



LABORATOIRE DES SCIENCES DU CLIMAT
& DE L'ENVIRONNEMENT



Uncertainties in Climate Modelling

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Inauguration du GIS “Quantification des Incertitudes”
October, 18, 2022

An aerial photograph taken from an airplane window, showing a vast expanse of white, fluffy cumulus clouds against a deep blue sky. Below the clouds, a dark green landscape of fields and possibly small bodies of water is visible.

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Hurricane Luis
NOAA GOES-8
Derived from Vis-Aura
NASA GSFC's Clouds and Atmosphere

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- More generally, **many human activities/interests** (agriculture, energy, water resources, etc.) **are strongly related to weather and climate**
(30% of the world economic activities are affected by meteo conditions, source: IPCC)



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 - ⇒ From ~60's: “*Global Climate Models*” (GCM) to model/understand past/present/future
 - ⇒ From 1988: “*Intergovernmental Panel on Climate Change*” (IPCC, last report in 2021/22)
 - Assess knowledge on CC, its causes, potential impacts and response options



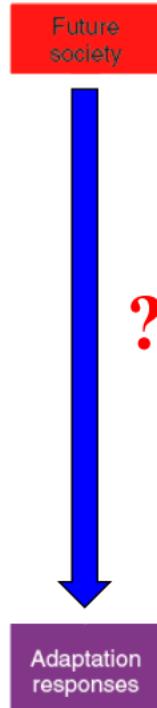
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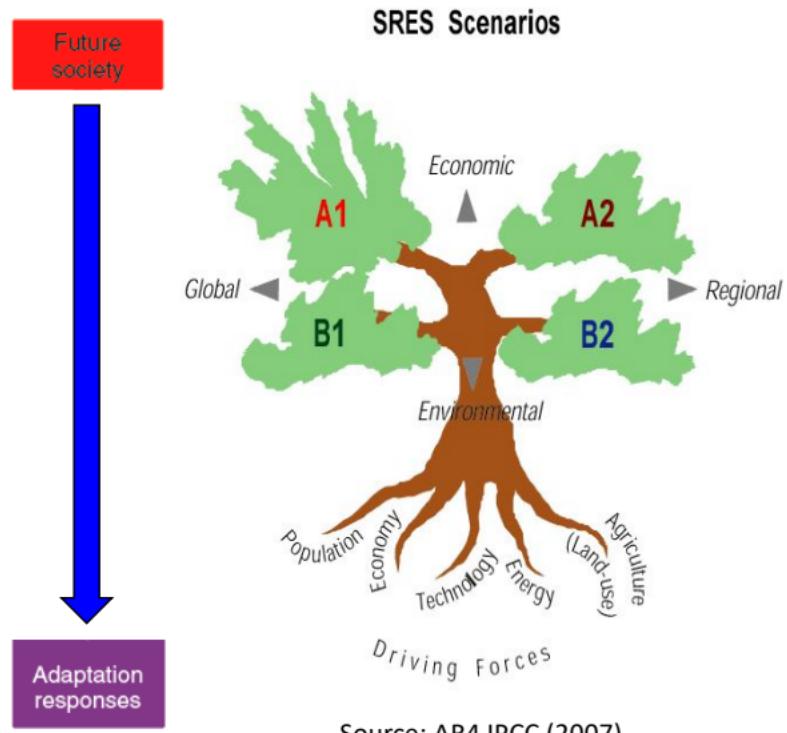
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- As in any (physical and statistical) modelling: **Uncertainties are present**

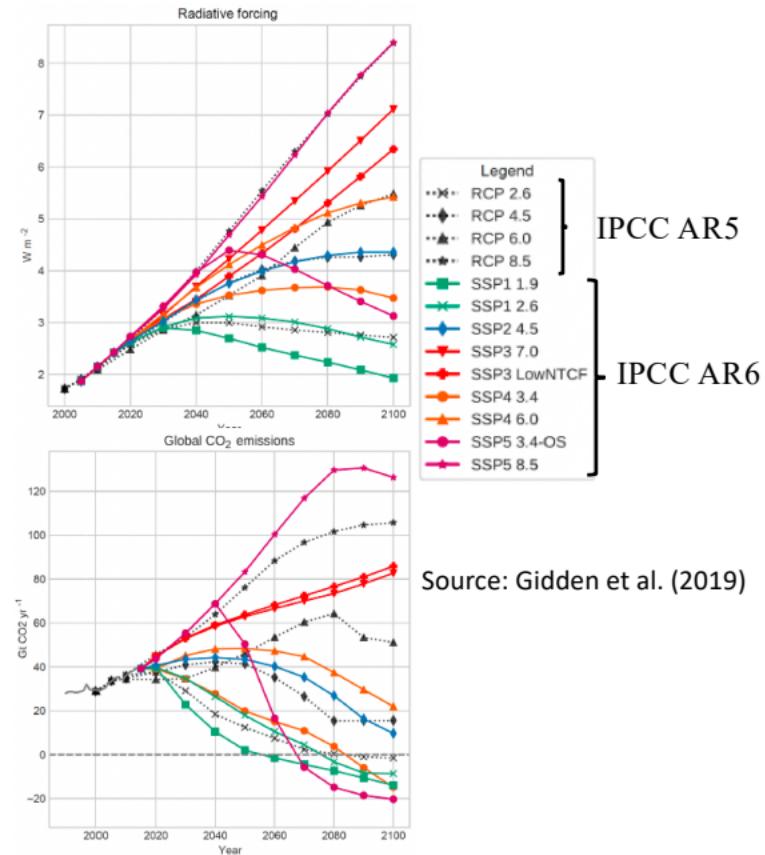
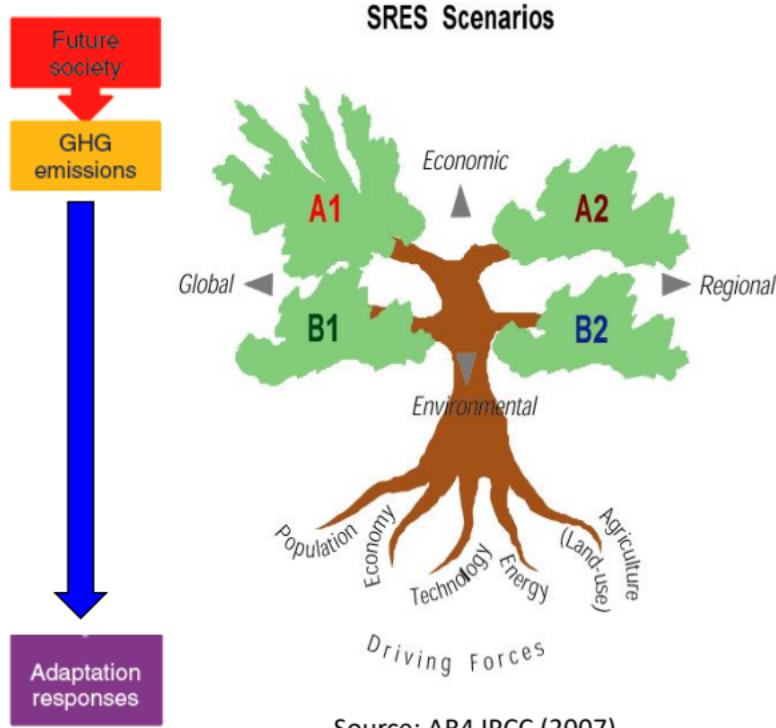
From scenarios to adaptations/mitigations



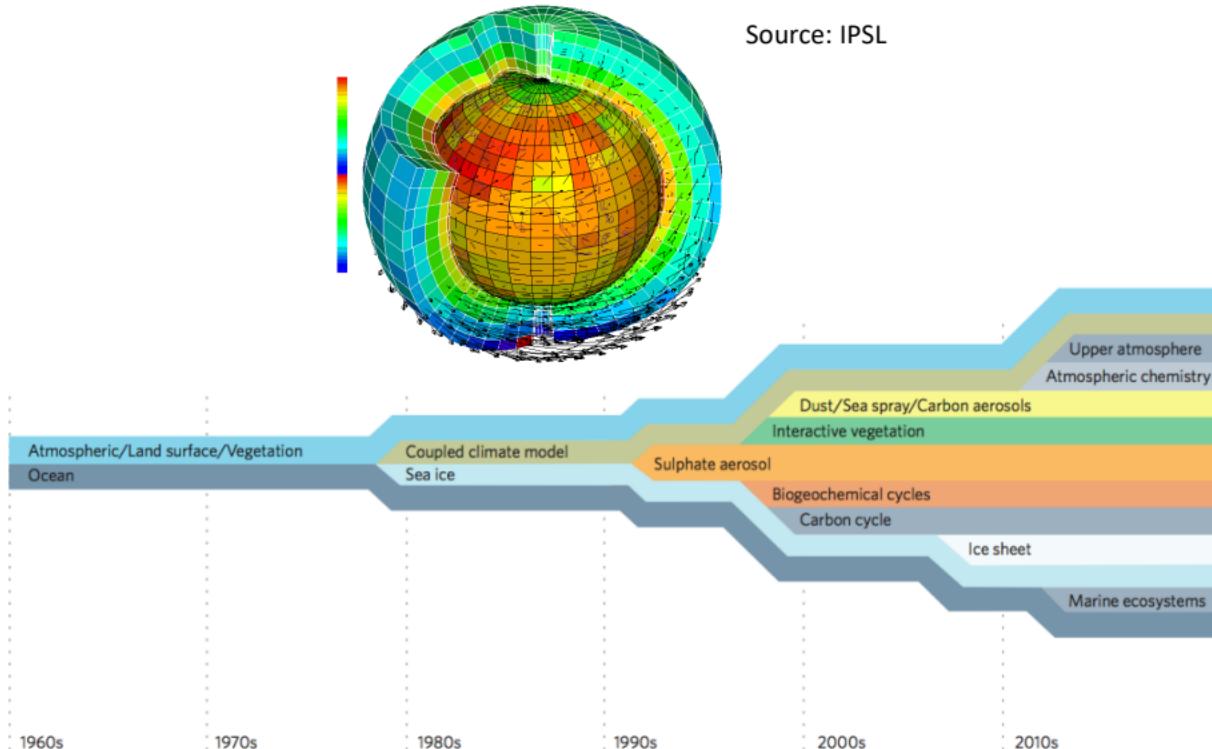
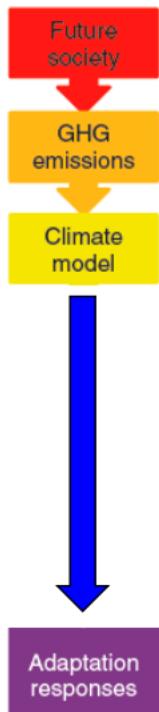
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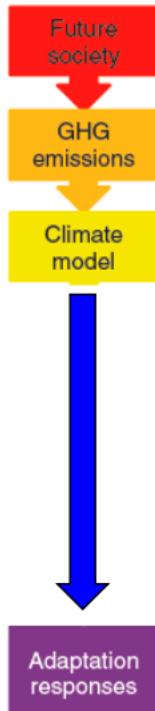
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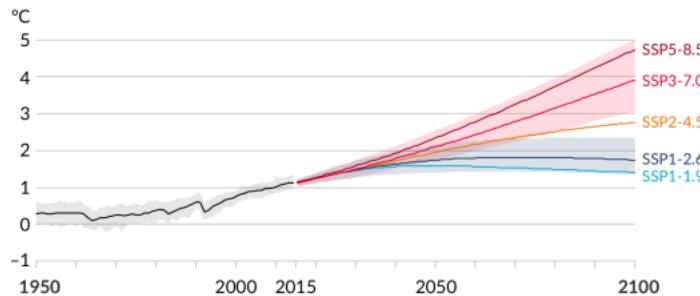
Source: AR4 IPCC (2007)

Source: IPSL

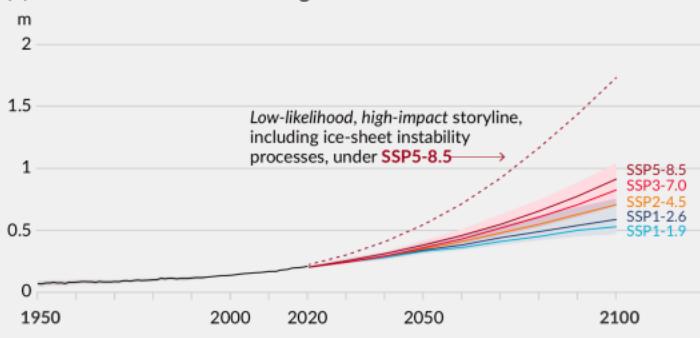
From scenarios to adaptations/mitigations



