BIOFEEDSTOCK SUPPLY CHAIN LOGISTICS

DYNAMIC MODELING: EASTERN REDCEDAR

By

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Abstract: A body of knowledge exists for the Eastern Redcedar supply chain; however, the available data is not sufficient to fully evaluate the numerous potential commercialization strategies. The ability to model a supply chain in its entirety, from identifying the facility location and feedstock availability through the harvest, transport, processing, and refining stages is a critical component of characterizing the feasibility of a given strategy. To facilitate the development of Eastern Redcedar commerce, a comprehensive, modular, commodity based supply chain model was developed as a computational tool for decision makers who are considering investing capital in developing or expanding Easter Redcedar markets. This model is web based, to provide improved accessibility and ease of use while its modular structure gives it the flexibility to evaluate niche markets. Geospatial programming is used to perform location allocation, develop service areas, routes, and biomass yield maps. This data, combined with user inputs, is used to approximate costs at each stage in the supply chain. Rejection sampling is used to generate random numbers according to empirical probability distribution functions for key cost variables in Monte Carlo simulations. The interdependency, cost impact and sensitivity of variables on total system cost are derived from one-way sensitivity analyses. All results are displayed as interactive bar graphs, line charts, and maps. The model is expected to reduce the risk associated with the production of Eastern Redcedar products and provide a strong foundation for expanding the model to include other biomass feedstocks and end products.

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GLOSSARY OF TERMS

Bone-Dry Tonnes (bdt): A Mass of one metric ton of material having zero percent moisture content (ASABE Standards, 2011).

Cold Loading: Logging operations where the logs are decked for some time before being processed or hauled to the mill (ASABE Standards, 2014).

Diameter at Breast Height (dbh): Tree diameter at 1.4 m (4.5 ft) above the ground (McKinley, 2012a).

Green Tonnes (gt): Mass of one metric ton of freshly collected biomass (ASABE Standards, 2011).

Higher Heating Value: The full energy content of a fuel. It is the amount of heat produced when a liquid fuel or oven dried solid fuel is fully combusted, all of the products of combustion are cooled to 25° C (77° F) and the water vapor formed during combustion is condensed into liquid water (ASABE Standards, 2011).

Hot Loading: Logging operations where the logs go from stump to mill with minimal delay (ASABE Standards, 2014).

Lignin: An amorphous polymer related to cellulose that provides rigidity and together with cellulose forms the woody cell walls of plants and the cementing material between them (Lignin, 2015).

Lignocellulose: Biomass composed primarily of cellulose, hemicelluloses and lignin (ASABE Standards, 2011).

Merchantable Bole: The portion timber species tree where diameter is greater than or equal to 5.0 inches in diameter, from a 1-foot stump to a minimum 4-inch top diameter of the central stem or where the central stem breaks into limbs all of which are less than 4.0 inches in diameter (McKinley, 2012a).

Residue: Wood products remaining after lumber fraction has been harvested (ASABE Standards, 2011).

Saccharification: The process of breaking a complex carbohydrate (as starch or cellulose) into its monosaccharide components (Saccharification, 2015).

CHAPTER I

INTRODUCTION

In the last 100 years Eastern Redcedar has transitioned from being “conspicuous by its absence” (Harper, 1912, p. 145) in the Great Plains region to covering a projected 3.5 million ha (8.6 million ac) in Oklahoma alone by 2013 (Starks, Venuto, Eckroat, & Lucas, 2011). Eastern Redcedar is a native Oklahoma tree species that has become an invasive nuisance species through poor management strategies, reduced prescribed burns, and cost prohibitive treatment protocols. Its uncontrolled spread has resulted in millions of dollars in economic damage to the state of Oklahoma in the form of water, cattle forage, hunting, and wildlife losses, as well as fire damage. Removal treatments can range in cost from \$7.40 to \$395.00 ha^{-1} (\$3.00 to \$160 ac^{-1}) depending on stand density and whether mechanical, fire-based, or herbicidal means are employed (Bidwell, Weir, & Engle, 2007). However, several commodities can be manufactured from Eastern Redcedar, which represent a potential method of removing the tree from native grasslands while aiding economic growth. Products that could be manufactured from Eastern Redcedar are mulch, lumber, biofuels, pharmaceuticals, cedar oil, animal bedding, particleboard, and wood flour (Drake et al., 2002; Gawde, Cantrell & Zheljiazkov, 2009; McNutt, 2012). As the value of end-products increase, so do capital cost, risk, and manufacturing complexity. Figure 1 shows the relative value and risk of potential commodities, based on expected production from Oklahoma trees greater than 15.25 cm (6 in) in diameter. Halting the current spread of Eastern Redcedar would require clearing 112,000 ha^{-1} (277,000 ac^{-1}) of land annually. Even more would be needed to reverse the spread (Drake et al., 2002).

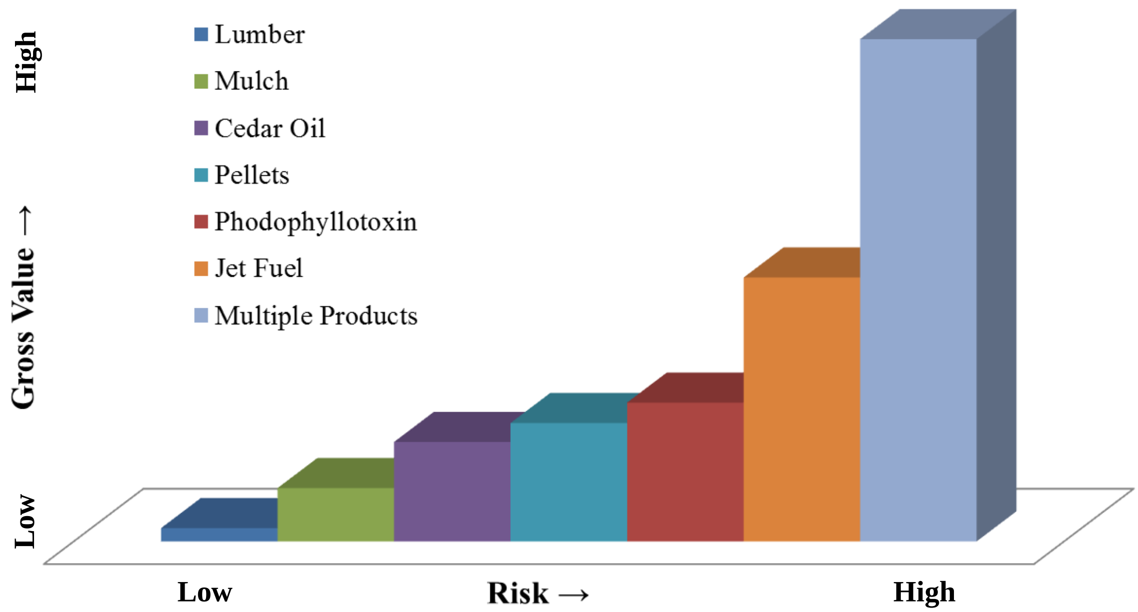

Figure 1. In general, as the gross value of the product(s) manufactured from Eastern Redcedar increases so does the risk and uncertainty associated with implementing the business plan.

To reverse the economic and ecological damage caused by Redcedar, the state of Oklahoma would need to develop industries that consume substantial quantities of Redcedar biomass. Due to the risk and uncertainty associated with production strategies with high throughput requirements, specialized industries utilizing Eastern Redcedar have not developed, despite public support for Redcedar removal and legislation, such as the Eastern Redcedar Initiative Act of 2010. Each stage of a hypothetical Redcedar supply chain presents unique implementation challenges. Eastern Redcedar is not generally grown in managed stands, and stand density may vary dramatically. These conditions make harvesting more difficult and raise concerns regarding the optimal location of processing facilities. Separating tree components, such as the needles and heartwood, to increase processing efficiency adds additional costs, but may ultimately result in a higher value product. The variability of a potential Redcedar supply chain is illustrated in Figure 2.

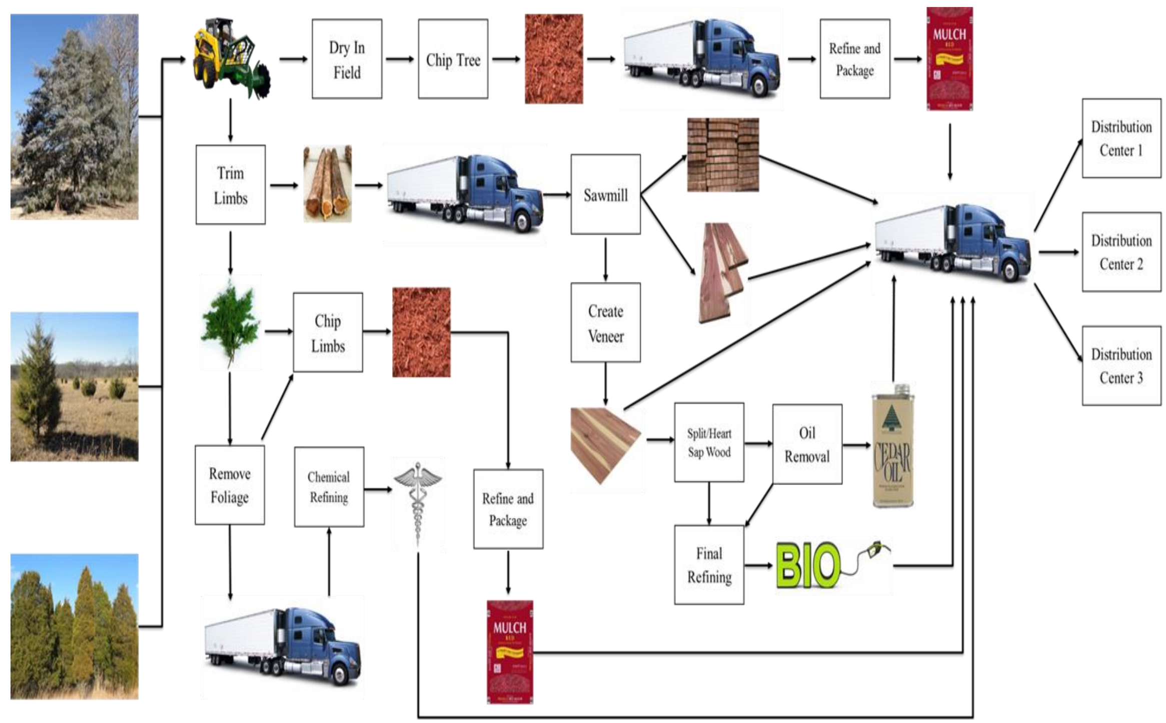

Figure 2. Simplified Eastern Redcedar supply chain. Trees may be harvested from low, medium or high density stands of various age, and an assortment of processing and refinement options are available.

To develop Eastern Redcedar enterprises, the costs associated with each supply chain stage should be evaluated with minimal simplification to accurately capture the production relationships between each stage, e.g. facility size is impacted by biomass accessibility, and transportation costs are affected by facility throughput. The computational technology exists to create a simulation model that can quickly and accurately evaluate the supply chain as a whole. The model should cover location of a facility, feedstock availability, harvest, processing, transport, and refinement of raw material into a finished product, and should provide the option for a single refinery to output multiple product streams. Developing a supply chain model for Eastern Redcedar commodities could be an effective method of providing businesses, entrepreneurs, and government entities the ability to evaluate and optimize alternative production strategies for Redcedar-based industries.

CHAPTER II

OBJECTIVES

The purpose of this project was to develop a web based model to evaluate the costs associated with utilizing Eastern Redcedar to produce value-added commodities, to help entrepreneurs, businesses, and government agencies better understand the economic potential of fully utilizing Eastern Redcedar. The specific objectives of this research were as follows:

1. To create a baseline model to evaluate harvesting, transport, pre-processing, and refining scenarios, to better assess the production costs associated with specific commodities.

2. To incorporate sensitivity analysis and economic optimization elements into the model to determine critical success factors.

3. To develop and deploy a user-friendly, online interface that generates economic reports and graphical displays of sensitivity analysis, supply chain performance, and other economic results produced by the model.

CHAPTER III

REVIEW OF LITERATURE

3.1 Eastern Redcedar

Eastern Redcedar is an evergreen that grows year-round when temperatures are above 5° C (40° F). It is semi-shade tolerant and can grow in forests and woodlands. It is easily ignitable because of its thin bark and fine flammable foliage, and will not sprout back when the top is killed by fire or when it is truncated below the lowest living branch (Division of Agricultural Science and Natural Resources [DASNR], 2012). However, as tree size increases, fire damage decreases (Buehring, Santelmann, & Elwell, 1971). It is a dioecious plant with seed reproduction beginning between 6 and 10 years of tree life. Seeds are spread extensively by small mammals and birds that eat the berries of the female tree (DASNR, 2012; Ferguson, Lawson, Maple, & Mesavage, 1968).

Eastern Redcedar occurs naturally in Oklahoma and is found in all but three or four counties, being the most widely distributed conifer in the Eastern United States (McKinley, 2012a) (Figure 3). It is slow-growing and typically not an aggressive competitor with hardwoods in deep soil. It is hardy, sprouting almost anywhere from dry rocks to swamps. Under high atmospheric demand, a 31 cm (12 in) Eastern Redcedar tree may use up to 150 liters (40 gal) of water per day from the soil profile when soil water content permits (Caterina, 2012; Truitt, 2011). It is susceptible to cedar-apple rust, but the disease is typically not life-threatening to Redcedar (Ferguson et al., 1968). Despite the tree’s resilience, it prefers deep, moist, well-drained, alluvial soils and may reach heights of 18.3 m (60 ft), with a bole diameter of 30.5 to 61.5 cm (12.0 to 24 in) within 50 years. This is a typical growth pattern, but on good sites, 1.22 m (4 ft) bole diameters and 36.6 m (120 ft) heights are possible.

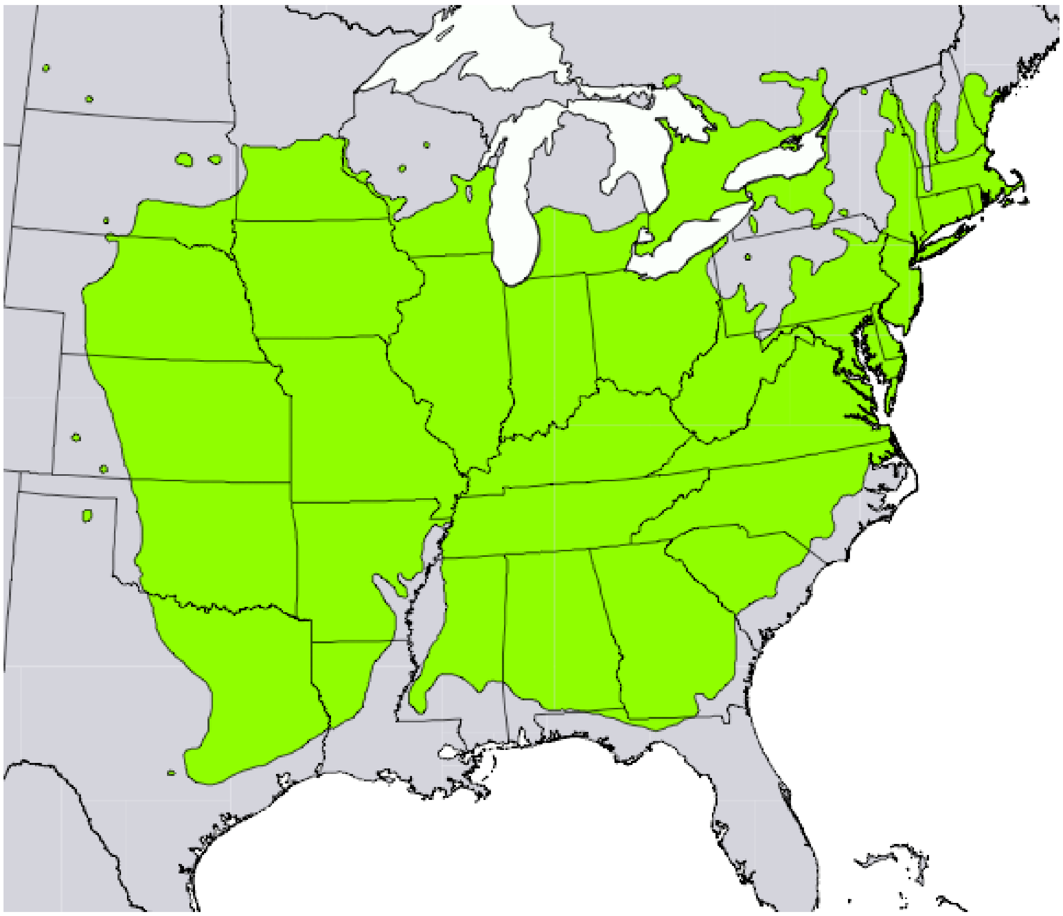

Figure 3. Native range of Eastern Redcedar in the United States.

Dr. David W. Stahle, University of Arkansas-Fayetteville, noted trees in Oklahoma from 500 to 1000 years old, with some of the oldest Eastern Redcedar stands in the south central United States located in Oklahoma (Drake et al., 2002). Individual Eastern Redcedar trees vary greatly in appearance based on stand density and competition from other species (Lawson & Law, 1983). Denser stands produce proportionally taller trees while thinner stands allow for more limb structure which has a slight effect on overall biomass. Ferguson et al. (1968) outlined equations for closed (3.1.1), dense (3.1.2) and open (3.1.3) stands,

$$H = 1.3716 + 23.317 \cdot (1 - e^{-0.03307*dbh}), \tag{3.1.1}$$

$$H = 1.3716 + 17.587 \cdot (1 - e^{-0.03543*dbh}), \tag{3.1.2}$$

$$H = 1.3716 + 15.24 \cdot (1 - e^{-0.0315*dbh}), \tag{3.1.3}$$

where H is height in m and dbh is diameter at breast height in cm. These equations suggest bole biomass increases relative to tree stand density (Figure 4). Conversely, branch and foliage biomass decreases as stand density increases. Lambert, Ung, and Raulier (2005) developed tree biomass equations relating height and dbh (3.1.4),

$$\begin{aligned} Y_{wood} &= B_{wood} \cdot dbh^{Bwood2} \cdot H^{Bwood3} + e_{wood} \\ Y_{bark} &= B_{bark} \cdot dbh^{Bbark2} \cdot H^{Bbark3} + e_{bark} \\ Y_{foliage} &= B_{foliage} \cdot dbh^{Bfoliage2} \cdot H^{Bfoliage3} + e_{foliage} \\ Y_{branches} &= B_{branches} \cdot dbh^{Bbranches2} \cdot H^{Bbranches3} + e_{branches} \\ Y_{total} &= Y_{wood} + Y_{bark} + Y_{foliage} + Y_{branches} + e_{total} \end{aligned} \tag{3.1.4}$$

where H is height in m, dbh is diameter at breast height in cm, e is error and Y_i is the dry biomass compoenent of a tree in kilograms, which enable comparison of tree biomass directly to stand density (Figure 5). The actual Eastern Redcedar biomass may vary, depending on location and other factors such as climate.

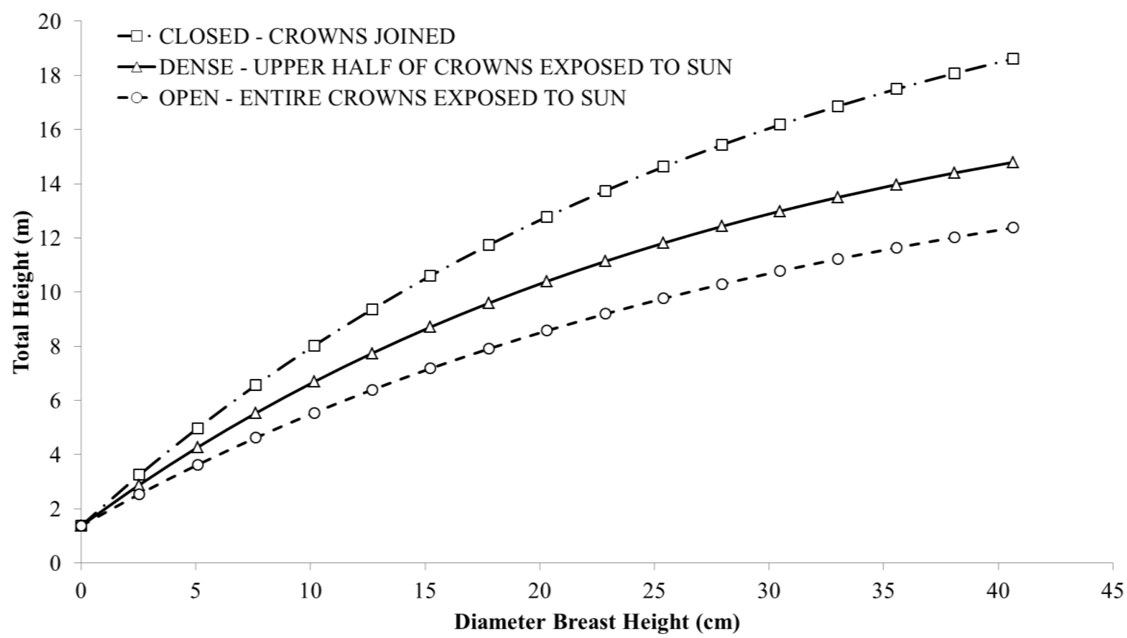

Figure 4. Representation of tree height and diameter to stand density (Ferguson et al., 1968).

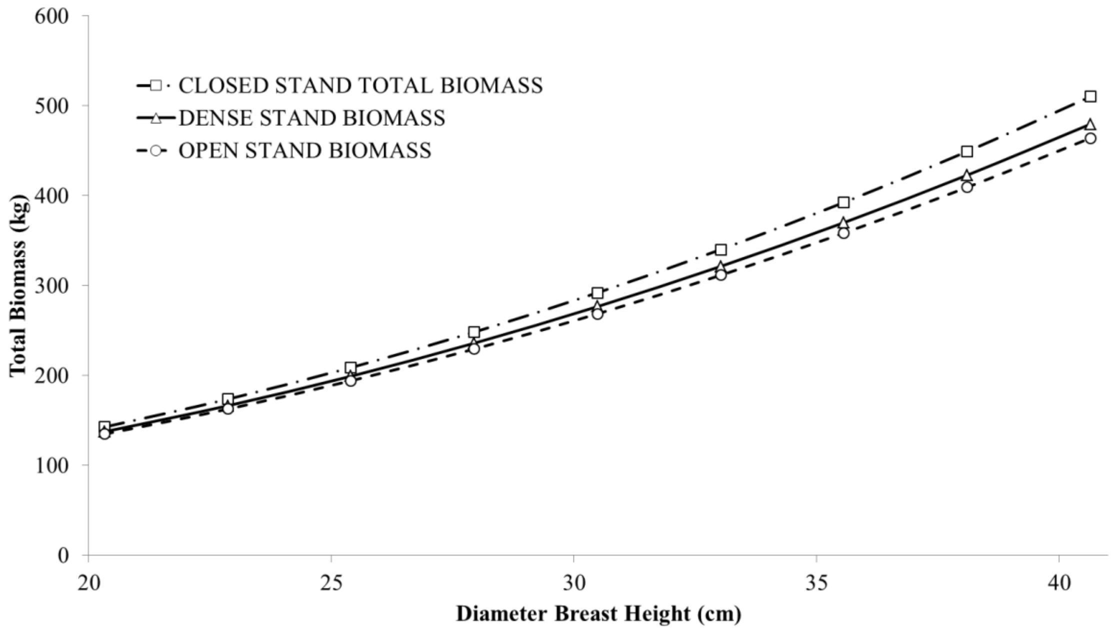

Figure 5. Graphical representation of equations to predict total biomass of Eastern Redcedar from 20.3 to 40.6 cm (8 to 16 in) dbh (Lambert et al., 2005).

Hardwood competition has a significant impact on Redcedar stand density, increasing growth by 2 m^3 ha^{-1} yr^{-1} (28 ft^3 ac^{-1} yr^{-1}) during a 14-year period in unthinned areas with hardwoods removed (Ferguson et al., 1968). Closed and dense stockings are optimal for post and saw log lumber, but given that seeds are commonly dispersed by birds and animals, low density stands could be expected (Lawson & Law, 1983). This would be especially true for Oklahoma, where unmanaged pastures are being taken over by Redcedar. Utilizing Eastern Redcedar in industrial markets could create a sustainable control strategy, but different products may prove more economically feasible for closed, dense, or open stands.

3.2 Environmental and Economic Impact

Eastern Redcedar is an aggressively spreading native species in Oklahoma grasslands and cross-timbers oak forests. The species reduces rangeland forage production and has been associated with stream flow and groundwater recharge reduction. As part of a project to quantify the projected growth and current quantities of Eastern Redcedar in Oklahoma, the Natural

Resource Conservation Service (NRCS) evaluated 17 counties to determine the available biomass based on satellite imagery (Starks et al., 2011). Table 1 shows the biomass availability for each of the 17 counties. The tree has a deep root system which captures more water than other trees, resulting in a decrease in soil water, groundwater storage, and groundwater recharge (Zou, Turton, & Engle, 2010). Little research has been conducted on rainfall interception by Eastern Redcedar, but a related species, Ashe Juniper (*Juniperus ashei*), may intercept over 60% of rainfall during low intensity (1.27 cm [0.5 in] per 19 hour period) storm events (Smith, 2011). Eastern Redcedar trees reduce forage by roughly 2.75 kg (6 lb) for a 1.8 m (6 ft) crown diameter tree (Stritzke & Bidwell, 1989). Briggs, Hoch, and Johnson (2002) reported that at densities of 1,500 trees ha^{-1} (607 trees ac^{-1}), herbaceous plants were virtually eliminated.

Table 1. Eastern Redcedar biomass data for selected Oklahoma counties as determined by the NRCS. The minimum, maximum and median expected biomass quantities were provided. (Starks et al., 2011).

County	Minimum	Maximum	Median
	----------------------Tonnes----------------------		
Blaine	875,667	1,434,271	1,154,969
Canadian	511,550	872,693	692,122
Dewey	1,478,173	2,642,928	2,060,551
Eliss	280,872	525,222	403,047
Garfield	237,985	420,806	329,396
Kingfisher	312,615	501,404	407,009
Lincoln	445,342	862,444	653,893
Logan	355,580	688,701	522,140
Major	438,851	789,240	614,046
Murray	483,698	796,548	640,123
Noble	203,616	347,688	275,652
Okfuskee	117,275	241,712	179,493
Oklahoma	322,075	509,764	415,919
Pawnee	763,224	1,395,217	1,079,221
Payne	643,436	1,224,562	933,999
Pottawatomie	210,730	403,953	307,342
Woodward	615,070	1,088,737	851,904
Total	**8,295,760**	**14,745,891**	**11,520,825**

Eastern Redcedar does have benefits. As a wind break, NRCS promoted Eastern Redcedar after the Dust Bowl to reduce wind erosion (Smith, 2011). However, the NRCS now estimates that with no control strategy and a takeover rate of 0.12 million ha yr^{-1} (0.3 million ac yr^{-1}), 28% of Oklahoma could be covered with Redcedar by 2013 (Drake et al., 2002). This land encroachment is expected to greatly alter the grassland water cycle (Hung, 2012). Eastern Redcedar leaf litter can alter soil-microbial feedbacks, resulting in reduction of post oak (*Quercus stellata*) and blackjack (*Quercus marilandica*), dominant oak species in the Oklahoma Cross-Timbers (Williams, Hallgren, Wilson, & Palmer, 2013). Since the 1950's, Redcedar tree density has increased over 3,100%, and sapling density has increased more than 4,400%. In contrast, the two dominant oak species increased in tree density by 19%, but the sapling density decreased by 66% (DeSantis, Hallgren, Lynch, Burton, & Palmer, 2010). Perhaps the most detrimental and noticeable impact comes at the expense of Oklahoma wildlife. The "Redcedar Task Force" (Drake et al., 2002) evaluated the impact of Redcedar on native wildlife to summarize wildlife displacement. Their comprehensive literature review on the subject cited these statistics:

- Invasion of junipers into native plant communities changes habitat structure and composition, resulting in displacement of some wildlife species (Bidwell, Engle, Moseley, & Masters, 1996).
- Juniper infestation in turkey roost sites has been known to displace entire turkey flocks (Smith, 2001).
- Grassland bird abundance and richness approached nonexistence with only 25% juniper cover present (Coppedge et al., 2002).
- At the current invasion rate of Eastern Redcedar and Ashe Juniper, Oklahoma could be losing up to 5,680 bobwhite quail coveys per year (Guthery, 2001).

