Carbon data assimilation using Maximum Likelihood Ensemble filter (MLEF)

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This research was funded by NASA Grant NNG05GD15G

Goals

- Develop an innovative general approach for carbon flux inversion
- Estimate and reduce carbon flux **uncertainty**
- Estimate and reduce **biases** in the carbon fluxes

Methodology
Maximum Likelihood Ensemble Filter (MLEF)

(M. Zupanski 2005, MWR; D. Zupanski and M. Zupanski 2006, MWR)

$$J=\frac{1}{2}[x-x_b]^T P_f^{-1}[x-x_b]+\frac{1}{2}[H[M(x)]-y_{obs}]^T R^{-1}[H[M(x)]-y_{obs}]=min$$

$x-x_b=P_f^{1/2}(I+C)^{-1/2}\zeta$ - Change of variable (preconditioning)

$C=Z^TZ$ - C is information matrix of dim $Nens \times Nens$

$z^i=R^{-1/2}H[M(x+p_f^i)]-R^{-1/2}H[M(x)]$ - z^i are columns of Z

$p_f^i=M(x+p_a^i)-M(x)$ - p^i_f and p^i_a are columns of P_f (forecast error cov) and P_a (analysis error cov)

y_{obs} - Observations vector of dim $Nobs$

x - Model state vector of dim $Nstate >> Nens$

ζ - Control vector in ensemble space of dim $Nens$

$x_n=M_{n,n-1}(x_{n-1})$ - Dynamical forecast model

$y_n=H_n(x_n)$ - Observation operator

For $N_{ens}=N_{state}$ (full-rank problem) and linear M and H :
MLEF = classical Kalman filter

For $N_{ens}=N_{state}$, non-linear M and H, constant P_f:
MLEF = 3d-var

Data assimilation experiments with an off-line Lagrangian Particle Dispersion Model (LPDM)

Bias estimation problem:

- **Integrate SiB-RAMS to pre-compute CO_2 fluxes (photosynthesis and respiration)**
- **Employ MLEF to estimate spatially dependent SiB-RAMS biases in carbon fluxes: β_{GPP} (photosynthesis bias) and β_{Resp} (respiration bias)**

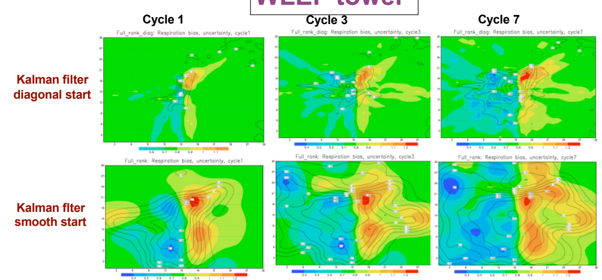
$$NEE(x,y,t)=\beta_{RESP}(x,y)RESP(x,y,t)-\beta_{GPP}(x,y)GPP(x,y,t)$$

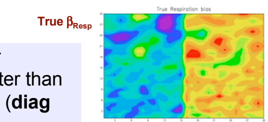
- **Employ LPDM as "observation operator" for CO_2 concentration observations (e.g., observations from ring of towers in northern Wisconsin)**

Experiments are performed for Single tower (WLEF) and Ring of Towers:

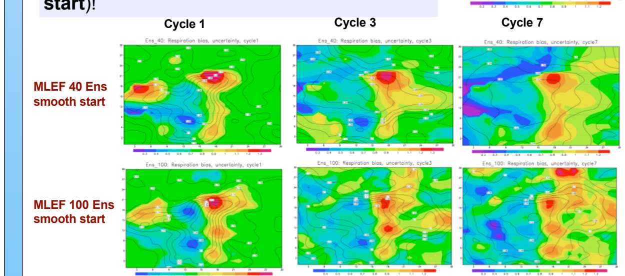
- **Simulated observations from WLEF tower and Ring of towers**
- **Real SiB-RAMS influence functions**
- **Data assimilation interval: 10 days**
- **Simulation over 70-day period starting 1 June 2004**
- **600km x 600km domain, Δx=20km**
- **N_{obs}=1200 (WLEF only) and N_{obs}=2640 (Ring of Towers)**
- **Obs_err varies between 1ppm and 45 ppm**
- **N_{state}=1800 (900 grid-points x 2 variables)**
- **Background values $\beta_{GPP}=\beta_{Resp}$ =0.75**
- **Background error for β_{GPP} and β_{Resp} assumed equal 0.2 in all 1800 grid-points**

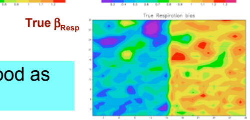
WLEF tower





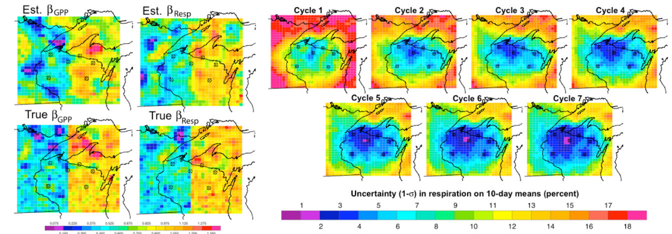
Using smooth initial background error covariance (**smooth start**) works better than using diagonal initial error covariance (**diag start**)!

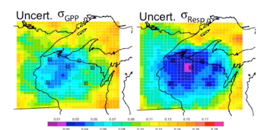




Reduced-rank MLEF results as good as full-rank Kalman filter results!

Ring of Towers





Uncertainties of the estimated biases decrease with time: the MLEF system has learning capability.

Conclusions

- ❑ MLEF approach is promising for carbon flux inversion problems: it can be used to estimate carbon fluxes, their biases, and the associated uncertainties.
- ❑ Using more data (from more towers) has a clearly beneficial impact. We need more towers!
- ❑ A relatively small ensemble size (100 ens) can produce results comparable to Kalman filter results (small ensemble size is a practical advantage over Kalman filter).
- ❑ No need to use adjont models (practical advantage over variational methods)

Future work

- ❑ Apply the same approach to the entire North American region.
- ❑ Use real observations.
- ❑ Employ a fully coupled atmospheric and carbon transport model (computationally demanding but could improve the results even further).

References

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