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

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Introduction

Canopy refers to the above-ground portion of plants, for example tree crowns.
Albedo describes the reflectivity of a surface as the ratio of reflected radiation to incident radiation.

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.

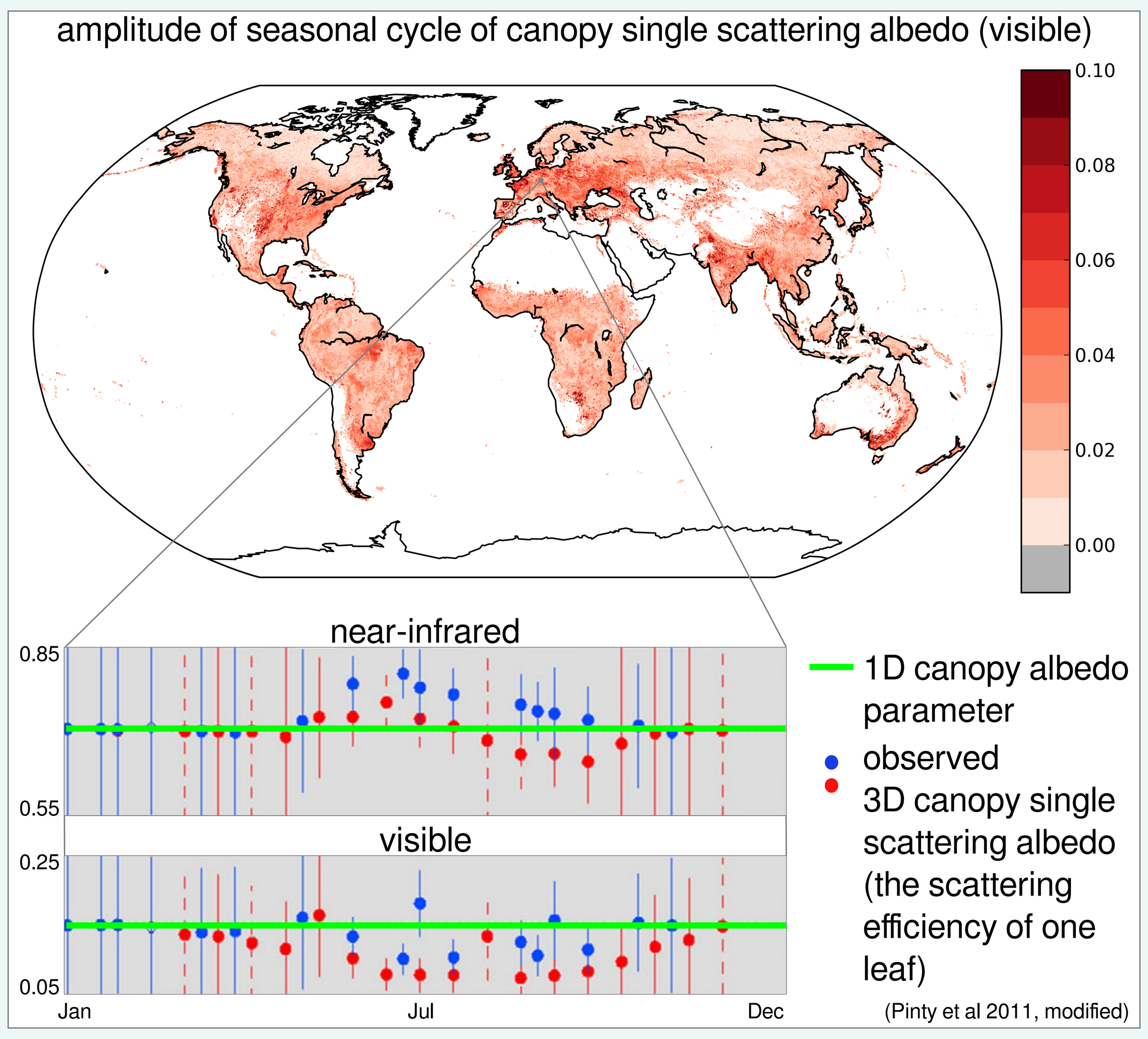

Figure 1: Seasonal cycles of canopy single scattering albedo.

Figure 2: The same forest canopy looks different at different times of the year.

The model

- The canopy albedo parameters of JSBACH describe the reflectivity of a homogeneous, 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 if 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.

