RCM-Emulators
A study of applicability to GCM ensemble

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Antoine Doury, Samuel Somot
CNRM Toulouse
antoine.doury@meteo.fr

RCM-Emulators: A Hybrid downscaling approach

Apply a statistical downscaling framework inside RCM simulations to emulate the relationship between the large scale atmospheric conditions and high resolution variables of interest.
(Walton et al, 2015; Babaousmail et al, 2021; Wang et al, 2021; Boé et al, 2022; Doury et al 2022)

- Train/calibrate the statistical model:
  → everywhere around the globe and for any variable (no need of observational data)
  → on various runs of the RCM allowing to explore better internal variability
  → in different climate using scenarios simulations

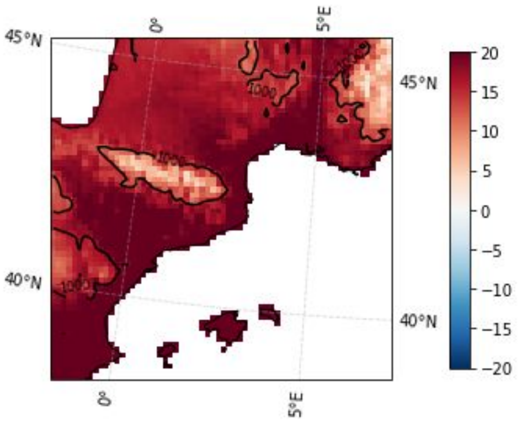
- Allows to downscale large GCM ensembles thanks to the efficiency of the statistical model.
  → Better exploration of different sources of uncertainties

Emulator conception

RCM: ALADIN63 (12km, driven by CMIP5 runs)

Target variables : Daily Temperature

Temperature



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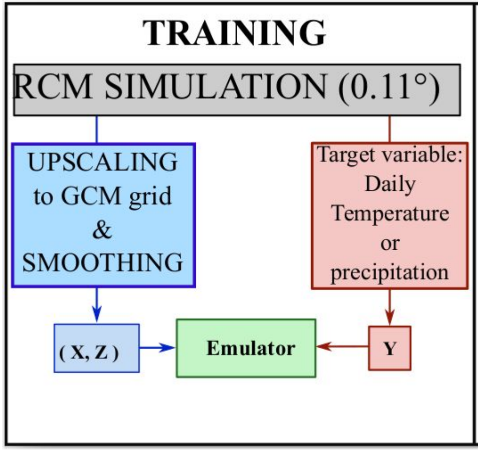
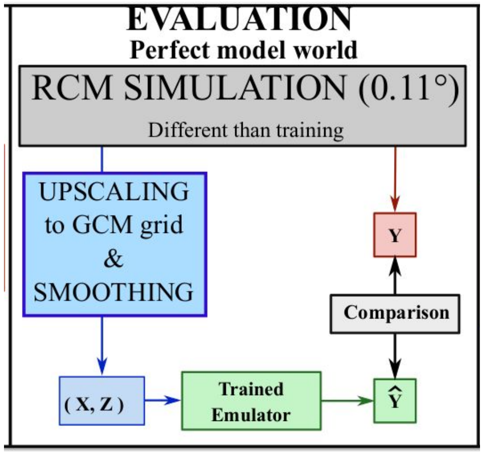
- Training in **Perfect model framework**
  - ➢ To ensure consistency between inputs and outputs as RCM tends to modify GCM large scale information





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Conceptual/Technical aspects :

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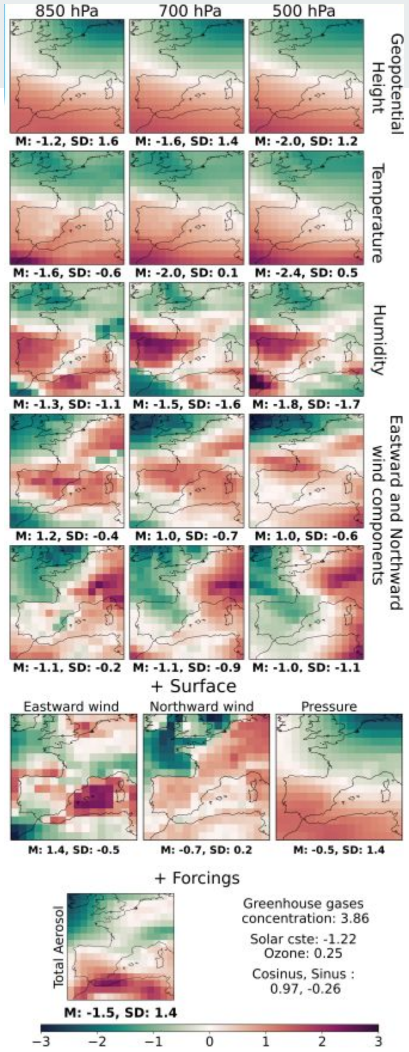
  - ➢ To ensure consistency between inputs and outputs as RCM tends to modify GCM large scale information (Laprise et al, 2008)
- Inputs : **Daily description of the atmospheric conditions**
  - ➢ Geopotential, temperature, wind components, humidity at 3 vertical levels + external forcing (aerosols, Greenhouse gases)
  - ➢ 2 steps standardization : Temporal and spatial information given separately



