Title: Can Regenerative Agriculture increase national soil carbon stocks? Simulated country-scale adoption of reduced tillage, cover cropping, and ley-arable integration using RothC

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ABSTRACT

Adopting Regenerative Agriculture (RA) practices on temperate arable land can increase soil organic carbon (SOC) concentration without reducing crop yields. RA is therefore receiving much attention as a climate change mitigation strategy. However, estimating the potential change in national soil carbon stocks following adoption of RA practices is required to determine its suitability for this. Here, we use a well-validated model of soil carbon turnover

(RothC) to simulate adoption of three regenerative practices (cover cropping, reduced tillage intensity and incorporation of a grass-based ley phase into arable rotations) across arable land in Great Britain (GB). We develop a modelling framework which calibrates RothC using studies of these measures from a recent systematic review, estimating the proportional increase in carbon inputs to the soil compared to conventional practice, before simulating adoption across GB. We find that cover cropping would on average increase SOC stocks by 10 $t.ha^{-1}$ within 30 years of adoption across GB, potentially sequestering 6.5 megatonnes of carbon dioxide per year ($MtCO_2.y^{-1}$). Ley-arable systems could increase SOC stocks by 3 or 16 $t.ha^{-1}$, potentially providing 2.2. or 10.6 $MtCO_2.y^{-1}$ of sequestration over 30 years, depending on the length of the ley-phase (one and four years, respectively, in these scenarios). In contrast, our modelling approach finds little change in soil carbon stocks when practising reduced tillage intensity. Our results indicate that adopting RA practices could make a meaningful contribution to GB agriculture reaching net zero greenhouse gas emissions despite practical constraints to their uptake.

Keywords: soil carbon sequestration, soil organic matter, Rothamsted carbon model, greenhouse gas abatement, United Kingdom (UK)

Abbreviations

CEH - Centre for Ecology & Hydrology (UK)

GB – Great Britain

GHG – greenhouse gas

$MtCO_2$ – megatonnes of carbon dioxide

PRI – plant residue input

RA – Regenerative Agriculture

RothC – Rothamsted carbon model (version 26.3)

SOC – soil organic carbon

TRM – tillage rate modifier

1. INTRODUCTION

Increasing terrestrial carbon sequestration is currently of global interest in efforts to mitigate anthropogenic greenhouse gas (GHG) emissions (IPCC, 2019). It has been demonstrated that there is substantial potential to increase soil carbon stocks on agricultural land (Griscom et al., 2017, Bossio et al., 2020, Kampf et al., 2016, Lal, 2004); a preferred setting since use for food production can continue, in contrast to interventions on natural and semi-natural habitats which can compromise biodiversity and ecosystem service delivery (Veldman, 2019, Veldman et al., 2015). Building soil organic carbon (SOC) through changes in agricultural land management practices is also important in mitigating widespread and costly soil degradation (Graves et al., 2015, Prout et al., 2020), thus safeguarding crop yields and promoting other ecosystem services such as water flow regulation and nutrient retention (Bradford et al., 2019, Smith et al., 2021). However, limitations of soil carbon sequestration for climate change mitigation include sink saturation, non-permanence following discontinuation of beneficial management, risk of displacement of emissions through compensatory cultivation elsewhere, and difficulties in verifying sequestration (Smith, 2012).

The Regenerative Agriculture (RA) paradigm is receiving increasing attention from land managers and policy makers due to its proposed ability to simultaneously contribute to climate change mitigation and ameliorate degraded soils by sequestering SOC through changes in management practices (Moyer et al., 2020, Newton et al., 2020, Giller et al., 2021). Although multiple definitions exist, RA can best be defined as "an approach to farming that uses soil conservation as the entry point to regenerate and contribute to multiple ecosystem services" (Schreefel et al., 2020).

A recent meta-analysis of RA practices in temperate regions demonstrated the potential to increase soil carbon concentration without any yield reduction in cropping years through reducing tillage intensity and incorporating a ley-phase into arable rotations (Jordon et al., 2021). However, evaluating the potential contribution of RA to climate change mitigation requires regional-scale simulation of the total potential change in soil carbon stocks following adoption.

