Introduction to Regional Climate Modelling and the Need of AI

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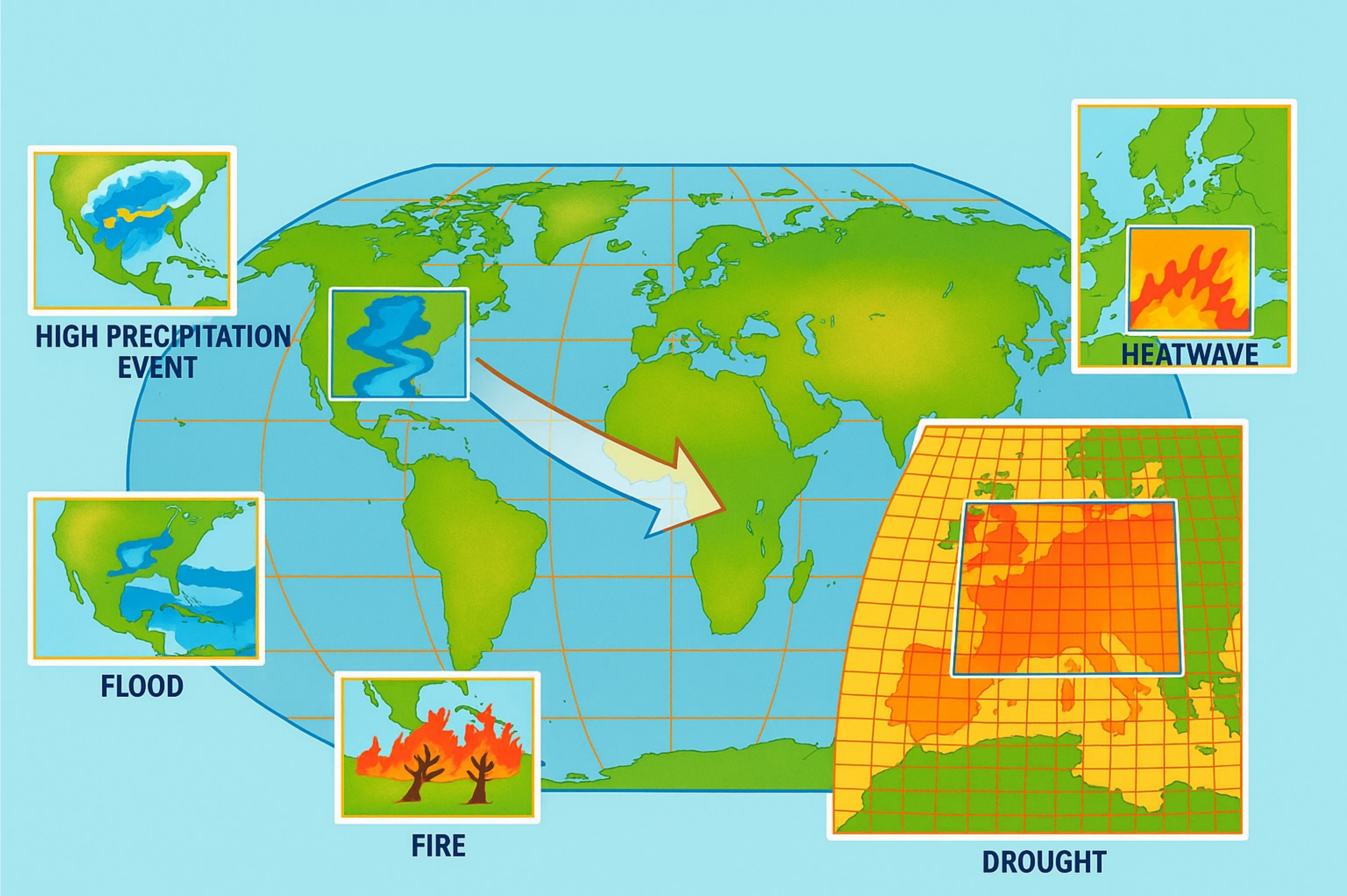
ICTP The Abdus Salam International Centre for Theoretical Physics
IAEA International Atomic Energy Agency
UNESCO United Nations Educational, Scientific and Cultural Organization

Regional Climate Models
… described by chatgpt



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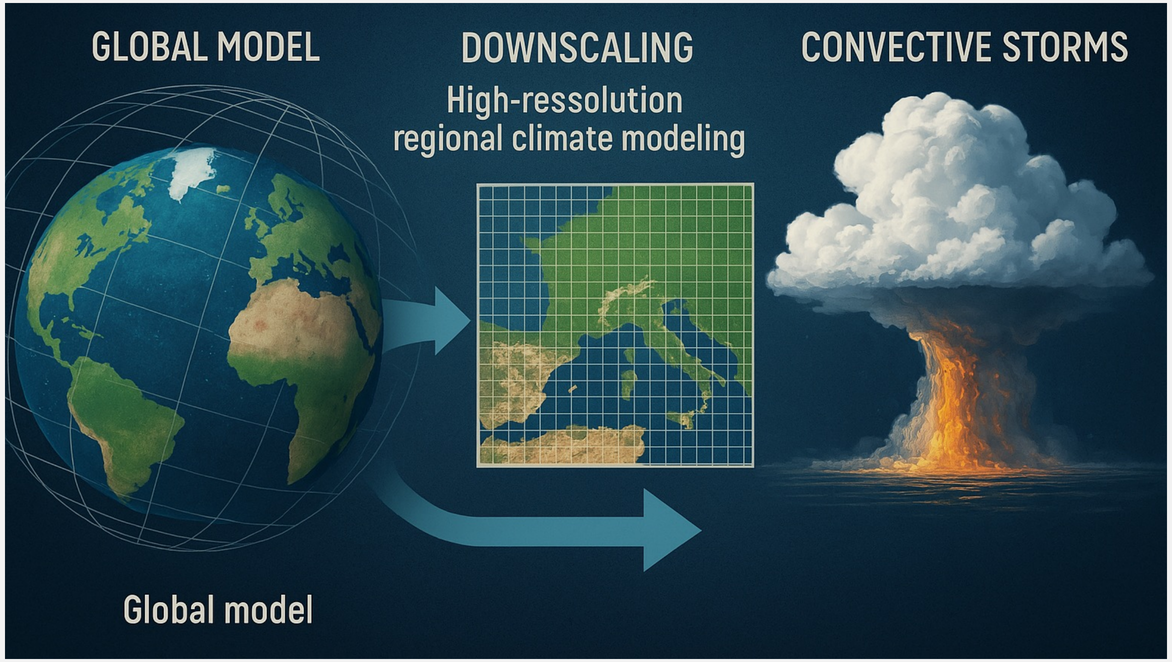
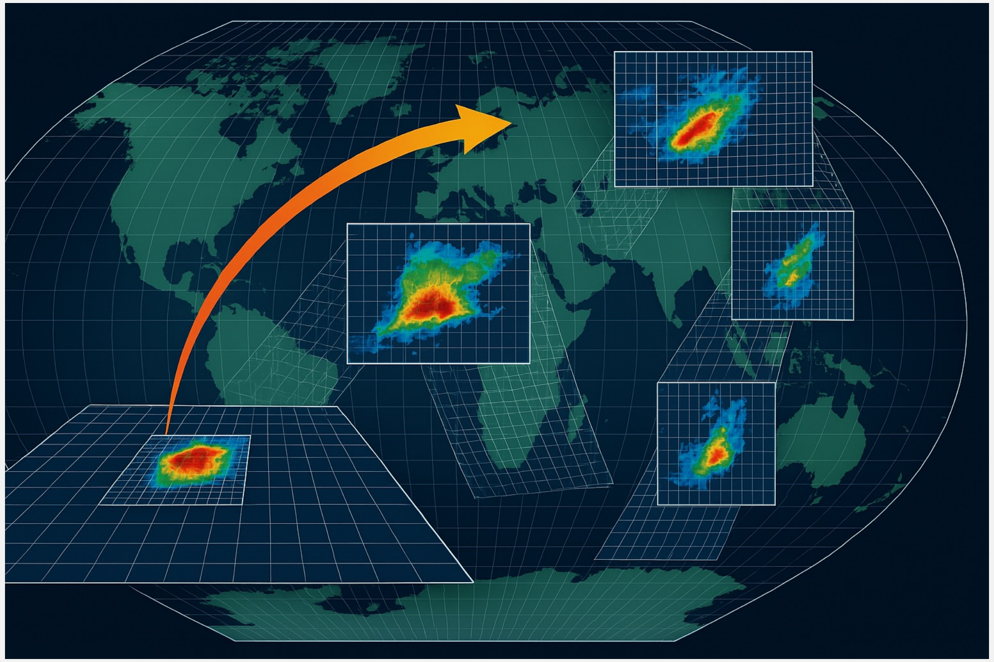
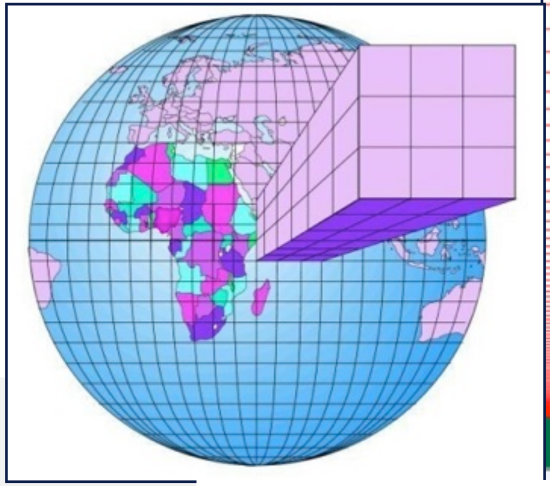
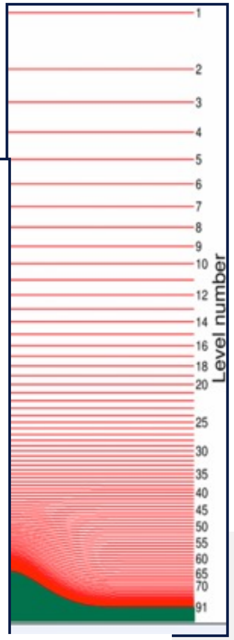




Why

Dynamical downscaling
Global Climate Model (GCM)





- or *General Circulation Model*
- Typical resolution between 50 and 250 km.
- "Cheap" models: Possible to make many long simulations
- Appropriate tool to study the climate from the global scale to sub-continental scale.
- Too coarse resolution for the local impacts of the global climate change.
- ⇒ Necessary to downscale those simulations.

Momentum

$$\frac{\partial \overline{V}}{\partial t} + \overline{V}\cdot\nabla\overline{V} = -\frac{\nabla p}{\rho} - 2\overline{\Omega}\times\overline{V} + \overline{g} + \overline{F}_{\overline{V}}$$

Energy

$$C_p\left(\frac{\partial T}{\partial t} + \overline{V}\cdot\nabla T\right) = \frac{1}{\rho}\frac{dp}{dt} + Q + F_T$$

Mass

$$\frac{\partial \rho}{\partial t} + \overline{V}\cdot\nabla\rho = -\rho\nabla\cdot\overline{V}$$

Water

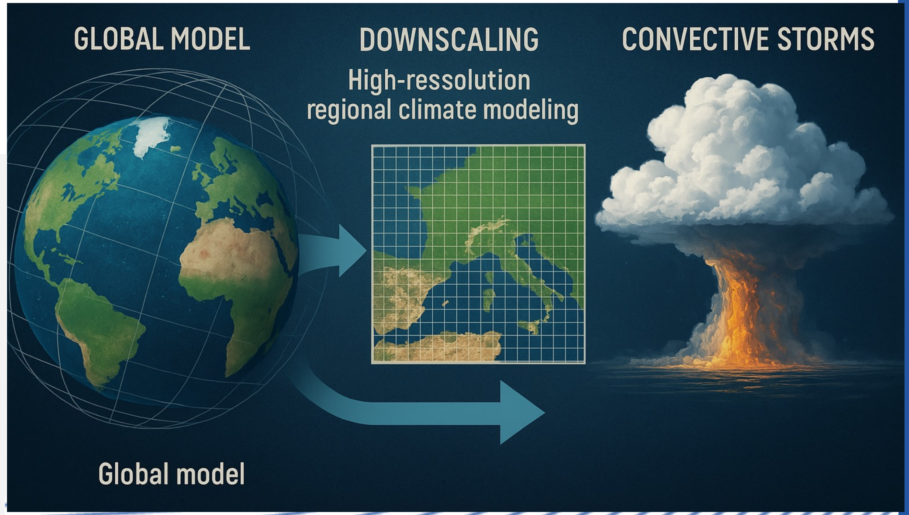
$$\frac{\partial q}{\partial t} + \overline{V}\cdot\nabla q = \frac{S_q}{\rho} + F_q$$

Ideal Gas Law

$$p = \rho R T$$

Regional Climate Models

What they are



- Computer programs performing a physical down-scaling over a limited domain region of the Earth
- Numerical discretized equations solved in a full 3D flattened box domain
- High resolution (50km - 1km).
- Limited Area Models
- Driven by a GCM simulation at the domain borders
- Same physical basis as global models.

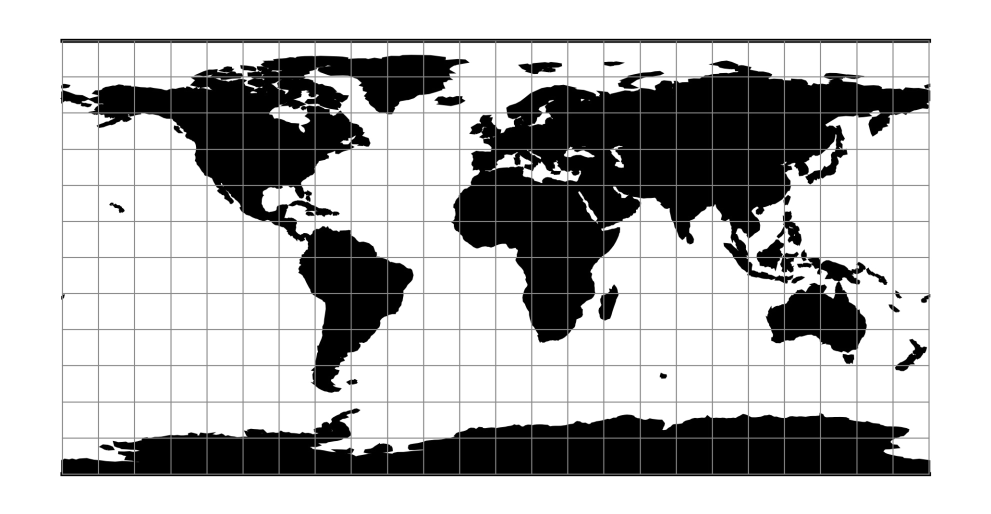
Regional Climate Models

Limited Area Models

- Same components of an earth system model
- Works in a box representing part of the earth surface
- Interacts with a coarse global model updating the boundaries
- Projects curved earth surface on a plane

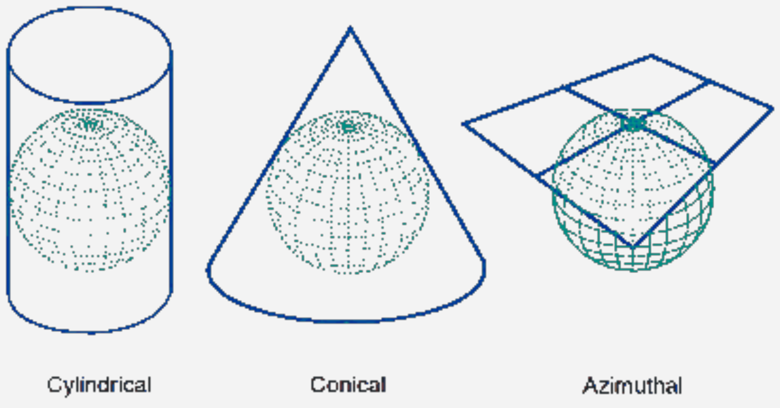
Flattening the Earth

- A map projection is a set of transformations employed to represent the curved two-dimensional surface of a Earth on a plane.
- All projections of a sphere on a plane necessarily distort the surface.

