**Regional carbon stock assessment and the potential effects of land cover change**

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## Abstract

Accurate assessment of carbon stocks remains a global challenge. High levels of uncertainty in Land Use, Land Use Change and Forestry reporting has hindered decision-makers and investors worldwide to support sustainable soil and vegetation management. Potential mitigation-driven activities and effects are likely to be locally/regionally unique. A spatially-targeted approach is thus required to optimise strategic carbon management. This study provides a new regional carbon assessment (tier 3) approach using biophysical-process modelling of high-resolution Land Cover (LC) data within a UK National Park (NFNP) to provide higher accuracy. Future Land Cover Change (LCC) scenarios were simulated. Vegetation-driven carbon dynamics were modelled by coupling two widely-used models, LPJ-GUESS and RothC-26.3. Transition and persistence analysis was conducted using Terrset’s Land Change Modeller to predict likely future LCC for 2040 using Multi-Layer Perceptron Markov-Chain Analysis. Current total carbon in the NFNP is 7.32-8.73 Mt C**,** with current trajectories of LCC leading to minor losses of up to 0.39 Mt C**.** Alternative LCC scenarios indicated possible gains or losses of 1.27 Mt C, or 136.7 t C ha-1. The importance of vegetation-driven carbon storage was greater than the national average, with a VegC pool 12-14% of the soil organic C pool, placing greater significance on local/regional LC and management policy. The potential storage capacity of each LC class was ranked (highest to lowest): Coniferous > Broadleaved/Mixed > Coastal > Semi-natural Grassland > Heath > Improved Grassland > Arable (Cropland). Opportunities were prioritised to inform landscape-scale management to reduce future carbon losses and/or to enhance gains through LCC. Balancing the carbon budget relies upon maintaining existing LC. The more detailed LC classification facilitated accounting of management through stock change factors and disaggregation of classes, achieving greater detail and accuracy. Forthcoming policy decisions must optimise carbon storage at a local/regional landscape-scale.

Keywords:

Soil organic carbon; terrestrial; Land use, land use change and forestry; land cover change; carbon budget

## Introduction

The importance of Soil Organic Carbon (SOC) has received increasing international attention as a valuable strategy to mitigate against climate change (Bispo et al., 2017), through initiatives such as the ‘4p1000’ (Chabbi et al., 2017; Rumpel et al., 2020) and the Global assessment of SOC sequestration potential (GSOCseq) programme (Smith et al., 2020). The global pool of SOC holds 4.5 times the amount of carbon in all living biomass and 3.1 times that in the atmosphere (McClean et al., 2015; Mayer et al, 2020); therefore, small changes in terrestrial carbon stocks (soils and vegetation) could significantly impact the concentration of atmospheric carbon (Lal et al., 2018). Through protection of existing land-based carbon stocks, as well as enhancing natural terrestrial sequestration, land managers and policy makers can reduce emissions and remove atmospheric carbon dioxide (while delivering other ecosystem services). Utilising Natural Climate Solutions (NCS) can provide one-third of the cost-effective mitigation needed by 2030 to stabilise warming to below 2 °C (Griscom et al., 2017). Although there is still a large range of uncertainty in the offset potential to reduce the global carbon budget, the maximum potential of NCS is estimated at 23.8 Pg CO2e yr-1 (6.49 Gt C yr-1) by 2030, with soil carbon representing 25% of this potential (Bossio et al., 2020). Further uncertainty exists between the technical and feasible potential, as well as the spatial variation between and within countries dictating whether protection or sequestration may be more significant (Crump, 2017).

Quantifying the capacity of plants to store atmospheric inorganic carbon in their biomass and eventually in the soil as organic carbon for an extended period is essential for climate change mitigation and soil fertility improvement (Mathew et al, 2020). An accurate assessment of carbon stocks, and any changes, is required annually to meet international commitments on carbon budgets for signatory countries under the Kyoto Protocol and UN Framework Convention on Climate Change (UNFCCC) (Moxley et al., 2014). The UK has additional domestic legal obligations to achieve net-zero emissions by 2050 (HM Government, 2019), with fundamental changes needed to meet future statutory emissions reductions targets (Thomson et al., 2018). A National Inventory Report (NIR) is submitted for annual emissions and includes the Land Use, Land Use Change and Forestry (LULUCF) sector, unique within carbon accounting in its capacity to be both a source and sink of Greenhouse Gases (GHGs). The LULUCF sector is key to achieving carbon neutrality by 2050, as prescribed by the Paris Agreement (Savaresi, Perugini and Chiriacò, 2020). Since 1990, the NIR has claimed the LULUCF sector to be a net sink, although with high uncertainty ranging from 25-55% (Ricardo, 2020). Recent changes in the methodology to account for peat-derived emissions has resulted in a tenfold increase (to 23 Mt CO2e yr-1), resulting in a significant shift of the whole LULUCF inventory to a net source (Evans et al., 2017). The updated method highlights the need for comprehensive accounting, and the particular importance of peat and high carbon organic soils.

