# Uncertainty Quantification of Convection Parameters within an Idealized Climate Model


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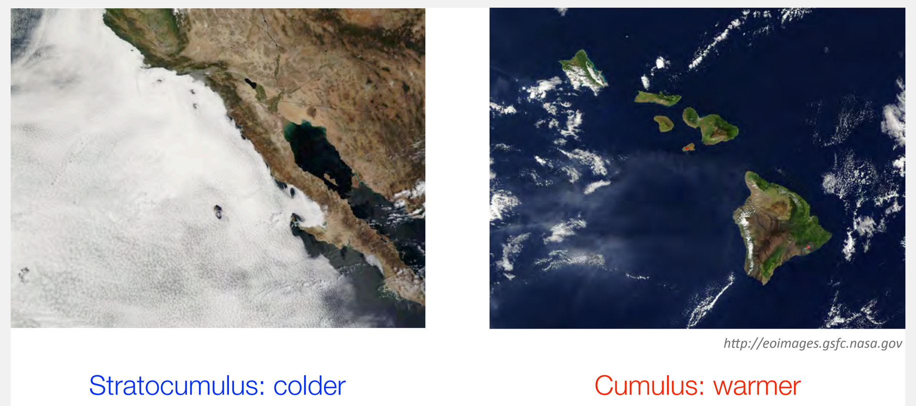
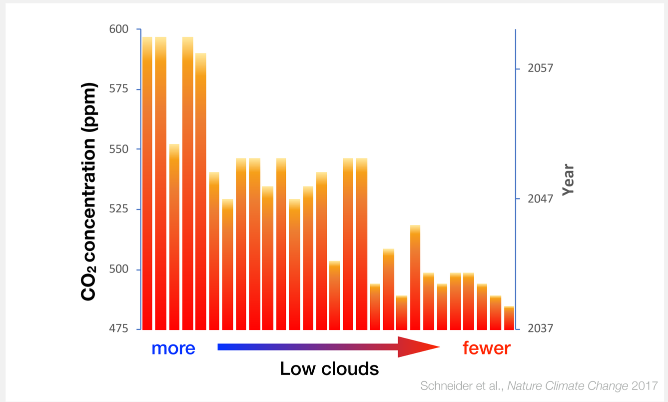
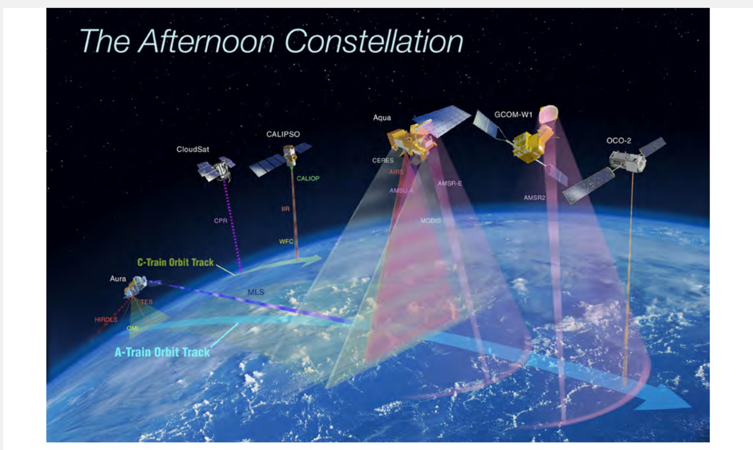
## Cloud parameter uncertainty dominates prediction uncertainty

