“All models are wrong, but some are useful”

-G. P. Box

Thoughts on the Use of Uncertainties in Models

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Ceci n'est pas une pipe.
Magritte

How do we know models are right?

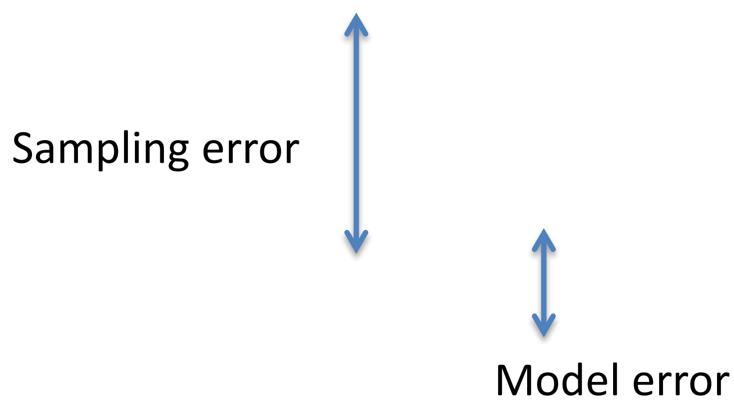
- All models are wrong, some are useful: models are fit for purpose
- How wrong are they? Or: what do we need to improve? Compare to observations
- Testable hypothesis: A model is valid (against an observation) if it is not statistically different from the observation
  - Easy: As long as we know the statistics of the models and observations

First: Sampling Issues

- Sampling issues need to be handled first
- E.g.: daytime or ocean only observations
  - Note daytime = seasonal cycle in polar regions
- Recall talks yesterday by Andrews and Schutgens

From N. Schutgens

Representativeness of observations



Schutgens et al ACP 2016a

Sampling: other issues

- Not just location and time
- Sampling is radiometric, can be masked and has a vertical component
- E.g.: averaging kernels (vertical structure)
- Masking (clouds)
- Spectral signature and thresholds
  - Different satellites see different things, not just geometry

Statistics

- Assuming we solve sampling issues, then is a model different than observations?

$$\sigma_{M_1-M_2} = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$$ Difference of two sample means

- Difference depends on the statistics (σ) of both model and observations
- Tell us the range in which truth lies. That tells us how certain we are (or not)
  - Don't sugar coat it
  - Qualitative reasoning is fine, maybe better than too much error propagation

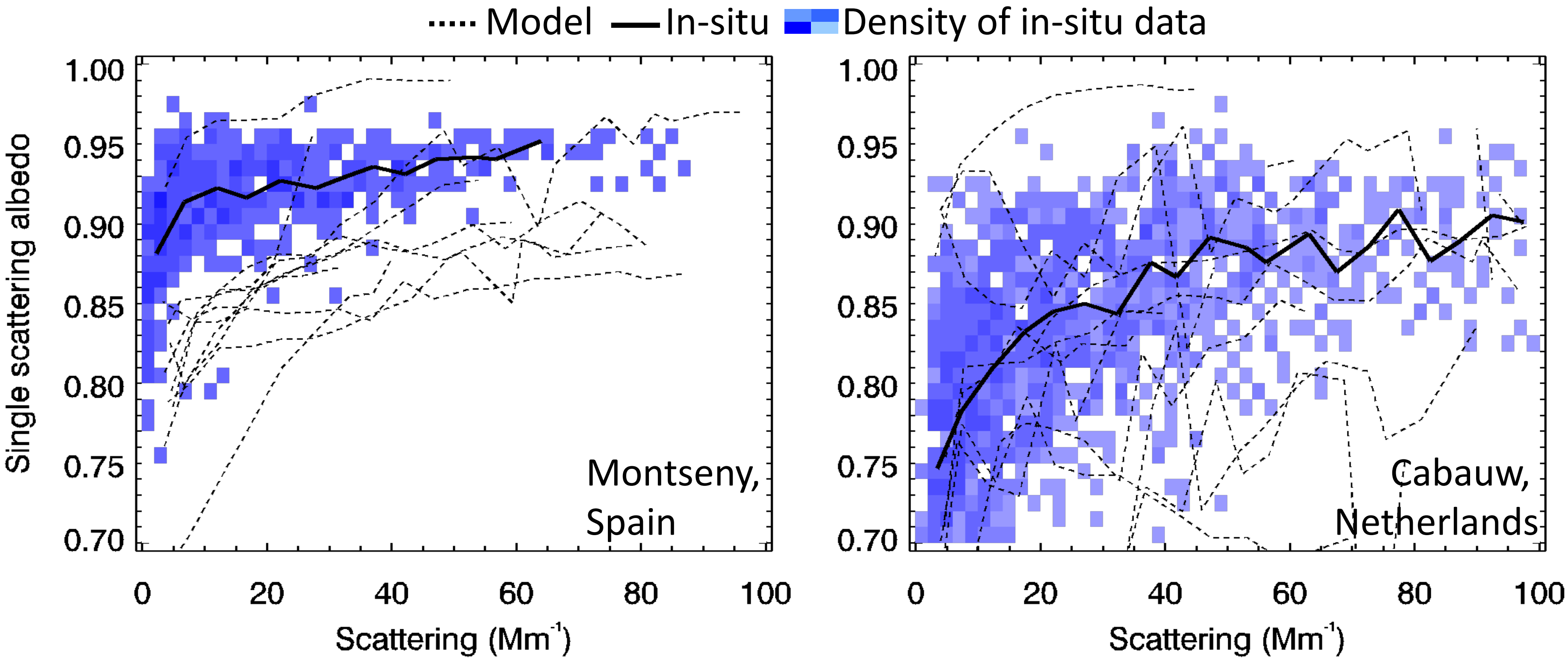
What quantities do we need to know?

- Stefan showed AOD
- Do we really want AOD? Or is it what we get?
  - When it differs what do we do?
  - Lots of physical factors built into a result
  - Surface downward radiation is another example
- Need to figure out what are the important metrics
  - Compare to what we can observe
  - Try to get observations for what we need
  - Then: go to process based metrics. Constrain the underlying model physics

Simulating observations (and error)

- If uncertainties are large (e.g. AOD), then let’s reduce them. Together.
- First eliminate the (spatial) sampling bias
- Then make sure the model can ‘simulate’ the observations (averaging kernel, masking etc)
  - This requires a forward model (e.g. Lidar equation)
- Then drill down to components (e.g. of AOD)
  - E.g.: aerosol optical properties

Aerosol Behavior: **Systematic Variability**



- Lower loading corresponds to darker (and smaller) particles

→ preferential scavenging of large, scattering aerosol by clouds/precipitation?

The co-variance observed between SSA and scattering for in-situ data is not necessarily reproduced by model output

From Betsy Andrews

Thoughts for Discussion

- Uncertainties can be reduced with sampling
  - Spatial and Temporal
  - Radiometric and Sensitivity
- Tell us a best estimate of uncertainty
  - Make it generous (no 3σ changes!)
- Let's simulate the data with a forward model
  - Think about a model in "data space"
- What metrics are the right place to start?
  - Are we even looking at the right thing?
  - Modelers say we want X, but if you are really producing Y, then just tell us Y really well. Don't make X = f(Y).
  - What metrics are grounded in physical process understanding? Optical properties?