On the challenges of producing (robust) Antarctic sea-level projections

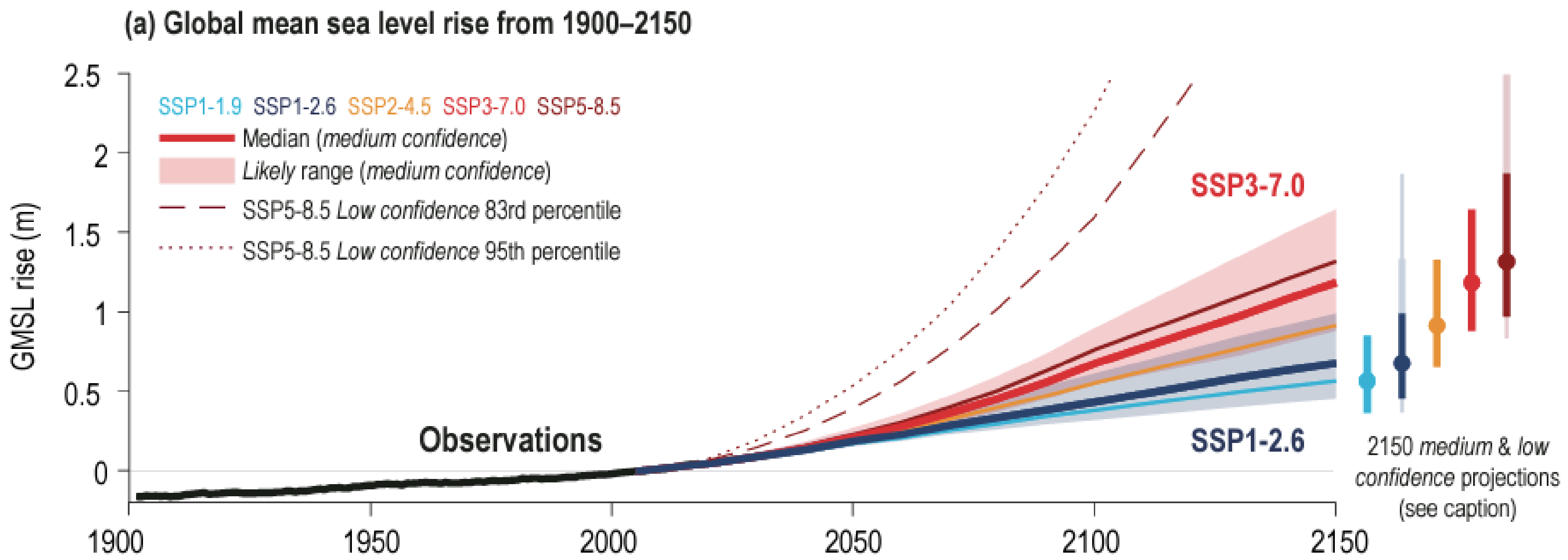
Vio Coulon

based on discussions with Frank Pattyn, Lars Zipf, Tamsin Edwards, Ann Kristin Klose, Fiona Turner, Christoph Kittel, Ricarda Winkelmann, and others

ISMASS workshop 2023, Trieste

Our goal: producing robust/credible projections of Antarctic contribution to future sea-level rise

The Antarctic ice sheet is the largest and most uncertain potential contributor to future sea level rise



AR6, IPCC (2021)

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The Cryosphere
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EGU

Brief communication: A roadmap towards credible projections of ice sheet contribution to sea level

Andy Aschwanden[1,★], Timothy C. Bartholomaus[2,★], Douglas J. Brinkerhoff[3,★], and Martin Truffer[1,★]

'Effective planning for coming sea level rise necessitates credible estimates accompanied by a robust assessment of uncertainty'

'accurate predictions of the cryosphere's contribution to sea level require that models
1. fully characterize uncertainties in model structure, parameters, initial conditions, and boundary conditions;
2. yield simulations that fit observations within observational uncertainty.
If the first point is not satisfied, then predictive uncertainties are likely to be underestimated. If the second condition is not satisfied, then the distribution of model predictions is likely to be biased relative to reality.'

Two requirements for such projections:

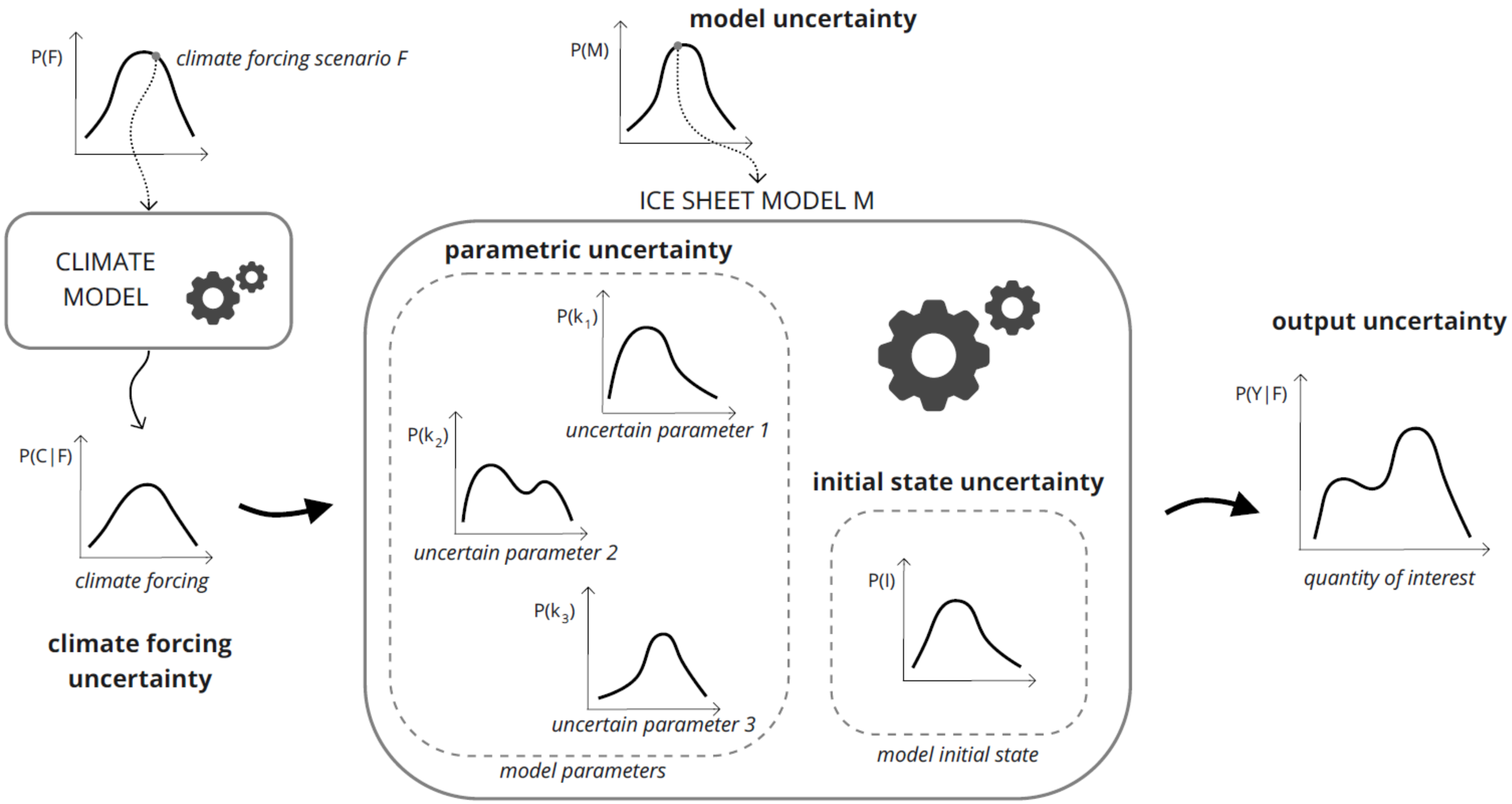
1. Accounting for all sources of uncertainty
   → uncertainty quantification framework
2. Conditioning simulations on observations

Goals of this talk

- Describe the **requirements** to produce robust/credible Antarctic sea-level projections
- Guide you through what are, according to me*, the **main challenges** to produce such projections
- Be a **support for discussion**

*this presentation is based on my (short) experience as an ice-sheet modeller and may be strongly biased or incomplete

1. Robust assessment of uncertainties
Propagation of uncertainty in ice-sheet model projections



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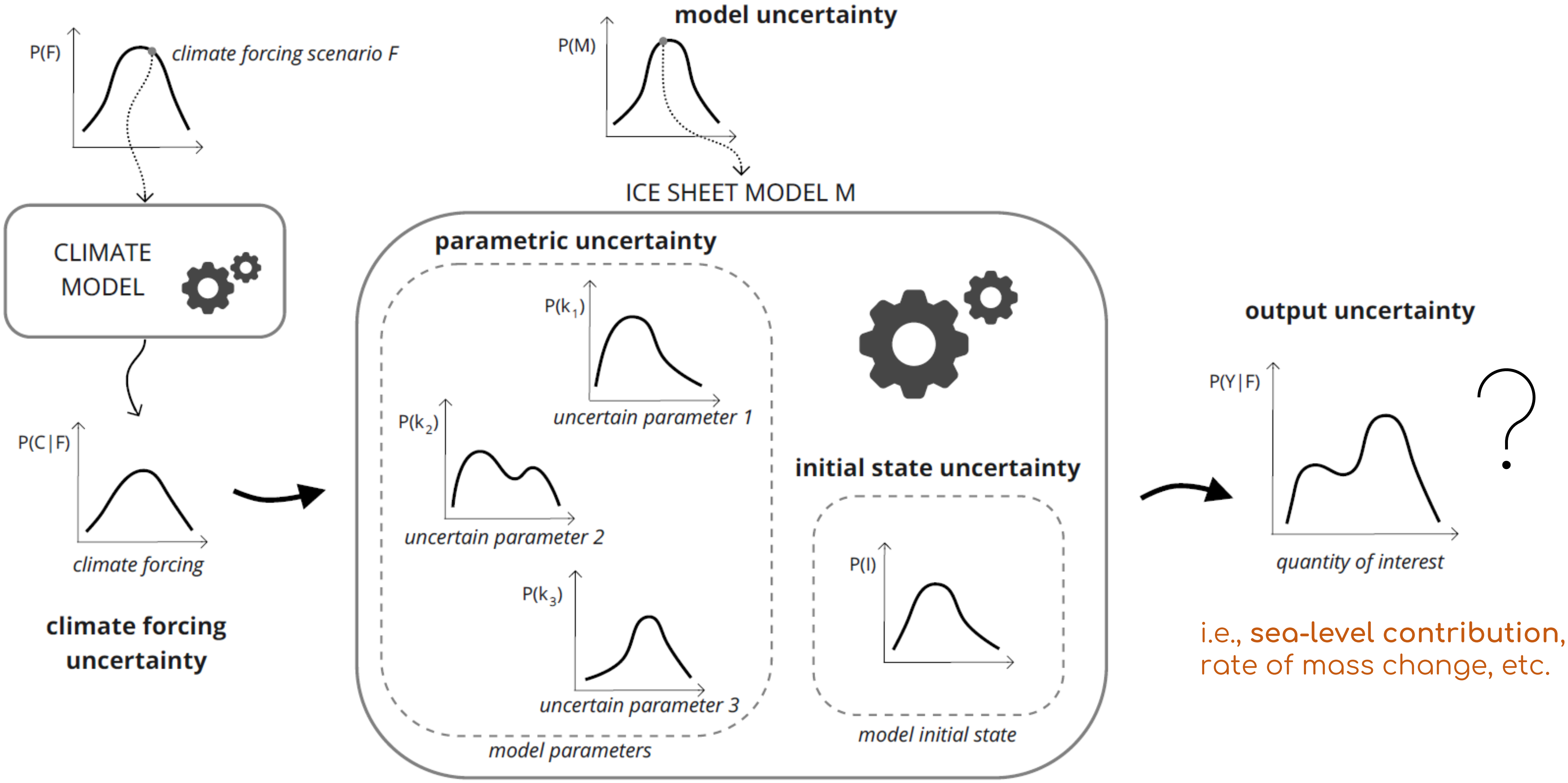

i.e., **sea-level contribution**, rate of mass change, etc.

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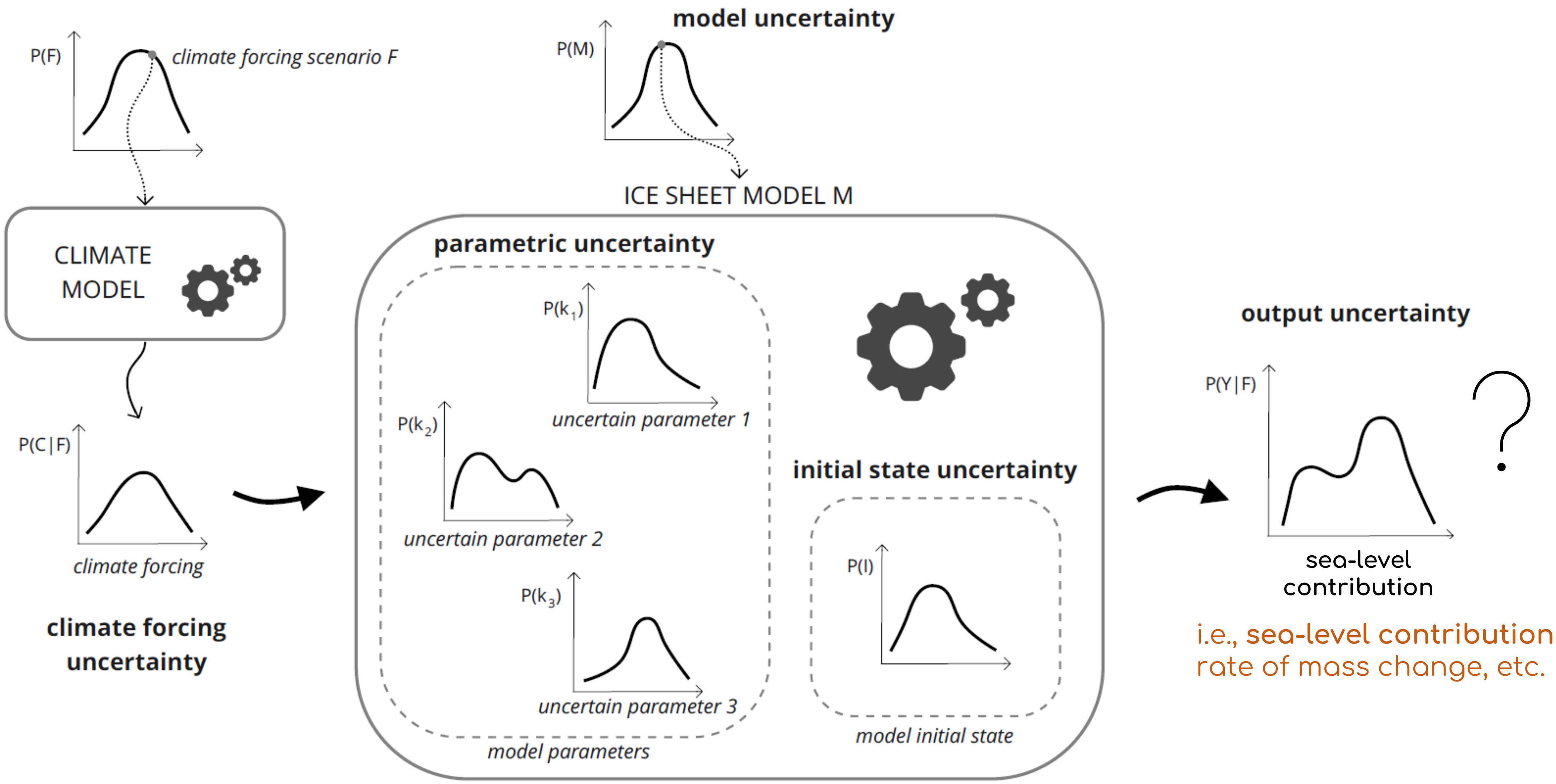

