

**Final Report for the  
National Center for Intermodal Transportation for Economic  
Competitiveness**

**Project Title:**

Analyzing the Impact of Intermodal-Related Risk to the Design and Management of Biofuel  
Supply Chain

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**NCITEC PROJECT Nr. 2012\_05**

**Project Period (Start Date, End Date):**

Aug 15, 2012 – Dec. 31, 2014

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## **ABSTRACT**

The objective of this research is to design a decision-support tool for identifying biorefinery locations that ensure a cost-efficient and reliable supply chain. We built mathematical models which take into consideration the benefits (such as, accessibility to different modes of transportation), and risks associated with locating a refinery near an intermodal facility. These mathematical models capture the impact of facility disruptions on biorefinery location and supply chain design. A visualization interface is developed and connected to the mathematical models. This web-based interface enables decision-makers to input the practical data related to the location problems and display chosen biorefinery locations after calculation of mathematical models.

The outcomes of this research are in compliance with the mission of the Intermodal Planning Division of MDOT to promote and support intermodal transportation by providing technical assistance which aims to improve and increase the usability of existing intermodal facilities. Through the decision-support tool, we will be able to identify under what conditions locating a biofuel plant near an intermodal facility is advisable; and what are the benefits/costs of such a decision. These results can be used to encourage biofuel plants to use intermodal facilities/transportation and make their investments accordingly.

## Introduction

The U.S. biofuel industry is expanding at a fast rate. The production of bio-ethanol in the U.S. has dramatically increased from 1.15 billion gallons in 2000 to 10.01 billion gallons in 2011 [76], and is projected to reach 11.67 billion gallons in 2020 [76]. Such an increase in bioethanol production mandates substantial expansion of existing biofuel supply chain infrastructure. The efficiency and reliability of a biofuel supply chain will be determined by the performance of an integrated biofuel production and transportation system that not only operates well under normal condition but also hedge against risks when a disruption occurs.

Biomass needs to be transported from a field to a biorefinery at a minimal cost. This requires a lean logistics network that efficiently connects origin fields and destination refineries with proper transportation modes. The biomass feedstock used for production of the first generation biofuels (corn- and soybean-based) is bulky, non-flowable and as a consequence difficult to load on a truck. This yields very high costs of loading, transporting and unloading biomass, which consequentially limits its economic transportation distance<sup>1</sup>. Brower [9] pointed out that moving biomass more than 50 miles to a conversion facility severely impacts profits. Due to this limited coverage radius, production capacities of the biorefineries are usually low. This restrains the biorefineries benefiting from economies of scale, and the unit cost of biomass keeps high. In order to alleviate this problem Idaho National Laboratory proposed a biomass delivery system [38]. This system relies on preprocessing biomass prior to transporting. Densified biomass has physical characteristics which are similar to corn, soybean and other grains; therefore, it is easy to load/unload and transport. Handling and transportation costs for densified biomass are smaller than those for unprocessed biomass; thus, long hauls become an option. Hess et al. [38] reported that depending on the amount and distance traveled, rail or truck can be used to deliver densified biomass to a biorefinery. As a result, large-capacity biorefineries can get shipments not only from local suppliers, but from suppliers located further away.

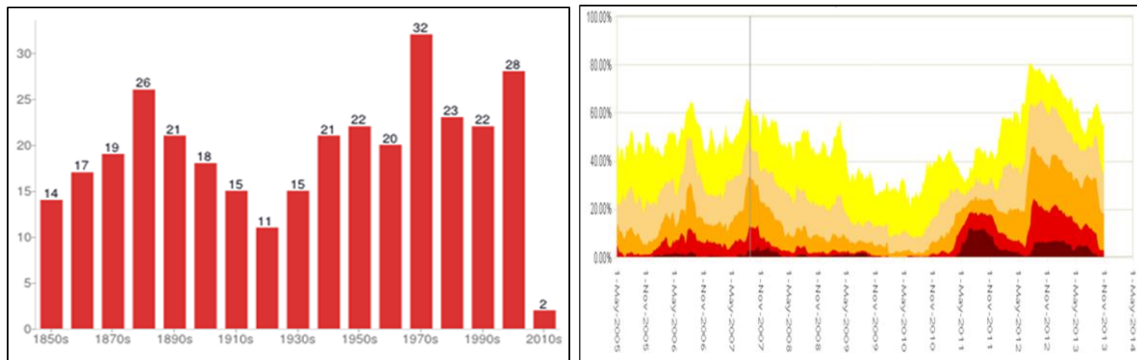
Large-capacity biorefineries require the development of a robust and integrated logistics system where the densified biomass is shipped via different modes of transportation such as truck, rail and barge. In case of unprocessed biomass, truck is considered as the only mode of transportation to ship biomass to biorefineries. Using rail or barge instead,

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<sup>1</sup> Economic transportation distance is the distance below which truck is considered as an economic mode of transportation.

not only reduces cost, but also alleviates congestion in the highways and as a result improves safety. Therefore, there is a need to establish intermodal hubs in a biofuel supply chain network where two or more transportation modes meet, such as rail ramps, in-land ports, sea ports, etc. Locating an intermodal hub close to the biorefinery allows it to use an economical transportation mode to replenish inventories. For example, the only biorefinery in Mississippi is the Bunge-Ergon located in Vicksburg, right on the Mississippi River at the port of Vicksburg, MS. KiOR Inc., a company of next-generation renewable fuel built its first plant near the Port of Columbus, MS. KiOR already announced to invest in building more biorefineries in Mississippi in the coming years.

Transportation infrastructures, particularly those bearing intermodal traffic, may be vulnerable to various disruption risks, such as natural disasters ([53], [77] e.g., 2005 Hurricane Katrina, 2008 China and 2009 Haiti Earthquakes) and human-caused disasters ([54], [58] e.g., 2003 U.S. Northeast blackout, 2010 Gulf of Mexico Oil Spill). Furthermore, some areas are recognized as disaster prone areas. For instance, Figure 1(a) shows that in total 39 different storms affected North Carolina between 2000-2008 [67]. Hurricanes in North Carolina history are responsible for over \$11 billion damage loss and almost 1,000 total fatalities. Similarly, the Mississippi river and its tributaries have flooded on numerous occasions in the past [72]. Hence, proper redundancy needs to be deployed among the biofuel supply chain to enhance the system reliability against infrastructure disruptions. This indicates that there is a need to develop a modeling framework for reliable design of a biofuel supply chain network. Such a design shall not only efficiently transport biomass under the normal Scenario (when every intermodal hub is functioning normally), but also hedge against possible losses due to unexpected infrastructure disruptions.



(a)

(b)

Figure 1: Figure shows (a) total storms affecting North Carolina between 1851-2012 [67], and (b) contiguous U.S. drought area (in %) [73]

## Literature Review

A major stream of research within the biofuel supply chain literature is to identify the best modes of transportation so as to minimize the transportation cost. To achieve this goal, a number of studies (e.g., [45], [50], [63]) analyzed the cost effectiveness of different modes of transportation to deliver biomass to biorefineries. Early studies mainly focus on supply chain decisions at operation level. Later studies further integrated both strategic planning and tactical decisions into the design of biomass supply chain networks in order to deliver biomass at a more competitive price to the end users. Work by [81], [27], [28], [39], [2], [5] and [79] analyze plant location and transportation issues in biofuel supply chain networks under a deterministic setting. These papers consider perfectly reliable facilities and known demand. Chen and Fan [12] and Kim et al., [44] extended those formulations by providing stochastic models that can be used to generate reliable solutions for the design and management of a biofuel supply chain network. Additionally, Gebreslassie et al. [32] incorporated financial risk in a hydrocarbon biorefinery supply chain system. All these models assume that supply chain infrastructure is always functioning perfectly and thus they fail to address unexpected transportation hub disruptions observed in reality [19], [58].

In the context of general network design, researchers have become increasingly interested in the effect of facility disruptions. Daskin [22, 23] was the first to consider facility unavailability in a maximal covering location problem. Drezner [26] has extended this work to reliable location design in a  $p$ -median problem. Snyder and Daskin [66] proposed an integer programming model for the stochastic fixed charge  $p$ -median location problem where the authors assumed that the facility disruptions occur independently and with an identical probability. Cui et al. [20] further extended this work to cases with site-dependent disruption probabilities by creating both discrete and continuous models. The continuous model has been generalized by Li and Ouyang [47] to incorporate spatially correlated disruption patterns. Shen et al. [64] proposed a two-stage stochastic program and a nonlinear integer program for problems where the open facilities fail at a certain probability. The authors proposed a 4-approximation algorithm and several heuristic approaches to produce near-optimal solutions in a reasonable amount of time. Most recently, Li et al. [46] provided nonlinear integer programming

models for a reliable  $p$ -median problem and a reliable uncapacitated fixed-charge location problem under disruption correlations. By using the rate of return on fortification investment, the authors also provided an alternative to assess the effectiveness of the design solutions.

