Instituto de Física de Cantabria

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WCRP CORDEX Coordinated Regional Climate Downscaling Experiment

Introducing eXplainable Artificial Intelligence to assess Deep Learning models for Statistical Downscaling

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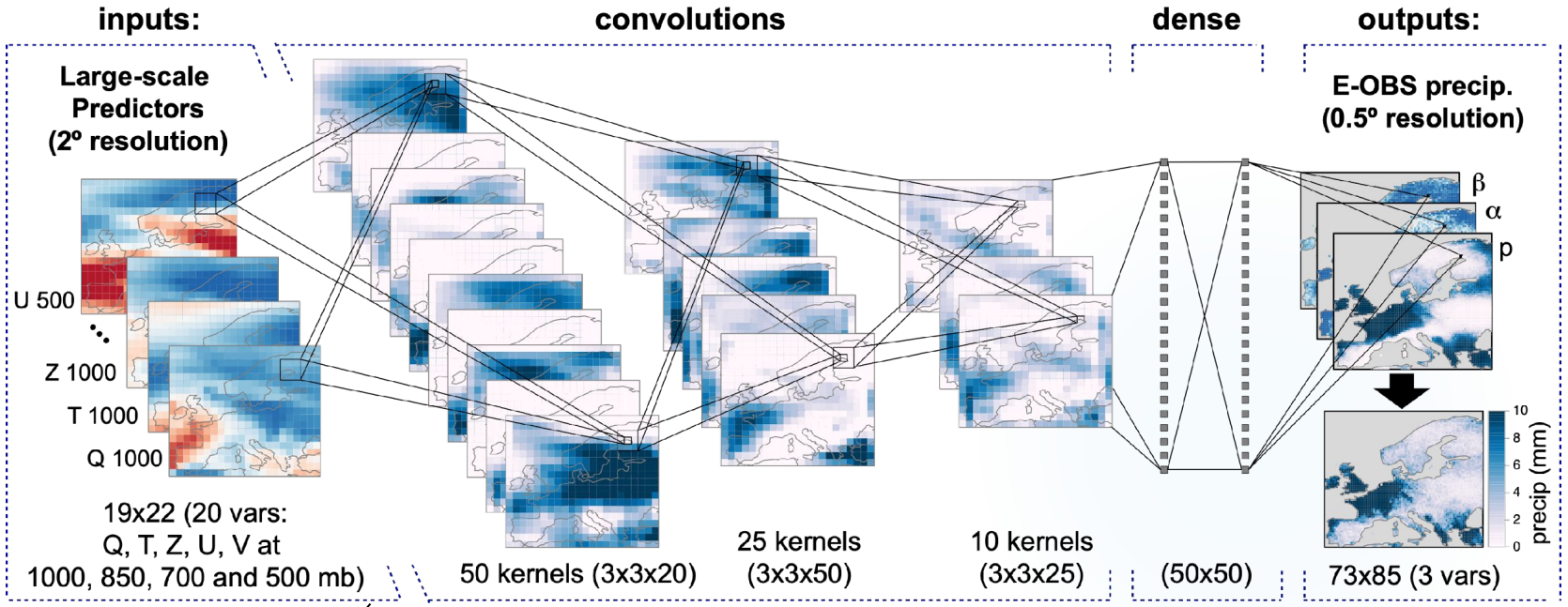
ICRC-CORDEX 2023:
Statistical Methods/Machine Learning techniques for RCM

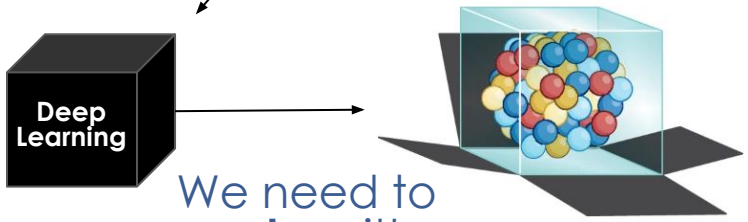
Perfect Prognosis downscaling

Source: Esterhuizen, J. A., Goldsmith, B. R., & Linic, S. (2022). Interpretable machine learning for knowledge generation in heterogeneous catalysis. Nature Catalysis, 1-10.

