TOWARDS IMPROVED ACCOUNTING OF ECOSYSTEM ENERGY IMPACTS

IN INDUSTRIAL-NATURAL SYSTEMS

by

JOSHUA J. DUNLAP

(Under the Direction of John R. Schramski and Ke Li)

ABSTRACT

In industrial-natural systems, energy measures both industrial efficiency and environmental impacts. However, these aspects are often studied disparately and across disciplines. This research addresses this gap by improving sustainability assessments of biomass production systems to account for ecosystem impacts and uncertainty in greenhouse gas emissions. First, system boundaries of forestry energy analyses are expanded to include changes in potential ecosystem biomass stocks, or foregone biomass, allowing for comparisons between forest management's human and ecological dimensions. Trade-offs show more intensive practices harvest more net energy and result in greater foregone biomass while less intensive practices are more efficient and reduce these impacts. Imbalances between the human and ecological metrics persisted across all managements, indicating that reducing intensity is insufficient for completely mitigating biomass losses. Nevertheless, this extended model identifies strategies that enhance industrial efficiency while minimizing ecological impacts, paving the way for more effective biomass production practices. Second, this research assesses uncertainty in the global warming impacts of biochemical production to identify factors ensuring emission reductions. Global warming impacts vary based on processing and modeling factors, but reductions are consistently achieved with low-intensity feedstocks, such as energy crops. Uncertainty in factors like enzyme production can negate these benefits, yet integrating coproducts emerges as a necessary factor for ensuring emission reductions. Identifying and producing coproducts is thus essential for a bioeconomy and global emission reduction efforts. Highlighting the interconnected nature between the human and environmental dimensions in industrial-natural systems provides invaluable insight into biomass production and current versus needed management strategies.

Keywords: industrial-natural systems, energy analysis, ecosystem energetics, global warming impacts, biomass production

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JOSHUA J. DUNLAP

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JOSHUA J. DUNLAP

Major Professor:	John R. Schramski
Co-major Professor:	Ke Li
Committee:	KC Das
	Ernest W. Tollner

Electronic Version Approved:
Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
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DEDICATION

To my father Scott W. Dunlap who instilled within me an undying thirst for knowledge, wonder, and above all, nature.

For this I remain forever grateful and miss you more than you know.

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Sir Isaac Newton once remarked that his accomplishments were the result of "standing on the shoulders of giants". With the same sensibility and utmost gratitude, I acknowledge that my own achievements are as much a testament to my teachers, peers, friends, and family as they are to my own efforts. To my parents, Sanda and Scott, I owe everything. You always supported my ideas, taught me to be endlessly curious, and gave me a love for science and nature. I would not be where I am without you. I am eternally grateful for my partner, Nancy, for your unending love and, most importantly, for entertaining my weekly rants on energy and ecosystems. You inspire me more than you know. To Dr. Schramski, for welcoming us to Athens and for being more than an advisor, but a mentor and a friend. You expanded my knowledge of energy and ecology and made me a better researcher. I am immensely honored to have had your guidance and mentorship over the past four years. To Dr. Li, for teaching me sustainability assessment methods and helping me grow as an environmental engineer. To my committee members, Dr. Das and Dr. Tollner, for your academic support throughout this process. Lastly, to everyone at the University of Georgia, the College of Engineering, and all of my newfound friends in Athens for your support, friendship, and encouragement.

PREFACE

This dissertation is motivated by the need for a deeper recognition of the role of energy in the interactions between humans and ecosystems. Such knowledge stands in stark contrast to energy's use throughout modern civilization, whose history has been marked by the increased orientation of energy science and engineering toward the obtainment, refinement, and utilization of ever-more energy resources. Yet, in the context of our interactions with nature, energy is, and describes, much more. Consider a typical design problem posed to countless decades of scientists, engineers, and builders – the diversion of a flow from a river for human purposes.

To the scientist, energy describes the physical properties and dynamics of the river and its flow. The potential energy gradient set by elevation differences controls the flows conversion to kinetic energy, setting limits to its flow rate. In turn, these properties shape the river's geomorphology. Meanwhile, to the engineer, energy analysis and theory are crucial. Bernoulli's equation, derived from the conservation of energy, facilitates the design of hydraulic structures to transport and deliver the flow through artificial channels, overcoming the energy losses dissipated by the channel's unnatural diversion. The builder, while not directly contending with energy, applies its power indirectly. The machines used for earthworks and construction require energy in the form of liquid fuels and electricity. The concrete, timber, rock, and steel construction materials require energy to extract, process, transport, and use, thereby embodying energy within the construction process.

Still, a broader context is missing. The thermodynamicist – a student of nature's energy – is required to model the missing, more fundamental, aspects of the involved physics. The diversion of water flow extracts energy from the river but in so doing, also diverts power away from natural processes that would have driven downstream sediment transport and erosional processes. This disruption of energy driving natural processes impacts ecological processes, reduces the energy available downstream to fertilize deltas and floodplains, and thereby alters the erosional processes which shape coastal ecosystems. How many rivers can be altered until the resulting environmental impacts are too large? What is the relationship or trade-off between the energy inputs required to alter the rivers flow and the resultant removal of energy from downstream processes?

In this context, energy is the ultimate indicator; its applications unparalleled in its descriptive power. It describes the river's flow and structural characteristics, enables the design of manmade structures to control it, embodies the inputs required for their construction, *and* describes the resultant downstream ecological impacts caused by human activities. Recognizing the foundational role of energy, this research aims to be an attempt at capturing and quantifying the multifaceted nature of energy together, along one process chain. Rather than a river, this work focuses on biomass production systems, which are crucial for the sustenance of civilization and also intrinsically embedded within ecosystems. Much like the river's diversion, energy expresses disparate aspects of biomass production; from the inputs invested to support its growth and maintenance to the impacts induced by its extraction and conversion to useful products.

It is my hope that this research serves as a foundation for future work and fosters a deeper consideration of the energetic implications of our interactions with ecosystems and nature. My own journey during this dissertation has been bountiful with support from amazing academic mentors, colleagues, friends, and family. The importance of this work extends beyond academic achievement, but instead marks the beginning of a lifelong career as an ecologically focused environmental engineer.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

> It [civilization] becomes possible only after an agelong accumulation of energy, by the supplementing of income out of capital. Its appetite increases by what it feeds on. It reaps what it has not sown, and exhausts, so far, without replenishing. Its raw material is energy and its product knowledge. The only knowledge which will justify its existence and postpone the day of reckoning, is the knowledge that will replenish, rather than further diminish, its limited resources.
>
> ― Frederick Soddy (*Matter and Energy*, 1911)

1.1 HUMANITY'S ENERGETIC METABOLISM AND ECOLOGICAL IMPACT

Despite being written a century ago, Frederick Soddy's insights are remarkably relevant today as human civilization now consumes energy at rates comparable with natural planetary processes. Consider, for example, the extraordinary annual consumption of ~600 exajoules (EJ, where 1 EJ = 10^{18} joules) of technical energy in 2021 (IEA, 2021), a magnitude that exceeds or is comparable to, the power of many geologic processes within the Earth System (Kleidon, 2010). Fundamentally, energy is defined as the *capacity to cause change*. Thus, the laws of physics necessitate that large energy consumption and discharge rates will also result in substantial environmental *changes* or impacts. Such large consumption underscores the critical need to better understand the relationship between human energy use and its ecological and environmental ramifications and is imperative for ensuring the future sustainability of human civilization.

Like all organisms, energy and material exchanges characterize humanity's most basic relationship with the natural environment and the broader biosphere. In this context, human civilization is a thermodynamically open, metabolic system (**Figure 1.1**). It extracts energy and materials from the environment, processes them to build and maintain internal structures within the global economy – the *technosphere* – and then discharges the wastes and low-quality degraded heat energy back to the environment, as set forth by the second law of thermodynamics (see for example, (Odum, 2007; Smil, 2007)).

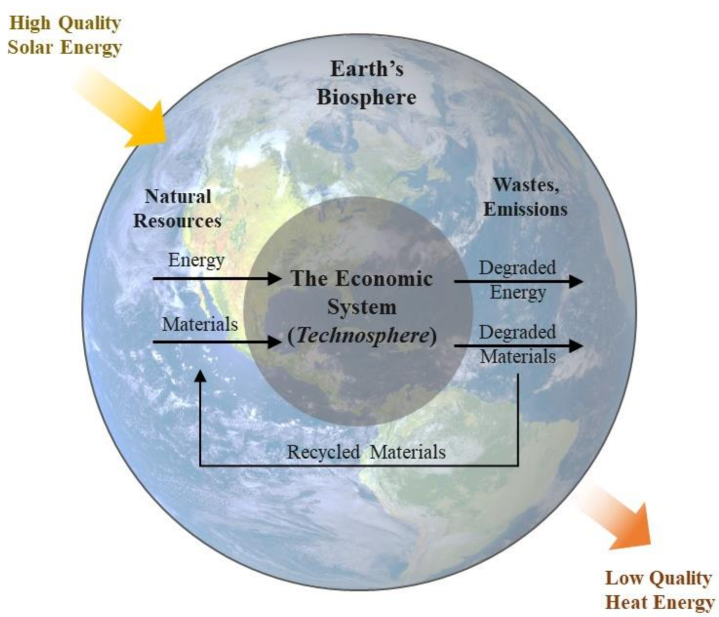

Figure 1.1 Civilization as an open thermodynamic system embedded in the biosphere. Figure re-adapted from (Cleveland & Ruth, 1997).

These transactions encapsulate the *sociometabolism* of human civilization embedded within its natural environment and are routinely studied by sociometabolic research (SMR) (Martinez-Alier & Schlüpmann, 1994; Fischer-Kowalski & Hüttler, 1999). This framework integrates human societal processes within the larger boundary of Earth's biosphere, illustrating humanity's interconnection with, and reliance on, surrounding ecosystems as sources of energy and materials, and sinks for assimilating wastes (Haberl et al., 2004).

Despite recognition of the interconnected exchanges between civilization and the biosphere, modern sustainability science adopts an anthropocentric perspective, focusing on issues such as energy quality (renewable vs nonrenewable), quantity (sufficient capacity to meet growing demand), and single environmental impacts such as carbon emissions (the output flows in **Figure 1.1**). However, in the context of our interactions with the biosphere, energy is far more complex and foundational. Unlike conventional energy statistics which account only for technical energy flows – e.g., energy combusted external to the human body in turbines or for heating – humanity's sociometabolism includes all energy carriers fueling civilization. This includes technical sources in addition to the flows of biological materials, or biomass, consumed as food and feed. Thus, human sociometabolism is comprised of two primary forms of energy; biomass from the biosphere to meet biological needs, and energy from technical sources including fossil fuels, hydropower, nuclear, and renewables utilized for industrial and socioeconomic purposes.

The magnitude of global biomass consumption can be estimated as the product of average per capita consumption and global population (Haberl, 2006; Haberl et al., 2011). Along with the ~600 EJ/year of annual technical energy consumption, biomass adds approximately ~550 EJ/year to our total energy consumption (**Figure 1.2**), bringing humanity's total sociometabolism to an extraordinary ~1,150 EJ/year[1] (Malhi, 2014). Of this total sociometabolic energy consumption, nearly 50% is still derived from biomass from the biosphere. This large consumption rate

[1] This magnitude of energy use by a single species cannot be overstated. For a point of reference, compare this to the entire terrestrial biosphere's annual production rate which has been estimated as 2,000 EJ/year!

quantifies humanity's total energy footprint and thus has profound thermodynamic implications for the biosphere.

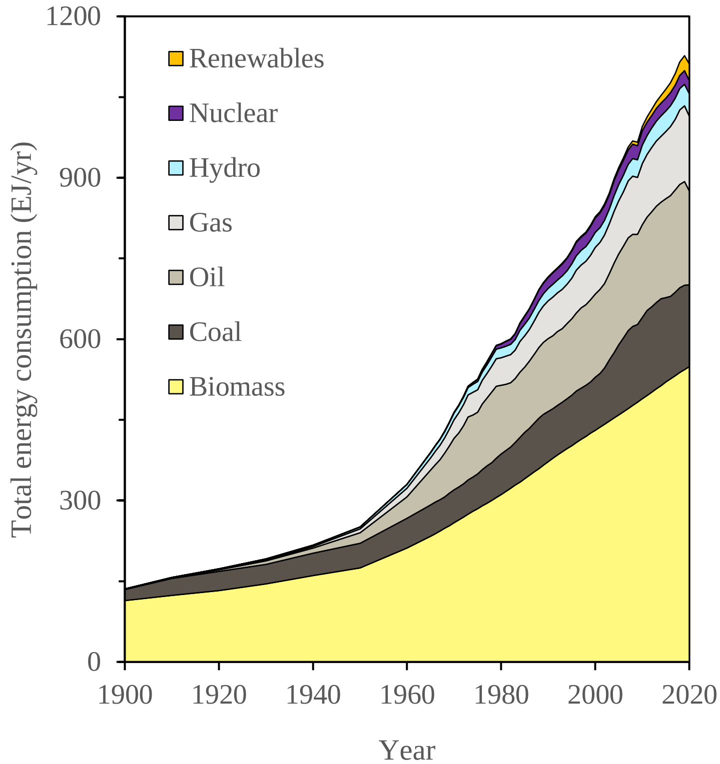

Figure 1.2 Humanity's total energy consumption from both technical energy sources (e.g., those reported in conventional energy statistics) and biomass extracted from the biosphere. Dataset reproduced from (Haberl, 2006) and extended to 2020 with updated data from (bp, 2023).

Like civilization, the biosphere is a thermodynamic system that converts and stores energy. Plants utilize solar radiation, converting it into high-quality chemical energy in the form of biomass, and releasing the resultant heat back into space. To meet their biological energy needs, humans extract these biomass flows, diverting a portion of this annual terrestrial net primary production (NPP) away from natural ecosystems. It is estimated that ~25% of terrestrial NPP is appropriated for human use (Krausmann et al., 2013). Additionally, intensive land-based activities such as land conversion and use, disrupt the total quantity of stored biomass (stored chemical energy) on land. The cumulative effect of these activities has reduced the global biomass store to approximately half of its historic level (Smil, 2012; Schramski et al., 2015; Erb et al., 2018). The total human energy impact on the biosphere is thus characterized by the diversion of a quarter of annual biomass production and the destruction of half of the land-based biomass store.

1.2 RATIONALE

As energy is the ability to cause change, the more energy a species has access to, the greater its capacity to impact and modify its environment. Humanity's energy impact on the biosphere is thus inextricably linked to the size of its sociometabolism. In this way, energy serves a dual function; fueling modern civilization while also increasing our ability to disrupt the biosphere's energy dynamics. Despite this crucial connection, the modern sustainability discourse overlooks the link between human energy consumption and resultant ecosystem and environmental impacts (Ehrlich, 1994; Makarieva et al., 2008; Kleidon, 2010). Overcoming this crucial knowledge gap requires clear examples that can more adequately capture the energy interactions between human/industrial systems and the ecosystems within which they are embedded.

In this dissertation, this gap is addressed by assessing natural energy stores in the form of biomass and the environmental performance of production processes along a modern industrial biomass supply chain. An industrial biomass supply chain was chosen as a straightforward example of humanity's most foundational thermodynamic relationship with ecosystems. With improvements to existing energy and environmental assessments to better account for deficiencies and uncertainties in ecosystem and environmental impacts, a more comprehensive analysis of biomass production systems sets the groundwork for an improved understanding of the coupled relationship between human energy use and ecological impacts.

The remainder of this chapter will provide an overview of the main energy and environmental assessment methods applied to biomass systems and their limitations, followed by an outline of the overall research goals and objectives. Finally, it will conclude with an overview of the structure of the remaining chapters.

1.3 EXISTING SUSTAINABILITY ASSESSMENT METHODS AND THEIR LIMITATIONS

The ability for energy to be used as an ecosystem health indicator to capture the human and ecological dimensions of industrial-natural systems more properly, emphasizes its value as a system-level indicator for evaluating the energetic and environmental impacts along a biomass supply chain. While several sustainability assessment methods have been developed over recent decades, energy analysis and life cycle assessment (LCA) are the most widely applied for quantifying the energetic and environmental performance of biomass production systems (Gheewala, 2023). However, both methods have limitations which can be improved for a more comprehensive understanding of the energy and environmental impacts of biomass systems.

Energy analysis is valued for its comprehensive accounting of all industrial energy flows within a system, but fails to root those flows within their broader environment. LCA, on the other hand, provides a detailed assessment of environmental impacts over a product's life cycle but can be limited by large variability and uncertainty, making it difficult to ensure environmental benefits. This research thus focuses on these two methodologies with special attention on these limitations. For less applied and more complex methods, the interested reader is directed to recent reviews of energy and environmental assessments of biomass production systems: (Hercher-Pasteur et al., 2020; Aghbashlo et al., 2022).

1.3.1 ENERGY ANALYSIS

Energy analysis, commonly referred to as ‘conventional’ or ‘net’ energy analysis, assesses the energetic performance of a system by quantifying and comparing the magnitudes of the system’s outputs against its required inputs (Hall & Cleveland, 1981; Cleveland et al., 1984). It is based on a core principle of ecosystem energetics; that any organism or ecosystem remains alive only through the production of an energy surplus (i.e., net energy) beyond its own metabolic requirements for growth and maintenance. This fundamental principle applies to all self-organizing systems, from ecosystems to industrial production processes to economic systems. A living organism must consume more than it expends for survival, and an energy production system must deliver more energy than is required to extract, process, and convert that energy in order to be energetically viable. It is within these omnipresent limits that all self-organizing systems operate and evolve. Any system that fails to meet these basic requirements inevitably decays and is unsustainable. In this way, energy analysis doesn’t just quantify the energetic viability of a production process; it serves as an ultimate measure of its sustainability.

A strength of energy analysis lies in its consideration of all energy and material flows within a system, including all direct (i.e., fuels, heat, electricity) and indirect (i.e., the energy embodied in materials) flows. The ability to capture a systems complete energy and material flows together, in consistent units, represents an advantage of energy analysis over conventional economic and material-based methods and can avoid potentially misleading conclusions when disparate inputs and outputs of differing units are compared. Accordingly, energy analysis is commonly used as a tool to optimize and improve the design of energy and material conversion systems by identifying opportunities for energy consumption reductions (Song et al., 2014). These strengths combined with its simplicity and ease of use have resulted in a wide range of research addressing the energetic sustainability of bioproducts, bioenergy, and crop and forestry systems (Marshall & Brockway, 2020).

Despite its extensive use throughout the literature, energy analysis falls short in linking biomass production systems with their surrounding environments (Dincer & Rosen, 2012). Conventional energy analyses capture only those inputs and outputs valued by the human/industrial system. In a biomass production system – as in an agroecosystem or managed forest – this includes the biomass yield of the system and the energy and materials invested in establishing, maintaining, and harvesting from the system (Tello et al., 2015; Galán et al., 2016).

Previous studies have attempted to account for environmental impacts, such as greenhouse gas (GHG) emissions, in energy analyses by accounting for the energetic costs of remediating or offsetting their negative effects (Cleveland & O'Connor, 2011; Moriarty & Honnery, 2019). While these approaches capture the indirect effects of environmental impacts, ecosystems are also thermodynamic systems striving towards states of maximal energy storage in the form of biomass (Odum, 1969; Fath et al., 2004; Jorgensen & Svirezhev, 2004). Intensive land management for biomass cultivation disturbs this process by altering the ecosystem's ability to accumulate biomass, maintaining the system at lower levels of energy storage (Doka et al., 2002). These energy impacts have thus far not been accounted for within the conventional energy analysis framework and therefore remain a substantial research gap (Golberg, 2015; Marshall & Brockway, 2020).

1.3.2 LIFE CYCLE ASSESSMENT (LCA)

In addition to their energetic viability, a main motivator contributing to the development of modern bio-based products is their role in reducing global warming impacts by replacing conventional fossil-intensive products and processes (Patel et al., 2006; Liu et al., 2017). Methods and tools that can accurately quantify the environmental impacts of biomass production processes have therefore received considerable scientific and engineering attention in recent decades. Environmental LCA is an internationally standardized method that captures the environmental impacts of a product or process over its entire process chain from raw material extraction to its end of life (Finkbeiner et al., 2006). Using a step-wise approach, LCA calculates the environmental burdens of the associated energies and materials used and discharged throughout a product's entire life cycle. Consequently, LCA's applications have encompassed several differing purposes including quantification of a product's total life cycle impacts, identification of impact hotspots at stages along a product's value chain, and serving as an aid in the design of more environmentally friendly products and processes.

The scientific rigor and standardization of LCA methodology has led to a proliferation of research assessing the environmental impacts of bioproducts, bioenergy, and biofuels in recent years. Evaluating the emission reduction potential of biochemicals and bioproducts relative to their conventional fossil-derived counterparts has emerged as an active research area to address issues of climate change and fossil energy scarcity (Weiss et al., 2012; Dunn, 2019). One of the earliest assessments of the potential emission savings of biochemicals indicated that savings of ~5 tons of CO_2 per ton of product were possible, with estimated global CO_2 savings of 500 – 1,000 million tons per year with future biotechnology (Hermann et al., 2007). However, conservation efforts require certainty to ensure and sustain these benefits over time. Despite the potential emissions savings and since that initial assessment, more recent research efforts have shown that considerable variability persists within individual biochemical LCA's, and can be enough to negate emissions benefits, thereby shifting the preference to favor conventional fossil-derived production in many cases (Ogmundarson et al., 2020).

Addressing these areas of uncertainty remains especially challenging due to the complex nature of biochemical life cycles (Heijungs & Huijbregts, 2004; Dunn, 2019). Typically, uncertainty analysis addresses parameter uncertainty, or variability in unit requirement data within a product's life cycle inventory (Groen et al., 2014). However, uncertainty also arises from model-based and technological factors, from methodological choices made by the LCA practitioner to differences in processing and conversion platforms. Previous studies have identified specific factors influencing the GHG emissions and energy use of biochemicals including the type of feedstocks, the handling of coproducts, downstream conversion technologies, system boundaries, and differences in geographic locations (Patel et al., 2006; Montazeri et al., 2016; Posen et al., 2016). Despite the recognition of these factors, few assessments have quantified their effects on an individual biochemical basis, particularly in comparison to their fossil-derived counterparts (Zuiderveen et al., 2023). The extent to which uncertainty affects the assurance of emission reduction benefits of biochemical production remains a substantive research gap. Understanding the combination of factors that ensure emission reduction benefits is crucial for sustainable biochemical production.

1.4 RESEARCH OBJECTIVES AND DISSERTATION OUTLINE

Given the importance of energy in capturing both the human and natural dimensions of industrial-natural systems and recognizing the present knowledge gaps in existing energy and environmental assessments, this work improves current sustainability assessments of biomass production systems. To achieve these goals, case studies are developed of differing biomass production processes along a biomass supply chain, including intensively managed forestry systems and biochemical production processes. Specifically, this dissertation aims to 1) develop an extended energy analysis model that integrates ecosystem energy impacts with conventional human/industrial energy metrics in managed forestry systems, 2) identify and assess areas of uncertainty and variability in the environmental impacts of biochemical production, and 3) apply these analyses to identify sustainable management practices that reconcile competing human and ecological energy dimensions along a biomass supply chain.

To better address these objectives within the context of the assessed case studies, more specific research questions are formulated:

a. How do the magnitudes of ecosystem energy impacts compare with conventional energy analysis metrics in managed forestry systems and what are the relationships between them (i.e., are any trade-offs present)?

b. What specific modeling factors contribute to uncertainty in sustainability assessments of bio-based production systems?

c. What types of management and production processes are most effective in balancing conventional energy metrics while also minimizing resultant ecosystem and environmental impacts?

The core studies and primary results of this work are developed in Chapters 2-4, each presented as standalone manuscripts or already published works. Integrating ecological and conventional energy metrics in industrial-natural systems requires an extended model capable of capturing both human and natural dimensions. Chapter 2 addresses this by extending the system boundaries of intensively managed forestry operations to encompass the physical area of the forest stand, allowing for the inclusion of ecosystem energy stores, in the form of biomass, within the system scope. Changes in potential biomass levels relative to baseline scenarios are then assessed alongside conventional industrial energy metrics under varying management regimes and time-horizons, enhancing interpretations of the energetics of managed forestry systems. In Chapter 3, this model is further refined to capture changes in food web biomass dynamics resulting from intensive management and directly compares them with the technical industrial energy inputs driving these changes. Chapter 4 shifts the focus to an important biochemical production process, and identifies and quantifies key methodological and technological factors contributing to uncertainty and variability in the global warming impacts. Finally, Chapter 5 provides a summary of the dissertation's main findings, discusses its broader significance, and outlines potential avenues for future research.

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CHAPTER 2

AN EXTENDED ENERGY ANALYSIS OF MANAGED FORESTRY SYSTEMS: ACCOUNTING FOR FOREGONE BIOMASS AS AN INDICATOR OF ECOSYSTEM IMPACT[2]

[2] **J. Dunlap** and J.R. Schramski. Submitted to *Biophysical Economics and Sustainability*, 04/12/24.

ABSTRACT

Conventional energy analyses of forestry systems capture only human inputs and harvests, neglecting impacts to forest biomass stocks resulting from intensive management. This gap is addressed by extending the boundaries of forestry operations to the whole forest ecosystem. These new boundaries allow for the quantification of cumulative foregone biomass (ΔB_c, the difference between accumulated potential and existing forest biomass stocks over time) under differing management scenarios to supplement the interpretation of conventional energy metrics such as net energy (*NE*) and the ratio of energy return to energy invested (*EROI*). Like existing models in the literature, our results confirm that less intensive management approaches achieve higher *EROI* values due to lower inputs. However, more significantly, magnitudes of ΔB_c remain 1-2 orders of magnitude larger than *NE* over 100 years regardless of management scenario, and thus highlight an imbalance between the industrial and ecological energy dimensions of managed forests. This extended energy model begins to illustrate the overlooked role of ecological energy storage in forest management and offers insights to identify and design more sustainable management practices that can balance energy efficiency while minimizing resultant ecosystem impacts.

2.1 INTRODUCTION

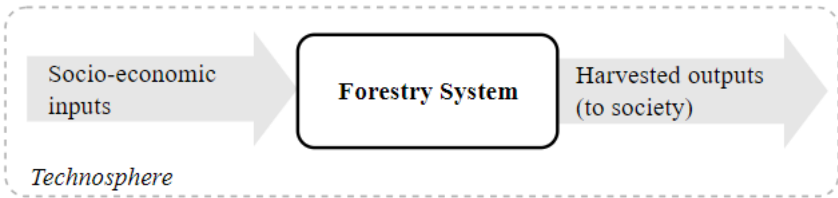
Energy plays a fundamental role in forestry systems. Through photosynthesis, atmospheric carbon dioxide is sequestered into biomass, which is the only renewable stored energy resource fueling the biosphere's food web of vast ecosystem biodiversity. However, through harvesting, forestry extracts a portion of this biomass to be used for various foods, fibers, and fuels (Bowyer et al., 2003; Easterling et al., 2007; Smil, 2012). Such transactions require extramural technical energy inputs invested by humans to establish, manage, and harvest from the system where a key objective is to improve operational efficiencies by minimizing inputs and maintaining or increasing harvested outputs (Sundberg & Silversides, 1988). As a result, energy analyses of managed forests predominantly focus on quantifying the amount of biomass produced and the energetic cost of obtaining that biomass.

Conventional energy analysis (e.g., net energy analysis, *NEA*), which quantifies the energetic performance of a system by comparing the useful outputs produced and the energy required to obtain those outputs, has been a key framework with which to assess the energetics of forestry (Mead & Pimentel, 2006; Marshall & Brockway, 2020). Specific indicators such as the ratio of energy return to energy invested (*EROI*) (Zavitkovski, 1979; Klopatek & Risser, 1981; Herendeen & Brown, 1987; Sundberg & Silversides, 1988; Mead & Pimentel, 2006; Balimunsi et al., 2012; Buonocore et al., 2014), net energy (*NE*) (Zavitkovski, 1979; Klopatek & Risser, 1981; Herendeen & Brown, 1987; Mead & Pimentel, 2006), and input-side indicators such as cumulative energy demand (*CED*) and gross energy requirements (*GER*) (Enger, 1983; Wells, 1984; Berg & Lindholm, 2005; Lindholm & Berg, 2005; González-García et al., 2014; Kouchaki-Penchah et al., 2023) have been applied to forestry systems. The *EROI* of forestry systems ranges from 10:1 to over 800:1 depending on the tree species, management type, system boundaries, and rotation period assessed (Klopatek & Risser, 1981; Herendeen & Brown, 1987; Mead & Pimentel, 2006). In all cases, *EROI* values remain positive, highlighting the positive energy returns of forestry to society.

