**Effect of Harvesting Schemes on Forest Residue Supply Chain for Biofuel Production:   
A Case Study in Tennessee**

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**Introduction**

Since the beginning of the last century, the world has based its development on fossil fuels, mainly petroleum. Even when the oil price has fluctuated, the electricity generated from oil has continued to increase, and transportation still primarily relied on petroleum derivatives. Intensive petroleum use has led to surging accumulation of greenhouse gases (GHG) in the environment that has already exceeded the "dangerously high" threshold of 450 parts per million (ppm) CO2 (Schenk, 2008), which has been linked to 1.5°C warming above pre-industrial temperatures (IPCC, 2019). Thus, governments around the world have attempted to explore new sources of energy to mitigate GHG emissions.

Blending conventional transport fuels with biofuels is believed to positively impact GHG emissions and related environmental issues (U.S. DOE, 2016). For example, the mixing of ethanol in gasoline can result in more efficient combustion of gas with less GHG emissions than conventional gasoline (Greene et al., 2004). With the increasing demand for reducing GHG emissions and increasing carbon sequestration, biofuel production has gained more attention over the past decade. However, the use of biofuel has walked through different phases. The first phase of biofuel produced from food crops has created controversy. The increased demand from using food crops as feedstock has pushed up food prices that generated social discontent and policy debates. The competition between feeding people and fueling cars and the impact of monoculture on biodiversity, and the uncertainty about first-generation biofuels’ contributions to mitigate GHG have encouraged second-generation biofuel development. The second-generation biofuel was expected to be less influential in land use for food crops and feedstuff (Carriquiry et al., 2014).

As approximately 70% of the total terrestrial biomass is considered lignocellulose (Pauly and Keegstra, 2008), feedstock from the forest has been considered to produce biofuel in the world. The land resources of the United States are capable of producing a sustainable supply of biomass sufficient to displace 30 percent or more of the country's present petroleum consumption (Perlack, 2005). The U.S. Southeast region can potentially contribute about 10.5 billion gallons (BG) of advanced biofuels (U.S. DOE, 2016). However, concerns regarding the intensive use of land, animal habitat loss, and reduction in the beautiful landscape have arisen.

Due to the negative perceptions of using trees for biofuel production, an alternative solution is using forest residues to generate biofuel. Forest loggers exploit timberland and generate tons of logging residues that can be used as biomass. Logging residues are mainly removals that are the unutilized wood volume from a cut or otherwise killed growing stock, or activities as timberland clearing, among others (Walsh et al., 2000). As residues produced by sawmills are typically used for commercial purposes, most of the available residues are from loggers in the forest, recovered in harvesting tasks, or commonly burned or left on the forest floor to decompose (Oswalt et al., 2014). The production of biofuel from logging residues has been shown as a potential option for biofuel production due to the abundance of forest residue resources, a relatively low cost compared with biofuel dedicated crops, potentials to diminish CO2 emissions, less competition for food crops, and one of the most unused biomasses on earth (Daioglou et al., 2016). However, forest residue feedstock for biofuel faces some challenges related to infrastructure, investment, feedstock availability, quality, and costs (Cambero et al., 2015).

In the biofuel supply chain, key activities are harvesting, transporting, storage, and converting (Nunes et al., 2020). Harvesting schemes could directly impact the management of transportation and storage. The impact of harvesting strategies on logging residues’ availability in the long term is one of the problems that demands additional research in the literature (Sun and Fan, 2020; Nunes et al., 2020). Thus, this present study intends to determine the optimal logistic operation considering different forest harvesting strategies for producing biofuel from forest residues. Given the availability and location of forest residues, the model determines the optimal location for a biorefinery with the minimum transportation cost. The framework runs for a multiperiod scope using high spatial resolution data. A mixed integer nonlinear programming model (MINLP) is developed to assess the effect of harvesting strategies on transportation costs and biorefinery location. We use Tennessee as a study case given its sizable inventory of hardwoods within the state and the state administrators’ goal of developing a sustainable bioenergy industry.