There remains a large gap between the capacity to enhance terrestrial carbon stocks, and commitment to establish SOC targets (with only 10 countries referring to SOC in their Nationally Determined Contributions (NDCs) (Wiese, 2019). A key barrier to increasing SOC is the need for reliable and credible measurement/monitoring, reporting and verification (MRV) platforms, for both national reporting and emissions trading (Bispo et al., 2017; Smith et al., 2020). Research such as this which reduces the uncertainty surrounding terrestrial carbon MRV is required to improve confidence for beneficial investments and public subsidies to support long-term climate change mitigation. There is incomplete process-level understanding of how carbon stocks are affected by variables including edaphic factors, climate, land use and management (Stockmann et al., 2013; Bispo et al., 2017). Simulation models have been increasingly used to predict SOC dynamics and evaluate changes in time and space (Campbell & Paustian, 2015), thereby helping to inform policy, land use and management decisions.

The terms land use and Land Cover (LC) are not synonymous. LC is directly observable and can be determined from satellite data, whereas land use requires additional information (Tomlinson et al., 2018). LC refers to the surface characteristics, such as vegetation or buildings, whereas land use describes the social and economic use of LC (van Soesbergen, 2016). Within the UK, the Vegetation Carbon (VegC) stock is relatively small (<5% of Soil Organic Carbon (SOC) (Ostle et al., 2009)), yet represents the most important source of carbon inputs for the soil (Leake et al., 2006). The balance between organic matter inputs and losses through decomposition determines the total terrestrial carbon reservoir (Lal et al., 2018). Therefore, policies that affect LC and management (its type, productivity, distribution and turnover) will influence the overall balance of vegetation-driven carbon storage, emissions or removals (Bispo et al., 2017).

Possible mitigation-driven activities and their effects are likely to be locally/regionally unique (Cantarello et al., 2011) and therefore a more spatially targeted approach is required to optimise strategic carbon management specific to local contexts (Brown, 2020). Nevertheless, there have been relatively few spatially explicit studies such as this undertaken in the UK that use detailed Land Cover Change (LCC) data to evaluate carbon stocks at a regional or landscape scale (Cantarello et al., 2011; Burke et al., 2020; Tomlinson et al., 2018), with the majority not going beyond a single devolved administration (Smith et al., 2011; Manzoor et al., 2019). However, the scale of assessment is increasing, with the NIR moving to local authorities for the first time in 2019 (Ricardo, 2020). Similarly, as the UK has exited the EU, assessments up to farm scale will be increasingly valued (Burke et al., 2020), as a new Agricultural Bill (CCC, 2019) seeks to financially support public goods, including soil management and carbon stewardship.

This study aimed to provide a regional carbon assessment (tier 3) using biophysical-process modelling of high-resolution LC data. The existing carbon stocks within the New Forest National Park (NFNP) were quantified and used as a baseline to model the future effects of likely and alternative LCC scenarios. Analysis of current management plans and alternative options estimated the technical potential changes from biophysical factors, but did not consider the feasibility through socioeconomic factors. Opportunities were identified that could inform landscape-scale management to reduce future carbon losses (avoiding GHG emissions) and/or to enhance gains (increasing sequestration).

## Methods

**2.1 Study area**

The New Forest National Park (NFNP) (Figure 1) covers 56,658 ha on the central south coast of England (Forest Farming Group, 2019) (latitude: 50o42’19” to 51o0’17”N, longitude: 1o17’59” to 1o48’8” W). Although one of the smallest of the nine national parks in England, it represents an important temperate ecosystem, with outstanding examples of 13 habitats (Cantarello et al., 2011) and 56% of the area designated under International and National nature conservation legislation (NFNPA, 2010). The complex mosaic of habitats consist predominantly of lowland heathland, grassland and woodland (Tubbs, 2001). Unique features include 75% of the valley-mire wetlands in Western Europe (90 out of 120) (Clarke & Allen, 1986; NFNPA, 2007) as well as one of the highest concentrations of ancient trees in the UK (NFNPA, 2019).

Furthermore, the NFNP is the largest area of extensively grazed semi-natural vegetation in lowland Britain (Cox and Reeves, 2000), characterised by freely roaming large herbivores including both deer and livestock. A rare pastoral system known as ‘commoning’ has survived due to protected grazing rights on common land. As a result, an area of unenclosed ‘Open Forest’ is defined within a ‘Perambulation’ boundary. Commoning as a form of land management has been supported by the largest environmental improvement scheme in England, the Higher Level Stewardship (HLS) scheme (NFNPA, 2019). The scheme cost £19 million from 2010-2020, and in some years covered up to 42% of the NFNP area (Howe, 2018).

The soil is a mixture of slightly acidic, well-drained clay and loam, with some continuous waterlogging and outcrops of neutral enriched soils (Natural England, 2014). Peat and humic soils occur where the water table comes to the surface, with seasonal or permanent waterlogging in the valleys (Forest Farming Group, 2019).