(a) Global surface temperature change relative to 1850–1900



(d) Global mean sea level change relative to 1900



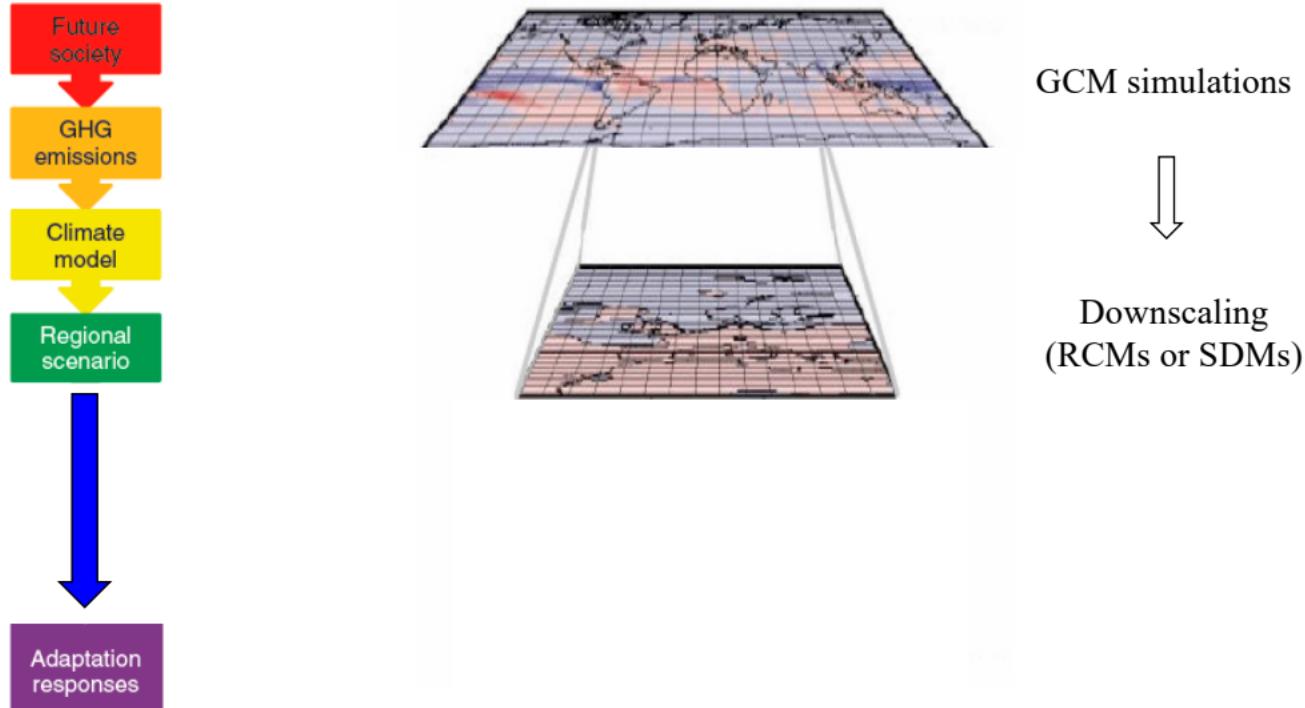
	Obs*	SSP1-2.6**	SSP5-8.5**
ΔT (K)	0.8 ± 0.1	1.0 ± 0.5	3.6 ± 1.2
ΔSL (m)	0.20 ± 0.05	0.47 ± 0.15	0.82 ± 0.19

* Obs = 1995–2014 vs. 1850–1900

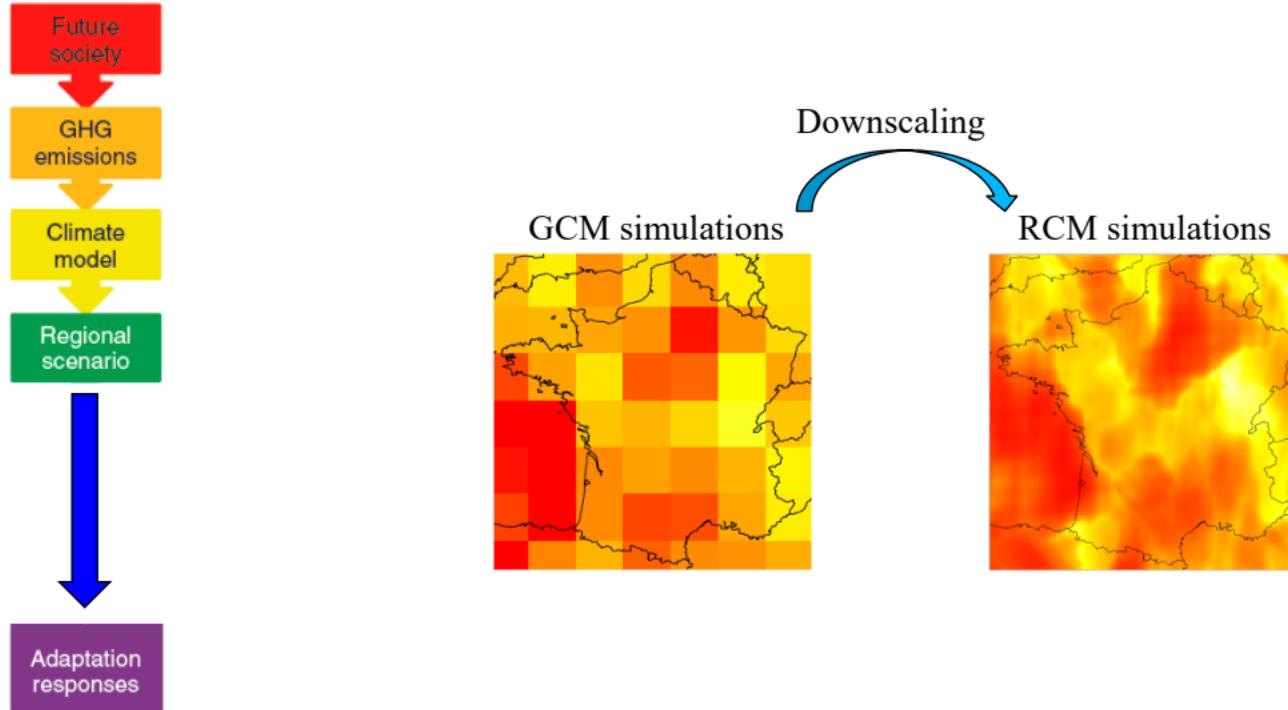
** SSP = 2081–2100 vs. 1995–2014

Source: AR6 IPCC (2021)

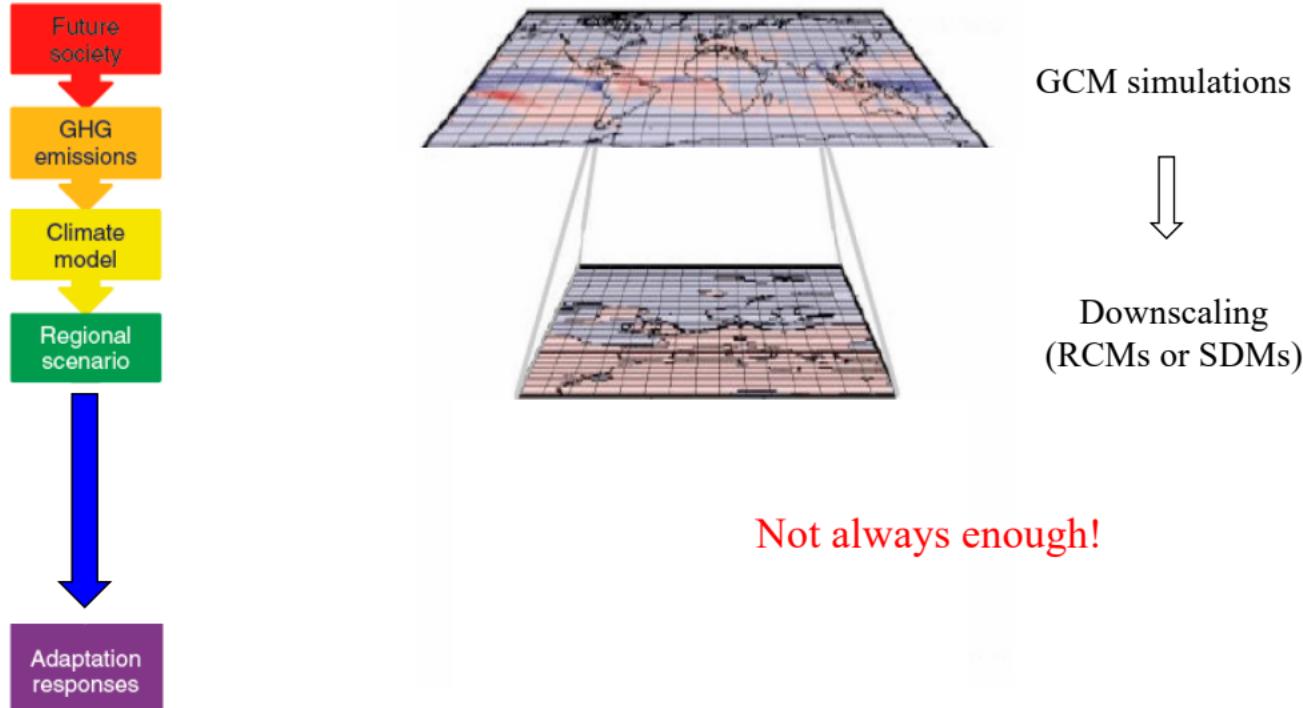
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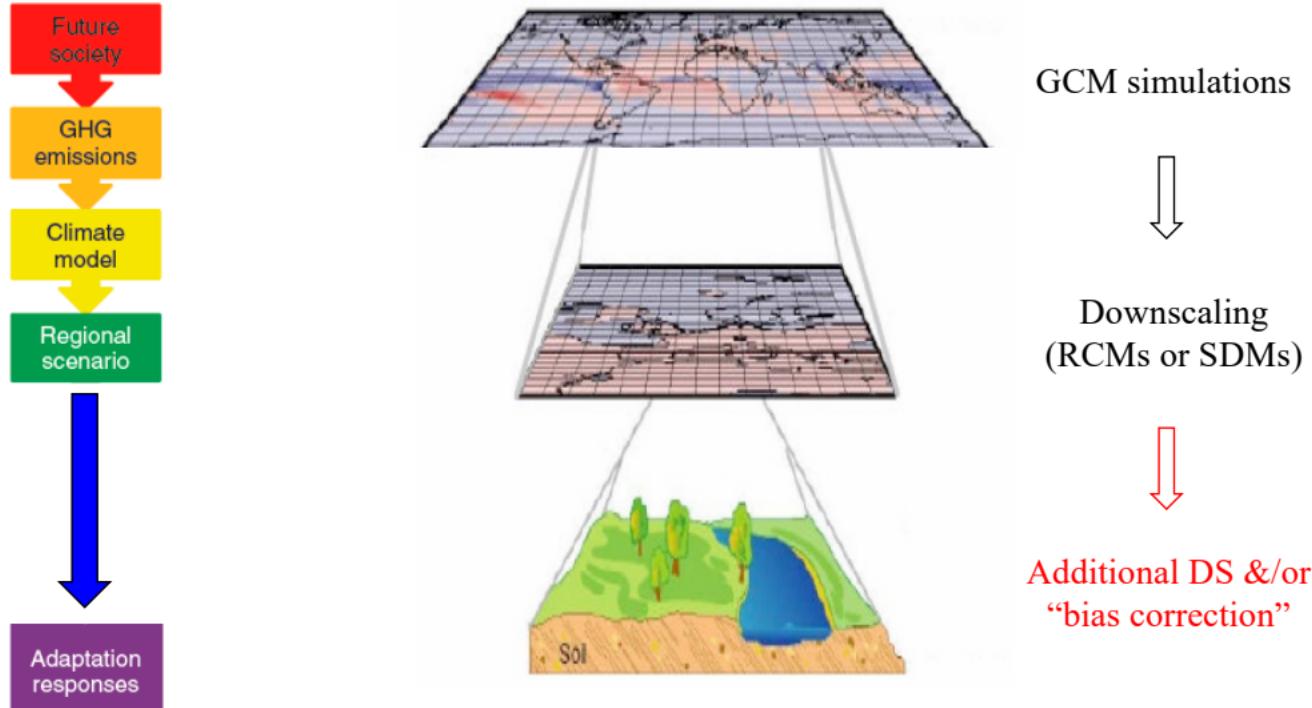
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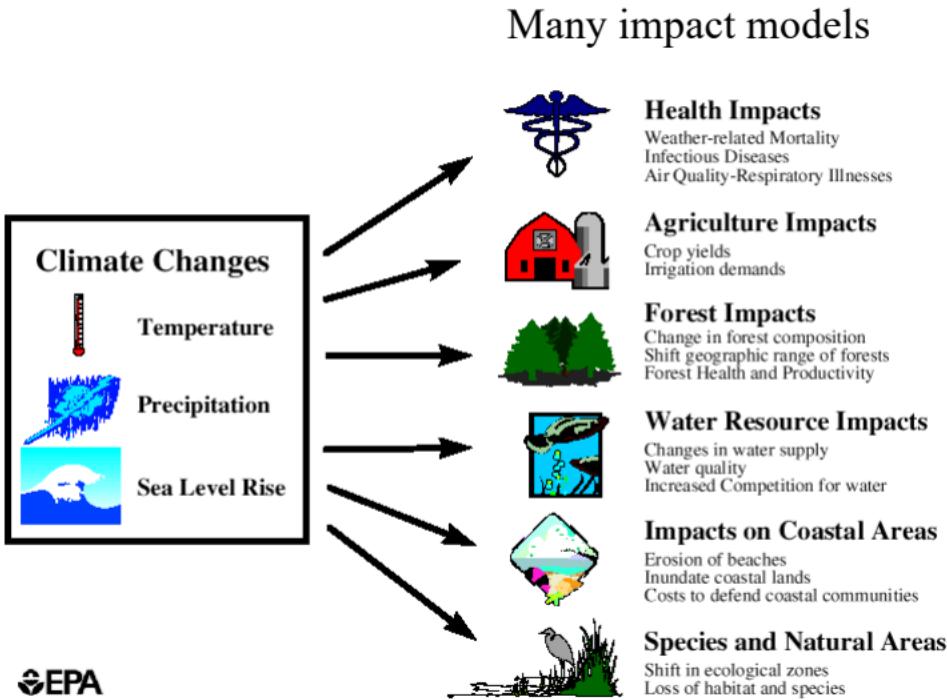
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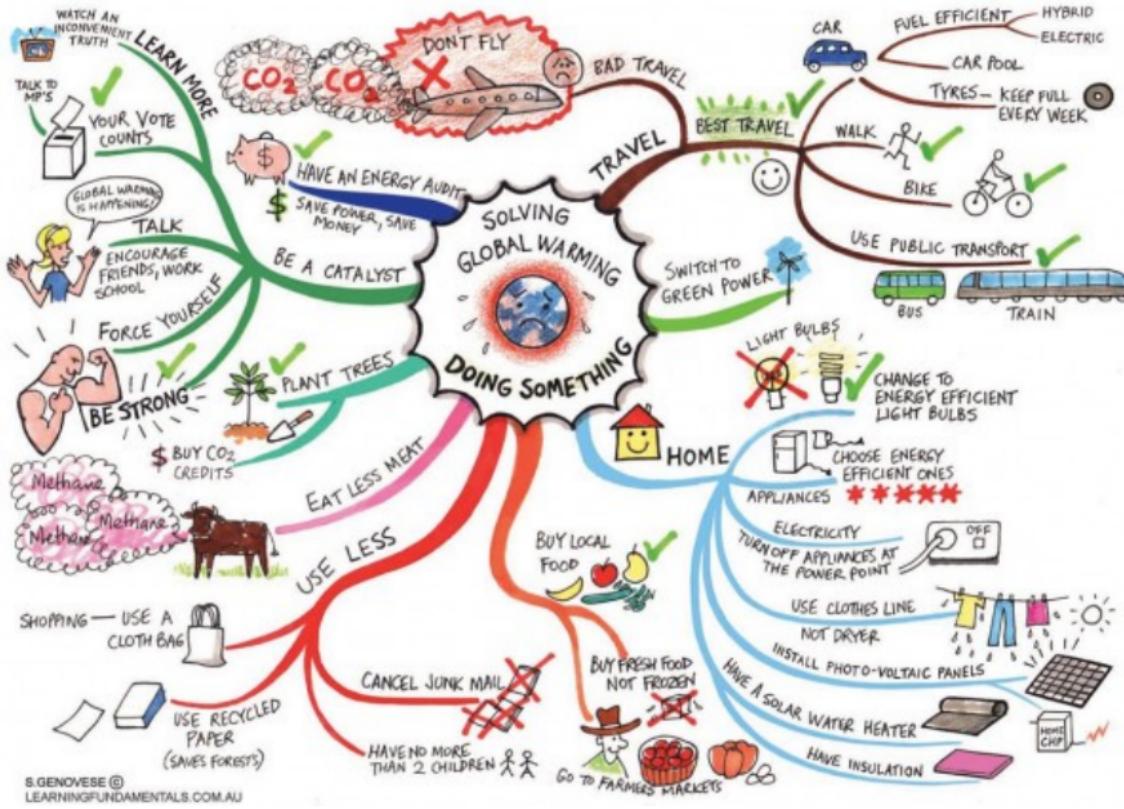