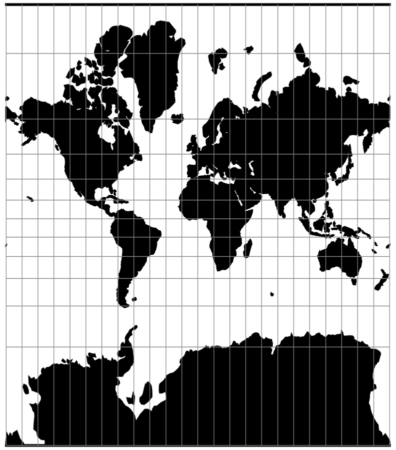


Local Area Projections

- Regional Climate Models use local projections which must
  - Provide high accuracy over model integration domain
  - Reduce to a minimum the deformation required to map vector quantities
  - Provide analytical formulas to map from/to the projected grid and the sphere
- Map projections are typically classified according to the geometric surface from which they are derived. The three classes of map projections are cylindrical, conical and planar or azimuthal



Mercator Projection

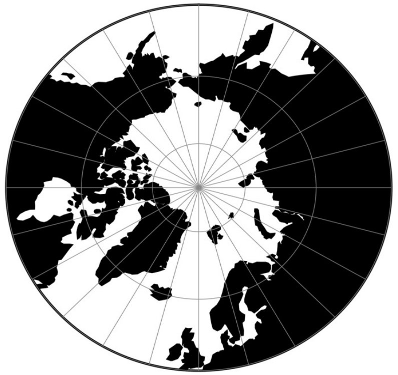


- Normal
  - The Mercator projection is a cylindrical map projection that origins from the 16th century. It is widely recognized as the first regularly used map projection. It is a conformal projection in which the equator projects to a straight line at constant scale.
  - It is best usable at low latitudes
  - The projection parameters are:
    - The central latitude
    - The central longitude
    - The ellipsoid description

Lambert conformal conical

- Lambert Conformal Conic projection (LCC) is a conic map projection used for aeronautical charts, and many national and regional mapping systems.
  - Projection parameters
    - Latitude of the center
    - Longitude of the center
    - Latitude (two for secant projection) of standard parallel
    - The ellipsoid description

Stereographic



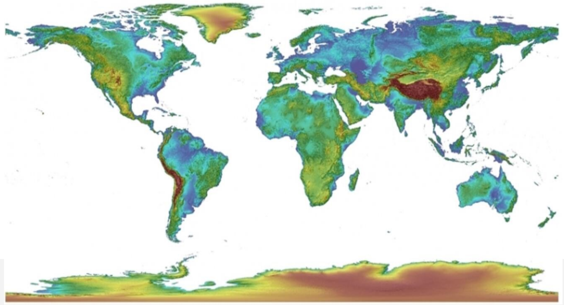
- Projection parameters
  - Latitude of the center
  - Longitude of the center
  - Latitude of the projection center
  - Longitude of the projection center
  - The reference ellipsoid

Map correction factor

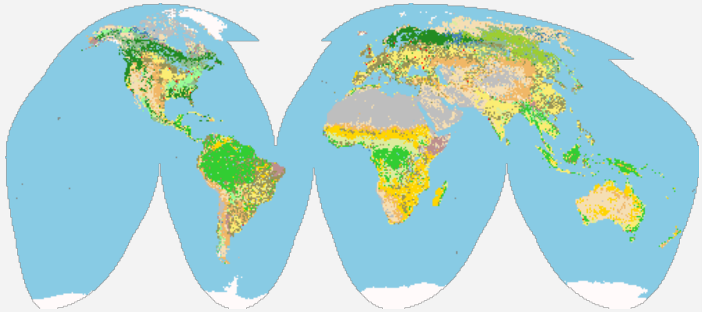
- In all projections, U and V components of the wind will be relative to the model grid, not relative to earth coordinates (where U would be west-east and V would be north-south).
  - In the case of a Mercator projection, the model grid does align with earth coordinates and no rotation of the winds is needed.
  - For the other projections, a rotation is necessary whenever one wants to back-project the output to calculate wind direction.
  - For the Coriolis effect, the wind in the equations must be earth relative
    - A constant mapping factor must multiply wind component in the equations

Static model information

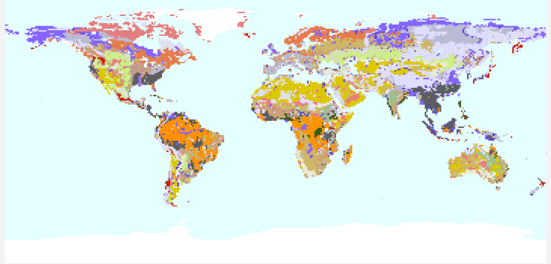
- **Topography** – Surface elevation generally comes form satellite radiometric estimation at high resolution, called global elevation model

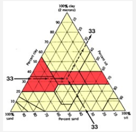


- Global **Land Cover Characterization** (GLCC) is a global land cover classification datasets that are based primarily on the unsupervised classification of 1-km AVHRR (Advanced Very High Resolution Radiometer) 10-day NDVI (Normalized Difference Vegetation Index) composites [1992-1993].



- The Zobler "World Soil File for Global Climate Modelling" shows the global distribution of **soil types**, including soil texture classes. These have been generalized from the FAO Soil Map of the World (FAO, 1974) and the Matthews Vegetation data (1984) into one-degree square latitude/longitude grid cells, using a dot grid overlay technique to determine the largest map unit of each one-degree cell.





Initial conditions

- The regional model needs an initial state
  - Reanalysis : Pick the interpolated status from global reanalysis
  - GCM : Pick the status from GCM at the particular initial date

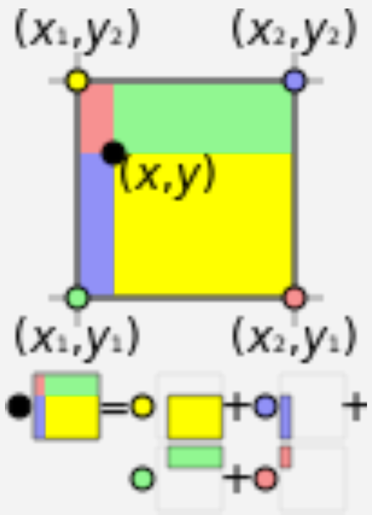
The two concepts are not equivalent

Variables for model run

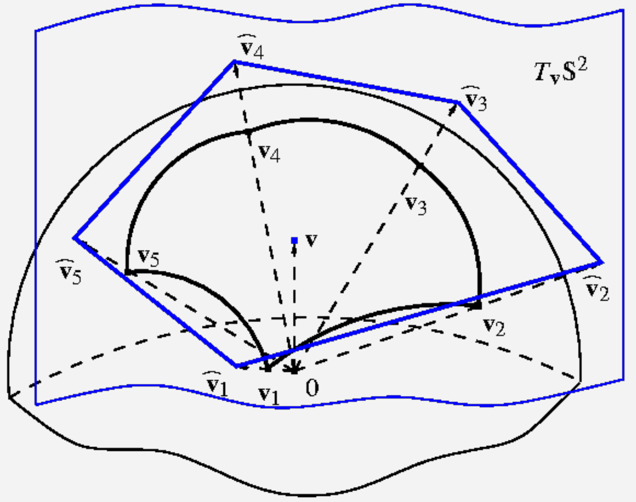
- Global 6 hourly
  - 3D
    - Temperature
    - Wind U (zonal) component
    - Wind V (meridional) component
    - Moisture (either mixing ratio, specific humidity, relative humidity)
    - [Geopotential height]
  - 2D
    - Sea Surface Temperature (SST)
    - Pressure
    - [Topography, Land mask]

Horizontal interpolation

- Data from file or OpenDAP protocol is horizontally interpolated
  - Bilinear interpolation



  - Spherical Baricentric Interpolation



Vertical interpolation

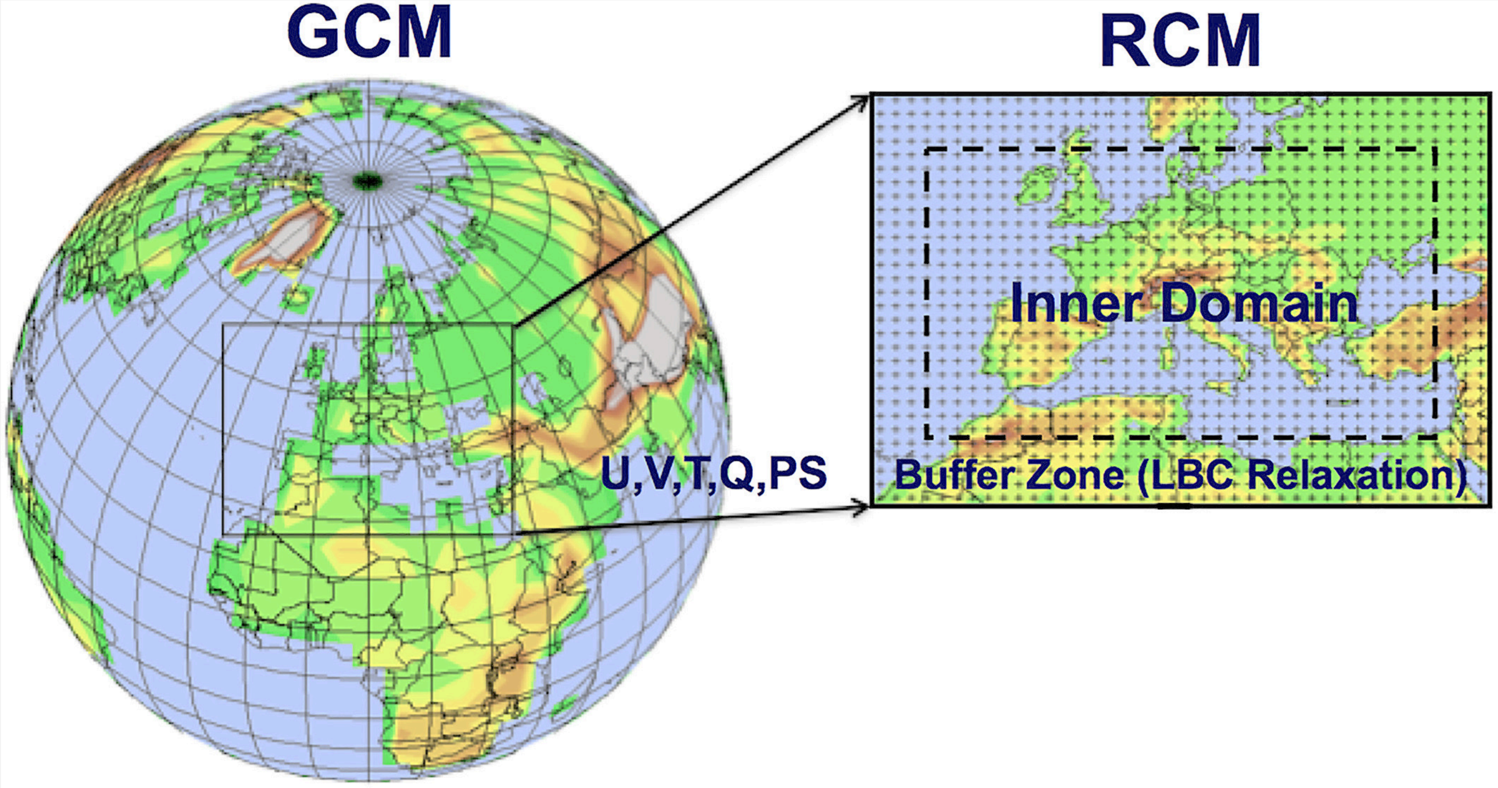
- Data horizontally interpolated on model grid is vertically interpolated from pressure or global model levels onto local area model levels

$$
\begin{aligned}
y &= y_0 + (x - x_0)\frac{y_1 - y_0}{x_1 - x_0} \\
&= \frac{y_0(x_1 - x_0)}{x_1 - x_0} + \frac{y_1(x - x_0) - y_0(x - x_0)}{x_1 - x_0} \\
&= \frac{y_1 x - y_1 x_0 - y_0 x + y_0 x_0 + y_0 x_1 - y_0 x_0}{x_1 - x_0} \\
&= \frac{y_0(x_1 - x) + y_1(x - x_0)}{x_1 - x_0},
\end{aligned}
$$

- Extrapolated afterward

Boundary conditions

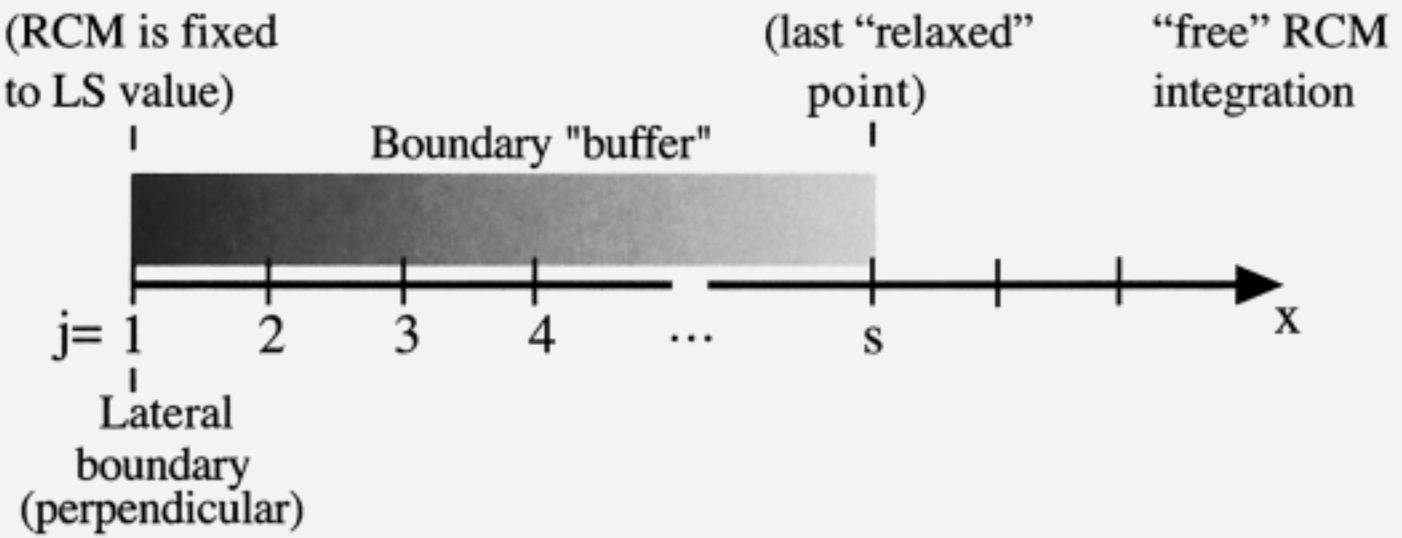
- Global Model derived; TIME DEPENDENT



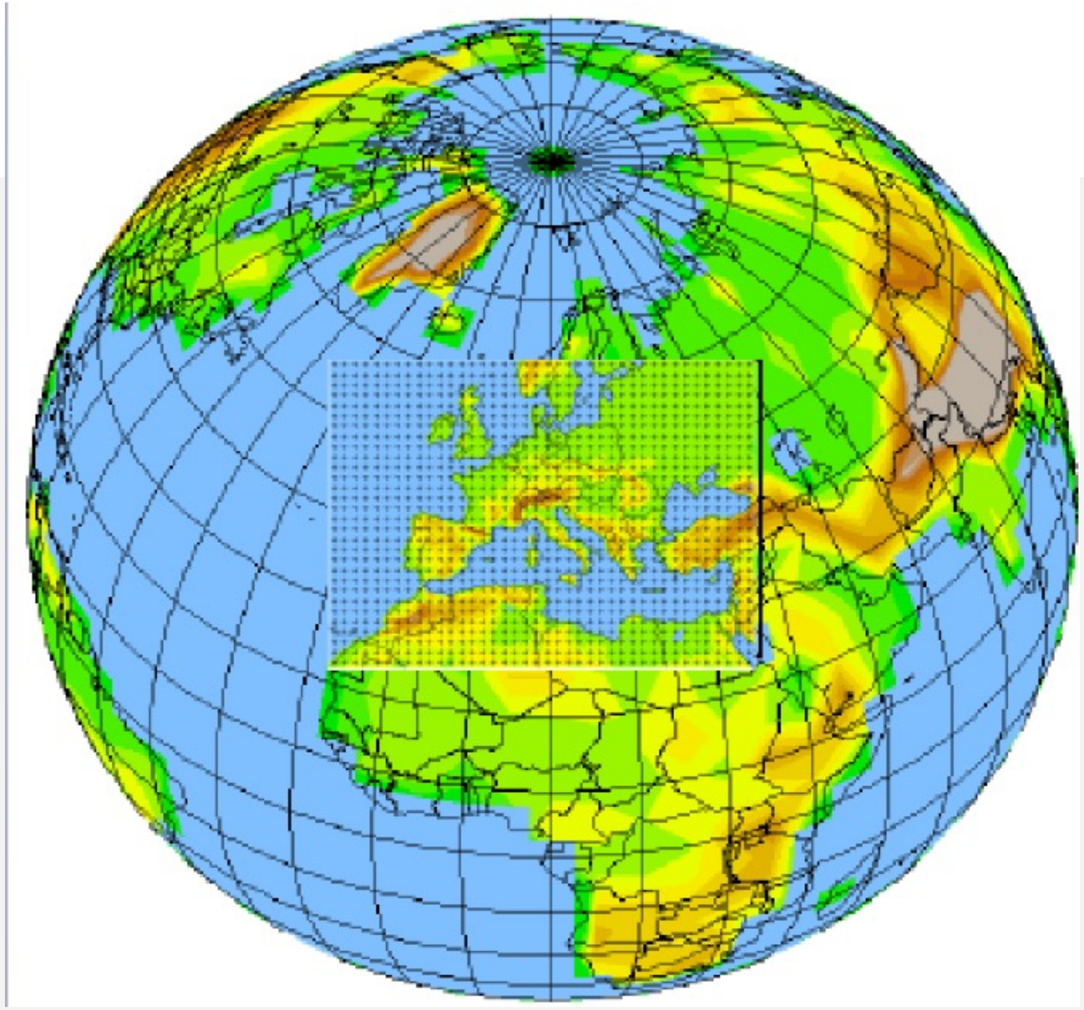
Boundary Scheme

- Global Model derived, TIME DEPENDENT

$$\frac{\partial \alpha}{\partial t} = \cdots + F(n)F_1(\alpha_{LBC} - \alpha_{mod}) - F(n)F_2\nabla^2(\alpha_{LBC} - \alpha_{mod})$$



Summary



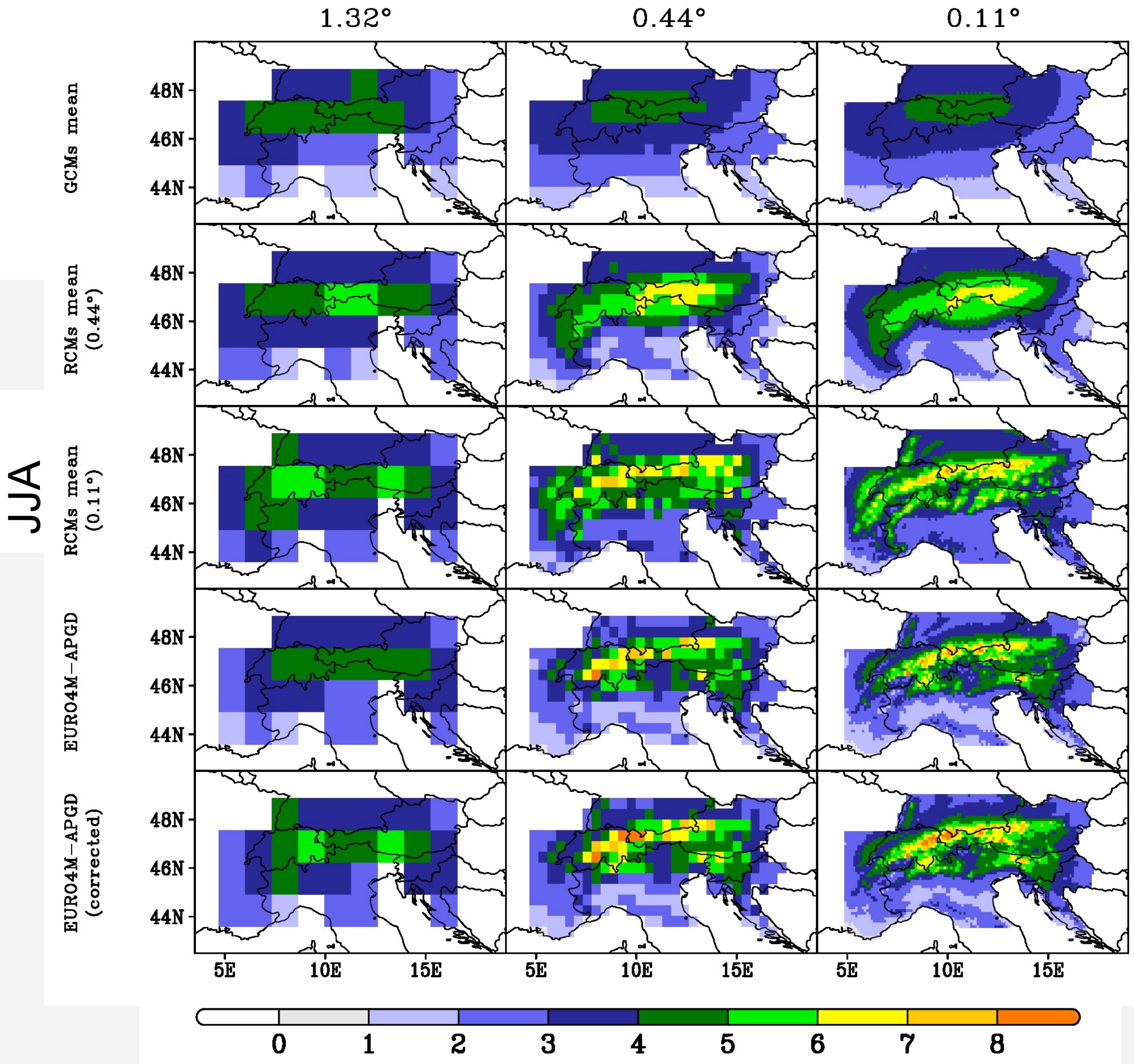
Motivation: The resolution of GCMs is still too coarse to capture regional and local climate processes.

