A MULTI-CRITERIA DECISION SUPPORT TOOL FOR BIOREFINERY SITING

By

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DOCTOR OF PHILOSOPHY

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To the Faculty of Washington State University:

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ACKNOWLEDGEMENT

This work is part of a larger effort under the Northwest Advanced Renewables Alliance (NARA) research group to develop wood-to-wing aviation biofuel supply chains in the Pacific Northwest. The work represented here is wholly interdisciplinary, drawing on research from various groups within NARA. I would like to thank Gevan Marrs and Tom Spink for their help with infrastructure assessments, understanding the workings of a pulp mill, and explaining their integrated biorefinery techno-economic analysis (TEA); Greg Latta for the countless hours he spent discussing biomass estimation techniques and running optimization models for me; John Sessions and Rene Zamora for their data and help in learning logging methods and logistics; Daisuke Sasatani for quickly developing an Economic Input-Output model for use in my last chapter; Indroniel Ganguly and his research assistants for sending me environmental impacts for various equipment; Kristin Brandt for her friendship and for being a sounding board in the last months of my program; and, Karl Olsen, Tammi Laninga, and Michele Vachon for their friendship and support throughout my program. Finally, I would like to thank my advisor, Michael Wolcott, for allowing me to pursue this degree from my home in Yakima. I am extremely grateful for his willingness to work with me over web technology, and for his help in my becoming a better writer and researcher.
Cellulosic and advanced biofuels must provide reduced life cycle greenhouse gas (GHG) emissions by 60% and 50%, respectively, over an equivalent petroleum baseline to meet regulations set by the U.S. Environmental Protection Agency’s Renewable Fuel Standard. Additionally, support at the community level can enhance or hinder a biorefinery’s success.

Repurposing existing industrial facilities into biorefineries may reduce capital expenditures, and selecting facilities based on biorefinery operational costs that vary geospatially may provide operational cost reductions. Additionally assessing facilities for their community social assets and GHG emissions along the supply chain can illuminate those best suited for repurposing based on multiple siting goals.

Considering economic, environmental, and social factors concurrently in biorefinery siting may further reduce investment risk and aid in meeting emission reduction standards. To this end, a decision support tool (DST) is developed at a strategic level to aid stakeholders in selecting existing industrial
facilities as biorefineries through assessing economic, environmental, and social metrics using criteria, weights, and scales. Criteria are selected as quantifiable siting metrics, weights define the relative importance of each criterion, and scale values allow for assessing facilities against each criterion based on location-specific values. Economic criteria are derived from biorefinery operational cost components that vary geospatially, including a criterion to assess each facility’s repurpose potential based on the infrastructure and assets present. The environmental metric is defined as GHG emissions aggregated along the supply chain, reported as 100-year global warming potential. The social metric is defined by two factors, the number of jobs created and three county-level social assets that together indicate a community’s potential receptivity to a new biorefinery. A score is created for each facility, and user-defined overall metric weights adjust the final scores based on stakeholder goals. The DST may be utilized in any region for assessing the repurpose potential of industrial facilities based on a given biofuel conversion process and regional feedstocks.
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Dedication

This dissertation is dedicated to my loving husband for his unwavering support during my pursuit of this degree through the “great recession” and the birth of our second son. I could not have maintained my sanity and completed this momentous task without you. This dissertation is also dedicated to my two energetic sweet young boys, Dane and Brooks. Thanks for keeping me grounded and exhausted over the last 5 years. I have learned the art of the power nap because of you. I am extremely grateful and indebted to my parents for supporting my dreams, no matter how big or how far. Thank you for being my life-long cheerleaders and support crew. I would also like to thank my mother- and father-in-law for being so supportive over the last five years. Their kind words, dinners, and grandparenting were all greatly appreciated. It has truly taken a village, and I am forever grateful.
CHAPTER ONE

GENERAL INTRODUCTION

The U.S. Environmental Protection Agency’s Renewable Fuel Standard (RFS) mandates annual cellulosic and advanced biofuel production targets [1], yet few biorefineries exist to meet the goals. Cellulosic and advanced biorefineries face significant challenges in the road to commercialization. Many have failed to reach or maintain commercialized status due to the significant upfront capital necessary for construction, high feedstock and production costs, and high risk associated with new technologies [2]. Cellulosic and advanced biofuels must provide life cycle greenhouse gas (GHG) emissions reductions of 60% and 50%, respectively, over an equivalent petroleum baseline to meet regulations set by the RFS [1]. Additionally, support at the community level can enhance or reduce a biorefinery’s success [3, 4].

Considering economic, environmental, and social factors in biorefinery siting may reduce investment risk and aid in meeting emission reduction standards. Developing siting criteria based on biorefinery operational costs that vary geospatially may reduce annual operational costs. Repurposing existing industrial facilities has been proposed as a means to reduce capital expenditures for biorefinery construction and to expand a facility’s product portfolio. Many have evaluated the technical and financial feasibility of repurposing facilities into biorefineries [5-11], however no methodology exists for assessing a facility’s repurpose potential based on compatibility with a specified biofuel conversion pathway measured through the infrastructure and assets present. Additionally, many have performed biorefinery siting analyses through selecting locations based on minimizing feedstock costs [12-17] or through minimizing environmental constraints and feedstock costs [18-22], yet all assume a greenfield biorefinery will be constructed in the town/county or pixel location identified as optimal. Greenfields are new construction on undeveloped lands.

Environmental constraints have been assessed in facility siting analyses by many through quantifying erosion potential, nutrient loss, and water quality, among others, [18-20, 23, 24] in addition
to minimizing delivered feedstock costs. As GHG emissions are regulated for biofuel production, either a detailed or screening Life Cycle Analysis (LCA) is often used to quantify emissions along the supply chain [22, 25-28]. Others quantify GHGs emitted through biomass procurement, processing, and transport equipment along a supply chain [21, 29]. While not a formal LCA, this approach is adequate for a strategic-level facility siting analysis to screen candidate biorefinery locations based on their total carbon footprint.

The number of jobs created through biorefinery implementation is the most consistently used social metric [25, 30, 31]. Martinkus et al. [4] proposed a methodology for measuring a community’s potential support for a biorefinery through three county-level social assets: social capital, cultural capital, and human health capital. Both approaches for quantifying social metrics are relevant in biorefinery siting, as regional economic development is an overarching goal of the U.S. government’s support for biofuel research [2, 32], and the U.S. Department of Energy states that community support for a biorefinery is necessary to obtain proper permits [3].

Two studies assess economic, environmental, and social factors concurrently in biorefinery siting analyses. You et al. [30] and Santibanez-Aguilar et al. [31] similarly developed regional biofuel supply chains through optimizing feedstock collection and transport costs, GHG emissions, and number of jobs created. Both developed pareto-optimal curves to assess the tradeoffs between the three metrics. However, You et al. [30] assumed each county centroid was a harvesting site, potential collection facility site, potential biorefinery site, and a demand zone. Santibanez-Aguilar et al. [31] specified cities for biorefinery locations and regions for harvesting sites and demand centers. In both studies, feedstock availability estimates may be less accurate when biomass is assigned to one location in a county or region as opposed to accounting for the spatial heterogeneity of biomass distribution across a landscape. Additionally, feedstock procurement and transport costs may be over- or under-
estimated when locations of biomass procurement, processing, and biofuel demand are generalized at the county or city level.

An alternative approach for addressing complex problems featuring conflicting objectives, different forms of data, and multiple interests and objectives is multi-criteria decision analysis (MCDA). Various forms of MCDA are often employed in the bioenergy field, where criteria are selected to evaluate a problem, weights define the relative importance of each criterion, and scale values allow for assessing alternatives [33]. Analytic Hierarchy Process (AHP) is a widely used MCDA method applied in bioenergy projects [19, 34, 35]. Weights are derived through pair-wise comparisons of criteria performed by experts and stakeholders. This approach is qualitative as personal opinions introduce bias and may skew the resulting relative importance of each criterion. Perimenis et al. [25] utilized a simple MCDA decision matrix to aid users in selecting a preferred biofuel production pathway from multiple feedstock and conversion pathways. Economic, environmental, and social measures served as criteria and were based on the annualized cost of the technology as well as its maturity, a screening-level LCA, and the number of jobs created, respectively. Weights were still derived through user-defined pair-wise comparisons, although through a much simpler form than the AHP method.

All previous studies referenced assume biorefineries to be greenfield facilities. Repurposing existing industrial facilities may provide a near-term solution to reducing many risks associated with cellulosic and advanced biorefineries and increase investor confidence while these biorefineries build up to economies of scale. The aim of this research is to develop a multi-criteria DST to aid stakeholders, investors, and researchers in selecting existing industrial facilities best suited for repurposing into biorefineries using economic, environmental, and social metrics as siting criteria and quantitative methods to develop criteria weights, and allowing for user-input to influence the overall importance of each metric. The following objectives and tasks guide this research.
Objective 1. Create an algorithm for assessing existing industrial facilities for their repurpose potential based on site and location characteristics.

Task 1a. Develop an algorithm for quantitatively assessing the compatibility of existing facilities with a biorefinery conversion process based on a facility’s infrastructure and assets.

Task 1b. Develop an algorithm to determine the weighted average delivered feedstock cost to a facility to meet the annual biorefinery feedstock demand.

Task 1c. Create a methodology for developing quantitative criteria and weights to assess existing facilities for their potential cost savings through becoming a repurposed biorefinery.

Objective 2. Develop quantifiable environmental and social metrics for assessing the biorefinery repurpose potential of existing industrial facilities.

Task 2a. Create a methodology for quantifying the environmental impact from greenhouse gases emitted during the procurement, processing, and transport of feedstock from biomass source points to a facility, and during the transport of biofuel from the facility to a petroleum terminal.

Task 2b. Create an algorithm to assess the social impact of a biorefinery through 1) estimating a community’s potential receptivity to a new biorefinery, and 2) determining the total number of jobs created through the installation of a biorefinery.

Objective 3. Create a multi-criteria DST to aid users in selecting existing industrial facilities best suited for repurposing through concurrently considering economic, environmental, and social siting criteria, and that allows for user-input to adjust the overall importance of the three metrics.

Task 3a. Develop a methodology for incorporating all three metrics into a DST that provides one overall score for each facility.
Task 3b. Incorporate stakeholder siting goals through the use of overall weights for economic, environmental, and social siting criteria.

An optimization model will give similar results as a decision matrix, but takes special training to properly write and execute the code. The simplicity of the decision matrix lends itself well to being utilized by stakeholders or researchers in many complicated problems without prior training required. The process of assessing major operational costs in a biorefinery techno-economic analysis enables a better understanding of the variables that influence the overall biofuel production cost and may identify limiting criteria in facility siting, such as the need for natural gas. Utilizing geospatial cost components as siting criteria provides a transparent and replicable method that may be applied for any biofuel conversion process.

In biomass supply chain planning, decisions at the strategic level include selecting potential facility locations and sizes, product and market development, and selecting the conversion technology [36, 37]. Tactical level planning reflects a medium-short term horizon, and includes final selection of a facility and size, and decisions on how to best address production and distribution issues [36, 37]. Operational level planning includes explicit delineation of the supply chain and contracts with suppliers and buyers for feedstock and fuel, respectively [36, 37]. This research is presented at the strategic level to aid stakeholders in identifying candidate facilities best suited for repurposing based on capital, operational, environmental, and social cost savings as compared to a greenfield biorefinery.

Chapter Three presents a methodology for assessing the compatibility of an existing industrial facility’s infrastructure and assets against a selected biofuel conversion process. Percent capital cost savings are estimated for each facility. The methodology utilizes a biorefinery techno-economic analysis combined with a factored approach to estimate biorefinery infrastructure and asset valuations for facility assessments.
Chapter Four compares two methods for determining delivered feedstock cost and volume of forest residuals to a biorefinery. The first method utilizes past timber harvest data as a reasonable prediction of the near future. The second method utilizes future projections of market timber demand both domestically and internationally for residuals estimation. A Total Transportation Cost Model (TTCM) is introduced to estimate delivered feedstock cost and volume to a facility through summing fixed costs at biomass source locations with a total variable transportation cost for delivering the biomass over a networked road or rail dataset to a facility.

Chapter Five introduces a DST to select existing facilities for their role in a depot-and-biorefinery supply chain. Depot and biorefinery operational cost components that vary geospatially are utilized as siting criteria. Additionally, facilities are assessed for their repurpose potential based on the infrastructure and assets present as compared to the selected biorefinery conversion process, which is then used as a siting criterion.

Chapter Six presents an approach for incorporating social assets into a biorefinery siting methodology. A step-wise approach is employed: 1) a DST is utilized to identify candidate facilities for repurpose based on economic siting criteria; and 2) county-level social, cultural, and human health capitals are applied to the ranked list of facilities to determine those facilities with high economic and social assets.

Chapter Seven presents a DST for identifying existing facilities best suited for repurpose through concurrently considering economic, environmental, and social metrics. The economic metric utilizes biorefinery cost components that vary geospatially as siting criteria. The environmental metric uses one siting criterion, GHGs emitted along the supply chain, which are quantified using the TTCM and reported as 100-year global warming potential. The social metric utilizes two siting criteria, the total number of jobs created through biorefinery implementation, and the social assets present in the county where the biorefinery will be constructed. Overall facility scores are developed through summing individual facility
metric scores. User-defined weights are applied to the three metrics based on stakeholder siting goals, and modify the facility scores to determine candidate facilities with the highest overall score.
References


CHAPTER TWO

Interdisciplinary Research Approach

2.1 Project Background

This work represents an interdisciplinary effort to develop “wood-to-wing” aviation biofuel supply chains in the Pacific Northwest states of Oregon, Idaho, Montana, and Washington under a grant from the U.S. Department of Agriculture (USDA) National Institute of Food and Agriculture. The Northwest Advanced Renewables Alliance (NARA) research team consists of multiple university and industry partners studying various aspects of aviation biofuel supply chain development in this region, from forestry operations to biofuel conversion processes. The research presented here is solely that of Natalie Martinkus, however others within NARA contributed text and/or data to enable the research to progress.

2.2 Data Contributions by Others

Infrastructure assessments performed in Chapter Three require a techno-economic analysis (TEA) for the lignocellulosic conversion process developed within NARA to convert woody biomass into iso-paraffinic kerosene, or aviation biofuel. Tom Spink and Gevan Marrs developed a TEA for the conversion process. Tom Spink additionally provided insight into common infrastructure present in various pulp mill types. Natalie applied major equipment cost estimates specified in the TEA to the methodology she presents for assessing existing facility infrastructure and assets against a greenfield biorefinery.

Biomass cost and volume estimation to a facility is compared through two modeling methodologies presented in Chapter Four. Todd Morgan is director of Forest Industry Research at the University of Montana’s Bureau for Business and Economic Research, and provided Timber Product Output reports for each state in the NARA region for use in the first modeling methodology. Natalie
used the TPO data to develop a geographic information system (GIS)-based methodology for biomass cost and volume estimation from TPO county-level forest residual volumes reported by ownership class.

The second methodology uses a bioeconomic market forecasting model that combines growth and yield data at Forest Inventory and Analysis (FIA) plot locations with national and international market demand for timber products to estimate the amount of residuals available. Greg Latta is a Forest Economist with the University of Idaho, and has been developing this model through work with the U.S. Environmental Protection Agency. He provided the FIA plot locations and forest residual volumes available at each location for average and low-yield years. Natalie used the FIA locations and residual volumes in a second GIS-based modeling methodology for biomass cost and volume estimation to a facility. John Sessions is a faculty member in the Forest Engineering, Resources and Management Department of Oregon State University, and together with his former student Rene Zamora, provided fixed costs for the various equipment used to convert forest residuals to wood chips at each forest landing. They also provided chip van haul costs over various road types, and recommended maximum speeds the chip van may go over the road types. This information is applied in the Total Transportation Cost Model developed by Natalie to estimate fixed and variable transport costs for supplying a biorefinery with forest residuals.

The decision matrix presented in Chapter Five is based on a facility siting decision matrix originally conceived in Washington State University’s Integrated Design Experience (IDEX) class, led by Karl Olsen and Tammi Laninga. The decision matrices used by the IDEX students to select facilities for repurpose into a biorefinery included many possible siting criteria with no defensible rationale for their inclusion. They also used a much wider scale range including negative and positive numbers for assessing facilities against each criterion, which led to less transparent resulting facility scores. Natalie refined their concept of the decision matrix to only include defensible facility siting criteria, and used a
scale range of 1 to 5 for assessing existing facilities against the criteria to provide more transparent facility scores. Additionally, Chapter Five presents a depot-and-biorefinery facility siting methodology. A depot TEA and a biorefinery TEA were developed by Kristin Brandt for use in the siting model developed by Natalie. The TEAs were used to identify geospatial operational costs as siting criteria and to develop weights for the criteria. The depot TEA was additionally used to estimate location-specific processing costs for converting forest residuals to micronized wood for inclusion in a siting criterion.

Chapter Six presents a novel approach to selecting an existing industrial facility for repurpose based on its economic, or biogeophysical, characteristics as well as the social assets of the community in which it resides. Community acceptance of a new biorefinery is estimated by quantifying county-level social assets through three capitals: social, cultural, and human health. Sanne Rijkhoff and Season Hoard of Washington State University’s Division of Governmental Studies and Services performed the statistical analysis of social asset datasets to develop a single score for each capital per county. Paul Smith, professor at Pennsylvania State University’s Agricultural and Biological Engineering Department and Michael Gaffney of Washington State University’s Division of Governmental Studies and Services provided general guidance and direction for the development of the social asset methodology.

Chapter Seven presents a decision matrix that concurrently assesses economic, environmental, and social metrics in one biorefinery site selection model. Life Cycle Inventory data reported as environmental impacts for the various equipment and vehicles used in the procurement, processing, and transport of forest residuals and biofuel was provided by Indroniel Ganguly, faculty in the School of Environmental and Forest Sciences at the University of Washington. An economic input-output (EIO) model developed for the NARA region to estimate job creation was provided by Daisuke Sasatani, also of the School of Environmental and Forest Sciences at the University of Washington. Environmental impact data were incorporated into the Total Transportation Cost Model developed by Natalie to estimate greenhouse gas emissions along the supply chain. Fixed and variable feedstock cost output
from the Total Transportation Cost Model was aggregated by county and input into the EIO model by
Natalie to determine the total direct, indirect, and induced number of jobs created through the
installation of a biorefinery.

2.3 Text Contributed by Others

In Chapter Three, Greg Latta edited text written by Natalie to describe the bioeconomic model
he is developing. He also provided general comments on the direction of the paper. In Chapter Five,
Season Hoard and Sanne Rijkhoff provided text on their social asset modeling methodology. They, as
well as Paul Smith and Mike Gaffney, also provided comments on the direction of the paper. Natalie
wrote the introduction, literature review, biogeophysical modeling methodology, results, discussion,
and conclusion.
CHAPTER THREE

A Framework for Quantitatively Assessing Existing Industrial Facilities for Their Repurpose Potential as a Biorefinery

Citation: Martinkus N, Wolcott M. A framework for quantitatively assessing the repurpose potential of existing industrial facilities as a biorefinery. Submitted to Biofuels, Bioproducts, and Biorefining (2016).

Abstract

Financing a commercial biorefinery involves significant financial and technical risk. Repurposing existing industrial facilities has been proposed as a means to minimize the investment risk in constructing a new biorefinery through reduced financial requirements and startup costs. An infrastructure and asset compatibility analysis was conducted at a strategic planning level to determine an estimated capital percent savings that may be realized through repurposing industrial facilities into biorefineries. A factored approach was employed to assign valuation to the major capital cost components of a biorefinery. Private and public databases and general facility process designs were used to determine the presence of equipment in each facility assessed. A yes/no analysis was performed to assign full cost to facility infrastructure and assets not present in the biorefinery and no cost to those that are present. The estimated accuracy of the factored approach is ± 20-30% for chemical plants in the range of $1 million to $100 million. While commercial-scale biorefineries undoubtedly cost more than $100 million to construct, the methodology for facility assessments is applicable as the cost percentage assignments provide a consistent and transparent valuation tool and enables a metric for facility comparisons.
3.1 Introduction

Financing a commercial biorefinery involves significant financial and technical risk. The initial financial commitment needed in large projects using unproven technologies increases investment risk and affects the willingness of private investors to commit funds \[1\]. This risk is exemplified in the many cellulosic biorefinery projects that have been cancelled or delayed due to funding difficulties \[2\]. Repurposing existing industrial facilities has been proposed as a means to minimize the investment risk in constructing a new biorefinery through reduced financial requirements and startup costs \[3-10\]. Additionally, existing facilities may offer a trained workforce, feedstock connections, and local support for retaining jobs \[3\].

Investors seeking to repurpose an industrial facility for a biorefinery may have difficulty selecting the most likely candidate from a field of potentially viable candidates. Each industrial facility being assessed has different sets of characteristics that make it feasible. Few methodologies exist \[4\] that provide a quantitative assessment of industrial facilities for repurposing potential.

The aim of this research is to develop a methodology for assessing industrial facilities for use as a biorefinery. This methodology is based on major physical characteristics and their use in a proposed process. The objective of this research is to create an algorithm for assigning a quantitative score to industrial facilities by comparing their infrastructure and assets to a given biorefinery conversion process. The scores represent relative capital cost savings, and can be used to assist in decision making regarding the suitability of a facility for repurposing. Here we define infrastructure as roads, water and sewer lines, storm drain system, etc., and assets as equipment and machinery.

3.2 Methodology

A variety of existing industrial facilities have been considered for retrofitting or repurposing into biorefineries, including but not limited to pulp and paper mills, sugar mills, and first generation biorefineries (i.e. corn ethanol and biodiesel) \[3-5, 8-19\]. While the methodology is equally applicable to
a number of processes and facility types, the example used here is the suitability of various pulp and paper mills. The pulp and paper industry uses a variety of process methods such as kraft, sulfite, and thermomechanical pulping for the degradation of wood to pulp [20]. Depending on the specific biofuel conversion process, significant capital cost savings may be realized by converting a specific pulp mill type to a biorefinery due to similarities in the mill’s characteristics.

Our methodology for assessing existing facility infrastructure and assets relies on assigning an economic valuation to capital assets present at a facility. This may be done using a detailed techno-economic analysis (TEA). For many new technologies, a factored approach is initially employed in TEA development to estimate ancillary capital costs associated with constructing a biorefinery as a product of the major total delivered process equipment cost. The factored approach is based on work initiated by Lang [21, 22] and expanded upon by others. Lang developed a technique to obtain order-of-magnitude cost estimates for constructing three main types of chemical processing plants (solid, solid-fluid, and fluid) by multiplying the known process equipment cost by a single factor, the Lang factor, to estimate the total capital investment. The single factor was derived from estimated factor components representing percentages of the process equipment cost for installed costs, piping, construction, and overhead. Peters et al. [23] builds on this methodology by expanding the factor derivatives to include additional direct and indirect plant costs for the same three plant types. When applied as a product of the total delivered equipment costs, the Lang factor can be used to estimate the total capital investment of a plant of similar configuration. Accuracy of this approach is in the +/- 30% range.

Recognizing that preliminary economics of new technologies are difficult to perform, Ereev and Patel [24] introduce a methodology for determining cost estimates for new and emerging technologies based on work by Peters et al. [23]. They assign direct cost items to either “inside-“ or “outside-battery-limits“ of the conversion process. Total delivered equipment cost estimates are required for all major equipment located inside the battery limits (ISBL), while expenses for items located outside the battery
limits (OSBL), such as yard improvements or service facilities, are estimated through percentages of the total delivered equipment cost (Figure 3.1).

Finally, de Jong et al. [25] assess the short-term feasibility of multiple biofuel conversion pathways to renewable jet fuel through a harmonized techno-economic analysis approach. They additionally examine capital and operational savings generally associated with varying degrees of co-production (co-locating, retrofitting, and repurposing) as compared to a greenfield facility. They define co-locating as installing a new facility adjacent to an existing facility, retrofitting as altering an existing facility for use of by-products or residuals in alternative processes, and repurposing as altering an existing facility to produce a new product. We adopt the same definitions in this paper.

The facility assessment methodology presented here builds upon the framework developed by Peters et al. [23] for assigning a consistent set of values to infrastructure and assets for the purpose of comparing against a greenfield biorefinery. We calculate a relative percent capital cost savings each facility may provide as the metric in determining site suitability. While de Jong et al. [25] assess capital and operational expenditure savings that may be realized through general co-production strategies, this methodology focuses on capital expenditure savings at specific industrial facilities. By reducing the initial capital expenditure needed to construct a biorefinery, the cost savings may translate into a lower minimum biofuel selling price. The analysis is intended to be performed at the scoping level to aid stakeholders in refining a list of candidate facilities based on potential cost savings.
3.2.1 Approach

The *Percentage of Delivered-Equipment Cost* method [23] is used to estimate the fixed-capital and total capital investment required to construct a biorefinery. The total delivered equipment cost (TDEC) for all ISBL processes in a greenfield biorefinery is required, and the additional components of capital investment are estimated based on average percentages of the total delivered equipment cost. The fixed capital investment – FCI ($C_n$) can be estimated from the total delivered equipment cost – TDEC ($E$) using the following equation:

$$C_n = \sum (E + f_1E + f_2E + \ldots + f_nE) = E \sum (100 + f_1 + f_2 + \ldots + f_n)/100$$  

*Equation 1*

where $f_1, f_2, \ldots, f_n$ are multiplying factors for all direct and indirect costs, such as installation, piping, engineering and supervision, etc. [23].

