Has the data outstripped the models? Or: What can possibly go wrong?

Recap from yesterday

- Data assimilation is an example of Bayesian Inference;
- BI itself follows from rules for combining PDFs;
- Techniques like least squares minimisation are special cases for particular types of PDF
- Most approaches such as Kalman Filtering and 4dVar can be expressed with this formalism.

Outline

- What *should* happen;
- The black triangle revisited;
- Things to watch for;
- Some real world cases;
- What can we do?

What should happen



PDFs for parameter with prior (blue) and after 1, 2 and 3 observations.

- Prior broad distribution hence weak constraint;
- Each observation refines the estimate (sharper peak);
- Each estimate is consistent with the previous ones;
- Final estimate casts doubt on prior estimate *but not the PDF*.

The black triangle revisited



- unknown on X-axis, obs on Y-axis;
- Light-blue = prior unknown;
- Light-red = obs;
- Green = model;
- Black = solution.

A problematic Case



- No overlap means no solution;
- Fundamental problem is at least one PDF is wrong;
- With a Gaussian we always get a solution but sometimes of very low probability;
- How can we tell?

Another problematic Case



- Parameter constrained by measurements of two different quantities;
- Either measurement alone is consistent with prior;
- 2 measurements + prior + model has no solution.

What to do?

- Look hard at each of the 3 input PDFs;
- Check the assumed PDF against the sample generated in the inversion;
- Check with independent data (often called cross-validation);
- A lot of examples.

First check the Priors

- Approach will differ depending on the unknowns;
- Sometimes you calculate actual PDFs, sometimes you use algorithms;
- Cases like weather prediction you can test these rules every day.

Example from Flux Inversions

- Chevallier et al. GRL, 2006;
- Compare ORCHIDEE at 50km resolution to CO₂ flux measurements;
- STD-dev of differences \approx 2.5 respiration;
- No spatial correlations in error;
- Temporal correlations of about 1 month.

The Measurement PDF

- PDF is that of the *true* value;
- Known errors (often called biases) must be removed first;
- This does *not* say there are no mean errors left, just that we don't know what they are.

Get to Know your Measurements

- Many "measurements" are themselves products of a model;
- Worry much more about the systematics than the noise;
- Systematics can be treated as correlated errors;
- Small signals on long records are the hardest things we do;
- Independent data is precious.

Comparison of SCIAMACHY and TCCON



Comparison of SCIAMACHY and ground-based spectrometer measurements of CO₂ at Park Falls Wisconsin

- Reuter et al., 2010, (in prep.);
- SCIAMACHY satellite on board ESA ENVISAT;
- Ground-based Solar Fourier Transform Spectrometer part of Total Carbon Column Observing Network (TCCON);
- Random and systematic errors but data are approaching usable.

Validating TCCON



Fig. 4. The TCCON calibration curve for CO₂. The smoothed aircraft value is \hat{c}_{s} from Eq. (7).

Comparison of TCCON measurements with simultaneous aircraft profiles

- D.Wunch et. al., (2010) discussion paper, Atmos. Meas.Tech.
- Aircraft measurements traceable to primary standards;
- Very good correlation but not one-one;
- Can correct but contributes to overall error.

Including measurement errors in Model

- Often you don't have independent data;
- Add extra unknowns to account for systematic errors, e.g.

$$q = q^* + \phi(\text{latitude})$$

to deal with consistent errors in latitude

• This sacrifices some information in q.

Combining SCIAMACHY and in situ \mbox{CH}_4 data



- Bergamaschi et al., JGR 2007;
- SCIAMACHY methane from Frankenberg05;
- Uses modelled CO₂ as reference;

Annually-averaged, column-integrated methane mixing ratio from SCIAMACHY alone (top) and from SCIAMACHY and surface data assimilated into a single flux inversion (bottom).

 Bias-corrected by simultaneously assimilating surface data into flux inversion.

