Travel Behavior Analysis of Agricultural Commodities in a Freight Activity Microsimulation Framework

BY

Seyed Mehdi Mahmoudifard
B.S., Hormozgan University, 2006
M.S., Sharif University of Technology, 2008

THESIS

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Defense Committee:
Dr. Abolfazl (Kouros) Mohammadian, Chair and Advisor
Dr. Kazuya Kawamura (Department of Urban Planning and Policy UIC)
Dr. Sriraj (Urban Transportation Center at UIC)
Dr. Sybil Derrible
Dr. Bo Zou

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To Zahra

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1. Introduction

The United States has the largest world economy with a total Gross Domestic Product (GDP) of $17.95 trillion in 2015 ("The New Global Economy" 2015). Between 1960 to 2013 the GDP increased almost 300% (Figure 1). This expansion is highly dependent on efficient U.S. transportation systems including ports, waterways, railroads, pipelines, and highways.

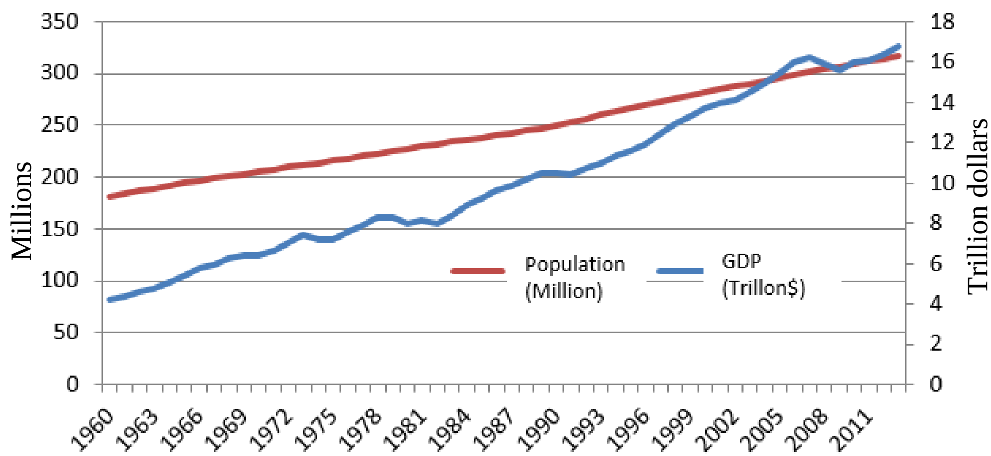


Figure 1 U.S. GDP 1960-2013 (trillion dollars) (Based on 2013-dollar value)

In 2013, farm-related industries contributed $789 billion to the U.S. GDP. Many other sectors of the economy also are dependent directly to the agricultural products including: food beverages, tobacco products, forestry, food services, fishing and related activities, textiles, and leather products (USDA 2015). About 9.2% of U.S. employment is related to agricultural industries involving 16.9 million full-time and part-time jobs.

Agricultural products are one of the largest consumers of freight transportation services in the U.S. The growth in agriculture cultivation during the last decades is primarily indebted to transportation system (Denicoff et al. 2010). It provides the opportunity to deliver farm products to urban centers and ports. Raw agricultural commodities also need to be moved to processing facilities like meat processors, grain mills, and fruit and vegetable processors.

An effective transportation system is vital to the U.S. economy. For example, in 2006 highway bottlenecks caused 226 million hours of delay in U.S. which resulted in $7.3 billion loss just for trucks (Cambridge Systematics 2008). Therefore, Metropolitan Planning Organizations (MPO) and state department of transportation are considering freight transportation modeling in their studies to improve the transportation system efficiency (Cambridge Systematics et al. 2008).

However, there are several problems with current freight models:

- They are too aggregate and new strategies and policy-changes cannot be tested on them (Windisch et al. 2010).
- Because of freight complexity, there is a big gap in modeling logistic elements such as determining the exact structure of supply chain.
- Despite the fact that agricultural commodities are a major component of freight flows, only few studies have mentioned them specifically.

Current study is the continuation of Freight Activity Microsimulation Estimator (FAME) designed at University of Illinois at Chicago (UIC) (Pourabdollahi et al. 2013). FAME while introducing stunning procedures and complex models into the freight simulation modeling, suffers from commodity aggregation issues and computational problems.

This study will improve the accuracy of models by disaggregating agricultural commodities and determining the exact supply chain for them. More data sources will be added to the framework to make the models more practical. A specific framework will be introduced to capture the effect of cereal grain movements in the U.S. transportation network. And finally, the computational problems of the previous model will be solved by introducing a new supplier selection model.

Following this introduction, the literature review on freight transportation studies will be presented. Next, it elaborates the research gaps and study`s objectives. Then, essential data sources needed for developing models will be introduced. In the next section, “Development of Model’s Components” a complete elaboration of models will be presented. Following that, model`s results will be discussed. And finally the last part, highlights the concluding points and suggests next possible future steps in this line of research.

2. Literature Review

This section highlights a comprehensive literature for freight transportation modeling. Freight models can be categorized by various aspects such as aggregate/disaggregate, urban/national, and even truck/multimodal models. This section will specifically review three types of freight models: logistics models, vehicle touring models, and agricultural freight models.

2.1. Logistics models

Logistic models possess different distribution channels and incorporate more than just a single origin and destination. They are equipped with behavioral specifications which apply to different decision makers within the supply chain. Furthermore, as the focus of supply chain is on the movements of goods, logistic models generally concentrate on units of commodities rather than vehicles (Chow et al. 2010).

Logistic models have been investigated differently by scholars. Some researchers use disaggregate logistic choices for generating commodity flows in regional supply chains (De Jong and Ben-Akiva 2007; Liedtke and Schepperle 2004; Tavasszy et al. 1998). Other researchers concentrate on urban logistics models which derived from disaggregate firm choice data (Wisetjindawat and Sano 2003; Boerkamps et al. 2000; Wisetjindawat et al. 2006).

2.1.1.Activity-based freight transport model

Liedtke and Schepperle (2004) developed a freight model that was based on activity passenger demand modeling. Then it was further developed to better capture the effects of new IT

(Information Technologies) on freight transport (Chow, Yang, and Regan 2010). The activity-based approach emphasizes on behavioral aspects of freight. These models were utilized to solve several problems in practice such as:

- Commodity flow conversion to vehicular flows,
- Empty vehicles flow in the system, and
- Insensitivity of aggregate models in forecasting the impacts of changes in logistic structures.

There are a lot of actors presented in activity based freight models and therefore Liedtke and Schepperle (2004) combined two methods to classify the tours:

- Classification of Product by Activity (CPA) and
- Standard Goods Classification for Transport Statistics (NST/R)

Employment data from the CPA was used to obtain annual commodity production in tons per employee. NST/R data, which contains the information of 1.7 million trips, was employed to define the tour type distribution.

Four tour types were defined using a fuzzy clustering: collection/distribution, consolidation, trucking segment, and shuttle tours. A gravity model was then used for trip distribution, which converts the economic-based CPA into transport-based tours. And in the final part, a microscopic simulation of commodity tours was conducted (Chow, Yang, and Regan 2010; Javanmardi, Fasihozaman Langerudi, et al. 2016; Shabanpour, Golshani, Derrible, et al. 2017).

The proposed framework employed the NST/R data to estimate the tour choice of different commodities, but was limited to Europe because the equivalent type of data was unavailable in the U.S. (Chow, Yang, and Regan 2010; Shabanpour, Auld, Mohammadian, et al. 2017).

2.1.2.GoodTrip model

City logistics models are defined as ‘‘the process of totally optimizing urban logistics activities by considering the social, environmental, economic, financial, and energy impacts of urban freight movement’’ (Taniguchi et al. 2001; Chow, Yang, and Regan 2010). The main core of these models is based on optimization methods rather than behavioral methods(Javanmardi, Langerudi, et al. 2016; Langerudi et al. 2016; Fasihozaman Langerudi et al. 2016).

Boerkamps et al. (2000) developed GoodTrip as an urban logistics model which incorporates logistics behavior like the regional logistics models, but focuses more on the urban setting with commodity-based truck tours.

The authors developed a four-step modeling framework for supply chain elements of urban freight movement and applied it to the city of Groningen in the Netherlands. The framework considers the behavior of multiple actors including: sender, transporter, receiver, and distribution channels. It also can analyze changes in demand patterns, supply chain organizations, distribution patterns, mode choice, and impacts of environmental improvements (Chow, Yang, and Regan 2010; Javanmardi et al. 2015).

The model starts with the consumer demand for a commodity where the production is related to the land uses in a zone. The idea of *commodity demand flows*, can be determined as a two-step process: supplier choice, and spatial choice. Then the commodities were combined together by group age probabilities, and assigned to mode of vehicle tours.

Several activity types were considered at the origin including: supermarkets, consumers, stores, offices, distribution centers of retailers, and producers. Commodities related to these activities were used to determine the transport mode, vehicle capacity, maximum load factor, and maximum number of stops per tour. However, the mode choice refers only to the truck types, such as traditional distribution trucks, urban trucks, or underground logistics trucks.

The model was validated for the food retail sector in the city of Groningen using 2 datasets: empirical data of food distribution and data from a four-step traffic model.

2.1.3.Strategic model for integrated logistic evaluations (SMILE)

Tavasszy et al. (1998) developed the Strategic Model for Integrated Logistic Evaluations (SMILE) to address three primary questions:

- Interaction between socioeconomic trends and the performance of transportation systems,
- Achieving performance measurements for analyzing policy implementations, and
- How a European distribution center could affect the transportation system.

The main modules of SMILE encompass 3 levels: *Production*, *Inventory*, and *Transport* (Chow, Yang, and Regan 2010).

In production level, a demand function was employed to generate the total volumes of produced and consumed commodities. The function consists of a Make/Use table, socioeconomic factors, and shipment value density (Tavasszy et al. 1998). Regional Input–Output Modeling System (RIMS II 1997) was developed to prepare regional I-O tables. And finally, according to price differences, a spatial distribution was achieved by trade theory.

At the Inventory level, transport demand obtained by finding optimal distribution locations. Three alternative channels were introduced: direct, single distribution center (DC), and two DCs. A multinomial logit model was used to determine the channel distribution choice considering inventory and transport costs.

At the transport level, the results of a survey were used to obtain the logistics cost for each commodity. The survey collected detailed information about shipment size and handling costs which helped to develop trade and network structure (Chow et al. 2010).

2.1.4. Joint shipment size and transport chain choice model

Since 1985, disaggregate join shipment size and mode choice models have been existent. De Jong & Ben-Akiva (2007) expanded the mode choice aspects into a set of commodity distribution chain choices. The motivation behind these models was the recent logistics challenges such as *just-in-time delivery*. In comparison to SMILE, this model focuses more on the decision-maker, from one sender to one receiver.

Aggregate supply-demand matrices were the inputs for the model. The choices that had been modeled were: shipment size/frequency, location of consolidation and distribution centers, number of legs or stops, and transport mode for each leg (Chow, Yang, and Regan 2010). Then by considering the number of employees per firm in each zone, aggregate production flows were disaggregated to annual firm-to-firm flows (Chow, Yang, and Regan 2010; De Jong and Ben-Akiva 2007; Shabanpour, Golshani, Auld, et al. 2017; Karimi et al. 2015).

After determining the flow between firms, shipment sizes were computed by employing an Economic Order Quantity (EOQ) model to be used in a logistic cost minimization. Transport costs depend on the transport chains and were assumed to be constant or approximated iteratively. The same EOQ model was used for determining the disutility in the discrete choice model.

Transport Chain (Vehicle Type/ Transshipment Location per Leg, Loading Unit per Leg / No. of Legs, Mode) = f (Available Modes, Destination Shipment Size, Firm Flows)

To consider the empty trucks movements in the system an additional commodity was defined as "empties". An Exogenously determined return model was used in this section that was based on the model represented by (Holguín-Veras and Thorson 2003).

In comparison to the previous two models, this model is more expensive regarding its data requirements. Not only the data on logistics costs and initial I-O tables need to be collected, but surveys also need to be conducted to collect the necessary data for individual sender-receiver pairs to estimate the transport chain models (Chow, Yang, and Regan 2010).

2.1.5. Urban freight micro-simulation

The urban freight micro-simulation was a three level process for modeling urban freight commodity flows (Wisetjindawat and Sano 2003; Shabanpour, Golshani, Fasihozaman Langerudi, et al. 2017). Later, it was improved by (Wisetjindawat, Sano, and Matsumoto 2006; Golshani, Sarwar, et al. 2017) to be compatible with fractional split distribution method. The model contains two core components: commodity generation and distribution.

For commodity consumption and production model, a regression model was proposed at firm level. The variables of the model include: firm size, floor area, and number of employees. The main difference between this model and GoodTrip is on their geographic definition. GoodTrip generates the productions at the zone level not the firm level.

Zone choice estimation was developed based on a spatial mixed logit model that employs the zonal attractiveness for utility function. Then, a logistic function was used to determine the shipper choice. For validation part, the flows were aggregated to zonal level to be compared with commodity flow survey (CFS) data.

The model is calibrated and validated with data from the Tokyo Metropolitan Goods Movement Survey (Chow, Yang, and Regan 2010). The survey collected data of 46,000 firms. It contained very detailed firm-based information such as: location, commodity type, number of employees, OD of freight trips, delivery frequency, and truck sizes, etc.