Only direct costs are used for facility assessment, as they represent the physical properties of a site that change with co-production strategy and biorefinery process. Indirect costs are negated because they remain constant regardless of facility location or type. Table 3.1 represents the summation of factors in the right-hand part of Equation 1, and illustrates the recommended percentages of TDEC for all direct and indirect cost items by plant type for new construction. Relative
cost savings for repurposing an industrial facility into a biorefinery are measured in the direct cost categories of Total Delivered Equipment Cost, Buildings, Yard Improvements, and Service Facilities. These items were selected as the degree to which they exist varies with facility location when compared to a biorefinery process. The associated percentages are assigned to the infrastructure and assets in a greenfield biorefinery design to provide a valuation tool for assessing against the physical characteristics in industrial facilities.

We expand on the list in Table 3.1 for a given conversion process by identifying the major ISBL equipment and associated costs, and by selecting the degree to which service facilities are required for OSBL processes from a list of recommended percentages. Buildings and yard improvements are also measured through recommended percentages. Direct cost items not included in the facility assessment remain in the Total Direct Costs calculation due to the necessary expenses incurred during any site redevelopment.
Table 3.1. Recommended percentages of Total Delivered Equipment Cost for a greenfield chemical plant. Adapted from Peters et al. [23].

<table>
<thead>
<tr>
<th>Processing Plant Type</th>
<th>Solid</th>
<th>Solid-Fluid</th>
<th>Fluid</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct Costs</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Delivered Equipment Cost (TDEC)</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Installation for TDEC</td>
<td>45</td>
<td>39</td>
<td>47</td>
</tr>
<tr>
<td>Instrumentation and Controls</td>
<td>18</td>
<td>26</td>
<td>36</td>
</tr>
<tr>
<td>Piping</td>
<td>16</td>
<td>31</td>
<td>68</td>
</tr>
<tr>
<td>Electrical Systems</td>
<td>10</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Buildings</td>
<td>68</td>
<td>47</td>
<td>45</td>
</tr>
<tr>
<td>Yard Improvements</td>
<td>15</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Service Facilities</td>
<td>40</td>
<td>55</td>
<td>70</td>
</tr>
<tr>
<td><strong>Total Direct Costs</strong></td>
<td>312</td>
<td>320</td>
<td>387</td>
</tr>
<tr>
<td><strong>Indirect Costs</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Engineering and supervision</td>
<td>33</td>
<td>32</td>
<td>33</td>
</tr>
<tr>
<td>Construction expenses</td>
<td>39</td>
<td>34</td>
<td>41</td>
</tr>
<tr>
<td>Legal Expenses</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Contractor’s fee</td>
<td>17</td>
<td>19</td>
<td>22</td>
</tr>
<tr>
<td>Contingency</td>
<td>35</td>
<td>37</td>
<td>44</td>
</tr>
<tr>
<td><strong>Total Indirect Plant Costs</strong></td>
<td>128</td>
<td>126</td>
<td>144</td>
</tr>
<tr>
<td>Fixed Capital Investment (FCI)</td>
<td>440</td>
<td>446</td>
<td>531</td>
</tr>
<tr>
<td><strong>FCI Lang Factor = FCI/TDEC</strong></td>
<td>4.40</td>
<td>4.46</td>
<td>5.31</td>
</tr>
<tr>
<td>working capital (17.6% of FCI)</td>
<td>77</td>
<td>78</td>
<td>93</td>
</tr>
<tr>
<td><strong>Total Capital Investment (TCI)</strong></td>
<td>517</td>
<td>524</td>
<td>624</td>
</tr>
<tr>
<td><strong>TCI Lang Factor = TCI/TDEC</strong></td>
<td>5.17</td>
<td>5.24</td>
<td>6.24</td>
</tr>
</tbody>
</table>

A systematic approach is proposed to score industrial facilities by their compatibility with a given biofuel conversion process. A greenfield biorefinery scenario is first developed with cost component percentages assigned for all direct cost categories based on preliminary process flow diagrams. Similar to Gonzalez et al. [4], facility assessments for the selected direct cost categories, except buildings, are performed on a present(0)/absent(1) basis (Figure 3.2). Full greenfield cost is assigned to components absent from a facility and no costs are assigned to components that are present. Each facility’s total direct plant cost is calculated by summing all direct cost percentages. Percent savings is calculated based on total greenfield cost (Table 3.2). The steps for facility
assessments are listed in Figure 3.2 with references to Tables 3.1 – 3.4 and Equations 2 – 7. Section 3.2.2 covers considerations for direct cost items assessed relative to the assignment of TDEC percentages.

Figure 3.2. Process flow for percentage of TDEC assignments to greenfield biorefinery and to facilities through site assessment.
Table 3.2. General form of Total Direct Plant Cost table for site assessments.

<table>
<thead>
<tr>
<th>Direct Cost Item</th>
<th>Greenfield</th>
<th>Site 1</th>
<th>Site 2</th>
<th>Site n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Delivered Equipment Cost (TDEC)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Equipment in process unit 1</td>
<td>$p_1$</td>
<td>$p_1 \cdot {0,1}$</td>
<td>$p_1 \cdot {0,1}$</td>
<td>$p_1 \cdot {0,1}$</td>
</tr>
<tr>
<td>% Equipment in process unit 2</td>
<td>$p_2$</td>
<td>$p_2 \cdot {0,1}$</td>
<td>$p_2 \cdot {0,1}$</td>
<td>$p_2 \cdot {0,1}$</td>
</tr>
<tr>
<td>% Equipment in process unit z</td>
<td>$p_z$</td>
<td>$p_z \cdot {0,1}$</td>
<td>$p_z \cdot {0,1}$</td>
<td>$p_z \cdot {0,1}$</td>
</tr>
<tr>
<td>TDEC Total</td>
<td>100</td>
<td>$P_1$</td>
<td>$P_2$</td>
<td>$P_n$</td>
</tr>
<tr>
<td>Installation for TDEC</td>
<td>$f_1$</td>
<td>$f_1$</td>
<td>$f_1$</td>
<td>$f_1$</td>
</tr>
<tr>
<td>Instrumentation and Controls</td>
<td>$f_2$</td>
<td>$f_2$</td>
<td>$f_2$</td>
<td>$f_2$</td>
</tr>
<tr>
<td>Piping</td>
<td>$f_3$</td>
<td>$f_3$</td>
<td>$f_3$</td>
<td>$f_3$</td>
</tr>
<tr>
<td>Electrical Systems</td>
<td>$f_4$</td>
<td>$f_4$</td>
<td>$f_4$</td>
<td>$f_4$</td>
</tr>
</tbody>
</table>

**Buildings**

<table>
<thead>
<tr>
<th></th>
<th>$g$</th>
<th>$f_5$</th>
<th>$f_5$</th>
<th>$f_5$</th>
<th>$f_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings Total</td>
<td>$f_5$</td>
<td>$f_5$</td>
<td>$f_5$</td>
<td>$f_5$</td>
<td>$f_5$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Yard Improvements</th>
<th>$f_6$</th>
<th>$f_6 \cdot {0,1}$</th>
<th>$f_6 \cdot {0,1}$</th>
<th>$f_6 \cdot {0,1}$</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Service Facilities</th>
<th>$s_1$</th>
<th>$s_1 \cdot {0,1}$</th>
<th>$s_1 \cdot {0,1}$</th>
<th>$s_1 \cdot {0,1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service Facility component 1</td>
<td>$s_1$</td>
<td>$s_1 \cdot {0,1}$</td>
<td>$s_1 \cdot {0,1}$</td>
<td>$s_1 \cdot {0,1}$</td>
</tr>
<tr>
<td>Service Facility component 2</td>
<td>$s_2$</td>
<td>$s_2 \cdot {0,1}$</td>
<td>$s_2 \cdot {0,1}$</td>
<td>$s_2 \cdot {0,1}$</td>
</tr>
<tr>
<td>Service Facility component y</td>
<td>$s_y$</td>
<td>$s_y \cdot {0,1}$</td>
<td>$s_y \cdot {0,1}$</td>
<td>$s_y \cdot {0,1}$</td>
</tr>
<tr>
<td>Service Facilities Total</td>
<td>$f_7$</td>
<td>$f_7 \cdot {0,1}$</td>
<td>$f_7 \cdot {0,1}$</td>
<td>$f_7 \cdot {0,1}$</td>
</tr>
<tr>
<td>Total Direct Plant Cost</td>
<td>$TG$</td>
<td>$TF_1$</td>
<td>$TF_2$</td>
<td>$TF_n$</td>
</tr>
<tr>
<td>Percent Savings from Greenfield</td>
<td>$1 - TF_1/TG$</td>
<td>$1 - TF_2/TG$</td>
<td>$1 - TF_n/TG$</td>
<td></td>
</tr>
</tbody>
</table>

\[
P_n = \sum p_z \cdot \{0,1\} \quad \text{Equation 2}
\]

\[
f_{5,n} = (g \cup c \cup r) \quad \text{Equation 3}
\]

\[
f_{6,n} = f_6 \cdot \{0,1\} \quad \text{Equation 4}
\]

\[
f_{7,n} = \sum s_y \cdot \{0,1\} \quad \text{Equation 5}
\]

\[
TG = 100 + \sum_{x=1}^{7} f_x \quad \text{Equation 6}
\]

\[
TF_n = P_n + \sum_{x=1}^{7} f_{x,n} \quad \text{Equation 7}
\]
where $P_n$ is the TDEC total percentage for facility $n$ derived by summing all equipment percentages ($p_z$) after site analysis; $f_{5,n}$ is the building percentage assigned to a site based on the estimated work needed to redevelop existing buildings into a biorefinery, with greenfield (g) needing the most work and retrofit/repurpose (r) needing the least; $f_{6,n}$ is the percentage assigned based on the presence of yard improvements; $f_{7,n}$ is the sum of all service facility component percentages after site analysis ($s_y$); $TG$ is the Total Direct Plant Cost for a greenfield biorefinery determined by summing TDEC Total with all direct cost component percentages ($f_x$); and, $TF_n$ is the Total Direct Plant Cost for Facility $n$ determined by summing all direct cost percentages of TDEC ($P_n, f_{x,n}$) assigned through site analysis.

3.2.2 Direct Cost Considerations

3.2.2.1 Total Delivered Equipment Cost (TDEC)

Cost estimates are required for all major process equipment, and may be obtained from vendor quotes, detailed TEAs such as [26-28] which may include cost estimate spreadsheets for download [29], or databases such as the SCENT tool [24]. Equipment costs are summed by process department, and the percentage cost of each process department is calculated. Process departments for an enzymatic hydrolysis biofuel conversion process, for example, typically include pretreatment, saccharification and fermentation, distillation, and solids recovery. Wastewater treatment can be a significant capital cost item [26, 27, 30]. Peters et al. [23] include wastewater treatment as a service facility item and estimate the cost through a range of recommended percentages of TDEC based on typical chemical plants. If wastewater treatment is unique to the conversion process, it should be included as an ISBL capital cost. Facility assessment is performed by comparing the major equipment in each ISBL process department to the major equipment present in each facility. Facility assets may be determined through industrial facility databases, such as [31], or through state-mandated facility permits for air and water which may include plant process descriptions. At the scoping level, facilities assessments are based on
publicly-available data. In cases where major processes are typical of all facilities of a given type, such as kraft pulp mills, literature may also be used to determine the presence of major equipment.

### 3.2.2.2 Buildings and Yard Improvements

All buildings, both ISBL and OSBL, are included in the buildings factor provided by Peters et al. [23]. When assessing the suitability of existing facilities, the user must determine the degree to which existing buildings will serve the greenfield scenario. If a majority of the buildings have been maintained, the site may be considered a retrofit/repurpose project, whereas if few buildings exist or have been maintained, a greenfield or co-locate designation may be more appropriate (Table 3.3). Aerial imagery and site photos can be used for assessment.

#### Table 3.3. Recommended building percentages of Total Delivered Equipment Cost for co-production strategies from Peters et al. [23]

<table>
<thead>
<tr>
<th>Process Plant Type</th>
<th>Percent of TDEC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Greenfield</td>
</tr>
<tr>
<td>Solid</td>
<td>68</td>
</tr>
<tr>
<td>Solid-Fluid</td>
<td>47</td>
</tr>
<tr>
<td>Fluid</td>
<td>45</td>
</tr>
</tbody>
</table>

Yard improvements include costs for fencing, grading, roads and sidewalks, railroad spurs, landscaping, etc. Access to multi-modal transportation is important for sending and receiving goods at a biorefinery. Therefore, facilities are assessed based on the presence of a rail spur, fencing, and roads. If not present, facilities are assigned the recommended percentage value from Table 3.1. Aerial imagery and geospatial data can be used for assessments.

### 3.2.2.3 Service Facilities

The service facilities category defines items that supply the plant with water, steam, power, and fuel, along with other miscellaneous items. The level of service facility components varies widely based on process plant design; therefore, ‘high’, ‘typical’, and ‘low’ percentages of TDEC are reported in Table
3.4 for each service facility component [23, 24]. The values originally reported in Peters et al. [23] are listed as percentages of fixed capital investment. To convert the values to percentages of delivered equipment cost, an average ratio of 0.27 fixed capital investment to purchased equipment cost was applied along with an assumed ten percent delivery charge [23]. The ratio was determined by comparing Peters et al. [23] recommended percentages for direct cost components reported as both fixed capital investment and purchased equipment cost.

**Table 3.4. Percentages of TDEC for service facility components. Adapted from Peters et al. [23].**

<table>
<thead>
<tr>
<th>Service Facilities</th>
<th>Low % of TDEC</th>
<th>Typical % of TDEC</th>
<th>High % of TDEC</th>
</tr>
</thead>
<tbody>
<tr>
<td>steam generation</td>
<td>10.6</td>
<td>13.2</td>
<td>26.4</td>
</tr>
<tr>
<td>steam distribution</td>
<td>0.8</td>
<td>4.4</td>
<td>8.8</td>
</tr>
<tr>
<td>process waste disposal</td>
<td>2.4</td>
<td>6.6</td>
<td>10.6</td>
</tr>
<tr>
<td>water supply, cooling and pumping</td>
<td>1.6</td>
<td>7.9</td>
<td>16.3</td>
</tr>
<tr>
<td>water treatment</td>
<td>2.0</td>
<td>5.7</td>
<td>9.2</td>
</tr>
<tr>
<td>water distribution</td>
<td>0.4</td>
<td>3.5</td>
<td>8.8</td>
</tr>
<tr>
<td>electrical substation</td>
<td>3.7</td>
<td>5.7</td>
<td>11.4</td>
</tr>
<tr>
<td>electrical distribution</td>
<td>1.6</td>
<td>4.4</td>
<td>9.2</td>
</tr>
<tr>
<td>gas supply and distribution</td>
<td>0.8</td>
<td>1.3</td>
<td>1.8</td>
</tr>
<tr>
<td>air compression and distribution</td>
<td>0.8</td>
<td>4.4</td>
<td>13.2</td>
</tr>
<tr>
<td>refrigeration including distribution</td>
<td>2.0</td>
<td>4.4</td>
<td>8.8</td>
</tr>
<tr>
<td>sanitary waste disposal</td>
<td>0.8</td>
<td>1.8</td>
<td>2.6</td>
</tr>
<tr>
<td>communications</td>
<td>0.4</td>
<td>0.9</td>
<td>1.3</td>
</tr>
<tr>
<td>raw material storage</td>
<td>1.2</td>
<td>2.2</td>
<td>14.1</td>
</tr>
<tr>
<td>finished product storage</td>
<td>2.9</td>
<td>6.6</td>
<td>10.6</td>
</tr>
<tr>
<td>fire protection system</td>
<td>1.2</td>
<td>2.2</td>
<td>4.4</td>
</tr>
<tr>
<td>safety installations</td>
<td>0.8</td>
<td>1.8</td>
<td>2.6</td>
</tr>
</tbody>
</table>

For a given biofuel conversion process, the level of each service facility component is selected to represent the capital cost percentage of that item. For a strategic level assessment, it is difficult to assess the extent to which many service facilities exist at a site. Industrial facility databases, such as [32], and state water and air permits can be used to determine the presence of some service facilities at given location. User judgment must also be employed for more common items such as communications, fire protection, and safety installations, which are typical at any given industrial site.
3.3 Case Study

The methodology is applied to a region in the Pacific Northwest representing western Oregon and western Washington (here called the Cascades-to-Pacific, or C2P, region). The C2P region is densely-populated, contains large areas of privately-owned working forests, and a number of pulp and paper mills. Five active and recently decommissioned pulp mills are assessed against a greenfield pretreatment facility that converts forest residuals into pulp fiber. The pulp mills represent the various pulp mill types in the region, including one thermomechanical (TMP), one magnesium sulfite (MgS), one kraft + neutral sulfite semi-chemical (NSSC), and two kraft mills.

The pretreatment facility is considered a solid-fluid facility, and may be co-located with a biorefinery that utilizes the pre-treated pulp fibers as feedstock for conversion into isoparaffinic kerosene (bio-jet fuel). The pretreatment process uses a mild bisulfite solution to pretreat forest residuals for subsequent enzymatic hydrolysis, creating free sugars [33]. These simple sugars can then be fermented into isobutanol (IBA), which is catalytically converted to isoparaffinic kerosene (IPK) [34]. This process is outlined as alcohol-to-jet synthetic paraffinic kerosene in ASTM D7566 A5 [35]. The process is scaled to produce approximately 135 million liters of IPK per year and has an annual feedstock demand of 757,500 bone dry metric tons (BDMt) of forest residuals to the biorefinery gate. Steam is generated in a hog fuel boiler as opposed to generating electricity and steam in a petroleum-fueled power boiler due to the low cost of hydropower electricity in the region.

All major equipment in the ISBL pretreatment process department are identified and a cost estimate is obtained for each (Table 3.6). The degree of each service facility component required for the pretreatment facility is selected from Table 3.4. A large wood yard is needed to facilitate the receiving and storage of wood chips [36]; therefore, raw material storage receives a high service facility percentage. Finished product storage consists of storage tanks to hold the pretreated pulp [27], and is assigned a low percentage. Electrical substation is low as electricity is not generated on-site. Air
compression/distribution and refrigeration/distribution are a low percentage due to their minimal requirement in the facility. All other components receive a typical percentage of TDEC (Table 3.5).

3.3.1 Pretreatment Assessment

The pretreatment process is designed using total sulfur dioxide and calcium bisulfite [37]. Sulfite and NSSC mills are most similar due to their use of a sulfite solution, however NSSC mills operate at a near-neutral pH (~6) while sulfite mills operate at low pH (~2.5). Kraft mills use sodium sulfide and sodium hydroxide to create an alkaline solution for pretreating wood at high temperature and pH (>12) [38]. Mechanical mills such as TMP use heat to loosen wood fibers before disc refining into pulp. Kraft + NSSC facilities are designed as a large kraft mill co-located with a small NSSC mill. For this strategic-level analysis, we broadly assume the same major pretreatment equipment are present within each specific type of pulp mill assessed (kraft, TMP, etc.). The pulp mill process flow diagrams used for comparison may be found in Kemmer [20] pgs. 30-8 to 30-18.

The pretreatment capital cost is disaggregated into three major equipment components in Table 3.6; (1) acid plant, (2) digester system, and (3) blow gas system. The acid plant and blow gas system are of similar design to those used in a sulfite-type pulp mill. The digester system lump sum includes chip washers, digester, blow tank, and high-density storage tank, among others, but is typically designed and sold as a single specialized unit. The digester in the biorefinery process is specific to the highly acidic conditions of a sulfite pretreatment method, therefore the magnesium sulfite (MgS) mill is uniquely suited to this process. Even though Kraft and Kraft + NSSC mills both possess digesters, the material of construction is not compatible with the acidic pretreatment method and is unsuitable for repurposing. Each facility’s pretreatment equipment cost percentages after assessment are summed to determine the total (Table 3.6).
### Table 3.5. Service facility components and selected percentages of Total Delivered Equipment Cost from Peters et al. [23]

<table>
<thead>
<tr>
<th>Service Facility Components</th>
<th>% of TDEC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steam generation</td>
<td>13.2</td>
</tr>
<tr>
<td>Steam distribution</td>
<td>4.4</td>
</tr>
<tr>
<td>Process waste disposal</td>
<td>6.6</td>
</tr>
<tr>
<td>Water supply, cooling and pumping</td>
<td>7.9</td>
</tr>
<tr>
<td>Water treatment</td>
<td>5.7</td>
</tr>
<tr>
<td>Water distribution</td>
<td>3.5</td>
</tr>
<tr>
<td>Electrical substation</td>
<td>3.7</td>
</tr>
<tr>
<td>Electrical distribution</td>
<td>4.4</td>
</tr>
<tr>
<td>Gas supply and distribution</td>
<td>1.3</td>
</tr>
<tr>
<td>Air compression and distribution</td>
<td>0.8</td>
</tr>
<tr>
<td>Refrigeration including distribution</td>
<td>2.0</td>
</tr>
<tr>
<td>Sanitary waste disposal</td>
<td>1.8</td>
</tr>
<tr>
<td>Communications</td>
<td>0.9</td>
</tr>
<tr>
<td>Raw material storage</td>
<td>14.1</td>
</tr>
<tr>
<td>Finished product storage</td>
<td>2.9</td>
</tr>
<tr>
<td>Fire protection system</td>
<td>2.2</td>
</tr>
<tr>
<td>Safety installations</td>
<td>1.8</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>77.2</strong></td>
</tr>
</tbody>
</table>

### Table 3.6. Pretreatment assessment of pulp mill types

<table>
<thead>
<tr>
<th>Pretreatment Equipment</th>
<th>% of Total Pretreatment Cost</th>
<th>Yes [0]/No [1] Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Kraft</td>
</tr>
<tr>
<td>Acid Plant</td>
<td>8.9</td>
<td>8.9</td>
</tr>
<tr>
<td>Digester System</td>
<td>79.7</td>
<td>79.7</td>
</tr>
<tr>
<td>Blow Gas System</td>
<td>11.4</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>100.0</strong></td>
<td>88.6</td>
</tr>
</tbody>
</table>

#### 3.3.2 Buildings, Yard Improvements, and Service Facilities

All of the facilities evaluated have maintained buildings and receive a cost percentage consistent with repurpose/retrofit projects. Aerial imagery was used to visually inspect for a rail spur, fencing, and roads. In the service facilities assessment, an online database was obtained to assess the boiler types and sizes present at each facility [32]. Only the Longview and Newburg mills operate hog fuel boilers.
Steam generation is therefore assigned full cost for all other mills. Raw material storage is assumed to be adequate at each site due to the selection of facilities with sites greater than 60.8 ha. None of the mills have adequate storage tanks for the pretreated pulp and are assigned full cost for finished product storage. The wastewater treatment system for each mill is defined in its state-regulated National Pollutant Discharge Elimination System (NPDES) permit. It was found that, regardless of pulping technology, all of the pulp mills assessed utilize primary and secondary clarifiers for wastewater treatment, and all are assumed adequate for the pretreatment facility. All other service facility components are assumed to be present at each facility.

3.4 Results and Discussion

3.4.1 Results of Facility Assessments

Table 3.7 shows the results of the facility assessments as percentages of TDEC. Percent savings are calculated against the greenfield scenario. As expected, the magnesium sulfite mill in Cosmopolis WA provides the most capital cost savings due to the presence of the pretreatment equipment. The Longview Mill contains some pretreatment equipment and a hog fuel boiler, which also makes it an attractive facility for repurpose. The Newburg mill is rather surprising in its similar cost savings to the Springfield and Toledo mills, as a TMP mill is not an intuitive choice due to its lack of pretreatment technology. However, the boiler is a significant capital cost item that offsets the lack of pretreatment equipment.

3.4.2 Discussion

The results reveal that when comparing facilities with similar characteristics, differences are measured in only one or two direct cost categories. When comparing facilities that differ significantly in type and status, more metrics are available for delineating potential cost savings. For example, disparate facilities such as a mining operation, a first-generation biorefinery, or an old wastewater treatment plant may all be considered for retrofit into a cellulosic biorefinery. Brownfields and
decommissioned industrial facilities also hold repurposing potential as local, state, and federal funds can be available for site cleanup and redevelopment [39, 40].

Table 3.7. Facility assessments and final estimated capital cost savings.

<table>
<thead>
<tr>
<th>Direct Cost Item</th>
<th>Greenfield</th>
<th>Cosmopolis WA mill</th>
<th>Longview WA mill</th>
<th>Springfield OR mill</th>
<th>Newburg OR mill</th>
<th>Toledo OR mill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Delivered Equipment Cost (TDEC)</td>
<td>100.0</td>
<td>39.0</td>
<td>26.0</td>
<td>31.0</td>
<td>10.0</td>
<td>77.2</td>
</tr>
<tr>
<td>Installation for TDEC</td>
<td>39.0</td>
<td>39.0</td>
<td>39.0</td>
<td>39.0</td>
<td>39.0</td>
<td>39.0</td>
</tr>
<tr>
<td>Instrumentation and Controls</td>
<td>26.0</td>
<td>26.0</td>
<td>26.0</td>
<td>26.0</td>
<td>26.0</td>
<td>26.0</td>
</tr>
<tr>
<td>Piping</td>
<td>31.0</td>
<td>31.0</td>
<td>31.0</td>
<td>31.0</td>
<td>31.0</td>
<td>31.0</td>
</tr>
<tr>
<td>Electrical Systems</td>
<td>10.0</td>
<td>10.0</td>
<td>10.0</td>
<td>10.0</td>
<td>10.0</td>
<td>10.0</td>
</tr>
<tr>
<td>Buildings</td>
<td>47.0</td>
<td>7.0</td>
<td>7.0</td>
<td>7.0</td>
<td>7.0</td>
<td>7.0</td>
</tr>
<tr>
<td>Yard Improvements</td>
<td>12.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Service Facilities</td>
<td>77.2</td>
<td>16.1</td>
<td>2.9</td>
<td>16.1</td>
<td>2.9</td>
<td>16.1</td>
</tr>
<tr>
<td>Total Direct Plant Cost</td>
<td><strong>342.2</strong></td>
<td><strong>129.1</strong></td>
<td><strong>204.5</strong></td>
<td><strong>217.7</strong></td>
<td><strong>215.9</strong></td>
<td><strong>217.7</strong></td>
</tr>
<tr>
<td>Percent Savings from Greenfield</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>62%</td>
<td>40%</td>
<td>36%</td>
<td>37%</td>
<td>36%</td>
<td></td>
</tr>
</tbody>
</table>

The accuracy of the TDEC method is estimated at ± 20-30% for chemical plants in the range of $1 million to $100 million [23]. While commercial-scale biorefineries undoubtedly cost more than $100 million to construct [41], the methodology for facility assessments is applicable as the cost percentage assignments provide a consistent and transparent valuation tool and enables a metric for facility comparisons. Estimated capital expenditure savings reported for each facility are approximate and meant for facility comparisons only. Actual costs for repurposing may differ greatly based on a more in-depth strategic-level assessment.

