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Integrated Techno-Economic and Life Cycle Analyses of Biomass Utilization for Value-Added Bioproducts in the Northeastern United States

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ABSTRACT

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A multi-stage spatial analysis was first conducted to select locations for lignocellulosic biomass-based bioproduct facility, using Geographical Information System (GIS) spatial analysis, multi-criteria analysis ranking algorithm, and social-economic assessment. A case study was developed to determine locations for lignocellulosic biorefineries using feedstocks including forest residue biomass and three energy crops for 13 states in the northeastern United States. In the entire study area, 11.1% of the counties are high-suitable, 48.8% are medium-suitable for biorefinery siting locations. A non-parametric analysis of cross-group surveys showed that preferences on biorefinery siting are homogeneous for experts in academia and industry groups, but people in government agencies presented different opinions. With the Maximum Likelihood test, parameters of distributions and mean values were estimated for nine weighted criteria. Social asset evaluation focusing on degree of rurality and social capital index further sorted counties with higher community acceptance and economic viability. A total of 15 counties were selected with the highest potential for biorefinery sites in the region.

A mixed-integer linear programming model was then developed to optimize the multiple biomass feedstock supply chains, including feedstock establishment, harvest, storage, transportation, and preprocessing. The model was applied for analyses of multiple biomass feedstocks at county level for 13 states in the northeastern United States. In the base case with a demand of 180,000 dry Mg/year of biomass, the delivered costs ranged from $67.90 to $86.97 per dry Mg with an average of $79.58 /dry Mg. The biomass delivered costs by county were from $67.90 to 150.81 per dry Mg across the northeastern U.S. Considered the entire study area, the delivered cost averaged $85.30 /dry Mg for forest residues, $84.47 /dry Mg for hybrid willow, $99.68 for switchgrass and $97.87 per dry Mg for Miscanthus. Seventy seven out of 387 counties could be able to deliver biomass at $84 per dry Mg or less a target set by US DOE by 2022. A sensitivity analysis was also conducted to evaluate the effects of feedstock availability, feedstock price, moisture content, procurement radius, and facility demand on the delivered cost. Our results showed that procurement radius, facility capacity, and forest residue availability are the most sensitive factors affecting the biomass delivered costs.

An integrated life cycle and techno-economic assessment was carried out for three bioenergy products derived from multiple lignocellulosic biomass. Three cases were studied for production of pellets, biomass-based electricity, and pyrolysis bio-oil. The LCA was conducted for estimating environmental impacts on cradle-to-gate basis with functional unit of 1000 MJ for bioenergy production. Pellet production had the lowest GHG emissions, water and fossil fuels consumption, for 8.29 kg CO_2 eq, 0.46 kg, and 105.42 MJ, respectively. Conversion process presented a greater environmental impact for all three bioenergy products. With producing 46,926 tons of pellets, 260,000 MWh of electricity, and 78,000 barrels of pyrolysis oil, the net present values (NPV) for all three cases indicated only pellet and biopower production cases were profitable with NPVs $1.20 million for pellet, and $81.60 million for biopower. The pellet plant and biopower plant were profitable only when discount rates are less than or equal to 10%, while it will not be profitable for a pyrolysis oil plant. The uncertainty analysis indicated that pellet production showed the highest uncertainty in GHG emission, bio-oil production had the least uncertainty in GHG emission but had risks producing greater-than-normal amount of GHG. For biopower production, it had the highest probability to be a profitable investment with 95.38%.

A study evaluated the environmental and economic impacts of activated carbon (AC) produced from lignocellulosic biomass was evaluated for energy storage purpose. Results indicate that overall “in-plant production” process presented the highest environmental impacts. Normalized results of life cycle impact assessment showed that the AC production had environmental impacts mainly on carcinogenics, ecotoxicity, and non-carcinogenics categories. We then further focused on life cycle analysis from raw biomass delivery to plant gate, the results showed “feedstock establishment” has the most significant environmental impact, ranging from 50.3% to 85.2%. For an activated carbon plant of producing 3000 kg AC per day in the base case, the capital cost would be $6.66 million, and annual operation cost was $15.46 million. The AC required selling price (RSP) was $16.79 per kg, with the discounted payback period (DPB) of 9.98 years. Alternative cases of KOH-reuse and steam processes had GHG emission of 15.4 kg CO_2 eq, and 10.2 kg CO_2 eq for every 1 kg activated carbon, respectively. Monte Carlo simulation showed 49.96% of the probability for an investment to be profitable in activated carbon production for supercapacitor electrodes.

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1. INTRODUCTION

Biomass, is a renewable energy sources that has the potential to remediate the greenhouse gas emissions (Elia et al. 2011). Carbon dioxide is absorbed from atmosphere during its growth and cultivation resulting in negative greenhouse gas emission. Biomass can also be utilized as a renewable feedstock for biopower, transportation fuels, and biomaterials, and biochemicals (Brown 2019; Putro et al. 2016). The commercially available biofuels are commonly made from rapeseed and corn. However, their production have drawbacks on failure in higher N_2O emission (Crutzen et al. 2008), or negatively land use changes (Searchinger et al. 2008). As a result, recent studies have turned to the use of other lignocellulosic feedstocks, such as perennial grasses or short rotation woody crops, and forest residues for bioenergy and value-added bioproducts (Higman and Burgt 2003). In the meanwhile, biomass-based high-value biochemical products have not been realized at a commercial scale due to economic and environmental challenges (Shen et al. 2015).

The northeastern region in United States has a wealth of existing biomass feedstocks and the potential to increase supplies in the future. Residues from timber industry, perennial grasses, or short rotation woody crops are the main sources easily accessible lignocellulosic feedstocks in the northeastern region of the U.S (Liu et al. 2017). Studies (Wang et al. 2006; Wu et al. 2012) on availability of woody biomass showed a great potential of woody biomass supply capability in this area. A study by Wang et al. (2006) analyzed the biomass resources in West Virginia, the third most heavily forested state in U.S. yields nearly 2.41 million dry tons of biomass per year. Energy grasses after drying can be used as the biorefinery feedstock, with the merits of high biomass yield, low moisture content (Miao et al. 2012). Switchgrass, the native perennial warm-season grass in United States, can be used as an energy crop with high productivity and low maintenance cost. Compared with switchgrass, miscanthus is another type of perennial rhizomatous grass, and its production is characterized by low fertilizer and pesticide requirement (Lewandowski et al. 2000).

Lignocellulosic biomass shows a great potential in bioenergy and high-value biochemical production. Based on an EIA study (2020a), the annual renewable energy usage in the U.S. had exceeded coal consumption since before 1885 in 2019. The consumption of renewable energy U.S. has increased 17.9% from year 2015, and biomass-based energy in renewable energy is the most promising resource especially, for 43.5% in total renewable energy usage (EIA 2020b). In addition to energy products, biomass can be used to create value-added bioproducts like chemicals and materials, and some popular carbon-based products including carbonaceous materials, sugar alcohols, and bioplastics (Irmak 2017). Furthermore, the production of bioenergy and bioproducts has the potential to revitalize rural communities as rural areas are in decline, especially when using products derived from multiple sources like forest residue and energy crop feedstocks locally.

1.1 Supply chain of biomass utilization

To successfully produce bioenergy products from various biomass feedstocks, supply chain configuration is the most important strategy before any further decisions. Gold and Seuring (2011) reviewed bioenergy production supply chain studies and summarized the main components of biomass supply chain: feedstock harvesting and collection, storage, transport, pretreatment and conversion. Though orders of process may change, repeat or more processes may be added, the main components of a biomass supply chain are similar in many respects (Rentizelas et al. 2009).

Delivered cost of biomass feedstock is an important factor in biomass supply chain, which affects the final product value greatly (Wright 2010; Swanson et al. 2010). In a study of biomass-based transportation fuel by Wright (2010), cost of biomass as feedstock showed its importance in the sensitivity analysis and feedstock cost varies among feedstock supply/demand locations all year round. Similarly, feedstock cost is an important parameter influencing the final product value from biomass (Swanson et al. 2010). The methods of biomass harvesting vary, depending on the types of biomass (Wang et al. 2013). For logging residues, studies have been primarily focusing on harvest and transportation systems such as whole-tree chipping and slash bundling to improve productivity and lower the cost (Yoshioka et al. 2006; Gan and Smith 2006). Harvesting systems and methods used for biomass harvesting activities affect overall harvesting cost, productivity, overall profitability of harvesting operations, returns to a landowner, and ecological impact (Herr and Carlson 2013). The existing harvest technology for short rotation woody crops (SRWCs) basically can be divided into logging, bundling, chipping and baling (Ehlert and Pecenka 2013). Chipping during harvest is the most cost-effective way to achieve chipped crops (Eisenbies et al. 2014). Eisenbies et al. (2014) thoroughly examined a single-pass, cut and chip harvest system of SRWC in New York State, and the results showed the harvester performance change and depend on machine capability, ground conditions, field layout, and so on. Harvesting switchgrass and miscanthus is similar to other grasses or crop residues (Sokhansanj et al. 2002). Brownell and Liu (2011a) evaluated four herbaceous biomass handling systems and found the “single-pass harvesting” equipment is a new trend in harvesting and collecting grass biomass.

Reducing the material size, increasing the bulk density, and increasing the energy density, make it possible to improve biomass feedstock characteristics and efficiency through the supply chain. Generally, chipping and baling can be done at the harvesting site. Chipping is a size reduction method for biomass that improves efficiency of thermally or chemical conversion (Hamelinck et al. 2005). Size reduction of the material from whole stems or large sections into chips is one of the most common methods to improve transportation properties. Chipping increases the feedstock density of woody biomass by 243 percent for transportation, and the larger surface area allows for more drying and improving the energy characteristics (Angus-Hankin et al. 1995; Richard, 2010). Baling is a key technology for crops to be handled in further logistics and get their density increased, as well as reducing the risks of feedstock deterioration (Forsberg 2000). Baling involves compressing a material and tightly binding the compressed material to maintain the compression, for woody biomass this process has the ability to double the bulk density over loose material (Angus-Hankin et al. 1995).

Moisture content would affect the cost in biomass supply chain operation. In the analysis of forest biomass delivery for bioenergy production, Sessions (2013) pointed out moisture management is a supply chain problem, and is affected by harvesting season and storage methods. Moisture content of biomass depends on a number of factors including species, diameter, season of year harvested, and length of time the material has been on the ground or in piles (Hakkila 1989). Reducing moisture content involves letting biomass dry in the field, on the landing, or in a satellite yard prior to delivery to the plant (Uslu et al. 2008).

There are two major pathways of converting biomass into biofuel and bioproducts: thermochemical and biochemical. Thermochemical conversion includes combustion, gasification, liquefaction, and pyrolysis (Goyal et al. 2008). Combustion is the direct burning of biomass in the presence of oxygen for the purpose of generating heat. Heat from combustion can then be used to generate mechanical power, which can be used to produce electricity (Goyal et al. 2008). Gasification partially oxidizes the feedstock to create a combustible gas mixture by heating the biomass in an environment that has an inadequate supply of oxygen to support combustion (Devi et al. 2003). Pyrolysis uses an oxygen free environment to thermally destruct biomass and is best suited for the production of liquid fuels, but also produces gasses and solids (Mohan et.al. 2006). Biomass biochemical conversion always involves the use of microbes, enzymes, or chemicals (Singh et al. 2015). When producing liquid fuels from biomass, lignocellulosic material could be converted to sugar via enzymatic hydrolysis (Cadham et al. 2016). Generally, a biochemical conversion system for lignocellulosic biomass produces the C6 and C5 sugars first, and then converts the polysaccharides into products like fuels or chemicals (Elbersen et al. 2017).

1.2 Life cycle assessment and techno-economic analysis

As a hand-on methodology for assessing environmental impacts, life-cycle assessment (LCA) accounts and manages environmental impacts associated with all the stages of the life-cycle of biomass-based products. The environmental impacts of bioenergy or bioproduct production are hotly-debated as methodologies for life cycle assessment vary widely (Caputo et al. 2014; You et al. 2011; Budsberg et al. 2012; Popp et al. 2011; Hsu et al. 2010). You (2012) built a multi-objective optimization model of a cellulosic biofuel supply chain that showed multiple factors affected the reduction of GHG emissions. Akhtari (2014) demonstrated that besides contributing to socioeconomic development, forest biomass utilization for district heating would support British Columbia's Clean Air program and would improve air quality within Williams Lake area.

A feasibility analysis is also called a techno-economic analysis, in which the technical aspects of a project are coupled to the economic aspects (Patel et al. 2011). First, the basic theoretical configuration is developed, and a mass-and-energy balance is performed. Second, cost estimation allows the investment and production cost of a biorefinery to be determined. Techno-economic models are built to establish production process and provide cost and performance boundaries (Kapila et al. 2017). Techno-economic analysis studies on biomass-based power plants could solve economic problems of real cases. To provide liquid transportation fuels and electricity, two gasification models of biomass-to-liquid production have been compared and shown that the product value is lower for high temperature gasification even though there is a higher investment cost than that for the low temperature gasification (Swanson et al. 2010). Liquid fuels or chemicals could be the most promising product in biomass conversion. A process model for a lignocellulosic biofuel production has been presented by Klein-Marcuschamer (2010) for the usage of lignocellulosic ethanol on energy related environmental and economic consultation. As in the study of naphtha and diesel fuels production with the feedstock of biomass via fast pyrolysis method, Wright (2010) built models with two fixed yearly production rates, which with respective capital costs and fuel product values for both nth plant and pioneer plant .

There appears a necessity to further analyze biomass utilization for bioenergy and bioproducts in the Northeast. Furthermore, it is crucial to analyze economic and environmental impacts of biomass-based bioenergy production in the region. Therefore, this dissertation focused on (1) identification of the suitable locations for new facilities of bioenergy and value-add products in the northeastern U.S., (2) supply chain configurations of multiple biomass as feedstocks with consideration of biomass harvest and logistics optimization, (3) real case studies of bioenergy productions in the aspects of economic feasibility and environmental impacts, and (4) integrated techno-economic and life cycle analyses of highly porous biomass-based activated carbon for high-performance supercapacitors.

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2. Optimization of facility siting of Bioenergy and Bioproducts in Northeast US[1]

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Abstract:

A multi-stage spatial analysis was conducted to select locations for lignocellulosic biomass-based bioproduct facility using Geographical Information System (GIS) spatial analysis, multi-criteria analysis ranking algorithm, and social-economic assessment. Site suitability indices were first created and evaluated for the entire study area using a linear fuzzy-logic prediction model. An integrated measure of stakeholder preferences was then identified and used for weighing the score adjustment of siting criteria in the Analytic Hierarchy Process. Surveys of expert's opinions from various stakeholder groups were collected to leverage their insights in biomass and bioproducts field and integrated into weight adjustment in site ranking.

A case study was developed to determine locations for lignocellulosic biorefineries using feedstocks including forest residue biomass and three energy crops for 13 states in the northeastern United States. In the whole study area, 11.1% are high-suitable, 48.8% are moderately-suitable for biorefinery siting locations. A non-parametric analysis of cross-group surveys showed that preferences on biorefinery siting are homogeneous for experts in academia and industry groups, but people in government agencies showed different opinions. With the Maximum Likelihood test, parameters of distributions and mean values were estimated for nine weighting criteria. Social asset evaluation focusing on degree of rurality and social capital index further sorted counties with higher community acceptance and economic viable. A total of 15 counties were selected with highest potential for biorefinery sites.

2.1 Introduction

To mitigate the challenges of energy security and increasing greenhouse gas emissions associated with burning fossil fuels, alternative energy sources such as biomass energy should be considered. Renewable energy from biomass has shown its potential to supply energy with a near carbon-neutral manner of greenhouse gas emissions (EIA 2019a; EIA 2019b), and create opportunities for rural development goals. According to EIA's Energy Review (2019c), renewable energy usage has increased to 20% of the overall energy consumption in the U.S., and biomass-based energy accounts for 44% of all renewable energy. Recent studies have highlighted the use of lignocellulosic biomass (e.g., perennial grasses, short rotation woody crops, forest residues) as feedstock for biofuel, bioproducts, or for bioenergy production (Jonker et al. 2016; Liu et al. 2017; Hanssen et al. 2019). However, to realize the transformational potential of these science and engineering breakthroughs, biofuel production technologies must be equally compatible with regional feedstock availability, transportation infrastructure, and relevant community assets.

Due to spatial dispersion of biomass, high transportation cost of the feedstock, and the possible negative environmental impacts for producing cost-effective bioproducts (Thomas et. al. 2013; Ruiz et al. 2013), selecting the optimal locations of the facility play a critical role in the biomass utilization supply chain (Gold and Seuring 2011). Siting bioenergy plants in optimal locations at optimum capacities is a challenging task. Due to high geographical dependence of many factors associated with optimal siting, the application of spatial information technologies such as remote sensing and geographical information system (GIS) have become important tools.

Determining the suitability of different locations for biomass-based facilities, and finding an optimal solution are the two prime aspects of optimum facility location analysis. Usually, the strategy of selecting suitable locations involves multiple criteria including economic and environmental impacts. A conventional way to select the facility locations is to use drawing and calculation tools (De Smith et. al. 2007), which is generally time and resource consuming. Single facility location decisions can be made by using a center-of-gravity approach as described by Drezner and Wesolowsky (1980). On the other hand, multi-facility location selection produces multiple solutions, including alternative location allocation, projection, p-median, genetic search, and different variable neighborhood searches (Brimberg et al. 2000). Drezner and Wesolowsky (1991) developed an approach to identify a single facility location with minimizing cost, using mathematical model to solve an objective function. In another study, a multiple-facility locating problem was solved by using p-median models, considering the uncertainty of demand over time (Drezner 1995). These methods use both quantitative and qualitative analyses in selecting locations without taking any advantages of spatial data features of the sites.

GIS-based methods can handle both spatial and non-spatial data. GIS-based methods have been used for various site selection applications. For example, McBean et. al. (1995) used both vector and raster data to define the location of a landfill. Other used raster data with Boolean logic map algebra based on suitability of topography and geographic features to make siting decisions (Şener et. al. 2006). Using multiple criteria in site suitability analysis to consider multiple possible conditions can aid decision-making for multi-stakeholder groups (Sharifi et al. 2009). The combination of GIS and multi-criteria decision analysis (MCDA) is an efficient way of assessing land suitability (Gomes and Lins 2002). In fact, this approach of combining different criteria from various disciplines including technical standards, social selection criteria and community acceptance has been used successfully for identifying site locations for landfills (Swallow et. al. 1992). The suitability index, usually calculated by GIS map algebra techniques, represents the relative usefulness for a particular land use. Suitability model can be built by Boolean or index overlay, as well as fuzzy logic. Fuzzy logic deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets (where variables may take on true or false values like Boolean), fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false (Novák, et. al. 2012). Fuzzy logic methods could improve the effectiveness in dealing with the imprecise values of qualitative criteria, compared to conventional approaches to facility location problems (Kahraman, et. al. 2003). One of the important tasks in the suitability analysis is the integration of different preference criteria by providing weight factors to the criteria, which expresses the importance of each factor relative to others. The most common procedure for multi-criteria evaluation is Weighted Linear Combination (WLC). The determination of criterion weights is an important part of this method.

The MCDA provides four methods for assessing criterion weights: ranking, rating, pairwise comparison, and trade-off analysis. One approach of incorporating weighting factor in the preference criteria is by employing the Analytic Hierarchy Process (AHP) introduced by Saaty (1980), and it has particular application in group decision making (Saaty 2008). In the context of AHP, the pairwise comparison technique is used in calculating criteria weights. Pairwise comparison method compares entities in pairs to judge the preferable of each entity, and is an important application of Analytic Hierarchy Process (Kou et al. 2016). Pairwise comparison has the advantage that only focus on the comparison of only two criteria at each time, but requires more comparisons than simply ranking or rating. However, this problem could be solved by integrating a GIS environment (Flitter et al. 2013). An optimal AHP-GIS approach was developed and applied to identify facility locations and scales for the power generation from biomass in Southern Italy (Delivand et al. 2015). GIS mapping techniques were applied to England at national scale, and results of analysis showed the spatial supply and demand relationships for biomass energy potential and identify spatial factors affecting potential generation from bioenergy (Thomas et. al. 2013).

Both social and economic factors and their interactions should be considered in the site selection process. Many researchers have examined the supply chains that link biomass to biofuel facilities using a sustainability approach by incorporating aspects of economic, environmental, and social criteria into their analyses (Raman et al. 2015; Martinkus et al. 2014). The social aspect of sustainability from a biorefinery site selection perspective needs to be focused along with regional feedstock availability and transportation infrastructure. The resistance or enthusiasm of a community could play an important role in determining the ideal location for a new biorefinery. Social capital index provides the positive outcome of human interaction on innovation (Wu, et. al. 2008), which has close associations with acceptance of a new biorefinery plant (Lovrich et al. 2012). The Index of Relative Rurality (IRR) is a continuous measurement of rurality (Waldorf and Kim, 2018), and being rural is an attribute with low economic activities. The new biofuel facilities could result in mitigating rural poverty by providing jobs, as well as direct and indirect economic gains (Martinkus et al. 2014).

Locating optimal sites for bioproduct facility is a complex process involving many factors like environmental, economic, and social constraints. For instance, biomass feedstock availability has significant impact on the location of a bioenergy plant (Delivand et al. 2015). Residents consistently prefer that bioenergy facilities be located a certain distance from residential areas (Ma et al. 2005). In addition, economic factors also play a critical role in determining the viability of potential biomass-based energy projects (Martinez-Gomez et al. 2014). With these restrictions and other considerations on land use, the study area is the northeastern U.S. In addition to abundant forest-based biomass resources, the region has over 2.8 million ha available marginal agricultural land (Skousen and Zipper 2014) and 0.5 million ha abandoned mine land (Drummond and Loveland 2010), respectively. These lands are generally characterized as rocky and sloped soils and are compatible to the development of perennial energy crops such as hybrid willow, switchgrass and Miscanthus. The temperate climate in this region also provides the conditions of producing biomass of higher yield (Somerville et al. 2010).

Therefore, this chapter is to evaluate the potential areas that are suitable for building biomass-based facilities in the northeastern US, considering economic, social and environmental factors. The specific objectives of this study were to: (1) conduct linear fuzzy-logic prediction model and apply site suitability index to identify suitable area for biorefinery facilities in the study area, (2) integrate the analytic hierarchy process (AHP) and stakeholder preferences from survey responses to perform multi-criteria analysis and determine the candidate locations in physical aspect, and (3) combine composite social-economic assessment measurements into the site selection and assess the selected biorefinery locations in Northeast US.

2.2 Methods and Data

2.2.1 Study Area

This study uses the multiple biomass supply chains in the Northeastern United States as a pilot case to illustrate the utility of the approach of integrating biogeophysical and social assets into bioproducts facility siting decisions. An estimated stock of social capital in each US county for year 2014 (Rupasingha, et. al. 2014) was used in this study. The measurement of rurality was the Index of Relative Rurality (IRR) summarized by Waldorf and Kim (2018). The county-level data generated as part of the social asset analysis process were then utilized to facilitate site selection optimization. This approach identifies counties that are “physically” and “socially” best prepared to accommodate potential biorefinery infrastructure/supply chain site development. The schematic overall flowchart of the approach used and implemented in the study is presented in Figure 2.1.

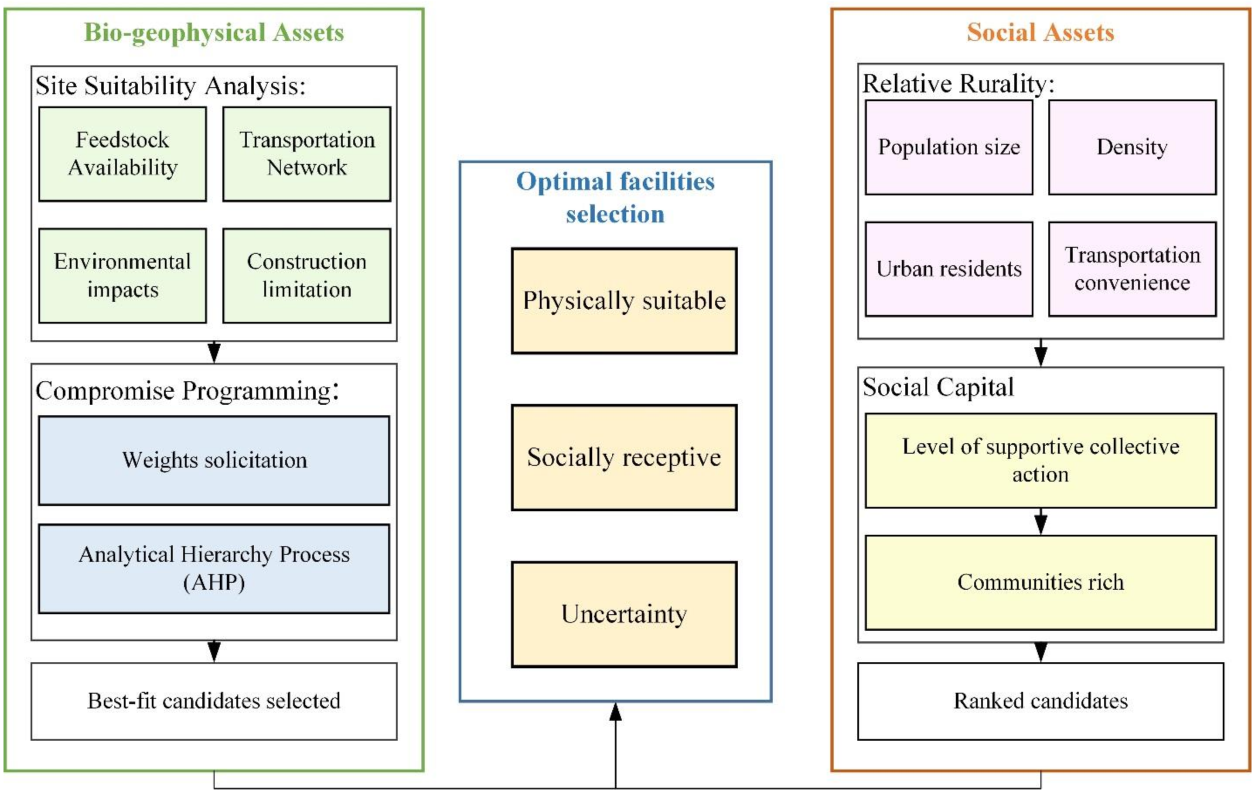


Figure 2.1 Flowchart of the conceptual model for selecting an optimal biomass biorefinery facility location.

The selection process of biomass biorefinery sites includes a GIS-based physical assessment of best-fit candidate selection, and an optimal facility selection from social assets analysis. In the GIS-based assessment phase, a multi-criteria analysis (MCA) is used to integrate the attribute measures for criteria relevant to decision- makers' objectives and measures of decision-makers' preferences. Based on a two-stage multi-objective decision model, a set of potential facility locations and candidate(s) can be optimized. On the other hand, the social asset metrics were used in the evaluation on community collaborative and acceptance of a potential facility biorefinery construction.

2.2.2 Site Suitability Analysis

The physical site selection was completed in a two-stage process that is similar to the method described by Wu et. al. (2011) and Hartley (2014). The process starts with computing the site suitability indices for the entire study area using a linear fuzzy-logic prediction model based on 11 criteria (Table 2.1). The fuzzy logic membership function (realized by map algebra) was used to achieve the site index in range 0-1, in which the smaller number represents the lower suitability and the larger number indicates the higher suitability, and all the index numbers are positive (Wu et al. 2011):

$$SSI = \sum (f_m w_m) * \prod b_n \tag{1}$$

f_m-The value of criteria m,
w_m -The weight of criteria m,
b_n - The criteria score of constraint n.

Where SSI is the site suitability index, f_m is the value of criteria m, w_m is the weight of criteria m and b_n is the criteria score of constraint n. Since the criteria were measured at different scales, the variables were transformed and normalized so that a positive change in a variable is reflected as a positive change accordingly in the suitability outcome.

Table 2.1 Site suitability criteria for biomass refinery facility.

Criteria		Acceptable range
Feedstock availability	Biomass Availability	Less than 80 km
Transportation network	Primary roads	Less than 5 km [a]
Construction limitation	Slope	Less than 10% [b]
	Powerlines	Less than 1.6 km [a]
	Water bodies	Less than 5 km [a]
	Distance from communities	2500-10,000 population less than 1 km; 10,000-20,000 population less than 2.5 km; >20,000 population less than 5 km
	Elevation	More than 100 m [c]
Environmental impacts	Flood Plain	More than 500 m [d]
	Public land	More than 500 m [e]
	Protected Area	More than 1 km [e]
	Wetland	More than 500 m [e]

a. (Koikai 2008)
b. (Stans, Siciliano, and Podesta 1969)
c. (Hendrix and Buckley 1992)
d. (Wu, Wang, and Strager 2011)
e. (Hartley 2014)

To obtain the suitability indices of criteria, fuzzy values of the criteria are used. The input variables for assessing site suitability of biorefinery facility usually consider: (a) feedstock availability; (b) transportation network; (c) construction limitation; and (d) environmental impacts. The site suitability is evaluated to minimize the variable cost and potential negative environmental impacts with considerations of all other related constraints. The variable cost in this study includes cost to purchase and transportation of feedstock and products, utility fee (power lines extension cost, water transportation cost), and cost for possible incidents (flood). The environmental impact could be anything like site and water pollution, and possible damages of wildlife. The variables considered as evaluation criteria are listed in Table 2.1 and were used to construct the fuzzy-logic membership functions, which were expressed as distance metrics and then normalized based on site preference.

The constraint for feedstock availability was based on the area which has feasibility of feedstock transportation. The importance of transportation and logistics in the biomass supply chain has been recognized, and transportation distance is one of the crucial factors affecting the cost of biomass delivery, and bioproducts marketing (Sharma et al. 2017). The transportation cost of processed biomass crops from the harvest site to facility would rise as round-trip distance increase (Kizha and Han 2016). With assuming transportation distance of less than 50 miles (80 km) in the base case (Bain et al. 2003), biomass feedstocks like residues or energy crops could potentially be available for energy uses at a reasonable delivered price.

When applying the suitability model to every layer of suitability analysis for each criterion, each grid/cell on map layer receives 1 or 0 for each variable based on whether the cell met the affirmative conditions of the variable (Heacock and Hollander 2011). For instance, when creating a suitability layer for criterion "biomass availability < 80 km", buffered polygons were created on map to show transport-feasibility zones (that biomass available with procurement distance less than 80 km) around counties with annual biomass availability exceeding 180,000 dry Mg (subject to the facility demand constraint). Therefore, all grids fell in these featured zones are assigned with a feasibility value 1, other grids receive 0. Site suitability is assessed as a function of general physical characteristics, proximity to infrastructure, and presence of utilities, raw materials, environmental factors and economic growth potential. Multiplied by 100 times of the suitability index for each cell, the site suitability index is then reclassified into three categories (non-suitable, low-suitable, and high-suitable) to create a GIS raster layer that can be used for future candidate analysis and selection.

2.2.3 AHP and Weight Solicitation

Analytical Hierarchy Process (AHP) was adopted as a robust and flexible MCDM tool to deal with this complex decision problem. AHP structures the complex decision as a hierarchy of goal, criteria and alternatives, pair-wisely compares elements at each level of the hierarchy with respect to each criterion, and vertically synthesizes the judgements over the different levels of the hierarchy (Sánchez-Lozano et. al. 2016). In this study, AHP was applied criteria weights.

In the context of Analytical Hierarchy Process (AHP), Saaty (2008) developed the pairwise comparison technique, which is used in calculating criteria weights. Compared to point allocation and rank ordering methods, the pairwise comparison has a strong theoretical foundation (Malczewski 1999). Scale of 1 to 9 is usually used in describing the preference. However, in some studies, 3-point weighting scheme based on 1-9 scale is applied to lessen the difficulty defining preferences with slight differences (Strager and Rosenberger 2006).

$$\text{Min}\left\{L_p(A_j) - \left[\sum_{i=1}^{N}(W_i)\left[\frac{(f_i^* - f_{ij})}{(f_i^* - f_i^{**})}\right]^p\right]^{\frac{1}{p}}\right\}$$

$L_p(A_j)$ -Distance metric as a function of the decision alternative A_j and the parameter p;

W_i -The standardized form of the criterion weight;
f_i^* - The ideal or best value for criterion i;
f_i^{**}- The minimum or worst value for criterion i;
f_{ij} – The actual value

In this study, intensity scale was ranging from 1-9 with detailed description showed in Table 2.2. A consistency test was performed to assure that choices were not randomly entered, which is based on whether the consistency ratio (CR) is less than 0.1. Only when there is consistency, the weights are valid with CR smaller than 1. Otherwise, the pairwise comparisons must be redone until the consistency condition is accomplished (Saaty 1980).

Table 2.2 Intensity scale for pairwise comparison and the creation of pairwise matrix.

Intensity	Definition	Explanation
1	Equal importance	Elements A and B are equally important
3	Moderate importance	Elements A is moderately more important than element B
5	Strong importance	Elements A is strongly more important than element B
7	Very strong importance	Elements A is very strongly more important than element B
9	Extreme importance	Elements A is extremely more important than element B
2,4,6,8	Intermediate values	N/A
Reciprocal	Inverse judgment	Element A is less important than element B

To better address the perspective of bioenergy and bioproduct siting selection from expertise in biomass and bioproduction field, a survey was designed targeting to research scientists and bioenergy industry was made and 30 responses were collected in order to compare stakeholders' preferences and summarize criteria weighting scores in overall view.

The weight of each criterion is determined by the pairwise comparison method, which compares each pair of two variables' importance in terms of the plant location selection. To integrate the preferences of the survey participants in the field of biomass, it is important to incorporate the inputs from different stakeholder's groups into the framework model. Preference weights measured for different land management alternatives or conservation criteria can vary significantly across the survey participants and across groups of these participants.

The weights from the AHP were analyzed to test the following three hypotheses: (1) if the individual survey participants could be grouped based on their affiliations, (2) whether the groups' preferences were substantially different from each other, and (3) if different, on which criteria they differed. By default, the weights for all criteria should follow normal distributions with population mean values estimated by sample average values. If the variation in individual responses is great within a group, and the hypothesis of normality fails, a new distribution was fitted and calculated for the expected value to represent the group.

