

Quantifying Parameter Uncertainty in a Glacier Evolution Model of High Mountain Asia with a Markov Chain Monte Carlo Method

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Abstract

Modeling future glacier changes on regional or global scales is challenging due to a scarcity of data for calibrating model parameters. This makes it difficult to derive accurate model parameters and also to convey the model uncertainty associated with those parameters. Previous global-scale models have typically optimized a single glacier or region specific set of model parameters to project global-scale glacier mass changes. As part of the development of a new open source global-scale glacier evolution model this research implements a Markov Chain Monte Carlo method to address this problem. We use geodetic mass-balance observations to determine probability distributions of a set of model parameters at each glacier. We then form an ensemble of model simulations by sampling parameters from these distributions. Using an ensemble allows us to create a range of mass balance changes for each glacier and quantify the model uncertainty. Applying this calibration technique, we use temperature and precipitation projections of one global climate model to model the mass changes until year 2100 of thousands of glaciers in High Mountain Asia. By using climate projections forced by multiple emission scenarios, we compare the uncertainties in changing climate caused by possible emission scenarios with the uncertainties in the glacier evolution model, and evaluate the results of different climate scenarios on glacier evolution.

Problems To Solve

Global-scale glacier models have been used to project how glaciers contribute to sea-level rise. Previous studies have calibrated model parameters using mass balance observations, but typically use a single best-fit parameter set per region or glacier. Here, we seek to:

- **Develop a calibration routine for global scale glacier evolution models that yields an ensemble of glacier specific parameters** based on mass balance data and prior knowledge.
- **Quantify the uncertainty** related to model calibration.
- **Demonstrate this method** on a large group of glaciers in **High Mountain Asia**, and compare the uncertainty from model parameters to the uncertainty in emissions scenarios.

Model and Data

Model: We use the Python Glacier Evolution Model (PyGEM)¹, which models the mass changes of all glaciers in a region. It uses a degree day model for melt, and accounts for glacier retreat, thinning, and geometry changes.

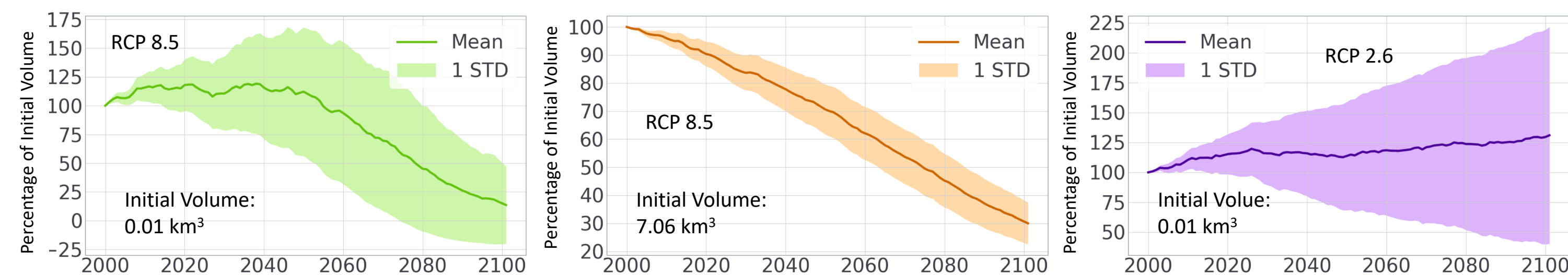
Data: We use monthly air temperature and precipitation data from ERA Interim² (past) and the MPI-ESM-LR model provided by CMIP5³ (future) using RCP 2.6 and 8.5 scenarios. We use the RGI 6.0 glacier inventory⁴ and geodetic mass balances from 2000-2015 for 640 glaciers^{5,6} for model calibration.

Quantifying and Comparing Uncertainty

Running Ensembles to Measure Uncertainty

We divided the joint probability distribution into N equal probability intervals in a manner that reflected the total spread of predicted mass balances. We then chose a parameter set from each interval to create an ensemble of N model runs. We ran 100 to 200 member model ensembles to determine means and standard deviations of volume over time. The plots below look at individual glaciers, and show a single standard deviation uncertainty margin.

