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On the use of Deep Generative Models for "Perfect" Prognosis Climate Downscaling

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Tackling Climate Change with Machine Learning

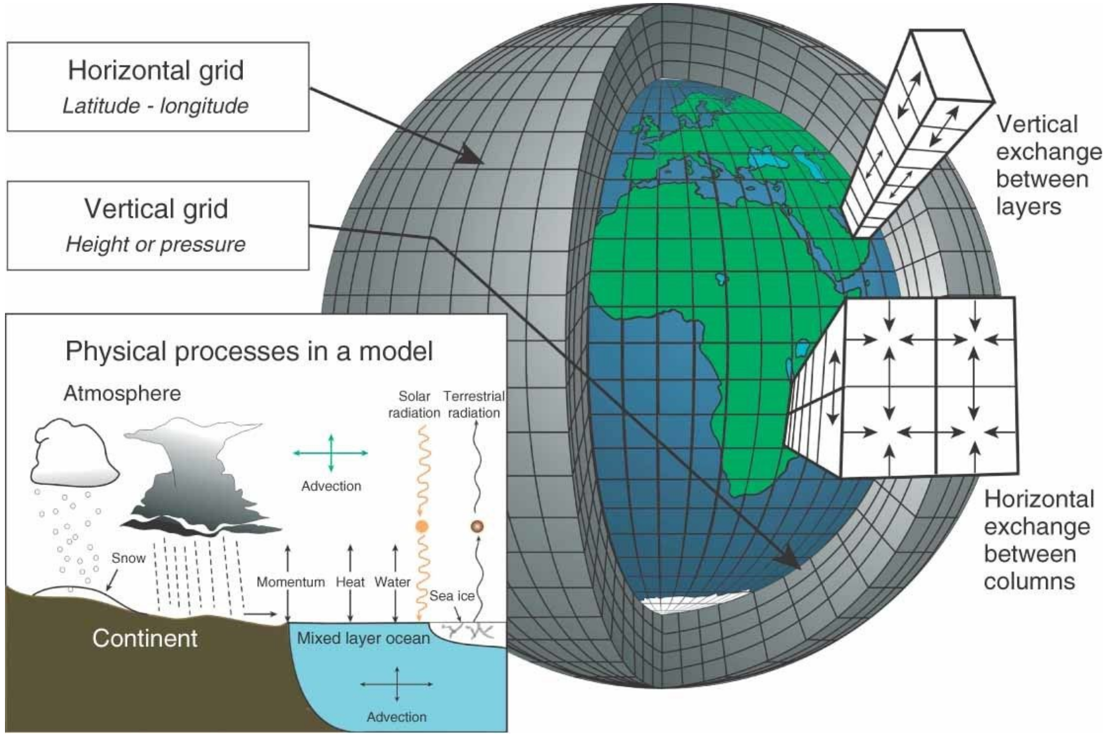
Global Climate Models

Global Climate Models (GCM) are the main tools available for simulating the response of the global climate system to different **greenhouse gas concentrations scenarios**.

Climate equations

$$
\begin{aligned}
\frac{d\boldsymbol{v}}{dt} &= -\alpha \boldsymbol{\nabla} p - \boldsymbol{\nabla}\phi + \boldsymbol{F} - 2\boldsymbol{\Omega} \times \boldsymbol{v} \\
\frac{\partial \rho}{\partial t} &= -\boldsymbol{\nabla} \cdot (\rho \boldsymbol{v}) \\
p\alpha &= RT \\
Q &= C_p \frac{dT}{dt} - \alpha \frac{dp}{dt} \\
\frac{\partial \rho q}{\partial t} &= -\boldsymbol{\nabla} \cdot (\rho \boldsymbol{v} q) + \rho (E - C)
\end{aligned}
$$