Despite the favorable returns, conventional energy analyses of forestry systems are incomplete (Dunlap & Schramski, 2024). In these analyses, the forestry system is a subsystem of the human industrial economy (i.e., the *technosphere*) (**Figure 2.1a**). Under these system boundaries, only the merchantable biomass valued to humans is considered and the rest of the forest stand is not included within the system's scope. As a result, conventional energy analyses capture only the industrial efficiency of forestry operations with respect to human society. In actuality, forestry systems are industrial-natural systems existing within a forest ecosystem that accumulates biomass through natural processes of ecosystem growth and development (**Figure 2.1b**). Thus, while conventional energy analysis has commonly been applied to forestry systems, this approach does not consider changes in natural capital stocks such as biomass. More comprehensive forestry energy analyses should include boundaries that capture forest biomass dynamics along with conventional industrial energy metrics.

There have been limited efforts to incorporate changes in natural capital stocks alongside conventional industrial energy metrics in agroecosystems (Hercher-Pasteur et al., 2020). Bulatkin (2012) and Fan et al. (2018) conducted embodied energy (emergy) analyses of agricultural systems, including changes in soil organic carbon stores, while Golberg (2015) argued for incorporating impacted species biomass levels in the exergy efficiency of bioenergy systems. In all cases, magnitudes of the change in natural capital stocks were substantial portions of the overall energy budget, underscoring their importance. However, a drawback of these studies involves using emergy and exergy-based indicators, which, compared to conventional energy indicators, demand additional modeling efforts and have been criticized for their complexity in conveying results to non-technical audiences.

a.)



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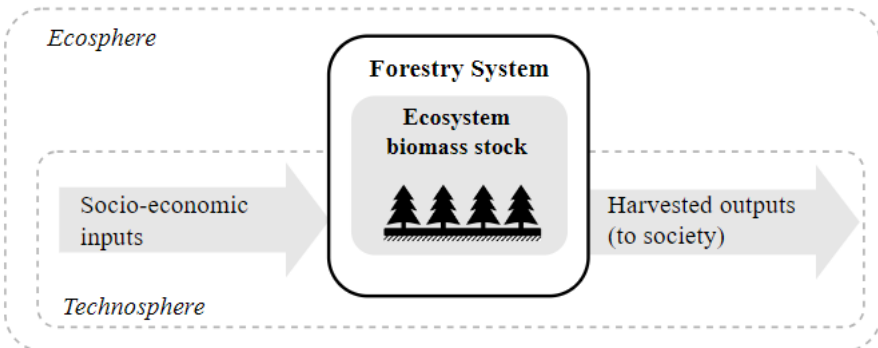

Figure 2.1 Contrasting system boundaries of forestry energy analysis approaches including, a) conventional boundaries where the forestry system is a sector of the technosphere, and b) extended boundaries where the forestry system is an industrial-natural system consisting of a forest ecosystem that accumulates biomass stocks.

In addition to describing the industrial efficiency of forestry systems, energy is also a state variable that conveys information about an ecosystem's thermodynamic state (Odum, 1983). Ecosystems are open, dissipative thermodynamic systems, degrading energy and material gradients while striving toward states of maximum stored energy in the form of biomass (Odum, 1969; Fath et al., 2004; Chen, 2007). These accumulated energy stores in the form of biomass quantify the system's distance from thermodynamic equilibrium (a state devoid of stored potential energy or biomass) and define a specific thermodynamic state operating away from equilibrium. However, intensive land management disrupts the ecosystem's ability to accumulate and store biomass, as managed forests typically accumulate less biomass than the natural system they have replaced (Doka et al., 2002; Erb et al., 2018; Erb & Gingrich, 2022). This results in a gap between potential and existing biomass stocks (**Figure 2.2**) as a direct consequence of intensive management. This gap represents the '*foregone'* quantity of stored energy in the form of biomass relative to a reference scenario where a natural ecosystem, absent human land-use activity, would exist. Globally, the gap between existing and potential biomass is substantial with anthropogenic activity estimated to have reduced terrestrial biomass by ~50% with most of the losses occurring in forests (Smil, 2012; Schramski et al., 2015; Erb et al., 2018; Erb & Gingrich, 2022). In other words, global forests would store double the quantity of energy, in the form of biomass, in the absence of human land-use activities. Intensive forest land management thus maintains the ecosystem at lower energy states closer to thermodynamic equilibrium.

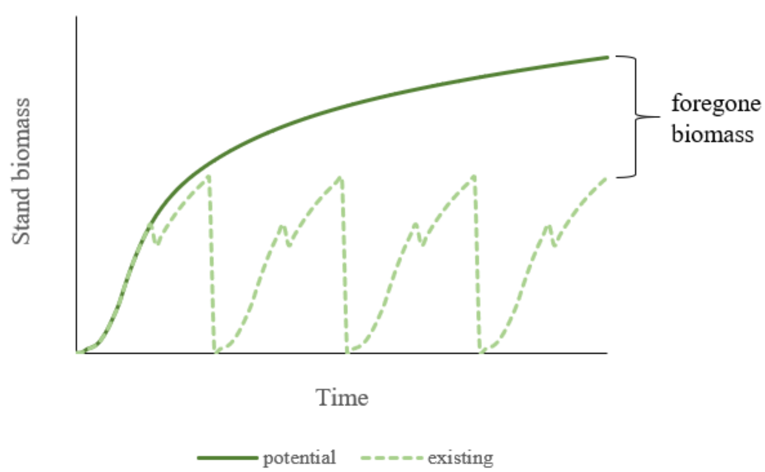

Figure 2.2 Conceptual diagram of foregone biomass as an indicator of the impact of intensive management on stand-level forest biomass over time. Foregone biomass is the difference between potential (solid green line) and existing (light green dashed line) biomass at any time.

In this context, energy is a systems-level indicator able to capture and express information about the industrial and ecological dimensions of forestry systems. Yet, few studies have assessed both aspects together in the context of intensive forest management. Including ecological aspects in conventional energy analyses contributes not just to our understanding of the resultant ecosystem impacts of differing types of forest management, but also adds context to our most fundamental energetic relationship with managed ecosystems and can help inform the design of sustainable forest management.

2.2 MATERIALS AND METHODS

An extended energy analysis is performed on one hectare (ha) of a managed forest stand under four different management scenarios in the southeastern U.S. To do this, a dynamic energy accounting framework (**Figure 2.3**) compares 1) the direct and indirect energy inputs invested in the stand by different forestry operations, 2) the total biomass harvested from the stand, and 3) the foregone biomass stocks relative to different baseline reference scenarios over time.

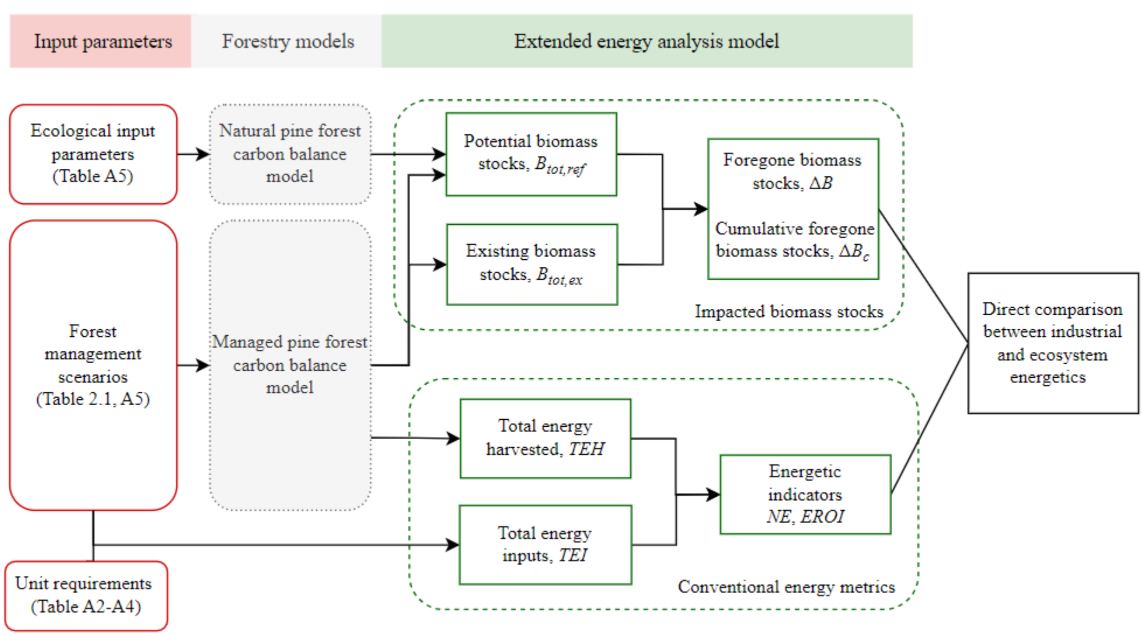

Figure 2.3 Process flow of the extended energy analysis model of forest management. Red boxes denote inputs and background data, grey boxes depict forest carbon balance models for calculating stand biomass stocks, and green boxes show the final calculated energy analysis metrics.

To this end, the system boundaries expand on conventional forestry energy analyses and include the existing, and potential biomass that would exist in the absence of intensive land occupation (**Figure 2.1b**). Existing stand biomass stocks include above and below-ground live trees (stem, bark, crown, and roots), understory, dead wood (standing trees, logging residues, and coarse woody debris), and forest floor biomass.

2.2.1 FOREST MANAGEMENT SCENARIOS

Four different forest management scenarios are selected to represent intensive pine management regimes in southeastern forestry in the U.S. Management scenarios vary in intensity with differing combinations of fertilizer and herbicide treatments, thinning intensities and applications, planting densities, and rotation lengths defined in total as less intensive saw timber (ST) and conventional (C) managements contrasted with more intensive heavy thinning (HT) and short rotation (SR) managements. Forest management data were collected from literature sources specific to southeastern pine forestry (**Table A1**).

For each scenario, management activities in the stand are grouped into four forestry operations, each supported by respective fuel and material inputs. Forestry operations and respective timelines include site preparation, stand management, thinning, and logging (**Table 2.1**).

Table 2.1 Timeline of inputs for each forest management scenario. Management scenario abbreviations include saw timber (ST), conventional (C), heavy thinning (HT), and short rotation (SR) scenarios.

Year	**0**	**1**	**4**	**6**	**8**	**10**	**15**	**16**	**25**	**35**
ST	Site prep						Thin	Fert		Log
C	Site prep		Fert		Fert		Thin		Log	
HT	Site prep	Herb	Fert			Fert Thin	Fert Thin		Log	
SR	Site prep	Herb	Fert	Fert				Log		

Site preparation includes initial groundwork to prepare the site for planting and re-establishment as well as initial fertilizer and herbicide treatments. Stand management includes additional fertilizer and herbicide treatments following the initial planting. Thinning involves the intermediate removal, typically 30% or 50%, of the stand while logging involves the final clear felling and removal of tree biomass.

2.2.2 ENERGY INPUTS

Following procedures from previous agroecosystem energy analyses, technical energy inputs include the direct and indirect fuel and materials supporting the system (Schramski et al., 2011; Schramski et al., 2013; Pimentel, 2019). Direct inputs include diesel fuel to drive machinery for site preparation, management, and logging activities while indirect inputs include the energy embodied in materials such as lubricating oils, nitrogen and phosphorus fertilizers, and herbicides. Human labor is excluded as an energy input based on 1) being a negligible term in previous literature studies and 2) that most of the work in intensive forestry is performed by machinery (Wells, 1984; Sundberg & Silversides, 1988). Infrastructural supporting activities such as forest road building and maintenance are not activities invested directly to support the forest stand, do not cross the system boundaries of the stand, and are thus excluded from the analysis.

Several assumptions are made regarding unit input requirements. First, fuel and material requirements for the initial groundwork and site preparations are assumed to be the same for all managements. Herbicide requirements are assumed constant while the number of herbicide applications varies by management. For logging operations, diesel and lubricant requirements are assumed constant across managements, however, similarly depend on the volume of harvested biomass at the time of final clear felling. Fuel and material requirements for thinning were not found in the literature and thus are assumed to be proportional to logging requirements as a function of thinning intensity, i.e., requirements for thinning 30% of the stand are assumed to be 30% of those required for logging.

All required unit inputs are converted to unit energy intensity values by multiplying each respective input of each management type with a specific energy conversion value (**Table A2** - **Table A4**). Then, for each forestry operation *k*, the sum of all unit energy intensity values *n*, determines the total energy input E_{tot} (GJ/ha) invested in the stand at time *t*,

$$E_{tot}(t) = \sum_{k}\sum_{n} E_{in,k,n}(t) \tag{2-1}$$

The total energy invested in the stand *TEI* (GJ/ha) over a given time period *t* is calculated as the sum of the total energy inputs over a given time period,

$$TEI(t) = \sum_{t} E_{tot}(t) \tag{2-2}$$

TEI is the sum of all direct and indirect energy inputs invested in the forest over a given period and thus represents the total human embodied energy inputs supporting the system.

2.2.3 ENERGY OUTPUTS

System outputs include the merchantable biomass harvested during thinning and clear felling at the rotation age of the stand. This consists of the stemwood and bark harvested from live pine trees. Logging residues were not included as harvested outputs. Instead, residues were burnt at the time of harvest, as is common practice in intensive forestry, and a small fraction fluxes to the dead wood pool. To convert biomass into energy units, an average energy content value of 17.5 MJ/kg (or 35 GJ/tonne C) is applied (Smil, 2007). For each management scenario, the total energy harvested *TEH* (GJ/ha) is then the sum of all biomass harvests E_{har} (GJ/ha) from the stand over a given period *t*,

$$TEH(t) = \sum_{t} E_{har}(t) \tag{2-3}$$

Thus, *TEH* represents the accumulated quantity of biomass harvested by humans from the system, in energy terms, over a given period.

2.2.4 ENERGY ANALYSIS METRICS

For each management scenario, net energy *NE* (GJ/ha) represents the cumulative net quantity of energy obtained through harvests after inputs are accounted for and *EROI* represents the energetic efficiency with which those outputs are obtained,

$$NE(t) = TEH(t) - TEI(t), \tag{2-4}$$

$$EROI(t) = \frac{TEH(t)}{TEI(t)} \tag{2-5}$$

In a forestry context, *NE* is a proxy for harvests yet is more descriptive as a systems-level indicator as it accounts for the net quantity of energy harvested after inputs invested to obtain those harvests are accounted for. Similarly, *EROI* is a systems-level indicator of the energetic efficiency of a biomass production system (Schramski et al., 2011; Schramski et al., 2013). *EROI* quantifies the quantity of energy obtained per unit of energy invested into the system and thus accounts for the capacity of the system to provide valued outputs despite external investments (Hall et al., 2009). Taken together, both indicators capture differing aspects of the system-level performance of forestry systems, aspects which are absent when considering only the gross quantity of harvests (i.e., yields) or inputs invested into a forestry system, as is often the case in forestry studies.

To account for differences in rotation lengths of each management, energy metrics are assessed in three different ways including on a per rotation basis, normalized over a consistent time-horizon, and a fixed 100-year period, for all managements. Energy metrics are normalized over a consistent time-horizon as follows,

$$normalized\ metric = \frac{energy\ metric * LCM}{rotation\ length} \tag{2-6}$$

Where LCM is the least common multiple of the different rotation lengths (equal to 2800 years for 16, 25, and 35-year rotations). Considering different temporal approaches to analyzing energy metrics ensures fair comparisons across different types of management and ensures that conclusions drawn regarding trends in energetic performance do not vary significantly under diverse types of analysis.

2.2.5 MODELING FOREST BIOMASS STOCKS

A carbon balance model of planted loblolly pines (*Pinus taeda*), from the University of Florida's Carbon Resources Science Center V1.32, is used to simulate stand-level biomass stocks under different forest management scenarios (Gonzalez-Benecke et al., 2011). Input parameters to initialize the models for each management scenario are detailed in **Table A5**. A key strength of the model is that it allows for the simulation and partitioning of biomass stocks beyond tree biomass and also includes understory, dead wood, and forest floor biomass, which comprise ~20% of total stand biomass (**Figure 2.4**). The total biomass stock in the forest at a given time is the sum of the biomass of all individual compartments in the stand and is reported as either tonnes/ha or tonnes C/ha. Where necessary, biomass stocks were converted to carbon mass units assuming an average carbon content of ~50% of biomass. As the stand consists of multiple biomass stocks with large variability in composition including water content, an average energy content value of 17.5 MJ/kg (or 35 GJ/tonne C) is applied to convert all biomass stocks to energy units (Smil, 2007).

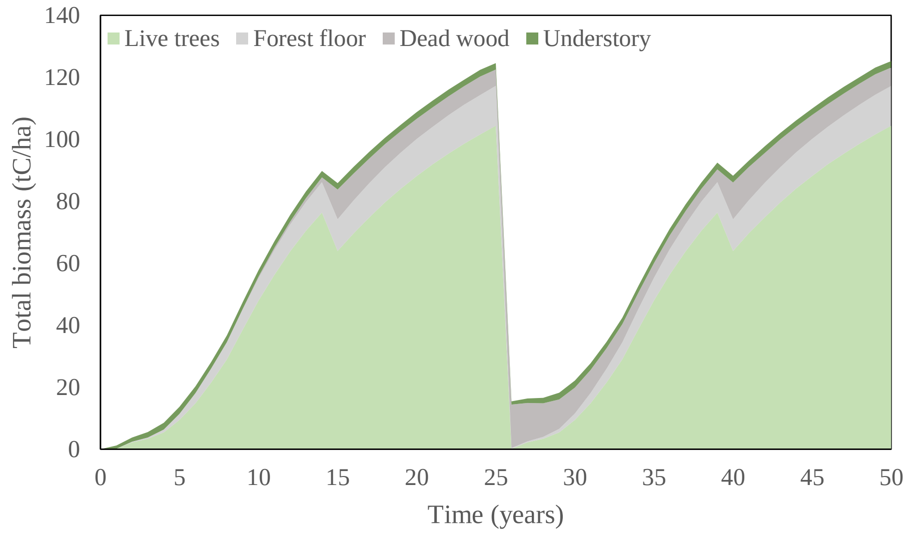

Figure 2.4 Example showing the composition of total existing stand biomass ($B_{tot,ex}$) over time in a managed forest for two harvest periods. The depicted scenario is for the conventional (C) forest management over two 25-year rotations. Total stand biomass consists of live pine trees, forest floor, dead wood, and understory compartments.

2.2.6 FOREGONE BIOMASS

To calculate foregone biomass, the total existing stand biomass is compared to potential biomass under a reference or baseline scenario. Potential biomass represents the natural unmanaged biomass that would have existed on the land if it had not been intensively managed. Foregone biomass $\Delta B(t)$ (GJ/ha) at time t is then,

$$\Delta B(t) = B_{tot,ref}(t) - B_{tot,ex}(t) \tag{2-7}$$

where $B_{tot,ref}(t)$ is the total potential biomass stock under a reference scenario and $B_{tot,ex}(t)$ is the total existing biomass stock in the managed stand. Two reference scenarios are simulated including a no-harvest scenario for each management and a natural regeneration scenario, where the land is allowed to return toward a natural state which would exist in the absence of land-use activity. The longleaf pine (*Pinus palustris*) ecosystem was chosen as the natural reference ecosystem that would exist in the hypothetical absence of intensive forest management as this ecosystem once dominated most of the southeastern coastal plains in the United States, but now occupies less than 5% of its original range (Outcalt, 2000). A carbon balance model was used to simulate biomass dynamics of the longleaf pine reference ecosystem (**Figure A1**) (Baldwin, 1983; Lauer & Kush, 2011). Further details of the inputs to parameterize the reference model can be found in the Appendix (**Table A5**).

Cumulative foregone biomass $\Delta B_c(t)$ at any time t is calculated for each management scenario,

$$\Delta B_c(t) = \sum_t \Delta B(t) \tag{2-8}$$

At any time, t, cumulative foregone biomass represents the total change in the forest's accumulated energy store that would have existed up to that point in time if the stand was either unharvested or not intensively managed. This magnitude quantifies the impact on the ecosystem's energy state resulting from intensive land occupation and management over time.

2.2.7 SENSITIVITY ANALYSIS

The quantity of ΔB_c is dependent upon the modeled potential biomass stocks of the baseline reference scenario. To provide validation for this quantity, a sensitivity analysis was performed for differing levels of biomass stocks under the natural regeneration reference scenario. Biomass stocks of the longleaf pine ecosystem depend on site index (SI) which is a measure of site productivity and can range from 16 to 29 m (Lauer & Kush, 2011; Gonzalez-Benecke et al., 2015; Samuelson et al., 2017). Thus, SI was varied between 16 and 29 m for the reference scenario and ΔB_c is recalculated for each management scenario to test the sensitivity of foregone biomass stocks to different SI values.

2.3 RESULTS

2.3.1 ENERGY ANALYSIS OF FORESTRY OPERATIONS ASSESSED OVER DIFFERENT TIME-HORIZONS

On a per-rotation basis, total energy inputs (*TEI*) to forest management are largest under more intensive heavy thinning (HT) and short rotation (SR) scenarios followed closely by less intensive saw timber (ST) and conventional (C) managements, respectively (**Table 2.2a**). In contrast, total harvests (*TEH*) are largest under the least intensive ST followed by HT, and lowest under C and SR management, respectively. These relationships are attributed to the longer rotation period of ST resulting in more biomass harvested at the rotation age, and the additional harvests obtained through the additional stand thinning under HT management (**Table A6**). As a result, the net energy (*NE*) obtained follows the same trend and is largest under the least intensive ST followed by the more intensive HT management scenario. The ratio of energy outputs to inputs (*EROI*) is largest under the least intensive ST and C managements and declines with increasing management intensity. Regardless of the *NE* obtained, lower-intensity management regimes are more energetically efficient at obtaining their outputs (i.e., have higher *EROI*) in comparison with the more intensive alternatives.

If energy metrics are normalized over a consistent time-horizon (i.e., 80 successive rotations for ST, 112 for C and HT, and 175 for SR management over 2800 years) previous input and output comparisons between management scenarios differ significantly (**Table 2.2b**). *TEI*, *TEH*, and *NE* values are lowest under low-intensity ST management and increase with increasing management intensity. These are due to the greater quantity of harvests that occur under more intensive management scenarios when assessed over a consistent time-horizon. Both the magnitude and trend in *EROI*, however, do not differ from the previous comparisons on a per-rotation basis and still decline with increasing management intensity (i.e., decline with declining rotation length). Like when analyzed on a per-rotation basis, lower intensity forest managements are more energetically efficient at obtaining their outputs (i.e., have higher *EROI*) than more intensive management.

Over 100 years, comparisons between energy metrics are consistent with normalized metrics although they differ substantially in magnitude. *TEI*, *TEH*, and *NE* increase with increasing management intensity and are the largest under more intensive HT and SR management (**Table 2.2c**) due to the greater number of harvests and greater outputs achieved over 100 years compared with their less intensive counterparts (**Table A7**).

Table 2.2 Conventional forestry energy analysis metrics assessed over different time-horizons.

	TEI (GJ/ha)	TEH (GJ/ha)	Net Energy (GJ/ha)	EROI (~)	# of rotations
	(1)	(2)	(3) = (2) - (1)	(2)/(1)	
a. Per harvest rotation					
Saw Timber (ST)	49	3,443	3,393	70	1
Conventional (C)	45	2,681	2,636	60	1
Heavy Thinning (HT)	63	3,406	3,343	54	1
Short Rotation (SR)	51	2,540	2,489	50	1
b. Normalized over a consistent time-horizon					
Saw Timber (ST)	3,943	275,403	271,460	70	80
Conventional (C)	5,006	300,266	295,260	60	112
Heavy Thinning (HT)	7,108	381,498	374,390	54	112
Short Rotation (SR)	8,927	444,442	435,515	50	175
c. Over 100 years					
Saw Timber (ST)	119	7,104	6,985	60	2
Conventional (C)	179	10,724	10,545	60	4
Heavy Thinning (HT)	254	13,625	13,371	54	4
Short Rotation (SR)	323	15,238	14,915	47	6

While trends in *EROI* remain consistent with previous analyses and decline with increasing management intensity, the magnitudes differ slightly for ST and SR. This is due to the truncation of their rotation cycles (i.e., which are not multiples of 100 years) when assessed over 100 years, thus leading to slightly lower *EROI* values compared with previous analyses.

Irrespective of how energy metrics are analyzed, *EROI* values are always largest under the least intensive (ST and C) management scenarios, indicating that lower-intensity forest management is more energetically efficient at obtaining their harvested outputs than more intensive ones.

2.3.2 FOREGONE BIOMASS – IMPACTS TO THE ECOSYSTEM'S STORED ENERGY POTENTIAL

The dynamics of foregone biomass (ΔB) depend on the reference scenario with which they are compared (**Figure 2.5**). Before the initial harvest, ΔB is negative under the natural regeneration reference due to lower biomass accumulated compared with fast initial growth in the managed stands. However, successive harvests quickly overcome these improvements. In contrast, ΔB is always positive under no-harvest references, as biomass continues to accumulate despite harvests. Although magnitudes of ΔB do not vary significantly between the two scenarios after 100 years, ΔB under natural regeneration outpaces ΔB under no-harvest scenarios due to its continued biomass accumulation as the ecosystem develops while biomass approaches a steady-state in the no-harvest scenarios.

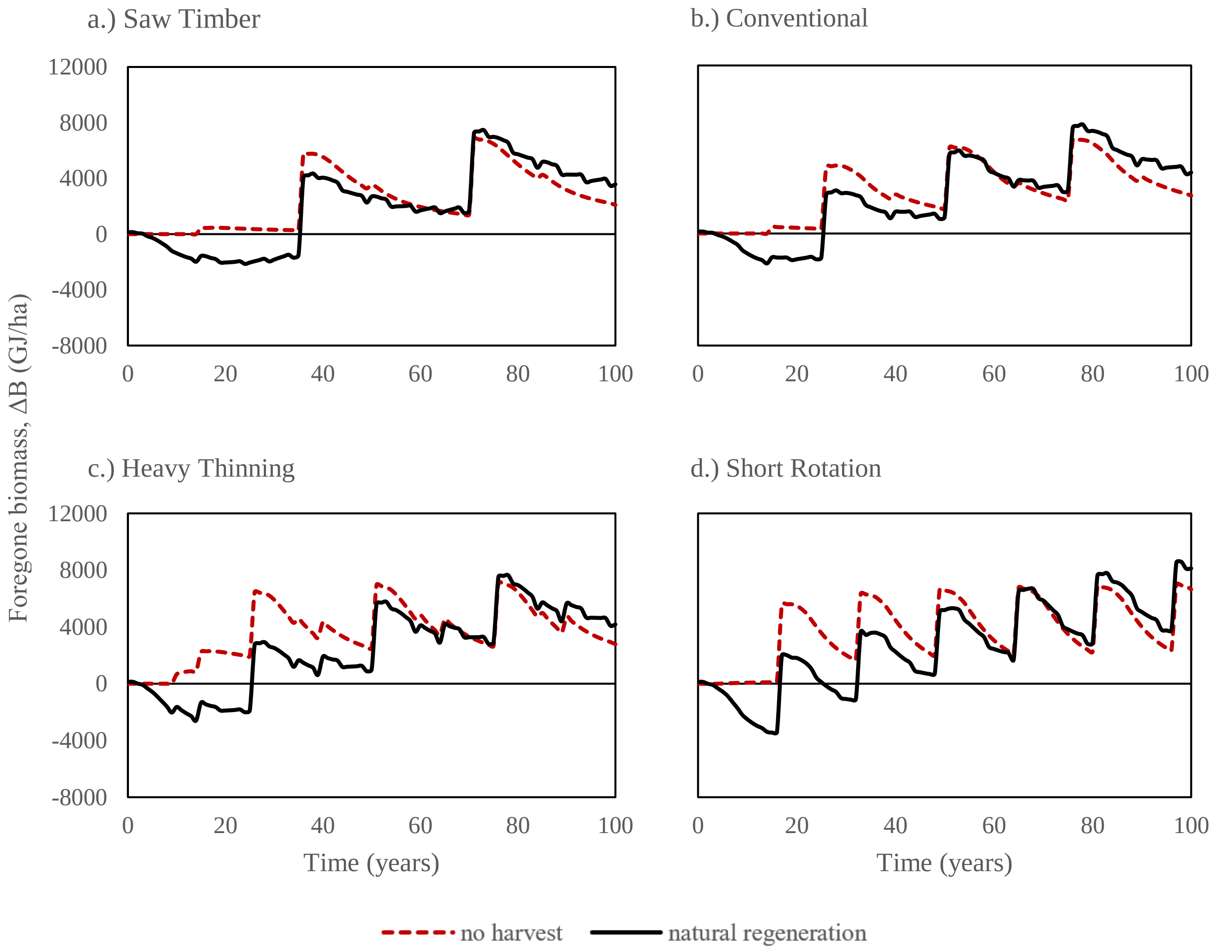

Figure 2.5 Foregone biomass under different forest management scenarios. Foregone biomass (ΔB) in GJ/ha (10^9 J/ha), is evaluated under two different reference scenarios: a no-harvest (dashed red line) and a natural regeneration scenario (solid black line).

