Data assimilation using coarse-resolution Earth Observations in heterogeneous ecosystems.

T. C. Hill[1,3], T. Quaife[2,3] and M Williams[1,3] ([1]University of Edinburgh, UK. [2] University of Exeter, UK. [3] NERC National Centre for Earth Observation NCEO, UK)

1. Introduction:

Satellite Earth Observations (EO) can extend site specific ecosystem knowledge to wider regions. However, the use of coarse scale observations is complicated by the spatial heterogeneity and non-linearity of natural ecosystems [1]. Unaccounted for, these characteristics bias predictions. The "disaggregation" approach that we describe allows the unbiased combination of multi-resolution EO [2].

2. Analysis:

We use observations from Abisko, Sweden. A 512 by 512 m (128 by 128 pixels), 4 m resolution NDVI image, gathered by the NERC ARSF aircraft, was combined with a time series of NDVI from a tower. From this 'true' dataset we drew daily observations of NDVI at various spatial resolutions. These observations were fed into a 'Particle filter' data assimilation scheme [3] to model the LAI [4] and then carbon uptake of the system [5]. The approach assesses the prediction accuracy obtained using a particular NDVI resolution. The analysis is repeated with the 'disaggregation' approach.

3. The observation scale problem:

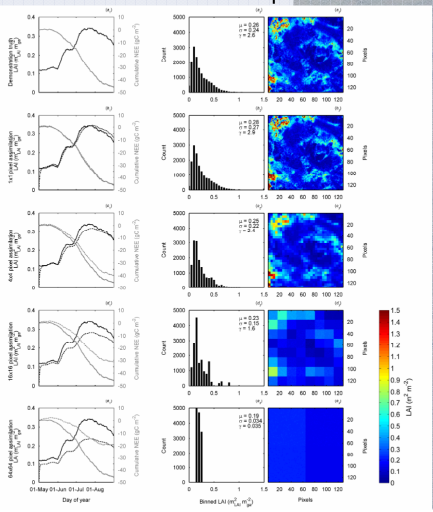


Figure 1: The top row shows 'truth'; the mean LAI and cumulative NEE time series, and the final LAI histogram and map. The mean (μ), standard deviation (σ) and skew (γ) for the final LAI distribution are shown. 1x1 pixel, 4x4 pixel, 16x 16 pixel and 64x64 pixel analyses are shown in the lower panels. The data assimilation analyses did not use the 'disaggregation' approach.

Assimilating 1x1, 4x4, 16x16 and 64x64 pixel observations shows that with coarse resolution observations leaf area index (LAI) and carbon flux estimates are severely biased (Fig 1). This results from the underestimate in LAI and the collapse in the variability of LAI. Fig. 2 shows how the estimated Gross Primary Production (GPP) will be biased if based on an averaged LAI.

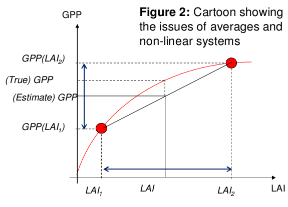


Figure 2: Cartoon showing the issues of averages and non-linear systems

4. The "disaggregation" solution:

To avoid biases the sub observation variability needs to be preserved. In our solution, we "disaggregate" coarse observations to the fine spatial resolution of the model. The disaggregated observation possesses the mean of the coarse observation, the spatial information from the model state and the variability from a prescribed PDF. The variability is estimated from (infrequent) fine resolution satellite/airborne observations, detailed field studies or 'expert knowledge'.

Step-by-step Example (Fig. 3):

Step 1: Extract current model state and coarse observation of the system state, X. Index the location of each element in the model state i.e. n = 1 to 9.

Step 2: Assign a PDF to coarse observation of X.

Step 3: Randomly draw n samples from the observation PDF.

Step 4: Sort the n model states according to their values of X.

Step 5: Assign the locations of the model states to the n observation samples according to the order of the sorted model and observation values.

Step 6: Reassemble the observation. This disaggregated observation can now be used as a normal measurement in the data assimilation scheme.

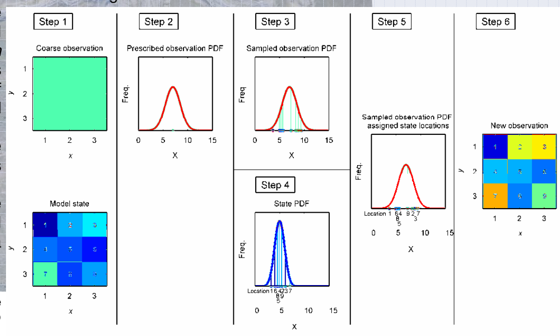


Figure 3: Schematic of the disaggregation approach to calculate the new observation.