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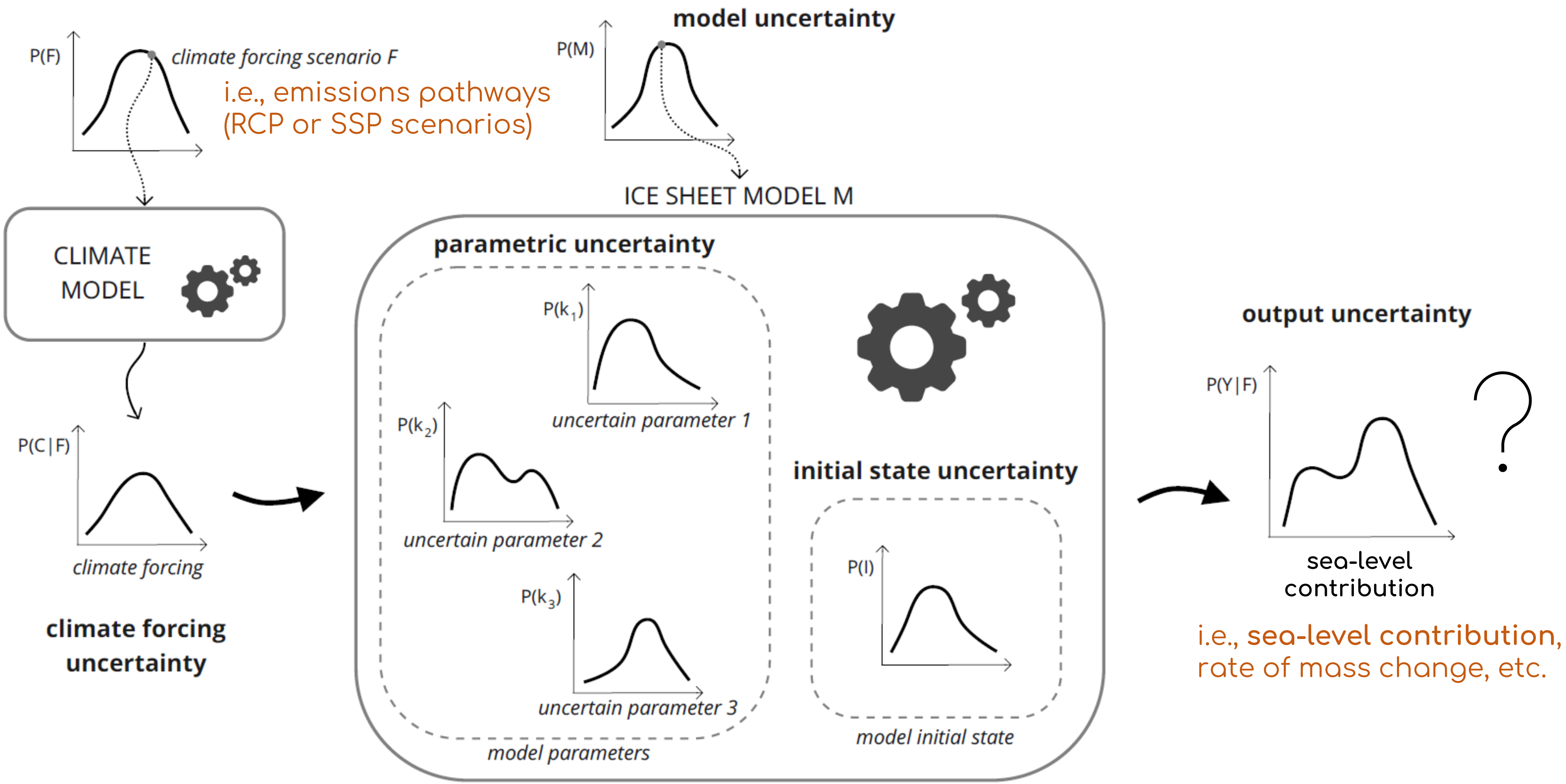

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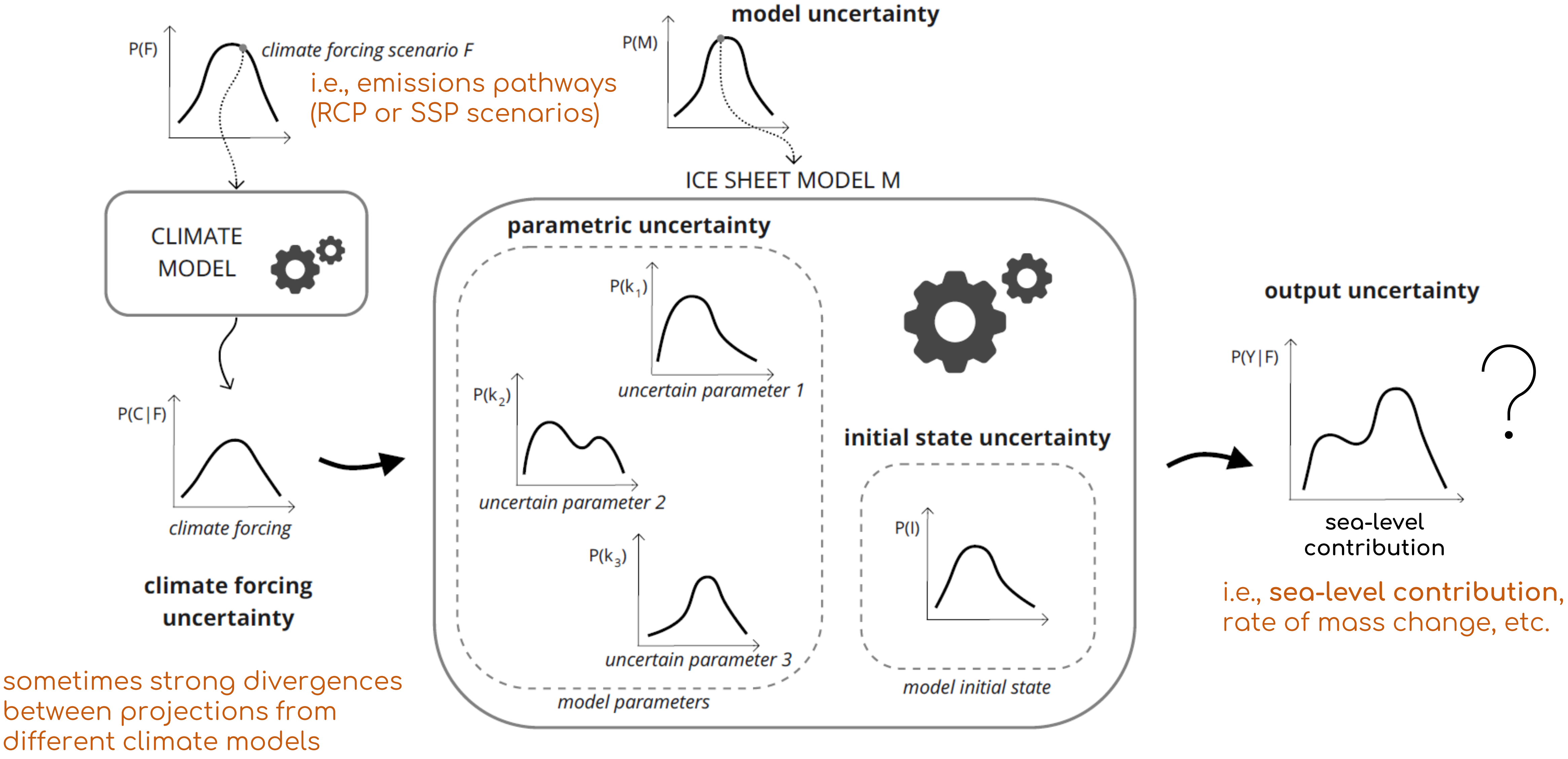

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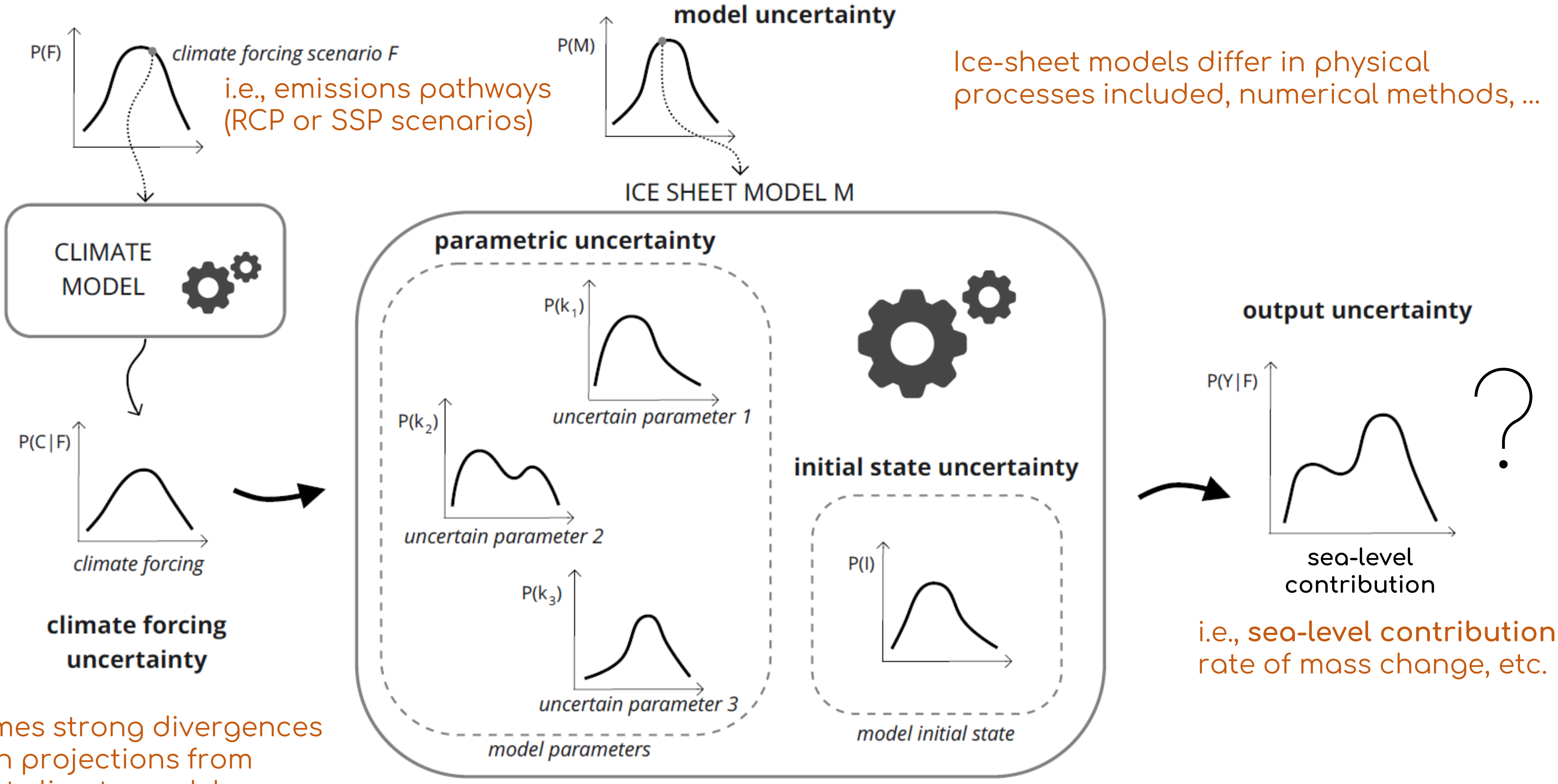

i.e., emissions pathways (RCP or SSP scenarios)

Ice-sheet models differ in physical processes included, numerical methods, …

i.e., **sea-level contribution**, rate of mass change, etc.

sometimes strong divergences between projections from different climate models

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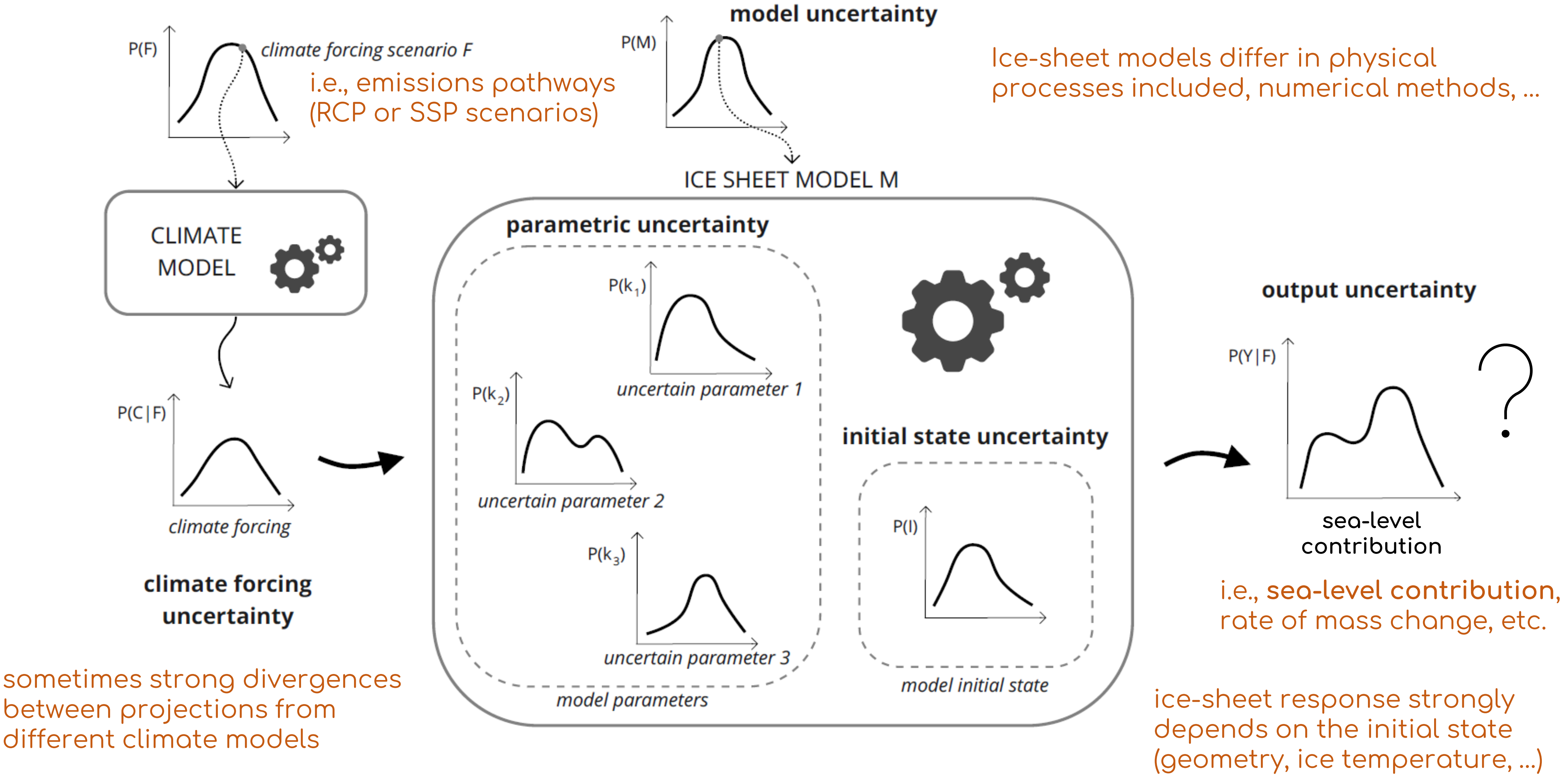

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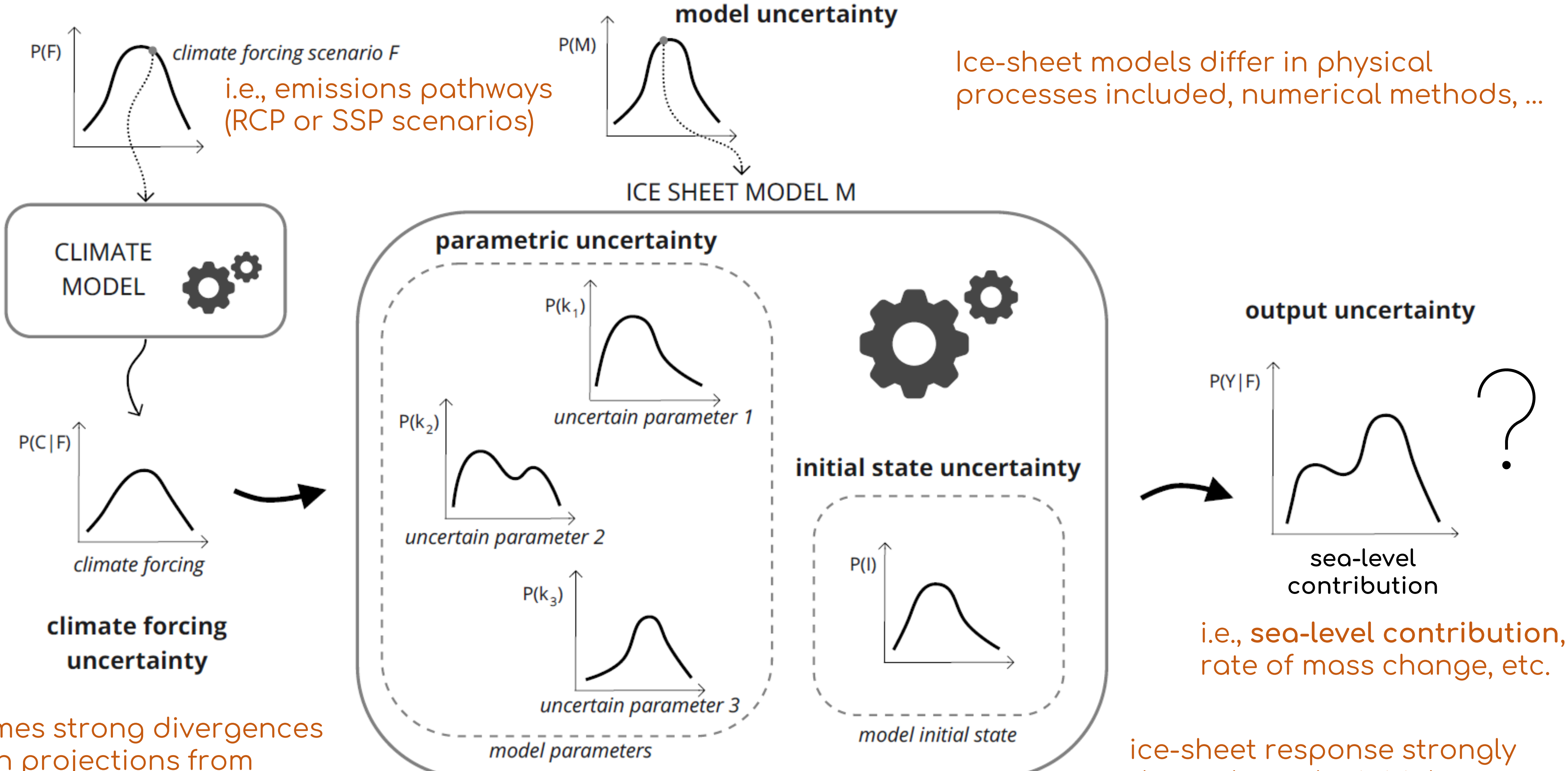


