

# The Impact of Satellite-Derived Land Cover Uncertainty on Carbon Cycle Calculations

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**Abstract**—A methodology is proposed for consistently including uncertainty in land cover, as described by confusion matrices, with other sources of input uncertainty in quantifying the uncertainty in model-based estimates of carbon fluxes. The approach is illustrated by calculating for each model grid-cell the Bayesian estimate of net biospheric carbon flux, its overall uncertainty and the proportion of uncertainty due to land cover for England and Wales in 2000. The methodology is generally applicable to other models of land surface fluxes, such as those of energy and water, and to other types of environmental calculation where land cover is an input.

**Index Terms**—Carbon cycle, Bayesian statistics, uncertainty, vegetation models, emulator, kriging.

## I. INTRODUCTION

THE land surface plays a central role in the Earth's carbon cycle. Globally, anthropogenic carbon dioxide ( $\text{CO}_2$ ) emissions due to fossil fuel burning, cement production and land use change (mainly from tropical deforestation) averaged around  $8.0 \text{ GtC y}^{-1}$  during the 1990s, but with large uncertainties, particularly in the land use change term [1]. (Throughout this paper,  $\text{CO}_2$  fluxes will be expressed in carbon units, in accordance with IPCC [1];  $1 \text{ GtC} = 10^9$  tonnes of carbon, equivalent to  $11/3 \text{ Gt}$  of  $\text{CO}_2$ .) However, only  $3.2 \text{ GtC y}^{-1}$  stayed in the atmosphere, the rest being taken up the ocean ( $2.2 \text{ GtC y}^{-1}$ ) and the land ( $2.6 \text{ GtC y}^{-1}$ ). The latter term, referred to as the residual terrestrial sink, suffers from large uncertainties in its magnitude, how it is distributed spatially and the biophysical processes which determine it. However, what is clear is that it represents a net imbalance between uptake of carbon by growth processes and emissions of carbon due to respiration from soils and vegetation.

Inferences on the location of terrestrial  $\text{CO}_2$  sources and sinks can be made by combining ground-based measurements of  $\text{CO}_2$  with atmospheric transport models [2], but sparsity of data means that this gives only coarse spatial resolution (thousands of km); it also gives no direct insight into the biophysical processes causing the fluxes. As a result, much of our understanding of terrestrial carbon fluxes and their geographical distribution comes from the use of a class of biophysical models known as Dynamic Vegetation Models (DVMs). These models calculate carbon fluxes between the atmosphere, vegetation and soil by mathematically representing the processes of photosynthesis, hydrology, gas and energy

exchanges with the atmosphere, vegetation dynamics at various time-scales (phenology, growth, death and replacement), disturbance, nutrient cycling and soil respiration [3]. Such DVMs also form core components of coupled climate models, so that quantifying their uncertainties is crucial in estimating the reliability of climate predictions.

DVMs require various types of input data to carry out their calculations. The major dynamic control is climate, and the model grid-cell size is therefore that of the climate data (typically from  $1/6$  to  $1$  degree). Other important external inputs are the atmospheric  $\text{CO}_2$  concentration (possibly varying for multi-year calculations), soil properties and solar illumination (both of which are determined by geographical location). Given these inputs, carbon fluxes at each grid-cell depend on the properties of the land cover within the cell, which have very strong effects on all aspects of model behaviour [4]. Typically, land cover is represented in terms of proportional occupancy by a small number of Plant Functional Types (PFTs), such as evergreen needleleaf trees, C3 grasses, crops, etc., with each PFT having its own set of parameters that control its response to the environment.

One approach to fixing the proportion of each PFT within a grid-cell is to use a set of biophysical rules to determine the likelihood of a given PFT existing at that location. However, this is only appropriate for 'natural' vegetation, whereas much of the land surface is heavily affected by human activities. Hence most DVMs exploit information on land cover derived from satellite data, of which there are numerous available sources ([5]–[7]; see also references in [4]). Using such a priori land cover data gives rise to uncertainty from three sources:

- the choice of land cover map: there are large differences between different land cover products [4], [8];
- the mapping from land cover types to PFTs [4];
- the uncertainty in each individual land cover map, which typically is poorly known; even in the best cases, it is described simply by a confusion matrix derived from a training set.

