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Short communication

Modelling soil carbon stocks following reduced tillage intensity: A framework to estimate decomposition rate constant modifiers for RothC-26.3, demonstrated in north-west Europe

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ABSTRACT

Simulating cropland soil carbon changes following a reduction in tillage intensity is necessary to determine the utility of this management practice in climate change mitigation. In instances where reduced or no tillage increases soil carbon stocks, this is typically due to reduced decomposition rates of plant residues. Although some soil carbon models contain a priori decomposition rate modifiers to account for tillage regime, these are typically not calibrated to specific climatic regions, and none are currently available for the Rothamsted Carbon Model (RothC). Here, we present a modelling framework to estimate a tillage rate modifier (TRM) for the decomposition rate constants in RothC-26.3 which determine decay between soil carbon pools. We demonstrate this for north-west Europe, using published data assembled through a recent systematic review with propagation of error from input parameters throughout the framework. The small magnitude of soil carbon change following a reduction in tillage intensity in this region is reflected in our TRM estimates for no-till of 0.95, with 95% Credible Intervals [0.91, 1.00], and reduced tillage of 0.93 [0.90, 0.97], relative to conventional high-intensity tillage with a default TRM of 1. These TRMs facilitate realistic simulation of soil carbon dynamics following a reduction of tillage intensity using RothC, and our simple, transparent, and repeatable modelling framework is suitable for application in other climatic regions using input data generalisable to the context of interest.

1. Introduction

Reducing tillage intensity in arable cropping systems can increase soil organic carbon (SOC) (Sanden et al., 2018, Haddaway et al., 2017, West and Post, 2002). Increased adoption could contribute to land-based climate change mitigation efforts (Bossio et al., 2020, Kämpf et al., 2016, Smith et al., 1998) although the SOC change identified is often small (Jordon et al., under review), with redistribution of SOC within the soil profile and a concurrent increase in bulk density resulting in little change in soil carbon stocks (Powlson et al., 2014, Xiao et al., 2020, Angers and Eriksen-Hamel, 2008, Meurer et al., 2018). Determining the potential contribution, or otherwise, of reducing tillage intensity to greenhouse gas mitigation at a regional or territorial level requires modelling approaches that adequately reflect the mechanisms driving soil carbon dynamics.

The principal mechanisms for increases in SOC are higher plant residue inputs (PRI) to soil and reduced rates of decomposition of organic carbon within the soil. Reduced tillage intensity favours the latter (Senapati et al., 2014, Van Groenigen et al., 2011), protecting SOC from degradation through enhanced soil aggregation and reduced soil temperatures (Huang et al., 2018), although simultaneous crop residue retention as part of a conservation agricultural also increases PRI (Lal, 2015). Widely-used and validated soil carbon models tend to simulate equilibrium soil carbon stocks following a change in management through adjusting PRI, with movement of carbon between conceptual pools determined by first-order kinetics (Smith et al., 1997). Decomposition rate constants are routinely adjusted or modified to account for the effect of soil moisture and temperature on decay, and can be amended to account for tillage regime (Jenkinson, 1990, Parton et al., 1988, Bolinder et al., 2012, Gerik et al., 2015, Li et al., 1994).

The Rothamsted Carbon Model (RothC) version 26.3 is a process-based five-compartment model with monthly timesteps (Fig. 1),

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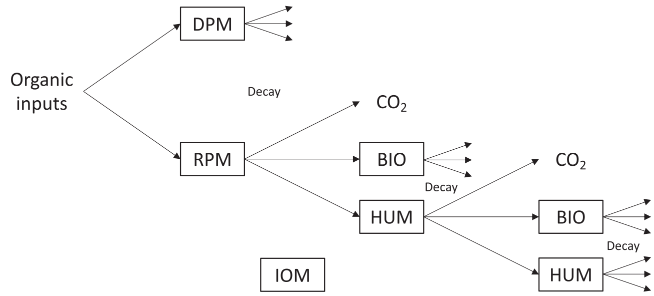

