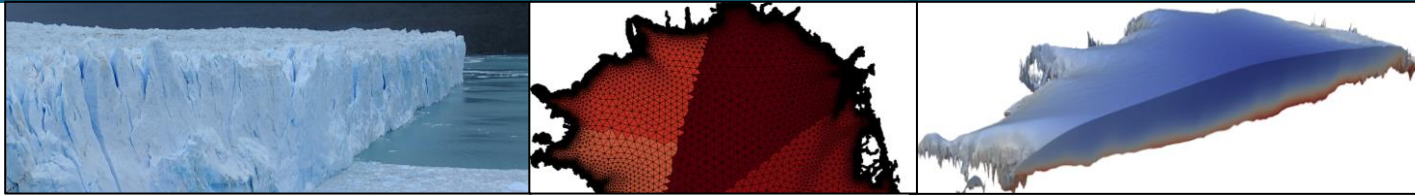




# Ice Sheet Models of Different Fidelity for Uncertainty Quantification



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# Talk Outline



- Brief motivation and introduction to ice sheet equations
- Hierarchy of ice sheet models (high to low fidelity)
- Introduction to multi-fidelity methods
- Results on Humboldt glacier

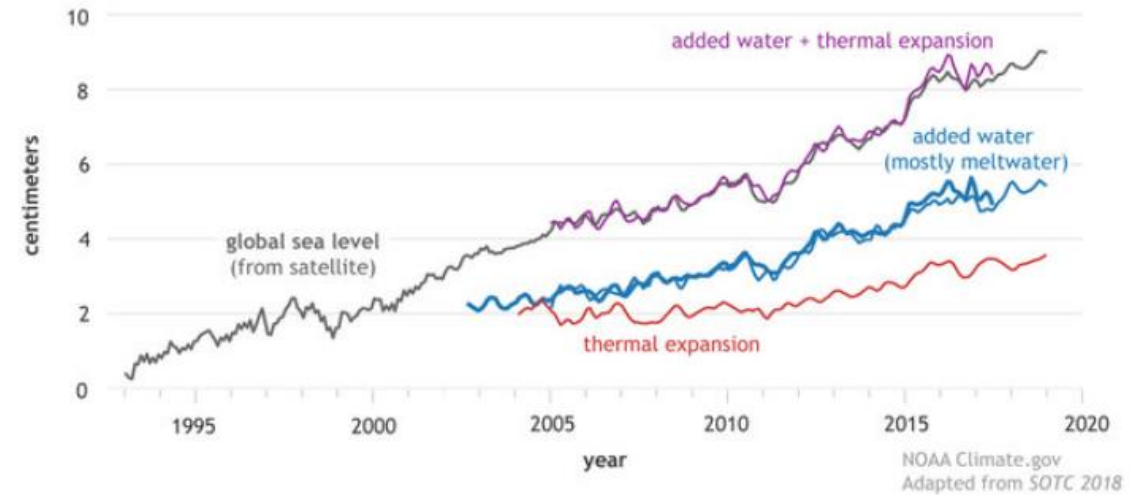
*Supported by US DOE Office of Science BER-SciDAC projects:*

- *FAnSSIE: Framework For Antarctic System Science In E3SM*
- *ProSPect: Probabilistic Sea-level Projection From Ice sheet And Earth System Models*

# Brief Motivation an basic physics

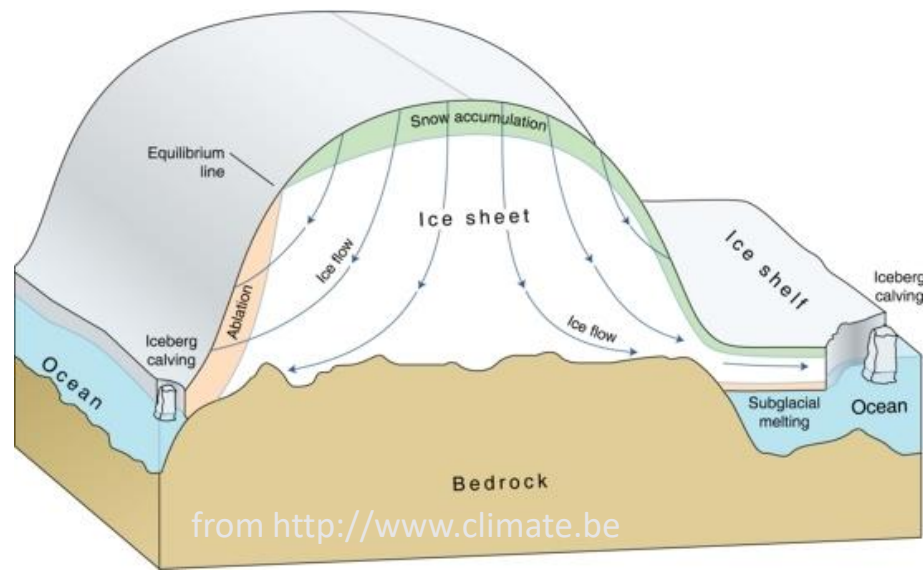
- Modeling ice sheets (Greenland and Antarctica) dynamics is essential to provide estimates for sea-level rise in next decades to centuries.