Similar to the literature on facility locations discussed above, biofuel supply infrastructure is also impacted by various adversary incidents, such as water scarcity, flooding, routine maintenance, or adverse weather condition [62]. However, there are very few studies that addressed the impact of biorefinery disruptions in a biofuel supply chain network. Li et al. [48] developed a discrete and a continuous location model for a reliable bio-ethanol supply chain network. The authors showed the impact of disruption probabilities on optimal refinery deployment decisions. Wang and Ouyang [78] proposed a game-theoretical based continuous approximation model to locate biorefineries under spatial competition and facility disruption risks. However, these studies only considered failure risks at biorefineries, and little has been done on disruptions at intermediate transportation hubs that can significantly impact this supply chain system.

The biofuel supply chain system from biomass production to biorefineries can be viewed as a hub-and-spoke transportation network. Other industries, such as, package delivery [65], telecommunication [43], and airline transportation [4], [10], [17] also used hub-and-spoke to design their distribution networks. A brief overview of the hub location problems and solution methodologies can be found from a recent study of SteadieSeifi et al. [68]. Recent studies focus on extending the classical single and multiple allocation hub location problems by incorporation several extensions in the modeling framework. These extensions attempt to determine the impact of congestion [10, 29, 30], nonlinear economies of scale [24], and presence of dynamicity in the hub location problems [14].

The existing literature focuses not only on modeling the hub location problem, but also on developing effective solution algorithms. Camargo et al. [24, 10] present a customized Benders decomposition algorithm to solve large instances of the multiple allocation hub-and-spoke network models in a reasonable amount of time. Contreras et al. develop a Benders decomposition algorithm and integrate it with reduction tests to solve the uncapacitated [16] and capacitated versions [15] of the hub location problem. The authors further extended these studies to develop a Monte-Carlo simulation-based algorithm that integrates a sample average approximation scheme with a Benders



decomposition algorithm to solve an uncapacitated hub location problem under uncertainty [13]. Elhedhli and Hu [29] and Elhedhli and Wu [30] used Lagrangian relaxation heuristics to solve a hub-and-spoke network design problem with congestion. Recently, a Lagrangian relaxation technique coupled with variable fixing and a Branch-and-Bound scheme is used to solve a dynamic hub location problem [14] and a reliable hub-and-spoke network design problem [3]. Other techniques used to solve hub location problems are dual-ascent technique [11], simulated annealing [42] and genetic algorithm [21].

All these studies assume that transportation hubs are always functioning and never fail, which however cannot adequately describe real-world systems that involve various uncertainties from the supply side. A few studies focused on managing and rescheduling rail and port operations during different disrupted scenarios such as equipment and operational failure and physical damage to the terminal berths [41], [61]. Peng et al. [57] propose a system dynamics approach to analyze the behaviors of disrupted disaster relief supply chain by simulating the uncertainties associated with predicting post-seismic road network and delayed information. Kim and O'Kelly [43] proposed a single and multiple allocation reliable p-hub location model. In the model, each arc and each hub is assigned a reliability factor. The authors derived an optimal network structure that maximizes network performance without considering backup hubs and alternative routes. An et al. [3] proposed a reliable single and multiple allocation hub-and-spoke network design problems where disruptions at hubs and the resulting hub unavailability can be mitigated by backup hubs and alternative routes. Different from the literature, the model presents in this paper considers the impact of intermodal hub failures on supply chain design context and provided a real life example for the densified biomass supply chain network. Furthermore, we estimate the disruption probability of intermodal hubs using a probabilistic model. We observed that previous studies assume a given disruption probability for each facility and seldom validate this value with real-world disaster mechanisms [66], [20], [47], [48]. Most recently, Huang and Pang [40] developed a mechanism to calculate disruption probability of a biorefinery which is prone to seismic hazard. In this study, we extend this concept and propose a methodology to calculate the disruption probabilities (caused by natural disasters) based on the real world data. The aim is to better estimate the disruption probabilities for the intermodal hubs.

## Methodology

The network design problem consists of locating a set of intermodal hubs and biorefineries among candidate locations and determining the routes of biomass flows from its origin (harvesting sites) to destination (biorefineries). The design shall minimize the total set-up cost and the expected long run transportation cost across all hub disruption scenarios. We assume that the intermodal hubs are subject to site-dependent probabilistic disruptions. Figure 2 presents the structure of the biofuel logistic network consisting of biomass suppliers, potential locations for intermodal hubs (rail ramps or ports) and biorefineries.

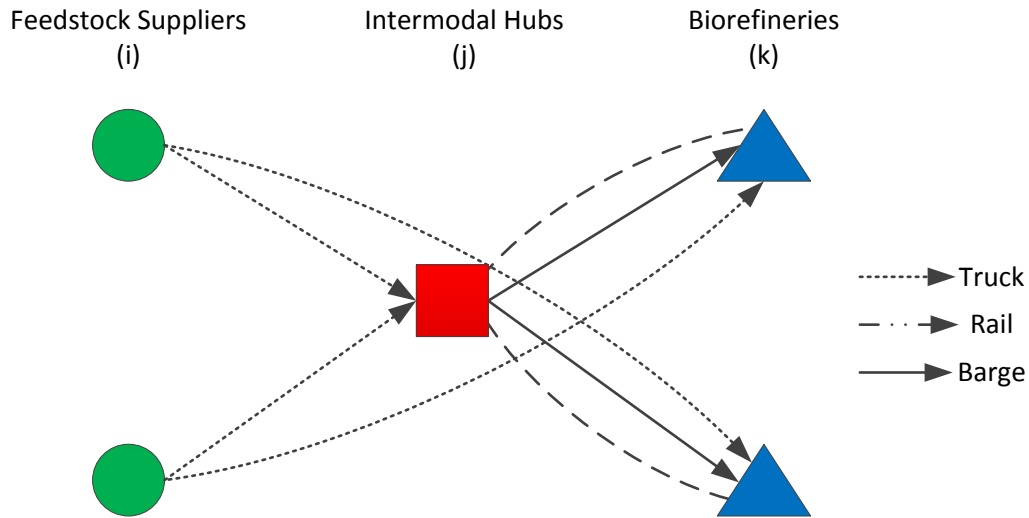


Figure 2: An example of intermodal supply chain network

We present two model formulations for the biofuel logistics network design problem, i.e., a basic hub-and-spoke model [HUB-B] that assumes that every hub is always functioning perfectly and a reliable hub-and-spoke model [HUB-R] that considers possible hub disruptions instead. The notation is summarized in Table 1. We will first introduce the basic model [HUB-B].

Consider a logistic network  $G = (N, A)$ , where  $N$  is the set of nodes and  $A$  is the set of arcs (shown in Figure 2). Set  $N$  consists of the set of harvesting sites  $I$ , the set of candidate intermodal hub locations  $J$  and the set of candidate biorefinery locations  $K$  (Let,  $H = J \cup K$ ). Each site  $i \in I$  produces  $s_i$  unit of densified biomass (we assume that biomass is densified right at the harvesting sites), and the total biofuel production in this

system is set to be no less than  $d$ . Locating an intermodal hub of capacity level  $l \in L$  at each location  $j \in J$  costs a fixed set-up cost  $\Psi_{ij}$ . Similarly, locating a biorefinery of capacity  $l \in L$  at each location  $k \in K$  costs a fixed set-up cost  $\Psi_{lk}$ . Each shipments from harvesting sites are consolidated at an intermodal hub in  $J$  before being delivered to a biorefinery in  $K$ . We assume that every biorefinery in  $K$  is co-located with an intermodal hub with a sufficiently large capacity, and the transportation expense between the refinery and its co-located intermodal hub is negligible. The set of arcs  $A$  is partitioned into three disjoint subsets, i.e.,  $A = A_1 \cup A_2 \cup A_3$ , where  $A_1$  represents the set of arcs joining harvesting sites  $I$  with intermodal hubs  $J$ ,  $A_2$  represents the set of arcs between intermodal hubs  $J$  and biorefinery  $K$ , and finally  $A_3$  represents the set of arcs that directly connect from harvesting sites  $I$  to biorefinery  $K$ . Each arc  $(i, j) \in A_1$  carries local collection low-volume traffic between a harvesting site and an intermodal hub that are usually spaced by a small distance (e.g., on the order of 10-20 miles). Therefore, trucks are preferable on  $(i, j) \in A_1$  and its unit-volume traffic cost is specified as the link length of  $c_{ij}$ . An inter-hub arc  $(j, k) \in A_2$  usually carries large-volume long-haul traffic and uses either rail or barge as their major transportation mode. We represent  $c_{jk}$  as a unit transportation cost along arc  $(j, k) \in A_2$ . Therefore, a unit flow along an origin-destination route  $\{(i, j), (j, k)\}$  costs  $c_{ijk} = c_{ij} + c_{jk}$ . Furthermore, we allow biomass to be shipped by trucks along a direct arc  $(i, k) \in A_3$  from harvesting site  $i \in I$  to biorefinery  $k \in K$ , which incurs a unit transportation cost  $c_{ik}$ . Since trucking usually has a higher unit cost than larger-volume rail and waterway modes, cost  $c_{ik}$  is likely to be much higher than regular cost  $c_{ijk}$ , and thus the long-haul trucking mode is mostly used only in emergency. Since densified biomass is usually transported in cargo containers between intermodal hubs, in addition to unit transportation cost we consider that along each inter-hub arc  $(j, k) \in A_2$ , sending each container with a capacity of  $v_{jk}^{cap}$  incurs a fixed cost  $\xi_{jk}$ . This fixed cost represents the costs associated with loading and unloading a single railcar. We introduce the following location and allocation decision variables in our model.

