# Modelling and Mapping of Multifunctional Landscapes: modelling carbon stocks and measuring and displaying uncertainty

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## 1. Introduction

This report summarises our work on the modelling and mapping of carbon in multifunctional landscapes, conducted as a contribution to the Nature Returns project by the Sussex LIMMMA team. "LIMMMA" stands for "Landscape Integrative Mapping and Modelling for Multi-Functional Analysis". It reflects the underlying methodology adopted by our multidisciplinary research team, which is also instantiated by the LIMMMA software system, a browser-based research and decision-support platform. Within the broader context of further developing the LIMMMA software platform, we conducted specific work on above-ground and below-ground carbon storage, supporting work conducted by teams of researchers at Wakehurst.

### Team Background

The Sussex LIMMMA team conducts, over the long-term, work on sustainable multifunctional landscapes. The cross-disciplinary team consists of academic specialists in the fields of ecology, science policy, geography, socio-ecological systems analysis, data science, machine learning, and computer programming, based at the University of Sussex and at Birkbeck, University of London. We work across the physical, biological and social sciences, with an emphasis on transdisciplinary approaches and community engagement. We have a particular interest in mapping and understanding the impact of landscape change on ecosystem services, well-being, and livelihoods, and opportunities for integrating nature recovery into sustainable multifunctional landscapes.

This work typically focuses on "critical transition" zones and moments, critical both spatially and temporally, and examines the impact of sustainability interventions on those transitions. We are also interested in understanding the use of different system framings and forms of knowledge or evidence across different scales when critical decisions are made.

Ideally, we hope our work will help lead to better decision-making to create resilient future landscapes which support both ecosystem services and wellbeing.

## Entry Point to Nature Returns: Building on the Wakehurst Living Laboratory

Our entry point to the Nature Returns project has been in supporting the scientific work conducted at the Living Laboratory by the team at Kew, Wakehurst, and in developing collaborative plans to complement and evolve this work. The Kew team are producing strong scientific data to inform and influence land management policies and practices, and are exposing a mosaic of issues associated with the sustainability and impact of nature-based solutions and nature recovery efforts. Working with local communities, land managers, policy makers and corporates they are considering the connectivity, co-benefits, and trade-offs that are achieved and required

With Kew colleagues we have been discussing how the Sussex LIMMMA team can complement such activities. For example, our LIMMMA 'virtual living lab' approach for multifunctional landscapes', provides a cross scale, cross stakeholder platform for assessment of the implications of different land use interventions. Dynamic mapping and modelling allows the platform to be updated with new evidence and stories of change. By facilitating engagement between scientists, practitioners, communities and policy makers, this can support a more responsive and participatory strategy for nature-based solutions over the longer term, supporting and contextualising Nature-based Solution policy and plans and their evaluation, gaining real-time feedback from policy interventions, and scaling up and extrapolating lessons from pilot sites.

## Nature Returns - our remit

Our work was conducted under Nature Returns  "WS3: Carbon Storage, flux and biodiversity" which has studied Carbon stocks and what influences them, the scaling of findings, and implications for nature recovery options. This work was conducted in the context of the broader ambitions for multifunctional landscape analysis outlined above. Our contribution was therefore twofold:

(i) Based on the findings of the Kew Wakehurst team, develop an approach to estimating carbon storage levels in natural environments in a manner that is simple, modifiable, scalable, and extendable across the UK, using a platform (LIMMMA) that is rapid, interactive, and dynamic. Specifically, we investigated how to model landscape carbon storage dynamically at field, local, and regional scale using consistent data sources, in a manner that can be extrapolated across the UK. In addition to visualise sources of uncertainty and their implications.

(ii) More broadly, continue the development of a system (LIMMMA) that allows the user to undertake landscape integrative mapping and modelling for multi-functional analysis. The scope of LIMMMA is therefore far broader than carbon storage measurement, which is just a particular incidental application of the platform; it is intended to support the broader multi-functional challenge for nature-based solutions. LIMMMA is designed to be able to "evolve with the science" and enhance our understanding of how different habitats contribute to the net zero and biodiversity goals and the interactions between them.

This report focuses primarily on contribution (i) to the Nature Returns project, which is one specific use of LIMMMA. A separate report provides a comprehensive overview of the LIMMMA platform itself, a summary of which is included here. The LIMMMA team welcomes opportunities to collaborate using the LIMMMA platform.

## 2. Executive Summary

Based on the findings of the Wakehurst teams, we have successfully developed generic models for estimating above-ground and below-ground carbon storage which can be deployed across a wide range of scales, and extrapolated across the UK. The specific raster-based approach that we adopted has exceeded our expectations; it seems to be capable of delivering highly detailed maps, provided that good quality feature height data sets are available. These approaches are neither fixed nor prescriptive; they can be readily updated to take advantage of new findings, modified or reconfigured by users to suit their specific needs, and combined with other approaches and other carbon-storage data sets to provide robust ensemble estimates.

When coupled with a technique that does not rely heavily on frequent habitat boundaries (in our case, this is the *feature-height* model), the approach we adopted seems capable of being used successfully across a very wide range of scales, here covering up to a region of 72 km x 72 km in a single model, without loss of consistency, in analysis of a patch of land. We feel the use of a single modelling approach across such a wide range of scales is both helpful and convenient for decision-makers, particularly as decisions typically involve consulting multiple geospatial analyses conducted at different scales.

For the below-ground carbon storage analysis, the LIMMMA approach makes it very straightforward to incorporate and combine data from existing external parties, and to combine these analyses with the above-ground work to provide effective combined carbon maps at differing scales. Our approach also allows us to rapidly incorporate new advances and techniques. We are in the process of making use of the emerging work by the below-ground team at Wakehurst and have created an additional mapping approach that can be used stand-alone or combined with other available data sets.

We have also identified suitable ways of specifying uncertainty, propagating it conservatively through these models, and displaying it in a way that helps decision-makers consider uncertainty without being overwhelmed by it.

Finally, the work recognises that carbon storage is only a single data type contributing towards multifunctional landscape decision-making. The LIMMMA system is primarily designed to bring together multiple data types and to allow them to be combined in novel, bespoke ways that help parties make decisions about the landscape where the full range of economic, cultural, socio-economic, and ecological factors can all be considered.

## 3. Overview of Contents

This report is divided into 5 chapters and one appendix.

Chapter 1 provides a brief introduction to the LIMMMA system.

Chapter 2 lays out the approach developed in this project for estimating “above-ground” carbon storage, that is carbon storage attributable to above-ground vegetation.

Chapter 3 introduces an approach to measuring and displaying uncertainty using LIMMMA.

Chapter 4 lays out the approach taken in this project to estimating “below-ground” carbon storage in the first 30 cm of soil

Chapter 5. describes how these approaches can be combined to provide a unified view of total carbon storage in the landscape, and outlines conclusions and next steps for our carbon storage work.

The appendix provides details on the approach taken at the end of this project to calibrate the above-ground model, based on preliminary work done by the Wakehurst team analysing its data. This calibration will be subject to further refinement of the Wakehurst analysis.

# Chapter 1. Introduction to LIMMMA

This chapter provides a brief introduction to key features of the LIMMMA platform.

## 1. Introduction

The system on which this work is built, the Landscape Integrative Mapping and Modelling for Multi-functional Analysis (LIMMMA) platform, is designed for dynamic geospatial assessment, integration of data sources, and modelling by the user to create novel geospatial data outputs. There is a very wide range of possible use cases, limited only by the user's needs and creativity, of which carbon storage is only a single example.

Users can build a model which takes existing data sources and allows them to be combined and manipulated in many ways to create novel outputs. LIMMMA provides the user a very wide degree of flexibility in respect of the modelling methodology adopted, the data sources used, and the manipulations applied. Data sources, equations and models are specified using a visual graphical interface. In practice, the output of a typical modelling exercise will likely be integrated with other results for landscape-based decision making.

It is intended to support bespoke decision-making in the context of uncertainty, enabling specialists and non-specialists to engage more quickly and easily with the evidence, assumptions and uncertainties involved in developing, selecting and monitoring land management options.

### Goal: Accelerate engagement with emerging evidence in transparent ways

We recognise the urgency for evidence-informed policy for sustainable multifunctional landscapes, including, for example, the major evidence gaps that exist and the challenges of translation to scale. LIMMMA supports visualisation, analysis and integrated learning across disciplines and site locations. It supports the rapid and timely use of new evidence. It supports the interpretation of evidence for Nature based Solutions and land use policy. Specifically, it makes assumptions visible and highlights uncertainties and trade-offs. Where possible, it avoids the use of black boxes.

### Goal: Accessible, flexible and extendable system

LIMMMA allows users to import, visualise and analyse diverse types of data and models. It offers an integrated mapping and transparent modelling user interface, with a low learning barrier for non-specialists. It allows the user to modify data sources, methodologies, parameters and outputs dynamically. It supports modification in real time with multiple users collaborating.

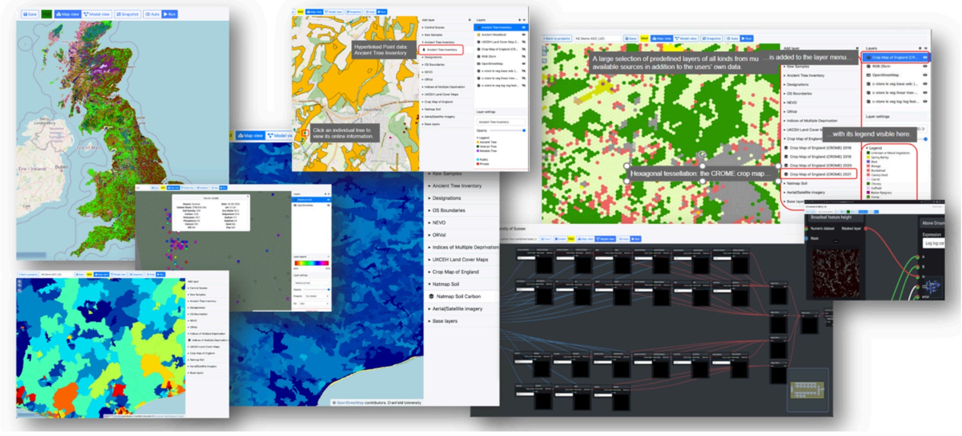
The system is initially a research and research-to-policy communication platform, with options to allow open access where public datasets are utilised. Likewise, the LIMMMA team is working towards multi-stakeholder dialogue and participatory assessments and evaluations of nature recovery options. For example we are working with the Sussex Local Nature Recovery Strategy to help refine context appropriate identification of opportunity areas for nature recovery interventions by connecting woodland fragments, as illustrated in the LIMMMA on-line manual.

## 2. Seven Illustrative Features of LIMMMA

### i. Work with multiple data datasets and models

Users can not only view datasets in the familiar map-view format but also, more importantly, as data source inputs to their own bespoke landscape models. See figure 1.1. The range of data sources available not only as traditional maps but also as data sources for new models is conceptually unlimited.

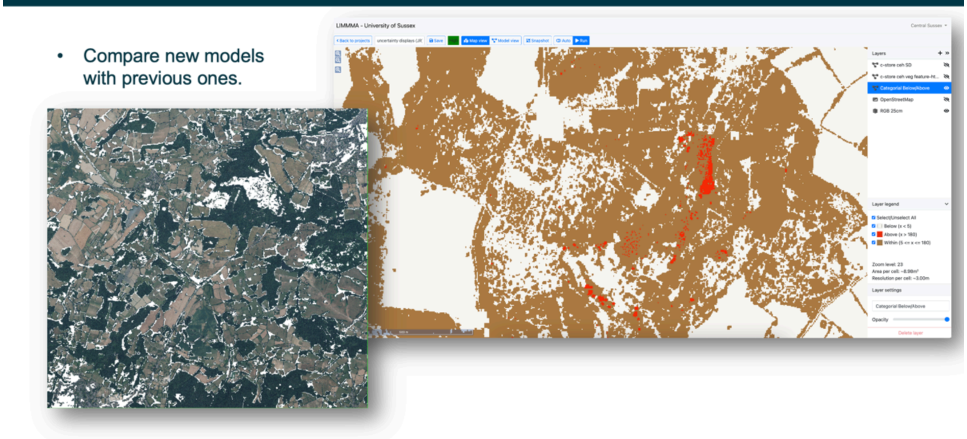
Figure 1.1 Work with multiple datasets and models.



### ii. Visualise and communicate uncertainty in multiple ways

The LIMMMA team is developing ways in which users can visualise and understand the location and impact of uncertainty in models, illustrating how that uncertainty is propagated through the landscape modelling process. See figure 1.2. This topic is examined in more detail in Chapter 3.

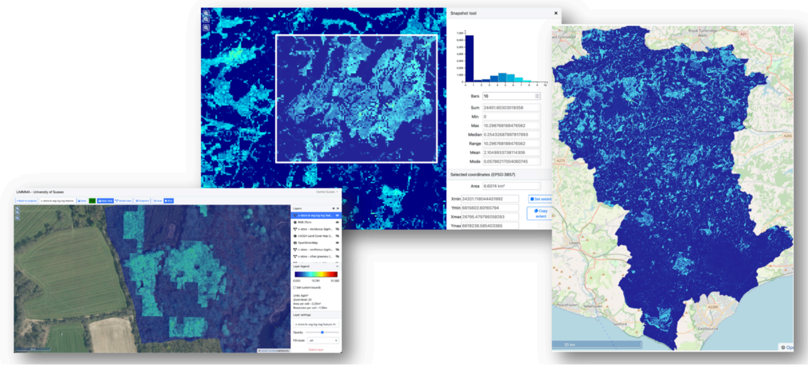
Figure 1.2 Visualise and communicate uncertainty in multiple ways



## iii. Scale models and explore their predictive limits

LIMMMA allows users to apply, dynamically and in real time, the same model (methodology, data sources, outputs) at widely different scales, ranging from field level (resolution of the order of 1 metre) to local or regional level (see figure 1.3). This allows users to integrate findings across different scales, and to understand the scale at which models reach their limits of predictive stability.

Figure 1.3 Scaling and exploring predictive limits of models.

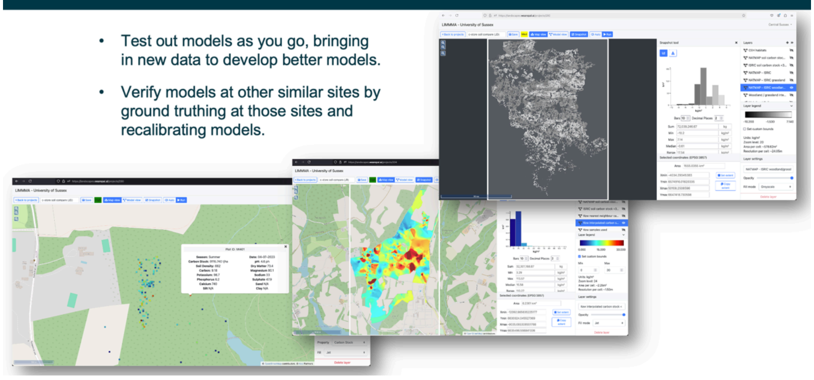


## iv. Extrapolate and refine models

The dynamic approach of LIMMMA allows users to verify models geographically at other sites, for example by establishing ground truths at other sites and recalibrating models, thereby extrapolating models across wider landscapes. The flexible and dynamic design also encourages users to test at models as they go, bringing in data and improved methodologies, as they become available, to develop better models. This iterative process is demonstrated further in Chapter 2.

The approach also allows you to bring together and compare raw data with established data sources, and to use interpolation methods to model extending samples across a site. Figure 1.4 on the left panel shows geospatially displayed individual pieces of data gathered by the Wakehurst team studying below-ground carbon storage on site in this project. The central panel shows a simple carbon storage map created by interpolating these individual results. The panel on the right illustrates comparable carbon storage maps from NATMAP, ISRIC and combinations of the two at a regional (Wealden District Council) scale.

Figure 1.4 Extrapolate and refine models

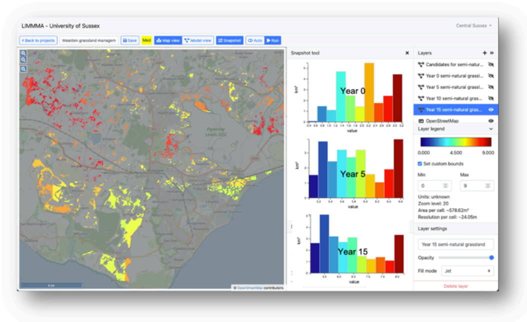


## v. Explore implications of land-use change over time and space

LIMMMA is being developed to support enhanced ‘what-if’ scenarios for nature recovery options. The strategy is to estimate at various scales the potential impacts of different strategies and to test out the implications, for example, of changing incentives. Figure 1.5 shows an illustrative example where strategies are explored in LIMMMA for the future management of grassland habitats in the Wealden region of East Sussex inspired by the potential extrapolation of chronosequence grassland experiments carried out by Natural England as part of Nature Returns.

**Figure 1.5 Exploring implications of land-use change over time and space**

- Supports enhanced ‘what-if’ scenarios for nature recovery options.
- Estimate potential impacts of different strategies at various scales.
- Test out implications of changing incentives.

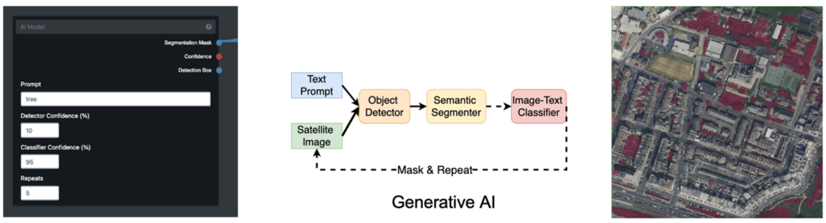



## vi. Enhance maps and models with AI and Machine Learning

LIMMMA has an integrated AI/machine learning capability, using a generative AI approach, to identify features in a landscape based on a combination of an English-language description and an optional reference image. Figure 1.6 illustrates how a text prompt (“tree”) (left side of diagram), with the optional addition of a reference image, allows the generative AI system to use an inbuilt processing pipeline (centre panel of diagram) to identify and label trees in an urban landscape (dark red shading, right panel of diagram). This capability can be used to identify features, such as lone trees or vineyards, not necessarily identified as standard in a landscape from existing available datasets.