A nonparametric, two-way analysis of variance by Friedman's Q statistic was used to test the differences of preference weights. The null hypothesis for the intra-group comparisons states that the preference of member i in a group (y) was represented by a population (P_y). Here are the alternative hypotheses:

$$H_0: y_i = P_y \quad \forall\, i \in P_y$$

$$H_1: y_i \neq P_y \quad \forall\, i \in P_y$$

And for the inter-group comparisons test whether the preferences comprising a group (P_y or P_z) are from the same population P:

$$H_0: P_y = P_z \quad \forall\, y_i \in P_y;\ z_i \in P_z; y \neq z$$

$$H_1: P_y \neq P_z \quad \forall\, y_i \in P_y;\ z_i \in P_z; y \neq z$$

The test statistic is given by Sheskin (2003). The test is described as given data $\{x_{ij}\}_{n\times k}$ matrix with n rows and k columns, and a single observation at the intersection of each block and treatment, calculate the ranks within each block.

$$Q = \frac{12n}{k(k+1)} \sum_{j=1}^{k} (\bar{r}_j - \frac{k+1}{2})^2$$

$$\bar{r}_j = \frac{1}{n} \sum_{i=1}^{n} r_{ij}$$

The nonparametric Mann–Whitney U-test is used for the differences of preference weights for each criterion across groups (Strager and Rosenberger 2006). The smaller value of U1 and U2 is the one used when consulting significance tables. The sum of the two values is given by Zar(1998):

$$U_1 + U_2 = R_1 - \frac{n_1(n_1 + 1)}{2} + R_2 - \frac{n_2(n_2 + 1)}{2}$$

R 3.5.1 (R Development Core Team 2008) and RStudio software (RStudio Team 2015) were used to aid the computation of both statistics.

2.2.4 Social assets analysis and MCDA

In social asset analysis, data collected at the county level were used to estimate the levels of degree of rurality and social capital for the biorefinery site selection. Degree of rurality was estimated for each county, based on four dimensions: population size, density, percentage of urban residents, and distance to the closest metropolitan area. Its score ranges from -1 to 1, 1 indicating the highest level of urbanization and while -1 representing the highest level of rurality. To specifically promote rural development, counties with scores nearer to -1 of these indices with spatial proximity to biomass sources and related structural assets should be considered as good candidates for biorefinery sites.

Social capital index shows the level of supportive collective action expected from a particular county, and it is measured through voter turnout, census response rate, the number of non-profit organizations, and a general consideration of the number of establishments in religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organization, fitness and recreational sports centers, and population. High social capital index reflects community reciprocity and easier access to human capital (Westlund and Larsson 2016), which can be considered as highly suitable locations.

2.3 Results

2.3.1. Weight solicitation from experts' survey

Multiple surveys were distributed to attendees during the 2017 Northeast Woody and Warm-Season Biomass Consortium annual conference together with the Mid-Atlantic Biomass Energy Conference and Expo in State College, PA, and 20 feedbacks were collected. Other professionals in bioenergy field were also reached in the following months of the conference. Graduate students emphasized in biomaterials, wood science, forestry, logistics modeling in the consortium were surveyed to provide diverse perspectives in biorefinery siting decision. A total of 30 survey responses were collected and categorized into three groups by their employer; 16 of which were graduate students or faculty members in academia, 7 worked for government agencies, and 7 were with biomass energy industries. 30 pairwise comparison matrices in total were created for each survey response. Table 2.3 showed one (out of thirty) pairwise comparison matrix and relative weights.

Table 2.3 Pairwise comparison matrix - an example from the survey.

Criterion	Biomass availability	Distance from main road	Distance from electric substation	Distance to waterbody	Flood risk of potential siting	Adjacent land uses of potential siting	Population in siting area	Landowner-ship	Unemploy-ment rate in potential siting
Biomass availability	1.00	9.00	0.20	9.00	9.00	5.00	9.00	0.20	0.20
Distance from main road	0.11	1.00	0.11	9.00	1.00	1.00	9.00	0.11	9.00
Distance from electric substation	5.00	9.00	1.00	9.00	9.00	5.00	9.00	9.00	9.00
Distance to waterbody	0.11	0.11	0.11	1.00	0.20	1.00	0.20	0.20	0.20
Flood risk of potential siting	0.11	1.00	0.11	5.00	1.00	0.20	1.00	1.00	9.00
Adjacent land uses of potential siting	0.20	1.00	0.20	1.00	5.00	1.00	0.20	1.00	5.00
Population in siting area	0.11	0.11	0.11	5.00	1.00	5.00	1.00	0.20	0.11
Landowner-ship	5.00	9.00	0.11	5.00	1.00	1.00	5.00	1.00	5.00
Unemploy-ment rate in potential siting	5.00	0.11	0.11	5.00	0.11	0.20	9.00	0.20	1.00

Histogram plots of the weighting score frequency failed to support the assumption of normality for all criteria and data was showed skewed. Like normal distribution estimated with parameters scale and shape, Weibull, lognormal, and gamma distributions are all commonly used in reliability and life testing problems for modeling skewed data (Siswadi and Quesenberry 1982). Therefore, Weibull, lognormal, and gamma distributions are used (Figure 2.2). Histograms showed a right skewed trend for “Distance from electric substation”, “Adjacent land uses of potential siting”, “Population in siting area”, and “Unemployment rate in potential siting”, which all showed that the weighting indexes for these criteria are clustered at a relative low level. Small weight score ranges for “Distance from main road”, “Distance to waterbody”, and “Unemployment rate in potential siting”, indicated people who took the survey had similar opinions on these criteria.

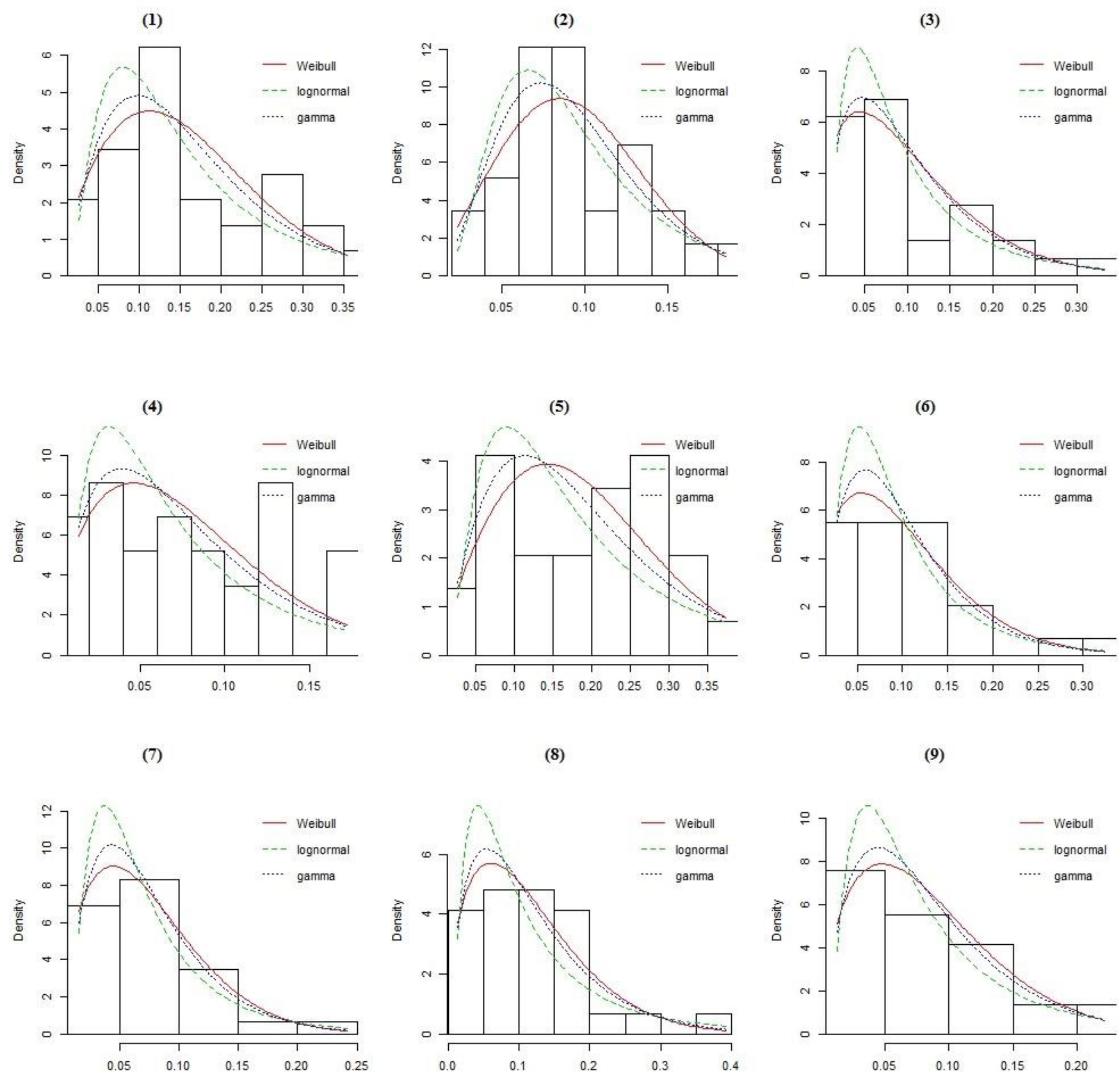


Figure 2.2 Frequency of the weighting scores for 9 criteria from 30 survey responses. From left to right, top to bottom, (1) Biomass availability, (2) Distance from main road, (3) Distance from electric substation, (4) Distance to waterbody, (5) Flood risk of potential siting, (6) Adjacent land uses of potential siting, (7) Population in siting area, (8) Landownership, and (9) Unemployment rate in potential siting

The Friedman's Q statistics for the intra-group comparisons showed that individuals within government agency group had varying levels of weighting preference at 95% significance level. The inter-group comparisons test rejected the hypothesis that all three groups are from the same population and significant differences showed in every paired groups with p-values all less than 0.05 (Table 2.4).

Table 2.4 Comparisons of intra-group and inter-group differences.

Group	Friedman chi-squared statistic	p-value
	Intra-group comparison	
Academia	12.776	0.1198
Government Agency	17.489	0.0254**
Industry	14.32	0.0738*
	Inter-group comparisons	
Academia vs. Government Agency	25.509	0.001274***
Academia vs. Industry	21.347	0.006281**
Government Agency vs. Industry	26.52	0.0008552***

*significant at p<0.1, ** significant at p<0.05, *** significant at p<0.005.

The weight scores were examined and varied by groups for nearly all criteria (Figure 2.3). By examining the pattern of single weighting values in each group, we found the opinions from the academic group were variable. Experts in government agencies and industry both agreed with a higher importance for "Biomass availability" and "Flood risk of potential siting", compared to opinions from academic people. Different from government and academic experts, industry people recognized criteria "Distance to waterbody" and "Unemployment rate" should have a higher weighting score in biorefinery selection. Participants of university professors and students viewed "Distance from electric substation" should be more important, and industry respondents admitted that "Landownership" is a critical factor. In average, similar weighting scores showed for “Distance from main road”, “Distance from main road”, and “Population in siting area” among all three groups.

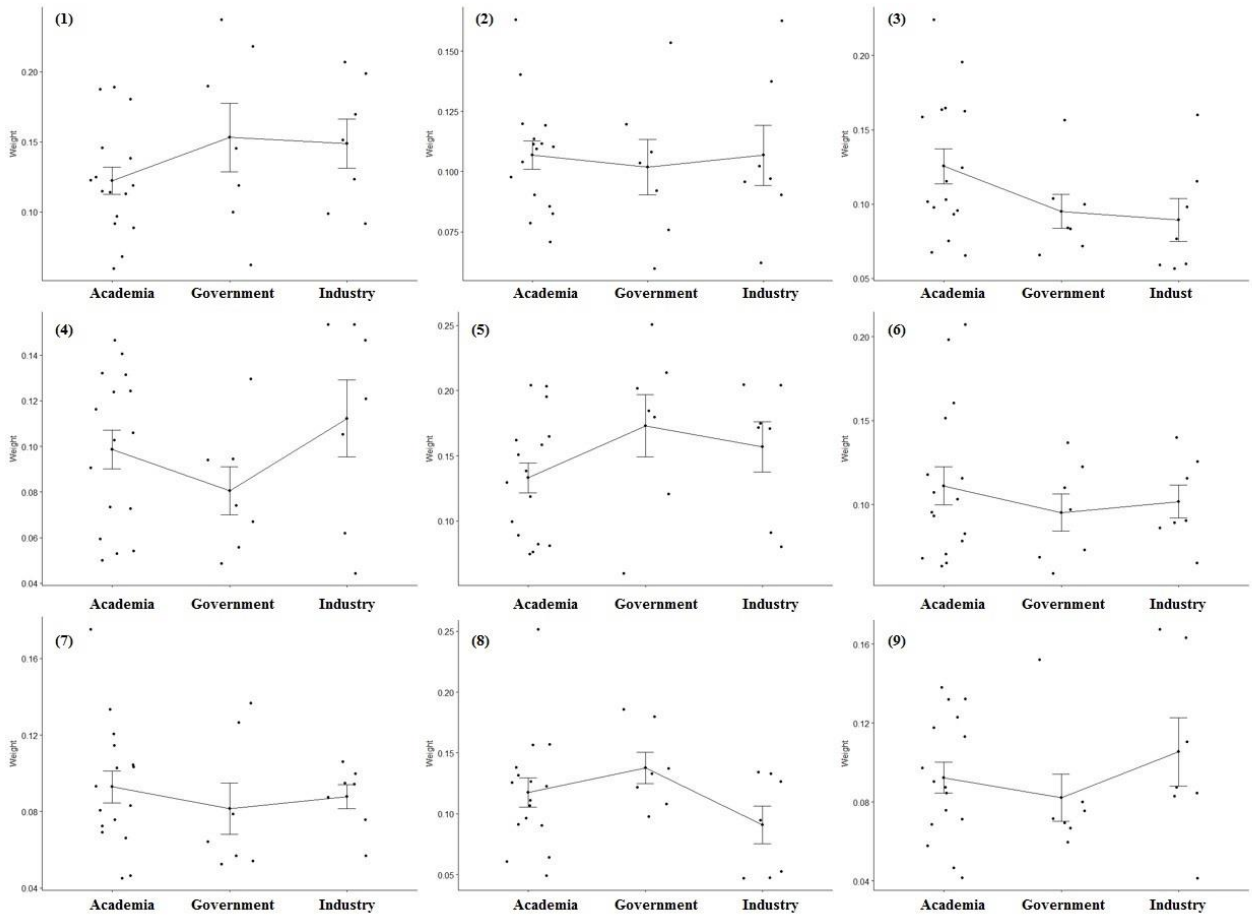


Figure 2.3 Weight scores comparison by survey groups. From left to right, top to bottom, (1) Biomass availability, (2) Distance from main road, (3) Distance from electric substation, (4) Distance to waterbody, (5) Flood risk of potential siting, (6) Adjacent land uses of potential siting, (7) Population in siting area, (8) Landownership, and (9) Unemployment rate in potential siting.

The statistical difference across groups for each criterion examined by Mann–Whitney U-test indicated that some criteria were statistically different (Table 2.5). Academic and industry responses differed only for one (“Distance from electric substation”, p=0.089) out of the nine total criteria. The only other differences among responding groups were between government agency and industry groups for the criteria of “Unemployment rate” (p=0.091) and for “Landownership” (p=0.082).

Table 2.5 Statistically different criteria and the aggregated group weights.

Criterion	Academia	Industry
Distance from electric substation	0.12553334	0.08946275*
	Government Agency	Industry
Landownership	0.13768094	0.09090278*
Unemployment rate in potential siting	0.08222107*	0.10541657

*significant at p<0.1.

By further examining the fitness for these criteria using Cullen and Frey graphs of the R package fitdistrplus (Delignette-Muller et al. 2018), we found that the criteria “Distance from electric substation” and “Unemployment rate in potential siting” fell into the lognormal distribution, and “Landownership” fitted well to loglogistic distribution (Figure 2.4).

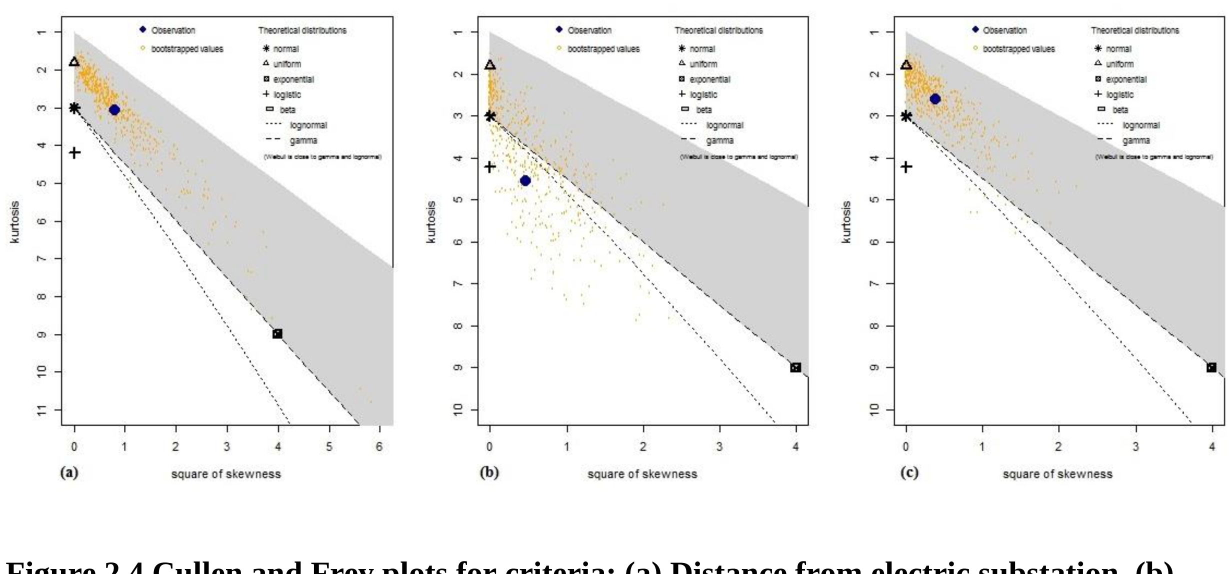


Figure 2.4 Cullen and Frey plots for criteria: (a) Distance from electric substation, (b) Distance from electric substation, and (c) Unemployment rate in potential siting.

With the Maximum Likelihood test, parameters of those distributions were calculated, and the expected values for all these criteria were derived accordingly (Table 2.6). It is showed that the weight score for "Distance from electric substation" is 0.1097, for "Unemployment rate in potential siting" is 0.1149 and 0.0932 for criteria "Landownership".

Table 2.6 Parameter adjustments for non-normal distributions with Maximum Likelihood test.

Criteria	Distribution	Parameter		Expected value
		Mean_log	**SD_log**	
Distance from electric substation	lognormal	-2.2795513	0.3760556	0.1096851
Unemployment rate in potential siting	lognormal	-2.4422441	0.3716554	0.1148819
		location	**scale**	
Landownership	loglogistic	0.11485348	0.02429281	0.09327594

A pairwise comparison matrix was created to reflect the preference or importance of the evaluation criteria in the suitability model. The normalized weights are listed in Table 2.7. The weights and tests for inconsistency were derived using the eigenvector method. All CR values are lower than 0.1, and therefore the evaluations of these criteria are consistent. Flood risk of potential siting has the highest weight value (0.1534), which was the most critical factor affecting a biorefinery plant location. Biomass availability (0.1405) was the second most important factor. The population near a siting area (0.0869) was the lowest weighted factor.

Table 2.7 Pairwise comparisons of the relative weights of the variables.

Criterion	Adjusted weight index
Flood risk of potential siting	0.1534
Biomass availability	0.1405
Unemployment rate in potential siting	0.1142
Distance from electric substation	0.1091
Distance from main road	0.1045
Adjacent land uses of potential siting	0.1021
Distance to waterbody	0.0966
Landownership	0.0927
Population in siting area	0.0869

2.3.2. Suitability analysis and reclassification

Boolean values (0 and 1) were assigned to the general conditions of feedstock availability, transportation network, construction limitation (slopes, elevation, utility, and water body), and environmental impact factors (floodplain, public land, protected area and wetland area). Slope and elevation were derived from an elevation dataset using GIS surface analysis and reclassified into two categories (suitable and non-suitable) on the basis of site preferences. The site suitability index (SSI) in the study area computed using GIS based spatial analysis ranged from 25 to 101 for each county.

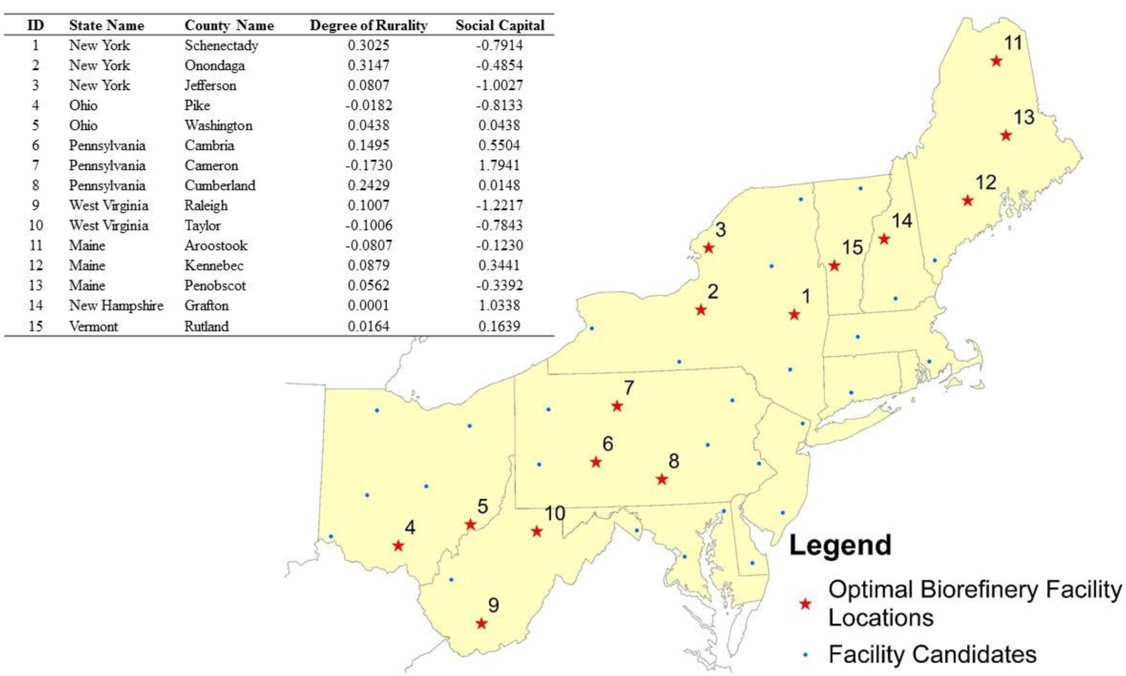
Figure 2.5 Candidate locations selected from suitability analysis.

In Figure 2.5, the SSI was then grouped into three categories by the Quantile classification method: low-suitable (25-50), moderately-suitable (51-75), and high-suitable (76-101). The zonal statistics indicated that the average distances of each alternative site to the desired location with consideration of spatial features and related criteria were between 32.53 km and 133.54 km. In 387 counties in the Northeast US, 155 counties are in low-suitable category, 189 counties are in medium-suitable category while 43 counties are in high-suitable category and were selected for further analysis.

2.3.3. Siting candidates based on social assets analysis

The degree of rurality for the entire United States ranged from -0.7800 to 0.9220 with an average of 0. In Northeast region was ranged between -0.22 and 0.92. Different from the large variation showed nationally, the social capital indices in the study area trended very close to the mean value 0 and ranged from -2.47 and 2.57. The degree of rurality and social capital index for 43 potential candidates with high suitability to build a biorefinery facility, were then ranked and summed into a single social asset ranking with equal weights.

An overall ranking for all selected facility locations were summarized with physical asset occupied 70% of importance and social asset is with 30% of weight. Fifteen out of 43 sites were selected based on social asset factors: degree of rurality and social capital scores (Figure 2.6).



ID	State Name	County Name	Degree of Rurality	Social Capital
1	New York	Schenectady	0.3025	-0.7914
2	New York	Onondaga	0.3147	-0.4854
3	New York	Jefferson	0.0807	-1.0027
4	Ohio	Pike	-0.0182	-0.8133
5	Ohio	Washington	0.0438	0.0438
6	Pennsylvania	Cambria	0.1495	0.5504
7	Pennsylvania	Cameron	-0.1730	1.7941
8	Pennsylvania	Cumberland	0.2429	0.0148
9	West Virginia	Raleigh	0.1007	-1.2217
10	West Virginia	Taylor	-0.1006	-0.7843
11	Maine	Aroostook	-0.0807	-0.1230
12	Maine	Kennebec	0.0879	0.3441
13	Maine	Penobscot	0.0562	-0.3392
14	New Hampshire	Grafton	0.0001	1.0338
15	Vermont	Rutland	0.0164	0.1639

Figure 2.6 Optimal biorefinery facility locations selected from biophysical assets and social assets with social asset scores.

2.4 Discussion

2.4.1. Differences of survey respondents in biorefinery siting selection

To estimate the mean value of a population that might not be normally distributed, the sample size should be sufficiently large and is usually greater than 30 samples (Israel 1992). In this study, the population mean was estimated based on a survey of 30 samples since these random samples could be approximately normally distributed according to the central limit theorem.

For comparisons among the three groups of respondents in the survey, each sample group had a relatively small size of samples, which was 16, 7 and 7 surveys for academia, government agencies, and biomass energy industries groups, respectively. Thus, parametric tests are not very robust to deviations from a Gaussian distribution with small samples and would be seriously affected by outliers. By applying the so-called distribution-free tests based on fewer assumptions, nonparametric tests were applied to compare among these three groups (Wobbrock et al. 2011). Specifically, Friedman test was used to test the differences of preference weights inter- and intra-groups while Mann-Whitney test was applied instead of two-sample t-test in parametric analysis to analyze the differences of preference weights for each criterion across groups.

The differences from the Friedman's Q statistics for the intra-group comparisons, could be caused by the participants' area of expertise that was reflected in their preference weights for the various criteria among the three groups. Therefore, individual participants from academia and industry were confirmed based on their homogeneity of preferences. The participants from the government agencies were categorized as a group more than who they represented for the homogeneity of their preferences.

2.4.2. Uncertainty in biorefinery siting

The variations in feedstock availability, biomass price, and many other parameters are among the major challenges in biorefinery siting selection. Even though a majority of recent studies on bioproduct facility siting and supply chain design assumed all the parameters in the system are known, there is a high level of uncertainty that can be encountered in practices. By considering cost efficiency, uncertainty of biomass feedstocks supply chain would have great impacts on feedstock delivery costs, and locations of a biorefinery facility would be affected when optimizing facility siting. Uncertain supply of biomass occurs because of many variables are comprised in the supply chain system. Biomass availability could be influenced by terrain, spatial location, harvest type and machinery combination, as well as weather conditions. The great variation in biomass supply due to seasonal harvest operation and environmental conditions may influence the facility location by reducing the demands.

There is a large amount of forest residue potentially available, and it is also promising to grow energy crops like shrub willow, switchgrass, or Miscanthus to alleviate the potential risk of biomass supply. However, costs in biomass supply chain are primarily affected by feedstock types due to different harvest and establishment systems. Facility locations with sufficient biomass supply are important in siting optimization, where feedstocks have higher yield rate and harvest efficiency. Price of fossil fuels like diesel would have impacts on both delivery costs and the economic feasibility of bioproducts. Based on our previous study, a change of $0.10 per liter diesel fuel would positively affect biomass delivery cost with an increase of $0.17 per dry Mg (Wang et al. 2019).

In addition, the uncertainty on selling price of biofuel, and logistic costs including transportation and operation costs related to the feedstock preparation at the field will directly impact the biomass supply chain system including both measurable and unmeasurable parameters. In this study, to improve the model's accuracy, measurable features such as "biomass availability", "distance from main road" were taken into consideration in the weighting criteria. However, some unmeasurable criteria like "stakeholder's lifestyle", or "sustainable levels" that cannot not be considered in the model due to related data availability, could have affected the spatial sensitivity to siting preference differences.

2.4.3. Social impacts in biorefinery siting decision process

Social assets analysis can further aid the siting decision process to optimize facility locations by potentially promoting rural development in supportive communities. To specifically support rural community development, a higher level of rurality and social capital index was used in ranking the most suitable locations. In this case, besides boosting rural economy, the investor might be also aware of situating a biorefinery plant near densely populated areas. But in some other cases, in an attempt to minimize the transport costs of moving bioproducts from a plant to final distribution centers or urban transit depots, the site would ideally not be far from major cities. An additional consideration should focus on the land type of a rural area. In some rural areas, the land mainly covers with biomass feedstocks, facilities could be possibly located around with low population density. But in some rural areas with majority characterized by natural areas with recreation and tourism as important economic drivers, decisions for biorefinery location should be more concerned about environmental amenities endangered and potential effects on tourism. At the local community level, biorefinery facility siting decisions should be made with consideration of the compatibility of the existing social and cultural assets of the people residing in those areas, along with the physical accessibility (Gomes and Lins 2002). The social asset scores utilized in this analysis provided better comparison and assessment of potential facilities while still accounting for regional differences that are better indicators of success between facilities in the region of interest. Social capital index can be higher even in rural regions due to a larger number of non-profit or social organizations. There should be less variation in both degree of rurality and social index for areas with high suitability to build a bioproduct facility. It implies that the suitability analysis can successfully filter candidate areas with potentials to be selected as biorefinery sites with homogeneous physical attributes.

2.5 Conclusions

The integrated physical and social assets analysis for biomass supply chain siting decisions fills the gap between spatial analysis-based facility siting and the lack of evaluation of the socioeconomic viability. A fuzzy-logic prediction model incorporating AHP is a viable tool to predict the site suitability index of county level or a smaller grid. Experts' opinions surveyed to leverage the experience in biomass energy and bioproducts increased the robustness of the weighting solicitation of evaluation criteria. Different from a single objective optimization analysis, multi-criteria decision-making method was applied in this study to solve the multi-objective problem in biorefinery siting selection and analyses all the trade-offs into the decision-making procedure of facility site selection.

The 43 counties or sites resulted from the suitability analysis in Northeast US could be used as potential candidates for biorefinery facilities in the region. When considering the social asset impacts, 15 locations were further identified for regional economic development featuring both environmental and social assets and impacts. The biomass-based biofuel/bioproduct plant location optimization provides the basis for the commercialization of biomass to bioenergy products. The modeling process and findings of this study could be employed in the community engagement efforts to promote the rural economic development in the northeastern U.S.

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3. OPTIMIZATION OF HARVEST AND LOGISTICS FOR MULTIPLE LIGNOCELLULOSIC BIOMASS FEEDSTOCK IN THE NORTHEASTERN UNITED STATES[2]

[1] Published in Energy, 197 (April). https://doi.org/10.1016/j.energy.2020.117260.

Abstract:

A mixed-integer linear programming model was developed to optimize the multiple biomass feedstock supply chains, including feedstock establishment, harvest, storage, transportation, and preprocessing. The model was applied for analyses of multiple biomass feedstocks at county level for 13 states in the northeastern United States. In the base case with a demand of 180,000 dry Mg/year of biomass, the delivered costs ranged from $67.90 to $86.97 per dry Mg with an average of $79.58 /dry Mg. The biomass delivered costs by county were from $67.90 to 150.81 per dry Mg across the northeastern U.S. Considered the entire study area, the delivered cost averaged $85.30 /dry Mg for forest residues, $84.47 /dry Mg for hybrid willow, $99.68 for switchgrass and $97.87 per dry Mg for Miscanthus. Seventy seven out of 387 counties could be able to deliver biomass at $84 per dry Mg or less a target set by US DOE by 2022. A sensitivity analysis was also conducted to evaluate the effects of feedstock availability, feedstock price, moisture content, procurement radius, and facility demand on the delivered cost. Our results showed that procurement radius, facility capacity, and forest residue availability were the most sensitive factors affecting the biomass delivered costs.

3.1 Introduction

Biomass utilization for bioenergy and bioproducts continues to grow due to environmental concerns of fossil fuel uses and rural development. With the need that biomass resources can be harvested and collected sustainably and should not compete with the food chain, forest residues, energy crops, and poultry litter are all viable biomass resources for energy.

Forest residues produced during timber harvesting is one of the important feedstocks for biofuels and bioproducts (Wu et al. 2010), with the potential to sufficiently produce 12 to 16 billion gallons of ethanol annually in the U.S. (Buchanan 2010). Hanssen et al. (2019) also showed that forest residue could play a large role in bioenergy supply with its cost-competitive attribute and potentially fulfill up to 50% of the total second-generation bioenergy demand by 2050. Perennial grasses, and short rotation woody crops can be grown on marginal agriculture land or disturbed mine land in the northeastern U.S (Lewandowski et al. 2003; Volk et al. 2006). Different from conventional woody biomass, growing energy crops on abandoned mine and marginal agricultural lands should help improve land uses from environmental protection perspective as well as filling the gap between insufficient supply of forest residues as biomass feedstock and the demand of a medium- to large-size biorefinery. The native perennial warm-season grass in northeastern United States, such as switchgrass ($Panicum\ virgatums$) and Miscanthus ($Miscanthus \times giganteus$), whose production is characterized by low fertilizer and pesticide requirement (Lewandowski et al. 2000), can be also used as an energy crop with high productivity and low maintenance cost (Stoof et al. 2015), especially for sustainable biomass production (Varnero et al. 2018). Short rotation hybrid willow also has the great potential to use as a feedstock for value-added bioproducts in the northeastern U.S. (Wang et al. 2006; Wu et al. 2012; Liu et al. 2017a). A number of trails for woody crops like shrub willow

($Salix\ sp$.) have been established with various breeding at multiple locations, and related studies are being developed at large scales (Volk et al. 2018). A techno-economic analysis that provides uncertainty of net present value (NPV) and minimum selling price (MSP) in bioenergy on shrub willow production could help promote the real-world applications (Frank et al. 2018).

Effective biomass harvest and logistics are the key to the success of biomass energy and bioproducts industry. A biomass supply chain typically consists of biomass feedstock establishment, harvesting, storage, transportation, preprocessing and conversion (Liu et al. 2017a). Biomass supply chain optimization is one way to improve the effectiveness of biomass logistics and involves simultaneous considerations of multiple supply chain components such as biomass cultivation and production facilities along with biomass flow through the chain. For example, an application of IBSAL simulation model for warm-season grass showed that supply chain optimization could decrease the baling cost by 21% and CO_2 emissions by 27% (Lautala et al. 2015). Jonker (et al. 2016) also indicated that supply chain optimization of sugarcane-based ethanol production in Brazil could reduce the production costs by 20.1% for first generation and 14.5% for second generation, respectively. Biomass supply chain optimization may vary according to stakeholders' needs, which usually have direct relationship with supply chain performance measures. The delivered cost of biomass is one of the most important measures (Neely 1995), subject to various environmental and operational constraints.

Feedstock cost is an important component when producing renewable biomass-based biofuels, and improvement of biomass logistics would dramatically boost the economic viability for bioproduction (Atashbar et al. 2018). Mathematical programming has long been used in optimizing forest and biomass supply chain management problems. One of the many challenges in biomass-to-bioenergy supply chain optimization, is to consider as many variables as possible in the entire supply chain that could lead to a really complicated problem (Yue et al. 2014). The mixed-integer linear programming (MILP) is being popularly employed in biomass logistics modeling with considerations of economic, environmental, and social impacts (Kim et al. 2011; Huang et al. 2010; Elia et al. 2013; Parker et al. 2010; Giarola et al. 2011; You et al. 2012).