The primary decision variables  $\mathbb{Y} := \{Y_{ij}\}_{i \in L, j \in J \cup K}$  determine the size and location to open intermodal hubs and biorefineries, i.e.,

$$Y_{lj} = \begin{cases} 1 & \text{if an intermodal hub of size } l \text{ is opened at location } j \\ 0 & \text{otherwise;} \end{cases}$$

$$Y_{lk} = \begin{cases} 1 & \text{if a biorefinery of size } l \text{ is opened at location } k \\ 0 & \text{otherwise;} \end{cases}$$

The second set of decision variables  $\mathbb{Z} := \{Z_{jk}\}_{j \in J, k \in K}$  decides the number of container flow between each pair of hubs. The remaining decisions are how to route the biomass flows from its origin to destination. Let  $\mathbb{X} := \{X_{lk}\}_{(l,k) \in A}$  denote the flow of biomass along each link  $(l, k) \in A$  in this network. With this, we can formulate the basic model [HUB-B] as follows,

$$\text{[HUB-B] Minimize } \sum_{(lk \in A)} c_{lk} X_{lk} + \sum_{l \in L, j \in H} \Psi_{lj} Y_{lj} + \sum_{j \in J, k \in K} \xi_{jk} Z_{jk}$$

Subject to

$$\sum_{j \in J_i} X_{ij} + \sum_{k \in K_i} X_{ik} \leq s_i \quad \forall i \in I \quad (1)$$

$$\sum_{k \in K} \sum_{j \in I_k \cup J_k} X_{jk} \geq d \quad (2)$$

$$\sum_{i \in I_j} X_{ij} - \sum_{k \in K_j} X_{jk} = 0 \quad \forall j \in J \quad (3)$$

$$\sum_{i \in I_j} X_{ij} - \sum_{l \in L} c_{lk}^{cap} Y_{lj} \leq 0 \quad \forall j \in J \quad (4)$$

$$\sum_{j \in I_k \cup J_k} X_{jk} - \sum_{l \in L} c_{lk}^{cap} Y_{lk} \leq 0 \quad \forall k \in K \quad (5)$$

$$v_{jk}^{cap} Z_{jk} - X_{jk} \geq 0 \quad \forall j \in J, k \in K \quad (6)$$

$$\sum_{l \in L} Y_{lj} \leq 1 \quad \forall j \in H \quad (7)$$

$$X_{lk} \in \mathbb{R}^+ \quad \forall (l, k) \in A \quad (8)$$

$$Y_{ij} \in \mathbb{B} \quad \forall j \in H \quad (9)$$

$$Z_{jk} \in \mathbb{Z}^+ \quad \forall j \in J, k \in K \quad (10)$$

Table 1: Summary of mathematical notations

Notation	Explanation
<b>Sets</b>	
$I$	set of harvesting sites (farms)
$J$	set of intermodal hubs
$K$	set of biorefineries
$L$	set of intermodal hub/biorefinery capacities
$J_i$	set of intermodal hubs connected to harvesting sites $i$ , $\forall i \in I$
$I_j$	set of harvesting sites connected to intermodal hubs $j$ , $\forall j \in J$
$K_j$	set of biorefineries connected to intermodal hubs $j$ , $\forall j \in J$
$J_k$	set of intermodal hubs connected to biorefineries $k$ , $\forall k \in K$
$K_i$	set of biorefineries directly connected to harvesting sites $i$ via the emergency transportation service, $\forall i \in I$
$I_k$	set of harvesting sites directly connected to biorefineries $k$ via the emergency transportation service, $\forall k \in K$
<b>Parameters</b>	
$s_i$	amount of biomass available at site $i \in I$
$d$	minimum total amount of biomass to be processed
$v_{jk}^{cap}$	maximum capacity of the cargo container transported along arc $(j,k) \in A_2$
$c_{lk}$	unit flow cost along arc $(l,k) \in A$
$\pi$	unit penalty cost for unsatisfied demand
$\Psi_{lj}$	fixed cost to open an intermodal hub of capacity $l \in L$ at location $j$ , $\forall j \in J$
$\Psi_{lk}$	fixed cost to open a biorefinery of capacity $l \in L$ at location $k$ , $\forall k \in K$
$\xi_{jk}$	fixed cost of a cargo container for transporting biomass along the arc $(j,k) \in A_2$
$c_{lj}^{cap}$	acquirable capacity of a hub of capacity level $l$ at location $j$ , $\forall l \in L, j \in H$
$q_j$	failure probability of hub $j \in H$
$\beta \geq 0$	penalty coefficient that reflects the risk aversion degree. The system is risk neutral if $\beta = 1$

The first term of the objective function is the total variable transportation cost, the second term is the total set-up cost of opening intermodal hubs and biorefineries and the third term is the fixed cost of sending cargo containers between the intermodal hubs and biorefineries. Constraints (1) indicate that the amount of biomass shipped from a harvesting site  $i \in I$  is limited by its availability. Constraints (2) set the minimum amount of biomass to be routed through the logistics network. Constraints (3) enforces flow-conservation at intermodal hubs  $j \in J$ . Constraints (4) indicate that the total amount of biomass shipped through an intermodal hub  $j \in J$  is limited by the hub capacity  $c_{lj}^{cap}$ ,  $\forall l \in L, j \in J$ . Similarly, Constraints (5) indicate that the total amount of biomass shipped to a biorefinery is limited by the refinery capacity  $c_{lk}^{cap}$ ,  $\forall l \in L, k \in K$ . Constraints (6) count the number of containers needed for shipping biomass on each arc.

Constraints (7) indicate that at most one intermodal hub/biorefinery of capacity  $l \in L$  is operating in a given location  $j \in H$ . Finally, constraints (8) are the standard non-negativity constraints, (9) are the binary constraints, and (10) are the integrality constraints.

To further incorporate intermodal hub disruptions observed in the real world, we will extend the basic model [HUB-B] to a reliable model [HUB-R] that hedges against disruption impacts by using back-up services. We assume that each hub in  $j \in H$  disrupts independently. The corresponding site-dependent probability is  $q_j$ . When either hub along route  $((i, j), (j, k))$  disrupts, this route is no longer operating, and we assume the traffic is detoured to the highway arc  $(i, k) \in A_3$ , which now serves as an emergency carrier. Since an emergency service usually costs much higher than a regularly scheduled service and may incur other risks to normal system operations, we consider that the unit emergency transportation cost is  $\beta$  times as much as the regularized cost  $c_{ik}$ , where the risk coefficient  $\beta \geq 1$  and  $\beta = 1$  denotes the risk neutral case. We further relax the minimum total biofuel production requirement and instead impose a penalty cost  $\pi$  per unit shortage of biomass. This penalty  $\pi$  can be also interpreted as a profit threshold such that if unit biomass transportation cost exceeds this threshold, producing biofuel will be no longer profitable and thus there is no point of shipping biomass at this transportation cost. To capture the hub disruption risks and biomass shortage penalty, we introduce additional decision variable as follows,

- $\mathbb{X} := \{X_{ijk}\}_{i \in I, j \in J, k \in K}$  flow from  $i$  to  $k$  via intermodal hub  $j$
- $\mathbb{U} := \{U\}$  total amount of unsatisfied demand