- Junipers are a dominant factor in the displacement of grassland birds and songbirds from the native prairie, and only three junipers per acre will displace some birds from their habitat (OSU Rangeland Ecology and Management, 2001).

The effects of Eastern Redcedar advancement on Oklahoma's prairie ecology, hydrology, and economy have been well noted by multiple studies. Without the implementation of control practices, Redcedar will continue its invasion of Oklahoma prairie, rangeland, and hardwood forests.

The Oklahoma insurance industry considers the Redcedar invasion a problem, similar to mold issues, which have cost other state insurance companies millions. Drake et al. (2002) stated the insurance industry expects higher financial costs as Redcedar becomes more prevalent and increases severe fire risks. As prairie and grasslands are overtaken by Eastern Redcedar, Oklahomans can expect to see the severity and frequency of severe fire outbreaks increase, incurring substantial monetary losses. Fire suppression alone can average \$420 ha^{-1} (\$170 ac^{-1}), excluding property losses, environmental damage, and loss of human life (Perlack et al., 2005). While increased fire danger is a real and legitimate concern (Table 2), in 2001 an estimated \$107 million was lost in lease hunting because of Redcedar, and another \$100 million was lost in forage production. Additionally, Eastern Redcedar may exacerbate drought conditions by depleting soil water supplies. The average Eastern Redcedar tree uses 27 liters of water, although usage varies from 4 liters (1 gal) for a 2 cm (0.75 in) dbh tree to 150 liters (40 gal) for a 31cm (12 in) dbh tree (Caterina, 2012). Forecasts in 2002 estimated multi-million dollar losses in several key economic areas by 2013 (Drake et al., 2002). Table 2 indicates that Eastern Redcedar has a negative impact on the Oklahoma economy.

Table 2. Estimated economic losses resulting from Redcedar spread in Oklahoma for 2013. (Drake et al., 2002).

Classification	Cost (Millions of $)
Wildfire	107
Cattle Forage	205
Lease Hunting	107
Recreation	17
Water	11
Total	**447**

The Oklahoma State University (OSU) department of Natural Resource Ecology and Management (NREM) reports that for land areas greater than 260 ha (640 ac) with Redcedar trees 1.8 to 6.1 m (6 to 20 ft) tall and 620 trees ha^{-1} (250 trees ac^{-1}), treatment can cost \$24.70 to \$42.00 ha^{-1} (\$10 to 17 ac^{-1}), depending on the prescribed burn technique implemented (Bidwell et al., 2007). For the same scenario, with trees greater than 6.1 m (20 ft) tall, NREM suggests helicopter ignition with helitorch and the application of paraquat herbicide, at a total cost of \$49.40 ha^{-1} (\$20 ac^{-1}). Fire is the cheapest treatment but is not recommended for areas greater than 260 ha (640 ac). In comparison, mechanical treatment of smaller areas can range from \$27.20 to \$395 ha^{-1} (\$11 to \$160 ac^{-1}) depending on the exact mechanical technique used (Bidwell et al., 2007).

3.3 Biofeedstock Supply Chain

Harvesting forestry biomass for energy is not a new concept, and extensive research has been conducted to determine the economics of harvest programs and the resulting environmental effects. Pine species are the most common biomass harvested for energy wood, but other tree species, such as Douglas-fir are commonly used (Mitchell & Gallagher, 2007; Conrad, Bolding, Aust, Smith, & Horcher, 2013; Pan, Han, Johnson, & Elliot, 2008; Adebayo, Han, & Johnson, 2007). A majority of these studies in the literature have focused on variations of integrated harvesting or thinning of undersized trees as a silviculture plan, although several evaluated new harvesting processes and techniques. The studies in the literature cover a multitude of geographic regions, soil types, and machinery.

The primary concern for a Redcedar based biofuel industry in Oklahoma is the ability to profitably harvest, transport, and process raw material. The delivery price of wood feedstock is typically the largest cost incurred when operating a biomass plant (Sessions, Tuers, Boston, Zamora, & Anderson 2012). Conrad et al. (2013) estimated the delivered cost of energy wood for a North Carolina whole tree chipping operation in 2010 was \$51.19 bdt^{-1} (\$46.44 bdt^{-1}), a loss of \$10.85 bdt^{-1} (\$9.84 bdt^{-1}) at the 2010 market price of \$40.34 bdt^{-1} (\$36.60 bdt^{-1}).[1] Similar delivery prices have been reported in other studies (e.g., Aman, Baker, & Greene, 2011; Mitchell & Gallagher, 2007). This suggests that traditional logging operations are not optimally suited for energy wood harvesting, and modifications need to be made to improve the economic feasibility of energy wood collection. However, the U.S. Billion-Ton Study Update considers a roadside cost of \$66.14 bdt^{-1} (\$60 bdt^{-1}) to be a “realistic, reasonable price” (p. 29), although the authors acknowledge that the actual market price will be dictated by numerous inputs (U.S. Department of Energy [DOE], 2011). This price does not include costs incurred through handling, transport, and preprocessing of material. An assumption of \$66.14 bdt^{-1} (\$60 bdt^{-1}) is reasonable considering the final delivered cost of comminuted Eastern Redcedar should be below \$110.23 bdt^{1} (\$100 bdt^{1}), with freight costs comprising roughly 30% of the delivered cost (J. Meibergen, personal communication, September 5, 2013). Considerable effort has been made to improve energy harvesting productivity through the use of specialized equipment, such as biomass balers, whole tree bundlers, and robust swath harvesters (Felker, McLauchlan, Conkey, & Brown, 1999; Patterson, Pelkki, & Steele, 2008; do Canto, Klepac, Rummer, Savoie, & Seixas, 2011).

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[1] Price was adjusted from green ton to bone dry ton based on an assumed 50% moisture content for Loblolly Pine (Clark III and Daniels, 2000).

3.3.1 Transportation

A large expense in energy wood logging operations is transportation of raw material to the refinery, which can be nearly half of total operating costs (Hall, Gigler, & Sims, 2001; Harrill & Han, 2012; Mitchell & Gallagher, 2007; Pan et al., 2008; Perlack et al., 2005). Factors noted to increase hauling rates include travel distance, fuel prices, load size, and material moisture content. Travel distance is the primary reason for high delivery costs in most instances. Pan et al. (2008) noted that for each additional mile of travel on spur or logging roads, production costs increased by $8.66 bdt1 ($7.86 bdt-1). Mileage increases on highway and unpaved roads also raised the bdt transport cost of energy wood, but at less than $0.47 km-1 ($0.75 mi-1). Forest roads and long round trip distances can lower hauling production rates appreciably (Harrill & Han, 2012).

To be profitable, the delivery price of energy wood should be no more than $22.05 gt-1 ($20 gt-1) (Conrad et al., 2013). In Arizona, Pan et al. (2008) reported delivery costs between $54.23 to $79.56 bdt-1 ($49.20 to $72.18 bdt-1) for a one-way hauling distance of 47.5 to 57.9 km (29.5 to 36 mi). With current energy wood chip prices, material can be transported 145 to 161 km (90 to 100 mi) before shipment becomes profit limiting (Ashton, Jackson, & Schroeder, 2007; J. Meibergen, personal communication, September 5, 2013; Rummer et al., 2003). Although 145 km (90 mi) is a relatively short distance, it encompasses over 20,000 km^2 (25,000 mi^2). A survey of researchers, industrialists, land owners, and policy makers involved in lignocellulosic bioenergy production (Bailey, Dyer, & Teeter, 2011) suggested that business models similar to pulp and paper mills, which have raw material transport radiuses of approximately 80.5 km (50 mi), would be good base models for a biomass industry. Although stand density and delays accounted for some price variation, biomass transportation comprised over 43% of total costs for the four study sites evaluated by Pan et al. (2008) in Springerville and Black Mesa Arizona (Table 3 and Table 4).

Table 3. Stump to market production costs for harvest units (Pan et al., 2008).

	Cost ($/bdt)					
	Feller-Buncher	Skidder	Loader	Grinder	Chip Van	Total
Unit 1	6.23	11.06	2.40	13.05	39.44	72.18
Unit 2	5.01	6.96	4.72	12.06	32.70	61.45
Unit 3	7.45	5.86	5.35	12.54	23.95	55.15
Unit 4	7.62	3.79	3.93	12.58	21.28	49.20
Overall	6.37	6.08	4.08	12.63	26.11	55.27

Table 4. Stump to market production percentages for harvest units (Pan et al., 2008).

	Percent of Total				
	Feller-Buncher	Skidder	Loader	Grinder	Chip Van
Unit 1	8.63	15.32	3.33	18.08	54.64
Unit 2	8.15	11.33	7.68	19.63	53.21
Unit 3	13.51	10.63	9.70	22.74	43.43
Unit 4	15.49	7.70	7.99	25.57	43.25
Overall	11.53	11.00	7.38	22.85	47.24

Conrad et al. (2013) suggested that railway access was one of the main reasons traditional energy facilities were more competitive than bioenergy facilities, which truck material. Rail transport was considered feasible beyond 500 km (310 mi) and could potentially increase the quantity of available biomass to a facility (Searcy, Flynn, Ghafoori, & Kumar, 2007). Railway transport would also limit the impact of fuel fluctuations on hauling prices. Harrill and Han (2012) reported a $0.86 bdt^{-1} ($0.78 bdt^{-1}) increase in production cost for every $0.10 l^{-1} ($0.38 gal^{-1}) increase in fuel cost. Fuel costs impacts total production costs less than travel distance and can be compensated for by utilizing fuel efficient vehicles. Loading trucking vehicles to the maximum legal limit will also ensure a lower delivery price (Figure 6). In a study by Aman et al. (2011), underweight trucks (19.4 gt [17.6 gt]) resulted in a total delivery cost of $32.85gt^{-1} ($29.80 gt^{-1}) for whole tree chipping operations, while increasing the load to 40 gt (36.3 gt) decreased delivery costs by $10.14 gt^{-1} ($9.20 gt^{-1}). The importance of maximizing load weight is critical, but raw material moisture content and material density significantly affect load weight and total system cost (Figure 6). Redcedar heartwood is approximately 33% moisture in green wood, meaning only two-thirds of transported material is useable (Simpson & TenWolde, 1999). Field drying for approximately one year could reduce cut tree moisture content to near zero percent (Starks et al., 2011). If material is chipped onsite, density will depend on chip size, chip moisture and whether any attempt is made to pack the chips. Wood chip bulk density can range from 150 to 200 kg m^{-3} (9.4 to 12.5 lb ft^{-3}), but densification can increase bulk density tenfold (Tumuluru, Wright, Kenny, & Hess, 2010a).

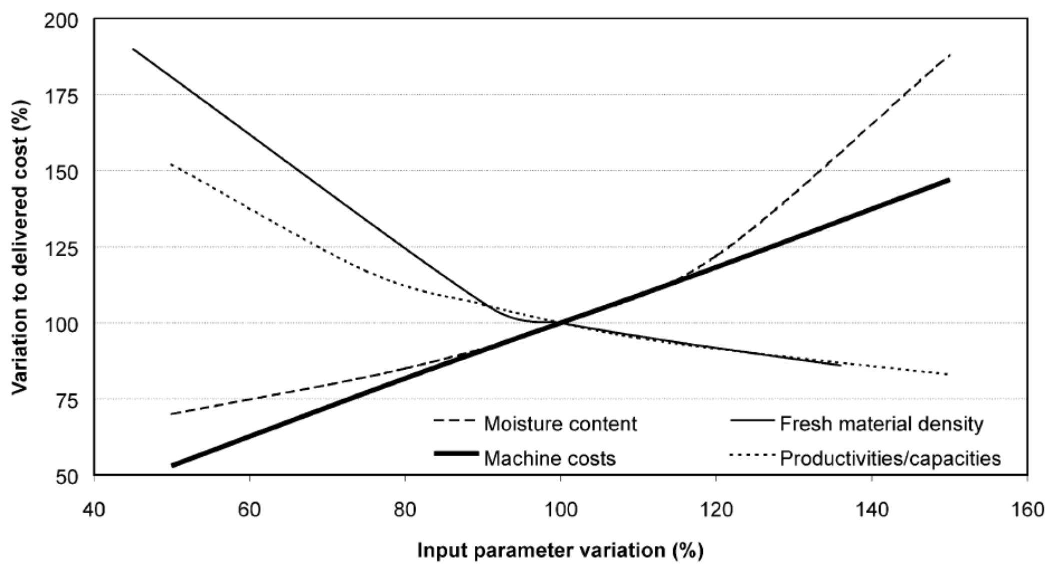

Figure 6. Sensitivity analysis of key factors that determine overall system cost for an energy wood harvesting operation (Hall et al., 2001).

There are a variety of methods to increase biomass density; including baling, pelletization, extrusion, and briquetting (do Canto et al., 2011; Tumuluru et al., 2010a; Clarke, Eng, & Preto, 2011). Densification would increase the economic feasibility of long distance transport by addressing technical limitations resulting from low density(150 to 200 kg m-3 [9.4 to 12.5 lb ft-3]) (Tumuluru et al., 2010a). The additional processing would increase energy consumption and therefore cost (Table 5) although some of the monetary loss would be reclaimed in reduced transportation expense (Clarke et al., 2011). Based on a specific energy consumption of 36.8 to 150 kW hr t^{-1} (40.6 to 165 kW hr t^{-1}) reported by Tumuluru et al. (2010a) and an electric rate of \$0.0667 kW hr (Energy Information Administration [EIA], 2015), biomass densification using a screw press could increase costs by \$2.45 to \$10 t^{-1} (\$2.70 to \$11 t^{-1}). This estimate does not include installation, maintenance, repairs, or labor, making this estimate conservative. However, unless chipping/pre-processing is conducted in the field, tree stand density and tree size will be the primary load density influence when transporting whole trees and residues to a central processing location. Closely grouped trees grow taller for a given dbh (Ferguson et al., 1968), suggesting more biomass concentrated in the bole compared to the limbs. An individual tree's volume increases as its dbh increases, from roughly 65.5 to 238 cm^3 (4.0 in^3 to 14.5 in^3) when comparing a 20.3 cm (8.0 in) and 35.6 cm (14.0 in) tree (McKinley, 2012a).

Table 5. Advantages and disadvantages of certain densification equipment (Tumuluru et al., 2010a).

	Screw Press	**Piston Press**	**Roller Press**	**Pellet Mill**	**Agglomerator**
Optimum moisture content of the raw material	8 to 9%	10 to 15%	10 to 15%	10 to 15%	No information
Particle size	Smaller	Larger	Larger	Smaller	Smaller
Wear of contact parts	High	Low	High	High	Low
Output from machine	Continuous	In strokes	Continuous	Continuous	Continuous
Specific energy consumption (kWh t^{-1})	36.8 to 150	37.4 to 77	29.91 to 83.1	16.4 to 74.5	No information
Through puts (t hr^{-1})	0.5	2.5	5 to 10	5	No information
Density of briquette (g cm^{-3})	1.0 to 1.4	1 to 1.2	0.6 to 0.7	0.7 to 0.8	0.4 to 0.5
Maintenance	Low	High	Low	Low	Low
Combustion performance of briquettes	Very Good	Moderate	Moderate	Very good	No information
Carbonization of charcoal	Makes good charcoal	Not possible	Not possible	Not possible	Not possible
Suitability in gasifiers	Suitable	Suitable	Suitable	Suitable	Suitable
Suitability for co-firing	Suitable	Suitable	Suitable	Suitable	Suitable
Suitability for biochemical conversion	Not Suitable	Suitable	Suitable	Suitable	No information
Homogeneity of densified biomass	Homogenous	Not homogenous	Not homogenous	Homogenous	Homogenous

3.3.2 Harvest

Machine utilization rates have been noted to greatly affect a harvest operation's ability to profitably deliver raw material to a processing facility (Aman et al., 2011; Harrill & Han, 2012; Mitchell & Gallagher, 2007). Increasing chipper utilization rates by 5% up to 70% has been shown to reduce delivered costs by \$1.10 bdt^{-1} (\$1.00 bdt^{-1}) (Harrill & Han, 2012). Aman et al. (2011) concurred with this finding, stating that a utilization rate of 70% would have reduced delivered cost by \$3.00 bdt^{-1} (\$2.72 gt^{-1}), compared to the average utilization rate of 40%. Maximizing utilization rates for other machinery can have even greater improvements. By maintaining all machines in a harvest system at a utilization rate of 85% versus an observed rate of 41%, Harrill and Han (2012) predicted savings up to \$35.33 bdt^{-1} (\$32.05 bdt^{-1}). A whole tree chipping operation, similar to what might be expected for Redcedar collection, would have lower delivery costs (Conrad et al., 2013). The average chipper machine utilization rate is about 73.8%, based on a study of 63 chipping productivity studies, of which 35 were whole tree chipping operations (Spinelli & Visser, 2009). This utilization rate is typical of other studies, but Spinelli and Visser (2009) also noted that organizational and miscellaneous delay accounted for 16.6% of lost productivity, with mechanical and operator delays comprising 8.0% and 1.6% of delay time respectively. Assuming mechanical and operator delays were a result of chance and could not be reduced, utilization rates near 90% were theoretically possible by minimizing organization delays. Skidding and felling components of energy wood harvest units were proportionately affected by similar delays. Pan et al. (2008b) reported waiting on load out trucks was the largest delay for skidder, loader, and grinder operation. Reducing delay, specifically organizational delays, would greatly reduce overhead costs (Mitchell & Gallagher, 2007; Pan et al., 2008b; Vitorelo, Han, & Elliott, 2011).

Hall et al. (2001) evaluated seven delivery systems on the three different forest density types most common in New Zealand (Figure 7). The most effective delivery model identified was to purchase forest residue → load of residue into trucks → transport to the refinery → truck unloading → chip residue. This model had a delivery price of \$13.95 bdt^{-1} (\$12.66 bdt^{-1}) (Hall et al., 2001). This method incorporates cold loading, which has been noted to improve efficiency compared to hot loading (Pan et al., 2008; Spinelli & Visser, 2009). A whole tree chipping operation would increase the quantity of energy wood biomass, compared to an integrated chipping and roundwood harvesting operation, further reducing price (Conrad et al., 2013). Incorporating a drying period raised the total delivery cost slightly (Hall et al., 2001). Hot and dry summers in Oklahoma could make field drying more feasible, reducing cedar moisture to near 20% (J. Meibergen, personal communication, September 5, 2013). Figure 8 shows the effects of moisture content on the heating value of woody biomass.

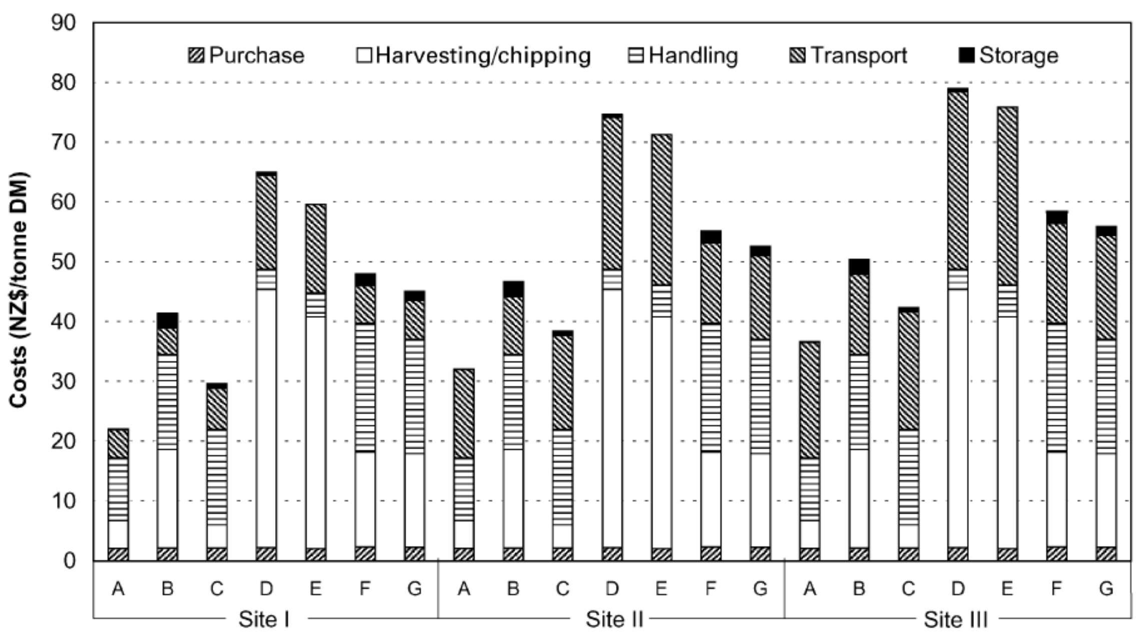

Figure 7. Cost of delivery systems according to site. 1 NZ\$ = \$0.42 USD in 2000. Full descriptions of site classification and delivery scenario can be seen in Appendix I (Hall et al., 2001).

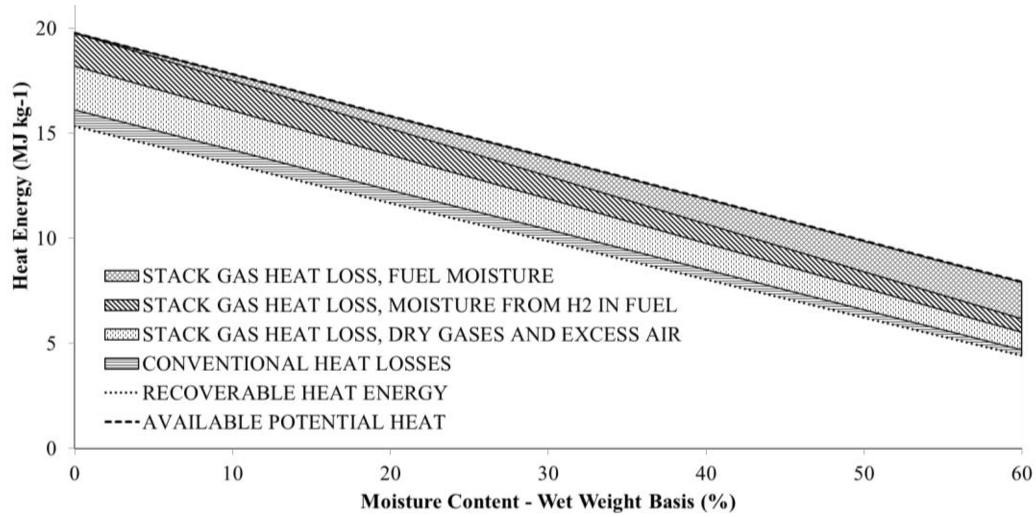

Figure 8. Heat energy in typical wood fuel per pound of wet fuel (Ince, 1979).

Many factors influence the cost and productivity of logging and energy wood harvesting operations. Two studies (Conrad et al., 2013; Vitorelo et al., 2011) determined that loggers with lower capital and more fuel efficient equipment could process energy wood more productively. Pan et al. (2008) estimated a \$0.64 bdt^{-1} (\$0.58 bdt^{-1}) increase in cost per 30.5 m (100 ft) of skidding distance. Terrain and topography conditions could also hinder energy wood production economically, although ground conditions were typically not technologically limiting (Perlack et al., 2005). A primary concern for traditional logging/skidding of Eastern Redcedar is tree size, since harvest cost is inversely related to dbh. As dbh decreases, production cost increases, often dramatically (Adebayo et al., 2007; Felker et al., 1999; Mitchell & Gallagher, 2007). Adebayo et al. (2007) specifically noted that harvest cost was affected by machine productivity, which in turn was a function of tree size and extraction distance (Figure 9).

Given that two thirds of Oklahoma Eastern Redcedar trees are 12.7 to 27.7 cm (5.0 to 10.9 in) in diameter and the relationship between tree dbh and machine productivity, Eastern Redcedar harvesting operations may have low productivity rates (McKinley, 2012a; Adebayo et al., 2007). Minimizing machine travel and utilizing fuel efficient equipment will aid in total system cost reduction (Conrad et al., 2013; Vitorelo et al., 2011; Pan et al., 2008).

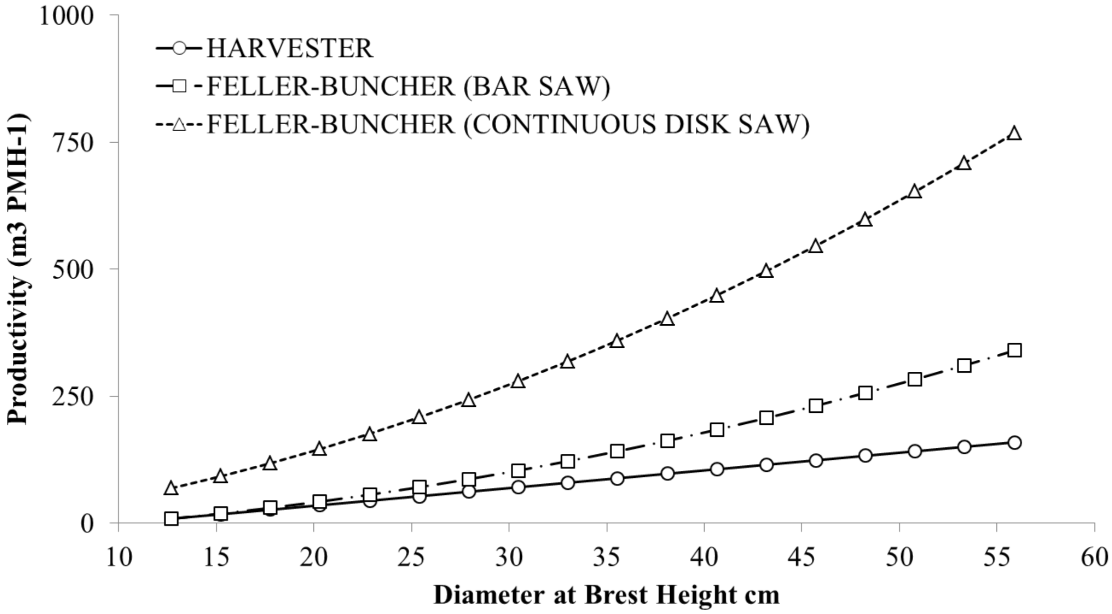

Figure 9. Representation of machine productivity to tree diameter for three distinct types of harvesting machines (Adebayo et al., 2007).

3.3.3 Processing

After the raw material (Eastern Redcedar) is harvested, chemical and/or mechanical pre-processing steps may be necessary prior to final product production. The type of pre-processing required is dependent upon the desired end-product. Biofuel, pharmaceutical, and cedar oil production may require several mechanical and chemical processing steps, such as grinding, chipping, dilute acid treatment, steam explosion, etc. to improve conversion or extraction efficiency (Zhu & Pan, 2010; Tumuluru et al., 2010b; Dunford, Hiziroglu, and Holcomb 2007).