A two-step process supply chain of biomass-based biofuel via fast pyrolysis and Fischer-Tropsch was modeled using the mix integer linear programming, including analysis of optimal design of biomass supply chain networks, optimized biomass locations and amounts, candidate sites and capacities for conversion, and the logistics of transportation in the Southeastern region of the United States (Kim et al. 2011). An ethanol supply chain was examined using a mixed integer linear programming model in multiple stages to minimize the total system cost for biomass feedstocks over the entire planning, demand, resource, and technology constraints (Huang et al. 2010). A mixed integer programming model was developed by Wu (2011) to minimize the delivered cost of woody biomass in central Appalachian region. They found that optimal plant location and minimum woody biomass delivered cost were closely associated with biomass handling systems. Zhang et al. (2013) studied switchgrass-based bioethanol supply chain in North Dakota at county-level using a MILP model. A MILP problem was also solved to identify biorefinery locations and make harvest/transportation decisions by maximizing net present value in the midwestern US, with uncertainty analysis emphasizing only on production aspects (Marvin et al. 2012). A MILP modeling process was also used in examining the economic and environmental benefits of utilizing energy crops in the northeastern United States. A techno-economic analyses were conducted for three feedstocks and three different bioproducts, along with the supply chain components. Up to 50% of the total cost was associated with the expenses of capital, operation and maintenance, while other costs included transportation, feedstock development (Liu et al. 2017a). Another study by Liu et al. (2017b) analyzed the economic feasibility and environmental benefits of converting coal and biomass to liquid fuels (CBTL), a mixed integer linear programming model was developed to conduct economic feasibility analysis, and results showed required selling price changed based on the differences of biomass to coal mix ratios, as well as the change of internal rate of returns. Although mathematical programming was usually involved for multi-criteria decision analysis (Atashbar et al. 2018), other analysis methods such as Geographic Information Systems (GIS) can also be a great supplement to solving multi-criteria decision problems. A biomass harvest and logistics system was developed by Karkee (2016) to apply a mixed integer non-linear programming model for management of switchgrass and corn/corn stover without consideration of storage cost. To address new perspectives in the multi-criteria decision-making process, the GIS-based analysis with mapping can help better understand the complexity of location-oriented problems and specific characteristics of these locations for biomass production and biorefinery (Ki 2018).

There are various feedstocks available in the Northeastern U.S. including high productivity perennial grasses, short rotation woody crops such as hybrid willow, and forest residues. To facilitate the regional rural economic development, there appears a necessity to further analyze multi-biomass feedstock supply chains in the northeastern U.S. Therefore, the objectives of this study were to (1) develop a mixed integer linear programming model to optimize multiple biomass feedstock harvest and supply chains logistics, (2) quantify and map the delivered costs of biomass feedstocks with regional case scenarios, and (3) conduct sensitivity analyses of the multiple feedstock harvest and logistics according to biomass availability, harvest rate, moisture content, procurement radius, and facility capacity.

3.2 Mathematical Model Development

A typical supply chain for multiple biomass feedstocks and the potential pathways include the following components: feedstock development, harvesting, storage, transportation, preprocessing, and conversion (Figure 3.1). The incorporation of multiple feedstocks into a single supply chain will improve the temporal supply of feedstocks, reduce the procurement radius needed to supply a facility and reduce the overall delivered cost.

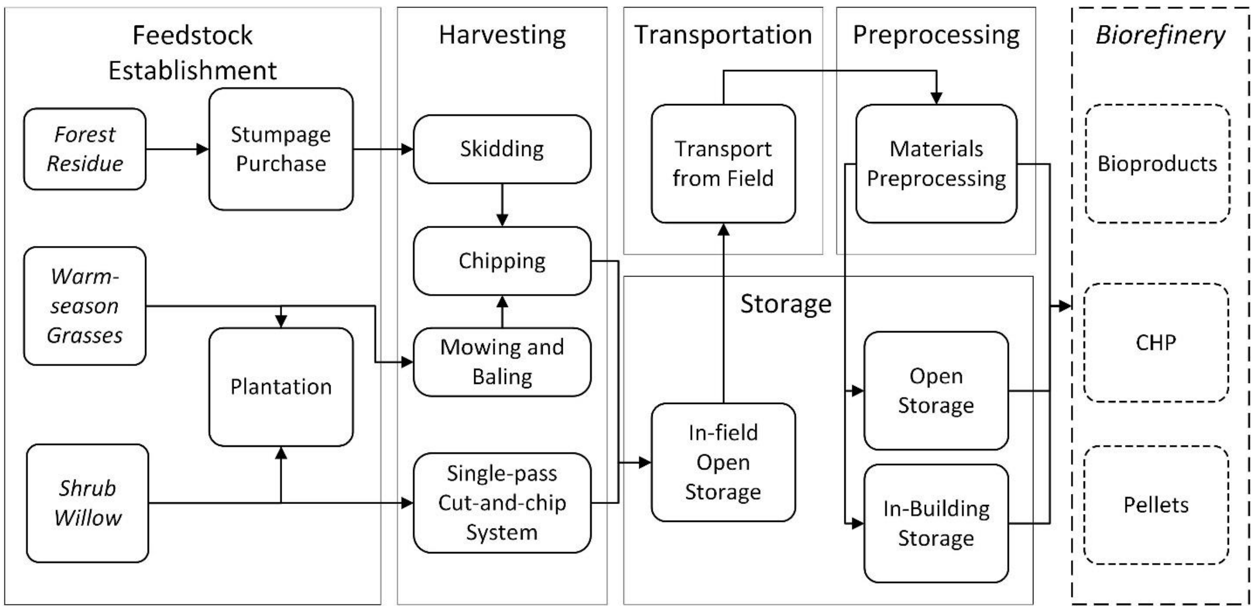

Figure 3.1 Multiple biomass feedstock supply chains in the northeastern U.S.

The multiple-feedstock harvest and logistics optimization is formulated as a mixed integer linear programming (MILP) model. The objective is to minimize the total delivered cost of biomass from biomass production site to the gate of a biorefinery facility with considerations of the number, location, and size of processing facilities, biomass availability and the amount of materials to be transported from the various supply nodes to optimized facility locations of the configured biomass supply chains.

3.2.1 Objective function

In this multiple feedstock supply chain, both woody and herbaceous materials are considered as feedstocks including forest residues, short rotation willow, switchgrass and Miscanthus. The objective of this mixed-integer linear programming model is to minimize the delivery cost of multiple feedstocks biomass along supply chains:

$$Min\ \mathrm{Z} = \alpha + \beta + \gamma + \delta + \theta \tag{1}$$

Where

Z – Delivered cost of biomass feedstock

α – Cost of feedstock establishment

β – Biomass feedstock collection cost

γ – Storage cost of biomass feedstock

δ – Transportation cost of biomass feedstock

θ – Preprocessing cost

For field handling of biomass, there are two parts: energy crop establishment or forest residues stumpage, and collection operations. In this model, the investment in crop establishment has calculated based on biomass grower payment as dollars per dry ton, and different handling systems are considered for each feedstock type. Feedstock establishment processes are similar among energy crops such as willow, switchgrass and Miscanthus, which consist of planting, fertilizing, weed clearing, etc. For forest residues, stumpage value was considered as the establishment cost substitute. Specifically, for forest residue stumpage, it is an estimated value that landowners would accept to trade the right to harvest for revenues with any private firms. Forest residues produced during forest operations were collected in three collection scenarios: whole-tree chipping, chipping of extracted residue, and integrated timber production and residue chipping. Both cable skidder and grapple skidder were considered for residue extraction. The feedstock establishment and harvest costs were calculated using the following equations:

$$\alpha = \sum_{t=1}^{T} \sum_{i=1}^{I} QE_{ti} * EC_t \tag{2}$$

$$\beta = \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{i=1}^{I} QH_{mti} * HC_t \tag{3}$$

To ensure a continuous, sufficient supply of feedstocks in bioenergy production, it is important to store biomass appropriately at certain locations relative to feedstock production and biorefinery sites (Inman et al. 2010). Biomass feedstock, especially seasonal crops are harvested in specific seasons each year. There is a storage need for biomass, to meet the production demand over the year (Rentizelas et al. 2009). The storage of biomass can occur at several locations along the supply chain, and suitable storage areas could be on the site or at a depot (Hoyne and Thomas 2001). At the harvest site, biomass can be stored at the landing for further transport. An intermediate facility that stores biomass before transportation to a conversion facility is another option (Eranki et al. 2011), but with a big amount of capital investment. The total storage cost consists of two parts: in-field storage costs of all biomass supply locations, and inventory costs in preprocessing facilities of each feedstock types along a year. Feedstock storage cost is expressed in equation (4):

$$\gamma = \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{i=1}^{I} QS_{mti} * SC_t + \sum_{m=1}^{M} \sum_{t=1}^{T} QIVD_{mt} * IDC \tag{4}$$

Feedstock transportation cost includes the cost of transporting feedstock to preprocessing facilities and the cost of from preprocessing facilities to conversion plants (Melero et al. 2012). Feedstock is transported mainly in three ways: (1) from collection sites to storage places or landing; (2) to the facilities for preprocessing; (3) to the conversion facilities. Hauling distance, along with feedstock mass and volume are the main economic factors affecting transportation cost. Three components were taken into consideration into transportation cost, which are feedstock transported directly to the preprocessing facility, transported from storage site to preprocessing facilities, and preprocessed feedstock transported to conversion plant. The biomass transportation cost can be calculated with the following equation (5):

$$\delta = \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{I}(QHD_{mti} + QSD_{mti}) * D_{ij} * tr + \sum_{m=1}^{M} QDC_m * tr * D_0 \tag{5}$$

Size reduction of biomass such as chipping and grinding is one of the most common preprocessing methods to improve transportation properties (Yancey et al. 2013). Generally, chipping or baling can be done at the harvesting site. Reducing moisture content of biomass that involves letting biomass dry in the field, on the landing, or in a satellite yard prior to delivery to the plant (Uslu et al. 2008), can also improve the biomass transportation. In this study, the feedstock preprocessing cost is expressed as:

$$\theta = \sum_{m=1}^{M}\sum_{t=1}^{T}(QD_{mt} * CC_t + QD_{mt} * DC_t) \tag{6}$$

3.2.2 Constraints

The objective function is subject to the following constraints:

a. Feedstock availability

In each year, there should be certain amount of feedstock available biomass t in county i so that the quantity of harvested feedstock at supply location i for each biomass type t will not exceed its availability.

In each year, there should be certain amount of feedstock available biomass t in county i so that the quantity of harvested feedstock at supply location i for each biomass type t will not exceed its availability.

$$\sum_{m=1}^{M} QH_{mti} - AVAL_{ti} * p_{ti} \leq 0 \,, \qquad \forall t, i \tag{7}$$

In each specific time period, the quantity of feedstock harvested in month m at supply location i cannot be greater than the quantity of available feedstock during this specific period.

$$QH_{mti} - AVAL_{ti} * p_{ti} * \gamma_{mt} \leq 0, \qquad \forall\, m, t, i \tag{8}$$

b. Biomass material balance along supply chain

In each month m, amount of harvested feedstock should be less than or equal to the amount of feedstock established or its yield.

$$QE_{ti} \geq QH_{mti}, \qquad \forall m, t, i \tag{9}$$

After harvesting, a certain proportion of harvested biomass will be directly transported to a preprocessing facility without storage process, and the rest of it will be stored on landing or in an intermediate storage. In month m, the amount of harvested feedstock transported to preprocessing facilities and to storage sites cannot exceed the total amount of harvested feedstock. The loss of feedstock due to degradation from on-site storage was also taken into consideration with a monthly dry-matter loss rate DM_t of each feedstock types. An estimate of matter loss during storage was considered into the supply chain balance, and 4.5% of mass loss per month for aerated unprotected chips (Eisenbies et. al. 2016), and 2% of mass loss per month for perennial grass bales (Sanderson et.al. 1997).

$$QH_{mti} - QHD_{mti} - QHS_{mti}(1 + DM_t) \geq 0, \qquad \forall m, t, i \tag{10}$$

The amount of the quantity of biomass stored in previous months and the quantity of biomass transported from harvesting, less than the quantity of feedstock transported to preprocessing facilities, should be greater than or equal to total amount of the quantity of biomass feedstock stored in month m.

$$QS_{(m-1)ti} + QHS_{mti}(1 + DM_t) - QSD_{mti}(1 + DM_t) \geq QS_{mti}, \forall\, m, t, i \tag{11}$$

At a preprocessing facility, biomass feedstock can be transported to a refinery facility either directly after harvesting or from an on-landing storage site. In the processing facility, inventory of feedstock and moisture content should be taken into consideration. The total quantity of biomass inventory at a preprocessing site and the newly-come biomass in month m, should be greater than or equal to the quantity of feedstock transported to a conversion plant.

$$\sum_{t=1}^{T} QD_{mt} * (1 - mc_t) - QDC_m * (1 - mc_0) \geq 0\,, \qquad \forall m \tag{12}$$

$$QIVD_{(m-1)t} - QIVD_{mt} + \textstyle\sum_{i=1}^{I}(QHD_{mti} + QSD_{mti}) - QD_{mt} \geq 0,\ \forall m, t \tag{13}$$

Quantity of feedstock transported from the preprocessing facility and the feedstock inventory at the conversion plant should be no less than the required amount for production each month.

$$\left(QDC_m + QIVC_{(m-1)} - QIVC_m\right)(1 - mc_0) - qc_m\ \geq 0, \forall\, m \tag{14}$$

c. Facility capacity

The quantity of stored feedstock in storage site cannot exceed the storage capacity.

$$QS_{mti} < CAPS_{mti}, \forall m, t, i \tag{15}$$

The amount of feedstock for preprocessing and conversion at a facility cannot exceed the facility capacity.

$$QD_{mt} * (1 - mc_t) < CAPD_{mti}, \forall m, t, i \tag{16}$$

The model was solved using the GAMS/CPLEX solver, and the delivered cost, and quantity of multiple biomass delivered were determined by site and operational factors. To perform MILP optimization with GAMS, a branch and cut algorithm was applied. The process divides the entire problem into a series of LP problems and solves them separately. This algorithm includes: problem size reduction by LP preprocessing, sub-LP problems solution, LP relaxation, and integer-feasible solutions (Mitchell 2002; Albert 2006). To examine solution quality, the proof of optimality is examined by GAMS/Examiner when lower constraint bound equals the upper's bound (Abdelmaguid 2018).

3.3 Methods and Materials

3.3.1 Study area

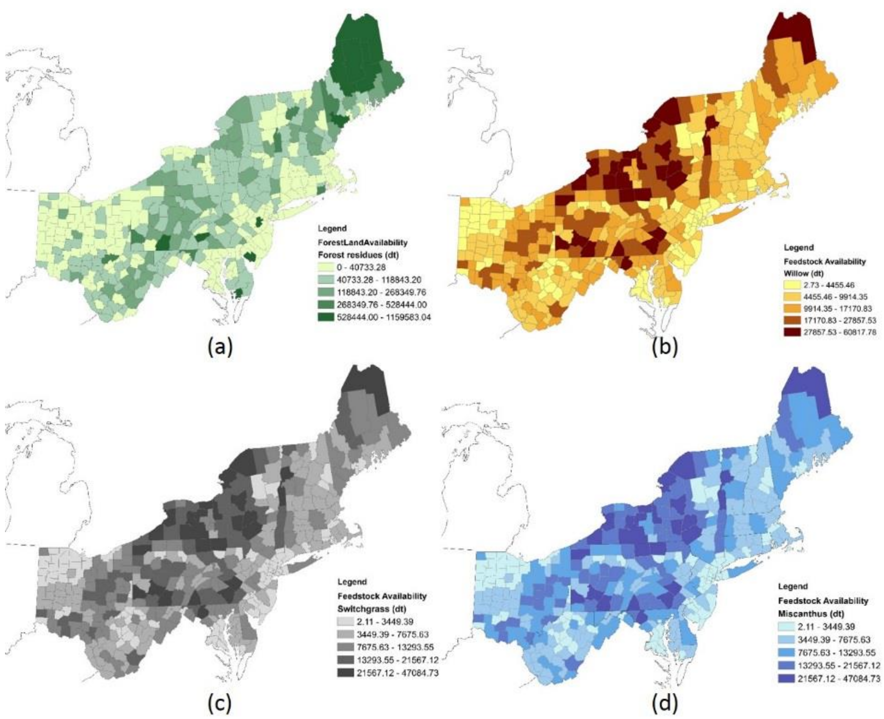

Figure 3.2 Study area and feedstock availability (a) forest residues, (b) short rotation willow, (c) switchgrass, and (d) Miscanthus.

The study area consists of 13 states in the northeastern United States, including Connecticut, Delaware, Maine, Massachusetts, Maryland, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia, and Ohio (NEWBio 2012). We considered two woody biomass feedstocks (forest residues, short rotation willow) and two perennial warm-season grasses switchgrass and Miscanthus. These feedstocks are with great potential for large amount of availability and use of widespread abandoned and marginal lands in the Northeastern U.S., with consideration of feedstock establishment, harvesting, storage, transportation, and processing (Figure 3.2).

Based on research studies by the USDA Forest Service, more than 40 percent of the 167.13 million ha (413 million acres) of land in the northeastern United States is forest. The northeastern U.S. has available marginal agricultural land of over 2.8 million ha (6.92 million acres) (Skousen and Zipper 2014) and abandoned mine land of 0.5 million ha (1.23 million acres) (Drummond and Loveland 2010), respectively. These lands are generally characterized as rocky and sloped soils and are compatible to the development of perennial energy crops. The temperate climate in this region also provides the conditions of producing biomass of higher yield (Somerville et al. 2010).

3.3.2 Data and Case Scenarios

The data on biomass availability were derived from the Billion-Ton 2016 report (U.S. Department of Energy 2016), which provides the distribution of potential biomass feedstock for all lignocellulosic resources available at county-level in the northeastern U.S. According to Forest Inventory and Analysis (FIA library, USDA Forest Service), the yield of forest residues is about 11.11-27.79 dry Mg/ year. Annual yield of hybrid willow is 11.89-15.67 dry Mg/ha (29.38-38.71 dry Mg /acre) (Timothy et al. 2004; Stoof et al. 2015; Kandel et al. 2016; Fahmi et al. 2008), 11.35-20.20 dry Mg/ha (28.06-49.91 dry Mg/acre) (Fike et al. 2006; Jung et al. 1990; Sanderson et al. 2006; Khanna et al. 2008) for switchgrass, and 12.11-27.44 dry Mg/ha (26.93-67.07 dry Mg/acre) (Khannaet al. 2008; Brosse et al. 2012; Miguez et al. 2009; Fahmi et al. 2008) for Miscanthus, respectively. Biomass establishment and harvesting data were based on our previous studies (Wang et al. 2008; Wu et al. 2011; Eisenbies et al. 2017) and EcoWillow simulations (Wu et al. 2011; Khanna et al. 2008; Heavey and Volk 2015). Storage data were based on a study by Pantaleo (2013), while preprocessing data were based on a previous study (Norman and Oscarsson 2002). Storage is considered as open storage and in-building storage, while preprocessing is considered as in-wood chipping and baling, and willow chipping are already included in the harvesting cost. Transportation rate of chips is \$0.106 per ton per kilometer (\$0.17 ton^{-1} /mile) , and for bales is \$0.066 per ton per kilometer (\$0.11 ton^{-1} /mile)in the base case (Hartley 2014, Duffy 2015). Other data were derived from the National Elevation Dataset, 2011 National Land Cover Database, and 2010 Census Data (Gesch et al. 2002, Homer et al. 2012, and U.S. Census Bureau 2017).

3.3.2.1 Base case scenario

The base case scenario was defined as delivering biomass to facilities that required 180,000 dry Mg per year with considerations of major parameters such as harvest area, feedstock rate, price, transportation distance and facility capacity (Table 3.1).

Table 3.1 Parameter configurations for the base case and other case scenarios for sensitivity analysis.

Parameters		Base Case	Sensitivity Analysis
Total harvested (million ha)	Forest residues[a]	37.75	N/A
	Willow[b,c]	0.63	
	Switchgrass[b,c]	2.52	
	Miscanthus[b,c]	3.14	
Feedstock yield rate (dry Mg/ha)	Forest residues[d]	11.11-27.79	N/A
	Willow[e]	11.89-15.67	
	Switchgrass[f]	11.35-20.20	
	Miscanthus[f]	12.11-27.44	
Feedstock price ($/dry Mg)	Forest residues[g]	23.62	1.6-2.4
	Willow[g]	42	33.6-50.4
	Switchgrass[f]	23.9	19.12-28.68
	Miscanthus[f]	29	23.2-34.8
Moisture content[h]		40%	30%-50%
Transportation distance(km)		75	10-150
Facility capacity (dry Mg)		180,000	144,000-216,000
Fossil fuel price ($/Liter)		0.946	0.757-1.136

a. (Burrill et al. 2017)
b. (Skousen and Zipper 2014)
c. (Drummond and Loveland 2010)
d. (2016 Billion Ton Report, Department of Energy)
e. (EcoWillow 2.0, Justin P. Heavey and Timothy A. Volk)
f. (Liu et al. 2017a)
g. (Hartley, 2014)
h. (Mosier et al. 2005)
i. (Mosier et al. 2005)

The choice of a biorefinery site is of great importance when trying to meet the goal of producing cost-effective multiple-biomass-based energy and products, due to spatial dispersion of the feedstock, the high transportation cost of feedstock, and the possible negative impacts on the environment. Each county in the study area was considered as a potential biomass supply location and it was also assumed that the feedstocks were aggregated to the centroid of the county. Geographic information system (GIS) is a viable tool to identify siting locations considering multiple criteria, for example, for minimizing the cost of dairy manure transportation (Paudel et al. 2009) and for optimizing an emergency facility location using a modified particle swarm optimization algorithm (Ma et al. 2019). In this study, the locations of the bioenergy plants were selected based on an integrated physical and social assets analysis, including suitability analysis, multi-criteria ranking, and social-economic assessment (Wang et al. 2019). First, 43 potential plant candidates were selected out of 387 locations in the study region with high-suitable indices, and then 15 locations were further identified for the regional economic development featuring both environmental and social asset impacts. The nine criteria considered were: biomass availability, distance from main road, distance from electric substation, distance to waterbody, flood risk of potential siting, adjacent land uses of potential siting, population in siting area, landownership, and unemployment rate in potential siting. To meet a necessary setting required by our mathematical model, all 15 sites selected were considered for medium size biorefinery plants with the same capacity of 180,000 dry Mg feedstock for the base case scenario (Figure 3.3).

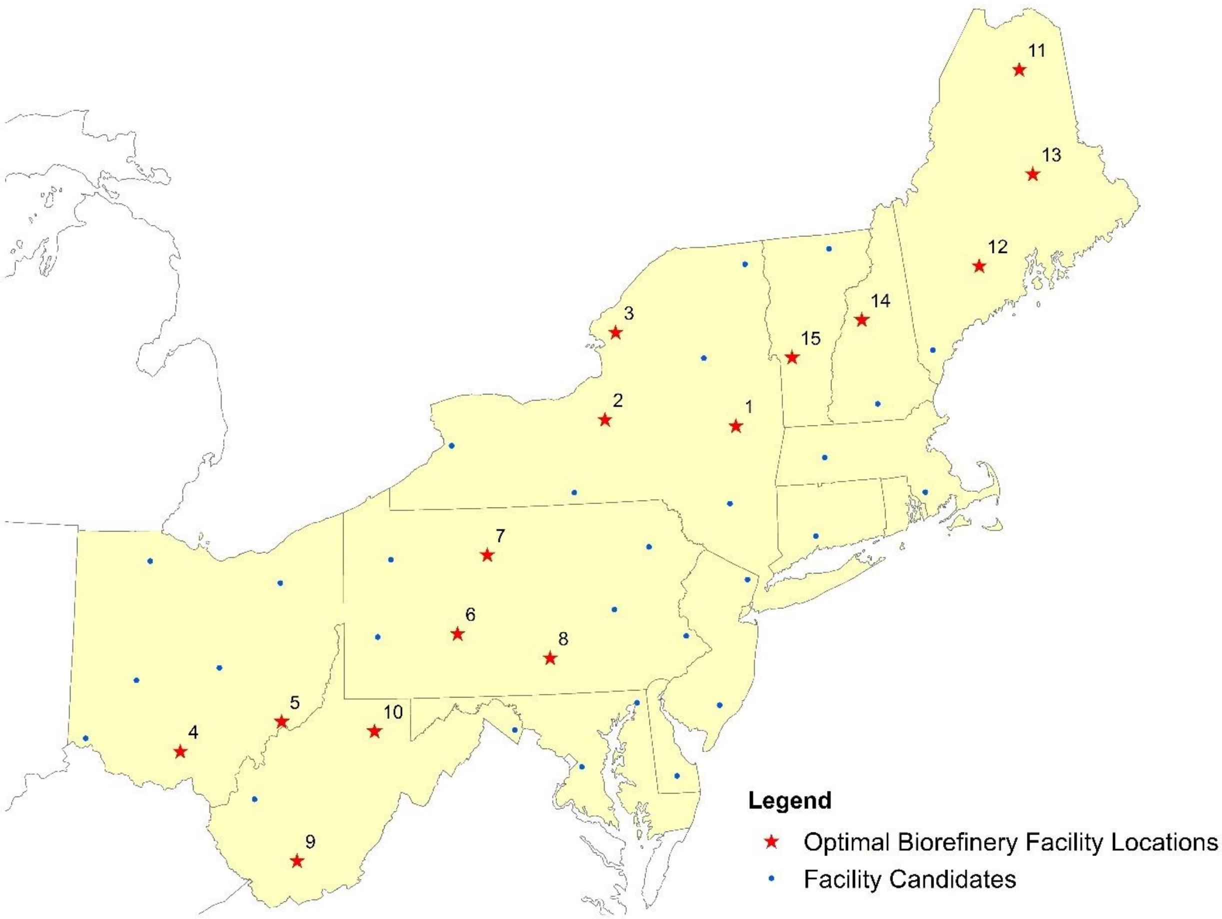

Figure 3.3 Locations of candidate facilities and optimal biorefinery siting within the study area.

3.3.2.2 Other case scenarios

The variation of feedstock availability, feedstock price, transportation distance, moisture content, facility capacity, and fossil fuel price were taken into consideration into multiple cases. Maximum and minimum feedstock price and facility capacity were examined for every feedstock material. Demand and siting location of biorefinery, along with feedstock availability will have effect on hauling distance, where a transportation distance range of 15-135 km (9.32-83.88 miles) was analyzed on delivered cost. Delivered cost along biomass supply chain will also be affected by moisture content and current fossil fuel price.

3.3.3 Sensitivity analysis

Several factors affect the delivered cost of multiple biomass feedstocks, including feedstock availability/demand, feedstock price, materials moisture content, procurement radius, facility capacity and fossil fuel price. Based on the base case, these factors were analyzed in terms of sensitivity and uncertainty under different case scenarios (Table 3.1).

3.4 Results

3.4.1 Base case scenario

The delivered cost of biomass for the 15 facility locations averaged $79.58 per dry Mg, ranging from $67.90 to $86.97 per dry Mg with consideration of a series of supply chain components of feedstock establishment, harvest, transportation, storage, and preprocessing (Figure 3.4).

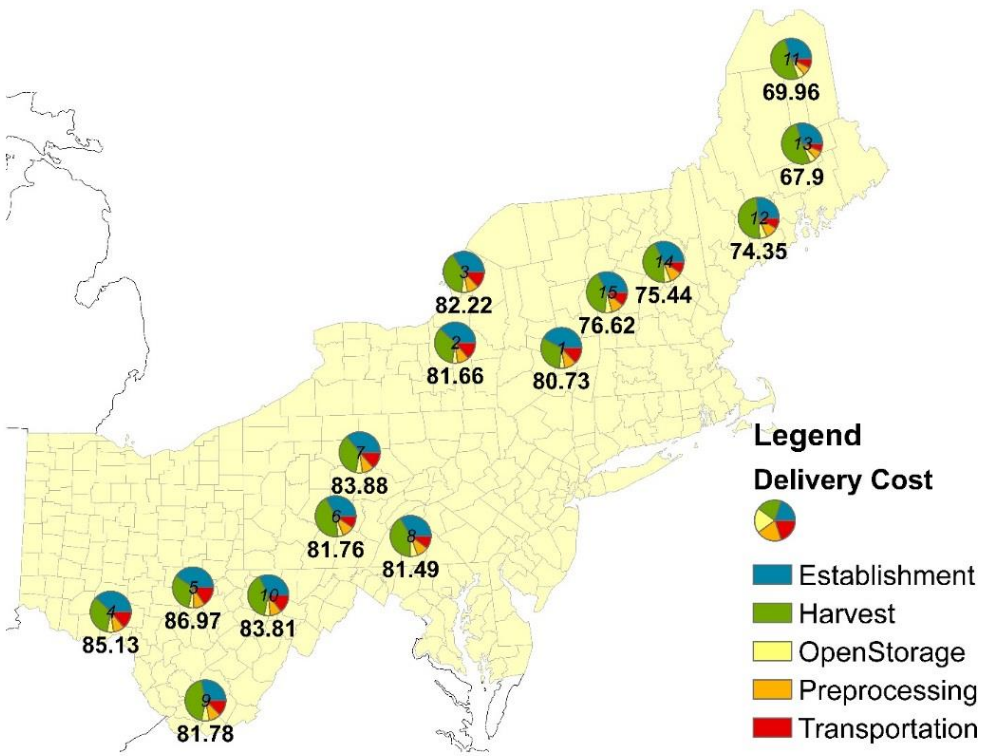

Figure 3.4 Spatial descriptions of biomass delivered costs of biomass within the study area.

The base case results showed that delivering biomass to facilities with longer transportation distances resulted in higher delivered costs (Table 3.2). The delivered cost would increase 28.1% if the average transportation distance increased from minimum 22.04 km (13.7 miles) to maximum 75.2 km (46.7 miles).

Table 3.2 Transportation distance and the delivered cost associated with optimally selected facility locations.

ID	Facility Locations	Min Transportation Distance (km)	Average Transportation Distance (km)	Max Transportation Distance (km)	Average Total Delivered Cost $/dry Mg
1	Schenectady	11.41	57.77	107.07	80.73
2	Onondaga	20.62	62.24	180.39	81.66
3	Jefferson	17.49	59.16	203.95	82.22
4	Pick	34.36	64.75	155.78	85.13
5	Washington	15.38	75.2	201.44	86.97
6	Cambria	9.43	42.05	127.49	81.76
7	Cameron	13.48	62.56	154.36	83.88
8	Cumberland	3.6	45.62	181.59	81.49
9	Raleigh	5.23	57.96	129.43	81.78
10	Taylor	5.32	65.65	192.33	83.81
11	Aroostook	2.34	28.11	85.63	69.96
12	Kennebec	5.62	35.62	88.54	74.35
13	Penobscot	2.17	22.04	89.22	67.90
14	Grafton	8.17	38.11	99.78	75.44
15	Rutland	7.93	46.15	108.92	76.62

Results of the base case also showed that both feedstock establishment and harvest costs accounted for over 70% of the total delivered cost (33.91% and 40.32%), which were $27.29, and $32.45 per dry Mg respectively. They were followed by 11.6%, and 9.04% of the total delivered cost for transportation and preprocessing costs. Biomass storage was the least cost component accounting for 5.11% (Table 3.3).

Table 3.3 Cost components of base case scenario

	Cost $ per dry Mg					
	Establishment	Harvest	Storage	Preprocessing	Transportation	**Average Total**
Min	18.62	25.63	3.47	4.74	5.26	**67.90**
Max	35.16	38.61	5.02	7.75	13.57	**86.97**
Average	26.40	32.45	4.12	7.28	9.34	**79.58**

Storage is employed in all cases to balance the conflict between the consistent demand from biorefineries, and the seasonal supply of bioenergy feedstocks. The use of storage allows for the materials that came from energy crops to be utilized well beyond the harvest window for the material. Outdoor storage was considered for the base case scenario, 56% of the material resided in storage before being used for conversion. Since there could be a certain amount of feedstock shortage in non-harvest season, storage inventory increased until the end of first quarter of the year to meet the full storage capacity, and gradually decreased until the end of third quarter when the inventory was exhausted, and the new harvest season began. In the view of energy crops inventory, during the harvesting season, there is no storage except for the safe inventory in biorefineries from May to September during a year.

Examining the cost components for each feedstock type, it showed the proportion of cost components varies from material types (Figure 3.5). Establishment cost of forest residues occupied the least proportion of the total delivery cost with 21.3% compared to other feedstock types. Harvest cost for willow proportion is 26.5% and is lower than that for with other feedstock materials. Storage cost for forest residues, willow, switchgrass and Miscanthus all occupied a small proportion (4.8% to 7.0%) of total delivered cost. Proportion of preprocessing cost is 10.5% and 9.2%, respectively, for forest residues and willow are higher than perennial grass with percentage. The transportation cost for forest residues is only 15.5%, compared to the proportion of 20-25% for others.

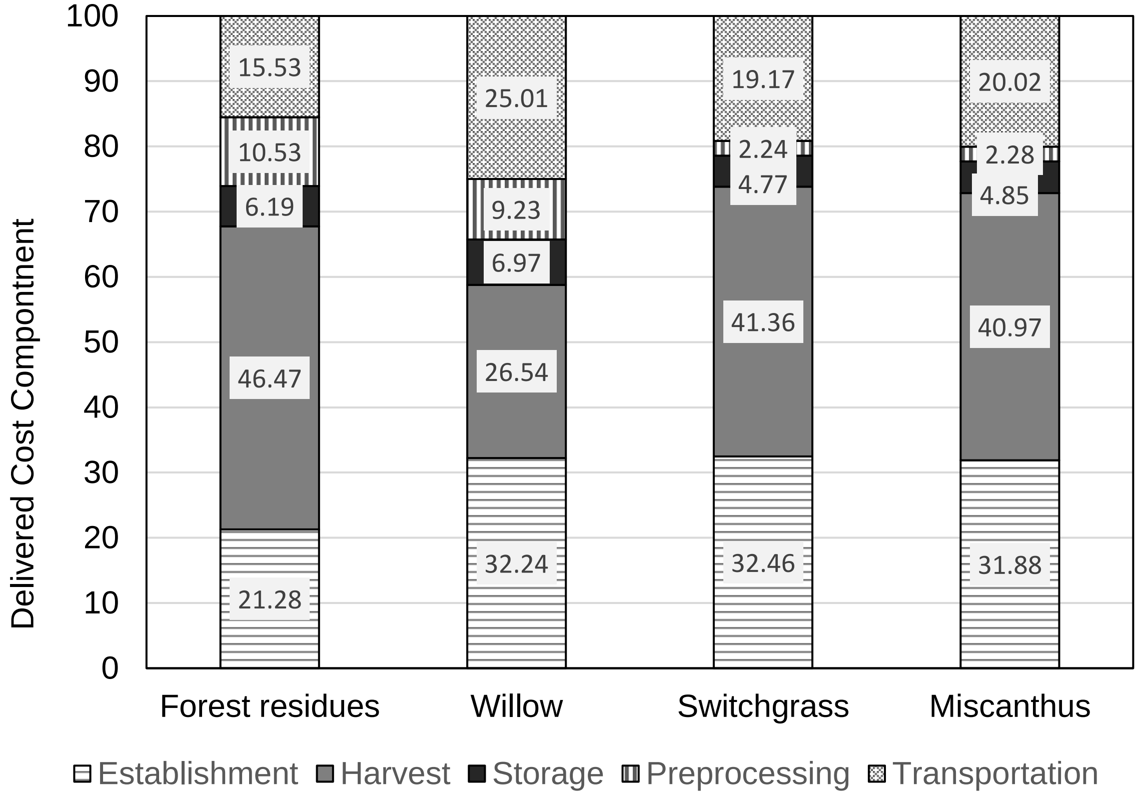

Figure 3.5 Biomass delivered cost components by feedstock types.