**Figure 1.6 Enhancing maps and models with AI and Machine Learning**

- Integrated AI and Machine Learning to identify specific landscape features and improve basemaps.
- Users are able to provide text prompts for "any" landscape features of interest.




User enters text prompt "tree"

Outputs

## vii. Apply socio-economic data and stakeholder-generated layers

LIMMMA's core functionality allows users to create novel, bespoke landscape maps of their own which can themselves act both as layers in a traditional mapping application, as geospatial data resources, and as inputs for further new models. As examples, in figure 1.7, on the left a map has been produced by LIMMMA identifying (in yellow) "green" areas which are both accessible and utilised according to user defined criteria. Here there is potential to complement the outputs from NE green infrastructure maps, lead to enhanced community engagement and understanding of benefits and trade-offs of intervention options for different groups.

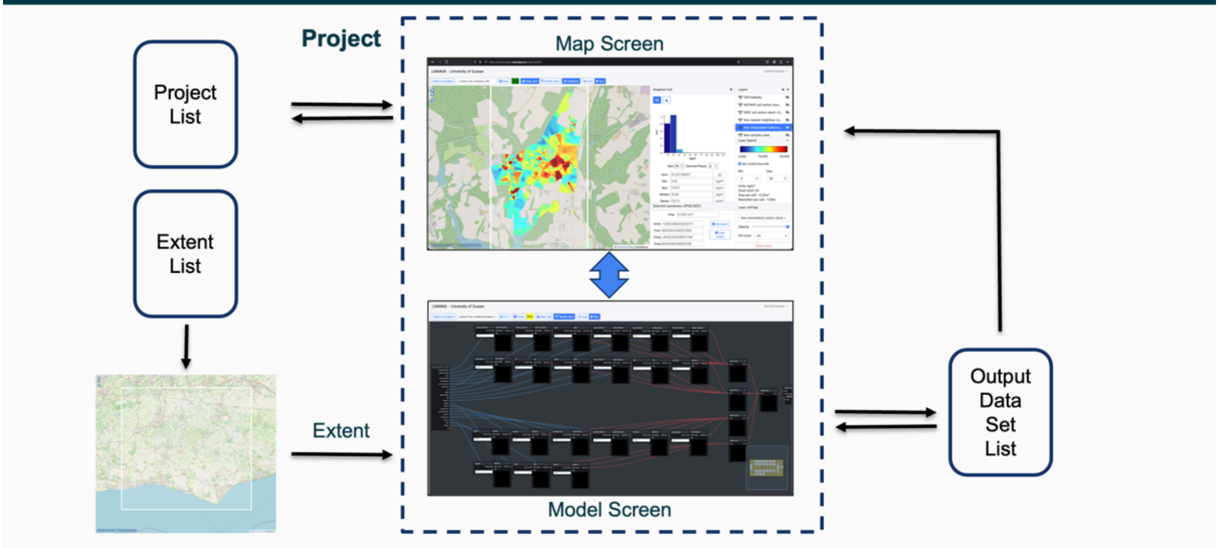
Figure 1.7 Apply to diverse multifunctional land use issues - with integrated socio-economic data and stakeholder generated layers.


The system is also in the process of being expanded to provide the ability to manually annotate and "paint" features onto maps. These processes will all be done dynamically and in real-time, allowing the creation in workshop settings of user-generated layers. Figure 1.7 provides illustrative schematics for how this will work. On the left, an illustrative example expands on current LIMMMA capabilities to envisage annotating existing maps with notations and photographs. On the right, the example proposes how manual annotations will be used to modify directly existing capabilities for identifying candidate woodland expansion sites.

## 3. Working with LIMMMA - the user interaction screens

Figure 1.8 provides an outline illustration of what LIMMMA looks like to work with. At its core, LIMMMA allows users to create their own bespoke geospatial data using a model, which the user defines, and then allows them to save the resulting output and analyse the results using a map screen.

Figure 1.8 What LIMMMA Looks Like




**Projects.** The central entity is a project, which is accessed through a map screen and a linked model screen (figure 1.8, centre). Projects are created, cloned, and loaded up via a project list (figure 1.8, top left).

**Project Model Screen.** The model screen (figure 1.8, centre below) lays out in a pictorial fashion the data sources, computational steps (methodology), and outputs of the project's model. The diagram shows visually how the data flows through the model and how it is manipulated. Each step in the process is represented by a component (box) which undertakes some piece of analysis; many components are available to the user. Outputs are map layers to be displayed on the map screen (figure 1.8, centre above), any number of which can be created simultaneously, and/or files saved to the system.

LIMMMA is dynamic and these outputs will need to be generated by running the model. The LIMMMA system automatically determines the highest model resolution at which a model extent of that size can be modelled (for more details, see below) and runs the model at that spatial resolution. A model typically takes 2-3 minutes to run.

**Project Extent.** A model can be pointed to any geographical area - users specify the precise area to be studied (the 'model extent') by either specifying it as a shape on a map (figure 1.8, lower left), or by choosing a pre-defined extent (e.g. a pre-loaded council boundary) from an extent list (figure 1.8, centre left). These extents can be any closed shape.

The report is based on project work that focused on three distinct areas: (i) Wakehurst, (ii) the area governed by Wealden District Council, in East Sussex, and (iii) a rectangular area covering parts of West Sussex, East Sussex, Surrey and Kent, labelled here the "Central South East Region". Areas (i) and (ii) both lie within area (iii). The work is intended to be extendable across all parts of the UK.

**Project: Map Screen.** The user can toggle between the project's model screen and the map screen (figure 1.8, top centre). The map screen displays a pre-loaded set of maps on top of one another as a set of layers. The order, visibility, and degree of transparency of each layer can be manipulated by the user, as can many aspects of the display (colour scheme, dynamic range). Most maps in this report were displayed with a colour scheme which ranges from dark blue (low values) through green and yellow (mid-range values) to red (high values).

These layers can be (i) external data sources; (ii) previously run model outputs (from this project or any other); and (iii) specified outputs from this project's model. The last of these only appear once the project model has been run. Because model outputs can be saved and then loaded in as a map layer, it is not always necessary to re-run a model to work with the results.

The data shown in the layers can be interrogated in several ways. If the layer is a model output, then the most significant of these is the snapshot control, which provides a statistical analysis, for each layer, of a user-defined geospatial area (a 'snapshot extent').

## 4. Using LIMMMA as an investigative platform

We use LIMMMA as an investigative platform to create simple, modifiable, scalable models using a process that is rapid, interactive and dynamic. Each LIMMMA model has three core components: a set of available data sources, a methodology for manipulating those data sources, and a set of desired model outputs. See figure 1.9.

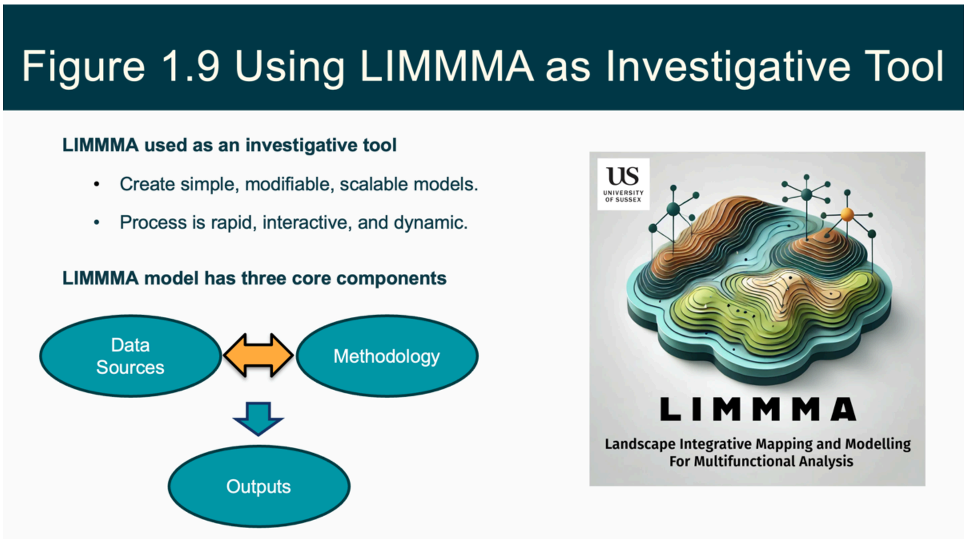



Figure 1.9 Using LIMMMA as Investigative Tool

Formulation of a methodology is in the hands of the user, who is free to develop innovative and bespoke ways to bring geospatial data sets together and create interesting outputs.

As an example, we can consider the broad methodological approach taken in the above-carbon work in the following chapter. Here the broad methodology is to take a habitat classification map and combine it with a topological estimation of feature height (e.g. tree canopy height) in the landscape and apply a carbon-storage estimation calculation for each small patch of land based on the habitat and feature height.

Figure 1.10 provides a figurative illustration of this methodology and the associated data sources that are available to undertake the analysis.

Figure 1.10 Above-Ground Carbon: Data & Methodology

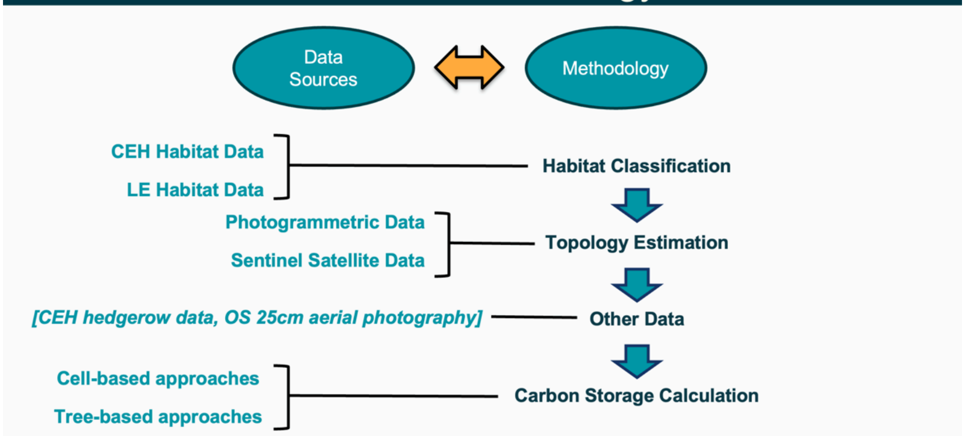
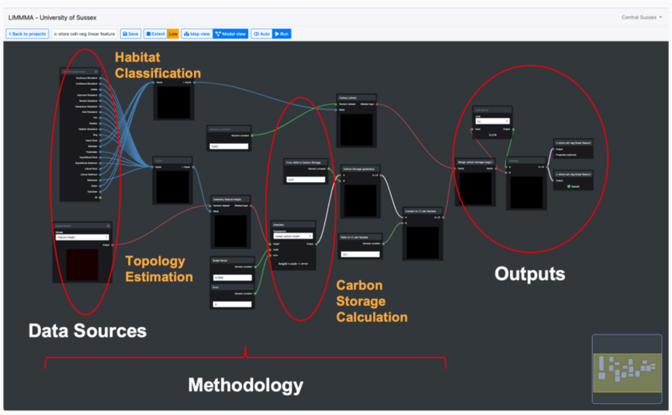



Figure 1.11 shows an implementation of one such version of this approach (the *feature-height* model) in the model screen of a LIMMMA project. Data sources are specified on the left. The flow of data is set out by the lines connecting data sources to components which undertake specific actions (figure 1.11, centre). Once the data has been processed, outputs are specified (figure 1.11, right). When an extent has been defined for the model, specifying the extent of the landscape being analysed, the model can be run. Running a model typically takes 2-3 minutes.

Figure 1.11 LIMMA Model Example



# Chapter 2. Above-Ground Carbon Storage

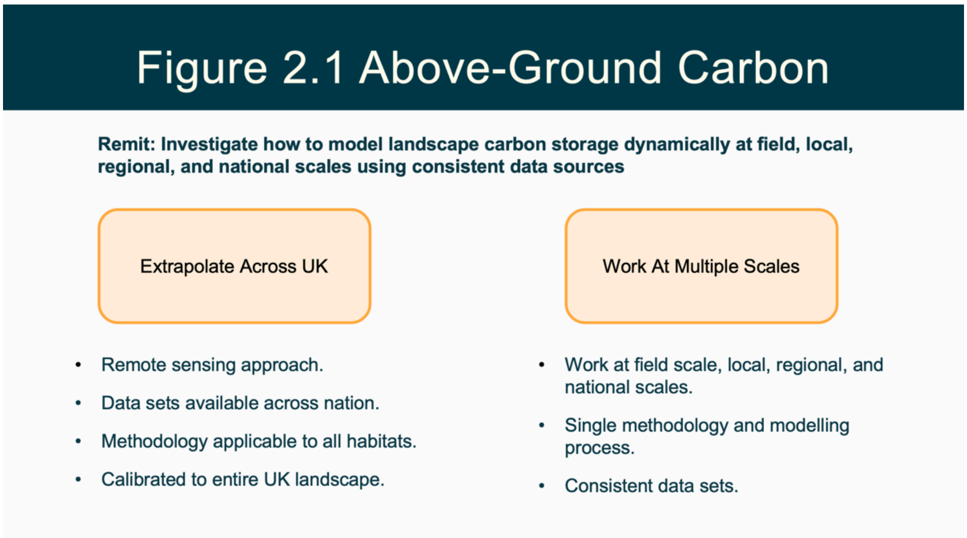
## 1. Introduction

In this report, we illustrate how users can develop and make use of simple transparent models of carbon storage in LIMMMA, using available national datasets and remote sensing data, that can not only measure at sufficiently high resolution to estimate the impact of very small-scale changes, such as the planting or removal of individual trees and hedgerows, but also measure at sufficiently large scales to estimate carbon storage at field, area, county, and regional levels in a single analysis. The models and their parameters can be interactively specified and dynamically modified to reflect the data sources that are available to the user, and their preferred modelling approach.

The use in any one study of a single model and consistent data sources at very high resolution for local areas, and simultaneously at regional levels, provides the ability to tie together local and regional measures, making it also much easier to model the potential impact of small changes across much larger landscapes. It further provides researchers, analysts and planners with a single, consistent view within a specific study at local and regional level across the UK.

In this chapter, we iteratively develop a series of models for estimating above-ground carbon storage, comparing their performance. The models offer trade-offs in terms of their differing levels of complexity, and differing reliance on data sources. We tentatively adopt the *feature-height* model as our preferred approach at this point for our own work, but all the approaches outlined have their contrasting merits.

This report compares dynamic models of above-ground vegetative carbon storage in illustrative regions within the Central South East region. Our remit is to work at multiple scales (field, local, and regional) and in a manner that can be extrapolated across the UK (figure 2.1). Accordingly, the models examined in this specific work, rely solely on remote-sensing data and are intended to provide rapid, dynamically adjustable approximate assessments of carbon storage. As such, they are an adjunct to, and not a replacement for, more accurate assessments using measurements in the field.




In this use case, modelling above-ground carbon storage, we developed a series of models that incrementally incorporated additional data sources to provide more useful and robust approaches. This reflects a typical working ‘evolving methodologies’ pattern with LIMMMA, working with and refining models as we learn more about the problem at hand.

At this point, the outputs are provisional, based on an initial calibration of underlying allometric equations (see Appendix) derived from work undertaken in this project by the research team at Wakehurst. The work undertaken in the project, and reported here, was based on this initial illustrative calibration early in the project. As the data has become available at the end of the project, we have now been able to use detailed results from the Wakehurst team to re-calibrate the models; this will adjust some of the figures presented here slightly but the recalibration has no material impact on the findings. Going forwards, further examination of outputs and more detailed calibration will be undertaken using field data to confirm the usefulness of the output from these remote-sensing methodologies.

The outputs of an above-ground carbon storage model are intended to be combined by decision-makers with those from below-ground storage models (see Chapter 4) and, more importantly, other multifunctional sources of landscape data.

## 2. Models Developed

Our goal is to estimate above-ground carbon storage levels in natural environments in a manner that is simple, rapid, modifiable, dynamic, interactive, and scalable. For scalability, we would like solely to use data sources that are available or can be acquired nationally; this allows the same model to be applied at field level, locally, and regionally in any single study or related set of studies.

### Models Developed: *base*, *base+tree-height*, *base+tree+hedge-height*, and *feature-height*

We start with an extremely simple model, the *base* model, which relies on no direct remote-sensing data, and then develop three simple derivative models: the *base+tree-height* mode, the *base+tree+hedge-height* model, and the *feature-height* model. These derivative models all incorporate processed remote-sensing data and incorporate allometric equations for estimation of carbon-storage in vegetation.

These four models aim to do the same thing: to estimate above-ground carbon storage by the landscape in a manner that works at different scales using a transparent, modifiable design. Each of the model methodologies used have advantages and disadvantages, but the approach provides an opportunity to examine in practical settings how these approaches work out.

Figure 2.2 provides a summary of the evolving methodologies examined here, showing how the components of the methodology (habitat, topology, other data, carbon storage calculation) differed across the model types.

