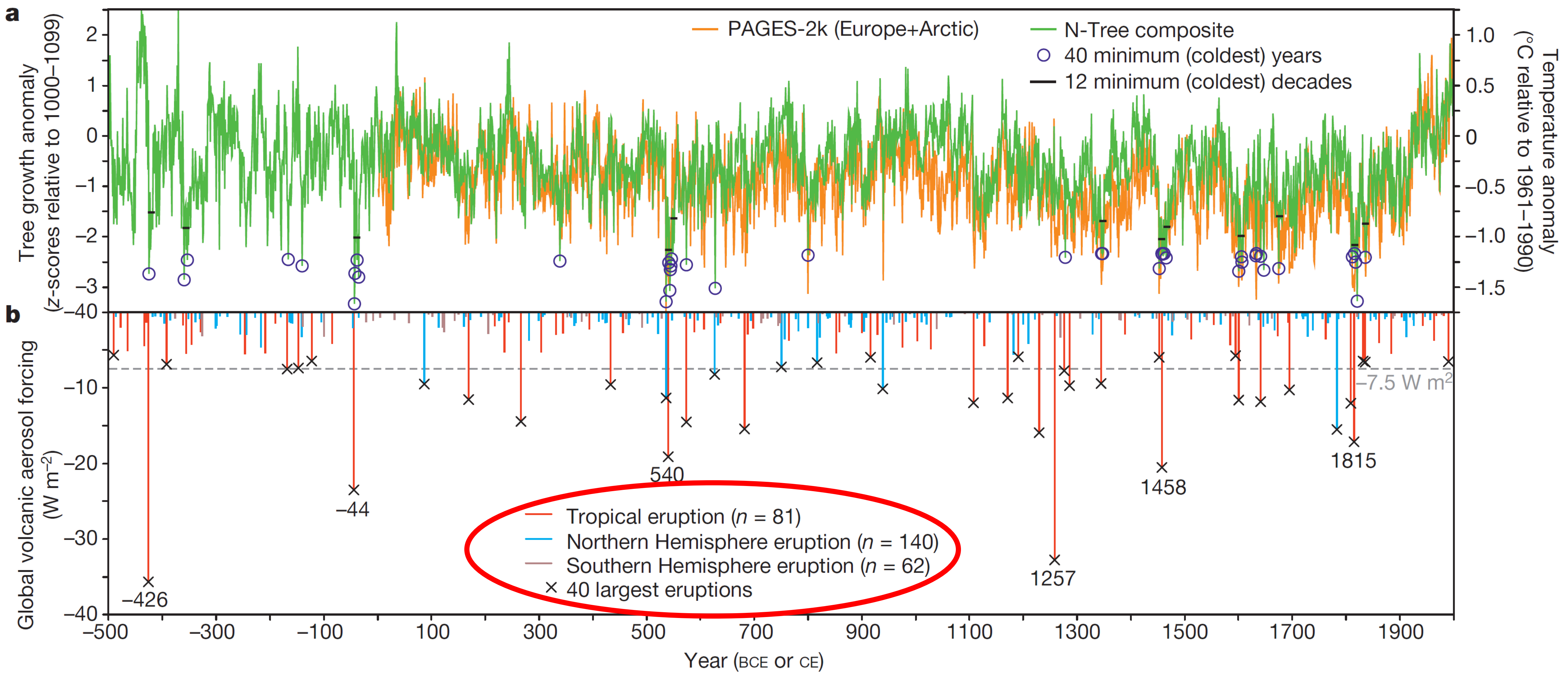
Combining Earth system modeling and machine learning to investigate volcanic sulfate deposition in polar ice cores

Malcolm Maas[1], **Kostas Tsigaridis**[2], Marcus Van Lier-Walqui[2]

