Quantifying parameter uncertainty within a climate model

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CliMA

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Eric and Wendy Schmidt, Mountain Philanthropies, NSF, ONR, Paul G. Allen Family Foundation

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The Climate Modelling Alliance (CliMA)

2018 Collaboration to produce a new Earth System Model[1]. clima.caltech.edu

Caltech MIT JPL Jet Propulsion Laboratory NPS PRAESTANTIA PER SCIENTIAM 1909

[1]Schneider et al. 2017.

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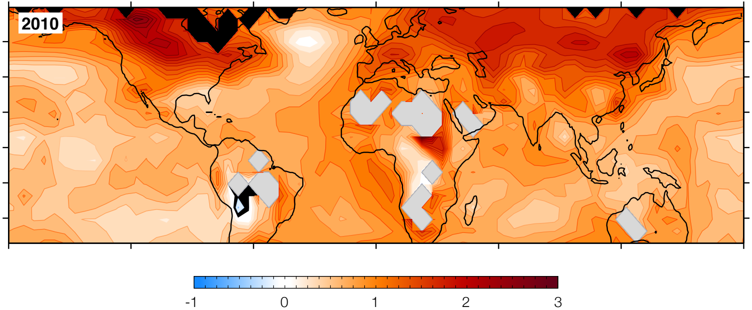
Global temperatures are increasing

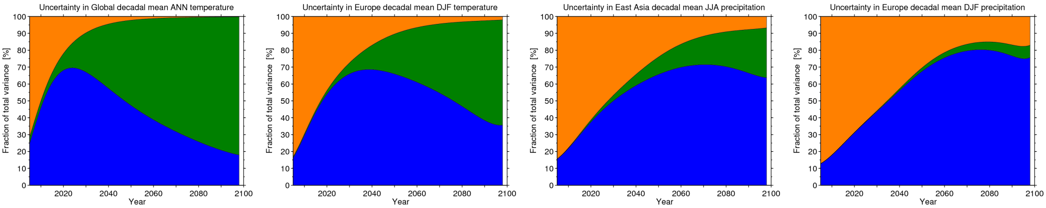


Temperature change (°C) from 1850s through 2010s

Schneider & Held, J. Climate, 2001; update http://climate-dynamics.org/videos

But climate model predictions are uncertain

( ) Internal Variability, ( ) Scientific (model) Uncertainty, ( ) Scenario Uncertainty.



[IPCC 2013, Climate Change 2013: The Physical Science Basis, Working Group 1 Contribution to the fith Assessment Report (AR5)]

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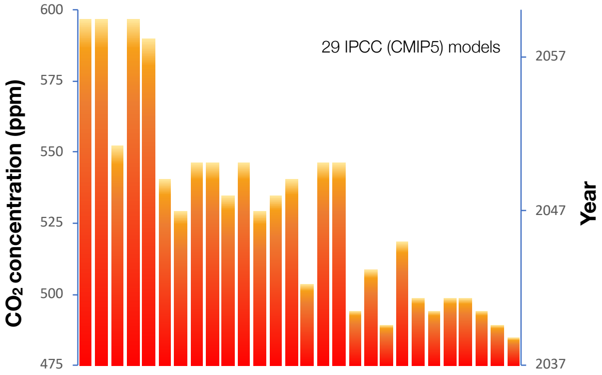
CO_2 concentration that breaches 2°C warming?



