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An Improved State-Parameter Estimation of Forest Carbon Dynamics in a Boreal Forest Ecosystem of Interior Alaska using Data Assimilation

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1. Introduction

Understanding how changes in the boreal forest ecosystem will affect global climate requires knowledge of boreal carbon dynamics. There are two principal approaches to understand boreal carbon dynamics: modeling and measuring. However, there are large uncertainties in quantifying boreal carbon dynamics using process-based models. The uncertainties result from model structure imperfection, poorly defined parameters, and driving force errors. Direct measurements of carbon stocks and fluxes usually are sparse, poorly distributed or biased. Data assimilation can mitigate the limitations of both approaches by incorporating the direct measurements into the modeling process.

2. Objective

This study uses a Smoothed Ensemble Kalman Filter (SEnKF) to sequentially assimilate measurements that characterize carbon flux and stocks, climate and soil into the General Ensemble Biogeochemical Modeling System (GEMS) to improve estimation of forest carbon dynamics in a boreal ecosystem of interior Alaska.

3. Data, Model, and Fusion Scheme

Site:

The site, known as Randerson's site, is located near Delta Junction (63°54'N,145°40'W) in Alaska and has a dominant cover of black spruce. Climate data, including air temperature, precipitation (both rain and snow components), radiation and vapor pressure deficit, were collected in the field and at the climate monitoring station in nearby Big Delta, Alaska from 2002 to 2004 (WRCC, 2007). Soils consist of well-drained silty loams on top of glacial moraines.

Data:

Assimilated data. First we used a flux partition model (Yuan et al., 2007) and field measurements of climate, soil, energy, and Net Ecosystem Exchange (NEE) collected at Randerson's site from 2002 to 2004 (Liu et al, 2008) to simulate Gross Primary Production (GPP) and Ecosystem Respiration (ER). Then we derived Net Primary Production (NPP), Autotrophic Respiration (AR), and Heterotrophic Respiration (HR) based on relationships between NPP and GPP (i.e., NPP = (0.525±0.05)*GPP, AR = (0.475±0.05)*GPP, HR = ER-AR). The relationships were calibrated from NPP (Mack et al., 2008) and simulated GPP.

All assimilated data errors are assumed to have Gaussian distributions with a mean of zero and a variance of 5 percent of the average data based on uncertainty analysis in eddy covariance measurements.

Model:

GEMS is a complex monthly biogeochemical model system based on the Monte Carlo technique. It includes a number of submodels (e.g., plant production and soil organic matter (SOM)), which are driven by various forces (e.g., climate conditions, soil properties, and various management options) (Liu et al., 2003). The plant production submodel assumes that NPP equals the monthly potential plant production multiplied by scalars related to moisture, temperature, stand age, and seasonal change. The SOM includes three soil organic matter pools (active, slow, and passive) with different potential decomposition rates, above and belowground litter pools, and a surface microbial pool which is associated with decomposing surface litter.

Fusion Scheme:

SEnKF is a sequential data assimilation method that combines an ensemble Kalman filter and a kernel smoothing technique (Chen et al., 2008). The SEnKF method is capable of estimating simultaneously the model states and parameters by concatenating unknown parameters and state variables into a joint state vector, recursively assimilating data into the model and thus detecting the possible time variation of parameters, and properly addressing various sources of uncertainties stemming from input, output and parameter uncertainties.

4. Results and Analysis

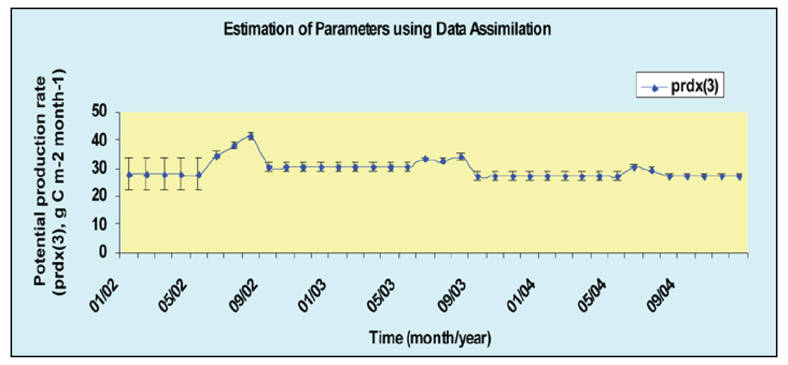

Figure 1. ***Potential Plant Production Rate.*** SEnKF can catch seasonal variations of the key parameter of the plant production submodel in GEMS and gradually reduces the error of the parameter. Conventional inverse methods typically derive a constant value of the parameter. In the SEnKF procedure, we explored the effects of ensemble size and initial values of parameters, and found that a moderate ensemble size (e.g.,30) and an arbitrary initial guess of a parameter can soon converge.