Technique: Regional Climate Model (RCM) is one way nested within a GCM in order to locallyincrease the model resolution.

• Atmospheric Initial conditions (IC) and lateral boundary conditions (LBC) for the RCM are obtained from the GCM (Climate projection) or Reanalysis (perfect LBC Hindcast).
• Climate boundary conditions are the same of the driving GCM : the RCPs in CMIP Strategy: The GCM simulates the response of the general circulation to the large scale forcings, the RCM simulates the effect of sub-GCM-grid scale forcings and provides fine scale regional information

Technique borrowed from NWP

RCM results (AV)



Mean Precipitation

Higher resolution

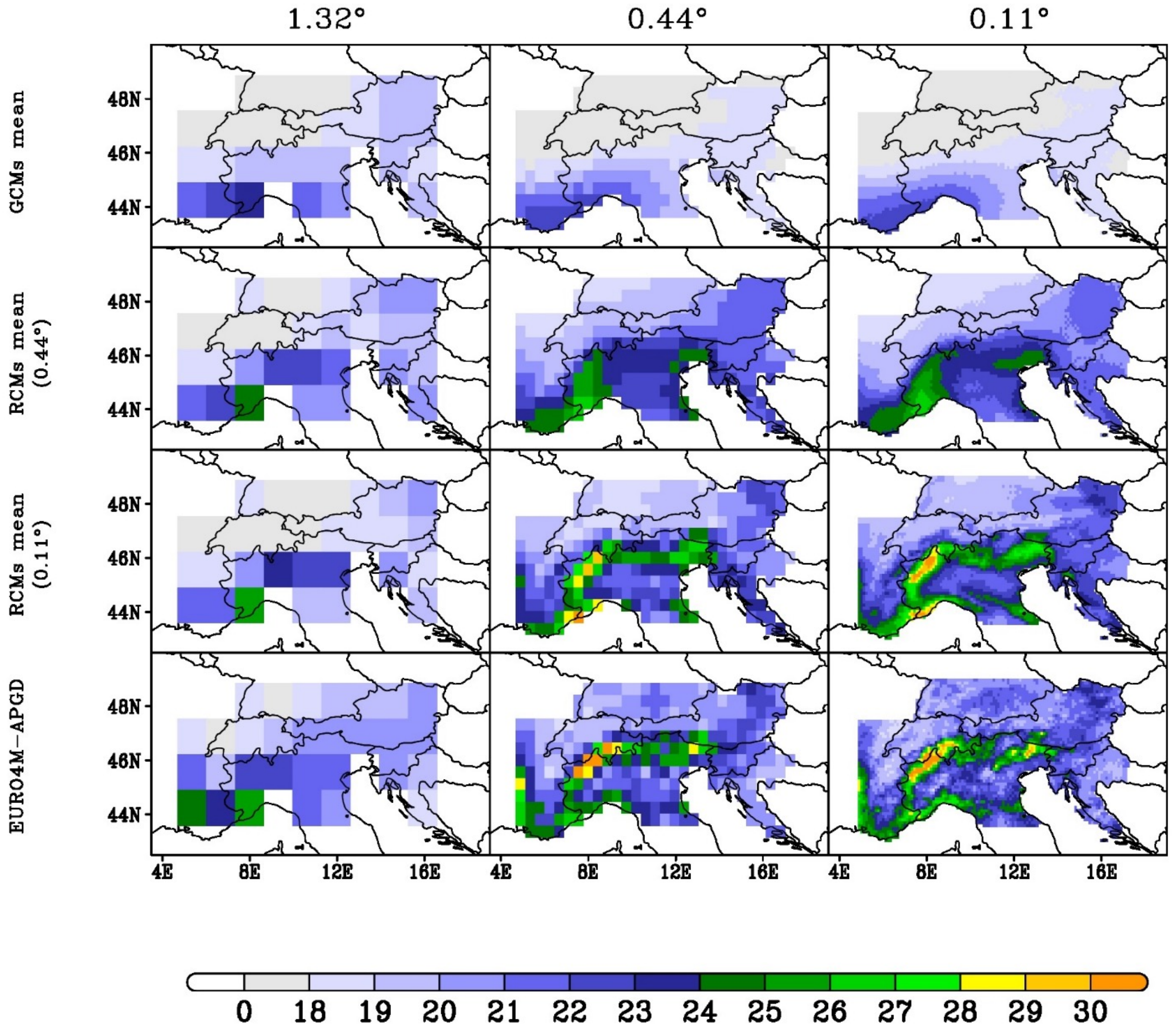
Increasing details in precipitation spatial distribution

Fine scale AV

Torma et al, 2015; Added value of regional climate modeling over areas characterized by complex terrain—Precipitation over the Alps; JGR https://doi.org/10.1002/2014JD022781

RCM results(AV)

Precipitation P95



GCM ensemble shows only SW gradient with lower values

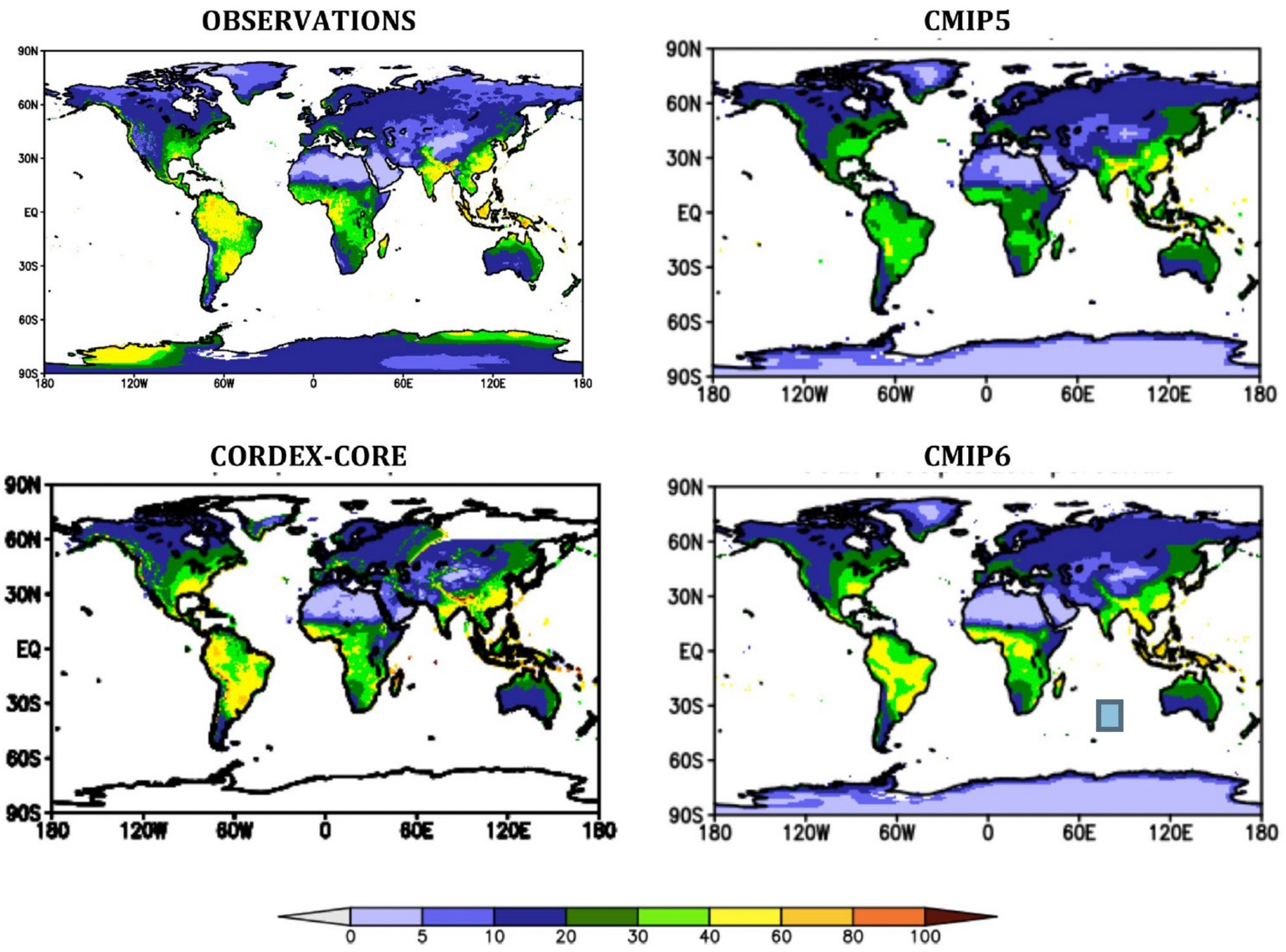
RCM11 captures well the magnitude and locations of max, min of R95

Spatial correlations highest fot **RCM11**

Torma et al, 2015; Added value of regional climate modeling over areas characterized by complex terrain—Precipitation over the Alps; JGR https://doi.org/10.1002/2014JD022781

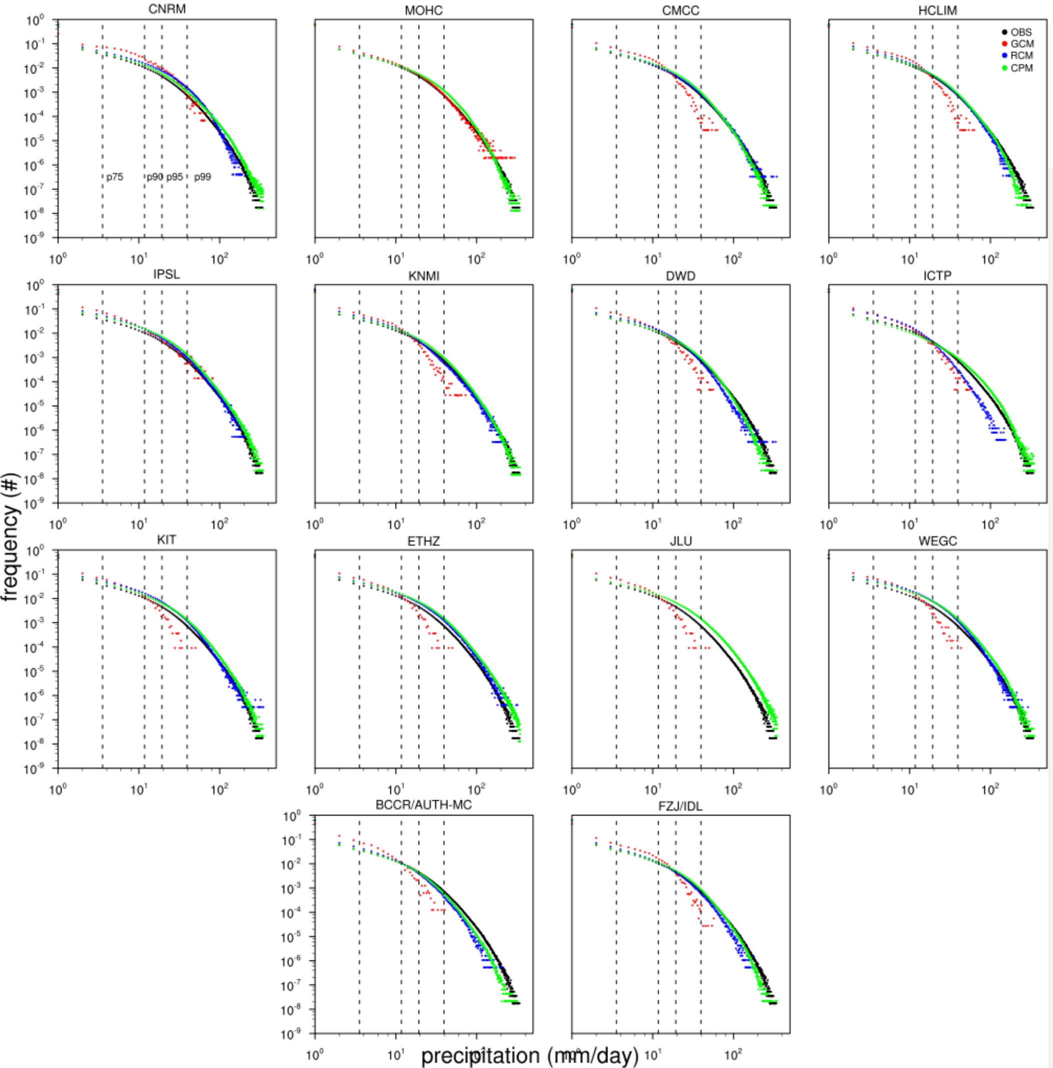
RCM results(AV)

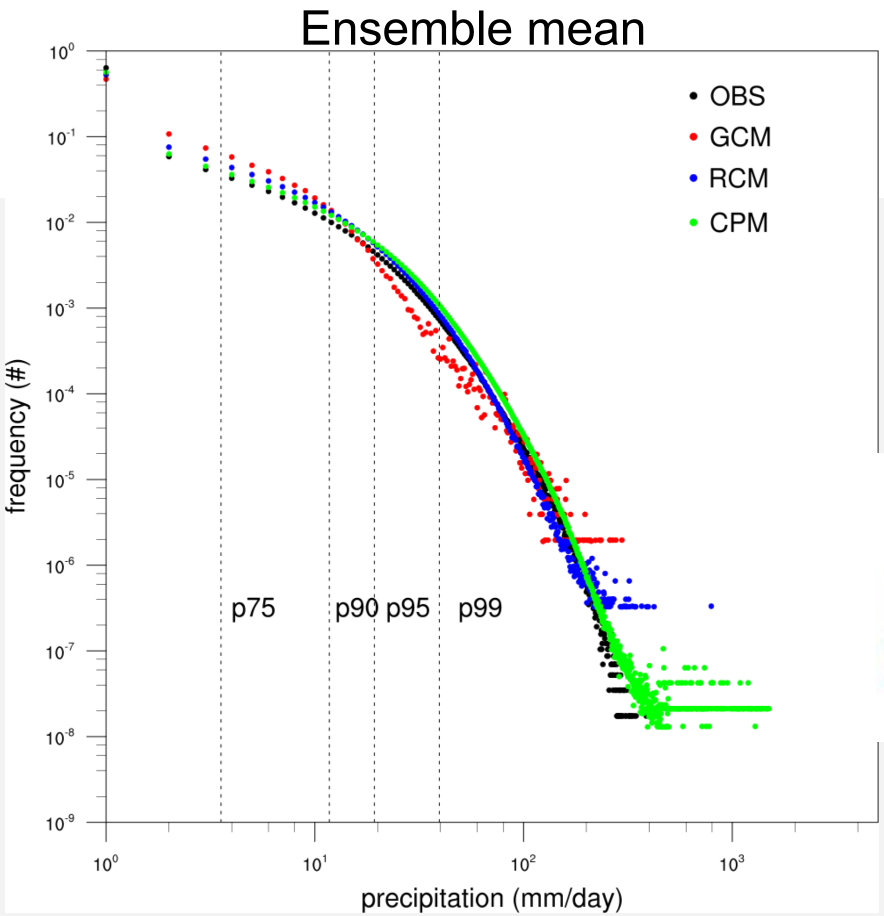
Precipitation P95

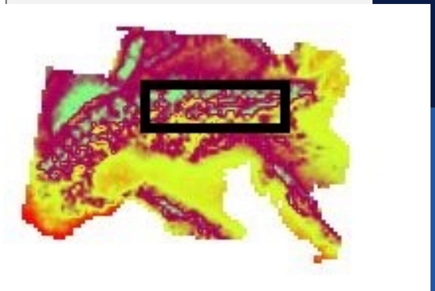


Coppola et al. 2021 Climate Dynamics (2021) 57:1293–1383 https://doi.org/10.1007/s00382-021-05640-z