Models of soil carbon turnover enable simulation of the effect of changes in land management on SOC stocks, while accounting for regional variation in climate and soils. The Rothamsted carbon model (RothC) version 26.3 is a process-based five-compartment model (Figure 1) with monthly timesteps, developed under temperate agricultural conditions and validated across climates and biomes (Smith et al., 1997b, FAO, 2019, Jenkinson, 1990, Jenkinson et al., 1999, Falloon and Smith, 2002). Advantages of RothC include its requirement for few, readily-available, parameters and its ability to run both in 'forward' (estimate change in SOC for known inputs) and 'inverse' (estimate inputs for known change in SOC) modes (Coleman and Jenkinson, 2014). Previous approaches to simulating the effects of land management changes on soil carbon include extrapolating an observed SOC change over a larger area (King et al., 2004, Smith et al., 2000b), *a priori* adjusting model input parameters in an effort to best represent management practices (Smith et al., 2005, Lugato et al., 2014), deriving soil carbon trends using data from long-term experiments (Smith et al., 1997a) or using average values from a meta-analysis of published literature (Poeplau and Don, 2015). However, more exact estimates of soil carbon changes can be generated by combining inverse and forward runs of a process-based model such as RothC, publicly available spatial datasets of required climatology and soil inputs, and empirical SOC measurements from published studies. This enables both the model calibration, using real-world data, and simulation stages to be based on site-specific inputs. Mirroring real-world dynamics as closely as possible in soil carbon modelling is important to prevent the contribution of land management changes to climate change mitigation from being overstated.

Here, we develop a modelling framework using RothC to estimate the total change in soil carbon stocks if three constituent practices of RA were adopted at a country-scale for Great Britain (England, Scotland and Wales, not including Northern Ireland). We use published SOC data obtained from studies of reduced tillage intensity, cover cropping and incorporation of grass-based leys into arable rotations conducted in temperate oceanic regions assembled by Jordon et al. (2021), to maximise generalisability to the context of interest. We aimed to evaluate the extent to which increased adoption of RA practices on temperate arable land can sequester carbon to mitigate GHG emissions.

2. METHODS

Changes in soil carbon are usually driven by one or a combination of changes in i) carbon entering the soil, most of which will be from plant residue inputs (PRI), or ii) the rate of decomposition of carbon pools within the soil. Cover cropping and ley-arable adoption affect SOC primarily *via* the former mechanism, while reducing tillage intensity favours the latter. Our framework comprised two stages: i) estimating the change in either PRI (following adoption of cover cropping or ley-arable rotations) or rate of SOC decomposition (following reduced tillage intensity) in the studies assembled by Jordon et al. (2021) then ii) using the resulting distributions of PRIs or tillage rate modifiers (TRMs) to simulate adoption of these practices at a 1 km resolution for arable land in Great Britain (GB).

RothC-26.3 was implemented in R version 4.0.3 using the *RothCModel* function in the package *SoilR* (Sierra et al., 2012, R Core Team, 2020). This function allows PRI, soil carbon pool sizes, and decomposition rates to be specified by the user. Inverse modelling steps (detailed below) were conducting *via* a linear optimisation process using the *optim* function with Brent method in base R (R Core Team, 2020). The R code and supporting data developed for and used here to implement our framework is publicly available online (Jordon, 2021a).

2.1. Model calibration

To estimate the change in PRI following adoption of cover crops and ley-arable, we implemented the first stage of our model framework for all treatments from each relevant study identified by Jordon et al. (2021). First, we used the baseline (i.e. pre-intervention) SOC stock reported in the study (assumed to be at equilibrium) to inverse model the PRI before the study began, using study-site-specific input parameters in RothC (Table 1). This PRI was used to initialise or ‘spin-up’ the conceptual pools of soil carbon (Figure 1), by running RothC in ‘forward’ mode for 1000 years, which when summed corresponds to the baseline SOC stock. Subsequently, we used these initial pool sizes to run RothC in 'inverse' mode for the duration of the study in years, to estimate the PRI which resulted in the endline (i.e. last available) SOC measurement for that treatment.

To propagate deterministic uncertainty (error already present in input data) through our modelling, we ran 100 model iterations per study treatment, using standard deviations associated with inputs to generate normally distributed random samples of parameters. These distributions were created using the *rnorm* function in base R (R Core Team, 2020), or the *truncnorm* function (Mersmann et al., 2018) bounded between zero and infinity, where negative values for those parameters are not possible (e.g. precipitation). Where clay and bulk density measurements were presented in studies, these were assumed to have standard deviations of zero, in order that error was only propagated for WISE30sec values (Batjes, 2016) to capture the uncertainty inherent in using these estimates rather than site-specific measurements. To derive standard deviations for the required climatology data (Table 1), we downloaded monthly averages for each year in the period 1981-2010 and calculated the mean and standard deviation across these 30 years.