**2.2 Model framework**

In order to model vegetation-driven carbon dynamics, two widely-used models were coupled (Smith et al., 2005; Smith et al., 2006; Werner et al., 2018; Forrest et al., 2020); a dynamic-vegetation model, LPJ-GUESS (Sitch et al., 2003; Smith et al., 2014), was used to simulate ecosystems of vegetation within specified parameters, or so-called plant functional types (PFTs). The Organic Matter (OM) litter derived from LPJ-GUESS was then applied to RothC-26.3 (Coleman and Jenkinson, 1996; Nemo et al., 2017) which modelled the turnover of organic carbon in soil. The PFT outputs for each carbon pool were assigned to a LC class following proportions from a cross-walking table (Poulter et al., 2015). In order to calculate total stock for each carbon pool, each LC class was multiplied by its area within the NFNP.

**2.3 Data collection**

**2.3.1 Climate data**

Monthly climate data was obtained (Met Office, 2011) from four weather stations in closest proximity to the NFNP for the period 1980-2010 (see Appendix B). The variables for temperature, sunshine and rainfall were averaged across all four stations and adjusted where necessary into the units required for modelling (e.g. hours/month to hours/day). Evapotranspiration rates were determined using an ETo calculator (FAO, 2009) in combination with the temperature and sunshine variables. Open pan evapotranspiration values were then found by dividing by 0.75 as recommended by Coleman & Jenkinson, (2014). Atmospheric carbon dioxide levels were acquired from the Mauna Loa station’s global mean for the year 2019, at 412 ppm (NOAA, 2020).

**2.3.2 Soils**

Soil data was obtained from the generalised soil map ‘SoilScapes’ rendered by the National Soil Resources Institute (Cranfield University, 2016). The range of clay content for the identified soil types ranged from 0-40%, therefore the median value of 20% was selected for the RothC-26.3 model. A depth of 30cm was assumed following IPCC guidelines (IPCC, 2006, 2019) and UK’s soil carbon database (Bradley et al., 2006). Due to the lack of available data for detailed spatial variation, a uniform soil code (6 – ‘fine-medium’) was used for LPJ-GUESS. This represented the closest fitting code to the mean of model outputs (for each soil code) following test-simulations (see Appendix G).

**2.3.3 Land Cover (LC)**

Land Cover Map (LCM) datasets from the UK Centre for Ecology and Hydrology (UKCEH) were selected as they have been used in the UK’s NIR and will continue to be used in future assessments (Ricardo, 2020). Other spatial datasets were considered (ESA-CCI, CORINE, MODIS) which have been used in recent attempts to improve reporting (e.g. Levy et al., 2017; Tomlinson et al., 2018). However, LCM was discerned to be the most accurate, with the highest kappa coefficient and resolution (Burke et al., 2020). The most recently released data from the LCM dataset (Morton, 2020) was selected to represent current land cover, at the highest resolution of 20m.

**2.4 Modelling**

**2.4.1 Dynamic Vegetation model**

The monthly climatic data collected (Appendix B) was used to construct an environmental driver file (Appendix C), with annual climate repeated for an initial ‘spin-up’ period of 1000 years. This allowed for vegetation, litter and soil pools to reach equilibrium with the climate data. Model evaluation (Appendix E) was then based upon the average of the following 100-year simulated ‘scenario phase’. The climatic change parameters were set to zero (for temperature, precipitation, CO2 and nitrogen deposition).

Simulations were run separately in cohort mode for each PFT, with selection of PFTs determined by the bioclimatic limits of the study area. Default parameters were used for temperate trees and grasses (Sitch et al., 2003), however shrub PFTs had to be created following parameters provided by Wolf (2008) (see Appendix G for PFT parameters).

LPJ-GUESS outputs the biomass of vegetation carbon (VegC) and Net Primary Productivity (NPP) of a PFT, allowing the litter inputs of Organic Matter (OM) to be calculated based on annual change in vegetative C (VegC):

***OM = VegC – NPP***

**2.4.2 Soil organic carbon model**

RothC-26.3 describes the process-based movement of carbon through different pools which vary in decomposition rates (Milne et al., 2012). A version of the model which applied the mathematical principles in Microsoft Office Excel was used (Appendix D) to facilitate ease of data analysis. The same climatic data (Appendix B) was used for temperature, rainfall and evapotranspiration. For each PFT the annual OM litter input derived from LPJ-GUESS was divided evenly per month and multiplied by a respective Decomposable Plant Material (DPM)/Resistant Plant Material (RPM) ratio. These parameters partition the incoming plant material into relevant pools. Standard ratios provided for most PFTs were used (Coleman & Jenkinson, 2014), with the exception of shrubs which were adopted from Wolf (2008) (Appendix E)**.** The same spin up time of 1000 years was used, with a 100-year scenario phase using monthly timesteps. Model output units were kg C m2 and converted to t C ha-1.