RCM results: extreme precipitation





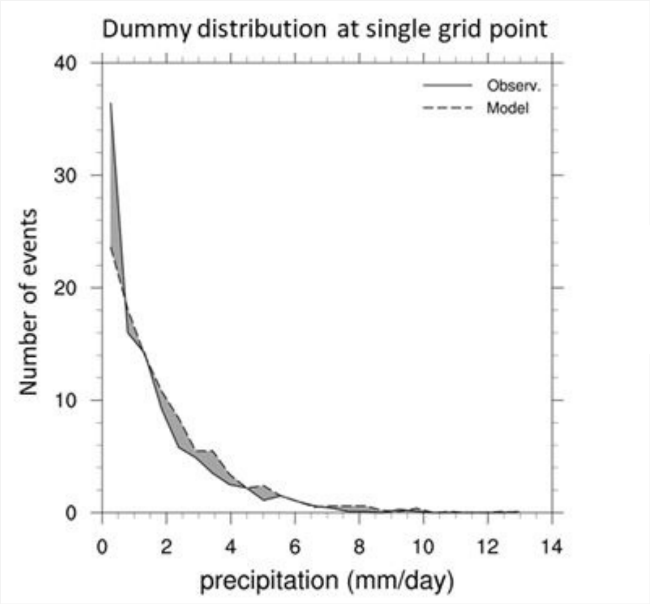


CPM v GCM 99-100 av

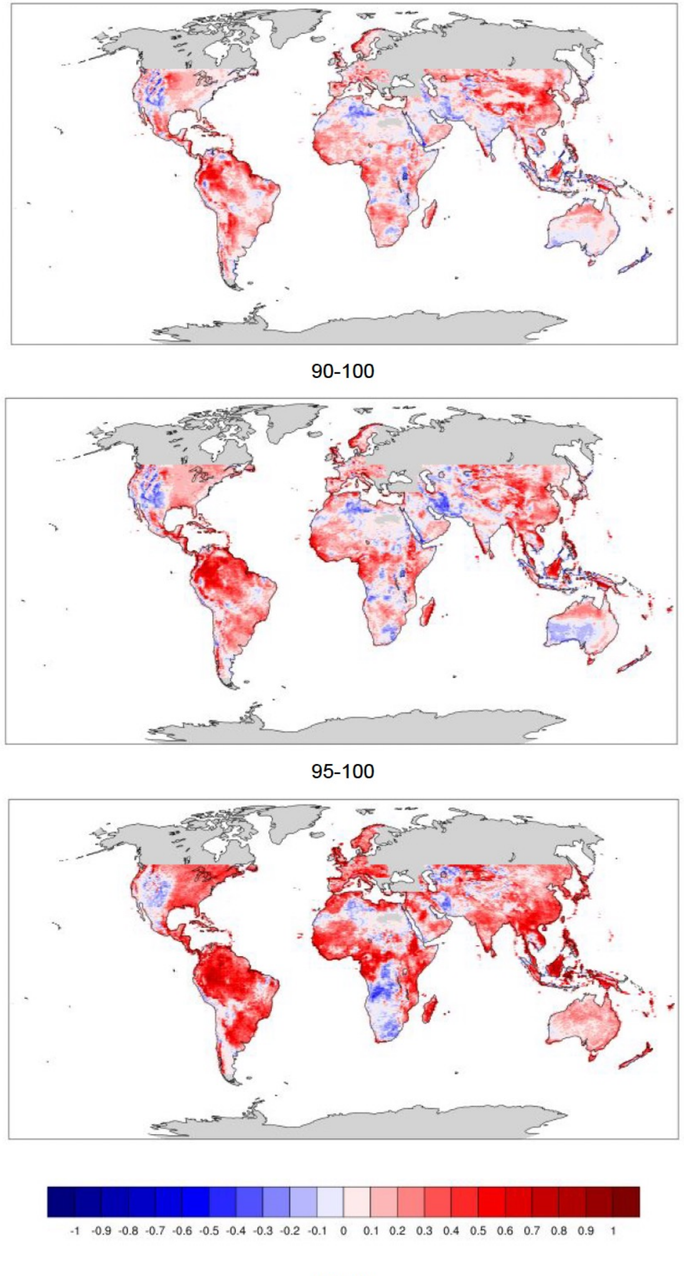
Ciarlò et al. *2021*

RCM results(AV)

Added value for RCM ensemble means of the CORDEX-CORE at different percentile intervals compared to CHIRPS at 0.22



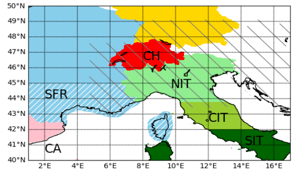
$$A_i = D_{GCM} - D_{RCM}$$

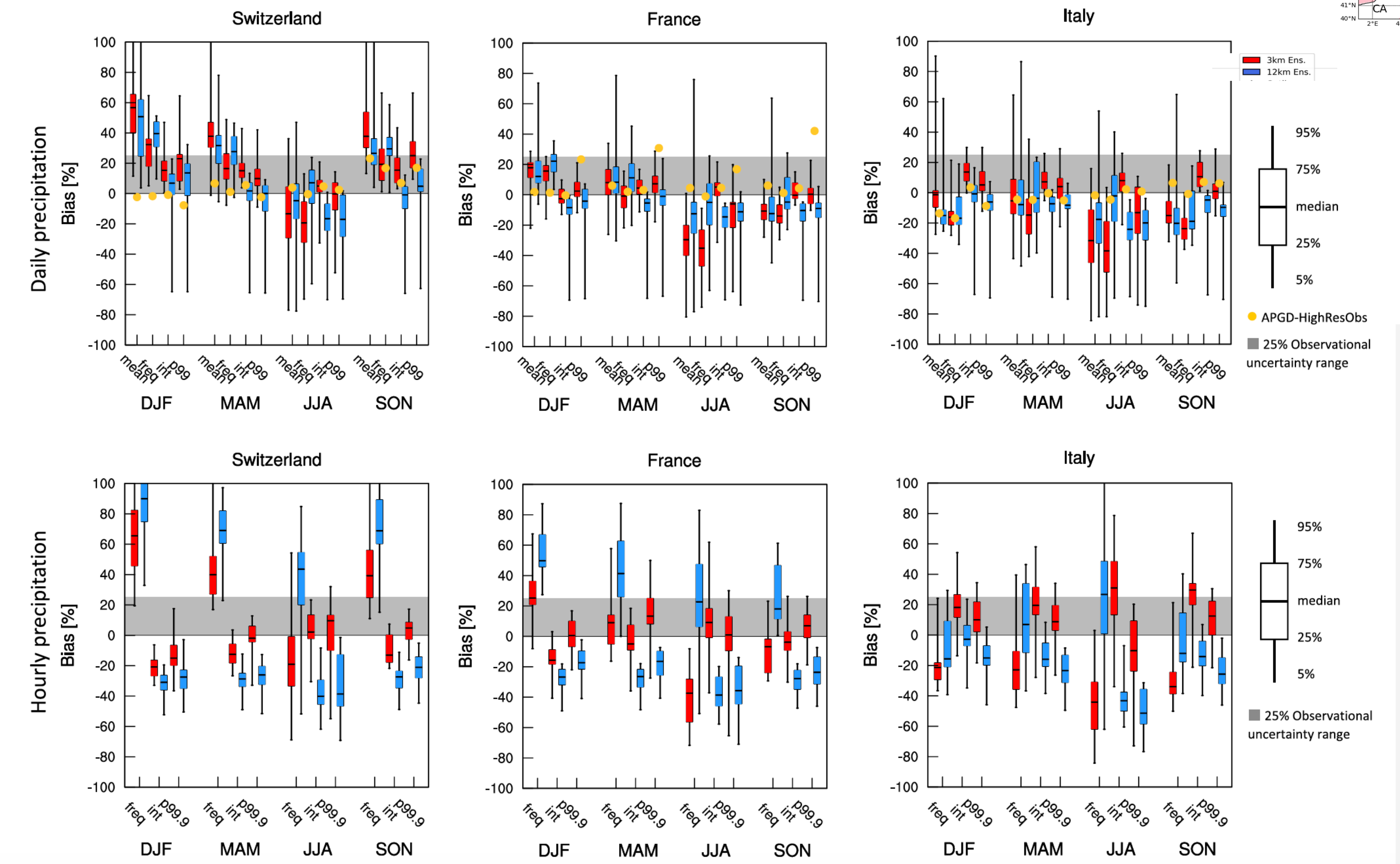


The shaded area represents the Sum of the Relative Probability Difference between the model and observation Dm

Ciarlo`, J.M., Coppola, E., Fantini, A. *et al.* A new spatially distributed added value index for regional climate models: the EURO-CORDEX and the CORDEX-CORE highest resolution ensembles. *Clim Dyn* **57**, 1403–1424 (2021). https://doi.org/10.1007/s00382-020-05400-5

Precipitation uncertainty





→ Larger differences between RCMs and CPMs at sub-daily scale;

→ Smaller biases for CPMs at the hourly scale;

→ **Smaller uncertainties** for CPMs at the hourly scale (all regions, most indices and seasons);

→ side note: differences between the two observations can be larger than 20%

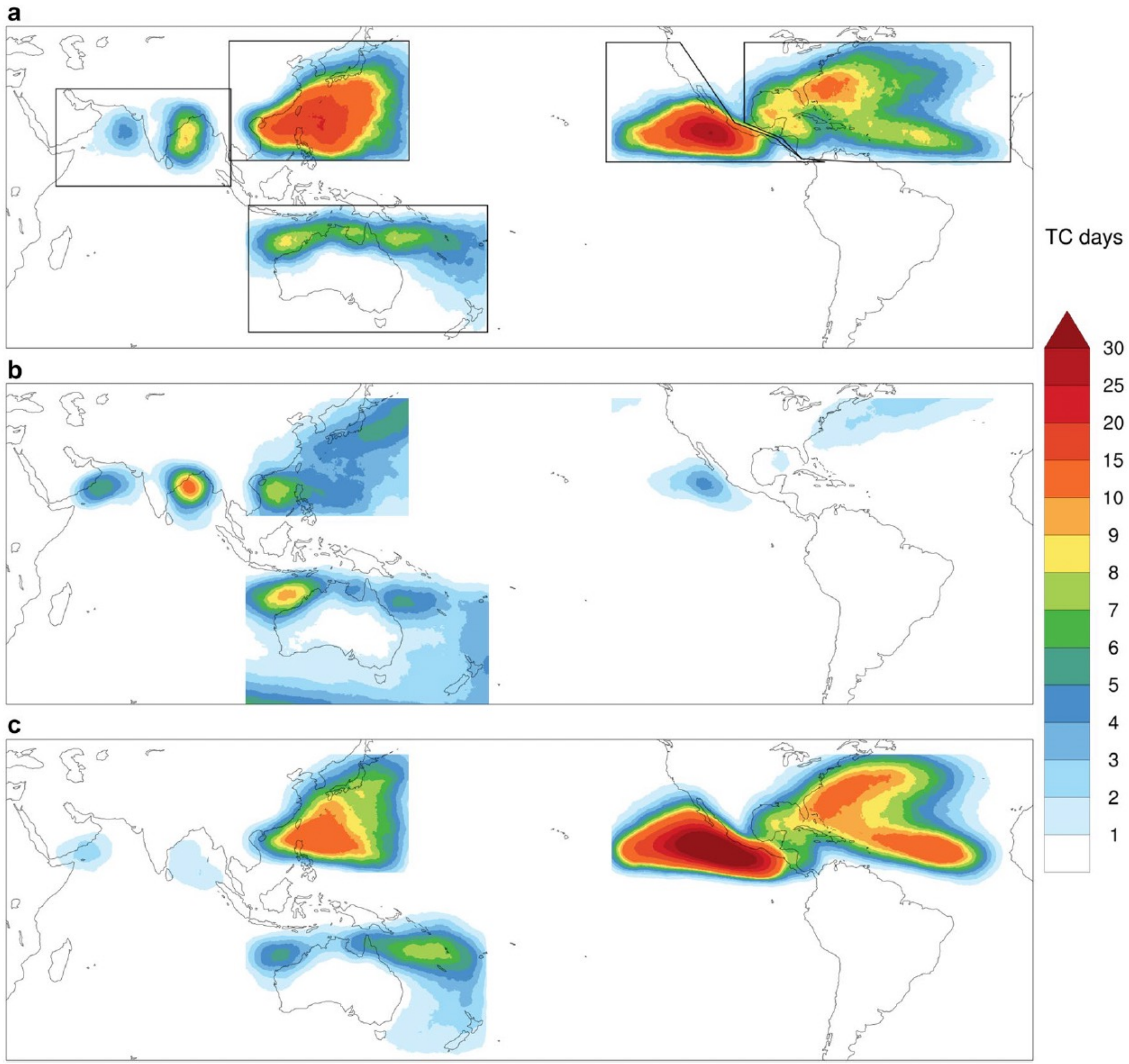
Ban, N., Caillaud, C., Coppola, E. *et al.* The first multi-model ensemble of regional climate simulations at kilometer-scale resolution, part I: evaluation of precipitation. *Clim Dyn* **57**, 275–302 (2021). https://doi.org/10.1007/s00382-021-05708-w

RCM results(Tropical Cyclones density)

IBTrACS, OBS

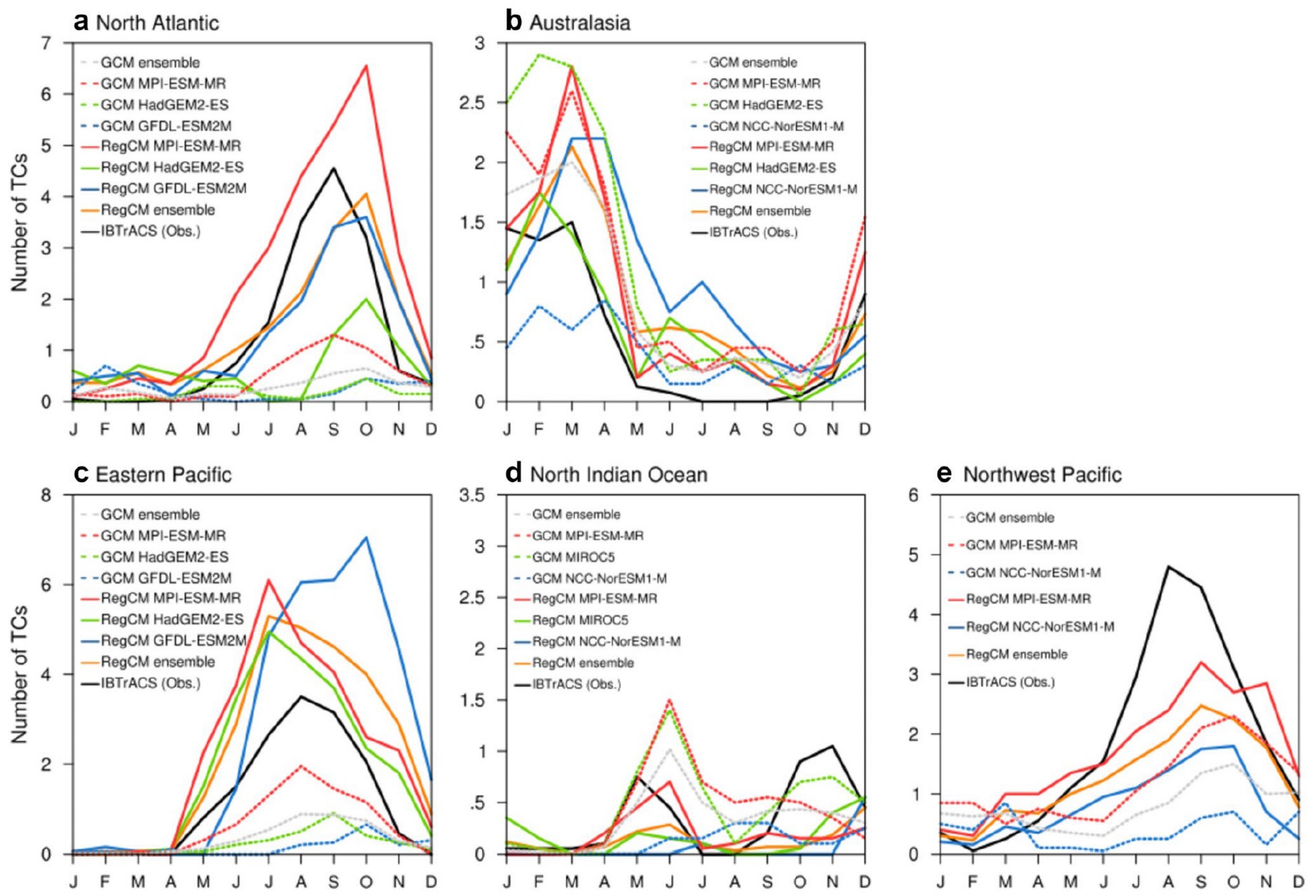
GCM

RCM



Torres-Alavez et al. 2021 , Climate Dynamics (2021) 57:1507–1531 https://doi.org/10.1007/s00382-021-05728-6

RCM results(Tropical Cyclones)



Torres-Alavez et al. 2021 , Climate Dynamics (2021) 57:1507–1531 https://doi.org/10.1007/s00382-021-05728-6

Regional Climate Model

Pros

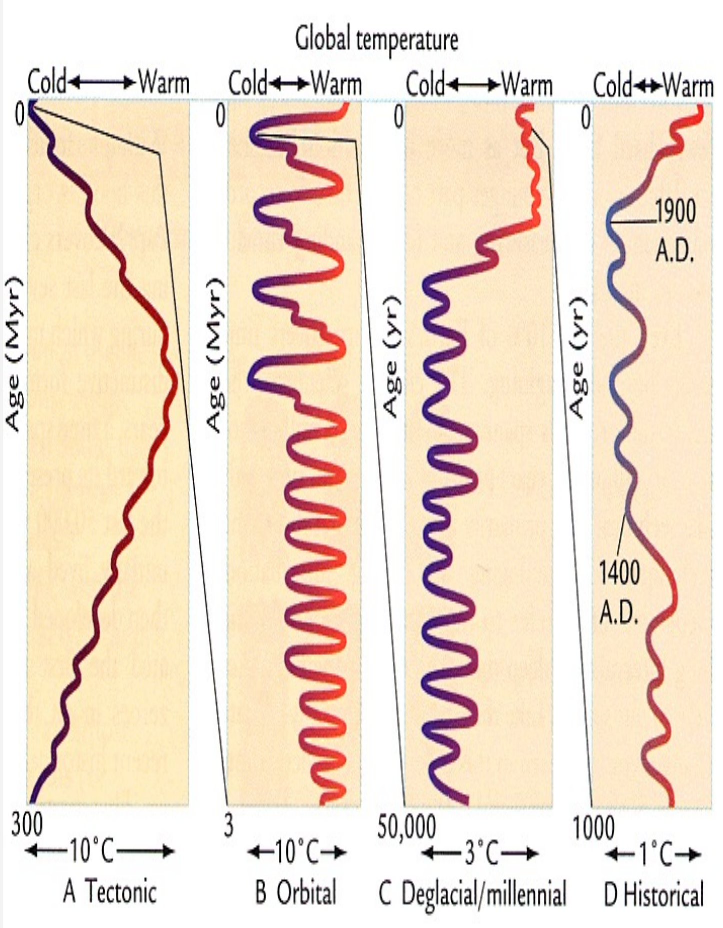
- Physically based down-scaling
  - Comprehensive climate modeling system
- Wide variety of applications
  - Process studies
  - Paleo-climate
  - Climate change
  - Seasonal prediction
- High resolution through multiple nesting
  - currently 3 to 50 km grid interval
- Simulation at very high km scale resolution with explicit convection

Cons

- One-way nesting
  - No regional-to-global feedbacks
- Technical issues in the nesting technique
  - Domain, LBC procedure, physics, etc.
- Not intended to correct systematic errors in the large scale forcing fields
  - ***Always analyze first the forcing fields***
- Computationally demanding

Natural Climate Change

- Tectonic-Scale Climate Changes
- Orbital-Scale Climate Changes
- Solar luminosity
- Aerosols from vulcanic eruption



(from *Earth's Climate: Past and Future*)

Natural Climate Change

Tectonic Control of Climate

- **Plate Tectonics** probably does influence climate over long time scales (on the order of **millions of years**).

