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GIS BASED DISCRETE EVENT MODELING AND SIMULATION OF BIOMASS SUPPLY CHAIN

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ABSTRACT

A consistent, reliable and low cost biomass supply chain is crucial for a sustainable biorefinery. Spatial and temporal variations in biomass yield, weather risk, transport network, machine capacity significantly impacts logistics cost and supply chain performances. The objectives of the study are to develop a sustainable biomass supply chain modeling framework coupled with GIS (Geographic Information System) to estimate feedstock flow rate and delivered cost. The supply chain model was developed and implemented in discrete event simulation platform and tested with Miscanthus crop (biomass) supply chain for 10 years from strip-mined lands in Ohio. The overall cost of biomass delivered to a biorefinery was estimated to 84 \$/dry Mg with an average annual plant demand of 200,000 dry Mg. The developed model will be further improved to include energy consumption and environmental impacts of entire biofuels supply chain.

1 INTRODUCTION

Biomass consisting of forest trees, energy crops and agricultural residues can be converted into drop-in biofuels to replace petroleum based liquid fuels. The US is mandated to replace 30% of current petroleum use by 2030 to spur rural bioeconomy, reduce greenhouse gas emissions and safeguard national energy security (Perlack and Stokes 2011). A biorefinery, synonymous to a petroleum refinery is envisioned to convert biomass feedstock into range of biofuels, biochemical and bioproducts. A typical biorefinery requires consistent and reliable supply of low cost feedstock. Unlike a petroleum crude oil supply chain, a typical biomass supply chain consists of series of complex operations from production, harvesting, transport and storage to delivery of feedstock to a plant. Biomass is also sparsely distributed across large landscape with changing productivity (biomass yield) and undesirable logistical characteristics (e.g. high moisture, low bulk density etc.). In addition, seasonal availability, local weather issues and machine performances further influence the feedstock delivery, inventory management and cost. For example yield of biomass from perennial energy crop like Miscanthus, switchgrass, etc. varies widely (i.e. 14.7 to 30.2 dry Mg/ha) in spatial as well as temporal (during its life cycle) scale (Arundale et al. 2014). Development of consistent, reliable and sustainable biomass supply chain is critical to improve machine performances, risk management & mitigation, and to reduce feedstock delivered cost (Lin et al. 2014; Sokhansanj, Turholow, and Wilkerson 2008). The cost of transportation is an another major contributor to the total cost of biomass that is often calculated by assuming fixed rectilinear distances or sometimes rectilinear distance multiplied with road winding factor/tortuosity factor (De Meyer et al. 2014; Sultana and Kumar 2012). Biomass transportation is a seasonal as well as year around operation where number of logistics

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equipment required is much larger during harvesting season than rest of the year. Modeling these operations by a single approach (seasonal or year around operation) may not be true representation of the actual transporting activities. Accurate estimation of transport cost require optimized transport network with practically feasible connecting road between biomass supply points and a biorefinery which can be accomplished by coupling Geographic Information System (GIS) and supply chain models. GIS based biomass supply chain model can reduce the error in estimation of resources by accommodating spatial and temporal biomass variability in the modeling/analysis. It will further facilitate to optimize biomass supply chain which can be effective and economical.

Previous supply chain simulation studies [e.g. SHAM (straw handling model), IBSAL (integrated biomass supply analysis and logistics)] have developed biomass supply chain models to estimate feedstock cost, energy use and fuel/diesel CO_2 emission to accommodate temporal variables but used static inputs data such as biomass yield, machine characteristics, fixed transport distance, etc. (Kumar and Sokhansanj 2007; Nilsson 1999; Sokhansanj, Turhollow, and Wilkerson 2008). In addition, the use of optimal network structure to simulate biomass supply chain was demonstrated by Ebadian et al. (2013) and reported that an integrated optimization and simulation model reduced the cost of biomass delivered by 6.6% as compared to only simulation result without an optimal network structure . The use of optimal structure & geographic information system (GIS) for actual road network distance and spatial & temporal variables can make these simulation model more reliable to accurately estimate cost and supply chain performance parameters. The main objectives of this paper are (i) to develop a consistent and reliable biomass supply chain model using a discrete event simulation platform coupled with GIS tool for perennial energy crops, and (ii) to evaluate and test the system performances and cost of feedstock delivery to a plant/biorefinery. Perennial crops have at least 10 years of production cycle once they are planted and the biomass yield significantly varies (± 30%) yearly and so the cost of feedstock delivered. In this study, a high yielding energy crop, Miscanthus grown in strip-mined land was selected.

2 BIOENERGY SUPPLY CHAIN

A typical bioenergy supply chain consists of biomass producers/farmers, biomass suppliers (logistics), energy producer/biorefinery, product distributors and customers (Figure 1). Usually a upstream bioenergy supply chain (biomass supply chain) for an energy crop includes crop establishment, maintenance/crop management, harvesting & collection, storage and transportation (An et al. 2011). Each major supply chain activity is a combination of different units of sub-processes.