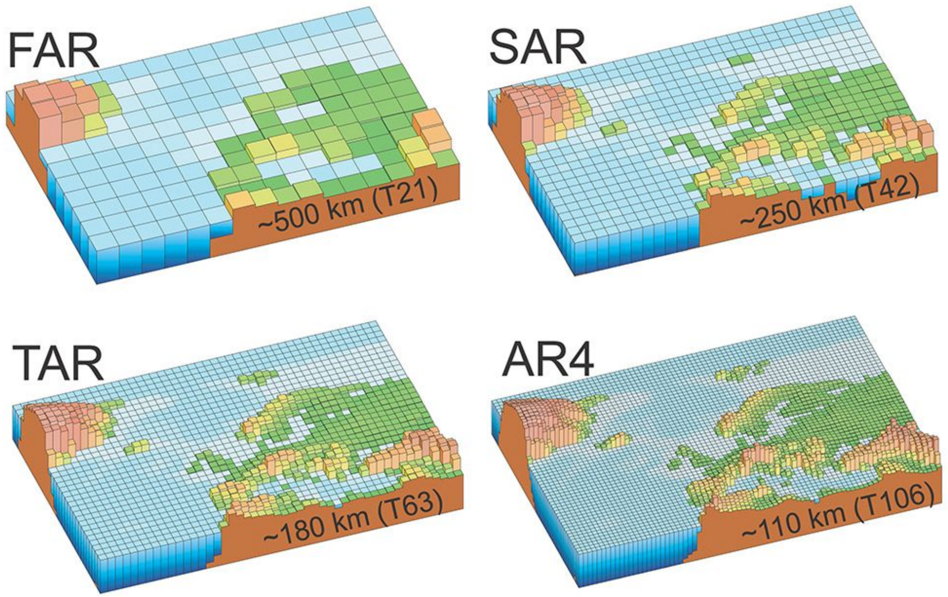
discretize over space and time



Source: Edwards, P. N. (2011). History of climate modeling. *Wiley Interdisciplinary Reviews: Climate Change*, 2(1), 128-139.

Global Climate Models

Due to computational limitations, GCMs suffer from **a coarse spatial resolution**.



Source

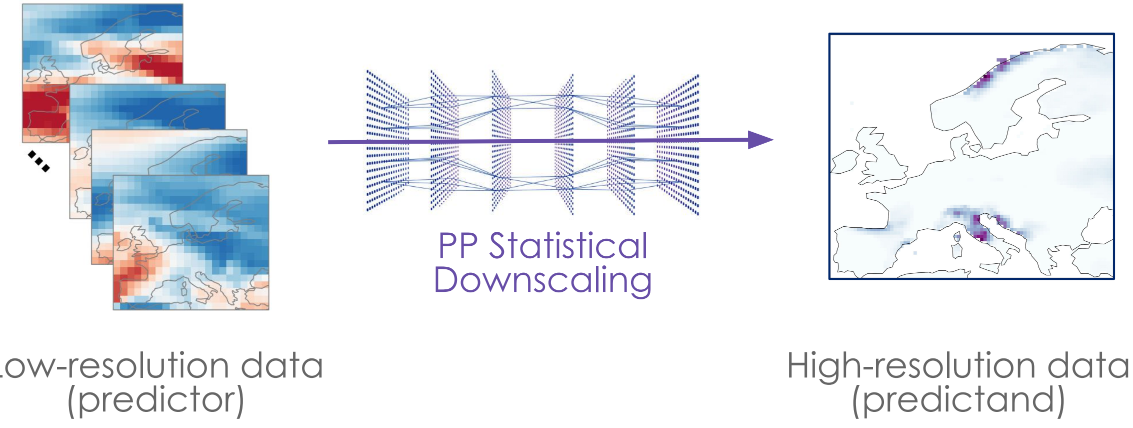
This makes it difficult to use GCMs in different socio-economical activities **to tackle climate change**.

Source

An increase in spatial resolution is needed

Statistical Downscaling

Statistical Downscaling learns the **empirical relationship** between a set of low resolution variables (*input/predictors*) and the local variable of interest (*output/predictands*).



In this study we focus on the **Perfect Prognosis (PP)** Downscaling where both predictors and predictand are **observational datasets**.

WARNING: PP-based downscaling is NOT a super-resolution problem (more details on PP assumptions in [1]).