Schneider et al., *Nature Climate Change* 2017

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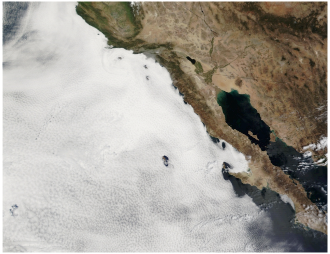
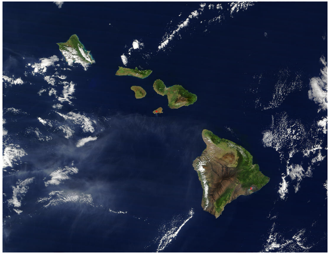
Ability to predict cloud cover is key





http://eoimages.gsfc.nasa.gov

Stratocumulus: colder

Cumulus: warmer

We don't know if we will get more low clouds (damped global warming), or fewer low clouds (amplified warming) with rising CO_2 levels

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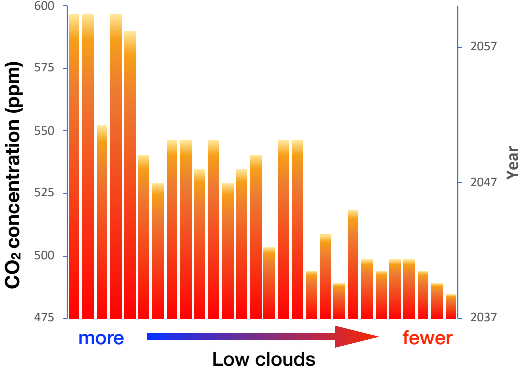
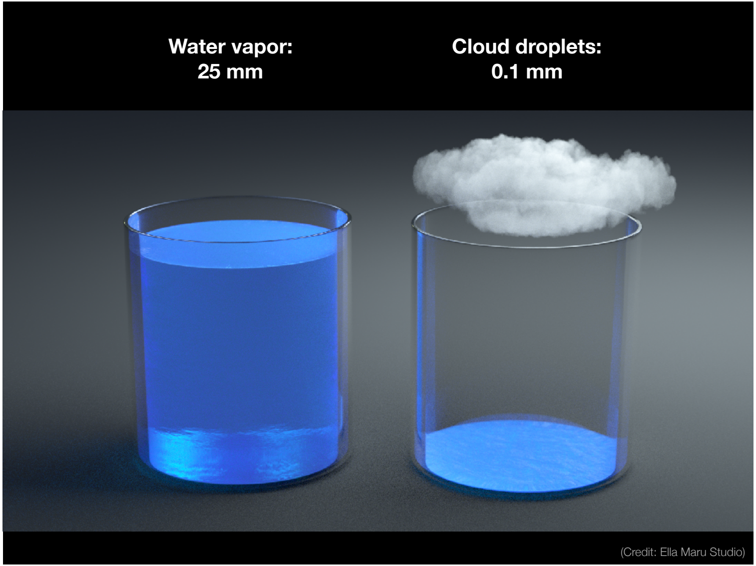
Cloud cover correlates with CO_2 concentration predictions



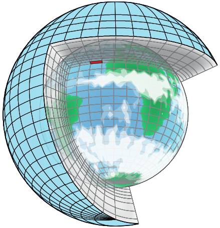
Schneider et al., *Nature Climate Change* 2017

Range of scales hampers ability to predict cloud cover

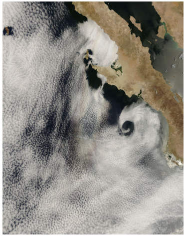


(Credit: Ella Maru Studio)

Range of scales hampers ability to predict cloud cover



Global model:
~10-50 km resolution

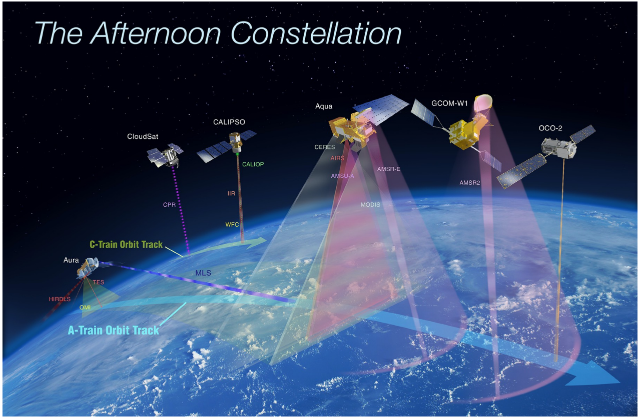


NASA MODIS

Cloud scales: ~10-100 m

Subgrid-scale processes (e.g., clouds and turbulence) are represented in ad-hoc fashion (not data-driven)

