Assimilating MODIS reflectance data into an ecosystem model to improve estimates of terrestrial carbon flux: recent progress

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Abstract—**This paper details recent progress in the assimilation of top of canopy reflectance data into an ecosystem model to constrain estimates of net carbon flux. Previous work has demonstrated the feasibility of such an approach but its application at wide spatial scales remains relatively un explored. Two aspects of this are examined in this paper: the requirement to provide spatialised reflectance model parameters and the restating of an ecosystem model to optimise it for assimilating EO data.**

Keywords-MODIS; data assimilation; NEP; GORT; Ensemble Kalman Filter.

I. Introduction

Ecosystem models are valuable tools for analysing the response and feedbacks of terrestrial vegetation to climate change. Typically these models are calibrated and tested against data from a small number of field sites and over a limited range of ecosystems. Consequently their performance away from the original field sites may be poorly constrained. Medium resolution earth observation (EO) data is an ideal source of information for integration with such models at regional to global scales, particularly as its relatively high temporal sampling frequency permits a detailed representation of seasonal dynamics.

Data assimilation (DA) techniques provide a framework for adjusting model behaviour on the basis of available observations, taking into account the error characteristics of both the model and the observation. Assimilating so-called "high level" EO data products, such as gross primary productivity (GPP) and leaf area index (LAI) into ecosystem models is an attractive option as they have a trivial relationship with a typical ecosystem model state vector and thus a framework to assimilate them is relatively straight forward to implement. Two key arguments against the use of such products are that: a) their error characteristics (critical for DA) are often only poorly known and, b) assumptions used in their derivation may contradict those of the ecosystem model itself. Both of these points may be addressed by using "low-level" EO products such as reflectance data. Whilst these data are still products *per se*, assumptions made in their derivation are independent of those made in the ecosystem model and so may be considered to simply be additional noise terms. To use these data in a DA framework, however, requires coupling a canopy reflectance model to the ecosystem model.

This paper highlights recent progress made in assimilating reflectance data into a simple ecosystem model. Proceeding work has assumed reflectance model parameters to be constant over a small area – this assumption is addressed by inverting the parameters for every pixel in a test site. In addition a modified ecosystem model is presented and the impacts on flux predictions using this model are shown.

II. Models and Assimilation Scheme

A. Ensemble Kalman Filter

The Ensemble Kalman Filter (EnKF) was used to assimilate MODIS reflectance data into the DALEC ecosystem model (see below). A requirement of the basic formulation of the EnKF is that observations are linear functions of model state vector, which is clearly not the case with reflectance. To overcome this limitation an augmented ensemble approach is used [1] where by the reflectance predicted by the hybrid Geometric Optic Radiative Transfer model (GORT) coupled to DALEC is made part of the state vector ensemble. This is described fully by [2].

B. DALEC model

DALEC is a simple ecosystem model designed to be constrained by the assimilation of frequent observations. It is fully described by [3]. In this paper a simplification of the model state vector is used. The restated model equations are:

$$C_f^+ = C_f + GPP\times(1-p_2)\times p_3 - C_f\times p_5 \quad (1)$$

$$C_r^+ = C_r + GPP\times(1-p_2)\times p_4 - C_r\times p_6 \quad (2)$$

$$C_w^+ = C_w + GPP\times(1-p_2)\times(1- p_4 + p_3) - C_w\times p_7 \quad (3)$$

$$C_s^+ = C_s + C_l\times p_1\times d - C_w\times p_6 - C_s\times p_9\times d \quad (4)$$

$$C_l^+ = C_l + C_f\times p_5 + C_r\times p_7 -+ C_l\times p_1\times d - C_l\times p_8\times d \quad (5)$$

This work was undertaken as part of the UK NERC Centre for Terrestrial Carbon Dynamics.