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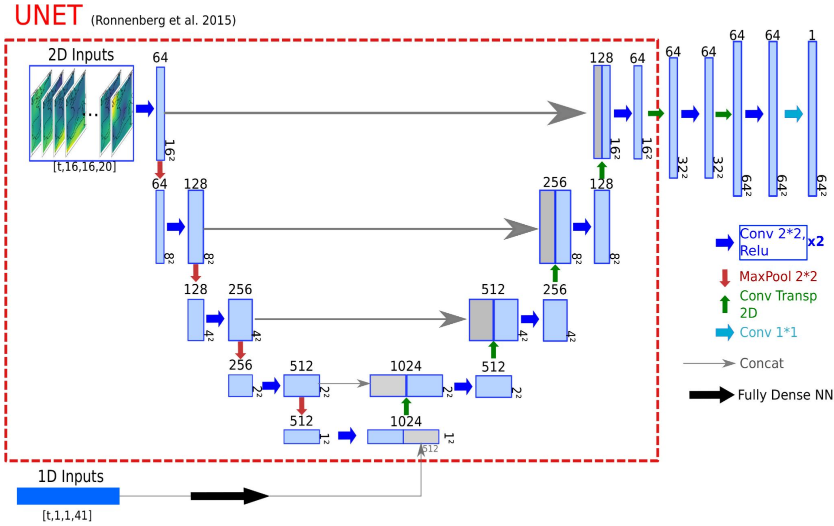
  - ➢ 2 steps standardization: Temporal and spatial information given separately
- **Neural network** architecture : **UNet** based
  - ➢ Efficient management of multidimensional data
  - ➢ **Fully convolutional** : helps the network to better catch the spatial structure



- ✤ ~ 25 million parameter
- ✤ ~ 1h to train on GPU (depends on the target domain size)
- ✤ ~ 1 min to predict

ALADIN63 EURO-CORDEX matrix

Vautard et al 2021, Coppola et al 2021

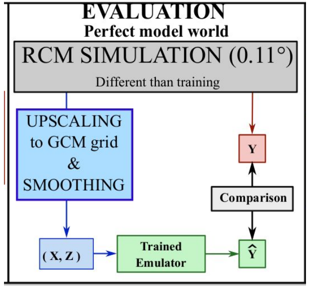
Scenarios	Driving GCM			
	CNRM (CNRM-CM5)	MPI (MPI-ESM-LR)	NCC (NorESM1-M)	HGM (HadGEM-ES2)
Historical (1950-2005)	X	X	X	X
RCP26 (2006-2100)	X			
RCP45 (2006-2100)	X			
RCP85 (2006-2100)	X	X	X	X

Training simulations : ALADIN63 driven by CNRM-CM5, historical and RCP85 simulations
→ the widest variety of climate in the CNRM-CM5/ALADIN63 family

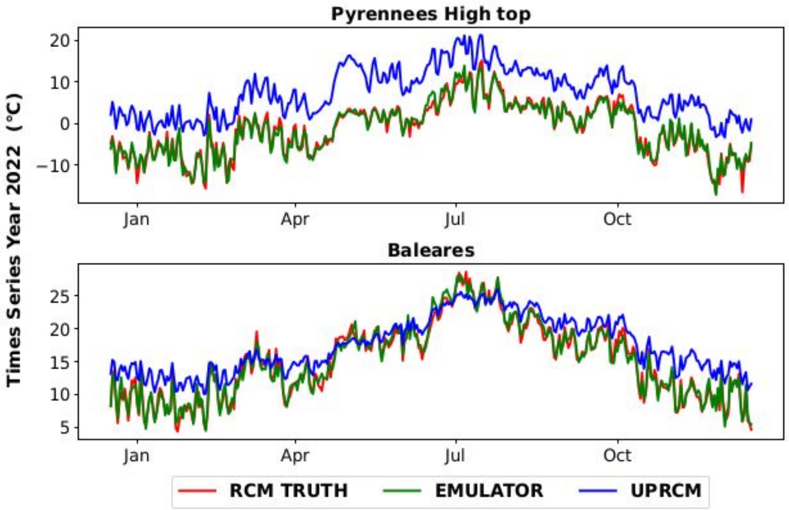
Evaluation 0 : CNRM-RCP45
→ the closest simulation especially in present climate (2006-2035)

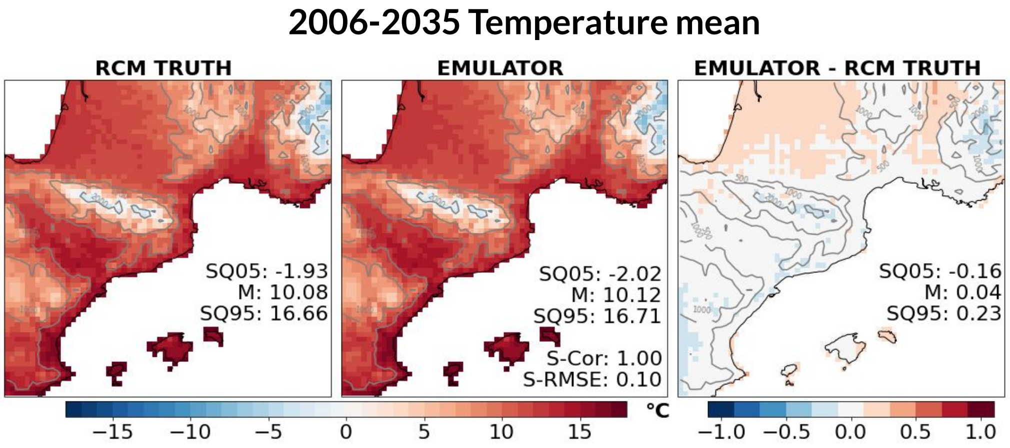
Study of transferability :
→ Scenario transferability (ALADIN63 driven by CNRM-CM5 RCP26 & RCP45)
→ GCM transferability (ALADIN63 driven by MPI, NCC & HGM)

PERFECT MODEL FRAMEWORK



Evaluation Step 0: CNRM-RCP45





A good ability to reproduce the RCM downscaling:

- Good reproduction of the spatial structure
- Almost perfect correlation with the RCM truth
- Good reproduction of the daily variance
- Good reproduction of the response to climate change

