Environmental Research Communications

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To cite this article: Will Rolls and Piers M Forster 2020 *Environ. Res. Commun.* **2** 045001

IOP Publishing Environ. Res. Commun. 2 (2020) 045001 https://doi.org/10.1088/2515-7620/ab7ff3

Environmental Research Communications

RECEIVED
24 January 2020

REVISED
4 March 2020

ACCEPTED FOR PUBLICATION
13 March 2020

PUBLISHED
6 April 2020

PAPER

Quantifying forest growth uncertainty on carbon payback times in a simple biomass carbon model

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Keywords: biomass fuels, LCA, forest model, payback period, carbon sequestration parity, forest carbon, soil carbon

Abstract

In 2018 Sterman *et al* (2018a) published a simple dynamic lifecycle analysis (DLCA) model for forest-sourced bioenergy. The model has been widely cited since its publication, including widespread reporting of the model's headline results within the media. In adapting a successful replication of the Sterman *et al* (2018a) model with open-source software, we identified a number of changes to input parameters which improved the fit of the model's forest site growth function with its training data. These relatively small changes to the input parameters result in relatively large changes to the model predictions of forest site carbon uptake: up to 92 tC.ha^{-1} or 18% of total site carbon at year 500. This change in estimated site carbon resulted in calculated payback periods (carbon sequestration parity) which differed by up to 54 years in a clear-fell scenario when compared with results obtained using previously published parameters. Notably, this uncertainty was confined to forests which were slower growing and where the model's training dataset was not sufficiently long for forests to reach maturity. We provide improved parameterisations for all forest types used within the original Sterman *et al* (2018a) paper, and propose that these provide better fits to the underlying data. We also provide margins of error for the generated growth curves to indicate the wide range of possible results possible with the model for some forest types. We conclude that, while the revised model is able to reproduce the earlier Sterman *et al* (2018a) results, the headline figures from that paper depend heavily on how the forest growth curve is fitted to the training data. The resulting uncertainty in payback periods could be reduced by either obtaining more extensive training data (including mature forests of all types) or by modification of the forest growth function.

Introduction

The use of biofuels is a significant element in global climate change mitigation strategies (Smith *et al* 2014, Rogelj *et al* 2018). These fuels have been attractive because, while biofuels do release CO_2 on combustion, the regeneration of biofuel feedstocks can result in the absorption of an equal quantity of CO_2. This regenerative ability in biofuels (unlike fossil fuels which do not regenerate during any meaningful timeframe: Rose *et al* 2014) has historically led to an assumption of 'carbon neutrality' of energy from biofuels (Buchholz *et al* 2016, Smith *et al* 2014).

While this assumption can be broadly true (assuming that the feedstock regenerates as expected, omitting supply chain emissions, and depending on the definition of 'carbon neutral': Malmsheimer *et al* 2011) a period of elevated atmospheric CO_2 may still exist because of the disparity between the rates of carbon emission and uptake relative to a counterfactual scenario. This has been described as a 'carbon debt' (Fargione *et al* 2008) site carbon is 'spent' on combustion, and takes a period of time to be 'repaid'. The time required to pay back the debt varies depending on the carbon emissions of the relevant supply chains, and recovery of the forest where the feedstock originated.

An extensive array of possible methodological choices (Buchholz *et al* 2016, Breton *et al* 2018) terminology (Malmsheimer *et al* 2011, Mitchell *et al* 2012, Bentsen 2017) and accounting assumptions (Lamers and Junginger 2013, Ter-Mikaelian *et al* 2015, Bentsen 2017) as well as the possibility of long periods of carbon debt, has led to a wide range of estimated payback periods (the time taken for a biomass scenario to outperform a counterfactual in terms of emissions over time: described as Carbon Sequestration Parity in Mitchell *et al* 2012) and conflicting opinions about the advisability of using forest biomass for energy. Variability in the results available from the literature, debate about the inclusion of different factors, and over-simplified communication of the benefits and costs of biomass use (Searchinger 2012, Searchinger and Heimlich 2015, Moomaw 2018a, Isaacs 2019) has been interpreted more widely as a lack of consensus. This has resulted in a range of responses in the policy sphere (e.g. FERN 2011, RSPB 2012, Brack 2017) which are not necessarily fully informed (Slade *et al* 2018).

In 2018 Sterman *et al* (2018a) published a simple dynamic lifecycle analysis (DLCA) model (Sterman *et al* 2018a) as an addition to an existing modelling framework (C-Roads Sterman *et al* 2012). Their intent was to allow policy makers to rapidly compare the climate effect of different policy alternatives over time, and to provide indicative results to guide regulatory development (Rooney-Varga *et al* 2019). The model has been widely cited since its publication (e.g. Norton *et al* 2019, Kalt *et al* 2019, Boumanchar *et al* 2019, Reid *et al* 2020, Maxwell *et al* 2020, Schlesinger 2018, Teske 2018). This publicity has included widespread reporting of the model's results within the media (Moomaw 2018b, Beeler and Morrison 2018, Smith 2020, Beswick 2018). Given the lack of clarity, agreement, and the degree of uncertainty which already exists in attempting to estimate payback periods, and the widespread acceptance of the findings of the Sterman *et al* (2018a) model: described as 'well documented and thorough' (Prisley *et al* 2018), we developed a replication of the Sterman *et al* (2018a) model in an open source framework to serve as a common foundation for future work, addressing the effects of differing assumptions, parameterisations, and scenarios.

While others have identified a number of potential weaknesses in the assumptions made by Sterman *et al* (2018a) (silvicultural practice Prisley *et al* 2018, responded to in Sterman *et al* 2018b, and biomass end-use efficiency Dwivedi *et al* 2019) little attention has been paid to the parameters governing simulated forest site regrowth. In testing our replication of the model, we identified uncertainties in the modelled forest growth curves, which have a profound impact on the reliability of results from five of the eight region/species combinations previously published by Sterman *et al* (2018a).

Research objectives

The work was carried out with reference to two key research objectives:

Firstly, the paper by Sterman *et al* (2018a) has been widely cited in the academic literature, policy briefings/recommendations and the press (as described above). We produced a model based on a similar framework which is simple/easy to modify; fully open source; and easy to calibrate to different assumptions. This tool was intended to facilitate comparisons between the wide range of different techniques, experimental decisions and assumptions which already exist in the literature.