Contributors to global sea level rise (1993-2018):

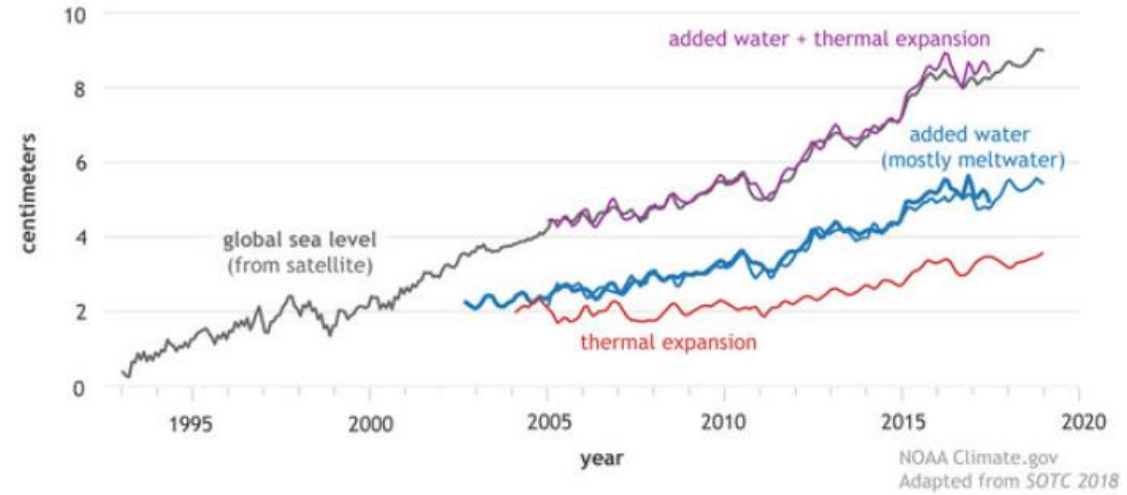


# Brief Motivation and basic physics

- Modeling ice sheets (Greenland and Antarctica) dynamics is essential to provide estimates for sea-level rise in next decades to centuries.
- Ice behaves like a very viscous shear-thinning fluid driven by gravity.



Contributors to global sea level rise (1993-2018):

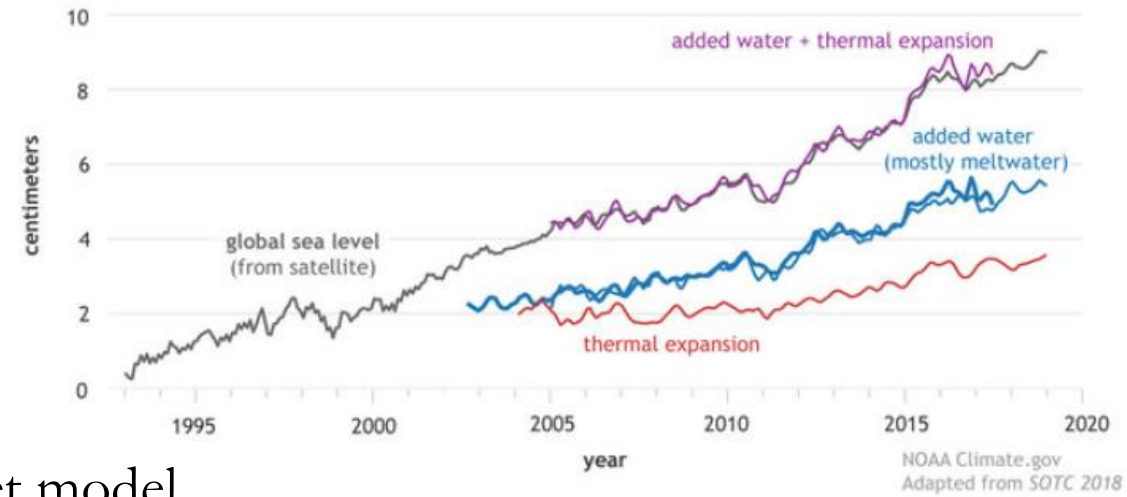


# Brief Motivation an basic physics



- Modeling ice sheets (Greenland and Antarctica) dynamics is essential to provide estimates for sea-level rise in next decades to centuries.
- Ice behaves like a very viscous shear-thinning fluid driven by gravity.
- There are several sources of uncertainties in an ice sheet model (e.g. uncertainties in sliding law, calving law, rheology) in addition to uncertainty in climate forcings.
- Quantifying the resulting uncertainty in the model prediction (e.g. sea-level rise) is a major challenges and computationally demanding as it requires the evaluation of the ice sheet model a large number of times.
- Here we explore the use of multi-fidelity approaches to accelerate the uncertainty quantification (UQ) analysis: we consider a hierarchy of model with different fidelity and cost, and develop a strategy to favor sampling of less expensive models over expensive ones, while maintaining a target accuracy.

Contributors to global sea level rise (1993-2018):





# Model: Ice velocity equations



Stokes equations:

$$\begin{cases} -\nabla \cdot \sigma = \rho \mathbf{g} \\ \nabla \cdot \mathbf{u} = 0 \end{cases}$$

gravit. acceleration

ice velocity

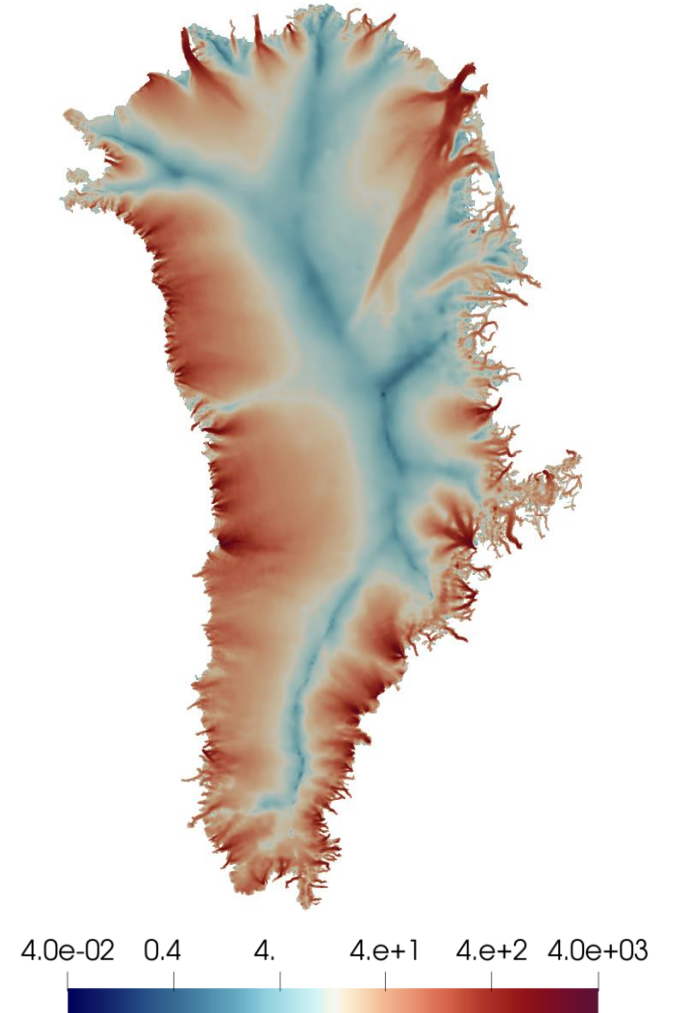
Stress tensor:

$$\sigma = 2\mu \mathbf{D} - pI, \quad \mathbf{D}_{ij}(\mathbf{u}) = \frac{1}{2} \left( \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right)$$

Ice viscosity (dependent on temperature):

$$\mu = \frac{1}{2} A(T) |\mathbf{D}(\mathbf{u})|^{\frac{1}{n}-1}, \quad n \geq 1, \quad (\text{typically } n \simeq 3)$$

Modeled surface ice speed [m/yr]  
(Greenland ice sheet)



# Model: Ice velocity equations



Stokes equations:

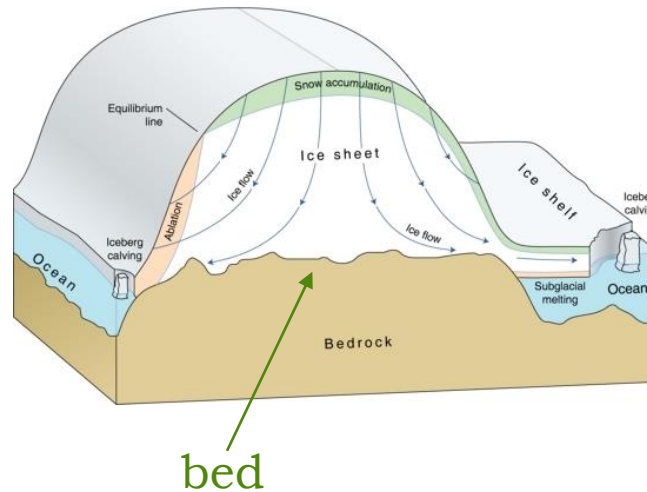
$$\begin{cases} -\nabla \cdot \sigma = \rho \mathbf{g} \\ \nabla \cdot \mathbf{u} = 0 \end{cases}$$

Sliding boundary condition at ice bed:

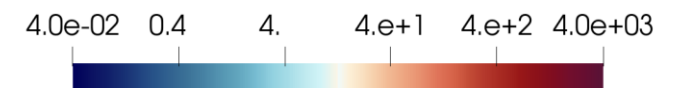
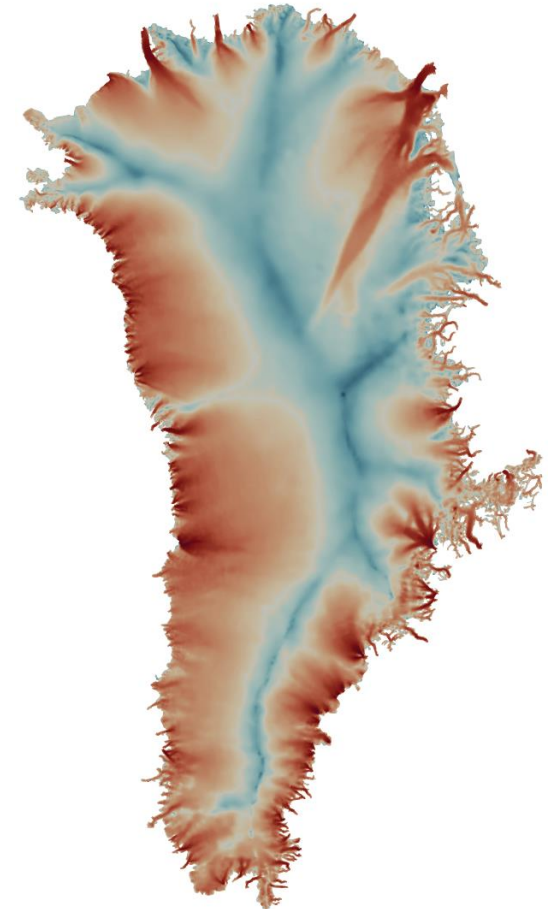
$$\begin{cases} \mathbf{u} \cdot \mathbf{n} = 0, & (\text{impenetrability}) \\ (\sigma \mathbf{n})_{\parallel} = \beta \mathbf{u} \end{cases}$$

Free slip:  $\beta = 0$

No slip:  $\beta = \infty$



Modeled surface ice speed [m/yr]  
(Greenland ice sheet)



# Model: Ice velocity equations



Stokes equations:

$$\begin{cases} -\nabla \cdot \sigma = \rho \mathbf{g} \\ \nabla \cdot \mathbf{u} = 0 \end{cases}$$

Thickness evolution equation:

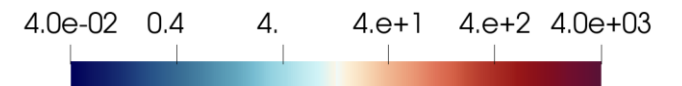
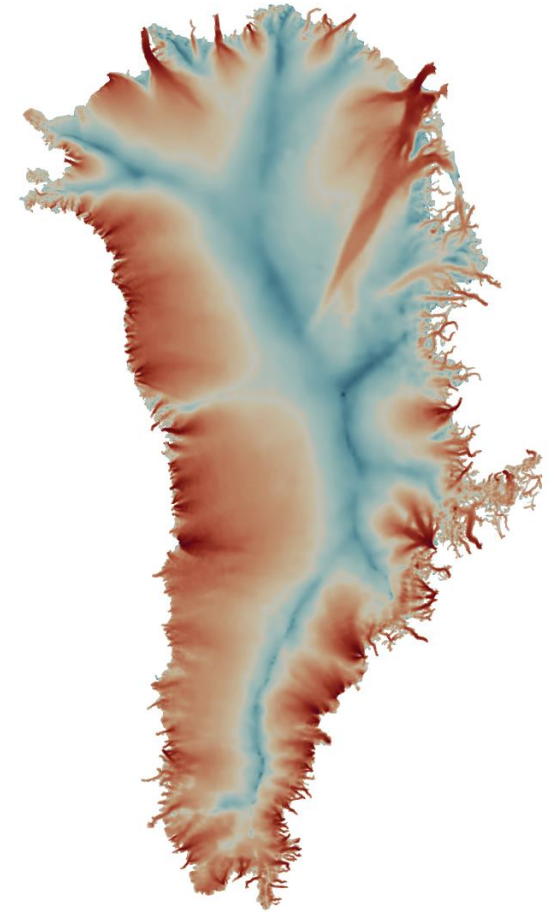
$$\partial_t H + \nabla \cdot (\bar{\mathbf{u}} H) = f_H$$

ice thickness

depth-averaged velocity

accumulation/ablation

Modeled surface ice speed [m/yr]  
(Greenland ice sheet)





# Multi-fidelity Models



Hierarchy of approximations of Stokes model, based on the fact that ice sheets are shallow

Increasing fidelity and cost

First Order (FO) model  
(3d PDE)

$$\begin{aligned} -\nabla \cdot (2\mu \tilde{\mathbf{D}}) - \partial_z(\mu \partial_z \mathbf{u}) &= -\rho g \nabla s \\ 2\mu \tilde{\mathbf{D}} \mathbf{n} &= \beta \mathbf{u}, \quad \text{on bed} \end{aligned}$$

Mono-Layer Higher-order (**MOLHO**) model  
(two 2d PDEs)

Solve FO with trial function

$$\mathbf{u} = \bar{\mathbf{u}}(x, y) + \mathbf{u}_{\text{def}}(x, y) \varphi(z)$$

Shallow Shelf Approx. (**SSA**)  
(2d PDE, for floating fast-flowing ice)

$$-\nabla \cdot (2\mu H \tilde{\mathbf{D}}(\bar{\mathbf{u}})) + \beta \bar{\mathbf{u}} = -\rho g H \nabla s$$

Shallow Ice Approx. (**SIA**)  
(for grounded slow-flowing ice)

$$\bar{\mathbf{u}} = - \left( \frac{2A\rho^3 g^3}{5} H^4 |\nabla s|^2 + \frac{\rho g}{\beta} H \right) \nabla s$$

# Problem setup

## (approximation and assumptions)



- Ice geometry is fixed (ice front can retreat but cannot advance, ice flux through margin allowed). No calving.
- Ice thickness and velocity model are solved implicitly (monolithic coupling), with backward Euler in time
- Problem discretized with piece-wise linear continuous finite elements on triangles.
- Thickness positivity is guaranteed using two methods:
  - Nonconservative: At each time step the thickness is updated at each node so that it is greater than 1m
  - Conservative: Thickness is constrained to be larger than 1m with an optimization-based<sup>1</sup> procedure that guarantees that mass changes are consistent with forcing terms and boundary fluxes

Ice-sheet models implemented in FEniCS<sup>2</sup>. The non-conservative methods are indicated with a “star” (SSA – conservative, SSA\* non conservative)



1. P. Bochev et al., CMAME, 2020

2. FEniCS code, developed by C. Sockwell and M. Perego from an original implementation by D. Brinkerhoff

# Set up of uncertainty quantification problem

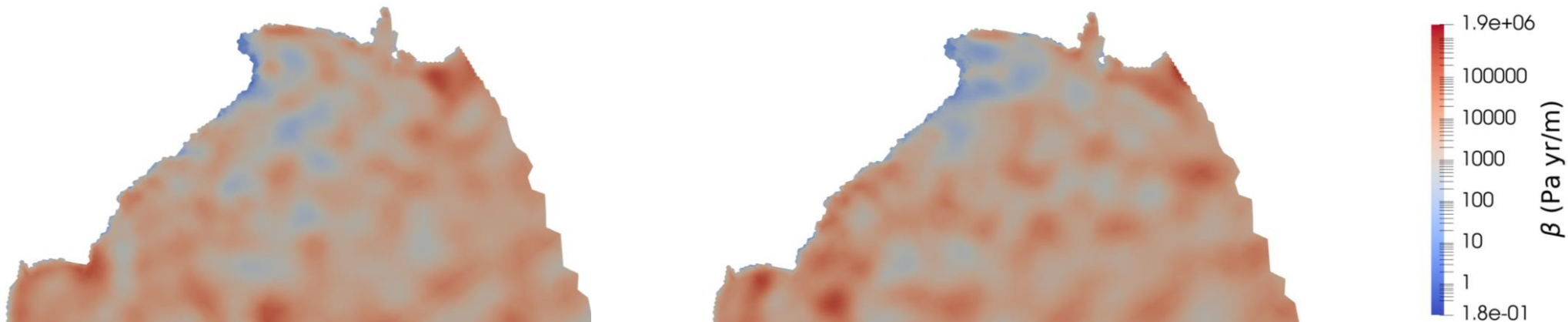


- We are interested in computing uncertainty in the ***total ice mass loss***, our Quantity of Interest (**QoI**), due to the uncertainty in the ***basal friction***.
- We assume that the basal friction distribution is lognormal, centered on the value  $\beta_{opt}$  obtained solving an inverse problem to match observations.

