2023

LIFE CYCLE ASSESSMENT OF AIR CLASSIFICATION AS A SULFUR MITIGATION TECHNOLOGY IN PINE RESIDUE FEEDSTOCKS

Ashlee Edmonson
University of Kentucky, 17aedmonson@gmail.com
Author ORCID Identifier:
https://orcid.org/0009-0005-4590-0074
Digital Object Identifier: https://doi.org/10.13023/etd.2023.124

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Ashlee Edmonson, Student

Dr. Jian Shi, Major Professor

Dr. Michael Sama, Director of Graduate Studies

LIFE CYCLE ASSESSMENT OF AIR CLASSIFICATION AS A SULFUR MITIGATION TECHNOLOGY IN PINE RESIDUE FEEDSTOCKS

THESIS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Biosystems and Agricultural Engineering in the College of Engineering at the University of Kentucky

By

Ashlee Edmonson

Lexington, Kentucky

Director: Dr. Jian Shi, Professor of Biosystems and Agricultural Engineering

Lexington, Kentucky

2023

https://orcid.org/0009-0005-4590-0074

ABSTRACT OF THESIS

LIFE CYCLE ASSESSMENT OF AIR CLASSIFICATION AS A SULFUR MITIGATION TECHNOLOGY IN PINE RESIDUE FEEDSTOCKS

Sulfur accumulation during biofuel production is pollutive, toxic to conversion catalysts, and causes the premature breakdown of processing equipment. Air classification is an effective preprocessing technology for ash and sulfur removal from biomass feedstocks. A life cycle assessment (LCA) sought to understand the environmental impacts of implementing air classification as a sulfur-mitigation technique for pine residues. Energy demand and material balance for preprocessing were simulated using SimaPro and the Argonne National Laboratory's GREET model, specifically focusing on comparing the global warming potential (GWP) of grid electricity versus bioelectricity scenarios. Overall, the grid electricity scenario had a GWP impact over 7 times that of the bioelectricity scenario with the largest source of impact from steam generation during rotary drying. Air classification represents 0.4% and 1.6% of total GWP impact for the grid electricity and bioelectricity scenarios, respectively. Therefore, air classification can facilitate significant sulfur reduction to improve rates of biofuel conversion and lessen corrosion of combustion equipment while contributing minimal GWP impact during preprocessing.

KEYWORDS: life cycle assessment, sulfur, air classification, feedstock variability, GWP, forest residues

Ashlee Edmonson

05/01/2023

Date

LIFE CYCLE ASSESSMENT OF AIR CLASSIFICATION AS A SULFUR MITIGATION TECHNOLOGY IN PINE RESIDUE FEEDSTOCKS

By
Ashlee Edmonson

Jian Shi

Director of Thesis

Michael Sama

Director of Graduate Studies

05/01/2023

Date

DEDICATION

To my family, who have supported me through it all

ACKNOWLEDGMENTS

The following thesis, while an individual work, benefited from the insights and direction of several people. First, my Thesis Chair, Jian Shi, exemplifies the high-quality scholarship to which I aspire. In addition, Mark Mba-Wright provided timely and instructive comments at every stage of the thesis process, allowing me to make thoughtful and accurate assumptions. Next, I wish to thank the complete Thesis Committee, and outside reader, respectively: Diana Byrne, Michael Montross, and Yingqian Lin. Each individual provided insights that guided and challenged my thinking, substantially improving the finished product.

In addition to the technical and instrumental assistance above, I received equally important assistance from family and friends. To Stan and Karen Pigman, who generously give disadvantaged students a chance to succeed and thrive in engineering. To Scott Bailey, who sparked my interest in engineering and has been a mentor and friend since. To my friends, who may not have known the respite they offered me during our time together. To my mom and Gracee, who keep me equally sane and insane. To my dad, who would be willing to help in any way he knew how. And finally, to my partner, Jacob. You provided unwavering support during every high and low. I will always be grateful to you all.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

1.1 Project Overview

This project, funded by the U.S. Department of Energy's (DOE) Office of Energy Efficiency and Renewable Energy, aims to correlate the form and fate of sulfur in pine feedstocks to thermochemical conversion performance and develop effective feedstock preprocessing and sulfur mitigation strategies. The long-term goals are to produce a detailed sulfur profile database and implement predictive models to guide the design of thermochemical conversion of biomass feedstocks with varying sulfur profiles.

Sulfur content in pine feedstocks varies based on a tree's age, location, growth and harvesting conditions, and anatomical fraction. Preliminary analyses of samples collected from Oregon by Red Rock Biofuels reveal wide variability (10 to 100-fold difference) in sulfur content in pine residues. This project includes 18 representative pine residue samples provided by FTX, North Carolina State University, Auburn University, and Red Rock Biofuels. The samples were collected from Georgia, South Carolina, North Carolina, Alabama, and Oregon and varied based on age, species, harvesting practices, and anatomical fractions.

Sulfur accumulation through the production of biofuels from pine feedstocks can be pollutive, toxic to conversion catalysts, and cause premature breakdown of processing equipment. Previous research has shown the effectiveness of air classification for the removal of sulfur, therefore the goal of air classification in this model is to facilitate a 30% reduction in feedstock sulfur. A life cycle assessment (LCA) was conducted to understand the environmental impacts of implementing air classification as a sulfur mitigation technique.

The first objective is to develop an LCA of the preprocessing of pine residue feedstocks using air classification. The second objective is to perform electrical grid mix and bioelectricity scenario analyses to compare efficiencies. The third objective is to determine the environmental advantages and disadvantages of the implementation of air classification technology for sulfur mitigation in pine feedstocks.

We expect this project will produce valuable information regarding tradeoffs between environmental impact categories from the implementation of air classification technology as well as determine the feasibility of implementing air classification technology in biofuel refineries to mitigate sulfur and emissions. This project will address a critical need in the cellulosic biofuel industry to improve efficiency and reliability and mitigate the environmental impacts of thermochemical conversion to produce biofuels.

1.2 Project Objectives

1.2.1 <u>Objective #1: Develop an LCA of the preprocessing of pine residue feedstocks using air classification.</u>

Air classification is an ash mitigation technique that separates materials based on particle density and size. Air classification is effective and economical for the separation of low and high ash content biomass fractions. The goal of implementing air classification is to reduce ash, and therefore sulfur, content mixed in the biomass fractions. The LCA in this study references the International Organization for Standardization's (ISO) series

14040:2006 and 14044:2006 standards and aims to glean information regarding environmental consequences associated with the implementation of air classification as a sulfur-mitigation technology.

1.2.2 Objective #2: Perform grid electricity mix and bioelectricity scenario analyses to compare efficiencies.

There is a gap in the literature regarding emissions associated with the implementation of air classification on an industrial scale. This objective will test a traditional and best-case scenario to weigh the environmental consequences of each.

1.2.3 Objective #3: Determine the environmental advantages and disadvantages of the implementation of air classification preprocessing technology for sulfur mitigation in pine residue feedstocks.

We expect that the outcomes of this project will elucidate the tradeoffs between environmental impact categories due to the implementation of air classification technology. This objective aims to look at the project holistically to weigh if the amount of sulfur/ash content being reduced before conversion is worth the environmental consequences of air classification. Additionally, this objective aims to perform sensitivity and uncertainty analyses to further understand which process parameters are most impactful to the environmental footprint.

1.3 LCA Goals and Scope

Defining the goals and scope is the first phase of an LCA that addresses the purpose and methods of including life cycle environmental impacts in the decision-making process (NRMRL, 2006).

1.3.1 Goals

Defining the goals of an LCA includes identifying the audience, objectives, applications, and how the results might be interpreted.

The intended audience for this study is biofuel refineries or researchers interested in technology to mitigate sulfur and/or emissions associated with biofuel production from forest residues.

The main objectives of this study are: 1) develop an LCA of preprocessing of pine feedstocks including air classification, 2) perform energy scenario analyses to compare efficiencies, and 3) determine the environmental advantages and disadvantages of air classification as a preprocessing technology for sulfur mitigation in pine feedstocks.

There are two main applications of this study. First, this study should provide information and direction to decision-makers. As stated, the intended audience for this LCA is biofuel refineries or researchers interested in technology to mitigate sulfur and/or emissions associated with biofuel production, therefore, this study should offer guidance for large-scale implementation of air classification. This study should also provide valuable information regarding the energy efficiency of preprocessing with air classification.

Second, this study should support broad environmental assessments by elucidating the change in environmental impact by implementing air classification at an industrial scale.

This study is conducted as an attributional LCA (ALCA). The ALCA is an LCA methodology for assessing what share of global environmental burdens belongs to a product. The model considers the environmental burden of preprocessing usable feedstock for conversion.

1.3.2 Scope

The scope of this LCA is pine wood chips (PWC) entering the biorefinery gate through preprocessing. Since the goals of this study pertain to gleaning information regarding the environmental effects of air classification, raw material acquisition and transportation of PWC to the biorefinery were not considered. Preprocessing includes the steps to prepare the biomass for conversion; in this case, the steps for preprocessing include air classification, drying, and size reduction. This LCA will consider the end-of-life of dry matter loss (DML) during air classification and wastewater treatment from drying. The scope of the LCA focuses on end-of-life of matter leaving the biorefinery, therefore, the mass discarded to combustion is not in the system boundary because it is assumed to be combusted to power other parts of the process. The system boundary is outlined in Figure 1 where the oval, rectangle, and parallelogram represent start/end points, processes, and inputs/outputs, respectively. The red color of the rectangles represent end-of-life processes. The rest of the document follows this flow diagram shape/color convention.

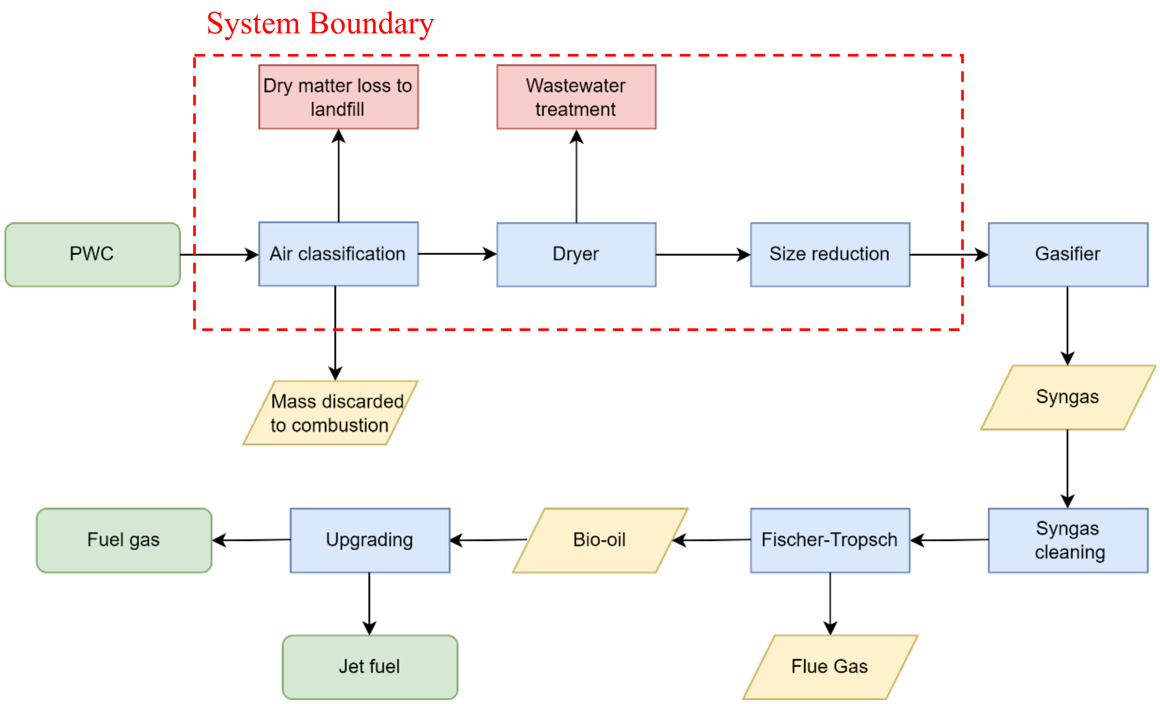


Figure 1. PWC conversion process flow diagram including the LCA system boundary.

1.3.3 Functional Unit

The ISO defines the functional unit as the "quantified performance of a product system for use as a reference unit" (ISO, 2006-07). A functional unit should be application-specific, quantitative, precise, and broad enough to encompass competing technologies. The function of the system within this LCA scope is to preprocess pine feedstock. However, a fraction of the processed feedstock will be "lost" during preprocessing due to high ash content and normal matter loss. This system should be normalized to the output of usable feedstock (feedstock that will continue to conversion processes) rather than the total feedstock going into the system (feedstock that will continue to conversion processes + feedstock lost during preprocessing). This process will be further explained in Chapter 3. Therefore, the functional unit is one dry metric tonne of usable feedstock.

1.3.4 Data Requirements

The data requirements of an LCA are resource and time intensive. The availability and utilization of data can greatly sway the accuracy of results; therefore, it is vital to carefully consider the time and resources required to complete an LCA. With this idea in mind, data was applied thoughtfully and at a carefully selected specificity level.

Only about two percent of annual energy consumption in the U.S. comes from wood-derived fuels (White, 2010). Therefore, this project currently has a niche-level application for researchers and biorefineries. The niche-level application means that the data used in this LCA is specific to equipment available to research facilities rather than based on common industrial practices. Assumptions had to be made at certain levels because no data currently exists for this system at an industrial level for preprocessing woody feedstocks. It is clearly noted where assumptions have been made.

Data sources for this project include Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET) life cycle model, SimaPro inventory databases, experiments, and literature. See Chapter 2 for more information about GREET and SimaPro.

CHAPTER 2. LITERATURE REVIEW

First, a brief history of biofuel policy in the U.S. and processes to convert cellulosic material to fuel will be presented. Next, the relationship between ash and sulfur content in feedstocks accompanied by methods for mitigation and additional considerations such as moisture content and size reduction will be explored. Last, LCA standards, relevant databases and software, and previous studies will be explained.

2.1 The Need for Biofuels

The relationship between population, consumption, and emissions is complex. Throughput is the flow of raw materials and energy from the global ecosystem's sources of low entropy (mines, wells, fisheries, croplands), through the economy, and back to the global ecosystem's sinks for high entropy wastes (atmosphere, oceans, dumps). While it seems that consumption fits the definition of throughput, the concept of consumption is more complex. If the quality or quantity of inputs is transformed in a system, then the resource has been partly or wholly consumed (Gößling-Reisemann, 2008). Consumption is accelerated by population growth (Khan et al., 2021). Higher levels of consumption lead to higher use of greenhouse gas (GHG)-intensive fossil fuels in the processing, manufacturing, transportation, usage, and/or disposal of goods and services (Khan et al., 2021). Current United Nations models predict an 80% probability of the world population rising to 9.6 to 12.3 billion by 2100 (Gerland et al., 2014). Therefore, by maintaining current reliance levels on fossil fuel-based energy, GHG levels will continue to rise from mounting population. However, as more research has been conducted regarding the repercussions of current energy trends, governments are incentivizing a transition to renewable fuels. This drives the need for comprehensive research on the harvesting, preprocessing, conversion, and distribution of lignocellulosic biomass for fuel production.

2.2 Biofuels Policy

The Renewable Fuel Standard (RFS) was the United States' first federal policy to begin transitioning to renewable fuels and lessen GHG emissions. In 2009, the U.S. required an annual production of 36 billion gallons of renewable fuel to be mixed into the motor fuel supply by 2022 (Schnepf & Yacobucci, 2013). Of these 36 billion gallons, 16 billion gallons were required to be cellulosic ethanol derived from lignocellulosic biomass demonstrating at least a 60% reduction in life cycle GHG emissions compared to gasoline (Schnepf & Yacobucci, 2013).

The targets set by the RFS were far overestimated. Various economic factors and technological setbacks have resulted in poor economics for biorefineries (Valdivia et al., 2016). However, it is generally agreed upon that cellulosic biofuels offer a promising route for energy security, support for farmers, and mitigation of GHGs if proper investments are made to support and expand efforts (Valdivia et al., 2016). The updated proposed volume targets set by the Environmental Protection Agency (EPA) for 2023 are 0.72 and 20.82 billion RINs for cellulosic biofuel and renewable fuel, respectively, where one RIN is one ethanol-equivalent gallon of renewable fuel.

2.3 Lignocellulosic Biofuels

Second-generation biofuels utilize feedstocks not suitable for human consumption. This includes feedstocks such as wood, forest waste, food crop waste, waste vegetable oil, and industrial waste (Antizar-Ladislao & Turrion-Gomez, 2008). The U.S. DOE's Billion-Ton Report concluded the U.S. can produce at least one billion dry tons of biomass, including agricultural, forestry, waste, and algal materials, annually without adverse environmental impact (Langholtz et al., 2016). Lignocellulosic feedstocks are of particular interest as cellulose is the most abundant biomass on the planet (Naik et al., 2010). It is estimated that there are over 36.2 million dry tons of recoverable logging residues and 37 million dry tons of forest thinnings in the U.S. each year (Lacey et al., 2015). This woody biomass offers a significant opportunity for energy conversion pathways.

Lignocellulosic, also known as cellulosic, biomass is composed primarily of lignin, hemicellulose, and cellulose (Basu, 2013). Cellulose is a polysaccharide consisting of chains of glucose monomers and occurs in nature surrounded by a polymer called hemicellulose. As shown in Figure 2, the cellulose and hemicellulose are embedded in the matrix of phenolic polymer lignin.

