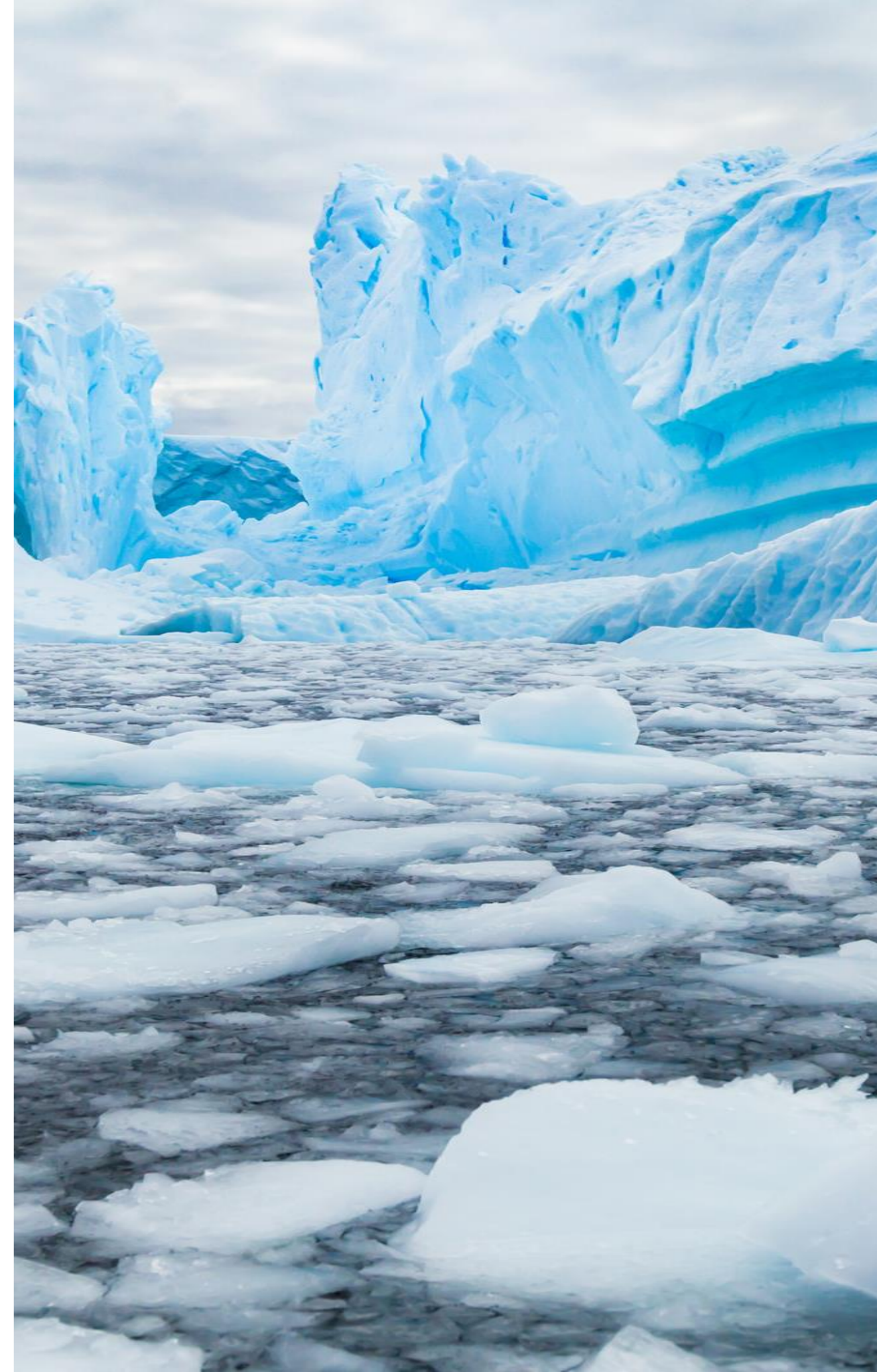


Improving interpretation of sea-level projections through a machine-learning-based local explanation approach

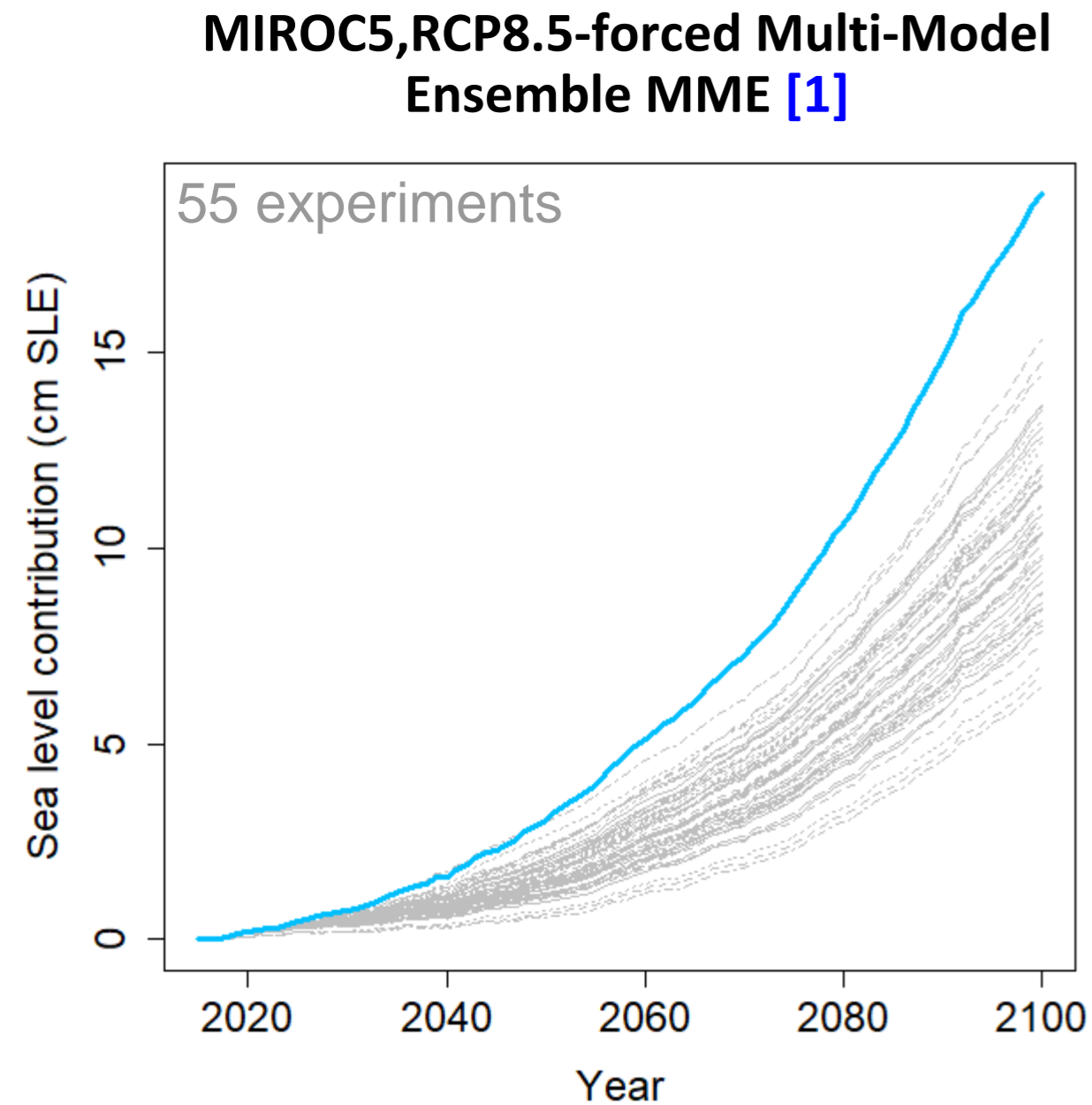
Jeremy Rohmer (BRGM), Remi Thieblemont (BRGM), Goneri Le Cozannet (BRGM), Heiko Goelzer (NORSAR), Gael Durand (IGE)