[1]University of Maryland, College Park

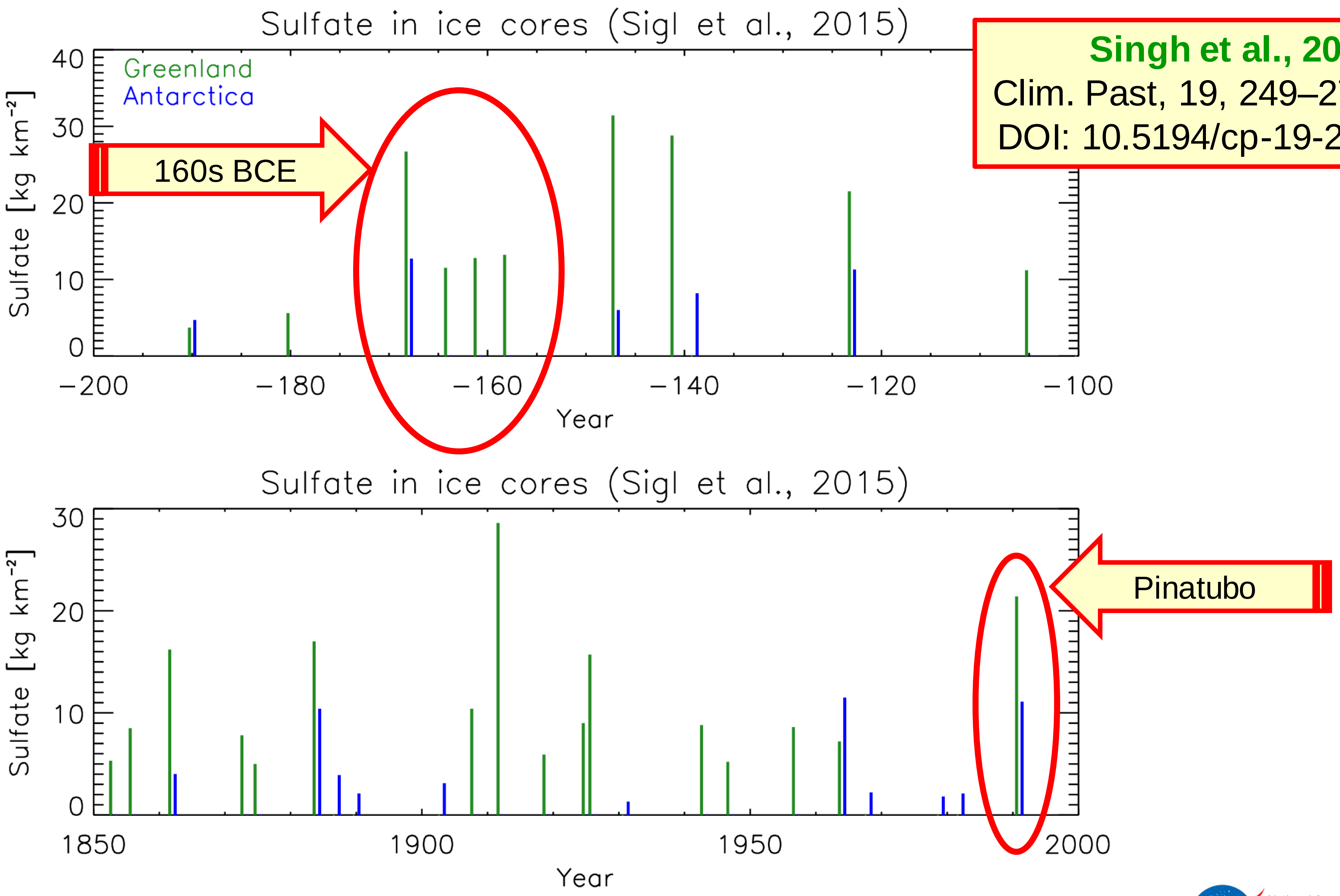
[2]Columbia University/NASA GISS

Sulfate in ice cores



Sigl et al., Nature, 2015

Sulfate in ice cores



Singh et al., 2023
Clim. Past, 19, 249–275, 2023
DOI: 10.5194/cp-19-249-2023

Latin hypercube sampling: 140 10-year-long simulations

Parameter	Min	Max	Pinatubo	Comments
Longitude [deg E]	-180	180	120.35	Land mask will be handled later.
Latitude [deg N]	-90	90	15.13	Normalized by cos(lat). Land mask will be handled later.
Julian day	1	365	166 (June 15)	
Plume bottom [km]	2	40	22	Above topography.
Plume thickness [km]	1	10	4	plume top = plume bottom + plume thickness
SO_2 amount [Tg]	0	100	18	
H_2O amount [Tg]	0	500	150	

Eruption duration: 1 day.