Secondly, our work identified a level of uncertainty in the results as obtained by Sterman *et al* (2018a) that they did not discuss. We draw attention to this discrepancy, identify possible solutions, and caution against undue reliance on the affected results.

Method

Sterman *et al* (2018a) model analysis

The Sterman *et al* (2018a) model is available under an open access licence, although it operates inside a closed-source framework which requires a full, 'professional', licenced copy of the VENSIM software (Venata Systems 2017) to work. The model is formed of two key components: (1) equations describing the supply chain, which are used to calculate the emissions associated with fuel production and use (a life cycle assessment: LCA calculation) and (2) a site model which calculates ongoing changes in carbon on a forest site and in the atmosphere after felling has taken place (a dynamic component to the LCA). While closer analysis of the supply chain variables and calculation may be warranted, here we focus on the forest site model.

The site model makes use of the flexible Chapman-Richards growth function (Richards 1959, Pienaar and Turnbull 1973, Zhao-gang and Feng-ri 2003) parameterised to represent aboveground carbon in forest sites. This function is used to represent gross primary productivity (GPP) of a forest site, while simple multiplication by dimensionless constants is used to approximate forest respiration; organic carbon deposition; and heterotrophic respiration.

Table 1. Species/region types covered by the Sterman *et al* (2018a) model.

Region of USA	Common name
North East	Maple/beech/birch Oak/hickory Oak/pine
South Central	Oak/hickory Oak/pine Short-leaved/loblolly pine plantation
South East	Short-leaved/loblolly pine plantation Long-leaved/slash pine plantation[a]

[a] Occasionally mislabelled in Sterman *et al* (2018a) supplementary information as long-leaved/loblolly pine.

The model was parameterised for eight different forest types in the USA (listed in table 1) by using a least-squares non-linear regression method, which is common ('invariably' used: Burkhart and Tomé 2012, p 239) within forest model development. The method uses a solution-finding algorithm to fit a mathematical representation of the forest growth curve to representative data-points with the minimum degree of error. This provides an approximation of actual forest growth behaviour which can be used to predict forest growth values where actual data is not present (e.g. in different time-steps, or over extended time periods). In this case, the model was trained using average values for forest and soil carbon produced by the USDA (Smith *et al* 2006). This dataset has been constructed using a combination of sample plots, and interpolation of data using the FORCARB2 model (Smith *et al* 2006, p 13). While uncertainties exist, and the data is unsuitable for smaller scale (stand-level) modelling, (Smith *et al* 2006, p 17) this data has been widely used in other projects (e.g. Jenkins *et al* 2010, Pan *et al* 2011, Lawler *et al* 2014, Adams *et al* 2018) for high-level estimates of carbon storage. The resulting model represents a high-level statistical approximation of forest growth (defined in Weiskittel *et al* 2011) which allows interpolation of values between the 5-year intervals in the data and extrapolation beyond the end of the dataset.

This approach has limitations, specifically resolution and predictive capacity. Generalisation implicit in the training data (average forest growth over a wide range of local site types) limits the applicability of the model to individual stands or spatially explicit areas - providing only high-level estimates. The lack of process-based calculation limits the model's ability to take account of varying site conditions (climate, soil, exposure), complex silvicultural systems (thinning, or selection fellings), and stochastic factors (e.g. fire or pest outbreak). This method does, however, have value as a tool to look at the approximate effect of management of large areas of forest to simple silvicultural systems in a more abstract/theoretical setting. This is particularly useful when looking at the carbon dynamics of biomass where a number of misconceptions persist (Ter-Mikaelian *et al* 2015, Bentsen 2017).

Replicating the Sterman *et al* (2018a) model

We recreated the model developed in Sterman *et al* (2018a) in a general-purpose, object-oriented, high-level programming language: Python. This was carried out using the Anaconda Python distribution (available from www.anaconda.com) which is already widely used in the research community and is distributed with an extensive ecosystem of open-source libraries and modules.

Our implementation: the 'Simple Biomass Comparison Model' (SBCM: included as supplementary material, most recent version downloadable from github.com/Priestley-Centre/SBCM) follows the same pattern as described above. SBCM compares emissions over time resulting from 1) fossil fuel production and use, and 2) biomass production, use, and subsequent forest site recovery.

The model was initially compared to the results published by Sterman *et al* (2018a) to check the success of the replication, this was carried out using a scenario based on a clear-fell of forest in order to supply biomass (equivalent to scenario S3 in Sterman *et al* 2018a). The biomass supply scenario was compared with a counterfactual (fossil fuel) scenario with energy derived from coal with an implicit assumption that there would be no emissions from the forest site in the absence of biomass production. While this may not always be an appropriate comparison (Ter-Mikaelian *et al* 2015, Koponen *et al* 2018) it was used to allow a direct comparison of results with those obtained by Sterman *et al* (2018a).

Table 2. Algorithms from the [scipy.optimize.leastsquares] function.

Algorithm	Notes
lm	Levenberg-marquardt algorithm (Moré 1978).
trf	Trust region reflective (Branch *et al* 1999).
dogbox	A trf implementation using a rectangular trust region (Voglis and Lagaris 2004, Nocedal and Wright 2006).

Table 3. Loss functions providing different weight to outliers (Scipy.org 2019).

Loss function	Formula
Linear	$\rho(z) = z$
Soft_l1	$\rho(z) = 2 \times ((1 + z)^{0.5} - 1)$
Huber	$\rho(z) = z \textit{ if } z \leqslant 1 \textit{ else } 2 \times z^{0.5} - 1$
Cauchy	$\rho(z) = \ln(1 + z)$
Arctan	$\rho(z) = \arctan(z)$

Agreement between SBCM and the Sterman *et al* (2018a) model (using the same parameters) in terms of forest growth over the first hundred years is very good ($<$1tC.ha^{-1}) but not exact in terms of maximum values for carbon over extended time periods (varying by up to 36tC.ha^{-1} for above-ground carbon at year 500). In view of this uncertainty, a curve fitting approach was developed in Python software to see whether improvements to the model parameterisation could be made, and whether a better fit of the training data would result in a closer agreement with Sterman *et al* (2018a).

