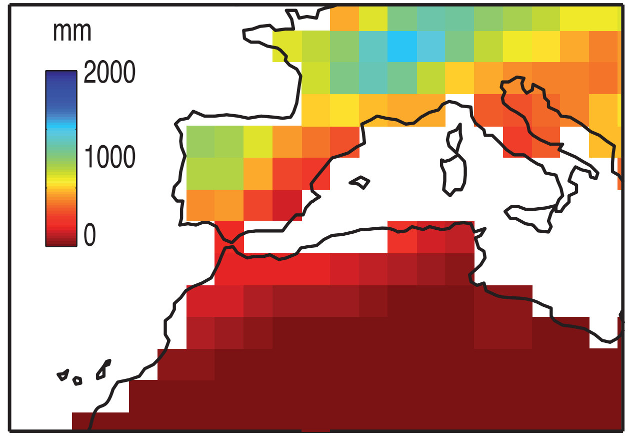
Statistical downscaling with deep learning: A contribution to CORDEX-CORE

Jorge Baño-Medina
bmedina@ifca.unican.es
Institute of Physics of Cantabria
Santander Meteorology Group

Jose M. Gutiérrez
gutierjm@unican.es
Institute of Physics of Cantabria
Santander Meteorology Group

UC UNIVERSIDAD DE CANTABRIA CSIC IFCA Instituto de Física de Cantabria

MODEL SPACE



GCM outputs (**~200 km**)

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

Dynamical Downscaling

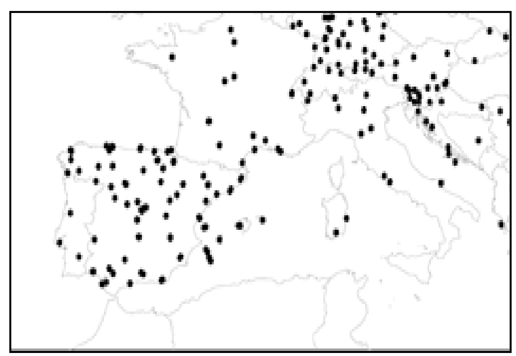
Statistical Downscaling

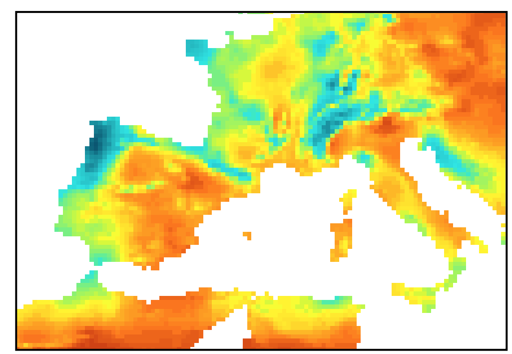
Approaches:

- Model Output Statistics (MOS)
Pred => OBS

- Perfect Prog
OBS (Rean.) => OBS

REAL WORLD

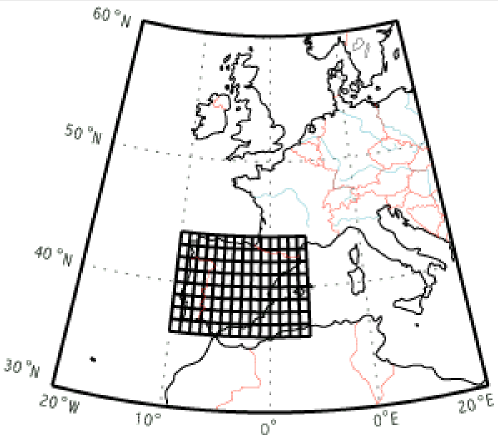

Local data (**points**)


Gridded data (**~10 km**)