3.3.3.1 Mechanical

Material size reduction may be necessary to effectively remove oils, bio-chemicals or produce biofuels. The smaller size allows for more effective penetration of pretreatment chemicals into the biomaterial, making the overall process more efficient (Zhu & Pan, 2010). There are a plethora of machines designed for size reduction of woody biomass, including hammer mills, chippers, knife mills, and disk or attrition mills (Ramachandriya, 2013). Each machine has distinct advantages and disadvantages, making it more or less suited for comminution of woody material. The desired end product is also a primary selection criterion for wood milling machinery. A chipper is commonly used in the field to produce hog fuel or energy chips, or occasionally a hammer mill, as shown by several productivity studies (Conrad et al., 2013; Spinelli & Visser, 2009; Vitorelo et al., 2011). The chippers are typically used in integrated harvest operations to comminute residues onsite, while merchantable bole wood is logged. In a mill setting, hammer or knife mills are typically used (Cadoche & Lopez, 1989). Dry biomass is easily refined by hammer and knife mills, but wet materials are better suited for disk mills (Schell & Harwood, 1994). Hammer mills are designed to exploit the shattering effect that occurs at low moisture content (Dooley, Lanning, & Lanning, 2013). Both hammer and disk mills are optimized for large scale production, with hammer mills commonly used in industry for production of pellets and composites, while disk mills are used for fiberization in pulping industries (Schell & Harwood, 1994).

One of the Eastern Redcedar pre-processing concerns is the size distribution of chipped particles (J. Meibergen, personal communication, September 5, 2013). While different strategies exist to reduce average particle size (mill type, screen filter size, two-stage processing, etc.) to the desired dimensions, they may have a broad particle size distribution. A study by Schell & Harwood (1994) found a particle size distribution of 1 to 4.8 mm for a hammer mill, and 0.4 to 2.3 mm for a disk mill. The energy consumption of these machines is a concern, since energy consumption equates to cost. The hammer mill and disk mill in the study by Schell and Harwood (1994) consumed 288 to 367 and 439 to 1984 MJ Mg^{-1} of dry wood respectively. Cadoche and Lopez (1989) reported 468 MJ Mg^{-1} of dry wood to comminute hardwood chips to 1.6 mm for both hammer and knife mills (Figure 10).

Specific energy consumption is inversely proportional to mill screen size and influenced by biomass moisture (Miao, Grift, Hansen & Ting, 2011). Zhu, Pan, and Zalesny (2010) reported milling wood chips typically requires 1800 to 2880 MJ Mg^{-1} of dry wood, 25 to 40% of the thermal energy of ethanol. Assuming a mechanical conversion efficiency of 30%, the authors calculated a net energy gain of zero. Another study found wood biomass size reduction for lignocellulosic ethanol production to be 32.9% of total refinery electric costs (Hinman, Schell, Riley, Bergeron, & Walter, 1992). Utilization of wood chips as a supplemental power source in coal-fired plants would not require substantial size reduction (25 x 75 x 12 mm chips); hence, preprocessing energy and cost would be less (Cadoche & Lopez, 1989; Toms & Lewis, 1987). However, this does not impact transportation fuel dependency (Perlack et al., 2005).

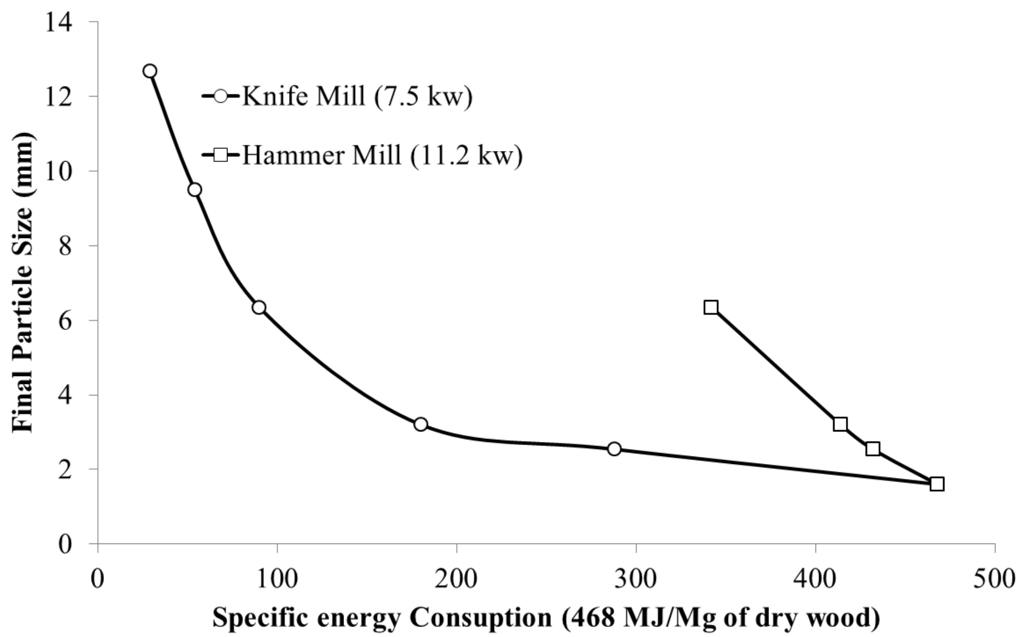

Figure 10. Specific energy consumption for comminution of hardwoods using a hammer and knife mill (Cadoche & Lopez, 1989).

Comminution of wood has traditionally been performed using methods detailed above, but Forest Concepts, LLC has developed a unique method of producing uniform feedstock particles from woody biomass. The system uses a rotary veneer lathe to peel the wood log, before passing the peeled surface through a rotary shear configurable Crumbler®[2] (Lanning, Dooley, & Lanning, 2012). Dooley et al. (2013) noted several advantages to using a veneer/Crumbler® combination, including the ability to process high moisture material, as well as reduced size distribution, energy consumption, and transport costs. Transportation of veneer is less expensive than chip transportation, primarily because veneer can be moved using flatbed trucks and does not require customized chip vans. It also has a higher bulk density than wood chips (150-200 kg m^{-3}) because there is no air space (Lanning et al., 2012; Tumuluru et al., 2010). The veneer has a Solid Volume Ratio of 1.0, much higher than slash (0.15 to 0.25), chips (0.35 to 0.45), or logs (0.70), making it more economical to transport (Dooley et al. 2013; Rummer, 2007).

While this in itself could increase the feasible transportation radius beyond 90 miles, the primary advantage is in reduced comminution energy and uniform size distribution (Figure 11and Figure 12). Figure 12 shows that 80% of chip particles are retained in No. 10 and No. 16 mesh by the Crumbler® technology, compared to 55% for traditional hammer milling. A more uniform chip size provides an opportunity for increased standardization in the refining process and addresses a key concern for the refining industry. Compared to traditional comminution methods, crumbling is much more efficient. The Crumbler® technique produces consistently-sized particles at a specific energy consumption of 150 MJ Mg^{-1} of dry wood, one-thirteenth the energy consumption of traditional comminution methods (Lanning et al., 2012).

[2] Crumbler® is a registered trademark of Forest Concepts, LLC, Auburn, WA

Figure 11. Crumbles produced using techniques developed by Forest Concepts, LLC (Lanning et al., 2012).

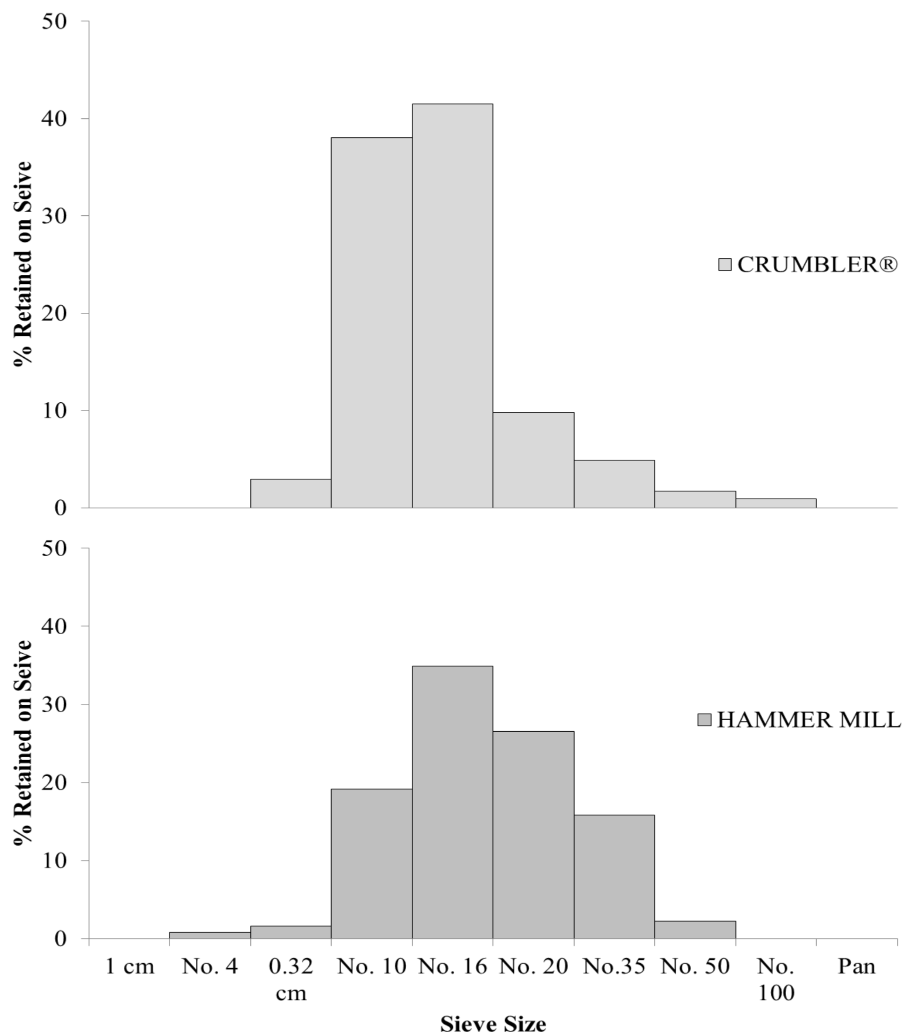

Figure 12. Size distribution for Crumbles compared to hammer mill processing for 2-mm nominal particle size.

Utilizing a Crumber® in pre-processing would enable separation of heartwood and sapwood from Eastern Redcedar, which has several benefits. Ethanol yield from Eastern Redcedar heartwood is lower than that of sapwood (Ramachandriya, 2013), and heartwood contains more essential oils than sapwood (Dunford et al., 2007; Semen & Hiziroglu, 2005). Separation of heartwood and sapwood would allow processes to be optimized for each tree component, improving oil and biofuel yield efficiency (Dunford et al., 2007; Ramachandriya, 2013). Despite the benefits of crumbing technology, there are several caveats for its implementation as the sole size reduction machinery in a pre-processing system. Oklahoma contains 8.2 million tonnes (7.4 million tons) of Eastern Redcedar biomass in trees 12.7 cm (5 in) or larger, of which 13% is tops, limbs, and stumps that cannot be processed in the same manner (McKinley, 2012a). Additionally, the Vermeer lathe can only process the log down to a 5 cm (2 in) diameter core, and the amount of material that can be recovered per log is proportional to log diameter (COE, 2013). However, the dowels could be utilized in other market areas.

3.3.3.2 Chemical

Representative pre-processing steps, especially for biofuel production or chemical extraction, typically include physical and chemical stages (Zhu & Pan, 2010). Dilute acid, steam explosion, and Sulfite pretreatment to overcome the recalcitrance of lignocellulose (SPORL) treatments are some common pretreatments for softwoods (Ramachandriya, 2013). Many other treatment methods exist, including concentrated acid, hydrothermal, auto-hydrolysis, wet oxidation, and various alkaline treatments (Carvalheiro, Duarte, & Gírio, 2008). The main purpose of dilute acid pretreatments is to make cellulose more accessible to enzymes without overly degrading products (Alvira, Tomás-Pejó, Ballesteros, & Negro, 2010). Hemicellulose breakdown using dilute acid is a promising chemical pretreatment process, despite the cost of acid and the production of fermentation inhibitors during the process (Carvalheiro et al., 2008). This method has been known since 1819 and can be conducted with several acids, including formic, nitric, phosphoric, sulphurous, sulphuric, hydrochloric, and hydrofluoric (Galbe & Zacchi, 2002). Table 6 shows conditions for acid pretreatment of certain softwoods.

Table 6. Acid pretreatment conditions for softwoods (Galbe & Zacchi, 2002).

Substrate	Pretreatment Conditions		
	Catalyst	Temperature (°C)	Time (min)
Pine	4.44% SO_2	200	10
Spruce + Pine	2.0 to 2.6% SO_2	188 to 204	2
Pine	0.5 to 12% SO_2	182 to 248	0.5 to 18
Pine	2.0 to 2.6% SO_2	150 to 208	2 to 20
Spruce	0.5 to 5% SO_2	190 to 220	0.8 to 4.2
Spruce	0.35% H_2SO_4	215	2.3
Fir + Pine	0.4% H_2SO_4	200 to 230	2.1 to 5.1
Spruce + Pine	1 to 6% SO_2	190 to 230	2 to 15
Spruce	0.5 to 4% H_2SO_4	180 to 240	1 to 20
Fir + Pine[a]	0.5 to 4% H_2SO_4 & 2.5% H_2SO_4	180 to 215, 210	1.7 to 4 & 1.7 to 2
Spruce[a]	0.5 to 4% H_2SO_4 & 1 to 2% H_2SO_4	180, 180 to 220	10 & 2 to 10

Steam explosion uses high pressure steam (20 to 50 bar, 210 to 290 °C [290 to 725 psi, 410 to 554 °F]) to break down the lignocellulose matrix (Carvalheiro et al., 2008). The technique is described as a "thermomechanochemical" process because of its mode of action (Chornet & Overend, 1988; Carvalheiro et al., 2008; Jacquet et al., 2012). The woody material's structure is broken down via heat, shear forces, and hydrolysis of glycosidic bonds (Carvalheiro, et al., 2008). Shear forces are generated during explosive decompression, after the material has been exposed to steam for several seconds to several minutes and rapidly depressurized (Alvira, et al., 2010). Jacquet et al., (2012) showed that char increased 16% after pyrolysis when the severity factor was increased from 5.14 to 5.55. This was quantified using a severity factor equation (3.3.1),

$$S=\log_{10} \int_{t_2}^{t_1} \exp\left(\frac{T(t)-100}{14.75}\right) dt, \tag{3.3.1}$$

where S is the severity factor, T(t) is process temperature (°C) and t_1 and t_2 are the start and end times of the reaction. Below a severity factor of 5.2, char levels ranged from 7.5 to 9.5% (Figure 13). Compared to other treatment technologies, steam explosion has less environmental impact, lower capital investment, and fewer hazardous chemicals (Alvira, et al., 2010).

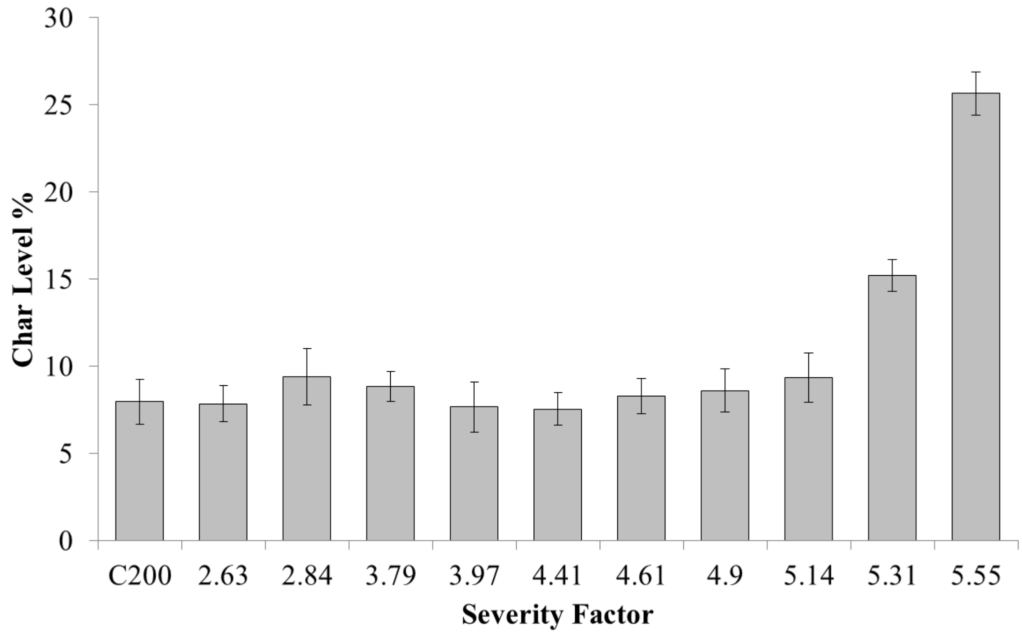

Figure 13. Carbonaceous residue levels after pyrolysis for cellulose C200 (control) and steam exploded samples (Jacquet et al., 2012).

In SPORL, wood material is mixed with a bisulfite solution (pH 2 to 5) at a temperature of 160 to 190 °C (320 to 374 °F) for 10 to 30 minutes (Zhu & Pan, 2010). The SPORL process is a recent chemical treatment processes, although pulp and paper industries have used similar processes for over 100 years (Zhu, Pan, Wang, Gleisner, 2009; Zhu & Pan, 2010). For this reason, much of the information produced in the study of sulfite pulping is transferable to SPORL pretreatments (Ramachandriya, 2013). In a study by Shuai et al. (2010), SPORL treatments had 91% cellulose to glucose conversion yields after 24 hours. In contrast, dilute acid yielded 55% conversion after 48 hours. Lodgepole pine was prepared for simultaneous fermentation and saccharification using SPORL, resulting in a calculated ethanol yield of 285 l t^{-1} (68.3 gal t^{-1}). Additionally, Shuai et al. (2010) noted 32% of lignin was dissolved to form lignosulfonate, a valuable co-product. Combining mechanical and chemical pretreatment, Zhu et al. (2010) examined the energy consumption of a post-chemical pretreatment size reduction, and found that energy consumption was reduced up to 80% (< 180 MJ Mg^{-1} of dry wood) by using a low pH SPORL pretreatment.

3.3.4 Industrial Market Potential

Eastern Redcedar is traditionally used for a variety of products, including wood furniture, fence posts, and mulch. Other more novel uses for the tree have been proposed including biofuel, pharmaceutical, particleboard, and essential oil production (Ramachandriya, 2013; Gawde et al., 2009; Hiziroglu et al., 2002; Hiziroglu, 2011). However, the current consumption of Redcedar for traditional end uses is not impacting the 121,000 ha yr^{-1} (300,000 ac yr^{-1}) encroachment rate and non-traditional industries have not developed (Drake et al., 2002). To begin restoration of land overrun with Redcedar and prevent its continued spread, 0.8 to 1.6 million ha yr^{-1} (2 to 4 million ac yr^{-1}) need to be treated (Drake et al., 2002). There are an estimated 462 million Redcedar trees in Oklahoma, approximately 6.5 million dry tonnes (5.9 million tons) in trees with diameters greater than 12.7 cm (5 in) (McKinley, 2012a). Expanding the use of low grade Redcedar logs in Oklahoma would aid in reducing the detrimental economic impact of this tree (Zhang & Hiziroglu, 2010). Figure 14 shows Potential Eastern Redcedar products while Figure 15 shows what would be considered a mature tree, with sections having significant economic potential labeled.

Figure 14. Commodities that can be produced from Eastern Redcedar. Top left to right: lumber, cedar oil, mulch, posts, medical chemicals, biofuel, veneer, and biofuel pellets.

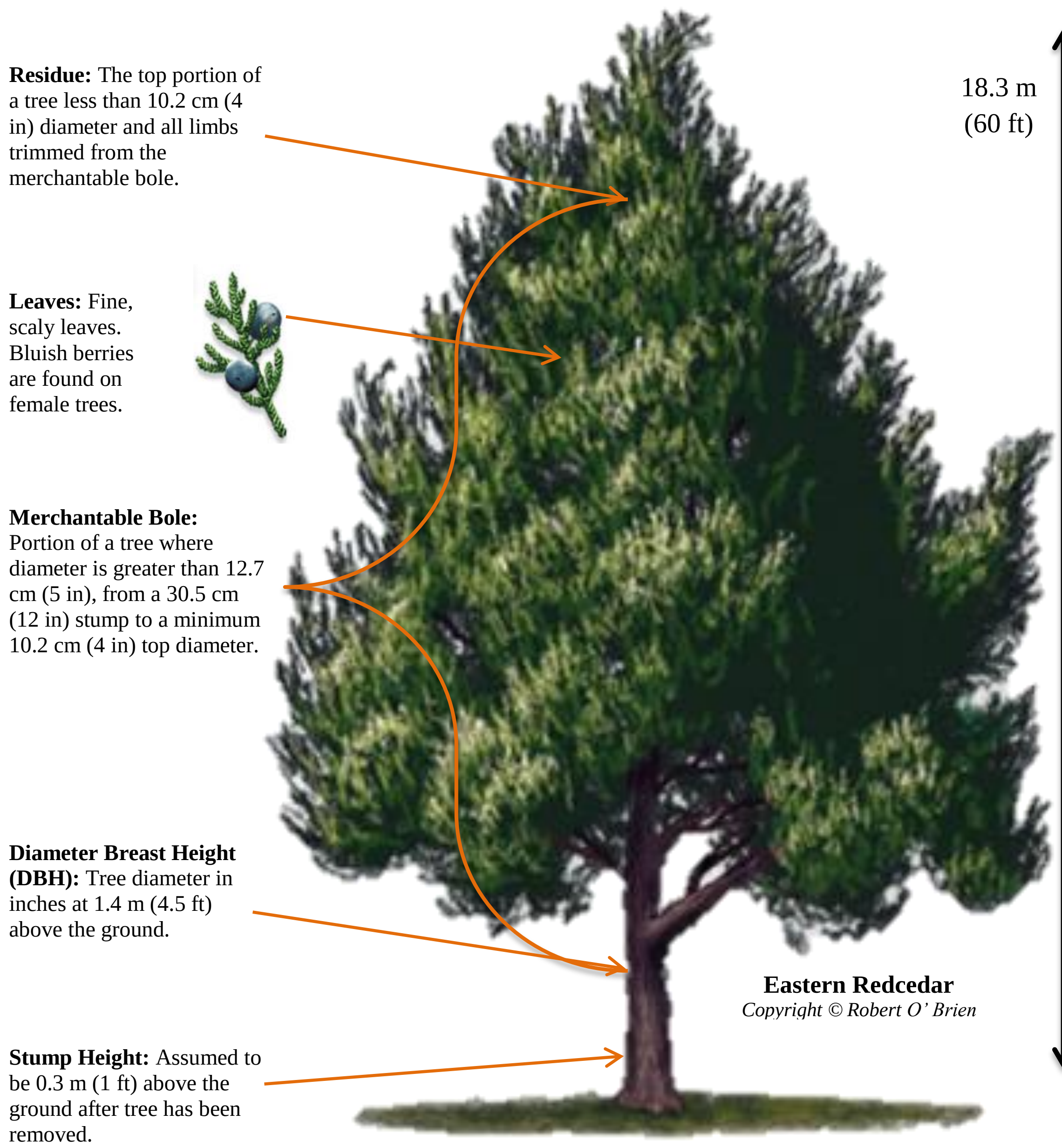

Figure 15. Components of an Eastern Redcedar tree. Different components may be more profitable for a specific end use, such as lumber for the merchantable bole or energy chips for the residue. Image from TAMU.

3.3.4.1 Wood Products

The largest source of demand for Redcedar in Oklahoma is for lumber products (Oklahoma Forestry Service [OFS], 2013). There are eight companies listed on the Eastern Redcedar Registry as of 2014 that purchase Redcedar logs to produce lumber, cants, posts, and poles (Figure 16). Demand for redcedar logs greater than 11.4 cm (4.5 in) in diameter and 244 cm (96 in) in length is over 100,000 for these businesses. Although this is a large quantity of redcedar logs, the vast majority (roughly 75%) of cedar trees in Oklahoma are 10.2 cm (4 in) dbh or smaller (McKinley, 2012a), making them unsuitable for posts. Only about 10% of Redcedar trees in Oklahoma can be marketed as quality lumber (McNutt, 2012). However, the marketable lumber can be sold for $5.91 and $7.28 per board meter ($1.80 and $2.25 per board feet) (T & A Sawmill, 2014) for lumber and beams respectively.

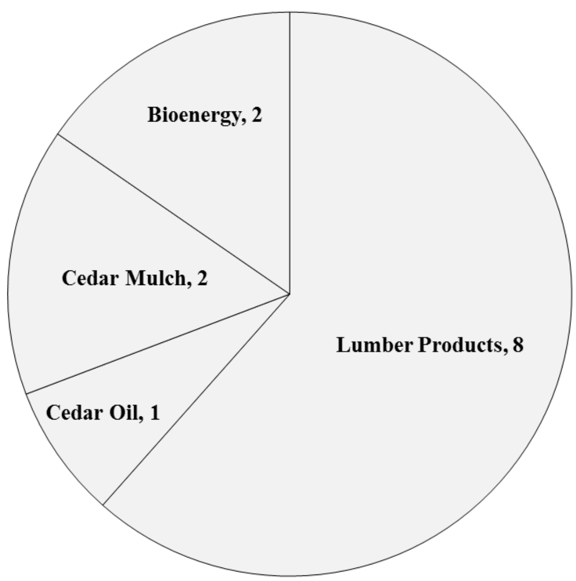

Figure 16. Oklahoma businesses utilizing Eastern Redcedar (OFS, 2013).

According to Drake et al. (2002), wood industry products would be more attractive business ventures than extraction of essential oil or bioenergy production, which were not evaluated. In 2002 a method to produce particleboard from Redcedar was developed and the material properties of the new particleboard quantified (S. Hiziroglu, personal communication, December 3, 2013). Using Redcedar is cheaper and faster than traditional methods because the entire tree is used, including limbs, bark, and even the needles. The material is structurally similar to those already on the market and has the added benefit of creating a “cedar chest” effect because of natural oils in the wood (Hiziroglu, Holcomb, & Wu, 2002; Zhang & Hiziroglu, 2010). However, to implement this technology, a particleboard mill would need to be constructed in Oklahoma at a cost of \$3 million to \$3.5 million (Mabra, 2002). Hiziroglu et al. (2002) estimated that the total delivered cost of material would be \$1145 m^{-3} (\$32.42 ft^{-3}), although this did not consider limbs or leaves that could be used in the manufacture of Redcedar particleboard. Although there is interest in these panels, there has been no major economic analysis or demand study conducted in Oklahoma (Zhang & Hiziroglu, 2010).

Table 7. Commercialization Attractiveness Index for potential Eastern Redcedar industries (Drake et al., 2002).