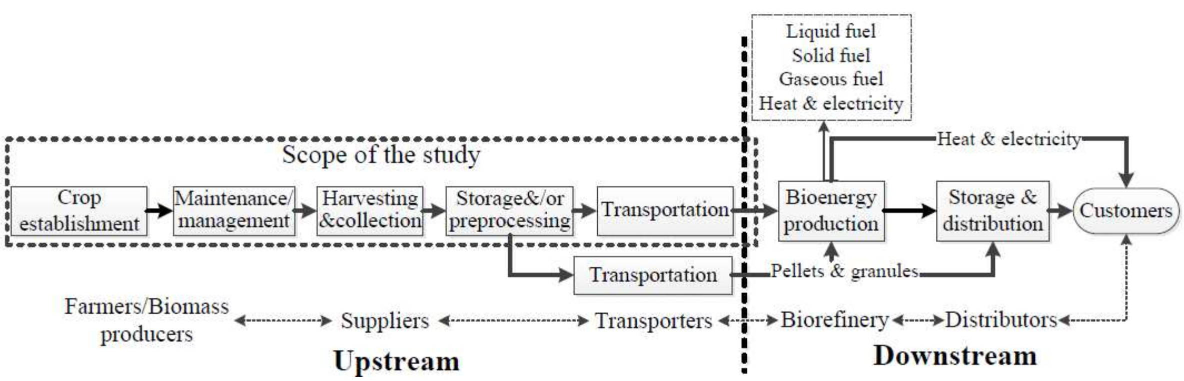

Figure 1: A typical bioenergy supply chain & scope of the study.

Harvesting and collection operation include cutting of grasses, baling (bundling into large items), stacking prior to long distance transport. While biomass can be transported by multi-model network (truck, train, barge and pipeline), truck transport is the most common operation to deliver biomass to a biorefinery or storage facility (Kumar and Sokhansanj 2007). Biomass is often stored in open space, but covered with tarps to protect it from weather.

3 MODEL DEVELOPMENT

3.1 Supply Chain Strategy and Model Structure

A combination of Push-Pull strategy was adopted for the biomass supply chain. In the push strategy, all lands are harvested and subsequently biomass was transported to storages irrespective of biomass demand at plant. But in the pull strategy, daily biomass demand of the plant was met from storages or field locations (during harvesting only). All land units were supposed to be harvested within the harvest time (typically, 2 months) and daily plant biomass demand during harvesting season should be transported from field to plant directly to reduce cost by skipping storage. The excess daily harvested biomass from fields is supposed to be transported to a assigned storage location for future use. The storage locations near to the plant were given more priority than remote ones for fulfilling the plant daily biomass demand. It was assumed that the plant started with an operating capacity (i.e. 50% of its maximum capacity) in 2nd year of simulation and its operating capacity increase to certain peak capacity after few years (i.e. 5th year) and maintain the capacity at this level till the end of plant life.

The framework/structure of GIS based discrete event simulation model is shown in Figure 2. Multi-criteria selection models developed in ArcGIS platform were used to find suitable available lands for specific crop cultivation and estimate biomass availability from these selected lands using average biomass yield along with field characteristics of individual land units. A multi-criteria inclusion & exclusion model was developed to find possible plants and storage locations (Sultana and Kumar 2012; Zhang et al. 2011). A facility location model using network analyst tool was developed to optimally locate plants and storage locations constraining maximum transport network distance or plant capacity to minimize the total weighted tonne-km for the studied region. The network analyst tool uses a combination of heuristics (vertex substitution method; Teitz and Bart algorithm) and a refining metaheuristics to find near-optimal solutions.

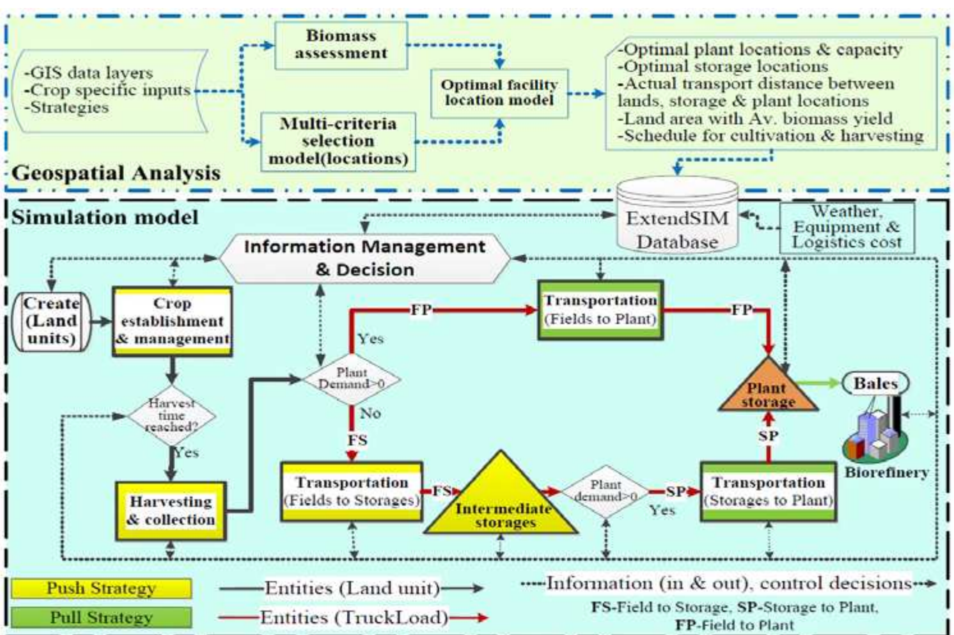

Figure 2: Framework of GIS based discrete event simulation model of biomass supply chain.

