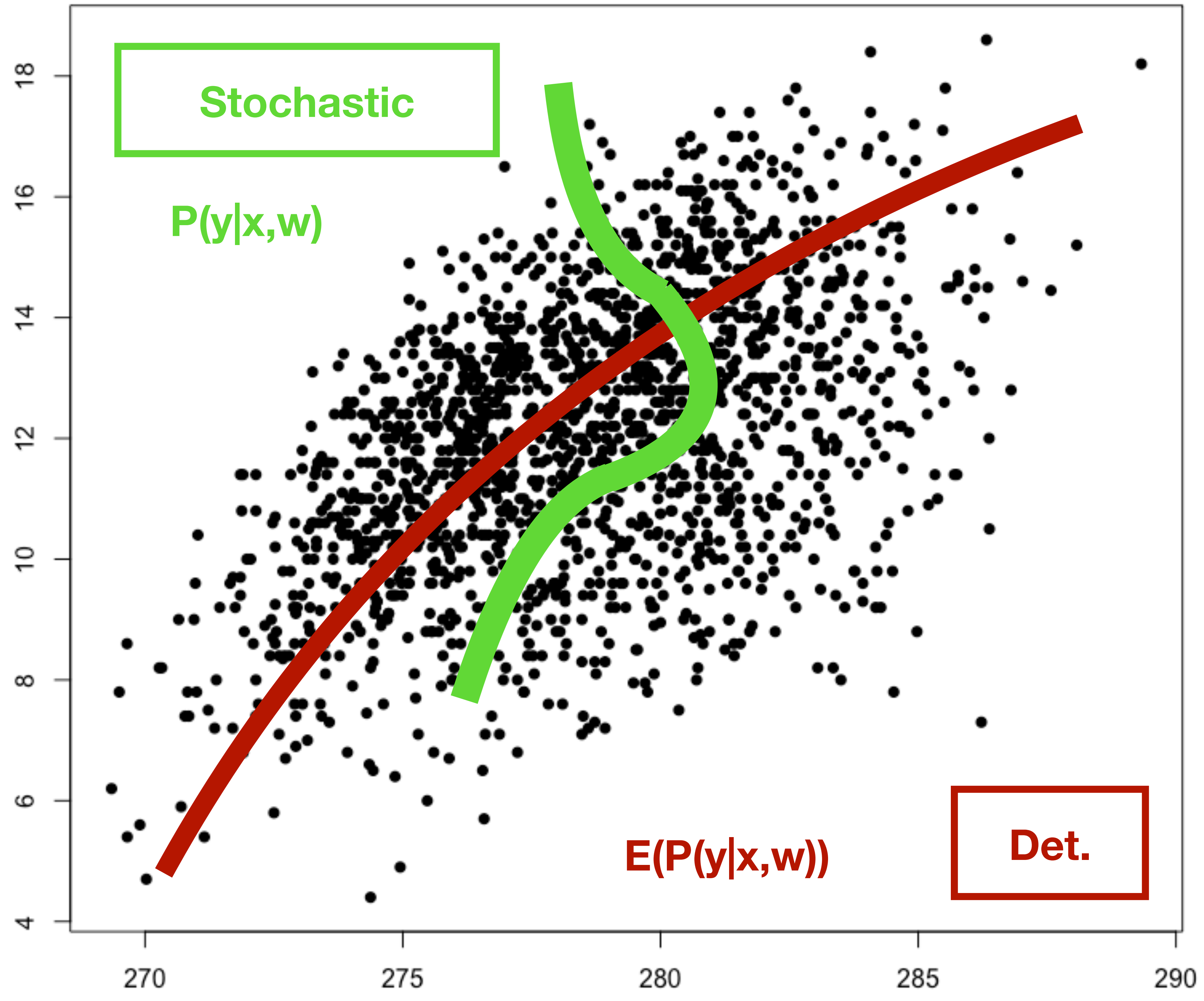

Stochastic downscaling of gridded precipitation to spatially coherent subgrid precipitation fields using a transformed Gaussian model

Matthew Switanek, Douglas Maraun, Emanuele Bevacqua

Climate impact models often require unbiased point-scale observations, but climate models typically provide biased simulations at the grid scale. While standard bias adjustment methods have shown to generally perform well at adjusting climate model biases, they cannot overcome the gap between grid-box and point scale. To overcome this limitation, combined bias adjustment and stochastic downscaling methods have been developed. These methods, however, are single-site methods and cannot represent spatial dependence. Here we propose a multisite stochastic downscaling method that can be applied to bias-adjusted climate model output for generating spatially coherent time series of daily precipitation at multiple stations, conditional on the driving climate model. The method is based on a transformed truncated multivariate Gaussian model and can also be used to downscale to a full field at finer-grid …

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Hybrid: Combining them

Emulators (GCM ➔ RCM)

Climate Dynamics (2023) 60:1751–1779
https://doi.org/10.1007/s00382-022-06343-9

Regional climate model emulator based on deep learning: concept and first evaluation of a novel hybrid downscaling approach

Antoine Doury[1] · Samuel Somot[1] · Sebastien Gadat[2] · Aurélien Ribes[1] · Lola Corre[3]

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Machine Learning: Data-driven modeling and prediction techniques

