

Ensemble transform Kalman filter parameter estimation of ocean optical properties for reduced bias in a coupled GCM

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COSIMA Conference 7th of May 2020, on-line

OCEANS AND ATMOSPHERE www.csiro.au





Problem: Model Biases Limiting Predictability

- In GCMs unresolved subgrid processes are parameterised.
- Many of the associated parameters are known with little precision, which contributes to **model biases and limits predictability**.
- For example, it is more difficult to produce realistic ENSO dynamics in coupled GCMs in which **air-sea fluxes** also need to be parameterised, as compared to OGCM or AGCM forced by appropriate boundary conditions.
- **Typical approach:** Run various simulations, each with manually tuned sets of parameter values, with a qualitative determination made on which produces the most realistic results.
- Present approach: Develop a systematic and objective means for model calibration / parameter tuning using the Ensemble Transform Kalman Filter (ETKF), focusing on parameters governing the air-sea fluxes.
- Presentation overview:
 - Estimated parameters in the coupled GCM.
 - Overview of Kalman filtering in state and parameter estimation.
 - Specifics of the Climate Analysis Forecast Ensemble (CAFE) system.
 - Demonstrate the sensitivity of climate forecast skill to estimating multiple parameters either individually or simultaneously.

Parameterisation of the Shortwave Flux

- Initial tests indicated that of the air-sea flux parameters, those governing the shortwave flux ($F_{\rm SW}$) exhibited the greatest influence.
- Estimating parameters of the other fluxes were found to be either ineffective, or produced numerical instabilities - indicative of model form error.

Representation of shortwave radiation:

- In the atmosphere solved using an energy balance model.
- The air-sea flux at the interface governed by

$$F^{SW} = F_0^{SW}(1 - \alpha)$$
, where ocean albedo $\alpha(\lambda, \phi, t) = \frac{0.037}{1.1\theta(\lambda, \phi, t)^{1.4} + 0.15}$
and θ is the zenith angle of the Sun.

• Shortwave fraction at a given depth z of the ocean given by

 $\frac{Q^{SW}(\lambda,\phi,z,t)}{Q^{SW}(\lambda,\phi,z=0,t)} = \exp\left(\frac{-z}{L_{SW}(\lambda,\phi,t)}\right) \text{ where } L_{SW} \text{ is an e-folding length}$

• In the following results we estimate α and $L_{\rm SW}$.

Ensemble Kalman Filter (Evensen, 1996)

• Data assimilation (DA) modifies imperfect simulations of reality with a series of incomplete and possibly noisy measurements (y), ideally resulting in a better representation of the true system state (x).

System structure: Non-linear with Gaussian process and observational noise.

$$\mathbf{x}(t) = \mathcal{F}(\mathbf{x}(t-1)) + \mathbf{w}(t)$$
, where $\mathbf{w}(t) \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}(t))$

$$\mathbf{y}(t) \;=\; \mathcal{H}\left(\mathbf{x}(t)
ight) + \mathbf{v}(t)$$
, where $\mathbf{v}(t) \sim \mathcal{N}(\mathbf{0}, \mathbf{R}(t))$

Analysis step: Sub-optimally minimises trace(\mathbf{P}^a), where \mathbf{P}^a is the error co-variance of the analysed / corrected state (\mathbf{x}_e^a).

$$\begin{aligned} \mathbf{x}_{e}^{a}(t) &= \mathbf{x}_{e}^{f}(t) + \mathbf{K} \left[\mathbf{y}_{e}(t) - \mathcal{H} \left(\mathbf{x}_{e}^{f}(t) \right) \right] & \text{for ensemble member } e \\ \mathbf{K} &= \mathbf{P}^{f} \mathbf{H}^{T} \left[\mathbf{H} \mathbf{P}^{f} \mathbf{H}^{T} + \mathbf{R} \right]^{-1} \text{, where } \mathbf{H} \text{ tangent linear operators of } \mathcal{H} \end{aligned}$$

Forecast step: The ensemble of forecast states (\mathbf{x}_e^f) evolved in time and associated error covariance (\mathbf{P}^f) is sampled

$$\begin{aligned} \mathbf{x}_{e}^{f}(t) &= \mathcal{F}\left(\mathbf{x}_{e}^{a}(t-1)\right) \\ \mathbf{P}^{f}(t) &= \mathbf{A}\mathbf{A}^{T}/(m-1) \text{, columns of } \mathbf{A} \text{ contains } \mathbf{x}_{e}^{f} - \langle \mathbf{x}^{f} \rangle \end{aligned}$$

with m the number of ensemble members, and $\langle \cdot \rangle$ the ensemble average.

Illustration of the Ensemble Kalman Filter



- Note, we adopt the ensemble transform Kalman (ETKF) filter (Bishop et al., 2001; Sakov, 2019) which does not require perturbed observations.
- Ensemble mean updated as above, with ensemble anomalies updated using the an alternate linear operator.