Where GPP is the Gross Primary Production ($g/m^2/day$), C_f, C_w, C_r, C_s and C_l are the foliar, woody, root, soil and litter biomass pools (g/m^2) respectively, p_n are model parameters and d is a temperature dependant decay rate. The superscript $^+$ is used to denote one time step in the future. The net ecosystem productivity (NEP) is the change in the total carbon held in these pools from one time step to the next. NEP is a useful metric for environmental change studies as it indicates whether or not an area is acting as a source or a sink of carbon. GPP is modelled using the aggregated canopy model of [4]. The model structure here is exactly the same as in [3] but the between-pool fluxes are not modelled as separate state vector members. This reduces the number of model state vector members from 15 to 5, which is more efficient in terms of the EnKF scheme. The removed fluxes are not observable using standard EO methods and so there is no loss in functionality.

C. *GORT model*

The canopy reflectance model used as the observation operator in the assimilation scheme was the hybrid geometric optic radiative transfer model, GORT [5]. Soil reflectance was calculated using the functions described by [6] and leaf reflectance was determined using the PROSPECT model [7]. The principal link between GORT and DALEC is LAI. The ancillary parameters of the reflectance model, i.e. those not determined by DALEC, such as cover fraction and leaf chlorophyll, must be determined prior to assimilation. This is done in [2] by inverting the GORT model against MODIS for a single pixel and assuming these parameters are a reasonable estimate for a small area ($4.5km^2$). Whilst practical, this is clearly not an ideal solution. Results given later show the impact of making this assumption is relatively small.

D. *Snow reflectance model*

The reflectance of snow was modelled from the refractive index [8] and Mie scattering coefficients [9] of ice particles and treating multiple scattering using the DISORT code [10]. The modelled reflectance was used to modify the lower boundary of the GORT model by assuming a fixed proportion of snow on the ground for all sites when snow contamination was indicated in the MODIS QA flags.

E. *MODIS data*

Three years of Terra-MODIS data for the Metolius site on the Oregon transect were used. In this paper results are taken from a $4.5km^2$ area (9×9 pixels) centred on an eddy covariance tower. For the central pixel, by way of example, there were 316 observations that contained no snow or cloud. Within this set there were no observations during winter months. Extracting pixels flagged in the MODIS QA data as being snow contaminated provided 18 additional observations evenly spread over the winter months of the three years considered. Uncertainties in the reflectance data were set as 0.004 and 0.015 for bands 1 and 2 respectively [11].

III. RESULTS

A. *Model structure*

The impact of the change in model structure on the DALEC predicted LAI is shown in fig. 1. Each point represents the mean LAI for one year for one of the pixels in the 9×9 study site. The models are almost identical from this perspective. This is not unsurprising as the LAI is well constrained by the reflectance observations. In turn, the GPP results (not shown) are also very similar for the two model structures. NEP results are shown in fig. 2. These data agree less well, but are still mostly cantered on the one to one line. Model uncertainties on NEP, determined by the EnKF, are in the region of ±80g of carbon per year at one standard deviation (σ) and only 22% of model predictions lie more than one σ away from the one to one line, indicting that the results are statistically similar.

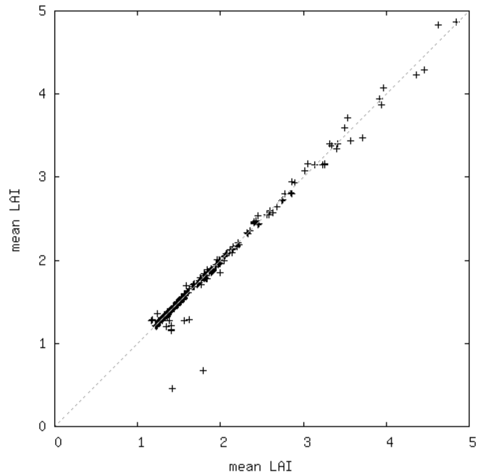

Figure 1. Comparison of predicted mean annual LAI between old (x-axis) and new (y-axis) model structures.