Peters et al. [23] state that the greatest errors in cost estimation are typically due to exclusions of equipment and service facilities rather than to large errors in estimation. The same philosophy applies here, where a detailed accounting of the major equipment and associated costs in the conversion process is important for accurate facility assessments. Also important is an understanding of the degree and type of service facilities required. Facility assessments are performed at the strategic level, with publicly available data used to assess the presence of infrastructure and assets. A strategic-
level analysis requires a detailed TEA with actual costs or refined estimates identified for all direct cost components. Facility assessments are then performed through communication with facility management to determine the type and size of major equipment, as well as the service facilities present. Stakeholders applying this methodology to assess existing facilities, especially decommissioned ones, will want to contact facility owners to determine the specific infrastructure and assets present, as well as the age and condition of each.

A major assumption is that the equipment in each facility is of the correct size and material to be repurposed into the design biorefinery. This is partially accounted for in the initial phase of facility selection, where facilities must be greater than 61 ha for consideration in the analysis. A facility selected for repurposing will undoubtedly need additional equipment and/or reconfiguring of the equipment to meet the biorefinery design process. However, the presence of needed equipment is still a cost savings over a greenfield.

Biorefineries must produce biofuel at a cost that is competitive against petroleum-based fuels to remain relevant in the marketplace and reach beyond pilot-plant status. In the long term, price parity will be achieved through technological innovations, economies of scale, policy support, and knowledge gained through production experience [25]. In the short term, repurposing existing facilities (pulp mills, sugar mills, etc.) into biorefineries may provide capital cost savings and translate into a reduced biofuel selling price. For example, when the pulp industry declines due to market demand, a co-located biorefinery is still producing biofuel and co-products [8, 12]. Additionally, sugar mills only operate a few months of the year, and a co-located biorefinery using stored bagasse will operate year round [17]. By-products from the mill become feedstock for the biorefinery, and heat, steam, and electricity generated in the biorefinery may be used in the mill. Retrofitting has the added benefit of multiple diverse revenue streams. Many studies have assessed the feasibility of retrofitting a pulp mill to produce ethanol and other derivatives such as acetic acid [9, 12, 13] along with pulp. Co-products are critical to
the financial success of biorefineries and traditional petroleum-based refineries alike [42-44]. The methodology may be applied to assess the retrofit potential of facilities for co-location through an analysis of infrastructure, assets, waste streams, and energy needs.

The initial financial commitment needed for construction of a biorefinery is significant; however, the annual operational expenses to run a facility are as well. Selecting a facility for repurpose based on compatible infrastructure characteristics aids in reducing the initial capital investment. Annual expenses for feedstock, energy, and labor vary geographically with facility location and may provide greater influence on site selection than evaluating capital cost savings alone. The total ISBL capital cost may be converted to an annualized cost using a capital recovery factor for comparison against the operational costs. A combined model that evaluates capital and operational savings at existing facilities will provide a more complete site selection framework and enable the selection of a facility for retrofit that produces biofuel at a minimized cost.

3.5 Conclusion

Cellulosic biorefineries are still in the early stages of commercialization. Until they become established in the marketplace and capitalize on economies of scale, biorefineries must take advantage of cost savings where possible to create biofuel at a price that is competitive with petroleum-based fuels. The methodology presented here provides a framework for quantitatively assessing existing facilities for their potential to be repurposed into a biorefinery. Cost savings are measured through similarities in infrastructure and assets to a design conversion process. The facility with the greatest cost savings is theoretically the least cost to repurpose and provides less risk in upfront capital to investors. The strength of this methodology is its ability to assess a range of industrial facilities through a quantitative and transparent process. The methodology is developed at the strategic level to aid stakeholders in refining a list of candidate facilities for further investigation as potential biorefineries.
References


CHAPTER FOUR

A Comparison of Methodologies for Estimating Delivered Forest Residuals Volume and Cost to a Wood-Based Biorefinery

Abstract

For industries with high raw material transport costs, such as large biorefineries using forest residuals as a feedstock, plant location can influence raw material cost. Forest residuals are a byproduct of timber harvests performed primarily to supply lumber and paper demand. Biorefineries sited near large amounts of forest residuals can better mitigate against the risk of reduced availability due to extraneous physical constraints such as forest fires and insect infestations, as well as market constraints such as low forest products demand. Two methodologies for estimating the amount and cost of delivered of forest residuals to a biorefinery are presented. Both methodologies are based on data provided by the U.S. Forest Service Forest Inventory and Analysis (FIA) program. The first methodology is past-predictive; it uses individual state Timber Product Output (TPO) reports, issued every five years, which provide county-level volumes of lumber harvested and residuals generated in a single year. The second methodology is future-predictive; the Land Use Resource Allocation (LURA) model uses a spatially explicit economic optimization model of the U.S. forestry sector coupled with stand data at FIA plot locations to project near- and medium-term residual volumes through forest growth and harvest regimes for public and private timber lands across the U.S. One total transportation cost model is used with both biomass estimation methods to enable comparison of facility supply curves. Average and low-yield scenarios were run in both methods to assess each model’s usefulness at projecting biomass supply to a facility.
4.1 Introduction

For industries with potentially high raw material transport costs, such as large biorefineries using forest residuals as a feedstock, plant location can influence raw material cost [1]. Forest residuals are a byproduct of timber harvests performed primarily to supply lumber and paper demand. Biorefineries sited near large amounts of forest residuals can better mitigate against the risk of reduced availability due to extraneous physical constraints such as forest fires and insect infestations, as well as market constraints such as low forest products demand. In contrast to agricultural feedstocks where annual production is planted in direct response to demand, forest residuals are recovered over a 20- to 50-year timber harvest rotation. This difference in planting and planning cycles may lead to a more spatially dispersed supply area for forest-based materials compared to agricultural residuals of energy crops. Therefore, methods to quantify forest residuals should account for both the spatial distribution of the biomass and future timber demand.

For a biorefinery to have a reliable annual feedstock supply, the plant should have access to low-cost feedstock at volumes in excess of the minimum annual demand, even in low-supply years. The goal of this research is to develop methods to estimate forest residuals availability for use in facilities such as a biorefinery. Specifically, we present two biomass estimation methodologies, one past-predictive and one future-predictive, to determine annual forest residual volumes¹ that would theoretically be available at a range of marginal feedstock prices. In addition, we evaluate each model’s relevance for use in facility siting. These methods only predict likely availability based upon a number of market assumptions and do not guarantee any buyer-seller relations that would inform tactical supply strategies.

¹ Forest products include measurements in both volume and mass for different products, and can also be reported for the same products in the case of pulpwood and residues. We refer to both mass and volume as volume for simplicity.
Both methodologies rely on public data supplied by the U.S. Forest Service (USFS) Forest Inventory and Analysis (FIA) Program. The first past-predictive methodology uses FIA Timber Product Output (TPO) reports [2], which provide county-level volumes of lumber harvested in a single year. Each state is assessed in five-year increments. The volumes are reported by land-ownership type and present a historical accounting of timber harvest over time. The second future-predictive methodology uses a spatially explicit economic optimization model of the U.S. forestry sector coupled with stand data at FIA plot locations to project near- and medium-term residual volumes through forest growth and harvest regimes for public and private timber lands across the U.S. The output from this model is a forest residuals volume estimate at each FIA plot over a projected time span of 20 years in one-year increments. An average volume is derived from the yearly increments. The two methodologies use the same transportation cost model to enable comparison of facility supply curves generated by the different biomass methodologies.

The aim of this research is to assess the applicability of the past-predictive and future-predictive biomass estimation methodologies for determining annual feedstock availability to a biorefinery. The objectives are to: 1) create a total transportation cost model that combines fixed and variable harvest and hauling biomass costs with a networked road dataset to estimate the delivered feedstock cost to the biorefinery gate; 2) develop algorithms for the two methodologies that integrate the spatial variability of forested biomass with the total transportation cost model to determine facility feedstock supply curves; and 3) assess the risk in feedstock supply to a biorefinery associated with each methodology. In this analysis, we define risk as the failure to procure the minimum annual feedstock demand, and is assessed through comparing facility supply curves to low-yield scenarios. The methodologies are applied in the Pacific Northwest (PNW) region of the United States, as it has abundant forest residuals that may serve as a sustainable biofuel feedstock [3-5].
4.2 Literature Review

Researchers have taken many approaches to estimate forest residuals and delivered feedstock costs to a facility. Many use historical biomass data, such as TPO datasets, applied generically over a county or grid to estimate feedstock volumes and transportation costs [6-9]. As harvest volumes change year to year, using a single year of data may significantly over- or under-estimate potential future biomass availability. Assigning biomass to the centroid of a county or to equally distributed grid points does not reflect the spatial heterogeneity of forest residuals. Similarly, using approximate transportation distances may introduce significant variability in the resulting delivered feedstock costs and thus biomass availability to a site.

Yoshioka et al. [10] estimated forest residual volumes from data similar to FIA plots, yet used a rasterized road network (50m cell size) to determine least cost paths from forest landings to a bioenergy plant. Unless the raster cell size is set to an average approximate road width, error may be introduced in travel time estimation as the sinuosity of the road network is lost in the larger cell size [11]. Small rasterized cell sizes, however, create excessively long computer processing times [11]. Therefore, using a vector-based approach can provide more accurate transportation costs in a reasonable amount of time.

A selection of studies combine refined feedstock estimates with a networked road dataset to estimate total delivered feedstock cost and volume [12-14]. Two studies use methodologies similar to those presented in this paper. Chung and Anderson [15] average three separate years of TPO datasets, and disaggregate the county-level roundwood and residue volumes by land ownership and land cover data. Thiessen polygons are created around evenly spaced nodes on a road network and are assigned the biomass volumes. Finally, Noon and Daly [16] use FIA plot locations and stand data to determine plot residue volumes based on stand characteristics and the likelihood of a stand being harvested, assuming that regional harvesting characteristics and levels would be similar to those occurring in the prior decade.
The methods presented below assess projections from two different biomass estimation methodologies; one based on the TPO approach of Chung and Anderson [15] and one based on the FIA plot inventories of Noon and Daly [16]. We present an alternative approach to biomass estimation using GIS-generated service areas rather than Thiessen polygons. We additionally utilize FIA plot inventories to simulate forest growth and future forest products demand through time to project likely logging and forest residuals availability as opposed to focusing on past harvest data. By accounting for potential market changes, the use of a coupled biological-economic model to estimate average feedstock volume over a longer time horizon may provide a more realistic annual feedstock volume. This paper aims to compare delivered feedstock volume and cost to a biorefinery using both historical logging data and a coupled bioeconomic model.

4.3 Methodology

The process of determining forest residual supply to a given facility is provided in two distinct steps: biomass availability followed by biomass supply. Availability is determined by the level of other forest harvesting activities, and supply is determined by the delivery of biomass to a facility at a given marginal cost. In both models, forest residue volumes from private and tribal-owned lands are included in the analysis while forest residue from Federal lands is not, due to feedstock sourcing regulations in the U.S. Environmental Protection Agency’s Renewable Fuel Standard [17]. The sections below discuss biomass availability, followed by a description of the Total Transportation Cost model, and concluding with biomass supply.

4.3.1 Biomass Availability

4.3.1.1 Timber Products Output Data – Historical Availability

Publicly available TPO reports [18] estimate roundwood use in each state through mill questionnaires, and stand inventory volume through logging utilization studies coupled with mill data. The reports provide county-level information on volumes of roundwood products harvested, logging
residues left on-site as slash piles, other timber products removed, and wood and bark residues
generated by primary wood-using mills for a single year of harvest [2, 19].

4.3.1.1.1 TPO Inputs

The TPO reports describe Montana, Oregon and Idaho’s timber harvests on a 5-year rotation. The Washington Department of National Resources provides Washington’s timber industry report on a biennial basis. Within the datasets, each county’s total volume of unused forest residue by ownership class (USFS, Other Public, Private, and Other Private) is determined for the following years of data: Oregon (2003, 2008, 2013), Idaho (2001, 2006, 2011), Montana (2004, 2009), and Washington (2002, 2010, 2012). Logging residue volumes are reported in thousand cubic feet; a conversion factor [20] is used to convert removals into bone dry metric tonnes (BDMt). While not reported as an ownership class, State forest residuals are included in the analysis due to stakeholder input. Each state’s multi-year datasets are averaged to create one average unused forest residue volume by ownership class for each county.

4.3.1.1.2 Disaggregation of County Data to Ownership-Level Density

In ArcGIS 10.2, a forested land ownership by county layer is created [21, 22]. The land ownership classes are re-classed into the TPO classes: USFS, Private, Other Public – State, and Other Public – Fed. Private lands include industrial forests, privately owned non-industrial forests, and tribal forests. Other Public – State lands include forested lands managed by the state. Other Public – Fed lands include forested lands managed and owned by federal agencies other than the USFS, including Bureau of Land Management and U.S. Fish and Wildlife.

Each county’s average forest residual volumes are converted into density measurements (BDMt/ha) (Table 4.1). Forest residues from State lands are not reported in the TPO. Therefore, State volumes are estimated by assuming the volume of forest residuals harvested from State lands will be proportional to the acreage of State lands in each county. Figure 4.1a displays a map of forest residual
density across the PNW. The density measurements are then used to calculate biomass supply to a facility.

Table 4.1. Forest Residuals Density Calculation for Five Counties in Idaho. (a) Land area and TPO-reported average forest residual volumes, respectively. State volumes may not equal percent-based calculation due to rounding. (b) Forest Residuals Density by County.

<table>
<thead>
<tr>
<th>County</th>
<th>Land Area (ha)</th>
<th>Forest Residue Supply (BDMt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>USFS</td>
<td>Other Public - Fed</td>
</tr>
<tr>
<td>ADA</td>
<td>1,345</td>
<td>583</td>
</tr>
<tr>
<td>ADAMS</td>
<td>372,100</td>
<td>14,552</td>
</tr>
<tr>
<td>BANNOCK</td>
<td>47,128</td>
<td>13,848</td>
</tr>
<tr>
<td>BEAR LAKE</td>
<td>142,508</td>
<td>4,237</td>
</tr>
<tr>
<td>BENEAH</td>
<td>36,318</td>
<td>9,614</td>
</tr>
</tbody>
</table>

### 4.3.1.2 Land Use Resource and Allocation (LURA) Model – Future Availability

The LURA model uses basic economic theory to balance forest resource supply with forest products demand. The spatially explicit resource supply is based on FIA plot-level data and is combined with forest products processing facility locations to generate a partial equilibrium market optimization mathematical programming problem. The model moves through time sequentially determining a static phase annual market-clearing level of forest resource utilization. This single-year static solution is accomplished through linear programming by minimizing costs associated with harvest, transportation, and manufacturing of primary and secondary forest-derived commodities to meet domestic and trade exogenous forest products demand levels. In the dynamic phase between time periods, forest
inventories are updated to account for static phase harvest levels and inter-period growth and demand. Trade levels are updated to account for changes in macroeconomic parameters, and forest products processing and port capacities are adjusted accounting for depreciation and changes in demand.

4.3.1.2.1 LURA Model Inputs

The LURA model uses FIA plot locations as sources for current and future raw forest products. The FIA monitors 315,352 plots across the conterminous United States [23]. In the western states, plots are measured approximately every ten years while in the eastern states plots are measured every five years. LURA uses data from just under 5 million trees measured on the 150,350 homogenous forested FIA plots as the basis for timber volume and biomass. Plot forest type and site productivity guide future growth and yield. The model uses primary wood-consuming mills (pulp mills, saw mills, etc.) as demand sources (Figure 4.1b). For each mill, the model includes product-specific capacity and input-output processing coefficients that correspond to the raw biomass or intermediate product requirement per unit of processed product output. The number of mills simulated in LURA is fixed as is each mill’s capacity in the static state (i.e., mills will not be shut down if they are not financially profitable), however in the dynamic phase only mills that are more profitable than average expand to meet new demand while unprofitable mills remain open but decrease in size. Dynamic phase forest demand for the nation is adjusted by key macroeconomic indicators from the 2015 Annual Energy Outlook [24] including gross domestic product (GDP) growth, population, housing starts, demand for forest bioenergy, and fossil fuel price using elasticities from Ince et al. [25] and Latta et al. [26].
Figure 4.1. (A) Forest residual density for state and private forested lands. (B) Primary wood processors and FIA points by forested ownership type.
4.3.2 Biomass Supply

4.3.2.1 Total Transportation Cost Model, TTCM

A total transportation cost model is used to determine delivered feedstock cost and volume between two nodes along a supply chain, i.e., between the forest plot and biorefinery. Similar to others ([27] and [28], e.g.), the TTCM utilizes a networked road dataset configured with variable transportation costs and a set fixed cost at each biomass procurement location. Variable costs are time- and/or distance-dependent. Fixed costs are typically time dependent, accounting for truck loading and unloading wait times, but may also include costs for biomass procurement and pre-processing. The Environmental Systems Research Institute (ESRI) provides a networked road dataset complete with road types and associated speed limits based on passenger vehicles [29]. Revised speed limits may be added to represent the maximum speed a truck, such as a fully loaded chip van, will travel across the various road types.

The general form of the TTCM between two nodes is shown in Equation 1, where \( TC_{ij} \) is the total delivered feedstock cost between the logging residue node \( i \) and potential biorefinery node \( j \), \( F_{ij} \) is the fixed cost associated with nodes \( i \) and \( j \), and \( V_{ij} \) is the total variable transport cost for the least cost route between nodes \( i \) and \( j \).

\[
TC_{ij} = F_{ij} + V_{ij} \quad \text{Equation 1}
\]
\[
V_{ij} = 2 \sum_{k=1}^{n} \sum_{l=1}^{n} V_{k,l} \quad \text{Equation 2}
\]

Each road segment in a networked road dataset is assigned a cost based on the road type, truck type for biomass transport, biomass moisture content and density, and speed limit of the assumed truck type on the given road type. As the variable cost is distance- and/or-time dependent, \( V_{ij} \) is represented by an equation to solve for the cost along each road segment. Equation 2 represents the general form of a variable cost equation, where \( k \) and \( l \) are beginning and ending nodes that define a road segment, \( n \) is
the total number of road segment nodes in the least cost path between nodes $i$ and $j$, and $2V_{k,l}$ is the roundtrip cost to traverse road segment $k,l$. $V_{k,l}$ may be derived from detailed truck costs [30, 31] divided by truck payload over various road types, or literature ([6, 9, 32] to name a few). The resulting time- and/or distance-dependent equation is then multiplied by the travel time or length associated with each road segment to determine a variable cost per unit biomass. The TTCM can then be used for transportation cost estimation to a facility using residue availability from the TPO and LURA models.

4.3.2.2 TPO Biomass Estimates

Biomass estimates are performed using GIS to generate a service area around each facility for a specified maximum “cost”, where “cost” can mean any impedance such as time (minutes, e.g.), distance (kilometers, e.g.), or, in this case, freight ($/BDMt). Dijkstra’s algorithm is used to solve the least-cost path problem along the road network [33] to generate service areas.

TPO residue volumes represent the total volume left on-site after a logging operation. Available residues are estimated by assuming a harvest system (ground-based vs. cable) based on terrain. Each land ownership polygon in the forested land ownership by county layer was assigned an average slope value by applying a terrain raster. See Equation 3, where $x$ denotes the average slope of polygon $y$, and $p_y(x)$ is the percentage of residuals available [34].

State and private land areas within the service area are multiplied by their respective forest residual densities and available residue percentages to determine the amount of forest residuals available, as seen in Equation 4.

$$p_y(x) = \begin{cases} 0.465, & x > 30 \\ 0.672, & x \leq 30 \end{cases}$$  \hspace{1cm} \text{Equation 3}$$

$$R_j = \sum_{y=1}^{z} \sum_{c=1}^{n} p_y(x) \cdot A_{y,c} \cdot D_{s,c} + p_y(x) \cdot A_{y,c} \cdot D_{p,c}$$  \hspace{1cm} \text{Equation 4}$$

where $R_j$ is the volume of forest residuals (BDMt) available to biorefinery $j$ within a service area at a specified marginal cost, $z$ is the total number of land owner polygons, $n$ is the total number of counties.
intersected by the service area, \( A_{y,s,c} \) is the polygon \( y \) area (ha) of State lands in county \( c \) within the service area boundary, \( D_{s,c} \) is the forested density (BDMt/ha) for State lands in county \( c \), \( A_{y,p,c} \) is the polygon \( y \) area (ha) of Private lands in county \( c \) within the service area boundary, and \( D_{p,c} \) is the forested density (BDMt/ha) for Private lands in county \( c \).

All biomass within the service area is assumed to be accessible and available. Only the variable transportation cost is utilized for polygon generation since there are no biomass source locations in which to assign the fixed cost. Polygons are generated for a range of variable costs, and biomass availability is calculated at each cost increment. A supply curve is generated by summing the fixed and variable cost at each increment, and plotting against the biomass volume, \( R_j \).

### 4.3.2.3 LURA Biomass Estimates

Similar to [15], we assume each FIA point is a roadside forest landing accessible by a chip van, and as such all points are projected onto the nearest road for use in the model. Least-cost paths are determined along the networked road dataset in GIS between each FIA point \( i \) and a candidate facility \( j \) using a multiple-origin, multiple-destination algorithm based on Dijkstra’s algorithm [33]. A fixed cost is added to each FIA point’s total variable feedstock cost to determine the total delivered feedstock cost to the biorefinery gate. LURA output similarly estimates total, not available, residue volumes. Equation 3 is applied to the volume at each FIA point based on the point’s average slope. The forest residual volumes are then joined to the total variable feedstock cost table. By sorting all total delivered feedstock costs from least to greatest, and tabulating the cumulative forest residual volume at each FIA point, a supply curve is generated.

### 4.4 Case Study

The two methodologies are applied to estimate biomass availability for four pulp mills in the PNW considered for retrofit into a biorefinery. See Figure 4.1a for locations. The biorefinery has an annual forest residuals demand of 757,500 BDMt to create 135 million liters of biojet fuel through an
enzymatic hydrolysis, fermentation and catalytic conversion process. At the forest landing, we assume a horizontal grinder is used to comminute limbs and tree tops into wood chips, which are then loaded onto a 6x4 chip van truck pulling a 13.7 m (45 ft) long drop center trailer that transports forest residuals to a biorefinery. The forest residuals are assumed to have a moisture content of 35%, which translates into a payload of 14.1 bone dry metric tonnes (BDMt). Fixed costs include transporting unmerchantable residuals to a forest landing ($16.5/BDMt), grinding residuals into chips ($22.4/BDMt), loading chips onto a waiting chip van ($3.9/BDMt), and a stumpage fee to the landowner ($4.4/BDMt).

A networked road dataset was acquired from ESRI [29], and the speed limits were modified for a chip van as follows: paved – 70 km/h (45 mph), gravel – 15 km/h (10 mph), and dirt – 10 km/h (6 mph) [31]. Variable unit trucking costs by road type were obtained from Zamora-Cristales et al. [30] and converted into roundtrip unit transportation costs for use in Equation 4. The total variable transportation cost ($/BDMt), $V_{ij}$, along a least-cost route between FIA point $i$ and facility $j$ is calculated through Equation 4.

$$V_{ij} = 0.258 \sum_{p=1}^{n} t_p + 0.194 \sum_{g=1}^{n} t_g + 0.184 \sum_{d=1}^{n} t_d \quad \text{Equation 4}$$

where $t_p$ is the time (min) travelled along all paved road segments, $t_g$ is the time (min) travelled along all gravel road segments, $t_d$ is the time (min) travelled along all dirt road segments, and $n$ is the total number of road segments in the least-cost route.

4.5 Results and Discussion

4.5.1 TPO Model Biomass Availability Results

Service area polygons are generated for a range of variable transportation costs at each facility. State and private land areas within each service area are aggregated by county, and the respective forest residual densities and slope percentages are applied to determine the estimated volume of forest
residuals available. The marginal cost for each service area analysis is determined by summing the fixed cost with each variable transportation cost. A supply curve is created by plotting each pair of marginal cost and respective feedstock volume (Figure 4.4). See Figure 4.2 for an example marginal cost service area and Table 4.2 for the calculation of volumes based on this service area.

![Map of Washington state with forest ownership and LURA study area]

Figure 4.2. $79/BDMt marginal cost service area for pulp mill in Cosmopolis, WA.

