Towards statistically robust constraints on climate model parameters from perturbed parameter ensembles

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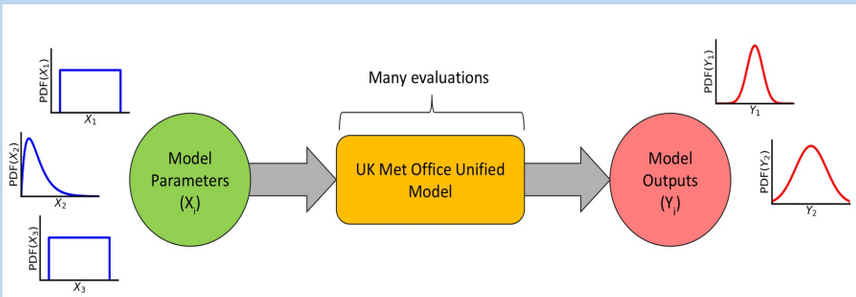
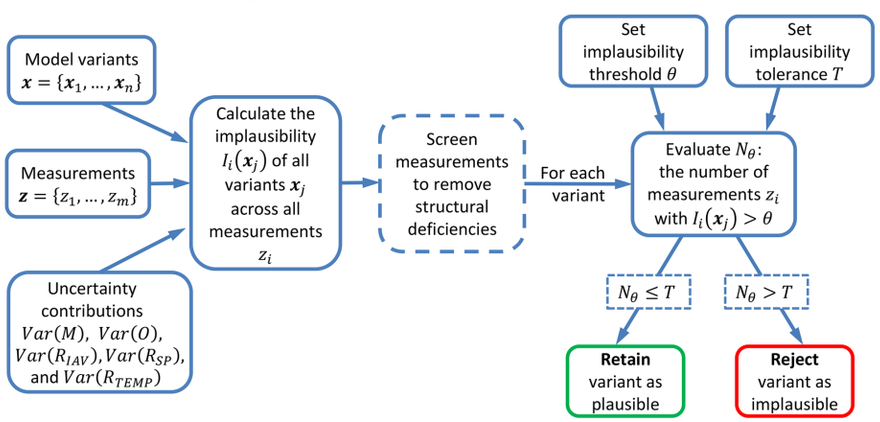


Aims: a) constrain parametric uncertainty in smoke radiative effects in SE Atlantic
b) Test potential improvements to `history matching' for parameter constraint

In brief: rule out parameter combinations for which implausibility exceeds a threshold

$$I(\boldsymbol{x}) = \frac{|M - O|}{\sqrt{[\mathrm{Var}(M) + \mathrm{Var}(O) + \mathrm{Var}(R) + \mathrm{Var}(S)]}}$$

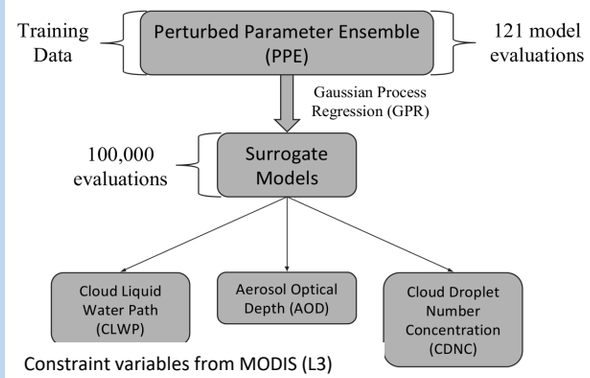
History matching (as applied by Johnson et al, ACP 2020):



Case study: smoke radiative effects in SE Atlantic

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



Constraint variables from MODIS (L3)
(plan to also add aircraft measurements)

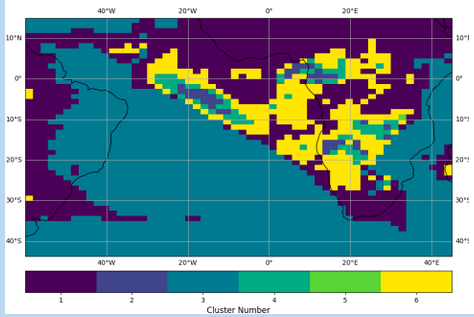


Figure shows area of interest. AOD is most sensitive to smoke in clusters 2,4,5,6; sea spray in cluster 3

Modifications to history matching approach

1. Account for non-Gaussian uncertainties

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

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

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

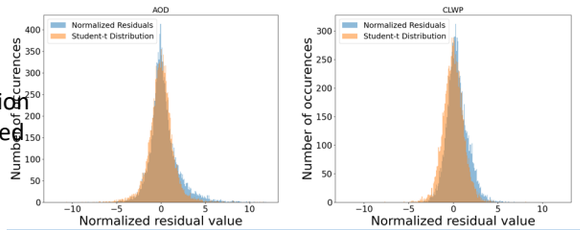
$$Sat. - Surr.\ Model \sim \mathcal{T} \quad (4)$$

$$Norm.\ Residuals_x = \frac{Sat._x - Surr.\ Model_{x,u^k}}{\sqrt{(\sigma^2_{Surr.\ Model\ at\ x,u^k} + \sigma^2_{Sat.\ at\ x} + \delta^2_{Model\ Discrep.})\frac{\nu-2}{\nu}}}$$

2. Estimate unaccounted-for ("structural") uncertainty by maximum likelihood

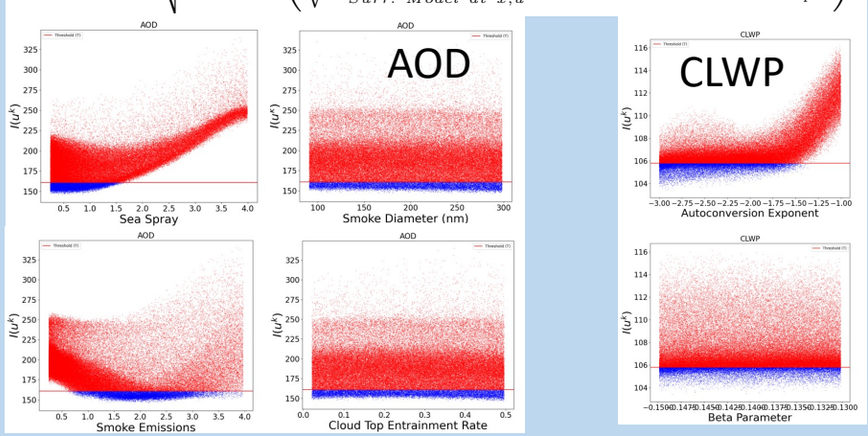
$L_{u_k} = \prod_{x \in M^*} f_t(x, \nu, \delta^2_{Model\ Discrep.})$ assuming T-distributed residuals

3. Obtain threshold for implausibility at 95% confidence as the 95th percentile of a distribution obtained by bootstrapped sampling of the distribution of residuals



4. Compare implausibilities to threshold to constrain parameters first with one then several observations, then constrain radiative effects (in progress)

$$I_{AOD}(u_k) = \sqrt{\sum_{x \in M^*} \left(\frac{AOD_{Sat.\ at\ x} - AOD_{Surr.\ Model\ at\ x,u^k}}{\sqrt{(\sigma^2_{Surr.\ Model\ at\ x,u^k} + \sigma^2_{Sat.\ at\ x} + \delta^2_{Model\ Discrep.})}} \right)^2}$$



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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