Random forests

Kernels and SVMs

Neural networks

The downscaling ecosystem

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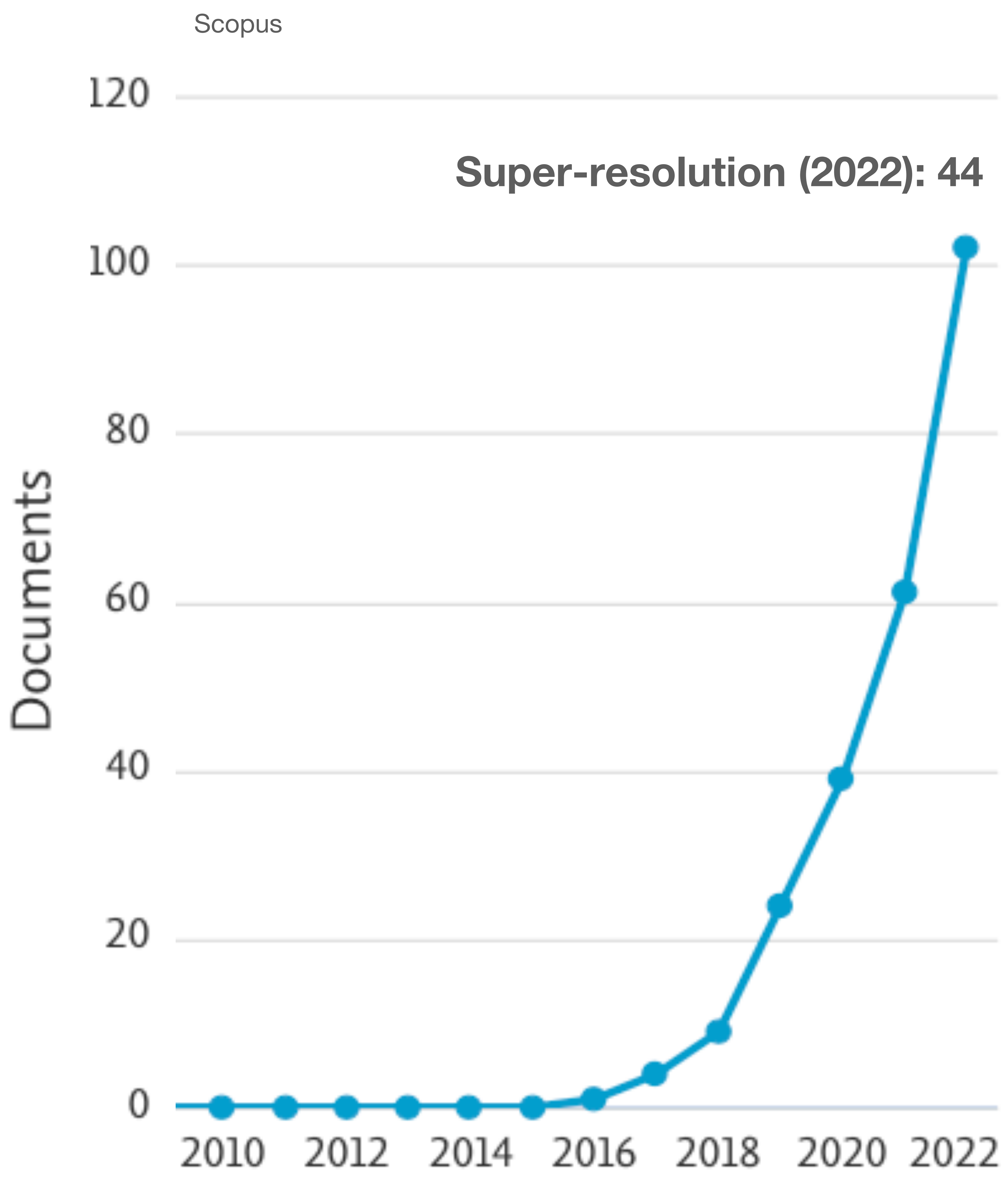
Machine Learning: Data-driven modeling and prediction techniques

- **Random forests**
- **Kernels and SVMs**
- **Neural networks**
- **Deep learning**

Deep downscaling is a very active topic that takes advantage of the rapid developments in the field and brings new members (fresh air) to the community.



The downscaling ecosystem

This momentum needs to be consolidated:

- Strengthening collaboration with ESD (**this conference**)
- **Coordination with ESD** protocols
- **Gaining trust** (methods are seen as black-boxes)

Machine Learning: Data-driven modeling and prediction techniques

Random forests	Kernels and SVMs	Neural networks	Deep learning

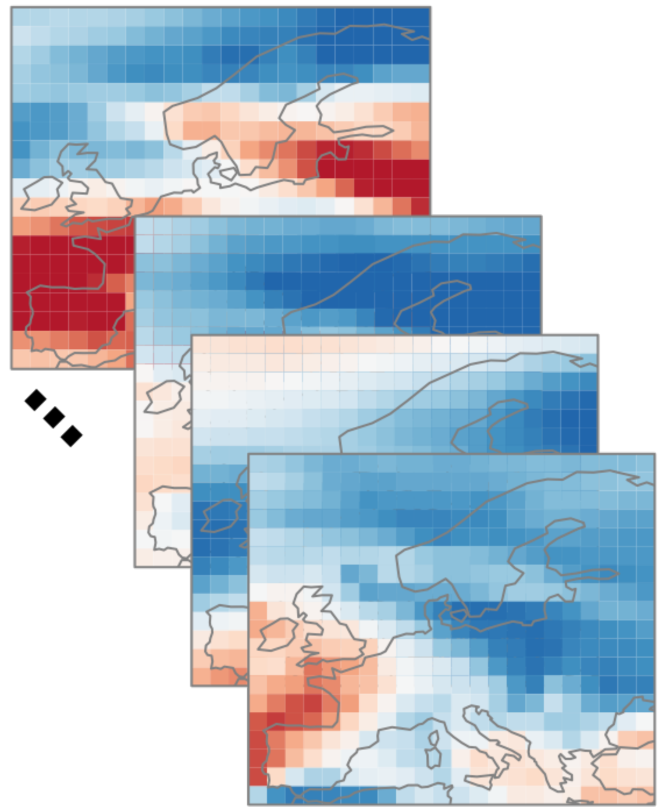
Deep downscaling is a very **active** topic that takes advantage of the **rapid** developments in the field and brings **new members** (fresh air) to the community.

Coordination with ESD protocols

Gutiérrez et al. (2013)
10.1175/JCLI-D-11-00687.1

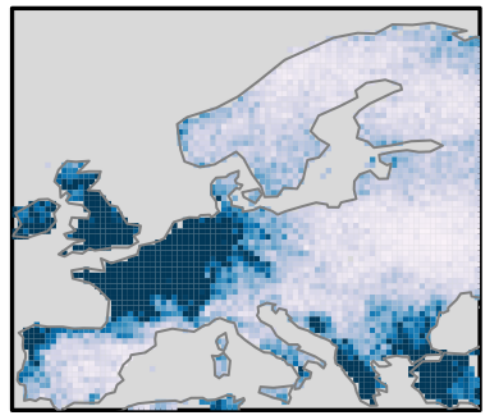
Large-scale **predictors** | Feature selection/reduction | Model Calibration and/or Prediction | High-resolution **predictands**

x (ERA5, 1°)



