

#### Estimation of Carbon Cycle Parameters in JULES

David Pearson, Chris D. Jones, John K. Hughes

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#### Abstract/Summary

- We are improving the terrestrial carbon cycle parameters in JULES by tuning them so we can simulate flux tower measurements.
- The tuning method is variational data assimilation.
- The usual formulation of Var is not applicable.
- A different weighting of prior and observation terms is needed.



This presentation covers the following areas

- Data assimilation: states or parameters?
- Data assimilation: sequential or variational?
- Var: the cost function.
- Var for parameter estimation.
- Weighting for the correlated problem.
- Results.
- What next?
- Q and A.



#### Data assimilation: states or parameters?



## Data assimilation: states or parameters?

- The state of a system is the set of relevant or interesting evolving variables. E.g.:
  - the CO<sub>2</sub> concentration field in the atmosphere;
  - the salinity field in the ocean;
  - the velocity field in either;
  - the moisture content in soil layers.
- Parameters are the fixed numbers in a model, that control the state. E.g.:
  - k<sub>sat</sub> in soil;
  - $q_{10}$  in soil or leaves.





• Sequential, e.g. the Kalman filter.





• Variational, e.g. 4D-Var.





- State vectors:
  - Sequential DA naturally accommodates model error;
  - Sequential DA does not naturally accommodate nonlinearity.
  - Var does not naturally accommodate model error;
  - Var naturally accommodates nonlinearity.
- Parameters:
  - Parameters are fixed, but sequential DA allows them to change;
  - Parameter-Var has fixed parameters;
  - JULES is more suited to variational parameter estimation than sequential estimation.



For parameter estimation in JULES, Var beats sequential



#### Var: the cost function.





#### Var for parameter estimation.



$$J(\mathbf{x}_0) = \frac{1}{2} (\mathbf{x}_0 - \mathbf{x}_b)^T \mathbf{B}^{-1} (\mathbf{x}_0 - \mathbf{x}_b) + \frac{1}{2} \sum_i [\mathbf{y}_i - H(\mathbf{x}_i)]^T \mathbf{R}^{-1} [\mathbf{y}_i - H(\mathbf{x}_i)]$$

$$J(\mathbf{p}) = \frac{1}{2}(\mathbf{p} - \mathbf{p}_b)^T \mathbf{B}^{-1}(\mathbf{p} - \mathbf{p}_b) + \frac{1}{2} \sum_i [\mathbf{y}_i - H(\mathbf{x}_i)]^T \mathbf{R}^{-1}[\mathbf{y}_i - H(\mathbf{x}_i)]$$



#### Var for parameter estimation.

- Q. Can we really do this?
- A1. State estimation theory [Jazwinski (1970)] can be manipulated to give a (nearly) identical parameter estimation theory.
- A2. "It just works", i.e. it is rational even if it is not optimal.
- A3. Equivalent least-squares problem.

$$\begin{split} J(\mathbf{p}) = & \frac{1}{2} (\mathbf{p} - \mathbf{p}_b)^T \mathbf{B}^{-1} (\mathbf{p} - \mathbf{p}_b) + \frac{1}{2} \sum_i [\mathbf{y}_i - H(\mathbf{x}_i)]^T \mathbf{R}^{-1} [\mathbf{y}_i - H(\mathbf{x}_i)] \\ & \text{A. Jazwinski, "Stochastic Processes and Filtering Theory" Chapter 5} \\ & \text{(1970)} \end{split}$$





- We want to optimise the terrestrial carbon cycle.
- Q. Which set of parameters do we work with?
- A1. Start with a set already studied [Booth (2009)];
- A2. Choose a few more;
- A3. Sensitivity analysis to find which subset had a strong effect on annual carbon pools and the timing and amplitude of seasonality.

[B. Booth et al., *Increased importance of terrestrial carbon cycle feedbacks under global warming.* Submitted to Nature (2009).]