**2.5 LC classification**

Two reclassification methods were used following the UKCEH’s aggregation (Appendix A) for 6 simplified classes (Rowland et al., 2020), and 10 dominant aggregate cover classes (Morton, 2020). These are hereafter referred to as Simplified Land Cover (SLC) and Disaggregated Land Cover (DLC) classes. The SLC classes provide the 3 classes required for LULUCF reporting (Grassland, Woodland, Cropland) (Rowland et al., 2020). The DLC classes were included as a comparison to discover if further disaggregation from 3 into 7 more detailed classes would affect reporting and therefore land management decisions (at a regional scale). Only classes reported in the LULUCF section of the NIR were considered with all ‘Other’ classes (e.g. built-up areas, inland rock) excluded.

A cross-walking table was then used to assign proportions of PFT outputs to LC classes (Table 1) which followed the standardised general framework of the United Nations Land Cover Classification System (UN LCCS) methodology (Poulter et al., 2015).

**2.6 Management Weightings**

Stock Change Factors (SCF) were applied to 4 LC classes to account for management through tillage (Arable) and grazing (applied to Heath, Semi-natural Grassland and Improved Grassland). These were calculated following the approach used in other models which assumes a grazing effect (G) on the NPP of non-woody vegetation reduced by 50% (Clark et al., 2011). The area (A) of each LC class accessible to freely-roaming ruminants was also considered, which for Semi-natural Vegetation was 37% and for Heathland was 98% (Forest Farming Group, 2019). Improved Grassland (defined as being managed for pasture or mown regularly) was assumed to be 100% accessible.

Therefore: ***SCF = 1 - (G \* A)***

e.g. Improved Grassland = 1 - (0.5 x 1) = 1 – 0.5 = 0.5

Where a LC class included a combined percentage of herbaceous vegetation *(H)* (shrubs and grass PFTs) and woody vegetation (tree PFTs), then:

***SCF = 1 - ((G \* A) \* H)***

e.g. Heathland = 1 - ((0.5 x 0.98) \* 0.74) = 1 - 0.363 = 0.636

The Arable (Cropland) class was deemed similar to Improved Grassland in having biomass (crops) removed annually. Therefore, the same SCF of 0.5 was applied. Notably, although the Arable SCF was applicable to both reclassification methods (SLC and DLC), grazing SCFs could only be applied under the more detailed DLC method which distinguished management of grassland classes (e.g. Improved Grassland).

**2.7 Model validation**

The initial modelled outputs and constrained results using SCFs to account for management were compared to results in the literature, including a systematic review for expected carbon stocks in the South West UK (Cantarello et al., 2011). Further comparison of modelled results for current carbon stocks was achieved through obtaining spatial datasets for SOC and Above Ground Biomass (AGB) within the NFNP boundary. The digital soil map datasets used were the Global assessment of SOC sequestration (GSOC) (1km grid to 30cm depth) (FAO, 2019), as well as the map ‘Soil Grids’ from the International Soil and Reference Information Centre (ISRIC) (250m grid, to 30cm depth) (ISRIC, 2020). Both use soil profile data and environmental layers, with the Soil Grids dataset applying machine learning methods for predictive ensemble modelling.

The two AGB ‘GlobBiomass’ datasets used were from the European Space Agency (ESA) Data User Element (DUE) (Santoro, 2018) and Climate Change Initiative (CCI) projects (ESA-CCI, 2018). The datasets calculate the mass of woody parts of living biomass based on combined earth observation data for the years 2010 (to 150m) and 2017 (to 100m) for CCI and DUE respectively.

The carbon stocks within the NFNP boundary derived from these SOC and AGB datasets were summed to give the TOC, and then compared to the modelled LPJ-RothC results and expected values (Mean, Min. and Max.) from the literature (Table 4).

**2.8 Land cover change scenarios**

Spatial analysis was conducted upon seven historical raster LCMs from the UKCEH’s dataset for the years 1990-2019 to determine the areas of LC classes for each period (Appendix H). Despite the LCM’s classification having been based on the UK Biodiversity Action Plan (BAP) Broad Habitats (Jackson, 2000), some inconsistencies in the number of classes were identified. Although the same classes have been used since 2015 with near matches to LCM 2007 and LCM 2000 (Morton et al., 2011), a recently updated dataset was selected which standardised the classification (and resolution of 25m) for the years 1990 and 2015 (Rowland et al., 2020). Furthermore, this enabled transition and persistence analysis to be conducted in Terrset’s Land Change Modeller (Clark Labs, 2015) in order to predict future land cover change for the year 2040. A combination of a Multi-Layer Perceptron (MLP) neural network to create transitional potential maps, as well as Markov-Chain Analysis (MCA) was used to model these transitions. The MLP-MCA calculated transition probabilities (Appendix I) to give a baseline ‘best-guess’ prediction of many highly plausible scenarios based upon current land cover changes. The net change was multiplied by the modelled carbon stocks to give the total net carbon gain or loss for each LC class.

To calculate gains and losses between all 42 possible LC transitions, a transition matrix was created to show the change in TOC between each LC class. Assumptions were made for the time to equilibrium according to the NIR methodology (Ricardo, 2020), with all changes to Woodland assumed to be slow (100 years to maturity) while changes to all other LC classes were fast (30 years). Scenarios were constructed to calculate the total and annual gains/losses from the effects of current planned management (e.g. Forest Design Plans 2019-2029 (Forestry England, 2020) and other alternative options which applied LC trends obtained from spatial analysis of the historical LCMs.