From scenarios to adaptations/mitigations



United States Environmental Protection Agency

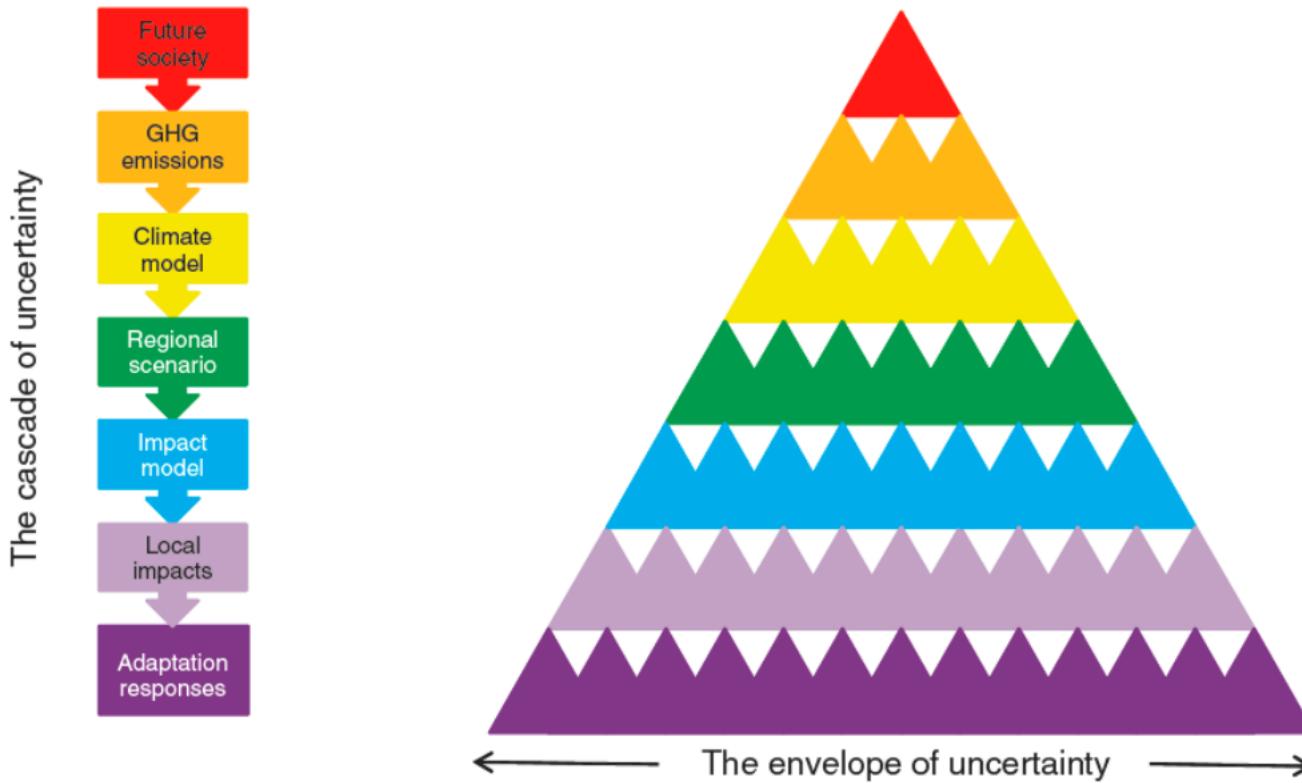
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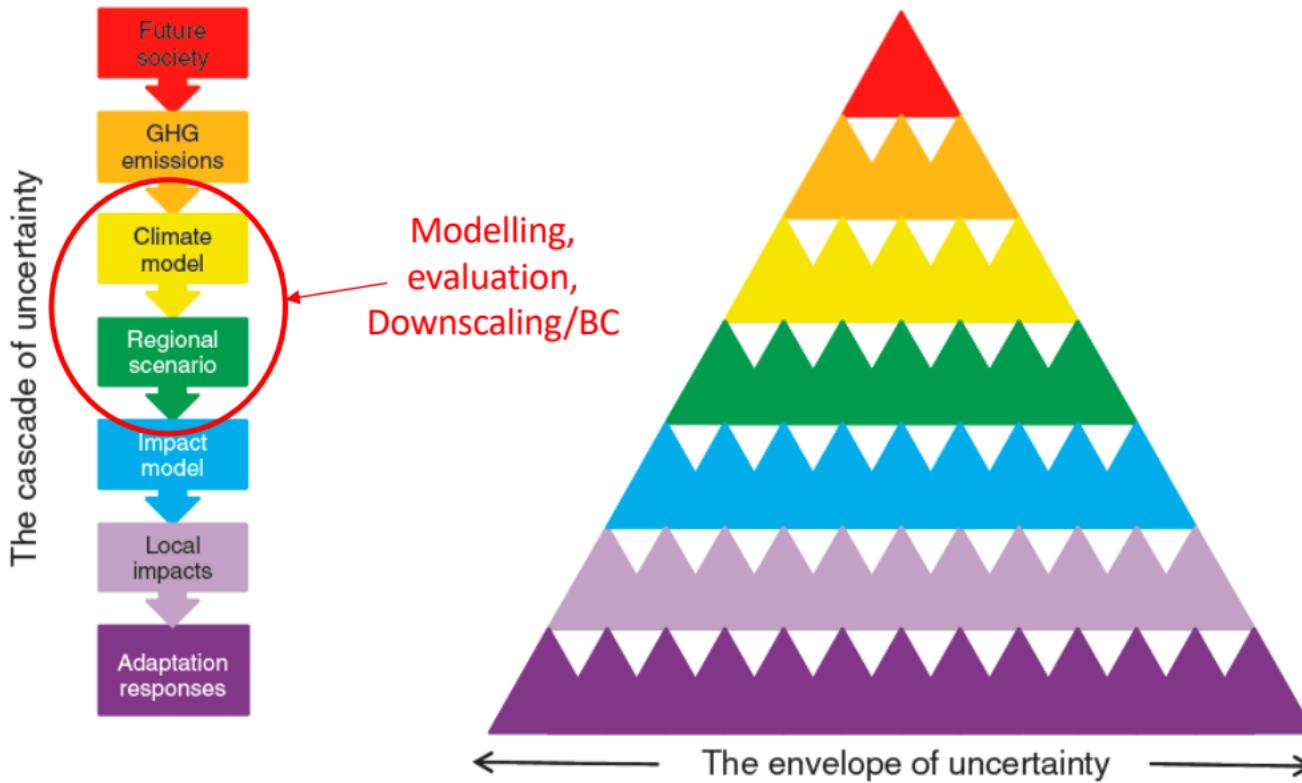
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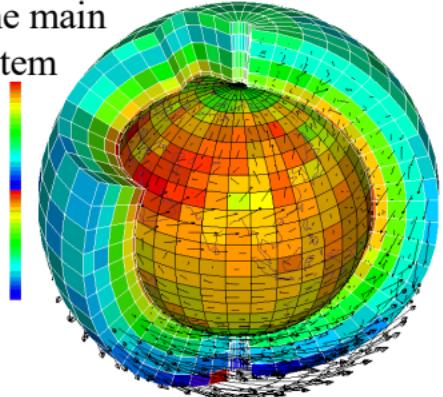


Uncertainties in “simulations” and in “references”

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Physical climate simulations

