Efficiently constraining parameter uncertainty in a General Circulation Model using targeted data

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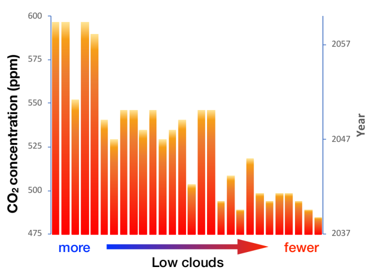
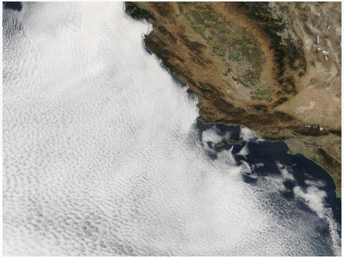
Why cloud parameters? Why uncertainty?

2015 Paris Agreement: $2^\circ C$ threshold temperature increase above preindustrial levels.





Schneider, Teixeira, et al. 2017 , https://worldview.earthdata.nasa.gov/

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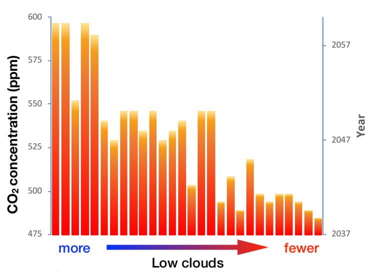

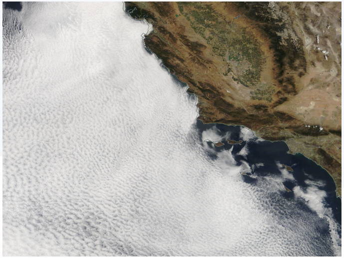

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Cloud parameter uncertainty $\implies$ prediction uncertainty

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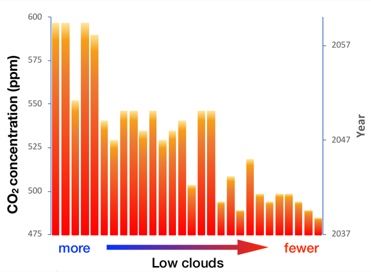

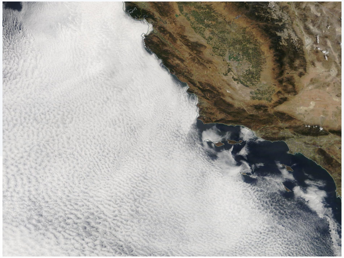

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Cloud parameter uncertainty $\Longrightarrow$ prediction uncertainty
All of these models give certain predictions.

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Climate Modelling Alliance (CliMA)

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

Caltech

Jet Propulsion Laboratory

NPS PRAESTANTIA PER SCIENTIAM 1909

Some aims

- Redesign physical models to better resolve clouds. ('physical over empirical')
- Data assimilation, uncertainty quantification and machine learning framework.
- Include data from high resolution simulation and observations.
- Julia programming language framework unified across all components.

[1]Schneider, Lan, et al. 2017.

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The abstract Bayesian setting[2]

Ingredients

- Prior parameters $\theta \sim \mu_0$.
- $\mathcal{G}_T(\theta)$ - **time averaged** data from GCM, (dimension reduction)
- Observational noise $\eta \sim N(0, \Sigma)$.

Recipe for observation y:

$$y = \mathcal{G}_T(\theta) + \eta \tag{1}$$

[2] Stuart 2010; Cleary et al. 2019.

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Our GCM example

Idealized moist GCM: Aquaplanet[3]. Moist convection scheme in quasi-equilibrium (Betts Miller type).

$$\text{flux}(x) \to \frac{x - x_{\text{ref}}(\alpha)}{\tau}, \qquad \theta = (\alpha, \tau)$$

Physical Priors

$$0 < \alpha < 1 \text{ relative humidity. Prior: } \text{logit}(\alpha) \sim \text{Normal}$$
$$0 < \tau \text{ relaxation time. Prior: } \log(\tau) \sim \text{Normal}$$