Some studies included in the database assembled by Jordon et al. (2021) do not present error terms for SOC estimates or baseline SOC measurements. Because discarding incomplete data can bias model estimates (Weir et al., 2018), we used multiple imputation methods to generate estimates for missing values, which has the advantage of explicitly representing the uncertainty associated with imputation in the model output (Lajeunesse, 2013). We imputed 30% and 53% of baseline SOC values, and 61% and 88% of error values, for the data used to estimate proportional changes in PRI following adoption of cover crops and ley-arable systems, respectively (Table 2). We used the *mice* package in R to generate ten imputed datasets (van Buuren and Groothuis-Oudshoorn, 2011) and extracted ten random samples using the imputed values from each of these datasets to arrive at the 100 samples per observation required.

Jordon et al. (2021) present cover cropping and ley-arable treatments as continuous variables in their dataset, with cover cropping expressed as a proportion of the rotation that cover crops are present (zero to one), and ley-arable as the duration of the ley-phase in the rotation (one to six years). We pooled endline PRI estimates across all treatments from all relevant studies (100 iterations per observation to allow propagation of error) and used the *brms* package to fit a Bayesian model to this data (Bürkner, 2018), with endline PRI as the response variable and a weakly informative normal prior distribution (mean 0, standard deviation 1). For cover cropping, cover crop proportion was the sole explanatory variable, but for ley-arable studies both ley and arable durations (years) within the treatment rotation were included as explanatory variables to allow two rotation types to be simulated: a three-year rotation with one year ley and two years arable (L1A2), and a six-year rotation with four years ley and two years arable (L4A2). We then extracted samples from the posterior distribution to calculate the proportional change in PRI if cover cropping or two ley-arable rotations were adopted, relative to 1 which represents 'conventional' practice with no cover crops or ley-phase. We do not explicitly represent different cover crop or ley compositions in our scenarios and therefore differences in quality of organic matter inputs which could influence the rate of decomposition (e.g. through the presence/absence of legumes). However, standard deviations of the proportional changes in PRI are used to capture variability in practices between study treatments used to calibrate our framework and are propagated through the GB simulation, reflecting likely diversity in practices if adopted in real-world conditions.

Due to our use of imputation for data with missing errors and/or baseline SOC for inclusion in our model framework we generated four estimates to test the sensitivity of the results to different data availability and quality (Table 2):

1. Baseline SOC present, errors present (BPEP)
2. Baseline SOC present, missing errors imputed (BPEI)
3. Baseline SOC imputed and/or missing errors imputed (BIEI)
4. Critical appraisal (CA): as in (3), but only observations that have high validity based on level of spatial replication and experimental design included (see Jordon et al. (2021) for details)

Note that for (1-3) endline SOC data is always present. We used the values generated from approach (4) in our GB simulation as a best compromise between input data quantity and quality (see footnotes of Table 2 for level of data imputation used to generate these estimates).

A similar approach was developed by (Jordon and Smith, under review) who estimated TRMs for adjusting the decomposition rate constants in RothC to account for reduced tillage intensity using the same dataset from Jordon et al. (2021). Here, we use their TRM estimates of 0.99 (Standard Deviation 0.02) for reduced tillage, and 1.02 (SD 0.03) for no-tillage, relative to 1 (i.e. default decomposition rate constants) for conventional full-inversion tillage (Jordon, 2021b).