2.2. Freight Vehicle Touring Models (VTM)

The underlying difference between the VTM and the aforementioned ones is based upon whether the unit of analysis is a vehicle or a shipment/commodity. Generally, commodity/shipment models emphasis on the agents' behavior over the perspective of logistics costs minimization. On the other hand, vehicle-touring models focus on capturing the vehicle movements and the decisions of carriers.

2.2.1.Space–time multinomial probit model

Garrido and Mahmassani (2000) developed a model that uses space and time to forecast the distribution of freight flows by linking service demand generation to various time intervals and zones. Their model is an econometric model which explains the service demand in terms of socioeconomic variables. It also uses an autoregressive discrete choice approach with a spatial lag operator.

Carrier's pickup and delivery plus the socioeconomic information are necessary for developing the model. The socioeconomic factors are: population, population density, number of private vehicles, unemployment rate, and average weekly wages. However, this model cannot explain the nature of logistics choices nor truck tours through different distribution channels.

2.2.2.Truck tour-based microsimulation model

The truck tour-based microsimulation model was estimated and implemented in the city of Calgary in Canada. The procedure then implemented in urban areas in the state of Ohio (Hunt and Stefan 2007; Gliebe et al. 2015). The model can also be used for analyzing various truck policies such as: increasing the gas price; congestion analysis; changing truck route accessibility; or toll pricing for specific zones (Chow et al. 2010).

The data within the Calgary model consists of interviews of freight vehicle movements for more than 3100 transport businesses, similar to household trip interviews. The survey contains information on purpose, commodity type, fleet, origin, and destination of the trip. It also contains the data of choice behavior for 64,000 commercial vehicle trips. Similar to Calgary, an establishment survey was conducted in the state of Ohio for 562 establishments.

The first module of the model requires an accessibility measure for each O-D pair to determine the number of tours. A logit regression model was used for the accessibility modeling. Then an aggregate exponential regression model used to calculate the number of tours generated in each zone. Each zone can have several land use such as: Industrial, Transport, Wholesale, Retail, and Services.

In order to determine the time period of a tour, a logit model have been used, considering that the carrier tries to maximize the utility function by choosing time period. Following that, a multinomial logit model was used to jointly assign a primary purpose and a vehicle type to each tour. These primary purposes include: Goods, Services, and Other. Vehicle types include: Heavy, Medium, and Light.

Start time simulation of each vehicle tour is performed by using Monte Carlo simulation. Then a logit model was used during each leg of the tour to determine the purpose of the following leg. The three general purpose outcomes include: Business, Other, and Return. The last one returns the vehicle to the depot for the rest of the day. Simulation continues till the return alternative is selected.

2.3. Agricultural transportation studies

In a study by Kruse et al. (2007) grain transportation on the upper Mississippi river and Illinois River were analyzed. According to their study about half of the total tonnage transported on Illinois Rivers comprises of “cereal grains”. The primary destination for these grains are ports at the Gulf of Mexico which handle two-thirds of U.S. soybean and corn exports (Remo and Pinter 2007).

The study also analyzed the effect of infrastructures improvements on Mississippi and Illinois river. They used a special equilibrium model for corn and soybean and provide information on revenue declination on Midwest grain producers in case of a catastrophe.

In a similar study by Shu (2013) the price of corn at the Gulf of Mexico were analyzed with respect to its transportation cost. According to their study;

- by an exogenous increase in the barge rates, the price between two markets increases;
- price response to barge rate changes according to the production location mainly in upstream river;
- there is an opposite relationship between the barge-rate effect with distance from the river; and
- effect of barge-rate is less viable in the markets that have less integration with the river system.

In a study by Meyer (2004), different options for transporting grains to the export facilities were discussed. They emphasized on the importance of Illinois and Mississippi Rivers for transporting grains to the ports for exports. They highlighted the necessity of improving the transportation systems efficiency to reduce the gap between local and foreign prices and consequently to make U.S. more competitive in the world grain markets.

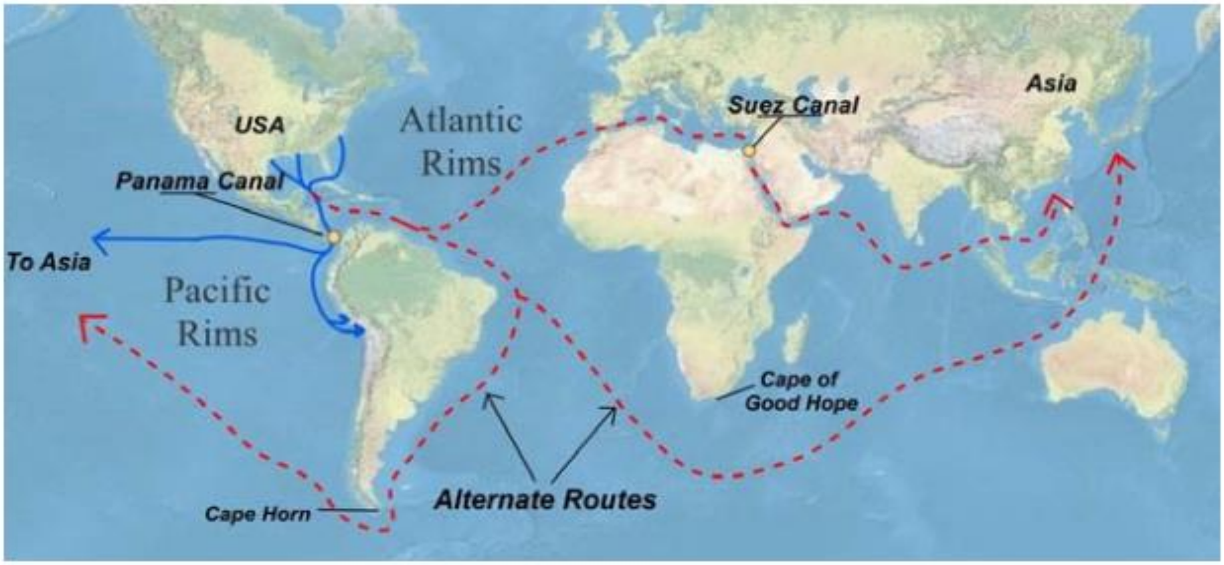
Fuller et al. (2003) studied different aspects of grain transportation for the state of Texas. The main focus of their study was on grain production and consumption trends. The study, however, is based on historical data patterns and no analyses were implemented to determine the reasons for these trends or if they are expected to happen again in the future.

The Texas elevator and feed mill surveys showed that 20% of the respondents did not have access to rail option because of rail-line abandonment, whereas 33% of the rice driers were placed on abandoned rail lines. As a result, truck shipments of grain have increased by nearly 60% in 5 years, while rail shipments have decreased by almost 3%.

In a study by Prater et al. (2013) rail mode share declination had been analyzed. According to their study, rail mode-share in the U.S. declined from 50% in 1980 to 29% in 2010 and the truck share increased from 30% to 58% at the same time period. They believed that several reasons resulted to this situation including: railroad deregulation, biodiesel and ethanol production; and the concentration of animal feeding.

Park et al. (1999) also studied the impact of various railroad mergers on grain carrying markets in the state of Kansas. They developed a network model to determine the least cost transportation paths between Kansas and Houston and a profit movement algorithm to measure the total raise that railroads can apply on their rates.

U.S department of agriculture also provides useful reports about grain transportation. For example, they analyzed the grain transportation through Panama Canal (USDA 2015). According to this report, the main user of the Canal is United States for transporting grain to Asia (Table 1 and Figure 2).



Source: USDA/AMS/TSD

Figure 2 Trade routes between Atlantic and Pacific Rims (USDA 2015)

Table 1 Grain Shipments from Atlantic Rim to the Pacific Rim through Panama Canal (USDA 2015)

	Fiscal Year		
	--Thousands of metric tons**--		
	2012	2013	2014
Corn	11,179	7,252	13,375
Soybean	16,375	14,111	19,268
Wheat	712	2,468	1,554
Rice	384	302	194
Sorghum	4,141	3,677	8,561
Barley	7	45	-
Other and unclassified	2,458	1,824	2,445
Total	35,256	29,679	45,397
% change from previous year		-16	53

**numbers may not exactly match those reported by the Panama Canal Authority due to conversion and rounding
Source: www.pancanal.com

Agricultural commodities are considered as one of the most important commodities transported through Panama Canal. Besides, with the expansion of the Canal in 2016, there is a great potential for the increase of grain export through Gulf ports (Rodrigue 2010; Salin 2010; Hricko 2012; Lindstad, Jullumstrø, and Sandaas 2013; Mahmoudifard, Ko, and Mohammadian 2014b; Shabanpour Anbarani et al. 2016; Mahmoudifard, Ko, and Mohammadian 2014a). However, these effects could not be seen in a comprehensive simulation framework because of data scarcity and incomplete freight simulation tools.

Maiyar et al. (2015) studied the process of transportation and distribution of grain by developing a cost minimization model. They used two variants of swarm optimization algorithm to solve the model. In another study by An et al. (2016), the supply chain problem for grains discussed by considering harvesting time equilibrium. They used a bi-level optimization model, in which a food firm maximizes its profit and minimizes the post-harvest loss.

3. Research Gaps and Objectives

3.1. Research Gaps

Literature review has shown that there are many gaps and deficiencies in freight transportation modeling that need to be covered. The focus of this research, however, is on improving FAME as one of the best freight frameworks. FAME while containing innovative, interesting, and sophisticated models, requires improvements in some parts. Figure 3 shows the FAME framework which consists of 3 main layers (Pourabdollahi 2015).

- *Economic activities*: agents and their features are generated, then consumption and production values of different commodities are calculated
- *Logistics decisions:* trade relationships between agents (firm) are formed and supplier-buyer sets are recognized. For each supplier-buyer set, the probability of partnership is determined. Next, using these probabilities, the commodity flow between supplier-buyers are calculated. Then, the logistics choices including mode choice, shipment size, shipping chain choice are estimated for disaggregate flows.
- Network analysis: commodity flows are converted into vehicle flows and assigned to the transportation network.

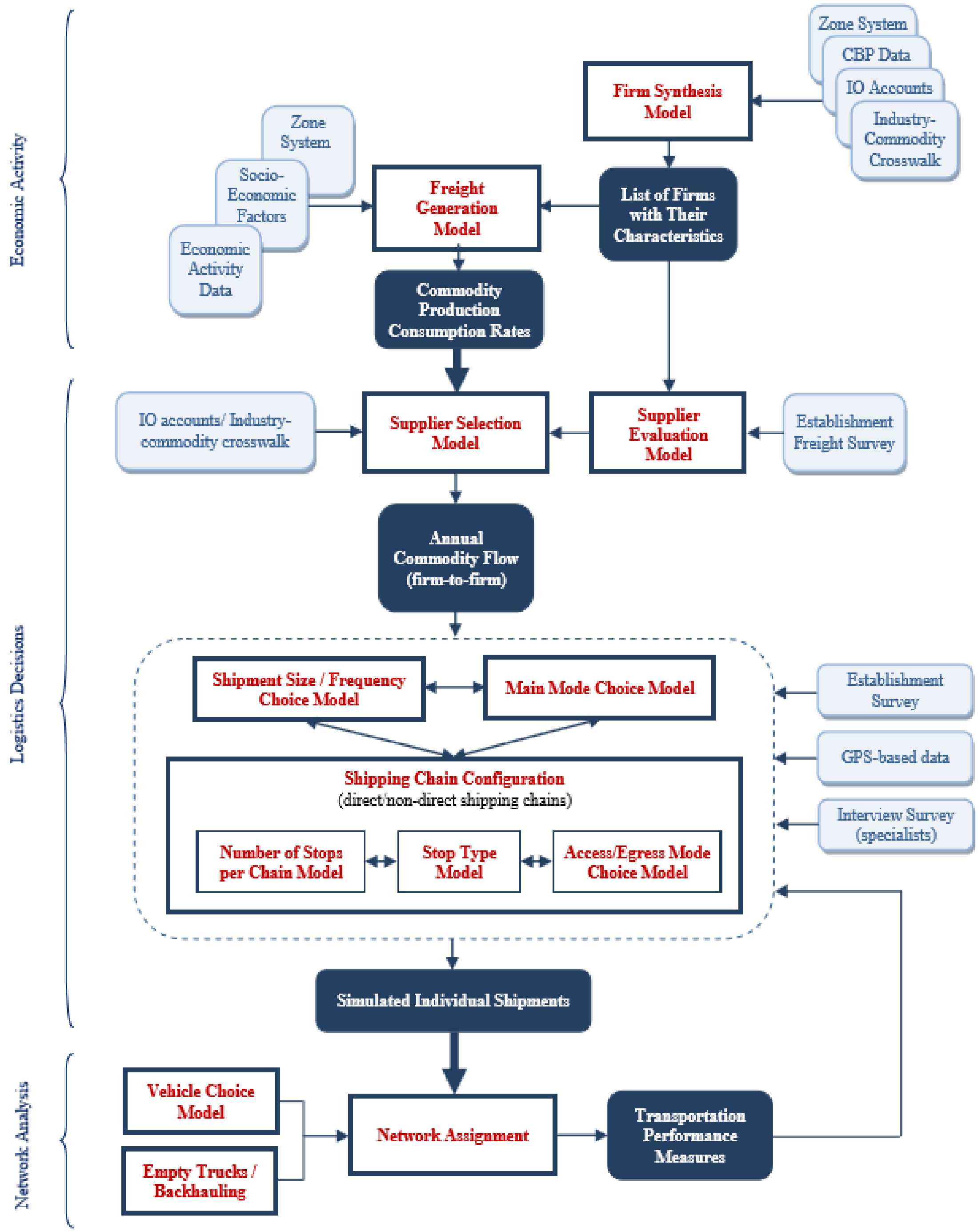


Figure 3 Freight Activity Microsimulation Estimator (FAME) (Pourabdollahi 2015)

3.1.1.FAME Commodity Aggregation

The Standard Classification of Transported Goods (SCTG) was used to categorize the commodities in FAME. SCTG at the most aggregate level has 43 types of commodities. However, in FAME these 43 types were aggregated to 15 types of commodities. This aggregation was justified because of the computational burden of the model and lack of information.