Motivation

“What is ‘easily explained’ with **words** is expected to increase the end-user’s level of **trust in the model**”

Sea-level projections for the Greenland ice sheet (GrIS) within ISMIP6



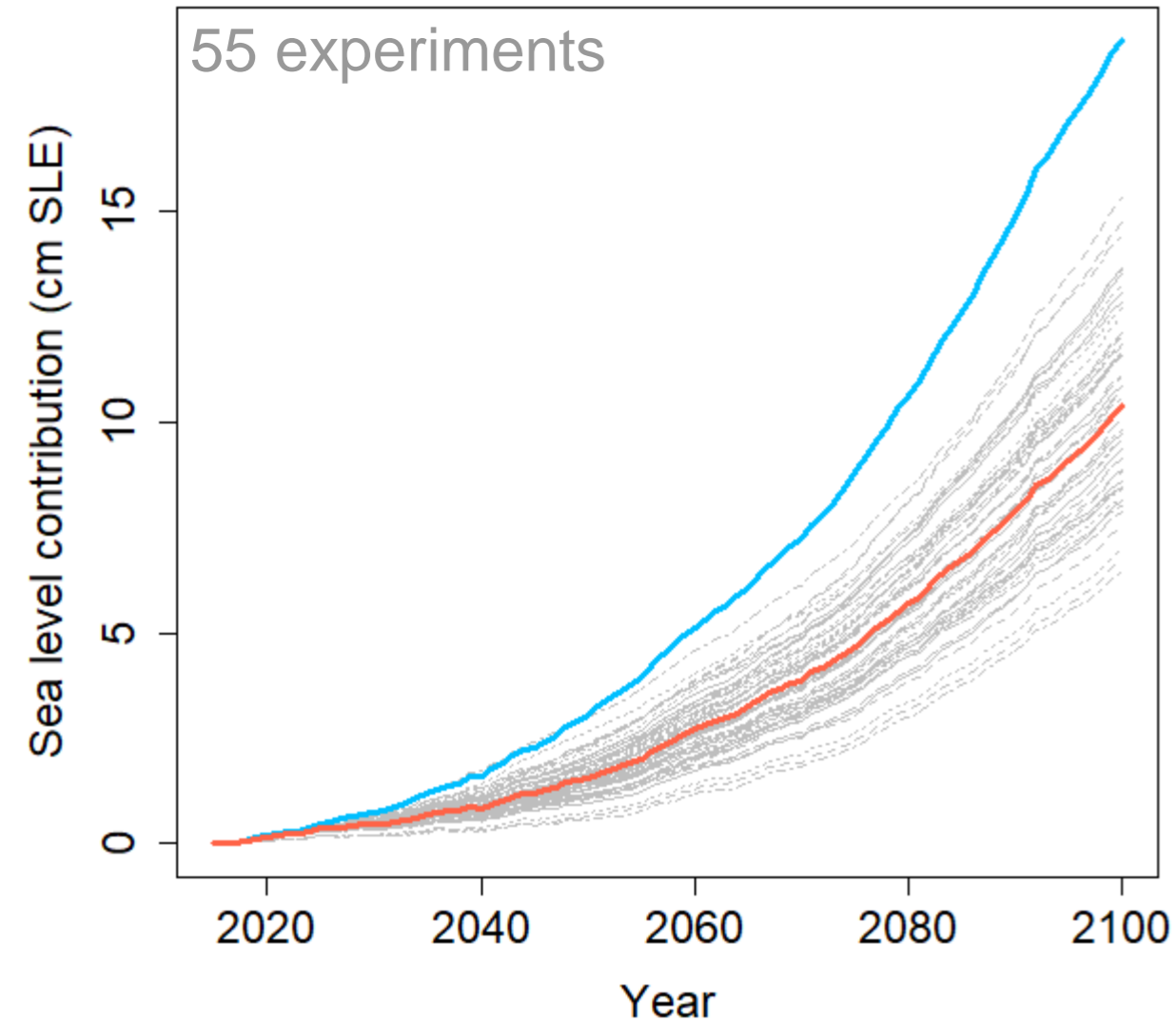
Experiment 1

Modelling choices

- **Numerical method** = Finite Difference (FD)
- **Ice Flow type** = shallow-ice approximation (SIA)
- **Type of initialization** = nudging to ice mask (NDm)
- **Min. grid size (resolution)** = 16km
- **Initial surface mass balance (SMB)** = RACMO anomalies (RA)
- **Retreat parameter** $\kappa = -0.9705 \text{ km (m}^3\text{.s}^{-1}\text{)}^{-0.4} \text{ }^{\circ}\text{C}$

Sea-level projections for the Greenland ice sheet (GrIS) within ISMIP6

MIROC5,RCP8.5-forced Multi-Model
Ensemble MME [1]



