Uncertainty Quantification and Climate Science

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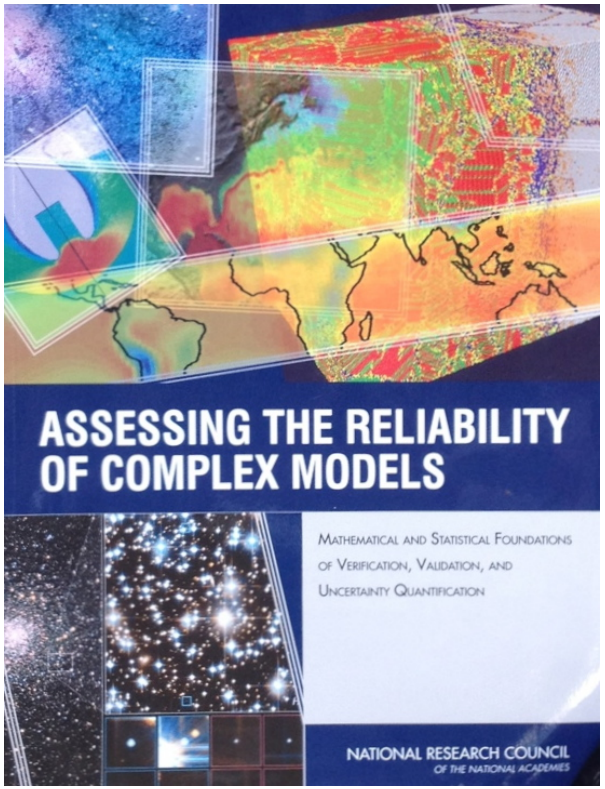
Introduction

- Climate models are deterministic, mathematical descriptions of the physics of climate.
- They provide a laboratory for experiments that we can't carry out in the real world. Also used to make predictions about future climate.
- Should we believe them? Can we quantify how uncertain their predictions are?
- SAMSI program: UQ as a discipline and UQ as practiced re: climate models.
- How can modern observational data sources be brought to bear?

UQ as a Discipline

- NRC study on verification, validation, and uncertainty quantification (2012).
- Verification = How well does computer code solve equations of the mathematical model?
- Validation = How well does the mathematical model represent the true physical system?
- UQ = “The process of quantifying uncertainties associated with model calculations of true, physical quantities of interest with the goals of accounting for all sources... and quantifying the contributions of specific sources."
- Climate modeling case study.



UQ as a Discipline

- Verification: two broad classes: code verification and solution verification.
- Validation:
  - How good is the underlying mathematical model? Leads to “structural" uncertainty.
  - Model calibration: ancillary unknowns must be estimated from data. Leads “parametric" uncertainty.
  - Interpolative predictions of primary unknowns $\leftrightarrow$ simulations of past and present (we have data).
  - Extrapolative predictions of primary unknowns $\leftrightarrow$ predictions of the future (we have no data).
- UQ:
  - Quantify uncertainties in model inputs.
  - Propagate these uncertainties through calculation.
  - Quantify variability of the true quantities of interest.
  - Aggregate uncertainties from different sources.

Simple Example

- Quantity of interest: time for a bowling ball to fall from 100m tower.
- Mathematical model: a function of g (gravitational constant). Assume it is imperfectly known and must be estimated.
- Data: experimental drop times from 10, 20, 30, 40, 50m.
- Validation experiment: drop time from 60m.
- Sources of uncertainty: mathematical model, true value of g, data on drop times used to estimate g, form of the estimate of g, extrapolation to 100m.

