Technical Report
Farm Carbon Storage Network

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Introduction

Farmers are increasingly aware of their need to help tackle the climate crisis, through a combination of reducing greenhouse gas (GHG) emissions and increasing sequestration of carbon dioxide on farms. A farm's soils, trees and hedges store significant amounts of carbon, which can be difficult to quantify, however, technology can help us improve the accuracy of these estimated carbon stocks.

Funded by the Scottish Government's Knowledge Transfer and Innovation Fund (KTIF), five farms were selected to participate in the network, each representing one of the main farming systems in Scotland. The project attempts to quantify the value of each farm's natural assets in terms of carbon storage, establishing a baseline for future monitoring.

By combining soil testing and LiDAR (Light Detection and Ranging) aerial surveys a model has been developed for quantifying carbon stocks within these natural assets. This report outlines the methods used and the model developed over the course of this project. The methods and model outlined below will be further developed and improved upon in the next phase of this project if approved.

Soil carbon stock analysis

To quantify the soil carbon stock across each of the selected farms soil samples were taken in each of identified field. Field boundaries were identified using land parcel shapefiles provided by each farm.

Samples were collected via the W-pattern sampling technique (Figure 1), avoiding patches with animas manure, animal pathways field entrances, areas near water / feed troughs and other uncommon features. Each sample was taken to a depth of 30cm as specified in the Food and Agriculture Organisation of the United Nations report on measuring carbon stock (NRM, 2023), before being prepped for processing by mixing the fields samples and removing plant material present in the sample.

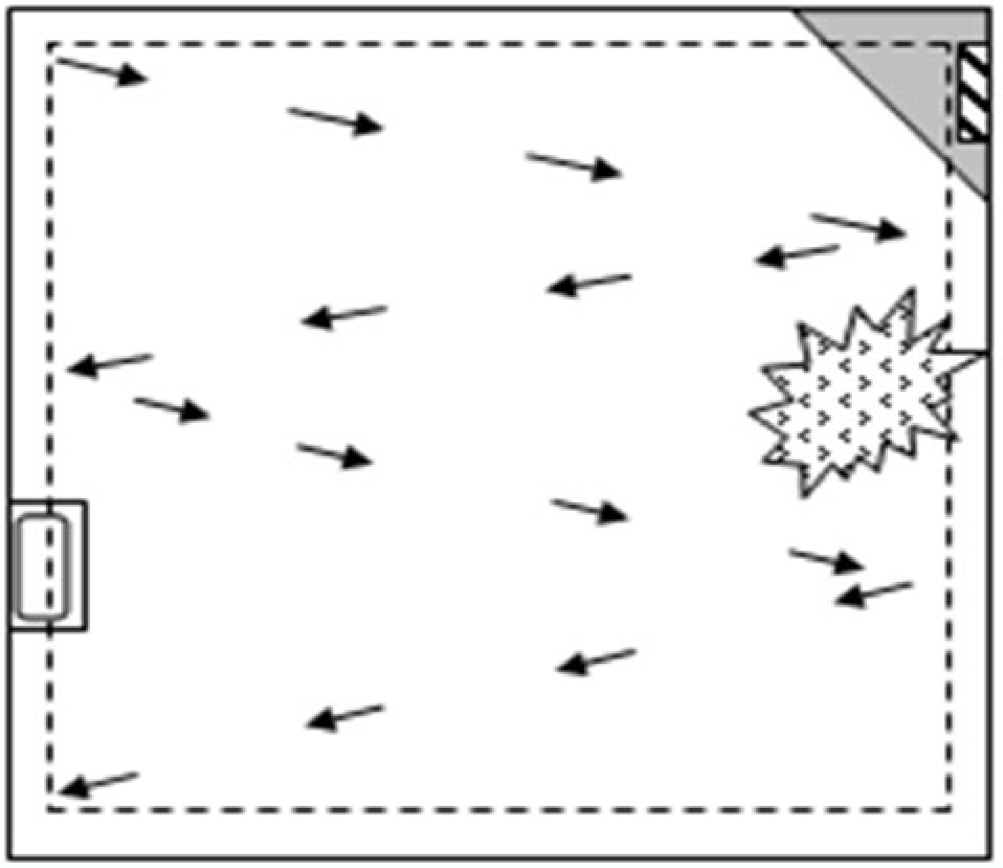

Figure 1. *W-Pattern soil sampling method (FFBC, 2022)*

Processed samples were sent to NRM (NRM part of Cawood, Bracknell, UK) for analysis using the laboratory scoop method. This method assumes densities for soil before using an elemental analyser to measure soil carbon. Using an elemental analyser allows for a far more thorough measurement of soil organic and inorganic carbon compared to other methods such as loss at ignition.

