

CRANFIELD UNIVERSITY

STYLIANI BEKA

Developing above and below ground carbon stock models and tools for  
farm and landscape management

School of Water, Energy and Environment (SWEE)  
PhD in Environment and Agrifood

PhD

Academic Year: 2019 - 2022

Supervisor: Prof Paul Burgess

Associate Supervisor: Prof Ron Corstanje

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PhD

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## ABSTRACT

Agriculture and land use are responsible for about 11% of the UK's territorial greenhouse gas emissions. Therefore, a policy measure to mitigate climate change is to incentivise additional soil organic carbon and biomass carbon storage on farms. However, physical measurements of soil organic carbon and biomass carbon can be difficult due to the high cost and labour requirements. Hence, this PhD aimed to review, develop, apply and evaluate scalable and robust methods for creating soil organic carbon and biomass carbon maps and models, to enable more informed farm and landscape management. Current methods for developing farm-scale carbon inventories are reviewed and it is demonstrated that few models provide spatial estimates with a level of uncertainty. Additionally, three spatial soil organic carbon models with different scales of input and output data, for the top 10 cm of the soil for nine grassland sites are developed and evaluated. Across the evaluation dataset, the fine-scale models were able to better predict the soil organic carbon (0-10 cm) variability found in the measured values. This difference has important implications if soil organic carbon values derived from models are used to provide a baseline from which carbon payments are derived. An integrated spatial approach using LiDAR data and two Bayesian Belief Network models is developed to quantify the total biomass carbon stock of different land covers and landscape features across five case studies. The two Bayesian Belief Network models successfully allocated the total biomass carbon values to one of four classes with an error rate of 6.7% and 4.3% for the land cover and landscape features respectively. An advantage of the approach is that the predicted values can be determined remotely using historic land cover and LiDAR height data. A novel tool is then established that combines the empirical SOC model with the probabilistic biomass carbon model for baseline farm carbon stock estimation. The derived results include itemised values and related uncertainty for each land cover parcel and landscape feature. Lastly, an investigation of the opportunities and obstacles for spatial farm level C accountancy is conducted.

**Keywords:**

Field-scale carbon accounting, spatial carbon inventory tool, soil organic carbon storage, spatial modelling, net-zero, carbon payments, biomass carbon, spatial carbon variation, integrated method, carbon storage, landscape features.

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## LIST OF ABBREVIATIONS

|                    |                                                                     |
|--------------------|---------------------------------------------------------------------|
| AGB                | Above ground biomass                                                |
| AGBC               | Above ground biomass carbon                                         |
| APEX               | Agricultural policy environmental extender                          |
| AR                 | Arable land                                                         |
| BBN                | Bayesian belief network                                             |
| bd                 | Bulk density                                                        |
| BGB                | Below ground biomass                                                |
| BGBC               | Below ground biomass carbon                                         |
| C                  | Carbon                                                              |
| °C                 | Degrees Celsius                                                     |
| CANDY              | Carbon Nitrogen Dynamics                                            |
| CAP                | Common Agriculture Policy                                           |
| CESAR              | Carbon Emission and Sequestration by Agricultural land use          |
| CH <sub>4</sub>    | Methane                                                             |
| CO <sub>2</sub>    | Carbon dioxide                                                      |
| CO <sub>2e</sub>   | Carbon dioxide equivalent                                           |
| C <sub>total</sub> | Total biomass carbon                                                |
| D                  | Depth                                                               |
| DEFRA              | Department for Environment Food & Rural Affairs                     |
| DNDC               | DeNitrification and DeComposition                                   |
| DOM                | Dead organic matter                                                 |
| DOMC               | Dead organic matter carbon                                          |
| DSM                | Digital surface model                                               |
| DTM                | Digital terrain model                                               |
| ECOSSE             | Estimation of Carbon in Organic Soils – Sequestration and Emissions |
| ELM                | Environmental Land Management                                       |
| EPIC               | Erosion-Productivity Impact Calculator                              |
| EU                 | European Union                                                      |
| EU ETS             | European Union Emissions Trading System                             |
| F                  | Function                                                            |
| GAECs              | Good Agricultural and Environmental Conditions                      |
| GHG                | Greenhouse gas                                                      |
| GIS                | Geographical Information Systems                                    |
| Gt                 | Gigatonnes                                                          |

|                  |                                                           |
|------------------|-----------------------------------------------------------|
| ICBM             | Introductory Carbon Balance Model                         |
| IG               | Improved grassland                                        |
| IPCC             | Intergovernmental Panel on Climate Change                 |
| InVEST           | Integrated Valuation of Ecosystem Services and Trade-offs |
| LAI              | Leaf Area Index                                           |
| LiDAR            | Light detection and ranging                               |
| LOI              | Loss on ignition                                          |
| LPIS             | Land Parcel Identification System                         |
| LULUCF           | Land Use, Land Use Change, and Forestry                   |
| MDGs             | Millennium Development Goals                              |
| MRT              | Mean residence time                                       |
| MRV              | Monitored, reported, and verified                         |
| Mt               | Megatonnes                                                |
| N                | Nitrogen                                                  |
| NDVI             | Normalised vegetation index                               |
| NFU              | National Farmers Union                                    |
| NH <sub>4</sub>  | Ammonium                                                  |
| NO <sub>3</sub>  | Nitrate                                                   |
| N <sub>2</sub> O | Nitrous oxide                                             |
| NSI              | National Soil Inventory                                   |
| NSIS             | National Soil Inventory of Scotland                       |
| NSRI             | National Soil Resources Institute                         |
| NUA              | New Urban Agenda                                          |
| OC               | Organic carbon                                            |
| OCC              | Organic carbon content                                    |
| OM               | Organic matter                                            |
| OT               | Other                                                     |
| P                | Phosphorus                                                |
| ppm              | Parts per million                                         |
| PUIs             | Pending Assurance Units                                   |
| R                | Coefficient for determination                             |
| RMSE             | Root mean square error                                    |
| RothC            | Rothamsted Carbon Model                                   |
| RPA              | Rural Payments Agency                                     |
| S                | Sulphur                                                   |
| SAVI             | Soil adjusted vegetation index                            |
| SCC              | Social cost of carbon                                     |

|         |                                                       |
|---------|-------------------------------------------------------|
| SDGs    | Sustainable development goals                         |
| SOC     | Soil organic carbon                                   |
| SOM     | Soil organic matter                                   |
| SSLRC   | Soil Survey and Land Research Centre                  |
| STOTEN  | Science of the Total Environment                      |
| t       | Tonnes                                                |
| TECO    | Terrestrial ECOsystem                                 |
| UK      | United Kingdom                                        |
| UKCEH   | UK Centre for Ecology & Hydrology                     |
| UNFCCC  | United Nations Framework Convention on Climate Change |
| Vis-NIR | Visible near – infrared                               |
| WBCSD   | World Business Council for Sustainable Development    |
| WRI     | World Resources Institute                             |
| W/RG    | Woodland and rough grazing                            |



# 1 Introduction

## 1.1 Climate change and carbon sequestration

Climate change is defined as ‘the long-term shift in average weather patterns across the world’ (Met Office, 2022). Greenhouse gases (GHG) absorb energy in the lower atmosphere and re-emit it, which warms the Earth (Montzka et al., 2011). Due to GHG emissions, primarily from anthropogenic activities, the concentration of carbon dioxide (CO<sub>2</sub>) has increased from 316 in 1959 to 400 parts per million by volume (ppm) in 2021 seen in Figure 1-1 (Soussana et al., 2019). Many of the emissions arise from our energy demand. Globally, one-quarter of the human-made GHG emissions arise from burning fossil fuels for electricity and heat production, while another quarter comes from agriculture, forestry and other land use (IPCC, 2019).

Between 1980 and 2000, the global rate of CO<sub>2</sub> emissions from the burning of fossil fuels increased by 40% (Wofsy, 2001; Lal, 2008). Before the Industrial Revolution, the average temperature across the earth was about 14°C; over time humans started burning up fossil fuels to produce energy, resulting in the increase of the planet’s average temperature by 1.5°C (IPCC, 2019).

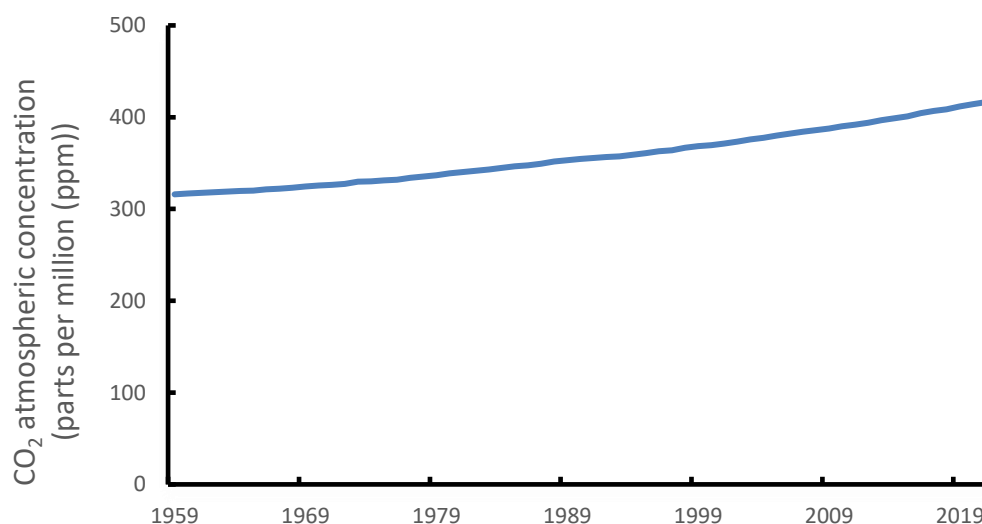


Figure 1-1 Global mean annual atmospheric concentration of Carbon Dioxide(CO<sub>2</sub>) (Modified from Tans and Keeling, 2022).

The increase in CO<sub>2</sub> emissions on the net level of atmospheric CO<sub>2</sub> is moderated in part through capture by carbon (C) sinks such as oceans, soils and forests (Battle et al., 2000). This process of capturing and locking away atmospheric CO<sub>2</sub> into stable C sinks that would have otherwise accumulated in the atmosphere is termed C sequestration. Because of the complexities related to ownership and use rights of oceans, the focus on enhancing the capacity of soil as a C sink is considered a more feasible approach to increase C sequestration (Bouffier et al., 2013).

## **1.2 Climate change mitigation**

Concern over climate change has led to regulated and voluntary reductions in GHG emissions. Negotiations in 1997 led to the Kyoto Protocol (United Nations, 1998), where 37 industrialised countries sought to reduce GHG emissions during 2008-2012 by a 5% average below their 1990 levels. Although emissions from countries that were part of the Protocol were reduced, emissions continued to increase in other countries. A second Kyoto commitment was agreed for the period 2013-2020, but there were fewer signatories (European Commission, 2019). In 2005, the EU established the world's first main C market called the European Union Emissions Trading System (EU ETS), which covered about 45 % of the EU's greenhouse gas emissions. It put a cap on the CO<sub>2</sub> emissions by businesses and produced a market and price for C allowances (Environment Agency et al., 2013).

In 2015, world leaders agreed on the 2030 Agenda for Sustainable Development which comprised 17 Sustainable Development Goals (SDGs) succeeding the Millennium Development Goals (MDGs) (United Nations, 2016). These goals focus on ending all forms of poverty along with building economic growth and addressing a variety of social needs such as education, health and job opportunities while tackling climate change and protecting the environment. In December 2016, the Paris Agreement (United Nations Framework Convention on Climate Change (UNFCCC), 2015) was negotiated to replace the Kyoto Protocol, by 196 state party representatives. The agreement aims to keep the

increase in global average temperature well below 2° C above pre-industrial levels and to limit the temperature warming to 1.5 °C.

The UK as part of the UNFCCC, through the Climate Change Act (Acts of Parliament, 2008) was the first major country to present long-term legally binding legislation to tackle climate change. Using this Act, the UK in 2019 legally committed itself to reach net zero territorial GHG emissions by 2050. This pledge includes a 78% reduction from 1990 levels by 2035, in line with the Sixth Carbon Budget (Climate Change Committee, 2020).

In 2021 world leaders gathered for the United Nation's Cop 26 in Glasgow where discussions about the climate crisis took place. The agreed decisions included strengthening efforts to build resilience to climate change, reducing GHG emissions and to providing the necessary funding to achieve the previous two points (United Nations, 2021 ) The conference concluded with signing the Glasgow Climate Pack agreeing the Paris Rulebook (United Nations, 2021). A year later world leaders gathered again in the Egyptian coastal city of Sharm el-Sheikh, for the United Nation's Cop 27. The key outcome of the conference was the Sharm el-Sheikh Implementation Plan, which reiterates the pledge to limit the global temperature rise to 1.5 °C above pre-industrial levels (United Nations, 2022)

### **1.3 The role of agriculture**

Achieving net-zero GHG emissions will require management change in each sector of the economy. GHG emissions from farmland are made up of two sectors, namely i) emissions from agriculture and ii) emissions from land use, land use change, and forestry (LULUCF). BEIS (2021) defines agricultural emissions as those arising from engine combustion, enteric livestock fermentation, livestock waste, direct soil emissions, and other practices, such as liming. By contrast, LULUCF emissions arise from C stock changes in forestlands, croplands, grasslands, wetlands, settlements and harvested wood products, and GHG emissions related to drainage and rewetting of soils, and fires.

In the UK, the agricultural sector (Figure 1-2) in 2019 emitted 46.3 Mt CO<sub>2e</sub> while the land use, land use change and forestry (LULUCF) emitted a much lower amount of 5.9 Mt CO<sub>2e</sub> (BEIS 2021). Moreover during 2019 agriculture contributed 10% of the total UK GHG emissions and LULUCF was a net source of 1.2%. Unlike many sectors, agriculture can be a sink as well as a source of emissions (Department for Environment, Food and Rural Affairs, 2012; National Farmers Union, 2019). Agricultural systems can capture C and actively use it to remove CO<sub>2</sub> and balance methane (CH<sub>4</sub>) and nitrous oxide (N<sub>2</sub>O) emissions. In this context, the National Farmers Union (NFU) in England and Wales has committed to reaching net-zero GHG emissions by 2040 (National Farmers' Union, 2019).

A recent Farm Practice Survey (UK Government, 2021) revealed that two-thirds of farmers consider the importance of GHGs in business decisions, yet individual farms lack methods to estimate emission levels. Hence there is a demand for simple and robust ways to estimate how much C is stored in their land, and possible opportunities to trade C (Chandra et al., 2017).

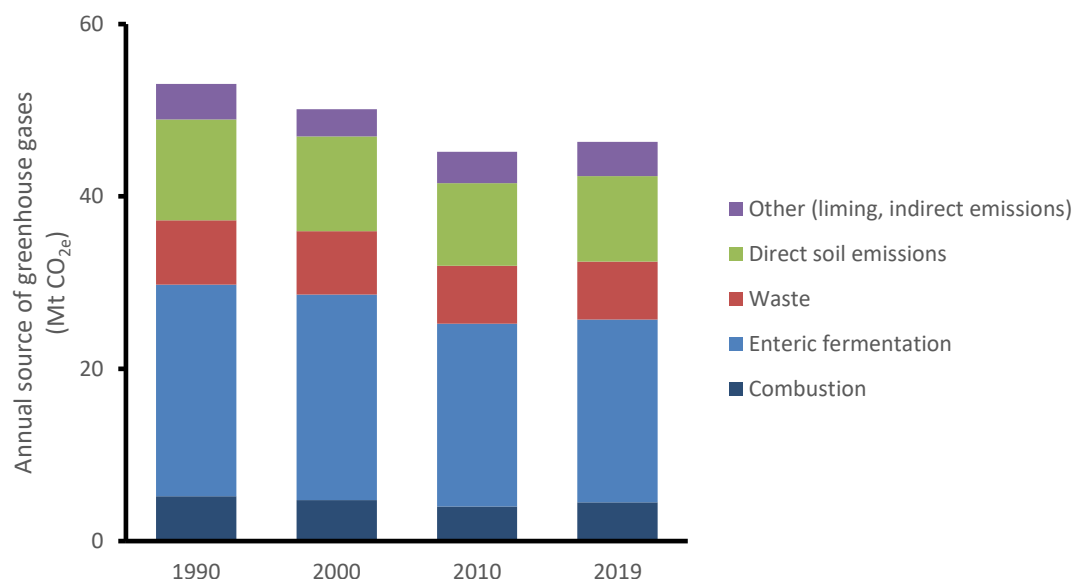


Figure 1-2 Greenhouse Gas (GHG) emissions arising from agriculture in the UK in 2019 where CO<sub>2e</sub> =Carbon Dioxide (Adapted by: BEIS, 2021).

## **1.4 Environmental reporting guidelines, frameworks and standards**

Globally, businesses are being required to account for and report their environmental impacts under the following principles: relevance, quantitative, accuracy, completeness, consistency, comparability and transparency (UK Government, 2019). The use of Environmental Management Systems (EMS) is also promoted to ensure good data management. Hence, many UK businesses are following environmental reporting guidelines and use methodologies and guidance from organisations such as the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD) (WBCSD and WRI, 2015). They are currently developing a GHG protocol for land sector guidance (WBCSD, 2020). The GHG protocol contains internationally accepted GHG inventory accounting and reporting standards together with tools to achieve a global low-emissions economy.

The International Organization for Standardization (ISO) has produced standards for the design and development of GHG inventories and procedures to quantify, monitor and report emissions reduction and removal. More specifically ISO 14064 -1 (British Standards Institute, 2020) sets out the principles of the design and development of GHG inventories for organisations. The document specifies how the GHG emissions and removals boundaries are defined, quantified, and calculated. It also specifies how the baseline year GHG inventory is established, the mitigation activities and finally the inventory quality management. According to ISO 14067 (British Standards Institute, 2019), all GHG emissions and removals will be assessed according to internationally recognised methods. The most recognised one is the reporting guidelines of national GHG stock and emissions inventories developed by the Intergovernmental Panel on Climate Change (IPCC, 2019).

## **1.5 Farm-scale carbon cycles**

On individual farms, the C cycle comprises changes from growth, decay and distinct events, such as land-use change or harvest (Figure 1-3). In a farm environment, terrestrial C is being moved between different major pools, namely aboveground

biomass (AGB), belowground biomass (BGB), dead organic matter (DOM), and soil organic matter (SOM) and out-of-the-farm products (Bartholomée et al., 2018; IPCC 2019). Carbon atoms move continually in this cycle, where various sinks store C fluxes or processes, and exchange C on several time scales. The mass of C stored for a specific amount of time refers to a C stock, while the transfer of C from one stock over a period of time to another refers to a C flux (IPCC, 2000).

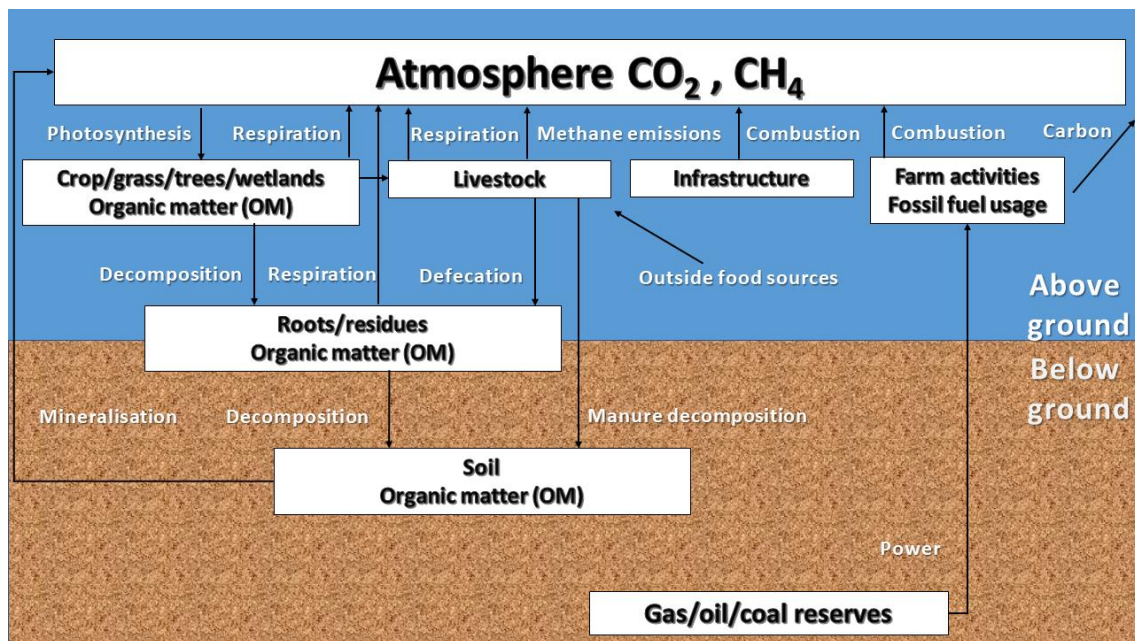


Figure 1-3 High-level conceptual model of the carbon cycle, where Carbon Dioxide  $\text{CO}_2$  = Carbon Dioxide and  $\text{CH}_4$  = Methane.

Major fluxes of C within a farm system include photosynthesis converting  $\text{CO}_2$  to organic C (OC) by vegetation, and the subsequent respiration of that OC which again releases  $\text{CO}_2$  (Figure 1-3). Vegetation consumed by ruminants can also be respired as  $\text{CO}_2$  or  $\text{CH}_4$  emissions (Cannell and Milne, 1995; Perez-Garcia et al., 2005; Ziegler et al., 2016; Dimassi et al., 2018). While these processes take place and C is moved through the different pools, C can also be stored as a stock.

Worldwide, the largest terrestrial OC pool is the soil, which stores around 2344 Gt of OC in its top 3 m from which 1700 Gt are found in the top 1 m (Jobbágy and Jackson, 2000; Stockmann et al., 2013; Paustian et al., 2019; Canadell et al., 2021). However, estimates

of the OC stored in the top 1 m of soil in 27 studies have ranged from 504 Gt to 3000 Gt (Scharlemann et al., 2014). The presence of OC helps agricultural ecosystems to function properly (Lacoste et al., 2013), but it also has a very significant impact on global C storage. Conant et al. (2011) proposed that improved soil and water quality together with a reduction in soil erosion, nutrient loss and an increase in water conservation and crop production could increase the amount of soil organic C (SOC). The enhancement of atmospheric C capture through photosynthesis (through land cover and land-use change), could increase the transfer of C to the soil (Craggs, 2016). Hence management practices to promote SOC storage have been a focus of substantial investigation (Sanderman and Baldock, 2010).

Methods for estimating C pools range from generalised approaches such as the IPCC Tier 1 method (IPCC, 2019) and the use of literature values (Adger and Subak, 1996; Milne and Brown, 1997; Bradley et al., 2005; Cantarello, Newton and Hill, 2011; Xu et al., 2011; Agostini, Gregory and Richter, 2015), to detailed methods including field sampling and laboratory analysis, to modelling and mathematical analyses (Patenaude et al., 2003; Upson and Burgess, 2013; Rytter, Rytter and Högbom, 2015; Fornara et al., 2017)

## **1.6 Rationale of this thesis**

For net-zero GHG emissions schemes on farms or in agriculture to be successful, farmers, regulators, and C traders require assessments of both GHG flows and C stocks. Theoretically, it is possible to take measurements of biomass C and SOC across all fields and farms, but this is expensive in terms of time, money and labour.

Whilst there are substantial assessments of national and international levels soil C stocks (Guo and Gifford, 2002; Grunwald, Thompson and Boettinger, 2011; Veronesi, Corstanje and Mayr, 2014; Wang et al., 2018; Adhikari et al., 2019), there is relatively little information on methods of determining farm-scale C inventories without measurement. At present in England and Wales, there are national datasets on SOC and there have been attempts to create spatial SOC maps (Keay et al., 2009; Hallett et al., 2017).

Experimental research exists to describe how changes in land use, such as tree planting on grass and arable land (Upson and Burgess, 2013; Upson, Burgess and Morison, 2016; Fornara et al., 2017) and hedges (Axe et al., 2017) can affect the biomass C stock. Also, studies such as Cantarello et al. (2011) have sought to explain how land use affects above and belowground C. This thesis seeks to bring together recent advances in biomass and SOC mapping and experimental research to address the research gap on how to create a rigorous C stock accounting tool at a farm scale.

## **1.7 Aims and Objectives**

Building on the above, this PhD aimed to review, develop, apply, and evaluate scalable and robust methods for creating fine-scale maps and models for below and aboveground C stocks that could be used by farm and landscape managers. Achieving improved spatial accounting for C should also enable more informed farm and landscape management. In this process, the research also addressed uncertainty and the implications for management and C accountancy.

The output of this research will be a C accountancy tool that will be used to develop baseline C stock inventories for farm and landscape management. The required data will be comprised of existing remotely sensed land parcel delineations, soil C estimates adjusted for land cover and soil properties, above, below and dead organic matter biomass C values for land covers and landscape features. The output will be a single total C stock value for each land parcel to the soil depth of 10 cm.

The aims were achieved by meeting the following six objectives:

- 1: to critically review and assess existing literature on carbon and greenhouse gas models and tools which could potentially be used to develop spatial farm carbon stock baseline inventories.
- 2: to develop calibrate and evaluate robust spatial soil organic carbon storage models, with different scales of input and output data and identify the impacts of downscaling national soil carbon information.

- 3: to determine how the developed spatial modelling approaches interact with the choice of accounting method and review their economic implications.
- 4: to develop and evaluate a method that combines probabilistic Bayesian Belief Network models with remotely sensed data and spatially estimates the total carbon stored in the biomass of different land covers and landscape features.
- 5: to establish a tool that provides a holistic view of the total farm carbon levels and allows the separate examination of each pool and field parcel.
- 6: to synthesise the above research and investigate any opportunities and obstacles for spatial farm level C accountancy.

From the above objectives, six research questions were derived:

Research question 1: What is the current capacity for developing a spatial farm C accounting tool?

Research question 2: What is the best way to establish SOC levels on farms without on-site measurements?

Research question 3: What is the implication of SOC modelling approaches on possible farm-level C payments?

Research question 4: What is the optimal way to determine biomass C levels of land cover and landscape features on farms without on-site measurements?

Research question 5: How can the SOC and biomass C models be combined in order to provide estimates of current C levels, and how could management options affect these levels in the future?

Research question 6: To what extent have the developed models improved capacity to spatially account for farm-level C?

## **1.8 General approach and thesis structure**

This thesis is comprised of a series of chapters (Figure 1-4) which were formatted as journal papers (published, submitted or in preparation) that address each one of the set objectives. The chapters were written by first author Styliani (Stelina) Beka and reviewed by first supervisor Paul Burgess and second supervisor Ron Corstanje.

Chapter 2 addresses objective 1 and examines the capability of existing farm C models and the capacity of developing a spatial C inventory tool. It then identifies the potential criteria for scalable farm-level C inventories, that are used to develop the SOC model and biomass C models in chapters 3 and 4.

Chapter 3 has been published in Science of the Total Environment (STOTEN) and addresses objectives 2 and 3. In the chapter, three spatial modelling approaches (models) were developed using either fine- (100 m x 100 m) or field-scale input soil data to produce either fine- or field-scale outputs across the four cardinal directions and to a soil depth of 10 cm. In addition, two approaches were examined across the nine study areas to determine the potential C payments.

Chapter 4 extends the spatial C stock accounting to the farm biomass, focuses on it with a level of uncertainty and examines the consequences for policy, and land uses. In this Chapter, objective 4 is addressed and two Bayesian Belief Network (BBN) models were developed to quantify biomass C stocks and their uncertainty at a farm scale. This chapter has also been published in the STOTEN journal .

Chapter 5 combines the results from Chapters 3 and 4 to develop a spatial C accounting inventory tool (objective 5). It also provides recommendations on management alterations to increase C storage in fields with low levels of C.

Chapter 6 synthesises and discusses the outputs and conclusions of the PhD, the contribution to knowledge and areas of future research (objective 6).

| Chapter        | Literature review                                       | Biomass carbon stock & soil organic carbon (SOC) stock | Integration of methods | Synthesis and recommendations |
|----------------|---------------------------------------------------------|--------------------------------------------------------|------------------------|-------------------------------|
| Objective      | 1                                                       | 2, 3 & 4                                               | 5                      | 6                             |
| Chapter number | Chapter 2                                               | Chapters 3 & 4                                         | Chapter 5              | Chapter 6                     |
| Stage          | Establishment ➡ Development ➡ Integration ➡ Conclusions |                                                        |                        |                               |

Figure 1-4 Schematic representation of the thesis with the different chapters and addressed objectives

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## 2 Review of carbon accounting tools

### Abstract

A literature review was conducted to examine the existing research landscape of spatial tools to develop farm-level carbon inventories. Firstly, the importance of globally recognised standards, guidelines and approaches are discussed. This is followed by the identification of 25 carbon and greenhouse gas accounting tools. These were then evaluated according to their i) resolutions, ii) tool platform and interface, iii) inputs/outputs iv) place of origin, and v) scientific robustness, and the spatial ones were identified. The spatial tools were further assessed in terms of i) horizontal resolution, ii) vertical resolution, iii) vertical extent, iv) temporal resolution, v) platform and interface, and vi) inputs and outputs. The review indicates that even though several greenhouse gas flux calculators exist, there are only a few carbon stock models. The potential farm, administrative, regulatory, and scientific related criteria for the development of the farm-scale spatial carbon stock tool are described.

**Keywords:** Desk-based review, assessing procedure, international and national greenhouse gas accounting approaches, carbon accounting research tools, carbon accounting decision support tools, spatial carbon accounting tools.

### 2.1 Introduction

Building on the Kyoto Protocol (United Nations, 1998), the Paris Agreement (United Nations, 2015), and the UK Climate Change Act (Acts of Parliament, 2008), in June 2019 the UK Government committed itself to reaching “net-zero” greenhouse gas (GHG) emissions by 2050.

In the UK, agriculture contributes to 10% of the net greenhouse gas (GHG) emissions and 1.2% of the total carbon dioxide (CO<sub>2</sub>) emissions (UK Government, 2021a). Moving towards a “net-zero emissions” goal is not easy, however, the NFU (National Farmers’ Union, 2019) proposed achieving this by 2040. For agriculture to achieve and

demonstrate net zero GHG emissions will require farmers and policymakers to find new ways of simply and robustly calculating farm-level carbon (C) stocks and to understand how different land uses and management practices affect storage and sequestration.

A carbon inventory provides a foundation for a farm business to understand its carbon stocks and build effective climate change strategies (WBCSD and WRI, 2020). The labour and cost involved in physical sampling can be high, and hence there is interest in the use of carbon calculator tools and models (Sukhoveeva, 2021). Carbon models are simplified representations of processes that occur in the real world, that can be used to account for, estimate, and predict carbon stocks above and below the ground in the soil, GHG emissions, and associated economic values. Whilst numerous tools and models describe GHG emissions, there are few models for developing farm carbon inventories (Malone et al., 2017; Leinonen et al., 2019; Wang et al., 2020). The objective of this chapter is to critically review existing literature on farm-level carbon (C) inventory models and tools and to establish the criteria for a spatial C inventory for use by farm and landscape managers.

## **2.2 Methodology**

The objectives were addressed using three steps as seen in Figure 2-1. In the first step, published literature was reviewed to identify globally and nationally recognised standards, guidelines and approaches, payment schemes, and field delineation methods for carbon accounting. In the second step, existing literature on models and accounting tools was reviewed to establish the criteria for a spatial C inventory for use by farm and landscape managers. The literature review was carried out using two search engines, Scopus and Google Scholar. This identified seven globally and nationally recognised standards, guidelines and approaches, three payment schemes, one delineation method and 25 tools and models. Economic models, livestock models and tools that do not account for C were not included in the review, as they were out of the project's scope.

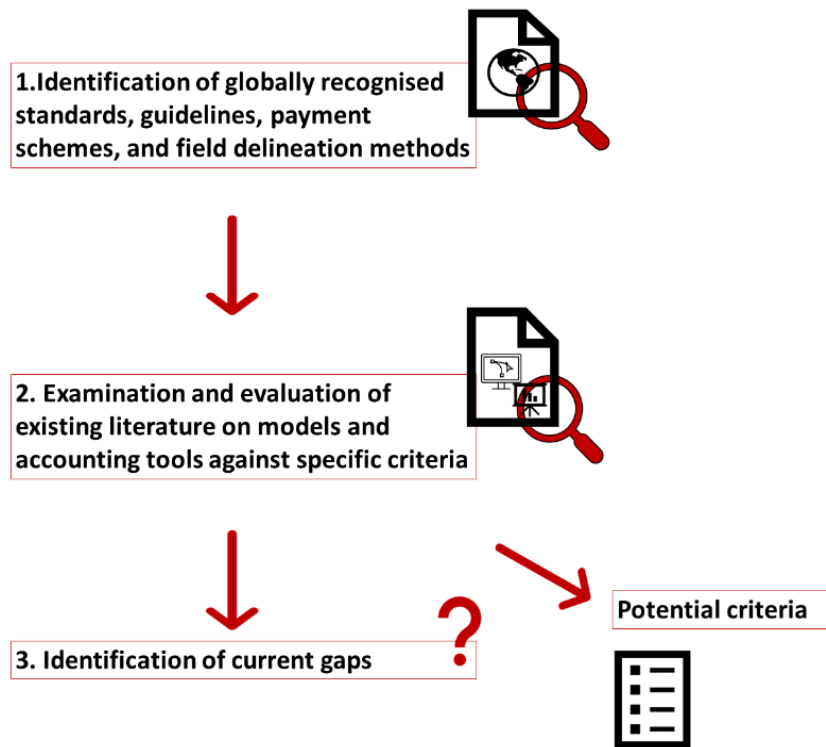


Figure 2-1 Three-step methodological approach

The identified models and tools were then evaluated against specific criteria. Graves et al. (2005) created a framework to categorise the characteristics of existing models and a similar approach was followed to identify the ones of most interest. Based on the analysis of the literature, three criteria for a spatial farm-level C stock inventory were established as seen in Table 2-1. Hence the 25 models and tools were evaluated against the criteria of: i) the background of the model, ii) the outputs and uncertainty, and iii) whether they were spatial.

Spatial models were those that were developed in a geographical information system (GIS) to describe fundamental processes and properties for a given set of spatial inputs. It must be noted that all models and tools can be integrated to a GIS interface, but only a few use spatial inputs to produce spatial outputs.

Table 2-1 Criteria for model and tool selection

| Evaluation criteria |                                                           |
|---------------------|-----------------------------------------------------------|
| 1                   | Background                                                |
|                     | What are the models and accounting tools developed under? |
|                     | When was it first mentioned?                              |
|                     | Where is its origin?                                      |
|                     | What was the first reference?                             |
|                     | Is it user-friendly?                                      |
|                     | Data requirements                                         |
|                     | Data comprehensiveness                                    |
| 2.                  | Outputs and uncertainty                                   |
|                     | What are the outputs of the model/tool?                   |
|                     | Is a level of uncertainty given to the derived outputs?   |
| 3                   | Is it a spatial model/tool?                               |

The spatial models and tools were then assessed according to their i) resolutions (spatial horizontal, vertical, and temporal), ii) their platform and interface (data comprehensiveness, data requirements, software requirements, result presentation), iii) inputs and outputs, iv) place of origin and v) scientific robustness (evaluation) data requirements. During the last step, any gaps that the present tools and models were identified.

## 2.3 Results

### 2.3.1 Standards and methodologies, payment schemes, and field delineation

The first part of the literature review focused on the development of carbon and GHG inventories in terms of international and national accepted standards and methodologies, payment schemes, and ways to delineate the land.

#### 2.3.1.1 Globally and nationally recognised standards, guidelines and approaches

Three major international and four UK accounting approaches for C and GHG inventories were identified (Table 2-2). Standards, guidelines and approaches acknowledged on an international level include the Intergovernmental Panel on Climate Change (IPCC). The fourth volume of the IPCC guidelines provides generic calculation methodologies, using

values from lookup tables and provides guidance for preparing annual GHG inventories (IPCC, 2019). The tables allow the calculation of GHG emissions and removals for different forms of agriculture, forestry, and other land uses. The quantification is classified into three different tiers, according to the level of accuracy and scale (global, national, regional) of the study area.

Table 2-2 Selected international and national approaches for Greenhouse Gas (GHG) accounting.

| Approach      | Year | Name                                                                                           | Origin         | Reference                           |
|---------------|------|------------------------------------------------------------------------------------------------|----------------|-------------------------------------|
| National      | 2019 | Environmental Reporting Guidelines: Including streamlined energy and carbon reporting guidance | United Kingdom | (UK Government, 2019)               |
| International | 2001 | Greenhouse Gas Protocol Corporate Accounting and Reporting Standard                            | Global         | (WBCSD and WRI, 2015)               |
| International | 2020 | Greenhouse Gas Protocol for Agricultural Guidance                                              | Global         | (WBCSD and WRI, 2020)               |
| International | 2019 | Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories                 | Global         | (IPCC, 2019)                        |
| National      | 2019 | ISO 14064                                                                                      | United Kingdom | (British Standards Institute, 2020) |
| National      | 2018 | ISO 14067                                                                                      | United Kingdom | (British Standards Institute, 2019) |
| National      | 2020 | UK GHG Inventory, 1990 to 2018                                                                 | United Kingdom | (Brown et al., 2020)                |

Two more international approaches include the Greenhouse Gas Protocol Corporate Accounting and Reporting Standard and the Greenhouse Gas Protocol for Agricultural Guidance. The World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD) have also established guidelines for the corporate sector via the Greenhouse Gas Protocol Corporate Accounting and Reporting Standard (WBCSD and WRI, 2015). The document contains internationally accepted best practice

GHG inventory accounting and reporting standards and tools. It aims to achieve a global low emissions economy. A recent guidance document has been developed specifically for agriculture (WBCSD and WRI, 2020). This version, summarizes and customizes the guidance from the main document and focuses on corporate or farm-level accounting. Since agriculture is comprised of diverse subsectors, it aims to establish a framework that is common in all of them.

The UK has developed its own national Greenhouse Gas Inventory (Brown et al., 2020) that uses Tier 1, 2, and 3 methods reported in the IPCC guidelines. The inventory is comprised of many models covering a range of sectors dating back to 1990. Estimates of each sector are presented each year in February and are updated in March. The agricultural one covers three major forms of agricultural land use i.e., pasture, grassland, and arable land. The land-use, land-use change, and forestry model covers the emissions and removals from current land uses land-use changes and forestry and is the only sector that reports net removals. Both models use data from matrices and tables stored in an SQL dataset server and estimate outputs in an Excel spreadsheet. Additionally, three more national guidelines exist in the UK. The Environmental Reporting Guidelines (UK Government, 2019) use methodologies from protocols produced by ISO 14064 (British Standards Institute, 2020). ISO has established standards for the design and development of GHG inventories and procedures to quantify, monitor, and report emission reduction and removal.

More specifically ISO 14064 -1 (British Standards Institute, 2020) sets the principles for the design and development of GHG inventories for organisations. This includes the following principles: relevance, completeness, consistency, accuracy, and transparency. The document specifies how GHG emission and removal boundaries are defined, quantified, and calculated. It also specifies how the baseline year GHG inventory is established, the mitigation activities, and finally the inventory quality management. According to ISO 14067 (British Standards Institute, 2019), all GHG emissions and

removals will be assessed according to internationally recognised methods, such as the IPCC Guidelines for National Greenhouse Gas Inventories (IPPC, 2019).

### **2.3.1.2 Payment schemes**

Farm-level carbon and GHG inventories take place in the context of a range of governmental support for farms. Farmers in the European Union can receive payments from Pillar I and II from the Common Agriculture Policy (CAP). In 2019, the UK left the European Union and UK farmers are currently transitioning from a payment system dictated by the CAP to a bespoke UK system. Under Pillar I of the CAP, UK farmers received “basic payments” for each hectare of agricultural land that they manage (Rural Payments Agency, 2019) and this can make up around 50% of the net farm income on many farms (Natural Capital Committee, 2017). Through this scheme they declare their owned land, the land uses (permanent grassland, arable, land permanent crops) and any non-agricultural features and in return receive money, in the UK, from the Rural Payments Agency (RPA) (HMG, 2018; Department for Environment Food & Rural Affairs and Rural Payments Agency, 2020). Under Pillar II of the CAP, some UK farmers still receive payments from the Countryside Stewardship, and Environmental Stewardship schemes, which were often agreed upon on a five-year basis.