Table 2 shows the commodity classification for FAME. For example, the commodity class 1 in FAME encompasses 138 commodities in SCTG (fifth level category). Logistic choices such as mode choice and shipment size, could be significantly different among these 138 commodities.

Table 2: commodity classes and Definitions (Pourabdollahi et al. 2013)

Commodity Class	**Definitions**	**Related SCTG**
1	Agricultural and Forestry products	1-9
2	Products of Mining	10-15
3	Petroleum Products	16-19
4	Chemical and Pharmaceutical Products	20-23
5	Wood Products	25, 26
6	Paper Products	27-29
7	Nonmetallic Mineral Products	31
8	Metal and Machinery Products	32-34
9	Electronic, Electrical and Precision Equipment	35, 38
10	Motorized and Transportation Vehicle Equipment	36, 37
11	Household and Office Furniture	39
12	Plastic, Rubber and Miscellaneous Manufactured Products	24, 40
13	Textiles and Leather Products	30
14	Waste and Scrap	41
15	Mixed and unknown Freight	43, 99

3.1.2.Computational Restrictions

To perform the simulation, a considerable number of firm-types should be paired together while minimizing the transportation cost. However, due to the significant computational burden, the mathematical program cannot perform the optimization. This problem was solved by reducing the number of firms to a manageable amount while keeping the total tonnage over 85%. This means that only main firms will stay in the simulation.

This process, however, reduces the total number of firm-types up to 92%. It may not significantly affect the total tonnage transported in the U.S., but it could lead to a very different origin-destination matrix. Table 3 shows the reduction in firm-type numbers for each commodity in FAME.

Table 3: Reduced number of firms due to computational limitation in FAME

Commodity type	Initial number of firms	Reduced number of firms	% Reduced
1	23747	9196	61.3
2	35107	5655	83.9
3	51078	4636	90.9
4	44436	4706	89.4
5	48126	4759	90.1
6	64960	9386	85.6
7	39122	6941	82.3
8	49093	10316	79
9	64749	9715	85
10	52963	3836	92.8
11	34539	5724	83.4
12	58729	9744	83.4
13	48864	9504	80.6
14	5813	573	90.1

3.1.3.FAF Inaccuracy

Inaccuracy in Freight Analysis Framework (FAF) data, which is a key input to FAME framework, is another major issue. As an example, grain products were compared with other reported data sources. Table 4 and Figure 4 show the comparison between the FAF data and the USDA reported data for 2007. Significant differences can be seen in this figure (ranging between 31% in

Vermont to up to 3872% in the state of Florida). Totally, the FAF data is almost 1.58 times larger than the real tonnage reported by USDA.

Table 4: difference between FAF and reported grain production

State	FAF*	USDA*	% Difference between FAF and USDA	State	FAF*	USDA*	% Difference between FAF and USDA
IA	146,180,440	65,392,770	123.5	LA	34,895,046	5,660,603	516.4
IL	171,910,787	62,684,908	174.2	NC	10,326,064	4,391,027	135.1
NE	103,213,748	45,754,814	125.5	VA	10,338,509	3,469,691	197.9
MN	119,623,913	37,788,217	216.5	TN	12,868,160	3,417,472	276.5
KS	96,148,611	37,551,007	156.0	OR	13,193,850	3,125,334	322.1
IN	61,941,596	28,086,062	120.5	NM	5,174,321	3,080,308	67.9
SD	56,907,495	25,425,748	123.8	GA	6,587,868	2,914,153	126.0
TX	61,149,589	24,893,925	145.6	MD	4,948,547	2,601,261	90.2
WI	43,575,269	24,371,957	78.7	AZ	4,472,746	1,760,566	154.0
ND	57,849,183	19,564,860	195.6	VT	2,172,031	1,653,000	31.3
OH	50,127,069	19,287,874	159.8	UT	4,093,458	1,411,229	190.0
CA	32,931,109	17,405,172	89.2	SC	2,972,613	1,336,726	122.3
MO	65,194,238	15,734,253	314.3	WY	4,242,600	1,095,178	287.3
MI	30,349,059	13,532,931	124.2	AL	3,079,732	855,495	259.9
CO	21,795,001	11,764,910	85.2	DE	1,065,058	771,039	38.1
PA	15,957,536	10,862,683	46.9	FL	25,698,828	646,953	3872.2
ID	33,328,191	10,762,728	209.6	NJ	2,750,274	503,955	445.7
NY	23,819,049	10,690,827	122.7	ME	1,622,570	474,058	242.2
AR	22,543,530	10,070,643	123.8	CT	3,171,339	468,000	577.6
WA	29,627,836	9,266,764	219.7	WV	1,340,561	374,739	257.7
MT	18,826,351	8,161,415	130.6	MA	594,117	300,000	98.0
OK	17,849,495	7,320,551	143.8	NH	386,381	267,000	44.7
KY	17,314,571	6,237,028	177.6	NV	1,888,448	194,726	869.7
MS	12,897,745	5,669,993	127.4	RI	58,311	40,000	45.7

*tons

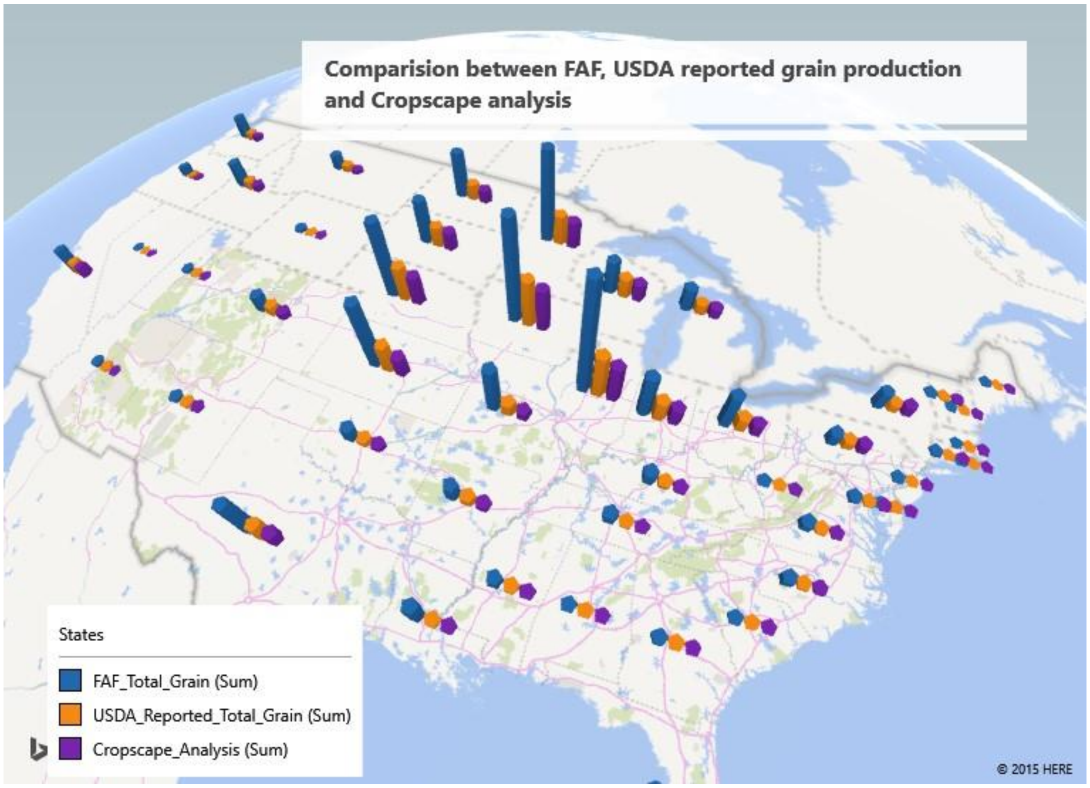


Figure 4 Grain Production Comparison between FAF, USDA, and CropScape Analysis

3.1.4.Network Assignment

Network Assignment is the last module of FAME that was not completed yet. Figure 5 presents the initial results developed by FAME`s authors. Comparing with Figure 6 (which is the assignment of Highway Performance Monitoring System (HPMS) data) reveals that there is a considerable difference between them. The reason for this difference could be due to elimination of firm-types in previous modules.

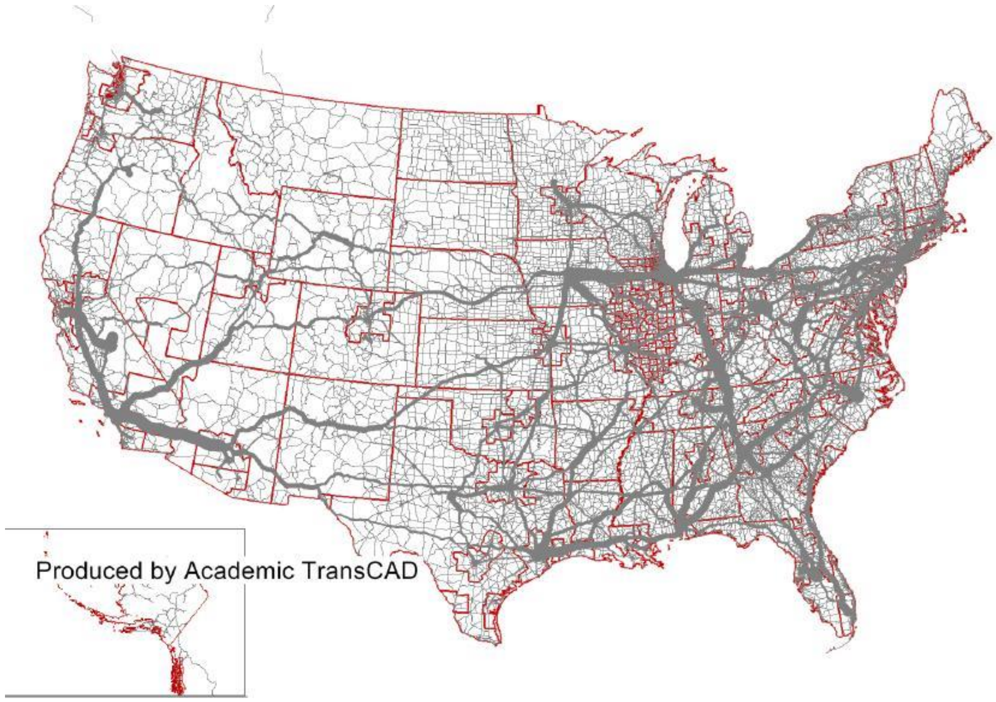


Figure 5 FAME truck network assignment 2007

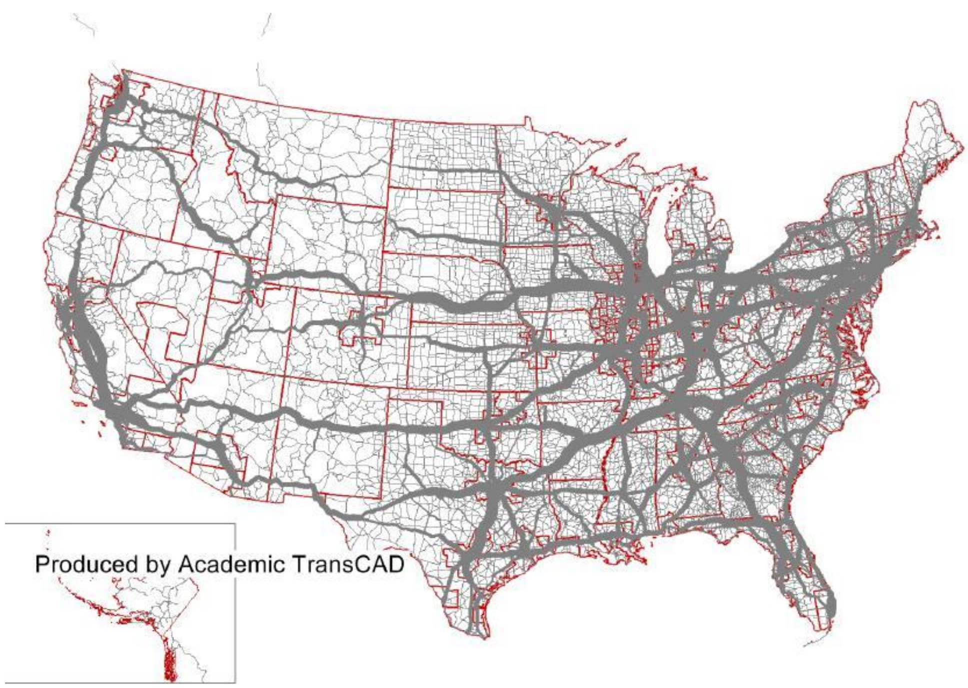


Figure 6 HPMS truck flows 2007

3.2. Objectives

The significant increase in freight modeling and their influence on socioeconomic schemes of our life have provided enough motivation to develop a reliable freight modeling framework. FAME will be used to estimate freight flows between zones and estimate future trends in commodity movements among regions. However, due to data constrains, the focus of this research will be specifically on SCTG 2 (which encompasses 45% of total tonnage of agricultural commodities). The main contribution and scope of the study could be categorized into 4 sub-sections:

3.2.1. Developing a comprehensive Grain Activity Microsimulation Framework

Logistic decisions of cereal grains comparing to other commodities are significant different. Therefore, the models that are related to logistic decisions such as firm synthetization, supplier evaluation, and supplier selection need to be revised in FAME. To perform this task, original agricultural commodities in FAME, disaggregated into 2 groups: cereal grains and other agricultural commodities. Furthermore, grain products are transported in large sizes and detailed disaggregated geographic zoning will not be necessary. In zone size simulation only 3007 zones in the U.S. will be analyzed which will consequently reduce the computational issues of the program.