The results from location allocation model were used as inputs to the simulation model developed in discrete event simulation platform software, ExtendSIM 8. The simulation model consists of crop establishment & management, harvesting, transport and storage. The create module in the simulation model generate entities (land units) and add all spatial values as attributes to entities (land units) based on inputs from GIS model. The management information & decision(IM&D) module (hexagonal box in Figure 2) acts as brain to the model where it control the movement of entities, provide resources requirements and weather delays to different process modules, collect & update all information to and from each modules, manage inventory at plant & storage locations, etc. In this study, two paths are considered for supplying biomass to the plant (i) Field to Plant (FP) and (ii) Field to plant via storage (FSP) [Storage (FS) and Storage to Plant (SP)].

3.2 Simulation Modeling Approach

The developed model is having many modules representing a specific task or operations and decisions for the supply chain. The descriptions of key modules are described below.

3.2.1 Information Management & Decision (IM&D)

IM&D module (Figure 2) is the brain of the simulation model which decides the path of entities, maximum number of equipment at process modules in a given day, manage inventory at each intermediate and plant storage locations, gather all information related to machines, processes, plant, etc. to manipulate different decisions to implement strategies. The module estimates number of equipment (establishment & harvesting) required on daily basis considering (a) maximum number of equipment allowed for a process in the system, (b) remaining operational time window for an operation at given point of time and (c) amount of work to finish before deadlines. It also estimates weather delay for each operation as estimated by Sokhansanj, Turhollow, and Wilkerson (2008).

3.2.2 Biomass Establishment & Management

This module is having number of sub-module which represents these once in a lifetime operations, i.e. lime application, spraying, primary tillage, secondary tillage and planting except fertilizer application (an annual operation). A processes where an implement is attached with a power unit, the sub-module is again split into attachment and power module. The process time is estimated based on land properties and input implement parameters. The costs are estimated based on process time and other material inputs, e.g. fertilizer, lime, etc. for few specific supply chain operations.

3.2.3 Harvesting & Collection

Three operations were considered for harvesting energy crops, i.e. (i) swathing, (ii) baling and (iii) stacking of bales. Disc header swather, square baler and bale stacker were selected for these operations. Swathing and baling equipment have limited maximum biomass handling capacity i.e. dry Mg of biomass per hour (Sunil et al. 2014a; Sunil et al. 2014b). So the field speed of the equipment is decided based on the biomass yield of a land unit and maximum biomass handling capacity. An equipment can increase its speed during field operation to reach maximum limit of biomass handling capacity but increase in speed reduce the field capacity due to decrease in field efficiency (Hunt 2008). The complex relationship between field capacity, field efficiency and field speed of equipment were addressed in the developed simulation model. The bale stacker field capacity depends on the number of bales in the field (i.e. biomass baled/bale weight), average field staking distance (size and shape of the field), bale holding capacity and field speed of the stacker. It was assumed that bale stacker follow the path of baler to collect the bales and move a certain field distance to unload bales at staking location of the field, every time the stacker reached its bale holding capacity. A schematic diagram of bale stacking process is shown in Figure 3. The process time and stacking field capacity is estimated as described below.

$$S1 = 10 * \frac{Area\ of\ land\ (ha)}{baling\ width\ (m)}$$

$$\mathrm{S2} = 0.5 * \mathrm{Sqrt}\left[Wi^2 + \left(\frac{Le}{2}\right)^2\right]$$

$$\mathrm{N}_{bale\ trips} = \frac{B_n}{\mathrm{S}_{bale\ Cap}}$$

$$\mathrm{S}_{total} = 0.001\left(\mathrm{S1} + 2 * \mathrm{S2} * \mathrm{N}_{bale\ trips}\right)$$