Sterman *et al* (2018a) use the [optimizer] function in Vensim to apply least squares non-linear regression and Markov Chain Monte Carlo methods to determine model parameters. This is described in detail in their supplementary material (Sterman *et al* 2018a available online at stacks.iop.org/ERC/2/045001/mmedia) but, in summary, they restricted the matching algorithm to parameters which generate values which satisfy two set conditions:

1. The initial values for forest and soil carbon must equal year zero values in the training data (from Smith *et al* 2006)
2. The curve must result in the smallest achievable root mean squared error (RMSE) values between the data and modelled output.

We used a similar approach in our replication of the model, using the [scipy] Python library. The [scipy.optimize] function for Python contains a number of different algorithms for curve fitting (table 2) and for the weighting given to outlying data (table 3). The training data produced by the USDA (Smith *et al* 2006) which in turn were based on a series of estimates from the Forestry Inventory and Analysis Database (USDA Forestry Service 2005) contains values for forest and soil carbon for forests over the first 90 or 125 years of growth (depending on forest type). This contains the full growth curve (planting to maturity) of plantation forests; however, natural forests (and forest soils) take far longer to reach equilibrium and data over this timescale was not present. This projection of the growth curve beyond the length of the fitting data results in additional uncertainties (as discussed below).

A full range of possible combinations of algorithm and loss function were attempted in two permutations: firstly, with the model parameters unconstrained (simply looking for the best fit possible, with very loose limits on possible parameter values) and, secondly with constraints applied—requiring the first value in the results to equal the first value in the USDA training data (±1 tC.ha^{-1}). In both cases the fit of the modelled output to the training data was assessed by calculating the RMSE.

Using a subset of possible parameterisations (40 of 240) which resulted in an improved RMSE score over Sterman *et al* (2018a) SBCM was run to determine: the changes over time in forest and soil carbon storage, the carbon storage when mature (at 'equilibrium' as discussed by Sterman *et al* 2018a–assumed to be reached when forest and soil carbon is 99% of the potential maximum value) and the effect that parameter changes have on payback period.

In each case, the supply-chain model used the original parameterisation for supply chain efficiencies and emissions (from Sterman *et al* 2018a) without incorporating the modification of the efficiency parameter used by Dwivedi *et al* (2019) to allow a comparison with the original model results.

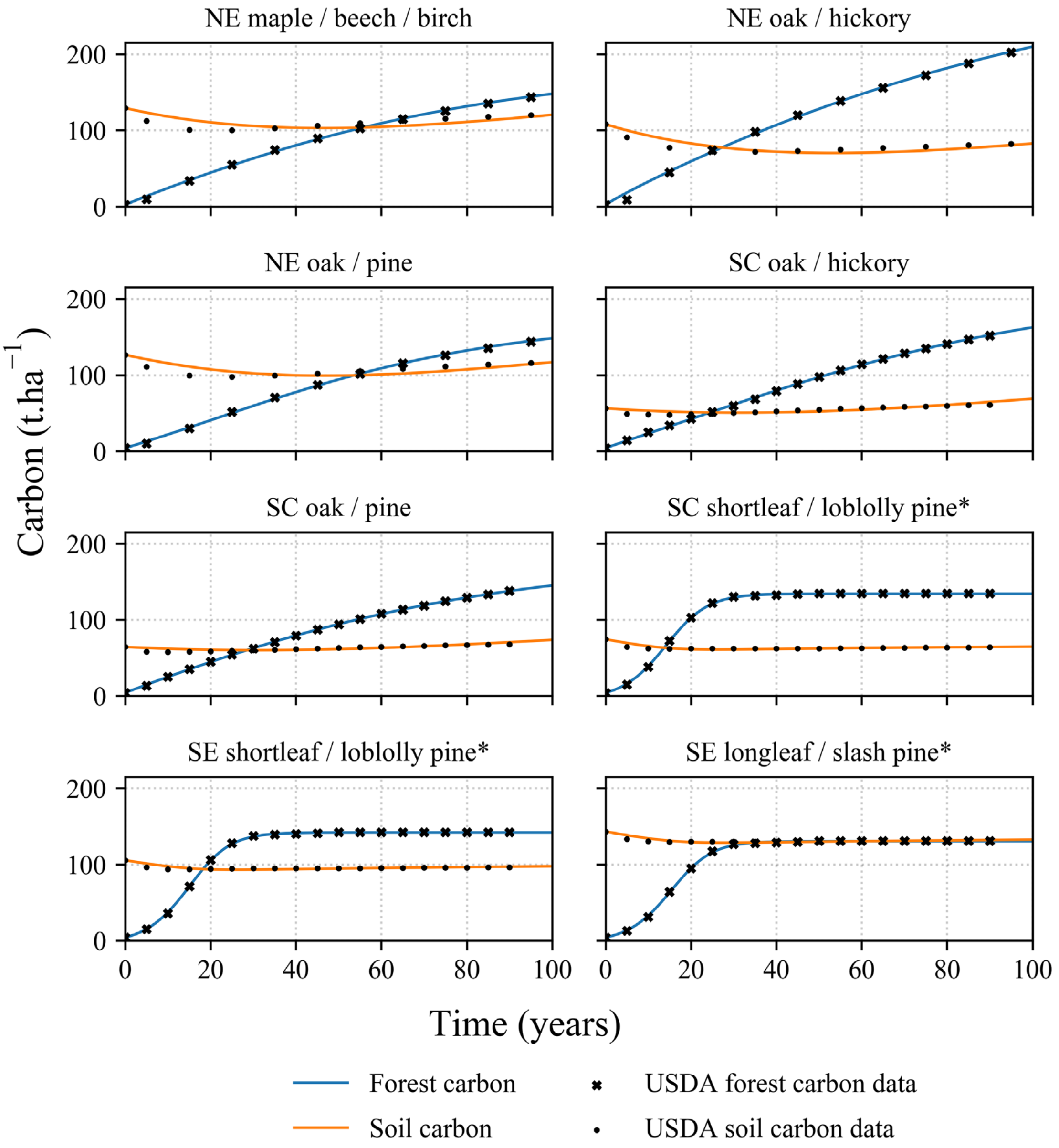

Figure 1. Forest and soil carbon values extrapolated using SBCM and the parameterisation used by Sterman *et al.* (2018a) Small discrepancies do exist, but growth over the first hundred years is visually indistinguishable from results published by Sterman *et al* (2018a supplementary material figure S2 page 11). Plantations are denoted with*.