2.2. Great Britain simulation

We used the UK Centre for Ecology & Hydrology (CEH) land cover map 1 km dominant target class raster (Rowland et al., 2017) to identify 1 km^2 pixels of GB which are predominantly arable (i.e. more than 50% of land cover within that pixel classified as arable). We assumed no current adoption of reduced tillage intensity, cover cropping or ley integration in GB arable rotations, which, although clearly erroneous, we considered appropriate as we were seeking to indicate the relative magnitude of SOC stock change by transitioning from no to complete adoption of these practices, rather than quantify the current unfulfilled potential for this in GB. Because RothC is not suitable for use with organic or organo-mineral soils (Falloon et al., 2006), we excluded 92 pixels with a WISE30sec SOC concentration above 100 $g.kg^{-1}$, and a further 389 pixels with artefact SOC concentrations below 0 $g.kg^{-1}$, resulting in 61,413 1 km^2 pixels for inclusion in our spatially-explicit simulation. RothC was unable to run for some of these pixels due to unreasonable input parameters; we give the number of pixels successfully run (n) for each intervention in Table 3. We anticipate these issues with the input data are due to limitations of the taxotransfer scheme applied in WISE30sec (Batjes, 2016). However, use of alternative proprietary data products such as the LandIS National Soil Map would potentially limit the reproducibility of our work and preliminary studies with soil models show little difference in simulated SOC change in GB when using either the Harmonised World Soil Database (precursor to WISE30sec) or LandIS Soil Map as model inputs (Smith, P. pers comm.). We assumed that using the dominant target class raster provided a good proxy of all arable land through non-arable land area within these squares being approximately matched by arable land in other squares with a different dominant target class. However, 61,413 1 km^2 pixels implies a total GB arable area of 6,141,300 ha, whereas the area of arable crops in the June 2021 census was 4,339,000 ha

(Defra, 2021). Therefore, we weighted the estimates of total soil carbon sequestration and GHG mitigation in Table 3 to reflect this actual arable area (Table S1).

We used WISE30sec SOC concentration ($g.kg^{-1}$) and soil bulk density ($g.cm^{-3}$) values to calculate SOC stocks ($t.ha^{-1}$) for 30 cm soil sampling depth at each pixel, which we assumed to be at equilibrium. We ran RothC in inverse mode using spatially explicit inputs (Table 1) to estimate the current PRI for each pixel. We then proportionally adjusted this site-specific PRI by the CA values in Table 2 to simulate adoption of cover cropping (present every year in arable rotation) or two ley-arable rotations (L1A2 and L4A2). A proportional adjustment rather than absolute increase was used to account for the inherent differences in Net Primary Productivity and therefore magnitude of PRI increase possible based on site pedological and climatic conditions, after Smith et al. (2005). To simulate reduced or no tillage, we assumed PRI remained constant and multiplied the default decomposition rate constants in RothC by the TRMs of 0.99 and 1.02, respectively (Jordon and Smith, under review). We executed this forward run for two time horizons: i) 30 years, to estimate the potential change in carbon stocks by the year 2050 which could contribute to national net zero emissions targets (Climate Change Committee, 2019), and ii) 1000 years, to estimate the total soil carbon change once this has reached a new equilibrium. We used the same method to propagate deterministic error as in the model calibration step, with 100 modelling iterations per pixel. We simulated interventions implemented in isolation rather than in combination because most studies used to parametrise our framework consider single interventions, preventing us from determining potential interactions in their effect on soil carbon. We ran the model in parallel for multiple pixels simultaneously using the *foreach* package (Microsoft and Weston, 2020), implemented on the University of Oxford's Advanced Research Computing facility (Richards, 2015)

We calculated the SOC stock at baseline, 30 years, and equilibrium (mean and standard deviation) from the 100 model iterations for each 1 km^2 pixel. We estimated mean and 95% Credible Intervals for average SOC stocks under each intervention by conducting an intercept-only analysis of pixel means that accounted for their standard error using the *brms* package (Bürkner, 2018). To estimate the total carbon sequestration and therefore carbon dioxide (CO_2) emissions abatement possible across all GB arable land (Table 3), we summed the mean SOC stock across all 1 km^2 arable pixels and weighted this by the actual area of GB arable land (Table S1). To calculate the standard deviation of these summed mean values, we assumed that pixels were independent of each other such that the variance of the sum equals the sum of variances. This is likely to be an underestimate because adjacent pixels are not independent (due to similarity in input parameters) and therefore have positive covariance. However, we feel this is a necessary approximation given the difficulty of calculating a covariance matrix for the large number of pixels summed here. We plotted the results of our simulations using the *ggplot* and *raster* packages (Hijmans, 2021, Wickham, 2016, FC and Davis, 2021). To decompose the sources of variation in our outputs, we fit linear models using the *lm* function (R Core Team, 2020) that contained different combinations of model input parameter distributions, and plotted the adjusted R^2 as a measure of the variation in the output explained by different inputs. All R code is available online (Jordon, 2021a).