Oklahoma Redcedar Commercialization Attractiveness Indexing							
Industry	Startup Capital (Millions)	Research Investment (Millions)	Net Annual Income (Millions)	Probability of Success	Time to Implement (Years)	Barriers	CAI[x]
Particleboard	7	0.5	1	80%	5	Est. Cos.	2.47
Wood Flour	1	0	0.25	90%	1	Est. Cos.	3.6
Mulch	1	0	0.25	95%	1	Est. Cos.	3.8
Cedar Oil for Perfume	1	0.1	0.2	70%	2	Est. Cos.	2.43
Cedar Oil for Preservative	2	0.5	0.4	70%	4	Unproven Tech.	1.58
Wood/Plastic Composite	2	0	0.25	80%	2	Est. Cos.	4.53
Paneling	1	0	0.25	80%	2	Est. Cos. & Raw Material	2.26
Lumber	0.5	0	0.1	80%	2	Est. Cos. & Raw Material	2.83

[x]Commercialization Attractiveness Index:

CAI=(((Startup Capital + Research Investment)/Net Annual Income) x Probability of Success)/(Time to Implement)$^{0.5}$

3.3.4.2 Biochemical

One of the more interesting potential uses of Redcedar is biochemical extraction of compounds from plant material. Redcedar leaves contain cedar oil and podophyllotoxin, an anticancer compound (Figure 17). This compound is typically harvested from the Indian Mayapple because of the high podophyllotoxin concentration. However, the Indian Mayapple has been declared endangered, renewing interest in alternative sources such as the American Mayapple and Eastern Redcedar. The chemical is found in concentrations of 56 mg g^{-1} plant matter in American Mayapple and 1.45 mg g^{-1} plant matter in Redcedar.

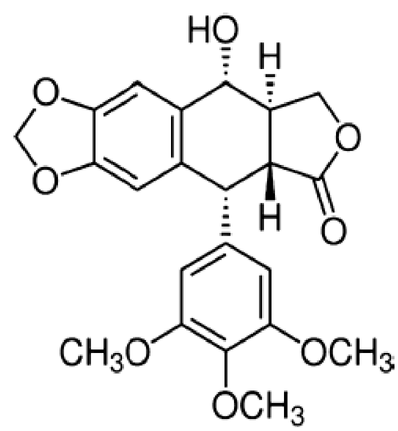

Figure 17. Podophyllotoxin structure (Gawde et al., 2009).

Experimentation by Gawde et al. (2009) showed it was possible to extract podophyllotoxin from Eastern Redcedar leaves with 72% recovery using steam distillation. Despite the low concentration of podophyllotoxin, Redcedar leaf biomass is more readily available, and available in larger quantities than American Mayapple, making it more desirable for chemical extraction (Cushman et al., 2003; Gawde, Zheljazkov, Maddox, & Cantrell, 2009). Aside from cancer treatment, podophyllotoxin is also used to treat rheumatoid arthritis, genital warts, psoriasis, and multiple sclerosis, making it a highly sought after commodity (Cushman et al., 2003).

Perhaps one of the most important products of Redcedar is cedar oil. Refined oil can be sold for up to \$11.9 l^{-1} (\$45 gal^{-1}) and has a wide range of applications, including pesticides, pharmaceuticals, and fungicides (McNutt, 2012). It is an active ingredient in five pesticide products used to control moths and fleas, and retard the growth of mildew (Environmental Protection Agency [EPA], 1993). It is also a major component of many non-pesticide products marketed in the U.S. It is a mixture of organic compounds and, as a food additive, is classified as GRAS or Generally Recognized as Safe. It repels insects via non-toxic modes of action, and the EPA does not consider its regulation worthwhile (EPA, 1993). Cedar wood oil is contained in varying concentrations throughout the tree, but most oil is obtained from shavings created during furniture manufacture. The highest concentrations of oil (2.2 to 3.8%) are found in the heartwood, with a lesser amount (1.3 to 2.3%) in sapwood. Older trees typically contain higher oil concentrations in each tree component (Dunford et al., 2007). Steam distillation is the most common method of Redcedar oil extraction, although continuous distillation is used by some commercial entities (Hiziroglu, 2011).

3.3.4.3 Bioenergy

Corporate interest in the growth of biofuel production from innovative feed stocks is being fueled by the Energy Independence and Security Act of 2007. This act mandates that 136 billion liters (36 billion gal) of renewable fuel be used annually by 2022 (U.S. Congress, 2007), a substantial portion of which must come from cellulosic ethanol production (EISA, 2007). Ethanol production could be a potential end use for harvested Redcedar in Oklahoma, eliminating a nuisance species, promoting economic growth, and safeguarding environmental resources. Studies have shown that Redcedar invasion rates and current biomass availability could support a substantial Redcedar-based economy (Drake et al., 2002; McKinley, 2012a; Starks et al., 2011). There are an estimated 462 million Redcedar trees in Oklahoma, roughly 8.7 million bdt (9.6 million bdt), with an additional 1.6 million bdt (1.8 million bdt) available in Ashe juniper, one-seed juniper, Pinchot juniper and pinyon pine (McKinely, 2012b). About 77% of Redcedar biomass is contained in trees with a diameter greater than 12.7 cm (5.0 in). From this 77%, merchantable bole is considered to be 80% of the biomass, while the remaining 13% is tops and limbs, and 7% is stumps. Figure 18 and Figure 19 show estimates made by NREM for total Eastern Redcedar biomass in Oklahoma and the estimated energy that could be produced (McKinley, 2012a). Approximately 143 billion MJ's (134 trillion btu) are available in trees with diameters greater than 2.54 cm (1.0 in), but 77% of this is contained in trees greater than 12.7 cm (5.0 in) in diameter. An assumed 16.28 MJ kg^{-1} (7,000 btu lb^{-1}) was used for the energy calculations, which takes into account potential heat losses during combustion (McKinley, 2012a). Although Eastern Redcedar is not listed, Table 8 shows higher heating values for similar wood species, such as Douglas-fir and Western Redcedar.

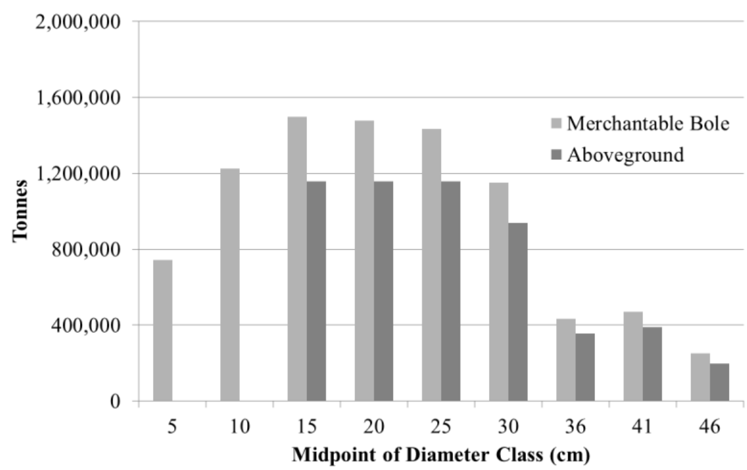

Figure 18. Estimate of Eastern Redcedar biomass availability (McKinley, 2012).

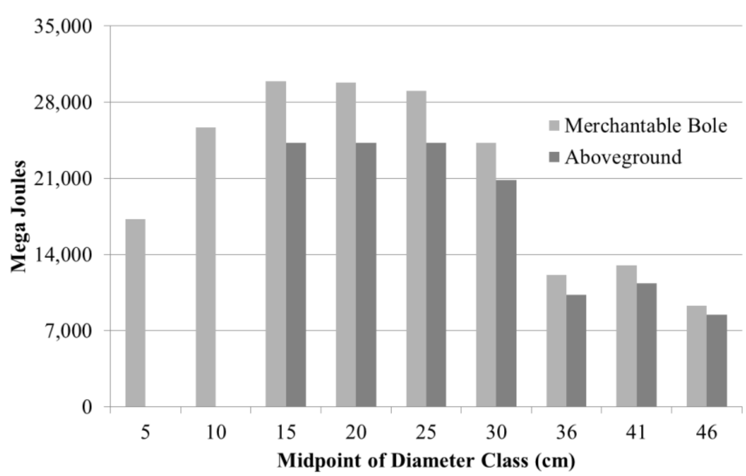

Figure 19. Estimate of potential energy available from Eastern Redcedar (McKinley, 2012).

Sessions et al. (2012) stated that the energy value of wood varies within a narrow range. This suggests that the energy estimates by McKinley (2012) may be conservative. The Redcedar Task Force determined that to break even with current Redcedar infestation in Oklahoma, juniper control measures need to be practiced on 121,400 ha yr^{-1} (300,000 ac yr^{-1}) (Drake et al., 2002). This would not reclaim infested lands, only prevent further infestations. To restore lands and keep them free of encroachment, 0.8 to 1.6 million ha yr^{-1} (2 to 4 million ac yr^{-1}) must be treated. For a 6-megawatt power plant, it would take 40,800 bdt (45,000 bdt) of wood, which could be removed from 800 to 1,000 ha (2,000 to 2,500 ac) annually (Drake et al., 2002). The initial investment for a plant of this magnitude would be between $2 million and $5 million per megawatt hour (Sessions et al., 2012).

Table 8. Higher heating values for certain wood species. (Sessions et al., 2012).

	Wood MJ kg^{-1}	Bark MJ kg^{-1}
Douglas-Fir *Pseudotsuga menziesii var, menziesii*	20.8	23.0
Western hemlock *Tsuga heterophylla*	19.5	21.7
Ponderosa Pine *Pinus ponderosa*	21.2	22.4
White Fir *Abies concolor*	19.0	---
Lodgepole Pine *Pinus contorta*	20.0	23.4
Bigleaf Maple *Acer macrophyllum*	19.6	---
Oregon White Oak *Quercus garryana*	18.9	---
Red Alder *Alnus rubra*	18.6	20.7
Western Redcedar *Thuja plicata*	22.6	20.2

There are several possibilities for wood chip energy production, including co-firing in coal plants, co-generation of steam and electricity, or liquid fuel production (Toms & Lewis, 1987). Wood chips act as a combustion promoter, reducing boiler slag, emissions, annual fuel costs, and the need for equipment modifications to meet clean air standards. Incorporating wood chips as a combustion promoter would allow for increased use of Oklahoma coal (which is high in sulfur) without violating clean air standards (Toms & Lewis, 1987). Alternatively, a facility such as Sun Rays 2 Oil using 40,800 bdt (45,000 bdt) of wood could produce 1,225 t (1,350 t) of cedar oil and 34 million liters (9 million gal) of jet fuel (McNutt, 2012). Yet another alternative would be production of cellulosic ethanol from Eastern Redcedar.

Nesbit, Alavatapati, Dwivedi, and Marinescu (2009) researched the economics of ethanol production from slash pine biomass, which is similar to Redcedar in some respects. Two conversion processes were simulated: a two-stage dilute sulfuric acid (2SDSA) process, and a synthesis gas ethanol catalytic conversion (SGECC). The former is well established, and commercial data was used in the model. The latter has not been used on an industrial scale, but showed promise to reduce ethanol prices. Nesbit et al. (2009) based the SGECC model parameters on a National Renewable Energy laboratory study conducted by Phillips, Aden, Jechura, Dayton, and Eggerman (2007). A delivery cost of \$47.60 gt^{-1} (\$43.18 gt^{-1}) was assumed for energy wood. Using standards typical for processing energy wood chips for ethanol, the 2SDSA and SGECC methods produced ethanol at \$0.93 l^{-1} (\$3.55 gal^{-1}) and \$0.46 l^{-1} (\$1.74 gal^{-1}) respectively. This included a price compensation factor to adjust for the higher energy content of gasoline. Nesbit et al. (2009) noted that the final delivered price of energy wood was a major component of unit ethanol cost (Table 9).

Table 9. Sensitivity analysis for price variations in ethanol production for two distinct processes (Nesbit et al., 2009).

Parameter Tested	2SDSA Process Original Value	2SDSA Process New Value	2SDSA Process Unit Cost ($/liter)	SGECC Process Original Value	SGECC Process New Value	SGECC Process Unit Cost ($/liter)
	($/tonne)			($/tonne)		
Feedstock stumpage rate (equivalent to PW rate)	5.51	8.94	0.66	5.51	8.94	0.32
Delivered feedstock cost (equivalent to corn ethanol)	47.60	0.00	0.32	47.60	47.60	0.31
Delivered feedstock cost (equivalent to switchgrass ethanol)	47.60	30.31	0.52	47.60	85.43	0.52
Delivered feedstock cost (+25%)	47.60	59.50	0.71	47.60	59.50	0.38
Delivered feedstock cost (-25%)	47.60	35.70	0.55	47.60	35.70	0.24
Ethanol conversion efficiency (liters/tonne) (+25%)	237	296	0.55	334	418	0.30
Ethanol conversion efficiency (liters/tonne) (-25%)	237	178	0.71	334	251	0.31

3.3.5 Additional Concerns

There are numerous minor parameters that have economic impacts on woody biomass utilization. Among these are biomass ash content and trash content, which affect refinery equipment maintenance costs, and the ability to quantify raw material moisture content for price adjustments. The ash content of woody biomass overall is about 2% by weight, but trash (dirt, rocks, etc.) increase ash content considerably (Ince, 1979; Naimi et al., 2009). The needles and bark comprise the majority of ash in pine and spruce, roughly 5% and 4% by weight, respectively. In comparison, the trunk is 1% by weight (Melin, 2008). As an evergreen, Eastern Redcedar should have comparable ash values. Ash content can be reduced to 1% of total weight by removing bark and tree needles. This would reduce particulates and slag in furnaces (Wood Pellet Association of Canada [WPAC], 2008). Beneficiation technology could be implemented to remove bark and leaves from chipped energy wood, reducing ash and improving yield for second generation cellulosic biofuel (Dooley et al., 2012). Trash should not be a major issue except for operations that involve extensive skidding and piling of material. Sessions et al. (2012) suggest eliminating this concern by separating residues into piles, for chipping and not for chipping. Moisture content affects several cost parameters, but in the southeastern U.S., most buyers do not adjust for moisture weight (Sessions et al., 2012). Compensation for feedstock moisture content is necessary, because the moisture evaporates and absorbs combustion energy (Ince, 1979). Sessions et al. (2012) found the cost of evaluating wood feedstock moisture content was $2 to 3 per sample. Another study by Olson (2006) showed moisture variability between truck loads warranted sampling each truck. The variability was such that, despite decreased sampling costs inherent in alternating sampling, sample bias resulted in increased cost to pulp chip purchasers (Table 10). Within a chip load there is considerable variability, and sampling protocols have not been standardized (Sessions et al., 2012). Sample location variability between sections of a chip trailer can be seen in Table 11. Each van had a sample moisture content range greater than 5%, indicating multiple samples are necessary to accurately estimate moisture.

Table 10. Unfavorable error from alternating chip moisture sampling in delivery trucks (Olson, 2006).

Trials	Two Trucks	Three Trucks	Five Trucks	Ten Trucks
10	0.12%	-0.04%	-0.18%	0.00%
50	0.10%	0.11%	-0.05%	-0.10%
100	0.15%	0.09%	0.08%	0.19%
250	0.12%	0.14%	0.12%	0.23%
500	0.11%	0.17%	0.17%	0.24%
1,000	0.11%	0.18%	0.19%	0.24%
1,500	0.10%	0.16%	0.19%	0.19%
2,500	0.10%	0.17%	0.18%	0.18%
5,000	0.11%	0.16%	0.17%	0.20%
8,000	0.11%	0.16%	0.19%	0.20%
10,000	0.11%	0.15%	0.19%	0.20%
20,000	0.11%	0.15%	0.19%	0.20%
30,000	0.11%	0.15%	0.19%	0.21%

Table 11. Moisture content for front and rear sections of 17 chip vans. (Sessions et al., 2012).

Van	Average for Van % dry	Average for van %MC	Front trailer %MC	Rear trailer %MC	Min %MC	Max %MC	Range %MC
1	65.0	35.0	34.1	35.9	32.0	37.0	5.0
2	66.0	34.0	38.7	29.3	28.1	40.0	11.9
3	76.1	23.9	27.2	20.6	19.8	29.0	9.3
4	74.9	25.1	22.9	27.3	16.8	32.8	16.0
5	79.6	20.4	19.0	21.9	18.5	25.3	6.8
6	74.2	25.8	29.2	22.4	21.6	30.4	8.8
7	70.5	29.5	32.8	26.3	25.1	35.3	10.2
8	77.6	22.4	22.5	22.2	21.3	25.8	4.6
9	62.3	37.7	44.6	30.8	29.7	47.0	17.4
10	72.7	27.3	23.4	31.1	21.7	32.2	10.5
11	71.2	28.8	27.7	29.9	26.6	30.8	4.1
12	65.0	35.0	36.2	33.8	31.4	37.1	5.7
13	65.4	34.6	36.7	32.4	31.9	38.8	6.9
14	67.4	32.6	30.5	34.7	26.3	37.3	11.0
15	73.7	26.3	25.7	26.8	24.1	27.8	3.7
16	62.2	37.8	34.4	41.3	33.0	42.9	9.9
17	75.2	24.8	30.7	19.0	18.0	31.7	13.7

3.4 Available Biomass and Logistics Models

Several models are available to estimate economic feasibility and logistics parameters for biomass transportation, processing, and biofuel production (Holcomb & Kenkel, 2008; Lau & Baldwin, 2014; Norris, 2009; Baker & Green, 2010). However, these models focus primarily on the evaluation of factors related to the utilization of energy crops for biofuels. There are no models to evaluate woody biomass utilization for bioenergy that account for harvesting, transport, storage, pre-processing, and end use variables. A potential reason for this lack of development is that fuel wood, wood wastes, and pulping liquors are already used for energy production in some way (DOE, 2011). Although the Integrated Biomass Supply Analysis and Logistics Model (IBSAL) provides methods to calculate costs incurred using woody biomass as a feedstock, review of the user manual indicates it is to be used primarily for energy crops such as wheat straw, switchgrass, and corn stover (Kumar, Sokhansanj, & Flynn, 2006; Sokhansanj, Turhollow, & Wilkerson, 2008).

Eastern Redcedar is also unique from other woody biomass in that it has multiple potential uses. Perfumes, pesticides, furniture, posts, bioenergy, mulch, preservatives, particleboard, and wood flour are all marketable commodities that could be products of a redcedar industry (Drake et al., 2002; EPA, 1993; McKinley, 2012a). Evaluating the economic feasibility of a redcedar-based industry for bioenergy alone would severely underestimate the economic potential of the industry. Essential oils can be produced from Eastern Redcedar using simple processes, such as steam distillation (Semen & Hiziroglu, 2005). This oil can then be sold at retail for \$53.95 kg^{-1} (\$24.47 lb^{-1}), representing a significant economic incentive (Texarome, 2013). Additionally, it is possible to extract podophyllotoxin, an anti-cancer compound, from the leaves. This chemical retails for \$6.29 mg^{-1} (Sigma-Aldrich, 2013) and would not be accounted for as a potential income in traditional biomass models.

3.4.1 Integrated Biomass Supply Analysis and Logistics Model (IBSAL)

IBSAL was developed by Oak Ridge National Laboratories to analyze biomass feedstock supply systems. The model simulates collection, transport, storage, and pre-processing of biomass and provides estimates of potential cost and energy consumption. The model's goal is to aid development of a sustainable and viable bioenergy industry in the United States (Sokhansanj et al., 2008). The IBSAL model uses spatial information such as weather data, farm size, crop yield, and transport data to evaluate relevant outputs. The platform used to develop IBSAL is EXTEND™, which has been linked with Microsoft Excel™ for data input and output (Sokhansanj et al., 2008).

This biomass model has been used to analyze the economic feasibility of a variety of potential biomass crops, harvesting, and transport techniques, and to develop new methods of collecting, storing, processing, and transporting biomass. An and Searcy (2012) developed parameters for a forage harvester pulling a module former, the module former itself and a module hauler. Using the newly developed machine elements, An and Searcy (2012) simulated the harvest of grass-type biomass for a refinery. A separate study (Kumar & Sokhananj, 2007) used IBSAL to evaluate multiple supply options for switchgrass: round and square bales, loaf piling of chopped material (a 2.4 x 6 x 3.6m compressed stack), and storage of silage. This study also reviewed three transportation options (bale, ground material, and chopped material transport) and evaluated several combinations of collection and transport methods. Delivered cost, energy consumption, and carbon emissions were the primary determinants for a best case scenario, which was to loaf material, grind the biomass using a mobile grinder, and transport it to the refinery. Factors other than cost have also been evaluated using IBSAL. Kumar et al. (2006) used both quantitative and qualitative information generated by IBSAL to rank biomass collection systems. The criteria included energy consumption, quality of material, maturity of technology, emissions, and delivered cost. However, despite the generally accepted performance of the IBSAL model, it was created to model straw and corn stover (Kumar et al., 2006). It has options to estimate woody biomass collection, transport, and pre-processing costs but it was not designed specifically for that task. A more focused model that explores in detail the costs associated with woody biomass utilization for energy would provide a more accurate estimate of feasibility.

3.4.2 Transportation Routing Analysis Geographic Information System (TRAGIS)

Transportation is a major factor in the economic analysis of biomass delivery for energy production. Numerous variables need to be accounted for when determining routes, including legal load limits. The Transportation Routing Analysis Geographic Information System (TRAGIS) has a database of 146,000 km’s (235,000 mi) of roadways, including all interstate highways and most U.S. and major state highways (Johnson, 2005). Building on two previous transportation models, HIGHWAY and INTERLINE, the TRAGIS model provides a graphical display of the route and allows for extra geographic route analysis (Johnson & Michelhaugh, 2000). The user interface and map data files are stored on the client’s personal computer, while the remaining data files and routing program are located on a network server (Shih et al., 2009).

The model is straightforward and allows the user to select options such as rail, highway, or waterway transport, road type, and avoidance of tolls (Johnson & Michelhaugh, 2000). However, one disadvantage of the model is that it cannot calculate routes for multiple transport modes, so highway, rail, and waterway routes can only be modeled singularly (Shih et al., 2009). It is an extensive and robust model, originally designed primarily for Department of Energy Operations (Dilger & Halstead, 2003). Although it is a useful model, the TRAGIS program was not designed for commercial use, and access is limited to registered users, of which there are just over 225, typically government agencies, subcontractors, and stakeholders (Johnson, 2005).

There are other transport routing models in addition to TRAGIS, such as GeoFreight, MOBCON, and ArcGIS for Transportation Analytics (Department of Transportation [DOT], 2014; Oak Ridge National Laboratory [ORNL], 2014; Environmental Systems Research Institute [ESRI], 2014). Although each one is different, they perform essentially the same function. The output data, distance, travel time, and road type/conditions can be used to estimate travel costs for freight material. These are powerful logistics models that could be used in conjunction with biomass harvesting and processing simulation functions to great effect.

3.4.3 Auburn Harvesting Analyzer (AHA)

The Auburn Harvesting Analyzer (AHA) estimates roundwood production costs according to specific harvesting parameters (Baker & Green, 2010). The primary parameters include quadratic mean diameter, tract size, tonnage per hectare, and quantity of trees removed per hectare (Baker Westbrook & Greene, 2010). Developed in 1984, the model uses Excel™ to estimate logging costs and can model virtually any system with few modifications (Wang, 2008). The main outputs of the model are loads and tons of wood produced day^{-1} and the cost to cut and load this material ton^{-1} (Baker et al., 2010).

The AHA was used by Bolding, Kellog & Davis (2009) to evaluate integrated fuel reduction operations in southwest Oregon. Using information collected during a productivity study, the AHA was used to calculate system productivity for the entire operation, and for harvesting or thinning saleable components of the stand only. Other studies have used the AHA to estimate total harvesting costs. Conrad et al. (2013) used the AHA to quantify harvest costs for integrated, energy wood, and conventional harvesting strategies. Comparison of integrated, conventional and energy chip only harvesting strategies employed the AHA to quantify harvest costs for each harvest prescription for comparison (Conrad et al., 2013). The system analysis by Bolding et al. (2009) using the AHA was extensive, including a feller-buncher, two skidders, loader, chipper, tub-grinder, and transport. The machine inputs by Conrad et al. (2013) were all-inclusive. The model was used to estimate costs for a feller-buncher, two skidders, two delimbers, two loaders, and two bucksaws, in addition to a chipper for the energy chip only prescription (Conrad et al. 2013). In a similar study evaluating integrated harvesting systems in pine stands (Baker et al., 2010), the AHA was used to estimate harvest costs for roundwood production and a modification to the program for chipping treatments. The model was used to conclude that biomass chips were less valuable than conventional wood products to landowners and loggers, and that the ratio of merchantable bole to chip weight ha^{-1} harvested was significant (Baker et al., 2010).

The AHA is a robust harvesting model that allows the user to simulate a wide variety of harvesting machines and harvesting scenarios. The model has been modified to evaluate chipping operations (Bolding et al. 2009; Conrad et al. 2013), but the main cost model generates roundwood production costs according to defined harvesting systems (Baker et al., 2010).

3.4.4 Other Models

One model of interest is the Cellulosic Ethanol Feasibility Template (CEFT). This model was developed at Oklahoma State University to aid agricultural producers, investors, leaders, and other decision makers in determining the feasibility of a cellulosic ethanol plant (Holcomb & Kenkel, 2008). The model provides a detailed analysis of costs associated with the development of an ethanol bio-refinery, but does not delve into harvesting, transportation, storage, or pre-processing of material. The CEFT accepts numerous inputs, such as equipment costs, up to four feedstocks, personnel costs, and even user-defined pre-treatment options (Holcomb & Kenkel, 2008). The large quantity of inputs and variable constraints necessitates that the model be complex and require some business and technical knowledge.

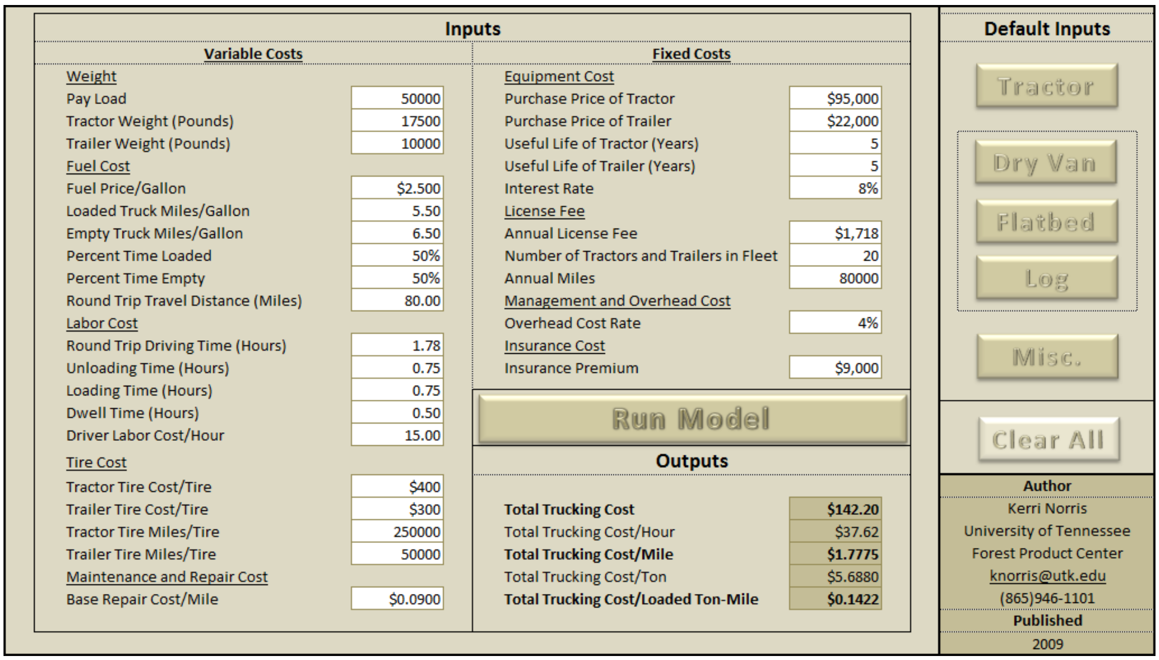

Figure 20. The BTCM trucking model utilizes Microsoft Excel™ and has one data input sheet (Norris, 2009).