This paper focuses on the third type of uncertainty and shows how it can be included in the uncertainty analysis of carbon fluxes calculated by a DVM on an equal footing with the other 'static' data inputs, i.e. soil descriptors and PFT parameters. We then demonstrate its use by producing maps of net biospheric carbon flux (often called the Net Biome Production or NBP) and NBP uncertainty for England and Wales (E&W) using the Sheffield Dynamic Global Vegetation Model, SDGVM [9]. It will be shown that, in this case, land cover uncertainty is not a major contributor to the uncertainty

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in the estimates of NBP. However, the key purpose of this paper is to provide a methodology by which land cover uncertainty, expressed by a confusion matrix, can be *consistently* embedded in analysis of overall model output uncertainty on an equal footing with other input data types. It is equally applicable to other DVMs and models of land surface water and energy fluxes. Moreover, the method is many orders of magnitude less computer intensive than, for example, Monte Carlo approaches. It therefore provides a practical approach to using the information in confusion matrices, which are often available but rarely exploited, in the uncertainty analysis of a wide range of land surface process calculations.

## II. DATA

Descriptions of the soil data and PFT parameters, including the uncertainties in these inputs, are given in [10]. Land cover is provided by the Land Cover Map 2000 (LCM2000) [11] and its uncertainty is derived from the Countryside Survey 2000 (CS2000) [12]. LCM2000 has a base spatial resolution of  $25\text{m} \times 25\text{m}$  with each pixel containing one of 26 subclasses of vegetation types classified from spectral information collected from various orbital sensors. To convert LCM2000 into a format compatible with the SDGVM, these 26 vegetation types are first grouped into the 5 PFTs used by the SDGVM, namely deciduous broadleaf (DcBl) trees, evergreen needleleaf (EvNl) trees, grassland, crops and a non-productive PFT called Bare to account for urban and barren areas that take no part in the natural carbon cycle (for the rules to convert LCM2000 vegetation types to PFTs see [4] or [13]). LCM2000 is then upscaled from its  $25\text{m} \times 25\text{m}$  resolution to  $1/6^{\text{th}}$  degree resolution in order to match the grid of the climate database used by the SDGVM. The transformed LCM2000 map used in our analysis thus takes the form of 707 sites of  $1/6^{\text{th}}$  degree resolution across England and Wales with each site characterised by the proportion of land covered by each of the 5 PFTs. As mentioned earlier, the SDGVM also requires additional inputs in the form of monthly climate data. These were taken from [14] and are treated as known, since the uncertainty in their values is believed to be small.

## III. METHODOLOGY

### A. Uncertainty analysis and components of uncertainty

Our analysis of uncertainty in the carbon flux for E&W in 2000 is based on NBP values output from SDGVM. The uncertainty in the flux arises from a number of sources:

- 1) *Uncertainty due to model inputs.* In common with other DVMs, uncertain inputs to SDGVM include soil data (bulk density and proportions of sand and clay), PFT parameters (describing such things as leaf lifetime for each PFT) and land cover. Our emphasis in this article is on uncertainty in the output NBP due to land cover uncertainty, but it is necessary to consider this in the context of uncertainty caused by other inputs.
- 2) *Computation uncertainty.* To compute the output uncertainty we need a method to propagate the input uncertainty through the model. One way of doing this is by Monte Carlo: random values are drawn for all the

uncertain inputs and the DVM is run to produce the required output; this is repeated many times, and the variance in the sample of outputs produced is the measure of output uncertainty. Because of random sampling, there is uncertainty in the Monte Carlo computation, which can be ignored only if we have a sufficiently large sample of outputs. In the case of the E&W carbon flux analysis using SDGVM, Monte Carlo would be completely impractical, since obtaining even a single output value entails a significant amount of computing time. An alternative, much more efficient, approach is developed in [10], based on building emulators [15] at a sample of sites and then interpolating the emulator results by geostatistical methods [16]. In this case, the computation error has two components, code uncertainty (arising from the emulation at the sample sites) and interpolation uncertainty.