Following Brexit, and as described in the new Agriculture Bill, the UK Government has been planning to replace basic payments with the Environmental Land Management (ELM) scheme with a focus on the delivery of the 25-Year Environment Plan (Department for Environment, Food & Rural Affairs and Rural Payments Agency, 2021). In England, the ELM comprises three schemes: the Sustainable Farming Incentive, Local Nature Recovery, and Landscape Recovery (UK Government 2022). In these schemes farmers are however not receiving government payments for C sequestration. In addition to the above, some farms are also securing payments from certified carbon sequestration schemes such as the Woodland Carbon Code (Woodland Carbon Code, 2022). In order to receive payments, farms must demonstrate the additionality and the permanence of C sequestration (Badgery et al., 2020). For the UK’s Carbon Registry two types of units exist. Firstly, there are pending issuance units (PIUs) which describe anticipated carbon

sequestration over given future periods, and secondly, there are full carbon credits which are verified accumulations of carbon storage (Woodland Carbon Code, 2022).

### **2.3.1.3 Delineation methods**

Farm C and GHG inventories across Europe also take place in the context of methods for delineating areas of land, typically on a field basis. The Land Parcel Identification System (LPIS) developed in 2005, is an EU-wide geospatial geographical dataset that holds records of all agricultural land parcels that are eligible to receive CAP payments (Grandgirard and Zielinski, 2008; European Court of Auditors, 2016). These parcels are uniquely identified and geographically enclosed (European Court of Auditors, 2016). The LPIS is based on orthoimagery (aerial or satellite) and designed to a) verify the CAP eligible parcels and b) calculate their maximum eligible area (Oesterle et al., 2005). Over the years, it has been found that some parcels can be under or over-declared by farmers compared with the registered referenced ones (Oesterle et al., 2005; Inan and Cete, 2007). Nevertheless, Grandgirard and Zielinski, (2008) report that LPIS is frequently proposed as the basis of effective spatial agricultural management.

## **2.3.2 Analysis of model and tool criteria selection**

### **2.3.2.1 Modelled components**

From the literature review, 25 models and accounting tools were identified. The analysis identified four types of modules with the models and tools as seen in Table 2-3. These were modules for i) carbon (C) and nitrogen (N) stocks or flows separate from the soil, ii) soil organic carbon (SOC) stocks or flows, iii) greenhouse gas (GHG) flows, and iv) crop growth. The C and N models describe the dynamics of carbon and nitrogen compounds such as ammonium ( $\text{NH}_4^+$ ) and nitrate ( $\text{NO}_3^-$ ) pools and the way that they are affected by farm management. The SOC models typically categorise soil carbon into several pools with specific properties. The GHG models and tools calculate emissions so farmers can produce carbon-neutral or low C footprint farming practices. Lastly, the crop growth models typically simulate plant growth, over different stages on a specific land unit..

Table 2-3 Reviewed research and decision support tools together with their characteristics. Where C = Carbon, N= Nitrogen, SOC= Soil Organic Carbon, and GHG =Greenhouse Gasses.

| Name                         | Modelled components |     |     |             | Origin      | Spatial |   | Reference                          |
|------------------------------|---------------------|-----|-----|-------------|-------------|---------|---|------------------------------------|
|                              | C, N & compounds    | SOC | GHG | Crop growth |             | Y       | N |                                    |
| Process based models         |                     |     |     |             |             |         |   |                                    |
| APEX                         | X                   |     |     | X           | USA         | X       |   | (Williams et al., 1995)            |
| CANDY                        | X                   |     |     |             | Germany     |         | X | (Franko, 1996)                     |
| CESAR                        |                     | X   |     |             | Netherlands |         | X | (Vleeshouwers and Verghagen, 2002) |
| CENTURY                      | X                   | X   |     |             | USA         |         | X | (Parton, 1996)                     |
| DAISY                        | X                   |     |     | X           | Denmark     |         | X | (Hansen et al., 1991)              |
| DayCent                      | X                   |     | X   | X           | USA         |         | X | (Parton et al., 2001)              |
| DNDC                         | X                   |     | X   |             | USA         | X       |   | (Li et al. 1992)                   |
| ECOSSE                       |                     |     | X   |             | UK          | X       |   | (Smith et al., 2010)               |
| EPIC                         | X                   |     |     | X           | USA         |         | X | (Williams et al., 1984)            |
| ICBM                         |                     | X   |     |             | Sweden      |         | X | (Andren and Katterer, 1997)        |
| InVEST                       | X                   |     |     |             | USA         | X       |   | (Tallis and Polasky, 2009)         |
| NCSOIL                       | X                   |     |     |             | USA         |         | X | (Molina et al., 1983)              |
| RothC                        |                     | X   |     |             | UK          | X       |   | (Jenkinson et al., 1977)           |
| TECO                         | X                   |     |     |             | USA         |         | X | (Weng and Luo, 2008)               |
| Statistical models and tools |                     |     |     |             |             |         |   |                                    |
| AgreCalc                     |                     |     | X   |             | UK          |         |   | (SAC, 2022a)                       |

|                                 |   |   |   |   |        |  |   |                                                  |
|---------------------------------|---|---|---|---|--------|--|---|--------------------------------------------------|
| COMET Farm                      |   |   | X |   | USA    |  | X | (Ziegler et al., 2016)                           |
| Cool Farm Tool                  |   |   | X |   | UK     |  | X | (Sustainable Food Lab et al. 2011)               |
| CropSyst                        |   |   | X | X | USA    |  | X | (Stöckle et al., 2001)                           |
| Farm Carbon Calculator          |   |   | X |   | UK     |  | X | (Farm Carbon Cutting Toolkit Organisation, 2022) |
| FaST                            | X |   |   | X | Europe |  | X | (Campos, 2020)                                   |
| Holos                           |   |   | X |   | Canada |  | X | (Janzen et al., 2006)                            |
| OFoot                           |   |   | X |   | USA    |  | X | (Carlson et al., 2017)                           |
| SCORPAN                         |   | X |   |   | USA    |  | X | (McBratney et al. 2003)                          |
| ScotFarm                        |   | X |   |   | UK     |  | X | (Shrestha, 2014)                                 |
| The Farm Tool Carbon Calculator |   |   | X |   | France |  | X | (Metayer and Haastrup, 2013)                     |

### 2.3.2.2 Process based models.

From the 25 selected models and tools, 15 as seen in Table 2-3 were classified as primarily process based models and 10 were primarily statistical models and tools. Within the identified research models, the first category tends to focus on describing the process that is taking place, whereas the statistical ones focus on producing easily understandable outputs. Additionally, the process-based models tend to include highly detailed accounting approaches and are modelled with a “process-oriented multicompartment” (Smith et al., 1997). Fourteen commonly cited process-based models, appropriate for arable and/or grassland systems, are: NCSOIL, EPIC, RothC, DAISY, DNDC, APEX, CANDY, CENTURY, ICBM, DayCent, CESAR, TECO, InVEST, and ECOSSE (Table 2-3). These are briefly discussed in terms of their modelled components.

The first group models C & N compounds. NCSOIL (Molina et al., 1983), replicates the flow of C, N,  $\text{NH}_4$ , and  $\text{NO}_3$  from seven processes. The Carbon-Nitrogen-Dynamics (CANDY) model, described by Franko (1996), was designed to calculate the short-term dynamics of nitrogen and long-term changes in soil C. The model was developed to provide information about crops, leaching and water quality to farmers. The Terrestrial Ecosystem (TECO) process-based ecosystem model aims to examine processes for interactive response regulation for high  $\text{CO}_2$ , warming, and changed precipitation. These interactive responses come from four main model components: canopy photosynthesis, soil water dynamic, plant growth (allocation and phenology), and soil C transfers. The model measures the C flow from the plant tissues to litter and soils and then to the atmosphere (Weng and Luo, 2008).

The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model comprises a collection of 18 spatially-explicit software models (Tallis and Polasky, 2009). These assist in mapping and evaluating ecosystem services, in addition to the preparation, processing, and visualisation of data. InVEST aims to explore how changes in ecosystems are likely to lead to changes that will provide benefits to people. One of the 18 models is for carbon storage and sequestration, where the storage is calculated

for each land parcel, according to the land cover classification maps provided by the user. In each parcel, the carbon is divided into four pools and the total stored amount, in each one of these pools, is calculated (Sharp et al., 2018).

The DeNitrification and DeComposition (DNDC) model creates similar outputs to NCSOIL, TECO, InVEST and CANDY in addition to modelling GHGs. It describes denitrification and decomposition processes to predict emissions of CO<sub>2</sub>, N<sub>2</sub>O, and N from farmed soils (Li et al., 1992). This agroecosystem process-based model is comprised of six sub-models and has a site and a regional mode. While running the regional mode, each region is divided into polygons. The model has also been integrated with a GIS dataset containing information about the location, climate, soil properties, cropping systems, and management practices of each polygon (Zhang et al., 2006; University New Hampshire, 2007; Topp and Rees, 2008). The Colorado State University developed the DayCent model as an evolved version of Parton's CENTURY model (Campbell et al., 2014). It uses a daily time step to simulate fluxes of C and N between the atmosphere, vegetation, and soil. It also simulates GHG emissions, crop growth, and biomass production for a range of agricultural systems (Wang et al., 2020).

CENTURY is a monthly step model developed for long-term grassland dynamics and has been subsequently extended and used for arable crops (Parton, 1996). The CENTURY biochemistry model is utilized to simulate C, N, phosphorus (P), and sulphur (S) dynamics, primary productivity, water balance, and plant growth (Dimassi et al., 2018). It comprises several major sub-models including Soil Organic Matter (SOM)/decomposition, water budget, and plant production. The SOM sub-model describes three carbon pools: active, slow, and passive, where the turnover time ranges from 1 -3 months (active) to 400 and 4000 years (passive) (Tizio and Grego, 2008; Gocht et al., 2016).

Another group produces outputs for C & N compounds together with crop growth. The Erosion-Productivity Impact Calculator (EPIC) model was developed to quantify the

relationship between soil erosion and soil productivity(Williams et al., 1984). Since its development, it has advanced to a comprehensive agroecosystem model that simulates crop growth, and soil C and N dynamics in complex management systems (Izaurrealde et al., 2006) with however no information about biomass C. The model operates on a field-scale basis and is designed to simulate homogeneous in terms of weather, soil, topography, plant cover, and management areas. DAISY was developed as a primary crop production model that includes soil water and N processes in various agricultural systems (Hansen et al., 1991). The model includes a soil dynamic module, but it does not account for soil C. Moreover, similar to the previous models it is not ideal for the development of farm baseline C stock inventories.

The Agricultural Policy Environmental eXtender (APEX) is a model that evaluates complex landscape and management scenarios and determines how current climate and management choices can affect the future of a farm (Leyton, 2019). The model extends EPIC's capabilities of simulating the impacts of management and land use for whole-farm systems and small watersheds (Williams et al., 1994). This was done due to two reasons. Firstly, to connect the simulation of soil C and N dynamics, to crop management, tillage methods, and erosion (Williams et al., 2014). Secondly, to explain more realistically the carbon and nitrogen transformation in the soil. This was something that Williams et al., (1995) had not described in their version which was focused on the effect of erosion on soil productivity. A study by Gassman et al. (2010) has shown the changes that the model has undergone since its creation. It can now simulate multiple spatially explicit fields with interactions between them. Additionally, it accounts for the main physical and biological processes including hydrology, crop growth and yield, water balance, nutrient transformations, storage, C, and nitrogen transport.

An additional group of models focuses on SOC modelling. The Rothamsted Carbon Model (RothC), calculates the turnover of organic C in the topsoil(Jenkinson et al., 1977). The model typically operates on a monthly time-step (Yokozawa et al., 2010; Mesfin et al., 2020; Mondini et al., 2012). It calculates the total organic carbon ( $\text{t ha}^{-1}$ ), the

microbial biomass C content ( $\text{t ha}^{-1}$ ), and the radiocarbon age of soil (Coleman and Jenkinson, 2014). It was originally used to calculate soil carbon turnover on arable topsoils but was later extended for grasslands and woodlands (Smith et al., 1997). This is an overall strong model but cannot be used on its own for the development of baseline C stock inventories due to its SOC estimation use.

The two-component Introductory Carbon Balance Model (ICBM) calculates steady-state C pool sizes together with model parameters from litter bag or C labelled litter decomposition data (Andren and Katterer, 1997; Kröbel et al., 2016). The Carbon Emission and Sequestration by Agricultural land use (CESAR) model focuses on C stocks and fluxes in soil organic matter. It contains the effects of the crop (species, yield, and rotation), climate (temperature, rainfall, and evapotranspiration) and soil (C content and water retention capacity) on the agricultural land's C budget (Vleeshouwers and Verghagen, 2002). According to Vleeshouwers and Verhagen (2001), the model calculates C input/output from the plant residues to the soil and from the topsoil layers, through the decomposition of the accumulated organic matter, into deeper layers.

The last model in this process-based category is the Estimation of Carbon in Organic Soils – Sequestration and Emissions (ECOSSE) model. It simulates how land use and climate change impact GHG emissions from mineral and organic soils in England, Scotland, and Wales (Smith et al., 2010 a,b). It aims to simulate soils with high organic levels and the method used for mineral soils was derived from the aforementioned RothC model. This model, similar to RothC can be adapted to perform spatially (Smith et al., 2010 a,b).

### **2.3.2.3 Statistical models and tools**

The second category of reviewed carbon and GHG models and tools (Table 2-3) is comprised of statistical models. These are generally used to predict the main sources of emissions, evaluate mitigation projects or report stocks and emissions, and raise awareness. Leinonen et al., (2019) reviewed 64 tools for quantifying GHG emissions and

removals in the agricultural sector, intending to find the most suitable for farm carbon audits. Of the 64 tools, only three satisfied all evaluation criteria and were considered applicable for carbon audits in farms: Agrecalc, Cool Farm Tool, and Solagro (JRC) Carbon Calculator.

The majority of models and tools in this category produce GHG emissions outcomes as seen in Table 2-3. The model named Holos (Janzen et al., 2006; Kröbel et al., 2016) aims to link Canadian farm characterization and the Intergovernmental Panel on Climate Change (IPCC) emission factors, for the generation of average annual GHG emissions and assessments. Agrecalc is a GHG emissions decision support tool originally developed in 2007 for the Scottish Beef Industry (SAC, 2022a) and in 2014 the first web version was launched (SAC, 2022a). The tool aims to assist the agricultural sector to deliver net-zero emissions and at the same time increase farm productivity. It is initially free for farmers, and non-farmer users might be required to pay. Three GHGs are modelled, namely CO<sub>2</sub>, N<sub>2</sub>O and CH<sub>4</sub> and the results are presented according to crop and livestock enterprises (SAC, 2022b).

The Cool Farm Tool, an empirical GHG calculation farm-scale tool aims to provide decision support in addition to investigating different management practices (Hillier et al., 2011). Being an online farm-level GHG calculator, it illustrates how farmer management decisions sequester soil C or reduce GHG emissions. However, farmers can only assess one production system at a time and not the whole farm even if the farm is comprised of many production systems. The model calculates the GHG emissions using IPCC Tier 1 -3 factor approaches (Sustainable Food Lab, University of Aberdeen and Unilever, 2011; Cool Farm Alliance, 2016). The Farm Carbon Calculator was developed in 2012 in the UK by a group of farmers with a mission to build future resilience by tackling climate change, improving environmental impacts and increasing profitability (Farm Carbon Calculator, 2022). All calculations are performed at an online interface where a spreadsheet with the required input data and results can be downloaded. The results are comprised of a GHG emissions and sequestration summary.

Three other tools worthy of mention are the Farm Tool Carbon Calculator, ScotFarm, COMET Farm, and OFoot. In France, the Farm Tool Carbon Calculator was developed to assess the life cycle GHG emissions from different European Union (EU) farming systems and proposes mitigation actions at a farm level. (Metayer and Haastруп, 2013). It has a similar name to the aforementioned Farm Carbon Calculator; however, they are not the same tool. Carlson et al. (2017) and Adewale et al. (2019) describe an online model called OFoot, which calculates GHG emissions from agricultural practices and farm products.

CropSyst (Stöckle et al., 2001) is a daily step cropping systems simulation model. It analyses the productivity, environmental impact and GHG emissions of crop rotations and systems management. It simulates many processes, namely: the soil water budget, crop phenology, canopy, and root growth, biomass production, crop yield, residue production and decomposition, soil erosion by water, and salinity. It also calculates economical values, in addition to simulating crop growth and having links to GIS software (ESRIs' ArcGIS software) representing the land block fragment.

ScotFarm is a linear programming tool created for maximizing farm profit by exploring the effects of different management practices (Shrestha, 2014). The tool takes into account all the interactions between farm structure, and management activities (Shrestha, 2014). Glenk et al. (2017) using Scotfarm reported how soil organic C management practices affect the farm's gross margin. COMET Farm was developed in 2016 to calculate C and GHG emissions for farms and ranches in the USA. The tool estimates the carbon footprint of all the parts of the farm/ranch and allows farmers to evaluate management options to minimise GHG emissions and sequester more carbon (Ziegler et al., 2016).

The SCORPAN model (McBratney, Mendonça Santos and Minasny, 2003) is a spatial quantitative model for soil mapping and uses machine learning to associate patterns to data for prediction. It uses a function of seven covariates: soil, climate, organisms and

vegetation, relief, parental material, age, and spatial location, for a specific point in space and time, which has been applied to both topsoil and subsoil studies (Sindayihebura et al., 2017). Flathers and Gessler (2018) explain that spatially explicit data can be collated in a raster format and can be processed using a Geographical Information System (GIS). The model enables the quantification of the relationships between the spatial covariates and therefore, the soil attributes are predicted in a spatial context (Avalos et al., 2018; Poppiel et al., 2019).

Lastly, one tool that has been proposed to be developed within the 2021 – 2027 CAP year period, under the Good Agricultural and Environmental Conditions (GAECs) framework, is called FaST. It targets assisting the sustainable use of fertilizers by EU farmers while enhancing the digitization of the agricultural sector (DG Agriculture and Rural Development, EU Space Programme and EU ISA<sup>2</sup> Programme 2022). The tool in development aims to provide information regarding the crops, the number of animals and the amount of manure produced by them, inside the selected LPIS parcel, and at the same time propose a nutrient management plan (Campos, 2020).

### **2.3.3 Characteristics of spatial models and tools**

The next step was to investigate in more depth those models and tools which were used spatially. As observed in Table 2-3, many of the examined models and tools were not spatially explicit. Of all those that were reviewed, eight models and tools were spatial as seen in Table 2-3 and Table 2-4. In the next sections, a more detailed comparison between them follows.

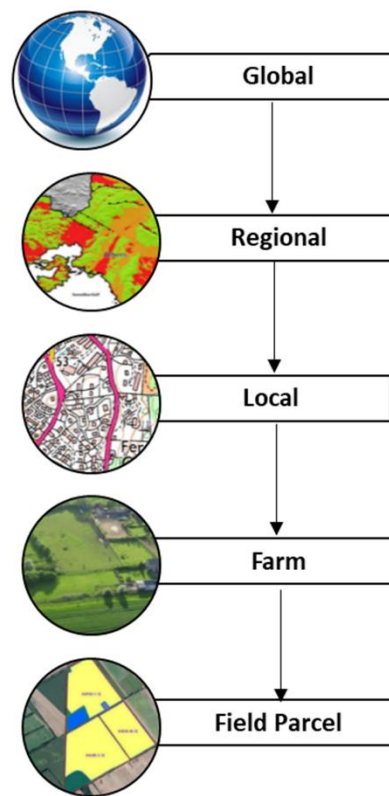


Figure 2-2 Schematic representation of horizontal spatial scales of modelling

### 2.3.3.1 Area

The area of the models and tools was divided into horizontal and vertical. The smallest area is the field level and above that in ascending order is the farm, local, regional, and global as seen in Figure 2-2. Analyses for APEX, CropSyst, and FaST (Williams et al., 1995; Stöckle, et al., 2001; Campos, 2020) have been reported at both site and farm levels, whereas SCORPAN (McBratney, Mendonça Santos and Minasny, 2003) has been reported to be used at a regional scale. DNDC and InVEST can be run on many different levels, site, regional and farm, regional and global respectively (Zhangs et al. 2006; Tallis and Polaskey, 2009). ECOSSE and RothC (Smith et al., 2010 a,b; Palma et al., 2018) can function at field, national and global scales.

Table 2-4 Eight C or GHG models and tools, which have been reported to be used spatially

| Tool     |              |                 | Spatial Resolution     |                             | Maximum Depth (cm) | Temporal Resolution      | Reference                  |
|----------|--------------|-----------------|------------------------|-----------------------------|--------------------|--------------------------|----------------------------|
| Name     | Primary use* | Place of Origin | Area                   | Minimum Depth Interval (cm) |                    |                          |                            |
| APEX     | PB           | USA             | Farm, Small Watersheds | n/a                         | n/a                | Daily                    | (Williams et al., 1995)    |
| DNDC     | PB           | USA             | Field Parcel, Regional | 10                          | 50                 | Daily                    | (Li et al. 1992)           |
| CropSyst | S            | USA             | Farm                   | 10                          | 300                | Daily                    | (Stöckle, et al., 2001)    |
| FaST     | S            | Europe          | Farm                   | No information released     | Topsoil            | Annual                   | (Campos, 2020)             |
| InVEST   | PB           | USA             | Farm, Regional, Global | 30                          | 30                 | Annual                   | (Tallis and Polasky, 2009) |
| ECOSSE   | PB           | Scotland        | Field, National        | 5                           | 300                | Monthly, Weekly or Daily | (Smith et al., 2010 a, b)  |
| RothC    | PB           | UK              | Field, National        | n/a                         | Topsoil            | Monthly                  | (Jenkinson et al., 1987)   |
| SCORPAN  | PB           | USA             | Regional               | Depends on the study        | 120                | Annual                   | (McBratney, et al., 2003)  |

\*PB=Process- Based, S= Statistical

### **2.3.3.2 Minimum Depth Interval**

The minimum depth interval for the models and tools is usually determined by the minimum depth interval for C values as seen in Table 2-4. ECOSSE (Smith et al., 2010 a,b) specifies that the analysis can be performed by dividing the soil into 5 cm layers, while RothC (Coleman and Jenkinson, 2014) does not specify the vertical resolution and requires the user to indicate the soil layer depth as model input. Moving on to SCORPAN (Minasny et al., 2013), the vertical resolution depends on the study. Both DNDC and CropSyst (University New Hampshire, 2007; Adewale et al., 2019), have a resolution of 10 cm, whereas InVEST (Sharp et al., 2018) follows the IPCC international guidelines and has a 30 cm resolution. Lastly, there is no information released yet for the FaST model (Campos, 2020). The model APEX (Williams et al., 1995) does not perform a below ground analysis, and it does not have a spatial vertical resolution and a vertical extent.

### **2.3.3.3 Maximum Depth**

The maximum depth refers to how deep below the ground C stocks are measured and modelled as seen in Table 2-4. InVEST (30 cm) typically examines the amount of C present in the first 30 cm of the soil. CropSyst (300 cm), ECOSSE (300 cm), DNDC (50 cm) and SCORPAN (120 cm) extend beyond the first 30 cm and study the processes in both the topsoil and the subsoil (European Court of Auditors, 2016; Flathers and Gessler, 2018; Sharp et al., 2018). RothC does not specify the exact extent, but it generates outcomes for the topsoil (Smith et al., 1997; Palma et al., 2018; Drexler, Gensior and Don, 2021). Lastly, Campos, (2020) specifies that the FaST model is focused on the topsoil.

### **2.3.3.4 Temporal resolution**

The temporal resolution identifies the time step of the required input data (Table 2-4). Fast Tool, InVEST and SCORPAN (Minasny et al., 2013; European Court of Auditors, 2016; Sharp et al., 2018; Campos, 2020) all run on an annual time step, whereas APEX, CropSyst, and DNDC (University New Hampshire, 2007; Gassman et al., 2010; Adewale et al., 2019) use a daily timestep. CropSyst (Adewale et al., 2019) can run simulations that

last from a year up to hundreds of years and DNDC (University New Hampshire, 2007) can run annual simulations. On the other extreme, FaST, InVEST and SCORPAN (Minasny et al., 2013; Sharp et al., 2018; Campos, 2020) all run simulations for the specific year that the management plan/ input data were made for. Lastly, RothC has a monthly time step and ECOSSE can run monthly, weekly or even daily.

#### **2.3.3.5 Platform and interface**

All of the reviewed spatial models and tools seem to be freely available to researchers and farmers under specific conditions. To access the Fast Tool (Campos, 2020) one needs to be a farmer or a landowner. APEX (Williams et al., 1995), RothC (Jenkinson et al., 1987), ECOSSE (Smith et al., 2010), CropSyst (Stöckle, Nelson and McCool, 2001) DNDC (Li et al. 1992), InVEST (Tallis and Polasky, 2009) and SCORPAN (McBratney, et al., 2003) are desktop-based software with a user-friendly interface. FaST is a web-based application for farmers (Campos, 2020). As it can be seen Table 2-5, most of the desktop software models are either scripted in C, FORTRAN, or Python and the web applications in Java.

#### **2.3.3.6 Inputs and outputs**

According to Gassman et al., (2010), APEX consists of more than 12 components that the user needs to input values. The 12 major ones are climate, hydrology, crop growth, pesticide fate, nutrient cycling, erosion–sedimentation, carbon cycling, management practices, soil temperature, plant environment control, economic budgets, and subarea/routing. CropSyst (Stöckle et al., 2003) requires five input text files: simulation control, location, soil, crop, and management, created by the user. DNDC's user guide (University New Hampshire, 2007) specifies that it needs relevant input information as CropSyst (weather, soil properties, crop acreage, and farming practices) with the only exception that the data are stored in a Geodataset. Information from Campos (2020) suggests that the in-development FaSTs' input data will be generated by the user and will include files relevant to farm information, soil sampling and management practices like the two aforementioned models.

SCORPAN (McBratney et al., 2003; Minasny et al., 2013; Sindayihebura et al., 2017) however, needs complex data to make predictions which are comprised of soil attributes, climatic values, organisms present, relief, parent material age and spatial location. Moving on to InVEST, according to the user guide (Sharp et al., 2018), it uses different “supply” and “service” data depending on the sub-model that is run by the user. What is common in all sub-models, are the current and future land use/land cover maps generated by the user. The input data are called “supply” and “service” where the first one represents what is potentially available from the ecosystem, while the second incorporates the demand, hence using information about the benefits of that service. RothC requires the user to insert data on the weather, soil properties, soil cover, plant residues, farmyard manure, and depth of the soil layer. Lastly, ECOSSE (Smith et al., 2010b) requires site-specific complex management, land use, crop parameters, soil parameters and water depth data.

The models and tools also have different kinds of outputs depending on the different processes considered. The outputs of APEX according to the latest user manual (Steglich and Williams, 2018) are simulations across a broad range of agricultural landscapes through a wide array of management practices and cropping systems. Stöckle et al. (2001) say that CropSyst focuses on outputs related to crops and their productivity. A closer look at DNDC and SCORPAN proves that they give outputs associated with soil dynamics (Smith et al., 1997; Sindayihebura et al., 2017). By contrast, the DNDCs’ user manual (University New Hampshire, 2007) specifies that has the extra feature of calculating GHG emissions. The FaST model (Campos, 2020) mostly concentrates on information about nutrient management farm plans and InVEST (Sharp et al., 2018) evaluates different ecosystem services. The RothC simulates results for the total organic carbon content in the topsoil, topsoil microbial biomass C content and radiocarbon age of the soil. Lastly, the ECOSSE outputs are comprised of simulations of changes in soil organic carbon and soil greenhouse-gas emissions.

Table 2-5 Spatial models and tools with their resolutions, platform, and outputs.

| Spatial tool | Tool platform and programming language                                                                          | Calculation uncertainty                                                                                              | Outputs                                                                       | Reference                  |
|--------------|-----------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|----------------------------|
| APEX         | <u>Desktop Software</u> – Written in FORTRAN it can be executed in Microsoft Windows and UNIX platforms.        | n/a                                                                                                                  | Evaluation of complex climate, landscape and management scenarios             | (Williams et al., 1995)    |
| DNDC         | <u>Desktop Software</u> – Written in Visual C ++ 6.0 and must be executed in the Microsoft Windows environment. | Uncertainty analysis by using input information from a site, and a regional dataset built up in the Shangrila format | Decomposition, denitrification, fermentation, nitrification and GHG emissions | (Li et al. 1992)           |
| CropSyst     | <u>Desktop Software</u> – Written in C++ and can be executed in Windows and UNIX                                | Uncertainty analysis is driven by input information from a site                                                      | Crop growth, yields, soil water, and N erosion                                | (Stöckle, et al., 2001)    |
| FaST         | <u>Web-Based or Mobile Phones/Tablets Application</u> – Written in Java can be executed in Windows and Mac      | n/a                                                                                                                  | A proposed tool to manage farm nutrients                                      | (Campos, 2020)             |
| InVEST       | <u>Desktop Software</u> – Written in Python code and can be                                                     | Monte Carlo uncertainty analysis by using input information                                                          | Ecosystem services model including yields, C storage, and sequestration       | (Tallis and Polasky, 2009) |

|             | executed in<br>Windows and<br>Mac                                                                                          | from the study<br>area                                                      |                                                                                                                              |                              |
|-------------|----------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------|------------------------------|
| ECOSSE      | <u>Desktop<br/>Software</u> – Can<br>be executed in<br>Windows.                                                            | Uncertainty<br>analysis is<br>driven by input<br>information<br>from a site | Simulates the<br>impacts of land use<br>and climate change<br>on GHG emissions<br>from both mineral<br>and organic soils. It | (Smith et al.,<br>2010 a, b) |
| RothC       | <u>Desktop<br/>Software</u> – Can<br>be executed in<br>Windows and<br>DOS.                                                 | Uncertainty<br>analysis is<br>driven by input<br>information<br>from a site | Turnover of organic<br>carbon in non-<br>waterlogged topsoil                                                                 | (Jenkinson et<br>al., 1987)  |
| SCORPA<br>N | <u>Desktop<br/>Software</u> –<br>Written in<br>Python, ArcPy<br>and R code and<br>can be executed<br>in Windows and<br>Mac | Uncertainty<br>analysis is<br>driven by input<br>information<br>from a site | Spatial<br>representation of<br>soil properties using<br>environmental input<br>data                                         | (McBratney, et<br>al., 2003) |

## 2.4 Discussion

### 2.4.1 Current landscape and gaps

The systematic literature review has examined and assessed the outputs of existing carbon and GHG models and tools which could potentially be used to develop farm carbon (C) stock inventories. The development of the reviewed models and tools started in the 1970s, but it wasn't until 1992 that a spatial component was introduced with DNDC (University New Hampshire, 2007). What is common in most of the statistical models and tools is that they follow a similar framework based on international guidelines and standards such as the IPCC (2019). Most of the reviewed inventory models and tools are focused on either C and GHG flows or other soil C processes. One major difference between the process-based and the statistical models and tools is the level of detail in the calculations. The statistical models and tools typically require data

that the farm owner or landscape manager can access, while research models typically need more specialised information.

One can notice the minority in spatial models and tools by observing Table 2-3 and Table 2-5, as they account for only 35% of the selected ones. The temporal scale of the spatial models and tools ranges from daily to annual and the level of uncertainty is not always stated. Many of the statistical models and tools do not calculate soil carbon stocks in detail, but many process-based models consider soil organic carbon dynamics.

The demonstrated spatial models and tools revealed that most studies have been done for the topsoil, as the IPCC (IPPC, 2019) guidelines recommend, and where the highest amount of carbon is stored. As Luedeling et al. (2016), described in their research, measurements of bulk density beyond 30 cm present many logistical problems. Also, short-cycling C is not included in most of the models, as it is generally identified as not relevant to the greenhouse effect. Most of the 25 reviewed models and tools have different conceptual soil C pools with similar chemical or physical characteristics (Franko, 1996; McBratney et al., 2003; Tizio and Grego, 2008; Weng and Luo, 2008; Stockmann et al., 2013). The first pool is typically called the active pool (fresh plant material, root exudates, microbial biomass) with a mean residence time (MRT) of one (1) year, where the following three forms of SOC are also categorised: surface plant residue, buried plant residue and particulate organic matter (POC). The second pool or slow pool (SOC that decomposes at an intermediate rate) typically has an MRT of 100 years and humus is the only form of SOC that is found in it. Lastly, the passive or inert pool (SOC with physical or chemical stability) with a typical MRT of 1000 years where like previously only one form of SOC is found (charcoal or charred materials).

Overall based on the above study, it is apparent that there are few existing spatial C models and few tools that provide farm-level C stock inventories and estimates of their uncertainty. Additionally, while there are often various GHG flux calculators there are only a few C stock models that have been published. Where they are published, their

accuracy is rarely presented. Hence there appears to be a need for scalable and easy-to-use farm-level C inventory tools. The following section examines potential criteria for such tools in terms of their administrative and farm-related, regulatory, and scientific/technical characteristics.

#### **2.4.2 Potential farm and administrative criteria**

In a study by Burbi et al. (2016), the interviewed farmers suggested that they want tools that will provide practical alternatives, speak their language and require limited or no direct input data. By contrast, a high level of expertise is required to understand the processes that take place in most of the selected process based models. Moreover, a lot of labour is needed to input all the data required for many decision support tools i.e., Holos, Cool Farm Tool, Farm Carbon Calculator, ScotFarm, COMET Farm, OFoot, APEX, CropSyst, and FaST.

For many farmers, the financial aspects of carbon storage may be of interest, something that most of the reviewed tools do not assess. This may be particularly important as government support for farms transitions to ELMs in England. Farmers and landowners may benefit from a tool that will assist them in creating the baseline inventory and at the same time provide assistance both in decision making and towards contributing toward the net-zero 2050 goal (Adewale et al., 2019).

#### **2.4.3 Potential regulatory criteria**

Any tool for creating a farm-level carbon inventory should align with criteria set by the international and national guidelines and protocols (British Standards Institute 2019,2020; IPPC, 2019; WBCSD and WRI, 2020). In all accounting protocols and guidelines, one of the initial steps is to set the boundaries of the farm business and delineate the land into managed and unmanaged. This can be performed using the LPIS system (European Court of Auditors, 2016). Ideally, a land classification system applicable to the six land cover categories specified in the IPCC guidelines (Forest land, cropland, grassland, wetlands, settlements and other land) would be useful. The IPCC

guidelines additionally specify that the developed inventory needs to cover the carbon stored in the following four pools: above ground biomass, below ground biomass, dead organic matter (made up of dead wood and litter), and soil.

Lastly, all guidelines specify that a level of uncertainty needs to be estimated, as this will allow users to make decisions with the appropriate level of confidence. Thus, the models and tools that will be used to develop the C stock inventory will need to be evaluated. This is something that many of the current tools are lacking, as the uncertainty was either not provided in most of the reviewed tools, or physical measurements to compare the results with were required as seen in Table 2-3. Transparency of the way that the calculations that were followed in the methodology and the data sources are also major criteria (WBCSD and WRI, 2015).

#### **2.4.4 Potential scientific criteria**

While there are often various GHG flux calculators, there are only a few C stock models that have been published i.e., the Cool Farm Tool. Even then, it is not evident whether they take into consideration landscape features such as hedges and trees, and only Holos takes into account trees, but not in a spatial way. Studies like Upson and Burgess (2013), Upson et al. (2016) and Axe et al. (2017) have highlighted the contribution of trees and other landscape features to total farm carbon, which should be considered when creating farm carbon stock inventories.

Since the aim here is to limit the amount of labour and economic effort that the farmer needs to put in, one option is to use remotely sensed data. Remote sensing can be easily accessible, continuous, and often freely available data with global coverage. Remote sensing data are comprised of satellite, aerial, LiDAR (light detection and ranging) and SAR (Synthetic Aperture Radar) technologies that have different spatial, spectral and temporal resolutions, making each one unique for different applications (Nasrallah et al., 2019; Karthikeyan et al., 2020). Vegetation and other spectral indexes, such as the NDVI (Normalised Vegetation Index) and SAVI (Soil Adjusted Vegetation Index) can be

used to monitor the vegetation and soil health, classify different crops and trees and monitor their phenology (Goswami et al., 2015; Mehta, 2020). Also, the usage of LiDAR data provides height and canopy information for trees, vegetation and farm infrastructure, while SAR data are suitable for estimates of soil and crop conditions and structure, soil moisture, crop classification and development stage through crop calendars (McNairn et al., 2019). Remote sensing can also be applied in order to obtain fine-scale information about LAI (leaf area index), agricultural practices such as tillage, crop yields, land cover, location and amount of crop residue (Veloso et al., 2017; Zhang et al., 2017).

Another consideration is the depth that the tool will account for the C. International guidelines and protocols (United Nations, 1998; British Standards Institute 2019,2020; Food and Agrifood Organization of the United Nations, 2019; IPPC, 2019; WBCSD and WRI, 2020), tend to report the C in the top 30 cm of the soil. The variety of studies that exist focus on different soil depths according to the level of complexity and accuracy that they want to achieve. Most studies aimed at decision support in farms are focused on the topsoil. Only when topsoil inversion or “deep ploughing” is considered, then they may be looking at depths up to 100 cm (Jones et al., 2009). Moreover, they do not separate soil organic matter (SOM) content with depth and mostly only include the top 30 cm of soil, which is the layer most affected by farm activities. Additionally, most of the short-term land use and management changes in soil C stocks are captured in that depth.

Process based models that predict crop growth and yield can consider SOC contents down to 3 m into the soil (Williams et al., 1984). These consider farm land management activities and the way that they affect the soil. However, studies such as Stockmann et al. (2013) have shown that as the soil depth increases the SOC found in it decreases as the mean residence time can be up to 2000 – 10000 years. Additionally, as the organic matter (OM) found in this passive pool has a turnover rate of centuries to millennia, evidence for its nature is hard to obtain (Malone et al., 2017). This long-time residence

is due to the subsoil C being stored much deeper than the layer affected by agricultural activities, climatic elements and erosion (Lal, 2008). Around 2344 Gt of organic C is stored in the top three meters of soil (Jobbágy and Jackson, 2000), from which more than half (1500 Gt), is stored within the first meter and 41% (615 Gt) in the top 20 cm. As a result, research studies are curious to analyse the soil profile in both topsoil and deep subsoil layers, something that an average farmer might not be interested in at the moment.

## 2.5 Conclusion

At present, there are many models and tools describing flows of C and GHGs. After reviewing the existing literature, it is apparent that there is a research gap in the development of tools that can be used to derive farm and landscape-scale C stock inventories. These inventories can provide a foundation on which farmers and land managers can better understand their land and build effective management strategies that promote C storage. This review has provided useful information for assessing C accounting tools that can be grouped into two categories; namely process based models and statistical models and tools. These are made up of a mixture of data, methodologies, and informed assumptions and represent a reflection of different perspectives on how to calculate emissions, flows, and stocks. The literature review highlighted that some areas require further research as the present models and tools do not have all required criteria for the development of validated spatial C stock inventories.

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### 3 Spatial modelling approach and accounting method affects soil carbon estimates and derived farm-scale carbon payments

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#### Abstract

Improved farm management of soil organic carbon is critical if national governments and agricultural businesses are to achieve net-zero targets. There are opportunities for farmers to secure financial benefits from carbon trading, but field measurements to establish soil organic carbon baselines for each part of a farm can be prohibitively expensive. Hence there is a potential role for spatial modelling approaches that have the resolution, accuracy and quantification of uncertainty to estimate the carbon levels currently stored in the soil. This study uses three spatial modelling approaches to estimate soil organic carbon stocks, which are compared with measured data to a 10 cm depth and then used to determine carbon payments. The three approaches used either fine- (100 m x 100 m) or field-scale (mean range: 3.74-12.39 ha) input soil data to produce either fine- or field-scale outputs across nine geographically dispersed farms. Each spatial model accurately predicted soil organic carbon stocks (range: 26.7-44.8 t ha<sup>-1</sup>) for the five case study farms where the measured soil organic carbon was lowest (range: 31.6 - 48.3 t ha<sup>-1</sup>). However, across the four case study farms with the highest measured SOC (range: 56.5-67.5 t ha<sup>-1</sup>), both models underestimated the soil organic carbon with the coarse input model predicting lower values (range: 39.8-48.2 t ha<sup>-1</sup>) than those using fine inputs (range: 43.5-59.2 t ha<sup>-1</sup>). Hence the use of the spatial models to establish a baseline, from which to derive payments for additional carbon sequestration, favoured farms with already high soil organic carbon levels, with that benefit greatest with the use of the coarse input data. Developing a national approach for soil organic carbon sequestration payments to farmers is possible but the economic impacts on individual businesses will depend on the approach and the accounting method.