3.4.2 Regional analysis of multiple feedstock supply chains

The biomass delivered costs varied from county to county and from state to state in the northeastern U.S. (Figure 3.6). It ranged from $67.90 to 150.81 per dry Mg by region across the northeastern U.S. The delivered cost was less than $90 per dry Mg in 311 counties, while 60 counties were shown with a delivered cost of $80-100 per dry Mg. There were 16 counties with a delivered cost of more than $100 per dry Mg. Considering the DOE's target to lower delivered cost for lignocellulosic biomass than $84 per dry ton in year 2022 (DOE 2016), and $71 per dry ton in year 2030, our results showed that 77 out of 387 counties in the region could deliver biomass with a cost of less $84/dry ton, and 2 counties with cost of below $71/dry ton.

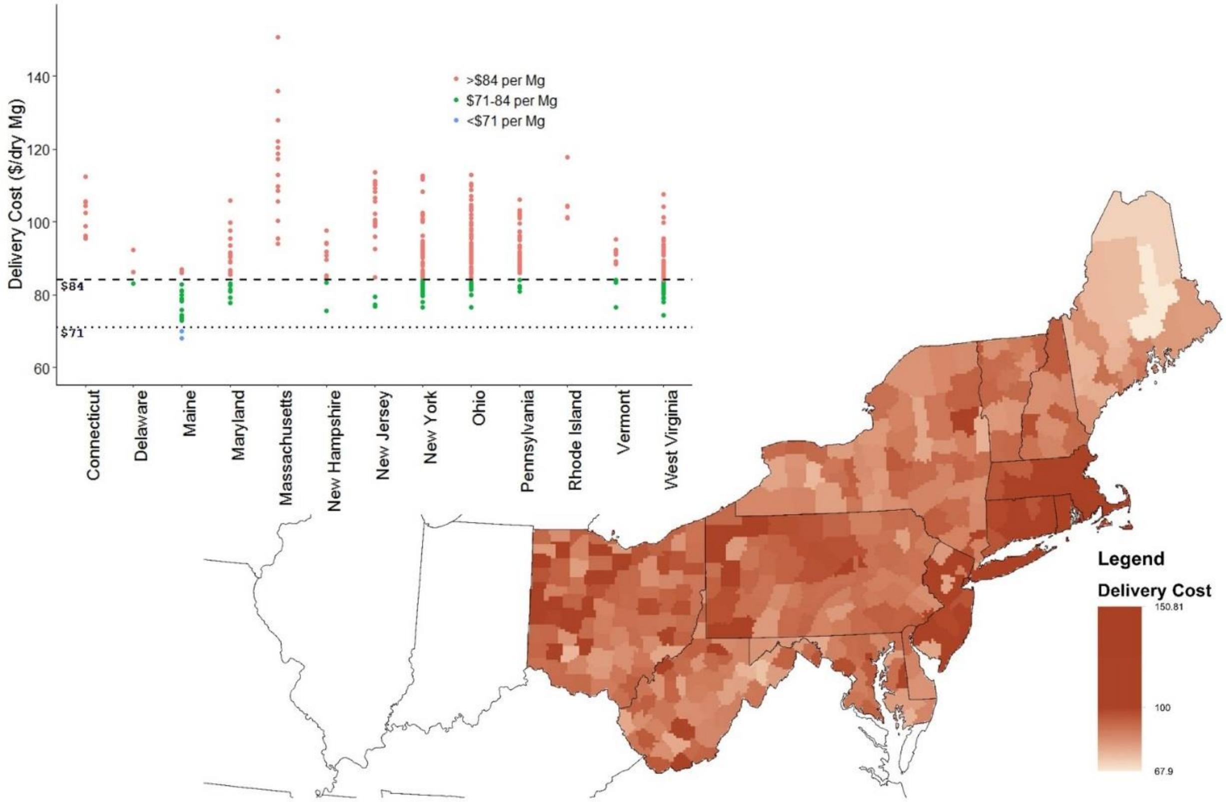

Figure 3.6 Spatial distribution of the regional biomass delivered costs.

The results show that the supply chain components followed a similar trend of the total delivered cost among regions (Figure 3.7).

Feedstock harvest cost is the primary cost component and accounted for 29% to 46% of the total cost. There are differences among these regions in harvest cost, from the lowest harvest cost of $34.96 per dry Mg in Maine to the highest harvest cost of $40.90 per dry Mg in New Jersey. The variation harvest cost mainly caused by different collection systems of feedstocks.

It followed by establishment (14.6% to 29.8%). Storage accounted for a small portion (3.3%-5.7%) of the total delivered cost ranging from $3.13 to $3.94 per dry Mg, and there was no much difference among regions. Preprocessing or size reduction cost in the supply chain in this study ranged from 5.7% to 9.4% of the total delivered cost, which is from $6.35/ dry Mg to

$7.36/ dry Mg. For comparisons of the biomass delivered among 13 states in the study area, both transportation cost and its proportion to the total delivered cost varied greatly among the states, with a range from the lowest $9.11 per dry Mg to the highest $47.22 per dry or from 10.3% to 43.0%.

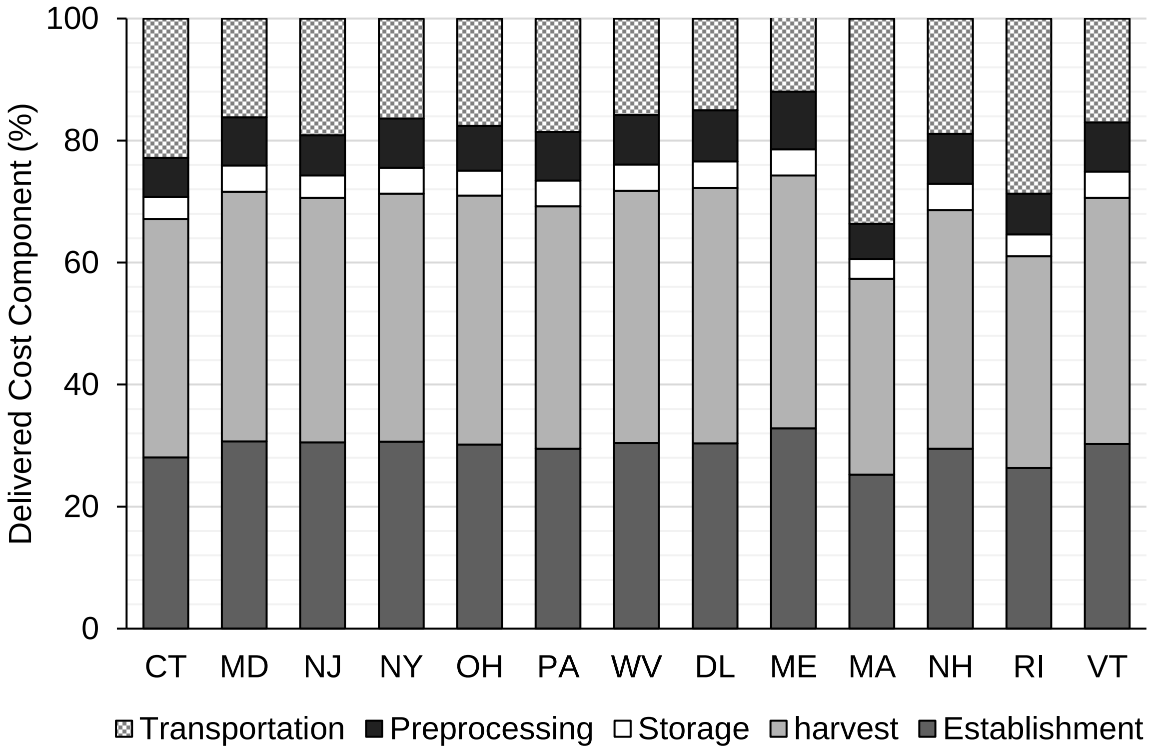

Figure 3.7 Percentage of cost components of biomass delivered cost by state.

The biomass delivered costs at county level was analyzed by feedstock type (Figure 3.8). Among four biomass feedstocks, delivered of forest residue chipped on landing averaged $81.78 per dry Mg, ranging from $67.74 to $125.88/dry Mg. The switchgrass delivered cost ranged from $63.89 to $149.83, with an average of $99.68 per dry Mg. For willow and Miscanthus, average delivered costs were $95.85/dry Mg and $97.87/dry Mg, ranging from $70.29 to $149.83/ dry Mg, and $66.39 to $153.39/ dry Mg, respectively.

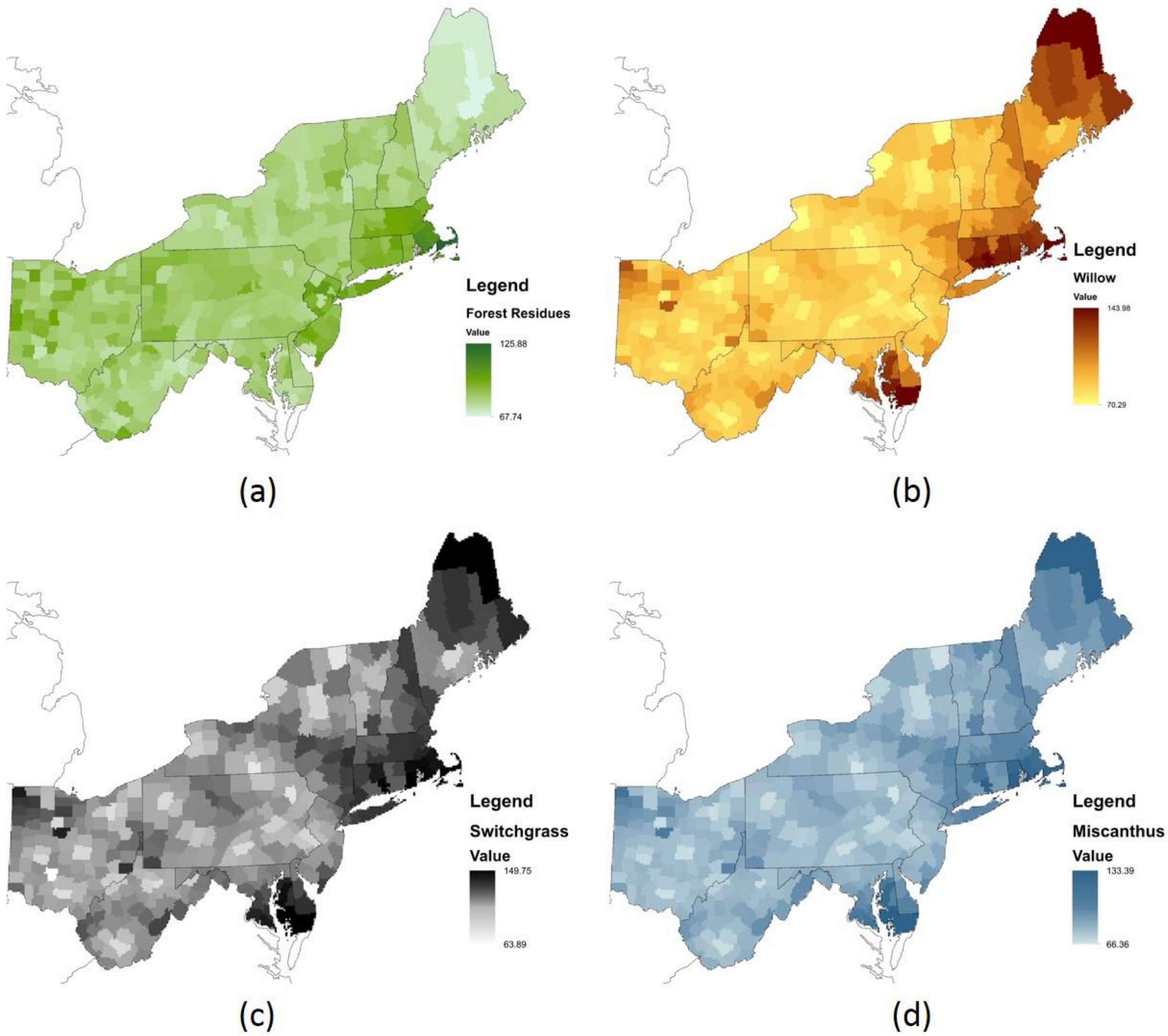

Figure 3.8 Regional biomass delivered costs by feedstock (a) Forest residues, (b) Short rotation willow, (c) Switchgrass, and (d) Miscanthus.

Across the entire study area, the delivered cost and its cost components were analyzed, and results were summarized in Table 3.4. Result showed that for feedstock of forest residues, it has the lowest average delivered cost of $ 88.79 per dry Mg, ranged from $67.74 to $125.88/dry Mg with a difference of $58. For willow, switchgrass, and Miscanthus, the delivered costs were $95.85/ dry Mg, $99.68/ dry Mg, and $97.87/ dry Mg, respectively.

Table 3.4 Delivered cost and cost components by feedstock types.

Feedstock		**Forest residues**	**Willow**	**Switchgrass**	**Miscanthus**
Cost components ($/dry Mg)	Establishment	18.15	27.23	32.36	31.20
	Harvest	39.64	22.42	41.23	40.10
	Storage	5.28	5.89	4.75	4.75
	Preprocessing	8.98	7.80	2.23	2.23
	Transportation	13.25	21.13	19.11	19.59
Total delivered cost $/dry Mg	Mean	**85.30**	**84.47**	**99.68**	**97.87**
	Min	65.74	70.29	63.89	66.39
	Max	125.88	143.98	149.75	133.39

In comparisons to other chain components, storage and preprocessing for all four feedstock types accounted for relatively smaller proportions of the total delivered cost. Willow feedstock had the highest establishment cost of $40.20 per dry Mg. Harvesting switchgrass and Miscanthus resulted in higher cost of $41.23/ dry Mg and $40.10/ dry Mg, and it followed by forest residues ($35.80/dry Mg), and willow ($22.42/dry Mg). If logging residues are collected from harvested sites, their stumpage price is a fraction of the whole-tree stumpage price that is based on the ratio of the yield from residues to the yield from a whole tree (Langholtz et al. 2016). Thus, the logging residue stumpage price could be ranging $5.5 to $22 per dry Mg. Harvesting costs for logging residues in this study include felling, skidder, delimbing, and loader costs. Our result is reasonable that the collection cost was similar to previous studies in the Northeast US, compared with the studies by Wu et al (2011; 2010) on forest residue handling cost in West Virginia that it is from $19.37 to $46.9 per dry Mg for collection systems: cable skidder-loader, grapple skidder-loader, and slash bundler- forwarder–bundles.

The utilization of multiple energy feedstocks varies in the region. While switchgrass and Miscanthus have a potential to grow as feedstocks, forest residues have been primarily utilized in most of the states. Less than 1% of Miscanthus was utilized in New York, Pennsylvania, West

Virginia, and Maine. For the rest of the northeastern states, Miscanthus was also utilized no more than 5.03%. The states of New York and Pennsylvania have a good growth potential for switchgrass and willow, while in Maine, Pennsylvania, and West Virginia there are large amount of forest residues available. With the tradeoff of feedstock availability, establishment cost, harvest and logistics, the delivered cost of specific biomass could be reduced in some areas with higher availability of forest residues and higher growth potential of energy crops.

3.5 Discussion

The model developed can provide the best fits of machines to select the most cost-efficient logistics for given tasks. Compared to the studies by Zhang et al. (2013) , Karkee (2016) and Marvin (2012), our study analyzed multiple feedstock resources including both woody and herbaceous biomass not only at state level but also at county level, which greatly fulfill the completeness of available biomass feedstock for energy and bioproducts production in the entire Northeastern US. A dynamic time-series attribute on monthly basis was considered in both the objective function and the constraints in this study, which was not thoroughly addressed in previous studies.

3.5.1 Biomass delivered cost

It showed that it is possible to lower the delivered cost of lignocellulosic biomass in 13 out of total 15 case scenarios with potential facility locations to meet the demand of a potential biorefinery facility with a capacity of 180,000 dry Mg per year in the northeastern United States. This can meet the U.S. DOE's target to lower the total delivered cost of lignocellulosic biomass especially for short rotation woody crops to $84 per dry ton (DOE 2016) by 2022 from site to throat of conversion reactor. In the minimum delivered cost case of $67.90 per dry Mg in Penobscot, Maine, 177,570 dry Mg of forest residue and 2,430 dry Mg of willow were delivered to the facility which includes $20.12 per Mg and $ 25.63 per Mg costs for feedstock establishment and harvest each year. Open storage and preprocessing incurred drying and chipping cost $3.47 per Mg and $4.74 per Mg. Average procurement radius of biomass is 22.04 km that cost $5.26 per Mg for a base case.

In the maximum delivered cost case of $86.97 per dry Mg in Washington, Ohio, the facility utilized 159,156 dry Mg of forest residue, 15,633 dry Mg of willow, 3127 dry Mg of Miscanthus and 2084 dry Mg of switchgrass. Harvest cost occupied the largest proportion of delivery cost, which was $ 38.61 per Mg annually, following by feedstock establishment of $35.16 per Mg. The storage cost was 44.7% more and preprocessing cost was 63.5% more than that of the minimum case. Average procurement radius of 75.2 km for this case was 241% longer than that for the minimum delivery cost case.

For the range of biomass delivered cost of $67.90 to $86.97 per dry Mg, the configuration of supply chain components varied. With the lowest delivery costs of $67.90 per dry Mg in Penobscot, Maine, the proportion that forest residue was 98.7% of biomass. In the highest delivery cost case in Washington, Ohio, 85.4% of utilized feedstock were forest residues. Willow was utilized as the second largest proportion of the supply chain ranged from highest as 10.1% to lowest as 1.0% among cases.

A combined whole-tree chipping and on-site residue collection was considered as one of the major collection system of forest residue. A mechanized harvesting system using a feller-buncher and grapple skidder is popular in the region to conduct conventional timber harvesting including small-diameter and low-quality trees. Small-diameter trees were harvested, and both harvested whole trees and on-site residues were extracted using cable/grapple skidders, and chips were produced at landing. In difficult terrains, chainsaws can fell trees to form a manual harvesting system with cable or grapple skidder. A cut-and-chip system was applied for willow shrub harvesting and chip collection. For perennial grasses, the harvest process included mowing and baling, while squared baling were considered for improvement of transportation capacity.

In a study of logging residue utilization in southern West Virginia (Grushecky et.al. 2007), the extraction cost ranged from $20.94 to 69.51 per dry ton with an assumption of 50% moisture content. This result is similar to the harvest/collection costs of logging residue form logistics optimization in this paper.

The biomass delivered cost is sensitive to biomass availability, feedstock price, transportation distance, biomass moisture content, facility capacity and fossil fuel price (Figure 3.9). A sensitivity analysis of the biomass delivered cost in base case was conducted for 12 factors with 10% change. If diesel price increased 10%, the delivered cost would increase 2.4%. When a 10% increase of facility capacity occurred, the delivered cost would increase 7.9%, but the delivered cost would reduce 6.8% if the facility capacity was down 10%. Transportation distance of biomass usually has a great impact on the biomass delivered cost. An addition of 10km (6.21 mile) of transportation distance would increase or reduce 8.6% of the delivered cost. If moisture content of biomass lowered 10%, it could reduce 2.5% of the biomass delivered cost. Feedstock availability had effect on the delivered cost and varied according to feedstock types. A 10% change of Miscanthus availability caused a change of 0.2-0.9% of the biomass logistics delivered cost, while a 10% change of switchgrass availability would either decrease 1.6% or increase 2.3% of the delivered cost. For forest residue, the delivered cost would reduce 3.6% with a 10% decrease of its availability or increase 3.2% with its availability increase 10%. Sensitivity analysis of feedstock price for other three energy crops indicated that a 10% change of feedstock price slightly affected the delivered cost (from -1% to 1%), while a 10% change of feedstock price for the base case of forest residue would affect the delivered cost from -3.3 to 3.3%.

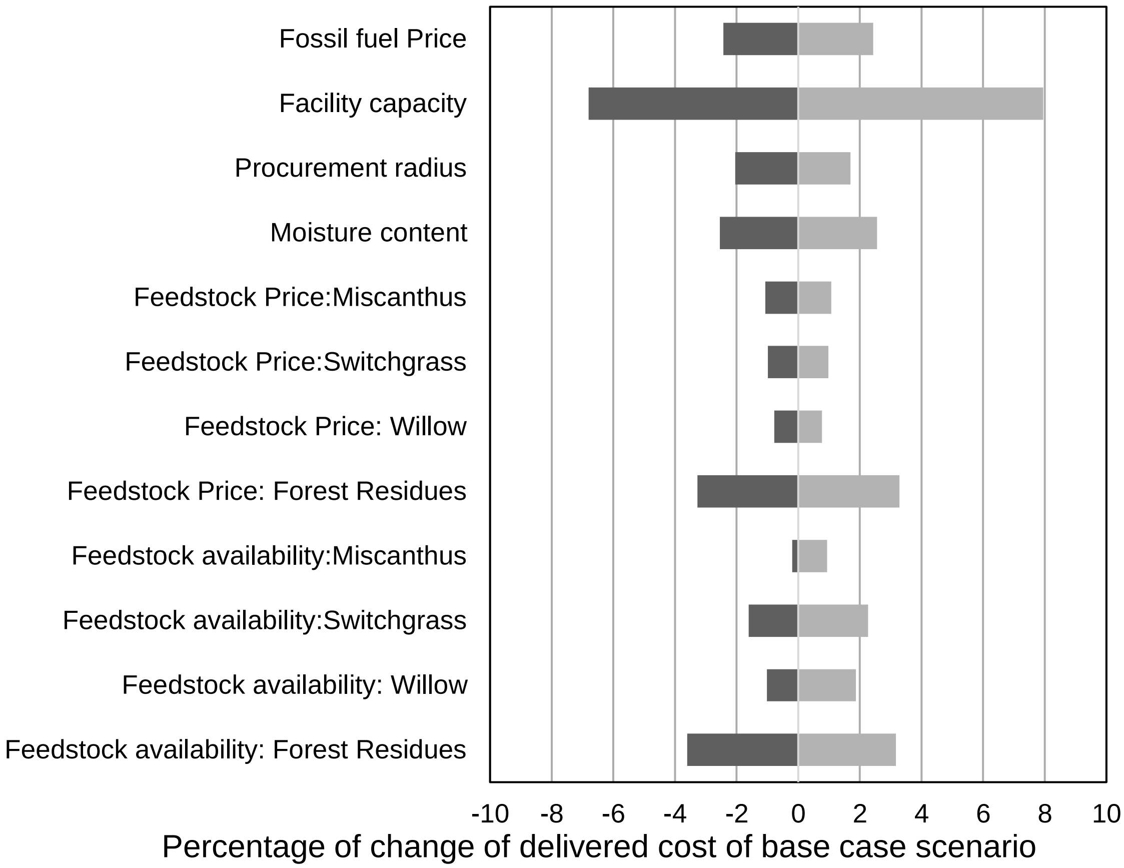

Figure 3.9 Sensitivities of the multiple biomass feedstock delivered cost according to feedstock availability, feedstock price, moisture content, procurement radius, facility capacity, and fossil fuel price.

The delivered cost of biomass is sensitive to facility capacity of biorefinery because the facility capacity affects feedstock demand, and further impact feedstock establishment, harvest, storage, as well as biomass procurement radius or transportation distance. Transportation of bulky biomass typically increases the cost dramatically depending on hauling distance. The longer the transportation distance is the higher the transportation cost will be. In the meantime, turnaround, loading and unloading times are also the key factors in biomass transportation logistics. It is essential to reduce the transportation cost through optimizing biomass logistics (Wu et al. 2011). Following the regional gross vehicle weight regulations, managing moisture content of biomass could effectively improve payload size of trucking and can significantly affect the delivered cost of biomass feedstocks.

In the base case scenario, the average delivered cost of multiple feedstocks ranged from \$67.90 to \$86.97 per dry Mg. Compared to previous studies with similar supply chain components and feedstock types, the delivered cost of biomass by this study is similar to the results 64.69 to \$98.31 per dry Mg (Hartley 2014) , and \$29.7 to \$97.1 per dry Mg (Grushecky et al. 2007) for the entire biomass supply chains from fields to biorefineries. However, our result is higher than that of \$44 to \$47 per dry ton (Kumar and Sokhansanj 2007) simulated by using IBSAL model, since they excluded transportation and collection cost components.

Since there is no adequate amount of energy crops planted for commercial purposes now in the region, the feedstock availability potential analyzed in this study was based on the Billion-Ton study by U.S. Department Of Energy (DOE 2016), and these availability potentials could be changed due to variations of some impact factors in the future, such as land use, supply and demand of biomass. Meanwhile, this study primarily focuses on the biomass delivered cost and does not include profit or other payment due to risk and policy uncertainties, and these factors would expect potentially to increase the biomass logistics costs. In 15 base cases of spatial biorefinery locations, delivered costs to 13 facility locations were lower than \$84 per dry ton. In these cases, forest residues accounted for a majority proportion of among multiple biomass feedstocks, due to low stumpage cost and large amount of availability. The total delivered cost of biomass from this study would be higher if alternative or additional pretreatments were used for feedstocks. For instance, further size reduction and hot water extraction would increase preprocessing costs for some specific treatments of biomass for specific bioproducts production (Kumar et al. 2009).

3.5.2 Cost components of biomass supply chain

Harvest and establishment costs were primarily affected by feedstock types. Perennial grasses of switchgrass and Miscanthus are both warm-season plant with high potential as a promising feedstock for bioproducts and bioenergy. In general, the yield of Miscanthus is higher than that of switchgrass, which could lead to a relatively higher collection cost for baling and a longer mowing time per acre basis. Forest residue collection after harvesting activities would cost more than collection activity incorporated into round wood harvesting. Increase in feedstock yield and harvest efficiency are important to the future economic viability of multiple feedstocks.

Field storage was chosen in the optimization of logistics and it only accounted for 5.1% of the total delivered cost at $4.12/dry Mg. However, attention should be paid to potential risks of biomass, while on-site storage could lead to extra mass loss. A dry-matter loss factor considered in the mathematical model intends to examine the uncertainty in potential energy loss during storage process.

Size reduction of grinding was considered as a major component in preprocessing of our modeling process. Chips of woody biomass and bales of perennial grasses were the materials for transportation. Within a certain procurement radius, biomass transportation could be economical, and it may require more connections/storage points (or depots) between biomass supply sources and bioenergy facilities. This makes the transportation an important component in the biomass supply chain. The impacts of sensitivity factors were examined on multiple cases (Figure 3.10).

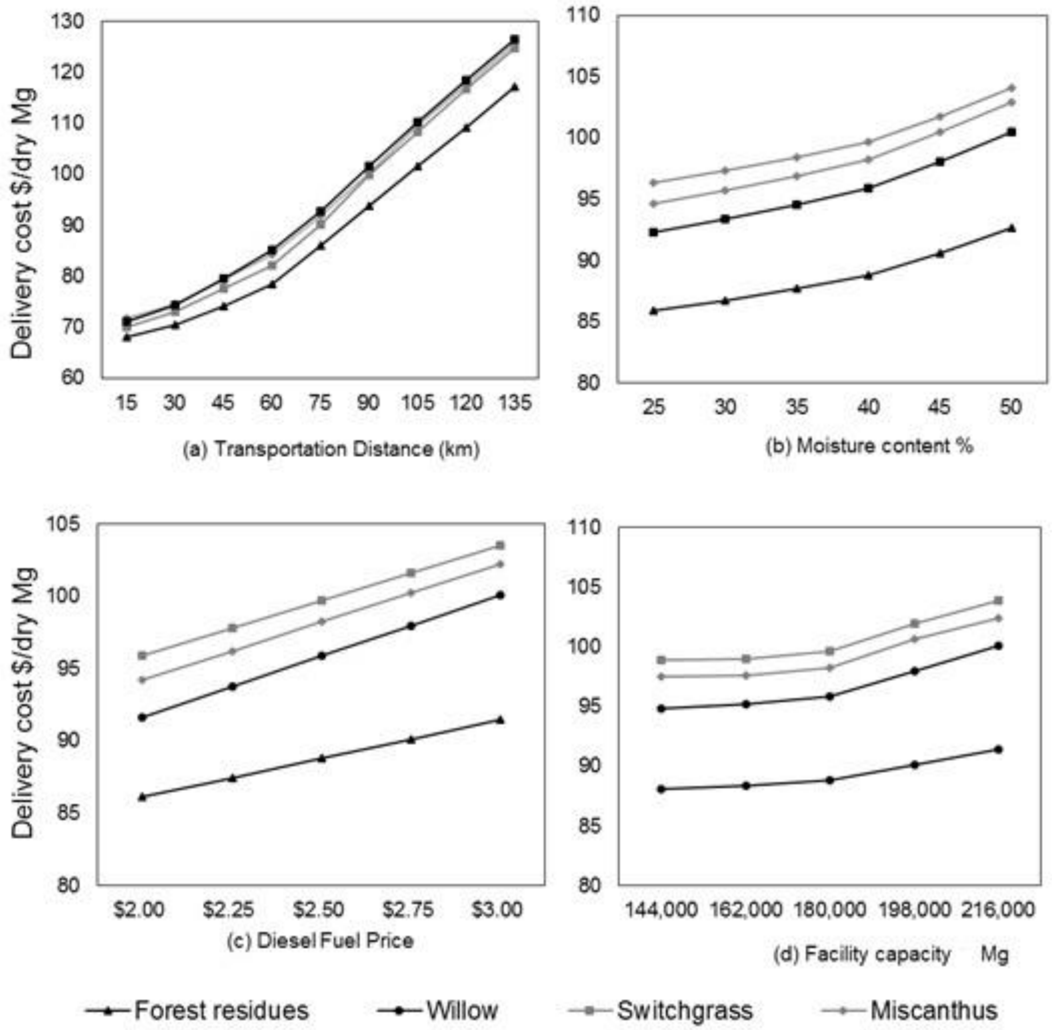

Figure 3.10 Impacts of sensitivity factors to transportation cost.

Four case scenarios were examined on the delivered cost for transportation distance ranged from 15 to 135 km (9.32-83.88 miles).

As transportation distance changed from 15 to 135 km (9.32-83.88 miles) with 75 km (46.60 mile) as the base case, the variation of delivered cost increased for all feedstock types. With moisture content from 25% to 50%, the delivered cost increased more quickly when moisture content was higher than 40%. The moisture content rate would affect the effective payload of transportation, and drying in field could reduce transportation cost as much as 20% (Hartley 2014).

In the meanwhile, uncertainties of fossil fuel price caused by international fuel market and policy would affect the economic feasibility of biomass utilization for bioenergy and bioproducts. Determination of “economies of scale” (Hartley 2014), of which the most economic facility capacity, would lead to a more effective logistics system and economical procurement radius of biomass. As biomass availability declines and/or facility demand increases, an increased transportation distance of biomass would incur the delivered cost to increase dramatically.

3.6 Conclusions

Focusing on entire biomass supply chains, the delivered cost of multiple biomass feedstocks was optimized with considerations of biomass supply/demand and potential biorefinery locations in the northeastern United States. Through supply chain and logistics optimization, 77 out of total 387 counties in the northeastern United States could be able to deliver biomass at a cost of $84 per dry ton - a target by US DOE by 2022. Additionally, two counties in the region could deliver at a cost of less than $71 per dry ton – a US DOE’s target by 2030. Fifteen spatially located biorefinery sites across the region further indicate the regional bioeconomic potentials. The optimized supply chains include integrated timber/forest residue production using feller-buncher for felling and grapple skidder for extraction, onsite chipping and chip van trucking at a cost of 70.74/dry Mg in Maine, 81.54/dry Mg in New York, and 82.80/dry Mg, in West Virginia.

The variance of biomass delivered cost is primarily affected by the differentiations of feedstock types, collection system and availability/accessibility. Feedstock establishment and harvest/collection are the two major cost components and generally account for 70% of the total delivered cost. The delivered cost was most sensitive to transportation distance or procurement radius and facility capacity. The procumbent radius of biomass is one of the most important factors affecting the total delivered cost. Transportation cost could be lower and overall economics could be feasible when supplying feedstocks to local and relatively small to medium size facilities, such as local pellet mills and co-firing power plants. Feedstock price, moisture content and fossil fuel price all have impacts on biomass delivered cost. If market for lignocellulosic biomass could be well developed nationwide, train would be another viable method to reduce the transportation cost of biomass. Trucking is usually preferred for short-distance transportation with its flexibility, while train can be used for long-distance of bulky biomass. For truck transportation, there are two key constraints - weight and dimension limitations regulated by the governments. Train is usually limited by volume instead of weight (Lin et al. 2016). Raw biomass like chips or bales has an inherently low mass and density, which would result in economic constraints for train transportation. Thus, densification of raw biomass such as bundling and pelletizing could be a solution to improve the cost effectiveness of biomass transportation.

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4. ENVIRONMENTAL AND ECONOMIC ASSESSMENTS AND UNCERTAINTIES OF MULTIPLE LIGNOCELLULOSIC BIOMASS UTILIZATION FOR BIOENERGY PRODUCTS: CASE STUDIES [3]

[3] To be submitted to Energies Special Issue "Analysis of Bio-based Products for the Circular Economy"

Abstract:

Life cycle assessment (LCA) and techno-economic analysis (TEA) were applied to assess economic feasibility and environmental benefits of utilizing multiple biomass feedstocks for bioenergy products under three different technological pathways with consideration of uncertainties. Three cases were studied for production of pellets, biomass-based electricity, and pyrolysis bio-oil. A Monte Carlo simulation was used to examine uncertainties of fossil energy consumption, bioenergy conversion efficiency, stochastic production rate, production increasing rate, sale price of bioenergy products, and discount rate, and to estimate the behavior of environmental and economic parameters considering the risk in project sustainability.