**Figure 2.2 Evolving Methodologies**

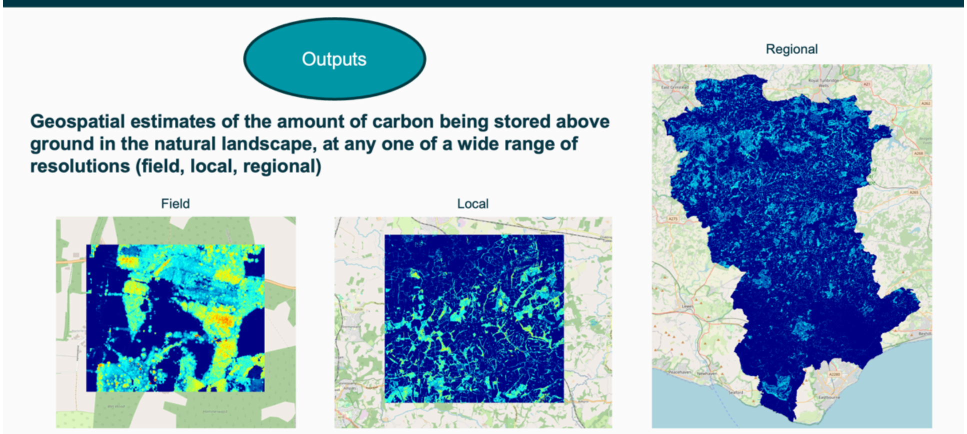
| | Base model | Tree Height | Tree + Hedge Height | Feature Height |
|---|---|---|---|---|
| **Habitat** | Fine-grained habitats | Fine-grained habitats | Fine-grained habitats | Broad 'arable' habitats |
| **Topology** | N/A | Woodland habitat tree height estimates | Woodland habitat tree height estimates | Arable habitat feature height estimates |
| **Other Data** | N/A | N/A | CEH hedgerow data | N/A |
| **Carbon Storage Calculation** | Fixed carbon storage figure per habitat | Woodland carbon storage estimate from feature height in cell. Fixed carbon storage figure other habitats | Woodland and hedge carbon storage estimate from feature height in cell. Fixed carbon storage others | Arable habitat features carbon storage estimate from feature height in cell. Fixed carbon storage others |

## 3. Model I: the *base* model

The *base* model starts with the observation that the above-ground carbon stored per unit area by vegetation in the landscape varies significantly by habitat type, and we have available published estimates of how much carbon, on average, each habitat type stores per unit area. These estimates are, of course, subject to future modification and refinement.

As already noted, a model consists of three components: methodology, data sources, and outputs. In this study, our desired outputs are geospatial estimates at a given spatial resolution of the amount of carbon being stored above ground in the natural landscape, and a measure of the uncertainty associated with that estimate (see Chapter 3). See figure 2.3 for example of above-ground carbon storage outputs at the field, local, and regional scale.

**Figure 2.3 Above-Ground Carbon: Outputs**




**Methodology.** The *base* model takes a habitat classification label for each patch of land and applies an expected value for carbon storage to that patch, enumerated as the expected (average) storage that would be seen for a habitat of that type. Overall carbon storage values for a larger area can then be determined by summing the values for each patch across the landscape.

**Data Sources.** This model requires only two data sources: a national land cover (habitat) classification scheme and a lookup table of estimates for expected carbon storage by habitat.

*National land cover classification scheme*. We have built models based on one or the other of two such schemes: the Living England habitat probability map (Living England Habitat Map, Phase 4, 2022), and the CEH land cover map (2021, 2022, 2023) (Morton, R.Det al., 2024, Land Cover Map 2023 (land parcels, GB)).

These schemes apply a habitat label to every patch of land and inland water in the UK. Both schemes have been derived, by other teams, from analysis of remote sensing data, specifically data from Sentinel satellites with an effective spatial resolution of approximately 10m, although subsequent processing and machine-learning classification can modify that underlying resolution, as can other factors, including the use in the Living England model of shape files. After processing, the underlying spatial resolution of both the Living England and CEH schemas are such that each labelled patch is a square of roughly 10m resolution (10m x 10m, an area of 100 $m^2$).

Note that, by using two different classification schemes we can compare the results obtained and assess the extent to which differences in habitat classification schemes are impacting our estimates (see below and Chapter 3).

*Estimates of expected carbon storage by habitat.* To each labelled patch of land, a figure from a key table is applied, that figure corresponding to the expected level of carbon storage associated with the land cover type. In this study we estimate specifically the expected above-ground, vegetation-driven carbon storage. The table key containing figures for expected carbon storage are based on (i) the figures provided in the Natural England Research Report NERR094, “Carbon storage and sequestration by habitat”, (Gregg et al., 2021); and (ii) user modifications for the purposes of local calibration. Importantly, these key table entries can be readily changed and the impact of these changes measured, allowing us to confirm which estimates are critical in different landscapes.

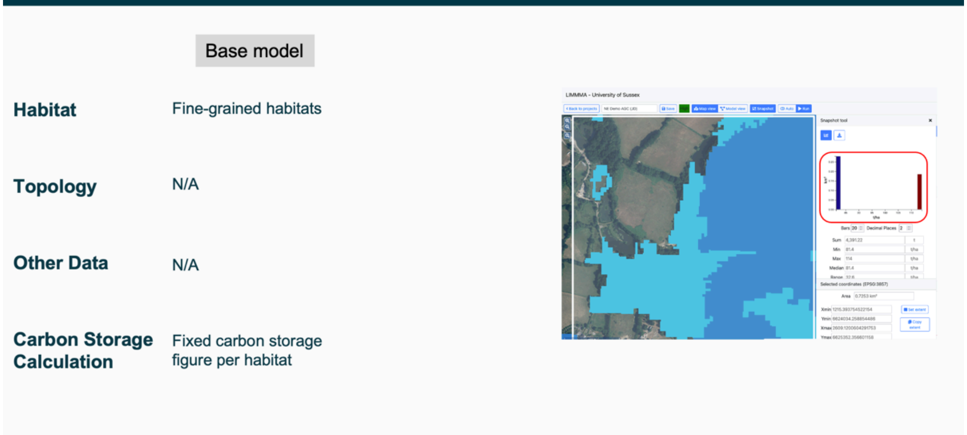
**Output.** The *base* model provides a baseline measure of estimated carbon storage across the landscape without direct recourse by the user to any additional remote sensing data.

*Spatial resolution.* The resolution of the resulting carbon storage maps is driven by the resolution of the land-cover classification data, estimated here for both schemes at a resolution of 10 m. This resolution limitation expresses itself at habitat borders. For the Living England scheme, the habitat landscape is mapped with many small, interleaved shapes. For the CEH scheme, the habitat landscape mapping is generally broader so although the resolution limit is expressed less frequently spatially. Within the habitat borders, spatial resolution is undefined as no attempt is made to estimate variations in carbon storage estimates within a habitat area.

*Usefulness of output.* The usefulness of the *base* model at a given level of resolution is therefore driven by (i) the correctness and spatial resolution of the habitat designation at a particular patch; and (ii) the reasonableness of the use of a single overall average figure for each land cover type at different scales. This is an empirical question: if the key table averages are properly estimated then the carbon storage estimates should be accurate as the area being examined increases towards a regional scale. This use, however, of a single average carbon storage figure for every patch of a particular habitat is likely to become less useful as we zoom in on the landscape to the field level.

Figure 2.4 provides a visual representation of vegetation carbon storage from the *base* model for a small patch of land, using a model with a 3 m x 3m cell size. We can see that the carbon storage signal is dominated by woodland, with two constant carbon storage intensities, reflecting the different average assumptions for deciduous and coniferous woodland. Visually, we can see the impact of using a single value for carbon storage by habitat type, dividing the countryside into monolithic blocks of carbon storage, flattening out variations in the landscape. The diagram shows underlying 25 cm resolution aerial photography (Bluesky International) for the area to provide scale and context.

Figure 2.4 Base Model




The biggest problem with the base model is the use of a single average carbon storage figure for every patch in a woodland habitat. From previous research and inspection of the *base* model in most habitats within our research area, trees provide by far the most important sources of vegetation carbon storage.

## 4. Model II: *base+tree-height* model

It is known that carbon storage varies greatly with the height of the trees, but this is not captured in the *base* model. This issue is addressed with the *base+tree-height* model, which introduces remote-sensing data to estimate tree heights.

**Methodology.** The *base* vegetation carbon storage model is adjusted to incorporate patch-by-patch estimates of average canopy height. These canopy height estimates are then used to estimate carbon storage, deploying an allometric equation that assumes a specific relationship between carbon stored and the remotely sensed average height of the canopy for that patch.

**Data Sources.** This model requires two additional data sources: a patch-by-patch estimate of woodland canopy height, and an allometric equation for estimating carbon stored by canopy height. We drop the *base* model's lookup table of estimates for expected carbon storage for woodland but retain them for all other habitats. As before, a relevant land-cover classification scheme (Living England, CEH) is used to identify the patches of land that are woodland.

*Canopy height estimates.* To date, we have built models based on one or the other of two schemes for estimating canopy height: (i) feature height estimates taken from taking the difference between the aircraft-gathered photogrammetric Digital Terrain Model and Digital Surface Model (Bluesky International Limited: 2 m photogrammetric DSM, 5 m photogrammetric DTM data sets), deriving an estimate of the canopy height at each patch within a woodland habitat ("photogrammetric source"); and (ii) canopy height estimates derived globally, including the UK, from sentinel satellite data (Lang et al., 2023) ("satellite source").

For the photogrammetric source, the DTM measures the altitude of the underlying terrain while the DSM measures the altitude of the surface features. The difference between the two therefore provides an estimate of surface feature height, which is taken as an estimate of canopy height in a woodland habitat. The resolution of the DTM/DSM combination is approximately 2 m where the underlying terrain is relatively flat, and 5 m where terrain height is rapidly changing, so within a habitat we typically enjoy a relatively high 2 m resolution of feature height.

*Allometric equation.* All the models except the *base* model contain an equation that estimates the amount of carbon stored in a patch of land, based on the estimated average height of canopy in that patch. The form of this equation has a major effect on the absolute carbon storage estimates. At high resolutions, most modelling of carbon storage to date has been tree-based, deriving direct estimates for the carbon stored within each tree. The models developed here are relatively unusual in that they remain cell-based (or "patch" or "raster") at high resolution. Models operating at 3 m resolutions, for example, might cover a single deciduous tree with 20 or more individual patches, the number of patches proportional to the area of the foliage seen from above i.e. the square of the crown radius.

The Appendix lays out in more detail our work on a calibration based on survey work for this project by the Wakehurst team. This work has so far found that best fits for this methodology are achieved with a linear model, i.e. a linear relationship between each patch's canopy height and the estimated amount of carbon stored by that patch. We find, however, that deciduous and coniferous woodland are best fit by different slopes. Note that these models can readily be adjusted to incorporate non-linear power relationships for the allometric equation.

**Output.** The *base+tree-height* model provides a measure of estimated carbon storage across the landscape making use of canopy height estimates and an allometric equation that estimates the relationship between carbon storage and canopy height.

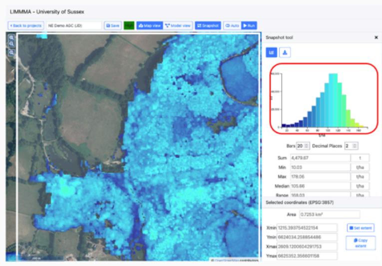
*Spatial resolution.* In areas where the woodland patch is very small, the effective resolution is governed by the resolution of the land-cover scheme (approximately 10 m). In areas of contiguous labelled woodland cover, however, a resolution of the order of 2 m might be inferred for the photogrammetric source as the feature height estimates govern apparent resolution, and 10 m for the satellite source. It should be noted, however, that patch-to-patch variation relative to the assumptions of the underlying simple equation will reduce resolution.

By using two different data sources for feature height estimation, we can compare the results obtained and assess the extent to which differences in the feature-height source are impacting our estimates (see below).

Figure 2.5 provides a visual map of vegetation carbon storage for the *base+tree-height* model for the same area. It is immediately apparent that the fine detail of the landscape topography, in particular the height and bulk of the woodland vegetation, is much more powerfully captured by this methodology, with a smooth near-Gaussian calculated distribution of carbon storage across the landscape. The spatial fidelity of this model instils much greater confidence that the impact of small and local changes in the landscape will be captured. Closer inspection, however, reveals that many trees and hedgerows are not being captured by this methodology.

Figure 2.5 Tree-Height Model

| | Base model | Tree Height |
|---|---|---|
| **Habitat** | Fine-grained habitats | Fine-grained habitats |
| **Topology** | N/A | Woodland habitat tree height estimates |
| **Other Data** | N/A | N/A |
| **Carbon Storage Calculation** | Fixed carbon storage figure per habitat | Woodland carbon storage estimate from feature height in cell. Fixed carbon storage figure other habitats |



A core problem with the *base+tree-height* model is that it fails to consider and incorporate hedgerows and isolated trees. Neither hedgerows nor isolated trees are typically identified as “woodland” habitats in either of the land classification schemes used here, so they are missed by this model.

## 5. Model III: the *base+tree+hedge-height* model

CEH has recently issued a UK hedgerows data set (Broughton et al., 2024) which applies machine-learning approaches to remote sensing data to produce a map of hedgerows in the UK. This can be incorporated in our modelling to produce a refinement of the *base+tree-height* model.

**Methodology.** This takes the *base+tree-height* model and adds in the CEH hedgerow data set, merging it with the existing deciduous (or broadleaf/mixed) woodland habitat. This then applies the same canopy equations to the hedgerow data as to the deciduous (or broadleaf/mixed) woodland habitats. We assume that the same height-based carbon storage formula developed for woodland canopy can be applied to these hedgerow features. If further empirical work leads to a new allometric equation for hedgerows then this can be easily applied.

**Data Sources.** This model requires one additional data source: a map of hedgerows for the UK made available by CEH in 2024. It would be ideal to have a hedgerow-specific allometric equation, which can be added if one becomes available.

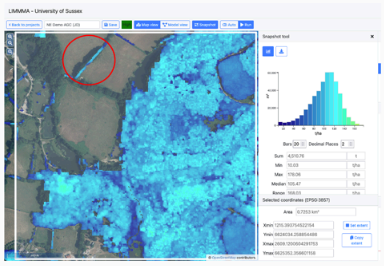
**Output.** Output is unchanged from the *base+tree-height* model. Spatial resolution from the CEH hedgerow dataset seems to be of the order of 2-5 m, but this is open to empirical confirmation.

The *base+tree+hedge-height* model only partially addresses the problem of hedgerows and isolated trees because the CEH hedgerow data doesn't capture all hedgerows or isolated trees. This is important, as individual trees are both key carbon-storing and aesthetic additions to the landscape.

Figure 2.6 also provides results for this model. The output for this model looks very similar to those for the *base+tree-height* model but closer inspection reveals that some hedgerows have been incorporated. Comparison with the aerial photography, however, shows that not all hedgerows or lone trees are captured by the model.

Figure 2.6 Tree+Hedge-Height Model

| | Tree Height | Tree + Hedge Height |
|---|---|---|
| **Habitat** | Fine-grained habitats | Fine-grained habitats |
| **Topology** | Woodland habitat tree height estimates | Woodland habitat tree height estimates |
| **Other Data** | N/A | CEH hedgerow data |
| **Carbon Storage Calculation** | Woodland carbon storage estimate from feature height in cell. Fixed carbon storage figure other habitats | Woodland and hedge carbon storage estimate from feature height in cell. Fixed carbon storage others |



Furthermore, we observe lower resolution at habitat boundaries than within habitats; for the *base+tree-height* model, the typical available spatial resolution is ~2 m within a habitat patch but much poorer on the habitat borders at approximately 10 m. Habitat borders therefore create greater resolution challenges and this inhibits the scheme from identifying and delineating accurately features at habitat edges at field-level scales.

## 6. Model IV: feature-height model

An attempt to address both the issue of missing isolated trees and habitat edge boundary effects has led to the development of the *feature-height* model.

**Methodology.** In this approach, the *base+tree-height* model methodology is changed in two ways:

1. We expand the repertoire of habitats that are assumed to contain features that can be treated as trees or their equivalent (e.g. hedgerow, lone tree). Features within a broad range of "arable" habitats are assumed either to be lone trees, hedgerows or other items equivalent to a woodland tree of the same height.
2. We assume that the same height-based carbon storage allometric equation developed for woodland canopy can be applied to these features.

A much larger number of habitats ("arable habitats") are therefore combined in this model and all treated as the equivalent of a single woodland habitat.

**Data Sources.** We use the same data sources as the *base+tree-height* model.

**Output.** These two changes have two principal effects relative to the *base+tree-height* model: improving effective spatial resolution and introducing false positive carbon signals.

*Spatial resolution and coverage.* The revised methodology reduces the number of habitat boundaries, increasing the available spatial resolution at those points where boundaries are effectively eliminated. The typical impact is to increase coverage of green foliage on the borders of habitats and improve accuracy at these locations.

It also increases the ability of the model to capture carbon storage contributions from important features, in particular isolated trees and hedgerows, the impact of which is to bring lone trees and hedgerows successfully into carbon capture calculations of high spatial resolution models (see below).

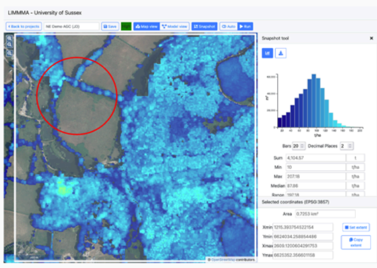
*False positives.* However, the *feature-height* model will register more false positives: features within non-woodland habitats that are not “woody”. For example, we have observed parked cars in a field registering a carbon storage contribution, pylons registering as small points of carbon storage contribution, and even green-roofed buildings that had been mis-classified as arable land registered by the model as a source of carbon storage.

The usefulness of this trade-off between better coverage and false positives is an empirical question. Initial observations, however, suggest that nearly all the increased carbon storage signals registered by the *feature-height* model are derived from the recognition of appropriate carbon storage sources, in particular trees on habitat boundaries and isolated trees and hedgerows within other rural habitats. As desired, this makes the model much more sensitive to carbon storage improvements from the planting of hedgerows and isolated trees.

Figure 2.7 illustrates that the *feature-height* model successfully captures many more of the carbon-storing landscape features omitted from the previous models. The *feature-height* model typically reports higher carbon storage readings and that these are along the edges of woodland, within fields and along hedgerows). As discussed earlier, this model will, however, identify more false positives than the *base+tree-height* model.