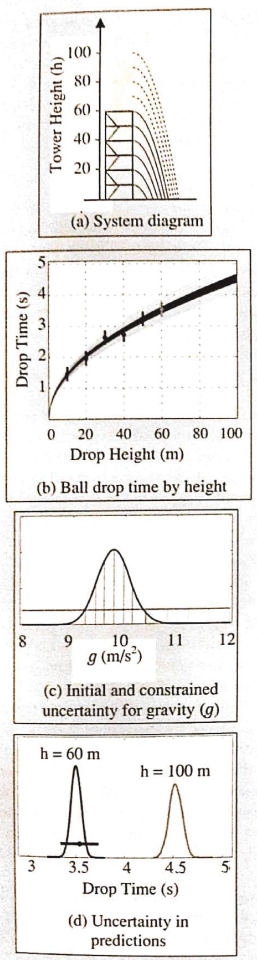


FIGURE 1.1.1

Box 1.1
Dropping a Bowling Ball from a Tower

The time that it takes for a bowling ball to fall from a tower 100 meters (m) high will be predicted by using experimental drop times obtained from a 60-m tower (Figure 1.1.1(a)). Drop times are recorded for heights of 10, 20, . . . , 50 m, and a validation experiment of dropping a ball from 60 m is also conducted. The uncertainty in the measured drop times is normally distributed about the true time with a standard deviation of 0.1 seconds (s). The quantity of interest (QOI) is the drop time for the bowling ball at a height of 100 m. Since the tower is only 60 m high, a computational model is used to help make this assessment.

The conceptual model incorporates only acceleration due to gravity g, allowing the computational solution used here to be compared to an analytical solution for a verification assessment of bowling ball drop times between 10 m and 100 m.

The physical constant g is assumed to be unknown, but between 8 and 12 m/s^2 (light lines). The five drop-time measurements (black dots; Figure 1.1.1(b) constrain the uncertainty about g to the probability density given by the dark line.

The drop times produced by the computational model (light lines in Figure 1.1.1(c)) are shown for 11 different values of g. The experimental data are shown with error bars of +2 standard deviations—the measurement error for the 60 m is not used. The constrained uncertainty for g results in a 95 percent prediction interval for the drop time (as a function of height) depicted by the dark region in Figure 1.1.1(b).

A validation experiment, dropping the bowling ball from 60 m, is conducted so that the prediction can be compared to the measured drop time. The drop-time measurement for 60 m (black dot in Figure 1.1.1(d)) is quite consistent with the prediction and its uncertainty.

A prediction with the uncertainty for the QOI (drop time at 100 m) is given by the light line in Figure 1.1.1(d). The uncertainty accounts for measurement error and parametric uncertainty. Numerical error and model discrepancy are not accounted for in this assessment.

From the 2012 NRC report, *Assessing the Reliability of Complex Models*, page 15.

Climate Model Example

- Quantity of interest: (say) annual precipitation in the western US in 30 years.
- Mathematical model: equations reflecting best physics understanding instantiated on a coarse grid in space and time. Many poorly understood feedbacks. Exchangeability of present and future; effects of different forcings/scenarios.
- Data: many heterogeneous sources (e.g., remote sensing, surface stations, radiosondes, aircraft) but massive yet incomplete, and themselves uncertain; often the result of inference.
- Validation experiment: CMIP5 decadal “experiments" and observations?
- Sources of uncertainty: process understanding over different spatial and temporal scales, model resolution, initial conditions, unknown parameters, inherent variability of (true) precipitation, and so on.

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2011-12 Program on Uncertainty Quantification: Climate Modeling

The area of climate modeling is a quintessential field of application for UQ. In fact, a sizable part of the research done in the quantification of uncertainty in computer models has been driven by the pressing needs of climate modelers. Climate models are computer codes based on physical principles that simulates the complex interactions between the many parts of the Earth system such as atmosphere and oceans. A significant issue of interest is for instance the problem of regional climate as the global models cannot on their own give enough information at the regional/local scales. Various strategies (downscaling and upscaling) can be considered whereby various combinations of global and regional models are combined to gain information on model uncertainty. Other issues include: development of reliable atmospheric and ocean models and interface between the two, regional and local risk assessment from models, paleoclimate models and how to best deal with models that have huge uncertainties and biases.

Organizers: Amy Braverman (JPL, California Institute of Technology, and UCLA), Xabier Garaizar (LLNL), Dave Higdon (LANL), Gardar Johanneson (LLNL), Donald Lucas (LLNL)

Workshops

- 2011-12 UQ Program: Climate Modeling Opening Workshop
- UQ: Observations Workshop - January 17-19, 2012

Working Groups

- Data Assimilation in IPCC Level Models - Climate UQ
- Parallel Computing Issues - Climate UQ
- Statistics of Extremes - Climate and Methodology UQ

The SAMSI Program

- Opening Workshop: review current landscape and state-of-the-art approaches.
- Working Groups: conduct research on specific topics of interest to participants.
- Observations Workshop: focus specifically on the role of observational data in UQ for climate models.