The cradle-to-gate LCA results showed that pellet production had the lowest GHG emissions, water and fossil fuels consumption, (8.29 kg CO_2 eq, 0.46 kg, and 105.42 MJ respectively). The conversion process presented a greater environmental impact for all three bioenergy products. The GHG emission, freshwater and fossil fuel consumptions in conversion process all accounted for more than half of the total environmental impacts, ranging from 52.66% to 89.57%. With producing 46,926 tons of pellets, 260,000 MWh of electricity, and 78,000 barrels of pyrolysis oil, the net present values (NPV) for all three cases indicated that only pellet and biopower production cases were profitable with NPVs $1.20 million for pellet, and $81.60 million for biopower. The pellet plant and biopower plant were profitable only when discount rates are less than or equal to 10%. The uncertainty analysis indicated that pellet production showed the highest uncertainty in GHG emission, bio-oil production had the least uncertainty in GHG emission but had risks producing greater-than-normal amount of GHG. Biopower production had the highest probability to be a profitable investment with 95.38%.

4.1 Introduction

The increasing global energy consumption has been resulting in the need to further develop bioenergy products using a variety of renewable materials, including forest residues (Searle and Malins 2016; Sowlati 2016), and energy crops (Robertson et al. 2017). Biomass is considered an environmentally friendly energy resource through its carbon mitigation function (Demirbaş 2001), and is a preferred alternative to fossil energy resources to reduce the greenhouse gas emissions (U.S. Department of Energy 2015). Biomass could be used to produce bioenergy products in a variety of forms, such as firewood, pellet, electricity, ethanol, and biofuels. Since carbon dioxide is consumed during biomass growth, biomass mitigates the amount of greenhouse gases (GHG) emission generated during the energy conversion (Morais et al. 2015). Thus, energy production from biomass has the advantage of emitting smaller amounts of GHG.

The utilization of lignocellulosic biomass for biofuels and bioproducts has been steadily increased (Cherubini 2010). Current production and application of first-generation biofuels from food crops for biodiesel and bioethanol are well understood (Novo et al. 2012; Elander and Putsche 2018). However, compared to food crops, lignocellulosic biomass like forest residues and energy crops is a major source of cheap and abundant nonfood materials available from plants (Naik et al. 2010). Therefore, lignocellulosic feedstock can offer the potential to provide novel biofuels or bioenergy, known as the second generation of biofuels (Sims et al. 2010).

In a biorefinery facility, biomass conversion processes and equipment are integrated to produce power, fuels, or any value-added products from biomass. The biomass conversion processes utilize physical, chemical, biological, and thermal pathways (Naik et al. 2010). Densification is a physical conversion that can help overcome the drawback of forest residues and other lignocellulosic biomass materials that always have uneven bulky characteristics

(Stevens and Verhé 2004). The densification of biomass improves the efficiencies in biorefinery facilities and reduces the handling costs of biomass (Yancey et al. 2013). Pellet is a bioproduct that intensifies the loose biomass and has become popular as solid biofuel (Goliński and Foltynowicz 2012). Combustion is a common means of converting biomass to energy, with a proven technology that low-cost, highly reliable, relatively well understood and commercially available (Bhaskar et al. 2011). Lignocellulosic biomass fired or co-firing power plants can produce electricity, heat or steam using either direct or indirect combustion systems (Liu et al. 2017). One major processing route for the production of biofuels from lignocellulosic feedstocks is thermo-chemical, which produces a wide range of long carbon chain biofuels, such as bio-oil, aviation fuel, ethanol, or reformed fuels (Sims et al. 2010). Thermochemical conversion using pyrolysis has been considered an important and promising technique for biofuel production (J. Zhang and Zhang 2019). In most cases, the pyrolysis process is a basic component of thermochemical conversion (Bhaskar et al. 2011). Fast pyrolysis is an approach to produce reliable higher energy content liquid fuels from biomass. The pyrolysis-derived liquid fuels can also be blended with petroleum-based fuels such as gasoline or diesel for transportation vehicles (Lehto et al. 2014).

Many analyses have been conducted on these conversion processes in terms of economics, environmental and life cycle assessments (Fantozzi and Buratti 2010; Sultana and Kumar 2012; Loock 2008; Sowlati 2016). Recent economic analyses indicated that the above mentioned bioenergy products have economic advantages to compete with other alternative fuels (Hill et al. 2006; Cadenas and Cabezudo 1998). A number of techno-economic studies demonstrated the economic feasibility of biomass-based bioenergy production (Arena et al. 2010; Pootakham and Kumar 2010; Brown and Wright 2014). With lower expected feedstock costs and no competition with food, lignocellulosic feedstock was studied as a major bioenergy resource. In a study of biomass-based energy production, techno-economic performance of different plant scale levels in UK were compared, and the economic viability of different processes through a discounted cash flow analysis was analyzed (Patel et al. 2012). Trippe et al. (2011) examined the biomass-to-liquid and chemicals production by adopting a two-stage concept, and concluded that the cost to produce one normal cubic meter (Nm^3) of syngas is \$25.07 (23€), with potential reducing costs 50% when coal as feedstock was introduced. As in the study of naphtha and diesel range fuels production with the feedstock of biomass via fast pyrolysis pathway, Wright et al. (2010) established the models with two fixed yearly production rates, respective capital costs and fuel product values for both nth plant and pioneer plant. Few studies were conducted to qualify the economic uncertainty and risks associated with a biomass-to-bioenergy project. Batan et al. (2016) studied microalgae-based biofuel and characterized the economic feasibility, and their results showed the economic performance and price and cost projections, that production cost reaches \$3.46 and \$3.69 per liter of algal raw oil and diesel, respectively.

Life-cycle assessment is a comprehensive procedure for estimating environmental impacts on either cradle-to-gate or cradle-to-grave basis for systematic energy production (Tan et al. 2004). Efforts have been made on life cycle assessment in productions of multiple conversion pathways of biomass (Caputo et al. 2014; You et al. 2011; Budsberg et al. 2012; Popp et al. 2011; Hsu et al. 2010). Caputo et al. (2014) constructed a life cycle assessment model of willow as a short rotation crop to estimate the footprints of willow for energy process, and the system consumed 445.0 to 1,052.4 MJ of fossil energy per oven-dry tonne (odt) biomass and provided a large carbon sink that more than compensated for carbon emissions. A life cycle assessment by Budsberg et al. (2012) on ethanol production with willow biomass as feedstock indicated that life-cycle carbon emissions of ethanol production from willow are carbon negative compared to gasoline equivalent energy but 169% more of life-cycle freshwater was consumed than the gasoline equivalent. Liu et al. (2017) conducted a study using life cycle inventory (LCI) to investigate the environmental load of multiple bioenergy products with three energy crops. Their results showed that willow to bio-product system usually had lowest environmental impacts and cost compared to perennial grasses.

Monte Carlo simulation was the most commonly recommended approach for uncertainty analysis (Lo et al. 2005; Sonnemann et al. 2003; Heijungs and Huijbregts 2004; M. Huijbregts 2002). Uncertainty analysis is not commonly performed in LCAs, although great efforts have been made on classification, definition, and sources of uncertainty as well as methodological aspects for expressing uncertainty (Huijbregts 1998; Geisler et al. 2005; Guo and Murphy 2012). At the life cycle inventory (LCI) phase, publicly available LCA databases only provide inventory data with no uncertain information. The LCA uncertainty of willow-based biomass production was investigated by Caputo et al. (2014), and the impacts of a series of parameters including additional herbicide treatment, planting densities and nursery module were examined. Nguyen et al. (2014) evaluated two scenarios for corn-based bio-ethanol supply chains in Kansas with Monte Carlo simulation to examine the uncertainty in greenhouse gas (GHG) emissions, and their results showed that the GHG emissions range from 24 g CO_2 eq/MJ to 41 g CO_2 eq/MJ depending upon the location, size and number of preprocessing depots. There are several economic challenges to overcome in bioenergy production associated with processing technologies (Gold and Seuring 2011), feedstock availability and its logistics cost (Sukumaran et al. 2010), feedstock sustainability (Puri et al. 2012), financial and technical issues for commercial scale production, and assessment of indirect impacts (Kandaramath Hari et al.2015).

Technological and economic uncertainties of eight cellulosic biofuel production pathways via both biochemical and thermochemical conversions were evaluated by Zhao et al. (2015). They reported that the distributions of NPV and breakeven fuel price for each case, and concluded that the fast pyrolysis and hydro processing pathways are with the relatively lower risk for investors. A techno-economic study (Zhang et al. 2013) with Monte-Carlo analysis compared two bio-oil pathways of two-staged and single staged upgrading and identified that the two-stage hydrotreating has a relatively low risk for project investment.

There appears a necessity to analyze and quantify the environmental and economic impacts and their uncertainties in utilizing multiple biomass feedstocks for major bioenergy products at a regional scale. The objectives of this study were to: (1) conduct a life cycle assessment (LCA) to examine the environmental impacts of utilizing the multiple biomass feedstocks for bioenergy products in the northeastern U.S., (2) perform an economic analysis of the bioenergy feedstock supply chains, and (3) quantify the uncertainties of the production of bioenergy products in terms of economic feasibility and environmental impacts.

4.2 Materials and Methods

In this study, multiple lignocellulosic bioenergy feedstocks (forest residues, hybrid willow, switchgrass and Miscanthus) were considered for producing three bioenergy products: pellets, bio-power, and liquid biofuels. Base cases were identified with parameter configurations listed in Table 4.1. Data were primarily collected from regional bioproduct companies - two companies for biomass to pellets, one for biomass to liquid fuels, and one for biomass to biopower in the northeastern U.S. For pellet production, a local pellet plant produced 46,926 tons of pellets with a sale price at $185 per ton. For biopower generation, the production yield was calculated as 260,000 MWh per year by setting plant capacity of 30 MW for 365 days operated annually, and the sale price was 10.5 cents per kilowatt hour (U.S. EIA 2020). 78,000 barrels of pyrolysis oil were produced with assumed sale price of $54/bbl, according to estimation of the potential minimum selling price by the U.S. government's NREL lab (Lorenz Bauer, 2017). According to information provided by a pellet fuel company, the retail price ranged from $180 to $210 per ton of pellets. In the electric power monthly report, it mentioned that in United States, the average price of electricity to ultimate customers was in the range of 8 cents to 26 cents per Kilowatt hour (U.S. EIA 2020). Recently, the crude oil price dropped to its lowest point at $11.26 per barrel on April 24, 2020, and it brings big challenge in producing economic feasible biomass-based pyrolysis oil. Based on a U.S. DOE's report (Wright et al. 2010), the NREL estimates the minimum selling price per gallon of a commercially finished fuel made from current fast pyrolysis oil is about $2.53 per gallon ($106/bbl). Thus, the price range for pyrolysis oil was $11.26-106.26 per barrel in this study. By feeding one dry ton of lignocellulosic biomass as feedstock, it produced 0.83 ton of pellet fuel, or 1.53 megawatt hours, or 0.46 barrel of fast pyrolysis oil. The feedstock price for all cases was assumed at $84 per ton based on the DOE's target to lower delivered cost for lignocellulosic biomass than $84 per dry ton in year 2022 (DOE 2016).

Table 4.1 Parameter configurations for base case analysis.

Parameter	Products		
	Pellets	Electricity	Pyrolysis oil
Production technology	Pellet mill	Combustion with steam turbine	Fast Pyrolysis
Annual yield	46,926 Ton	260,000,000 KWh	78,000 bbl
Product sale price	$185/ton[a]	$0.105/KWh[b]	$54/bbl [c]
Price Range	$180-210/ton	$0.08-0.26/KWh	$11.26-106.26/bbl
Product yield rate (from per dry ton of feedstock)	0.83 ton of pellet[a]	1.53 MWh of electricity	2.17 bbl of pyrolysis oil
Capital Investment	$4,403,744	$71,616,960	$106,015,291
Annual operation cost	$4,046,745	$3,560,469	$612,069
Feedstock price	$84/ton	$84/ton	$84/ton

(a) Provided by Greene Team Pellet Fuel Company

(b) U.S. Energy Information Administration 2020

(c) (Lorenz Bauer 2017)

The baseline model was then coupled with Monte Carlo simulation to conduct uncertainty analysis of greenhouse gas emission (GHG) and Net Present Value (NPV) for bioenergy products derived from lignocellulosic biomass feedstock (Figure 4.1).

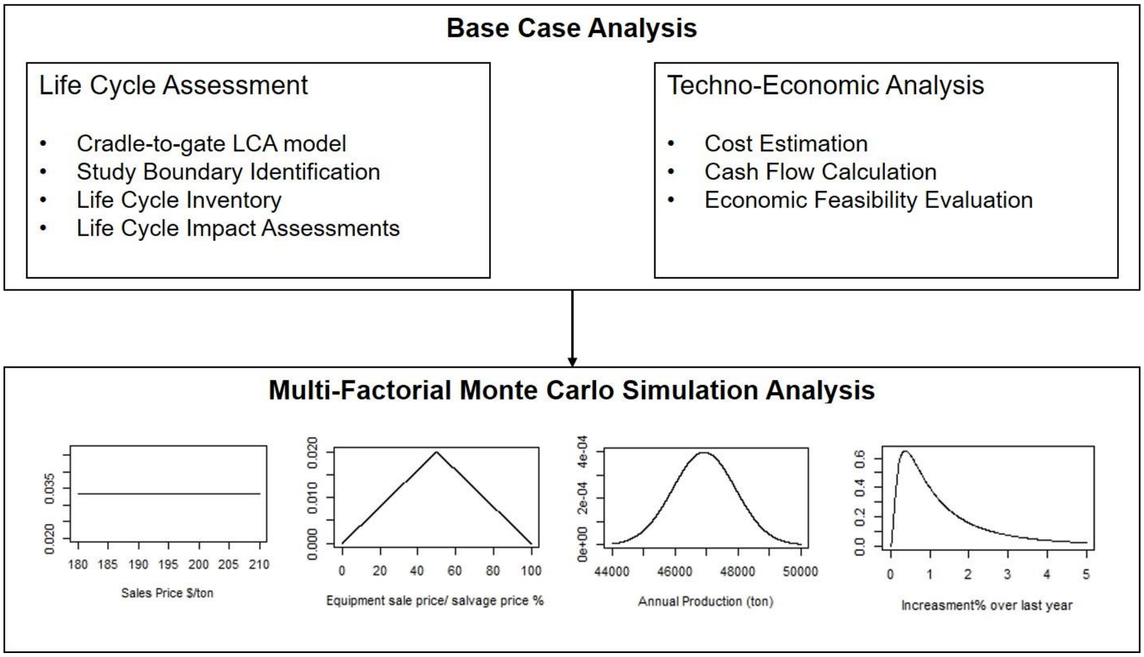
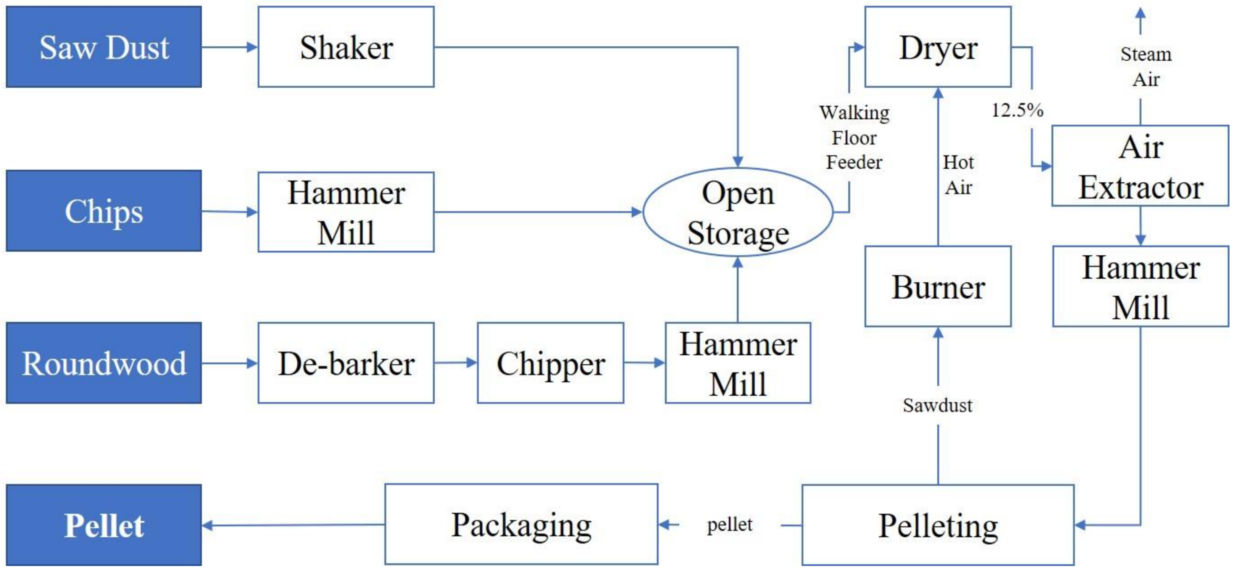


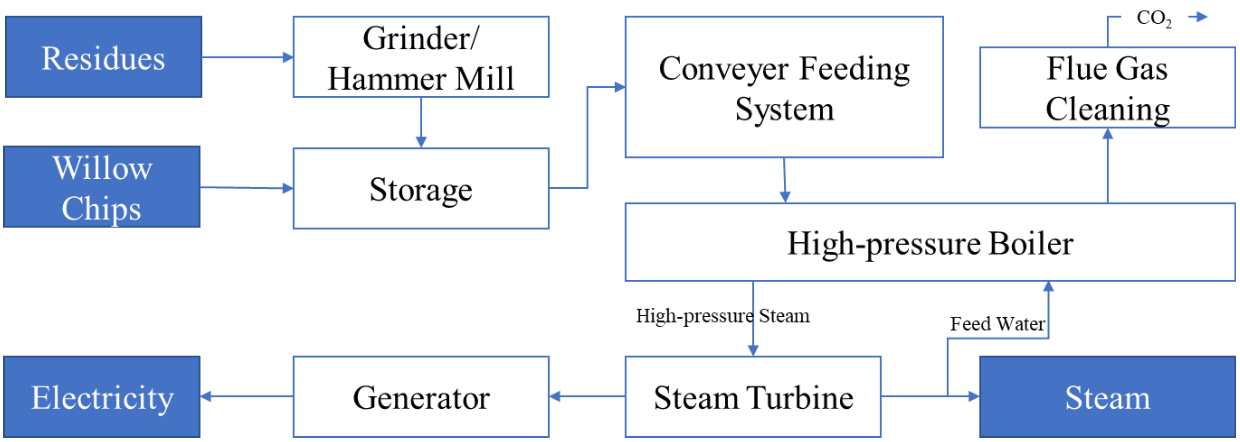
Figure 4.1 Flow chart of the economic and environmental impacts of biomass for bioenergy products.

4.2.1 Life Cycle Assessment

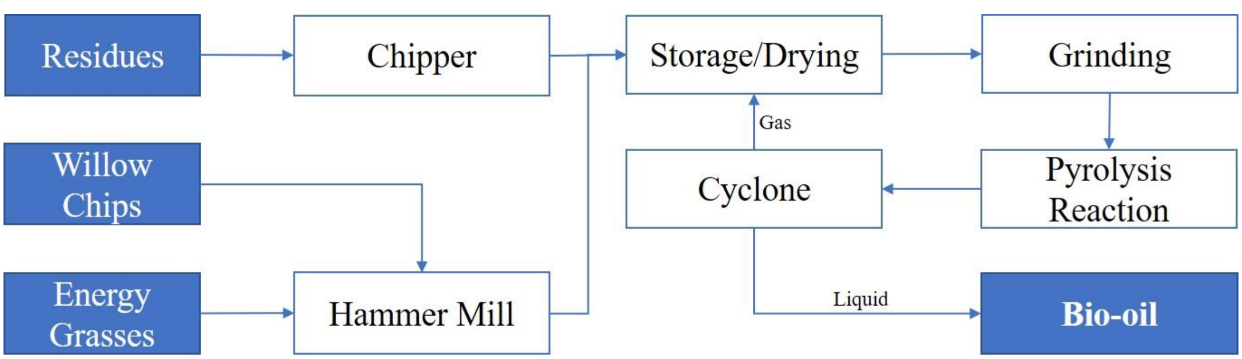
A cradle-to-gate LCA model framework developed includes feedstock collection, transportation, storage and preprocessing, bioenergy production (Figure 4.2). This study focuses on the GHG emissions, water and fossil fuel consumption. The functional unit (f.u.) of the system is 1,000 MJ of energy products. The boundary of this LCA includes raw feedstock handling (harvest/collection), storage, transportation, preprocessing, and conversion, following the International Organization for Standardization (ISO)'s LCA standards (Klöpffer 1997).



(a) Pellet



(b) Bio-Power



(c) Pyrolysis oil

Figure 4.2 Block flow diagram of multiple-feedstock logistics and production processes, (a)Pellet, (b)Bio-Power, and (c) Pyrolysis oil

Life cycle inventory of feedstock collection includes harvesting of logging residues using grapple loader, grapple skidder and chipper, while establishment of energy crops consists of site preparation, planting, fertilization and cut-and-chip or harvest-and-baling. The fuel consumption of residues harvest system was based on a study by Wu et al. (2011). The US LCI database was also used for the biomass transportation process (National Renewable Energy Laboratory 2012). The composition of multiple biomass feedstock was based on a study by Wang et al. (2020) for an optimized solution of the minimized delivered cost of biomass in the northeastern U.S.
The LCA model was developed using the environmental modeling tool SimaPro and database ecoinvent (PRé Consultants 2016, Wernet et al. 2016). The impact of GHGs was calculated using 100-year global warming potentials (Liu et al. 2017). All the emissions were converted into the carbon dioxide equivalent (kg CO_2 eq). The reduction of GHG emissions was calculated as the difference between the emissions from petroleum-derived-diesel and the emissions from the energy products by the three technologies in this study. The calculation of water consumption (kg) followed the method by Boulay et al. (2011). Fossil energy consumption (MJ) was calculated based on the Frischknecht's studies (Frischknecht et al. 2007; 2015; Frischknecht et al.1998).

4.2.2 Mathematical model for Techno-economic analysis

To evaluate the economic feasibility, the processes of the selected bioenergy pathways were first defined (Figure 4.2) and a range of NPVs was estimated for each pathway scenario based on stochastic analysis of the commodity prices and economic parameters.

The NPV method is a good way to analyze the profitability of an investment with unique advantages comparing across other economic methods, in counting time value of investment and ranking capability (Žižlavský 2014). The formulation of the NPV for biomass to bioenergy products is as follows:

$$NPV = -TIC + \frac{Q_1}{(1+\gamma)} + \frac{Q_2}{(1+\gamma)^2} + \cdots + \frac{Q_n}{(1+\gamma)^n} - EC + SV$$

$$= -TIC + \sum_{j=1}^{n} \frac{Q_j}{(1+\gamma)^j} - EC + SV \qquad (1)$$

Where,

TIC–the total initial cost for a bioenergy plant project;
n–bioenergy plant lifetime;
Q_j–net cash flow at any year j after project startup, without equipment replacement costs;
γ–interest rate;
EC–present value of equipment replacement costs;
SV–salvage value.

The annual net cash flow Q_j for a bioenergy plant production after the project startup shows difference between cash inflows and outflows by operating a bioenergy plant over each year, and it was calculated as:

$$Q_j = \left(\left(PQ_j * (1+\delta_j) * p\right) - FC_j - OC_j\right)(1+\epsilon)^j \qquad (2)$$

Where,
PQ_j–Quantity of product produced and sold for year j, for instance, tons of pellets, or amount of electricity in KWh, or number of barrels of bio-oil;
δ_j–Production increased rate based on previous year;
p –Unit selling price;
FC_j–Lignocellulosic feedstock cost for year j in dry matter basis;
OC_j–Operation and maintenance cost at the bioenergy plant for year j;
ϵ–Inflation rate.

And a constraint was set that the increased annual production shouldn't be exceeded the yearly capacity for bioenergy plant.

$$PQ_j * (1 + \delta_j) \leq \ Capacity \tag{3}$$

For quantity of bioenergy products produced and sold PQ_j,

$$PQ_j = FQ_j * (\tau) \tag{4}$$

Where,

FQ_j–Feedstock quantity in dry Mg transported to and utilized in facility for year j;

τ –Conversion rate, fuels produced by each dry Mg of feedstock.

For feedstock cost FC_j at year j,

$$FC_j = \varphi * FQ_j \tag{5}$$

Where, φ is Feedstock price per ton.

The total present value of equipment replacement costs, EC can be calculated from Equation (6) using the acquisition value for equipment at year zero AV. The EC takes into account the equipment initial costs plus the inflation in the period since it began to operate until its replacement, and for each replaced equipment it will be calculated.

$$EC = \sum_y AV \frac{(1+\epsilon)^y}{(1+\gamma)^y} \tag{6}$$

Where,

y–year of the equipment replacement;

AV- The acquisition value for equipment at year zero, which means the purchased value of the asset.

The salvage value was calculated by the following equation:

$$SV = \sum_i^N EIC_i \ (1 - \tau)^n \tag{7}$$

Where,

N- Total amount of equipment;

EIC_i- Equipment purchase cost for equipment i;

τ- Depreciation rate;

The total annual cost consists of annualized capital costs (calculated assuming an interest rate of 10% (Mahmoudi et al. 2009; Mobini et al. 2011)), operating and maintenance costs, and biomass feedstock cost. The total installed costs were calculated by a factored estimation (McKendry 2002a; 2002b; 2002c), based on the major equipment required for various production processing. All capital costs are in 2020 U.S. dollars with the equipment cost inflation calculated using the Chemical Engineering Plant Cost Index (CEPCI) (Anderson 2014).

4.2.3 Monte Carlo simulation for uncertainties

Monte Carlo simulation is a mathematical technique which performs risk analysis by building models with random variables for decision (Rubinstein and Kroese 2016). In this study, we used this computational algorithm to estimate the environmental impacts and techno-economic benefits of biomass-based energy production. Separate simulation runs with 5,000 iterations were conducted. Monte Carlo analysis was performed for both environmental impacts and economic feasibility in this study (Table 4.2).

Table 4.2 Descriptions of parameters for uncertainty analysis.

Variable	Scenarios	Minimum	Base Case	Maximum	Distribution
Parameters of Life Cycle Inventory					
Diesel Consumption in Collection (per ton biomass, L)	All	4.97	6.21	7.45	Uniform
Lubricant Oil Consumption (per ton biomass, kg)	All	0.048	0.06	0.072	Beta
Pellet Annual Production (ton)	Pellets	37,543	46,929	56,314	Triangular
Electricity Annual Production (MWh)	Bio-power	208,000	260,000	312,000	Triangular
Pyrolysis oil Annual Production (bbl)	Biofuel	62,400	78,000	93,600	Triangular
Parameters of Techno-economic Assessment					
Pellet Conversion Rate (tons per dry ton feedstock)	Pellets	0.81	0.83	0.90	Beta
Electricity Conversion Rate (MWh per dry ton feedstock)	Bio-power	1.37	1.53	1.68	Beta
Liquid Bio-oil Conversion Rate (bbl per dry ton feedstock)	Biofuel	1.89	2.17	2.56	Beta
Increase over previous year	All	0%	0%	5%	Lognormal
Pellets Sales Price (per ton)	Pellets	$180	$185	$210	Beta
Electricity Sales Price (per KWh)	Bio-power	$0.08	$0.105	$0.26	Beta
Liquid Bio-oil Sales Price ($/bbl)	Biofuel	11.26	54	106	Beta
Biomass Feedstock Price (per dry Mg)	All	$69	$84	$136	Beta
Discount rate	All	0%	5%	N/A	Lognormal

Greenhouse gas (GHG) emissions from bioenergy supply chains are critical, since climate change and energy policies often encourage bioenergy as a sustainable GHG mitigation option (Röder et al. 2015). The conventional life cycle assessment (LCA) does not perform quantitative uncertainty analysis. However, the reliability of life cycle assessment results can be improved by characterizing the associated uncertainty (Lo et al. 2005). The uncertainty of GHG was quantified using various probabilistic methods, including Monte Carlo simulation with knowledge of the underlying probability distribution functions that characterize the model parameters. A total of 1,000 random trials were conducted to study the effect of uncertainty. Several factors affecting the life cycle GHG emissions of biomass-derived fuel products were examined, including the production technology, and the efficiency of production, the operation and maintenance of bioenergy production.

Yearly cash flows were generated for the three productions, and the NPVs were derived from these cash flows. Stochastic production rate, production increasing rate, sale price, feedstock price, and discount rate were used to adjust the models. The Monte Carlo implementation results in a set of NPV values, which are represented by their corresponding probability distributions. The greater the number of iterations performed, the better the precision of the uncertainty would be examined.

4.3 Results

4.3.1 Life cycle analysis

The environmental impacts of the three bioenergy technological pathways were listed in Table 4.3, and all environmental impacts were calculated with f.u. of 1000 MJ for bioenergy production. Pellet production presented the lowest GHG emissions with 8.29 kg CO_2 eq and consumed the least amount of fresh water and fossil fuels. Pyrolysis oil production had the highest environmental impacts for all impact factors. The pyrolysis oil production emitted the highest amount of greenhouse gas, which was double that of biopower production, and 3.87 times that of pellet production. Both biopower and pellet production consume a small quantity of fresh water compared with pyrolysis oil production, for 0.73, and 0.46 kg, respectively.

Table 4.3 LCA results for bioenergy products: Pellet, Biopower, and Pyrolysis oil.

Products	Impact Factor	Bioenergy Supply Chain Components				Total LCA Impacts
		Feedstock Collection	Transportation	Storage and Preprocessing	Conversion	
Pellet	Greenhouse Gas Emission	1.239	0.294	2.394	4.368	**8.295**
	Blue Water Consumption	0.01	0.04	0.01	0.41	**0.46**
	Fossil Energy Consumption	2.37	6.08	2.55	94.42	**105.42**
Bio-Power	Greenhouse Gas Emission	3.24	6.33	2.14	3.87	**15.58**
	Blue Water Consumption	0.05	0.36	0.07	0.25	**0.73**
	Fossil Energy Consumption	2.26	17.98	6.14	35.68	**62.06**
Pyrolysis oil	Greenhouse Gas Emission	2.93	3.74	0.62	23.29	**30.58**
	Blue Water Consumption	0.12	0.36	0.08	3.84	**4.40**
	Fossil Energy Consumption	2.82	7.24	2.71	100.40	**113.16**

The percentages of the total impacts were analyzed and summarized by supply chain components for pellets, biopower and bio-oil (Figure 4.3). Feedstock transportation contributed most to the greenhouse gas (GHG) emission and blue water consumption (BWC) when producing biopower with 40.66% of total GHG emission, and 48.81% of blue water consumption. It was different from pellet and biofuel production in which the conversion process attributed more GHG (with 52.66% and 76.17%, respectively) and BWC (with 88.53% and 87.27%, respectively) . All four processes (including feedstock collection, transportation, storage and preprocessing, and conversion) for biopower production contributed more than 10% of GHGs. Storage and preprocessing for pellet and bio-oil production accounted for both very low portions of the total GHG emission, for 2.00% and 2.03%, respectively. When producing electricity from lignocellulosic biomass, the top two processes transportation (48.81%), and conversion (34.64%) consumed the most water. Conversion was the process in bioenergy supply chain consuming the largest amount of fossil energy in all three bioenergy productions, and all exceeded 50% of total fossil fuel consumption. Specifically, the conversion processes consumed 89.57% and 88.72% of total fossil energy to produce pellet and bio-oil. For biopower production, 57.49% of fossil energy was consumed in combustion and 28.79% of fossil fuel was used in feedstock transportation process, following with 9.90% for storage and preprocessing, and 3.64% for feedstock collection.

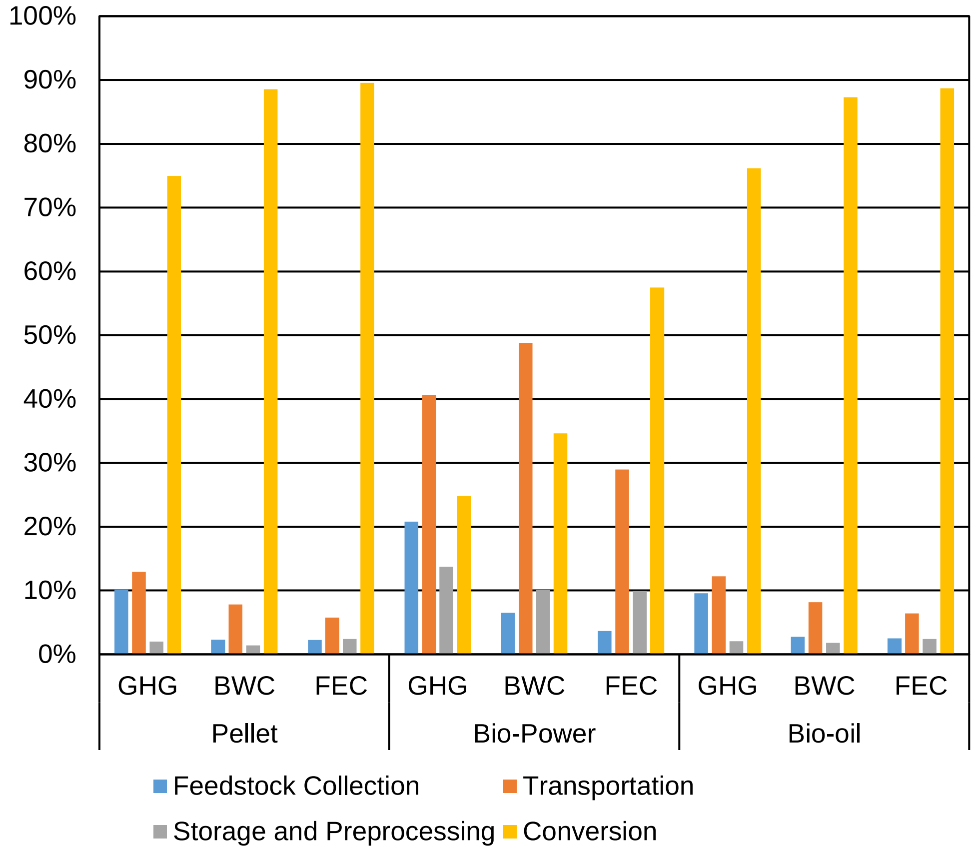


Figure 4.3 Percentages of the total impact of Greenhouse Gas Emission (GHG), Blue Water Consumption (BWC), and Fossil Energy Consumption (FEC) by supply chain components for Pellet, Biopower, and Bio-oil.

4.3.2 Techno-economic analysis

Based on economic assessment for multi-feedstock multi-pathways bioenergy production, the economic evaluations were summarized in Table 4.4.

Table 4.4 Economic evaluation for three products: Pellet, Biopower, and Pyrolysis oil.