Figure 2.7 Feature-Height Model

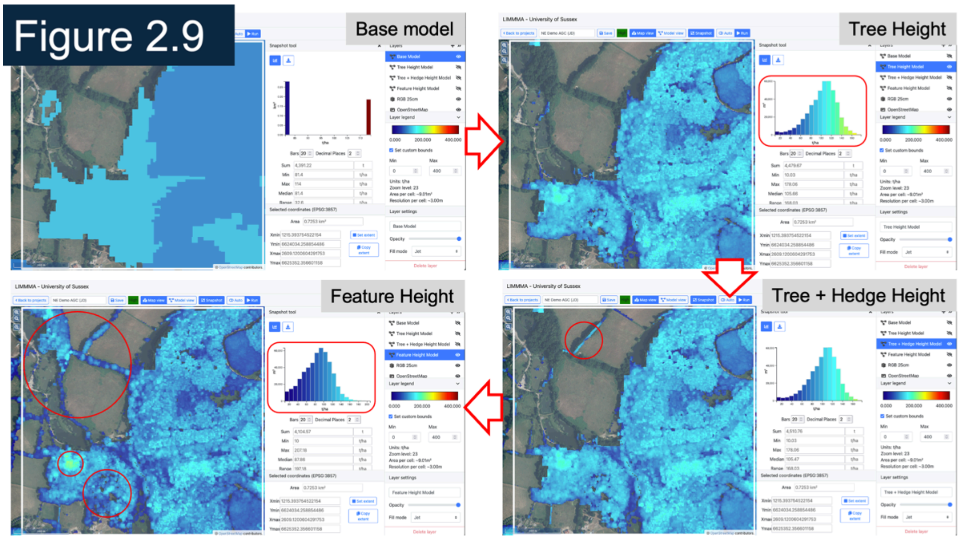
| | Tree + Hedge Height | Feature Height |
|---|---|---|
| **Habitat** | Fine-grained habitats | Broad 'arable' habitats |
| **Topology** | Woodland habitat tree height estimates | Arable habitat feature height estimates |
| **Other Data** | CEH hedgerow data | N/A |
| **Carbon Storage Calculation** | Woodland and hedge carbon storage estimate from feature height in cell. Fixed carbon storage others | Arable habitat features carbon storage estimate from feature height in cell. Fixed carbon storage others |



Observed illustrative examples of false-positive signals include cars parked in a field, buildings with green roofs, and electricity pylons. Initial impressions and estimates are that these false positives form an acceptably small proportion of the additional carbon storage signal identified; work is ongoing to examine this initial view.

Figure 2.9 summarises the evolution of methodologies and results exemplified by these four models. All these models contain simplifying assumptions that can be improved upon. For example, within built-up areas carbon storage from gardens and other green spaces is ignored unless separately identified by the underlying habitat map scheme (Living England, CEH). More sophisticated modelling methodologies and the use of additional data sets are being explored to address these limitations.

Figure 2.9




## 7. Limitations on resolution created by the modelling (“analysis resolution limits”)

Ideally, given the scalability ambition, we would like to be able to model with sufficient spatial resolution to be useful at field level as well as all the way up to large-scale regional modelling.

One limitation to resolution is the spatial resolution of the available data sources, as noted earlier. But model resolution is also a factor. The model analysis process itself imposes resolution limitations derived from storage and computational complexity considerations. The LIMMMA platform is designed to be used by researchers on their local machines or laptops in real time. This design imposes practical limitations on the size of the geospatial array that can be processed in any one analysis. For this reason, a single analysis divides the area to be analysed into an array containing 10 million cells; the geographical extent chosen for analysis therefore determines the size of each modelled “patch” of land.

Theoretically, it would be possible to create a national map by stitching together a collage of such tiles, but LIMMMA isn’t really designed or intended for creation of static data sets so, in practice, we will generally undertake large scale analyses using large-scale models, albeit with the same methodology. The overall resolution of a model is therefore typically a combination arising from the interaction between the spatial resolutions of interacting data sets and the model resolution being used.

This analysis resolution limit therefore interacts with data resolution factors to determine the overall spatial resolution of the resulting carbon storage model. The smaller the geographical extent, the more spatially detailed the model output and the higher the analysis resolution, and vice versa. Of course, modelling large parts of the countryside in a single analysis, which typically takes only 2-3 minutes to run, is often useful and appropriate. If fine detail is required, however, a smaller extent and correspondingly higher resolution analysis is appropriate.

To give a feel for this trade-off, an area the size of Wealden District Council can be modelled in a single analysis at a particular zoom level ("zoom level 20" or "z20") with a model resolution of 24m. This zoom level can be used to analyse any area fitting within a rectangle of total area up to 5,770 $km^2$. The table below shows the model resolution for areas (extents) that fit into a rectangle of up to the area specified in the column "Total Area of Analysis". For a model zoom level above 23, the data sources will typically be the acting constraint on resolution. For model zoom 23 and below (analytical area of 90 $km^2$ and greater), the model itself will be the gating resolution for output. The following table summarises the approximate extent that can be covered at each zoom level and the resulting analysis resolution limit.

| Zoom | Total Area of Analysis (km2) | Dimensions of Area Analysed (km) | Analysis Unit Area (m2) | Analysis Resolution Limit (m ) |
|---|---|---|---|---|
| 20 | 5,770 | 76.0 | 580 | 24.1 |
| 21 | 1,443 | 38.0 | 145 | 12.1 |
| 22 | 361 | 19.0 | 36 | 6.0 |
| 23 | 90.2 | 9.5 | 9.07 | 3.0 |
| 24 | 22.5 | 4.75 | 2.27 | 1.5 |
| 25 | 5.63 | 2.375 | 0.57 | 0.75 |
| 26 | 1.41 | 1.188 | 0.142 | 0.38 |

The analysis resolution limits for z20, z21, z22, and z23 are 24 m, 12 m, 6 m, 3 m and 1.5 m, respectively. In practice, therefore, the z22 and z23 zoom settings are required to be able to model individual hedgerows and lone trees with good fidelity. At z26, a single analysis can theoretically model an area of ~1.2 km x 1.2 km at 38 cm analysis resolution, but data resolution limits generally dominate at these levels.

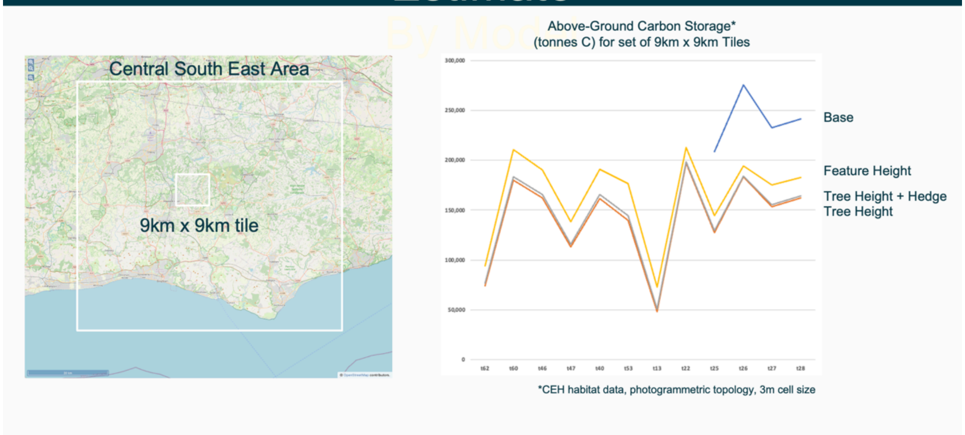
## 8. Comparing Above-Ground Storage Estimates by Model Type

What is the impact on carbon storage estimates as we move from *base* to *base+tree-height*, to *base+tree+hedge-height*, and to *feature-height* models?

We address this question by sampling results across a set of 12 local-level extents. Our geographic region of interest consists of a broad rectangular area covering parts of West Sussex, East Sussex, Surrey and Kent ("Central South East Region"). We divided this region into a set of 64 tiles, each measuring 9 km x 9 km. A tile of this size can be modelled by LIMMMA at z23 scale (3 m spatial resolution per model pixel). For this analysis we chose a subset of these tiles covering our area of interest. These were tiles numbered 24, 25, 26 and 27, covering the Wakehurst area and immediate surroundings, and tiles numbered 13, 22, 40, 46, 47, 53, 60 and 62. These latter 8 tiles were chosen at random from the remaining available tiles, with the protocol of excluding from the candidates any tiles containing only sea.

Figure 2.10 quantifies the observed differences between these different models across the 12 sampled tiles. We see large variations between tiles, ranging from ~50,000 tonnes of carbon in a 9 km x 9 km tile to over 200,000 tonnes in another. For these results, we use the CEH habitat data and photogrammetric topology. The model is operating with a 3 m cell size (zoom 23 in LIMMMA).

Figure 2.10 Above-Ground Carbon Storage Estimate




Within that large range, we see consistent relationships between the different models within a tile, with the base configuration showing the highest estimates, then *feature-height* > *tree+hedge-height* > *tree-height*. The relationship between the latter three models is expected, as the models are progressively more restrictive in the habitats and data sources considered as candidates for carbon storage. The high values for the *base* model suggest a local calibration error or deviation, specifically that the average height of woodland cover in the landscape surveyed here is lower than that of the woodland used to gain the National England estimates in Gregg et al. (2021), and as here implemented, and/or the calibrated allometric equations lead to a lower carbon storage intensity than that estimated in the National England report.

## 9. Impact of Scaling

What is the impact on fidelity as we change the analysis zoom level from high to low resolution?

As we noted before, one of two key requirements for our remit is to create models that work at multiple scales. We note three broad requirements. First our models must work simultaneously at field, local, and regional scales. Second, we must be able to use the same data sources at each scale. Third, our models must be able to use a single methodology and produce the same outputs. These requirements have been met through design choices; they determined some aspects of the design of the LIMMMA platform and dictated the use of the cell-based or raster allometry equation approach.

Ideally, however, we would like our models to obey as closely as possible a fourth restriction, namely that the same analysis conducted at different scales should produce, on average, the same result. Models produced at our working ‘field’ resolution (3 m cell size, LIMMMA zoom 23) have a high enough resolution to be able to register individual features such as lone trees and hedgerows, while still modelling in a single analysis an area of up to 9.5 x 9.5 km. Models produced at our working ‘regional’ resolution (24m cell size, LIMMMA zoom 20) can model in a single analysis an area up to 76 km x 76 km. (For comparison, the county of East Sussex is 75 km by 40 km). We would like, on average, the estimate for a given patch of land for the ‘field’ model to be comparable to that produced by the ‘regional’ model.

To examine this, we calculated the total estimated carbon storage for each of the 12 chosen zoom 23 tiles ( 9km x 9 km) in our region, using the same models but run at different scales as outlined in the following table:

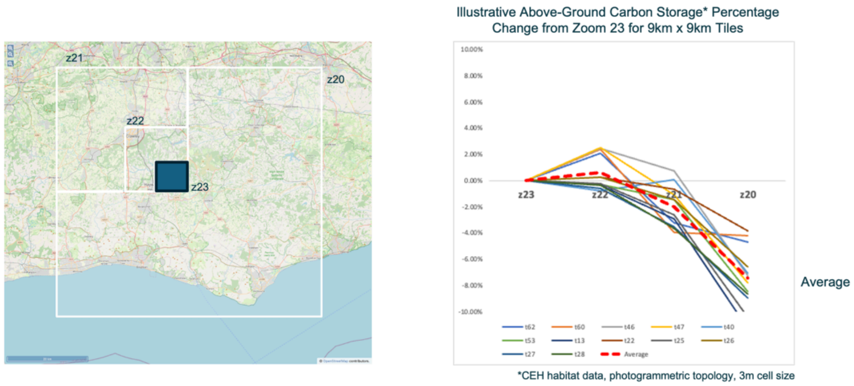
| Model Scale | Max Area Modelled | Cell dimension | Tile area as % |
|---|---|---|---|
| ‘Field’ z23 (Zoom 23) | 9.5 km x 9.5 km | 3 m x 3 m | 100% |
| ‘Local’ z22 | 19 km x 19 km | 6 m x 6 m | 25% (1/4) |
| ‘Local’ z21 | 38 km x 38 km | 12 m x 12 m | 6.25% (1/16) |
| ‘Regional’ z20 | 76 km x 76 km | 24 m x 24 m | 1.56% (1/64) |

Therefore, the field model was calculating the carbon storage across 100% of the area being modelled at a 3 m x 3 m resolution, while the regional model was calculating carbon storage for the same area, but this was only 1.56% of the area being modelled, the model working at a 24 m x 24 m resolution.

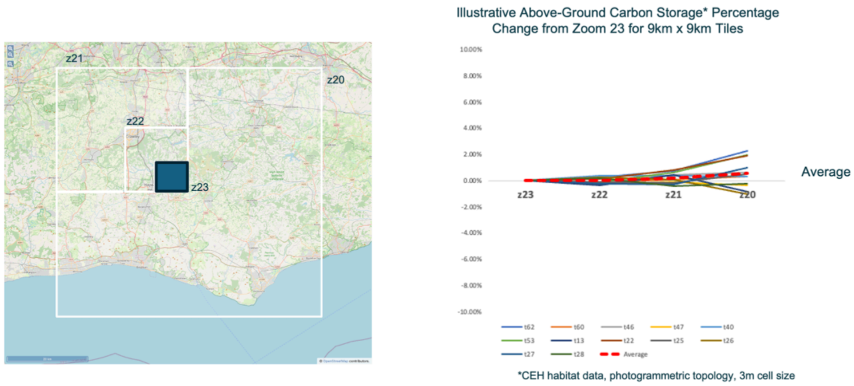
We don’t have an *a priori* right to expect this behaviour - it is an empirical question. We know that as we model at greater scales (and larger resolutions) we are going to lose landscape details. Models that behave better in this respect, however, are fundamentally much more valuable to our purpose so this should influence our choice of preferred model.

Figures 2.11 and 2.11a show the results of our analysis for two key models: *tree-height* and *feature-height*. For these results, we use the CEH habitat data and photogrammetric topology. We find that the *feature-height* model behaves extremely well in this regard, with minimal change in the estimated carbon storage estimate for a tile across a 64-fold increase in model size. The *tree-height* model likewise shows minimal variation for a 16-fold increase, but a 64-fold increase in modelled area leads to, on average, an 8% decrease in the estimated carbon storage for the tile. This trend of underestimating carbon storage at the lower resolution is consistent across all tiles although varying from -4% to -12% from tile-to-tile.

## Figure 2.11 Scaling: Tree Height Model




## Figure 2.11a Scaling: Feature Height Model




We suggest that the superior performance of the *feature-height* model may reflect its lower exposure to distorting effects arising from habitat borders. Either way, we feel that this is a strong rationale for preferring the ‘top-down’ *feature-height* approach over the bottom-up *tree-height* model, notwithstanding the presence of false positives in the *feature-height* model.

## 10. Extrapolation Across UK - Data Source Quality

Are the data sources useful and consistent? What are the differences observed when using the photogrammetric source feature height data as compared to the satellite source canopy height data? What are the differences observed when using the CEH land cover classification scheme as compared to the Living England habitat map?

The second requirement for our remit is that we can extrapolate the findings and the models across the entire UK landscape. We identified three issues for meeting this requirement: (i) a remote sensing approach using data sets available across the nation; (ii) a methodology applicable to all habitats; and (iii) models calibrated to the entire UK landscape.

At this point the requirement for calibrations across the UK has not yet been met. We have, however, used data and models developed by the Wakehurst team to undertake preliminary calibrations of the above-ground and below-ground carbon models (Appendix and Chapter 4, respectively).

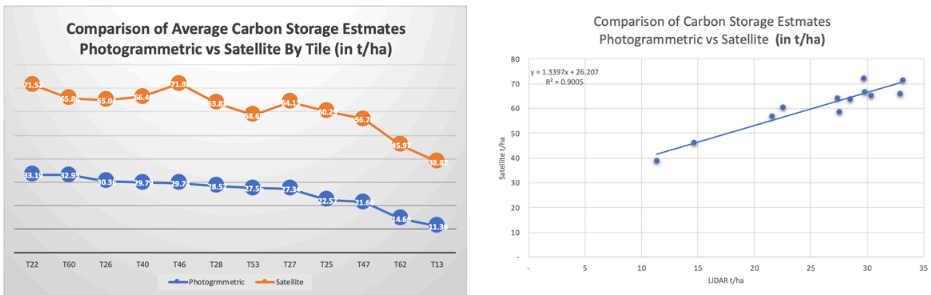
To extrapolate successfully across the UK, the methodology must be applicable everywhere and the data available across the nation; specifically, the data on which it relies must be available and consistent. For the present methodology (see figure 1.10) we rely on two principal data types: an estimation of the topology of the landscape (terrain, height of landscape features on the terrain), and a habitat classification map.

With respect to each of these data types, we have investigated the two data sources as candidates.

### *Topology Estimation*

Either photogrammetric, LiDAR, or satellite data can be used to assess the terrain and derive an estimate of the height of features above the terrain. We have, separately, deployed in our methodology worldwide satellite-derived canopy height estimates from Lang et al. (2023) (“satellite source”) and UK photogrammetric-derived feature height estimates from Bluestar International Limited (DSM and DTM data sets) (“photogrammetric source”). Figure 2.12 provides a comparison of estimated above-ground carbon storage using the same methodology with each source. The right panel of figure 2.12 shows the relationship between these two sets of estimates.

Figure 2.12 Data Sources: Photogrammetric vs Satellite

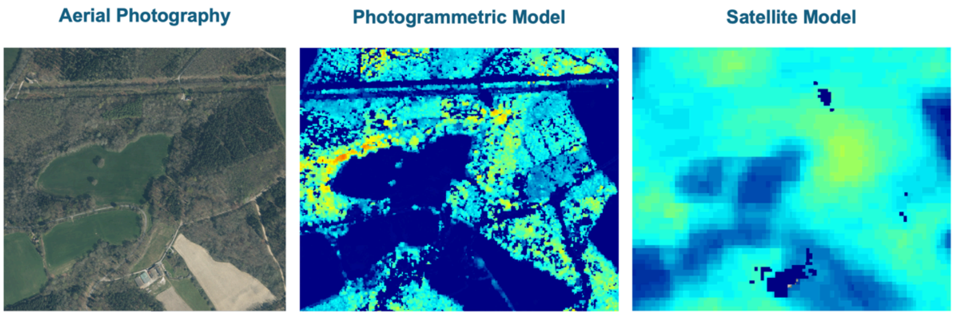



*CEH habitat data, photogrammetric topology, 3m cell size

We tentatively conclude from this work that the satellite-derived canopy data is not suitable, at present, for the current use case. Using the feature model (CEH habitat data set, 3 m cell size model), we found that estimates for carbon storage were 2-3.5x higher using the satellite data than photogrammetric feature-height data. A best-fit model of carbon-storage estimates, for the same tiles using these two different data sources, suggested that carbon storage estimates increased at 1.3x the rate for satellite over photogrammetric-measured landscapes as carbon storage intensity increased, with an intercept offset of 26 tC/ha, implying a satellite derived estimate of this when photogrammetric measured 0 tC/ha.