**Literature Review**

As climate change problems become more evident, the pressure for mitigating GHG emissions increases, and new actions have to be executed. The Renewable Fuel Standard (RFS), introduced in the Energy Act in 2005 (Energy Policy Act of 2005) and reinforced in the Energy Independence and Security Act of 2007 (EISA), mandates 36 BG of renewable fuels to be available for use by 2022. Besides, the 36 BG of renewable fuels need to include at least 21 BG of advanced biofuel with a 50% reduction in life-cycle emissions. Some private sectors have also engaged in the reduction of GHG. For instance, the International Air Transportation Association (IATA) established a goal for diminishing GHG emissions by 50% from 2005 to 2050. (IATA, 2015).

The USDA Biomass Crop Assistance Program in 2008, along with other state policies, encourages the production of liquid fuels from woody biomass and wood-based electricity generation (He et al., 2016). Perlack et al. (2005) suggested that the United States could produce about 1.3 billion dry tons (dt) of biomass per year, while maintaining food export and domestic demands with only subtle changes in land use. The updated "Billion-ton report” in 2016 (U.S. DOE, 2016) indicates that nearly 360 million tons of biomass were utilized for power and heat in 2014. The southern U.S. has a significant part of timber forest resources and reliable woody biomass supply sources. According to the Forest Inventory Analysis (FIA) database (FIADB), there are more than 100 million acres of hardwood, 60 million acres of softwood, and 20 million acres of mixed woods growing in this region.

Many researchers have assessed the potential of logging residues used for bioenergy production. Daioglou et al. (2016) forecast the energy available from residues worldwide for different forestry and agriculture production scenarios using global supply curves. Results show that potential energy could vary from 120 EJ year-1 in 2015 to 140-170 EJ year-1 by 2100. Skog et al. (2013) calculated county-level supply curves for forest-based biomass for the U.S., based on the billion-ton report for evaluating contributions to producing renewable fuels that would be needed to meet cellulosic biofuels production targets under the 2007 EISA. Results show that 20 BG targets of advanced biofuels could be met by producing 4 BG from forest biomass and 16 BG from agricultural biomass at $44 per dt.

Different models have been developed for evaluating costs and operations for facilities fueled by forest resources. For example, Huang et al. (2010) designed a model that uses spatial and temporal dimensions planning of biofuel supply chains to minimize the cost of the entire supply chain of biofuel from second-generation biomass from feedstock fields to gas station users. The model assessed the potential and requirements for biofuel production in California as a case study and concluded that second-generation biofuel can be available at the cost of around $1.1 per gallon to the final user through the optimal supply chain. Forest residues biomass is considered a promising option for producing biofuel due to the abundance in supply and its relatively low cost compared to another biomass feedstock. However, forest-based biofuel is still not cost competitive compared to conventional fossil fuels (Stockinger and Obernberger, 1998; Sambra et al., 2008). Gan (2007) developed an analytical framework to determine the optimal dimension of a power plant deriving the supply of biomass feedstock, electricity production, and CO2 reduction from forest residues by minimizing the cost of feedstock and electricity production. Cost of electricity generated from logging residues is $51/MWh, higher than the $36/MW electricity generated from fossil fuels. Frankó et al. (2016) analyzed the technical and economic feasibility of a forest residues ethanol biorefinery fueled in Sweden, considering different bark contents. The biorefinery was assumed to be driven by residues and produce different outcomes like ethanol, pellets, biogas, and electricity. The ethanol production cost varied considerably from 0.77 to 1.52 USD per liter. All the forestry residues, except for sawdust and shavings, produced a negative net present value.

High-resolution spatial information has been used for determining the facility’s location of the biofuel supply chain. Zhang et al. (2016) applied a Geographic Information System (GIS) methodology to select potential forest biofuel locations. Results served as inputs for an optimization model to determine the optimal cost, energy consumption, and emissions for candidate locations. Yu et al. (2014) developed a GIS-based MIP model to measure the impact of the spatial and geographic attributes on the biofuel supply chain's optimal location and configuration based on switchgrass. Results indicate that the type of agricultural land converted to feedstock production and the transportation cost of hauling feedstock and biofuels were influential factors in optimizing the supply chain configuration. Zhong et al. (2016) developed a multi-objective optimization model to high-resolution spatial data, which considered the environmental advantages of switchgrass and the economic challenges in its logistics in the design of a switchgrass supply chain in the state. He et al. (2018) used GIS and MIP for determining the optimal location of facilities, subject to market demand, land suitability for biomass production, and transport costs for at high spatial resolution in a two-stage optimization procedure. Results were used to obtain a feasible solution of multiple feedstocks over a geographic region in less computer time than required by conventional algorithms.