Parameter	Products		
	Pellets	Electricity	Pyrolysis oil
Bioenergy production summary			
Plant life (year)	16	25	20
Feedstock consumption (dry tons)	848,114	4,079,847	666,900
Bioenergy production	703,935 ton	6,240,000 MWh	1,760,564 bbl
Economic feasibility summary			
Total investment cost ($)	4,403,744	149,550,000	106,015,291
Total feedstock cost ($)	71,241,614	342,707,175	56,019,600
Total operating cost ($)	60,701,175	85,451,256	11,629,319
Total revenue ($)	139,236,253	694,526,976	80,028,000
Net Present Value (NPV) ($)	1,201,069	81,598,262	(98,998,847)
Discount rate (%)	5	5	5

Total biomass feedstock consumption and bioenergy mass production were summarized. With consumed 848,114 dry Mg of biomass feedstock, a pellet plant could produce 703,935 ton of pellet products, which bring a total of $139.23 million revenue, and the net present value was $9.64 million in 16 year. Via biomass combustion to produce electricity, a biopower plant could utilize around six times of feedstock, which could bring 4.7 times of revenue ($657,69 million) than a pellet plant. For biopower production, the net present value was $108.77 million with discount rate of 5%. The total amount of biomass feedstock consumed for bio-oil production was similar to pellet production but resulted with a much lower NPV at -$98.14 million. Among all the cost components, the operating cost represents the largest contribution (52-63%) to the total production cost, and it is followed by the capital investment ranging from 30-36.5%. The production costs averaged $14.81 per ton for pellets, $0.04 per KWh for biopower, and $40.11 per barrel for pyrolysis fuels.

Usually, a discount rate is used in discounted cash flow analysis to compute a net present value, and it reflects the opportunity costs, inflation, and risks accompanying of time (Rasheed et al. 2016). With the general rule of thumb for selecting an appropriate discount rate that the discount rate equals investors' required rate of return (Jagannathan et al. 2016), the product net present values (NPV) of bioenergy plants via three conversion pathways were analyzed based on 0%-30% discount rate (Figure 4.4). Results showed that the pellet plant and biopower plant would be profitable when the discount rate was less than or equal to 10%. For pellet production, the NPV ranged from $2.89 million to $0.21 million for discount rate 0% to 10% accordingly. The biopower plant would be profitable with NPV ranged from $106.04 million to $15.75 million only when the discount rate was less than or equal to 10%, and the NPV dropped dramatically as discount rate increased. For pyrolysis oil production, it was never profitable even though the discount rate as low as 0%.

Figure 4.4 The impacts of discount rate on Net Present Value for three products: Pellet, Biopower, and Pyrolysis oil.

4.3.3 Uncertainties of the environmental and economic impacts

GHG emissions from bioenergy supply chains are critical to their sustainability and GHG mitigation potential. Uncertainty of GHG for three bioenergy products were examined using Monte Carlo simulations (Figure 4.5). In Figure 4.5, the right tail of pellet and the left tail of Bio-power were very close to each other. The largest value of the three impact factors among the three technologies were 51.2 kg CO_2 eq greenhouse gas emissions for bio-oil production. The results presented here show a small variation in emissions from electricity generated from lignocellulosic biomass ranging from 15.4 to 15.9 CO_2 kg eq GHG emission of per 1000 MJ. Bio-oil production had a compacted distribution of GHG emission simulated from Monte Carlo, and its GHG emission distribution is right skewed, ranging from 21.9 to 51.2 CO_2 kg eq per 1000 MJ. The GHG emission simulation for pellet production showed a large variation with GHG from 7.4 to 10.5 CO_2 kg eq per 1000 MJ. Among three bioenergy products, pellet production showed the highest uncertainty in GHG emission, bio-oil production had the least uncertainty in GHG emission but had risks producing greater-than-normal amount of GHG.

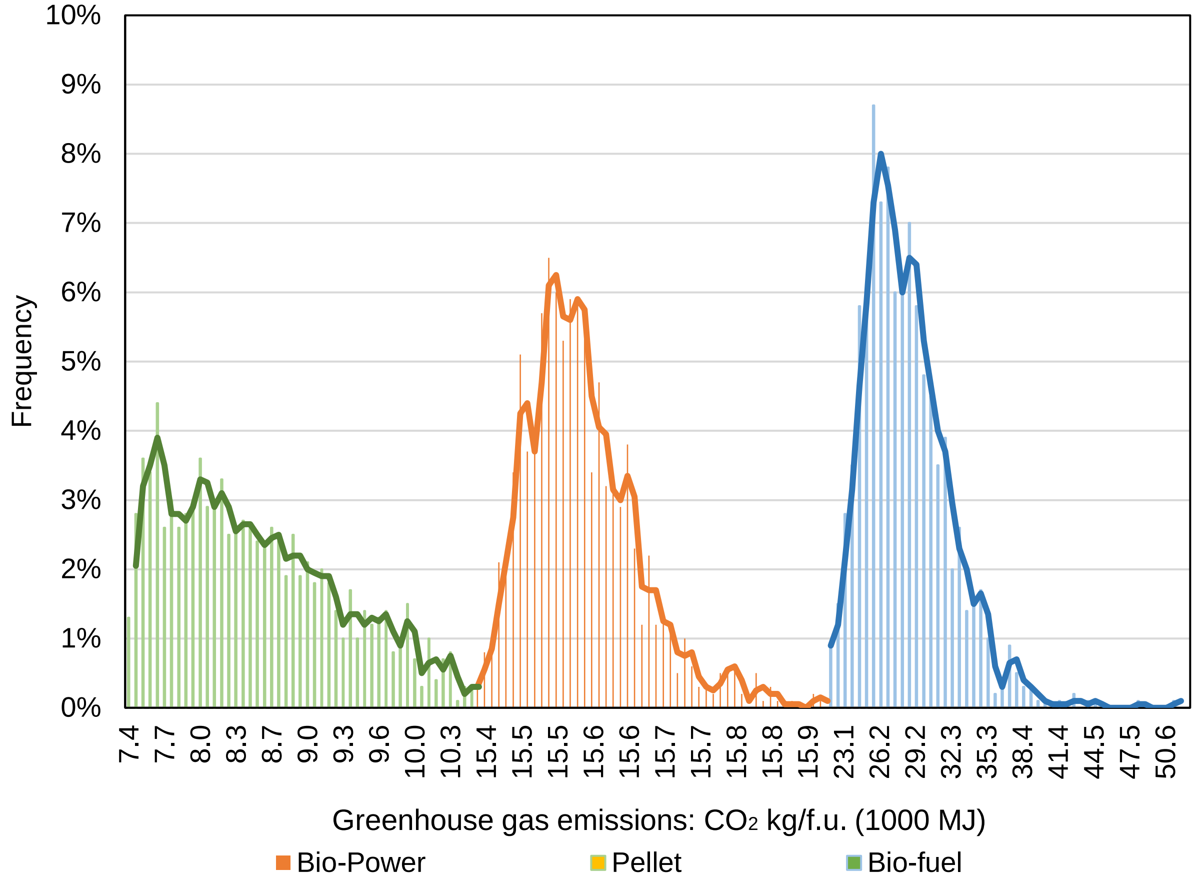


Figure 4.5 Uncertainty of Greenhouse gas emission of three biofuel products

Five sensitive variables were accessed in terms of NPVs. After 5,000 iterations the MC converges to the NPV results with the behavior of the NPV under consideration of related parameter uncertainties (Figure 4.6).

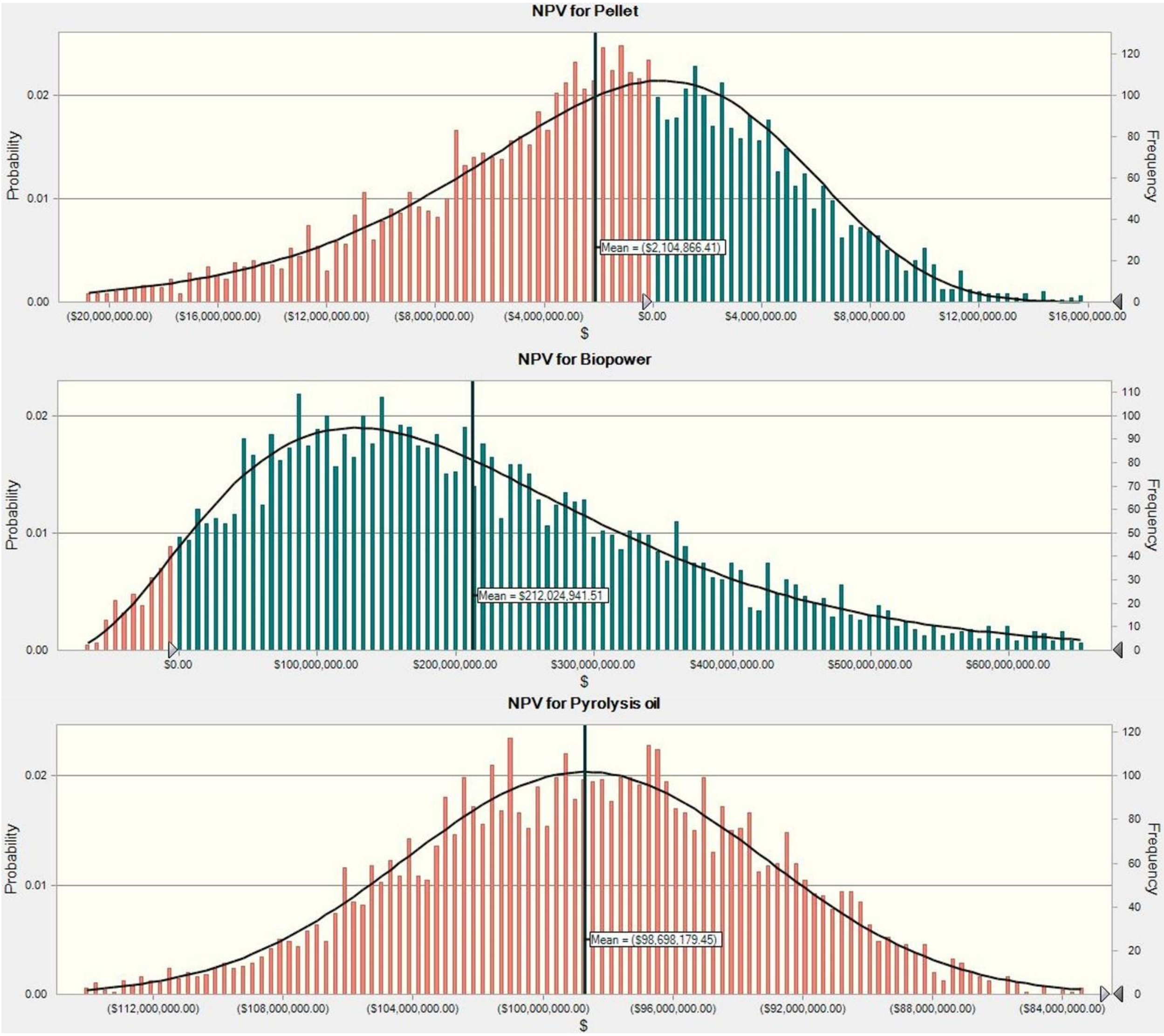


Figure 4.6 Fitness of statistical distributions of uncertainties: (a) pellet fuel, (b) biopower, (c) biofuel.

For pellet fuel production, the distribution presents an average NPV of -$2,104,886 with 39.58% of probability to be a profitable investment. The Anderson-Darling factor was calculated to figure out the best fitted distribution. A Weibull distribution showed the best fit with lowest A-D factor of 4.04. In the biopower production pathway, the profitable probability was 95.38% with uncertainty factors introduced. For an 80% credible interval, the simulation results of NPV ranged from $34.02 million to $425.92 million (for percentile 10% to 90%). A Gamma distribution with parameters location value of \$89.42 million, and scale value of \$84.42 million, could be used for the probability prediction of the biopower production. The probability for a biofuel plant to be profitable was zero. A beta distribution can represent the uncertainty distribution.

4.4 Discussion

4.4.1 Environmental impacts

Power generation emits significant amounts of greenhouse gases (GHGs), which are combination of CO_2, CH_4, and N_xO . The global warming potential with GHG has taken into account the upstream processes of power generation. Spath and Mann (2004) studied the GHG emissions for biomass and conventional fossil systems to generate electricity, and found the biomass direct-fired system have the global warming potential -148% lower compared to traditional coal-fired power plant, and 99% lower of fossil fuels combustion. Hsu (2012) studied the GHG emissions for biomass-based pyrolysis oil, and showed that greenhouse gas emissions could be reduced around 50% from pyrolyzed biofuels compared to fossil fuels. To produce every 1000 MJ of bioenergy, bio-oil production generated the highest GHG emission, and consumed most fresh water and fossil energy among all three bioenergy products. In a pyrolysis oil study by Steele et al. (2012), the results showed the global warming potential for pyrolysis bio-oil production is 32 kg CO_2 eq, which is very close to 30.58 kg CO_2 eq of GHG emission in this study. Though with higher GHG emission than the other two bioenergy products, pyrolysis technology is advancing at a rapid rate and has a promising potential for commercial conversion of biomass to fuels.

Contributions to the total GHG emissions of biorefinery systems were different based on conversion pathways. For bio-oil production, pyrolysis conversion was the only crucial process to determine how much GHG emits. However, when producing pellet, feedstock collection, storage and processing, and pelletizing all played large role in determining the final GHG balance. It is the same for biopower production that all processes contribute more than 10% of the total GHG emission. These changes among different bioenergy products could be explained by different utilization of energy at the facilities. Based on the study by Cherubini and Jungmeier (2010), the largest fraction of total GHG emission originated from diesel/gasoline consumption, followed by electricity from natural gas, heat and others. The production of pellet showed lower GHG emissions than the other two products, and the reason was there is only a low level of electricity consumption in pellet mill with less processing (Fantozzi and Buratti 2010; Steele et al. 2012). Even though energy consumption is usually high for biomass power generation (Nuss et al. 2013), the heat and electricity could be self-sufficient, with more feedstock required.

4.4.2 Economic feasibility

For bioproduct investment, the major capital cost items for a bioenergy production system include various processing and controlling equipment. System cost intensity tends to decrease as the system size increases, but this could increase significantly with feedstock costs (Tidball et al. 2010). Usually the scale of a biopower plant or a biofuel refinery is much larger, and a larger facility will demand more biomass with more biomass handling cost (Sultana et al. 2010). A few smaller size facilities will be able to reduce the transportation distance of biomass delivery. The capital and operational and maintenance costs were adjusted from previous-studies, and the costs for pellet facility were much lower than these of the other two bioenergy products.

Feedstock cost occupied a large proportion of the total impact on the final production costs. In a study of biomass-based transportation fuel by Wright et al. (2010), the cost of biomass as feedstock is an important factor affecting the sensitivity of the total cost and the feedstock cost varies among feedstock supply/demand locations all year round. Consequently, the feedstock cost was also proved as an important parameter influencing the final product value from biomass (Swanson et al. 2010). It is critical to lower feedstock cost by minimizing delivery cost through logistic optimization (Wang et al. 2020). Biomass logistics modeling and optimization have long been on a single biomass feedstock at a relatively small scale, and this study showed that it is necessary to focus on multiple feedstocks at relatively large commercial scale. In biomass logistics optimization, biomass feedstock with issues such as low bulk density, spatially dispersed, high mass loss during handling always needs to be considered to lower the biomass delivered cost. There are various feedstocks available in the northeastern U.S. including energy grass, short rotation woody crops such as hybrid willow, and forest residues.

4.4.3 Uncertainty and risks analysis

In bioenergy production with renewable sources, the use of the MC method has advantages when compared to traditional sensitivity analysis. Monte Carlo simulation provides a dynamic approach to assessment of bioenergy production environmentally and economically.

With counting uncertainty factors for three bioenergy products, 10,000 iteration of MC simulation was made. The pellet production showed more flat distribution than other two cases implied its highest uncertainty in GHG emission. This suggests that any slight change of environmental impact factors for pellet fuel production could easily raise the GHG emission. For the biofuel scenario, its environmental impacts would be less affected with little uncertainty, even though it had highest GHG emission.

Fossil fuel price have a great impact on bioenergy market, especially for pyrolysis oil production from biomass. In this study, the biofuel case always showed negative NPV for sale price ranged $11.26 to $106/bbl. However, the bio-oil plant would be profitable if the market price could rise to $135 per barrel, and the NPV would be as high as $2.52 million with 5% discount rate. Accounting multiple economic uncertainty factors, the relative low probability with 49.57% for a pellet plant to be profitable implies a relatively high risk in investment. Compared to the high probability (over 80%) to be profitable for biopower plant, it could due to the smaller scale for bioenergy plant would show much more fragile to the changes of financial environment and biomass and bioenergy market. To increase assurance of investment profitability, adding additional processing to upgrade products that could lead to a premium price would provide financial benefits.

4.5 Conclusion

This paper provides a dynamic approach to conduct an integrated life cycle and techno-economic assessment for three bioenergy products utilizing multiple lignocellulosic biomass as feedstock. Results of the LCA and TEA provide insights for commercial-level decision making with regards to bioenergy production alternatives and investment potentials. Results can also inform potential policy makers aimed at facilitating growth in the bioenergy and bioproducts industries in the Northeast United States.

The life cycle assessments for each supply chain component show different patterns for pellet, biopower, and biofuel production. The variance of environmental burden and cost were mostly explained by the differences of conversion pathways of the products. Biopower production presented the lowest GHG emissions, but with the highest water and fossil energy consumptions. Results of the LCA present that pyrolysis bio-oil production has the highest environmental impacts for GHG emission water and fossil fuel consumption, and pellet production has the lowest environmental impacts.

The economic feasibility of multiple biomass feedstocks for bioenergy products is essential for scale-up of various technologies. Separate process-based technical cost models were developed for the three established bioenergy production processes, and cases pellet and biopower production showed profitable under certain plant assumptions and circumstances. The net present value was most sensitive to discount rate when producing biopower, which implies higher risk when investors require a higher rate of return.

Analytical approaches like Monte Carlo simulation could make more accurate decisions by applying a large number of iterations. For GHG emission, pellet production shows higher uncertainty than the other two bioenergy products. For financial evaluation, there is higher chance to be a profitable investment for biopower production.

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5. Quantifying Environmental and Economic Impacts of Highly Porous Activated Carbon from Lignocellulosic Biomass for High-Performance Supercapacitors[4]

[4] To be submitted to Renewable Energy.

Abstract:

Activated carbons (AC) from lignocellulosic biomass feedstocks have been used as supercapacitor electrodes. This chapter evaluated the environmental and economic impacts of AC produced from lignocellulosic biomass for energy storage purpose. The life cycle assessment (LCA) was employed to quantify the potential environmental impacts associated with AC production via the proposed processes including feedstock establishment, harvest, transport, storage and in-plant production. A techno-economic model was constructed to analyze the economic feasibility for AC production, which included the processes in the proposed technology, as well as the required facility installation and management. A base case together with two alternative scenarios of KOH-reuse and steam processes for carbon activation were evaluated for both environmental and economic impacts, while the uncertainty for the net present value (NPV) of the AC production was examined with seven economic indicators.

Our results indicated that overall "in-plant production" process presented the highest environmental impacts. Normalized results of life cycle impact assessment showed that the AC production had environmental impacts mainly on carcinogenics, ecotoxicity, and non-carcinogenics categories. We then further focused on life cycle analysis from raw biomass delivery to plant gate, the results showed "feedstock establishment" has the most significant environmental impact, ranging from 50.3% to 85.2%. For an activated carbon plant of producing 3000 kg AC per day in the base case, the capital cost would be \$6.66 million, and annual operation cost was \$15.46 million. The AC required selling price (RSP) was \$16.79 per kg, with the discounted Payback Period (DPB) of 9.98 years. Alternative cases of KOH-reuse and steam processes had GHG emission of 15.4 kg CO_2 eq, and 10.2 kg CO_2 eq for every 1 kg activated

carbon, respectively. Monte Carlo simulation showed 49.96% of the probability for an investment to be profitable in activated carbon production for supercapacitor electrodes.

5.1 Introduction

Lignocellulosic materials such as energy grasses and woody biomass are widely recognized as environmentally friendly feedstocks for value-added bioproducts (Liu et al. 2017a), including for bioenergy production (Liu et al. 2017b) and carbon sequestration (Zhao et al. 2019), and as an essential element for the production of active carbon-based material (Gu et al. 2018). Utilizing biomass to develop alternative energy storage devices with high energy densities is a viable solution due to the uncertainty of fossil fuels and increased environmental concerns (Subramanian et al. 2007). Supercapacitors are intermediate systems between electrochemical batteries and dielectric capacitors, which can deliver high power during few milliseconds (Kötz and Carlen 2000). Carbon supercapacitors are one of the three different types of supercapacitors (Gamby et al. 2001). Among the variety of carbonaceous materials such as carbon aerogel, activated carbon (Obreja 2008), and carbon nanotubes (Portet et al. 2005) currently investigated for supercapacitor electrode, activated carbon is the most widely used material mainly because of its cost effectiveness, good conductivity and potential environmental improvement (Teo et al. 2016). Despite the fact that carbon electrode is mostly produced from nonrenewable materials like coal and petroleum, lignocellulosic biomass has been known as a renewable and inexpensive feedstock for AC-based supercapacitor electrodes.

Fundamentals behind activation of carbon materials have been well studied and the activation of carbon materials is generally done either by a physical or chemical process (Chen et al. 2011; Alhashimi and Aktas 2017). In the case of physical activation process, a large amount of internal carbon mass in carbon structures are removed with activators such as steam or carbon dioxide (Bergna et al. 2018), while in the chemical activation process, chemicals agents used in both carbonization and activation steps so the raw material is thermally decomposed

(Świątkowski 1999). The synthesis protocol of the biomass-based AC capacitors usually includes pyrolysis (for carbonization) and activation processes (Yakaboylu et al. 2019). Various studies on activated-carbon supercapacitors have investigated the integration pyrolysis and activation processes, and all showed high specific capacitances of biomass derived carbon (Cao et al. 2016; Sun et al. 2013; Li et al. 2011).

Though efforts have been made by researchers to study on biomass-based activated carbon for energy storage applications (Teo et al. 2016; Hassan et al. 2020), the production of lignocellulosic activated carbon for energy storage purpose still faces many technical, economic, and environmental challenges. Studies have focused on using lignocellulosic material for activated carbon production due to its voluminous amounts (González-García 2018) and environment-friendly attributes (Hjaila et al. 2013). However, the downside of using lignocellulosic material for activated carbon production is the low carbon yield (Hassan et al. 2020), which could result in economic and environmental issues. Meanwhile, the other key challenge towards the carbon supercapacitor is the development of low cost activated carbon compared to other electrode materials (Rufford et al. 2008).

Life Cycle Assessment (LCA) is an approach that accounts and manages environmental impacts by considering all the aspects of resource uses and emissions associated with an industrial system from either cradle-to-gate or cradle-to-grave (Curran 2008). A full LCA study typically includes four steps: goal and scope, inventory analysis, impact assessment, and the interpretation of results (Muralikrishna and Manickam 2017). Life Cycle Assessment has been widely applied to analyze the environmental impact of the utilization of biomass to various biomass-based products (Liu et al. 2017b; Budsberg et al. 2012). Liu et al. (2017a) compared three bioenergy products from three lignocellulosic feedstocks and found that pellet production presented the lowest greenhouse gas (GHG) emissions and fossil energy consumption than biopower and biofuels. A LCA of ethanol production via bioconversion of willow biomass showed a 1.69 times greater of water consumption compared to the gasoline production of using the same feedstock (Budsberg et al. 2012). The environmental impacts associated with the activated carbon production vary depending on different feedstocks and synthetic processes. A cradle-to-gate LCA study of activated carbon from woody biomass has showed that the cumulative energy demand would potentially decrease by 35% compared to coal-based activated carbon (Gu et al. 2018). A study on the environmental impacts of activated carbon from olive-waste cakes showed that the impregnation using H_3PO_4 as chemical activation agent is a major process responsible for the majority of the impacts (Hjaila et al. 2013). Another LCA study of activated carbon from coconut shells implied that using renewable resources to produce AC would reduce both human toxicity and global warming (Arena, Lee, and Clift 2016).

Previous studies have focused on cost estimation of biomass derived activated carbon (Ng et al. 2003; Stavropoulos and Zabaniotou 2009). A process flow diagram was developed for AC production from pecan shells in a plant with a capacity of 10000kg/day, with a production cost of \$2.89/kg (Ng et al. 2003). The activated carbon production processes were compared using various feedstocks with the production costs ranging from \$1.56 to \$2.24 per kg of activated carbon (Stavropoulos and Zabaniotou 2009).

However, a comprehensive assessment of the economic feasibility and life cycle analysis for carbon supercapacitors is still lacking. As the electrodes industry continues to grow, it is critical to develop a baseline analysis of the biomass derived activated carbon for energy storage purpose and evaluate its performance economically and environmentally. The objectives of this study were to: (1) perform a life cycle assessment analyzing the environmental impacts of biomass-based activated carbon; (2) conduct a techno-economic analysis for utilizing the energy crops for carbon supercapacitors, (3) compare environmental impacts from alternative scenarios of the activated carbon productions, and (4) quantify the economic uncertainty of the AC productions.

5.2 Materials and Methods

In this study, an entire process of activated carbon production was defined with utilizing energy crops of switchgrass and miscanthus to produce highly porous activated carbon for supercapacitor electrodes. The processes of the AC production include biomass establishment, harvest, transport, storage, and in-plant production.

The raw feedstock: switchgrass and miscanthus, has been established in the field and was harvested and stored before delivery to the activated carbon (AC) plant, and then it is ground and blended into relatively fine material of smaller particle size in order to facilitate the carbonization and activation thereafter. Biochar is prepared by intermediate pyrolysis in a fixed bed with raw materials. After being impregnated with the potassium hydroxide (KOH) solution for chemical activation with the precursor-to-KOH ratio always kept constant at 1:4 by weight (Yakaboylu et al. 2019), the intermediate carbon is activated in at 850 °C. In the base case, it was assumed the plant production rate of 3000 kg per day, which is a capacity to meet the demand of a small-to-medium supercapacitor electrode market (Sun et al. 2013).

Two alternative scenarios of life cycle impacts were examined relative to the base case in terms of sensitivity. In the activation process of the baseline, the potassium hydroxide (KOH) was used as an activation agent and the KOH was not recycled, which would bring a great amount of environmental burden due to the chemical consumption and waste water created (Montes and Hill 2018). For the first case scenario, the introducing chemical recycling and reusing of potassium hydroxide with a mass loss of 10% was considered. The steam activation was used in the second alternative scenario and it is a common process to produce activated carbon for general purposes at commercial scale (Nor et al. 2013).

Then the uncertainty of the economic impacts was examined according to the changes of stochastic production rate, production increase rate, sale price, equipment salvage price, and discount rate in the models. Monte Carlo (MC) simulation results in a set of values for the NPVs, are represented by their corresponding probability distributions (Table 5.1).

Table 5.1 Impact factors for the TEA uncertainty analysis.

Item	Base Case Value	Prob Distribution
Labor rate	\$18.58/hr	Beta(4.8,2.7) min=7.25 max=25
Raw materials Delivery cost	\$80/dry Mg	Beta(2,9) min=69 max=130
KOH price	\$750/dry Mg	Uniform(500,1000)
Lang factor	3.63	Beta(2.3,5) min=3 max=5
Days operated	320 days	Beta(3,3) min=310 max=330
Production Price	\$17/kg	Beta(6,6.5) min=5 max=30
Discount Rate	5%	Uniform(0.05,0.1)

5.2.1 Life Cycle Assessment

5.2.1.1 Goal and scope definition

A cradle-to-gate LCA model was developed to estimate the environmental impacts of active carbon production for supercapacitors from lignocellulosic biomass. The entire study boundary for producing high-performance activated carbon includes two major components: biomass feedstock production and in-facility AC production (Figure 5.1). The cradle-to-gate LCA considers feedstock establishment, harvest, transportation, and storage, in-plant production, and final products. In an AC production plant, raw materials were processed through: (1) size reduction, (2) thermochemical conversion into biochar via pyrolysis, and (3) chemical activation. The functional unit (f.u.) of the system was 1000 kg of energy-storage-purpose activated carbon.

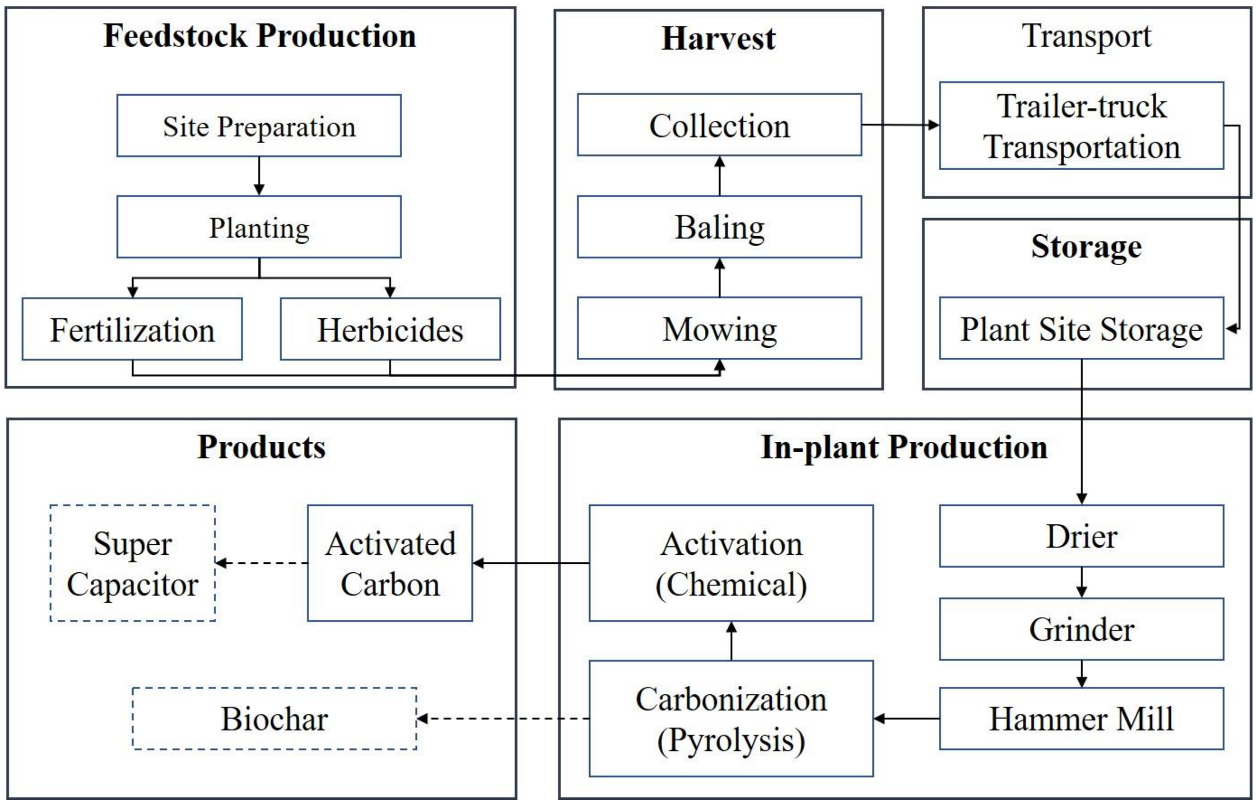

Figure 5.1 Study boundary of the activated carbon production from lignocellulosic biomass.

5.2.1.2 Life cycle inventory

With producing 1000 kg of highly porous AC, the material inputs were carried out to estimate the environmental output over the AC production (Table 5.2). Diesel and lubricating oil were consumed by machine handling in almost every process. The utilization of fertilizer and herbicide was also considered and could potentially have great environmental impacts. Electricity and potassium hydroxide (KOH) were the materials consumed in size-reduction, carbonization, and activation. Data of input was from the studies by Liu et al. (2017a), Arena et al. (2016), Yakaboylu et al. (2019), and the US LCI database (US NREL 2012).

Table 5.2 Environmental inputs and outputs for energy-storage activated carbons (ACs) from cradle-to-gate, on a per ton (1000 kg) basis (f.u.).

		Amount	Unit
Product			
	AC	1000	kg
Feedstock consumed			
	Multiple Lignocellulosic Biomass	8.94	Dry Mg
Input			
	Diesel	80.56	L
	Lubricating oil	0.78	kg
	Ammonium sulphate, as N	51.00	kg
	Glyphosate	0.18	kg
	Electricity, medium voltage	669.83	kWh
	Potassium hydroxide (KOH)	22,560.00	kg
Output			
	Butadiene	3.39E-05	kg
	Acetaldehyde	6.65E-04	kg
	Acrolein	8.02E-05	kg
	Benzene	8.09E-04	kg
	Carbon dioxide, fossil	1.03E+04	kg
	Carbon monoxide, fossil	4.58	kg
	Formaldehyde	1.02E-03	kg
	Methane, fossil	8.31E-03	kg
	Nitrogen oxides	3.35	kg
	Nitrogen oxides	2.76	kg
	PAH, polycyclic aromatic hydrocarbons	1.46E-04	kg
	Particulates, > 2.5 um, and < 10um	9.57E-02	kg
	Propene	2.24E-03	kg
	Toluene	3.55E-04	kg
	Sulfur monoxide	4.96E-02	kg
	VOC, volatile organic compounds, unspecified origin	9.79E-02	kg
	Xylene	2.47E-04	kg
	Dinitrogen monoxide	2.08E-03	kg
	water	3.21E+03	kg
	Oxygen	1.14E+03	kg
	Nitrogen	3.15E+04	kg
	Dust	9.24E+01	g
	Tar (as naphthalene)	9.23	kg

Lignocellulosic feedstock was considered as raw materials to produce energy-storage purpose activated carbons. Energy crops of switchgrass and Miscanthus, feedstock establishment and collection were considered containing site preparation, planting, fertilization and herbicides, mowing, baling and collection. Equipment used in these processes included plow, disk, horrow, hopper, tedder, rake, baler, wheel loader, and tractor (Liu et al. 2017a). Feedstock was then transported by truck for 50 miles to processing facility, and active drier, grinder, and hammer mills were included in the storage and preprocessing process. Feedstocks were pyrolyzed at 450ºC for carbonization process, then activated by being mixed and heated with potassium hydroxide (KOH) at 800 ºC. The feedstock-to-KOH ratio was 1:4 by weight and KOH would be discarded after usage (Yakaboylu et al. 2019). The fuel and materials consumption of the harvest system was modified from the studies by Liu et al. (2017a). The transportation process was also applied based on the data in the US LCI database (US NREL 2012). The fuel and materials consumption of carbonization and activation process were adjusted based on the studies by Arena et al. (2016) and Yakaboylu et al. (2019).

5.2.2 Economic Feasibility Analysis

A mass flow diagram was developed to identify the yield values at each step in the carbon production and activation process and to determine the basic process equipment for constructing a manufacturing facility (Figure 5.2). According to this diagram, producing one kg of powdered activated carbon requires 12.96 kg of raw materials on wet basis. Feedstock establishment and harvesting, transportation, and storage, were considered in feedstock production component, and 3% of dry matter loss was accounted in each process (Wang et al. 2020). Based on the pyrolysis and chemical activation of lignocellulosic biomass by Yakaboylu et al. (2019), the highly porous activated carbon for energy-storage was synthesized from lignocellulosic biomass following the route of pyrolysis, and chemical activation with Potassium hydroxide (KOH) solution.

