Data assimilation for parameter estimation: useful for Mars?

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Parameter estimation

- GCMs typically require specification of O(10²) parameters
- Parameterizations fall into two kinds of category
 - "Rational" based on a traceable set of approximations to the exact problem [e.g. radiative transfer for gaseous constituents]
 - "Non-rational" based on *heuristic* representations with *ad hoc*, empirically adjustable coefficients [e.g. boundary layer mixing, gravity wave drag....]
- All parameters are uncertain to some degree, but....
 - Uncertainties in parameters for "rational" parameterizations can usually be quantified objectively
 - Uncertainties in "non-rational" parameterizations may be difficult to assess from first principles theory – parameters need to be adjusted empirically to optimize agreement between model and observations

• But How....?

- Brute force trial and error....?
- But optimal parameters may be state-dependent and depend on time and space?
- Better to find a more objective approach adapted from data assimilation

Parameter estimation and DA

• Data assimilation is typically designed for **state estimation**, based on minimization of a cost function:

•
$$J(x) = (x - x_b)^T B^{-1} (x - x_b) + (y - H[x])^T R^{-1} (y - H[x])$$

for dynamical system represented by

•
$$x^{n+1} = f[x^n; \lambda_i]$$
; where λ_i are parameters

- But we can also treat parameters as variables in the system
 - $x^{n+1} = f[x^n; \lambda^n]$
 - $\lambda^{n+1} = \lambda^n$

and minimize the cost function by varying λ as well as x.

BUT

- for highly nonlinear systems, J(x) may have multiple local minima need sophisticated minimization algorithms?
- Observations may not be well correlated with λ (so J not much affected by λ) value of λ uncertain but perhaps not critical?
- Optimal λ may be state dependent..... need state-dependent DA?

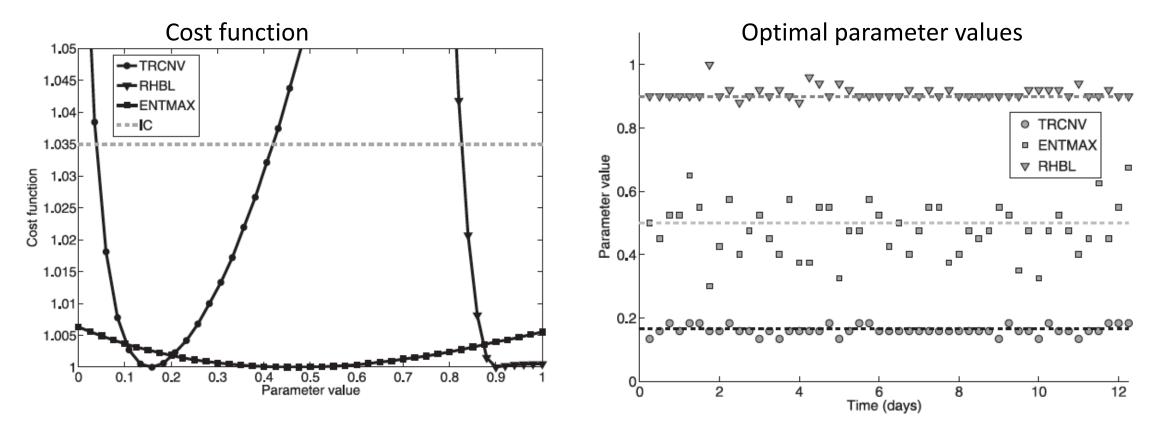
Methods for DA parameter estimation

- 4D-var minimizes a J(x) over a time interval
 - Takes state dependence into account
 - Uses clever minimization algorithms for high dimensional dynamical system
 - Needs tangent linear and adjoint versions of full model (including gradients w.r.t. parameters)
- EnKF and its variations (LETKF etc.)
 - Uses ensembles to estimate uncertainties
 - Takes state dependence into account
 - Relatively straightforward to code and inexpensive to run
- Particle filters (PFs)
 - Doesn't need to assume Gaussian errors
 - Better at coping with strong nonlinearity
 - Needs many "particles" (i.e. model simulations) to converge expensive!

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An example [Ruiz et al. JMSJ 2013]



- Uses "SPEEDY" intermediate GCM and assimilates for 3 convective parameters
- Based on LETKF assimilation
- Minimises cost function to recover simultaneous optimal values of parameters

Questions?

- Perfect vs imperfect models?
 - Bias correction?
- Interfering effects of other parameters....?
 - Important if set of parameters being optimized is incomplete....
 - Which parameters need to be included....?
- Good for optimizing climate models but may not improve forecasts much....?
- Which parameters would be most important to optimize for Mars models?
- Several groups already using LETKF for assimilation, but....
 - Size of ensembles?
 - How nonlinear?
 - Gaussian assumptions OK.....?