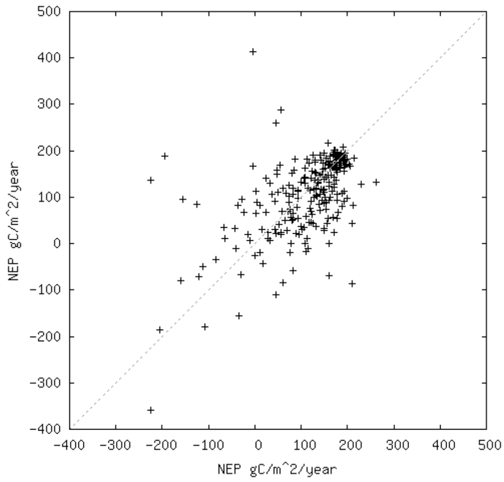

Figure 2. Comparison of predicted annual NEP values between old (x-axis) and new (y-axis) model structures.

The change in NEP is quite surprising given the similarity in LAI and GPP. It appears to be the case that the soil carbon pool is very sensitive to small random fluctuations in the ensemble and that these cause some instability during the Kalman analysis step. To counter this it may be necessary to pre-filter the ensemble covariance matrix prior to analysis.

B. Spatialised parameters.

Results in this section use both the new model structure and spatialised GORT parameters generated from a look up table inversion. Fig. 5 shows the fractional crown cover inverted from GORT for the study area. This is clearly different from the assumption that the cover is uniform for the area as in [2], which is quoted as 0.63 (in the middle of the range seen in fig. 5).

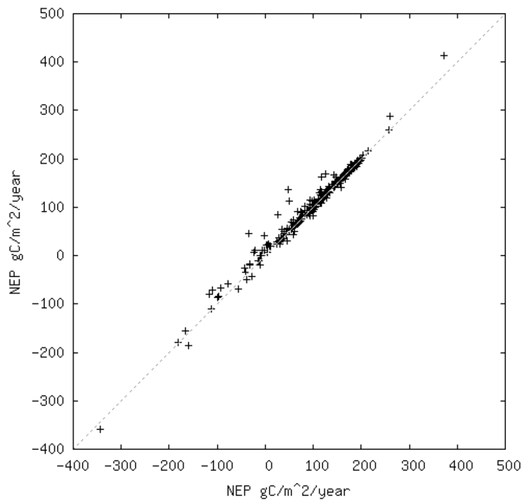

Figure 3. Scatter plot of predicted annual NEP values between the assimilation with spatialised GORT parameters (x-axis) and assimilation without spatialised GORT parameters (y-axis)

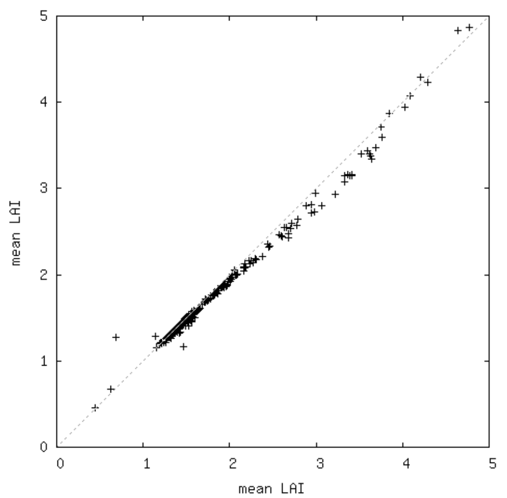

Figure 4. Scatter plot of predicted mean LAI values between the assimilation with spatialised GORT parameters (x-axis) and assimilation without spatialised GORT parameters (y-axis)

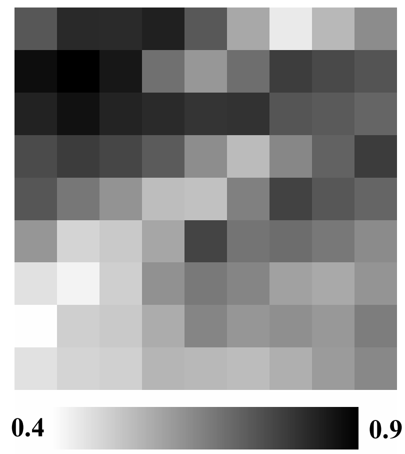

Figure 5. Fractional tree crown cover inverted from the GORT model using MODIS data.