Deep Learning (DL) has recently emerged as a promising PP technique:

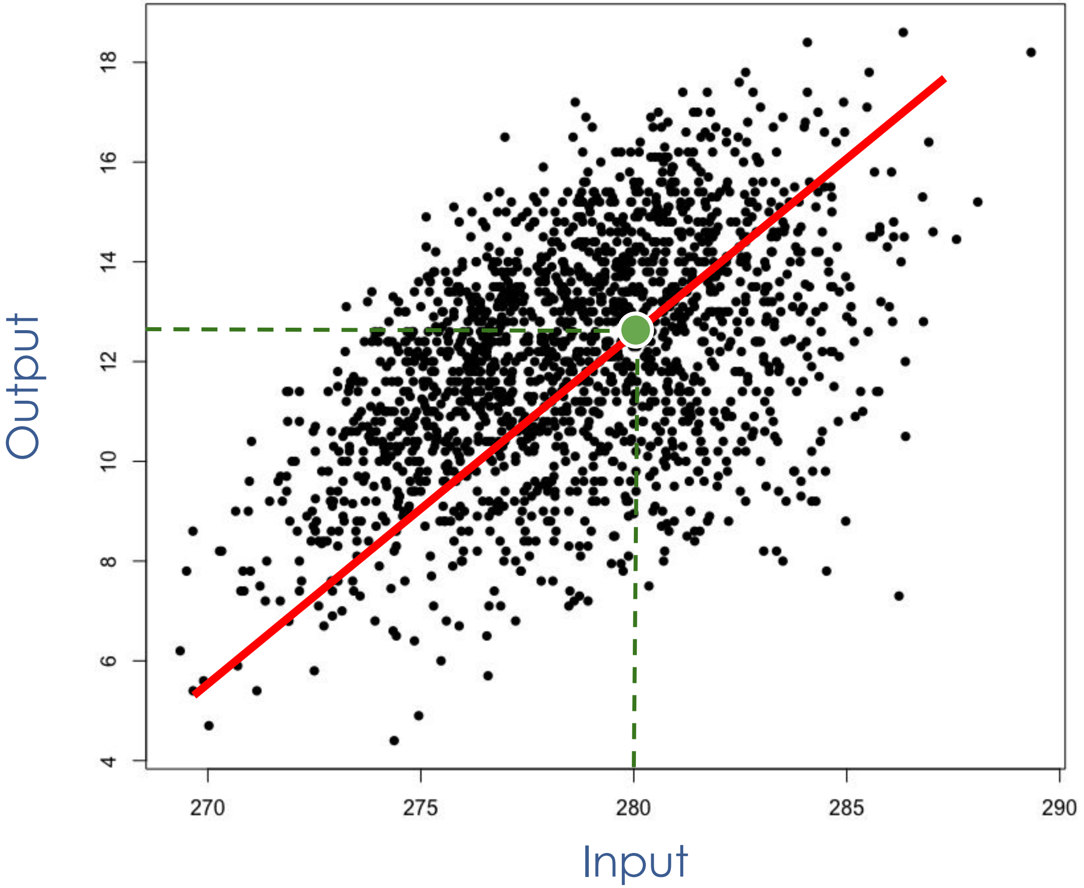
- Allows to **reproduce the observed local climate**.
- Shows **plausible climate change projections** of precipitation and temperature over Europe.

[1] Maraun, D., & Widmann, M. (2018). Statistical downscaling and bias correction for climate research. Cambridge University Press.