One major challenge of applying the mathematical programming model to the high-resolution data for biomass supply chains is these methods have been restricted to small-scale problems because computation time dramatically increases with problem size. Bordon et al. (2020) developed a Mixed Integer Linear Programming (MILP) model that determines the planning in forest industry decisions about raw material allocation, vehicle routing, and scheduling of truck arrivals to both harvest areas and the plants in Argentina. A hierarchical approach was adopted to divide the problem into two stages: in the first phase, the raw material allocation and vehicle routing problems were solved through a MILP model; while the schedule of truck arrivals based on the routes identified in the first phase was determined through another MILP model in the second phase. The results show the approach is practical and could be easily applied in the industry. Other researchers have faced the similar challenge when using metaheuristic and approximate methods. Contreras et al. (2008) solved the forest transportation problem considering financial aspects and environmental impact by applying the ant colony optimization metaheuristic that efficiently solves large and complex forest transportation problems with side constraints.

Harvesting is a crucial activity in biomass supply chains that consists of collecting crops and moving them to storage or a pre-processing plant (Atashbar et al., 2018). Forestry harvesting problems are classified into three categories: forest harvesting schedule, crop harvesting, and equipment schedule for harvesting (Sun and Fan, 2020). The crop harvesting schedule intends to achieve the minimum cost or maximum profit by selecting resource allocation, harvest period, or location to be harvested. Due to its importance, harvesting activities have been studied by many researchers. Spinelli et al. (2008) found that crop density affects harvesting costs. Areas denser implies lower costs than less dense areas. Spinelli and Magagnotti (2013) also explored the effect of tree-selection patterns on harvesting productivity. Two patterns were studied; uniform spatial distribution across the whole site and clustered distribution, where trees were concentrated along strip roads. Results suggest that the distribution of harvested trees had no significant effect on harvesting productivity. In turn, tree size and harvesting intensity affected the harvesting performance. Aalmo et al. (2020) evaluated the efficiency of harvesting operations in Norway. Among their findings, results suggested that harvesting inefficiency increases when the ratio to actual travel distance to minimal travel distance increases.

**Method**

The objective of the model is to determine the optimal harvesting scheme that minimizes cost of the forest residue biomass supply chain. The optimization problem was divided into two stages: the first subproblem evaluates different harvesting schemes adopted by loggers to determine wood locations for supplying sawmills demand with minimal costs. The forest residues generated are inputs for the second stage problem. The objective of the second subproblem is to calculate the minimum transportation costs location for a biorefinery. Figure 1 shows an input/output diagram of the model.