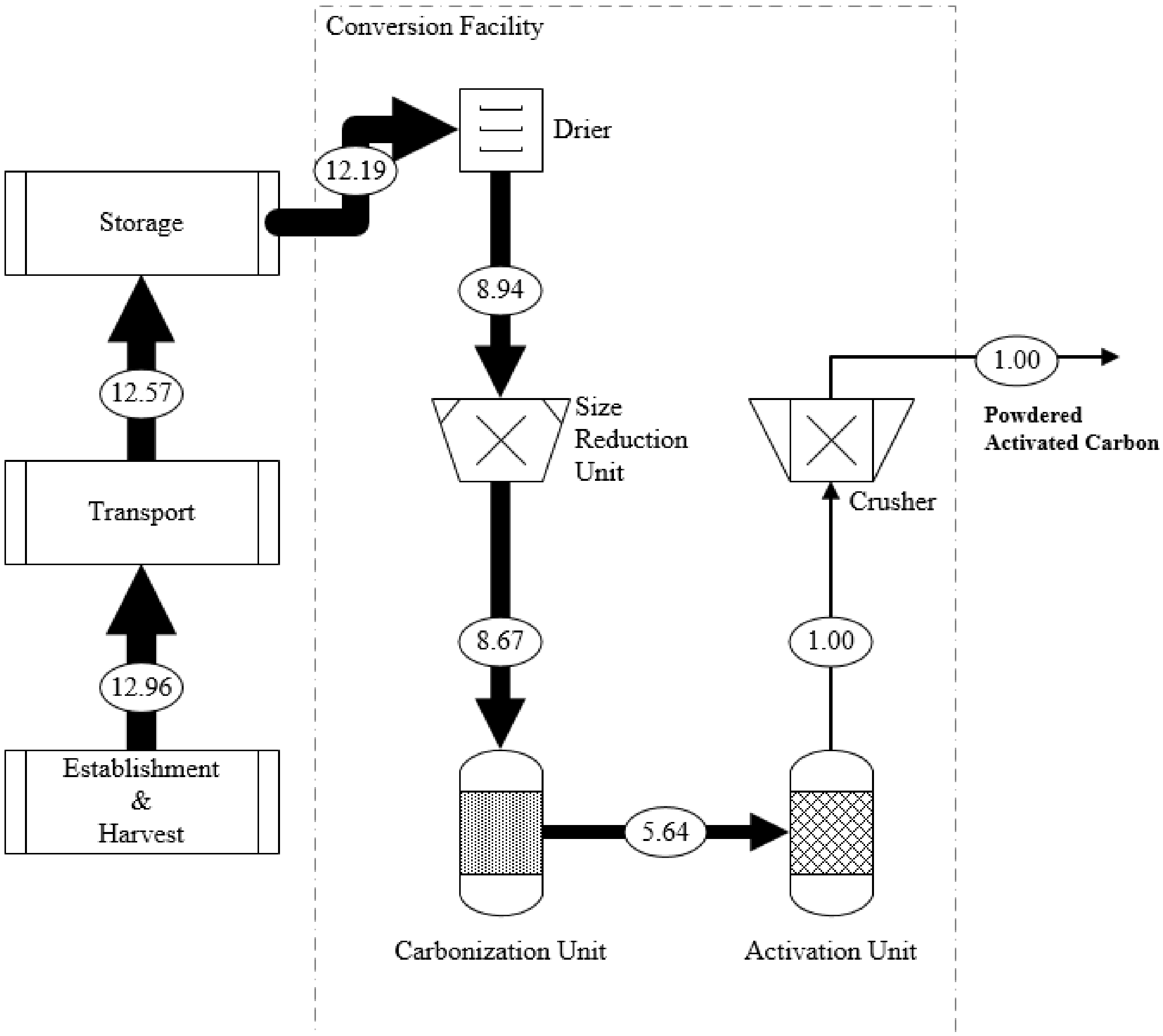

Figure 5.2 A Mass flow of activated carbon production for high-performance supercapacitor.

5.2.2.1 Cost Estimation

In the base case, it was assumed the plant life was 10 years with a discount rate of 5%, and an annual production yield of 960,000 kg (3,000 kg per day for 320 days operated) of high-performance ACs (Table 5.3). To support an AC plant with this size, it required a supply of 8,579 dry Mg of lignocellulosic biomass as feedstock.

Table 5.3 Assumptions of the base case for an AC plant for energy-storage material.

Parameter	Unit	Amount
Plant Capacity	Tons/day	3
Days Operated	Days/year	320
Plant Life	Year	10
Feedstock Delivery Cost	$/dry Mg	80
KOH Purchase Price	$/dry Mg	750
AC Yield Rate	% of dry feedstock	11.19

Equipment cost was estimated from a combination of vender quotes and literature estimates (Ng et al. 2003; Stavropoulos and Zabaniotou 2009), and capital cost was estimated for all major technical components and processes within the plant using the Lang Factor method (Turton et al. 2018). The total cost was determined by multiplying the total purchase cost for all the major items of equipment by a constant called Lang factor.

$$C_{TM} = F_{Lang} \sum_{i=1}^{n} C_{P,i} \quad (1)$$

Where, C_{TM} is the capital cost of the plant, $C_{P,i}$ is the purchased cost for the major equipment unit i, n is the total number of individual units, and F_{Lang} is the Lang Factor. Lang factor varies regarding three process plant types: solid processing plants ($F_{Lang} = 3.10$), solid-fluid processing plants ($F_{Lang} = 3.63$), and fluid processing plants ($F_{Lang} = 4.70$) (Turton et al. 2018). In this study, $F_{Lang} = 3.63$ was used for this combined fluid-solid system. Equipment costs derived from literatures were adjusted by multiplying the Producer Price Index (by Commodity for Machinery and Equipment: General Purpose Machinery and Equipment) (U.S. Bureau of Labor Statistics 2019).

The cost associated with the day-to-day operation refers to the cost of manufacturing (COM) can be obtained by adding together three cost components: direct manufacturing cost, fixed manufacturing cost and total general manufacturing cost (Turton et al. 2018). It is denoted in the following equation:

$$COM(Cost\ of\ Manufacture) = 0.280C_{TM} + 2.73C_{OL} + 1.23(C_{RM} + C_{UT}) \qquad (2)$$

Where, C_{TM} is the capital cost of the plant, C_{OL} is the labor cost for plant operation, C_{RM} is the raw material costs for feedstock and chemical solution, and C_{UT} is the utility cost for electricity, water, and natural gas. In this equation, the coefficients for each variable were derived from "total general manufacturing cost" by Turton et al. (2018).

With the assumption that a single operator works 40 hours per week for 49 weeks annually, the number of required labor (N_{OL}) were calculated based on (Turton et al. 2018):

$$N_{OL} = 4.5(shifts) \times \left(6.29 + 31.7P^2 + 0.23N_{np}\right)^{0.5} \qquad (3)$$

Where P=0 is the number of processing steps involving particulate solids, $N_{np} = 10$ is the number of other processing steps. To estimate the number of operators per shift. In this study, there were ten non-particulate processes: hammer mill, soak tanks, rotary dryer, two-rotary-kilns, rotary cooler, wash tanks, recovery tanks, storage tanks, rotary dryer, and sieve. For each of the N_{OL} operators assigned an 8-hour shift with a typical 3-week leave, there are 4.5 operators required for a plant that runs 24 hours per day. After calculation, the number of labors per shift was 2.93 and then rounded up to 3 for later calculation.

5.2.2.2 Economic evaluation

To systematically measure and valuate the inputs and outcomes of the production of activated carbon, and determine how much the benefit of the investment would outweigh its costs, we examined several economic indicators including the return on investment (ROI), net present value (NPV), internal rate of return (IRR), and discount pay-pack period (DPB). The use of these economic indicators is to connect to the fact that not only the investment return must be assured, but the risk in its execution should also be considered.

Return on investment (ROI) is a performance measurement used to evaluate the efficiency of an investment or compare the efficiency of a number of different investments. The ROI can directly measure the amount of return on a particular investment, relative to the investment's cost. To calculate the ROI, the benefit (or return) of an investment is divided by the cost of the investment. It is expressed as a percentage or a ratio.

$$ROI = \frac{I_t - C_p}{C_{TM}} \tag{4}$$

Where,

C_p is total production cost;

I_t is total income during the time period t;

C_{TM} is total investment cost.

To analyze the profitability of the investment of an activated carbon plant from biomass, the net present value (NPV) was calculated by calculating the difference between the present value of cash inflows and outflows over the whole plant life (Ross and Westerfield 1988). The net present value brings to the present difference between incoming and outgoing cash flows during a project lifetime.

$$NPV = -C_{TM} + \sum_{t=1}^{N} \frac{I_t}{(1+d)^t} \tag{5}$$

Where,

C_{TM} is total investment cost;

I_t is the cash flow at single period t;

d is the discount rate.

Internal rate of return (IRR) measures the performance of the efficiency of an investment, and it directly estimates the amount of return on a particular investment. This matric is calculated over the whole plant life that the returns from an investment fluctuate from one year to the other, and is expressed as a percentage range (Phillips 2012). A general rule-of-thumb is that the higher IRR the higher return, and the lower IRR the lower risk.

Discounted pay-pack period (DPB) is the time period required for the pay-back of investment and interest, and it takes into account the present value of cash flow. It is calculated by setting NPV=0 and a trial and error procedure is applied. The shorter the payback, the more desirable the investment. Conversely, the longer the payback, the less desirable it is. The DPB was formulated using the logarithm with consideration of the time value of money, which is superior compared to simple payback period formula (Gallo 2016).

$$DPB = \ln\left(\frac{1}{1-\frac{C_{TM}\times d}{CF}}\right) \div \ln(1+d) \quad (6)$$

Where,

C_{TM} is total investment cost;

d is the discount rate;

CF is the cash flow during the whole period.

5.3 Results

5.3.1 Life cycle impacts

The environment assessment for producing 1000 kg of supercapacitor electrode carbon products with the KOH activation was assessed using SimaPro 9 (PRé Consultants 2019), the database Ecoinvent 3.5 (Wernet et. Al. 2016), and the environmental assessment tool TRACI 2.1 (Bare 2012) in terms of the cradle-to-gate environmental performance.

Table 5.4 LCA impact indicators for the activated carbon production.

Impact category	Unit	Total
Ozone depletion	kg CFC-11 eq	2.62E-03
Global warming	kg CO_2 eq	6.28E+04
Smog	kg O_3 eq	2.23E+03
Acidification	kg SO_2 eq	2.06E+02
Eutrophication	kg N eq	1.07E+02
Carcinogenics	CTUh	2.27E-03
Non carcinogenics	CTUh	1.04E-02
Respiratory effects	kg PM2.5 eq	1.41E+01
Ecotoxicity	CTUe	2.26E+05
Fossil fuel depletion	MJ surplus	7.18E+04

Assessments were examined in the following 10 impact categories: ozone depletion, global warming, smog, acidification, eutrophication, carcinogenics, non-carcinogenics, respiratory effects, and ecotoxicity (Table 5.4). The emitted gases contributed to the depletion of the ozone layer was 2.62E-03 Kg CFC-11 equivalent. The total global warming potential when producing 1000 kg of high-performance activated carbon (AC) was 62.78 tons of CO_2 equivalent, including greenhouse gases CO_2, N_2O, NH_4, and volatile organic compounds (VOCs). The measurement of smog indicated photochemical ozone creation potential (POCP)(Simon et al. 2010), accounting for 2226.50 kg O_3 equivalent. Acidification emission to the atmosphere and subsequently deposited in surface soils and waters (Dissanayake and Summerscales 2013) was 206.37 kg SO_2 equivalent. Eutrophication potential was 106.73 kg N equivalent, which referred to the over-fertilization in aquatic ecosystems over the entire life cycle (La Rosa 2016). Both Carcinogenics and Non-carcinogenics are human-toxicological effect factors for LCA purposes (Huijbregts et al. 2005), and they were 2.27E-03 and 1.04E-02 CTUh (Comparative Toxic Unit for human), respectively. Respiratory effects caused by inorganic substances was resulted as 14.09 kg PM2.5 equivalent, and the ecotoxicity potential was

2.26E+05 CTUe (Comparative toxic unit for ecotoxicity). The amount of consumed fossil fuel was 7.18E+04 MJ surplus.

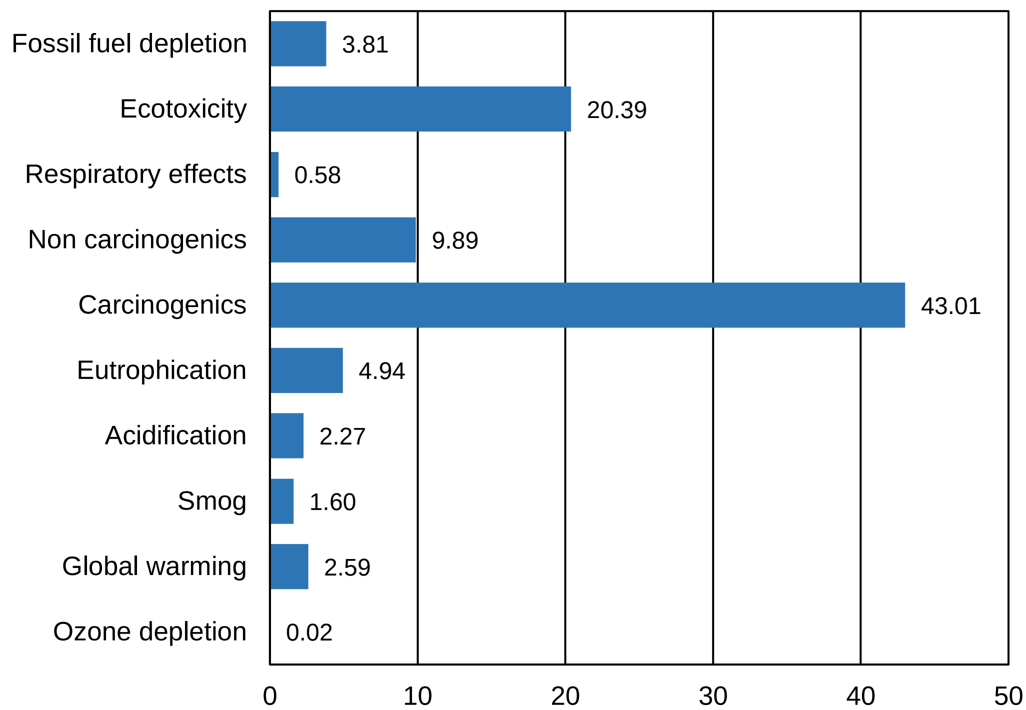

Figure 5.3 Normalized results of life cycle impact assessment of energy-storage activated carbon, in ten impact categories.

Environmental indicators were normalized for each impact categories at midpoint level (Figure 3). Midpoint results include a large number of impacts and more details (ten factors in this study), and endpoint impacts are usually shown as impact on human health, global warming and resource depletion (Ellen Meijer 2014). The normalized factor can relate the impact scores to the average impact of a person has to environment per year (Ryberg et al., 2014). Result showed that the top three categories with highest potential impacts were carcinogenics, ecotoxicity, and non-carcinogenics, with values 43.01, 20.39, and 9.89 per person per year equivalent, respectively. The emission of both carcinogenics and non-carcinogenics has impacts on human health at endpoint level (Huijbregts et al. 2005), and accounted for over 60% of the total environmental impacts. Ozone depletion, respiratory effects, and smog were the three factors that had the least effects on environmental emissions. When considering endpoint levels categorized as human health (including carcinogenics, non-carcinogenics, smog, respiratory effects, and ozone depletion), ecosystem quality (including acidification, eutrophication, and ecotoxicity), resource (referring to fossil fuel depletion), and GHG emission (referring to global warming), the results showed that their normalized environmental effects were 55.09, 27.60, 3.81, and 2.59, respectively at each endpoint level.

Among the five process components including feedstock establishment, harvest, transportation, storage, and AC production, the process of AC production (carbonization and activation) resulted in a majority of the environmental impacts in all ten impact categories, with 95.8 to 99.6% of the total normalized environmental impacts while 96.70% of the GHG emission occurred in the process of "carbon production" phase at a facility site (Table 5.5).

Table 5.5 Percentage of life cycle environmental impacts of environmental indicators by process components.

Impact category	Establishment %	Harvest %	Transport %	Storage %	AC Conversion %
Ozone depletion	0.3311	0.0051	0.0066	0.0459	99.6112
Global warming	0.4091	0.1135	0.1574	0.0167	99.3033
Smog	2.1094	1.3609	0.7072	0.0192	95.8034
Acidification	0.8647	0.4516	0.2648	0.0222	98.3966
Eutrophication	0.3011	0.0678	0.0486	0.0237	99.5588
Carcinogenics	0.3499	0.0541	0.0697	0.0268	99.4996
Non carcinogenics	0.4891	0.1122	0.1452	0.0282	99.2253
Respiratory effects	0.5847	0.1313	0.0607	0.0276	99.1957
Ecotoxicity	0.5218	0.1319	0.1710	0.0239	99.1513
Fossil fuel depletion	0.6907	0.1995	0.2586	0.0160	98.8352

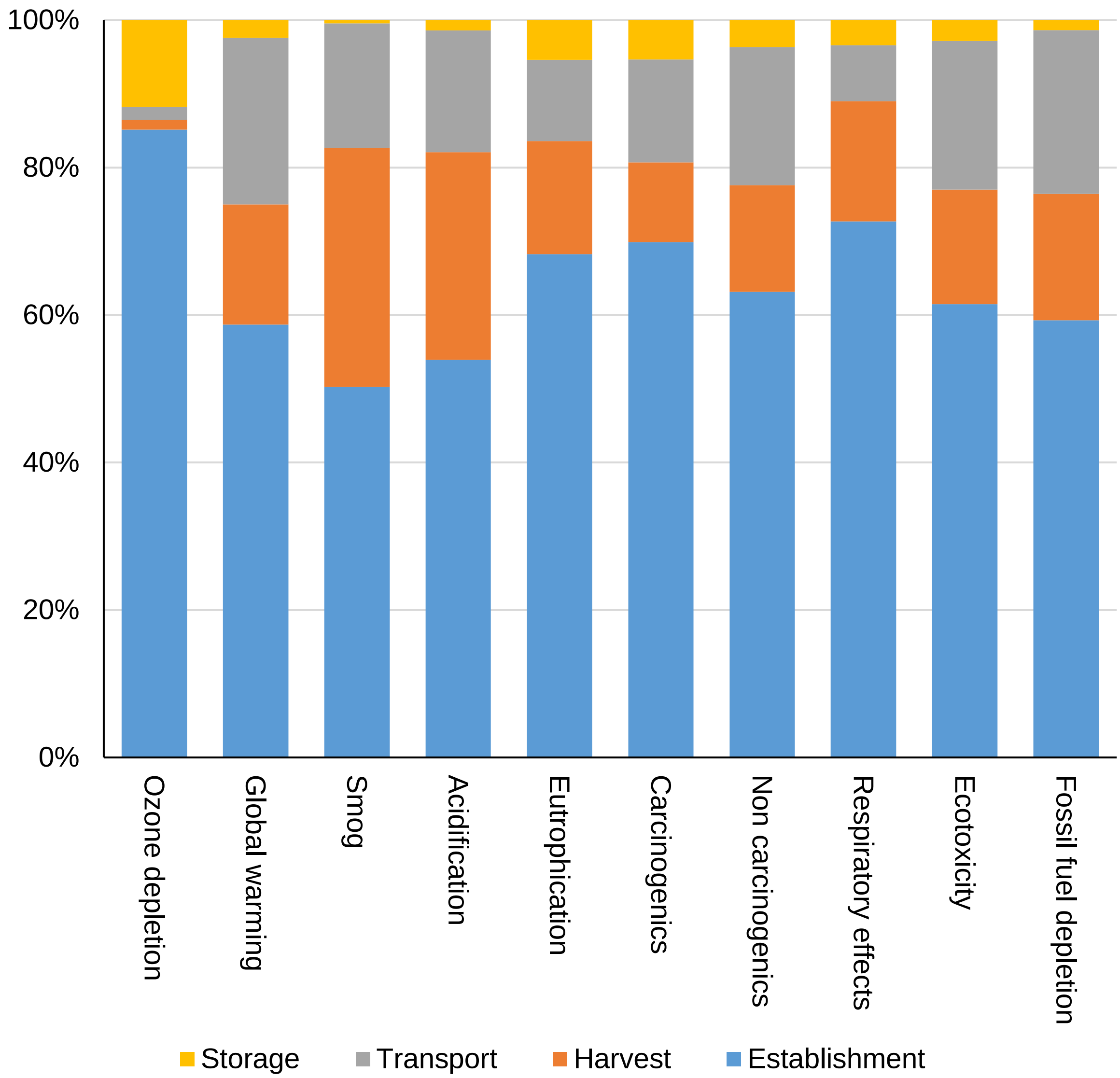

Figure 5.4 Percentage of life cycle environmental impacts of environmental indicators by process components, for biomass feedstock logistics only.

Then the further analysis of environmental impacts on feedstock logistics (Figure 5.4), showed that "feedstock establishment" process had the most significant impact, ranging from 50.3 to 85.2%. In "feedstock establishment" process, site preparation, fertilizing, and herbicide were counted in life-cycle inventory. According to a study by Schmidt Rivera et. al (2017), the use of fertilizer (ammonium sulphate) and herbicide (glyphosate) could affect the climate change, eutrophication, acidification and ecotoxicity, which have been proved that they are the main cause of highly environmental impacts by feedstock establishment. The top three impact categories by feedstock harvest were smog (32.43%), acidification (28.17%), and greenhouse gas emission (16.29%). With the assumption of a 50-mile transportation distance for the base case, feedstock transport caused 15.12% of the environmental impacts in feedstock logistics. This could be increase as transportation distance of biomass increases. The impacts of global warming, fossil fuel depletion and ecotoxicity accounted for more than one fifth of the total environmental impacts by feedstock logistical activities.

5.3.2 Techno-economic impacts

Equipment costs were estimated based on a study by Ng (et al. 2003) and adjusted by multiplying producer price index by commodity for machinery and equipment (U.S. Bureau of Labor Statistics 2019), which measure the average change over time of the purchase prices of required machines in AC production (Table 5.6). The equipment costs for a total of 16 machines were $1.83 million for a high-performance AC plant with a productivity of 3000 kg/day. Adding installation costs, the total capital costs for this AC plant would be $6.66 million.

Table 5.6 Capital costs for a biomass derived AC plant for energy-storage.

Item		**Amount**	**Cost**
Hammer mill		2	$28,657
Two-glass-lined, soak tanks		2	$254,727
Rotary dryer		1	$23,881
Two-rotary-kilns		2	$652,739
Rotary cooler		1	$103,483
Two-glass-lined, wash tanks		2	$254,727
Two-glass-lined, recovery tanks		2	$264280
Two-glass-lined, storage tanks		2	$222886
Rotary dryer		1	$23881
Sieve		1	$4776
Equipment Cost			*$1,834,037*
Capital Cost	C_{TM}		***$6,657,555***

Table 5.7 Annual operating costs for an AC plant for energy-storage purpose.

Item			**Annual Cost**
Lignocellulosic Feedstock			$686,327
KOH			$11,915,401
Raw Materials	$\boldsymbol{C_{RM}}$		***$12,601,728***
Electricity			$77,000
Water			$14,000
Natural Gas			$268,000
Utility	$\boldsymbol{C_{UT}}$		***$359,000***
Operating labor	C_{OL}		$94,944
Direct supervisory and clerical labor		$0.18 \times C_{OL}$	$17,090
Operating Supplies		$0.009 \times C_{TM}$	$59,918
Maintenance and repairs		$0.06 \times C_{TM}$	$399,453
Laboratory charges		$0.15 \times C_{OL}$	$14,242
Plant overhead costs		$0.708 \times C_{OL} + 0.036 \times C_{TM}$	$306,892
Local taxes and insurance		$0.032 \times C_{TM}$	$213,042
Patents and royalties		$0.03 \times COM$	$102,272
Depreciation		$0.1 \times C_{TM}$	$665,755.50
a. Administration costs		$0.177 \times C_{OL} + 0.009 \times C_{TM}$	$76,723
b. Distribution and selling costs		$0.11 \times COM$	$374,997
c. Research and development		$0.05 \times COM$	$170,453
General Manufacturing Expenses			***$1,287,929***
Total Operation costs			**$15,456,509**

The total operation cost for producing highly porous activated carbon was $15.45 million annually (Table 5.7). Annually, the raw materials cost was estimated at $12.60 million for lignocellulosic feedstock and potassium hydroxide (KOH), and it accounted for the largest portion of the total operating cost, 81.53%. Besides raw material cost, adding the costs of utility, operating labor, direct supervisory and clerical labor, operating supplies, maintenance and repairs, laboratory charges, and plant overhead costs, the total direct manufacturing costs were $13.85 million. The fixed manufacturing costs accounting for local taxes and insurance, patents and royalties, and depreciation with rate at 10%, were $981,069. And the general manufacturing expenses were $1.29 million.

5.3.3 Economic feasibility

Based on economic assessment for activated carbon production, the required selling price (RSP) was $16.79 per kg ($16,794.02/ton). Even though the price for general-purpose activated carbon could be as low as $1.65/kg, the market price of carbon for supercapacitor electrode can be higher with its premium grade ranging from $15 to $50/kg (Zhi et al. 2014; Weinstein and Dash 2013).

Table 5.8 Economic evaluation for an AC plant for energy-storage purpose.

Economic Indices	Amount
Total Investment Cost $	6,657,555
Total Operating Cost $	154,565,090
Total Income $	163,200,000
Return on Investment (ROI)	129.70%
Net Present Value (NPV) $	9,613
Internal Rate of Return (IRR)	5%
Discounted Payback Period (DPB) years	9.98

The economic performance of the activated carbon production plant was evaluated in terms of ROI, NPV, IRR, and DPB (Table 5.8). It was assumed that all activated carbon products were characterized with the same surface area and are sold on a weight basis of $17/kg.

The return on investment (ROI) of 129.7%, (or annual ROI of 12.97%) shows the net return of the AC plant could bring financial gain and the project would be potentially profitable. By comparing the difference between the cash inflows and cash outflows over the whole plant life, the net present value (NPV) of $9,613 also indicates that it is a profitable project, and this investment should be considered financially. The internal rate of return (IRR) shows the expected compound annual growth rate of return that will be earned on the AC project is 5%. By discounted to present values of cash flows with return rate of 5%, the discounted payback period (DPB) is 9.98 years, which also shows the potential profitability of the AC plant.

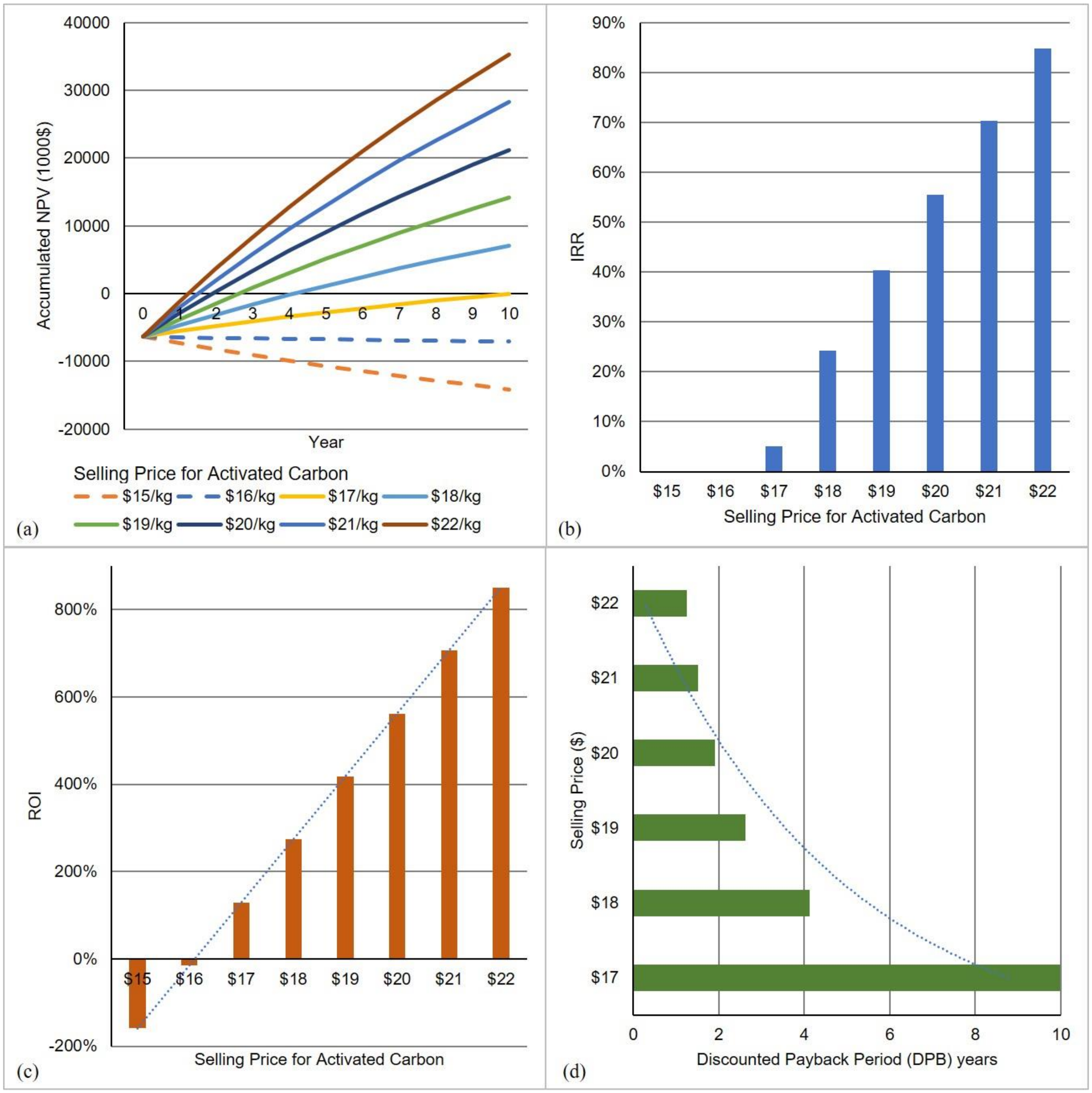

Figure 5.5 The impacts of activated carbon selling price on economic indices: (a) Accumulated NPV, (b) IRR, (c) ROI, and (d) DPB.

The product selling price's impacts on the economic assessment were analyzed based on -15%-30% change of $17 per kg (Figure 5.5). The economic indices of the AC selling price range from $12 to $22/kg. At a selling price $15 or $16/kg, all the economic indices indicate that the AC plant would not be profitable due to the negative NPV, ROI, and longer DPB (longer than plant lifetime). The discounted payback period would be less than two years once the product selling price reaches to $20/kg and greater. At $20/kg, the internal rate of return would be greater than 50%, ranging from 56% to 85%.

5.4 Discussion

5.4.1 Sensitivity of life cycle impacts

Results of life cycle assessment showed the differences of GHG emissions compared to other studies (Ng et al. 2003; Alhashimi and Aktas 2017; Gu et al. 2018). It was mainly because of the use of different activation technologies. The usage of potassium hydroxide without recycling would lead to a great environmental impact not only on GHG emission, but also on human toxicity. Meanwhile, the wastewater containing resulted KOH in aqueous mix was disposed of by the refineries as a hazardous waste (Montes and Hill 2018). Thus, recovering the KOH for reuse could benefits AC production economically and environmentally. If 50% of potassium hydroxide was recycled, the annual material cost could be reduced to $5.96 million. And if an AC plant could reuse 90% of the chemical agent, it would save $10.72 million for material cost every year.

The normalized results of the environmental impacts by the two alternative scenarios were compared with the base case (Figure 5.6). The two alternative scenarios demonstrated significant decreases of environmental impact in each of the 10 categories. Specifically, for greenhouse gas emission, both partial-recycling KOH activation and steam activation had emission of 15.4 kg CO_2 eq, and 10.2 kg CO_2 eq for every 1 kg activated carbon production, respectively. These are 13.33% and 42.30% lower than the coal-based activated carbon of 18.3 kg CO_2 eq/kg (Gu et al. 2018), and are also similar to the GHG emission of 11.15 kg CO_2 eq from wood-chip-based activated carbon (Gu et al. 2018).

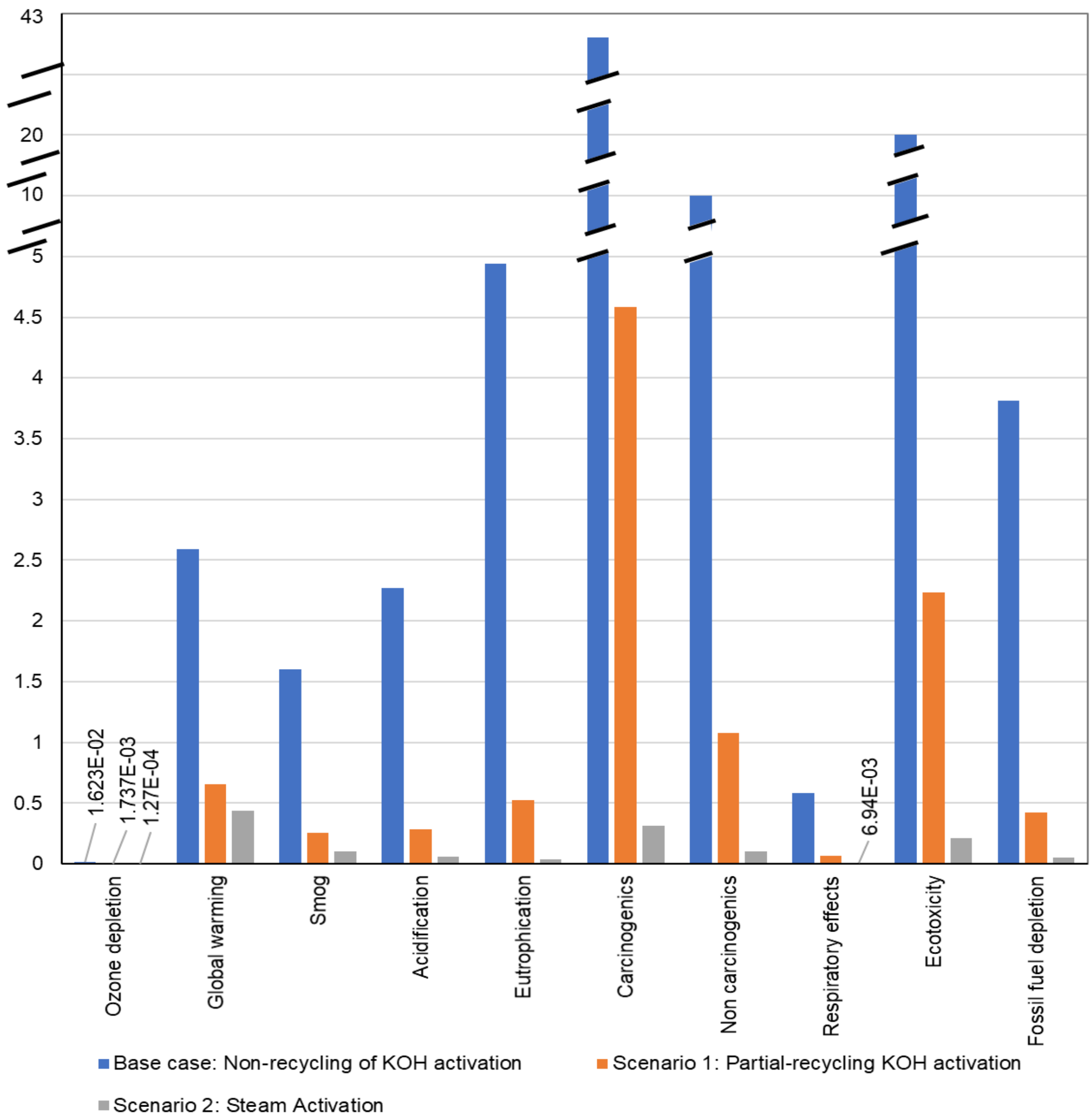

Figure 5.6 Normalized results of life cycle impacts of activated carbon production using alternative scenarios: (1) Non-recycling of KOH activation – baseline case, (2) Partial-recycling KOH activation, and (3) Steam activation for general purpose AC.