There is available satellite data (JPL)



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

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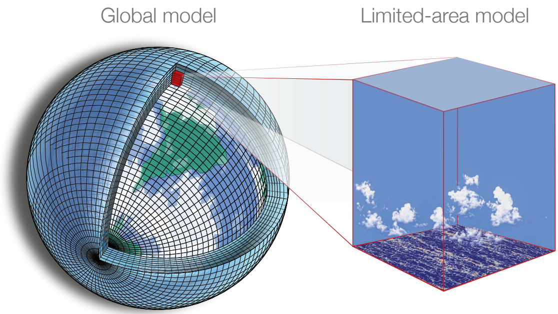
There are affordable limited-area simulations



Thousands of high-resolution simulations can be embedded in global model in a distributed computing environment (cloud), and the global model can learn from them

The Climate Modelling Alliance (CliMA)[2]

Our Aims

- Redesign physical models to better resolve clouds.
- Data assimilation, uncertainty quantification and machine learning framework to learn about parameter uncertainty within physical models.
- Include data from both high resolution simulation and observations.
- Julia language framework unified across all components. (v0.1.0 released!)

[2] Schneider et al. 2017.

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Going from parameters to data[3]

Ingredients

- Parameter (prior) distribution $\theta \sim \mu_0$, parameter space $\theta \in \Theta$.
- Data space $y \in \mathcal{Y}$.
- Forward map $\mathcal{G}\colon \Theta \to \mathcal{Y}$,
- Noise covariance Σ.

Recipe for data y:

$$y = \mathcal{G}(\theta) + N(0, \Sigma) \tag{1}$$

[3] Stuart 2010; Garbuno-Inigo et al. 2019.

The perfect climate model setting[4]

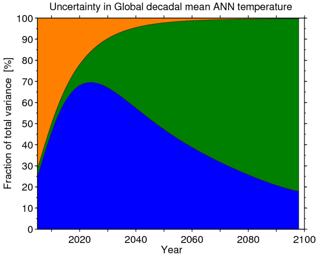
Recipe for data y:

$$y = \mathcal{G}_T(\theta; z_0) = \mathcal{G}_\infty(\theta) + N(0, \Sigma) \quad (2)$$

- Forward map $\mathcal{G}_T$, T time averaged forward run of length T.
- No observational noise η ('perfect setting'), **but** $\mathcal{G}_T$ is noisy $N(0, \Sigma)$.

Perfect doesn't mean easy!

- $\mathcal{G}_T$ is noisy, no access to $G_\infty(\theta)$.
- $\mathcal{G}_T$ expensive, especially for large T.
- $\mathcal{G}_T$ is non-differentiable.



[4] Dunbar et al. 2020.

An idealized GCM[5]

Idealized moist GCM: Aquaplanet. T21 Spectral discretization (32 discrete latitudes).

Moist convection in quasi-equilibrium (Betts Miller type). Features sources in temperature and humidity equations