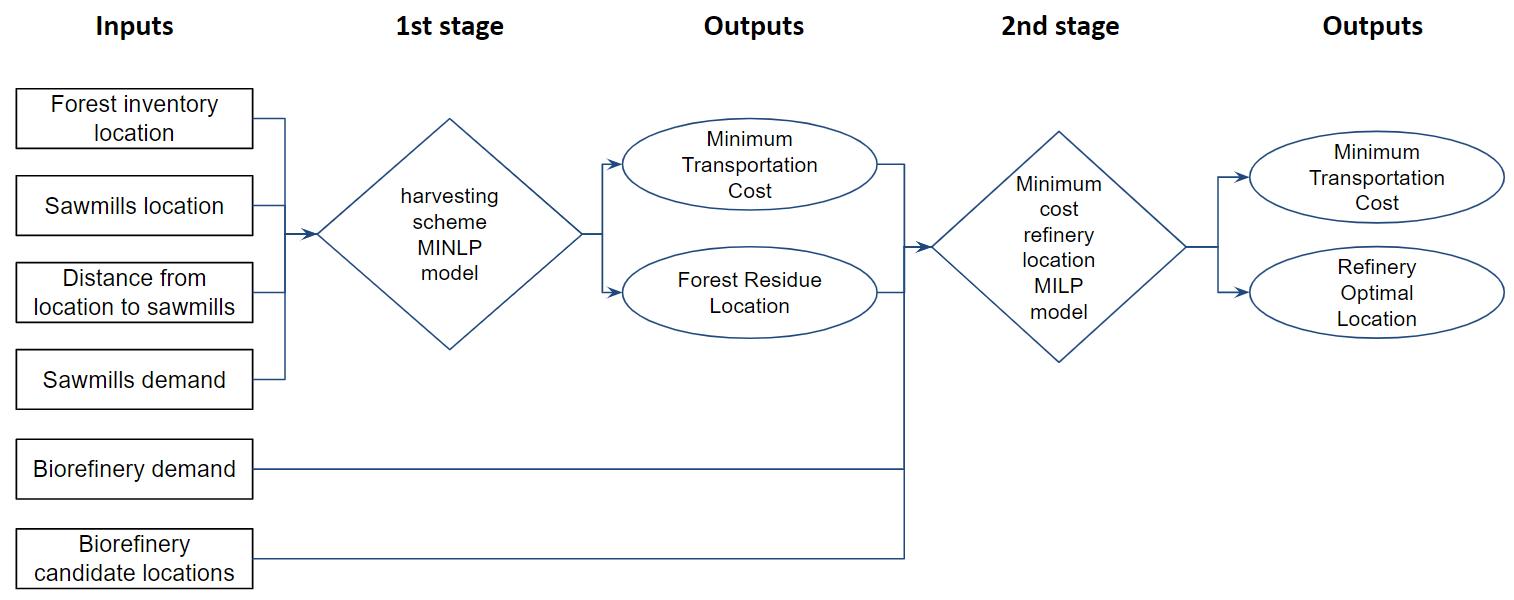


Fig 1. Framework for the Forest Residues Supply Chains

The optimization model presents an annual decision for over ten years. Two wood types are considered, hardwood and softwood, in the study. The growth of forest inventory over the 10-year horizon is incorporated in the model. The Tennessee area is divided into 8,435 hexagons; each hexagon will be modeled as an integer variable. The analytical method used for optimization is the MINLP, used before in the biomass supply chain with relative success (NG and Maravelias, 2017). Besides, the distance from hexagon to hexagon in the grid is precalculated. The language programming to be used is Python 3.8, which has numerous libraries for optimizing and spatial information processing and abundant references and support.

**First Stage**

Criteria considered for harvesting schemes are “Shortest distance area” and “highest density area.”. Harvesting activities are affected by the availability and location of trees, transportation costs, distance from the forest to the sawmills.

1. **Shortest distance scheme**

The scheme considers that loggers would prefer the nearest trees to further ones, regardless of their size. Thus, areas closer to mills will be harvested first rather than farther ones. Only locations between the n-miles buffer around roads will be considered, where n is a parameter to be set up. This scheme can be expressed as the following equation.

(1) Min [ [Xiktw1×(DMik × TCw1 + Ew1) × Yit]

S.T.

(2) (Xiktw) = DEktw for location i = 1 to b, year t = 1 to 10, sawmill k from 1 to m, and wood type w from 1 to 2 (softwood =1, hardwood = 2).

(3) AVitw = AVi(t-1)w – Xi k(t-1)w for location i = 1 to b, year t = 1 to 10, sawmill k from 1 to m, and wood type w from 1 to 2 (softwood =1, hardwood = 2).

(4) Xiktw <= AVitw  for location i = 1 to b, year t = 1 to 10, sawmill k =1 to m, and wood type w from w =1 to 2 (softwood =1, hardwood = 2).

(5) AVipt = AVi(t-1)w×(1 + GRw) for location i = 1 to b, year t = 1 to 10, and wood type w from 1 to 2 (softwood =1, hardwood = 2).

(6) Xitw, AVitw >= 0 for location i = 1 to b, year t = 1 to 10, and wood type w from 1 to 2 (softwood =1, hardwood = 2).

where,

Xiktw1: Amount of wood harvested from location i to sawmill k in the year t, and for wood type w under “shortest distance” harvesting scheme.

DMik: shortest distance from location i to sawmill k.

AVitw: Available wood type w inventory in location i for year t.

DEktw: Wood type w demand for sawmill k in year t.

Yit: Binary variable that indicates if hexagon i was harvested in year t.

TCt1: Per-unit transportation cost for wood type w under the “shortest distance” harvesting scheme.

Et1: Per-unit loading and unloading cost for wood type w under the “shortest distance” harvesting scheme.

GRw: annual growth rate for type wood w.

b: Number of locations.

m: Number of sawmills.