Source

Probabilistic regression-based models

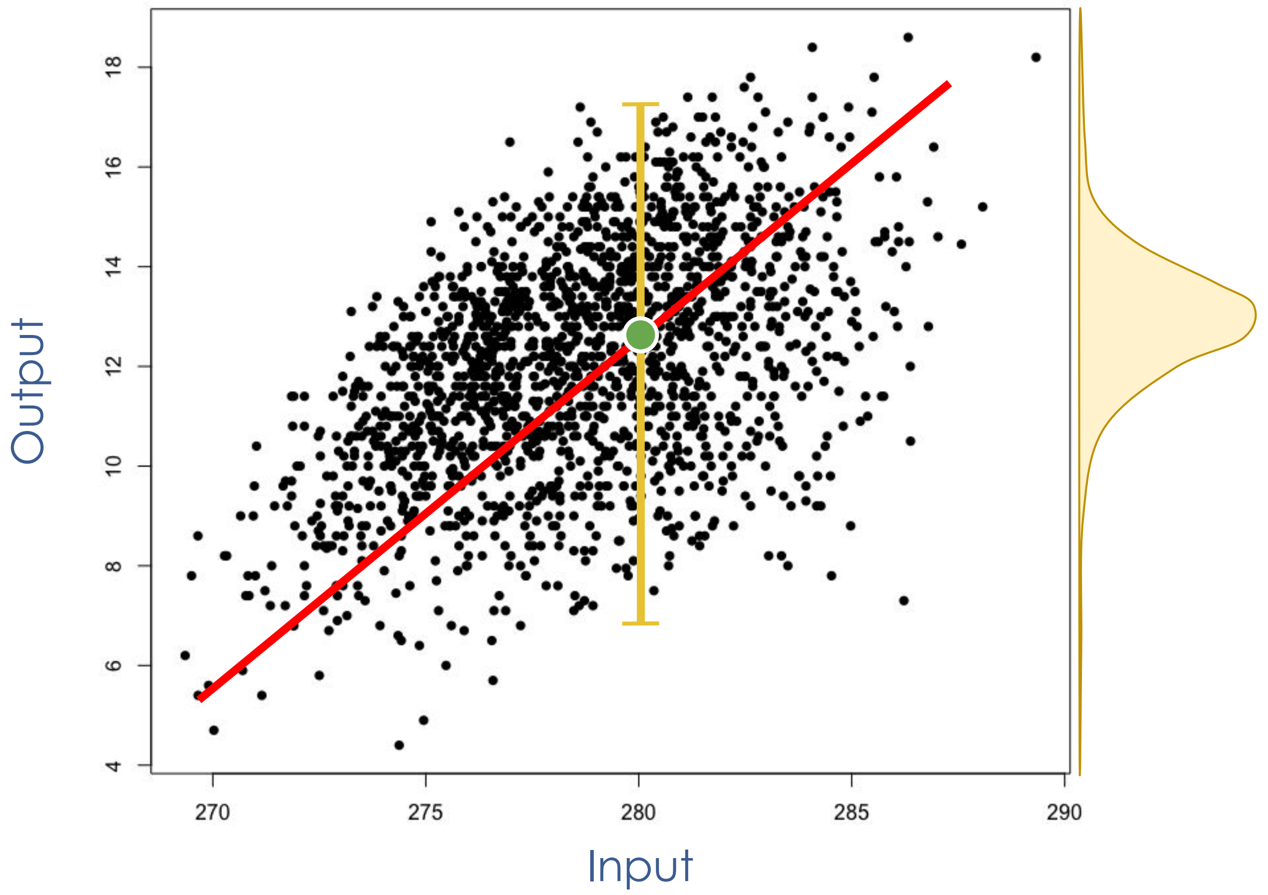
Unfortunately, deterministic DL techniques applied to PP Downscaling may fail to **account for extremes**.



Conditional mean does not express the variability of data.