**Keywords:** soil organic carbon, storage, farm-scale, spatial modelling, net-zero, carbon payments

### 3.1 Introduction

To reduce the effects of climate change, many countries are implementing policies to achieve net-zero greenhouse gas (GHG) emissions by 2050 (Smith et al., 2012; Van Soest et al., 2021). A key policy measure in those countries is to incentivise land managers to sequester more soil carbon as some sectors of the economy will remain a source of GHG even in 2050 (Chambers et al., 2016). This planned increase in soil carbon will be in contrast to a previous historic global loss of soil carbon of about 133 Gt, primarily because of agricultural practices (FAO and ITPS, 2021). Globally it is estimated that about 1700 Gt of carbon is stored in the soil to a depth of 1 m (Canadell et al., 2021), although the mean estimates of 27 global studies have ranged from 504 Gt to 3000 Gt (Scharlemann et al., 2014).

Because increasing soil carbon storage can be a very effective climate change mitigation strategy (Amin et al., 2020), many national governments are planning to pay farmers to increase the amount of carbon stored on their land (e.g. UK Government, 2021a). There are two practical challenges that need to be addressed for this policy to be successful. Firstly, it is expensive to develop a robust soil C baseline from which to evaluate the success of C sequestration measures at farm level. Measurement of soil carbon in every field can be costly and measurements can vary widely within small areas due to the inherent soil variability. Secondly, the policy formulations around farmer incentives need to consider both the retention of existing soil C as well as encouraging farmers and land managers to sustainably increase soil C over the medium to long term. Hence, national incentivization schemes need to have means of producing robust, auditable information on the amount of current levels of soil C stored on farms, and an accounting procedure to quantify the amount of carbon that has been or will be sequestered.

The cost of using physical field measurements of SOC and bulk density to establish a baseline can be high, moreover; it may be more cost-effective to use spatial models. Such spatial models, and their underlying data sets, are often derived from national-level soil C datasets such as national soil maps (Veronesi et al., 2014). These need to be downscaled to farm, field and within field-level soil C estimates which are sufficiently robust, policy-relevant and useful for farmer decision making. Whereas there is a substantive body of research on national and international level soil C stocks (Adhikari et al., 2019; Bárcena et al., 2014; Chen et al., 2019; Guo and Gifford, 2002; Wang et al., 2018); and in site-specific and soil process specific C sequestration processes (Baisden et al., 2002; Coleman et al., 2017; Laskar et al., 2021; Muhammed et al., 2018; Muhlbachova et al., 2015; Pschenyckyj et al., 2020), there is surprisingly little information on the implications of using national-level datasets at local and farm-level decision making, and the economic consequences of using different national datasets to support decisions at farm level.

This study investigates the hypothesis that there are consequences concerning policy, payments and land users when national-level soil C information is downscaled to a farm and a field level. To test the hypothesis, three spatial modelling approaches were developed and compared to quantify SOC stocks and their associated uncertainty at a farm-scale. This was followed by an examination of how the modelling approach and accounting method for carbon payments could affect farm revenue and the societal cost of promoting carbon sequestration.

## **3.2 Materials and methods**

### **3.2.1 Description of study areas and soils datasets**

Existing measurements of SOC and bulk density were collated from nine locations to form a calibration and an evaluation dataset. The calibration dataset comprised of SOC and bulk density data (0-10 cm) taken at five farms across the UK, following a method described by Hodson et al. (2021). The farms or sites were Hodgson's Fields near Skeffling in Yorkshire (SKF), the Allerton Project farm at Loddington, Leicestershire

(LOD), Manor Farm near Bath in Somerset (MAN), Elm Farm Organic Research Centre in Berkshire (ELM), and a farm near Swanage in Dorset (SWA). The evaluation dataset included another two sites described by Hodson et al. (2021): a site at Craibstone in Aberdeenshire (ABE) and Torr Organic Farm near Auchencairn in Dumfries and Galloway (TORR) (Figure 3-1). The evaluation dataset also included SOC and bulk density obtained from Clapham Park and Silsoe in Bedfordshire (Upson, 2014). The site at Clapham Park comprised areas of 14-year-old woodland, grassland and silvopasture agroforestry with widely-spaced trees planted on grassland (Upson et al., 2016). The site at Silsoe comprised an arable area that had recently been converted to grassland and an area of widely-spaced poplar trees with a grass understorey (Upson and Burgess, 2013). Soil samples were taken over a depth including 0-10 cm and analysed as described by Upson et al. (2016) and Upson and Burgess (2013).

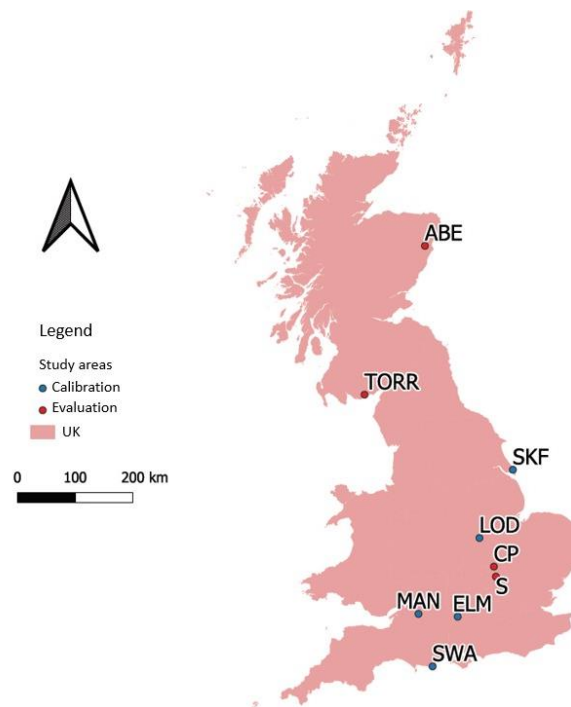


Figure 3-1 Measurements of soil organic carbon and bulk density for a calibration dataset (blue dots) were taken on grassland areas near Skeffling (SKF), Loddington Farm (LOD), Manor Farm (MAN), Elm Farm Organic Research Centre (ELM), and a farm near Swanage (SWA). Evaluation measurements (red dots) were taken at Craibstone near Aberdeen (ABE), Torr Organic Farm (TORR), Clapham Park (CP), and Silsoe (S).

### 3.2.2 Spatial modelling approaches

Three spatial modelling approaches were used to predict the SOC stock at the nine sites across four cardinal directions and to a soil depth of 10 cm. The three approaches included different combinations of two distinct sources of spatial soil data inputs and two output scales (Figure 3-2). A depth of 10 cm was chosen because this was the depth available in the measured datasets used for the calibration and evaluation of the approaches (Table\_Apx A-1).

Many existing digital soil maps describe soil organic carbon at a relatively coarse scale of 1 km x 1 km. For example, in England and Wales, field surveys between 1979 and 1983 were used to create a national soils map (NATMAP) of soil associations, and a National Soil Inventory was made on a 5 km x 5 km grid describing soil properties such as soil organic content (Keay et al. 2009; Hallett et al. 2017). Using these two sources, and information from the National Soil Inventory of Scotland (NSIS) (Lilly et al., 2010), a map of SOC at a 1 km x 1 km scale was created for Great Britain (Bradley et al. 2005; Gregory et al. 2014). However, it is possible to use additional variables, such as meteorological data and altitude, and using random forest and artificial neural networks to determine the soil variability at a finer scale of 100 m x 100 m (Taalab et al., 2013). Using such techniques, Campbell (2018) developed a dataset of soil organic C content for Great Britain using a 100 m x 100 m grid.

#### 3.2.2.1 Spatial modelling approach 1

Spatial modelling approach 1 used input vector data in the form of field delineations from the Rural Payments Agency in the UK, land cover (UK Centre for Ecology & Hydrology, 2017), and NATMAP soil associations (Farewell et al., 2011; Hallett, 2010). During the first step, (Figure 3-3) the field parcels were categorised in one of the four land cover groups of the national soil map of England and Wales: arable (AR), improved grassland (IG), woodland and rough grazing (W/RG), and other which included water (OT) (Farewell et al., 2011).

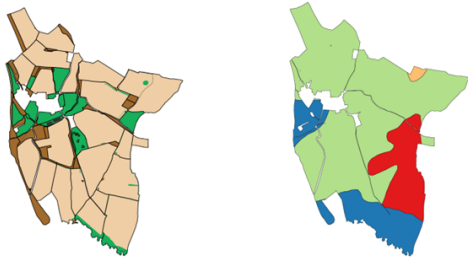
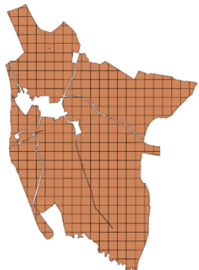
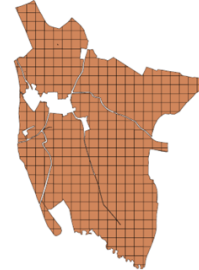
| Approach | Input                                                                                                                                                      | Output                                                                                                                      |
|----------|------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------|
| 1        | <p>Land cover &amp; soil associations (coarse scale)</p> <p><b>a</b></p>  | <p>RPA parcels (coarse scale)</p>        |
| 2        | <p>100 m x 100 m soil properties (fine scale)</p> <p><b>b</b></p>        | <p>100 m x 100 m grid (fine scale)</p>  |
| 3        | <p>100 m x 100 m soil properties ( fine scale)</p> <p><b>c</b></p>      | <p>RPA parcels (coarse scale)</p>      |

Figure 3-2 Farm scale spatial modelling approaches (Models) of soil organic carbon (SOC) stocks with the datasets used to develop them illustrated for the study site at Loddington: a) Spatial modelling approach 1 (Model 1) using land cover and coarse-scale soil association designations, and coarse-scale land parcel boundary data derived from the Rural Payments Agency (RPA), b) Spatial modelling approach 2 (Model 2) using fine-scale 100 m x 100 m soil properties data with predicted values of loss on ignition (LOI), clay and sand content, and fine-scale 100 m x 100 m grid squares data, and c) Spatial modelling approach 3 (Model 3) using input data from a 100 m x 100 m square grid with predicted values of loss on ignition (LOI), clay and sand content, and outputs using coarse-scale Rural Payments Agency (RPA) land parcel boundary data

The next step (Figure 3-3) was to identify the soil series that each soil association was made up from and fit splines to the whole soil profile, to derive a value for the organic carbon content (OCC) and bulk densities for the depth of 0-10 cm. The soil profile data contain OCC values on a soil horizon basis and thus the depths are variable. Hence, the splines were able to predict the OC values at specific depth intervals. In England and Wales, each soil association comprises one or more soil series with an indicative proportion of those series (Table\_Apx A-2) each with a specified OCC and bulk density value to a depth of about 150 cm (Figure\_Apx A-1) (Farewell et al., 2011; Hallett, 2010). The original measurements of organic carbon used in the National Soil Resources Institute (NSRI) dataset were made using the Tinsley loss on ignition (LOI) method, (Kalembasa and Jenkinson, 1973) and to standardise the results the LOI values (units: g (g soil)<sup>-1</sup>) were converted to an organic carbon content (OCC; unit: g C (g soil)<sup>-1</sup>) using Equation (3-1 (Ball, 1964) with a correlation coefficient of 0.99 for an LOI range of 5.8 to 88.5 g (g soil)<sup>-1</sup>

$$\text{OCC} = 0.476 \times \text{LOI} - 1.87 \quad (3-1)$$

The values of bulk density in the NSRI dataset were measured using the pedogenic Soil Survey and Land Research Centre (SSLRC) method (Avery and Bascomb, 1982). In order to derive a value for the OCC and bulk densities for the same depth as the field measurements of 0-10 cm, we fitted a relationship between OCC (Figure\_Apx A-1a) and bulk density (Figure\_Apx A-1b) with depth for each land cover and soil association. This was done using the R packages *ithir* (Malone, 2019), *agp* (Gramacy, 2016), *dplyr*

(Wickham et al., 2021) sp (Pebesma et al., 2021) and openxlsx (Schauberger et al., 2021). Creating these splines, allowed the prediction of the SOC for any specified soil depth with a 1 cm precision depth interval.

The overall OCC and bulk density of each soil association for the specified depth (Figure 3-3) were derived from the weighted mean average of the component soil series using the propagate (Spiess, 2018) package in R. The SOC stock (0-10 cm; unit t ha<sup>-1</sup>) was then derived using Equation 2 (Taalab et al., 2013).

$$\text{SOC}_i\text{stock} = \text{BD} \times \text{OCC} \times d_i \times 10 \quad (3-2)$$

Where SOC<sub>i</sub>stock is the soil organic carbon stock for the depth increment *i* (t C ha<sup>-1</sup>), BD is the soil bulk density (g cm<sup>-3</sup>), OCC is the organic C content per unit mass of dry soil (g C (g soil)<sup>-1</sup>), and *d<sub>i</sub>* is the soil thickness of the depth increment *i* (cm). Lastly, the SOC for each delineated field was the multiplication product of the per hectare SOC stock with the area of the field shapefile.

The soil associations across the nine locations were primarily clays or loams, and none were characterised by a large gravel or stone content. Hence it was unnecessary to include the gravel content during the estimation of the SOC stocks. A diagrammatic representation of the steps followed for this approach can be found in Figure 3-3.

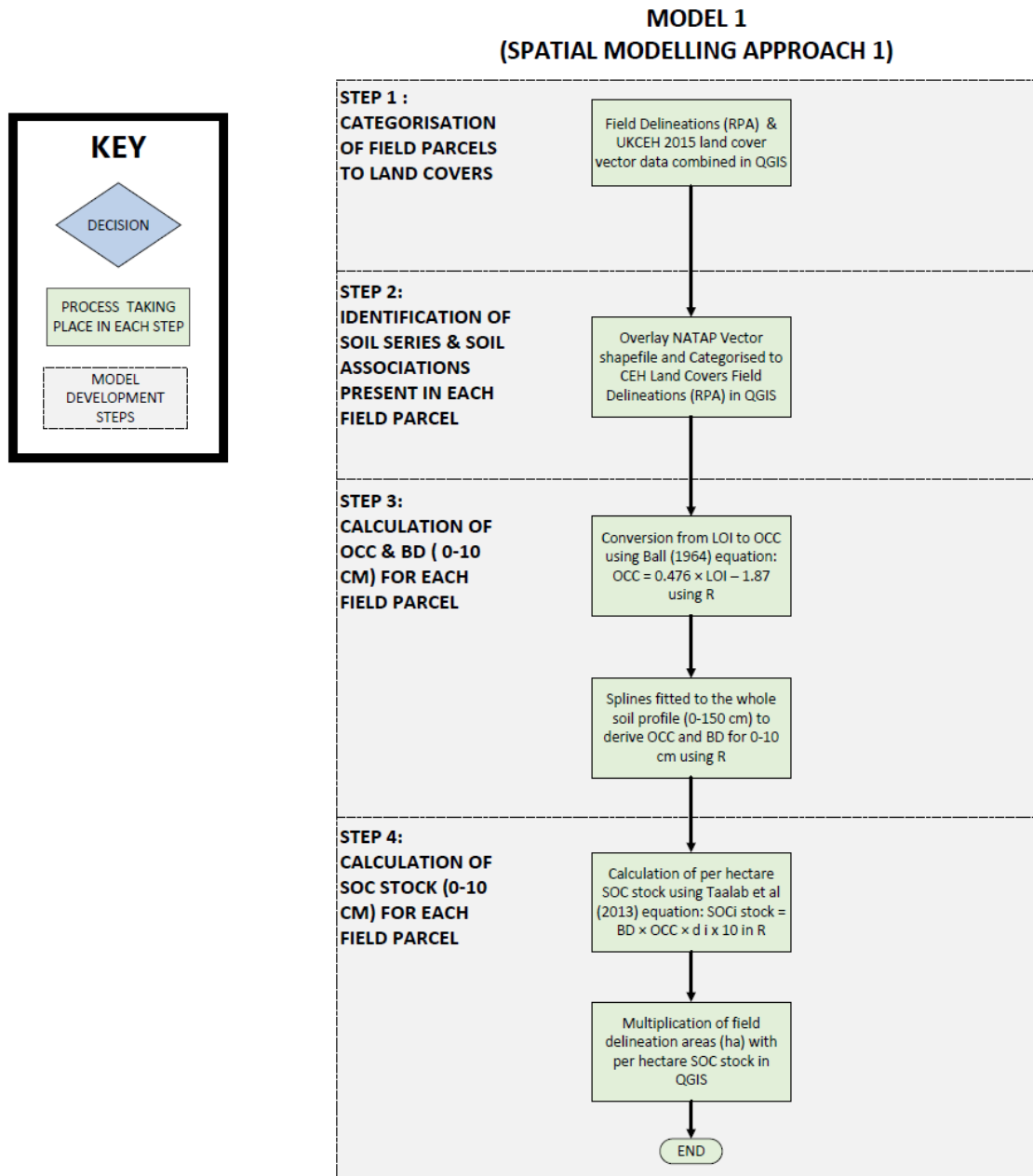


Figure 3-3 Flow chart representing the operational process of spatial modelling approach 1 (Model 1)

### 3.2.2.2 Spatial modelling approach 2

Spatial modelling approach 2 (Model 2), used Digital Soil Mapping (DSM) to create a 100 m x 100 m raster grid dataset of soil properties in Great Britain, at set depth intervals to a depth of 150 cm, as described by Campbell (2018). The dataset combines the above NSRI data, with representative soil series profiles from the equivalent National Soil Inventory from the Scotland dataset (Lilly et al., 2010), and data from the National Soil Inventory (NSI). The soil properties, which included LOI values and soil and clay contents, were predicted by a combination of the spline method described earlier (for the fixed depth intervals) and then through DSM, by utilising the Boosted Regression Trees Models (Elith et al, 2008) method using climate, organisms, relief, parent material, and landscape position and environmental covariates (Campbell, 2018).

In order to obtain the soil properties for a depth of 0-10 cm (Figure 3-4), we used a depth weighted sum of the discrete 0-5 and 5-15 cm depths and aggregated the value for the 0-15 cm depth. We then produced a 100 m x 100 m grid raster, for the depth of 10 cm with the calculated LOI, clay, sand values, model uncertainties and the horizontal x and y coordinates for each pixel using the *rgl* (Murdoch et al., 2021), *raster* (Hijmans et al., 2021) and *sp* (Pebesma et al., 2021) R libraries. This was followed by the production of three 100 m x 100 m grid point shapefiles that were merged using the QGIS 3.20 (QGIS, 2021) software. For the creation of the grid with the known LOI, clay and sand values, Thiessen polygons from the points were created with an influence area of 1 ha (100 m x 100 m squares) and were later overlaid to the vector land cover/soil association layer in QGIS. This resulted in every 1 ha square grid being made up of a combination of land covers and soil associations Figure 3-2b.

The *propagate* package in R (Spiess, 2018) was used to calculate the OCC and its uncertainty using Equation (3-1(3-1) as seen on the second step in Figure 3.4. The bulk density of non-arable mineral soils ( $B_{D\text{arable}}$ ; g cm<sup>-3</sup>) in England was calculated using a pedotransfer function (Hollis et al., 2012; Equations (3-3) and (3-4)) where OCC is

measured in g C (g soil)<sup>-1</sup>, and Sand and Clay is measured in terms of g sand (g soil)<sup>-1</sup> and g clay (g soil)<sup>-1</sup> respectively.

$$\begin{aligned} \text{BD}_{\text{mineral}} = & 0.69794 + (0.750636 \times \text{Exp}(-0.230355 \times \text{OCC})) \\ & + (0.0008687 \times \text{Sand}) - (0.0005164 \times \text{Clay}) \end{aligned} \quad (3-3)$$

In those cases where the land use was arable, a modified equation was used to calculate the bulk density (Equation (3-4)).

$$\begin{aligned} \text{BD}_{\text{arable}} = & 0.80806 + (0.823844 \times \text{Exp}(-0.27993 \times \text{OCC})) \\ & + (0.0014065 \times \text{Sand}) - (0.0010299 \times \text{Clay}) \end{aligned} \quad (3-4)$$

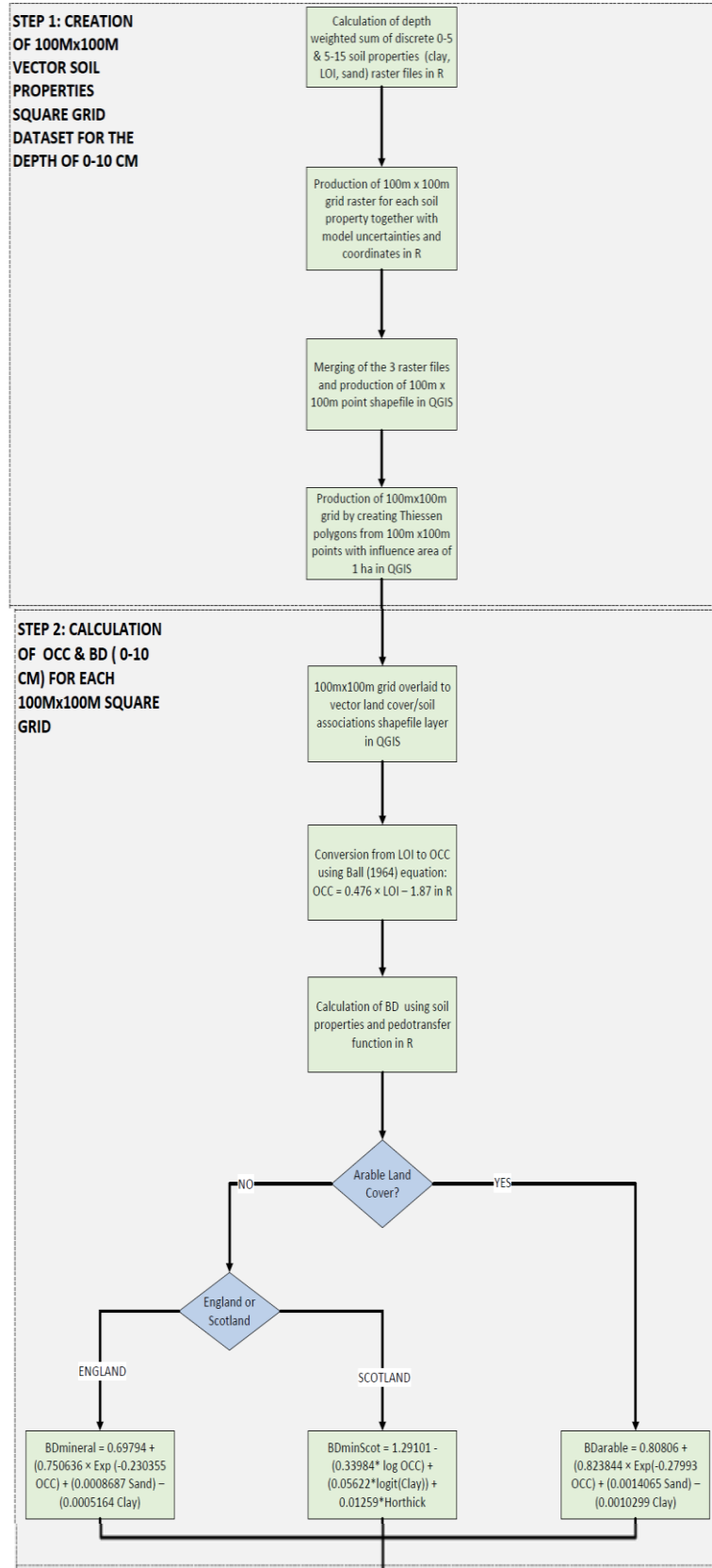
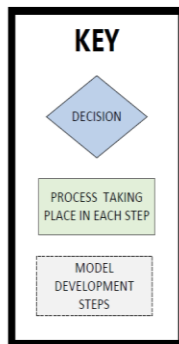
Because of different environmental conditions in Scotland, Equation (3-5) was used to derive the bulk density of mineral soils ( $\text{BD}_{\text{minScot}}$ ). The equation included the horizon thickness ( $\text{Hor}_{\text{thick}}$ ; cm), the natural logarithm (log) of the OCC measured in g C (100 g soil)<sup>-1</sup> and the logarithm of the odds ratio (logit) of the Clay (g clay (100 g soil)<sup>-1</sup>) as inputs (Gagkas and Lilly, personal communication 2021).

$$\begin{aligned} \text{BD}_{\text{minScot}} = & 1.29101 - (0.33984 \times \log \text{OCC}) \\ & + (0.05622 \times \text{logit}(\text{Clay})) + 0.01259 \times \text{Hor}_{\text{thick}} \end{aligned} \quad (3-5)$$

$$\text{Logit} = \log ((\text{Clay}/(100 - \text{Clay}))) \quad (3-6)$$

The propagate package in R (Spiess, 2018) was used to calculate the bulk density and the uncertainty of each 100 m square grid by using first/second-order Taylor expansion including the covariates. To allow comparison with Model 1, a SOC stock value was derived for each land cover and soil association combination using the land cover and soil association layer in QGIS (Figure 3-2b). These SOC stock values were distributed according to the area of each combination within the square grid. This method allowed an estimation of the RMSE uncertainty of the stocks by propagating it in all four cardinal directions and to a soil depth of 10 cm. A diagrammatic representation of the steps followed for this approach can be found in Figure 3-4.

## MODEL 2 (SPATIAL MODELLING APPROACH 2)



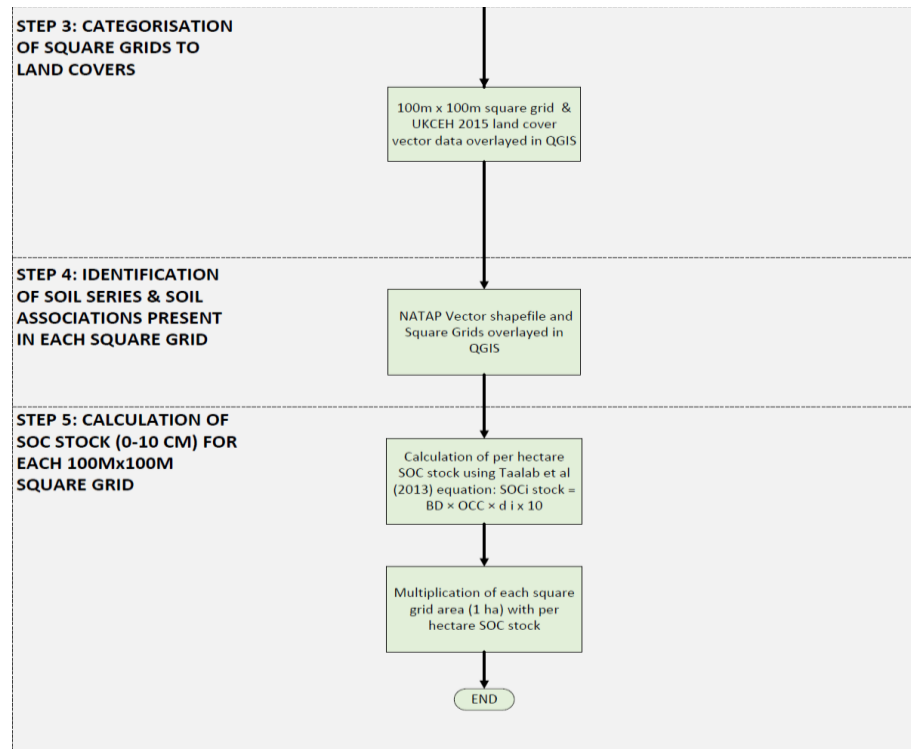


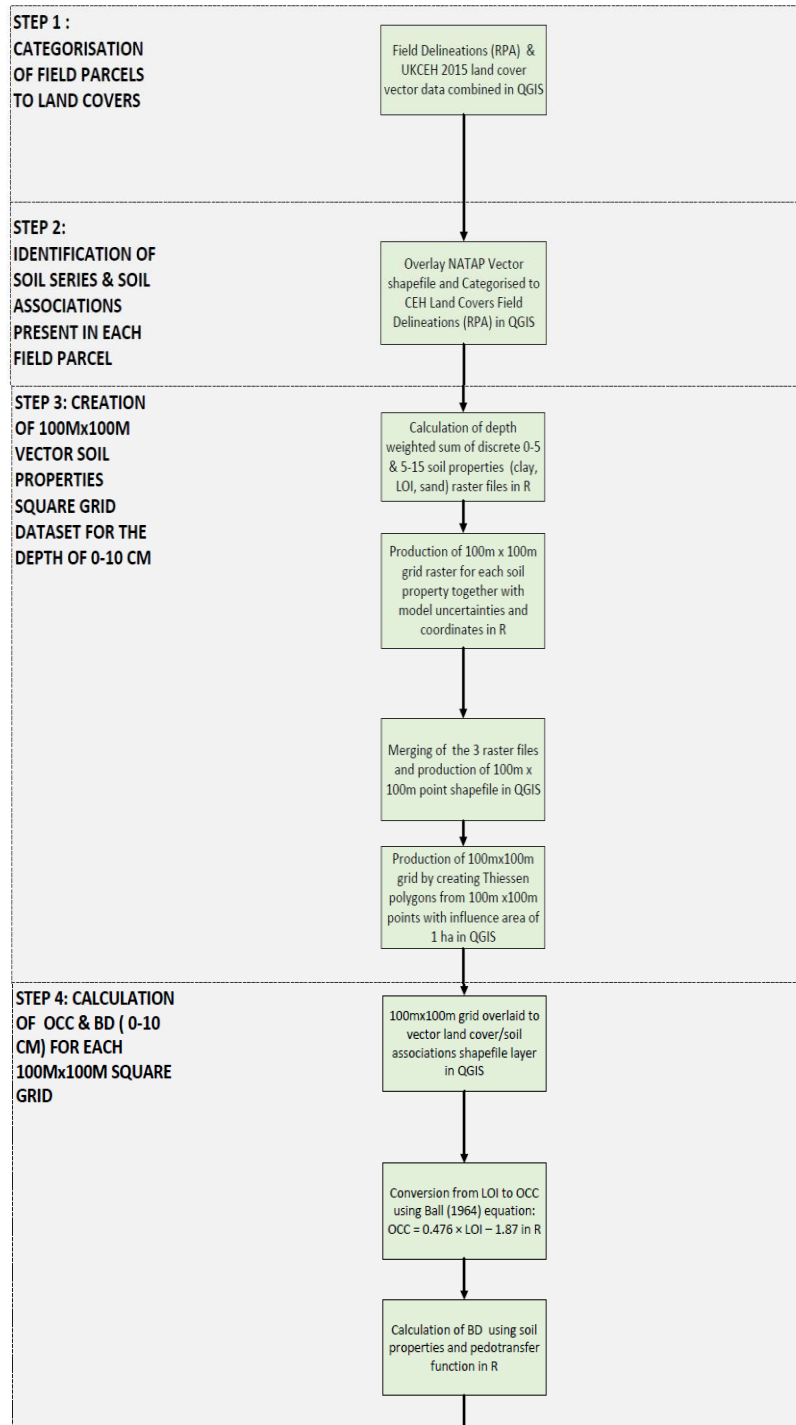
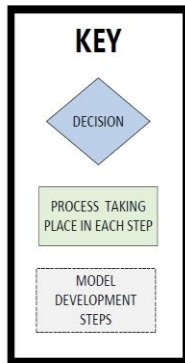
Figure 3-4 Flow chart representing the operational process of spatial modelling approach 2 (Model 2)

### 3.2.2.3 Spatial modelling approach 3

Spatial modelling approach 3 (Model 3) used the same soil properties described for the 100 m square grid raster in Model 2. However, whereas Model 2 delineated areas using the 100 m grids, Model 3 delineated the farm into fields that contained one or more areas of a combination of a land cover and soil association (Figure 3-2c). This resulted in each field parcel having an LOI, clay and sand value that was calculated as the mean of all the 100 m x 100 m grid squares that fell inside the field boundaries. We then used the same calculation steps (e.g. (3-3) - (3-6)) as in Model 2 to obtain the OCC and the bulk density datasets.

The calculation of the SOC for the area of each land cover/soil association combination, for the 0-10 cm depth, was again performed by using Equation (3-2). Here, the uncertainty associated with the area (ha) was that of the UKCEH land cover classification, as the soil associations dataset was assumed unbiased, and not having any uncertainty related to its landscape (x, y) placement. Similar to Model 2, this last method was used to estimate the uncertainty of the stocks by propagating it across the four cardinal directions and to a depth of 10 cm. A diagrammatic representation of the steps followed for this approach can be found in more in Figure 3-5.

**MODEL 3**  
**(SPATIAL MODELLING APPROACH 3)**



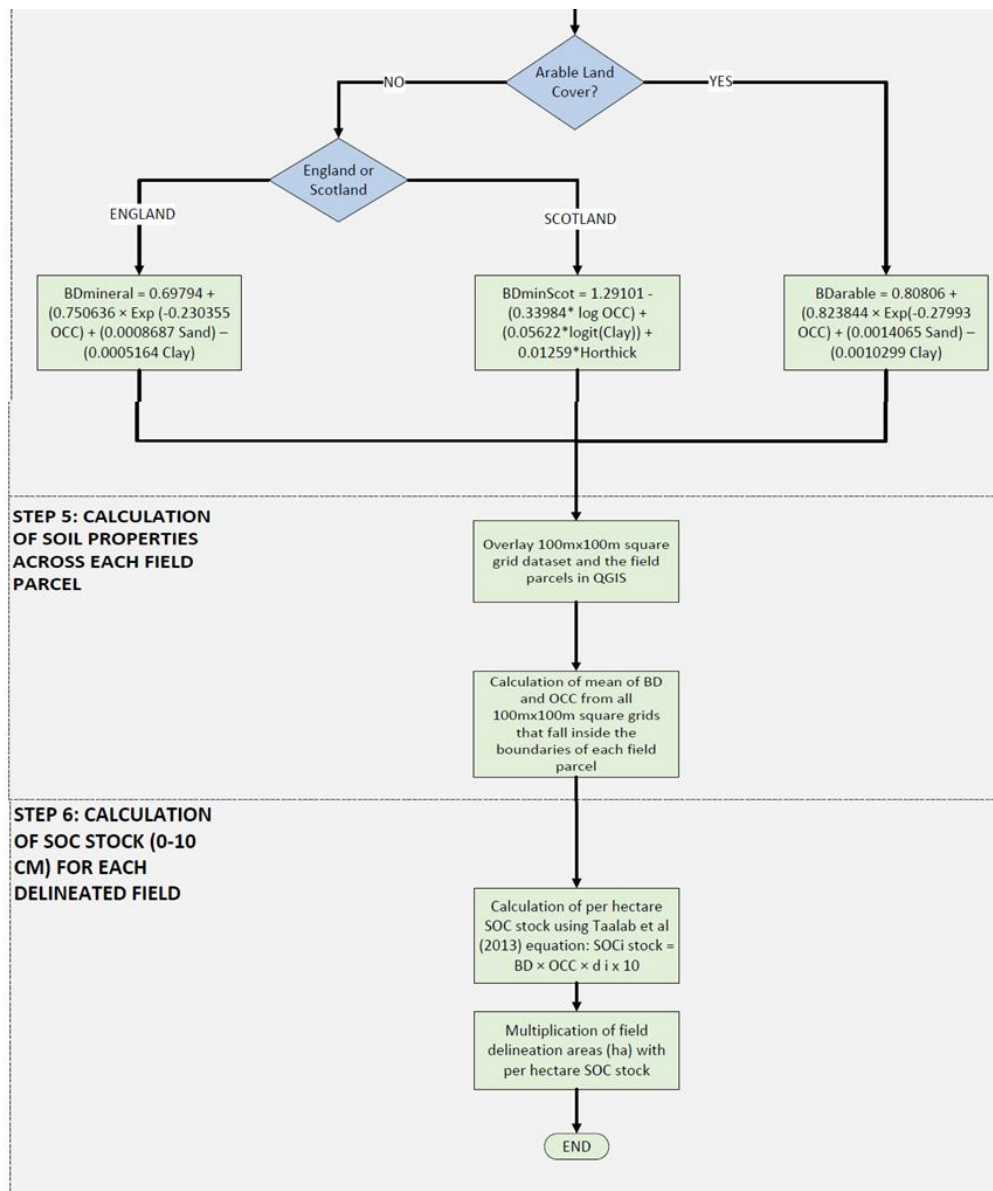


Figure 3-5 Flow chart representing the operational process of spatial modelling approach 3 (Model 3)

### 3.2.3 Comparison of spatial model outputs with measurements

The measurements from Skeffling (SKF), Loddington Farm (LOD), Manor Farm (MAN), Elm Farm Organic Research Centre (ELM), and the farm near Swanage (SWA) previously described, were used as calibration datasets (Figure 3-1). The measurements from Craibstone near Aberdeen (ABE), Torr Organic Farm (TORR), Clapham Park (CP), and Silsoe (S) were used as evaluation datasets (Figure 3-1).

In addition, the measurements of three fields present in the Loddington Farm (LOD), Fig 3.8 were used to look at how well the spatial modelling approaches were behaving when deployed in a specific farm and the level of in-farm stored SOC variation that they could pick up.

For Models 1 and 3, where the outputs were expressed at a field scale, we assumed that the SOC stock was constant within each land parcel. For the calibration and evaluation datasets, we performed a linear regression of the estimated values against the calculated mean of the measured SOC of the sampled points within each land parcel of interest. For the fine management scale Model 2, we assumed that the SOC stock was constant within the boundaries of each 100 m square grid. For the calibration and evaluation of all three models, the  $R^2$  and RMSE values were calculated and used to compare the spatial modelling approaches.

#### **3.2.4 Spatial accounting approach of carbon stocks**

Voluntary certified carbon sequestration schemes are typically concerned with i) the additionality of the change i.e. the change has only occurred as a result of the certification process, and ii) the permanence of change e.g. can the change be maintained for the next 100 years? (Gren and Aklilu 2016; Badgery et al. 2020). Within the UK Land Carbon Registry, there are two types of units: i) pending issuance units (PIUs) which describes an anticipated carbon sequestration over 5-10 year periods in the future, and ii) full carbon credits which are verified accumulations of carbon storage (Woodland Carbon Code 2022). For the three spatial methods, we compared the assumed SOC, and the value of the additional carbon stored assuming i) the level of soil carbon is increased by  $10 \text{ t C ha}^{-1}$  over the measured value, and ii) the same level of carbon compared with a baseline derived from the models.

To illustrate the financial and economic implications of the approaches, we selected an indicative value of carbon of  $\text{£}100 (\text{t C})^{-1}$ , which lies within a wide range of values reported in the literature. Graves et al. (2015) estimated the value of soil carbon in terms

of positive effects on crop yields, soil water storage and soil conservation, and assumed a value of £51 (t CO<sub>2</sub>e)<sup>-1</sup>, equivalent to £187 (t C)<sup>-1</sup> for the effect of carbon sequestration on climate change. The UK Government has provided guidance on the social value of soil carbon in reducing atmospheric CO<sub>2</sub> for policy analysis (Department of Energy and Climate Change, 2009). For 2000, Stern (2007; page 323) quoted a social value of carbon (2000 prices) of £100 t C<sup>-1</sup>, and the current mid-range estimate for policy appraisal in the UK using 2022 prices) is about £250 (t CO<sub>2</sub>e)<sup>-1</sup>, equivalent to £916 (t C)<sup>-1</sup> (UK Government, 2021b). In December 2021, the mean quoted price on the UK Emissions Trading Scheme and the EU Emissions Trading Scheme, covering the power generation sector, was £68-74 (t CO<sub>2</sub>e)<sup>-1</sup>, equivalent to £250-270 (t C)<sup>-1</sup> (EMBER, 2022). The UK Department for Business Energy and Industrial Strategy (2019) reported a marginal abatement cost of reducing atmospheric CO<sub>2</sub> levels with a mean value of £70 t C<sup>-1</sup> for 2021 within a range of £35-105 t C<sup>-1</sup>. The price currently received in the UK for verified woodland carbon ranges from £17 to £24 (t CO<sub>2</sub>e)<sup>-1</sup>, equivalent to £62 to £88 (t C)<sup>-1</sup> (Woodland Carbon Code 2022).

### 3.3 Results

#### 3.3.1 Calibration sites

Across the five calibration sites, there was a positive relationship between the measured and estimated soil organic carbon values to a depth of 10 cm for all three spatial modelling approaches (Table 3-1). The lowest correlation ( $R^2 = 0.39$ ) was obtained from the coarse input; coarse output Model 1 which had a root mean square error (RMSE) of 16.0 t ha<sup>-1</sup>. Model 2, with the combination of fine input data and fine output data, had a higher correlation ( $R^2 = 0.50$ ) with an RMSE of 15.8 t ha<sup>-1</sup>. The highest coefficient of determination ( $R^2 = 0.64$ ) was obtained using Model 3, comparing fine input data with coarse outputs, with an RMSE of 17.2 t ha<sup>-1</sup>. Model 3 had the highest RMSE value, followed by Model 1 and Model 2. The higher RMSE value of Model 3 meant that its regression line was further away than the other two from the 1:1 line. The 95% confidence interval of the regression equation is illustrated by the grey shaded area together with the 1:1 line in Figure 3-6.

