Forests and Fuel

Development of a Simple Biomass Comparison Model

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The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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Abstract

Forest-sourced biomass combustion is a popular climate change mitigation technology used to decarbonise electricity generation. Disagreement in the literature on the sustainability of biomass deployment limits policy development. (Chapter 1). The project addresses this uncertainty by development of the Simple Biomass Comparison Model (SBCM) to explore the effect of contrasting assumptions and experimental designs.

An existing model first developed by Sterman et al. (2018a) was identified, analysed in detail and replicated in Python to form SBCM (Chapter 2). SBCM produced a good (but inexact) match for the training data and previously published results. To improve this, the forest growth component of SBCM was re-parameterised (Chapter 3) against the original training data. A significant divergence ($p = 0.00002$) in species with long growth curves arising from numerical instability in the forest growth function was identified. Analysis of the original supply-chain (Chapter 4) revealed a number of parameterisation errors. These were corrected, and new scenarios for BECCS and gas were developed. These led to large decreases in payback period.

SBCM was modified to improve several inaccurate assumptions in the original model (Chapter 5) by introducing variable rotation length and silvicultural thinning. Shorter rotation lengths resulted in a mean increase in modelled yield of 10.9 $GJ.ha^{-1}.a^{-1}$ for non-plantation forests and 7.7 $GJ.ha^{-1}.a^{-1}$ for plantations. This highlights the weakness of payback as a suitable metric for biomass uptake.

The study concludes (Chapter 6) that conventional biomass use may be more appropriate than other technologies in some contexts over some time-periods, but that this is by no means certain. Without some form of BECCS technology, biomass remains a low carbon option at best, and is heavily dependent on a sustainable supply chain to achieve positive environmental outcomes.

Further work to develop clear methods and processes is strongly recommended.

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Chapter 1. Background and a review of the literature

In which the Author embarks on a perilous endeavour

1.1 Introduction

Wood fires are a fundamental part of human history, pre-dating virtually every other technology. Evidence exists that suggests that fire has been used by hominids over hundreds of thousands of years (James et al., 1989) and that the controlled use of fire may have had a significant influence on the evolution of modern humans (Wrangham, 2017; Sandgathe and Berna, 2017; Stepka et al., 2022). Wood fires have been in regular use across recorded history and this traditional use of wood still contributes around 6% of the world's energy needs today (Ritchie et al., 2022b).

While it is hard to deny the atavistic appeal of traditional fires (or their utility to some of the poorest people on earth) a less aesthetically pleasing industrial scale use of wood as a fuel has been steadily increasing in recent years. This has been described as an economic use for poor quality timber, and as an alternative "carbon neutral" source of energy to address climate change concerns (Reid et al., 2020). The sustainability of this course of action has been the subject of debate (Slade et al., 2018; Mather-Gratton et al., 2021) and much research (Welfle et al., 2020) with little prospect of a simple set of conclusions in the near future (Robledo-Abad et al., 2017).

This chapter seeks to identify the core issues at stake in the debate and review the current literature in order to identify the various arguments, assumptions, and interpretations which has led to such a confusing range of conclusions. This includes a review of the background, addressing the underpinning elements of the debate (Section 1.2), followed by a detailed assessment of the terminology and assumptions used in the scientific literature (Section 1.3). Based on this review, a number of conclusions are drawn (Section 1.4) which are used to outline a programme of research to identify how model parameters, assumptions and reporting metrics affect the apparent sustainability of biomass supply chains (Section 1.5).

1.2 Background

1.2.1 Climate change

The global climate is undergoing a period of rapid change, and it is now "unequivocal" that human activities are the primary cause (Cubasch et al., 2013; Arias, Bellouin, Coppola, R. Jones, et al., 2021). This is taking place because of changes to Earth's energy budget through alteration of absorption spectra of the atmosphere and land surface. These changes to the quantities of energy trapped by the atmosphere are primarily caused by anthropogenic emissions of greenhouse gases (GHGs) which are transparent to visible light, but opaque in the infra-red wavelengths and changes in land use which alter the surface albedo (Arias, Bellouin, Coppola, R.G. Jones, et al., 2021). For example (as shown in Figure 1.1) annual emissions of carbon dioxide (CO_2) – the most significant GHG (Arias, Bellouin, Coppola, R. Jones, et al., 2021) have been rising since the dawn of industrial revolution (Ritchie et al., 2022a).

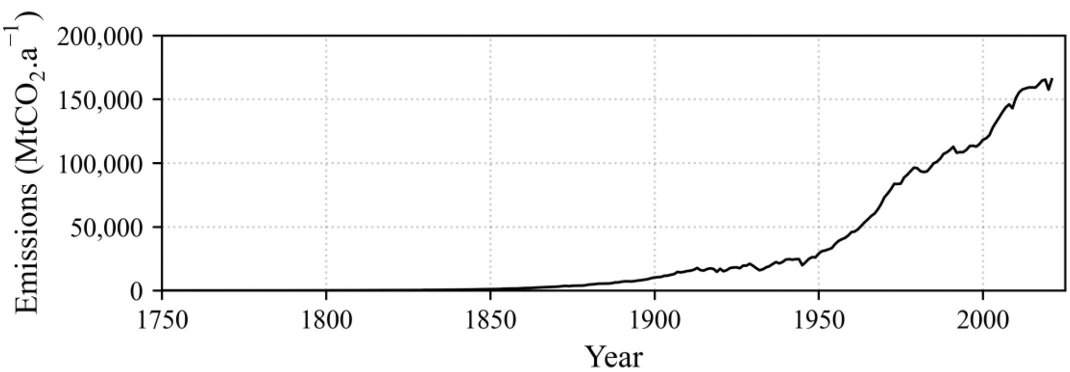

Figure 1.1. Annual global CO_2 emissions 1750-2021 (data from Ritchie et al., 2022a). Global emissions of CO_2 have shown no appreciable decrease since the start of the industrial revolution. These emissions are primarily caused by the combustion of fossil fuels.

The result of these changes is that "Human-induced warming reached approximately 1°C … above pre-industrial levels in 2017, [and is] increasing at [around] 0.2°C … per decade…" (Hoegh-Guldberg et al., 2018) shown in Figure 1.2.

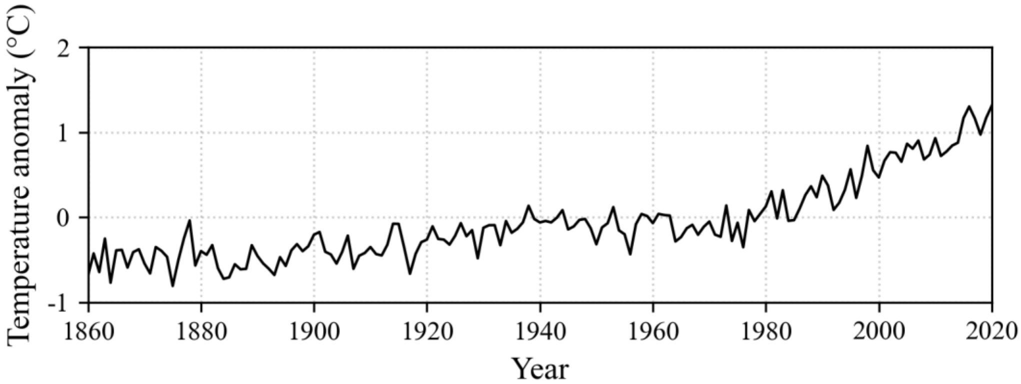

Figure 1.2. Global temperature anomaly 1860-2019 relative to 1960-1990 mean value (data from Osborn et al., 2021) Global temperatures, while showing variation, exhibit a strong correlation with CO_2 emissions over the post industrial revolution period.

This significant and rapid alteration of the earth's energy balance is already having far-reaching consequences in terms of weather events, the cryosphere, and sea levels; with substantial repercussions for the biosphere and human societies (Field et al., 2014; Pörtner et al., 2022)

An international effort is underway to address the challenges posed by climate change. This effort, centred about the United Nations Framework Convention on Climate Change (UNFCC, Kuyper et al., 2018) aims to develop policies and activities which 1) mitigate: "reduce the sources or enhance the sinks of greenhouse gases" (Edenhofer et al., 2014) or 2) adapt: "[adjust] to actual or expected climate and its effects" (Field et al., 2014).

The transition away from activities which emit climate forcing agents (primarily CO_2) is far from certain, and projections suggest that – depending on future policy decisions about technologies and activities, the range of possible outcomes is substantial (Stocker et al., 2013; Riahi et al., 2017; Arias, Bellouin, Coppola, R. Jones, et al., 2021; Shukla et al., 2022).

A common feature of scenarios which result in lower emissions and less severe warming, is a decarbonised energy (Meckling et al., 2017) and transport (Gota et al., 2019) infrastructure. Another is the removal of CO_2 from the atmosphere directly through negative emissions technologies (Daggash et al., 2019; Fawzy et al., 2020; Carton et al., 2020) and enhancement of existing biospheric carbon sinks such as forests (Doelman et al., 2020).

1.2.2 Climate change, carbon, and the terrestrial biosphere

Anthropogenic climate change is caused through a number of different pathways, these include: the release of greenhouse gases (e.g. CO_2, CH_4, N_2O, halocarbons, ozone); changes to the hydrological cycle (drainage of wetlands, contrails, and stratospheric water vapour); the release of particulate matter (aerosols); and changes to the global surface reflectivity (albedo) - mainly through land use changes (LUC), and black carbon deposition on snow (Myhre et al., 2013; Arias, Bellouin, Coppola, R. Jones, et al., 2021) The relative impact of these factors is shown in Figure 1.3 below.

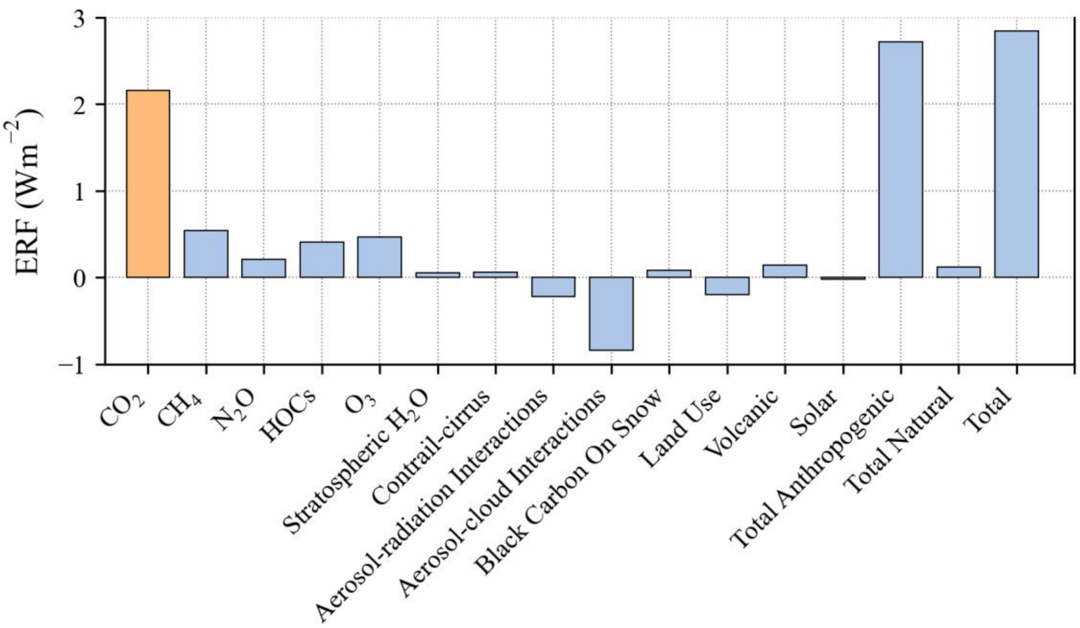

Figure 1.3. Effective Radiative Forcing (ERF) values for different climate forcers plotted using data from (Arias, Bellouin, Coppola, R. Jones, et al., 2021, table. AIII.3). CO_2 the principle focus of this study is the most significant climate forcer, primarily due to its abundance.

The majority of climate forcing is caused by CO_2 but this is primarily due to the quantity emitted. Methane, nitrous oxide and halocarbons all have greater global warming potentials than CO_2, but have a smaller overall effect because of their lower relative abundance (Arias, Bellouin, Coppola, R. Jones, et al., 2021, table. 7.15).

CO_2 is primarily emitted as a result of carbon release from geological storage by the extraction and combustion of fossil fuels (Arias, Bellouin, Coppola, R. Jones, et al., 2021), and the cement and steel industries (van Ruijven et al., 2016; Bataille, 2020) – all of which generate significant quantities. Other sources of CO_2 include the decomposition of methane released from permafrost (Holm et al., 2020; Ridolfi et al., 2021) and agriculture (Jackson et al., 2020), and directly from combustion of recently living matter from the terrestrial biosphere through wildfires (Volkova et al., 2021), LUC (Shukla et al., 2019) land clearance and the use of wood products as fuel (Reid et al., 2020) as shown in Figure 1.4 below.

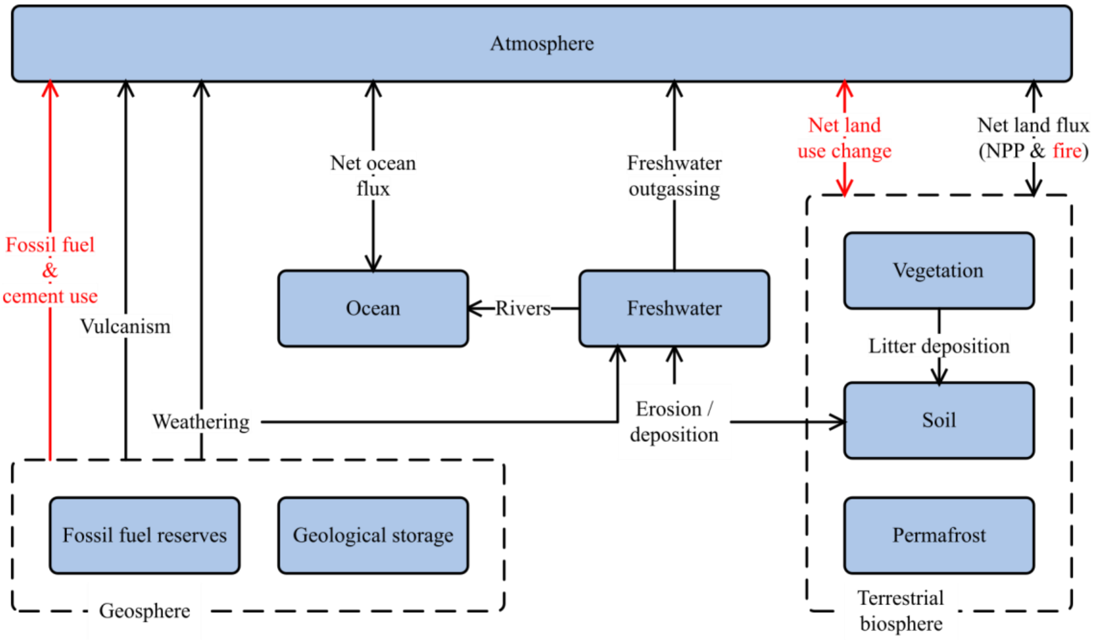

Figure 1.4. A simplified schematic of the global carbon cycle (adapted from Ciais et al., 2013 fig. 6.1). Flows which are primarily human mediated are shown in red, the overwhelming majority of these result in a net gain in atmospheric carbon.

The climate sensitive interactions which take place within the terrestrial biosphere are extremely complex, and this complexity is exacerbated by human influences and processes.

The net ERF of the terrestrial biosphere is not static, as growth, mortality, and seasonality are continually taking place. This includes a range of factors such as albedo change due to seasonal forest senescence and snow cover (Jääskeläinen and Manninen, 2021); changing carbon stocks due to growth, and mortality (Matthews et al., 2016), carbon fertilisation (Ziegler et al., 2021), the release of biological volatile organic compounds (Scott et al., 2018; Rap et al., 2018) and the release of methane and CO_2 from the decomposition of organic material (Megonigal and Guenther, 2008).

Human interactions further increase this complexity by deliberate (and accidental) changes in land use (Kassas, 1995), harvesting crops and timber, artificial fertilisation, soil disturbance, and changes in site hydrology (Shukla et al., 2019). Wider landscape-scale stochastic factors such as fire, pests, and diseases while being natural features of undisturbed landscapes also tend to change in terms of frequency, intensity, and duration as a result of human land management practices (Brankatschk, 2019).

Of the radiative forcing factors caused by human interactions with the terrestrial biosphere, the emissions of CO_2 are the most significant (as shown in Figure 1.3). These take place primarily when changes occur in the soils of wetland and permafrost dominated habitats and during deforestation (Olsson et al., 2019) or forest harvesting operations (Buchholz et al., 2014).

As with the controlled use of fire, human interactions with forests have been taking place since before recorded history (Williams, 2006; Ellis, 2011; Ellis et al., 2013), and these interactions have had a profound influence on the nature of forest carbon storage. However, the assessment of forest carbon stocks is not an exact science, and margins of error when estimating carbon volumes remain high (Parrott et al., 2012; Olschofsky et al., 2016). As such the forest carbon cycle is commonly simplified to account for the most significant flows of carbon, while omitting minor factors which occur well within the uncertainty range of larger effects. An example of a simplified schematic used for modelling the forest carbon cycle is shown below in Figure 1.5.

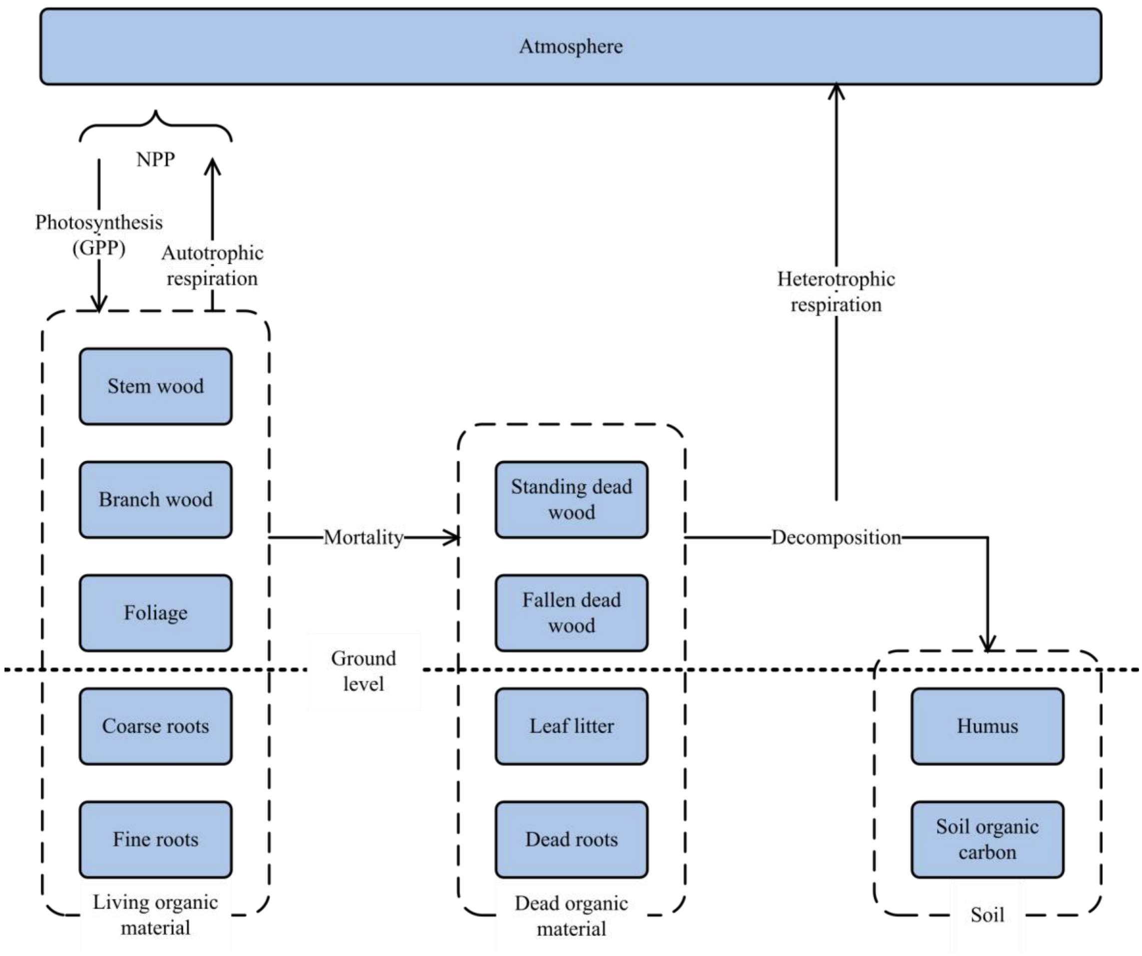

Figure 1.5. A simplified schematic of the carbon cycle within an undisturbed forest (derived from Smith et al., 2006; Matthews et al., 2016)

This schematic shows an approximation of the carbon stocks and flows within a forest at stand level, but omits a great deal of detail and context. Many forest modelling approaches exist (described more fully in section 3.2.3 below) for different purposes and these focus on different aspects of forest growth and management. Suffice to say at this point, that forests and the climate are intimately linked and this this linkage is very strongly affected by human influences.

1.2.3 Forest growth and retention as a climate change mitigation strategy

Deforestation is a significant driver of climate change (Shukla et al., 2019). Forests currently cover around 30% of the global ice-free land surface (Shukla et al., 2019; FAO and UNEP, 2020). This area is a substantial reduction on historical forest cover as an area of approximately 1.8 billion ha had been felled prior to 2010 (Martin et al., 2012). Large scale deforestation has been responsible for the release of an estimated 180 GtC into the atmosphere between 1750 and 2011 (Stocker et al., 2013) and the trend towards deforestation has been consistent over the whole of human history (Williams, 2006; Ellis, 2011; Ellis et al., 2013).

A large international effort is underway to prevent further deforestation and to replant significant areas of forest (Angelsen, 2014; UNFCCC, 2021b). The effort is intended to reduce emissions from deforestation, restore damaged carbon sinks, and provide greater resilience and adaptability to terrestrial ecosystems and human societies (FAO, 2018). This has been primarily carried out via the reducing emissions from deforestation and forest degradation in developing countries (REDD+) framework in developing nations – although this approach has been widely criticised (Asiyanbi and Lund, 2020) and via nationally implemented forestry strategies within the developed world, which are reported on via the UNFCCC (IPCC, 2006).

1.2.4 Biofuels as a climate change mitigation strategy

Increasing the scale and significance of bioenergy technologies has also become a key element of the global effort to decarbonise transport fuels and energy supplies in the face of climate change (Chum et al., 2011; Craggs and Gilbert, 2018; Funk et al., 2022). These technologies derive energy from a wide range of biological feedstocks including

'…the biodegradable fraction of products, waste and residues from biological origin from agriculture (including vegetal and animal substances), forestry and related industries including fisheries and aquaculture, as well as the biodegradable fraction of industrial and municipal waste' (EU, 2009 article 2e).

The logic of using biologically sourced fuels as opposed to fossil fuels is relatively straightforward: a crop regrows, reabsorbing carbon from the atmosphere. This means that over a complete cycle of harvest, combustion, and regrowth the total amount of carbon added to the atmosphere is approximately zero (Fargione et al., 2008). This simple rationale (as shown in Figure 1.6) has been used to justify a significant development of biofuel supply chains worldwide (Slade et al., 2018).

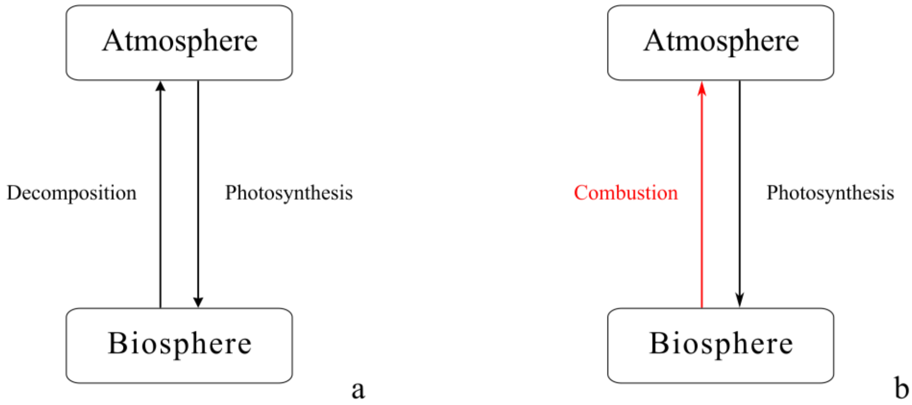

Figure 1.6. *The logic of the carbon neutrality of energy derived from biomass fuels. As shown in the schematic, over time, the carbon absorbed by photosynthesis is approximately equal to the carbon released during decomposition of dead material (a). If this material is burned to provide useful energy (b) we simply increase the rate of a process (decomposition) which would have occurred in any case. This simplistic logic ignores the change in rate of transfer of carbon from the biosphere to the atmosphere, supply chain emissions, and a potential decrease in the biospheric carbon pool which occurs through deforestation if this material has an economic value.*

Biofuels have been popular globally because they allow direct substitution for existing fossil fuelled systems with a minimum of infrastructure modification and expense (Slade et al., 2018). This has led to an extremely rapid uptake which has resulted in a number of unintended consequences and uncertainties about

1. Their efficacy as an emission reduction technique (Holtsmark, 2015).
2. The effect on land use (Creutzig et al., 2015).
3. The effect on global biodiversity and existing carbon stocks (Searchinger et al., 2018).

These concerns have become a significant underpinning of anti-biomass energy campaigns, largely as a result of work by environmental NGOs (Mather-Gratton et al., 2021 e.g. Brack, 2017a; Dogwood Alliance, 2012; RSPB et al., 2012 and others) as discussed further below (Section 1.2.6).

1.2.5 Forest-sourced biofuels (biomass)

Solid biofuels are derived from a very wide range of different feedstocks (EU, 2009). These include agricultural residues (Werther et al., 2000), woody post-consumer waste (Röder and Thornley, 2018) dedicated woody energy crops (Bajwa et al., 2018), and woody by-products of manufacturing and secondary processing (Malkki et al., 2003). While a number of these feedstock sources are relatively uncontroversial; others raise significant questions. Biomass fuel, defined here as: solid, *forest-sourced* material (broadly equivalent to "woodfuel" FAO, 2001 or 'forest fuel'; BSI, 2014) represents an extreme case due to its extended rotation length (Thornley, 2018).

The use of forest-sourced biomass has been widely supported globally (Reid et al., 2020) and use of this material has shown a marked increase as a result, as shown in Figure 1.7 below. In particular the UK has become the largest importer of biomass pellets globally (circa 8.8 million tonnes or 21% of global output in 2019 - Forest Research, 2020; FAO, 2020) principally for use in power generation (Figure 1.8). All future projections under the shared socioeconomic pathway (SSP) scenarios assume a substantial increase in the use of biomass fuels both with and without the implementation of carbon capture and storage (CCS) technologies (see also Chum et al., 2011). Under scenarios which meet the 1.5°C (>50%) target, global carbon dioxide removal (CDR) from bioenergy with carbon dioxide capture and storage (BECCS) is estimated at 30–780 $GtCO_2$ by 2100 (Shukla et al., 2022) as shown in Figure 1.9.

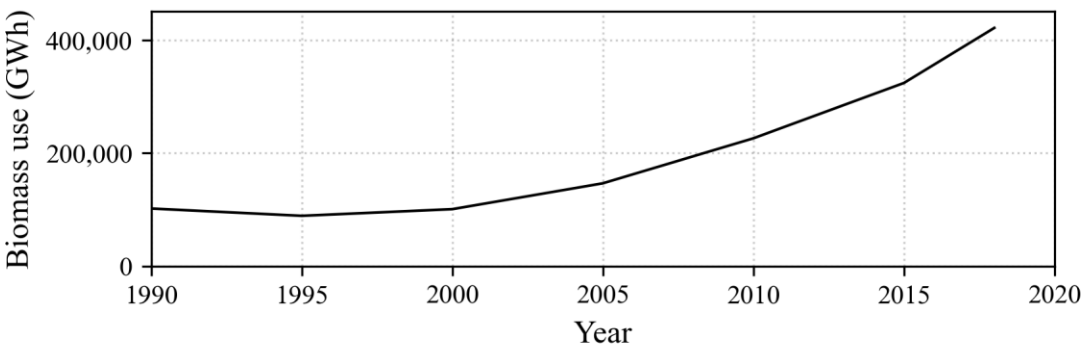

Figure 1.7. Global primary solid biomass fuel consumption for electricity generation 1990-2018 (data from IEA, 2020). The global demand for biomass used in electricity generation (as opposed to traditional uses such as cooking etc.) has quadrupled since 1990.

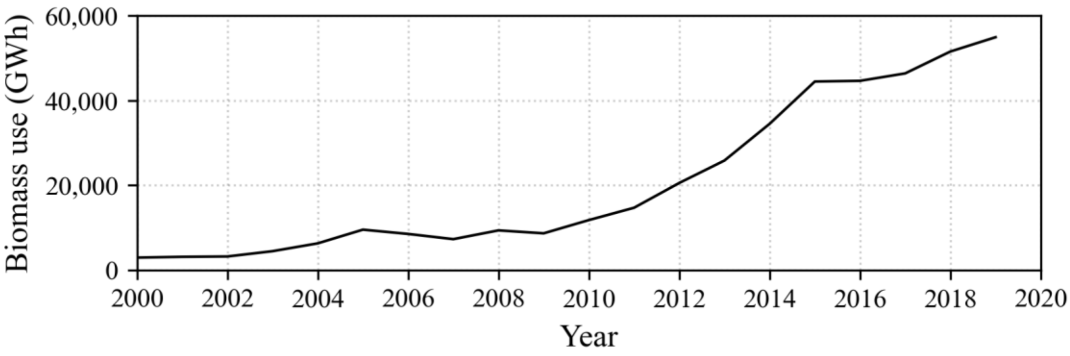

Figure 1.8. Primary biomass fuel use, UK (data from BEIS, 2022a). Biomass use in the UK has risen from around 3,000 GWh.a^{-1} in 2000 to around 55,000 GWh.a^{-1} in 2019 (an eighteen-fold increase)

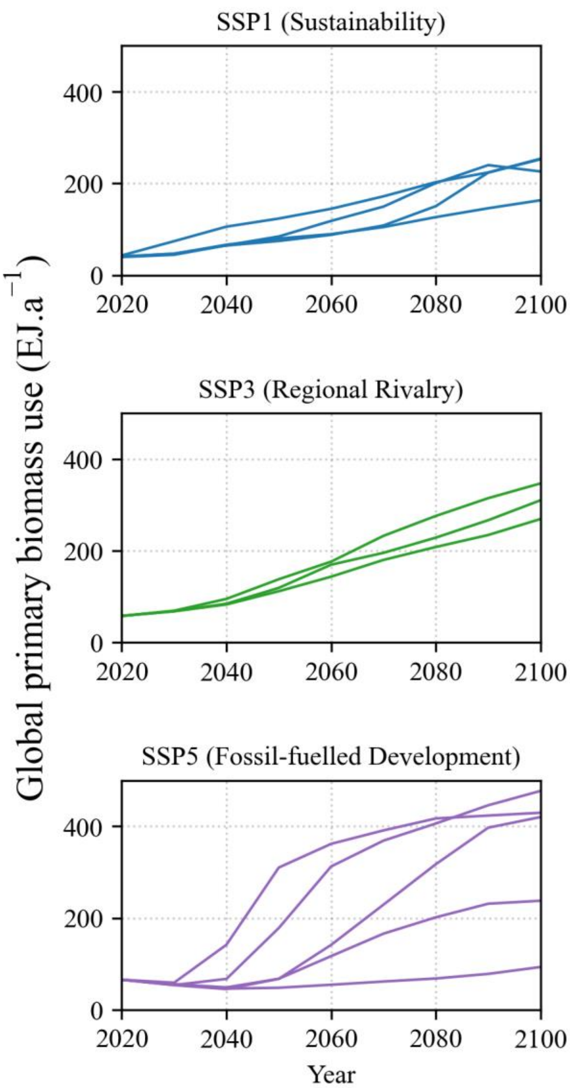

Figure 1.9. Projected future use of global biomass demand for electricity generation (data from van Vuuren et al., 2017; Fricko et al., 2015; Fujimori et al., 2017; Calvin et al., 2017; Kriegler et al., 2017; Rogelj et al., 2018; Gidden et al., 2019). Significant increases in energy derived from biomass are projected under virtually all the SSP scenarios. This may take the form of conventional first-generation biomass to power (notably in SSP3-60) or as bioenergy with carbon capture and storage (BECCS, notably in SSP4-26)

1.2.6 The debate

The extraction of silvicultural thinnings, branch wood, brash, roundwood, and stumps (see Appendix A for definitions) directly from the forest as a feedstock has highlighted a striking contradiction inherent in the dual objectives of biomass use and forest carbon storage (Taeroe et al., 2017; Schlesinger, 2018; Favero et al., 2020)

On one hand biomass is an attractive alternative to fossil fuels which regenerates over time allowing a single area of land to replace fossil fuel emissions a number of times over (Timmons et al., 2016). It has also been generally welcomed by the forestry sector as a marketable use for poor quality timber (Malmsheimer et al., 2011). Biomass has been perceived as a potential revenue stream encouraging active forest management, displacing fossil fuels, and effectively utilising material which previously may have been left in the forest to rot (Abt et al., 2012; Dupuis et al., 2021) contribute to forest fire risk (USDA Forestry Service, 2009; Mitchell et al., 2009) or otherwise be excluded from supply chains (Lamers et al., 2014).

On the other hand, production of biomass fuel requires release of carbon from an existing sink (Ter-Mikaelian et al., 2015). Felling within forests may affect biodiversity, and fears exist that primary forests may be converted to intensively managed plantations, or felled and removed altogether (Olden, 2016; Brack, 2017b; Brack, 2017a). While it is true that forests will often regenerate, if re-planted or left undisturbed, this may take a very long time (Norton et al., 2019); resulting in elevated atmospheric carbon concentrations for decades or even millennia (Mitchell et al., 2012). The regenerative loop which led biofuels to be described as carbon neutral still exists, but the disparity in speed between combustion and regrowth results in a long period of elevated atmospheric CO_2 within the cycle – during which elevated radiative forcing takes place (Beddington et al., 2018). The production of biomass may also displace material otherwise destined for longer lived harvested wood products (HWPs) conceivably reducing potential carbon storage in the "anthropospheric" carbon pool (Sathre and Gustavsson, 2006; Gustavsson et al., 2017).

Over-simplified communication derived from the academic literature looking at this issue, and a poorly constrained range of results has led to a polarised and confused debate within the public sphere about the environmental effects of biomass use, and the advisability of support (Cătuţi et al., 2020). For example, in 2012, Searchinger wrote a discussion paper (Searchinger, 2012) on the UK Government Bioenergy Strategy (DECC, 2012) his (un-reviewed) paper was critical of the strategy which failed (in his opinion) to correctly model the payback times for biomass use. Searchinger's paper (which was based on a single extreme-case scenario in the original report) was then used by Friends of the Earth, Greenpeace, and the Royal Society for the Protection of Birds (RSPB) among others, to inform their policy report "Dirtier than coal?" (RSPB et al., 2012). This report, gained national publicity in the press (EJNow, 2012; Kinder and

Gray, 2012; Huyton, 2013) and has since been quoted in other influential policy documents (Brack, 2017b).

This simplification of the complexities of biomass carbon cycling risks turning the discussion around the sustainability of biomass fuel into a polarising series of “biomass is good / bad” statements in the public sphere (e.g. Galeon, 2018; Stock, 2017; Moomaw, 2018a; Moomaw, 2018b; Slade et al., 2018; Olden, 2016; Sterman et al., 2022).

1.3 Bioenergy emission accounting frameworks

As we might expect, the apparent contradiction between supporting forest retention, and forest felling for use as fuel has been discussed extensively. The debate can best be summarised in the question: Is energy from forest-sourced biomass sustainable, and does it produce a net benefit in terms of atmospheric carbon dioxide within a timeframe consistent with our greenhouse gas emission targets?

A substantial body of literature has grown around this apparently simple question (Welfle et al., 2020) and has a very wide range of possible answers (Buchholz et al., 2016; Bentsen, 2017). The discussion has been further hampered by a lack of clarity; this is due to the heterogeneity of the terms, methods, assumptions, system boundaries, and metrics (not to mention misconceptions, as described by Ter-Mikaelian et al., 2015) evident within the literature (Holtsmark, 2013; Laganière et al., 2017; Giuntoli et al., 2020).

The two main methods (O’Brien et al., 2012; Liu et al., 2018) for assessing the carbon balance of human activity are 1) the method as produced by the IPCC (Eggleston et al., 2006; refined by Buendia et al., 2019) and 2) Life Cycle Assessment (LCA: ISO, 2006a; ISO, 2006b). These methods differ primarily in terms of system boundaries, and the inclusion / exclusion of non-CO_2 GHGs (Cellura et al., 2018). In practice, biomass carbon accounting does not sit comfortably in either camp.

In using the IPCC framework, firm boundaries are introduced around geographical territories which separates the forest and the end user into different accounting silos in the case of internationally traded commodities. For example, forest biomass harvesting is reported as a loss in stored carbon under “agriculture / forestry and other land use” (Eggleston et al., 2006 Volume 4) “biomass combustion for power generation” however, is calculated at a zero rate (to prevent double counting: Eggleston et al., 2006 Volume 2). This gives rise to a potential “accounting error” if forest loss is not accurately reported: extensively discussed by Searchinger and others (Searchinger et al., 2009; Haberl et al., 2012).

Using an LCA method would appear to be an obvious solution, LCA boundaries are tailored to the supply chain, rather than a specific territory. However, LCA is predicated on the concept of units of impact (tCO_2e, tN_2O etc.) per unit of product (Bjørn et al., 2018). This value when looking at a biomass fuel with a long forest recovery time is not static, and if a static value is used, considerable uncertainty then exists about what time horizon is most appropriate (Liptow et al., 2018; Albers et al., 2020). The use of Dynamic Life Cycle Assessment (DLCA) couples existing LCA techniques with a temporal element to identify the changes, but a plethora of different assumptions, data sources, specific supply chain circumstances and methods, does not lend itself to clear comparisons (Hauschild, 2018; Perkins and Suh, 2019).

A significant number of authors have attempted to bridge this gap with the majority opting to develop independent hybrid solutions (Welfle et al., 2020); based on, but not limited by existing methods.

To briefly summarise, the mechanics of biomass carbon accounting lies in mass balance of four distinct carbon pools: fossil carbon, the terrestrial biosphere, the anthroposphere (Guest, Bright, et al., 2013), and the atmosphere; over time (Paustian et al., 2006; Watson, 2009) as shown in Figure 1.10.

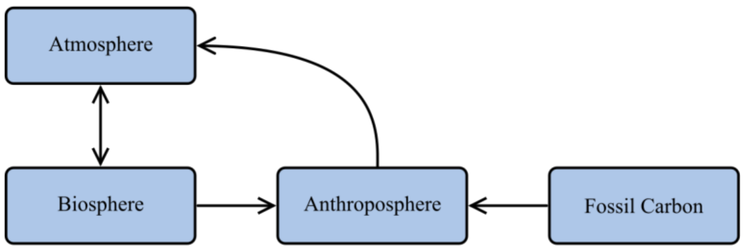

Figure 1.10. A schematic of the carbon accounting mass balance showing the four carbon pools and the direction of flows between them.

Based on this method the mass balance of carbon over time can then be described as in Equation 1.1 below. The sum of the changes of carbon at each point within the supply chain dictates the resulting change in total emissions. Crucially, ΔC_{site} is not static over time as the biomass crop regrows and reabsorbs carbon. Equation 1.1 has been written with reference to carbon – the main source of climate impact when burning biomass, but a number of other terms could be added to include other on-site effects such as albedo, aerosols, and non-CO_2 GHGs although these effects are small by comparison (Gutierrez et al., 2005)

$$\Delta C_{\text{site}} + \Delta C_{\text{fossil}} + \Delta C_{\text{supply chain}} + \Delta C_{\text{products}} = \Delta C_{\text{atmosphere}}$$

Equation 1.1. Biomass carbon accounting mass balance.

Ter-Mikaelian, et al. (2015) describe seven "errors" in the interpretation of this mass balance which they encountered in the literature at the time of writing. While it is not entirely clear to what extent all of these "errors" are indeed erroneous; some being deliberate methodological choices, they are useful in illustrating the extent of disagreements over the underlying systems, metrics, and assumptions surrounding system boundaries (a common one being the assumption that one or more of the elements of Equation 1.1 are equal to zero). Considerable divergence exists within the literature over terminology, metrics, assumptions and experimental design as discussed below.

1.3.1 Terminology and metrics

One of the key attractive qualities of biomass fuels is their regenerative capacity. This means that (as discussed earlier in Section 1.2.4) they have previously been described as "carbon neutral" (Lippke et al., 2011). They have also been described in terms of the time taken for them to reach a more beneficial atmospheric carbon balance than fossil fuels, this has been reported in terms of "payback period" (Jonker et al., 2014), "carbon debt repayment" (Mitchell et al., 2012; Malcolm et al., 2020), and "carbon sequestration parity" (Hanssen et al., 2017). These terms have been used inconsistently within the literature (Giuntoli et al., 2020), and it seems likely that a number of misunderstandings have taken place as a result of this; both within the scientific discourse and the wider public / policy sphere.

It should be noted that the majority of this terminology describes "stand level" models of forest growth. This is a mid-scale approach between a model which describes the behaviour of individual trees and a model which describes a forested landscape. There are a number of strengths and weaknesses to this approach, which are discussed on page 22.

Carbon neutrality

The term "carbon neutral" is widely used in both the scientific and grey literature (Agostini et al., 2014; Johnston and van Kooten, 2015; Nabuurs et al., 2016). This term is problematic, and given widespread use, is likely to be defined far more by common usage than as an actual technical term (Murray and Dey, 2009; Miner and Gaudreault, 2013). The ambiguity in defining "carbon neutral" may lead to misconceptions, and without explicit description of the underlying assumptions it becomes potentially misleading. For example (Malmsheimer et al., 2011) writing more than a decade ago identified six different possible definitions of carbon neutrality, each addressing different system boundary conditions and timescales.

Biomass has historically been described as carbon neutral (Gunn et al., 2012; Miner and Gaudreault, 2013; Klein et al., 2015; Bjørn et al., 2018; Liu et al., 2018) and this argument has been used to support a number of different policy decisions (Giuntoli et al., 2014; Agostini et al., 2014).The ambiguity of the term, when combined with the uncertainties and slow rate of turnover of the carbon cycle when applied to forest carbon, has rendered future use questionable. Additionally, as described by Ter Mikaelian et al. (2015) there has been an assumption in the past that wood is inherently carbon neutral, and thus biomass use incurs no carbon debt (often also neglecting supply chain emissions). This has been (rightly) criticised (e.g. Murray and Dey, 2009) and it is arguable that new references to carbon neutrality tend to be identified with this simplistic position. As such, it is doubtful whether the term carbon neutral should be used at all in this context, since it is so open to misinterpretation and misrepresentation.

Carbon debt and carbon sequestration parity

Carbon debt is a term (popularised by Fargione et al., 2008) used to describe the temporal imbalance between carbon release and sequestration from bioenergy systems (Lamers et al., 2016).

While a wide range of versions and uses of the term exist (Domke et al., 2008; Malmsheimer et al., 2011; Ter-Mikaelian et al., 2011; Jonker et al., 2014; Bentsen, 2017 all use subtly different terminology for example); Mitchell et al. (2012) describe an internally consistent nomenclature using four key terms to define carbon debt as shown below in Table 1.1, and Figure 1.11

Table 1.1. Definition, and comparison, of terms and metrics

Term	**Definition**	**Alternative nomenclature**
Carbon debt (gross)	A loss of carbon storage when compared with the maximum equilibrium carbon storage possible on the site (Mitchell et al., 2012). Based on this definition virtually all sites which are not undisturbed wilderness will carry some level of carbon debt in perpetuity (unless abandoned over a very long time) as shown in Figure 1.11a.	• A reduction in the 'Stable ecosystem carbon level' (Jonker et al., 2014) • 'Foregone carbon sequestration' (AEBIOM, 2013) • 'Persistent carbon debt' (Reid et al., 2020)

Carbon debt (net)	A temporary loss of carbon storage when compared with pre-harvesting (reference baseline) site conditions (Fargione et al., 2008; AEBIOM, 2013) shown in Figure 1.11b	• Typically referred to in the literature simply as 'carbon debt' (as in Nabuurs et al., 2016) However, a substantial number of authors do not specify or define which kind of carbon debt they are using. • 'Cyclical carbon debt' (Reid et al., 2020)
Carbon debt repayment	The point at which there has been no net emission of carbon from the site over time – where regrowth has reabsorbed the carbon removed through harvesting. This can be described in terms of gross (Figure 1.11a) or net (Figure 1.11b) carbon debt. This is analogous to using a static point or reference baseline (Ter-Mikaelian et al., 2015) i.e. comparing a scenario with its own pre-existing conditions.	• Carbon cycle neutrality (Malmsheimer et al., 2011) • Carbon Neutral Period (Ter-Mikaelian et al., 2011). • Carbon Payback Period (Jonker et al., 2014) • Carbon debt repayment time (AEBIOM, 2013) • Payback period (Reid et al., 2020)
Carbon sequestration parity (CSP)	The point at which carbon savings through substitution and site regrowth are equal to the estimated carbon emissions of what would have occurred otherwise. Generally used to describe the point at which biomass production becomes more advantageous than alternative options. This is analogous to using a dynamic anticipated future baseline (EPA, 2011; Miner and Gaudreault, 2013; Buchholz et al., 2016)	• Carbon offset parity point (Mitchell et al., 2012) • Carbon Parity (Nabuurs et al., 2016) • Break-Even Period (Ter-Mikaelian et al., 2011) • Years to [carbon] neutrality (Domke et al., 2012) • Life-cycle neutrality (Malmsheimer et al., 2011) • Substitution neutrality (Malmsheimer et al., 2011)

	or comparing the scenario with a counterfactual. This is generally defined in terms of time and is also described as a payback period (as shown in Figure 1.11c).	• Payback time (Agostini et al., 2014; Bentsen, 2017) • Payback period (Reid et al., 2020) • Fossil fuel parity (Agostini et al., 2014)

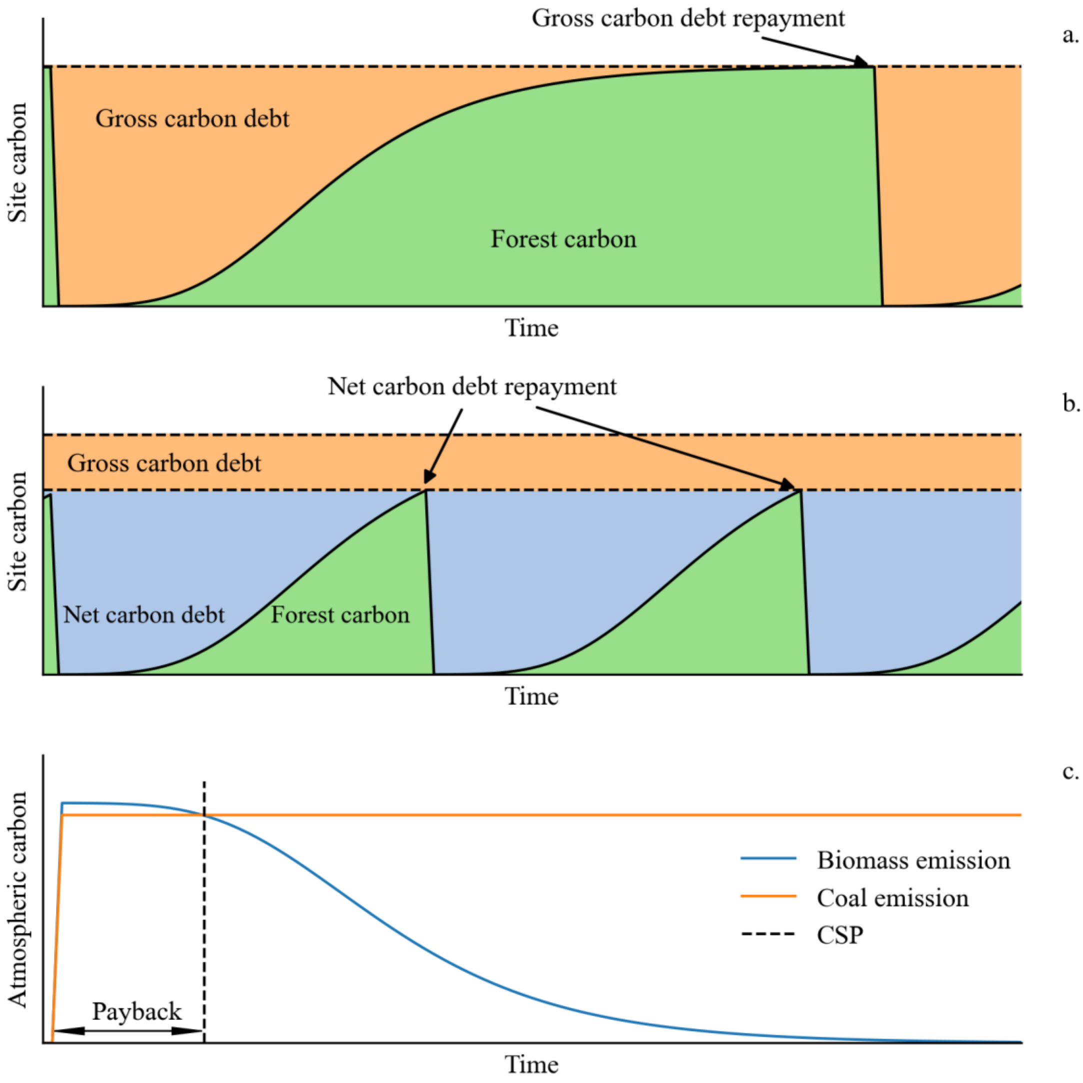

Figure 1.11. Illustrations of gross / net carbon debt, and carbon sequestration parity at stand level. Gross carbon debt (a) is the difference between current managed forest site carbon and maximum possible natural ecosystem forest site carbon. Gross carbon debt repayment takes place when gross carbon debt is equal to zero, however in the absence of an existing mature ecosystem on site, the point at which this takes place is uncertain. Net carbon debt (b) is the difference between current site carbon and the carbon on site before operations take place. This is prone to error due to the dividend then debt perspective described by Ter Mikaelian et al. (2015) discussed on page 24. Net carbon debt repayment takes place when site carbon returns to the level measured before changes took place. Carbon Sequestration Parity (c) occurs when biomass becomes the most advantageous strategy with respect to atmospheric carbon, i.e. where the biomass scenario reaches parity with the alternative. The time taken for this to occur is described as the payback period. All graphs are illustrative and not to scale

The critical difference between these metrics is the comparison carbon pool. Net carbon debt, and net carbon debt repayment compare a site with itself in a pre-defined state, whereas gross carbon debt and CSP account for comparison relative to some other scenario (a hypothetical maximum, or counterfactual using a different fuel type). While comparison of a scenario with itself may show whether it has a net carbon loss or gain, it does not show whether the scenario is an optimal use of site NPP (Haberl and Geissler, 2000; Mitchell et al., 2012) as discussed in Chapter 5.