- Global (GCM) or Regional (RCM) Climate Models
 - Based on physical equations, computer code(s) *simulating* the main characteristics (pressure, temp., prec., etc.) of the Earth system
 - **Structure of the model / parametrizations / scale**



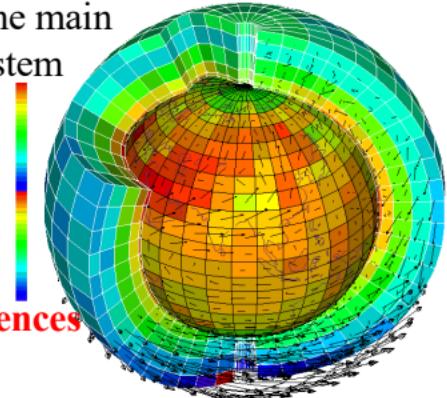
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- Statistical downscaling/Bias correction
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 - Uncert. sources: **Stat./ML approach (linear, non-linear, distribution assumptions), choice of the predictors, references**



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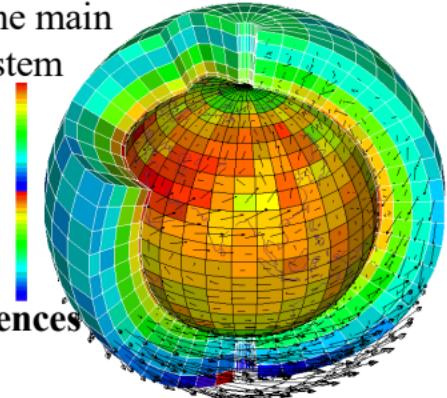
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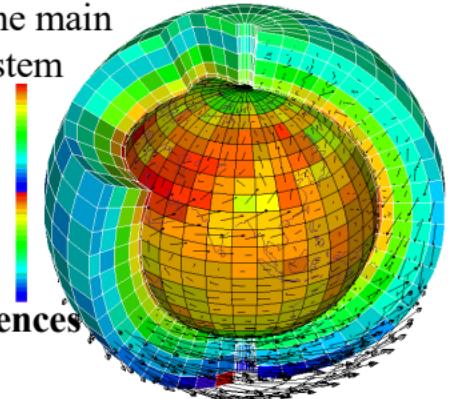
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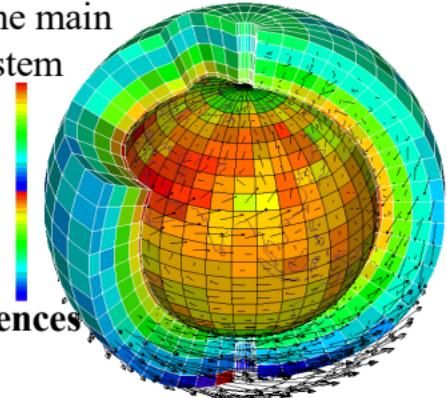
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- Note: Climate ≠ Meteo !! (even though, same variables)



Meteorology ≠ Climate

- Time: ~1 week vs. 100 years



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But...

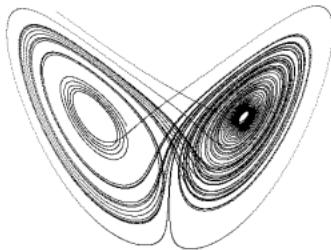


*“Climate is what you expect,
weather is what you get.”*

E. Lorenz
(1917–2008)

Meteorology ≠ Climate

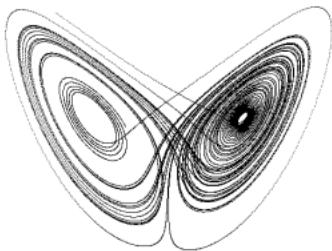
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- Dynamics: 1 trajectory vs. the “attractor”

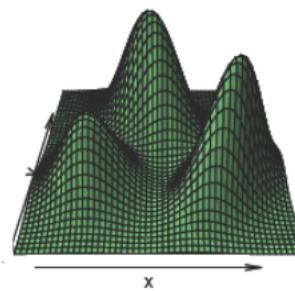
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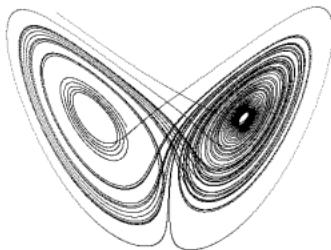
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1 realization vs. its **random variable**



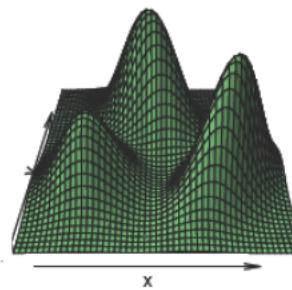
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Main thread of various statistical modellings climate variables & evaluations:

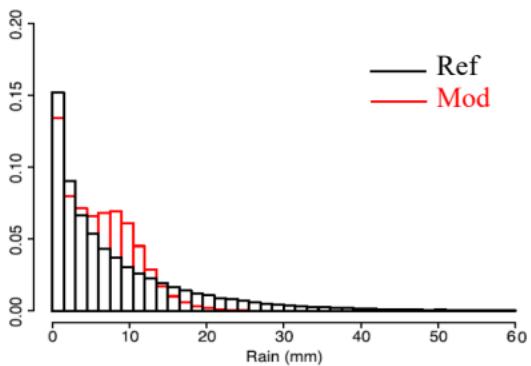
What we need is the correct **pdf or CDF** (or at least properties)

Uncertainty vs. Variability vs. Bias

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Systematic statistical error (e.g.
approximated parametrizations,
spatial scale, etc.)

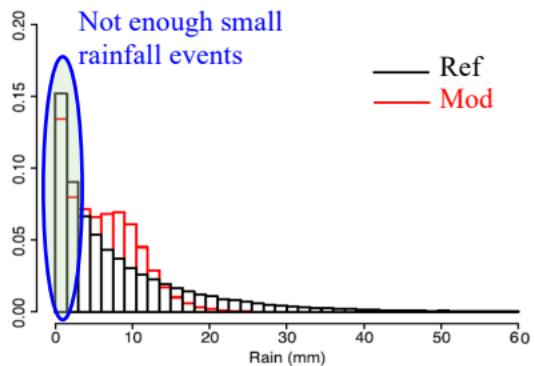
Systematic (distributional) biases
Scale issue (e.g., grid vs. station)



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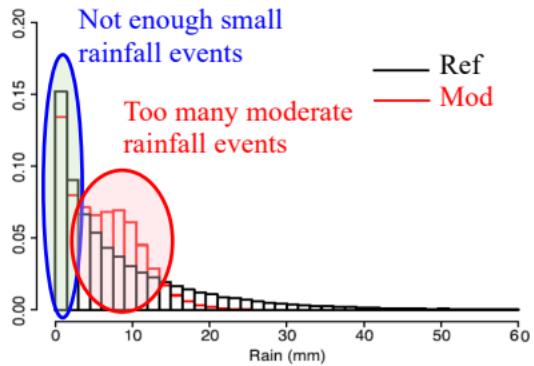
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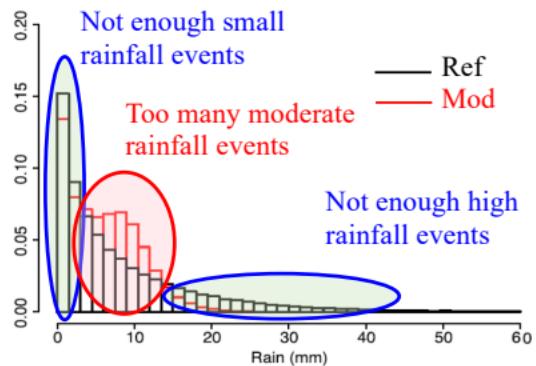
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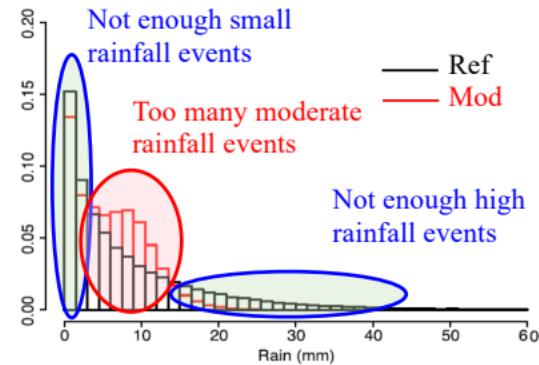
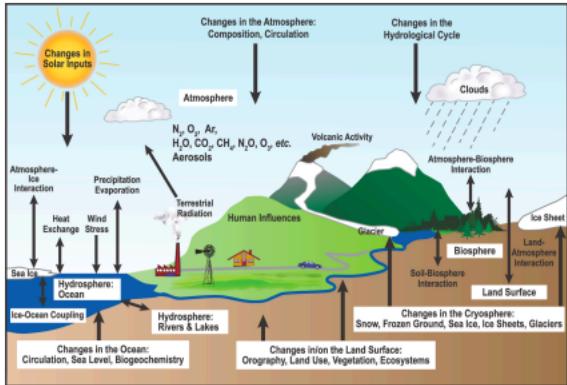


Uncertainty vs. Variability vs. Bias

Hyp.: We don't have all the relevant knowledge (e.g., predictors and/or processes are not necessarily fully fixed or known) → the results are impacted by this lack of knowledge

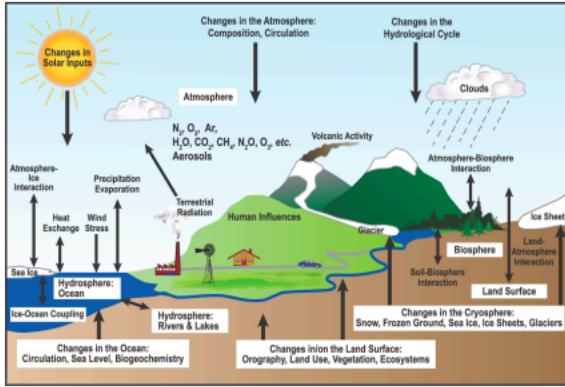
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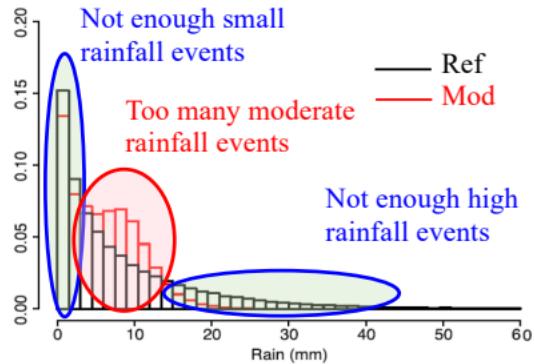
Hyp.: We have all the relevant information (i.e., predictors) but there is a stochasticity inherent to the system



In practice, we have **uncertainties on the variability** (e.g., does the dice have 12 or 6 sides?)

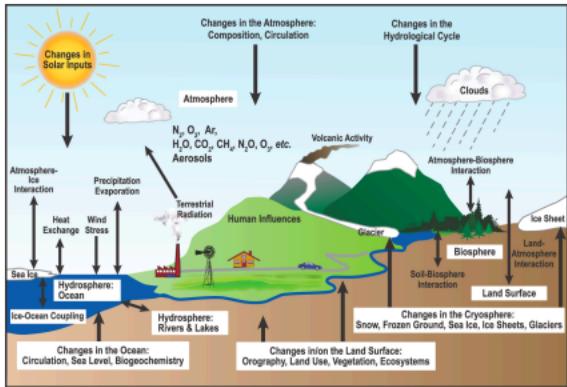
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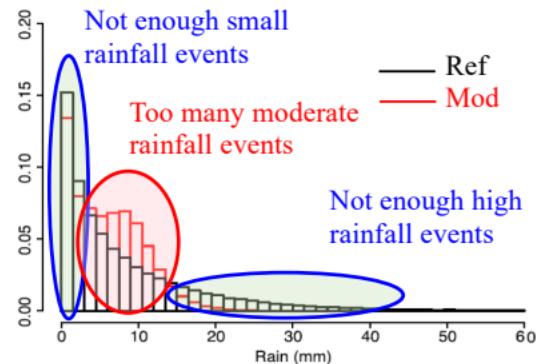


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➤ Not always easy to separate them!

Variabilities, forcings, etc.