$$\mathrm{PT}_{stacking} = \frac{\mathrm{S}_{total}}{Sp_{stacking}}$$

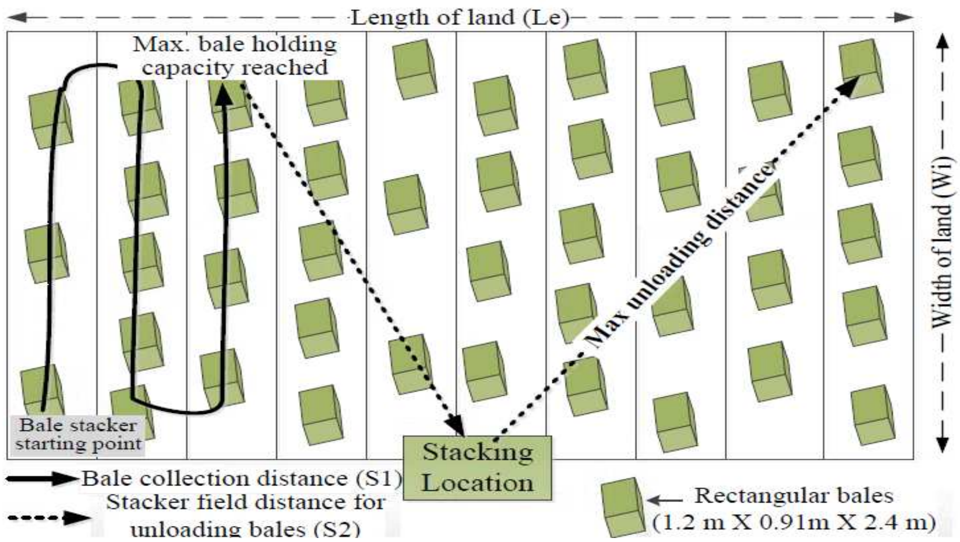

Figure 3: A schematic diagram of stacking operations bales.

Where Wi and Le are length and width of a land unit. S1 and S2 represent travelling distances (m) by the bale stacker for bale collection and bale unloading respectively. B_n, $\mathrm{S}_{bale\ Cap}$, $\mathrm{N}_{bale\ trips}$ and S_{total} are number of bale per land unit, stacker bale capacity, total number of trips a stacker required to complete the stacking process and total travel distance (km) respectively by a stacker for a land unit to complete the stacking process. $\mathrm{PT}_{stacking}$ and $Sp_{stacking}$ are total process time (hr) and field velocity of the stacker (km/hr) respectively.

3.2.4 Transport

After harvesting, the total harvested biomass was divided into number of truckloads. Based on the inventory at plant location and its daily demand, the IM&D module controls the amount of biomass to be supplied directly from field to plant during harvesting season. Each entity/truckload of biomass was having three distance attributes i.e. actual distances from field to plant, field to assigned storage and storage to plant based on the optimal supply chain network (GIS output to the simulation model). A priority was assigned to these three destinations for assigning resources (bale loaders, tractors and trailers) during transportation operation. The orders of priority from highest to lowest are FP, SP and FS respectively. The transport resource selection and its management were modeled with advanced resource module (ARM) of ExtendSIM8. The transportation operation was modeled as combination of sub-processes, i.e. loading bales into trailer, transport the loaded trailer to a destination with tractor and unload the bales from trailer at the destination location and return transport of truck & trailer to the starting location. The transport equipment are categorized into two categories i.e. dedicated (only few) & non-dedicated (large number) transport logistics to accommodate large fluctuation of equipment requirement between harvesting window and rest of time in a year.

3.2.5 Storage (At Intermediate & Plant Locations)

Outdoor-tarped storage method with unlimited storage capacity was considered to store bales at each storage location in the supply chain. There are two types of cost associated with storage of biomass i.e. (i) fixed cost (stacking, rent & overhead cost; irrespective of storage duration) and (ii) variable cost (dry matter loss cost; depend on storage duration). The biomasses from storage locations were consumed by the plant based on their location distances from the plant (priority to nearer storage locations from plant) controlled by the IM&D module. The IM&D module also maintain the storage inventory at each storage locations by scarping the old storage bales (i.e. 1.5 years old) and bales excess to the limiting maximum storage biomass in the system (i.e. 250 dry Mg in storages for an annual 200 dry Mg plant capacity). The model also considers a temporary storage at the plant which acts as a buffer for supply uncertainty, variable plant demand and shortage during extreme weather events.

4 MODEL INPUTS

The complete supply chain model implemented in discrete event simulation software was tested for producing Miscanthus biomass from strip-mined lands in the state of Ohio, USA and supply to a plant/biorefinery. The spatial analysis with GIS estimates the biomass availability and optimal location of plants and its storages. One plant and its storage locations were chosen (highest biomass availability) for simulating its biomass supply chain. The model runs for 20 iterations and each iteration considered for a time frame of 10 years, i.e. life cycle of the energy crop to estimate cost and other supply chain performance indices. Some critical assumptions & input data for simulation model were:

- The plant was scheduled to run for 330 days and 24X7 in a year with 30 days of downtime for maintenance. The logistics operations were scheduled from 8.00AM to 6.00PM (10 hours daily) for 5days in a week. The maximum harvesting window for Miscanthus was 4 months.
- The plant started with 50% of its highest annual biomass processing capacity (200,000 dry Mg) and achieved peak level at 5th year of simulation time. The storage capacity of the plant was about 2 weeks of its biomass demand.
- Annual biomass yield of Miscanthus from strip-mined land was considered on average 5 dry Mg/ha in 2nd year and the yield increase rapidly to 17 dry Mg/ha in 5th year after planting and then decreased slowly to about 10 at 10th year of establishment (Arundale et al. 2014).