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



However, its **black box** nature makes it **difficult** to gain a **comprehensive** understanding of their inner functioning, **particularly for downscaling climate change projections.**

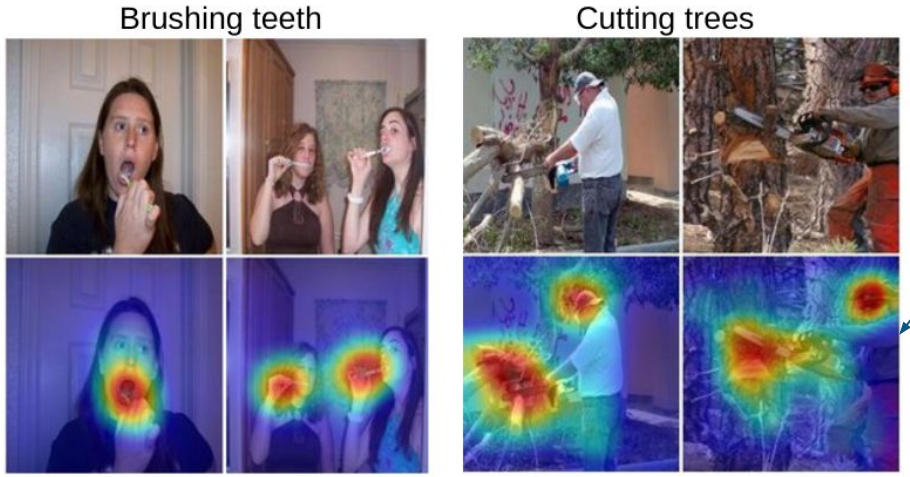


We need to **unbox** it!

Can we **trust** these models?

Interpretability techniques

Interpretability techniques emerged in the computer vision field to **explain the functioning and results of deep learning** models



Source: Zhou, Bolei, et al. "Learning deep features for discriminative localization." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016

Saliency maps assign to each feature a **relevance score** representing its influence on the computed prediction

For downscaling: features ⇒ gridpoints

Relevance *R* of feature *x_i* can be computed as follows:

$$R(x_i) = \frac{\partial f(\mathbf{x})}{\partial x_i}$$

Sensitivity of the prediction to the input

where ***f*** is the model to explain

Temperature downscaling over North America

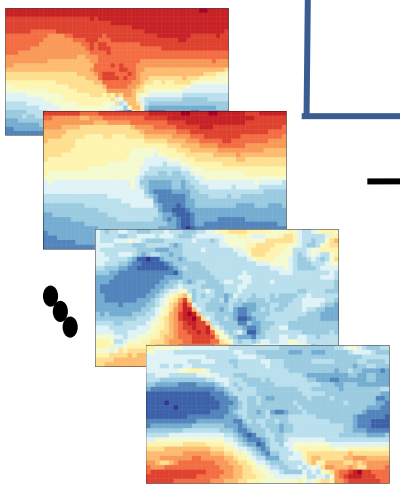
Deep learning models

CNN-DeepESD
CNN-PAN

UNet

Convolution + dense

Fully-convolutional

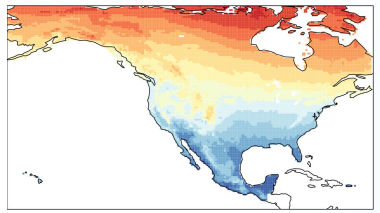


ERA-Interim (2° resolution)

5 thermodynamical variables
× 4 different vertical levels

Deep Learning

PP Empirical Statistical Downscaling



Observations (0.5° resolution)

Mean temperature (land)