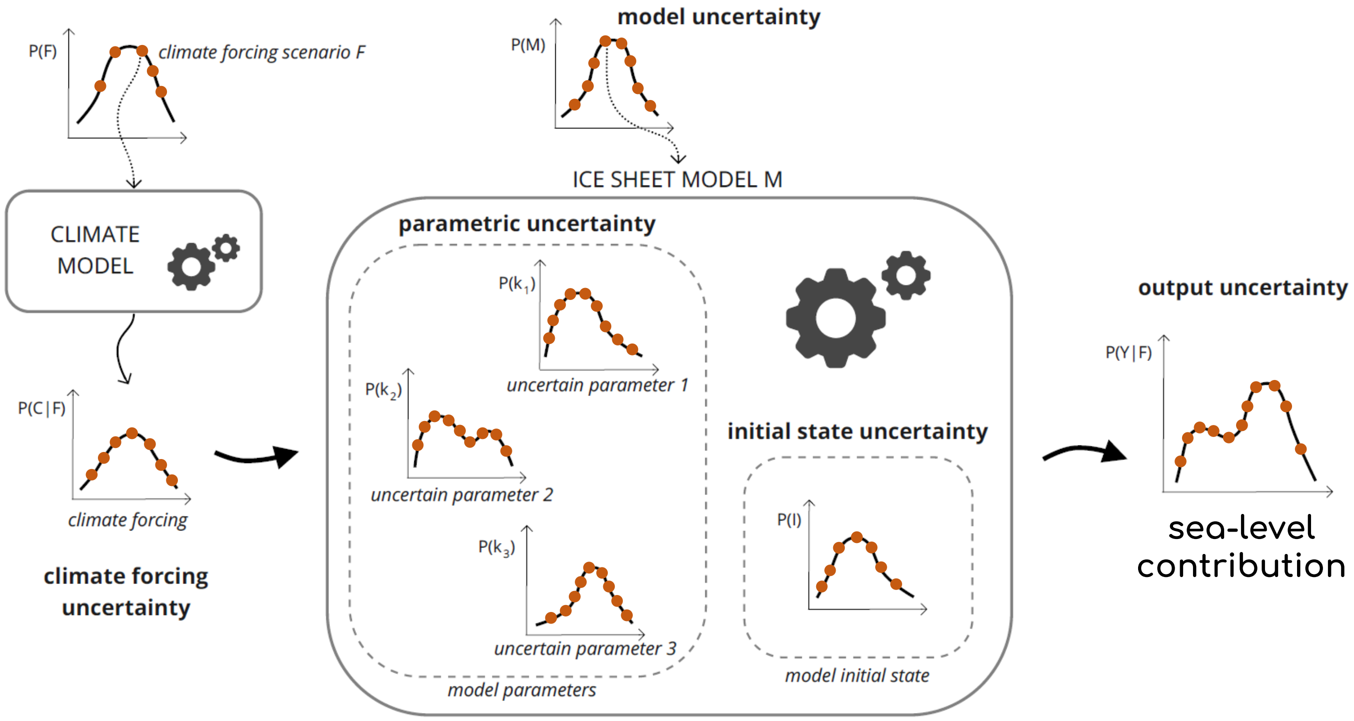
sometimes strong divergences
between projections from
different climate models

all models contain parameters
whose values are uncertain

ice-sheet response strongly
depends on the initial state
(geometry, ice temperature, ...)

1. Robust assessment of uncertainties

.. implies that the complete probability distributions of the different sources of uncertainty are considered



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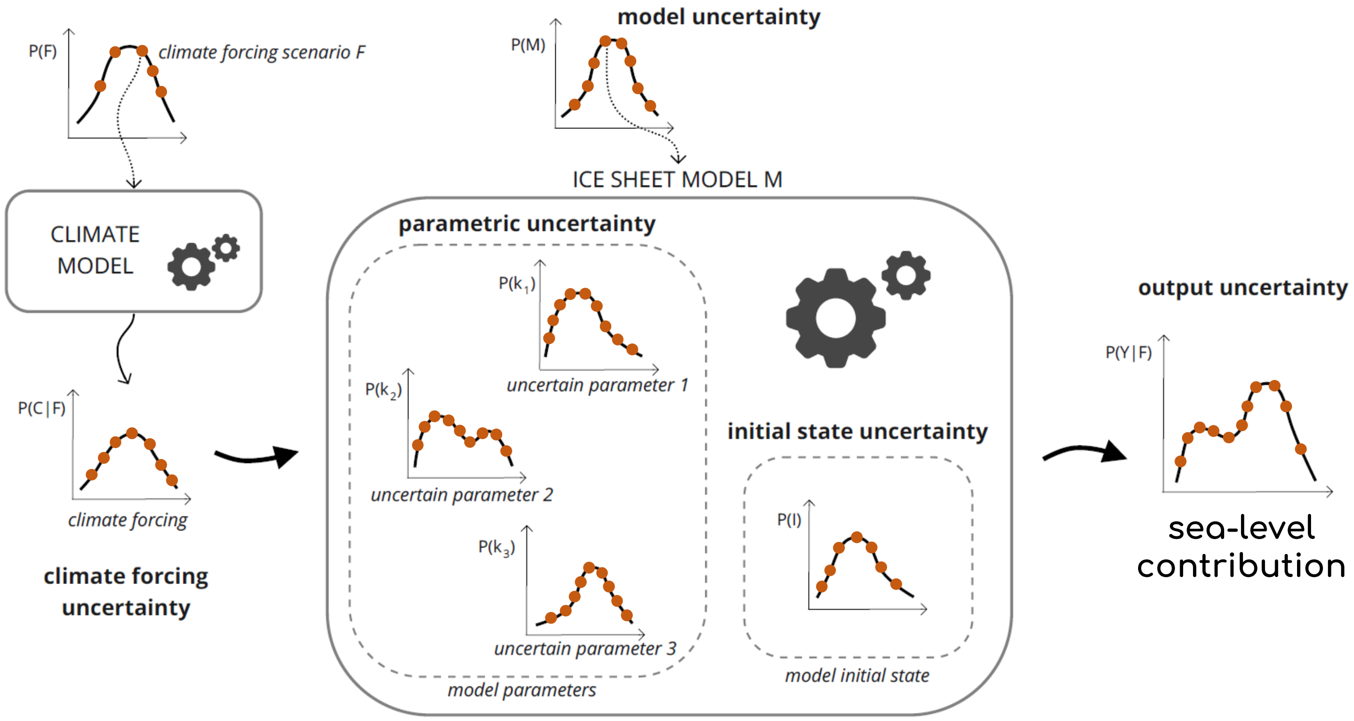
- **In theory**, very **simple**
  - Estimate Y for many samples from each source of uncertainty



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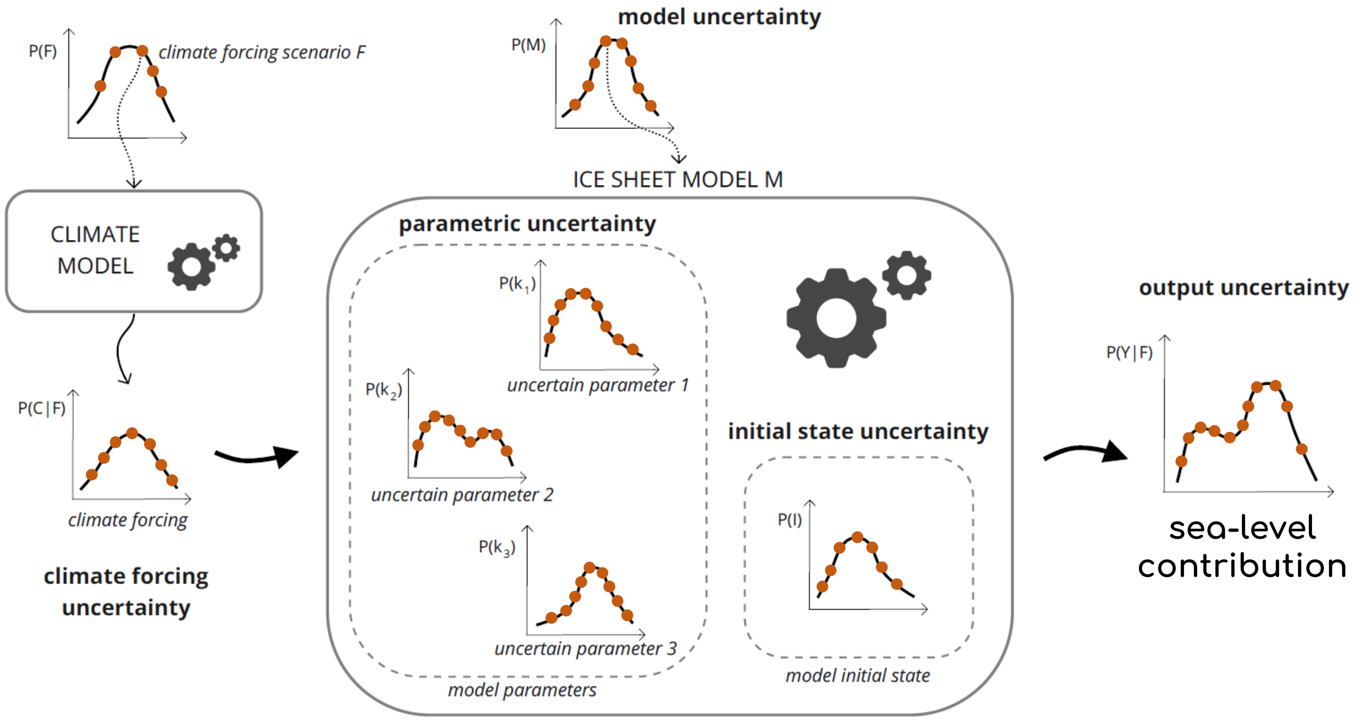
  → relatively recent in ice-sheet modelling community



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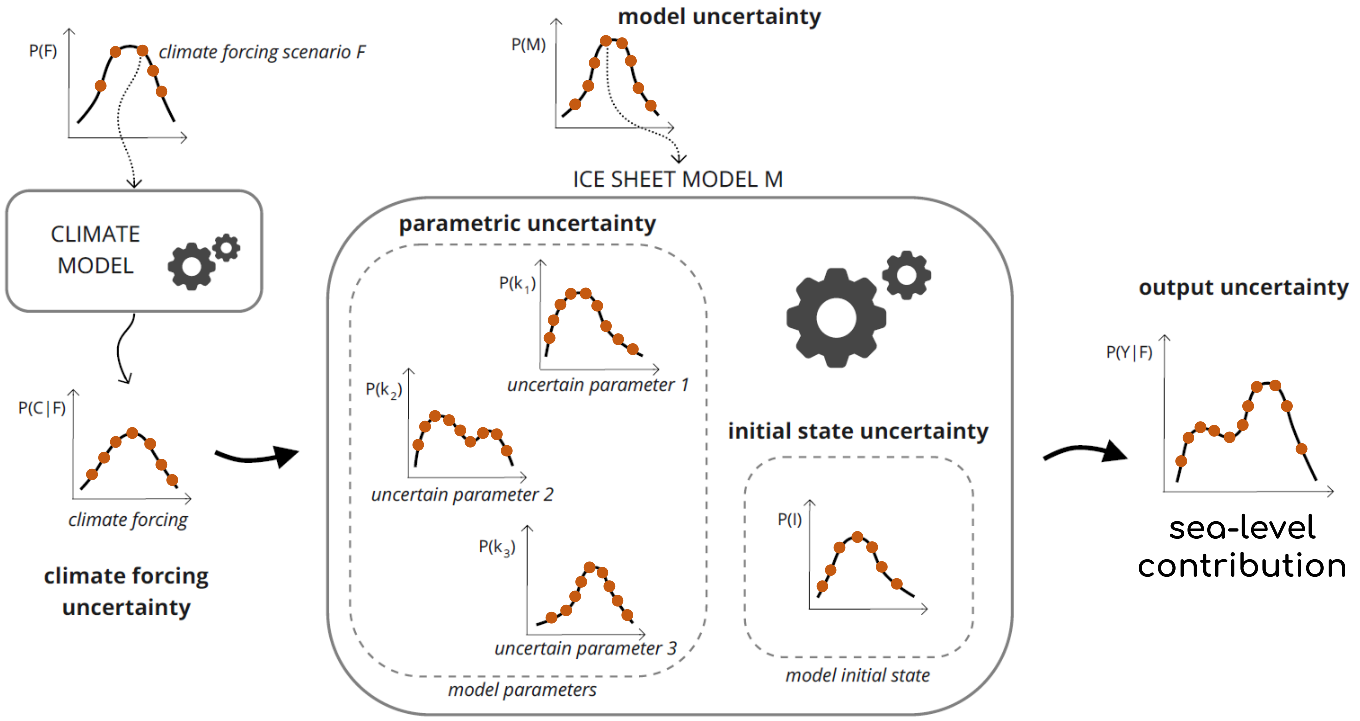
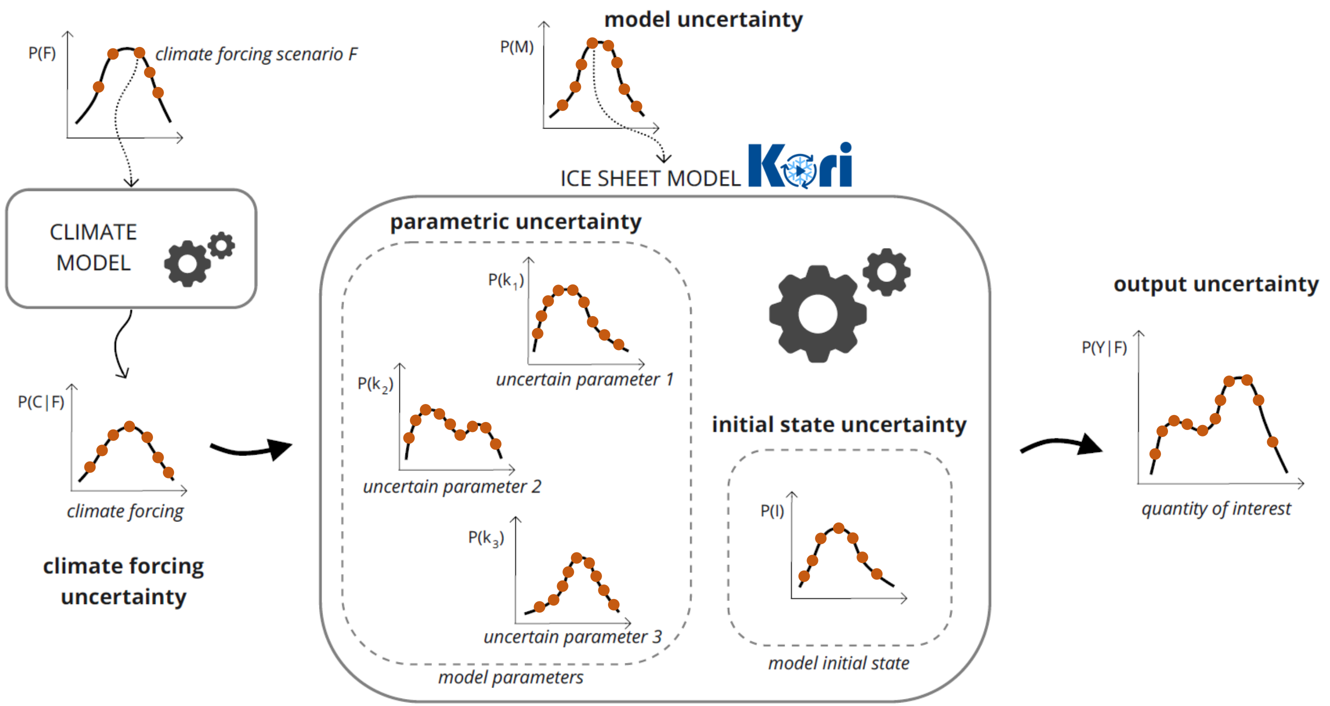


- Typically, some compromises must be made:
  - Regional/short timescale focus (e.g., Nias et al., 2019; Hill et al., 2021, Bevan et al., 2023)
  - Coarse spatial resolution (e.g., Ritz et al., 2015; Pollard et al., 2016; Bulthuis et al. 2019, Coulon et al. 2021, 2023)
  - Simplified approaches and/or parameterisations (e.g., Bulthuis et al. 2019, Coulon et al. 2021, 2023)
  - Focus on specific sources of uncertainty (all so far)

An example case: Coulon et al. (2023)



- 1000-yr Antarctic simulations under SSP scenarios
- Latin hypercube sampling (100 samples over 9 inputs)
- No emulation

Compromises/limitations:

- Coarse spatial resolution (16 km)
- Simplified approaches (PDD model, ELRA model)
- Parametric uncertainty focused on ice-climate interactions
- Only one ice-sheet model and 2 initial states

CMIP6 GCM applied for the climate forcing	MRI-ESM2-0 UKESM1-0-LL CESM2-WACCM IPSL-CM6A-LR	
Atmospheric present-day climatology	RACMO2.3p2 MAR3.11	
Atmospheric lapse rate	5-12 °C/km	
Refreezing thermally-active layer	0 - 15 m	
PDD ice melt factor	4 - 12 w.e. mm/PDD	
PDD snow melt factor	0 - 6 w.e. mm/PDD	
Oceanic present-day climatology	Schmidtko et al. (2014) ISMIP6 (Jourdain et al., 2020)	
Sub-shelf melt parameterisation	PICO model (Reese et al., 2018) Plume model (Lazeroms et al., 2019) Quadratic local (Burgard et al., 2023) ISMIP6 non-local (Jourdain et al., 2020) ISMIP6 non local slope (Jourdain et al., 2020)	
Effective ice-ocean heat flux	γ_T^* $C_d^{1/2}\Gamma_{TS}$ K γ_0 γ_0	0.1 – 10 x 10^{-5} m/s 1 – 10 x 10^{-4} 1 – 10 x 10^{-4} m/s 1 – 4 x 10^{4} m/yr 1 – 4 x 10^{6} m/yr