## Results

### 3.1 Carbon pools per LC

Comparison of initial results for PFTs showed soil carbon was on average 4 times greater than vegetation carbon (141.0 t C ha-1 = Mean SOC and 35.3 t C ha-1 = Mean VegC). A Mann-Whitney test showed a significant difference across all PFTs (U < critical value (p) = 8 < 12 (where (p) > 99.9% confidence)). When PFT proportions were then assigned to LC classes (Table 1), SOC was on average 8.3 and 7.1 times greater than VegC, for SLC and DLC respectively (Table 2). However, despite the effect of reduced NPP through management factored into more DLC than SLC classes, the total mean VegC pool was slightly higher for DLC classes (17.4 > 15.6 t C ha-1).

The highest initial TOC by LC class was Coniferous (217.4 t C ha-1) and the lowest was Improved Grassland (157.3 t C ha-1). Once management was factored in**,** the effect of grazing constrained values (Figure 2)to be within the ranges of a systematic review (Cantarello et al., 2011), closely matching the mean (for Semi-natural vegetation, Improved Grassland and Heathland). Although the TOC for Improved Grassland and Arable were both reduced, Arable became the lowest value for TOC at 80.7 t C ha-1 (see Table 2 for all ranked classes).

There was variation in carbon pools between the two aggregation methods (Table 2). The mean of ‘Woodland’ DLC classes gave a higher estimate for all carbon pools compared to Woodland under the SLC method (TOC = 187 t C ha- 1 for SLC and mean of 201.2 t C ha- 1 for DLC). For Grassland, the mean for the DLC classes was lower for SOC and TOC, yet higher for VegC. Values for Arable were the same for both aggregation systems.

The disaggregation of Woodland (187 t C ha- 1) into Coniferous and Broadleaved estimated a higher TOC for Coniferous (217.4 t C ha- 1) with Broadleaved slightly lower (185 t C ha- 1). Overall, Woodland classes (green) had the largest overall TOC, yet this was not always true for the SOC, with the SLC Grassland class (164.6 t C ha- 1) higher than the Woodland SOC (148.9 t C ha- 1). Where management was accounted for in the associated ‘Grassland’ DLC classes (for Heathland, Semi-natural Grassland and Improved Grassland), the mean SOC (118.5 t C ha- 1) was then less than Woodland classes. Notably, the Coastal class, which was exempt from grazing, was higher in SOC (159 t C ha-1) than the Broadleaved (146.2 t C ha- 1). Similarly, the Coastal class (172.9 t C ha- 1) also had more than twice the TOC of Improved Grassland (83.9 t C ha- 1), which highlighted the large range (83.9 t C ha- 1) within the multiple ‘Grassland’ classes normally aggregated into one Grassland class.

**3.2 Land Cover of the New Forest National Park (NFNP)**

This study followed IPCC guidelines (IPCC, 2006, 2019) for land cover considered in the national LULUCF reporting, with ‘Other’ categories excluded. Therefore, the percentage of the NFNP included was 89.46% for the SLC classes, and 92.87% for the DLC classes due to the additional inclusion of Coastal classes (Appendix A).

Under the SLC method, Grassland (49.26%) and Woodland (36.83%) account for most of the NFNP area (85%). The DLC method gives more detail and showed that Heath was the most dominant cover (26.6%). Additionally, approximately two thirds of Woodland was Broadleaved/Mixed (23.3%), with Coniferous 13.5%. Aside from Improved Grassland (22.5%), the remaining classes represent a combined minority of 6.93%.

**3.3 Total carbon pools in the New Forest National Park (NFNP)**

The total carbon stock in the NFNP is estimated to be 8.73 and 7.32 Mt C by the SLC and DLC methods, respectively (Table 3). Analysis of the difference from SLC to DLC classes highlighted a change in the dominant carbon stock, with a reduction in ‘Grassland’ TOC to 3.07 Mt C and a small increase to 4.11 Mt C for ‘Woodland’ classes. The significance of Heath was exposed within DLC classes as the second highest TOC stock (1.66 Mt C), equal to the TOC of Coniferous. Despite the Coastal class having the highest carbon of ‘Grassland’ classes, the relatively small areas within the study area meant that total carbon was only 0.33Mt C, although this is still more than twice that stored within Arable land.

The LPJ-RothC model simulations used to quantify current TOC stocks in the NFNP (7.3-8.7 Mt C) compared well with results derived from a systematic review (X̄ = 8.3 Mt C) (Cantarello et al., 2011). Furthermore, comparison to the other spatial data for SOC (GSOC/Soil Grids) and AGB (ESA DUE/CCI) gave a combined total of 7.49 and 7.99 Mt C (see Table 4). The SLC and DLC methods represented the highest and lowest total estimates respectively, however the difference was relatively small (1.4 Mt C) and quite close (-1 to +0.4 Mt C) either side of the mean expected value (Cantarello et al. 2011). All comparison values fell within this range, and well within the possible minimum and maximum values expected (Cantarello et al., 2011).