The overall uncertainty, as measured by the total variance of the output accounting for all these sources of uncertainty, can be decomposed into uncertainties due to different sources. The basic approach for this is known as variance-based sensitivity analysis, and is described in [17]; variance-based sensitivity analysis using emulators is presented in [18]. Formally, the component of variance due to a given source is the proportion of the total output variance that we should expect to remove if we were to remove the corresponding source of uncertainty. So the component due to input uncertainty is the proportion of total variance that we would expect to remove if we were able to find out the true values of all uncertain inputs. Similarly, the component due to computation uncertainty is the proportion of total variance that we would expect to remove if we could compute without error (equivalent to using an infinitely large Monte Carlo sample).

The input and computation uncertainties can be further decomposed, for instance by calculating components due to code uncertainty and interpolation uncertainty. The analysis in [10] treated the land cover as fixed (according to the values obtained from LCM2000), so the total uncertainty and its decomposition derived therein do not include a component due to land cover uncertainty.

### B. Land cover uncertainty

In order to propagate input uncertainties through the model, the uncertainties in the inputs must be fully characterised statistically. We use the methodology of [13] to quantify the uncertainty in the PFT map derived from LCM2000, and to aggregate from the  $25\text{m} \times 25\text{m}$  LCM2000 pixels to the  $1/6^{\text{th}}$  degree resolution sites used by SDGVM. The result of this analysis is an estimate of the proportion of each site that is covered by each of the PFTs, together with variances and covariances that quantify the uncertainties in those estimates. Thus, if  $\gamma_{tk}$  is the proportion of site  $k$  that is covered by PFT  $t$ , then we have estimates  $E(\gamma_{tk})$ , which when summed over all PFTs  $t$  for a given site  $k$  add to 1 (or 100%). Uncertainties in each estimate are expressed first in variances  $\text{var}(\gamma_{tk})$ . However, another important feature of uncertainty is captured in the covariances  $\text{cov}(\gamma_{tk}, \gamma_{t'k'})$ , because we are interested

in aggregated carbon fluxes over the whole of England and Wales. Covariances (or, equivalently, correlations) strongly affect the uncertainty in such aggregate values. For instance, since the  $\gamma_{tk}$ s must sum to 1 across  $t$  for a given  $k$ , there are negative covariances between the proportions of different PFTs covering a given site. On the other hand, there will generally be positive covariances between the proportions of the same PFT at two neighbouring sites. The Bayesian method of [13] is, to our knowledge, unique in being able to quantify uncertainty in land cover maps fully, accounting for covariances/correlations as well as variances.

### C. Combining land cover and other input uncertainties

The major purpose of this article is to show how the two methodologies set out in Sections IIIA and IIIB can be put together. In principle this is straightforward. Uncertainty in land cover, as formulated using the method of [13], can be propagated through the DVM on an equal footing with other uncertainties, and the additional components of uncertainty due to land cover isolated from those due to other sources.

The carbon flux at any given site is a weighted sum of fluxes obtained by running the DVM assuming that the whole site is covered by each land cover type (PFT) separately, weighted by the proportion of the site that is covered by each PFT. Uncertainty about land cover is therefore manifest in uncertainty about these weights. Standard statistical formulae allow us to compute expectations and variances of weighted sums. Furthermore, all of the formulae for calculating components of uncertainty due to other uncertain inputs and computation uncertainties are also linear or quadratic functions of the land cover weights, whose expectations with respect to land cover uncertainty may be readily computed. The details of all these computations are set out in [19].