The challenges of a UQ framework

- Computational cost to run sufficiently large ensembles (10^2-10^3)

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  - Solution: use **emulators** (e.g., Bulthuis et al., 2019; Hill et al., 2019; Edwards et al., 2019, 2021)
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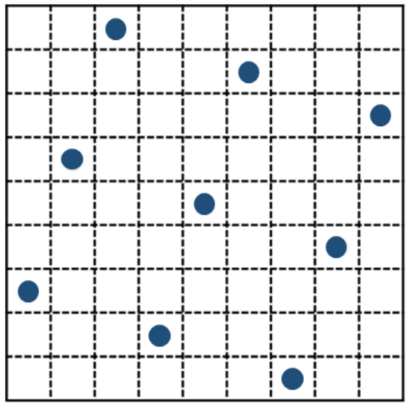
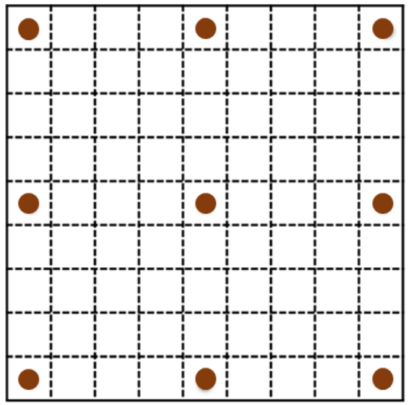
- Requires a **specific design**: an optimal ensemble design has
  - **wide ranges** of uncertainties
  - a **space-filling ensemble design**

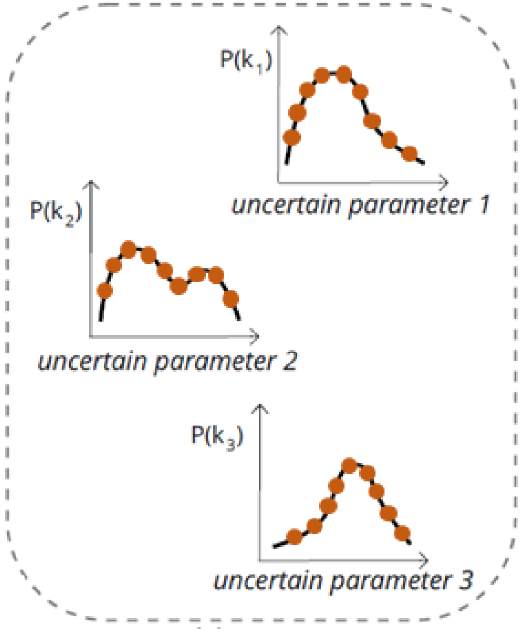


maximin Latin Hypercube

VS



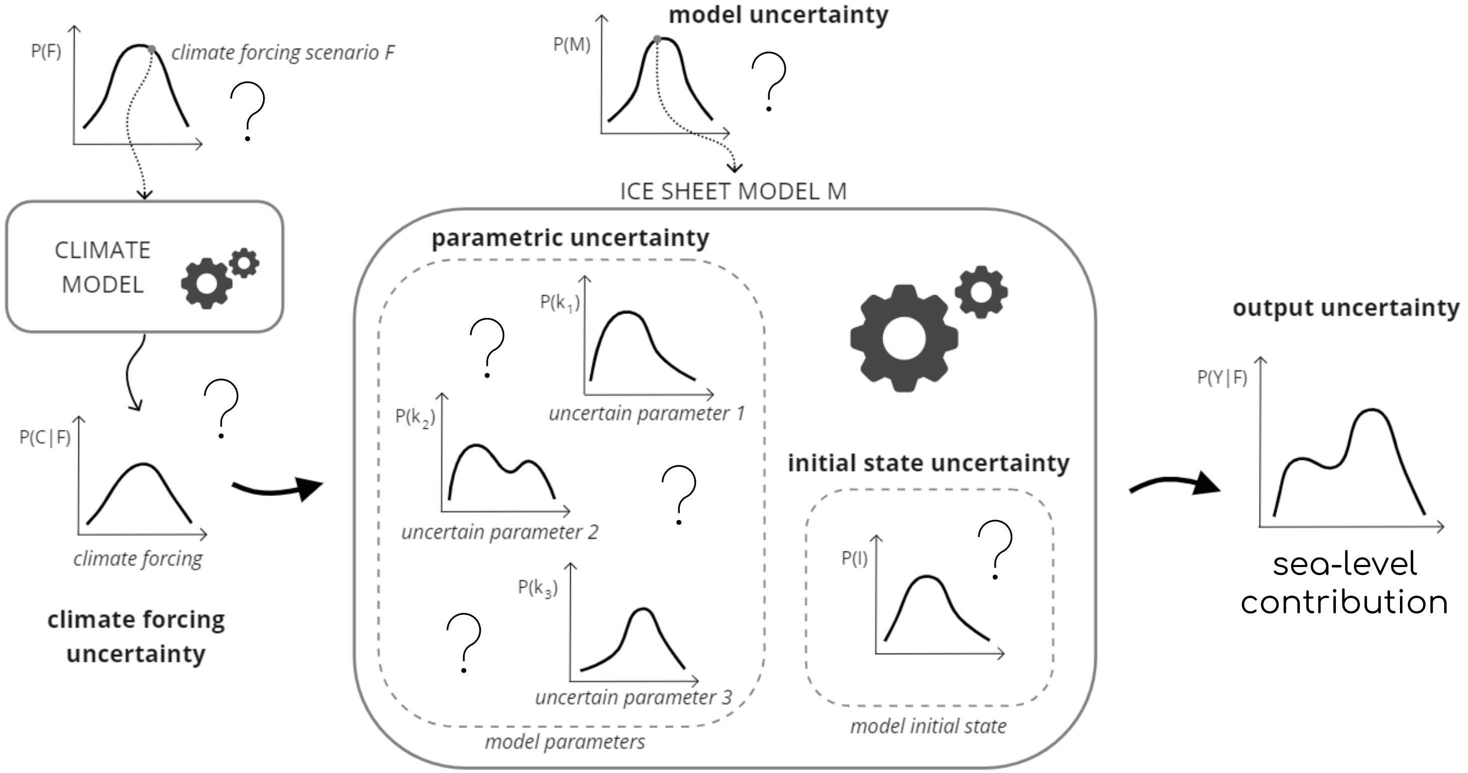
grid (factorial) design



2. Conditioning simulations on observations

1. Robust assessment of uncertainties: the complete probability distributions of the different sources of uncertainty are considered

PROBLEM: the PDFs of the sources of uncertainty are not always known...



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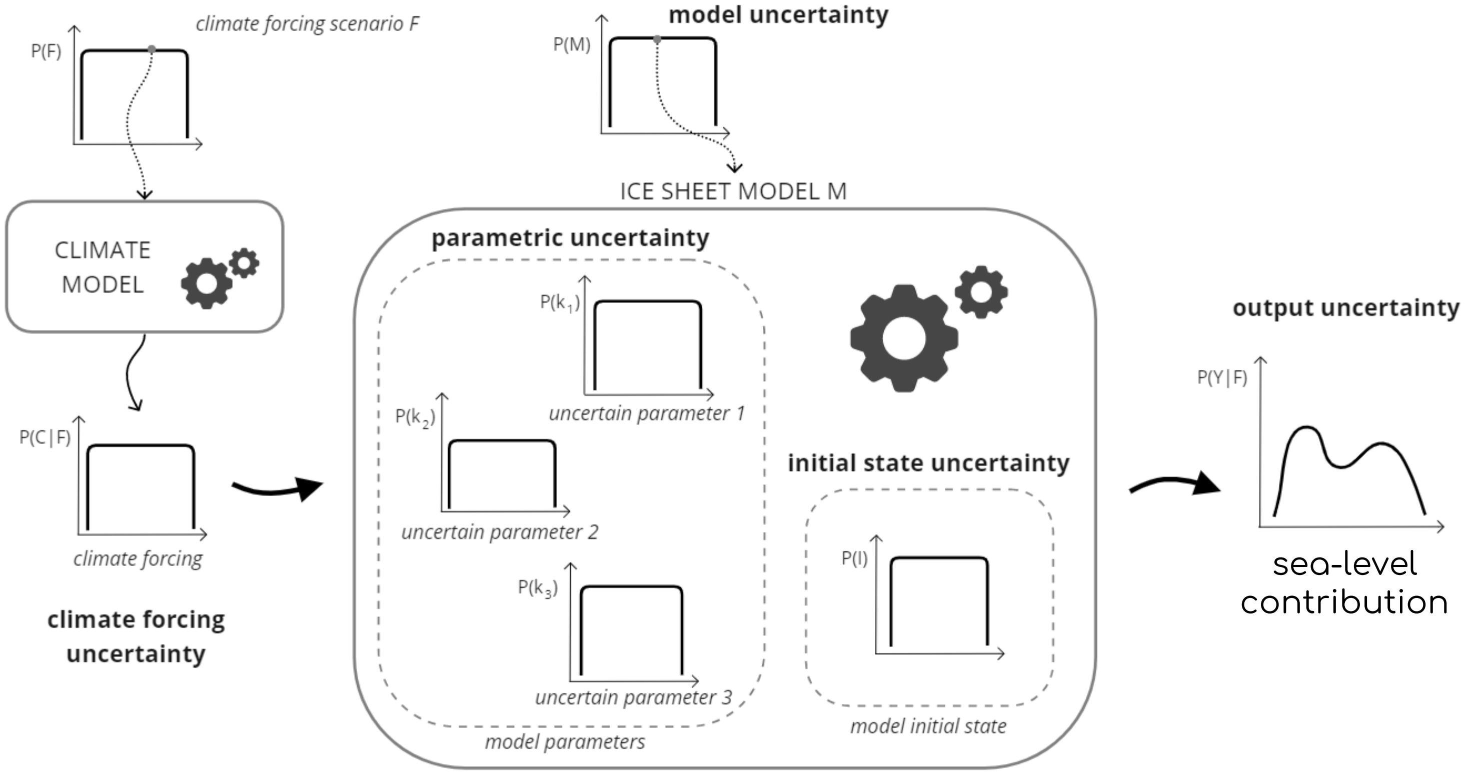

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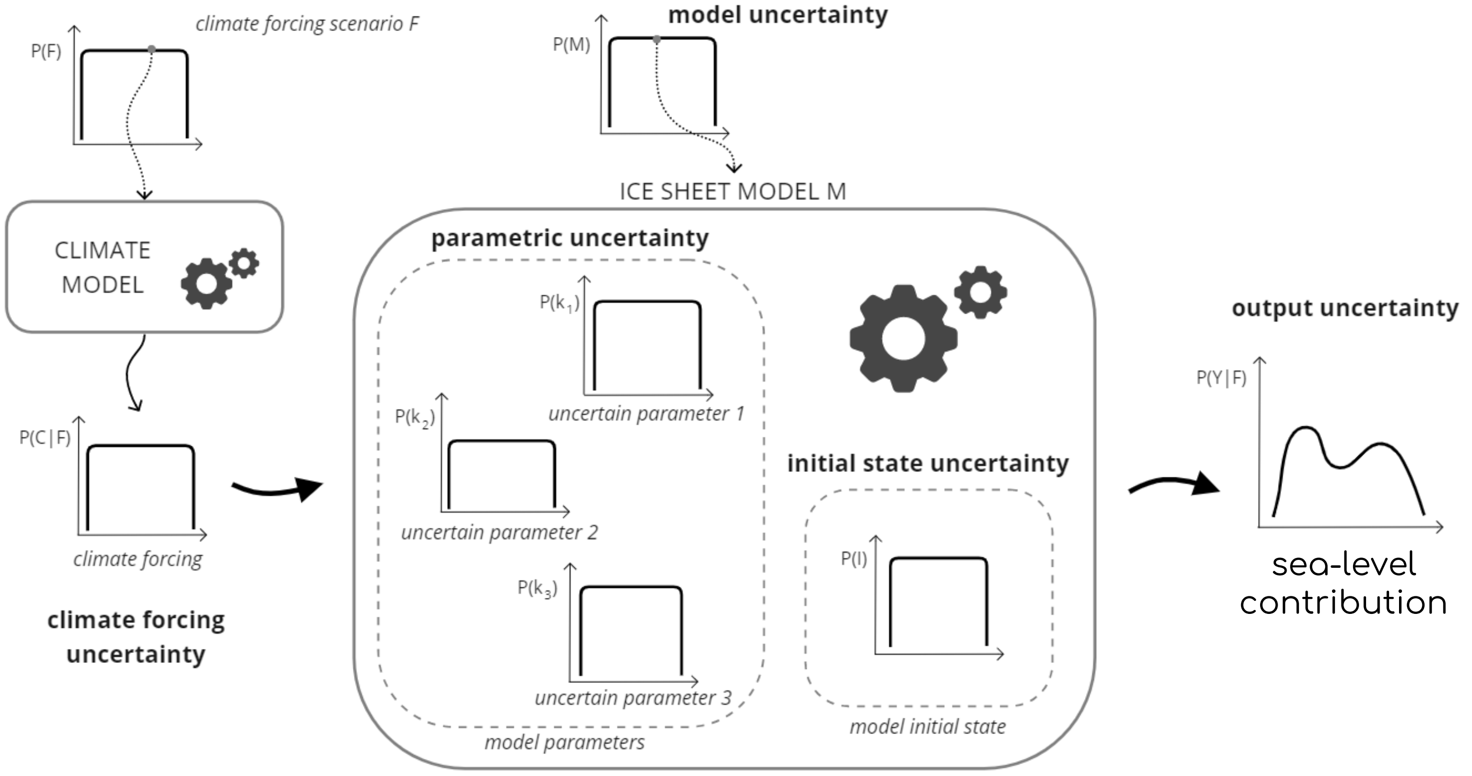
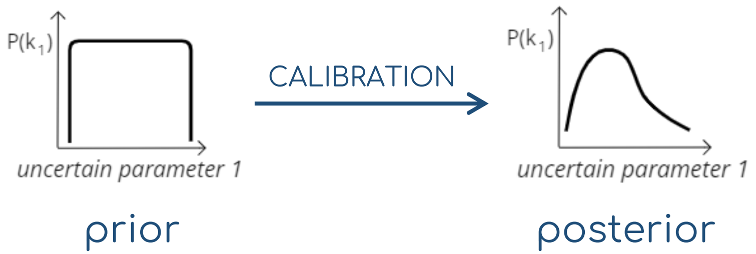


STEP 2: calibrate

After an initial guess, approximate the PDFs of the different sources of uncertainty according to how well the parameter space matches observations

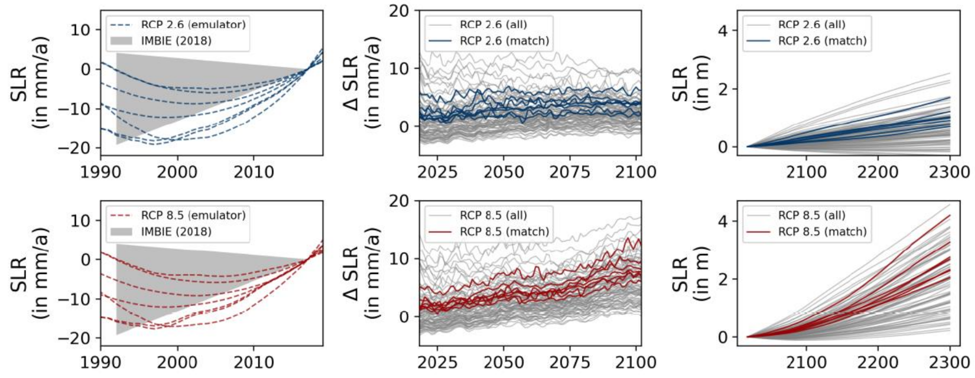


→ **Next step in a UQ framework**

Two alternative approaches to calibrate projections

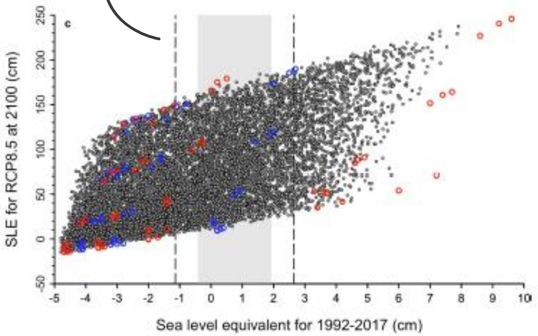
Two alternative approaches to calibrate projections

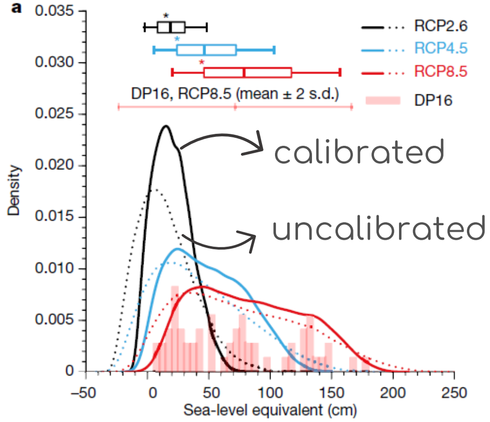
HISTORY MATCHING
rules out inadequate values of the parameters (i.e., ensemble members judged too dissimilar to observations)



Lowry et al. (2021)

Threshold for implausibilility





calibrated

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Edwards et al. (2019)