Then we adapt [HUB-B] to the following mixed integer linear programming (MILP) formulation for our reliable intermodal hub and spoke problem:

$$\begin{aligned}
\text{[HUB-R] Minimize } & \sum_{l \in L, j \in H} \Psi_{lj} Y_{lj} + \sum_{j \in J, k \in K_j} \xi_{jk} Z_{jk} + \sum_{\forall i \in I, j \in J_i, k \in K_j} c_{ijk} (1 - q_j)(1 - q_k) X_{ijk} \\
& + \sum_{\forall i \in I, k \in K} c_{ik} \left[ X_{ik} + \beta \sum_{j \in J_i \cap J_k} (q_j + q_k - q_j q_k) X_{ijk} \right] + \pi U
\end{aligned}$$

Subject to

$$\sum_{j \in J_i, k \in K_j} X_{ijk} + \sum_{k \in K_i} X_{ik} \leq s_i \quad \forall i \in I \quad (11)$$

$$\sum_{k \in K} \left[ \sum_{i \in I_k} X_{ik} + \sum_{j \in J_k, i \in I_j} X_{ijk} \right] + U = d \quad (12)$$

$$\sum_{i \in I_j, k \in K_j} X_{ijk} - \sum_{l \in L} c_{lj}^{cap} Y_{lj} \leq 0 \quad \forall j \in J \quad (13)$$

$$\sum_{i \in I_k} X_{ik} + \sum_{i \in I_j, j \in J_k} X_{ijk} - \sum_{l \in L} c_{lk}^{cap} Y_{lk} \leq 0 \quad \forall k \in K \quad (14)$$

$$v_{jk}^{cap} Z_{jk} - \sum_{i \in I_j} X_{ijk} \geq 0 \quad \forall j \in J, k \in K \quad (15)$$

$$\sum_{l \in L} Y_{lj} \leq 1 \quad \forall j \in H \quad (16)$$

$$X_{ijk} \in \mathbb{R}^+ \quad \forall i \in I, j \in J_i, k \in K_j \quad (17)$$

$$X_{ik} \in \mathbb{R}^+ \quad \forall i \in I, k \in K_i \quad (18)$$

$$U \in \mathbb{R}^+ \quad (19)$$

$$Y_{lj} \in \mathbb{B} \quad \forall l \in L, j \in H \quad (20)$$

$$Z_{jk} \in \mathbb{Z}^+ \quad \forall j \in J, k \in K_j \quad (21)$$

In [HUB-R], the objective function minimizes the total expected system cost, including the expected transportation cost across both normal and disruptive scenarios and the investment of opening hubs and using inter-hub arcs. More specifically, the first and second terms represent respectively the total set-up cost of establishing the intermodal hubs and biorefineries and the fixed cost of transporting cargo containers between the intermodal hubs. The third term is the regular transportation cost which is weighted by  $(1-q_j)(1-q_k)$ , the probability that both hubs operate normally along each route  $(i, j, k)$ . When either or both the intermodal hub  $i$  and biorefinery  $k$  disrupt, which occurs at a probability of  $(q_j + q_k - q_j q_k)$ , flow  $X_{ijk}$  originally assigned to route  $(i, j, k)$  will be diverted to direct route  $(i, k)$  at a higher variable cost  $\beta c_{ik}$ , while route  $(i, k)$  in addition carries the planned regular flow  $X_{ik}$  at variable cost  $c_{ik}$ . This is reflected by the fourth and fifth terms of the objective function. The sixth term is the penalty cost for biomass supply shortage.

Again, constraints (11) indicate that the amount of biomass shipped from a harvesting site  $i \in I$  is limited by its availability. Constraints (12) indicate that the total demand for biomass will be fulfilled either through the hub-and-spoke distribution network or through emergency shipments. Constraints (13) indicate that the total amount of biomass shipped through intermodal hub  $j \in J$  is limited by the hub capacity  $c_{lj}^{cap}$ ,  $\forall l \in L, j \in J$ . Similarly, constraints (14) indicate that the total amount of biomass shipped to a biorefinery is limited by the refinery capacity  $c_{lk}^{cap}$ ,  $\forall l \in L, k \in K$ . Constraints (15) set a limit on the amount of biomass to be routed on the arcs  $(j, k) \in A_2$ . Constraints (16) indicate that at most one intermodal hub/biorefinery of capacity  $l \in L$  is operating in a given location  $j \in H$ . Finally constraints (17) to (19) are the standard non-negativity constraints, (20) are the binary constraints, and (21) are the integrality constraints.



## Visualization Decision-Support Tool

On the basis of the proposed models, we developed a visualization decision-support tool consisting of two parts: a web-based interface and a problem solution server. The web-based interface is coded using HTML, JavaScript and PHP and published on the internet. The web-based interface is connected to a biofuel supply chain problem solver which is coded using C++, CPLEX and MySQL and running on the server used by the research team.

Figure 3 is the initial user interface when users firstly open the webpage, showing data of our base case example in default. Initially, the webpage shows all the locations of feedstock suppliers and candidate locations of intermodal hubs and biorefineries. The data of locations are stored in MySQL database which is running on our server. The users are able to input their own problem data and change model parameters though the left side panel of the user interface, as shown in Figure 4.

By using the decision-support tool, we are able to identify under what conditions locating a biofuel plant near an intermodal facility is advisable; and what are the benefits/costs of such a decision. Furthermore, we can clearly and visually observe how changes on different conditions impact the biofuel supply chain network.