Currently about 118,267 ha of strip-mined land in Ohio State, USA is suitable for cultivating Miscanthus. The location allocation model developed with the help of network analyst tool in ArcGIS 10.1 optimally located 7 plants (Figure 4). Among seven optimally located plants, one location (selected for simulating its downstream supply chain) is assigned to about 20,696 ha (272 unit lands with area varies from 10 ha to 660 ha) of land with 10 optimally located storage facilities of un-limited capacity. Other input data for the simulation model as a resulted from spatial analysis were (i) actual road network distances from individual land units to storages & plant and direct distances from storages to plant location. (ii) The area & shape factor (length and width) of each individual land, (iii) land schedule based on adjacency (assumed that after finished an operation at certain land the equipment will move to its adjacent land to save idle time). The model generated daily stochastic plant demand by using a triangular distribution using average demand ±10% of average demand. The dry matter loss in the supply chain was due to implement inefficiencies as well as natural biochemical activities in the biomass. The dry matter loss during swathing, baling, stacking, transportation and storages were assumed to be on average 6%, 9%, 2%, 2% and 7% respectively (Ebadian et al. 2013; Sokhansanj, Turhollow, et al. 2008). The daily weather data (temperature, rainfall and snow accumulation) were collected from the weather station near to the plant location and its surrounding nearby weather stations from 2004 to 2014 and input to the simulation model (MRCC 2015). The type of equipment and its number, hourly total cost of operation and maximum number of equipment used in the simulation model are presented in Table 1.

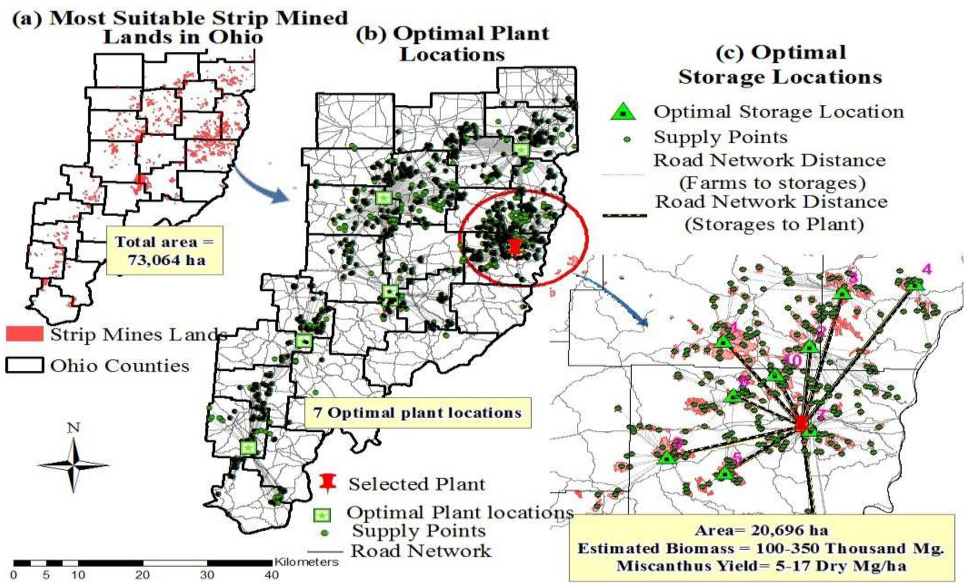

Figure 4: (a) Spatial distribution of Strip-mined lands, (b) Optimal number and location of plants and (c) Selected plant and its storage locations for simulating its supply chain.

Table 1: Crop establishment, harvesting and logistics equipment used in simulation model.

Operation Name	Equipment	Operation Cost ($/hr)Ɨ	Max. No of Equipment
Pre-Establishment			
Lime spreader	Fertilizer spreader +Tractor	486.42	6
Spraying	Self-propelled sprayer	252.38	3
Primary tillage	MB plough +Tractor	137.72	30
Secondary tillage	Tandem disc + Tractor	245.77	10
Rhizome planting	Rhizome planter + Tractor	97.49	40
Post Establishment			
Fertilizer spreader	Fertilizer spreader +Tractor	322.77	
Swathing	Disc header + SP Swather	273.86	16-24
Baling	Large square baler +Tractor	173.76	9-41
Field stacking	Auto stack + Tractor	118.41	15-52
Loading	Frontend loader	105.7	15[a]& 38[b]
*Transport	Flatbed trailer + Tractor	1.61*	Trailers(18[a] + 50[b]) Tractors(10[a]+ 27[b])
**Storage		4.61**	

*Transport cost was estimated as $/km; ** storage cost was estimated as $/dry Mg, Ɨ Estimated as per as ASAE standards (ASABE 2011; Lazarus 2013); [a] Dedicated (used throughout the year), [b] Seasonal use.

The model used the average, minimum and maximum equipment field speed and field efficiencies as described in ASAE standards (ASABE 2011). The model may not use all these equipment during simulation run which was discussed earlier. A fixed rate of fertilizer inputs were applied during only establishment year. But a variable rate (i.e. yield dependent) of fertilizer was applied during rest of the life cycle years to maintain nutrient balance in the soil and sustainable biomass production (Cadoux et al. 2012). Miscanthus establishment and annual management inputs materials and its related costs are given in Table 2.

Table 2: Annual input raw materials and respective prices for crop establishment (1st year) and annual management (2nd year onwards) [(USDA-NASS 2015), (Arundale et al. 2014; Cadoux et al. 2012; Khanna et al. 2008)].