The slope of the regression equation for Model 1 was 0.293, compared to 0.403 for Model 2 and 0.436 for Model 3, indicating that in each case the observed variation in the estimated soil carbon contents was less than the measured values. For example, for Model 1 ( $n = 19$ ), while the averages of the measured values within each sampled field parcel ranged from 28 to 90 t C ha<sup>-1</sup>, the estimated values only ranged from 29 to 52 t C ha<sup>-1</sup>. For Model 2, the larger number of samples ( $n = 90$ ) increased the measured range (20 to 98 t C ha<sup>-1</sup>), but this was still larger than the range of estimated values (21 to 78 t C ha<sup>-1</sup>). For Model 3 ( $n = 19$ ), the estimated values ranged from 26 to 57 t ha<sup>-1</sup> while the average measured values within each sampled field parcel ranged from 28 to 90 t ha<sup>-1</sup>. Due to the different output scale of Model 2, the number of values used for its validation were more than in Models 1 and 3

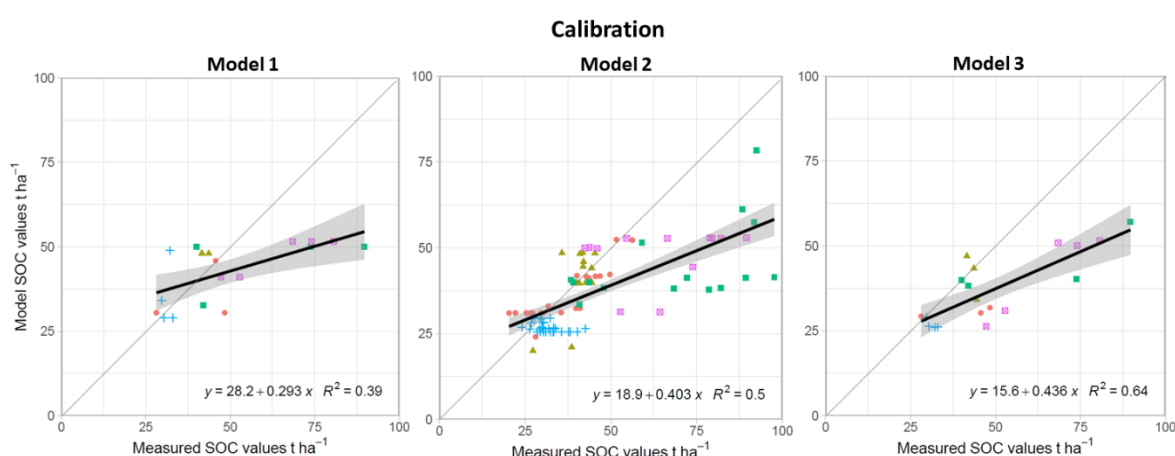


Figure 3-6 Calibration dataset: relationship between estimated and measured soil organic carbon (SOC) values (0-10 cm) using spatial modelling approaches 1 (Model 1), 2 (Model 2) and 3 (Model 3) across five calibration sites: ● Elm Farm (ELM), ◆ Loddington (LOD), ■ Manor Farm (Man), + Skeffing (SKF), and ⊠ Swanage (SWA)

### 3.3.2 Evaluation sites

The evaluation dataset also showed a positive correlation between the estimated and the measured soil organic carbon contents (Table 3-1 and Figure 3-7). The poorest correlation ( $R^2 = 0.43$ ) was again obtained using Model 1, while Models 2 and 3 with the fine input data had  $R^2$  values of 0.68 and 0.69 respectively. The RMSE ranged from 18.3 t ha<sup>-1</sup> for Model 1, to 11.0 and 8.3 t ha<sup>-1</sup> for Model 2 and 3 respectively. Model 1 had

the highest RMSE value, followed by Model 2 and Model 3. The higher RMSE value of Model 1 meant that its regression line was further away than the other two from the 1:1 line. Due to the different output scale of Model 2, the number of values used for its evaluation were more than in Models 1 and 3.

The value of the slope ranged from 0.048 for Model 1 to 0.668 for Model 2 and 0.744 for Model 3. Hence the range of the estimated values was again less than the measured values. For Model 1 ( $n = 13$ ) the estimated values ranged from 38 to 40  $\text{t ha}^{-1}$ , while the mean measured values in each field parcel ranged from 40 to 75  $\text{t ha}^{-1}$ . For Model 2 ( $n = 54$ ), the estimated values ranged from 32 to 84  $\text{t ha}^{-1}$  broadly similar to the range of measured values from 26 to 94  $\text{t ha}^{-1}$ . For Model 3 ( $n = 13$ ), the predicted values ranged from 36 to 70  $\text{t ha}^{-1}$  similar to a range of measured values from 40 to 75  $\text{t C ha}^{-1}$ . Overall, each of the models predicted lower levels of SOC stocks than the measured levels. The mean reduction was 19% with Model 1, 15% for Model 2, and 14% for Model 3.

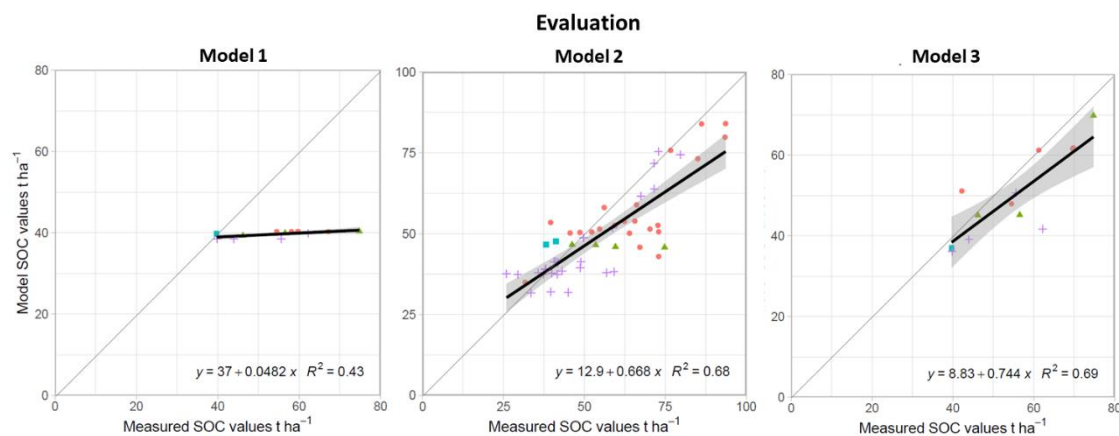


Figure 3-7 Evaluation dataset: relationship between estimated and measured soil organic carbon (SOC) values (0-10 cm) using spatial modelling approaches 1 (Model 1), 2 (Model 2) and 3 (Model 3), across four evaluation sites: ● Aberdeen (ABE), ◆ Clapham Park (CP), ■ Silsoe (S), and + Torr Organic Farm (TOR)

Table 3-1 Analytical representation of the calibration and evaluation performance results of the three spatial modelling approaches (models) of soil organic content (SOC). The regression equations describe the relationship between the estimated ( $SOC_{pred}$ ;  $t\ ha^{-1}$ ) and measured ( $SOC_{meas}$ ;  $t\ ha^{-1}$ ) soil organic carbon values to the depth of 10 cm. The number of observations (n), coefficient of determination ( $R^2$ ), root mean square error (RMSE), and upper and lower confidence limits of the intercept and the slope, and the range of measured and estimated values are also presented.

| Model       | Regression equation                                  | n  | R <sup>2</sup> | RMSE | Intercept<br>confidence<br>limits<br>(95%) | Slope<br>confidence<br>limits<br>(95%) | SOC Range (t ha <sup>-1</sup> ) |            |
|-------------|------------------------------------------------------|----|----------------|------|--------------------------------------------|----------------------------------------|---------------------------------|------------|
|             |                                                      |    |                |      |                                            |                                        | Estimated                       | Measured   |
| Calibration |                                                      |    |                |      |                                            |                                        |                                 |            |
| 1           | SOC <sub>pred</sub> =0.293*SOC <sub>meas</sub> +28.2 | 19 | 0.39           | 16.0 | 18.2-38.1                                  | 0.1-0.5                                | 29.0-51.6                       | 28.1-89.7  |
| 2           | SOC <sub>pred</sub> =0.403 SOC <sub>meas</sub> +18.9 | 90 | 0.50           | 15.8 | 14.8-23.0                                  | 0.3-0.5                                | 20.0-78.3                       | 20.3 -97.7 |
| 3           | SOC <sub>pred</sub> =0.436 SOC <sub>meas</sub> +15.6 | 19 | 0.64           | 17.2 | 6.8-24.5                                   | 0.3-0.6                                | 26.1-57.1                       | 28.1-89.7  |
| Evaluation  |                                                      |    |                |      |                                            |                                        |                                 |            |
| 1           | SOC <sub>pred</sub> =0.048 SOC <sub>meas</sub> +37.0 | 13 | 0.43           | 18.3 | 35.0 - 39.1                                | 0.0-0.1                                | 38.5-40.4                       | 39.7-74.8  |
| 2           | SOC <sub>pred</sub> =0.668 SOC <sub>meas</sub> +12.9 | 54 | 0.68           | 11.0 | 5.5 - 20.2                                 | 0.5-0.8                                | 31.6-84.1                       | 25.9-93.6  |
| 3           | SOC <sub>pred</sub> =0.744 SOC <sub>meas</sub> +8.83 | 13 | 0.69           | 8.3  | -9.6 - 27.3                                | 0.4-1.1                                | 36.0-69.8                       | 39.7-74.8  |

### 3.3.3 Quantity and value of carbon stock across farms

The next step of the analysis was to determine how the three modelling approaches interact with the choice of accounting method. Using 100 m x 100 m grids as an output (Model 2), the lowest mean measured SOC (0-10 cm) of 31.6 t ha<sup>-1</sup> was at Skeffing, with the highest measured SOC value of 65.3 t ha<sup>-1</sup> at Aberdeen. The mean measured SOC (0-10 cm) at a field scale (as used in Models 1 and 3) ranged from 31.6 t ha<sup>-1</sup> at Skeffing to 59.5-67.5 t ha<sup>-1</sup> at Aberdeen, Swanage and Manor Farm (Table 3-3).

As previously indicated, the estimated values of SOC were less than the measured values, with a tendency of the spatial modelling approaches to underestimate the value of SOC at sites with high soil organic carbon. Hence Model 2 predicted a SOC (0-10 cm) of 59.2 t ha<sup>-1</sup> at Aberdeen, compared to a measured value of 65.3 t ha<sup>-1</sup>. Model 1 predicted a SOC (0-10 cm) of 40.3 t ha<sup>-1</sup> at Aberdeen, compared to a measured value of 59.5 t ha<sup>-1</sup>, and Model 3 predicted a SOC of 58.9 t ha<sup>-1</sup> at Aberdeen compared to a measurement of 59.5 t ha<sup>-1</sup> (Table 3-2).

Two approaches were analysed to determine the potential receipts of carbon payments that could be received by the farms. The first assumed that the level of soil carbon is increased by 10 t C ha<sup>-1</sup> over the measured value, and the second approach assumed the same final level of carbon but compared to the modelled values as a baseline. In approach 1, assuming a measured increase in SOC of 10 t C ha<sup>-1</sup> and a carbon value of £100 (t C)<sup>-1</sup>, would have resulted in a carbon value benefit of £1000 ha<sup>-1</sup> on each farm and with each method. The new SOC content to achieve this varied between farms, but the values from the three spatial approaches for a given farm were broadly similar (Table 3-3).

Using approach 2 resulted in noticeable differences between farms and spatial modelling methods. Using Model 2 as the initial baseline, the calculated mean increase in SOC was worth £1657 ha<sup>-1</sup>, ranging from £1010 ha<sup>-1</sup> at Loddington to £2570-2670 ha<sup>-1</sup> at Manor Farm, and Swanage (Table 3-3). Using Model 1, the mean derived value was

marginally higher than with Model 2, and the calculated value of the assumed increased in carbon ranged from £500 ha<sup>-1</sup> at Loddington to £2670-2950 ha<sup>-1</sup> at Clapham, Swanage, Aberdeen and Manor Farm (Table 3-3). The mean value of the increase (£1760 ha<sup>-1</sup>) based on Model 3 was similar to Model 1 (£1750 ha<sup>-1</sup>), but the value was more consistent across seven of the sites ranging from £1010-1630 ha<sup>-1</sup>, but it reached £3200-3350 ha<sup>-1</sup> at Manor Farm and Swanage.

Table 3-2 Weighted mean measured and estimated soil organic content (SOC) (0-10 cm) and its value of sampled fields using the three spatial modelling approaches (Models). Fields are ranked according to measured values using Model 2.

| Farm/ Site          | Weighted mean SOC content value of sampled fields (t ha <sup>-1</sup> ) |       |          |       |          |       |
|---------------------|-------------------------------------------------------------------------|-------|----------|-------|----------|-------|
|                     | Model 1                                                                 |       | Model 2  |       | Model 3  |       |
|                     | Measured                                                                | Model | Measured | Model | Measured | Model |
| Skeffing (SKF)      | 31.6                                                                    | 35.7  | 31.6     | 26.8  | 31.6     | 26.7  |
| Elm Farm (ELM)      | 35.4                                                                    | 33.9  | 35.9     | 31.6  | 35.4     | 29.9  |
| Silsoe (S)          | 39.7                                                                    | 39.8  | 39.7     | 37.6  | 39.7     | 36.9  |
| Loddington (LOD)    | 43.0                                                                    | 48.0  | 40.5     | 40.4  | 43.0     | 39.5  |
| Torr Organic (TORR) | 41.2                                                                    | 39.2  | 48.3     | 44.8  | 41.2     | 41.1  |
| Clapham (CP)        | 56.5                                                                    | 39.8  | 58.5     | 52.7  | 56.5     | 50.2  |
| Manor Farm (MAN)    | 67.5                                                                    | 48.0  | 61.4     | 45.7  | 67.5     | 44.0  |
| Swanage (SWA)       | 65.5                                                                    | 48.2  | 64.5     | 47.8  | 65.5     | 43.5  |
| Aberdeen (ABE)      | 59.5                                                                    | 40.3  | 65.3     | 59.2  | 59.5     | 58.9  |
| Mean                | 48.9                                                                    | 41.4  | 49.5     | 42.9  | 48.9     | 41.2  |

Table 3-3 Assumed new SOC, based on measured values and assuming an increase in SOC of 10 t ha<sup>-1</sup>, and the value of the change to new SOC starting from the modelled baseline.

| Farm/ Site          | Model 1                               |                                                    | Model 2                               |                                                    | Model 3                               |                                                    |
|---------------------|---------------------------------------|----------------------------------------------------|---------------------------------------|----------------------------------------------------|---------------------------------------|----------------------------------------------------|
|                     | Assumed new SOC (t ha <sup>-1</sup> ) | Value above modelled baseline (£ha <sup>-1</sup> ) | Assumed new SOC (t ha <sup>-1</sup> ) | Value above modelled baseline (£ha <sup>-1</sup> ) | Assumed new SOC (t ha <sup>-1</sup> ) | Value above modelled baseline (£ha <sup>-1</sup> ) |
| Skeffing (SKF)      | 41.6                                  | 590                                                | 41.6                                  | 1480                                               | 41.6                                  | 1490                                               |
| Elm Farm (ELM)      | 45.4                                  | 1150                                               | 45.9                                  | 1430                                               | 45.4                                  | 1550                                               |
| Silsoe (S)          | 49.7                                  | 990                                                | 49.7                                  | 1210                                               | 49.7                                  | 1280                                               |
| Loddington (LOD)    | 53.0                                  | 500                                                | 50.5                                  | 1010                                               | 53.0                                  | 1350                                               |
| Torr Organic (TORR) | 51.2                                  | 1200                                               | 58.3                                  | 1350                                               | 51.2                                  | 1010                                               |
| Clapham (CP)        | 66.5                                  | 2670                                               | 68.5                                  | 1580                                               | 66.5                                  | 1630                                               |
| Manor Farm (MAN)    | 77.5                                  | 2950                                               | 71.4                                  | 2570                                               | 77.5                                  | 3350                                               |
| Swanage (SWA)       | 75.5                                  | 2730                                               | 74.5                                  | 2670                                               | 75.5                                  | 3200                                               |
| Aberdeen (ABE)      | 69.5                                  | 2920                                               | 75.3                                  | 1610                                               | 69.5                                  | 1060                                               |
| Mean                | 58.9                                  | 1750                                               | 59.5                                  | 1657                                               | 58.9                                  | 1760                                               |

\*Carbon value was assumed to be 100 £ (t C)<sup>-1</sup>

### 3.3.4 Application at a farm-scale

The estimated SOC stock (0-10 cm) in t ha<sup>-1</sup> determined by each spatial modelling approach for each field at Loddington is shown in Figure 3-8. These values were used to determine the stored SOC (0-10 cm) for the 317 ha at Loddington. The estimate was 12,356 t using Model 1, 13,815 t using Model 2, and 13,472 t using Model 3. The use of coarse data inputs with Model 1 resulted in less within-farm variation than the two spatial modelling approaches using input data at a finer spatial resolution.

From the three measured parcels, land parcel B comprised two soil associations, returned the highest mean SOC values and stocks in all three models, and land parcel C

the lowest. As can be observed in Table\_Apx A-3, the spatial modelling approach with the combination of coarse input data and coarse management scale (Model 1), gave similar SOC values to all land parcels with the same land cover/soil association combination. By contrast, the use of fine-scale input data enabled the identification of within field and between field variations.

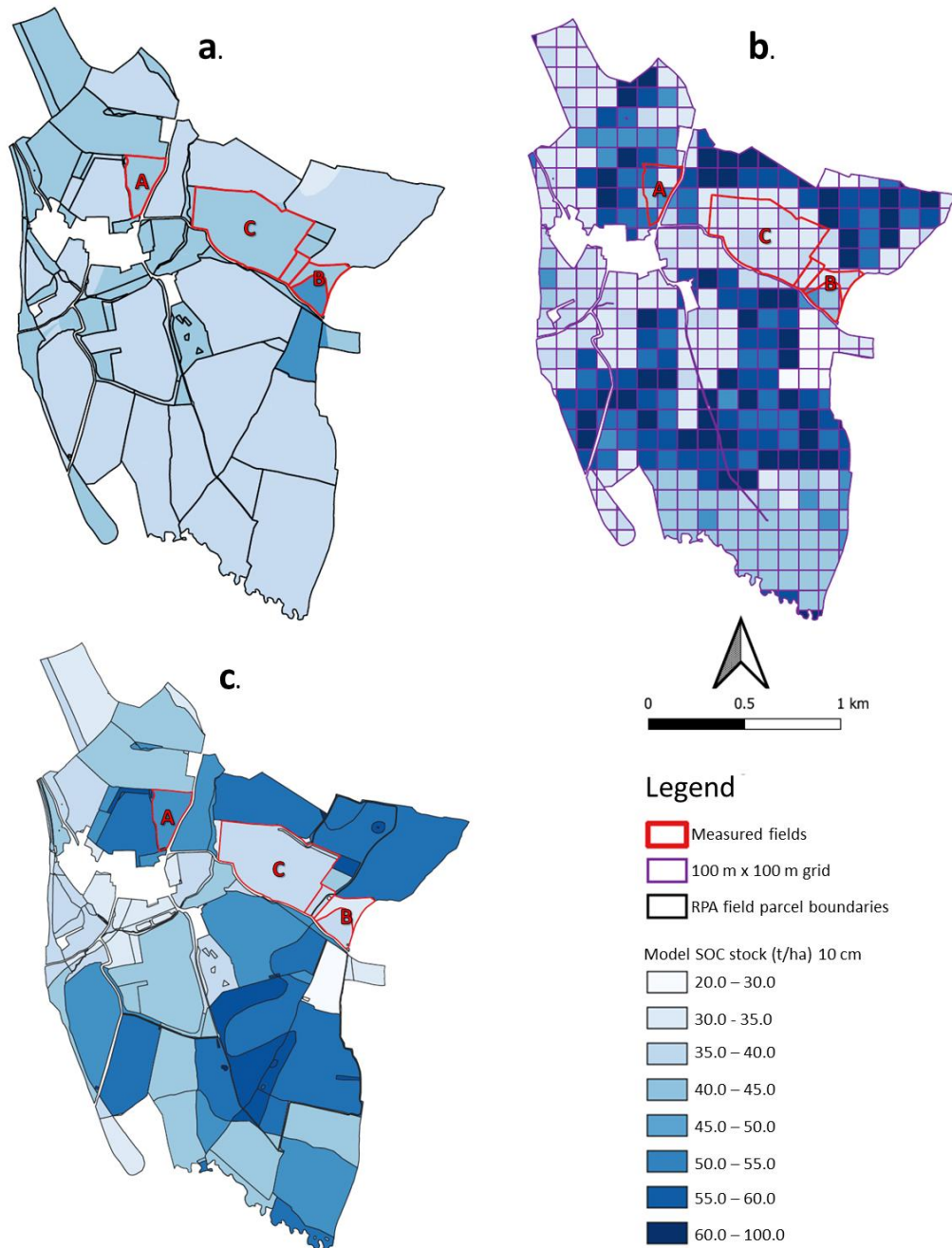


Figure 3-8 Predicted soil organic carbon (SOC) stock (t ha<sup>-1</sup>) (0-10 cm) for a) each field parcel and highlighted measured parcels (in red) in the Loddington farm using spatial modelling approach 1 (Model 1), b) each 100 m x 100 m square grid using spatial modelling approach 2 (Model 2), and c) each field parcel using spatial modelling approach 3 (Model 3). The SOC stock values are shown using a 5 t ha<sup>-1</sup> increment for values between 30 and 60 t ha<sup>-1</sup> and greater increments at the extremes.

### 3.4 Discussion

This discussion starts by examining the benefits of using fine resolution inputs to develop farm-level inventories of SOC. It then examines sources of error and uncertainty, the benefits of the final predictions being provided at a field or 100 m grid-square scale, and the implications of spatial modelling approach use on carbon sequestration payments.

#### 3.4.1 Benefits of fine resolution input data for farm-scale inventories

In the context of national targets for net-zero GHG emissions, there is a need to develop robust farm-scale SOC inventories of soil carbon storage. Ideally, it would be best to have standardised measured values of soil carbon and bulk density for each field on specified dates to specified depths, but such data are costly in terms of time and resources. A potential cost-effective alternative is to use validated approaches that can predict SOC levels, with a stated level of uncertainty, moderated by spatial inputs which can be derived more easily. For both calibration and evaluation datasets, using a 100 m x 100 m input dataset (Campbell 2018) increased the proportion of the variation in SOC that could be explained to 50-69% (Models 2 and 3), compared to 39-43% with the coarser NATMAP dataset (Model 1). Across the calibration and evaluation dataset, the RMSE associated with Model 2 (11.0-15.8 t SOC ha<sup>-1</sup>) and Model 3 (8.3-17.2 t SOC ha<sup>-1</sup>) tended to be less than with coarse-scale Model 1 (16.0-18.3 t SOC ha<sup>-1</sup>).

In addition to explaining a higher proportion of the variation, the slopes of the regression equation of the estimated to measured stocks using Model 2 (0.40-0.67) and 3 (0.44-0.74) were substantially greater than that using Model 1 (0.05-0.29). This increased slope means that Models 2 and 3 were better able to differentiate between areas of low and high soil carbon, which has important implications for carbon payments. For example, as demonstrated for Loddington, Models 2 and 3 were able to pick up field-to-field and in-field variation not captured by Model 1. Hence it seems that the finer resolution models can enable more informed management of soil carbon.

One reason why Models 2 and 3 were able to estimate a higher proportion of variation than Model 1 is that the soil properties dataset developed by Campbell (2018) considered the local variation of soil formation characteristics such as altitude, climate, relief, parent material, and time (Jenny 1941). In addition, the Campbell dataset accounted for spatial variation in bulk density, OCC and the soil associations, both across the landscape (x, y) and with depth (z). It is particularly important to account for variations in bulk density when determining values of SOC from OCC measurements (Taalab et al., 2013).

Although Model 2 and 3 were able to explain a higher proportion of the variation in SOC than Model 1, overall, both spatial modelling approaches still predicted lower variation than the measured SOC values. This is demonstrated by the slope values of less than 1, and large intercepts for the regression line of 28.2-37.0 t SOC ha<sup>-1</sup> for Model 1, 12.9-18.9 t SOC ha<sup>-1</sup> for Model 2, and 8.8-15.9 t SOC ha<sup>-1</sup> for Model 3. This means that although the finer resolution dataset was better able to account for SOC differences, Models 2 and 3 still tended to underestimate the SOC value of soils high in soil carbon. The tendency for spatial models to underestimate areas of high soil carbon has previously been noted by Gregory et al. (2014).

Potential sources of error and uncertainty when comparing estimated predictions with measured results can arise from three sources. Firstly, regarding the measured data, the SOC and bulk density measurements are within typical analytical mean probable errors (2.7–5.8%) (Schrumpf et al., 2011) and the methods and location of the measurements were also clearly recorded in the studies where the sampled data were taken from. Secondly, in terms of the input data, the soil association dataset used in Model 1 assumes definite borders making the predicted SOC step changes abrupt, while they are typically gradual. The 100 m x 100 m dataset (Campbell 2018), used in Model 2 and 3 assumed land covers as they existed in 2000 (LCM 2000), whereas the measured values were obtained between 2013 and 2016. However, to our knowledge, all of the grassland sites were grassland in both 2000 and 2013-2016. In addition, the spatial modelling

approaches do not address the temporal aspects of SOC decline or increase resulting from a land cover change. To account for such effects would require additional data on the timing of land cover changes.

Lastly, the third source of error relates to the algorithms used in the modelling approaches. The data used to create the spatial modelling approaches with the fine-scale input data (Models 2 and 3), performed much better in predicting the texture properties (clay and sand) than the LOI with RMSE values equal to  $\pm 9.1 \text{ g clay (g soil)}^{-1}$  and  $\pm 15.6 \text{ g clay (g soil)}^{-1}$  respectively (Campbell, 2018). Similarly, the equations used for the calculation of these models' parameters had a correlation coefficient of 0.99 for the LOI / OCC calculation (Ball, 1964) and an  $R^2$  ranging from 0.40 to 0.68, for the bulk density depending on the type and the characteristics of soil (Hollis et al., 2012).

### **3.4.2 Benefits and costs of different carbon baseline estimates**

On a traditional farm where decisions are taken at a field level, farmers might be more interested in estimates of SOC for individual fields (e.g., Model 3) rather than each 100 m x 100 m square grid (Model 2). However, by using a model with the combination of fine-scale input data and fine management scale, like Model 2, a farmer can pick up the in-field variations and be able to adjust their management practises according to factors like the topography and the soil type of that location. The mean measured field sizes of the nine study areas ranged from 3.74 ha for the farm in Swanage to 12.39 ha for the Torr Organic Farm.

### **3.4.3 Implications of spatial modelling approach choice on financial payments**

Carbon farming can potentially provide an income to farmers and landowners who can sell the credits they earn in carbon markets where large scale GHG emitters can purchase them to offset their own emissions. One major challenge is that soils depending on their texture, depth and mineral content absorb different amounts of carbon (Choudhury et al., 2016; Jobbágy and Jackson, 2000; Yu et al., 2020). While certain practices such as no-till and cover cropping (Hillier et al., 2011; Jian et al., 2020;

Zhang et al., 2006) can increase C storage, quantifying the stored amount is crucial in order to assign the value of the change.

Although soil carbon markets are not yet fully developed, one example includes the Emissions Reduction Fund in Australia (Australian Government Department of Industry, Science, Energy and Resources, 2021). In the UK, there are plans for the Sustainable Farming Incentive to pay farmers and landowners for adding organic matter in the soil (Department for Environment Food & Rural Affairs, 2021), and the Environmental Agency is funding a consortium to develop a soil carbon code that will provide farmers with an additional income (Sustainable Soils Alliance, 2021). In the US, the Senate passed the Growing Climate Solutions Act of 2021 (US Government, 2021) and voluntary companies such as IndigoAg and Nori have already enabled farmers to receive carbon credit payments (Farmers Weekly, 2021). However, as Paustian et al. (2019) highlighted there are still no global standards for measuring, verifying or reporting SOC credits in agricultural lands.

In the few existing farm-scale soil carbon modelling studies, predictions are typically limited to averages over the whole farm area (Vandenbygaart et al., 2004). In some cases, the coefficients of correlation ( $r$ ) and determination ( $R^2$ ) are reported between the measured and predicted values, but there is no information about the level of precision (Adewale et al., 2019; Correndo et al., 2021; Mikhailova et al., 2016), even though model uncertainty can be derived by propagating the uncertainty of input values. Moreover, rigorous approaches validated against measured values are needed in order to avoid someone claiming carbon credits that do not occur in practice. A possible method is to develop approaches to spatially predict and value SOC that is appealing to farmers and landowners, who can both be paid for maintaining or increasing soil carbon, whilst also benefiting from improved soil health and increased crop yields.

In this paper, we assumed a carbon value of £100 (t C)<sup>-1</sup>, which is equivalent to £27 (t CO<sub>2</sub>e)<sup>-1</sup>. This is marginally higher than prices (£17 and £24 (t CO<sub>2</sub>e)<sup>-1</sup>) received for verified woodland carbon sequestration in the UK (Woodland Carbon Code 2022), but less than the traded price for carbon in the electricity generation sector (£74 (t CO<sub>2</sub>e)<sup>-1</sup>), and about 11% of the social cost of carbon (SCC) (£250 (t CO<sub>2</sub>)<sup>-1</sup>) used in policy analysis. At present, the prices received for reducing GHG emissions through tree and soil management are less than the penalties for emissions in electricity generation, but over time these values should converge. Similarly, if carbon emissions are viewed from a societal perspective, the value of traded carbon sequestration or cost of carbon emissions should converge to the social costs of carbon.

The choice of whether to measure or model the baseline SOC from which to derive a value of an increase in the SOC by 10 t C ha<sup>-1</sup> above the initial measured value could have different financial implications between farms, and the effect also varied with choice of model. Underestimation of high SOC values, using the spatial modelling approaches, described in Section 3.4.1 has important financial implications. Using Model 2, because the mean modelled SOC (42.9 t ha<sup>-1</sup>) was less than the mean measured value (49.5 t ha<sup>-1</sup>), an increase to a new measured value of 59.5 t ha<sup>-1</sup> assuming the initial modelled values would result in a mean payment of £1657 ha<sup>-1</sup>, i.e., 66% higher than if the results were only based on measurements. Because Model 2 tended to show a greater underestimation of the measured SOC at high SOC sites, using the model as a baseline meant that the derived carbon benefit was a mean of £1296 ha<sup>-1</sup> for the five sites with low SOC compared to a mean of £2108 ha<sup>-1</sup> for the four sites with the highest SOC. Hence in this example, using the model as a baseline favoured sites that already had a high SOC.

Using both coarse level inputs and outputs with Model 1 resulted in a lower mean estimate of SOC of 41.4 t ha<sup>-1</sup> compared to 42.9 t ha<sup>-1</sup> with Model 2. Hence assuming final measured values of SOC (that were 10 t ha<sup>-1</sup> above the original measured value), and baseline values based on Model 1 would result in an assumed mean increase worth

£1750 ha<sup>-1</sup>, 75% higher than the actual increase worth £1000 ha<sup>-1</sup>. Again, because Model 1 underestimated the initial SOC of sites with high SOC values, assuming a modelled baseline benefited the four farms with the highest SOC (range: £2670-2950 ha<sup>-1</sup>) than the five farms with the lowest SOC (range: £500-1200 ha<sup>-1</sup>).

The mean values of measured and modelled SOC using Model 3 were similar to Model 1 (Table 3-2), and hence the mean benefit to the farmers of the explained increase in carbon, based on Model 3 baseline of £1760 ha<sup>-1</sup>, was 76% higher than the increase if based on measurements. However, because Model 3 was better able than Model 1 to predict the high SOC of some high SOC sites, for seven of the nine sites, the calculated increase in value ranged from £1010 ha<sup>-1</sup> to £1630 ha<sup>-1</sup>. However, by contrast, Model 3 substantially underestimated the initial SOC at Manor Farm and Swanage (by between 22.0 and 23.5 t (C ha<sup>-1</sup>), where the assumed increase in SOC was worth £3200-3350 ha<sup>-1</sup>).

Overall, the use of models rather than measurements to determine an initial baseline for increases in soil carbon benefitted farmers, but such an approach would be more costly than expected for purchasers of carbon credits. In this example, a coefficient of 0.57-0.62 would need to be applied to mean calculated increases, so that the calculated increases matched the actual increase of 10 t C ha<sup>-1</sup>. The appropriate coefficient will vary depending on the increase in SOC.

#### **3.4.4 Limitations of the developed spatial modelling approaches and how to overcome them**

Each of the examined spatial modelling approaches have potential limitations, and there are errors and uncertainty with the measured data and the inputs and the algorithms in the approaches. International soil carbon accounting approaches such as used by the IPCC (IPCC, 2019) focus on a soil depth of 0-30 cm. However, in this study, the three spatial modelling approaches were only applied to a depth of 0-10 cm as this was the only spatially explicit available measured dataset. Acquisition of complete measured

SOC data to greater depths is hard to come across due to the labour intensity and expenses that are required. The methodology can be applied at deeper depths, if complete spatially explicit datasets to greater depths become available. Further research is recommended to compare the spatial modelling approaches with measured soil carbon values to a depth of at least 30 cm and across a wider range of land covers.

Models 2 and 3 were based on a soil dataset established for land cover at a specific date. However, land cover on farms is not static, and even if the land cover remains the same, management practices can modify the SOC (Badgery et al., 2020; Hamburg et al., 2019; Kirk and Bellamy, 2010; Upson et al., 2016). Hence it is likely that physical measurements will be needed to validate current levels of SOC. However there is an argument that having modelled SOC values calculated for a specific date can be useful in establishing a common baseline from which to predict subsequent change. In order for this to be useful, it will be important to understand the uncertainty associated with such SOC values and the associated financial valuations. One way is to address the financial uncertainty associated with modelled values would be to apply a discounting coefficient. Although this will reduce the financial value of estimated change, it may still be more cost-effective for the farmer than incurring additional costs to derive a more accurate value through other methods.

The three spatial modelling approaches developed in this study take a screenshot of a farm or site at a specific point in time and estimate the amount of carbon currently stored in it. The approaches do not directly determine the permanence of the SOC, and changes in climate and management may modify current levels (Badgery et al. 2020). Hence, in most carbon sequestration schemes, current or future carbon levels eventually need to be monitored, reported, and verified (MRV) by measurements to demonstrate genuine abatement. The measurements associated with this process of MRV could be collected by farmers themselves or by an accredited organisation. The proposed field sampling will need to address both changes in bulk density and OCC and record any changes in land cover. Some authors have examined ways to reduce MRV

costs through the potential of non-destructive soil carbon measurements such as in-field visible- near-infrared (vis-NIR) spectroscopic sensors and gamma-ray attenuation (England and Viscarra, 2018) and novel remote sensing techniques (Angelopoulou et al., 2019). In practice, a combination of approaches may be cost-effective.

### **3.5 Conclusion**

In this study we have demonstrated our hypothesis that downscaling national-level soil C information to a farm and field level has different impacts depending on both the spatial modelling approach and the accounting method. From the three spatial modelling approaches to pay farmers for soil carbon sequestration, the models using fine-scale resolution input data appeared to provide a more robust estimate of the measured SOC than the one using coarse-scale input data. Additionally, the capacity of the fine input and output approach (Model 2) to pick up in-field variations could assist farmers adjust their management practices according to within-field variations in topography and soil type.

The use of spatial models of SOC to predict the baseline for subsequent payments based on measured values of SOC tended to favour farms with high initial values of SOC, because the models tended to underestimate the SOC when the actual SOC was high. By contrast farms with initially low values of SOC tended to be unfavoured by the use of models to predict their initial baseline, as the models tended to predict SOC values close to the actual values on such farms. Further research is recommended to compare the spatial modelling approaches with measured soil carbon values at depths greater than 10 cm and across different land covers as data become available. However, spatially explicit measured soil carbon and bulk density data from deeper depths are relatively rare.

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## 4 Robust spatial estimates of biomass carbon on farms

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### Abstract

The drive for farm businesses to move towards net zero greenhouse gas emissions means that there is a need to develop robust methods to quantify the amount of biomass carbon on farms. Direct measurements can be destructive and time-consuming and some prediction methods provide no assessment of uncertainty. This study describes the development, evaluation and use of an integrated spatial approach, including the use of LiDAR data and Bayesian Belief Networks to quantify total biomass carbon stocks of i) land cover and ii) landscape features for five case study sites in lowland England. The results demonstrated that it is possible to develop and use a remote integrated approach to estimate biomass carbon at a farm scale. The highest achievable prediction accuracy was attained by applying both current literature and measured information about the variables that most influence the total biomass carbon stocks. The two Bayesian Belief Network models successfully predicted the test values of the total biomass carbon with propagated error rates of 6.7% and 4.3% for the land cover and landscape features respectively. These error rates were lower than in other studies indicating that the six predictors are strong determinants of biomass carbon. The LiDAR data also enabled the spatial presentation and calculation of the variable carbon stocks along the length of hedges and within woodlands.

**Keywords:** biomass carbon, spatial variation, integrated method, land cover, landscape features

### 4.1 Introduction

Efforts to mitigate climate change have been enacted by many countries across the world with the aim of achieving net-zero greenhouse gas (GHG) emissions by 2050 (Brandão et al., 2013; Smith et al., 2012; Van Soest et al., 2021). Achieving this will

require management changes across each sector of the economy. This is particularly the case in agriculture, which was the source of about  $1.07 \times 10^9$  tonnes of carbon dioxide equivalent (Gt CO<sub>2</sub> eq) emissions in 2019, and in the long-term, it could provide a net sink (Food and Agriculture Organization of the United Nations, 2021).

Since management practices under the control of farmers can reduce GHG emissions at a farm level (Burbi et al., 2016), a key policy measure is to incentivise land managers to store more carbon on their farms and reduce emissions (Ziegler et al., 2016; Petrokofsky et al., 2012). For these policies to be successful, robust and accurate information on the current carbon (C) stock levels and methods to quantify the amount of C that has been or will be stored are required. Ideally, the quantified baseline inventories will be developed according to industry-accepted best practices and will be auditable (World Business Council for Sustainable Development and World Resources Institute, 2020). Physical sampling of soil and biomass carbon might provide the most accurate assessments, but such methods can be destructive, expensive and/or labour intensive (Rosenstock et al., 2016). There may be more cost-effective alternative methods that can provide the required accuracy more cheaply.

There is a substantive body of research on approaches using generic carbon storage values (Adger and Subak, 1996; Cannell and Milne, 1995; Cantarello et al., 2011; Cruickshank et al., 2000; Dewar and Cannell, 1992; Gregory et al., 1995; IPCC, 2019; Jian et al., 2020) and highly detailed emission factor tools and calculators (Campos, 2020; Carlson et al., 2017; Janzen et al., 2006; Shrestha, 2014; Stöckle et al., 2001; Sustainable Food Lab et al., 2011; Ziegler et al., 2016). However, the generic approach tends to present a very broad range between the minimum and maximum values, often without defining the levels of uncertainty. Similarly, the use of farm carbon calculators can be labour, time and cost-consuming and too complicated for some farmers to use. Additionally, the residual uncertainty surrounding the validity of carbon calculators is sometimes hard to determine.

Given the above, farmers need tools that can be adapted to changing technical, social, and economic environments whilst being able to specify the level of certainty in the carbon estimates. This study determines the potential of accounting for farm biomass carbon stocks with a level of uncertainty and examines the consequences for policy, payments and land users. This was achieved by developing two Bayesian Belief Network (BBN) models to quantify biomass carbon stocks and their uncertainty at a farm scale.

## **4.2 Materials and Methods**

### **4.2.1 Methodology formulation**

Probabilistic BBNs provide a way of understanding social-environment interactions where complex sets of geospatially interdependent variables can affect environmental outcomes and consequently human decisions in landscape management (Grafius et al., 2019; Karimi et al., 2021). The capability of BBNs to describe complex systems (Borsuk et al., 2004; Heckerman 1997; Pearl 1988; Taalab et al., 2015a; 2015b) potentially provide an approach to quantifying biomass stocks and their certainty for a situation where we typically have incomplete knowledge and information (Hassall et al., 2019; Korb and Nicholson, 2010). Moreover, when BBNs are combined with Geographical Information Systems (GIS) they can be used to guide on-farm decisions by providing an idea of the probability of events, defining key variables and conditional dependencies, and identifying how these could affect the outcomes (Grafius et al., 2019).

