COLUMBIA CLIMATE SCHOOL LAMONT-DOHERTY EARTH OBSERVATORY

Observation proxies for high-resolution simulations and satellite observations

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Observation proxies for kilometer-scale models and/or EarthCARE informed by COSP

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Swales et al. 2018, 10.5194/gmd-11-77-2018

Observing system characterization



Swales et al. 2018, 10.5194/gmd-11-77-2018

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Swales et al. 2018, 10.5194/gmd-11-77-2018

Scale-matching

Observing system characterization



Swales et al. 2018, 10.5194/gmd-11-77-2018

Summarization

Observing system proxies map model state to observables

I.e. for clouds:

From cloud state $q^{l,i,\dots}(z), r_e^{l,i,\dots}(z)$

to (potentially multi-variate) observable $f(\tau, r_e, Z, ...; \Delta x, \Delta y, \Delta t)$

via radiative properties $\sigma^{\lambda}(z), \omega_0^{\lambda}(z), \beta^{\lambda}(z), \dots$

Mapping seeks to account for conditional biases e.g. masking, sensitivity, ...

Proxies and simulators

See also:

- simulators for sensor design (e.g. ECSIM) or mission design (OSSEs)
- forward operators in data assimilation

Notes:

- Some observables (e.g. radiative fluxes) don't use proxies
- Comparisons to active sensors tend to be closer to instrument signals
- Summaries may be multi-faceted (definitional, multi-variate, ...)



after Suzuki et al. 2010, 10.1175/2010JAS3463.1

Proxy precision and underlying uncertainty

Some quantities are well-measured*:

$$\tau = \int_{\mathsf{TOA}}^0 \sigma(z) dz$$

Some observational estimate are hard to/not worth replicating in detail

$$P = \int_{\mathsf{TOA}}^{\tau=1} P(z)\sigma(z)dz$$

Some biases are hard to anticipate

 $r_e = F^{-1}(F(r_e(z), P(z)))$

Some comparisons are most easily made in observation space

$$Z_l^a = Z_l e^{-2\tau_l} \frac{1 - e^{-2\Delta h_l \alpha_l}}{2\Delta h_l \alpha_l}$$

Data assimilation for understanding uncertainty budgets

Data assimilation is effective when observations are unbiased^{*} and conditional uncertainties are known

$$\begin{aligned} \mathscr{J}(\delta \mathbf{x}_0) &= \frac{1}{2} (\delta \mathbf{x}_0)^T \mathbf{B}^{-1} (\delta \mathbf{x}_0) + \frac{1}{2} \sum_i (H_i' \delta \mathbf{x}_i - \mathbf{d}_i)^T R_i^{-1} (H_i' \delta \mathbf{x}_i - \mathbf{d}_i) \\ \text{with } \mathbf{d}_i &= \mathbf{y}_i^o - \mathbf{H}_i(\mathbf{x}_i^b) \end{aligned}$$

Efforts to quantify uncertainty for data assimilation might inform proxies/operators for other contexts



after Fielding and Janisková 2020, 10.1002/qj.3878









Pincus et al. 2023, 10.5194/essd-2022-282



Illingworth et al. 2015, 10.1175/BAMS-D-12-00227.1

From COSP to km-scale models

Innovation is endless - experience suggests enabling experimentation and iteration

At resolved scales:

What is required for ergodicity to defeat limited sampling?

To what extent can vertical motion and microphysics be unfolded?

At unresolved scales:

Can confidence in observations and/or models be categorized?

Effort spent in mapping model to observations can be targeted (observing system proxy is not always the largest source of uncertainty)

What lightweight proxies for km-scale models?