Results

SBCM evaluation

Results for forest growth obtained by running SBCM using the standard parameters in Sterman *et al* (2018a) supplementary information table S3 show good agreement with values published by Sterman *et al* (2018a) over a modelled period of 100 years (as shown in figure 1). Notably; however, the forest carbon levels at equilibrium (maturity) are consistently higher than those reported by Sterman *et al* (2018a as shown in figure 2). This raises questions, as SBCM also returns lower RMSE values than were originally published in some cases (figure 3).

The effect of re-parameterisation

Of the 240 permutations assessed using our method (30 per forest type) 40 returned results with a better RMSE error than that reported by Sterman *et al* (2018a) shown in figure 4 (the full range of results are available online).

The increased range of possible parameterisations, while achieving marginal improvements in RMSE over the original Sterman *et al* (2018a) model resulted in a high degree of uncertainty in terms of the changes in forest

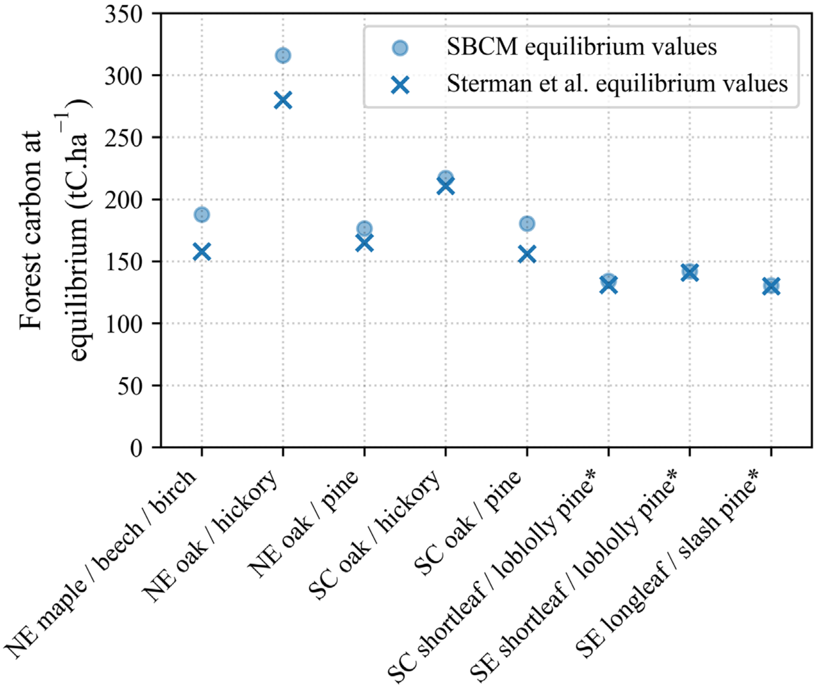

Figure 2. A comparison between forest carbon equilibrium values published by Sterman *et al* (2018a) supplementary information table S3 and results from SBCM using the same parameters. All values are of forest carbon at year 500 (plantations are denoted with*).

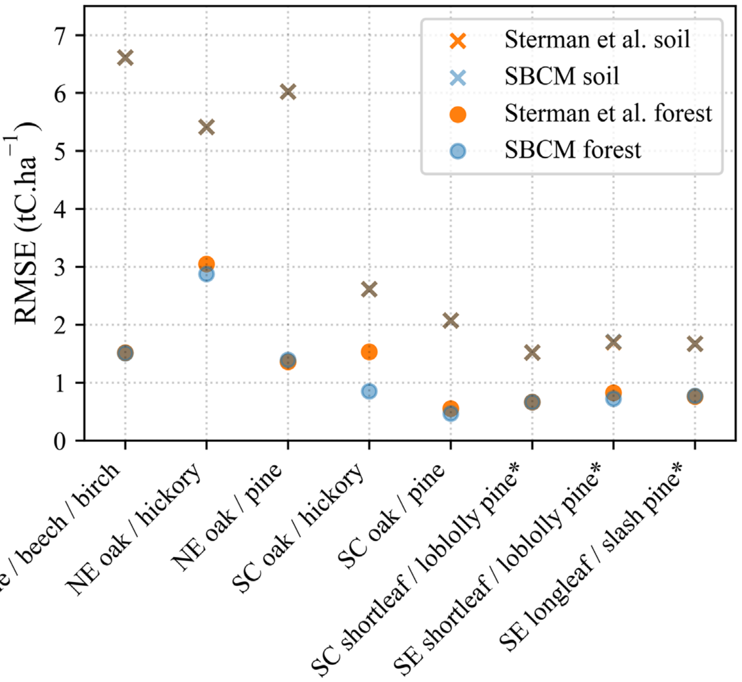

Figure 3. A comparison between RMSE values published by Sterman *et al* (2018a supplementary information table S3) and SBCM using the same parameters. Some variability exists between models which prompted further work. Plantations are denoted with*.

and soil carbon predicted by SBCM (which is unsurprising due to the numerical instability of the Chapman - Richards growth function: Ratkowsky 1983, Burkhart and Tomé 2012). In five of the eight forest types assessed, revised parameterisation resulted in substantial expansions of the uncertainty associated with site carbon, particularly in levels of soil carbon (see figure 5, which shows the range of possible outcomes using improved parameterisations). It is notable that this increase in uncertainty is confined to slower growing species mixtures