3.2.2. New Supplier Evaluation Model

The problem of supplier selection has received an excessive deal of attention by researchers. It is also one of the main components of FAME. However, these models face computational issues. Using the result of UIC establishment survey, the supplier selection model will be revised. A decision tree model and an order probit model will be developed to capture the buyer's behavior on selecting the distance-range in which the trades are forming.

3.2.3. Seasonality analysis

In order to perform the traffic assignment, first tonnages of commodities need to be converted to units of trucks. FAME and FAF use the same procedure for this conversion. They assume that the distribution of commodities is uniform during a year. This assumption seems to be a highly questionable one. One can argue that many commodities have seasonal patterns during a year. An obvious example is agricultural commodities. Seasonality analysis is a task that can be added to the last module of the framework and enhance the accuracy of network assignment. It will not be dedicated only for grain commodities but will be implemented for any other commodity in which the seasonal data are available.

3.2.4. Importing new dataset to the framework

Agricultural specific data such as CropScape data, USDA data, grain consumer's data such as biofuel production information, and ports of entry data are the most important data sets that will be entered to the framework to enrich the analysis. CropScape is a huge source of data for land use and agricultural analysis. This dataset has important information which will be explained on section 4.9.

4. Data

4.1. UIC Establishment Survey

In order to develop a freight activity microsimulation framework, Samimi et al. (2010) conducted an establishment survey back in 2009. The first wave of the survey focused primarily on collecting the essential data for developing the basic components of FAME.

Initially, three methods of data collection were evaluated: telephone interview, mail questionnaire, and web-based methods. Due to lower cost and higher response rate, a web-based method was selected (Samimi et al. 2010; Pourabdollahi 2015).

Two new waves of the survey were completed in 2010-2011 by another team at UIC. The collected data were used to fill the gaps of previous research and to collect detailed information about logistic choices and supply chain formation. More than 219,000 contacts were attempted, using all different contact techniques such as: web crawling, telephone introductions, and e-mail blast campaigns. One introductory e-mail and two reminders were directed to the representatives of freight handling in the companies. In total, 657 surveys were completed which resulted in 970 useable shipment forms (Pourabdollahi 2015).

The survey comprised of three major parts.

- In the first part, questions about the characteristics of the business establishment (e.g. firm location, value of total annual shipments, employee size, number of weekly internal/outbound shipments, supply chains, and major suppliers etc.) were asked.
- The second part of the survey collected the information about the five most recent shipments and their corresponding attributes, such as origin, destination, mode of transportation, commodity type, weight and value of the shipment, etc.

- In the third part, several new questions were added to collect the information on the features of decision-makers and the other logistics modules of supply chain (Pourabdollahi 2015).

One of the main purposes of the survey was to collect data to understand the process of decision-making in a supply chain. Eight potential criteria were asked to be scaled from one to five. These criteria were: cost, credit and finance, distance and convenience, delivery, loyalty, manufacturing capacity and reliability, management and service, and technology and quality.

As presented in Figure 7, the results show a very interesting picture of how suppliers are selected. Quality, delivery, manufacturing capacity, and cost have been given values higher than 4. In addition, Figure 8 shows how respondents have assigned scores on each criterion.

Using the origin and destination zip code, the distance range is calculated as the Great Circle Distance (GCD). The distance in which the major supplier is selected categorizes into 6 ranges (i.e., “200 miles or less,” “200-500 miles,” “500-1000 miles,” “1000-1500 miles,” “1500-2000 miles,” and “2000 miles and more”). The survey results were used to determine the distance range in which the trades are forming by developing a decision tree model and an ordered probit model.

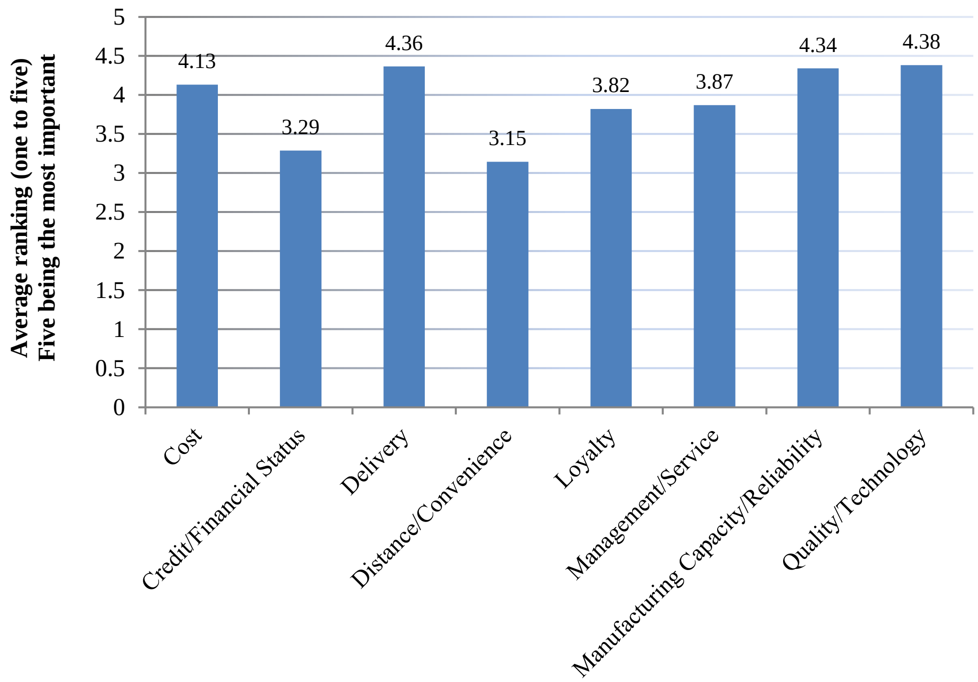


Figure 7 Average scores of supplier selection criteria (Pourabdollahi et al. 2016)

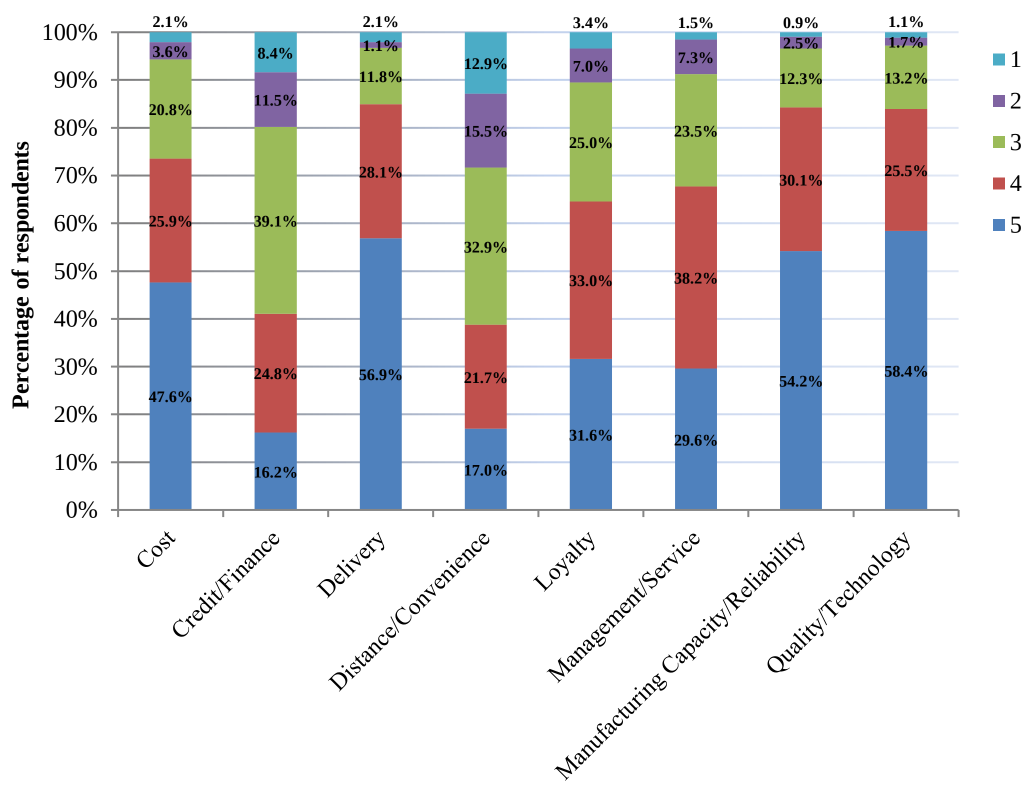


Figure 8 Rankings of supplier selection criteria (Pourabdollahi et al. 2016)

4.2. FAF

FAF is an aggregate picture of freight movement between states and major metropolitan areas. It was created by Federal Highway Administration (FHWA) using different data sources including: Commodity Flow Survey (CFS), Transborder Freight Transportation Data, Rail Waybill, Waterborne Commerce, Vehicle Inventory and Use Survey, Highway Performance Monitoring System, National Transportation Atlas Database, Transportation Satellite Account.

FAF contains flows of commodities in terms of tonnages and values by different modes of transportation. Figure 9 shows the top ten transported commodities in terms of tonnage in 2012. These 10 commodities encompass a total of 78% of entire tonnages transported in the U.S. As one can observe in this figure, coal (SCTG 19 and SCTG 15) shows the highest commodity flow that is reported in FAF dataset. Following that is gravel (SCTG 12) and then petroleum products (SCTG 16).

Table 5 also describes the top heaviest commodities transported by different transportation mode in 2012. Gravel and other minerals represent approximately 15.84% of the total tonnage flows in the U.S. and 27.43% of tonnages that are transported by trucks. Coal is the dominant user of rail transportation services and petroleum products are using waterways instead.

Figure 10 indicates top ten precious commodities transported in the U.S. in 2012. Electronics are the dominant commodity type. Table 6 also indicates the top valuable commodities transported by truck, rail and water. Mixed freight and motorized commodities are the most valuable commodities transported by truck and rail. However, Fuel oils and crude petroleum are the dominant commodity transported by water.

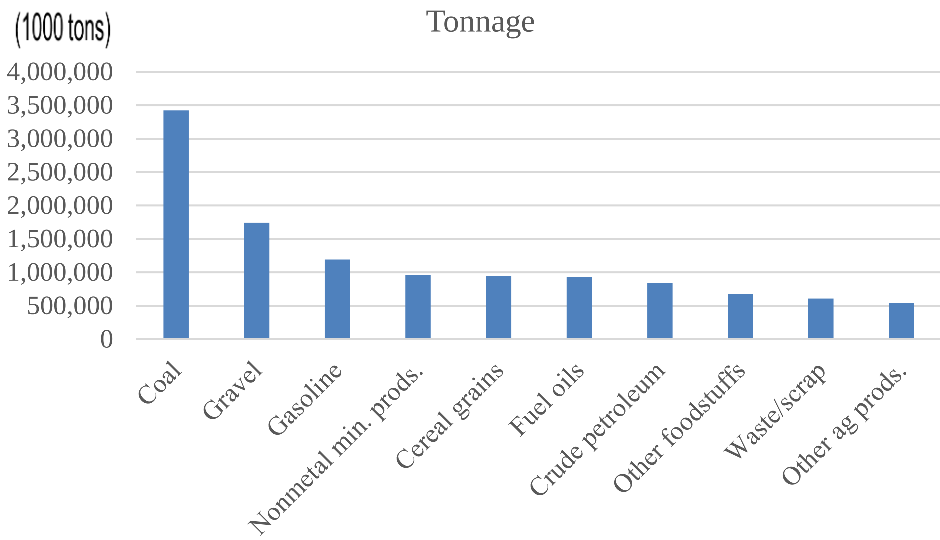


Figure 9 Top ten heavy commodities transported in the U.S. in 2012

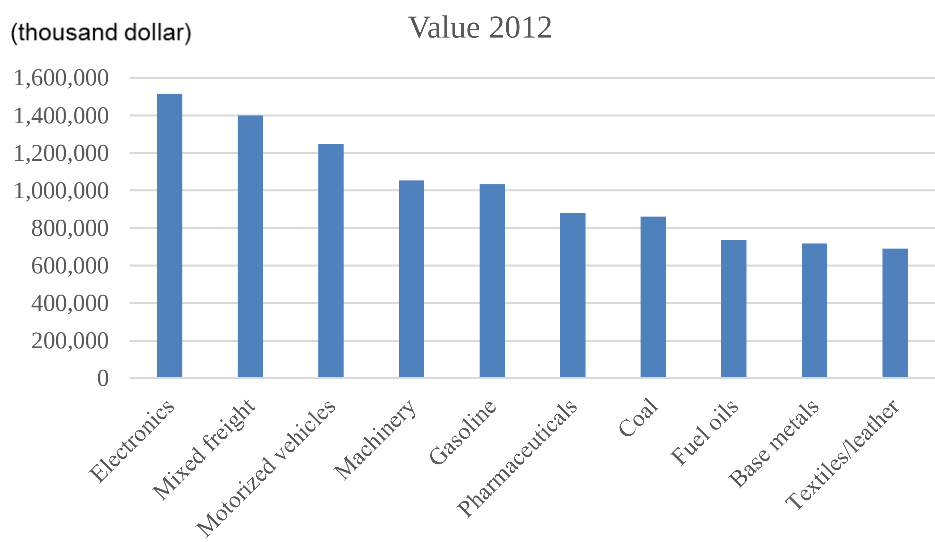


Figure 10 Top ten precious commodities transported in the U.S. in 2012

Table 5 Top 10 heavy commodity transported by different modes (1000 metric tons) (2012)