$$\text{Source}(x) = \frac{x - x_{\text{ref}}(\alpha)}{\tau}$$

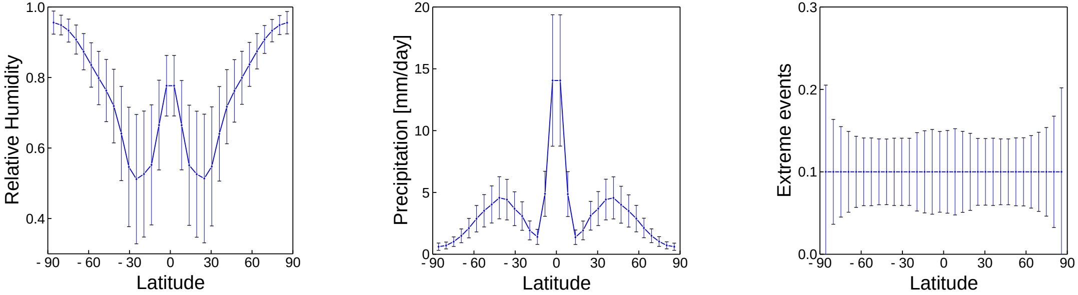
$0 < \alpha < 1$ relative humidity. $0 < \tau$ relaxation time. Priors enforce constraints.

Properties: stationary statistics, zonally symmetric, $\theta = (\alpha, \tau)$

[5] Frierson 2007; O'Gorman and Schneider 2008.

The data y

3 time averaged ($T = 30$ day) quantities



$$y^\dagger = \mathcal{G}_T(\theta^\dagger; z_0), \text{ where } \theta^\dagger = (\alpha^\dagger, \tau^\dagger) = (0.7,\ 2\text{hours})$$

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(Traditional) Optimization approach: find optimal parameter set

Calibration objective: Find optimal $\theta^* \in \Theta$ that best fits with prior μ_0 and data $y^\dagger$.

Ensemble Kalman Inversion[6] (EKI) to find θ^*:

- $(+)$ Cheap! $\sim$ 500 evaluations of $\mathcal{G}_T$,
- $(+)$ Doesn't require differentiation! $\mathcal{G}_T$ non-differentiable,
- $(+)$ Works with noisy model evaluations! noisy objective function,

But...

- $(-)$ **Uncertainty greatly underpredicted.** (Ensemble Collapse)

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[6] Iglesias, Law, and Stuart 2013.

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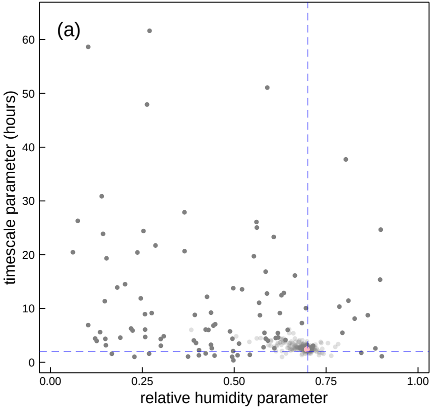
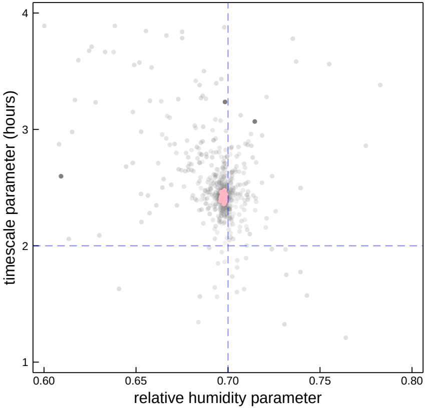
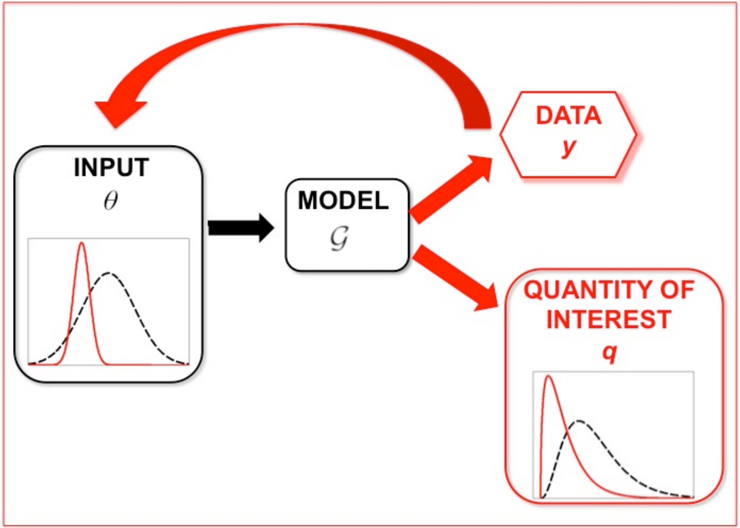
EKI optimization



Zooming in...