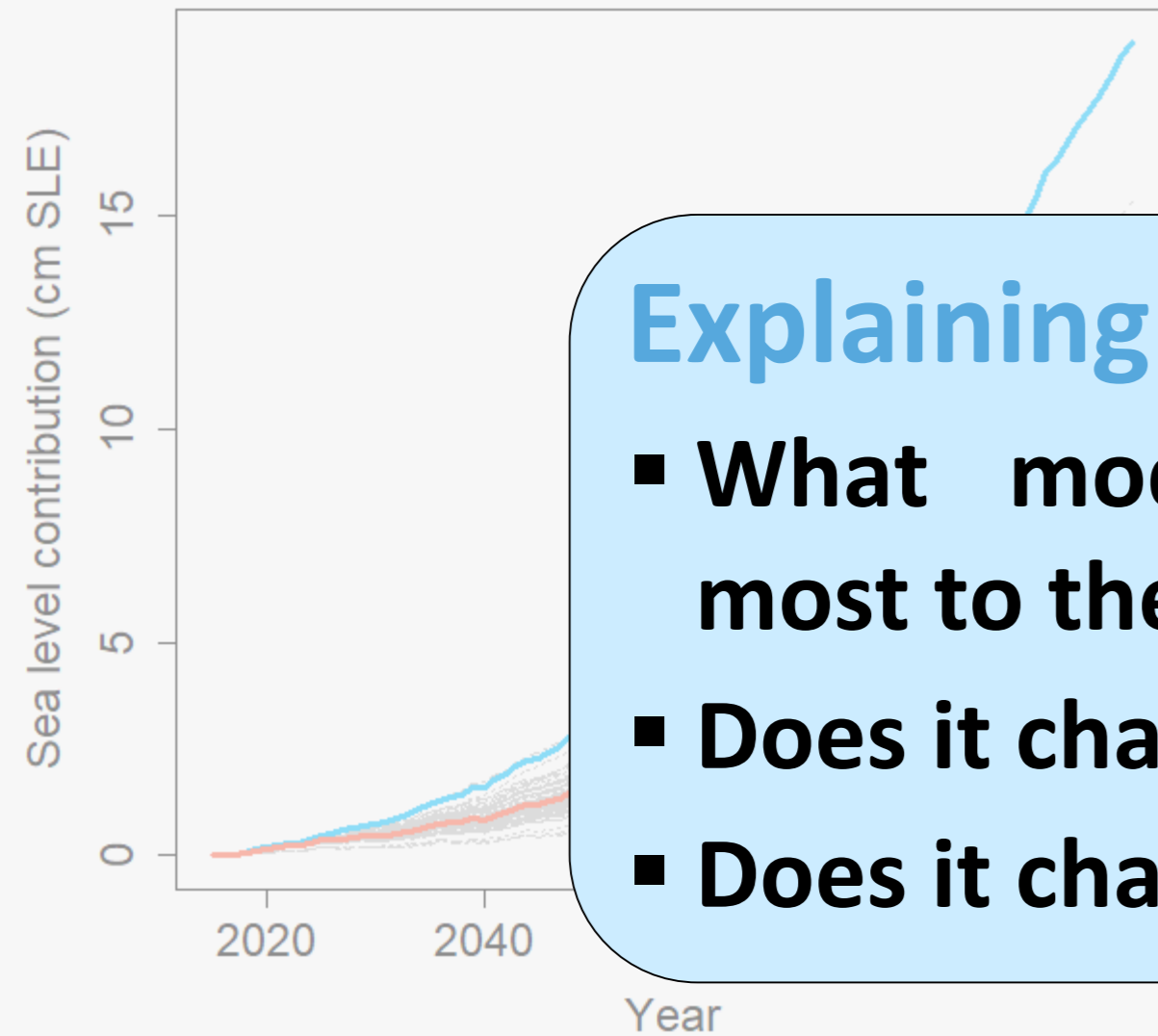
Experiment 2

Modelling choices

- **Numerical method** = Finite Difference (FD)
- **Ice Flow type** = shallow-ice approximation (SIA)
- **Type of initialization** = nudging to ice mask (NDm)
- **Min. grid size (resolution)** = 16km
- **Initial surface mass balance (SMB)** = RACMO anomalies (RA)
- **Retreat parameter** $\kappa = -0.06 \text{ km (m}^3\text{.s}^{-1})^{-0.4} \text{ }^{\circ}\text{C}$

...Etc...

Sea-level projections for the Greenland ice sheet (GrIS) within ISMIP6



Explaining the projections:

- What modelling assumptions contribute the most to the sea level value?
- Does it change from one experiment to another?
- Does it change over time?

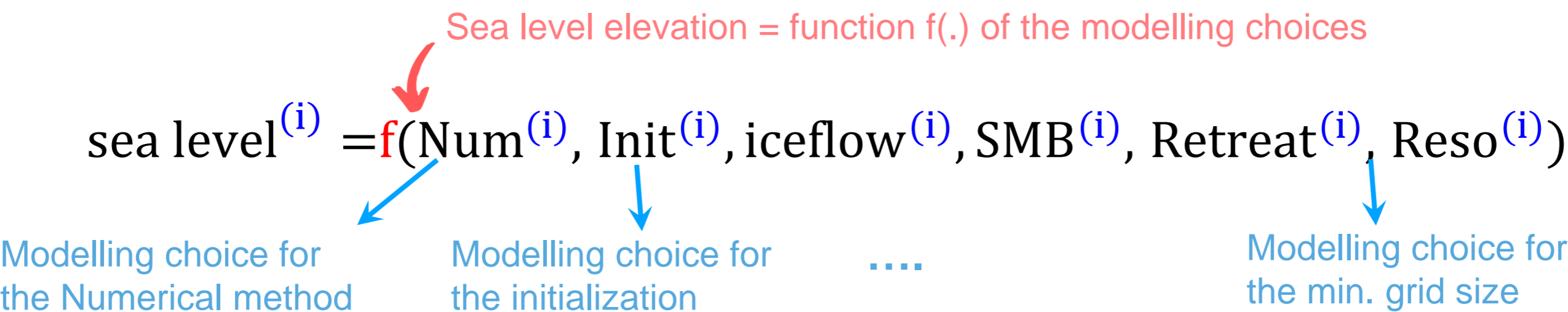


...Etc...

Methods

Local explanation approach

For each experiment (i)




Objective:


$$\text{sea level}^{(i)} = \mu_0 + \mu_{\text{Num}^{(i)}} + \mu_{\text{Init}^{(i)}} + \mu_{\text{iceflow}^{(i)}} + \mu_{\text{SMB}^{(i)}} + \mu_{\text{Retreat}^{(i)}} + \mu_{\text{Reso}^{(i)}}$$

‘additive’ contribution of each input to the seal level value
= influence of the modelling choice

Difficulties

1 $f(\cdot)$ is a **complex** chain of numerical models 

2 $f(\cdot)$ is long running, and the number of experiments is **limited** 

3 Design of experiments is **unbalanced** + **dependence** betw. the inputs 

Proposed method

Approximate $f(\cdot)$ by a **Machine Learning ML** [1]
model $\tilde{f}(\cdot)$

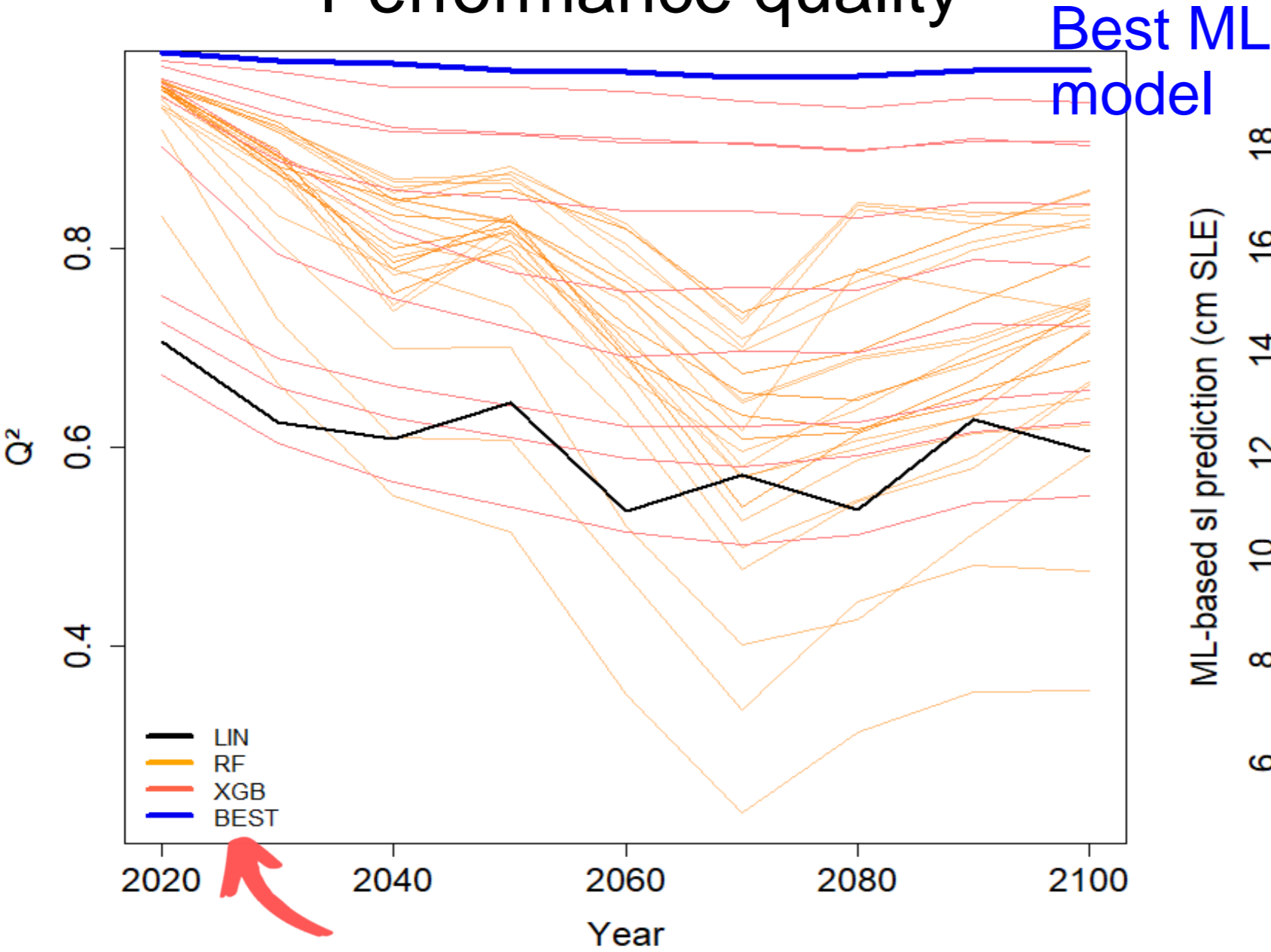
Use tools of **XAI***:

decompose the ML predictions
using SHAP **local attribution**
approach [2,3]