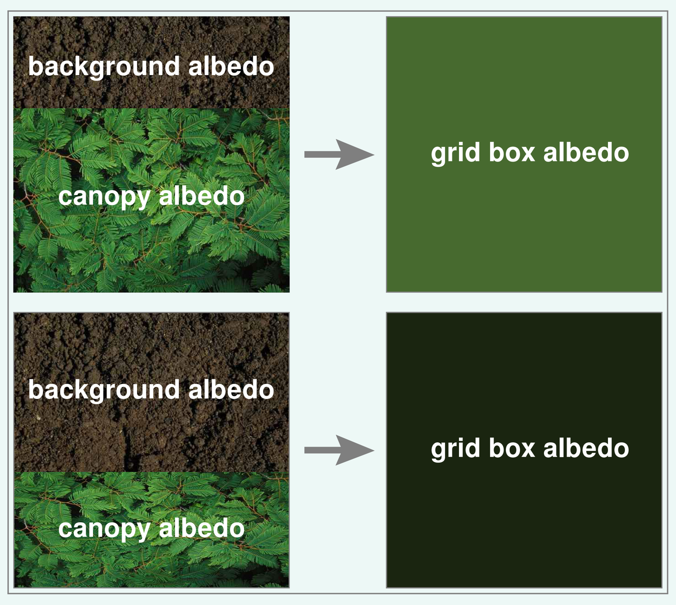

Figure 3: Simplified land surface albedo scheme of JSBACH.

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 parametrization 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.

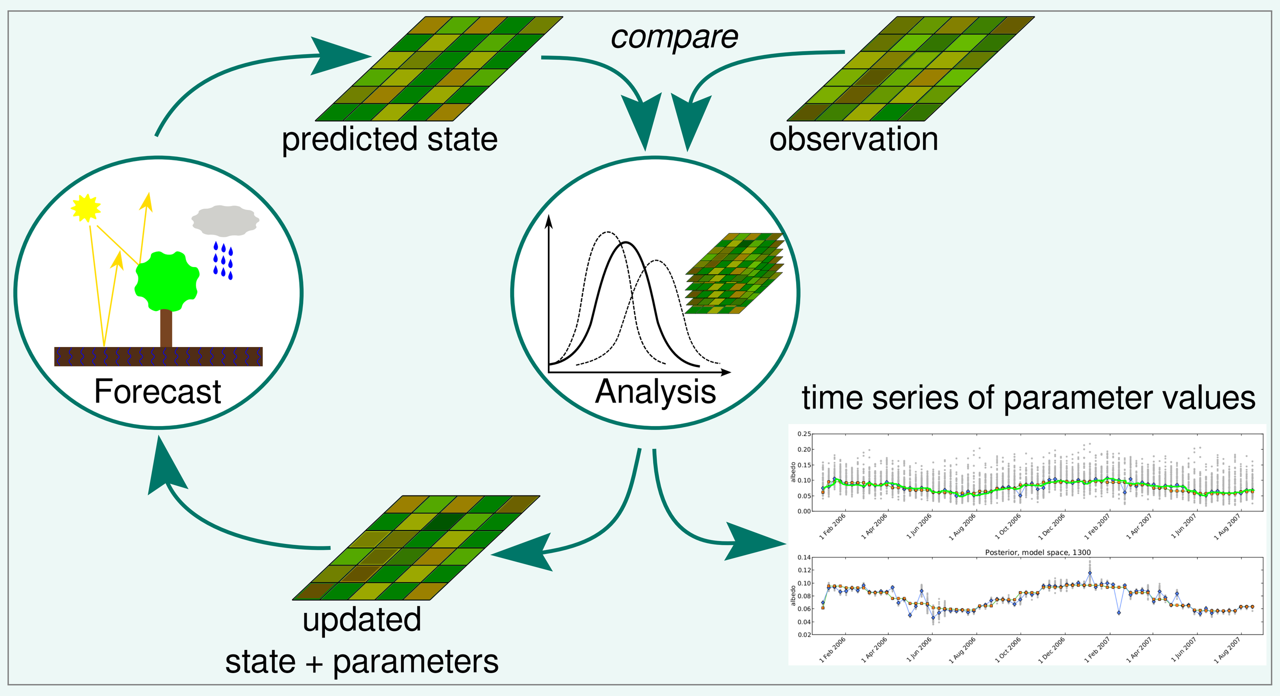

Figure 4: The data assimilation cycle.

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.