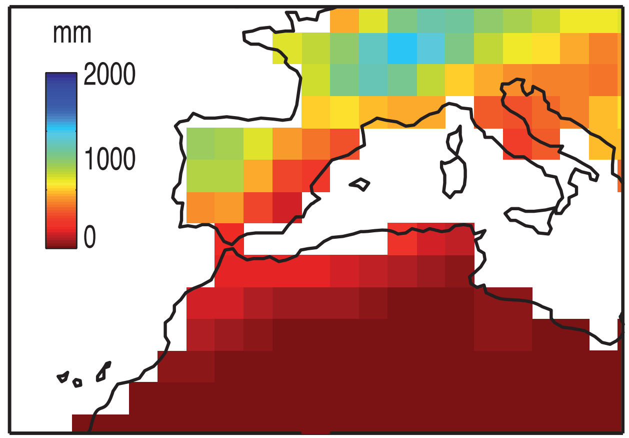
– Hydrology – Energy
– Agriculture – Health

Statistical Downscaling

MODEL SPACE



T(1000 mb),..., **T**(500 mb);
Z(1000 mb),..., **Z**(500 mb);
.......;
H(1000 mb),..., **H**(500 mb)



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$$

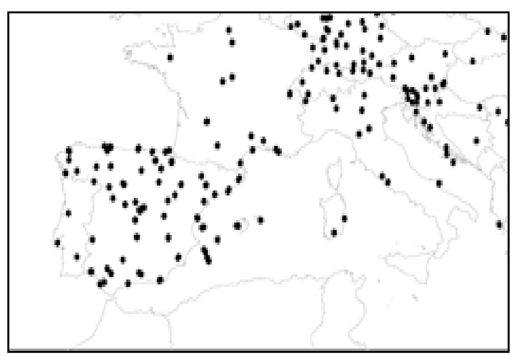
X_n

Predictors (from a renalysis, **ERA-Interim**):
- Large-scale variables well reproduced by GCMs.

REAL WORLD

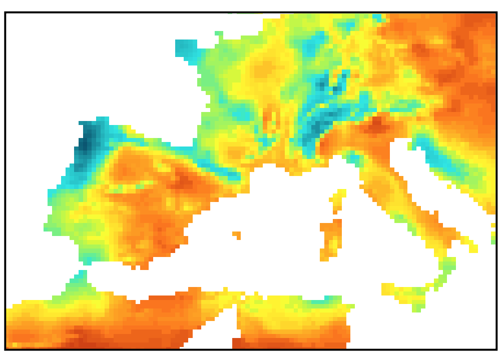
Linear regression
K-NN (analogs)
SVMs,
NNs,
RFs

$$\hat{Y}_n = a\, X_n + b$$



Local data (**points**)

Precip



Gridded data

E-OBS (0.5º ~50km)

Y_n

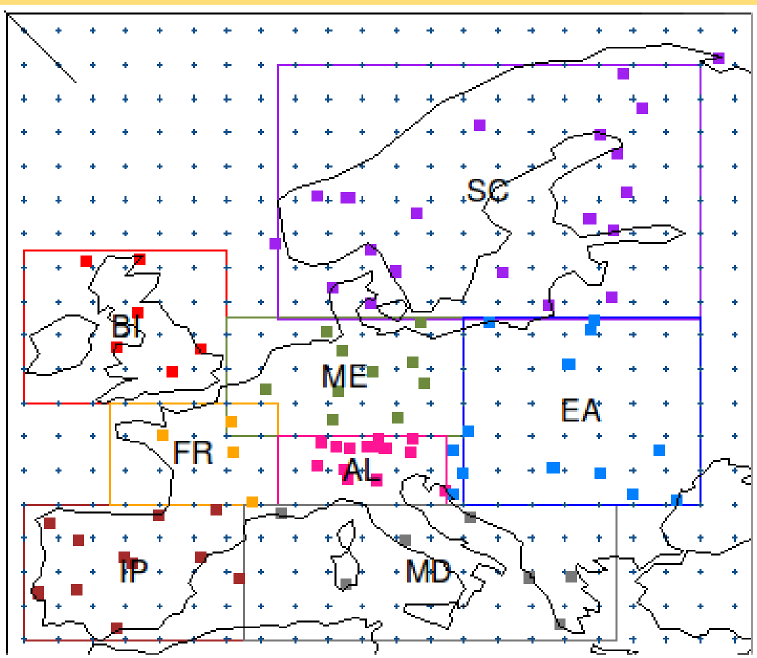
Common Methods:

Linear regression
K-NN (analogs)
SVMs,
NNs,
RFs

Limitations:

- High-Dimensonality
  - Feature Selection
    (e.g., selection of gridboxes)
  - Feature Reduction
    (e.g., PCs)

- No method clearly outstands
  against the other



Traditional approaches **can not treat continental-sized domains**

Therefore, the **spatial information** is very **limited**

¿**How** can we **statistically downscale continental-sized domains**?

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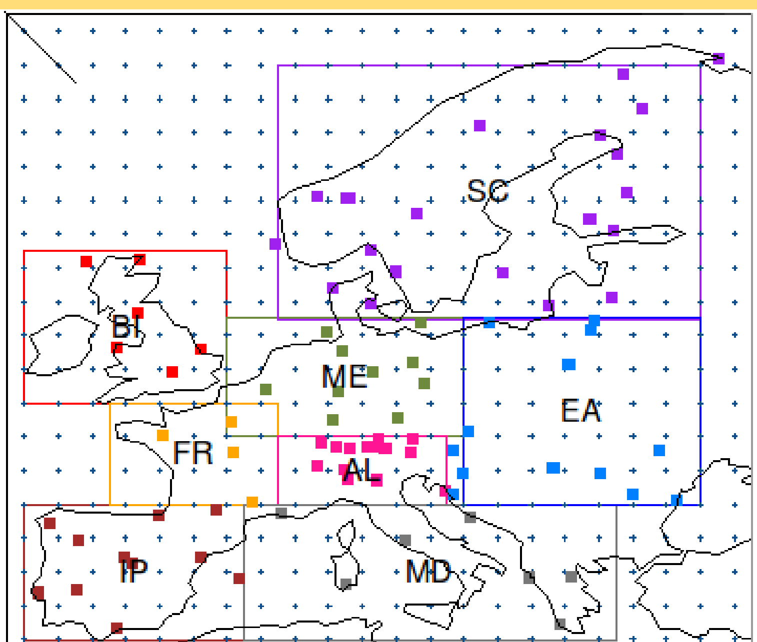
Deep Learning?



Can deep learning treat continental-sized domains?

Therefore, **contribute** to **CORDEX-CORE**

Deep Learning Statistical Downscaling

Common Methods:

Linear regression
K-NN (analogs)
SVMs,
NNs,
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Deep Learning?

A recent **Nature** publication outlined future **research** towards the **applicability of deep learning in the climate science**

Reichstein et al., 2019

Simple illustrative examples of applications of deep learning in statistical downscaling have been developed in the last years

Vandal et al., 2017
Rodrigues et al., 2019

Pros:
Outline the possible benefits of using deep learning in statistical **downscaling under big domains**

Cons:
Not applicable in more realistic applications

Downscale GCMs future climate projections

Deep Learning Statistical Downscaling

Article

Improving Monsoon Precipitation Prediction Using Combined Convolutional and Long Short Term Memory Neural Network

Qinghua Miao [1], Baoxiang Pan [2,*], Hao Wang [1,3], Kuolin Hsu [2] and Soroosh Sorooshian [2]

Statistical downscaling of precipitation using long short-term memory recurrent neural networks

Saptarshi Misra[1] · Sudeshna Sarkar[1] · Pabitra Mitra[1]

Improving Precipitation Estimation Using Convolutional Neural Network

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Downscaling rainfall using deep learning long short-term memory and feedforward neural network

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Intercomparison of Machine Learning Methods for Statistical Downscaling: The Case of Daily and Extreme Precipitation

Thomas Vandal[*1], Evan Kodra[†2], and Auroop R Ganguly[‡1]

[1]Sustainability and Data Science Lab , Civil Engineering Dept Northeastern University
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More realistic applications under the perfect-prognosis approach