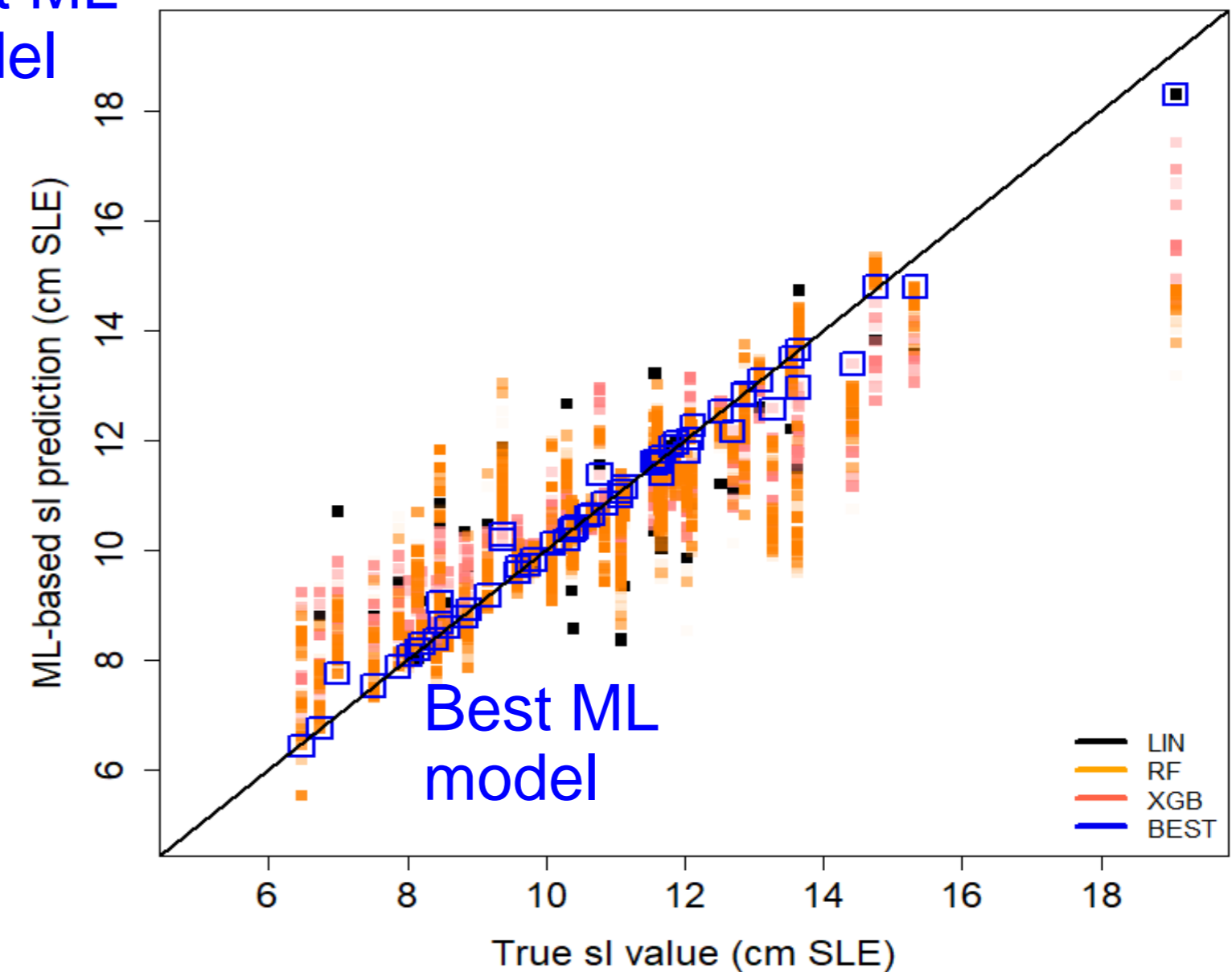
\approx regression coefficients with
accounts for **dependence between**
inputs