This is a generic methodology that may be applied to quantify uncertainties in fluxes obtained from environmental models, to account for uncertainty in land cover in addition to other inputs, and to partition the resulting flux variance according to the contributory sources of uncertainty. It has the following steps:

- 1) *Quantification of land cover uncertainty.* Apply the method of [13] to a suitable confusion matrix to compute uncertainty in land cover at each model site.
- 2) *Analysis of uncertainty due to other sources.* Using the emulation methods of [10], quantify flux uncertainty due to uncertainty in other inputs, in the form of expectations, variances and variance components for flux at each site under each land cover type.
- 3) *Propagation of land cover uncertainty.* Apply the formula presented in [19] to account for land cover uncertainty in addition to the other uncertainties.

The result is a comprehensive analysis of uncertainty in flux at the level of individual sites (which may be presented as maps) or aggregated over the whole region or any collection of sites.

TABLE I  
ESTIMATED FLUX FOR ENGLAND AND WALES, AND UNCERTAINTY FROM COMPONENT SOURCES INCLUDING LAND COVER UNCERTAINTY.  
VARIANCE COMPONENTS: LCOV = LAND COVER, INTRP = INTERPOLATION, EMUL = EMULATION, SPFT = SOIL AND PFT INPUTS.

PFT	Mean (GtC)	Variance components				Total variance
		LCOV	INTRP	EMUL	SPFT	
Grass	4.37	0.0076	0.0080	0.0001	0.2296	0.2453
Crop	0.43	0.0006	0.0084	0.0001	0.0236	0.0327
DcBl	1.80	0.0071	0.0056	0.0000	0.0095	0.0221
EvNI	0.86	0.0043	0.0000	0.0000	0.0006	0.0048
Covar		-0.0091			0.0010	-0.0081
TOTAL	7.46	0.0105	0.0220	0.0002	0.2642	0.2968

TABLE II  
ESTIMATED FLUX AND OVERALL UNCERTAINTY FOR ENGLAND AND WALES USING FIXED LAND COVER ESTIMATES, EITHER FROM LCM2000 (FROM [10]) OR FROM THE METHOD OF [13].

PFT	LCM2000		Cripps et al	
	Mean (GtC)	Total variance	Mean (GtC)	Total variance
Grass	4.64	0.2689	4.37	0.2371
Crop	0.45	0.0338	0.43	0.0320
DcBl	1.68	0.0128	1.80	0.0142
EvNI	0.78	0.0005	0.86	0.0006
Covar		0.0010		0.0010
TOTAL	7.55	0.3170	7.46	0.2849

## IV. RESULTS - UNCERTAINTY ANALYSIS OF BIOSPHERIC FLUXES FOR ENGLAND AND WALES

### A. England and Wales uncertainty

The primary results for the net biospheric flux (NBP) for England and Wales in 2000 are presented in Table 1. Table 2 gives some corresponding results before incorporating uncertainty in land cover.

Looking first at the total across all PFTs, the estimated total flux for England and Wales in 2000 is 7.46 MtC, with uncertainty from all sources amounting to a standard deviation of  $\sqrt{0.2968} = 0.54$  MtC. This contrasts with the earlier result of [10] in the columns labelled ‘‘LCM2000’’ in Table 2, which estimated the total flux as 7.55 MtC with a standard deviation of  $\sqrt{0.3170} = 0.56$  MtC. The differences in both the estimated flux and the overall uncertainty deserve comment. First, the estimate has reduced slightly. This occurs because taking account of uncertainty in land cover using the methods of [13] has led to different estimates of PFT proportions compared with those obtained directly from LCM2000 as used in [10]. This is due to asymmetry in the error probabilities as discussed in [13]. The small changes in estimated land cover proportions overall have resulted in a modest change in the estimated total flux.

The change in the overall uncertainty appears paradoxical at first sight, because adding uncertainty in land cover has decreased the overall uncertainty in NBP. To understand this paradox, Table 2 also presents the results of repeating the analysis of [10] but with the estimated land cover proportions from applying the method of [13]. We see that this analysis gives the same estimates of flux as in Table 1 but with a lower overall variance of 0.2849. Hence uncertainty about land cover has increased the overall variance by only 0.0119, increasing

the standard deviation from 0.53 to 0.54 MtC. Notice that the figure for variance due to land cover uncertainty in Table 1 is not 0.0119 but 0.0105. This difference is attributable to interaction between land cover and other sources of uncertainty, particularly soil and PFT inputs.