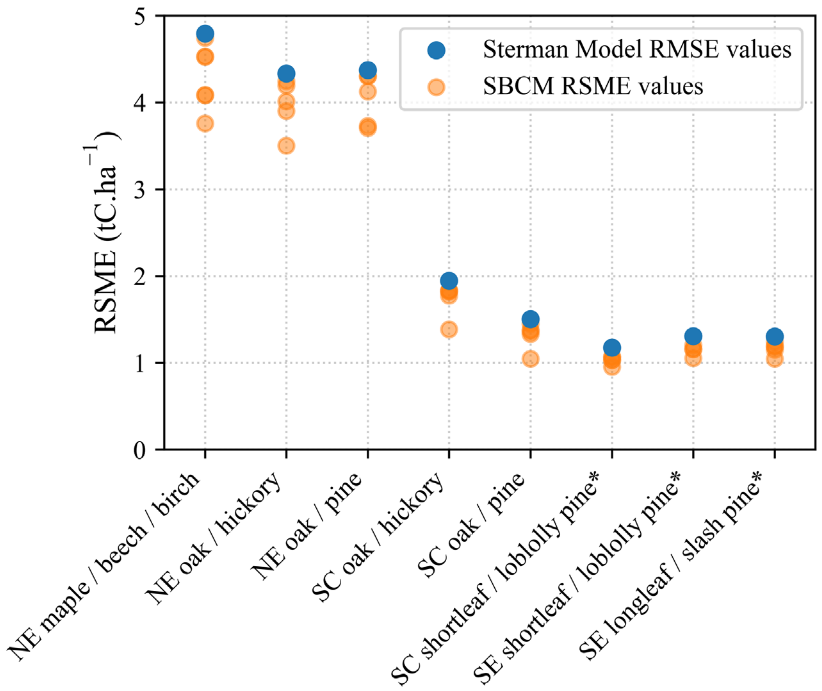

Figure 4. A comparison of RMSE values published by Sterman *et al* (2018a) supplementary information table S2) and those obtained by re-parameterisation of the model. All values are restricted to parameterisations with a better fit than Sterman *et al* (2018a) (40 in total) for clarity. Plantations are denoted with*.

where the entire growth curve was not present within the training dataset. In contrast, all three plantation forests show very similar outcomes regardless of parameterisation (figure 5 below). This supports the assertion in Burkhart and Tomé (2012) that the Chapman—Richards growth curve can result in more accurate outcomes when an estimated asymptote is added, as these forest types contain values close to the asymptote within the training data.

Changes in payback periods

Taking the range of growth curves into account and running the model for the full range of improved parameterisations (again using a 95% clear-fell scenario: equivalent to Sterman *et al* 2018a scenario S3) we found that the range of possible payback periods expands (figure 6). In each case, the values obtained using the Sterman *et al* (2018a) parameterisation fall at the top of the range of possible outcomes, and multiple estimates of shorter payback periods also fit the available data to a comparable degree. This is due primarily to the rate of emission to the atmosphere from the soil carbon pool. The rate of emission is directly proportional to the carbon pool size and, since this size and the time required for the pool to saturate are uncertain, this has a strong effect on the net emissions of the system shortly after felling.

There is a considerable difference between forests labelled by Sterman *et al* (2018a) as 'natural' (predominantly naturally regenerated hardwoods) and plantations (planted pine forests in the southern USA). Natural forests showed greater variation in terms of the time taken to reach maturity, the embodied carbon in a mature forest site, and the payback times associated with their use for biomass fuel. In contrast, plantation forests exhibited very low levels of uncertainty throughout. We argue that this pattern is due to extension of growth curves beyond the end of the fitting data. Of the forest types studied, all of the natural forests required long periods of time to reach maturity (equilibrium). The length of the datasets available to train the model were either 90 or 125 years, and this often fell short of capturing the entire growth curve. The faster growing plantation forests reached maturity comfortably within the timeframe available. A summary of the dataset length and years required to reach maturity is shown in table 4.

A further illustration of this effect can be seen in figure 7. There is a statistically significant correlation ($p = 6.26 \times 10^{-6}$) between the degree to which data has been extrapolated and standard deviation of the site carbon at equilibrium.