The totals estimated for SOC (7.83 and 6.21 Mt C) were more than the values from Soil Grids (3.8 Mt C) and GSOC (4.3 Mt C), yet closer to the mean estimate (X̄ = 6.03 Mt C) derived from the literature (Cantarello et al., 2011). Conversely, the totals estimated for VegC (0.89 and 1.11 Mt C) were less than the values from ESA-DUE (3.76 Mt C) and ESA-CCI (3.62 Mt C), but still closer to Cantarello’s (2011) mean estimate (X̄ = 2.23 Mt C).

The spatial distribution of the carbon was mapped according to the two different aggregation methods (Figure 3), with the location of existing carbon stocks quantified for each type of land cover. The most noticeable differences for the DLC map was the dominance of Heathland (purple) and the addition of Coastal (light blue) areas which would otherwise have been classified as Grassland (bright green). In addition, the area of Coniferous (dark green) was also distinct from Broadleaved areas, whereas Arable remains the same, and Semi-natural Grassland was hard to distinguish.

**3.4 Land cover change scenarios**

The potential TOC gains or losses between LC changes calculated in a transition matrix ranged from 80.7 to 217.4 t C ha-1. The LC transitions that lead to losses of carbon were ranked (from smallest to largest losses): Coniferous < Broadleaved/Mixed < Coastal < Semi-natural Grassland < Heath < Improved Grassland < Arable (Cropland). Conversely, any LC cover changes made in the reverse order improved carbon gains; the highest potential LC change (from Arable to Coniferous, or vice versa) would change TOC by 136.7 t C ha-1. In addition, transitions between LC classes which accounted for management were ranked as the four classes with the lowest total carbon stocks.

The MLP-MCA predicted a net area change of 1789 ha lost by 2040 from the classes of Grassland, Woodland and Arable, equal to 3.52% of the study area (Table 5). Although a small gain was predicted from Arable transitioning to other LC classes, overall there was a net loss of 0.39 Mt C (predicted net change graphs between 1990-2040 and transition maps are included in Appendix J). The results presented had an accuracy of 51% based on the Markov-Chain probabilistic tables (Appendix I), therefore they were treated as an indicative baseline with low confidence.

The results from spatial analysis of LCM datasets indicated an increase in the area of Improved Grassland and Heathland, with a decrease in Woodland and relatively constant Arable (Appendix H). There was also an increase in ‘Other’ classes implying increased urban development. Based on these trends identified and current management plans (Forestry England, 2020), hypothetical transition scenarios were constructed to calculate possible changes (Table 6). The current Forest Design Plans (conifer removal) until 2029 will lose a relatively small 0.04 Mt C (0.03 t C ha-1 yr-1),which is 10% of another deforestation scenario where half of the area of Conifers transition to Heathland (-0.41 Mt C). The highest loss of carbon was through deforestation from Woodland to Arable (-1.26 Mt C, or -1.84 t C ha-1 yr-1)**.** Conversely, afforestation could lead to gains of up to 1.27 Mt C (or 0.26 t C ha-1 yr-1)**.** Notably, the difference results between the DLC and SLC methods could be large (up to 1 Mt C), particularly with transitions involving Grassland.

The DLC method allows for more transitions beyond the six possible with the SLC method, for example from Heath to other classes. If succession was allowed through reduced grazing on 50% of the NFNP, the storage potential would increase through changes to woodland classes and those with less grazing (and agriculture); annual gains would range from 0.19 – 0.36 t C ha-1 yr-1 resulting in a total gain of 0.56-0.81 Mt C (an 8-11%increase of current TOC).

## Discussion

**4.1 Context**

The purpose of conducting a tier 3 assessment to quantify existing carbon stocks provides a higher accuracy baseline to improve MRV. In addition, a spatially explicit approach at a regional scale allows for land managers to target carbon pools and prioritise respective management opportunities. Attempts to remotely assess current carbon stocks and estimate future storage potential at the landscape scale are needed to optimise land-based climate mitigation strategies (Tomlinson et al., 2018; Burke et al., 2020). Accurate assessment is particularly relevant for the UK given its exit from the EU and transition to domestic payment schemes for ecosystem services.