Validation of using the machine learning (ML) model

10-fold Cross validation
Performance quality

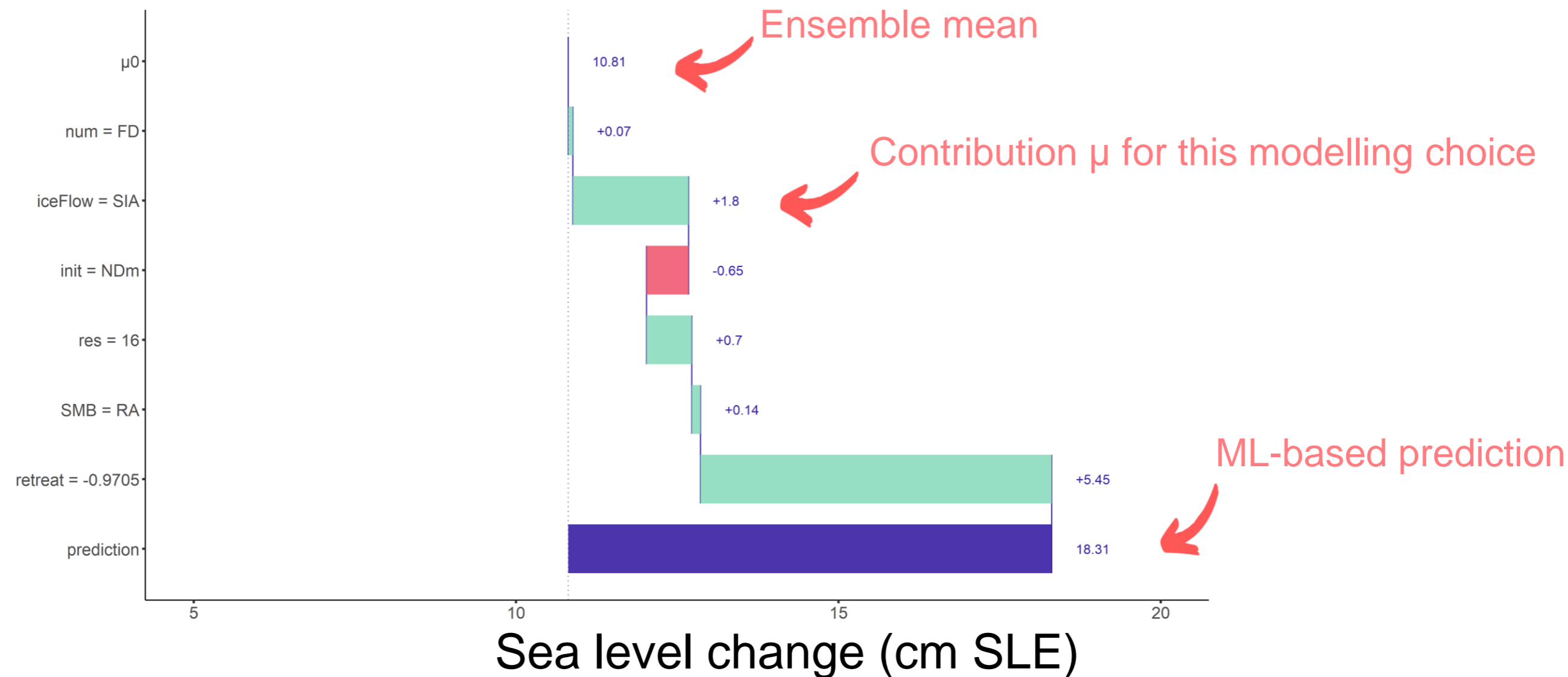


For 2100



Application

Experiment (1), prediction time = 2100

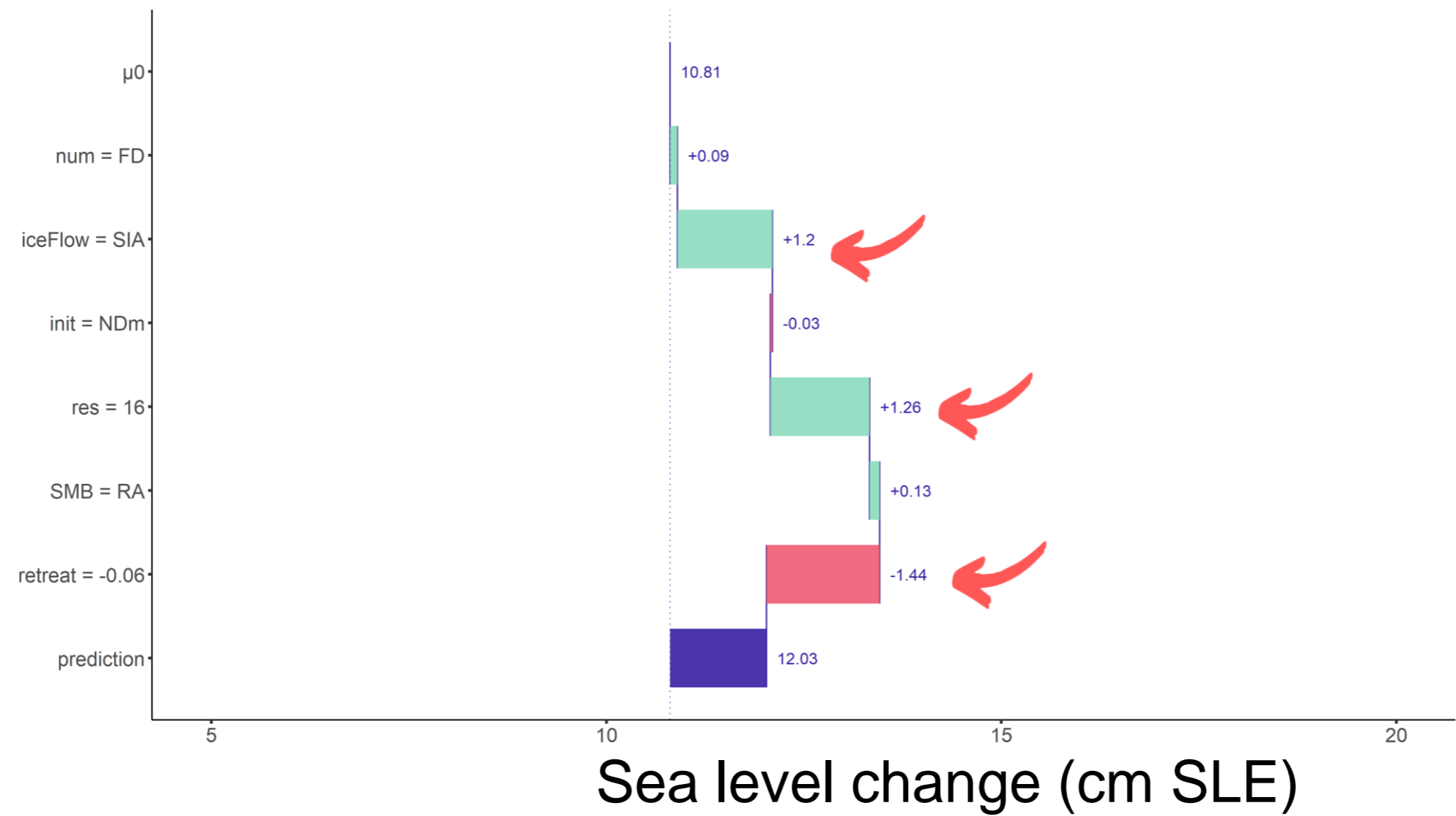


With words

"The largest sea level value is mostly influenced by the assumption of a retreat parameter set up at its largest absolute value"

"The contribution of this assumption reaches >5cm"