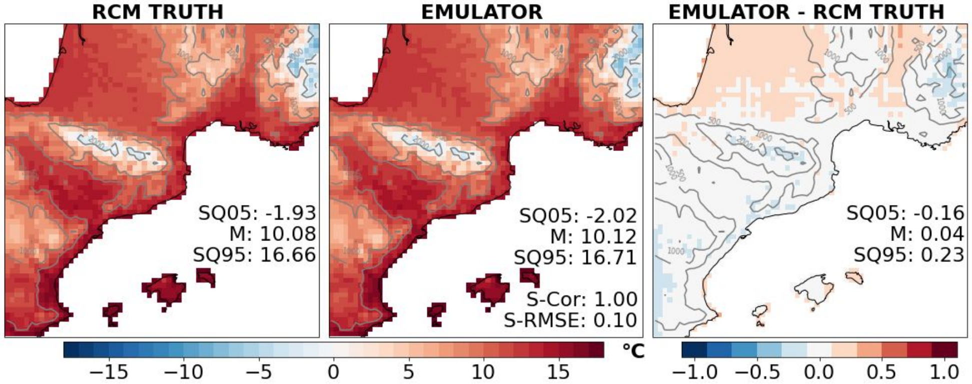
Some limitations:

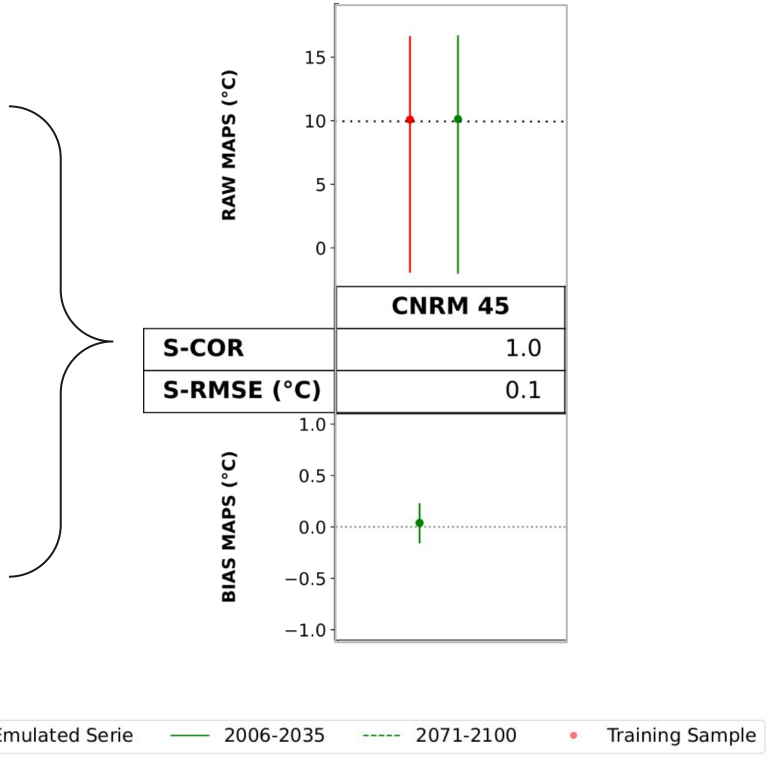
- Underestimation of extremes events
- More difficulties on mountains regions

More complete evaluation in Doury et al, 2022

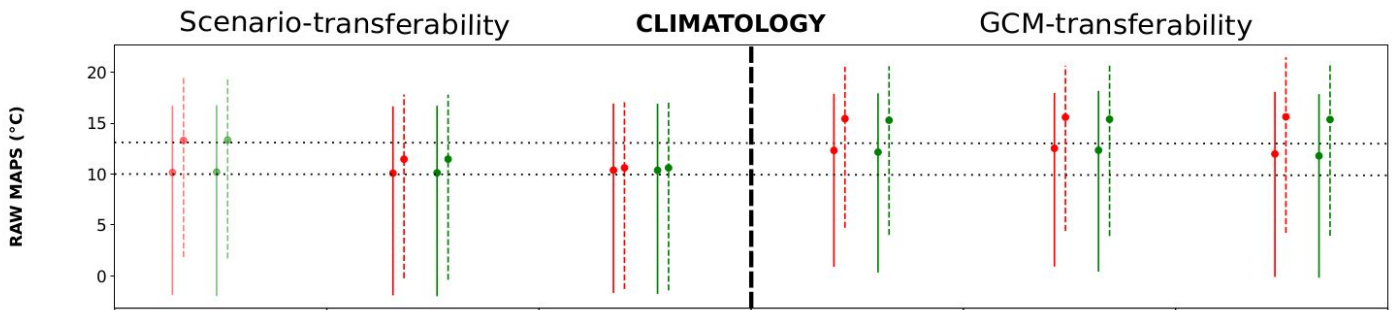
Study of transferability

2006-2035 Temperature mean

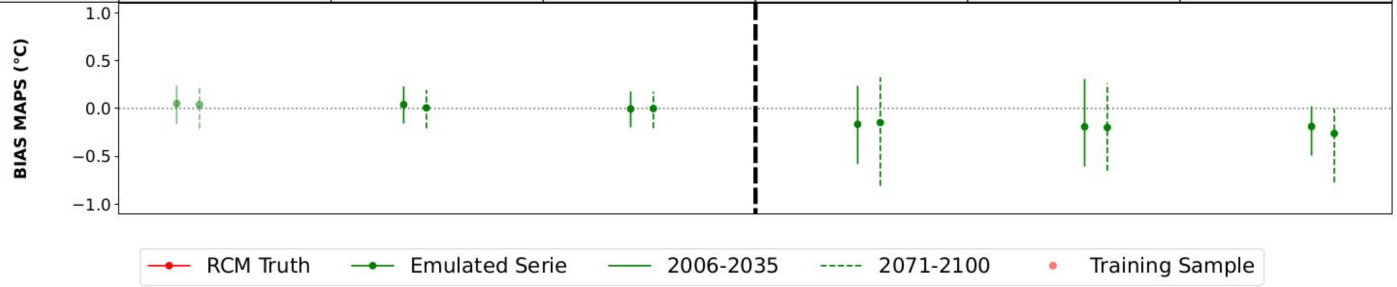




Study of transferability



	CNRM 85	CNRM 45	CNRM 26	MPI 85	NCC 85	HGM 85
S-COR	1.0/1.0	1.0/1.0	1.0/1.0	1.0/1.0	1.0/1.0	1.0/1.0
S-RMSE (°C)	0.11/0.12	0.1/0.1	0.09/0.09	0.24/0.29	0.27/0.28	0.22/0.31



