Optimization of vegetation model parameters through sequential assimilation of surface albedo observations

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Introduction

Canopy
Albedo

The observations
- Leaves change their colour not only before they are shed but over the whole seasonal cycle. Also the structure of the canopy changes over the seasons. Both effects lead to a seasonally changing canopy albedo.
- Inversions of remote sensing observations also indicate that the radiative properties of individual leaves change over the seasons.

The model
- The canopy albedo parameters of JSBACH describe the reflectivity of a homogenous, dense, closed canopy.
- The model considers background albedo and canopy albedo as fixed parameters.
  - The albedo of grid box only varies due to variations in leaf area index, that is the fraction of closed canopy within a grid box changes.
  - Because canopy albedo as used in JSBACH is an effective parameter, we cannot infer it directly from observations. We can only observe land surface, meaning grid box albedo.

Uncertainty in processes and data

Processes - Do canopy albedo variations matter?
- How large is the seasonal variability in canopy albedo as used in JSBACH?
- Do we need to include a seasonally varying parameterization or not?
  - Derive a parameter time series to judge seasonal variability.

Data - How can we derive parameters from observations?
- We can only observe grid box albedo but not canopy albedo on its own.
- How can we use observations with state dependent errors?
- How can we include crude, uncertain prior knowledge?
  - Use probability distributions to include initial and observational uncertainty.

Sequential data assimilation

Data assimilation combines model forecasts with observations to yield improved estimates. In a sequential data assimilation system, this happens cyclically:
  - Run the model to generate a forecast.
  - Compare the forecast to the observation.
  - Update states and parameters according to the observation.
  - Produce a new forecast for the next observation.

Because the parameters are also updated every time, his cycle produces the desired time series of parameter values.

The Ensemble Kalman Filter (EnKF) and Gaussian anamorphosis

- The EnKF uses an ensemble of model states to represent the prior distribution of the state vector.
- The observation likelihood is given by the observed value and its error covariance.
- Bayes Theorem yields the posterior or conditional distribution of the state given the observation.
- Unobserved states and parameters are updated according to their correlations with observed states as estimated from the ensemble.
- If the prior distribution and the observation likelihood are Gaussian, the conditional distribution is Gaussian.
  - Mean and covariance are sufficient to characterise all distributions.
  - The ensemble can be easily updated by shifting and scaling.
  - Because albedo is a double-bounded quantity and the sought after parameters are close zero, we cannot use Gaussian distributions.
  - To use the EnKF with the non-Gaussian, bounded distributions, we use the logit transform, $t(x) = \ln(x) - \ln(1-x)$, to map albedo from $[0,1]$ to an unbounded interval such that the transformed variables follow a Gaussian distribution.

Results and Conclusion

- We assimilated synthetic observations (perturbed truths) with an observation error variance of 0.03.
- With adequate inflation of the ensemble (not shown here), we were able to retrieve the seasonal evolution of the canopy albedo parameters.

Conclusion

- The assimilation quickly corrects the initial error and reacts well to seasonal changes of the parameters.
- The retrieval of canopy albedo parameters from real observations appears to be possible if other error sources such as shifted phenological cycles can be minimized.