**4.2 Results analysis**

**4.2.1 Model performance**

Overall, LPJ-RothC model outputs for each carbon pool compared well with previous values, including the UK’s soil carbon database (Bradley et al., 2006; Cantarello et al., 2011). Carbon pools of Grassland and Arable classes were initially higher than mean values from a systematic review (Cantarello et al., 2011). However, where management (e.g. grazing) could be accounted for through stock change factors, values then fitted more closely with the expected mean for each carbon pool (Figure 2). As the DLC method distinguishes between otherwise aggregated classes, accounting for their respective management is facilitated. This improves on the current LULUCF/SLC method that uses Grassland as a buffer class, allocating any LC other than Woodland or Cropland (Ricardo, 2020). Furthermore, the DLC method enables additional LC classes to be ranked, thereby providing extra information to prioritise LC by their potential storage capacity (e.g. Grassland is disaggregated to: Coastal > Semi-natural Grassland > Heath > Improved Grassland). Other classes can be included in this ranking, assuming data availability (e.g. bogs or peatland). When classes in the two methods are ranked by TOC, the DLC classes were more accurately aligned to the order expected from the literature (Woodland > Grassland > Arable) (Guo & Gifford, 2002; Berhongaray et al., 2013; Cantarello et al., 2011)**.**

One exception to the otherwise successful model-framework performance was for the VegC of Broadleaved (38.8 tC ha-1) which was below the minimum expected value (57 tC ha-1) of Cantarello et al., (2011), yet still within the range of 36.4-90.6 tC ha-1provided by Milne et al.(1997). A suggested cause is the prescribed allocation of solely the Broadleaved Summergreen PFT, but not the Evergreen PFT, which had a higher value of 66.7 tC ha-1 within the expected range. Furthermore, while carbon stocks were estimated to be higher for Coniferous than Broadleaved, some studies suggest that Broadleaved has the capacity for higher SOC and VegC than Coniferous, although the range is highly variable (Guo & Gifford, 2002; Ostle et al., 2009; Cantarello et al., 2011)**.** However, it is possible for Coniferous to store more carbon than Broadleaved (Dorji et al., 2014), with higher values for carbon stocks found under Coniferous in agreement with the UK’s forest survey (Vanguelova et al., 2013). Forestry management may explain differences between managed plantations and undisturbed natural forests caused by thinning and harvesting. Although forestry management was not accounted for, there was an assumption that if well managed and harvest residues are left behind it is not significant (Lal, 2010).

Model-data agreement was found for the modelled TOC stocks (7.3-8.7 Mt C) through validation against other spatial datasets (7.49, 7.99 Mt C). Comparison by carbon pools indicated an overestimation for modelled SOC and underestimation for VegC, though these estimates may be more accurate by capturing landscape variation at a higher resolution (20m2). The modelled ratios of SOC to VegC seem appropriate, on average 8.3 and 7.1 times greater for SLC and DLC respectively. The global ratio of carbon in soils is 4.5 times that of VegC (McClean et al., 2015) yet estimates in the UK are 20 times or more (Ostle et al., 2009). As the NFNP represents an area of higher than national average terrestrial biomass, with modelled results (3.2 Mt C) approximately 2% of the UK’s total woodland stock (Vanguelova et al., 2013), there is greater significance of vegetation-driven carbon storage for regional LC and management policy. The significance of LC as a main driver of carbon dynamics was demonstrated as the TOC results of LPJ-RothC were similar to more complex predictive models (FAO, 2019; ISRIC, 2020) which include many other covariates but operate at a lower resolution (250m2/1km2).

**4.2.2 Land Cover Change**

Transitions between LC classes were broadly in line with other studies of LCC, with potential total carbon storage highest under afforestation scenarios and lowest under deforestation (Guo & Gifford, 2002; Cantarello et al., 2011). The transition matrix highlighted that these LC changes could avoid or gain up to 136.7 t C ha-1. The MLP-MCA prediction based on the current trajectory of LCC was relatively minor, indicating a net loss of 0.39 Mt C (or 1.43 Mt CO2e) which is off-track for the NFNPA to achieve their aim of ‘net-zero with nature’ by 2050 (NFNPA, 2020). Current management plans are likely to lead to small losses through reduced woodland (-0.03 t C ha-1 yr-1). Alternative hypothetical transition scenarios leading to gains were identified including a reduction in grazing and any form of afforestation, particularly Coniferous woodland. Ranking of scenarios by annual change (highest to lowest) indicated: allowing succession (no grazing) > afforestation > partial grazing > woodland management > agricultural management > deforestation**.** However, some caution in interpreting these results may be needed, as scenarios are averaged to equilibrium and time-to-maturity is assumed; therefore short to medium term losses from an initial disturbance may not be accounted for (e.g. Broadleaved to Coniferous may have higher potential storage eventually, but significantly lose carbon initially before regaining it gradually over decades or centuries (Guo & Gifford 2002)). The rate of loss being greater than rate of gain is evident by the difference in annual losses from deforestation being significantly larger than annual gains from afforestation.

**4.3 Uncertainty**

LCC analysis requires selection of appropriate datasets and standardised classification methods which present challenges at both national and regional levels (Herold et al., 2008). The UKCEH’s LCM was understood to be the most accurate dataset available (Burke et al., 2020) with an impressive national average of ~80% (Morton, 2020); accuracy validation within the NFNP was slightly lower at 74%, attributed to classification difficulties (between a higher than average proportion of) ‘Heather’ and ‘Heather grassland’). This still compares well with global LC mapping accuracy which aims for <30% error (Fritz et al., 2011; Santoro, 2019). Furthermore, the recent LCM datasets use automated machine learning classification (Random Forest) which improves the accuracy of spatial assessment and produces maps rapidly therefore allowing for annual comparison.