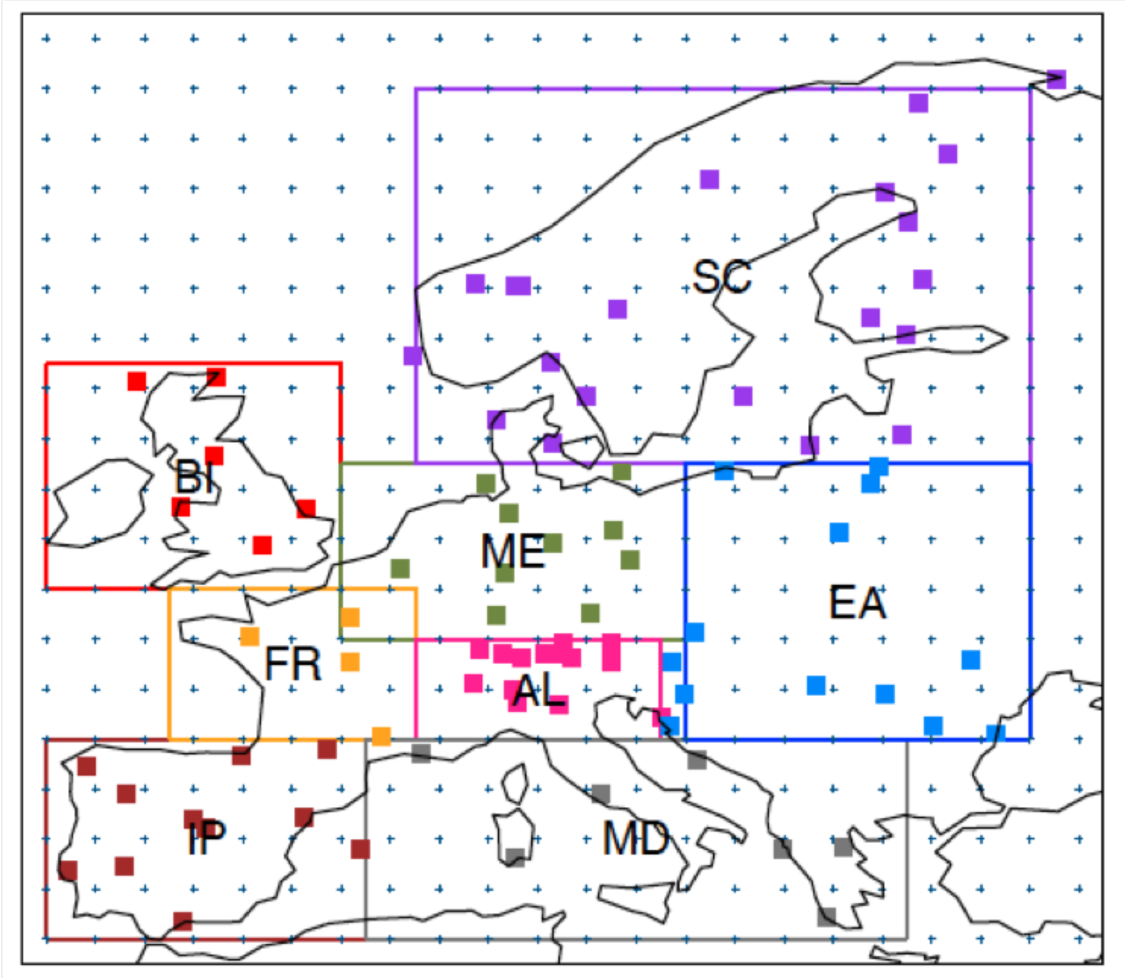
$$y = \mathbf{f}(x)$$

y (E-OBS, 0.1°)



Predictor selection is a bottleneck for continental-wide applications: NNs, EOFs, ...

Which domain?



Which variables?

T(1000hPa),…, T(500hPa);
Z(1000hPa),…, Z(500hPa);
H(1000hPa),…, H(500hPa);
U(1000hPa),…, U(500hPa);
V(1000hPa),…, V(500hPa);

Most applications of statistical downscaling are on small domains.

Coordination with ESD protocols

Large-scale **predictors** → Feature selection/reduction → Model Calibration and/or Prediction → High-resolution **predictands**

Standard Statistical Downscaling

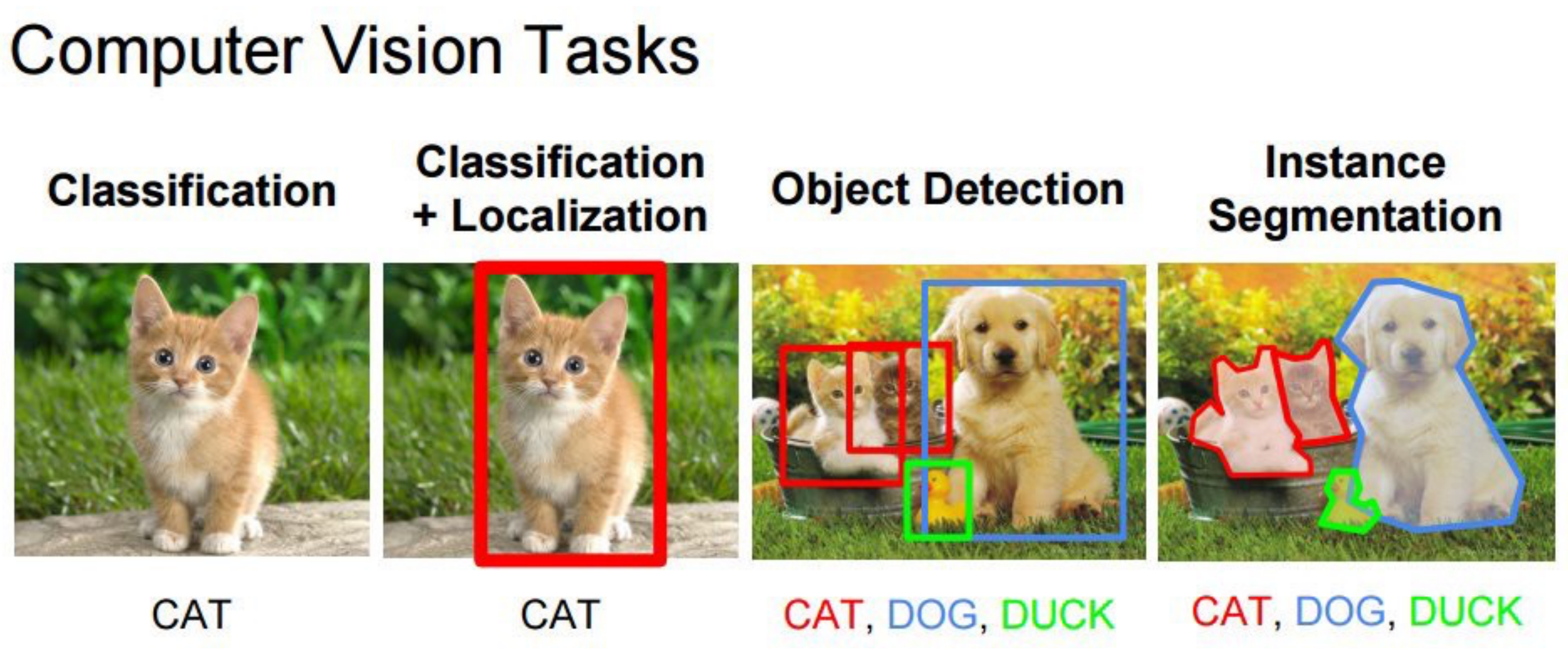
Convolutional Neural Networks + Deep Learning technological developments