Visual inspection of patches of landscape photography and the corresponding photogrammetric and satellite derived pictures of carbon storage, as illustrated in figure 2.13, suggests that the satellite-derived canopy height estimates have had too much spatial smoothing applied to them. For typical English countryside of small woods frequently interrupted by small fields, the result of this aggressive smoothing is that empty fields are shown to have significant "canopy height". This problem is going to be exacerbated by the *feature-height* methodology, which treats all arable country habitats as "wood-like".

Figure 2.13 Data Sources: Photogrammetric vs Satellite




An implication is that the *tree-height* model would be less profoundly impacted. Results confirm this to be the case. Using the *tree-height* model, we found estimates were 1.2-1.7 x higher using the satellite data than when using photogrammetric data for estimating the carbon storage in a 9km x 9 km tile. (The model again used the CEH habitat data set and a 3 m cell size). The best fit linear least squares model for satellite-derived carbon estimates conditioned on photogrammetric-derived estimates had a slope of 1.45, setting the intercept to zero.

The satellite-derived canopy work (Lang et al., 2023) was optimising its canopy height estimation worldwide and chose a spatial smoothing approach that is not appropriate for the UK for these purposes. It should be possible to reconstitute satellite-derived canopy height estimates with much lower spatial smoothing, more suitable for rapidly shifting English countryside, and we shall be exploring this possibility. Until then, our approach remains reliant on photogrammetric data as a single source of topology estimation information.

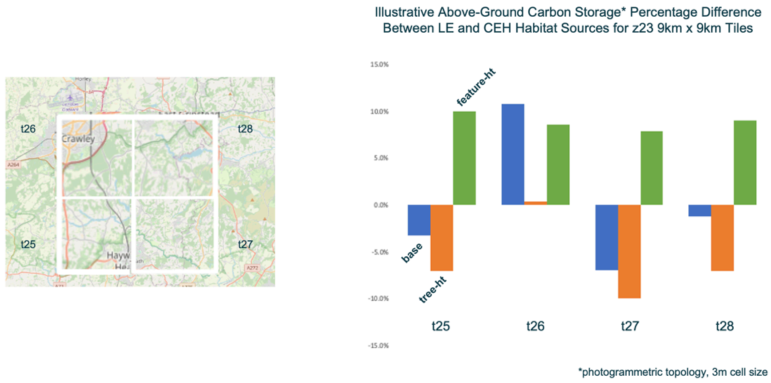
### *Habitat Classification*

With respect to habitat classification, we have identified and made use of two sources of habitat maps: Living England (Living England Habitat Map, Phase 4, 2022) and CEH (Morton, R.D et al., 2024). The two approaches differ slightly in terms of the habitats included in their classification schemes, and in terms of the precise manner of their outputs, but share a fundamentally similar approach to classification, and produce maps that are, in our eyes, of equal validity. They therefore provide a valuable double source of habitat classification data and an opportunity to compare outputs from the two sources using the same methodology.

Figure 2.14 compares the above-ground carbon storage estimates for four of the 9 km x 9 km tiles in our sample. Each estimation for each tile was derived using photogrammetric topology and 3 m cell size models), and we estimated carbon storage using three methodologies: *base* model, *tree-height* model, and *feature-height* model.

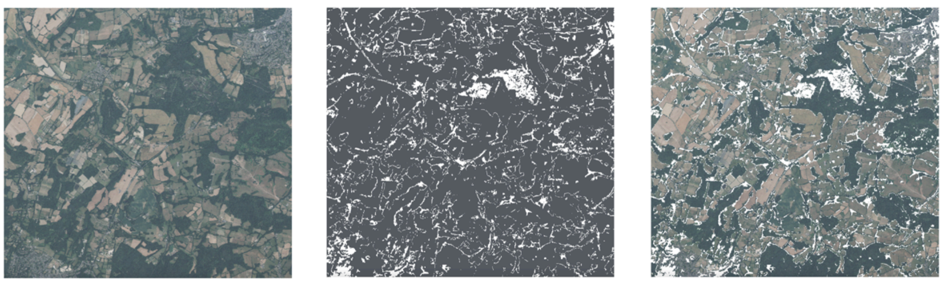
There is no consistent pattern of difference between the two data sources. For the *feature-height* model, the LE data source provides estimates that are 5-10% higher than the CEH data across all methodologies. For the *tree-height* methodology, the trend is reversed, with LE providing between 0-10% lower estimates for the same tiles. The base model is in-between with, on average, no difference across the four tiles.

## Figure 2.14 Data Sources: Habitat Classification




We think this pattern reflects the interaction between two different aspects of the data sources. In the case of the *tree-height* model, the *tree-height* methodology is very sensitive to the accuracy of habitat boundaries between woodland and other arable land (grassland, arable etc.) because carbon is only ‘counted’ in the woodland habitats. The two data sources disagree precisely where these habitat boundaries lie, and therefore which patch of landscape is deemed in woodland scope. For the *tree-height* model, Figure 2.15 illustrates these points of habitat disagreement in one of the tiles examined, and we find that it covers over 12% of the landscape. We believe that the CEH data source is more inclusive with respect to these boundaries i.e. it captures more of the woodland foliage found on these habitat edges. As a result, estimates using the CEH data source with this methodology are generally higher.

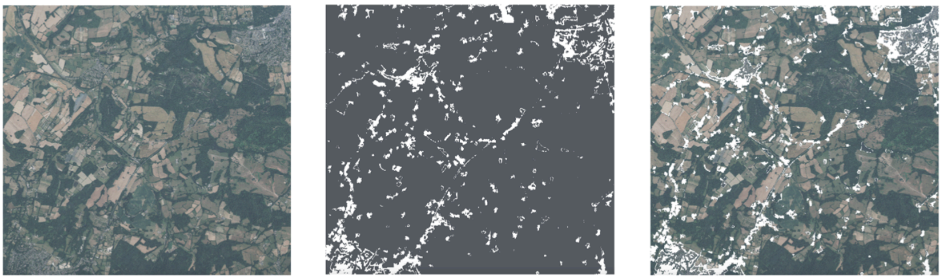
## Figure 2.15 Habitat Disagreement (tree-ht model)



**OS Aerial Photoraphy** | **Habitat Source Disagreement (12.3%)** | **Superposition**

For the *feature-height* model, however, these habitat boundaries are no longer important because all woodland and arable habitats are treated inclusively, i.e. features in all such habitats are treated as carbon storing. Habitat disagreement now is focused primarily on buildings, with the LE data set much more aggressive at identifying patches of the environment containing trees and shrubbery around buildings or within urban areas (figure 2.16). As a result, for the *feature-height* model, estimates using the LE data source are generally higher.

Figure 2.16 Habitat Disagreement (feature-ht model)



**OS Aerial Photoraphy** | **Habitat Source Disagreement (8.9%)** | **Superposition**

We choose, therefore, not to prefer one data source systematically over the other, but we use these habitat disagreement plots to identify locations in the landscape where uncertainty in the level of carbon storage is higher (see Chapter 3).

### 11. Do the models produce carbon-storage maps of sufficient resolution and accuracy that they are likely to be useful?

The utility of these carbon storage maps is an empirical question. In terms of visual resolution, however, they highlight in striking detail and at fine spatial detail the parts of the vegetative landscape that are storing significant carbon. Analytically, we find this allows us to use these maps to answer useful follow-on questions. The shift in visual fidelity from the *base* model to the *base+tree-height* is striking. The improvements in capturing fine landscape details, lone trees and hedgerows are likewise striking as we move from the *base+tree-height* to the *feature-height* models. From the perspective of higher resolution analysis with the aim of capturing small details and incremental changes in the landscape, it appears that each model is progressively more useful.

The accuracy of these maps is likewise an open question. The ability to model at high resolution will allow us to make direct comparisons between these approaches and detailed high resolution on-the-ground analyses, work that is ongoing (see below). These comparisons should allow us to improve the models and gain a better understanding of their likely accuracy and uncertainty ranges.

# Chapter 3. Incorporating Uncertainty into Landscape Models

## 1. Introduction

Policymakers must often take decisions under conditions of high uncertainty, making trade-offs between competing interests for the allocation of scarce resources, for example. Unfortunately, attempts to quantify the impact of a decision may be so prone to error that the value of that quantification as a support for a decision is questionable. We know that all models are wrong, but when are they useful?

Notwithstanding these concerns, decisions must be made. The goal of this chapter is to explore approaches for providing, in a landscape analysis, quantitative evidence that is accompanied by estimates on the degree of uncertainty associated with that evidence, in a manner that is useful and visually intuitive, such that policymakers can decide relatively easily what weight to place on the available evidence in their decision-making.

The intention is that uncertainties are propagated appropriately through a model and are traceable back to their original source, where possible. Here, we implement these approaches into our four above-ground carbon storage models from the previous chapter and offer some initial conclusions.

## 2. Statement of the problem

**Need to combine uncertainty and level-of-confidence.** Uncertainty is sometimes divided into a numerical estimate of the range of values associated with some quantified evidence, together with the statistical implications arising, and a qualitative estimate of confidence in the reliability of the evidence. For example, in the Natural England Research Report NERR094, "Carbon storage and sequestration by habitat", (Gregg et al., 2021), estimates of the average carbon stored and sequestered by vegetation are gathered from reviews of the available literature, and these estimates are accompanied by an important summary of the authors' confidence in the figures ("low", "medium", "high").

These qualitative assessments provide an important warning for decision-makers, but it is difficult for policymakers to make use of evidence in decisions if the qualitative warning isn't folded into quantitative estimates of uncertainty. Ideally, we would like to do this, giving policymakers an improved sense of the uncertainty identified.

**Need to make locations and implications of uncertainty as clear as possible.** We are looking for visually intuitive but useful ways of portraying geospatial landscape uncertainty in a manner that assists with decision-making.

## 3. Contributions to addressing the problem

**Need to combine uncertainty and level-of-confidence.** We propose a simple framework that combines all sources of uncertainty into one figure, providing a single measure of uncertainty that incorporates degree of confidence. We structure sources of uncertainty into two categories: (i) "data uncertainty", uncertainty attributable to problems with the data, including measurement errors, natural variation, and missing or otherwise problematic data; and (ii) "methodological uncertainty", which is primarily driven by our limited confidence in our models. The latter sources of uncertainty are typically signalled qualitatively (e.g. "low confidence") so this approach attempts to integrate such concerns into a numerical framework.

These differing sources of uncertainty need to be estimated and then propagated appropriately and/or conservatively through a model to capture a realistic approximation of uncertainty that is of some value to a decision-maker.

**Need to make locations and implications of uncertainty as clear as possible.** We propose how evidence and uncertainty might be displayed visually to convey data and uncertainty in a visually intuitive but useful fashion for the decision-maker.

**Specific application.** We currently apply these approaches to incorporate uncertainty estimates into the following assessments:

- What is the uncertainty (standard deviation) associated with a measurement of something at a single unit patch of landscape (a single cell in our LIMMMA model, typically varying in size from 1.5 m (field level, zoom 24) to 24 m (regional level, zoom 20).
- What is the uncertainty (standard deviation) associated with the measurement of the total (sum) of something across an extent made up of multiple modelled patches?
- What is the uncertainty (standard deviation) associated with the estimation of the average value of something across an extent made up of multiple modelled patches?

## 4. Summary of method to combine estimates of uncertainty into one figure

Under our simple scheme, the process of propagating uncertainty through a model is as follows:

- identify the key sources of uncertainty to be quantified (both data and methodological)
- Provide a reasonable best-guess estimate of their size
- Propagate the variances appropriately through the model to the output
- Combine uncertainties with a method for combination

### Identify key sources of uncertainty to be quantified

This is an (incomplete) list of uncertainty sources that we may wish to specify, quantify, and combine in a model:

| Type<br>*Sub-Type* | Description |
|---|---|
| **Data**<br>*measurement* | measurement error / uncertainty |
| **Data**<br>*natural / statistical* | variability around model parameter fit to data due to natural variation or other parameterization issues |
| **Data**<br>*Missing data* | missing data requires interpolation or other assumptions |
| **Methodological**<br>*miscalibration* | model not calibrated to local conditions |
| **Methodological**<br>*alternatives* | models of equivalent credibility produce differing values |
| **Methodological** | poor scientific understanding of the phenomenon being modelled |

| Type<br>*Sub-Type* | Description |
|---|---|
| *understanding* | |
| **Methodological**<br>*black box* | “black box” ML model with unpredictable failure modes |
| **Methodological**<br>*proxy* | proxy values used in a model for some known causal factor |
| **Methodological**<br>*simplification* | deliberately simplified models used due to limitations in available data |

In some circumstances, identified uncertainties may also suggest an increase or decrease in the modelled figures themselves to offset for miscalibration arising from the uncertainty.

### Method for combination

We combine uncertainties under the conservative assumption of independence, adding together the variances of each separate component of uncertainty to estimate the variance of the whole.

For an individual patch in the model, the standard deviation of the estimate for the patch (uncertainty estimate) is then the square root of this sum.

For an extent, the uncertainty of the sum of the estimated figure is the square root of the sum of each patch’s total variance.

The uncertainty of the average (the standard error) is this figure divided by the square root of the number of patches in the extent.

## 5. Case Study: Above-Ground Carbon feature-height model

We have implemented a preliminary uncertainty analysis of the above-ground feature-height carbon storage model.

### Identifying and Estimating Uncertainty in the feature-height model

We identified and estimated uncertainty around several features in the model, outlined in the table below. We identified four sources of uncertainty:

i. Uncertainty around the measurement of carbon-storing feature heights (tree canopy etc.) We estimated it as 4% of height for 1 standard deviation (sd) i.e. a 60 cm uncertainty on a 15 m tree.
ii. Uncertainty around the best fit model parameter for the allometric equation (see Appendix), considering natural variation. We modelled this as 1 sd equivalent to a 15% change in the slope estimate for the best fit relationship between carbon storage and feature height.
iii. Uncertainty around the possible presence of false positive signals for carbon storage in non-woodland arable, grassland habitats. We estimated this as small: a 1 sd equivalent to 1 tC/ha.

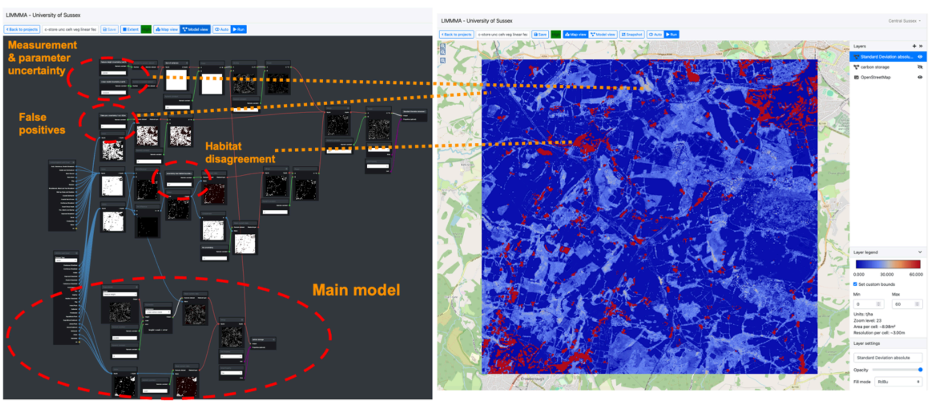
iv. “Black box” uncertainty from disagreement in critical habitat classification between our two reference maps (CEH, Living England). For this model, it is present most notably around buildings and in urban/suburban areas, where LE may identify woodland or grassland which CEH more conservatively labels as urban or suburban. We estimated this as a large effect on uncertainty, 1 sd = 60 tC/ha, where it occurs.

| Type<br>*Sub-Type* | Description | Estimate |
|---|---|---|
| **(i) Data**<br>*measurement* | Measurement of feature height (photogrammetric terrain, surface) | 1 sd = 4% of height (e.g. 60cm on 15m tree). variance (var) = 0.0016 |
| **(ii) Data**<br>*natural / statistical* | variability around model parameter fit to data due to natural variation or other parameterization issues | Parameter fit 1.s.d = +/- 15% multiplier. variance = 0.02225 |
| **(iii) Data**<br>*missing data* | missing data requires interpolation or other assumptions | False positives on arable, grassland 1 sd =1 tC/ha. Var = 0.1 |
| **(iv) Methodological**<br>*black box* | “black box” ML model with unpredictable failure modes | locations of disagreement in habitat map. 1 sd = 60 tC/ha var = 3600 |

### Propagating uncertainty through the model

The left panel of figure 3.1shows the model view for this version of the *feature-height* model. The bulk of the modelling is now devoted to estimating and propagating uncertainty, with the main model, estimating the carbon storage, occupying the lower part of the model view. The sections of the model processing and propagating the four identified uncertainty types are identified in the left-hand panel.

Figure 3.1 Feature-Height Uncertainty




### Output: a complex uncertainty map

The panel on the right-hand side of figure 3.1 shows the resulting uncertainty map, which is relatively complex geospatially notwithstanding the simplicity of the approach.

Uncertainty items (i) and (ii) in the table (measurement and parameter uncertainty, top left) give rise to uncertainty typically in the region of 20-30 tC/ha in the woodland areas, showing up as uncertainty the magnitude of which is proportional to the height of the features.

For item (iii) in the table, false positive signals would be seen on arable and grassland areas; these typically have minimal carbon signals except where there are hedgerows and lone trees. The false positive assumption adds a small 1 tC/ha uncertainty across these entire habitats, which is not noticeable on the 0-60 tC/ha colour scale.

For item (iv), most significantly, we see strong uncertainty signals in those regions of the map where the CEH and LE habitat maps disagree with one another. These disagreements are largely confined to built-up areas, specifically in three areas of this 9 km x 9 km tile.