Steam activation is a physical process, and the lignocellulosic precursor is carbonized at high temperature with controlled gasification. According to the González-García's study (2018), steam-activated carbon products are characterized with only 776-1122 m^2/g of surface area, which are not adequate to meet the energy-storage requirement for supercapacitor. On the other hand, the KOH-activated carbon products showed high specific surface area of up to 3265 m^2/g, and exhibited great performance for electricity capacitance (Yakaboylu et al. 2019). However, problems may occur in KOH recycling related to impurities originated and immature potassium recovery. During chemical activation process, the ratio between KOH and precursor mass, temperature time and stirring are strictly controlled (Tran et al. 2017), and this would bring even more difficulties to KOH recycling and reuse.

5.4.2 Uncertainty of economic impacts

With the production yield rate at 3000 kg of AC per day, and a minimum annual demand of 8,579 dry Mg of lignocellulosic biomass as feedstock, a reasonable capital cost was estimated at $6.66 million. Compared to the study (Stavropoulos and Zabaniotou 2009) that a wood-based chemical activated carbon plant with 4500 kg/day capacity needs a total investment cost of $6.29 million, the capital cost for AC plant in this study is 5.56% higher mainly because of higher feedstock delivery price. Meanwhile, the required selling price at the break-even point for highly porous AC is $16.79 per kg, which is in the range of the market price of supercapacitor carbon of $15 to $50. Therefore, the RSP of this study provides a considerable margin from the actually potential selling price of electrode-purpose activated carbon products.

The uncertain economic environment could arise risks for investment decisions. The Monte Carlo (MC) simulation, a proper tool enclosing the net present value (NPV) analysis (Shaffie and Jaaman 2016) was employed to achieve reliable cash flows estimation when considering the investment of the plant for AC supercapacitors. The Monte Carlo simulation was conducted using Crystal Ball (Goldman 2002) in this study, and our results show the behavior for the NPV with consideration of related parameter uncertainty (Figure 5.7). After 4,982 iterations on calculating NPVs, the MC simulation converges to a properly scaled normal distribution of NPV, which means the appropriate sample size was adopted in this study. The distribution presents that the average NPV is $9,612.86 for this investment with 49.96% probability to be profitable.

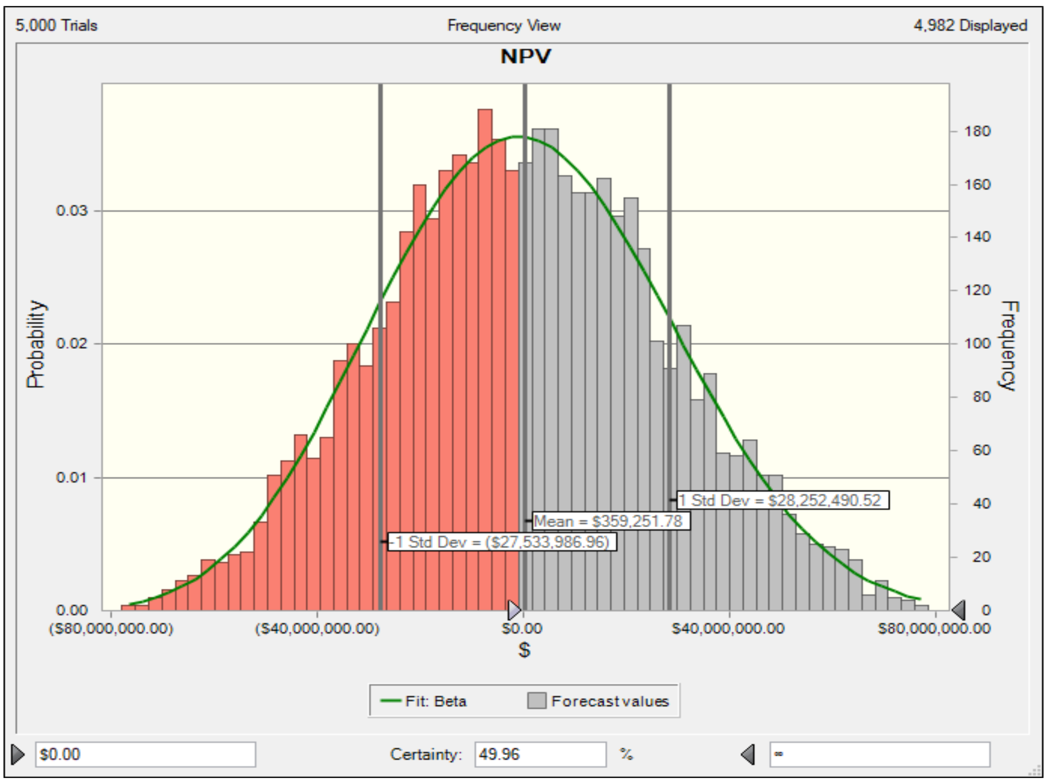

Figure 5.7 Net present value (NPV) uncertainty for an AC plant using lignocellulosic biomass.

For activated carbon production from renewable lignocellulosic biomass sources, the use of the Monte Carlo simulation has advantages when compared to traditional methods such as sensitivity analysis. While in traditional methods the uncertainties are taken as deterministic values, the MC simulation considers them with a probabilistic behavior and makes the results more realistic.

5.5 Conclusions

An integrated life cycle and techno-economic analysis was carried out for a small-to-medium market of activated carbon for supercapacitor derived from lignocellulosic biomass. The lack of robust information on environmental and economic performance of a chemical-activated carbon production chain for energy-storage purpose limits the AC market potential using lignocellulosic feedstock as raw materials.

In the entire supply chain of AC production, "activated carbon conversion" is the single process component resulted in the most impacts in all 10 environmental categories. Carcinogenics, ecotoxicity, and non-carcinogenics accounted for over 60% of the total environmental impacts related to human health. If just focusing on biomass feedstock logistics portion of the entire supply chain, "feedstock establishment" had the most significant impact on environment, especially for ozone depletion, respiratory effects, and carcinogenics. The RSP of $16.79/kg for activated carbon from lignocellulosic biomass is comparable with the market price of $15-50 per kg for supercapacitor carbons. Our base case study indicates a profitable investment of $6.66 million might occur with the economic performance indicators of ROI 129.7%, NPV $9,613, IRR 5%, and DPB 9.98 years.

The analysis of alternative scenarios suggests that the sustainability of activated carbon for supercapacitors production could be improved greatly via reducing the environmental emissions and fossil energy consumption. For instance, the GHG could be further lowered for 83.76%, with a potentially upgraded AC conversion technology in the alternative cases. The Monte Carlo simulation also provides a practical way to strategize risks for AC plant investment, as well as project the possibilities of the outcome from the investment. Comparisons of sensitivity and uncertainty among case scenarios further prove that chemical agents in AC activation play a critical role in the overall environmental performance of the production chain, which accordingly imply that the economic and environmental sustainability of highly porous AC production could be improved through enhancing innovative carbon activation technologies.

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6. SUMMARY

The studies in this dissertation were motivated by four factors: (1) the need of selecting the optimal facility locations for biomass utilization with overcoming spatial dispersion of biomass, high transportation cost of the feedstock, and the possible negative environmental impacts, (2), a knowledge gap related to analyzing biomass supply chains with considerations of multiple feedstocks to boost the regional rural economic development in the northeastern U.S. (3) the lack of detailed and robust techno-economic analysis (TEA) and life cycle analysis (LCA) of diverse biomass feedstocks to support a sustainable bioenergy and bioproduct industry, and (4) the possibility of integrating frameworks from spatial analysis, mathematic programming, TEA and LCA, to aid in further understanding of biomass development.

A set of modeling techniques were applied in this dissertation to assess the economics and environmental impact of the utilization of biomass for bioenergy and value-added products in the northeastern United States. According to the results from this dissertation and case scenarios, as well as uncertainty and sensitivity analyses, the following conclusions can be drawn:

(1) The facility siting decision for biomass-based production can be made using integrated physical and social assets analysis. Via Experts' opinions surveying, the participants' area of expertise was reflected in their preference weights for the various criteria, and the to leverage the experience via this type of survey could increase the robustness of the weighting solicitation of evaluation criteria in biorefinery siting decision. It is proved that the fuzzy-logic prediction model incorporating AHP is a viable tool to predict the site suitability index at county level. A total of 43 counties or sites resulted from the suitability analysis in the study area could be used as potential candidates for biorefinery facilities in the region. To support rural community development, social assets analysis taking account a higher level of rurality and social capital index can further aid the siting decision process to optimize facility locations by potentially

promoting rural development in supportive communities. By accounting the social asset impacts, 15 out of 43 locations were further identified for regional economic development featuring both environmental and social assets and impacts. The modeling process and findings of this study could be employed in the community engagement efforts to promote the rural economic development in the northeastern U.S.

(2) The multiple biomass feedstock logistics is optimized with focus on entire biomass supply chains. With considerations of biomass supply/demand and potential biorefinery locations in the northeastern United States, the delivered costs were optimized with an average of $79.58 per dry Mg, ranged from $67.90 /dry Mg to $86.97 /dry Mg. With the US DOE target to lower the total delivered cost of lignocellulosic biomass to $84 per dry ton by 2022, seventy seven out of 387 counties could be able to deliver biomass at a cost of this goal. Additionally, two counties in the region could even deliver at a cost of less than $71 per dry ton – the DOE's target by 2030. Sensitivity analyses showed biomass delivered cost was mostly affected the differentiations of feedstock types, transportation distance and facility capacity. The biomass delivered cost was most sensitive to feedstock availability of forest residues among all feedstock materials. Feedstock transportation procurement radius and facility capacity had the most sensitive impacts to delivery costs. A reduction of procurement radius of 10 km could change biomass delivery cost by 8.65 %. The decrease of facility capacity by 10% from base case could lead to a 6.81 % reduction of biomass delivery by $74.16 per dry Mg. In the meanwhile, other impact factors like feedstock price, moisture content and fossil fuel price have impacts on biomass delivered cost as well.

(3) An integrated life cycle and techno-economic assessment for bioenergy products utilizing multiple lignocellulosic biomass as feedstock was conducted. Three potential cases of

lignocellulosic biomass for commercial scale production of bioenergy analyzed for the economic and environmental effects. The integrated LCA and TEA provides insights for decision making for alternative bioenergy production at commercial level. Results of life cycle assessments on cradle-to-gate basis showed the pellet production had the lowest greenhouse gas emissions, as well as water and fossil fuels consumption, for 8.29 kg CO_2 eq, 0.46 kg, and 105.42 MJ respectively with function unit of 1000 MJ of bioenergy products. Among biomass supply chain, the process of conversion process presented the greatest environmental impact for all three bioenergy products. The different patterns of life cycle assessments by supply chain components for pellet, biopower, and biofuel, could be mostly explained by the differences of bio-productions. A mathematical TEA model to calculate net present value (NPV) was applied to three study cases, and only two out of three cases showed profitable with NPVs of $1.20 million for pellet, $81.60 million for biopower. Results showed both the pellet plant and biopower plant have higher chance to keep being profitable with discount rate changed from 0% to 10%, and there's higher investment risks for producing biopower when the investors require a higher rate of return between these two bioenergy productions. Monte Carlo simulation could help with more accurate decisions by applying analytical approaches with many iterations. The uncertainty analysis of GHG emission implied pellet production with highest uncertain in environmental impacts, and bio-oil production had the least uncertainty in GHG emission but was with higher risks to produce extreme large amount of greenhouse gas. The uncertainty of investment showed biomass-based electricity production had the highest probability to be a profitable investment with 95.38%, and the probability for a profitable pellet plant was only 39.58%.

(4) The environmental and economic impacts analyses of activated carbons (AC) from lignocellulosic biomass feedstocks demonstrate the AC as a promising product for energy

storage purpose as supercapacitor electrodes. It fills the knowledge gap related to robust information on environmental and economic performance of a chemical-activated carbon product for supercapacitor and helps to improve the limitation for potential AC market using lignocellulosic feedstock as raw materials. A base case for a small-to-medium market of highly porous AC with KOH-activation was applied for LCA and TEA. Among all supply chain components, “AC conversion” resulted in the most impacts in all 10 environmental categories. And three environmental categories related to human health, including carcinogenics, ecotoxicity, and non carcinogenics accounted for over 60% of the total environmental impacts. The RSP of highly porous AC was16.79/kg, and it is comparable with the market price of $15-50/kg for supercapacitor carbons. Also, the base case study indicated the AC plant is a profitable investment with the economic performance indicators of return of investment (ROI) 129.7%, net present value (NPV) $9,613, internal rate of return (IRR) 5%, and discounted period if payback time (DPB) 9.98 years. The life cycle analysis of alternative cases of reusing-KOH-activation and steam-activation showed that the sustainability of AC production for supercapacitors could be improved greatly via reducing the environmental emissions to 24.52% and 16.24% of the base case, respectively. The Monte Carlo simulation is a viable method to strategize risks for AC plant investment. Results showed there was 49.96% of probability for an AC plant investment to be profitable for supercapacitor electrodes.

APPENDIX A. SUPPLEMENTAL INFORMATION FOR CHAPTER 2

Table A-1 Survey sheet for experts' opinions in biorefinery siting selection

Parameter A	A is extremely more important than B	A is moderately more important than B	Equally important	B is moderately more important than A	B is extremely more important than A	Parameter B
Biomass availability	O	O	O	O	O	Distance from main road
Biomass availability	O	O	O	O	O	Distance from electric substation
Biomass availability	O	O	O	O	O	Distance to waterbody
Biomass availability	O	O	O	O	O	Flood risk of potential siting
Biomass availability	O	O	O	O	O	Adjacent land uses of potential siting
Biomass availability	O	O	O	O	O	Population in siting area
Biomass availability	O	O	O	O	O	Landownership
Biomass availability	O	O	O	O	O	Unemployment rate in potential siting
Distance from main road	O	O	O	O	O	Distance from electric substation
Distance from main road	O	O	O	O	O	Distance to waterbody
Distance from main road	O	O	O	O	O	Flood risk of potential siting
Distance from main road	O	O	O	O	O	Adjacent land uses of potential siting
Distance from main road	O	O	O	O	O	Population in siting area
Distance from main road	O	O	O	O	O	Landownership
Distance from main road	O	O	O	O	O	Unemployment rate in potential siting
Distance from electric substation	O	O	O	O	O	Distance to waterbody
Distance from electric substation	O	O	O	O	O	Flood risk of potential siting
Distance from electric substation	O	O	O	O	O	Adjacent land uses of potential siting
Distance from electric substation	O	O	O	O	O	Population in siting area
Distance from electric substation	O	O	O	O	O	Landownership
Distance from electric substation	O	O	O	O	O	Unemployment rate in potential siting
Distance to waterbody	O	O	O	O	O	Flood risk of potential siting
Distance to waterbody	O	O	O	O	O	Adjacent land uses of potential siting
Distance to waterbody	O	O	O	O	O	Population in siting area
Distance to waterbody	O	O	O	O	O	Landownership
Distance to waterbody	O	O	O	O	O	Unemployment rate in potential siting
Flood risk of potential siting	O	O	O	O	O	Adjacent land uses of potential siting
Flood risk of potential siting	O	O	O	O	O	Population in siting area
Flood risk of potential siting	O	O	O	O	O	Landownership
Flood risk of potential siting	O	O	O	O	O	Unemployment rate in potential siting
Adjacent land uses of potential siting	O	O	O	O	O	Population in siting area
Adjacent land uses of potential siting	O	O	O	O	O	Landownership
Adjacent land uses of potential siting	O	O	O	O	O	Unemployment rate in potential siting
Population in siting area	O	O	O	O	O	Landownership
Population in siting area	O	O	O	O	O	Unemployment rate in potential siting
Landownership	O	O	O	O	O	Unemployment rate in potential siting

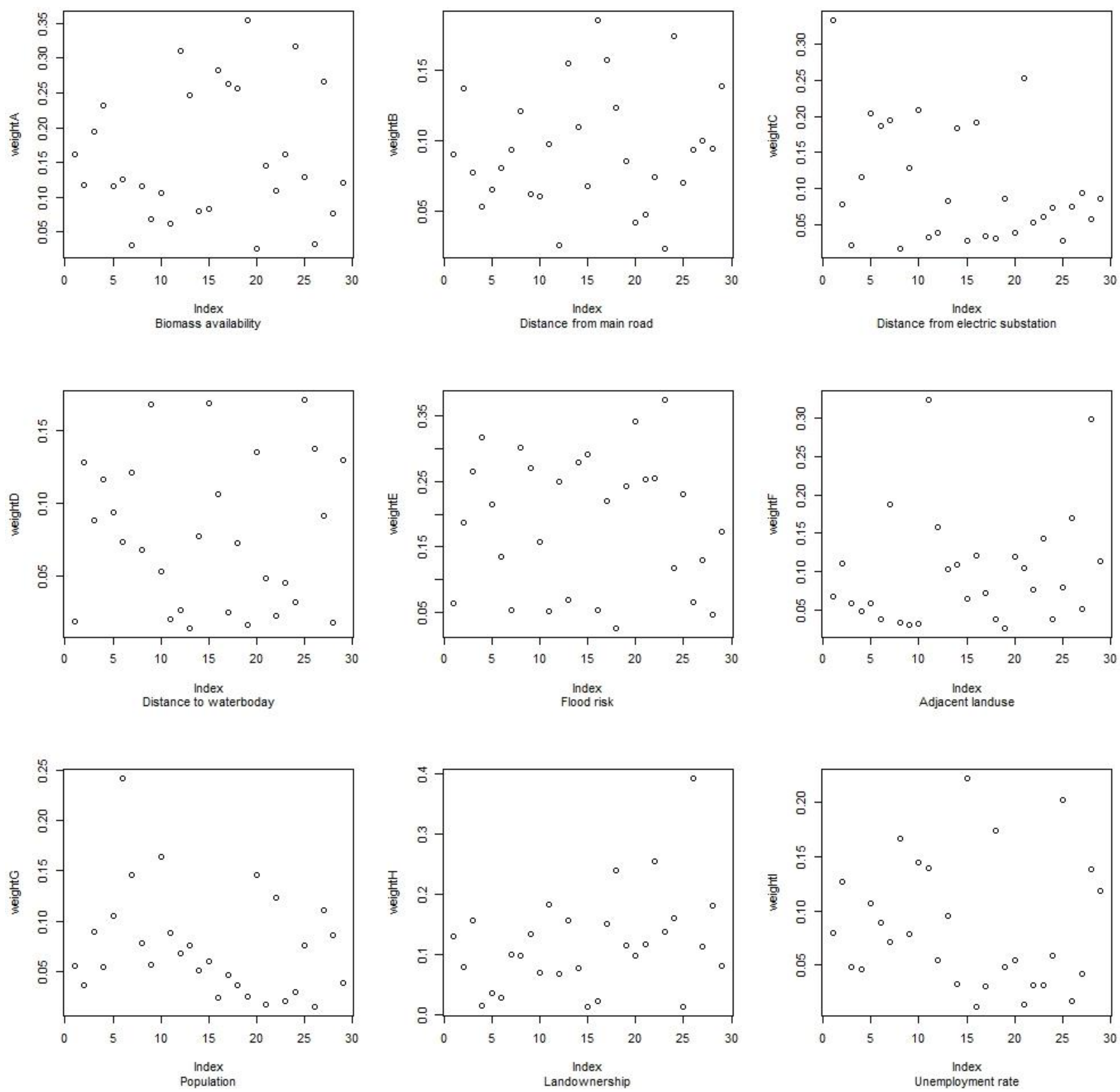

Figure A-1 Scatter plot for survey summary for creation of pairwise matrix

APPENDIX B SUPPLEMENTAL INFORMATION FOR CHAPTER 3

Table B-1. Descriptions of parameters and variables in the MILP model.

Parameters/Variables	Description
Objective Function	
α	Feedstock establishment cost; ($)
β	Feedstock harvest cost; ($)
γ	Feedstock storage cost; ($)
δ	Feedstock transportation cost; ($)
θ	Feedstock preprocessing cost; ($)
Z	Delivered cost of biomass feedstock
Feedstock establishment (α)	
QE_{ti}	Quantity of biomass t established in county i (dry Mg);
EC_t	Establishment cost of biomass t ($/Mg)
Feedstock harvest (β)	
QH_{mti}	Quantity of collected/harvested biomass t in county i in month m (dry Mg);
HC_t	Collected/Harvest cost of biomass t ($/ Mg);
Feedstock storage(γ)	
QS_{mti}	Quantity of biomass t stored on-landing site in county i in month m (dry Mg);
SC_t	In field storage cost of biomass t ($/dry Mg);
$QIVD_{mt}$	Quantity of biomass t inventory in month m at preprocessing facility;(Mg)
IDC	Inventory cost at preprocessing facility;($/dry Mg)
Feedstock transportation(δ)	

QHD_{mti}	Quantity of feedstock transported directly to the preprocessing facility in county i at month m for biomass t after harvesting; (dry Mg)
QS_{mti}	Quantity of biomass t transported from storage site to preprocessing facilities in month m (dry Mg);
D_{ij}	Distance from county i to facility j (km);
tr	Transportation rate ($*Mg^{-1}/km);
QDC_m	Quantity of preprocessed feedstock transported to conversion plant in month m ; (dry Mg)
D_0	Distance from preprocessing facility to conversion site (km);
Feedstock transportation (θ)	
QD_{mt}	Quantity of biomass t in facility for preprocessing in month m (dry Mg);
CC_t	Preprocessing cost for chipping of biomass t ($/dry Mg);
DC_t	Preprocessing cost for drying of biomass t ($/dry Mg);
Constraints	
$AVAL_{ti}$	Biomass t availability at location i (dry Mg);
p_{ti}	The proportion of biomass t available for harvest at supply location i;
γ_{mt}	A percentage shows the limitation that for biomass t can be harvest in month m of whole year; (%)
QHS_{mti}	Quantity of harvested feedstock transported to field for storage in county i at month m for biomass t; (dry Mg)
DM_t	Dry-matter loss rate for each feedstock type per month; (%)
mc_t	Moisture content rate for biomass t;
mc_0	Moisture content rate for after-preprocessing biomass;
$QIVD_{mt}$	Quantity of biomass t inventory in month m; (dry Mg)
qc_m	Monthly demand of feedstock used for conversion process; (dry Mg)
$CAPS_{mti}$	Storage site capacity for biomass t in county i in month m; (dry Mg)

$CAPD_{mti}$	Preprocessing facility capacity for biomass t in county i in month m; (dry Mg)
Parameters	
T	Biomass feedstock type; $t = \{logging\ residues, SRWC, switchgrass, miscanthus\}$
M	Month; $m = \{all\ months\ in\ a\ year\}$
I	Biomass supply locations; $i = \{all\ counties\ in\ the\ study\ area\}$
J	Biomass processing facility locations; $j = \{all\ facility\ locations\ in\ the\ study\ area\}$

APPENDIX C. SUPPLEMENTAL INFORMATION FOR CHAPTER 4

Table C-1 Cash flows for for bioenergy products: Biopower, Pellet, and Pyrolysis oil.

Pellet Production

Year	1	2	3	4	5	6	7	8	9	10
Production										
Pellets per year (ton)		0.05M	0.05M	0.05M	0.05M	0.05M	0.05M	0.05M	0.05M	0.05M
Increase over previous year			0	0	0	0	0	0	0	0
Revenue										
Sales		9.25M	9.25M	9.25M	9.25M	9.25M	9.25M	9.25M	9.25M	9.25M
Equipment sales										
Operation costs										
Feedstock costs		-3.68M	-3.68M	-3.68M	-3.68M	-3.68M	-3.68M	-3.68M	-3.68M	-3.68M
Fixed operation costs		-1.29M	-1.29M	-1.29M	-1.29M	-1.29M	-1.29M	-1.29M	-1.29M	-1.29M
Variable operation costs		-3.01M	-3.01M	-3.01M	-3.01M	-3.01M	-3.01M	-3.01M	-3.01M	-3.01M
Capital Investment										
Equipment purchase	-1.59M									
Installation cost	-0.60M									
Cash Flow										
Net Cash Flow	-2.19M	1.26M	1.26M	1.26M	1.26M	1.26M	1.26M	1.26M	1.26M	1.26M

Year	11	12	13	14	15	16	17
Production							
Pellets per year (ton)	0.05M	0.05M	0.05M	0.05M	0.05M	0.05M	0.00M
Increase over previous year	0	0	0	0	0	0	0
Revenue							
Sales	9.25M	9.25M	9.25M	9.25M	9.25M	9.25M	0.00M
Equipment sales							0.56M
Operation costs							
Feedstock costs	-3.68M	-3.68M	-3.68M	-3.68M	-3.68M	-3.68M	0.00M
Fixed operation costs	-1.29M	-1.29M	-1.29M	-1.29M	-1.29M	-1.29M	0.00M
Variable operation costs	-3.01M	-3.01M	-3.01M	-3.01M	-3.01M	-3.01M	0.00M
Capital Investment							
Equipment purchase		-0.97M					
Installation cost		-0.35M					
Cash Flow							
Net Cash Flow	1.26M	-0.06M	1.26M	1.26M	1.26M	1.26M	0.56M

Biopower Production

Year	1	2	3	4	5	6	7	8	9	10
Production										
Electricity per year (MWH)		260,000	260,000	260,000	260,000	260,000	260,000	260,000	260,000	260,000
Increase over previous year %			0	0	0	0	0	0	0	0
Revenue										
Sales $		28.94M	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M
Equipment sales $										
Operation costs										
Feedstock costs $		-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M
Operation costs $		-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M
Capital Investment										
Equipment purchase $	-30.08M									
Installation cost $	-12.89M									
Cash Flow										
Net Cash Flow $	-42.97M	11.10M	11.10M	11.10M	11.10M	11.10M	11.10M	11.10M	11.10M	11.10M

Year	11	12	13	14	15	16	17	18	19	20
Production										
Electricity per year (MWH)	260,000	260,000	260,000	260,000	260,000	260,000	260,000	260,000	260,000	260,000
Increase over previous year %		0	0	0	0	0	0	0	0	0
Revenue										
Sales $	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M	28.94M
Equipment sales $										
Operation costs										
Feedstock costs $	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M
Operation costs $	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M
Capital Investment										
Equipment purchase $						-20.05M				
Installation cost $						-8.59M				
Cash Flow										
Net Cash Flow $	11.10M	11.10M	11.10M	11.10M	11.10M	-17.54M	11.10M	11.10M	11.10M	11.10M

Year	21	22	23	24	25	26
Production						
Electricity per year (MWH)	260,000	260,000	260,000	260,000	260,000	0
Increase over previous year %		0	0	0	0	0
Revenue						
Sales $	28.94M	28.94M	28.94M	28.94M	28.94M	0
Equipment sales $						0
Operation costs						
Feedstock costs $	-14.28M	-14.28M	-14.28M	-14.28M	-14.28M	0
Operation costs $	-3.56M	-3.56M	-3.56M	-3.56M	-3.56M	0
Capital Investment						
Equipment purchase $						
Installation cost $						
Cash Flow						
Net Cash Flow $	11.10M	11.10M	11.10M	11.10M	11.10M	0

Pyrolysis Oil Production

Year	1	2	3	4	5	6	7	8	9	10
Production										
Liquid Fuel (bbl)		78,000	78,000	78,000	78,000	78,000	78,000	78,000	78,000	78,000
Increase over previous year %			0	0	0	0	0	0	0	0
Revenue										
Sales $		4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M
Equipment sales $										
Operation costs										
Feedstock costs $		-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M
Operation costs $		-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M
Capital Investment										
Equipment purchase $	-37.11M									
Installation cost $	-15.90M									
Cash Flow										
Net Cash Flow $	-53.01M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M

Year	11	12	13	14	15	16	17	18	19	20	21
Production											
Liquid Fuel (bbl)	78,000	78,000	78,000	78,000	78,000	78,000	78,000	78,000	78,000	78,000	0
Increase over previous year %		0	0	0	0	0	0	0	0	0	0
Revenue											
Sales $	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	4.21M	0
Equipment sales $											0
Operation costs											
Feedstock costs $	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	-3.02M	0
Operation costs $	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	-0.61M	0
Capital Investment											
Equipment purchase $	-37.11M										
Installation cost $	-15.90M										
Cash Flow											
Net Cash Flow $	-52.43M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M	0.58M	0

APPENDIX D. SUPPLEMENTAL INFORMATION FOR CHAPTER 5

Table D-1 LCA impact assessment for 1000 kg Activated carbon with 100% KOH consumption

Calculation:	Analyze
Results:	Impact assessment
Product:	1 p Activated carbon with KOH consumed 100% (of project Highly porous AC)
Method:	TRACI 2.1 V1.05 / US 2008
Indicator:	Characterization
Skip categories:	Never
Exclude infrastructure processes:	No
Exclude long-term emissions:	No
Sorted on item:	Impact category
Sort order:	Ascending

Impact category	Unit	Total	Plantation	Harvest Grass	Transport Grass	Storage Grass	AC Production, at Plant-koh100%
Ozone depletion	kg CFC-11 eq	2.62E-03	8.67E-06	1.34E-07	1.74E-07	1.20E-06	0.00260737
Global warming	kg CO2 eq	6.28E+04	256.82098	71.246226	98.815934	10.487938	62340.824
Smog	kg O3 eq	2.23E+03	46.965337	30.29994	15.745106	0.42770795	2133.0583
Acidification	kg SO2 eq	2.06E+02	1.7844581	0.93196766	0.54649583	0.045915906	203.0588
Eutrophication	kg N eq	1.07E+02	0.32140202	0.072371741	0.051863772	0.025309735	106.26164
Carcinogenics	CTUh	2.27E-03	7.93E-06	1.23E-06	1.58E-06	6.07E-07	0.002255893
Non carcinogenics	CTUh	1.04E-02	5.08E-05	1.17E-05	1.51E-05	2.93E-06	0.010304661
Respiratory effects	kg PM2.5 eq	1.41E+01	0.082384561	0.018496899	0.008555499	0.003890875	13.977314
Ecotoxicity	CTUe	2.26E+05	1177.9144	297.78842	385.92735	54.057577	223807.09
Fossil fuel depletion	MJ surplus	7.18E+04	495.89877	143.2553	185.63398	11.46323	70957.576

Table D-2 LCA impact assessment for 1000 kg Activated carbon with 10% KOH consumed

Calculation:	Analyze
Results:	Impact assessment
Product:	1 p Activated carbon with 10% KOH consumed (of project Highly porous AC)
Method:	TRACI 2.1 V1.05 / US 2008
Indicator:	Characterization
Skip categories:	Never
Exclude infrastructure processes:	No
Exclude long-term emissions:	No
Sorted on item:	Impact category
Sort order:	Ascending

Impact category	Unit	Total	Plantation	Harvest Grass	Transport Grass	Storage Grass	AC Production, at Plant-koh10%
Ozone depletion	kg CFC-11 eq	0.000280201	8.67E-06	1.34E-07	1.74E-07	1.20E-06	0.000270025
Global warming	kg CO2 eq	15863.693	256.82098	71.246226	98.815934	10.487938	15426.322
Smog	kg O3 eq	352.48604	46.965337	30.29994	15.745106	0.42770795	259.04795
Acidification	kg SO2 eq	25.725235	1.7844581	0.93196766	0.54649583	0.045915906	22.416397
Eutrophication	kg N eq	11.403756	0.32140202	0.072371741	0.051863772	0.025309735	10.932809
Carcinogenics	CTUh	0.000241622	7.93E-06	1.23E-06	1.58E-06	6.07E-07	0.000230276
Non carcinogenics	CTUh	0.001133582	5.08E-05	1.17E-05	1.51E-05	2.93E-06	0.001053129
Respiratory effects	kg PM2.5 eq	1.5604246	0.082384561	0.018496899	0.008555499	0.003890875	1.4470968
Ecotoxicity	CTUe	24714.074	1177.9144	297.78842	385.92735	54.057577	22798.386
Fossil fuel depletion	MJ surplus	8020.5797	495.89877	143.2553	185.63398	11.46323	7184.3284

Table D-3 LCA impact assessment for 1000 kg Activated carbon with steam activation

Calculation:	Analyze
Results:	Impact assessment
Product:	1 p Activated carbon with steam activation (of project Highly porous AC)
Method:	TRACI 2.1 V1.05 / US 2008
Indicator:	Characterization
Skip categories:	Never
Exclude infrastructure processes:	No
Exclude long-term emissions:	No
Sorted on item:	Impact category
Sort order:	Ascending

Impact category	Unit	Total	Plantation	Harvest Grass	Transport Grass	Storage Grass	AC Production, at Plant-steam
Ozone depletion	kg CFC-11 eq	2.05E-05	8.67E-06	1.34E-07	1.74E-07	1.20E-06	1.03E-05
Global warming	kg CO2 eq	10650.97	256.82098	71.246226	98.815934	10.487937	10213.599
Smog	kg O3 eq	144.26	46.965337	30.29994	15.745106	0.42770795	50.824571
Acidification	kg SO2 eq	5.65	1.7844581	0.93196766	0.54649583	0.045915906	2.3450189
Eutrophication	kg N eq	8.12E-01	0.32140201	0.072371741	0.051863771	0.025309735	0.34071632
Carcinogenics	CTUh	1.66E-05	7.93E-06	1.23E-06	1.58E-06	6.07E-07	5.21E-06
Non carcinogenics	CTUh	1.06E-04	5.08E-05	1.17E-05	1.51E-05	2.93E-06	2.52E-05
Respiratory effects	kg PM2.5 eq	1.68E-01	0.082384561	0.018496899	0.008555499	0.003890875	0.054850421
Ecotoxicity	CTUe	2379.77	1177.9144	297.78842	385.92735	54.057577	464.08524
Fossil fuel depletion	MJ surplus	934.66	495.89877	143.2553	185.63398	11.46323	98.412026