On completion of analysis, detailed results were returned that included the following data:

- Bulk density (kg/l)
- Sample depth (cm)
- Stone content (%)
- Carbonate class
- Soil inorganic carbon (%)
- Total carbon (%)
- Total nitrogen (%)
- C:N ratio
- Organic matter (%)
- Soil organic carbon (%)
- Organic carbon stock (t/ha)

Results were then converted in a suitable GIS format to be incorporated into the projects carbon stock database.

Above ground biomass carbon stock

A key objective of this project was to develop a method for estimating above ground biomass (AGB) carbon stocks using remotely sensed data collected by drone mounted LiDAR. To achieve these various methods were tested leveraging published research in this area. The methodology can be broken down into four steps outlined in Figure x below.

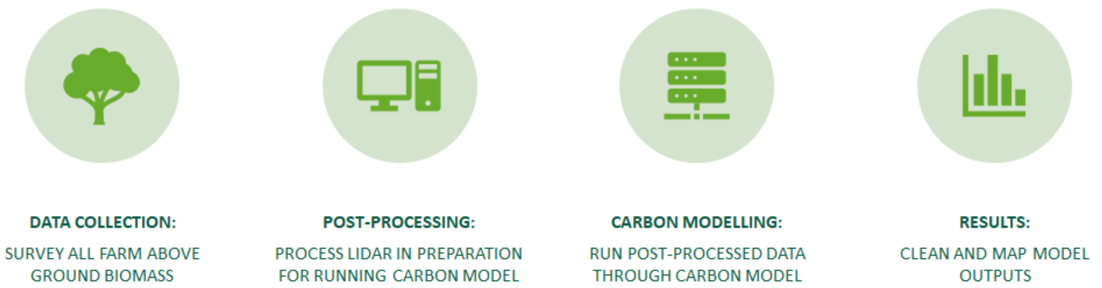

Figure 2. *Above ground biomass methodology*

Drone data collection

The drone used for all surveys was the Matrice 300 RTK drone manufactured by DJI (SZ DJI Technology Co. Ltd, Shenzhen, China) coupled with their Zenmuse L1 LiDAR sensor. Thorough mission planning was completed in preparation for each drone survey. This involved compiling relevant data of each site including, AGB locations, topography, flight restrictions, and any other potential hazards such as pylons and wind turbines. Once collected this information is then fed into the decision making for mapping out and planning each flight mission. Each mission boundary was marked out in QGIS (QGIS, 3.28) before being imported into DJI Pilot 2 (DJI Pilot 2 v2.5.1.15), the programme used to complete the missions. Once input into DJI Pilot 2 the flight and sensor parameters were optimised for biomass capture (Table 1).

Surveys were conducted during periods of good weather during leaf-off season (October-February). Completing surveys in these conditions maximised the ground point detection through the canopy. Each site was flown over the course of 2-3 days, with a total of 3 additional days where flights had to be halted due to poor weather conditions. Once collected the data was exported onto our workstation for cleaning and post processing.

Table 1. *Lidar Survey Settings*

Setting	Value	Description
IMU calibration	On	IMU calibration is a prerequisite for LiDAR accuracy and impacts the final point cloud accuracy.
Terrain-follow	On	Uses a pre-loaded elevation model of the survey area to ensure the drone stays at the prescribed height over complex topography.
Height (m)	50-60	Survey height was set to 50-60m to improve ground point detection.
Speed (m/s)	6	Speed that the drone flies. A speed of 6 m/s was selected as a midpoint between speed of survey and number of points collected.
Side overlap (LiDAR) (%)	50	This increases the time to complete the survey but allows for an RGB side overlap to 61% which is required to create high quality google earth style images of the survey area.
Forward overlap (RGB) (%)	70	This increases the time to complete the survey but is required to create high quality google earth style images of the survey area.
Photo mode	Timed interval shot	Set to take an image on a timer rather than over distance.
Return mode	Triple	Set to maximise the LiDAR's penetration in vegetated areas.
Sampling rate	160 KHz	Sampling rate of 160,000 points per second.
Scanning mode	Repetitive	Scanning repeats approximately every 0.1s and captures slightly more detail than non-repetitive scanning.
RGB colouring	On	Set to colourise the LiDAR point cloud
RTK	On	Real-time kinematic positioning was enabled using a VRS network connection to improve accuracy of the survey. When signal was not available the data was post-processed using OS base station RINEX data.