Probabilistic regression-based models

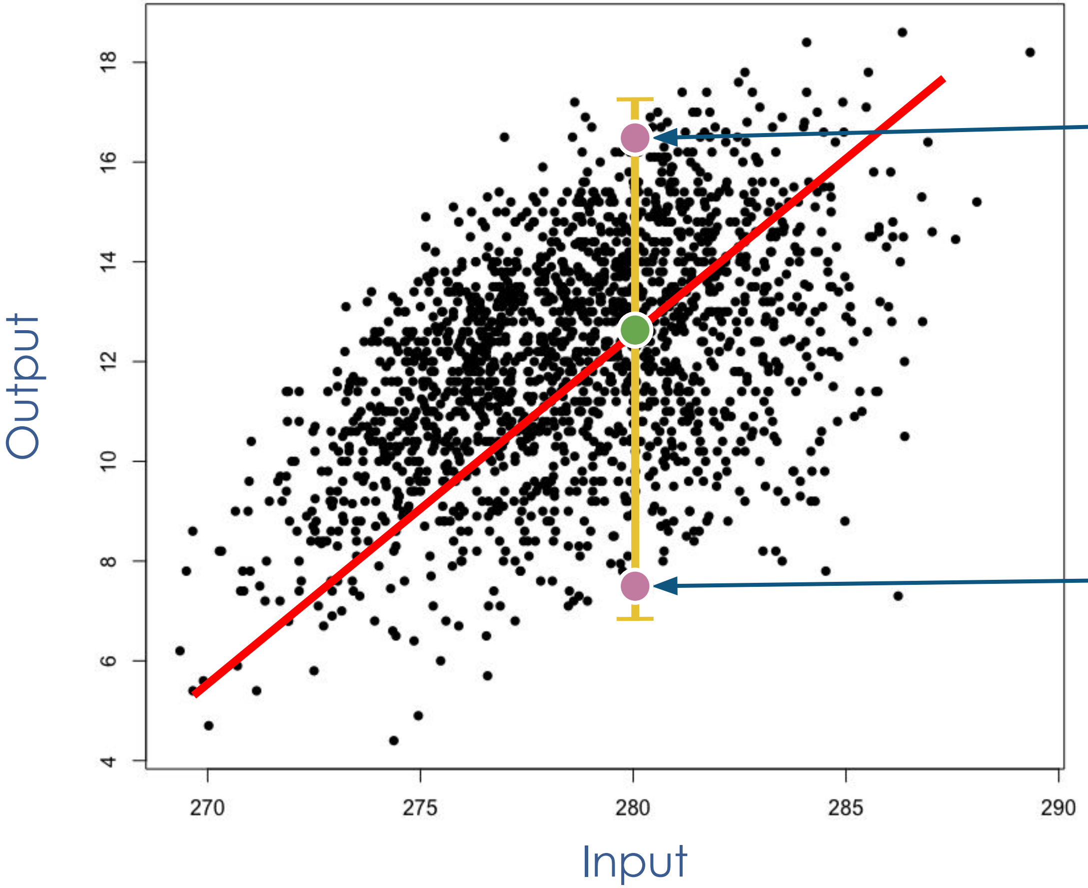
To account for the uncertainty describing these extremes **probabilistic regression-based modeling** started to be adopted.



Modelling the distribution allows to account for the **uncertainty**, thus describing the possible **extremes**.

Probabilistic regression-based models

Taking into account these **extremes** helps in the decision-making **to tackle climate change**.



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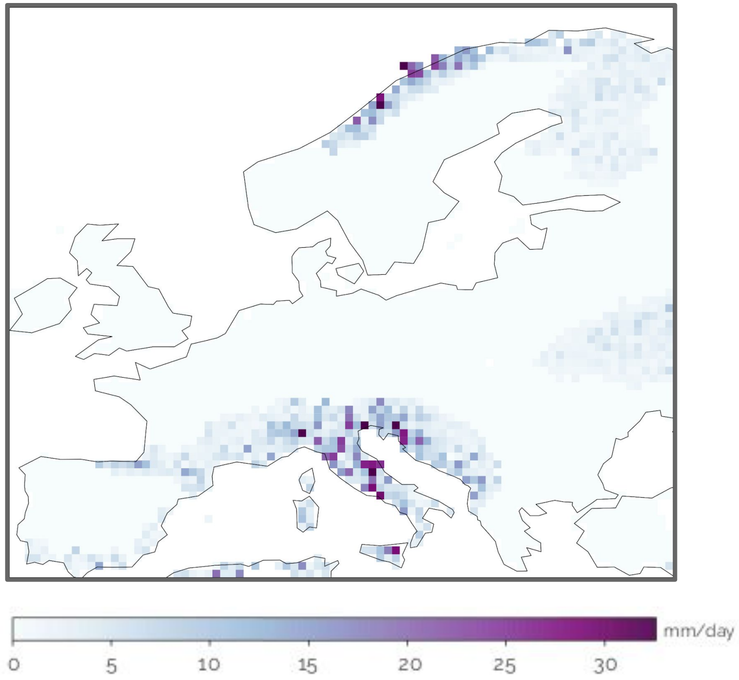
Deep Generative Models for PP Downscaling

The state-of-the-art probabilistic DL approach [2] **independently** modeled the distribution at each predictand site.