4.5.2 LURA Model Biomass Availability Results

The volume of forest residuals available at each FIA point designated as State or Private ownership was determined from the LURA model. The least-cost path from each FIA point to a mill was determined in ArcGIS 10.2 (Figure 4.3). The total variable transportation cost at each FIA point is summed with the fixed cost to determine total delivered feedstock cost. The total costs are then sorted from least to greatest, and the respective forest volumes summed (Table 4.3). The marginal cost is the total delivered feedstock cost associated with the annual facility demand of 757,500 BDMt. A supply curve is generated by plotting cumulative volume versus total delivered feedstock cost for all FIA points (Figure 4.4).
Table 4.2. Biomass calculation for Cosmo pulp mill at $79/BDMt marginal Cost. Volumes may differ slightly due to rounding.

<table>
<thead>
<tr>
<th>Row Labels</th>
<th>Forested Land Ownership</th>
<th>Density</th>
<th>Estimated Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Other Public State (ha)</td>
<td>Private (ha)</td>
<td>Other Public - State (BDMt/ha)</td>
</tr>
<tr>
<td>Clallam County WA</td>
<td>50</td>
<td>79</td>
<td>0.163</td>
</tr>
<tr>
<td>Clatsop County OR</td>
<td>6,003</td>
<td>17,909</td>
<td>1.416</td>
</tr>
<tr>
<td>Columbia County OR</td>
<td>91</td>
<td>699</td>
<td>0.611</td>
</tr>
<tr>
<td>Cowlitz County WA</td>
<td>2,468</td>
<td>20,552</td>
<td>1.265</td>
</tr>
<tr>
<td>Grays Harbor County WA</td>
<td>19,887</td>
<td>97,755</td>
<td>0.965</td>
</tr>
<tr>
<td>Jefferson County WA</td>
<td>12,288</td>
<td>9,848</td>
<td>0.072</td>
</tr>
<tr>
<td>King County WA</td>
<td>83</td>
<td>2,561</td>
<td>0.141</td>
</tr>
<tr>
<td>Kitsap County WA</td>
<td>3,782</td>
<td>15,830</td>
<td>0.492</td>
</tr>
<tr>
<td>Lewis County WA</td>
<td>9,723</td>
<td>65,183</td>
<td>0.525</td>
</tr>
<tr>
<td>Mason County WA</td>
<td>6,990</td>
<td>41,770</td>
<td>0.540</td>
</tr>
<tr>
<td>Pacific County WA</td>
<td>13,047</td>
<td>52,610</td>
<td>0.542</td>
</tr>
<tr>
<td>Pierce County WA</td>
<td>1,837</td>
<td>28,238</td>
<td>0.188</td>
</tr>
<tr>
<td>Thurston County WA</td>
<td>9,604</td>
<td>26,472</td>
<td>0.800</td>
</tr>
<tr>
<td>Wahkiakum County WA</td>
<td>6,184</td>
<td>13,293</td>
<td>0.978</td>
</tr>
<tr>
<td><strong>Total Est. Biomass</strong></td>
<td><strong>63,669</strong></td>
<td><strong>448,224</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3. Marginal cost at Cosmopolis, WA pulp mill to meet biorefinery demand.

<table>
<thead>
<tr>
<th>FIA Plot No.</th>
<th>Pulp Mill</th>
<th>Total Length (km)</th>
<th>Fixed Cost ($/BDMt)</th>
<th>Total Variable Cost ($/BDMt)</th>
<th>Total Delivered Feedstock Cost ($/BDMt)</th>
<th>Volume (BDMt)</th>
<th>Cumulative Volume (BDMt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>134969</td>
<td>Cosmopolis pulp mill</td>
<td>8</td>
<td>$47.2</td>
<td>$2.3</td>
<td>$49.5</td>
<td>1,471</td>
<td>1,471</td>
</tr>
<tr>
<td>134978</td>
<td>Cosmopolis pulp mill</td>
<td>11</td>
<td>$47.2</td>
<td>$2.3</td>
<td>$49.5</td>
<td>9,411</td>
<td>10,882</td>
</tr>
<tr>
<td>135019</td>
<td>Cosmopolis pulp mill</td>
<td>11</td>
<td>$47.2</td>
<td>$2.8</td>
<td>$50.0</td>
<td>311</td>
<td>11,194</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>138538</td>
<td>Cosmopolis pulp mill</td>
<td>136</td>
<td>$47.2</td>
<td>$36.0</td>
<td>$83.2</td>
<td>3,042</td>
<td>761,012</td>
</tr>
<tr>
<td>134286</td>
<td>Cosmopolis pulp mill</td>
<td>136</td>
<td>$47.2</td>
<td>$36.1</td>
<td>$83.3</td>
<td>2,614</td>
<td>753,626</td>
</tr>
<tr>
<td>135601</td>
<td>Cosmopolis pulp mill</td>
<td>136</td>
<td>$47.2</td>
<td>$36.2</td>
<td>$83.4</td>
<td>5,320</td>
<td>758,946</td>
</tr>
</tbody>
</table>

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4.5.3 Risk Assessment

A major risk assessed when selecting a biorefinery location is lack of sufficient feedstock to meet annual demand. Here risk is measured in terms of the estimated additional amount a biorefinery must pay in a low-yield year, as measured from the average-yield cost as a baseline, to meet biorefinery demand. By selecting a location that minimizes this risk, a biorefinery is better able to maintain operations when external variables affect timber harvest and forest residual availability.

A low yield scenario was modeled in the TPO and LURA datasets (Figure 4.5). The LURA model was modified based on the 2015 Annual Energy Outlook low economic scenario [24]. Similar to Stephen et al. [35], each state’s lowest-yield TPO reporting year was used to determine forest residual densities for each county. These years coincide with the four years after the 2008 Great Recession (OR 2008, MT 2009, WA 2010, ID 2011) (Figure 4.6).

The supply curve results indicate that Longview is estimated to procure the annual biorefinery demand at the least cost of all mills evaluated during an average year, followed by Cosmopolis. The mills in Lewiston and Usk are estimated to procure biomass at almost double the cost of the mills in Cosmopolis and Longview (Table 4.4).
Figure 4.4. TPO and LURA model supply curves with marginal cost comparison at annual biorefinery demand for average yield scenario.

Table 4.4. Comparison of Biomass Estimation Modeling Results

<table>
<thead>
<tr>
<th>Pulp Mill</th>
<th>Average Yield Scenario ($/BDMt)</th>
<th>Low Yield Scenario ($/BDMt)</th>
<th>Difference Between Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LURA</td>
<td>TPO</td>
<td>Diff.</td>
</tr>
<tr>
<td>Cosmopolis pulp mill</td>
<td>83.4</td>
<td>88.5</td>
<td>6%</td>
</tr>
<tr>
<td>Longview pulp mill</td>
<td>78.1</td>
<td>77.2</td>
<td>1%</td>
</tr>
<tr>
<td>Lewiston pulp mill</td>
<td>123.6</td>
<td>150.7</td>
<td>18%</td>
</tr>
<tr>
<td>Usk pulp Mill</td>
<td>133.3</td>
<td>161.7</td>
<td>18%</td>
</tr>
</tbody>
</table>
4.5 Discussion

The two biomass estimation methodologies produce similar results for the west-side mills while diverging significantly for the east-side mills in both average and low yield years (Table 4.4). This may be due to several factors. First, the conversion of total residue volumes to available residue is based on logging operations in western Oregon and Washington. The forests west of the Cascade mountain range differ greatly from those east of the Cascades, where the climate is drier and the forests less productive. Further research should be performed to determine allometric equations for estimating available residue volumes from logging operations in forests more similar to those in northern Idaho and western
Montana. Additionally, the TPO average residual volumes are influenced by the historically-low yield years of 2008 – 2012 [35] (Figure 4.6), while the LURA model projects a recovery in harvest levels. The west-side has continued at substantially higher harvest levels than the east-side during this time frame due largely to the significant proportion of industrial timber land owners and a strong log export market to China, mainly in Oregon [36]. Longview procures approximately half of its biomass from Oregon while Cosmopolis only procures about 25% from Oregon. This may explain the strong correlation between the LURA and TPO supply curves for Longview and a slight divergence in curves for Cosmopolis.

![Graphs showing forest residuals for Montana, Idaho, Washington, and Oregon (Figure 4.6).](image)

**Figure 4.6. Total private and state forest residuals for each TPO reporting year in this study.**

The results indicate that the Longview mill is estimated to procure biomass at the least cost in average and low yield years to meet the annual biorefinery demand. It therefore poses the lowest risk of insufficient feedstock availability. Both west-side mills, or mills west of the Cascade Mountain Range,
are projected to procure feedstock to meet annual demand at less than $90/BDMt. The two east-side mills are projected to procure biomass at well over $100/BDMt, making them infeasible for the biorefinery scenario presented. When selecting a final location, the biorefinery owner must determine the maximum amount able to be spent on feedstock, or consider a smaller mill constructed around a lower feedstock cost.

The low-yield scenario in the TPO datasets is a good measure of low forest harvest in each state. The strong national markets of 2004 through 2006 were followed by the Great Recession of 2008 [36]. During 2009 and 2010, lumber harvest and production were at their lowest levels in the West since the 1940s [36]. The LURA model’s low-yield scenario reflects a low market demand for timber products. The LURA and TPO models correlate most strongly for Cosmopolis in the low yield scenario, most likely due to Washington’s steady forest harvest levels beginning in 2010. Longview’s results reflect its use of Oregon residuals, which in the TPO model are most likely higher than projected by the LURA low yield model.

While both methodologies can be used to estimate future availability and cost at the strategic level, the TPO model is more limited in its flexibility to generate biomass availability scenarios. Fuel costs and road speeds can be modified in the Total Transportation Cost model to influence biomass availability. Technological advances in biomass procurement and preprocessing can be modeled as reductions in the fixed cost. Policy support is demonstrated to the extent that residuals from federal lands are not included in the analysis. Significant changes in market trends and decimation of timber supply due to insect infestations or wildfires are captured in the historical datasets, as evidenced in the PNW in the recent past. Figure 4.6 also indicates the challenge with using a single year from historical datasets and the need for facility siting methodologies that take biomass availability into account in low- and average-yield years.
The LURA model is capable of evaluating scenarios for a wide range of market drivers. Fuel prices can be modeled for biomass availability based on transport costs, but can also be modeled to examine the effect on primary product harvest as well. Policies relating to forest health management, biofuel demand, and feedstock sources influence the amount of forest residuals potentially available from Federal lands. The recent decline of newsprint and printing paper can be modeled to evaluate the future supply of pulpwood available to biorefineries and other industries such as pellet and torrefied wood pellet manufacturers. Additionally, the LURA model can play out scenarios for biomass and pulp wood/round wood availability using non-connected factors such as gross domestic product (GDP), housing starts, and specific mill closures.

The TPO methodology is most applicable in regions where allometric equations to estimate available residuals are known, and when using TPO datasets more representative of average yield years. The recent past is assumed to be indicative of the near future. Therefore, this model is most relevant in refining a list of candidate biorefinery facilities or locations for further consideration. The LURA model is applicable in any region. It is recommended that regional allometric equations be applied to estimate residual availability from logging operations on varying terrain. This model was built using economic metrics and historical timber growth and yield patterns. It is capable of projecting available residuals under varying economic and policy scenarios. Ecological influences consistent with climate change may also be incorporated into the timber availability model and used for scenario runs as well. The LURA model thus enables a more thorough site selection investigation to ensure the final site is best buffered against the risk of low feedstock supply.

4.6 Conclusions

This research provides two forest residual biomass estimation methodologies for use in a biorefinery site selection analysis. The first methodology uses historical data with the assumption that the recent past is indicative of the near future, while the second methodology uses a bioeconomic
model over a 20 year time horizon. Both methodologies utilize a GIS-based total transportation cost model to estimate the amount of residuals available to a facility over a range of marginal feedstock costs. The TPO model is most applicable when using datasets representing average yield years, and is best suited for refining a list of candidate sites based on biomass availability. The LURA model is applicable in any region as it provides a refined approach to biomass estimation, and can simulate a multitude of economic, environmental, and policy scenarios. This model may be used at the strategic or tactical level where a few select facilities are assessed for their biomass procurement potential under a range of circumstances, including their risk of low feedstock supply.

Constructing a biorefinery involves significant financial risk. According to the U.S.D.A. Economic Research Service, the variable cost of biomass coupled with unproven technologies and high initial capital costs increases investment risk and the affects the willingness of investors to commit funds [37]. Minimizing the risk of low biomass availability reduces the overall risk of investing in a facility. A site selection analysis, where multiple sites are assessed for biomass availability, is one method for ensuring a biorefinery location is buffered against low availability. The site with the highest biomass procurement potential at the least cost may provide the greatest buffer against feedstock risk in low-yield years.
References


34. Miller, C. and K. Boston, *The quantification of total and available forest residues following forest operations in Oregon with impacts on sustainability and biomass availability to supply raw material for future biomass energy projects* For Prod J, 2016. In review.


CHAPTER FIVE

A Multi-Criteria Decision Analysis Approach to Facility Siting in a Biorefinery-and-Depot Supply Chain Model

Abstract

Feedstock supply variability and significant upfront capital expenses can affect investor willingness to commit funds to cellulosic and advanced biorefinery projects. Utilizing depots in a biorefinery supply chain to procure and preprocess feedstock has been found to mitigate supply risk in regions of low biomass availability. Repurposing existing industrial facilities may reduce the upfront capital needed to construct a biorefinery, and operational cost savings may be gained through the selective siting of depots and biorefineries at existing facilities based on cost components that vary geospatially, such as energy rates and feedstock availability. A multi-criteria decision support tool is presented to assess industrial facilities for their role in a depot-and-biorefinery supply chain. Geospatial operational cost components are identified in both a depot and a biorefinery techno-economic analysis (TEA) for use as siting criteria. Depots are assumed to be greenfields co-located with an active biomass processing plant, such as a saw mill. Biorefineries are assumed to be repurposed facilities, therefore the repurpose potential of industrial facilities is included as a siting criterion. Overall, the DST was found to select similar depots for each potential biorefinery as an optimization model, with the overall cost to procure, process, and transport the biomass and biofuel being approximately the same.
5.1 Introduction

Feedstock supply variability and significant upfront capital expenses can affect investor willingness to commit funds to cellulosic and advanced biorefinery projects [1]. Utilizing depots in a biorefinery supply chain to procure and preprocess feedstock has been found to mitigate supply risk in regions of low biomass availability [2-4]. Repurposing existing industrial facilities has been proposed as a means to reduce the upfront capital needed to construct a biorefinery [5-8]. Additionally, operational cost savings may be gained through the selective siting of depots and biorefineries at existing facilities based on cost components that vary geospatially, such as energy rates and feedstock availability. By selecting existing facilities that maximize capital and operational cost savings, biorefineries and depots may be constructed with reduced financial risk.

Potential biorefinery locations are often selected based on city or location characteristics (e.g., population, proximity to rail, etc.) with the assumption that a greenfield site can be found within the city boundaries [9-13]. Others assume every pixel, grid point or county centroid is a potential biorefinery location in a study region or along a roadway [14-19]. Still others [20, 21] expand on the pixel approach by performing an exclusion analysis using rasterized layers to identify potential biomass-based facilities. These approaches may be adequate for siting an $n^{th}$ biorefinery plant, however, pioneer-plant biorefineries must identify the costs within their operation that can be minimized through selective siting. Many studies [22-24] determined that location characteristics and economic determinants influence the final location selection. Therefore, siting decisions must include considerations for location-specific variables and minimization of feedstock costs to reduce capital and operational expenses. Stephen et al. [25] assessed potential biorefinery locations based on capital and operational cost variables through the use of a techno-economic model to determine the minimum ethanol selling price at each facility. However, generic transportation costs were utilized in conjunction with greenfield biorefinery locations for the analysis.
A centralized, or integrated, biorefinery’s feedstock collection area is the immediate radius surrounding the biorefinery, whereas depots draw biomass from geographically separate locations and marginal lands previously inaccessible [26]. The technical feasibility of depots in a biorefinery supply chain model has been explored in depth by many for preprocessing and pretreating cellulosic material to reduce the biorefinery footprint and operational costs [2-4, 26-30]. All studies assume the biorefineries and depots are greenfield facilities. One study assumes depots can co-locate with farms for biomass drying and densification [13], yet does not provide any siting criteria for farm selection. Facilities in all studies are sited in optimized locations based on minimizing transportation and feedstock costs without considering other facility expenses that may impart more influence on the overall cost to procure and process feedstock.

Finally, a multi-criteria decision analysis (MCDA) is a quantitative tool for complex decision-making through weights and scores for disparate criteria. The most-often MCDA tool used in biorefinery siting is the Analytic Hierarchy Process [20, 31, 32]. This tool relies on users to perform pairwise comparisons between all criteria in an analysis to determine the relative importance of each criterion, from which criteria weights are derived. While these methods provide a quantitative facility scoring method, the criterion weights are inherently biased due to user-determined relative importance. We build on the MCDA approach by developing a scoring methodology where facility siting criteria and weights are derived from cost components identified in biorefinery and depot techno-economic analyses (TEAs). By removing user influence, the decision-making process becomes more transparent and replicable.

Researchers have studied the benefits of repurposing facilities into biorefineries, applied MCDA to site selection, and utilized depots in biorefinery supply chain analysis, but none to our knowledge have combined all three approaches into one siting model. This research utilizes an MCDA approach through the use of decision matrices to assess industrial facilities and biomass processing facilities for
their potential to be repurposed into a biorefinery and to host a co-located depot, respectively. Coupled with a transportation cost model, supply chains are developed. The supply chain that procures and processes biomass into biofuel at the least cost can then be identified.

The aim of this research is to develop an algorithm to assess existing facilities for their potential role in a regional biomass supply chain. The objectives are to 1) develop an assessment tool for quantitatively scoring facilities based on infrastructure, assets, and location characteristics to identify the top-ranking facilities for use in a supply chain, and 2) identify the depot-and-biorefinery configuration that provides the least processing and transportation costs from an array of potential depot and biorefinery locations. In biomass supply chain planning, decisions at the strategic level include selecting potential facility locations and sizes, selecting the conversion technology, and product and market development [33, 34]. This research is performed at the strategic level to aid stakeholders in identifying potential facilities for participation in regional biofuel supply chains.

5.2 Methodology

The facility siting methodology is comprised of a series of steps (Figure 5.1) that center around two decision matrices, one for the biorefinery and one for the depots. Each decision matrix defines criteria, weights, and scale values. The criteria provide a means to compare facility assets against a design greenfield biorefinery or depot. Weights indicate the importance of each criterion relative to all other criteria. Integer scale values from 1 to 5 provide a means for assessing each facility’s assets against each criterion. A 5 indicates an asset that either best matches that scenario component or reduces risk significantly, and a 1 indicates an asset that may add significant additional cost or increased risk to the construction and operation of a biorefinery.

Potential depot and biorefinery locations are first assessed through an initial screening process to identify candidate locations based on site development needs. A Total Transportation Cost Model is used to determine the least-cost routes between biomass source nodes, depots, biorefineries, and the
end user. A weighted average delivered feedstock cost is determined for each depot at a set capacity for use in the depot TEA and decision matrix. Depot siting criteria represent operational costs only, as the depots are co-located with existing facilities yet are greenfields. Facility assessments are performed by translating location-specific criteria values into scaled values specified in the decision matrix. A final score for each facility is calculated as the sum of each criterion’s weight multiplied by its scaled value. The facility scores illuminate the depots that procure and process feedstock at the least cost for each potential biorefinery. An optimization routine allocates biomass source points to each biorefinery’s selected depots based on minimizing each source point’s total delivered feedstock cost to the biorefinery, including processing costs at the depot.

Biorefinery siting criteria represent geospatial operational costs, but also include a metric for assessing facility retrofit potential. Weights are derived similarly as for depots. The “retrofit potential” weight is determined by annualizing the total biorefinery capital cost for comparison with the geospatial operational costs. Facility assessments are performed similarly as for depots. The following sections discuss the major components of the siting model, namely the general form of the decision matrix, weight and scale derivation, and the Total Transportation Cost Model.
5.2.1 Generalized Form of Decision Matrix

The decision matrix presented here is similar in form to Wang et al. [35], with criteria, weights, and scale values (Table 5.1).

<table>
<thead>
<tr>
<th>Scale, s</th>
<th>Criterion 1 (C₁)</th>
<th>Criterion 2 (C₂)</th>
<th>Criterion 3 (C₃)</th>
<th>Criterion n (Cₙ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>aₘₐₓ</td>
<td>bₘᵢₙ</td>
<td>cₘᵢₙ</td>
<td>dₘᵢₙ</td>
</tr>
<tr>
<td>4</td>
<td>aₘₐₓ - B₁</td>
<td>bₘᵢₙ + B₂</td>
<td>cₘᵢₙ + B₃</td>
<td>dₘᵢₙ + B₄</td>
</tr>
<tr>
<td>3</td>
<td>aₘₐₓ - 2B₁</td>
<td>bₘᵢₙ + 2B₂</td>
<td>cₘᵢₙ + 2B₃</td>
<td>dₘᵢₙ + 2B₄</td>
</tr>
<tr>
<td>2</td>
<td>aₘₐₓ - 3B₁</td>
<td>bₘᵢₙ + 3B₂</td>
<td>cₘᵢₙ + 3B₃</td>
<td>dₘᵢₙ + 3B₄</td>
</tr>
<tr>
<td>1</td>
<td>aₘₐₓ - 4B₁</td>
<td>bₘᵢₙ + 4B₂</td>
<td>cₘᵢₙ + 4B₃</td>
<td>dₘᵢₙ + 4B₄</td>
</tr>
</tbody>
</table>

Facility scores are calculated using the Weighted Sum Method [36], which represents the sum of individual criterion weights multiplied by location-specific scaled values (Equation 1).
where $F_j$ is the score for facility $j$, $w_i$ is the weight for criterion $i$, $s_{ji}$ is the scaled value for criterion $i$ at facility $j$, and $n$ is the total number of criteria.

5.2.2 Weight and Scale Derivation

Depot and biorefinery geospatial operational costs must be identified, typically through a TEA ([37-39], e.g.). A regional average annual cost is determined for each major component and applied in the TEA for weight derivation (Equation 2), where $c_i$ is the annual average cost of criterion $i$, $n$ is the total number of criteria, and $s_{\text{max}}$ is the maximum scale value. The last term is used to normalize the weights. In the biorefinery analysis, facilities are assessed based on their infrastructure compatibility for retrofit into a biorefinery. Similar to others [9, 13, 40], the total capital expenditure to construct a greenfield biorefinery ($C_k$) is converted to an annualized expense ($A_k$) assuming a plant life ($n$) and a discount rate ($r$) using the capital recovery equation (Equation 3) for inclusion in weight derivation as an operational expense.

$$W_i = \left( \frac{c_i}{\sum_{i=1}^{n} c_i} \right) \times \frac{100}{s_{\text{max}}}$$ \hspace{1cm} \text{Equation 2}

$$A_k = C_k \times \frac{r(1 + r)^n}{(1 + r)^n - 1}$$ \hspace{1cm} \text{Equation 3}

Each criterion’s range of regional values is used to determine the criterion-based value designation associated with each scale value. Where others translate facility-specific values into scaled values through linear transformation [32, 35], we use criterion-based “bin” values ($B_i$), determined by dividing the range of regional values ($a_{i,\text{max}}$, $a_{i,\text{min}}$) by the maximum scale value ($s_{\text{max}}$) for each criterion $i$ (Equation 4).

$$B_i = \frac{a_{i,\text{max}} - a_{i,\text{min}}}{s_{\text{max}}}$$ \hspace{1cm} \text{Equation 4}
In the decision matrix, the maximum scale value for each criterion is assigned to the minimum or maximum range value that denotes the most positive influence on facility siting, such as high biomass availability or low electricity rate. The subsequent scale values are calculated by either adding or subtracting $B_i$, depending on the positive or negative influence of the criterion (Table 5.1). Where regional values are not available or possible, as in infrastructure assessments or delivered feedstock cost, bin values are determined from the range of facility values.

**5.2.3 Total Transportation Cost Model, TTCM**

A supply curve is used at each depot and biorefinery to assess biomass availability. Similar to others [12, 16, 20], we use a least-cost routing method to develop supply curves. The TTCM determines the delivered feedstock cost and biomass volume between two nodes along the supply chain. Nodes are locations of biomass procurement or processing, and linkages are the road or rail network that connect nodes (Figure 5.2). The delivered cost and volume of biomass between two nodes is determined through a multiple-origin, multiple destination algorithm based on Dijkstra’s algorithm for finding the shortest path between two points [41, 42]. Biomass source locations are input as points or translated to point locations if areal biomass representations are used. Some translate biomass areal volumes to county centroid locations ([10, 15, 16, 43], e.g.); however, finer spatial resolution should be attained if possible to increase the accuracy of the transportation costs.
A networked road dataset is utilized in a GIS environment, and must include a transport cost for each road segment by truck or rail type used in the analysis. The truck type may change based on the form of biomass being transported between the different nodes. The general form of the TTCM between two nodes for road or rail transport is shown in Equation 5 [20].

\[ TC_{bj} = F_{bj} + V_{bj} \]  

Equation 5

where \( TC_{bj} \) is the total delivered feedstock cost between node \( b \) and node \( j \), \( F_{bj} \) is the fixed cost associated with nodes \( b \) and \( j \), and \( V_{bj} \) is the total variable transport cost for the least cost route between nodes \( b \) and \( j \). Each road segment is assigned a cost based on the road type, biomass transport truck type, biomass moisture content and density, and speed limit of the assumed truck type on the given road type. As the variable cost is distance- and/or-time dependent, \( V_{bj} \) is represented by an equation to solve for the cost along each road segment. Equation 6 represents the generic form of a variable cost equation, where \( 2*V_x \) is the roundtrip transport cost for road segment \( x \), and \( n \) is the total number of road segments in the least cost path between nodes \( b \) and \( j \). \( V_x \) is doubled to account for back-haul, yet is not doubled if assessing rail transport.