Although it is more simplistic than the TRAGIS routing model, the BioSAT Trucking Cost Model (BTCM) could be easily incorporated into any cost model that utilizes a similar software platform, such as Excel™ (Figure 20). The program accepts nineteen variable costs that affect transportation costs, including pay load, fuel cost, labor, maintenance, and tire cost (Norris, 2009). Trucking operation and trip characteristics must be defined by the user, and based on this information, the model calculates costs. Sensitivity analysis can be conducted using the BTCM, varying multiple options to determine the optimum trucking configuration (Berwick & Farooq, 2003). The ability to conduct sensitivity analysis on transportation costs represents a significant benefit to users.

3.5 Summary

Eastern Redcedar is a rapidly spreading juniper tree in Oklahoma, occurring naturally in all but three or four counties (McKinley, 2012a). It is spread largely through small mammals and birds that eat the berries of female trees (Ferguson et al., 1968). Although it is native to the state, Redcedar is aggressively spreading through Oklahoma grasslands and cross-timbers. This rapid spread is causing extreme changes in native ecology through displacement of native flora and fauna. Herbaceous plants are eliminated at roughly 1500 trees ha^{-1} (600 trees ac^{-1}) , and a 1.8 m (6.0 ft) crown diameter tree can reduce aboveground plant biomass by 2.75 kg (6.0 lb) (Briggs et al., 2002; Stritzke & Bidwell, 1989). While certain birds benefit from Redcedar, Oklahoma’s obligate grassland bird species do not. Five bird species are negatively impacted by the spread of Eastern Redcedar, including the Bobwhite Quail, Song Sparrow, House Sparrow, American Goldfinch, and White-crowned Sparrow (Coppedge et al., 2001; Engle, Coppedge, & Fuhlendorf, 2008; Guthery, 2001). Beyond these detrimental impacts, Redcedar is a water wasting tree and increases wildfire hazards. Eastern Redcedar has a deep root system which allows a 31 cm (12.2 in) diameter tree to capture up to 150 liters (40 gal) of water per day from the soil profile, which can significantly change the grassland water cycle (Caterina, 2012; Hung, 2012; Zou et al., 2010). The tree’s thin bark and fine flammable foliage make it easily ignitable and can complicate wildfire control according to the Division of Agricultural Sciences and Natural Resources (DASNR, 2012). Drake et al. (2002) estimated the economic damage directly resulting from Redcedar was $447 million annually. Costly management techniques, which ranged from $7.40 to $395 ha^{-1} ($3.00 to $160 ac^{-1}) depending on stand condition and treatment technique, have resulted in the uncontrolled spread of Redcedar throughout Oklahoma (Bidwell et al., 2007).

Many studies have estimated the cost of transporting energy wood to a refinery to be nearly half the total operating cost (Felker et al., 1999; Hall et al., 2001; Harrill & Han, 2012; Mitchell & Gallagher, 2007; Pan, Han, Johnson, & Elliott, 2008; Perlack et al., 2005). Estimates for energy wood delivery cost vary from \$22 gt^{-1} (\$20 gt^{-1}) (Conrad et al., 2013) to \$100 bdt^{1}, with freight costs comprising roughly 30% of the delivered cost (J. Meibergen, personal communication, September 5, 2013). The high variability in cost estimates was due to the many factors noted to increase hauling rates, including travel distance, fuel prices, load size, and material moisture content. Travel distance is the primary reason for high delivery costs in most instances. By minimizing non-highway transportation, the total cost of material transport can be effectively minimized and transport distance increased (Pan et al., 2008). A survey by Bailey et al. (2011) suggested that a raw material transport radius of approximately 80.5 km (50 mi) would be a good base model for the biomass industry. Machine utilization rates have a significant effect on the profitability of delivering raw material to processing facilities (Aman et al., 2011; Harrill & Han, 2012; Mitchell & Gallagher, 2007). Increasing chipper utilization rates by 5% up to 70% have been shown to reduce delivered costs by \$1.10 bdt^{-1} (\$1.00 bdt^{-1}) and predicted total savings up to \$35.33 bdt^{-1} (\$32.05 bdt^{-1}) if utilization were maintained at 85% for all machines in the system. Conrad et al. (2013) noted that whole tree chipping operations had lower energy wood delivery costs compared to integrated harvesting systems. Spinelli & Visser (2009) also noted that organizational and miscellaneous delays accounted for 16.6% of lost productivity and that utilization rates near 90% were theoretically possible by minimizing the delay. Reducing delays, specifically organizational delays, would greatly reduce overhead costs (Mitchell & Gallagher, 2007; Pan et al., 2008; Vitorelo et al., 2011).

Eastern Redcedar presents additional complications, considering it is not grown in managed stands. Additionally, the wide array of value-added commodities which can be produced from Eastern Redcedar, including biofuel, cedar oil, wood flour, lumber, mulch, pesticides, particleboard, animal bedding, and pharmaceuticals (Drake et al., 2002), further complicates supply chain logistics. An incipient Redcedar industry exists in Oklahoma, with the largest demand being for lumber products (OFS, 2013). However, only about 10% of Redcedar trees in Oklahoma can be marketed for lumber (McNutt, 2012). Biofuel and pharmaceutical production from Eastern Redcedar are possible but are much riskier than other commodities. Drake et al. (2002) reported that a 6-megawatt power plant could consume 49,600 bdt^{-1} (45,000 bdt^{-1}) from 800 to 1000 ha (2,000 to 2,500 ac) annually. The capital cost would be between $2 million and $5 million per megawatt hour (Sessions et al., 2012). Experimentation by Gawde et al. (2009) showed it was possible to extract podophyllotoxin from Eastern Redcedar leaves using steam distillation with a 72% recovery rate. Redcedar leaf biomass is available in higher quantities than the current source, Indian Mayapple, despite the lower chemical concentration. This makes it much more desirable for chemical extraction (Cushman et al., 2003; Gawde et al., 2009). Essential oils could be removed from Redcedar using steam distillation for additional revenue (Hiziroglu, 2011), with a lesser amount (1.3 to 2.3%) in sapwood (Dunford et al., 2007).

Several logistics models are available to evaluate transportation, harvesting/processing, and refinement costs. TRAGIS is a GIS based transportation model that provides graphical displays of routes and includes all major U.S. highways (Johnson, 2008; Johnson & Michelhaugh, 2000). The model is straightforward and allows the user to select options such as rail, highway, or waterway transport, road type, and avoidance of tolls (Johnson & Michelhaugh, 2000). Other models such as GeoFreight, IBET, and MOBCON provide similar capabilities and are more readily accessible than TRAGIS, which is not intended for commercial use. The AHA can be used to estimate logging costs and models many different logging systems (Wang, 2008). It can be used to evaluate wood production and production costs for thinning operations and integrated logging systems (Baker et al., 2010; Bolding et al., 2009; Conrad et al., 2013).

A more comprehensive model, IBSAL, was developed by Oak Ridge National Laboratories to analyze biomass feedstock supply systems. It has been linked with Excel™ for data input and output and can simulate collection, transport, storage, and pre-processing of biomass (Sokhansanj et al., 2008). It has been used to model grass-type bio-refineries (An & Searcy, 2012), to multiply supply options for switchgrass (Kumar & Sokhananj, 2007), and to rank supply systems (Kumar et al., 2006). However, it was created to model straw and corn stover

(Kumar et al., 2006), and while it has options to evaluate a woody biomass supply chain, it was not specifically designed for that task.

A concern with the reviewed logistics models is that, with the exception of IBSAL, they focus only on a single stage of the supply chain, i.e. harvest or transport. In reality, each stage of the supply chain will be influenced by the previous stage, depending on the raw material, whether it is dried in-field, pre-processing steps, storage losses, handling losses, facility location, and other factors. IBSAL provides this capability to a degree, but its complexity may hinder its use in evaluating business ventures. Furthermore, there is no simple method of optimizing parameters or conducting extensive sensitivity analysis without considerable effort on the part of the user. An attempt should be made to incorporate probability distributions into the model to capture the real world variability inherent in any supply chain. Providing a simple yet comprehensive model with sensitivity analysis and optimization capabilities is essential to evaluate an Eastern Redcedar commodity supply chain and realize the full potential of Eastern Redcedar-based industries.

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CHAPTER IV

Manuscript to be submitted to Applied Energy

CONCEPTUAL DESIGN OF A BIOFEEDSTOCK SUPPLY CHAIN MODEL: EASTERN REDCEDAR

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Abstract

The ability to model a supply chain in its entirety, i.e. determining biomass availability, location selection, and the harvest, transport, processing, and refining costs, is a critical component of determining the economic feasibility of a given production strategy. To facilitate development of Eastern Redcedar commerce, a comprehensive, modular, commodity based supply chain model was developed as a computational tool. The conceptual model is web-based and has a modular design structure that gives it the flexibility to evaluate niche markets. Geospatial programming is used to perform location allocation, develop service areas, routes, and biomass yield maps. This data and user input data was employed to approximate costs at each stage in the supply chain. Users are provided the option to input their own operational data into the model or use distribution based data provided in the model. The distribution based data uses rejection sampling to generate random numbers according to empirical probability distribution functions for key cost variables in the Monte Carlo simulations. The interdependency, cost impact and sensitivity of variables on total system cost are derived from one-way sensitivity analysis. All results are displayed as interactive bar graphs, line charts, and maps. The conceptual model is focused on fully utilizing Eastern Redcedar by providing the user the ability to evaluate the economic feasibility of producing multiple end products simultaneously. The dynamic and modular framework of the model provides a strong foundation for expanding the model to other biomass feedstocks.

4.1 Introduction

Eastern Redcedar is a naturally occurring Oklahoma evergreen and the most widely distributed conifer in the Eastern USA (McKinley, 2012). Formerly limited to rocky outcrops and islands of land untouched by fire, it is rapidly spreading throughout the Great Plains region and currently covers an estimated 3.5 million ha (8.6 million ac) in Oklahoma (Starks, Venuto, Eckroat, & Lucas, 2011). The unchecked spread of Eastern Redcedar has incurred significant economic losses to the Oklahoma Economy in the form of enhanced wildfire, lost cattle forage, lost wildlife habitat, and decreased water availability. Volatile oils, thin bark, and fine foliage make it easily ignitable, complicating wildfire control efforts (Division of Agricultural Sciences and Natural Resources [DASNR], 2012). A tree with a 1.8 m (6 ft) crown may reduce plant biomass in the direct vicinity of the tree by 2.75 kg (6 lb); herbaceous plants are virtually eliminated at a density of 1500 trees ha^{-1}(600 trees ac^{-1}) (Briggs, Hoch, & Johnson, 2002; Stritzke & Bidwell, 1989). Eastern Redcedar is known to negatively impact Bobwhite Quail, Song Sparrow, House Sparrow, American Goldfinch, and White-Crowned Sparrow populations (Coppedge, Engle, Masters & Gregory, 2001; Engle, Coppedge, & Fuhlendorf, 2008; Guthery, 2001). In 2001, the economic impact of Eastern Redcedar on the Oklahoma economy was estimated at $218 million and expected to increase to $447 million annually by the year 2013 (Drake et al., 2002). Costly management techniques, ranging from $7.40 to $395 ha^{-1} ($3 to $160 ac^{-1}) are dependent on stand density and treatment method. These high management costs have led to Eastern Redcedar to spreading rampantly, despite the obvious economic, environmental, and social implications (Bidwell, Weir, & Engle, 2007). Reducing and reversing the advancement of Eastern Redcedar requires an alternative solution.

Eastern Redcedar lumber has long been valued for its color, aroma, decay resistance, and insect repellant attributes. As an industrial biofeedstock, tree components can be used to manufacture essential oils, wood flour, pesticides, particleboard, pharmaceuticals, animal bedding, and biofuels, in addition to traditional wood products such as lumber and posts. Many of the higher value products, e.g. composite panels, essential oils, or pharmaceuticals could be manufactured on an industrial scale to control the spread of Eastern Redcedar while simultaneously providing economic stimulus. Due to the risk and uncertainty associated with the industrial scale production of these bio-products, commercial ventures have not developed despite public support and business interest.

A biofeedstock supply chain presents unique logistical challenges, depending on the facility location, existence of processing hubs, transport, processing, harvest, storage, and refining costs. To garner confidence in Eastern Redcedar and other biofeedstock enterprises, the cost, variance, and risk of each stage in the supply chain must be characterized without over simplification. The purpose of this project was to develop an online, dynamic, robust, whole-system supply chain model to provide techno-economic data for a variety of alternative Eastern Redcedar supply chain scenarios.

4.2 System Architecture

Development of the Geospatial Logistics and Agricultural Decision Integration System (GLADIS) consisted of three stages: literature review current biofeedstock supply-chain systems and identify key model requirements, database development, and decision support system (DSS) development. The purpose of the literature review was to identify and gather information needed to create a biofeedstock model that uses specific user input data, model generated stochastic data or a combination user and model generated data. It was decided the supply chain model should be modular, i.e. individual cost sections for each supply chain stage: location, transport, harvest/process, and refining. Software and specific costing equations for each module were identified during this stage. The second stage focused on empirical data acquisition to develop probability distribution functions (PDFs) for costing variables, e.g. equipment, tire, and fuel, and the collection of biomass, potential facilities and finished product information.

The decision support system (DSS) was created using a MySQL database, HTML, CSS, JavaScript, and PHP. MySQL was selected to store production and distribution data because it is open-source, and capable of storing a large number of records. HTML, CSS, and JavaScript are the de-facto programming languages for web development. The web interface was built and styled using HTML and CSS. JavaScript functions and sub-modules process user inputs and data from the MySQL database before uploading the outputs to a server. This data is processed in PHP, a server side scripting language compatible with MySQL, and stored in the MySQL database.

The DSS refers to the modeling system as a whole and is divided into modules, e.g. site selection, transportation, harvesting, processing, and refining. A module is an independent component of the system that includes all database information, user inputs, and models required to generate specific outputs. The modules capture aspects of specific supply chain nodes, such as site selection or material harvesting. A module is composed of models, which provide abstraction from the main module. One or more modules exist within a module to evaluate sub-components of the supply chain node, e.g. labor, fuel, and maintenance costs, or to enhance functionality in another model. Each module was developed using a bottom up approach; outputs were defined,

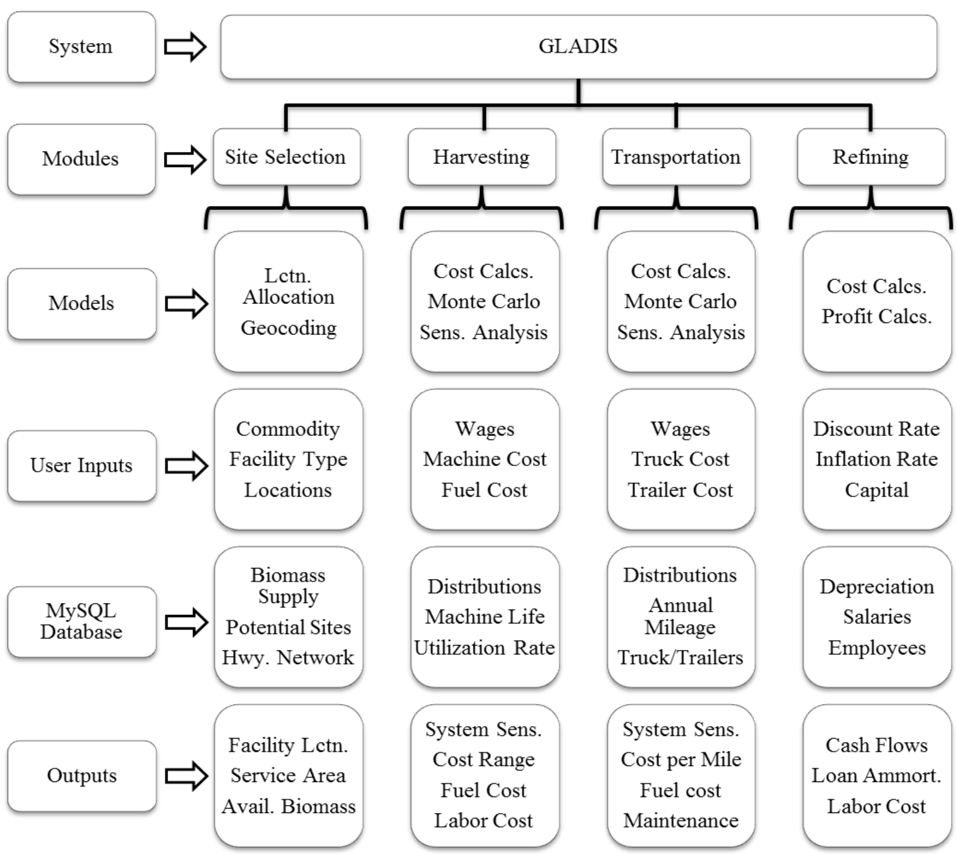

Figure 21. Hierarchy of system components. The system is broken into modules which comprise data inputs, functions, and sub-modules to produce module specific outputs. Not all variables or components are shown.

used to identify required inputs, and the database structure defined based on the required inputs and desired outputs. This approach facilitated development by providing a defined information and structural template. A basic outline of the modules, models, and module interaction were delineated as shown in Figure 21.

The site selection, harvesting/processing, transportation, and refining modules represent the primary nodes in a supply chain. The first step in GLADIS is to identify the optimal location for a biofeedstock facility. The ArcGIS JavaScript API (Environmental Systems Research Institute [ESRI], 2014a) includes network analysis tools which provided a straightforward means of implementing location-allocation. The location-allocation feature is a complex combinatorial problem that requires, at a minimum, a highway network, impedance limit, biomass supply, and a list of potential facilities (ESRI, 2014b). This information is formatted in JavaScript Object Notation (JSON) and transferred to ArcGIS servers via a PHP proxy page. Results from the analysis are used to generate visual representations of facility service area, calculate average annual truck mileage and approximate the number tractor-trailer combinations.

The transportation module uses the Husseign and Petering (2009) Milwaukee fuel cost approximation model and a modification of the Berwick and Farooq (2003) truck costing model for transportation managers. Harvesting and processing costs are evaluated in a similar manner using a machine rate model (Miyata, 1980). Using the database compiled during literature review and additional data (Table 12) listed in Brinker, Kinard, Rummer, and Lanford (2002), the machine rate variables are automatically populated when the client selects a machine and an approximate machine size, namely small, medium, and large. The models within the harvesting module were validated by comparing cost outputs with the machine rate form in Brinker et al. (2002).

Table 12. Subset of data obtained from Brinker et al. (2002) used in the machine rate model.

Machine	Size	Insurance[1]	Lube & Oil[2]	Repair & Maint.[3]	Fuel Cons.[4]	Hp	Salvage Value[1]	Life (yrs)	Util.[5]
Skidder	L	10	0.3677	90	0.028	148	20	5	60
Feller Buncher	M	10	0.3677	100	0.02633	140	20	5	65
Harvester	NA	10	0.3677	30	0.02633	120	20	6	80

[1]Pct. of retail price, [2]Pct. of fuel cost, [3]Pct. of annual depr., [4]gal per hp-hr, [5]Pct. of scheduled machine hours

The refining cost module is comparable to the Holcomb and Kenkel (2008) Cellulosic Ethanol Feasibility Template but more general, e.g. there is not a cost breakdown of the chemical products or physical steps required to manufacture a specific commodity. However, multiple product streams can be evaluated with specific product inflation rates, tax credits, production rates, and unit production cost. This is achieved by dynamically adding a data input form for each commodity output specified by the client. Additionally, the refining cost equations include variables for land, equipment, labor, construction, wage inflation, time value of money, tax rates, and product market value among other items. The JavaScript costing models in the refining module were checked for validity against the original template outputs.

To quantify variability within the supply chain, Monte Carlo and one-way sensitivity analysis were implemented for the harvesting and transportation modules. This required development of probability distribution functions (PDFs) for model variables. Determining the PDF for cost variables began with the compilation of raw, empirical data from the literature and online equipment listings. Distributions were fitted to the data using MATLAB® data analysis software (MATLAB, 2014) and a specialized program written by Sheppard (2012) for selecting the best fitting distribution. MATLAB® provides built-in functions to fit distributions to empirical data and rank them using Bayesian Information Criterion (BIC) (MATLAB, 2014). The program written by Sheppard (2012) utilizes these functions, but loops through all valid parametric probability distributions provided in MATLAB® and sorts them by BIC. These empirical distributions were stored in a MySQL database with the PDF name, range, and parameter values.

Monte Carlo simulations were conducted using a JavaScript distribution library which implemented rejection sampling to generate random values following a specific PDF. One-way sensitivity analysis characterized the impact of individual variables on overall system cost by incrementing cost variables through a plausible range and holding all other variables constant. From these analysis methods, relative cost impact, relative sensitivity, and the expected mean, variance, and quartile cost values were derived.

4.3 System Interface

Users enter information for simulations through a series of forms as shown in Figure 22 Clients may use a default input values or modify inputs to match their actual or estimated operating structure and costs; including distributed pre-processing hubs, drop and hook transport, custom harvesting machines, and/or multi-product production facilities. An auto-fill data option is available in the harvesting module for small, medium, and large skidders, feller-bunchers, forwarders, loaders, harvesters, dozers, chippers, and grinders, while the refining module provides auto-fill data for employee salaries and benefits. Relevant data from each module feeds into subsequent modules for calculations, e.g. facility throughput is used by the transportation module to estimate the tractor-trailers required for biomass transport. This layout enables users to run simulations using default values or customize data inputs. The user interface allows the user to auto-populate all required inputs, however, they are provided the ability to adjust system input data based on their actual or planned operation.

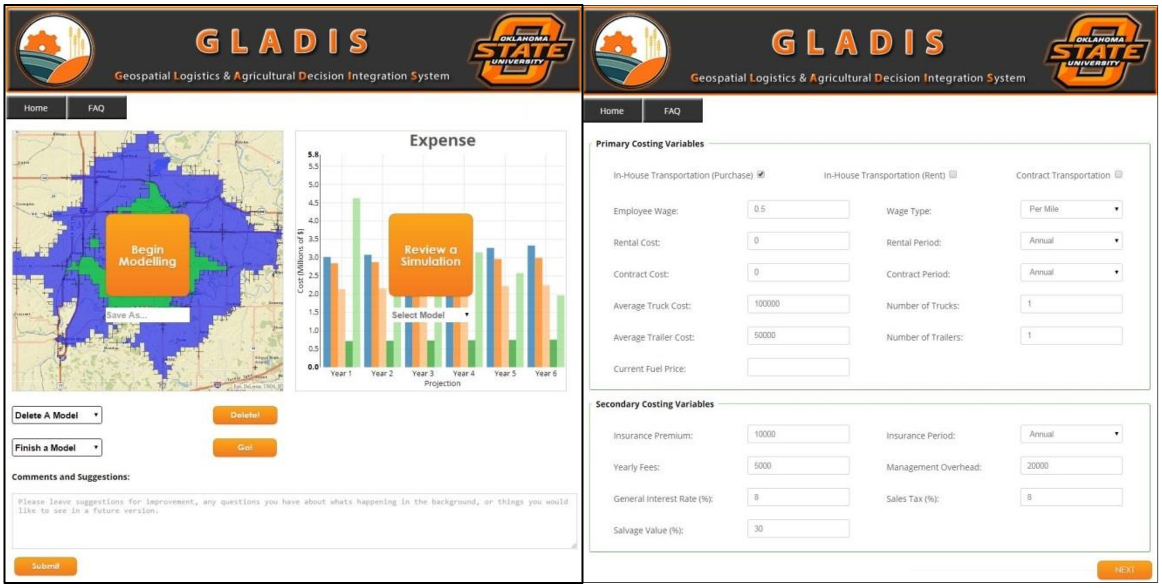

Figure 22. Model home page (left) and transportation module interface (right).

4.4 System Outputs

Economic results produced by GLADIS include graphical cost outputs for harvest/processing, transport, and refining. Currently, the output interface provides limited drilldown capabilities to view individual cost variables and system costs. If deemed important, this capability will be expanded in a future release. Harvesting costs are presented on a per hour basis and include total cost estimates for productive machine hours (PMH) and scheduled machine hours (SMH). The analysis represents the aggregate costs for all machines in the harvesting operation. These costs include fuel, labor, maintenance and machine ownership costs for the harvesting system. Transportation costs are displayed in a similar format with different cost components. The average fixed, labor, fuel, maintenance, and tire cost estimates for tractor-trailers is provided on a per mile basis.

Outputs generated from the refining module include loan amortization, and discounted expense/profit cash flows. For these projections, discounted cash flow is calculated using the loan term and a discount rate. The expense cash flow provides projected labor, production, maintenance, insurance, property, loan interest and miscellaneous costs. Profit projection includes the present value of income, gross sales, after tax profit and present value of expenses for

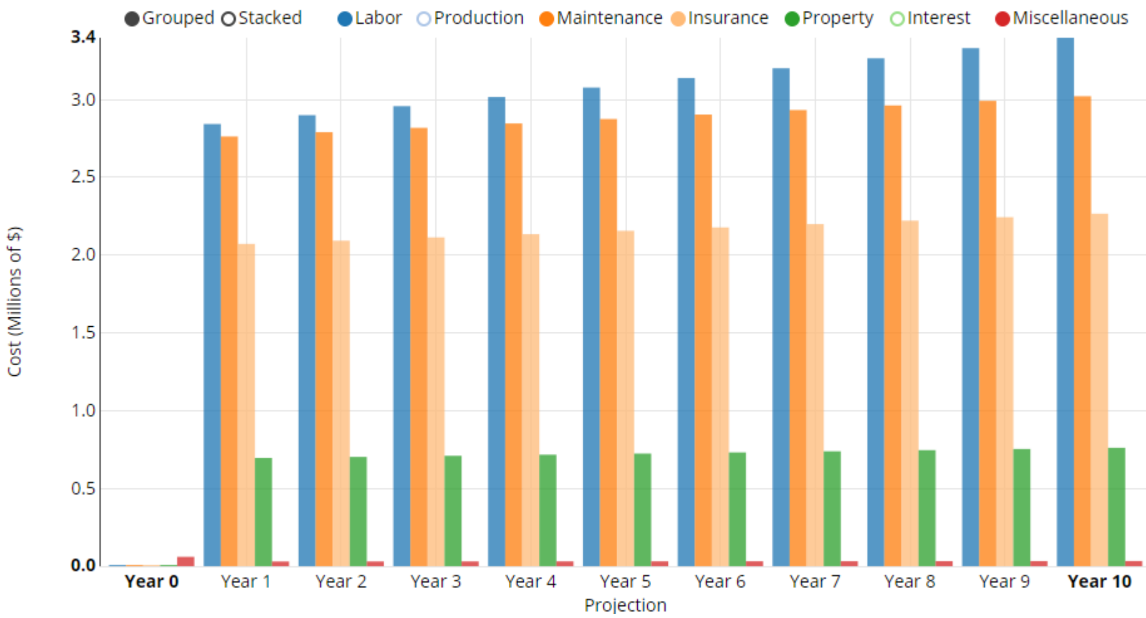

Figure 23. Example of refining discounted expense cash flow in the grouped view style.

comparison. To compare expenses across the supply chain, a composite chart is provided which contains the total cost of harvest/processing, transportation, and refining on an annual basis. Annual harvest/processing and transportation costs are calculated using default or user specified information such as facility throughput, scheduled machine hours, and number of tractor-trailers to convert per hour and per mile units to annual costs. Average annual refining expense was calculated by dividing the net present expense by the projection periods. An example of the techno-economic outputs produced is shown in Figure 23. Large cost components, such as labor or maintenance cost, may be removed to compare smaller cost components, such as property or miscellaneous costs. Hovering their computer mouse over the chart bars allows users to see the exact cost for each item.