Individual compositions of ΔB, averaged over 100 years, vary between management types and reference scenarios (**Table 2.3**). Under the no-harvest reference, ΔB is positive for all stocks and managements (except understory for SR management), indicating biomass losses for all management scenarios. However, for natural regeneration, understory, forest floor, and dead wood biomass improve for all management scenarios (except forest floor biomass under SR management), as indicated by negative values of ΔB in **Table 2.3**. These improvements can be attributed to frequent fires (every 5 years), leading to lower biomass quantities under the natural regeneration scenario compared to the managed stands.

Table 2.3 Compositions of foregone biomass (*ΔB*) in GJ/ha (10^9 J/ha) averaged over 100 years for different management scenarios under two different reference scenarios. Negative values indicate improvements in biomass.

	Reference scenario							
	no-harvest				**natural regeneration**			
	ST	**C**	**HT**	**SR**	**ST**	**C**	**HT**	**SR**
Trees	2163	2684	3259	3190	2373	3029	2996	3028
Forest floor	118	161	161	296	-157	-92	-122	25
Dead wood	154	131	179	266	-202	-211	-359	-256
Understory	1	2	1	-2	-57	-57	-57	-61
Total	2436	2978	3601	3751	1957	2669	2458	2737

Impacts to the ecosystem's energy stores, measured as cumulative foregone biomass (ΔB_c), while larger in magnitude than ΔB, follow a similar trend over time (**Figure 2.6**). Under no-harvest reference scenarios, ΔB_c increases with increasing management intensity and is comparable in magnitude for more intensive HT and SR managements. In comparison to no-harvest scenarios, ΔB_c under natural regeneration scenarios display lower magnitudes due to the initial improvements in ΔB before harvest. Under a natural regeneration reference, ΔB_c is lowest under least intensive ST management, increasing with increasing management intensity, but displaying less variability between managements than the no-harvest references. Interestingly, for natural regeneration, ΔB_c for the less intensive C management scenario is comparable in magnitude to the most intensive SR management. This is attributed to the lower quantity of biomass stocks under the C management compared to the natural regeneration reference. Trends in the individual compositions of ΔB_c for each management are similar to those under the no-harvest references and can be found in the Appendix (**Table A8**).

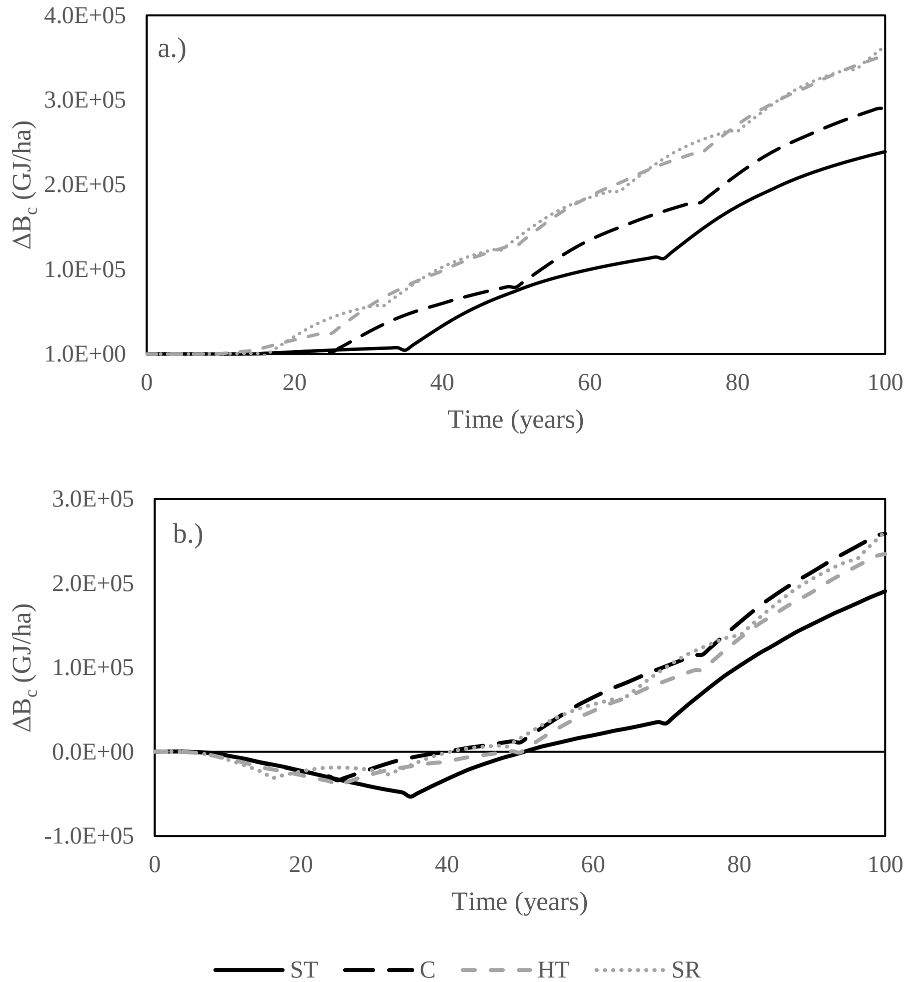

Figure 2.6 Cumulative foregone biomass for various forest management scenarios assessed under two reference scenarios including, a.) no-harvest and b.) natural regeneration scenarios. Management scenario abbreviations are: saw timber (ST, solid black line), conventional (C, dashed black line), heavy thinning (HT, dashed grey line), and short rotation (SR, dotted grey line).

2.3.3 COMPARING THE ENERGETICS OF FORESTRY OPERATIONS AND ECOSYSTEM IMPACTS

While trends in *NE* and ΔB_c between management scenarios depend on the time-horizon and reference scenario over which they are analyzed, comparing their magnitudes over a consistent timespan can reveal insight into the energy dynamics between the human/industrial and ecological dimensions of forestry operations. Regardless of the reference scenario or the type of management, impacts to forest biomass stocks ΔB_c are 1-2 orders of magnitude larger than *NE* from forestry operations over 100 years (**Table 2.4**). These results signify a strong energy imbalance, as the quantity of *NE* obtained from the ecosystem through intensive management also leads to substantial reductions in the ecosystem's accumulated energy stores. In essence, reductions in ecosystem energy storage resulting from intensive management greatly exceed the magnitudes of the technical energies invested and harvested by humans from the system.

Table 2.4 Comparison of net energy (*NE*) and cumulative foregone biomass in GJ/ha over 100 years for differing management scenarios.

		ΔB_c	
	NE	no-harvest	natural regeneration
Saw Timber (ST)	6,985	238,932	190,558
Conventional (C)	10,545	290,085	258,817
Heavy Thinning (HT)	13,371	350,034	234,652
Short Rotation (SR)	14,915	363,600	261,149

2.3.4 SENSITIVITY ANALYSIS RESULTS

A sensitivity analysis assessed the variability in ΔB_c under the natural regeneration reference scenario for different SI values. SI was varied from 16 to 29 m and resulting values of ΔB_c were recalculated for each management scenario. For all management scenarios, variation in SI varies ΔB_c from a minimum of -50% to a maximum of +127% compared to an SI of 20 m applied in the main study (**Figure A2**). This variability holds regardless of whether ΔB_c is calculated over 100 years or on a per-rotation basis. While the relative changes in ΔB_c are high under large SI values, such variability is not enough to alter the magnitudes of ΔB_c more than an order of magnitude in either direction (**Figure A3**). Thus, variation in site productivity alone is not enough to alter the conclusions drawn between comparisons of *NE* and ΔB_c. Regardless of SI, the *NE* of forestry operations remains 1-2 orders of magnitude smaller than ΔB_c across all management scenarios.

2.4 DISCUSSION

Conventional energy analyses of forestry systems are incomplete, as they account only for the technical energy inputs and biomass harvested from the system (Zavitkovski, 1979; Herendeen & Brown, 1987; Sundberg & Silversides, 1988; Mead & Pimentel, 2006; Balimunsi et al., 2012; Buonocore et al., 2014). In these analyses, the forest system is treated as another sector of the economy (Hercher-Pasteur et al., 2020). However, forestry operations take place within a forest ecosystem which, through natural ecological processes, accumulates and strives toward states of maximal energy storage over time. Therefore, a more complete energy model should include forest biomass and their resultant impacts under differing types of intensive management. Our approach differs from previous approaches by extending the system boundaries to encompass the whole forest ecosystem. Doing so allows for direct comparisons of the resulting reductions in potential biomass stocks (i.e., foregone biomass) alongside conventional energy metrics, highlighting the coupled energy interactions between the industrial and ecological dimensions of managed forests.

Despite its applications, the model is not without limitations. Foregone biomass is calculated as the difference between potential and existing biomass and therefore depends on the biomass of the modeled reference scenario. While variability in biomass of the natural reference ecosystem was accounted for with no impact on overall conclusions, this may not be the case for all forests or management types. In cases of afforestation, or where the managed forest replaces an ecosystem with lower biomass stocks, such as grassland or degraded land, biomass stocks are likely to be improved when compared to the natural baseline reference, resulting in negative impact values. As the purpose of the study was to capture impacts to biomass in typical intensive southeastern forestry scenarios, such cases were not considered but should be explored in future research. The developed model applies to cases where intensive management occupies land where the historical baseline would include a mature ecosystem, as is the case throughout much of the southeastern and northeastern United States (Rathbun, 1993; Hanberry et al., 2018). Additionally, the model was developed at the stand scale, as the stand represents the primary spatial unit in forest management. Since biomass stocks at the landscape scale are simply the sum of those at the stand scale, extension of the model to the landscape scale is an important next step. However, differing land uses and forest age distributions across the landscape will require additional consideration and modeling efforts that were beyond the scope of this study.

When analyzed over 100 years, results revealed trade-offs between management intensity, industrial energetics, and ecosystem impacts. In general, intensive management produces greater net energy returns through more frequent harvests, but this comes at the expense of greater biomass losses over time. While less intensive managements reduce biomass losses, they also achieve higher *EROI* values in comparison with more intensive regimes, regardless of how they were analyzed. This is a significant finding as it illustrates that less intensive managements are more energetically efficient at obtaining their harvests per unit of input invested compared to their more intensive counterparts. These findings agree with previous assessments indicating an increase in energy ratio with increasing rotation ages (i.e., for less intensive management) (Herendeen & Brown, 1987). However, earlier studies compared energy performances across different forest types (i.e., pine vs oak) (Klopatek & Risser, 1981; Herendeen & Brown, 1987), while this study compared the energetic performance of differing management scenarios within the same forest and under different study scopes. Considered together, our results further support the hypothesis that less intensive forest managements exhibit greater energetic efficiency, whether considering various forest types, different management scenarios within the same forest, and regardless of the time-horizon over which energy metrics are analyzed.

This extended energy model has applications in forest management and decision-making which involve increasingly diverse objectives, requiring managers to balance conflicting goals such as sustainability, yields, and economic efficiency (Chaudhary et al., 2016). The use of an extended energy framework in forestry systems offers valuable insights for decision-makers by facilitating direct comparisons between magnitudes of the human/industrial and ecological dimensions of different management regimes. An energy model captures and expresses, in consistent units, the human inputs and outputs supporting and harvested from the stand, the existing energy stored as biomass in the stand, and the resultant impacts to the energy storage potential of the stand as an outcome of intensive management. In this way, the usefulness of energy models extends beyond traditional forest yield, carbon, and ecological models which are often assessed disparately and across multiple disciplines. Furthermore, quantifying impacts to the forest's energy state as the distance from potential energy stores establishes a benchmark for restoration potential which goes beyond considering only carbon stocks but also recognizes the foundational role of energy in maintaining ecosystems away from thermodynamic equilibrium (Odum, 1983; Jorgensen & Svirezhev, 2004).

2.5 CONCLUSION

Quantifying and understanding ecosystem impact together with the industrial efficiency of forestry operations requires an extended framework and indicators that can capture both the human/industrial and ecological energy dimensions of managed forests. Such a framework extends beyond the traditional perception of intensively managed forests as merely industrial production systems producing human-valued outputs while requiring external energy and material inputs.

Results showed improved energy efficiency under less intensive management approaches, while also highlighting substantial disparities between the human-extracted net energy and ecosystem impacts resulting from intensive management. Quantifying such imbalances is crucial, as permanent reductions in ecosystem biomass can lead to an irreversible return to thermodynamic equilibrium. Natural ecosystems required significant timespans, over millions of years, to accumulate substantial energy stores in the form of biomass. While human activities such as deforestation directly destroy biomass, intensive management, and land occupation permanently reduce and alter the ecosystem's ability to store biomass, as intensively managed ecosystems typically store less biomass than their natural counterparts (Smil, 2012; Poorter et al., 2016; Erb et al., 2018; Lewis et al., 2019).

Despite these stark thermodynamic realities, the global state of forests is deteriorating, with natural forests experiencing ongoing losses of biomass and forest cover while the area of intensively managed forests expands by ~1% per year (FAO, 2020; UNEP, 2020). Although some degree of intensive management will likely always be necessary to meet biomass demands, this extended energy framework provides context to our most fundamental interactions with managed ecosystems and is essential for further understanding of the coupled energy interactions between the industrial forest management operations required to sustain and extract biomass for society and their resultant impacts to the ecosystem’s overall energy state.

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CHAPTER 3

ENERGY-SYSTEMS ACCOUNTING IN INDUSTRIAL-NATURAL SYSTEMS: AN ENERGY ANALYSIS OF A MANAGED FOREST ECOSYSTEM INCLUDING FOOD WEB BIOMASS DYNAMICS[3]

[3] **J. Dunlap** and J.R. Schramski. 2024. *Ecological Modelling* 488: 110598.
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ABSTRACT

Managed forests are industrial-natural systems established and maintained by human inputs that provide biomass to society while, given their long-successional growth period, also supporting a multitude of interacting species in food webs. Yet, energy analyses have overlooked food web impacts resulting from forest management. Addressing this gap, a dynamic energy analysis of a managed forest stand together with its supported food web was performed under differing forest management scenarios over a 100-year period. The model allows for a dynamic comparison of the exogenous energies invested to establish, manage, and harvest the stand, alongside the time-series impacts on food web biomass stocks compared to a reference no-harvest scenario. Over the first 25 years, food web biomass improved by ~18 to 31 GJ/ha under management scenarios with forest thinnings prior to the initial harvest, which enhanced dead wood production relative to no-harvest scenarios. However, after 100 years, magnitudes of food web biomass losses exceeded exogenous investments in the forest stand by factors of three to five depending on management type. These results highlight a critical imbalance between the external inputs supporting the forest and the resultant food web impacts driven by those inputs. Taken together, such results suggest a large-scale losing energy tradeoff between civilization and the biosphere.

3.1 INTRODUCTION

Forests are one of the most important biomes on Earth, covering less than a third of the land surface, yet comprising most of the global biomass, and supporting most of the planet's terrestrial biodiversity (MEA, 2005; Smil, 2007; Bar-On et al., 2018; FAO, 2020). Human land-use activities and demands for forest products continue to impact and transform forests in significant ways, driving net losses of global forests at a rate of ~5 Mha/yr (FAO, 2020). In spite of the loss of global forests, the area of human planted forests has increased by ~120 Mha since 1990, now comprising 7% of total forest area (~4 Gha) (FAO, 2020; UNEP, 2020).

Plantation forests are intensively managed, planted forests, consisting of even-aged monocultures of tree species grown for production purposes. Different from natural forests and established by humans, plantation forests are considered "techno-ecosystems" or human-dominated systems "*competitive with and parasitic on*" nature (Odum, 2001). These systems use technology to concentrate human-valued outputs, and are established and supported by fossil energy and material inputs. Thus, managed forest systems are best understood as coupled industrial-natural systems whose dynamics are dependent on and driven by external, or exogenous human inputs. In such systems, exogenous technical energy inputs are invested to support and maintain the growth of forest stands which are ultimately harvested for products valuable to humans.

As a result, conventional energy analyses of managed forests treat the forest as an industrial production system, generating useful outputs (i.e., wood, residues, energy etc.) while requiring energy and material inputs (Klopatek & Risser, 1981; Herendeen & Brown, 1987; Mead & Pimentel, 2006). Consequently, these approaches have focused on input-output based metrics such as the energy return on energy invested (EROI), which quantifies the energy efficiency with which energy outputs are obtained, and net energy analysis (NEA), which determines the quantity of energy obtained from the system after inputs (costs) are subtracted (Hall et al., 2009; Gupta & Hall, 2011; Marshall & Brockway, 2020). An advantage of these approaches is the application of consistent metrics to compare different types of forestry operations across space and time. In doing so, they provide decision-making information regarding forestry operations (Mead & Pimentel, 2006). In the context of forests, however, these metrics account only for the quantity and incurred "energy cost" of tree biomass produced for the benefit of society.

In addition to describing the efficiency of forestry operations, energy also expresses information regarding a (eco)systems thermodynamic state (Odum, 1983; Perryman & Schramski, 2015). Ecosystems are dissipative systems which use energy and materials to maintain themselves at states far from thermodynamic equilibrium while dissipating degraded energy as heat to the environment (Smil, 2007, 2012; Wiesner et al., 2019). Over successional time, this dissipative activity results in the accumulation and maximization of stored chemical energy in the form of biomass which serves as the foundational energy source supporting trophic communities of interacting organisms in food webs. In forests, the growth of primary producers (i.e., vegetation and trees) supply the energy available for food web organisms (i.e., consumers and decomposers) where biomass is maximized during food web growth (Fath et al., 2004). Thus, the magnitude of biomass within ecosystems represent the systems stored energy content and characterize its overall energy state (Odum, 1983; Jørgensen & Nielsen, 1998; Jørgensen, 1999; Schramski, Gattie, et al., 2015). Reductions in forest biomass, such as through intensive management, alter the energy available for food webs, ultimately impacting their biomass (i.e., energy) stores and driving them to states closer to thermodynamic equilibrium.

This dual role of energy in capturing the external inputs and resultant changes in the systems energy state emphasize the significance of energy analyses in assessing the coupled interactions in industrial-natural systems. The use of energy to simultaneously account for different aspects of a systems dynamics, expressed in consistent energy units, represents an advantage of energy analysis over mass-based and economic assessment approaches. However, while energy analyses exist for forest products, supply chains, and ecosystems, research has occurred disparately, in separate disciplines, and without context regarding their industrial-ecological coupling (Chen, 2007; Franzese et al., 2009; May et al., 2012; Marshall & Brockway, 2020; Malhi et al., 2022). Engineers focus on the supply and demand of energy along forest supply chains and the energy embodied within and obtained by forest products, whereas ecologists have traditionally focused on the distribution and diversity of individual species and how they are affected by human activities. As coupled systems, energy analyses of managed forests require approaches to assess both the external inputs supporting the system and resultant changes in the systems energy state driven by those inputs.

Here, we address this gap of growing importance and assess the energetics, including food web energetics, of an intensively managed pine plantation in the southeastern United States. We construct a dynamic model linking forestry activities to a forest stand that supports its corresponding food web (**Figure 3.1**). The model allows us to compare over time the total exogenous energy invested to plant, manage, and harvest the stand under differing management scenarios together with the resulting loss of food web biomass. Harvest of the stand results in a clear-cut of above-ground biomass, but also impacts the energy stores and flows available to support the rest of the food web operating in the forest. Varying impacts to stand biomass stocks (i.e., tree, vegetation, and dead wood biomass) alter the biomass dynamics (i.e., stored energy dynamics) of food web organisms. Including these impacts in energy analyses allows for the quantification of previously unconsidered energy aspects of industrial-natural systems, with potential implications for the future sustainable management of forest systems.

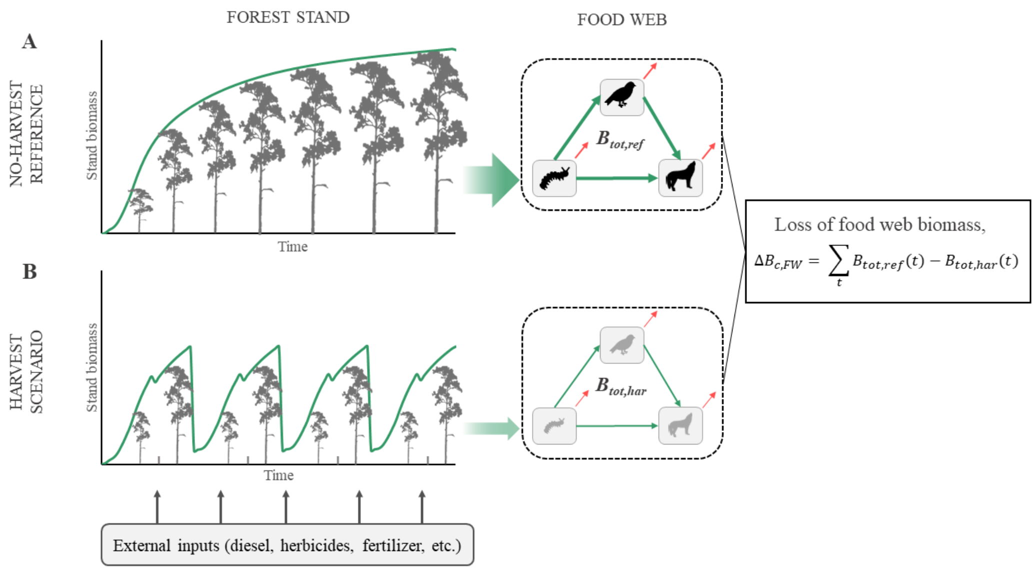

Figure 3.1 Conceptual diagram of a coupled industrial-natural forestry system. External energy inputs (black arrows) support forest operations invested to plant, manage, and harvest a forest stand over time. The forest stand supplies biomass which provides the energy to support interacting organisms at the base of the ecosystem's food web (green arrows). Under a no-harvest reference (**A**), and following natural forest succession, food webs organize maximizing biomass stores over time, $B_{tot,ref}$. Periodic harvesting alters the natural energy available subsequently impacting food web biomass, $B_{tot,har}$ (**B**). The total industrial external energy input to this system, *TEI*, is compared to the natural food web biomass energy losses, $\Delta B_{c,FW}$.

3.2 MATERIALS AND METHODS

An energy-systems accounting model is introduced of forestry operations which includes the exogenous energy invested for forest management, the biomass stocks of vegetation, and the disturbance induced energy losses in the forest ecosystem food webs. Stand biomass models of four different forest management scenarios are coupled to their commensurate food webs using ecological network analysis and metabolic theory methods. Stand-level models simulate biomass stocks of trees, understory vegetation, and dead wood (i.e., primary producer and dead wood compartments) while ecological network analysis and metabolic theory simulate the structural and functional characteristics of organisms including their biomass, energy throughflows, and respiration during food web interactions (i.e., consumer and decomposer compartments) (Gonzalez-Benecke et al., 2011; Gonzalez-Benecke et al., 2015; Schramski, Dell, et al., 2015; Woodson et al., 2020).

3.2.1 SIMULATING STAND-LEVEL BIOMASS STOCKS AND FOREST MANAGEMENT SCENARIOS

University of Florida's Carbon Resource Center carbon balance model (version 1.32) was used to simulate stand dynamics of one-hectare of loblolly pine under differing management scenarios (Gonzalez-Benecke et al., 2011). Stand-level biomass stocks were simulated for four different management scenarios in the southeastern US (**Table A5** and **Figure B1**) (Scott & Tiarks, 2008; Energy, 2011; Mills et al., 2013; Lu et al., 2015; Jonker et al., 2018). Management scenarios covered a range of site intensities with varying levels of herbicide and fertilizer treatments, thinning intensities and frequencies, and harvest frequencies. Simulated biomass stocks included those that directly supported the forest food web organisms and thus included above ground biomass of live pine trees, understory vegetation, and the dead wood pool. Above ground biomass of trees included stemwood, bark, and crown biomass. Where necessary, carbon mass values are calculated assuming a carbon content of ~50% for all biomass compartments (Smith, 2006). Biomass stocks are converted to energy units with the common conversion factor of 35 MJ/kg C (~17.5 MJ/kg biomass) (Smil, 2007).

3.2.2 ENERGY ANALYSIS OF FOREST MANAGEMENT SCENARIOS

Energy analysis of forest management includes the exogenous energy and material inputs invested in the stand. Forestry operations were grouped into four activities including site preparation, management, thinning, and logging (**Figure A4**). Site preparation includes the energy and material inputs for initial stand groundwork such as planting, replanting, initial herbicide and fertilizer treatments. Subsequent management includes treatments occurring after site preparation. Thinning activities remove a portion (typically 30% or 50%) of stand biomass and were assumed to be proportional to thinning intensity as a percentage of logging activities (i.e., requirements for thinning 30% of a stand are assumed to be 30% of those required for logging activities). Logging operations include those resources needed to harvest biomass. Only operations directly invested to support and maintain the stand are included in the energy analysis. Indirect supporting and infrastructure activities such as road building and maintenance were not quantified.

Individual fuel and material requirements of forestry operations included diesel, lubricants, N-fertilizer, P-fertilizer, and herbicides and were collected from literature sources for southeastern forestry operations (**Table A1**) (Lan et al., 2021; Xu et al., 2021). Individual inputs for each management scenario were converted to energy units as the product of each individual requirement with their corresponding specific energy coefficients (**Table A2** - **Table A4**). Requirements of thinning and logging operations were reported per volume of wood harvested and required an additional conversion step by multiplying each input with the quantity of wood harvested. Harvests from the stand model were converted to volume by dividing the harvested quantity by the average specific gravity (SG) at a given age from allometric equations (Gonzalez-Benecke et al., 2011). The total energy invested in the stand at any time t, $E_{in,tot}(t)$ (GJ/ha) is

$$E_{in,tot}(t) = \sum_{k}\sum_{n} E_{in,k,n}(t) \tag{3-1}$$

Then $E_{in,k,n}(t)$ (GJ/ha) is the energy investment at time t, of each individual fuel and material input, n, for each forestry operation, k. The cumulative or total energy invested TEI in the stand is then determined for four different management scenarios as the sum of all energy investments over a prescribed period

$$TEI = \sum_{t} E_{in,tot}(t) \tag{3-2}$$

3.2.3 SIMULATING FOOD WEB BIOMASS (ENERGY) STORES

Ecological network analysis (ENA) was used as a modeling framework to analyze compartment biomass stores of each trophic level and the food web in total (**Figure 3.2** & **Figure 3.3**). An empirically derived southern pine food web with 8 compartments (S) and 21 links (L) was constructed from literature sources. Trophic compartments represent aggregated functional groups based on their primary feeding habits while links represent flow connections between groups, i.e., "who eats who" (Fath, 2004; Ulanowicz, 2004; Fath et al., 2007). The dead wood pool was treated as a primary producer compartment and an input for decomposers. Live tree crown biomass (i.e. foliage) was assumed to be the edible portion of tree biomass by grazing species. Following previous approaches, metabolic theory was used to simulate steady-state biomass stores, energy flows, and respiration of each trophic compartment in the food web (Schramski, Dell, et al., 2015; Woodson et al., 2020).