Accounting for Discontinuities



 Two external references necessary for final measurement;

 Great effort made to maintain continuity across changes but never perfect;

 Can be handled either with extra unknowns or correlations.

Checking the Model PDF

- Need PDF of simulated value given *true* value for unknowns;
- Rarely have such cases;
- Use model ensembles as proxy; *risky*;
- More tomorrow.

T1 fossil and biosphere





Zonal mean concentration from fossil fuel source Zonal mean response to annually balanced biosphere source

Checking Posterior PDFs

- Basic assumption is that the samples of posterior values for unknowns and simulated observations are drawn from the relevant populations;
 - Posterior prior \leftrightarrow prior PDF
 - Model observed \leftrightarrow data PDF
- Must hold for all aspects of the PDF;
- Take note of sample size.

A problematic Case



- No overlap means no solution
- With a Gaussian we always get a solution but sometimes of very low probability;
- How can we tell?
- Fix by increasing uncertainties but which ones and how much?

Plot the Residuals



- Plot of normalised innovations (posterior — prior)/(prior-uncertainty) and normalised residuals (simulation — obs)/(data-uncertainty) for flux inversion;
- Use cumulative frequency rather than raw PDF, easier to look at;
- Compare with standard normal distribution;
- The steep slope corresponds to smaller variance;
- Also numerical tests.

Value of the cost function

Minimise

$$J = (\vec{x} - \vec{x}_0)^T \mathbf{C}^{-1} (\vec{x}_0) (\vec{x} - \vec{x}_0) + (\mathbf{M}\vec{x} - \vec{y})^T \mathbf{C}^{-1} (\vec{y}) (\mathbf{M}\vec{x} - \vec{y})$$

Yields

$$\vec{x} = \vec{x}_0 + \mathbf{C}(\vec{x}_0)\mathbf{M}^T \left[\mathbf{M}\mathbf{C}(\vec{x}_0)\mathbf{M}^T + \mathbf{C}(\vec{y})\right]^{-1} (\vec{y} - \mathbf{M}\vec{x}_0)$$

Substituting

$$J_{MIN} = (\vec{y} - \mathbf{M}\vec{x}_0)^T \left[\mathbf{M}\mathbf{C}(\vec{x}_0)\mathbf{M}^T + \mathbf{C}(\vec{y}) \right]^{-1} (\vec{y} - \mathbf{M}\vec{x}_0)$$

Properties

$$J_{MIN} = (\vec{y} - \mathbf{M}\vec{x}_0)^T \left[\mathbf{M}\mathbf{C}(\vec{x}_0)\mathbf{M}^T + \mathbf{C}(\vec{y}) \right]^{-1} (\vec{y} - \mathbf{M}\vec{x}_0)$$

- Numerator difference between obs and prior simulation;
- Denominator uncertainty in that quantity;
- Should be consistent $J_{MIN} \approx N_{OBS}$, if not, posterior uncertainty inconsistent with inputs;
- Michalak et al., JGR, 2005 has algorithm for scaling uncertainty.

Example of Bias



Amplitude Example



Residuals and their correlations



Cross Validation

- Use of independent data to test results of assimilation;
- If assimilation is for state data is rare but if for function we can apply the model elsewhere;
- Sometimes independent data is for the unknowns but usually other observables;
- As always, need to consider the problem statistically.

Independent Measurements of the unknowns



- Lauvaux et al., GRL, 2009;
- Compare inverse fluxes
 with independent
 measurements from
 aircraft;
- Posterior estimates closer to aircraft fluxes.

That — triangle again



- Unknown on X-axis, obs on Y-axis;
- Now imagine light blue was posterior PDF from previous inversion;
- If just used central value (0) would not overlap obs;
- Must consider posterior uncertainty in unknowns when comparing to other obs.

Summary

- Problems with data assimilation usually sign of incorrectly specified statistics;
- Where possible check input statistics against independent data;
- Check output statistics against assumed PDFs;
- Check as many elements as possible, not just quality of fit;
- Uncertainties are a necessary component of cross-validation.