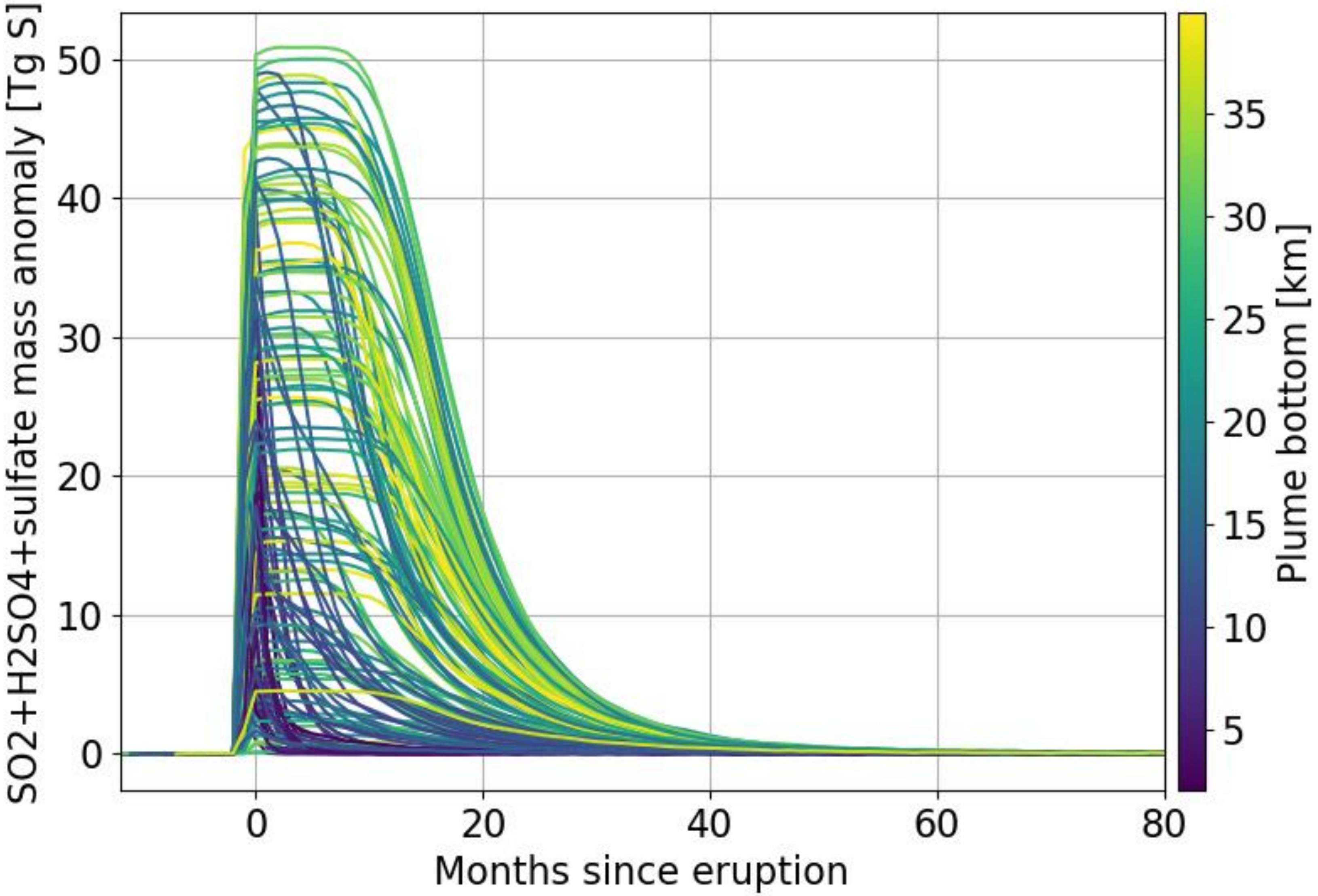
Total sulfate burden (anomaly from control)

Time series of global atmospheric sulfur anomaly for all 140 simulations.

Color: injection bottom altitude.

Demonstrates varied sulfur injections.

Roughly exponential decay.