Fig. 1. Conceptual soil carbon pools in RothC-26.3, after Coleman and Jenkinson (2014). DPM: decomposable plant material, RPM: resistant plant material, BIO: microbial biomass, HUM: humified organic matter, IOM: inert organic matter. Decay of pools determined by first-order kinetics with decomposition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

developed under temperate agricultural conditions and demonstrated to perform well across climates and biomes (Smith et al., 1997, Fao, 2019, Jenkinson, 1990, Jenkinson et al., 1999). Advantages of RothC-26.3 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). An inverse modelling approach has previously been applied directly to the decomposition rate constants in RothC-26.3 to capture the effects of different tillage intensities (Rampazzo Todorovic et al., 2014), although this approach risks overfitting model parameters to the data. Alternatively, the decomposition rate constants could be multiplied by a single tillage rate modifier (TRM) based on tillage intensity. Soja et al. (2010) calibrated such TRMs in RothC to account for different tillage practices in Austrian vineyards, and rate modifier terms have also been developed to better capture SOC dynamics in saline soils (Setia et al., 2011), and aluminium-rich and paddy soils (Yokozawa et al., 2010). Further, generalisable estimates for RothC input parameters have previously been calculated using data from multiple study sites (Falloon et al., 1998).

Here, we present a modelling framework to estimate tillage rate modifiers for 'reduced tillage' and 'no tillage' practices on arable farmland, to be used as multipliers for the decomposition rate constants in RothC-26.3. We demonstrate this approach for north-west Europe, using SOC data from studies of tillage intensity in temperate oceanic regions identified by a recent systematic review (Jordon et al., under review). The TRM estimates presented here are appropriate for use in north-west Europe and have been applied elsewhere to simulate adoption of no and reduced tillage practice across arable land in Great Britain (Jordon et al., 2022). Further, our framework is intended to be applicable in other regions using data appropriately generalisable to the context of interest.

2. Methods

Jordon et al., under review identified 19 studies that measured soil organic carbon (and crop yield) under differing arable tillage intensity regimes in regions of north-west Europe with a temperate oceanic climate (Köppen-Geiger classification Cfb (Peel et al., 2007)). Studies identified were conducted in the UK, France, Belgium, Germany, the Netherlands, Denmark and Spain. From this, we extracted 23 paired observations of soil carbon under conventional tillage (CT) vs no-till (NT) treatments (12 studies), and 20 observations under CT vs reduced tillage (RT) treatments (14 studies), available in the Zenodo online repository (Jordon, 2022). We selected paired observations where the only difference between study treatments was tillage regime, such that where studies applied tillage treatments factorially with other treatments, paired observations were extracted for each level of the factor(s) not of interest. Where studies presented observations for CT, RT and NT treatments, they were included both in the CT-NT and CT-RT analyses.

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), which allows plant residue input (PRI), soil carbon pool sizes, and decomposition rates to be explicitly specified. We ran our model framework for each study site, using site-specific input parameters from global databases extracted using site coordinates where required parameters were not provided in article texts or available on request from the corresponding author (Table 1).

We propagated error through our model framework using standard deviations associated with inputs to generate normally distributed random samples of parameters for 100 model iterations per observation. Where clay and bulk density estimates were given in study articles, their respective standard deviations were assumed to be zero, such that error is only propagated for WISE30sec values to capture this estimation uncertainty. To derive standard deviations for the required climatology data, 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 systematic review database assembled by Jordon et al., under review do not present error terms for SOC estimates. Since discarding incomplete data can bias model estimates (Weir et al., 2018), we used multiple imputation methods to generate estimates for missing values, which explicitly represents the uncertainty associated with imputation in the model output (Lajeunesse, 2013). We used the *mice* package in R to generate ten imputed datasets (Van Buuren and Groothuis-Oudshoorn, 2011) and drew ten random samples of imputed values from each dataset to generate the 100 samples required.

Our modelling framework and assumptions are presented in Table 2 and the full R code we used is provided online (Jordon, 2022). Inverse modelling was conducting via a linear optimisation process using the optim function with Brent method in base R (R Core Team, 2020). We used CT 'endline' SOC (i.e. most recent measurement in study) to inverse model PRI. We assumed PRI to be the same within each CT-NT/RT paired observation due to the only difference in management between study treatments being tillage regime. Although crop residue retention alongside reduced tillage intensity in conservation agriculture may increase PRI, our pairing of study treatments ensured similar crop residue fate between treatments, i.e. both removed/burnt, or incorporated in CT/RT and left on surface in NT. Further, if reduced tillage intensity (RT or NT) resulted in higher crop Net Primary Productivity (NPP) compared to CT, this would likely increase PRI (Bolinder et al., 2007). However, meta-analysis of the yield data from the study treatments used here found no difference in crop yield (Jordon et al., under review) (found to relate to NPP (Bolinder et al., 2007)) between tillage treatments, in

Table 1
Input parameters for RothC-26.3 in our model framework. Global spatial data are at 1 km resolution, and were extracted for each study site using degree decimal coordinates.