The metabolic model was initialized with inputs of environmental (temperature and net primary productivity) and ecological (individual body mass size, trophic transfer efficiencies, endo/ectothermy) parameters. Steady-state of network flows were achieved by enforcing mass and energy balances on the input and output flows of each compartment in the food web until input and output flows balanced. Resulting steady-state biomass stores of each compartment were then determined as the product of the compartments individual abundance and its average individual body mass. All biomass flows and stores were converted to energy units with the common conversion factor of 35 MJ/kg C (Smil, 2007). A full description of the network construction, metabolic model, and steady-state analysis can be found in the Appendix (see Appendix B1).

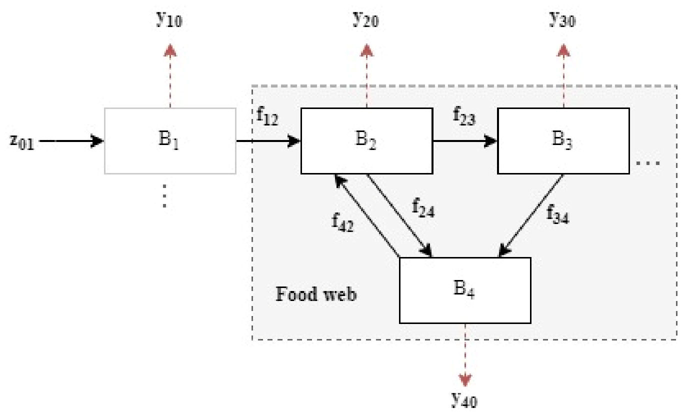

Figure 3.2 Ecological network analysis (ENA) notation of food web energy parameters. Energy storage (B_i); intercompartmental flows (f_{ij}); respiration (y_{i0}); insolation (z_{0i}); and system boundaries of an ecosystem network. In this study, all trophic compartments downstream of (i.e., excluding) the primary producer compartments are grouped and labelled "food web" (shaded region).

After steady-state of network flows and biomass stores was reached, donor-controlled flow rate and respiration rate coefficient constants, c_{ij} and k_i, respectively (1/yr) were calculated for each compartment,

$$c_{ij} = \frac{f_{ij}}{B_i} \tag{3-3}$$

$$k_i = \frac{y_i}{B_i} \tag{3-4}$$

Where, for a given compartment, i, f_{ij} (GJ/ha·yr) is the energy flow from compartment i to j, y_i is the respiration to the environment (GJ/ha·yr), and B_i is the compartment biomass (GJ/ha). These donor-controlled rate coefficients determine a linear relationship between a given compartment and each of its outgoing flows and control the rate at which transfers occur to other compartments or to the environment as respiration.

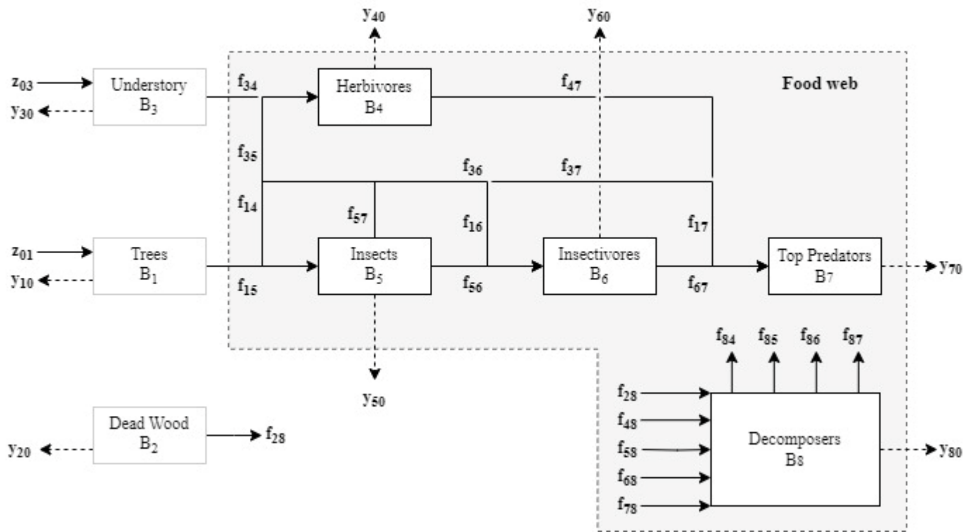

Figure 3.3 Network model of a 1-hectare forest ecosystem depicting energy stores and flows. Network includes S = 8 trophic compartments (storages) and L = 21 links (intercompartmental flows, f_{xx}). Stand biomass compartments, B_1, B_2, and B_3, are the edible portion of tree biomass, dead wood, and understory vegetation, respectively. Insolation, z_{01} and z_{03}, and respiration, y_{10} through y_{80}, are system inputs and outputs, respectively. The food web (shaded area) consists of all heterotrophic compartments, B_4 through B_8, downstream of stand compartments.

Rate coefficients were then applied in a simple bioenergetic model to simulate food web biomass dynamics over time,

$$\frac{dB_i}{dt} = \overbrace{\sum\nolimits_{j\forall prey} c_{ij}B_i}^{gain\ by\ consumption} - \overbrace{\sum\nolimits_{j\forall predators} c_{ij}B_i}^{loss\ by\ predation} - \overbrace{k_iB_i}^{respiration\ loss} \tag{3-5}$$

Where the change in a given compartments biomass, $\frac{dB_i}{dt}$ is determined by the balance between the energy gained by the compartment through consumption and losses through predation and respiration. Rearranging, the biomass of compartment i at a time t is

$$B_i(t) = B_i(t-1) + c_{ij}B_i(t-1) - c_{ij}B_i(t-1) - k_iB_i(t-1) \quad (3\text{-}6)$$

Similarly, at time t, compartment energy flows, f_{ij}, and respiration, y_i, are determined from their respective steady-state rate coefficients,

$$f_{ij}(t) = c_{ij}B_i(t) \quad (3\text{-}7)$$

$$y_i(t) = k_iB_i(t) \quad (3\text{-}8)$$

For the whole food web, at any time t, total food web biomass B_{tot} (GJ/ha) was calculated as the sum of all compartment biomass values, B_i,

$$B_{tot}(t) = \sum_i B_i(t) \quad (3\text{-}9)$$

The model approaches steady-state over time with parameter output trajectories matching well known asymptotic trends in the energetics of successional forest growth (Odum, 1969; Fath et al., 2004).

3.2.4 FOOD WEB IMPACTS

Food web model initialization began by coupling the time series biomass outputs of the forest carbon models as inputs to the producer and dead wood compartments (compartments B_1, B_2, and B_3, see **Figure B1**) of the dynamic network model for each management scenario. Total food web biomass was then calculated (eq. 3-9) over the simulated time period for each management scenario under, first, a no-harvest reference scenario $B_{tot,ref}$ and then again for each management scenario with harvest included $B_{tot,har}$. Cumulative values of total food web biomass were then calculated over the simulated period for each reference and harvest scenario, respectively. The difference between the cumulative food web biomass without and with harvest $\Delta B_{c,FW}$ (GJ/ha) was taken to represent the impact of harvest on food web energetics,

$$\Delta B_{c,FW} = \sum_{t} (B_{tot,ref}(t) - B_{tot,har}(t)) \qquad (3\text{-}10)$$

Magnitudes of the cumulative loss of total food web biomass are then compared with the magnitudes of the total energy invested *TEI* (GJ/ha) for each management scenario over 25, 50, 75, and 100-year intervals.

3.2.5 UNCERTAINTY ANALYSIS

To account for variability and uncertainty in food web functional and structural characteristics, monte carlo analysis was performed for $n = 1000$ model runs while varying individual body mass sizes ($M_{ind,i}$) of each trophic compartment and differing trophic transfer efficiencies (ε_i) within noted but realistic ranges. Further details of the parameter variations for each scenario can be found in the Appendix (see Appendix B3). Food web biomass losses $\Delta B_{c,FW}$ are reported as the mean and standard deviation (mean ± st.dev) following 1000 simulations for each management scenario.

3.3 RESULTS

3.3.1 COMPARISON OF FOOD WEB BIOMASS LOSSES TO TOTAL ENERGY INVESTED

After 100 years, more intensive management regimes require greater energy investments and result in greater food web impacts (**Figure 3.4**). However, these dynamics vary over time and across management regimes. Over the first 25 years, food web biomass losses ($\Delta B_{c,FW}$) are lower than total energy investments (*TEI*) for all management scenarios. For saw timber (ST), conventional (C), and heavy thinning (HT) scenarios, $\Delta B_{c,FW}$ remained negative over the first 25 years indicating food web biomass improvements of ~18 GJ/ha for ST and C and ~31 GJ/ha for HT relative to no-harvest reference scenarios. However, this was not the case under the most-intensive short rotation

(SR) scenario, which never achieved improvements to food web biomass instead quickly surpassing total energy invested.

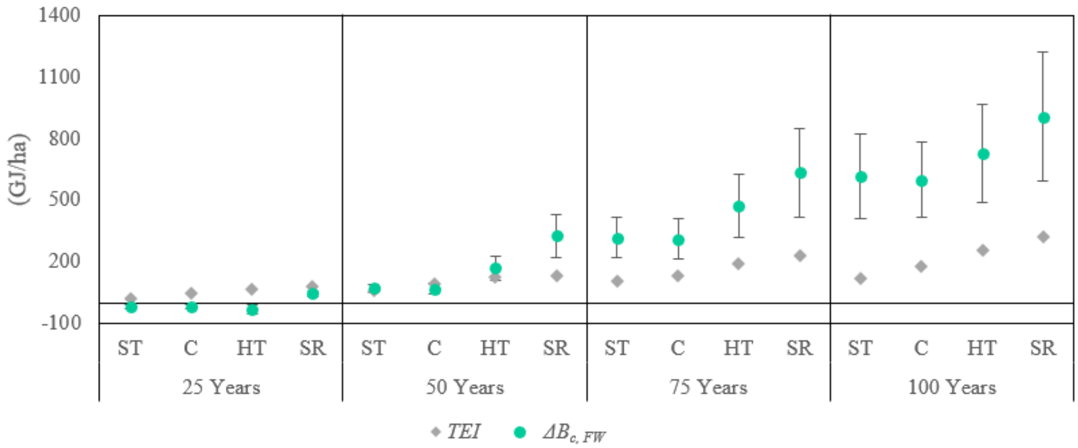

Figure 3.4 Comparison of total energy invested (*TEI*) and food web biomass losses (*$\Delta B_{c,FW}$*) from a forest stand (in GJ/ha) under four management scenarios each over 25, 50, 75, and 100-year intervals. In order of increasing intensity from left to right, management regimes include saw timber (ST), conventional (C), heavy thinning (HT), and short rotation (SR) scenarios with harvest rotations every 35, 25 (for both C and HT managements) and 16 years, respectively. Error bars represent the standard deviation (95% confidence interval). Negative values indicate improvements in food web biomass under a given management.

Such improvements to food web biomass are due to increased dead wood production immediately following early stand thinnings prior to the initial harvest under these scenarios. Increased dead wood production stimulates decomposer biomass leading to greater food web biomass compared with the reference scenarios. However, in these scenarios, improvements are quickly outpaced by losses in tree crown and understory biomass following successive harvests which clear cut the stand. By year 50, $\Delta B_{c,FW}$ is comparable to or exceeds *TEI* while by year 75, $\Delta B_{c,FW}$ exceeds *TEI* for all managements. By year 100, food web biomass losses are three to five times greater than energy invested in the stand regardless of forest management.

3.3.2 DYNAMICS OF FOOD WEB BIOMASS LOSSES AND TOTAL ENERGY INVESTED

Over time, food web biomass losses accumulate at faster rates than energy invested in the stand and thus exceed them at different points in time depending on management regime. To examine this further, the ratio of food web biomass lost to the total energy invested ($\Delta B_{c,FW} / TEI$) was calculated for each scenario over time. This dimensionless ratio quantifies the food web biomass lost per unit of total energy invested in the stand over a given time period. Thus, the ratio describes the relationship between the impacted food web biomass supported by the stand and the exogenous inputs supporting the stand (i.e., a ratio of *impacts* to the *drivers* supporting those impacts). While the numerator and denominator consist of disparate energy types (i.e., biomass and technical energy), the ratio provides insight to the relationship between food web impacts resulting from different types of forest management, which are ultimately driven by differing quantities of external inputs. When this ratio exceeds 1, food web biomass losses exceed total energy invested. Conversely, a negative value indicates improvement of food web biomass under the given management regime.

After 100 years, this ratio is greater under the least intensive (ST and C) and roughly equivalent under more intensive (HT and SR) management regimes (**Table 3.1**). In other words, less intensive managements result in greater food web biomass impacts per unit of energy invested compared with more intensive management regimes. This is due to the much lower energy invested under less intensive managements. Over the short-term, the ratio remains negative under managements with thinning, indicating improvements in food web biomass under these management regimes and further demonstrating the role of improving dead wood production in forest management prior to harvest.

Linearly interpolating between time intervals determines the approximate time at which food web biomass losses exceed total energy investments, or when the $\Delta B_{c,FW}/TEI$ ratio exceeds a value of 1 for each management scenario. Under less intensive management regimes, food web biomass losses take longer to exceed total energy invested (i.e., for $\Delta B_{c,FW}/TEI > 1$). For ST and C management this occurred at years 48 and 55, respectively. While for HT and SR this occurred at years 46 and 31, respectively (**Table 3.1**). In other words, food web impacts exceed energy invested sooner under more intensive management regimes.

Table 3.1 Ratio of food web biomass lost to total energy invested ($\Delta B/TEI$) in the forest stand for different management scenarios at differing time intervals. The last column displays the approximate time at which food web biomass losses begin to exceed total energy investments ($\Delta B_{c,FW}/TEI > 1$).

	Time interval (years)				
Management Scenario	25	50	75	100	Approx. time (years) at which $\Delta B_{c,FW}/TEI > 1$
Saw Timber (ST)	-0.9	1.2	2.9	5.2	48
Conventional (C)	-0.4	0.8	2.3	3.4	55
Heavy Thinning (HT)	-0.5	1.3	2.5	2.9	46
Short Rotation (SR)	0.6	2.5	2.7	2.8	31

3.4 DISCUSSION

This study advances the understanding of the relationship between the external technical energies invested in industrial-natural forestry production systems and the resultant energetic impacts to their supported food webs. Results showed that more intensive management regimes not only require greater external energy inputs for system maintenance, but also support greater losses of food web biomass. These losses accumulate over time, eventually surpassing in magnitude external energy investments and widening an energy gap between intensive management and ecosystem impacts. Thus, our results begin to quantify a fundamental energy imbalance between the intensive management of forests and their supported food webs necessary for sustenance at the base of an otherwise healthy ecosystem. Understanding the coupled energetics of such interactions is crucial given the global decline of natural forests, rapid biodiversity loss, and increasing establishment of managed forests now underway due to ever-increasing human demands for forest products. Altogether, these results indicate a losing energy trade-off between the human use and management of forest ecosystems and their continued ecological health.

Despite these coupled interactions, no studies have directly compared the external energies invested to support the system with their resultant impacts to food web energy stores (i.e., biomass stores) over time. While previous attempts have been made to capture impacts to ecosystem's energy states resulting from human activity, such attempts occur in isolation to the broader exogenous technical inputs supporting them. Further, impacts to consumer biomass are often ignored due to their much lower quantities in comparison with vegetation and tree biomass (Woodwell & Whittaker, 1968; Schaubroeck et al., 2012; Smil, 2012). However, rather than being of a negligible magnitude, our results demonstrate that food web biomass losses are in fact comparable to, and eventually exceed, the exogenous energy inputs invested in the system over time. These results agree with a previous study which calculated significant energy losses associated with the biomass and biodiversity loss of avian species due to agricultural bioenergy production systems in Europe and argued for the inclusion of such disruptions in energy analyses (Golberg, 2015). Thus, as an energy term, food web biomass losses are indeed significant in magnitude and should be included alongside conventional technical energy terms in future energy analyses of industrial-natural systems.

The study has limitations. As semi-natural systems, managed forests are supported and driven by both natural inputs (such as solar radiation, nutrients, water, etc.) and technical inputs invested by humans. However, the natural inputs were not included as explicit inputs in the energy analysis as the modeled food web biomass dynamics were already indirectly driven by the natural resources supporting the food webbed network system. This is possible and appropriate as the carbon balance models used to simulate stand biomass dynamics already included natural resources based on geographical data to simulate stand growth. The management scenarios consisted of only clear-cut harvests of stand biomass. Yet, harvest intensity and distribution have been shown to have large impacts on food webs and biodiversity (Simard et al., 2020; Canelas & Pereira, 2022). As such, less intensive harvest practices such as through selective logging or retention forestry, will reduce the exogenous energy inputs invested in the stand due to reduced logging requirements, but further study is needed to compare food web biomass impacts with exogenous technical inputs under managements with less intensive harvest practices.

Additionally, limitations and challenges exist for the modeled food web biomass dynamics. Other management factors, such as from fertilizer and herbicide applications or environmental changes induced by clear cutting (such as changes in surface temperatures), are likely to impact food web biomass dynamics. However, these will require substantial work requiring additional models linked to food web biomass and thus, were not included. Further, the food web network structure in this study was based on literature data of pine forest ecosystems throughout the southeastern US and is likely more complex than networks in intensively managed forests where high levels of land-use intensity result in more homogenized and less connected networks (Felipe-Lucia et al., 2020). Given that additional impacts and simpler food webs would result in greater losses of food web biomass, our model results and conclusions are conservative, accounting only for the contribution of stand biomass changes, driven by different managements, to the resultant changes in food web biomass. Still, the fact that food web biomass losses exceed external energy investments by large margins, regardless of the type of management, highlights the fundamental existence of an energy imbalance between the inputs driving intensive management and the resulting food web impacts supported by those managements.

3.5 CONCLUSION

By assessing the human inputs invested to manage forests together with the resultant changes in food web biomass supported by those inputs, our work differs from previous forestry energy analyses which only focus on the energetic performance and efficiency of forestry operations. We performed a dynamic energy analysis of an intensively managed forest stand together with and supporting a food web under differing management scenarios over a 100-year period. Our model compared magnitudes of the total exogenous technical energy inputs invested to support the stand and the resultant changes in food web biomass driven by those inputs. Key findings can be summarized as follows:

- Over the first 25 years and prior to the initial harvest, food web biomass improved under management scenarios with thinning. These improvements were due to enhanced dead wood production from thinning which increased decomposer biomass, leading to improvements in total food web biomass.
- Following successive harvests and by year 75, across all management scenarios, regardless of intensity, magnitudes of food web biomass losses exceeded the magnitudes of exogenous technical energy inputs invested. However, the times at which food web biomass losses began to exceed the exogenous energy inputs occurred sooner under more intensive managements.
- For all management scenarios, over the long-term (i.e., after 100 years), food web biomass losses exceeded the exogenous energy invested by factors of three to five suggesting a critical energy imbalance in forestry production systems.

By directly comparing the magnitudes of two seemingly disparate aspects of the energetics of intensively managed forestry systems over time and across differing managements, our results demonstrate the importance of energy analysis in capturing both the inputs supporting the system and the resultant impacts driven by those inputs. These results highlight a fundamental, yet perhaps typical, large-scale energy imbalance in modern industrial-natural systems as energy inputs invested for system management also support increasing losses of food web energy stores (i.e., biomass) over time. While these losses were improved over the short-term under less intensive managements, the magnitudes of food web biomass losses eventually exceeded the external energy investments with subsequent harvests, regardless of the type of management. Less intensive managements, however, delayed the timing of when food web biomass losses exceeded external inputs.

Given the magnitudes of food web biomass losses in comparison with exogenous technical energy inputs, it is no longer permissible to ignore resultant ecosystem impacts in industrial-natural systems. Future energy analyses should strive to include resulting ecological impacts alongside conventional energy metrics as much as possible. Likewise, future work is needed to further explore these energetic relationships under wider selections of forest managements and different food web networks. Doing so will help enable the design and selection of managements to reduce resultant impacts to the ecosystems energy stores, improving overall sustainability in intensively managed industrial-natural systems.

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CHAPTER 4

IDENTIFYING UNCERTAINTY IN THE GLOBAL WARMING IMPACTS OF BIOMATERIALS: AN ANALYSIS OF BIO-SUCCINIC ACID[4]

[4] **J. Dunlap**, J.R. Schramski, G. Li, K. Li. 2024. *International Journal of Life Cycle Assessment* Reprinted here with permission of publisher.

ABSTRACT

Life cycle assessments of bio-succinic acid (bioSA) report a range of emissions compared to their fossil-based counterparts. Such uncertainty results from multiple factors including different processing options and modeling choices, making it difficult to interpret results and ensure emission reductions. Identifying uncertainty is thus crucial to ensuring the environmental benefits of biomaterials and is a crucial step toward a future bioeconomy. Comparing 15 life cycle assessments of bioSA production, factors such as feedstocks, downstream processing technologies, study scopes, coproduct handling, coproduct types, and study locations were assessed to identify the impact of different modeling choices and processing options on the global warming impacts of bioSA. Emissions were referenced to a fossil-derived equivalent product and selected case studies were developed for a more in-depth analysis of the impact of individual factors, such as enzymes, coproducts, and grid location on overall emissions. Global warming impacts varied across differing processing and modeling factors. BioSA from sugar cane and energy crops consistently showed emission reductions while from corn starch, corn stover, and food waste, bioSA displayed impacts above and below fossil-based production depending on processing and modeling options. Uncertainty in individual factors such as enzyme production was significant, potentially resulting in impacts exceeding conventional fossil-based production. However, coproduct inclusion and handling methods were necessary for several feedstocks to ensure emissions remained lower than the fossil-based route. This study highlights the importance of identifying and quantifying uncertainties in the global warming impacts of bio-based products. Doing so serves not only to ensure emission reduction benefits, but also strengthens trust in LCA studies and encourages more accurate and trustworthy results for policy makers, industrial partners, and LCA practitioners.

4.1 INTRODUCTION

A transition to a bioeconomy is a crucial solution to address fossil-fuel depletion and global climate change. As an alternative to petroleum-based products, bio-based equivalents can reduce fossil fuel use and sequester CO_2 in biomass (Musonda et al., 2020; Bello et al., 2022). Bio-succinic acid (bioSA), $C_4H_6O_4$, is one chemical that is derived from biorefinery carbohydrates and is a growing platform chemical due to the high value of its derivative products (Bechthold et al., 2008; Bozell & Petersen, 2010). Currently, succinic acid (SA) is petrochemically produced from n-butane/butane through catalytic hydrogenation of maleic acid or maleic anhydride (Bechthold et al., 2008). However, increasing conservation efforts toward transitioning to a bioeconomy have called for increasing production of bioSA derived from several renewable feedstocks and microorganisms (de Jong et al., 2020).

BioSA production is still in its early phases with no commercial scale production, despite several previous pilot and demonstration plants (Li & Mupondwa, 2021). However, interest in bioSA is continuing to be driven by both its potential for reducing emissions compared with fossil-derived SA, it's wide applications in a variety of industries, and as a building block for a wide range of high value products and bulk chemicals (Choi et al., 2015; de Jong et al., 2020). BioSA can serve as renewable source for a wide range of chemicals and products in the production of food, pharmaceutical products, detergents and solvents, and biodegradable polymers, such as polybutylene succinate (PBS) and polyamides (Ahn et al., 2016; Mazière et al., 2017). As an intermediate bio-monomer, the process chain of bioSA is simpler than the full production of bio-polymers and thus, assessing the environmental impacts of bioSA can serve as a necessary starting point for chemicals with more complex structures. As a result, bioSA has previously been recognized by the Department of Energy (DOE) as a top ten priority biochemical whose production is crucial for a future bioeconomy (Werpy & Petersen, 2004). However, in order to ensure bio-based solutions remain environmentally beneficial, it is crucial to examine their total life cycle impacts. Given its early stage of development, wide industrial applications, and potential to serve as a starting point for more complex bio-based polymers, bioSA represents an ideal candidate for assessing the environmental impacts of biomaterials more broadly.

Early life cycle assessment (LCA) studies of bioSA indicated that global emissions savings of 5 kg CO_2/kg were possible when replacing their functionally equivalent fossil-derived counterparts (Hermann et al., 2007). Later assessments showed emissions savings up to 86% for bioSA from corn stover feedstocks compared to a conventional fossil reference (Adom et al., 2014; Dunn et al., 2015). However, despite promising emission reductions, more recent assessments expanded to include multiple feedstocks, processing options, and methodological choices and display a range of emissions, even when produced from similar feedstocks (Weiss et al., 2012; Ogmundarson et al., 2020; Walker & Rothman, 2020). In a recent review of biomaterials, global warming impacts of bioSA were both above and below its fossil counterpart regardless of the life cycle stages considered (Ogmundarson et al., 2020). Such large variations can lead to difficulty in drawing meaningful conclusions and highlight the need for identifying and quantifying significant areas of uncertainty.

Uncertainty in the life cycle emissions of bioSA and biomaterials, more broadly, arise from processing options (i.e., from differing feedstocks, processing technologies, and biorefinery locations) and methodological choices (i.e., differing study scopes and system boundaries, inclusion of coproducts, and different methods for handling coproducts) (Montazeri et al., 2016; Dunn, 2019; Ogmundarson et al., 2020; Bishop et al., 2021). In existing LCA's, however, only uncertainty in the quantities of individual material and energy flows in the inventory assessment phase are considered. Yet, several individual choices, often made by the LCA practitioner, such as the chosen conversion technology, system boundaries, and inclusion of coproducts have also been shown to significantly influence comparisons of bio-based with fossil based products (Janssen et al., 2016; Montazeri et al., 2016; Tecchio et al., 2016; Dickson et al., 2021). In Germany, for example, bioSA has been shown to only produce significant emission savings when substituting its fossil counterpart if it is recycled at the end of its life and several cascading coproducts are obtained from its production (Musonda et al., 2020).

Addressing these issues, this study aims to identify areas of uncertainty in the greenhouse gas emissions of bioSA as a guide for future impact assessments of biomaterials. We survey the published environmental literature of bioSA production to answer two questions which address current gaps in knowledge: 1) What are the formative individual areas of uncertainty within LCA's of bioSA production and 2) Do the magnitude of uncertainties in emissions hinder conclusions regarding the environmental benefits afforded by bioSA compared to its fossil-derived counterparts? Compared to previous analyses, we analyze a much larger sample size of studies than has been previously considered (Montazeri et al., 2016; Ogmundarson et al., 2020). Where adequate, existing assessments are used as case studies to discuss and quantify priority areas of uncertainty and their magnitudes.

4.2 MATERIALS & METHODS

4.2.1 STUDY OVERVIEW

Life Cycle Assessment (LCA) is a systematic way to quantify the environmental impacts of a process or product over its lifespan (ISO, 2006). **Figure 4.1** shows an overview of the main LCA steps and processes of bioSA considered in this study. First, we contrast and examine the results of fifteen environmental assessment and LCA models (**Table C1**) of bioSA production to determine the variability of greenhouse gas emissions (GHG) due to different modeling choices and processing options. This is a substantial improvement over previous analyses which have considered only five and eight studies for bioSA in total (Montazeri et al., 2016; Ogmundarson et al., 2020). The examined modeling choices and processing options were those that have been previously identified as potentially having a large impact on the emissions of bio-based systems. A total of six factors impacting bioSA emissions including feedstock, downstream processing technology, study scope, coproduct handling method, type of coproduct, and study location were examined. Finally, using existing samples as case studies, a more in-depth analysis is performed to further quantify the impact of several individual factors on the overall emissions of bioSA.