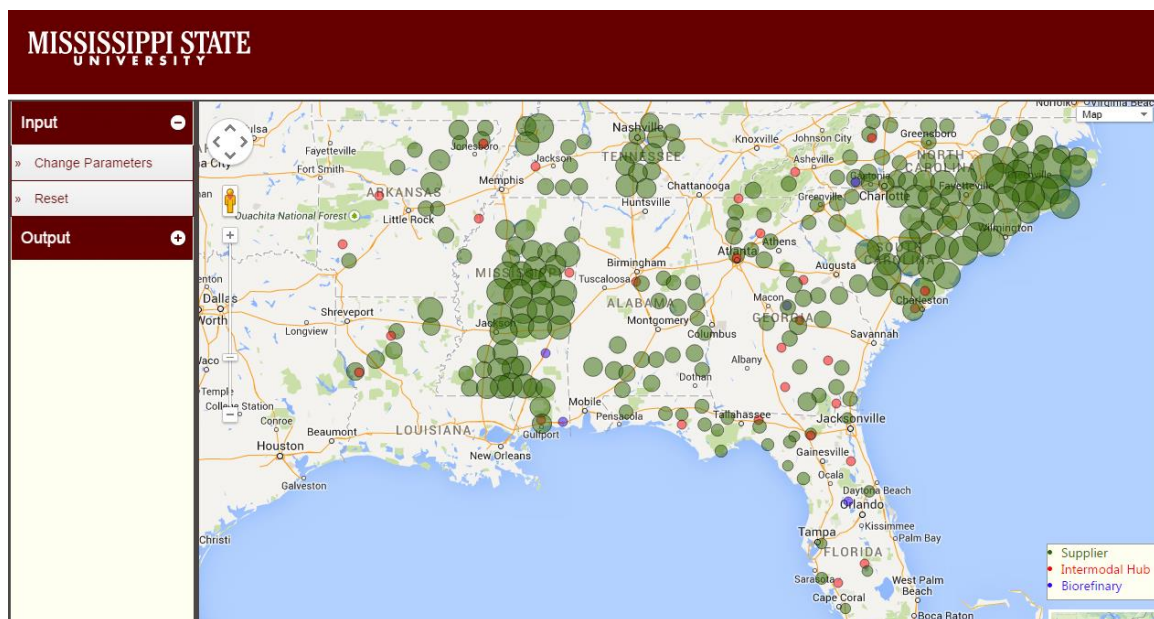


Figure 3 Main user interface

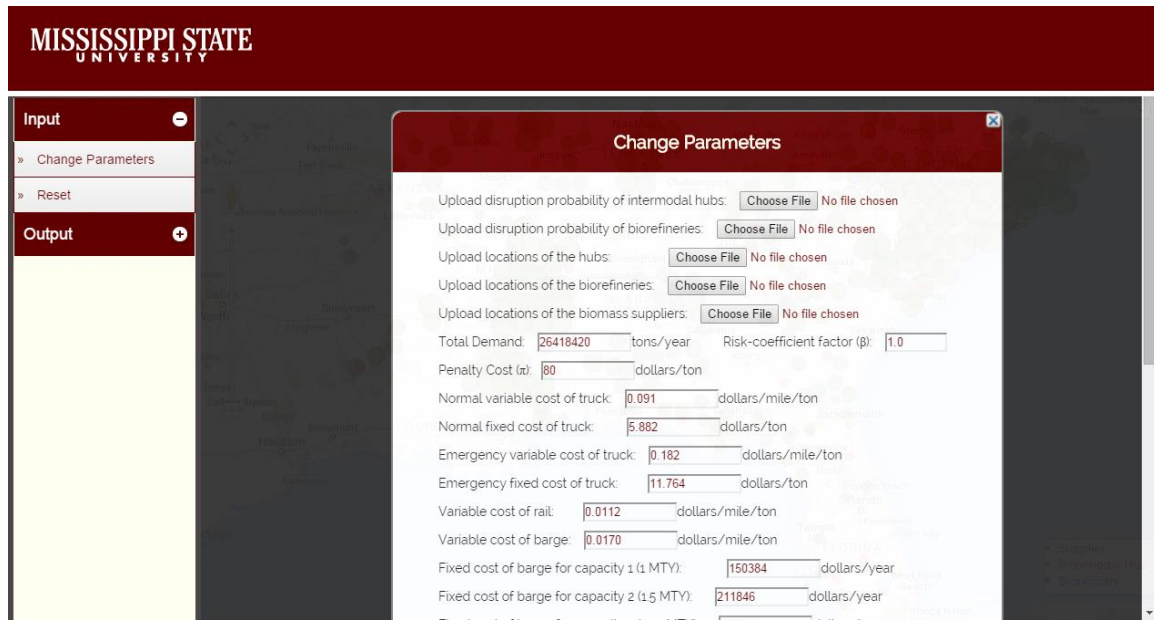


Figure 4 Interface of changing model parameters

Through the internet, the webpage transmits input data of biofuel supply chain problem parameters to the problem solver. When the solver receives the data, it calls CPLEX to solve the optimization problem. Then the solver connects to MySQL database which stores all the location information and we are able to find the location information of selected intermodal hubs and biorefineries. When the server has the information of selected intermodal hubs and biorefineries, it transmits the result information to the webpage and display all the selected location on the map of the user interface. The data flow between various system components are demonstrated in Figure 5.

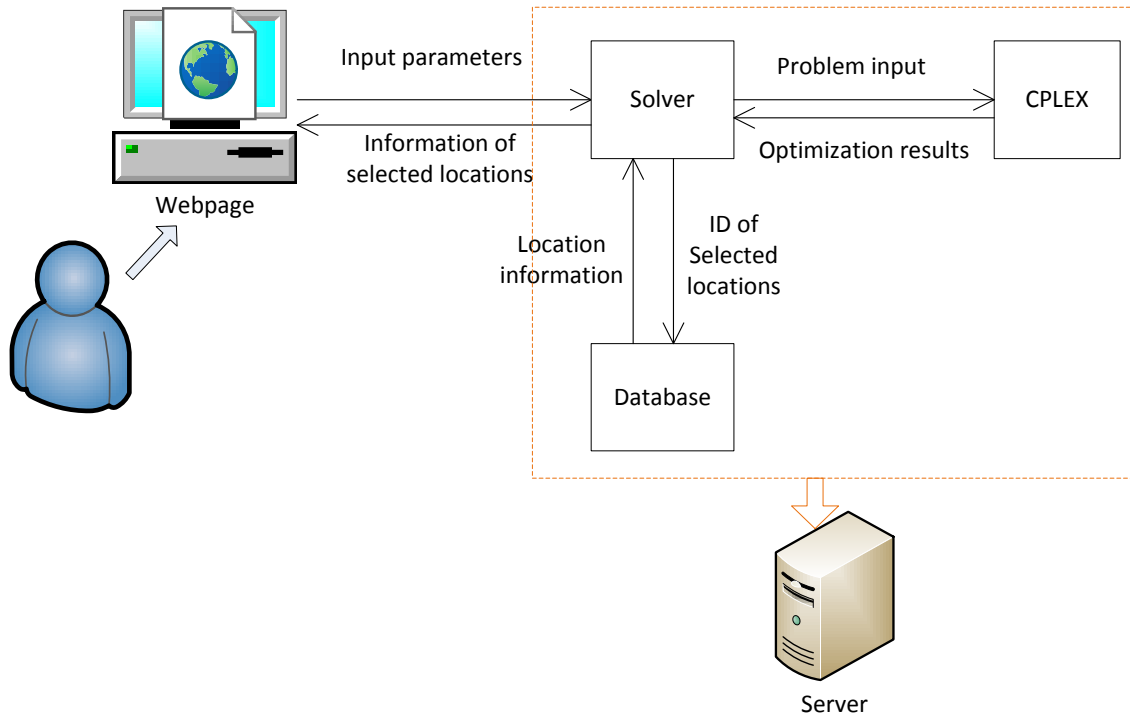


Figure 5 data flow between various system components

## Research Findings

In this section, we use data and map of the southeast region of the U.S as a case study of our visualization decision-support tool. We will focus on how the risk impacts biorefinery locations in Mississippi. To understand the impact of intermodal hub disruption on biofuel supply chain network, we conduct three different experiments: (a) Demand increases/decreases; (b) Increases of variable truck cost (to reflect an increase in gas price since it has a great impact on this variable cost); (c) Increases of fixed truck costs (to reflect the increase in the salary of drivers).

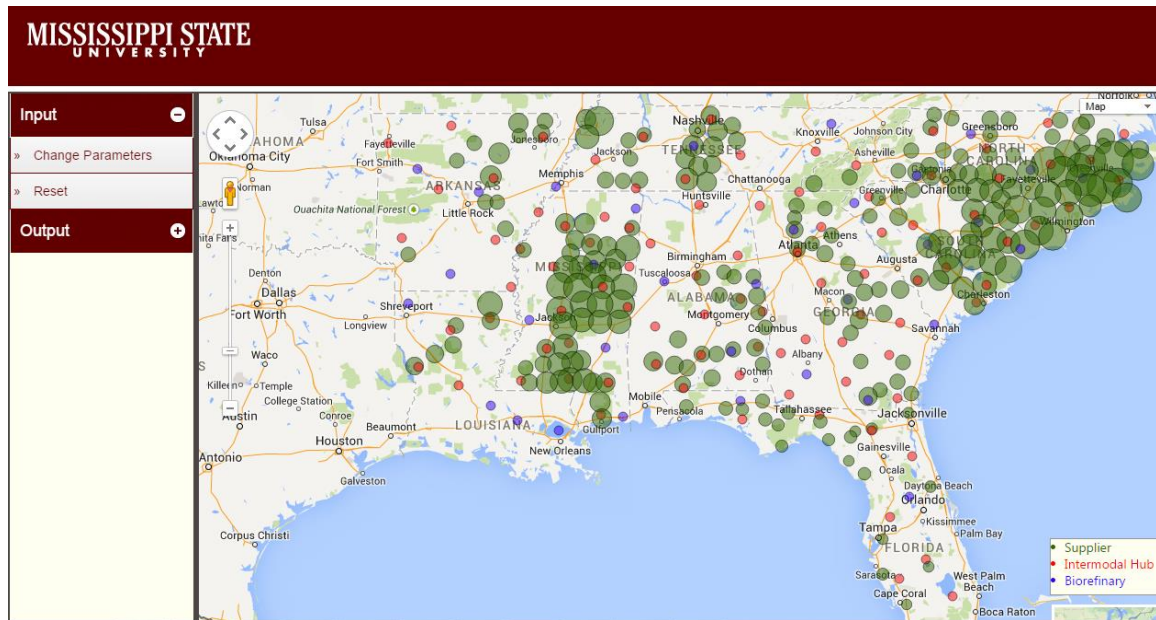


Figure 6: Feedstock suppliers locations and potential locations of intermodal hubs and biorefineries in the southeast region of the U.S

### Scenario 1: Basic input

We use this Scenario as the benchmark. Using basic input parameters as shown in Figure 7, after calculation, we have results of biorefinery locations showed in Figure 8.