The usefulness of metrics is also closely tied to scale (Cherubini, Guest, et al., 2013). Assumptions of large-scale biomass use, which are more applicable to policy makers at the national level, include greater uncertainty than those made at a small landscape or stand level. Equally, stand-level calculations while potentially carrying a lower level of uncertainty may prove misleading when expanded to landscape scale (Cintas et al., 2017).

1.3.2 Assumptions and experimental design

Scale

Spatial scale is a significant factor in forest modelling techniques. Forest models exist which range in detail from the description of biological processes within individual trees (Somers, 1994; Perttunen, 1996; Elkin et al., 2012), to the rates of growth across entire biomes (e.g. Mladenoff, 2004; Scheller and Domingo, 2005; Best et al., 2011; Clark et al., 2011; Xiao et al., 2017). In each case, limits of understanding and computational resources, as well as potential margins of error and the intended purpose of the model largely dictate the scale and scope (Burkhart and Tomé, 2012).

The majority of biomass studies adopt a stand-level approach. These models are generally far simpler than models describing individual trees, and require fewer parameters (and a less complete understanding of underlying biological processes). It is arguable that the methods of forest mensuration already have a high margin of error, and that this justifies a statistical approach (Weiskittel, 2011) or that models are designed to be a general representation for describing trends and characteristics rather than an exact simulation for accurate measurement (Borges et al., 2014). Stand level models do not have to be spatially explicit beyond a general approximate growth curve for a woodland area, and can be scaled up to describe a landscape relatively quickly by assuming that the landscape is composed of a number of discrete stands (as in Eliasson et al., 2013). There is a long history of the use of “yield tables” in forestry (Edwards and Christie, 1981; Matthews and Mackie, 2006; Smith et al., 2006; Matthews et al., 2016) and their strengths and limitations are well known.

Stand level models; however, have limited spatial resolution and generally fail to represent mixtures of species or age classes well, unless those mixtures have been directly studied (Matthews and Mackie, 2006). The statistical approximation of forest behaviour is often based on a very specific “prescription” of silvicultural operations (closely defined thinning years, patterns and quantities for example) and when a stand is managed differently, then the statistical representation of future growth becomes progressively less reliable (Vanclay, 1994). This is also true where site conditions vary (in topography, altitude, soil type, precipitation, climate change etc.) as the statistical relationship will have been determined with a specific set of site conditions in mind. Finally, when extrapolating a stand level model to a landscape scale, a number of large-scale influencing factors may not be handled correctly. Stochastic events such as fire, pests, diseases, and other natural threats such as high winds are not homogeneous across a forested landscape (Salas et al., 2016; Buchholz et al., 2016). The growth of individual stands is partially determined by their location, stochastic risk, and the behaviour of adjacent stands and this may represent limitations in the resulting landscape-scale model, unless it is being used for idealised representation rather than a detailed analysis of real-world predicted yield.

Spatial Boundaries

It is well documented that the scale of modelling changes the apparent emissions of biomass production and use (AEBIOM, 2013; Hammar et al., 2019; Kalt et al., 2019), this poses two potential inconsistencies. Stand level modelling shows a clear fluctuation in site carbon over the full rotation (as shown in Figure 1.12a) this results in the characteristic saw-tooth graph common in forest carbon accounting (Lamers and Junginger, 2013). When stands are aggregated into a landscape scale model, this pattern is obscured by the accumulated growth in other stands, leading some (Strauss, 2011; Nabuurs et al., 2016) to argue that “carbon neutrality exists on a landscape scale”. This assertion depends entirely on the baseline assumptions (not to mention the specific definition of carbon neutrality) as it counts from a fixed reference point, and does not take into account forgone sequestration potential of trees if they are not felled.

This inconsistency, described well by Cintas et al. (2017) lies in the geographical area being studied. Some studies assume that the boundary of the study area increases as more forest areas are dedicated to biomass production as shown in Figure 1.12b

(Cherubini, Guest, et al., 2013; Jonker et al., 2014). while others assume fixed boundary to the study area - as Cintas et al. (2017) recommend shown in Figure 1.12c. This distinction is important because it effectively also determines the system boundary. In using a fixed area, a measured biomass system either takes credit for regrowth in forests which were not felled for biomass (leading to an incoherent system boundary) or assumes that the site carbon reference point lies at the point of planting: the dividend then debt approach - one of the “errors” described by (Ter-Mikaelian et al., 2015). This is discussed further in Chapter 6.

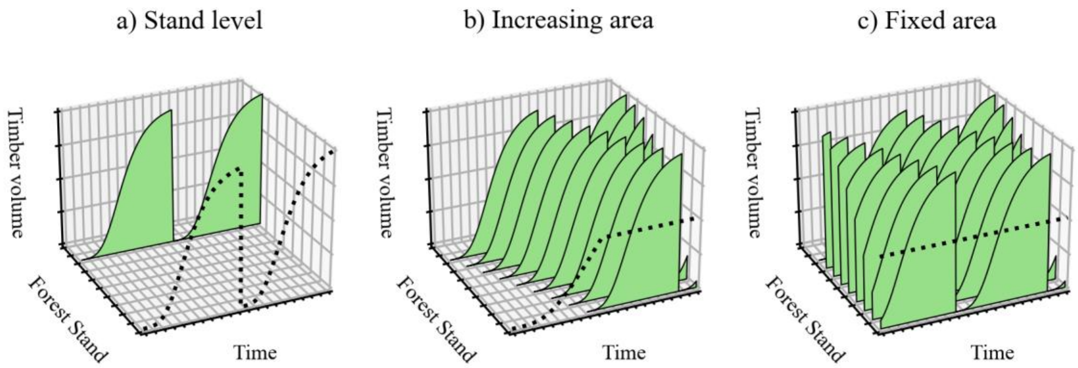

Figure 1.12. An illustration of stand-level, increasing area, and fixed area approaches to the spatial boundary question. Apparent fluctuation in carbon stock over time decreases as we increase the area studied (mean values across the study area are represented by the dotted lines). This obscures the loss of carbon caused by felling, because it becomes less significant when compared to the landscape annual increment. The resulting loss of potential carbon sequestration is handled inconsistently in the literature.

Temporal boundaries

Temporal boundaries in forest sourced biomass also have a profound influence over the apparent sustainability of use. This is not so much caused by the long rotation periods typical in forest management as an implicit assumption of baseline. Forestry professionals, concerned with the successful planting and growth of a crop, tend to assume a “bare site” baseline with no pre-existing carbon – the “dividend then debt” approach (Strauss, 2011; Ray, 2012; Strauss, 2013; Dwivedi et al., 2019). According to this perspective a site accumulates carbon over a forest rotation, which is then released on felling and combustion; this ties in naturally with forest management calculations of yield (as in Broadmeadow and Matthews, 2003). The dividend then debt approach is a minority view, however; as it assumes that the site is bare (not forested) without human action, and that the important factor is the amount of carbon stored *on site* (Ter-Mikaelian et al., 2015). In contrast, the more widely used “debt then dividend” perspective assumes that the baseline condition for a forest is as a large carbon store, and that any release of that carbon incurs a debt that must be repaid. This perspective takes a longer view (assuming most sites capable of growing trees will have been forested before human intervention) and one more relevant to the climate (forest carbon is only important in this case because it is directly linked to atmospheric carbon).

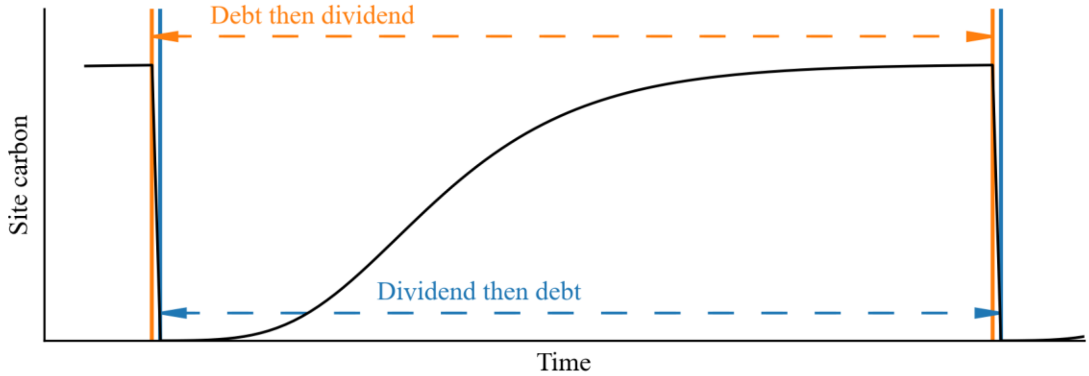

Figure 1.13. Illustration of temporal boundaries. Assuming a site is bare before intervention is common when the perspective is on a final crop (which has an economic value)- the dividend then debt approach. This, however, implies that the site has always been bare when we look at it with respect to atmospheric carbon. Most studies looking at climate change and forest carbon use the debt then dividend approach as the focus is on the atmospheric carbon pool and not specific site conditions.

System boundaries

System boundaries, while affected by spatial and temporal considerations, are also heavily influenced by the range of different products included within the analysis. Products such as coal may not have any large markets that do not result in combustion (World Coal Association, 2020) the same is not true of wood. Biomass fuels are frequently described as occupying a single (less valuable) niche within the forestry and timber processing industries (Simangunsong et al., 2017; Lu and El Hanandeh, 2017) however, use of timber for combustible fuel precludes its use for alternative products. The range of possible uses for timber is heavily influenced by the species and size of tree harvested (Lal and Alavalapati, 2014) as well as current market values (Colnes et al., 2012), and this in turn is largely dictated by silvicultural practice (Matthews, 1989). The principle of silvicultural thinning is that removal of a proportion of the crop (Usually about 30% - Hart and Evans, 1991) concentrates growth in the remaining trees, and allows selection of the final crop for improved “form” (better sawmilling characteristics) leading to increased production of material at the lowest grades (the thinnings) and material at the highest grades (the final crop). The simple fact that forest harvesting operations typically produce multiple fractions of material suitable for different uses and influence the range of fractions produced in future years leads to a complex picture.

A consequence of this complexity has been the widespread use of simple models which omit nuanced silvicultural systems. By omitting other harvested wood products (HWPs) and any non-fuel products from the calculation, such studies (e.g. Peñaloza et al., 2019) effectively remove a wide range of variables which allows easier understanding of the process. This is analogous to a use of an attribution LCA (LCA-A) approach – simply considering the emissions caused by the use of the product compared to the use of an alternative product – over a consequential LCA (LCA-C) which also takes into account the effect of consumption on the production and impacts of other related products (Brander et al., 2009; Peñaloza et al., 2019). While both approaches are valid and can be adapted to become dynamic LCA (as in most studies that incorporate forest growth Beloin-Saint-Pierre, Albers, et al., 2020; Beloin-Saint-Pierre, Padey, et al., 2020) they vary in scope and as such are not directly comparable with one another.

Counterfactual choice

The effects of biomass use are highly dependent on what we assume to take place when biomass is *not* used (Lamers and Junginger, 2013; Bentsen, 2017; Mather-Gratton et al., 2021). This includes a counterfactual fuel type, supply chain, and end use efficiency (Sterman et al., 2018a) and, as described above, also includes implicit assumptions about the alternative use of the forest (Lamers and Junginger, 2013). This may include other HWPs but also may not – assumptions of non-intervention management regimes in the counterfactual being reasonably common (e.g. Sterman et al., 2018a). It should be noted that a counterfactual including non-intervention is effectively an assumption that forest management is driven solely by biomass production (AEBIOM, 2013) which, given the low value of biomass in comparison to other wood products (Timber Update, 2021) seems a less likely scenario. The assumptions inherent in the choice of counterfactual (as in Berndes et al., 2016) reference case (as in Lamers and Junginger, 2013) or baseline (as in Ter-Mikaelian et al., 2015) has a significant impact on the apparent costs and benefits of biomass fuel use.

The infrastructure required to convert biomass to electricity is considerable, but is frequently excluded from studies: generally being assumed to be of a comparable magnitude to that required for fossil fuels (Reid et al., 2020). While it could be argued that this is a reasonable assumption in the case of coal infrastructure, it is not necessarily reasonable in the case of gas, and even less so in the case of nuclear, or renewables such as solar and wind. This may be a convincing reason for the popularity of coal as a counterfactual fuel choice, although it has also been argued (Sterman et al., 2018b) that coal has been used specifically because of its low end use efficiency in comparison to other fossil fuels which increases the attractiveness of biomass fuels by comparison. Setting the system boundary at the point of fuel delivery rather than infrastructure development is a limitation shared by many studies although given the wider existing issues of inconsistency of assumptions, approach, and experimental design, a simplification of this aspect of the assessment is not unreasonable.

Modelling approaches

The need to provide quantifiable estimates of future forest yield has been recognised for many years (Evelyn, 1664; von Carlowitz, 1713) and has stimulated the development of a range of a theoretical structures to enable forest valuation and planning forest operations (Assmann, 1970; Taylor et al., 2009). Forest models have significantly advanced since the development of computers, which has allowed the use of increasingly complex methods, and greater volumes of data (Vanclay, 1994; Peng, 2000). However, even with substantial increases in computing power that have taken place during the last forty years, forests remain difficult to model (Mitchard, 2018). Forests are heterogeneous, dynamic systems which incorporate a large number of processes, and are subject to a wide range of external factors. in addition to this, growth takes place on multi-decadal timescales which limits opportunities for empirical testing (Somers, 1994; Perera et al., 2015).

Growth models seek to represent the growth of trees or a group of trees by some combination of process simulation of causal relationships (described as mechanistic models by Porté and Bartelink, 2002) and statistical representation (Weiskittel, 2011). These models reflect the assumptions of the writers and have parameters based on a wide range of different data sources; they also reflect the limitations present in our ability to model natural systems accurately.

While a number of different models and methods are used to estimate forest growth (Assmann, 1970; Weiskittel, 2011; Burkhart and Tomé, 2012), the inclusion of resulting estimates of forest carbon change in a model which describes the wider context of a biomass supply chain is relatively uniform; however, 99.5% of bioenergy modelling research published between 2000 and 2018 used bespoke models (around 44,000 papers Welfle et al., 2020). These models are designed for use on different operating systems and software platforms, using different mathematical methods and using different combinations of assumptions (as discussed above) but will generally include a forest model with a series of wider assumptions about growth rates, system boundaries, silvicultural systems, harvested wood products, counterfactuals and occasionally other factors such as economic drivers (Holmes et al., 2008; Abt et al., 2010; Abt et al., 2012; Duden et al., 2017) and stochastic tree mortality (Burkhardt et al., 2014).

1.3.3 The range of results

Based on the very large number of papers published on the subject, and the extensive range of methods, assumptions, and metrics used, it is difficult to arrive at a series of direct comparisons. Indeed, it is arguable that the scale of the analysis required would justify a significant research project in its own right. A small sample of superficially comparable papers where payback periods are quoted (or can be derived from the experimental design) is shown in Figure 1.14. While it would not be appropriate to draw firm conclusions from an unrepresentative sample of papers; based on the range of possible results it seems reasonable to accept that the potential payback period for forest-sourced biomass fuel is, at best, poorly constrained (as argued by Bentsen, 2017; Buchholz et al., 2016; Lamers and Junginger, 2013; Giuntoli et al., 2020).

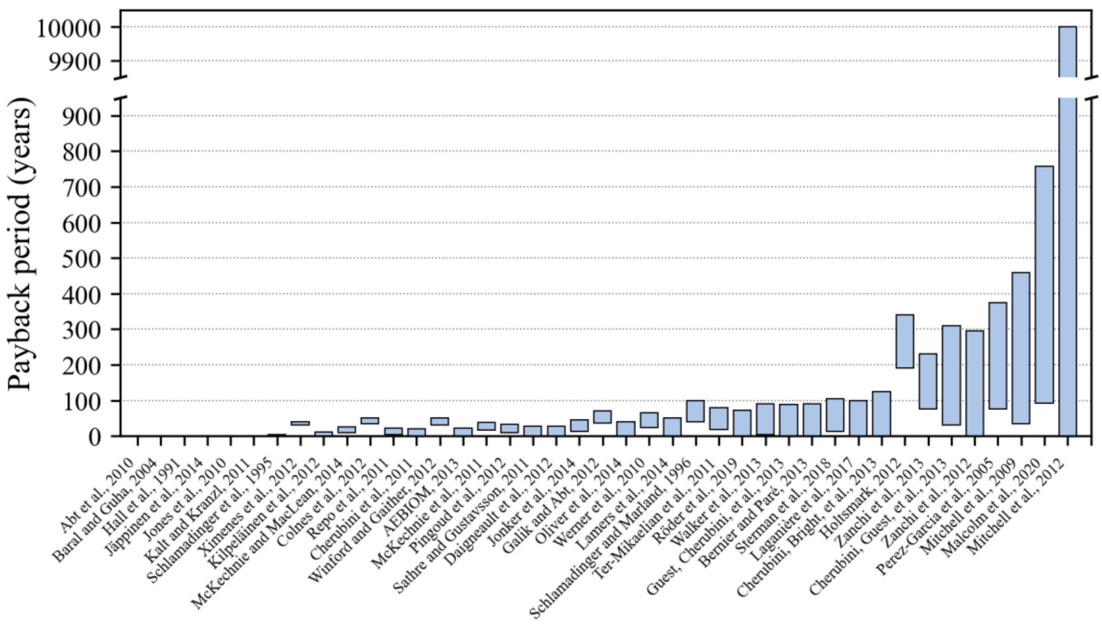

Figure 1.14. *A small sample of the published payback periods. Many of these studies use differing modelling methods and experimental assumptions, and are based on differing scenarios. The resulting range of payback periods extends from <1 year to 10,000 years.*

Based on the literature assessed, it is possible to provisionally identify a number of themes which reoccur and seem worthy of further research. A number of studies show (or strongly imply) that payback period is shortest where relative carbon debt is minimised. This may occur because the initial carbon debt is small (i.e. a small proportion of forest carbon is used as fuel, or there is little carbon on site to begin with) if the debt is repaid quickly (as in shorter rotational management of fast-growing crops) or if counterfactual scenarios have particularly high emissions (e.g. stochastic tree mortality is high in the counterfactual, and the comparison fuel is very low efficiency Mitchell et al., 2012; Buchholz et al., 2016; Sterman et al., 2018a).

1.4 Conclusions

Forest-sourced biomass combustion is a widely used climate change mitigation technology used to decarbonise electricity generation, with global use of biomass fuels expected to continue increasing for decades to come (as shown in Figure 1.9 above). It has been argued that this development is incompatible with enhancement of the terrestrial biosphere as a carbon pool (e.g. Favero et al., 2020).

Given that biomass use removes carbon from the terrestrial biosphere and emits that carbon to the atmosphere as CO_2, there is an obvious risk that developing global biomass supply chains will undermine international climate change mitigation efforts. As such, action should be taken to ensure that biomass payback times are as short as possible.

In the scientific literature, there is a high level of variation between published payback periods and other sustainability metrics (as shown in Figure 1.14). This level of variation means that, while it is possible to identify scenarios which have particularly high or low probabilities of a sustainable outcome, the boundary between these two states is poorly constrained. The diverse range of models, methods, assumptions, and parameterisations used in the literature is likely to be, in part, driving the high level of variations in results (Giuntoli et al., 2020).

The heterogeneity of reported results and apparently conflicting conclusions has led to over-simplified communication of the benefits and costs of biomass production and use, which has undermined public support (Slade et al., 2018). As a result, the sustainability of forest-sourced biomass fuels is now hotly contested (Mather-Gratton et al., 2021).

The lack of clarity in the literature, and the existence of well-funded campaigns both for and against biomass use (Mather-Gratton et al., 2021) limits the ability of policy makers to make informed choices regarding forest management and support / regulation for biomass development. As Buchholz et al. point out:

"for carbon payback period calculations to provide operational insights to decision makers, future research should focus on creating consistent accounting principles including the consideration of stochastic disturbance, temporal scales, quantifying and reporting uncertainties, standardization of carbon pools evaluated, GHG emission metrics considered, and baseline definition." (Buchholz et al., 2016, p.288).

A large degree of variation does still exist in the reported outcomes, and it remains unclear to what extent this variation is driven by real-world conditions such as site, species, and silviculture, and to what extent it is driven purely by diverse perspectives and assumptions made while modelling the outcomes.

As such there is a demonstrable need for a simple replicable modelling framework to facilitate comparisons between modelling assumptions and methods using the same underlying parameters and data. This work can then be used to identify the degree to which the apparent variation in biomass carbon studies is due to different formats and assumptions, and the degree to which real-world variation exists.

1.5 Research outline

The core research goal is to develop a robust modelling framework which is adaptable to account for a wide range of different methodological assumptions while remaining simple and freely available, enabling intercomparisons between approaches. The primary, overarching research question being:

How do model parameters, assumptions and reporting metrics affect the apparent sustainability of biomass supply chains?

Model development (Chapter 2)

Outline

Rather than undertake the ground-up development of yet another model, an assessment of existing work was undertaken in order to find an appropriate structure to adapt and modify. Chapter 2 describes the process of identifying an appropriate model and includes a detailed analysis of the model chosen, a description of the model replication as the Simple Biomass Comparison Model (SBCM), and testing to ensure that results from both models match.

Research Questions

1. Given the need for an adaptable modelling framework to compare the sustainability of biomass fuel supply chains; which existing, published model is the most appropriate for conversion and adaptation?

2. How does the selected model work, what are its strengths and weaknesses, and what assumptions are implicit in the model structure?

3. How can this model be enhanced, making use of its strengths while addressing its weaknesses?

4. Can the existing published results from the model be reproduced in a replicated version?

Forest model (Chapter 3)

Outline

The model chosen in Chapter 2 (as published by Sterman et al., 2018a) is formed of two main elements describing the forest site, and the biomass supply chain from forest to end use.

On testing the model in Chapter 2, small discrepancies were observed between the original results from the forest site model as published by Sterman et al., and results obtained from SBCM. Chapter 3 seeks to address these inconsistencies and identify the cause.

Research Questions

1. How is the data used to train the model by Sterman et al. derived, and is it the most appropriate?

2. Are the parameters obtained by Sterman et al. the most appropriate to replicate the forest growth curves supplied by Smith et al. (2006) or can improvements be made?

3. To what extent does uncertainty exist between the training data, forest growth as described by Sterman et al. (2018a) and forest growth described in SBCM?

4. What effect does an improved choice of parameters have on predicted carbon storage values, and payback times for different region and species combinations?

Supply chain model (Chapter 4)

Outline

The second of the two main model components is a series of functions describing emissions released by the biomass supply chain, and the emissions caused by an equivalent counterfactual scenario. Chapter 4 describes an assessment of the parameterisation of this aspect of the model and a critique of the counterfactual scenarios developed by Sterman et al.

Research Questions

1. Are the parameters used by Sterman et al. the most appropriate for the supply chains they describe, and should they be modified in SBCM?

2. Sterman et al. rely heavily on a counterfactual of electricity generated using coal. Is this still the most appropriate counterfactual?

3. Are there any other supply chains which could be modelled using SBCM that would be more appropriate than those currently in use?

4. How does revision of the supply chain parameters within the model change the apparent sustainability of biomass fuels

Silvicultural assumptions (Chapter 5)

Outline

The Sterman et al. model as originally written was designed to identify the area of forest needed to supply a specified value of energy. The assumption implied by this configuration is that forest area is elastic, while energy demand is fixed. Chapter 5 includes an assessment of this assumption, as well as an examination of the broader silvicultural assumptions in the model (which have been criticised in the wider literature; see Prisley et al., 2018)

Research Questions

1. What do Sterman et al. assume about silvicultural systems in developing their model?

2. What are the implications of these assumptions, are they justified, and could they be improved?

3. How does modification of these assumptions within the model change the apparent sustainability of biomass fuels?

Conclusions (Chapter 6)

Outline

Chapter 6 summarises the conclusions as identified in earlier chapters and applies them to the overall research question. This analysis is used to examine the strengths, weaknesses, and limitations of the work as carried out; and to identify lessons learned and future research opportunities.

Research Questions

How do model parameters, assumptions and reporting metrics affect the apparent sustainability of biomass supply chains?

Chapter 2. Model development

In which the Author dismantles everything,
and (contrary to his own expectation) reassembles it in good order.

Elements of this chapter have been previously published as Rolls, W. and Forster, P. M. 2020. Quantifying forest growth uncertainty on carbon payback times in a simple biomass carbon model. *Environmental Research Communications*. 2(4), p.045001. DOI 10.1088/2515-7620/ab7ff3. This paper was primarily the work of W. Rolls, with support, editorial comments, and oversight by P. M. Forster

2.1 Introduction

As previously discussed, forest-sourced biomass combustion is a widely supported climate change mitigation technology used to decarbonise electricity generation (Rogelj et al., 2018). While uptake of this technology has been rapid and is expected to continue for many years to come (as shown in Figure 1.9) the sustainability of this course of action has not yet been fully determined. A high level of variation between published payback periods and other metrics exists in the scientific literature (Bentsen, 2017) and this is likely to be, in part, driven by the diverse range of models, methods, assumptions, and parameterisations used (Giuntoli et al., 2020).

The apparently conflicting conclusions reached in the literature, has led to confusion within the public discourse and as a result, the sustainability of forest-sourced biomass fuels is widely contested (Mather-Gratton et al., 2021).

In order to identify to what extent this variation is driven by real-world conditions such as site, species, and supply chain emissions, and to what extent it is driven purely by diverse perspectives and assumptions made while modelling the outcomes, there is a demonstrable need for a simple replicable modelling framework. This will facilitate comparisons between modelling assumptions and methods using the same underlying data.

2.1.1 Research questions

The broad operational objective for this chapter is to identify, analyse, replicate, and test a simple model to allow further comparison of biomass carbon payback periods, specifically addressing the research questions:

1. Given the need for an adaptable modelling framework to compare the sustainability of biomass fuel supply chains; which existing, published model is the most appropriate for conversion and adaptation?
2. How does the selected model work, what are its strengths and weaknesses, and what assumptions are implicit in the model structure?
3. How can this model be enhanced, making use of its strengths while addressing its weaknesses?
4. Can the existing published results from the model be reproduced in a replicated version?

2.2 Initial analysis

2.2.1 Identifying a model

A very large range of different models, assumptions and approaches exists in the literature (Welfle et al., 2020) rendering an exhaustive categorisation and analysis beyond the scope and capacity of this study. The extensive range of different approaches reinforces the argument in favour of an intercomparison tool and, since one of the core requirements of the tool is an ability to be configured for a range of different settings, the specific model chosen for adaptation is less important than its ease of use and accessibility.

A number of criteria were used to assess the suitability of published models for modification and adaptation. Models were assessed using a cross section of the literature on the basis of a series of questions:

1. Is the model freely available, and does it require proprietary software to run?
2. Is the model licenced for modification / adaptation / re-distribution?

3. Is the model code open-source with a full description of the internal assumptions, logic, and processes?
4. Is the model relatively simple and easy for an end user to grasp?
5. Can the model be configured for a range of different site / forest growth types?
6. Does the model operate on a platform that requires advanced knowledge of a low-level or little-used programming language to modify?
7. Does the model produce values comfortably within the range of published results?

A substantial number of published papers make use of bespoke modelling techniques which are perhaps more usefully referred to as "calculations". These are studies making use of a mathematical model without developing software or distributable code (e.g. Abt et al., 2010; Cherubini, Bright, et al., 2013; Cherubini, Guest, et al., 2013; Laganière et al., 2017; Malcolm et al., 2020). While there is no fundamental reason why these papers should not provide the relevant information to develop a more widely applicable tool, in the overwhelming majority of examples assessed, the implementation of the work in these papers was either designed to work within a specific development environment or answer highly specific research questions. This tended to result in extremely brief discussion of the underlying mathematical component of the model without the full description of logic, assumptions and calculation order needed for a wider or more general-purpose application.

The majority of published papers which did use a more comprehensive modelling framework were deemed inappropriate for this exercise, based on the criteria above. These included systems which were:

- Proprietary and therefore not available outside the relevant institutions and not necessarily subject to peer review e.g. CARBINE (Forest Research, n.d.) and C-Flow (CEH, n.d.)
- Closed-source: while the finished model is publicly available, the source code is hidden or compiled and therefore cannot be modified e.g.: CO2fix (European Forest Institute, 2004; Schelhaas et al., 2004), G4M (Turkovska and Gusti, 2015; IISA, 2022), CBM-CFS3 (Kurz et al., 2009; Canadian Forest Service,

2019). These models tended to have additional licencing restrictions limiting modification and redistribution.

- Highly complex: including a significant level of detail, functions, or add-ons requiring a high level of background knowledge for modification / customisation e.g.: LANDIS (Mladenoff, 2004), EFIScen (European Forest Institute, n.d.), Landcarb (Pacific Northwest Research Station, n.d.)
- Developed using programming languages that require a high level of technical knowledge to modify: limiting the accessibility of the software even if it has been distributed freely e.g. G4M ([C++] IISA, 2022), LANDIS II ([C#] LANDIS-II Foundation, 2022), FORCARB2 ([FORTRAN] Heath et al., 2010)
- Based on system boundaries not appropriate for this study – e.g. forest models with no supply chain modelling (Gonzalez-Benecke et al., 2010; 2011; 2012; 2015) or a very broad range of functions extending into other areas of forest and energy decision making beyond the scope of this study e.g. BVCM (ETI, 2015)

A short overview of assessed models is included in Appendix B

The Sterman et al. model

In an exception to these barriers and limitations, Sterman et al. (2018a) describe a model which they developed to address the lack of clear guidance for policy makers, showing the effects of biomass production and use. This simple model is designed to be incorporated into a wider framework (C-ROADS), but can be easily configured and run quickly as an independent model to give indicative results. Sterman et al. suggest the use of the model as a "flight simulator" (Sterman et al., 2013) to inform policy scenarios in a real time iterative development process, without recourse to more in-depth and resource intensive modelling resources.

The Sterman et al. model: strengths

This model fits the choice criteria above well since it is: freely available (Sterman et al., 2018a); licenced for modification / redistribution (Creative Commons, 2018; Sterman et al., 2018a), open-source and provides a well-described simple framework for development of future work. (Prisley et al., 2018). The model has been configured using publicly available data (Smith et al., 2006) for a range of site types and species mixtures in the USA and produces results which are comfortably within an indicative range of published payback periods.

The Sterman et al. model: weaknesses

While the Sterman et al. model has a number of strengths in terms of reproducibility, transparency of logic, and access to the code, the model is written in the VENSIM software (Venata Systems, 2017) developed for systems dynamics modelling. It requires a full professional license of VENSIM to run the code distributed with Sterman et al., 2018a which is expensive, and the setup requires detailed knowledge of both this less commonly used development framework and terminology and notation used within system dynamics. Assumptions about spatial, temporal, and systems boundaries are hard-coded into the model and these require re-evaluation given that the model itself has been criticised (primarily for an oversimplification of silvicultural systems [Prisley et al., 2018] addressed later in Chapter 5) and has a number of questionable decisions made in parameterisation (in particular the values for efficiency of fuel use, which are quietly corrected in Dwivedi et al., 2019 - addressed in Chapter 4). These weaknesses indicate that the Sterman et al. model is not, as published, appropriate to meet the selection criteria as described above, but that it could be used as a starting point for an alternative implementation of the logic and structures of a model (and be re-parameterised).

Summary

Based on this evaluation, the Sterman et al. model was deemed suitable for further development. The model was first analysed in detail and then replicated using the basic framework and mathematical structure of the original in a more accessible format. This allowing for detailed modification of calculation order, scenario settings, and parameterisation.

2.3 The Sterman et al. model: full analysis

The Sterman et al. model is available under an open access licence, and is shown as implemented in VENSIM below (Figure 2.1). The graphical nature of the VENSIM software, while potentially useful in visualising complex systems, is limited in that every variable must be visually present on the schematic. This can lead to complex diagrams as shown below.

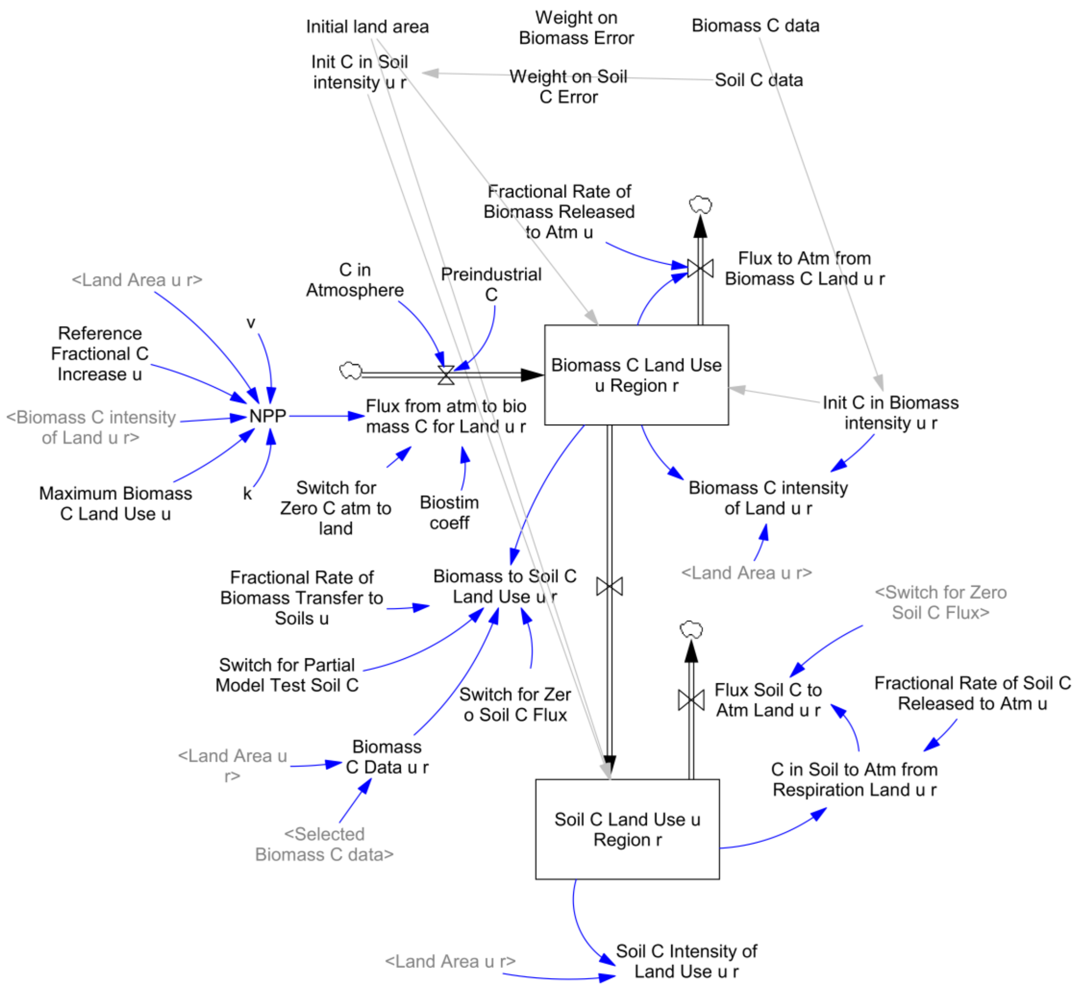

Figure 2.1. *Schematic of the Sterman et al. model as implemented in Vensim by Sterman et al. (2018a). The model is relatively simple (although a full graphical representation of the model is somewhat confusing)*

The modelling framework can be conceptualised as containing two discrete components:

1. A supply chain model handling a calculation of the volume of fuel required to meet a specified electricity demand and the resulting carbon emissions associated with production and use.
2. A forest site model calculating the area of forest required to meet a defined fuel demand, and the changes in forest, soil, and atmospheric carbon over time as the forest used for fuel production regrows.

These components are linked and used to compare distinct emissions scenarios. The model estimates the carbon emissions associated with meeting a defined energy demand from biomass, and this is then compared with a counterfactual scenario in which electricity is generated using a fossil fuel (usually coal) instead. In the biomass scenario, the model goes on to estimate the rate of carbon reabsorption on the forest site, and to calculate the time required for the scenario to result in a lower net carbon emission than the counterfactual. This is described as reaching "carbon payback" (carbon sequestration parity as described by Mitchell et al., 2012) as discussed in Chapter 1.

2.3.1 Supply chain

The Sterman et al. model derives the total quantity of energy required (including allowances for waste / losses) from efficiency parameters and a user-defined energy demand. It then determines the emissions (tonnes of carbon) associated with the production and end use of the fuel required to generate this quantity of electricity. When assessing biomass supply chains, the model uses the fuel requirement to determine the forest area needed to meet demand. This is shown in schematic form in Figure 2.2 and in Equations 2.1 to 2.3.

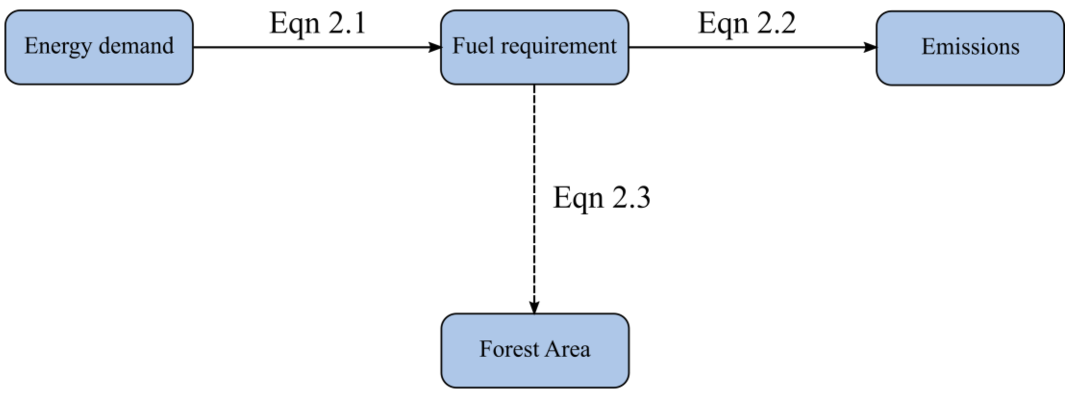

Figure 2.2. Schematic of the supply chain in the Sterman et al. model. An external input: energy demand, and the efficiencies of the supply chain are used to determine the total amount of fuel energy that is required to meet electricity demand (Equation 2.1). The emissions associated with producing the required quantity of fuel energy, and from combustion, are then calculated (Equation 2.2) to produce an emissions value per unit of energy supplied. In the case of biomass fuel, the total quantity of fuel needed to meet demand (incorporating all supply chain and end use losses and forest carbon storage) are used to calculate the area of mature forest required to meet demand (Equation 2.3).

$$\text{fuel energy demand} = \frac{\text{energy demand}}{\text{efficiency}_{\text{production}} \times \text{efficiency}_{\text{use}}}$$

Equation 2.1. Input fuel energy required to meet electricity demand. The efficiencies of production and use are dimensionless variables, both energy demand and fuel energy required are expressed in GJ.

$$\text{total emission} = \text{fuel energy} \times (\text{emission}_{\text{production}} + \text{emission}_{\text{use}})$$

Equation 2.2. Carbon emissions arising from energy generation. The emissions arising from the production of each unit of fuel energy (the result of Equation 2.1) and the final use (tC), based on emissions (tC.GJ^{-1})

$$\text{forest area} = \text{emission}_{\text{use}} \times \left(\frac{\text{fuel energy}}{\text{felling intensity} \times \text{forestC}}\right)$$

Equation 2.3. Area requirement. The total area (ha) of forest required to meet the fuel demand is calculated from the fuel energy required to meet demand (in GJ: the result of Equation 2.1) the fuel available per ha (felling intensity is dimensionless, forest carbon in tC.ha^{-1}) and the carbon intensity of biomass fuel combustion i.e. the tonnes of carbon needed to produce 1 GJ of energy (emission$_{use}$)

Once the necessary area of mature forest has been determined, the model combines the emission of carbon associated with fuel combustion to meet the desired energy demand and the ongoing negative emissions over time from the regrowth of the calculated area of forest (using the forest sub-model).

The default parameters used by Sterman et al. for the supply chain model are examined in more detail in Chapter 4.

2.3.2 Forest Site

The Sterman et al. model calculates the rate of four different carbon flows as the forest regenerates, and uses these to maintain running yearly totals of the carbon stored in the forest (above-ground); soil (below-ground); and atmosphere as shown in Figure 2.3. Carbon flows are described below in Equations 2.4-2.8.

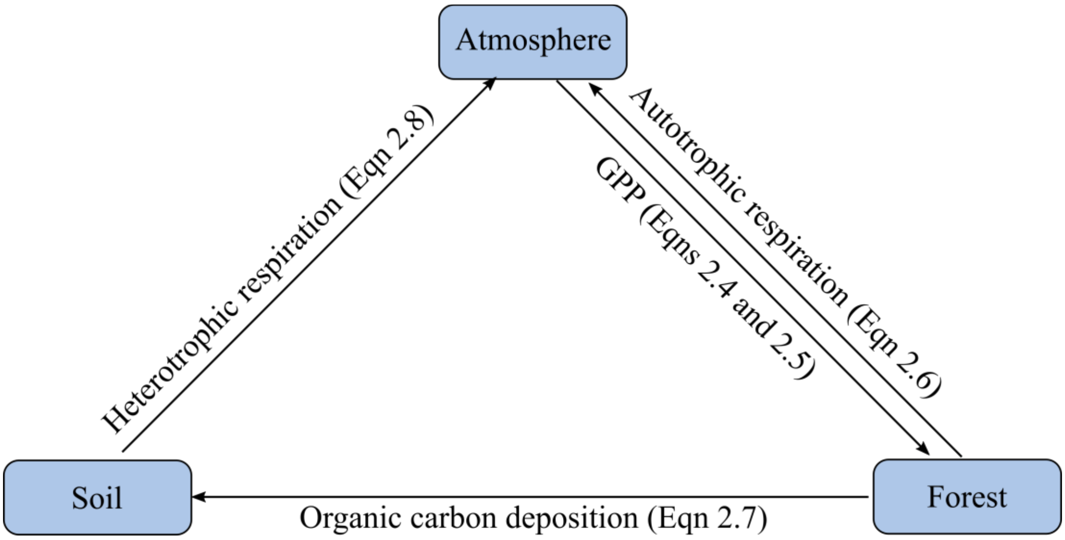

Figure 2.3. Schematic of the forest site carbon balance in the Sterman et al. Model. Each of the flows labelled is governed by equations described below.

The total flux of carbon from atmosphere to forest (Net Primary Productivity or NPP) is equal to Gross Primary Productivity (GPP) minus a value for autotrophic respiration.

GPP is calculated using a growth function to model the increase in forest mass over time (tonnes of carbon: the result of Equation 2.4) multiplied by a function to account for carbon fertilisation (Equation 2.5). This is then converted to NPP by subtracting the result of a simple proportional transfer of carbon from forest to atmosphere (Equation 2.6)

$$\text{growth per ha} = (\varphi_{ab} \times \text{forestC} + K \times \text{forestC}_{max}) \times \left(1 - \left(\frac{\text{forestC}}{\text{forestC}_{max}}\right)^{V}\right)$$

Equation 2.4. Forest growth. The rate of forest growth is a function of the existing forest carbon on site (forestC in $tC.ha^{-1}$) the maximum potential biomass for the site (forest C_{max} in $tC.ha^{-1}$) and the dimensionless constants K, V, and φ_{ab} (a fractional rate of carbon flux from atmosphere to biomass). This function is based on a stand-level, statistical approximation of growth (Weiskittel, 2011) using a Chapman-Richards growth function (Richards, 1959; Pienaar and Turnbull, 1973; Zhao-gang and Feng-ri, 2003) modified to include a "fractional carbon flux from atmosphere to biomass" (Sterman et al., 2018a).

$$\text{GPP} = \text{growth}\left(1 + \text{biostim} \times \ln\left({}^{C_1}/_{C_0}\right)\right)$$

Equation 2.5. Gross Primary Productivity. Total GPP ($tC.ha^{-1}$) as equal to the growth per ha multiplied by a function to account for carbon fertilisation. This is based on a "bio-stimulation coefficient" – Sterman et al. use a value of 0.42 (Sterman et al., 2018a) and the relative change between current (C_1) and pre-industrial (C_0) atmospheric CO_2 concentrations (after Wullschleger et al., 1995).

$$\text{respiration} = \varphi_{\text{ba}} \times \text{forestC}$$

Equation 2.6. Autotrophic respiration. The rate at which biomass carbon is released into the atmosphere via respiration (in Figure 2.3) is based on the current forest carbon on site ($tC.ha^{-1}$) and φ_{ba} a dimensionless fractional rate of carbon flux from biomass to atmosphere

The remaining flows in figure 2.4 representing heterotrophic respiration, and organic carbon deposition from the forest to soil carbon pools are calculated in a similar way: as a proportion of the total carbon in each pool per year (Equations 2.7 and 2.8)

$$\text{organic carbon deposition} = \varphi_{\text{bs}} \times \text{forestC}$$

Equation 2.7. Organic carbon deposition. The rate at which forest carbon is deposited in forest soils (in Figure 2.3) based on the current forest carbon on site ($tC.ha^{-1}$) and φ_{bs} a dimensionless fractional rate of carbon flux from biomass to soils.

$$\text{heterotrophic respiration} = \varphi_{\text{sa}} \times \text{soilC}$$

Equation 2.8. Heterotrophic respiration. The rate at which decomposition releases biomass carbon from forest soils into the atmosphere (in Figure 2.3) is based on the current soil carbon on site ($tC.ha^{-1}$) and φ_{sa} a dimensionless fractional rate of carbon flux from soil to atmosphere.

2.3.3 Parameters

Sterman et al. parameterised the forest site model for eight different forest types (listed in Table 2.1) in three different regions of the USA (shown in Figure 2.4). This was done 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 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 was constructed using a combination of sample plots, and interpolation of data using the FORCARB2 model (Smith et al., 2006, p.13; Heath et al., 2010). While uncertainties exist, and the data is not appropriate for site specific (stand-level) modelling, (Smith et al., 2006, p.17) it 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 statistical approximation of forest growth (as defined by Weiskittel, 2011) which allows interpolation of values between the 5-year intervals in data points and extrapolation beyond the end of the dataset (although this is subject to considerable uncertainty in some species, as discussed in Chapter 3.)