Volume Evolution Projection (Percentage of Year 2000 Volume) from 2000 to 2100 for 3 Example Glaciers



Markov Chain Monte Carlo (MCMC) Method

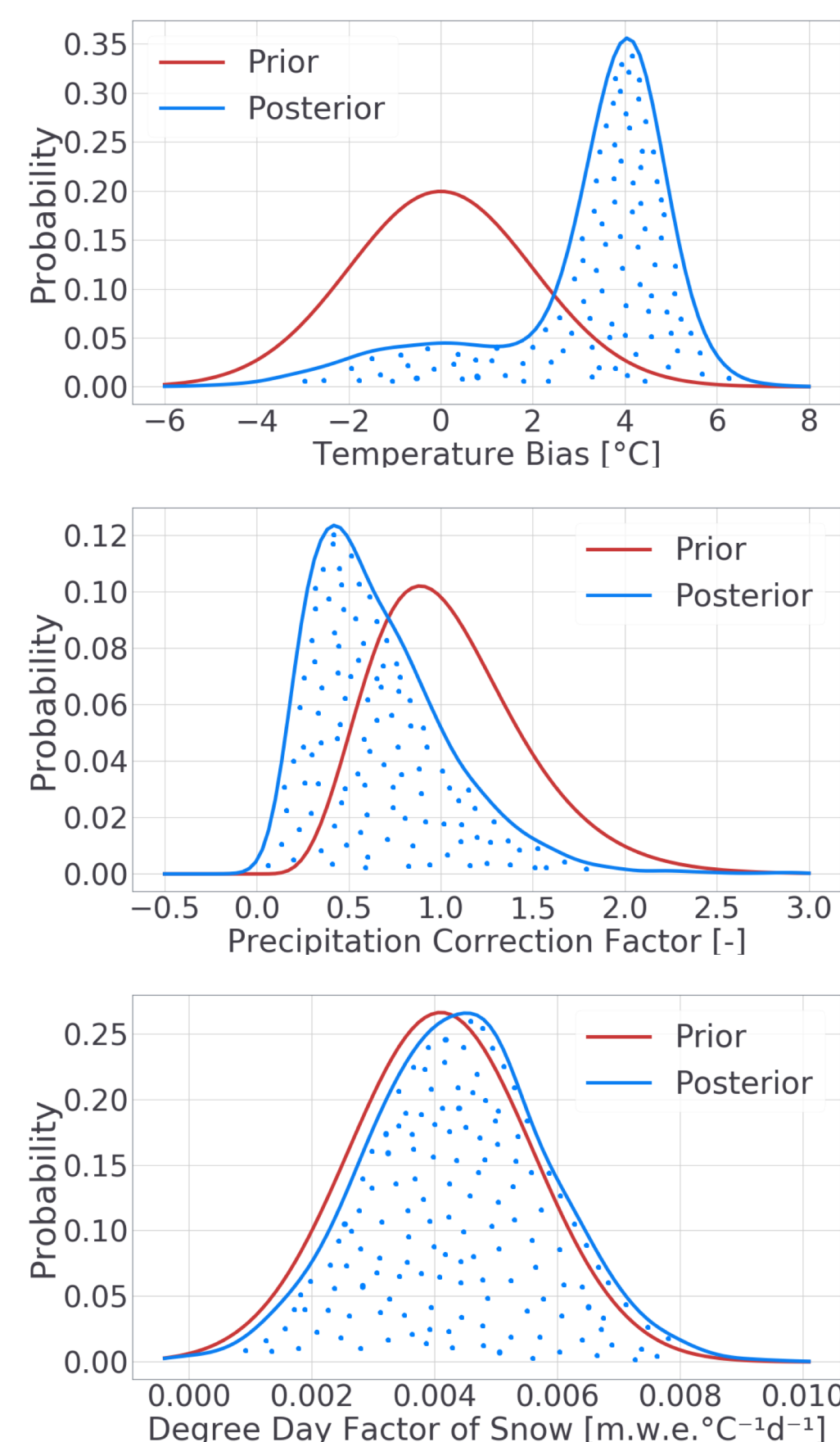
Theory

- Based on our existing knowledge, we generate *prior* probability distributions of three model parameters: temperature bias correction, precipitation correction factor and degree day factor of snow.
- We use geodetic mass balance observations.
- A likelihood is specified which ties together the mass balance data and the model parameters.
- We want to determine the Bayesian *posterior* probability distribution of the model parameters. MCMC methods provide algorithms to estimate the desired distribution.