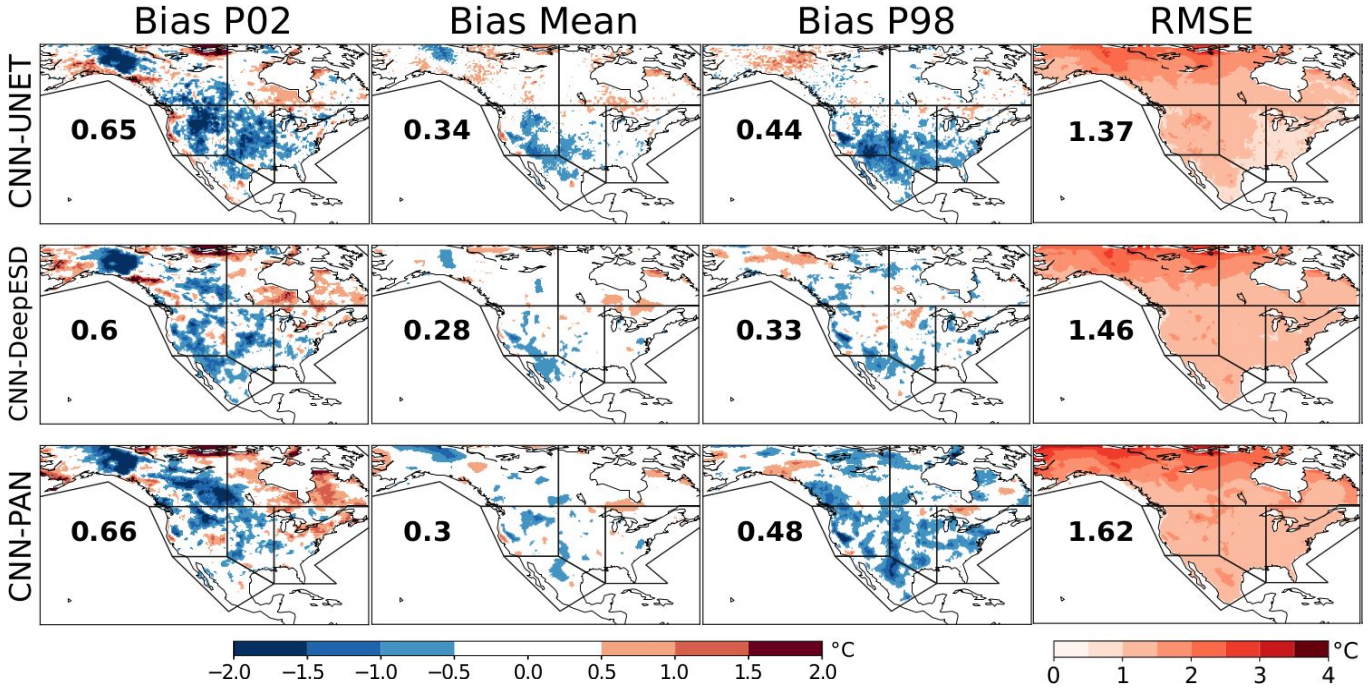
Training set
1979-2002

Test set
2003-2008

EC-Earth (CMIP5) RCP8.5

2006-2040
2041-2070
2071-2100

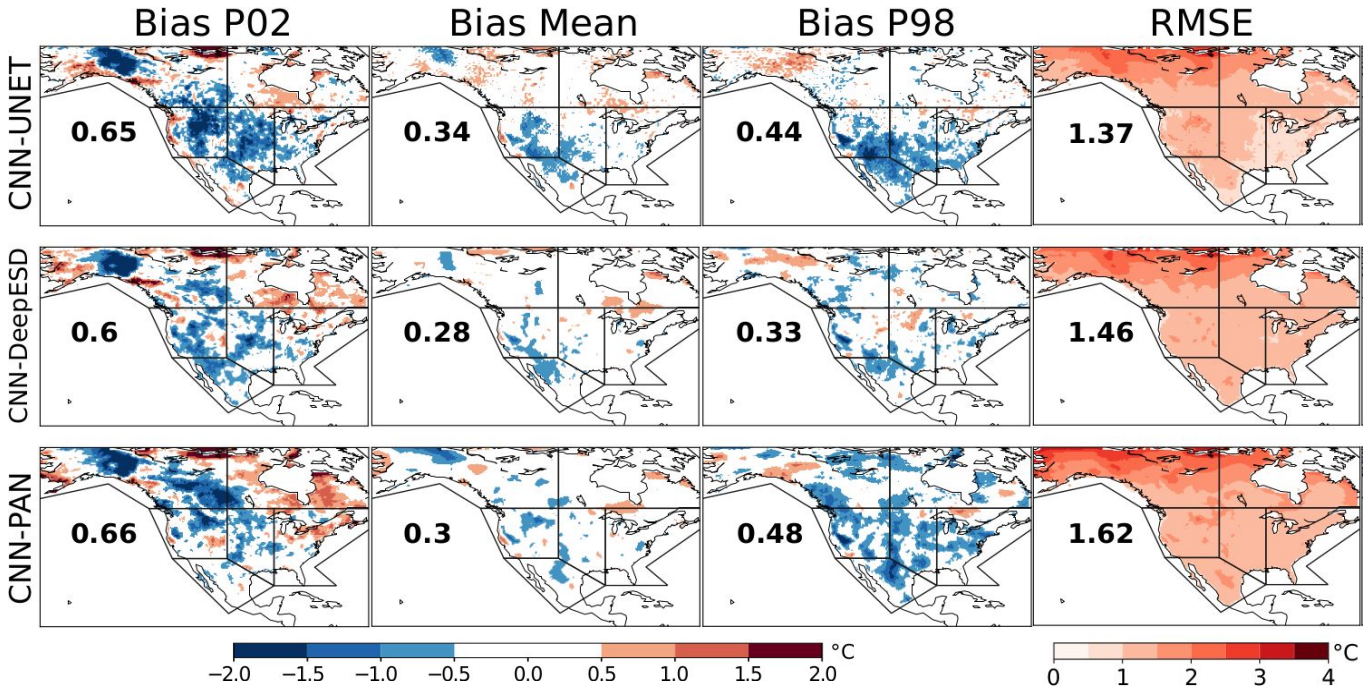
Evaluation on the test set