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More realistic applications under the perfect-prognosis approach

Different conclusions about their performance

Lack of a common validation framework and small case studies

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More realistic applications under the perfect-prognosis approach

Different conclusions about their performance

- Lack of a common validation framework and small case studies

Complex off-the-shelf deep learning topologies

- Not clear the role of every element in the net

Deep Learning Statistical Downscaling

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Complex off-the-shelf deep learning topologies

Not clear the role of every element in the net

Do not test the extrapolation capability

Crucial in **climate change**

More realistic applications under the perfect-prognosis approach

Configuration and Intercomparison of Deep Learning Neural Models for Statistical Downscaling

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Different conclusions about their performance

- Lack of a common validation framework and small case studies

The largest-to-date downscaling intercomparison project: VALUE

Complex off-the-shelf deep learning topologies

- Not clear the role of every element in the net

Develop and intercompare deep learning topologies of increasing level of complexity

Do not test the extrapolation capability

- Crucial in **climate change**

Evaluate a simple test to evaluate the extrapolation capability of classical and deep learning models

Deep Learning as a statisical downscaling model

1) Can Deep Learning explain the local variability with NO PREDICTOR SELECTION?

State-of-the-art methods overfit with no predictor selection

2) Can Deep Learning show a stable behaviour when projecting to future climate with NO PREDICTOR SELECTION?

State-of-the-art methods show unstable behaviour with no predictor selection when extrapolating

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Validation framework
- VALUE

Deep Learning
- Continental-sized domains
- Different DL topologies

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RESEARCH ARTICLE

VALUE: A framework to validate downscaling approaches for climate change studies

OPEN

Douglas Maraun[1,*], Martin Widmann[2], José M. Gutiérrez[3], Sven Kotlarski[4], Richard E. Chandler[5], Elke Hertig[6], Joanna Wibig[7], Radan Huth[8] and Renate A.I. Wilcke[9]

Article first published online: 7 JAN 2015
DOI: 10.1002/2014EF000259

Issue

Earth's Future

Early View (Online Version of Record published before inclusion in an issue)