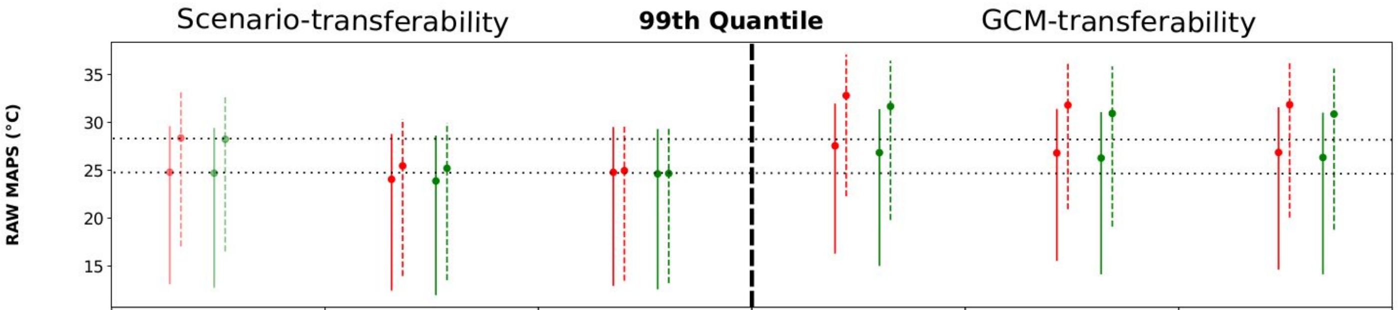
Good reproduction of the spatial structure on all simulations

Good ability to reproduce the specificity of each simulations

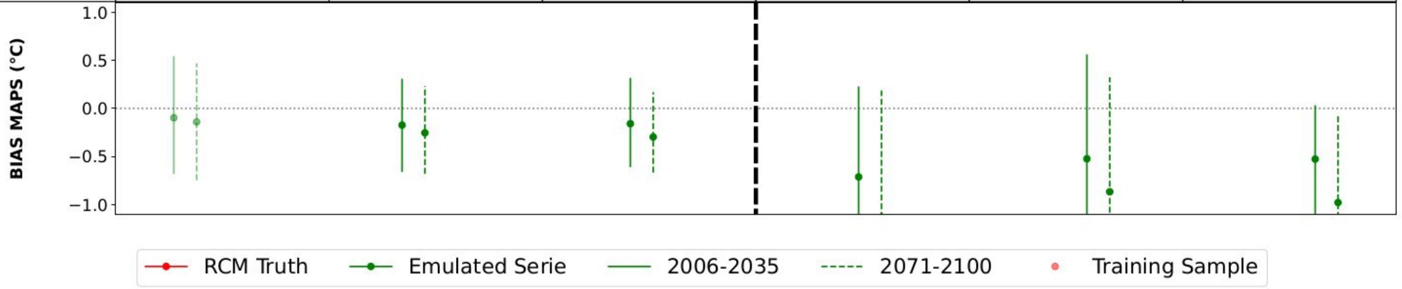
Good transferability to intermediate scenarios

Cold bias in warmer simulations

Study of transferability



	CNRM 85	CNRM 45	CNRM 26	MPI 85	NCC 85	HGM 85
S-COR	1.0/1.0	1.0/1.0	1.0/1.0	1.0/0.99	1.0/0.99	1.0/0.99
S-RMSE (°C)	0.31/0.33	0.29/0.35	0.27/0.36	0.81/1.32	0.69/1.03	0.62/1.09