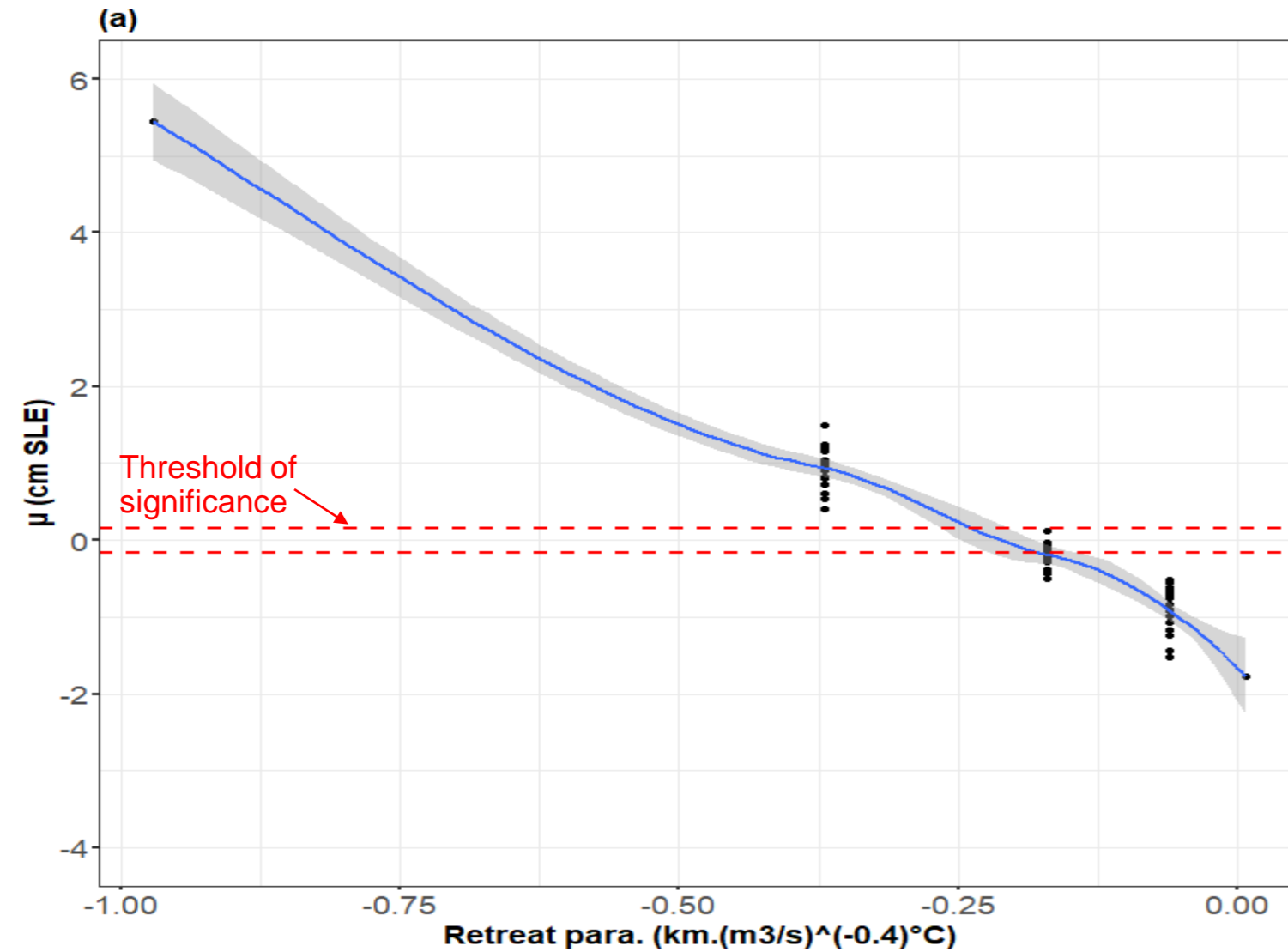
Experiment (2), prediction time = 2100



With words

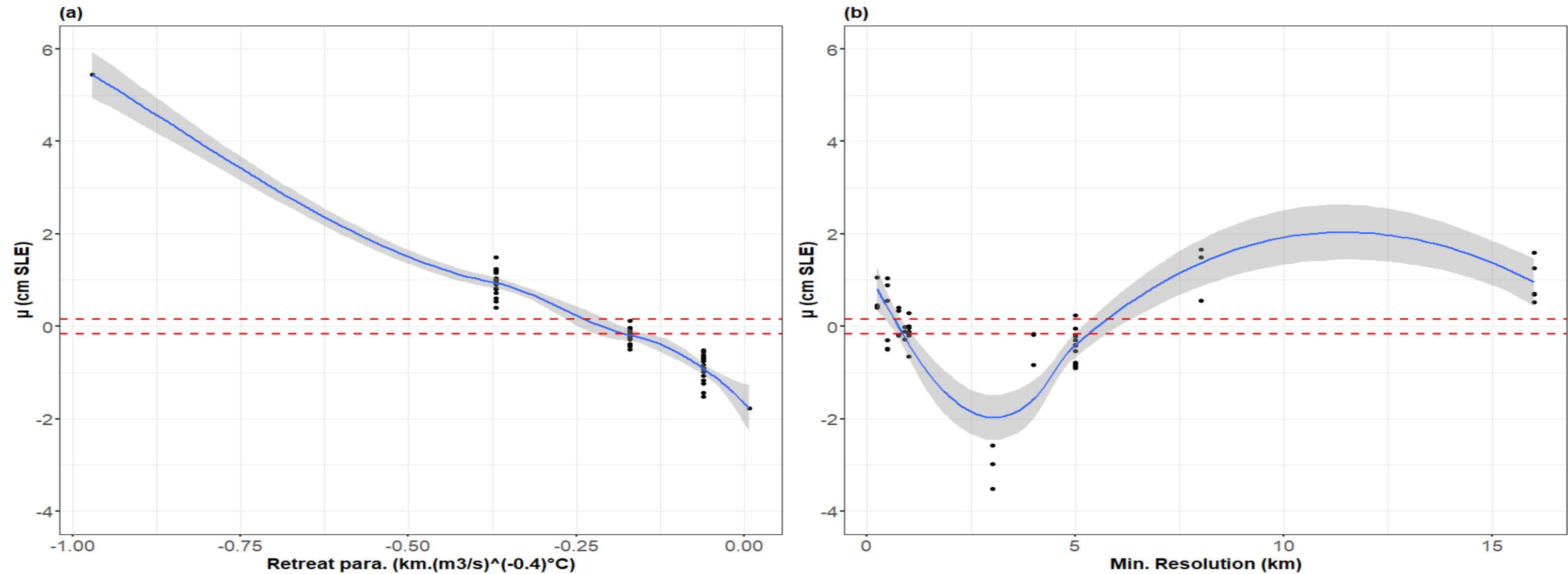
"The sea level value of 12cm is mostly controlled by 3 modelling choices with an equal contribution of 1-1.5cm"

Aggregation of all 55 experiments, prediction time = 2100



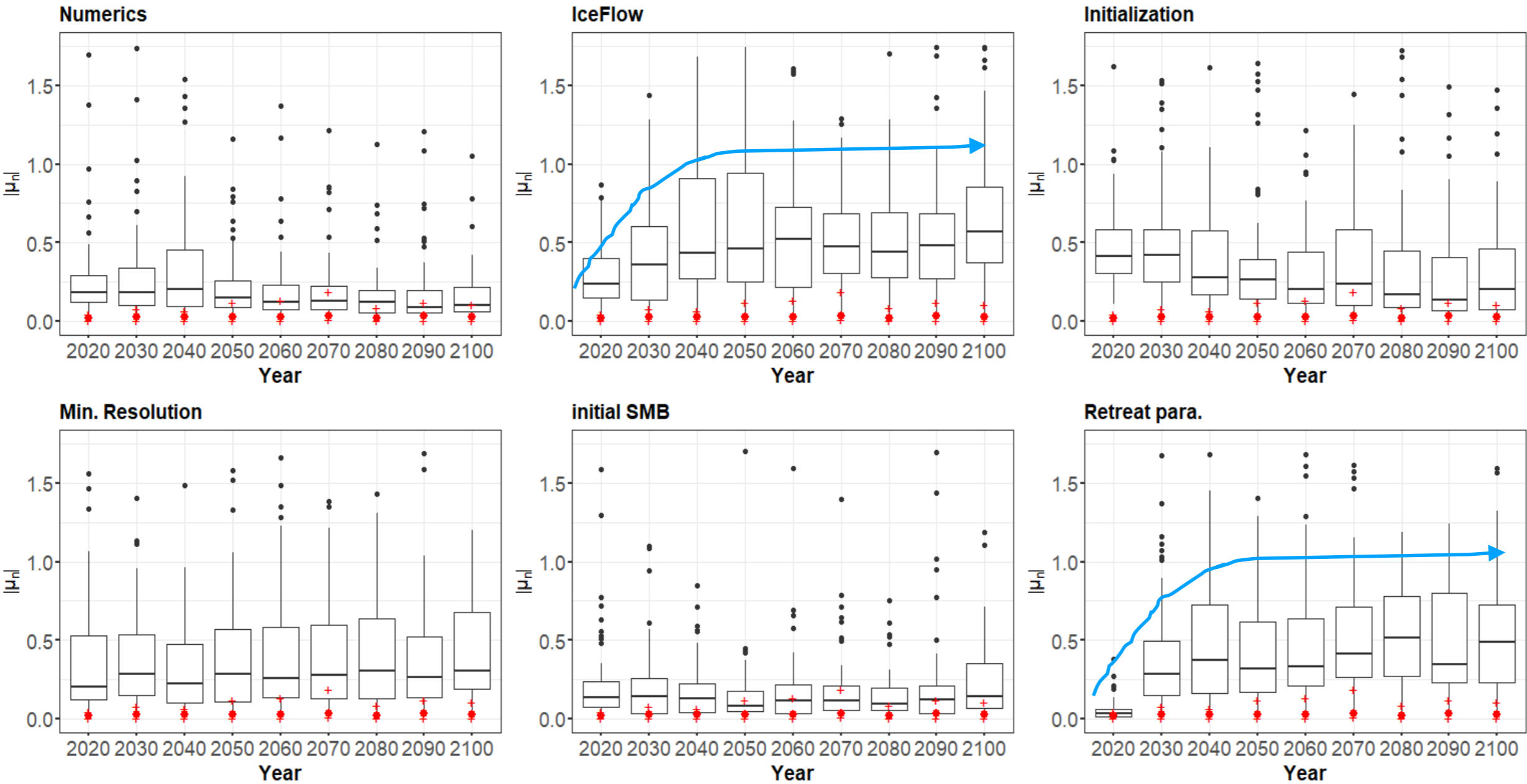
"Increasing the absolute value of the retreat parameter increases its contribution to the sea level value"

Aggregation of all 55 experiments, prediction time = 2100



"Too high mesh grid size (>5km) might bias the computed sea level value"

Aggregation of all 55 experiments, over time



"Influence increase of ice flow and retreat parameter over time"

"Influence of the numerical method only in the short term"

"Quasi-constant influence of the min. grid size"

Summary

- For each experiment (i) of the considered MME we decompose:

$$\text{sea level}^{(i)} = \mu_0 + \mu_{\text{Num}}^{(i)} + \mu_{\text{Init}}^{(i)} + \mu_{\text{iceflow}}^{(i)} + \mu_{\text{SMB}}^{(i)} + \mu_{\text{Retreat}}^{(i)} + \mu_{\text{Reso}}^{(i)}$$