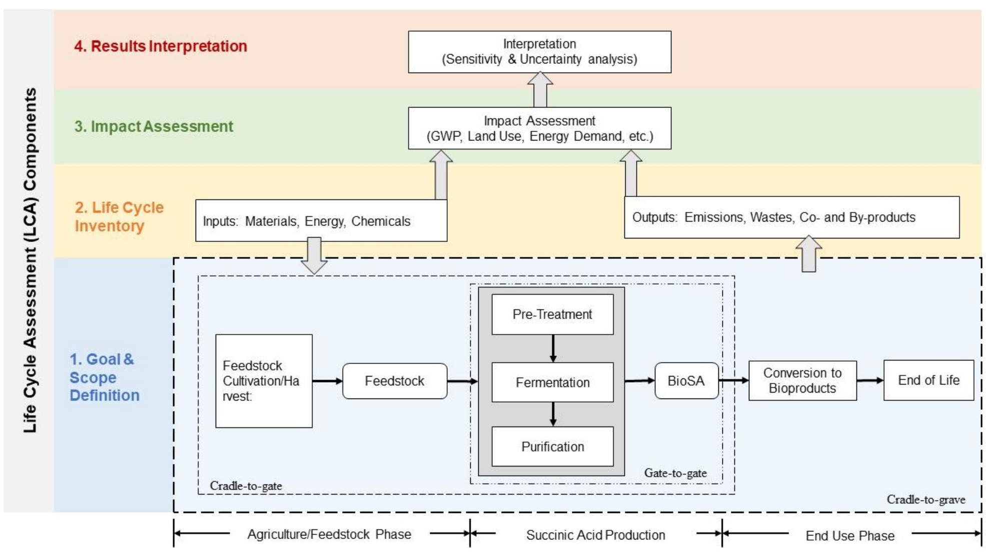

Figure 4.1 Primary life cycle assessment components of bioSA from production to end of life.

The examined studies canvassed all three generations of feedstocks in the US, Europe, and Brazil with one paper focused on India, yielding a total of $n = 64$ individual data points for the GWP of bioSA (**Table C1**). Only studies focusing exclusively on the production of succinic acid were included in the analysis. Studies whose primary focus was to assess an end product of bioSA were not included as these studies simply applied the results from those that focused on bioSA. The majority of examined studies adopted an attributional modeling approach, however, consequential studies were also included in the sample. In consequential modeling, the primary difference involved substitution of bioSA with a fossil reference. For these studies, the substitution with fossil SA was excluded to maintain consistency with the rest of the studies.

4.2.2 MEASURING GLOBAL WARMING IMPACTS

Impact assessments of bioSA most commonly included the 100-year global warming potential (GWP), which represents the cumulative radiative forcing of the total life cycle emissions of a process over a 100-year period. For this study and due to data availability, GWP was used to represent the GHG emissions of bioSA.

4.2.3 DIFFERENCES IN FUNCTIONAL UNITS

While nearly every study applied a mass-based functional unit of 1 kg of produced and purified bioSA, a single study applied a functional unit of the feedstock (Maria Ioannidou et al., 2021). In this case, inventory and impact results were rescaled to the functional unit of 1 kg of bioSA using yield data to maintain consistency with the rest of the studies. One study compared two different functional units including impacts per kg of produced bioSA and per kg of feedstock (Brunklaus et al., 2018). While the choice of functional unit can impact broad study outcomes, the purpose of this study was to assess variability in the global warming impacts of bioSA production itself. Further, the choice of functional unit does not introduce uncertainty to the impacts of bioSA production, but rather depends on the overall research question to be answered. Thus, only the former functional unit was included.

4.2.4 FEEDSTOCK GROUPING

Feedstocks were categorized into eight broad groups (sugar cane, energy crops, corn starch, corn stover, food waste, sugar beet, seaweed, and waste wood) based on the number of studies, sample size, and crop type. Due to a low number of data points, bread waste, waste cooking oil, apple cider waste, and winery waste were grouped into the broader category of "food waste". Similarly, fast growing crops such as sorghum grain, canary grass, and giant reed grass were grouped into the "energy crops" category. Due to its small sample size (only a single sample) and structural similarity to other lignocellulosic energy crops, sugar cane bagasse was also included in the "energy crops" category.

4.2.5 STUDY SCOPES AND CARBON SEQUESTRATION

The majority of the assessed studies used cradle-to-gate system boundaries which start with raw materials extraction and end with the production of purified succinic acid from the biorefinery. Only four studies used cradle-to-grave boundaries which included the degradation of bioSA in an end-of-life (EOL) scenario (Patel et al., 2006; Adom et al., 2014; Musonda et al., 2020; Dickson et al., 2021). A key difference between the two study scopes involved the treatment of biogenic carbon sequestration, or the carbon sequestered into the bioSA product itself during its production. In cradle-to-gate studies, biogenic carbon can be applied as a credit, reducing the overall emissions. For bioSA, biogenic carbon amounts to ~1.5 kg CO_2 eq./kg SA (Cok et al., 2014; Zucaro et al., 2017; Patel et al., 2018). In nearly all cradle-to-grave studies, bioSA was assumed to be landfilled at the end of its life, releasing the biogenic carbon sequestered during its production and thus being carbon neutral. In many cradle-to-gate studies, however, it was unclear whether biogenic carbon was included or not as many studies simply did not specify or mention biogenic sequestration. In these cases, and to avoid double counting, a conservative approach was taken, and it was assumed that biogenic carbon was included allowing for a consistent comparison with the other studies.

In addition to biogenic carbon, soil carbon sequestration may be an important factor in the carbon balance of many first- and second-generation feedstocks. However, issues of soil carbon sequestration were not included in most studies due to data availability issues (Moussa et al., 2016; Chrysikou et al., 2018; Maria Ioannidou et al., 2021). Only a single study considered changes in soil carbon storage (SCS) due to the cultivation of giant reed grass (Zucaro et al., 2017). In this case, SCS accounted for a relatively minor proportion ~11% (0.44 kg CO_2 eq./kg SA) of the gross global warming impact of bioSA. Thus, due to the lack of data and the minor contribution to overall emissions, issues of SCS were not considered in this study but still may represent an important future research avenue to consider.

4.2.6 FOSSIL-BASED REFERENCE PRODUCT

To quantify the impacts of modeling choices and processing options on emissions of bioSA, GWP values were referenced to those of fossil-derived SA. However, uncertainty regarding the GWP of fossil SA does exist. Production of fossil-derived SA was based on the current conventional hydrogenation of maleic anhydride method (Pinazo et al., 2015). From the literature, a total of four values of the emissions of fossil-derived SA were found ranging from ~1.9 to ~7.1 kg CO_2 eq./kg SA (Patel et al., 2006; Cok et al., 2014; Dickson et al., 2021). The values on the upper range used by Patel et al. (2006) were based on SA from the ecoInvent database (Althaus et al., 2007). Since then, these values have been updated to more accurately account for the coproduced steam (Cok et al., 2014). The fossil reference values used by Patel et al. (2006) are likely outdated and were thus excluded from this analysis. Therefore, we used values from Cok et al. (2014) and Dickson et al. (2021), who independently calculated the GWP of fossil SA based on proprietary industrial and literature data (Cok et al., 2014; Pinazo et al., 2015; Dickson et al., 2021). To account for the uncertainties in the GWP of fossil SA, the range of the reported values, from ~1.9 to ~3.9 kg CO_2 eq./kg SA with a mean of ~2.9, were taken as representative values for the conventional fossil-based route to produce SA.

4.2.7 ISOLATING THE EFFECT OF INDIVIDUAL FACTORS ON GWP

A more in-depth analysis regarding the impact of individual methodological choices and processing options on the overall emissions was performed using data from selected studies. These factors included the influence on emissions of changing the geographic location of the biorefinery, variability in the emissions of highly uncertain processes such as enzyme production, and the contribution of the inclusion of coproducts to overall emissions. Full details of the descriptions and modeling procedures of each of these factors can be found in Appendix C.

4.3 RESULTS

4.3.1 VARIATION IN GLOBAL WARMING POTENTIAL (GWP) DUE TO MODELING CHOICES AND PROCESSING OPTIONS

Figure 4.2 and **Figure 4.3** show the variability in GWP under each of the six different modeling choices and processing options for bioSA production. Summary statistics of the variability in GWP for all factors can be found in the Appendix (**Table C2** & **Table C3**). While GWP variability is high for each factor, several broad trends in the emissions of bioSA in comparison with fossil SA are noted:

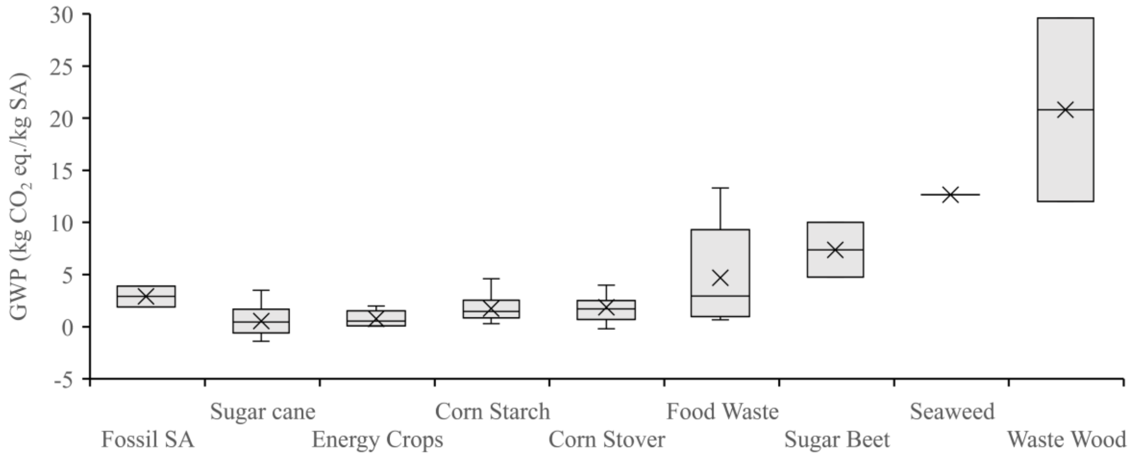

Figure 4.2 Overview of bioSA GWP by feedstock. Mean GWP values (X markers, in kg CO_2 eq./kg) of bioSA per feedstock from the existing literature. For comparison, the GWP of fossil-derived succinic acid (fossil SA) is also shown.

4.3.1.1 FEEDSTOCK

BioSA GWP varies significantly when produced from different feedstocks (**Figure 4.2**), ranging from -1.4 to ~30 kg CO_2 eq./kg SA for bioSA from sugar cane and waste wood, respectively. Compared to fossil SA (ranging from ~1.9 to ~3.9 kg CO_2 eq./kg), the mean values of four feedstocks – sugar cane, energy crops, corn starch, and corn stover – remain below the lower range of fossil SA. However, wide variability exists within the results of each feedstock. Despite having mean values below fossil SA, the range of GWP's of corn starch and corn stover, for example, vary from ~0.3 to ~4.6 and ~-0.2 to ~5.7 kg CO_2 eq./kg SA, respectively. For these feedstocks, such wide variability in GWP is enough to shift the comparison from favoring bioSA to favoring fossil SA. Four feedstocks – food waste, sugar beet, seaweed, and waste wood - display mean values above the mean and upper range of fossil SA. However, few data points exist for these feedstocks with only a single sample for seaweed, five for food waste and two for sugar beet and waste wood.

4.3.1.2 STUDY SCOPE

The analyzed system boundaries have a minor impact on bioSA (**Figure 4.3a**), varying GWP from a mean of ~2.3 to ~3.0 kg CO_2 eq./kg SA under cradle-to-gate and cradle-to-grave boundaries, respectively. This variability was due to the fact that nearly all cradle-to-grave studies assumed bioSA was landfilled at the end of its life, releasing the biogenic carbon sequestered during its production (a value of ~1.5 kg CO_2 eq./kg SA). As a result, cradle-to-grave studies displayed higher emissions than cradle-to-gate studies, placing the mean GWP slightly above the mean of fossil SA and shifting the preference more in favor of fossil-based SA.

4.3.1.3 DOWNSTREAM TECHNOLOGY

Significant variability exists for bioSA produced using different downstream processing technologies, with mean GWP's ranging from ~1.4 to ~7.3 kg CO_2 eq./kg SA for reactive distillation (RD) and reactive extraction (REX), respectively, values ranging both below and above the lower and upper ranges of fossil SA (**Figure 4.3b**). In addition to the large variation across technologies, considerable variation exists amongst studies which used the same technology. This is largely attributed to differences in feedstocks as bioSA produced from different feedstocks may also have been produced with the same downstream technologies (see Section 4.3.2.). It is important to note, however, that large disparities exist in the assessed sample sizes with only 1, 3, and 4 samples present for RD, membranes (MEM), and REX while 8, 21, and 26 samples were available for ion exchange (IX), electrodialysis (ED), and crystallization (CR) (**Table C3**).

4.3.1.4 COPRODUCTS

Both the method of handling coproducts (**Figure 4.3c**) and the type of coproduct obtained (**Figure 4.3d**) are essential for ensuring emission reductions compared with fossil SA. Under different coproduct handling methods, mean GWP varied from ~0.1, ~1.8, and ~4.2 kg CO_2 eq./kg SA for studies which used multiple, system expansion, and allocation-based (either mass or economic) methods, respectively. Studies using allocation-based methods showed the largest variation in GWP, particularly influenced by the relationship between the coproduct and bioSA. For example, in the case of food waste, the mass of coproduced feed was more than 10x that of the main bioSA product, yet their economic values were nearly identical at $4.8/kg and $5.0/kg, respectively (Gadkari et al., 2021). Mass and economic allocation would allocate ~10% and ~51% of the gross impacts to bioSA, respectively, leading to a 480% increase in impacts if economic rather than mass allocation was applied (Gadkari et al., 2021). Despite such large differences, mass allocation was chosen due to the high impacts resulting from economic allocation. Other studies have also noted the unfavourability of economic allocation citing the high selling price of bioSA in comparison with many of its coproducts, resulting in large allocation factors applied to bioSA (Cok et al., 2014; Gadkari et al., 2021). Although the price of bioSA is expected to decrease with increasing production, in scenarios where its price greatly exceeds its coproduct (as is the case of ammonium sulfate), decreases in selling price are unlikely to reduce the environmental burden of bioSA under economic allocation approaches (Cok et al., 2014).

The mean GWP of obtained coproducts ranged from ~0.2 to ~1.4 kg CO_2 eq./kg SA for processes which produced multiple coproducts and energy coproducts, respectively, all values below the lower range of fossil SA. Studies which did not include or assess any coproducts, displayed a mean GWP of ~9.5 with a significant range from ~2.0 to ~12 kg CO_2 eq./kg SA, values above the lower and upper ranges of fossil SA. For studies which generated feed as a coproduct, GWP displayed significant variability, ranging from ~1.3 to ~13.3 with a mean of ~8.2 kg CO_2 eq./kg SA, values both below and above the lower and upper range of fossil SA. Such large variability is explained by the method used to treat the coproduct and the quality of the coproduct itself. Existing production of feed is not a fossil intensive process. Thus, in the studies which treated the co-produced feed using the system expansion approach, the applied credit from substitution of feed with the existing production was not large enough to significantly reduce the overall GWP of bioSA (Dickson et al., 2021).

Taken together, these results highlight not just the importance of the inclusion of coproducts in reducing overall emissions, but of the quality of the obtained coproduct and the method used to handle the issue of coproduction in LCA. Obtaining multiple or high value coproducts (such as fertilizers) from the process chain is preferred and can be identified as a goal for securing emission reductions of bioSA and biomaterials, more broadly.

4.3.1.5 STUDY LOCATION

While the majority of studies analyzed were from European countries, significant variability in the GWP of bioSA production exists, regardless of the study location (**Figure 4.3e**). The mean GWP values varied from ~0.6, ~1.4, ~3.0, and ~4.6 kg CO_2 eq./kg SA for studies from Brazil, India, Europe, and the United States, respectively. However, studies from the United States and India are constrained by small sample sizes as only a single study and sample exists for bioSA from India while seven samples exist across four feedstocks in the United States (**Table C1**).The low impact of bioSA from Brazil can be attributed to the use of sugar cane as the sole feedstock, whose production is much less energy intensive than corn-based feedstocks typical of Europe and the United States (Patel et al., 2006; Cok et al., 2014; Smidt et al., 2016).

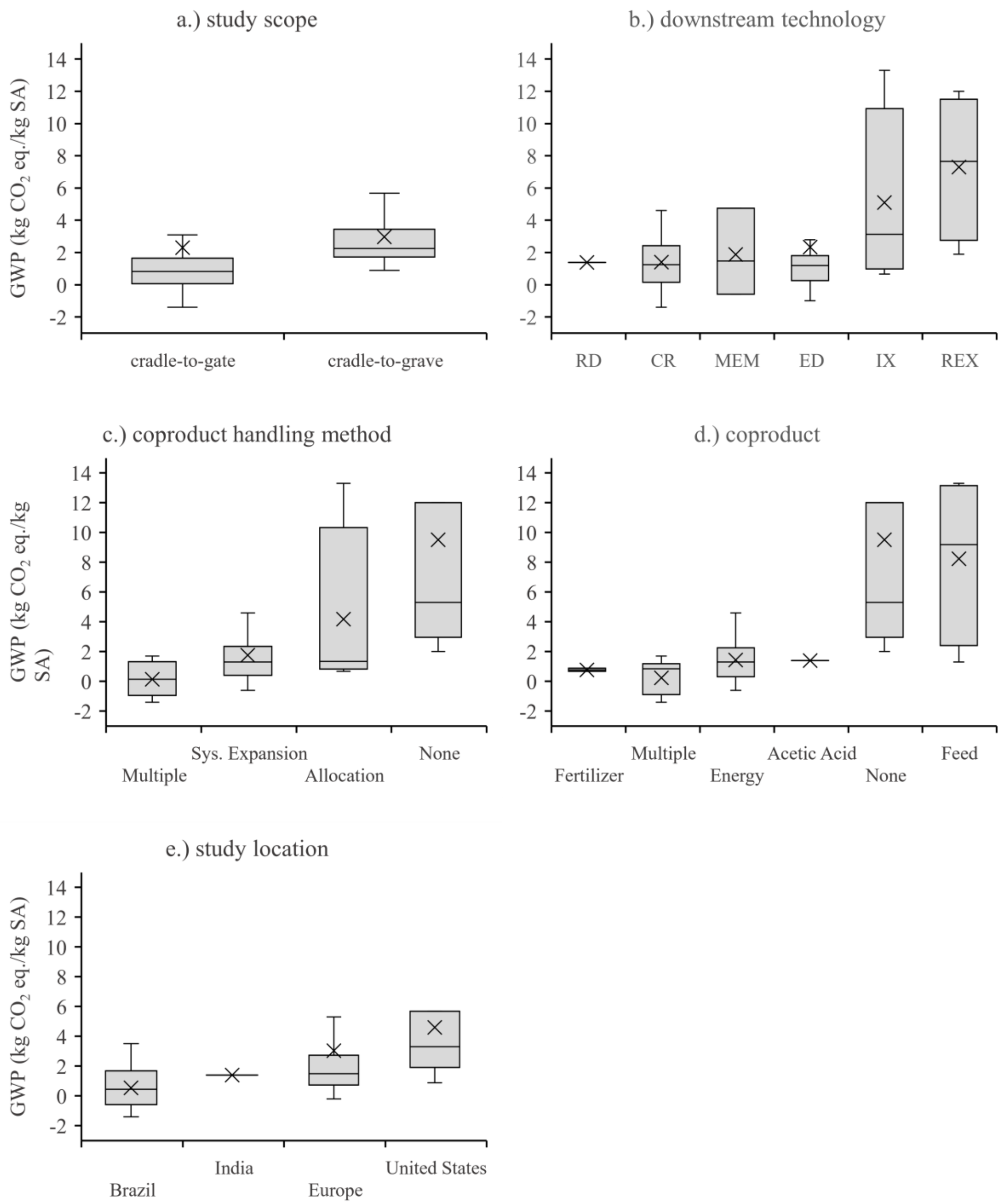

Figure 4.3 Variation and mean GWP's by uncertainty factor a.) study scope, b.) downstream technology, c.) coproduct handling method, d.) coproduct, and e.) study location. Abbreviations for downstream technologies are: reactive distillation (RD), crystallization (CR), membranes (MEM), electrodialysis (ED), ion exchange (IX), and reactive extraction (REX). For readability, the full range of GWP values (i.e., outliers) are not displayed on graphs. Corresponding ranges and summary statistics of each factor can be found in Appendix C.

4.3.2 COMPARISON OF MULTIPLE FACTORS WHICH IMPACT THE VARIABILITY OF GWP BENEFITS

While the results thus far identify variability in each of the modeling and processing factors which contribute to the global warming impacts of bioSA, the combination of factors behind the variability is crucial to ensuring emission reductions. **Figure 4.4** shows a breakdown of the GWP values of bioSA from each feedstock paired with each modeling choice and processing option in comparison with fossil SA. For bioSA derived from energy crops, emission reductions are nearly always secured compared to fossil SA irrespective of the considered modeling choices or processing options. For sugar cane, emission reductions are likely secured, but display more variability depending on the chosen downstream technology, coproduct handling method, and coproduct obtained.

While many studies have noted the potential environmental benefits of bioSA derived from corn starch (Patel et al., 2006; Cok et al., 2014; Smidt et al., 2016; Musonda et al., 2020), these benefits are highly variable where the inclusion of multiple coproducts and the use of less energy intensive downstream technologies such as membranes are essential for securing emission reductions. BioSA from corn stover and food waste produce widely variable emissions that range from both better-than to worse-than fossil SA across nearly all factors. While for bioSA derived from sugar beet, seaweed, and wood waste, emissions are worse than fossil SA regardless of the considered modeling and processing factors, however, these feedstocks may be constrained by a relatively small sample size of data points in comparison with the others (**Table C1**) and additional GWP data are needed as more studies become available for these feedstocks.

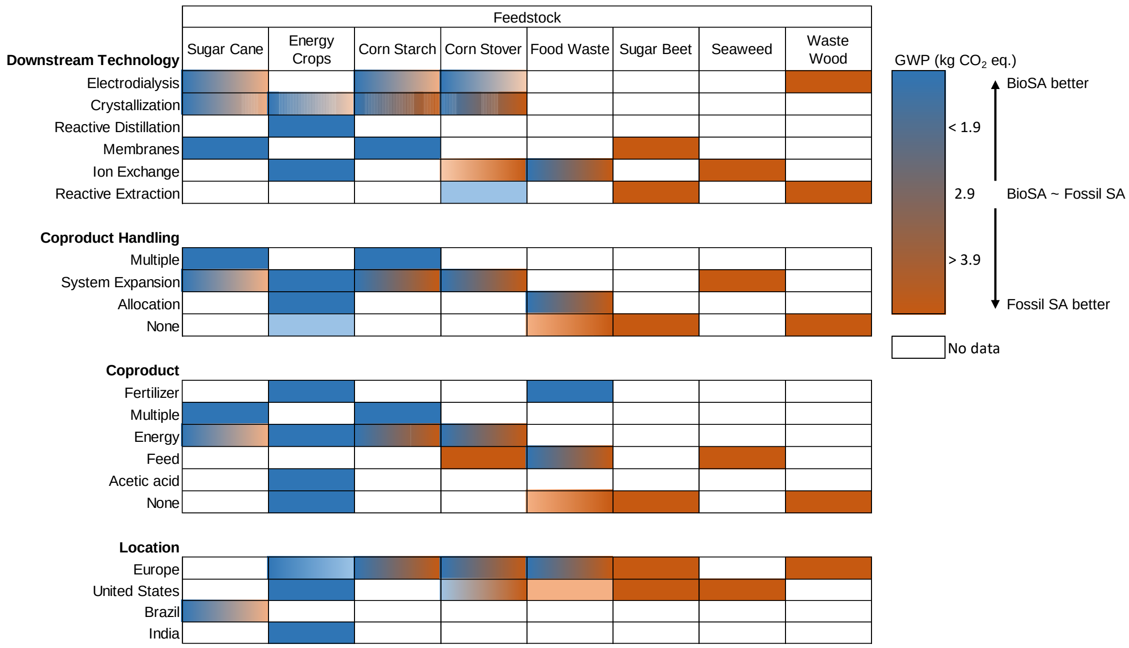

Figure 4.4 Comparison of modeling and processing factors impacting emissions. The color of each box represents the range in GWP of bioSA in comparison with fossil SA. Solid blue boxes represent those cases where GWP remained below the low end of fossil SA (1.9 kg CO_2 eq.) while solid red boxes are those where GWP was above the upper end (3.9 kg CO_2 eq.) of fossil SA. Boxes with gradients from blue to red are cases with multiple samples which displayed GWP values ranging from better than to worse than fossil SA.

4.3.3 IMPACT OF INDIVIDUAL FACTORS ON OVERALL GWP

Finally, a more in-depth analysis was performed on selected case studies to isolate the effects of several individual factors on the overall emissions of bioSA. These factors include 1.) a change in the location of the biorefinery to regions with differing power grids (**Table C4**) resulting in variations in overall emissions 2.) variation in the emissions of enzyme production, a process whose carbon footprint has previously been identified as highly uncertain, and 3.) the impact of including/excluding coproducts on overall emissions of bioSA.

4.3.3.1 PLANT LOCATION

GWP of bioSA varies with biorefinery location from ~0.1 to ~3.4 kg CO_2 eq./kg SA (**Figure 4.5**). At the extremes, using direct crystallization (DC) technology, moving from the average European

(RER) power mix to that of Greece (GR) increases GWP by 0.9 generating a total of ~1.7 kg CO_2 eq./SA and conversely, changing plant location to Switzerland (CH) decreases GWP by 0.8 resulting in a total of ~0.1 kg CO_2 eq./SA.

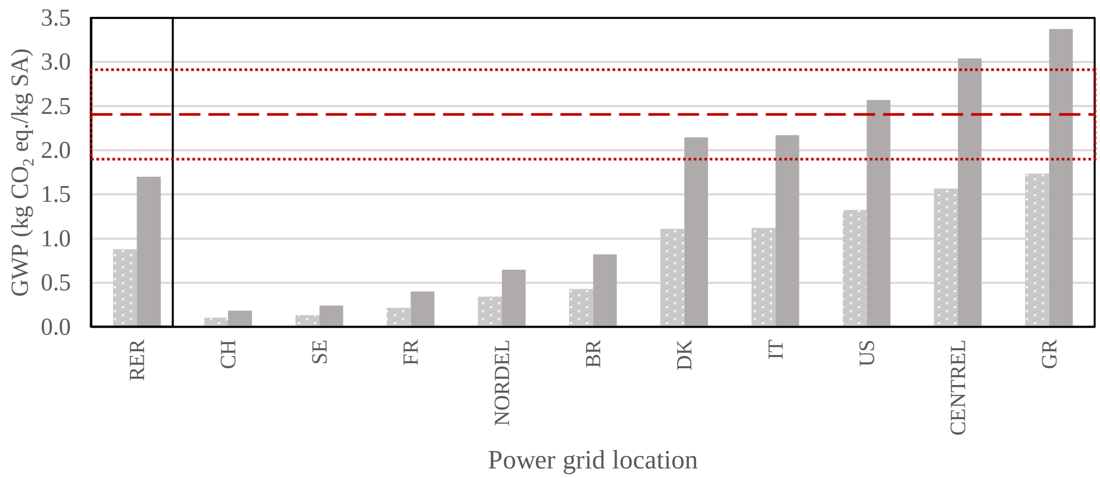

Figure 4.5 Location dependent effects on GWP of bioSA production. Direct crystallization (DC, light grey dotted bars) and electrodialysis (ED, dark grey solid bars) as downstream technologies. GWP values are compared to the average European power mix (RER, black box) and the mean (red, dashed line) and upper and lower ranges (red, dotted lines) of fossil-derived succinic acid.