Model parameter	Source	Citation
Soil organic carbon (g 0.100 g^{-1})	Studies in systematic review database	(Jordon et al., under review)
Soil clay content (%)	WISE30sec*	(Batjes, 2016)
Soil bulk density (g.cm^{-3})[a]		
Mean monthly air temperature (^{o}C)[b]	TerraClimate	(Abatzoglou et al., 2018)
Mean monthly precipitation (mm)		
Potential evapotranspiration (mm)		

*where not presented in study
[a] Soil bulk density was required to convert soil carbon data from concentration (g 0.100 g-1) to stocks (t.ha-1) in order to input to RothC
[b] TerraClimate only provides monthly minimum and maximum temperatures, so we approximated monthly mean temperature by averaging the minimum and maximum

Table 2
Modelling framework used to estimate tillage rate modifiers (TRM), parametrised with paired observations of conventional tillage (CT) with no-till (NT) or reduced tillage (RT). PRI: plant residue input.

Stage	SOC input[a]	Output	Model run time	Initial soil carbon pools	Plant residue input	Decomposition rate constants	Assumptions
1. Inverse model PRI for CT endline	CT endline	CT endline PRI	1000 years	0[b]	*Inverse modelled*	Model defaults	CT SOC is at equilibrium at study endline
2. Spin up NT/RT baseline SOC pool sizes	*na*	NT/RT baseline SOC pool sizes	1000 years	0[b]	CT endline PRI **(1)**	Model defaults	NT/RT baseline SOC is at equilibrium; PRI is same as CT treatment
3. Inverse model decomposition rate modifier for NT/RT treatment	NT/RT endline	NT/RT rate modifier	Study years	NT/RT baseline SOC pool sizes **(2)**	CT endline PRI **(1)**	Model defaults multiplied by single rate modifier	PRI is same as CT treatment

[a] Inert organic matter (IOM) pool estimated as $IOM = 0.049(SOC^{1.139})$ following Falloon et al. (1998), where SOC is the soil organic carbon stock (t.ha-1)
[b] used in inverse modelling stage

agreement with the findings for this region from another recent meta-analysis (Sun et al., 2020). This allowed us to inverse model TRMs for the RothC decomposition rate constants for NT and RT endline SOC values by keeping the PRI constant. Our approach assumes a TRM of 1 for conventional tillage, as the decomposition rate constants in RothC were originally calibrated in arable systems with cultivation.

We used the *brms* package to fit a Bayesian intercept-only model to estimate the average tillage rate modifier across all paired observations (Bürkner, 2018). Due to the large amount of data with missing errors imputed for use in our model framework we generated three estimates to test the sensitivity of the results to different data availability and quality:

1. Errors present (EP)
2. Errors imputed where missing (EI)
3. Critical appraisal (EIHV): as in (2), but only observations that have high validity based on level of spatial replication and experimental design (see Jordon et al., under review for details)

3. Results and discussion

We present a simple, transparent, and repeatable framework for estimating TRMs to uniformly adjust the decomposition rate constants in RothC-26.3. We demonstrate our approach using data from north-west Europe, identifying a TRM for no-tillage in the range 0.95 [0.91, 1.00] to 1.02 [0.97, 1.07] and for reduced tillage between 0.93 [0.90, 0.97] and 0.99 [0.95, 1.03] (Table 3). Of these, only the reduced tillage TRM from the EI analysis has 95% Credible Intervals not overlapping with 1 so is significantly different from the rate of decomposition under conventional tillage. This is unsurprising given meta-analysis of the data used here identified only a very small increase in SOC *concentration* following adoption of reduced or no tillage in temperate oceanic regions (Jordon et al., under review), without accounting for any concurrent increase in bulk density which can result in little or no change in soil carbon *stocks* on an equivalent soil mass basis (Powlson et al., 2014, Meurer et al., 2018). Nevertheless, our TRM estimates give realistic soil carbon dynamics (i.e. modest increase with plateauing dynamic (Smith, 2014)) when used in RothC to simulate equilibrium soil carbon stocks following adoption of no- or reduced-tillage (Fig. 2). Further, our framework is applicable to data from other regions where reduction of tillage has a greater influence on SOC (Sun et al., 2020, West and Post, 2002), which we would expect to result in larger TRMs.