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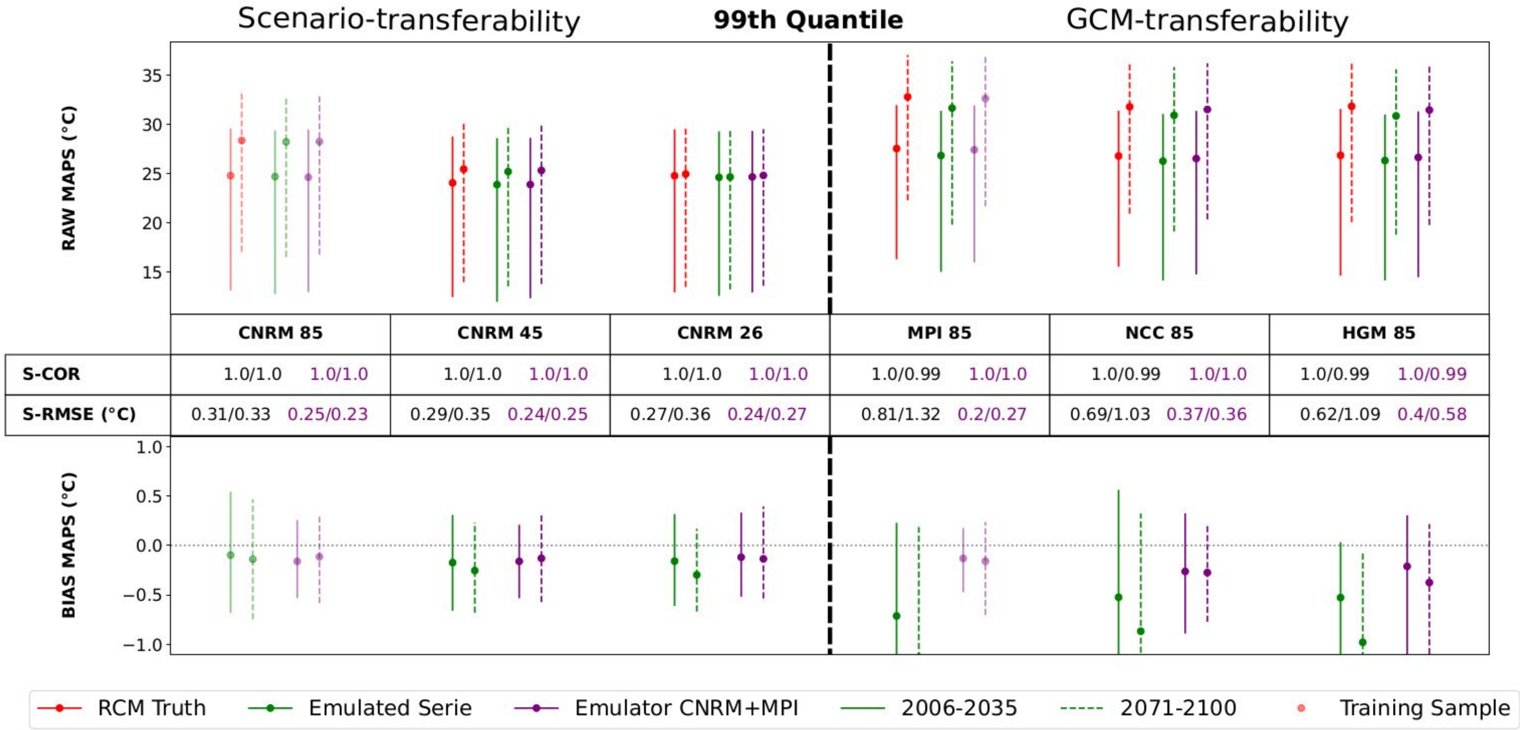
Cold bias in warmer simulation

⇒ Difficulties to extrapolate outside of the training domain?

Study of transferability



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S-COR	1.0/1.0 1.0/1.0	1.0/1.0 1.0/1.0	1.0/1.0 1.0/1.0	1.0/0.99 1.0/1.0	1.0/0.99 1.0/1.0	1.0/0.99 1.0/0.99
S-RMSE (°C)	0.31/0.33 0.25/0.23	0.29/0.35 0.24/0.25	0.27/0.36 0.24/0.27	0.81/1.32 0.2/0.27	0.69/1.03 0.37/0.36	0.62/1.09 0.4/0.58

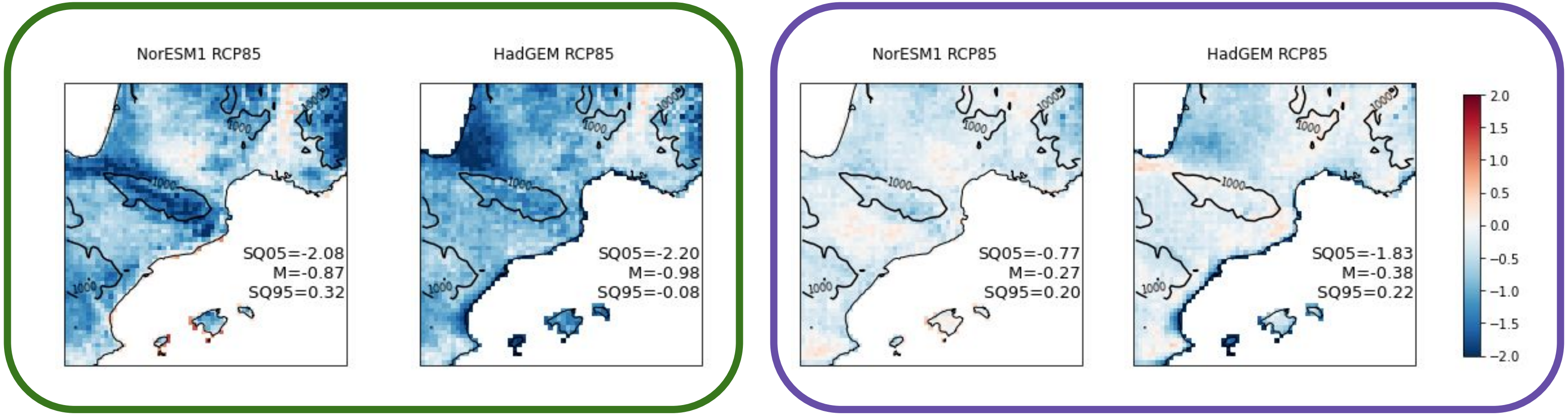
PURPLE Emulator : Trained on CNRM-CM5 and MPI, HISTORICAL + RCP85

Clear improvement of the 99th quantile maps for all simulations, especially for NCC and HGM, in historical and scenarios.

Study of transferability

2071-2100 99th quantile BIAS

CNRM-CM5 EMUL | **CNRM-CM5+MPI EMUL**



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Conclusion

- RCM-Emulators are able to **capture and reproduce the RCM downscaling** function
  - ➢ Good ability to reproduce the high resolution spatial structure
  - ➢ Good reproduction of the daily variability
  - ➢ Ability to reproduce the entire distribution of daily temperature..
  - ➢ .. Progress can be done for the extremes

- The perfect model framework allows to properly **evaluate the transferability** of the trained emulator in the EURO-CORDEX matrix:
  - ➢ Good transferability across members (similar scenario and same GCM than training set)
  - ➢ Good transferability across intermediate scenarios (Same GCM)
  - ➢ Good transferability to other GCM simulations..