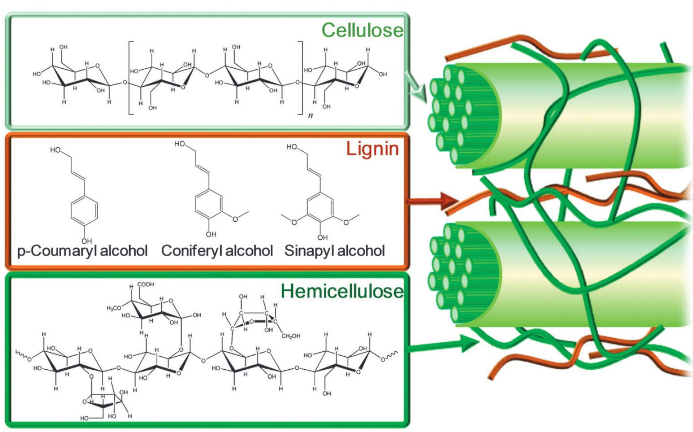


Figure 2. Structure of lignocellulosic biomass with cellulose, hemicellulose, and lignin represented (Alonso et al., 2012).

Biomass conversion occurs biochemically or thermochemically (Basu, 2013). Biochemical processing does not require much external energy and relies on bacteria or enzymes to break down biomass molecules (Basu, 2013). This is accomplished through aerobic or anaerobic digestion, fermentation, or enzymatic or acid hydrolysis. Cellulose is composed of thousands of glucose units connected by β-(1→4) glycosidic linkages (Wertz & Bedue, 2013). By breaking up cellulose, sugars are made available for biochemical conversion. However, the structure of cellulose is recalcitrant to conversion due to the tightly packed structure of the β-(1→4) linkages. Additionally, lignin acts as a barrier holding together the cellulose and hemicellulose and has evolved to be resistant to microbial attack. Therefore, breaking down the lignin matrix is an added complication when pretreating cellulosic biomass for biochemical conversion.

Thermochemical processing requires significant thermal energy to convert biomass into gases (Basu, 2013). The gases can be used directly or synthesized into desired chemicals (Basu, 2013). This is accomplished through combustion, gasification, torrefaction, pyrolysis, or liquefaction. Conversion pathways are outlined in Figure 3.

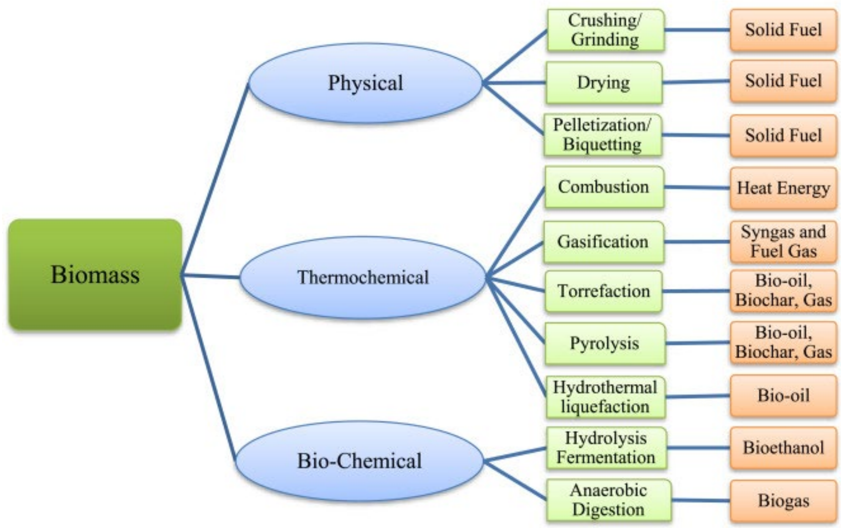


Figure 3. Pathways for conversion of biomass into fuel gases or chemicals (Ong et al., 2019).

Thermochemical conversion using gasification is the pathway considered in this model. Gasification uses high heat and an oxidizing agent (air, oxygen, or steam) to produce combustible gas, volatiles, biochar, and ash in an enclosed gasifier (Boerrigter & Rauch, 2006). After gasification, the Fischer-Tropsch (F-T) process converts syngas to bio-oil. Bio-oil is preferred over biochar and syngas because of higher energy density and ease of transport/storage (Ahamed et al., 2021).

The primary types of gasification are entrained flow, fixed bed, moving bed, and fluidized bed. Entrained flow gasification is the chosen technology in this model. Entrained flow gasification transforms the feedstock into syngas at high temperatures (1200-1500°C) with a residence time of a few seconds (Boerrigter & Rauch, 2006). The resulting syngas is mainly composed of carbon monoxide (CO), hydrogen (H_2), carbon dioxide (CO_2), and water (H_2O) (Boerrigter & Rauch, 2006). Small amounts of tar and ash are also present (Kumar & Aarthi, 2020). Entrained flow is preferred to other gasification technologies due to low tar production and high carbon conversion efficiency (Kumar & Aarthi, 2020). However, it is difficult to prepare the required feedstock for entrained flow gasification due to a small required particle size and variability in ash content. Elevated ash content in biomass can deactivate necessary catalysts during conversion processes, corrode equipment, and increase pollutants.

2.4 Ash Content

The variability of ash content in woody biomass creates complications for thermochemical conversion. Elevated ash content is known to have significant negative effects on thermochemical conversion efficiency (Lacey et al., 2015). Ash causes slagging, bed agglomeration, fouling, and corrosion of combustion equipment (Werkelin et al., 2010). While there are major benefits to utilizing logging residues and forest thinnings as feedstocks, the issue of elevated ash content must be addressed before commercial implementation to avoid such consequences.

Ash content is composed of "physiological ash" and "exogenous ash" (Thompson et al., 2016). Physiological ash is innate to the plant and derived from plant tissue. Physiological elements present due to biological processes include calcium (Ca), potassium (K), magnesium (Mg), sulfur (S), manganese (Mn), and phosphorous (P) (Lacey et al., 2015). Exogenous ash is acquired from soil contamination during harvest. Exogenous elements present due to external processes include silicon (Si), aluminum (Al), iron (Fe), sodium (Na), and titanium (Ti) (Lacey et al., 2015). This information is summarized in Table 1.

Table 1. Ash content in woody biomass.

	Physiological Ash	Exogenous Ash
Definition	Ash that is innate to the plant and derived from plant tissue.	Ash that is acquired from soil contamination during harvest and collection.
Elements	Ca, K, Mg, S, Mn, and P	Si, Al, Fe, Na, and Ti

Many carbon footprint studies have been completed examining the detriment of high ash content on conversion efficiency and yield. One study examined the correlation between ash content and GHG emissions from 346 different feedstocks grouped into six representative categories: treated wood, untreated wood, husk/shell/pit, grass/plant, straw (stalk/cob/ear), and organic residue/product (Li et al., 2017). As ash content increases for each biomass type, GHG emissions decrease (apart from husk/shell/pit due to indirect land use change from food production). This relationship is due to the increase in carbon sequestration credits from the production of biochar. Biochar is charcoal produced by the pyrolysis of plant matter in the absence of oxygen and sequesters CO_2 when stored in the soil. Therefore, high ash content biomass produces lower biofuel yields and emissions per unit of fuel (Li et al., 2017). This relationship is shown in Figures 4 and 5.

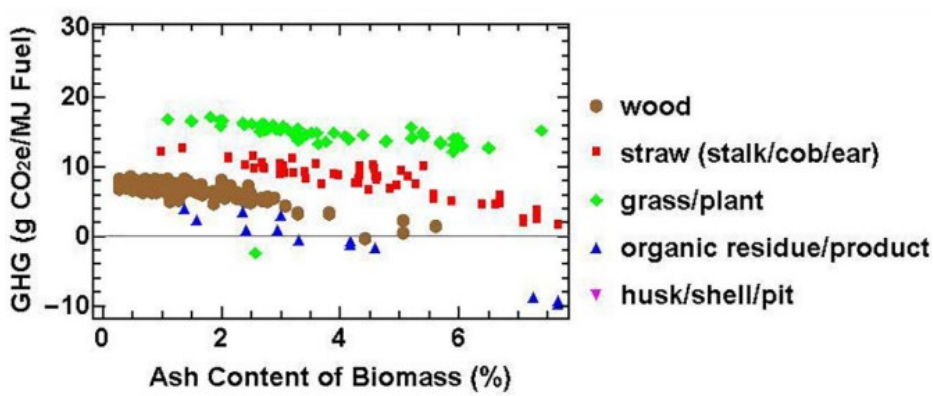


Figure 4. The impact of ash content (%) of biomass on GHG emissions (g CO_2 e/MJ fuel) (Li et al., 2017).

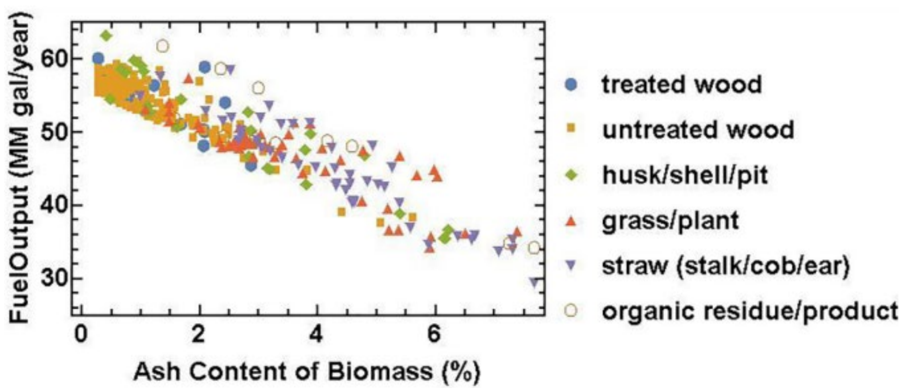


Figure 5. The impact of ash content (%) of biomass on fuel output (MM gal/year) (Li et al., 2017).

While the increase in biochar from elevated ash content decreases GHG emissions from sequestration credits, the fuel output also dramatically decreases. This is problematic for conversion efficiency. Therefore, it would be beneficial to devise alternative methods to lower emissions while simultaneously maintaining high fuel outputs.

2.5 Sulfur

Sulfur in particular contributes to reactions during combustion that lead to fouling and slagging (Lacey et al., 2015). Sulfur comprises 0.3%-0.5% of plant dry weight and is an essential macronutrient for plant growth and development (Ma et al., 2020). Sulfur is absorbed from the plant's root system in the form of inorganic sulfate (SO_4^{2-}) and from the air in the form of sulfur dioxide (SO_2). Fertilizers can also supply elemental sulfur, but the plant must convert the sulfur to inorganic sulfate for uptake (Ma et al., 2020). The inorganic sulfate is distributed across the plant where it is reduced to sulfide and absorbed into the protein-building amino acids cysteine and methionine (Kaufman Rechulski et al., 2014). While the plant converts much of the inorganic sulfate to sulfide, as much as 65% of the total sulfur remains in inorganic form (Kaufman Rechulski et al., 2014). Sulfuric products such as hydrogen sulfide (H_2S) and carbonyl sulfide (OCS) are highly corrosive gases formed during thermochemical processes and pose major concerns to catalysts in downstream upgrading processes such as F-T.

Furthermore, sulfur content and utilization vary according to biomass type. Sulfur content ranges from 0.02% dry weight for softwood and hardwood to 1.0% or more dry weight for municipal solid wastes (Patton et al., 2009; Liu et al., 2017). Additionally, sulfur content varies based on growth/harvesting conditions in woody biomass. For example, sulfur content is higher for loblolly pine forest thinnings than for logging residues (Lacey et al., 2015). The sulfur content of each anatomical fraction also varies, with the highest content for loblolly pine occurring in the needles and bark (Lacey et al., 2015). The variable nature of sulfur across different biomass types as well as within the anatomical fractions adds significant challenges to designing and sizing sulfur mitigation systems.

Sulfur mitigation technologies exist for coal gasification: sulfur scrubbers, feed washing, and coal separation; however, the technologies do not translate directly to mitigation in biomass feedstocks. Overall, there is a research gap in evaluating ash-mitigation preprocessing technology for reductions in sulfur content and changes in environmental impact for woody biomass. It is necessary to complete an LCA to determine the environmental burden from the implementation of air classification technology before thermochemical conversion.

2.5.1 Air Classification

There are previously studied ash removal techniques. Air classification is a well-studied and economical separation technology that separates materials based on particle density and size (Lacey et al., 2015). Air classification uses the physical characteristics of biomass to isolate fractions based on chemical compositions, such as low or high ash content (Lacey et al., 2015). One study found that over 40% of ash content by mass was concentrated into less than 7 wt% of the total biomass (Lacey et al., 2015). If the high ash content fractions are separated from the low ash content fractions before thermochemical conversion, the high content fractions can undergo further extractive treatment before being sent to conversion or be used in other value-added processes. A drawback to this technology is it is more effective at the differentiation of exogenous ash than physiological ash (Lacey et al., 2015).

Another study examined air classification as a method to improve feedstock quality of high moisture short rotation woody crops hybrid poplar (HP) and shrub willow (SW) (Emerson et al., 2018). It was found that the optimal air classification air velocity of ~4.7 m/s reduced ash content from 2.34% to 1.67% for HP and 2.60% to 2.14% for SW (Emerson et al., 2018). Increased air velocity correlates to increased ash removal, however, this is at the expense of biomass losses exemplified in Figure 6.

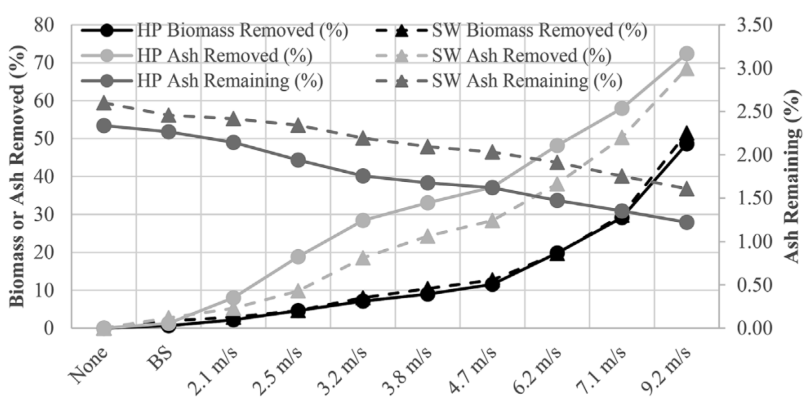


Figure 6. Biomass and ash removed or remaining for sequential air classification air velocity for hybrid poplar (HP), shrub willow (SW), and below screen (BS) fractions (Emerson et al., 2018).

For example, a 6.2 m/s air velocity resulted in a ~10% rate of ash removal, but biomass loss was increased by a factor of four (Emerson et al., 2018). This is an important consideration for an LCA as the reduction in ash content alongside air classification speed must be optimized for minimum biomass loss.

The air classifier assumed in this study is a two-piece system produced by Key Technology. The biomass is fed onto the Iso-Flo dewatering vibratory conveyor which lands in the Model 2x Hi-Flo Air Cleaner. The machine is pictured in Figure 7 with key areas defined.

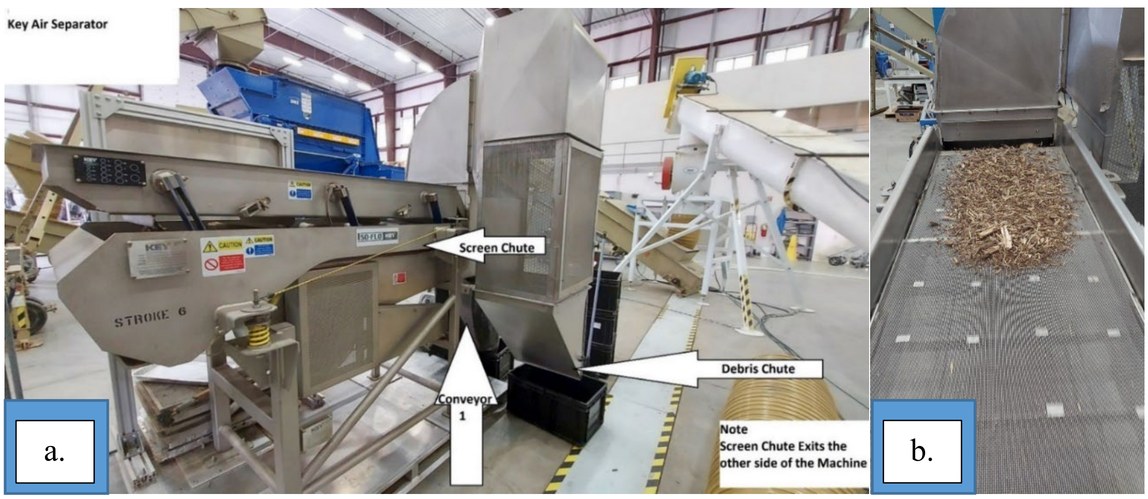


Figure 7. Key Technology a) air separator setup and b) example of woody feedstock on conveyer. (Image source: Idaho National Laboratory's Bioenergy Program).

2.5.2 Bioleaching

In addition to air classification, bioleaching is an ash-mitigation technology that is well-studied in the mining industry but has been recently utilized for cellulosic biomass (Zhang et al., 2019). Bioleaching uses a range of microorganisms with varied leaching capabilities to separate metals from ore or recover elements from solid waste materials

(Zhang et al., 2019). This technique has shown promising results for cellulosic biomass. One study found that up to 96% of silica was leached from rice husks within 24 hours using the microbe *Fusarium oxysporum* (Bansal et al., 2006). Additionally, recent studies have explored bioleaching for switchgrass, corn stover, sorghum, and wheat straw, with *Aspergillus niger* proving to be most efficient at removing most relevant elements by 80% in 48 hours (Zhang et al., 2019). Therefore, it would be beneficial for the high ash content fractions (mass discarded portion) separated in air classification to undergo bioleaching before continuing to thermochemical conversion processes.

