

The role of prior and observation error correlations in improving a forecast of forest CO₂ balance

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Introduction

We present the Data Assimilation Linked Ecosystem Carbon model (DALEC2) [1] in a Four-Dimensional Variational (4d-Var) data assimilation framework for parameter and state estimation. We assimilate a single year (1999) of daily Net Ecosystem Exchange (NEE) measurements, which represent the carbon balance of a forest, and then forecast the next 14 years (2000-2013). We run a set of experiments including correlations in the prior information (between parameter and state errors) and between NEE observation errors in time to assess the impact of these correlations on assimilation results and forecasts [2]. For this work we use NEE measurements taken at the NERC CASE partner Forest Research's Alice Holt deciduous forest CO₂ flux site.

Experiments

Novel techniques were used to create background and observation error covariance matrices (**B** and **R** respectively) including correlations. We used a set of previously postulated dynamical constraints from [1] to include correlations in **B** between prior parameter and state errors and a Gaussian correlation function to include time correlations between NEE observation errors in **R**.

Experiment	Uncorrelated background errors, \mathbf{B}_{diag}	Uncorrelated observation errors, \mathbf{R}_{diag}	Correlated background errors, \mathbf{B}_{corr}	Correlated observation errors, \mathbf{R}_{corr}
A	X	X		
B		X	X	
C	X			X
D			X	X

Table 1: Combination of error covariance matrices used in each experiment.

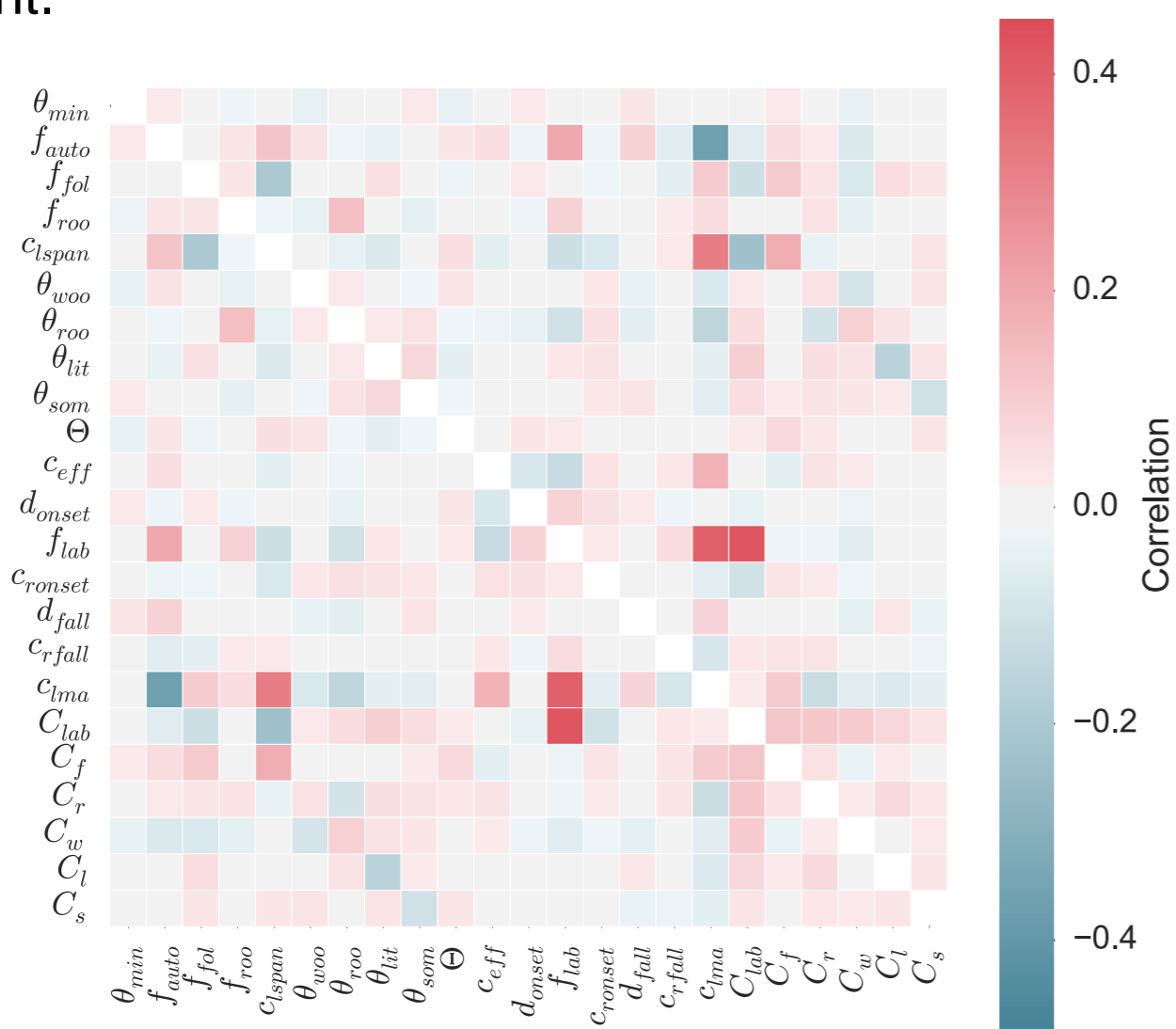


Figure 1: Background error correlation matrix, \mathbf{B}_{corr} , created using ecological dynamical constraints from [1].