Large-scale **predictors** → Model Calibration and/or Prediction → High-resolution **predictands**

Predictor selection is performed automatically during the trainning

…similar experiences in **other applications** with **successful** results

LeCun et al. (1995)



Coordination: CORDEX domains (EUR-44)

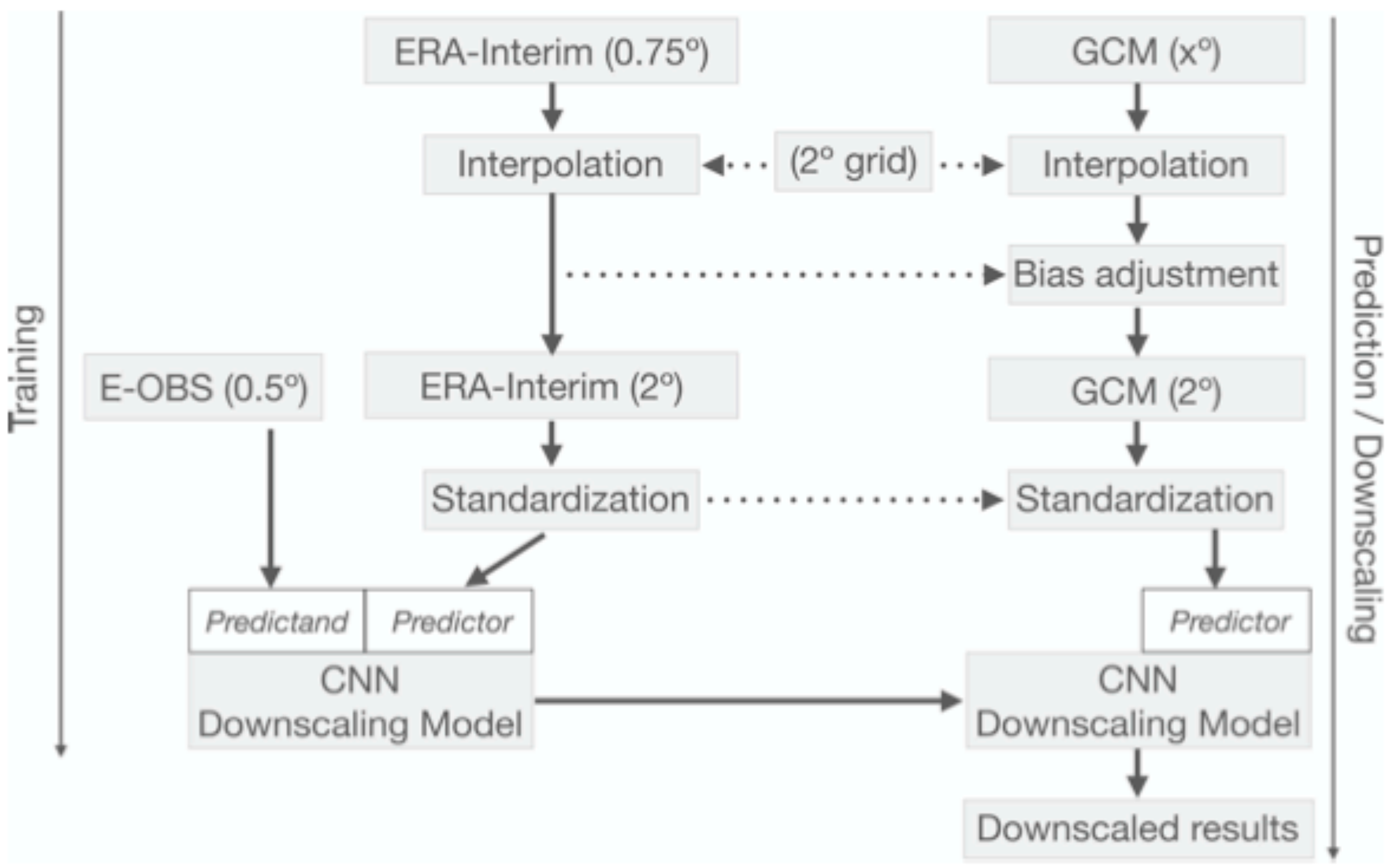
Geosci. Model Dev., 15, 6747–6758, 2022
https://doi.org/10.5194/gmd-15-6747-2022

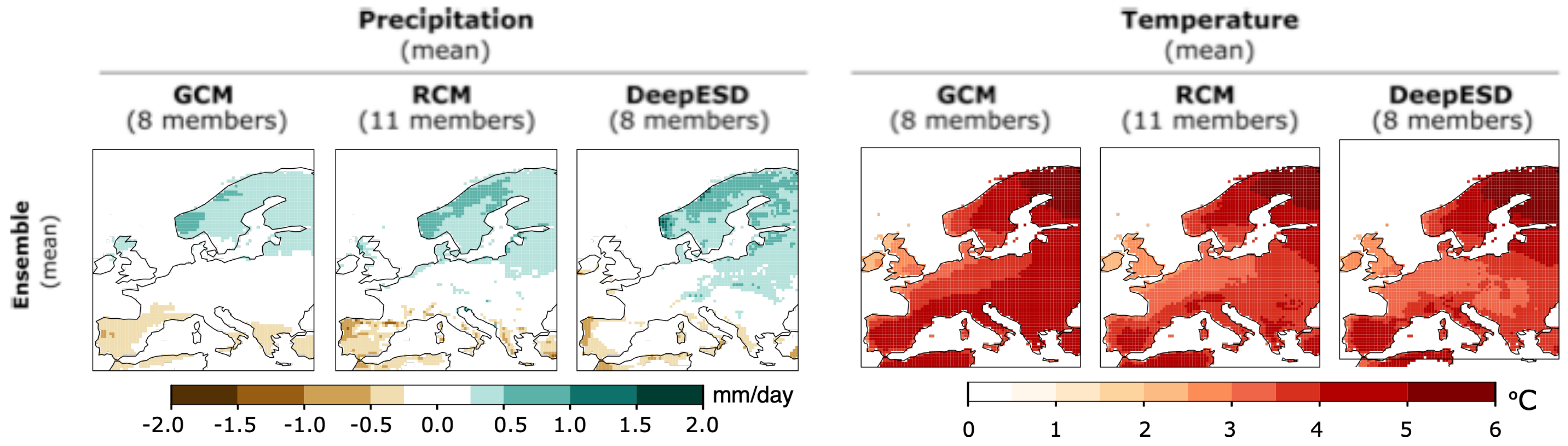
Geoscientific Model Development
Open Access
EGU

Downscaling multi-model climate projection ensembles with deep learning (DeepESD): contribution to CORDEX EUR-44