Implementation

- We combine *prior* probability distributions and the above likelihood to create a joint *posterior* probability distribution of the model parameters.
- As part of the MCMC process, a Markov Chain is created in which each step is a sample from the desired distribution. With enough steps, the points in the chain converge to approximate the joint *posterior* probability distribution of model parameters.
- We can now use these samples from the posterior distribution for model calibration.
- We use the PyMC software library to carry out the above MCMC method using a Metropolis-Hastings algorithm.

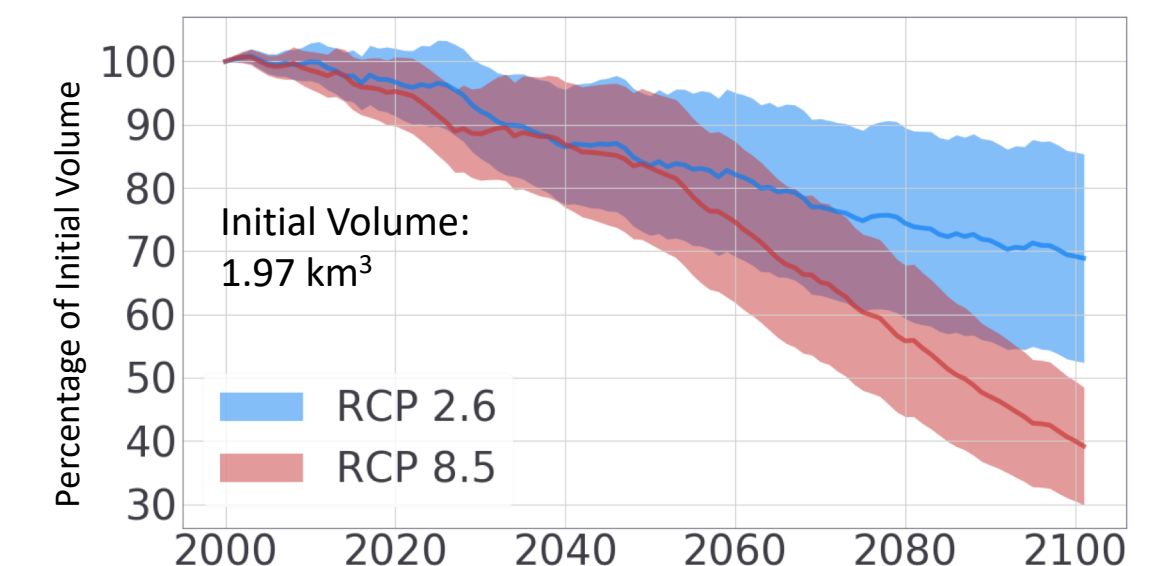
Example of Prior vs Posterior Distributions for a Single Glacier



