Data assimilation experiments of the dynamic global vegetation model SEIB-DGVM with simulated GPP observations

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Overview

A simple data assimilation experiment of a vegetation model

SEIB-DGVM + SIS filter + simulated GPP observation

Dependence on the number of particles and observation interval is discussed

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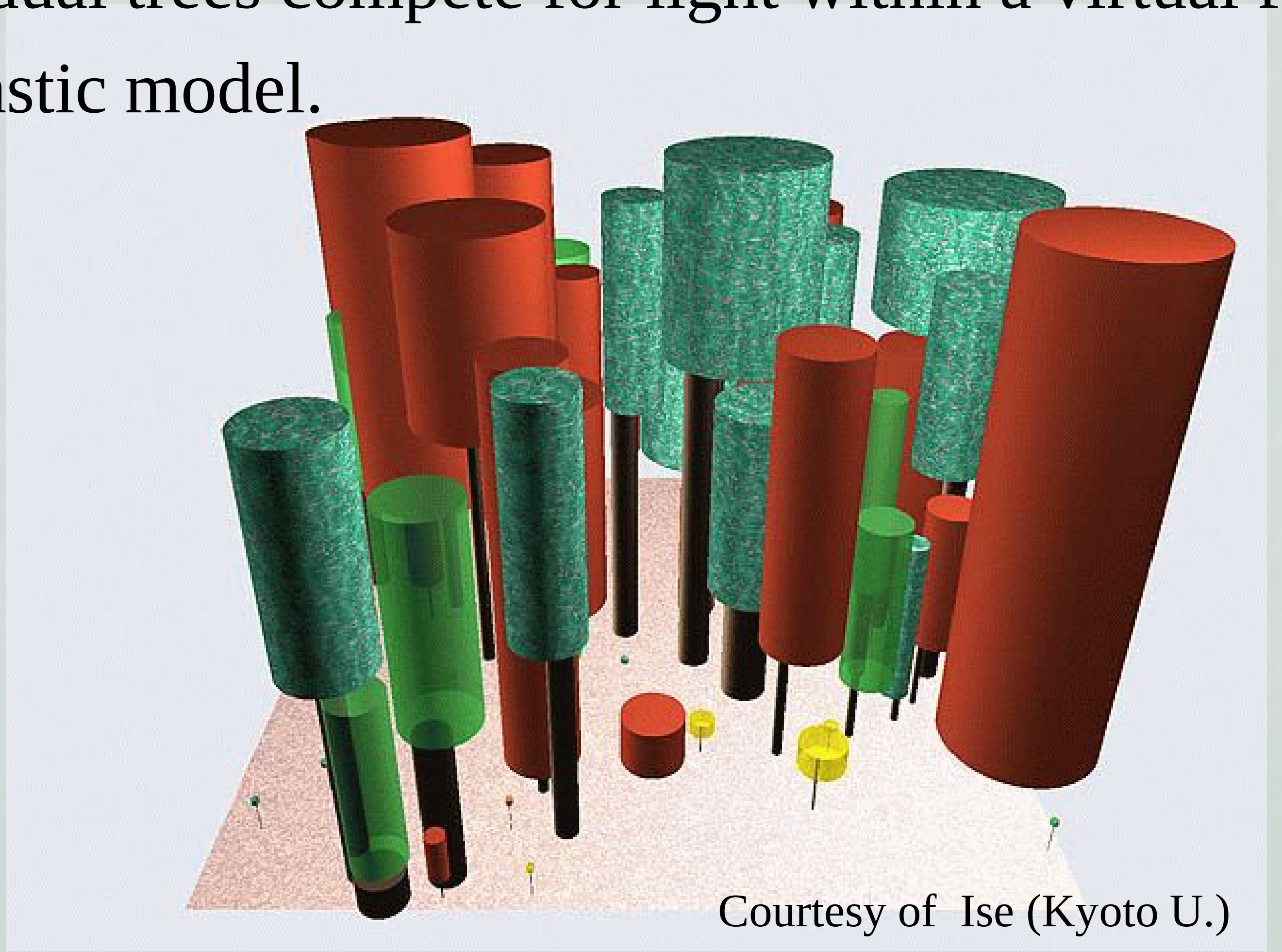
1. Introduction

SEIB-DGVM (Spatially-Explicit-Individual-Base Dynamic-Global-Vegetation-Model) (Sato et al., 2007)

Individual trees compete for light within a virtual forest.

Stochastic model.



Courtesy of Ise (Kyoto U.)