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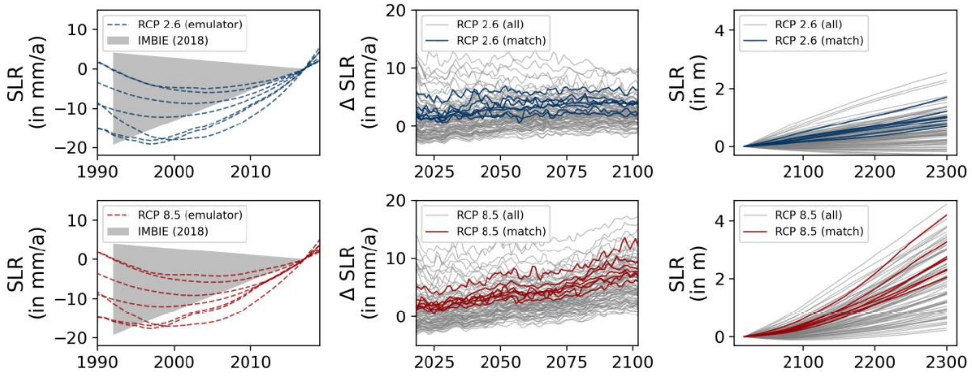

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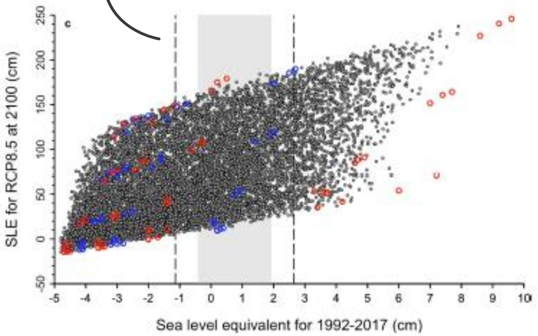

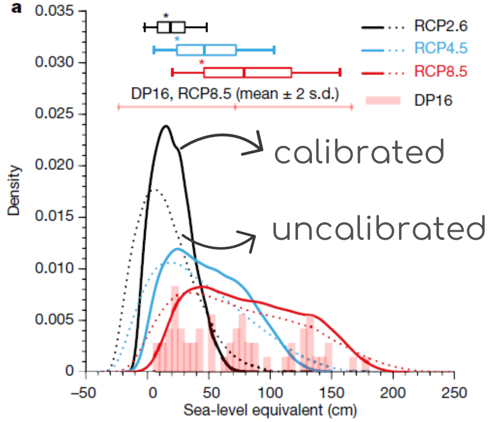

calibrated

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BAYESIAN CALIBRATION

weights ensemble members according to their distance from observations

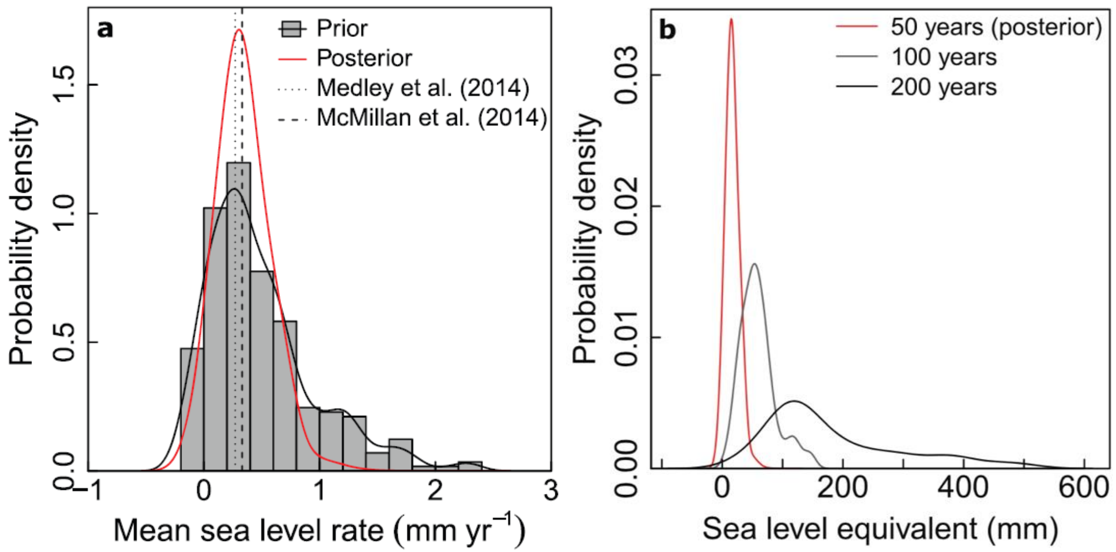
BAYES' THEOREM:

posterior

Likelihood function

$$P(Y|O) \propto P(O|Y)P(Y)$$

prior



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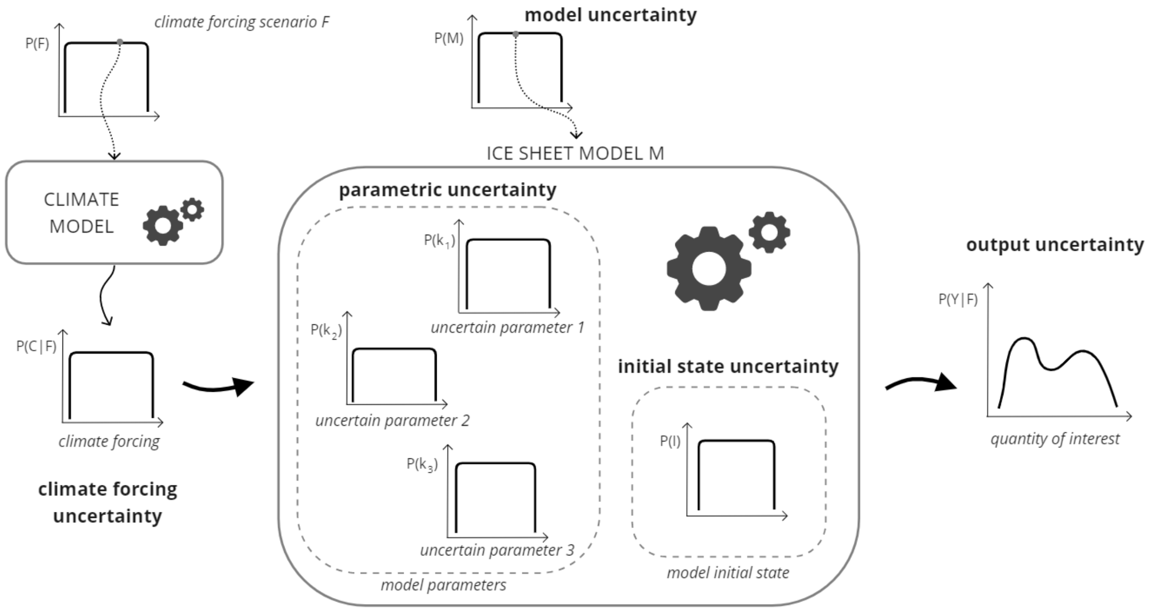

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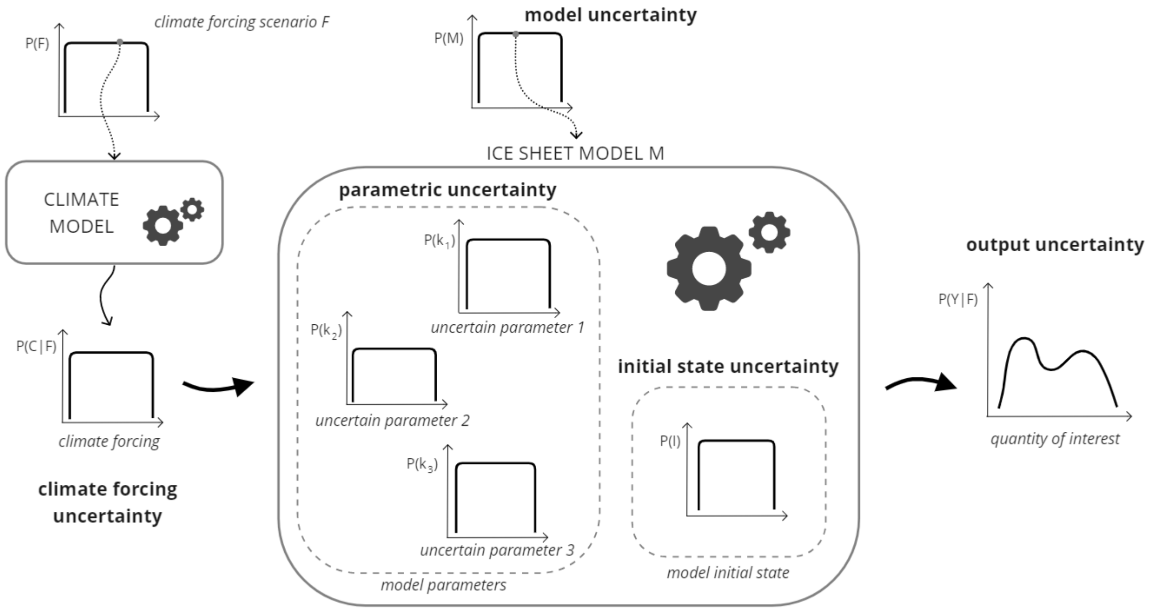

2 Observational constraints

Data used for the calibration: rates of ice sheet mass change
(IMBIE – Otosaka et al., 2023)

	WAIS (Gt/yr)	EAIS (Gt/yr)	Peninsula (Gt/yr)
1992 – 1996	-37 ± 19	-27 ± 33	-7 ± 11
1997 – 2001	-42 ± 19	21 ± 32	2 ± 11
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2007 – 2011	-129 ± 23	19 ± 36	-21 ± 12

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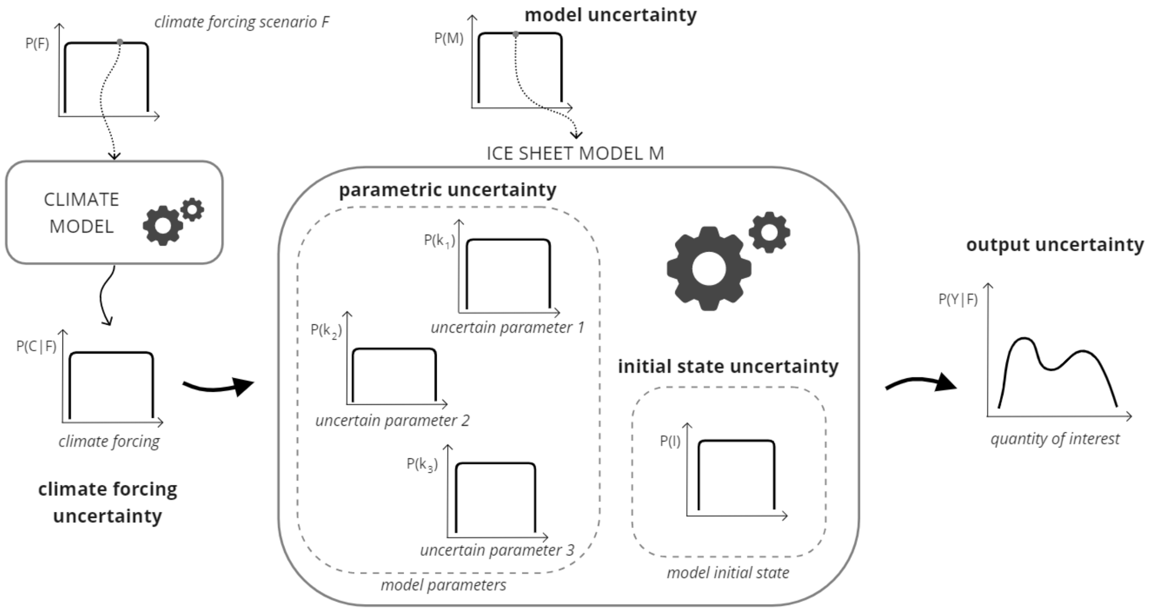

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3 Gaussian likelihood function

similar to, e.g., Nias et al. (2019), Bevan et al. (2023)

$$s_j = \exp\left(-\frac{1}{2}\sum_{i=1}^{N_{\text{obs}}}\left(\frac{\text{mod}_i^j - \text{obs}_i}{\sigma_i}\right)^2\right)$$

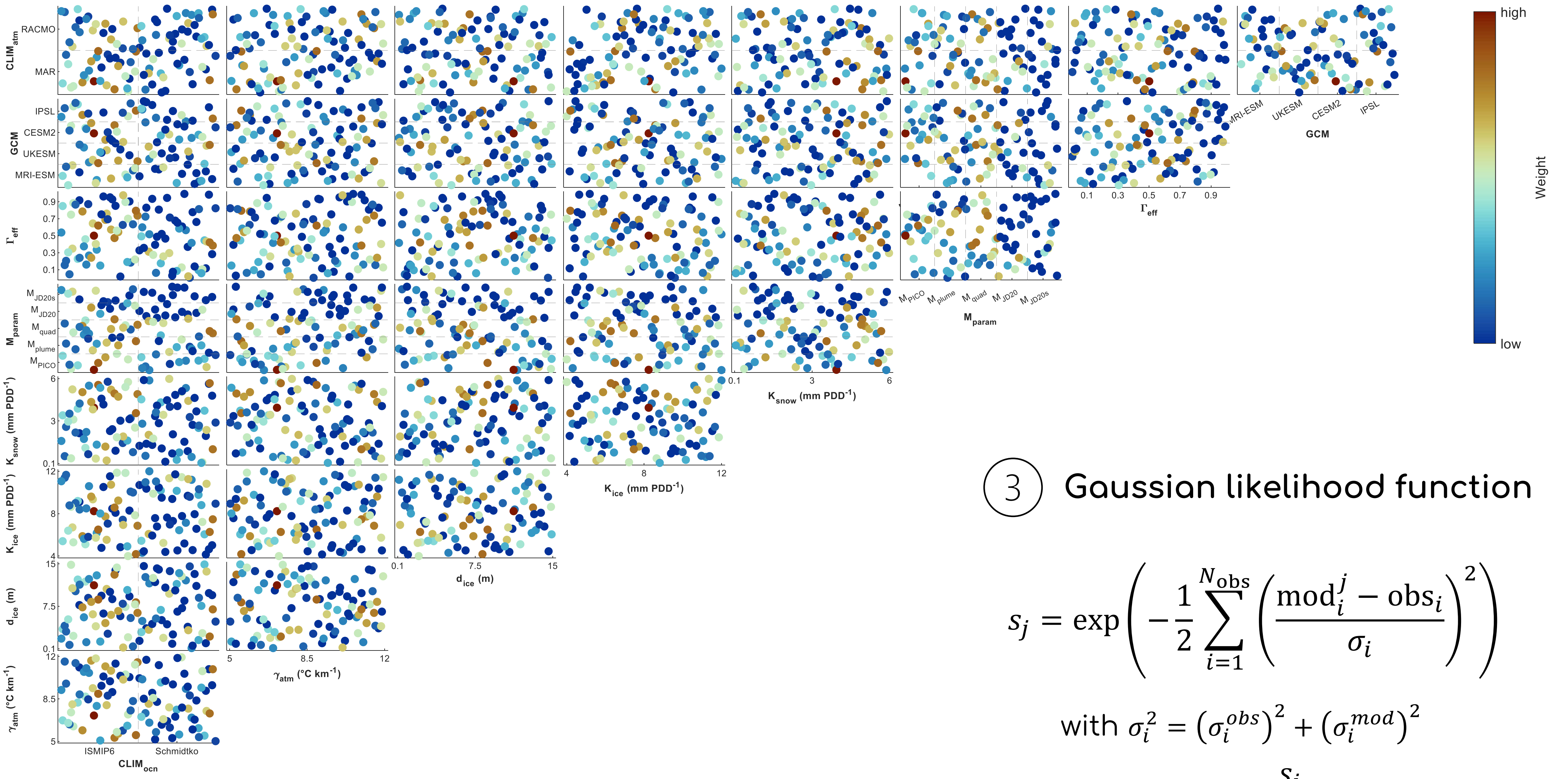
with $\sigma_i^2 = \left(\sigma_i^{obs}\right)^2 + \left(\sigma_i^{mod}\right)^2$

Discrepancy variance

$$w_j = \frac{s_j}{\sum s_j}$$

$\sigma_i^{mod} = 8\sigma_i^{obs}$

An example case: Coulon et al. (2023)