On-farm carbon storage can occur as soil carbon and in the form of biomass of relatively homogenous land covers and landscape features. In this study, a BBN modelling approach was used for predicting the total amount of biomass carbon stocks of i) homogeneous land covers such as arable crops, woodland and grassland, and ii) landscape features such as lone trees and hedges. The methodological approach involved five steps as shown in Figure 4-1. Initially, key influence predictor variables were identified from a literature search, followed by the construction of the BBN models using those literature values. We then quantified the conditional probabilities before (the naive model) and after (the informed model) adding some additional measured

values. Lastly, we used the informed model to spatially predict the total biomass carbon stocks across five case studies. A more detailed description of the steps is provided in the following sections.

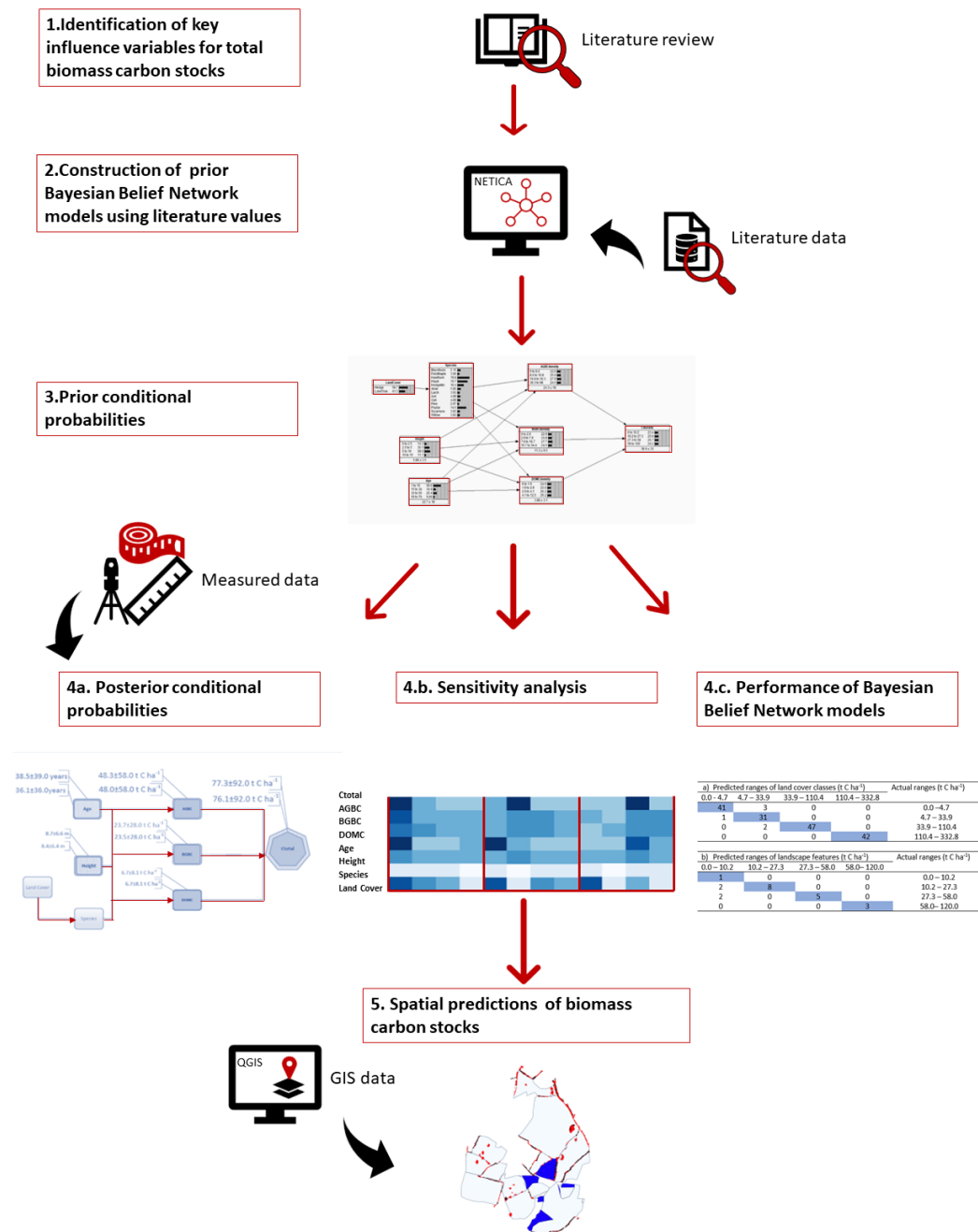


Figure 4-1 Schematic representation of the methodological approach.

#### 4.2.2 Identification of ‘state’ values

In the first step, we analysed published studies to identify the variables that were reported to affect the amount of biomass carbon. The key variables identified were land cover, species, age, height, above ground biomass carbon (AGBC), below ground biomass carbon (BGBC), and dead organic matter carbon (DOMC).

Secondly, we used two search engines (Scopus, 2022, Google Scholar, 2022) and a keyword approach to inform the BBNs. The literature was focused on UK studies and we identified eight broad types of homogeneous land cover using the classification of UKCEH (UK Centre for Ecology and Hydrology, 2020). These were: arable land, improved grassland, semi-natural grassland, broadleaf woodland, coniferous woodland, mixed woodland, mountain heath and bog, and shrubland. Additionally, we completed a similar literature search for the landscape features which were classified as hedgerows or lone trees (Brewer et al. 2017).

Within the land cover types, subdivisions were sometimes included down to species levels. Arable land cover was subdivided into cereals, crops for stock feed, horticulture, miscanthus, orchard, short rotation coppice (SRC), unspecified arable, vegetables, and vines. The broadleaf woodland species were separated into ash, beech, elm, oak, poplar, sweet chestnut, sycamore, unspecified broadleaf, willow, and a mixed group called SAB comprising sycamore, ash, and birch. The coniferous woodland species were separated into Corsican pine, Douglas fir, larch, lodgepole pine, Norway spruce, Scots pine, Sitka spruce, and unspecified coniferous. The improved grassland subdivisions included pasture, switchgrass, and unspecified improved grassland. The semi-natural grassland, mixed woodland, shrubland, mountain heath and bog covers were not subdivided. Lastly, for the woody landscape features, the hedgerow class was subdivided into: blackthorn, field maple, hawthorn, hazel, and “mixed hedge” unspecified hedge, and the lone trees were classified as either alder, ash, larch, oak, pine, poplar, sycamore, willow, or unspecified lone trees.

For each land cover and landscape feature, values were derived for the species, age, height, AGBC, BGBC, DOMC and total biomass carbon stock ( $C_{total}$ ). When a value for a variable was unknown, they were calculated using equations from Table\_Apx B-1 found in Appendix B. All the values, their descriptive properties and their references were inserted into Microsoft Excel spreadsheets (Microsoft Office, 2022), and were subsequently converted into the same format in order to be used as ‘cases’ in the next step.

#### **4.2.3 Construction of the Bayesian Belief Network models using literature values**

We then developed predictive knowledge-based BBN probabilistic models using Netica software (Norsys 2022) for the homogeneous land covers and the landscape features. These graphical models link a set of nodes called variables to a set of directed edges that represent the conditional probabilities between the nodes (Taalab et al., 2015a). In order to derive the structure of the probabilistic models, relationships between the variables were established as presented in Equations (4-1) - (4-5). The species variable was a function (f) of the land cover as seen in Equation (4-1), while the AGBC, BGBC and DOMC were a function of the species, age and height (Equations (4-2)- (4-4)). Lastly,  $C_{total}$  was a function of the three forms of biomass carbon (Equation (4-5)).

$$\text{Species} = f(\text{Land cover}) \quad (4-1)$$

$$\text{AGBC} = f(\text{species, age, height}) \quad (4-2)$$

$$\text{BGBC} = f(\text{species, age, height}) \quad (4-3)$$

$$\text{DOMC} = f(\text{species, age, height}) \quad (4-4)$$

$$C_{total} = f(\text{AGBC, BGBC, DOMC}) \quad (4-5)$$

The influence network for the homogeneous land covers contained seven variables as predictor nodes i.e., land cover type, species class, age, height, AGBC, BGBC, and DOMC.

Each node contained four bins as considered good practice (Constantinou et al., 2016; Marcot et al., 2012). The value of  $C_{total}$  was selected as the response variable node. The influence network for the landscape features contained similar predictor and response variable nodes, although the land cover type node contained only two states (hedgerow or lone trees) instead of the CEH land cover classes

Using only literature data, prior conditional probabilities were defined for “naive” models for the homogeneous land cover and the landscape features. For the naive models, 576 literature-derived values were used for land cover and 68 values for the landscape features model.

#### **4.2.4 Addition of measured values**

The next stage was to include additional measurement inputs of land cover and landscape features from five study areas (Figure 4-2) to create an “informed” model. The measured values were derived from five study areas all in lowland England identified by the names: Silsoe (S), Clapham Park (CP), Hanhill Manor Farm (HM), Crowmarsh Battle Farm (CB), and Elm Farm (E).

The site at Silsoe comprised an arable field planted with widely-spaced (6.4 m x 10 m) poplar trees, which 19 years after planting, measured in 2011, had a grass understorey (Upson and Burgess, 2013). The measurements at Clapham Park, taken in 2012, comprised a 14-year-old broadleaf woodland, a grassland area at least 50 years old, and a silvopasture agroforestry system with 14-year trees planted on grassland (Upson et al., 2016). At Harnhill Manor Farm measurements during the winter of 2013 were taken from three 12-18-year-old hawthorn and blackthorn hedges, and a 30 m adjacent area which included a grassland field margin and a small part of the arable land with a mix of forbs and legumes (Axe et al., 2017). At Crowmarsh Battle Farm, measurements were taken from five mixed 10-year-old hawthorn and mixed hedgerows in 2012 (Alexa Varah, personal communication 2021). Lastly, at Elm Farm, two blackthorn, two hawthorn and

two hazel hedgerows aged 15-40 years were measured in 2014 (Westaway and Smith, 2020).

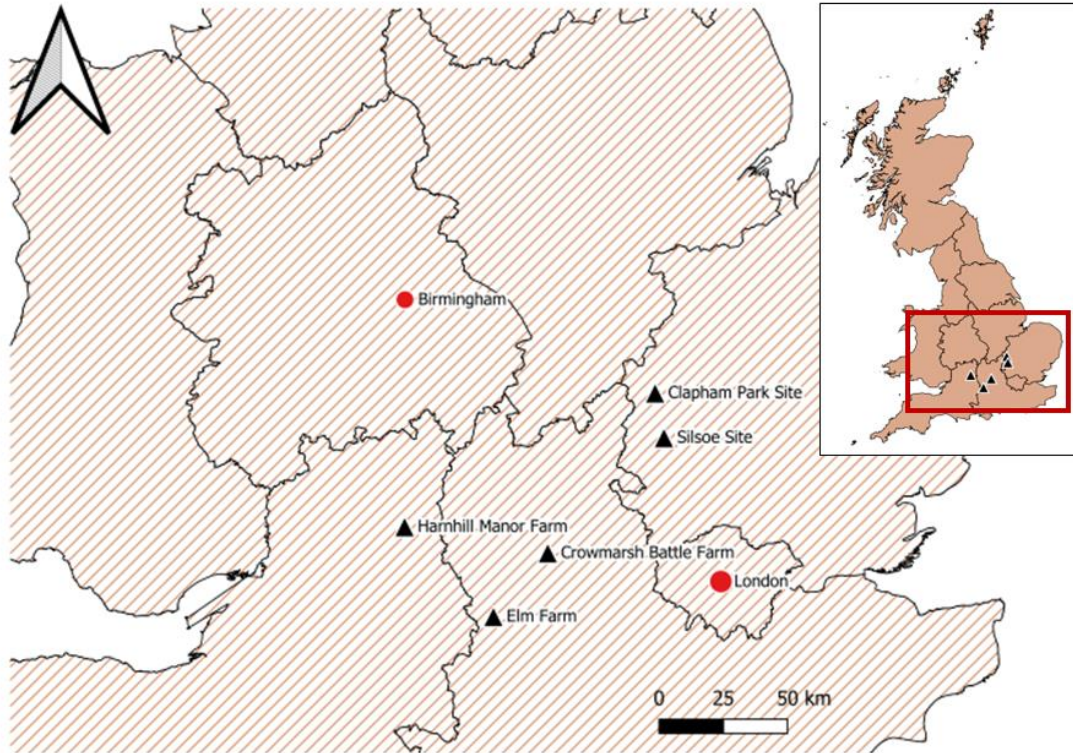


Figure 4-2 Map showing the location of the five study areas ▲ where measurements of the carbon biomass, dry biomass, dimensions, age and height of landscape features were collected.

In total, there were an additional 5 measured values of land cover and 26 measured values for landscape features. The 31 measured values were used to update the parameter distribution and predict the posterior probabilities by the application of Bayes' Theorem (Equation (4-6)).

$$p\left(\frac{\theta}{D}\right) = c p\left(\frac{D}{\theta}\right) p(\theta) \quad (4-6)$$

where  $p\left(\frac{\theta}{D}\right)$  is the posterior probability density function (pdf) for the model's parameters  $\theta$  after incorporating the new measured information  $D$ ,  $p(\theta)$  is the prior pdf

from the literature information for  $\theta$  before the arrival of the new information  $D$ . The likelihood of  $D$  for given values of  $\theta$  is  $p\left(\frac{D}{\theta}\right)$  and  $c$  is a proportionality constant (Koller and Friedman, 2009).

#### **4.2.5 Performance of Bayesian Belief Network models and sensitivity testing**

For both informed models, the predictors' influence on the  $C_{total}$  was examined by developing heat maps of the probabilistic associations. Output maps of the predicted total carbon across the five case studies were also generated using the QGIS 3.20.3 software environment (QGIS, 2022).

The performance of the models was then assessed using the “Test with cases” feature within Netica. The feature can be used to determine the performance of the two models by comparing the total carbon stored in the biomass predicted by the informed BBN models to the “true” value within a confusion matrix. For each case processed, Netica generated beliefs from which the most probable was selected and presented in the confusion matrix. Thereafter, it was compared with the true value of that case. For a network to perform well, the entries along the main diagonal would need to be larger to those off of it.

An error rate was defined for each network as the percentage of the cases where the measured value occurred outside of the range of the allocated “bin” (Norsys Software Corp., 2003). Although this process does not validate the results in the same way as determined in modelling, due to the Bayesian probabilistic inference base (Grafius et al., 2019), it provides a measure of confidence similar to model predictions. To rank the influence of the seven predictors on  $C_{total}$ , their sensitivities and correlations were assessed using the sensitivity feature of the Netica software (Norsys Software Corp., 2003).

#### **4.2.6 Spatial accounting approach of biomass carbon stocks**

The prior naïve model and the posterior informed model were used to estimate the total biomass carbon stocks of the study areas in order to identify the advantages of incorporating measured data.

##### **4.2.6.1 Land cover input data**

A mixture of raster and vector input data was used to depict the estimated total carbon stored in the biomass of the homogeneous land cover features found in the five case study sites. In more detail, vector data in the form of field delineations from the Rural Payments Agency in the UK, the 2015 land cover dataset (Centre for Ecology and Hydrology, 2017) and raster data in the form of the 1 m resolution Digital Surface Model (DSM) and a Digital Terrain Model (DTM) (Department for Environment Food & Rural Affairs, 2022) were collected for each study area.

During the first step, the field parcel information was combined in the QGIS 3.20.3 software environment (QGIS, 2022) with a land cover shapefile. This resulted in the field parcels being categorised in one of the land cover states of the BBN land cover node. The age and species of the homogeneous land cover species present at each land parcel were taken from the information provided from the sampling of the areas. The age of the arable crops was assumed to be 1 year. The age of the grassland (3-50 years) was determined using aerial images from previous years from Google Earth (Google Earth Pro, 2022).

In order to derive the height data for land cover features such as the woodland, the DTM was subtracted from the DSM and a raster with the height was derived. This was then segmented using the ENVI Version 5.6 (ENVI, 2022) software and was overlaid to the land cover/parcel vectors to classify the different height objects in land covers. Following, the vector shapefile with the segments was clipped to the boundaries of each field parcel and the mean height of the segments that fell within each field parcel was derived (height BNN predictor variable). The relationship between the aboveground

biomass for all woodland ( $AGB_{allwood}$ ;  $t\ ha^{-1}$ ) and the mean canopy height ( $H_{mean}$ ; m), was determined using Equation (4-7) from Lefsky et al. (2002) which had an  $R^2$  of 84%.

$$AGB_{allwood} = 0.378 H_{mean}^2 \quad (4-7)$$

Lastly, the predicted range of  $C_{total}$  was spatially depicted in QGIS for each study area.

#### 4.2.7 Landscape features input data

The height of landscape features such as hedges and lone trees and their spatial location were derived using the method described for homogeneous land covers. The height segments were overlaid with the parcel boundaries and everything on the edge of each parcel boundary was classified as a hedge, while everything away from parcel boundaries was defined as a lone tree. The age, species, and C stored in the biomass were obtained using a similar method as in the homogeneous land cover features and the predicted total carbon range was again spatially depicted.

### 4.3 Results

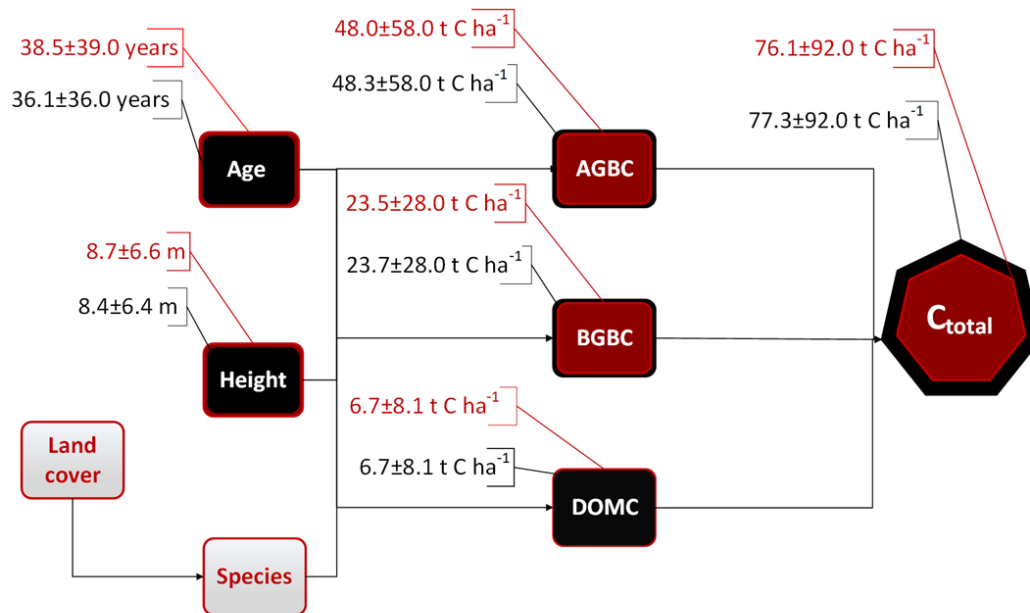
#### 4.3.1 Bayesian uncertainty quantification and predictor sensitivity

For the BBN of the homogeneous land cover classes, a sensitivity analysis showed that the most influential predictor variables in descending order were AGBC, DOMC, BGBC, height, species, age, and land cover. For the landscape features the three predictor variables with the most significant influence were the three forms of biomass C, followed by age, species, height, and land cover.

Figure 4-3 presents the five continuous variables of the two BBN models. The prior probability values, indicated in red in Figure 4-3, present the mean value of each one of the naive model's parameters together with the uncertainty expressed as standard deviation (sd) associated with each prediction using just literature values. After

incorporating the measured information into the naive models, an updated informed model and newly updated uncertainties were derived as indicated in black in Figure 4-3. A more detailed description of the values can be found in Table\_Apx B-2 and Table\_Apx B-3 in Appendix B. The combination of literature and additional measured information seemed to marginally improve the precision of estimation of the mean value of the total biomass C stock, as the mean value increased and the standard deviation stayed the same. In terms of the landscape features, the addition of measured values also increased the precision of the estimated total C stock value, as the mean value increased and the standard deviation decreased. Similarly, the precision of the estimate of the three forms of biomass C stock also improved as the values increased but the standard deviation stayed the same.

a.



b.

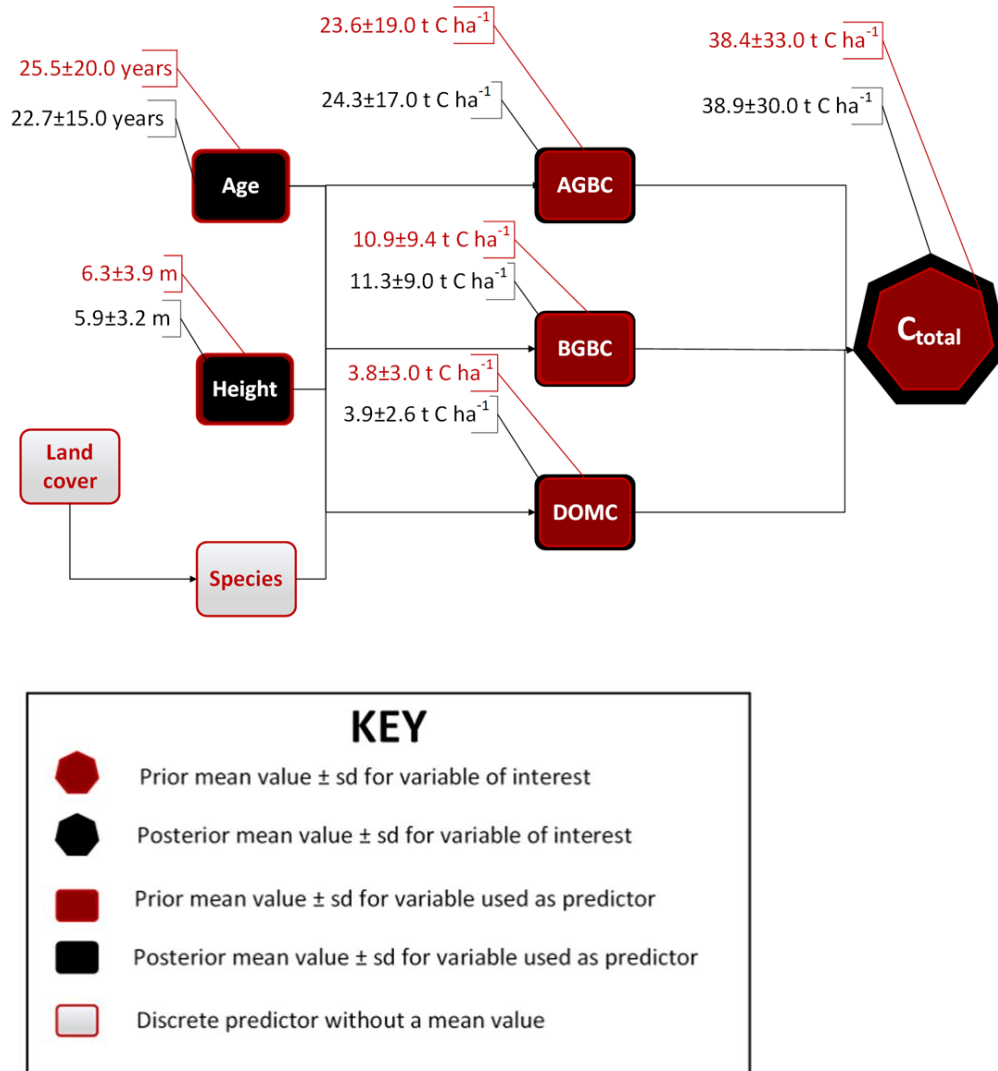


Figure 4-3 Graphic representation for mean prior and posterior probability values and standard deviation for the parameters of the Bayesian Belief Network (BBN) model for a) the homogeneous land cover classes ( $n_{\text{prior}} = 576$ ,  $n_{\text{posterior}} = 576 + 5$ ) and b) landscape features ( $n_{\text{prior}} = 68$ ,  $n_{\text{posterior}} = 68 + 26$ ). Where AGBC = Above Ground Biomass Carbon, BGBC= Below Ground Biomass Carbon, DOMC= Dead Organic Matter Carbon and C<sub>total</sub> = Total Biomass Carbon Stock

#### 4.3.2 Drivers of carbon density

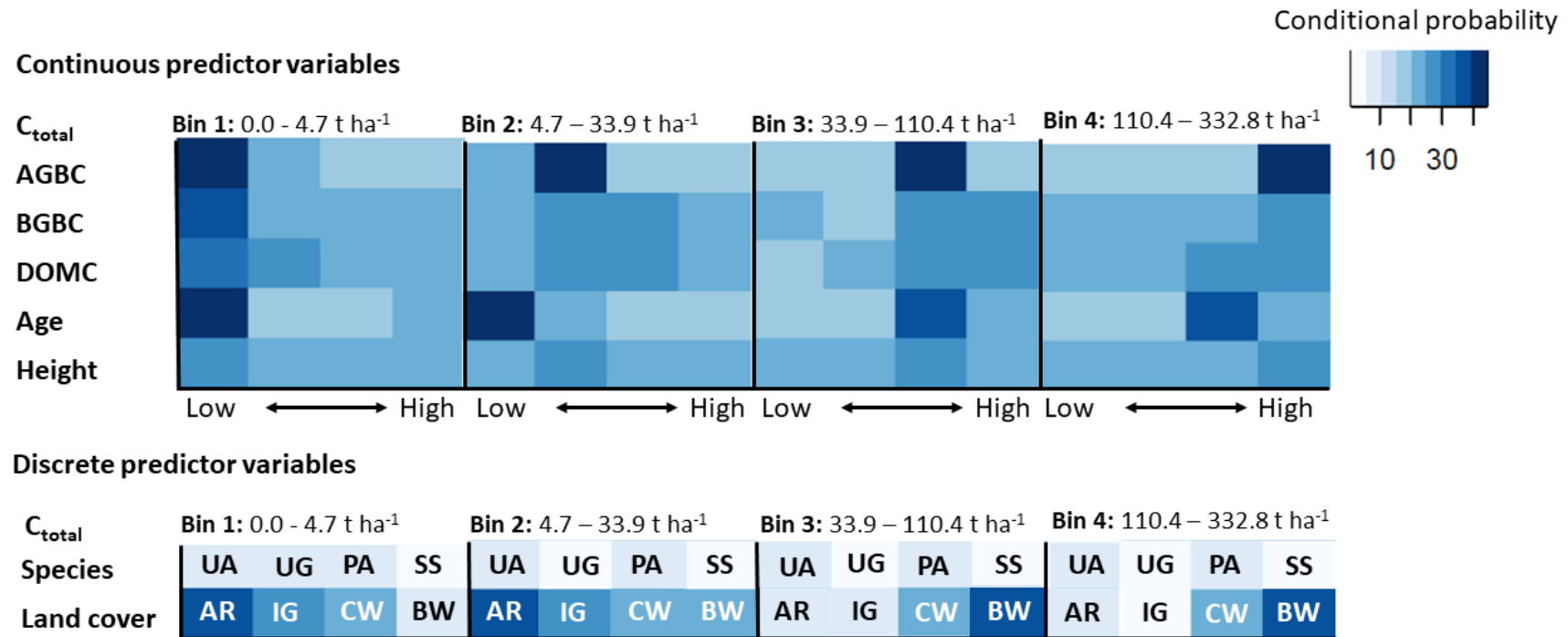
Using the posterior models, heat maps were generated to describe the probabilistic associations between the predictor variables and the predicted total biomass C stock (C<sub>total</sub>) for the homogeneous land cover classes (Figure 4-4a) and the landscape features

(Figure 4-4b). The conditional probabilities of an outcome given a set of parent node states are presented with shades of blue, with low and high probabilities indicated in light and dark blue respectively. For the homogeneous land cover features, although there were more than four states on the land cover and species nodes, only the four most common land covers are presented in the heatmaps. The four probabilistic ranges that the  $C_{total}$  can take are referred to as “bins”.

For the homogeneous land covers, Bin 1 comprised 0-4.7 t C ha<sup>-1</sup>, and Bins 2, 3, and 4 comprised 4.7-33.9, 33.9-110.4, and 110.4-332.8 t C ha<sup>-1</sup> respectively. The heat map shows that low values of  $C_{total}$  were associated with arable land (AR) and that high values of  $C_{total}$  were associated with high values of aboveground biomass carbon and age and with broadleaf woodland (Figure 4-4a). Differences between the effect of the four most common species in the dataset (UA: unspecified arable; UG: unspecified grassland, PA: pasture, and SS: Sitka spruce) on  $C_{total}$  were relatively small. The low-level ‘bin’ of  $C_{total}$  (0.0 - 4.7 t C ha<sup>-1</sup>) was dominated by short and young land covers that store low amounts of C as above ground, below ground, and dead organic matter (Figure 4-4a). By contrast, the high level ‘bin’ of  $C_{total}$  (110.4 - 332.8 t C ha<sup>-1</sup>) comprised tall land cover classes typically in the age range of 40-60 years and with high levels of aboveground biomass (AGBC).

For the heatmap created for the landscape features (Figure 4-4b), Bin 1 comprised 0-10.2 t C ha<sup>-1</sup>, and Bins 2, 3, and 4 comprised 10.2-27.3, 27.3-58.0, and 58.0-120.0 t C ha<sup>-1</sup> respectively. As with the land cover, the highest values of  $C_{total}$  were associated with high values of aboveground biomass, belowground biomass and dead organic matter (Figure 4-4b). High values of age and height were also associated with high values of  $C_{total}$ . Hence, young lone trees and hedges below a height of 5 m tended to have low values of  $C_{total}$ , and older tall features had high values. Lone trees like poplar and hedges like hawthorn and hazel and in an age group of greater than 30 years tended to have high values of  $C_{total}$ .

a.



b.

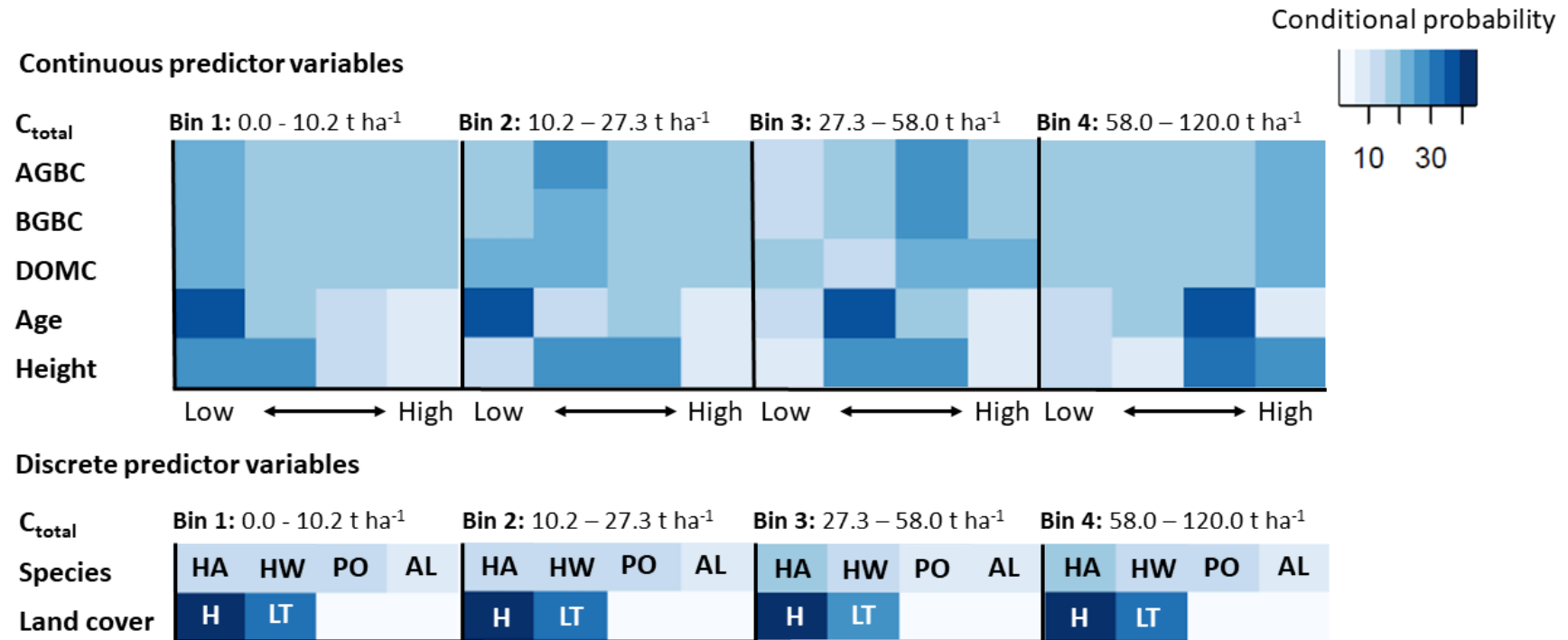


Figure 4-4 a. Informed heat map presenting the four bins of the total biomass carbon stock ( $C_{total}$ ;  $n = 581$  of homogeneous land cover, and the conditional probabilities of five continuous predictor variables, and two discrete predictor variables showing the four most common species (UA: unspecified arable; UG: unspecified grassland, PA: pasture, and SS: Sitka spruce) and four most common land cover classes (AR: arable, IG: improved grassland, CW: coniferous woodland, and BW: broadleaf woodland) b. Informed heat map presenting four bins of the total biomass carbon stock ( $C_{total}$ ) of landscape features ( $n = 94$ ), the conditional probabilities of five continuous predictor variables, and two discrete predictor variables showing the four most common species (HA: hazel; HW: hawthorn; PO: poplar, and AL: alder) and

whether the landscape feature is a hedge (H) or lone tree (LT). Where AGBC = Above Ground Biomass Carbon, BGBC= Below Ground Biomass Carbon, DOMC= Dead Organic Matter Carbon and Ctotal = Total Biomass Carbon Stock.

### 4.3.3 Model performance

The performance of the BBN models in determining  $C_{total}$  can be partly assessed using the error rate derived from a confusion matrix. The confusion matrices produced for each model contained four possible ranges for  $C_{total}$ . For each one of the 581 cases in the land cover dataset, the use of the BBN model in Netica generated beliefs for each possible state and the one with the highest probability value most likely was chosen as its prediction. This value was then compared with the measured value taken from the test file. The confusion matrix (Table 4-1) shows that 542 out of the 581 datum points were correctly allocated to the correct “bin”.

A total of 37 values were not estimated correctly, 15 of which were predicted to have a higher value and the other 22 a lower value than their actual one. A similar matrix (Table 4-1) was produced for the landscape features, where a total of 94 cases were processed, and in this case, 90 features were correctly allocated, but four features were incorrectly allocated to Bin 1. Hence, the error rate for the BBN model was 6.7% for the homogeneous land cover classes and 4.3% for the landscape features indicating that, in general, the BBNs were able to match the allocated  $C_{total}$  value to the same bin as the measured  $C_{total}$  test values.

Table 4-1 Confusion matrix demonstrating the success of the posterior Bayesian Belief Network (BNN) to predict the total biomass carbon stock ( $C_{\text{total}}$ ) values for a) the land cover classes ( $n = 581$ ) as inputs and b) the landscape features as inputs ( $n = 94$ ).

| Predicted carbon stock (t C ha <sup>-1</sup> ) |            |              |               | Actual carbon stock (t C ha <sup>-1</sup> ) |
|------------------------------------------------|------------|--------------|---------------|---------------------------------------------|
| 0.0 - 4.7                                      | 4.7 – 33.9 | 33.9 – 110.4 | 110.4 – 332.8 |                                             |
| 130                                            | 15         | 0            | 0             | 0.0 – 4.7                                   |
| 18                                             | 127        | 0            | 0             | 4.7 – 33.9                                  |
| 0                                              | 2          | 142          | 1             | 33.9 – 110.4                                |
| 0                                              | 0          | 1            | 143           | 110.4 – 332.8                               |

| Predicted carbon stock (t C ha <sup>-1</sup> ) |             |             |             | Actual carbon stock (t C ha <sup>-1</sup> ) |
|------------------------------------------------|-------------|-------------|-------------|---------------------------------------------|
| 0.0 – 10.2                                     | 10.2 – 27.3 | 27.3 – 58.0 | 58.0– 120.0 |                                             |
| 9                                              | 0           | 0           | 0           | 0.0 – 10.2                                  |
| 2                                              | 24          | 0           | 0           | 10.2 – 27.3                                 |
| 2                                              | 0           | 29          | 0           | 27.3 – 58.0                                 |
| 0                                              | 0           | 0           | 28          | 58.0– 120.0                                 |

#### 4.3.4 Quantity and value of total carbon density

The next step in the analysis was to compare the measured values of  $C_{\text{total}}$  with the predicted results of  $C_{\text{total}}$  using the informed BBNs (Table 4-2) and calculate the RMSE. More details about the measured values can be found in Table\_Apx B-4 in Appendix B. For each land cover and landscape feature type, the most probable out of the four  $C_{\text{total}}$  bins is presented together with the weighted median value. This was calculated as the weighted median of all probable bins with their probabilities assigned as weights. The highest predicted value of  $C_{\text{total}}$  (72 t C ha<sup>-1</sup>) was for an ash broadleaf woodland, compared to a measured value of 58 t C ha<sup>-1</sup> (Table 4-2). The lowest predicted value of  $C_{\text{total}}$  of 2 t C ha<sup>-1</sup> was for an arable field, compared to the measured value of 3 t C ha<sup>-1</sup>. For the landscape features, the mean measured  $C_{\text{total}}$  of all hedges was 65 t C ha<sup>-1</sup> and that for the lone trees was 100 t C ha<sup>-1</sup>. The mean predicted value using the informed model was 62 t C ha<sup>-1</sup> for the hedges and 85 t C ha<sup>-1</sup> for the lone trees. The RMSE for the overall predictions of the land covers was 7.89 t C ha<sup>-1</sup> while for the landscape features it was equal to 10.58 t C ha<sup>-1</sup>:

Table 4-2 Measured and predicted by the informed Bayesian Belief Network models total biomass carbon stock ( $C_{\text{total}}$ ) for homogeneous land cover classes and landscape features at five study sites.