5. Solution:

We demonstrate the data assimilation disaggregation method by repeating the earlier analysis. The approach is robust and clearly out performs standard approaches that do not use disaggregation (Fig. 4). Using the disaggregation approach results in a 1% overestimate of carbon uptake, compared to the 58% underestimate using the standard assimilation of coarse observations.

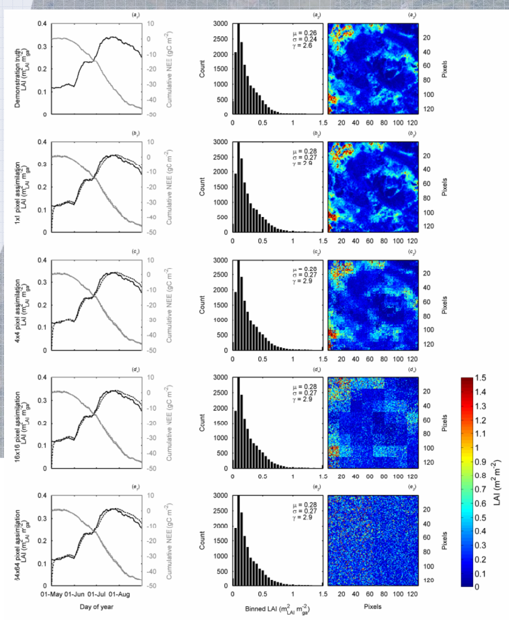
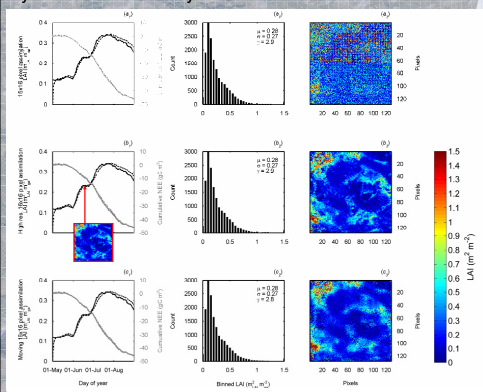


Figure 4: The top row shows 'truth'; the mean LAI and cumulative NEE time series, and the final LAI histogram and map. The mean (μ), standard deviation (σ) and skew (γ) for the final LAI distribution are shown. 1x1 pixel, 4x4 pixel, 16x 16 pixel and 64x64 pixel analyses are shown in the lower panels. The data assimilation analyses all used the 'disaggregation' approach.

6. Additional benefits:

The performance of the disaggregation assimilations is further improved with the addition of infrequent high resolution NDVI imagery (Fig. 5, panels b2 and b3). The high resolution imagery imprinted the model state with finer resolution spatial information. This performance increase will be of benefit for field studies where infrequent (e.g. airborne, IKONOS) imagery is available, but at an insufficient frequency to capture the temporal dynamics of the ecosystem.



Using shifting observations, which are located on a grid that moves between observation times, allowed the assimilation to improve the spatial information in the analysis (Fig. 5, panel c3). The shifting observations improved the spatial resolution of the assimilation. This result makes it attractive to consider non-collocated observations from multiple satellites, even if they are of a similar resolution, provided that their geo-location is accurately known.

Figure 5: The top row (panels b1, b2 and b3) shows the 16x16 pixel (with additional high resolution NDVI "snap shot") data assimilation analysis. The bottom row (panels c1, c2 and c3) shows the 16x16 data assimilation analysis where successive NDVI observations shift in location rather than being collocated between observation times.

7. Conclusions

In our data assimilation disaggregation method, frequent, coarse resolution observations are combined with an estimate of their sub-pixel variability and the fine resolution model state. The sub-pixel variability can be derived from (infrequent) fine resolution Earth observation, detailed field studies or expert knowledge. The methodology is robust and out performs standard approaches that do not make use of the disaggregation method. The approach is easily implemented in most data assimilation schemes and benefits from combining multiple observations at differing spatial and temporal resolutions.

Acknowledgements

We would like to thank, the Natural Environment Research Council (NERC), the National Centre for Earth Observation (NCEO) and the Centre for Terrestrial Carbon Dynamics (CTCD). In particular we are grateful to B Huntley and R Baxter, C Lloyd, J Evans and R Harding, M Disney and A Prieto-Blanco for access to the necessary data.

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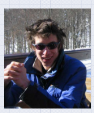

CONTACT:
Timothy Hill
School of GeoSciences, The University of Edinburgh
The Crew Building, The Kings Buildings
West Mains Road, Edinburgh
EH9 3JN, UK
+44 (0) 131 6507721
thill@staffmail.ed.ac.uk