Figure 5.2. Nodes and linkages along the biorefinery and depot supply chain.
Each depot’s weighted average delivered feedstock cost is required in the depot TEA for use in determining the overall depot decision matrix weights and for determining the average processing cost at each depot. Equation 7 calculates the weighted average cost based on the design capacity of the facility [20].

$$W_A_j = \frac{\left(\sum_{i=1}^{y} TC_{bj}B_b\right)}{B_j}$$

Equation 7

where $W_A_j$ is the weighted average total delivered feedstock cost to depot $j$, $TC_{bj}$ is the total delivered feedstock cost of biomass source point $b$ to depot $j$, $B_b$ is the biomass volume at source point $b$, $y$ is the total number of biomass source points supplying depot $j$, and $B_j$ is the total volume of feedstock delivered to depot $j$. Where rail and road are evaluated along a linkage, the minimum of the two transport methods is selected to provide the least-cost route along the supply chain.

### 5.3 Case Study

The depot-and-biorefinery siting model is applied to a region in the Pacific Northwest (PNW) that includes western Montana, the panhandle of Idaho, and eastern Washington. The forest residuals in this region have a low density as compared to forest residual densities in western Washington and Oregon [44] due to the federal government being the major land-holder. A depot model is utilized to procure forest residuals for an annual biorefinery demand of 254,000 bone dry metric tonnes (BDMt), accounting for 12% losses at the depots. Each depot in the supply chain is assumed to provide 50,790 BDMt of wood flour to the biorefinery annually. We assume one large depot is co-located at the biorefinery to capitalize on nearby biomass, with an annual demand of 152,400 BDMt. The biorefinery will create approximately 11.3 million liters of isoparaffinic kerosene (IPK), or biojet fuel, per year using an enzymatic hydrolysis, fermentation, and separation process [45]. Depots will perform preprocessing.
and pretreatment through dry-milling the wood into wood flour (~40 microns) [46]. The IPK will supplement the Spokane, WA regional annual jet fuel demand with approximately 20% of their year 2025 demand [47, 48]. A petroleum terminal is located near the town’s airport and military base to receive, blend, and store the fuel.

Biorefinery site requirements include a minimum lot size of 40.5 ha, access to natural gas, and a rail spur. Three facilities are evaluated as potential biorefineries: a decommissioned pulp mill in Frenchtown, MT, a greenfield site in Spokane, WA, and an active kraft pulp mill in Lewiston, ID. Primary wood processors (e.g., sawmills and plywood mills) are considered as potential depot locations. Depot siting considerations include access to natural gas, at least 5 ha of unused land for depot site development, and a rail spur. Additionally, where multiple mills reside in the same town or in close proximity, one representative mill is selected for analysis. Of the twenty-seven primary processors in the region, eleven meet the siting requirements. Additional depots are included at the greenfield and Frenchtown Mill for co-location with the biorefineries (Figure 5.3).
Figure 5.3. Potential Biorefinery and Depot Locations and State and Privately-Owned Biomass Source Points in the Study Region.

5.3.1 Total Transportation Cost Model, TTCM

U.S. Forest Service Forest Inventory and Analysis (FIA) plot locations represent biomass source points. FIA plots exist across the U.S. and are specific locations where tree growth, mortality, and harvest removals are recorded periodically over time [49]. The Land Use Resource Allocation (LURA) bioeconomic model determines the projected 20-year average annual forest residual volume available at each FIA plot based on future timber market influences [44].Similar to Chung and Anderson [43], each FIA point is assumed to be a forest landing and is projected onto the nearest road for use in the TTCM. Each road segment is assigned a variable transversal cost based on the material being hauled and associated truck type. Fixed and variable cost calculations for the three supply chain linkages are discussed below.
5.3.1.1 FIA Plot-to-Depot

Based on work by Zamora et al. [50], a 6x4 chip van truck pulling a 13.7 m (45 ft) long drop center trailer is assumed for wood chip transport. The wood chips are assumed to have a moisture content of 35%, which translates into a payload of 14.1 BDMt. Fixed costs include transporting unmerchantable residuals to a forest landing ($16.5/BDMt), grinding the residuals into chips ($22.4/BDMt), and loading the chips onto a waiting chip van ($3.9/ BDMt). The speed limit of the networked road dataset was modified based on average chip van speed and tractor-trailer weight loaded and unloaded on paved (70 km/h), gravel (15 km/h), and dirt (10 km/h) roads [50]. The roundtrip variable unit trucking cost for each road type is based on known truck operating costs when loaded and unloaded [50]. See Equation 8.

\[
TC_{bj} = 42.8 + 0.284 \sum_{p=1}^{n} t_p + 0.214 \sum_{g=1}^{n} t_g + 0.203 \sum_{d=1}^{n} t_d \tag{Equation 8}
\]

where \(TC_{bj}\) is the total delivered feedstock cost ($/BDMt) along a least-cost route between FIA point \(b\) and depot \(j\), \(t_p\) is the travel time (min) along all paved road segments, \(t_g\) is the travel time (min) along all gravel road segments, \(t_d\) is the travel time (min) along all dirt road segments, and \(n\) is the total number of road segments in the route.

5.3.1.2 Depot-to-Biorefinery

A 30,280 liter liquid tanker truck is assumed for transporting milled wood flour to the biorefinery. This truck type was selected as a sealed vessel is needed to contain the flour during transport and the flour must be pneumatically loaded and unloaded. Milled wood has a moisture content of 10% and bulk density of 585 kg/m\(^3\) which translates to a payload of 16.3 BDMt. The road network was modified with speeds representative of this truck type (interstate - 96.5 km/h, U.S. highways – 80.5 km/h, and local roads, state, and county highways – 48 km/h). Fixed and variable
transportation costs are derived from Parker et al. [9], with liquid truck capacity converted to dry capacity (Equation 9). The fixed cost represents loading and unloading wait times.

$$TC_{jk,t} = 8.54 + 2 \left[ 1.98 \sum_{t=1}^{n} x_t + 0.05 \sum_{d=1}^{n} x_d \right] \quad \text{Equation 9}$$

where $TC_{jk,t}$ is the total delivered feedstock cost ($/BDMt) between depot $j$ and biorefinery $k$ using truck transport, $x_t$ is the travel time (hrs) along road segment $x$, $x_d$ is the distance (km) along road segment $x$, and $n$ is the total number of road segments in the least-cost route.

Rail transport was also assessed for this linkage using an equation derived from Parker et al. [9]. A 124,740 liter rail tanker is assumed to haul the milled wood flour with a payload of the 80.5 BDMt (Equation 10). The fixed cost includes loading, unloading, and a charge for use of the railcar.

$$TC_{jk,r} = 50.13 + 0.023 \sum_{r=1}^{n} y_r \quad \text{Equation 10}$$

where $TC_{jk,r}$ is the total delivered feedstock cost ($/BDMt) between depot $j$ and biorefinery $k$ using rail transport, $y_r$ is the distance (km) along rail segment $y$, and $n$ is the total number of rail segments in the least-cost route.

5.3.1.3 Biorefinery-to-Petroleum Terminal

The same rail and truck liquid tanker types are assumed to transport IPK to the petroleum terminal in Spokane, WA. Therefore, the equations are the same with unit costs modified based on IPK volume. See Equations 11 and 12.

$$TC_{kt,t} = 0.56 + 2 \left[ 0.10 \sum_{t=1}^{n} x_t + 0.003 \sum_{d=1}^{n} x_d \right] \quad \text{Equation 11}$$

$$TC_{kt,r} = 2.92 + 0.001 \sum_{r=1}^{n} y_r \quad \text{Equation 12}$$
where $TC_{kl,t} (\$/BDMt)$ and $TC_{kl,r} (\$/BDMt)$ are the total delivered feedstock cost between biorefinery $k$ and petroleum terminal $l$ for truck and rail, respectively, $x_t$ is the travel time (hrs) along road segment $x$, $x_d$ is the distance (km) along road segment $x$, $y_r$ is the distance (km) along rail segment $y$, and $n$ is the total number of road or rail segments in the least-cost route.

A multiple origin, multiple destination least-cost algorithm [41, 42] is run in ArcGIS to determine the total variable truck and rail transportation cost for each linkage. A fixed cost is then added to each total variable cost to determine the total delivered feedstock cost for all linkages of the supply chain.

### 5.3.2 Depot TEA and Decision Matrix

Table 5.2 lists the depot operational cost components as identified in the TEA. The first four cost components vary geographically, thus are the siting criteria in the depot decision matrix. To determine weightings, each criterion’s regional average value is input into the TEA, with the resulting annual operational costs converted into percentages of the total cost and then into weights (Equation 2). Average county-level energy data (2010-2014) [51, 52] and average county-level weekly labor rates (2012-2014) [53] are utilized, along with the weighted average delivered feedstock cost. The feedstock cost is the average of all weighted average delivered feedstock costs for 50,790 BDMt of forest residuals to each depot (Equation 7). At this stage of the analysis, competition for feedstock is not considered. While labor is used as a site selection metric, location-specific labor rates are not utilized in the TEA. Labor costs are defined in the TEA through annual salaries, therefore average county rates are not applicable.
Table 5.2. Depot Operational Costs and Conversion into Decision Matrix Weights.

<table>
<thead>
<tr>
<th>TEA Cost Components</th>
<th>% of Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating Cost Component</td>
<td></td>
</tr>
<tr>
<td>Feedstock</td>
<td>34%</td>
</tr>
<tr>
<td>Electricity</td>
<td>27%</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>10%</td>
</tr>
<tr>
<td>Labor</td>
<td>7%</td>
</tr>
<tr>
<td>Other (maintenance, diesel)</td>
<td>8%</td>
</tr>
<tr>
<td>Fixed Costs (Overhead, Property Tax, Insurance)</td>
<td>13%</td>
</tr>
<tr>
<td>Total Operating Costs</td>
<td>100%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Criteria Weightings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Siting Criteria</td>
</tr>
<tr>
<td>Feedstock</td>
</tr>
<tr>
<td>Electricity</td>
</tr>
<tr>
<td>Natural Gas</td>
</tr>
<tr>
<td>Labor</td>
</tr>
<tr>
<td>Total Criteria Cost</td>
</tr>
</tbody>
</table>

Each criterion’s range of regional values is used to determine the depot decision matrix bin values (Equation 4) for facility assessments (Table 5.3). The feedstock criterion is here measured as the weighted average delivered feedstock cost to depot $j$ at 50,790 BDMt plus the total delivered cost from the depot to biorefinery $k$. See Equation 13. This measurement assesses each depot’s feedstock procurement potential as well as its location relative to the biorefinery. Depot feedstock processing costs are not included as they are accounted for in each cost component criterion.

$$TC_{bk} = WA_j + TC_{jk}$$  \hspace{1cm} Equation 13

Eleven potential depot locations are assessed for inclusion in each biorefinery supply chain. Location-specific criterion values are translated into scale values. Facility scores are determined using Equation 1 and are ranked from greatest to least (Table 5.4).

Table 5.3. Depot Decision Matrix.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Total Delivered Feedstock Cost, $TC_{bk}$ ($/BDMt$)</th>
<th>Electricity ($/kWh$)</th>
<th>Natural Gas ($$/k.c.m.$$)</th>
<th>Avg. Wage ($$/week$$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>56</td>
<td>0.042</td>
<td>0.19</td>
<td>459</td>
</tr>
<tr>
<td>4</td>
<td>72</td>
<td>0.047</td>
<td>0.21</td>
<td>536</td>
</tr>
<tr>
<td>3</td>
<td>87</td>
<td>0.052</td>
<td>0.24</td>
<td>612</td>
</tr>
<tr>
<td>2</td>
<td>102</td>
<td>0.057</td>
<td>0.26</td>
<td>689</td>
</tr>
<tr>
<td>1</td>
<td>118</td>
<td>0.062</td>
<td>0.29</td>
<td>765</td>
</tr>
<tr>
<td>weights</td>
<td>8.7</td>
<td>6.9</td>
<td>2.5</td>
<td>1.9</td>
</tr>
</tbody>
</table>
Table 5.4. Top 5 Depot Facility Scores Per Biorefinery.

<table>
<thead>
<tr>
<th>Spokane Greenfield</th>
<th>Lewiston Active Pulp Mill</th>
<th>Frenchtown Decommissioned Mill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facility</td>
<td>Score</td>
<td>Facility</td>
</tr>
<tr>
<td>IFG Laclede</td>
<td>84.3</td>
<td>IFG Laclede</td>
</tr>
<tr>
<td>Idaho Veneer Co.</td>
<td>84.3</td>
<td>Idaho Veneer Co.</td>
</tr>
<tr>
<td>Riley Creek Chico Sandpoint</td>
<td>84.3</td>
<td>Riley Creek Chico Sandpoint</td>
</tr>
<tr>
<td>Bennett Lumber Products</td>
<td>81.2</td>
<td>Bennett Lumber Products</td>
</tr>
<tr>
<td>IFG Moyle Springs</td>
<td>80.7</td>
<td>IFG Moyle Springs</td>
</tr>
</tbody>
</table>

The depots chosen for the Spokane supply chain are Bennett and IFG Laclede. While IFG Laclede, Idaho Veneer, and Riley Creek all score the highest for both Spokane and Lewiston, Idaho Veneer and Riley Creek are in close proximity to Spokane and would compete with the biorefinery co-located depot for biomass. Therefore IFG Laclede, the farthest top-ranking depot from the greenfield, and Bennett Lumber are selected for supply chain analysis. The top two ranking depots for Lewiston and Frenchtown are used in their respective supply chain analyses. An optimization routine then assigns FIA points to the top two satellite depots and biorefinery co-located depot to meet the overall biorefinery demand of 254,000 BDMt based on minimizing the total delivered feedstock cost from each FIA point to the biorefinery gate (Equation 14).

\[ TC_{bjk} = TC_{bj} + PC_j + TC_{jk} \]  \hspace{1cm} \text{Equation 14}

where \( TC_{bjk} \) is the total delivered feedstock cost from FIA point \( b \) to biorefinery \( k \), \( TC_{bj} \) is the total delivered cost from FIA point \( b \) to depot \( j \), \( PC_j \) is the feedstock processing cost at depot \( j \), and \( TC_{jk} \) is the total delivered cost of wood flour to biorefinery \( k \). \( PC_j \) is determined from the depot TEA by applying the depot-specific weighted average delivered feedstock cost and energy rates.

5.3.3 Biorefinery TEA and Decision Matrix

In addition to energy, labor, and feedstock, facility infrastructure is included as a biorefinery siting criterion (Table 5.5). This criterion is measured as the percent reduction in capital costs from a greenfield facility and is determined through an assessment of the infrastructure and assets present at each site assessed, following methodology by Martinkus et al. [54]. Weights for the biorefinery decision
matrix are developed using Equation 2. The feedstock cost is the average of each biorefinery’s weighted average delivered cost \((TC_{bjk})\), along with regional averages for electricity and natural gas. Facility infrastructure is measured as the biorefinery’s annualized total capital cost, as identified in the TEA, assuming a plant life of 30 years and a discount rate of 10\% (Equation 3).

Bin values for energy and labor rates are the same as for the depot decision matrix. Feedstock is now measured by the weighted average total delivered feedstock cost of all depots to the biorefinery gate \((TC_{bjk})\) plus the cost to transport IPK to the petroleum terminal \((TC_{kl})\). Processing costs at the biorefinery are not included as they are measured through the siting metrics. The range of facility values for feedstock and infrastructure assessment are used for bin value determination. Biorefinery site assessments are performed the same as for depot facilities.

**Table 5.5. Biorefinery Operational Expenses and Conversion to Weights.**

<table>
<thead>
<tr>
<th>Operating Cost Components</th>
<th>% of Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feedstock</td>
<td>60%</td>
</tr>
<tr>
<td>Electricity</td>
<td>5%</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>12%</td>
</tr>
<tr>
<td>Labor</td>
<td>3%</td>
</tr>
<tr>
<td>Annualized Infrastructure</td>
<td>3%</td>
</tr>
<tr>
<td>Other (steam, enzymes, etc.)</td>
<td>10%</td>
</tr>
<tr>
<td>Utilities</td>
<td>1%</td>
</tr>
<tr>
<td>Fixed Costs (overhead, property tax, insurance, etc.)</td>
<td>6%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Siting Criteria</th>
<th>% of Total Criteria Cost</th>
<th>Normalized to 20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feedstock</td>
<td>73%</td>
<td>14.5</td>
</tr>
<tr>
<td>Electricity</td>
<td>6%</td>
<td>1.2</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>14%</td>
<td>2.8</td>
</tr>
<tr>
<td>Labor</td>
<td>3%</td>
<td>0.7</td>
</tr>
<tr>
<td>Annualized Infrastructure</td>
<td>3%</td>
<td>0.7</td>
</tr>
<tr>
<td><strong>Total Criteria Cost</strong></td>
<td><strong>100%</strong></td>
<td><strong>20</strong></td>
</tr>
</tbody>
</table>

**5.4 Results and Sensitivity Analysis**

See Table 5.6 for the biorefinery decision matrix and results. Spokane was found to be the least-cost location for processing feedstock into IPK. Although it is a greenfield, infrastructure was found in this scenario to not be a significant annual expense due to the disaggregation of the pretreatment unit from the biorefinery. Spokane is centrally located among large amounts of biomass and near primary
processors with lesser energy rates. Frenchtown incurs the greatest expense to procure and process feedstock due to its location amid federally-owned forests and high energy rates.

Table 5.6. (a) Biorefinery Decision Matrix, (b) Site-Specific Values, and (c) Scaled Values with Final Facility Scores.

(a)

<table>
<thead>
<tr>
<th>Biorefinery Decision Matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Milled Wood + IPK Transport Cost ($/BDMt)</td>
</tr>
<tr>
<td>---------------------------------</td>
</tr>
<tr>
<td>Scale</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>weights</td>
</tr>
</tbody>
</table>

(b)

<table>
<thead>
<tr>
<th>Facility</th>
<th>Total Milled Wood + IPK Transport Cost ($/BDMt)</th>
<th>Electricity Rate ($/kWh)</th>
<th>Natural Gas ($/k.c.m.)</th>
<th>Infrastructure: % reduction from Greenfield Cost</th>
<th>Avg. Wage ($/week)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frenchtown</td>
<td>298.3</td>
<td>0.068</td>
<td>0.33</td>
<td>9</td>
<td>660</td>
</tr>
<tr>
<td>Lewiston</td>
<td>279.5</td>
<td>0.055</td>
<td>0.25</td>
<td>48</td>
<td>709</td>
</tr>
<tr>
<td>Spokane</td>
<td>269.7</td>
<td>0.055</td>
<td>0.28</td>
<td>0</td>
<td>782</td>
</tr>
</tbody>
</table>

(c)

<table>
<thead>
<tr>
<th>Facility</th>
<th>Total Milled Wood + IPK Transport Cost ($/BDMt)</th>
<th>Electricity Rate ($/kWh)</th>
<th>Natural Gas ($/k.c.m.)</th>
<th>Infrastructure: % reduction from Greenfield Cost</th>
<th>Avg. Wage ($/week)</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frenchtown</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>21.4</td>
</tr>
<tr>
<td>Lewiston</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>60.7</td>
</tr>
<tr>
<td>Spokane</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>83.6</td>
</tr>
</tbody>
</table>
A sensitivity analysis was performed to assess the variables and assumptions that influence the decision matrix results, including biomass availability, scale values, and weights. Additionally, an assessment of the decision matrix results is made through comparing the decision matrix-selected depots to depots selected through an optimization routine by minimizing total feedstock processing and transport costs. The results of the sensitivity analysis indicate the usefulness of the decision matrix as a strategic-level facility siting tool.

5.4.1 Sensitivity Analysis

5.4.1.1 Biomass Availability

Biomass availability is a function of biomass supply and the Total Transportation Cost Model (TTCM). Biomass supply is considered to have a medium uncertainty due to the many variables that comprise it, including the seasonality of harvest operations and the amount of residuals available and accessible at varying slopes and distances from the forest landing. A high-cost scenario was run to determine the increase in feedstock cost each biorefinery incurs to meet annual demand during years of low biomass availability. A low-cost scenario was run assuming the use of a blower for loading ground chips into the chip van, which was found to increase payload by 25% over traditional gravity-fed loading methods [55]. See Figure 5.4.

![Figure 5.4. Biomass Sensitivity Analysis with Low-Cost, Average, and High-Cost Results.](image)
The TTCM aggregates fixed and variable costs for each linkage of the supply chain. The fixed cost at the forest landing is based on an assumed off-road diesel cost, equipment types and efficiencies, and a landowner payment assuming a weak market for forest residuals. The variable cost for residuals transport to depots is based on a 30-year average diesel cost of $0.93/liter and a set chip van size. Han and Murphy [56] found that a 10 percent increase in fuel cost resulted in a 3 percent increase in total transportation costs. The fixed and variable costs for the forest-to-depot linkage are used with low uncertainty, as time-motion studies were performed to determine the costs [50, 57]. The fixed and variable costs for the linkages between the depots, biorefineries, and petroleum terminal are used with medium uncertainty, as only one reference was used [9] to develop the tanker truck total cost equation and only a diesel cost of $0.66/liter was provided as insight into their cost derivations. The rail costs from [9] were compared against other sources [58-60] and determined to be mid-range among all costs and therefore acceptable for use.

5.4.1.2 Scaling Analysis

Lewiston and Spokane have the same depot rankings in their decision matrix results. Refinement is lost due to the five bins in which each location-specific cost is applied. Additional bins would increase the amount of refinement in facility scaling. An alternative scaling approach that translates location-specific values into dimensionless scaled values from 0 to 1 based on each criterion’s regional range of values [35] was employed to compare depot ranking results. See Table 5.7. The results indicate that the same top five depots are selected, however the order of depots is different. IFG Moyie Springs now ranks first in the alternative analysis for all biorefineries due to having the lowest energy and labor rates in the region.
Table 5.7. Alternative Scaling Factor Results.

<table>
<thead>
<tr>
<th>Facility</th>
<th>Spokane Greenfield</th>
<th>Lewiston Active Pulp Mill</th>
<th>Frenchtown Decommissioned Mill</th>
</tr>
</thead>
<tbody>
<tr>
<td>IFG Moyie Springs</td>
<td>77.1</td>
<td>IFG Moyie Springs</td>
<td>IFG Moyie Springs</td>
</tr>
<tr>
<td>Idaho Veneer Co.</td>
<td>76.9</td>
<td>Idaho Veneer Co.</td>
<td>Idaho Veneer Co.</td>
</tr>
<tr>
<td>IFG Laclede</td>
<td>75.3</td>
<td>IFG Laclede</td>
<td>IFG Laclede</td>
</tr>
<tr>
<td>Riley Creek Chilco Sandpoint</td>
<td>74.9</td>
<td>Riley Creek Chilco Sandpoint</td>
<td>Riley Creek Chilco Sandpoint</td>
</tr>
<tr>
<td>Ceda Pine Veneer</td>
<td>71.3</td>
<td>Ceda Pine Veneer</td>
<td>Ceda Pine Veneer</td>
</tr>
</tbody>
</table>

5.4.1.3 Weighting Analysis

Electricity, natural gas, and labor rates all come from reputable government agencies and are considered to have low uncertainty. The importance of region definition was assessed through applying PNW regional energy averages in both TEAs. The electricity average increases significantly ($0.056/kWh to $0.071/kWh) with the change in region boundary while the natural gas average decreases slightly ($0.27/k.c.m. to $0.26/k.c.m.). The overall effect in the depot decision matrix due to electricity is substantial, as the electricity and feedstock weights become equal. In the biorefinery TEA, feedstock costs are significantly higher than all other costs, therefore an increase in electricity or natural gas is not significant in overall weighting. The feedstock weight is evaluated through both the high- and low-cost scenarios (Table 5.8).

Table 5.8. Weighting Sensitivity Analysis for Depot and Biorefinery Decision Matrices.