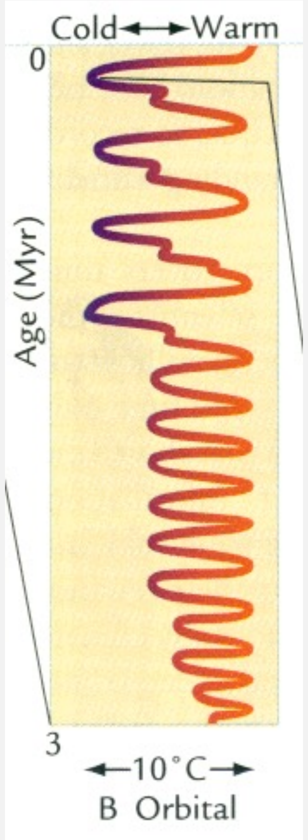
- The main influence of plate tectonics on climate appears to be indirect: by modulating CO_2 levels in the atmosphere through the chemical weathering process.

- This, in turn, affects climate by way of the greenhouse effect.

- Such change, in combination with the long-term increase in solar luminosity, can account for the main features of the long-term climate changes.

Natural Climate Change

Orbital-Scale Climate Change



(from *Earth's Climate: Past and Future*)

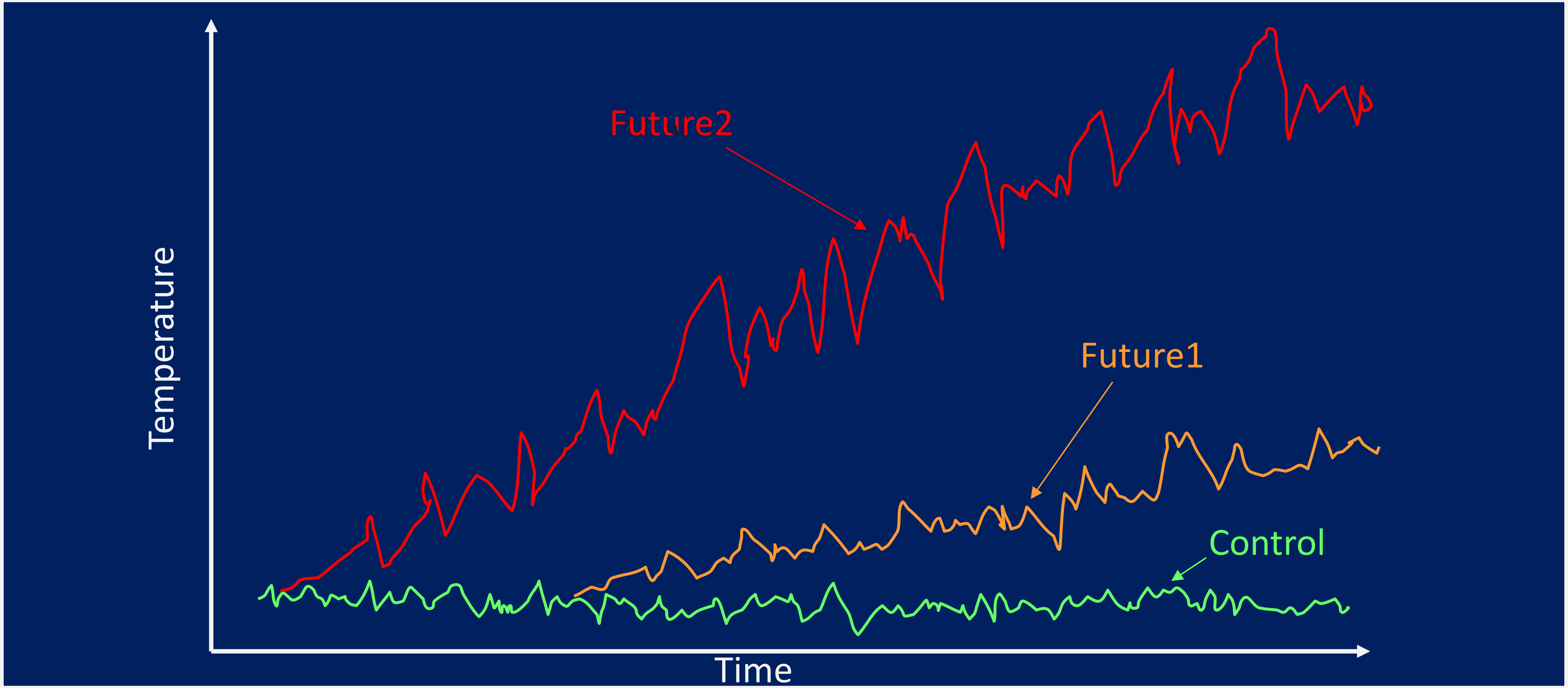
- Changes in solar heating driven by changes in Earth's orbit are the major cause of cyclic climate changes over time scales of tens to hundreds of thousands of years (23k years, 41k years, and 100k years) .
- Orbital-scale climate changes are caused by subtle shifts in Earth's orbit.

- Three features of Earth's orbit around the Sun have changed over time:
  - the tilt of Earth's axis,
  - the shape of its yearly path of revolution around the Sun
  - the changing positions of the seasons along the path.

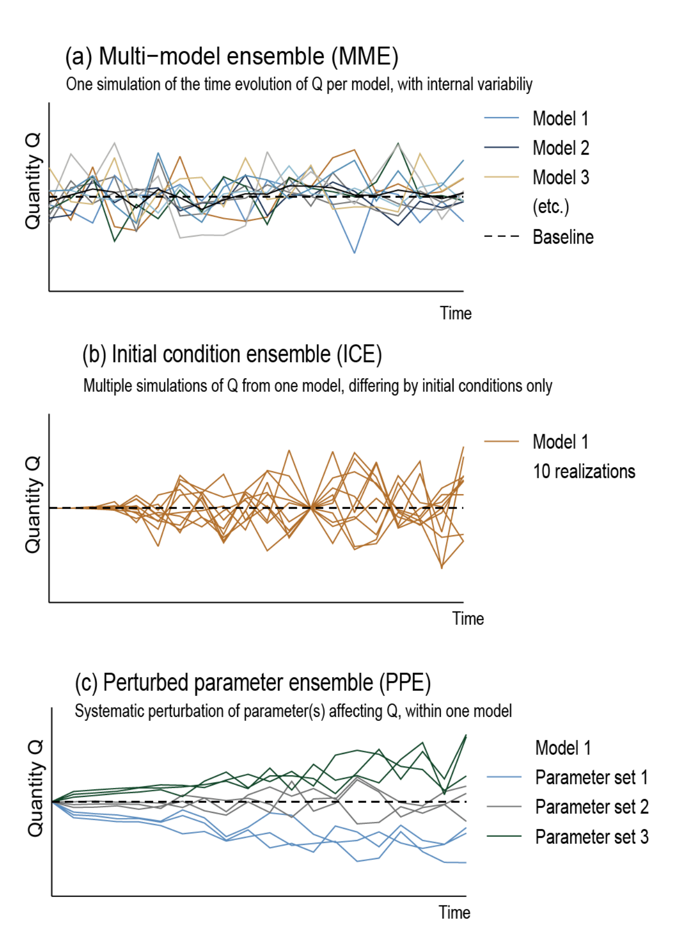
- **Orbital-scale climate changes** have typical cycles from **20,000 to 400,000 years.**

Anthropogenic Climate Change

Running a climate scenario simulation : Initial conditions



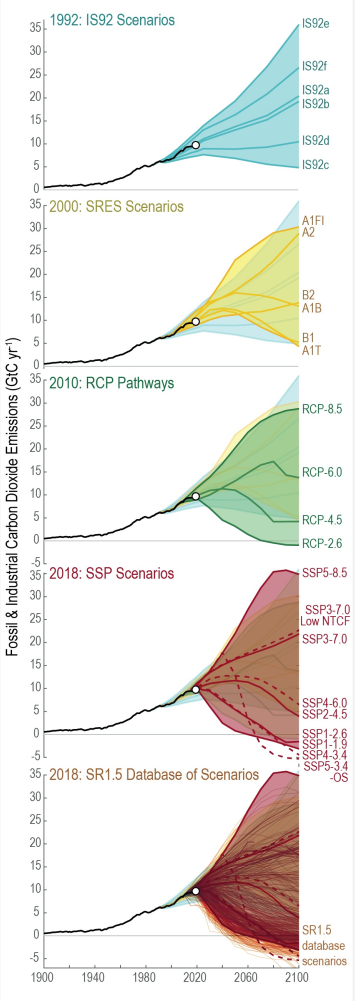
Anthropogenic Climate Change

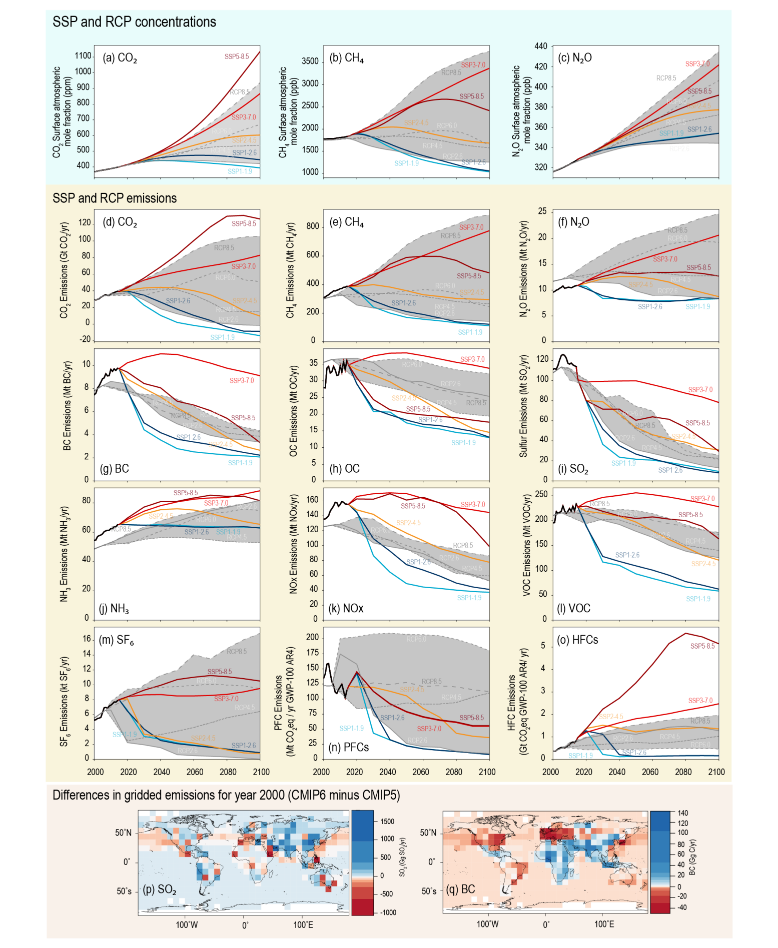


IPCC AR6 WGI Figure1.21 | Illustration of common types of model ensemble, simulating the time evolution of a quantity Q (such as global mean surface temperature)

Anthropogenic Climate Change

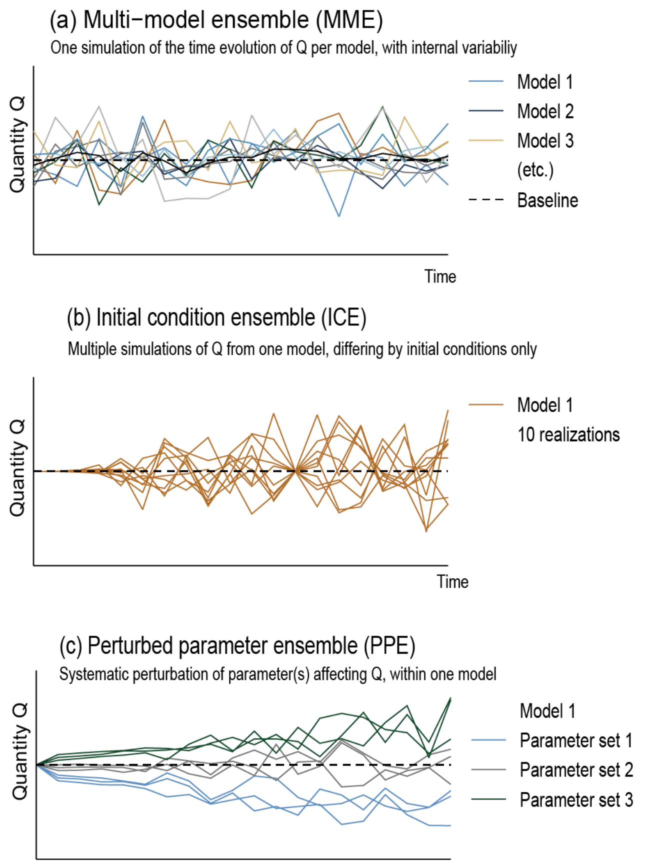
IPCC AR6 WGI Cross-Chapter Box 1.4, Figure 2 | Comparison between the Shared Socio-economic Pathways (SSP) scenarios and the Representative Concentration Pathway (RCP) scenarios





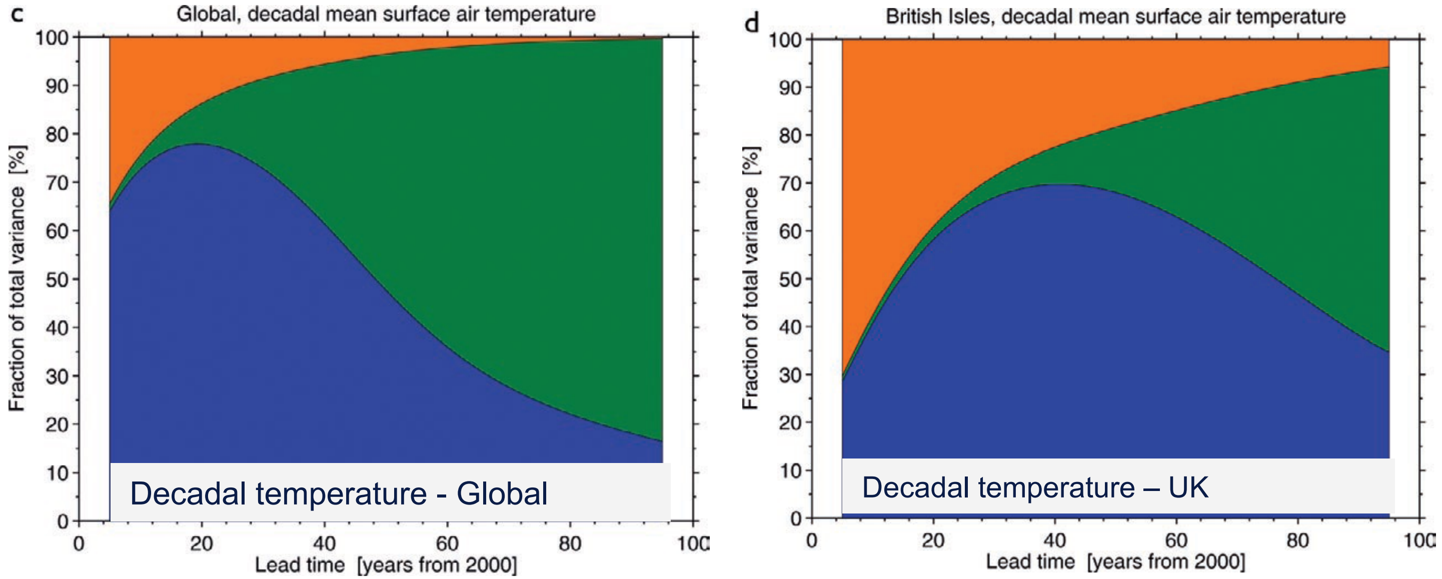
IPCC AR6 WGI Figure1.28 | Comparison of the range of fossil fuel and industrial CO2 emissions from scenarios used in previous assessments up to AR6

Dynamical downscaling
Ensemble approach for uncertainty estimate



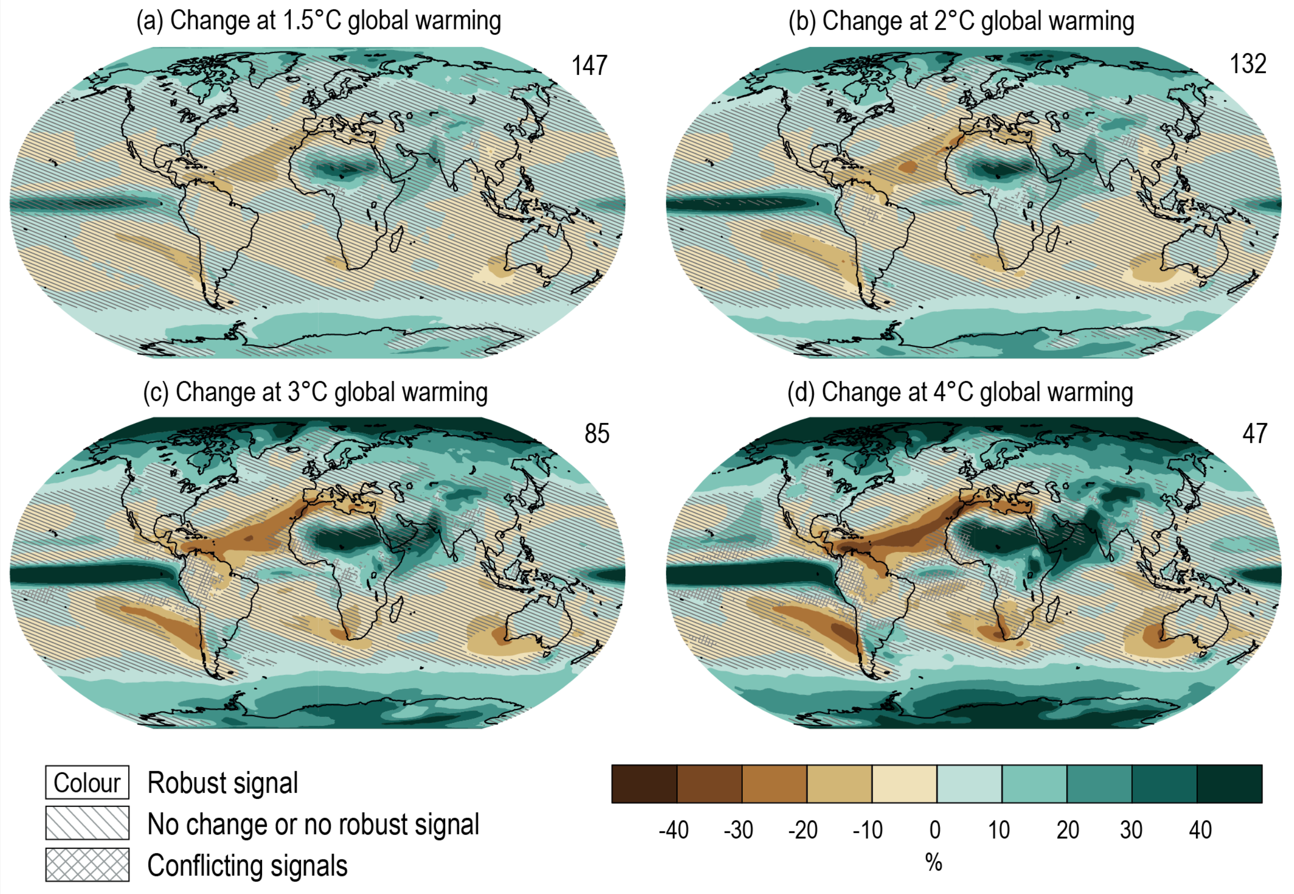
IPCC AR6 WGI Figure1.21 | Illustration of common types of model ensemble, simulating the time evolution of a quantity Q (such as global mean surface temperature)