Total Demand:	26418420	tons/year	Risk-coefficient factor ( $\beta$ ):	1.0
Penalty Cost ( $\pi$ ):	80	dollars/ton		
Normal variable cost of truck:	0.091	dollars/mile/ton		
Normal fixed cost of truck:	5.882	dollars/ton		
Emergency variable cost of truck:	0.182	dollars/mile/ton		
Emergency fixed cost of truck:	11.764	dollars/ton		
Variable cost of rail:	0.0112	dollars/mile/ton		
Variable cost of barge:	0.0170	dollars/mile/ton		
Fixed cost of barge for capacity 1 (1 MTY):	150384	dollars/year		
Fixed cost of barge for capacity 2 (1.5 MTY):	211846	dollars/year		
Fixed cost of barge for capacity 3 (1.75 MTY):	240288	dollars/year		
Fixed cost of barge for capacity 4 (2 MTY):	266769	dollars/year		
Fixed cost of barge for capacity 5 (2.34 MTY):	306000	dollars/year		
Fixed cost of rail for capacity 1 (0.6 MTY):	41212	dollars/year		
Fixed cost of rail for capacity 2 (0.8 MTY):	46707	dollars/year		
Fixed cost of rail for capacity 3 (0.9 MTY):	50553	dollars/year		
Fixed cost of rail for capacity 4 (1.04 MTY):	54949	dollars/year		
Fixed cost of rail for capacity 5 (1.2 MTY):	60444	dollars/year		
Fixed cost of biorefinery for capacity 1 (0.62 MTY):	14324613	dollars/year		
Fixed cost of biorefinery for capacity 2 (1.24 MTY):	22919381	dollars/year		
Fixed cost of biorefinery for capacity 3 (1.86 MTY):	30559174	dollars/year		
Fixed cost of biorefinery for capacity 4 (3.1 MTY):	42782844	dollars/year		
Fixed cost of biorefinery for capacity 5 (4.65 MTY):	55617697	dollars/year		

Figure 7: Basic input parameters



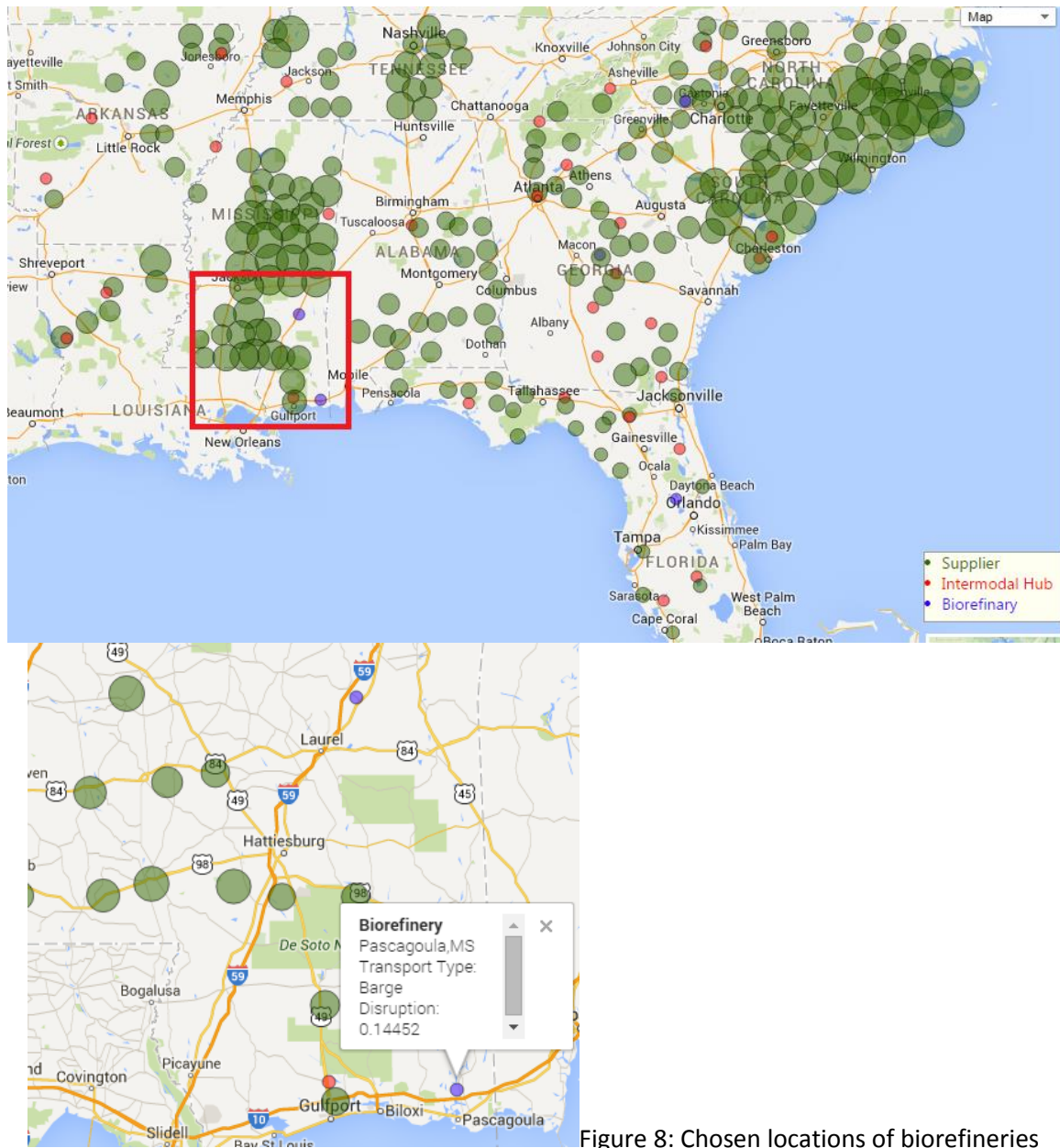


Figure 8: Chosen locations of biorefineries and intermodal hubs

We can find that there are 2 biorefineries and 1 intermodal hub in Mississippi. The first biorefinery is in Heidelberg, MS with capacity 1.24 MTY and the second is in Pascagoula, MS with capacity 4.65 MTY. The total supply chain cost is 1.10955e+009 dollars. For the whole supply chain network in the southeast region of the U.S, 29 intermodal hubs are selected and 5 biorefineries are selected. The total number of transported containers is 44,132. The total amount of biomass shipped through intermodal hub is 6.6822e+006 tons. The total amount of biomass shipped through truck (direct shipment) is 1.71926e+007 tons. The total amount of demand shortage is 2.54362e+006 tons.

## Scenario 2: Total demand decreases/increases

(1) Total demand decreases from 26,418,420 tons to 16,418,420 tons.