### B. Uncertainty maps

The overall differences can be explored in more detail by mapping the means and variance components.

In Figure 1(a) we see the change in estimated flux due to using the estimates of land cover proportions in [13] instead of those derived directly from LCM2000. Differences on a site by site basis range from  $-10$  to  $+15$   $\text{gC m}^{-2}$  (for comparison, the estimated fluxes range from  $-100$  to  $+200$   $\text{gC m}^{-2}$ , so on a site basis the changes can be 10% or more). We see that the majority of values are negative, in accord with a reduction in total, but with more positive values in the North of England.

Figure 1(b) shows the standard deviation in NBP at each site attributable directly to land cover uncertainty. Values are mostly less than  $10$   $\text{gC m}^{-2}$  (for comparison, the site standard deviations due to uncertainty in soil and PFT parameters are mostly above  $20$   $\text{gC m}^{-2}$ ). We tend to find low uncertainty in regions where one PFT dominates.

A more complex story emerges in Figure 1(c), which shows the difference in standard deviation at each site between our analysis and that of [10]. As noted above, the overall uncertainty is actually reduced, due to a combination of the change in estimates (which in this case reduces uncertainty) and the addition of land cover uncertainty. We see that at the site level the change is by no means uniformly negative, but instead has a broadly similar pattern to Figure 1(b). The main exception to this is a group of sites in the North-East of England, which show a much stronger reduction in uncertainty. In Figure 1(d) we see conversely that these sites are the ones with greatest uncertainty from all sources. The estimation in these sites seems to be more unstable, with large uncertainty after incorporating land cover effects, but with even more uncertainty in the earlier analysis of [10].

### V. CONCLUSION

The principal contribution of this work is to demonstrate how the analysis of uncertainty in remotely sensed land cover maps in [13] can be combined with the methods of [10] in order to quantify the impact of possible errors in such maps on the estimates of biospheric carbon flux produced by a Dynamic Vegetation Model. We have illustrated our approach using the net carbon flux for England and Wales in 2000, as estimated by SDGVM with land cover data from LCM2000.

Possible errors in LCM2000 affect both mean fluxes and their uncertainty. As regards mean fluxes, asymmetry in error rates causes LCM2000 to overestimate the proportion of land covered by some PFTs and underestimate the proportion covered by others. The result of replacing the raw land cover proportions from LCM2000 by the estimates in [13] is to reduce the estimate of total flux from 7.55 to 7.46 MtC. Although this is a small correction, and well within the bounds of uncertainty around these figures, it indicates that

the technique can be used to improve estimates of land cover for input to environmental models such as SDGVM.

By quantifying the uncertainty due to possible land cover errors, the analysis further shows that uncertainty in soil and PFT parameters contributes much more to the overall uncertainty in the carbon flux than does land cover uncertainty. This is important, since it tells us that improving land cover accuracy is not a priority if we wish to reduce the error budget for this particular environmental application. However, England and Wales are unusual in that an accurate high resolution digital landcover map is available. This not the case in many other parts of the world, and then the balance between the impact of land cover uncertainty and other sources of input uncertainty may shift. More generally, the techniques presented here are able to show whether a remotely sensed land cover product provides adequate accuracy (after adjustment of proportions as in [13]) for calculations by a range of complex environmental models.

A final important point is that these techniques allow the production of *maps* of flux uncertainties arising from uncertainties in land cover, and hence indicate where improved knowledge about land cover would have the biggest impact (for example, in our calculations, the group of sites on the coast of North-East England with particularly uncertain flux estimates).