Table 2.1. Species / region types covered by the Sterman et al. model

Region of USA	Common name	Scientific name
North East (NE)	Maple / beech / birch	*Acer / Fagus / Betula*
	Oak / hickory	*Quercus / Carya*
	Oak / pine	*Quercus / Pinus*
South Central (SC)	Oak / hickory	*Quercus / Carya*
	Oak / pine	*Quercus / Pinus*
	Short-leaved / loblolly pine plantation	*P. taeda / P. echinata*
South East (SE)	Short-leaved / loblolly pine plantation	*P. taeda / P. echinata*
	Long-leaved / slash pine plantation*	*P. palustris / P. elliottii*

**Occasionally incorrectly labelled in Sterman et al. (2018a supplementary material) as long-leaved / loblolly pine.*

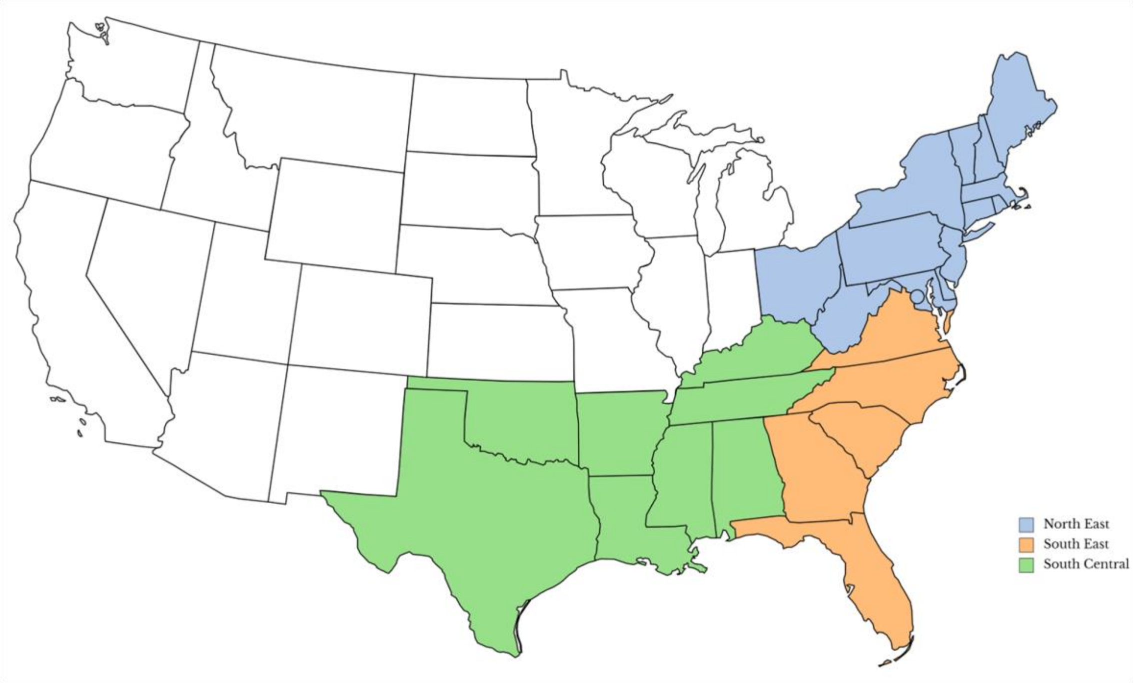

Figure 2.4. *Map showing regions of the USA covered by the Sterman et al. model. These regions include three of the eight biogeographical areas covered by the forest carbon data (Smith et al., 2006) species / region types are listed in Table 2.1 above.*

The curve-matching methods are described in more detail in their supplementary material (Sterman et al., 2018a) but, in summary, Sterman et al. restricted the matching algorithm to parameter values which resulted in two set conditions:

- The first value of the points forming the matched curve ($y_{(x=0)}$) must equal the first value of the Smith et al. (2006) data.
- The curve must result in the smallest achievable root mean squared error (RMSE) values between the data and modelled output.

Their method resulted in values for carbon with RMSE errors generally less than 3.1 $tC.ha^{-1}$ for forest (above-ground) carbon and 6.7 $tC.ha^{-1}$ for soil (below-ground) carbon.

2.3.4 Scenarios

Sterman et al. applied their model to a number of scenarios representing a range of potential biomass production and use mechanisms (described fully in Appendix C). These include a coal-based counterfactual (scenario cf), several scenarios which are most appropriate for diagnostic purposes: S0 (zero carbon energy), S1 (regenerating coal), and S4 (non-regenerating biomass); four stand-level scenarios: S2 (25% thinning)

S3 (95% clear-fell), S5 (deforestation and conversion to agriculture) and S6 (clear-fell, with subsequent species change). Two additional scenarios are also considered, looking at landscape level impacts of biomass use based on long term projections of energy demand, S7 (sustained yield with ongoing demand growth) and S8 (sustained yield with attenuating demand growth). Broadly speaking, the scenarios are not as well described as the rest of the model, and there are a number of elements which bear closer consideration. These are examined in more detail in Chapter 4.

2.3.5 Assumptions

A number of implicit assumptions are evident in the Sterman et al. model, and these are reflected in where the system boundaries and baselines are set.

The Sterman et al. model is not spatially explicit (all forest stands are assumed to be equivalent to each other). Total forest area is assumed to remain unchanged over the modelled timeframe in scenarios S0 to S6, and assumed to grow with demand in scenarios S7 and S8 an expanding forest boundary (described in Jonker et al., 2014 and criticised by; Cintas et al., 2017) discussed on page 23.

Sterman et al. assume that 1) all forest growth not directly related to a felling for biomass fuel should be omitted; and 2) all forests are completely mature at the point of felling (where the baseline is set). Given the stated aim of prioritising model simplicity this represents a valid interpretation of the argument as stated by Ter-Mikaelian et al. (2015).

One further assumption made by Sterman et al. (2018a) bears additional consideration. In the counterfactual case, forest growth is omitted entirely. This is an "error" (according to Ter-Mikaelian et al., 2015) as it "*fails to account for changes in forest carbon stocks in the absence of harvest for bioenergy*": that is, the flux of carbon from forest to atmosphere is assumed to equal zero in the counterfactual scenario. This is arguably sensible: if we assume that all forests have reached an "equilibrium point" before felling, then the flux should be equal (or close) to zero in any case. However, potential variations in the time taken to reach equilibrium (as discussed later in Chapter 3) changes in the carbon fertilisation over time (a proposed addition to the model governed by Equation 2.5) and the potential inclusion of more nuanced silvicultural systems turn this into a potential source of error; as it assumes that in the absence of bioenergy production, the forest carbon pool is completely outside the system boundary. This issue is difficult to resolve and is examined in more detail in Chapters 5 and 6.

2.3.6 Comparison with other published results

Direct comparison of the payback times calculated by Sterman et al. with other published work is extremely difficult. This is due to the wide variation in terms of method, assumptions, and site type present in the literature as discussed in Chapter 1. Sterman et al. (2018a) state that their results (from scenarios S2 and S3: thinning and clear-fell) vary between 4 years (Southern USA pine plantations scenario S2) and 104 years (North-Eastern oak / hickory forest scenario S3) as shown in Table 2.2. This is comfortably within the (admittedly large) range of published values (as illustrated in Figure 2.5 below).

Table 2.2. Payback periods calculated by Sterman et al. (2018a supplementary material table S7)

Region / species mix	**Scenario S2 (25% fell) payback period (years)**	**Scenario S3 (95% fell) payback period (years)**
Northeast maple / beech / birch	79	101
Northeast oak / hickory	87	104
Northeast oak / pine	52	85
South-central oak / hickory	52	82
South-central oak / pine	44	64
South-central shortleaf / loblolly pine plantation	4	12
Southeast shortleaf / loblolly pine plantation	4	12
Southeast longleaf / slash pine plantation	4	12

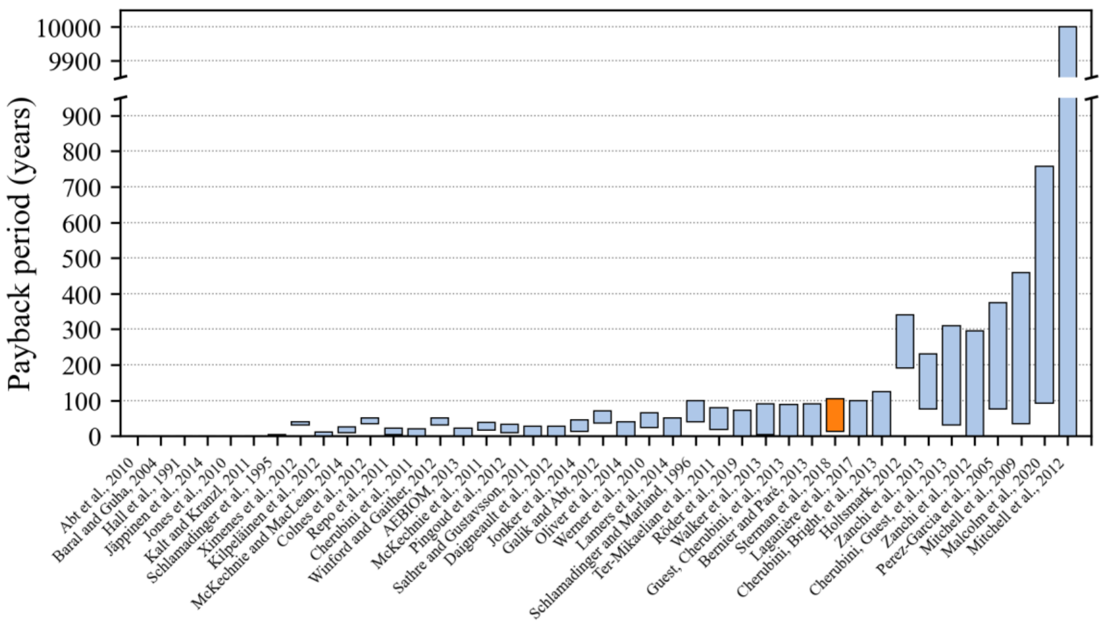

Figure 2.5. Published payback periods highlighting the results obtained by Sterman et al. (2018a). These results (as also shown in Figure 1.14) were comfortably within the middle of the range of papers assessed.

2.4 Method

The model as published by Sterman et al. (2018a) was first replicated using a general-purpose, object-oriented, high-level programming language (Python) and released as the Simple Biomass Comparison Model (SBCM). This is further described in Rolls and Forster (2020) and is available to download from github.com/Priestley-Centre/SBCM.

Python is the most popular (i.e. accessible) programming language globally, with around a 30% market share (Carbonnelle, 2021). While a huge range of different open-source libraries are available to add to existing Python capabilities, use of these was kept to a minimum to prevent potential future compatibility issues developing. Project functionality primarily depends on the “SciPy stack” (Jones et al., 2001) although a number of other additional minor elements were implemented using other libraries, all of which are available as standard elements of the Anaconda Python distribution (Anaconda Inc., 2018). Full documentation for the project was written to ensure that third parties are able to access, use, and modify the project which was made available under an open-source (MIT) licence (as used by Sterman et al.).

2.4.1 SBCM Structure

SBCM 1.0 is based on four files in the `Core_Model` folder. These are usable with the Python libraries which come bundled with the anaconda Python distribution (Anaconda Inc., 2018) and should be platform and operating system independent.

The required libraries are:

- `Matplotlib` 3.3.2 (Hunter et al., 2019)
- `NumPy` 1.19.2 (part of the SciPy stack: Jones et al., 2001)
- `Pandas` 1.1.3 (Augspurger et al., 2019)
- `Warnings`, and `Math` – both part of the Anaconda 1.7.2 distribution (Anaconda Inc., 2018).

The files that form the core of SBCM are

SBCM.py	The main model file. Contains the scenario object which is used to run the simulation and generate results.
Variables.py	A file containing all of the parameters for forest growth, the original model training data from the USDA (Smith et al., 2006) and supply chain efficiency and emissions parameters.
Functions.py	Contains all the functions for calculations used by SBCM.py
Formatting.py	A small file containing housekeeping functions for formatting output correctly

All code was configured using the Black code formatter (Langa et al., 2019) to standardise formatting for ease of editing.

SBCM.py

In its simplest form, SBCM.py contains a `scenario` object which describes a comparison between counterfactual emissions, based on coal, and a biomass scenario based on a user-selected forest region / species combination. It imports default variables for forest growth and supply chain efficiency from `variables.py`, and uses these variables to describe energy demand, starting conditions, felling regime and other scenario values. These default to conditions used by Sterman et al. but can be modified to represent alternative or specialised scenarios.

Once the scenario parameters and starting values have been determined (or altered by the user) the `initialise` function calculates emissions from the counterfactual and biomass scenarios, and the forest area required to meet demand (Equations 2.1 to 2.3). It also builds a series of lists to keep track of:

- Time (year)
- Counterfactual emissions (tC)
- Biomass emissions (tC)
- Forest carbon ($tC.ha^{-1}$)
- Soil carbon ($tC.ha^{-1}$)
- Gross carbon debt ($tC.ha^{-1}$)
- Carbon saved (counterfactual emission – biomass emission in tC)

After initialisation, the model is run for a set number of years using the `runstep` function. For each year the model calculates a value for forest regrowth (using Equations 2.4 and 2.5) and appends updated values to the lists described above.

Once the model has been run, the report function converts the values to a `pandas` `DataFrame` and saves the result to a comma delimited (.csv) file for further analysis.

Variables.py

`Variables.py` (as the name suggests) contains a list of variables to run the model. For each of the forest types assessed by Sterman et al. (2018a) the file contains: a forest / species code, a series of variables for the growth function, equilibrium values, and training data values from Smith et al. (2006). `Variables.py` also contains values for emissions and efficiency of biomass and coal systems and a pre-calculated carbon fertilisation value (the result of Equation 2.5 for 2018 to allow comparison with the results published by Sterman et al.). These are discussed in more detail in Chapter 4.

Functions.py

`Functions.py` contains all the mathematical functions that make the model work. Forest site equations remain unchanged from Sterman et al. as described above in Equations 2.1 to 2.8 and Figure 2.3. The supply chain component of the model has been expanded to include the inverse calculations as described below in Equations 2.9 to 2.11 and Figure 2.6.

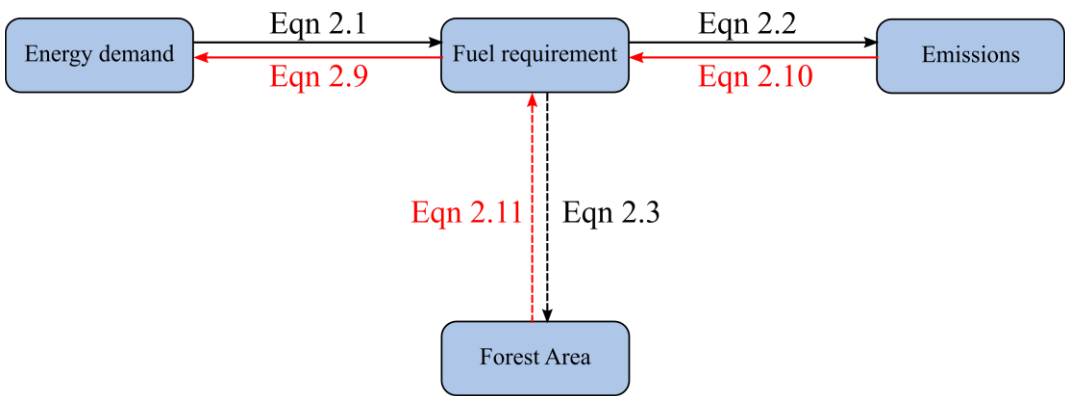

Figure 2.6. Schematic of the supply chain model used in SBCM. Three additional functions (in red) have been added (as described by Equations 2.9, 2.10, 2.11). These are the inverse of existing equations 2.1, 2.2 and 2.3

$$\text{energy produced} = \text{fuel energy} \times \text{efficiency}_{\text{production}} \times \text{efficiency}_{\text{use}}$$

Equation 2.9. Electricity produced from a known quantity of fuel. Energy is in GJ (electric), and efficiencies of production and use are expressed as dimensionless constants. This is the inverse of Equation 2.1.

$$\text{fuel used} = \frac{\text{total emission}}{(\text{emission}_{\text{production}} + \text{emission}_{\text{use}})}$$

Equation 2.10. Fuel used to generate a known emission. GJ of fuel based on a total emission (tC) and the carbon intensities of production and use (both in $tC.GJ^{-1}$). This is the inverse of Equation 2.2.

$$\text{fuel supplied} = \frac{(\text{area} \times \text{felling intensity} \times \text{forest carbon})}{\text{emission}_{\text{use}}}$$

Equation 2.11. Fuel supplied by a known area of forest. Fuel (GJ) is calculated from the intensity of emission ($tC.GJ^{-1}$), area (ha), felling intensity (%), and biomass present on a forest site ($tC.ha^{-1}$). This is the inverse of Equation 2.3.

Formatting.py

`Formatting.py` simply contains a function to correctly manage fonts within the `matplotlib` visualisation library and function to return the full forest type / species description when handed a model input code (`forest_labels`). These have no effect on the model results, they are simply included to correctly format output for display.

A note on execution order and resolution

While the Sterman et al. model has no specified execution order, it is necessary to define one to ensure that all coding is consistent and results are transparent. In SBCM, operations take place at the *end* of the year. In each year, operations take place in the order: fell, plant, grow, thus we assume that the starting condition values represent conditions where trees were planted at the very beginning of year 0 and have grown for the duration of that year.

The tightest temporal resolution possible in SBCM is one year. While it is possible to code for shorter timesteps, without extensive modification to account for seasonal variation in woodland growth, results from these timesteps would suffer from substantially reduced accuracy.

2.4.2 Testing SBCM

SBCM was configured to reproduce output from Sterman et al. (2018a) to allow direct comparisons with their range of published results and check that the model was functioning as expected.

100-year growth curve comparison

For each region / species combination SBCM was initialised using the parameters as published by Sterman et al. The model was then run for a 100-year period, tracking above-ground and below-ground carbon. The resulting values were displayed graphically and compared with the equivalent results as published by Sterman et al. (2018a supplementary material figure S2 on page 11). As the values used to generate the original graphical output were not available, this was carried out by setting the background of the SBCM output to transparent and overlaying the two images.

Forest carbon equilibrium values comparison

For each region / species combination SBCM was set up with a felling age of 500 years. This was then run for 10 rotations, to allow any variability in soil carbon to stabilise. Forest (above-ground) equilibrium values were then compared with those already published (Sterman et al., 2018a supplementary material table S3 on page 12).

Root Mean Squared Error (RMSE) comparison

Root Mean Squared Error (shown in Equation 2.12) is a simple calculation based on the average residual (difference between expected and observed values) for a given dataset.

$$\mathrm{RMSE} = \sqrt{\overline{(e-o)^2}}$$

Equation 2.12. Root mean squared error (RMSE) is equal to the square root of the mean squared difference between expected (e) and observed (o) values (the residuals). The units are whatever the values of e and o are expressed in.

This can be expressed using the `math` and `sklearn` libraries included in Anaconda in Python as:

```
from sklearn.metrics import mean_squared_error
from math import sqrt
rmse = sqrt(mean_squared_error(predictions-observations))
```

For each region / species combination, SBCM values for forest and soil carbon were compared with the original training data from Smith et al. (2006) based on carbon predictions at stand age intervals of 5 or 10 years to either 90 or 125 years (depending on species). The RMSE for this comparison was then compared with results from the same exercise as published by Sterman et al. (2018a supplementary material table S2 on page 10).

Supply chain scenarios comparison

For each region / species combination SBCM was initialised using the parameters and scenario information as published by Sterman et al. for scenarios cf and S0 to S5 (Sterman et al., 2018a supplementary material table S6 on page 19) and described more fully in Appendix C.

The resulting values were displayed graphically and compared with the equivalent results as published by Sterman et al. (2018a supplementary material figure S3 on page 21). As when testing the growth curves above, the values used to generate the original graphical output were not available, so this was carried out by setting the background of the SBCM output to transparent and overlaying the two images.

Payback period comparison

Finally, SBCM was initialised using the parameters published by Sterman et al. and run for the two most “realistic scenarios” (Prisley et al., 2018): S2 (a 25% felling) and S3 (a 95% felling) to calculate the payback period relative to a coal counterfactual. These payback periods were compared with the results as published by Sterman et al. (2018a supplementary material table S7 on page 22).

2.5 Results and Discussion

2.5.1 100-year growth curves

The forest growth model match was initially very good, resulting in a very close duplication of the Sterman et al. model for periods of less than 100 years. Soil and forest carbon storage values (Figure 2.7) are visually indistinguishable from the equivalent results published by Sterman et al. (as shown in Sterman et al., 2018a supplementary material figure S2 on page 11) when overlayed.

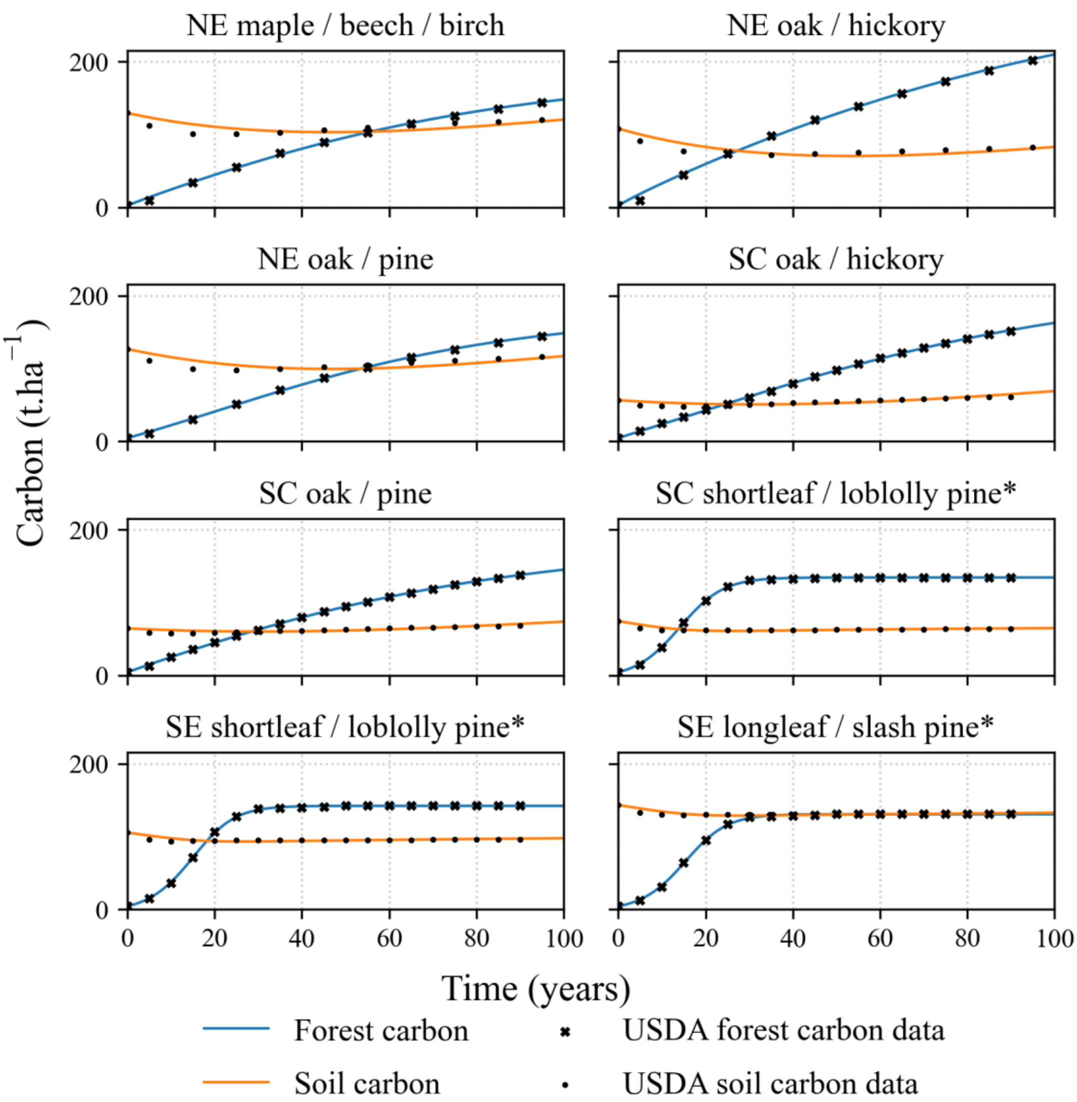

Figure 2.7. *A comparison of results from SBCM and underlying USDA training data from (Smith et al., 2006) when applied to eight forest types in the USA. Plantations are denoted by *. These results are visually indistinguishable from results obtained by Sterman et al. (as shown in Sterman et al., 2018a supplementary material figure S2 on page 11).*

2.5.2 Equilibrium values

SBCM, however; did not produce an exact match for "equilibrium values" (i.e. the total carbon storage in a fully mature woodland) over extended time periods. The values calculated by the Sterman et al. model (Sterman et al., 2018a supplementary material table S3) were published without reference to the time frame over which they were obtained, but discussion with the authors revealed that the time period used for the published values was 500 years (Sterman, 2018). Values from SBCM did not agree over the same time period and exhibited a discrepancy of up to 36 $tC.ha^{-1}$ in forest carbon (as shown in Table 2.4, and Figure 2.8).

Table 2.3. Equilibrium values from the Sterman Model vs results from SBCM.

Region / species	**Forest carbon equilibrium ($tC.ha^{-1}$ at 500 years)**		**Discrepancy ($tC.ha^{-1}$)**
	Sterman et al.	**SBCM**	
NE maple / beech / birch	158	188	+30
NE oak / hickory	280	316	+36
NE oak / pine	165	176	+11
SC oak / hickory	211	217	+6
SC oak / pine	156	180	+24
SC shortleaf / loblolly pine plantation	131	134	+3
SE shortleaf / loblolly pine plantation	141	142	+1
SE longleaf / slash pine plantation	130	130	+0

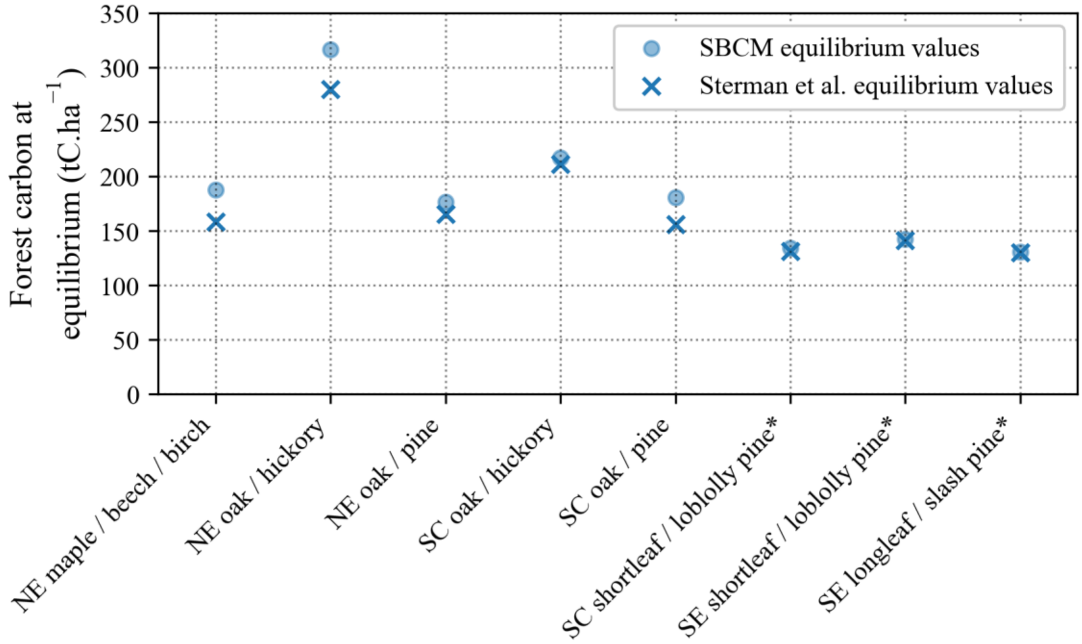

*Figure 2.8. Equilibrium values from the Sterman Model compared with SBCM for above-ground carbon at 500 years. Plantation forests marked with *.*

It is notable that the three plantation species / site combinations (marked with * in Figure 2.8) do not exhibit this variation, which is as high as 19% of above-ground carbon in the most extreme case. This is examined in greater detail in Chapter 3.

2.5.3 Root Mean Squared Error

Agreement between the models in terms of RMSE was found to be good, but a number of small differences were apparent between values generated by SBCM and those published by Sterman et al. (Sterman et al., 2018a Supplementary material table S2) as shown below in Figure 2.9 and table 2.4.

The maximum divergence (found in south-central oak / hickory forests) was a decrease of RMSE by 680 kgC.ha^{-1} (or a decrease of 0.3% of above-ground carbon at equilibrium for that forest type) when using SBCM. In each case this divergence is well within the margin of error for the measurement of standing forests – calculations of forest carbon precise to the nearest kilogramme per hectare seem naive in their optimistic implication of accuracy – but the difference in RMSE values indicates a possible variation in procedural accuracy between the two models. This suggests that more substantial variability is possible, and this is more extensively addressed in Chapter 3.

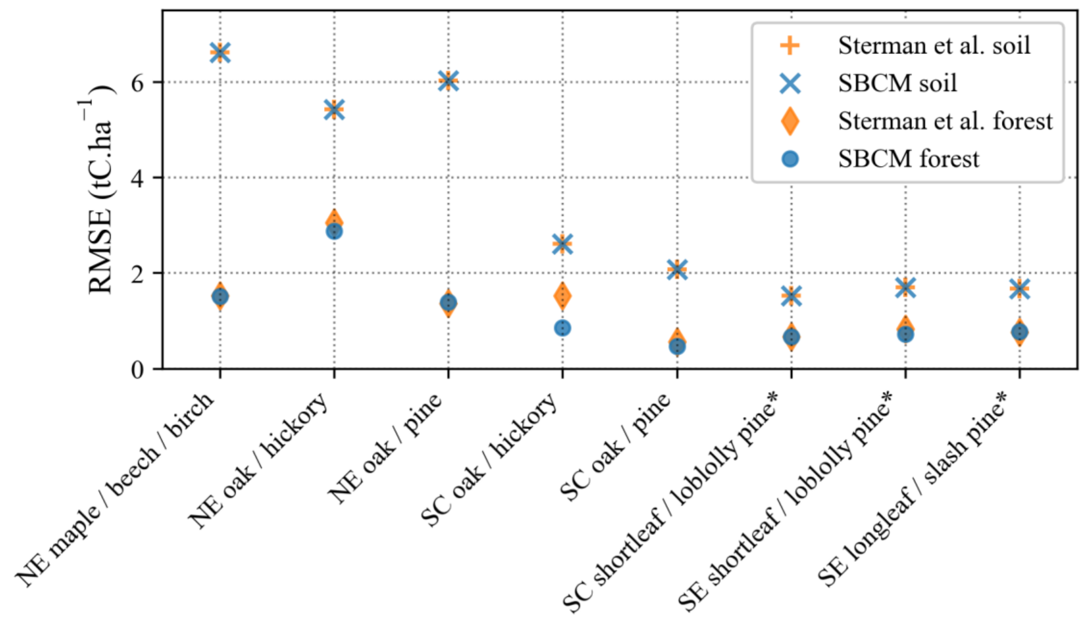

Figure 2.9. RMSE relative to the training data for SBCM and the Sterman et al. model. The degree of disagreement is not consistent across the forest types studied, but in every case, it is less than 0.3% of standing timber mass.

Table 2.4. RMSE relative to the training data for SBCM and the Sterman et al. model (all values are in tC.ha^{-1}). No observable differences were present in the soil RMSE scores, some small discrepancies were present when comparing forest (above-ground) carbon.

	Sterman et al.		**SBCM**		**Change ***	
	Soil	**Forest**	**Soil**	**Forest**	**Soil**	**Forest**
NE maple / beech / birch	6.611	1.518	6.611	1.511	0.000	-0.007
NE oak / hickory	5.415	3.046	5.415	2.873	0.000	-0.173
NE oak / pine	6.026	1.358	6.026	1.395	0.000	0.037
SC oak / hickory	2.615	1.531	2.615	0.851	0.000	-0.680
SC oak / pine	2.072	0.554	2.072	0.465	0.000	-0.089
SC shortleaf / loblolly pine plantation	1.522	0.666	1.522	0.663	0.000	-0.003
SE shortleaf / loblolly pine plantation	1.7	0.826	1.700	0.722	0.000	-0.104
SE longleaf / slash pine plantation	1.672	0.759	1.672	0.773	0.000	0.014
Mean	3.454	1.282	3.454	1.157	0.000	-0.126

**Change columns are equal to the (SBCM RMSE value - Sterman et al. RMSE value)*

2.5.4 Supply chain scenarios

When SBCM was applied to the scenarios described in (Sterman et al., 2018a) again the match with the Sterman Model was good, but not perfect. A reproduction of the scenarios which incorporate a single forest stand and a single energy demand (no species change or sustained yield) is shown in Figure 2.10.

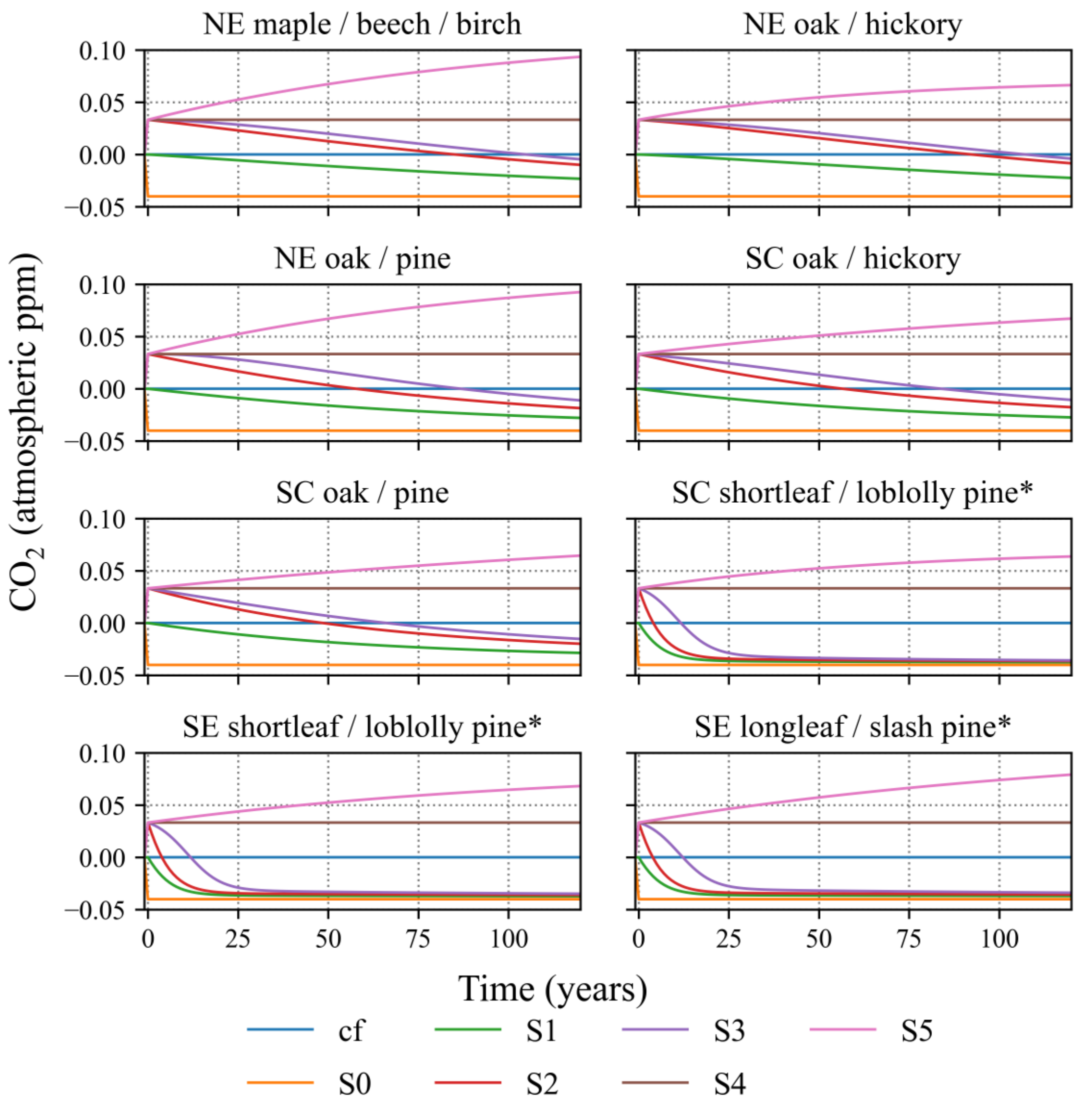

Figure 2.10. A reproduction of Sterman et al. scenarios S0-S5 using SBCM (Sterman et al., 2018a supplementary information page 19).

SBCM results compare well with results published by Sterman et al. (2018a supplementary information: Figure S3 on page 21) but do show very minor discrepancies, particularly in scenario S5 (deforestation, with soil carbon emissions enabled). Because the change in above-ground and below-ground carbon over the first hundred years of growth is essentially identical in the two models when starting from a common point, and because of the known discrepancies in equilibrium values for above-ground carbon (shown in section 2.5.2), this suggests that soil carbon or equilibrium values are not well constrained in the Sterman et al. model either. Varying starting conditions between the models, and growth rates are addressed in more detail in Chapter 3.

2.5.5 Payback periods

The disagreement between the Sterman et al. model, and SBCM results in a margin of error of <7 years when calculating payback periods for Sterman et al. scenarios S2 and S3 (shown in Figure 2.11). This is proportionally less significant on sites with longer rotation duration, but remains concerning. In every case, SBCM calculates a longer payback period than that reported by Sterman et al. and this is believed to be a result of the calculation order as described on page 53. The discrepancy implies that the Sterman et al. model contains an off-by-one error which effectively assumes that the initial value of above-ground carbon on site is greater than zero. Essentially assuming that the initial values in the training data represent the total carbon stored in planted trees (at the beginning of the first modelled year) rather than the first year's growth (at the end of the first modelled year).

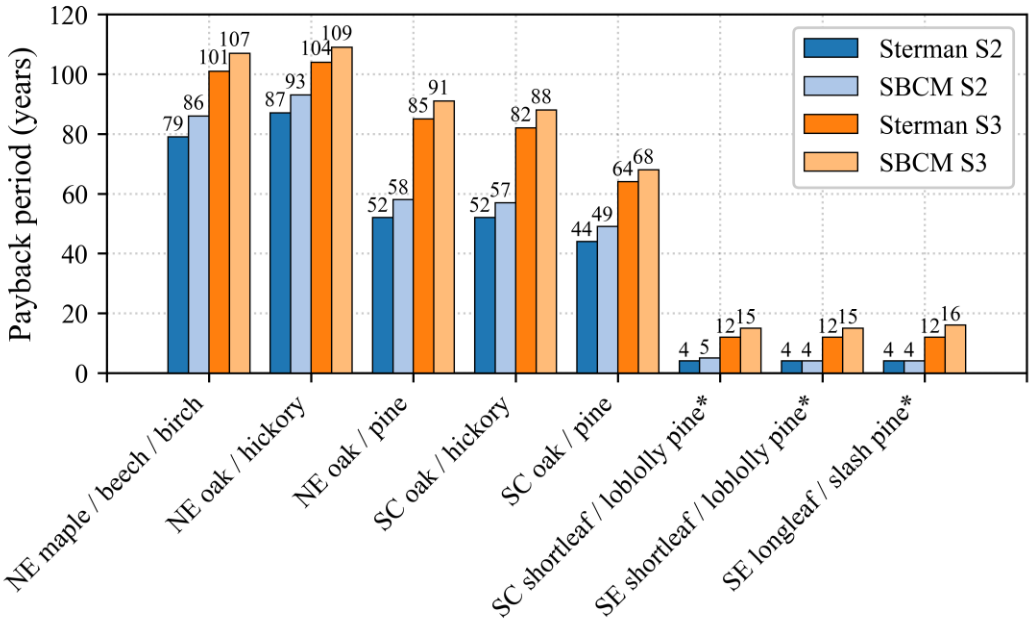

Figure 2.11. Payback periods from Sterman et al. and SBCM (2018a supplementary material table S8). Results are shown for scenarios S2 and S3: a 25% "thinning" and a 95% clear-fell.

2.6 Conclusions

Given the need for an adaptable modelling framework to compare the sustainability of biomass fuel supply chains, the model as published by Sterman et al. (2018a) was identified as a good starting point for modification.

As described in detail in Section 2.2, the Sterman et al. model represents an attempt to produce a simple framework to calculate the effects of displacing coal with a forest-sourced biomass fuel. It is freely available, open-source, is licenced for modification, and a detailed description of the internal assumptions, logic, parameters, and processes has been published (Sterman et al., 2018a). The model is relatively simple, makes use of publicly available data for training (Smith et al., 2006) and produces results which fall comfortably within the range of outcomes in the literature.

The model suffers from a number of weaknesses and while these are not insurmountable, they do require additional work to correct. Firstly, implementation is via a less well-known coding language which is a proprietary system which, while free for a basic version, carries a substantial financial cost to the end user to replicate the work in Sterman et al. (2018a). This limits access to what is otherwise very well documented code. Secondly, attention has also been drawn to assumptions in parameterisation and scenario development (Prisley et al., 2018; Dwivedi et al., 2019). In particular, a number of the scenarios detailed by Sterman et al. are of questionable utility in real-world situations, as they rely on assumptions about forest management which are "unrealistic" (Prisley et al., 2018).

The Sterman et al. model was enhanced by recoding the model in a more accessible language. This ability to revise conditions easily, as well as modifying assumptions and scenarios is an important requirement if the model is to accurately compare different modelling techniques and approaches.

SBCM represents a more accessible implementation of the Sterman et al. model, it was coded in Python and thoroughly tested against the results published by Sterman et al. (2018a). Based on these tests SBCM was found to match the existing published results closely, but not exactly.

The forest site sub-model in SBCM reproduces Sterman et al. results well for the first hundred years (Figure 2.7) and achieves a near-identical fit to the training data to that reported by Sterman et al. (Figure 2.9). Equilibrium values for forest carbon, on the other hand, do not match published results precisely (Figure 2.8) and it seems likely that values for soil carbon also disagree.

When the supply chain sub-model is incorporated into the calculation, SBCM reproduces a close approximation of results published by Sterman et al. (Figure 2.10). A small degree of uncertainty remains however; particularly in scenarios which are strongly focussed on the emissions of carbon from soils (e.g. Sterman et al. scenario S5). The disagreement between implementations of the model, results in a noticeable variation in payback period (Figure 2.11).

While SBCM is an acceptable approximation of Sterman et al. model, in that it produces very similar results, these results do not match exactly. As such, further research was deemed necessary to address these discrepancies.

Chapter 3. Assessing the forest model

In which the Author goes down a hole in search of a rabbit,
and is, instead, ambushed by a hydra.

Elements of this chapter have been previously published as Rolls, W. and Forster, P.M. 2020. Quantifying forest growth uncertainty on carbon payback times in a simple biomass carbon model. *Environmental Research Communications*. 2(4), p.045001. DOI 10.1088/2515-7620/ab7ff3. This paper was primarily the work of W. Rolls, with support, editorial comments, and oversight by P. M Forster

3.1 Introduction

As discussed in Chapter 1, the measurement and modelling of forest growth has been used to give indications of future yield for a many years (Samuelson, 1976). The application of these models to biomass production and carbon accounting is more recent, but has become widespread (Welfle et al., 2020). This has resulted in a need (as identified in Chapter 1) for a modelling framework to compare methodologies addressing the sustainability of biomass fuel supply chains. The model as published by Sterman et al. (2018a) was identified as a suitable candidate for modification as described in Chapter 2. This model was analysed in detail, replicated, and tested, the results from these tests indicating that while the new model (SBCM) produced a good match for the training data and results as published by Sterman et al., this match was not exact. In particular, discrepancies were observed in “equilibrium” carbon (i.e. the total carbon present in mature forest), and reported payback period.

These findings raise a number of questions about the forest modelling techniques and data used by Sterman et al. (2018a). A core requirement of the modelling framework as described in Chapters 1 and 2 is reproducibility and, while the discrepancies between the Sterman et al. model and SBCM are not excessive, they remain persistent.

This chapter includes a more detailed overview of forest modelling techniques in this context, an analysis of the baseline data and how this was translated into the model by Sterman et al. and an attempt to rebuild a new parameter set for SBCM from the same data.

3.1.1 Research questions

The central objective for this chapter is to explore the parameterisation of the SBCM model and its relationship with the model published by Sterman et al. and its training data. This is to identify whether the parameters developed by Sterman et al. are justified; whether a better model fit with the training data is possible, and whether this eliminates previously observed disagreement.

This work specifically addresses the research questions:

1. How is the data used to train the model by Sterman et al. derived, and is it the most appropriate?

2. Are the parameters obtained by Sterman et al. the most appropriate to replicate the forest growth curves supplied by Smith et al. (2006) or can improvements be made?

3. To what extent does uncertainty exist between the training data, forest growth as described by Sterman et al. (2018a) and forest growth described in SBCM?

4. What effect does an improved choice of parameters have on predicted carbon storage values, and payback times for different region and species combinations?

To assess the quality of the growth model parameters used by Sterman et al. in fitting their model to the training data, and to identify whether a closer match is possible, SBCM was re-parameterised. This was carried out using the original training data (from Smith et al., 2006) and a dual-response non-linear regression based on the `scipy` Python library. The resulting growth curves were assessed in terms of their fit to the original training data, and the effects of these changes on predicted carbon storage and payback periods were compared. The observed increase in uncertainty resulting from this exercise was then analysed and used to inform future research objectives.

3.2 Forests, silviculture, and modelling

3.2.1 Forests

While the original use of the word "forest" referred to a legal demarcation between jurisdictions rather than any specification of actual land-cover (Schama, 1996; Rackham, 1998) general usage has grown to define it as a geographical unit dominated by the presence of trees. Technical definitions vary between different countries, incorporating different biomes, but the definition used by the UNFCCC is:

"…a minimum area of land of 0.05-1.0 hectares with tree crown cover (or equivalent stocking level) of more than 10-30 per cent with trees with the potential to reach a minimum height of 2-5 metres at maturity in situ. A forest may consist either of closed forest formations where trees of various storeys and undergrowth cover a high proportion of the ground or open forest. Young natural stands and all plantations which have yet to reach a crown density of 10-30 per cent or tree height of 2-5 metres are included under forest, as are areas normally forming part of the forest area which are temporarily un-stocked as a result of human intervention such as harvesting or natural causes but which are expected to revert to forest" (UNFCCC, 2001 Annex, Section A:1.a).

This formal definition has been the subject of some criticism (Sasaki and Putz, 2009) as it depends heavily on the application of country or biome-specific criteria for local conditions (stocking density and tree size varies significantly between dryland forests and tropical rainforest for example). This, they argue, can lead to severe degradation of some forest areas before a change of land-use occurs under the formal definition. The UNFCCC definition is, however, is broadly equivalent to definitions in use by United Nations Food and Agriculture Organization (FAO, 2012) the United Nations Convention on Biological Diversity, and the International Union of Forest Research Organizations (Chazdon et al., 2016).

Forests vary in terms of their characteristics, however, they do have a number of common features in terms of ecosystem services (Raum, 2018). These are defined by the Millennium Ecosystem Assessment as supporting, provisioning, regulating, and cultural services (Reid et al., 2005) as shown in Figure 3.1 below.

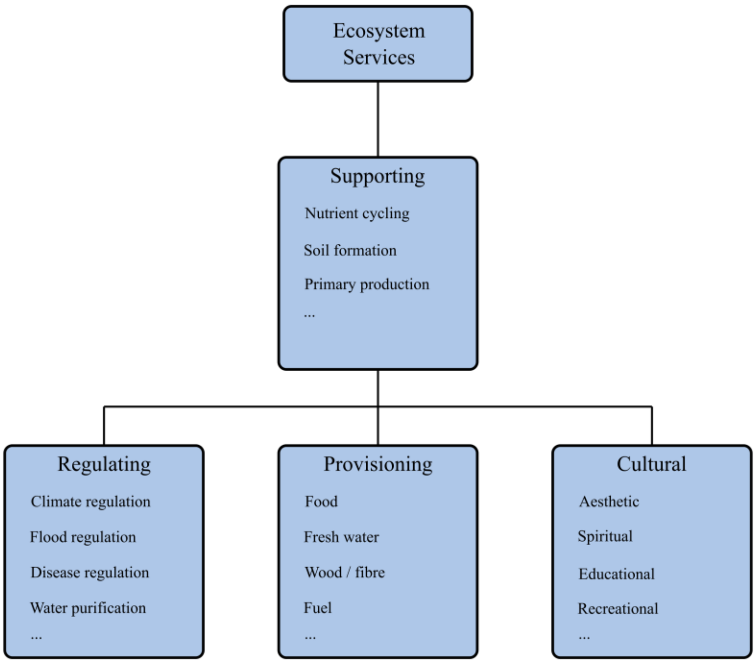

Figure 3.1. *Ecosystem services provided by forests (after Reid et al., 2005)*

Forests cover a significant proportion of the global land surface (about 30%) or an area of approximately 4 billion ha (FAO, 2016). However, since the beginning of human civilisation, the trend towards deforestation has been consistent and widespread (Williams, 2006; Ellis, 2011; Ellis et al., 2013). Fuelled by the industrial revolution, the industrialisation of the agricultural sector, and dramatic increases in human population pressures, the area of global forested land has been decreasing at some level ever since (FAO, 2012).