2.6 Moisture Content and Drying

Preprocessing within the scope of this project includes air classification, drying, and size reduction steps. Preprocessing far outweighs the costs of other steps in a woody feedstock supply chain system. Conventional preprocessing of logging residues includes rotary drying and size reduction using a hammer mill and is estimated to produce ~180 kg CO_2 eq/dry ton and cost ~$39/dry ton (Hartley et al., 2021). For reference, the next highest emitter in the supply chain is field-side preprocessing to field dry and chip the feedstock at just ~18 kg CO_2 eq/dry ton and ~$12/dry ton (Hartley et al., 2021). Drying is often the most expensive and GHG-intensive step of preprocessing.

Drying is critical for the efficient gasification of biomass. The goal of drying before gasification is to dry biomass to at least 10% moisture content wet basis. Higher moisture content could result in low gas heating values due to reduced thermal efficiency from the heat being used to drive off water instead of for conversion reactions (FAO). The higher the moisture content, the more energy will be expended during drying. Additionally, size reduction steps are sensitive to biomass moisture content, with energy consumption increasing dramatically with increasing biomass moisture content (DOE, 2014).

Direct-heating rotary dryers are the most commonly used in woody feedstock biorefineries due to superior heat and mass transfer, high processing capacity, and low electrical power (Yi et al., 2020). Biomass is fed into an inclined rotating shell where the heating medium, either flue gas/hot air or steam, flows in the concurrent or countercurrent direction to dry the biomass (Yi et al., 2020).

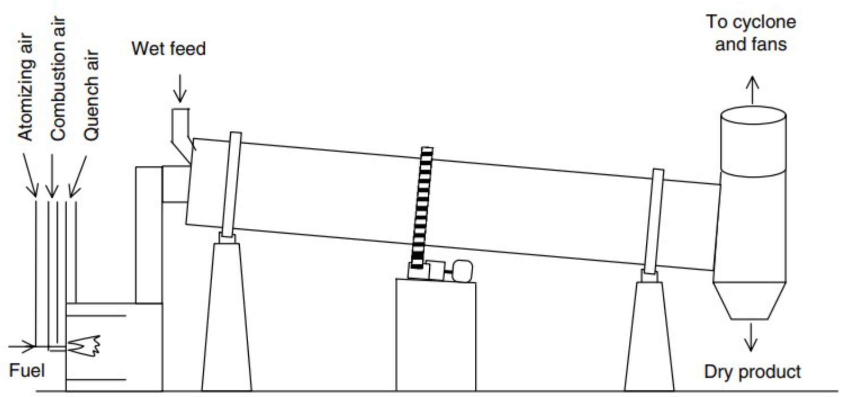


Figure 8. Simplified diagram of direct-heat rotary dryer (Mujumdar, 2006).

Drying is often the most challenging step in the pretreatment of biomass due to considerations regarding energy efficiency, emissions, heat integration, and dryer performance (Fagernäs et al., 2010). However, it can be beneficial to integrate the drying process with the energy infrastructure of the main process (Fagernäs et al., 2010). For example, after gasification, leftover biochar can be separated using a cyclone and unconverted syngas can be fed to a boiler to generate steam for rotary drying and/or bioelectricity generation using a steam turbine. The LCA considers both options in a best-case scenario explored in Chapter 4.

2.7 Size Reduction

Biomass moisture content, incoming size of particles, degree of size reduction, type of grinding, and biomass type all affect energy consumption when size reducing biomass (Naimi et al., 2016). There are also specifications for particle size based on the type of conversion process. For example, fluidized bed and downdraft gasification require 10-mm particles, while entrained flow gasification is more stringent and requires a 1-mm grind. There is a balance that must be established between these parameters.

Also called comminution, milling theory is based primarily on equations originally intended for the ore industry proposed by Rittinger, Kick, and Bond (Temmerman et al., 2013). These equations have since been applied to biomass. Rittinger's theory asserts the energy consumed by grinding is proportional to the surface area created and is considered the most accurate for predicting the energy uptake of grinding woody biomass (Naimi et al., 2016). The Rittinger equation is expressed below where E is the energy demand (kWh/tonne), C_{VR} is a constant characteristic of the material, L_p is the mean product particle size (mm), and L_f is the mean feed particle size (mm).

$$E = C_{VR}\left(\frac{1}{L_p} - \frac{1}{L_f}\right)$$

Size reduction typically occurs in two steps when preparing woody biomass for energy production using gasification (Naimi et al., 2016). In this LCA, the pine residues are course ground to two-inch (50.8-mm) chips at the harvest site and directly fed to a truck for transportation to the biorefinery (Hartley et al., 2021). The chips are further refined to one inch or smaller during a fine grinding step. Forest residues are contaminated with dirt and stones, therefore hammer mills should be used over knife mills to avoid dulling the knives and lowering efficiency (Naimi et al., 2006). This process is outlined in Figure 9.

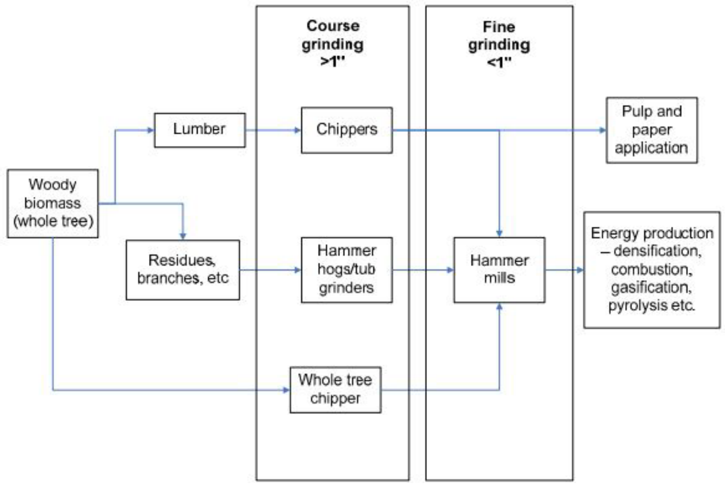


Figure 9. Two stage size reduction process of woody biomass (Naimi et al., 2006).

Not much literature data have been produced regarding biomass moisture content's effect on comminution energy consumption, however, it is correct to assume higher moisture content means more energy consumption due to increased shear resistance of the material (Temmerman et al., 2013). Assumptions for the energy demand of size reduction steps in this LCA model will be based on an iteration of the Rittinger equation developed by Temmerman that also accounts for the moisture content of feedstocks (Temmerman et al., 2013). Temmerman's equation is expressed below where E is the energy demand (kWh/tonne), H is the moisture content (%), M is a constant characteristic of the material (9.65 for pine), L_p is the mean product particle size (mm), and L_f is the mean feed particle size (mm).

$$E = HM\left(\frac{1}{L_p} - \frac{1}{L_f}\right)$$

This study used a hammermill equipped with six T-shaped swinging hammers at 2800 rpm. Using five different moisture content scenarios ($0<H_1<4.99\%$, $5<H_2<9.99\%$, $10<H_3<14.99\%$, $15<H_4<19.99\%$, and $20<H_5<24.99\%$), Temmerman correlated grinding power consumption with particle size distribution medians at moisture contents H_1 to H_5 (Temmerman et al., 2013). The correlation is shown in Figure 10 accompanied by each scenario's coefficient of determination (R^2) value.

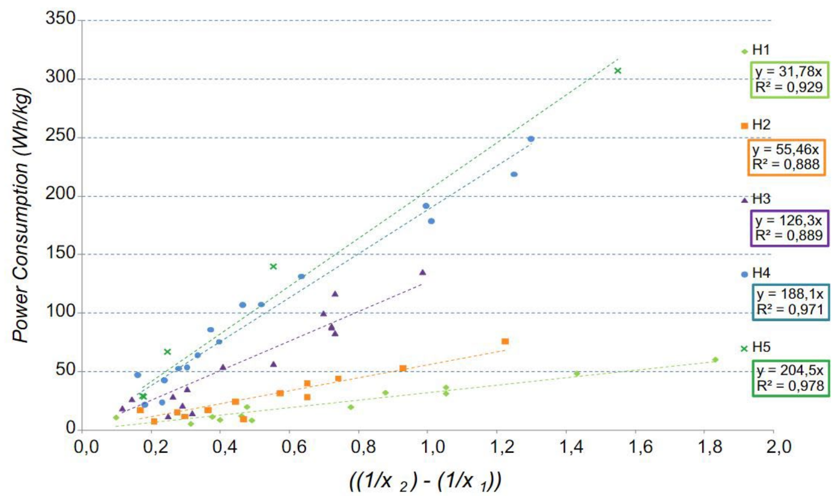


Figure 10. Pine grinding energy consumption for five moisture content scenarios (Temmerman et al., 2013).

An important consideration is Temmerman's equation does not account for other factors such as feed rate or hammer speed. However, no fully comprehensive equation exists, and Temmerman's equation has been used in other recent biorefinery LCA studies (Ou & Cai, 2020a).

2.8 LCA Standards

2.8.1 ISO

The LCA was conducted according to the ISO series 14040:2006 and 14044:2006 standards (ISO, 2006). These standards describe the principles and framework for a successful LCA. The standards include information on the limitations of the LCA, reporting and critical review of the LCA, and relationships between the LCA phases. The four steps to the LCA are 1) Goal and Scope Definition, 2) Life Cycle Inventory (LCI), 3) Life Cycle Impact Assessment (LCIA), and 4) Interpretation.

Defining the goals of the LCA includes identifying the audience, application, objectives of the study, and how the results might be interpreted. Defining the scope identifies the function and functional unit, system boundaries, and any data requirements or assumptions. Goal and scope definitions are outlined in Chapter 1. The LCI quantifies relevant inputs and outputs for the chosen system throughout its life cycle. LCIA focuses on classification and characterization. Classification sorts the inputs/outputs from the LCI into classes based on how they impact the environment such as global warming potential (GWP), acidification, ozone depletion, etc. Next, characterization models the inventory results for each category in terms of a category indicator. For example, substances contributing to acidification will be measured according to their kg SO_2 equivalent (eq) per kg of substance. Last, an interpretation of the LCI and LCIA can be made based on the defined goals and scope accompanied by uncertainty and sensitivity analyses. While the steps to an LCA appear to occur linearly, they often do not. It is important to incorporate flexibility while performing an LCA and adjust parameters as needed. Phases of the LCA along with direct applications are shown in Figure 11.

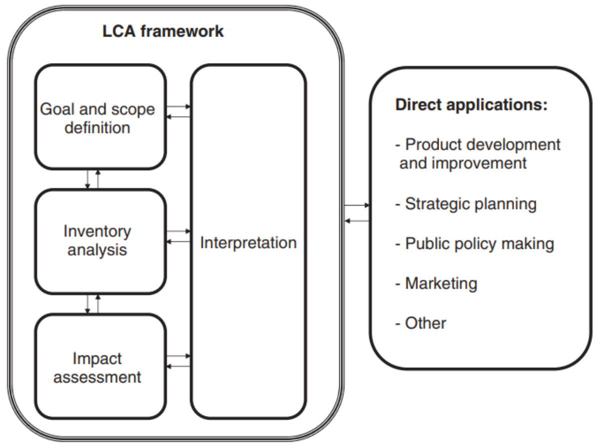


Figure 11. Phases of the LCA according to ISO 14040 (Klöpffer & Grahl, 2014).

2.8.2 EPA

The U.S. EPA protects land, air, and water resources while striving to implement a harmonious balance between human activities and natural systems (NRMRL, 2006). The National Risk Management Research Laboratory (NRMRL) is an agency under the EPA that investigates preventing and reducing risks associated with pollution. In accordance with the goals of the NRMRL, the agency produced the document "Life Cycle Assessment: Principles and Practice" as an educational tool for conducting LCAs. It includes the four main stages of LCA along with examples. This document was referenced in conjunction with the ISO standards for LCA.

The EPA also developed the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) for LCIA (Bare, 2011). TRACI uses characterization factors to quantify impacts that inventory items have on TRACI impact categories in common equivalence units. The ten impact categories for TRACI with associated units are listed in Table 2.

Table 2. TRACI impact categories and units.

Impact Category	Unit
Ozone depletion	kg CFC-11 eq
Global warming	kg CO_2 eq
Smog	kg NO_x eq
Acidification	kg SO_2 eq
Eutrophication	kg N eq
Carcinogens	CTUh
Non-carcinogens	CTUh
Ecotoxicity	kg $PM_{2.5}$ eq
Respiratory effects	CTUe
Fossil fuel depletion	MJ surplus

2.9 LCA Databases and Software

2.9.1 SimaPro

Developed by PRé Sustainability, SimaPro has been a leading LCA software for over 30 years. SimaPro is a powerful LCA tool that combines inventory analysis and impact assessment to output comprehensive environmental impact data. SimaPro incorporates various inventory databases such as U.S. Life Cycle Inventory (USLCI), Ecoinvent, and Agri-footprint for a comprehensive selection of life cycle inventory data. Then, through the user's selected impact assessment method, inventory results are translated to impacts. This LCA used TRACI as the impact assessment method because data is U.S.-based. SimaPro was used extensively to build this model.

2.9.2 GREET

The Greenhouse Gases, Regulated Emissions, and Energy use in Technologies (GREET) model was developed by the Argonne National Laboratory for the performance of LCAs regarding transportation fuels, feedstocks, and vehicles. GREET translates inputs to three traditional GHGs: CO_2, methane (CH_4), and nitrous oxide (N_2O). The GHGs are aggregated to calculate the GWP equivalent of a process, expressed as the CO_2 eq. GREET was referenced primarily to obtain impacts associated with steam production from natural gas and production of bioelectricity. Figure 12 shows the groupings used in GREET for fuel pathways.

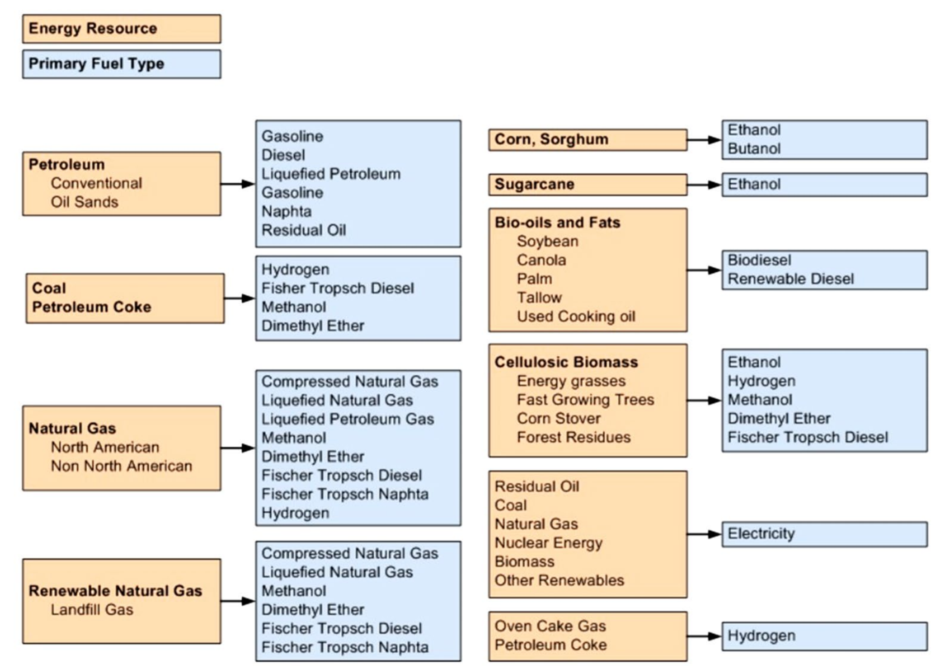


Figure 12. GREET grouping by feedstock used for pathways in the model (*GREET Model*).

2.10 Previous LCA Studies

It is difficult to directly compare previous LCA studies due to differences in assumptions, scope, time-horizons, and data sources. This section will explore previous LCA studies related to this work, but the studies will not be directly comparable to the results of this LCA due to the reasons listed above.

The Idaho National Laboratory (INL) releases an annual Woody Feedstocks State of Technology Report that uses data and experimental results to update the status of feedstock supply system technology development for biomass to biofuels (Hartley et al., 2021). In 2020, INL reported on three distinct woody feedstock conversion pathways: indirect liquefaction (IDL), catalytic fast pyrolysis (CFP), and algal-blend hydrothermal liquefaction (AHTL). The AHTL assumes a conventional feedstock supply system and is most similar to the pathways used in this LCA. Therefore, the AHTL will be explored in more detail. The AHTL pathway is outlined in Figure 13.

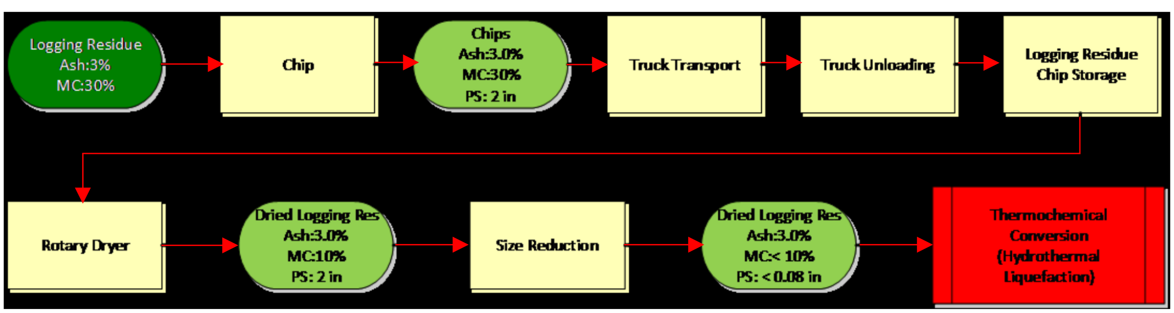


Figure 13. INL 2020 Woody State of Technology feedstock supply system design supporting AHTL (Hartley et al., 2021).