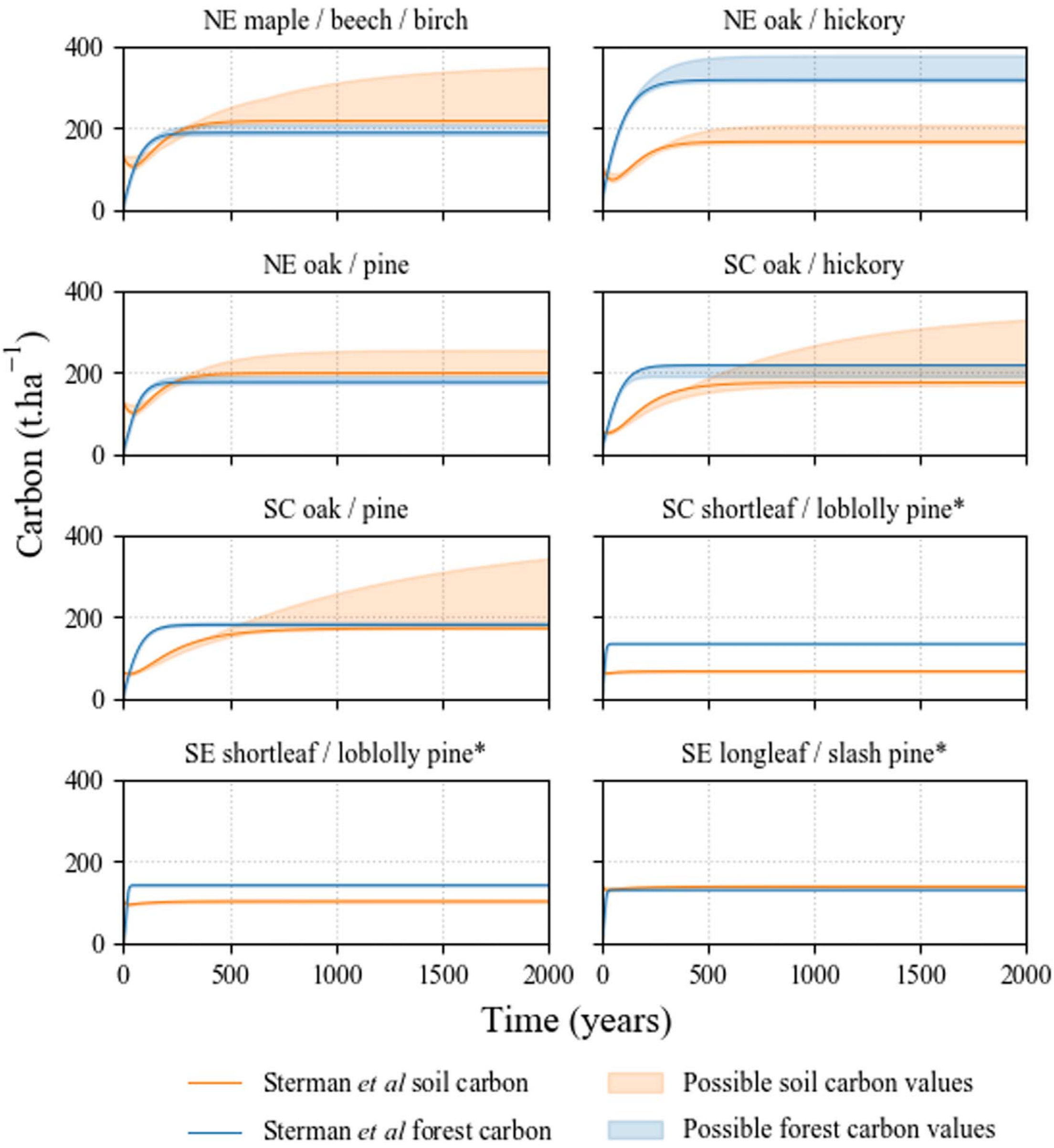

Figure 5. Full uncertainty of forest and soil carbon levels under all improved parameterisations Shaded areas contain the full range of outcomes possible from extrapolating parameterisations with a better fit than those obtained by Sterman *et al* (2018a) ±RMSE. Solid lines indicate the results obtained from SBCM under the Sterman *et al* (2018a) parameterisation. Plantations are denoted with*.

Discussion and conclusions

While there are small discrepancies between the forest site model results from the newly developed SBCM and Sterman *et al* (2018a) the overall match is good (figure 1), and we conclude that SBCM replicates the earlier model well.

In investigating disagreements between previously published results (Sterman *et al* 2018a) and the output of SBCM, we were not able to adjust the model parameterisations to achieve a large improvement in the fit with the training data (figure 4). It is significant, however; that the small improvements that were achieved, resulted in substantial changes to carbon uptake estimates generated by the model (figure 5). New parameterisations revealed large uncertainties in terms of the time carbon stocks take to reach equilibrium as well as the quantity of carbon stored on forest sites. This is believed to be due to the sensitivity of the growth function used within the model to minor changes in input parameters (numerical instability: discussed in Ratkowsky 1983).

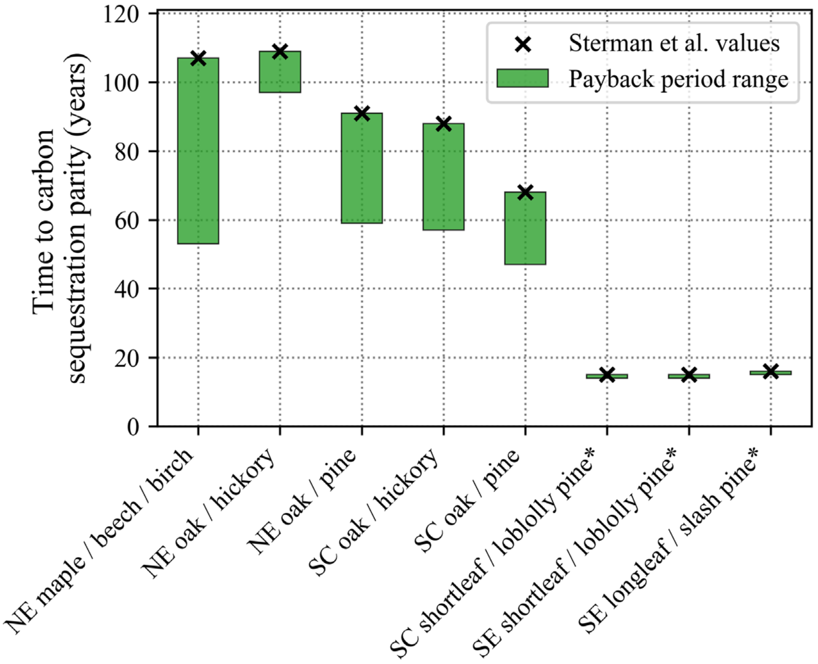

Figure 6. Carbon payback period (carbon sequestration parity) under different parameterisations. Once again, the variation between minimum and maximum values is far lower in the plantation forests (*).

Table 4. Comparison of time taken for forests to reach maturity and the length of the dataset used to train the model NB. The time required for forest soils to reach an equilibrium is substantially longer.

Region/species		Min	Mean	Max	Length of training dataset
		(years)			
NE maple/beech/birch	forest	263	316	342	125
	soil	513	1118	2403	
NE oak/hickory	forest	374	476	573	125
	soil	480	602	768	
NE oak/pine	forest	212	235	250	125
	soil	477	709	1073	
SC oak/hickory	forest	196	223	271	90
	soil	713	1310	3309	
SC oak/pine	forest	247	261	271	90
	soil	946	1796	4176	
SC shortleaf/loblolly pine (plantation)	forest	35	35	35	90
	soil	148	160	169	
SE shortleaf/loblolly pine (plantation)	forest	34	34	35	90
	soil	256	281	324	
SE longleaf/slash pine (plantation)	forest	34	34	35	90
	soil	244	278	305	

It is notable that the wide variation in possible growth rates exists only in the forests described by Sterman *et al* (2018a) as 'natural'. The common feature in these forests is that the full growth curve is not fully represented within the training data, as forest growth to maturity takes longer than the 125 years available from Smith *et al* (2006). This failure to specify a value on or near the asymptote of the curve is known to provide less accurate results when using the Chapman—Richards growth function (Burkhart and Tomé 2012). Faster growing 'plantation' forests do not suffer from this problem: the entire growth curve (including the asymptote) is contained within the training dataset; and consequently, the variation in output is very low. We conclude that the modelled outputs for these site types are more reliable and less prone to error than those from slower