Intercomparison of over 50 methods

VALUE

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Validation framework
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Deep Learning
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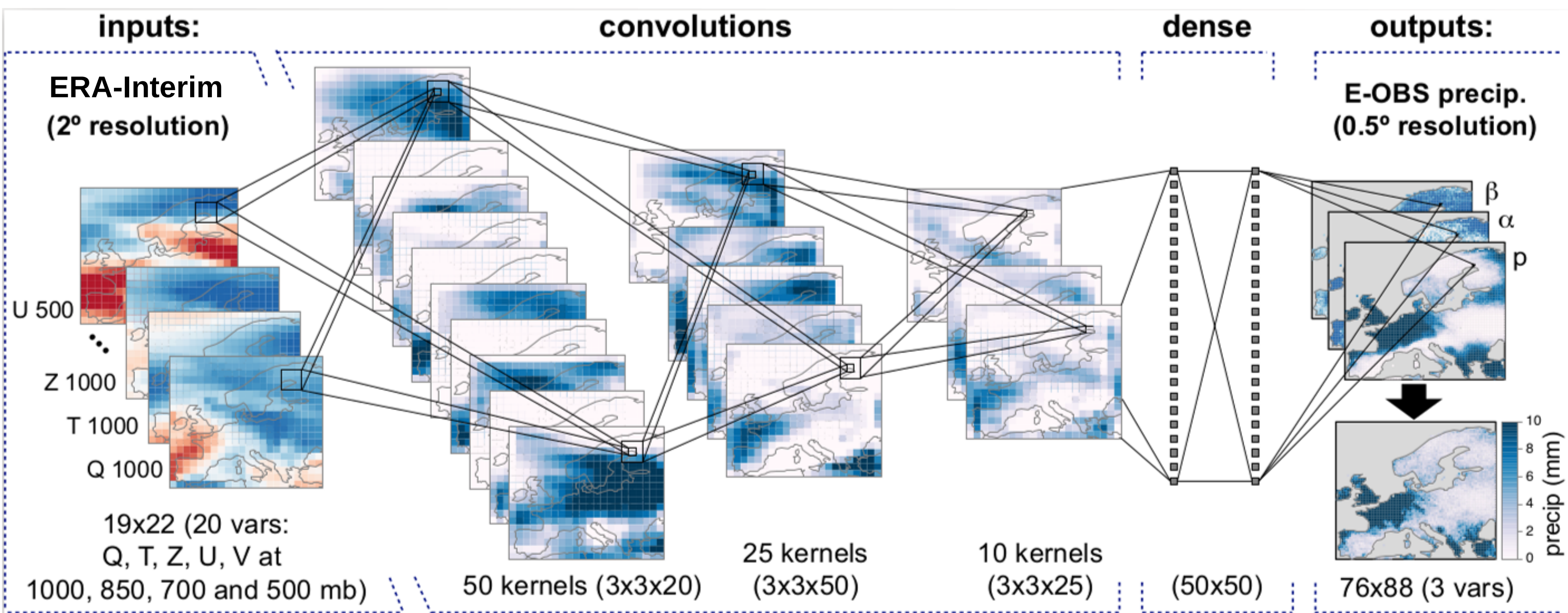
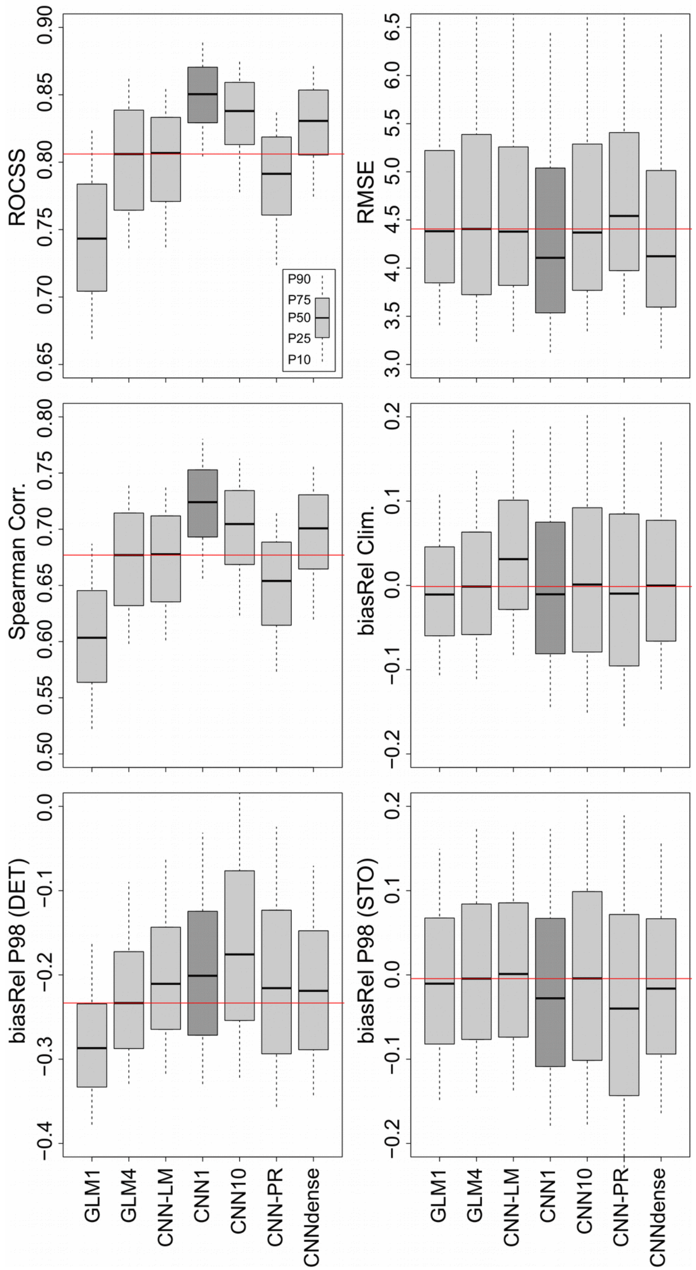
Train: 1979-2002 **Test:** 2003-2008 **Cost function:** Negative log-likelihood of a Bernouilli-Gamma distribution





Classical ….