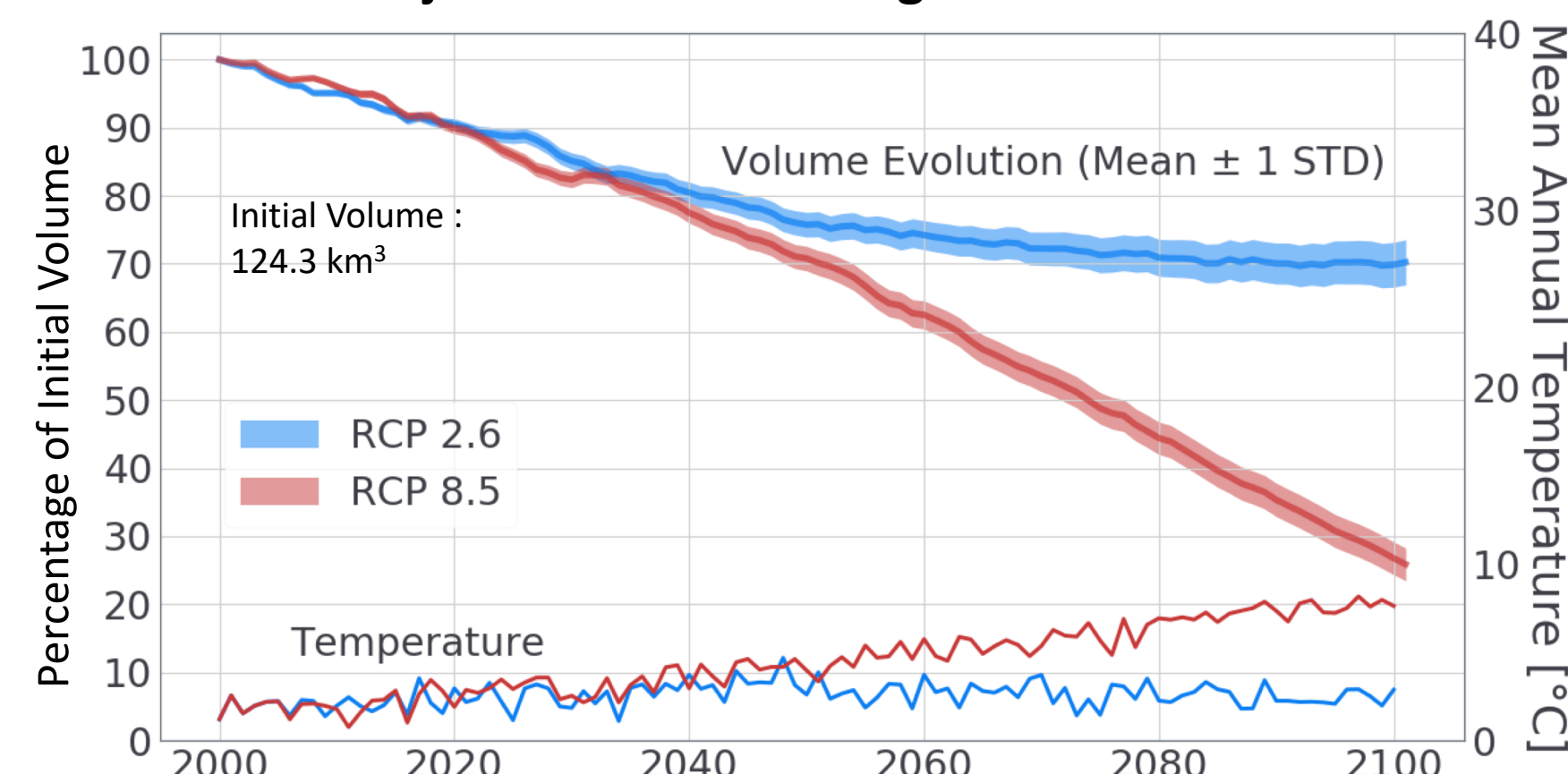
Comparing Model Uncertainty with Emissions Uncertainty

By running the model using climate data from different RCPs, we can compare model uncertainty with uncertainty due to future emission scenarios. The plot on the right depicts a single glacier's predicted evolution under different RCPs. At the bottom we look at the total volume change of 640 glaciers in High Mountain Asia RGI region 15. Notice that in the aggregate, we see a relatively smaller uncertainty. Results indicate that the uncertainty in model parameters is much smaller than the difference in glacier volume by 2100 due to the two alternative emissions scenarios.

Projected Volume Change: 1 Glacier



Projected Volume Change: 640 Glaciers



Conclusions

- MCMC methods provides a useful tool for glacier specific model calibration and quantifying parameter uncertainty in regional or global scale glacier evolution modeling.
- Results for 640 glaciers in High Mountain Asia RGI region 15 show volume reductions by 2100 of 30(±3)% for RCP2.6 and 73(± 2)% for RCP 8.5. This indicates that the relative uncertainty due to model parameters is much smaller than volume differences due to alternative emissions scenarios.

References

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