Input Materials	Av. Cost ($/kg)	Average inputs (kg/ha):Year 1	Average inputs(kg/dry Mg biomass removed):Year 2 to Onwards
Rhizomes (for planting crop)	0.09 ($/pcs)	16000 (nos/ha)	0
Lime	0.06	4500	0
Nitrogen	1.27	52	3.8
Phosphorous	1.38	33	0.5
Potash	0.99	81	8.0
Glyphosate	12.5	5.8	0
2-4-D	6.4	3.5	0

5 MODEL TESTING & VALIDATION

The extreme weather events (rain & snow) occurs during (December-April) in USA which coincides with biomass harvesting season for Miscanthus. Figure 5 illustrates the influence of snow and rain on different logistics operations. A significant portion of working hour was lost due to bad weather conditions (i.e. about 27% of working hour lost in 5th year due to bad weather) during harvesting season at respective geographic location.

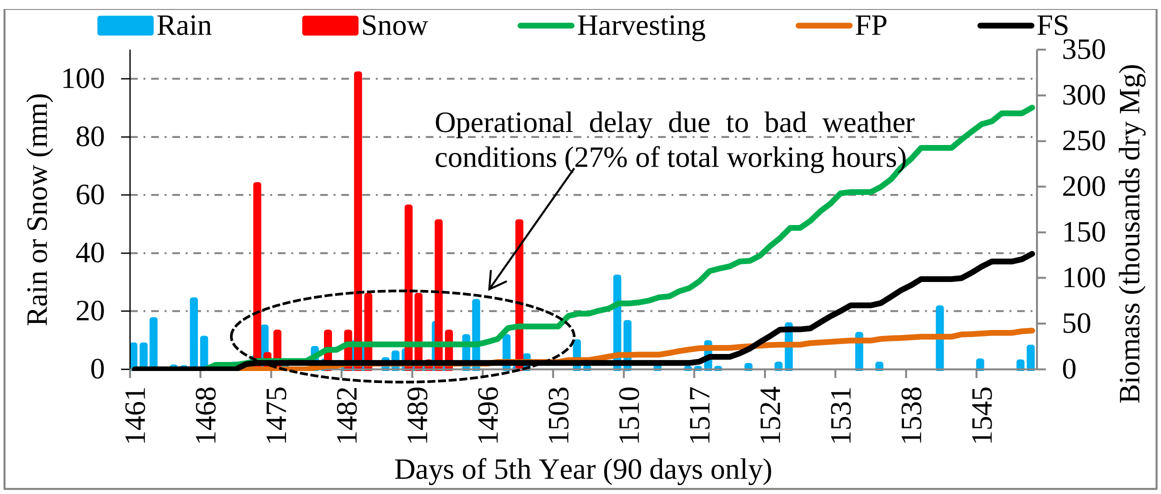

Figure 5: Effect of weather events on different supply chain operations [transportation of biomass from field to plant (FP) and field to storage (FS)].

The current model not only capture the discrete weather delay but also delay due to consecutive weather events for series of days in a year. Miscanthus is a perineal energy crop and every year it grows from its remaining underground rhizomes in the field. So extending harvest window in a year will adversely affect the biomass yield for subsequent years. Therefore harvesting should be complete before emergence of new shoots (~ month of May every year).

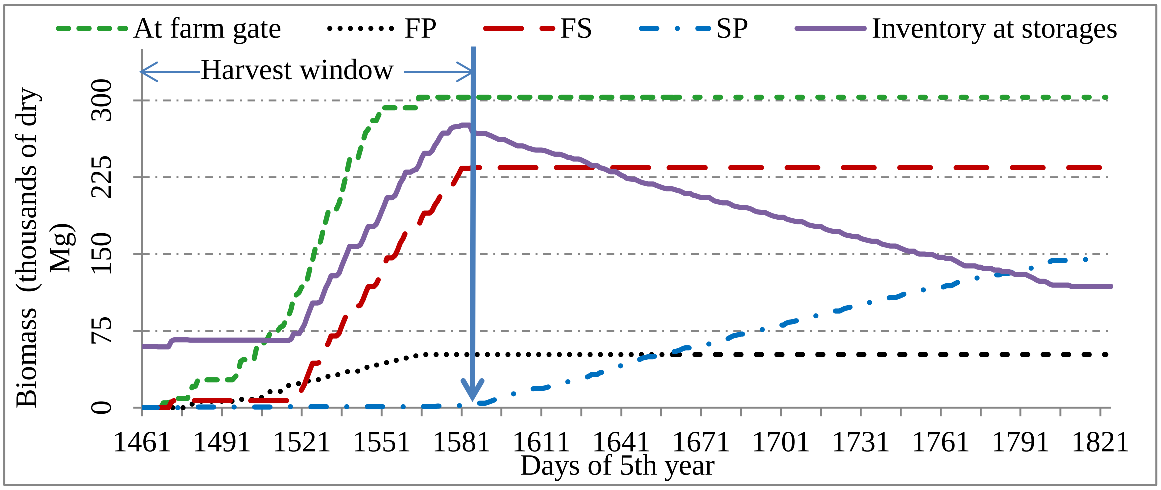

Figure 6: Temporal biomass accumulation at farmgate, biomass transported and stored in the downstream bioenergy supply chain (5th year only) [biomass transported from field to plant (FP), field to storage (FS) & storage to plant (SP)].