We see, therefore, that uncertainty is very unevenly distributed across the landscape. The analysis highlights a key weak aspect of this model, namely that it under-examines the carbon storage contribution from built-up areas. This is particularly important when examining habitats in the UK in general, and England in particular, where built-up and rural landscapes are intimately intertwined. A more precise modelling of these built-up areas, considering urban treescapes and gardens, should lead to a better and more accurate assessment of the impact of changes to these mixed landscapes.

## 6. Case Study: Above-Ground Carbon tree-height model

We have implemented, for comparison purposes, a slightly simplified version of the standard *tree-height* model, with propagation of uncertainty estimates through the model. (This version of the model treats non-woodland habitats in a simplified manner.) The analysis reveals an appropriate method for locally re-calibrating the tree-height model and illustrates the better performance of the *feature-height* model in the rural landscape.

### Identifying and Estimating Uncertainty in the *tree-height* model

The uncertainties labelled (i), (ii) and (iv) in the *feature-height* model, were of the same form and magnitude here. Recall, however, that the form of habitat disagreement here is different (see discussion in Chapter 2); the geographical distribution of the habitat disagreement uncertainty therefore suffers for this model. Uncertainty (iii) from the *feature-height* model is not relevant.

The fact that this model captures neither hedgerows nor lone trees in the arable and grassland habitats is a new and relevant source of uncertainty, however. We capture this in two ways. First, we re-calibrate the model by adding a background carbon storage intensity of 15 tC/ha across these arable and grassland habitats; this calibration offset compensates for the inability of the model to locate hedgerows and lone trees (item (iii) in table, below). This area of the UK countryside has a high density of mature hedgerows and lone trees; such a level of local re-calibration would overstate carbon storage in other parts of the UK, reflecting a weakness in the *tree-height* model. Second, we add uncertainty to this background figure across these habitats (1 sd = 7.5 tC/ha) (item (iv)), to reflect the fact that we don’t know where or whether the lone trees and hedgerows are in fact to be found here (they might be playing fields, and so forth).

The following table captures our uncertainty assumptions:

| Type<br>*Sub-Type* | Description | Estimate |
|---|---|---|
| **(i) Data**<br>*measurement* | Measurement of feature height (photogrammetric terrain, surface) | 1 sd = 4% of height (e.g. 60 cm on 15 m tree). variance (var) = 0.0016 |
| **(ii) Data**<br>*natural / statistical* | variability around model parameter fit to data due to natural variation or other parameterization issues | Parameter fit 1.s.d = +/- 15% multiplier. variance = 0.02225 |
| **(iii) Methodological**<br>*miscalibration* | model not calibrated to local conditions | Add background 15 tC/ha to arable and grassland habitats |
| **(iv) Data**<br>*missing data* | missing data requires interpolation or other assumptions | Uncertainty around missing hedges & lone trees. 1 sd = 7.5 tC/ha for arable and grassland habitats |
| **(v) Methodological**<br>*black box* | "black box" ML model with unpredictable failure modes | locations of disagreement in habitat map. 1 sd = 60 tC/ha var = 3600 |

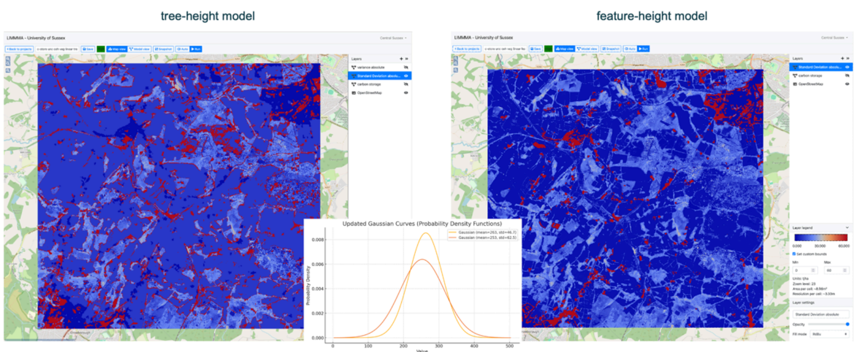
### Propagating uncertainty through the model

The model is extremely similar to the *feature-height* model with changes to handle the calibration offset and greater uncertainty for arable and grassland habitats, while removing the very small false positive signal.

### Output: comparing the *tree-height* and *feature-height* models

Figure 3.2 compares the uncertainty maps for the *tree-height* and *feature-height* models across an example 9 km x 9 km tile. We see a higher level of background uncertainty across the arable and grassland landscape for the tree-height model, reflecting the uncertainty as to the location of hedgerows and trees. We also see a different and more widespread pattern of large uncertainty attributable to habitat uncertainty. We calculate the estimated total carbon storage for this tile for the two models (centre panel) and we see that the offset calibration has had the desired effect. Total carbon storage is now estimated at 253 ktC for the *tree-height* model and 263 ktC for the *feature-height* model. The uncertainty distribution, however, is broader for the *tree-height* (62.5 ktC) versus the *feature-height* (46.7 ktC) model, reflecting overall greater precision for this model.

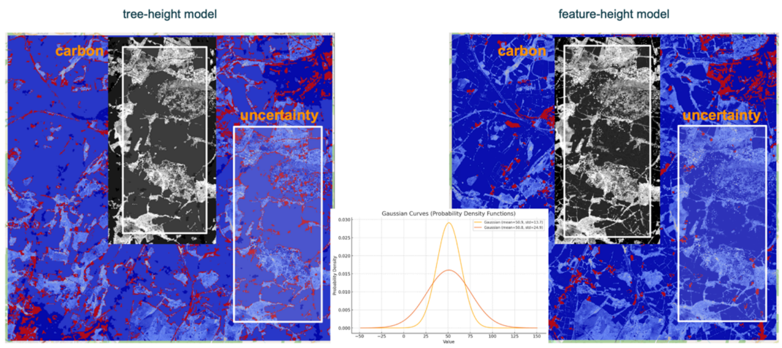
Figure 3.2 feature-height v tree-height uncertainty




Under this analysis, the estimate of above-ground carbon stored (ktC) for the tree-height model has a slightly lower mean and a broader uncertainty distribution

This advantage for the *feature-height* model is demonstrated more clearly if we focus on a purely rural patch of landscape (figure 3.3). Here we see much finer detail in the *feature-height* carbon storage landscape (grayscale landscape on right) versus the *tree-height* model (grayscale landscape on left). The total estimated carbon storage agrees precisely for the two models, but we see much less uncertainty in the readout for the *feature height* model (mean 50.9, standard deviation 13.7) versus the *tree-height* model (mean 50.8, standard deviation 24.9).

Figure 3.3 feature-height v tree-height uncertainty




For purely countryside landscape, the benefit of the feature-height model is more readily apparent. Carbon storage for outlined area (ktC).

The advantages of the *feature-height* model seem clear: only a large reassessment of the probability of false positives is likely to move the analysis.

The analysis to date, however, clearly understates problems in built-up areas. The models were not designed to handle built-up areas - and it shows. Our experience here with the intertwined rural / built landscape of southern England demonstrates that this approach can be improved by more detailed examination of built-up areas.

## 7. Visualisation of uncertainty

We propose how evidence and uncertainty might be displayed visually to convey data and uncertainty in an intuitive but useful fashion for the decision-maker.

### Core offering: the mixin display on LIMMMA

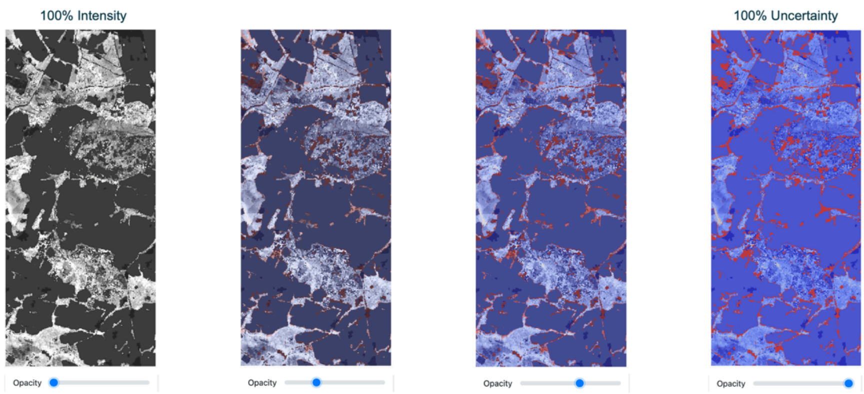
For the core visualisation requirement, we propose that false colouration can be used to indicate areas on the map of higher and lower uncertainty.

Specifically, we display the value being measured (e.g. carbon storage, in tC/ha) using grayscale as one layer on the map view. We then also display the uncertainty associated with the estimate (e.g. standard deviation of the estimate, also in tC/ha) as the next highest layer on the map view. This is displayed using a colour palette that shows blue at the lower end, grey in the middle, and red at the upper end of the scale.

The transparency of this uncertainty layer can then be adjusted using a slider control to mix the grayscale intensity and the false colour uncertainty. Setting the slider at one end shows just the (grayscale) intensity map, setting it at the other end shows just the (false colour) uncertainty may, while intermediate settings mix the two.

Figure 3.4 shows a practical example with both ends and two intermediate settings shown.

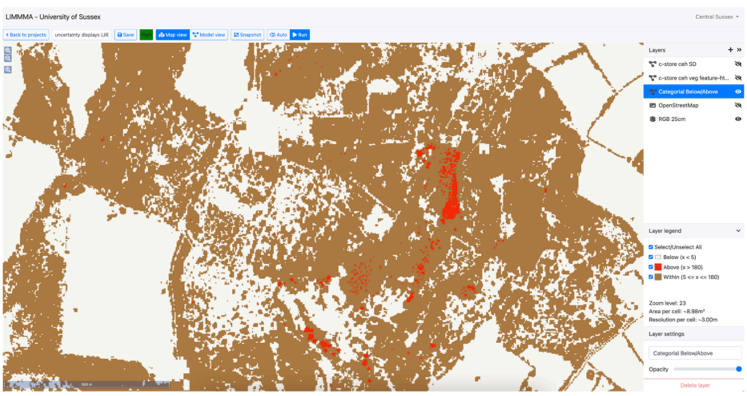
Figure 3.4  mixin display




## Greater-lower display on LIMMMA

A secondary display can be used to identify patches of landscape that are significantly lower or higher than either a fixed figure (known precise amount) or the estimated figure of another patch of landscape (an estimate with an uncertainty distribution). This ‘greater-lower’ approach is under development in LIMMMA; it is being reviewed to determine its practicality and usefulness. Figure 3.5 shows an example of the display.

Figure 3.5  greater-lower display



# Chapter 4. Below-Ground Carbon Storage

This chapter summarises our work developing below-ground estimates of carbon storage in soil; this can then be combined with the above-ground work to produce a view on total landscape carbon storage (see Chapter 5).

We outline our use of existing external data, review work derived from the Wakehurst team's investigations for this project, and provide simple additional models that make use of some of these insights and can usefully be applied, or combined with the other data sources, for an integrated view on below-ground carbon storage.

## 1. Using available data sources: NATMAP and ISRIC

Our approach is to make use where possible of standard external data sources, and to allow researchers to use them for bespoke analysis. Where possible, therefore, we make use of established external data sets. For below-ground carbon storage, several well-resourced external agencies have developed UK-wide geospatial data sets for below-ground carbon storage. Our first port of call, therefore, is to make use of these.

We currently have access to data sets from NATMAP and ISRIC. Available geospatial data include both estimates of below-ground carbon storage in the soil and estimates of uncertainty. The ISRIC data is prepared on a grid basis, while the NATMAP data set is habitat driven, so the pattern of estimates is driven by the shape of the underlying habitat map that was used.

Our preferred approach is to combine these two independent assessments, working on the grounds that a combination of the two approaches should reduce uncertainty. It also helps to increase the spatial frequency of the map, although this may be as much noise as signal.

Figure 4.1 provides carbon storage mixin maps for 0-30 cm (the first 30 cm of soil depth) in LIMMMA from NATMAP (left panel), ISRIC (middle panel), and an equally weighted combination of the two models (NATMAP/ISRIC – right panel) for a sample tile from the South East Sussex area.

Figure 4.1 ISRIC, NATMAP and combo display

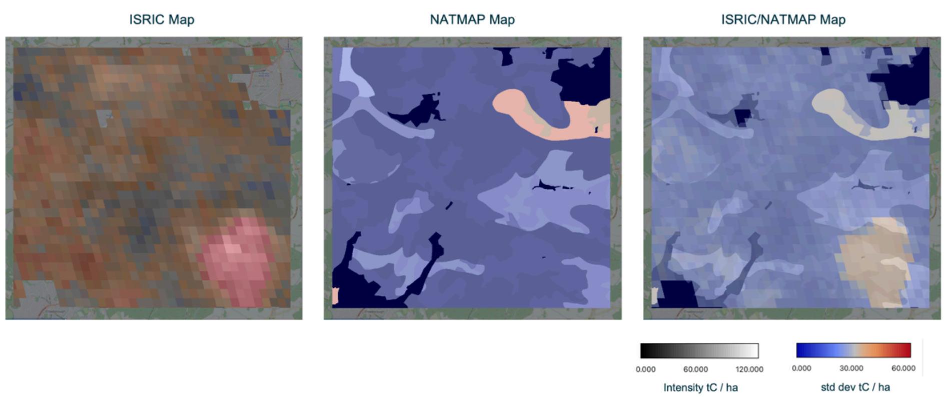
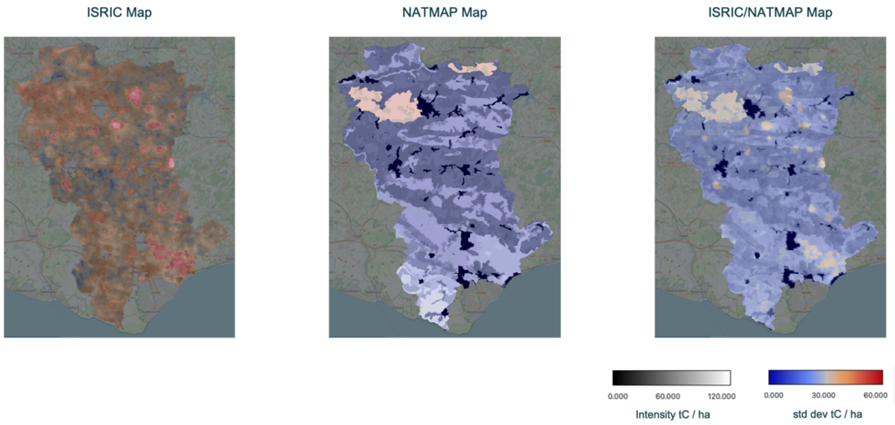


Figure 4.2 gives a larger-scale view, plotting the same data for the whole Wealden District Council area in East Sussex.

Figure 4.2 ISRIC, NATMAP and combo display




The two maps provide independent analyses, and we assume that this combination therefore reduces the underlying associated uncertainty.

A challenge is that the NATMAP data, unlike the ISRIC data, is not in general freely available for researchers and decision-makers. Additional soil databases are likely to remain behind paywalls. In addition, the mechanisms underpinning below-ground carbon storage are poorly understood. All these factors spur on further approaches to understanding the relationship between observable landscape features and below-ground carbon storage.

## 2. Insights from Wakehurst team investigations

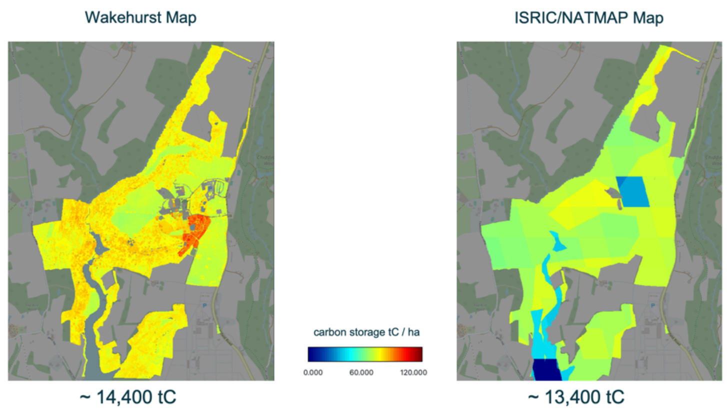
As a component of the Nature Returns project, the Wakehurst team undertook detailed sampling activities across the site. The team is focused on advancing our scientific knowledge of underlying mechanisms for carbon storage but also conducted, in collaboration with us, a piece of work looking at using simple, nationally available data types and their relationship to below-ground carbon storage, as seen on the Wakehurst site.

For this particular piece of work, the Wakehurst team looked at five variables for regression analysis: (i) woodland canopy height; (ii) terrain moistness; (iii) soil nitrogen; (iv) soil pH; and (v) sand/clay content ratio. These variables are known or believed to be associated with below-ground carbon storage.

Using a mixed-effect regression analysis, regression slopes were derived for these variables, each of which was statistically significant in the analysis, with additional offsets for: (i) the Wakehurst habitats, and (ii) soil depth (0-15 cm, 16-30 cm).

Using sample interpolation, for variables (iii) to (v), to estimate values for these input variables across the whole Wakehurst site, the Wakehurst team derived the following modelled map of below-ground carbon for the Wakehurst site using these equations (figure 4.3, left panel). In this figure, the map produced for this analysis by the Wakehurst team is compared to an equivalent map created in LIMMMA by combining the ISRIC and NATMAP 0-30 cm maps for the Wakehurst site (figure 4.3, right panel). The two approaches produce estimates of total below-ground carbon storage in the first 30 cm of soil that are within 7% of one another.

Figure 4.3 below-ground carbon storage




## 3. Replication of work by Wakehurst team

We have replicated preliminary versions of the work undertaken by the Wakehurst team, with the aim of implementing the model in LIMMMA and both scaling and extrapolating the findings. This version is based on 4 of the 5 regression variables used in the Wakehurst model: (i) woodland canopy height; (ii) soil nitrogen; (iii) soil pH; and (iv) sand/clay content ratio. A 5-variable version will follow once the terrain moistness measure has been implemented in LIMMMA.