3. RESULTS and DISCUSSION

3.1. Changes in SOC stocks

We demonstrate substantial increases in soil organic carbon (SOC) stocks across Great Britain (GB) are possible if Regenerative Agriculture (RA) practices are adopted on arable land in an illustrative temperate region. Growing over-winter cover crops in every year of an arable rotation has the potential to increase cropland SOC stocks in GB by an average of 20.3% after 30 years, compared with no cover cropping (Figure 2). Including grass-based leys in an arable rotation with low frequency (one year ley followed by two years arable, L1A2) increases SOC stocks by 6.9%, or 33.4% if at high frequency (four years ley followed by two years arable, L4A2) within 30 years compared with continuous arable cropping (Figure 2). We identify less potential for reducing tillage intensity to affect SOC stocks, with an average increase of 0.36% over 30 years when reduced tillage is adopted, and a decrease of 0.72% when no till is implemented, compared to conventional full-inversion tillage (Figure 2).

3.2. Sources of uncertainty and limitations

Our results are not directly comparable with the findings of similar studies due to differences in i) the area of arable land that management changes are modelled over, ii) assumptions regarding level of adoption of management change (e.g. length of ley phase in ley-arable rotation or proportion of rotation that cover crops are included), and iii) soil and climate inputs in other study countries (Dendoncker et al., 2004, Taghizadeh-Toosi and Olesen, 2016, Smith et al., 2000a, Robertson and Nash, 2013). Furthermore, our estimate of total baseline (i.e. current) SOC stock in GB arable farmland (Table 3) does not match other estimates (Bradley et al., 2005, Smith et al., 2000a), in part because, to be conservative, we used survey data of the area of arable crops grown in 2021 to weight our output, rather than total croppable area. However, our baseline per area average of 49.3 t $C.ha^{-1}$ in the 0-30cm horizon is close to the European average of 53 t $C.ha^{-1}$ (Smith et al., 2000b). Further, our estimate of baseline Plant Residue Input (PRI) for GB arable land was 3.30, 95% Credible Intervals [3.295, 3.298], which is acceptably similar to Falloon et al. (2006)'s estimate of 3.67 (Standard Deviation 1.71).

Spatial heterogeneity in the magnitude of SOC stock change across GB (Figure 3) is predominantly due to existing variation in GB soil carbon stocks (Figure S1). In the cover crop simulation, baseline SOC stock (determined from WISE30sec SOC concentration and bulk density data) alone explains 99.7% of total variation in SOC stocks after 30 years of treatment implementation (Figure S2). WISE30sec values are derived from the Harmonised World Soil Database, and therefore the European Soil Database for GB, using a taxotransfer scheme (Batjes, 2016) and come with standard deviations that capture the uncertainty in these estimates, which we propagated through our modelling framework. However, our large sample size (>61,000 pixels, 100 model iterations per pixel) means the uncertainty around our overall estimates is acceptably small (Table 3). Our modelling approach used baseline SOC to calculate initial PRIs, which were then proportionally increased for cover crops and ley-arable scenarios, resulting in variation within the soils input data being amplified in our modelling outputs (Figure 3). Although climatology inputs (monthly average temperature, precipitation, and evapotranspiration (Abatzoglou et al., 2018)) explained 7.25% of variation in GB baseline PRI estimates, these parameters explained only 0.1% of variation in SOC stock estimates at 2050 (Figure S2). Conversely, in our model calibration stage, climatology inputs explained 38% and 25% of variation in estimates of study baseline and endline PRI, respectively (Figure S3). This is likely because studies used for model calibration were from across temperate oceanic regions, which have greater variation in climate than within GB, aligning with previous sensitivity analyses with RothC that have demonstrated a strong influence of climate variables on predicted SOC (Janik et al., 2002). Soil carbon concentration ($g.100g^{-1}$) explained 27% and 35% of variation in baseline and endline PRIs respectively (Figure S3).