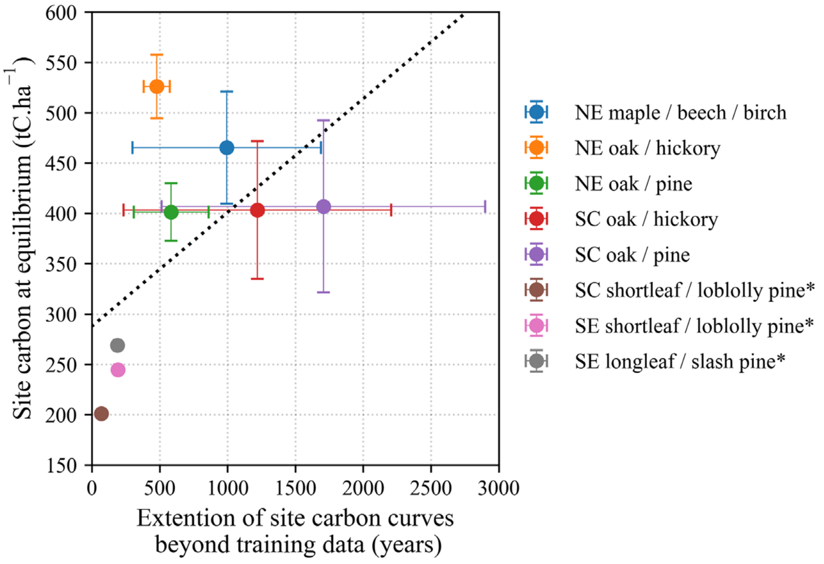

Figure 7. Comparison of the change in site carbon storage with extent to which values have been extrapolated beyond the training data. Values on the x axis is equal to the time taken for the site to reach full maturity (including soil), minus the number of years for which the fitting data is available. Error bars represent standard deviation. Plantation forests (denoted with*) show very low variation, and the error bars are obscured by the data-point. The dotted line is a linear best fit for the data points ($r^2 = 0.986$).

growing forests. In all forest types, the degree of variation is well correlated with the degree to which the growth curve has been extrapolated beyond the available training data (as shown in figure 7).

The variability exhibited by the 'natural' forest types is significant given the reliance of the original model on the assumption that forests are biologically mature (at equilibrium) before felling and that this has occurred by year 500. In the absence of an extended input dataset, we conclude that it is not possible to determine which parameterisation for 'natural' forests is most appropriate when using the current growth function (indeed, the values preferred by Sterman *et al* (2018a) may be the best fit with real-world situations).

We acknowledge the argument by Prisley *et al* (2018) that the lack of more nuanced silvicultural systems is a weakness in the model. We suggest that this, when combined with the uncertainty inherent in the slower growing 'natural' forests, raises important questions about the ability of the model to accurately predict payback times in these forest types. Based on our range of possible parameterisations, the range of possible carbon payback periods when modelling 'natural' forests expanded by between 21 and 54 years. This is in contrast to range of possible payback periods when modelling 'plantation' forests, which in each case was within one year (figure 6). We found that in every case the values published by Sterman *et al* (2018a) represented the maximum payback period achieved, suggesting a potential bias in their parameterisation. We conclude that, while the paper produced by Sterman *et al* (2018a) has been widely cited and discussed, its headline figures contain a level of uncertainty which is not apparent. This uncertainty can be limited by use of a growth function which does not suffer from the same instability, or collection of an extended dataset for very old forests (to provide an asymptote, limiting the range of possible growth curves produced).

We recommend the inclusion of robust error/uncertainty reporting (included in tables 5a and 5b) when discussing the climate effect of biomass fuel production from these site types when using this model. We have provided a summary of our best parameterisations below (table 6) and these are also available in the supplementary information.

This work sits within a wider programme of research to address the large uncertainties in the literature when calculating the carbon dynamics of forest growth and biomass fuel use. This work is ongoing, and is being carried out through expansion of the SBCM model framework. In the short term we intend to mitigate the uncertainty addressed in this paper by restricting assessments to either time horizons which do not extrapolate beyond the training data (max 125 years) or are based on forest types which are not affected (the 'plantation' forests). Future work will be based around incorporation of an alternative growth function, development of a wider range of silvicultural options (as per Prisley *et al* 2018), modification of the scenarios available (as per Dwivedi *et al* 2019) and better reflection the effect of biomass production on different forested sites and wider landscapes.

Table 5a. Calculated values for soil and forest carbon with margins of error based on the range of parameterisations identified above. Margins of error were calculated using highest and lowest estimates ± appropriate RMSE value.

year	NE maple/beech/birch forest (tC.ha^{-1})				NE oak/hickory forest (tC.ha^{-1})				NE oak/pine forest (tC.ha^{-1})				SC oak/hickory forest (tC.ha^{-1})			
	forest		soil		forest		soil		forest		soil		forest		soil	
25	62.4	+4.2 −7.5	117.9	+13.0 −13.3	84.6	+3.5 −6.9	86.6	+8.8 −10.0	59.1	+3.9 −8.4	118.5	+3.9 −17.2	57.3	+2.9 −1.5	56.4	+1.4 −6.7
50	101.7	+4.3 −6.5	116.1	+15.3 −15.1	138.9	+3.7 −6.8	79.6	+9.5 −10.6	100.0	+3.9 −6.2	117.4	+4.0 −20.3	102.4	+2.3 −1.6	59.3	+1.4 −7.5
100	150.3	+4.6 −5.0	128.5	+11.0 −10.1	215.8	+3.6 −5.2	87.9	+6.1 −6.8	150.9	+3.8 −5.4	127.9	+3.9 −13.3	162.9	+4.6 −1.7	71.6	+1.4 −4.7
150	174.5	+6.1 −6.9	149.0	+5.3 −8.3	263.8	+6.9 −6.9	107.3	+5.9 −5.4	173.1	+3.9 −9.1	145.3	+3.7 −8.7	184.4	+13.6 −1.4	87.7	+8.0 −3.1
200	186.4	+7.6 −9.6	169.9	+6.8 −12.0	293.8	+11.8 −11.0	126.9	+6.4 −6.3	181.6	+4.0 −11.9	162.9	+5.8 −6.9	189.9	+20.9 −1.4	104.1	+12.4 −3.2
250	192.2	+8.7 −11.7	188.1	+4.7 −15.4	312.4	+16.6 −15.7	143.2	+4.6 −5.2	184.7	+4.1 −13.4	178.6	+3.7 −8.0	191.2	+24.7 −1.4	119.8	+13.3 −5.5
500	197.4	+10.4 −14.5	235.5	+15.0 −26.2	340.1	+30.4 −28.4	177.5	+16.5 −17.3	186.4	+4.2 −14.5	224.7	+4.2 −32.5	191.6	+27.5 −1.4	185.0	+1.4 −34.0
1000	197.5	+10.5 −14.6	249.7	+60.3 −38.0	342.9	+34.1 −30.5	182.5	+24.3 −21.1	186.5	+4.2 −14.5	246.7	+5.1 −52.9	191.6	+27.5 −1.4	265.2	+1.4 −98.6