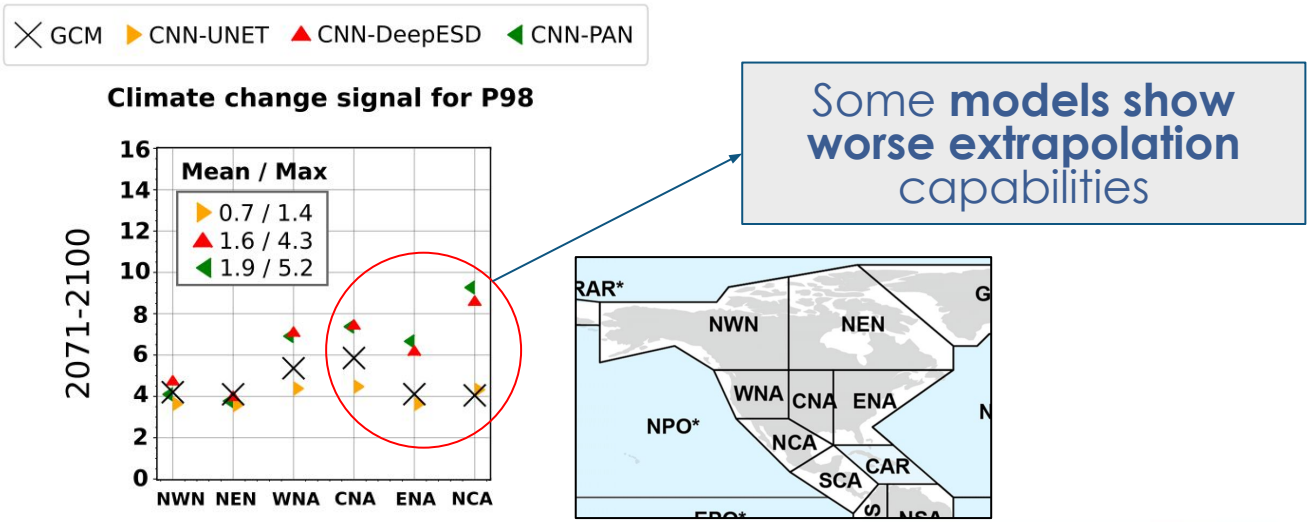


- **Similar spatial distribution** of biases across DL models

No best performing model for all regions and metrics

Evaluation on the test set