What is uncertainty quantification?



Bayesian approach: find the data-informed distribution μ^y

Sampling objective: Sample the distribution $\theta \mid y^\dagger$, given a prior μ_0.

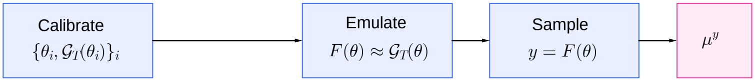
Markov Chain Monte Carlo (MCMC):

- $(+)$ **Uncertainty is quantified!**

But...

- $(-)$ Expensive. $\sim 500,000$ evaluations of $\mathcal{G}_T$,
- $(-)$ Gets stuck in local minima. noisy objective function.

Calibrate-Emulate-Sample[7]



Calibrate-Emulate-Sample (CES):

- (+) **Uncertainty is quantified!**
- (+) Cheap! $\sim$ 500 evaluations of $\mathcal{G}_T$,
- (+) Doesn't require differentiation! $\mathcal{G}_T$ non-differentiable,
- (+) Works with noisy model evaluations! Emulator smoothes the objective.

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[7] Cleary et al. 2019; Dunbar et al. 2020.

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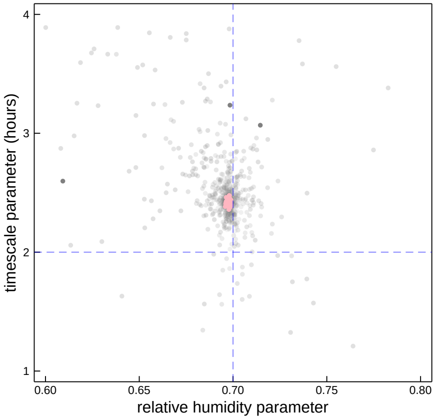
Calibrate-Emulate-Sample[7]

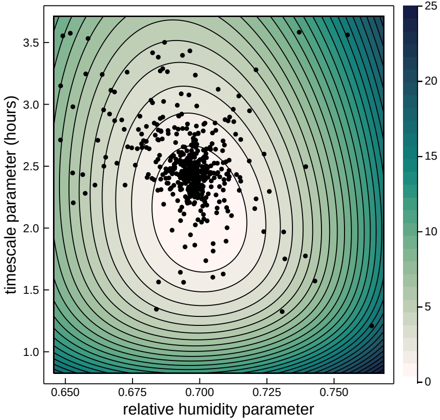
Calibrate $\{\theta_i, \mathcal{G}_T(\theta_i)\}_i$ → Emulate $F(\theta) \approx \mathcal{G}_T(\theta)$ → Sample $y = F(\theta)$ → μ^y

Calibrate **EKI** → Emulate **GP** → Sample **MCMC** → μ^y

[7] Cleary et al. 2019; Dunbar et al. 2020.