Jorge Baño-Medina[1], Rodrigo Manzanas[2,3], Ezequiel Cimadevilla[1], Jesús Fernández[1], Jose González-Abad[1], Antonio S. Cofiño[1], and José Manuel Gutiérrez[1]

Name	Institution	Spatial resolution
CanESM2 (Christian et al., 2010)	Canadian Centre for Climate Modelling and Analysis	(2.81°, 2.79°)
CNRM-CM5 (Voldoire et al., 2013)	Centre National de Recherches Météorologiques and Centre Européen de Recherche et de Formation Avancée	(1.4°, 1.4°)
MPI-ESM-MR (Müller et al., 2018)	Max-Planck-Institut für Meteorologie	(1.87°, 1.87°)
MPI-ESM-LR (Müller et al., 2018)	Max-Planck-Institut für Meteorologie	(1.87°, 1.87°)
NorESM1-M (Bentsen et al., 2013)	Norwegian Climate Center	(2.5°, 1.9°)
GFDL-ESM2M (Dunne et al., 2013)	National Oceanic and Atmospheric Administration Geophysical Fluid Dynamics Laboratory	(2.5°, 2.02°)
EC-EARTH (Doblas Reyes et al., 2018)	European-wide consortium	(1.12°, 1.12°)
IPSL-CM5A-MR (Dufresne et al., 2013)	Institut Pierre-Simon Laplace Climate Modelling Center	(2.5°, 1.27°)



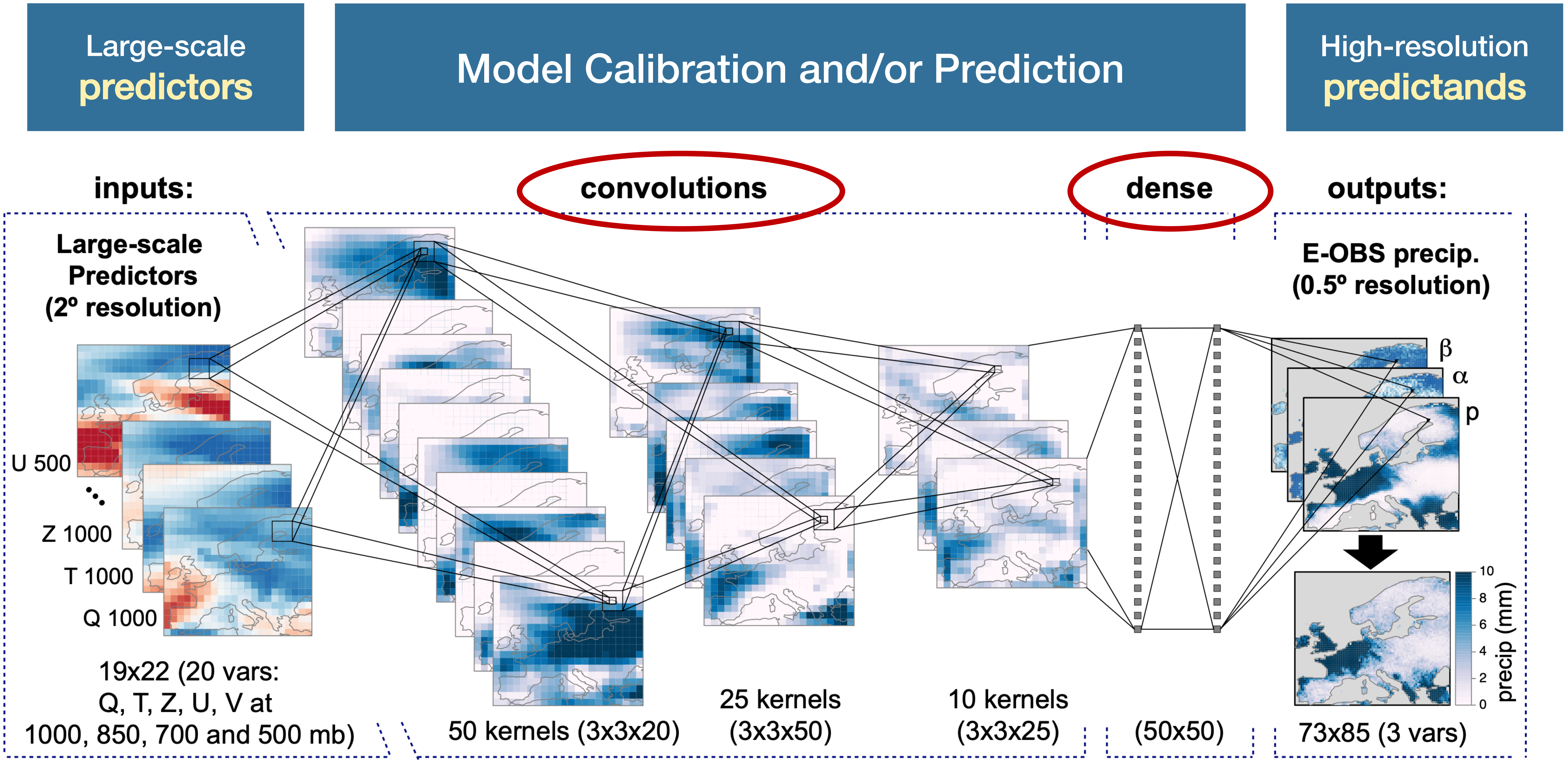


Baño-Medina et al. (2022)
[10.5194/gmd-15-6747-2022](https://doi.org/10.5194/gmd-15-6747-2022)

DeepESD_vEE (ERA-Interim – E-OBS)

ESGF
Earth System Grid Federation

Gaining trust: Interpretability



Baño-Medina et al. (2020) https://doi.org/10.5194/gmd-13-2109-2020

Gaining **interpretability** for the models

González-Abad et al. (submitted)
[10.48550/arXiv.2208.05424](https://doi.org/10.48550/arXiv.2208.05424)