Post processing

In preparation for running the data through the carbon model the collected Lidar data went through a post processing process. DJI Terra (DJI Terra, v3.6) was used to process the Raw LiDAR, producing a colourised point cloud. Data collected using DJIS Zenmuse L1 sensor is saved in a proprietary file format, requiring DJI terra to process it into a recognised file format.

The point cloud data was then imported into TerraSolid (Terra Solid, v023.003) for further cleaning. Using Tera Solid Scan package, overlapping points were removed followed by manual cleaning to remove any visible noise present within the data.

Results were then exported into QGIS where the point cloud were clipped to vegetation boundaries to remove areas surveyed without any above ground biomass. Following this the point cloud was split up into each site's different biomass types (broadleaves, conifers, hedgerows), for separate processing through the model.

Carbon model

Following the post-processing of the LiDAR point cloud, analysis and biomass calculations were performed using a program written in R (R Core Team, 2022) with lidR (Roussel et al., 2023), terra (Hijmans, 2022), and sf (Pebesma et al., 2023) as its core dependencies. Firstly, ground points in the point cloud were classified using Cloth Simulation Filtering and interpolated using inverse distance weighted k-nearest neighbours to create a DTM. Following this, the point cloud was normalised and used to create a canopy height model (CHM) using the pitfree algorithm (Khosravipour et al., 2013). Given the lack of continuity between sections of the point cloud, a minimum point interpolation distance was set for the DTM and CHM creation to avoid forming random artifacts. A median filter was applied to the CHM to reduce noise and allow for better tree detection. This smoothed CHM was then used within two different methods to calculate AGB for hedgerows and individual trees. For both methods, site wide AGB was calculated and converted to carbon stores using equation 1.

Equation 1

$$C(kgC) = AGB(kg) * 0.5$$

Tree carbon

To calculate tree carbon across the site, individual trees were detected and used to create input data for allometric equations. A local maximum filter with a variable window size was used to identify high points, assumed to be treetops, within the canopy height model. The variable window allowed for the filter size to increase with tree height based on the assumption that taller trees generally have larger crowns. These high points were then used to segment the full trees in the point cloud. Multiple different segmentation algorithms and parameters were tested to achieve the best segmentation results based on visual analysis of the outputs. Of the algorithms tested, watershed-based object detection performed with the highest visual accuracy and lowest computation requirements.

Algorithm parameters were then fine-tuned for each site and tree type to optimize segmentations. Convex hull crown area, crown diameter, and tree height were extracted for each segmented tree.

Given the importance of diameter at breast height (DBH) in many allometric equations, an equation was first used to estimate DBH. Two different equations were tested to calculate DBH based on the LiDAR derived metrics. The chosen equation (Equation 2) fit the ground-truth data with an R^2 of 0.87 and a residual standard error of 9.88 (Figure 3). It should be noted that the ground truth data for DBH was limited to 35 observations across one site, and observations were primarily broadleaves (n = 32). Using this equation, DBH was calculated for each tree using LiDAR tree height and crown diameter.

Equation 2

$$DBH(cm) = (0.557 * (Tree\ Height\ (m) * \ Crown\ Diameter(cm))^{0.809} * \exp\left(\frac{0.056^2}{2}\right)$$