3.2.2 Silviculture

The nature of human interaction with forested areas varies significantly. It may involve no active management, or various silvicultural and arboricultural management techniques up to and including total species replacement or deforestation (Martin et al., 2012). Because of the long-lived nature of most tree species, the majority of sites will carry a legacy of previous management in addition to the contemporary management patterns, and this is likely to have a lasting effect on species mixture and age-structure. (Duncker, Raulund-Rasmussen, et al., 2012)

Forests can be categorised based on the intensity and degree of regulation of human interactions as shown below in Figure 3.2.

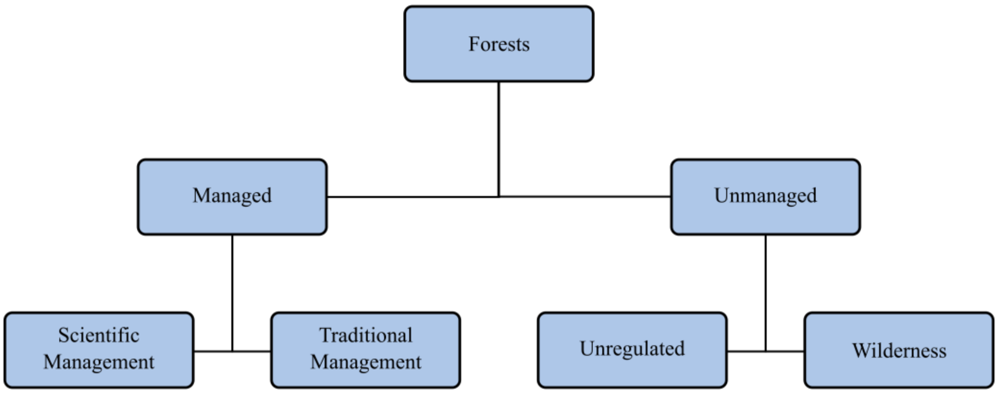

Figure 3.2. A schematic categorisation of forest management definitions based on the degree of planned management and intensity of human interaction.

It is important to recognise that a significant proportion of global forest area is unmanaged, that is: either human interactions are either not taking place at all (as in wilderness areas: see Luyssaert et al., 2014; Cherubini et al., 2016) or that they are taking place without planned management (Ter-Mikaelian et al., 2008). These "unregulated" forest areas being subject to site clearance for other industries, un-restricted deforestation, or felling specific valuable species (Wunder et al., 2012)

Of the managed forest areas, many are managed according to "traditional" or non / pre-industrial management practices such as coppicing, or silvo-pastoral methods (Richardson et al., 2002). This study specifically focusses on the remaining forests which are managed "scientifically" (Siiskonen, 2007; Klooster, 2009) i.e. carefully planned silvicultural operations intended to optimise a specific outcome.

Management of forests according to "scientific" silvicultural methods represent one of the main sources of biomass fuels for industrial use (World Bioenergy Association, 2020). Silvicultural systems are generally designed to maximise either yield or economic return (discussed in Chapter 5) and rely on accurate measurement of standing timber volume and estimates of the rate of forest growth.

3.2.3 Forest Models

While it is not impossible for experienced foresters to gain a general sense of the growth trajectory of a forest stand by eye, this is not an easy skill to learn, and a qualitative assessment is difficult to translate into a reliable quantitative figure (Weiskittel et al., 2011). The need to provide quantifiable estimates of future forest yield has been recognised for many years (e.g. von Carlowitz, 1713) and has stimulated the development of a range of a theoretical structures to enable forest valuation and planning forest operations (Assmann, 1970; Taylor et al., 2009).

As discussed in Section 1.3.2, the simplest (and earliest) forms of forest model are simple statistical tables, indicating expected yield based on known silvicultural prescriptions, species, and site conditions (Burkhart and Tomé, 2012). Yield tables remain in use within large sections of the forest industry (Porté and Bartelink, 2002). For example in the UK, the Forestry Commission has published (and continues to maintain) yield tables for commercially grown species (Hamilton and Christie, 1971; Edwards and Christie, 1981; Matthews et al., 2016). While these tables can provide useful estimates of growth, they rely on rigid scenarios, which do not account for unscheduled silvicultural operations, previous management, variations in allometric relationships, or changes in growing conditions. Yield tables are also less common for mixtures of species, or for forests where age classes are spatially mixed, so their use is largely confined to even-aged, monoculture forestry. This is of particular concern given the expected changes to the climate which on some sites may take place within the duration of a single forestry rotation.

Yield tables, while giving some useful statistics on likely tree mortality and timber volume, rarely provide information on any variable which is not directly linked to saleable timber output. While this is (perhaps) acceptable in commercial softwood stands, it does not account for a large amount of information outside the model which has a bearing on modern forest management. These omissions are deeply relevant to this study as total carbon storage is not equal to the saleable proportion of stem volume, but also includes branch-wood, particularly in decurrant species (e.g. Corbyn et al., 1988; Fowler and Rennie, 1988; Dahle and Grabosky, 2009) and soil carbon (Peckham and Gower, 2011).

While yield tables have remained in use in some areas of a sector comfortable with slow rates of change, the wider forestry industry has moved away from simple sustained-yield management of monocultures towards more complicated management structures intended to provide multiple ecosystem services (Timsina et al., 2022; Tebėra and Semaškiene, 2023)

The advent of computational modelling and a recognition of the limitations In such simple techniques (Pretzsch et al., 2015) has led to a rapid increase in the number and sophistication of forest models since the late 20th century (Vanclay, 1994; Peng, 2000). Forests however, remain difficult to model since they are dynamic natural systems incorporating a large number of processes and are subject to a wide range of potential external factors.

In assessing more sophisticated models, it is important to distinguish between the formula or function describing the growth of a forest, and the model (its application). While the use of these terms is not by any means standardised (Weiskittel, 2011; Burkhart and Tomé, 2012) in this study *function* applies to the broadest application of a mathematical framework, *formula* or *equation* refers to the specific expression of that function and, and *model* refers to an operational computer-based application of the formula.

Models are typically composed of one or more differential equations (Borges et al., 2014) which describe the behaviour of trees based on different parameters and existing growth. These seek to represent the growth of trees or a group of trees by some combination of process simulation of causal relationships (Porté and Bartelink, 2002) and statistical approximation. Taylor et al. (2009) categorise the latter as “empirical” models, in that they do not attempt to describe actual physical processes, but merely the end result. This categorisation is criticised by Weiskittel et al. (2011) who point out that the more appropriate description of this kind of models is statistical (based on probable outcomes) as all models must be validated against empirical data to be useful. In reality, however, these terms define where models sit in terms of a continuum rather than discrete categories, and most models can be considered to be hybrids of the two methods (Weiskittel et al., 2011).

A number of competing categorisations of models have been used in the past (Porté and Bartelink, 2002). Categorisations range from the three category system as proposed by Munroe (1974) which makes simple distinctions about the distance dependency (whether or not spatial distribution of trees is taken into account) and scale; to the twenty nine categories proposed by Vanclay (1994). Porté and Bartelink (2002) identify seven different criteria that have been used to categorise models in the past and then propose their own as shown in Figure 3.3 below.

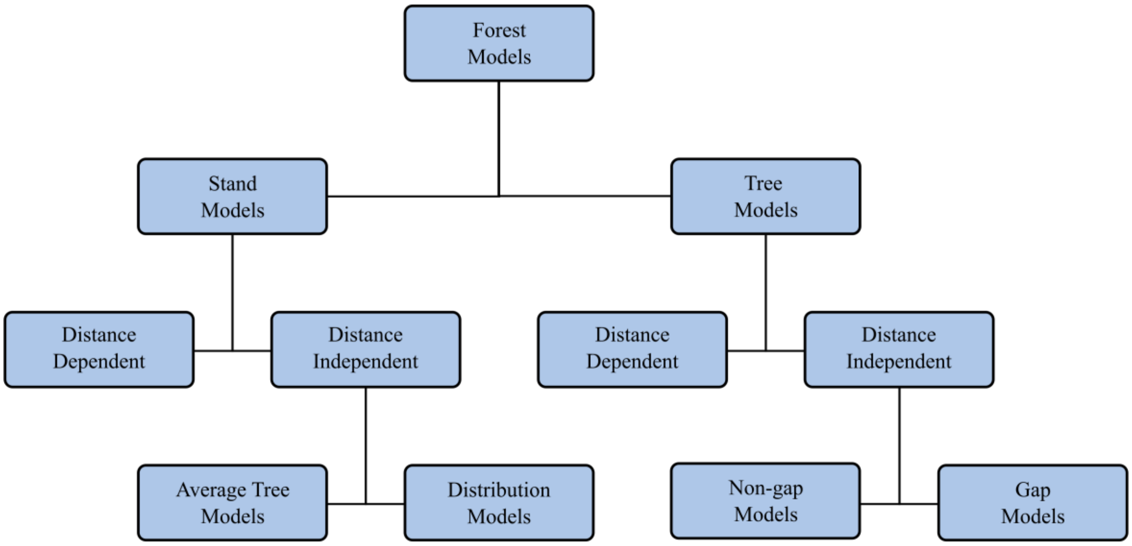

Figure 3.3. Different modelling strategies for woods and trees after Porté and Bartelink (2002)

This hierarchy, while omitting some detail in terms of methodology, does allow for clear terminology when discussing different models. According to this nomenclature Sterman et al. (2018a) use data from a stand-level, distance independent, average tree yield table (Smith et al., 2006) to parameterise a growth curve (a modified Chapman-Richards function, see Burkhart and Tomé, 2012, sec. 6.4.4). This is used to generate results for a conceptual landscape, distance independent, landscape scale model.

3.3 Method

3.3.1 Training data

For growth functions to give meaningful and useful indications of future yield, they must be calibrated (trained) to data from forests in the real-world. This is a particularly difficult task, partly because of the long rotation length of many commercially grown species (Somers, 1994; Perera et al., 2015), partly because of the heterogeneity of site conditions and growth characteristics of tree species (Skovsgaard and Vanclay, 2013), and partly because non-destructive measurement of trees and soil carbon results in lower accuracy measurement (Matthews and Mackie, 2006). A range of (somewhat uncomfortable) solutions to these issues exist, but the underlying difficulties associated with forest measurement mean that the accuracy of predictions is relatively low when compared to annual agricultural crops.

The multi-decadal study periods required to measure a forest stand from planting to felling are a significant barrier to data collection (Somers, 1994; Perera et al., 2015). To measure the same stand at recurrent intervals may require a commitment to a particular management regime of over a century and, particularly in the light of climate change, there is no guarantee that site conditions, ownership, stochastic factors, management objectives, and measurement protocols will remain consistent throughout.

Forests have generally been a lower-priority land use when compared to agriculture (Rackham, 1998), which means the diversity of forest site types is typically high, being relegated to areas with uneven topography, marginal soils, etc. (Evans et al., 2015). Due to this lower prioritisation, and an extended lifecycle, trees have generally received less attention in terms of selective breeding than agricultural crops, this means that many tree species tend to exhibit significant heterogeneity of form (Larson, 1963)

The variation in growth characteristics between (and within) species and the size of mature trees makes accurate non-destructive measurement difficult (Matthews and Mackie, 2006). This is further compounded by disagreements in terms of measuring conventions (Brokaw and Thompson, 2000) and the wide range of literature describing allometric relationships (Globallometree.org, 2018).

Given the high degree of natural variation in the rate and nature of tree growth and the logistical issues surrounding measurement of individual trees, the standard response has been to take a statistical approach to sampling. A proportion of the total population is considered to be a representative sample and this has been measured and used as a proxy. This takes place spatially, but also temporally in the form of a chronosequence of sites: samples of the population with similar characteristics and site types at different stages of maturity (Chazdon, 2013). This allows the collection of data from trees in a broad series of age categories, but sacrifices control of factors such as topography, geology and soils, precipitation, management history etc.

The incorporation of soils into forest models is a relatively recent development. Early forest models treat soils as a site characteristic which is not subject to change, and assume that any reduction in soil fertility for multiple forestry rotations can be accounted for by simply adjusting yield in the forest model (as in Hamilton and Christie, 1971; Edwards and Christie, 1981; Matthews et al., 2016). Soil carbon stocks have not been widely considered in the context of land use and climate change until relatively recently (Guo and Gifford, 2002) and while a range of soil carbon modelling approaches exist (e.g. Schmid et al., 2006) their relationship with forest models is far from mature.

A consequence of these problems has been a lack of reliable data to calibrate or “train” mathematical functions used in modelling forest carbon dynamics over large areas. Locally relevant datasets have been published in the literature, but these are often limited in scope to specific species or geographical regions. Larger scale datasets, such as those used by national governments in reporting under climate change commitments are often either reported as a fixed inventory, rather than as a complete dataset showing the change over time (McCullagh et al., 2017) or are not spatially linked – so soils and forest carbon are reported independently of one another (Mills-Novoa and Liverman, 2019; Pauw et al., 2020).

The Smith et al. data used by Sterman et al. is a widely used dataset (e.g. Jenkins et al., 2010; Pan et al., 2011; Lawler et al., 2014; Adams et al., 2018; Tinkham et al., 2018) published by the United States Department of Agriculture (USDA). This dataset provides generic growth curves for a range of biogeographical regions and species mixtures across the contiguous USA including an estimate of soil carbon. These were developed using the Forest Inventory and Analysis (FIA) database (Miles et al., 2001) which incorporates data from many thousand sample plots across the country. These datapoints were then analysed using the Aggregate Timberland Analysis System (Mills, 1992; Haynes, 2003) and the FORCARB2 model (Smith and Heath, 1990; Heath et al., 2002; Woodbury et al., 2007) to produce high level approximations of mean growth curves for each of the species / region combinations. This dataset is unusual in that it has a clear sampled growth curve for a range of different species, and includes soil carbon at a national level (although the estimates of soil carbon as opposed to forest floor detritus remain somewhat simplistic). While the data is provided for large biogeographical regions, the authors caution against using the data to predict growth on specific sites - emphasising that since they have been based on national averages, they are unlikely to provide accurate results at stand or local level. Nevertheless, the result is an accessible dataset giving indications of growth for different forest sites over the first 90-125 years which can be widely adapted to allow researchers access to similar data for intercomparison and generic use.

The Smith et al. data (an example of which is shown below in Table 3.1 and Figure 3.4) includes values for age and standing forest volume, followed by estimates of carbon in tonnes partitioned into different categories: live trees, standing dead wood, understorey down (fallen) dead wood, forest floor, and soils. No management activity is modelled, so stands are assumed to be unthinned, and planted at an average spacing for sites of that type (or regenerated naturally). This, again, is an extremely simple rendering of a forest growth curve, but as the authors are at pains to point out, it is designed to give a generic picture, rather than a detailed projection for a specific site

Table 3.1. An example of the Smith et al. (2006) dataset: Regional estimates of timber volume and carbon stocks for maple / beech / birch stands with reforestation of land in the Northeast biogeographical region of the USA. Blue shaded areas were combined into an "above-ground" carbon figure, and orange shaded areas are considered "below-ground" by Sterman et al. (2018a).

Stand age	**Volume**	**Live tree**	**Standing dead**	**Under-story**	**Down dead wood**	**Forest floor**	**Soil**	**Total non-soil**
Years	$m^3.ha^{-1}$	------------------------------------ $t.ha^{-1}$ ------------------------------------						
0	0	0	0	2.1	32	27.7	69.6	61.8
5	0	7.4	0.7	2.1	21.7	20.3	69.6	52.2
15	28	31.8	3.2	1.9	11.5	16.3	69.6	64.7
25	58.1	53.2	5.3	1.8	7.8	17.6	69.6	85.7
35	89.6	72.8	6	1.7	6.9	20.3	69.6	107.8
45	119.1	87.8	6.6	1.7	7	23	69.6	126
55	146.6	101.1	7	1.7	7.5	25.3	69.6	142.7
65	172.1	113.1	7.4	1.7	8.2	27.4	69.6	157.7
75	195.6	123.8	7.7	1.7	8.8	29.2	69.6	171.2
85	217.1	133.5	7.9	1.7	9.5	30.7	69.6	183.2
95	236.6	142.1	8.1	1.7	10.1	32	69.6	193.9
105	254.1	149.7	8.3	1.6	10.6	33.1	69.6	203.4
115	269.7	156.3	8.5	1.6	11.1	34.2	69.6	211.7
125	283.2	162.1	8.6	1.6	11.5	35.1	69.6	218.8

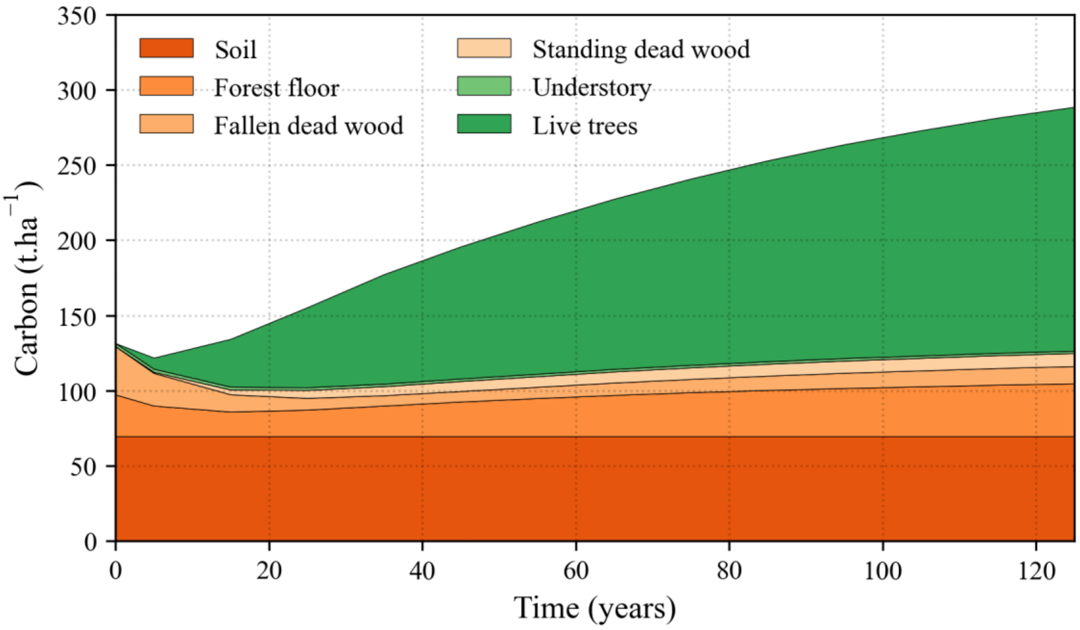

Figure 3.4. Carbon stocks in NE maple / beech / birch forest . Based on data published by USDA (Smith et al., 2006) carbon partitioning into above-ground (green)and below-ground (orange)as used by Sterman et al. (2018a).

As shown in Figure 3.4 above, Sterman et al. combined the live tree / understorey values as above-ground biomass and also combined the standing dead timber, down dead wood, forest floor, and soil values as below-ground carbon. This is a further simplification, and it could be argued that it misses some nuances: the live trees category includes stumps and coarse roots and standing dead wood, which can often be incorporated into the biomass supply chain; and the understorey could reasonably be expected to include herbaceous plants as well as woody shrubs and young trees. In general, however, this simple partitioning of material into above-ground (i.e. fit for fuel production) and below-ground (not considered) is in keeping with the generic character of the dataset.

Sterman et al. then use the growth tables for replanting an existing forest site. This is consistent with their assumption that forests are only felled when mature (as described in Section 2.3.5 p47) but does raise some complexities around the spatial boundary conditions (see Section 1.3.2 p23) in order to meet demand, this deserves further consideration and is examined further in Chapter 5. While a method for partitioning felled material into different harvested wood product (HWP) categories is included by Smith et al., this was not used by Sterman et al., presumably for reasons of simplicity.

This represents an opportunity for further development of the model as discussed later in Chapter 6.

Following determination of the basic values to be used in the growth curves, Sterman et al. then used a non-linear regression technique to ensure the best possible fit between the results from the growth function (Equation 2.4) and the training data published by Smith et al. (2006).

Using the same assumptions as Sterman et al. SBCM was reconfigured to identify parameter sets which matched the training data from Smith et al. (2006).

3.3.2 Fitting the curve

In the work published in their 2018 paper, Sterman et al. used the `optimizer` function in Vensim (Venata Systems, 2017) to test a range of possible parameterisations against the training dataset described above and choose values which obtained the closest match. Their method tested this using a combination of least squares non-linear regression and Markov Chain Monte Carlo methods. This is described in more detail in their supplementary material (attached to Sterman et al., 2018a) but, in summary, they restricted the matching algorithm to parameter values which resulted in two set conditions:

- The first value of the points forming the matched curve ($y_{(x=0)}$) must equal the first value of the Smith et al. (2006) data.
- The curve must result in the smallest achievable root mean squared error (RMSE) values between the data and modelled output.

A similar approach was used in SBCM using the `scipy` Python library (Jones et al., 2001). This library includes a range of different methods for curve fitting, and how to handle outlying data. The process was complicated by the nature of the dataset and matching function. A match of a single function to a single dataset, is relatively straightforward, however the functions governing below-ground and above-ground carbon in SBCM are intimately linked (using overlapping parameters). This required an adaptation of the code to introduce a dual-response matching above-ground and below-ground carbon values simultaneously.

A full set of possible combinations was used to identify new parameters which when applied to the growth function resulted in a fit with the Smith et al. data which was as good as or better than that provided by Sterman et al.

The `optimize.leastsquares` function from the Python `scipy` library contains a range of different algorithms for curve fitting (Table 3.2). These represent methods for identifying parameter sets which achieve a good degree of agreement with the training data based on a given formula.

Table 3.2. Algorithms from the `scipy.optimize.leastsquares` function (discussed in detail in Scipy.org, 2019).

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

`Scipy` also provides a range of "loss functions" (described in Table 3.3). These decrease the relative importance given to outliers when fitting the model to the data depending on the distance between each point and the residual. This is more important in noisy data sets which contain a lot of outliers and less certain trends, but were included to provide the maximum range of possible outcomes.

Table 3.3. Loss functions providing different weight to outliers (discussed in detail in Scipy.org, 2019). The weighted value of a data point (ρ(z)) changes relative to the residual (z).

Loss function	**Formula**
linear	$\rho(z) = z$
soft_l1	$\rho(z) = 2 \times ((1+z)^{0.5} - 1)$
Huber	$\rho(z) = z \text{ if } z <= 1 \text{ else } 2 \times z^{0.5} - 1$
Cauchy	$\rho(z) = \ln(1+z)$
arctan	$\rho(z) = \arctan(z)$

The quality of the match between the modelled trend and the training data is assessed during the curve fitting exercise by attempting to minimise the RMSE. Since the process assesses the training data point by point, is insensitive to error location, and uses overlapping parameter sets, it is possible for the system to identify a good match at a local level rather than globally (for the trend as a whole) and provide skewed results. This is where one part of a data-series achieves a very good fit, while the cumulative error is simply propagated to another part of the series. The RMSE method is limited in this regard as it gives equal weighting to each residual; this weakness, however is relatively simple to detect by simply plotting the results and observing any wide divergence (as shown later in Figure 3.5).

3.4 Results and analysis

For each of the eight region / species combinations as used by Sterman et al. (described in detail in Section 2.3.3 on page 45), a full range of possible combinations of algorithm and loss functions (as described above in Tables 3.2 and 3.3) 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 training data (±1 $tC.ha^{-1}$). This resulted in 240 specific combinations of region / species, algorithm, loss function, and constraints. In each case, the fit of the modelled output to the training data was assessed by calculating the RMSE. Of the 240 permutations assessed, 93 failed to reach a solution, and of the 147 successful attempts, 41 achieved a lower RMSE score than reported by Sterman et al. (2018a) as shown in Table 3.4.

*Table 3.4. RMSE results from a full suite of curve fitting methods and loss functions. Constrained runs are marked with (c), cells shaded in orange represent an improvement on the RMSE achieved by Sterman et al., cells shaded in blue are the best results obtained in the exercise. NB No iterations using the Levenberg-Marquardt algorithm were successful in finding a workable solution and cells marked with [a b] (trf / Huber iterations for SC oak / pine forest) while achieving a better RMSE than Sterman et al., were discarded due to clear anomalies in soil carbon levels. Plantations are denoted with *.*

	NE maple / beech / birch	**NE oak / hickory**	**NE oak / pine**	**SC oak / hickory**	**SC oak / pine**	**SC shortleaf / loblolly pine***	**SE shortleaf / loblolly pine***	**SE longleaf / slash pine***
Sterman	4.79	4.33	4.37	1.94	1.50	1.17	1.31	1.30
trf / linear	3.76	3.50	-	1.39	1.05	0.95	1.05	1.05
trf / linear (c)	4.53	4.01	4.13	1.78	1.33	1.03	1.16	1.15
trf / soft_l1	4.08	55.32	3.71	32.74	-	34.15	36.90	1.24
trf / soft_l1 (c)	4.75	4.19	4.30	1.82	1.36	8.35	9.17	8.61
trf / Huber	4.09	3.90	3.73	32.74	0.61[a]	34.33	37.09	34.43
trf / Huber (c)	4.74	4.25	4.31	1.83	0.86[b]	1.07	1.20	1.19
trf / Cauchy	-	107.09	51.12	36.26	-	97.12	1.54	1.51
trf / Cauchy (c)	77.92	23.84	75.66	2.00	1.45	1.18	1.32	1.30
trf / arctan	27.98	61.76	37.70	61.69	32.30	47.30	86.81	78.70
trf / arctan (c)	77.54	113.76	11.48	36.34	25.42	84.41	48.64	80.38
lm (all 10 runs)	No iterations of the Levenberg-Marquardt algorithm achieved a workable result							
dogbox / linear	221.50	-	77.89	243.36	216.81	220.41	209.08	63.85
dogbox / linear (c)	40.65	34.10	41.13	85.87	86.46	1.03	1.16	136.21
dogbox / soft_l1	195.94	207.01	226.92	250.63	251.73	230.49	218.23	217.04
dogbox / soft_l1 (c)	175.51	161.58	15.83	-	1.78	109.16	107.76	1.19
dogbox / Huber	-	-	-	70.67	37.29	77.52	60.87	181.61
dogbox / Huber (c)	176.65	98.14	-	1.83	-	1.07	14.88	19.55
dogbox / Cauchy	237.78	202.54	228.28	241.62	224.50	224.20	216.44	209.67
dogbox / Cauchy(c)	15.12	-	6.95	-	69.51	75.11	10.01	7.11
dogbox / arctan	234.88	211.64	238.83	252.02	253.21	231.76	223.96	231.55
dogbox / arctan (c)	207.40	181.43	208.46	474.17	240.29	316.85	195.35	153.74

In virtually every case, the best results were obtained by the Trust Region Reflective (Branch et al., 1999) method. No iterations of the Levenberg-Marquardt algorithm (Moré, 1978) were successful in reaching a useful result.

In two cases when using the Trust Region Reflective algorithm and Huber loss function for SC oak / pine forest the resulting RMSE was lower than the value achieved by Sterman et al. but it quickly became apparent that the results were badly skewed. These cases (labelled a and b in Table 3.4) resulted in a strong upward linear trend in soil carbon (as shown in Figure 3.5). The model was run for a long time-horizon (5,000 years) and no evidence of this upward trend attenuating was found. Regardless of the excellent RMSE score, these results were deemed anomalous and discarded.

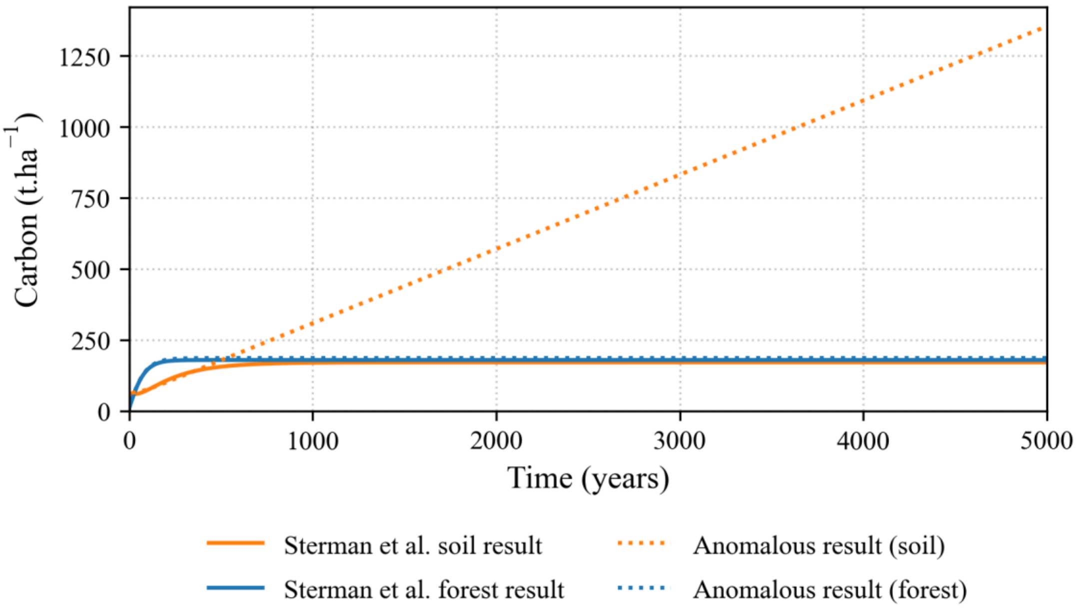

Figure 3.5. An example of anomalous result for south-central oak/pine forest. Using the Trust Region Reflective algorithm and Huber loss function; the match between forest carbon results and the training data is good, however the value for soil carbon increases linearly with no attenuation.

At this point, for each region / species combination there exists a number of possible solutions all of which improve the fit of the model to the training data. For example, Figure 3.6 shows six different modifications to the parameters for North East maple / beech / birch forest (as well as the training data, and the fit as published by Sterman et al.) While the forest (above-ground) carbon values are relatively well clustered, the uncertainty associated with below-ground (soil) carbon is around 90 tC.ha^{-1} at maturity.

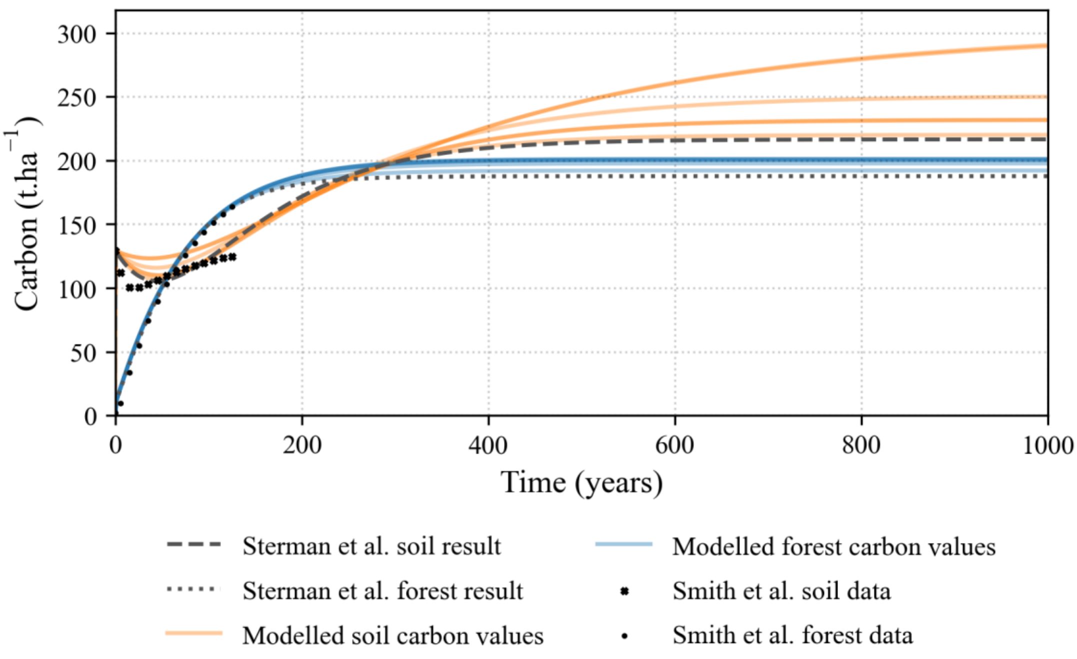

Figure 3.6. Results from curve fitting to North East maple / beech / birch forest data. Six possible curves were identified which fit the data better than the parameters identified by Sterman et al. While agreement on above-ground carbon levels is reasonably good, there is notable variation in predicted below-ground carbon values.

3.4.1 Quantifying the effects of re-parameterisation

Having identified a subset of 39 possible parameterisations which resulted in an improved RMSE score compared to Sterman et al. (as shown in Table 3.5 and Figure 3.7); SBCM was run to determine the effects of these changes on predicted carbon storage and payback period.

*Table 3.5. Subset of results from Table 3.4 which show a measurable improved RMSE compared to Sterman et al. Constrained runs are marked with (c), cells shaded in blue are the best results obtained for each species / region combination. Plantations are denoted with *.*

	NE maple / beech / birch	**NE oak / hickory**	**NE oak / pine**	**SC oak / hickory**	**SC oak / pine**	**SC shortleaf / loblolly pine***	**SE shortleaf / loblolly pine***	**SE longleaf / slash pine***
Sterman	4.79	4.33	4.37	1.94	1.50	1.17	1.31	1.30
trf / linear	3.76	3.50		1.39	1.05	0.95	1.05	1.05
trf / linear (c)	4.53	4.01	4.13	1.78	1.33	1.03	1.16	1.15
trf / soft_l1	4.08		3.71					1.24
trf / soft_l1 (c)	4.75	4.19	4.30	1.82	1.36			
trf / huber	4.09	3.90	3.73					
trf / huber (c)	4.74	4.25	4.31	1.83		1.07	1.20	1.19
trf / cauchy (c)					1.45			
dogbox / linear (c)						1.03	1.16	
dogbox / soft_l1 (c)								1.19
dogbox / huber (c)				1.83		1.07		

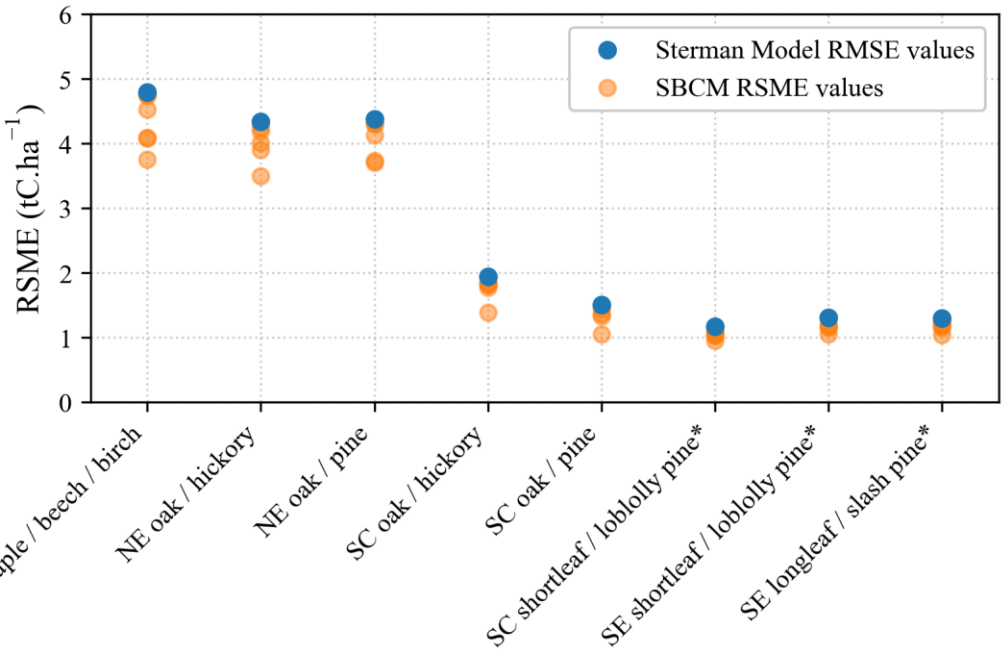

*Figure 3.7. A comparison of RMSE values from SBCM and published by Sterman et al. (2018 Supplementary table S2) and those obtained by re-parameterisation of the model. Only values of parameterisations with a better fit than Sterman et al. are shown for clarity. Plantations are denoted with *.*

The Sterman et al. model assumes that forests are fully mature when felled. As such the quantity of carbon stored in the forest is directly related to the area of forest required to meet energy demand (Equation 2.3). This takes place because the model is designed to quantify forest area required to meet a defined energy need: if the quantity of carbon per hectare is high, the model will assume that fewer hectares are needed to meet demand, and conversely if the quantity of carbon per hectare is low, the model will assume that more hectares are required. This directly affects the rate of carbon reabsorption because two hectares of forest will tend to have a greater annual growth increment than a single hectare – so forests with large pre-existing carbon pools will tend to take longer to recover. This issue surrounding the elasticity of area in the model is addressed in more detail in Chapter 5.

To assess the variation in mature forest carbon storage, the model was first run for a 5000-year timescale using the full range of parameter sets identified above. It was not possible to calculate payback period at this point, because the model's starting ("equilibrium") conditions were unknown, so the model was run with incorrect starting values for soil and forest carbon for a sufficient length of time to ensure that maximum stored carbon given the site and species selected had been reached. A substantial variation was observed in the estimated carbon storage on site at maturity for model runs using parameters which achieved similar RMSE scores. This was particularly noticeable in non-plantation forests (as shown in Table 3.6) where the range of possible results exceeded 100 $tC.ha^{-1}$ in three cases.

*Table 3.6. Variation in site carbon based on different parameter sets for SBCM. The possible outcomes in terms of on-site carbon show very different results depending on parameterisation used. Plantations are denoted by **

	Below-ground carbon min – max ($tC.ha^{-1}$)	**Above-ground carbon min – max ($tC.ha^{-1}$)**	**Whole site variation ($tC.ha^{-1}$)**
NE maple / beech / birch	216 - 303	188 - 202	101
NE oak / hickory	166 - 183	317 - 350	50
NE oak / pine	197 - 272	176 - 189	88
SC oak / hickory	158 - 349	191 - 217	217
SC oak / pine	172 - 394	180 - 186	228
SC shortleaf / loblolly pine*	65 - 67	134 - 134	2
SE shortleaf / loblolly pine*	100 - 104	142 - 142	4
SE longleaf / slash pine*	136 - 139	130 - 131	4

Having established the carbon storage at maturity for each of the parameter sets, the model was run again using these values to define correct starting conditions. In each case, the supply-chain model used the original parameterisation for supply chain efficiencies and emissions as published in Sterman et al. (2018a) to allow a comparison with the original model results. The scenario used was based on a clear-fell of mature forest in order to supply biomass (equivalent to scenario S3 in Sterman et al., 2018a, described in detail in Appendix C). This was compared with a coal-based counterfactual scenario with an implicit assumption that there would be no emissions from the forest site in the absence of biomass production (discussed further in Chapter 5). While it is acknowledged that this may not be appropriate (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). Payback periods (as shown in Table 3.7) varied by up to 48 years depending on model parameters used. As when looking at mature site carbon, this degree of divergence was striking in the non-plantation forests.

Table 3.7. Payback periods using different growth model parameters in SBCM. The parameterisations with the lowest RMSE score are highlighted in blue. All values are in years.

	NE maple / beech / birch	NE oak / hickory	NE oak / pine	SC oak / hickory	SC oak / pine	SC shortleaf / loblolly pine*	SE shortleaf / loblolly pine*	SE longleaf / slash pine*
Sterman	107	109	91	88	68	15	15	16
trf / linear	80	103		57	47	14	14	15
trf / linear (c)	106	108	90	82	62	14	15	15
trf / soft_l1	60		60					15
trf / soft_l1 (c)	98	107	58	76	59			
trf / huber	59	97	59					
trf / huber (c)	98	107	85	75		14	15	15
trf / cauchy (c)					56			
dogbox / linear (c)						14	15	
dogbox / soft_l1 (c)								15
dogbox / huber (c)				75		14		
max	107	109	91	88	68	15	15	16
min	59	97	58	57	47	14	14	15
Range of results (max-min)	48	12	33	31	21	1	1	1
mean	87	105	74	76	58	14	15	15

3.4.2 Addressing the wide uncertainty range

Based on these observations, further analysis was undertaken to address possible causes of this discrepancy. Simply: what is different about the non-plantation forests which could explain the variation, and is there any quantifiable effect that could cause it?

As described above, the time taken for a site to fully recover from felling and return to maturity is variable, based on the speed of forest growth and the total carbon on site to be re-captured. This has a significant impact on payback periods, since the time to reach carbon sequestration parity is closely related to the time for a forest site to return to a pre-felling state (discussed in more detail in Chapter 5).

The non-plantation forests, in contrast to plantations, take longer to reach maturity and have higher carbon stocks per ha when fully grown. Sterman et al. assumed maturity of both forest and soil at year 500 (Sterman, 2018) and based their starting conditions on carbon stocks estimated at this point. When identifying starting conditions in SBCM (as described above) a 5000-year cut-off was used, because; while the time taken for above-ground carbon to stabilise is indeed approximately 500 years (as shown in Figure 3.8), soil carbon takes substantially longer in some cases (as shown in Figure 3.9).

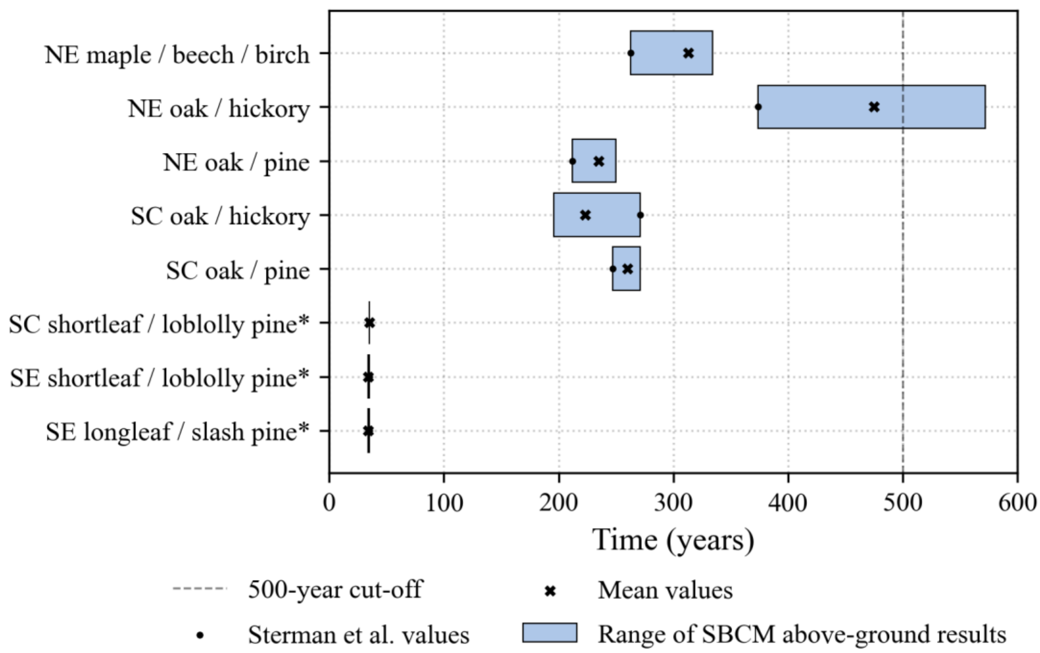

Figure 3.8. Time required for above-ground carbon to reach maturity on forest sites. The bars represent the maximum and minimum possible outcomes based on the range of parameterisations described in Table 3.5. In each case the parameters chosen by Sterman et al. result in maturity before 500 years.

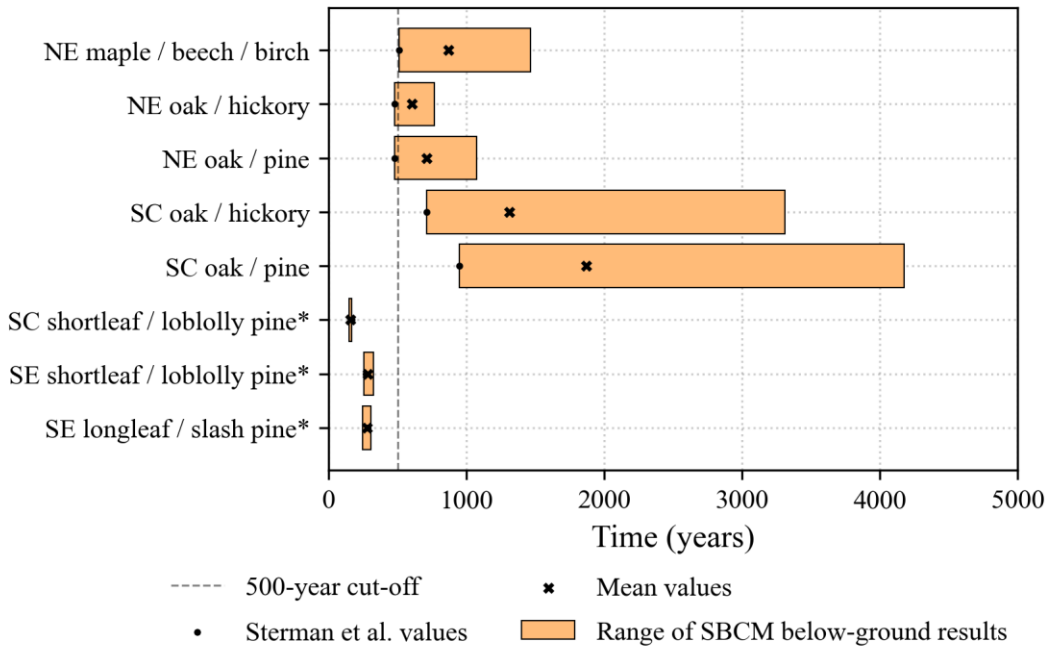

Figure 3.9. *Time required for below-ground carbon to reach maturity on forest sites in terms of below-ground carbon. The bars represent the maximum and minimum possible outcomes based on the range of parameterisations described in Table 3.5. The time required for non-plantation sites to reach maturity is close to or in excess of the 500-year assumption used by Sterman et al.*

This observation raises a further question: If SBCM has been trained using the same data as the Sterman et al. model, why is the time required for a site to reach equilibrium, and the total carbon stored on site when mature so uncertain? All of the parameterisations of the growth curve identified in Table 3.5 fit the available data as well as, or better than, those published by Sterman et al., so why do they not agree more closely?

Figure 3.10 shows the range of possible outcomes based on the range of growth curves listed in Table 3.5. Each of the plantation forests show a tight agreement between different model runs, while the non-plantation forests show a much poorer level of agreement, particularly with respect to soil carbon. The vertical lines on each graph represent the limit of the training data used to predict these curves, either 90 or 125 years depending on region / species. The degree of extrapolation which takes place in the non-plantation forests is variable, but is generally extremely large, while plantation forests have all reached maturity within the limit of the training data.