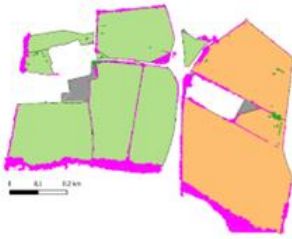
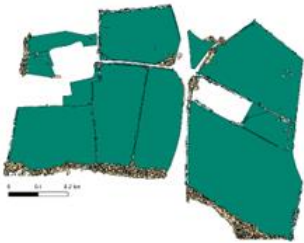
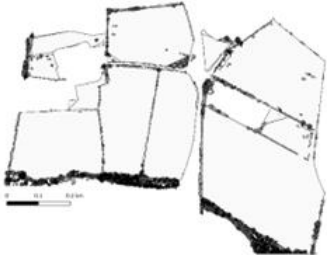
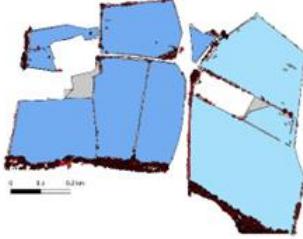
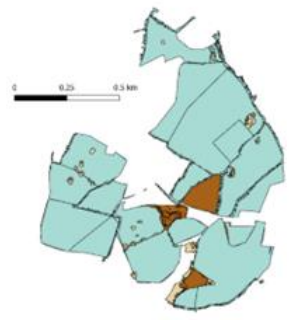
| Farm                   | Land cover/<br>feature | n | Total biomass carbon stock (t ha <sup>-1</sup> ) |                                            |                                   |
|------------------------|------------------------|---|--------------------------------------------------|--------------------------------------------|-----------------------------------|
|                        |                        |   | Measure<br>d                                     | Most probable bin<br>range and probability | Weighted<br>Median value<br>± sd* |
| Homogeneous land cover |                        |   |                                                  |                                            |                                   |
| HM                     | Arable: cereal         | 1 | 3                                                | 0-5 (96%)                                  | 2 ± 2.68                          |
| S                      | Arable: stockfeed      | 1 | 5                                                | 0-5 (57%)                                  | 4 ± 7.12                          |
| CP                     | Improved<br>grassland  | 1 | 8                                                | 5-34 (96%)                                 | 15 ± 9.97                         |
| HM                     | Improved<br>grassland  | 1 | 7                                                | 5-34 (67%)                                 | 15 ± 25.97                        |
| CP                     | Broadleaf: ash         | 1 | 58                                               | 34-110 (97%)                               | 72 ± 29.11                        |
|                        |                        | 5 |                                                  |                                            |                                   |
| Landscape features     |                        |   |                                                  |                                            |                                   |
| CB                     | Hedge: hawthorn        | 1 | 19                                               | 10-27 (67%)                                | 20 ±24.78                         |
| CB                     | Hedge: hawthorn        | 1 | 42                                               | 27-58 (84%)                                | 42 ± 17.36                        |
| CB                     | Hedge: hawthorn        | 1 | 44                                               | 27-58 (75%)                                | 41 ± 20.76                        |
| CB                     | Hedge: hawthorn        | 1 | 51                                               | 27-58 (75%)                                | 41 ±20.76                         |
| CB                     | Hedge: mix             | 4 | 34-40                                            | 27-58 (84%)                                | 42 ± 17.36                        |
| E                      | Hedge: hazel           | 1 | 39                                               | 27-58 (84%)                                | 42 ± 17.36                        |
| CB                     | Hedge: mix             | 1 | 87                                               | 58-120 (90%)                               | 85 ± 27.02                        |
| E                      | Hedge: hawthorn        | 2 | 61-105                                           | 58-120 (75%)                               | 85 ± 36.5                         |
| E                      | Hedge: hazel           | 1 | 97                                               | 58-120 (75%)                               | 85 ± 36.5                         |
| E                      | Hedge: blackthorn      | 2 | 99-106                                           | 58-120 (75%)                               | 85 ± 36.5                         |
| HM                     | Hedge: hawthorn        | 1 | 79                                               | 58-120 (75%)                               | 85 ± 36.5                         |
| HM                     | Hedge: blackthorn      | 1 | 94                                               | 58-120 (75%)                               | 85 ± 36.5                         |
| HM                     | Hedge: mix             | 1 | 103                                              | 58-120 (75%)                               | 85 ± 36.5                         |
|                        | Mean                   |   | 65                                               |                                            | 62                                |
| CP                     | Lone tree: ash         | 1 | 69                                               | 58-120 (90%)                               | 85 ± 27.02                        |
| S                      | Lone tree: poplar      | 7 | 98-111                                           | 58-120 (75%)                               | 85 ± 36.5                         |
|                        | Mean                   |   | 100                                              |                                            | 85                                |

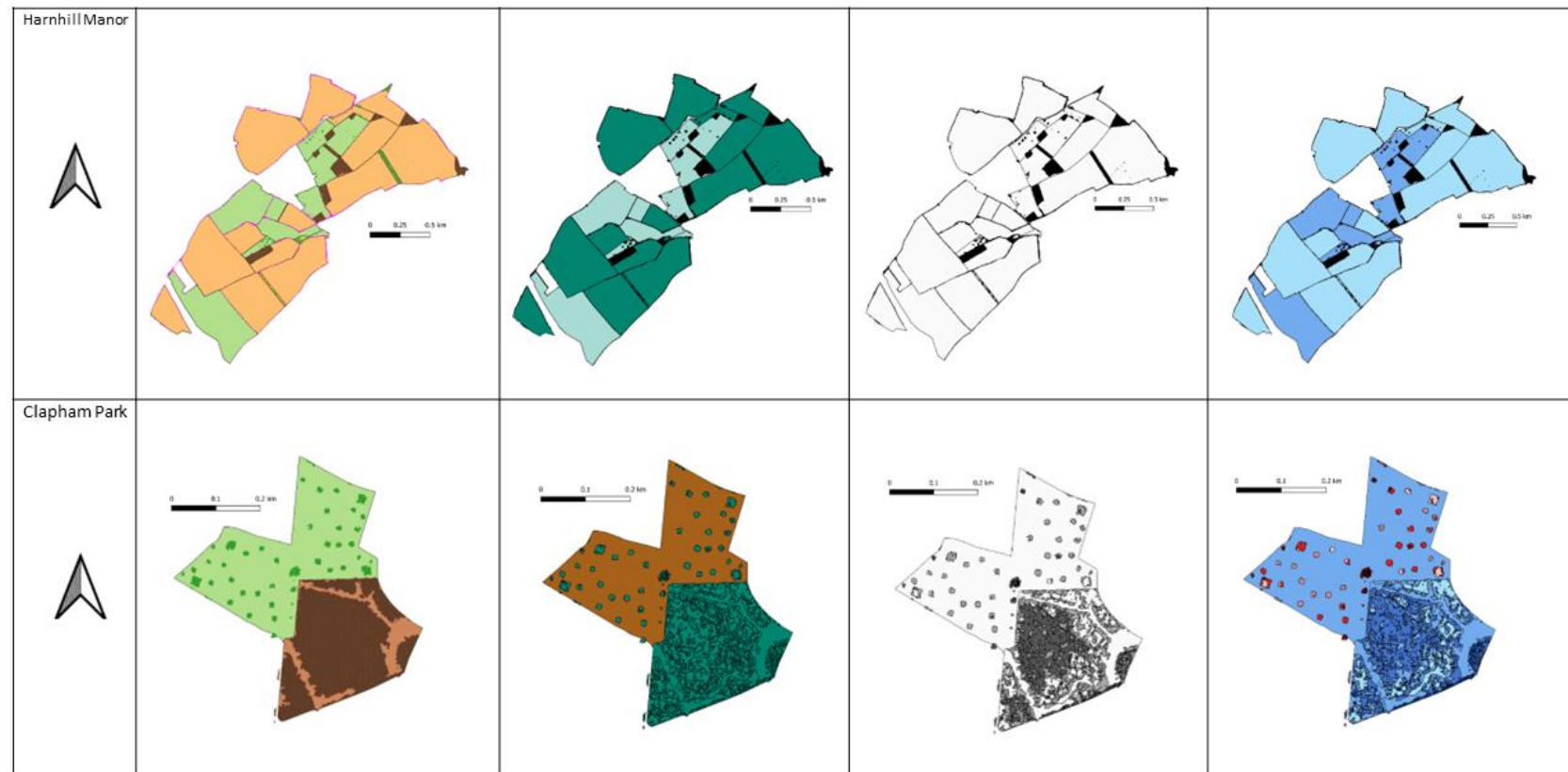
HM: Harnhill Manor Farm; S: Silsoe; E: Elm Farm; CP: Clapham Park; CB: Crowmarsh Battle, \* sd = standard deviation

The last stage of the analysis was to predict the total biomass carbon stock ( $C_{\text{total}}$ ) found across all of the land covers and landscape features on each of the five case study farms. As presented in Table 4-3 and presented visually in Figure 4-5 together with the age and height predictors, Crowmarsh Battle, Harnhill Manor and Elm Farm had quite similar levels of  $C_{\text{total}}$  per hectare stored in the biomass of the homogenous land covers, ranging from 11.4 to 13.5 t ha<sup>-1</sup>, while Silsoe had the lowest levels of just 2.4 t ha<sup>-1</sup> (Table 4-3). Clapham Park had the highest stored biomass  $C_{\text{total}}$  of 21.7 t ha<sup>-1</sup>. For the landscape features Crowmarsh Battle and Elm Farm had the highest per hectare values ranging from 59.4 to 60.6 t ha<sup>-1</sup> and Harnhill Manor together with Clapham Park had the lowest, ranging from 32.1 to 35.9 t ha<sup>-1</sup>. The level of  $C_{\text{total}}$  stored at the poplar trees of Silsoe was 52.3 t ha<sup>-1</sup>.

Table 4-3 Mean per hectare and total biomass carbon stock ( $C_{\text{total}}$ ) present across all the land cover and landscape features of five case study farms, together with the proportion of the area and the total biomass carbon stored in landscape features.

| Farm           | Total area (ha) | Total area landscape features (ha) | Mean carbon of land cover (t ha <sup>-1</sup> ) | Mean carbon of landscape feature (t ha <sup>-1</sup> ) | Total Carbon (t) | Total carbon of land cover (t) | Total carbon of landscape feature (t) |
|----------------|-----------------|------------------------------------|-------------------------------------------------|--------------------------------------------------------|------------------|--------------------------------|---------------------------------------|
| Crowmarsh      | 42.46           | 5.44 (13%)                         | 11.4                                            | 59.4                                                   | 807              | 484                            | 323 (40%)                             |
| Elm Farm       | 80.06           | 4.46 (6%)                          | 13.5                                            | 60.6                                                   | 1,354            | 1,084                          | 270 (20%)                             |
| Harnhill Manor | 394.86          | 7.50 (2%)                          | 11.8                                            | 32.1                                                   | 4,882            | 4,641                          | 241 (5%)                              |
| Clapham Park   | 15.25           | 0.67 (4%)                          | 21.7                                            | 35.9                                                   | 354              | 330                            | 24 (7%)                               |
| Silsoe         | 4.71            | 2.66 (57%)                         | 2.4                                             | 52.3                                                   | 150              | 11                             | 139 (93%)                             |
| Mean           | 107.47          | 4.15 (4%)                          | 12.2                                            | 48.1                                                   | 1,509            | 1,310                          | 199 (13%)                             |

| Farm or site                                                                                                 | Land cover                                                                         | Age                                                                                | Height                                                                               | Total biomass                                                                        |
|--------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|
| Crowmarsh<br>Battle<br><br> |   |  |   |   |
| Elm<br><br>                 |  |  |  |  |



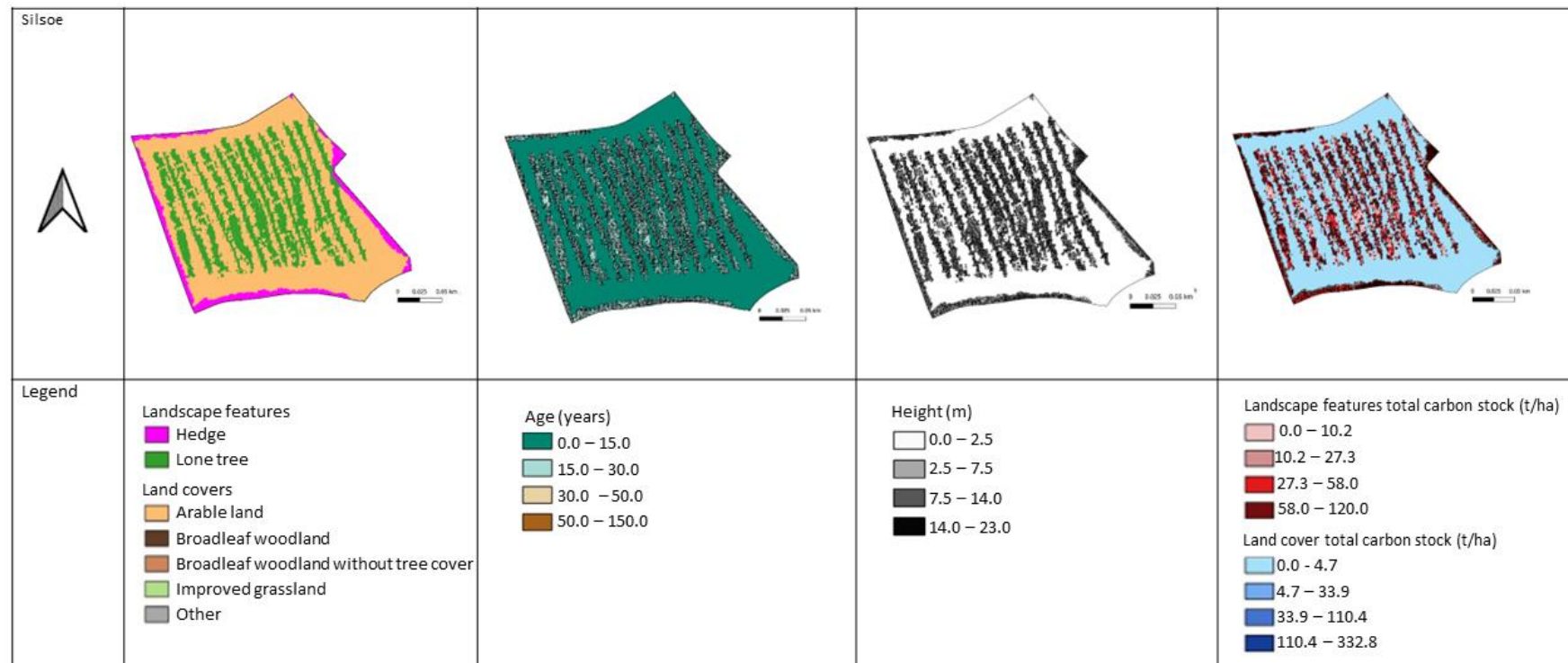


Figure 4-5 Maps presenting the land cover types and species together with their age, height and the simulated levels of the total biomass carbon stock ( $C_{total}$ ) across five studies.

## 4.4 Discussion

The results are discussed in terms of the key drivers determining  $C_{total}$ , the development of an integrated spatial model, the importance of landscape features for carbon storage, the benefits of using LiDAR data, and the benefits and disadvantages of using Bayesian Belief Network models.

### 4.4.1 Key drivers

The identification of important predictor variables influencing  $C_{total}$  and the structure of the BBN models were informed by published literature. The creation of heatmaps (Figure 4-4a and b) is one method to illustrate the influence of each predictor on  $C_{total}$ . The developed heatmaps highlight that aboveground biomass carbon (AGBC) is the most influential predictor of  $C_{total}$  for both homogenous land covers and landscape features. For arable land and woodlands, the aboveground biomass carbon was typically 2-5 times higher than the belowground biomass carbon, as also indicated by algorithms in Table\_Apx B-1 in Appendix B. High values of  $C_{total}$  were also positively associated with height and large values for belowground and dead organic biomass. The least influential predictor, of those considered, was the species for land cover classes and underlying land cover for the landscape features, presumably because these predictors were less directly linked to  $C_{total}$ .

### 4.4.2 Development of an integrated spatial method for biomass carbon

The approach described in this paper shows that it is possible to determine both the biomass C stock of land covers and landscape features in an integrated logical format using remotely sensed data. Within our approach, we assumed that a lone tree is an additive feature, and the  $C_{total}$  of the tree is added to the  $C_{total}$  of the underlying land cover. By contrast, we considered that the  $C_{total}$  of a hedgerow was not additive but that it effectively represented a different type of land cover. This integrated method also incorporates the spatial aspect, as we have demonstrated that the BBNs can be successfully combined with a GIS interface across the five study areas to spatially apply the influence network of the  $C_{total}$ .

The development of such robust farm-scale biomass carbon storage inventories is useful to farmers who wish to achieve net-zero GHG emissions and move to being “carbon” positive. Theoretically, it would be possible to organise on-site measurements of AGBC, BGBC, and DOMC of each land cover or landscape feature on a farm, but this would be costly in terms of time and resources and could be destructive. There are also potential accessibility issues (Kumar and Saran, 2014; Timothy et al., 2016). For woodlands, species-specific allometric equations have been developed to derive tree biomass from measurements such as stem wood, stem bark, branches, and the cross-sectional area (Zianis 2005, 2008; Vargas Larreta et al., 2017). However, in practice woodlands on many farms comprise a mixture of species.

Farmers who wish to sell “carbon credits” from the accumulation of biomass carbon need to demonstrate both the additionality and the permanence of carbon storage. For example, within the Woodland Carbon Code in the UK, it is necessary to demonstrate that increases in biomass carbon arising from tree planting have only occurred because of carbon credits; that is, it would not have occurred without the credits. In addition, it is necessary to ensure the permanence of C storage. In contrast to woodland establishment, which can involve a redesignation of land use from agriculture to woodland, it is more difficult for a farmer to demonstrate the permanence of carbon storage in landscape features. Hence, in many cases, the drive for increasing biomass carbon storage on farms through landscape features is likely to be more useful in demonstrating that an individual farm or group of farm businesses is achieving net-zero greenhouse gas emissions rather than to profit from the sale of carbon credits.

#### **4.4.3 Importance of landscape features**

Landscape features such as hedgerows and lone trees are well-recognised for their landscape, biodiversity and cultural value. However, this paper also highlights that they can store large quantities of carbon similar, on a per hectare basis, to woodlands and substantially higher than the mean biomass carbon levels of farms (Table 4-3). Hence increasing the area of hedgerows and agroforestry systems can be a useful on-farm

strategy to increase the storage of carbon biomass (Axe et al., 2017; Drexler et al., 2021). Although the case study farms were not randomly selected, the results demonstrate that landscape features could comprise 5-93% of the biomass carbon storage on farms. On average, the mean value was 13% across the five case studies.

#### **4.4.4 Benefits of using LiDAR data**

A useful innovation described in this paper is the capacity to spatially present the variation in carbon stocks along the length of hedges and within woodlands using remote sensing and LiDAR data (Figure 4-5) (Petrokofsky et al., 2012). Airborne LiDAR data can reduce the costs and effort required to conduct whole-farm surveys (Arenas-corralliza et al., 2020; Timothy et al., 2016) and can provide a remote screenshot of vegetation heights. LiDAR data have been used in forest studies to estimate timber volumes (Naesset et al., 1997), canopy cover (Arenas-corralliza et al., 2020; Lefsky et al., 2002), forest aboveground carbon content (Patenaud. et al., 2004; Urbazaev et al., 2018), and above ground biomass (Lu et al., 2012; Timothy et al., 2016).

The combined method of LiDAR and BBN models is relatively new. Woodland studies such as Wang et al. (2019), and Zapata-Cuartas et al. (2014) have proved the potential of improving the estimation of above ground biomass through LiDAR data by incorporating a BBN method instead of using the traditional allometric equations. In this study, we have extended this work by using the BBN method and estimating the total biomass carbon in additional land cover categories together with landscape features. Moreover, a useful attribute of the methodology described in this paper is that the required variables (such as age and height) can potentially be determined remotely using historic land cover and LiDAR height data.

The use of LiDAR data allows the derivation of different levels of biomass within land units that have a single designated “land cover”. For example, within a single parcel designated as “woodland” at Clapham Park (Figure 4-5), the incorporation of height data from LiDAR enabled the BBN for land cover to distinguish between areas of trees and

grass walkways. The vegetation height in the walkways was less than the surrounding trees, with corresponding lower values of  $C_{total}$ . The process was also able to infer different values of  $C_{total}$  along the length of the individual hedges across four of the farms because of differences in the LiDAR height data (e.g. Crowmarsh Battle in Figure 4-6). This process of including variable heights within woodlands and along hedges can be more informative than previous studies in the UK (Cannell and Milne, 1995; Milne and Brown, 1997), Ireland (Cannell et al., 1996; Cruickshank et al., 2000), and in other parts of the world (Vargas-Larreta et al., 2017) where one value is given to the whole woodland with the same age.

#### **4.4.5 Advantages and disadvantages of the Bayesian approach**

This paper shows that it was possible to develop an approach which could quantify biomass carbon stocks and their certainty. Such a Bayesian approach can be useful for integrating information and measured values to derive relationships between parameters (McCandless and Gustafson, 2017), aggregating uncertainty of information across complex networks when information is limited (De Campos et al., 2004; Friedman and Koller, 2003; Jiang et al., 2011), and as a means of preventing overfitting (Borsuk et al., 2004; Melody et al., 2011).

The way that BBN models quantify uncertainty is different from deterministic models as the uncertainty is directly embedded in the predictions and the generated error boundaries (Taalab et al., 2015b). The two informed BBN models developed in this paper were able to predict successfully the test values with propagated error rates of 6.7% for  $C_{total}$  for the homogeneous land features model and 4.3% for the landscape features. These error rates were lower than in studies where BBN models have been applied to soil systems (Taalab et al., 2015b) where the error ranged from 15% to 36% and in environmental systems of ecosystem service trade-offs and synergies where the error rate ranges from 41 to 45% (Karimi et al., 2021). Despite the reliance on only six predictors, the relatively lower error rates of BBN models reported in this paper suggests that the selected predictors are strong determinants of  $C_{total}$ .

The developed BBN models generate distributions of  $C_{\text{total}}$  that were not based on pre-determined relations and correlations between parameters. This can be an advantage when the relationships between parameters are complex. One example of a potential non-intuitive response in terms of biomass carbon is that the land cover model (Figure 4-4a) suggests that expanding the continuity of a land cover beyond 40 years did not necessarily result in a higher value of  $C_{\text{total}}$ . Such relationships could be a result of the carbon biomass of woodlands plateauing once a woodland has reached 40 years or the confounding effects of tree harvests.

Within our approach, we developed models that provide a “snapshot” of the values of  $C_{\text{total}}$  within a given year. The model does not account for temporal variation in  $C_{\text{total}}$  within the year. However, in practice, the biomass of a growing arable crop can change from effectively zero before the seeding of cultivated soil to maximum values just before harvest. This temporal limitation is a common feature of most carbon accounting methods. For example, the standard practice in the IPCC guidelines (IPCC, 2019; Chapter 5 page 7), is to assume the C density value of arable crop after harvest, i.e. the biomass is primarily related to the weight of the roots and the stubble of the crop. In using the model, we also assumed a uniform species type and constant age within a land cover area. Although in practice, there may be changes in tree species within a woodland or a hedge, the logic generally follows the methodology described in the UK’s Woodland Carbon Code Assessment Protocol (Jenkins et al., 2011).

Looking forward, we anticipate two avenues where the model could be further developed or used. Firstly, there is the potential to use the model to predict the effect of management interventions on  $C_{\text{total}}$  at a farm level. For instance, a farm manager could use it to identify the height and species mix of a specific hedgerow or woodland that would tend to achieve a specific level of  $C_{\text{total}}$ . Secondly, for this study, we used the Netica BBN software (Norsys Software Corp., 2003) that categorised the outputs into discrete “bins”. The advantage of this categorisation is that the computing of the relationships becomes far more feasible on a standard desktop computer or laptop.

However, more computationally demanding software programmes exist (Thomas et al., 2003), where the outputs can be expressed as continuous variables. As the computational capacity of computers increases, future studies may be able to apply the described in this paper techniques in order to derive continuous predictions of  $C_{total}$ .

#### 4.5 Conclusions

This study supports the hypothesis that a probabilistic approach for accounting for farm biomass carbon stocks is feasible. A particularly useful attribute of the demonstrated approach is that the estimation of the total biomass carbon stocks ( $C_{total}$ ) of both land cover and landscape features is performed in an integrated logical format. The described BBN approach, which seeks constantly to improve prediction accuracy, provided a method for applying current literature and measured information about the variables that most influence the  $C_{total}$  values of land cover classes and landscape features.

An advantage of the approach described in this paper is that the required variables (such as age and height) can potentially be determined remotely using historic land cover and LiDAR height data. Additionally, in this paper, we have demonstrated that the BBNs can be successfully combined with a GIS interface across the five study areas to spatially apply the influence network of the  $C_{total}$ . A useful attribute of the methodology described in the paper, including the use of LiDAR data, is that it was possible to predict differences in  $C_{total}$  across hedgerows and land parcels. As the computational capacity of computers increases, there may be future opportunities to use forms of BBN analysis that produces continuous rather than discrete estimates of  $C_{total}$ .

## 4.6 References

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## 5 Integration of soil and biomass carbon accounting

### Abstract

To reduce the effects of climate change, many countries such as the UK, are implementing policies to achieve net-zero greenhouse gas emissions by 2050. Achieving net-zero emissions will require management change in each sector of the economy. Agriculture has a particularly important role as it can be a source and a sink of greenhouse gas emissions. Moreover, a key policy measure is to incentivise land managers to sequester more carbon. In the context of achieving net-zero emissions, farmers and policymakers need improved ways of simply and robustly calculating how much carbon is stored on farmland and how different land uses affect storage and sequestration. There is a wide range of C accounting tools that enable predictions of the annual rate of GHG emissions and sequestration on the farm however, there are fewer tools that predict the absolute farm carbon stock. This chapter combines the two approaches described in Chapters 3 and 4, to develop a scalable tool that estimates the current levels of C stocks at a farm scale. It additionally investigates the potential of using the tool to compare the effect of farm management options. Finally, it describes the advantages and disadvantages of farm C certification as well as the possibility of farmers participating in a worldwide C market.

**Keywords:** farm carbon certification, baseline farm C stock levels, spatial total carbon stock, spatial carbon pool integration

### 5.1 Introduction

To reduce the effects of climate change, many countries including the UK, are implementing policies to achieve net-zero greenhouse gas (GHG) emissions by 2050 (Smith et al., 2012; UK Government, 2019; Van Soest et al., 2021). Agriculture contributes to about 10% of the net greenhouse gas (GHG) emissions in the UK (UK Government, 2019a). Hence, there is a focus on reducing GHG emissions associated with agriculture, land use, and land use change. Farmers seeking to reduce emissions can

benefit from both an understanding of i) the current stock of carbon on their farm, and ii) the flows of GHGs. There is a need for methods that can simply and robustly calculate how much carbon (C) is stored on farmland and how different land uses affect storage. Such methods could help landowners calculate how their farm business contributes to net-zero emissions, and if sufficiently robust provide a basis for C certification and sale of C credits.

There is a wide range of C accounting tools which enable predictions of the annual rate of GHG emissions and sequestration on farms. For example, Leinonen et al. (2019) reviewed 64 farm-level carbon accounting tools. Dynamic process-oriented tools and models include DAISY (Hansen et al., 1991), APEX (Leyton, 2019), TECO (Weng and Luo, 2008), and INVEST (Tallis and Polasky, 2009). Examples of decision support tools and models of GHG flows include CropSyst (Stöckle et al., 2001), Agrecalc (SAC, 2022), the Cool Farm Tool (Hillier et al., 2011), Farm Carbon Cutting Toolkit team (Metayer and Hastrup, 2013), ScotFarm (Shrestha, 2014) and OFoot (Adewale et al., 2019). By contrast, there are fewer tools which predict the absolute stock of carbon on farms. Farm C storage occurs in the soil as soil organic carbon (SOC) and the biomass as roots and above ground biomass of crops, woodland, and landscape features.

Tools for predicting the absolute amount of carbon on farms can be based on physical measurements. However typically many physical measurements are required and the uncertainty surrounding the validity of the results can be hard to define (Campos, 2020; Carlson et al., 2017; Janzen et al., 2006; Shrestha, 2014; Stöckle et al., 2001; Sustainable Food Lab et al., 2011; Ziegler et al., 2016). It is also useful for the farmer to know how management can be used to increase the level of C storage. For example, changes in the level of tree cover (Fornara et al., 2017; Upson et al., 2016; Upson and Burgess, 2013) and the management of hedgerows (Axe et al., 2017) can affect the stored C.

Chapter 3 compared three approaches to estimate soil C storage (Beka et al., 2022), and Chapter 4 described a probabilistic approach to quantify biomass carbon stocks and

their uncertainty at a farm scale (Beka et al., 2023). This chapter has the objective of combining the two approaches to develop a scalable tool that estimates the current levels of C stocks at a farm scale. It also explores the potential of using the tool to compare the effect of farm management options. Lastly, it identifies opportunities and constraints for farm C certification and the potential of farmers being part of a global C market.

## 5.2 Methodology

### 5.2.1 General approach

A decision support tool was developed, for potential use by farmers or advisors, to predict the total carbon stored on different parts of a farm, and to identify areas of relatively high or low carbon levels. The tool was developed using a four-stage approach to estimate the soil C and the biomass (above and below ground) of land covers and landscape features.

A land parcel polygon was selected as the basic unit of analysis (Figure 5-1, stage 1). These polygons are registered and referenced in the Land Parcel Identification System (LPIS) for farmers as part of the payment system within the European Common Agricultural Policy (CAP) (Grandgirard and Zielinski, 2008). Each farmer in the European Union needs to report crop areas annually using the Land Parcel Identification System (LPIS) (European Court of Auditors, 2016) which has been developed using satellite or aerial photographs.

The second stage was to estimate the level of soil organic carbon (Figure 5-1, stage 2). The approach used at this stage was based on the spatial modelling approaches described in Chapter 3 (Beka et al., 2022a).

The third stage was to estimate the carbon stored in the total biomass ( $C_{\text{total}}$ ) for land covers and the fourth stage was to estimate the C stored in landscape features using the Bayesian Belief network approach described in Chapter 4 (Beka et al., 2023). The total C

per spatial area was then assumed to be the sum of the SOC values and biomass  $C_{total}$  values. For the initial analysis, field management practices for a given crop were assumed to be constant.

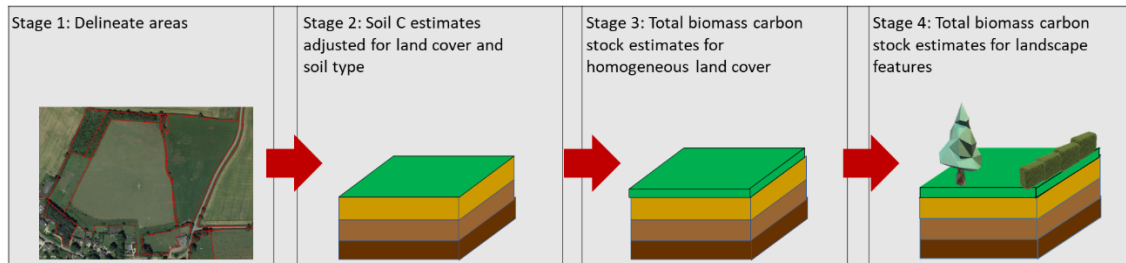


Figure 5-1 The tool uses a four-stage approach to estimate the total carbon present on a farm or agricultural site, where C= Carbon.

### 5.2.2 Tool implementation

The implementation of the approach was performed in QGIS 3.20.3 software environment (QGIS, 2022) for the 317 ha Allerton Project arable farm located in Loddington, Leicestershire (Figure 5-2). Vector data were used to describe the field delineations from the Rural Payments Agency in the UK. Details of the land cover and species data for each arable field for the year 2019 were provided by the Allerton Project (Personal communication Chris Stoate, 2019). Raster data were collated for the study area in the form of the 1 m resolution Digital Surface Model (DSM) and a Digital Terrain Model (DTM) (Department for Environment Food & Rural Affairs, 2022). To have temporal consistency, the DTM and DSM derived from LiDAR data from 2019 were also used. To be consistent with other C assessment studies (Cantarello et al., 2011; Milne and Brown, 1997) all man-made features and water bodies were not considered in the C accounting process.

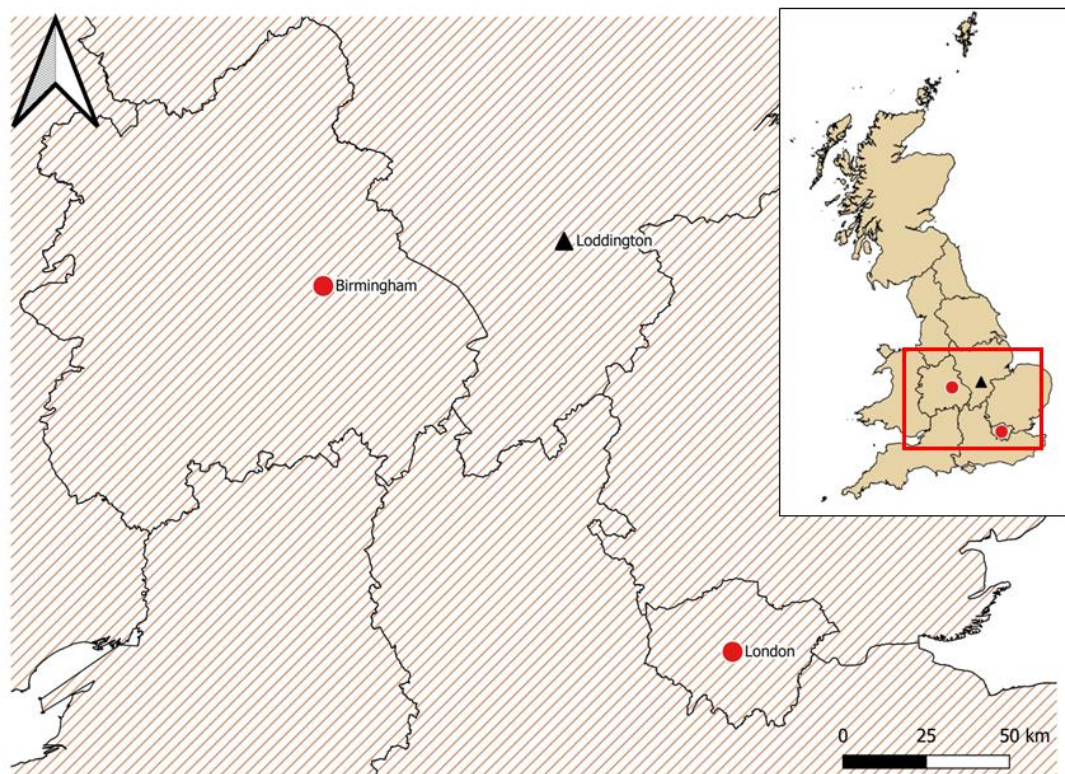


Figure 5-2. Map showing the location of the study area ▲ where the developed tool was applied.

The SOC stock for the Allerton Project Farm was calculated using each of the three approaches described in Chapter 3 (Beka et al., 2022), that is a coarse input/output approach called “Model 1”, a fine input/fine output approach called “Model 2”, and a fine input/coarse output method called “Model 3”. To maintain continuity with the results in Chapter 3, the values of SOC were restricted to only the top 10 cm. The  $C_{total}$  stored in biomass was determined using the probabilistic approach described in Chapter 4 (Beka et al., 2023), where each land cover and landscape feature was assigned to the most probable of four Bayesian Belief Network bins and assigned the median value (Table 5-1). For the biomass, the uncertainty of the estimations was described as probabilities (Marcot, 2012; Taalab et al., 2015), as demonstrated by the heat maps in Chapter 4.

Table 5-1 Values for biomass were categorised into one of four ranges or “bins”, and provided with a median value.

|                   | Range (t ha <sup>-1</sup> ) | Median (t ha <sup>-1</sup> ) |
|-------------------|-----------------------------|------------------------------|
| Land cover        | 0.0 - 4.7                   | 2.4                          |
|                   | 4.7 - 33.9                  | 19.3                         |
|                   | 33.9 - 110.4                | 72.2                         |
|                   | 110.4 - 33.8                | 221.6                        |
| Landscape feature | 0.0 - 10.2                  | 5.1                          |
|                   | 10.2 - 27.3                 | 18.8                         |
|                   | 27.3 - 58.0                 | 42.7                         |
|                   | 58.0 - 120.0                | 89.0                         |

Lastly, the sum of the SOC and biomass C was calculated for each delineation unit, using Model 3 for the calculation of SOC. Model 3 was selected because it was able to explain more of the variation in SOC than Model 1 (see Chapter 3), and the results were presented in terms of the delineation unit rather than the grid structure used for Model 2. Even though hedgerows were considered landscape features, the total C was calculated for a separate land parcel (without a ground-storey land cover). By contrast, the biomass C value of the lone trees was added to the SOC of the understory.

### 5.2.3 Visualisation and analysis of practices to increase carbon storage

To visualise the results, the total C values were categorised into classes in QGIS using the Jenks optimization method (QGIS Project, 2022), which seeks to reduce the variance within classes, while maximising it between classes (Jenks, 1967). To examine the effects of land management options, further analysis focused on those fields where the value of carbon (including SOC to a depth of 10 cm) was less than 50 t ha<sup>-1</sup>. The fields in that group were categorised into those with relatively low SOC, low biomass C, and both low SOC and biomass C. A recent study by Prout et al. (2020) highlighted that level of SOC depends on the soil clay content, and that the “appropriate” level of SOC can be related to a SOC/Clay coefficient. Hence the SOC/Clay coefficient for each field was calculated.

Lastly, the potential of using four farm practices to increase field C was examined in relation to specific fields. These farm practises have different effects according to the present soil type. The first practice (Option A) to be examined was the implementation of silvoarable agroforestry using poplar hybrid trees on a previously arable field. Upson and Burgess (2013) and Burgess and Graves (2022) predicted that 30 years after planting poplar in an arable field, there would be an increase in biomass carbon storage equivalent to  $2.1 \text{ t C ha}^{-1} \text{ y}^{-1}$ . The second practice (Option B) considered was the incorporation of legume cover crops on arable fields with already existing cover crops to enhance the SOC (Moxley et al., 2014; Jian et al., 2020). Glenk et al. (2017) reported that legume cover crops could increase SOC by  $0.4 - 0.8 \text{ t C ha}^{-1} \text{ y}^{-1}$ . They additionally reported a 5-20 % increase in the biomass which translated to a 5-20% increase in biomass C (IPCC, 2019).

The third practice (Option C) considered the implementation of a silvopastoral agroforestry system on grassland. Beckert et al. (2016) reported that 24 years after planting 400 hybrid larch trees per hectare on grassland, resulted in an additional  $96 \pm 4.2 \text{ t C ha}^{-1}$  of biomass C. Burgess et al. (2022) used the Yield-SAFE model and predicted that after 30 years the planting of the hybrid larches will store about  $160 \text{ t C ha}^{-1}$ , equivalent to  $5.3 \text{ t C ha}^{-1} \text{ y}^{-1}$ . Tree planting on grassland mineral soils has a mixed effect on SOC levels. Studies such as Beckert et al. (2016), found that the planting of trees resulted in a non-significant 19% (0-60 cm) and 30% (0-30 cm) higher level of SOC compared to adjacent pasture. Similarly Fornara et al. (2017) also reported no major change of SOC in the top 20 cm, 26 years after planting ash trees in Northern Ireland. Upson et al., 2016 found that the SOC of a lowland grassland site in England was reduced within the first 14 years after tree planting. In the absence of a consistent effect, it was assumed that planting trees on grassland did not affect the SOC.

The last option (Option D) comprised an increase in the height and width of existing managed hedges. Axe et al. (2017) demonstrated that the above ground biomass carbon (AGBC) storage of hawthorn hedges could increase by  $1.4 \text{ t C}$  per hectare per year over

five years by increasing the height from 1.9 m to 3.5 m. Axe et al. (2017) also reported that increasing the width of a 3.5 m hedge from 2.6 to 4.2 m would result in an additional AGBC stock of 9.7 t C km<sup>-1</sup>. Biffi et al. (2022) compared the SOC stock beneath hedges and adjacent grassland fields and found that 2-4-year-old hedges stored 3.3% more carbon in the top 50 cm of soil than the grasslands.

## **5.3 Results**

### **5.3.1 Baseline carbon stock inventory**

The first component of the calculated baseline carbon stock at the study site is the soil organic carbon (SOC). As described in Chapter 3 (Beka et al. 2022), using coarse field-level input data in Model 1 resulted in lower values of predicted SOC than using finer resolution input data with Model 2 and Model 3 (Figure 5-3).

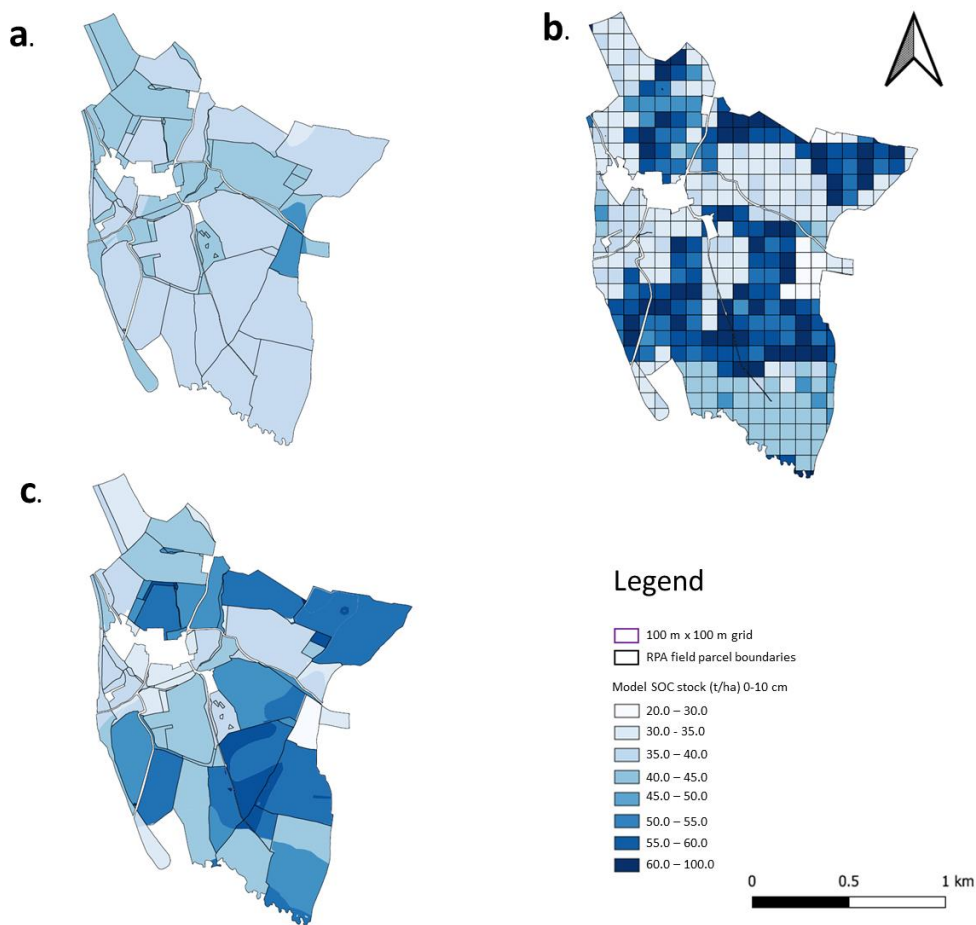


Figure 5-3 Predicted soil organic carbon (SOC) stock ( $\text{t ha}^{-1}$ )(0–10 cm) for a) each field parcel in the Loddington farm using Model 1, b) each  $100 \text{ m} \times 100 \text{ m}$  square grid using Model 2, and c) each field parcel using Model 3. The SOC stock values are shown using a  $5 \text{ t ha}^{-1}$  increment for values between 30 and  $60 \text{ t ha}^{-1}$  and greater increments at the extremes.