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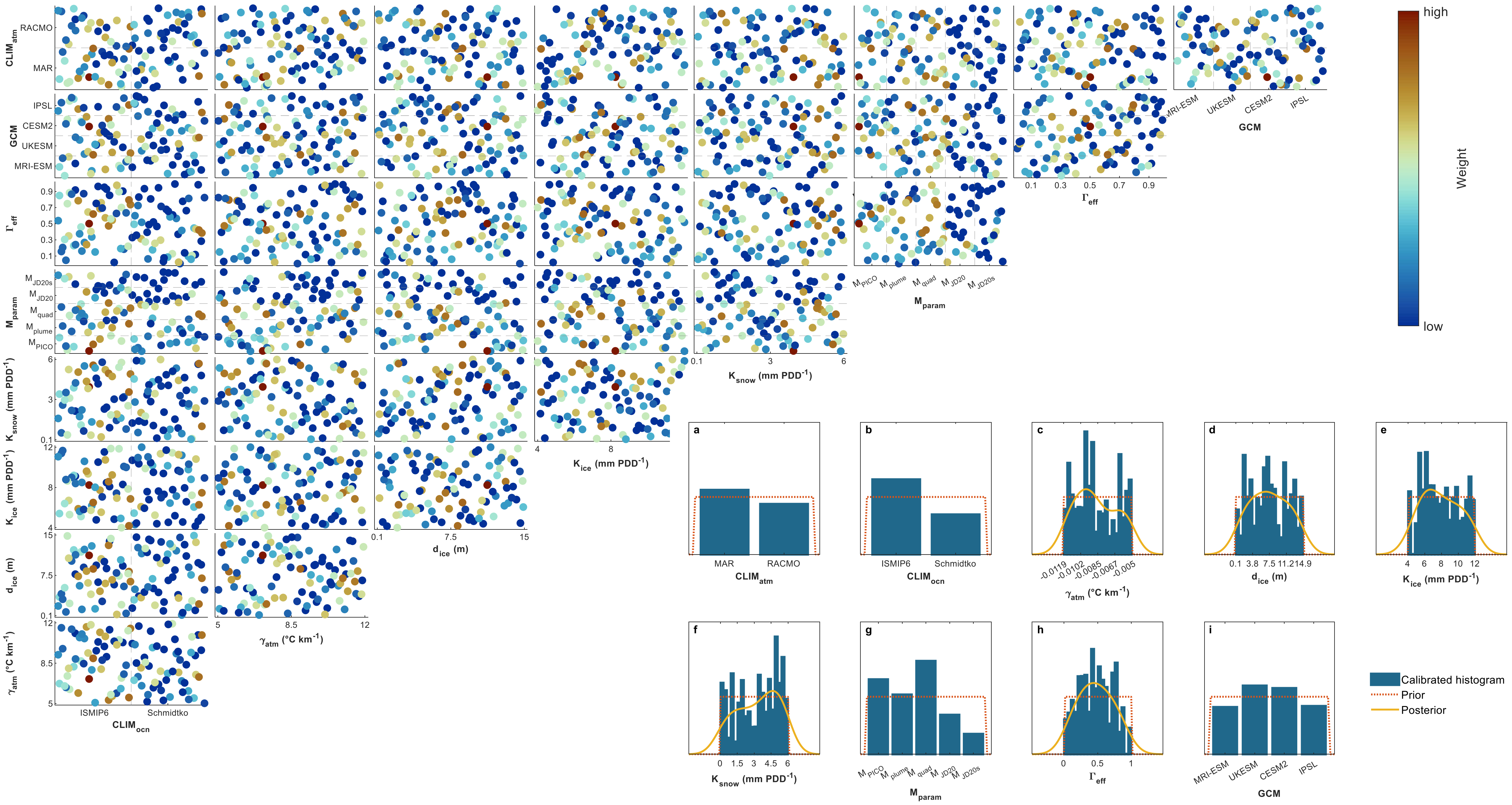

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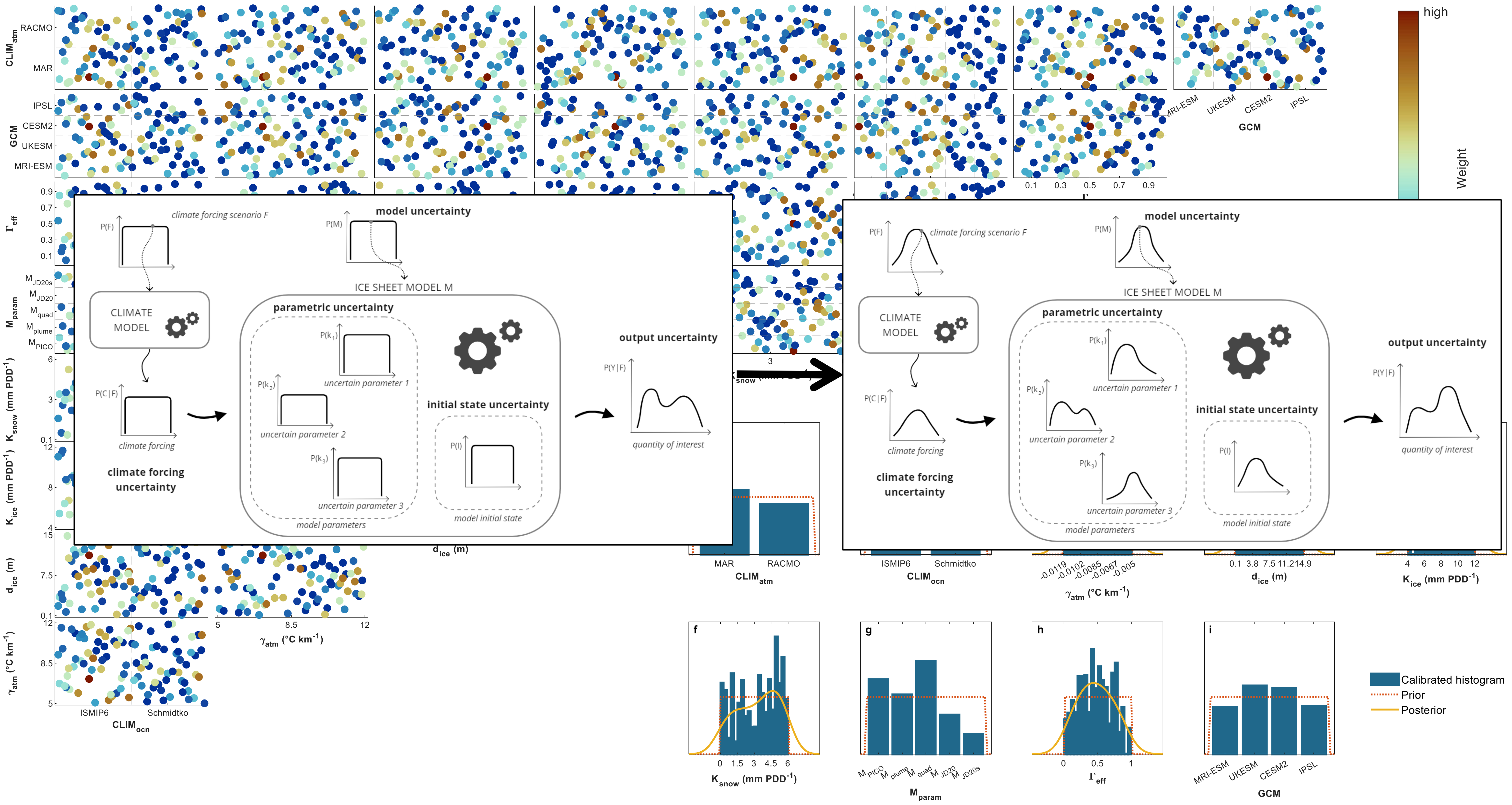
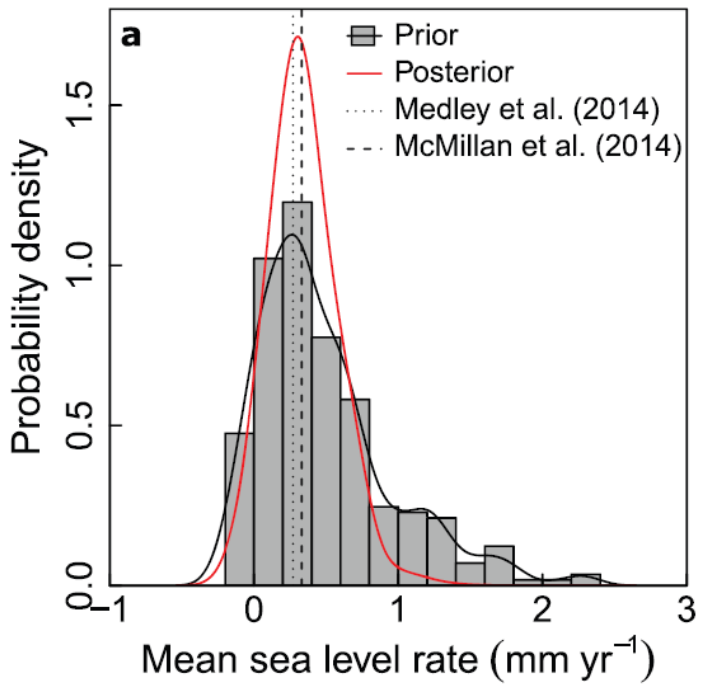


Calibrating allows to reduce the spread in ice-sheet response



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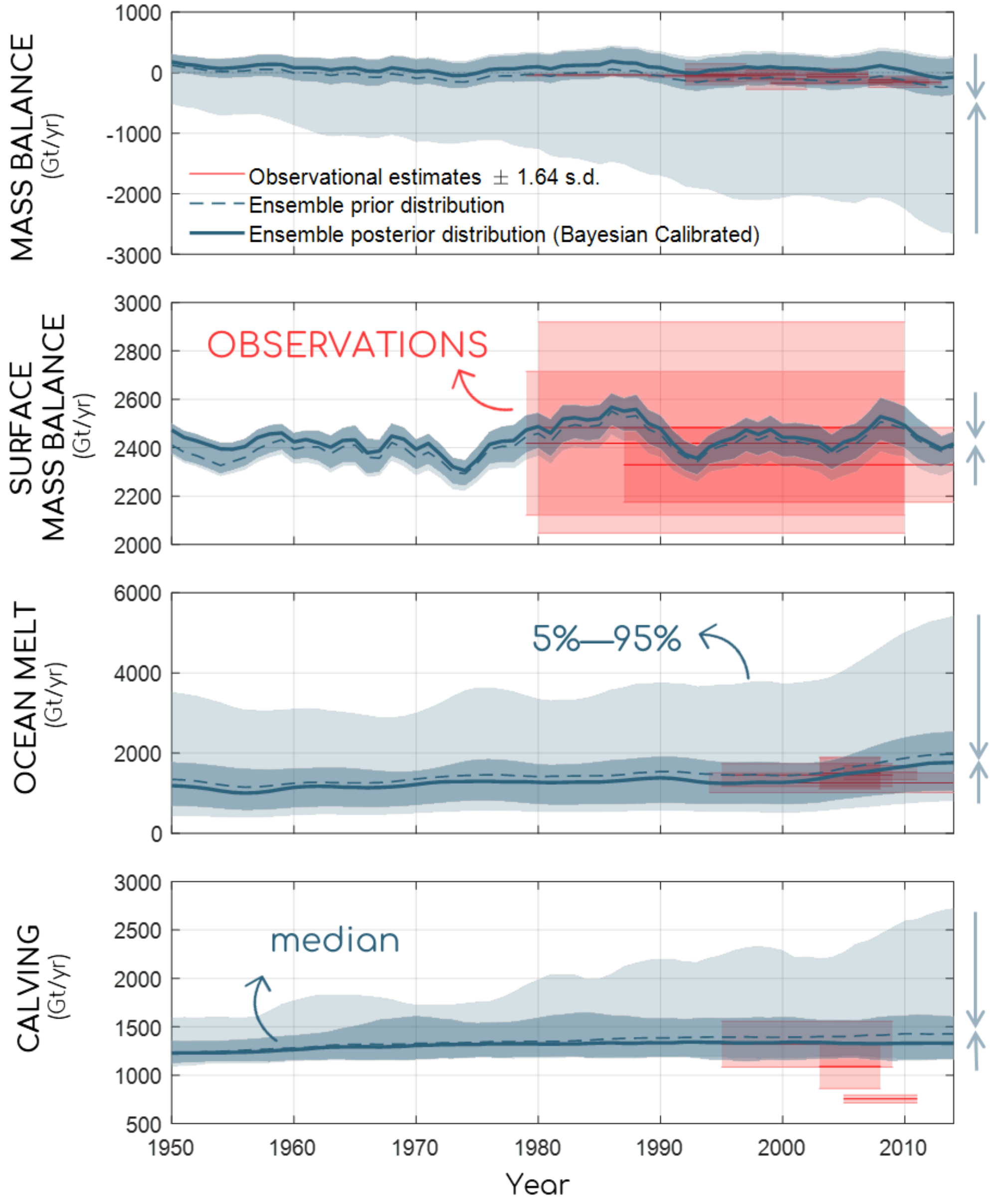

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HINDSCASTS

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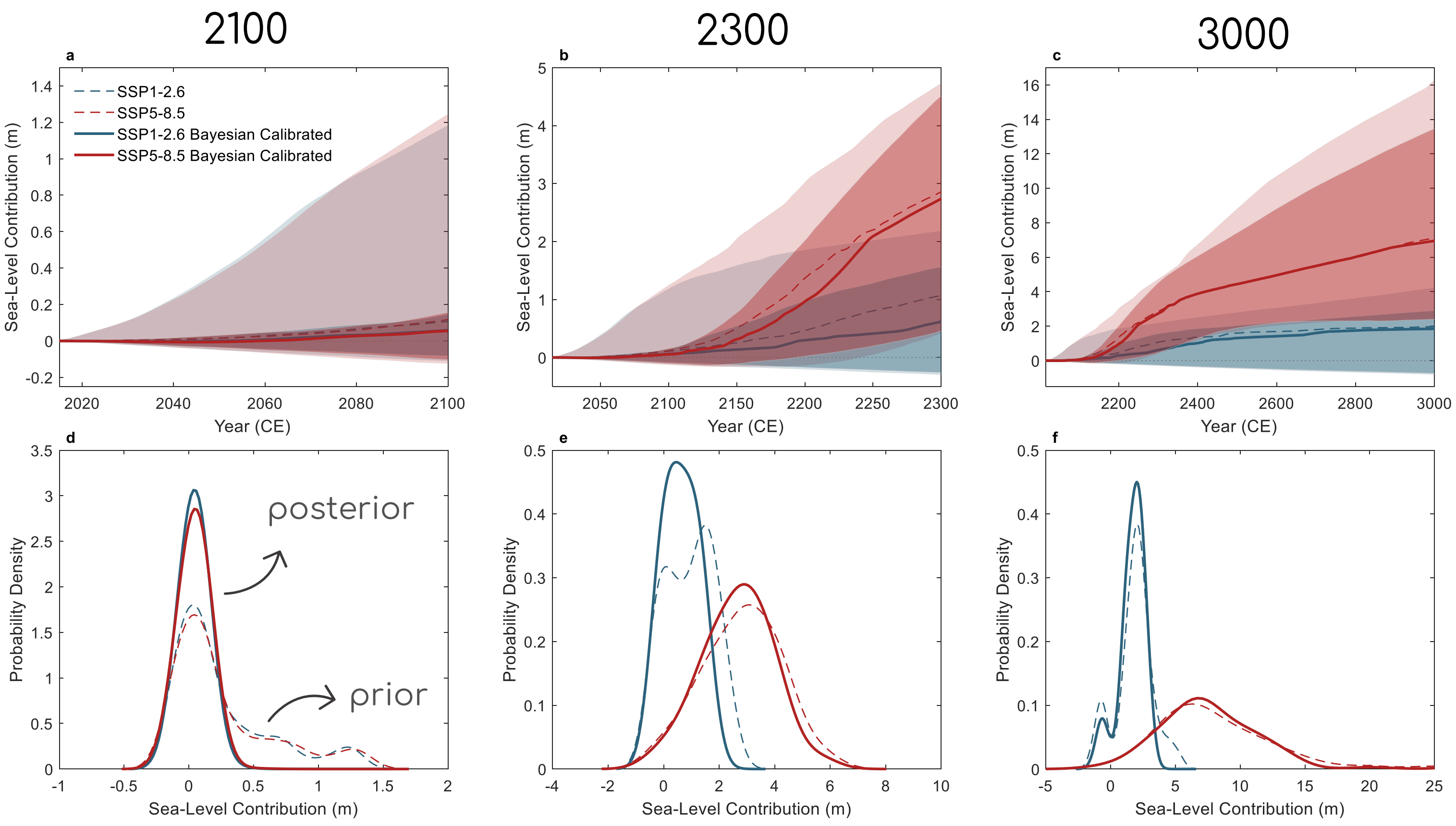

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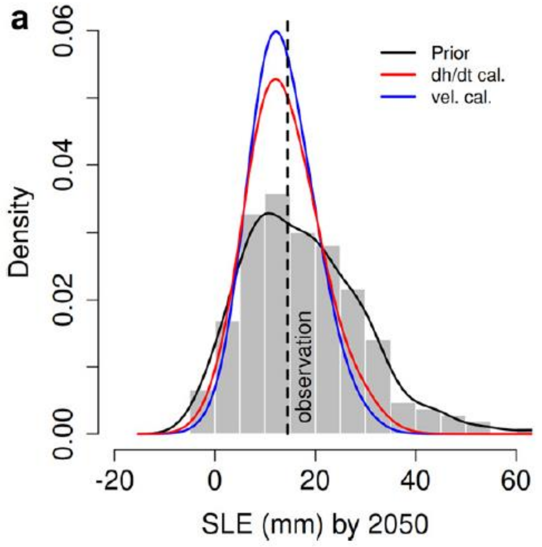
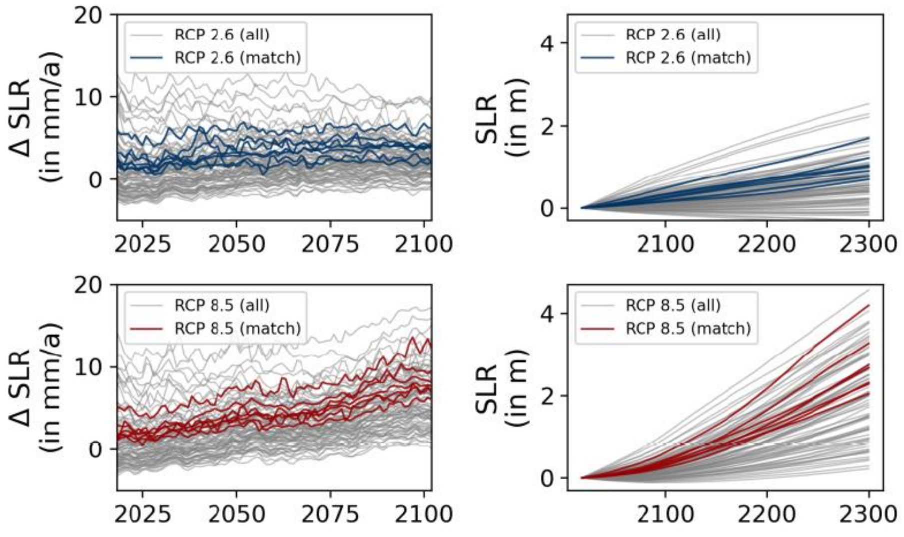


Bevan et al. (2023)



Lowry et al. (2021)

PROJECTIONS

One big challenge of calibration: simulations need to start in the past..