Using an inverse modelling approach to estimate PRI in RothC assumes that SOC stocks are at equilibrium. If SOC is in fact increasing or decreasing, then the PRI would be overestimated or underestimated respectively (Falloon et al., 2006). We use this inverse modelling step both in our model calibration and spatially explicit simulation. Studies used to calibrate our model framework ranged in duration from 2 to 70 years (mean 15) (Jordon et al., 2021) which is insufficient for SOC to reach a new equilibrium following a change in management (50-150 years for a decrease, 100-750 years for an increase (Falloon et al., 2006)), and therefore the proportional changes in PRI we calculated from studies of cover crops and ley-arable duration are at risk of being overestimated. Further, there is evidence that SOC in much of GB's arable land is still in the process of decline following conversion from grassland in previous decades (Skinner and Todd, 1998), and therefore our estimates of baseline PRI for proportional adjustment are possibly underestimates. Conversely, there are two additional mechanisms by which the baseline PRIs we calculated for GB arable soils could be overestimates. Firstly, use of 1 km^2 resolution soil data means that some squares may in reality contain a combination of mineral and organic soils. RothC is not suited for use on organic and organo-mineral soils because it over-predicts the PRI required to maintain the high SOC concentration in these soils. Although we excluded WISE30sec pixels with a SOC concentration above 100 $g.kg^{-1}$ from our analysis, pixels with mixed soil types could result in a SOC concentration higher than a typical mineral soil but under our 100 $g.kg^{-1}$ threshold, leading to an overprediction of current PRI for these pixels. This could also potentially explain the clustered rather than Gaussian distribution of baseline SOC stocks (Figure 2), although the derivation of WISE30sec soil properties using taxotransfer rules is also likely responsible for this clustered distribution by reflecting underlying discreet soil type categories. Secondly, using the CEH dominant land class product means that each 1 km^2 could contain large areas of other land uses with typically higher SOC, such as permanent pasture or woodland, again inflating the SOC concentration used to infer PRIs on arable land. Because our modelling framework proportionally adjusted baseline PRI to simulate cover cropping or ley-arable adoption, any overestimation of PRI would in turn lead to an overestimate in the SOC stock change possible from adopting these interventions on mineral arable soils alone. Despite this, our estimates of GB baseline SOC stocks and potential changes following adoption of RA practices are consistent with previous studies using other approaches and input datasets, and we are confident in our results as indicative of the trends possible.

Our modelling framework does not identify significant GHG mitigation potential from reducing tillage intensity or no till, in contrast with previous estimates (e.g. Smith 2000, Dendonker 2004). This could be because the tillage rate modifiers (TRM) developed in Jordon and Smith (under review) were calibrated to empirical data which, when recently meta-analysed, show only very small increases in SOC concentration when reduced or no tillage are adopted in temperate oceanic regions compared to conventional full-inversion tillage (Jordon et al., 2021). Alternatively, although Jordon and Smith (under review) endeavoured to best represent the mechanism of soil carbon increases following a reduction in tillage intensity by developing a TRM rather than adjusting PRI, in reality these two mechanisms are likely to be confounded in some instances. This is because reduced tillage or no till are often implemented as part of a broader conservation agriculture approach where arable stubble is retained instead of removed as straw, thus potentially increasing carbon inputs to the soil alongside decreasing the rate of decomposition. Identifying these two mechanisms *via* an inverse modelling approach would require a dataset with factorial treatments of tillage intensity and straw retention to establish the PRI increase from straw retention, tillage rate modifier from reduced tillage intensity, and any interaction between these. Further, a depth-distributed model would likely better account for SOC dynamics following reduced tillage intensity (Angers and Eriksen-Hamel, 2008), but would similarly require calibration from depth-distributed studies.

We do not include scenarios to account for the impact of near-future climate change on soil carbon stocks and the way this could interact with the efficacy of land management changes to sequester soil carbon. We would expect increases in average temperature and/or precipitation to increase the rate of decomposition of carbon inputs to the soil, resulting in a modest decline in soil carbon for a given PRI (Zhong and Xu, 2014, Sakrabani and Hollis, 2018, Smith, 2012) and any increase in PRI following adoption of cover crops or ley-arable system to deliver less of an increase in SOC stocks.