SIS (Sequential Importance Sampling) filter

- A version of particle filter
- Probability density is represented by **weighted particles**
- Easy to implement and assumption-less, but costs a lot

Design of our experiment

- Assimilate observations to SEIB-DGVM using SIS filter
- Observations are simulated by SEIB-DGVM
- We estimate the state and a parameter of the truth

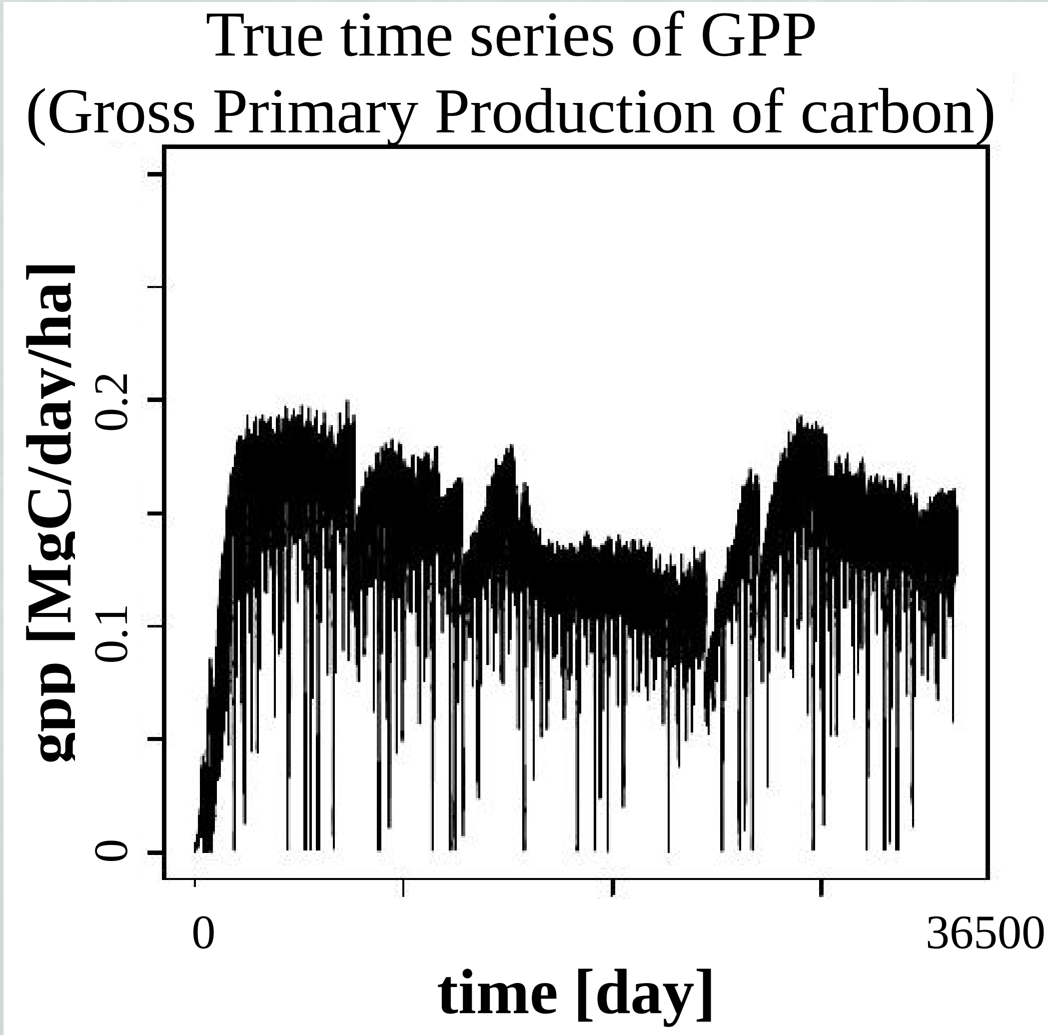
Objective

- Assess the performance of this assimilation system
  - How many particles are needed?
  - How often do we have to observe the system?
  - Is the probability density function (PDF) Gaussian like?

2. Setup of the Experiment

Truth

One specific run of SEIB-DGVM is regarded as the truth



Observation

Observe the true GPP every Δt (1,7,30[day]) for 100 years

Gaussian noise of σ=0.1[MgC/day/ha] is added to truth

y_t denotes the t-th observation

Prediction model

SEIB-DGVM

Assume a parameter Pmax is uncertain

Photosynthesis parameter of a specific plant type

Initially, Pmax is uniformly distributed in [6.0,46.0]

Pmax=26.0 is the truth

$\boldsymbol{x}_t$ denotes the state of the system at the t-th observation time

Observation model

$p(y_t|\boldsymbol{x}_t)$: PDF to get an observation y_t for a given $\boldsymbol{x}_t$

Gaussian with σ=0.1[MgC/day/ha], same as observations

Data assimilation scheme

What interests us the most is $p(\boldsymbol{x}_t|y_{1:t})$:

PDF of x_t, given the observations $y_{1:t}=\{y_1,\ldots,y_t\}$

Based on Bayes' theorem, $p(\boldsymbol{x}_t|y_{1:t})$ satisfies

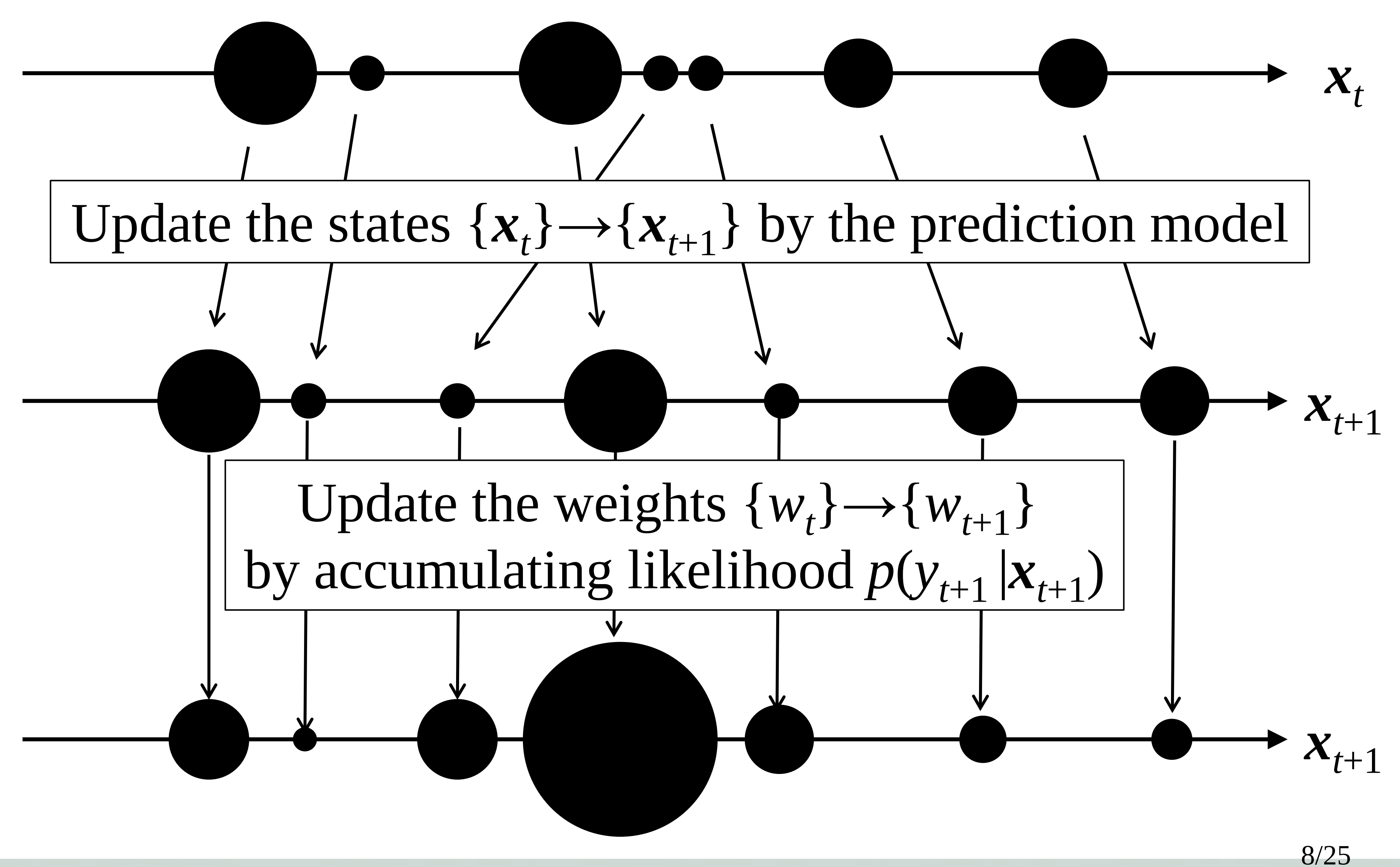
$$p(\boldsymbol{x}_t|y_{1:t}) = \frac{p(y_t|\boldsymbol{x}_t)p(\boldsymbol{x}_t|y_{1:t-1})}{\int p(y_t|\boldsymbol{x}_t)p(\boldsymbol{x}_t|y_{1:t-1})d\boldsymbol{x}_t}.$$

SIS filter evaluate this eq. straightforwardly

- PDF is represented by **weighted particles**
- As # of particles $N\rightarrow\infty$, any PDF can be reproduced.
- Easy to implement, but costs a lot

…cont. (Data assimilation scheme)

Procedure of SIS filter



Control parameters

Number of particles N=41, 410, 4100, 41000, 205000

Observation interval Δt=1day, 7days, 30days

4. Concluding Remarks

Summary

Data assimilation experiments of the SEIB-DGVM was done

Simulated GPP is used for the observations

SIS filter is used for the assimilation

# of particles: at lease *N*=410, but 41000 could be enough

If we use SIR filter, we can reduce *N*

Observation interval Δt≦7days seems to be better.

PDF of Pmax is skewed a bit but unimodal

Kalman filter can be used?

Future plan

Now ready to use real observation