Due to the independence between distributions, the downscaled variables are **not spatially consistent**.



We propose the use of **Deep Generative Models** as tractable alternatives to model multivariate conditional distributions over the high-dimensional space of the predictand (in a PP setting). This could bring us certain advantages:

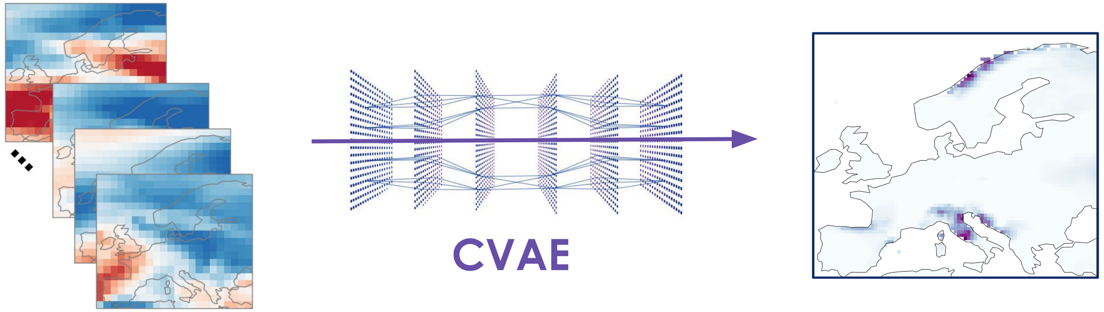
- Improved **spatial consistency** in comparison with previous approaches
- **Stochasticity**, which allows us to account for uncertainty (extremes)
- Taking advantage of **recent developments** in generative modelling

[2] Baño-Medina, J., Manzanas, R., & Gutiérrez, J. M. (2020). Configuration and intercomparison of deep learning neural models for statistical downscaling. *Geoscientific Model Development*, *13*(4), 2109-2124.

Downscaling case study over Europe with CVAE

To illustrate these points we develop a simple **use-case** of PP Downscaling over Europe using a Generative Model, more specifically a **Conditional Variational Autoencoder (CVAE).**

We compare our CVAE model with the CNN1 **state-of-the-art** model in [2] under the same conditions:



Train period
1979-2002

Test period
2003-2008

ERA-Interim (2° resolution)