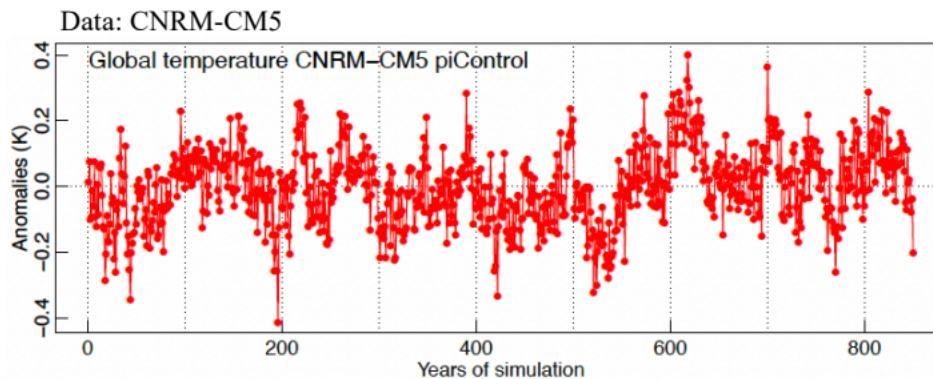
Some “wording”:

- Climate = Mean state + climate variability
- Climate variability = internal variability + external forcings
- External forcings = Natural forcings + anthropogenic forcings
- Natural variability = Internal variability + Natural forcings

Inter-model variability vs. Internal variability

Stationary climate: lots of variations anyway!

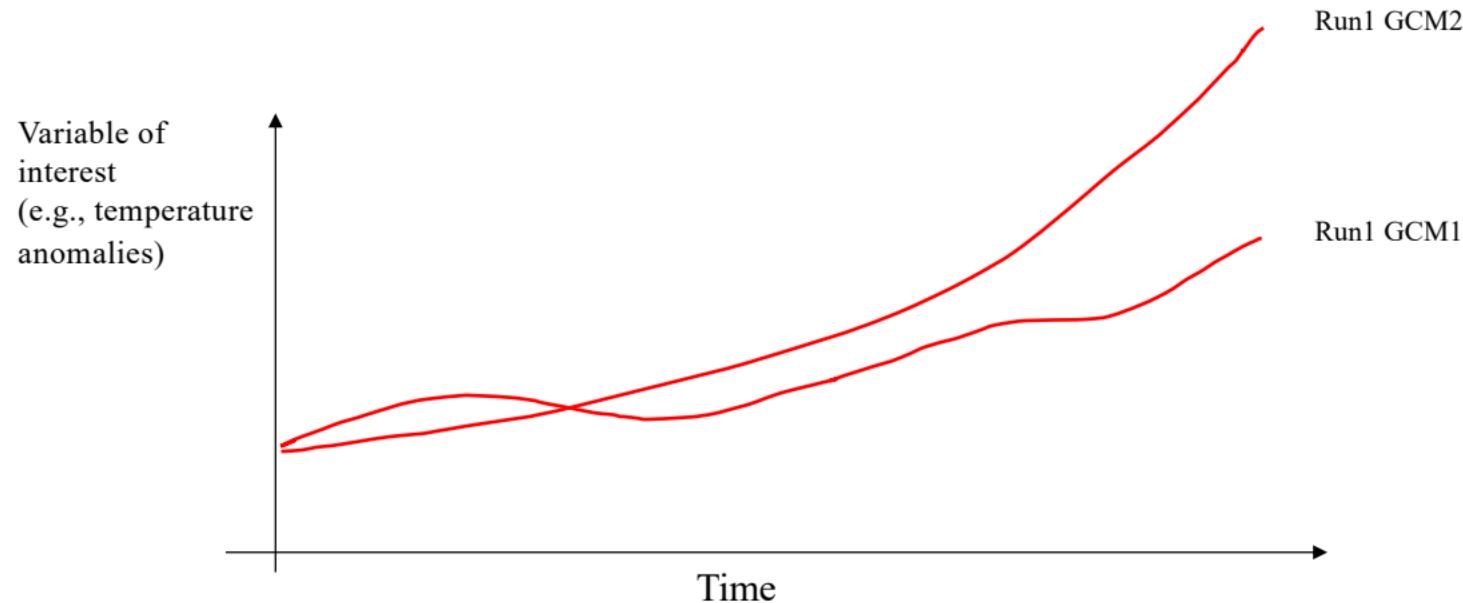
(= mean state + **internal variability**)



Many internal variabilities:

- from global and multi-decadal (mostly from the ocean)
- to regional and inter-annual (mostly from the atmosphere)

Inter-model variability vs. Internal variability

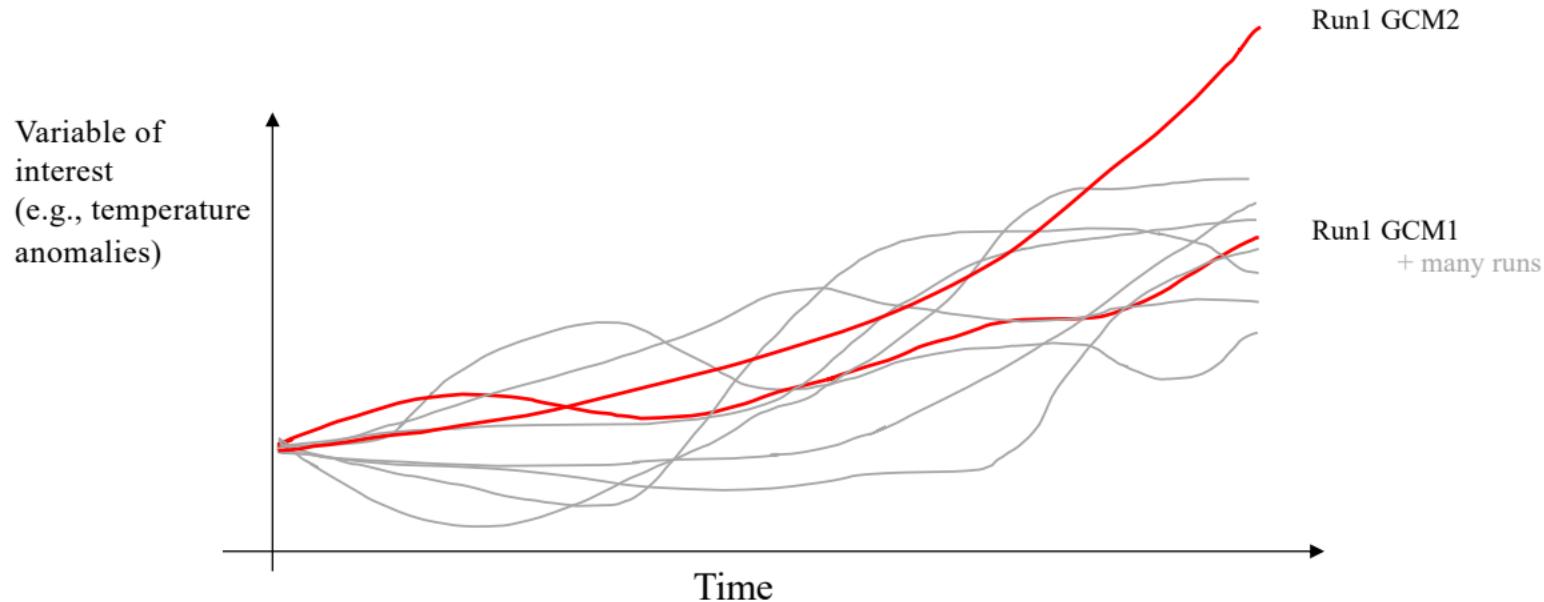


- Single runs of 2 GCMs (one scenario only)



This is a schematic view (i.e., not based on actual simulations)

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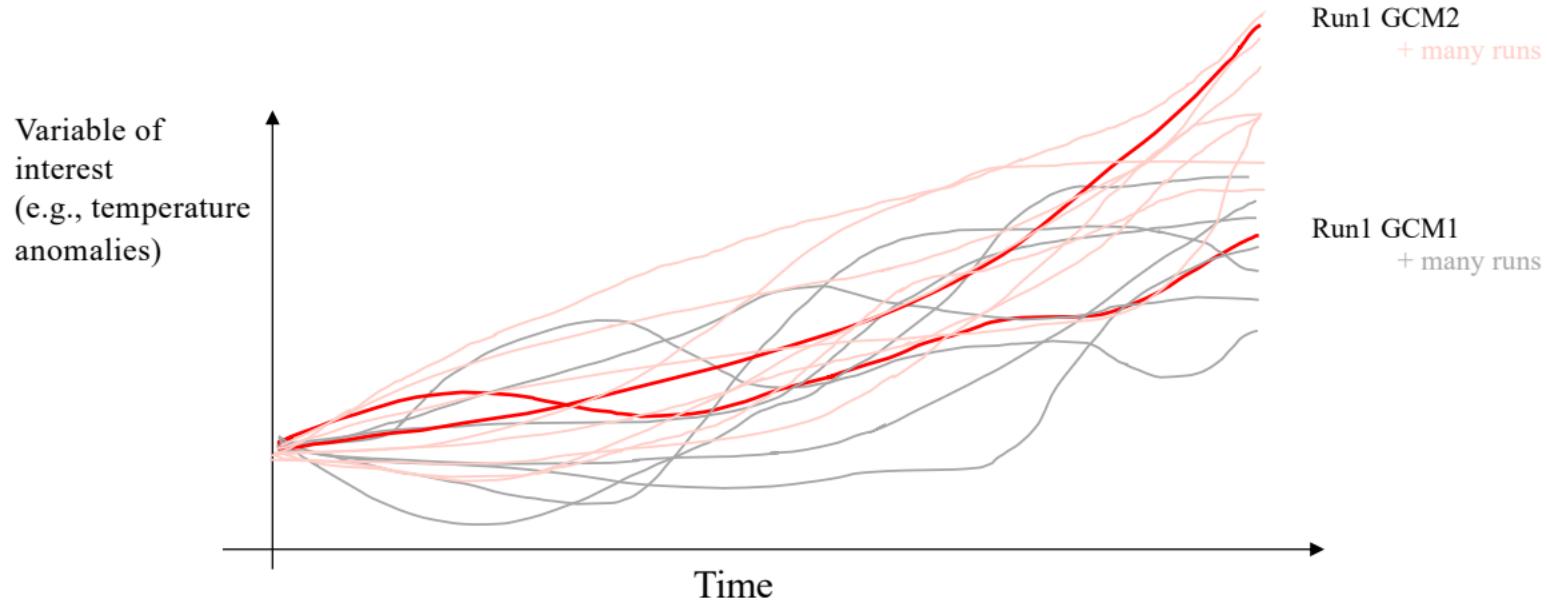


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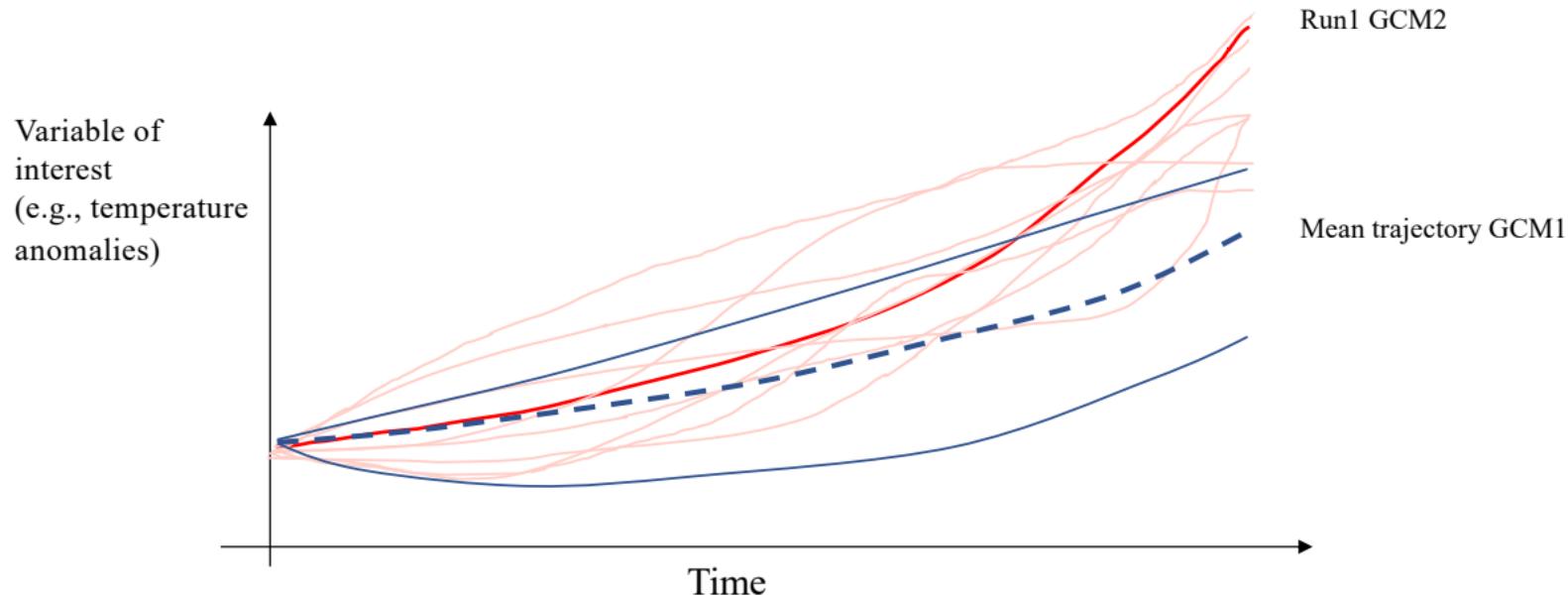