Internal Variability
Scenario uncertainty
Model uncertainty



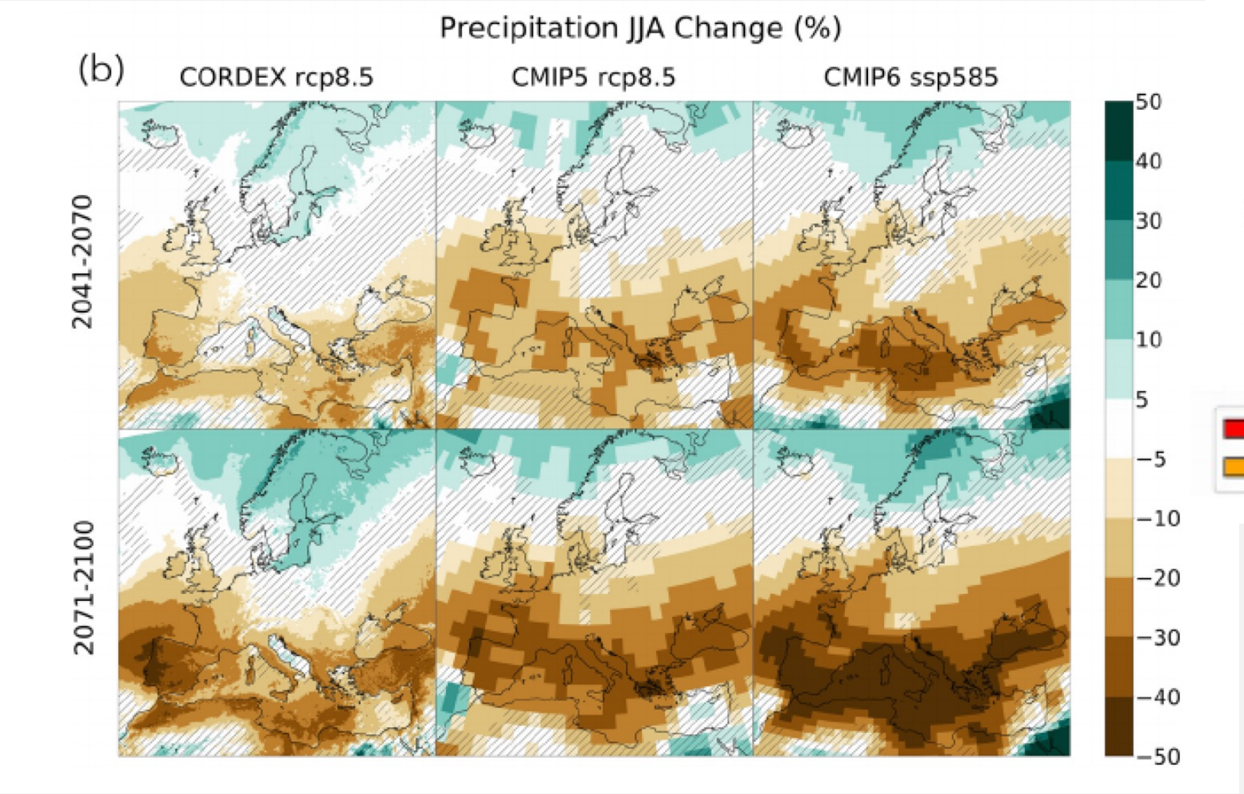
Hawkins and Sutton 2009

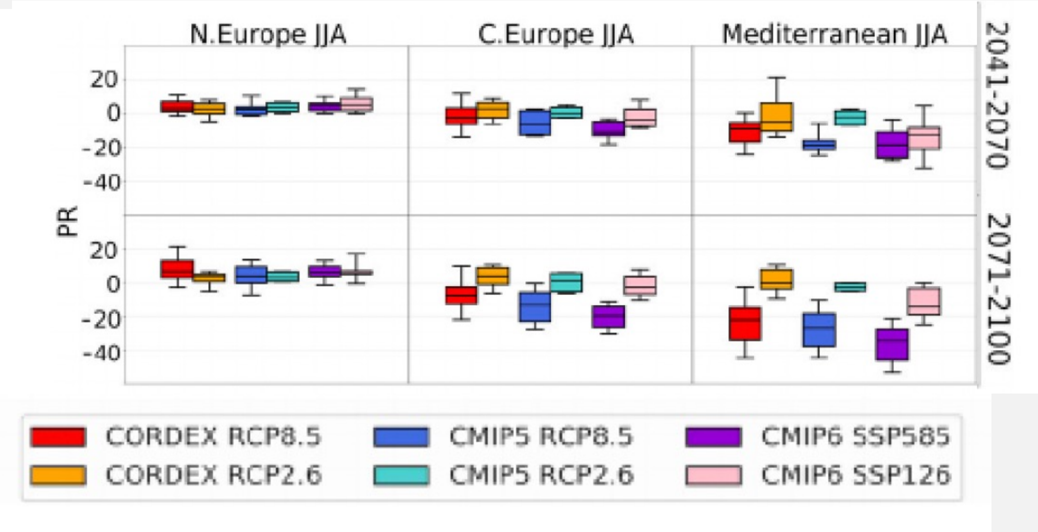
Anthropogenic Climate Change:GCM models



IPCC AR6 WGI Figure 4.32 | Projected spatial patterns of change in annual average precipitation (expressed as a percentage change) at different levels of global warming

Anthropogenic Climate Change: GCM&RCM

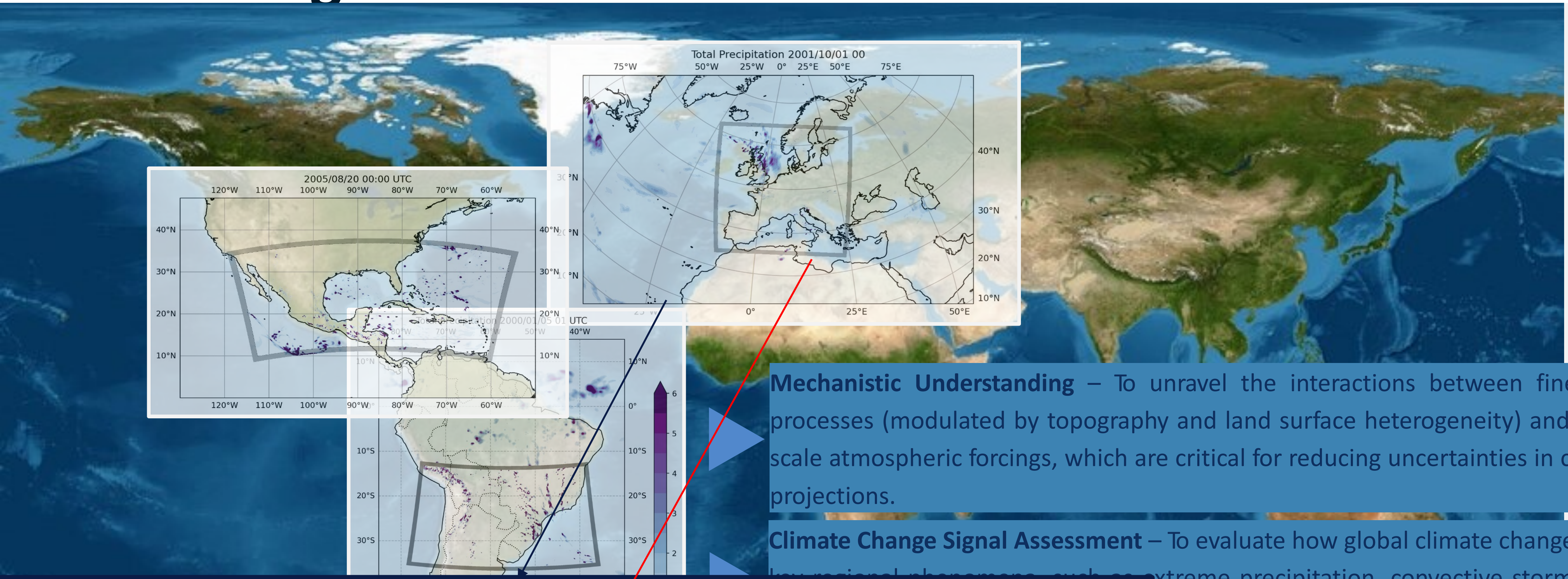




Coppola, E., Nogherotto, R., Ciarlo', J. M., Giorgi, F., van Meijgaard, E.,Kadygrov, N., et al. (2021).Assessment of the European Climate Projections as Simulated by the Large EURO□ CORDEX Regional and Global Climate Model Ensemble. Journal of Geophysical Research: Atmospheres, 126, e2019JD032356. https://doi.org/ 10.1029/2019JD032356

A New Scientific Frontier in Climate Science

High-Resolution Kilometer-Scale Regional Climate Modeling



Mechanistic Understanding – To unravel the interactions between fine-scale processes (modulated by topography and land surface heterogeneity) and large-scale atmospheric forcings, which are critical for reducing uncertainties in climate projections.

Climate Change Signal Assessment – To evaluate how global climate change alters ... xtreme precipitation, convective storms, and ... n are poorly resolved in coarser models.

... o generate decision-relevant data for impact, ... essments, supporting policymakers, urban ... e resilience planning.

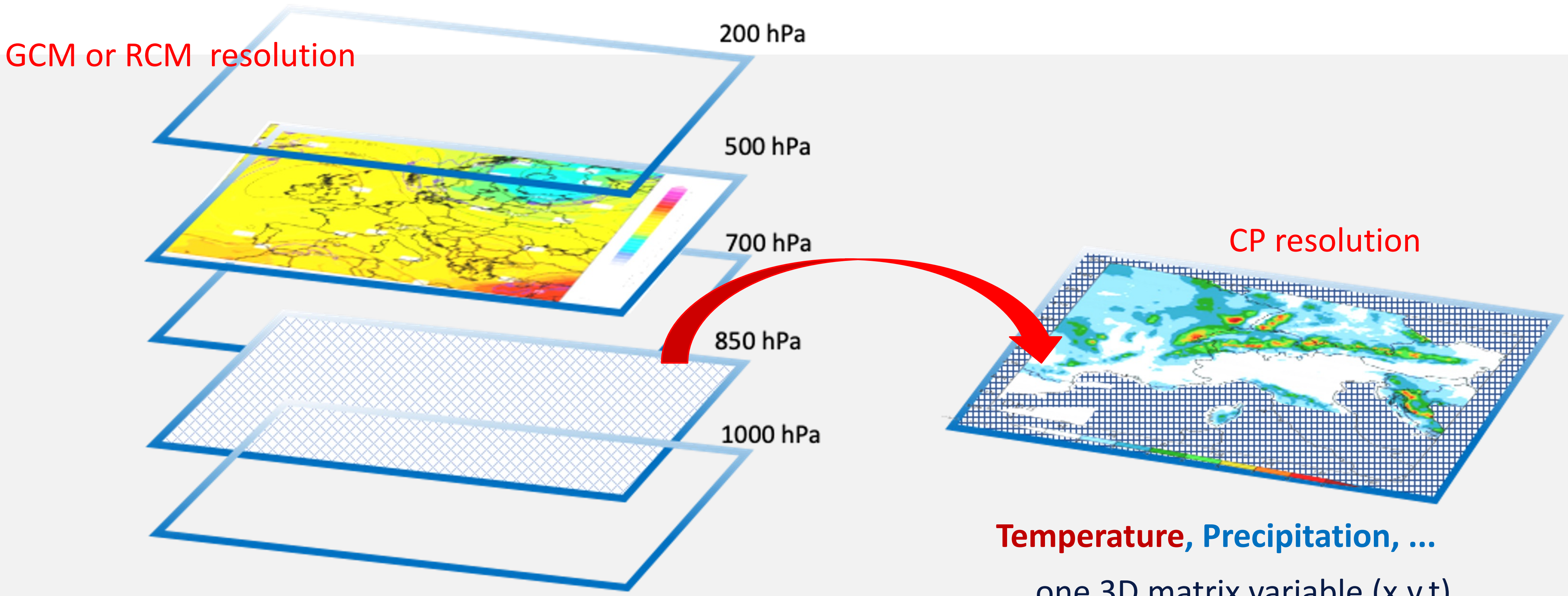
Domain	CPU h per year	Raw output per year (Tb)
EUR 12 km	7500 h	1 T

CP domain	CPU h per year	Raw output per year (Tb)
EUR - 3km	207000 h	8.8

How

Machine Learning Emulator

The scetch



Temperature, Precipitation, ...

n 4D matrix variable (x,y,z,t) corresponding to *n* large scale variables

one 3D matrix variable (x,y,t) corresponding to *one* local scale high resolution variable

How

Machine Learning Emulator
The approaches

- Perfect Prognosis (PP) downscaling approach : high-resolution RCM variables as target and upscaled large-scale variables from the same RCM as predictors
- Imperfect approach or Model Output Statistics (MOS) : high-resolution RCM variables as target and driving GCM large-scale fields as predictors
- Hybrid imperfect approach (HIA): high-resolution observed variable as target and driving reanalysis large-scale fields as predictors

Machine Learning Emulator

The PP approache

The RCM can be seen as a function (F_{RCM}) that creates a high resolution simulation (Y) from a low resolution one (X).

$$Y = F_{RCM}(X)$$

It can be decomposed as a **Large Scale Transformation** and a **Downscaling** functions (Laprise et al, 2008).

$$\Rightarrow \quad F_{RCM} = F_{RCM,T} + F_{RCM,D}$$

courtesy of Antoine Doury

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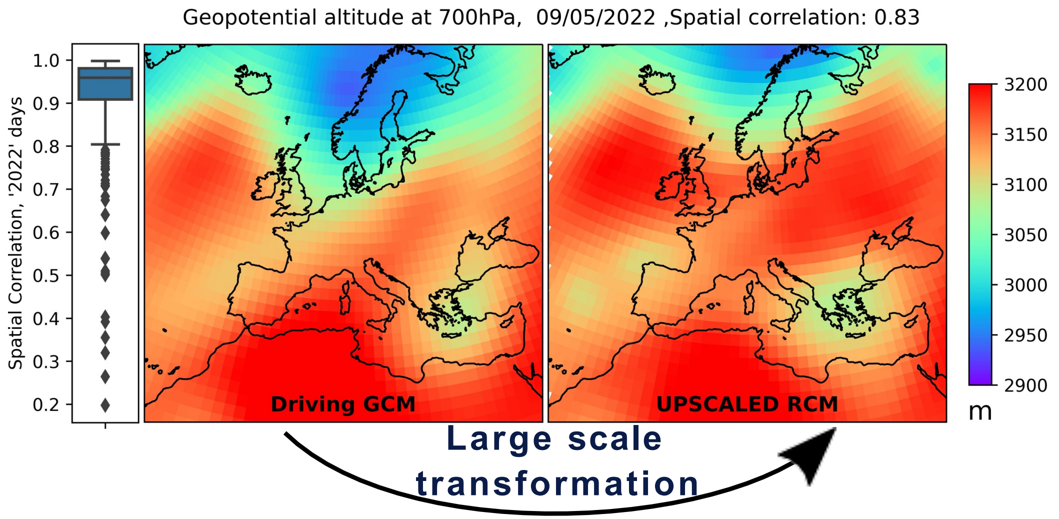

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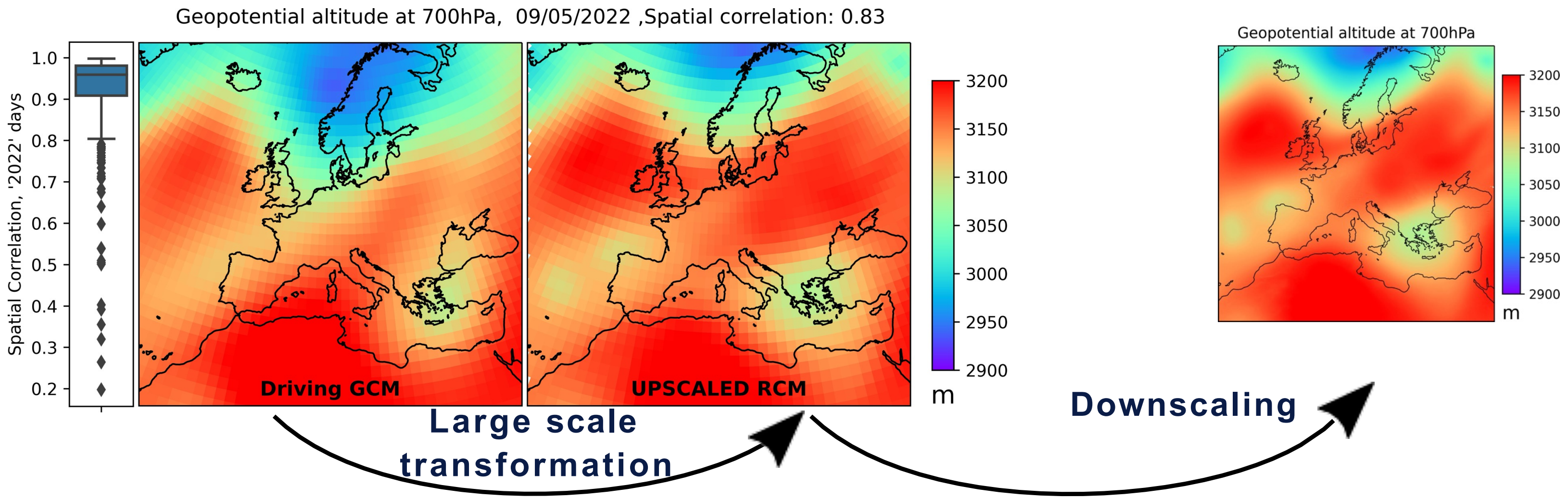