Some **models show worse extrapolation** capabilities

- **Similar spatial distribution** of biases across DL models

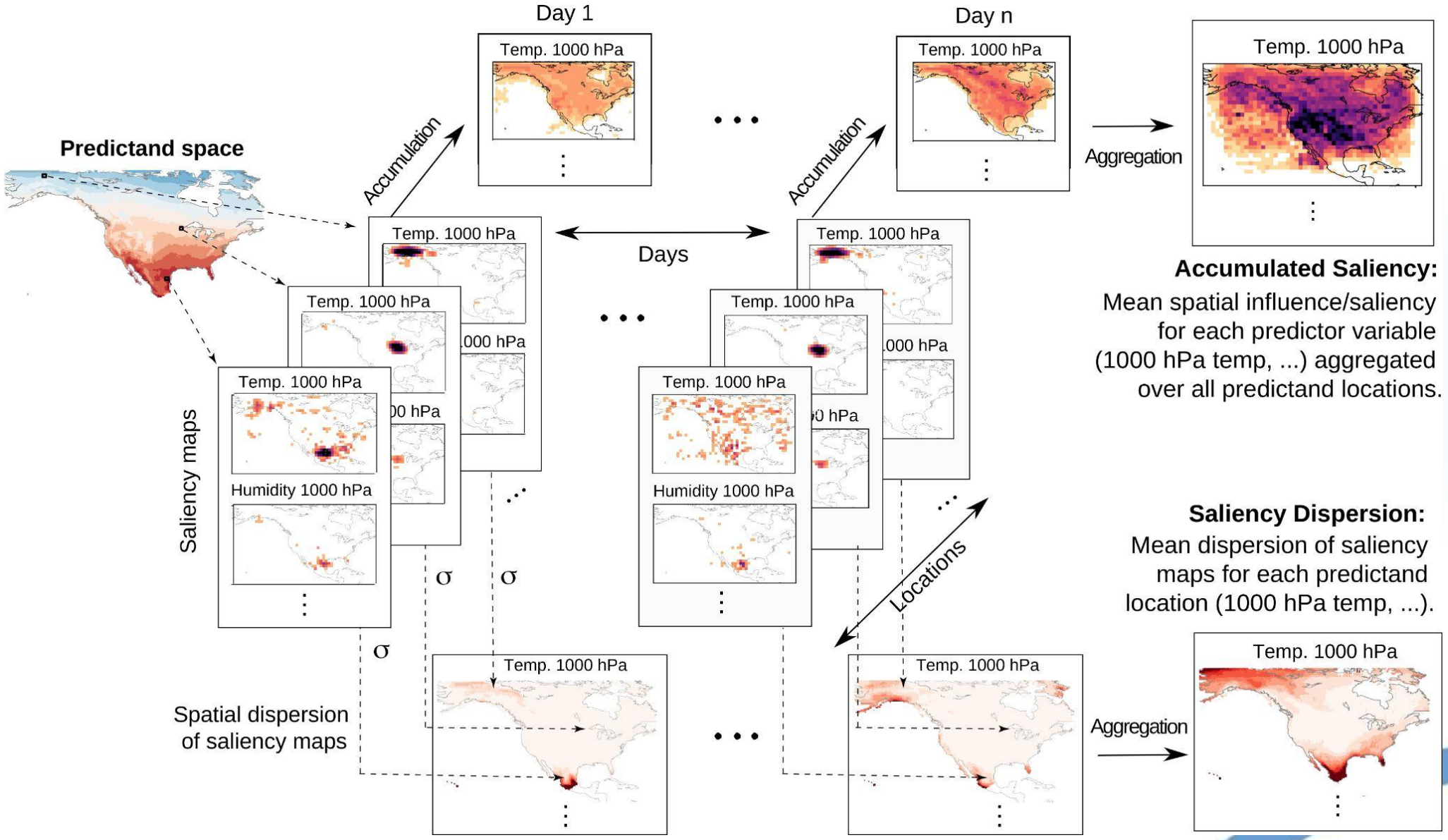
~~**No best performing model for all regions and metrics**~~