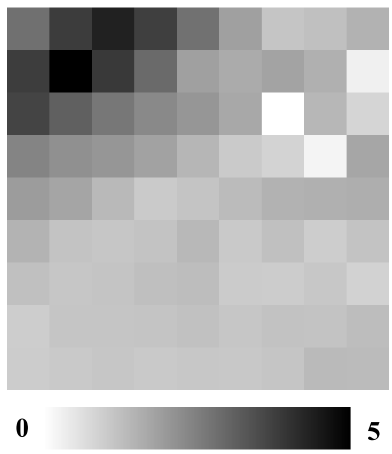

Figure 6. Mean LAI predicted from DALEC for the year 2002 assimilating MODIS reflectance data.

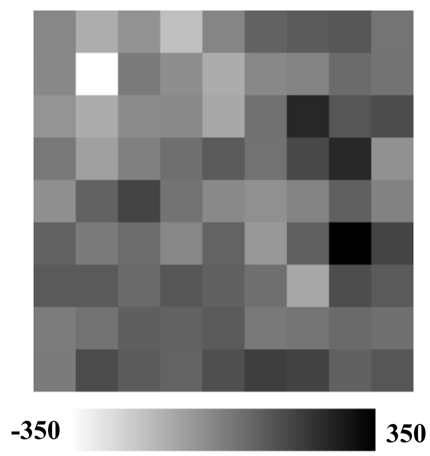

Figure 7. Total NEP predicted from DALEC for the year 2002 assimilating MODIS reflectance data.

The LAI predicted from the model/data assimilation scheme (fig. 6) varies loosley with the retrieved estimates of cover from the look up table inversion. Some relationship is expected between the two variables as the LAI of a pixel is a function of the total tree cover and the density of leaves within a tree crown. Note that GORT is parameterised by the crown shape, the number of crowns (stem density) and the foliage area volume density.

Total NEP (fig. 7) looks very similar to that shown in [2]. Most of the region is acting as a sink (+ve NEP) of carbon, but a small region to the North East is acting as a source. Although there is no clear relationship between LAI and NEP these results seem to suggest that areas of high LAI are acting as a source of carbon.

The scatter plots (figs. 3 and 4) show that there is only very marginal difference between using the spatialised GORT parameters produced independently for each pixel or using the parameters inverted from the central pixel to represent the entire area. The suggests that the assimilation scheme is relatively insensitive to these parameters as long as some reasonable value is used.

IV. CONCLUSIONS

The model predicted carbon balance of the ecosystem appears to be relatively insensitive to the parameterisation of the GORT model. This may be because the set of GORT parameters in [2] that are assumed to be constant across the study area provide a reasonable estimate of the observations. The results of this paper justify the approach taken in [2]. A further sensitivity analysis is required to determine exactly how robust the assimilation scheme is to mis-specification these ancillary parameters. For regional to global scales it will be critical to understand the errors introduced in the carbon budget by the uncertainties in the observation operator parameters. If the errors in the carbon budget are small *despite* high uncertainties in the observation operator parameters this may permit further simplification and optimisation of the observation operator itself. Currently, ensemble predictions of top of canopy reflectance by the GORT model are the most computationally expensive part of the assimilation scheme.

Restating the model so that the state vector is reduced in size is also a step toward spatialisation of the model. Various elements of the state vector that are not directly observable using EO techniques are no longer explicitly considered. This change had a higher level of impact on the predicted carbon flux than using the spatialised GORT parameters. The changes induced are evenly distributed about the one to one line however and so no bias has been introduced into the model. In addition, a large majority of samples lie within one standard deviation of the line. Our working hypothesis is that this is caused by an instability in the model's soil pool, but this needs further testing to be confirmed. Assuming this is the case it may be necessary to pre-filter the ensemble covariance matrix prior to the Kalman analysis step.

The smaller the model state vector the more viable it becomes to run the model at multiple sites in parallel. This has the potential to provide a mechanism for assimilating spatial information in addition to point observations, allowing the ensemble to build up a statistical representation the spatial dependencies of the ecosystem. Current work is focused on building on the work presented in [2] and [3], using a spatialised version of the DALEC model, to develop a regional data assimilation scheme that used low-level EO data.

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