The AHTL pathway assumes a 90% algae-10% woody feedstock blend with ≤10% moisture content (wet basis) and a particle size requirement of ≤¼ inch (Hartley et al., 2021). The forest residues have been chipped to 2 inches upon arrival to the biorefinery where they are stored for preprocessing. Preprocessing includes drying in a rotary dryer to 10% moisture content (wet basis) and grinding to ¼ inch particles. Preprocessing GHG emissions reported for this scenario are 180.03 kg CO_2e/dry ton (Hartley et al., 2021).

Another recent study assessed life cycle GHG emissions from drop-in fuel production via fast pyrolysis of pine residues followed by hydroprocessing (Ou & Cai, 2020a). This study was completed as a dynamic life cycle analysis and calculated GHG emissions from over 4600 simulated runs varying the moisture content of incoming feedstock from 25 to 35% and product particle sizes from 0.5 to 5 mm. Case A in this study is most similar to this LCA and will be explored in more depth. Case A assumes drying the feedstock from 30 to 10% moisture content (wet basis) and rotary shearing to 2 mm particle size. Preprocessing accounts for about 18 g CO_2e/MJ of fuel (Ou & Cai, 2020a). A key finding of the study is that the energy penalty associated with a small particle size requirement outweighs the benefit of increased fuel yields (Ou & Cai, 2020a). Additionally, the study found that increased field drying saves energy consumption during feedstock transportation and preprocessing (Ou & Cai, 2020a).

There are many other LCA studies on conversion of woody feedstocks to biofuels, however the studies above were referenced the most. There is a gap in the literature on large-scale implementation of air classification assuming a conventional feedstock supply system. This study aims to complete an LCA on pine residue preprocessing that incorporates air classification as a sulfur mitigation technology.

CHAPTER 3. LIFE CYCLE INVENTORY

A life cycle inventory (LCI) is the quantification of relevant energy and material flows and the associated emissions for a chosen life cycle (NRMRL, 2006). The key steps to complete an LCI include the development of detailed process flow diagrams, data collection, and consolidation of results. The LCI feeds directly into the results outlined in the LCIA in Chapter 4, so it is critical to ensure accurate and well-assumed data for the LCI. First, the process overview will be described. Then, detailed information regarding each of the LCI steps for preprocessing will be outlined.

3.1 Process Overview

The process of making biofuels from harvested pine residues is complex. Chapter 1 outlined the chosen scope and scope justification for this LCA. For the sake of full process comprehension, a flow diagram overview will be presented along with the basis of calculations, then more detailed flow diagrams for each subsystem within the scope of this LCA will be presented.

3.1.1 Process Overview Flow Diagram

Process flow diagrams should model the inputs and outputs of a system which includes materials and energy flowing in (electricity, water, gas, etc.) and out (finished parts/components, waste, etc.) of the system or subsystem. A generic unit process flow diagram is shown in Figure 14.

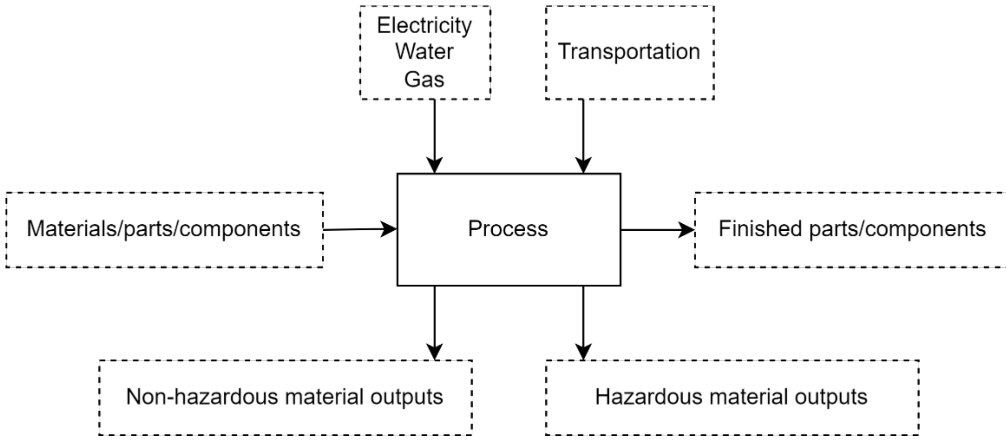


Figure 14. Generic unit process diagram (NRMRL, 2006).

The primary steps in converting pine residue feedstocks to biofuels are preprocessing (including air classification, drying, and size reduction), gasification, syngas cleaning, F-T catalysis, and upgrading to obtain the final products of fuel gas and jet fuel. A byproduct of the F-T process is flue gas which is processed for power. An overview of the process is shown in Figure 15.

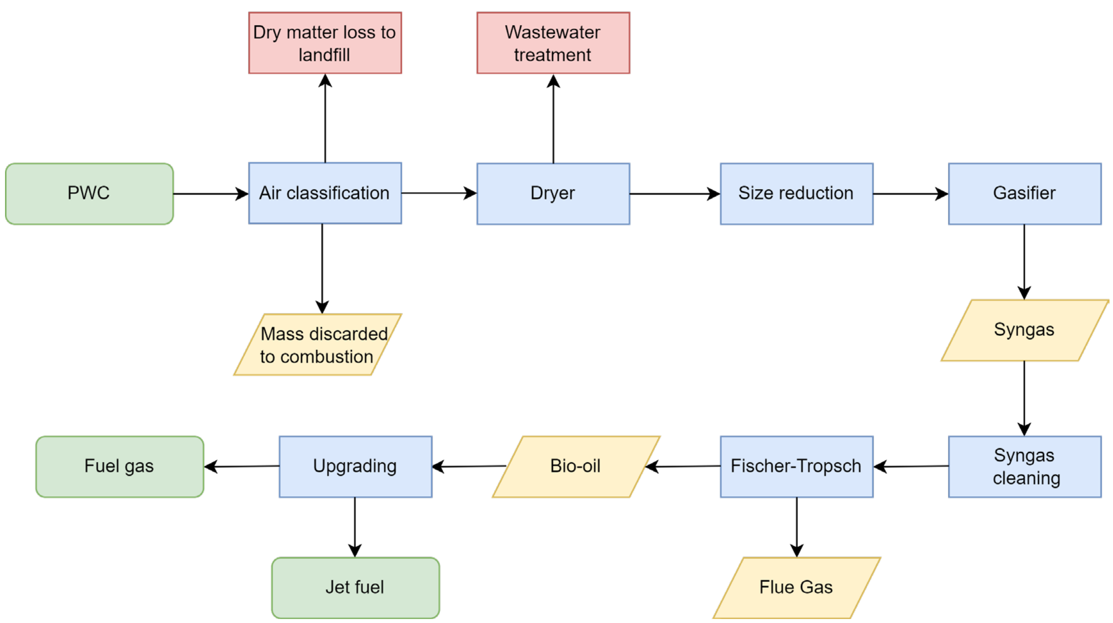


Figure 15. PWC conversion process flow diagram.

3.1.2 Basis of Calculations

FTX, North Carolina State University, Auburn University, and Red Rock Biofuels provided 18 pine residue samples. The samples were sourced from Georgia, South Carolina, North Carolina, Alabama, and Oregon and varied according to species/genetics, age, growth location (soil type), harvesting practices, and anatomical fractions. Refer to Appendix 1 for a link to an ArcGIS story map sharing all feedstock sample information.

As described in Chapter 1, a milestone of this project is to quantify baseline sulfur content in pine residue samples and verify a 30% reduction in sulfur using air classification. Three samples from FTX were chosen for air classification experiments – Samples 1, 2, and 8 shown on the story map. These samples were chosen as they share a similar makeup of anatomical fractions, but vary in age, location, and harvesting practice. Each sample was run according to the air classification process flow diagram shown in Figure 17. A 30% sulfur reduction occurred in Samples 1 and 2. Based on these experiments, Sample 1 will serve as the representative sample in this LCA. See section 3.2.1 on Air Classification to read more about this study. It is listed in the assumptions when data from these experiments are used.

The basis of calculations are data that process inputs and outputs are based upon. Outlined below are the basis of calculations for plant operations, incoming feedstock, and outgoing feedstock.

The plant availability is 310 days per year (85%) with a plant capacity of 2000 dry metric tonnes/day (Swanson et al., 2010). For simplicity's sake, "dry metric tonnes" will simply be referred to as "tonnes."

Table 3. Basis of calculations for plant operations.

Plant Operation	Average	Unit	Reference
Operating hours	7440	hours/year	(Swanson et al., 2010)
Tonnage processed	2000	tonnes/day	(Swanson et al., 2010)
Mass flow rate	83.33	tonnes/hour	Calculated

The incoming feedstock has a moisture content of 30% wet basis (Hartley et al., 2021). The forest residues are size reduced at the harvesting site with a mobile chipper to two-inch (50.8-mm) PWC and fed directly to a truck for transport to the biorefinery (Hartley et al., 2021).

Table 4. Basis of calculations for incoming feedstock.

Incoming Feedstock	Average	Unit	Reference
Moisture content	30	percent	(Hartley et al., 2021)
PWC	50.8	mm	(Hartley et al., 2021)

The outgoing feedstock (feedstock that has been preprocessed for conversion) has been dried to a moisture content of 10% wet basis (Hartley et al., 2021). This is the required moisture content for gasification. It is assumed the feedstock is being prepared for entrained flow gasification which requires size reduction to 1-mm particles (Swanson et al., 2010).

Table 5. Basis of calculations for outgoing feedstock.

Outgoing Feedstock	Average	Unit	Reference
Moisture content	10	percent	(Hartley et al., 2021)
Particle size requirement	1	mm	(Swanson et al., 2010)

3.2 Preprocessing LCI

The scope of the LCA is outlined below. Seeing that the goals of this study pertain to gleaning information regarding the environmental effects of air classification and preprocessing, raw material acquisition and transportation of PWC to the biorefinery were not considered. The LCI will inventory energy demand for operating equipment, wastewater treatment, steam generation, end-of-life of DML from air classification to a landfill, and, in the bioelectricity scenario, transportation associated with feedstock delivered. Transportation associated with feedstock delivered is considered for the bioelectricity scenario because burning the biomass is biogenic except for the emissions released during transport of the pine residue to the biorefinery. The scope of the LCA focuses on end-of-life of matter leaving the biorefinery, therefore, the mass discarded to combustion is not in the system boundary because it is assumed to be combusted to power other parts of the process. Process flow diagrams along with data collection for each step will be presented.

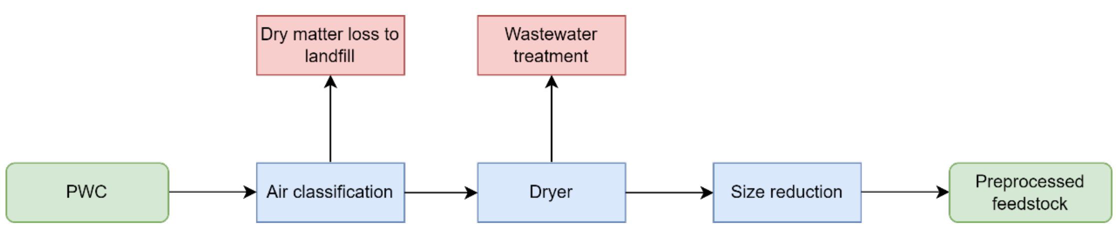


Figure 16. Scope of LCA.

This model collects LCI data on air classification, drying, and size reduction. The grinder and dryer steps (highlighted in Table 6) conventionally use electricity and natural gas, respectively. Air classification is a novel technology in LCA feedstock preprocessing, but it is assumed to be powered by electricity.

Table 6. Fuel type for steps in preprocessing (Meyer et al., 2016).

Machine	Fuel Type
Air Classifier	Electricity
Dryer	Natural gas
Grinder	Electricity

3.2.1 Air Classification

3.2.1.1 Process Flow Diagram

Air classification experiments were carried out to separate fractions with higher sulfur contents. Pine residue samples were fed through the air classifier four times, each time labeled as heavy, light, or below screen. This process recovered four distinct fractions: white wood rich, bark rich, needle rich, and fines/dirt rich. Runs 1 and 2 separated most of the heavy and large biomass, while Runs 3 and 4 sorted the remaining lighter and dirt-heavy fractions. Figures 17 and 18 depict flow diagrams of the materials being air classified along with visual examples of the air classified fractions.

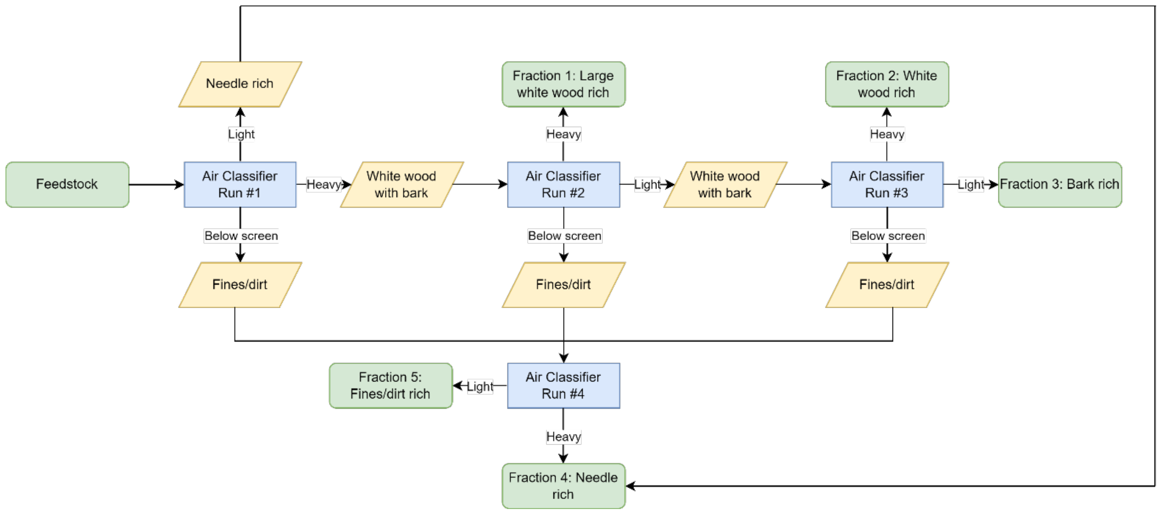


Figure 17. Air classification experiments to separate large white wood rich, white wood rich, bark rich, needle rich, and fines/dirt rich fractions.

Figure 18. Air classified fractions including a) fines/dirt rich, b) needle rich, c) white wood rich, and d) bark rich.

There was also dry matter loss (DML) and mass discarded fractions from air classification. DML represents biomass lost due to clogging in the equipment, falling on the ground, etc. The mass discarded portion represents biomass that is considered too "dirty" from high ash/sulfur content and sent to other value-added processes. This is shown in Figure 19.

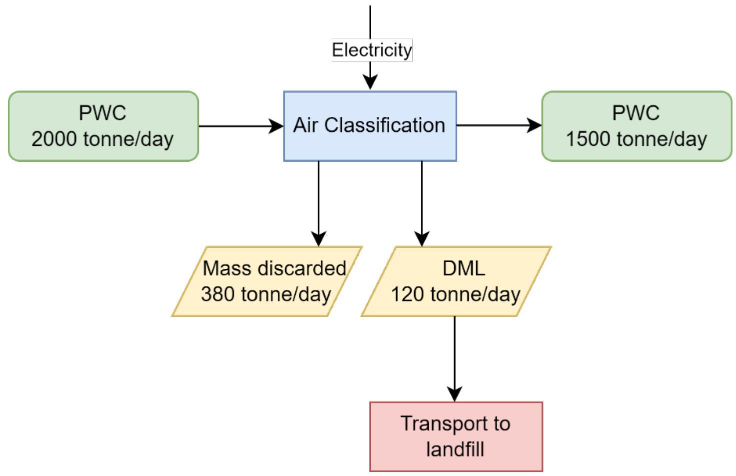


Figure 19. Air classification process flow diagram.

3.2.1.2 Data Collection

An overarching goal of the project is for air classification to facilitate at least a 30% reduction in the sulfur content of the biomass. From experimental data based on the representative Sample 1, it was determined 4% of Fraction 3 (bark rich fraction), 100% of Fraction 4 (needle rich fraction), and 100% of Fraction 5 (fines/dirt rich fraction) must be "discarded" to achieve the 30% sulfur reduction goal. The mass discarded fraction represents 19% of the total feedstock sample mass and is the percentage assumed discarded in this model (380 tonne/day). When normalized to the functional unit of usable tonnes per day, this becomes 25%. The mass discarded fraction is not included in the scope as it is assumed to be combusted to power other parts of the process while this LCA focuses on the end-of-life of materials. See Chapter 5 for future work incorporating the mass discarded portion into the model.

DML, on the other hand, is assumed to be landfilled after air classification. Experimental data determined about 6% of biomass was lost during air classification, so that is the amount assumed for DML in this model (120 tonne/day). However, when scaled to industrial size, it is likely the fraction will be even higher than 6% (Lin et al., 2021). This uncertainty is explored further in Chapter 4. When normalized to the functional unit of usable tonnes per day, this fraction becomes 8%. It is assumed that end-of-life landfill emissions are biogenic and, therefore, carbon-neutral. However, transportation of the DML to a landfill is accounted for. Based on recommendations from the National Renewable Energy Laboratory (NREL), for distances less than 15 miles (24.14 km), trucks can transport either wet or dry material without disrupting traffic (Atchison & Hettenhaus, 2003). Therefore, it is assumed the DML is transported 24.14 km to a landfill using USLCI's transport process for a short-haul, diesel-powered combination truck for the Southeast region.