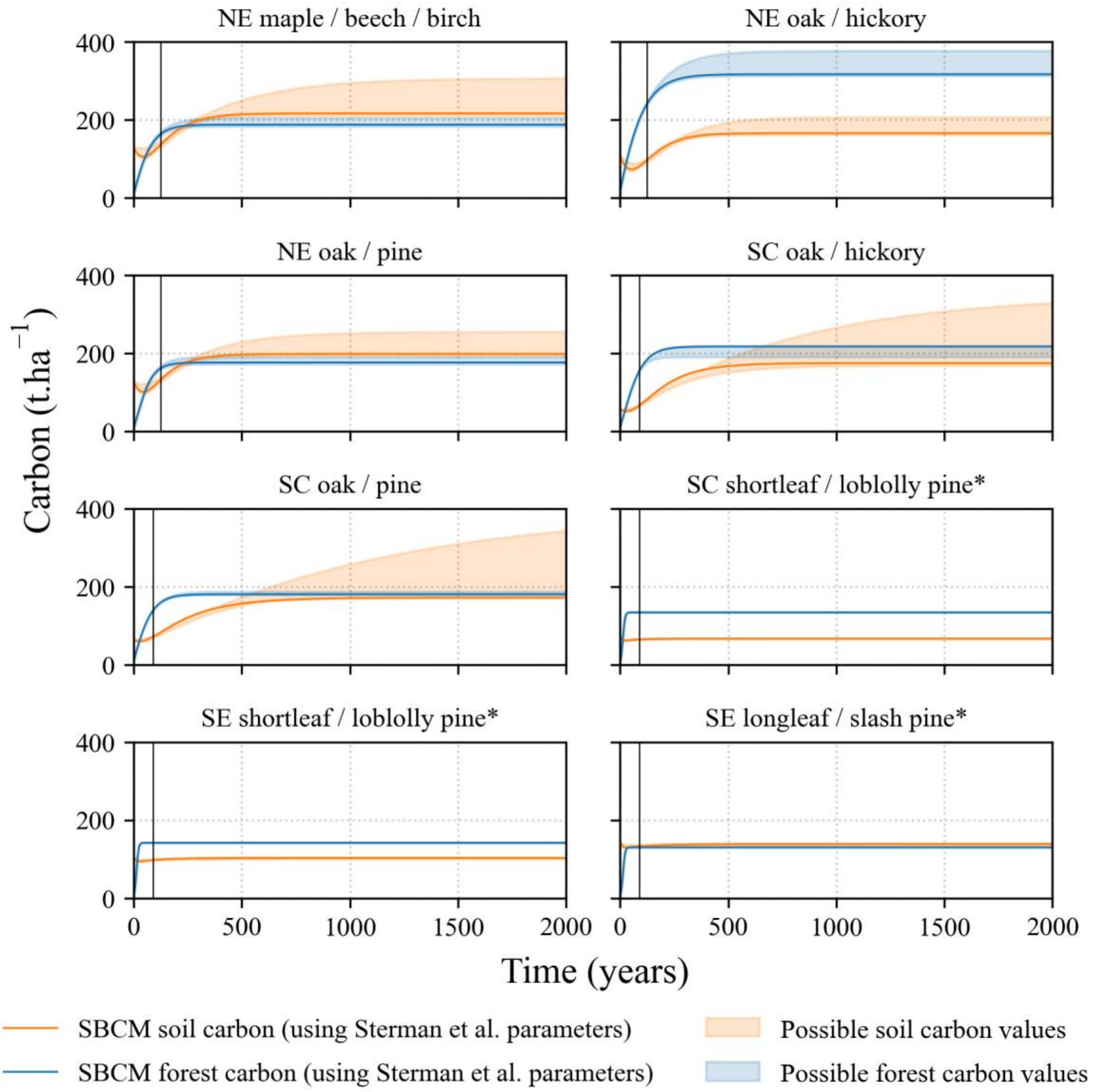

Figure 3.10. A range of possible outcomes based on the parameters identified for SBCM in Table 3.5 Shaded areas contain the full range of outcomes possible with a better fit than those obtained by Sterman et al. ±RMSE. Solid lines indicate the results obtained from SBCM under the Sterman et al. parameterisation. The vertical lines represent the temporal limit of the training data: any values to the right of the line are the result of extrapolations.

3.4.3 Significance

The observation that uncertainty in outcome appeared to be higher in cases where the training data was not available for a full growth curve, was assessed to identify any statistical significance. Data was available for all species / region types for a period of at least 90 years, although three species mixtures in the north-east region had training data to 125 years. In five of eight cases (the non-plantation forests) both SBCM and Sterman et al. were making predictions of forest growth over a substantially longer period of time. In each of these cases, the level of uncertainty arising from re-parameterisation was also high. In contrast, faster growing species mixtures (the plantation forests) which all reached maturity within the 90-year timeframe showed much higher degrees of agreement between parameterisations. This observation implied that the projecting growth curves too far beyond the training data could produce more variable output.

The strength of the relationship between the degree to which results were extrapolated from the training data and uncertainty was assessed using a simple linear regression from the `linregress` function embedded in the `scipy` library.

The results of this test (shown in Figure 3.11) indicate a strong relationship ($r^2 = 0.99$) with a very high confidence ($p < 0.00002$).

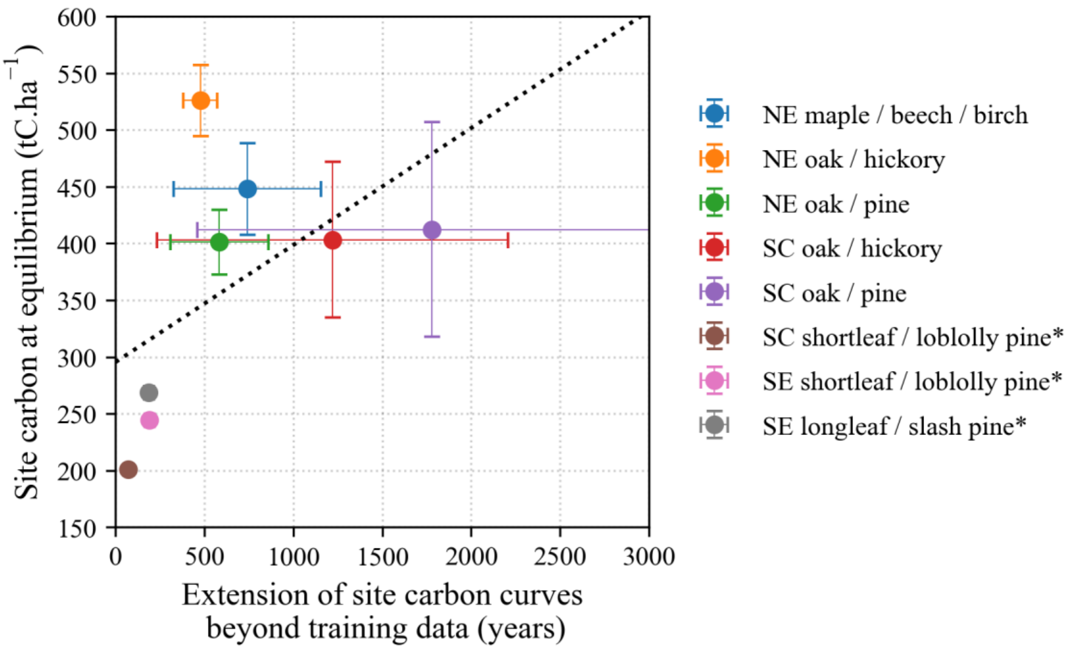

Figure 3.11. Mean extension of time to maturity beyond the training data compared with mean site carbon at maturity for different region / species types. Error bars represent standard deviation, and although they are not visible in the plantation forests (*) this is because the deviation is too small to extend beyond the graph marker (not because they were omitted). A strong correlation (high r^2, very good confidence) was found to exist, trend line formula is $y \approx 295.52 + 0.10x$ (scalar values are rounded for brevity).

This significant relationship raises a number of questions about the validity of results produced for the non-plantation forests.

3.5 Discussion

3.5.1 Results in context

Sections 3.3 and 3.4 represent a detailed analysis of the process of fitting growth curves to the Smith et al. training dataset. A large number of analyses were conducted and require some interpretation. This section is intended to summarise the earlier findings, discuss the implications, and put them in context to improve clarity and provide a basis for later conclusions.

Using the same training data as Sterman et al. in their 2018 paper (Smith et al., 2006) a non-linear regression was developed using Python and SBCM to see if the match between SBCM and the Sterman et al. model (as reported in Chapter 2) or the fit of the growth curve with the training data could be improved.

A full suite of methods and loss functions from the `scipy.optimize` function were used to attempt 240 individual matching attempts. 41 of these returned results with a smaller RMSE value than that reported by Sterman et al. (see Table 3.4). Two of these results were discarded due to anomalous results as illustrated in Figure 3.5 and the remaining 39 results (approximately five per species / region combination) were used to construct representative growth curves (an example of this is shown in Figure 3.6).

The increase in the range of possible parameterisations achieved a modest decrease in RMSE over the original Sterman et al. model and an improved fit with the training data. It also, however, resulted in a substantial increase in the range of possible outcomes. In particular, the predicted carbon stored in mature forest sites (at “equilibrium” Sterman et al., 2018a) and payback period. This expanded range of uncertainty is illustrated in Tables 3.6 and 3.7.

3.5.2 Impacts on carbon storage

Figure 3.12 below shows the range of possible carbon storage values at maturity based on the parameterisations described in Table 3.5 for each region /species combination. In each of the non-plantation forests the range of possible outcomes in terms of carbon storage increases, largely due to an expansion in estimated soil carbon. The values published by Sterman et al., are, in most cases, at the extreme minimum end of carbon storage for each forest. In contrast, the variation between plantation forests remains low.

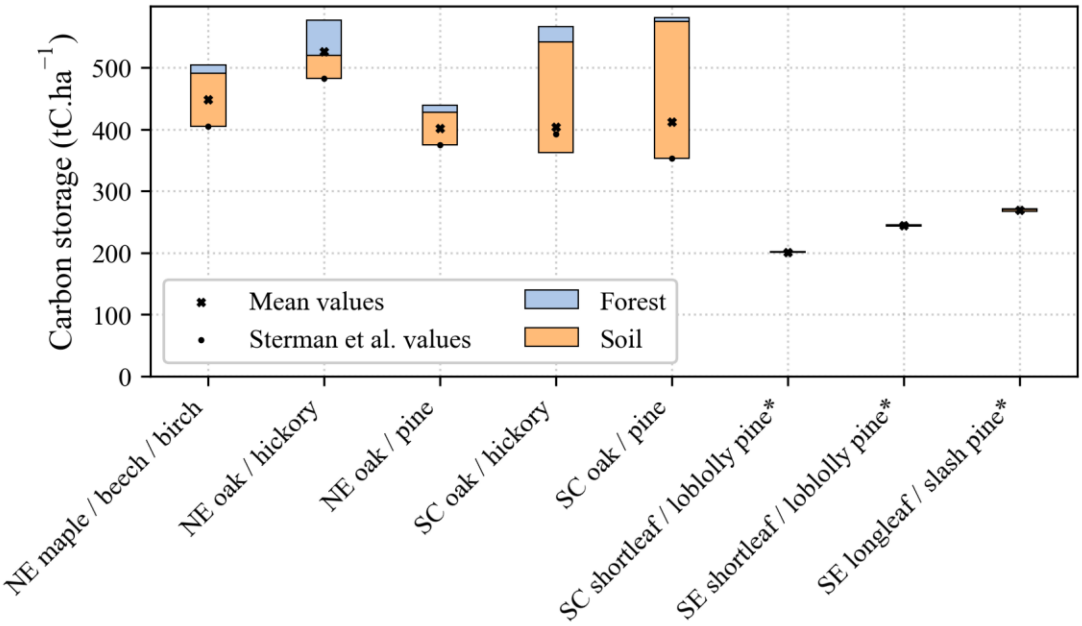

Figure 3.12. An illustration of the range of potential site carbon storage at maturity based on the parameterisations used in Table 3.5. Bars indicate the upper and lower boundaries of total site carbon (both above-ground: blue and below-ground: orange carbon). Mean values are for the entire site. The range of potential carbon storage is substantially larger for the non-plantation forests, and the values published by Sterman et al. tend to be at the lowest end of these estimates.

The time required for a site to reach maturity varies substantially depending on parameterisation. In most cases this took far longer than was accounted for in the initial Vensim based model (recall that Sterman et al. used a 500 year time horizon: Sterman, 2018) as shown in Figures 3.8 and 3.9.

3.5.3 Changes in payback periods

Taking the range of growth curves into account and running the model for the full range of improved parameterisations using a 95% clear-fell scenario (equivalent to Sterman et al. scenario S3 which is described more fully in Appendix C) it becomes apparent that the range of possible payback periods expands, particularly in the non-plantation forests (as shown in Table 3.8 and Figure 3.13).

*Table 3.8. Payback period ranges from figure 3.13. showing the number of years for different parameterisations to reach payback when compared to a coal counterfactual. In every case the value obtained using the parameters published by Sterman et al. results in the longest payback period. All values are in years, plantations are denoted with *.*

	NE maple / beech / birch	**NE oak / hickory**	**NE oak / pine**	**SC oak / hickory**	**SC oak / pine**	**SC shortleaf / loblolly pine***	**SE shortleaf / loblolly pine***	**SE longleaf / slash pine***
Max payback	107	109	91	88	68	15	15	16
Sterman et al. payback	107	109	91	88	68	15	15	16
Mean payback	87	105	74	76	58	14	15	15
Min payback	59	97	58	57	47	14	14	15

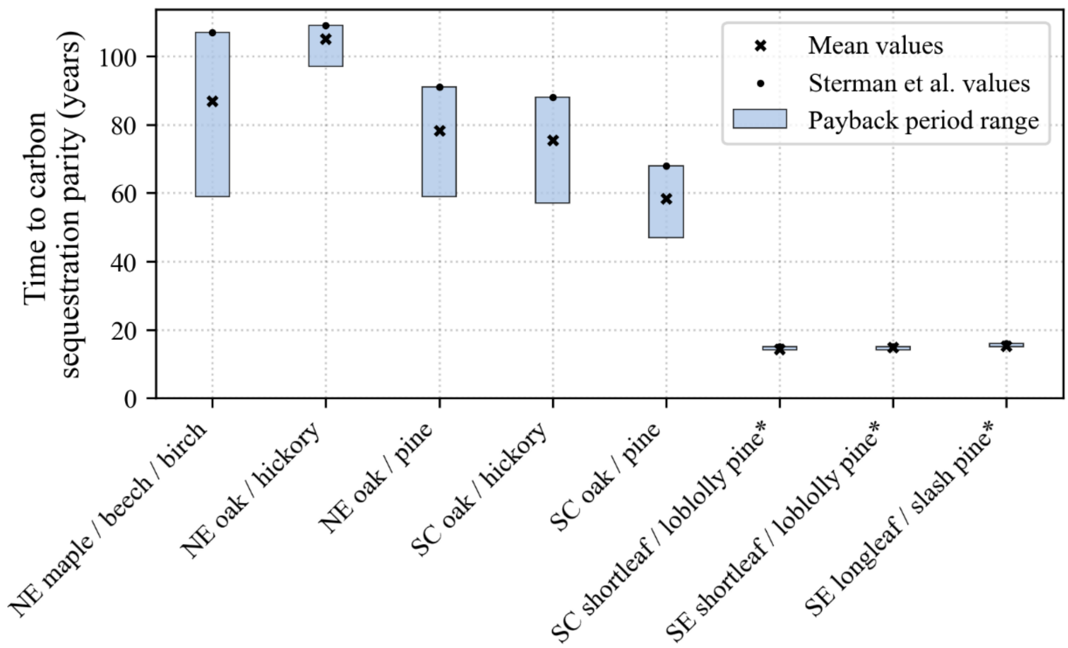

Figure 3.13. Time for biomass usage to pay back (reach carbon sequestration parity) under different parameterisations. In all cases the payback periods reported by Sterman et al. are higher than payback periods represented by other parameterisations. Once again, the variation between minimum and maximum values is far lower in the plantation forests (*).

In each case, the values obtained using the Sterman et al. parameterisation fall at the top of the range of possible outcomes, and multiple estimates of shorter payback periods also fit the available data at least as well.

3.5.4 Causes of uncertainty

As shown in Figure 3.11, there is a clear, statistically robust, relationship between the degree to which the growth curves have been extrapolated beyond the training data and the degree to which different model runs disagree.

The Sterman et al. model and SBCM both make use of a Chapman – Richards growth function (Richards, 1959; Pienaar and Turnbull, 1973; Zhao-gang and Feng-ri, 2003; Sterman et al., 2018a) to estimate forest growth rates. The results shown in Figure 3.10 appear to support the assertion in Burkhart and Tomé (2012) that the Chapman – Richards growth function results in more accurate outcomes when an asymptote is included in the training data, due to the function's tendency toward numerical instability (Ratkowsky, 1983). In this case, the training data for all of the non-plantation forests is effectively incomplete because it does not include a value at (or close to) the asymptote, while the training data for plantations (with their faster growth rate) does include an asymptotic value.

3.6 Conclusions

Analysis of the training data published by Smith et al. (2006) and used by Sterman et al. (2018a) shows that it is a widely used (Jenkins et al., 2010; Pan et al., 2011; Lawler et al., 2014; Adams et al., 2018) high-level regional dataset from the USA. The dataset is based on a large-scale network of sample plots with additional software-based analysis, and is designed to provide consistent generic values for a range of species mixtures across ten biogeographical regions. While the authors caution against reliance on the data at smaller site-specific scales, it does provide a useful tool for comparison across studies. Given the aim of Sterman et al. to assess the carbon balance of transatlantic biomass trading, this dataset is appropriate, particularly in view of the limited alternatives available.

Based on the work above, it is possible to produce a range of parameterisations which improve the fit of estimated forest and soil carbon levels to their training data over the earlier approach adopted by Sterman et al. (2018) as shown in Table 3.5. A number of these improvements are modest, but SBCM consistently achieves a lower RMSE score compared to the training data than those published by Sterman et al.

In improving the fit of the growth model to its training data (as shown in Table 3.5 and Figure 3.7) a striking divergence was identified between results for plantation and non-plantation forests. Plantations typically show very little disagreement between the results; values published by Sterman et al. the training data published by Smith et al., and results from SBCM generally agree well. This is evident in estimates of: site carbon at maturity (overall variation <=4tC.ha^{-1} as shown in Table 3.6) payback period (variation <= 1 year Table 3.7) and time to reach site maturity (variation <=1 year for above-ground carbon Figure 3.8 and <=53 years for below-ground carbon Figure 3.9)

In contrast, the non-plantation ("natural") forests show substantial variation between different parameter sets with comparable RMSE scores. Estimates of: site carbon at maturity (overall variation 50-228 tC.ha^{-1} as shown in Table 3.6) payback period (variation 21-48 years Table 3.7) and time to reach site maturity (variation 24-198 years for above-ground carbon Figure 3.8 and 287-3230 years for below-ground carbon Figure 3.9) all show a larger degree of uncertainty in the later phases of growth.

In assessing these differences (shown in Figure 3.10) it became apparent that a strong statistical correlation exists ($r^2 = 0.99$, $p < 0.00002$.) between the range of possible outcomes and the degree to which growth curves have been projected beyond the training data. A likely reason for this increase in uncertainty is the susceptibility of the Chapman-Richards growth function to numerical instability where the asymptote is not known (Ratkowsky, 1983) Burkhart and Tomé (2012) - as in the case of the slower growing forest types.

It is reasonable to conclude on this basis that it is not possible to determine which parameterisations for these forests are more likely to be accurate from this training data alone when using either the Sterman et al. model, or SBCM. It is even possible that the values preferred by Sterman et al. may be the best fit with real-world situations; we simply do not have enough information to tell without either improving the training data or modifying the growth function used by the model.

Improvements to the training data would include site carbon measurements over a longer time-series to include the asymptote of forest growth – although collecting this data could prove problematic due to the relative scarcity of forest sites meeting the necessary criteria. This could be due to a lack of forests of sufficient age to form robust conclusions, a lack of forests with documented similar management histories, and the increased likelihood of some stochastic interruption to forest management over an extended time period.

A more realistic option would be to modify the growth function used by the model to predict future growth. While it seems reasonable to expect that this would result in a better agreement between models, it could not conclusively be said to improve model accuracy without some form of real-world measurement to confirm any predictions.

SBCM produces results which are similar to those published by Sterman et al. (2018a) and can be used to calculate a range of parameter sets which improve the model fit with the training data. The underlying growth function used by Sterman et al. and replicated in SBCM relies heavily on the completeness of this training data, as without access to values late in the growth curve, results become increasingly inconsistent. While a number of issues affecting the reliability of the work carried out by Sterman et al. (2018a) have been identified; particularly the efficiency of biomass use (alluded to by Dwivedi et al., 2019 discussed in Chapter 4) and the plausibility of forestry supply chains (Prisley et al., 2018 discussed in chapter 5) the inconsistency of results from non-plantation forests has not been widely discussed (with the obvious exception of Rolls and Forster, 2020 which represents the published version of Chapters 2 and 3)

This disagreement was reflected in the variability of estimated carbon storage in mature forests and forest soils (Figure 3.6), as well has having a significant impact on the time required for sites to return to this mature state post felling (Figures 3.8 - 3.9). Uncertainties of carbon storage rate and magnitude have a substantial impact on the payback periods for non-plantation woodlands, and in each of the cases studied the parameters reported by Sterman et al. (2018a) resulted in the longest possible payback periods (as shown in Figure 3.13, and Figure 3.8) of between 68 and 107 years for non-plantation forests.

Based on these findings, it is reasonable to assume that the parameter values with the lowest RMSE are the most appropriate for use elsewhere in this study (see Appendix D), but that results referring to the non-plantation forests should be treated with an abundance of caution due to the high degree of uncertainty at longer rotation lengths.

These conclusions identify a number of limitations to the model and present a number of potentially fruitful avenues for further research, including modifications to the forest growth function to reduce uncertainty, and re-parameterisation for additional forest types in new biogeographical regions. These are discussed in more detail in Chapter 6.

Chapter 4. Assessing the supply-chain model

In which the Author considers how hard it is to move things around and then set fire to them.

4.1 Introduction

As discussed in Chapter 1, the development of bioenergy technologies has become a key element of the global effort to decarbonise energy supplies in the face of climate change (Craggs and Gilbert, 2018). Bioenergy has risen in popularity globally because it allows direct substitution for existing fossil fuelled (often coal-based) systems with a minimum of infrastructure modification and expense (Slade et al., 2018).

In their paper of 2018, Sterman et al. use the model described in Chapter 2 to analyse a range of different scenarios and cite payback periods when compared to a counterfactual case predicated on transatlantic supply of biomass to replace coal use in western Europe (see Figures 2.10 and 2.11). Based on parameters derived in Chapter 3 describing forest growth in a set of eight site / species combinations on the eastern continental USA, this chapter examines the parameters chosen by Sterman et al. to describe the supply chains for biomass fuels and coal (their preferred counterfactual case).

4.1.1 Research questions

The broad operational objective of chapter is to assess the validity of parameters for the supply chain component of the model as published by Sterman et al. (described in Section 2.3.1) the degree to which the counterfactual scenarios employed by them are appropriate for future use, and whether others may be more useful. Specifically addressing the research questions:

1. Are the parameters used by Sterman et al. the most appropriate for the supply chains they describe, and should they be modified in SBCM?

2. Sterman et al. rely heavily on a counterfactual of electricity generated using coal. Is this still the most appropriate counterfactual?

3. Are there any other supply chains which could be modelled using SBCM that would be more appropriate than those currently in use?

4. How does revision of the supply chain parameters within the model change the apparent sustainability of biomass fuels?

4.2 Initial analysis

4.2.1 Supply chain modelling in SBCM

The Sterman et al. model derives the total quantity of energy required (including allowances for waste / losses) from the supply chain component of the model described in Section 2.3.1. This uses a specified demand for the final quantity of electricity required, then modifies it using variables for efficiency and supply chain losses to determine the initial biomass needed to meet demand and the emissions resulting from generation (as shown in schematic form in Figure 2.3, Figure 4.1and in Equations 2.1 to 2.3).

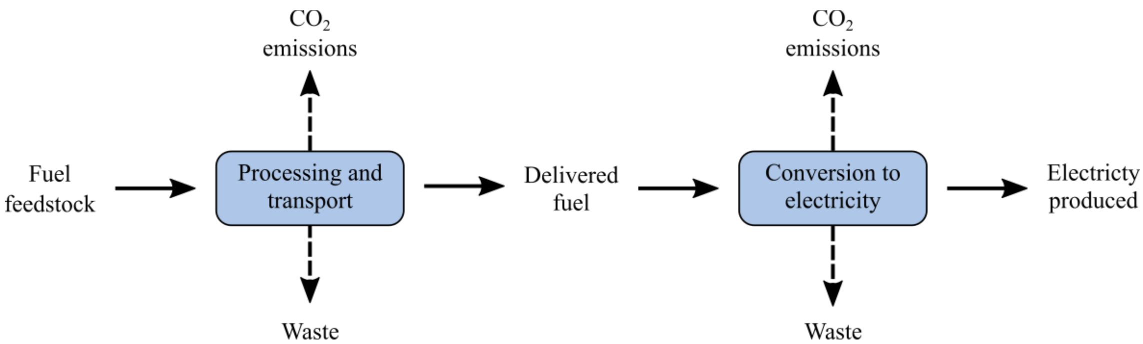

Figure 4.1 Block diagram showing the SBCM approach to supply chain. A fuel feedstock is harvested / mined and then processed and transported to the point of use. This results in emissions ($tC.GJ^{-1}$ handled by the $Emission_{production}$ parameter) and losses caused by production inefficiencies, use of some biomass fuel for drying, decomposition, etc. (handled by the $Efficiency_{production}$ parameter – a dimensionless proportional loss). The conversion of fuel to electricity is handled in a similar way with a dimensionless variable describing whole process efficiency ($Efficiency_{use}$) and a carbon intensity parameter describing the associated emissions ($Emission_{use}$).

Sterman et al. use a total of ten scenarios to test their model and illustrate their results; these vary in quality and usefulness (Table 4.1 and Appendix C).

Table 4.1. A summary of the Sterman et al. supply chain scenarios. These are described in more detail in Appendix C

Code	Name	Scenario description
Cf	Counterfactual	The emissions from electricity generation from coal combustion.
S0	Zero-carbon energy source	Electricity is assumed to be supplied with no associated carbon emission. While this is superficially applicable to renewables, it does not take into account building and infrastructure emissions so the comparison is incomplete.
S1	Regenerating coal	A combination of the supply chain emission and efficiency values for coal, with the regenerative capacity of biomass (the opposite of S4). Possible utility for diagnostic purposes.
S2	25% "thinning"	The emissions associated with electricity generation from biomass combustion, where biomass is sourced from forests with a 25% felling intensity.
S3	95% clear-fell	The emissions associated with electricity generation from biomass combustion, where biomass is sourced from forests with a 95% felling intensity.
S4	Inert biomass	A combination of the supply chain emission and efficiency values for biomass, with the regenerative capacity of coal i.e., none in this model (the opposite of S1). Possible utility for diagnostic purposes.
S5	Deforestation and land use conversion	The emissions associated with electricity generation from biomass combustion with total site deforestation, without regeneration, but with subsequent release of carbon from soils (e.g. following conversion to agriculture).
S6	Clear-fell with species conversion	As modelled in scenario S3, however, the species (at full biological maturity) which is felled, is replaced with a different species. This leads to a disparity between the carbon released by felling, and the potential uptake available through regrowth. Sterman et al. apply this to a "natural" forest replaced by a plantation and use it as an illustration of a loss of site carbon storage potential.

Code	Name	Scenario description
S7	Sustained yield (continued demand growth)	Instead of modelling the emissions associated with a one-off pulse of supplied electricity, the model is modified to produce a sustained yield of energy on an annual basis. This annual demand is either assumed to continue to increase over time (scenario S7) or increase to a pre-determined point, and then remain the same (scenario S8). These scenarios are limited because they do not reflect rotational forest management accurately (as discussed in Chapter 5)
S8	Sustained yield (attenuating demand growth)	

In order to test the supply chain aspects of the model (rather than run diagnostic tests on the model itself) scenarios S2 (25% fell) and S3 (95% fell) were chosen as being the closest to real-world conditions (Prisley et al., 2018). While it is acknowledged that scenarios S5 and S6 could potentially occur, it is debatable as to whether these scenarios would tell us anything new. It is already widely acknowledged that deforestation and reduction of stored carbon from mature forests is unsustainable (UNFCCC, 2021a) and exploring these scenarios further does little to reduce the uncertainty identified in earlier chapters.

4.2.2 Supply chain parameters

Coal variables

Sterman et al. derived parameters for the coal counterfactual from a variety of sources as shown in Table 4.2. These were largely derived from global statistics and generic conversion factors, as well as an LCA assessment of UK based coal-fired power plants (Odeh and Cockerill, 2007)

Table 4.2. Sterman et al. published parameters for coal supply chains. Adapted from Sterman et al. (2018a supplementary material table S5).

Parameter	Description	Value	Source
$Efficiency_{production}$	Processing efficiency representing supply chain losses (d'less)	0.89	IEA, 2016
$Efficiency_{use}$	Combustion and conversion efficiency (fuel energy to electricity d'less)	0.35	IEA, 2016
$Emission_{production}$	Supply chain carbon intensity ($tC.GJ^{-1}$)	0.0015	Odeh and Cockerill, 2007
$Emission_{use}$	Carbon intensity of combustion and electricity generation ($tC.GJ^{-1}$)	0.025	EIA, 2016; IEA, 2016

The bulk of these values were calculated using simple conversion factors to express values in common terms (Sterman et al., 2018a, supplementary information pp 16-17) and require little further explanation. The only exception to this is the derivation of the efficiency of production which was calculated using global data from 2014 (IEA, 2016) as shown in Equation 4.1.

$$\text{efficiency}_{\text{production}} = 1 - \left(\text{TPED} - \frac{\text{TFC} + \text{PG}}{\text{TPED}}\right)$$

Equation 4.1. The efficiency of global coal production was calculated using Total Primary Energy Demand from coal (TPED) Total Fuel Consumption (TFC) and Power Generated from coal (PG). The result is a unitless measure of coal production efficiency. Sterman et al. calculate 0.89 (or 89%) efficient (Sterman et al., 2018a, supplementary material table S5)

The parameters chosen by Sterman et al. for coal are of variable quality. IEA figures, while likely to be reliable, were not particularly recent when the paper was published (in 2018, data was from 2014) and are now quite dated. They also represent global averages, and while it is arguable that this is appropriate to estimate the efficiency of a global supply chain, when the paper specifically addresses the transatlantic supply of fuel to western Europe and the UK more local values would be more appropriate if available. The paper by Odeh and Cockerill while more locally appropriate, is even older (2007). Based on these concerns, a revision of the parameters describing the coal supply chain was undertaken as described in Section 4.3.1.

Biomass variables

As with the parameters describing the coal supply chain above, Sterman et al. identified values from a variety of sources (as shown in Table 4.3).

Table 4.3. Sterman et al. published parameters for biomass supply chains. Adapted from Sterman et al. (2018a supplementary material table S5).

Parameter	Description	Value	Source
$Efficiency_{production}$	Processing efficiency representing supply chain losses (d'less)	0.725*	Röder et al., 2015
$Efficiency_{use}$	Combustion and conversion efficiency (fuel energy to electricity d'less)	0.25	FPL, 2004; NEA, 2011
$Emission_{production}$	Supply chain carbon intensity ($tC.GJ^{-1}$)	0.0012	Röder et al., 2015
$Emission_{use}$	Carbon intensity of combustion and conversion to electricity ($tC.GJ^{-1}$)	0.027	EPA, 2014; Leturcq, 2014

**On closer examination of the data source this value may be incorrect. Recalculating and assuming a 8.5% supply chain loss, and 18% of the fuel used for drying, it appears that this value should be 0.735 (Röder et al., 2015, table 1)*

Again, the parameters chosen by Sterman et al. for the biomass supply chain are of variable quality. In some cases, the values are likely to be relatively robust (the value for processing efficiency from Röder et al., 2015 for example - although it appears to have been miscalculated) others are less certain and require further scrutiny. In particular, the variable for combustion efficiency is simply incorrect. This parameter was derived from a combination of an unreferenced information note published by the US Department of Agriculture (FPL, 2004), and the "power" component of medium scale wood-pellet CHP system in another unreferenced calculation tool published by the Netherlands Energy Agency (NEA, 2011). Neither of these values are appropriate, one because it refers to small / medium systems running in the USA and is out of date, the other because it refers to medium scale systems using CHP technologies, which are less efficient at generating electricity alone. This can be seen in NEA (2011) in the contrast between the 25.4% efficiency quoted by Sterman et al. (cell H12 on the "Wood Pellets – CHP" tab) and the 39.2% efficiency provided by the same source for wood pellet co-firing (cell H12 on the "Wood Pellets – Cofiring" tab). In both of these references, values were cited without references to other work, so it is impossible to see how they were derived.

Again, due to concerns about the relevance and appropriateness of these values, a revision of the parameters describing the biomass supply chain was undertaken as described in Section 4.3.1.

4.2.3 New counterfactual scenarios

Coal represents nearly half of the world's primary energy supply (44% - Birol, 2022) as shown in Figure 4.2 and is expected to remain a significant component of global energy infrastructure for some time to come (Rentier et al., 2019; Brauers et al., 2020). It is however the "dirtiest" of the fossil fuels, and the UNFCC has reached broad agreement that unabated coal combustion should be phased out as soon as possible (UNFCCC, 2021a).

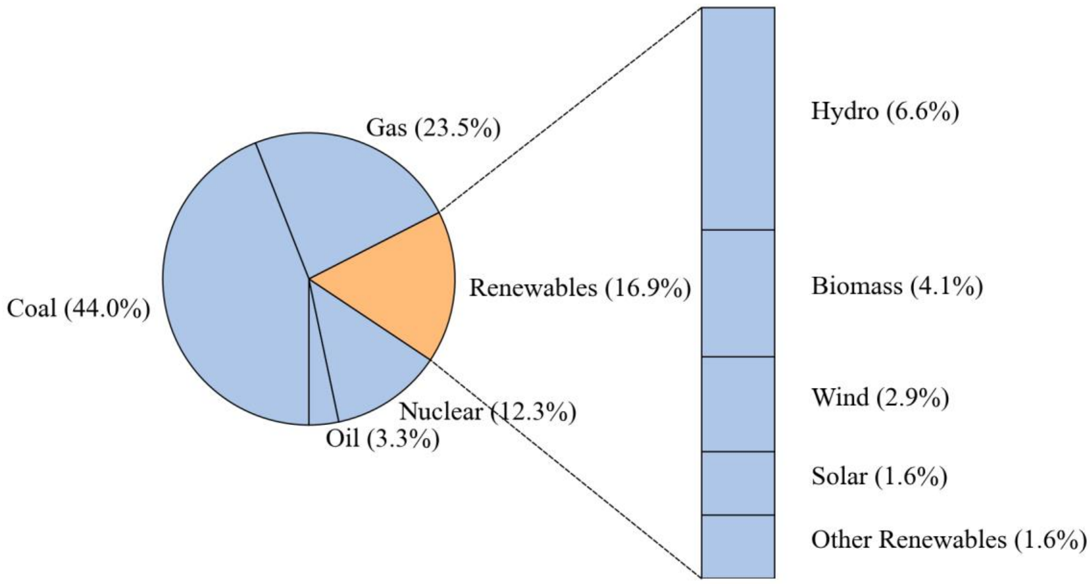

Figure 4.2. Global energy supply 2021 breakdown by energy source (Birol, 2022)

Coal has been a popular benchmark for assessing the sustainability of forest sourced biomass use (Reid et al., 2020) and, while it has been argued that this is appropriate because of the similarities between biomass and coal supply chains and use (Slade et al., 2018), it has also been suggested that coal represents the most polluting fossil fuel, and as such it is easier to portray biomass use in an attractive light by comparison (Sterman et al., 2018b).

Since coal remains such an important commodity in terms of global fuel supply, retention of this counterfactual is reasonable (assuming an improvement in the parameters used as described in 4.3.1), but it also represents the lowest bar in terms of emissions. A wide range of other power generation technologies exist and it is difficult to argue in favour of biomass by simply stating that it less bad than the fuel with the highest carbon emissions. To address this issue, a natural gas counterfactual was also developed (described in 4.3.2). Gas is the second most widely used primary energy source globally (13%, Birol, 2022) and is the cleanest of the fossil fuel technologies.

Biomass Energy with Carbon Capture and Storage (BECCS) has been widely described as being a true carbon dioxide removal (CDR) technology (Shukla et al., 2022). Engineering solutions vary but the essential logic is: forest growth removes carbon from the atmosphere, the resulting woody biomass is burned for energy, but the carbon is stored to prevent re-release into the atmosphere. This process results in lower efficiencies (since a proportion of the electricity generated is used to compress and store the resulting CO_2) but this is less important because emissions are being captured.

BECCS has been assumed by IPCC to be a core transition technology over the coming years to reduce emissions (Fricko et al., 2015; van Vuuren et al., 2017; Fujimori et al., 2017; Calvin et al., 2017; Kriegler et al., 2017; Rogelj et al., 2018; Gidden et al., 2019) while other CDR technologies are still being developed and are not yet fully market ready (Ganeshan et al., 2023). Two BECCS scenarios (described in 4.3.2) were developed to allow for a range of efficiencies of conversion and use.

4.3 Method

4.3.1 Part 1. revising the existing variables

As discussed in Section 4.2.2 a number of concerns were identified with respect to the parameters used by Sterman et al. in their published data. These parameters are variable in quality due in part to their age, and partly due to the data sources chosen by Sterman et al. In each case, the calculation or conversion undertaken by Sterman et al. was replicated and where newer or more reliable data sources were available, these were used instead.

Coal variables

Coal Efficiency$_{production}$

The calculation carried out by Sterman et al. (Equation 4.1) using 2014 values from the IEA (2016) data was replicated using more recent data (2021) also from the IEA (Birol, 2022). This resulted in an apparent improvement in the efficiency of coal supply chains from 0.89 to 0.97. While the reasons for this improvement are not described, it is reasonable to assume that low efficiency coal supply chains are becoming less financially viable. Since this value is calculated from values for *unabated* coal use it is not influenced by potential changes introduced by the development of coal CCS programmes.

Coal Efficiency$_{use}$

The existing value for the conversion of fuel to electricity was revised for a UK context using the Digest of UK Energy Statistics (DUKES) data published by the UK government (BEIS, 2022a, table 5.6). This resulted in a small drop in efficiency from 0.35 to 0.334. Again, this is not surprising as the UK has spent considerable resources on reducing a national reliance on coal for energy generation (DESNZ, 2023). This change of efficiency implies that the remaining operational units are no longer being invested in at the same rate and are being nursed to the end of their operational lives rather than being actively developed.

Coal Emission$_{production}$

The emissions associated with coal production were revised using the UK government greenhouse gas reporting conversion factors (BEIS, 2022b). This resulted in a large increase in the "well to tank emissions" associated with coal from 0.0015 $tC.GJ^{-1}$ to 0.0040 $tC.GJ^{-1}$. While this is a more generic figure than that published by Odeh and Cockerill (2007) and other authors (e.g. Venkatesh et al., 2012) it does represent a consistent methodological framework to assess the difference between coal, gas, and biomass supply chains (since values are supplied for each).

Coal Emission$_{use}$

The emissions associated with coal fired electricity generation are apparently well established. Sterman et al. cite three sources all quoting 0.25 $tC.GJ^{-1}$. This was confirmed using more recent data and replicating the calculation carried out by Sterman et al. The calculated emissions from use changed from 0.02467 $tC.GJ^{-1}$ calculated by Sterman et al. using 2014 data to 0.0242 $tC.GJ^{-1}$ from 2021 (BEIS, 2022b).

Biomass variables

Efficiency$_{production}$

In assessing this value, a wide range of variation was observed. A number of studies have addressed the issue of dry matter loss during biomass supply chains (e.g. Thörnqvist, 1985; Jirjis, 1995; Nurmi, 1999; Hirsmark, 2002; Hamelinck et al., 2005; Sikkema et al., 2010; Filbakk et al., 2011; Nurmi, 2014; Röder, 2018; Routa et al., 2018; Liu et al., 2018; Beagle and Belmont, 2019; Sgarbossa et al., 2020). The majority of work carried out on this area focusses on the loss of dry matter to decomposition rather than waste, and does not include additional losses due to fuel use in the drying process. Values were identified from

- Röder et al. (2015): 8.5% supply chain loss, 18% drying loss
- Hamelinck et al. (2005) 12.8% supply chain loss, 12.5% drying loss
- Sgarbossa et al. (2020) 16% drying loss

Data on decomposition losses was heavily dependent on fuel type and site conditions, and thus highly variable (see Table 4.3)

Table 4.4. Examples of the variation of dry matter losses in biomass supply chains in the literature due to decomposition

Study	Range of decomposition losses (%)
Filbakk et al., 2011	15-30
Hirsmark, 2002	21
Jirjis, 1995	12-21
Nurmi, 1999	20
Sikkema et al., 2010	7
Thörnqvist, 1985	7-21

In view of this wide range of results the parameter for the efficiency of biomass supply chains was revised upward slightly from 0.725 to 0.738 based on average supply chain losses from Röder et al. (2015) and Hamelinck et al. (2005) and drying losses based on these two sources with the addition of Sgarbossa et al. (2020). This value represents one of the greater areas of uncertainty within the supply chain model parameterisation.

Efficiency$_{use}$

The existing value for electricity generation from biomass was revised for a UK context using the Digest of UK Energy Statistics (DUKES) data published by the UK government (BEIS, 2022a, table 5.6). This resulted in a substantial increase in efficiency in the conversion of biomass fuel to electricity from 0.25 to 0.369. In contrast to the flawed data used by Sterman et al. the DUKES data represents measurements of fuel use and energy output reported under a statutory mechanism for power stations in the UK, and is considered to be significantly more reliable.

Emission$_{production}$

The emissions associated with biomass fuel production were revised using the UK Government greenhouse gas reporting conversion factors (BEIS, 2022b). This resulted in a large increase in the "well to tank" emissions associated with biomass from 0.0012 $tC.GJ^{-1}$ to 0.0028 $tC.GJ^{-1}$. While this is a more generic figure than that published by Röder et al. (2015) it again, represents a consistent methodological framework to assess the difference between coal and biomass supply chains.

$\text{Emission}_{\text{use}}$

The emissions arising from biomass combustion for electricity generation were recalculated using data from the Phyllis2 database (ECN, n.d.). Based on a mean calorific value for untreated wood of 20.12 $GJ.t^{-1}$ (daf or dry, ash-free higher heating value or HHV) and a mean carbon content of 50.76% daf, these were calculated as 0.0252 $tC.GJ^{-1}$. This is a slight decrease when compared to Sterman et al. since the value used in their model apparently used the lower heating value (LHV) for wood.

The LHV is a less appropriate metric in this case, because it double counts a factor reducing the efficiency of biomass conversion to electricity. Moisture content within fuel changes the apparent calorific value per tonne because of the heat required to remove it before combustion. This can be mitigated to some extent by heat recovery systems so it could be argued that large users can gain more energy per tonne of fuel by using these technologies. However, in this case SBCM (and the Sterman et al. model) calculate based on tonnes of carbon into the system and GJ of electricity leaving it. As such, including a loss of efficiency for moisture content which is already included in the absolute values is redundant.

4.3.2 Part 2. New counterfactuals

Natural gas variables

$\text{Efficiency}_{\text{production}}$	As with the coal parameter, the gas supply chain efficiency parameter was derived from IEA data (Birol, 2022) using Equation 4.1 and values for natural gas
$\text{Efficiency}_{\text{use}}$	As described above, the efficiency of combustion and electricity generation was derived from the DUKES data (BEIS, 2022a)
$\text{Emission}_{\text{production}}$ $\text{Emission}_{\text{use}}$	As with coal and biomass parameters, well to tank efficiency and electricity generation emissions were derived from the UK government conversion factors (BEIS, 2022b)

BECCS variables

$\text{Efficiency}_{\text{production}}$	The same variables were used as for the revised biomass scenario as described above
$\text{Efficiency}_{\text{use}}$	As described above, combustion efficiency was derived from the DUKES data (BEIS, 2022a) with between 10% and 34% of electricity generated assumed to be used in capturing emissions (Slameršak et al., 2022)
$\text{Emission}_{\text{production}}$	The same variables were used as for the revised biomass scenario as described above
$\text{Emission}_{\text{use}}$	Emissions associated with combustion and electricity generation were assumed to have been reduced by 90% due to carbon capture, with a 1.4% leakage factor in handling before long terms storage – a total reduction of 88.6% (Slameršak et al., 2022)

4.3.3 Revised parameters summary

The new parameters as calculated for each of the scenarios described above are summarised in Table 4.5

Table 4.5. Revised parameters for the supply chain model as calculated in sections 4.3.1 and 4.3.2 The values used by Sterman et al. are included in brackets for comparison

Parameter	**$\text{Efficiency}_{\text{production}}$**	**$\text{Efficiency}_{\text{use}}$**	**$\text{Emission}_{\text{production}}$**	**$\text{Emission}_{\text{use}}$**
Descrip-tion (units)	Processing efficiency representing supply chain losses (d'less)	Combustion and conversion efficiency (fuel energy to electricity d'less)	Supply chain carbon intensity ($tC.GJ^{-1}$)	Carbon intensity of combustion and conversion to electricity ($tC.GJ^{-1}$)
Biomass	0.738 (0.725)	0.369 (0.25)	0.0028 (0.0012)	0.0252 (0.027)
Coal	0.97 (0.89)	0.334 (0.35)	0.004 (0.0015)	0.0242 (0.025)
Gas	0.884	0.485	0.002	0.014
BECCS	0.738	0.244 - 0.332*	0.0028	0.0029

** Upper and lower boundaries as per (Slameršak et al., 2022)*

4.3.4 Testing

Using the new parameters for forest growth as identified in Chapter 3 (detailed in Appendix D) a suite of comparisons was undertaken to compare the old and new parameter sets for the supply-chain sub model and the new scenario options of BECCS implementation and natural gas (as shown in Figure 4.3). Each comparison was undertaken using an assumed energy demand of 10^6 GJ as a one-off pulse and then no further energy required over time; for a total of 8 Species / region combinations. This was carried out simulating a 95% clear-fell scenario, and a 25% selection felling scenario (equivalent to Sterman et al. scenarios S3 and S2 as described in Appendix C) this resulted in 192 possible comparisons (8 region-species combinations, 12 parameter combinations and 2 felling intensities.

	Coal (old params)	**Coal (new params)**	**Natural Gas**
Biomass (old params)			
Biomass (new params)			
BECCS (lower efficiency estimate)			
BECCS (higher efficiency estimate)			

Figure 4.3. A schematic of the biomass / counterfactual scenarios. Each combination was run using each of the species / region cases, under a 25% and 95% felling scenario

4.4 Results and discussion

As described above, an SBCM model run was carried out for each of the species / region cases using both the original and revised parameters for biomass and coal, as well as three new possible scenarios: natural gas, and a high / low efficiency range for BECCS. These runs were carried out assuming either a 25% or 95% felling rate as per Sterman et al. scenarios S2 and S3. An example of the output is shown in Figure 4.4 and Figure 4.5 below.

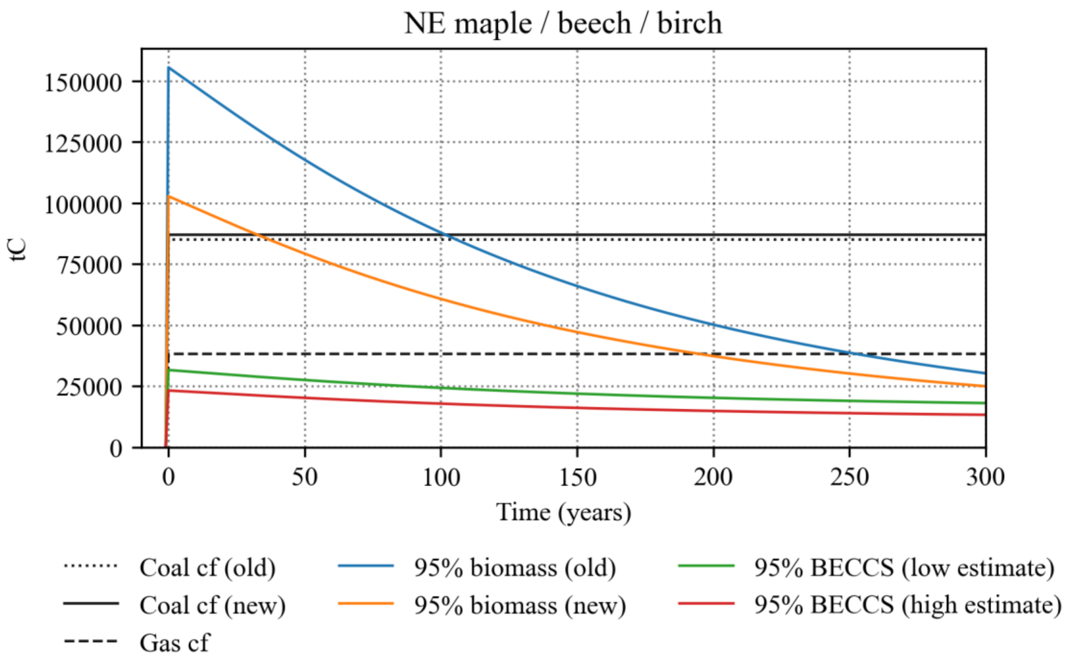

Figure 4.4. Results for a NE maple / beech / birch forest 95% clear-fell scenario. Payback periods using new parameterisations are 195 years vs natural gas, 33 years vs coal, and 0 years for both BECCS scenarios.