Learning: calibrate for training points





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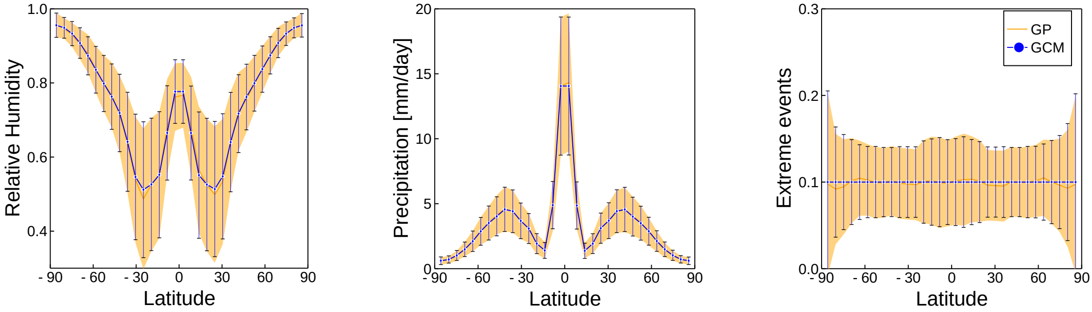
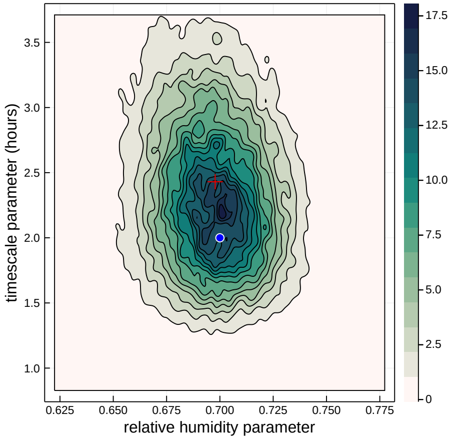
Learning: emulate with Gaussian process



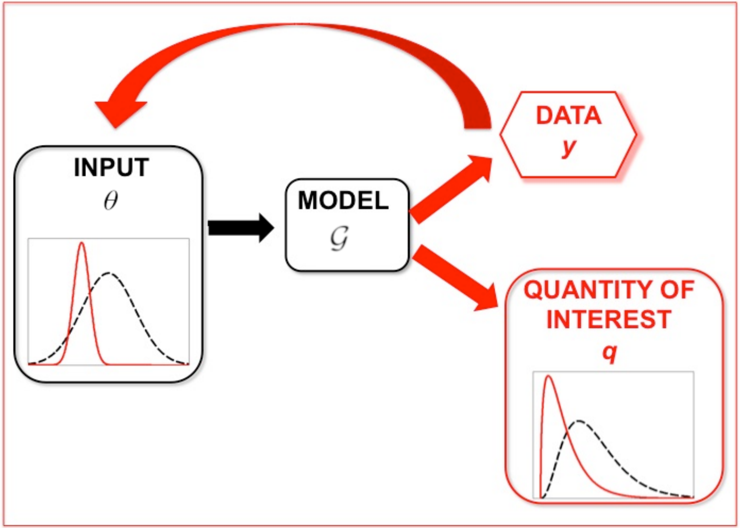
Learning: Sample with MCMC



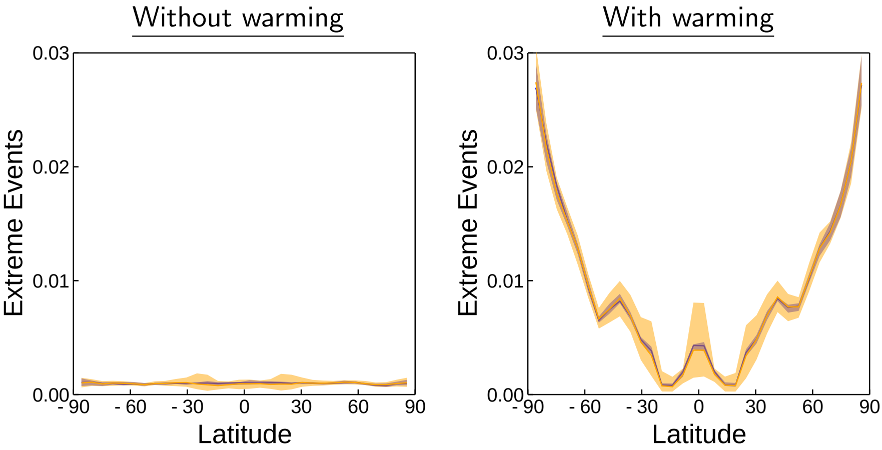
(+) EKI Optimal θ^*,

(●) Truth $\theta^\dagger$.