3.3. Greenhouse gas mitigation potential

We identify GHG mitigation potential for Great Britain (GB) in the next 30 years of 6.48 million tonnes of carbon dioxide equivalent per year ($MtCO_2e.y^{-1}$) if cover crops were grown on arable land (Table 3), assuming no prior adoption. A scenario of low ley-arable integration (L1A2) would deliver 2.19 $MtCO_2e.y^{-1}$ over 30 years, or 10.6 $MtCO_2e.y^{-1}$ if higher adoption (L4A2) (Table 3). In contrast, our results imply that adopting no till could result in net GHG *emissions* of 0.234 $MtCO_2e.y^{-1}$ due to decreases in SOC stocks, and reduced tillage only limited sequestration of 0.11 $MtCO_2e.y^{-1}$, over 30 years (Table 3). Although SOC changes would continue for longer than 30 years for all interventions until a new equilibrium is reached, we focus on a 30-year time horizon to assess the potential climate change mitigation potential of these RA practices due to the significance of the year 2050 for meeting domestic and international net zero GHG emission targets (IPCC, 2018, Climate Change Committee, 2019). Furthermore, because soil carbon dynamics are non-linear and the time to reach a new equilibrium varies between interventions, expressing the final total change in SOC stocks as an annualised rate does not best reflect the timescale of SOC changes.

To contextualise our results, the total GHG emissions of Great Britain were 433.4 $MtCO_2e$ in 2019, of which agriculture comprised ~40 $MtCO_2e$ (United Kingdom emissions (BEIS, 2021) minus Northern Ireland (Daera, 2019)). Full adoption of cover crops from a baseline of zero adoption could therefore mitigate around 16% of GB agriculture’s emissions between now and 2050, and high inclusion of leys in arable rotations could mitigate 27% of current agricultural emissions. This comes with the major caveats that these interventions are in fact already implemented to some extent in GB and assumes an ability to achieve immediate adoption across all remaining arable land, which is unrealistic. Nevertheless, we identify emissions abatement potential from adopting RA practices of a comparable magnitude to previous scenarios of changes in UK land management, which have estimated 10 $MtCO_2e.y^{-1}$ from soil carbon sequestration (Royal Society and Royal Academy of

Engineering, 2018) and 10 $MtCO_2e.y^{-1}$ from adoption of low-carbon farming practices (Climate Change Committee, 2020) for the UK. Alternatively, adopting cover crops and a high frequency of ley-phase in arable rotations through our 'land-sharing' approach to carbon sequestration would sequester 9 and 14%, respectively, of the ~74 $Mt.CO_2e.y^{-1}$ abatement theoretically possible under an upper-bound scenario of agricultural yield increases sparing UK land for afforestation with coniferous woodland (Lamb et al., 2016). Furthermore, our findings concur with previous work that have found limited potential for carbon sequestered through changes in farm management to mitigate even agricultural GHG emissions (MacLeod et al., 2010, Franks and Hadingham, 2012), much less provide carbon offsets to other sectors (Schlesinger and Amundson, 2019).

In addition to previously characterised barriers to adoption of RA practices by land managers (Mills et al., 2019), there are key practical limitations to the implementation of practices considered here for climate change mitigation. Establishing cover crops rather than leaving bare arable stubbles or cultivated soil over winter benefits water quality and soil nutrient retention (Abdalla et al., 2019), with this practice already being promoted for these reasons. However, many crops commonly grow in GB arable rotations are established in the autumn (e.g. winter wheat or winter oilseed rape) (Defra, 2019) which are less compatible or incompatible with over-winter cover crops. A shift to spring-sown cultivars would likely incur a yield penalty e.g. (Vijaya Bhaskar et al., 2013, Cormack, 2006), which is a disincentive for farmers and risks displacing cultivation elsewhere. Similarly, ley-arable rotations are already commonplace in organic farming systems due to the fertility-building properties of the ley phase (particularly if containing legumes) benefiting the following arable crop and are increasingly being adopted in conventional systems as a tool to control crop weeds displaying herbicide resistance, such as blackgrass (*Alopecurus myosuroide*). However, each year of ley phase in a rotation has an ‘opportunity cost’, with possible revenue streams from a ley (e.g. grazing with livestock, harvesting fodder for livestock or as anaerobic digestor feedstock) typically less profitable than producing an arable crop. Furthermore, if demand for arable crops did not decrease in proportion to the increase in ley-phase in arable rotations (e.g. through a restructuring of livestock production away from indoor rearing or finishing on cereal-based rations to grazing or ranging over temporary leys in arable systems (Lee et al., 2021, Karlsson and Röös, 2019), this would result in compensatory cultivation of pasture in GB or displaced land use change overseas, the emissions from which would likely more than offset any carbon sequestration from ley-arable adoption (Carlton et al., 2011, Ostle et al., 2009). Our modelling approach suggests that reduced tillage intensity does not substantially build soil carbon stocks, if at all, in this temperate region. A further limitation of implementing this practice on soils with compromised structure is the risk of increased soil compaction leading to higher emissions of nitrous oxide (Huang et al., 2018, Powlson et al., 2014). This could potentially result in a net increase in GHG emissions, limiting the role of reduced tillage intensity for climate change mitigation in this context. We do not consider environmental or policy restrictions on the implementation of these practices or features of current GB farm structure which have been shown elsewhere in Europe to further limit GHG mitigation potential of these practices (Dendoncker et al., 2004, Taghizadeh-Toosi and Olesen, 2016). Further work could combine our approach here with data on current farm management and cropping practices, in addition to economic and behavioural models, to estimate the likely capacity for further adoption of these practices in a GB context.