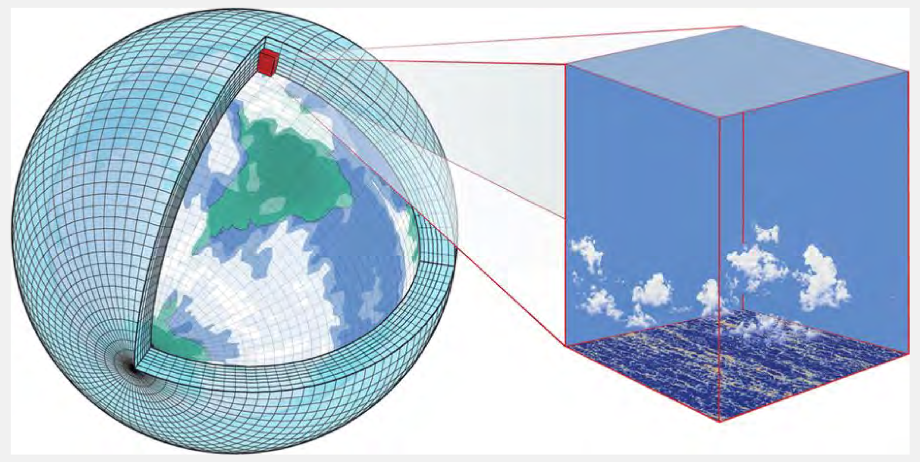



Climate model predictions are correlated with **unresolvable** cloud features.

## There is available data we can use to learn these parameters [7]

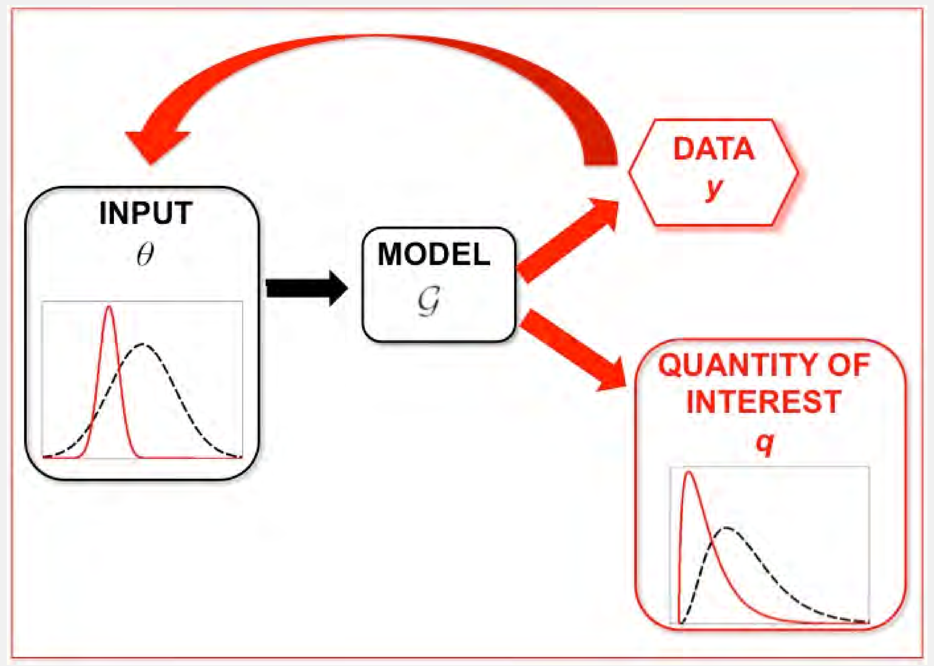


[https://atrain.nasa.gov/]

## Parameter uncertainty quantification (UQ) [8]

UQ is a loop: The spread (- -) of prior $\theta$ is refined to (—) by using a data sample $y$:

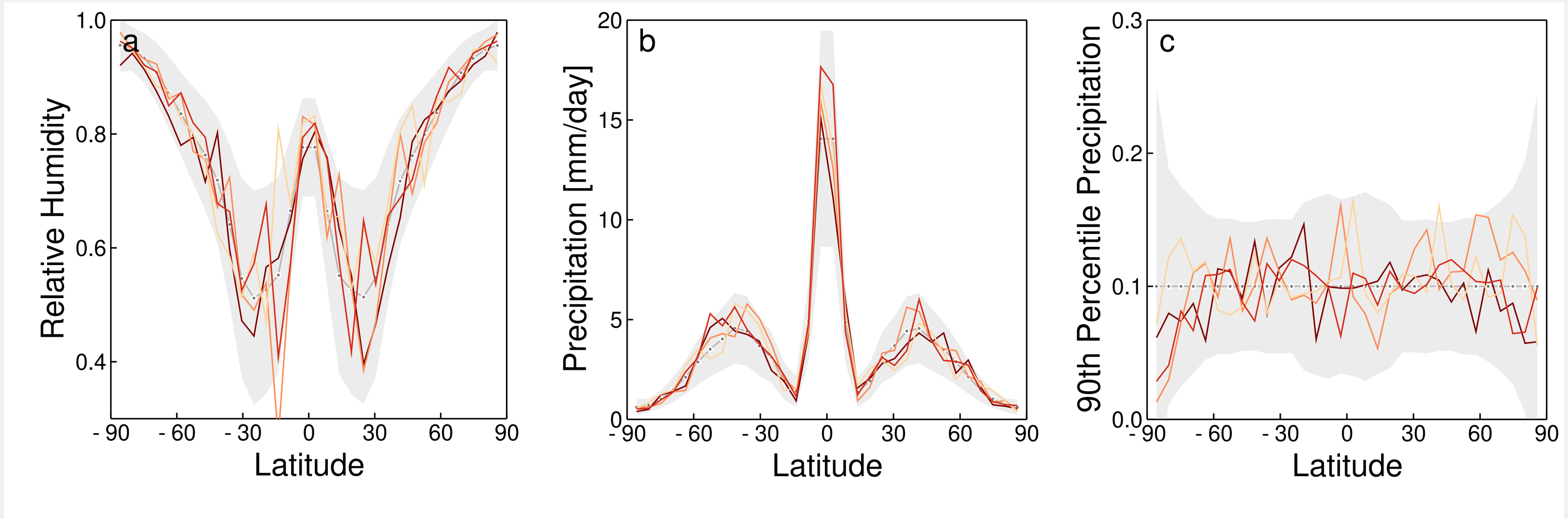



Climate setting:

- Convection parameters $\theta$, defined by prior distribution over space $\Theta$,
- Initial condition $z$, time $T > 0$,
- Aggregated observations in data space $y \in \mathcal{Y}$,
- Forward map containing a climate model $\mathcal{G}_T(\cdot; z)\colon \Theta \to \mathcal{Y}$.

## An idealized aquaplanet (GCM) scenario [4, 6]

In color: ($T = 30$ day) quantities $y_i$ at four initial conditions $z_i$




$y_i = \mathcal{G}_T(\theta; z_i)$, when $\theta$ **is fixed.**

Central Limit Theorem: removes $z$ dependence

$$y = \mathcal{G}_T(\theta; z) \approx \mathcal{G}_\infty(\theta) + N(0, \Sigma) \qquad (1)$$

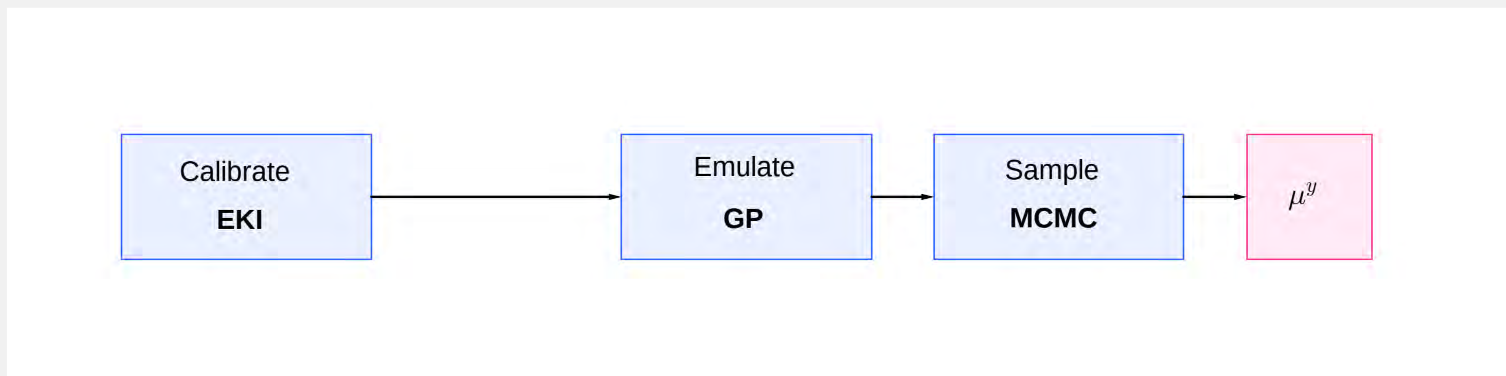
## Our goal: to solve (1) for $\theta$ given a sample $y_i$.