<table>
<thead>
<tr>
<th>Facility</th>
<th>Cost Component</th>
<th>Cost Variance</th>
<th>Feedstock</th>
<th>Electricity</th>
<th>Natural Gas</th>
<th>Labor</th>
<th>Annualized Infrastructure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depot</td>
<td>Average</td>
<td>Average</td>
<td>8.7</td>
<td>6.9</td>
<td>2.5</td>
<td>1.9</td>
<td></td>
</tr>
<tr>
<td>Depot</td>
<td>Feedstock</td>
<td>Low Cost Biomass</td>
<td>8.5</td>
<td>7.1</td>
<td>2.5</td>
<td>1.9</td>
<td></td>
</tr>
<tr>
<td>Depot</td>
<td>Feedstock</td>
<td>High Cost Biomass</td>
<td>9.0</td>
<td>6.8</td>
<td>2.4</td>
<td>1.8</td>
<td></td>
</tr>
<tr>
<td>Depot</td>
<td>Electricity</td>
<td>High Electricity</td>
<td>8.0</td>
<td>8.1</td>
<td>2.2</td>
<td>1.7</td>
<td></td>
</tr>
<tr>
<td>Depot</td>
<td>Natural Gas</td>
<td>High Natural Gas</td>
<td>8.4</td>
<td>6.7</td>
<td>3.0</td>
<td>1.8</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Facility</th>
<th>Cost Component</th>
<th>Cost Variance</th>
<th>Feedstock</th>
<th>Electricity</th>
<th>Natural Gas</th>
<th>Labor</th>
<th>Annualized Infrastructure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biorefinery</td>
<td>Average</td>
<td>Average</td>
<td>14.6</td>
<td>1.2</td>
<td>2.8</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Biorefinery</td>
<td>Feedstock</td>
<td>Low Cost Biomass</td>
<td>14.5</td>
<td>1.2</td>
<td>2.8</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Biorefinery</td>
<td>Feedstock</td>
<td>High Cost Biomass</td>
<td>14.7</td>
<td>1.2</td>
<td>2.8</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Biorefinery</td>
<td>Electricity</td>
<td>High Electricity</td>
<td>14.5</td>
<td>1.5</td>
<td>2.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Biorefinery</td>
<td>Natural Gas</td>
<td>High Natural Gas</td>
<td>14.1</td>
<td>1.2</td>
<td>3.4</td>
<td>0.7</td>
<td>0.7</td>
</tr>
</tbody>
</table>
5.4.1.4 Depot Selection Analysis

Depots that provide the least cost biomass to each biorefinery were selected through the optimization routine as a comparison against the decision matrix-selected depots. The optimized Spokane run identified IFG Laclede and Vaagen Brothers as the least-cost mills, however the total delivered cost to the biorefinery was $0.01/BDMt less than the decision matrix-selected depots. The optimized depots for the other two biorefineries were the same as their decision matrix-selected depots.

5.5 Discussion

The results and depot optimization comparison show the strength of the decision matrix methodology. The use of bins removes some refinement; however, it provides a facility ranking that can then be assessed qualitatively for feedstock competition and proximity to a biorefinery. The depot optimization run illustrated that different facilities may be selected and still provide least-cost delivered biomass. Trade-offs occurred in the decision matrix-selected versus optimized depots in terms of depot processing costs and variable transportation costs. The assessment of high-cost biomass gives an indication of the additional amount biorefineries must pay during low-yield years, and the low-cost assessment shows how technological advances along the supply chain can translate into reduced costs. The weighting sensitivity analysis illustrates the importance of region definition when performing supply chain analysis. Misrepresenting the study region and associated regional average costs can skew weights and result in a depot list that does not reflect the true least-cost facilities.

While infrastructure is an important component of biorefinery siting in a retrofit project, the overall annualized capital cost is small relative to operational costs in this depot scenario due to the disaggregation of pretreatment from the biorefinery. In an integrated biorefinery, infrastructure may play a larger role as pretreatment can be a significant capital cost depending on the conversion technology. Cost sharing that may occur between depots and primary processors was not modeled here.
Significant operational cost savings may be realized, including sharing of staff, energy, residuals, etc. Further research is necessary to quantify this cost savings potential.

Rail was found to be utilized only for the furthest depot from the biorefinery in each supply chain analysis. Similar to Richardson et al. [61], we found that fixed costs account for a significant portion of the delivered feedstock cost, especially from the forest to the depot. Technological advances may reduce this cost. However, as the biomass market becomes commercialized, landowner payments may increase [62] and processing costs may decrease due to economies of scale.

The TEAs are constructed using Lang Factors from methodology presented by Peters et al. [63] to estimate total capital investment. Operational expenses are estimated from equipment quotes and literature references. The accuracy of the Lang methodology is stated at ±20-30%. This TEA-development approach is reasonable at the strategic level of analysis presented here for identifying facilities with a potential role in a regional biorefinery supply chain. The results clearly indicate Spokane is the preferred location while Frenchtown cannot procure sufficient feedstock at a reasonable price to meet the biorefinery demand necessary for producing IPK. A strategic analysis would involve discussions with primary processors to determine their interest in a co-location scheme and a more in-depth feasibility analysis of the top-ranked potential biorefinery. A tactical analysis would involve purchasing a facility or land for biorefinery construction and negotiating contracts with depots for feedstock.

5.6 Conclusions

We propose a selective facility siting methodology to identify the least-cost regional biorefinery supply chain from an array of potential depot and biorefinery locations. Co-location and retrofit strategies are assumed for existing primary processors and pulp mills, respectively, as a means to reduce capital and operational costs. Decision matrices provide a quantitative, transparent MCDA tool for assessing the geospatial operational cost components that vary at each location. A total transportation
cost model is utilized to quantify the feedstock procurement and processing costs at each linkage of the supply chain.

Both the depot and biorefinery geospatial cost components comprise approximately 80% of their respective total facility operational costs. By performing facility siting through minimizing feedstock as well as energy and labor costs, biorefinery supply chain development can be better directed to select facilities that provide the greatest cost reductions. Any cost reductions gained during the early phase of commercialization may translate into a more cost-competitive biofuel for cellulosic and advanced biorefineries.
References


CHAPTER SIX

Biorefinery Site Selection Using a Stepwise Biogeophysical and Social Analysis Approach

Abstract

Sustainable and economically viable aviation biofuel supply chains require careful consideration of several assets to make siting decisions that increase the likelihood of success. Given the importance of aviation biofuels in future emission goals, it is imperative that siting tools incorporate both economic and social measures. The proposed biorefinery siting tool builds on previous research by incorporating site-specific natural, built, and financial, or biogeophysical, measures and more complete and comprehensive social measures of community innovation and capacity for collective action. A refined biogeophysical analysis assesses pulp mills for their potential as retrofitted biorefineries; the social asset components of site selection are enhanced and disaggregated through the use of multiple indicators of community collective action capacity and propensity for change; and the refined measures are integrated into a single biorefinery site-selection tool. Pulp mills that rank highly in both the biogeophysical and social asset measures may be considered more suitable candidates for retrofit into a biorefinery. This methodology has been applied to biorefinery siting decisions in the U.S. Pacific Northwest region; however, it may be applied to other infrastructure development projects in any region of the U.S.
6.1 Introduction

In the United States’ Pacific Northwest region (PNW), woody biomass residuals from logging operations are proposed as a potential feedstock for conversion into iso-paraffinic kerosene, or sustainable aviation biofuel [1, 2]. A key factor in the production of economically viable and environmentally sustainable biofuels is site selection for an integrated lignocellulosic biorefinery. Many have noted the potential for repurposing chemical-based pulp mills into wood-based biorefineries due to their scale, pretreatment infrastructure, and feedstock logistics [3-6]. Repurposing a facility as opposed to a constructing a greenfield biorefinery may significantly reduce capital costs to allow production of a more competitively priced biofuel.

The location of a facility is primarily driven by access to feedstock, proximity to customers, and local incentives [7]. While economic constraints will always be major factors in site selection, incorporating social measures may further reduce the cost of installing a biorefinery. A community’s favorable disposition toward a biorefinery development project may significantly impact implementation success. That is, grassroots support can lower implementation costs, while opposing attitudes can increase the costs of permitting blockages and other scale-up delays [8].

Social measures are rarely incorporated into siting decisions due to the qualitative nature of the data and a lack of experience and expertise in applying the metrics. Acknowledging the difficulties in adequately measuring social assets, Martinkus et al. [9] were the first to create a single metric, the Social Asset Factor score, to measure community capacity for collective action. The authors developed a facility siting tool that combined biogeophysical, or natural, built, and financial, assets with a Social Asset Factor score to identify communities in a region with the highest potential for successful biorefinery implementation. While this tool was the first to identify potential sites using biogeophysical and social assets, its measurement of communities’ capacity for collective action remains incomplete and does not fully capture this important, yet under-utilized, resource. Given the demonstrated importance of social
assets to economic development and successful environmental policy implementation [10-18], this study provides a refined and enhanced facility siting tool by incorporating more complete and robust measures of social assets and enhancing biogeophysical measures through site-specific analysis.

Specifically, this research aims to do the following: (1) refine the biogeophysical analysis by including location-specific variables, (2) enhance and disaggregate social asset components of site selection through multiple indicators of community collective action capacity and propensity for change, and (3) integrate the refined measures into a single biorefinery site-selection tool. The improved methodological framework is applied to the PNW states of Oregon, Idaho, Washington, and Montana. The current analysis provides an opportunity to examine how the enhanced metrics improve on community selection, while the PNW provides a case study for community and county-level analysis of biorefinery site selection.

6.2 Literature Review

As noted by Hutchins and Sutherland [19], supply chain decisions traditionally focus on the economic measure of sustainability. Environmental considerations have gained strength through life cycle assessments, yet social measurements remain ill-defined [19]. This is evident in biorefinery siting research. While community characteristics and social assets are acknowledged, the inclusion these assets is often minimal and does not incorporate characteristics that adequately predict success of these projects.

Many location studies have examined the impact of various biogeophysical variables on site selection in the ethanol industry. Sarmiento and Wilson [20] and Kenkel and Holcomb [21] similarly found that major siting factors include feedstock availability, access to biofuel and coproducts markets, utility costs and availability, and state and local incentives. Stewart and Lambert [22] expand on these findings, concluding that availability of feedstock and absence of operating ethanol plants dominates siting decisions; however, state and federal incentives also are important. Additionally, access to multi-
modal transportation, product markets and producer credit can provide a comparative advantage in attracting ethanol plants. Facility siting analyses using variations of the aforementioned siting criteria have been performed nationally and at the state or regional level using a combination of geographic information system (GIS) software and/or optimization routines to identify ideal locations for biorefinery siting [7, 23-26]. Additional studies incorporated environmental constraints into facility siting analyses through measuring greenhouse gasses emitted along the supply chain [27, 28], or measuring soil erosion, nutrient loss, runoff, or pesticide movement off-site [29, 30]. All studies assume a greenfield biorefinery will be constructed at the location identified as ideal.

Some studies used imprecise measures to either quantitatively or qualitatively assess social metrics in facility siting analyses. Van Dael et al. [31] developed bioenergy facility siting criteria and weights in Belgium with the assumption that early stakeholder buy-in would result in increased acceptance of the final decision. They defined a society criterion as the willingness of communities to accept the project in their area. However, their measurement of this criterion included variables such as community acknowledgement of the local Kyoto protocol, total number of unemployed job seekers, and total free industrial area. Sultana and Kumar [32] assumed that social acceptability of establishing a bioenergy plant was contingent on proper treatment of man-made, natural and environmental elements. Fortenbery et al. [33] modeled biodiesel siting decisions through examining several biogeophysical resources, political resources, and socioeconomic variables, including proxies of market measures and community acceptance. They used percentage of houses owner-occupied and education level as indicators of potential opposition to the construction of a biodiesel refinery. Few studies incorporate economic, environmental and social criteria through quantifiable means for facility siting analysis. You et al. [34] and Perimenis et al. [35] approach facility siting differently, yet both incorporate quantifiable economic, environmental and social measures through minimizing costs, measuring greenhouse gas emissions along the supply chain, and estimating the total number of jobs created.
through an installed biorefinery, respectively. While these studies identify facility locations through assessing economic, environmental and social criteria, they assume the communities surrounding the final location will be accepting of a new biorefinery. In particular, using total number of jobs created or measuring acceptance via education-levels and owner-occupied housing as a social measure offers very poor proxies of the indicators needed to predict success of the biorefinery installation.

Martinkus et al. [9] developed the first biorefinery siting tool to integrate biogeophysical and social assets through quantitative measures for prediction of biorefinery implementation success. Their tool used a step-wise approach to facility siting, first identifying suitable communities for biorefineries through a biogeophysical assessment of feedstock, population, infrastructure, and other measures. Next, county-level social assets (social capital, creative leadership, and public health status) were combined into a single Social Asset Factor score and applied to the ranked community list to identify communities with the highest potential for biorefinery investment. However, limitations of this first integrated biorefinery site selection tool include a lack of several important indicators of social capital, such as the number of non-profit organizations and associational groups. Additionally, the creative leadership construct did not fully capture the adaptability and creativity of a community, and the human health measure relied on self-assessments of health rather than widely available objective measures of community health, such as obesity, premature deaths and low birth weights by county. Finally, the biogeophysical assessment was performed at the community level with the assumption that a valid location could be found to site a biorefinery, rather than considering existing industrial sites to gain capital and operational cost savings and expedite the permitting process. In the nascent biofuel industry, any cost savings are critical, thus underscoring the need to consider repurposing pulp mills in the biogeophysical site selection process. Our proposed model will greatly improve site-selection decision making and may contribute to the likelihood of success for these important biofuel
infrastructure projects. See Table 6.1 for a description of the measures used in the Initial Model [9] and in the Refined Model presented here.

Table 6.1. Assets in Initial and Refined Model.

<table>
<thead>
<tr>
<th>Community Assets</th>
<th>Initial Model</th>
<th>Refined Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biogeophysical (Financial, Natural &amp; Built Capital)</td>
<td>Cities selection criteria: Population greater than 1,000; located within 1.6 km of major road and rail; near large quantities of biomass; near petroleum terminals</td>
<td>Pulp mills assessment criteria: annual biomass availability; labor quality; electricity rate; proximity to multi-modal transportation infrastructure; and facility type.</td>
</tr>
<tr>
<td>Social Capital</td>
<td># Rent-Seeking Groups: political, labor, professional and business organizations</td>
<td># Rent-Seeking Groups: political, labor, professional and business organizations</td>
</tr>
<tr>
<td></td>
<td>• Rupasingha et al, 2006</td>
<td># Non-Rent Seeking Groups: civic organizations, bowling centers, golf clubs, fitness centers, sports organizations and religious organizations</td>
</tr>
<tr>
<td></td>
<td>• 2009 data used</td>
<td># Non-Profit Organizations</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Voter Turnout</td>
</tr>
<tr>
<td>Cultural Capital</td>
<td>$ Average annual revenues of arts-related goods and services based on all revenues between 2002 and 2010</td>
<td># Arts related organizations</td>
</tr>
<tr>
<td></td>
<td>• WESTAF</td>
<td># Arts related business</td>
</tr>
<tr>
<td></td>
<td></td>
<td># Occupational employment in the arts</td>
</tr>
<tr>
<td>Human Capital</td>
<td>% Self reports of poor health condition (physically and mentally)</td>
<td>$ Revenues of arts related goods and services</td>
</tr>
<tr>
<td></td>
<td>• County Health Ranks</td>
<td></td>
</tr>
</tbody>
</table>

All counts (#) and amounts ($) are calculated as a rate of the population per 10,000

6.3 Methodology

The Community Capitals Framework, developed by Emory and Flora [36], models community capacity using seven “capitals” that combine various resources, such as social, biogeophysical and financial assets (Figure 6.1). The decision tool presented in this paper incorporates six of the seven capitals in a step-wise process. First, a biogeophysical assessment of selected pulp mills, addressing natural, built, and financial capital, is performed in the U.S. PNW study region. A decision matrix is used to assess and score each facility based on site-specific assets. The output consists of a ranked list of mills by their biorefinery retrofit potential. Second, refined county-level social metrics are applied to each
facility to assess the collaborative and creative capacity of communities to accommodate a biorefinery by measuring cultural capital, human capital, and social capital. The output of step two is a selection of facilities that are both biogeophysically and socially well-suited for biorefinery implementation.

![Community Capitals Framework](image)

**Figure 6.1. Community Capitals Framework. Based on work by Emory & Flora [36].**

### 6.3.1 Biogeophysical Siting Analysis

A list of all pulp mills in the PNW [37] were assessed based on a defined biorefinery scenario [38] as follows:

- An annual feedstock demand = 757,500 bone dry metric tons (BDMt) of forest residuals to the biorefinery gate;
- Access to natural gas for use in the conversion process;
- Mild bisulfite pretreatment converts wood into pulp to produce approximately 132.5 million liters of biojet fuel per year; and,
- At least 60.7 hectares are required for site development.

Of the 21 pulp mills identified, eight were removed based on acreage or natural gas limitations (Figure 6.2).
6.3.1.1 Facility Siting Decision Matrix

Multi-criteria decision analysis (MCDA), combined with GIS, is a powerful tool in bioenergy projects [31, 39]. Based on work by Martinkus et al. [40], a decision matrix is constructed based on criteria and weights to assess each pulp mill (Table 6.2). Criteria provide a means to compare facility assets against the design biorefinery scenario, and weights denote the importance of each criterion relative to all criteria. An integer scale value from 1 to 5 is assigned to each facility for each criterion based on its location-specific assets relative to the range of regional values. A ‘5’ indicates an asset that best matches that biorefinery component, and a ‘1’ indicates an asset that may add significant additional cost to the construction and operation of a biorefinery.
Siting criteria and weights are developed from the major capital and operational cost components that vary geospatially, as identified in a greenfield biorefinery techno-economic analysis (TEA) [41]. Criteria include total delivered feedstock cost, electricity rate, natural gas rate, average weekly wage, and infrastructure retrofit potential. Regional average values for feedstock and energy costs are input into the TEA to determine the annual cost of each criterion. Each criterion’s weight represents the percentage of its annual cost relative to the total cost of all criteria. Weights are multiplied by 20 to normalize facility scores. The weight for infrastructure retrofit potential is developed by consolidating the total capital expenditure, \( C_k \), into an annual average payment, \( A_k \), over an assumed lifetime of the plant using the capital recovery equation (Equation 1) [34, 35, 42]. The values for discount rate \( i \) and assumed plant life \( n \) are set at 10% and 30 years, respectively [34, 42]. The annualized cost is then included in the total cost of all criteria. Scaled “bin” values for each criterion are derived by equally dividing the range of facility values.

\[
A_k = C_k \frac{r(1 + r)^n}{(1 + r)^n - 1} 
\]

\textit{Equation 1}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
 & Wtd. Avg. Delivered Feedstock Cost ($/BDMt) & Electricity ($/kWh) & Natural Gas ($/k.c.m.) & Infrastructure: % reduction from Greenfield Cost & Avg. Wage ($/week) \\
\hline
\textit{Scale} & & & & & \\
5 & 65.8 & 0.047 & 0.252 & 41% & 571 \\
4 & 74.4 & 0.051 & 0.268 & 37% & 627 \\
3 & 82.9 & 0.055 & 0.284 & 33% & 683 \\
2 & 91.4 & 0.060 & 0.300 & 30% & 739 \\
1 & 99.9 & 0.064 & 0.316 & 26% & 795 \\
\textit{weights} & 7.0 & 2.3 & 1.1 & 7.5 & 2.1 \\
\hline
\end{tabular}
\caption{Biorefinery Decision Matrix.}
\end{table}

Overall facility scores are determined using the Weighted Sum Method [39] (Equation 2), where \( j \) represents a criterion, \( n \) represents the total number of criteria, \( s_{mj} \) is the assigned scale value based on
the assets present at facility $m$, and $w_j$ is the weight associated with criterion $j$. The facilities are then ranked from highest to lowest based on facility score.

$$F_m = \sum_{j=1}^{n} w_j s_{mj}$$

\textit{Equation 2}

\textbf{6.3.1.2 Criteria Development}

Biomass availability is a measure of the risk associated with a facility’s ability to procure feedstock in the face of feedstock shortages due to natural disasters or changes in market demand. The weighted average delivered feedstock cost to each facility at the biorefinery annual demand is determined using a Total Transportation Cost Model (TTCM) [43]. This model combines GIS-based variable least-cost routes, $V_{bj}$, along a networked road dataset between biomass source points, $b$, and an IBR, $j$, with a fixed cost, $F_b$, to procure and process the biomass at each source point (Equation 3).

$$TC_{bj} = F_b + V_{bj}$$

\textit{Equation 3}

The result is a table of total transport costs and associated volumes for all biomass source points supplying a biorefinery. By sorting the total costs from least to greatest, a weighted average delivered cost can be determined for each facility at the annual IBR demand of 757,500 BDMt. The facilities that procure sufficient feedstock at the least cost are best-situated to maintain annual production in low-yield years.

Electricity and natural gas (2010–2014) and weekly wage (2012-2014) are average rates by county derived from national datasets [44-46]. Each facility’s repurpose potential as a percent reduction from the greenfield IBR is performed utilizing methodology presented by Martinkus et al. [47]. They present a factored approach to estimate percentage costs for major capital cost components in the construction of a biorefinery based on known major delivered equipment costs. Facility assessments are performed using a yes/no approach, where full cost is assigned to infrastructure and asset cost components that do not match those of the biorefinery, and no cost is assigned where infrastructure
and assets are the same. The potential cost savings is reported as a percent reduction from the greenfield capital construction cost.

6.3.2 Social Asset Analysis

Site-selection literature thoroughly addresses financial and biogeophysical resources; however, social resources remain inadequately addressed. This is problematic given the wealth of scholarly literature that supports the importance of social, cultural, and human capital in community success and project sustainability. Following the Community Capitals Framework, the social assets in our decision tool consist of multiple indicators of community collective action capacity and receptiveness to change measured through social capital, cultural capital and human capital.

Social capital, which refers to the number, strength and type of social networks present within a community based on norms of trust, communication and reciprocity, has been found to increase the capacity for cooperation, promote economic growth, aid in city sustainability, and promote natural resource management [10, 11, 13-15, 48]. Scholars have argued that social capital predicts variation in environmental policy success [16, 17]; therefore, it is important to include complete measures of this concept in biorefinery siting models. Cultural capital, based on the attributes and traditions of a community that influence creativity and innovation [17], is an important component of success because highly technical projects require adaptability and creativity. Research has found that creativity contributes to successful sustainability programs [49], which is why Martinkus et al. [9] include it in their model. Lastly, human capital, which includes several measures that analyze the skills and ability of a community [36], is included because of its importance in natural resource management [50]. A number of potential measures capture different skills and abilities within a community, including education and health. Therefore, human capital is perhaps the more complex social asset due to the number of important measures that can be included.
Ideal data for each of these capitals is qualitative in nature (see also [35]); however, even the best qualitative measures lack precision and accuracy, are not widely available, and are expensive and time-consuming to obtain at the community level. Therefore, we use county-level data from nationwide databases as close proxies for the qualitative measures. Data developed by Rupasingha et al. [51] was used to measure social capital. Cultural capital was measured using the Creative Vitality Index from WESTAF [52], and human capital was measured using the County Health Rankings dataset [53]. For each capital, we created one scale by summing relevant indicators and providing a single score for the latest year available.

6.3.2.1 Refinement of Social Assets

The measures provided here for social, creative and human capital are more refined than the single social asset factor score provided previously by Martinkus et al. [9]. Following Martinkus et al. [9], we calculated reliability scores for a potential single social asset factor score based on their measures of the three capitals; however, the low reliability of the scale, with a Cronbach’s $\alpha$ of 0.043, and the single indicators per capital were limitations of this initial work. For instance, the social capital score included only one component of social capital: the sum of political organizations, labor organizations, business organizations and professional organizations (known as Olson groups) divided by the population in 1997. This excludes components such as the “Putnam groups”, which are non-rent-seeking groups and include civic organizations, bowling centers, golf clubs, fitness centers, sports organizations, religious organizations, and non-profit organizations. These are often viewed as the most important measures of social capital. Furthermore, the creative capital indicator consisted of only 40% of the Creative Vitality Index, and the human capital score combined the percentage of adults reporting to have fair or poor health, reported physically poor days per month and reported mentally poor days per month for 2012 into a single score without standardizing the original variables. This second iteration of social assets scores provides more inclusive and precise indicators for the three capitals.
6.3.2.1.1 Social Capital

This analysis uses the most current indicators available from Rupasingha et al. [51] (2009), including organizations and associations, non-profit organizations and voter turnout. To keep the model parsimonious, an aggregate social capital score per county is calculated. The social capital score consists of the aggregate of the count of organizations and associations, voter turnout, and the number of non-profit organizations. This scale is reliable (cronbach’s $\alpha = 0.67$) and an exploratory factor analysis resulted in a single factor solution (eigenvalue = 1.33) explaining 44.2% of the total variance. Factor loadings are acceptable ranging from 0.442 to 0.837. Each county score of the three indicators was multiplied by its factor loading and summed to represent one social capital score per county.

6.3.2.1.2 Creative Capital

As with social capital, creativity and innovation can be difficult to measure and observe. Florida [54] argues that creative communities are the centers of diversity, innovation and economic growth. Therefore, Florida [54] uses the creative vitality index (CVI) created by WESTAF [52], which measures the health of the creative economy as it compares to the national index, and creates a benchmark for future measurement. This multifaceted measure of community creativity includes indicators of level of arts participation (e.g. revenues of arts related goods and services) and occupational employment in the arts. Overall, the index reflects creative economy employment which involves creative thinking, originality and fine arts. We use the index available for the most current year (2010).

6.3.2.1.3 Human Capital

Measures of community health can be used to represent human capital as an indicator of the ability and skills within a community. This measure provides a picture of a community’s labor force, as a healthy person is more reliable at work and less expensive for the biorefinery in terms of insurance and time off. The health score includes measures of obesity, low birth weight, premature deaths, adults reporting to have fair or poor health, and counts of physically and mentally unhealthy days per month.
These data are from the 2013 County Health Rankings [53], from which we develop a scale reflecting health scores per county. This scale is measured by negative scores, thus lower scores indicate healthier counties overall.

The health scale consists of six indicators, of which three are measured by the National Center for Health Statistics while the other three come from the Behavioral Risk Factor Surveillance System. The six health indicators were found to form a reliable scale (cronbach’s $\alpha = 0.86$) and an exploratory factor analysis resulted in a single factor solution (eigenvalue = 3.17) explaining 52.8% of the total variance. Factor loadings are acceptable ranging from 0.584 to 0.916. For each county, the scores of the individual indicators were multiplied by their respective factor loadings and then summed for one health score per county.