$$\beta = \exp(\gamma), \text{ where } \gamma \sim \mathcal{N}(\log(\beta_{opt}), k), \text{ and } k(\mathbf{x}_1, \mathbf{x}_2) = \sigma^2 \exp\left(-\frac{|\mathbf{x}_1 - \mathbf{x}_2|^2}{2 l^2}\right)$$

variance
correlation length

Samples of basal friction  $\beta$  near Humboldt glacier outlet ( $\sigma^2 = 1, l = 10$  km):



# Multi-fidelity Approach

## Multi-level Monte Carlo



Models of different fidelity for the QoI (total mass change):

$$f_0, f_1, \dots, f_M$$

high-fidelity

$$E[f_0] = E[f_1] + E[f_0 - f_1]$$

$$E[f_0] \approx \hat{Q}(\mathbf{z}) = \frac{1}{N_1} \sum_{k=1}^{N_1} f_1(\mathbf{z}_k^1) + \frac{1}{N_0} \sum_{k=1}^{N_0} f_0(\mathbf{z}_k^0) - f_1(\mathbf{z}_k^0)$$

If  $\mathbf{z}^0 \cap \mathbf{z}^1 = \emptyset$

$$\text{Var}[\hat{Q}(\mathbf{z})] = \frac{1}{N_1} \text{Var}[f_1] + \frac{1}{N_0} \text{Var}[f_0 - f_1]$$

Model is cheap,  
can evaluate a large  
number of times


If models are well correlated  
this variance is small

# Multi-fidelity Approach

## Generalized approximate control variate



Models of different fidelity for the QoI (total mass change):

$f_0, f_1, \dots, f_M$   
 high-fidelity

$$\hat{Q}_i(\mathbf{z}_i) := \frac{1}{N} \sum_{k=1}^N f_i(\mathbf{z}_{i,k})$$

$$\begin{aligned} \hat{Q}_0(\boldsymbol{\alpha}, \mathbf{z}) &= \hat{Q}_0(\mathbf{z}_0) + \sum_{k=1}^M \alpha_i \left( \hat{Q}_i(\mathbf{z}_i^1) - \hat{Q}_i(\mathbf{z}_i^2) \right) \\ &= \hat{Q}_0(\mathbf{z}_0) + \sum_{k=1}^M \alpha_i \Delta_i(\mathbf{z}_i) = \hat{Q}_0(\mathbf{z}_0) + \boldsymbol{\alpha}^T \boldsymbol{\Delta} \end{aligned}$$

Minimize variance of estimator by

1. Selecting what models to use
2. Selecting the sampling strategy

Optimal weights that minimize variance of estimator

$$\boldsymbol{\alpha}^{ACV} = -\text{Cov}[\boldsymbol{\Delta}, \boldsymbol{\Delta}]^{-1} \text{Cov}[\boldsymbol{\Delta}, \hat{Q}_0]$$

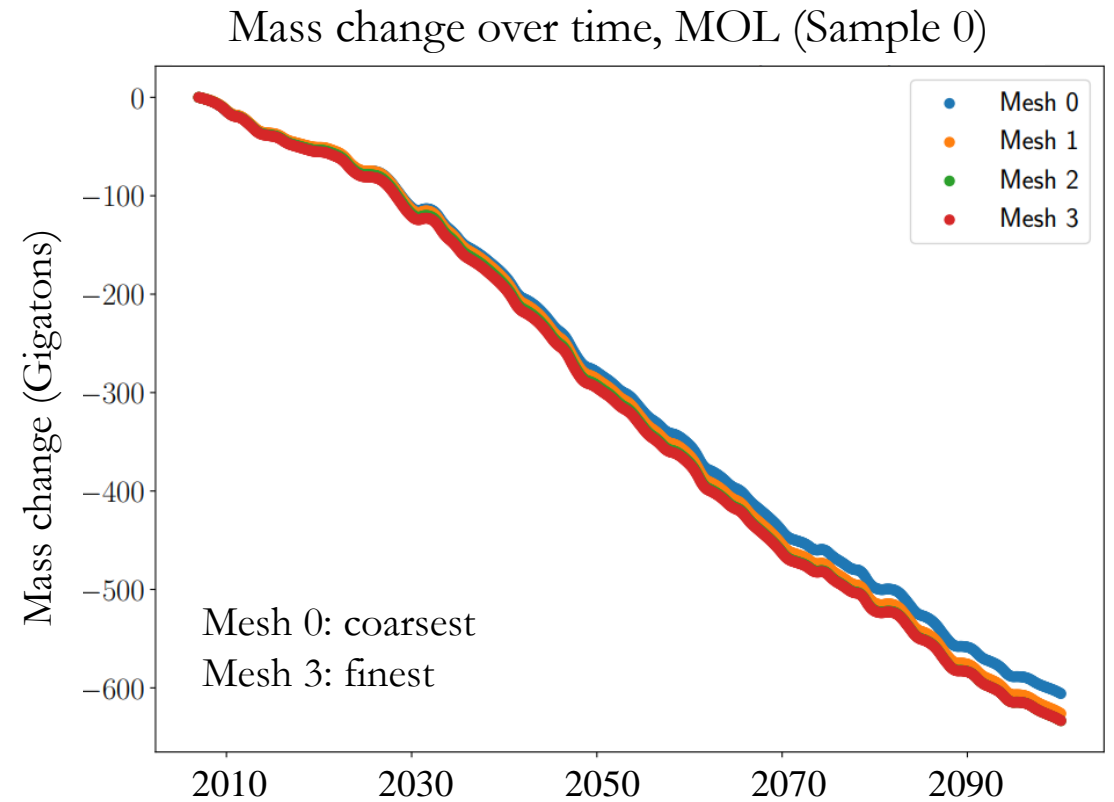
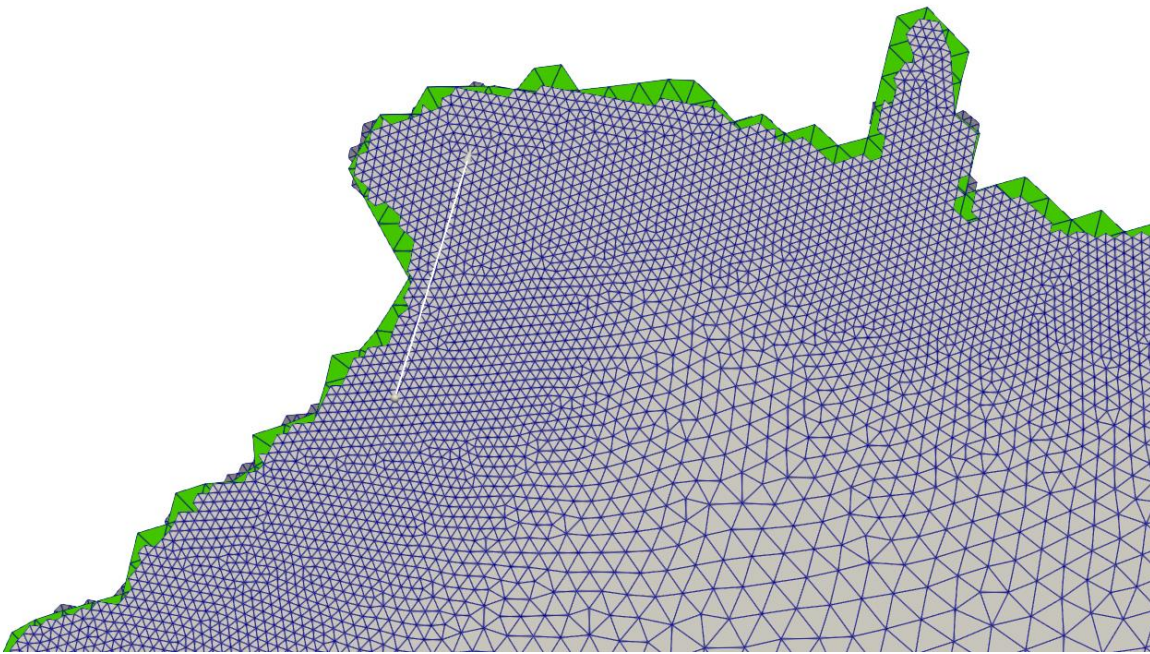
Methods implemented in  
**PyApprox** by J. Jakeman  
<https://sandialabs.github.io/pyapprox/intro.html>