- Three levels of analysis

1. μ (expressed in cm SLE) measures the contribution of the modelling choices in the sea level value = **local importance analysis**
2. Analysing all decompositions at a given prediction time helps understanding how the influence relates to the modelling choices = **model structure**
3. Aggregating all decompositions for any prediction time helps getting insights in the **global influence** of the modelling choices

- Applicable to any MME with

- a **limited number** of experiments (50-100)
- **unbalanced** design
- presence of **dependence** between the inputs

Acknowledgements

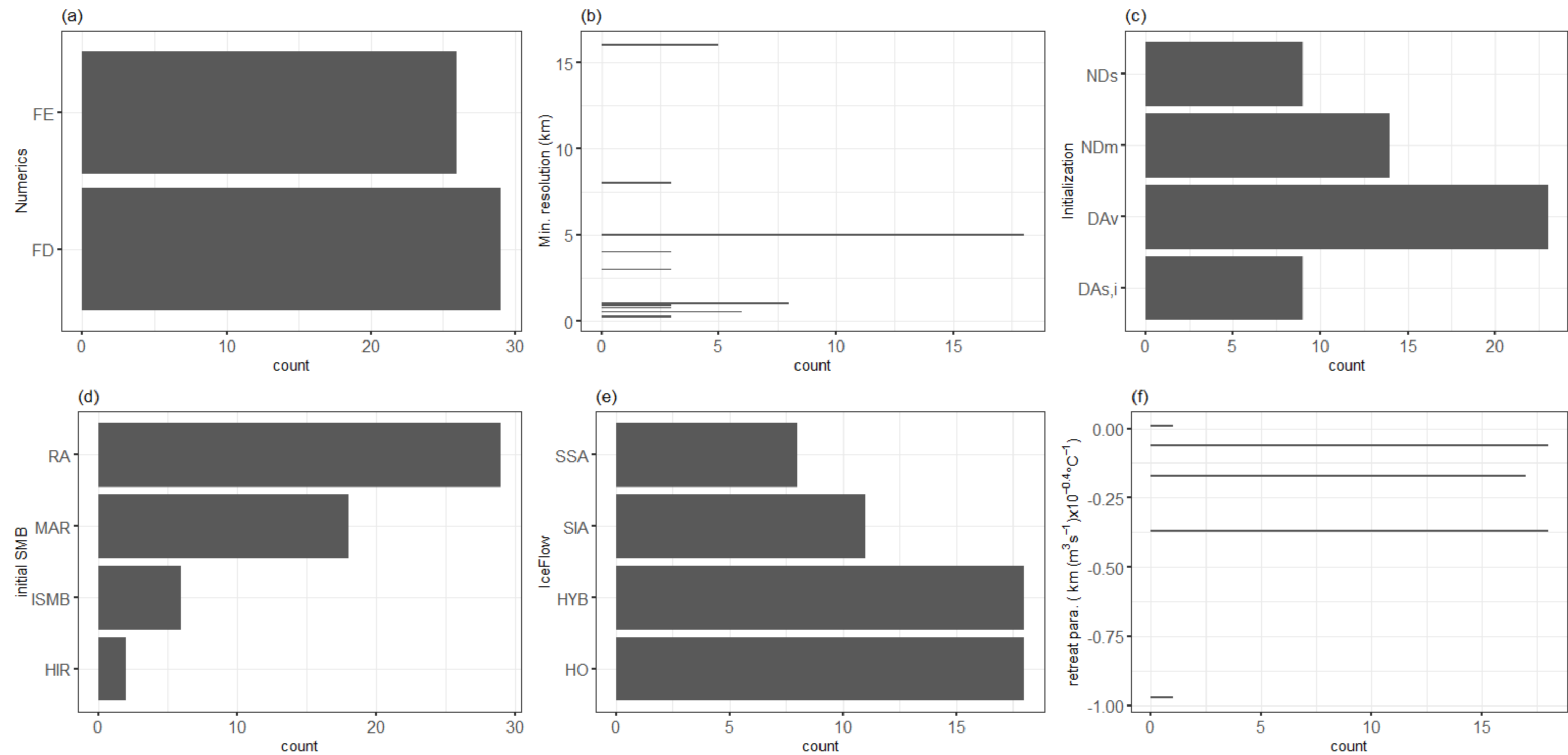