The energy demand for the air classifier was assumed as "Air Classifier – Large" from the INL Woody Feedstocks 2021 State of Technology Report (P. H. Burli et al., 2022). Material and energy inputs and outputs per usable tonne of feedstock are listed in Table 7.

Table 7. Process inputs and outputs for air classifying feedstock.

Process Inputs/Parameters	**Average**	**Unit (per usable tonne of feedstock)**	**Reference**
Energy	0.923	kWh	(P. H. Burli et al., 2022)
Process Outputs/Parameters	**Average**	**Unit**	**Reference**
DML	8	percent	Experimental
Mass discarded	25	percent	Experimental
Transport of DML to landfill	0.016	tonne-km	(Atchison & Hettenhaus, 2003)

3.2.2 Dryer

3.2.2.1 Process Flow Diagram

The dryer used in the process is a direct-contact steam rotary dryer that dries the biomass to 10% moisture content using steam generated in a boiler. Electricity is needed to power the dryer and a heating source is needed to generate steam. Steam is constantly evaporating and recirculating between the dryer and boiler for reheating. Excess water is sent to wastewater treatment. This process is shown in Figure 20.

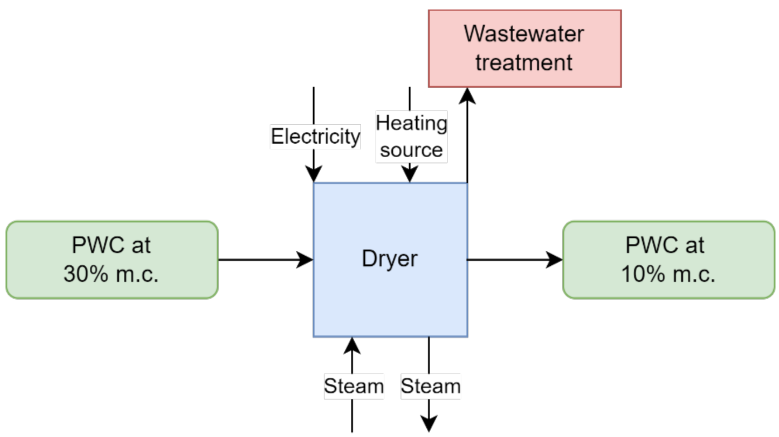


Figure 20. Dryer process flow diagram.

3.2.2.2 Data Collection

This model assumes moisture content is measured on wet basis. Wet basis is assumed as this follows most assumptions made in related literature and for the sake of simplicity, as wet basis moisture content is always between 0% and 100%. The formula for calculating the wet basis of biomass is as follows:

$$mc_{wb} = \frac{mass\ of\ water}{mass\ of\ wet\ sample} * 100\%$$

Pine feedstocks typically arrive at biorefineries with a moisture content ranging from 30-60% based on location, time of harvest, and storage time after harvest (Fagernäs et al., 2010). This model assumes biomass is entering the system boundary at 30% moisture content. This is an estimate that is in line with related studies conducted by the DOE (Hartley et al., 2021). However, this uncertainty is explored further in Chapter 4.

The dryer used in the process is based on a direct-contact rotary steam dryer that uses a 9:1 steam to evaporated moisture ratio resulting in a 4000-tonne per day steam loop for a 2000-tonne per day biomass input drying from 25% to 10% moisture content from recommendations provided by NREL (Amos, 1999). This means that 90% of steam leaving the dryer is reheated and recirculated while the remaining 10%, representing moisture evaporated from the biomass, is removed to be condensed or used in other parts of the plant (Amos, 1999). See Appendix 2 for calculations scaling the steam requirements to this model.

Two scenarios are considered in this LCA. The first scenario assumes a natural gas/grid electricity mix to dry the feedstock. Natural gas is used to generate steam while grid electricity powers the rotary dryer. The second scenario assumes a combusted biomass/bioelectricity mix to dry the feedstock. In this case, steam is heated in a boiler from the combustion of biochar and unconverted syngas after the gasification process. The techno-economic analysis (TEA) team confirmed there is enough excess unconverted syngas to meet the steam requirements for drying based on Swanson's "Techno-Economic Analysis of Biofuels Production Based on Gasification" (Swanson et al., 2010). In both cases, steam enters the dryer at 200°C, drops to 120°C during drying, and is fed to the boiler for reheating. The dryer efficiency was used to estimate the energy needed to dry the feedstock based on the above parameters. The dryer efficiency is 3838 kJ/kg of evaporated water. When normalized to the functional unit, the efficiency is 1,220,484 kJ/tonne of usable feedstock. This calculation is found in Appendix 2.

Steam dryers produce organic compound emissions as inert gases dissolved in the condensed wastewater stream or floating on the condensed water as tar; therefore, the majority of emissions will appear in the steam condensate (Fagernäs et al., 2010). It is recommended the condensed evaporated moisture undergo biological filtration (Fagernäs et al., 2010; Vidlund, 2004). It is assumed that the 10% fraction representing moisture evaporated is sent to biological filtration water treatment. The biological filtration water treatment process was found in Ecoinvent. Material and energy inputs and outputs per usable tonne of feedstock are listed in Table 8.

Table 8. Process inputs and outputs for drying feedstock.

Process Inputs/Parameters	**Average**	**Unit (per usable tonne of feedstock)**	**Reference**
Dryer efficiency	1,220,484	kJ	(Worley, 2011); (Ou & Cai, 2020a); Calculated, see Appendix 2
Energy	339	kWh	Calculated, see Appendix 2
Steam (recirculating)	2.86	tonnes H_2O	(Amos, 1999); Calculated, see Appendix 2
Process Outputs/Parameters	**Average**	**Unit**	**Reference**
Evaporated moisture to wastewater treatment	0.32	tonnes H_2O	(Amos, 1999); Calculated, see Appendix 2

3.2.3 Size Reduction

3.2.3.1 Process Flow Diagram

This model assumes size reduction to 1-mm particles. The incoming feedstock is composed of 50.8-mm PWCs at 10% moisture content. This process assumes one size reduction step using a hammer mill based on recommendations from INL's Woody Feedstocks State of Technology Report (Hartley et al., 2021).

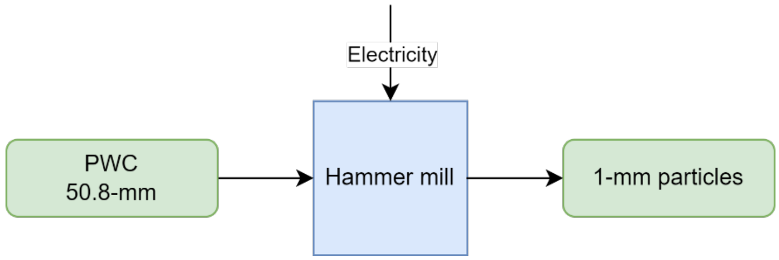


Figure 21. Size reduction process flow diagram.

3.2.3.2 Data Collection

Size reduction energy assumptions are based on the article "Von Rittinger theory adapted to wood chip and pellet milling, in a laboratory scale hammermill" (Temmerman et al., 2013). Refer to Chapter 2 to read about this study. The energy demand for grinding is based on the following equation where E is the specific grinding energy (kWh/tonne), H is moisture content (%), M is a constant for pine feedstocks (9.65), L_p is the mean product particle size (mm), and L_f is the mean feed particle size (mm).

$$E = HM\left(\frac{1}{L_p} - \frac{1}{L_f}\right)$$

A summary of energy usage for size reduction for entrained flow gasification is shown in Table 9.

Table 9. Size reduction power requirement equation parameters.

Equation Parameter	Average
Moisture content (%)	10
Pine feedstock constant	9.65
Mean product particle size (mm)	1
Mean feed particle size (mm)	50.8
Specific grinding energy (kWh/tonne)	**94.6**

It is assumed no DML occurs during size reduction. It is also assumed moisture content stays the same, although there is some evidence that size reduction steps can facilitate further drying (Esteban & Carrasco, 2006), therefore energy estimates are assumed to be conservative. Material and energy inputs and outputs per usable tonne of feedstock are listed in Table 10.

Table 10. Process inputs and outputs for size reduction of feedstock.

Process Inputs/Parameters	Average	Unit (per usable tonne of feedstock)	Reference
Energy	126	kWh	(Temmerman et al., 2013); Calculated, see Appendix 2

CHAPTER 4. LIFE CYCLE IMPACT ASSESSMENT

Most of the LCIA was performed using TRACI embedded in SimaPro (Bare, 2011). SimaPro sets up calculations to output each of the TRACI impact categories, however only GWP impact will be compared across scenarios in this analysis because it is the most used in related studies. Additionally, the International Life Cycle Data Handbook classifies GWP as Level I for recommended and satisfactory in terms of best available characterization models to midpoint. GREET software, literature values, and experimental data were used when inventory data from Ecoinvent or USLCI were unavailable.

Two scenarios were considered for evaluation. The first scenario is considered more traditional and is based on natural gas and grid electricity. The second scenario is a best-case scenario based on the combustion of biochar and bioelectricity.

4.1 Electrical Grid Scenario

It is assumed the biorefinery is in the state of South Carolina in the United States. The energy portfolio of South Carolina for the year 2021 was obtained from the Energy Information Administration (EIA). The total electric power industry percentages are shown below. This is the makeup that will be assumed when calculations are made with grid electricity. It is unclear what the “other” and “other biomass” categories encompass, so they are excluded from the analysis. Therefore, 99.85% of the grid makeup is accounted for. Refer to Appendix 3 for complete energy source data from the EIA.

Table 11. South Carolina energy portfolio for 2021.

Electric Power Industry	Contribution (%)
Nuclear	55
Natural gas	24
Coal	15
Hydroelectric conventional	3
Solar thermal and photovoltaic	2
Wood and wood derived fuels	2
Other biomass	0.1
Petroleum	0.1
Other	0.04
Pumped storage	-1

The GWP values associated with each electric industry per kWh of energy were found in either Ecoinvent or USLCI. See Appendix 3 for specific product assumptions. Respective GWP values were multiplied by the contribution percentage in the grid makeup to obtain the GWP of the South Carolina electrical grid makeup per kWh of energy. The final GWP value for the South Carolina grid per kWh of energy was multiplied by the respective energy demand for each process.

4.1.1 Impact Assessment

The air classification impact represents equipment electricity usage and transport of DML to a landfill based on assumptions listed in Chapter 3. The electricity usage and transportation of DML were normalized to the functional unit. These calculations can be found in Appendix 3.

The dryer impact represents wastewater treatment and natural gas/grid electricity energy demand to heat steam and power the rotary dryer. GWP values were calculated through TRACI for the Ecoinvent wastewater pathway conventional tap water production with biological treatment for one tonne of water. The output values were then multiplied by a ratio to normalize to the functional unit. The process assumptions and calculations can be found in Appendix 3. The ratio of natural gas to electricity to produce steam and power the dryer, 87.4% and 12.6%, respectively, was determined from INL's Woody Feedstocks State of Technology Report (Hartley et al., 2021). GWP values for natural gas to generate steam are from the "Production of Displaced Steam from NG at DME/FTD plant" process in GREET.

The size reduction impact represents the electricity required to power the equipment and mill the fractions to the required particle size of 1 mm for entrained flow gasification. The grinding energy values were normalized to the functional unit.

The GWP of each process is listed in Table 12 as kg CO_2 eq per tonne of usable feedstock. A visual of the relative GWP for the grid electricity scenario is shown in Figure 22.

Table 12. GWP of preprocessed feedstock assuming grid electricity.

Process	**GWP (kg CO_2 eq per tonne of usable feedstock)**
Air Classification Total	**0.53**
Grid electricity	0.31
Transport DML to landfill	0.22
Dryer Total	**92.46**
Natural gas	77.83
Grid electricity	14.45
Wastewater treatment	0.19
Size Reduction Total	**42.67**
Grid electricity	42.67
Total	**135.66**

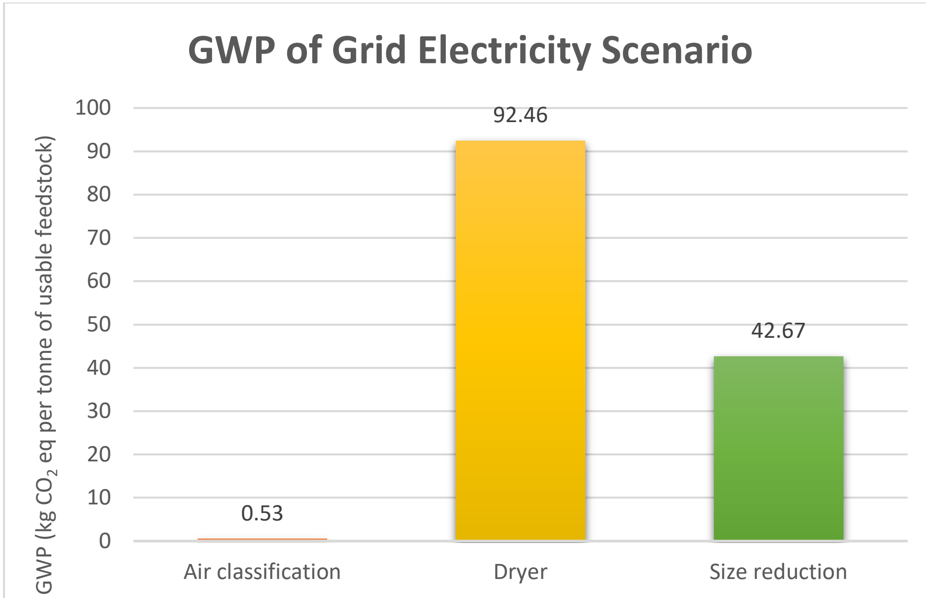


Figure 22. GWP of preprocessed feedstock for the grid electricity scenario.

A sensitivity analysis was completed with key decision parameters grouped based on feedstock/product parameters and energy demand parameters. The feedstock/product parameters include particle size requirement (mm), moisture content requirement (%), DML (%), and feedstock particle size (mm). The energy demand parameters include dryer efficiency (kJ) and energy demand (kWh) for drying, size reduction, and air classification. A one-at-a-time sensitivity analysis changed the decision parameters by ±20% from the respective baseline values to understand the impact of each parameter on the overall GWP. The sensitivity analysis results for the grid electricity scenario are shown in Figure 23.

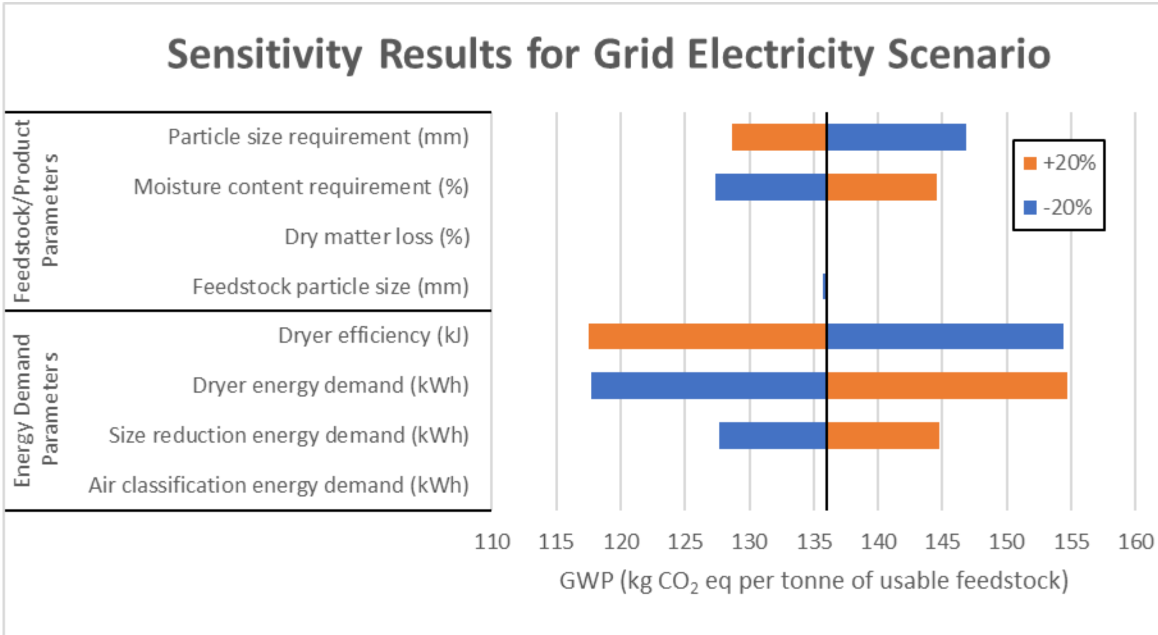


Figure 23. Sensitivity analysis results for the grid electricity scenario where the centerline represents the baseline preprocessing GWP value.

The Monte Carlo method for repeated random sampling predicts outcomes based on an estimated range of probability distributions for variables with inherent uncertainty. Monte Carlo simulations were implemented to obtain uncertainty associated with the GWP results. GWP values were calculated 5000 times using a range of values assuming uniform distributions for the following parameters: feedstock moisture content (30 to 60% wet basis), moisture content requirement (5 to 15% wet basis), and DML (5 to 15%). The range for feedstock moisture content was chosen based on variation explored in “Drying of biomass for second generation synfuel production” and INL’s Woody Feedstocks State of Technology Report (Fagernäs et al., 2010; Hartley et al., 2021). Moisture content requirement was varied by ±5% from the baseline value. It is likely that the DML will be higher than the experimental results of 6% found in this study considering INL recently reported a 12% DML value (P. Burli et al., 2022). Therefore, the values for DML considered up to 15% loss. Uniform distributions were assumed for each parameter as a conservative estimate. For future iterations of this model, it may be beneficial to obtain normal distributions for the parameter values.