Equation (2) indicates that the total wood type w harvested to supply the sawmill k has to meet sawmill demand. Equation (3) is the time-link constraint assuring that available wood inventory in location i in year t is equal to wood inventory in location i in the year (t-1), subtracting the wood harvested in the location. Equation (4) is the inventory availability constraint that requires the total wood harvested at location i must be less or equal to the wood inventory. Equation (5) is the inventory growth equation that considers the available wood resource from the year (t-1) to year t.

1. **Highest density scheme**

Under the scheme, forest loggers consider the density of available woods as the decision criteria for harvesting area. The scheme prefers more tree-dense sites over less dense ones. As in the “shortest distance” scheme, areas are restricted to the n-miles buffer around roads. For simulating this scheme, available forest inventory locations are ordered from highest to lowest values. Ordering forest inventory will be a preprocessing operation for running the model.

Let j be the index variable for the forest inventory ordered data. Thus, position one has the highest value. Ordered data can be expressed as (7).

(7) AVjtw >= AV(j+1)tw for year = t, j =1 to b-1, and for wood type w.

(8) Xjtw - X(j+1)tw <= AVjtw -Xjtw for year = t, j =1 to b-1, and for wood type w.

The highest density scheme can be expressed by (8), subject to (2), (3), (4), (5), (6), (7) and (8).

(9) Min [Xjktw2 × (DMjk × TCw2 + Ew2) × Yjt]

where,

Xiktw2: Amount of wood harvested from location i to sawmill k in the year t, and for wood type w under “shortest distance” harvesting scheme.

TCw2: Per-unit transportation cost for wood type w under the “highest density” harvesting scheme.

Ew2: Per-unit loading and unloading cost for wood type w under the “highest density” harvesting scheme.

**Second Stage**

Given the forest residues produced in the first subproblem, the second subproblem consists of selecting the refinery location among m candidate options for minimizing transportation costs. The formula can express it:

(9) Min { for i = 1 to locations b, t = 1 to 10, and f = 1 to number of candidate refinery d.

S.T.

(10) Zit) = DBt for i = 1 to locations b, and t = 1 to 10.

(11) AZit = 𝛼w× Xi(t-1)w + AZi(t-1) for i = 1 to locations b, w = 1 to 2 wood types, and t = 1 to number of 10.

(12) Zit <= AZit

Where,

Zit: Amount of forest residue harvested from location i for fueling the candidate biorefinery location at year t.

AZit: Amount of forest residue available in location i in year t.

DMif: Shortest distance from location i to candidate biorefinery location f.

CR: Transporting feedstock per-unit cost.

ER: Loading and unloading per unit cost.

DBp: Biorefinery demand in year t.

𝛼w: of forest residues generated by harvesting wood type w in the first subproblem.

Equation (10) represents the demand restriction for the refinery (10), equation (11) represents the time–link for available forest residues, the amount of forest residues available in year t is equal to forest residues available in the year (t-1) plus forest residues produced in the year (t-1). Finally, equation (12) is the available inventory constraint.

**Data**

Tennessee is divided into 8,435 hexagons (5-mi2) for calculating the distance between forest supply and sawmills or distance between forest residue supply and the biorefinery candidates. Hexagons are primary location units represented by an integer id for the model. For this research, hexagons farther than 200 miles from a sawmill or biorefinery candidate location are not considered. The data used in the model include (1) forest inventory spatial data for softwood and hardwood in Tennessee; (2) sawmill demand, type of wood, and location; (3) annual woody growth for hardwood and softwood in Tennessee; (4) harvesting costs for hardwood and softwood in Tennessee.

Softwood and hardwood inventory spatial data in Tennessee are obtained from the FIA database (FIADB). The spatial data contains the amount of hardwood and softwood in different locations in Tennessee. GIS processing operations need to be performed for having the forest inventory in the hexagon level. The shortest road distances between hexagons along with the street network were input provided by the FORSEAM model (He et al. 2014). These distances were calculated, favoring major roads when possible. Distances are required for calculating transportation costs. As the structure for a biorefinery requires services and logistics, not all the state locations are appropriate for establishing that industry. Only sites within industrial parks were considered candidates’ biorefinery locations.