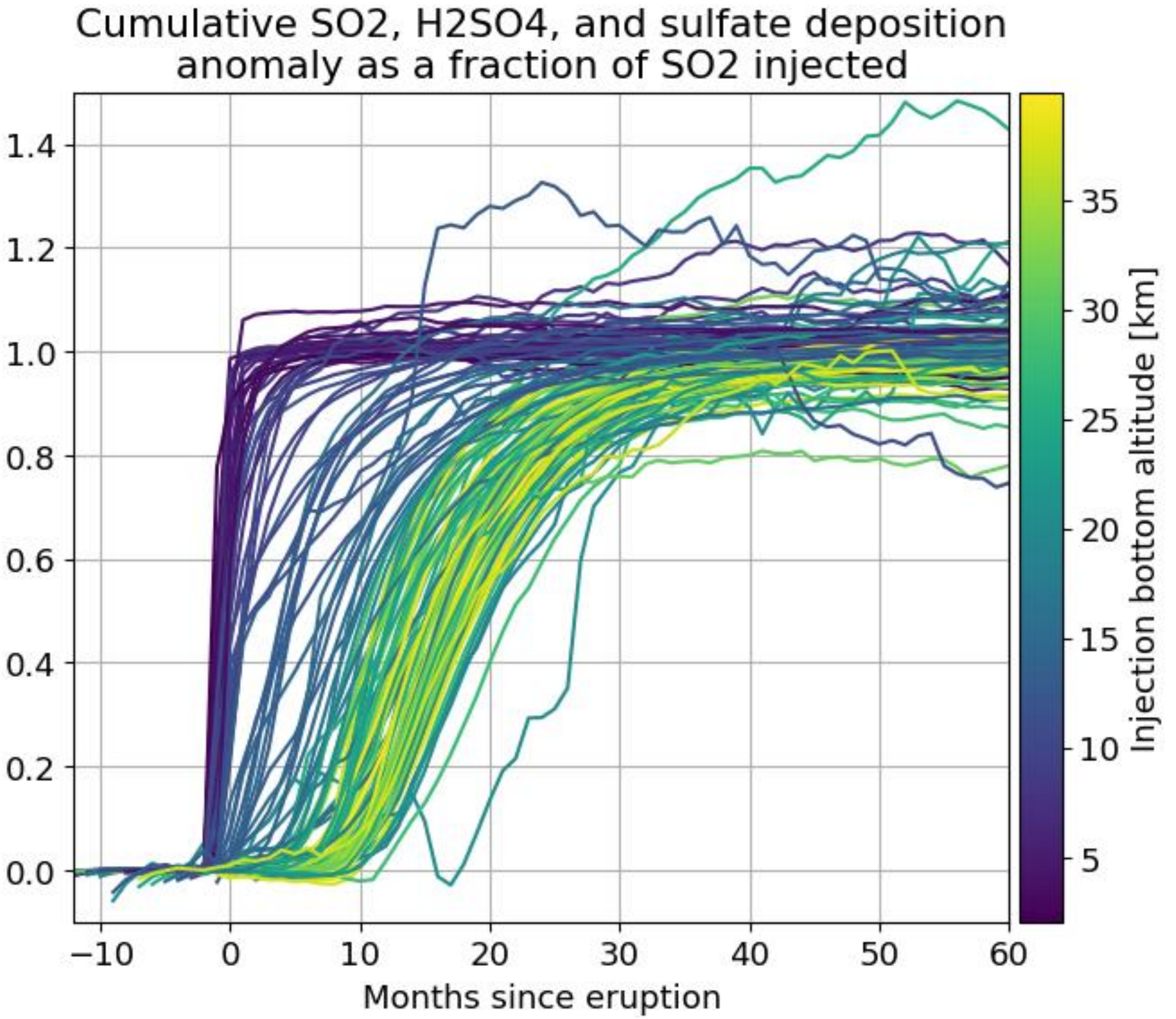
Cumulative sulfate deposition (anomaly from control)

Time series of global sulfur deposition anomaly as a fraction of injected SO_2.

Color: injection bottom altitude.

Bifurcation between tropospheric and stratospheric plumes.

Rather noisy for low-SO_2 eruptions.