Figure 6 demonstrates the model exactly followed the supply chain strategy and completed the harvesting operation within the time frame, transport biomass from field to plant during harvesting season and remaining sent to storage locations. During harvesting season, the priority to transport biomass was given in the order of FP & FS. The annual plant demand, biomass delivered and yearly excess biomass stored are shown in Figure 7.

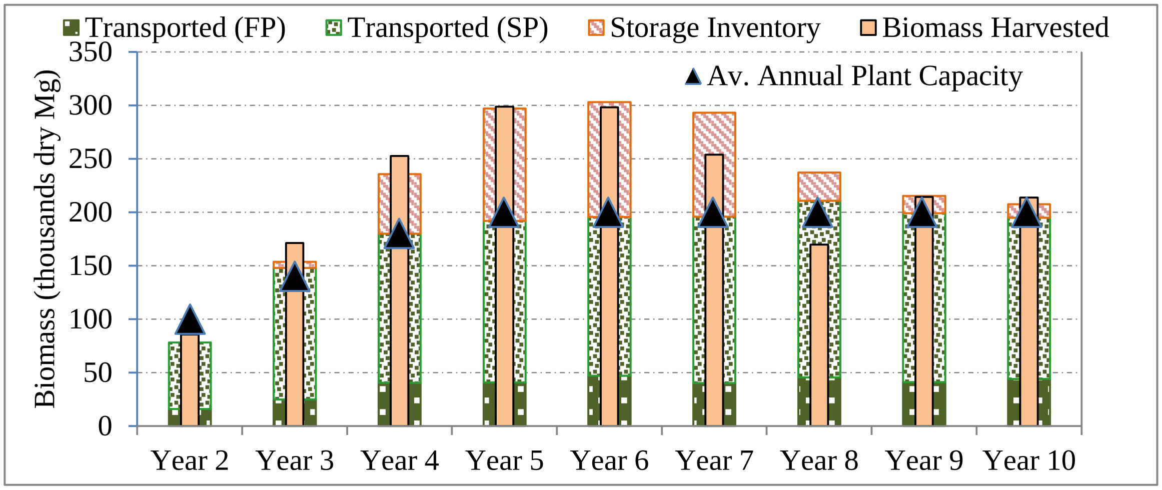

Figure 7: Annual biomass budget (biomass harvested, transported and in storage).

On average 21% (17-24%) of the total annual plant biomass demand was supplied directly from field to plant. The excess amount of biomass after fulfilling the plant demand were stored for future use which leads to increase in biomass delivered cost (Figure 9). Overall, the present set of harvesting & transport logistics equipment (Table 1) were able to fulfill the plant annual average demand. The estimated biomass cost at farm gate and plant gate is presented in Figure 8 which exclude the establishment cost but include the annual inputs raw materials, i.e. fertilizers (NPK : nitrogen, phosphorous and potassium) .

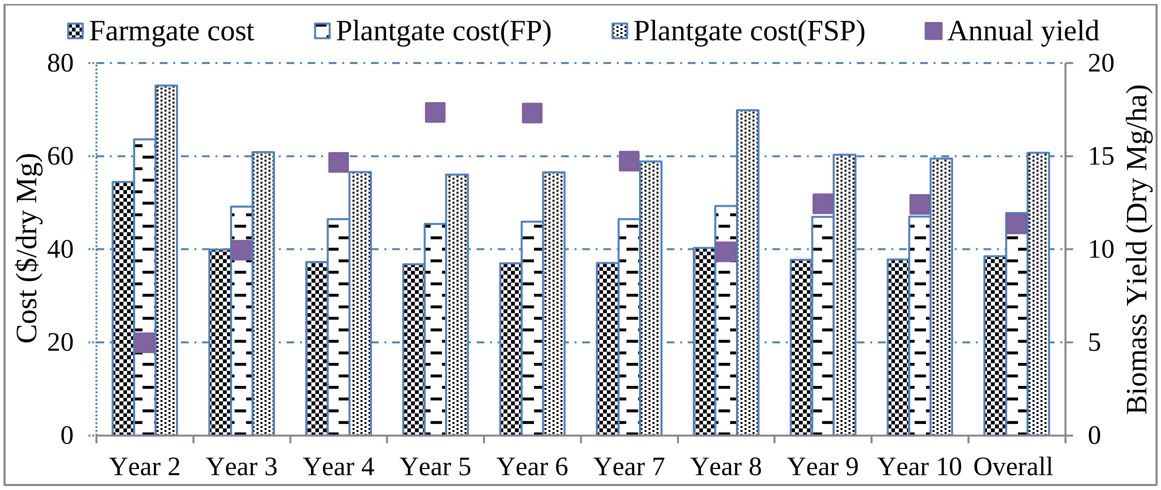

Figure 8: Annual average cost of biomass at farm gate & plant gate [field to plant (FP) & field to storage to plant (FSP)] with respective annual average biomass yield.