The wood demand is considered at the sawmill level. Information about sawmills as wood type required, and capacity come from the U.S. Forest Service, United States Department of Agriculture (USDA) (Spelter et al., 2009). Annually sawmill demand is estimated as 50% of the maximum sawmill capacity. Sawmills locations were received from the FORSEAM model. Inventory growth rate and yield will be calculated from the FIA database (FIADB), which collects information at the county level. Annual average growth will be used for the period of the study for hardwood and softwood. Transportation costs and loading and unloading costs will be obtained from The U.S. Forest Service, which provides average forest operations costs from the Fuel Reduction Cost Simulator (FRCS) harvest cost model.

**Preliminary Results**

For testing the model, an arbitrary forest inventory data was generated in a 10 ×10 rectangular grid, and hypothetical sawmill A and sawmill B were located on the cells (1, 5) and (10, 5), respectively and a road that connects sawmills is shown in Figure 2. In the figure, the darker green areas correspond to higher density areas of woods. The “shortest distance” harvesting scheme model was applied for loggers to collect trees for satisfying the sawmills demand while minimizing their costs. One day demand for sawmill A is 2,500 tons, and demand for sawmill B is 2,000 tons. The daily demand for a hypothetical biorefinery is 150 tons. Figure 3 shows the amount of wood harvested to satisfy the demands in one day. As it is expected under the “shortest distance” criteria, loggers harvest closer areas first than further ones. Assumptions considered and results are shown in table 1.

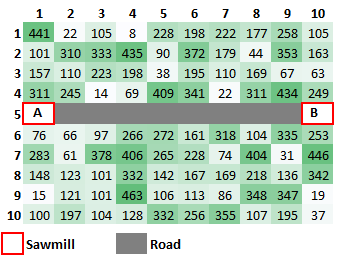


Fig2. Arbitrary forest inventory data for testing the model.

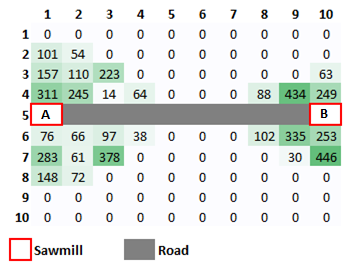


Fig3. Wood harvested for supplying the sawmills demand.

Table 1. Assumptions and results for Phase 1.

|  |  |
| --- | --- |
| Transportation cost | 0.054 $ per ton km |
| Wood density | 0.4 ton per m3 |
| Truck capacity | 35 m3 |
| Loading and unloading cost | 0.76 $ per ton |
| Phase 1 Truck loadings | 322 |
| Phase 1 Transportation costs | $86,091 |
| Phase 1 Loading and unloading costs | $3,420 |
| Phase 1 Total costs | $89,511 |
| Phase 1 Forest-wood per unit cost | 19.89 $/ton |

In the second stage, the optimal biorefinery location and forest residues collected were determined Residues generated from harvesting activity are shown in Figure 4. Those residues fueled the biorefinery. Figure 5 shows the minimal cost biorefinery location; as is expected, the biorefinery is placed close to the sawmill A, which has a higher demand than sawmill B. For this hypothetical case a truck with capacity of 35 m3 considered for transportation. Table 2 summarizes assumptions and results obtained. The estimated total supply chain costs are 94,025$.

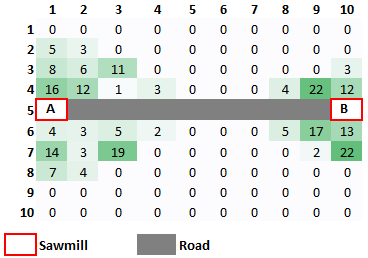


Fig4. Forest residues generated by sawmills.

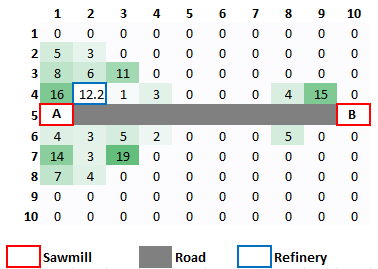


Fig5. Forest residues harvested and biorefinery location for minimizing transportation costs.

Table 2. Assumptions and results for Phase 2.

|  |  |
| --- | --- |
| Transportation cost | 0.054 $ per ton km |
| Truck capacity | 35 m3 |
| Forest residues density | 0.17 ton per m3 |
| Loading and unloading cost | 0.76 $ per ton |
| Phase 2 Truck loadings | 25 |
| Phase 2 Transportation costs | $4,400 |
| Phase 2 Loading and unloading costs | $114 |
| Phase 2 Total costs | $4,514 |
| Phase 2 Forest Residues per unit cost | 30,12 $/ton |

**References**

Aalmo, G. O., Kerstens, P. J., Belbo, H., Bogetoft, P., and Talbot, B. “Efficiency Drivers in Harvesting Operations in Mixed Boreal Stands: A Norwegian Case Study.” International Journal of Forest Engineering 1494-2119 (June 2020).