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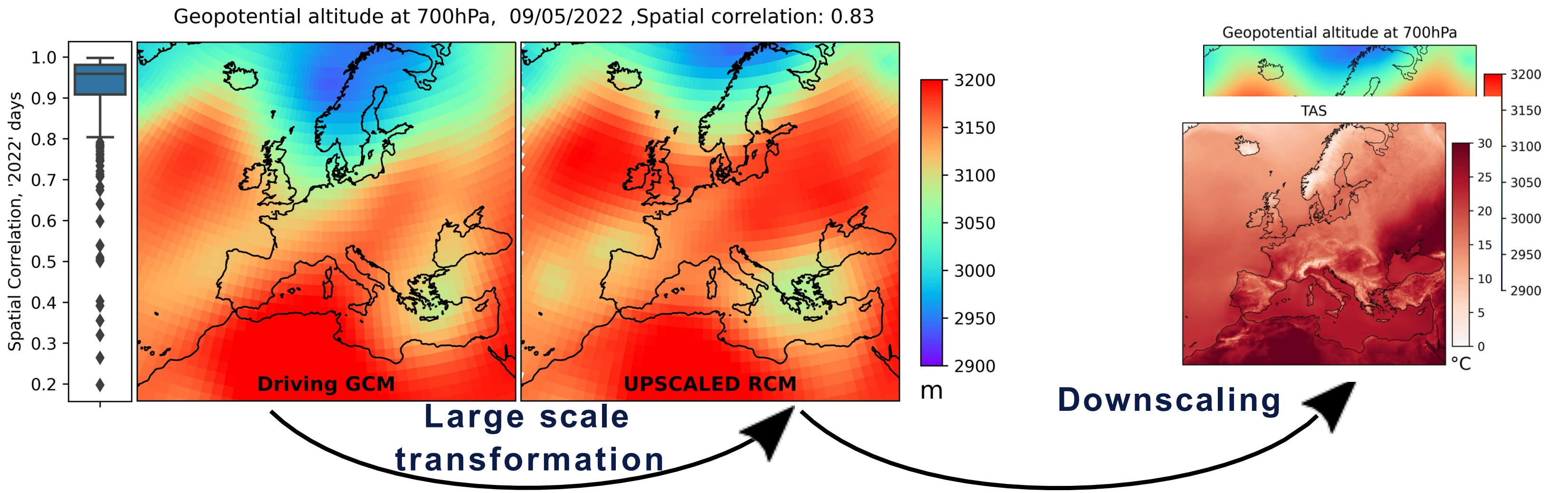

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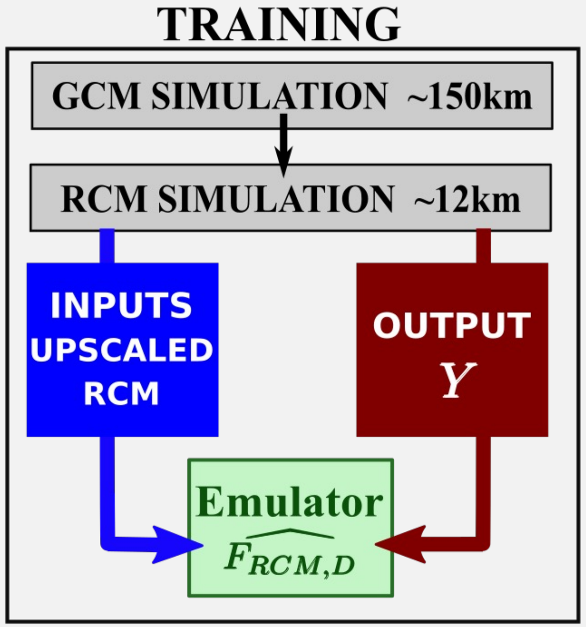
How

Machine Learning Emulator

The PP approache

- $F_{RCM,T}$: chaotic, depends on the driving GCM simulation. (Boé et al, 2020; Taranu et al, 2022)
- RCM-emulator: find the best estimator $F_{RCM,D}$
- Perfect prognosis strategy : link a set of predictors (LR) with the expected target variable (HR).
- Supervised learning approach in a perfect model framework.



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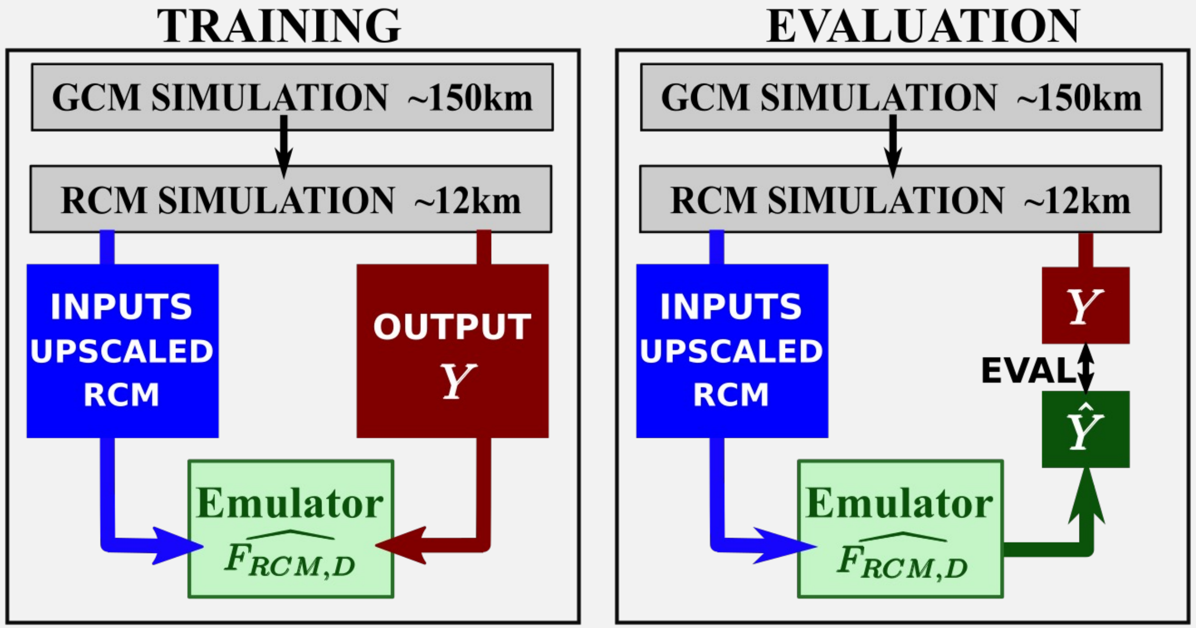

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Machine Learning Emulator
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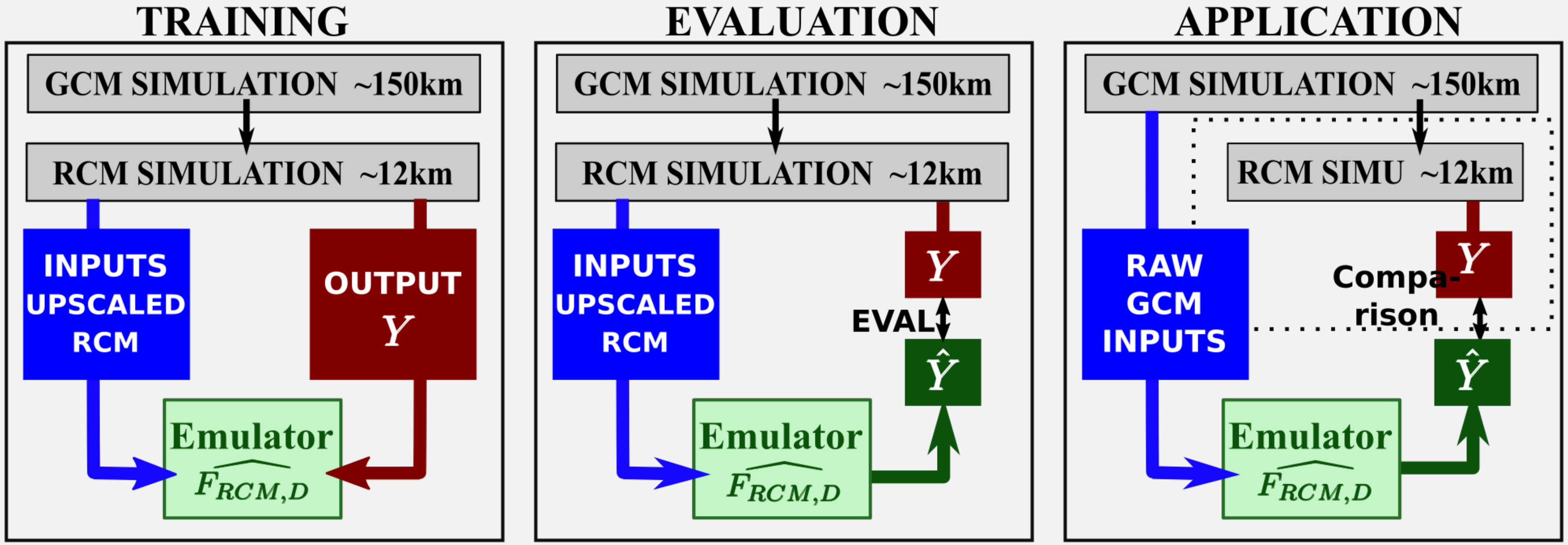
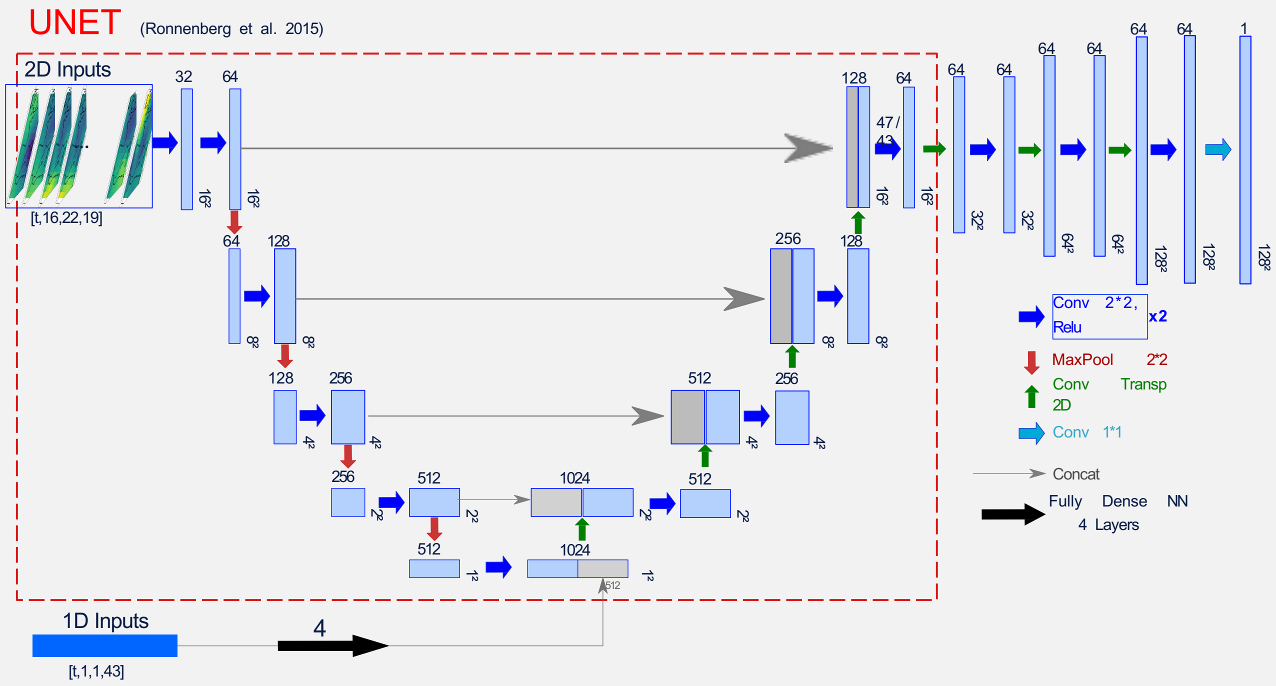


How

Machine Learning Emulator

The PP approache

Adapted from the Unet architecture (Ronneberger et al, 2015).

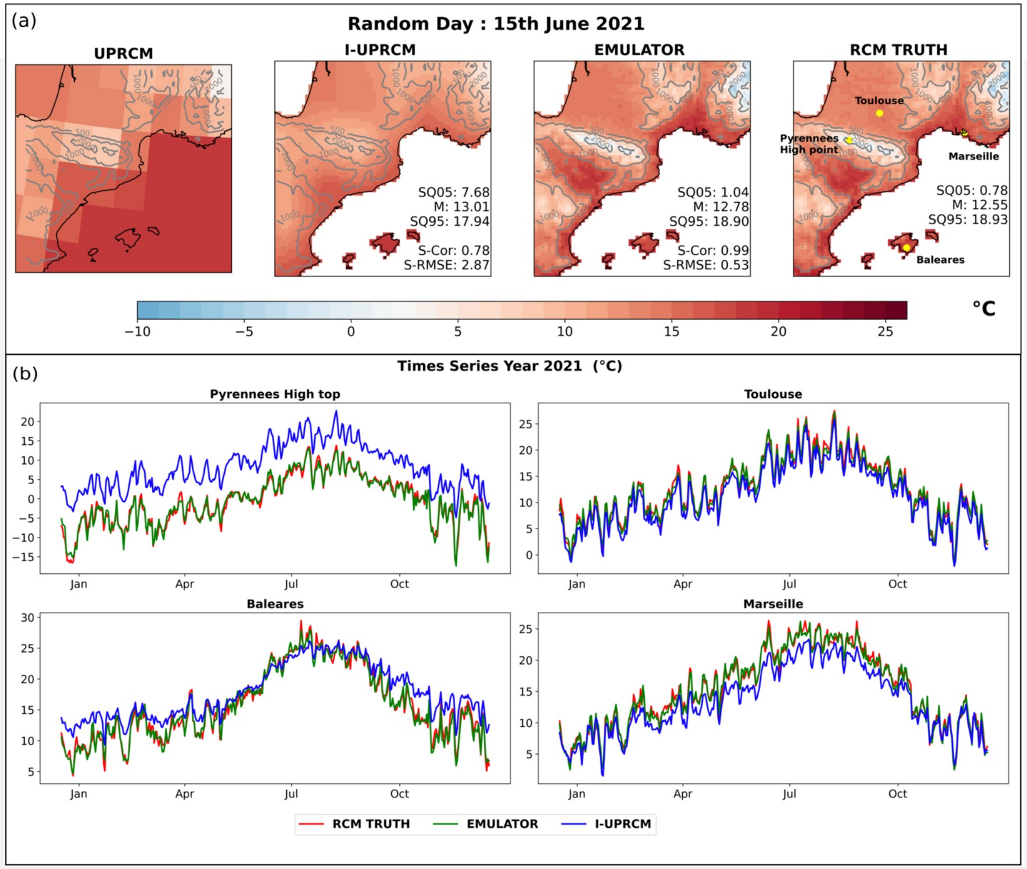


- ~ 25 millions parameters
- ~ 60 epochs for calibration
- ~ 2h for the large domain (1h for the small one)
- ≤ 1min for production

How

Machine Learning Emulator

The PP approache: validation



Doury, A., Somot, S., Gadat, S. et al. Regional climate model emulator based on deep learning: concept and first evaluation of a novel hybrid downscaling approach. Clim Dyn (2022). https://doi.org/10.1007/s00382-022-06343-9