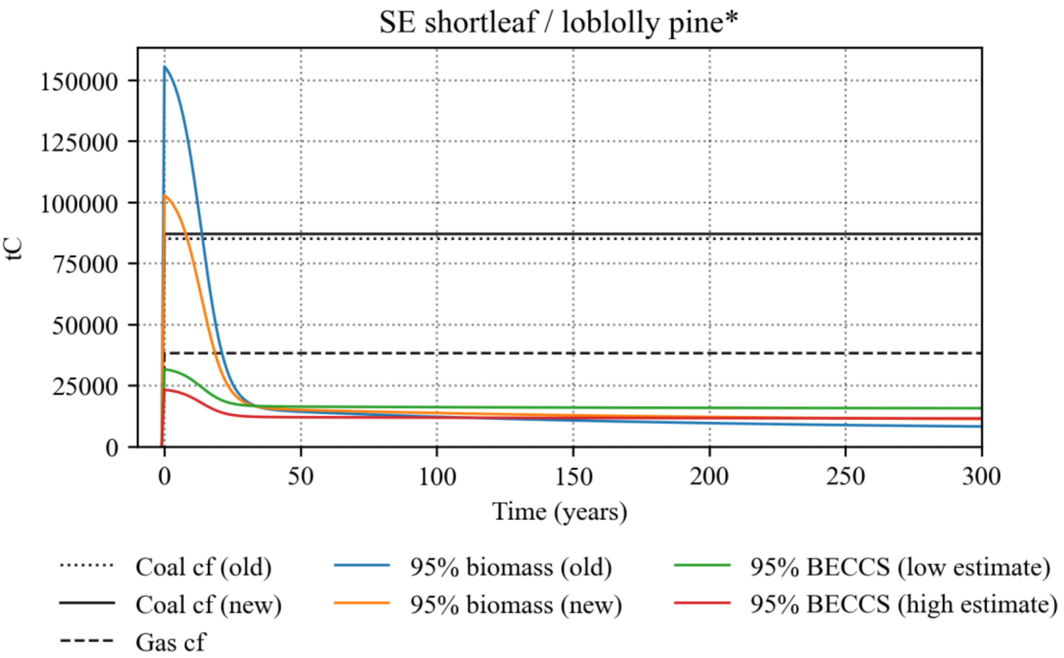

Figure 4.5. Results for a SE shortleaf / loblolly pine plantation 95% clear-fell scenario. Payback periods using new parameterisations are 20 years vs natural gas, 9 years vs coal, and 0 years for both BECCS scenarios.

Using this output, payback periods were calculated for a range of scenarios (see Appendix E for results in full). As expected, the emissions associated with natural gas were much lower than either biomass or coal, and the emissions associated with the BECCS scenarios were much lower than any other cases studied. This disparity in emissions was reflected in the payback periods as shown in Figure 4.6 and Figure 4.7.

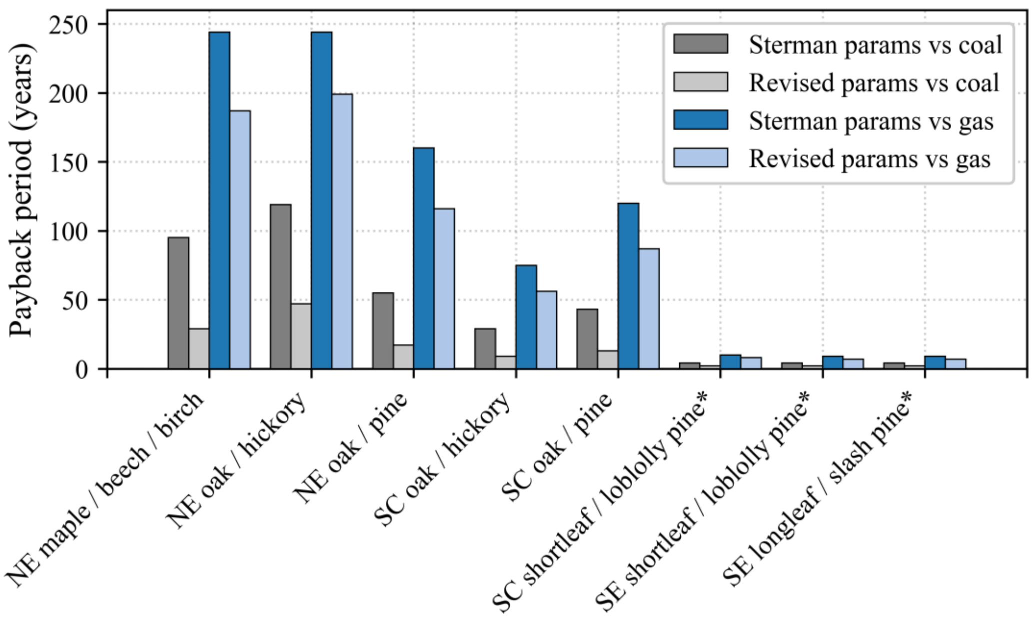

*Figure 4.6. Payback periods based on a 95% clear-fell. Payback periods decrease substantially when using a revised biomass efficiency value, but this is offset by the increase in payback periods when compared with a natural gas counterfactual. BECCS scenarios are not shown in this graph since in every case the payback was 0 years. Plantations are denoted with **

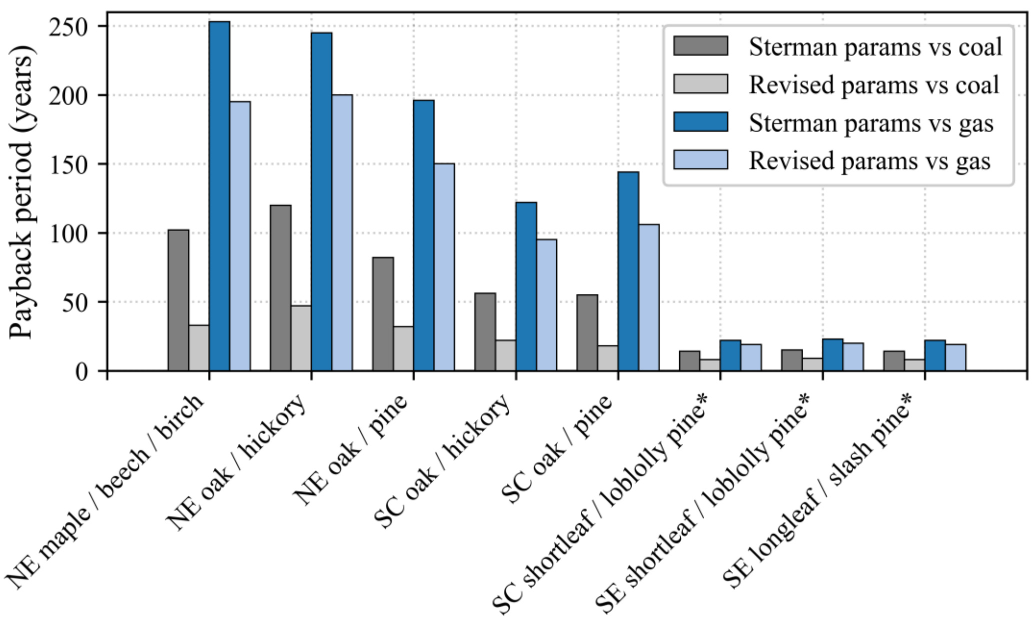

*Figure 4.7. Payback periods based on a 25% fell. Payback periods decreased by an average of 14 years compared to clear-felled sites (discussed in more detail in Chapter 5). As above BECCS scenarios are not shown in this graph since in every case the payback was 0 years. Plantations are denoted with **

The revision to the coal counterfactual parameters has a small impact on payback periods resulting in an overall reduction of between 0 and 4 years depending on species and felling intensity. The modification of the biomass parameters however, resulted in a large decrease in emissions per unit of energy (around 33%) and this had a strong influence on payback period when compared with the parameters used by Sterman et al. This was expected, since the parameter they used for efficiency was extremely low (as described in Section 4.2.2). In the case of "natural" forests, changes in the biomass parameter resulted in payback periods decreasing by between 20 and 73 years. This was less obvious for plantation forests, where reductions were more modest (between 2 and 6 years).

The new counterfactual comparison using natural gas led to a large increase in payback periods (as might be expected). Gas usage for power generation is between 11% and 15% more efficient than the solid fuels studied, and the emissions resulting from production and use are both substantially lower (see Table 4.5). In the case of natural forests, payback periods increased by between 47 and 162 years when compared with natural gas, and again, this increase was less marked in plantation forests (between 5 and 11 years).

The emission reduction associated with the capture and storage of emissions from BECCS had a profound impact on the payback period: in every case, the initial emission associated with BECCS was lower than the emission generated by the counterfactual case. This means that there is no payback period per se, because we are no longer considering a marginal case, BECCS results in lower emissions than the counterfactual at the point of combustion which goes on to decrease further over time i.e., payback period is instantaneous. This illustrates a weakness in using the payback period as a metric because it is impossible to tell using the payback period alone whether the high or low efficiency BECCS scenario is better, we can only say that they both outperform natural gas and coal. This weakness is discussed further in Chapter 5 as it also relates to the cumulative emissions associated with multiple rotations.

A disparity exists between payback periods of a 95% clear-fell and a 25% felling (as shown in Figure 4.6 and Figure 4.7). Felling intensity has an impact on payback period because it is intrinsically linked to site recovery time and the area required to meet demand as discussed in Chapter 5. The failure of Sterman et al. to properly account for thinning – relying instead on an assumption that 25% of a mature forest would be felled has an effect on payback period because it occurs at a different point on the forest growth curve. Again, this is discussed further in Chapter 5.

4.5 Conclusions

The parameters used by Sterman et al. to describe supply chains show significant weaknesses. The existing parameters were recalculated to address these weaknesses and this resulted in substantial implications for payback periods estimated by the model for biomass compared with a coal counterfactual. In all cases, the modification of existing parameters resulted in a decrease in payback periods compared to those reported by Sterman et al.

The widespread use of coal counterfactuals in studies of this type is perhaps understandable due to the similarities of supply chains handling solid fuels, but it has been suggested that coal is used because it represents the most carbon intensive counterfactual (Sterman et al., 2018b). The validity of this criticism is debatable but based on this, and in view of international commitments to phase out coal use (UNFCCC, 2021a), it is becoming clear that coal can no longer be used in isolation as a valid business as usual scenario.

Given the limited usefulness of comparisons with coal, another counterfactual based on natural gas was added to the model. Gas is the cleanest and most efficient fossil fuel technology; as such this was deemed to give a more robust comparison and forestall any allegations of “cherry-picking” counterfactuals.

While simple combustion for primary energy generation remains the dominant use of biomass globally, use of carbon capture and storage technology is expected to become widespread in the near future (Shukla et al., 2022). To account for this, two further parameter sets were developed to provide indications of the change in payback periods associated with BECCS (based on high and low estimates of efficiency).

The modifications to scenarios resulted in a range of changes to the apparent sustainability of biomass use in this context.

- Updates to the coal and biomass parameter sets resulted in a dramatic fall in payback period compared to the results published by Sterman et al. (2 to 33 years compared with 4 to 104 years in Sterman et al., 2018a supplementary material table S7)
- Introduction of a natural gas counterfactual scenario demonstrated that other technological solutions can result in lower emissions over extended periods of time when compared to conventional biomass use in some forest types (up to 253 years in NE maple / beech / birch forest under a 95% fell: Figure 4.7 and Appendix E).
- While the efficiency value for BECCS is poorly constrained compared to other supply chain parameters (Table 4.5), initial indications are that BECCS outperforms a gas counterfactual by a substantial margin leading to payback within a year in all cases.

There are however, some limitations to these findings. It is arguable that gas is a less appropriate fuel to be compared directly with biomass. Since a core assumption of the modelling framework is that the emissions associated with building the infrastructure for consumption and conversion to electricity are broadly comparable. Alternative energy sources such as wind, solar, and hydro have no direct emissions from use, and operate differently in terms of infrastructure and distribution (which is a key argument in rejecting the use of Sterman et al. scenario S0). Nuclear power has high infrastructure and well to pump emissions, emits no carbon directly from use, but is likely to have substantial additional post-use emissions associated with spent fuel storage. These other energy sources were deemed to be too different to biomass for a direct comparison to be drawn without an expansion of the system boundary to include development of a power station or equivalent installation.

While payback periods showed a substantial reduction, none of the conventional biomass scenarios resulted in negative emissions. The model does not allow for this, because it is based on a single pulse of CO_2 at the beginning of the run. A single rotation beginning at full biological maturity can recover virtually all of the carbon released on combustion, but cannot recover supply chain emissions as well, so while it can be said to be “carbon lean” in relation to the counterfactual, without some element of BECCS, it will not achieve true negative emissions. This is addressed by modifications to the silvicultural assumptions in the model described in Chapter 5.

Finally, the model works on a basis of energy supplied. This has a substantial impact on the scenarios available for testing, because it limits the silvicultural management of the forest area to the simplest operation available – a single clear-fell. It is not possible to increase the complexity of the silvicultural operations (as called for by Prisley et al., 2018) to integrate thinning, or vary felling age within the model as it currently stands because only one operation is modelled per run. This limits both an assessment of the effect of forest yield on payback period, and whether some scenarios can result in negative emissions over a reasonable timeframe. Again, these issues are addressed more completely in Chapter 5.

Chapter 5. Including Silviculture

In which the Author carefully cuts down a hypothetical forest. Repeatedly.

5.1 Introduction

As discussed in Chapter 1, the global deployment of bioenergy has been rapid due to the prospect of low carbon energy generation as a climate change mitigation technology (Chum et al., 2011; Craggs and Gilbert, 2018; Funk et al., 2022). This has not been without controversy as a number of authors have highlighted concerns about the efficacy of biomass use, as an emission reduction technique (Holtsmark, 2015), the effect on other land uses (Creutzig et al., 2015) and their effect on global biodiversity and existing carbon stocks (Searchinger et al., 2018). A critical concern raised in this debate is the sustainability of forest management operations in producing biomass fuel, and while the IPCC recognises that trade-offs may exist as part of the integration of biomass production (Calvin et al., 2023), a number of authors (e.g. Olden, 2016; Brack, 2017a; Brack, 2017b) now simply equate biomass production with unsustainable forest management.

The need to manage forests sustainably has been recognised for a very long time (Evelyn, 1664; von Carlowitz, 1713). Although definitions of sustainability have evolved (Grober, 2012) and have long been a subject of some debate among foresters (Samuelson, 1976). In this case, sustainable forest management is loosely based on Brundtland's famous definition of sustainability (Brundtland, 1987)[*] as: the ability to produce ecosystem services (specifically carbon regulation) without degrading the forest's ability to continue producing those services in the future.

It is clear that the ecosystem services of carbon sequestration and storage which this study addresses are part of a range of other benefits derived from forests (see Figure 3.1) and production of one service may preclude maintenance or production of others. A qualitative judgement is therefore required to identify which scenarios may be

[*] "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*" (Brundtland, 1987)

considered acceptable or not. As such, it is arguable that of the scenarios described by Sterman et al. some can simply be described as unsustainable in terms of carbon management without undertaking further study. For example, scenario S5 – (deforestation with land use conversion) eliminates the forest's ability to regrow, and cannot be considered sustainable forestry (even if there are excellent reasons for adopting this management strategy e.g. open habitat restoration). Others such as scenarios S2 and S3 (25% and 95% fell) are more debatable: their payback periods described in Chapter 4 suggest that they can result in a more beneficial carbon balance, but the implicit assumption of forest maturity before felling suggests that other regulating and cultural ecosystem services may be adversely affected (not to mention biodiversity in forest ecosystems.)

As discussed in Chapter 3, this study focuses on forests under "scientific management" (Figure 3.2) and on the carbon balance of different management decisions. It does not address wider qualitative questions regarding the desirability of different ecosystem services, concentrating specifically on the effects of emissions arising from biomass production and use.

The scenarios used by Sterman et al. (2018a) make a number of assumptions about forest management (described in Chapter 4 and Appendix C) which vary in terms of their applicability to real-world forest management systems. This is well described by Prisley et al. (2018) who conclude that "*many of the assumptions on which their primary wood bioenergy scenario is based are not realistic*". This chapter is concerned with addressing these assumptions and addressing the implications for carbon balances when they are modified.

At this stage the model represents either an area required to supply a single pulse of energy, or a single stand producing an intermittent energy supply depending on management decisions. While it does not yet represent a model which can handle a forested landscape (discussed further in Section 6.4), the modifications described in this chapter allow stand-level calculations to assess the model against known forest management practices.

5.1.1 Research questions

This chapter describes an analysis of the forest management practices assumed by Sterman et al. followed by a number of modifications made to SBCM to broaden the range of possible silvicultural systems that may be considered. Research questions for this chapter are specifically:

1. What do Sterman et al. assume about silvicultural systems in developing their model?

2. What are the implications of these assumptions, are they justified, and could they be improved?

3. How does modification of these assumptions within the model change the apparent sustainability of biomass fuels?

5.2 Background

5.2.1 Sustainable forest management

Historically, it is difficult to overstate the importance of timber as a natural resource (Schama, 1996; Rackham, 1998). As such, the economics of timber production and management have been the subject of close study since the Enlightenment. The development of the modern science of forestry has been attributed to the need for yield regulation to protect forests during the late Early Modern Period (From around 1650: Grober, 2012). A number of significant changes in land management were taking place during this period, heavily influenced by first the agricultural and later the industrial revolutions, and this resulted in codification of existing methodologies (e.g. Evelyn, 1664) or the development of new paradigms of sustainable forest management (e.g. von Carlowitz, 1713). These changes were primarily concerned with the sustainability of ongoing production (Grober, 2012) and led to silviculture as it exists today.

Current best practice in well-regulated forestry maximises the forest's value to society in terms of ecosystem services, (UN, 2011) but this is often of secondary concern to the economic demands of forest owners who (perhaps understandably) often prioritise personal benefits over those to the wider community (Rojas et al., 2016).

While a range of different variations in forest management exist to ensure specific results (which are by no means limited to timber production or any other single ecosystem service); where forests are managed from a production standpoint, they tend to fall within two clear categories. Either maximisation of biological productivity of a site (yield) or maximising economic performance.

Yield maximisation

Sustained yield is very easy to conceptualise: the forest is divided into a number of compartments equal to the rotation age, divided by the felling frequency; thus, a 50 ha forest which is managed on a 50-year rotation would be composed of 50, 1 ha compartments if felling takes place every year, or 25 2 ha compartments if felling takes place every other year and so on. Felling takes place in the oldest compartment in each management period, and results in a number of age classes within the forest equal to the number of compartments. This is known as a “normal” forest, or a forest which exists in a “steady state” (Newman, 2002; Pommerening and Murphy, 2004)

The timber output from such a forest is maximised in perpetuity if the compartments are felled at the point of maximum mean annual increment (i.e. the age where the mean growth over the rotation is as high as possible as shown in Figure 5.1) This basic structure can then be varied depending on the species, site variables, and desired timber size, but changes will often result in a loss of total timber volume (although not necessarily of value).

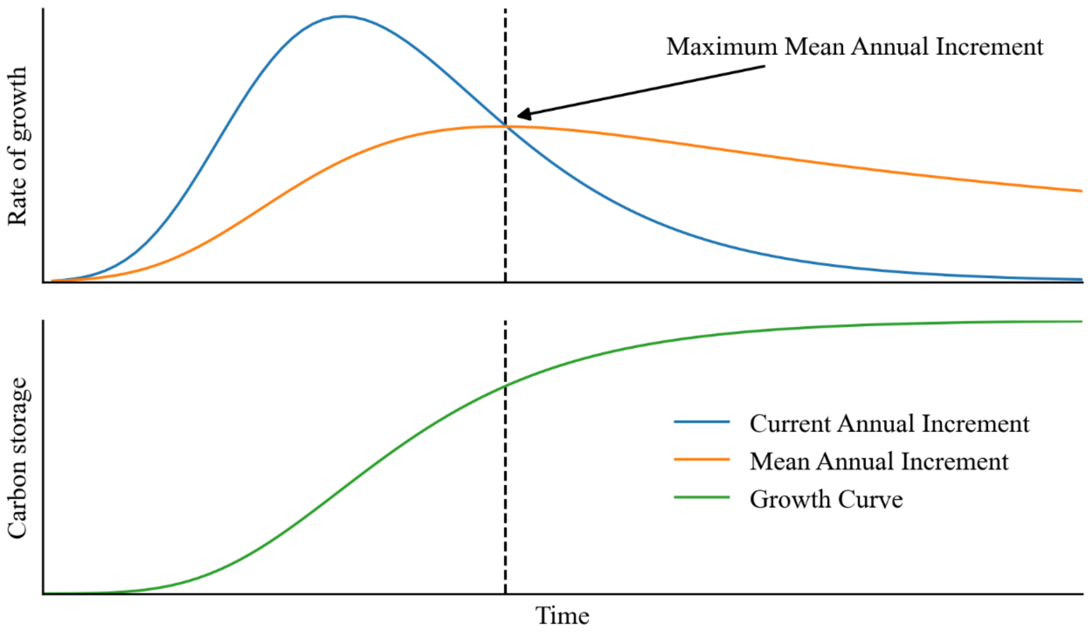

Figure 5.1. *An illustration of the current annual increment and mean annual increment. Current Annual Increment (CAI: blue) represents the per year growth of the forest (green). Mean Annual Increment (MAI: in orange) is the expanding (or cumulative) mean of all earlier values of CAI. The point of Maximum Mean Annual Increment (MMAI) as shown by the dotted line, is the long-term maximum yield of the site.*

Note that this only works for forests which have a growth pattern which follows a logistic curve. Mixtures of tree species which are more likely to follow a logarithmic curve (as shown in Figure 5.2) will always have a MMAI at year 1, because that is the point of fastest growth. In these more complex cases, a different approach is necessary, and these forests tend to be managed to favour specific objectives such as target timber diameter (Duncker, Barreiro, et al., 2012)

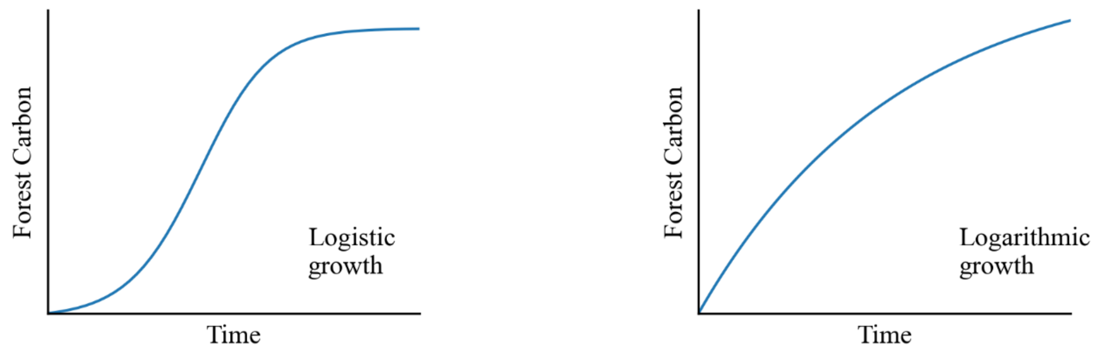

Figure 5.2. *A comparison of growth curves for different species / region cases in the training data. The plantation forests tend to follow a logistic growth pattern (left) while the non-plantation forests – which include a range of different species with different growth rates – tend to follow a logarithmic curve (Smith et al., 2006).*

Economic maximisation

The yield maximisation approach does not necessarily result in the same outcomes as the calculation of an optimum economic rotation age. This approach, originally developed by Martin Faustmann in 1849 (Viitala, 2006), and later refined by Pressler in 1860 and Ohlin in 1921 (Amacher et al., 2009) results in the rule that *'The landowner should clear-cut an even-aged stand at an age where the marginal return of delaying harvest is equal to the opportunity cost of delaying harvest, where the latter is given by foregone rents accruing to the future value of the stand and the land'* (Amacher et al., 2009 proposition 2.1, p21) This is shown graphically in Amacher *et al.* (2009 fig. 2.5 p16) and further described qualitatively by Vukina et al. (2001, p.55)

This economic approach depends on the maximisation of the net present value (NPV) or the discounted costs and revenues associated with forest management in perpetuity. This calculated NPV of a forest may be based on a number of different parameters such as timber price, product assortment, forest yield, rotation age and discount rate. At its most basic, NPV is equal to the sum of discounted future costs and revenues over future years as described in Equation 5.1 below.

$$\mathrm{NPV} = \sum_{t=0}^{n} \left(\frac{\text{future revenue}_{(t)}}{(1 + \text{discount rate})^{t}} \right)$$

Equation 5.1: The simplest version of the discounting formula; where, NPV equals the sum of discounted costs and revenue at each future year (t) where the discount rate (representing the time preference) is expressed as a dimensionless variable (Price, 1989).

Theoretically, this should be calculated for every year from 0 to some indefinite point in the future, but in practice revenues and costs which are at a distant future point will (assuming a positive discount rate) become so small as to become negligible. More complex methods exist to model the NPV over whole rotations, or a perpetual series of operations (Price, 1989), but since the magnitude of costs and revenues tend toward zero the further we look into the future and forestry operations are rarely a symmetrical series of events, this simple form of the equation is usually the most practical.

This economic assessment may result in different outcomes to the biological maximisation approach as it depends on the economic value of the timber, rather than simply its size (Lal and Alavalapati, 2014; Buongiorno et al., 2014). As such it has been criticised by the forestry industry (Samuelson, 1976) as producing a maximised economic output which is not necessarily in keeping with sustainable silvicultural practice. This is because a strong preference for early revenue (a high discount rate) can have a severe downward pressure on optimal rotation lengths, to the point where simply felling the forest and investing the money elsewhere is the optimum economic course of action.

Using Equation 5.1, it is possible to show that the point of maximum mean annual increment is equal to the point of maximum NPV when the discount rate is equal to 0 as shown in Equation 5.2.

$$\lim_{\text{discount rate} \to 0} \quad \max\left(\frac{\text{future revenue}_{(t)}}{(1+\text{discount rate})^{t}}\right) = y_{(\text{MMAI})}$$

Equation 5.2. Maximised mean annual increment and net present value equivalence. If the discount rate → 0, then the term (1+discount rate)^t → 1. The point of maximum NPV (based on a number of potential values of t) is then equal to the point of maximised future revenue with no time preference; thus, the strategy of felling at MMAI is valid from an economic point of view, if no time preference (or variable timber value) is expressed.

However, when time preferences are expressed (discount rate is > 0) in the absence of an increasing economic value for more mature timber, the rotation length providing the maximum NPV decreases rapidly (as shown in Figure 5.3), until it becomes apparent that the rate of economic growth in forest investments is less than other alternatives (see Hotelling, 1931; Vukina et al., 2001). It is worth pointing out that while conventionally discount rates are positive (denoting a time preference nearer the present) there is no mathematical reason why they should not be negative, denoting an increasing value the longer a resource is maintained, or a greater importance at some time in the future (Price, 2017). It is arguable that this may be applicable to carbon in the context of forestry (Anthoff et al., 2009; Timmons et al., 2016) which would tend to increase optimum rotation lengths from an economic maximisation point of view.

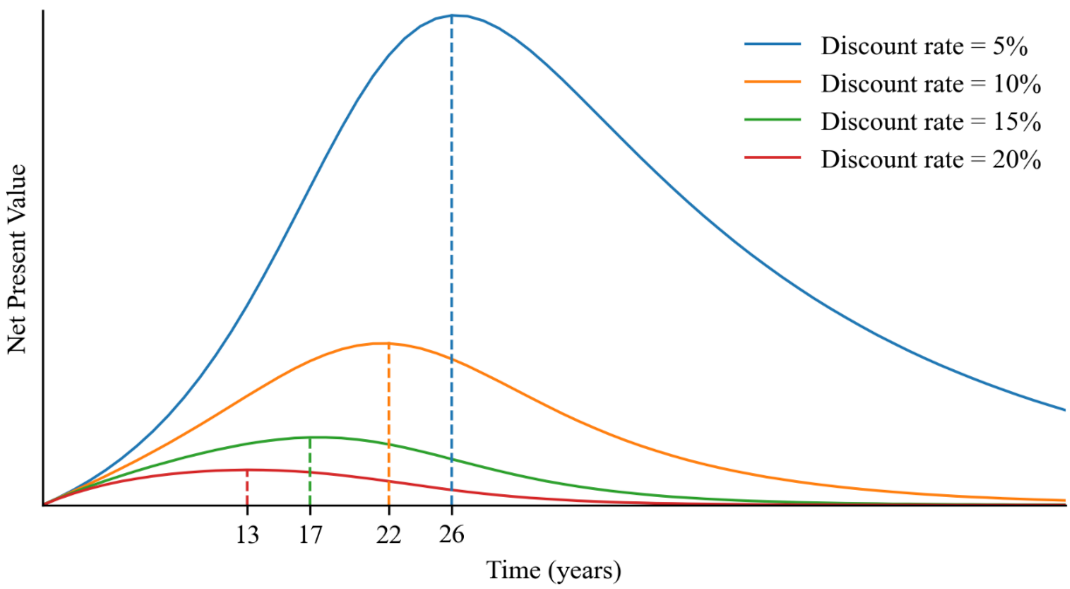

Figure 5.3. The value of the forest as shown in Figure 5.1 under different discount rates. The point of maximum net present value (assuming 1 m^3 of wood = 1 [unspecified] monetary unit) based on four different time preferences (discount rates) As discount rate increases, optimal rotation length (annotations) decreases.

Thinning

Thinning is a silvicultural tool used to enhance the value of a stand of trees at the final felling stage (Matthews, 1989). A proportion of trees in a forest stand are removed during the rotation, which reduces competition between trees for light and nutrients, this means that the remaining trees are able to grow more rapidly. The length of the rotation will generally then be extended to allow the forest to take advantage of this reduction in competition (Hart and Evans, 1991). The overall effect is that the growth of the stand is concentrated among fewer, larger stems. These are typically more valuable from an economic point of view, but are also more likely to be converted into high quality products with a long life-expectancy (storing carbon). Thinning generally removes trees with poor timber quality, health issues, and other defects (Gonçalves, 2021). This improves the resilience of the stand as a whole to stochastic natural disturbance (fires, pests, etc.) by removing more susceptible trees from the site while also introducing opportunities for the forest composition to be modified to cope with changing management objectives, climatic factors etc. (Szmyt, 2021).

The interrelationships between site, species, rotation length, thinning operations and forest yield are extremely complex, and the subject of a substantial body of literature (e.g. Matthews, 1989; Hart and Evans, 1991; Kerr and Haufe, 2011; Matthews et al., 2016).

5.2.2 Sustainable forest management in the context of biomass production

As discussed in Chapter 3, forests are complex natural systems which are managed with varying skill and efficiency for a wide array of different management objectives. These objectives can change quickly relative to the rate of forest growth and have a strong impact on management techniques and regimes.

The increase in demand for biomass fuels has influenced timber markets, and as such is likely to have had an impact on forest management decisions. Assessments of this impact have been made (e.g. Galik et al., 2009; Abt et al., 2010; Abt et al., 2012; Duden et al., 2017) but disagreement remains over its nature and whether the impact is positive.

The introduction of a market for poor quality timber can arguably support an increase in forest management activity, increasing the forest area through new planting, and management for high quality timber through providing value for thinnings (Abt et al., 2012). On the other hand, an increasing value for poor quality timber could lead to a downward pressure on rotation length by incentivising early felling of forests to meet demand (Schulze et al., 2012) it could also result in previously unmanaged, ecologically valuable forests being brought under active management resulting in a loss of ecosystem services and stored carbon (as alleged in EIA, 2022; Anon, 2022).

A full assessment of the impact of these market forces on forest management in this context is outside the scope of this study, but it is notable that both the yield and economic maximisation strategies described above have the effect of reducing rotation length relative to that assumed by Sterman et al.

It is arguable that managed forests do not ever become fully biologically mature, carrying a very long-term gross carbon debt and repaying a net carbon debt relatively rapidly. If this is the case, then modelling a scenario where fully mature forest is felled for biomass is inaccurate and unhelpful. However, a transition of long-neglected, old-growth or primary forest to active management would indeed incur a substantial new gross carbon debt. Forestry governance and sustainability are also outside the scope of this study, but it is argued some environmental campaign groups that this does take place (FERN et al., 2011; RSPB et al., 2012; Dogwood Alliance, 2012; Brack, 2017a; Brack, 2017b; EIA, 2022).

5.3 Analysis

Sterman et al. observe forests from an end user's point of view. While this is perhaps understandable, given the debt then dividend approach described in Chapter 1, in their assessment of forest production, they make a number of assumptions about forests and forest management which do not reflect conventional forestry practice (Prisley et al., 2018).

Firstly, and most obviously, they assume that the forest area available for biomass production is completely elastic i.e., infinite in potential area, and there are no biophysical, economic, regulatory, or other constraints on fuel availability. Fuel availability is simply determined by fuel demand.

Secondly, all forests are assumed to be fully mature ("at equilibrium") before felling. This implies that the forests concerned remain unthinned, are not managed under either of the silvicultural systems described above and are essentially wild. Since under the Sterman et al. model, forests are felled once and then allowed to regenerate back to full maturity, this effectively ignores the rotational aspect of forest management as any mature forest is interchangeable with any other mature forest of the same type.

Thirdly, in spite of an assertion that scenario S2 comprises a 25% thinning (Sterman et al., 2018a; Sterman et al., 2018b) it simply does not. The operation as specified takes place in a mature forest, and no further subsequent action takes place: this is a felling operation removing 25% of the final crop. It is not specified, but this could represent either a partial clear-fell of the forest area, or a selection felling targeting a particular species or growth pattern, some hybrid of the two, or even a prelude to species conversion as partially described in scenario S6. Such operations do take place in managed stands (Matthews, 1989), but without a clearer description it is not possible to determine which is intended. The functional use of thinning as a management tool is essentially either ignored or misinterpreted in the original Sterman et al. model. Where results relating to a “25% thinning” are reported (scenario S2) they seem to indicate a general decrease in payback period (as shown in Figures 2.11, 4.5 and 4.6) over a clear-fell (scenario S3) operation. This is to be expected; as area is elastic in the Sterman et al. model, the 25% felling takes place over a much wider area of forest (3.8 times the area used by a 95% fell) in order to meet the pre-defined energy requirement. The increase in area means that the potential NPP available for site recovery is substantially larger resulting in a lower payback period.

Finally, uncertainty remains about the fate of material harvested from woodlands. 100% of felled material is described as going to biomass. This neglects the wide range of potential end uses for felled timber, the majority of which have a higher economic value (Jasinevičius et al., 2017) and a greater value in terms of carbon storage (Parobek et al., 2019; Paluš et al., 2020). This is perhaps understandable in an illustrative model, since the assumptions required to account for harvested wood products would require a significant increase in the complexity of the model as well as potentially obfuscating the results of minor changes to the end user. More concerningly, Sterman et al. do not describe the fate of the 5% of forest carbon remaining after their 95% clear-fell scenario (S3). Whether the 5% remains as living biomass (remaining in the forest carbon pool as assumed in SBCM), is converted to dead wood (part of the soil carbon pool) or is assumed to be burned (moving to the atmospheric carbon pool) is not specified and is left unclear.

5.4 Method

Sterman et al. make three key assumptions about forest management in their model:

1. That forest area managed for biomass production is infinite and elastic.

2. Forests are only felled when completely mature

3. Thinning (as traditionally understood) does not take place

These assumptions were adjusted by introducing two substantial modifications to SBCM: to allow it to operate on a fixed area basis (producing a variable amount of energy based on a fixed forest area as described in 5.4.1) and to allow repeated felling of an existing stand on an ongoing basis to a variable degree – supporting repeated felling and thinning (described in 5.4.2).

A number of further modifications were made to SBCM* to consolidate earlier work. These included some incremental upgrades to the code to improve usability of the model, a template system to allow for standard scenarios to be pre-coded separately, the full incorporation of new growth function parameters as defined in Chapter 3, new scenarios using gas and BECCS as described in Chapter 4, and code to calculate mean annual increment, payback periods, and some other cosmetic adjustments.

5.4.1 Energy vs area basis

The SBCM code was modified to allow operation in one of two different modes for biomass fuel.

Energy basis

The energy required is provided by the user. Equation 2.1 is used to determine the fuel required to meet demand, and Equation 2.3 is used to determine the area of forest needed to harvest that quantity of fuel. Equation 2.2 is used to determine the emissions from both the biomass and counterfactual scenarios. This is the default approach used by Sterman et al. (shown in Figure 5.4)

* SBCM 2.0 is available from the author and included in electronic supplementary materials.

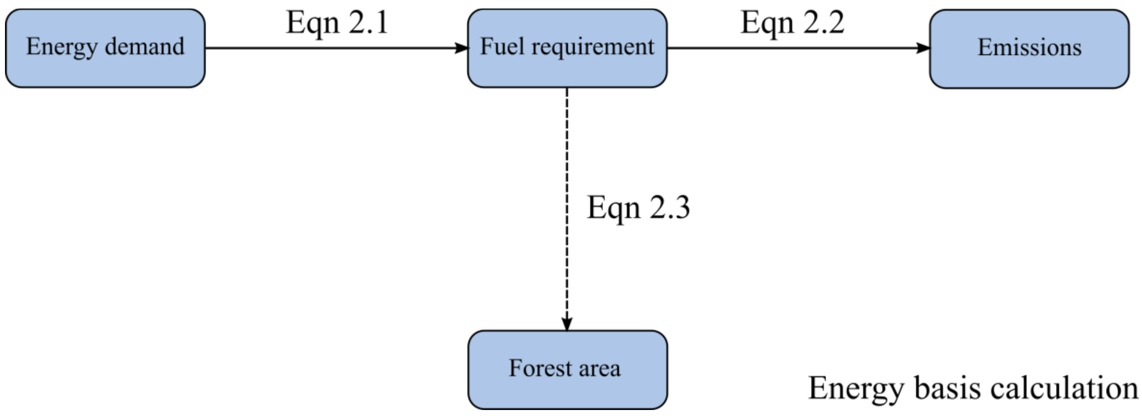

Figure 5.4. *The energy basis calculation. Fuel requirement, forest area and resulting emissions are determined by energy requirement.*

Area basis

The forest area is supplied by the user. Equation 2.11 is then used to determine the amount of fuel available, and Equation 2.9 is used to describe the total amount of energy available from this much fuel. As with the energy basis calculation, Equation 2.2 is then used to determine the emissions from both the biomass and counterfactual scenarios.

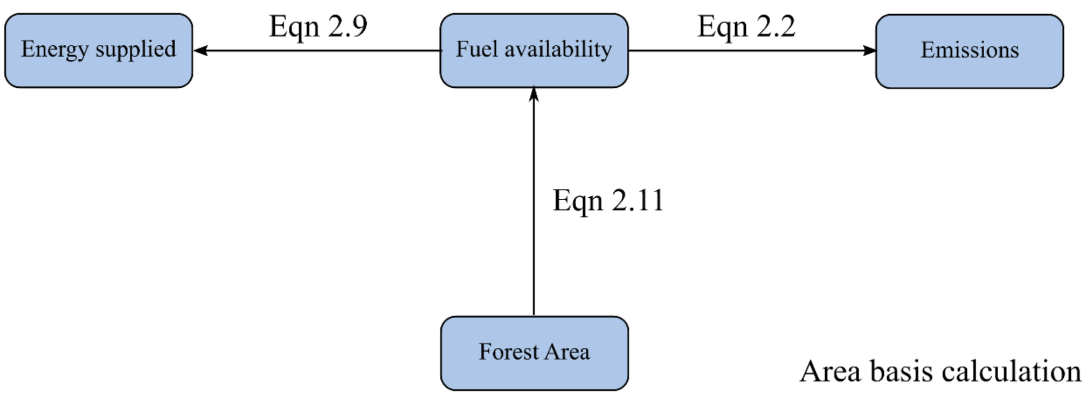

Figure 5.5. *The area basis calculation. Fuel availability, energy supplied and resulting emissions are determined by available forest area.*

This code was then run for a full range of site/species cases at different stages of maturity to demonstrate the interrelationships between area requirement, energy production, and payback period. At this stage all model runs were run as a single felling per model run in isolation – no rotations were applied.

5.4.2 Rotations

An additional function `fell` was added to SBCM 2.0 as well as an independent tracker of stand age (as distinct from the modelled time period relied on by SBCM 1.0). On each `runstep` the model was modified to check whether the stand is to be thinned or clear-felled and call the `fell` function as required. This function recalculates the forest carbon value based on felling intensity, and calculates additional emissions from both biomass and counterfactual sources.

By using this new method, a range of forest rotation lengths were tested and used to describe the relationships between rotation length, site yield, carbon saved, and payback period.

For each site / species case, two rotation lengths were identified (as shown in Table 5.1). A long rotation based on the time taken for forests to reach at least 99% maturity – a near-end estimate of the fully mature assumption, and a short rotation. The short rotations were calculated in two ways: the non-plantation forests which are highly mixed in terms of species, predominately follow a logarithmic curve growth pattern (as shown in Figure 5.2 above). In these cases, the rate of growth begins quickly and then steadily decreases over time without an inflection point, as such, any calculation of MMAI will be during the first modelled year: the point of maximum increment. For these forests, felling was assumed to take place when the forest was at 66% of maturity by mass. This is not intended to represent an optimum rotation length for these forests, but to provide a more realistic hypothetical for comparison with the extended rotation lengths required for full maturity. The plantation forests, being typically composed of a small number of more closely related pine species, showed a much clearer growth pattern on a logistic curve, and these were assumed to have a shorter rotation length equal to MMAI.

Table 5.1. Rotation lengths used to assess forest yield and payback period.

Tree species	Age of MMAI	Age of 66% maturity by mass	Age of 99 % maturity by mass
NE maple / beech / birch	2	80	323
NE oak / hickory	2	115	484
NE oak / pine	2	71	238
SC oak / hickory§	40§	72	202
SC oak / pine	2	76	273
SC shortleaf / loblolly pine*	26	23	41
SE shortleaf / loblolly pine*	28	24	41
SE longleaf / slash pine*	32	28	45

** Denotes plantations which were calculated using MMAI, all other forest types were assumed to be worked on a rotation length resulting in 66% of mature yield by mass.*
§SC oak / hickory is an edge case. While it does appear to have a growth curve which fits the logistic pattern a 66% maturity value was used to allow comparison with the other non-plantation forests.

5.4.3 Thinning

The results published by Sterman et al. suggest that a 25% thinning results in a decrease in payback period compared to a simple clear-fell. However, as discussed in 5.3 above their model does not simulate a true thinning, merely a 25% final felling. Using the modifications to SBCM and rotation lengths described in section 5.4.2 a hypothetical series of thinnings were introduced in a more realistic way compared to the original model. These were assumed to take place when the forest reached 50% and 75% of mass at final felling age. In each case, 25% of the crop was assumed to be removed and the final rotation length was extended to allow stand recovery before final felling. This extension to the rotation length is intended to allow the remaining trees to take advantage of additional light and other site resources made available through thinning. In the illustrative example in Figure 5.6, the time required for the forest stand to recover from the first thinning (time A) and second thinning operations (time B) is added to the overall rotation length, which extends the rotation by C years. The total amount of timber removed from site is equal to two thinnings plus a final felling, but over an extended period of time.

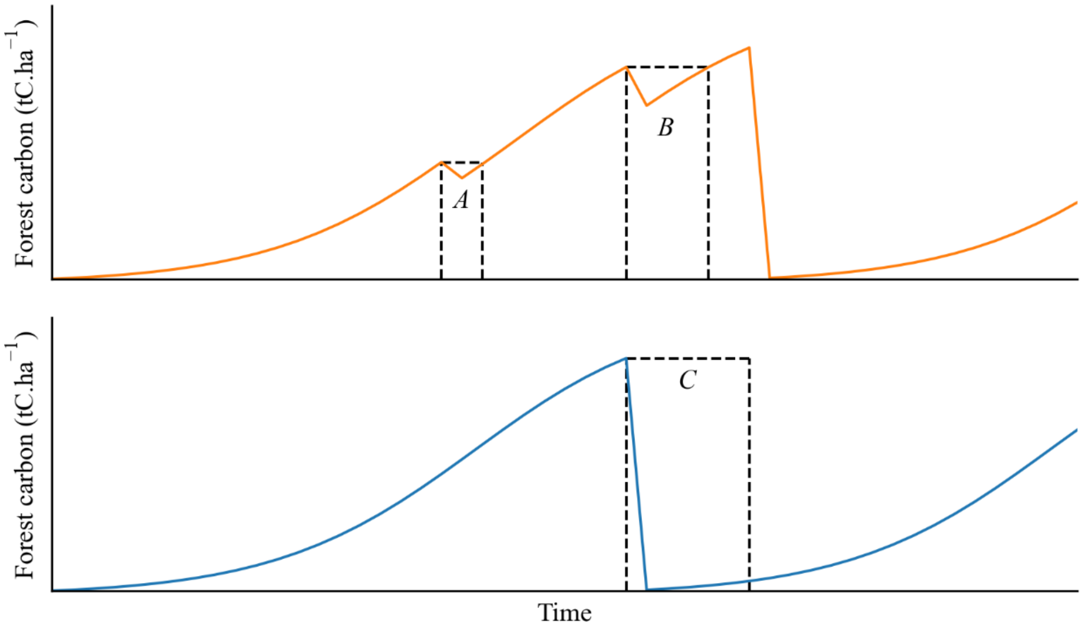

Figure 5.6. Rotation length modification with thinning. The time taken for a forest stand to recover from a first (A) and second (B) thinning was added on to the overall rotation length (C = A+B) to allow the remain trees in the forest stand to take advantage of site resources made available during the thinning.

A full range of rotations used and thinning years is shown below in Table 5.2

Table 5.2. Rotations lengths (years) used to assess the impact of thinning on forest yield and payback period.

Species	Short rotation (unthinned)	Short rotation (thinned at [ages])	Long rotation (unthinned)	Long rotation (thinned at [ages])
NE maple / beech / birch	80	127 [31, 110]	323	379 [52, 118]
NE oak / hickory	115	184 [43, 156]	484	564 [73, 167]
NE oak / pine	71	109 [31, 95]	238	281 [48, 100]
SC oak / hickory	72	106 [35, 95]	202	241 [52, 99]
SC oak / pine	76	118 [32, 103]	273	321 [50, 109]
SC shortleaf / loblolly pine*	26	32 [18, 27]	41	47 [19, 27]
SE shortleaf / loblolly pine*	28	34 [19, 28]	41	47 [21, 29]
SE longleaf / slash pine*	32	38 [23, 32]	41	47 [24, 32]

** denotes plantations which were calculated using MMAI, all other forest types were assumed to be worked on a rotation length resulting in a felling of 66% of mature mass.*

5.5 Results and Discussion

5.5.1 Area vs. energy basis and forest age

Area and energy basis calculation is a pre-determined setting in SBCM 2.0. This means that an area basis calculation will calculate an initial energy supplied, and an energy basis calculation will calculate the required area (as described in 5.4.1). If SBCM is run for a single mature stand under energy basis, and the resulting area required to meet demand is used as an input variable for a similar single mature stand on an area basis, there are no differences between models results. If, however, the age of the felled area is varied, a number of aspects of the relationship between payback, area requirement, and energy supply can be observed, as shown below in Figure 5.7

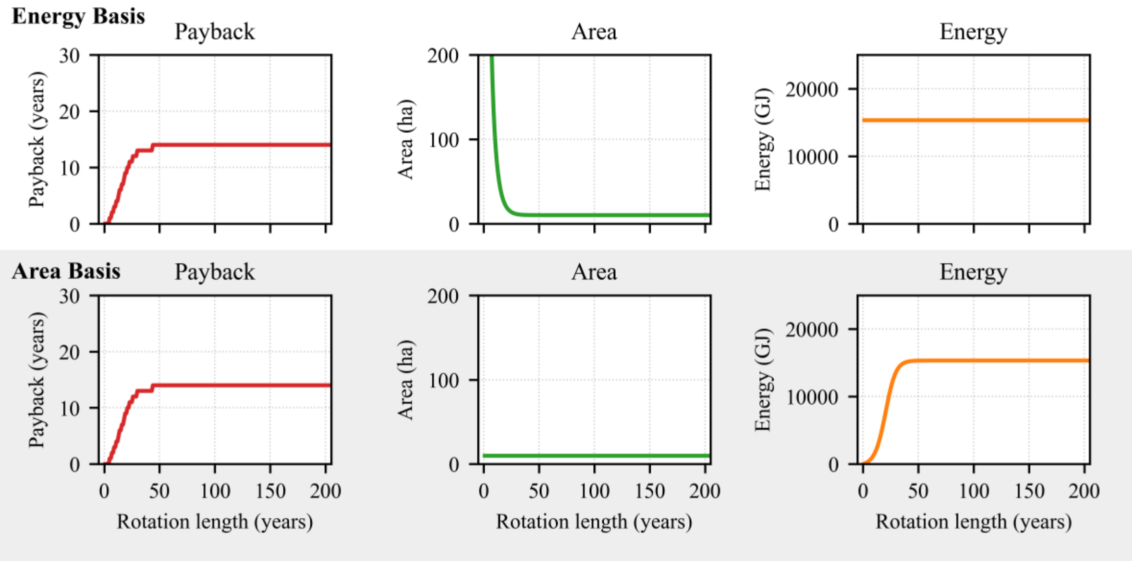

Figure 5.7. Payback, area requirement and energy output on energy and area bases. Calculations were carried out for conventional biomass supplied from a southeast short-leaved / loblolly pine plantation and a coal counterfactual using both energy (top row) and area basis (bottom row) calculations for a range of different rotation lengths. The relationship between energy and area is stable once the forest is biologically mature, but varies significantly when forests are felled earlier.