Commodity	Truck	Commodity	Rail	Commodity	Water
Gravel	1,586,797	Coal	733,523	Fuel oils	139,046
Nonmetal min. prods.	892,313	Cereal grains	184,560	Crude petroleum	92,762
Cereal grains	706,726	Basic chemicals	108,632	Coal	126,005
Gasoline	682,754	Gravel	72,168	Gasoline	71,517
Other foodstuffs	605,118	Fertilizers	71,345	Basic chemicals	50,914
Waste/scrap	565,038	Plastics/rubber	57,811	Gravel	50,667
Natural sands	514,276	Metallic ores	52,640	Cereal grains	39,883
Fuel oils	485,501	Other foodstuffs	49,369	Other ag prods.	30,760
Other ag prods.	453,277	Base metals	46,210	Nonmetallic minerals	21,069
Mixed freight	373,709	Nonmetal min. prods.	35,879	Metallic ores	14,518

Table 6 Top 10 precious commodity transported by different modes (1000 dollars) (2012)

Commodity	Truck	Commodity	Rail	Commodity	Water
Mixed freight	1,306,798	Motorized vehicles	87,755	Fuel oils	89,720
Motorized vehicles	982,641	Basic chemicals	79,918	Crude petroleum	62,106
Electronics	966,607	Plastics/rubber	77,051	Gasoline	61,101
Machinery	848,579	Base metals	51,341	Basic chemicals	40,632
Other foodstuffs	625,200	Coal	48,312	Coal	37,255
Base metals	624,149	Cereal grains	46,662	Transport equip.	14,098
Gasoline	607,374	Other foodstuffs	31,911	Other ag prods.	9,672
Textiles/leather	519,278	Fertilizers	22,586	Cereal grains	8,750
Plastics/rubber	492,970	Motorized vehicles	87,755	Fertilizers	5,064
Pharmaceuticals	489,763	Basic chemicals	79,918	Base metals	2,942

4.3. Commodity Flow Survey (CFS)

Commodity Transportation Survey was the name of a program that was initially conducted by the Census Bureau. In this program the flow of goods and commodities by modes of transportation was determined from 1963 to 1977. Afterwards, in 1990 the Census Bureau and Department of Transportation tried to create a survey that could answer questions for planners and decision makers. This effort resulted in the first CFS in 1993 that has information on the value, weight, classification of the shipment, and origin and destination of the shipments.

4.4. SCTG

The SCTG was developed by 4 groups including: U.S. Department of Transportation, Statistics Canada, U.S. Bureau of the Census, and Transport Canada. They wanted to replace this coding system instead of Standard Transportation Commodity Codes (STCC) for 1997 and later CFS surveys. FAF uses this method of classification for the commodities.

SCTG has a hierarchical Structure with 4 sub layers (2- to 5-digits). At 2-digit level, SCTG is designed for the purpose of having an overview of transported goods (Southworth et al. 2010). As the digits grow in this structure, more details will appear and the commodities become more disaggregated. In the 5-digit level, SCTG was designed to capture the details of transportation specifications and industry patterns. Four and Five- digit categories of SCTG are generally unpublished mainly because of data confidentiality, data-reliability issues, and insignificant sample size. Table 7 summarizes the number of categories in each SCTG level as used in the 2002 CFS.

Table 7: number of categories in each SCTG level (Southworth et al. 2010)

Level of Hierarchy	**Number of Categories**	**Information Provided**
First level, 2-digits	42	Analytical overview
Second level, 3-digits	133	U.S.-Canadian product groups
Third level, 4-digits	283	Transportation characteristics
Fourth level, 5-digits	504	CFS 2002 collection leve

4.5. North American Industry Classification System (NAICS)

After the United States, Mexico, and Canada signed the North American Free Trade Agreement (NAFTA) in 1994, a new set of classifications for categorizing the industries was created (U.S. Census Bureau 2015). Before this agreement, U.S. was using Standard Industrial Classification (SIC) system for categorizing the industries.

The SIC was established in 1939 and the last update was in 1987 (Bhojraj et al. 2003). As the technology grew, new industries were created and there was a need for adding new codes for them. Switching from SIC to NAICS added 350 new industries. Therefore, NAICS also has the new classification for high-tech industries.

NAICS has a hierarchal structure. They are composed of 6 digits beginning with general categories and move to more details (i.e. from sector to industry). This may be clarified by an example from (Miller and Blair 2009).

"The first two digits indicate the sector (for example, manufacturing). The third digit indicates the sub-sector (for example, food manufacturing), the fourth, the industry group (for example, dairy product manufacturing), and the fifth, the NAICS industry (for example, ice cream and frozen dessert manufacturing). The sixth-digit indicates a country-specific industry; most of the data at this level are not comparable among all three countries." (Miller and Blair 2009).

In order to understand the preceding example, it is important to clarify the difference between an establishment and an industry. By definition, a group of establishments with related production processes is called an *industry*. On the other hand, an *establishment* is a physical location in which the business is organized. Establishments are the existing locations for industrial operations or providing the services. They, however, are different from enterprises (Miller and Blair 2009).

Enterprises are legal units, such as companies or nonprofit institutions. Usually, an enterprise is made up of only one establishment, but can also have more. For example, General Motors is considered as an enterprise, while the factory in Ohio State which actually produces the Chevrolet, is defined as one of its establishments (Miller and Blair 2009).

4.6. County Business Patterns (CBP)

The U.S. Census bureau integrates information from different data sources to create CBP. These data sources include: Business Register, Company Organization Survey (COS), and other various Census Bureau programs, including the four annual surveys, Internal Revenue Service (IRS) and Social Security Administration (SSA) records.

Number of establishments, employment, and the amount of payrolls in the Census years are captured in the CBP dataset. It provides data on zip code and county. But there are some limitations in this dataset. For example, it does not include the employment of agricultural production workers, service workers, ocean-borne vessels, and railroad employees. Also, because of confidentiality, most governmental employees are not reflected in this dataset (Division 2015).

4.7. Input-Output Data

The Bureau of Economic Activities (BEA) integrates the Annual Industry Accounts and the National Income and Products account to create the benchmark Input-Output (IO) tables. IO tables provide detail information on the inputs and outputs to an industry. Information in this data set will help determining the supply chain of commodities.

One of the most important features of IO tables is Input Category Controls (ICC). It is an estimate of the total costs for one input category, such as purchases of specific materials for an industry. For agriculture, the ICCs are computed by the Department of Agriculture from the Farm Costs and Returns Survey. For most service establishments and for wholesale and retail trade, the ICCs are based on the Business Expenses Survey (BES) (Miller and Blair 2009).

4.8. CropScape Data

CropScape is an interactive visualization portal created by National Agricultural Statistics Service (NASS) and George Mason University. It is a web-based interactive map visualization and querying system. This web service offers geospatial and navigation access, statistical analysis, online mapping, data retrieval and change detection. Figure 11 shows a screen shot of the website interface and the available tools provided in the website.

Cropland Data Layer (CDL) is the crop-specific land cover which is produced by NASS annually since 1997. More than 100 crop categories are presented in CDL for the entire U.S. at a 0.09-hectare pixel resolution. CDL combines the satellite imagery with data from Landsat, and Disaster Monitoring Constellation (DMC). Also, Common Land Unit (CLU) data is used for verification and validation.

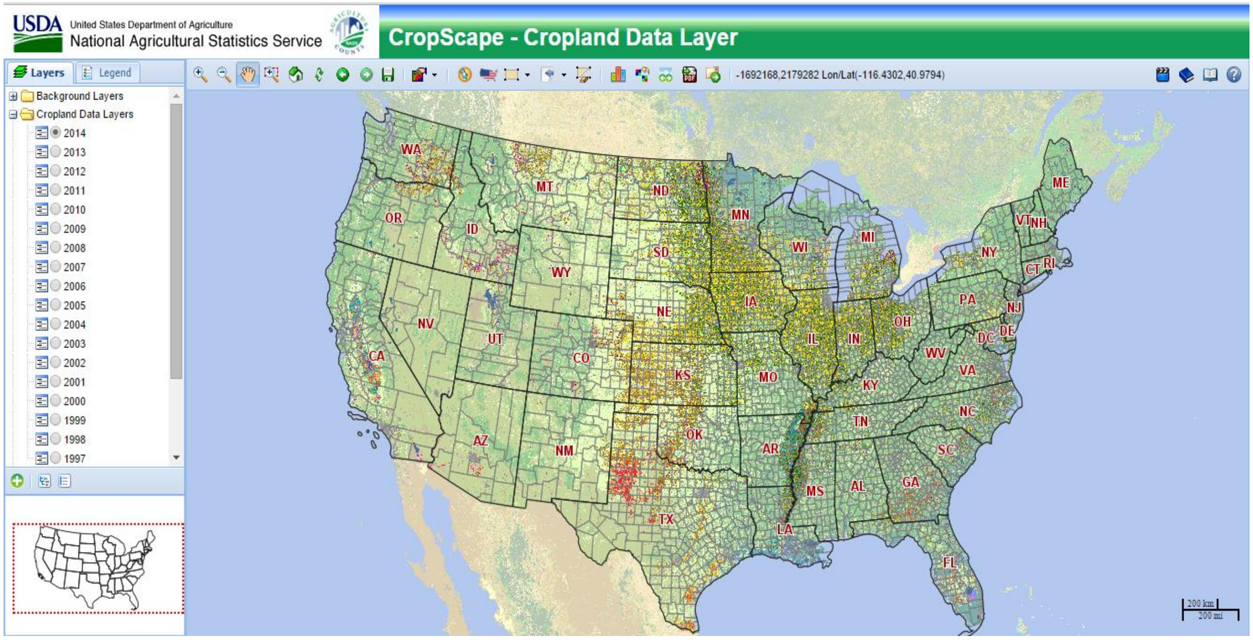


Figure 11 snapshot of the CropScape web service page

Since 1997 the CDL usage has improved in methods and accuracy of data. It was also incorporated with Geographic Information System (GIS) (Boryan et al. 2011). CDL can be used for many purposes such as agricultural sustainability studies, land conversion assessment, studying environmental issues, crop rotations, farmer surveys, disaster studies, decision support, bioenergy studies, ecology, and biodiversity studies. Some of these studies are presented here:

Hartz et al. (2011) used CDL data in West Virginia to identify the agricultural production areas and Fitzgerald et al. (2013) used CDL data for studying water resources in Montana`s Tongue River Basin. Painter et al. (2013) at the University of Idaho used CropScape for designing an oilseed survey in order to help processors and producers in growing oilseed. Becker et al. (2010) used CDL data to identify mask wheat fields. These data then used to achieve an empirical regression model for Kansas. Lunetta et al. (2010) used the CDL data across Great Lakes Basin to characterize crop distributions and fluctuations in crop rotations.

5. Development of Model's Components

5.1. Activity Microsimulation Framework for the U.S. Grain Transportation

5.1.1.Introduction

About 17% of word's arable land is located in the North American continent, which makes this region a major producer and exporter of grain crops (Wrigley et al. 2015; Mahmoudifard, Shabanpour, Golshani, and Mohammadian 2017). Between 2002 and 2013, about 82.2 million hectares (Mha) of cereal grains were harvested in North America, accounting for 20% of world's production. In North America, the U.S., Canada, and Mexico contain almost 70%, 18%, and 12% of the total harvested area, respectively. Corn is the most commonly grown grain in the region, accounting for about 50% of the area followed by wheat with approximately one-third of the area.

During the last decade, grain production has increased by 6.6 Mha (i.e., 8.5%) in North America. Most of the increase occurred in the U.S., where the area of corn cultivation has increased from 28 Mha to 35 Mha. In fact, the U.S. is the largest producer and exporter of cereal grains in the world.

U.S. domination in production and export is primarily indebted to the efficient transportation systems. Fuller et al. (2003) investigated the effects of improvements in transportation on U.S. competitiveness in the world grain market. In their study, the effect of increasing supply of grain –offered by Southern American countries– were found to cause a loss of 1.4% of U.S. grain export revenues.

Furthermore, a major concern in grain transportation is the biofuel ethanol production. Biofuel production faces a variety of challenges including biomass harvesting, storage, biomass transportation and shipment of the final product to the consumption points (Hajibabai and Ouyang 2013). Many new biorefineries are constructed near cornfields– mostly Midwest– and they use truck to transport biomass feedstock shipment to manufacturing sites. This process has resulted in mode shift from rail to truck in many states (Kang et al. 2010).

Several researchers studied the biofuel production problem considering the grain shipment to the processing sites. The focus of these studies were mostly on biorefinery location finding problem (Sokhansanj et al. 2006; Tembo et al. 2003; Mapemba et al. 2002; Searcy et al. 2007; Mahmudi and Flynn 2006; Brown et al. 2007; Tursun et al. 2008).