Angus-Hankin C., Stokes B., and Twaddle A. “The transportation of fuelwood from forest to facility.” Biomass and Bioenergy, Volume 9 (1995): 191-203.Cambero, C., Sowlati, T., Marinescu, M., and Röser, D. “Strategic optimization of forest residues to bioenergy and biofuel supply chain.” International Journal of Energy Research, Volume 39 (2015): 439– 452.

Atashbar, N. Z., Labadie, N., and Prins, C. “Modelling and optimization of biomass supply chains: a review.” International Journal of Production Research, Volume 56 (2018): 3482-3506.

Bordon, M. R., Montagna, J. M., and Corsano, C. “Mixed integer linear programming approaches for solving the raw material allocation, routing and scheduling problems in the forest industry.” International Journal of Industrial Engineering Computations, Volume 11, Issue 4 (2020): 525-548.

Carriquiry, M., Xiaodong D., and Govinda R.T. “Production Costs of Biofuels. The Impacts of Biofuels on the Economy, Environment, and Poverty.” Natural Resource Management and Policy, Volume 41 (2014): 33-46.

Contreras, M, Chung, W, and Jones, G. “Applying ant colony optimization metaheuristic to solve forest transportation planning problems with side constraints.” Canadian Journal of Forest Research, Volume 38 (2008): 2896-2910.

Daioglou, V., Stehfest E., Wicke, B., Faaij, A., and Van Vuuren, D.P. “Projections of the availability and cost of residues from agriculture and forestry.” GCB Bioenergy, Volume 8 (2016): 456–470.

FIADB, Forest Inventory and Analysis Database, St. Paul, MN: U.S. Department of Agriculture, Forest Service, Northern Research Station. https://apps.fs.usda.gov/fia/datamart/datamart.html. (Accessed October 01, 2020).

Frankó, B., Galbe, M., and Wallberg, O. “Bioethanol production from forestry residues: A comparative techno-economic analysis.” Applied Energy, Volume 184 (2016): 727–736.

Gan, J. “Supply of biomass, bioenergy, and carbon mitigation: Method and application.” Energy Policy, Volume 35 (2007): 6003–6009.

Greene, N., Celik, F.E., Dale, B., Jackson, M., Jayawardhana, K., Jin H., Larson, E.D., Laser, M., Lynd, L, and MacKenzie, D. “Growing energy: how biofuels can help end America's oil dependence.” Natural Resources Defense Council, New York, 2004.

He, L., English, B.C., De La Torre Ugarte, D.G., and Hodges, D.G. "Woody biomass potential for energy feedstock in the United States." Journal of Forest Economics, Volume 20 (2014): 174-191.

He, L., English, B. C., Lambert, D. M., Shylo, O., Larson J. A., Yu, T. E., and Wilson, B. “Determining a geographic high resolution supply chain network for a large scale biofuel industry.” Applied Energy, Volume 218 (2018): 266-281.

He, L., English B. C., Menard, R. J., and Lambert, D. M. “Regional woody biomass supply, and economic impacts from harvesting in the southern U.S.” Energy Economics, Volume 60 (November 2016): 151-161.

Huang, Y.A., Chen, C., and Fan, Y. “Multistage optimization of the supply chains of biofuels.” Transportation Research Part E, Volume 46 (2010): 820–830.

IATA. Sustainable Aviation Fuel Roadmap (2015). https://www.iata.org/contentassets/d13875e9ed784f75bac90f000760e998/safr-1-2015.pdf (Accessed October 03, 2020).

IPCC, The intergovernmental Panel on climate change. “Special Report Global Warming of 1.5 ºC.” (2019). https://www.ipcc.ch/report/sr15/ (Accessed October 01, 2020).

Ng, R., and Maravelias, C. “Design of biofuel supply chains with variable regional depot and biorefinery locations.” Renewable Energy, Volume 100 (January 2017): 90-102.