The plan is to extrapolate this model in LIMMMA across the UK, using nationally available data sets that capture each of these variables, specifically:

| Variable | Available data source |
|---|---|
| woodland canopy height | Estimated from photogrammetric Digital Terrain and Surface models |
| soil nitrogen | ISRIC soil data |
| soil pH | ISRIC soil data |
| sand/clay content ratio | ISRIC soil data |
| *terrain moistness* | *Use photogrammetric data and replicate known algorithms - not yet included* |

The Wakehurst model was derived for a set of specific Wakehurst habitats. For the first iteration of the UK-wide model, we map these on to standard CEH and Living England habitats as follows:

| Wakehurst Habitat | Maps on to CEH Habitat | Maps on to Living England Habitat | Notes |
|---|---|---|---|
| Broadleaved Woodland<br>Hedgerow | Deciduous Woodland | Broadleaved, Mixed and Yew Woodland | |
| Coniferous Woodland | Coniferous Woodland | Coniferous Woodland | |
| Meadow<br>Pasture | Arable, Improved Grassland, Neutral Grassland, Acid Grassland, Heather Grassland | Acid, Calcareous, Neutral Grassland, Arable & Horticultural, Bare Ground, Improved Grassland, Scrub | |
| Garden Woodland<br>Garden Bed<br>Lawn | | | Not used in general |
| | Fen<br>Heather, Bog, Saltmarsh | Bog, Bracken, Coastal Saltmarsh, Coastal Sand Dunes, Dwarf Shrub Heath, Fen, Marsh & Swamp | Use habitat estimates in Natural England (2021) |
| | Inland Rock, Saltwater Freshwater, Supralittoral Rock, Littoral Rock, Supralittoral Sediment | Bare sand, Water | Set to zero |

Note that the two variables that are directly derivable by remote sensing (woodland canopy height, terrain moistness) contribute only weakly to the variation in carbon storage figures observed on the Wakehurst site. An equivalent model limited to only these two regression variables, accounts for only 1.1% of the variance (after adjustment of the correlation coefficient).

In short, the power of this regression model is dominated by the soil nitrogen reading, and a national model will likewise be dominated by the soil nitrogen estimate, which here we take from the ISRIC data. ISRIC already provides its own direct estimates of organic carbon storage in the first 30 cm, which we are already using. It therefore remains to be seen whether this new model will provide a useful addition to the available ISRIC estimates in these circumstances.

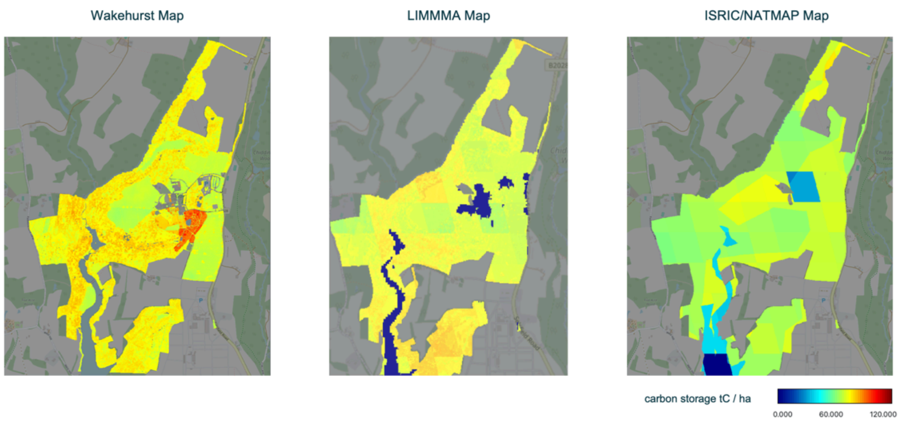
We do note, however, that while the effect of canopy height is small in the regression model, it is consistent. In the 5-variable, 4-variable and in the 2-variable versions of the model, the coefficient attributable to canopy height remained constant, suggesting that the effect is likely independent of the other variables and therefore plausibly adding useful information.

## 4. Comparison of Maps: Wakehurst team, LIMMMA implementation, ISRIC, NATMAP

Figure 4.4 provides a visual example of the output from the new LIMMMA generic model. On the left we show the Wakehurst map, developed from the illustrative model provided by the Wakehurst below-ground research team. On the right, we show the output obtained from mixing the available ISRIC and NATMAP below-ground carbon storage maps. The centre panel shows the output of the LIMMMA generic model.

The comparison shows clearly the familial relationship between these three models. The LIMMMA model captures four of the five variables used in this Wakehurst model (soil nitrogen, soil pH, sand/clay ratio, and canopy height; terrain moistness not implemented). Note, however, that the LIMMMA map is not using the figures gathered for these variables by the Wakehurst team on site, but rather is using nationally-available estimates. The ISRIC database is providing estimates for the first three of these four variables and the characteristic rectangular shape of these data points from ISRIC help give the LIMMMA map a familial resemblance to the ISRIC/NATMAP below-ground carbon map.

Figure 4.4 Wakehurst, LIMMMA, ISRIC/NATMAP




Further investigation suggests that the LIMMMA map tracks the Wakehurst map well. In figure 5.3 (next chapter) we compare the readouts of the Wakehurst and LIMMMA carbon storage models in smaller sub-plots within the site. We focus there on total carbon storage (above- and below- ground), but we also looked specifically at the isolated below-ground carbon storage estimates for the whole site and for each of the sub-plots outlined in figure 5.3. We find good agreement between models:

| Below-Ground Carbon Storage (0-30cm) tC | Wakehurst Model | LIMMMA Model | Percentage Difference |
|---|---|---|---|
| Main Area | 14,393 | 14,361 | +0.2% |
| Sub-Area 1 | 452 | 459 | -1.5% |
| Sub-Area 2 | 396 | 372 | +6.5% |
| Sub-Area 3 | 747 | 768 | -2.7% |
| Sub-Area 4 | 640 | 654 | -2.1% |

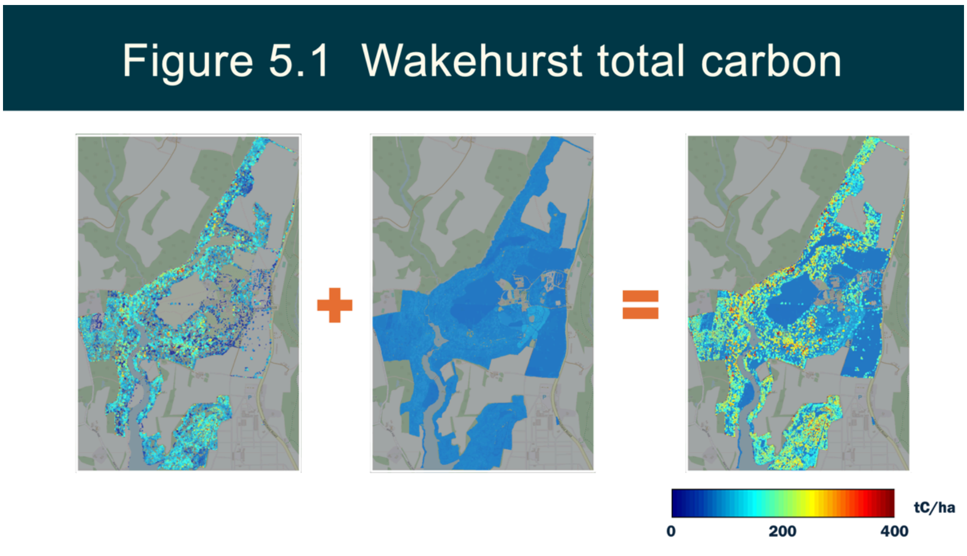
# Chapter 5. Total Carbon: Combining Above- and Below-Ground Storage

In general, we are interested in understanding the total carbon stored in the landscape above-ground and in the upper soil below-ground, because changes in landscape use affect both. It makes sense, however, to measure each separately before combination, because different variables drive the carbon take-up and different observations are used to measure carbon storage. The approach adopted here is, therefore, as outlined above - using quite different methods to measure each and then combining the two sets of estimates for a total carbon storage map.

It is a simple matter to combine above-ground and below-ground carbon maps in LIMMMA through the model interface. This chapter offers summary illustrative combinations of above-ground and below-ground carbon storage maps (a) for Wakehurst, using both Wakehurst team analyses and our LIMMMA-implemented equivalents (field level), (b) for an even higher-resolution view (field level), (c) for a sample tile from the Central South East Region (local level), and (d) for the administrative area of the Wealden District Council (regional level). The chapter concludes by summarising the strengths of the approach, the outstanding challenges, and the proposed next steps.

## 1. Wakehurst Team total carbon storage on Wakehurst site

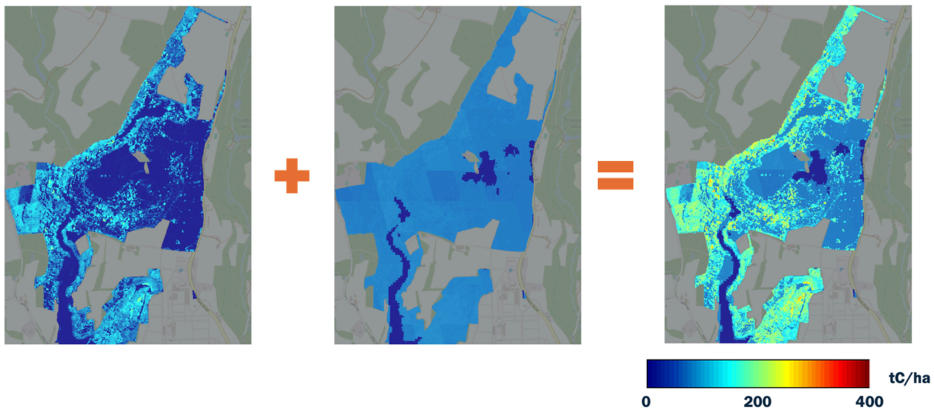
For figure 5.1, we were able to import into LIMMMA the illustrative carbon storage maps generated separately by the above-ground and below-ground Wakehurst teams, as outlined in Chapters 3 and 4 above, and combine them to provide a detailed analysis and geospatial map of total carbon storage across the Wakehurst site. This provides a detailed, high resolution, estimate of the carbon stored across the estate.




## 2. Scalable and extendable mapping: Wakehurst site

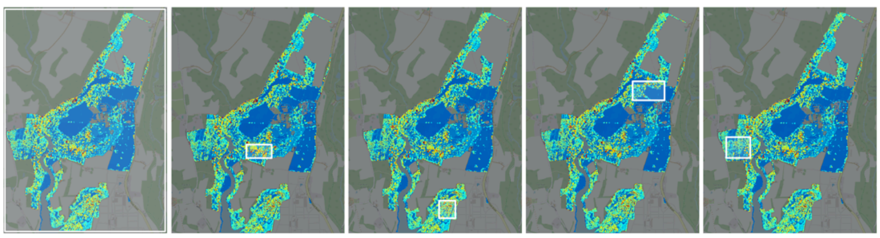
The remit for our work was to create a set of generic projects in LIMMMA that allow us to generate as-close-as-possible to equivalent maps at multiple scales (field, local and regional), with an approach that is extendable across the UK. Looking first at the Wakehurst site itself, figure 5.2 shows our analysis of the Wakehurst site, using nationally available data sets and our generic above-ground and below-ground approaches, implemented in LIMMMA.

## Figure 5.2 LIMMMA total carbon




In figure 5.3, below, we examine in more detail the closeness in agreement between the Wakehurst detailed analysis and the LIMMMA generic mapping of the site. For the site as a whole, and for a selection of small sub-areas within the Wakehurst site, the Wakehurst and LIMMMA models agree quite closely in terms of the absolute amounts of carbon estimated as being stored, and the split between above- and below-ground (0-30 cm) carbon storage. The last sub-area examined here is the only one where a significant discrepancy is found, with LIMMMA apparently over-estimating above-ground storage.

## Figure 5.3 Wakehurst vs LIMMMA



| | | | | | | |
|---|---|---|---|---|---|---|
| above-ground as % total | Wakehurst | 43% | 51% | 58% | 32% | 45% |
| | LIMMMA | 41% | 47% | 57% | 30% | 55% |
| total carbon tC | Wakehurst | 25,100 | 931 | 884 | 1,062 | 1,183 |
| | LIMMMA | 24,600 | 860 | 926 | 1,124 | 1,435 |
| % disagree LIMMMA/Wakehurst | | -2.4% | -7.6% | +4.8% | -5.5% | +21% |

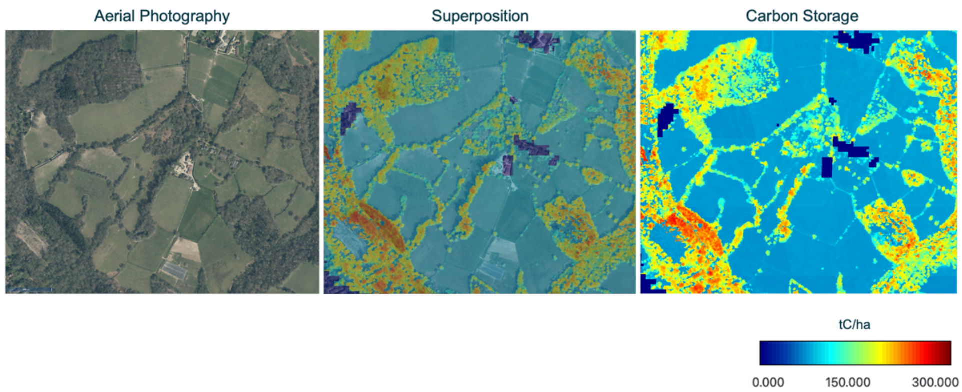
These comparisons are taken with LIMMMA models before the final re-calibration (see the Appendix); the discrepancy in this last sub-area may, in part, be attributable to over-estimation of coniferous carbon storage in the LIMMMA model before re-calibration. Overall, after re-calibration, we would expect the LIMMMA above-ground model landscape maps typically to increase significantly in signal strength in this part of the country, but this will depend on the amount of woodland and mix between coniferous (-10% signal strength) and deciduous (+21% signal strength) woodland in the landscape being studied.

## 3. Scalable and extendable mapping: field, local and regional scales

Ultimately, the goal is to demonstrate this capability across field, local and regional scales and a diverse range of habitats. For illustrative purposes, the following figures provide demonstrations of our current capabilities.

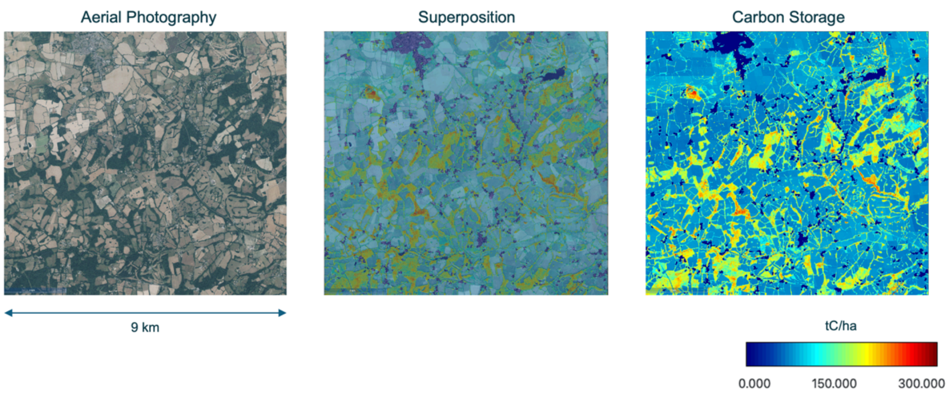
**Capabilities at field level.** In addition to the field-level analysis of the Wakehurst site itself above (figure 5.2), figure 5.4 shows an analysis at very high field resolution for a small patch of terrain just to the east of the Wakehurst site. The left-hand panel shows aerial photography of the area (Bluesky International 25cm aerial imagery). The right-hand panel shows the LIMMMA total carbon model for the landscape. The centre panel superimposes the two views, confirming that all of the visible relevant carbon-storing landscape features have been captured at high resolution in the assessment including lone trees, bushes and small hedgerows.

Figure 5.4 total carbon: field-level



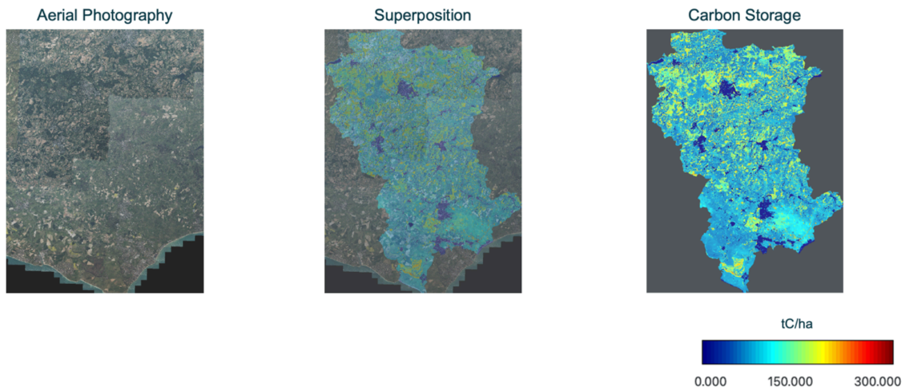

**Capabilities at local level.** Figure 5.5 shows a sample tile (9km x 9km) from the Central South East Region, our overall area of study. The same generic LIMMMA above-ground and below-ground models have been applied to this local area view as were applied to the examples above, the only difference being the extent, the specification of the landscape. Run-time for each model is 2-3 minutes.

Figure 5.5 total carbon: local-level



**Capabilities at regional level.** Figure 5.6 shows model output and analysis for the entire Wealden District Council region (835 $km^2$). As before, the same generic models are applied with the only change being the specification of the extent. The time taken to produce a map is likewise unchanged. The LIMMMA system is capable of mapping up to an area of over 5,000$km^2$ at this level of detail.

Figure 5.6 total carbon: regional-level




## 4. Challenges and Next Steps

There are several identified opportunities to improve the performance of our carbon storage approach.