What's new about this: data (observations) are becoming more important!

Observations

- Two major roles:
  - Estimate pdf's (or parameters of those pdf's) of processes that are not well enough understood to model directly. (Model "calibration" in UQ-speak, "parameterizations" in climate-model-speak.)
  - Compare against climate model simulations to characterize uncertainties in model output. (Model "validation" in UQ-speak.)
- Issues:
  - *Uncertainty in the observations needs to be quantified and accounted for in any analysis that uses them.* How best to capture/communicate this? (Asheville: provide an ensemble of observations from which to sample?)
  - Observational data sets are massive and heterogeneous (e.g., different support, measurement error, sampling).

Observations

Inferred (e.g., remote sensing)

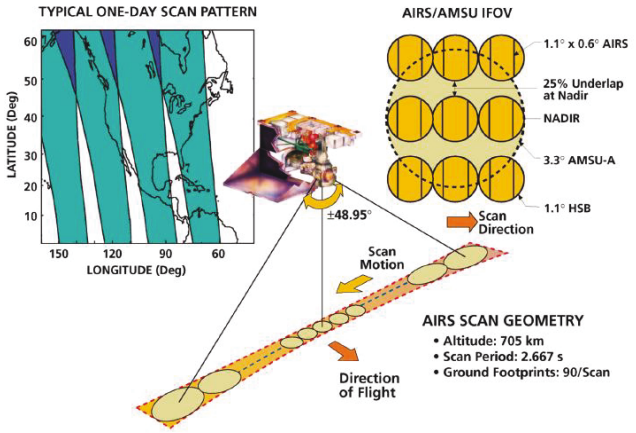
- radiance measurement error
- underlying forward model
- method of inference (“retrieval")
- spatial and temporal aggregation (satellites)
- massive size
- distributed storage
- sampling relative to “true" field
- spatially coarse, but often dense
- often temporally sparse
- relatively short record

Directly measured (e.g., surface stations, aircraft)

- measurement error
- “point-level" spatial support
- spatially dense in places
- temporally dense in places
- records as long as hundreds of years

Observations

UQ for climate observations (remote sensing):



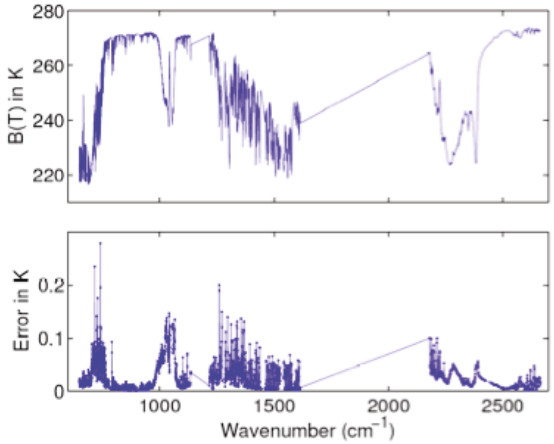
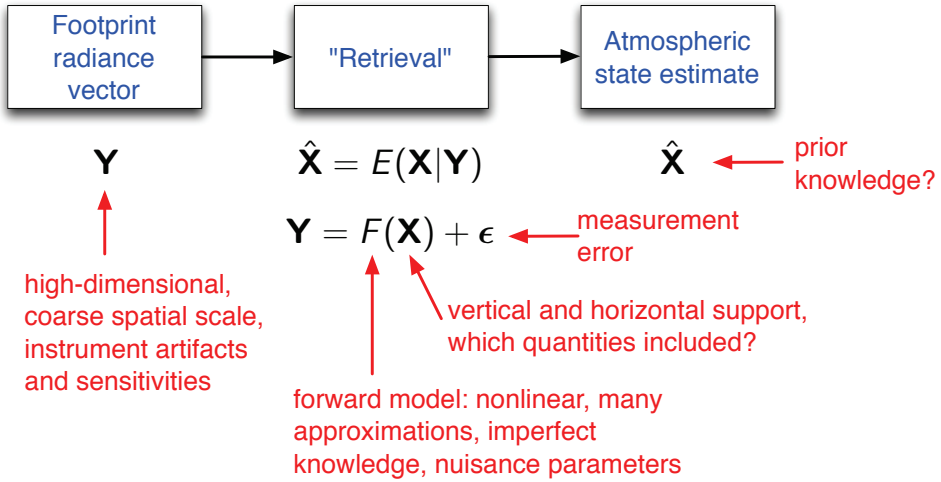


Figure 4.2.4. RMS Errors of the AIRS-RTA Model



How to "validate" $\hat{\mathbf{X}}$? How to quantify its uncertainty?