Geospatial outputs include map representations of location allocation, service area and county level biomass yield maps. Spatial analysis determines biomass accessibility, maximum transport distance, and optimal facility location by maximizing biomass resources within a service area cutoff distance. The geocoding, location-allocation, service area and mapping tools incorporated in this model are a key component of the overall supply chain analysis, especially for facility location. Location allocation provides a means of location selection for a biomass facility based on the accessibility of raw feedstock material, such as Eastern Redcedar. This model minimizes biomass transportation distance and thus the overall cost of feedstock delivery. The model can be used to conduct a global or local optimization. The global optimization defines a population center as a city with a population greater than 500 and within the borders of Oklahoma. The local optimization includes only specified locations entered by the user. This configuration provides greater flexibility and provides the user the ability to account for qualitative parameters such as personal preference, community support, and government incentive. Both global and local analysis options may included distributed processing hubs in the simulation. Distributed processing hubs are smaller depot stations strategically located around the main facility preprocess biomass, thereby reducing transportation costs.

The maps generated in the site selection module provide users with much more than an optimized facility location address (Figure 24). The location allocation output indicates the distribution of biomass allocated to the facility or processing hub through lines connecting biomass points (circles) and the facility or hub (square). The relative quantity of biomass at each location is represented by the circle size, indicating how biomass quantities vary within the service area. The service area polygon map shows regions of inaccessibility and is broken into three equal distances, with the outer limit being the full service area. A county map with Eastern Redcedar data indicates the biomass quantity in each county by color intensity from green (low) to red (high). Clicking on a county displays Eastern Redcedar tonnage and acreage for the county.

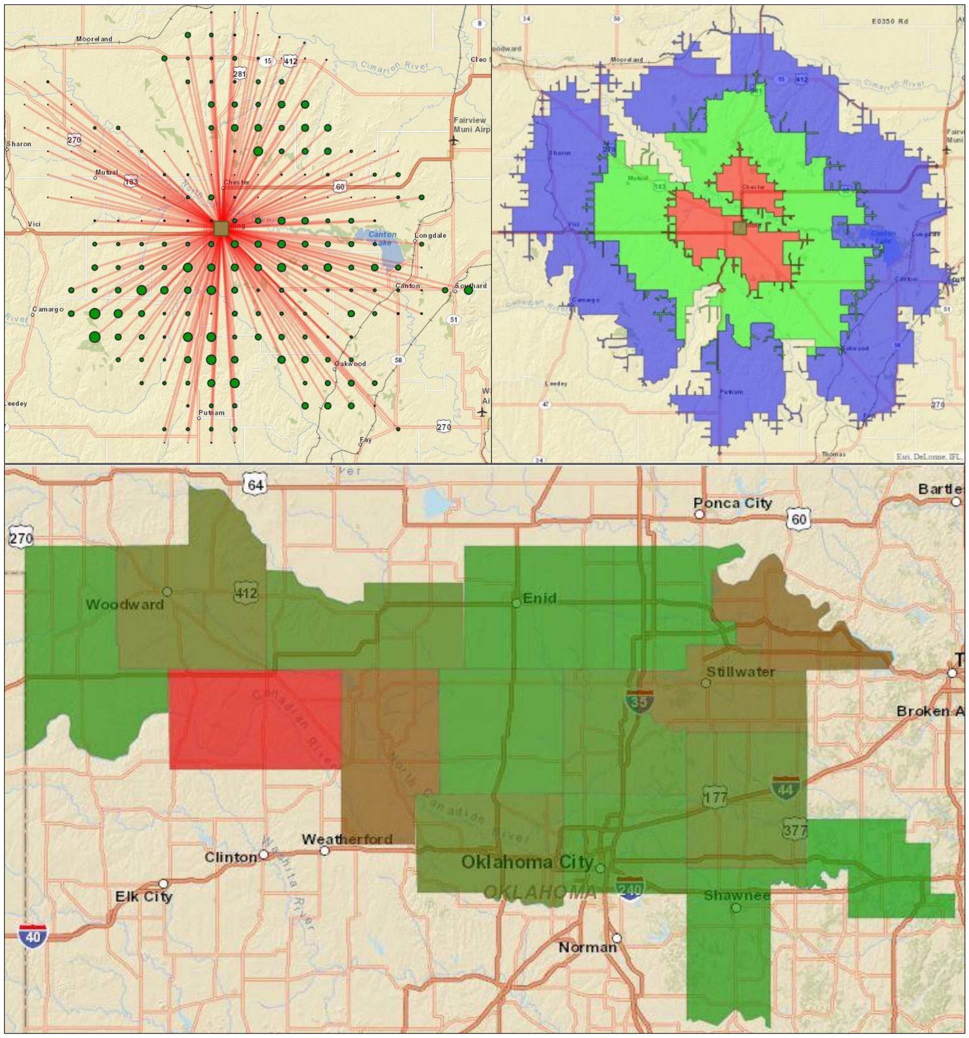

Figure 24. Location allocation, service area and county based Eastern Redcedar biomass maps.

Despite the algorithmic complexitity of this analysis, the user may run a simulation by, at a minimum, selecting "optimize" and specifying a service area limit. The model will identify a single facility location that minimizes biomass hauling distance within the service area limit. Results generated from this analysis include allocated biomass, average weighted transportation distance, and the location of each the facility and/or pre-processing hubs.

Variability in baseline data used in biofeedstock logistics systems like GLADIS is a critical issue that impacts the system's capability to provide reliable techno-economic outputs. This is due to uncertainty in cost factors such as fuel, machine life, productivity, and labor costs. The uncertainty of a given system can be quantified through Monte Carlo simulation and one-way sensitivity analysis, which are done automatically for the transportation and harvesting modules and based on the baseline data input into the system. This provides users the ability to determine the expected system cost based on stochastic probability distribution functions. The relative impact of variables on total cost, system sensitivity to variable changes and the overall dollar impact on system cost are also determined (Figure 25).

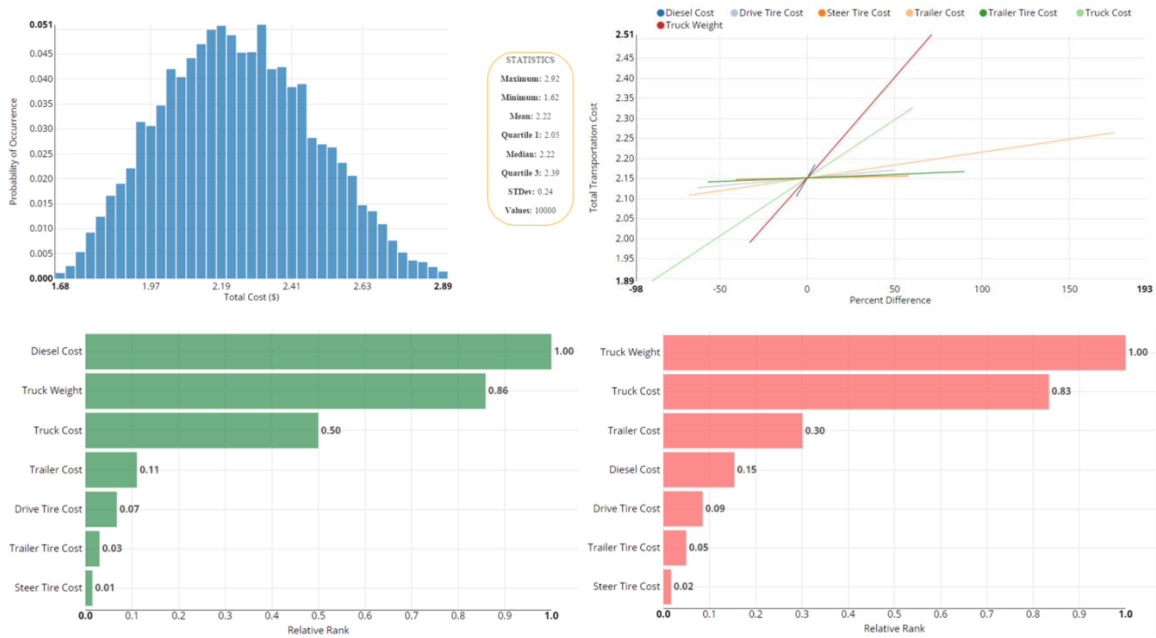

Figure 25. Monte Carlo analysis (top left), one-way sensitivity spider chart (top right), system sensitivity ranking (bottom left) and cost impact ranking (bottom right) of key transportation variables.

The Monte Carlo simulations use PDFs selected in stage two of development and a JavaScript library to generate random values that follow a specified distribution. Rejection sampling is used to generate the random values and allows virtually any PDF to be modeled. 10,000 simulations are run for the transportation and harvesting modules, using a randomly chosen value for variables with PDFs. A lack empirical of data prevents the use of distributions for all variables, but harvesting machine horsepower, truck weight, fuel, tire, and labor costs represent some of the model variables with distributions. Summary statistics reveal the expected cost variance, average, quartiles, and distribution of the supply chain stage. One-way sensitivity analysis provides an additional level of detail. This is done by incrementing a single variable is through its range while holding all other values constant. The range of values is assumed to be from the minimum to the maximum value in the empirical data compiled for the variable. This describes the relationship of the selected variable to total cost and indicates where efforts should be focused to minimize cost or maximize profit.

4.5 Conclusion

The GLADIS provides techno-economic, geospatial, and sensitivity analysis data for an Eastern Redcedar supply chain. Techno-economic data is generated for harvesting, processing, transport, and refining of Eastern Redcedar. Modeling information is entered through a simple user interface or default values from a database may be used. Results are displayed in interactive graphics with drill-down capability. Geospatial analysis provides an optimized facility location, facility service area, and county maps of Eastern Redcedar biomass. Uncertainty within supply chain nodes is quantified through Monte Carlo simulations and one-way sensitivity analysis, which ranks variables by cost impact and sensitivity. The modular design of GLADIS allows for quick expansion of analytical capacity and the inclusion of additional feedstocks, such as switchgrass or miscanthus. The model is expected to facilitate development of Eastern Redcedar industries and aid businesses, entrepreneurs, and government entities in stimulating the state economy. A beta version of the model is available at www.gladis.okstate.edu.

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CHAPTER V

Manuscript to be submitted to Biomass & Bioenergy

INCORPORATING GEOSPATIAL NETWORK ANALYSIS IN AN ONLINE BIOFEEDSTOCK SUPPLY CHAIN MODEL

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Abstract

Interactive GIS analysis is a key feature missing from the majority of biofeedstock supply chain models due to software costs and the need for specialized training. Incorporating GIS analysis into supply chain models could enhance their capabilities and value. Oklahoma State University has developed the Geospatial Logistics and Agricultural Decision Integration System (GLADIS) to provide facility selection, service area, and mapping features in a web-based supply chain model. Some of the primary analysis features included in GLADIS are location-allocation, service area determination, and mapping functionality. Location-allocation is used to identify the optimal location for a biofeedstock facility based on highway networks, trucking restrictions, service area distance cutoff, and biomass supply. Distributed processing hubs are modeled using a two level location-allocation solver to optimize their location relative to the main facility. The solver identifies total biomass available to the facility and processing hubs, and determines an average weighted transportation distance. A service area around the central facility is calculated to identify inaccessible regions according to the user specified distance cutoff limit. The results of each function are then displayed in interactive maps.

5.1 Introduction

There is a robust body of literature examining the various components of a biofeedstock supply chain, such as facility design and location, harvesting, transport, processing, storage, refinement, and distribution of bio-products. Despite this information, biofeedstock supply chain uncertainty continues to limit the development of bio-industries. The primary reason for this is a lack of consolidated information to accurately estimate a system's economic feasibility. A comprehensive method of applying existing research data to evaluate the interdependency of supply chain components, and the impact of these relationships on end product cost is needed. An effective means of closing the gap between economic potential and economic reality is the development of a logistics model to evaluate supply chain strategies. One of the most important aspects in supply chain development is bio-facility location.

Several software and modeling systems exist with the ability to optimize facility locations and several studies have detailed facility optimization procedures using these systems. One research group used a two stage GIS process to optimize facility location (Zhang, Johnson & Sutherland, 2011). The first stage identified potential facility locations based on specific criteria including population, rail and highway access. The second stage used a transportation cost relationship to identify the optimal location. Another study by Voets, Neven, Thewys, and Kuppens (2013) followed a similar methodology as Zhang et al. (2011) to identify the optimal location for a biomass refinery for phytoremediation of heavy metals. Integrated suitability analysis and location-allocation was used by Sultana & Kumar (2012), to identify facility size, location, and material transport costs.

Other site selection models include a mathematical model that considered distributed and centralized facility configurations simultaneously (Bowling, Ponce-Ortega, & El-Halwagi, 2011). The model was programmed using the General Algebraic Modeling System (GAMS, 2014) and included 38 binary variables, 219 continuous variables and 325 constraints (Bowling, et al., 2011). Another mixed integer linear programming model used GIS software to generate a distance matrix, biomass availability and production costs which are stored in a spreadsheet (Lin, Rodriguez, Shastri, Hansen, & Ting, 2013). This information can be read by GAMS, which can solve the optimization model. Data outputs can then be visualized using GIS software after exporting results to a spreadsheet. Location optimization with uncertain demand over multiple periods is considered by Baron, Milner, and Naseraldin (2011) in a capacitated facility location problem. Taking into account environmental sustainability concerns, Xifeng, Ji, and Peng (2013) developed a model which included CO_2 emissions as a minimization parameter.

These models provide robust methods of identifying an optimal facility location based on a given set of criteria. However, individuals without technical training in mathematical modeling, or modeling software may find use of the models challenging. In general, these models are limited by a) complexity, b) software availability and/or c) model versatility. Mathematical models (Bowling et al., 2011; Baron et al., 2011; Xiefeng et al., 2013) may need to be incorporated into programming or spreadsheet software to be useable. Bowling et al. (2011) and Lin et al. (2013) overcome this limitation by presenting the facility location optimization models in GAMS, but simulation of customized scenarios may be challenging and software accessibility to the user is a concern. GIS software reduces the complexity of location-allocation problems by providing a user interface to set parameters and manipulate data, but a substantial knowledge base is still required. The usability of site selection models could be increased by limiting model complexity from a user perspective, utilizing widely available software technologies, developing a scalable and customizable modeling system, while retaining the GIS software and location optimization model benefits.

Geospatial analysis has been incorporated into an Oklahoma State University's (OSU) web-based, techno-economic model, the Geospatial Logistics and Agricultural Decision Integration System (GLADIS). This system is currently focused on biofeedstock supply chain modeling with the target feedstock being Eastern Redcedar. The current use of GIS in this web application is focused on optimizing the location of a facility, the first stage of supply chain development. However, the modular framework of GLADIS has been designed so GIS analytics could be expanded to provide additional functionality such as multi-modal transport and spatial statistics. The objective for the GIS module in GLADIS was to provide GIS location-allocation and service area analysis to users in a simple interface without the need for additional software or technical training.

5.2 Database Development

The location-allocation component requires biomass supply points, potential facility locations, and potential preprocessing hub locations as input variables. Biomass supply points represent geographic locations with a quantity of Eastern Redcedar biomass associated with the point. This supply may be transferred according to a defined street network to geographic points that represent the location of a hypothetical preprocessing station or biofeedstock facility. To minimize user input requirements, a MySQL database of biomass supply points, potential facilities, and preprocessing hub locations was created. Biomass supply points for Eastern Redcedar were produced from canopy coverage maps made available by the Natural Resources Conservation Service (NRCS) using ArcGIS 10.2 (Environmental Systems Research Institute [ESRI], 2014a). These maps are comprised of approximately 2.3 million polygons representing Eastern Redcedar groves in three classes: 10 to 30%, 30 to 70%, and greater than 70% canopy cover in 18 Oklahoma counties (Staks, Venuto, Eckroat, & Lucas, 2011). An allometric equation relating canopy cover to aboveground dry biomass was developed by Starks et al. (2011) and is provided in Equation 5.2.1.

$$y = 639.1x + 4962.1 \qquad 5.2.1$$

Where y is aboveground dry biomass in t per ha and x is percent canopy cover. Available tonnage for each map polygon was estimated using the median canopy cover of the classes, i.e. 20%, 50% and 85%. To reduce data storage and processing overhead requirements, polygons were converted to centroid points. Each centroid point was grouped in a grid of 16.2 km^2 cells, and the biomass associated with each point summed. The total tonnage was stored in a MySQL database using the centroid of each grid cell as a point location, resulting in 2,343 supply points.

Potential facility and processing hub locations were developed using a similar approach. A dataset of Oklahoma population areas was downloaded and converted to centroid points (ESRI, 2014b). Although Zhang et al. (2011) used a population cutoff of 1,000 to constrain potential facility locations, 67% of the locations in the Oklahoma population areas dataset had a population below 1000, so a cutoff of 500 was chosen (ESRI, 2014b). All population centers meeting this criterion were stored in a MySQL database as potential facility locations. Potential processing hub locations included both potential facility locations and transportation network nodes, points where vehicles may enter or change route, from the Freight Analysis Framework Network (Department of Transportation [DOT], 2013). The transportation network nodes were included as potential processing hub locations because the hubs require highway access but do not have the labor demands of the main facility. The database tables contain 360 potential facility locations and 3,116 potential processing hub locations.

5.3 Application Development

GLADIS leverages the network analyst functions available through ArcGIS for Developers (ESRI, 2014c). Specifically, GLADIS uses the location-allocation, service area, and geocoding features to determine the optimal facility location and then generates map visualizations. The location-allocation solver identifies the optimal facility location by minimizing impedance (biomass quantity multiplied by transport distance) from supply points to the main facility (ESRI, 2014c; ESRI, 2014d). This procedure selects a facility such that the largest quantity of biomass is available within a given service area, which will minimize biomass acquisition costs (Searcy, Flynn, Ghafoori, & Kumar, 2007).

Users interact with the site selection component of GLADIS through a web interface (Figure 26). At a minimum, the user must select “optimize” and specify a service area limit to run a simulation. Alternatively users can run a more complex analysis by selecting a facility type, service area, product(s) to manufacture, estimated throughput, or entering user identified potential facility locations. The interface enables users to simulate distributed processing hubs or a single central processing facility using the database of potential facility locations (global) or user specified locations (local). To prevent entry of non-real locations, a Google Maps API predicts the location being entered based on the user's keystrokes (Google, 2014). The Google Maps API also ensures custom locations are in the proper format to be geocoded into latitude and longitude coordinates by the ArcGIS JavaScript API. After data entry is completed, potential facility locations, biomass supply points, and other parameters (Table 13) are converted to a JSON object. Currently, only the facilities to find and impedance limit are specified by the user; other values are preprogrammed into the model.

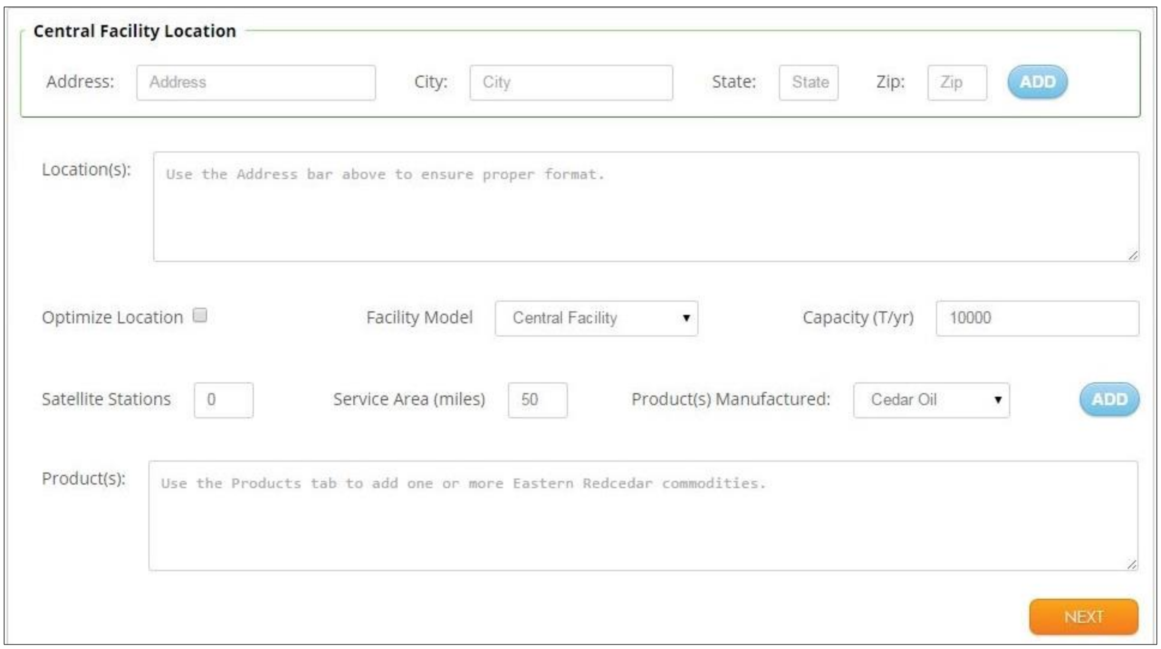

Figure 26. Web interface for users to enter parameters for optimizing a facility location.

Table 13. Analysis options specified for location-allocation solver.

Parameter	Value
Format	JSON
Measurement Units	Miles
Travel Mode	Trucking
Facilities to Find	1[a]
Analysis Region	North America
Problem Type	Minimize Impedance[a]
Impedance Limit	Integer, i.e. 35

[a]Dependent on facility model

A Hypertext Preprocessor (PHP) Proxy is used to transfer the JSON object variable to ArcGIS servers for processing (ESRI, 2014e). A proxy configuration file routes data for each GIS service to the appropriate server using web urls specific to the location-allocation, service area, and geocoding services. The PHP proxy is responsible for appending an identification token to the GIS service request and entering the JSON object into a processing queue on the server. The identification token is generated using OAuth 2.0 standards, enabling application authentication, i.e. users do not need to be associated with ArcGIS Online to use the services. The data transfer is asynchronous, so a job status query is sent to the server once per minute until the job is completed (1-3 min.) and the optimal facility location(s) returned.

A simplified schematic of this process is shown in Figure 27. Solving for the globally or locally optimal facility is a straightforward process, and requires data formatting, transfer to ESRI servers, and result retrieval. Optimizing the location of a central facility with distributed processing hubs is a two stage process. The first stage is identical to the process for optimizing a single facility location and determines the primary facility location for the second stage. The next step creates a buffer around the optimized location calculated in stage one that is 25% larger than the user specified service area, primarily to improve processing performance. Supply points and potential processing hub locations within the buffer are used to create a new JSON object variable. The location returned by the solver in stage one is specified as a required facility in the new JSON object.

Three solver parameters are modified before transferring the variable to the GIS server: facilities to find, problem type and service area. The “facilities to find” option is set to one plus the number of satellite stations specified by the user and the “problem type” is specified as maximize coverage. The service area limit for each processing hub and main facility is set to two-thirds of the original service area, effectively increasing the transport range of the main facility by 33%. This increase in the effective service area of the main facility is conservative considering the expected increase in biomass availability when utilizing a distributed processing hub facility model (Hess, Kenney, Ovard, Searcy, & Wright, 2009). Specifying these options distributes the processing stations around the main facility such that the maximum land area is accessible within the adjusted service area distance limit.

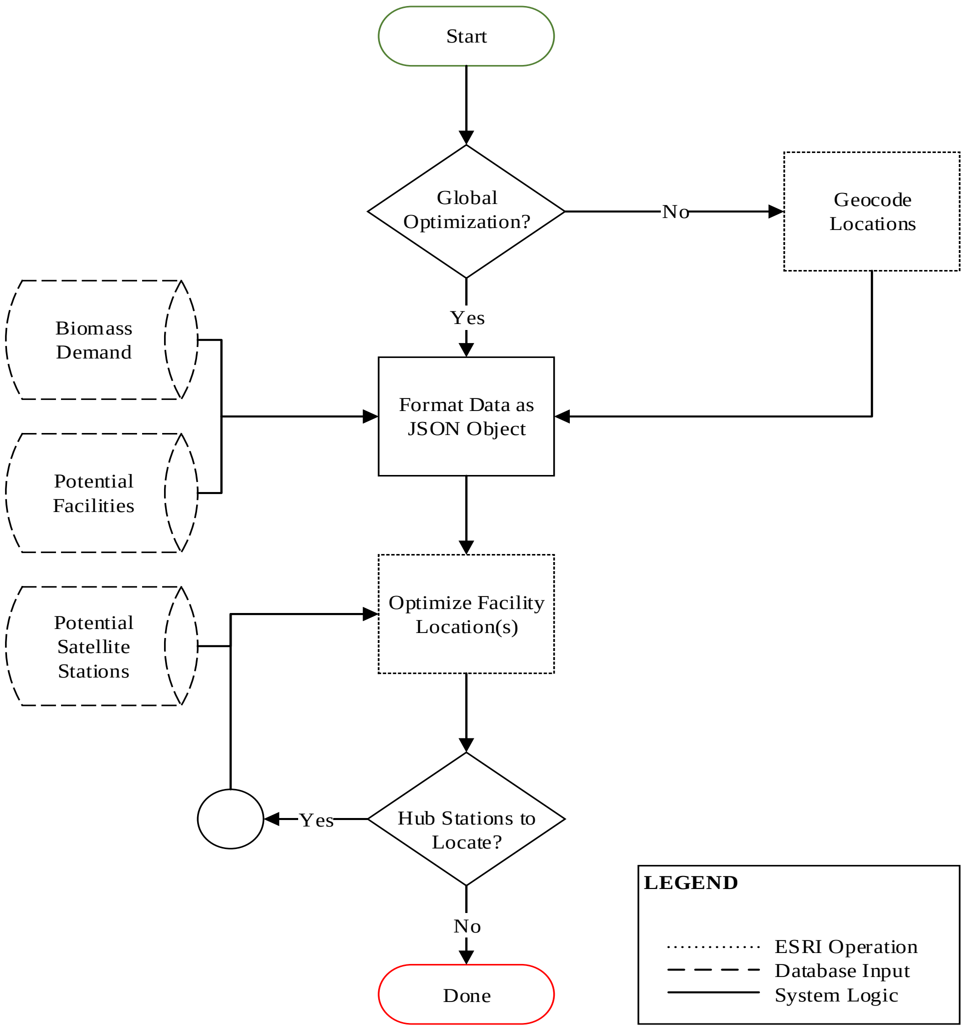

Figure 27. Schematic of operations to determine the optimal facility location and satellite station locations.

The final GIS analytical component creates a visual service area outline for the optimal facility and distributed processing hub locations generated by the location-allocation function. The service area is calculated using the same general procedure as the location allocation; create a JSON variable, specify parameters, transfer data to a GIS service, and retrieve the result. It uses the same service area distance limit specified by the user and all other applicable parameters remain constant.

5.4 Outputs

The results generated from the location-allocation provide the optimal facility location, its service area, accessible biomass, and weighted transportation distance (biomass tonnage multiplied by distance). The weighted transportation distance is used in the GLADIS trucking module to estimate the number of tractor-trailers required for a facility. A summary of the location-allocation results include the main facility location, available biomass, how long the facility can be supplied with biomass, and a brief statement of assumptions. However, the primary benefit is the graphical representation of facility service area and biomass allocation.

Figure 29 shows the location-allocation result for a single facility in Seiling Oklahoma, with a 48 km (30 mi) service area distance cutoff. The biomass supply allocation is shown by straight lines from the facility. The biomass assigned to the facility is represented as a point, the size of which indicates the relative quantity of biomass in that location. Although the location-allocation solver provides an indication of biomass accessibility, experimentation during the development of GLADIS suggested additional analysis was needed. Using the location-allocation parameters, a generalized service area representation was created for the facility (Figure 28). The added geospatial analysis was done for two reasons. First, the online location-allocation service has a snap tolerance of 20 km (12.4 mi) (ESRI, 2014c). Therefore, all supply points within 20 km (12.4 mi) of a street may be allocated to a facility location if the supply point is within the service area distance limit. Secondly, biomass data used for analysis is currently at least 10 years old (Starks et al., 2011). During that time, the quantity and location of available Eastern Redcedar biomass may have shifted due to new tree growth, controlled burns, and drought. GLADIS currently cannot account for new growth; however, the service area (Figure 28) provides an up-to-date graphic of accessible land. ESRI (2014f) states the highway network used for site selection and service area analysis is updated every four months, making old Eastern Redcedar biomass data the primary source of uncertainty when determining the facility location.