### a. Improve carbon storage calculations in built-up areas

Our preferred *feature-height* model is much less susceptible to uncertainties in the precise habitat boundaries and habitat classifications than the other models studied. In this respect we believe it to be more accurate at field level than our other approaches, even after local calibration. Issues remain around habitat designation, however. Disagreements are found between CEH and LE habitat data sets that are relevant to the model; these focus on built-up areas - suburban and urban environments, but also small clusters of buildings, hamlets, and villages. The original remit of the work was restricted to “rural landscapes” but, in the region of the country where this work has been covered (an area we termed the Central South East Region), rural and built-up areas are closely intertwined.

Accuracy would be increased, and uncertainty reduced, therefore, by tackling carbon estimation in these built-up areas directly. Our plan is to tackle this challenge separately to the existing rural above-ground and rural-below-ground approaches, because the data sources and approaches will likely differ. A composite picture can then be created by combining the three model outputs (above-ground rural, below-ground rural, built-up areas).

### b. Improve below-ground carbon storage calculations using freely available national data

The work from the below-ground Wakehurst team has allowed us to specify a new below-ground carbon model using available national data sets. This work is described in Chapter 4 and is currently being refined further. Further emerging work from the same team will likely throw more light on the underlying mechanisms and open prospects for improved assessment of below-ground carbon storage. Our approach, and its implementation in LIMMMA, should allow new findings to be rapidly integrated into existing models.

### c. Diversify sources of topology estimation information

These remote-sensing approaches are all highly reliant on data that allows estimations of feature height in the landscape. This is achieved using either photogrammetric data, LiDAR data, satellite data, or a combination of them. At present our system works well with selected high-quality 2m photogrammetric data sets (Bluesky International Limited, photogrammetric DSM, photogrammetric DTM data sets), but we would like to diversify sources. Other photogrammetric data sets, LiDAR data sets, and satellite data sets are available; satellite data, for example, can potentially be updated more frequently and therefore is likely to offer more up-to-date topological information. In this project, we assessed a recently published data set derived from satellite data but found it unfortunately to be inaccurate. It should be possible, however, to derive more accurate data from available satellite feeds.

### d. Perform calibration across more diverse habitats and support investigations at other sites

The intensive Wakehurst pilot site investigation has allowed us to perform a detailed calibration of above-ground and below-ground carbon storage estimation at a field level, and check model stability across local and regional spatial scales, with the aim of extrapolating across the UK. Ongoing work from the above-ground team at Wakehurst may lead to further minor adjustments to settings. Further calibration work at other sites and diverse habitats and regions would be valuable for confirming and refining settings. The broader capabilities of LIMMMA are also ideal for supporting investigatory work at other locations and pilot sites in the UK.

## 5. Summary

Based on the findings of the Wakehurst teams, we have successfully developed generic models for estimating above-ground and below-ground carbon storage which can be deployed across a wide range of scales, and extrapolated across the UK. The specific raster-based approach that we adopted has exceeded our expectations; it seems to be capable of delivering highly detailed maps, provided that good quality feature height data sets are available. These approaches are neither fixed nor prescriptive; they can be readily updated to take advantage of new findings, modified or reconfigured by users to suit their specific needs, and combined with other approaches and other carbon-storage data sets to provide robust ensemble estimates.

When coupled with a technique that does not rely heavily on frequent habitat boundaries (in our case, this is the *feature-height* model), the approach we adopted seems capable of being used successfully across a very wide range of scales, here covering up to a region of 72 km x 72 km in a single model, without loss of consistency, in analysis of a patch of land. We feel the use of a single modelling approach across such a wide range of scales is both helpful and convenient for decision-makers, particularly as decisions typically involve consulting multiple geospatial analyses conducted at different scales.

For the below-ground carbon storage analysis, the LIMMMA approach makes it very straightforward to incorporate and combine data from existing external parties, and to combine these analyses with the above-ground work to provide effective combined carbon maps at differing scales. Our approach also allows us to rapidly incorporate new advances and techniques. We are in the process of making use of the emerging work by the below-ground team at Wakehurst and have created an additional mapping approach that can be used stand-alone or combined with other available data sets.

We have also identified suitable ways of specifying uncertainty, propagating it conservatively through these models, and displaying it in a way that helps decision-makers consider uncertainty without being overwhelmed by it.

Finally, the work recognises that carbon storage is only a single data type contributing towards multifunctional landscape decision-making. The LIMMMA system is primarily designed to bring together multiple data types and to allow them to be combined in novel, bespoke ways that help parties make decisions about the landscape where the full range of economic, cultural, socio-economic, and ecological factors can all be considered.

L **Landscape**
I **Integrative**
M **Mapping** and
M **Modelling** for
M **Multi-functional**
A **Analysis**

# Appendix. Detailed Re-Calibration of Above-Ground Carbon Storage

## 1. Introduction: tree-based vs cell-based modelling

Most remote-sensing landscape measurement is undertaken using a cell-based, also known as raster-based, approach. The properties of a particular small patch, or cell, of land are measured, estimated, or otherwise modelled. The patch is typically, but not exclusively, a square as seen from above; this is the case in the approach used by the LIMMMA platform. The properties of an entire landscape are then processed by aggregating together each of these patch (cell) measurements. In the case of the LIMMMA platform, a single model consists of an array of up to 10,000,000 such cells, contained in a rectangular spatial array that encompasses the extent, the area of landscape, being modelled.

This cell-based approach is straightforward and uncontroversial for most physical, economic, socio-economic and ecological forms of data. In the case of above-ground carbon storage, however, high resolution (field scale) detailed surveys have traditionally taken a “tree-based” approach, in which carbon storage is evaluated with a tree-by-tree, object-by-object approach. There are sensible reasons beyond custom for the tree-based approach; it is easier to calibrate tree-based approaches to a known amount of carbon storage when the carbon stored in individual trees can be reasonably well estimated on the ground using established field techniques. A tree-based approach therefore maps most readily onto these calibrated tree measurements.

### Tree-based modelling

Many detailed tree-based approaches are deployed for remote sensing techniques. Typically, a tree’s above-ground carbon storage, s(t), is estimated from the remote measurement of two variables: (i) the height of the tree, t, at its highest point, h(t); and (ii) the effective radius of the tree canopy as seen from above, r(t). The “effective radius” is the radius for a circle that would have the same area as that observed for the tree canopy from above. Again, several suitable allometric equations have been derived, but a typical equation would be of the form:

$$\log(s(t)) = a.\log(h(t).r(t)) + \log(b) \qquad \text{(i)}$$

where (a, b) are constants for a particular type of tree (e.g. temperate coniferous woodland, temperate deciduous woodland, …).

To summarise, using the tree-based approach for remote sensing, above-ground carbon storage is typically estimated by (i) splitting the landscape into individual “trees”; and then (ii) for each tree, measuring the maximum height of the tree and the effective radius of the tree canopy, as seen from above. The total above-ground carbon storage of a landscape is therefore calculated by summing together the carbon storage estimates for all the trees identified in the landscape.

### Cell-based modelling

The cell-based approach to remote-sensing estimation of above-ground carbon storage, that we use here for the LIMMMA platform, is somewhat different. For each cell, c, it is first determined whether above-ground carbon is being stored by some landscape feature in the cell. If so, the average height of the feature in the cell, j(c), is estimated. (We use “j” in preference to “h” to emphasize that the height of a feature in a cell bears no direct relation to the maximum height of a tree.) A simple allometric equation, using just a single variable, is used to estimate the carbon storage density sd(c) for the cell, from which the amount of above-ground carbon being stored in that cell can be derived by multiplying out by the unit area of the cell:

$$\log(sd(c)) = e.\log(j(c)) + \log(f) \quad \text{and}$$
$$s(c) = sd(c).u \qquad \text{(ii)}$$

where u is the unit area of the cell, and (e, f) are constants for a particular type of woodland (e.g. temperate coniferous woodland, temperate deciduous woodland, …).

Note that in the cell-based approach, there is no explicit concept of a “tree object” here, just that of a cell, or patch, containing stored carbon, where the carbon stored is estimated based on the measured average height of the feature storing the carbon. That feature is typically deemed to be a part of a “tree canopy” or something deemed equivalent e.g. the top of a hedge.

In other words, we are asking the question “how much carbon is being stored in this cell (patch) such that a feature (e.g. tree canopy) of this average height in this cell is observed?”. We might summarise this also as “how much carbon must be being stored to raise a patch of canopy to this height?”. The total above-ground carbon storage of a landscape is then calculated by summing together the carbon storage estimates for all the cells in the landscape.

### Comparing tree-based and cell-based modelling

We can make a direct comparison of the two approaches if we consider a landscape containing just a single lone tree.

For the tree-based approach summarised here, the total carbon estimate would be gained by estimating two variables, h(t) and r(t), and then applying allometric equation (i).

For the cell-based approach, it depends on the scale of the model. The cell size for a typical field-level model might be 3 m x 3 m. At this model scale (“z23”), seen from above the number of cells containing a part of a mature deciduous tree’s canopy might be of the order of 20 cells, in which case, the total carbon estimate would be gained by estimating 20 variables, j(c), one for each cell c containing tree canopy, applying equation (ii) to each cell, and then summing across those 20 cells.

For a much larger scale, where the size of the cell is significantly larger than the size of the canopy from above, then, in this case, the total carbon estimate might be based on a single, or a very few, such cells.

## 2. Initial Calibration

At an early stage in the current project, the Wakehurst team provided an illustrative initial calibration estimate for equation (ii) for our LIMMMA implementation of a cell-based approach.

This Wakehurst estimate gave the following values for (e, f):

$$e = 1$$
$$f = 0.560 \quad \text{where } sd(c) \text{ is measured in kg of C per } m^2$$

Data was very limited at this stage, so the same equation was used for all the feature types being modelled, namely temperate deciduous woodland, temperate coniferous woodland, hedges, lone trees and any other features. These simplified equations underlie all the calculations and figures presented in the current version of the report.

Note that, with e = 1, equation (ii) is linear and can be simplified to:

$$sd(c) = f.j(c) \quad \text{and}$$
$$s(c) = sd(c).u \qquad \text{(iii)}$$

where u is the unit area of the cell, and f is a constant for a particular type of tree (e.g. temperate coniferous woodland, temperate deciduous woodland, …).

## 3. Detailed re-calibration

By the end of this project, the above-ground Wakehurst team had gathered detailed estimates of the above-ground carbon stored in the entire woodland estate, with separate estimates for coniferous and deciduous woodland.

This was achieved by the Wakehurst team through a two-step process. In the first step, they undertook direct estimates of the carbon stored in a sample selection of deciduous and coniferous woodland trees on the estate, using established QSM (Quantitative Structure Modelling) techniques. They used these direct estimates to construct models, using a best fit analysis, for the deciduous and coniferous trees on the estate, which were of the form shown in equation (i).

For the deciduous and coniferous woodland, therefore, they derived separate estimates of the parameter pairs (a, b). Using these two models, it was therefore possible, for each tree in the estate, to measure h(t) and r(t) using photogrammetric data and thereby plot out the modelled distribution of the carbon stored across the estate, using photogrammetric data to identify the precise canopy shapes and place them in the landscape.

For each tree in the estate, therefore, the Wakehurst team were able to provide us an estimate of the total carbon stored s(t), and a geospatial shape file for the tree’s canopy, We were then able to turn this into a map of carbon density across the estate by averaging the carbon stored across the canopy shape such that the carbon density multiplied by the area of the canopy was equal to s(t).

By superimposing the cell structure for our LIMMMA model across this map, we were therefore able to create a map of sd(c) for each cell across Wakehurst according to the Wakehurst model and use that model to freshly calibrate our cell-based model.

For each cell, therefore, we had the Wakehurst-derived “gold standard” carbon storage density, sd(c), and for each cell our own photogrammetric measurement of feature height, j(c). We could therefore plot log(sd(c) against log(j(c)) for all relevant cells, and read off directly the variables (e, f) in equation (ii) from the least squares best-fit regression line.

We expect the data to be considerably scattered as the “gold standard” for each cell is always just the average density across the whole canopy; the average slope and intercept, nevertheless, should represent the aggregate relationship. Some issues arise, however, with clipping of habitats (deciduous vs coniferous), and along the edges of the estate. Also, there is the issue of very slight misalignments between the two data sets (the Wakehurst model data coordinates and our photogrammetric feature height coordinates). To address these issues, we applied filtering to the data, excluding a cell if one or more of the following conditions applied:

- The feature height, j(c), in the cell was < 2m
- The difference between the measured feature height in the cell, j(c), and the tree maximum height, h(t) was > 15 m
- The carbon density estimate, s(c) was in the top 1 percentile, or in the bottom 1 percentile

The re-calibration provides an opportunity to derive separate indices for deciduous and coniferous woodland. We split the data into trees identified accordingly by the Wakehurst team.

We felt it was possible that the size of the cell chosen as the unit of analysis might affect the result. To examine this possibility, we performed the same analysis using three different model scales: 1.5 m x 1.5 m (“z24”), 3 m x 3 m (“z23”), and 6 m x 6 m (“z22”). We then compared the results obtained for each scale and re-calibrated accordingly.

## Deciduous woodland

For our deciduous woodland analysis, we found excellent fits for a linear equation. Best fit least squares regression lines for y on x, sd(c) on j(c), were as follows in the table below.

| Scale | slope (e) | intercept log(f) | $r^2$ |
|---|---|---|---|
| z24 | 1.0391 | -0.2383 | 63% |
| z23 | 1.0145 | -0.1737 | 59% |
| z22 | 0.9596 | -0.0443 | 44% |

Figure A1 shows the scatter diagrams and best fit curves.

Figure A.1 calibration plot - deciduous

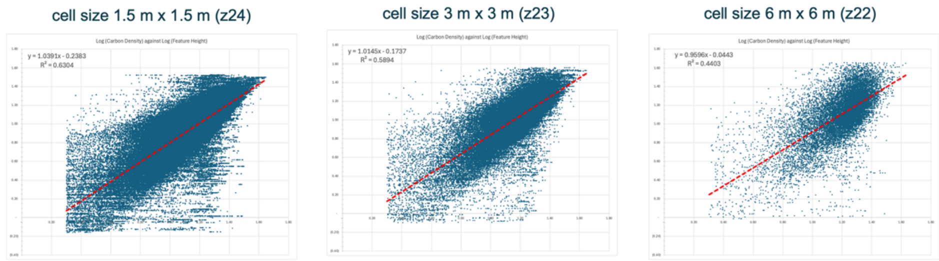



Figure A.3, below and overleaf, left panel summarises the results, showing the relationship implied by these equations between the carbon storage density and the feature height in the cell. Least regression lines for the three scales are shown. We also plot the “old” line representing the first illustrative calibration, and a proposed “new” calibration line, for which the values (e, f) from equation (ii) are (1, 0.676).

A linear equation is therefore retained, but with a 21% increase in the slope (the rate at which carbon storage density increases with feature height).

## Coniferous woodland

For our coniferous woodland analysis, we also found excellent fits for a linear equation, albeit at a 30% lower slope than the deciduous tree findings. Best fit least squares regression lines for y on x, sd(c) on j(c), were as follows in the table below.

| **Scale** | **slope (e)** | **intercept log(f)** | **$r^2$** |
|---|---|---|---|
| z24 | 1.0017 | -0.3037 | 54% |
| z23 | 0.9059 | -0.1231 | 38% |
| z22 | 0.9662 | -0.2584 | 36% |

Figure A.2 shows the scatter diagrams and best fit curves.

**Figure A.2 calibration plot - coniferous**

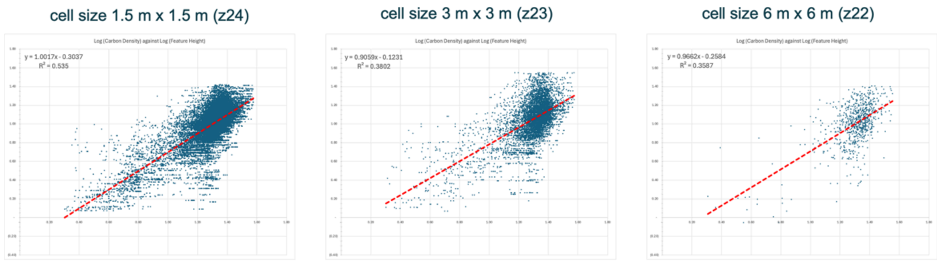
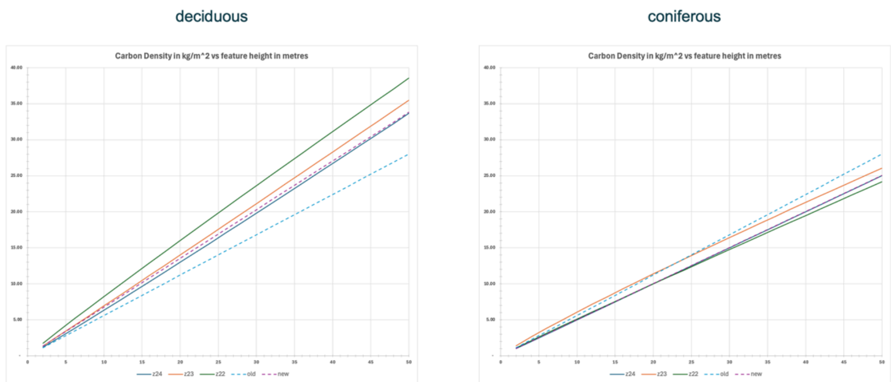



Figure A.3, right panel summarises the results, showing the relationship implied by these equations between the carbon storage density and the feature height in the cell. Least-square regression lines for the three scales are shown. We also plot the “old” line representing the first illustrative calibration, and a proposed “new” line for which the values (e, f) from equation (ii) are (1, 0.501).

A linear equation is therefore retained, but with a 10% decrease in the slope (the rate at which carbon storage density increases with feature height).

**Figure A.3 calibration model parameters**




## Hedges, copses, lone trees and other features

No data was available, so we estimate carbon density for these other features by using the (revised) deciduous woodland feature values. Most hedges, copses, and lone trees are deciduous in the Central South East region.

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Bluesky International Limited. 25cm Aerial photography, 2 m photogrammetric DSM, 5 m photogrammetric DTM data sets. See https://www.blueskymapshop.com/products/height-data
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