PROBLEM: **reproducing the past is difficult!**

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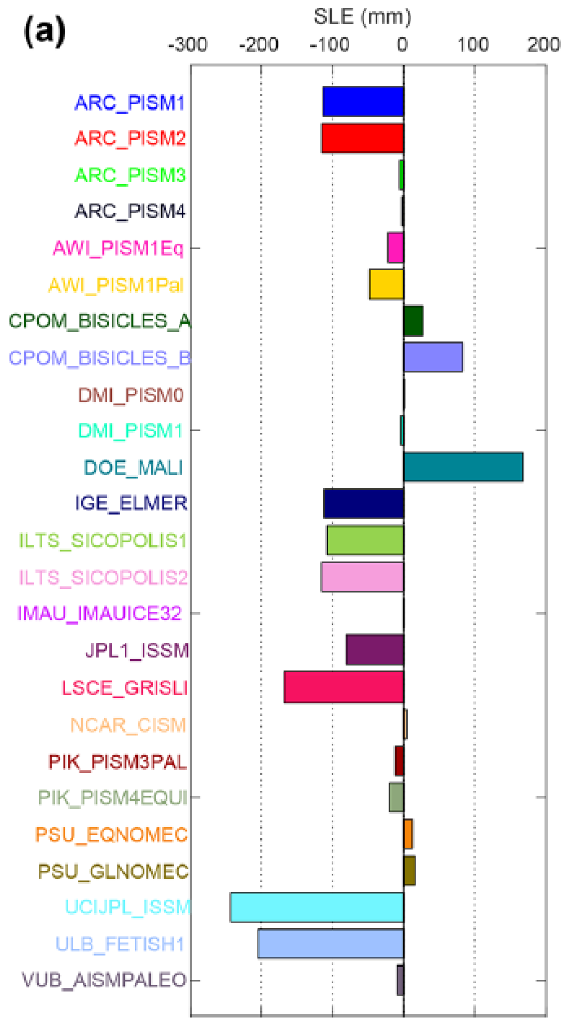
PROBLEM: **reproducing the past is difficult!**

One of the culprits: the initialisation

- Small mass balance signal over the historical period
- Requires limited model drift/noise



initMIP-Antarctica ctrl experiment
Seroussi et al. (2019)

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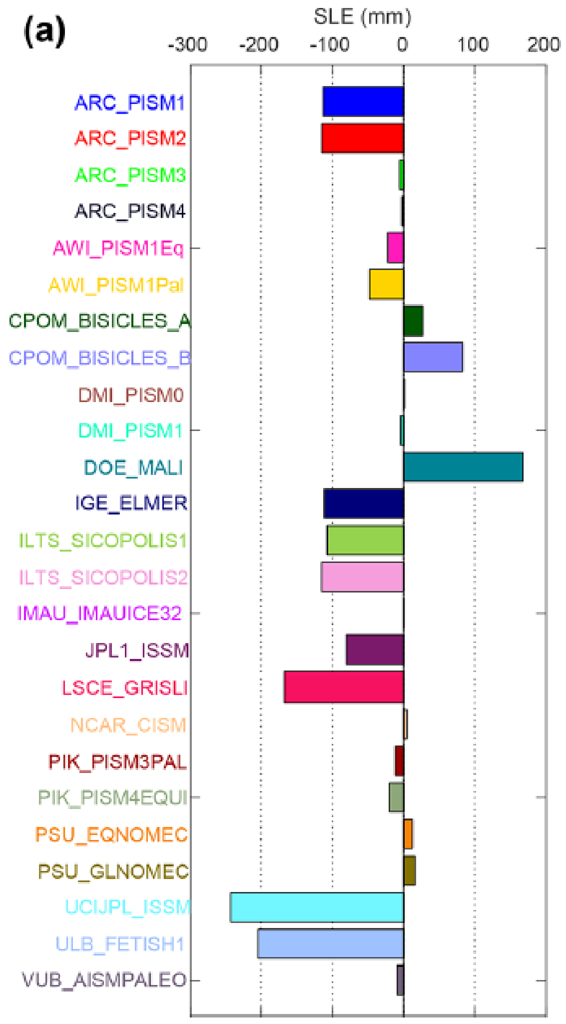
Some additional challenges/questions when producing historical hindcasts:

- How to initialise an ice-sheet model for a past unknown state?
- What forcing to use for the hindcasts
  - One single forcing as the ‘truth’, if yes, which one?
  - Forcing from several climate models and include in calibration?



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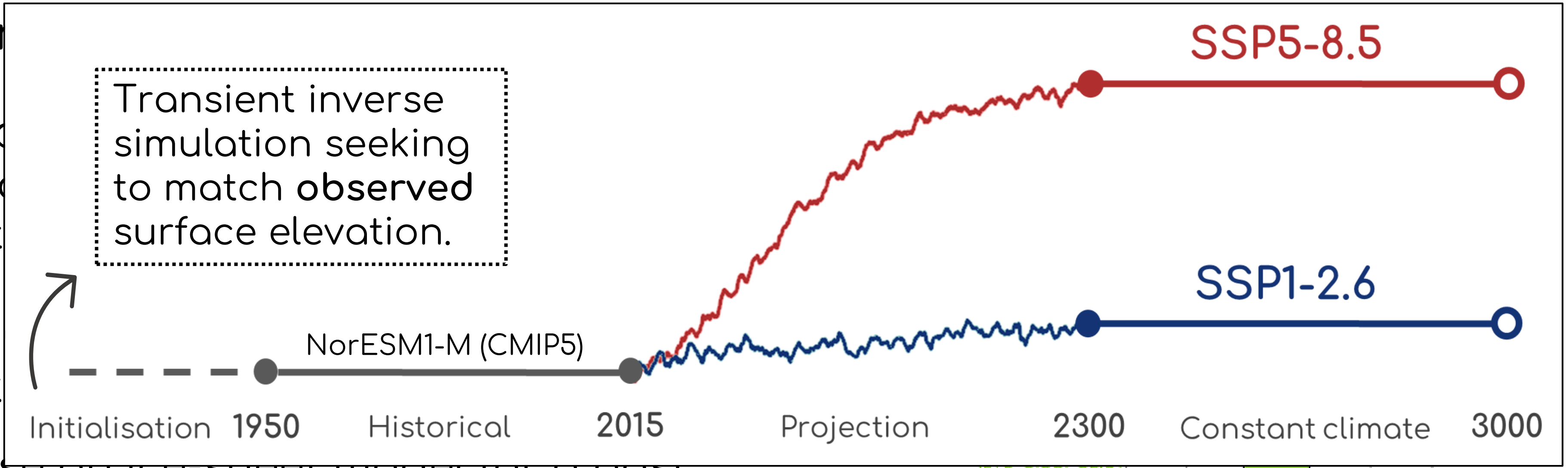

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- What forcing to use for the hindcasts
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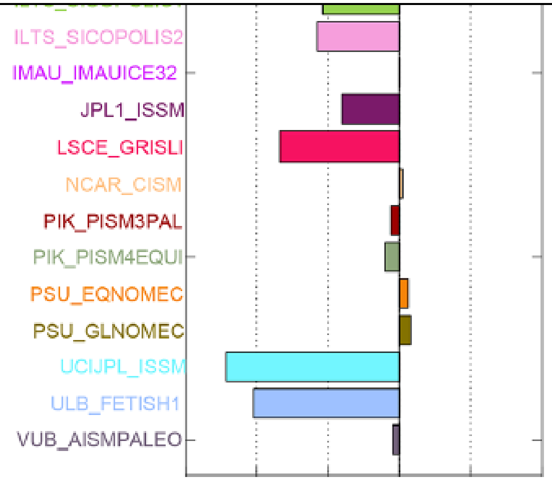
  - Forcing from several climate models and include in calibration?



initMIP-Antarctica ctrl experiment
Seroussi et al. (2019)

Other challenges of calibration…

- **A simulation may be evaluated as well-matching observations 'for the wrong reasons'**, i.e., it compensates for
  - some drift from the initialisation
  - biases in imposed climate forcing

  → assess the evolution of the sources of mass change

- **Precise satellite data only available for short modern periods**
  - Modern conditions may not reflect the future ones,
    i.e., simulations that do not match observations may yet better perform at reproducing the future

  → ensemble members that do not match the historical trends should not be discarded too strictly

- **We may be missing something**
  - Simulations may reproduce observations but lack accounting for processes that may be triggered in the future (e.g., MICI, …)

→ Avoid overfitting!

CONCLUSIONS

- Robust Antarctic projections should ideally
  1. Include as many sources of uncertainty as possible in a probabilistic framework
  2. Calibrate the simulations with observational constraints
- This is quite challenging:
  - Computation time, ensemble design, initialisation, historical forcing, …

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- We are making progress: AIS projections are increasingly
  - evaluated or calibrated with observations
  - designed to quantify uncertainties
    - Model intercomparison projects
    - Statistical emulation
    - Large ensembles with space-filling PPE

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    - evaluated or calibrated with observations
    - designed to quantify uncertainties
        - Model intercomparison projects
        - Statistical emulation
        - Large ensembles with space-filling PPE
- Next step/challenge:
  multi-model PPE starting in the past
    - ISMIP7
    - PROTECT
    - …

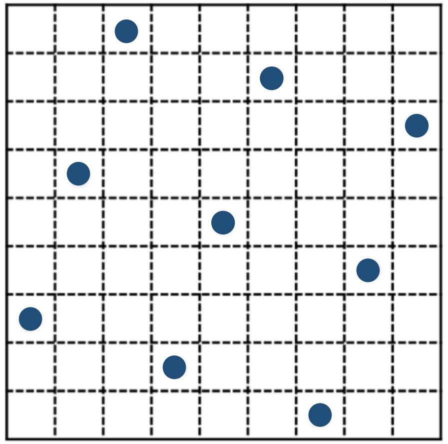
> ‘We propose for the future a ‘**grand ensemble’, designed across multiple, diverse ice-sheet models, that simultaneously and systematically samples parameters, structures, boundary conditions and initial conditions. Co-ordinated design** would enable multi-model emulation—a statistically rigorous method for interpreting and combining different model projections—to estimate probability distributions that account for structural uncertainties across multiple models.’

Edwards et al. (2019)

Thank you for your attention!

ADDITIONAL SLIDES

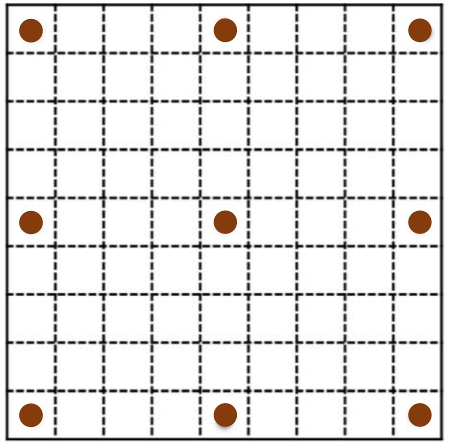
The challenges of a UQ framework



maximin Latin Hypercube

- ? divides the sample space of each variable into *n* evenly spaced regions
- ✓ spreads points efficiently throughout the input space
  → far better for building emulators
- ✓ does not require too many simulations (in contrast to, e.g., Monte Carlo sampling)
- ✗ Cannot be changed once defined

VS



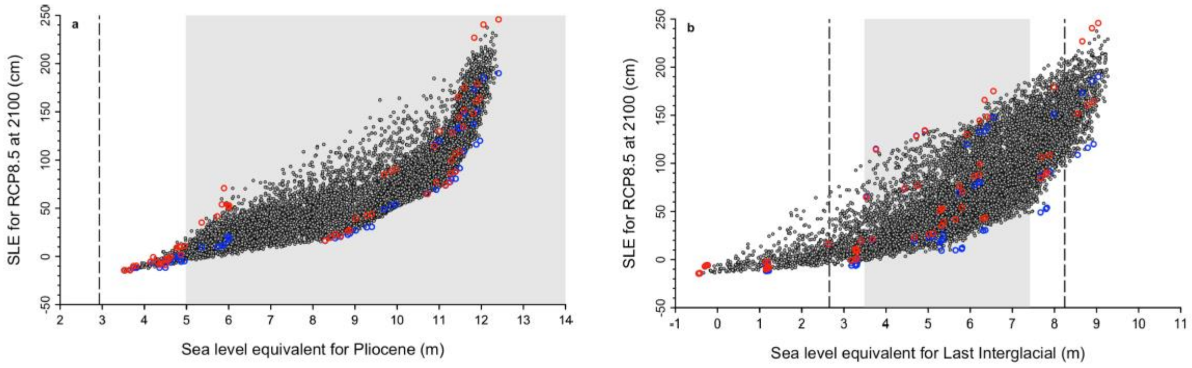
grid (factorial) design

- ? fixed values of each parameter are chosen and sampled in every combination
- ✗ Not a good coverage of input space
- ✓ Easy to isolate the effect of a process and understand its influence

→ Is UQ compatible/complementary with process understanding?

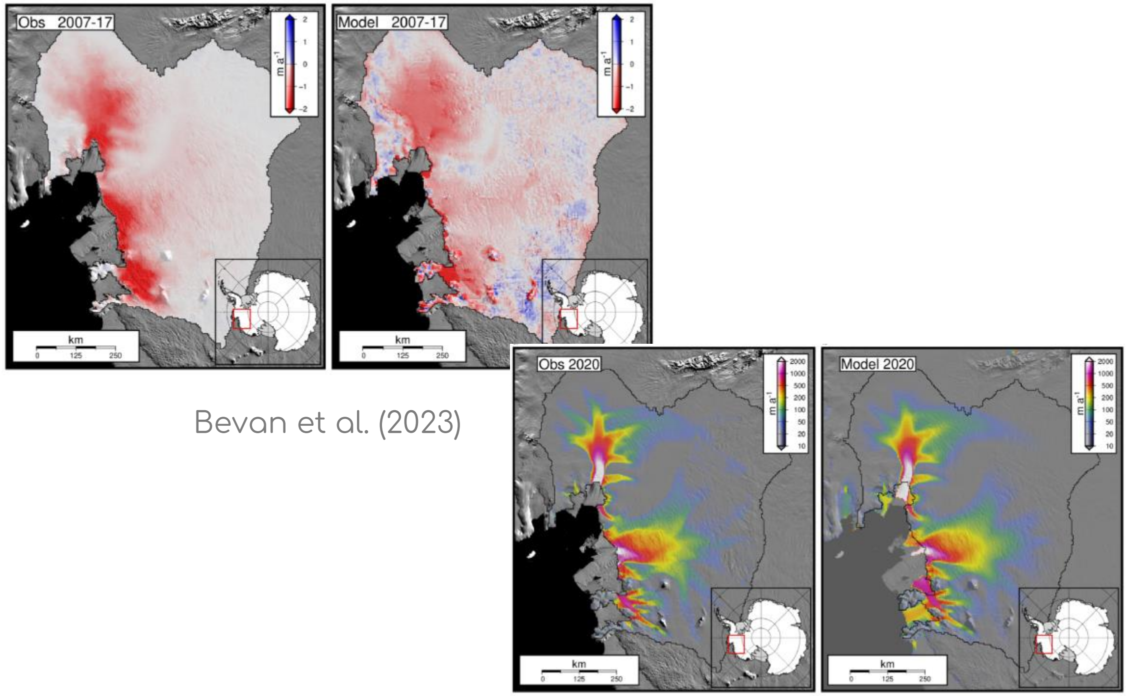
What data can we use for calibration ?

- **Paleo-constraints**
  - large variety of observational constraints (e.g., AntICE2)
  - sparse data in both time and space
  - covering periods of significant ice-sheet changes



Edwards et al. (2019)

- **Precise satellite data over the past decades**
  - e.g., surface elevation change, surface velocities, mass change
  - very short time period…
  - … with limited changes (non-linear changes, e.g., MISI and MICI, currently not observed)



Bevan et al. (2023)

avoid use of observational data
that have been used for the initialisation!