For the more energy intensive electrodialysis (ED) process, GWP increases by 1.7 and decreases by 1.5 kg CO_2 eq./SA for the Greek and Swiss grids, respectively. For ED processing, a change from the European average to Central Europe (CENTREL), Greece, and the United States (US) resulted in GWP values above the mean and upper range of fossil-derived SA (**Figure 4.5**, red dashed and upper dotted line) while a change to Denmark (DK) and Italy (IT) resulted in values above the lower range (**Figure 4.5**, lower dotted line). ED processing is more energy intensive, requiring almost double the electricity as the DC process (3.3 compared to 1.7 kWh) (Cok et al., 2014). For DC processing, changes in location had a large impact on total GWP but were not enough to increase the GWP above the lower range of fossil-derived SA. Despite the large impact of biorefinery plant location on overall process GWP, the electricity mixes of the above countries are likely to become cleaner over time as the proportion of renewables in the production mixes increase, reducing the GWP's for the energy intensive technologies.

4.3.3.2 ENZYME PRODUCTION

For two selected feedstocks, bread waste and corn stover, the overall emissions of bioSA production were recalculated accounting for uncertainty within the GWP of enzyme production (see Appendix C1.2). Uncertainty in the GWP of enzyme production displays wide variation, ranging from ~1.2 to ~22 kg CO_2 eq./kg of enzyme (**Table C5**). For bioSA from bread waste, this variability is not enough to significantly alter the GWP due to the very low quantity (0.007 kg per kg of SA) of enzymes required (Gadkari et al., 2021). For corn stover, however, the uppermost estimate of enzyme production is enough to increase GWP above fossil SA, shifting the preference to favor fossil SA (**Table 4.1**). However, these results are dependent upon the production technology used. For bioSA from a less energy intensive liquid-liquid extraction (LLE) technology, variability in enzyme production is enough to vary GWP from ~1.9 to ~2.6 kg CO_2 eq./kg SA, values ranging from slightly below the lower range to below the mean of fossil SA. Under a more energy intensive electro-deionization (EDI) technology, however, GWP varies from ~3.3 to ~4.1 kg CO_2 eq./kg SA, values above the mean and upper range of fossil SA.

Compared to the original GWP values reported for these feedstocks of ~1.9 and ~3.3 kg CO_2 eq./kg SA under each respective technology, uncertainty in enzyme production alone is enough to increase the GWP of bioSA from corn stover by ~39% and ~24% on the extreme ends (**Table 4.1**). Thus, as a single process, uncertainty in the GWP of enzyme production can have a large impact on overall GWP of bioSA production and can significantly hurt the performance of bioSA when compared to fossil SA. Despite the large uncertainty attributed to enzyme production, many studies did not include enzymes within the study scope or considered their impact to be negligible. The case studies above considered enzyme production as a background process, where enzymes were produced off-site and added as an input to the pre-treatment reactor. Bioethanol studies have shown that reductions in GWP of ~20% and ~60% can be achieved if enzymes are recycled or produced on-site (Janssen et al., 2016). Future research is needed to assess whether such scenarios can ensure GWP reductions remain below that of the conventional fossil-based SA route when uncertainty in enzyme production is considered.

Table 4.1 Variation in GWP due to uncertainty in enzyme production. Mean and range of recalculated GWP values of bioSA production (in kg CO_2 eq./kg SA) for two different feedstocks resulting from variation in the GWP of enzyme production. The original reported GWP values from each feedstock are included for comparison (left column). The rightmost column represents the percent difference between the upper end of the resulting GWP due to variation in the emissions of enzymes and the originally reported values. Thus, this value represents the extreme impact of the uncertainty in enzymes on the GWP of bioSA.

		Recalculated GWP values				
Feedstock	**Reported GWP**	**Lower GWP**	**Mean GWP**	**Upper GWP**	**% Change between upper and reported**	**Reference**
Bread Waste	1.3	1.3	1.3	1.4	9.4	(Gadkari et al., 2021)
Corn Stover (LLE)	1.9	1.9	2.2	2.6	39	(Adom et al., 2014)
Corn Stover (EDI)	3.3	3.3	3.6	4.1	24	(Adom et al., 2014)

4.3.3.3 COPRODUCT INCLUSION

The coproduct(s) produced in seven selected studies were removed to isolate the effect of coproduct inclusion on the overall emissions of bioSA (see SI section 1.3). Regardless of the handling method or coproduct type, the impact of including a coproduct was substantial and variable, ranging from ~7% to ~91% lower GWP (**Table 4.2**).

Table 4.2 The isolated effect of coproduct inclusion on bioSA GWP. Bold values represent those cases where inclusion of the coproduct reduced GWP below the lower range of fossil-based SA (~1.9 kg CO_2 eq.). Units are kg CO_2 eq./kg SA. For corn starch, coproducts included fertilizer and excess electricity.

Feedstock	Coproduct Method	Coproduct	Without Coproduct	With Coproduct	% Change	Reference
Seaweed	System Expansion	Feed	14.5	12.7	13	(Dickson et al., 2021)
Corn Stover	System Expansion	Feed	6.11	5.68	7	(Dickson et al., 2021)
Corn Starch	Multiple	Multiple	2.50	**1.47**	41	(Cok et al., 2014)
Sugarcane Bagasse	Economic Allocation	Acetic acid	1.93	**1.39**	28	(Shaji et al., 2021)
Bread Waste	Mass Allocation	Feed	15.1	**1.30**	91	(Gadkari et al., 2021)
Sorghum Grain	System Expansion	Fertilizer	4.89	**0.87**	82	(Moussa et al., 2016)
Bread Waste	Mass Allocation	Fertilizer	5.00	**0.67**	87	(Brunklaus et al., 2018)

For example, the inclusion of coproducts for four feedstocks (sorghum grain, food waste, sugarcane bagasse, corn starch) was required to reduce emissions below the lower range of the conventional fossil-based SA route. The cases where coproduct inclusion displayed the largest reduction in GWP were those where either a small fraction of the total impact was allocated to bioSA (as in the coproduction of large quantities of feed and fertilizers from bread waste) or where large credits were applied when the coproduct substituted for the existing conventional production of fossil-intensive fertilizers (Moussa et al., 2016; Brunklaus et al., 2018; Gadkari et al., 2021). As a single factor, inclusion of coproducts is potentially the most important factor for reducing the emissions of bioSA. More broadly, for a future bioeconomy, identification and management of useful coproducts can be seen as a requirement to ensuring sufficient emission reductions of bioSA and associated biomaterials.

4.4 DISCUSSION

This analysis identifies uncertainty in the emissions of various reported bioSA production processes and has limitations. To contrast production processes, this study used only GWP as a comparative metric and specifically did not include other impact categories. This is a limitation and is due to data availability in the literature. The concern would be that trade-offs between greenhouse gas (GHG) emissions and other ecosystem-based impact categories (such as land use, ecotoxicity, and eutrophication) are especially relevant for bio-based products and may shift the preference to favor the conventional fossil-based routes (Smidt et al., 2016; Ogmundarson et al., 2020). To this point, a variety of impact factors are reported inconsistently across the literature. However, GWP performance was reported in all of the studies cited, and this is why GWP is used exclusively in our analysis. Notably only a single cradle-to-grave study of bioSA included full coverage of impact categories beyond just GHG emissions and fossil-energy consumption, highlighting a critical avenue for future research (Dickson et al., 2021).

The factors identified which impact bioSA emissions in this study were based on those previously identified in existing assessments. Yet, the suite of factors considered in this study were not exhaustive and other factors such as land-use change (LUC) emissions and scale were not included. While LUC emissions have been shown to be significant for biofuels (Valin et al., 2015), including the impacts of direct and indirect LUC into a biomaterial LCA still remains challenging (Montazeri et al., 2016; Dunn, 2019). Further, many of the assessed feedstocks in this study included low impact crops and waste products such as sorghum grain, corn stover, and food waste, feedstocks for which LUC issues may not apply. LUC emission factors are also not readily available in most existing databases and would require product-specific and location-specific data on behalf of the LCA practitioner. As a result, none of the assessed studies have included LUC emissions in their analyses of bioSA. However, given their importance, LUC emissions do represent a significant area of uncertainty for feedstocks such as sugar cane (Valin et al., 2015). Future research should focus on assessing whether the inclusion and variability of LUC emissions are enough to significantly increase the emissions of bioSA.

Study scale is an important factor which can drive the emissions of bioSA and is not addressed herein (Curran, 2013; Brunklaus et al., 2018). Scale impacts downstream conversion yields which then varies energy and material requirements to produce the same functional unit. Increases in yield reduce energy and material inputs leading to lower overall emissions (Janssen et al., 2016; Brunklaus et al., 2018). Thus, as bioSA production matures, increases in conversion yields are expected, leading to decreases in GWP and other impact categories in comparison to fossil derived SA, whose production has already reached commercial scale (Tecchio et al., 2016). Currently, bioSA production is still in the early phases with only pilot plant and lab-scale data available. Thus, while GWP may be sensitive to the scale chosen in existing LCA models, its sensitivity alone does not negate the benefits of bioSA compared with fossil-derived SA. The fact that many existing studies already display emissions comparable to, or lower than, fossil SA despite their early stage of development is promising and will continue to improve over time.

4.5 CONCLUSION & RECOMMENDATIONS

4.5.1 CONCLUSIONS

The bioeconomy is a solution to concerns over fossil-fuel depletion and global climate change. Bio-based succinic acid (bioSA) has been identified as a key platform chemical, with the potential to compete both economically and environmentally with fossil-based production. However, uncertainties in life cycle assessments (LCA's) of bioSA, resulting from differences in processing options and modelling choices, make it difficult for decision makers to interpret results.

Addressing these concerns, this study assessed existing LCA's of bioSA production to identify areas of uncertainty and variability due to different processing and modelling options. The subsequent goal was to clarify areas of uncertainty in the LCA's of bioSA and most importantly whether such uncertainties negate previous conclusions regarding the emissions savings of bioSA compared with their fossil-derived counterparts.

Despite the large variability in emissions, bioSA from sugar cane and energy crop feedstocks display the lowest emissions and are likely to reduce emissions compared to the conventional production of fossil-derived SA, regardless of the considered processing options or methodological choices. Emissions of bioSA produced from corn starch, corn stover, and food waste feedstocks are less certain and display more variability depending on processing technology, coproduct handling, and coproduct type. Conversely, bioSA from sugar beet, seaweed, and waste wood feedstocks display emissions above the upper range of the conventional fossil-based route, however, these results may be hindered by a lack of studies and small sample sizes for these feedstocks indicating the need for further research.

Several individual factors were associated with large uncertainty with potential to have large impacts on overall emissions. As an individual process, variability in the emissions of enzyme production represent a large source of uncertainty for bioSA from food waste and corn stover. For food waste, this uncertainty was not enough to increase GWP above the conventional fossil route. However, for corn stover, uncertainty was enough to shift the preference to favor the conventional fossil-based production route. Similarly, changes in biorefinery location can have significant impacts on emissions due to differences in the regional power mixes of different geographic locations. A switch in plant location from the European average to Central Europe, Greece, Denmark, Italy, and the United States resulted in emissions greater than that of fossil-derived SA for bioSA produced with an energy intensive downstream technology. This was not the case for a less energy-intensive downstream technology, demonstrating the importance of the downstream processing technology in ensuring emission reductions of bio-based materials.

Finally, inclusion of coproducts was essential in ensuring emissions below that of fossil-derived SA. However, the quality of the obtained coproduct and the method used to handle the issue of coproduction in LCA was also significant. High quality coproducts such as bio-based fertilizers and energy that can substitute for existing fossil-intensive products can provide substantial credits to the bio-based product, making them crucial for ensuring emissions reductions.

4.5.2 RECOMMENDATIONS

Given the uncertainties present in the LCA's of bioSA and the subsequent conclusions, four key recommendations will help to direct future environmental assessments and production of bioSA and biomaterials, more broadly (**Table 4.3**). First, despite its early stage of development, bioSA from several feedstocks including sugar cane and energy crops consistently exhibit lower emissions than the conventional route. It is recommended that future production focus on these feedstocks, which can already guarantee emission reductions.

For bioSA derived from corn starch, corn stover, and food waste, however, impacts are more uncertain. For these feedstocks, securing emission reductions requires careful consideration of coproducts, coproduct handling methods, and downstream technology. Further collaboration between industrial partners and LCA researchers is needed for selecting factors that ensure emissions reductions. Additionally, uncertainty in individual processes such as enzymes can have a significant impact on overall emissions, making them large enough to shift the preference toward fossil production. However, strategies such as on-site production and recycling of enzymes can also be effective for reducing emissions. Thus, additional care should be taken when considering enzymes in bio-based LCA's and future research should prioritize better integration of enzymes into the overall production process chain.

Table 4.3 Conclusions and recommendations for LCA's of future biomaterials.

Main Conclusion	Recommendation and Future Research
BioSA from sugar cane and energy crops display emissions lower than the conventional route, regardless of other factors, whereas feedstocks such as corn starch, corn stover, and food waste are less certain.	Future production should focus on feedstocks that can already guarantee emission reductions while future research is needed to clarify the emissions of those that are less certain.
For bioSA from corn starch, corn stover, and food waste, combinations of the coproduct, handling method, and downstream technology are crucial for ensuring emission reductions.	Collaboration between industrial partners and LCA researchers is required to ensure the selection of factors which will help guarantee emission reductions in these cases.
The uncertainty in single processes such as enzymes can be enough to shift the preference toward fossil production. However, research from biofuels suggests that producing and recycling enzymes on-site can reduce emissions.	Additional care should be taken when considering enzymes for bio-based processes. Future studies and production plants should consider better integration of enzymes into the overall production process chain.
Obtainment of multiple, high value coproducts is essential for securing emission reductions for several feedstocks. Inclusion of coproducts alone may be the single most important factor in ensuring reducing emissions of bioSA.	Industry practitioners should strive to not only identify and produce as many coproducts as possible from the bio-based production process but should ensure that as many high-quality coproducts (such as fertilizers) as possible are obtained.

Finally, attainment of multiple high-value coproducts is essential for securing the emission reductions of biomaterials. Industry practitioners are encouraged not only to identify and produce a variety of coproducts from the bio-based production process but also to ensure that many high-quality coproducts, such as fertilizers, are obtained. Inclusion of these recommendations into future LCA studies of biomaterials will appropriately strengthen LCA methodology, encourage more accurate and trustworthy results for policy makers, industrial partners, and LCA practitioners, and help ensure the sustainable future production of bioSA and biomaterials.

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CHAPTER 5

CONCLUSIONS

An improved understanding of the human energy impact on ecosystems requires sustainability assessments that account for both the industrial and ecological dimensions of industrial-natural systems. This research has played an important role in advancing the accounting of the coupled energetics and resultant ecological and environmental impacts in biomass production systems by assessing the energy dynamics of forestry operations (Chapters 2 & 3) along with areas of uncertainty in the global warming impacts of a biochemical production process (Chapter 4). Throughout the rest of this conclusion, brief overviews of each chapter and their conclusions are provided, followed by a discussion of important perspectives and future research.

5.1 CHAPTER 2 - CONCLUSIONS

An extended energy accounting model was developed and applied to a 1-hectare managed loblolly pine (*pinus taeda*) stand in the southeastern United States. The model improved conventional energy analyses of forestry systems by extending the system boundaries to include ecosystem biomass stocks including above and below ground tree biomass, understory, dead wood, and forest floor compartments. This allowed for a dynamic comparison between conventional energy indicators, such as net energy (*NE*) and the ratio of energy return to energy invested (*EROI*), which account only for the human/industrial dimension of forestry operations, alongside changes in potential ecosystem biomass (i.e., the forest's stored energy) resulting from intensive management. Impacts to ecosystem biomass were quantified as foregone biomass (ΔB) by comparing them to potential stocks under no-harvest and natural regeneration reference scenarios.

In this way, biomass impacts represent potential reductions in the forest's energy storage under differing management approaches.

Case studies were performed assessing the energetics of four forest management scenarios, common throughout the southeastern United States, varying from low to high intensity over a 100-year period. The quantity of *NE* harvested depended on the time horizon that indicators were assessed over. On a per-rotation basis, *NE* was the largest under management practices which achieved larger harvest quantities at their rotation age, including a long-rotation saw timber and heavy thinning scenario. However, when normalized over a consistent time horizon or assessed over a 100-year period, *NE* increased in direct proportion with increasing management intensity. Regardless of the temporal scope, less intensive management practices consistently achieved higher *EROI* values due to their lower input requirements compared with their more intensive counterparts. These results agree with previous forestry energy analyses which also found increases in *EROI* with increasing rotation ages and thus add additional support to the hypothesis that less intensive management practices are always more energetically efficient than more intensive ones (Herendeen & Brown, 1987).

Cumulative values of foregone biomass (ΔB_c) also depended on the chosen reference scenario. Under no-harvest scenarios, ΔB_c was directly proportional to management intensity, increasing with increasing intensity. Compared to a natural regeneration scenario, impacts still increased with increasing intensity but displayed more variability, with a less intensive conventional management approach displaying comparable impacts as an intensive short rotation management due to its lower quantity of accumulated biomass compared to the natural regeneration reference ecosystem. Regardless of the reference scenario or type of management, impacts to biomass stocks after 100 years remained 1-2 orders of magnitude larger than the harvested *NE*, thus revealing a large energy imbalance between the human/industrial and ecosystem energy dimensions in intensively managed forestry systems.

By extending the system boundaries of conventional energy analyses of intensively managed forestry systems under varying management practices and timeframes, these findings underscore the significance of energy analysis in contributing to a more comprehensive understanding of the energy dynamics of managed ecosystems. This analysis revealed the importance of including ecosystem biomass impacts alongside conventional industrial energy indicators, illustrating trade-offs between management intensity, industrial efficiency, and ecosystem impacts. However, in addition to capturing only stand-level biomass, forest ecosystems also accumulate biomass in supported food webs. Additional approaches are needed to account for the resultant impacts on food webs driven by intensive management (Schaubroeck et al., 2012; Golberg, 2015).

5.2 CHAPTER 3 - CONCLUSIONS

Intensive management of forest land requires exogenous technical energy inputs while also disrupting the ecosystem's energy state, leaving less energy available for downstream food webs. Building on the previously extended energy model, a more in-depth energy accounting model was developed to further incorporate food web biomass dynamics. The model allowed for direct comparisons between impacts on food web biomass dynamics alongside the exogenous technical energy inputs (*TEI*) invested to support forestry operations. Accounting for food web biomass dynamics, multi-trophic network models representing food webs in southern pine forests were constructed using the metabolic theory of ecology and literature data. Food web models were initialized with outputs of stand biomass dynamics (i.e., trees, vegetation, and dead wood) from forest carbon balance models for managed loblolly pine forests. Linking food web biomass to stand biomass dynamics allowed for unique food webs individualized to, and representative of, specific forest management regimes. Similar to the previously developed methodology, impacts to food web biomass were quantified as the difference between potential and actual biomass compared to no-harvest reference scenarios. Food web impacts thus represented reductions in the ecosystem's potential stored energy (i.e., biomass) resulting from intensive management. Cumulative values of food web biomass losses ($\Delta B_{c,FW}$) were then compared to the exogenous technical energy inputs (*TEI*) invested to support forestry operations for four different forest management scenarios, varying from low to high intensity, over a 100-year period.

Prior to the initial harvest, improvements to food web biomass stores were achieved by management regimes that involved stand thinning. These improvements were due to increased dead wood production following thinning which stimulated decomposer biomass. Increasing decomposer biomass buffered biomass losses through the rest of the food web and thus resulted in greater quantities of total biomass compared with the reference scenarios. However, following subsequent harvests and by year 75, $\Delta B_{c,FW}$ exceeded *TEI* across all management scenarios. After 100 years, the magnitudes of $\Delta B_{c,FW}$ exceeded *TEI* by factors of three to five across all managements. This large disparity indicates a critical imbalance between the human energy invested for system management and the resultant ecological impacts they support. Despite such a fundamental imbalance, less intensive management approaches delayed when food web biomass impacts began to exceed technical energy inputs.

Expanding on the previously developed framework, a more in-depth analysis comparing the magnitudes of two seemingly disparate energy terms further highlights the role of energy analysis in capturing and comparing the inputs sustaining forestry operations together with the resultant ecosystem impacts they support. Rather than being a negligible energy term, reductions in food web biomass stores resulting from intensive management were comparable to and eventually exceeded, technical human energy inputs. These findings bolster recent calls for energy assessments of managed ecosystems to better account for ecological impacts alongside conventional energy metrics and address a much-needed knowledge gap in further understanding the coupled human and nature interactions in managed ecosystems (Bulatkin, 2012; Schaubroeck et al., 2012; Golberg, 2015). Although these results shed light on the unsustainable nature of intensive forest management over time, they also point to areas of improvement for the design of management regimes which can reduce resultant ecosystem impacts and improve the sustainability of intensively managed industrial-natural systems.

5.3 CHAPTER 4 – CONCLUSIONS

In addition to biomass growth occurring within managed ecosystems, biochemical production also requires energy and materials that result in global warming impacts. To contribute to a sustainable bioeconomy, biochemical production requires assessment methods that consider the entire value chain. Ensuring the environmental benefits of biochemicals requires improved environmental performance compared with their conventional fossil-based counterparts. Environmental life cycle assessment (LCA) has been a primary method to assess the environmental impacts of a product over its entire life cycle and has been widely applied to many biochemicals (Weiss et al., 2012; Dunn, 2019). However, global warming impacts over biochemical life cycles display large variability, making it difficult to interpret results and ensure future emission reduction benefits.

Chapter 4's purpose was to identify and quantify major areas of uncertainty in existing LCA's of an important biochemical, and to determine whether such uncertainty hindered previous conclusions regarding its emission reduction benefits. Using bio-based succinic acid (bioSA) as a case study and starting point for more complex biochemicals, the main factors contributing to uncertainty and variability in greenhouse gas emissions were identified in existing LCA's of bioSA production. Such factors arose from a multitude of differing processing options (different feedstocks, geographic locations, and processing technologies) and modeling choices (study scopes, coproducts, and methods of handling coproducts) throughout the life cycle of bioSA production. Variability in greenhouse gas emissions were quantified with the 100-year global warming potential (GWP) and compared with the conventional production of fossil-based succinic acid as a benchmark for emission reduction targets.

Considerable variability in GWP persisted across all examined model-based and technological factors, with magnitudes ranging both below and above the conventional fossil-based production route. Across feedstocks, for example, mean values of bioSA GWP displayed a two-order of magnitude range. Uncertainty in the emissions of individual factors such as enzymes and geographic location, were substantial and enough to increase GWP above the conventional route for bioSA produced from corn stover or with an energy-intensive downstream technology.

In addition to individual factors, the combination of factors ensuring emission reduction benefits for bioSA under each feedstock was identified. Emission reductions were nearly always secured for bioSA when produced from low-intensity sugar cane and energy crop feedstocks, irrespective of any examined methodological or process-based factors. For bioSA from corn stover, corn starch, and food waste feedstocks, emission reductions were more variable, depending on variations in downstream technology, the type(s) of coproducts obtained, coproduct treatment methods, and geographic location. Conversely, emissions were always worse than the conventional fossil-based route for sugar beet, seaweed, and waste wood feedstocks.

Despite the large variability in GWP across all factors, the obtainment and handling of coproducts was identified as a necessary factor for ensuring the emission reductions of bioSA. For several feedstocks, the very inclusion of coproducts was required to ensure GWP remained below the conventional fossil-based route, while cases with no coproducts consistently displayed GWP values above the conventional route. Moreover, the quality of the obtained coproduct was crucial. High-quality coproducts which substitute for conventional fossil-intensive products (e.g., fertilizers and energy), provide large credits to the bioSA product significantly reducing its overall emissions.

By assessing uncertainties in the global warming impacts stemming from both methodological and technological choices, this research extends beyond typical uncertainty analyses of bioproducts and identifies the critical underlying factors necessary to secure future emission reduction benefits. This study thus serves as a valuable resource for LCA practitioners and industry partners, allowing them to target and improve areas within the production process that yield the greatest emission savings. In doing so, this research strengthens confidence in the effectiveness of LCA in ensuring the environmental benefits of biomaterials and contributes to the advancement of a sustainable bioeconomy.

5.4 PERSPECTIVES AND FUTURE RESEARCH DIRECTIONS

Sustainability assessments of biomass systems typically focus on individual indicators such as energy, carbon, or GHG emissions. However, ensuring the sustainability of biomass systems necessitates more comprehensive assessments that include their energetic and environmental performance, as well as their broader ecological impacts. This dissertation improved existing energy and environmental assessments by incorporating ecosystem energy impacts into conventional energy analyses and identifying areas of uncertainty in the global warming impacts of biochemical production. Consequently, several broader perspectives were gained including a deeper understanding of the coupled relationship between the industrial and ecological energy dimensions of intensively managed forests and the underlying factors contributing to uncertainty in the environmental impacts of biochemical production; both with implications for sustainable future biomass production and management strategies.

5.4.1 APPLICATIONS OF IMPROVED SUSTAINABILITY ASSESSMENTS

The extended energy model, developed in Chapters 2 and 3, offers several advantages over conventional forest energy analyses. By expanding the system boundaries of forestry operations to encompass the whole ecosystem, the model integrates ecological factors directly alongside industrial energy-based metrics. It recognizes managed forests not merely as industrial production systems, but as semi-natural ecosystems driven and maintained by external technical inputs while also accumulating ecological energy stores in the form of biomass. Given that managed forests consist of both ecosystems and industrial production systems, multi-dimensional and integrated assessment approaches are needed by forest managers who must increasingly balance ecological and technical considerations (Buonocore et al., 2014). The extended energy model developed in this work can be implemented together with or alongside existing forest carbon assessments, which have traditionally been central to sustainable forestry. In doing so, this approach would broaden the scope of forest carbon studies to further include considerations of ecosystem energy impacts and the industrial viability of forestry production systems, thus allowing for more informed decision-making when comparing different management practices.

In Chapters 2 and 3, ecosystem impacts were quantified as cumulative foregone biomass losses. This indicator represents the cumulative reduction in the ecosystem's stored biomass (in vegetation or organism biomass) over a given period, relative to a natural baseline ecosystem. From a thermodynamic perspective, it measures the gap between the potential and actual stored energy in the ecosystem, thus quantifying the total impact of intensive management on the ecosystem's ability to maximize energy storage in the form of biomass over time. Current impact models typically calculate ecosystem impacts through cause-effect relationships that are based on generic ecological processes or species-specific toxicological effects (Huijbregts et al., 2017). While these approaches capture specific ecological damages induced by industrial activities, they reveal little about the impacts of intensive management on ecosystem structure and function (Schaubroeck et al., 2012; Schaubroeck et al., 2013).

Cumulative foregone biomass can serve as an improved impact indicator for assessing the human impact on ecosystems because it directly reflects the lost potential energy storage of an ecosystem due to human management practices. Compared to existing impact indicators, it provides an absolute and tangible measure of how far current practices deviate from natural ecosystem functioning. Impact assessment characterization models could then link this indicator to different functional units, such as biomass yields or intensities of different management practices across different forests and geographic regions. This would enable its direct incorporation into the life cycle impact assessment (LCIA) phase of LCA, alongside other ecosystem-based indicators, thus better capturing the full environmental impacts of forestry systems.

In addition to improving energy analyses of managed forests, quantifying the factors contributing to uncertainty in the global warming impacts of biochemical production (Chapter 4) improves environmental assessments of bioproducts and helps ensure their environmental benefits. Addressing uncertainties arising from modeling and technological factors goes beyond inventory and data-based uncertainty and instead addresses factors that can be influenced and controlled by project stakeholders, including LCA practitioners and business managers. This provides greater transparency and trust in LCA, as it clarifies how individual choices and decisions can influence overall environmental impacts. Furthermore, identifying which factors contribute to large variability in impacts can pinpoint opportunities along the production process where interventions can improve environmental performance, thereby supporting better overall decision-making.

Focusing on areas of uncertainty related to modeling and technological factors also contributes to the design of more sustainable process chains as the complexity of bio-based production is often hindered by the numerous combinations of differing model-based and technological options available (Dickson et al., 2021). By quantifying the specific underlying factors contributing to uncertainty, stakeholders can make more informed decisions regarding feedstock options, coproduct utilization and handling methods, and technology selection. This allows for the identification of the combinations of factors that guarantee improved environmental performance compared to conventional fossil-based production routes. This approach is more comprehensive than traditional uncertainty analyses, which focus only on uncertainty in data or impact factors and can empower stakeholders to design processes that ensure the future environmental benefits of bioproduct and biomass production processes.