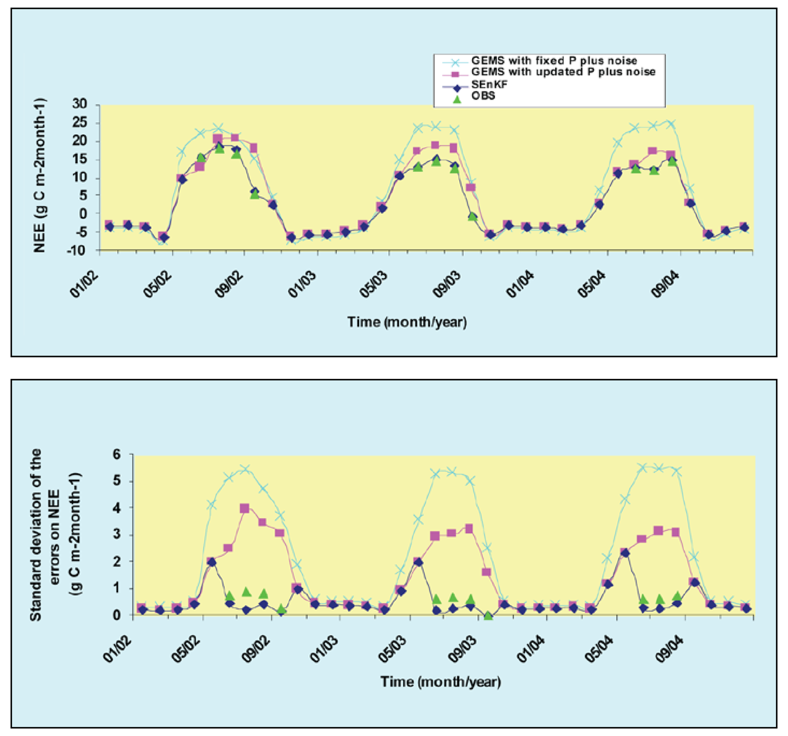

Figure 2. ***Net Ecosystem Exchange Estimation.*** The upper figure shows monthly variations of ensemble means of NEE estimated by GEMS (one case with fixed parameters estimated by conventional inverse method and the other with updated parameters by SEnKF), SEnKF and observation, respectively. We see that predictions of GEMS with updated parameters are closer to observations than those of GEMS with fixed parameters. SEnKF further improves the predictions of GEMS with updated parameters. The lower figure shows that the standard deviation of NEE estimated by GEMS is up to 30 percent of the mean during summer when the fixed parameter is added with a perturbation error of 10 percent of the parameter value. Using the updated parameter reduces 40 percent of the deviation caused by the parameter uncertainty and SEnKF reduces further up to 70 percent of the deviation.