Firstly, there are no differences between payback periods when comparing area and energy basis calculations. This is because payback is intimately tied to site recovery rate and SBCM is either confining felling to a single area and reducing energy output or maintaining energy output and increasing the area of a homogeneous forest type. Since there is no variation in any forest recovery parameters, no variability is shown in recovery rate. As shown in Figure 5.8 below payback is influenced by three key factors; the depth of the initial trough is determined by amount of carbon on site (per ha), and the comparative efficiencies of production and use from the base and counterfactual cases. The time taken to reach payback (carbon saved >0) is then determined by the rate of growth (equivalent to the rate of site recovery).

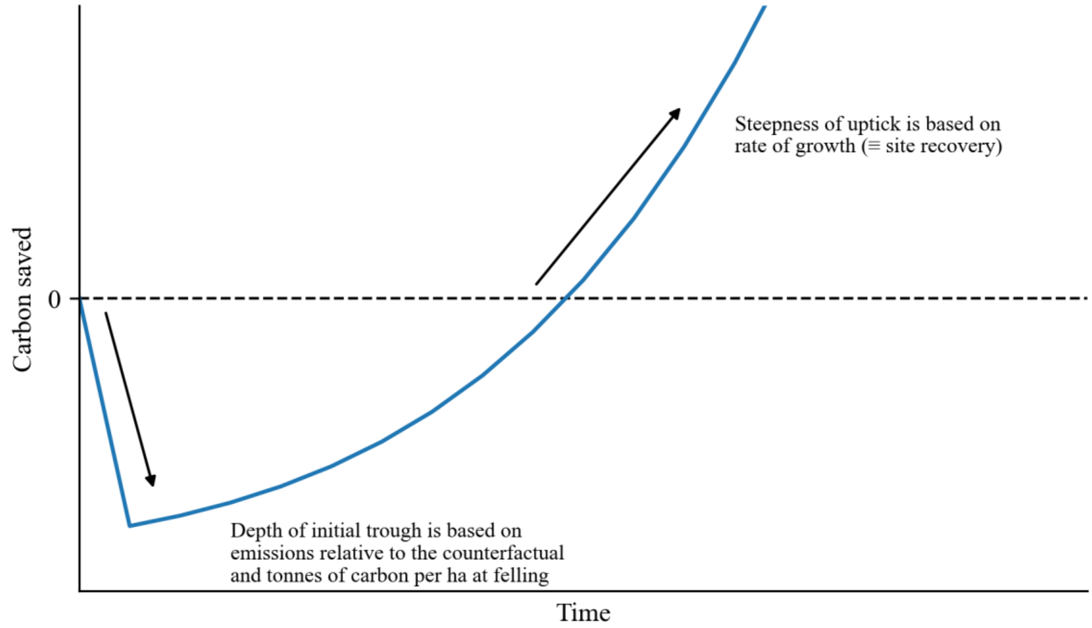

Figure 5.8. The anatomy of payback. An initial drop in saved carbon occurs where the counterfactual results in a lower carbon emission than biomass fuel. This is determined by the relative emissions of supply and use, and the total carbon present in the felled stand. The steepness of the recovery phase is a directly linked to forest regrowth. Carbon Sequestration Parity (or payback) occurs when saved carbon >0. Not to scale

Site recovery rate is dictated by the quantity of carbon removed and the forest growth parameters, which are calculated per hectare and as such it is not affected by the basis of model calculation used.

When energy production is fixed, however; the area required to meet demand becomes extremely high in very young forests; to the point where it is analogous to mowing an annual crop. A very small harvest per ha over a wide area is quickly recovered and payback of less than a year is common in forests younger than 5 years. It is likely that modelled rotation lengths of less than this are essentially meaningless since the underlying assumptions about planting and harvesting are no longer valid.

When the area of forest is fixed, the energy supplied in short rotations is very low, because we are again, felling a very small quantity of timber. This rises as the felled forest grows with age increasing the available fuel from the site. As with the energy basis calculation, the model becomes unreliable for very young forests.

Based on these results it becomes apparent that the age of a forest when felled has an impact on the payback period, and either the quantity of energy supplied, or the area of forest required (depending on calculation basis). It is possible to optimise biomass supply chains simply for energy supplied, carbon per hectare, or low payback periods, but without a combined metric which takes account of several key variables, this optimisation tends to result in unintended consequences elsewhere. Sterman et al. have implicitly assumed an extremely long rotation length (to full forest maturity) which based on these results would suggest that they report a maximum possible payback period for each species / region case.

5.5.2 The effect of rotations

By applying an area basis calculation and setting SBCM to model repeated felling of the same site, the utility of shorter rotations becomes apparent. In the scenario shown in Figure 5.2 a single ha of south eastern plantation of short-leaved and loblolly pine was managed on two different rotation lengths (28 years and 41 years, as described in Section 5.4.2). Payback is achieved at either 12, or 13 years, and the quantity of carbon saved (the difference between biomass and counterfactual emissions) continues to rise on a step-wise basis at each point of felling. The emissions do not become negative because, while the forest site is able to recoup virtually all of the carbon released by felling and combustion, it does not recover supply chain emissions.

In contrast, Figure 5.10 shows a scenario using the same region / species case, but compares a natural gas counterfactual against a high efficiency BECCS scenario. Since the BECCS scenario emits less carbon than natural gas at the point of combustion, the payback period is equal to zero. The biomass still emits carbon from combustion (even if it is less than the counterfactual) but becomes carbon negative between 10 and 12 years into the first rotation. Rather than simply comparing the relative merits of different scenarios, this allows use of negative carbon emissions as a metric by direct comparison with an absolute value. Each rotation then incrementally reduces biomass carbon emissions while the counterfactual emissions continue to rise.

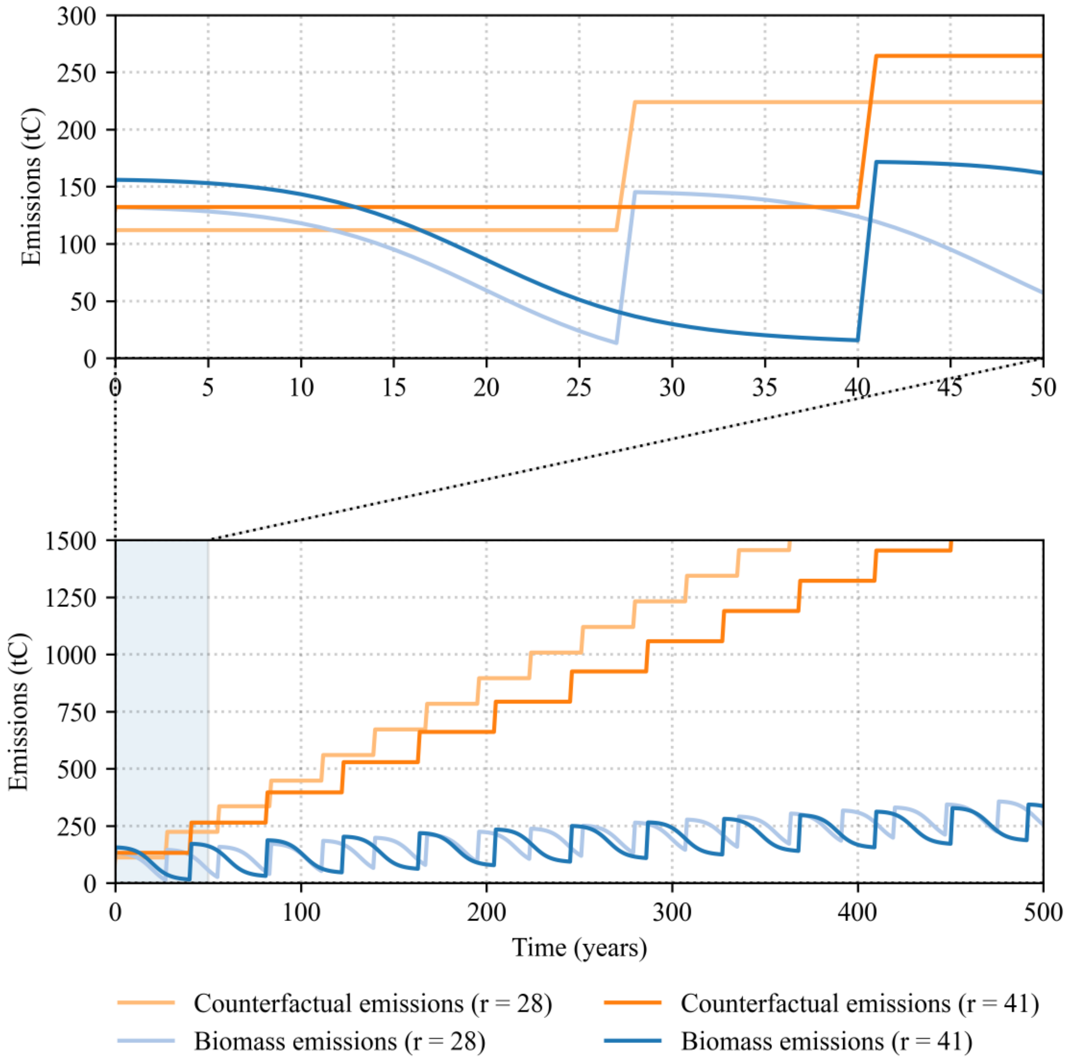

Figure 5.9. The effect of multiple rotations on payback period (conventional biomass) . In this case (a coal counterfactual and a conventional biomass supply chain based on 1 ha of SE shortleaf / loblolly pine plantation) payback is achieved between years 12 and 13 depending on rotation length (r). Subsequent rotations increase the carbon saved compared to the counterfactual (the difference between cumulative emissions) but remain positive in terms of carbon emissions. The upper graph shows the early stages of the rotation in greater detail.

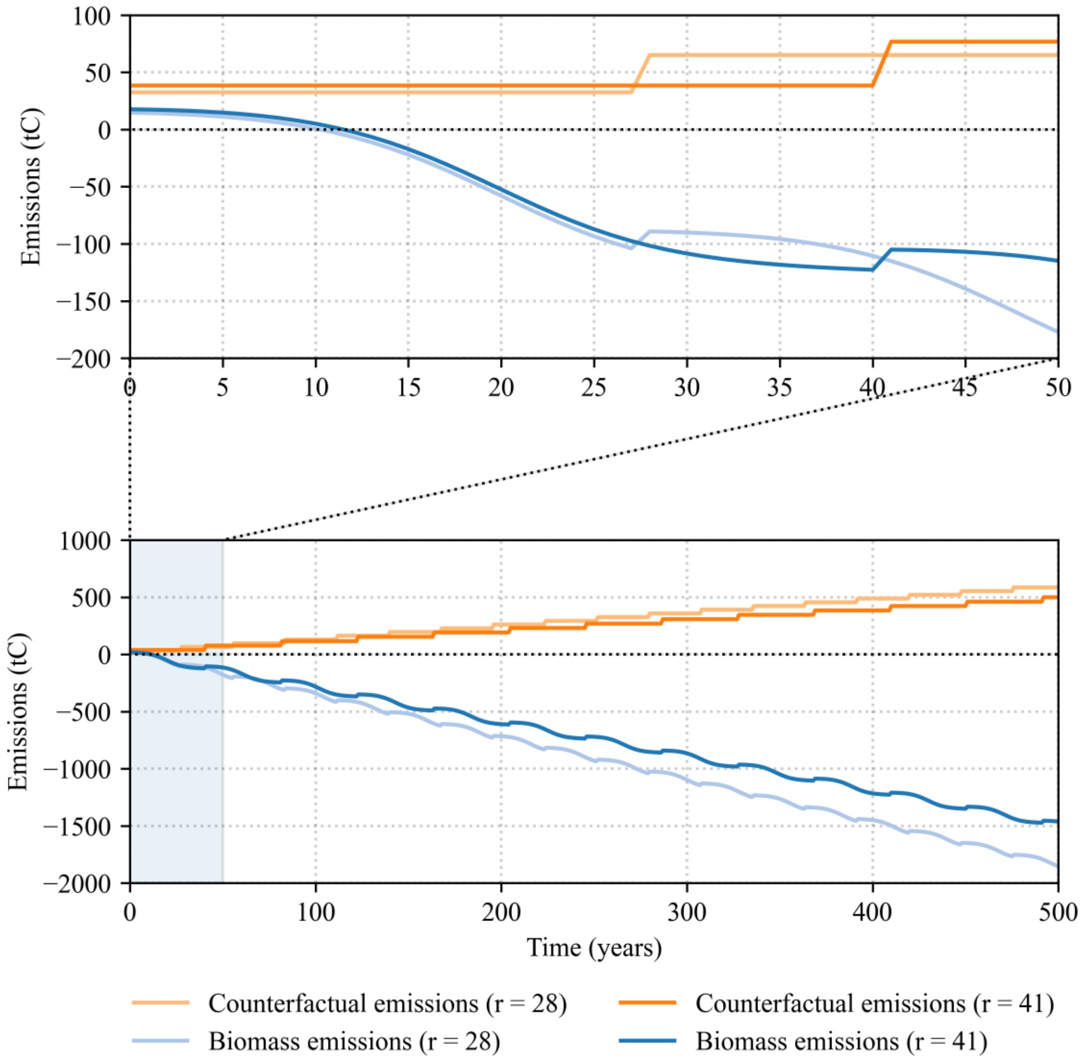

Figure 5.10. The effect of multiple rotations on absolute emissions (BECCS). In this case (a natural gas counterfactual and a high efficiency BECCS case based on 1 ha of SE shortleaf / loblolly pine plantation) payback is achieved in year zero and carbon negative operation occurs between years 10 and 12. As above, subsequent rotations still increase the carbon saved compared to the counterfactual, but also result in an ongoing reduction in atmospheric carbon. The upper graph shows the early stages of the rotation in greater detail.

5.5.3 Varying rotation length

Varying rotation length is a standard tool in forest management. As described above, foresters aim to optimise timber production or economic value through felling forests at the right age. This may be calculated in a purely biological sense, or in an economic sense, based on the change in value of the crop over time.

The forests described on a single-rotation basis as used by Sterman et al. have been assumed to reach full biological maturity before felling, with no further subsequent felling taking place (or at least not within the modelled timeframe). These assumptions essentially assign an extremely long rotation period to modelled forests which has a number of effects. Firstly, when applied to the non-plantation forests with very long growth periods they imply that felling is restricted to stands of mature trees (notably those with the greatest economic value, and value in terms of ecosystem services). Secondly, the extended rotation lengths suggest that productive land ceases to be productive when trees have been felled on site – basically, a forest can only be used once. This ignores the extensive history of land management described earlier and the core rationale behind using biomass fuels: that an area of land can produce energy multiple times.

As described in Section 5.4.2, SBCM was configured for an area basis (1 ha) calculation and run for the rotation lengths in Table 5.1: a “to maturity” long rotation and a more plausible short rotation based on either the point of MMAI or a 66% of estimated final growth by mass. This resulted in a number of forest growth curves with associated energy production (examples are shown below in Figure 5.11 and Figure 5.12), as well as values for energy supplied per hectare per year, and payback periods (Table 5.3).

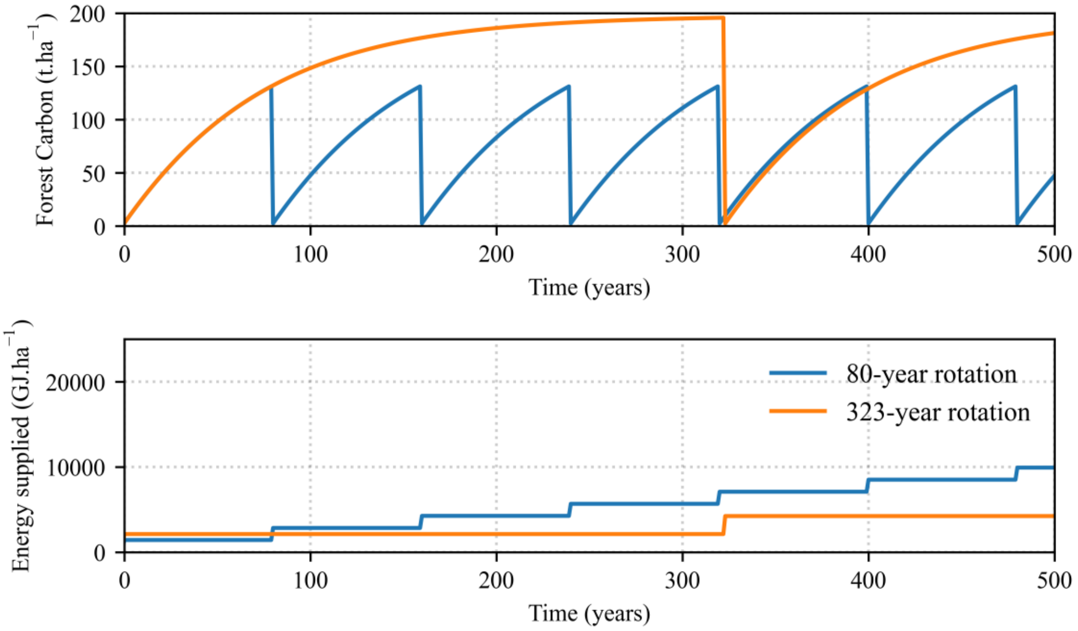

Figure 5.11. Growth and energy production for NE maple / beech / birch forest under a 66% mature (80 year) and an extended full maturity (323 year) rotation. The shorter rotation results in a substantial increase in yield over time as it repeats the early (rapid) phase of growth four times while the long rotation spends a significant period (about 240 years) with a much slower growth rate.

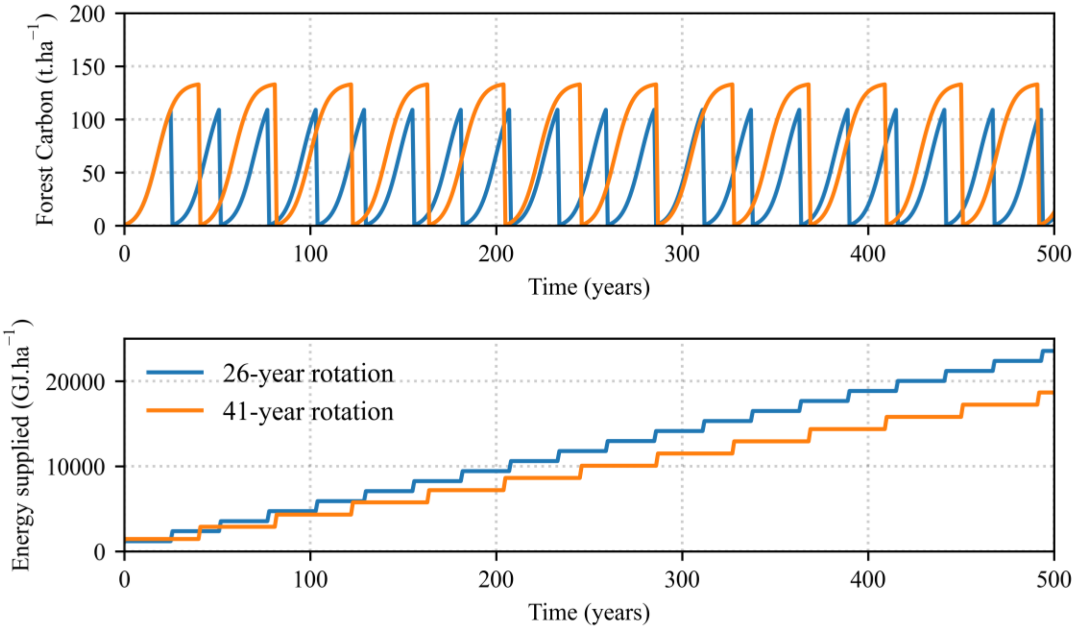

Figure 5.12. Growth and energy production for SC shortleaf / loblolly pine plantation under a MMAI (26 year) and an extended full maturity (41 year) rotation. The difference between these rotation lengths is less marked than in Figure 5.11 due to the faster general growth rate of these forests, however the short rotation still outperforms the longer one over a number of rotations.

*Table 5.3. The effect of rotation length on yield and payback. In every case, a longer rotation length results in a decrease in energy yield per year, and an increase in payback period when compared to the counterfactual. The BECCS counterfactuals are all omitted from this table since in every case payback is <1 year. Plantations denoted with **

	Rotation length (years)	**Realised energy yield ($GJ.ha^{-1}.a^{-1}$)**	**Coal payback (years)**	**Gas payback (years)**
NE maple / beech / birch	80	17.7	11	52
	323	6.5	28	62
NE oak / hickory	115	21.4	17	75
	484	7.6	44	90
NE oak / pine	71	18.5	12	48
	238	8.2	28	58
SC oak / hickory	72	19.0	13	51
	202	10.1	21	57
SC oak / pine	76	17.6	10	50
	273	7.3	17	56
SC shortleaf / loblolly pine*	26	45.3	11	20
	41	35.0	12	22
SE longleaf / slash pine*	32	37.4	16	26
	41	33.6	17	27
SE shortleaf / loblolly pine*	28	45.9	12	22
	41	37.0	13	23

Because of the variation in growth curve type (as described in Figure 5.2) and the associated impact of growth rates on payback periods (described in Figure 5.8) the relationship between rotation length and payback period shown in Table 5.3 is not immediately clear. It is notable that in every case, the shorter rotation outperforms the longer on a species-by-species basis; however, this reveals less about the strengths and weaknesses of different management techniques than the limitations of payback as an indicator of effective forest management. By changing the metric to an average energy yield per hectare per year (as in Table 5.3) it becomes easier to see the correlation between rotation length and actual energy output (shown in Figures 5.13 and 5.14).

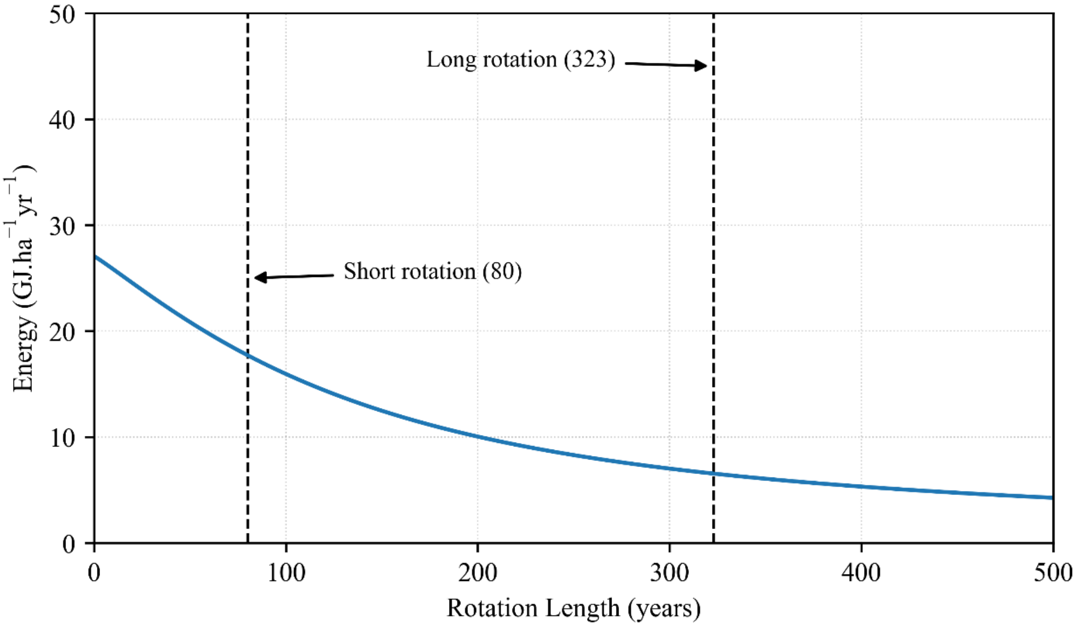

Figure 5.13. *realised energy yield for a NE maple / beech / birch forest under varying rotation lengths. A 66% mature (80 year) and an extended full maturity rotation (323 years) are shown for comparison. As discussed in Section 5.2.1, forests with a logarithmic growth pattern reach maximum yield at year 1, so a 66% mature rotation length was used instead.*

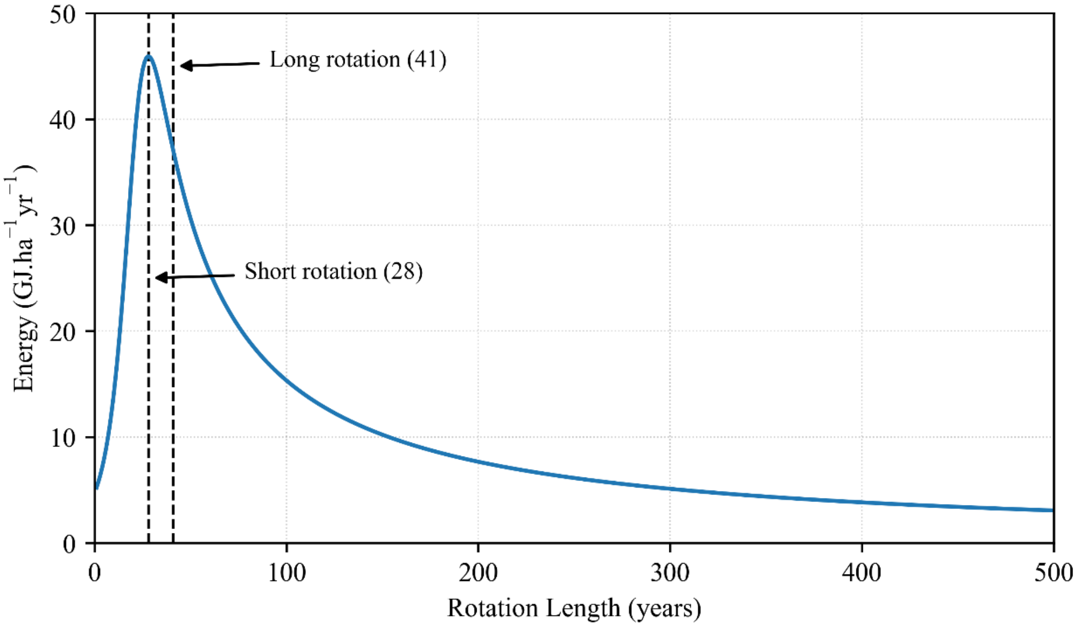

Figure 5.14. *realised energy yield for a SE shortleaf / loblolly pine plantation under varying rotation lengths. A MMAI (28 year) and an extended full maturity rotation (41 years) are shown for comparison. The graph shows a clear peak at the point of maximum yield, which corresponds to the MMAI used to determine the shorter rotation length.*

Based on this analysis, it is clear that while payback gives indication as to the relative time required for biomass to break even in terms of carbon emissions compared to the counterfactual case, it does not provide enough information to determine an appropriate forest management strategy. A measurement of mean annual energy supply per hectare for each rotation (as shown in Figure 5.14) suggests that an optimised solution for yield does not conform directly to payback period in all cases. For example, north-east maple / beech / birch forest yields 17.7 $GJ.ha^{-1}.a^{-1}$ on an 80-year rotation while south-central shortleaf / loblolly pine yields 45.3 $GJ.ha^{-1}.a^{-1}$ on a 26-year rotation (as shown in Table 5.3 above) however, both species show a payback period of 11 years. This further demonstrates the weaknesses of payback period as a metric, as it fails to account for cumulative gain in carbon savings which takes place over multiple rotations (as shown in Figures 5.11 and 5.12).

5.6 The effect of thinning

Sterman et al. cite their scenario S2 as an example of 25% thinning and assign lower payback values to these results. As discussed earlier in Section 5.3, this application of "thinning" is actually a 25% clear-fell. As the payback period metric is directly influenced by the quantity of carbon removed per hectare it will tend to show a more rapid recovery (the initial trough in the graph will be less extreme as indicated in Figure 5.8). This is because of the energy basis calculation used by Sterman et al. - the 25% "thinning" uses 3.8 times the land area of the 95% clear-fell resulting in a substantial increase in the NPP available for regrowth.

The primary function of thinning is not to increase yield, but to modify the forest site to encourage a change in the growth of the remaining trees in a stand (as described in section 5.2.1). There is however a clear relationship between the timing of a felling, payback periods, and yield. As such, a short series of trials were undertaken to identify possible impacts of thinning on wider modelled yield. It should be noted that these scenarios were not intended to reflect real-world forestry practice exactly. Thinning can be a time consuming and expensive operation (Chang et al., 2023) and undertaking it for the purposes of producing a comparatively low-value product such as biomass fuel as a final crop seems unlikely in real-world conditions.

As described in section 5.4.3 above, a range of indicative thinning ages were determined (see Table 5.2) based on MMAI or stand mass. These were modelled and compared to equivalent unthinned stands examples of the results are shown below in Figures 5.16 and 5.17)

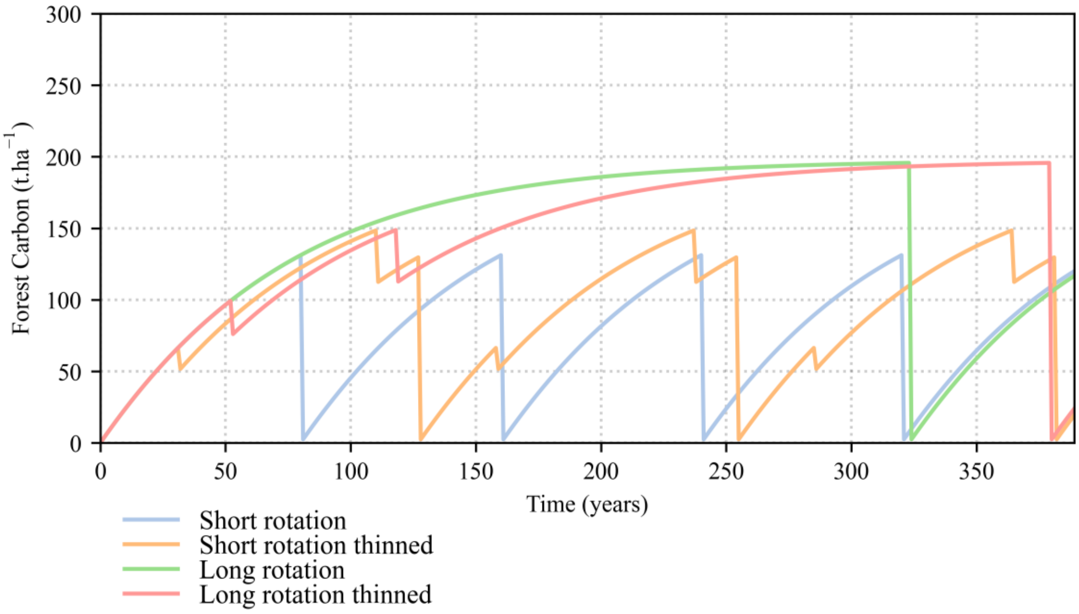

Figure 5.15. Forest growth in a stand NE maple / beech / birch forest under thinning and no-thin scenarios on long and short rotations.

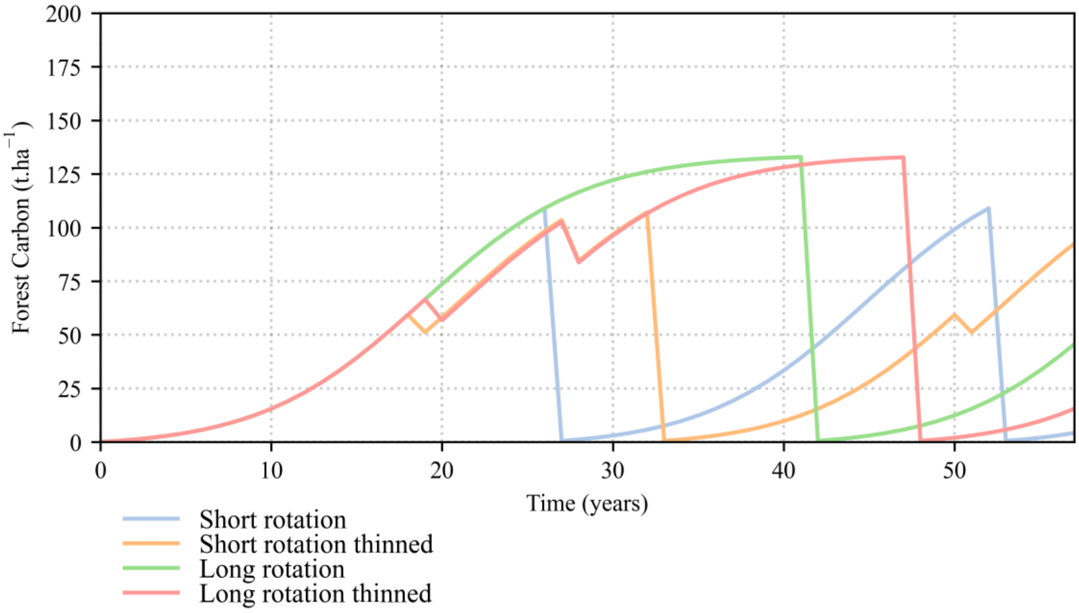

Figure 5.16. Forest growth in a stand SC shortleaf / loblolly pine plantation under thinning and no-thin scenarios on long and short rotations. Note that all rotation lengths are substantially shorter than those used in Figure 5.15. Forest growth in a stand NE maple / beech / birch forest above.

Since the timing and yield of biomass is dependent on independently derived variables for each region / species case, an annual energy yield (GJ.ha^{-1}.a^{-1}) was calculated for each case, under each management regime. This included the sum of energy derived from thinnings and then from a final felling per rotation and is shown in Figure 5.17 below.

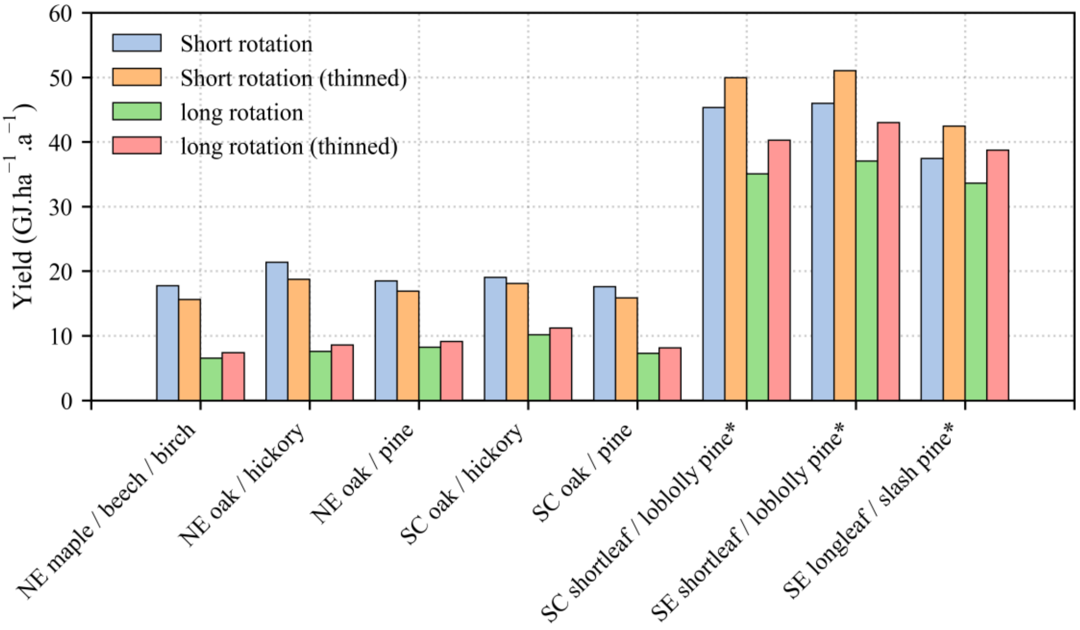

Figure 5.17. *Energy yield from thinned and unthinned forest stands on a long rotation (to full maturity) and a short rotation (to either 66% of final mass, or the point of MMAI as described in 5.4.2).*

The results were consistent with the themes which have been observed in earlier chapters. These is a clear separation between plantation and non-plantation forests in terms of yield and behaviour.

The non-plantations all showed the highest yield when unthinned under a short rotation. Thinning resulted in a very minor change in yield with a commensurate change in payback period (≤ 2 years) in some cases. This may be because of the timing of the thinnings; the slow growth rate of these species at higher maturities may not have allowed full recovery after thinning before the final felling.

Conversely, the energy yield per ha from plantation forests was improved by thinning in every case, but this increase was not large enough to result in a change in payback period (as shown in Table 5.4 below).

These findings are in clear contrast to the results published by Sterman et al. where thinning of a forest resulted in a (sometimes very substantially) shorter payback period in all cases.

Table 5.4. Payback periods under different felling regimes and rotation lengths compared to the revised coal and gas counterfactuals described in Chapter 4. In spite of measurable changes in yield, relatively minor changes in payback period took place.

	Short rotation unthinned		**Short rotation thinned**		**Long rotation unthinned**		**Long rotation thinned**	
	Coal	**Gas**	**Coal**	**Gas**	**Coal**	**Gas**	**Coal**	**Gas**
NE maple / beech / birch	11	52	12	62	28	150	27	182
NE oak / hickory	17	85	19	90	44	190	44	234
NE oak / pine	12	48	13	58	28	115	28	141
SC oak / hickory	13	51	13	57	21	88	21	95
SC oak / pine	10	50	10	56	17	97	17	104
SC shortleaf / loblolly pine*	11	20	11	22	12	23	12	25
SE shortleaf / loblolly pine*	12	22	12	23	13	24	13	26
SE longleaf / slash pine*	16	26	16	27	17	28	17	29

Based on these results, it is apparent that thinning results in a minimal change in the total energy realised per hectare when compared to no-thin scenarios. Contrary to the findings of Sterman et al., the resulting changes in payback period are minimal.

It should be noted that these results are based on the assumption that all felled biomass is used for biomass fuel. As discussed earlier, the primary purpose of thinning is not to increase yield *per se*, but to change the type of yield (Gonçalves, 2021). This mechanism is designed to produce timber with higher economic value to the forest manager which argues strongly against it being used for fuel, and in favour of use for higher value items. As such the increased cost associated with thinning to produce a higher quality final crop is essentially wasted if the final crop is also used to produce biomass. This is discussed in more depth in section 5.7 below.

5.7 Conclusions

As originally written, the Sterman et al. model contains several inbuilt assumptions which do not allow for a more nuanced assessment of forest management techniques:

The model was designed to identify the area of forest needed to supply a specified value of energy. The assumption implied by this configuration is that forest area is infinitely elastic, while energy demand is fixed.

The model also assumes that all forests are felled at biological maturity (an “equilibrium” point) and are then allowed to return to this state. This, is in effect, an assumption that only mature forests (aged between 45 and 484 years depending on species and region) are felled for biomass fuels. In making these assumptions, they ignore studies which suggest that multiple rotations of fast-growing species may be more sustainable than fewer rotations of slower growing species (e.g. Mitchell et al., 2012) and a significant and long standing body of research on forestry and silvicultural practice (Prisley et al., 2018).

Sterman et al. assume that felling takes place on a site at the beginning of the model run and does not occur again within the modelled timeframe. This is partially offset in their scenarios S7 (sustained yield with continued demand growth) and S8 (sustained yield with attenuating demand growth); although in both of these cases, new forest blocks are generated to meet demand, rather than old ones being reused. In each case, this means that forests can only be felled at the point of biological maturity and as such, they track the effects of site regrowth, rather than the effect of forest management. Rotational forest management and partial felling (thinning) of forest stands is completely omitted. While Sterman et al. do identify a scenario as thinning (their S2) since the forest is mature when felled this is simply a selection felling or a clear-fell of 25% of the forest area.

These assumptions suggest a number of implications for the results as published by Sterman et al. specifically:

1. Unreliable estimates of forest area required for biomass production due to an increasing area without reusing existing sites.

2. Unreliable estimates of payback periods for forests with particularly long growth curves. This is because the assumption of a larger carbon stock on a forest site results in an unrealistically high net carbon debt before repayment (see Table 5.3, and Figure 5.8).

3. Incorrect statements about the impacts of forest thinning on energy production. The elasticity of area and assumption of “thinning” at maturity used by Sterman et al. means that the reduction in payback period shown in their findings is at best uncertain (as shown in Table 5.4).

Payback is used as the primary metric for judging sustainability of biomass supply chains. This does take account of the relative emissions from biomass and counterfactual supply chains as well as the rate of site regrowth, and is robust for the scenarios that Sterman et al. use. However, it does not take account of the efficiency of fuel production with respect to land use, and is limited to scenarios where the counterfactual initially appears more attractive. When the biomass scenario has a lower initial emission than the counterfactual (as with BECCS) the payback period allows no comparison between scenarios.

As discussed in Section 5.5.1, in calculating area requirement based on energy demand Sterman et al. have reached an incomplete solution for the forested area required to meet demand. This is based on an erroneous assumption that forested areas must return to a point of maturity following felling.

Modifying rotation lengths changes the average rate of growth for an area of land (Section 5.5.2). Reducing rotation length has a variable effect (depending on growth curve type) but generally results in an increase in forest production allowing a forest to regrow and displace emissions from the counterfactual case many times, rather than the single time assumed when using a long rotation. As shown in Figure 5.17 and Table 5.4, reducing rotation lengths (described in Section 5.4.3) resulted in an mean increase in yield of 10.9 $GJ.ha^{-1}.a^{-1}$ for non-plantation forests and 7.7 $GJ.ha^{-1}.a^{-1}$ for plantations.

The timing and intensity of thinning operations are variable and imply questions about the final use of timber (as discussed in Section 5.5.3). While the use of thinnings and a final crop for biomass fuel is unlikely in real-world scenarios, this cannot be explored more completely without additional work to add harvested wood products to the modelled supply chain. Based on a limited range of possible thinning strategies using the assumption that all felled carbon is destined for biomass use, it is clear that in most cases the introduction of a thinning regime has a minor effect on yield across a rotation (as shown in Figure 5.17). This does not support the findings of Sterman et al. who suggest that thinning substantially reduces payback periods in all cases.

SBCM 2.0 is able to model a fixed area able to supply a single pulse of energy, or an intermittent energy supplied depending on management decisions. This could be improved to simulate a wider forested landscape of many stands required to produce an annual supply and represents a step towards the inclusion of harvested wood products and economic factors within the model framework. These and a number of further improvements are discussed in more detail in Chapter 6.

Chapter 6. Conclusions

In which the Author has a long, hard, think about what he did.

6.1 Introduction

As discussed in detail in Chapter 1, forest-sourced biomass combustion is a widely used climate change mitigation technology used to decarbonise electricity generation. While the literature reflects a substantial level of uncertainty as to the sustainability of this course of action (Bentsen, 2017; Giuntoli et al., 2020), global use of biomass fuels is expected to continue increasing for decades to come (Rogelj et al., 2018).

The uncertainty surrounding the sustainability of biomass fuels (reported payback periods which span four orders of magnitude - Mitchell et al., 2012) has been poorly communicated with little reference to the wide range of different assumptions, methods and approaches used. This has led to a lack of clarity in the public sphere and among policy makers. As a result, the sustainability of forest-sourced biomass fuels is now hotly contested (Mather-Gratton et al., 2021).

The aim of this thesis is to address uncertainty by attempting to identify how model parameters, assumptions and reporting metrics affect the apparent sustainability of biomass supply chains.

This chapter includes a summary of work carried out as part of this research programme on a chapter-by-chapter basis, with direct reference to the research questions described in Section 1.5. The work is then critically assessed with regard to limitations and this assessment is used to propose future research topics and avenues of exploration.

6.2 Summary of research

6.2.1 Chapter 2: Model development summary

Chapter 2 describes the identification, analysis, replication, and initial testing of a simple model to assess the sustainability of biomass supply chains as described in Chapter 1.

Given the need for an adaptable modelling framework to compare the sustainability of biomass fuel supply chains; which existing, published model is the most appropriate for conversion and adaptation?

As discussed in Section 2.2, a large range of different models, calculations, and approaches exists in the literature (Welfle et al., 2020). As such, an exhaustive categorisation and analysis is beyond the scope and capacity of this study. Models were identified based on a snowball search of the current literature on the basis of a series of questions (Section 2.2.1) largely intended to select for accessibility and ease of modification. A strong candidate for adaptation was identified (Sterman et al., 2018a) which fit the requirements well. The Sterman et al. model is simple, free, licenced for modification, has open-source code and is well documented. Weaknesses in the model do exist, but because of the quality of the documentation, these are not insurmountable.

Given the proliferation of models designed to address the sustainability of biomass fuels, it is reasonable to assume that other candidates for adaptation are available. Since the initial choice of model was very much a starting point for future work, the specific model chosen was rather less important than subsequent modification.

How does the selected model work, what are its strengths and weaknesses, and what assumptions are implicit in the model structure?

The Sterman et al. model (described in detail in Section 2.3) is composed of two parts. A fuel supply chain model (Figure 2.2) is used to estimate fuel requirement, emissions, and the counterfactual scenario. A forest growth model (Figure 2.3), is used to estimate the mass balance of carbon moving between the atmosphere, forest, and soil carbon pools. The model has some strengths in that it provides a clearly defined, transparent framework under an open-source licence with logical well documented code, and freely available training data (Smith et al., 2006). Of all the models assessed, the Sterman et al. model was by far the most transparent in terms of documentation and application. Conversely, the model also suffers from a number of structural weaknesses, being reliant on less well-known proprietary modelling software to run (Vensim - Venata Systems, 2017) and relying on a number of parameters, assumptions and scenarios of questionable reliability. Initial analysis of the model identified clear issues with the supply chain parameters (particularly for biomass combustion) and assumptions about silvicultural practices discussed by Prisley et al. (2018).

How can this model be enhanced, making use of its strengths while addressing its weaknesses?

After a detailed analysis of the Sterman et al. model (Section 2.3) a redeveloped version of the model was built using Python: The Simple Biomass Comparison Model (SBCM)[*] This replication was intended to improve accessibility as well as be easily configurable for a wider range of parameters and scenarios.

SBCM specifically utilises the strengths of the Sterman et al. model (i.e. open-source, licenced for modification, simple) while addressing previously identified weaknesses (such as inaccessible coding language) and allowing further study of the parameters and scenarios used. Later chapters (3, 4, and 5) describe how work was carried out to address weaknesses in the forest model, supply chain model, and silvicultural assumptions.

Can the existing published results from the model be reproduced in a replicated version?

SBCM was tested against results published by Sterman et al. (2018a) to ensure that the replication of earlier work was successful. The initial match between results from SBCM and the Sterman et al. model was very good – producing visually identical growth curves over the first 100 year-period. SBCM, however; did not produce an exact match for "equilibrium values" (i.e. the total carbon storage in a fully mature woodland) over extended time periods, and payback periods did not agree. After testing, this discrepancy was isolated to the forest growth model and was investigated in detail in Chapter 3

6.2.2 Chapter 3: Assessing the forest model summary

Chapter 3 describes a detailed analysis of the forest growth sub-model and the investigation of minor discrepancies between the results from SBCM and those originally published as described in Chapter 2.

[*] available at https://github.com/Priestley-Centre/SBCM

How is the data used to train the model by Sterman et al. derived, and is it the most appropriate?

The data used to train the model is a high-level regional dataset from the USA, based on a combination of direct measurement using chronosequence values from a large scale network of sample plots, interpolated using the LANDCARB model (Smith et al., 2006). While it does not provide spatially explicit stand level information (beyond biogeographical region) it does provide a robust, easily accessible indicative values for above and below-ground carbon for a range of forests of different ages in the continental USA. This dataset is unusual in that it includes estimated values for soil carbon as well as carbon in forest biomass, and no more appropriate datasets were identified.

Are the parameters obtained by Sterman et al. the most appropriate to replicate the forest growth curves supplied by Smith et al. (2006) or can improvements be made?

Using this data, a dual-response least squares non-linear regression was carried out in Python to produce revised parameters for SBCM to plot curves for forest and soil carbon over time. In every case, SBCM was able to produce at least one parameterisation which improves the fit of estimated forest and soil carbon levels to their training data over the Sterman et al. model. A number of these improvements are modest, but the growth curves generated using SBCM parameterisations developed in Chapter 3 consistently outperform those using parameterisations published by Sterman et al. (2018a).

To what extent does uncertainty exist between the training data, forest growth as described by Sterman et al. (2018a) and forest growth described in SBCM?

In improving the fit of the SBCM growth model to its training data, a clear difference was observed between results for plantation and non-plantation forests. Plantations typically show good agreement between the values published by Sterman et al. the training data published and results from SBCM (variation in site carbon at maturity <=4tC.ha^{-1} variation in payback period <= 1 year). In contrast, the non-plantation forests show substantial variation between different parameter sets with comparable

RMSE scores (variation in site carbon at maturity 50-228 $tC.ha^{-1}$ variation in payback period 21-48 years) all show a larger degree of uncertainty in the later phases of growth.