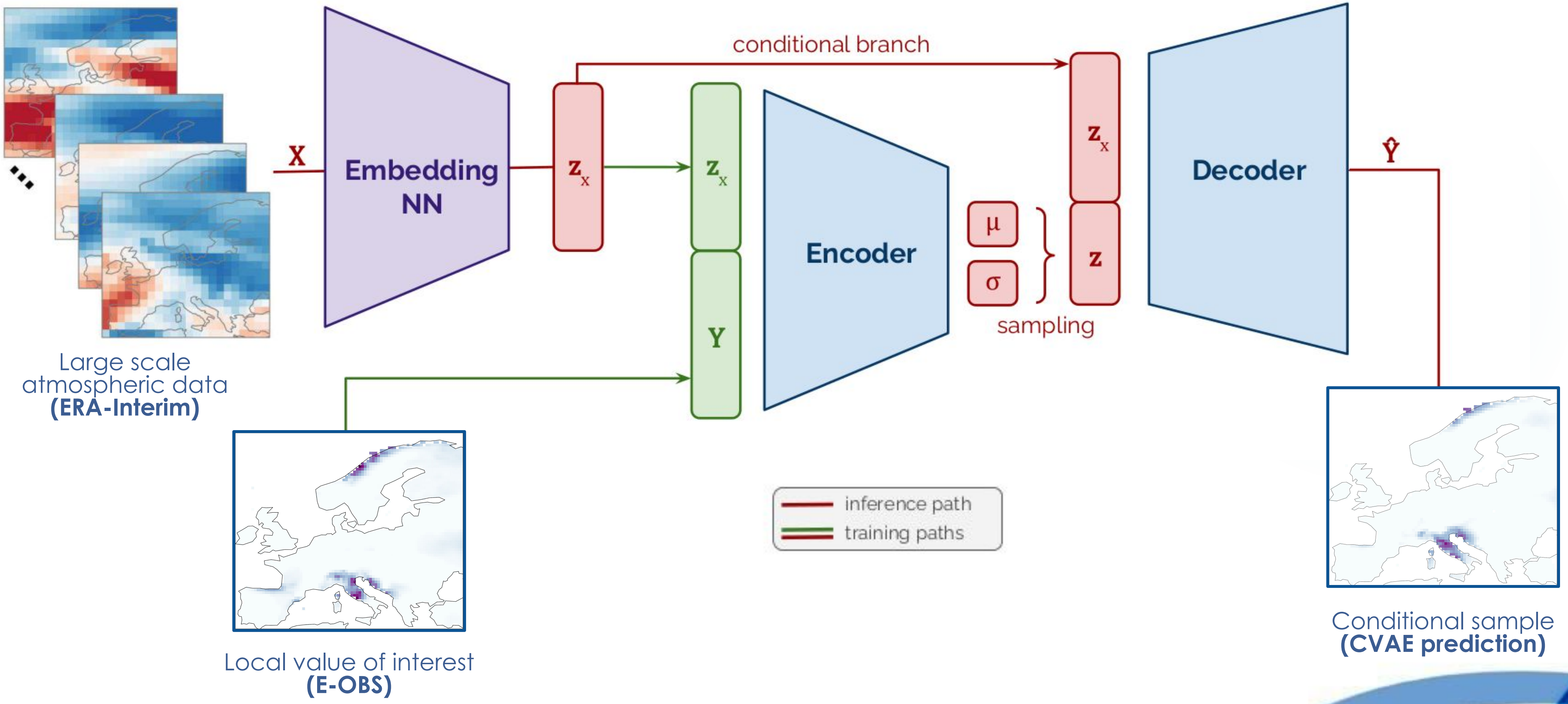
5 thermodynamical variables
× 4 different vertical levels

EOBS (0.5° resolution)