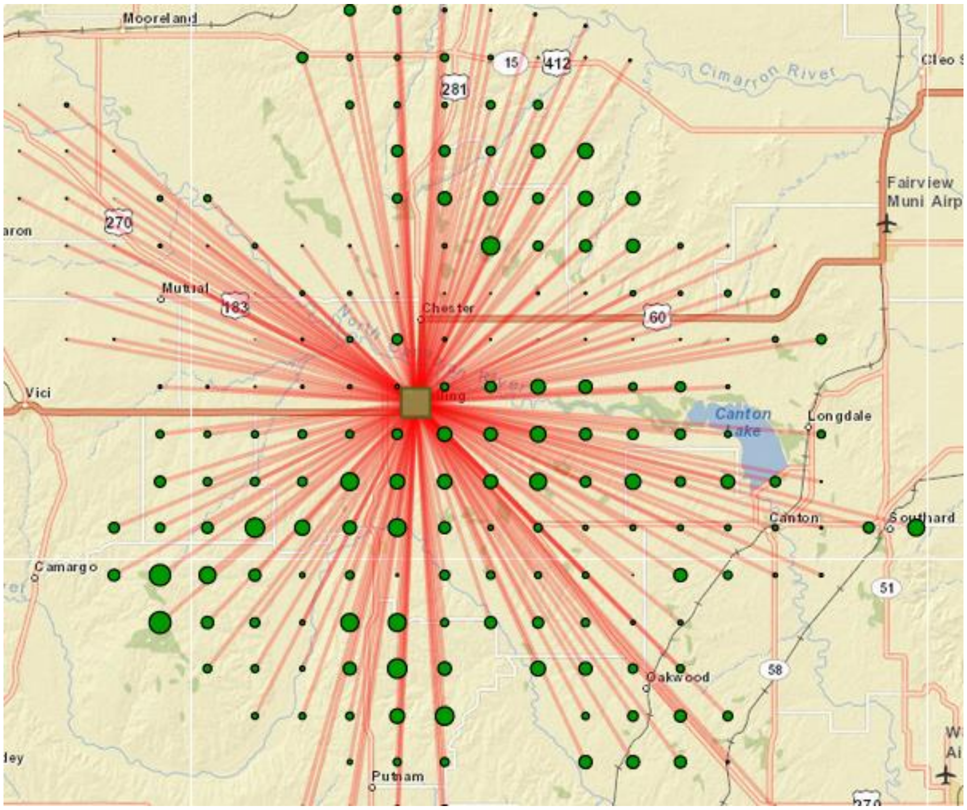

Figure 29. Biomass allocation to a hypothetical facility located in Seiling, OK.

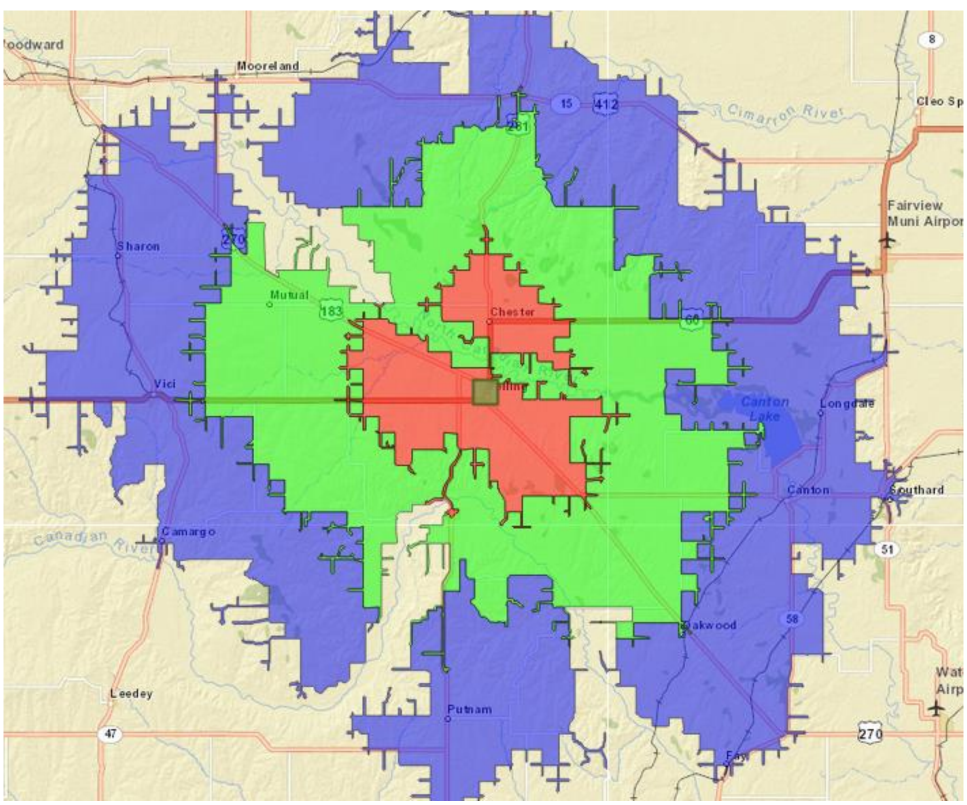

Figure 28. Service area for a hypothetical facility located in Seiling, OK.

GLADIS provides the ability to simulate distributed processing stations, which was noted to increase the feasibility of transporting biomass over long distances (320 km) (Hess et al., 2009). The resulting facility model is presented in Figure 30. Satellite stations are represented by blue squares and the main facility by a green square. The corresponding service area representation is shown in Figure 31. For the same location (Seiling, OK) and service area distance limit (48 km [30 mi]), the distributed hub model (Figure 31) results in fewer regions of inaccessibility and encompasses a greater overall area than the central facility model (Figure 28). This is most likely the result from a combination of the specified problem type, maximize coverage versus minimize impedance, and the addition of processing hubs. Future versions of GLADIS will provide advanced options allowing the user to modify more of the default parameters, e.g. problem type, highway restrictions, travel mode, and impedance transformations.

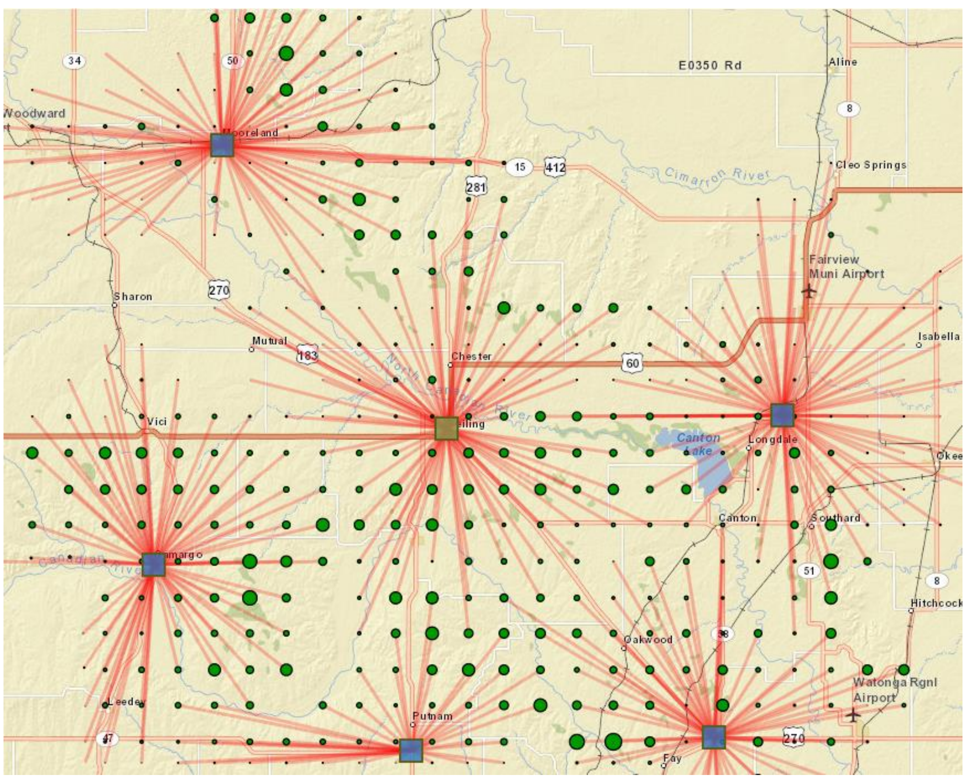

Figure 30. Biomass allocation for a facility with five processing hubs in Seiling, OK.

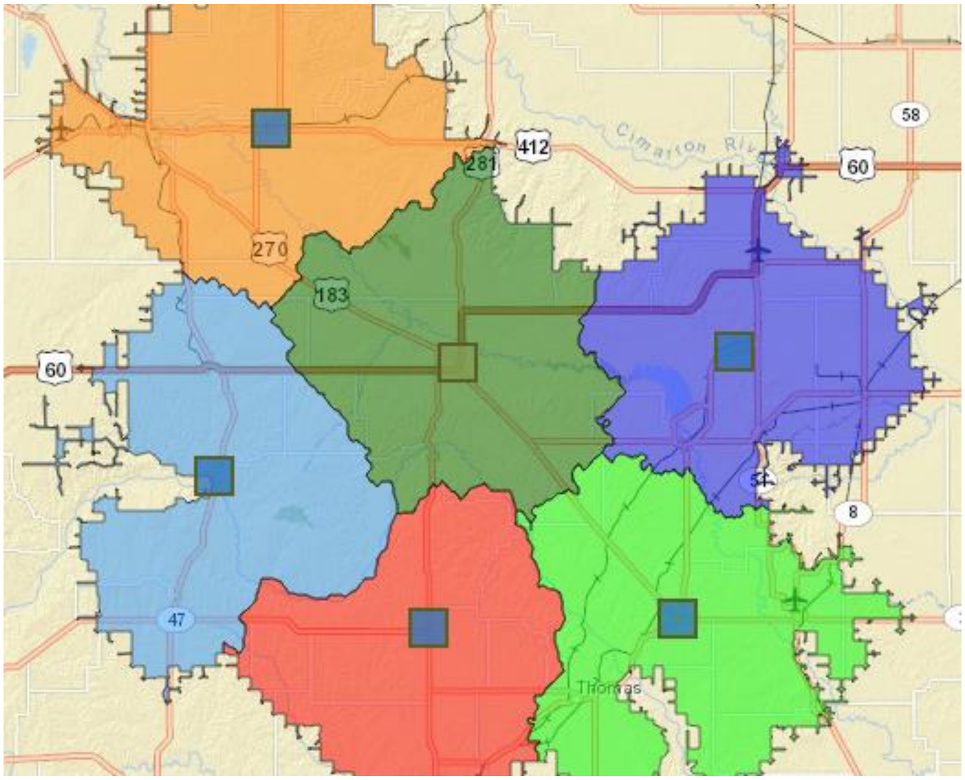

Figure 31. Service areas for a hypothetical five processing hub facility in Seiling, OK.

5.5 Conclusion

GIS network analysis provides a method of determining the optimal location of a biofeedstock facility that maximizes available biomass and minimizes transport cost. The GIS analysis is complemented by the creation of a facility service area to provide a more detailed representation of accessible land regions within a specified impedance limit. The inclusion of processing hubs can be modeled using a two level location-allocation solver to identify the best regional location and then the optimal location of hubs to maximize service area coverage. Incorporating these features into a web-based supply chain model makes high level GIS analysis available in a simple format to non-GIS specialists, without reducing the viability of results. The generated outputs are used in other sectors of the web-module and improve the overall simulation. Future work includes expansion to model multi-modal transportation networks, suitability analysis, and crop yield predictions. A beta version of the GLADIS model has been released and is available at www.gladis.okstate.edu.

5.6 References

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CHAPTER VI

Manuscript to be submitted to International Journal of Production Economics

WEB-BASED DEPLOYMENT OF SINGLE-FACTOR BIOFEEDSTOCK SUPPLY CHAIN SENSITIVITY ANALYSIS USING MONTE CARLO SIMULATION

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Abstract

There is a high degree of uncertainty in biofeedstock supply chains that is not easily quantified in current modeling systems. Monte Carlo and one-way sensitivity analysis can be used to quantify supply chain uncertainty and identify critical cost factors. To improve current supply chain modeling capabilities, Monte Carlo and one-way sensitivity analysis were incorporated into an online, modular, commodity based supply chain model. Empirical data was compiled to create distribution functions for key system variables so a stochastic solution could be determined using Monte Carlo simulations. The sensitivity analysis programs were written in JavaScript to facilitate online development. Sensitivity analysis results for biofeedstock transportation indicated the system was most sensitive to changes in fuel cost while truck weight had the highest potential cost impact. Minimum, maximum, average, and quartile cost estimates were calculated from the Monte Carlo simulation. Analysis results are displayed graphically and include the system cost distribution, variables ranked by both sensitivity and potential cost impact. The inclusion of robust sensitivity analysis techniques in a web-based supply chain modeling system is an improvement over current systems. Additional value is provided to users for better quantitative analysis of biofeedstock supply chains.

6.1 Introduction

Monte Carlo analysis is a deterministic method of evaluating a complex system by calculating a finite number of outcomes using parameter values randomly generated according to their defined probability distribution (Metropolis & Ulam, 1949). The law of large numbers indicates that subsequent statistical analysis of the resulting outcomes will be representative of the overall system. The effect of system parameter value inaccuracies can be quantified using one-way sensitivity analysis, which systematically varies each parameter through its probability range (Kjaerulff & van der Gaag, 2000). Each of these methods has been used to evaluate uncertainty in biofeedstock supply chain systems in prior studies (Hess, Kenney, Ovard, Searcy & Wright, 2009; Awudu & Zhang, 2012; Kim, Realff, & Lee, 2011; Awudu & Zhang, 2013). Hess et al. (2009) outlines an approach to transition biofuels industries to an advanced supply chain infrastructure, designed to overcome current economic, sustainability, and logistics concerns. Researchers used Monte Carlo and one-way sensitivity analysis to determine the cost distribution and rank supply chain variables by their relative sensitivity and cost impact. Kim et al. (2011) used sensitivity analysis to determine high impact variables as part of a two stage process to maximize profit for a given scenario. The identified high impact variables were then incorporated into a Mixed Integer Linear Programing (MILP) model programmed in the General Algebraic Modeling System (GAMS, 2014). Another methodology was also used to solve a deterministic and stochastic model (Awudu & Zhang, 2013). The stochastic model was solved using Monte Carlo simulation, specifically due to the existence of uncertainties in the model parameters. These techniques are useful for ranking system variables by importance and determining the overall system distribution. Each of these outputs are integral to understanding a biofeedstock supply chain and implementing best management practices.

Oklahoma State University (OSU) has developed the Geospatial Logistics and Decision Integration System (GLADIS) a modular, systems-based logistics and techno-economic model to evaluate biofeedstock supply chain components, with a specific focus on Eastern Redcedar. A biofeedstock supply chain presents unique logistical challenges, depending on the facility location, existence of processing hubs, transport, processing, harvest, storage, and refining costs. Companies looking to invest in Eastern Redcedar industries have expressed a need for characterization of the cost and cost variance at each stage in the supply chain, without over simplification. An effective means of addressing this critical, stakeholder identified need is through the development of an online, whole chain logistics system that is flexible and sufficiently robust to provide techno-economic data for a variety of alternative supply chain scenarios. One of the primary outputs required by users of this web-based model is quantitative information from sensitivity analysis for risk management, such as cost variance, and the minimum and maximum possible costs. The impact of individual variables on total cost can be determined and system variability quantified to evaluate the likelihood of specific outcomes. The purpose of this manuscript is to describe the approach used to develop and implement single-factor sensitivity analysis in an online supply chain model and provide an overview of analysis results.

6.2 System Distribution Development

Prior to implementing Monte Carlo simulation and one-way sensitivity analysis in the supply chain model, it is necessary to know the properties of certain system variables. Specifically, it is desirable to know the probability distribution function (PDF) that characterizes each variable. Determining the PDF for cost variables began with the compilation of raw, empirical data from the literature and online equipment listings. Distributions were fitted to the data using MATLAB® data analysis software (MATLAB, 2014) and a specialized program written by Sheppard (2012) for selecting the best fitting distribution. MATLAB® provides built-in functions to fit distributions to empirical data using maximum likelihood estimates and determining rankings for model selection, such as Bayesian Information Criterion (BIC) (MATLAB, 2014). The program written by Sheppard (2012) utilizes these functions, but loops through all valid parametric probability distributions provided in MATLAB® and sorts them according to a specified ranking parameter. BIC was chosen as the ranking criterion because it penalizes for model complexity (number of parameters), considers goodness-of-fit, and sample size. The equation for BIC is given in Equation 6.2.1.

$$\mathrm{BIC} = -2(logL) + (X * \log(Y)) \qquad 6.2.1$$

Where *logL* is the log-likelihood, *X* is the number of parameters, and *Y* is the number of observations (MATLAB, 2014). It should be noted that the BIC does not determine the "best" probability distribution, but serves as quantitative method of choosing one distribution over another. These empirical distributions were stored in a MySQL database with the PDF name, range, and parameter values.

6.3 System Implementation

To perform Monte Carlo simulations, the PDF data was extracted as an associative array, and the distribution name matched to a random number generator. Simulating a specific distribution was achieved through the implementation of rejection sampling as illustrated in Figure 32. Rejection sampling entails defining a grid from zero to the maximum probability value of the distribution on the y-axis, and constraining the x-axis to the minimum and maximum values of the empirical data. Programmatic implementation of rejection sampling was performed in JavaScript and a PDF specific random number generator programmed for each distribution. The pseudo-code for the procedure is given by:

Procedure (Continuous Case)

- Choose $g(x)$ (a density function that is easy to sample from)
- Determine a constant c such that: $c \cdot g(x) \geq f(x)$

1. Let Y ~ $g(y)$
2. Let U ~ Unif [0, 1]
3. If $U \leq f(x) / c \cdot g(x)$ then X=Y; else reject and return to step 1

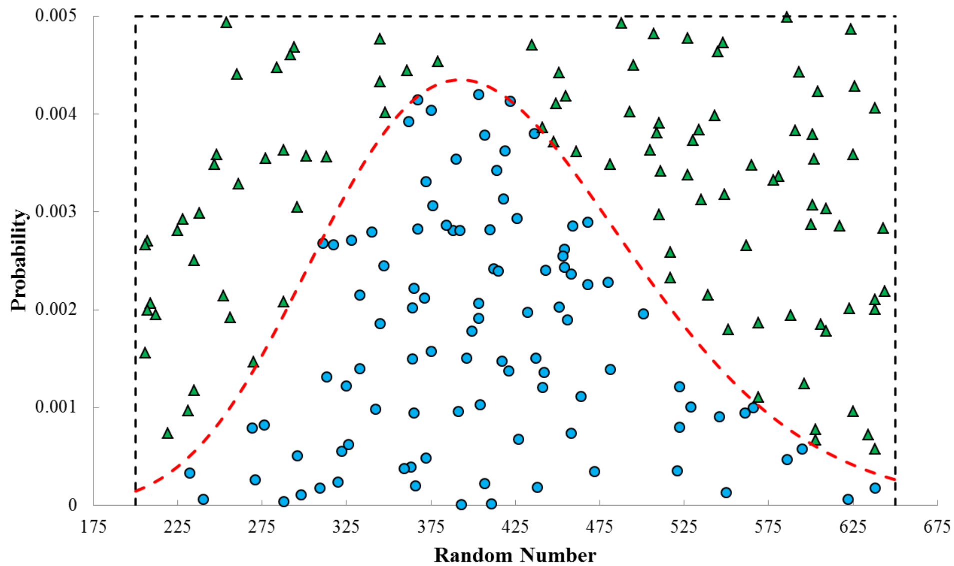

Figure 32. Graphical example of rejection sampling. Points beneath the probability density function (dashed line) are kept while points above are rejected.

To improve processing performance, step two in the pseudo-code is modified to be a uniform distribution from zero to the distributions mode. Closed form equations for each distributions mode were determined from the literature. If a closed form equation could not be identified, the maximum probability of occurrence was set to one. To verify correct programmatic implementation, simulation values were downloaded into Microsoft Excel™ and compared against native Excel™ distribution functions as shown in Figure 33. By visual inspection, it was determined generated values approximated a distribution, e.g. normal, exponential, or gamma.

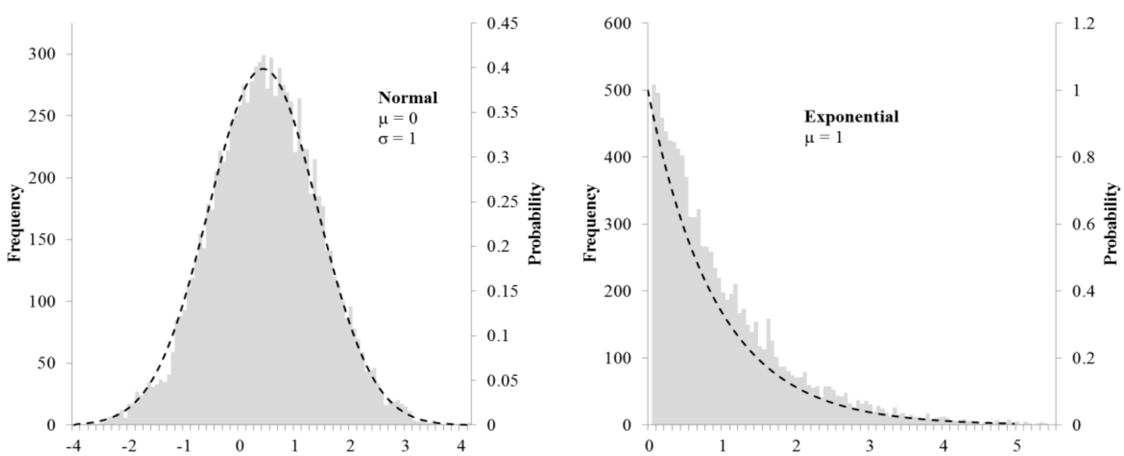

Figure 33. A histogram of simulated data is overlaid with a Microsoft Excel™ generated distribution curve for programming verification.

The second major component of sensitivity analysis for the supply chain modules was a one-way sensitivity analysis. This was accomplished by incrementing a single variable through its distribution range while holding all other variables constant. Sufficient data to derive the relative cost and sensitivity impact of each variable was generated by dividing each variable's distribution range into 100 increments. Relative sensitivity of the supply chain to changes in a single variable was determined by calculating the rate of change in system cost incurred by the variable, and then normalizing it against the other cost variables. Similarly, relative cost impact was calculated from the difference in total system cost at the upper and lower end of the variable's cost range and then normalizing the result against the other variables. Pseudo-code for the procedure is given by the following:

Procedure

- Let N be the number of distributions to analyze
- Let Dist[N] be an array of distributions

```
For i = 0 to N
    Let UB = upper range limit of Dist[i]
    Let LB = lower range limit of Dist[i]
    Let Step = (UB – LB) / 100
    # Increment through the distributions range
    # Keep all other variables constant at the baseline
    For j = 0 to 100
        Let value = LB + Step
        Data[j] = Function( value )
    Next j
Next i
```

Data generated during the Monte Carlo and one-way sensitivity analysis are kept in ordered arrays and stored in a MySQL database. One-way sensitivity analysis data is stored in data columns for each variable; however, to minimize storage requirements, the Freedman-

Diaconis bin size rule (Equation 6.3.1) was used to transform the Monte Carlo data prior to storage (Freedman & Diaconis, 1981).

$$\text{Bin size} = 2 \cdot IQR \cdot n^{-0.333} \tag{6.3.1}$$

Where *IQR* is the interquartile range of the sample and *n* is the number of observations in the sample. Bin midpoint, sample frequency, and probability of occurrence are then stored in the database. The information is later extracted to generate visualizations of the analysis results.

6.4 Results and Discussion

There are three major requirements for incorporating Monte Carlo simulation into a web model. Namely, evaluation of mathematical equations for the system, probability distributions for system variables, and a method of generating stochastically independent random variables for each distribution. Additionally, the website structure, user interface and database interactions should also be created. The backbone of the online Monte Carlo analysis is a JavaScript random number generator to simulate specific distributions. There are several mathematical methods of simulating continuous random variables such as the inverse transformation method, rejection method, hazard rate method, and other special techniques for the normal, gamma, beta, and exponential distributions (Ross, 2010). Each of these methods has advantages; however, rejection sampling was chosen for its relative simplicity and robustness. It must be noted that it is a less efficient approach than other methods and may require multiple iterations. However, modern computer processors have rendered this a trivial concern.

Currently, PDF data for key system variables are stored in a MySQL database to be extracted for simulation. During the Monte Carlo simulation, programming logic evaluates each database variable in a loop to determine if it has an assigned distribution. If a match is found a JavaScript Object Notation (JSON) variable containing the minimum and maximum empirical data values, PDF name, and its parameters is created. If no match is identified the variable's value is not changed from the original default or user specified value. The JSON variable is then passed to a JavaScript function that can generate random numbers following the distribution curve. Including additional variables such as equipment utilization, wages, or interest rates in the Monte Carlo analysis requires adding a logic check for the new variable. The same logic check controls one-way sensitivity analysis, so no additional program modifications are required after the initial update. Currently, the primary limitations of the system are a lack of empirical data to develop PDFs for variables and the inability of users to specify distributions for variables within GLADIS. Incorporating additional variable distributions in the model would make GLADIS more robust and enhance its capabilities, while allowing distributions to be specified by the user would make it more customizable.

6.4.1 System Application to a Transportation Operation

The results of Monte Carlo simulation and one-way sensitivity analysis are given in the context of a truck transportation system to more effectively demonstrate the outputs generated by the modeling system. The algorithms used to calculate costs are derived primarily from Berwick & Farooq (2003) with the exception of fuel cost which utilizes the method outlined by Hussein & Petering (2009). Distributions developed for system analysis included truck weight, fuel cost, truck retail value, trailer retail value, and tire costs. The distribution functions and corresponding parameters can be seen in (Table 14). Based on the original Monte Carlo data, the cost distribution is provided, as shown in Figure 34.

Table 14. Transportation variables with assigned PDF and parameter values used in Monte Carlo simulation.