- **GLM1:** generalized linear model using as predictor the closest gridpoint.
- **GLM4:** generalized linear model using as predictor 4 closest gridpoints.

… and **deep learning methods** are intercompared

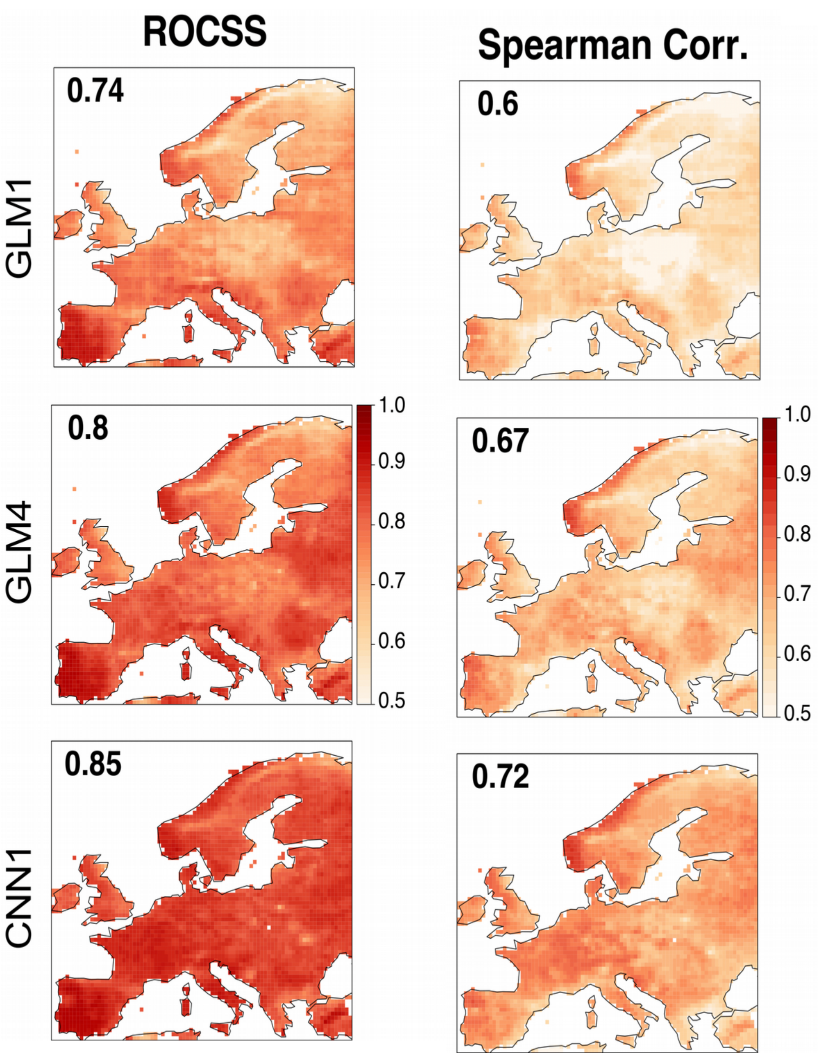
- **CNN-LM**, **CNN1**, **CNN10**, **CNN-PR**, **CNNdense**

According to these metrics…

Deep Learning outperform classical methods

The model **CNN1** achieves the best validation scores

We chose this one (CNN1) for downscaling climate change scenarios



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CNN1 achieves ↑ **ROCSS** and ↑ **spearman correlation** over the whole domain than **classical** approaches

CNN1 is…. able to **treat** the **whole domain** simultaneously

Why? → *Baño-Medina et al., 2019* → **Convolutions** → *Baño-Medina and Gutiérrez, 2019* → **Convolutions + Multi-task**