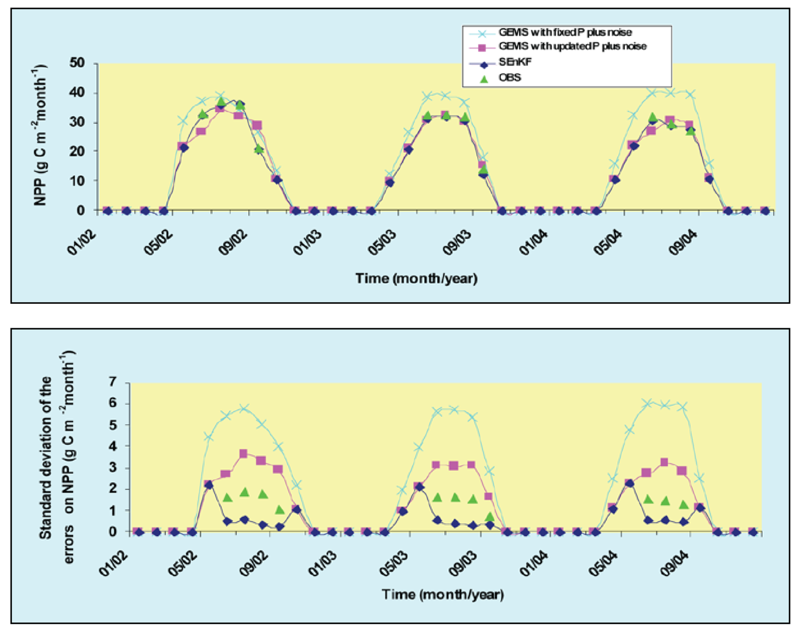

Figure 3. ***Net Primary Production.*** Comparison of monthly variation of ensemble means (upper figure) and standard deviations (lower figure) of NPP. Both predictions of GEMS with updated parameters and estimates by SEnKF are better approximations to observations than those of GEMS with fixed parameters. The lower figure shows that NPP is quite sensitive to perturbation of the parameter (potential production rate) because standard deviations of NPP reach 25 percent of the mean during summer when the fixed parameter has a perturbation error of 10 percent of the parameter value. Using the updated parameter reduces 45 percent of the deviation and SEnKF reduces further up to 75 percent of the deviation.

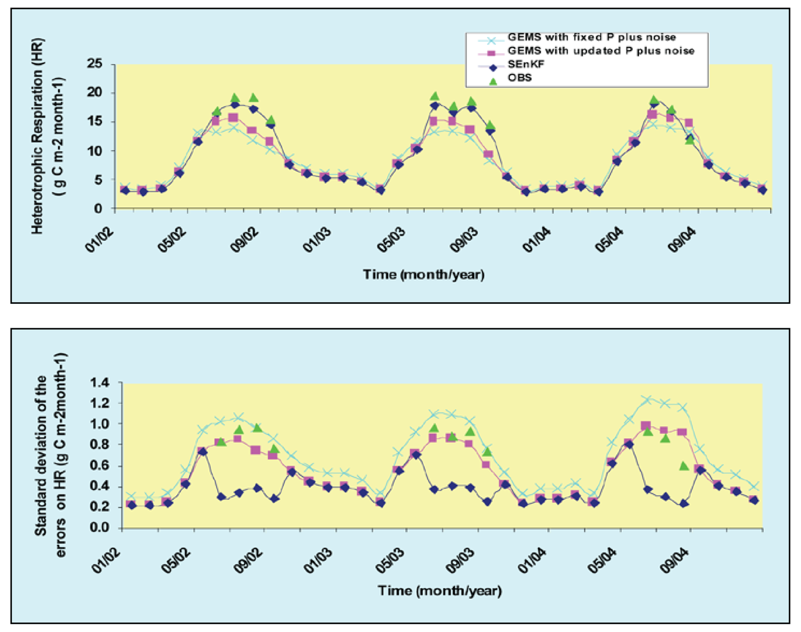

Figure 4. ***Heterotrophic Respiration.*** Comparison of monthly variation of ensemble means (upper figure) and standard deviation (lower one) of HR. GEMS derived predictions that incorporated updated parameters are better approximations to observations than those that incoporated fixed parameters. Application of SEnKF prior to modeling produces the estimated values which are even closer to the observations. The lower figure shows that HR is not quite sensitive to perturbation of the parameter (potential production rate). However, Application of SEnKF significantly reduces ensemble variance.

5. Conclusion

After using SEnKF to assimilate sequentially eddy covariance measurements into GEMS, the estimates of state variables, such as NEE, NPP, and HR (see fig. 2~4), are substantially improved over GEMS alone for the boreal forest site. Especially, predictions using updated parameters match observations better than model runs with fixed parameters (see fig.1) because SEnKF takes into account seasonal variations of the parameters. Through Monte Carlo analysis, NEE and NPP estimated by GEMS are quite sensitive to the perturbation of parameters (e.g., potential production rate) during summer. However, SEnKF can reduce the uncertainty of NEE and NPP by 50 percent stemming from the uncertainty of the parameter. The estimates of NEE from the SEnKF analysis suggest the forest site was a net sink for three years.

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