- BUT it is not designed to extrapolate too far from its training set.

RCM-Emulators are **powerful tools** to create large ensemble of high resolution simulations

⚠️ **Importance of Scenario/GCM/RCM matrices design**.

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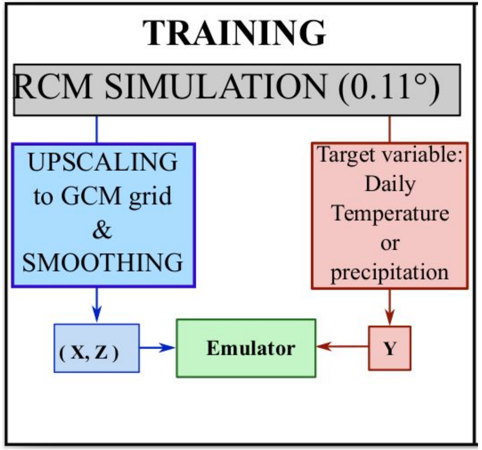

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Target variables : Daily Temperature

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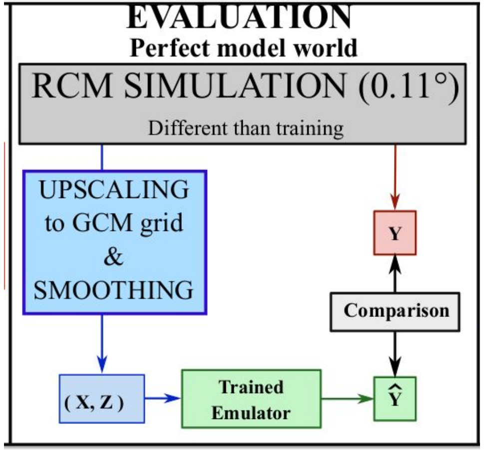
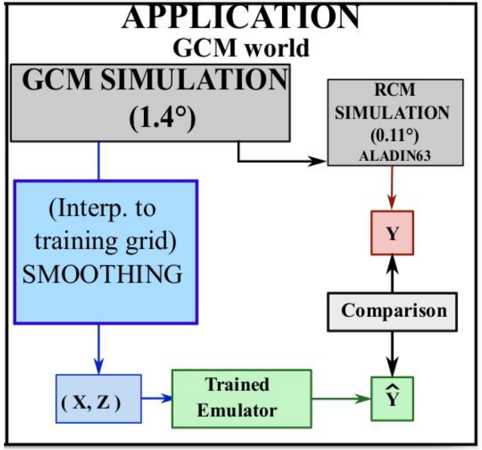




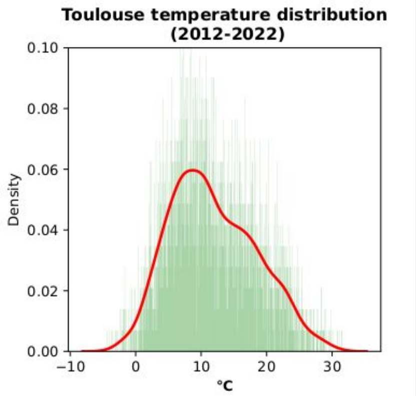
Emulator conception

RCM: ALADIN63 (12km, driven by CMIP5 runs)

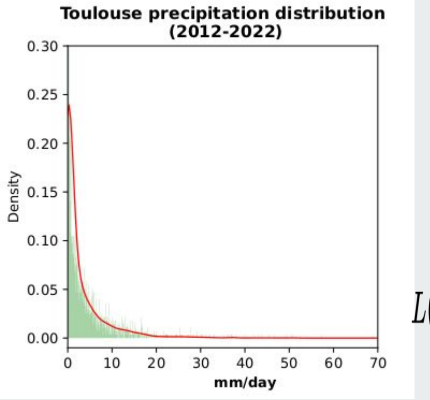
Target variables : Daily Temperature & precipitation

Conceptual/Technical aspects :

- Training in Perfect model framework
  - ➢ To ensure consistency between inputs and outputs as RCM tends to modify GCM large scale information
- Inputs choice, "organisation" and standardization:
  - ➢ Daily description of the atmospheric conditions
  - ➢ Geopotential, temperature, wind components, humidity at 3 vertical levels + external forcing (aerosols, Greenhouse gases)
  - ➢ 2 steps standardization: Temporal and spatial information given separately
- Neural network architecture : Unet based
  - ➢ Fully convolutional : helps the network to better catch the spatial structure
- Loss function designed for precipitation



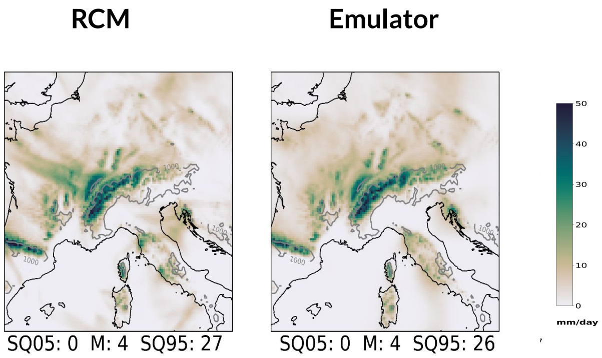
Normally distributed ⇒ MSE is well adapted