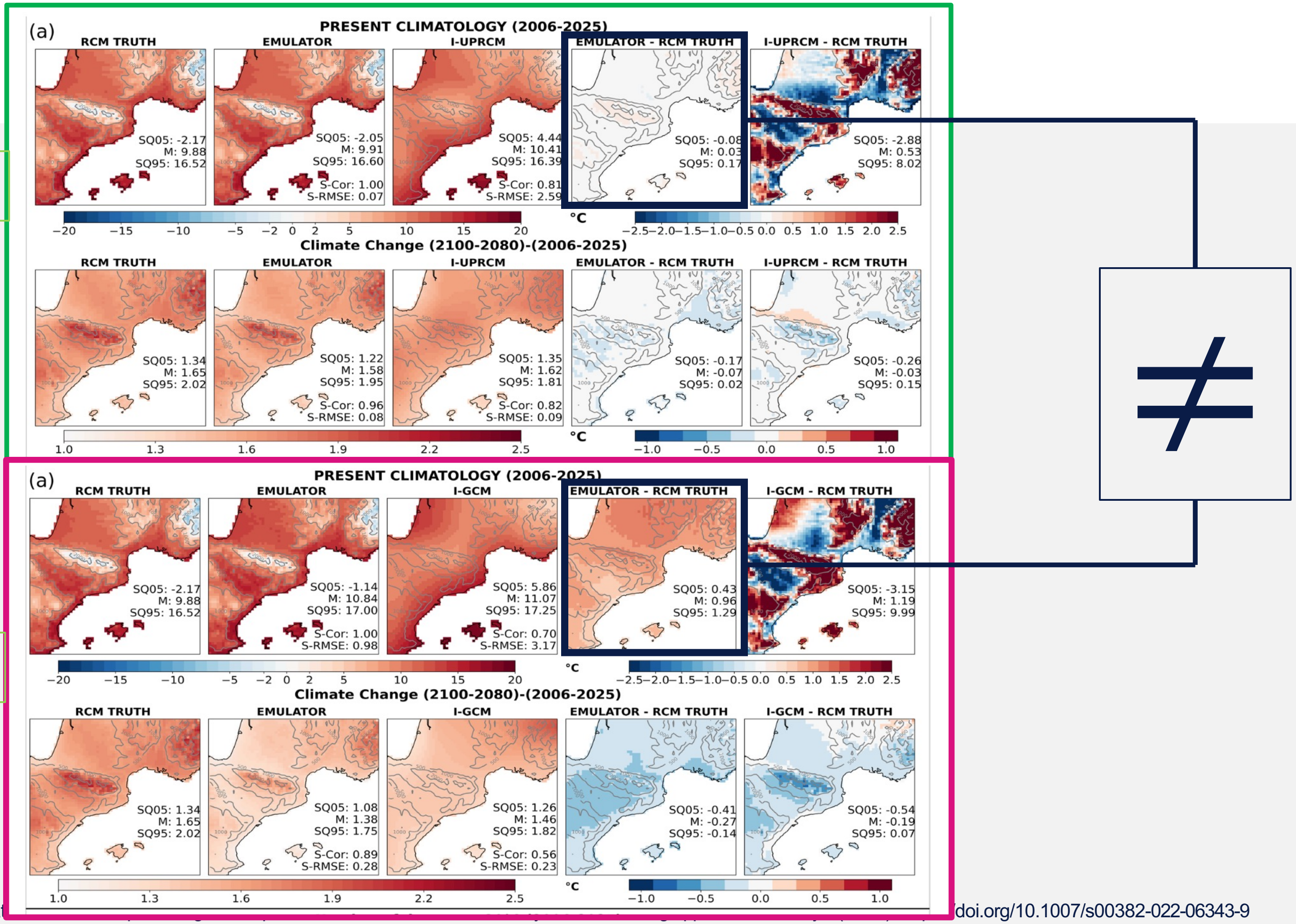
How

Machine Learning Emulator

The PP approache: validation

Perfect model

GCM world



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How

Machine Learning Emulator

The PP approache: validation

Perfect model

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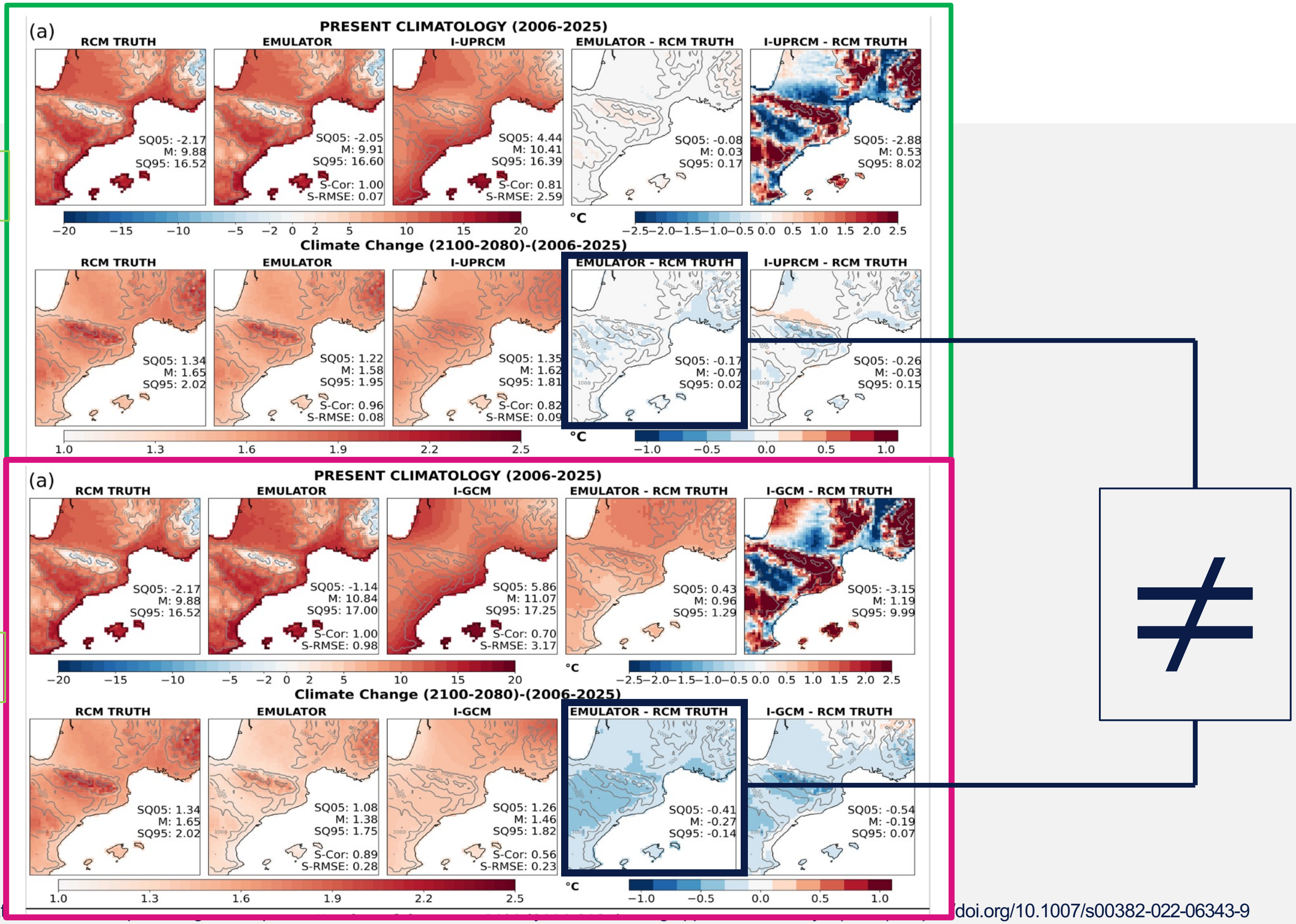

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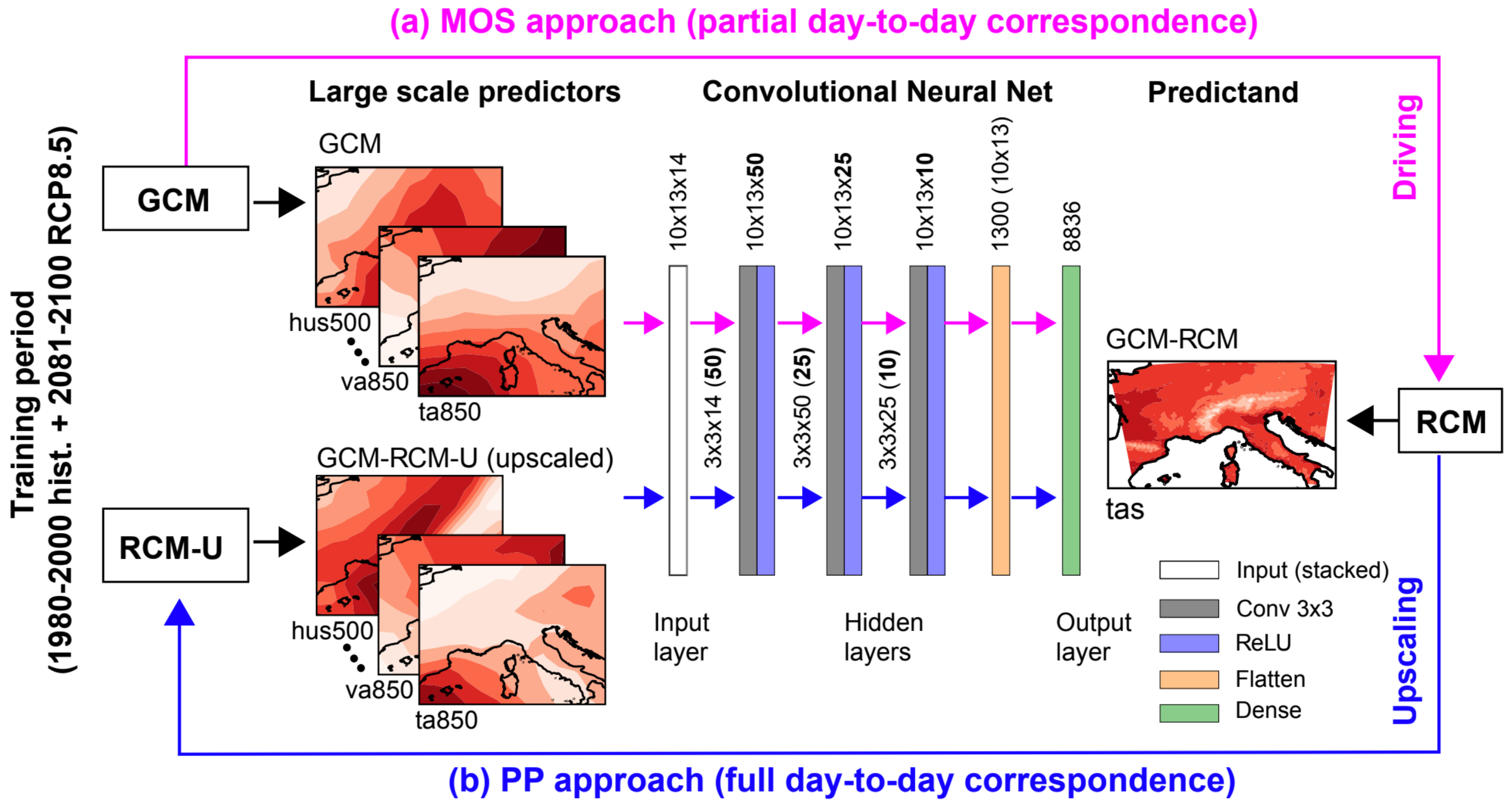
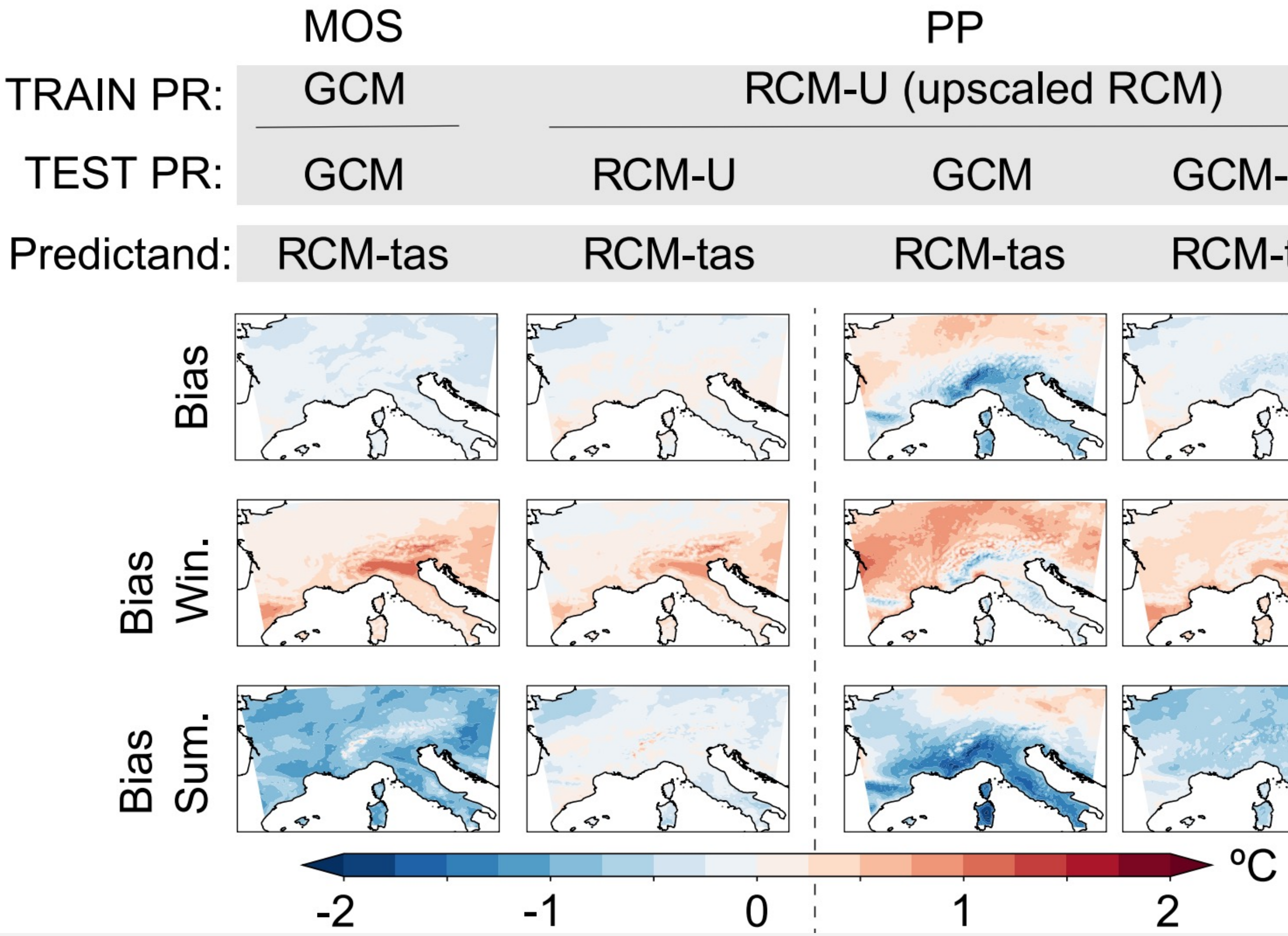
Machine Learning Emulator
The PP vs MOS approache



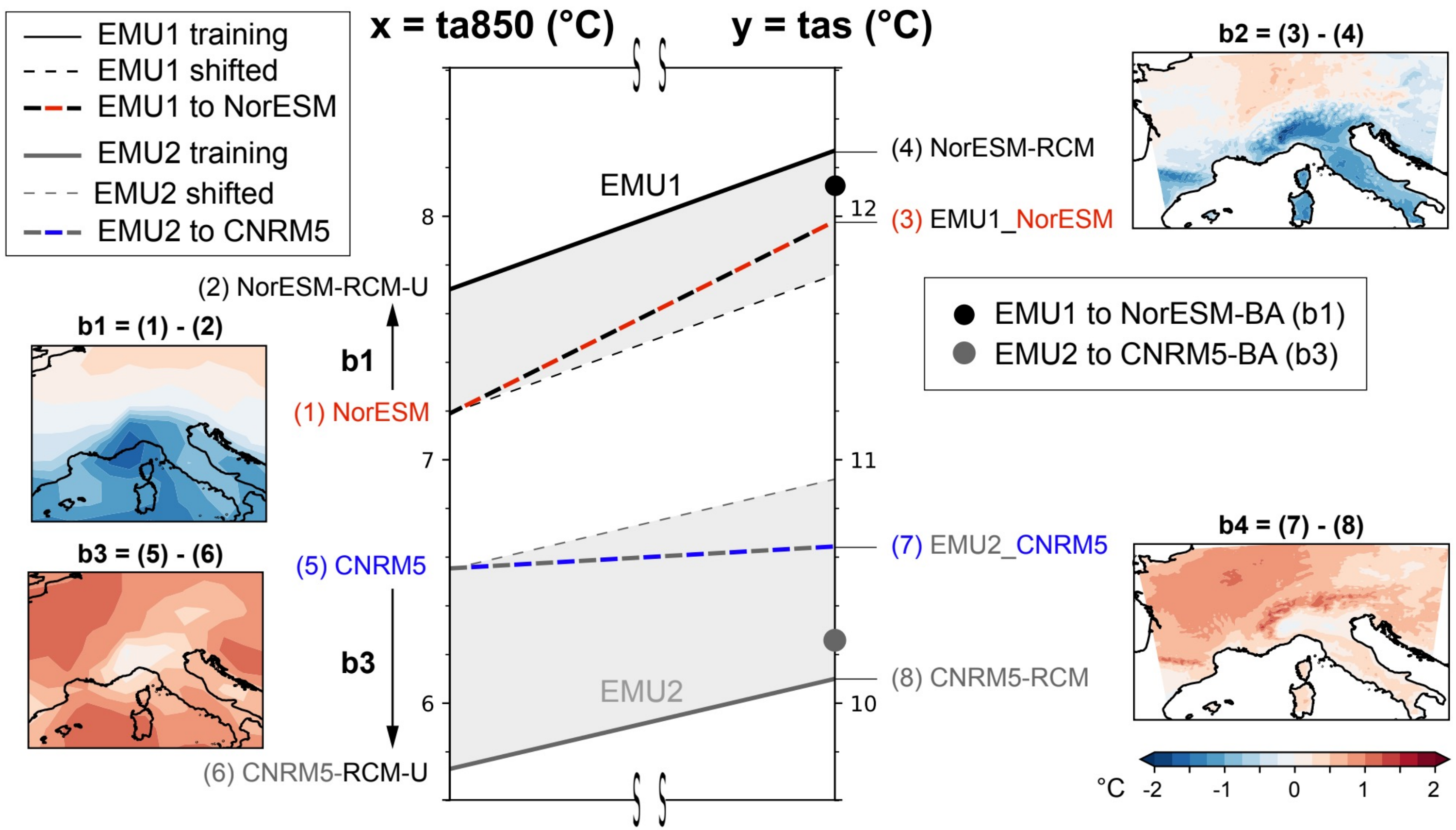
Bano-Medina et al., Transferability and explainability of deep learning emulators for regional climate model projections: Perspectives for future applications (2023). Submitted to Artificial Intelligence for the Earth Systems https://doi.org/10.1007/s00382-022-06343-9

How

Machine Learning Emulator
The PP vs MOS approache



Machine Learning Emulator
The PP vs MOS approache



PP approach is suitable for emulating RCM outputs when using bias-adjusted predictors from the same driving GCM used for learning. But this cannot be done in the Hard transferability framework to emulate a new GCM

Machine Learning Emulator

The PP vs MOS approache

Summary so far

- PP approach learns the same robust predictor patterns for different driving GCMs thus increasing confidence. These predictor patterns are locally connected to the predictand, resembling more closely the functioning of the RCM
- MOS yields model-dependent patterns which, in some cases, are more difficult to interpret and lack from physical consistency.
- both approaches face problems in emulating the results for different driving GCMs, thus limiting their applicability to fill the GCM-RCM combination matrix of regional climate projections.
- way forward could be:
  - ✓ train the emulator under non-biased driving fields, which could be used later also to de-bias newpredictors → **training with reanalysis data**
  - ✓ train the emulator with a wider variety of GCM biases.

Wednesday 14 May: AI And Regional Climate Downscaling, by Blasone Valentina

Erika Coppola • You
Scientific Researcher at The Abdus Salam International Centre f...
4w •

📣 ICTP ESP section is hiring two post-docs to work under the LIQUIDICE project to evaluate the future century-long impacts of climate change on the Greenland ice sheet and climate-sensitive regions in the Alps, Norway, High Mountain Asia (HMA), and Svalbard.

📚 Required qualifications are PhD in Atmospheric Physics and Climate sciences, geophysical science or related disciplines. Specific requirements are expertise in high resolution regional climate modelling, coupled regional earth system modelling for one position and expertise in ML (with a focus on DL) theory and application for climate science for the other.

📅 Application deadline is 31 May 2025

ℹ️ For further information please visit the Abdus Salam International Centre for Theoretical Physics (ICTP) web site at https://lnkd.in/dcUbkbAX

🔗 Application link https://lnkd.in/dFbGSn53

Earth System Physics Postdoctoral Fellowship starting fall 2025
ictp.it

Thank you