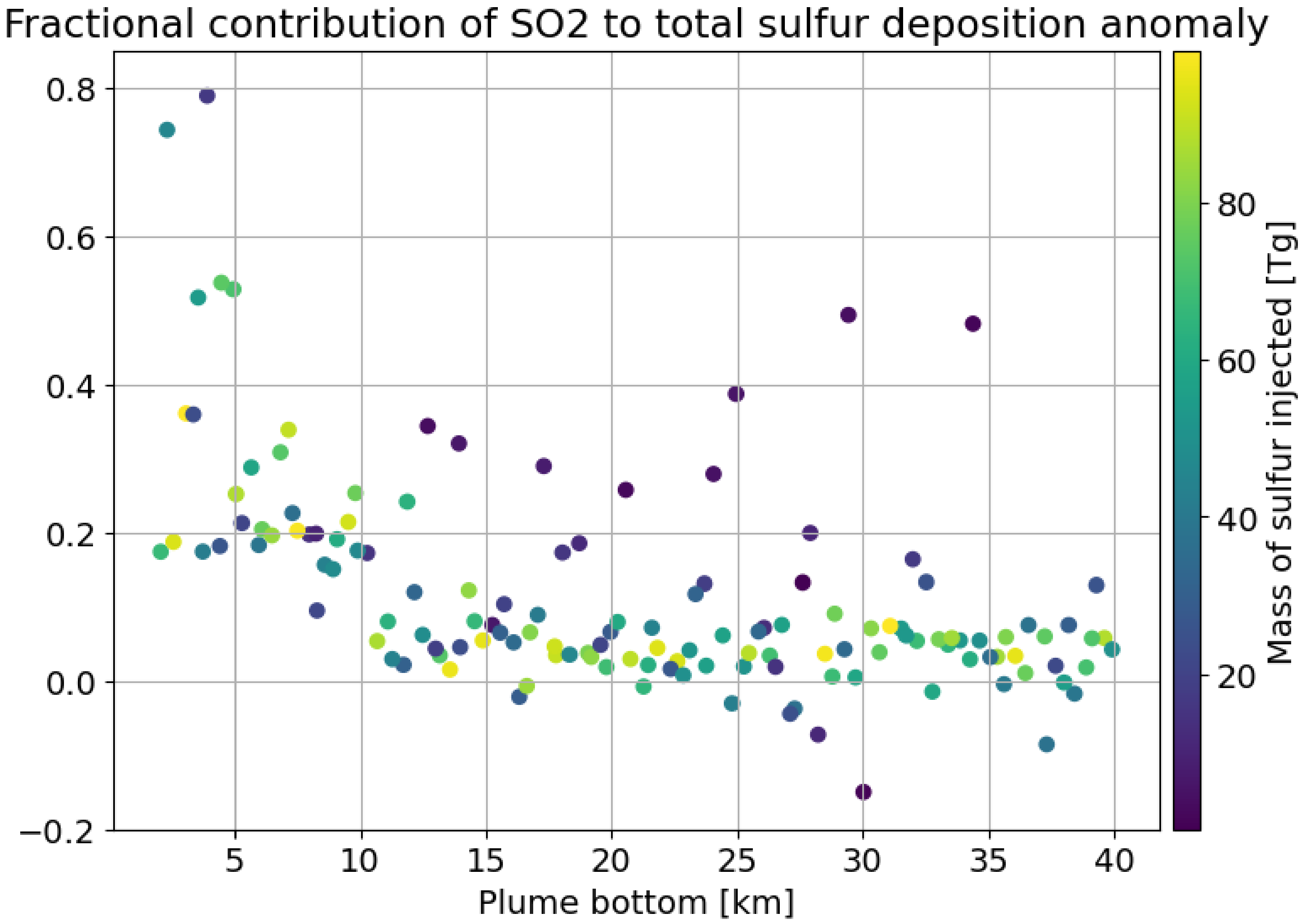
Fractional SO_2 deposition (anomaly from control)

Global SO_2 deposition anomaly as a fraction of total global sulfur deposition versus injection bottom altitude.

Color: injected SO_2 mass.

For tropospheric plumes, much of the sulfur is washed out as SO_2, not as much aerosol.

Low-SO_2 eruptions (darker points) noisier.