Due to the great importance of grain`s transportation to the U.S. economy and lack of a comprehensive freight simulation framework, this part of the dissertation suggests an extension module to FAME framework to capture the essential needs for modeling grain transportation in the U.S. The suggested framework captures the grain transport behavior and presents a detailed supply chain for grains by adding additional models and data sources to the FAME framework.

5.1.2.Data Preparation

In order to develop a reliable freight transportation framework and to form the connections between grain suppliers and consumers, vast data mining and data analysis efforts are required. The first step of developing the supply chain for cereal grains is to determine the amount of grain that suppliers produce in each zone. The zoning system that is chosen for this step is the U.S. counties.

The estimation procedure of supply and demand amounts at the county level can be divided into two steps.

- First the USDA databases are employed to collect information on grain production in each county. Then, a 3-dimensional commodity-industry crosswalk is developed for the commodity consumption by 6-digits NAICS industry.
- In the second step, the developed crosswalk is used to apportion aggregate consumption amounts between firms.

Unlike the production part, the consumers can be of a vast variety of firms such as biorefinery firms, U.S. ports, food processors, and milling firms. For more information on the procedure, readers can refer to (Pourabdollahi 2015; Pourabdollahi et al. 2013; Pourabdollahi et al. 2012).

The data on the annual biomass demand for biorefinery firms contains information on the exact address of the firms, total storage capacity, total annual fuel production, projected capacity expansion, and available transportation facilities on the sites ("Ethanol Biorefinery Locations" 2015).

Since the zoning system considered as county level, the total demand for biorefinery firms is aggregated from zip code level to the county level. Notably, most of these firms are located in the Midwest region. As an example, Figure 12 visualizes the distribution of biorefinery sites in the state of Illinois and the grain production at the county level.

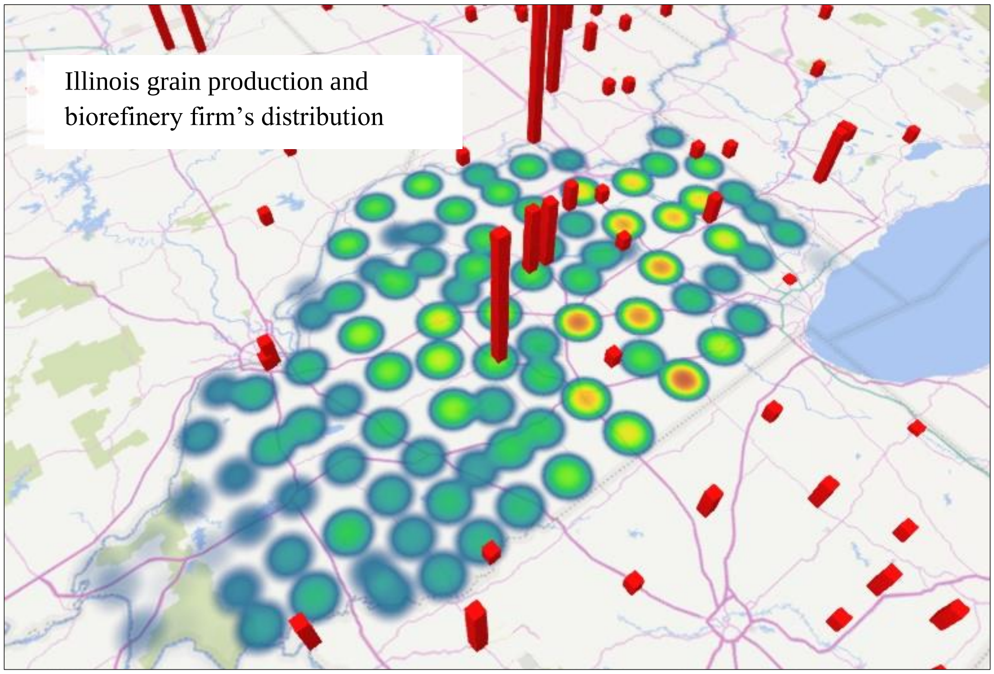


Figure 12 Illinois grain production[1] and biorefinery[2] firm's distribution.
1- green circles show the grain production density 2- bars show the biorefinery firms

According to 4th version of FAF, about 7.3% of U.S. grain production, was exported to other countries in 2012. About 50% of all U.S. grains exports, shipped through New Orleans, 25% through Pacific Northwest and the Texas Gulf Coast handles about 11%. The remainder was exported through California and East Coast ports. (U.S. Grains Council 2015).

Another useful data source is the Bureau of Transportation Statistics (BTS) that provides information on incoming-crossings at the U.S.-Mexican and U.S.-Canadian border at the port level (U.S. DOT 2016). U.S. grain trades in the ports are extracted from these data sources. Then, the amount of grain is assigned –as grain demand– to the county in which the port is located.

Estimating grain storage capacity for each county is useful in supply chain determination. Grain storage is divided into 2 parts: off-farm storage and on-farm storage. Off-farm storage mainly refers to grain elevators with rail or water facilities (Figure 13). On-farm storage refers to smaller bin storages that exist on the farms.

To estimate the storage capacity for each county in the U.S., the storage data in two states of Illinois and Missouri were collected including a total of 216 counties. Then a regression model is estimated to evaluate the total storage capacities at the county level with respect to the total grain production of that county. Table 8 presents the results of the regression model.

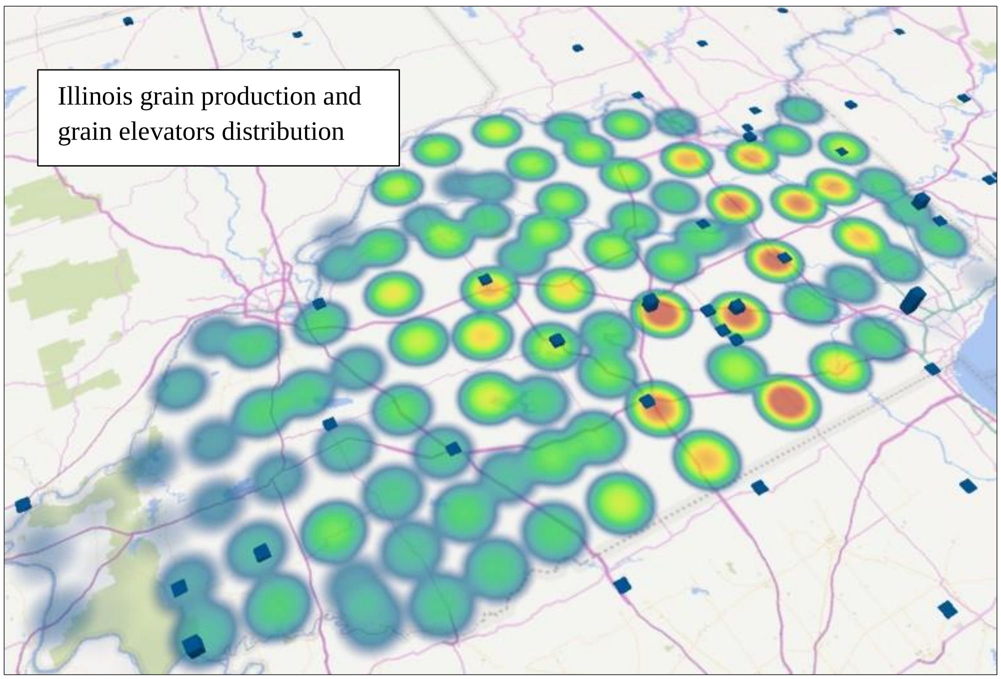


Figure 13 Illinois grain production[1] and grain elevators[2] distribution.
1- green circles show the grain production density   2- bars show the grain elevators

Table 8 Storage Capacity Estimation at County Level

Regression Statistics				
Multiple R	0.883			
R Square	0.780			
Adjusted R Square	0.779			
Standard Error	94337.72			
Observations	216			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	72876.13	8079.15	9.020271	1.09E-16
Grain production	0.737307	0.026694	27.62118	1.69E-72

5.1.3.Methodology

Figure 14 shows the revised framework for grain transportation modeling. The structure of the framework is almost the same as FAME with proper changes. Grain Activity Microsimulation Estimator (GAME) consists of 3 main layers.

The first layer, economic activity, will result in grain production and consumption rates. In this layer different databases added to the framework including CropScape data and USDA data. These data sources include the total acreage and yield per acreage for every county in the U.S. for several years. Regression models were used for predicting the total grain production. Another important component of this layer involves synthesizing grain-related firms. These firms can be identified through the NAICS look up tables and then be located through ZBP (Zip Code Business Pattern) data. One of the advantages of GAME's framework is that the firms can be identified more easily because of commodity disaggregation.

The second layer of GAME is logistic decisions. This layer is the heart of the model in which the grain producers and the grain consumers are connected to each other. This connection is based on an optimization model which in general, minimizes the transportation cost between suppliers and consumers. In the optimization process, it is common that a small amount of commodity, here grains, is assigned to an origin-destination, which may not be realistic. To address this issue, a new decision tree was developed and some other assumptions were considered that will be explained here.

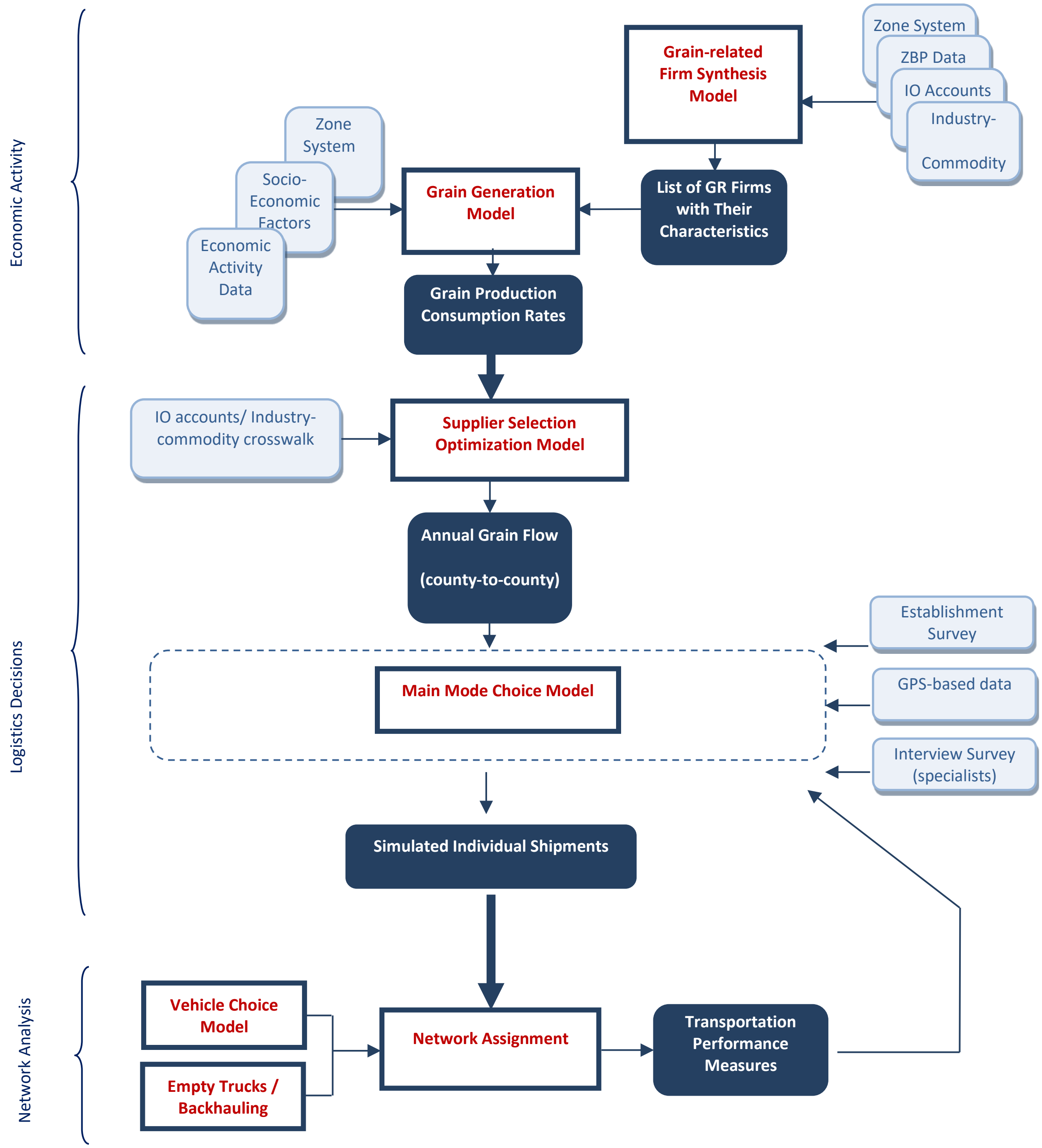


Figure 14 Outline of the proposed framework

Grain is transported by three major modes including trucks, rail and water. In FAF4, information about mode split and corresponding distances was reported. This information enables us to create a decision tree that relates mode choice with respect to distance between origins and destinations.

Figure 15 shows the results of the new mode choice decision tree. This model enabled us to define a new constrain for the optimization model. If the model assigns a flow between an origin-destination, it should consider the probable mode between them with respect to corresponding distance. For example, if rail was chosen as the transportation mode, the flow could not be less than 25 railcars. Or if the selected mode is truck, then the minimum amount of flow between those origin-destination should not be less than 26 tons. 25 railcar loads and 26 tons for truck are the assumptions made for the model.