References

1. A. Bloom and M. Williams: Constraining ecosystem carbon dynamics in a data-limited world, *Biogeosciences*, 12, 1299-1315, doi:10.5194/bg-12-1299-2015, 2015.
2. E. Pinnington, E. Casella, S. Dance, A. Lawless, J. Morrison, N. Nichols, M. Wilkinson, and T. Quaife. Investigating the role of prior and observation error correlations in improving a model forecast of forest carbon balance using four dimensional variational data assimilation. *Agricultural and Forest Meteorology*, accepted 2016.

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Results

Figure 2 shows a one year assimilation and 14 year forecast for experiment D when all correlations are included in the data assimilation scheme.

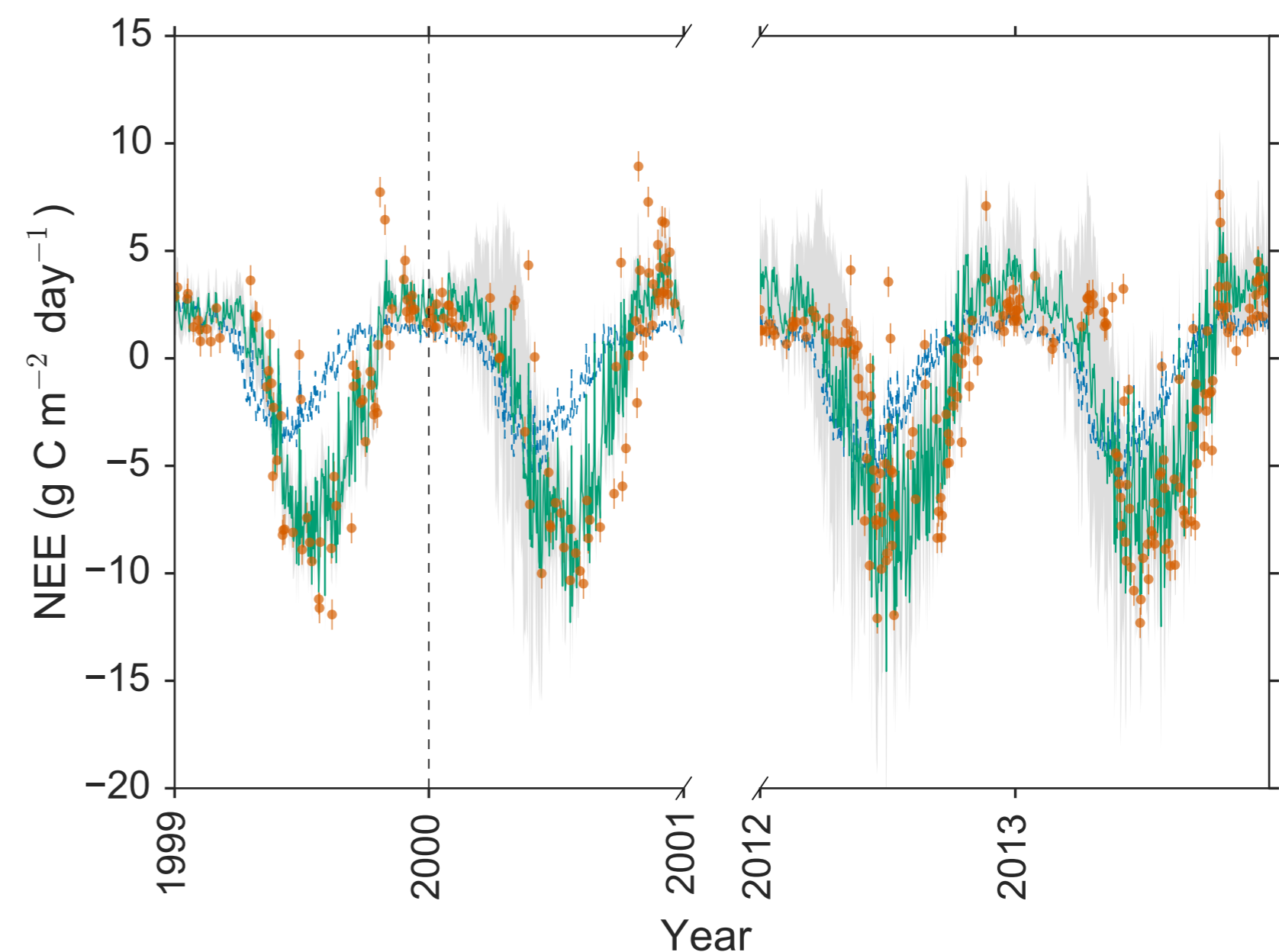


Figure 2: One year assimilation and fourteen year forecast of Alice Holt NEE with DALEC2, blue dotted line: prior model trajectory, green line: analysis and forecast after assimilation, red dots: observations from Alice Holt flux site with error bars.