We need **further insights** on the **models behaviour**

↓

Interpretability

Interpretability-based metrics

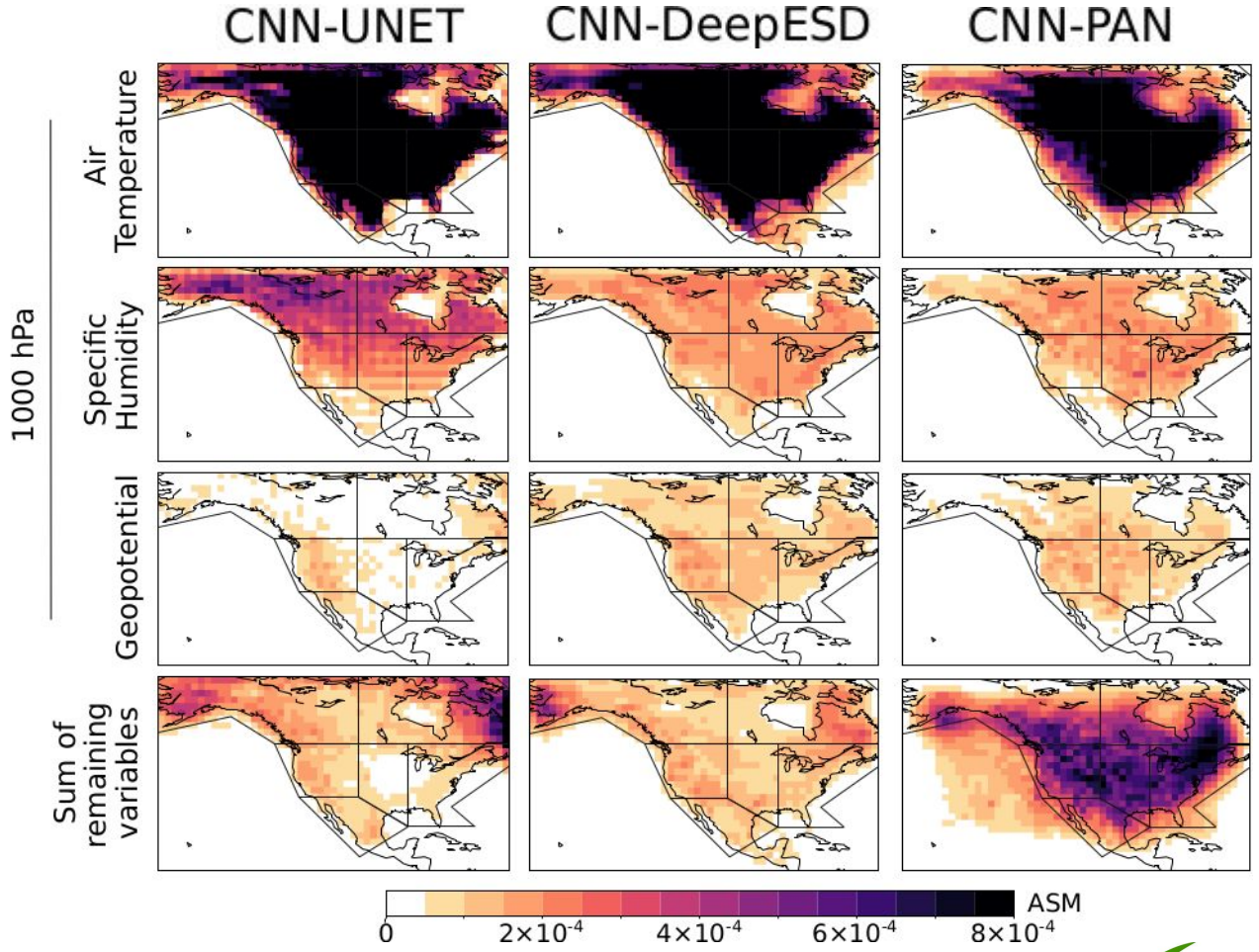


Accumulated Saliency:
Mean spatial influence/saliency for each predictor variable (1000 hPa temp, ...) aggregated over all predictand locations.

Saliency Dispersion:
Mean dispersion of saliency maps for each predictand location (1000 hPa temp, ...).

Source: González-Abad, J., Baño-Medina, J., & Gutiérrez, J. M. (2023). Using Explainability to Inform Statistical Downscaling Based on Deep Learning Beyond Standard Validation Approaches. arXiv preprint arXiv:2302.01771.