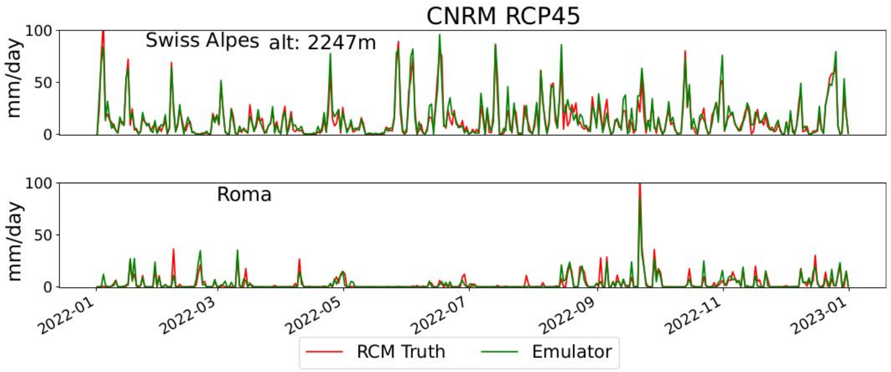


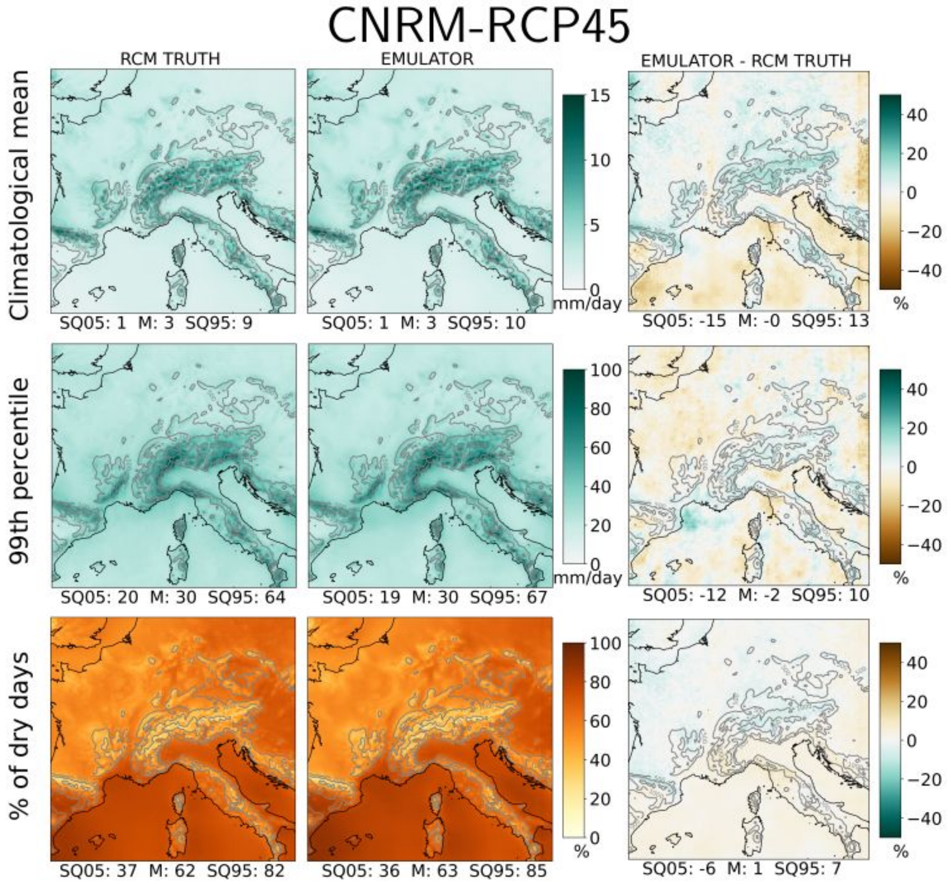
Right skewed ⇒ Asymmetric loss function, to specifically focuses on extremes