We consider *four different mesh resolutions* and *three different formulations*: **MOLHO**, **SSA**, **SIA**.



# Models

(different mesh resolutions)

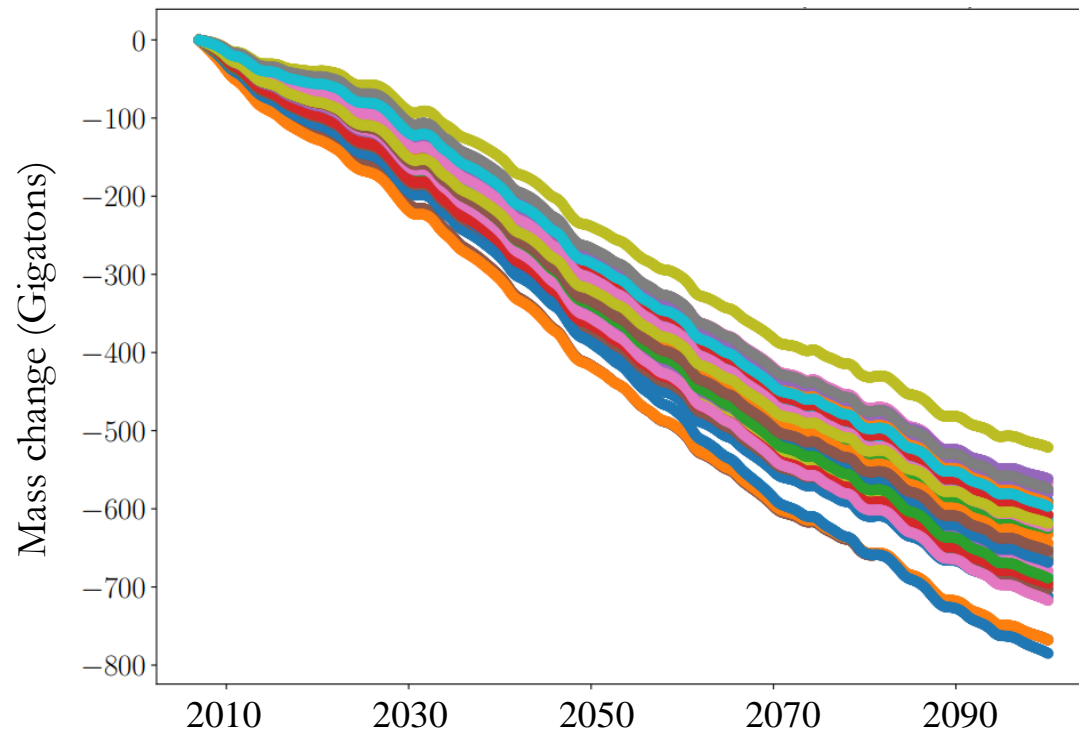


We consider four different mesh resolutions.