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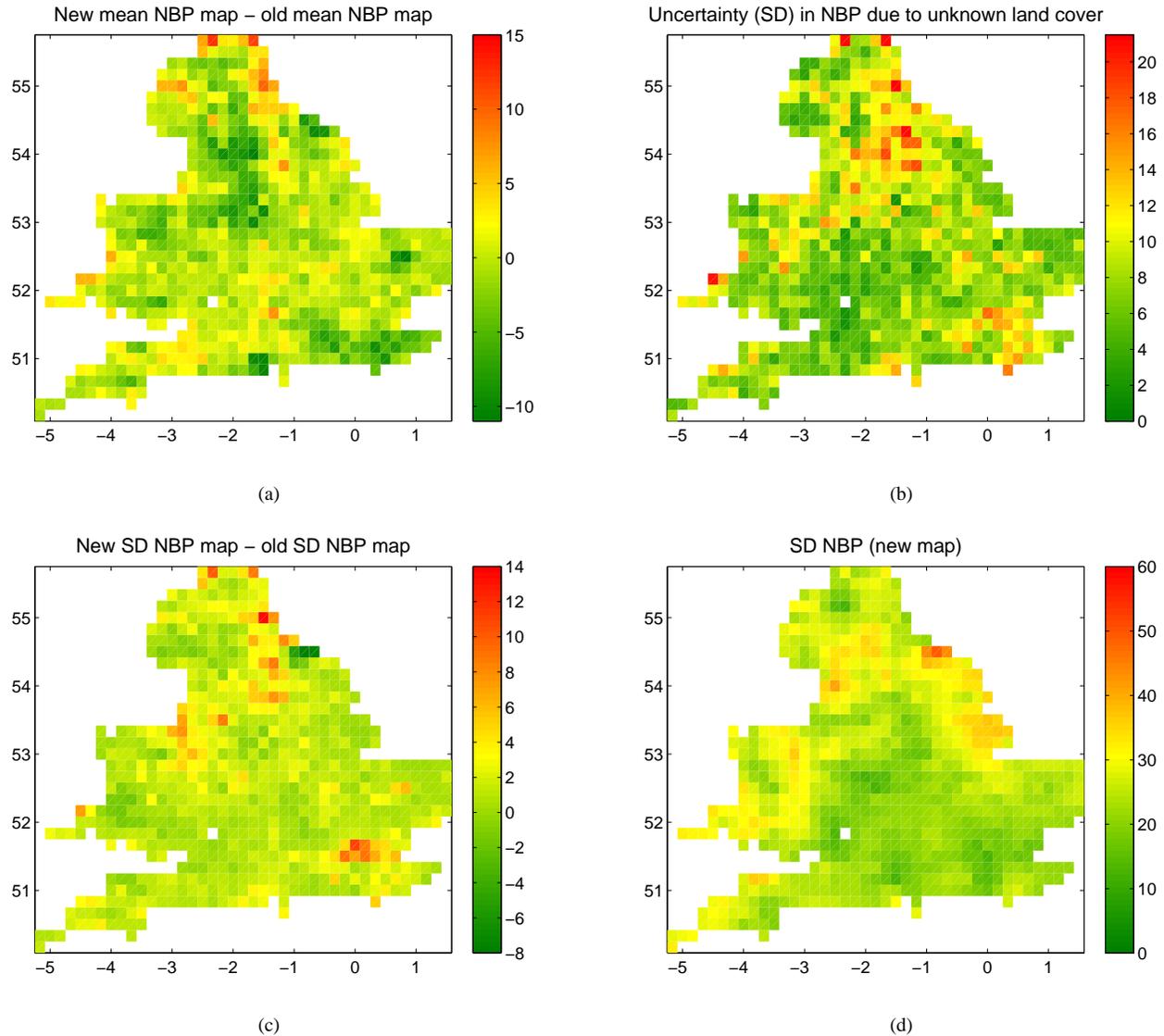


Fig. 1. Maps of the effect of possible errors in LCM2000. (a) Difference in estimated flux, (b) standard deviation directly attributable to land cover uncertainty, (c) difference in total standard deviation and (d) total standard deviation.

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