$$L(y,\hat{y}) = |y-\hat{y}| + (\beta * max(0, y-\hat{y}))$$

Precipitations







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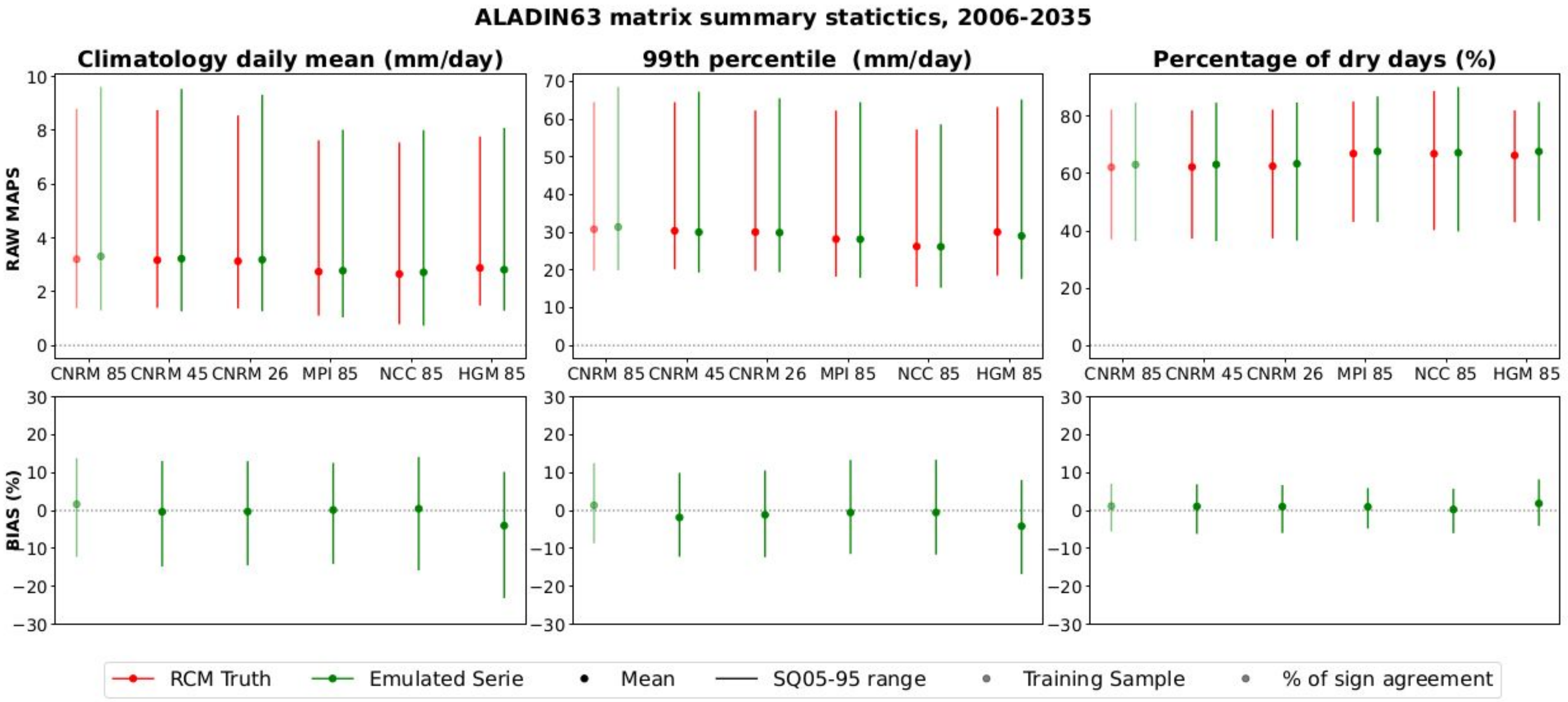
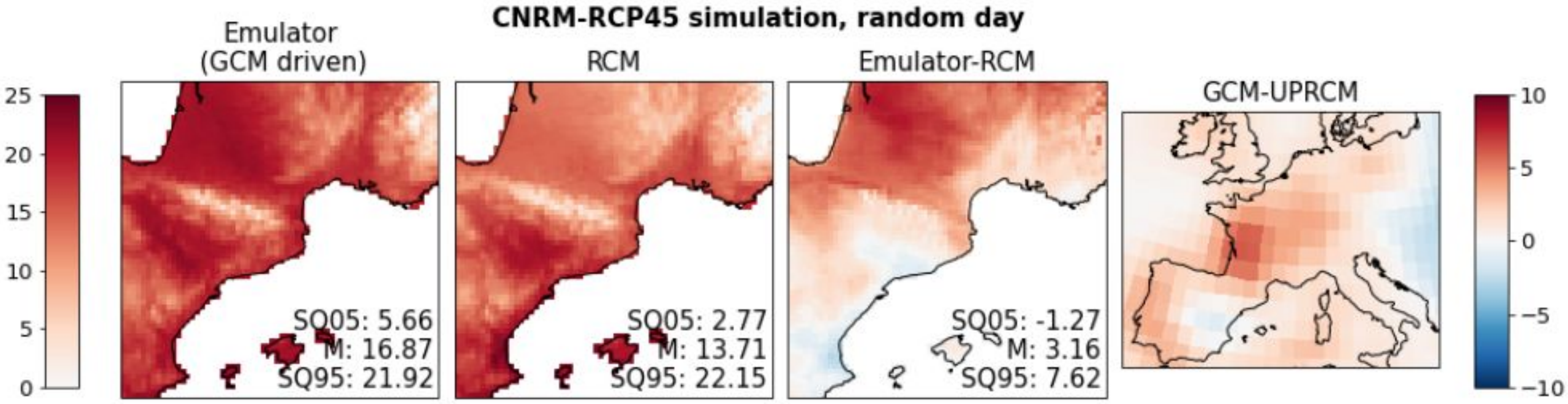


Application to GCM

Downscaling GCM simulation with the emulator produces a different results than with the RCM.
⇒ Large scale transformation from the RCM is not reproduced.



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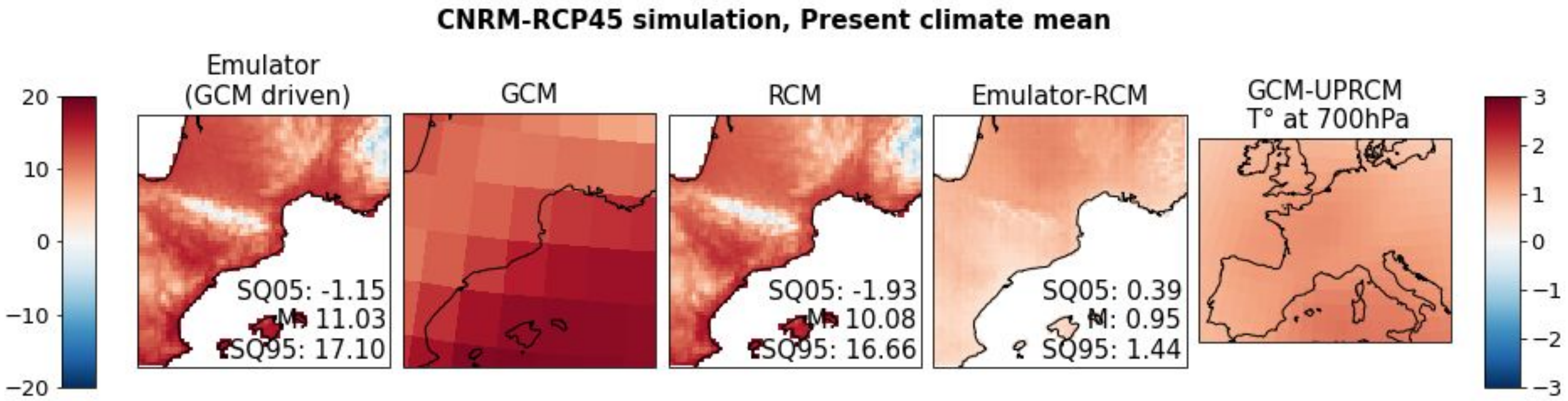

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Training only historical

Delta TAS

Historical emulator

Historical + RCP85 emulator