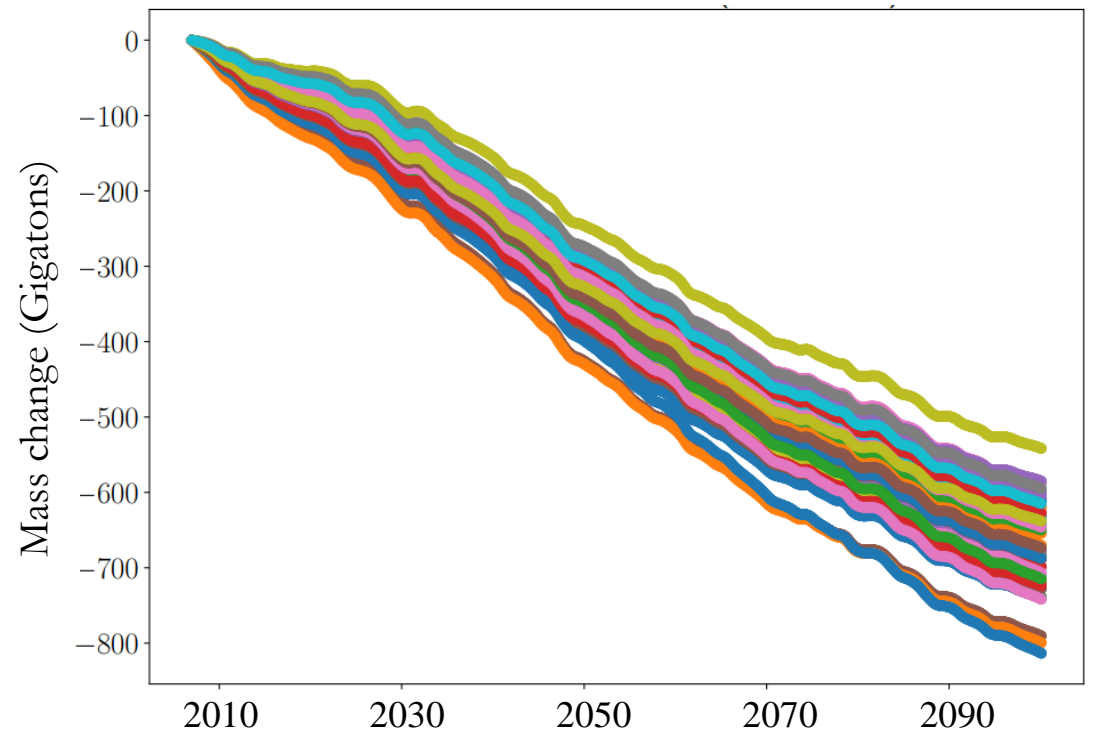
# Models (different formulations)



Mass change over time SSA (finest mesh)



Mass change over time MOL (finest mesh)



Mass change over time for different samples

# Correlation of different models



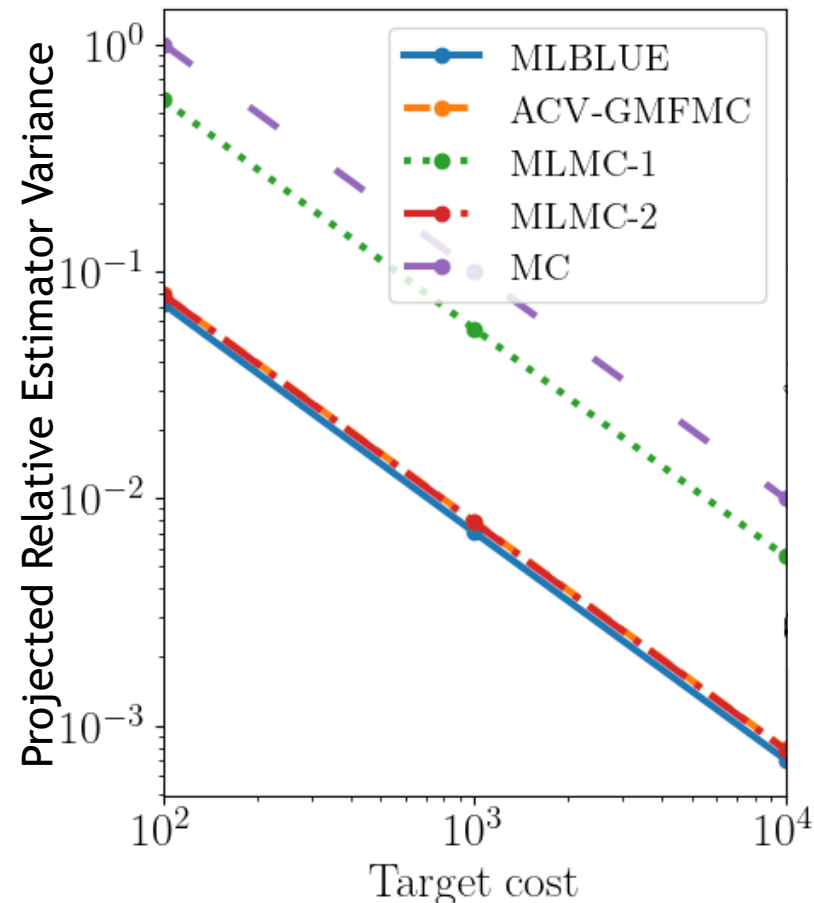
Correlation between models, based on 100 samples of basal friction

# Multi-fidelity Results



We compare different multi-fidelity approaches with the vanilla Monte Carlo approach.

The best approach is projected to be about **14x** faster than the Monte Carlo approach and **7x** times faster than the classic Multi-level Monte Carlo approach.