Table 5b. Calculated values for soil and forest carbon with margins of error based on the range of parameterisations identified above. Margins of error were calculated using highest and lowest estimates±appropriate RMSE value.

year	SC oak/pine forest (tC.ha^{-1})				SC shortleaf/loblolly pine plantation (tC.ha^{-1})				SE shortleaf/loblolly pine plantation (tC.ha^{-1})				SE longleaf/slash pine plantation (tC.ha^{-1})			
	forest		soil		forest		soil		forest		soil		forest		soil	
25	58.5	+1.5 −2.0	64.6	+1.0 −5.4	125.3	+1.1 −2.3	64.5	+1.0 −3.7	132.4	+1.2 −2.4	97.4	+1.1 −4.4	121.2	+1.3 −2.6	133.2	+4.5 −4.4
50	97.8	+1.4 −1.8	66.9	+1.0 −6.2	134.2	+1.2 −1.2	65.0	+1.0 −3.0	141.9	+1.3 −1.3	98.1	+1.1 −3.7	130.4	+1.3 −1.3	133.7	+4.1 −3.9
100	146.9	+1.3 −2.0	76.1	+1.0 −4.6	134.2	+1.2 −1.2	66.0	+1.0 −2.0	141.9	+1.3 −1.3	99.7	+1.1 −2.9	130.5	+1.3 −1.3	135.1	+3.3 −3.0
150	169.6	+1.5 −3.5	88.2	+4.7 −4.3	134.2	+1.2 −1.2	66.5	+1.0 −2.1	141.9	+1.3 −1.3	100.8	+1.1 −3.0	130.5	+1.3 −1.3	136.1	+2.8 −3.0
200	179.2	+1.6 −4.9	101.2	+7.6 −4.5	134.2	+1.2 −1.2	66.8	+1.0 −2.1	141.9	+1.3 −1.3	101.6	+1.1 −3.2	130.5	+1.3 −1.3	136.9	+2.4 −3.1
250	183.1	+1.7 −5.8	114.3	+8.0 −5.6	134.2	+1.2 −1.2	67.0	+1.0 −2.1	141.9	+1.3 −1.3	102.2	+1.1 −3.3	130.5	+1.3 −1.3	137.5	+2.1 −3.2
500	185.6	+1.9 −6.7	172.9	+1.0 −21.4	134.2	+1.2 −1.2	67.3	+1.0 −2.2	141.9	+1.3 −1.3	103.5	+1.1 −3.7	130.5	+1.3 −1.3	138.9	+1.8 −3.6
1000	185.6	+1.9 −6.7	256.5	+1.0 −87.2	134.2	+1.2 −1.2	67.3	+1.0 −2.2	141.9	+1.3 −1.3	103.8	+1.1 −3.9	130.5	+1.3 −1.3	139.4	+1.9 −3.8

Recommended margins of error and parameters.

Table 6. Best achieved values for model variables. NB these values have been rounded to 5 decimal places (the [scipy.optimize.leastsquares] function operates to 35 decimal places). The model is highly sensitive to input parameters, and full values obtained are available with the supplementary information. Plantations are highlighted.

Variable	NE maple/beech/ birch	NE oak/ hickory	NE oak/pine	SC oak /hickory	SC oak/pine	SC shortleaf /loblolly pine (plantation)	SE shortleaf /loblolly pine (plantation)	SE longleaf /slash pine (plantation)
Initial forest carbon (tC.ha^{-1})	0.00000	0.00000	0.34027	5.42946	3.65256	4.01355	4.28585	4.08908
Initial soil carbon (tC.ha^{-1})	118.44336	99.35253	112.43524	50.74496	59.95396	71.49007	102.08017	139.90835
Forest carbon$_{max}$ (tC.ha^{-1})	381.41778	999.97326	245.82447	525.90193	207.35840	174.73552	146.11936	158.35607
φ_{ab} (d'less)	0.00000	0.00092	0.00635	0.05255	0.00367	0.28448	0.20793	0.26133
k (d'less)	0.00591	0.00292	0.00793	0.00299	0.00943	0.00275	0.00299	0.00101
v (d'less)	1.38027	0.92458	1.30275	1.50000	1.22833	0.72667	0.90271	0.81340
φ_{ba} (d'less)	0.00000	0.00000	0.00000	0.05000	0.00000	0.05000	0.00153	0.03644
φ_{bs} (d'less)	0.00753	0.00656	0.00562	0.00243	0.00199	0.00562	0.00453	0.00590
φ_{sa} (d'less)	0.00594	0.01232	0.00420	0.00133	0.00093	0.01121	0.00619	0.00553
RMSE (tC.ha^{-1})	3.75833	3.50038	3.70652	1.38643	1.04564	0.95397	1.05174	1.04512

Acknowledgments

The authors would like to gratefully acknowledge the work carried out by Prof J Sterman, Dr L, Seigel, and Prof J Roony-Varga. Without their clear and comprehensive model description, this work would not have been possible.

Funding statement

The work was carried out by the Priestly Centre which is based within the University of Leeds. Work was partially funded by grants from the United Bank of Carbon, and the sustainability department at Drax Group plc.

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