The Monte Carlo simulation results were ranked by relative size of the numbers, and each of the parameter's ranks were correlated to the GWP ranks to obtain Spearman's rank correlation coefficients (SCC). SCC measures the strength and direction of monotonic association between two ranked variables for a range between -1 and +1. The closer the SCC is to ±1, the stronger the relationship is between the variables based on an increase in the associated parameter. Multiple 5000-time simulations were run to ensure similar correlation results. Figure 24 shows the SCC for the uncertainty parameters with red representing increased impact.

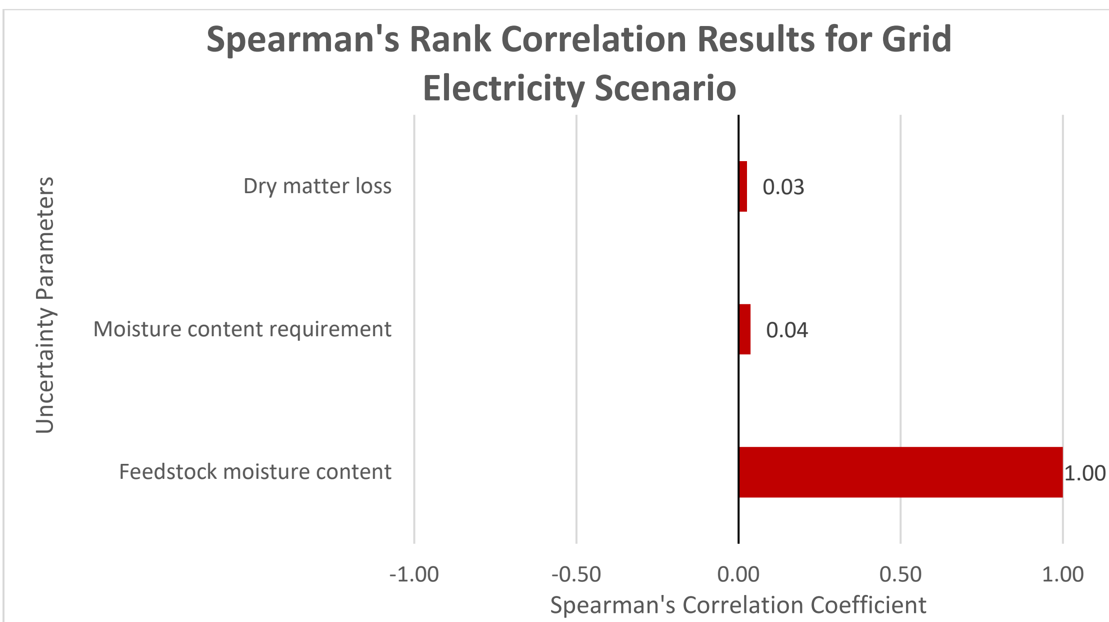


Figure 24. Spearman's rank correlation coefficient results for dry matter loss, moisture content requirement, and feedstock moisture content in the grid electricity scenario.

4.1.2 Analysis

Drying by far has the highest GWP in this scenario due to the use of natural gas for steam generation. As a result, the model is most sensitive to the dryer efficiency and dryer energy demand. Size reduction has a GWP almost half of drying, but it is still a high-impact process because it requires high energy demand to power the hammer mill. Relatively, air classification has a trivial GWP. Air classification represents just 0.4% of preprocessing GWP, therefore, the model is least sensitive to changes in air classification energy demand. Furthermore, the SCC supports the finding that the grid electricity scenario is sensitive to changes in parameters surrounding drying. The sensitivity analyses showed that GWP is highly sensitive to uncertainty in feedstock moisture content (SCC=1.00). However, it is interesting that the impact of feedstock moisture content far outweighs that of the moisture content requirement. See section 4.3 for further interpretation and comparison of scenario results.

4.2 Bioelectricity Scenario

The second scenario assumes power provided is bioelectricity generated from combusted biomass driving shaft work in steam turbines attached to electric generators (Swanson et al., 2010). The combustion of biomass emits carbon that is part of the biogenic carbon cycle, so the only GWP associated with the combustion of biomass is the transportation of biomass to the biorefinery. To account for transportation in each process, the ratio of the energy demand to the higher heating value (HHV) of pine (~23,260 kJ/kg) was multiplied by total transportation emissions (19.91 kg CO_2 eq/dry tonne) reported in

INL's 2021 Woody Feedstocks State of Technology Report (P. Burli et al., 2022). Calculations can be found in Appendix 3. The GWP impact associated with bioelectricity generation was found in GREET. The GWP value per kWh of energy was multiplied by the respective energy demand for each process.

4.2.1 Impact Assessment

GREET was used for bioelectricity GWP impact values within the process "Forest residues to bioelectricity (North Carolina)" and subprocess "Pine (Steam Turbine) Power Plant." This process links power plant electricity generation data with emissions data to represent the combustion of pine to drive steam turbines attached to electric generators (Ou & Cai, 2020b).

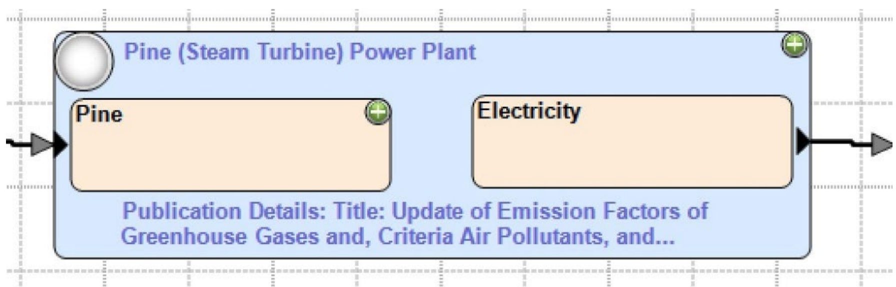


Figure 25. Pine to electricity process in GREET.

Air classification impact represents equipment bioelectricity energy demand, transportation of DML to a landfill, and transportation of biomass delivered. These values were normalized to the functional unit. This process follows the same format as found in the electrical grid scenario.

The dryer impact represents wastewater treatment, bioelectricity energy demand to power the rotary dryer, and transportation of biomass delivered. Drying in this scenario assumes steam is heated in a boiler from the combustion of biochar coming off a cyclone after the gasification process. Identical to the electrical grid scenario, emission factors were found from Ecoinvent within SimaPro for wastewater using the pathway conventional tap water production with biological treatment for one tonne of water. These values were normalized to the functional unit.

The size reduction impact represents the bioelectricity energy demand to power the equipment and transportation of biomass delivered. These values were normalized to the functional unit.

The GWP of each process is listed in Table 13 as kg CO_2 equivalent per tonne of usable feedstock. A visual of the relative GWP for the bioelectricity scenario is shown in Figure 26.

Table 13. GWP of preprocessed feedstock assuming bioelectricity.

Process	**GWP (kg CO_2 eq per tonne of usable feedstock)**
Air Classification Total	**0.31**
Bioelectricity	0.09
Transport DML to landfill	0.22
Transport of biomass delivered	0.003
Dryer Total	**5.41**
Bioelectricity	4.18
Wastewater treatment	0.19
Transport of biomass delivered	1.04
Size Reduction Total	**12.72**
Bioelectricity	12.33
Transport of biomass delivered	0.39
Total	**18.44**

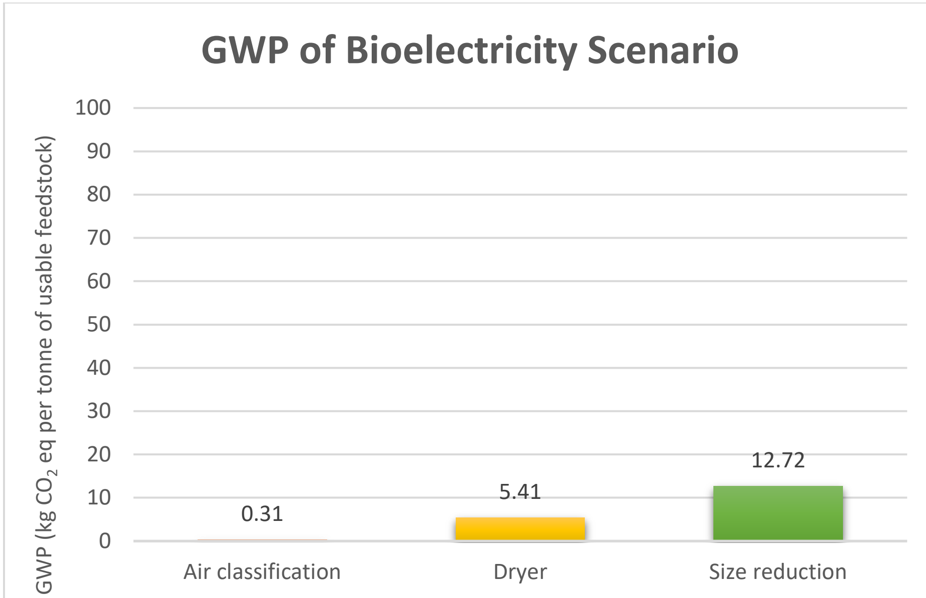


Figure 26. GWP of preprocessed feedstock for the bioelectricity scenario.

Identical to the grid electricity scenario, a one-at-a-time sensitivity analysis changed the decision parameters by ±20% from the respective baseline values to understand the impact on the overall GWP. The sensitivity analysis for the bioelectricity scenario is shown in Figure 27.

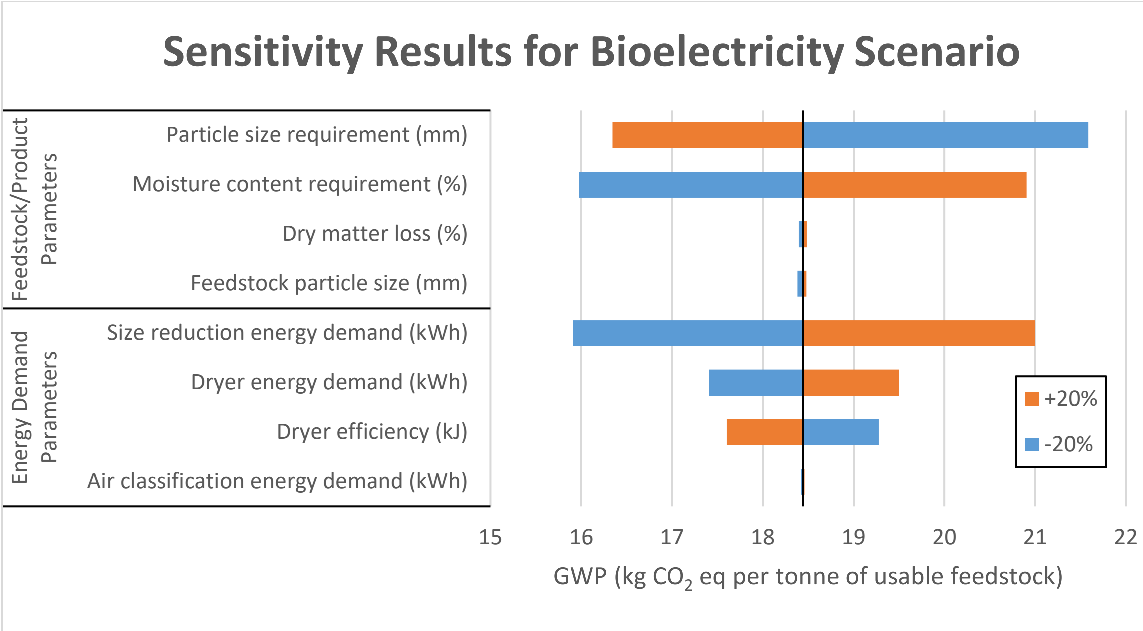


Figure 27. Sensitivity analysis results for the bioelectricity scenario where the centerline represents the baseline preprocessing GWP value.

Identical to the grid electricity scenario, an uncertainty analysis was completed using the Monte Carlo method for repeated random sampling over 5000 simulations to predict GWP based on the following parameters assuming uniform distributions: feedstock moisture content (30 to 60% wet basis), moisture content requirement (5 to 15% wet basis), and DML (5 to 15%). Again, uniform distributions were assumed for each parameter as a conservative estimate; however, it may be beneficial to obtain data on normal distributions of parameter values for future iterations.

SCCs were then determined for each parameter. Multiple 5000-time simulations were run to ensure similar correlation results. Figure 28 shows the SCCs for the uncertainty parameters with red representing increased impact.

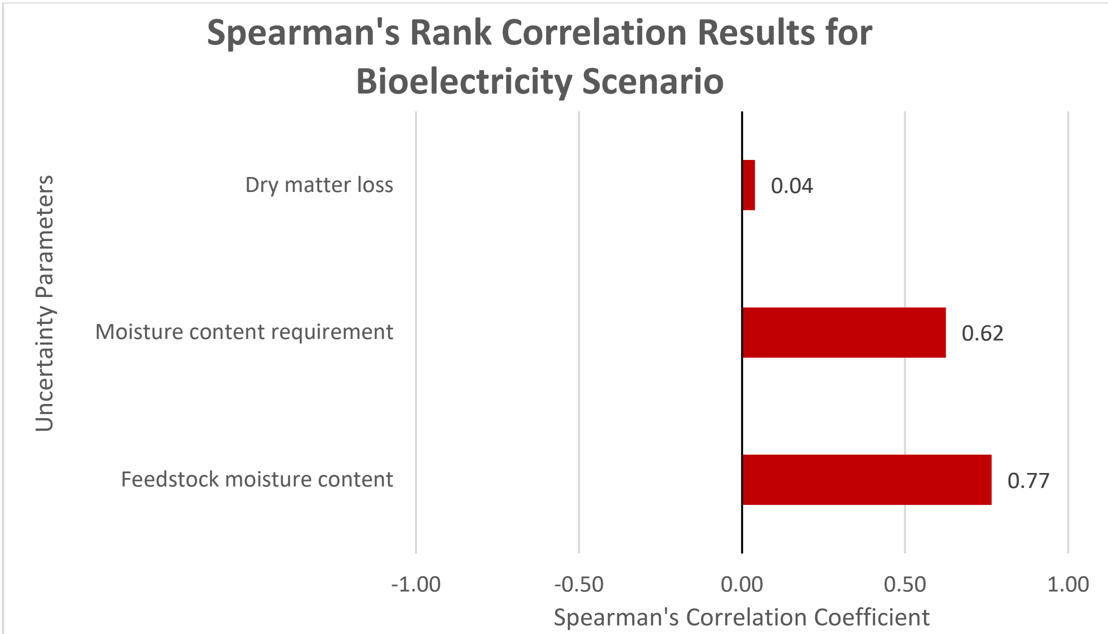


Figure 28. Spearman's rank correlation coefficient results for dry matter loss, moisture content requirement, and feedstock moisture content in the bioelectricity scenario.

4.2.2 Analysis

Size reduction has the highest GWP in this scenario. As a result, the model is most sensitive to the particle size requirement and size reduction energy demand. Size reduction has a higher GWP than drying in this scenario because steam generation for drying is considered biogenic except for the small impact associated with transportation of feedstock to the biorefinery. Moisture content requirement is also sensitive to change because size reduction energy demand accounts for moisture content of the feedstock. The model shows that if the moisture content of the feedstock is increased by 20%, then total GWP will significantly increase. Air classification represents just 1.6% of preprocessing GWP in this scenario. Therefore, the model is least sensitive to air classification energy demand of the energy demand parameters. Furthermore, the SCC results support the finding that the bioelectricity scenario is sensitive to changes in parameters surrounding size reduction.

The sensitivity analyses showed that GWP is sensitive to uncertainty in moisture content requirement (SCC=0.63) and feedstock moisture content (SCC=0.85). The model supports the finding that moisture content requirement is sensitive to uncertainty, as size reduction parameters have the greatest effect on GWP impact in the bioelectricity scenario. However, it is interesting that the impact of feedstock moisture content is so high for this scenario because that is not seen directly in the GWP results or one-at-a-time sensitivity analysis. Therefore, it is important the feedstock moisture content reaches the biorefinery at 30% wet basis to ensure GWP is not significantly increased during preprocessing. See section 4.3 for further interpretation and comparison of scenario results.

4.3 Interpretation and Comparison

The GWP of each step was compared according to the kg of CO_2 eq per tonne of usable feedstock as shown in Figure 29.

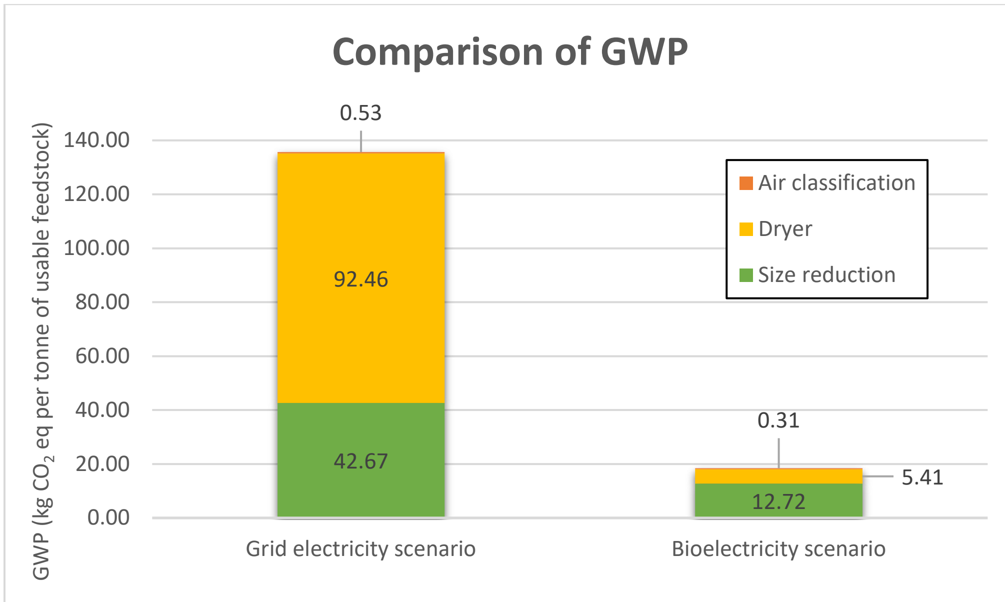


Figure 29. Comparison of GWP for grid electricity and bioelectricity scenarios.