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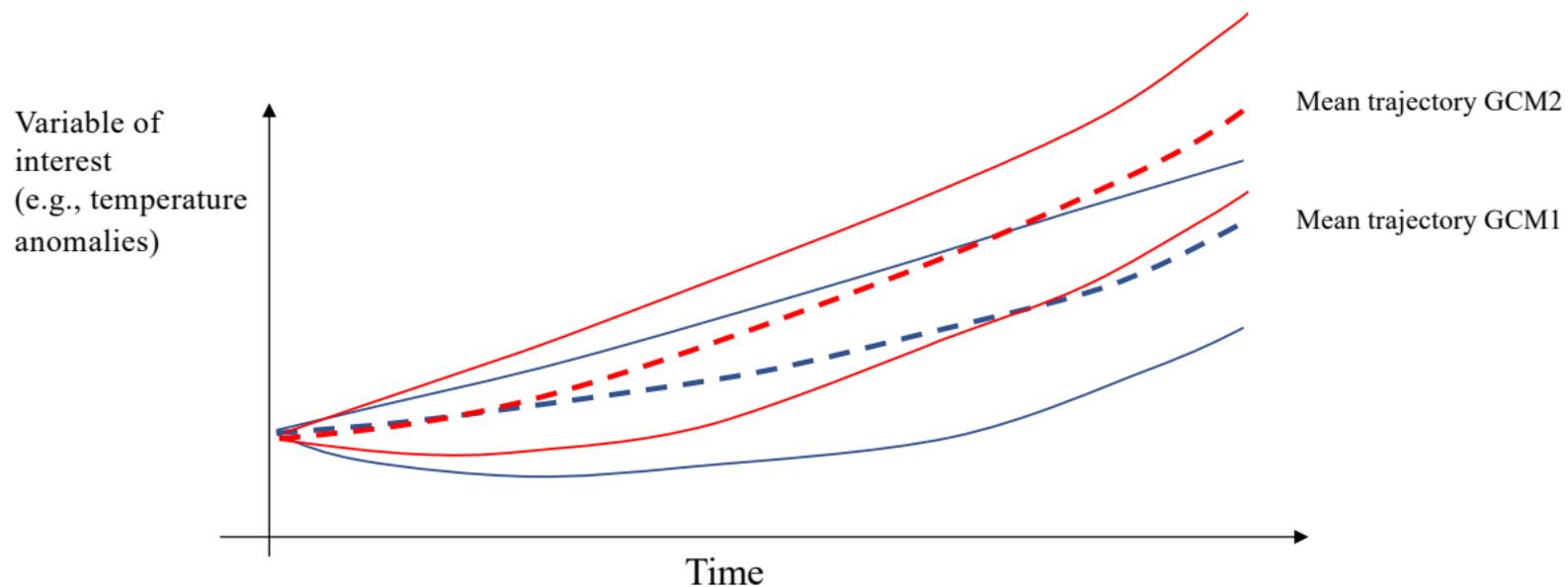


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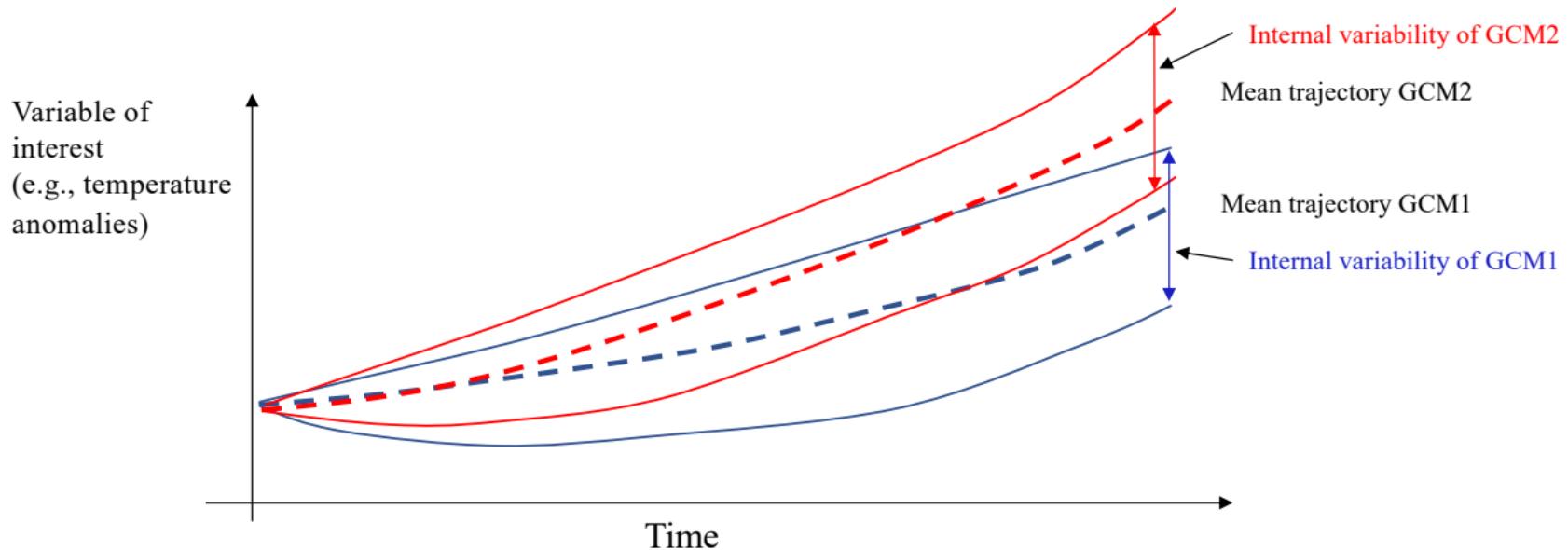


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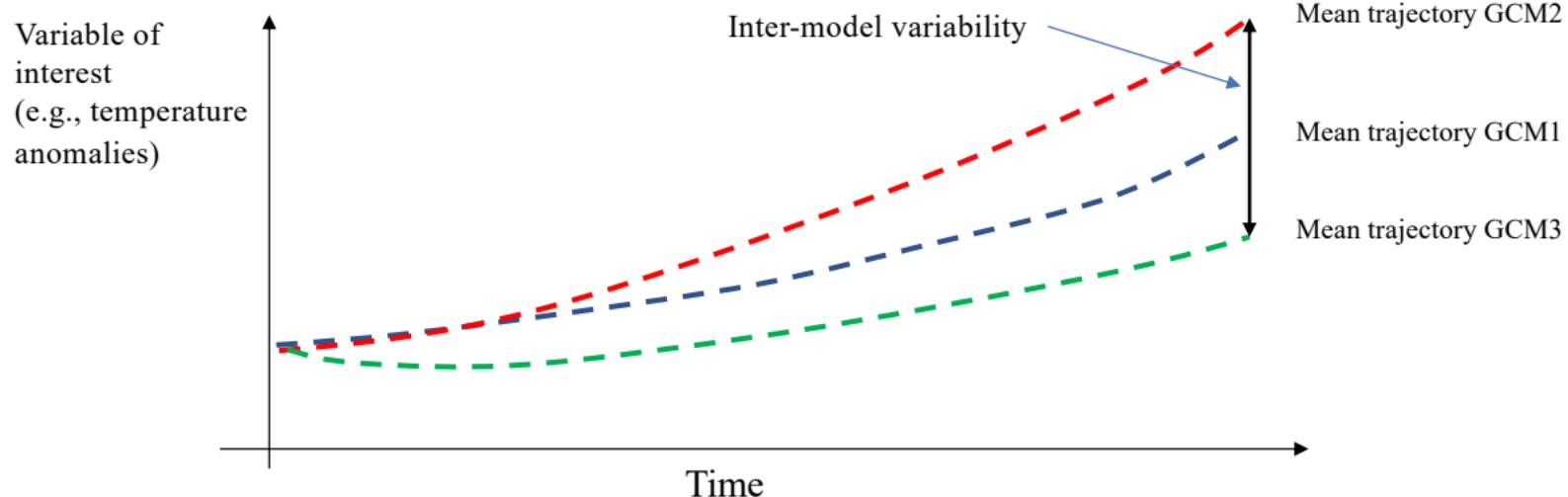
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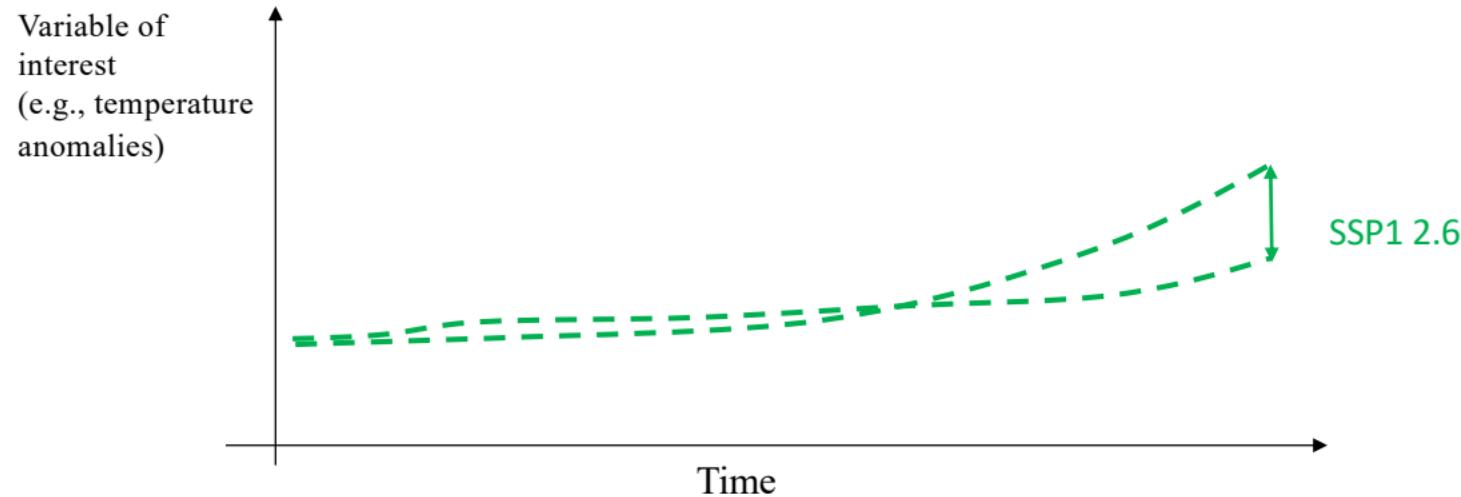
Inter-model variability vs. Internal variability