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

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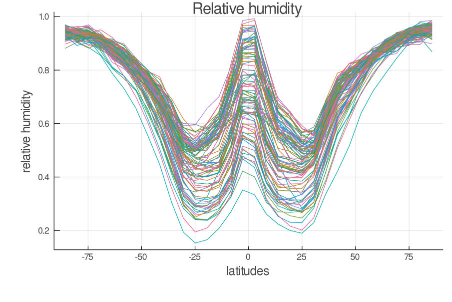
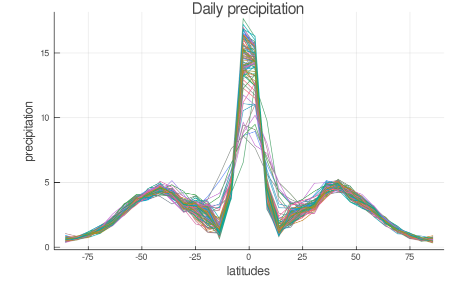
Our GCM example

Forward map $\mathcal{G}_T$: 2 time averaged (20 day) quantities: relative humidity at 5km, and daily precipitation.





100 samples of $\mathcal{G}_T(\theta)$ at $\theta \sim \mu_0$.

Observed data point: $y = \mathcal{G}_T((0.7, 7200s))$

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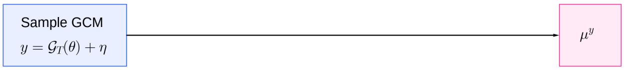
The Bayesian inverse problem setting[5]

Learning objective: Sample $\theta | y \sim \mu^y$ posterior, constrained by data y.



[4] Cleary et al. 2019.

[5] Stuart 2010; Cleary et al. 2019.

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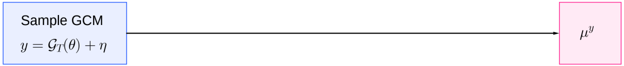
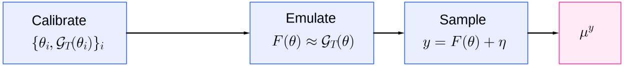


Calibrate **E**mulate **S**ample framework (CES)[4]



[4]Cleary et al. 2019.
[5]Stuart 2010; Cleary et al. 2019.

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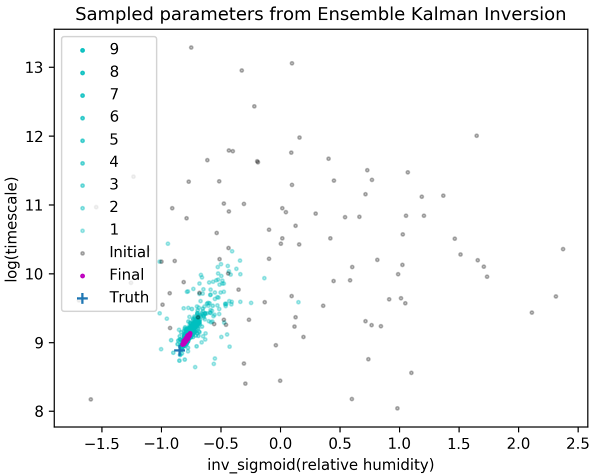
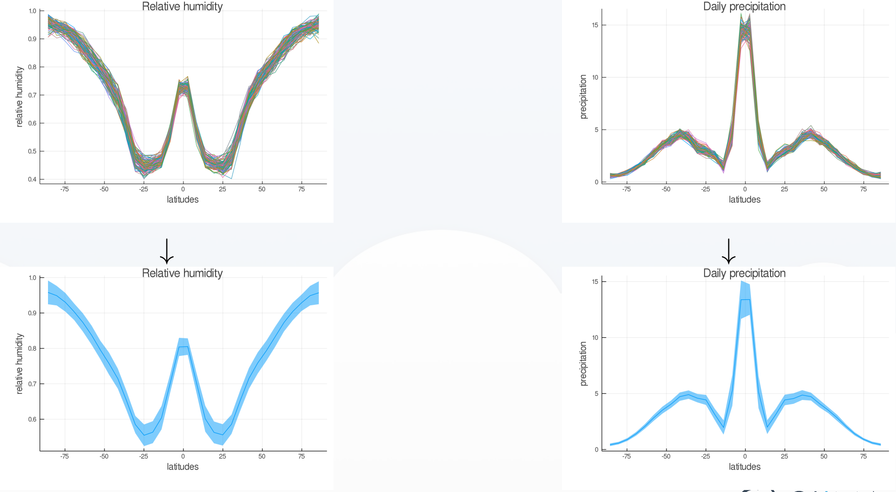
Calibrate: Ensemble Kalman Inversion of the GCM parameters.[6]



[6] Iglesias, Law, and Stuart 2013.