The grid electricity scenario has a GWP impact over 7 times higher than the bioelectricity scenario. Therefore, for each usable tonne of feedstock preprocessed, the traditional grid electricity scenario has a much higher GWP impact than the best-case bioelectricity scenario.

The highest GWP step for preprocessing feedstock from grid electricity is drying. Production of steam from natural gas accounts for about 84% of dryer emissions or 57% of total emissions in this scenario. This makes the electrical grid scenario highly sensitive to the dryer efficiency and dryer energy demand. Assuming a 20% decrease in the dryer efficiency (from 3838 kJ/kg of evaporated water to 4606 kJ/kg of evaporated water) and a

20% increase in dryer energy demand (from 255 kWh/tonne to 306 kWh/tonne), GWP would increase by about 14% for each parameter. The GWP of drying is about 17 times higher in the grid electricity scenario than in the bioelectricity scenario. Emissions can be significantly reduced in preprocessing by using biogenic sources to generate steam for drying.

Size reduction is another significant source of GWP in both the electrical grid and bioelectricity scenarios. Both scenario models are sensitive to product particle sizes. In the grid electricity scenario, by increasing product particle size by 20% to 1.2 mm, the total GWP could be reduced by 6%. In the bioelectricity scenario, product particle size is the parameter most sensitive to change. If the product particle size is increased by 20% from 1 mm to 1.2 mm, the total scenario GWP decreases by 17%. Therefore, the required particle size is a key consideration when choosing a type of gasifier. For example, entrained flow gasification requires a particle size of 1 mm, whereas fluidized bed and downdraft gasification have less stringent standards of 10 mm. Assuming grid electricity, the GWP of size reduction for a biorefinery preparing biomass for entrained flow gasification would be about 12 times higher per year than for fluidized bed or downdraft gasification. Similarly, for the bioelectricity scenario, the GWP of size reduction for entrained flow gasification would be about 5 times higher per year than for fluidized bed or downdraft gasification.

Air classification has a relatively trivial contribution in both scenarios, representing just 0.4% and 1.6% of GWP for the grid electricity and bioelectricity scenarios, respectively. The small contribution to the GWP is significant because air classification facilitated a 30% reduction in sulfur content in this model which will potentially improve rates of biofuel conversion and lessen corrosion of combustion equipment. Therefore, the small GWP of the process further points toward the industrial implementation of air classification technology in biorefineries.

The Monte Carlo method elucidated uncertainty associated with each scenario by random sampling from a range of values for the following parameters: feedstock moisture content (30 to 60% wet basis), moisture content requirement (5 to 15% wet basis), and DML (5 to 15%). The GWP was calculated for each of the 5000 scenarios. The results are shown in Figure 30.

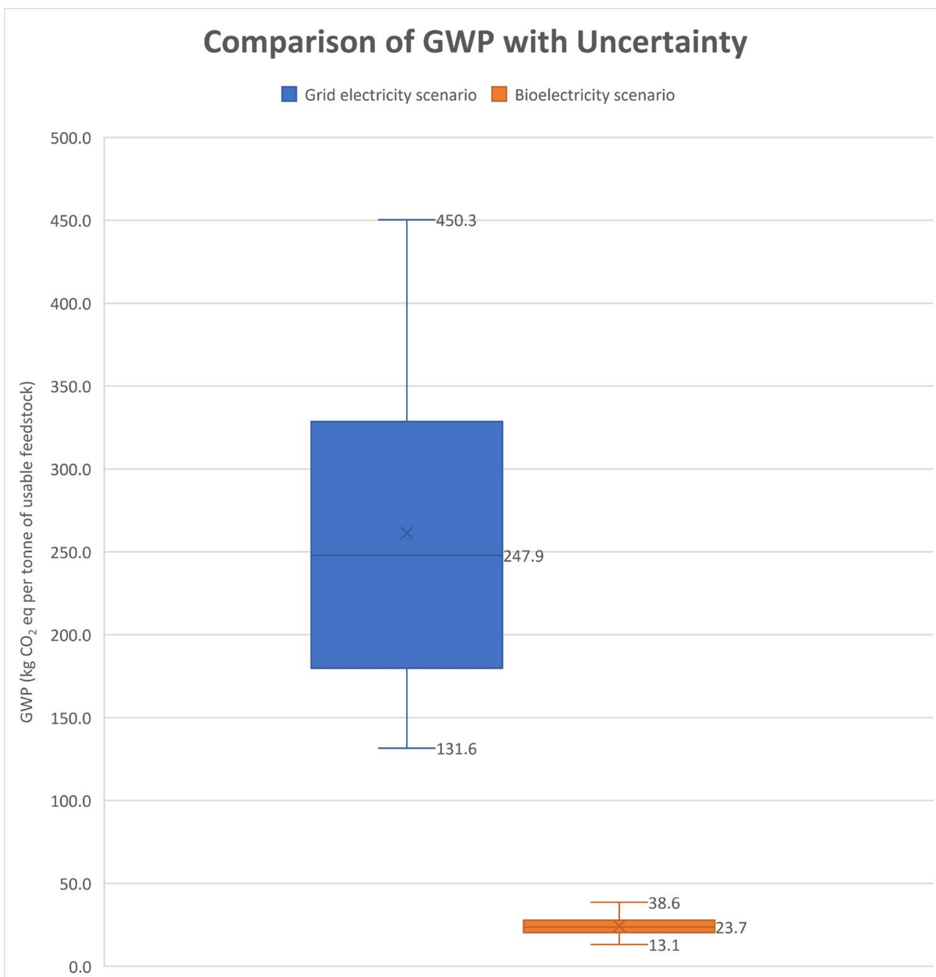


Figure 30. Comparison of GWP with the minimum, 25th and 75th percentiles, median, and maximum represented for the grid electricity and bioelectricity scenarios.

The grid electricity scenario minimum and maximum GWP are 131.6 and 450.3 kg CO_2 eq per tonne of usable feedstock, with a median of 247.9 kg CO_2 eq per tonne of usable feedstock. The bioelectricity scenario minimum and maximum GWP are 13.1 and 38.6 kg CO_2 eq per tonne of usable feedstock, with a median of 23.7 kg CO_2 eq per tonne of usable feedstock. These analyses showed that there is no overlap in GWP between the grid electricity and bioelectricity scenarios even considering uncertainty. The maximum GWP in the bioelectricity scenario will still be lower than the minimum GWP in the grid electricity scenario.

The SCCs explained the amount of DML transported to the landfill has very little impact on the overall uncertainty of GWP (SCC=0.03 for grid electricity; SCC=0.04 for bioelectricity). Moisture content requirement also has very little impact on the uncertainty of GWP in the grid electricity scenario (SCC=0.04). However, the moisture content requirement has a much larger impact on GWP in the bioelectricity scenario (SCC=0.62). This is explained by the contributions of GWP in each scenario coupled with the energy demand parameters for size reduction. Size reduction accounts for 69% of GWP in the bioelectricity scenario, but only 31% of GWP in the grid electricity scenario. Additionally, energy demand for size reduction increases as moisture content of the feedstock increases. Therefore, the model supports the finding that uncertainty in moisture content requirement could lead to uncertainty in overall GWP.

Both scenarios are most sensitive to the feedstock moisture content (SCC=1.00 for grid electricity; SCC=0.77 for bioelectricity). Drying is the largest contributor to GWP in the grid electricity scenario; therefore, it aligns that increasing the feedstock moisture content would significantly impact overall GWP. Size reduction is the largest contributor to GWP in the bioelectricity scenario; however, the feedstock moisture content has the largest impact on GWP. This was an interesting finding of the sensitivity analyses because size reduction does not account for feedstock moisture content. This could be explained by the large range of uncertainty for feedstock moisture content (30 to 60% wet basis). Regardless, this finding is important because increasing the moisture content of feedstock entering the biorefinery has a significant impact on overall GWP in both scenarios.

CHAPTER 5. CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

Sulfur accumulation in feedstocks can be pollutive, toxic to conversion catalysts, and cause premature breakdown of processing equipment. The LCA evaluated the environmental impact of air classification facilitating a 30% reduction in feedstock sulfur content. The LCA found that air classification represented 0.4% and 1.6% of GWP for the grid electricity and bioelectricity scenarios, respectively. This small contribution to GWP supports the large-scale implementation of air classification as a sulfur-mitigation technology at biorefineries.

Furthermore, this model sought to compare efficiencies between a traditional scenario using grid electricity/fossil fuels and a best-case scenario using bioelectricity/biogenic sources. Overall, the grid electricity scenario had a GWP over 7 times that of the bioelectricity scenario. The largest source of emissions in the grid electricity scenario, representing over 57% of total GWP, is from natural gas to produce steam for drying. This finding supports the transition to biogenic heating sources for steam production.

As the cellulosic biofuel industry moves forward, it is important to consider how the electrical grid is changing. Historically, coal-fired power plants supplied most of the grid electricity. This benefited cellulosic biorefineries because the fuels received significant carbon offset credits derived from excess electricity. However, as the U.S. grid transitions to primarily renewables, carbon offset credits are shrinking. Additionally, carbon markets in the past have treated biofuels as zero-emission fuels, however, agencies are beginning to step away from this concept as more information is gleaned regarding emissions associated with land use change and transportation (EPA). Therefore, it is vital to focus on lowering the carbon footprint of biofuels to maintain biofuel production as a net-negative process.

5.2 Future Work

The data requirements of an LCA are resource and time intensive. The availability and utilization of data can greatly sway the accuracy of results; therefore, it is vital to carefully consider the time and resources required to complete the LCA. Careful effort was made throughout the model to provide transparency about data sources and flexibility for change. Additionally, it is important to consider this model focuses on the GWP impact, but there could be tradeoffs between other impact categories that are not reflected in this study. With this in mind, iterations of this model should incorporate several processes to increase accuracy.

First, it should be considered how the mass discarded portion will be handled as this process was not included in the scope of this study. It would be beneficial to compare the efficiencies of sending the discarded mass portion to bioleaching versus combustion. There will be pros and cons to each pathway. Bioleaching will provide increased sulfur mitigation, possibly further increasing biofuel yield or generating co-products. However, it is unknown if the amount of sulfur leached out would be worth the time/cost of implementation and processing. Combustion, on the other hand, is a process that is already incorporated into the model and could create excess energy.

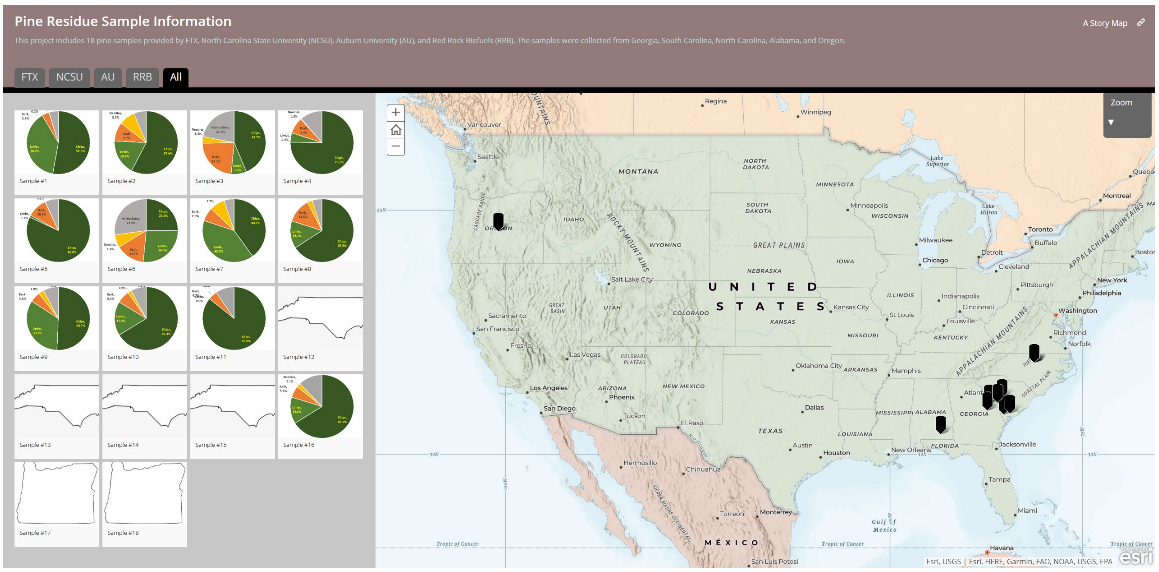
Next, it would be beneficial to characterize the pollutants in the steam condensate that is sent to wastewater treatment. The condensate contains particulate matter that is not well-characterized. This would be beneficial for a more accurate representation of the emissions associated with the steam condensate and taking appropriate measures for wastewater treatment.

Furthermore, this work should be combined with a holistic LCA of the cradle-to-gate process. This would include harvest, transportation, preprocessing, gasification, syngas cleaning, F-T catalysis, and upgrading to obtain the final products of fuel gas and jet fuel. It would be interesting to investigate the opportunity to air classify feedstock at the harvesting site prior to transport to the biorefinery and compare cost savings. Eventually, it would be beneficial to compare burned biofuels with and without air classification to compare emissions.

APPENDICES

APPENDIX 1. PINE RESIDUE SAMPLE STORY MAP

https://www.arcgis.com/apps/Shortlist/index.html?appid=21917fe655bb41c3b95982a6b01a4e86



APPENDIX 2. LIFE CYCLE INVENTORY CALCULATIONS

Dryer energy requirements

The energy requirements for the dryer were calculated using rotary dryer efficiency numbers reported from Worley (Worley, 2011). Worley reported rotary dryers have an efficiency of 3489 to 4187 kJ/kg of evaporated water. The average of 3838 kJ/kg of evaporated water was assumed. The calculations are shown below where q is evaporation heat (kJ), m is mass of liquid (kg), and h_e is evaporation heat (kJ/kg).

$$q = mh_e$$

$$3838 \frac{kJ}{kg\ evaporated\ water} * 477\ \frac{tonnes\ evaporated\ water}{day} * \frac{1000\ kg}{1\ tonne}$$

$$= 1{,}830{,}726{,}000 \frac{kJ}{day} = 508{,}535\ \frac{kWh}{day} = 254\ \frac{kWh}{tonne}$$

$$254 \frac{kWh}{tonne} * \frac{2000\ tonnes}{1500\ tonnes\ usable\ feedstock} = 339 \frac{kWh}{tonne\ usable\ feedstock}$$

Dryer efficiency calculations

The average of 3838 kJ/kg of evaporated water was assumed. The following calculation was used to normalize the efficiency to the functional unit.

$$1{,}830{,}726{,}000\,\frac{kJ}{day} * \frac{day}{1500\ tonnes\ usable\ feedstock} = 1{,}220{,}484\ \frac{kJ}{tonne\ of\ usable\ feedstock}$$

Steam Calculations

$$\frac{1500}{0.7} = 2142.857\ \frac{tonnes}{day}\, of\ biomass\ at\ 30\%\ moisture$$

$$\frac{1500}{0.9} = 1666.67\ \frac{tonnes}{day}\, of\ biomass\ at\ 10\%\ moisture$$

$$2142.857\ \frac{tonnes}{day} - 1666.67\ \frac{tonnes}{day} = \mathbf{477}\ \boldsymbol{\frac{tonnes}{day}}\, \boldsymbol{of\ evaporated\ moisture}$$

$$Assuming\ a\ 9{:}\,1\ recicrulating\ steam\ to\ evaporated\ moisture\ ratio.$$

$$477\ \frac{tonnes}{day} * 9 = \mathbf{4286}\ \boldsymbol{\frac{tonnes}{day}}\ \boldsymbol{of\ recirculating\ steam}$$

$$Normalizing\ the\ evaporated\ moisture\ to\ the\ functional\ unit:$$

$$477\ \frac{tonnes\ H2O}{day} * \frac{day}{1500\ tonnes\ usable\ feedstock}$$

$$= \mathbf{0.32}\ \boldsymbol{\frac{tonnes\ H2O}{tonne\ usable\ feedstock}}$$

$$Normalizing\ the\ recirculating\ steam\ to\ the\ functional\ unit:$$

$$4286\ \frac{tonnes\ H2O}{day} * \frac{day}{1500\ tonnes\ usable\ feedstock}$$

$$= \mathbf{2.86}\ \boldsymbol{\frac{tonnes\ H2O}{tonne\ usable\ feedstock}}$$

Size Reduction Energy Requirements

The energy demand for grinding is based on the following equation where E is the specific grinding energy (kWh/tonne), H is moisture content (%), M is a constant for pine feedstocks (9.65), L_p is the mean product particle size (mm), and L_f is the mean feed particle size (mm).

$$E = HM\left(\frac{1}{L_p} - \frac{1}{L_f}\right)$$

$$E = 10 * 9.65\left(\frac{1}{1} - \frac{1}{50.8}\right) = 94.6\frac{kWh}{tonne} = 126\frac{kWh}{tonne\ usable\ feedstock}$$

APPENDIX 3. LIFE CYCLE IMPACT ASSESSMENT CALCULATIONS

South Carolina Energy Portfolio

https://www.eia.gov/electricity/data/state/

“Net Generation by State by Type of Producer by Energy Source” for 2001-present. Averaged monthly energy source data for the year 2021. Divided by total to get the energy portfolio percentages.