Variable	Distribution	Parameters		
Steer Tire	Gamma	a = 19.5,	b = 21.2	
Drive Tire	Weibull	a = 500,	b = 4.9	
Trailer Tire	Gamma	a = 14,	b = 28.1	
Fuel Cost	Rician	s = 3.9,	σ = 0.11	
Truck Cost	Birnbaum Saunders	Β = 39730,	γ = 0.59	
Trailer Cost	Gamma	a = 10.7,	b = 2570	
Truck Weight	Generalized Extreme Value	k = 0.28,	σ = 5730,	μ = 36000

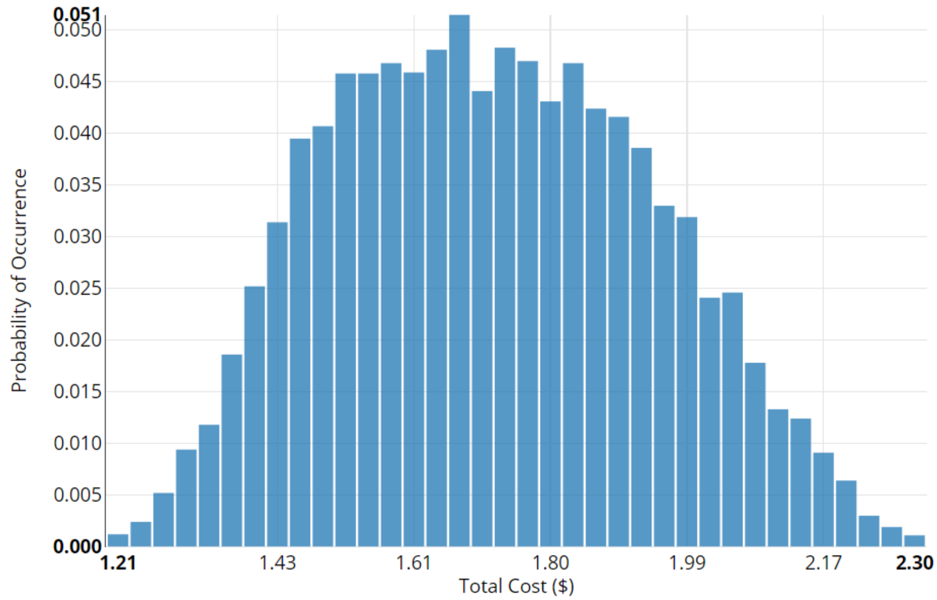

Figure 34. Transportation system cost distribution derived from Monte Carlo simulation.

Based on the generated data, several important factors can be determined regarding the distribution of cost for transportation. The mean transportation cost is $1.70 per mile with a standard deviation of $0.22. Therefore, the model user can expect total transportation costs to be between $1.26 and $2.14 approximately 95% of the time. This range covers nearly the entire distribution of probable values, indicating high variance in the system. Given this information, a user can compare their base cost estimate to the systems distribution to determine if their underlying cost variable inputs are reasonable. The base cost is determined from the user's initial inputs for costing variables, e.g. truck retail, trailer retail, insurance, and tax rates. One-way sensitivity analysis provides additional information regarding the interrelation of cost variables. This analysis indicates the interdependency of variables, their relative impact on total system cost and the relative sensitivity of total system cost to changes in the variables as shown in Figure 35. Relationships between variables can be seen as the curvature of the lines, where non-linear variable relationships have a more noticeable curve. The maximum change in total cost on the y-axis indicates the variables cost impact, effectively the cost change incurred by a variable change.

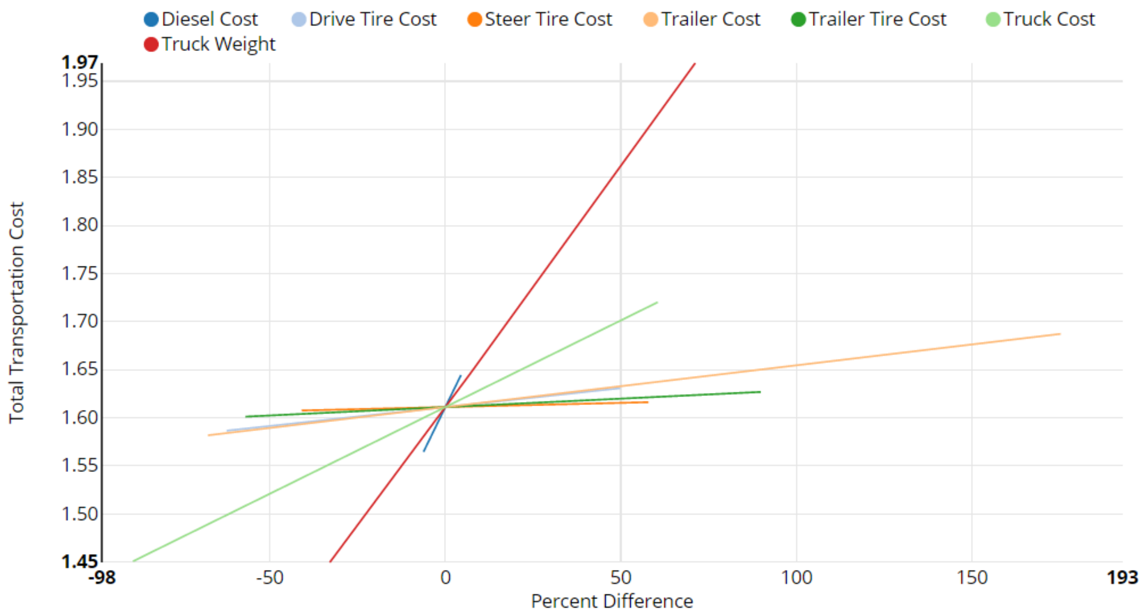

Figure 35. Spider chart representation of one-way sensitivity analysis results.

This contrasts with the variables sensitivity, represented by the rate of change in total cost resulting from base changes in the variable. These last two sensitivity measures can be separated to rank the variables relative to one another (Figure 37 and Figure 36). As an be observed from these figures, diesel fuel cost is ranked as the transportation cost variable that is most sensitive while it is ranked fourth in terms of overall cost impact. This is somewhat intuitive considering small changes in the cost of diesel may cause a large change in total operating cost, indicating high sensitivity; however, the limited range of expected diesel fuel prices constrains its effect somewhat resulting in a much lower cost impact ranking than, for instance, truck cost. Additionally, these rankings can reveal unexpected results, such as the ranking of truck weight as the most significant influence on total transport cost. Such findings reflect the algorithms used to calculate total transportation cost, for which truck weight is a variable in the maintenance, fuel and tire cost equations. This means truck weight affects cost in three areas, while changes in other variables may only affect one or two sectors. Including Monte Carlo and one-way sensitivity analysis in GLADIS enhances the models functionality and provides users a method of quantifying supply chain uncertainty.

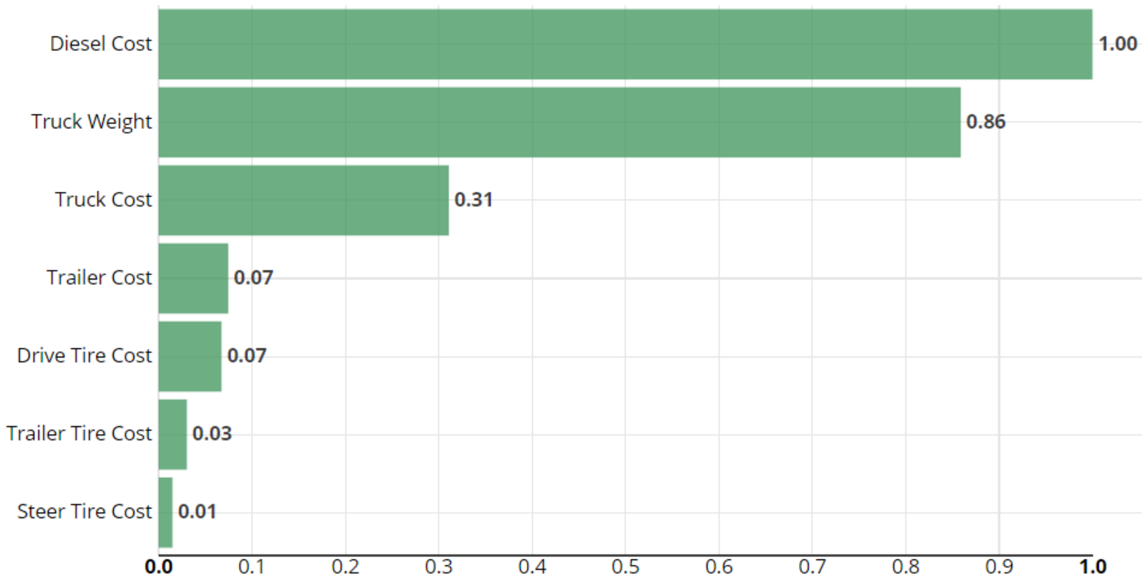

Figure 37. Relative sensitivity of transportation cost variables.

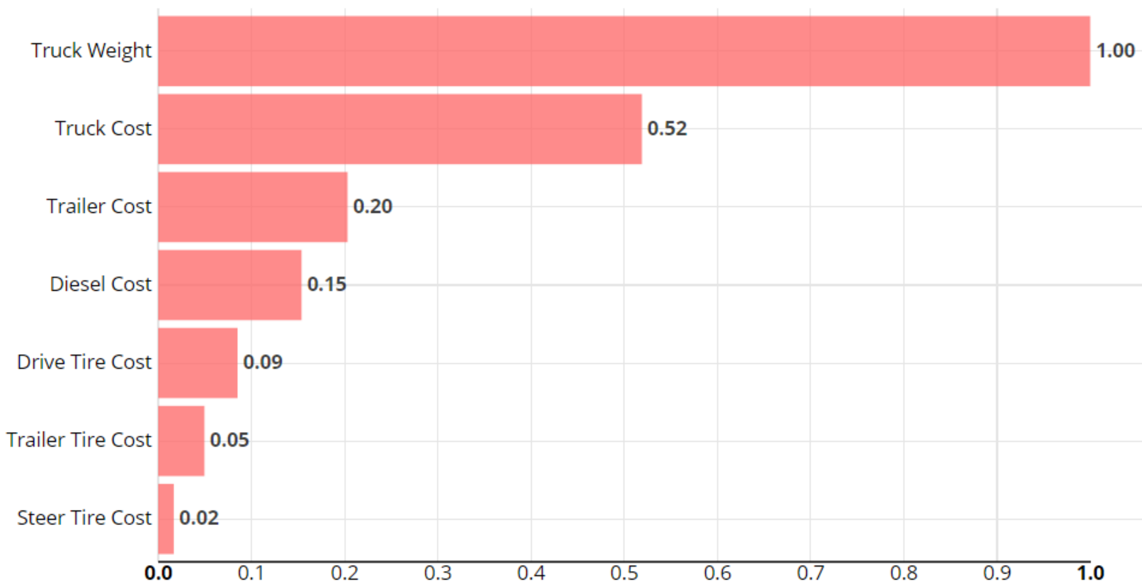

Figure 36. Relative cost impact of transportation cost variables.

6.5 Conclusion

The Monte Carlo and single-factor sensitivity analysis built into GLADIS provides users with quantitative information about the harvesting and transportation stages of a supply chain. Variables are ranked by their relative sensitivity and cost impact using one-way sensitivity analysis. Monte Carlo analysis provides the systems expected cost distribution and summary statistics that include the minimum, maximum, mean, median, standard deviation, and quartiles. The results are displayed graphically so users may see a visual representation of the analysis. Algorithms were programmed in JavaScript, so the user is not required to download any software packages. As an online modeling system, the sensitivity analysis components of GLADIS may be accessed from any electronic device with a data connection. Future work will supplement the model by adding the ability to specify custom variable distributions and increasing the number of variables that have an assigned distribution. The beta version of the model has been deployed and is available at www.gladis.okstate.edu for review and supply chain simulation.

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CHAPTER VII

CONCLUSION

The beta version of GLADIS provides users with techno-economic, geospatial, and sensitivity analysis for an Eastern Redcedar supply chain. Techno-economic data is generated for the harvesting, processing, transport, and refining of Eastern Redcedar. Modeling information is entered through a simple user interface or default values from a database may be used. This gives GLADIS more flexibility and allows users to select default values or enter inputs based on personal knowledge of their operation. The analysis results are displayed in interactive graphics with drill-down capability.

GIS network analysis provides a method of determining the optimal location of a biofeedstock facility that maximizes available biomass and minimizes transport cost. The GIS analysis is complemented by the creation of a facility service area to provide a more detailed representation of accessible land regions within a specified impedance limit. The inclusion of processing hubs can be modeled using a two level location-allocation solver to identify the best regional location and then the optimal location of hubs to maximize service area coverage. Incorporating these features into a web-based supply chain model makes high level GIS analysis available in a simple format to non-GIS specialists, without reducing the viability of results.

Uncertainty within supply chain nodes is quantified through Monte Carlo simulations and one-way sensitivity analysis. The Monte Carlo and single-factor sensitivity analysis built into GLADIS provides users with quantitative information about the harvesting and transportation stages of the supply chain. Variables are ranked by their relative sensitivity and cost impact using one-way sensitivity analysis. Monte Carlo analysis provides the systems expected cost distribution and summary statistics that include the minimum, maximum, mean, median, standard deviation, and quartiles.

The modular design of GLADIS allows for quick expansion of analytical capacity and the inclusion of additional feedstocks, e.g. switchgrass, forage sorghum, miscanthus, and canola. As an online modeling system, GLADIS may be accessed from any electronic device with a data connection. The analysis results are displayed in interactive graphics with drill-down capability. It is expected that the model will facilitate development of Eastern Redcedar industries and aid businesses, entrepreneurs, and government entities in stimulating the state economy. The beta version of the model has been deployed and is available at www.gladis.okstate.edu for review and supply chain simulation.

CHAPTER VIII

FUTURE WORK

8.1 Overview

Currently, the primary focus is review and incorporation of client comments and suggestions to enhance the usability of GLADIS. Additional steps are being taken to enhance database security and improve processing performance, such as transitioning to server processing, consolidating the model into a PHP framework, and utilizing CSRF tokens. Expanding the model to include multiple feedstocks is a key objective for future versions. Many of the models current features could be improved, such as increased options for location-allocation, geospatial yield statistics, projected biomass yields, discount cash flow for all modules, and custom stochastic distributions for cost variables. Future editions will see more calculations implemented server side to provide greater processing power and limit lag.

8.2 Geospatial Information System

The GIS components included in GLADIS are a limited example of the capabilities that can be provided to government, business, and research institutions. Foremost, the location-allocation feature could be expanded to provide options for the client to specify solver type, custom travel restrictions, alternative demand points, competing facilities, facility capacity, and measurement transformations (Environmental Systems Research Institute [ESRI], 2014a). Adding

GIS data for alternative biomass feedstocks would have the greatest impact on the current system and be the simplest modification to implement. Expanding the solver types available for analysis would provide users a means of tailoring the model simulation to better match their business objectives, such as maximizing their market share or minimizing the number of facilities. The measurement transformation could be used to more accurately represent the impact of travel distance on transportation cost by specifying a linear, exponential or power relationship. These variables should be incorporated as options so the user may control the complexity and level of detail in their analysis. With the current foundation, these improvements should be straightforward to incorporate into the GLADIS model. To add additional detail to the model, optimized routes could be incorporated from any processing hubs to the main facility or facilities then to distribution centers. This could be used to account for shipping and handling costs associated with distribution of the final product(s).

In the literature, multi-modal transportation networks are considered in biomass transportation logistics when selecting a facility location (Bowling, Ponce-Ortega, & Halwagi, 2011; Zhang, Johnson, & Sutherland, 2011; Voets, Neven, Thewys & Kuppens, 2013; Hess, Kenney, Ovard, Searcy, & Wright, 2009). This functionality should be incorporated into GLADIS in future versions to provide advanced options to clients for supply chain analysis, without requiring a high level of technical knowledge or software expertise. The additional network datasets would allow GLADIS to determine the feasibility of multi-modal transport and/or the range at which multi-modal transport becomes feasible. Per mile costs, fixed costs, and variable handling costs could be accounted for with minimal input. Aside from network analyst functions, the most obvious benefit of GIS in an online modeling system is mapping. Biomass yield maps for forage sorghum, switchgrass, miscanthus, corn stover or any other biomass could be approximated for a given year, land area or soil type using a technique known as fuzzy logic. Fuzzy logic is typically used in suitability analysis (ESRI, 2014b) but it could be used to estimate biomass yield with Oklahoma Mesonet and USGS data such as precipitation, temperature, solar radiation, relative humidity and soil composition. A similar concept was presented by Kenkel (2014) which used Mesonet data to simplify estimation of switchgrass biomass yields. Using fuzzy logic, each variable could be assigned a distribution specific to how it affects a certain feedstock yield, e.g. switchgrass growth is highest when temperatures in a certain range. The primary advantages of using fuzzy logic to estimate yield is that it accounts for spatial variance, may include many (or few) variables, and is ideal for circumstances where a variable has a known impact but the relationship is not clear. The generalized methodology would involve conducting suitability analysis for specific biomass crops under known conditions with fuzzy logic and then determining empirical relationships between crop yield and the fuzzy membership calculated from all variables. Once this relationship is established, yield estimates could be obtained for that crop in any location where data for the fuzzy membership variables is available.

8.3 Sensitivity Analysis

There remains considerable room for improvement and expansion in the current sensitivity analysis module. One such change is server side processing which would increase the speed of processing and reduce the client's computer lag during analysis of very large systems. Additionally, simulations are currently limited to variables with a distribution assigned in the model's database. Including a method for the user to assigned distributions to specific variables would enhance the analysis detail and enable them to more closely simulate a specific scenario. This would also make it possible to provide analysis data for sub-systems, e.g. maintenance, fuel, tire wear, etc. The ultimate goal for future model versions is to link the model with a robust and extensive database repository that stores empirical data for the system variables. Distributions could be determined dynamically from this information for simulation, limiting input requirements from the user. These modifications would make the Monte Carlo simulation and one-way sensitivity analysis more robust, detailed and accurate, resulting in a better quantification of risk in supply chain systems. More sophisticated sensitivity analysis could also be easy incorporated into the model since the programming foundation has been laid. This could include n-way analysis to determine the joint impact of parameters, non-parametric statistics to model systems using fewer assumptions, and geometric Brownian motion to model commodity prices. Inclusion of these capabilities would provide a very robust set of analysis tools for modeling complex systems.

8.4 References

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APPENDIX I – DELIVERY SYSTEMS FOR FOREST RESIDUE

Site Descriptions

Site I: A large forest area (> 125,000 ha) covered by private forest roads which allows high transport speeds (> 100 km/h) and large payloads (up to 60 tonnes). These sites are not open to the public. The total amount of arisings available in such an area would be sufficient to supply up to 100,000 green tonnes per annum of feedstock to a centrally located energy plant without the need to use public roads. Hence the system is not constrained by legal maximum axle weights on transport vehicles. Total transport distance is 25 km on average of which 2 km is on forest tracks and 23 km on good forest roads.

Site II: A large forest area (200,000+ ha) consisting of a number of separate forests, small and large (3000–140,000 ha), within a small region. Arisings from the different forest areas would be combined to achieve enough feedstock to supply an energy plant. Transport on public roads is necessary which requires maximum transport vehicle weights and dimensions to comply with New Zealand legislation. Total transport distance is 50 km on average of which 4 km is on forest tracks, 26 km on good forest roads and 20 km on public roads.

Site III: Scattered forests (from 100 to 20,000 ha each to give a regional total of 150,000 ha) necessitating public road transport over larger distances. Total transport distance is 75 km on average of which 4 km is on forest tracks, 26 km on good forest roads and 45 km on public roads.

Scenario Descriptions

Delivery systems for landing residues:

A: load residues into truck—transport to power plant—unload truck—chip residues;

B: load residues into truck—transport to a central processing yard—store residues for 3 months—chip into truck—transport to power plant—unload truck;

Delivery systems for cutover residues:

C: forward residues to landing—unload forwarder—store residues for 3 months—load into truck—transport to power plant—unload truck—chip residues;

D: forward to landing by chipper-forwarder—unload chips from chipper-forwarder—store chips for 1 month—load into truck—transport to power plant—unload truck;

E: forward to landing by chipper-forwarder—transfer chips into truck—transport to power plant—unload truck;

F: forward to landing—unload forwarder—store residues for 6 months—chip residues—store chips for 1 month—load into truck—transport to power plant—unload truck;

G: forward to road side—unload forwarder—store residues for 6 months—chip into truck—transport chips to power plant—unload truck.

This is a partial methodology description of research conducted by:

Hall, Peter, Jörg K. Gigler, and Ralph E. H. Sims. 2001. Delivery Systems of Forest Arisings for Energy Production in New Zealand. *Biomass and Bioenergy*. 21 (2001) 392-399.

APPENDIX II – DATABASE INFORMATION

Harvesting Module Data

Table 15. Database information for the harvesting module. Input are provided for by machine size and type if the user specifies the automatic inputs option.

Machine Class	Tracked	Size	Hp	Life (yrs)	Salvage[a]	Utilization%)	Repair[b]	Ins. (%)[c]	Fuel Cons.[d]	Lubrication[e]	Interest (%)	Tax (%)
feller_buncher	F	s	175	3	20	65	100	5	0.02633	36.77	10	0
feller_buncher	F	m	200	4	20	65	100	5	0.02633	36.77	10	0
feller_buncher	T	l	225	5	15	60	75	5	0.02633	36.77	10	0
forwarder	F	m	180	4	20	65	100	4	0.02488	36.77	10	0
slasher_loader	F	m	150	4	0	65	35	2	0.03104	36.77	10	0
iron_gate_delimber	F	m	0	5	20	90	65	0	0	36.77	10	0
harvester	F	m	250	4	20	65	110	4	0.02917	36.77	10	0
loader	F	s	NA	5	30	65	90	1.5	0.02166	36.77	10	0
loader	F	m	NA	5	30	65	90	1.5	0.02166	36.77	10	0
loader	F	l	NA	5	30	65	90	1.5	0.02166	36.77	10	0
chipper	F	s	100	5	20	75	100	NA	NA	36.77	10	0
chipper	F	m	150	5	20	75	100	NA	NA	36.77	10	0
chipper	F	l	200	5	20	75	100	NA	NA	36.77	10	0
crawler_tractor	T	s	100	5	20	25	100	3.5	0.03932	36.77	10	0
crawler_tractor	T	m	150	5	20	60	100	3.5	0.03932	36.77	10	0
crawler_tractor	T	l	200	5	20	60	100	3.5	0.03932	36.77	10	0
skidder	F	s	80	4	20	65	75	5	0.028585	36.77	10	0
skidder	F	m	90	4	20	65	90	5	0.028585	36.77	10	0
skidder	F	l	120	5	10	60	90	5	0.028585	36.77	10	0
grinder	F	s	600	5	20	75	100	NA	NA	36.77	10	0
grinder	F	m	700	5	20	75	100	NA	NA	36.77	10	0
grinder	F	m	700	5	20	75	100	NA	NA	36.77	10	0

Probability Distribution Data

Table 16. Distributions used in Monte Carlo analysis, with the minimum and maximum values used in one-way sensitivity analysis. Distributions were developed using MATLAB™

Description	Distribution Name	Distribution Parameters	Parameter values	Minimum	Maximum
chainsaw_cost	rayleigh	B	575	143	2030
chainsaw_horsepower	birnbaumsaunders	beta;gamma	4.34;0.365	2.2	8.6
chainsaw_weight	loglogistic	mu;sigma	2.54;0.113	8.6	22.7
chipper_cost	generalizedextremevalue	k;sigma;mu	0.80;22,516;32,150	10,900	569,700
chipper_weight	generalizedextremevalue	k;sigma;mu	0.60;4,007;6,713	2,425	84,000
chipper_current_life	exponential	mu	1,324	0	11176
diesel_cost	rician	s;sigma	3.90;0.108	3.58	4.15
drive_tire_cost	weibull	A;B	499;4.9	162	683
feller_buncher_cost	inversegaussian	mu;lambda	147,318;519,170	49,999	550,000
feller_buncher_weight	generalizedextremevalue	k;sigma;mu	2.0;4,740;27,117	24,900	244,000
feller_buncher_current_life	rayleigh	B	5,364	127	16,400
forestry_tire_cost	gamma	a;b	2.29;1047	168	9,585
forwarder_cost	inversegaussian	mu;lambda	200,928;2,049,913	125,000	339,116
forwarder_weight	extremevalue	mu;sigma	38,108;8,410	3,600	50,900
forwarder_current_life	rayleigh	B	7,703	2,036	16,500
grinder_cost	rayleigh	B	228,514	49,900	595,000
grinder_weight	extremevalue	mu;sigma	72,955;17,505	5,540	100,000
grinder_current_life	weibull	A;B	2,764;1.25	100	8,000
harvester_cost	inversegaussian	mu;lambda	234,259;1,974,993	115,500	455,000
harvester_weight	tlocationscale	mu;sigma;nu	40,000;0.000227;0.24	30,644	66,690
harvester_current_life	rayleigh	B	5005	566	12,900
skidder_cost	birnbaumsaunders	beta;gamma	120372;0.54646	38,000	335,598

Table 15 (cont.)

Description	Distribution Name	Distribution Parameters	Parameter values	Minimum	Maximum
skidder_weight	logistic	mu;sigma	36156;2604	22,780	48,281
skidder_current_life	nakagami	mu;omega	0.42;60,956,436	2	17,226
skidsteer_cost	inversegaussian	mu;lambda	35,136;144,143	10,250	86,000
skidsteer_weight	weibull	A;B	8,394;3.9	1,800	11,630
skidsteer_current_life	nakagami	mu;omega	0.3;2,804,177	1	4,988
skidsteer_tire_cost	birnbaumsaunders	beta;gamma	245;0.45	105	526
steer_tire_cost	gamma	a;b	19.5;21	230	643
trailer_cost	gamma	a;b	10.7;2,572	7,500	69,500
trailer_tire_cost	gamma	a;b	14;28	163	763
truck_cost	birnbaumsaunders	beta;gamma	39,727;0.585	8,700	130,422
truck_finance_cost	birnbaumsaunders	beta;gamma	29,796;0.585	6,525	97,817
truck_weight	generalizedextremevalue	k;sigma;mu	0.28;5,731;35,991	26,001	69,000

[A] units given as percent of purchase price.

[B] units given as a percent of yearly purchase price.

[C] units given as a percent of purchase price.

[D] units given as gallons per horsepower hour.

[E] units given as a percent of fuel costs.

Employee Salary Data

Table 17. Database information used to populate labor inputs for users.

Title	Employees	Salary
Plant Manager	1	100,000
Plant Engineer	1	80,000
Maintenance Supervisor	1	75,000
Lab Manager	1	60,000
Shift Supervisor	1	45,000
Maintenance Technician	1	35,000
Shift Operator	20	30,000
Yard Hand	32	25,000
General Manager	1	120,000
Secretary	5	23,000

Depreciation Data

Table 18. Annual depreciation rates used for calculating discounted cash flows in the refining module.

Year	Equipment Depreciation	Special Building
1	0.1429	0.1
2	0.2449	0.14
3	0.1749	0.14
4	0.1249	0.14
5	0.0893	0.14
6	0.0892	0.14
7	0.0893	0.14
8	0.0446	0.14
9	0	0.14
10	0	0.14

VITA

Charles Collin Craige

Candidate for the Degree of

Master of Science

Thesis: **BIOFEEDSTOCK SUPPLY CHAIN LOGISTICS DYNAMIC MODELING: EASTERN REDCEDAR**

Major Field: **BIOSYSTEMS ENGINEERING**

Education:

Completed the requirements for the Master of Science in your Biosystems and Agricultural Engineering at Oklahoma State University, Stillwater, Oklahoma in May, 2015.

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- Development of an economic supply chain model for Eastern Redcedar
  - Analyze location, harvest, transport, processing and refinement costs
  - Drop-in costing modules transferable to alternative biomass feedstocks
  - Designed for online deployment to improve public accessibility
  - Risk management through Monte Carlo simulation
  - Supervised four employees in web design, data acquisition and dynamic programming
- Biomass Research and Development Initiative
  - Characterization of moisture and dry matter loss in bioenergy bales during storage
  - Team design of summary form to display 3-D moisture variability, bale/stack shrinkage, and statistical summary of results.
  - Collection of stack height, bale dimensions, and biomass samples
- General Projects
  - Drafting of SolidWorks schematics for Ammonia Acid Scrubber
  - Creation of 3-D visualizations of Cotton Gin total suspended particle emissions

Professional Memberships: American Society of Agricultural and Biological Engineers.