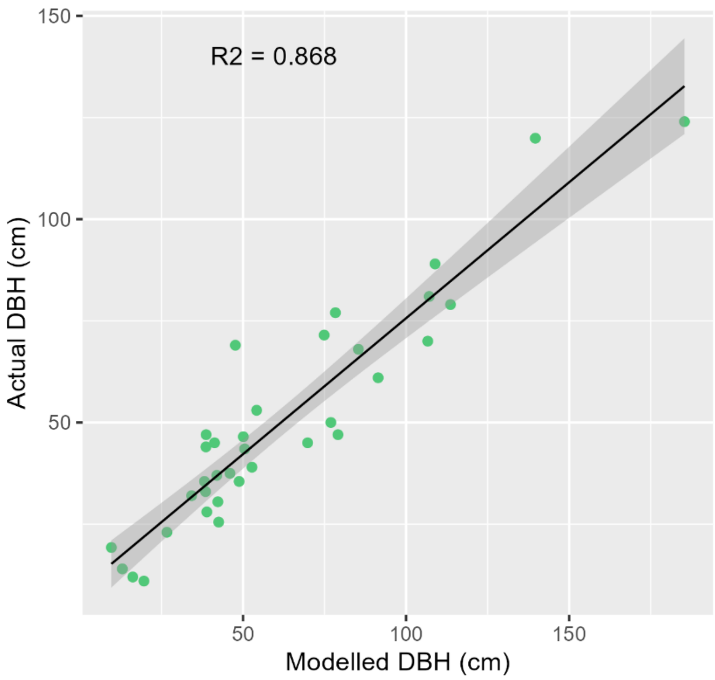

Figure 3. *Relationship between measured DBH and modelled DBH at Auchinbay Farm*

The calculated DBH values, along with height, were used within allometric equations to calculate AGB. Suitable allometric equations were chosen from studies and forest carbon models in a similar biogeographic region to Scotland. Equations from the Carbware forest model were specific to broadleaves (Equation 3) and conifers (Equation 4) (Black et al., 2011). Equation 5 uses a density constant for species where ρ = 0.740 was used for broadleaves and ρ =

0.510 for conifers from the wood density database developed by Chave *et al.* (2009). This resulted in a total of two equations to be tested for each tree type.

Due to a lack of AGB validation data, there is a high degree of uncertainty in which of the equations is most correct. Provided this limitation, it was determined that calculating biomass using both equations and assessing the variance in the results was best practice. However, initial project outputs have used results from Equation 5. Further analysis in phase 2 will explore the variance between equations further in an effort to reduce error.

***Equation 3** – Broadleaf (Black et al., 2011)*

$$AGB(kg) = 0.08 + \frac{(25{,}000 * DBH(cm)^{2.5})}{DBH(cm)^{2.5} + 246872}$$

***Equation 4** – Conifer (Black et al., 2011)*

$$AGB(kg) = 0.022 * DBH(cm)^{2.73} + 0.19 * Tree\ Height(m)^{2.06}$$

***Equation 5** (Jucker et al., 2017)*

$$AGB(kg) = 0.0673 * (\rho * DBH(cm) * Tree\ Height(m))^{0.976} * \exp\left(\frac{0.357^2}{2}\right)$$

Hedgerow carbon

Following the methodology of Black et al. (2014) the calculations for AGB and above ground carbon in hedgerows was calculated using a random height sampling approach and an allometric equation developed for broadleaf trees (Equation 6). Random points over 1.3m in height were randomly sampled from the CHM with a minimum distance of 2m between points. Points were sampled until the minimum distance rule prevented the creation of new points. The values of these points were then used as height within the allometric equation, and the outputs of the equation were summed to create a site-wide biomass estimation. Mean biomass and the standard deviation were then calculated across 30 iterations of random sampling to get the final AGB estimates and statistics for each site.

***Equation 6** (Jucker et al., 2017)*

$$AGB(kg) = (0.179 * Tree\ Height(m)^{3.3})$$

Repeatability and scaling-up

The methods outlined above have been designed to be repeated and improved upon through further in-house or third-party development in the future. All methods and code are available on request to enable replication or improvement by anyone with access to suitable equipment. Naturally there are barriers to this as LiDAR is still a relatively expensive technology, however year on year the cost and accessibility related to this technology is improving.

It should be noted that carbon model developed in this phase of the project is a first version. If phase 2 of the project is approved the model will be developed further, increasing efficiencies and incorporating localised tree data to improve and tailor biomass carbon estimates. The next phase will also expand the network to 10 farms, strengthening the dataset, and ensuring the data derived is relevant to farmer's from across Scotland.

Overall, there is potential for this project to be scaled up to larger regions incorporating manned aerial vehicle LiDAR data collection. Though considerable improvements will be required to scale data collection and improve the ability of the model to run larger datasets. The soil sample methodology was specifically chosen for its simplicity while producing good results. This ensures that farmers and other landowners will be able to sample their own field in the event of scale up. This would bring significant time and cost savings; however, quality assurance measures will need to be developed to safeguard the integrity of soil data collected.

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