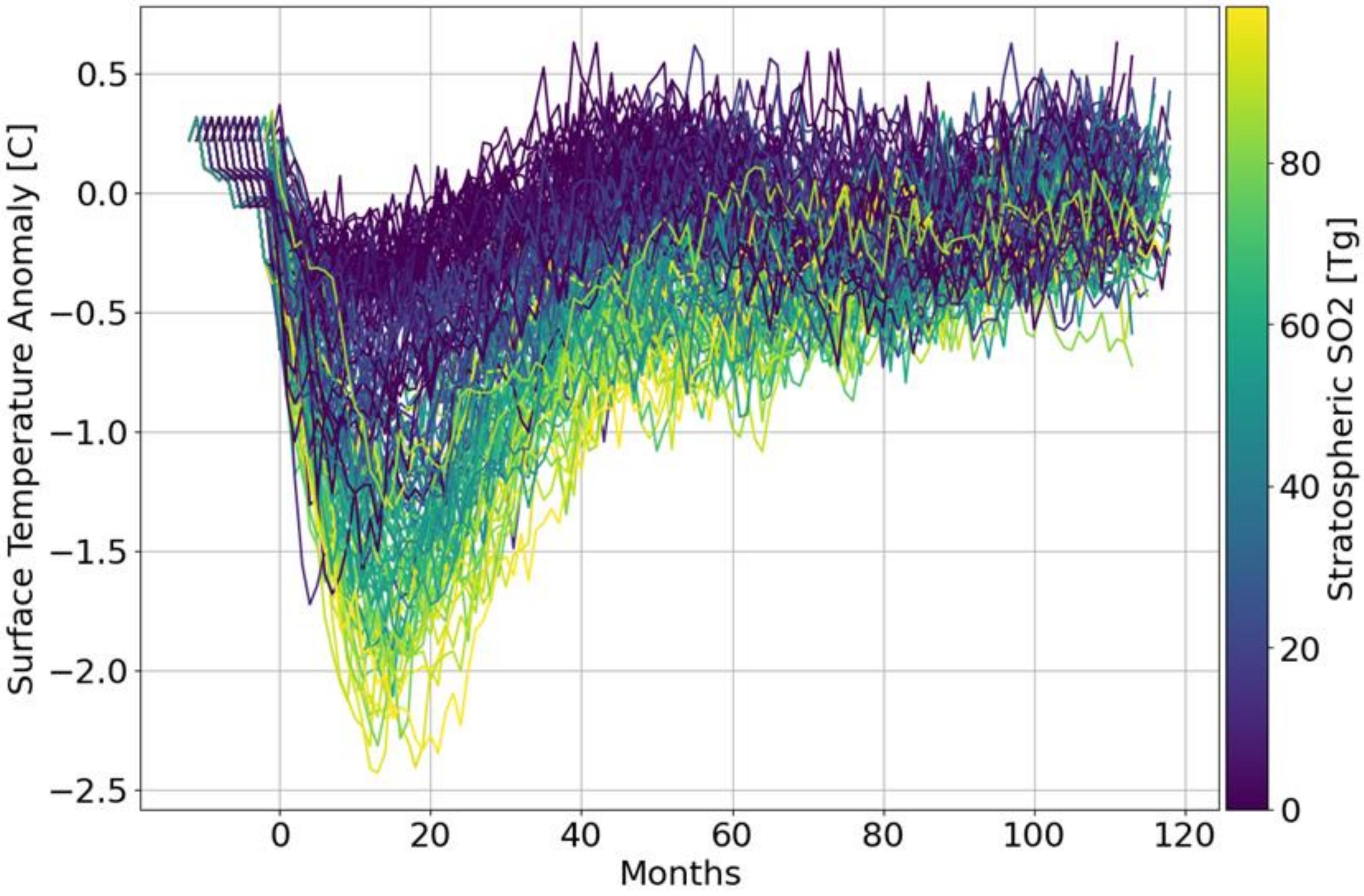


Climate effect: global mean surface temperature

Time series of global surface temperature anomaly for all 140 simulations.

Color: mass of SO_2 injected into the stratosphere.

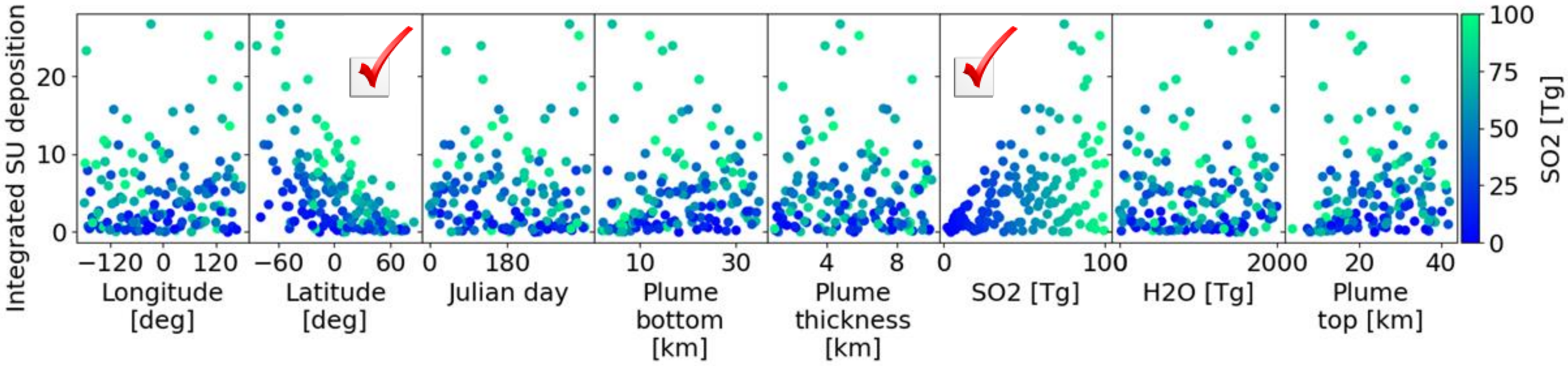
Stratospheric sulfur strongly linked with global cooling.



Deposition-parameter connections

- Scatter plot of Antarctic sulfate aerosol deposition anomaly across all parameter space dimensions.

- Stronger correlation: injected SO_2, latitude.
- Weaker correlation: plume bottom, plume top.
- No clear correlation: longitude, Julian day, plume thickness.



Machine Learning (ML)

- Think of ModelE as a mapping from eruption parameters to polar sulfate deposition.
- An ML model (e.g. neural network) is also just a mapping from input to output.
- We train a ML model on ModelE runs that map eruption parameters to sulfate deposition, giving us a simplified but performant model that emulates ModelE.
- This is surrogate modeling: replacing a complex, computationally expensive model with an approximate (e.g. ML) one that lets us "simulate" eruptions much faster.
- For accuracy, need to train with many runs of the complex model first.