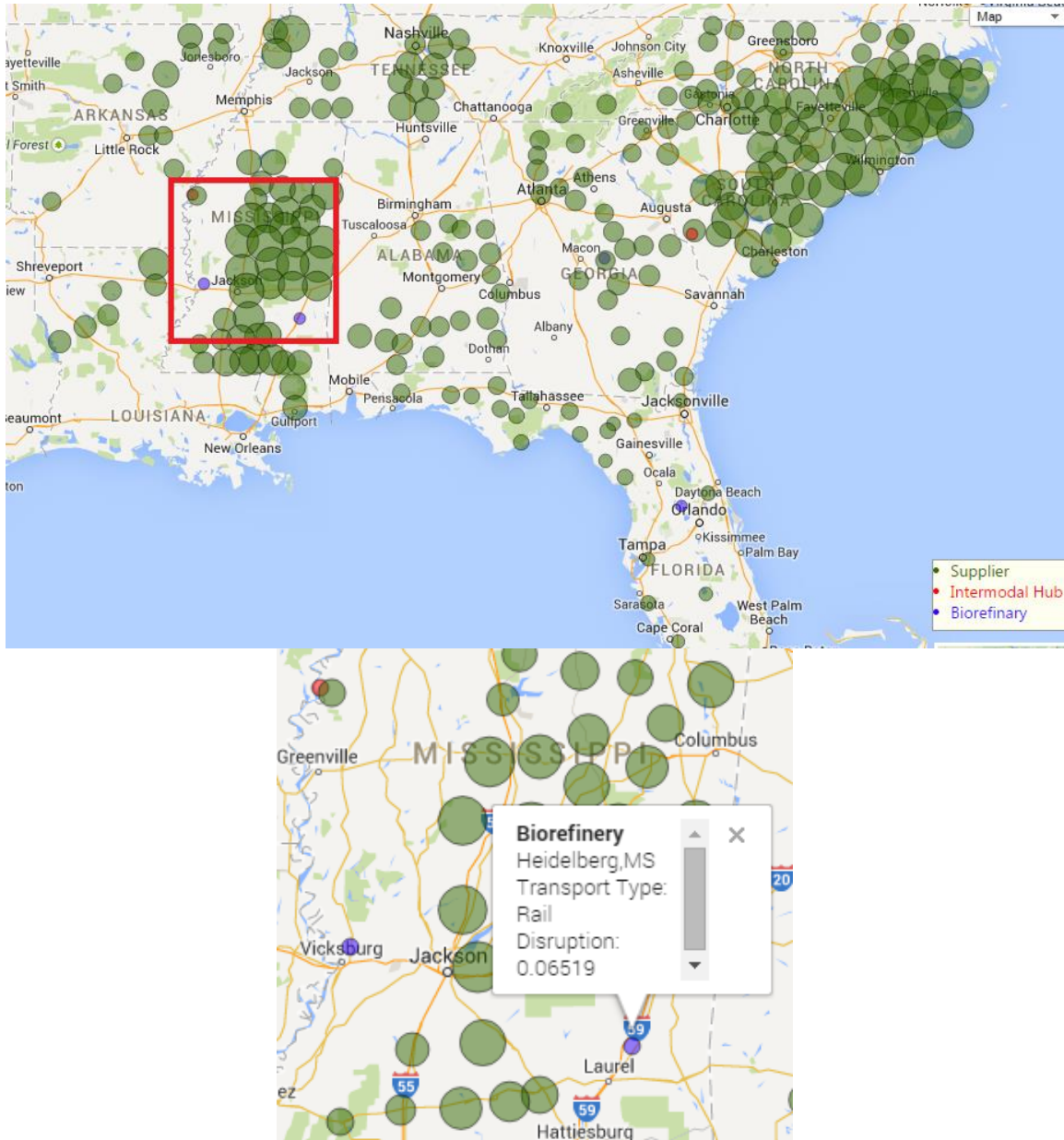
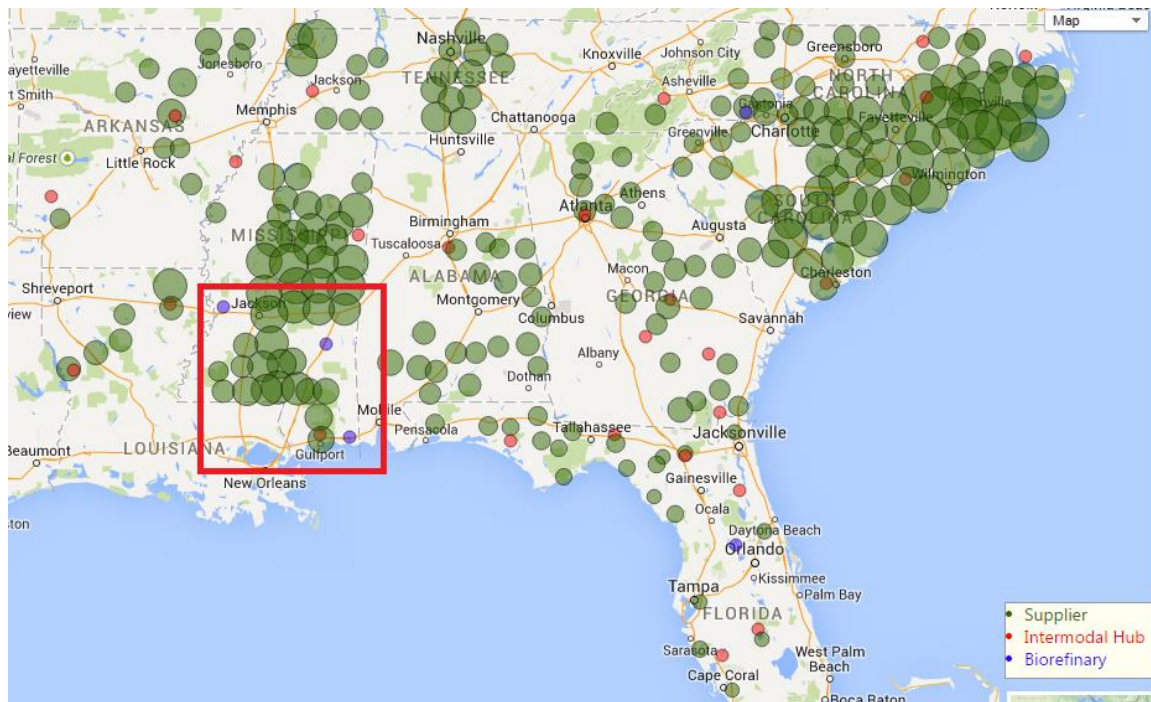


Figure 9: Chosen locations of biorefineries and intermodal hubs

We can find that there are 2 biorefineries and 1 intermodal hub in Mississippi for this scenario. The first biorefinery is in Heidelberg, MS with capacity 0.62 MTY and the second is in Blakely, MS with capacity 4.65 MTY. The total supply chain cost is 5.60812e+008 dollars.

Compared with Scenario 1, due to the decrease of total demand, the locations of biorefinery and intermodal hub are changed and the capacity scale decreases (which could decrease the fixed cost of biorefineries). Both biorefineries use rail in this Scenario while in Scenario 1 one uses rail and the other uses barge. The reason is that because the total demand decreased, rail can transport all needed biomass and it is cheaper than barge. Therefore, choosing biorefineries that use rail is more cost-efficient. Hence, the total system cost of this Scenario is less than Scenario 1. Also, the number of total selected intermodal hubs and biorefineries is less than in Scenario 1.

(2) Total demand increases from 26418420 to 36418420





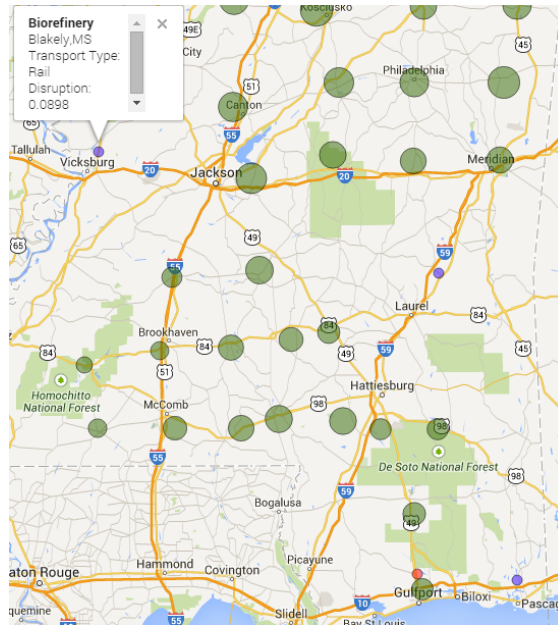


Figure 10: Chosen locations of biorefineries and intermodal hubs

For this scenario, there are 3 biorefineries and 1 intermodal hub in Mississippi. The first biorefinery is in Heidelberg, MS with capacity 1.24 MTY, the second is in Blakely, MS with capacity 4.65 MTY, and the third is in Pascagoula, MS. The total supply chain cost is 1.91618e+009 dollars.

Compared with Scenario 1, due to the increase of total demand, the number of selected biorefineries increases in Mississippi. Also, the capacity scale increases as well to meet the increased demand.

### Scenario 3. Increases of Variable Truck Cost

In this scenario, we increased normal variable cost of truck from 0.091 dollars per mile per ton to 0.131 dollars per mile per ton.

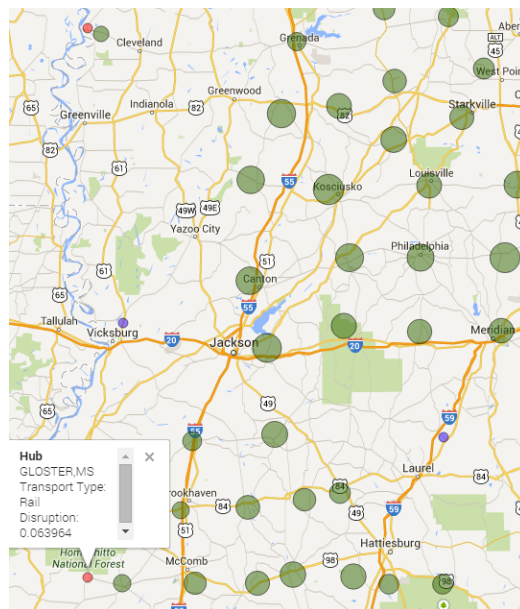
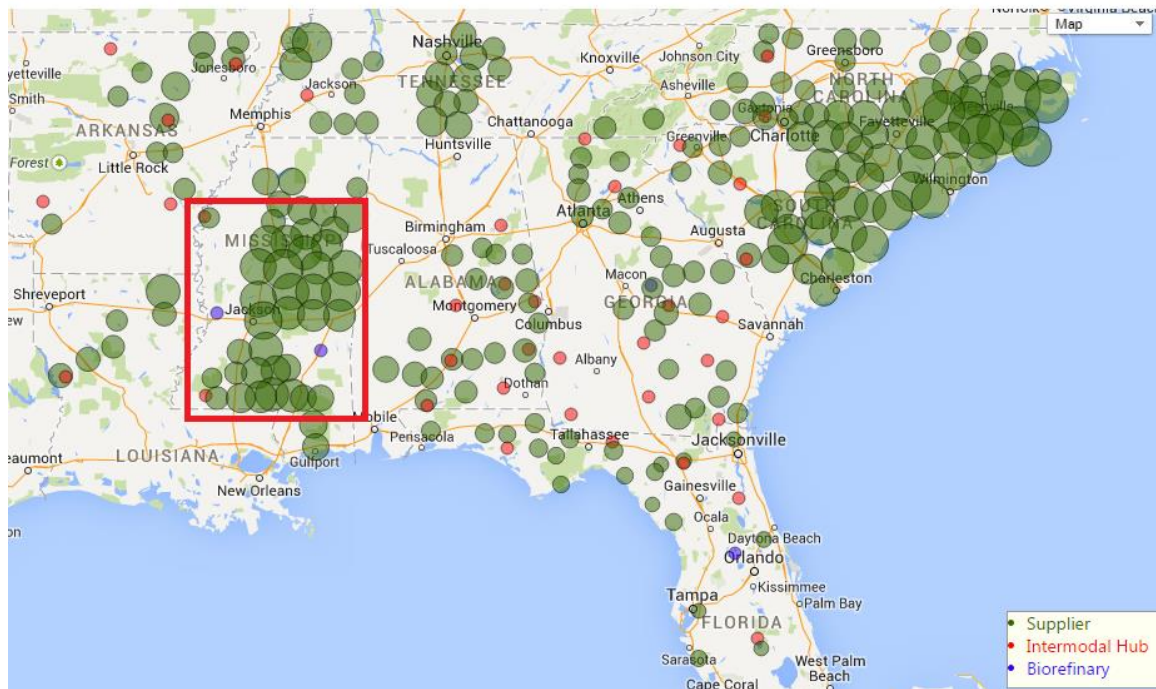