- No access to $\mathcal{G}_\infty(\theta)$. Only have access to "noisy" $\mathcal{G}_T$,
- $\mathcal{G}_T$ expensive for large $T$,
- $\mathcal{G}_T$ is non-differentiable.

Practical problems prevent **direct application** of sampling methods!

## Overcome these hurdles with Calibrate, Emulate, Sample [1, 2]

Idea: A **Judicious** use of machine learning can **accelerate** UQ.

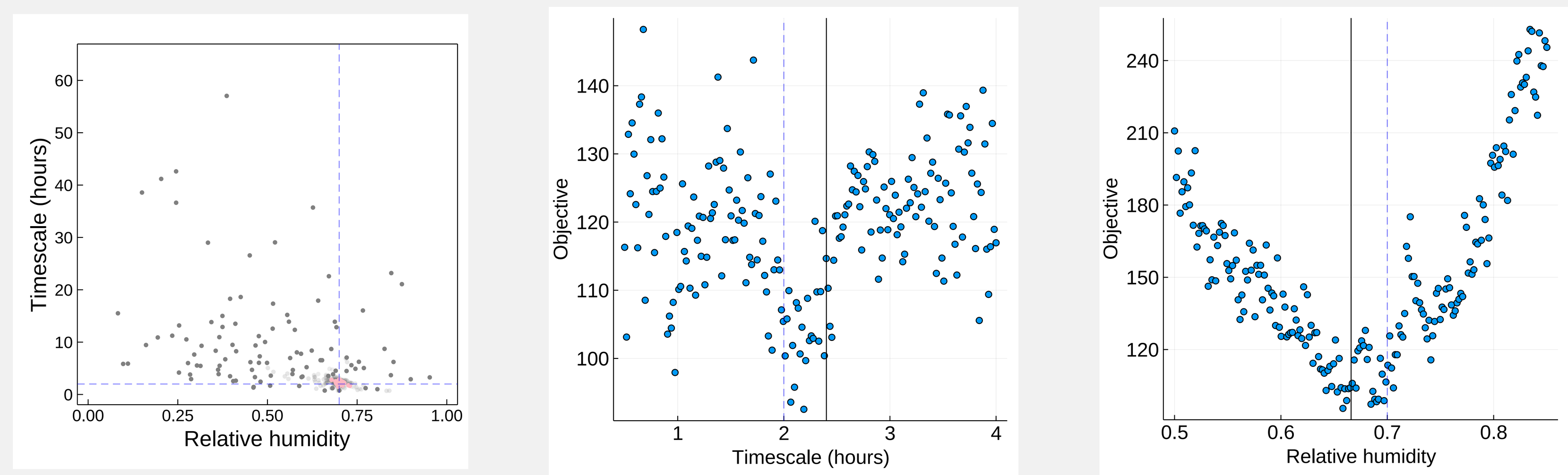



Calibrate, Emulate, Sample (CES):

- ✓ Works with noisy model evaluations, as emulator smoothes the objective.
- ✓ Cheap, $\sim 500$ evaluations of $\mathcal{G}_T$, Emulator is cheap online.
- ✓ Doesn't require differentiation, as $\mathcal{G}_T$ is used as a black box.