6.3.2.2 Determining cutoff scores

To determine the levels of human capital, cultural capital, and social capital necessary to increase the likelihood of biorefinery implementation success, we previously conducted a retrospective analysis of community projects within the PNW region [55]. No discernable means were identified for comparing county scores within a category, therefore cutoff scores, or minimum values selected to denote positive capital attributes, were based on regional averages. Communities with values above the regional average are considered more likely to successfully implement a biorefinery. See Table 6.3 for the average social asset scores by nation, the West, and the PNW. The National score includes all 3,007 U.S. counties, less the 632 counties with missing data, located outside the PNW region. The West is a U.S. Census Bureau-designated region, and includes all states from the Pacific Coast, Hawaii, Alaska, Montana, Wyoming, Colorado and New Mexico. The PNW region includes Oregon, Washington, and Idaho, and the twelve forested counties in western Montana.
Table 6.3. Social Capital Score Measures.

<table>
<thead>
<tr>
<th>Asset</th>
<th>National</th>
<th>West</th>
<th>Pacific Northwest (PNW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N = 3,108</td>
<td>N = 413</td>
<td>N = 128</td>
</tr>
<tr>
<td>Social Capital</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. Score (2009)</td>
<td>-0.004</td>
<td>0.041</td>
<td>0.082</td>
</tr>
<tr>
<td>Minimum score</td>
<td>-4.29</td>
<td>-3.06</td>
<td>-2.51</td>
</tr>
<tr>
<td>Maximum score</td>
<td>23.08</td>
<td>7.88</td>
<td>3.52</td>
</tr>
<tr>
<td>Missing counties</td>
<td>40</td>
<td>35</td>
<td>0</td>
</tr>
<tr>
<td>Creative Capital</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CVI score (2010)</td>
<td>0.491</td>
<td>0.686</td>
<td>0.573</td>
</tr>
<tr>
<td>Human Capital</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. Health (2013)</td>
<td>0.084</td>
<td>-1.425</td>
<td>-1.593</td>
</tr>
<tr>
<td>Minimum score</td>
<td>-7.66</td>
<td>-7.66</td>
<td>-6.11</td>
</tr>
<tr>
<td>Maximum score</td>
<td>12.50</td>
<td>6.21</td>
<td>2.71</td>
</tr>
<tr>
<td>Missing counties</td>
<td>632</td>
<td>82</td>
<td>15</td>
</tr>
</tbody>
</table>

Note: missing values are mostly all counties in Alaska and Hawaii, plus seven counties in Georgia

6.4 Results and Discussion

Table 6.4 shows the overall facility and respective county-level social asset scores. The results indicate that Cosmo, a magnesium sulfite mill, is the most viable candidate for retrofit into the design biorefinery based on biogeophysical assets. The mill’s pretreatment infrastructure is most similar to the biorefinery’s pretreatment process, and it has low feedstock procurement costs, wages, and electricity. Weyerhaeuser, a kraft mill, has hog fuel boilers that may be repurposed for the biorefinery, is estimated to procure feedstock for $3/BDT less than Cosmo, yet has a higher average weekly wage than Cosmo. Georgia-Pacific (GP) Wauna and SP Fiber Technologies share similar characteristics in feedstock cost, energy, and wages, however SP Fiber Technologies also has a hog fuel boiler suitable for repurpose.
Table 6.4. Combined Biogeophysical and Social Asset Analysis Scores with Capital Standard Deviations Shown in Parentheses.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Site name</th>
<th>Facility Score</th>
<th>County and State</th>
<th>Social Capital</th>
<th>Creative Capital</th>
<th>Human Capital Health</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cosmo Specialty Fibers</td>
<td>94.6</td>
<td>Grays Harbor County, WA</td>
<td>-0.30 (-0.03)</td>
<td>0.308 (-0.602)</td>
<td>1.49 (1.72)</td>
</tr>
<tr>
<td>2</td>
<td>Weyerhaeuser - Longview Mill</td>
<td>88.3</td>
<td>Cowlitz County, WA</td>
<td>-0.66 (-0.59)</td>
<td>0.331 (-0.550)</td>
<td>1.67 (1.82)</td>
</tr>
<tr>
<td>3</td>
<td>SP Fiber Technologies</td>
<td>87.2</td>
<td>Yamhill County, OR</td>
<td>-0.68 (-0.61)</td>
<td>0.510 (-0.144)</td>
<td>-2.88 (-0.72)</td>
</tr>
<tr>
<td>4</td>
<td>Georgia-Pacific – Wauna Mill</td>
<td>87.0</td>
<td>Clatsop County, OR</td>
<td>0.64 (0.45)</td>
<td>0.985 (0.934)</td>
<td>-2.61 (-0.57)</td>
</tr>
<tr>
<td>5</td>
<td>Georgia-Pacific – Camas Mill</td>
<td>81.8</td>
<td>Clark County, WA</td>
<td>-1.29 (-1.09)</td>
<td>0.600 (0.060)</td>
<td>-2.40 (-0.45)</td>
</tr>
<tr>
<td>6</td>
<td>KapStone Kraft Paper Mill</td>
<td>80.8</td>
<td>Cowlitz County, WA</td>
<td>-0.66 (-0.59)</td>
<td>0.331 (-0.550)</td>
<td>1.67 (1.82)</td>
</tr>
<tr>
<td>7</td>
<td>International Paper - Springfield Mill</td>
<td>80.3</td>
<td>Lane County, OR</td>
<td>-0.15 (-0.19)</td>
<td>0.961 (0.879)</td>
<td>-1.62 (-0.01)</td>
</tr>
<tr>
<td>8</td>
<td>Cascade Pacific Pulp Halsey Mill</td>
<td>78.0</td>
<td>Linn County, OR</td>
<td>-0.46 (-0.43)</td>
<td>0.300 (-0.620)</td>
<td>-0.71 (0.49)</td>
</tr>
<tr>
<td>9</td>
<td>Georgia-Pacific – Toledo Mill</td>
<td>77.5</td>
<td>Lincoln County, OR</td>
<td>0.29 (0.16)</td>
<td>0.901 (0.743)</td>
<td>-0.58 (0.56)</td>
</tr>
<tr>
<td>10</td>
<td>RockTenn</td>
<td>72.8</td>
<td>Pierce County, WA</td>
<td>-1.10 (-0.94)</td>
<td>0.655 (0.185)</td>
<td>-0.91 (0.38)</td>
</tr>
<tr>
<td>11</td>
<td>Clearwater Paper Lewiston Mill</td>
<td>65.0</td>
<td>Nez Perce County, ID</td>
<td>-0.08 (-0.13)</td>
<td>0.526 (-0.107)</td>
<td>-0.79 (0.45)</td>
</tr>
<tr>
<td>12</td>
<td>Boise Wallula Mill</td>
<td>52.4</td>
<td>Walla Walla County, WA</td>
<td>-0.56 (-0.51)</td>
<td>0.690 (0.265)</td>
<td>-2.25 (-0.37)</td>
</tr>
<tr>
<td>13</td>
<td>Frenchtown Kraft Mill</td>
<td>26.3</td>
<td>Missoula County, MT</td>
<td>0.11 (0.03)</td>
<td>0.262 (-0.706)</td>
<td>-0.10 (0.84)</td>
</tr>
</tbody>
</table>

The individual social asset standard deviations are reported to easily assess whether the capital score for each county meets or exceeds the regional benchmark (highlighted in grey). The human capital measure is a negative index score, meaning negative standard deviation scores indicate communities that perform better than the regional average. Weyerhaeuser scores well in the biogeophysical analysis, yet scores low in social asset measures. Cosmo’s social capital score is 0.03 standard deviations below the mean, which may indicate sufficient social capital for community support of a biorefinery. SP Fiber Technologies scores high in human health capital, indicating a healthy
workforce and potential cost savings from less paid sick leave. While GP Wauna scores lower in the biogeophysical assessment due to lack of infrastructure repurpose potential, it scores the highest in all social assets. Additionally, it has lesser electricity and feedstock procurement costs than Cosmo, thus making it a preferred location for repurposing into a biorefinery. The additional cost to retrofit the pulp mill may be offset by operational cost savings and a faster permitting and construction process due to a more supportive and healthier community.

The social asset analysis informs stakeholders of the social, creative, and human capital present in a location, yet is but one component in a larger facility siting analysis. A biorefinery must be capable of procuring its minimum annual feedstock demand and have access to additional feedstock sources during low-yield years. Therefore, facilities with high social capital that cannot meet the annual biorefinery demand, such as the Boise Wallula Mill, would not make good candidate sites for the proposed biorefinery. However, a smaller biorefinery with a lower annual feedstock demand may be successful due to higher social capital. While Cosmo is theoretically the least-cost to repurpose, the top four sites procure ample biomass above the minimum annual demand. The additional cost to repurpose a different pulp mill type may be offset through a facility with high social capital, and thus, potentially lower start-up costs through a supportive community. The Georgia Pacific-Wauna mill may experience an easier transition into a biorefinery than other sites due to the collaborative and creative nature of the community.

It is worth noting that initially the study region was divided geographically into the counties west of the crest of the Cascade Mountain Range (here called the C2P region) and the counties in eastern Washington, the panhandle of Idaho and western Montana (here called the WMC region). When creating regional cut-off values, it was found that the three social asset measures vary considerably between the two regions. The WMC has higher levels of social capital than the C2P and the PNW; however, cultural capital is higher in the C2P. These differences are likely due to the
respective population densities. The C2P is more densely populated while the WMC is more rural. Since one component of cultural capital is creative occupations, this capital is likely to be higher in areas more densely populated as these types of occupations are more common in larger cities. Conversely, an important component of social capital are the Putnam groups, which include non-profit organizations and social organizations, such as churches, which tend to be higher per capita in rural counties. Since few active pulp mills exist in the WMC, we selected the PNW as the study region for all facilities. The importance here is that social asset assessments will differ based on the study region and resulting regional averages.

6.5 Conclusions

Sustainable and economically viable aviation biofuel supply chains require careful consideration of several assets to make siting decisions that increase the likelihood of success. Given the importance of aviation biofuels in future emission goals, it is important that siting tools incorporate both biogeophysical and social measures. The proposed biorefinery siting tool builds on previous research by incorporating site-specific biogeophysical measures and more complete and comprehensive social measures of community innovation and capacity for collective action. As mentioned in the literature review, biorefinery siting analyses that incorporate economic, environmental, and social metrics provide a holistic approach to selecting a final location that is socially acceptable, environmentally responsible, and economically equitable. Future work will involve developing a single facility siting decision matrix that simultaneously assesses all three metrics.

Social capital represents a community’s ability to work together on contentious issues and influence a resolution; creative capital represents a community’s ability to develop creative solutions to a problem; and, human capital represents a community’s ability to be effective employees. Together, these capitals provide a measure of each county’s willingness to accept a new biorefinery through the communities’ abilities to develop creative solutions to contentious issues surrounding the installment of
a biorefinery. When combined with biogeophysical analysis, it gives stakeholders and investors insight into each candidate site’s potential for added implementation cost due to extra community education or delays caused by litigation conflicts.

The initial, groundbreaking work combining biogeophysical with social assets for biorefinery siting decisions identified two counties in the Western Montana Corridor (WMC) with the biogeophysical and social assets necessary for successful biorefinery implementation: Missoula and Flathead. The assumption was that a facility or greenfield site could later be identified within those counties for repurpose or construction, respectively. This paper builds on that work and utilizes more nuanced biogeophysical measures that incorporate site-specific assets. Thirteen active pulp mills were assessed for their repurpose potential as a lignocellulosic biorefinery through siting criteria such as biomass availability and facility infrastructure. The highest scoring facilities are theoretically are the least cost to repurpose and provide the least risk in terms of operational costs.

Additionally, the social asset components were refined by adding additional measures that more fully capture each of the key assets: social capital, cultural capital and human capital. These additional measures allow our model to more precisely depict the county-level measures of each of these capitals, and more accurately predict implementation success. Through this analysis, we narrowed the 13 initial pulp mill sites identified to one site that possess the optimal combination of biogeophysical and social assets for siting a biorefinery: Georgia Pacific –Wauna Mill (Clatsop County, OR).

Both the initial model [9] and the refined model presented here use social asset regional averages as cutoff values for assessing the strength of each capital present in a county. By incorporating standard deviations, one can begin to see varying degrees of strength. Future work will utilize standard deviations in a retrospective analysis of multiple projects with successes and failures in multiple counties to determine if more refinement can be achieved in assessing a cutoff value for each capital.
References


[52] Creative Vitality Index Database [Internet]. updated 2010 ed. Denver (CO): Western States Arts Federation.


CHAPTER SEVEN

A Multi-Criteria Decision Support Tool for Biorefinery Siting

Abstract

Cellulosic and advanced biorefineries face significant challenges in the road to commercialization. Many have failed to reach or maintain commercialized status due to the significant upfront capital necessary for construction, higher operational costs, and high risk associated with new technologies. A multi-criteria decision support tool (DST) that simultaneously assesses economic, environmental, and social metrics is introduced to evaluate the repurpose potential of existing facilities as a biorefinery. This chapter introduces an environmental metric and a new social metric in addition to the county-level social assets developed in Chapter 6.

Economic siting criteria are represented by biorefinery operational cost components that vary geospitally. The environmental criterion is the Global Warming Potential of the supply chain, as measured through the greenhouse gases emitted from feedstock procurement, preprocessing, and transport equipment and vehicles. Social criteria are represented by the number of regional jobs created through the deployment of a biofuel supply chain, and county-level social assets. Weights and scaled values are derived for each set of metrics through transparent and quantifiable methods. An overall facility score is produced by compiling the scores of the three metrics. Additionally, overall user-defined metric weights relay the importance of the three metrics, thus altering the overall facility scores. The DST provides a holistic approach to biorefinery siting through incorporating quantifiable economic, environmental, and social siting criteria, and allowing stakeholder goals to be reflected in final facility scores through the use of overall metric weights.
7.1 Introduction

Cellulosic and advanced biorefineries face significant challenges in the road to commercialization. Many have failed to reach or maintain commercialized status due to the significant upfront capital necessary for construction, high operational costs, and high risk associated with new technologies [1]. Cellulosic and advanced biofuels must provide reduced life cycle greenhouse gas emissions by 60% and 50%, respectively, over an equivalent petroleum baseline to meet regulations set by the U.S. Environmental Protection Agency’s (EPA) Renewable Fuel Standard [2]. Additionally, support at the community or regional level can enhance or reduce a biorefinery’s success in constructing a plant [3]. Policy support for bioenergy projects continues to wax and wane, also impacting investor willingness to commit funds.

Repurposing existing facilities into biorefineries has been proposed to reduce capital expenditures [4, 5]. Selecting existing facilities based on biorefinery production costs that vary geospatially has been proposed to reduce operational expenses [6]. Considering economic, environmental, and social factors in biorefinery siting may further reduce investment risk and aid in meeting emission reduction standards. Decision support tools (DST) are useful in biorefinery siting as they provide a means for concurrent consideration of qualitative and quantitative criteria in a complex problem. Through creating metrics for economic, environmental, and social factors, biorefinery siting can be performed in a DST to identify existing facilities that meet the goals of stakeholders and reduce investment risk.

Biorefinery siting has been performed by many through identifying sites that procure the most feedstock at the least delivered cost [7-12]. Environmental constraints have been assessed through quantifying erosion potential, nutrient loss, and water quality, among others, [13-17] in addition to minimizing delivered feedstock costs. As biofuel greenhouse gas (GHG) emissions are regulated, either a detailed or screening Life Cycle Analysis (LCA) is often used to quantify emissions along the supply chain.
Others quantify greenhouse gases emitted through biomass procurement, processing, and transport along a supply chain [23, 24]. While not a full LCA, this approach is adequate for a strategic-level facility siting analysis since the fixed and variable GHG emissions along each facility's supply chain can be used to identify locations that procure feedstock efficiently while producing lower emissions.

The social component of facility siting is often discussed or measured qualitatively. Sultana and Kumar [17] assumed that inclusion of strong socio-environmental considerations in facility siting would enhance social acceptability of a project. Van Dael et al. [25] quantified social metrics through proxies such as the number of unemployed people, community acknowledgement of the Kyoto protocol, and total unutilized industrial area. Martinkus et al. [3, 26] proposed a method for quantifying a community's acceptance of a new biorefinery through developing a Social Asset Factor Score, which combines social, creative, and health capital metrics. The number of local jobs created is the most consistently used social metric [19, 27, 28].

Some have modeled environmental, economic, and social metrics in supply chain analysis using optimization routines. You et al. [27] and Santibanez-Aguilar et al. [28] similarly developed regional biofuel supply chains through optimizing feedstock collection and transport costs, GHG emissions, and number of jobs created. Both developed pareto-optimal curves to assess the tradeoffs between the three metrics. Alternatively, multi-criteria decision analysis (MCDA) is a DST often used in the bioenergy field, where criteria are selected to evaluate a problem, weights define the importance of each criterion, and scale values allow for assessing alternatives [29]. Perimenis et al. [19] applied MCDA to aid users in selecting biofuel production pathways from multiple feedstock and conversion pathways. The economic, environmental, and social measures were based on the annualized cost of the technology as well as its maturity, a screening-level LCA, and the number of jobs created, respectively.

Other than Martinkus et al. [6, 26], all previous studies assume biorefineries to be greenfield facilities. The aim of this research is to develop a DST to aid stakeholders in selecting existing industrial
facilities as biorefineries through user-defined preferences for economic, environmental, and social criteria. The objectives are to: 1) develop a DST that includes metrics for economic, environmental, and social criteria, and accepts user-input for the overall weight of the three measures; 2) determine the most suitable facility for repurposing in a region based on varying the overall weights for the three metrics; and 3) evaluate an alternative policy scenario where GHG reduction requirements are increased under the Renewable Fuel Standard [2]. In biomass supply chain planning, decisions at the strategic level include selecting potential facility locations and sizes, selecting the conversion technology, and product and market development [30, 31]. This methodology is performed at the strategic level to aid stakeholders in refining a list of candidate facilities based on user-defined siting goals.

7.2 Methodology

We present a DST that utilizes weight and scale values to assess existing facilities against biorefinery siting criteria and incorporates user-defined overall weights, as seen in Table 7.1. This methodology is based on work by Martinkus et al. [6] and Perimenis et al. [19]. Criteria are selected as quantifiable metrics, and weights define the relative importance of each criterion. Scale values provide a means for assessing facilities against each criterion based location-specific values relative to the range of values present.

Table 7.1. General form of decision matrix.
Facility scores are calculated using the Weighted Sum Method [29], which represents the sum of individual criterion weights multiplied by location-specific scaled values (Equation 1).

\[ F_j = \sum_{x=1}^{3} \theta_x \sum_{i=1}^{n} w_i s_{ji} \quad \text{where} \quad \sum \theta_x = 1 \quad \text{Equation 1} \]

where \( F_j \) is the score for facility \( j \), \( w_i \) is the weight for criterion \( i \), \( s_{ji} \) is the scaled value for criterion \( i \) at facility \( j \), \( n \) is the total number of criteria, and \( \theta_x \) is the overall user-defined weight for metric \( x \).

### 7.2.1 Criteria Development

Economic criteria and weights are developed from the biorefinery annual operational expenditures that vary geospatially, as typically identified in a techno-economic analysis (TEA). A regional average annual cost is determined for each major cost component and applied in the TEA for weight derivation (Equation 2), where \( c_i \) is the average annual cost of criterion \( i \), \( n \) is the total number of geospatial criteria, and \( s_{\text{max}} \) is the maximum scale value. The last term is used to normalize the weights.

Facilities are assessed based on their infrastructure compatibility for repurposing into a biorefinery. Similar to others [12, 18, 24], the total capital expenditure to construct a greenfield biorefinery \( (C_k) \) is converted to an annualized expense \( (A_k) \) assuming a plant life \( (n) \) and a discount rate \( (r) \) using the capital recovery equation (Equation 3) for inclusion in weight derivation as an operational expense.

\[ w_i = \left( \frac{c_i}{\sum_{i=1}^{n} c_i} \right) * \frac{100}{s_{\text{max}}} \quad \text{Equation 2} \]

\[ A_k = C_k * \frac{r(1 + r)^n}{(1 + r)^n - 1} \quad \text{Equation 3} \]

Each criterion’s range of regional values is used to determine the criterion-based value designation associated with each scale value. The criterion-based “bin” values \( (B_i) \) are determined by dividing the range of regional values \( (a_{i,\text{max}}, a_{i,\text{min}}) \) by the maximum scale value \( (s_{\text{max}}) \) for each criterion \( i \) (Equation 4).
The maximum scale value is assigned to the minimum or maximum value in each criterion’s range of values that denotes the most positive influence on facility siting, such as high biomass availability or low electricity rate. The subsequent scale values are calculated by either adding or subtracting $B_i$ based on the positive or negative influence of the criterion (Table 7.1). Where regional values are not available or possible, as in infrastructure assessments or delivered feedstock cost, bin values are determined from the range of facility values.

Similar to others [19, 23, 24, 27], the environmental metric is defined as the global warming potential (GWP) of the biorefinery supply chain. Greenhouse gas emissions for CO$_2$, NH$_4$, and NO$_x$, expressed as kg CO$_2$ equivalent, are aggregated along the supply chain and reported as a single GWP value. Equipment emissions may be determined from various Life Cycle Inventory (LCI) databases [32-34] or transportation models [35, 36], and are then translated into environmental impact indicators.

Biorefinery emissions are not included in this analysis, but may be incorporated for a screening level or full life cycle analysis (LCA). Other environmental impact indicators, such as smog or acidification, may be used in addition to GWP to evaluate the broader environmental impacts of a biofuel supply chain.

The social metric is defined by two criteria: 1) the regional number of jobs created due to the installation of a biorefinery, and 2) potential community support for the bioenergy project. To determine the number of jobs created (full-time equivalent for one year), an economic input-output (EIO) multiplier analysis is employed. This analysis relies on known multipliers for specific industry sectors at the county level. For a given economic expenditure in a county, e.g., constructing a biorefinery, multipliers quantify the overall effect in the county through three impacts: direct, indirect, and induced. Direct impacts measure the economic activity and employment created through constructing a biorefinery, e.g., salaries for laborers and contractors. Indirect impacts measure the effects of direct...

\[ B_i = \frac{a_{i,max} - a_{i,min}}{s_{max}} \]  \hspace{1cm} \text{Equation 4}
economic impacts on other connected businesses, and induced impacts measure the spending effects by households associated with direct and indirect impacts. The total effect from a single expenditure is calculated by summing all three impacts using county-level multipliers and personal expenditure patterns [27]. EIO multipliers and expenditure patterns may be obtained from private [37] or public [38] sources.

The second social metric is a measure of a community’s potential receptivity to the construction of a biorefinery. Based on work by Martinkus et al. [3, 26], this measure is evaluated through county-level values for three capitals: social, cultural, and human. Social capital refers to the number, strength, and type of social networks present within a community, and has been found to increase capacity for cooperation and promote economic growth [26]. Cultural capital measures the attributes of a community that influence creativity and innovation, and indicates a community’s ability to overcome problems through creative thinking [26]. Human capital includes several measures that analyze the skills and ability of a community [26]. Exploratory factor analysis was performed on the individual datasets to determine a single factor value for each capital. Together, the three capitals indicate a community’s ability to work collaboratively to solve contentious issues, such as the proposed construction of a biorefinery. While Martinkus et al. [3] used cut-off values based on regional averages to determine a capital’s influence on facility siting, we use the range of regional capital values in the DST for facility assessments. Each social metric is assigned a weight of 50%, as no additional data is available to judge the importance of one criterion over the other. Within the community receptivity metric, the three capitals are each assigned a weight of 16.67% as again there is no data to support different weightings.

7.2.2 Total Transportation Cost Model, TTCM

A Total Transportation Cost Model (TTCM) is used to develop facility supply curves to assess biomass availability, GWP along the supply chain, and regional number of jobs created. The TTCM determines the delivered cost and biomass volume between two nodes along the supply chain, where cost can be units of dollars per bone dry metric tonnes ($/BDMt) or GWP/BDMt. Nodes are locations of
biomass procurement, processing, and fuel distribution. Linkages are the road or rail network that connect nodes. The delivered cost and volume of biomass between two nodes is determined through a multiple-origin, multiple destination algorithm based on Dijkstra’s algorithm for finding the shortest path between two points [39, 40].

Networked road and rail datasets are utilized in a GIS environment, and include a transport cost for each road or rail segment by transport vehicle type. Vehicle type may change based on the form of biomass being transported between the different nodes. The general form of the TTCM is shown in Equation 5, where $TC_{bj}$ is the total cost between node $b$ and node $j$, $F_{bj}$ is the fixed cost associated with nodes $b$ and $j$, and $V_{bj}$ is the total variable transport cost for the least cost route between nodes $b$ and $j$ [17].

$$TC_{bj} = F_{bj} + V_{bj}$$  \hspace{1cm} \text{Equation 5}

Each road segment is assigned a cost based on the road type, biomass transport truck type, biomass moisture content and density, and speed limit of the assumed truck type on the given road type. As the variable cost is distance- and/or-time dependent, $V_{bj}$ is represented by an equation to solve for the cost along each road segment. Equation 6 represents the generic form of a variable cost equation, where $2 \times V_x$ is the roundtrip transport cost for road segment $x$, and $n$ is the total number of road segments in the least cost path between nodes $b$ and $j$. $V_x$ is doubled to account for back-haul, yet is not doubled if assessing rail transport. Rail cost calculations are similarly performed using Equation 5. Each rail segment is assigned a cost based on the rail car type and capacity, biomass moisture content and density, and rail segment length.

$$V_{bj} = 2 \sum_{x=1}^{n} V_x$$  \hspace{1cm} \text{Equation 6}

The output of the TTCM is a table of fixed and total variable costs between nodes along the supply chain. In the economic metric, the output is utilized to determine the weighted average delivered
feedstock cost to meet the annual feedstock demand at each potential biorefinery. This cost is input into the TEA for determining criteria weights, and is additionally used as a siting criterion. In the environmental metric, the output is reported as total GWP aggregated along the least-cost routes between nodes along the supply chain. The social metric utilizes the total fixed and variable transport costs aggregated by county of origination to determine the total number of jobs created based on supply chain configuration. Each biomass source point’s total fixed cost is applied to the commercial logging sector in the EIO model and the total variable cost is applied to the trucking sector for the county in which the source point resides. See Figure 7.1 for a flow diagram of data derivation for the DST.