Nunes, L. J. R., Causer, T. P., Ciolkosz, D. “Biomass for energy: A review on supply chain management models.” Renewable and Sustainable Energy Reviews, Volume 120, Article 109658 (2020).

Oswalt, S., Smith, B.W., Miles, P.D., and Pugh, S.A. *Forest Resources of the United States, 2012: A Technical Document Supporting the Forest Service Update of the 2010 RPA Assessment.* (Gen. Tech. Rep. WO-91). Washington, DC: U.S. Department of Agriculture, Forest Service, Washington Office. 2014.

Pauly, M., and Keegstra, K. “Cell-wall carbohydrates and their modification as a resource for biofuels.” The Plant Journal, Volume, 54 (2008): 559-568.

Perlack, R., Wright, L., Turhollow, A., and Graham, R. *Biomass as feedstock for a bioenergy and bioproducts industry: the technical feasibility of a billion-ton annual supply.* (Tech. Rep. ORNL/TM 2006/66). Oak Ridge National Laboratory:  Oak Ridge, TN. 2005.

Sambra, A., Sorensen, C. A. G., and Kristensen, E.F. “Optimized harvest and logistics for biomass supply chain.” Proceedings of European Biomass Conference and Exhibition, Valencia, Spain, May 2-6, 2008.

Schenk, P., Thomas-Hall, S., Stephens, E., Marx, U., Mussgnug, J., Posten, C., Kruse, O., and Hankamer, B. “Second Generation Biofuels: High-Efficiency Microalgae for Biodiesel Production.” BioEnergy Research (2008): 20–43.

Skog, K., Barbour J., Buford M., Dykstra, D., Lebow, P., Miles, P., Perlack, B., and Stokes, B. “Forest-Based Biomass Supply Curves for the United States.” Journal of Sustainable Forestry, Volume 32 (2013): 14-27.

Spelter, H., McKeever, D., and Toth, D. *Profile 2009: Softwood Sawmills in the United States and Canada.* (Res. Pap. FPL-RP-659). USDA Forest Service, Forest Products Laboratory, Madison, Wisconsin, 2009.

Spinelli, R., Nati, C., and Magagnotti, N. (2008). “Harvesting Short-Rotation Poplar Plantations for Biomass Production.” Croatian Journal of Forest Engineering, Volume 29 (2008): 129-139.

Spinelli, R., and Magagnotti, N. “The effect of harvest tree distribution on harvesting productivity in selection cuts.” Scandinavian Journal of Forest Research, Volume 28 (2013):701-709.

Stockinger, H., and Obernberger, I. “Life cycle Analysis of district heating with biomass.” Proceedings of the 10th European Bioenergy Conference, Würzburg, Germany, June 8-11, 1998.

Sun, O., and Fan, N. “A Review on Optimization Methods for Biomass Supply Chain: Models and Algorithms, Sustainable Issues, and Challenges and Opportunities.” [Process Integration and Optimization for Sustainability](https://link.springer.com/journal/41660), Volume 4 (2020): 203–226.

U.S. Congress. Energy Policy Act of 2005. Public Law 109, 109th Congress, Washington DC, USA.

U.S. Congress. Energy independence and security act of 2007. Public Law 110, 110th Congress, Washington DC, USA.

U.S. Department of Energy (DOE), 2016 Billion-ton report https://bioenergykdf.net/billionton2016/2/1/table (Accessed October 04, 2020).

Walsh, M.E., Perlack, R.L., Turhollow, A., De la Torre U. D., Becker, D.A., Graham, R.L., Slinksy, S.E. and Ray, D.E. “Biomass Feedstock Availability in the United States: 1999 State Level Analysis.” Oak Ridge National Laboratory: Oak Ridge, TN (2000).

Yu, T.E., He, L., English, B.C., and Larson, J.A. “GIS-based optimization for advanced biofuels supply chains: a case study in Tennessee.” Management Science, Volume 6 (2014): 217–227.

Zhang, F., Johnson, D., Johnson M., Watkins D., Froese, R., and Jinjiang W. “Decision support system integrating GIS with simulation and optimization for a biofuel supply chain.” Renewable Energy, Volume 85 (January 2016): 740-748.

Zhong J., Yu T. E., Larson, J. A., English, B. C., Fu J. S., and Calcagno J. “Analysis of environmental and economic tradeoffs in switchgrass supply chains for biofuel production.” Energy, Volume 107 (2016): 791-803.