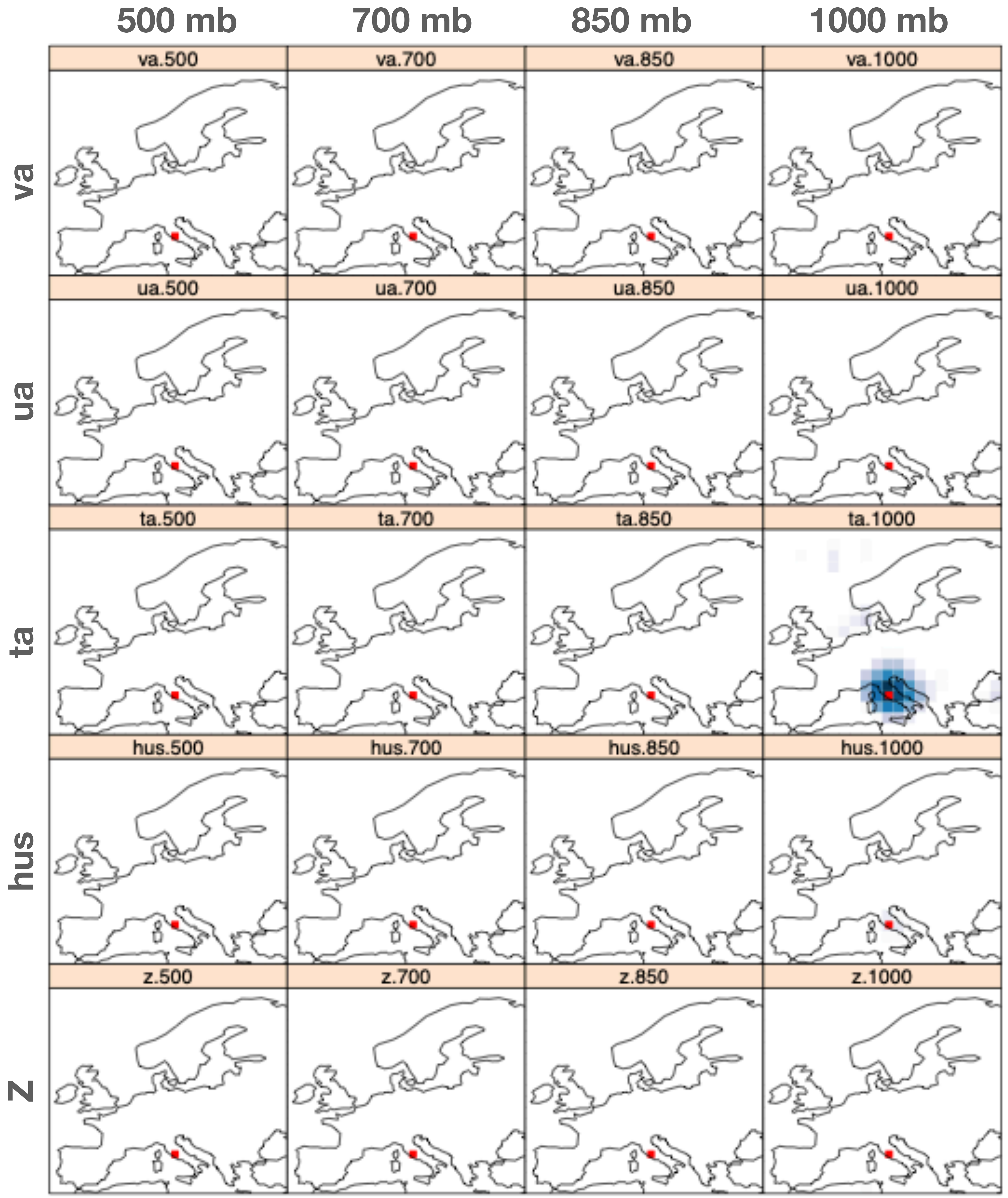
- What predictor variables are the most important ones?
- Do CNNs perform automatic spatial selection of features?

Explainable Artificial Intelligence (XAI)

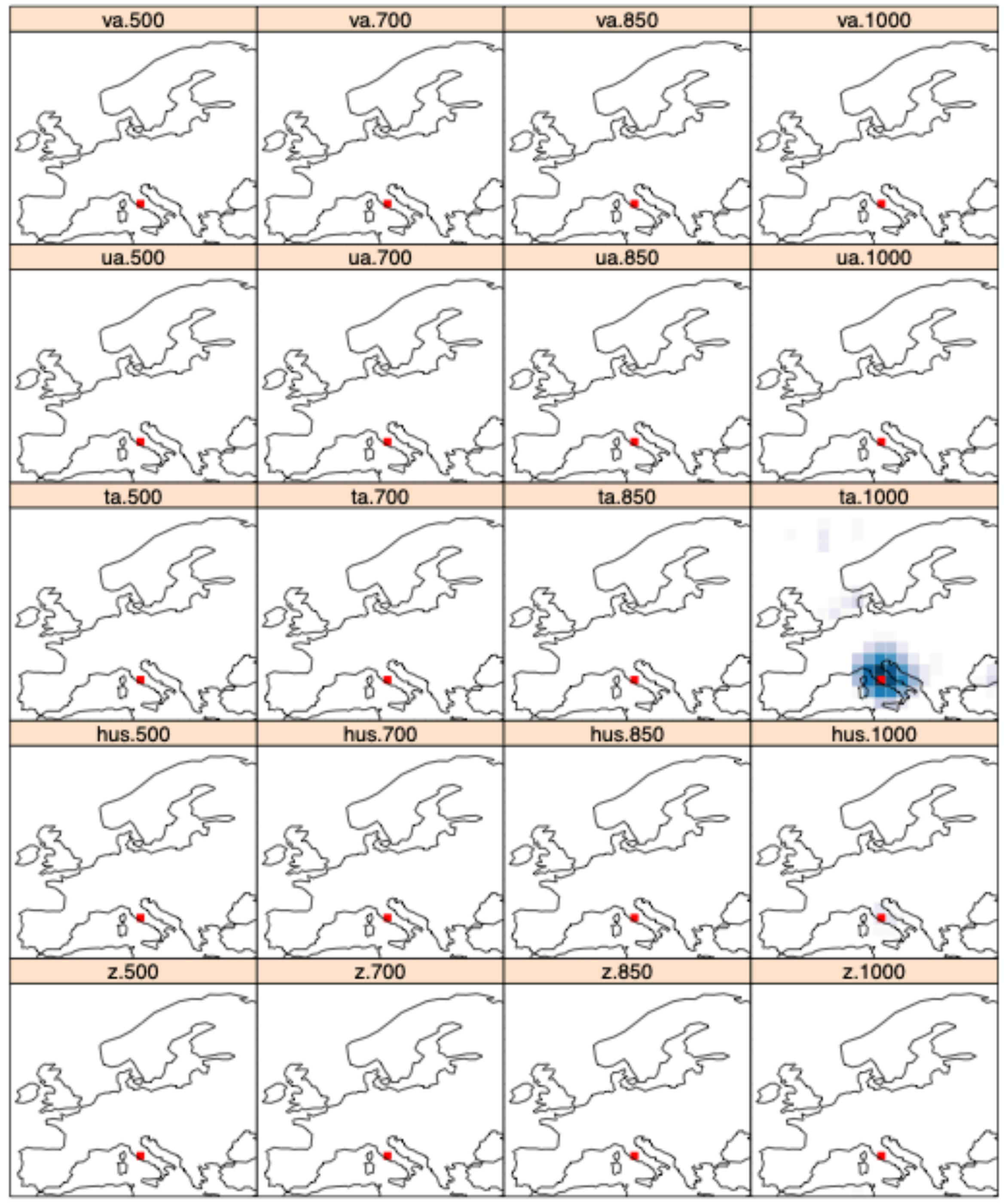
A **saliency map** is a spatial representation of the influence of the inputs in the model output.