Deep Learning as a statisical downscaling model

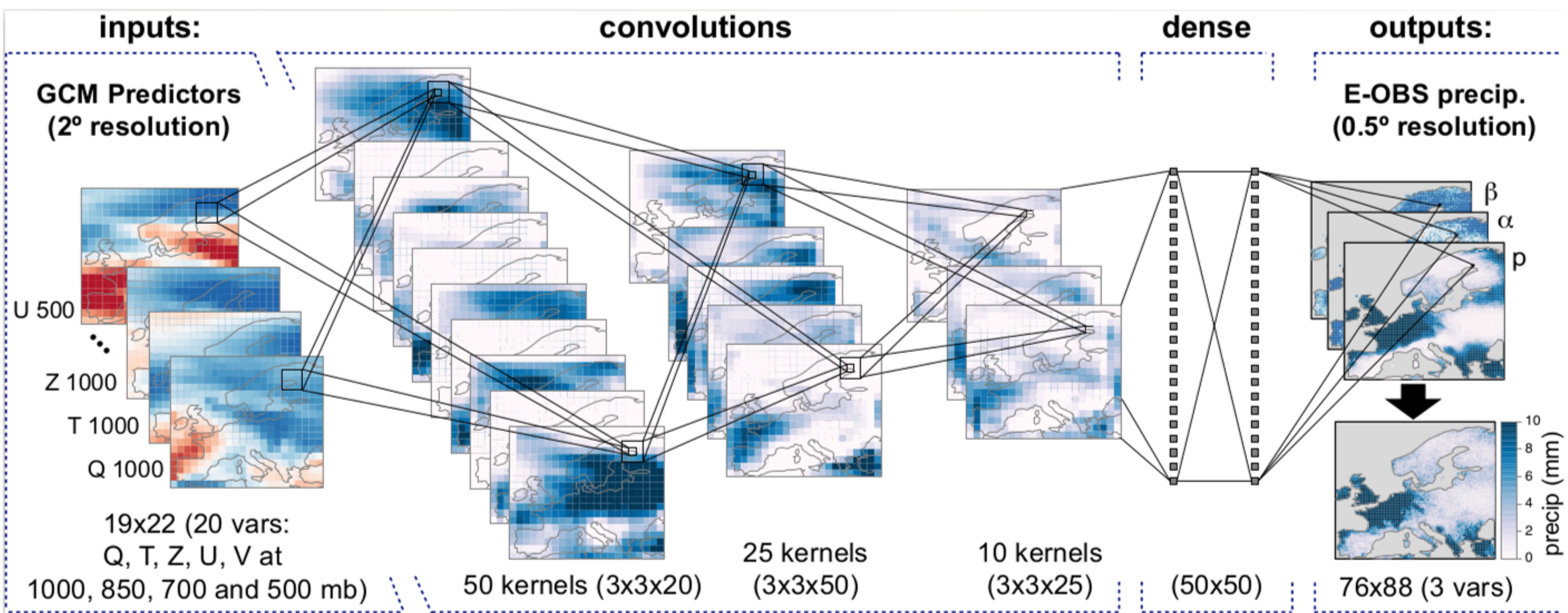
Predictor

EC-EARTH 2º
HISTORICAL: 1986-2005
FUTURE(RCP8.5): 2071-2100

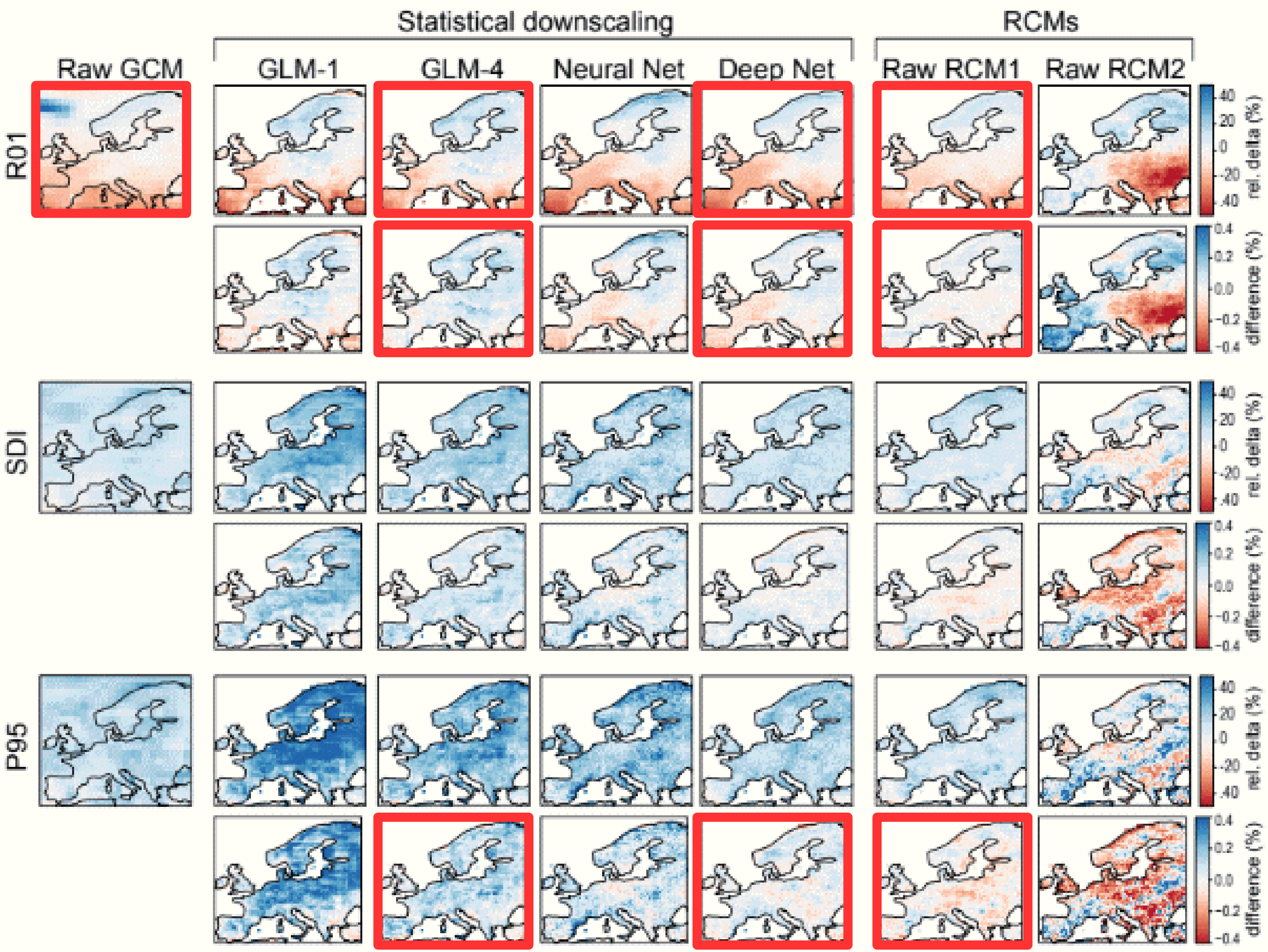
2) Can Deep Learning show a stable behaviour when projecting to future climate with NO PREDICTOR SELECTION?

State-of-the-art methods show unstable behaviour with no predictor selection when extrapolating

Can the statistical models preserve the deltas (i.e., ratio between future and historical values)? INSTABILITY DETECTOR



We apply the function learned in **perfect conditions** to the GCM predictors → **Downscaling GCM**



Deep Net preserves the deltas and thus it does not show instabilites in future conditions!

Conclusions

- Deep Learning can handle continental-sized domains without leading to overfitting
- Deep learning explains better the local variability than classical approaches
- The extrapolation capability of deep learning seems plausible
-

Future Work

- Extend the study to other CORDEX domains