Precipitation

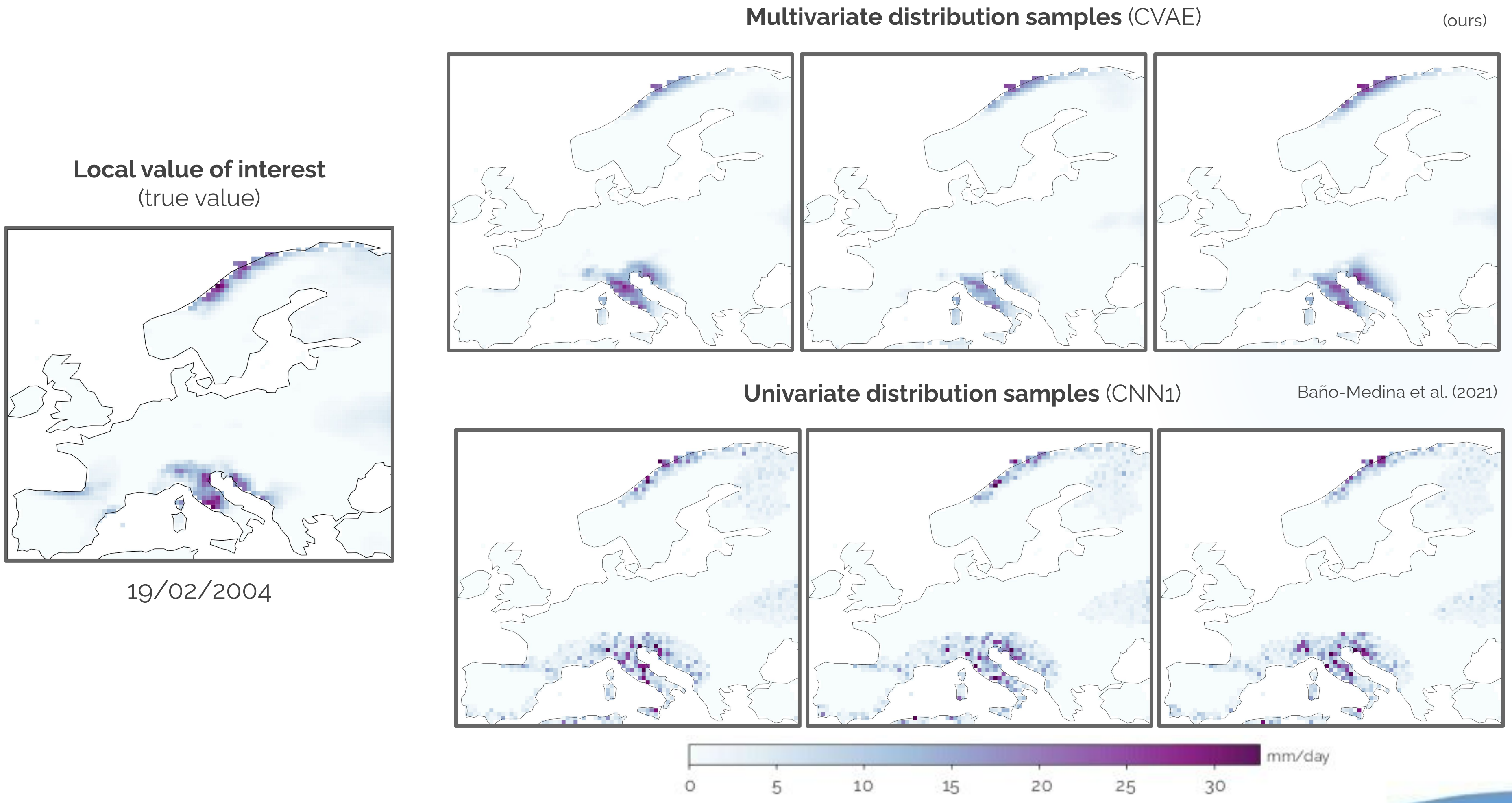
[2] Baño-Medina, J., Manzanas, R., & Gutiérrez, J. M. (2020). Configuration and intercomparison of deep learning neural models for statistical downscaling. *Geoscientific Model Development*, *13*(4), 2109-2124.

CVAE model



X
Embedding NN
z_x
conditional branch
z_x
Y
Encoder
μ
σ
sampling
z_x
z
Decoder
Ŷ
Large scale atmospheric data
(ERA-Interim)
Local value of interest
(E-OBS)
inference path
training paths
Conditional sample
(CVAE prediction)

Comparison: **CVAE** vs **CNN1**



CNN1 fields, being sampled from independent Bernoulli-Gamma distributions, present a **noisy spatial structure**. In contrast, CVAE, while still allowing for sampling, gives much **smoother predictions**.

Future Work

We propose the use of **Deep Generative Models** to produce **spatially consistent** stochastic fields in PP Statistical Downscaling. Future work will explore:

- Robust **quantitative comparison** of the **spatial consistency** of generative models with respect to non-generative ones.
- Evaluating the models with respect to **temporal consistency** and **reproducibility of extremes**.
- A proper study of the model's **extrapolation capabilities** in order to apply it to climate change projections.
- Further **tuning of the CVAE architecture** may translate into improvements. Additional mechanisms such as **Normalizing Flows** could help modelling a more **flexible latent distribution** which would capture better the complex distribution of precipitation fields.
- Explore **GAN-based** models to further improve the results obtained with CVAEs (e.g Conditional GANs).

Thank you!

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