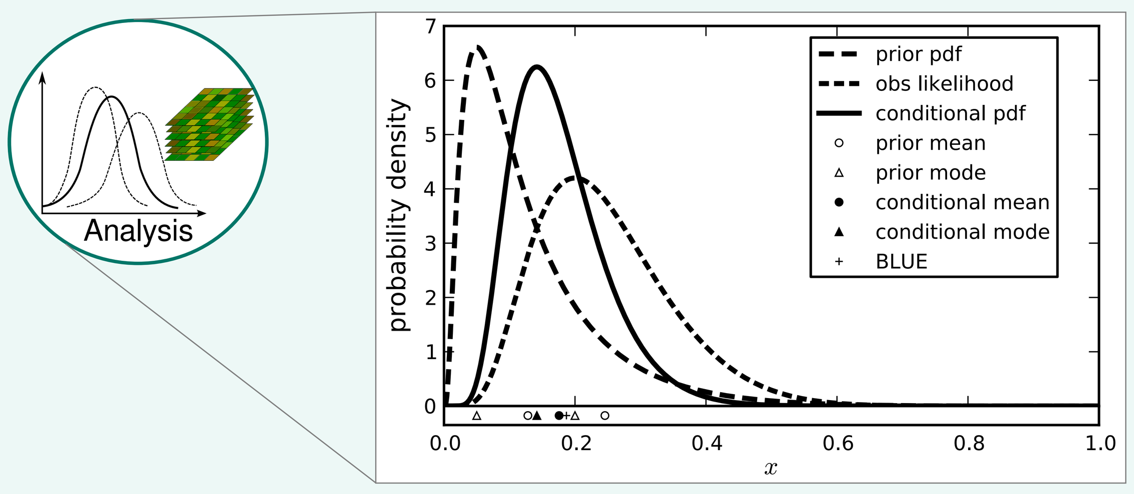

Figure 5: Bayesian update applied in the EnKF.

- 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.

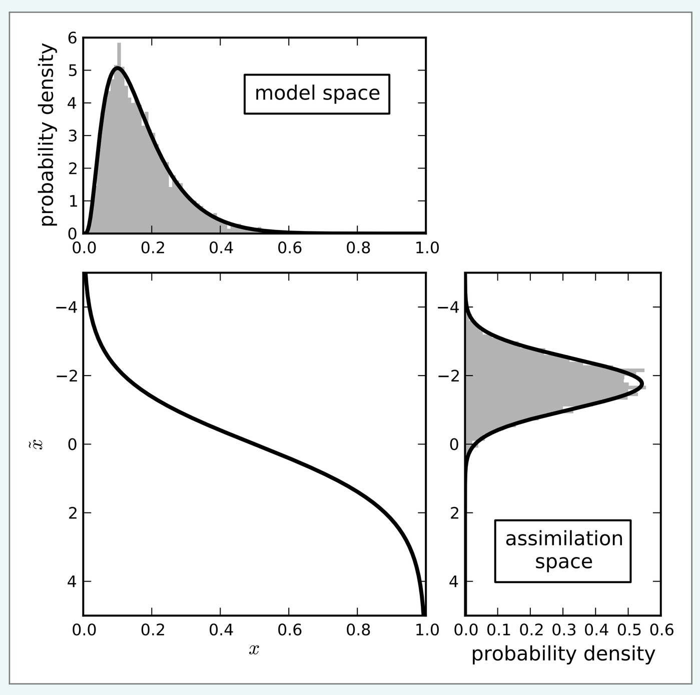

Figure 6: Logit transform to map albedo from [0, 1] to an unbounded interval.

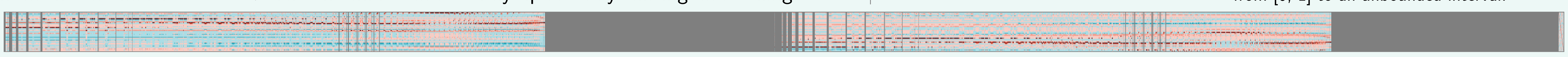
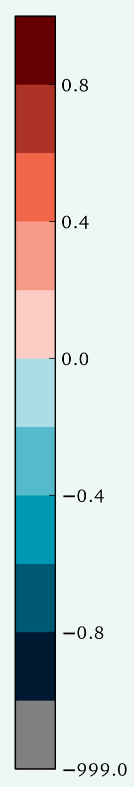

Figure 7: Correlations of canopy albedo parameters (vertical) with model state vector (grid box albedo, horizontal).

Results and Conclusion

- We assimilated synthetic observations (perturbed truths) with an observation error variance of 0.01.
- 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 minimised.