LCI Process Assumptions Translated to LCIA using TRACI in SimaPro

Process	Product	Amount	Unit	Database
Nuclear in grid mix	Electricity, nuclear, at power plant/US	1	kWh	USLCI
Natural gas in grid mix	Electricity, natural gas, at power plant/US	1	kWh	USLCI
Coal in grid mix	Electricity, bituminous coal, at power plant/US	1	kWh	USLCI
Hydroelectric conventional in grid mix	Electricity, high voltage {SERC}| electricity production, hydro, run-of-river | APOS, U	1	kWh	Ecoinvent 3 – allocation at point of substitution - unit
Solar thermal and photovoltaic in grid mix	Electricity, low voltage {SERC}| electricity production, photovoltaic, 570kWp open ground installation, multi-Si | APOS, U	1	kWh	Ecoinvent 3 – allocation at point of substitution - unit
Wood and wood derived fuels in grid mix	Electricity, biomass, at power plant/US	1	kWh	USLCI
Petroleum in grid mix	Electricity, residual fuel oil, at power plant/US	1	kWh	USLCI
Pumped storage in grid mix	Electricity, high voltage {SERC}| electricity production, hydro, pumped storage | APOS, U	1	kWh	Ecoinvent 3 – allocation at point of substitution - unit
Transportation of DML to landfill	Transport, combination truck, short-haul, diesel powered, Southeast/tkm/RNA	24.1402	tkm	USLCI
Wastewater treatment	Tap water {RoW}| tap water production, conventional with biological treatment | APOS, U	1000	kg	Ecoinvent 3 – allocation at point of substitution - unit

Dryer normalizing to functional unit calculations

First, we take the ratio of biomass moisture evaporated to dry tonnage processed per day.

$$\frac{477\ tonnes\ H_2O\ per\ day}{1500\ tonnes\ usable\ feedstock\ per\ day} = 0.318\ \frac{tonnes\ H_2O}{tonne\ of\ usable\ feedstock}$$

Therefore, to normalize to the functional unit of 1 dry metric tonne of usable feedstock, the values for impact categories are multiplied by 0.318 to get tonnage of H_2O per tonne of usable feedstock. It is assumed the moisture evaporated from biomass is equivalent to tap water being sent to biological treatment. For example, take the following calculation for GWP to receive kg CO_2 eq per tonne of usable feedstock processed.

$$\frac{0.585917\ kg\ CO2\ eq}{1\ tonne\ H_2O} * 0.318\ \frac{tonne\ H_2O}{tonne\ usable\ feedstock}$$

$$= 0.18632\ \frac{kg\ CO2\ eq}{tonne\ usable\ feedstock}$$

Product	1000 kg Tap water | tap water production, conventional with biological treatment | APOS, U (of project Ecoinvent 3 - allocation at point of substitution - unit)		
Impact category	**Unit**	**Value**	**Value * 0.318**
Ozone depletion	kg CFC-11 eq	4.52E-08	1.44E-08
Global warming	kg CO2 eq	0.585917	0.18632
Smog	kg O3 eq	0.035048	0.01115
Acidification	kg SO2 eq	0.002838	9.03E-04
Eutrophication	kg N eq	0.002353	7.48E-04
Carcinogenics	CTUh	6.37E-08	2.03E-08
Non carcinogenics	CTUh	1.69E-07	5.39E-08
Respiratory effects	kg PM2.5 eq	0.000925	2.94E-04
Ecotoxicity	CTUe	5.274152	1.67718
Fossil fuel depletion	MJ surplus	0.488244	0.15526

Air classification energy normalizing to functional unit calculations

The electricity usage should be normalized to the functional unit. To do this, first multiply the given electricity usage by the tonnage processed per day.

$$0.692\frac{kWh}{tonne\ feedstock} * 2000\frac{tonne\ feedstock}{day} = 1384\frac{kWh}{day}$$

Next, multiply by the amount of usable feedstock per day to get the kWh of electricity needed per tonne of usable feedstock.

$$1384\frac{kWh}{day} * \frac{1\ day}{1500\ tonne\ useable\ feedstock} = 0.923\frac{kWh}{tonne\ usable\ feedstock}$$

Air classification transport of DML normalizing to functional unit calculations

It is assumed that the transport of the DML occurs in a diesel-powered combination truck in the Southeast region of the United States. It is assumed the truck travels 24.1405 km (15 miles) to reach a landfill. Emissions values for transport of 1 tonne of DML traveling 24.1405 km were calculated. This yields the unit of each impact category per tonne of DML. However, the unit should be normalized to the unit of each impact category per tonne of usable feedstock. Therefore, each value was multiplied by the ratio of DML to tonnes of usable feedstock. The following calculation was made to each impact category value, taking GWP as an example calculation.

$$\frac{120\ tonne\ DML}{2000\ tonne\ feedstock} * \frac{2000\ tonne\ feedstock}{1500\ tonne\ usable\ feedstock}$$

$$= 0.08\ \frac{tonne\ DML}{tonne\ usable\ feedstock}$$

$$\frac{2.7204512\ kg\ CO2\ eq}{1\ tonne\ DML} * 0.08\ \frac{tonne\ DML}{tonne\ usable\ feedstock}$$

$$= 0.217636096\ \frac{kg\ CO2\ eq}{tonne\ usable\ feedstock}$$

Product	24.1402 tkm Transport, combination truck, short-haul, diesel powered, Southeast/tkm/RNA (of project USLCI)		
Impact category	**Unit**	**Value**	**Value * 0.08**
Ozone depletion	kg CFC-11 eq	1.14E-10	9.10599E-12
Global warming	kg CO2 eq	2.7204512	0.217636096
Smog	kg O3 eq	0.76351717	0.061081374
Acidification	kg SO2 eq	0.030312307	0.002424985
Eutrophication	kg N eq	0.001809192	0.000144735
Carcinogenics	CTUh	4.07E-08	3.25996E-09
Non carcinogenics	CTUh	3.93E-07	3.14368E-08
Respiratory effects	kg PM2.5 eq	0.000943807	7.55046E-05
Ecotoxicity	CTUe	7.5949646	0.607597168
Fossil fuel depletion	MJ surplus	5.7155621	0.457244968

Transport of biomass delivered for bioelectricity scenario

The HHV is a measure of heat content based on the gross energy content of a combustible fuel. It is assumed each process's energy use value is divided by pine's HHV of 23,260 kJ/kg (or 6461.1 kWh/tonne). When multiplied by 100%, this ratio represents the percentage of energy needed for the process out of the gross energy content. Last, the calculation was normalized to the functional unit. The following calculation was made for air classification, drying, and size reduction, taking drying as an example calculation.

$$\frac{338\ \frac{kWh}{tonne}}{6461.1\frac{kWh}{tonne}} = 0.05$$

$$\frac{19.91\ kg\ CO2\ eq}{tonne} * 0.05 = 1.04\frac{kg\ CO2\ eq}{tonne}$$

$$1.04\frac{kg\ CO2\ eq}{tonne} * \frac{2000\ tonne\ feedstock}{1500\ usable\ tonnes} = 1.39\frac{kg\ CO2\ eq}{tonne\ usable\ feedstock}$$

BIBLIOGRAPHY

Ahamed, T. S., Anto, S., Mathimani, T., Brindhadevi, K., & Pugazhendhi, A. (2021). Upgrading of bio-oil from thermochemical conversion of various biomass–Mechanism, challenges and opportunities. *Fuel*, *287*, 119329.

Alonso, D. M., Wettstein, S. G., & Dumesic, J. A. (2012). Bimetallic catalysts for upgrading of biomass to fuels and chemicals. *Chemical Society Reviews*, *41*(24), 8075.

Amos, W. A. (1999). *Report on biomass drying technology*.

Antizar-Ladislao, B., & Turrion-Gomez, J. L. (2008). Second-generation biofuels and local bioenergy systems. *Biofuels, bioproducts and biorefining*, *2*(5), 455-469.

Atchison, J. E., & Hettenhaus, J. R. (2003). *Innovative methods for corn stover collecting, handling, storing and transporting*.

Bansal, V., Ahmad, A., & Sastry, M. (2006). Fungus-Mediated Biotransformation of Amorphous Silica in Rice Husk to Nanocrystalline Silica. *Journal of the American Chemical Society*, *128*(43), 14059-14066.

Bare, J. (2011). TRACI 2.0: the tool for the reduction and assessment of chemical and other environmental impacts 2.0. *Clean Technologies and Environmental Policy*, *13*(5), 687-696.

Basu, P. (2013). *Biomass gasification, pyrolysis, and torrefaction practical design and theory* (2nd ed.). Elsevier/AP.

Boerrigter, H., & Rauch, R. (2006). Review of applications of gases from biomass gasification. *ECN Biomassa, Kolen en Milieuonderzoek*, *20*, 211-230.

Burli, P. H., Hartley, D. S., & Thompson, D. N. (2022). *WOODY FEEDSTOCKS 2021 STATE OF TECHNOLOGY REPORT*.

Emerson, R. M., Hernandez, S., Williams, C. L., Lacey, J. A., & Hartley, D. S. (2018). Improving bioenergy feedstock quality of high moisture short rotation woody crops using air classification. *Biomass and Bioenergy*, *117*, 56-62.

EPA. *Economics of Biofuels*.

Esteban, L. S., & Carrasco, J. E. (2006). Evaluation of different strategies for pulverization of forest biomasses. *Powder technology*, *166*(3), 139-151.

Fagernäs, L., Brammer, J., Wilén, C., Lauer, M., & Verhoeff, F. (2010). Drying of biomass for second generation synfuel production. *Biomass and Bioenergy*, *34*(9), 1267-1277.

FAO. Food and Agriculture Organization of the United Nations.

Gerland, P., Raftery, A. E., Sevčíková, H., Li, N., Gu, D., Spoorenberg, T., Alkema, L., Fosdick, B. K., Chunn, J., Lalic, N., Bay, G., Buettner, T., Heilig, G. K., & Wilmoth, J. (2014). World population stabilization unlikely this century. *Science (American Association for the Advancement of Science)*, *346*(6206), 234-237.

Gößling-Reisemann, S. (2008). What Is Resource Consumption and How Can It Be Measured?: Theoretical Considerations. *Journal of industrial ecology*, *12*(1), 10-25.

Hartley, D. S., Thompson, D. N., & Cai, H. (2021). *Woody Feedstocks 2020 State of Technology Report*.

ISO. (2006-07). Environmental management — Life cycle assessment — Principles and framework (ISO 14040:2006). In.

Kaufman Rechulski, M. D., Schildhauer, T. J., Biollaz, S. M. A., & Ludwig, C. (2014). Sulfur containing organic compounds in the raw producer gas of wood and grass gasification. *Fuel (Guildford)*, *128*, 330-339.

Khan, I., Hou, F., & Le, H. P. (2021). The impact of natural resources, energy consumption, and population growth on environmental quality: Fresh evidence from the United States of America. *The Science of the total environment*, *754*, 142222-142222.

Klöpffer, W., & Grahl, B. (2014). *Life cycle assessment : a guide to best practice*. Wiley-VCH.

Kumar, R. N., & Aarthi, V. (2020). From biomass to syngas, fuels and chemicals–A review. AIP conference proceedings,

Lacey, J. A., Aston, J. E., Westover, T. L., Cherry, R. S., & Thompson, D. N. (2015). Removal of introduced inorganic content from chipped forest residues via air classification. *Fuel (Guildford)*, *160*(C), 265-273.

Langholtz, M. H., Stokes, B. J., & Eaton, L. M. (2016). *2016 billion-ton report: advancing domestic resources for a thriving bioeconomy*.

Li, W., Dang, Q., Brown, R. C., Laird, D., & Wright, M. M. (2017). The impacts of biomass properties on pyrolysis yields, economic and environmental performance of the pyrolysis-bioenergy-biochar platform to carbon negative energy. *Bioresource technology*, *241*(C), 959-968.

Lin, Y., Roni, M. S., Burli, P. H., Hartley, D. S., & Thompson, D. N. (2021). *Herbaceous Feedstock 2021 State of Technology Report*.

Liu, C., Huang, Y., Wang, X., Zhang, S., Xia, W., Sun, C., & Liu, H. (2017). Dynamic Experimental Investigation on the Volatilization Behavior of Lead and Cadmium in the Simulated Municipal Solid Waste (MSW) Influenced by Sulfur Compounds during Incineration. *Energy & fuels*, *31*(1), 847-853.

Ma, Q., Luo, Y., Wen, Y., Hill, P. W., Chadwick, D. R., Wu, L., & Jones, D. L. (2020). Carbon and sulphur tracing from soil organic sulphur in plants and soil microorganisms. *Soil biology & biochemistry*, *150*, 107971.

Meyer, P. A., Snowden-Swan, L. J., Rappé, K. G., Jones, S. B., Westover, T. L., & Cafferty, K. G. (2016). Field-to-fuel performance testing of lignocellulosic feedstocks for fast pyrolysis and upgrading: techno-economic analysis and greenhouse gas life cycle analysis. *Energy & fuels*, *30*(11), 9427-9439.

Mujumdar, A. (2006). Handbook of Industrial Drying.

Naik, S. N., Goud, V. V., Rout, P. K., & Dalai, A. K. (2010). Production of first and second generation biofuels: A comprehensive review. *Renewable & sustainable energy reviews*, *14*(2), 578-597. (Renewable and Sustainable Energy Reviews)

Naimi, L. J., Collard, F., Bi, X., Lim, C. J., & Sokhansanj, S. (2016). Development of size reduction equations for calculating power input for grinding pine wood chips using hammer mill. *Biomass Conversion and Biorefinery*, *6*(4), 397-405.

Naimi, L. J., Sokhansanj, S., Mani, S., Hoque, M., Bi, T., Womac, A. R., & Narayan, S. (2006). Cost and performance of woody biomass size reduction for energy production. 2006 ASAE Annual Meeting,

NRMRL. (2006). Life-cycle assessment: principles and practice. In: National Risk Management Research Laboratory, Office of Research and ….

Ong, H. C., Chen, W.-H., Farooq, A., Gan, Y. Y., Lee, K. T., & Ashokkumar, V. (2019). Catalytic thermochemical conversion of biomass for biofuel production: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *113*, 109266.

Ou, L., & Cai, H. (2020a). Dynamic life-cycle analysis of fast pyrolysis biorefineries: impacts of feedstock moisture content and particle size. *ACS sustainable chemistry & engineering*, *8*(16), 6211-6221.

Ou, L., & Cai, H. (2020b). *Update of Emission Factors of Greenhouse Gases and Criteria Air Pollutants, and Generation Efficiencies of the U.S. Electricity Generation Sector*.

Patton, R., Steele, P., & Yu, F. (2009). Coal vs. Charcoal-fueled Diesel Engines: A Review. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *32*(4), 315-322.

Schnepf, R., & Yacobucci, B. D. (2013). *Renewable Fuel Standard (RFS): Overview and Issues*.

Swanson, R. M., Platon, A., Satrio, J., Brown, R., & Hsu, D. D. (2010). *Techno-economic analysis of biofuels production based on gasification*.

Temmerman, M., Jensen, P. D., & Hebert, J. (2013). Von Rittinger theory adapted to wood chip and pellet milling, in a laboratory scale hammermill. *Biomass and Bioenergy*, *56*, 70-81.

Thompson, V. S., Lacey, J. A., Hartley, D., Jindra, M. A., Aston, J. E., & Thompson, D. N. (2016). Application of air classification and formulation to manage feedstock cost, quality and availability for bioenergy. *Fuel (Guildford)*, *180*(C), 497-505.

Valdivia, M., Galan, J. L., Laffarga, J., & Ramos, J. L. (2016). Biofuels 2020: biorefineries based on lignocellulosic materials. *Microbial biotechnology*, *9*(5), 585-594.

Vidlund, A. (2004). *Sustainable production of bio-energy products in the sawmill industry* Kemiteknik].

Werkelin, J., Skrifvars, B.-J., Zevenhoven, M., Holmbom, B., & Hupa, M. (2010). Chemical forms of ash-forming elements in woody biomass fuels. *Fuel (Guildford)*, *89*(2), 481-493.

Wertz, J.-L., & Bedue, O. (2013). *Lignocellulosic biorefineries*. CRC Press.

White, E. M. (2010). *Woody biomass for bioenergy and biofuels in the United States: A briefing paper* (Vol. 825). DIANE Publishing.

Worley, M. (2011). Biomass Drying Presentation.

Yi, J., Li, X., He, J., & Duan, X. (2020). Drying efficiency and product quality of biomass drying: a review. *Drying Technology*, *38*(15), 2039-2054.

VITA

Ashlee Edmonson

Born in Irvine, Kentucky

EDUCATION:

Bachelor of Science, Biosystems and Agricultural Engineering, University of Kentucky, 2021.

RESEARCH EXPERIENCE:

Graduate Research Assistant, Biosystems and Agricultural Engineering, University of Kentucky, 2021-2023.

Municipal Solid Waste Intern, Energy and Environment Science & Technology, Idaho National Laboratory, 2022.

SCHOLASTIC HONORS:

Outstanding Experiential Learning Award, Biosystems and Agricultural Engineering, University of Kentucky, 2019.

Pigman Scholarship Recipient, College of Engineering, University of Kentucky, 2017-2021.