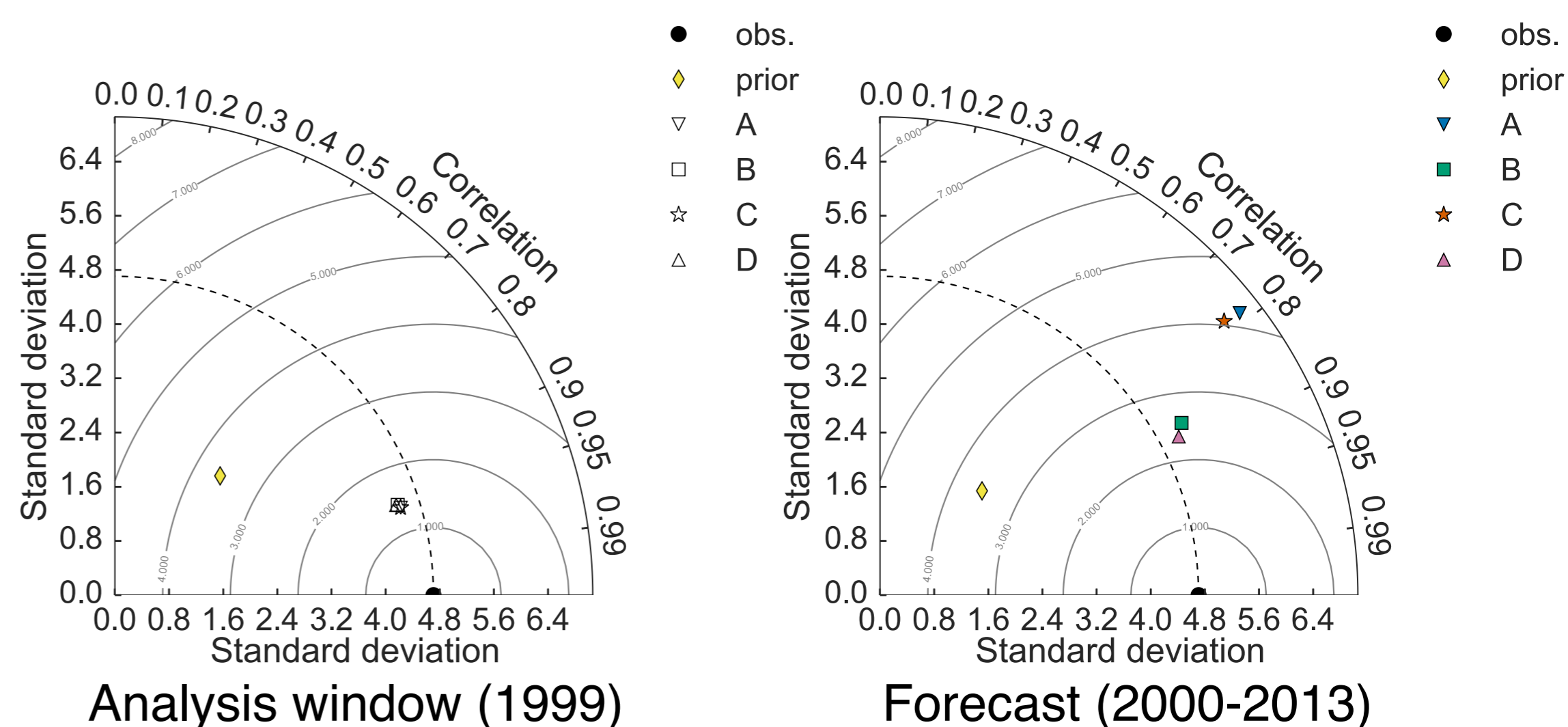


Figure 3: Taylor diagrams displaying statistical comparison of the four experiment and prior results with the observed NEE ($\text{g C m}^{-2} \text{ day}^{-1}$) in both the analysis (left) and forecast (right) period. The dotted line represents the standard deviation of the observations and the contours represent values of constant root mean square error between model and observations.

From Figure 3 we can see that experiment D (with all correlations) gives us the best forecast results. We also see there is no significant difference for the experiments in the analysis window after assimilation.

Conclusion

- Including both prior and observation error correlations reduces the root-mean square error in the 14-year forecast of NEE by 44%, decreasing from 4.22 to 2.38 $\text{g C m}^{-2} \text{ day}^{-1}$.
- More work needed into observation error correlations in time, with the development of a diagnostic tool for the calculation of time error correlations being important.