4. CONCLUSIONS

Adopting the Regenerative Agriculture practices of cover cropping and ley-arable rotations on cropland in Great Britain has potential to substantially increase carbon stocks within 30 years, mitigating up to a quarter of agricultural GHG emissions. Although the modelling uncertainty within our estimates is acceptably small, there are clear practical barriers to achieving complete adoption of these practices across all GB arable land. While gains in SOC stocks from adopting such practices are worth pursuing where trade-offs with current management systems and rotations can be minimised, our results demonstrate the challenges of relying on boosting soil carbon sequestration to abate ongoing agricultural emissions.

FIGURE LEGENDS

Figure 1. Conceptual soil carbon pools in RothC-26.3. DPM: decomposable plant material, RPM: resistant plant material, BIO: microbial biomass, HUM: humified organic matter, IOM: inert organic matter, after Coleman and Jenkinson (2014). Decay of pools determined by first-order kinetics with decomposition rate constant, apart from small inert pool resistant to decomposition.

Figure 2. Distribution of Great Britain arable soil organic carbon (SOC) stocks (t.ha^{-1}). Baseline (assumed current, using WISE30sec values) (Batjes, 2016) and following implementation of cover crops, ley-arable rotations and reduced tillage intensity after 30 years (i.e. around the year 2050) and once a new equilibrium is reached, to 30 cm depth. Violin plots show distribution of mean values from each 1 km^2 model run for in Great Britain. Two ley-arable systems are modelled: L1A2, one year ley-phase and two years

arable cropping, and L4A2, four years ley-phase and two years arable cropping. Simulations for two ley-arable scenarios and two reduced tillage scenarios were run together, respectively, hence shared baselines.

Figure 3. Great Britain arable soil organic carbon (SOC) stocks (t.ha^{-1}) at 1 km^2 resolution. Colour indicates difference from baseline (0-30 cm), following implementation of cover crops, ley-arable rotations and reduced tillage intensity after 30 years and once a new equilibrium is reached. The two scenarios for ley-arable rotations are one year ley-phase and two years arable cropping (L1A2), and four years ley-phase and two years arable cropping (L4A2). 1 km^2 resolution for arable land in Great Britain identified using the CEH land cover map (Rowland et al., 2017). Scale bar in km.

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6. SUPPLEMENTARY MATERIAL

Table S1. Calculations used to convert SOC stocks summed across all 1 km2 pixels run for each intervention to results presented in Table 3.

Figure S1. Baseline Great Britain arable soil organic carbon (SOC) stocks (t.ha^{-1}) at 1 km^2 resolution. Averaged across simulations for each intervention for 0-30 cm. Calculated from SOC concentration (g.100g-1) and bulk density data from the WISE30sec dataset (Batjes, 2016), for all GB arable land at 1 km^2 resolution identified through the CEH land cover map (Rowland et al., 2017). Scale bar in km.

Figure S2. Proportion of uncertainty in RothC model output for Great Britain simulation explained by input parameter variation. Estimated from 6,137,400 observations (61,374 1 km^2 pixels) from the cover crop simulation. Adjusted R^2 from linear model with (**a**) baseline Plant Residue Input, and (**b**) soil carbon stock after 30 years of intervention, as response variables, and specified input parameter distributions as explanatory variables.

Figure S3. Proportion of uncertainty in RothC model output for model calibration explained by input parameter variation. Estimated using 61 observations from 8 studies with cover crop treatments identified by Jordon et al. (2021), i.e. CA data (see Table 2 and Methods text for details). Adjusted R^2 from linear model with (**a**) treatment baseline Plant Residue Input, and (**b**) treatment endline Plant Residue Input, as response variables, and specified input parameter distributions as explanatory variables.

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