Now we can make predictions of QoIs!



A warming experiment



(■) without parameter uncertainty, (■) with parameter uncertainty.

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Summary

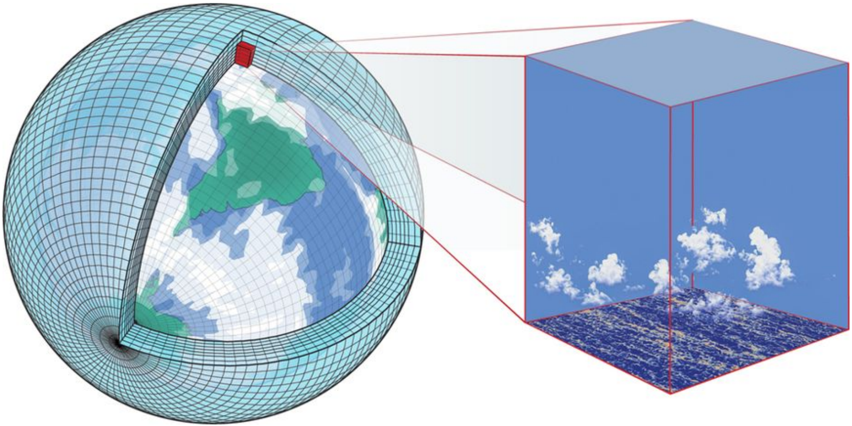
- Uncertainty is important, particularly parameter uncertainty.
- To make trustworthy predictions we must quantify it.
- CES pipeline automates and accelerates uncertainty quantification for expensive and noisy models in a black-box fashion.[8] (Julia package forthcoming on Github)
- We benchmarked this for moist convection in an idealized aquaplanet.[9]

Looking ahead

- Structural model error,
- Higher dimensional parameter learning (and non-parametric function learning),
- Online learning,
- **Automated optimal design...**

[8] Cleary et al. 2019.
[9] Dunbar et al. 2020.

Optimal placement of limited-area simulations



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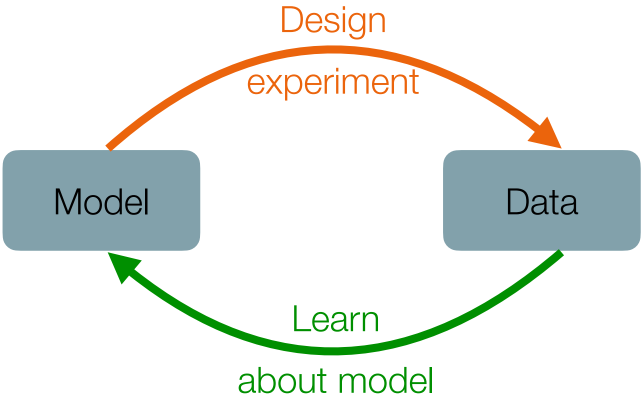
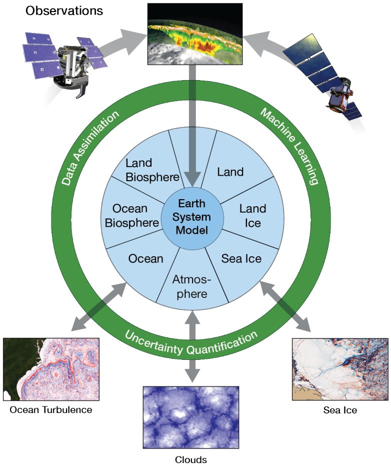
CES automates and accelerates the scientific loop!



The bigger picture



Targeted High-Resolution Simulations

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