The uncertainty involved in prescribing PFT proportions to LC classes can be greater in cross-walking than in LC classification (Hartley et al., 2017). LCM class definitions make it difficult to distinguish between fractional cover precisely, with wide ranges within a class (e.g. >20%) that do not account for regional variations in PFT fractions (Hartley et al., 2017). Classification is therefore likely to be subjective and based upon expert judgement at best. A solution may be to have regional cross-walking tables, or alternatively using a blend of continuous vegetation maps rather than just categorical LC classes (Hansen et al., 2003). Improvements in remote sensing, or vector-based approaches in combination with ensemble models, may improve efficiency through direct assessment of LCC per cell (Levy et al., 2017).

Spatial heterogeneity and depth of soils was poorly described in available data, however test simulations determined there was minimal variation between soil types, apart from organic soil which produced higher biomass per PFT (Appendix G). Organic soils, in particular those containing peat, have the highest saturation of SOC (Parry & Charman, 2013). The significance of accurately assessing peat has been raised in the UK’s NIR (Evans et al., 2017), yet quantifying peat through remote sensing can be difficult, as with bogs and saturation levels (Burke et al., 2020). Peat distribution and depth has been relatively poorly mapped within the NFNP (Tubbs, 2001), with surveys observing deposits from 30cm up to 5m (Natural England, 2014). The uncertainty around peat remains potentially significant and unaccounted for, with SOC values of up to 300 t C ha-1 yr-1 found in shallow peat (to 30 cm) in a similar national park, Dartmoor (Parry & Charman, 2013).

**4.4 Future research**

Developments to specific LPJ-GUESS model versions could be used to better account for disturbances from wildfire or intentional burning (LPJ-LMfire), as well as saturation (LPJ-Why). To improve Arable biomass modelling, specific Crop Functional Types (CFTs) may improve accuracy. Furthermore, regional and species-specific parameters could be modelled (Hickler et al., 2012)**.** Available software has advanced the capacity of LPJ-GUESS to model current and future climatic changes using gridded data (Bagnara et al., 2019). Consideration of different climatic pathways and their effect on SOC would be useful, given that predictions of future carbon sequestration are still highly uncertain (Lal, 2008).

Additional data to fill gaps in remote sensing may be helpful, such as for peatlands and saturation. Advances in peatland assessment have been made through ground-penetrating radar(Parry et al., 2014), with dynamic soil layers improving the ability to account for seasonal and saline flooding (Snell et al., 2013)**.** Development of MLP-MCA probabilities with other such covariates would increase model complexity but will likely increase the accuracy and plausibility of future LC maps.

The focus of LULUCF has primarily focused on LCC rather than management of terrestrial carbon stocks (Moxley et al., 2014). Beneficial management practices are known (Dawson & Smith, 2007) and their importance increasingly recognised (Ricardo, 2020), yet further research is required to build an evidence base for the complex range of existing options (Burgess et al., 2019).

## Conclusions

A new regional carbon assessment (tier 3) approach using biophysical-process modelling of high-resolution LC data within a UK National Park has demonstrated higher accuracy. Current total carbon in the NFNP was between 7.32-8.73 Mt C**,** with current trajectories of LCC leading to relatively minor losses up to 0.39 Mt C**.** Alternative LCC scenarios indicated possible gains or losses of up to 1.27 Mt C, or 136.7 t C ha-1. The importance of vegetation-driven carbon storage was greater than the national average, with a VegC pool 12-14% of the SOC pool, placing greater significance on regional LC and management policy. The potential storage capacity of each LC class was ranked (highest to lowest) as: Coniferous > Broadleaved/Mixed > Coastal > Semi-natural Grassland > Heath > Improved Grassland > Arable (Cropland). Similarly, prioritised transition scenarios for spatially explicit areas were ranked: succession (no grazing) > afforestation > partial grazing > woodland management > agricultural management > deforestation**. K**nowledge of potential carbon storage, along with spatial maps, can support landscape-scale management decisions globally to reduce carbon losses (avoiding GHG emissions) and enhance gains (increasing sequestration) through LCC. The benefits of maintaining LC to protect existing carbon stocks are demonstrated, particularly with higher priority classes. Thus, nations’ strategies, policy decisions and payments to land managers must carefully reconsider the value (and costs) of habitat management, whilst simultaneously optimising carbon storage (and other ecosystem services).

Improvements to the current LULUCF reporting were achieved using a more detailed classification method which improved accuracy, through differentiation between classes, as well as accounting for their respective management. Reducing the biophysically modelled output within the context of local management factors constrained the biomass simulated to within expected values. While additional classes such as heath and coastal regions were included, some difficulties were found in accounting for peatland and wetlands through remotely sensed data which remains an area of uncertainty. The significance of omitting peat-derived emissions from accounting has been highlighted previously (e.g. in the UK’s NIR), with comprehensive accounting required to improve future accuracy. Overall, the increased complexity introduced through disaggregation of classes obtained increased detail and accuracy of results.

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