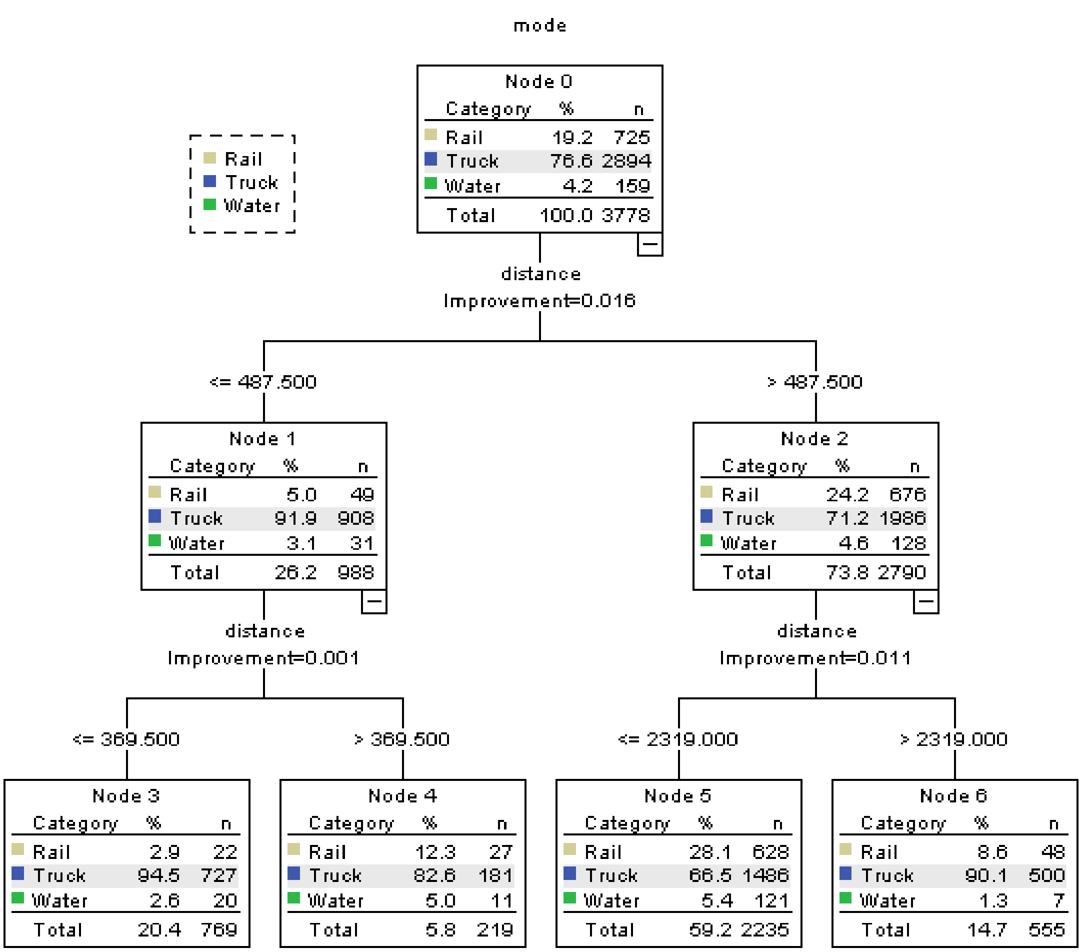


Figure 15 Decision tree for mode choice versus distance (in miles).

5.1.4.Optimization Model formulation

The objective function for the optimization problem was defined as:

$Minimize\ z = \sum_{i \in I} \sum_{i \in J} X_{(i,j)}\, d_{(i,j)}$ Eq. (5.1)

Subject to

$\sum_{i \in I} X_{(i,j)} \geq Demand_j \qquad (\forall\, j \in J)$ Eq. (5.2)

$\sum_{j \in J} X_{(i,j)} \leq Supply_i \qquad (\forall\, i \in I)$ Eq. (5.3)

$m_{(i,j)} = \{r_{(i,j)} | d_{(i,j)}\}$

$\sum_{i \in I} X_{(i,j)} \geq 26 \qquad if\ \ m_{(i,j)} = truck$ Eq. (5.4)

$\sum_{i \in I} X_{(i,j)} \geq 2500 \qquad if\ \ m_{(i,j)} = rail$ Eq. (5.5)

$\sum_{i \in I} X_{(i,j)} \geq 1500 \qquad if\ \ m_{(i,j)} = water$ Eq. (5.6)

where the variables used in the model were defined as follows;
$d_{(i,j)}$: average distance between county i and county j
$X_{(i,j)}$: grain flow between county i and county j
$m_{(i,j)}$: selected mode with respect to the distance between origin and destination.
$r_{(i,j)}$: a random number between 0 to 1 that assigns the probability for mode selection for origin-destination
$Demand_j$: total grain demand at county j
$Supply_i$: total grain supply at county i

The last layer of GAME includes assigning corresponding grain traffic to the network. It is assumed that the first step for transporting the grains are covered by truck mode. Meaning that the harvested grains go directly from farms to grain elevators or biorefinery firms by truck mode. The elevator`s manager then decide to choose whether to send the grain by truck, rail or ships to the markets or ports. The results of this layer are then compared with FAF data.

5.1.5. Results

The first output of the framework resulted in estimates of each county's grain supply and demand. Figure 16 shows the aggregated grain supply and demand in U.S. states. As it can be seen in this figure, the main grain producers are also the main grain consumers. States such as Louisiana, Texas and Washington have a higher demand for grains mainly because they are the destinations for grain export.

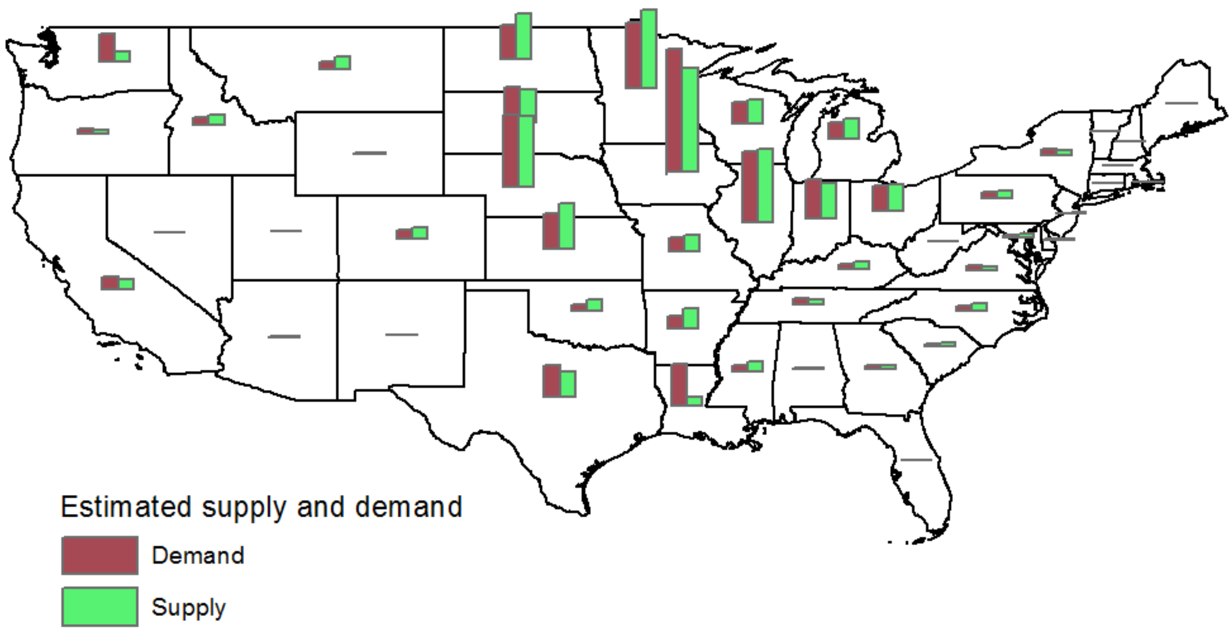


Figure 16 Aggregated supply and demand values for "Grains".

The estimated Grain supply and demand was compared to FAF4 data in Figure 17 and 18. The results show reasonable and similar trends and the total difference between estimated numbers and FAF4 data are acceptable.

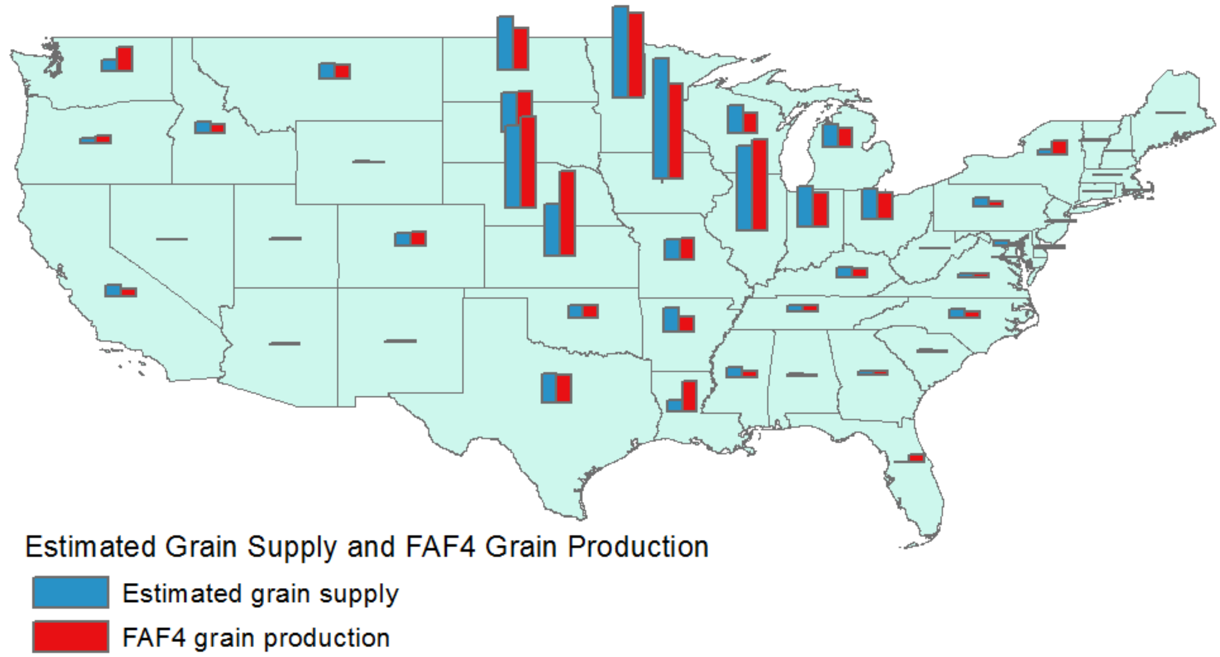


Figure 17 Comparison of estimated and FAF4 production values for “Grains”.

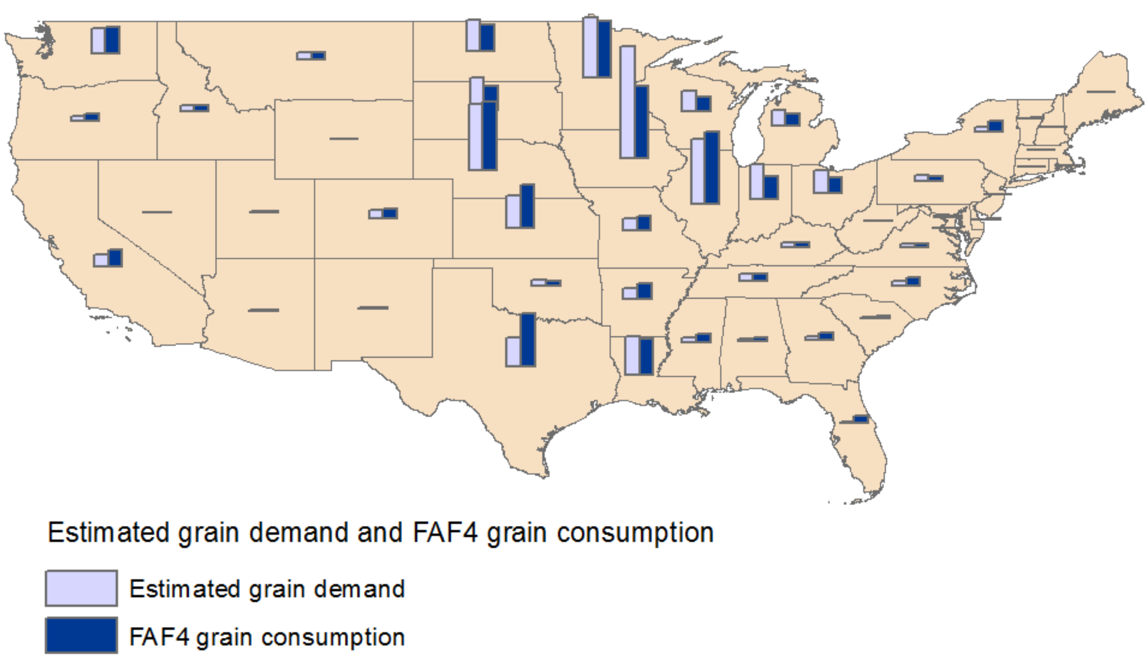


Figure 18 Comparison of estimated and FAF4 demand values for “Grains”.