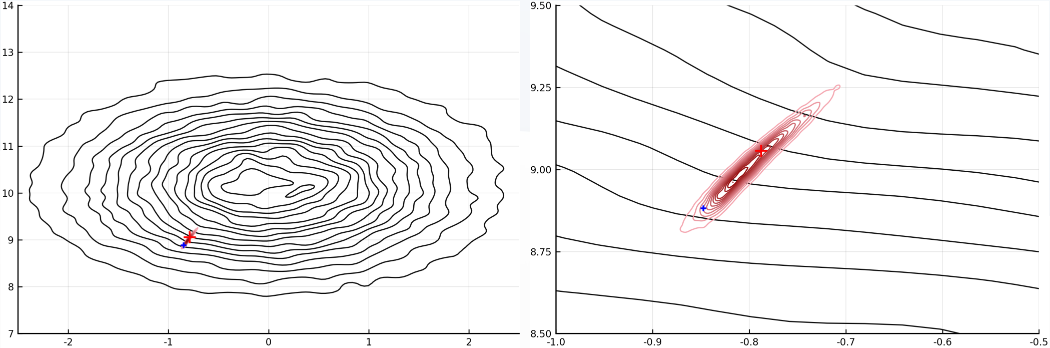
Emulate: Gaussian Process emulator.[7]



[7] Kennedy and O'Hagan 2001; Santner et al. 2018.

Sample: Random Walk Metropolis

Blue + Truth, Red + Optimal,
Black – Prior, Red – Posterior



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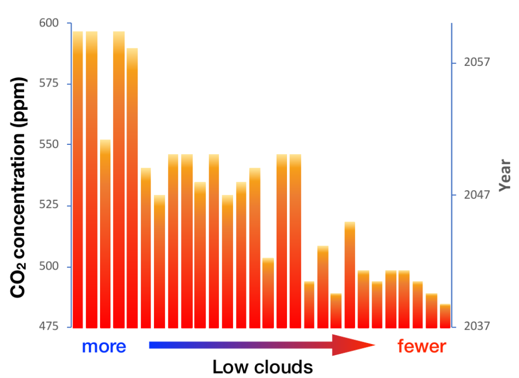
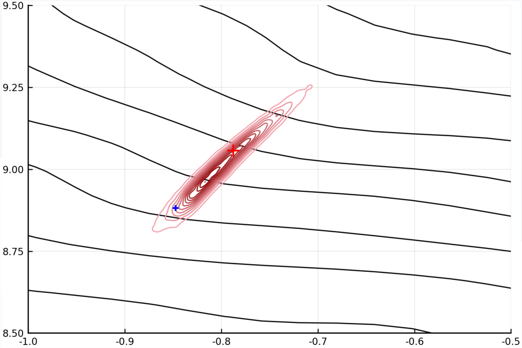
We can now make predictions with uncertainty





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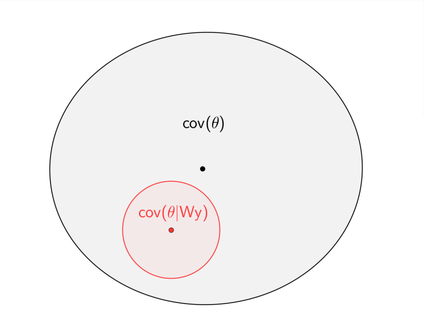
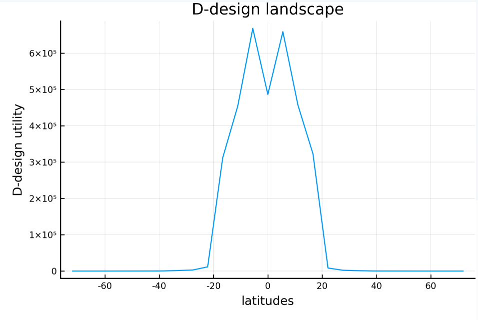
Design objectives

Design objectives:

1. Find design W so that $\theta | Wy$ is **maximally** informative.





$\Longrightarrow$ Equatorial region is highly informative.