Other models generally assume a larger effect of tillage on the rate of decomposition of soil carbon pools.[1] For example, the Century model multiplies decomposition rates by up to 1.6 (Metherell et al., 1993), the Environmental Policy Integrated Climate (EPIC) model applies an exponential coefficient in the range 5–15 (Gerik et al., 2015), the DeNitrification-DeComposition (DNDC) model increases rates by 1.5 times for disk cultivation and by 3 times for ploughing (Li et al., 1994), and an optimised rate modifier of 1.2 has been used in the Integrated Carbon Balance Model (ICBM) for rotations with more frequent tillage (Bolinder et al., 2012). Other approaches include increasing the proportion of net primary productivity retained as crop residues, from 35% for conventional tillage to 55% for conservation tillage as in SOCRATES (Grace et al., 2006). Although these higher adjustments have been found to perform well, this could be due in part to their development using datasets from different climates or cropping systems to our demonstration region, and underlying differences between models in their core decomposition rate constants. Where future research uses data from warmer or drier climates to parametrise our framework, this may result in a greater magnitude of TRM than we identify here (Sun et al., 2020). Although some syntheses have found little influence of temperature or rainfall (Luo et al., 2010), or climate zone (Haddaway et al., 2017), on SOC changes under different tillage regimes, this could be due to their focus on predominantly temperate regions.

Key advantages of our approach include the use of a systematic review database to parametrise our modelling and ability to propagate error from the underlying studies. However, our results are sensitive to which, and how many, observations are used to estimate TRMs, with a trend towards a greater magnitude of TRM when more observations are included (Table 3). This highlights the issue of data completeness when attempting to derive model parameters from published studies; six NT studies and eight RT studies in our dataset did not present error terms for SOC measurements, necessitating multiple imputation methods for inclusion. Further, it would be more mechanistically accurate to initialise baseline (i.e. pre-intervention) soil carbon pools for the CT and NT/RT treatments using baseline SOC measurements, to enable PRI to be estimated for the study duration rather than over a 1000-year spin-up. This was not possible as 13 CT-NT observations and 12 CT-RT observations did not present baseline data. We were unable to use imputed baseline values as this led to a modelling artefact where it appeared that SOC greatly increased in the CT treatments, resulting in unrealistically high estimates of study PRI which led to incorrect dynamics of increased decomposition in NT and RT treatments in order to match study SOC measurements. Where sufficient baseline SOC data is available in future work, this should be incorporated when implementing our framework. Although we feel that assuming PRI is constant within each CT-NT/RT paired observation is reasonable here due to the reasons outlined in the Methods, in instances where PRI is anticipated to differ due to differences in crop residue management or known changes in crop yield, a modified approach would be required to implement our framework. Identifying the effect of reduced tillage intensity vs crop residue retention via an inverse modelling approach would require a dataset with

[1] Most models increase tillage rate modifiers to account for higher tillage intensity rather than decrease to account for reduced tillage intensity as in our approach.

Table 3
Tillage rate modifier (TRM) estimates for no-till (NT) and reduced tillage (RT) with 95% Credible Intervals in square brackets. * denotes where not overlapping with 1.

	NT TRM	Observations	Studies	RT TRM	Observations	Studies
Error present (EP)	1.02 [0.97, 1.07]	16	6	0.93 [0.75, 1.09]	12	6
Error imputed (EI)	0.95 [0.91, 1.00]	23	12	0.93 [0.90, 0.97]*	20	14
Error imputed, high validity (EIHV)	1.02 [0.97, 1.07]	18	8	0.99 [0.95, 1.03]	14	8