$T_{low}$ and $T_{upp}$	Maximum and minimum temperature constraints on
	photosynthesis. These were covaried. [°C]
dQ <sub>crit</sub>	Critical humidity deficit for photosynthesis. [kg water / kg air]
$f_0$	Controller of stomatal carbon dioxide concentration. [unitless]
LAI <sub>min</sub>	Minimum leaf area for vegetation areal expansion. [unitless]
n <sub>10</sub>	Top leaf nitrogen concentration . [kg N / kg C]
q <sub>10,leaf</sub>	Base for leaves in q <sub>10</sub> model of respiration. [unitless]
q <sub>10,soil</sub>	Base for soil in q <sub>10</sub> model of respiration. [unitless]
α	Soil albedo. [unitless]
g <sub>grow</sub>	Rate of leaf growth. [/360 days]
groot	Turnover rate for root biomass. [/360 days]
gwood	Turnover rate for woody biomass. [/360 days]



$$J(\mathbf{p}) = \frac{1}{2}(\mathbf{p} - \mathbf{p}_b)^T \mathbf{B}^{-1}(\mathbf{p} - \mathbf{p}_b) + \frac{1}{2} \sum_i [\mathbf{y}_i - H(\mathbf{x}_i)]^T \mathbf{R}^{-1}[\mathbf{y}_i - H(\mathbf{x}_i)]$$

• 
$$\mathbf{p} = (T_{low}, dQ_{crit}, f_0, n_{l0}, q_{10.leaf}, q_{10.soil})$$

- Find p that minimises J(p) by the Nelder-Mead method over the 6-dimensional parameter space.
- Target functions: daily  $\rm R_{eco},\,GPP$  and NEE over as many years as are available.
- (Note: NEE = -NEP)



• Hyytiala: "standard" parameters





• Hyytiala: "best" parameters





• Hyytiala: "best" parameters ...but ...



• ... the cost is completely dominated by the observations.





- Var derivation assumes the system is  $1^{st}$ -order Markov:  $\mathbf{x}_{k+1} = f(\mathbf{x}_k) + \mathbf{e}_k$ .
- OK for NWP and other autonomous systems.
- Not correct for systems driven by seriallycorrelated phenomena (e.g. the land surface is driven by weather and radiation).
- Correlated inputs → correlated outputs, containing less information.
- Therefore we should give less weight to observation terms.
- But how much?



• Numerical experiment: weight prior and obs terms by chosen factors:

$$\begin{aligned} & \text{Multiply by B.fac} & \text{Multiply by R.fac} \\ & J(\mathbf{p}) = \frac{1}{2} (\mathbf{p} - \mathbf{p}_b)^T \mathbf{B}^{-1} (\mathbf{p} - \mathbf{p}_b) + \frac{1}{2} \sum_i [\mathbf{y}_i - H(\mathbf{x}_i)]^T \mathbf{R}^{-1} [\mathbf{y}_i - H(\mathbf{x}_i)] \end{aligned}$$

- R.fac is small.
- Only the ratio is important.



• What happens when we vary the weights?





• What happens when we vary the weights?





- Changes in the relative weights cause changes in the results (of course!).
- The changes are systematic (good!)
- What are the best weights? (Difficult problem!)



- Michalak et al., Maximum likelihood estimation of covariance parameters for Bayesian atmospheric trace gas surface flux inversions. JGR 110, D24107 (2005).
- NWP experience of correlated obs errors.
- Least-squares parameter estimation for time series.







#### Met Office • Hyytiala, Finland: NL forest





#### Results

#### • Vaira Ranch, CA: grazed C3 grass





#### • Fort Peck, Montana: mixed C3/C4 grass







- Resolve the weighting problem.
- Gather more flux tower data over different PFTs.
- Take advantage of "JULES-TAF" (discussed by Tim Jupp in this session) for faster convergence.
- Examine the response of large-area carbon cycles (e.g. Europe or World).



#### Questions and answers



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#### Spare Slides

f 0 and dqcrit  
Met Office  
Hadley Centre
$$\left\{\frac{c_i - \Gamma}{c_c - \Gamma}\right\} = F_0 \left\{1 - \frac{D_*}{D_c}\right\}$$

- c<sub>i</sub> is the internal partial pressure of CO<sub>2</sub>
- c<sub>a</sub> is the external partial pressure of CO<sub>2</sub>
- $\Gamma$  is the photorespiration compensation point
- F<sub>0</sub> is a tuning parameter
- $D_*$  is the humidity deficit at the leaf's surface
- D<sub>c</sub> is a tuning parameter