Figure 11: Chosen locations of biorefineries and intermodal hubs

According to the results, we find that the number of selected intermodal hubs increases. For the whole supply chain network in the southeast region of the U.S, there are 37 selected intermodal hubs, an increase of 27.6% compared with Scenario 1. In Mississippi, there are 2 selected biorefineries and 2 selected intermodal hubs while in Scenario 1, there is only 1 selected intermodal hub. Because the cost of truck increases, it is better

to have more intermodal hubs to maintain a higher inventory level. Although the truck cost increases, the total system cost is 1.10602e+009 dollars and maintains at the same level with a small decrease of 0.3%.

#### Scenario 4: Increase of Fixed Truck Cost

In this scenario, we increase normal fixed cost of truck from 5.882 dollars per mile per ton to 6.882 dollars per mile per ton.

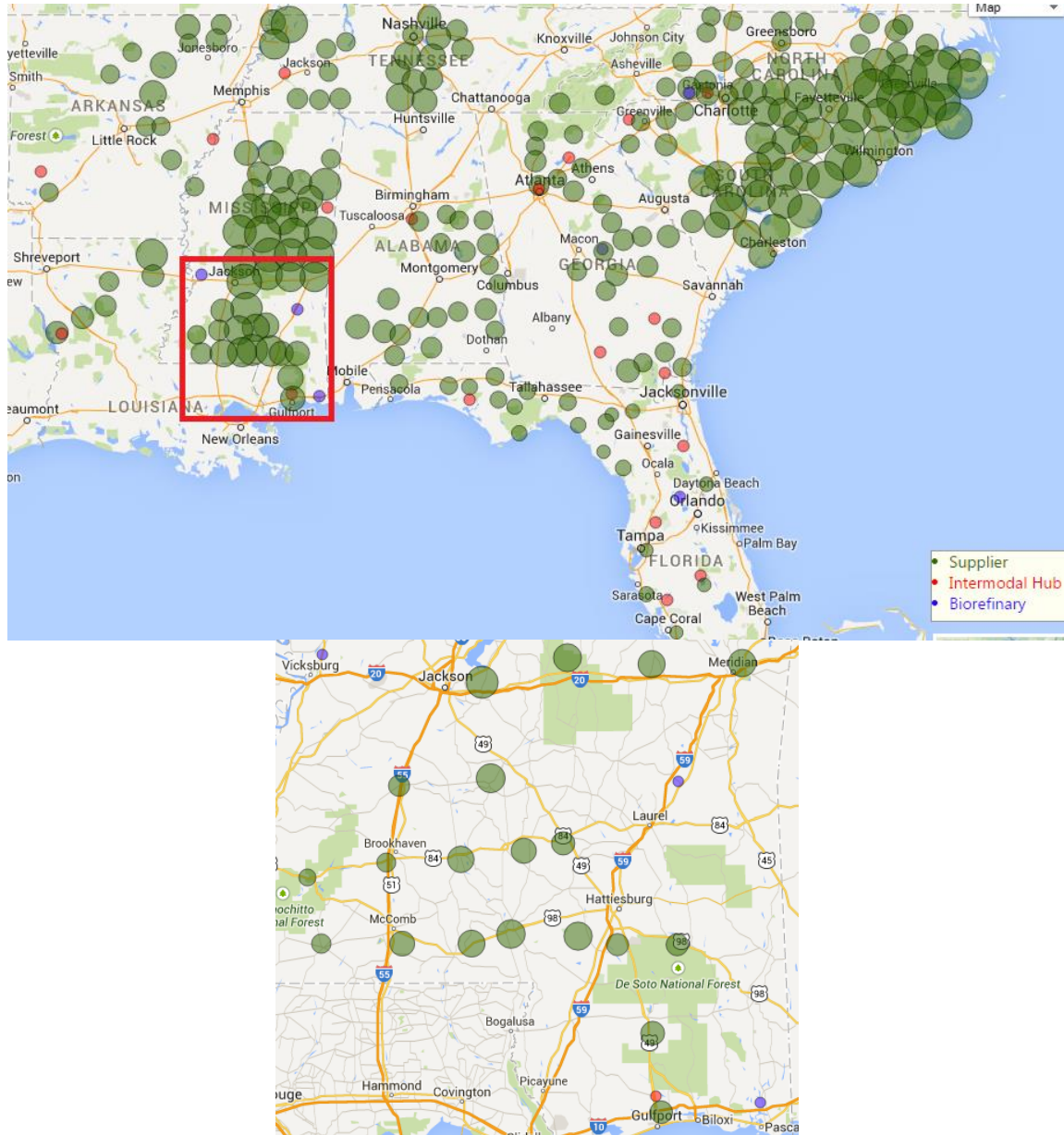


Figure 12: Chosen locations of biorefineries and intermodal hubs

Compared with Scenario 1, due to the increase of fixed truck cost, the number of selected biorefineries increases while the number of selected intermodal hubs decreases. In Mississippi, there are 3 selected biorefineries and 1 selected intermodal hub. The fixed truck cost is the fixed cost sending cargo containers between the intermodal hubs and biorefineries. Thus, the decrease of the number of intermodal hubs will decrease the total fixed cost of truck to deal with the impact of increased fixed cost of truck. In this scenario, the total supply chain system cost is 1.10359e+009 dollars, which is similar to Scenario 1 with a minor decrease of 0.5%. The number of selected intermodal hubs is 34.5% less than it in Scenario 1.

## Conclusions

This research is to analyze the impact of intermodal disruption risks to the design and management of a biofuel supply chain network, and to design a decision-support tool that assist identifying biorefinery locations to ensure a cost-efficient and reliable supply chain. A mixed integer linear programming model [HUB-R] is developed to determine the optimal intermodal hub locations and shipment routes for delivering biomass in order to optimize system's performance under normal conditions but also hedge against losses when intermodal hubs are disrupted because of natural disasters (e.g., flooding, hurricane, draught).

We have designed and developed a visualization decision-support tool combining a web-based interface displaying the original candidate and chosen biorefinery locations, and a problem solver running in the server solving reliable intermodal hub location problems. Computational results showed that our visualization decision-support tool can be used to solve realistic instances of large size problems and clearly and intuitively display the results of supply chain network. Furthermore, decision makers can solve specific supply chain problems by inputting their own data of feedstock suppliers, intermodal hubs and biorefineries through the web-based interface and obtain visualized results for analysis.

By using the data and map of the southeast region of the U.S, we conducted thorough computational experiments to test our visualizatoin decision-support tool and draw managerial insights. Our computational experiments revealed some insightful results about the impact of intermodal disruption risks on a biofuel supply chain network. Based on the results, the model selects to use intermodal hubs located in areas with low

disruption probabilities. Moreover, when the total demand changes, it greatly impacts the number and locations of selected biorefineries. When the normal variable truck cost or fixed truck cost increases/decreases, the number and locations of selected intermodal hubs are also influenced to a large extent. The sensitivity analyses further reveals how different parameters affect the location and performance of the biofuel supply chain network, and the developed decision-tool enables decision makers to capture such sensitivities and choose optimal plans for the design of biofuel supply chain.

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