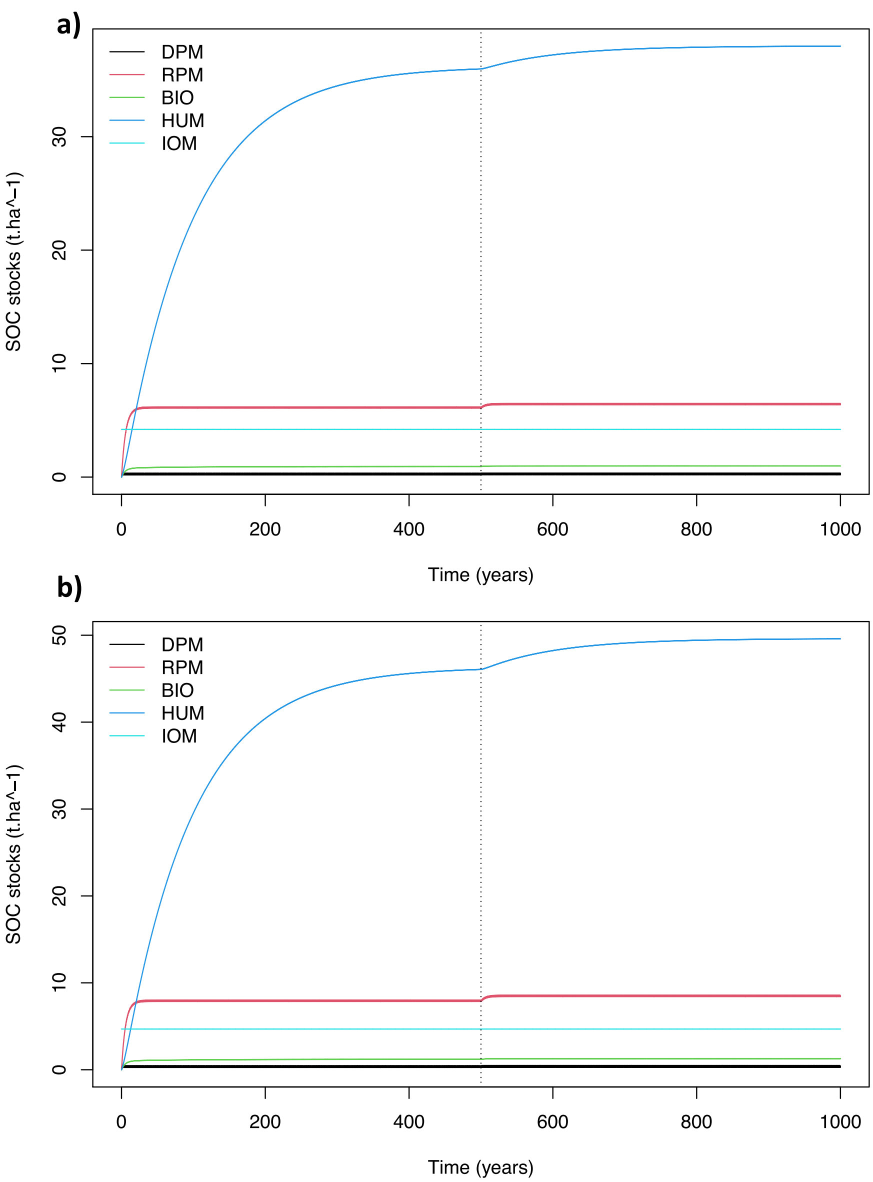

Fig. 2. RothC soil carbon pool dynamics, initialised for 500 years using conventional tillage (CT) plant residue input (PRI) from dataset, followed by simulated reduction of tillage intensity using tillage rate modifier (TRM) from year 500 (dashed vertical line). All parameters are mean values from implementation of respective modelling framework. **(a)** No-till: CT PRI 2.68 t.ha^{-1}.year^{-1}, TRM 0.95, SOC_{500} 47.4 t.ha^{-1}, SOC_{1000} 49.8 t.ha^{-1}. **(b)** Reduced tillage: CT PRI 3.52 t.ha^{-1}.year^{-1}, TRM 0.93, SOC_{500} 60.2 t.ha^{-1}, SOC_{1000} 64.4 t.ha^{-1}. DPM: decomposable plant material, RPM: resistant plant material, BIO: microbial biomass, HUM: humified organic matter, IOM: inert organic matter. Figure after Sierra (2015).

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, where differences in crop yield between tillage regimes are known to exist, a method similar to that described by Bolinder et al. (2007) could be implemented to estimate a proportional tillage factor for *PRI* using crop yield data, thus accounting for this effect in an additional step between stages 2 and 3 in our framework (Table 2).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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