In the case of downscaling, saliency maps allow identifying the **relevant predictor variables** and the spatial regions of influence, thus **facilitating diagnostic and explainability** of the downscaled results.

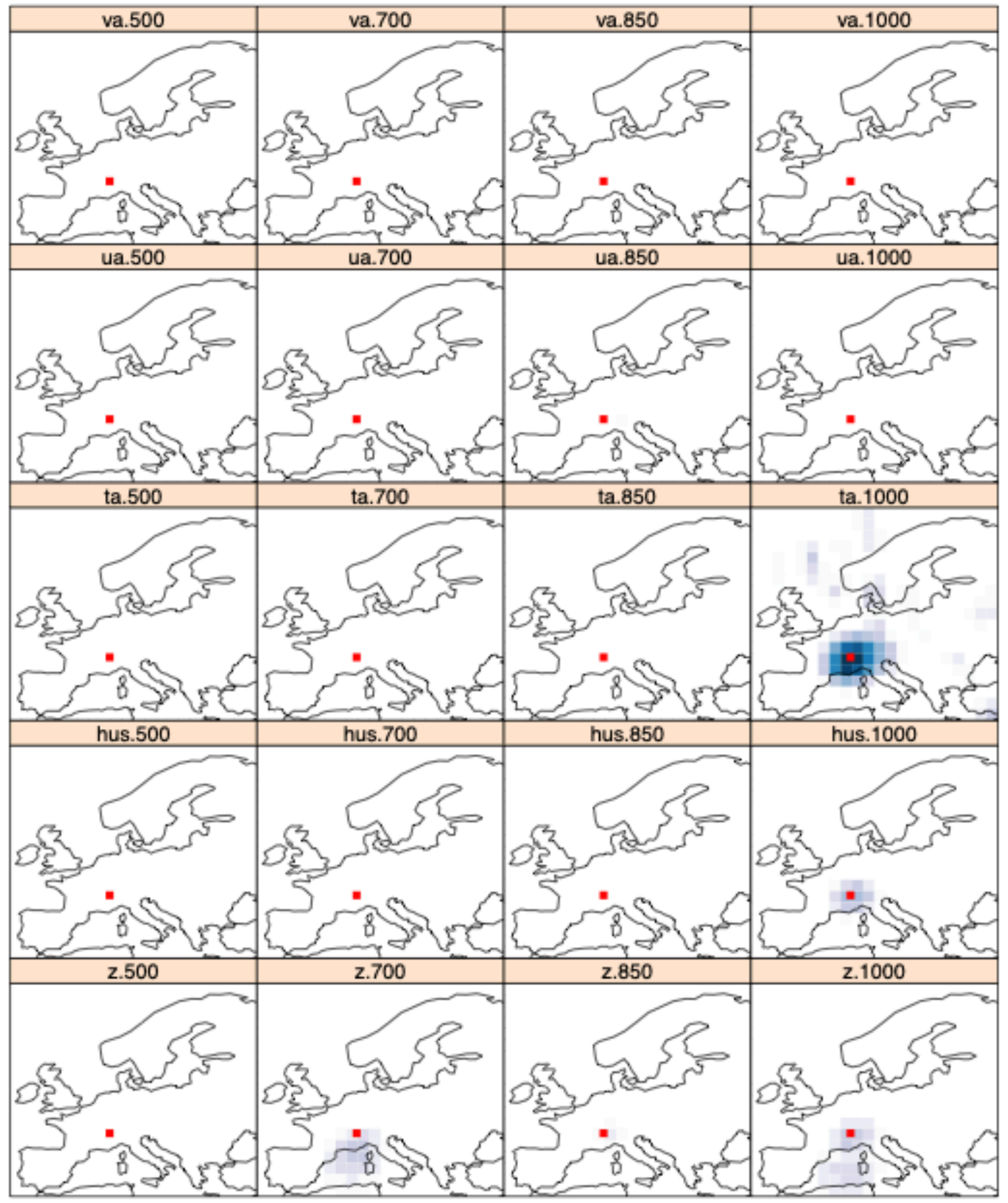
We yse a gradient-based technique known as Integrated Gradients (IG; **Sundararajan et al., 2017**), since it is known to overcome inherent problems of standard gradient-based methods —e.g. gradient saturation (Glorot & Bengio, 2010)— and has been used in other climate-CNN applications (**Kondylatos et al., 2022**).



TEMPERATURE



Rome



Alps

- Air temperature at 1000 hPa is the most relevant variable

- This predominancy of T° at 1000 hPa is also observed for the other locations studied (*see the manuscript*).