The majority of the land at the Allerton Project Farm is arable (Table 5-2). The mean SOC value (0-10 cm) for the arable fields ranged from  $36 \text{ t C ha}^{-1}$  using Model 1 to  $42 - 46 \text{ t C ha}^{-1}$  for Models 2 and 3. The mean SOC value (0-10 cm) for the grassland fields was also lower using Model 1 ( $43.6 \text{ t C ha}^{-1}$ ) than that  $46 \text{ t C ha}^{-1}$  using Model 2 and  $47 \text{ t C ha}^{-1}$  using Model 3. In total across the 317 ha of farmland, the predicted total SOC stored in the top 10 cm ranged from 12,078 t C using Model 1 to 13,743 t C using Model 2 and 14,817 t C using Model 3 (Table 5-2).

Table 5-2 Areas of land cover and landscape features and the calculated mean soil organic carbon (SOC) stock (0-10 cm) together with Root Mean Square Error at the farm in Loddington.

| Land cover/ feature type | Area (ha) | Mean SOC (t ha <sup>-1</sup> ) |           |          | Total SOC (t) |                |                |
|--------------------------|-----------|--------------------------------|-----------|----------|---------------|----------------|----------------|
|                          |           | Model 1                        | Model 2   | Model 3  | Model 1       | Model 2        | Model 3        |
| Homogeneous land cover   |           |                                |           |          |               |                |                |
| Arable land              | 246.56    | 36 ± 18.3                      | 46 ± 11.0 | 42 ± 8.3 | 8,876 ± 4,512 | 11,366 ± 2,712 | 10,429 ± 2,046 |
| Improved grassland       | 41.26     | 44 ± 18.3                      | 47 ± 11.0 | 46 ± 8.3 | 1,799 ± 755   | 1,947 ± 454    | 1,890 ± 342    |
| Woodland                 | 22.62     | 41 ± 18.3                      | 45 ± 11.0 | 42 ± 8.3 | 934 ± 414     | 1,009 ± 249    | 950 ± 188      |
| Shrub                    | 5.80      | 41 ± 18.3                      | 44 ± 11.0 | 42 ± 8.3 | 240 ± 106     | 253 ± 64       | 242 ± 48       |
| Other                    | 1.12      | n/a                            | n/a       | n/a      | n/a           | n/a            | n/a            |
| Sub-total                | 317.36    |                                |           |          | 11,849        | 14,575         | 13,511         |
| Landscape features       |           |                                |           |          |               |                |                |
| Hedge                    | 5.76      | 40 ± 18.3                      | 42 ± 11.0 | 40 ± 8.3 | 229 ± 105     | 242 ± 63       | 232 ± 48       |
| Farm total               | 323.00    |                                |           |          | 12,078        | 14,817         | 13,743         |

*The mean SOC for each land cover/ soil association combination and landscape feature/soil association was used. n/a = not applicable.*

The median total biomass C values for the land cover ranged from 9 t ha<sup>-1</sup> for arable land to 48 t ha<sup>-1</sup> for woodland areas, the median value for hedges was 46 t ha<sup>-1</sup>, and that for lone trees was 34 t ha<sup>-1</sup> (Table 5-3). The total biomass C stored in the farm was predicted to be 4,522 tonnes of which 4,221 tonnes were associated with homogeneous land cover with 301 tonnes in the hedges and lone trees.

Table 5-3 Areas of land cover and landscape features and the calculated biomass carbon (C) stock at the Allerton Project Farm

| Land cover or feature  | Area (ha) | Median total biomass C (t ha <sup>-1</sup> ) with sd * | Total biomass C (t) |
|------------------------|-----------|--------------------------------------------------------|---------------------|
| Homogeneous land cover |           |                                                        |                     |
| Arable                 | 246.56    | 9 ± 4.4                                                | 2,214 ± 1,085       |
| Improved grassland     | 41.26     | 19 ± 8.7                                               | 796 ± 359           |
| Woodland               | 22.62     | 48 ± 19.1                                              | 1,088 ± 433         |
| Shrub                  | 5.80      | 21 ± 8.4                                               | 123 ± 49            |
| Other                  | 1.12      | n/a                                                    | n/a                 |
| Sub-total              | 317.36    |                                                        | 4,221               |
| Landscape features     |           |                                                        |                     |
| Hedge                  | 5.76      | 46 ± 10.6                                              | 267 ± 61            |
| Lone tree              | 0.99      | 34 ± 7.2                                               | 34 ± 7              |
| Sub-total              | 6.75      |                                                        | 301                 |
| Farm total             | 323.12    |                                                        | 4,522               |

*The median value is the median found in one of four bins. Land cover biomass C model classifier error rate= 6.7%, Landscape features biomass C model classifier error rate= 4.3 %, sd = standard deviation*

Adding the total SOC (0-10 cm) from Model 3 (13,743 t C) with the biomass total (4,522 t C) resulted in a total farm C stock of 18,271 tonnes (Table 5-4 and Figure 5-4d). As about 69% of the farm is arable, the carbon associated with arable land formed the largest stock. Although woodland comprised only 7% of the farmed area (Figure 5-4a), it comprised about 11% of the total C stock. The lone trees were incorporated into the land parcels with arable and improved grassland land covers.

Table 5-4 Areas of land cover and landscape features and the calculated total carbon (C) stock including soil organic carbon (SOC) (0-10 cm) and biomass carbon (C) stock together with propagated uncertainty at the farm in Loddington

|                    | Area (ha) | Mean total C (t ha <sup>-1</sup> )* | Total C (t)*   |
|--------------------|-----------|-------------------------------------|----------------|
| Land cover         |           |                                     |                |
| Arable             | 246.56    | 51 ± 9.9                            | 12,649 ± 2,441 |
| Improved grassland | 41.26     | 65 ± 12.1                           | 2,686 ± 499    |
| Woodland           | 22.62     | 90 ± 21.5                           | 2,038 ± 486    |
| Shrub              | 5.8       | 63 ± 11.8                           | 355 ± 68       |
| Other              | 1.12      | n/a                                 | n/a            |
| Sub-total          | 317.36    |                                     | 17,723         |
| Landscape features |           |                                     |                |
| Hedge              | 5.76      | 8 ± 19.7                            | 487 ± 113      |
| Lone tree          | 0.99      | 34 ± 7.2 **                         | 34 ± 7         |
| Farm total         | 323.12    |                                     | 18,271         |

*\*Adding SOC derived from Model 3, \*\*Lone tree value does not include a SOC value*

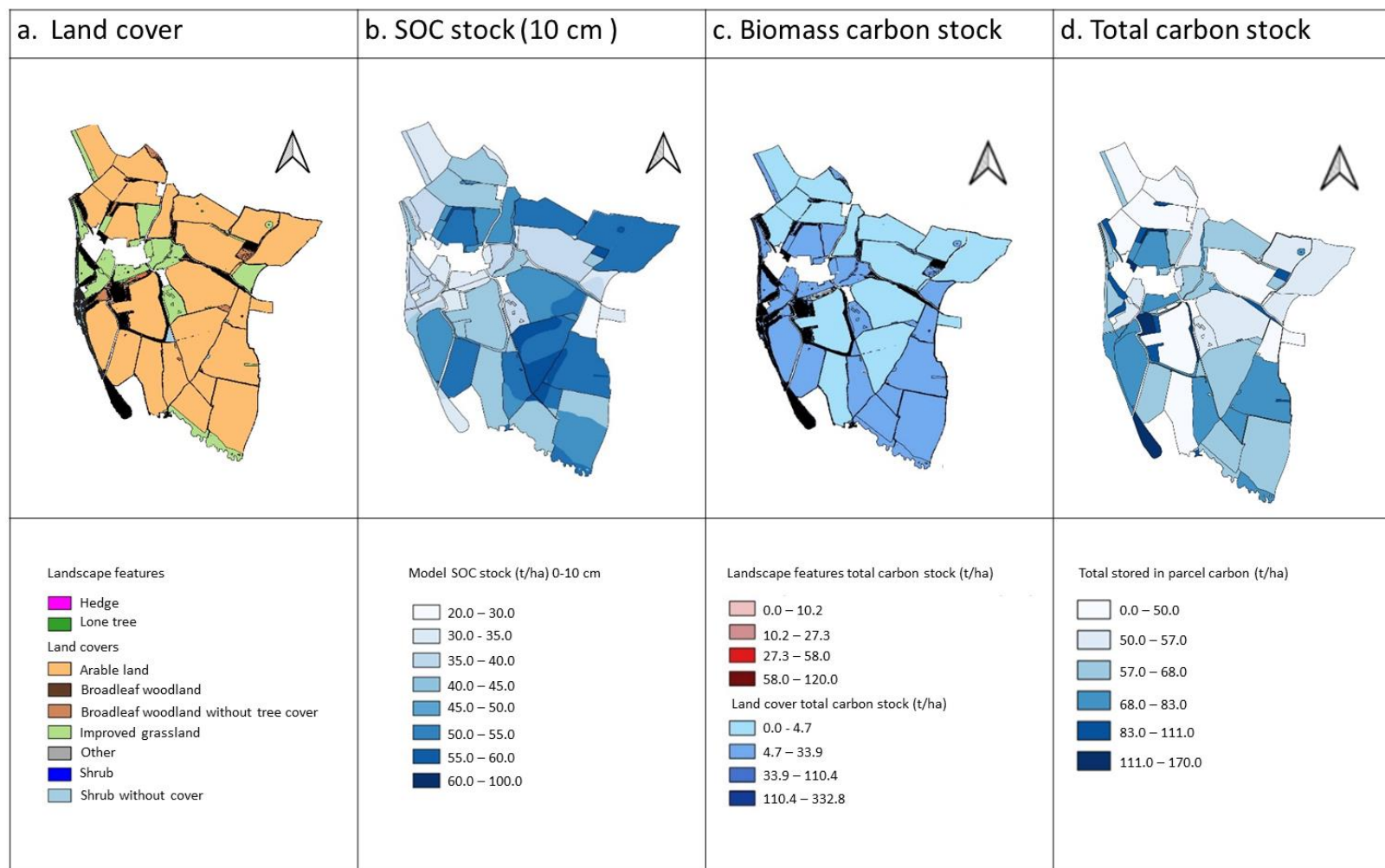


Figure 5-4 Maps presenting **a.** the land cover types across the study area, with **b.** the SOC stock levels to the depth of 10 cm using Model 3, **c.** the simulated levels of the total biomass carbon stock ( $C_{total}$ ) and **d.** the per parcel total stored carbon ( $C$ ).

### 5.3.2 Options to increase farm carbon storage

The options to increase farm storage were examined by focusing on 13 land parcels where the calculated value of C was less than 50 t C ha<sup>-1</sup> (Figure 5-5). The SOC/clay value in these fields ranged from 0.30 to 0.47 (Table 5-5). This is higher than the threshold of 0.13, which Prout et al. (2020) indicated as the threshold between a “very good” and a “good” level of soil carbon. Hence it appears that the soil carbon levels are not specifically an area of concern. Prout et al. conducted their research over the topsoil (0-15 cm depth), which is quite similar to the 0-10 cm depth used with the SOC model.

Table 5-5 Parcels with low levels of carbon together with the SOC/clay ratio , where SOC= Soil Organic Carbon.

| Field ID | Land cover         | SOC/ clay value |
|----------|--------------------|-----------------|
| 1285     | Arable             | 0.33            |
| 1410     | Arable             | 0.34            |
| 1492     | Arable             | 0.33            |
| 1829     | Arable             | 0.43            |
| 3065     | Arable             | 0.32            |
| 6304     | Improved grassland | 0.30            |
| 6838     | Arable             | 0.36            |
| 7324     | Arable             | 0.33            |
| 7473     | Arable             | 0.35            |
| 8224     | Improved grassland | 0.33            |
| 9382     | Arable             | 0.36            |
| 9382     | Improved grassland | 0.47            |
| 9382     | Improved grassland | 0.32            |
| 9991     | Arable             | 0.38            |

The 13 land parcels with C values less than 50 t C ha<sup>-1</sup> were subdivided into three groups, i.e. fields with relatively low SOC (green stripes), fields with relatively low biomass C (red stripes), and fields distinguished by both relatively low SOC and biomass C (both red and green stripes) (Figure 5-6). Eight of the fields comprised arable land and five fields comprised improved grassland.

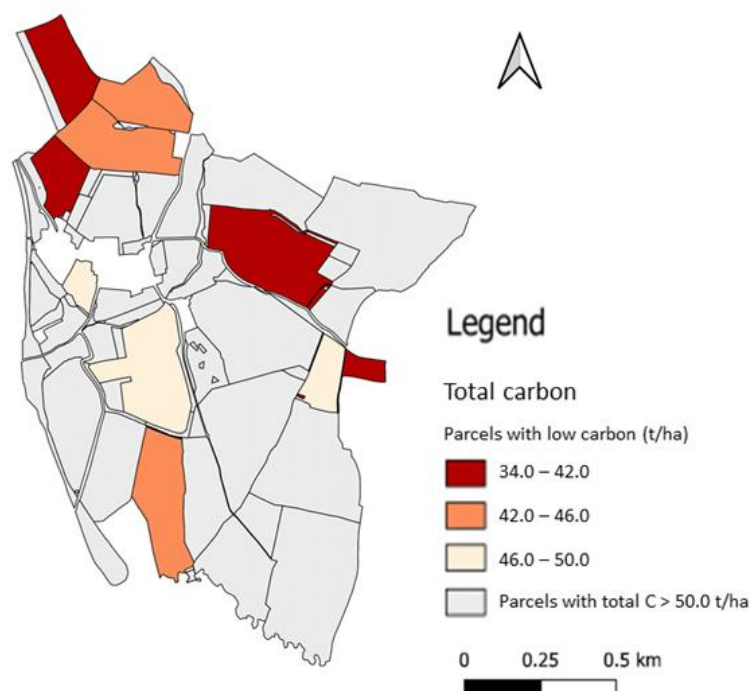


Figure 5-5 Identified farm parcels with low levels of total carbon (C) ( $\text{t ha}^{-1}$ ).

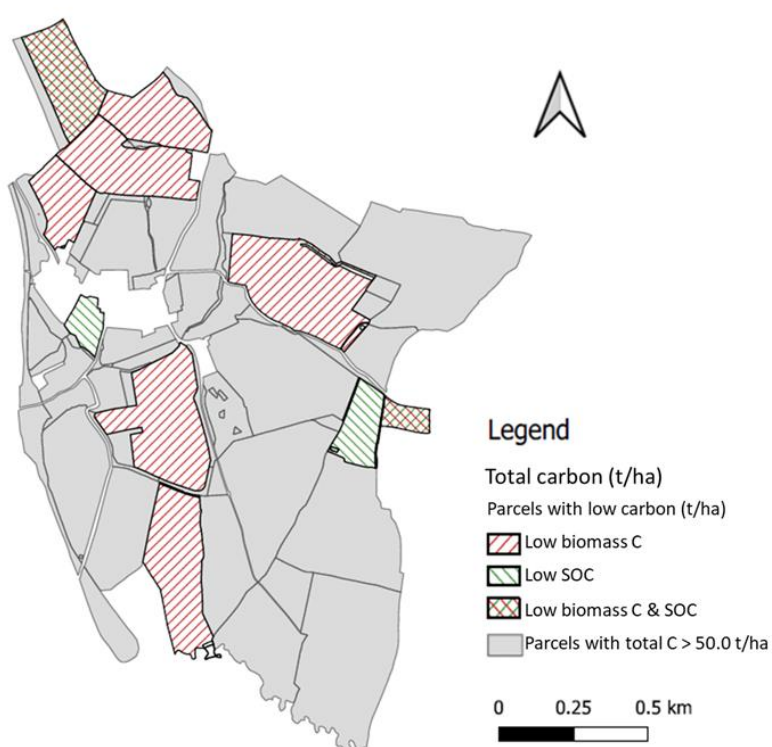


Figure 5-6 Categorisation of 13 fields with low carbon (C) in terms of whether the dominant effect is low SOC, low biomass C or both.

Across the 13 land parcels, the first of the four land management interventions considered silvoarable agroforestry using poplar trees in the arable fields marked with the black “A” star in Figure 5-7. Over a 30 year period from tree planting, this was predicted to result in the accumulation of an additional total of 111.0 t C ha<sup>-1</sup>, equivalent to a mean increase of 2.4 t C ha<sup>-1</sup> per year (Table 5-5).

Table 5-6 Predicted effect of four management interventions relative to a baseline on increase in carbon (C) storage either as soil organic carbon (SOC) or as biomass over a stated time period.

| Baseline                                   | Management intervention |         | Current value<br>(t ha <sup>-1</sup> ) | Final value<br>(t ha <sup>-1</sup> ) | Time period<br>(yr) | Annual change<br>(t ha <sup>-1</sup> y <sup>-1</sup> ) |
|--------------------------------------------|-------------------------|---------|----------------------------------------|--------------------------------------|---------------------|--------------------------------------------------------|
| Arable with poplar hybrid trees<br>(n = 8) | A: Silvoarable          | SOC     | 39.3                                   | 48.0                                 | 30                  | +0.3                                                   |
|                                            |                         | Biomass | 3.0                                    | 63.0                                 |                     | +2.1                                                   |
|                                            |                         | Total   | 42.3                                   | 111.0                                |                     | +2.4                                                   |
| Arable with cover crop<br>(n = 1)          | B: Legume cover crop    | SOC     | 29.8                                   | 32.9                                 | 1                   | +3.1                                                   |
|                                            |                         | Biomass | 19.4                                   | 24.3                                 |                     | +4.8                                                   |
|                                            |                         | Total   | 49.3                                   | 57.2                                 |                     | +7.9                                                   |
| Grassland<br>(n = 4)                       | C: Silvopasture         | SOC     | n/a                                    | n/a                                  | 30                  | n/a                                                    |
|                                            |                         | Biomass | 0.0                                    | 160.0                                |                     | +5.3                                                   |
|                                            |                         | Total   | 0.0                                    | 160.0                                |                     | +5.3                                                   |
| Hedge<br>(n = 6)                           | D: Enlarge hedge        | SOC     | 38.4                                   | 39.7                                 | 5                   | +0.3                                                   |
|                                            |                         | Biomass | 19.8                                   | 29.0                                 |                     | +1.8                                                   |
|                                            |                         | Total   | 58.2                                   | 68.7                                 |                     | +2.1                                                   |

*n.a = not applicable, n = amount of samples collected in each study where the values were derived from.*

A second option (marked with a green “B” in Figure 5-7) was the incorporation of a legume cover crop in the arable field with existing cover crops. This was assumed to result in an additional 7.9 t ha<sup>-1</sup> of C in total after one year of incorporating the legume cover crops together with the existing cover crops.

The third option was silvopastoral agroforestry using larch trees in the grassland fields marked with the yellow “C” star. Over a 30 year period, this was predicted to result in

an additional 160 t ha<sup>-1</sup> of biomass C, equivalent to a mean increase of 5.30 t ha<sup>-1</sup> per year. The fourth option “D” of enlarging hedges was predicted to store an additional 0.3 t ha<sup>-1</sup> yr<sup>-1</sup> from a baseline of 38.4 t ha<sup>-1</sup> of SOC over 5 years, in addition to 19.8 t ha<sup>-1</sup> of biomass C, equivalent to 1.8 t C per hectare per year.

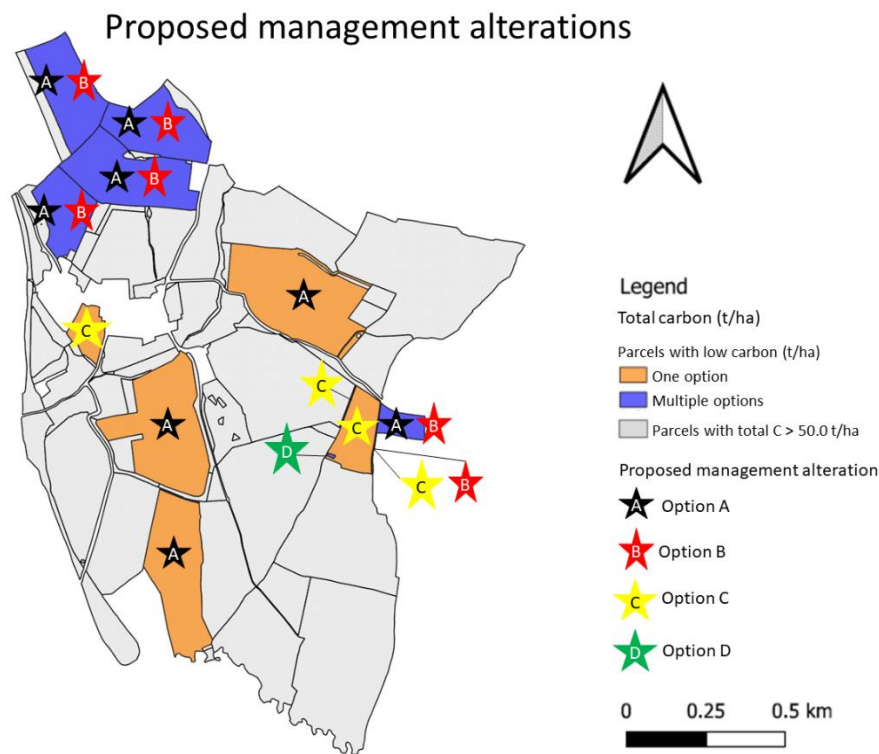


Figure 5-7 The proposed implementation of four management interventions were examined across the farm.

## 5.4 Discussion

### 5.4.1 Advantages of the developed tool

In order to support national targets for net-zero GHG emissions, farmers would benefit from creating farm inventories to understand the current stock of carbon on their farms. This study describes the development and use of a remote approach to determine the carbon inventory of a farm in England. The main parameters required to determine SOC was access to a soil data base for Great Britain, and a description of land cover at a field scale (Beka et al. 2022). The use of a fine resolution 10 m x 10 m soil dataset of SOC

enabled a greater capacity to identify field to field variations than a dataset based on current NATMAP soil associations data (Farewell et al., 2011; Hallett et al., 2017).

The four parameters to establish the biomass carbon were land cover and/or species, height, and age which were in turn related to the above ground biomass, the below ground, and dead organic matter (Beka et al., 2023). The value of height was derived using LiDAR data, which offers advantages compared to methods where height is not considered (Scholefield et al., 2016).

In this Chapter, the above two models were combined to give an estimation of the baseline farm C stocks on a field by field basis for a case study farm. The process was able to identify differences in carbon storage across the farm, and it examined four methods for enhancing C storage while maintaining food production. The most accurate inventories are likely to require detailed site measurements of soil organic matter which, even if only the uppermost 10 cm is considered, accounted for 13534 t out a total of 18244 t C (i.e. 74% of the carbon) on the Allerton Project Farm. If deeper soil depths are considered, then the proportion of SOC would be even higher. However detailed measurements of SOC are costly in terms of time and resources and can be destructive (Kumar and Saran, 2014; Timothy et al., 2016). In the new soil standards under the Sustainable Farming scheme (Department for Environment, Food & Rural Affairs and Rural Payments Agency, 2022) there is a requirement for farmers to measure soil organic matter. So these measurement could become available in the future. These measurements can potentially be converted to SOC and be used to validate the predictions derived by the tool.

The C inventory tool described here allows the spatial detection of differences in the levels of C between fields, unlike non-spatial GHG auditing methods such as the Cool Farm Tool (Cool Farm Alliance, 2016), Farm Carbon Calculator (Farm Carbon Calculator, 2022) and Agrecalc (SAC, 2022). This spatial capability allows the calculation and spatial representation of the total amount of C present in any land parcel. This in turn allows

an initial assessment of which parts of the farm are likely to have particularly low or high levels of carbon storage.

A potential utilisation of the tool can be by land managers and farmers to quantify a change in SOC stocks. At the initial stage, they can benefit from a baseline SOC audit and derive present stocks. Thereafter, a future change in stocks is needed for them to be branded as “net zero” or “C positive”. Since the tool is not able to address the temporal change of SOC, it can be connected to the RothC (Jenkinson et al., 1977) model and derive possible future SOC states.

#### **5.4.2 Considerations when using the tool**

Using Soil Model 3, the predicted SOC (0-10 cm) of the land parcels comprising grassland (45.8 t ha<sup>-1</sup>) was greater than either woodland (42.0 t ha<sup>-1</sup>) or arable fields (42.3 t ha<sup>-1</sup>). The higher value of SOC for grassland than woodland aligns with results such as Upson et al. (2016) who reported a decrease in surface SOC when planting trees on grassland, which they related in part to the reduction in root turnover by the high quantity of grass roots. Additionally due to a lack of acquiring more measured data the derived SOC values were only considered for the depth of 0-10 cm (Beka et al., 2022), while international accounting approaches focus on a soil depth of 0–30 cm (IPCC,2019).

The tool uses the predictions from the BBN models and classifies each parcel into one of the four  $C_{total}$  bins, where the median value of the bin range is given as seen in Table 5-1. This lack of precision can result in overestimation or underestimation of values. The mean value for arable land ( $9.0 \pm 4.4$  t ha<sup>-1</sup>) is higher than values of 2.0 – 6.57 t ha<sup>-1</sup> reported for mean arable crop categories in the UK GHG Inventory (Brown et al., 2020), and studies by Cruickshank et al. (2000), Cantarello et al. (2011) and Adger and Subak (1996). The value of 9.0 t ha<sup>-1</sup> seems particularly high as we followed the guidance of the IPCC guidelines (IPCC, 2019; page 5.7) which seeks to represent the C density value of the arable crop after harvest. The derived mean value for improved grassland of 19.3 t ha<sup>-1</sup> (Table 5-3) is also higher than values of 4.2-8.4 t ha<sup>-1</sup> in the aforementioned

studies. By contrast, the value of 48.1 t ha<sup>-1</sup> for woodland is close to values of 52.9-74.0 provided by Milne and Brown (1997) and Morisson et al. (2012).

A limitation of the tool is that it only provides a “snapshot” of C storage in a nominal year with no consideration of temporal change and permanence, for example, it does not account for the temporal aspects of SOC change due to land cover change. Addressing the temporal change of SOC from a change in land use from grassland to woodland would require additional data on the timing of that change.

The last part of the chapter considered the effect of how some management practices, for a given land cover, can modify the SOC or the biomass C. These would typically require physical measurements to validate the levels of SOC and biomass C (Badgery et al., 2020; Bellamy et al., 2005; Hamburg et al., 2019). In this study, we used results derived from models validated against UK-based experimental studies found in the literature. These models potentially allow the prediction of the change in the C stocks with the time from planting by the tool. For the management intervention process, we predicted the management change for up to 30 years which matches the UK Government’s net zero goal for 2050. The effect of Options B and D were restricted to a one-off change over 1 or 5 years.

### **5.4.3 Quantification of uncertainty**

Farm C modelling involves a synthesis of knowledge about various aspects of the soil and biomass pools. The developed tool simplifies several spatially and temporally complex processes involved in the C stored in these two pools. Moreover, it comes as no surprise that the derived results carry a level of uncertainty. There are two components to model and express uncertainty namely bias and variance. Bias indicates how accurate the results are compared to the “true” value, with “accurate” results potentially having a low bias (Ogle et al., 2006; Petrokofsky et al., 2012). Variance assesses the precision in the results of the model, which in most cases is presented as a confidence interval (Clermont and Sudret, 2007; Malone et al., 2018; Webster, 2001). A

low value of variance can be related to precise results. There are many sources of uncertainty coming from the variance of the input data, the measured data and the imperfect nature of the developed models.

In deterministic models like the ones used for the estimation of the SOC, the uncertainty was expressed by comparing the continuous measured vs the modelled data. The performance of the models was assessed using the RMSE, which expresses the standard deviation of the residuals or the prediction error (Uusitalo et al., 2015). By contrast, the standard deviation variance measure was chosen to assess the biomass C predictions derived from the BBN models. These confidence ranges were derived based on the probability distribution functions of the two BBN model parameters (Das, 2004; Ogle et al., 2006). The uncertainty of the BBN models' outputs was derived by the stochastic measure of uncertainty of the BBN predictors used to estimate the  $C_{total}$  (Vandenbygaart et al., 2004).

The results obtained by the tool demonstrate that a level of uncertainty were derived by propagating the uncertainty of the biomass and soil models using Taylor series (Schenkendorf, 2014). This is something that existing farm-scale tools are lacking (Whittaker et al., 2013).

#### **5.4.4 Business opportunities and incentives for carbon inventories**

At present, there is no requirement for farm businesses in the UK and the EU to perform GHG and C audits, but there can be business opportunities for those that do. C markets related to agriculture and land use are being developed (Mcdonald et al., 2021) including the Emissions Reduction Fund in Australia (Australian Government Department of Industry, Science, Energy and Resources, 2021) and the Woodland Carbon Code, which is now part of the UK Land Carbon Registry, in the UK (Woodland Carbon Code, 2022).

It is anticipated that eventually most farm businesses in the UK will be required to undertake regular GHG audits, and inventories of C stocks. In this study, four different

management alteration options according to the current situation of the fields with low C stocks were explored. In the future, the selection of options could be expanded to cover a wider range of area-related farm management possibilities with estimates of their pattern.

In the UK farmers can currently receive “basic payments” for each hectare of agricultural land that they manage (Rural Payments Agency, 2019) and this can comprise about 50% of their net farm income (Natural Capital Committee, 2017). Following Brexit, the UK Government has been replacing basic payments with a three-tier Environmental Land Management (ELM) scheme related to the delivery of the 25-Year Environment Plan (Department for Environment, Food & Rural Affairs, Rural Payments Agency, 2020). The UK Government has indicated plans to develop a hedgerow carbon code (Game and Wildlife Conservation Trust, 2021) and the first round of applications for the Sustainable Farming Incentive Scheme opened in June 2022 (Department for Environment Food & Rural Affairs, 2021). These schemes can provide incentives to increase on-farm carbon sequestration.

Secondly, once a farm business has achieved net zero, there could be business opportunities to sell “C credits” and receive a financial return from private buyers who want to pay for mitigation measures (Cevallos, Grimault and Bellassen, 2019; Indigo, 2022). Within the Woodland Carbon Code (Forestry Commission, 2014), farmers are incentivised to sequester C by planting and managing trees through two payments. The first payment is made when a farmer plants a new area of woodland and retains it until a set amount of C has been stored. The second payment is based on the additional amount of C sequestered by a set number of years from the baseline.

#### **5.4.5 Cross-cutting challenges for farm carbon certification**

The proposed tool can potentially assist farmers in developing farm baseline C stock inventories together with field management options that can increase C storage. However, a few considerations arise that need to be carefully examined.

Even though farm carbon certification offers a significant contribution toward net zero, there is still uncertainty related to the scale of the opportunity; there are also liabilities. For the farm C certification to be fair and credible to everyone, accurate monitoring, reporting and verification (MRV) methods need to be implemented (WBCSD and WRI, 2020). This process can be expensive as high MRV accuracy requires money and time (Directorate-General for Climate Action -European Commission, 2019; Menon and Lim, 2017; Rosenstock et al., 2016) and poses a key barrier to both funders and farmers. In addition, countries can specify a required time period to ensure the permanence of C storage.

The development of economically attractive, scientifically robust farm-based C credits is likely to require governments working closely with research organisations and farmer groups. Any established system will need to demonstrate the additionality, credibility and permanence of the C storage (WBCSD and WRI, 2020, 2015). Certified farmers and landowners can potentially derive an income by selling their credits in carbon markets where large scale GHG emitters can purchase them to offset their emissions. Additionally, governments will need to be responsible for the MVR until the certification process is completed. The described approach could end up being a way for carbon traders and governments to sense-check the values of SOC and biomass C being claimed by farmers. If the values calculated by the farmers very substantially differ from predictions derived by the approach, then a more detailed investigation or a site visit could be warranted. Moreover, careful planning needs to be considered as the C market will be comprised of three different audiences namely the landowners, the carbon market makers and the governments.

Farm C certification can deliver benefits to both farmers and society but at the same time, some risks arise. Methods to enhance on-farm C storage may lead to farm productivity improvements, reduced costs and improved farm resilience (Adewale et al., 2016; Toensmeier, 2016; Young et al., 2021) but some practices can reduce food production (Burgess and Graves, 2022). National and agricultural sectors' goals for net zero GHG emissions could potentially reduce food security, sustainable food production,

and biodiversity enrichment (NFU, 2019a; UK Government, 2021a). During 2022, the UK Government has indicated that food imports should not exceed 40% of the UK's total food consumption (Nature Friendly Farming Network, 2022), and this should reduce the extent of C leakage where reduced food production in the UK increases the C footprint of food produced elsewhere (Dimbleby, 2021). The above highlight the importance of adopting a holistic approach as climate change mitigation targets, together with environmental and social benefits are interlinked. Additionally, a farmer or landowner needs to consider the implications of having sold farm-credits, if the farm is not C-neutral anymore.

## 5.5 Conclusions

Farm businesses must start to establish carbon (C) inventories to support progress towards net zero. To do so, reliable and scalable farm scale C stock estimation tools are required that follow systematic approaches and methods and at the same time provide an estimate of uncertainty. This study supports the hypothesis that an empirical SOC accounting approach can be combined with a probabilistic biomass carbon stock approach and produce a scalable tool that estimates the current levels of farm C soil and biomass stocks.

The novelty of this work lies in its simple but systematic approach which spatially integrates the C stored in the biomass of land covers and landscape features together with that found in the soil. This allows to spatially present the total amount of C present in any land parcel together with a level of uncertainty. A major advantage of this tool is the land parcel unit of analysis, as it not only allows the farmer to derive a single total C value for each parcel but can additionally easily be broken down to the amount of C present in each pool. This individual examination of each pool allows farmers to rank areas with low or high levels of C and thereby take particular management actions. Lastly, the use of LiDAR and remotely sensed data can assist in determining both the biomass C stock of homogeneous land covers and landscape features such as trees and

hedges in an integrated logical format, in addition to minimising the labour of physical measurements.

Applied at a farm level, the tool can assist farmers in achieving net zero GHG emissions. However, governments, farmer organisations, research institutes and economists still need to work together to develop sustainable C certification and farm-based schemes. The first step for most farm businesses is to ensure that their farm achieves net zero GHG emissions rather than selling their C credits to C trading schemes.

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## 6 Synthesis

### 6.1 Thesis rationale and revisit of aims and objectives

Many countries around the world, including the UK, are implementing policies to tackle climate change and achieve net-zero greenhouse gas (GHG) emissions by 2050 (Smith et al., 2012; van Soest et al., 2021; UK Government 2019). Achieving net-zero emissions will require management change in each sector of the economy. Agriculture has a particularly important role as it is a source of about 10% of UK net emissions, and land use and land-use change can also provide a sink for GHG (Department for Environment, Food & Rural Affairs, 2021). Hence, a key policy measure is to incentivise farmers and land managers to store more carbon (C), as some sectors of the economy (including potentially agriculture) will remain a source of GHG even in 2050 (Chambers et al., 2016). For net-zero schemes to be successful, it would be ideal to take measurements of biomass C and SOC across the required fields and farms. However, this can be difficult in terms of time, money and labour. Moreover, to achieve net zero, farmers and policymakers need improved scalable ways of predicting how much C is stored on farms and how different land management practices affect storage and sequestration. Hence, this PhD aimed to review, develop, apply, and evaluate scalable and robust methods for creating fine-scale maps and models for below and aboveground carbon stocks that could be used by farm and landscape managers.

The thesis aim was addressed by six objectives. The first objective was: 1) To critically review and assess existing literature of carbon and greenhouse gas models and tools; which could potentially be used to develop spatial farm carbon (C) stock baseline inventories. The next objectives were 2) to develop calibrate and evaluate robust spatial soil organic carbon storage models, with different scales of input and output data and identify the impacts of downscaling national soil carbon information, 3) to determine how the developed spatial modelling approaches interact with the choice of accounting method and review their economic implications., and 4) to develop and evaluate a method that combines probabilistic Bayesian Belief Network models with remotely sensed data and spatially estimate the total carbon stored in the biomass of different

land covers and landscape features.. The last two objectives were 5) to establish a tool that provides a holistic view of the farm carbon levels and allows the separate examination of each pool and field parcel and lastly, 6) to synthesise the above research and investigate any opportunities and obstacles for spatial farm level carbon accountancy. Hence, this Chapter discusses each objective in turn.

## **6.2 Current carbon inventories and criteria development**

The first research question to be addressed was: What is the current capacity of developing a spatial farm C accounting tool?

### **6.2.1 Existing carbon inventory tools**

Chapter 2 sought to find an answer to research question 1. The first part of Chapter 2 examined the characteristics of 25 existing C accounting and/or inventory tools and models. Due to the major differences in the level of detail and accuracy during the calculations, the tools were grouped into two categories: process based models (Chapter 2, Table 2-3, first 17 lines) and statistical models and tools (Chapter 2 Table 2-3, last 8 lines). The process based models tend to require specialised information, they tend to emphasise the processes in the calculations, and it can take substantial time to collect and enter all required information. By contrast, statistical models and tools can often draw on pre-existing datasets that are available to the farm owner or land manager and produce results often without a level of uncertainty.

The review indicated that only 35% of the reviewed farm-scale C stock models and tools were spatial, and only InVest (Tallis and Polasky, 2009) provided estimates of C stocks and estimates of their uncertainty. While there are various GHG flux calculators/tools (DNDC, DayCENT ECOSSE, CropSyst, Holos, Cool Farm Tool, Farm Tool Carbon Calculator, COMET Farm and OFoot), there are only a few published C stock tools (DayCent and the Cool Farm Tool) which are non-spatial. Hence, the development of spatial C inventory tools is a research gap.

### **6.2.2 Farm level spatial carbon tool criteria development**

The focus of the second part of Chapter 2 was to establish criteria for a successful carbon inventory tool, which could be used to inform Chapters 3 to 5. Burbi et al. (2016) reported that farmers preferred tools that “speak their language”, require as little as possible new input data, and provide practical management alternatives and financial assessments. Additionally, there is a need for the incorporation of novel approaches, such as open source hardware and data for agriculture (Fisher et al., 2012) and models (Haigh et al., 2018; Dalyn M. et al., 2019) to strengthen the adaptability, profitability and resilience of farmers

In accounting protocols and guideline methodologies (IPCC 2019; WBCSD and WRI, 2015) the recommended first steps are: i) the setting of boundaries, ii) the classification of the land into managed and unmanaged, and iii) the identification of the land covers. In any accounting or inventory system, it is important to identify the boundaries in the system. In the agricultural sector, farm boundaries within Europe are set by using the LPIS system (European Court of Auditors, 2016). In the UK, one method of assessing land cover is the land cover classification system managed by the UK Centre for Ecology and Hydrology (2020). Lastly, ideally, an estimate of stock should be associated with a statement of the level of uncertainty, as this will allow users to make decisions with reasonable confidence regarding the reliability of the reported information.

### **6.3 Robust spatial modelling of soil organic and biomass carbon**

The principal forms of on-farm C storage are soil organic carbon (SOC), and biomass C in the form of above ground biomass, below ground biomass, and dead organic matter (made up of dead wood and litter). In the next sections, the outcomes of the development of models to estimate the C in the four pools are discussed. Also, the following three research questions were addressed:

Research question 2: What is the best way to establish SOC levels on farms without on-site measurements?

Research question 3: What is the implication of SOC modelling approaches on possible farm-level C payments?

Research question 4: What is the optimal way to determine biomass C levels of land cover and landscape features on farms without on-site measurements?

### **6.3.1 Soil organic carbon models**

In Chapter 3 research question 2 was addressed by developing, calibrating and comparing the evaluation of three spatial modelling approaches to estimate soil organic carbon (SOC) storage. The approach also examined the hypothesis that downscaling national-level soil C datasets to a farm and field level has different impacts depending on both the spatial modelling approach and the accounting method.