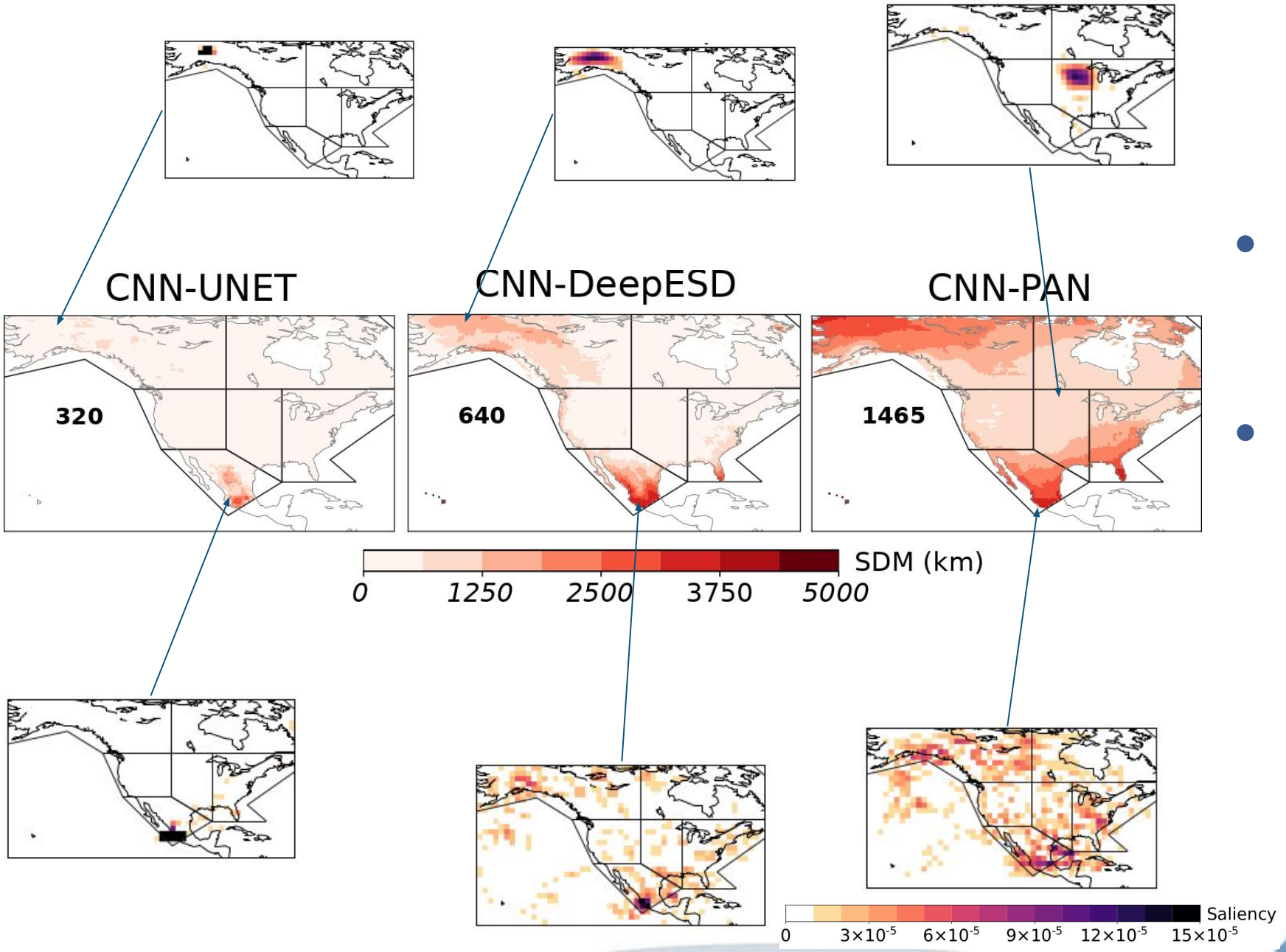
Accumulated saliency map (ASM)



- **Air temperature at 1000 hPa** is the **most relevant variable** → ✓ across seasons and DL models

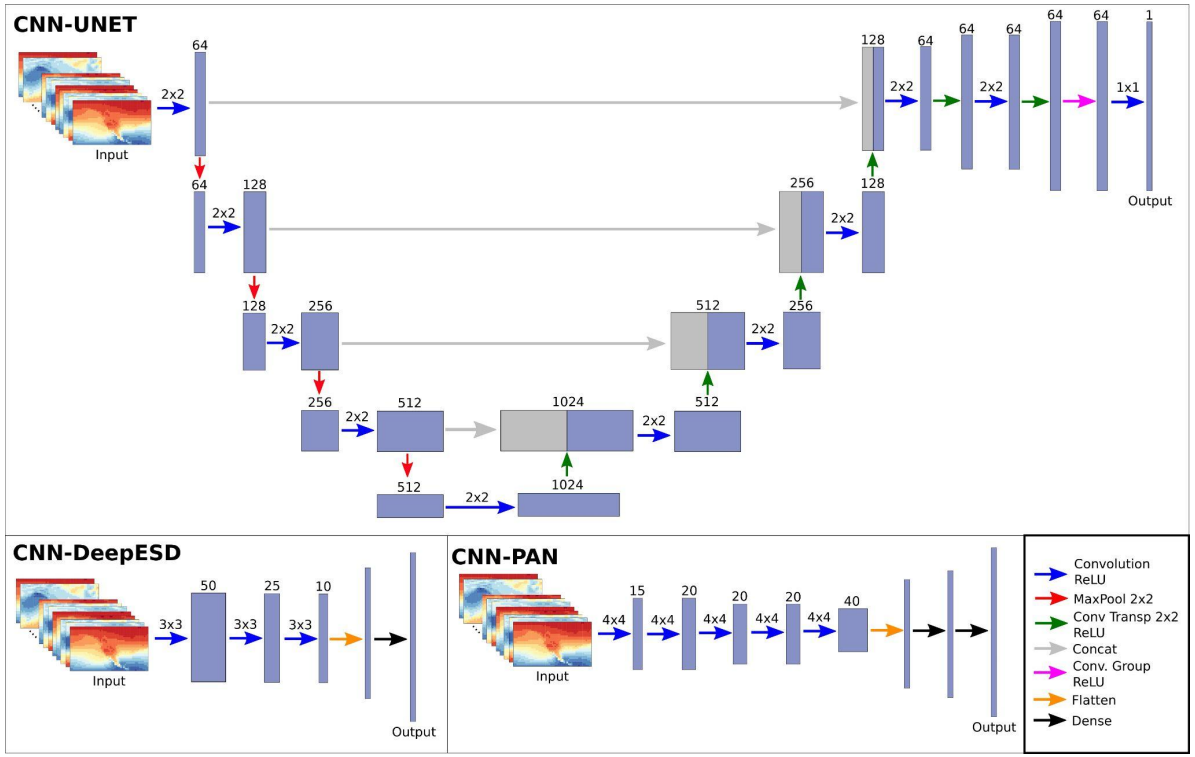
→ **It aligns with the scientific literature**