Eruption parameters

Longitude
Latitude
Julian day
Plume bottom
Plume thickness
SO_2
H_2O

Markov Chain Monte Carlo (MCMC) parameter estimation ←

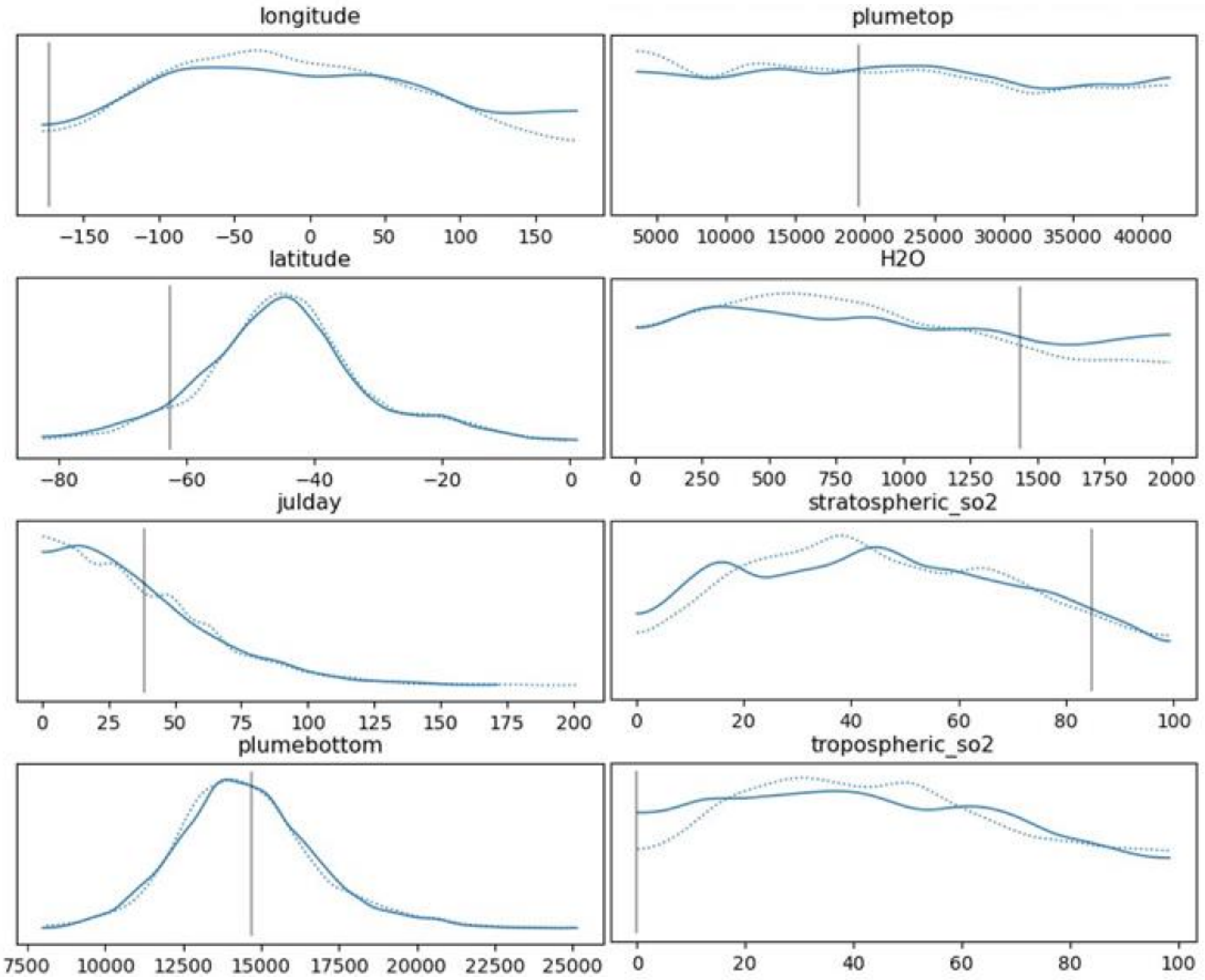
→ ~~Earth system model (ESM)~~ →

Machine learning model trained on a large set of ESM simulations

Polar sulfate deposition

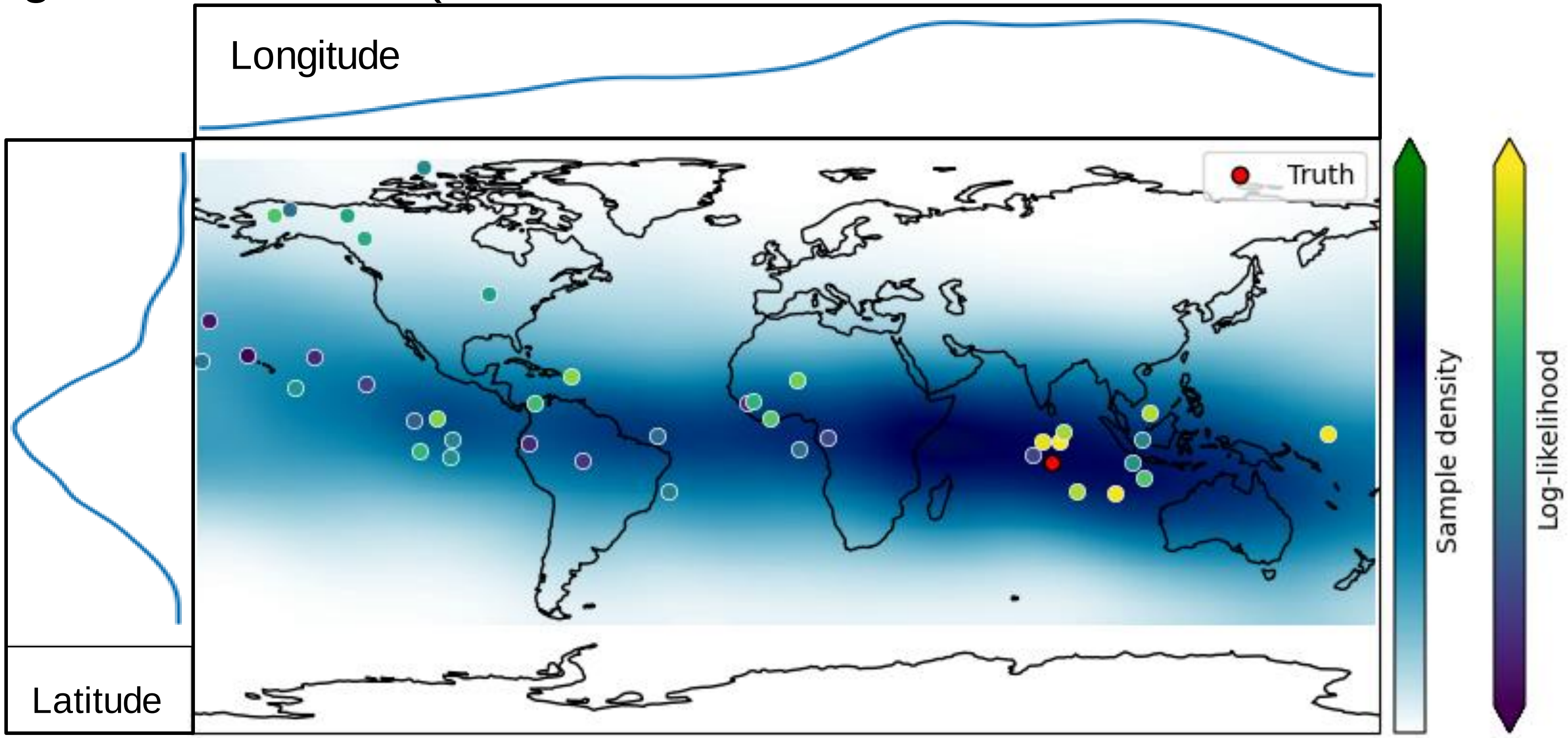
Parameter estimation

- Trained neural network that maps parameters → Antarctic and Greenland simulated sulfate deposition.
- MCMC strategically samples neural net thousands of times using a sulfate deposition sample and uncertainty as input.
- These samples can be plotted as distributions for each parameter.
- Plot represents a parameter estimation for a single simulation.
- True values marked.



Parameter estimation

- Combined latitude and longitude distributions to produce a heatmap.
- Find samples with highest likelihood (best matches to observed sulfate deposition).
- Plot true latitude and longitude parameters for this simulation.



Conclusions and future work

- Simulated 140 volcanic eruptions with various parameters.
- Trained neural network on eruption parameters and polar sulfate deposition.
- Set up parameter estimation given some observed sulfate deposition.
- Parameter estimation performs best with high sulfate.

- **Future extensions:**
- Improve quantification of uncertainty in both the machine learning and ESM.
- Test with real ice core data from known eruptions (e.g. Tambora, Pinatubo).
- Identify regions in parameter space with stratified responses.
- Estimate parameters based on climate impact instead of sulfate deposition.
- Predict climate response from ice core sulfate.