- Multiple runs of 2 GCMs (one scenario only)
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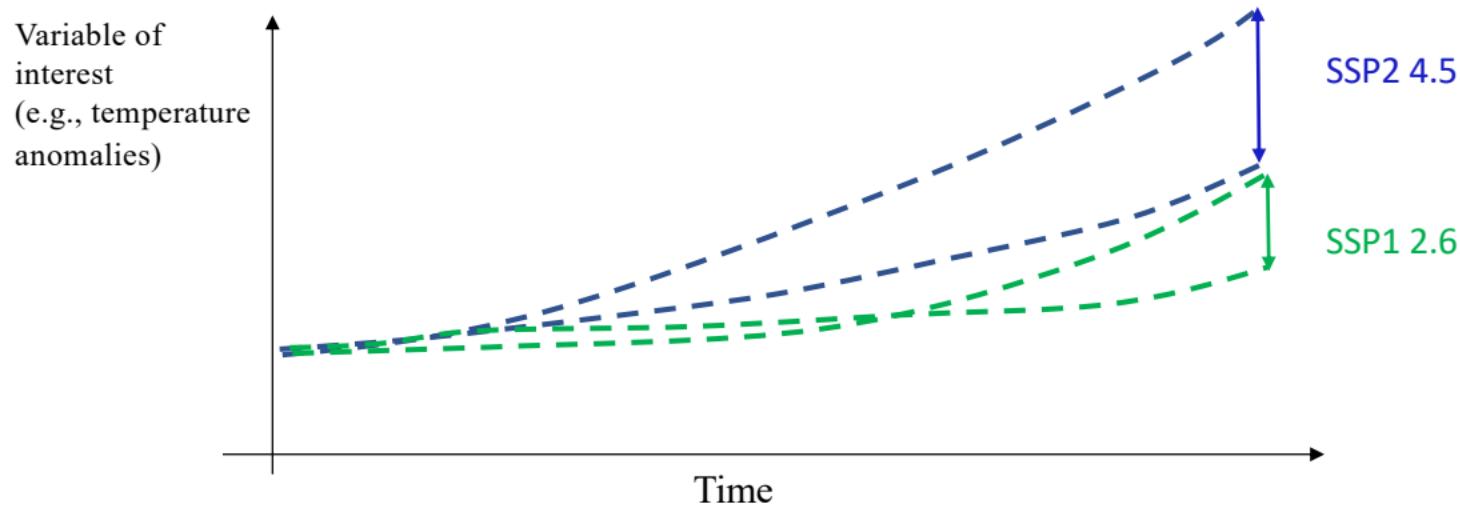


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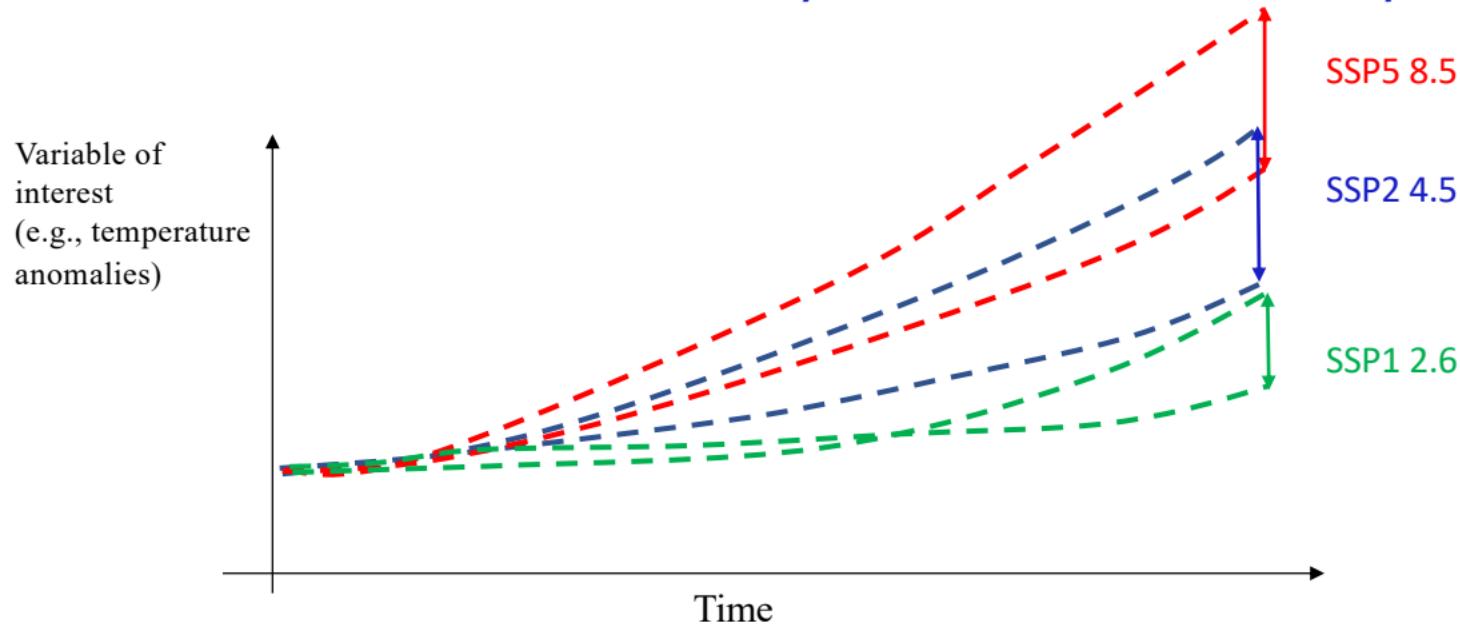


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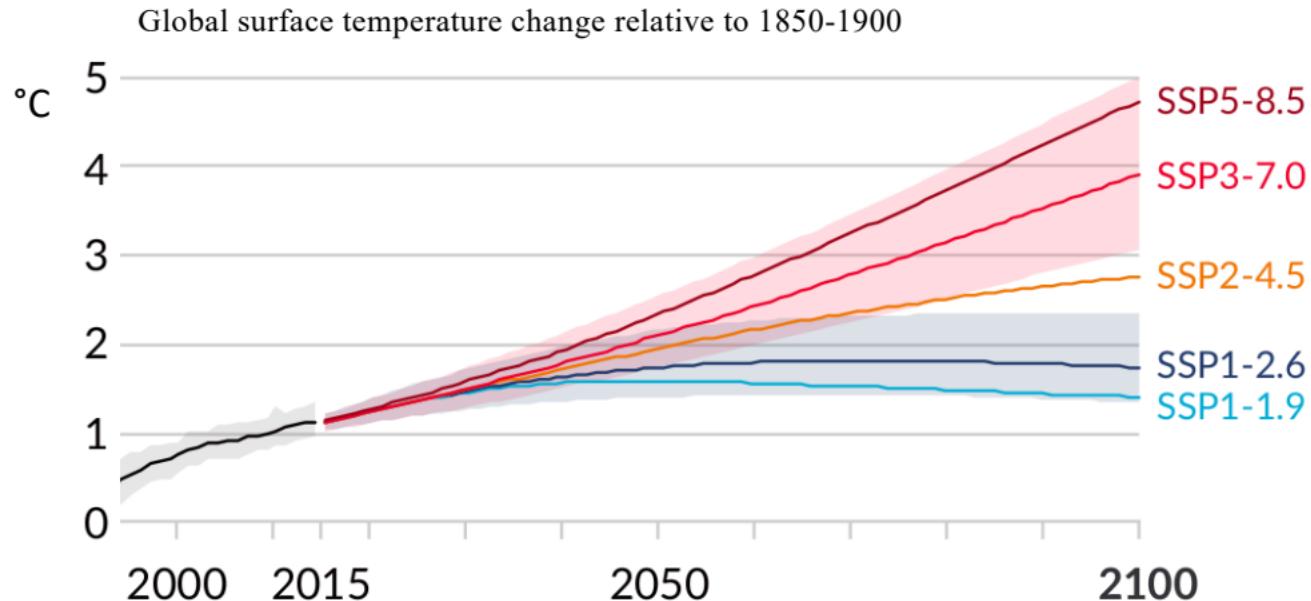


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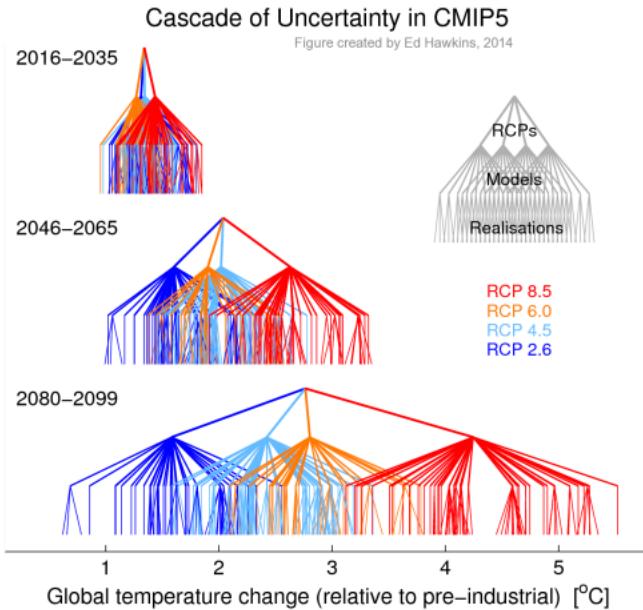


- Multiple runs of GCMs & multiple scenarios
- How to quantify the contribution of the different variabilities/uncertainties?

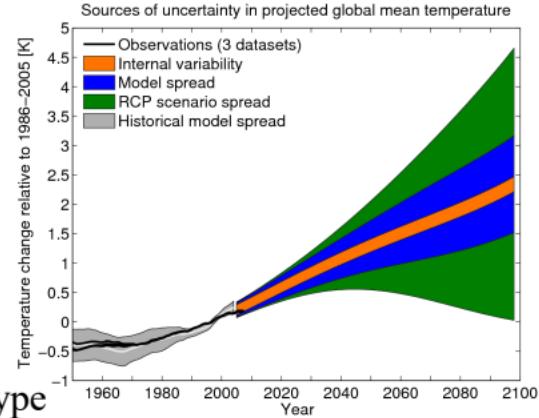
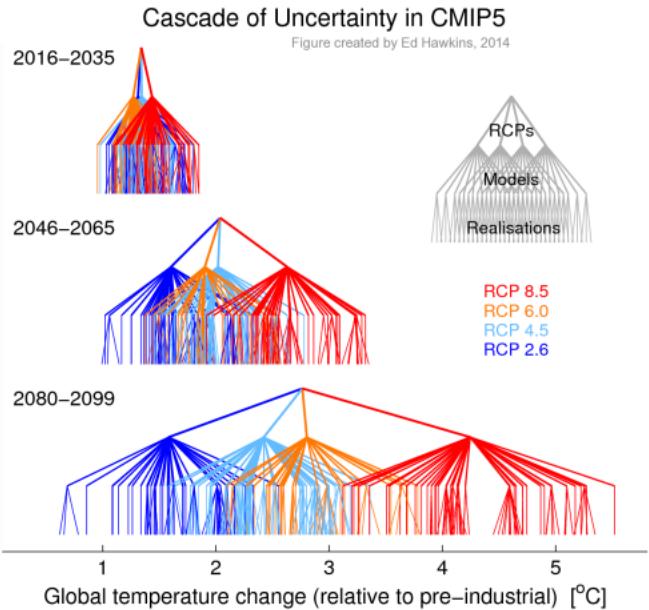


This time, this is based on actual CMIP6 simulations (adapted from AR6 IPCC, 2021)

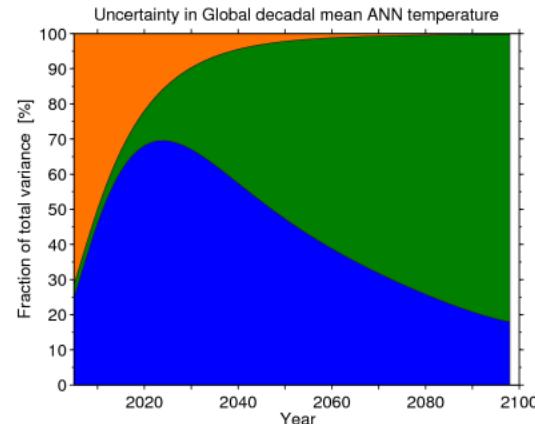
Contributions of the different uncertainties...



Contributions of the different uncertainties...