**Produces a parameter distribution with quantified uncertainty!**

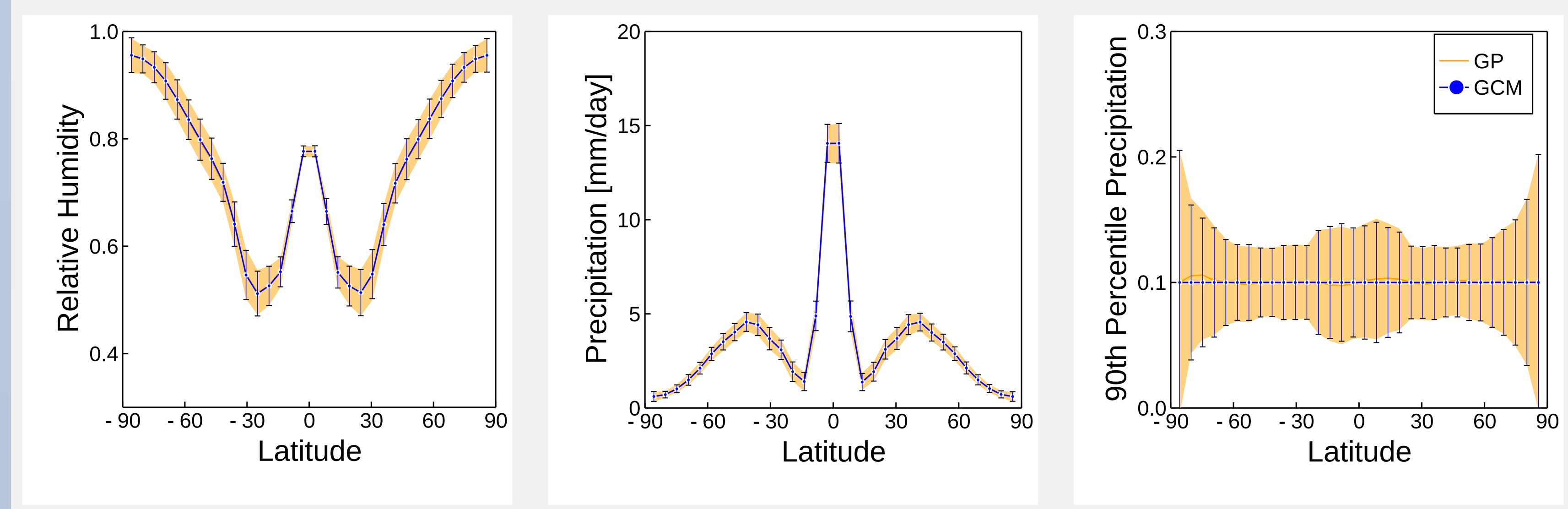
## Calibrate: Ensemble Kalman Inversion [5]




Robust: locates minimizer (|) with **noisy** objective function! [3]

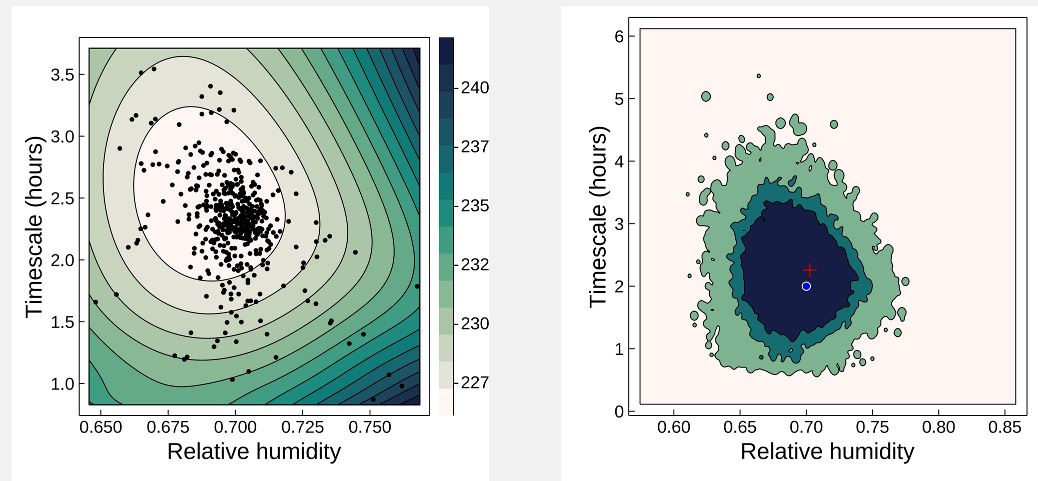
## Emulate: $\mathcal{G}_T$ with Gaussian processes (GP) [9]

Idea: Use the **Calibrate** evaluations as training points.




GP-prediction is $10^4\times$ faster than climate model evaluation!

## Sample: GP-based Markov chain monte carlo




Stored posterior samples can be later sampled to predict quantities of interest, with **quantified uncertainty.**

## General tools: open software (Julia)

```
https://github.com/CliMA/EnsembleKalmanProcesses.jl
https://github.com/CliMA/CalibrateEmulateSample.jl
```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