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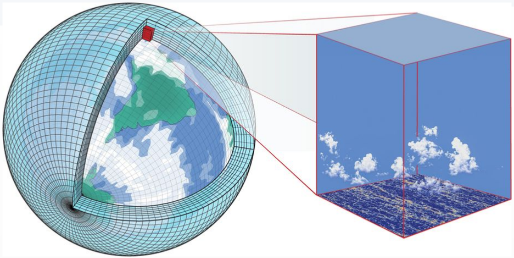
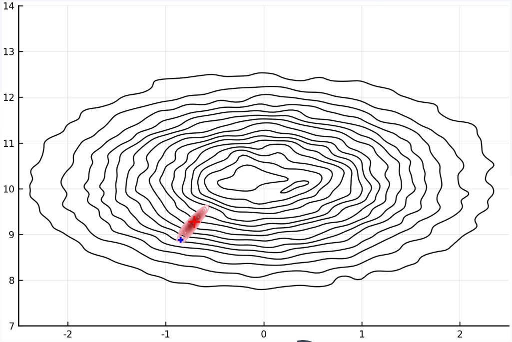
Design objectives

Design objectives:

1. Find design W so that $\theta | Wy$ is **maximally** informative.
2. **Target computation:** Uncertainty quantification **only** at optimal location:





Looking ahead

1. Using imperfect data in the design stage. (model error)
2. Targeted simulation independent of parameterization. (LES/DNS)
3. More complex GCM, with $\mathcal{O}(100)$ parameters (Gaussian Process?)
4. Online (sequential) design (Multiple design locations)

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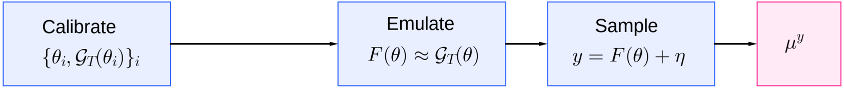
Calibrate Emulate Sample methods (CES)[10]

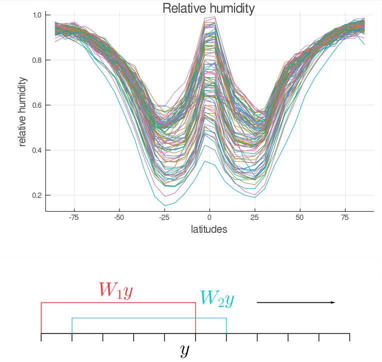
- (Calibrate) Ensemble Kalman Inversion of the GCM parameters.[8]. Derivative free. Optimal parameters in 100s of samples.
- (Emulate) Gaussian Process emulator.[9]
- (Sample) Random Walk Metropolis.

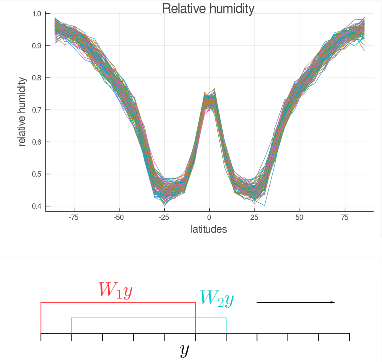


[8] Iglesias, Law, and Stuart 2013.
[9] Kennedy and O'Hagan 2001; Santner et al. 2018.
[10] Cleary et al. 2019.

Finding the optimal design

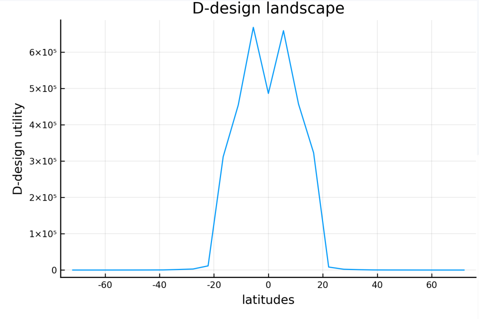
Regional (in latitude) data $W_i y$ give different posterior distributions $\mu^{W_i y}$

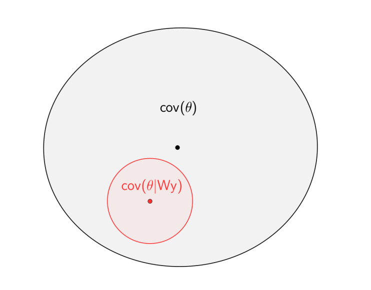




Maximal information

W^* that maximizes an information entropy[11] gives the most concentrated posterior distribution





E.g $W* = \arg\max(U(W))$ where $U(W) = \det(\mathrm{cov}(\theta|Wy))^{-1}$

[11] Chaloner and Verdinelli 1995; Huan and Marzouk 2013; Alexanderian, Gloor, and Ghattas 2016.