ANOVA type analyses

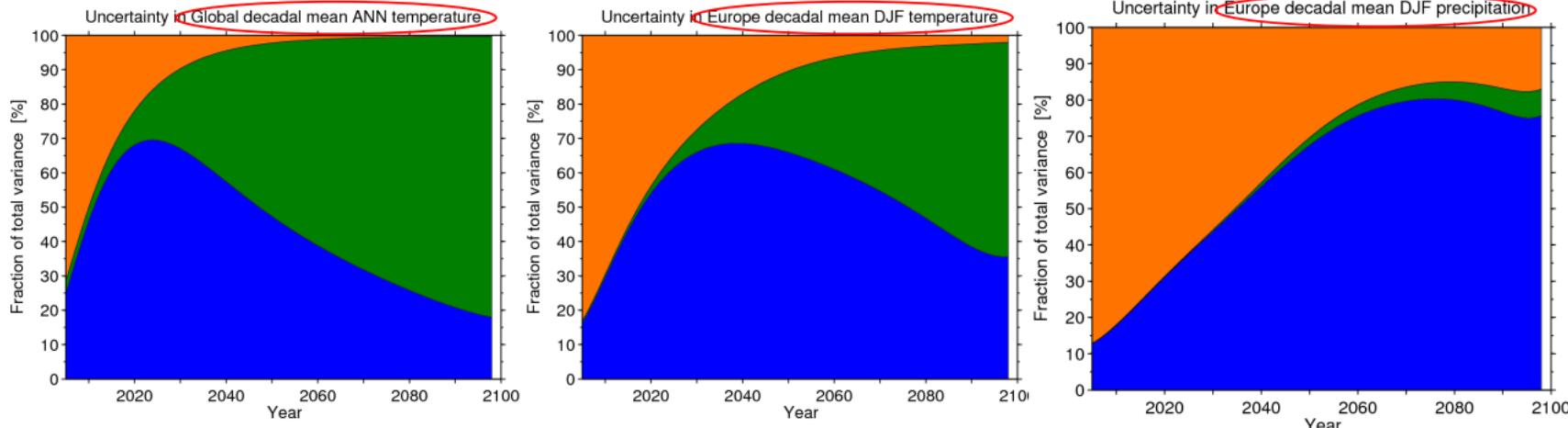


Source:
Hawkins
(2014)

For temperature:

- Short term: uncertainty on *internal variability* is predominant
- Medium term: uncertainty on *modelling* dominates
- Long term: uncertainty on *scenario* is the largest

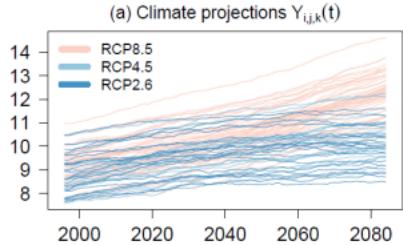
... Different for each variable & region



Source: Figures from E. Hawkins, to find on his blog.

A recent tool to characterize contributions

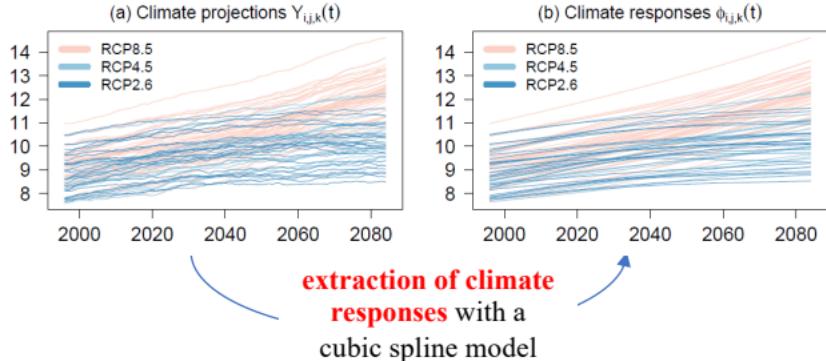
QUALYPSO : partitioning uncertainty components in an ensemble of climate projections (Evin et al., 2019)



- **Provides:** **Uncertainty sources**; individual **climate response** of each model:
uncertainties as a function of **global warming level** (e.g. in a +2°C world)
- **Suits:** Incomplete ensembles with multimodel simulation chains (GCM x RCM x ...) for any kind of projections (weather, hydrology, ecology)
- **Links:** Package R “QUALYPSO” available on CRAN

A recent tool to characterize contributions

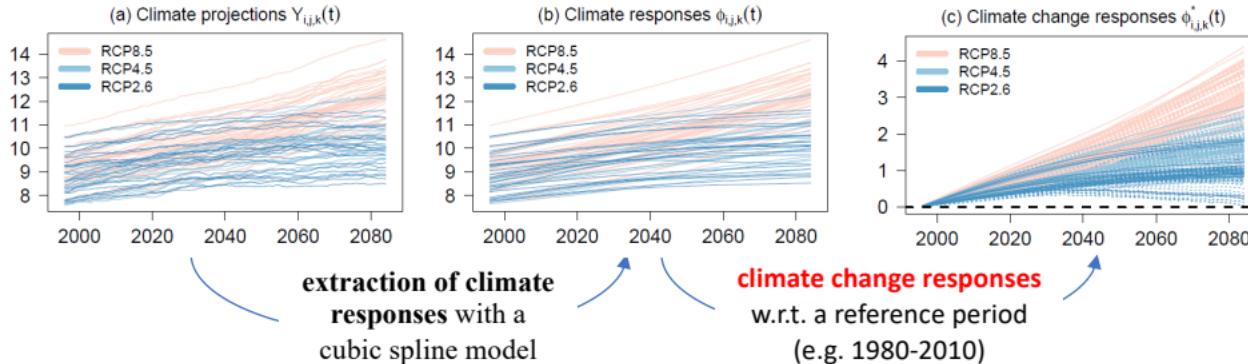
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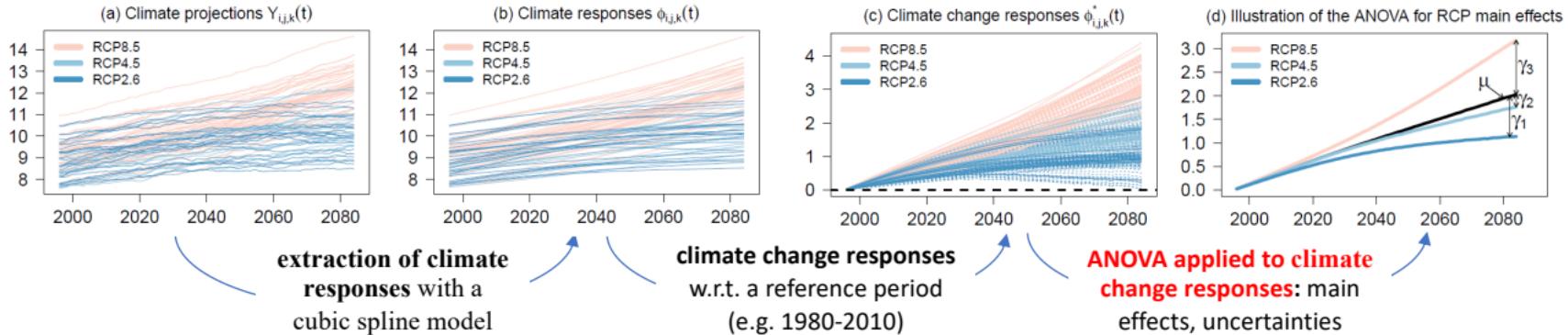
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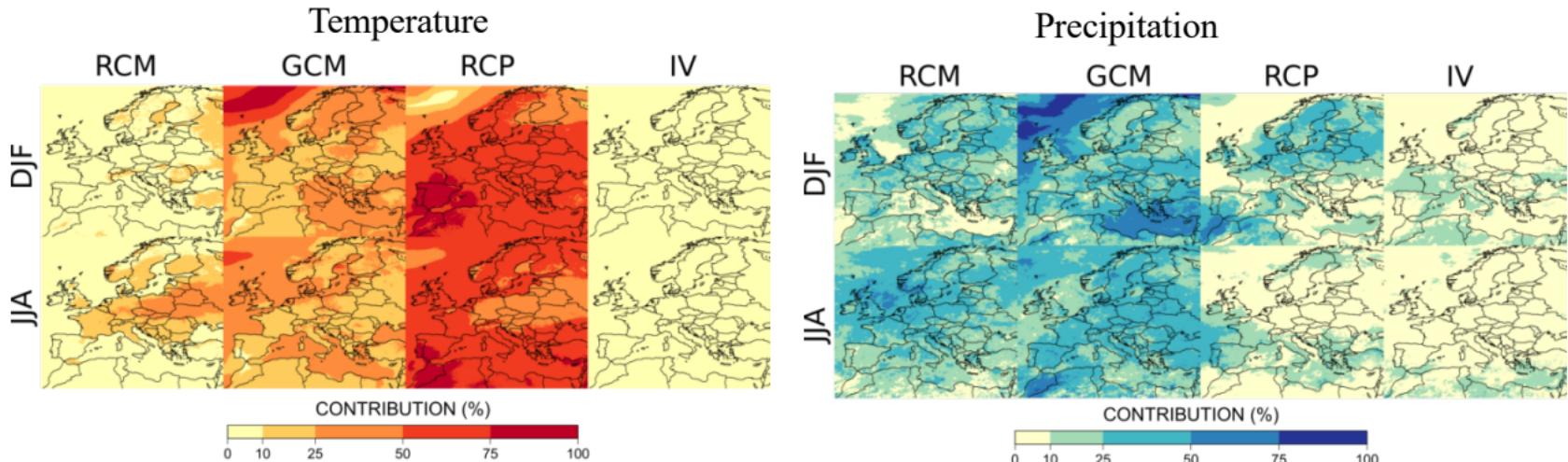
μ = mean response in change from the whole ensemble inter-models / inter-scenarios

γ_1, γ_2 and γ_3 = individual effects of the 3 RCP scenarios wrt μ (e.g., $\gamma_3 \Rightarrow$ RCP8.5 implies a T change of +1°C wrt μ)

A recent tool to characterize contributions

QUALYPSO : partitioning uncertainty components in an ensemble of climate projections (Evin et al., 2019)

Examples for seasonal changes (2071-2099 wrt 1981–2010) of precipitation and temperature in Europe



Source: Evin et al. (2021, ESD)

Uncertainty vs. Variability vs. Bias

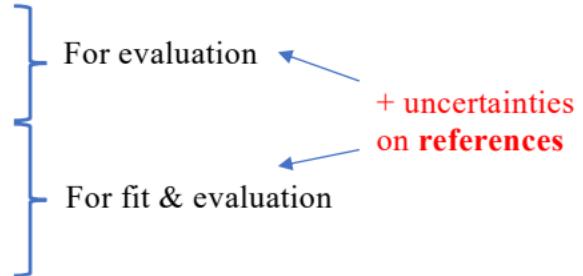
Present in most components of the modelling chain...

- Global Climate Models (GCM)
- Regional Climate Models (RCM, "Dynamical downscaling")
- Statistical Downscaling Models (SDM, including Mach. Learning)
- Bias Correction (BC) methods
- Impact models (hydrology, ecology, economy, etc.)

Uncertainty vs. Variability vs. Bias

Present in most components of the modelling chain...

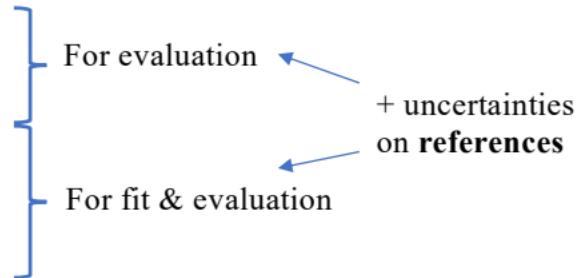
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... & in most processes

- Precipitation / Wind / (Temperature) /...
- Circulation (SLP, Z500, jet, etc.) patterns
- Clouds / aerosol / ice / ...
- Etc.

Uncertainty vs. Variability vs. Bias

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 - Regional Climate Models (RCM, "Dynamical downscaling")
 - Statistical Downscaling Models (SDM, including Mach. Learning)
 - Bias Correction (BC) methods
 - Impact models (hydrology, ecology, economy, etc.)
-
- For evaluation
- + uncertainties on references
- For fit & evaluation

... & in most processes **and/or statistical properties**

- Precipitation / Wind / (Temperature) /...
- Circulation (SLP, Z500, jet, etc.) patterns
- Clouds / aerosol / ice / ...
- Etc.
- Univariate distributions and basic properties
- Multivariate dependencies
- Temporal properties (persistence, reccurrence, etc.)
- Extremes (return levels/period, HW, storms, etc.)

Uncertainty vs. Variability vs. Bias

Present in most components of the modelling chain...

- Global Climate Models (GCM)
 - Regional Climate Models (RCM, "Dynamical downscaling")
 - Statistical Downscaling Models (SDM, including Mach. Learning)
 - Bias Correction (BC) methods
 - Impact models (hydrology, ecology, economy, etc.)
-
- + uncertainties
on **references**

... & in most processes and/or statistical properties

- Precipitation / Wind / (Temperature) /...
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 - Etc.
 - Univariate distributions and basic properties
 - Multivariate dependencies
 - Temporal properties (persistence, reccurrence, etc.)
 - Extremes (return levels/period, HW, storms, etc.)
- Especially in a climate change context! (trends, non-stationarity, etc.)

Thank you...