Confidence intervals on uncertain parameters in atmospheric simulations of African fires

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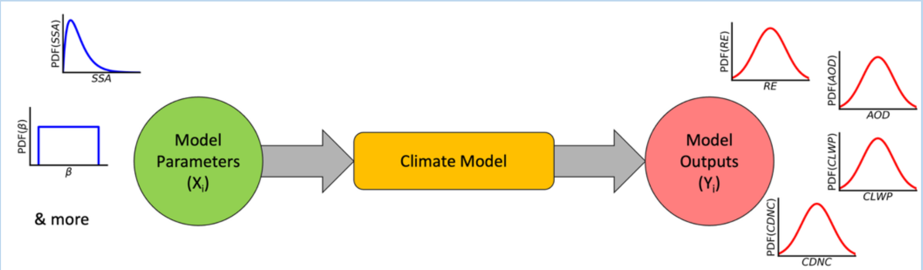
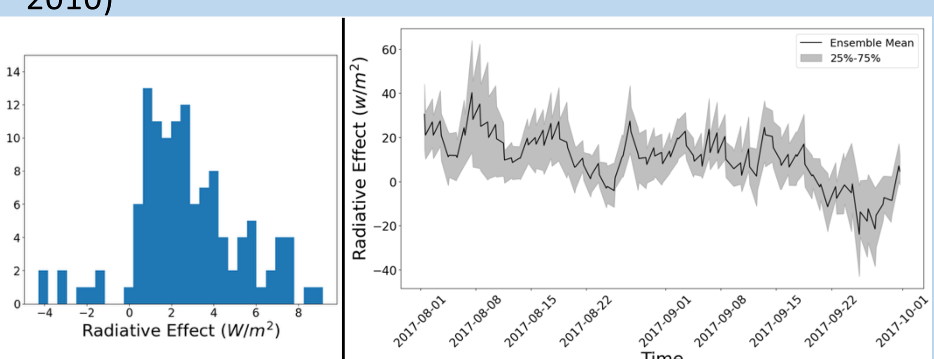


Aims: a) Reduce parameter uncertainty for simulations of biomass burning fires in Southern Africa
b) Observe reduction in radiative effect uncertainty with reduced parameter uncertainties

Background & Motivation

Previous Method:
-Theoretical guarantees of previous methods ("history matching") were not clearly understood
Case Study:
-Biomass Burning Fires are used by local population in Southern Africa for agriculture on a seasonal basis
-Southern Africa accounts for largest portion of planet's biomass burning aerosol budget (Van der Werf et al. 2010)



Case study: 2017 Biomass Burning Fires in Southern Africa

Interest: Smoke interacting with stratocumulus clouds, complex direct and cloud radiative effects; period coincides with intensive aircraft measurements
PPE: 121 2-month-long global Unified Model simulations in 2017, 1.88x1.25° resolution, atmosphere-only, winds nudged to ERA5 above the boundary layer

Parameters	Minimum Value	Maximum Value
Smoke Emissions*	0.25	4
Smoke Diameter (nm)	90	299
Std. Dev. of Updraft Velocity*	0.4	1.2
Dry Deposition of Accumulation Mode Aerosol*	0.1	10
Sea Spray Emissions*	0.25	4
Cloud top Entrainment Rate*	0.02	0.5
Beta Parameter	-0.15	-0.13
Kappa-Kohler Coeff. for Organic Carbon	0.2	0.65
Dimethyl Sulfide Ocean Surface Concentration*	0.33	3
Anthropogenic SO_2*	0.6	1.5
Autoconversion Exponent	-3	-1
Black Carbon Refractive Index	0.4	1

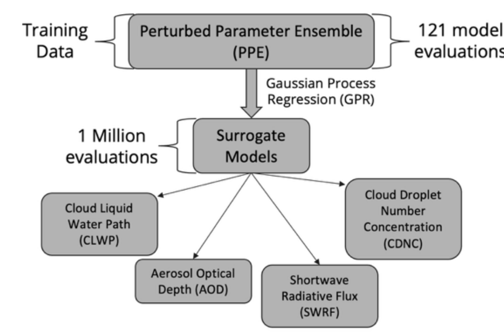


Fig. A: Data currently compared with MODIS (L3) (plan to also add aircraft measurements)

$$H_0 : u = u^* \qquad H_1 : u \neq u^*$$

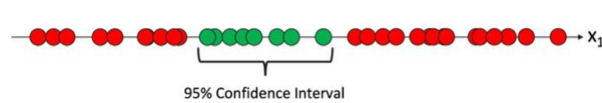


Fig B: Describing an inverted hypothesis test

Methods and Results

1. **Statistical Model**

$$Sat. = Surr.\ Model(u) + \varepsilon_{Surr.\ Model}(u) + \varepsilon_{Sat.} + \varepsilon_{Model\ Discrep.} \quad (1)$$