Ensemble Kalman Filter for Parameter Estimation

• Redefine the state vector to include both the model states (\mathbf{x}_S^f) and parameters (\mathbf{x}_{ψ}^f) , and associated observational operator (i.e. a satellite cannot observe a model parameter)

$$\mathbf{x}_{e}^{f}\equiv\left[egin{array}{c} \mathbf{x}_{S}^{f}\ \mathbf{x}_{\psi}^{f}\end{array}
ight]_{e}$$
 , and $\mathbf{H}=\left[\mathbf{H}_{S}~\mathbf{0}
ight]$

Substituting above redefinitions

$$\langle \mathbf{x}^a
angle = \langle \mathbf{x}^f
angle + \mathbf{K} \left[\mathbf{y} - \mathbf{H}_S \langle \mathbf{x}_S^f
angle
ight]$$
, with $\mathbf{K} = \left[egin{array}{c} \mathbf{P}_{SS}^f \mathbf{H}_S^T \ \mathbf{P}_{\psi S}^f \mathbf{H}_S^T \end{array}
ight] \left[\mathbf{H}_S \mathbf{P}_{SS}^f \mathbf{H}_S^T + \mathbf{R}
ight]^{-1}$

- Kalman gain for the states is unchanged, but gain for the parameters is proportional to the covariance between the states and parameters \mathbf{P}^{f}_{wS} .
- For parameter estimation, the choice of forecast window $(t_1 t_0)$ is not obvious. In general, as the forecast window increases, $\mathbf{P}_{\psi S}^f$ decreases, associated K decreases, but the bias $\mathbf{y} \mathbf{H}_S \langle \mathbf{x}_S^f \rangle$, increases.

Climate Analysis Forecast Ensemble (CAFE) system

Data Assimilation System: (Sandery et. al., 2020)

- ETKF designed for high dimensional geophysical models (Sakov, 2019).
- 96 ensemble members (i.e. climate models).
- $\approx 10^8$ model states, with many parameters.
- $\approx 10^4$ CPUs required to simulate the GCM ensemble and solve EnKF.

Observations:

- Satellite and sub-surface observations of the ocean (Cabanes, 2013).
- JRA55 reanalysis treated as atmospheric observations (Kobayashi, 2015).
- Satellite sea-ice concentration observations from Norwegian and Danish Meteorological Institutes.

General Circulation Model:

- Modified version of the Geophysical Fluid Dynamics Laboratory Coupled Model version 2.1 (Delworth et. al., 2006).
- Atmosphere: 2° latitude ; 2.5° longitude ; 24 vertical levels,
- Ocean: 1° longitude; finer latitudinal in specific regions; 50 vertical levels.
- Sea-ice: ocean horizontal resolution; 5 ice thickness categories.

Individual verses Joint Parameter Estimation

- DA undertaken from 1/1/2010 to 31/12/2011, on a 28-day cycle.
- Globally averaged mean bias $(y H\langle x^f \rangle)$ over the second year of the DA experiments to remove "spin up" period.
- Note, the bias is evaluated prior to the analysis step, therefore, it is a true measure of the forecast error.
- Only experiments estimating $L_{\rm SW}$ have reduced bias in both sea-ice concentration (SIC) and in-situ temperature.



Spatio-temporal Properties of the Parameters

• Parameters have a weak dependence upon time. Structure broadly similar, with specific differences between the individual and joint estimation.

Out-of-sample Multi-year Monthly Average SST Bias

• Only $L_{\rm SW}$ case has reduced positive and negative SST bias.

Out-of-sample Multi-year Monthly Average SIC Bias

• Only $L_{\rm SW}$ case has reduced bias in both hemispheres.

90°E 180°

Concluding Remarks

- Ensemble Transform Kalman filter used to estimate spatio-temporally varying parameter maps of **ocean albedo** and the **ocean shortwave e-folding length scale** (L_{SW}) on the basis of short term 28-days forecasts of a coupled climate atmosphere / ocean / sea-ice GCM.
- Estimated parameter maps in these data assimilation experiments resemble known model biases, and have been shown to **improve the in-sample fit of the coupled GCM** to a network of real world observations during 2010-2011.
- However, only the multi-year forecast using the individually estimated map of L_{SW} systematically **improves out-of-sample skill** during 2012-2020.
- To our knowledge, this is the first attempt at undertaking parameter estimation on GCMs of this size and complexity.
- Whilst the parameter maps may appear aphysical, there is a precedent for aphysical parameters in subgrid turbulence modelling, where the eddy viscosity is in general anisotropic and also negative for certain scales (Kitsios et. al., 2016).
- We have demonstrated some promising results, and will continue to assess other parameters that are potentially more appropriate and effective.

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Thank You

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