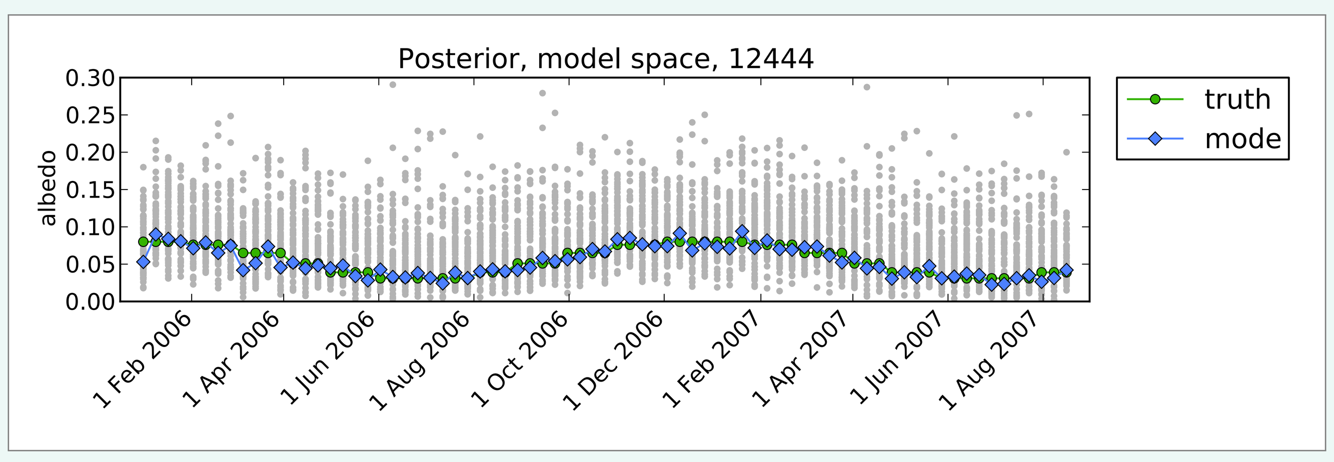

Figure 8: Evolution of the posterior ensemble and the posterior mode compared to the synthetic truth for the canopy albedo of tropical evergreen trees (TropEv).

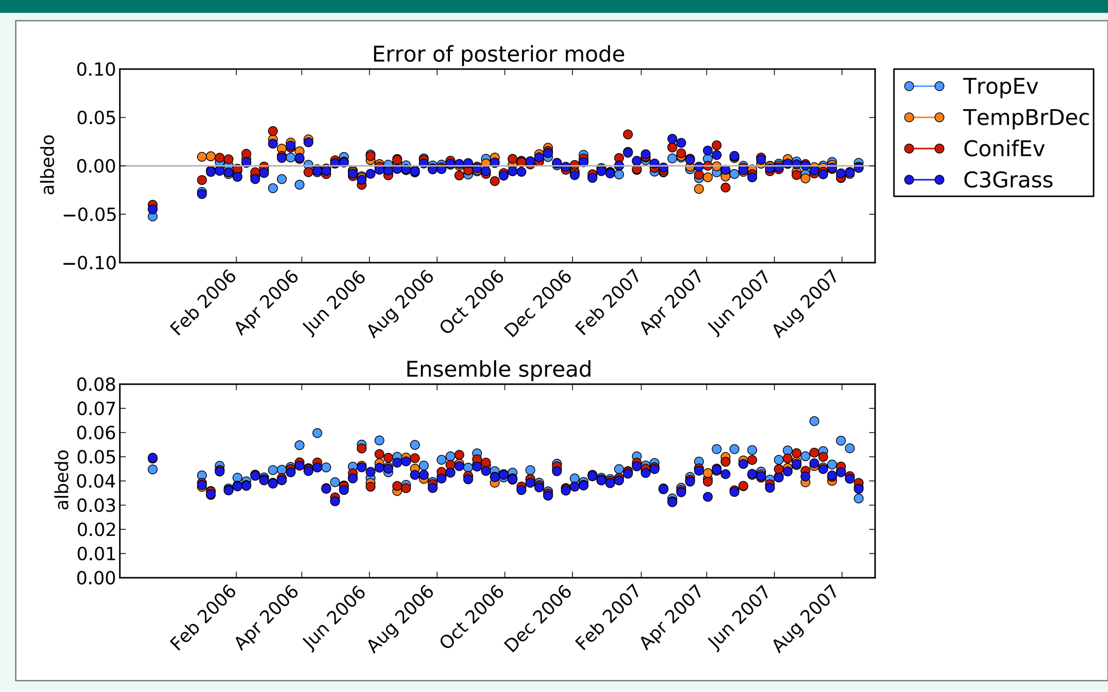

Figure 9: Error of the posterior mode and ensemble spread for 4 parameters.

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