$$Sat. - Surr.\ Model(u) = \varepsilon_{Surr.\ Model}(u) + \varepsilon_{Sat.} + \varepsilon_{Model\ Discrep.} \quad (2)$$

$$Sat. - Surr.\ Model \sim \mathcal{N} * \mathcal{T} \quad (3)$$

Here we approximate: $Sat. - Surr.\ Model \sim \mathcal{T}$ (4)

2. **Maximum Likelihood Estimation**: Estimate model discrepancy and bias

$$L_{\mathrm{AOD}}(u, \delta, \beta) = \sum_{x \in M} log(f_t(x, u, \delta_{AOD}, \beta_{AOD}))$$

$$L_{\mathrm{Total}} = L_{\mathrm{AOD}}(u, \delta_{\mathrm{AOD}}, \beta_{\mathrm{AOD}}) + L_{\mathrm{CLWP}}(u, \delta_{\mathrm{CLWP}}, \beta_{\mathrm{CLWP}}) + L_{\mathrm{CDNC}}(u, \delta_{\mathrm{CDNC}}, \beta_{\mathrm{CDNC}}) + L_{\mathrm{SWRF}}(u, \delta_{\mathrm{SWRF}}, \beta_{\mathrm{SWRF}})$$

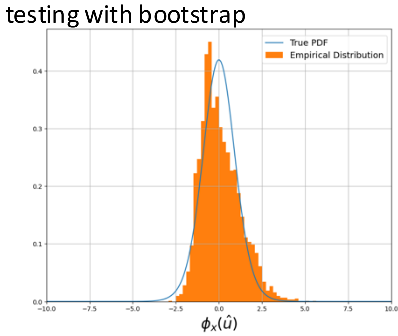
$$\hat{u}, \hat{\delta}_i, \hat{\beta}_i = \underset{u, \delta_i, \beta_i}{\operatorname{argmax}} \ L_{\mathrm{Total}} \quad \text{s.t. } u \in U_{\text{Surrogate Sampling}},\ \delta_i > 0,\ \beta_i \in \mathbb{R}$$

3. **Estimate critical value** for hypothesis testing with bootstrap

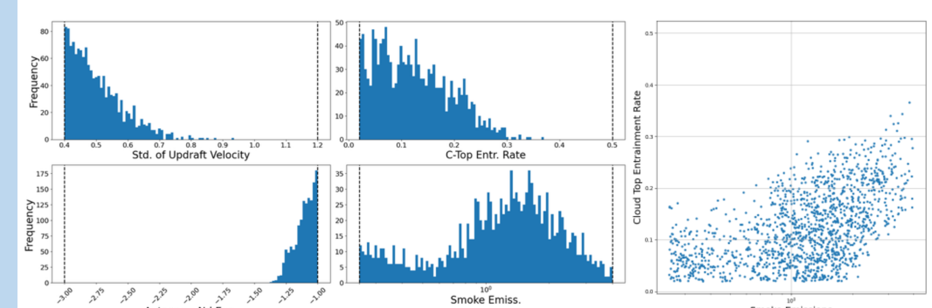
$$\phi_x(u) = \frac{\mathrm{AOD}_{Sat.,x} - \mathrm{AOD}_{Surr.,x}(u) - \hat{\beta}_{\mathrm{AOD}}}{\sqrt{(\sigma^2_{Surr.,x}(u) + \sigma^2_{Sat.,x} + \hat{\delta}^2_{\mathrm{AOD}})}}$$

$$I_{\mathrm{AOD}}(u) = \sqrt{\sum_{x \in M} (\phi_x(u))^2}$$

$$I_{\mathrm{AOD}}(u) \ \text{ vs } \ I_{\mathrm{AOD,\ crit.}}$$



4. **Visualize constrained parameter space** for model variants that pass all tests



Funding acknowledgements:
NASA Roses 80NSSC21K1344
GEM Fellowship
C3.ai Digital Transformation Institute

References: this approach: Carzon et al, Env Data Sci 2023; https://doi.org/10.1017/eds.2023.12
History matching: Johnson et al, Atmos Chem Phys 2020 https://acp.copernicus.org/articles/20/9491/2020/; Regayre et al, Atmos Chem Phys 2023; https://doi.org/10.5194/acp-23-8749-2023