Chapter 3 compared how three spatial SOC models estimated the organic carbon in the top 10 cm of the soil, along with a level of uncertainty. The models were based on an existing soil dataset, which potentially offers cost and labour savings relative to physical sampling. The models used either fine- (100 m x 100 m) or field-scale input soil data to produce either fine- or field-scale outputs across the four cardinal directions and to a soil depth of 10 cm (Beka et al., 2022). Across the evaluation dataset, the RMSE associated with Model 2 (11.0 t SOC ha<sup>-1</sup>) and Model 3 (8.3 t SOC ha<sup>-1</sup>) tended to be less than with coarse-scale Model 1 (18.3 t SOC ha<sup>-1</sup>). As seen in Chapter 3, the fine resolution models can enable more precise management of soil C due to their capacity to identify field-to-field and in-field variation. In addition, Models 2 and 3 showed slopes of regression (0.67 - 0.74) between modelled and actual measurements that were closer to 1:1 lines than Model 1 (Slope = 0.05). Hence the greater sensitivity of Models 2 and 3 enables a greater capacity to differentiate between areas of low and high soil C which could have important implications for C payments.

Before this PhD, the existing method for predicting SOC was Model 1 (Bradley et al., 2005), and the benefits of the fine-scale model had not been established. Another useful advance as described in Chapter 3 is its capacity to identify field-to-field and within-field variation with much greater detail than the current recognised method of Model 1. The

100 m x 100 m raster grid soil properties datasets were developed using DSM (Campbell, 2018) to a depth of 150 cm and are held at Cranfield University. An alternative data source that could be used for the SOC model development is the freely available topsoil (0-15 cm) C concentration estimates from the 2007 Countryside Survey of Great Britain (Thomas et al., 2020). However, its 1 km resolution, raster format and missing information for important parameters such as bulk density mean that it lacks the potential precision of the Campbell dataset.

Using a fine scale (100 m × 100 m) dataset as a model's input provided a better prediction of farm-level SOC that derived from previous studies like Bradley et al., (2005) and Gregory et al. (2014) which used a coarser dataset. However, even so, both fine-scale input models still predicted lower variation than the measured SOC values and tended to underestimate the SOC value of soils high in soil C. This limitation of spatial models has previously been noted by Gregory et al. (2014). In a similar way to data and labour-demanding models like CENTURY (Parton et al., 2001), RothC (Coleman and Jenkinson, 2014) and EPIC (Williams et al., 1984), Models 2 and 3 considered the local variation of soil formation characteristics on soil characteristics (Jenny, 1941), and this was one potential reason why Models 2 and 3 estimated a higher variation than Model 1.

A limitation of the current study is that all the models were only calibrated and validated for the top 10 cm of soil in grassland fields, as this was the only available dataset available to the author. By contrast, the criteria identified in Chapter 2 suggest that ideally, the model should consider a deeper depth at least covering the depth of soil to the depth of a plough e.g. about 30 cm. This is where the greatest amount of carbon is stored and as demonstrated by Cai et al. (2022), cultivation practices can modify the distribution of SOC within the top 0-30 cm. Ideally, estimates should be made to depths of 100-150 cm. However, the acquisition of complete measured SOC data to greater depths and across more land covers is hard to come across due to the labour intensity and expenses that are entailed.

Additionally Models 2 and 3 were based on a soil dataset established for land cover at a specific date. However as many studies have shown (Badgery et al., 2020; Hamburg et al., 2019; Kirk and Bellamy, 2010; Upson et al., 2016) land cover on farms is not static, and management practices can modify the SOC over time.

To address research question 3, two approaches were analysed in Chapter 3 to determine the potential receipts of C payments to farmers. The first one considers a payment assuming a  $10 \text{ t C ha}^{-1}$  SOC increase over the measured value, while the second assumed a payment based on the difference between the measured value and a “baseline” value derived from the model. As seen in Chapter 3, choosing whether to measure or model the baseline SOC in order to derive a SOC increase by  $10 \text{ t C ha}^{-1}$  had different financial implications between farms. The effect also contrasted with the choice of the model. Overall, using models rather than measurements to determine an initial baseline for increases in soil C, benefitted farmers. Using Model 2 as a baseline favoured sites that already had a high SOC. The C benefit using Model 2, was a mean of  $\text{£}1296 \text{ ha}^{-1}$  for the five sites with low SOC compared to a mean of  $\text{£}2108 \text{ ha}^{-1}$  for the four sites with the highest SOC. Using Model 1 resulted in a lower mean estimate of SOC. Therefore, assuming final measured SOC values and baseline SOC values based on Model 1 would result in a 75% higher mean increase worth  $\text{£}1750 \text{ ha}^{-1}$ . Similarly, Model 3 resulted in a lower mean estimate of SOC and assuming final measured SOC values and baseline Model 3 SOC values, would result in a 76% higher increase of  $\text{£}1760 \text{ ha}^{-1}$ .

Farmers with access to a statement of their net greenhouse gas emissions and a carbon inventory may be able to access new markets or government grants. These incentives can come from public funds such as the Common Agricultural Policy (CAP) (Cevallos, Grimault and Bellassen, 2019), private payments (Indigo, 2022), or a combination of the two. Whilst the development of a national approach for C sequestration payments to farmers is possible, this research demonstrates that the economic impacts on individual businesses will depend on the chosen tool, the data and methods used, and the accounting method.

### 6.3.2 Biomass carbon models

Chapter 4 developed and validated a scalable spatial modelling approach to estimate the total C stored in the biomass of different land covers and landscape features. The spatial modelling approach described in the chapter addressed research question 4 by integrating LiDAR data, and Bayesian Belief Networks (BBNs) to quantify total biomass carbon stocks ( $C_{total}$ ) of i) land covers and ii) landscape features. The two BBN models successfully predicted the test values of the  $C_{total}$  with propagated error rates of 6.7% and 4.3% across four groupings of  $C_{total}$  for the land cover and landscape features respectively which were much lower than other BBN studies. Aboveground biomass carbon (AGBC) was identified as the most influential predictor of  $C_{total}$  for both land covers and landscape features.

An advantage of a Bayesian approach is that it constantly seeks to improve the prediction accuracy, by utilising current literature and measured information about the variables that most influence the  $C_{total}$ . A potential alternative to this approach would have been to use either generic C storage values, (Cannell and Milne, 1995; Cantarello et al., 2011; Gregory et al., 1995; IPCC, 2019) or highly detailed calculators such as CENTURY (Parton, 1996), Cool Farm Tool (Sustainable Food Lab et al., 2011), ScotFarm (Shrestha, 2014), OFoot (Carlson et al., 2017).

The use of historic land cover and LiDAR height data was also an advantage of the developed approach. Airborne LiDAR data and land cover maps are capable of reducing the costs and effort required to conduct on-site surveys (Arenas-corralliza et al., 2020; Timothy et al., 2016). Additionally, the probabilistic associations between the predictor variables and the  $C_{total}$  of both land covers and landscape features were easily derived by the generated heat maps presented in Chapter 4.

Chapter 4 also illustrated the importance of landscape features. In the case study sites, landscape features comprised 5-93% of the total biomass C, with the 93% value obtained

for a silvoarable experimental site. The described spatial methodology in Chapter 4 and then its usage for the C stock tool in Chapter 5 is a major advantage compared to non-spatial tools like the Cool Farm Tool and Holos (Hillier et al., 2011; Kröbel et al., 2016). This spatial process of including variable heights along hedges can be more informative in terms of farm management.

A limitation of the current BBN methodology was that the modelled  $C_{total}$  values were estimated as a discrete ranges of values and not as a continuous variable, as the software used (Norsys Software Corp., 2003) did not have the capability of deriving continuous results. An advantage of a discrete categorisation is that the computing of the relationships becomes far more feasible on a standard desktop computer or laptop. However, more computationally demanding software programmes exist such as WinBUGS (University of Cambridge, 2022) where the outputs can be expressed as continuous variables (Thomas et al., 2020). Overall the categorisation approach worked fine, however as the computational capacity of computers increases, future studies could use forms of BBN analysis that produce continuous rather than discrete estimates of  $C_{total}$ .

## 6.4 Integration of the models

The integration of the models addressed the following two research questions:

Research question 5: How can the SOC and biomass C models be combined in order to provide estimates of current C levels, and how could management options affect these levels in the future?

Research question 6: To what extent have the developed models improved capacity to spatially account for farm-level C?

### 6.4.1 Use of the integrated tool

Chapter 5 sought to find an answer to research questions 5 and 6 by describing the integration of the SOC and BBN biomass C model and its application to a case study farm. An advantage of the tool is that it primarily relies on pre-existing data in terms of soil

types, land covers (Beka et al. 2022a), and all seven predictors that affect the C stored in the biomass (Beka et al. 2023). The reliance on these datasets allows the approach to be applied and used remotely.

Also within Chapter 5, the integrated tool was used to identify parts of the farm with relatively low levels of C, and the implications of using four methods (identified from the literature) to increase C storage were examined. Tools such as the Cool Farm Tool (Cool Farm Alliance, 2016), Farm Carbon Calculator (Farm Carbon Calculator, 2022) and Agrecalc (SAC, 2022a) can be used to look at the effect of different farm management practices. However, an advantage of this tool is that it can allow the spatial presentation of the results. The integrated approach described in Chapter 5 allows the calculation and spatial presentation of the total amount of C in both the biomass and soil of each land cover and landscape feature present in any land parcel. This also permits a farmland owner to derive a single value for the total C stock for any or all land parcels.

The tool as described in Chapter 5 was originally developed as a farm-based tool. As discussed in Chapter 3, the models can potentially assist farmers in establishing a baseline for their C inventory. The initial intention of the tool was to be open source and to use freely available datasets as far as possible. Unfortunately, that was not possible as some datasets and software used to develop the models described in Chapters 3 and 4 needed to be purchased or required a license. The geospatial analysis, the statistical analysis and the development of the SOC and biomass C models were performed using open-source software (QGIS 2022; R 2022; Norsys Software Corp. 2003 ). However, the segmentation of the LiDAR data into objects performed in Chapter 4 was accomplished using the ENVI Version 5.6 (ENVI, 2022) licensed software. The land cover (UK Centre for Ecology and Hydrology, 2017; 2020 ) and most LiDAR data (Department for Environment Food & Rural Affairs, 2022) except for the 2011 LiDAR data for Silsoe used in Chapter 4 were also open data. In general, the literature data used for the development of the biomass C models in Chapter 4 were derived from open-access journals. By contrast, the data used for the calibration and evaluation of the SOC models namely the National Soils

Map (Keay et al., 2009; Hallett et al., 2017), and the 100 m x 100 m soil properties dataset described by Campbell (2018) required a license from Cranfield University.

Potentially a model similar to that described in Chapter 5 could also be used as a public policy tool. Policymakers might want to implement the tool on a nationwide scale. This would require the tool to be upscaled. Although a dataset for the C stored in biomass was developed for this project, it is not as extensive as the national soils map (NATMAP) (Hallett et al., 2017; Keay et al., 2009). The biomass data used in the BBN models in Chapter 4 represent only a proportion of the values that the 7  $C_{total}$  predictors can take across the whole UK. Moreover, a larger range is needed to cover all possible values that the predictors can take. Developing a national dataset of all representative combinations would be useful.

The soil properties (LOI, sand, clay) and soil association data used for the development of the SOC models (Beka et al., 2022a) are available from the National Soil Inventory held by Cranfield University, and hence the data are limited to most people. Additionally, the R scripts used to create and run the SOC models require a level of coding knowledge. Similarly, all tasks performed in QGIS require the user to be familiar with the open-source software.

The developed integrated method was primarily based on the use of existing data, rather than requiring new whole-farm surveys that can be time consuming, labour intense and expensive, as described by Arenas-Corraliza et al. (2020) and Timothy et al. (2016). The required variables (such as age and height) can potentially be determined remotely using historic land cover and LiDAR height data. The combined method of LiDAR and BBN models is relatively new, and the research described in Chapter 4 has extended previous woodland studies such as Wang et al. (2019), and Zapata-Cuartas et al. (2014) by using the BBN method and estimating the total biomass C in additional land cover categories together with landscape features. A further innovation of the developed tool described in Chapter 5 is the capacity to spatially present the variation

in C stocks along the length of hedges and within woodlands using remote sensing and LiDAR data, as described in Chapter 4.

#### **6.4.2 Uncertainty**

The quantification of uncertainty as described in Chapters 3, 4 and 5 played a major role in this PhD, as this was one of the identified literature gaps, as existing farm-scale tools are lacking it (Whittaker et al., 2013). The results obtained by the tool demonstrate that a level of uncertainty can be derived by propagating the uncertainty of the biomass (Chapter 4) and soil (Chapter 3) models using Taylor series (Schenkendorf, 2014). In more detail, the uncertainty of the deterministic SOC models described in Chapter 3 was assessed using the RMSE (Uusitalo et al., 2015) that describes the scatter of the mean data points. The uncertainty of the BBN models' outputs was derived from the standard deviation variance which is a stochastic measure of uncertainty of the predictors (Vandenbygaart et al., 2004).

In general, uncertainty can be separated into two parts: namely its sources and the way that it is expressed (Ogle et al., 2006). It can be expressed or quantified as a variance (e.g. range, standard deviation), a performance measure ( $R^2$ , RMSE, confusion matrix for a probabilistic uncertainty, Chi-square measure, etc), or as a monetary value, which is sometimes used in climate change studies for risk management (Petrokofsky et al., 2012; Piñeiro et al., 2008; Schrumpf et al., 2011; Smith and Heath, 2001).

In deterministic models like the ones used for the estimation of the SOC, the uncertainty was expressed with the RMSE measure that ranged from 8.3 – 18.3 t ha<sup>-1</sup> and arises from the errors and uncertainty within the measured data, together with the inputs and the algorithms used to develop and validate the models (Schrumpf et al., 2011). Consideration must be given to the fact that the data used to train and validate them resulted in the models seeing only a portion of the existing soil types and land covers present in the UK. Additionally, the data used to create the two fine-scale models performed much better in predicting the texture properties (clay and sand) than the LOI.

The RMSE values of the texture properties were equal to  $\pm 9.1 \text{ g clay (100 g soil)}^{-1}$  and  $\pm 15.6 \text{ g sand (100 g soil)}^{-1}$  respectively, compared to  $\pm 19.4 \text{ g LOI (100 g soil)}^{-1}$  (Campbell, 2018).

In the published paper, the fine resolution soil dataset described by Campbell performed well. However, subsequent to the publication of the paper, a group project was undertaken by MSc students at Cranfield University in May 2022. Jones et al., (2022) have questioned the reliability of the Campbell LOI soil properties dataset (Campbell, 2018) to describe the LOI values of soils in the clay basin area of Marston Vale in Bedfordshire. For this particular 16,000 ha area, the predicted values of LOI for the surface soil were about four times higher than the measured values. The reasons for this discrepancy have still to be established, and there are plans for Cranfield staff to re-run the Campbell model and seek to resolve this issue.

The way that the BBN models in Chapter 4 expressed the uncertainty is different to Chapter 3, as it is directly embedded in the predictions and the generated error boundaries (Taalab et al., 2015). For the BBN models, the standard deviation variance measure was chosen to assess the biomass C predictions. These confidence ranges were derived based on the probability distribution functions of the two BBN model parameters (Das, 2004; Ogle et al., 2006). The uncertainty of the models' outputs was moreover obtained by the stochastic measure of uncertainty of the BBN predictors used to estimate the  $C_{\text{total}}$  (Vandenbygaart et al., 2004). The BBN models were able to predict the test values with propagated error rates across four categories of 6.7% for the land covers and 4.3% for the landscape features. These error rates were lower than in other environmental studies where they ranged from 15 % across five categories (Taalab et al., 2015b) to 45 % across three categories (Karimi et al., 2021).

A challenge that a farmer is faced with is the need to demonstrate the permanence and additionality of the C storage (Beka et al., 2022). No matter how perfect a tool might be, there will still be a level of uncertainty, addressed with a coefficient. A way to avoid

claiming C credits that do not occur in practice, the derived results described in Chapter 5 will need to be validated against measured values through accurate monitoring, reporting and verification (MRV) methods (WBCSD and WRI, 2020). This, however, as thoroughly described in Chapter 5, comes with financial and time implications (Directorate-General for Climate Action -European Commission, 2019; Menon and Lim, 2017; Rosenstock et al., 2016)

### **6.4.3 Carbon balance sheet analysis**

Carbon farming can potentially provide an income to farmers and land-owners who can sell the C credits in markets where large-scale emitters can purchase them to offset their emissions. However, current or future C levels will ultimately need to be monitored, reported and verified (MRV) to demonstrate genuine abatement (Beka et al., 2022). In financial accounting there are two types of practices, that are used in parallel, to calculate cash flow. These are the profit and loss analysis and the balance sheet analysis, also referred to as double bookkeeping (Houdet et al., 2020; Hasanaj et al., 2019; Hayden, 2014). Something similar can potentially be used on farms, with a C inventory model providing a balance sheet, and GHG emissions models providing an estimate of annual GHG flows in a similar way to a cash-flow account.

At present, as discussed in Chapter 2 and section 6.2.1 of this Chapter, there are many tools to calculate annual GHG flows, but only a few tools that provide farm-level C stock inventories and estimates of their uncertainty. Through the thesis, the methods developed and examined in Chapters 3 and 4 have followed a "balance sheet analysis" for C stocks. The balance sheet analysis followed in Chapter 4 for the C stored in the biomass of land covers and landscape features already has a strong foundation. That is the differences in tree height or the changes in crop type can already feed through to differences in biomass C stock estimates. However, the SOC stock analysis described in Chapter 3 is still largely static, as it is based on measurements taken at a fixed point in time, which in most cases were collected decades ago. Moreover, there remains a need

to develop a balance sheet way of accounting for SOC stocks for specified land use, that takes into account annual flows.

## **6.5 Recommendations**

This section includes suggestions for further work that came out of this PhD thesis.

### **Investigate the Loss On Ignition abnormal values**

Further work is needed to investigate the apparent large discrepancy between measured values and modelled soil LOI values derived by Campbell, (2018) observed in the Marston Vale in Bedfordshire by Jones et al. (2022). The reasons for the discrepancy should be determined before substantial use of the fine-scale SOC Models (Chapter 3) across other sites.

### **Further development of the Bayesian Belief Network models**

The BBN models from Chapter 4 used the Netica BBN software (Norsys Software Corp., 2003) and represented the biomass C value as a discrete and not a continuous variable. Future studies to apply the described techniques using more computationally demanding software (Thomas et al., 2003) that supports the production of BBN models with continuous and not discrete outputs is suggested.

### **Development of a national dataset of SOC and biomass C values**

The results in Chapter 3 indicated that it would be beneficial to validate and train the SOC models using depths greater than 30 cm and across a wider range of land covers and farms throughout the whole UK. Additionally, the probabilistic fit that the BBN models in Chapter 4 use tends to favour values that have been observed more by the model. In order to eliminate the models being less responsive to some land covers or landscape features, more measured values need to be incorporated from all across the UK. It is understood that spatially explicit measured soil carbon and bulk density data from deeper depths and across all the varieties of land covers are relatively rare (Paustian et al., 2019). Additionally, physical sampling of biomass carbon can be

destructive, expensive and/or labour-intensive (Rosenstock et al., 2016). Further research is recommended on how to develop a nationwide sampling program for the development of a biomass C dataset and an updated version of the UK's Land Information System (LandIS) (Keay et al., 2009).

### **Upgrade to forecasting tool**

The SOC models developed in Chapter 3 in addition to the BBN models in Chapter 4 provide a “snapshot” of the values of the C within a given year. Many studies have shown (Badgery et al., 2020; Hamburg et al., 2019; Kirk and Bellamy, 2010; Upson et al., 2016) that land cover on farms is not static, and management practices can modify the SOC. Additionally, the biomass of growing crops can change from effectively zero before the seeding of cultivated soil to maximum values just before harvest. Indeed, the standard practice in the IPCC guidelines (IPCC, 2019; Chapter 5-page 7) assumes the C density value of arable crops after harvest. However, further research is recommended to incorporate the time element in both SOC and biomass models and consideration on how the tool can potentially provide C storage forecasts according to specific criteria. Additionally, more research on the development of a balance sheet way of accounting for SOC stocks that takes into consideration annual flows of C is recommended.

## **6.6 Conclusions**

The principal conclusions from the research are summarised in relation to each objective below:

### **Objective 1**

- There are various GHG flux calculators, but the accuracy of such models is rarely published.
- There are even fewer published accounts of spatial C inventory models and tools that provide farm-level C stock inventories and estimates of their uncertainty.
- There are few spatial farm scale C stock models that consider landscape features.

- There is a need to develop a scalable tool to derive farm and landscape-scale C stock inventories that specify the level of uncertainty.
- Farmers value tools that require minimal levels of additional data and which can provide baseline estimates and highlight practical management alternatives.
- Tools need to align with criteria set by international and national guidelines and protocols (British Standards Institute 2019,2020; IPPC, 2019; WBCSD and WRI, 2020).
- Procedures that delineate the area using RPA land parcels and estimate C stocks with a degree of uncertainty across all cartesian directions to specified soil depths is desirable.

## **Objective 2**

- Downscaling national-level soil C information to a farm and field level has different impacts depending on both the spatial modelling approach and the accounting method.
- SOC models using fine-scale resolution input data appeared to provide a more reliable estimate of the measured SOC than an model using coarse-scale input data.
- Although the fine input Models 2 and 3 were able to explain a higher proportion of the variation in SOC (68-69%) than the coarse input Model 1 (43%), all models still predicted lower variation than the measured SOC values.
- The capacity of Model 2 (RMSE= 11 t SOC ha<sup>-1</sup> ) to pick up in-field variations could assist farmers in adjusting their management practices according to within-field variations in soil attributes.

## **Objective 3**

- The use of the spatial SOC models to establish a baseline, from which to derive payments for additional carbon sequestration, favoured farms with already high SOC levels, with that benefit greatest with the use of the coarse input data.

- Developing a national approach for SOC sequestration payments to farmers could be possible but the economic impacts on individual businesses will depend on the approach and the accounting method.

#### **Objective 4**

- It was possible to develop an integrated spatial probabilistic approach including LiDAR data, to quantify  $C_{total}$  of i) land cover and ii) landscape features at a farm scale.
- BBN models can be successfully combined with a GIS interface to spatially apply the influence network of the  $C_{total}$ .
- A higher prediction accuracy was attained by applying both current literature and measured information about the variables that most influence the  $C_{total}$ , than just using literature values alone.
- BBN models successfully predicted the test values with propagated error rates of 6.7% and 4.3% across four categories of land cover and landscape features respectively.
- BBN error rates are lower than in other BBN studies, indicating the six selected predictors are strong determinants of  $C_{total}$ .
- LiDAR data enabled the spatial presentation and calculation of the variable C stocks along the length of hedges, within woodlands and across land parcels.
- The required variables can potentially be determined remotely using historic land cover and LiDAR height data.

#### **Objective 5**

- The empirical SOC accounting approach can be combined with a probabilistic biomass carbon stock approach to produce a tool for estimating baseline farm C stock levels.

- A systematic approach was developed which allows spatial representation of the total amount of C present in the soil, land cover and landscape features of any land parcel.
- The spatial detection of fields with low levels of C could be related to management options to increase C storage.
- The derived approach could spatially integrate biomass and soil C stocks together with specified levels of uncertainty.

### Objective 6

- The tool investigated how carbon farming can provide an income to farmers
- The research undertaken confirmed the need for an MRV method to access genuine abatement of current or future C levels
- The research determined that a balance-sheet analysis can be used to estimate annual GHG flows

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## APPENDICES

### Appendix A : Spatial modelling approach and accounting method affects soil carbon estimates and derived farm-scale carbon payments

Table\_Apx A-1 Source of soil data and area delineation method for the three modelling approaches

| Scale                      | Method 1                                     | Method 2                                                       | Method 3                                                       |
|----------------------------|----------------------------------------------|----------------------------------------------------------------|----------------------------------------------------------------|
| Input data scale           | Coarse - NATMAP UK data on soil associations | Fine - 100 m gridded soil properties data from Campbell (2018) | Fine - 100 m gridded soil properties data from Campbell (2018) |
| Output or management scale | Coarse - field parcel boundaries             | Fine - 100 m square grid                                       | Coarse - field parcel boundaries                               |

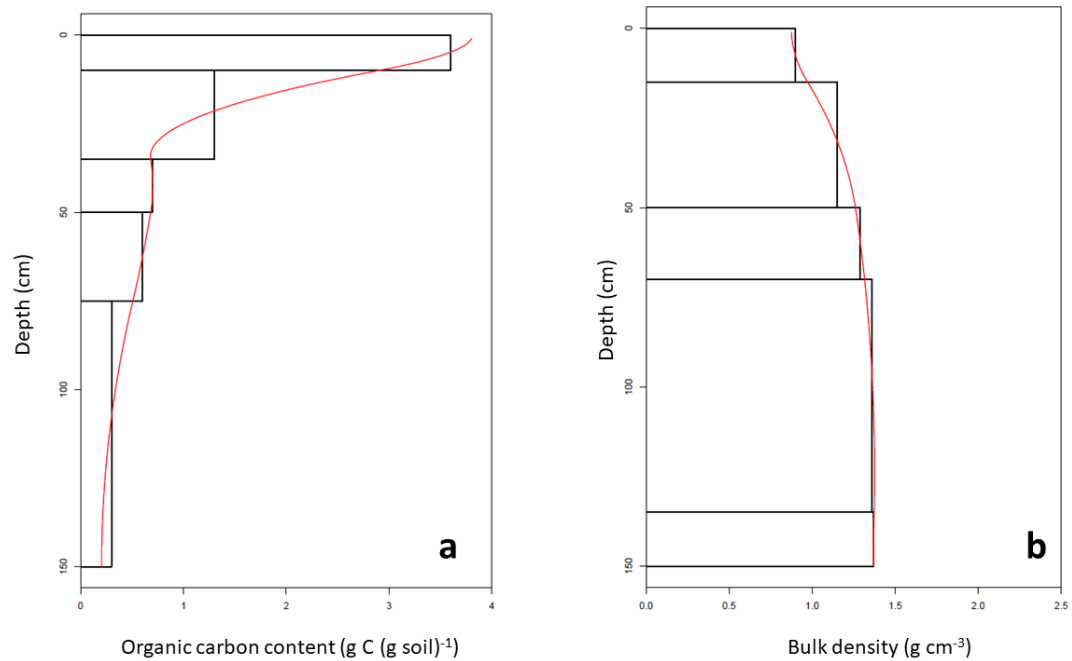
Table\_Apx A-2. Soil associations in the case study (Loddington) are made up of different soil series (LandIS, 2020)

| Soil association | Constituent soil series with proportion indicated in brackets                  |
|------------------|--------------------------------------------------------------------------------|
| Denchworth       | Denchworth (38%), Wickham (19%), Lawford (15%), Eversham (14%), Oxpasture 14%) |
| Hanslope         | Hanslope (77%), Faulkbourne (23%)                                              |
| Oxpasture        | Oxpasture (47%), Wickham (23%), Holdenby (15%), Denchworth (15%)               |
| Ragdale          | Ragdale (44%), Beccles (33%), Hanslope (23%)                                   |

Table\_Apx A-3 Calculated mean soil organic carbon (t ha<sup>-1</sup>) (0-10 cm) stock, together with the total SOC stock (0-10 cm) for each land cover/soil association combination in the four selected parcels in the Loddington farm. The land cover was improved grassland in each case.

| Land Parcel ID | Soil Association | Area (ha) | SOC (t ha <sup>-1</sup> ) |           |         | Stock (t) |         |         |
|----------------|------------------|-----------|---------------------------|-----------|---------|-----------|---------|---------|
|                |                  |           | Model 1                   | Model 2   | Model 3 | Model 1   | Model 2 | Model 3 |
| A              | Denchworth       | 3.63      | 40.6                      | 33.7-55.2 | 47.1    | 147       | 122-200 | 171     |
| B              | Denchworth       | 1.84      | 40.6                      | 30.9-45.3 | 41.3    | 75        | 57-83   | 76      |
|                | Hanslope         | 2.08      | 49.8                      | 31.2-47.7 | 44.6    | 104       | 65-99   | 93      |

|   |            |       |      |               |      |     |              |     |
|---|------------|-------|------|---------------|------|-----|--------------|-----|
| C | Denchworth | 17.26 | 40.6 | 30.9-<br>60.5 | 43.4 | 701 | 533-<br>1044 | 749 |
|---|------------|-------|------|---------------|------|-----|--------------|-----|



Figure\_Apx A-1 Development of a mass preserving spline for a) organic carbon content (OCC) and b) bulk density to a depth of 150 cm for the Denchworth soil series, and for the improved grassland (IG) land cover

## Appendix B : Robust spatial estimates of biomass carbon on farms

Table\_Apx B-1 Coefficients used to derive belowground biomass carbon (BGBC; t C ha<sup>-1</sup>), aboveground biomass carbon (AGBC; t C ha<sup>-1</sup>) and dead organic matter carbon (DOMC; t C ha<sup>-1</sup>) from AGBC or aboveground biomass (AGB; t ha<sup>-1</sup>)

| Type | BGBC/AGBC |                          | DOMC/AGBC |                          | AGBC/AGB |              |
|------|-----------|--------------------------|-----------|--------------------------|----------|--------------|
| AR   | 0.2       | (Gregory et al., 1995)   | 0.114     | (Barel et al., 2019)     |          |              |
| BW   | 0.46      | (Patenaud. et al., 2004) | 0.14      | (Patenaude et al., 2003) | 0.48     | (IPCC, 2019) |
| CW   | 0.349     | (Qi et al., 2019)        | 0.14      | (Patenaude et al., 2003) | 0.51     | (IPCC, 2019) |
| G    | 1.5       | (Brown et al., 2020)     |           |                          |          |              |
| H    | 0.94      | (Axe et al., 2017)       |           |                          |          |              |

\*AR: arable, G: grassland, CW: coniferous woodland, BW: broadleaf woodland, and H=hedge)

Table\_Apx B-2 Prior and Posterior probability distributions for the parameters of the Bayesian Belief Network (BBN) model for the land cover classes

| BBN model parameters |                      | Bin |       | Prior probability distribution |      |       | Posterior probability distribution |       |
|----------------------|----------------------|-----|-------|--------------------------------|------|-------|------------------------------------|-------|
| Symbol               | Unit                 |     | Lower | Upper                          | Mean | sd    | Mean                               | sd    |
| C <sub>total</sub>   | t C ha <sup>-1</sup> | 1   | 0.0   | 4.7                            | 76.1 | ±92.0 | 77.3                               | ±92.0 |
|                      |                      | 2   | 4.7   | 33.9                           |      |       |                                    |       |
|                      |                      | 3   | 33.9  | 110.4                          |      |       |                                    |       |
|                      |                      | 4   | 110.4 | 332.8                          |      |       |                                    |       |
| AGBC                 | t C ha <sup>-1</sup> | 1   | 0.0   | 2.6                            | 48.0 | ±58.0 | 48.3                               | ±58.0 |
|                      |                      | 2   | 2.6   | 19.9                           |      |       |                                    |       |
|                      |                      | 3   | 19.9  | 67.3                           |      |       |                                    |       |
|                      |                      | 4   | 67.3  | 208                            |      |       |                                    |       |
| BGBC                 | t C ha <sup>-1</sup> | 1   | 0.0   | 1.3                            | 23.5 | ±28.0 | 23.7                               | ±28.0 |
|                      |                      | 2   | 1.3   | 11.0                           |      |       |                                    |       |
|                      |                      | 3   | 11.0  | 33.1                           |      |       |                                    |       |

|        |                      | 4 | 33.1 | 99.5 |      |       |      |       |
|--------|----------------------|---|------|------|------|-------|------|-------|
| DOMC   | t C ha <sup>-1</sup> | 1 | 0.0  | 0.3  | 6.7  | ±8.1  | 6.7  | ±8.1  |
|        |                      | 2 | 0.3  | 2.8  |      |       |      |       |
|        |                      | 3 | 2.8  | 9.4  |      |       |      |       |
|        |                      | 4 | 9.4  | 29.1 |      |       |      |       |
| Height | m                    | 1 | 0.0  | 2.6  | 8.7  | ±6.6  | 8.4  | ±6.4  |
|        |                      | 2 | 2.6  | 7.2  |      |       |      |       |
|        |                      | 3 | 7.2  | 13.3 |      |       |      |       |
|        |                      | 4 | 13.3 | 22.7 |      |       |      |       |
| Age    | years                | 1 | 0.0  | 20.0 | 38.5 | ±39.0 | 36.1 | ±36.0 |
|        |                      | 2 | 20.0 | 40.0 |      |       |      |       |
|        |                      | 3 | 40.0 | 60.0 |      |       |      |       |
|        |                      | 4 | 60.0 | 80.0 |      |       |      |       |

*sd= standard deviation*

Table\_Apx B-3 Prior and Posterior probability distributions for the parameters of the Bayesian Belief Network (BBN) model for the landscape features classes

| BBN model parameters |                      | Bin |       | Prior probability distribution |      | Posterior probability distribution |      |       |
|----------------------|----------------------|-----|-------|--------------------------------|------|------------------------------------|------|-------|
| Symbol               | Unit                 |     | Lower | Upper                          | Mean | sd                                 | Mean | sd    |
| C <sub>total</sub>   | t C ha <sup>-1</sup> | 1   | 0.0   | 10.2                           | 38.4 | ±33.0                              | 38.9 | ±30.0 |
|                      |                      | 2   | 10.2  | 27.3                           |      |                                    |      |       |
|                      |                      | 3   | 27.3  | 58.0                           |      |                                    |      |       |
|                      |                      | 4   | 58.0  | 120.0                          |      |                                    |      |       |
| AGBC                 | t C ha <sup>-1</sup> | 1   | 0.0   | 8.6                            | 23.6 | ±19.0                              | 24.3 | ±17.0 |
|                      |                      | 2   | 8.6   | 16.8                           |      |                                    |      |       |
|                      |                      | 3   | 16.8  | 36.3                           |      |                                    |      |       |
|                      |                      | 4   | 36.3  | 68.0                           |      |                                    |      |       |
| BGBC                 | t C ha <sup>-1</sup> | 1   | 0.0   | 2.9                            | 10.9 | ±9.4                               | 11.3 | ±9.0  |
|                      |                      | 2   | 2.9   | 7.8                            |      |                                    |      |       |
|                      |                      | 3   | 7.8   | 16.7                           |      |                                    |      |       |
|                      |                      | 4   | 16.7  | 34.4                           |      |                                    |      |       |
| DOMC                 | t C ha <sup>-1</sup> | 1   | 0.0   | 1.9                            | 3.8  | ±3.0                               | 3.9  | ±2.6  |
|                      |                      | 2   | 1.9   | 2.9                            |      |                                    |      |       |
|                      |                      | 3   | 2.9   | 4.1                            |      |                                    |      |       |
|                      |                      | 4   | 4.1   | 12.5                           |      |                                    |      |       |
| Height               | m                    | 1   | 0.0   | 2.5                            | 6.3  | ±3.9                               | 5.9  | ±3.2  |

|     |       |   |      |      |      |            |      |            |
|-----|-------|---|------|------|------|------------|------|------------|
|     |       | 2 | 2.5  | 5.0  |      |            |      |            |
|     |       | 3 | 5.0  | 10.0 |      |            |      |            |
|     |       | 4 | 10.0 | 15.0 |      |            |      |            |
| Age | years | 1 | 0.0  | 15.0 | 25.5 | $\pm 20.0$ | 22.7 | $\pm 15.0$ |
|     |       | 2 | 15.0 | 30.0 |      |            |      |            |
|     |       | 3 | 30.0 | 50.0 |      |            |      |            |
|     |       | 4 | 50.0 | 70.0 |      |            |      |            |

sd= standard deviation

Table\_Apx B-4 Details of homogeneous land covers and landscape features measured across the five study areas

| Measured landcover/<br>feature         | Species                        | Age (years) | Height (m) | AGBC (t ha <sup>-1</sup> ) | BGBC (t ha <sup>-1</sup> ) | DOMC (t ha <sup>-1</sup> ) | C <sub>total</sub><br>(t ha <sup>-1</sup> ) |
|----------------------------------------|--------------------------------|-------------|------------|----------------------------|----------------------------|----------------------------|---------------------------------------------|
| Clapham Park Broadleaf Woodland        | Ash                            | 14          | 7.4        | 35.9                       | 17.2                       | 5.0                        | 58.2                                        |
| Clapham Park Improved Grassland        | Unspecified Improved Grassland | 50          | 0.5        | 3.2                        | 4.8                        | 0.4                        | 8.3                                         |
| Harnhill Manor Farm Improved Grassland | Unspecified Improved Grassland | 23          | 0.5        | 2.6                        | 3.9                        | 0.3                        | 6.8                                         |
| Harnhill Manor Farm Arable Land        | Cereal                         | 1           | 0.5        | 2.3                        | 0.5                        | 0.3                        | 3.0                                         |
| Silsoe Site Arable Land                | Crops for Stockfeed            | 1           | 0.5        | 3.7                        | 0.7                        | 0.4                        | 4.9                                         |
| Clapham Park Lone Tree                 | Ash                            | 14          | 8          | 42.7                       | 20.5                       | 6.0                        | 69.2                                        |
| Crowmarsh Battle Farm Hedgerow         | Hawthorn                       | 10          | 1.5        | 12.0                       | 5.7                        | 1.7                        | 19.4                                        |
| Crowmarsh Battle Farm Hedgerow         | Hawthorn                       | 10          | 2.5        | 31.3                       | 15.0                       | 4.4                        | 50.7                                        |
| Crowmarsh Battle Farm Hedgerow         | Hawthorn                       | 10          | 2.5        | 27.4                       | 13.1                       | 3.8                        | 44.3                                        |
| Crowmarsh Battle Farm Hedgerow         | Hawthorn                       | 10          | 2.5        | 25.8                       | 12.4                       | 3.6                        | 41.8                                        |

|                                |              |    |      |      |       |     |       |
|--------------------------------|--------------|----|------|------|-------|-----|-------|
| Crowmarsh Battle Farm Hedgerow | Hedgerow Mix | 10 | 2.5  | 22.5 | 10.8  | 3.2 | 36.5  |
| Crowmarsh Battle Farm Hedgerow | Hedgerow Mix | 10 | 2.9  | 21.2 | 10.2  | 3.0 | 34.4  |
| Crowmarsh Battle Farm Hedgerow | Hedgerow Mix | 10 | 2.9  | 23.8 | 11.4  | 3.3 | 38.5  |
| Crowmarsh Battle Farm Hedgerow | Hedgerow Mix | 10 | 3.5  | 24.9 | 12.0  | 3.5 | 40.4  |
| Crowmarsh Battle Farm Hedgerow | Hedgerow Mix | 10 | 4.2  | 53.5 | 25.7  | 7.5 | 86.6  |
| Elm Farm Hedgerow              | Hawthorn     | 40 | 2.85 | 64.7 | 31.0  | 9.1 | 104.8 |
| Elm Farm Hedgerow              | Blackthorne  | 28 | 3.59 | 65.3 | 31.4  | 9.1 | 105.8 |
| Elm Farm Hedgerow              | Hazel        | 19 | 3.93 | 60.1 | 28.9  | 8.4 | 97.4  |
| Elm Farm Hedgerow              | Hawthorn     | 15 | 4.65 | 37.4 | 18.0  | 5.2 | 60.6  |
| Elm Farm Hedgerow              | Blackthorne  | 39 | 5.39 | 61.4 | 29.5  | 8.6 | 99.4  |
| Elm Farm Hedgerow              | Hazel        | 19 | 5.73 | 24.0 | 11.54 | 3.4 | 38.9  |
| Harnhill Manor Farm Hedgerow   | Hawthorn     | 12 | 3.4  | 48.8 | 23.4  | 6.8 | 79.1  |
| Harnhill Manor Farm Hedgerow   | Blackthorn   | 18 | 3.5  | 58.3 | 28.0  | 8.2 | 94.4  |
| Harnhill Manor Farm Hedgerow   | Hedgerow Mix | 14 | 3.6  | 63.4 | 30.4  | 8.9 | 102.7 |
| Silsoe Site Lone Tree          | Poplar       | 19 | 6.6  | 67.4 | 34.4  | 9.4 | 111.3 |
| Silsoe Site Lone Tree          | Poplar       | 19 | 8.4  | 59.3 | 30.3  | 8.3 | 97.9  |
| Silsoe Site Lone Tree          | Poplar       | 19 | 8.6  | 60.8 | 31.0  | 8.5 | 100.4 |

|                       |        |    |     |      |      |     |       |
|-----------------------|--------|----|-----|------|------|-----|-------|
| Silsoe Site Lone Tree | Poplar | 19 | 8.7 | 67.2 | 34.3 | 9.4 | 110.9 |
| Silsoe Site Lone Tree | Poplar | 19 | 8.9 | 61.9 | 31.5 | 8.7 | 102.1 |
| Silsoe Site Lone Tree | Poplar | 19 | 9.1 | 61.2 | 31.2 | 8.6 | 101.1 |
| Silsoe Site Lone Tree | Poplar | 19 | 9.4 | 67.8 | 32.5 | 9.5 | 109.8 |

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