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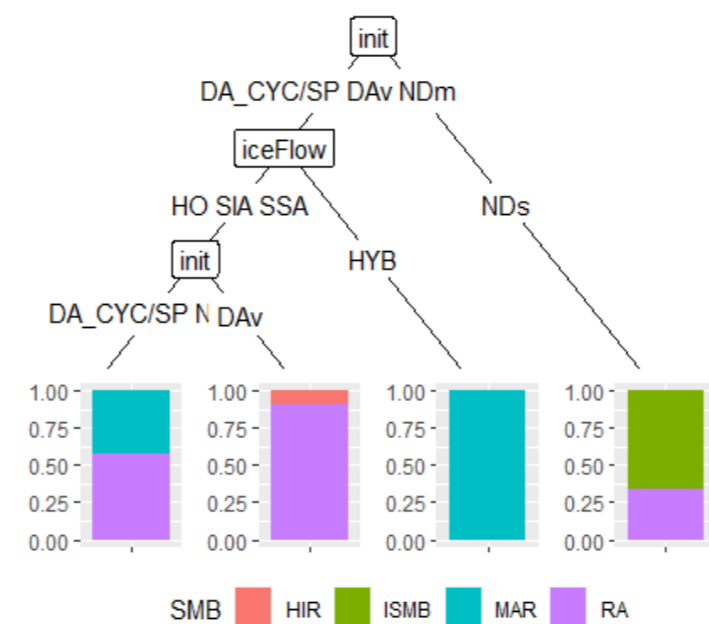
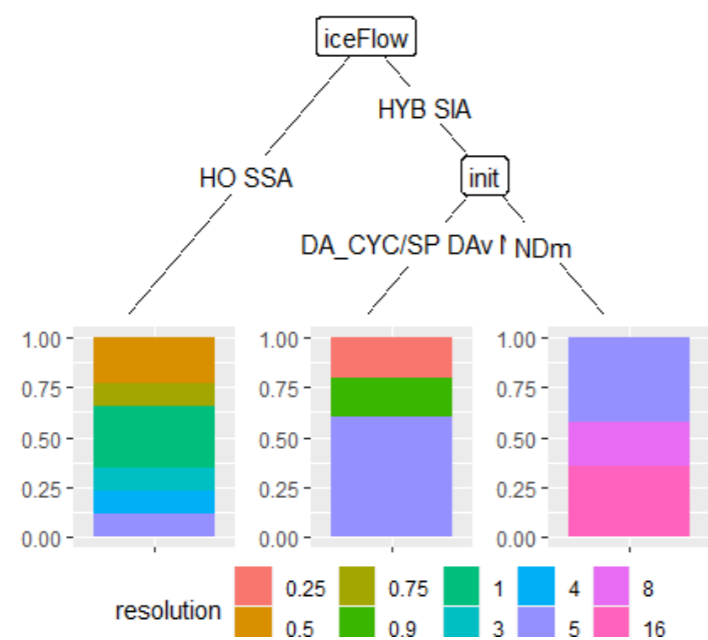
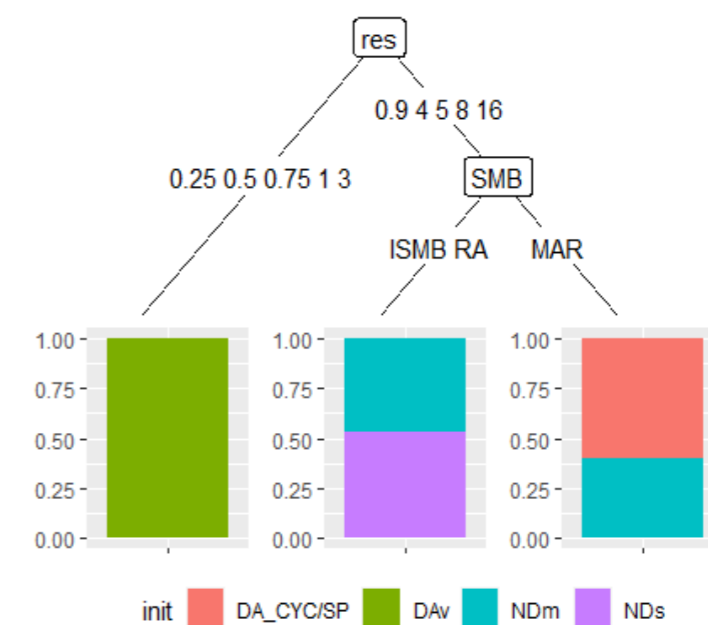
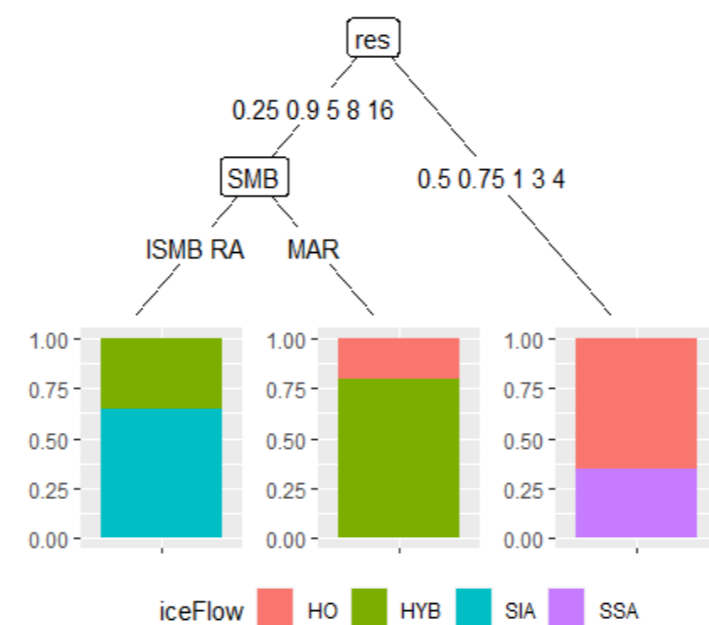
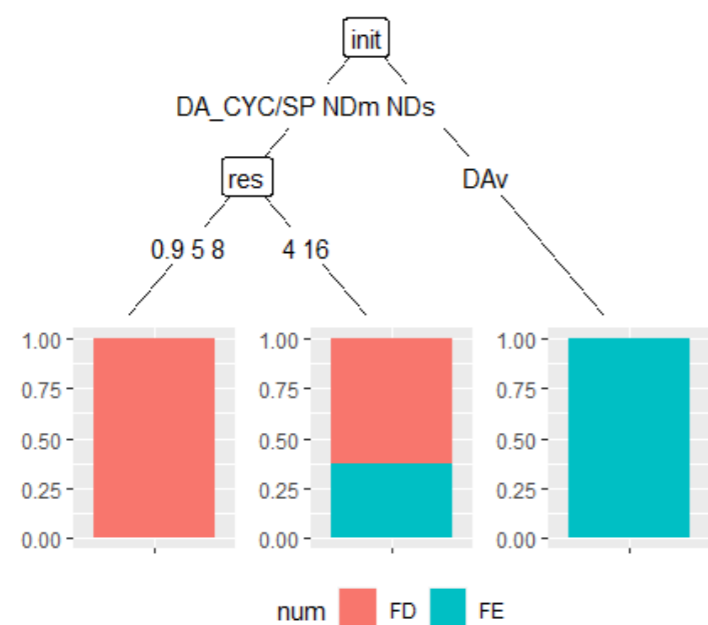
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Appendices

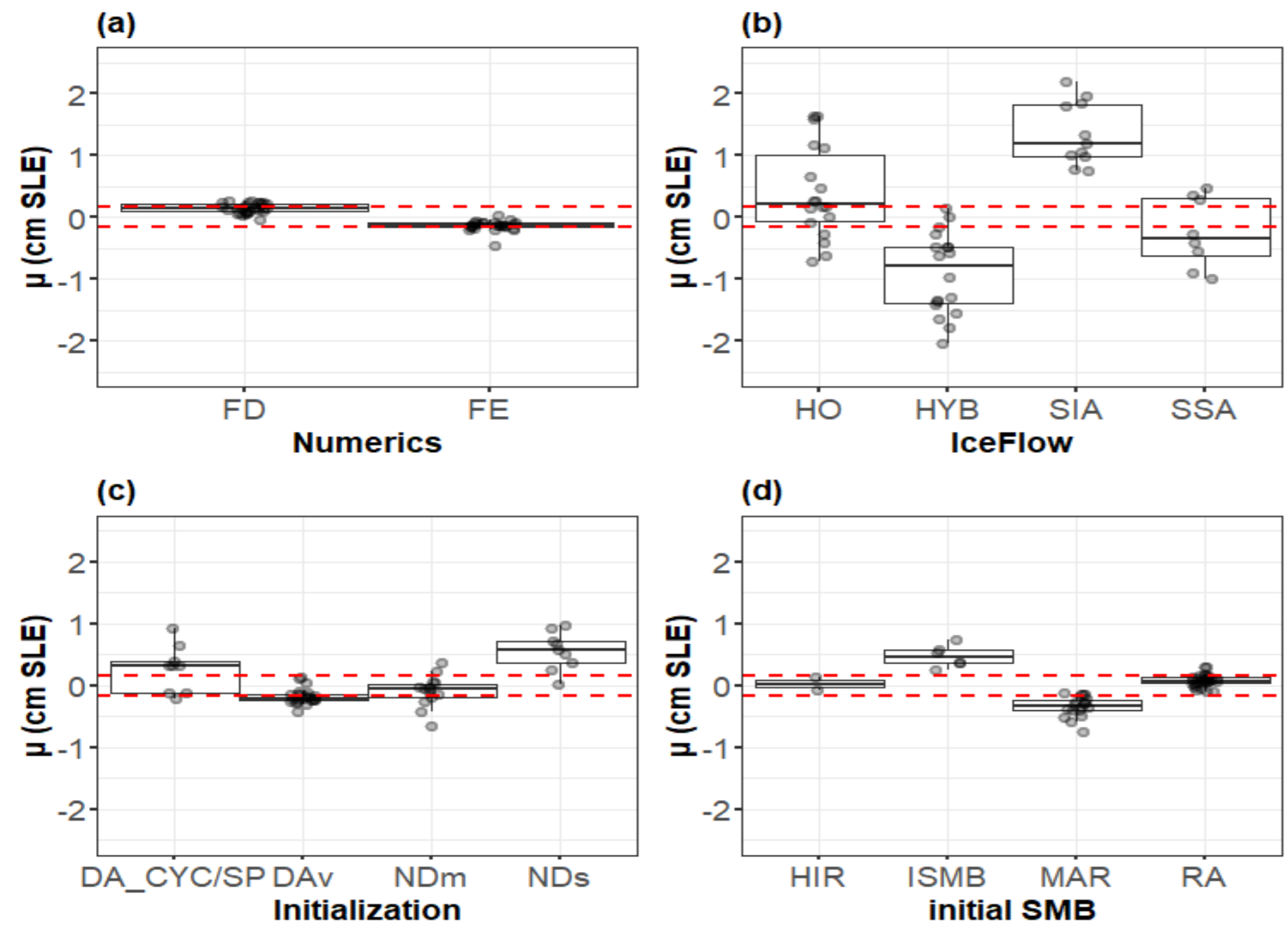
Unbalanced design of experiments in the considered MME GrIS case [1]



Evidence of dependence



Aggregation of all 55 experiments, prediction time = 2100



"The choice in the numerical method does not influence much"

"Setting the ice flow type to HYB or SIA has the largest impact"