Method	Description	Models
MC	Monte Carlo	MOL <sub>3</sub> - highest fidelity model
MLMC-1	Multi-level Monte Carlo	MOL <sub>3</sub> , MOL <sub>2</sub> , MOL <sub>1</sub>
MLMC-2	Multi-level Monte Carlo	MOL <sub>3</sub> , SSA <sup>*</sup> <sub>2</sub> , SSA <sup>*</sup> <sub>0</sub>
ACV-GMFCM	Generalized Approximate Control Variate <sup>1</sup>	MOL <sub>3</sub> , MOL <sup>*</sup> <sub>0</sub> , SSA <sup>*</sup> <sub>2</sub> , SSA <sup>*</sup> <sub>0</sub>
MLBLUE	Multilevel Best Linear Unbiased Estimators <sup>2</sup>	MOL <sub>3</sub> , MOL <sup>*</sup> <sub>0</sub> , SSA <sup>*</sup> <sub>2</sub> , SSA <sup>*</sup> <sub>0</sub>

➤ SSA<sup>\*</sup><sub>0</sub> is **30x** faster than MOL<sub>3</sub>

1. G. Bomarito, P. Leser, J. Warner, W. Leser, *JCP*, 2022

2. D Schaden, E Ullmann, *SIAM/ASA J. Uncertainty Quantification* 8 (2), 601 - 635, 2020

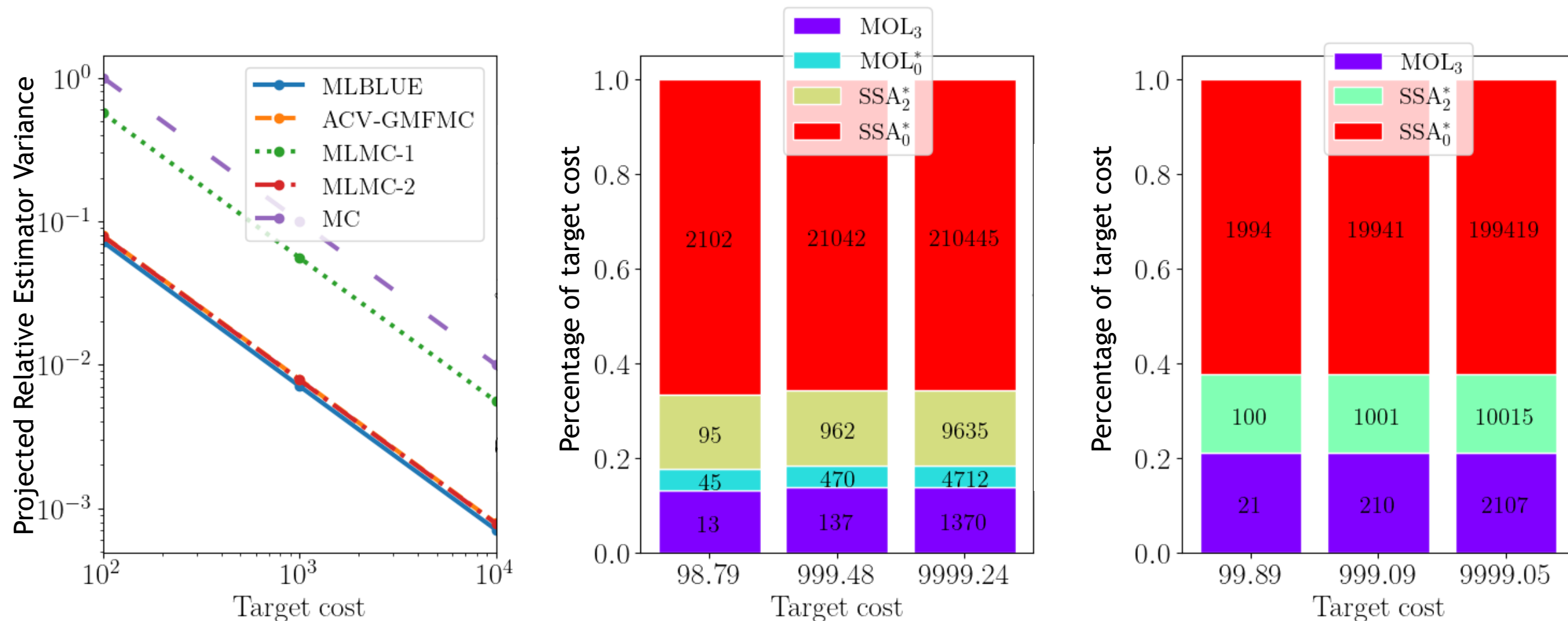


# Multi-fidelity Results



We compare different multi-fidelity approaches with the vanilla Monte Carlo approach.

The best approach is projected to be about **14x** faster than the Monte Carlo approach and **7x** times faster than the classic Multi-level Monte Carlo approach.







- Demonstrated effectiveness of multi fidelity approach in ice-sheet application.
- Correlations between models is very high in our example. Correlation will likely be lower when considering high-order model for velocity (e.g. FO), more physics (e.g. calving) and when allowing the geometry to change.
- TODO: Use the multi-fidelity approach on different glaciers with improved accuracy for high-fidelity model.
- TODO: Include NN surrogate in our multi-fidelity strategy.

	MOL <sub>3</sub>	MOL <sub>2</sub>	MOL <sub>1</sub>	MOL <sub>0</sub>	MOL <sub>3</sub> <sup>*</sup>	MOL <sub>2</sub> <sup>*</sup>	MOL <sub>1</sub> <sup>*</sup>	MOL <sub>0</sub> <sup>*</sup>	SSA <sub>3</sub>
Realtive Cost	1.0e+00	6.3e-01	4.3e-01	1.2e-01	8.1e-01	5.1e-01	3.5e-01	9.7e-02	4.7e-01
	SSA <sub>2</sub>	SSA <sub>1</sub>	SSA <sub>0</sub>	SSA <sub>3</sub> <sup>*</sup>	SSA <sub>2</sub> <sup>*</sup>	SSA <sub>1</sub> <sup>*</sup>	SSA <sub>0</sub> <sup>*</sup>	SIA <sub>0</sub>	SIA <sub>0</sub> <sup>*</sup>
Realtive Cost	2.9e-01	1.9e-01	5.6e-02	2.7e-01	1.6e-01	1.1e-01	3.1e-02	4.7e-02	2.3e-02