Saliency dispersion map (SDM)



- **CNN-UNET** shows **local patterns** across the region
- **CNN-DeepESD** and **CNN-PAN** shows **non-local patterns** for the **southern region** (NCA)

Overfitting of CNN-DeepESD and CNN-PAN



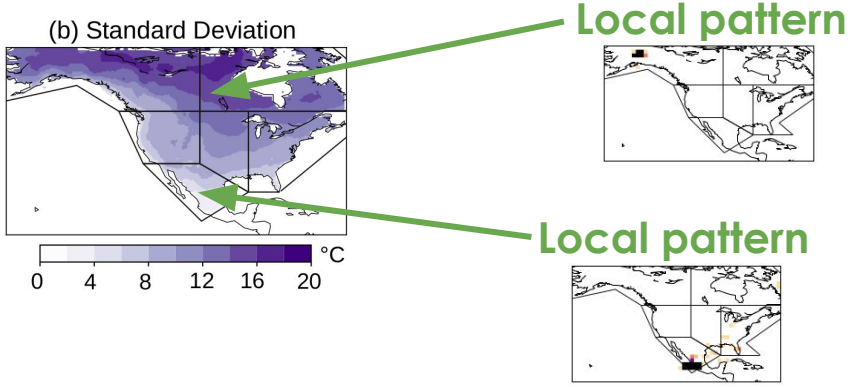
- **Convolutional layers** incorporate an inductive bias toward capturing **local relationships**
- **Dense layers** allow learning **non-local relationships**

CNN-UNET is implicitly local

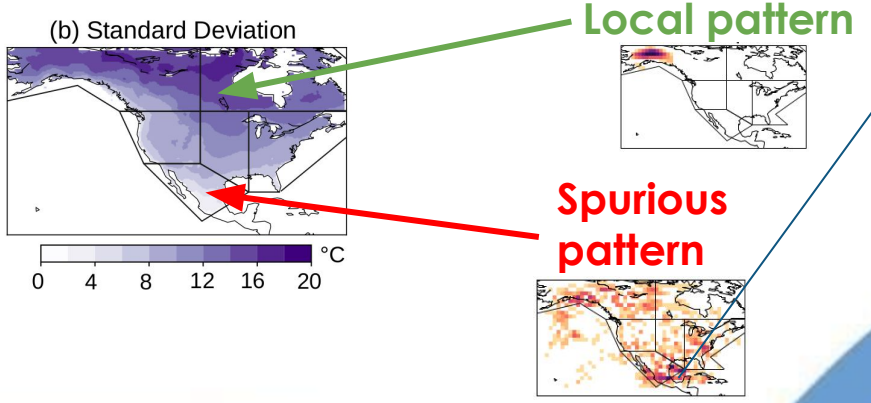
Temperature downscaling is local

Plausible relationships

CNN-UNET



CNN-DeepESD / CNN-PAN



Non-plausible relationships

Conclusions

- **Interpretability techniques** allow **expanding the standard evaluation techniques** for assessing deep learning models in statistical downscaling

- **Interpretability techniques** can help us gain **confidence** in deep learning models when **extrapolating** to GCMs in future scenarios

- Although **interpretability techniques** can be useful in offering transparency for DL models, they must be used with **caution** given their **limitations**

Can we **trust** these models?

→

Standard validation metrics
+
Interpretability

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Thank you!

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