Bottom-up: propagate input uncertainties through retrieval.

Top-down: compare $\hat{\mathbf{X}}$ to "truth". ("Truth"? Really?)

Observations

Data “fusion" and “homogenization":

- Fusion: combine multiple heterogeneous observational data sets, in a way that exploits their complementary strengths, to estimate true geophysical fields with minimum uncertainty.
- Homogenization: remove biases (or other artifacts) due to non-climate sources, from climate data.
- These are related- they are both about inferring the true field (or getting closer to it).

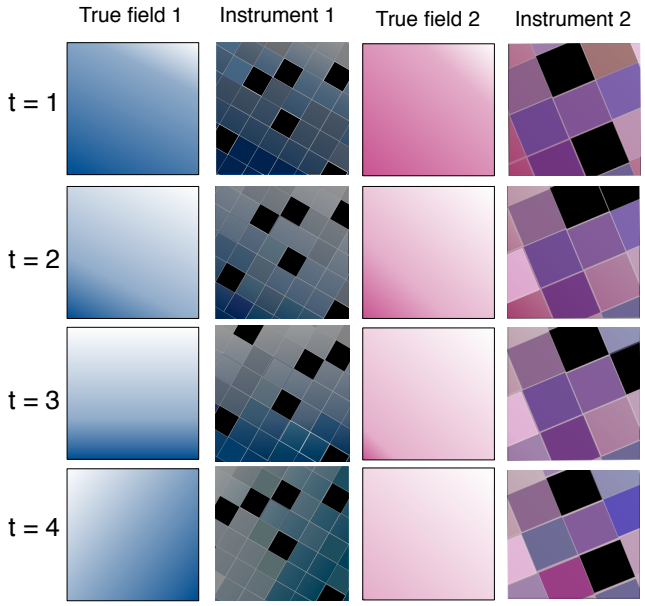
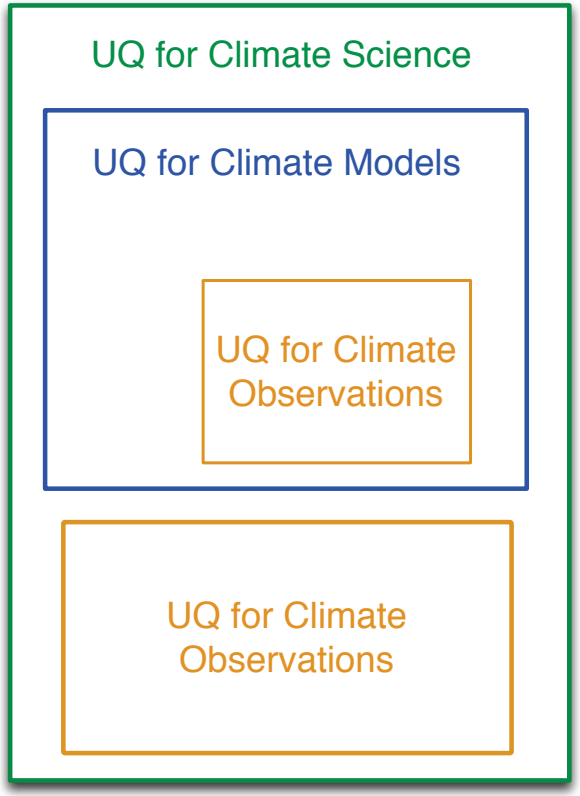


Image credit: Project SCREEN, Center for Climate Change, Universitat Rovira i Virgili, Spain.

Closing thoughts



- Uncertainty quantification for climate observations is important in both model “calibration"/parameterization and model “validation".
- Uncertainty quantification for climate observations is important upstream: observations used to formulate hypotheses ultimately instantiated in climate models.
- Is UQ the same for all these purposes?
- UQ for simulations of past/present vs. UQ for predictions of the future?

Comments?

Contact Amy.Braverman@jpl.nasa.gov.

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