Figure 7.1. Process Flow Diagram for Multi-Criteria DST.
7.3 Case Study

This methodology is applied to a region within the Pacific Northwest (PNW) region of the United States, here called the Cascades-to-Pacific (C2P). This region is characterized by highly productive privately-held forests, a moist climate, and dense population. It represents western Oregon and Washington (Figure 7.2). The C2P region is best suited to host a large centralized (integrated) biorefinery as there is ample biomass to meet an annual forest residual demand of 757,500 BDMt [41]. The biorefinery will create 135 million liters of isoparaffinic kerosene (IPK), or biojet fuel, through an enzymatic hydrolysis, fermentation and catalytic conversion process.

![Figure 7.2. Cascades-2-Pacific Study Region.](image)

7.3.1 C2P Analysis

Ten active or recently decommissioned pulp mills are assessed for their repurpose potential as an integrated biorefinery (IBR). The biofuel end user is the Seattle-Tacoma International Airport (Sea-Tac). The mills are evaluated to identify the facility best suited to serve the airport based on varying the overall
weights for the economic, environmental, and social criteria. The airport fuel terminal does not have rail access, therefore rail is not considered as a transportation mode.

7.3.2 DST Development

The economic metric criteria are derived from the operational cost components in the IBR TEA that vary geospatially. These include: feedstock, electricity, natural gas, and labor. Additionally, the total capital cost to construct an IBR is converted to an annualized operational cost using Equation 3 for inclusion in weight derivation. This provides a metric to assess each mill’s repurpose potential based on the infrastructure and assets present.

The feedstock criterion is defined as the weighted average cost to process and transport chipped forest residuals to an IBR, plus the cost to transport biofuel to the petroleum terminal. The last cost is included to give preference to those facilities that procure biomass efficiently and are located close to an end-user. These costs are determined using the TTCM, assuming a 13.7 m (45 ft) chip van truck transports forest residuals to a biorefinery [41], and a 30,200 liter tanker truck transports biofuel to the terminal [6]. Electricity and natural gas criteria are defined through average (2010-2014) county-level energy data [42, 43] and the labor criterion is defined as the average (2012-2014) county-level weekly labor rate [44]. The infrastructure assessment criterion is defined using methodology presented by Martinkus and Wolcott [45] for quantitatively assessing the infrastructure and assets present at a facility against a greenfield IBR. Potential cost savings are estimated based on compatibility with the IBR. The regional average energy rates and regional weighted average delivered feedstock cost are input into the TEA to determine the resulting annual expenditures and criteria weights using Equation 2. While labor rate is used as a siting metric, location-specific rates are not input into the TEA. Representative annual salaries are used in the TEA for the different labor classes. The DST bin values for energy and labor rates are determined from the range of values present in the C2P. The bin values for feedstock and infrastructure are determined from the range of values for the facilities assessed.
The environmental metric is measured as the weighted average GWP emitted between the forest landings and IBR to meet annual feedstock demand plus the GWP between the IBR and petroleum terminal. GWP is aggregated along the supply chain for the least-cost ($/BDT) routes between nodes. Emissions at the biorefinery and from unloading the biofuel at the terminal are not included in this analysis. The range of values is used to set the bin values in the DST.

The first social metric, number of regional jobs created, is developed through employing an EIO model for the logging and trucking industries. These industries are most economically impacted by the construction of a biorefinery, and a biorefinery industry is not yet represented in the community spending pattern data. Fixed procurement and variable transport costs are aggregated separately for each county in which biomass is sourced to supply a specific facility with feedstock. The direct, indirect, and induced number of jobs created based on the county-level expenditures are summed for both industries to determine the total number of jobs created. The second social metric combines county-level scores for social, cultural, and human capital by assigning each of the three criteria a weight equal to one-third of the first social metric weight. Human capital is measured as a negative scale, where lower scores indicate healthier counties overall. The range of facility values is used to set the bin values in the DST for the first metric, while the range of regional values is used for the second metric. See Table 7.2 for the DST.

Table 7.2. DST for assessment of potential biorefinery locations in the C2P Region.
7.3.3 Scenarios

Two scenarios are evaluated using the DST. The first scenario assumes a biorefinery will locate where transport costs are minimized to the greatest extent possible. Each facility’s resulting supply chain is then assessed for GHG emissions and number of jobs created. The range of values for each metric is used to create the bin values in the decision matrix. The second scenario assumes GHG emission regulations are increased under the Renewable Fuel Standard and a biorefinery must locate where GHG emissions are minimized to the greatest extent possible. In this scenario, least-cost routes between biomass source points, biorefineries, and end-users are created based on minimizing GWP as opposed to cost. The resulting supply chains are again reflected in the metrics for feedstock, GWP, and the number of jobs created.

Within each scenario, the overall weights are modified for four potential stakeholder goals. The first goal is to identify a facility where all three metrics are weighted equally. The top-ranked facilities provide reduced capital and operational costs, reduced GWP, and higher social assets and job creation. The second goal imparts more importance on the economic criteria, thus siting a facility where costs are the least. The third goal seeks to identify facilities that provide the least GWP along the supply chain, and the fourth goal emphasizes the job creation and social assets as the highest priority. The DST bin values are modified based on the resulting reduced GWP range of values and increased cost to procure and transport biomass and biofuel between nodes.

7.4 Results and Discussion

7.4.1 Scenario Results

In the economic scenario, Weyerhaeuser (WY) and Cosmo consistently rank the highest for repurposing due to their high infrastructure compatibility, lower feedstock/transport and energy costs, and lower GWP (Table 7.3). Weyerhaeuser scores higher than Cosmo in the number of jobs created, however, both facilities have low social asset scores. Weyerhaeuser and Kapstone are located on
adjacent parcels in the same county, therefore their social assets, energy rates, and feedstock costs are the same. However, Weyerhaeuser has more infrastructure and assets compatible with the IBR than Kapstone, thus scoring higher. Georgia-Pacific (GP) Wauna has the highest social, cultural, and human capital of the facilities assessed, and slightly higher feedstock/transport costs and GWP than Weyerhaeuser, thus making it a candidate facility for retrofit as well.

In the environmental scenario, Cosmo and Weyerhaeuser would pay 13% and 11% more, respectively, for feedstock as a tradeoff for a 17% and 11% respective reduction in GWP. RockTenn would incur a 67% increase in feedstock/transport cost to receive a 25% reduction in GWP. In both scenarios RockTenn provides the least GWP as it is located nearest to the petroleum terminal. This mill ranks highest in the environmental scenario by also providing the most regional jobs, which together offset its poor economic metrics. However, it also has one of the highest feedstock procurement costs. See Appendix A for raw facility values.

**Table 7.3. C2P scenario results with reported metrics that vary based on scenario.**

<table>
<thead>
<tr>
<th>Economic Scenario - Costs are Minimized</th>
<th>Environmental Scenario - GWP is Minimized</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Feedstock and Transport Cost ($/BDMt)</strong></td>
<td><strong>Total Feedstock and Transport Cost ($/BDMt)</strong></td>
</tr>
<tr>
<td><strong>Total GWP (kg CO₂e/BDMt)</strong></td>
<td><strong>Total GWP (kg CO₂e/BDMt)</strong></td>
</tr>
<tr>
<td><strong>Total Number of Jobs</strong></td>
<td><strong>Total Number of Jobs</strong></td>
</tr>
<tr>
<td><strong>Rank</strong></td>
<td><strong>Facility</strong></td>
</tr>
<tr>
<td>1</td>
<td>WY</td>
</tr>
<tr>
<td>2</td>
<td>Cosmo</td>
</tr>
<tr>
<td>3</td>
<td>GP Wauna</td>
</tr>
<tr>
<td><strong>Econ: 0.5 Env: 0.25 Soc: 0.25</strong></td>
<td><strong>Econ: 0.5 Env: 0.25 Soc: 0.25</strong></td>
</tr>
<tr>
<td>1</td>
<td>WY</td>
</tr>
<tr>
<td>2</td>
<td>Cosmo</td>
</tr>
<tr>
<td>3</td>
<td>Kapstone</td>
</tr>
<tr>
<td><strong>Econ: 0.25 Env: 0.50 Soc: 0.25</strong></td>
<td><strong>Econ: 0.25 Env: 0.50 Soc: 0.25</strong></td>
</tr>
<tr>
<td>1</td>
<td>WY</td>
</tr>
<tr>
<td>2</td>
<td>RockTenn</td>
</tr>
<tr>
<td>3</td>
<td>Cosmo</td>
</tr>
<tr>
<td><strong>Econ: 0.25 Env: 0.25 Soc: 0.50</strong></td>
<td><strong>Econ: 0.25 Env: 0.25 Soc: 0.50</strong></td>
</tr>
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<tr>
<td>1</td>
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<td>2</td>
<td>GP Wauna</td>
</tr>
<tr>
<td>3</td>
<td>Kapstone</td>
</tr>
</tbody>
</table>
7.4.2 Discussion

When considering economic, environmental, and social metrics in biorefinery siting, tradeoffs must occur. Consistent with You et al. [27], it was found that the number of regional jobs is positively correlated with feedstock procurement and transport costs. GWP is not linearly correlated with feedstock costs, as the distance between the IBR and petroleum terminal drives GWP while procurement and transport costs between the forest landing and the IBR drive feedstock costs.

Weyerhaeuser and Cosmo are the pulp mills best situated for retrofit into an IBR due to their low feedstock, energy, and GWP, and low increased cost to reduce GWP even further if necessary. The sites also have low social asset scores. The mill owner must gauge the potential increased expense incurred under strong opposition to repurposing the mill into a biorefinery against the annual operational cost savings at one of these sites. If the mill is facing closure, as many have in the region, the potential for maintained or increased jobs may offset the potential for opposition, which typically concerns increased traffic, odor, noise, and air and water pollution [46]. An alternative choice for repurposing is GP Wauna. For roughly the same delivered feedstock costs and slightly higher GWP as Cosmo or Weyerhaeuser, the communities near this mill are more likely to support a new wood-based biorefinery or work together to overcome opposition to the mill. Their labor force is significantly healthier than the communities near Weyerhaeuser or Cosmo, indicating less paid sick leave and more productive employees. GP Wauna achieves a 10% reduction in GWP for approximately a 15% increase in delivered feedstock/transport costs in the environmental scenario.

The U.S. Department of Agriculture identified feedstock supply and high production and capital costs as two major challenges in the success of second-generation biorefineries [1]. The proposed facility siting DST aims to reduce these start-up challenges through utilizing major operational and construction costs, regulatory requirements, and social assets as siting criteria to identify locations that provide the least cost to construct and operate. By repurposing existing industries that may be failing or wanting to
expand their product portfolio to maintain profitability, such as pulp and paper mills, capital costs may be reduced. Quantifying feedstock, labor, and energy costs by location allows a biorefinery to be sited such that operational costs are reduced. Quantifying each industrial facility’s supply chain carbon footprint and minimizing supply routes based on delivered feedstock cost and GWP additionally aid in selecting a location where mandated carbon emission reductions can be met under varying regulations. Finally, quantifying the potential number of jobs created and evaluating a county’s social assets can indicate the resistance a biorefinery may face when moving forward into the permitting and construction phase.

While social assets may not be high in the counties where many mills are located, local communities are accustomed to the forest products industry and may be more tolerant of a wood-based biorefinery. Additionally, existing facilities may have sufficient water rights, permits, and feedstock contracts already in place, thus reducing construction delays.

The DST is flexible in the number and type of criteria that may be used. Only one customer (petroleum terminal) was modeled in the case study, however the tool can accommodate multiple customers. The environmental metric is represented by GWP, however, additional impacts such as smog formation and ozone depletion may be included for a more robust representation of the supply chain’s environmental impacts. Additional social assets may also be included to more fully represent the social characteristics of a community, such as education or obesity levels.

7.5 Conclusions

Most biorefinery siting research assumes greenfield facilities will be sited in the location determined to be optimal. Repurposing existing industrial facilities may provide a near-term solution to reducing risks associated with cellulosic and advanced biorefineries and increase investor confidence while these biorefineries build up to economies of scale. The proposed facility siting DST is developed at the strategic level to aid stakeholders in identifying candidate biorefinery locations that reduce economic, environmental, and social costs and potentially increase investor assurance in the new
biotechnologies. Locations that procure feedstock and deliver fuel efficiently, and have low energy and labor rates, are preferred as they provide low annual operating costs. Locations with low supply chain GWP are better situated against the risk of federally-regulated increases in carbon reductions. Finally, locations with high social capital and that provide significant new jobs are more likely to have community support for a new biorefinery and a faster permitting and construction process. By providing a transparent and quantitative methodology for selecting siting criteria and weights, the DST can be replicated in other regions for various biofuel conversion processes and feedstocks.

Future work may be performed to incorporate the GWP of a biorefinery for a more inclusive reporting of the supply chain’s carbon footprint. The social asset metrics may be refined to more fully represent the characteristics of a community that indicate its collective attitude towards a new biorefinery. The EIO model lacks biorefinery multipliers due to this industry still being relatively new in the U.S. marketplace. Future work will incorporate biorefinery multipliers for a better estimate of the jobs created due to the installation of a biorefinery. Finally, the tool is static in that all inputs and outputs are derived using Excel. Future work may involve creating a dynamic web-based tool for deployment in different regions of the U.S. to develop regional supply chains utilizing existing facilities and region-specific feedstocks and conversion processes.
References


Appendix A

Raw Facility Values
### Economic Scenario - Feedstock Costs are Minimized

<table>
<thead>
<tr>
<th>Facility</th>
<th>Wtd. Avg. Delivered Feedstock Cost + Cost to Terminal ($/BDT)</th>
<th>Economic Metric</th>
<th>Env. Metric</th>
<th>Social Metric</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cascade Pacific</td>
<td>$69</td>
<td>0.066</td>
<td>7.8</td>
<td>34%</td>
</tr>
<tr>
<td>Cosmo</td>
<td>$66</td>
<td>0.048</td>
<td>8.8</td>
<td>41%</td>
</tr>
<tr>
<td>GP Camas</td>
<td>$68</td>
<td>0.055</td>
<td>7.5</td>
<td>34%</td>
</tr>
<tr>
<td>GP Wauna</td>
<td>$65</td>
<td>0.053</td>
<td>7.8</td>
<td>34%</td>
</tr>
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<td>GP Toledo</td>
<td>$75</td>
<td>0.062</td>
<td>7.8</td>
<td>34%</td>
</tr>
<tr>
<td>IP Springfield</td>
<td>$70</td>
<td>0.062</td>
<td>7.8</td>
<td>34%</td>
</tr>
<tr>
<td>Kapstone</td>
<td>$63</td>
<td>0.047</td>
<td>8.8</td>
<td>34%</td>
</tr>
<tr>
<td>RockTenn</td>
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</tr>
<tr>
<td>SP Fiber</td>
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### Environmental Scenario - GWP is Minimized

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<th>Economic Metric</th>
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CHAPTER EIGHT

OVERALL CONCLUSIONS

Given the challenges associated with advanced and cellulosic biorefineries reaching and maintaining commercialized status, repurposing existing industrial facilities may provide a near-term solution to reducing risks and increasing investor confidence while these biorefineries build up to economies of scale. Major risks include maintaining profitability during the initial phases of commercialization when capital and production costs are high; variable feedstock costs in average and low-yield years; and, an ever-changing political climate where mandated reductions in greenhouse gas emissions may vary [1]. To reduce these risks, we present methodologies for selecting existing industrial facilities as repurposed biorefineries in place of constructing greenfield biorefineries. To assess facilities for their repurpose potential, we created methodologies to determine:

- facility infrastructure and asset compatibility with a biorefinery conversion process;
- delivered feedstock volume and cost to meet annual biorefinery demand during average and low-yield years;
- total GHGs emitted along the supply chain;
- the influence social assets may have on facility selection; and
- a transparent and quantitative approach for concurrently assessing economic, environmental, and social facility siting metrics for selecting candidate facilities best-suited to meet stakeholder goals through a DST.

Chapter Three presented an infrastructure and asset compatibility analysis conducted at a strategic level to determine an estimated capital percent savings that may be realized through repurposing industrial facilities into biorefineries. A factored approach was employed to assign valuation to the major capital cost components of a biorefinery. Private and public databases and general facility
process designs were used to determine the presence of equipment in each facility assessed. A yes/no analysis was performed to assign full cost to facility infrastructure and assets not present in the biorefinery and no cost to those that are present. The estimated accuracy of the factored approach is ±20-30% for chemical plants in the range of $1 million to $100 million [2]. While commercial-scale biorefineries undoubtedly cost more than $100 million to construct [3], the methodology for facility assessments is applicable as the cost percentage assignments provide a consistent and transparent valuation tool and enables a metric for facility comparisons.

Two methodologies for estimating the amount and cost of delivered forest residuals as feedstock to a facility were presented in Chapter Four. Both methodologies are based on data provided by the U.S. Forest Service Forest Inventory and Analysis (FIA) program. The first methodology is past-predictive in that it uses individual state Timber Product Output (TPO) reports, issued every five years, which provide county-level volumes of lumber harvested and residuals generated in a single year. The second methodology utilizes the Land Use Resource Allocation (LURA) model and is future-predictive in that it uses an economic optimization model of the U.S. forestry sector coupled with FIA plot locations to project near- and medium-term residual volumes through forest growth and harvest regimes on timber lands across the U.S. A Total Transportation Cost Model is developed for use with both biomass estimation methods to enable comparison of facility supply curves. Average and low-yield scenarios were run in both methods to determine the facility best suited for repurpose based on total delivered feedstock cost and volume to meet the annual biorefinery feedstock demand. It was found that average forest residual volumes generated using TPO data are largely influenced by the recent “Great Recession”. Selecting TPO reporting years that better represent average fluctuations of the timber market is critical to estimating forest residual volumes to a biorefinery in any given year. In the states where the forest products market was not as significantly affected by the Great Recession, the supply curves between the two methods compared well. As TPO data are publicly available and the LURA model is not, the TPO
methodology is adequate for reducing the number of facilities in a siting analysis based on each facility’s procurement potential of the annual biorefinery feedstock demand. It is recommended that the LURA model be used in more detailed siting analyses as it estimates future timber products demand and associated residuals. It is a more refined approach to biomass and delivered cost estimation, as points represent biomass source locations where fixed costs may be applied while the TPO model uses service area polygons based on specified maximum variable costs with the assumption that all biomass within the polygon is accessible.

Chapter Five presents the concept of the DST applied to biorefinery siting. The DST is used to assess industrial facilities for their role in a depot-and-biorefinery supply chain. Geospatial operational cost components are identified in both a depot and a biorefinery techno-economic analysis (TEA) for use as siting criteria. Depots are assumed to be greenfields co-located with an active biomass processing plant, such as a saw mill. Biorefineries are assumed to be repurposed facilities, therefore facility repurpose potential is included as a siting criterion. Through assessing geospatial cost components, the use of natural gas in both depot and biorefinery conversion processes was found to be a limiting factor for potential facilities. Natural gas is not available in all counties, therefore many candidate facilities were removed from analysis. Additionally, the defined region used for deriving weights and scaled bin values in the DST was found to greatly affect facility ranking. Regional values for criteria such as natural gas or labor rates are used to assess a facility’s location-specific attributes against all other facilities in an analysis. When a defined region is much larger than the immediate study area and the range of values includes outliers, refinement can be lost as all facilities are assigned to one or two scaled criterion values and the resulting facility rankings are skewed. Criteria weights are also affected as undue importance may be applied to a cost criterion that is a much lesser or greater cost in the immediate study area region. An optimization model was run to assess the usefulness of the DST. Overall, the DST was found to
select similar depots for each potential biorefinery as an optimization model, with the overall cost to
procure, process, and transport the biomass and biofuel being approximately the same.

Chapter Six introduces a novel approach for estimating the potential receptivity of a community
towards the construction of a biorefinery. This research builds on methodology introduced by Martinkus
et al. [4], where three county-level social assets (social capital, cultural capital, and human capital) were
combined into one Social Asset Factor score for use with an economic biorefinery siting analysis. The
refined approach, presented here, maintains a separate score for each capital, thus allowing for a more
refined assessment of the social assets present. Facility assessments are performed in a stepwise
approach. First, a DST is utilized to assess existing facilities for their usefulness as a biorefinery based on
geospatial siting criteria. Second, each facility’s county-level social assets are applied to the ranked
facilities. The facilities that are economically efficient and have high social assets are theoretically the
least cost to repurpose overall. The assumption is that within counties having high social assets reside
communities that can work together to develop creative solutions to contentious economic development
issues, e.g., installing a biorefinery.

Chapter Seven introduces a multi-criteria DST that incorporates economic, environmental, and
social metrics concurrently for assessing the biorefinery repurpose potential of existing facilities. The
economic criteria are the geospatial cost components identified in Chapter Three. The environmental
criterion is the Global Warming Potential of the supply chain, as measured through the greenhouse gases
emitted from the feedstock procurement, preprocessing, and transport equipment, and the vehicle for
transporting biofuel to a petroleum terminal. The social criteria are the number of regional jobs created
through the deployment of a biofuel supply chain, and county-level social assets. Weights and scaled
values are derived for each set of metrics through transparent and quantifiable methods. An overall
facility score is produced by compiling the scores of the three metrics. Additionally, overall user-defined
metric weights relay the importance of the three metrics, thus altering the overall facility scores. The
DST provides a holistic approach to biorefinery siting through incorporating quantifiable economic, environmental, and social siting criteria, and allowing stakeholder goals to be reflected in final facility scores through the use of overall metric weights.

The DST may be applied to regional supply chain development based on any feedstock and biofuel conversion process. Future work may involve converting the static biorefinery siting tool presented here into a dynamic tool with a geographic user interface (GUI) for regional supply chain analysis. Significant work would have to be completed on the back end to create datasets in databases for the different regions across the U.S for use in the GUI. The datasets for regional feedstocks would include feedstock geospatial location and average yield; a networked road dataset modified based on representative truck transport vehicles and average speeds by road type for hauling each type of feedstock; moisture content and density of feedstock in various stages of processing which require transport; and fixed and variable costs associated with the procurement, processing, and transport of the feedstock. Conversion facility datasets would include a techno-economic analysis for each conversion process considered using an assumed facility size or multiple TEAs for a range of sizes; regional average costs for energy, labor, and feedstock; and, fixed and variable processing costs at the biorefinery and depots, if applicable. A geospatial list of industrial facilities must be developed and paired with the conversion technologies considered, with the infrastructure and assets of each facility listed. A comparison of facilities to each conversion technology must be performed to determine the percent reduction from greenfield. The decision matrix datasets would require transport costs along the supply chain for each facility and feedstock combination assessed, the greenhouse gas emissions from each supply chain, the number of jobs created based on each supply chain, and the social assets for each county in the region of analysis. An economic input-out model may need to be incorporated into a database to generate the number of jobs created based on various supply chain configurations. The model would need to be sufficiently robust to include a number of environmental impacts, such as smog.
and acidification, which may be beneficial to users for assessing specific policy implications. The GUI would also need to be capable of accepting datasets provided by users for use in siting analyses, such as GHG emissions at a depot or biorefinery. Before rolling out the dynamic DST to the public, each dataset used in the tool must be verified for its legal use and sharing rights. Additionally, consideration must be given to the time relevance of each dataset used in the analysis. A schedule would need to be developed to ensure the data represented in the tool are kept current.

As this research is part of the larger Northwest Advanced Renewables Alliance (NARA) project, it builds on work by others and in turn has been incorporated into other research projects. Regional supply chains developed in both the western and eastern NARA regions are being utilized to estimate the sectoral emissions of various primary and precursor to secondary air pollutants through mobile source emissions, area source emissions, and emissions from slash pile burning. Biorefinery emissions will be combined with emissions from the above sectors to assess the additional air quality impacts or benefits that can be attributed to the entire NARA supply chain for various criteria pollutants and air toxics. Additionally, the Total Transportation Cost Model (TTCM) methodology is being applied to forest residual estimation on the Confederated Salish and Kootenai Tribal lands. The ability of the TTCM to aggregate carbon dioxide equivalent emissions as well as transportation costs lends itself for use in a detailed Life Cycle Analysis to determine the GWP of a potential or actual biorefinery.

Geospatial cost components comprise approximately 80% of total biorefinery operational costs for the conversion process used in the case studies. By performing facility siting through minimizing feedstock as well as energy and labor costs, biorefinery supply chain development can be better directed to select facilities that provide the greatest cost reductions. Incorporating environmental metrics in facility siting will identify facilities with low GWP, and selecting sites with high social assets may translate into capital cost savings through a faster permitting and construction process. Any cost reductions gained
during the early phases of commercialization may translate into a more cost-competitive cellulosic or advanced biofuel and further the development of the biofuel industry.
References