5.4.2 FOREST MANAGEMENT IMPLICATIONS

The improved energy analysis confirmed a previously identified imbalance between the industrial and ecological energy metrics of managed ecosystems (Gorshkov & Dol'nik, 1980; Makarieva et al., 2008; Kleidon, 2010; Golberg, 2015), as magnitudes of ecosystem impacts, measured as cumulative foregone biomass, ultimately exceeded the industrial energies invested in and harvested from the system over a given period. While less intensive management practices reduced these impacts compared with more intensive approaches, large imbalances persisted across all managements, thus indicating that reducing management intensity is a necessary, but insufficient, strategy for completely mitigating ecosystem impacts. The act of intensive management for biomass production within a given stand supports large and increasing reductions of ecosystem biomass over time.

Despite the persistent energy imbalance across all management practices, these results also highlight a fundamental thermodynamic trade-off between management intensity and ecosystem impacts, as more intensive management practices extract more net energy for society through greater and more frequent harvests but also result in greater ecosystem biomass reductions. These results agree with the sustainable forestry literature that managing forests for biomass production at the stand scale is at odds with optimizing biodiversity and thus requires landscape-scale planning to ensure adequate portions of the landscape remain unmanaged or zoned for conservation (Betts et al., 2021; Stokely et al., 2022). While the extended energy approach in this dissertation was developed at the stand scale, further application of the model can provide insight into regional forest management by quantifying the number of unmanaged and regenerating stands required to offset reductions in the ecosystem's energy stores (i.e., biomass stocks) while meeting a given level of harvested net energy. Offsetting foregone biomass losses through the regeneration of native and natural ecosystems across a forest landscape would begin to rectify the imbalance between the extracted net energy and resultant impacts of forest management and serve as a starting point for the extension of the model to larger spatial scales.

The extended energy model captures additional information, applicable to forest management, not examined in existing studies. Many forestry studies have noted the ability of less intensive managements to retain some level of floral and faunal biodiversity, particularly following early stand regeneration (Ellis & Betts, 2011; Stokely et al., 2022). However, the focus on ecological factors alone ignores broader aspects of the industrial energy performance of differing management approaches, making it difficult to directly compare ecological and non-ecological (i.e., industrial) aspects required for the design and selection of sustainable management practices. Moreover, few studies have explored quantitative relationships between biomass production and ecosystem impacts in intensively managed forests. Our results showed that while less intensive managements obtain less net energy than more intensive approaches, they do so at higher levels of energy efficiency (i.e., achieve higher *EROI* values). Compared with more intensive approaches, less intensive management practices both reduce ecosystem impacts and are more efficient at extracting biomass for society. Therefore, in areas of the landscape where intensive management is necessary, less intensive management practices are preferable from both an industrial and ecological energy perspective and should be prioritized over more intensive practices.

5.5 CONCLUDING REMARKS

Energy is the ultimate arbiter of change, sustaining and enabling the growth and development of civilization within the biosphere. Nowhere is such a profound recognition more apt than for the production of biomass, which serves as the most foundational energy resource for humankind and all other living organisms. By expanding upon and improving energy and environmental assessments of biomass production systems, this dissertation has deepened our understanding of the coupled energy relationships between industrial and natural systems while ensuring their continued environmental benefits. Together, these improvements strengthen our capacity to sustainably harness biomass resources and reinforce the broader imperative for a more harmonious balance between civilization and the biosphere going forward.

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APPENDIX A

FOREST MANAGEMENT SCENARIOS

A1 REFERENCE SCENARIO DESCRIPTION – LONGLEAF PINE ECOSYSTEM

The longleaf pine savanna ecosystem was chosen as the natural mature reference ecosystem as it represents the potential natural ecosystem that would have existed in the absence of intensive human land-use activity throughout the southeastern coastal plains. Compared to managed pine forests and hardwood forests, this ecosystem is unique and is maintained by frequent fire intervals every few years. Frequent fires maintain a sparse understory interspersed with fire-adapted longleaf pine trees, giving the system its characteristic open park-like structure.

To model dynamics of the biomass stocks of the longleaf pine ecosystem, a biomass dynamics model for even-aged natural longleaf pine (*pinus palustris*) stands from University of Florida's Carbon Resource Center was utilized (Lauer & Kush, 2011). Many of the default parameters of the base model were kept the same including a site index SI = 20 m at a reference age of 50 years and 7 years to reach dbh (**Table A5**). For tree density and fire frequency, values of 170 trees/ha and 5-year fire frequencies were applied as representative of natural longleaf pine forests (Gonzalez-Benecke et al., 2015; Samuelson et al., 2017). Biomass dynamics of the forest floor, dead pool, and understory compartments from the model are displayed in **Figure A1a**. Live tree biomass included both above and below ground biomass and followed trajectories expected of ecosystem growth and development (**Figure A1b**). The model was run for a total of 100-years to allow for comparisons with the managed stand biomass stocks. Similar to the managed stands and due to variability in biomass compositions, an average energy content value of 17.5 MJ/kg was applied for all biomass stocks. Together, these dynamics represent the biomass stocks of the natural regeneration reference scenario used to calculate the foregone biomass under differing forest management scenarios.

Table A1 Data sources for energy and material inputs of forestry operations, management scenarios, and carbon balance models.

Item	Data Source
Energy and material inputs	
Diesel, lubricant, and pesticide use for site preparation and stand management	(Xu et al., 2021)
Diesel and lubricant use for logging	(Lan et al., 2021)
Fertilizer use	(Scott & Tiarks, 2008; Energy, 2011; Mills et al., 2013; Lu et al., 2015)
Management scenario data	
Saw timber	(Mills et al., 2013)
Conventional	(Energy, 2011)
Heavy thinning	(Scott & Tiarks, 2008)
Short rotation	(Lu et al., 2015)
Longleaf pine baseline	(Gonzalez-Benecke et al., 2012; Gonzalez-Benecke et al., 2015; Samuelson et al., 2017)
Carbon balance models	
Loblolly pine plantation	(Gonzalez-Benecke et al., 2011)
Natural longleaf pine	(Lauer & Kush, 2011)

Table A2 Unit fuel and material requirements of forestry operations for differing management scenarios.

Item	Management scenarios: Saw Timber (ST)	Conventional (C)	Heavy Thinning (HT)	Short Rotation (SR)
Site preparation				
Diesel (L/ha)	123.1	123.1	123.1	123.1
Lubricants (L/ha)	2.500	2.500	2.500	2.500
N-fertilizer (kg/ha)	50.00	-	-	-
P-fertilizer (kg/ha)	57.00	-	-	-
Herbicide (kg/ha)	1.360	1.360	1.360	1.360
Stand management				
N-fertilizer (kg/ha)	224.0	155.0	199.0	199.0
P-fertilizer (kg/ha)	-	17.50	22.00	22.00
Herbicide (kg/ha)	-	-	1.360	1.360
Logging				
Diesel (L/m^3)	1.980	1.980	1.980	1.980
Lubricants (L/m^3)	0.040	0.040	0.040	0.040
1st Thinning				
Diesel (L/m^3)	0.594	0.594	0.990	-
Lubricants (L/m^3)	0.012	0.012	0.020	-
2nd Thinning				
Diesel (L/m^3)	-	-	0.594	-
Lubricants (L/m^3)	-	-	0.012	-

Table A3 Specific energy conversion factors of fuel and material inputs.

Item	Specific energy factor	Ref.
Diesel (MJ/L)	38.60	(Ulbanere & Ferreira, 1989)
Lubricant (MJ/L)	38.60	(Ulbanere & Ferreira, 1989)
N-Fertilizer (MJ/kg)	51.47	(Hill et al., 2006)
P-Fertilizer (MJ/kg)	9.170	(Hill et al., 2006)
Herbicide (MJ/kg)	476.0	(Heller et al., 2003)

Table A4 Unit energy intensities of forestry operations for differing management scenarios.

Item	Management scenarios			
	Saw Timber (ST)	**Conventional (C)**	**Heavy Thinning (HT)**	**Short Rotation (SR)**
Site preparation				
Diesel (GJ/ha)	4.752	4.752	4.752	4.752
Lubricants (GJ/ha)	0.097	0.097	0.097	0.097
N-fertilizer (GJ/ha)	2.574	-	-	-
P-fertilizer (GJ/ha)	0.523	-	-	-
Herbicide (GJ/ha)	0.647	0.647	0.647	0.647
Stand management				
N-fertilizer (GJ/ha)	11.53	7.978	10.24	10.24
P-fertilizer (GJ/ha)	-	0.160	0.202	0.202
Herbicide (GJ/ha)	-	-	0.647	0.647
Logging				
Diesel (GJ/m^3)	0.076	0.076	0.076	0.076
Lubricants (GJ/m^3)	0.002	0.002	0.002	0.002
1st Thinning				
Diesel (GJ/m^3)	0.023	0.023	0.038	-
Lubricants (GJ/m^3)	0.000	0.000	0.001	-
2nd Thinning				
Diesel (L/m^3)	-	-	0.023	-
Lubricants (L/m^3)	-	-	0.000	-

Table A5 Overview of silvicultural input parameters of different forest managements to initialize the carbon balance models.

Management item	Management scenarios				
	Longleaf reference (LL)	**Saw Timber (ST)**	**Conventional (C)**	**Heavy Thinning (HT)**	**Short Rotation (SR)**
Planting density (trees/ha)	170	1500	1500	3000	3000
Site index, m	20	17	17	17	17
Herbaceous weed control	-	Banded, no grass Year 1	Banded, no grass Year 1	Banded, no grass Year 1, 2	Banded, no grass Year 1, 2
P-fertilizer kg/ha, (year of application)	-	57 (1)	17.5 (4, 8)	22 (4, 10, 15)	22 (4, 6)
N-fertilizer kg/ha, (year of application)	-	50 (1) 224 (16)	155 (4, 8)	199 (4, 10, 15)	199 (4, 6)
Thinning, year of application (% intensity)	-	15 (30%)	15 (30%)	10 (50%) 15 (30%)	N/A
Harvest, year of application	-	35	25	25	16
Age to reach DBH (years)	7	-	-	-	-
Ring count at DBH	10	-	-	-	-
First prescribed fire (year)	9	-	-	-	-
Burning frequency (year)	5	-	-	-	-

Table A6 Breakdown of the cumulative energy inputs and harvests of forestry operations over one rotation period of different management scenarios.

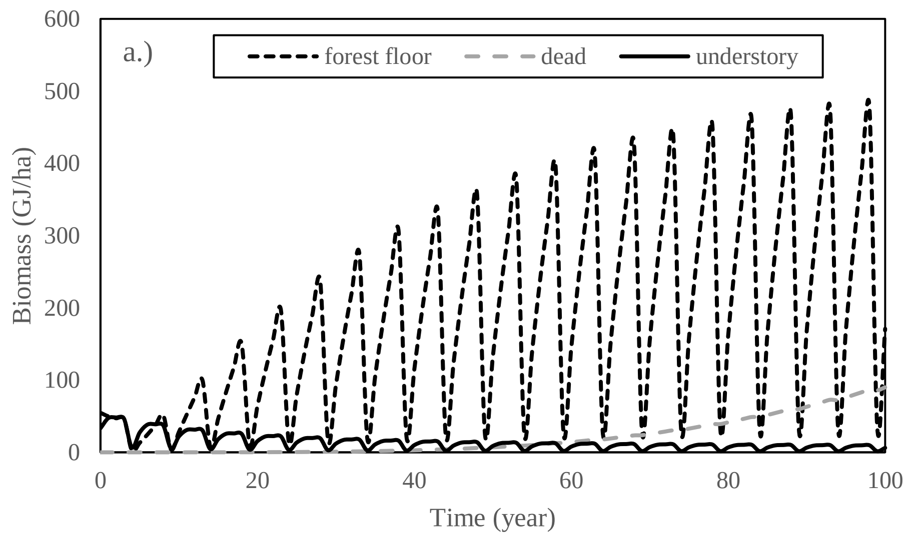
Item	Management scenarios			
	Saw Timber (ST)	**Conventional (C)**	**Heavy Thinning (HT)**	**Short Rotation (SR)**
Site preparation				
Diesel (GJ/ha)	4.752	4.752	4.752	4.752
Lubricants (GJ/ha)	0.097	0.097	0.097	0.097
N-fertilizer (GJ/ha)	2.574	-	-	-
P-fertilizer (GJ/ha)	0.523	-	-	-
Herbicide (GJ/ha)	0.647	0.647	0.647	0.647
Subtotal	**8.592**	**5.496**	**5.496**	**5.496**
Stand management				
N-fertilizer (GJ/ha)	11.53	15.96	30.73	20.49
P-fertilizer (GJ/ha)	-	0.321	0.605	0.403
Herbicide (GJ/ha)	-	-	0.647	0.647
Subtotal	**11.53**	**16.28**	**31.98**	**21.54**
Logging				
Biomass harvested (m^3)	366.1	285.4	295.0	307.5
Biomass harvested (GJ/ha)	218.9	2445	2527	2540
Diesel (GJ/ha)	27.98	21.81	22.54	23.50
Lubricants (GJ/ha)	0.565	0.441	0.455	0.475
Subtotal	**28.542**	**22.253**	**22.998**	**23.979**
1st Thinning				
Biomass harvested (m^3)	26.65	28.74	30.62	-
Biomass harvested (GJ/ha)	3224	236.1	243.3	-
Diesel (GJ/ha)	0.611	0.659	1.170	-
Lubricants (GJ/ha)	0.012	0.013	0.024	-
Subtotal	**0.623**	**0.672**	**1.194**	**-**
2nd Thinning				
Biomass harvested (m^3)	-	-	77.45	-
Biomass harvested (GJ/ha)	-	-	636.2	-
Diesel (GJ/ha)	-	-	1.776	-
Lubricants (GJ/ha)	-	-	0.036	-
Subtotal	**-**	**-**	**1.812**	**-**
Total inputs (GJ/ha)	49.29	44.70	63.48	51.01
Total harvests (GJ/ha)	3443	2681	3406	2540

Table A7 Breakdown of the cumulative energy inputs and harvests of forestry operations over 100-years under different management scenarios

Item	Management scenarios			
	Saw Timber (ST)	**Conventional (C)**	**Heavy Thinning (HT)**	**Short Rotation (SR)**
Site preparation				
Diesel (GJ/ha)	14.25	19.01	19.01	33.26
Lubricants (GJ/ha)	0.290	0.386	0.386	0.676
N-fertilizer (GJ/ha)	1.942	-	-	-
P-fertilizer (GJ/ha)	7.721	-	-	-
Herbicide (GJ/ha)	1.568	2.589	2.589	4.532
Subtotal	**25.78**	**21.98**	**21.98**	**38.47**
Stand management				
N-fertilizer (GJ/ha)	-	63.82	122.9	133.2
P-fertilizer (GJ/ha)	34.59	1.284	2.421	2.623
Herbicide (GJ/ha)	-	-	2.589	4.532
Subtotal	**34.59**	**65.11**	**127.9**	**140.3**
Logging				
Biomass harvested (m^3)	732.1	1142	1180	1845
Biomass harvested (GJ/ha)	6447	9779	10107	15238
Diesel (GJ/ha)	55.95	87.25	90.17	141.02
Lubricants (GJ/ha)	1.130	1.763	1.822	2.849
Subtotal	**57.08**	**89.01**	**91.99**	**143.9**
Thinning				
Biomass harvested (m^3)	79.94	115.0	432.3	-
Biomass harvested (GJ/ha)	656.7	944.4	3518	-
Diesel (GJ/ha)	1.833	2.636	11.78	
Lubricants (GJ/ha)	0.037	0.053	0.238	-
Subtotal	**1.870**	**2.689**	**12.02**	**-**
Total inputs (GJ/ha)	119.3	178.8	253.9	322.6
Total harvests (GJ/ha)	7104	10724	13625	15238

Table A8 Compositions of ΔB_c over 100 years under different reference scenarios.

	Reference scenario							
	no-harvest				natural regeneration			
	ST	**C**	**HT**	**SR**	**ST**	**C**	**HT**	**SR**
Trees	211,366	260,407	315,559	306,954	232,579	295,213	288,955	290,634
Forest floor	11,900	16,257	16,234	29,944	-15,823	-9,257	-12,347	2,528
Dead wood	15,541	13,214	18,092	26,916	-20,421	-21,345	-36,216	-25,853
Understory	126	207	149	-214	-5,776	-5,795	-5,741	-6,161
Total	238,932	290,085	350,034	363,600	190,558	258,817	234,652	261,149



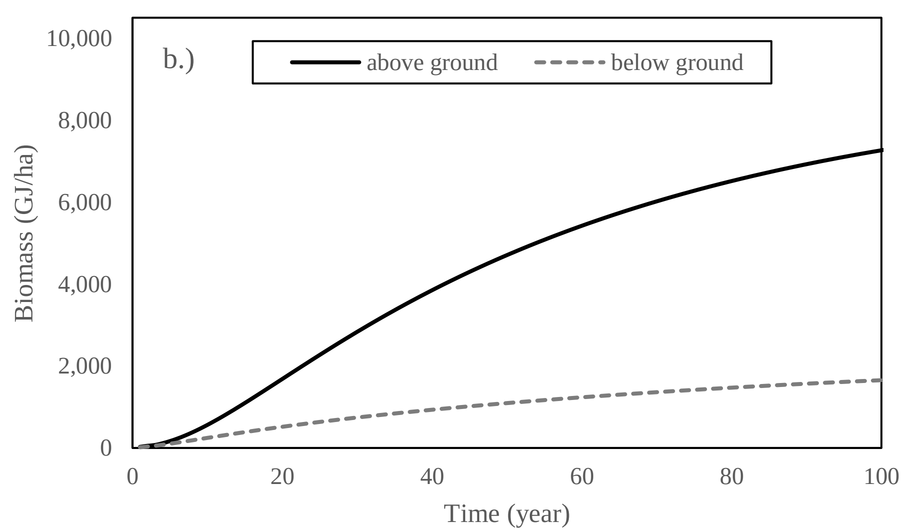


Figure A1 Biomass dynamics (in GJ/ha) of a.) forest floor, dead, understory and b.) above and below ground tree compartments over time in the natural regeneration baseline scenario.

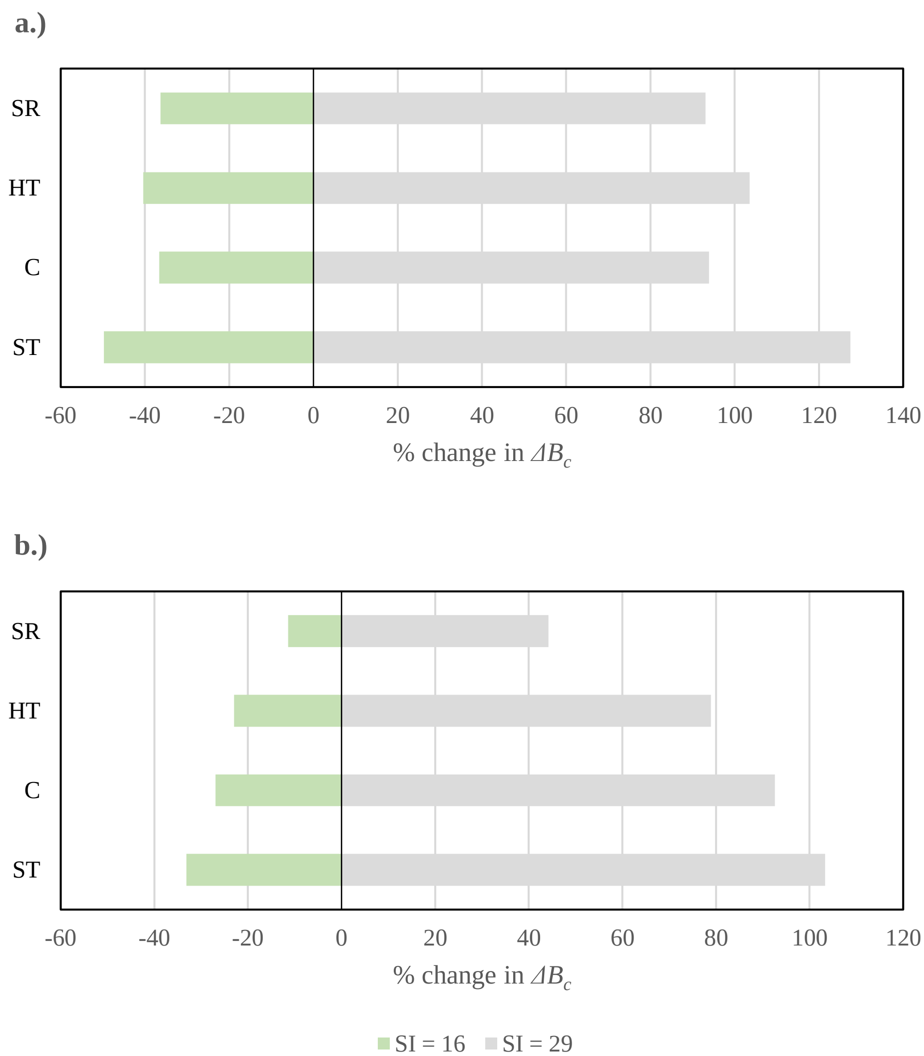


Figure A2 Percent (%) change in ΔB_c under the natural regeneration reference scenario for site index (SI) values ranging from SI = 16 to SI = 29 m for different forest management scenarios. Percent change values are measured against ΔB_c for SI = 20 m, as applied in the main study. The top panel a.) displays the percent change in ΔB_c for each management calculated over a 100-year period while the bottom panel b.) is calculated over one rotation.

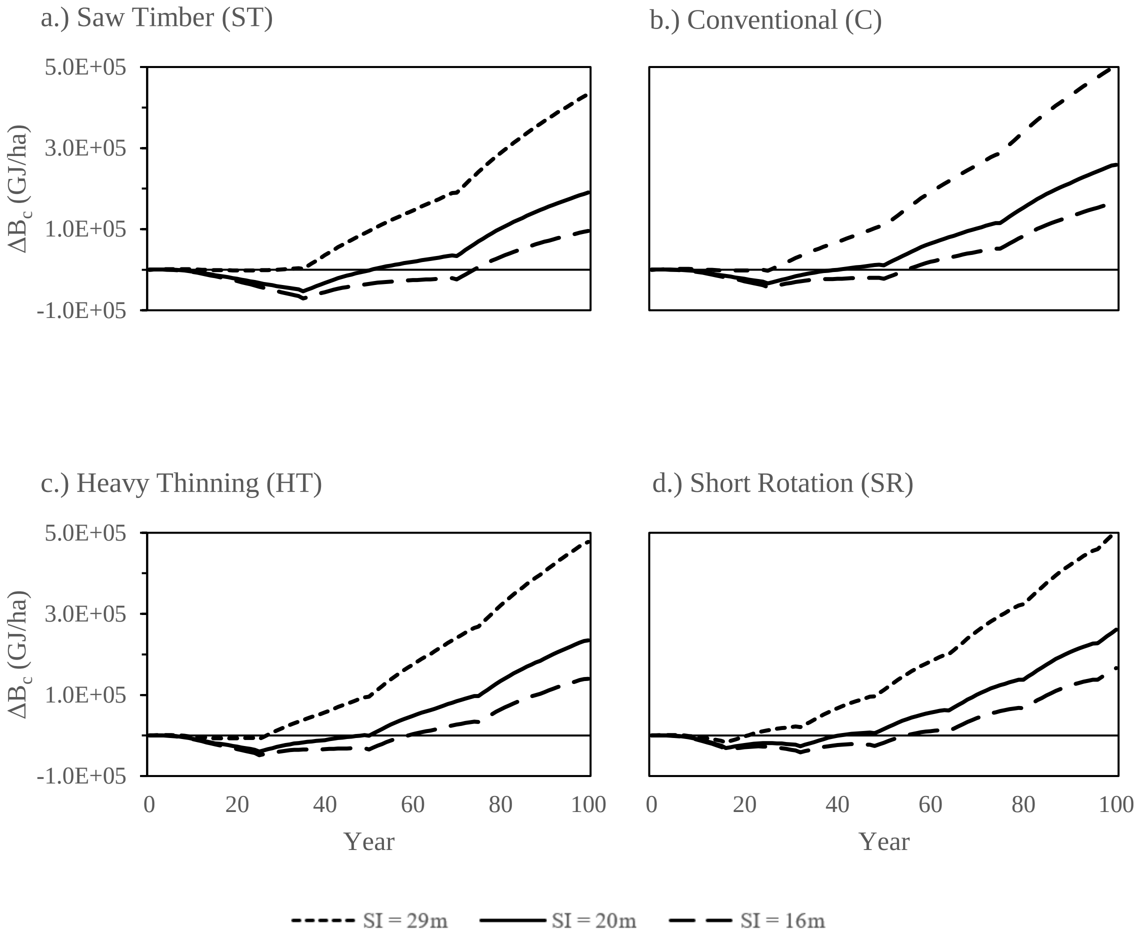


Figure A3 Variability in the magnitude of ΔB_c under the natural regeneration reference with differing site index (SI) values. Solid lines represent ΔB_c with SI = 20 m, as applied in the study and dashed lines represent the lower and upper ranges of ΔB_c for SI values ranging from 16 to 29 m, respectively.

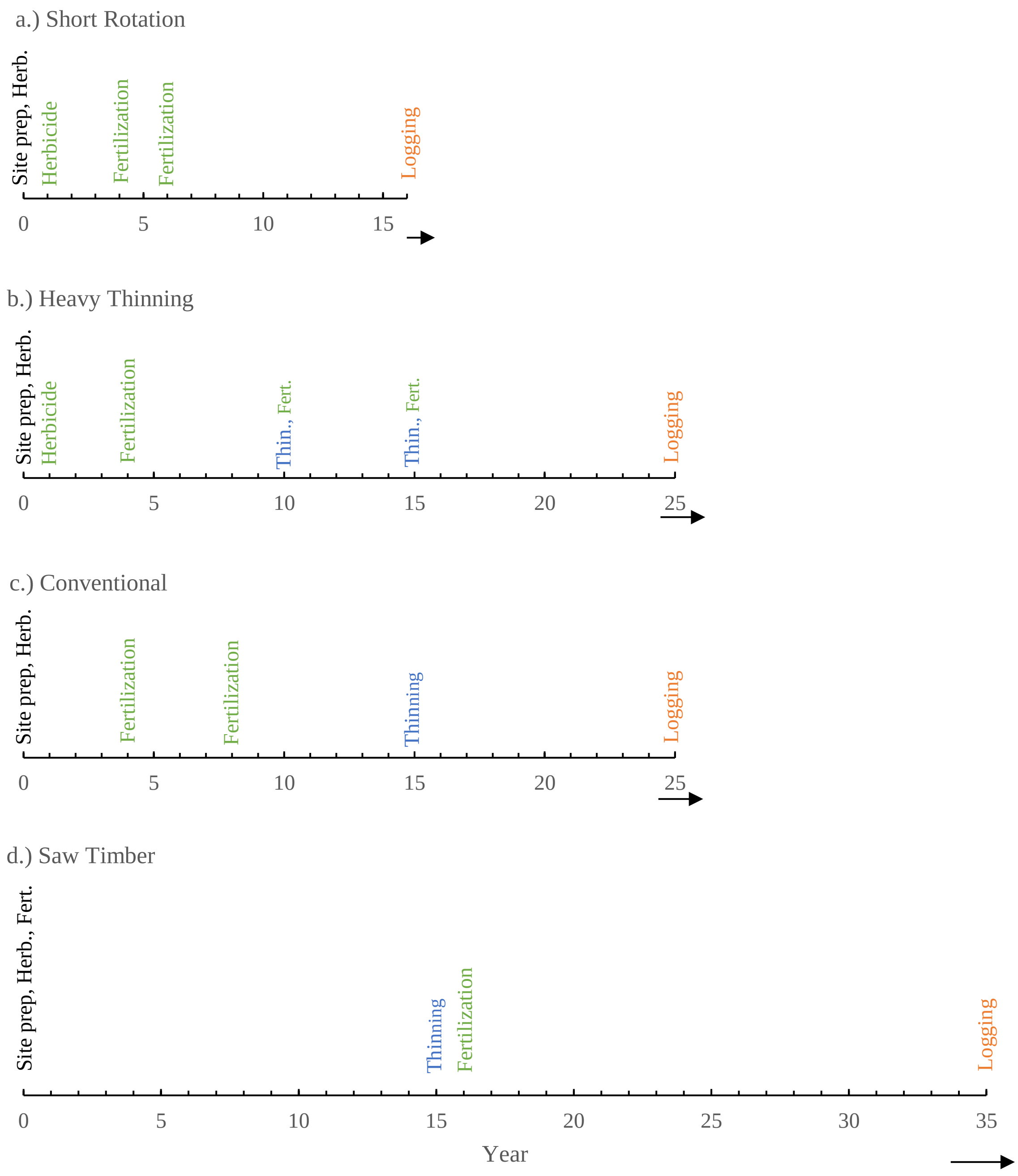


Figure A4 Timeline of forestry operations and individual treatments over one rotation period for four management scenarios (a-d). Forestry operations are denoted by the color of the symbols as follows; site prep (black), stand management (green), thinning (blue) and logging (orange). Individual treatments include initial site prep (site prep), herbicide (herb.), fertilization (fert.), thinnings (thin.) and logging.