A statistically significant correlation was identified ($r^2 = 0.99$, $p < 0.00002$) between the range of possible outcomes and the degree to which growth curves have been projected beyond the training data. A likely candidate for this increase in uncertainty is the susceptibility of the Chapman-Richards growth function to numerical instability where the asymptote is not known (Ratkowsky, 1983; Burkhart and Tomé, 2012) as in the case of the slower growing forest types.

It is reasonable to conclude on this basis that it is not possible to determine which parameterisations for these forests are more likely to be accurate from this training data alone when using either the Sterman et al. model, or SBCM. It is even possible that the values preferred by Sterman et al. may be the best fit with real-world situations; we simply do not have enough information to tell without either improving the training data or modifying the growth function used by the model.

What effect does an improved choice of parameters have on predicted carbon storage values, and payback times for different region and species combinations?

Uncertainties of carbon storage rate and magnitude have a substantial impact on the payback periods for non-plantation woodlands, and in each of the cases studied the parameters reported by Sterman et al. (2018a) resulted in the longest possible payback periods of between 68 and 107 years for these forest types.

Based on these findings, it is reasonable to assume that the parameter values with the lowest RMSE are the most appropriate for use elsewhere in this study (see Appendix D) but, that these parameters are only reliable for non-plantation forests when the length of the rotation is less than 100 years, in contrast to the biological maturity assumption used by Sterman et al. (this is discussed in Chapter 5).

6.2.3 Chapter 4: Assessing the supply-chain model summary

Having assessed the reliability of the forest growth sub-model in Chapter 3, a number of assumptions used in the supply-chain sub-model were assessed in Chapter 4.

Are the parameters used by Sterman et al. the most appropriate for the supply chains they describe, and should they be modified in SBCM?

The parameters used by Sterman et al. to describe supply chains were assessed and significant weaknesses were identified. Values for the coal counterfactual were out of date in some cases, and the value for biomass end use efficiency was found to be incorrect by nearly 12%. In each case, values were updated where more appropriate and recent sources were available.

Sterman et al. rely heavily on a counterfactual of electricity generated using coal. Is this still the most appropriate counterfactual?

The widespread use of coal counterfactuals in studies of this type is perhaps understandable due to the similarities of supply chains handling solid fuels, but in view of international commitments to phase out coal use (UNFCCC, 2021a), it is becoming clear that coal can no longer be used in isolation as a valid business as usual scenario.

Are there any other supply chains which could be modelled using SBCM that would be more appropriate than those currently in use?

Given the limited usefulness of comparisons with coal, another counterfactual based on natural gas was added to the model. Gas is the cleanest and most efficient fossil fuel technology, and was deemed to give a more challenging comparison.

While simple combustion for primary energy generation remains the dominant use of biomass globally, use of carbon capture and storage technology is expected to become widespread in the near future (Ganeshan et al., 2023). To account for this, two additional parameter sets were developed to provide indications of the change in payback periods associated with BECCS.

How does revision of the supply chain parameters within the model change the apparent sustainability of biomass fuels?

Using more reliable data sources, payback periods for electricity generated from conventional biomass combustion were shown to decrease relative to coal when compared to the results published by Sterman et al. for 25% and 95% felling scenarios.

Payback periods decreased by between 20 and 73 years in the non-plantation forests and between 2 and 6 years in plantations.

Unsurprisingly, payback periods increased substantially when conventional biomass use was compared with natural gas: by between 47 and 162 years for non-plantations, and between 5 and 11 years in plantation forests.

In every case, the initial emission associated with BECCS was lower than the emission generated by the counterfactual; resulting in a payback period of less than 1 year. This highlights the potential of BECCS as a CDR technology, but also illustrates the limitations of payback period as a metric. Payback only shows the relative difference between a biomass scenario and a counterfactual when the counterfactual produces less CO_2 initially than the biomass system. As such, it is not possible to identify which of the two BECCS scenarios was more advantageous using this metric. This limitation is discussed more completely in Chapter 5.

6.2.4 Chapter 5: Including silviculture summary

Sterman et al. make a number of contested statements about forestry management practices (Sterman et al., 2018a; Prisley et al., 2018; Sterman et al., 2018b). In view of these, and having established limitations to the validity of the forest model for very long rotations on non-plantation sites (Chapter 3) this chapter describes an analysis of the forest management practices assumed by Sterman et al. followed by a number of modifications made to SBCM to broaden the range of possible silvicultural systems considered. The limitations of payback period as a metric, the use of energy and area basis calculation, and the optimisation of forest yield are discussed in more detail.

What do Sterman et al. assume about silvicultural systems in developing their model?

In the Sterman et al. model, forest area is assumed to be infinite and fully elastic, forests are assumed to be felled at full biological maturity and silvicultural thinning as it is traditionally understood is replaced with a partial felling of mature forest. This ignores conventional forestry practice (described in Section 5.2.1) which aims to maximise forest yield (either in volume or financial terms) for a limited area rather than simply waiting until the forest has stopped growing before felling.

What are the implications of these assumptions, are they justified, and could they be improved?

First SBCM was updated to version 2.0* to allow it to run with a fixed area (and elastic energy production) and to allow repeated felling of a single area. This change in perspective allows an analysis of forest yield, rotation length, and silvicultural thinning in the context of biomass production (these modifications are described in section 5.4).

The assumptions made by Sterman et al. have a number of effects. Extremely long rotation lengths result in the maximum possible payback period for each species / region case and can effectively waste potential yield from a forest site. This is obscured by a reliance on the energy basis calculation which simply recalculates area to compensate, and can lead to unreliable estimates of area requirement. In simulating a 25% felling, the model assumes an increase in area requirement by a factor of 3.8 compared to a 95% clear-fell scenario. This meets the energy demand, but skews the site recovery (and thus payback period) since NPP from a much greater area is available to support regrowth.

How does modification of these assumptions within the model change the apparent sustainability of biomass fuels?

In calculating area requirement based on energy demand Sterman et al. have reached an incomplete solution for the forested area necessary to supply fuel. In real-world conditions forest area is finite, and limits potential energy production rather than the other way round. This has minimal effect on results if we assume that forested areas must return to a point of maturity following felling, but when very short rotation lengths are applied, it can lead to excessive area requirements (as shown in Figure 5.7).

Varying rotation lengths is a standard silvicultural technique (Section 5.2.1) and this practice changes the average rate of growth for an area of land over time. The effect is harder to observe when operating on an energy basis, and when measuring the effect of a single felling operation, but becomes increasingly important when working on a fixed area and modelling a series of felling operations on the same site. Rotation lengths can generally be tailored to optimise forest NPP, allowing a site to regrow and displace emissions from the counterfactual case many times, rather than the single time assumed

* Available from the author and included in electronic supplementary materials.

when using a long rotation. As described in Section 5.4.2 modified rotation lengths resulted in a mean increase in yield of 10.9 $GJ.ha^{-1}.a^{-1}$ for non-plantation forests and 7.7 $GJ.ha^{-1}.a^{-1}$ for plantations.

While conventional biomass use does not lead to negative carbon emissions, the relative difference between biomass emissions and the counterfactual increases every rotation leading to a cumulative carbon saving over time. This cumulative effect is maximised when forests are managed to maximise yield. The same is true for BECCS scenarios, except that the divergence between counterfactual emissions and BECCS emissions is more marked and BECCS also functions as a CDR technology i.e., the cumulative BECCS emissions become negative.

The work in this chapter highlights a number of weaknesses inherent in the use of payback as a metric. Without detailed control over other variables, it is possible to show very low payback periods at the expense of extremely low energy production or extremely high area requirement. When biomass emissions are lower than the counterfactual (as in BECCS scenarios) payback cannot be used in isolation to identify the most advantageous course of action.

6.3 Addressing the overarching research question

The research goal described in Chapter 1 was to identify how model parameters, assumptions and reporting metrics affect the apparent sustainability of biomass supply chains. While the research conducted was not exhaustive (limitations and next steps are discussed in Section 6.4) a number of firm conclusions can be identified.

6.3.1 Parameters

The model parameters used in SBCM fall into two clear categories based on the forest and supply chain sub models. This can be generalised to describe specific impacts on payback (as shown in Figure 5.8) as the depth of the initial drop in carbon saved depends principally on relative emissions of biomass use and the counterfactual scenario – governed by the supply chain parameters, and the steepness of the recovery is based on the rate of forest growth – governed by the forest growth model.

As such, minor changes in the forest model parameters (Chapters 2 and 3) result in substantial effects in terms of the apparent sustainability of the biomass scenario. As shown in Figure 5.8, this is partly caused by the total carbon emitted on combustion i.e. the net carbon debt; and partly on the rate of regrowth – which depends on the intensity of felling, site, and species. Payback periods are also highly sensitive to counterfactual scenario (shown in Chapter 4). While some supply chain parameters are not well constrained (biomass supply chain losses being particularly difficult to quantify) the general effect of moving away from a conventional biomass: coal counterfactual scenario is significant.

Based on this finding, it is reasonable to conclude that the apparent sustainability of conventional biomass depends to a great extent on the accuracy of these parameterisations (as explored in Chapters 3 and 4).

6.3.2 Assumptions

As discussed in Chapter 1, there are a wide range of different assumptions made in studies of this type. It is possible to produce results which appear to be based on comparable methods, while making radically different assumptions about system boundaries, counterfactual operation, silvicultural practice, and metric calculation. In particular, the assumptions about how forests are managed in response to biomass fuel production (as explored in Chapter 5) have a strong influence on the apparent payback period.

The complexity of modelling required to develop a fully coherent / exhaustive set of possible assumptions is very high, and as such many studies (including this one) opt to simplify the possible range of scenarios in favour of reducing complexity to a more manageable level. For example, it is not possible to fully take into account forest management and growth in a counterfactual scenario without including assumptions about management for a range of alternative HWPs. Failure to do so restricts the model to an implicit assumption that forests are unmanaged (or simply carbon inert) in the counterfactual. This limitation is discussed in more detail in Section 6.4.

6.3.3 Metrics

Payback period is a useful metric for communicating results but only when adequately contextualised. While no consensus of minimum acceptable payback period or standardised counterfactual case were identified, the idea that shorter payback periods are generally better is easy to understand and intuitive. Care needs to be taken that counterfactual cases are stated for clarity, but continued use of this metric is advisable. The metric does have limitations which are evident when comparing scenarios where biomass emissions are smaller than the counterfactual. When the biomass scenario incorporates BECCS, a time to reach carbon negative operation may be more appropriate. While it is tempting to see this as a separate metric, it is essentially a payback period against a hypothetical energy source with zero initial emissions. It is important to recognise that this is not the same as a comparison with wind or solar energy, because this would imply an assumption of equality in infrastructure emissions which is not valid.

Based on these conclusions, a recommended form of reporting is suggested as:

The "payback" time required for electricity generated by biomass to result in a lower emission than the alternative was estimated at [X] years, when compared with an equivalent amount of energy generated using [counterfactual]. This estimate assumes that the biomass fuel is sourced from sustainably managed forests which will regenerate over time.

or

The time required for electricity generated by biomass with carbon capture and storage to result in a net reduction in CO_2 *from the atmosphere was estimated at [X] years. This estimate assumes that the biomass fuel is sourced from sustainably managed forests which will regenerate over time.*

6.3.4 Comparison with other work

Based on the findings described in earlier chapters, the payback periods for conventional biomass as calculated by SBCM have reduced from those published by Sterman et al. when compared to coal in both duration and uncertainty (Figure 6.1).

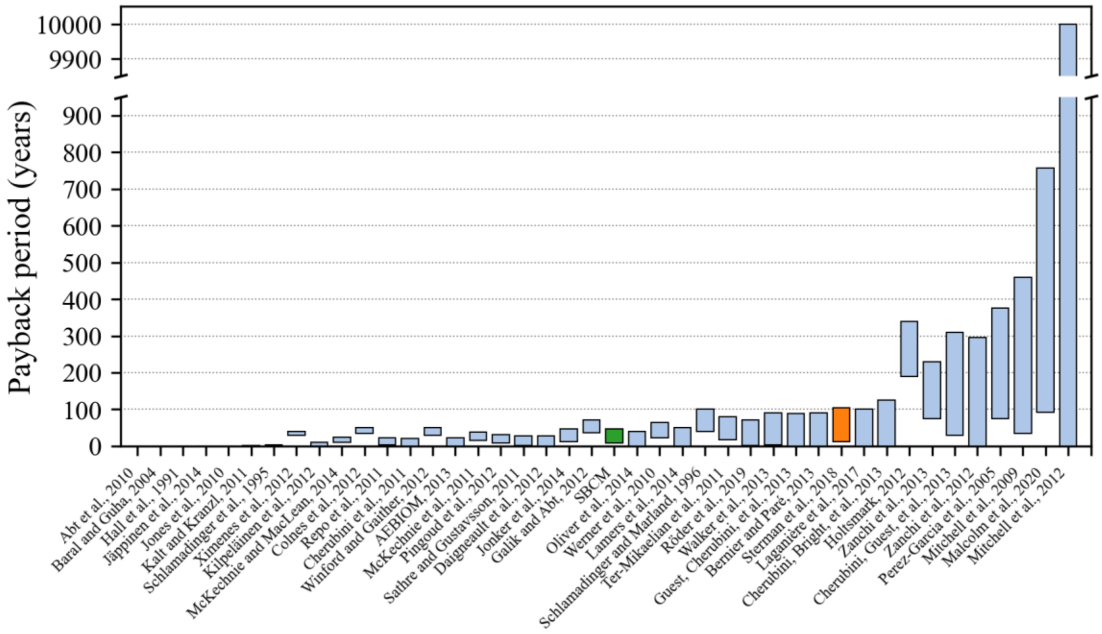

Figure 6.1. SCBM comparison with other published results (coal scenario). SBCM (in green) shows a marked reduction in payback period compared to the Sterman et al. model (orange) as well as a decrease in the range of possible outcomes.

In contrast the comparison with a gas counterfactual (Figure 6.2) shows a substantial increase, although this is not consistent across the forest types studied.

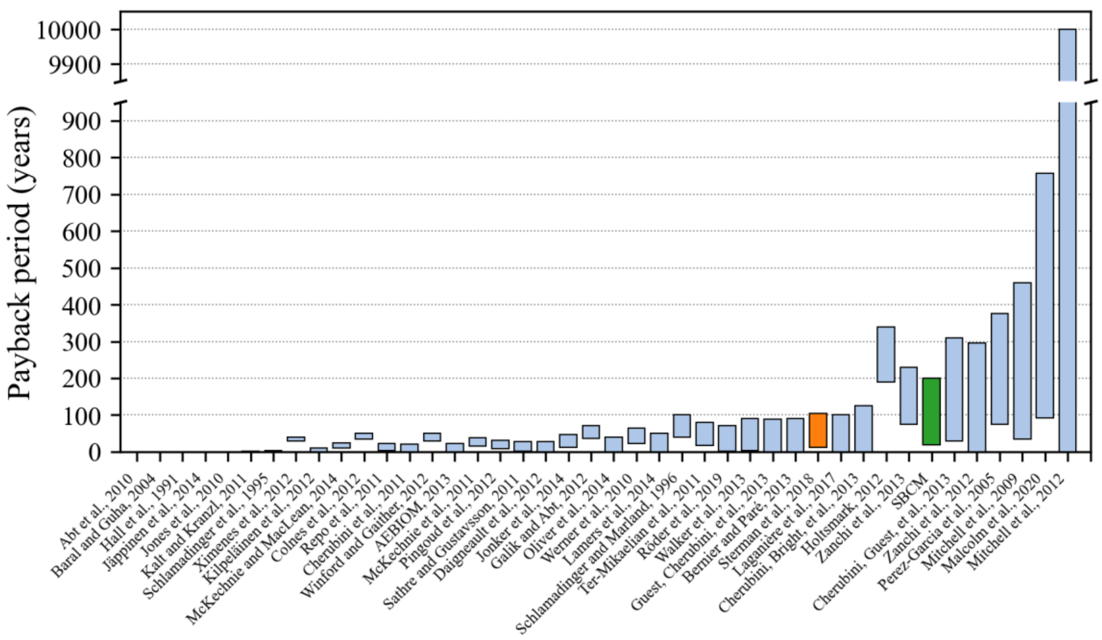

Figure 6.2. SCBM comparison with other published results (gas scenario). SBCM (in green) shows an increase in payback periods, as well as substantial increase in the range of possible results.

It should be noted that these examples do not show BECCS scenarios due to the inability of payback to describe negative emissions meaningfully. The BECCS scenarios resulted in negative absolute emissions by between 10 and 44 years.

6.4 Model application and usefulness

This work clearly demonstrates the need for better comparisons between different models, techniques, and experimental assumptions. This is particularly true in an increasingly polarised and toxic public debate on the sustainability of biomass fuels. While it is tempting to express surprise that so little agreement has yet been reached in the academic literature over accepted conventions when conducting this kind of study, this is perhaps explained by difficulties in conceptualisation, particularly in view of their superficial simplicity.

The development of SBCM is primarily intended to address this issue and allow researchers to compare their work with existing findings and to properly and completely articulate the assumptions they make when publishing new work.

SBCM provides a fully documented, accessible starting point for researchers working on the sustainability of forest-sourced solid biofuels, and it is hoped that it will provide some common ground when addressing this subject. It is also hoped that further work on this subject will allow the simplification of the terms used in this area to be clearer when disseminating the findings to policy makers and an increasingly sceptical public.

6.5 Limitations and further research possibilities

As with any work of this kind, the research undertaken has boundaries and limitations. In most cases these limitations also represent a range of interesting and potentially fruitful avenues for further research. These have not been pursued further due to constraints of time, capacity, scope, and budget, but could provide opportunities for further development.

6.5.1 Forest growth modelling

SBCM 2.0 provides a robust model for forest growth and soil carbon in eight forest types as discussed in Chapter 2. However, as identified in Chapter 3, the application of the Chapman-Richards growth curve to training data without a clear asymptote is problematic and this means that for the non-plantation forests, the model becomes unreliable for periods longer than 100 years. This does not preclude its use for shorter periods, but does call into question the extremely long rotations used by Sterman et al. as discussed in Chapter 5.

An obvious opportunity for further research would be to upgrade SBCM with one or more alternative growth functions and additional training data (if available) to provide a comparison for balance and to check whether the different growth functions are able to further improve the model over longer periods.

In addition to this, SBCM could relatively simply be adapted to include forest types elsewhere in the USA, using the original training data, or for other world regions and forest types. In particular, the UK does not appear to have an open-source peer-reviewed software-based model available to the forest industry and this could provide a useful tool. Further work would need to take place to improve the accessibility of the model, calculate parameterisations for a range of growth rates for each species, and identify high quality soil data or an appropriate soil carbon model such as YASSO (Viskari et al., 2022), but an approximation based on existing yield tables would not be difficult to achieve.

6.5.2 Improve the response to climate change

SBCM as it stands includes the code to correct for carbon fertilisation (Equation 2.5). This was not used in this research to minimise confusion when results were compared directly with existing published work. This could be the subject of further work to simulate the expected response of specific forest types to changing atmospheric CO_2 and coupled with a model dealing with atmospheric carbon such as FaIR (Leach et al., 2021). This would allow further research looking at the long-term effects of forest management and biomass use over time. Further additions could be made to include other non-CO_2 GHGs and other climate effects such as albedo change, although this would risk adding a spatially explicit component to the model which is not supported by the existing training data.

6.5.3 Supply chain modelling

The supply chain modelling in SBCM is very simple. This is beneficial during development, when attempting to identify clear causes and effects, or when dealing with hypothetical scenarios, but less useful when addressing real-world conditions. If work is carried out to improve the forest growth component of the model – to provide site-specific data to inform management decisions for example, further work would also be needed to improve the resolution of the supply chain model. At present SBCM would not be an appropriate tool to guide decisions about processing technologies, transport routes, or infrastructure site. Work of this kind has been used by the UK government for reporting purposes in the (now rather dated) B2C2 Calculator (E4Tech, 2015) but has not been clearly coupled with a forest management model.

6.5.4 Harvested wood products

SBCM follows the assumption that all felled material is used for fuel purposes. While this may sometimes be the case the low value of biomass fuel compared to other HWPs would suggest that it is not the preferred market for timber. HWPs have different life expectancies usually modelled by half-life (Braun et al., 2016) and require different types / qualities of timber for production. The life expectancy of HWPs could well be expected to have a profound impact on the mass balance of carbon following woodland management. Biomass fuels in SBCM are assumed to have a life-span of <1 year, but a range of other products (building timber for example) could be expected to immobilise carbon for a much longer period. The interrelationship between this variable lifetime, the counterfactual scenario and forest management is extremely complex as it could potentially include a range of forest supply chains for different products and a cascade of post-use products re-entering the supply chain, as well as a larger number of different counterfactual products

The product assortment available from forests depends on the shape of felled trees (form) the species, length and diameter. These are all dictated by site conditions, particularly initial spacing, and the timing and intensity of silvicultural thinning. This links closely with the enhancements proposed in Section 6.5.1

6.5.5 Economics

A number of authors (Schulze et al., 2012; Roberge et al., 2016) have suggested that increasing the economic value of poor quality timber will lead to a downward pressure on rotation length. This is impossible to quantify with any certainty without the addition of an estimate of economic value for different HWPs and an estimate of product assortments defined by different management decisions as described in 6.5.1 and 6.5.4. While economic valuation of different product streams is likely to be relatively simple, the implications for inclusion of other HWPS make this modification of the model extremely difficult to develop in a coherent and comprehensive way.

6.5.6 Forested landscapes

SBCM operates at a stand level – an intermediate spatial scale which models a homogenous area of forest at the same age. This can, in theory, be expanded simply to cover a forested landscape by simulating a number of stands with different ages simultaneously (as illustrated in Figure 1.12). Combining these in a coherent system boundary raises difficulties because different methods imply different assumptions about attribution of carbon flows and baselines.

As discussed in Section 1.3.2 a landscape scale model is difficult to justify without the inclusion of HWPs since omission risks either assuming forest growth does not exist in the counterfactual, that biomass use can take advantage of the net carbon flux generated by producing products outside the temporal system boundary, or adopting the widely rejected dividend then debt approach (as shown in Table 6.1)

Table 6.1. The implications of spatial boundaries and HWPs

	Static boundary	**Expanding boundary**
HWPs excluded	Forest areas are included within the boundary which are either fully mature, or are partially grown. This means we either assume that mature forests blocks are being felled solely for biomass, or the (negative) carbon flux from part grown forests can be counted towards biomass use when they were felled for some other reason. The only coherent way of handling this is by adopting the dividend then debt perspective.	Forest areas are added to the model as they reach a baseline (rotation age). Again, this implies that biomass fuel is the only reason for felling, and also fails to take account of forest growth in the counterfactual case. It is arguable that we could assume forest growth is more or less static in the counterfactual but the only situation when this would take place is if these forests had reached full biological maturity i.e. an assumption that old growth forest is felled exclusively for biomass use.
HWPs included	This is coherent, but we will need to make some assumptions about existing HWPs already in circulation	Again, this does not take account of forest management in the counterfactual case.

6.5.7 More counterfactual nuance

A number of other scenarios could be added (as discussed in 4.5). These could be developed to reduce supply chain uncertainties for biomass production, further constrain the value for the efficiency of BECCS, and increase the number of cases studied. To develop this fully would require modification of the model to include an estimate of infrastructure emissions, since SBCM currently assumes that the emissions inherent in installation and development of infrastructure are equal across all technologies. This assumption while plausible for a coal counterfactual and (slightly less so) for a gas counterfactual is not valid when looking at other fuels. Renewables have no fuel supply emissions per se, and nuclear energy which generates no direct CO_2 from use, has radically different infrastructure requirements including long-term spent fuel storage. This could be combined with modifications to the supply chain modelling to allow greater variability in assumptions regarding transport and processing emissions for different fuel types as discussed in Section 6.5.3.

6.5.8 Additional extensions / possible minor changes

Finally, a number of extensions, updates, and modifications of the code would allow wider comparisons / analysis, and improve accessibility for an end user.

Add new metrics

SBCM currently uses payback period as the primary metric. This has weaknesses as described in Chapter 5, but is intuitive and easily understood. An additional metric of “absolute payback” or time to negative carbon emissions could be added to the model to compensate for these weaknesses (particularly when addressing the effectiveness of BECCS). Alternatively, other metrics exist such as gross and net carbon debt (described in Chapter 1), and the GWP_{bio} (as promoted by Cherubini et al., 2012). These are less widely used (and less easy to conceptualise) but could facilitate wider comparisons with other published work.

Usability / UI improvements

While SBCM is a simple model, which is easy to conceptualise and configure. It does require a working knowledge of Python to modify and operate. Introduction of a user-interface (UI) would remove this barrier and increase accessibility to a wider audience.

Code optimisation

One of the most common criticisms of Python as a coding language is that execution of code is slow compared to lower-level languages. Considering the simplicity of the model, some aspects of SBCM take a long time to run in a Python environment (the identification of new parameters described in Chapter 3 takes around 10 minutes for example). It seems likely that bottlenecks exist in the code, and that these could be addressed by optimisation of the code as written, by conversion of some modules to Cython (which compiles Python code to .exe format) or by some other method.

Automated margins of error

As described in Chapters 3, and 4 uncertainties exist in both the forest site sub model, and in the parameterisation of supply chains. This can be communicated, but at present relies on the end user to intimately understand the methods and processes used in the model and address them manually. An extension to SBCM could include more structured sensitivity testing and automated error bar reporting (potentially including standardised graphical output). This would improve the clarity of results communication and allow more robust comparisons with other tools.

Higher level assumption / methodological choice

The majority of comparisons in this study have been developed manually based on explicit descriptions of assumptions, parameters, and the like. A useful further development of SBCM would be to separate out parameter use, assumptions, and methods used – essentially setting them as higher-level functions rather than requiring a more detailed understanding of SBCM implementation to deliver.

6.6 Final Conclusions

The development and use of SBCM to assess the impacts of different parameters, assumptions, and metrics on biomass supply chains has successfully illustrated a number of critical points. The highly heterogeneous set of different methods present in the literature effectively obfuscates the sustainability of biomass use, and while it is possible (without much effort) to identify scenarios which are clearly sustainable or otherwise, the range of uncertainty leads to a substantial grey area. This work attempts to articulate the effects of different assumptions made which have an effect on the apparent desirability of biomass supply chains as a sustainable climate change mitigation technology.

This study reinforces the conclusion that conventional forest-sourced biomass use does not generally result in negative emissions over any timeframe and as such never reaches a point where net emissions equal zero (which some might call "carbon neutrality"). Referring to Equation 1.1 (page 16) ΔC_{site} is able to (though does not always) return to zero if full site recovery occurs, the supply chain however inevitably involves emissions of some type and there is no mechanism for reversing these without an increase in ΔC_{site}

above pre-felling (or pre human) levels or some other form of carbon removal. As such, conventional biomass sourced directly from forests is best viewed as a low(er) emission energy technology, rather than a panacea for zero emission global energy generation. Alternative sources of biomass fuel (such as energy crops, agricultural waste, and post-consumer woody waste) are expected to have different carbon emission profiles, but are outside the scope of this study.

Given that this work focusses primarily on the payback periods associated with different biomass and counterfactual comparisons, it seems reasonable to make some recommendations on the forest / region cases which could be deemed to be acceptable. These recommendations will not remain static, and if we take 2050 as the functional deadline for net zero operation of international energy generation technologies, the obvious solution would be to adopt a gradual reduction in acceptable payback period or time to net zero operation to ensure that this deadline is not breached.

Based on the results of this work, when operating conventional biomass to electricity supply chains, some plantation forests could continue to be used in the short term when compared to natural gas (payback periods indicate continued use for the next 2-4 years) and a wider range of forests remain acceptable when compared to coal (payback periods suggest continued use for the next 9-26 years: see Table 5.3). While this makes sense in principle, the limitations of payback period as a metric are once again apparent. A payback period of zero is not equivalent to a net emission of zero, and the times required for negative emissions operation with BECCS range between 10 and 44 years.

In all cases, conventional biomass combustion without CDR technologies should be halted before 2050. It is hoped that supply chains these could be converted to BECCS operation. BECCS scenarios including the storage of a high proportion of site carbon post combustion allows the $\Delta C_{atmosphere}$ (from Equation 1.1) to become negative when the initial carbon debt is repaid. This certainly has a more attractive carbon profile than conventional biomass, and represents a CDR technology which could be implemented at scale. This is not to say that a wholescale reliance on BECCS is automatically desirable, for a number of reasons:

- Global forests provide a wide range of ecosystem services (Figure 3.1) and use of biomass for fuel may preclude the maintenance and production of these other services. There are a worrying number of allegations of mature forests with a high value for other ecosystem services being felled for biomass production. As described elsewhere, deforestation for fuel production is not a sustainable strategy.

- Global fertile land area also provides a number of services, and an expansion of forest planting while advantageous in some cases, could lead to reductions in agricultural productivity and hardship to human populations in others.
- The volatility of carbon stored via CCS is variable depending on technology, but in many cases is not geologically stable. This suggests that BECCS might be a temporary fix rather than a permanent solution
- The rate of global forest growth does not allow a wholescale switch to any form of biomass technology because it simply is not large enough. This emphasises the conclusion that biomass use represents, at best, part of a climate change mitigation solution.
- Depending on a wider range of assumptions and counterfactual scenarios (described in Section 6.4) other uses for forest products may prove to be a more effective use for the NPP represented by the Earth's forests. This study does not take account of HWPs or the emissions associated with their equivalents if the supply chain is diverted into fuel production.
- While BECCS has a payback period of zero years, as described above, this is not the same as net zero operation with respect to carbon. Some perturbation of the atmospheric carbon pool still exists. The net damage caused by BECCS may be relatively small when compared with conventional fossil fuels, but this is not the same as saying that no damage occurs.

This study highlights and reinforces the need for a more comprehensive understanding and agreement on the appropriate methods and assumptions to make in this context.

Electricity generated using biomass fuels is clearly not an optimum long-term solution to decarbonising the world's energy generation. BECCS is an improvement on conventional biomass combustion and can result in a net reduction in atmospheric carbon levels, but this takes time to accomplish and relies on close monitoring of forest sites and supply chains. These findings are consistent with the approach that forest-sourced biomass should be considered a transition technology rather than a desired end point.

There is a clear need for tight regulation of the use of biomass fuels, with a consensus on the methods used to compare alternative supply chains. Acceptable payback periods or times taken to achieve negative emissions should be clearly defined and reduced annually to conform to international emission targets. This should be harmonised with wider work assessing the carbon impacts of burning energy crops, post-consumer woody waste, and agricultural residues.

In the face of strong political, social, and business interests competing to define coherent (and favourable) narratives, the scientific community must reach a consensus on best practice in this field. Further research to provide definitive guidance for policy makers and clearly articulate the costs and benefits for this technology is urgently needed.

quod erat demonstrandum

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Appendix A: Glossary and abbreviations

Term	**Description**
Age class	Trees within a forest which were planted in the same year.
Arboricultural	Relating to the care and management of individual trees (as opposed to silviculture, which is the management of forests)
BECCS	Biomass Energy with Carbon Capture and Storage (discussed in section 4.2.3)
Branch-wood	Wood from tree branches, far more branch-wood is present in decurrant tree species, and this is not always well quantified in forest growth models.
Bioenergy	Energy derived from biological material. May be used for heat only applications, combined heat and power (CHP), and electricity generation. May be used as gas (biogas), liquid (e.g. biodiesel and bioethanol) or solid (e.g. wood chips, pellets, or logs). See Section 1.2.4
Biomass	May simply refer to the mass of biological material in a system (the original ecological meaning) or as it is used here: *energy from the combustion of solid, forest-sourced* material. See section 1.2.5
(Forest) Block	A management unit of forest
Brash	Residues from forest harvesting, usually composed of small diameter branches, leaves, and twiggy material arising from silvicultural operations. Occasionally called “lop and top”.
BVOC	Biological Volatile Organic Compounds
Carbon debt (net and gross)	The loss of carbon incurred between felling and regrowth of a forest site (see Section 1.3.1)
Carbon neutrality	An operation with no net carbon emission -though a wide range of definitions exist: see Section 1.3.1
Carbon Sequestration Parity (CSP)	The point at which a biomass scenario results in a lower emission than the counterfactual. Discussed in Section 1.3.1
CDR	Carbon Dioxide Removal [technology]
CH_4	Methane (a GHG)

CHP	Combined Heat and Power. Refers to technologies which utilise the waste heat from combustion in addition to generating electricity.
Clear Fell	A forest felling operation which removes all trees from a site.
Closed / Open-source	Refers to whether the underlying code used for a piece of software is available publicly (open) or not (closed)
CO_2	Carbon Dioxide (a GHG)
Compartment	A forest management area (sometimes called a block)
Coppicing	A traditional forest management system which relies on tree species which regrow from the stump after felling. Historically this has been used to produce straight low diameter poles for a large range of purposes.
Decurrant	Tree species with large spreading branches (typically hardwoods in the UK). The opposite of Excurrant
DLCA	Dynamic Life Cycle Assessment. An LCA approach which estimates emissions associated with a product and includes subsequent emissions over time.
DUKES	Digest of UK Energy Statistics (e.g. BEIS, 2017)
ERF	Effective Radiative Forcing
Excurrant	Tree species with large spreading branches (typically hardwoods in the UK). The opposite of Decurrant
GHG	Greenhouse Gas
GPP	Gross Primary Productivity. The rate of photosynthesis on site
Form	Used in forestry to describe good or bad sawmilling characteristics. Trees with good form will generally have a straight stem with minimal side branches. Poor form could include excessive branching, rot or disease, an uneven shaped stem, multiple stems etc.
HWP	Harvested Wood Product
IPCC	Intergovernmental Panel on Climate Change

LCA	Life Cycle Assessment. A method for estimating the emissions associated with production of a product, its use, and disposal.
LCA a	Attributional Life Cycle Assessment. A simple assessment of the emissions associated with production of a product in isolation
LCA c	Consequential Life Cycle Assessment. An assessment of the emissions associated with production of a product including a range of indirect effects such as the changes in the use of other products which result
LUC	Land Use Change
LULUCF	Land Use, Land Use Change, and Forestry
N_2O	Nitrous Oxide (a GHG)
NPP	Net Primary Productivity (equal to GPP minus carbon emitted through autotrophic respiration)
NPV	Net Present Value. The value of an asset based on the discounted income and costs expected in the future
O_3	Ozone (a GHG)
Payback (period)	The time taken to reach CSP (discussed in Section 1.3.1)
Plantation	A human-planted regularly spaced, even-aged forest (often a monoculture).
RMSE	Root Mean Square Error (see Equation 2.12) a statistic measuring the fit of observed and expected values. Used here to judge the success of a non-linear regression
Rotation	A full managed lifecycle of a forest including planting, growth, and final felling. Used to describe the length of time a forest is left to grow (rotation-length) and when it is due to be felled (rotation age)
Roundwood	Timber as it grows in the tree (i.e., in the round rather than having been processed)
SBCM	Simple Biomass Comparison Model
Silvicultural	Relating to the care and management forests (as opposed to arboriculture, which is the management of individual trees)

Silvicultural Thinning	A silvicultural tool used to enhance the value of a stand of trees at the final felling stage. A proportion of trees are felled early which changes the growth patterns of remaining trees (discussed in Section 5.2.1). Trees removed for this purpose are described as "thinnings"
Silvo-pastoral	A historical forest management practice which combines the management of land for useful timber, and grazing / shelter for livestock.
SSP	Shared Socioeconomic Pathway(s). Scenarios developed by the IPCC to estimate the changes in a range of different technologies relating to climate change (see Section 1.2.5)
Stand	A general description of a unit of forest
Stem-wood	Wood that comes from the stem of a tree (as opposed to the branches)
Stocking density	The number of trees per unit of area
Understorey	Plant species which grow under the forest canopy
UNFCCC	United Nations Framework Convention on Climate Change
Yield class	A classification of growth rate used in UK forestry, based on estimated average increment in $m^3.ha^{-1}.yr^{-1}$ over the rotation.

Appendix B: Biomass supply chains model analysis

Table B.1 An overview of biomass supply chain models with reference to the selection criteria described in Section 2.2

Name	**Publisher(s)**	**Open source**	**Platform**	**Notes**
Biomass and Biogas Carbon Calculator (B2C2)	(Denvir et al., 2015)	No	Unknown	Hard coded assumptions in compiled software (.exe) No site regrowth factored in (assumes biomass is carbon neutral at source following IPCC accounting convention) Used to calculate processing and end use emissions for UK Renewable Heat Incentive qualification.
Biomass Environmental Assessment Tool (BEAT / BEAT2)	(Defra, 2010)	No	VBA (with MS Access and Excel	Technoeconomic planning tool – identifies economic and environmental costs and benefits for a range of different biomass supply chains. No site regrowth factored in (assumes biomass is carbon neutral at source following IPCC accounting convention) Includes a wide range of different bioenergy feedstocks and end uses which are not required for this programme of research
Air emissions, Greenhouse gas emissions, and Energy use model for the Bioeconomy (Bioeconomy AGE)	(Zaimes, 2015)	No	MS Excel	Whole bioeconomy model which includes a range of feedstocks and processes. Focussed mainly on transport biofuel (not solid biofuels) Described briefly in (Rogers et al., 2017; Dunn et al., 2020)
UK and Global Bioenergy Resource Model	(Bates and Gandy, 2017)	No	MS Excel (& VBA)	National – level model estimates the potential UK and global bioenergy fuel resource available to the UK from 2015 to 2050 under different scenarios.

Name	Publisher(s)	Open source	Platform	Notes
Biomass Value Chain Model (BVCM)	(ETI, 2015)	No	AIMMS	Proprietary model for high-level assessments of biomass supply, processing, and use model including forest regrowth. Growth is limited to the first 50 years in the case of forest rotations, maximum temporal resolution is 5 years. Described in (Samsatli et al., 2015)
CARBINE	(Forest Research, n.d.)	No	Fortran	Proprietary research owned by FR, not available for research or modification Described in (Robertson et al., 2003)
CBMCFS3	(Canadian Forest Service, 2019)	No	Unknown	Proprietary research owned by CFS, free to use, not available for modification Described in (Kurz et al., 2009)
C-Flow	(CEH, n.d.)	No	Excel	Proprietary research owned by CEH, not available for research or modification Described in (Robertson et al., 2003)
CO_2fix	(European Forest Institute, 2004)	No	C++	Closed source model (although free to use) produced by the EFI Described in (Schelhaas et al., 2004)
EFI GTM	European Forest Institute	No	Unclear	Global forest sector model, includes a very wide range of different elements including international trade, market pricing and HWP recycling. Described in (Kallio et al., 2004)
EFIScen	(European Forest Institute, n.d.)	Yes	C++	Open-source but requires detailed knowledge to use (and knowledge of C++) Described in (Sallnäs, 1990)
FORCARB2	USDA	Yes	FORTRAN	Described in (Heath et al., 2010)
Global Forest Model (G4M)	(IISA, 2022)	Yes	C++	Described in by (Kindermann et al., 2006; Kindermann et al., 2013; Gusti and Kindermann, 2011)
GORCAM	Oak Ridge Laboratory /	Not available	Unknown	Described by (Schlamadinger et al., 2003) Older model no longer available

Name	Publisher(s)	Open source	Platform	Notes
	Joanneum Research			
Growth, Yield and Carbon Balance Models for Southern Pine Stands	(Carbon Resources Science Center - IFAS - University of Florida, n.d.)/	Yes	MS excel	Very thorough set of model for the growth of a range of pine species in the southern USA. Limited to forest growth, without biomass supply chains or counterfactual scenarios. Described in (Gonzalez-Benecke et al., 2010; Gonzalez-Benecke et al., 2011; Gonzalez-Benecke et al., 2012; Gonzalez-Benecke et al., 2015; Gonzalez-Benecke et al., 2017)
Land Carb	(Pacific Northwest Research Station, n.d.)	No	?	Not clear whether this is still available, website is broken link Optimised for Pacific North West
Landis PRO	University of Missouri	Yes	c#	Described in (Mladenoff, 2004) Not clear whether this is still available, website is broken link
Landis II	(LANDIS-II Foundation, 2022)	yes	c#	Large scale forest landscape model Very complex Features in many publications (available here: https://www.landis-ii.org/publications) but initially described in (Scheller and Domingo, 2005)
Sub-Regional Timber Supply (SRTS)	Southern Forest Resource Assessment Consortium	Yes	MS Excel	Landscape scale model giving long term, high-level estimates of timber forest yield in the south eastern USA Does not include supply chains or end use
Sterman et al. model	Sterman et al.	Yes	Vensim	Analysed in the main document Described in (Sterman et al., 2018a)
ToSIA	European Forest Institute	No	Java	Optimised for the north-west Atlantic coast of Europe (Ireland, Iceland, Scotland, and parts of Norway, Sweden and Finland) Proprietary software, not open source.

Name	Publisher(s)	Open source	Platform	Notes
Woodland carbon code calculator	(UK Woodland Carbon Code, 2021)	Yes	MS Excel	An Excel version of the UK forest yield tables (Matthews et al., 2016) Provides rough (and heavily padded) estimates of woodland carbon sequestration in a UK context. Does not include biomass supply chains or end use.

Appendix C: Sterman et al. scenarios

Table C.1. Scenarios used by Sterman et al. (2018a) with added names and descriptions

Code	**Name**	**Scenario description**
Cf	Counterfactual	The emissions from coal combustion.
S0	Zero-carbon energy source	The emissions associated with producing an equivalent amount of energy from a hypothetical energy source with zero carbon emissions per unit of energy. Since the emissions cited in Sterman et al. (2018a) are indexed to a counterfactual baseline, this is included to provide an indication of the emissions associated a baseline of zero.
S1	Regenerating coal	This hybrid scenario is a combination of the supply chain emission and efficiency values for coal, with the regenerative capacity of biomass fuel (essentially the opposite of scenario S4). Since there are fundamental differences between coal and biomass supply chains, its utility is questionable. This scenario assumes a 25% felling intensity of mature forest.
S2	25% thinning	The emissions associated with biomass use, where biomass is sourced from forests with a 25% felling intensity. The assumptions made by Sterman et al. regarding the nature of thinning, are not correct since this seems to be a 25% fell of a fully mature forest and a thinning takes place before the trees are mature. This is discussed at greater length in Chapter 5
S3	95% clear-fell	The emissions associated with biomass use, where biomass is sourced from forests with a clear-fell management plan. This is assumed to recover 95% of the standing biomass for fuel use. The assumed fate of the remaining 5% is not described by Sterman et al.
S4	Inert biomass	The emissions associated with total site deforestation, without regeneration or subsequent release of carbon from soils. This hybrid scenario is a combination of the supply chain emission and efficiency values for biomass, with the regenerative capacity of coal (i.e. none within the modelled timeframe) essentially the opposite of scenario S1.

Code	Name	Scenario description
S5	Deforestation and land use conversion	The emissions associated with total site deforestation, without regeneration, but with subsequent release of carbon from soils (e.g. following conversion to agriculture). This leads to a loss of site carbon without the opportunity to recover carbon through the negative emissions associated with forest regrowth.
S6	Clear-fell with species conversion	As modelled in scenario S3, however, the species (at full biological maturity) which is felled, is replaced with a different species. This leads to a disparity between the carbon released by felling, and the potential uptake available through regrowth. As in scenario S3, the assumed fate of the remaining 5% is not described by Sterman et al.
S7	Sustained yield (continued demand growth)	Instead of modelling the emissions associated with a one-off pulse of supplied energy, the model is modified to produce a sustained yield of energy on an annual basis. This annual demand is either assumed to continue to increase over time (scenario S7) or increase to a pre-determined point, and then remain the same (scenario S8). These scenarios are limited because they do not reflect rotational forest management accurately (as discussed in Chapter 5)
S8	Sustained yield (attenuating demand growth)	

Appendix D: Revised forest model parameter values (from Chapter 3)

Table D.1 Revised parameterisations for the forest growth model as described in Chapter 3

	NE maple / beech / birch	NE oak / hickory	NE oak / pine	SC oak / hickory	SC oak / pine	SC shortleaf / loblolly pine*	SE shortleaf / loblolly pine*	SE longleaf / slash pine*
forest_start	0.0	0.0	0.340281301096724	5.42945516622011	3.65268974558872	4.0135458190631	4.28585292676176	4.08908392634156
soil_start	118.447213201702	99.3525392306797	112.435248693524	50.7449560638913	59.953955472225	71.4900652676356	102.080169133964	139.908346501841
B	391.120695434745	999.98066533353	245.824688209949	525.902073071337	207.437397248961	174.735497838745	145.058305977820	158.381546556469
phi_ab	0.000000403802129175386	0.000915177518296519	0.0063476052809224	0.0525499310427132	0.00365515757620042	0.284482533957661	0.206569020813397	0.261363046096014
k	0.0057664386372377	0.00292198301404347	0.00792870522461342	0.00298640631404372	0.00942813788630074	0.0027517036240606	0.00301352269954644	0.00100611255289063
v	1.38571943653264	0.924633593893648	1.30275288757678	1.49999999999999	1.22984447502163	0.726671377676232	0.902693651454447	0.813397397057516
phi_ba	0.000183124443593115	0.0	0.000000000029945935021	0.0499965643738088	0.0000105004470048127	0.0499999569334574	0.000000000004410111289	0.0364802871181941
phi_bs	0.00753710354311497	0.00655935870360692	0.0056205453767558	0.00243237936614515	0.00199235840621598	0.00561918616334578	0.00452915503914184	0.00590304833703096
phi_sa	0.0059431566238568	0.0123179468226925	0.004195988464765840000	0.001331958318115520000	0.000929724539265572000	0.011209041027797500000	0.006191643539750210000	0.005525104654706860000
RMSE	3.75847703888947	3.50037731470384	3.70651663369493	1.38643291574463	1.04563944496873	0.953968451997551	1.05173974551195	1.04512436809478

Appendix E: Full results from supply chain parameter modelling (Chapter 4)

Table E.1 Payback periods under a 25% fell scenario

Counterfactual fuel	**25**	**BECCS (high efficiency)**	**BECCS (low efficiency)**	**Conventional biomass (new params)**	**Conventional biomass (Sterman et al. params)**
Natural Gas	NE maple / beech / birch	0	0	187	244
	NE oak / hickory	0	0	199	244
	NE oak / pine	0	0	116	160
	SC oak / hickory	0	0	56	75
	SC oak / pine	0	0	87	120
	SC shortleaf / loblolly pine*	0	0	8	10
	SE shortleaf / loblolly pine*	0	0	7	9
	SE longleaf / slash pine*	0	0	7	9
Coal (new params)	NE maple / beech / birch	0	0	29	95
	NE oak / hickory	0	0	47	119
	NE oak / pine	0	0	17	55
	SC oak / hickory	0	0	9	29
	SC oak / pine	0	0	13	43
	SC shortleaf / loblolly pine*	0	0	2	4
	SE shortleaf / loblolly pine*	0	0	2	4
	SE longleaf / slash pine*	0	0	2	4
Coal (old params)	NE maple / beech / birch	0	0	33	98
	NE oak / hickory	0	0	52	122
	NE oak / pine	0	0	19	58
	SC oak / hickory	0	0	10	30
	SC oak / pine	0	0	15	44
	SC shortleaf / loblolly pine*	0	0	2	4
	SE shortleaf / loblolly pine*	0	0	2	4
	SE longleaf / slash pine*	0	0	2	4

Table E.2 Payback periods under a 95% fell scenario

Counterfactual fuel	95	BECCS (high efficiency)	BECCS (low efficiency)	Conventional biomass (new params)	Conventional biomass (Sterman et al. params)
Natural Gas	NE maple / beech / birch	0	0	195	253
	NE oak / hickory	0	0	200	245
	NE oak / pine	0	0	150	196
	SC oak / hickory	0	0	95	122
	SC oak / pine	0	0	106	144
	SC shortleaf / loblolly pine*	0	0	19	22
	SE shortleaf / loblolly pine*	0	0	20	23
	SE longleaf / slash pine*	0	0	19	22
Coal (new params)	NE maple / beech / birch	0	0	33	102
	NE oak / hickory	0	0	47	120
	NE oak / pine	0	0	32	82
	SC oak / hickory	0	0	22	56
	SC oak / pine	0	0	18	55
	SC shortleaf / loblolly pine*	0	0	8	14
	SE shortleaf / loblolly pine*	0	0	9	15
	SE longleaf / slash pine*	0	0	8	14
Coal (old params)	NE maple / beech / birch	0	0	37	106
	NE oak / hickory	0	0	52	123
	NE oak / pine	0	0	36	85
	SC oak / hickory	0	0	24	58
	SC oak / pine	0	0	20	57
	SC shortleaf / loblolly pine*	0	0	8	14
	SE shortleaf / loblolly pine*	0	0	9	15
	SE longleaf / slash pine*	0	0	9	14