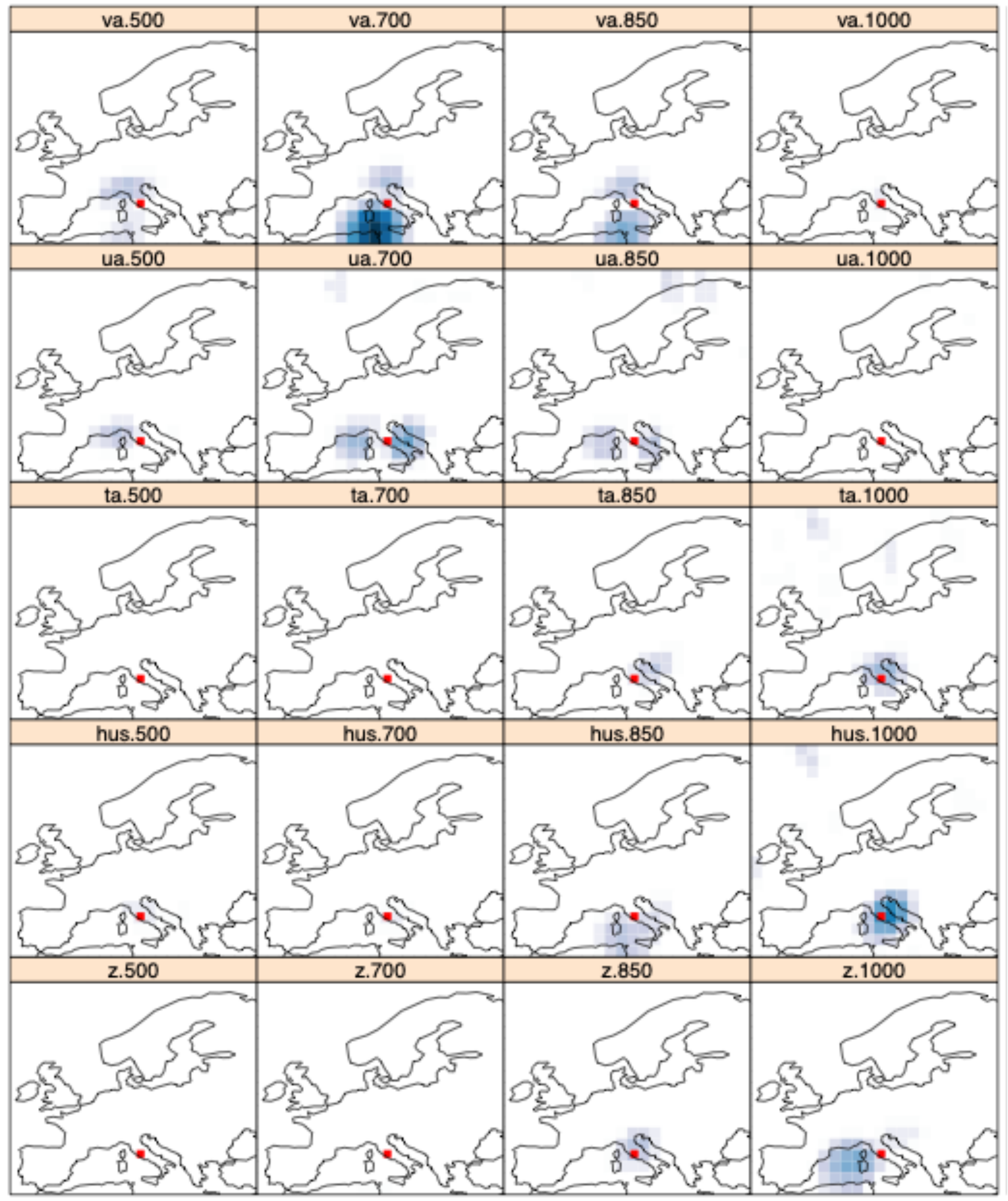
- The relevant spatial domain is located around the location of interest.

PRECIPITATION

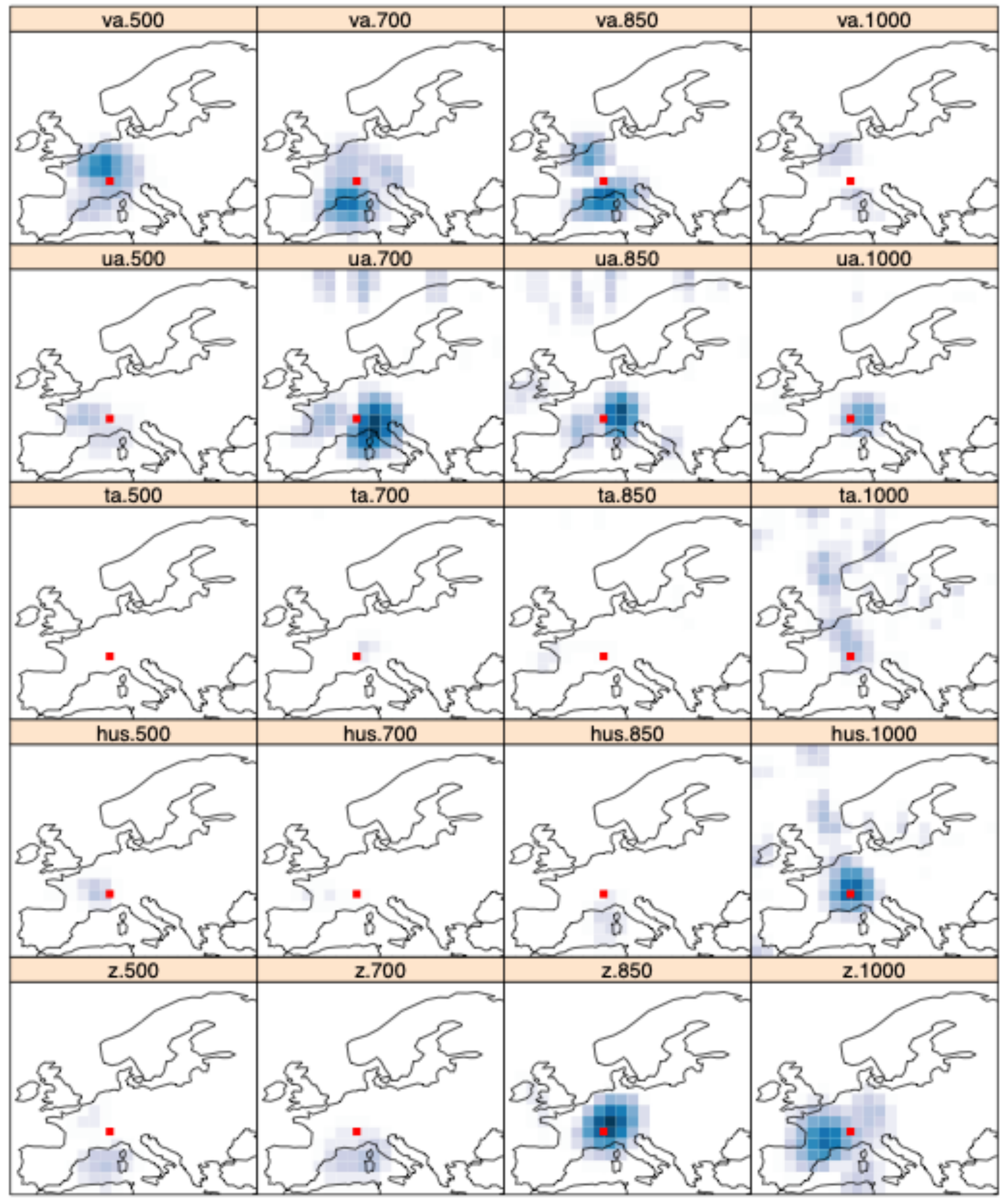
- Wind velocity, especially the meridional component at 700 and 850 hPa, together with the specific humidity and the geopotential height at 1000 hPa seem the most informative to downscale over Rome.

- For the Alps, zonal velocity is also relevant.

Rome



Alps



Questions (machine learning):

- How do we ensure/evaluate that the automatization of predictor selection and feature extraction captures the right physical phenomena needed for downscaling? **[physical constrains]**
- How do we ensure/evaluate that machine learning methods produce plausible projections generalizing to future climates? **[experimental protocols]**
- Can we advance in the understanding of machine learning methods to gain interpretability of results? **[XAI]**
- Can we build RCM **emulators** suitable for certain tasks (e.g. filling-up temporal gaps or the SCEN/GCM/RCM matrix, to create large ensembles over areas poorly covered by RCM runs, or for CPRCM runs)?

IMPETUS 4CHANGE

Thank you for your attention!