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  - ... (no MI

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EGUsphere

Choice of observation type affects Bayesian calibration of ice sheet model projections

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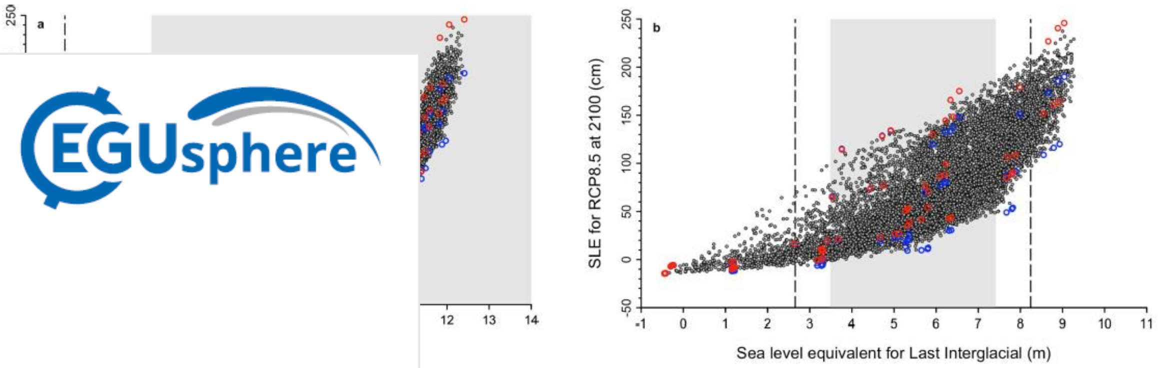
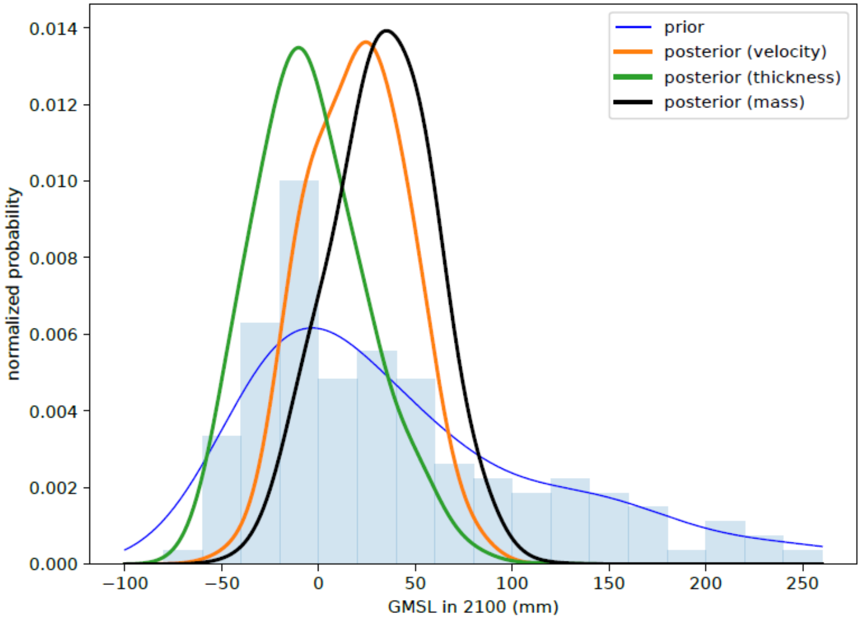
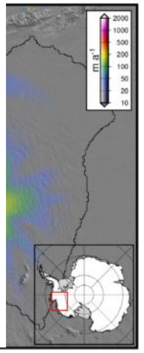


Edwards et al. (2019)



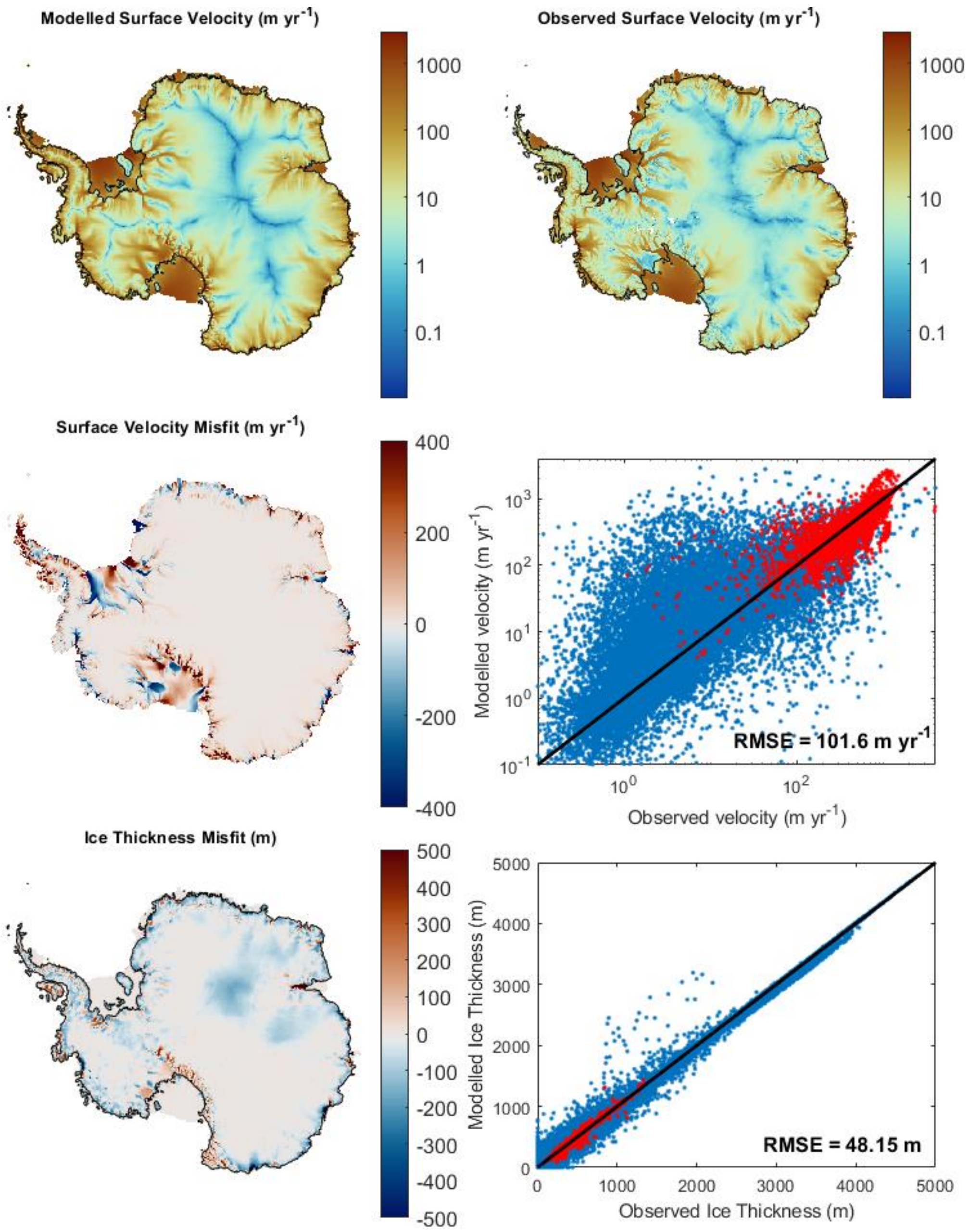


avoid use of observational data
that have been used for the initialisation!

An example case: Coulon et al. (2023)

1950-2014 hindcasts with Kori

- Initial state in year 1950 ($CLIM^{1995\text{-}2014}$ + aNorESM1-M)
    - **Transient inverse simulation** following Pollard&DeConto (2012) and Bernales et al. (2017)
        - **Basal sliding coefficients under grounded** ice and **sub-shelf melt rates under floating ice** obtained by solving an **inverse problem seeking to match observed surface elevation.**
        - Full model physics and freely moving grounding lines
    - ...until reaching a **steady-state**



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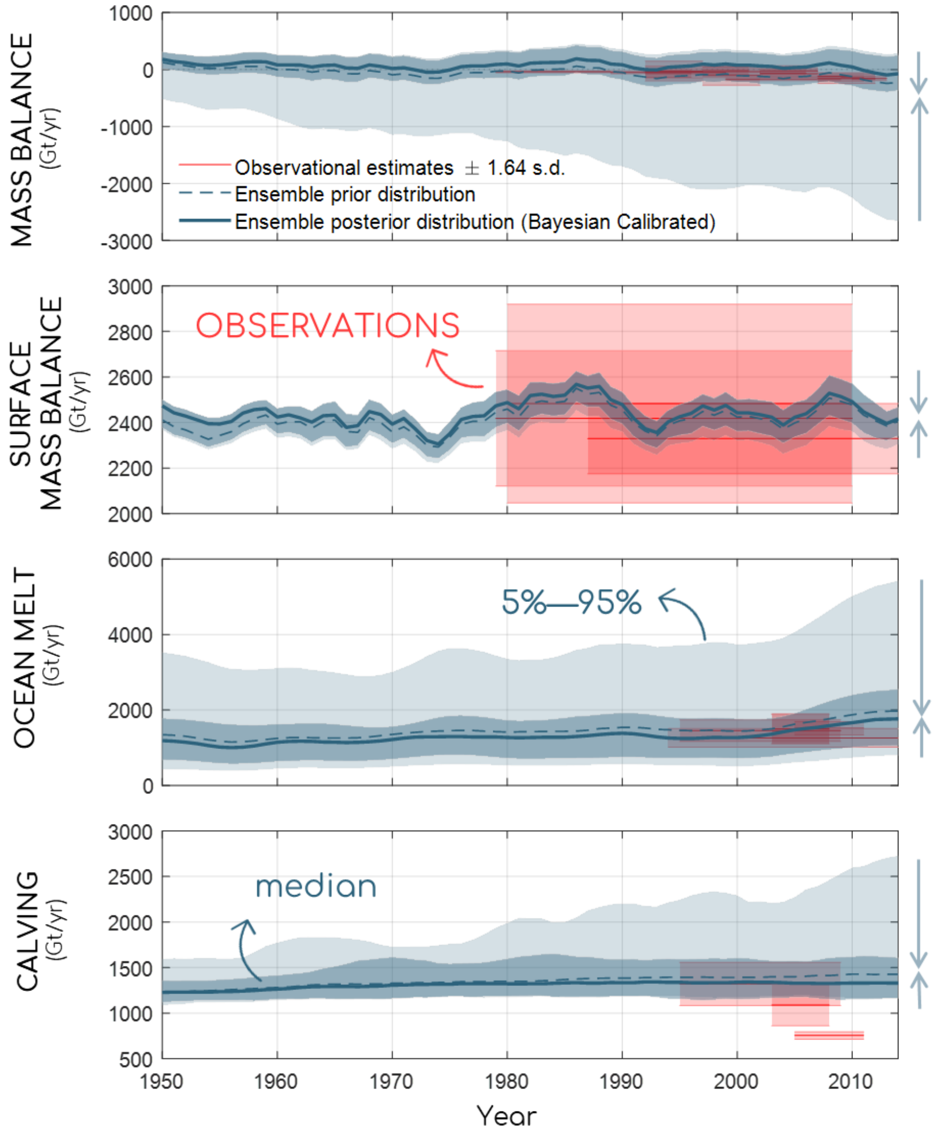
  - ...until reaching a **steady-state**
  - 10-year relaxation to limit shock caused by transition from balance sub-shelf melt rates to melt rates derived from a parameterisation
- Historical run using anomalies derived from CMIP5 NorESM1-M

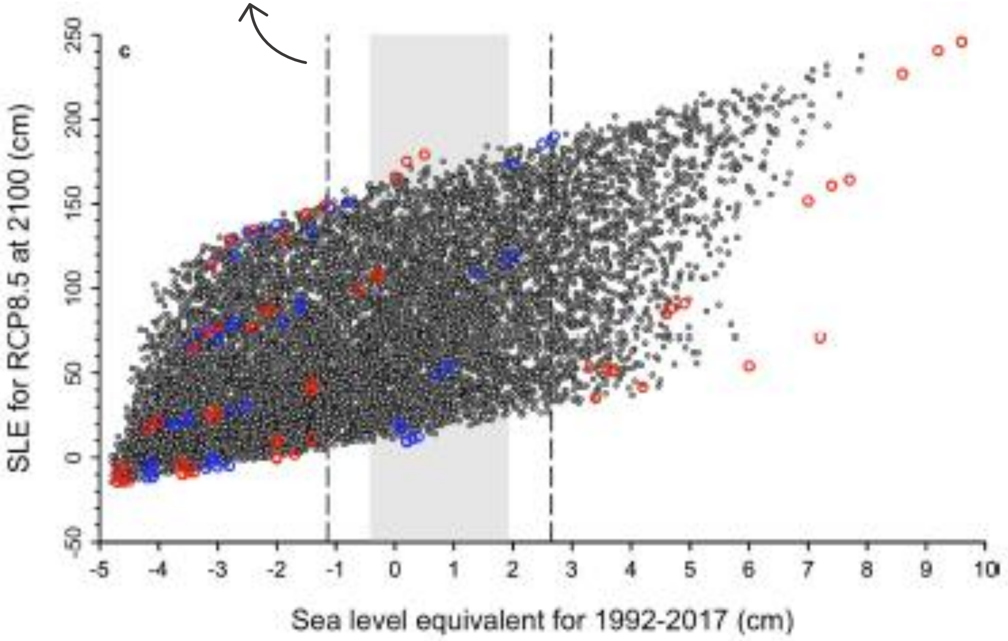


Validation of our hindcasts with observational estimates not used in the calibration

The importance of accounting for structural error

Any type of calibration should incorporate both observational and model errors
→ models are imperfect
→ even the best simulations would not be expected to match the observations perfectly

Threshold for implausibilility



Edwards et al. (2019)

$$P(Y|O) \propto P(O|Y)P(Y)$$

Likelihood function

$$s_j = \exp\left(-\frac{1}{2}\sum_{i=1}^{N_{\text{obs}}}\left(\frac{\text{mod}_i^j - \text{obs}_i}{\sigma_i}\right)^2\right)$$

with $\sigma_i^2 = \left(\sigma_i^{obs}\right)^2 + \left(\boldsymbol{\sigma_i^{mod}}\right)^2$

Discrepancy variance

The importance of accounting for structural error

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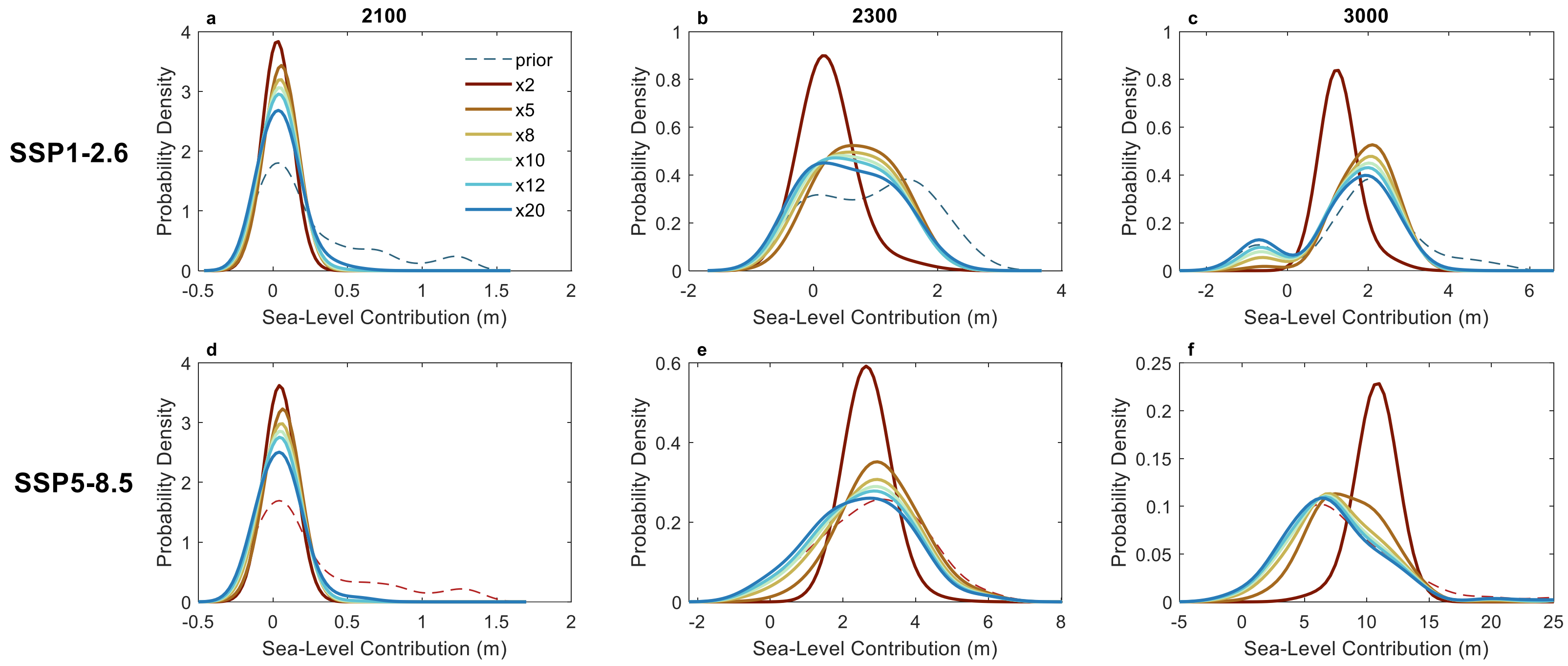

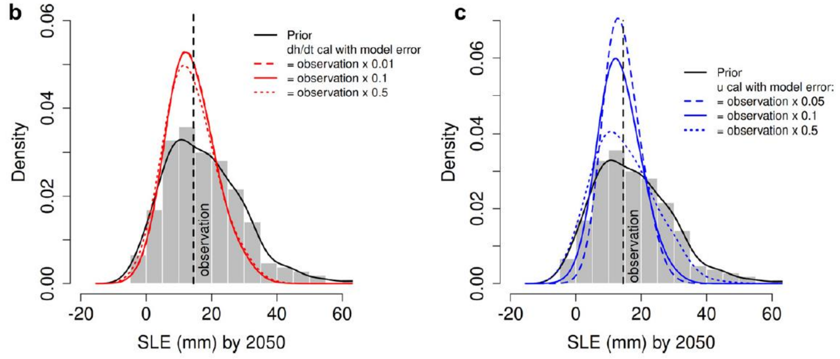

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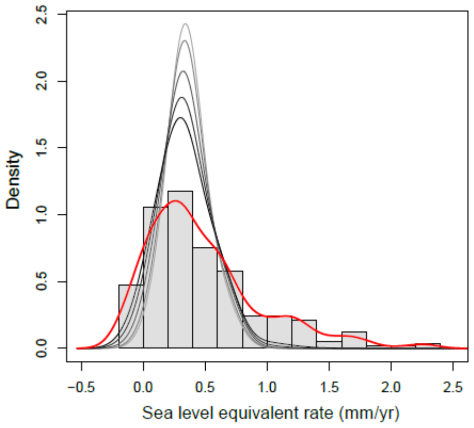

Nias et al. (2019)

Problem: arbitrary choice to be made..