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APPENDIX B

FOOD WEB NETWORK MODELS

B1 FOOD WEB METABOLIC MODEL DESCRIPTION

B1.1 NETWORK STRUCTURE

The structure of an ecological network representing a food web in a pine forest ecosystem was built using literature data (**Table B1**). The network consisted of 8 total trophic compartments (*S*) with 3 primary producer compartments (trees, understory, and dead wood) and 5 food web compartments (herbivores, insects, insectivores, top predators, and decomposers), and 21 links (*L*) or connections. Trophic compartments represent aggregated functional groups of species, based on feeding relationships of the group, while links represent predator-prey relationships or energy flow connections between them. An *8* x *8* connectance matrix, A_{ij}, (**Table B2a**) was designated to represent connections or links between compartments (0 – for no link, 1 – for link). For each compartment, individual body masses of groups of species within a functional group (M_{ind}) were collected from surveyed literature sources (**Table B1**). Average individual body mass values were calculated (**Table B3**) and assumed to represent the typical individual body mass of that compartment.

B2 STEADY STATE METABOLIC MODEL

Using representative species for each trophic compartment, dietary and stomach analysis data from the literature (**Table B4**) were used to construct a diet matrix, D_{ij}, for the food web. For each predator (columns), the sum of prey items (rows) down the column add to 1, such that the column values in the diet matrix represent the proportion of each prey item comprising the predators' diet

(**Table B2b**). For each prey item (rows), each value of the diet matrix was normalized to the sum of predator preferences for that prey such that each row of the matrix then summed to 1. Each value of the matrix now represents the proportion of energy from each prey flowing to each predator, i.e. the proportion of each prey consumed by each predator (**Table B2c**). This energy allocation matrix, α_{ij}, is similar to trophic interaction strength matrices common in the ecological modeling literature.

Finally, an energy flow matrix, f_{ij}, was constructed as the product of the energy allocation matrix with the corresponding production rate of the trophic compartment and a trophic transfer efficiency value (ε_{ij}), representing the percentage of energy transferred between trophic compartments. Energy flows, f_{ij}, are read from compartment *i* (rows, prey) to *j* (columns, predators) so that each flow represents the amount of energy flowing from i to j through consumption. Production rates of each producer compartment (i.e., compartments 1, 2, and 3) were taken as the average values from the carbon balance models for each management scenario. Transfer efficiency values were assigned commonly assumed values of ~10%, 40%, and 50% for flows between consumers, from consumers to decomposers, and from decomposers to consumers, respectively. Thus, this energy flow matrix represents the quantity of energy flowing between all compartments of the network (**Table B2d**).

Metabolic theory was then used to calculate the individual uptake rate (kg C/m^2 ind) of each trophic compartment downstream of producers as follows;

$$P_{ind} = P_0 M_{ind}^{\beta} e^{-E/k_b T} \tag{B1}$$

Where P_0 is a normalization constant (~2.16x10^9), β is a mass scaling exponent (~0.75), E is the metabolic activation energy (~0.65 eV for heterotrophs), k_b is Boltzmanns' constant (8.62x10^{-5} eV/K), and T is the environmental temperature (set to 295 K for ectothermic and 310 K for endothermic organisms).

Next, the carrying capacity or abundance of individuals (ind/m^2) in each trophic compartment was calculated as;

$$N_i = P_{tot}/P_{ind} \tag{B2}$$

Where P_{tot} is the total energy flow into a trophic compartment. The biomass of each trophic compartment (kg C/m^2) was then determined as;

$$B_i = N_i M_{ind,i} \tag{B3}$$

Finally, energy flow balance was imposed on all input and output flows of each compartment to determine respiration flows, y_i. Following the above procedure, all carbon flows and stores were then converted to energy units using a conversion factor of 35 MJ/kg C.

The above metabolic model procedure was run for each of the four forest management scenarios in this study. The main difference between management scenarios was in the production rates and biomass stores of the primary producer and dead wood compartments (compartments B_1, B_2, and B_3). These values were derived from the forest carbon models and calculated as the average production rates and biomass of each compartment and then input to the metabolic model for each management scenario. Doing so allowed for the metabolic model to be parameterized with realistic inputs capturing differences in stand growth and resulting in unique food webs representative of each management practice.

B3 UNCERTAINTY ANALYSIS

To account for uncertainty in food web properties, monte carlo analysis was performed while varying individual body mass sizes (**Table B3**) and trophic transfer efficiencies within realistic ranges representative of forest ecosystems. Typically, in network analysis, transfer efficiencies are commonly randomly selected from uniform or lognormal distributions. However, as the goal was to use more realistic ranges representative of forest ecosystems, transfer efficiency values were varied from 1% - 10% for flows between consumers, 10% - 40% for flows from consumers to decomposers, and 10% - 50% for flows from decomposers to consumers. Similarly, individual body mass sizes were varied over ranges derived from literature data for each trophic compartment.

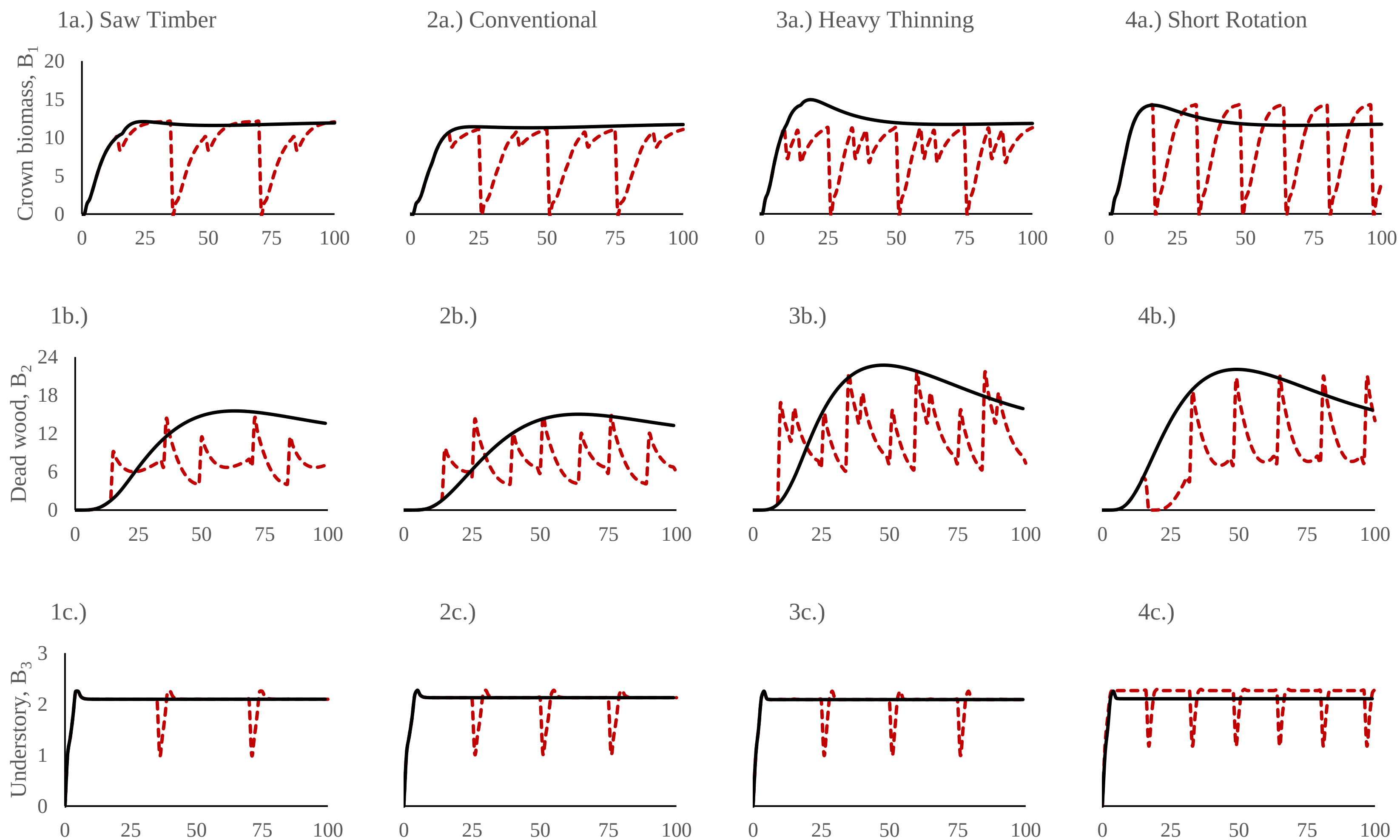

Figure B1 Stand biomass of producer and dead wood compartments (rows) under different management scenarios (columns) for 100 years. Biomass curves are outputs of the carbon balance model and display no-harvest reference (solid black) and harvest (red dashed) scenarios coupled as inputs to the dynamic network model. All units are in tonnes C/ha.

Table B1 Species used to represent functional groups of the trophic model.

Model Compartment	Taxa	Common Name	Scientific Name or Order	Individual Mass (g)	Temp (ºC)	Ref
Insect	Insect	Spider	Pisaruidae	1.4E-01	22	(Uiterwaal & DeLong, 2019)
Insect	Insect	Scorpion	Centruroides vittatus	7.0E-01	22	(Miller et al., 2016)
Insect	Insect	Carpenter Ant	Camponotus floridanus	7.5E-03	22	-
Herbivore	Mammal	Gray Squirrel	Sciurus carolinensis	3.6E+02	37	(Hayssen, 2008)
Herbivore	Mammal	Fox Squirrel	Sciurus niger	2.4E+02	37	(Hayssen, 2008)
Herbivore	Mammal	White Tailed Deer[5]	Odocoileus virginianus	6.4E+04	37	(Purdue, 1987)
Herbivore	Mammal	Cottontail Rabbit[6]	Sylvilagus floridanus	1.2E+03	37	(Swihart, 1986)
Insectivores	Bird	Wild Turkey	Meleagris gallopavo	6.1E+03	37	(Dunning Jr, 2007)
Insectivores	Bird	Cardinal	Cardinalis cardinalis	4.4E+01	37	(Sgueo et al., 2012)
Insectivores	Bird	Carolina Wren	Thryothorus ludovicianus	2.0E+01	37	(Dunning Jr, 2007)
Insectivores	Bird	Tufted Titmouse	Baoelophus bicolor	2.2E+01	37	(Dunning Jr, 2007)
Insectivores	Bird	Blue Jay	Cyanocitta cristata	8.8E+01	37	(Dunning Jr, 2007)
Insectivores	Bird	Summer Tanager	Piranga rubra	3.0E+01	37	(Dunning Jr, 2007)
Insectivores	Bird	Pileated Woodpecker	Dryocopus pileatus	2.9E+02	37	(Dunning Jr, 2007)
Insectivores	Bird	Northern Bobwhite Quail	Colinus virginianus	1.8E+02	37	(Dunning Jr, 2007)
Insectivores	Mammal	Wild Hogs	Sus scrofa	3.8E+04	37	(Mayer, 2021)
Top Predator	Mammal	Bobcat	Lynx rufus	8.2E+03	37	(Larivière & Walton, 1997)
Top Predator	Bird	Bald eagle	Haliaeetus leucocephalus	5.5E+03	37	(FWS, 2021)
Top Predator	Bird	Osprey[7]	Pandion haliaetus	2.0E+03	37	-
Top Predator	Mammal	Red Wolf	Canis rufus	5.7E+04	37	(Hinton et al., 2017)
Top Predator	Mammal	Coyote	Canus latrans	3.0E+04	37	(Hinton et al., 2017)
Decomposers	Detritivore	Springtails	Collembola	1.5E-04	22	(Wolff et al., 2014)
Decomposers	Detritivore	Beetles	Tenebrionidae	2.0E-02	22	(Hu, 2019)

[5] Mass of deer vary considerably, average values of combined sexes from 9 measurement sets were used.

[6] Average of northernmost and southernmost latitude populations.

[7] Based on best estimate of 4.5 lbs per individual.

Table B2 Examples of connectance (a), diet (b), trophic interaction strength (c), and energy flow matrices (d) for the metabolic network model. Example shown is for the conventional (C) management scenario. Compartment abbreviations are as follows: (1) tree crown, (2) dead wood, (3) understory vegetation, (4) herbivores, (5) insects, (6) insectivores, (7) top predators, (8) decomposers/detritivores.

a. Connectance Matrix, A_{ij}

	1	2	3	4	5	6	7	8
1				1	1	1	1	
2								1
3				1	1	1	1	
4							1	1
5						1	1	1
6							1	1
7								1
8				1	1	1	1	

b. Diet Matrix, D_{ij}

	1	2	3	4	5	6	7	8
1				0.60	0.25	0.55	0.05	
2								0.20
3				0.35	0.50	0.37	0.05	
4							0.67	0.20
5						0.03	0.01	0.20
6							0.21	0.20
7								0.20
8				0.05	0.25	0.05	0.01	

c. Interaction Strength Matrix, α_{ij}

	1	2	3	4	5	6	7	8
1				0.41	0.17	0.38	0.03	
2								1.00
3				0.28	0.39	0.29	0.04	
4							0.77	0.23
5						0.13	0.04	0.83
6							0.51	0.49
7								1.00
8				0.14	0.69	0.14	0.03	

d. Energy Flow Matrix, f_{ij}

	1	2	3	4	5	6	7	8
1				9.9E-04	4.1E-04	9.1E-04	8.3E-05	
2								8.8E-03
3				1.1E-04	1.6E-04	1.2E-04	1.6E-05	
4							1.3E-04	1.5E-04
5						4.3E-05	1.4E-05	1.2E-03
6							8.4E-05	3.2E-04
7								1.8E-04
8				5.8E-04	2.9E-03	5.8E-04	1.2E-04	

Table B3 Range and mean of individual body mass sizes (kg C/ind) used in the metabolic network model and monte carlo analysis.

	$\mathbf{M_{mean}}$	$\mathbf{M_{low}}$	$\mathbf{M_{high}}$
Herbivores	8.2E+00	1.2E-01	3.2E+01
Insects	1.4E-04	3.8E-06	3.5E-04
Insectivores	2.5E+00	1.0E-02	1.9E+01
Top Predators	1.0E+01	1.0E+00	2.9E+01
Detritivores	5.0E-06	7.5E-08	1.0E-05

Table B4 Representative functional groups of species/trophic compartments and data sources used to construct the diet matrix in this study.

Functional Group	**Representative Species**	**Data source**
Herbivores	White Tailed Deer (Odocoileus virginianus)	(Jenks et al., 1996)
Insects	Harvester Ants[8]	(MacKay, 1981)
Small mammals/Insectivores	Feral Hogs (Sus scrofa), Bob-white Quail (Colinus virginianus)	(Wood & Roark, 1980) (Laessle, 1944)
Top Predators	Coyotes (Canis latrans)	(McVey et al., 2013)

[8] Dietary data for ant species could not be found in the southeastern US. Data from the southwest were taken as comparable.

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APPENDIX C

GWP LITERATURE AND CASE STUDIES

C1 IMPACT OF INDIVIDUAL FACTORS ON OVERALL GWP

C1.1 PLANT LOCATION

Electricity use has been shown to be a key contributor to total the overall emissions of bioSA production (Patel et al., 2006; Shen et al., 2019). Several studies noted the sensitivity of GWP to the geographic location of the power grid available (Cok et al., 2014; Moussa et al., 2016; Smidt et al., 2016). The impact of plant location on GWP was assessed by varying the geographic location of power grids supplying electricity for bioSA production. Based on the availability of inventory data for electricity requirements, two production technologies, direct crystallization (DC) and electrodialysis (ED) for bioSA from corn starch were selected as case studies to compare the impact of different grid locations on overall GWP (Cok et al., 2014).

Unit GWP values for eleven different power grid geographic locations were obtained from the EcoInvent database and displayed large variability in GWP (**Table C4**), with values ranging from ~0.02 to ~1.0 kg CO_2 eq./kWh (a nearly 60-fold difference) between the power grids of Switzerland (CH) and Greece (GR). In the existing study, values for the average European grid intensity (RER) were used to calculate the GWP of bioSA. Using inventory data from Cok et al. (2014), the existing contribution to GWP from electricity was removed from the total GWP for each technology. The resulting GWP for each geographic location was then recalculated by multiplying the electricity requirements with each corresponding unit GWP value of **Table C4** and adding it back to the overall GWP without electricity. This was done for both production technologies in order to recalculate the impact of different plant locations on bioSA from the same feedstock.

C1.2 ENZYME PRODUCTION

Inclusion of enzymes required for enzymatic hydrolysis of biomass can have a significant impact on the carbon footprint and energy demand of bioSA production primarily due to their high energy requirements (Janssen et al., 2016; Gilpin & Andrae, 2017). Based on availability of data for enzyme requirements and transparency regarding the database used for enzyme production, variability in the GWP of enzyme production was assessed for bioSA produced from bread waste and corn stover feedstocks (Adom et al., 2014; Gadkari et al., 2021). Two samples of bioSA produced from corn stover were chosen with two different downstream technologies, liquid-liquid extraction (LLE) and electro-deionization (EDI) while one sample was used for bread waste (Adom et al., 2014). A total of $n = 17$ values for the GWP of enzymes were extracted from a variety of environmental databases and literature sources (**Table C5**). The values from Harding et al. (2008) were excluded as outliers. From these values, the mean GWP of enzyme production was calculated as ~9.3 kg CO_2 eq./kg enzyme with a standard deviation of 7.4 and lower and upper ranges of ~1.2 to 22 kg CO_2 eq./kg enzyme. Using three existing samples as case studies, the resulting GWP values of bioSA production were then recalculated with the above mean, lower, and upper ranges replacing the original values. The recalculated upper and lower ranges for each sample were then compared to the original GWP values of each sample to determine the contribution of the variability of enzyme production to total GWP.

C1.3 COPRODUCT INCLUSION

Multifunctionality occurs when more than one product, or coproduct, is produced from the same production process. When this occurs, the question of how the environmental impacts associated with such processes should be partitioned and distributed arises. Though different approaches to the handling of coproducts have been proposed, ISO 14044 presents a hierarchy of methods for handling coproducts (Finkbeiner et al., 2006). While it has generally been shown that the production of bioSA from starch-based sugars entails GHG emission benefits in comparison to those of petroleum based succinic acid, this result depends on the allocation procedure and handling of coproducts (Cok et al., 2014; Montazeri et al., 2016; Moussa et al., 2016; Posen et al., 2016). Several analyses have noted the large impact of coproduct treatment on GWP and energy use of bioSA (Cok et al., 2014; Montazeri et al., 2016; Brunklaus et al., 2018; Gadkari et al., 2021).

To assess the effect of coproduct treatment in reducing GWP, seven literature studies, which included three different coproduct treatment methods (mass allocation, economic allocation, and system expansion) and common bioSA coproducts (such as biomass for fertilizers and feed, electricity, and acetic acid) were assessed. For each sample, the effect of the coproduct(s) was removed using the treatment method of each study and the resulting GWP without the coproduct was recalculated. For studies that included more than one coproduct, the effects of both coproducts were removed. For each study, the resulting GWP values without inclusion of coproducts were then compared to the original reported values of each study to assess the impact of coproduct inclusion on the total GWP.

Table C1 Publication summary.

Year	Location	Feedstock	Scope (cradle to-)	GWP	Coproducts	Coproduct Treatment	Reference
2006	Brazil	Sugar cane	gate/grave	-0.6 - 3.5	Energy	System expansion	(Patel et al., 2006)
2014	Brazil		gate	-1.0 - 1.4	Multiple	Multiple[9]	(Cok et al., 2014)
2015	Brazil		gate	-0.8	Multiple	Multiple	(Smidt et al., 2016)
2006	Europe	Corn	gate/grave	0.3 - 4.6	Energy	System expansion	(Patel et al., 2006)
2014	Europe		gate	0.9 - 1.7	Multiple[10]	Multiple	(Cok et al., 2014)
2015	Europe		gate	0.9	Multiple	Multiple	(Smidt et al., 2016)
2020	Germany		gate/grave	0.9	Multiple	System expansion	(Musonda et al., 2020)
2006	Europe	Corn Stover	gate/grave	-0.2 - 4.0	Energy	System expansion	(Patel et al., 2006)
2014	United States		grave	1.9 - 3.3	Energy	System expansion	(Adom et al., 2014)
2021	United States		grave	5.7	Feed	System expansion	(Dickson et al., 2021)
2018	Sweden	Food Waste[11]	gate	0.7	Fertilizer	Mass allocation	(Brunklaus et al., 2018)
2018	Spain		gate	5.3	None	None	(Gonzalez-Garcia et al., 2018)
2021	Europe		gate	13.3	Feed	Economic allocation	(Ioannidou et al., 2020)
2021	United States		grave	3.0	None	None	(Dickson et al., 2021)
2021	United Kingdom		gate	1.3	Feed	Mass allocation	(Gadkari et al., 2021)
2016	United States	Energy Crops [12]	gate	0.9	Fertilizer	System expansion	(Moussa et al., 2016)
2017	Italy		gate	2.0	None	None	(Zucaro et al., 2017)
2018	Greece		gate	0.1 - 1.9	Energy[13]	System expansion	(Chrysikou et al., 2018)
2022	India		gate	1.4	Acetic acid	Economic allocation	(Shaji et al., 2021)
2016	Europe	Sugar beet	gate	10	None	None	(Morales et al., 2016)
2021	United States		grave	4.7	None	None	(Dickson et al., 2021)
2016	Europe	Wood waste	gate	12 - 30	None	None	(Morales et al., 2016)
2021	United States	Seaweed	grave	13	Feed	System expansion	(Dickson et al., 2021)

[9] Considered different treatment methods for the corn wet mill and downstream biorefinery processes

[10] Include differing coproducts from the corn wet milling and biorefinery processes

[11] Food waste includes bread waste, waste cooking oil, cider industry waste, and winery waste

[12] Includes dedicated fast-growing crops and other lignocellulosic materials such as canary grass, sorghum grain, sugarcane bagasse, and giant reed crops

[13] In this study, the production of SA was itself a coproduct from a process producing both ethanol and SA from the same feedstock. We have isolated SA and considered only the coproduct from SA chain of the biorefinery (i.e. coproduced steam)

Table C2 Summary statistics of bioSA GWP by differing feedstocks.

Uncertainty factor	Mean GWP	Standard Error	Median	St. Dev.	Sample Variance	Range	Min.	Max.	Sample size
Feedstock									
fossil SA	2.90	1.00	2.90	1.41	2.00	2.00	1.90	3.90	2
sugar cane	0.55	0.34	0.45	1.37	1.88	4.90	-1.40	3.50	16
energy crops	0.76	0.33	0.53	0.80	0.65	1.94	0.06	2.00	6
corn starch	1.74	0.27	1.47	1.12	1.25	4.30	0.30	4.60	17
corn stover	1.87	0.41	1.70	1.59	2.53	5.88	-0.20	5.68	15
food waste	4.71	2.29	2.96	5.13	26.29	12.63	0.67	13.30	5
sugar beet	7.37	2.63	7.37	3.72	13.80	5.25	4.75	10.00	2
seaweed	12.67	-	-	-	-	-	-	-	1
waste wood	20.80	8.80	20.80	12.45	154.88	17.60	12.00	29.60	2

Table C3 Summary statistics of bioSA GWP under different modeling options and processing options.

Uncertainty factor	Mean GWP	Standard Error	Median	St. Dev.	Sample Variance	Range	Min.	Max.	Sample size
Study scope									
cradle-to-gate	2.30	0.86	0.83	5.46	29.76	31.00	-1.40	29.60	40
cradle-to-grave	2.97	0.49	2.25	2.41	5.79	11.77	0.90	12.67	24
Downstream technology									
ED	2.33	1.38	1.20	6.33	40.04	30.59	-0.99	29.60	21
CR	1.41	0.29	1.25	1.49	2.23	6.00	-1.40	4.60	26
RD	1.39	-	-	-	-	-	-	-	1
MEM	1.88	1.55	1.47	2.69	7.22	5.33	-0.58	4.75	3
IX	5.09	1.82	3.13	5.14	26.38	12.63	0.67	13.30	8
REX	7.30	2.28	7.65	4.57	20.85	10.10	1.90	12.00	4
Coproduct handling									
multiple	0.14	0.43	0.14	1.21	1.47	3.10	-1.40	1.70	8
system expansion	1.76	0.32	1.30	2.15	4.64	13.27	-0.60	12.67	45
allocation	4.17	3.05	1.35	6.10	37.19	12.63	0.67	13.30	4
none	9.51	3.62	5.30	9.57	91.64	27.60	2.00	29.60	7
Coproduct									
fertilizer	0.77	0.10	0.77	0.14	0.02	0.20	0.67	0.87	2
multiple	0.22	0.39	0.85	1.16	1.35	3.10	-1.40	1.70	9
energy	1.44	0.20	1.30	1.26	1.60	5.20	-0.60	4.60	41
acetic acid	1.39	-	-	-	-	-	-	-	1
none	9.51	3.62	5.30	9.57	91.64	27.60	2.00	29.60	7
feed	8.24	2.89	9.18	5.77	33.32	12.00	1.30	13.30	4

Table C4 Variation in unit GWP values from different geographic grid locations.

Location	**Abbreviation**	**GWP** (kg CO_2 eq./kWh)
Switzerland	CH	0.02
Sweden	SE	0.03
France	FR	0.08
Nordic (except Iceland)	NORDEL	0.16
Brazil	BR	0.21
Europe	RER	0.48
Denmark	DK	0.62
Italy	IT	0.63
United States	US	0.75
Central Europe	CENTREL	0.89
Greece	GR	0.99

Table C5 Summary of the GWP of enzyme production from literature and environmental databases including the calculated mean and standard deviation (95% confidence) of all samples. Bold values represent the lower and upper bounds used to determine the variability of enzyme production.

Description	**GWP** (kg CO_2 eq./kg enzyme)	**Reference**
Calculated mean and standard deviation	9.3 ± 7.4	-
Enzyme, Alpha-amylase, Novozyme Liquozyme	**1.2**	(Nielsen et al., 2007)
Enzyme, Cellulase, Novozyme Celluclast	4.1	(Nielsen et al., 2007)
Enzyme, Glucoamylase, Novozyme Spirizyme	4.4	(Nielsen et al., 2007)
	-1240[14]	(Harding, 2008)
	924.0	(Harding, 2008)
	2.3	(MacLean & Spatari, 2009)
	16.0	(Kim et al., 2009)
	25.0	(Kim et al., 2009)
	3.7	(Dunn et al., 2012)
	2.2	(Wang et al., 2012)
	10.2	(Hong et al., 2013)
	16.0	(Hong et al., 2013)
	21.9	(Agostinho et al., 2015)
	5.5	(Olofsson et al., 2015)
	7.9	(Gilpin & Andrae, 2017)
	9.1	(Gilpin & Andrae, 2017)
	10.6	(Gilpin & Andrae, 2017)

[14] Both GWP values by Harding, 2008 are excluded from the calculation as outliers.

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