The overall cost (Figure 8) of biomass delivered from field to plant (FP) is about 21 % (15 - 29%) less than the delivered biomass from field to storage to plant (FSP). The cost benefit was due to skipping storage and reduction of handling cost during bale loading/unloading at storages. But the cost saving is only for about 1/4th of total biomass delivered to a plant as mentioned in Figure 7.

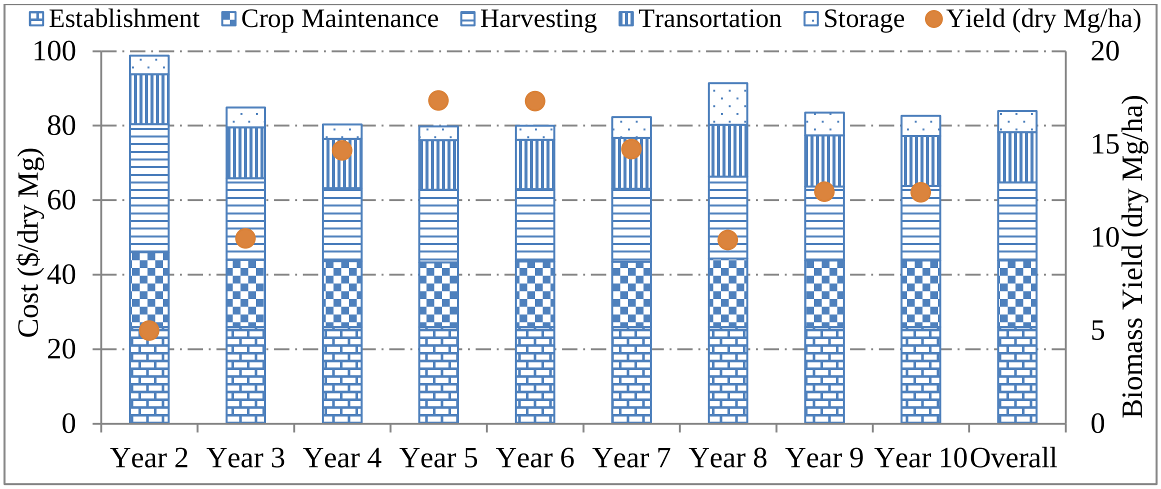

Figure 9: Annual & overall (for 10 years lifecycle) average cost of biomass delivered to the plant including establishment cost of Miscanthus.

The increase in harvest window may increase the total potential saving where more biomass can be delivered directly from field to plant. The costs are significantly influenced by the yield of biomass which decreased with higher yield. But the relationship between the increase in yield and decrease in cost is not linear (Figure 9). The cost of harvesting and plant delivery (FP & FSP) decreased by 27% and 21% by doubling the biomass yield respectively. Sokhansanj, Turholow and Wilkerson (2008) reported a decrease in harvesting cost by 20% with 33% increase in biomass yield. In this study, comparatively small decrease in cost was due to variable machine field capacities (changes with biomass yield) and relatively high biomass yield of Miscanthus as compared to crop residues. The model estimated establishment cost of Miscanthus which was around 31% of total cost of biomass delivered to the plant. The estimated average cost of biomass delivered to the plant was about 84 (80 to 100) $/ dry Mg (Figure 9) which was much larger than cost estimated by Kumar and Sokhansanj (2007) of similar biomass yield. The higher cost was due to inclusion of establishment cost & fertilizer inputs. Khanna, Basanta, and John (2008) used analytical model to estimate cost of delivery of Miscanthus biomass which was about half as compared to current study but the assumed biomass yield was about double than the present study. The storage cost of biomass in the supply chain varied between 5 to 12% of total cost. The very high cost of storage in 7^{th} year of simulation was due to accumulation of excess biomass from previous years resulted in high dry matter loss. Transportation cost of biomass remains unchanged among different simulation years as it is independent of biomass yield. The cost of establishment will decrease if the lifecycle years of Miscanthus will increase beyond 10 years. The biomass delivered cost estimated here is slightly higher than the target cost given by the Department of Energy (DOE) but this can be reduced by improving machine capacities, increase biomass yield, etc. The study indicates that the available strip-mined lands are a promising source for biomass production to generate bioenergy as well as reclamation of degraded strip-mined lands in USA.

6 CONCLUSION & FUTURE RESEARCH

The GIS based biomass production and logistics simulation model was developed to evaluate the spatial and temporal variability of Miscanthus yield, cost of delivery to a biorefinery. The model has demonstrated that the increase in biomass yield did not significantly increase the total delivered cost. Total delivered cost can be reduced by avoiding storage and by considering reverse logistics approaches, while significantly improving weather related delays and machine utilization rate. Future research is focused on incorporating the estimation of energy use, soil and water quality and greenhouse gas emissions of delivered biomass for building a sustainable biorefinery. The developed model can be further used to optimize minimum machinery required for efficient operation of biomass supply logistics system while extending the downstream biofuel supply chains.

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