The supplier-consumer pair formation conducted in the optimization process. Unlike FAME, the computational burden of the model was reasonable and the software could handle the optimization process. As it was mentioned previously, the zoning system of the GAME considered to be at U.S. county level. Therefore, a matrix of 3007*3007 was solved in CPLEX environment. The results of this optimization could be seen in Figures 19 to 21.

Total grain tonnage flows between counties were obtained from the simulation outputs. These flows are then aggregated to state level in order to compare them with FAF4 data. Figure 19 compares the optimization results with FAF4 in terms of each state`s grain export. The figure shows that the results are very similar to each other. As expected, states such as; Kansas, Iowa, Minnesota, Illinois which are the primary grain producers, are also among primary grain exporters.

The results of optimization and the data of FAF4 are compared in Figure 20 which shows each state`s grain imports. For example, state of Louisiana and Texas are among the states with a considerable amount of imports. This is mainly because these states are the major destinations for cereal grain export to other countries.

Internal grain flows refer to the internal grain circulation in a state. Figure 21 shows the comparison between FAF4 and optimization results in terms of internal grain flows. As it can be seen in this figure Illinois, Iowa, Nebraska, Minnesota, and Kansas are among the top five states in terms of internal grain circulation. Notably, the most ethanol production plants are located in these states.

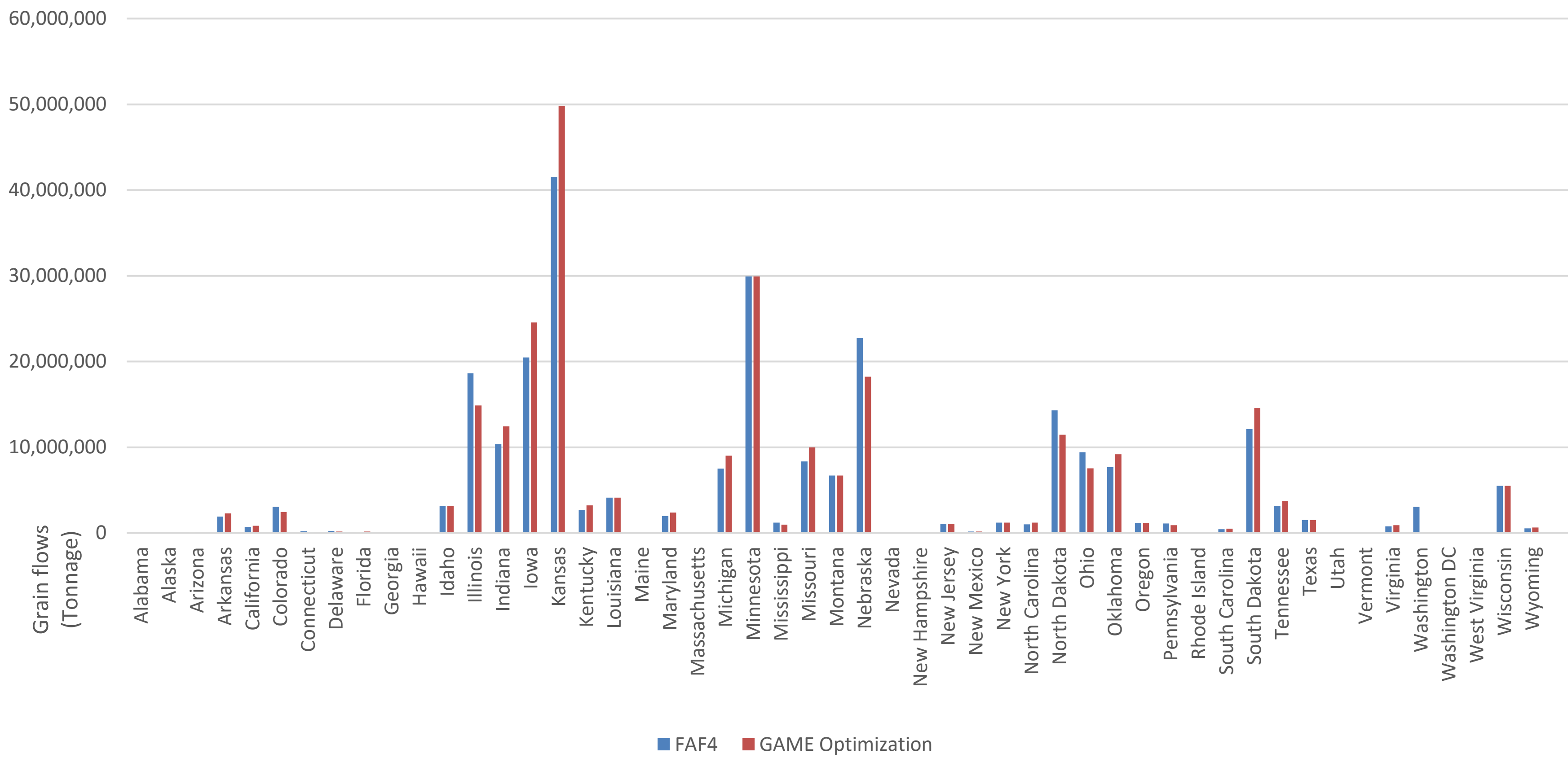


Figure 19 State`s grain export (comparison between FAF4 and optimization results).

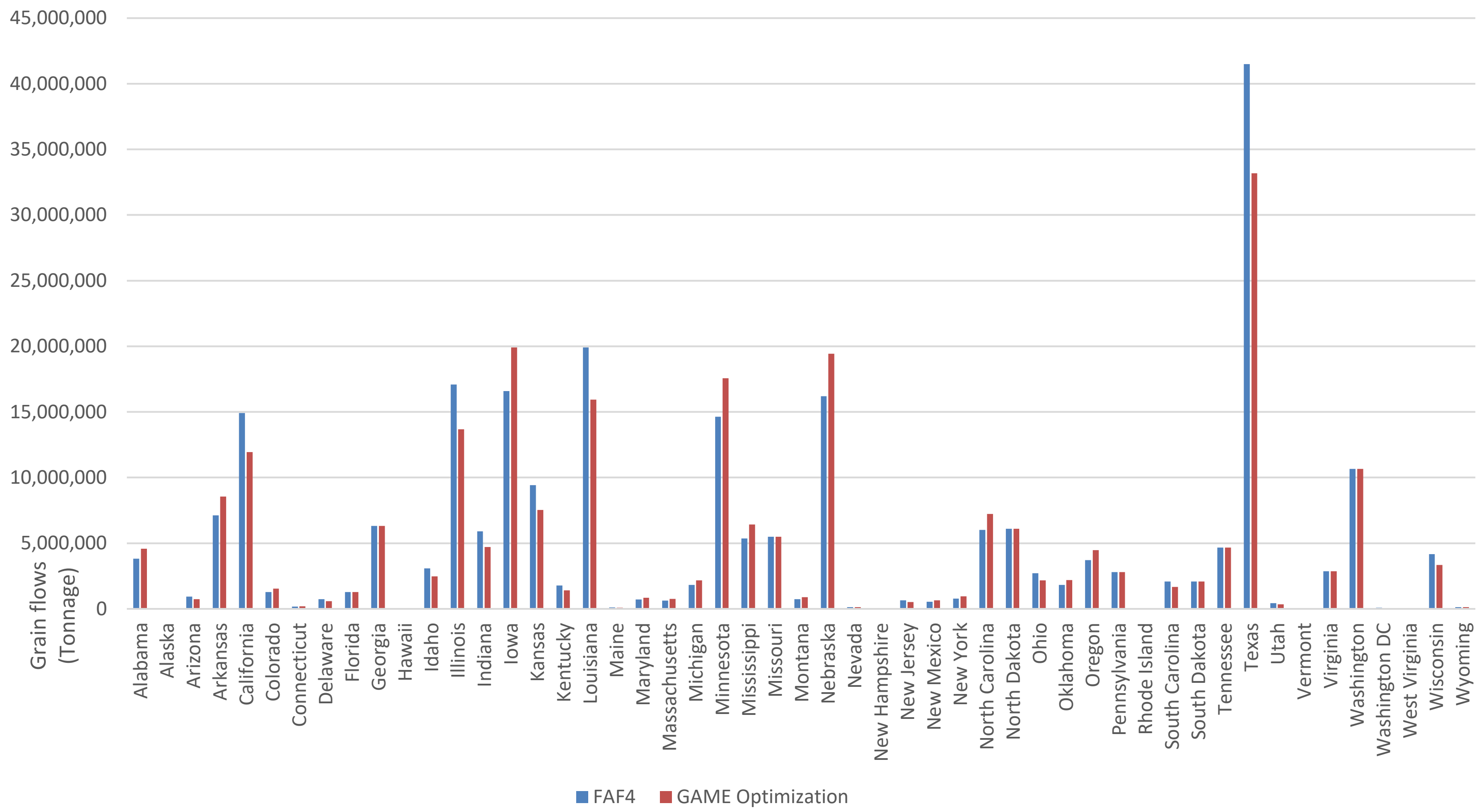


Figure 20 State`s grain imports (comparison between FAF4 and optimization results).

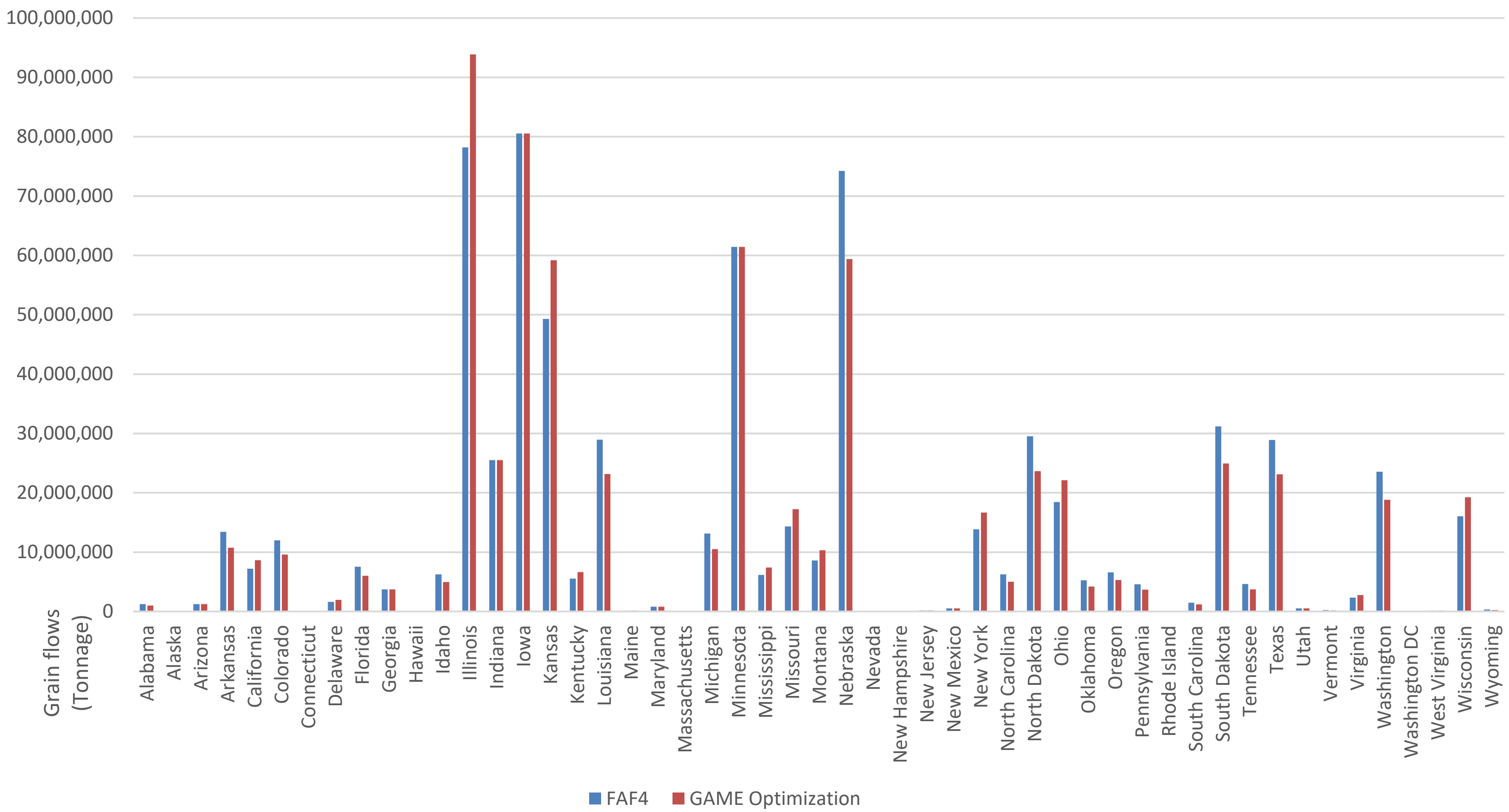


Figure 21 State`s grain Internal flow (comparison between FAF4 and optimization results).

5.2. Supplier Evaluation

5.2.1.Introduction

Supplier selection is one of the most critical stages of supplier management process. It directly affects the profit of a company and the final quality of products. Therefore, poor decision making in the supplier selection process could widely affect a company`s failure (Gonzalez et al. 2004).

For a company, selecting the right supplier comprises much more than skimming a series of price lists. The decision-maker’s choices will depend upon a wide range of features such as quality, reliability, and service attributes of the supplier. How the business weighs up the importance of these features will be based on its priorities and strategies. For instance, if a company wants to cut down the service time to customers, suppliers which offer faster delivery will rank higher than those who compete only on price.

A vast variety of studies have been focused on how companies weigh the importance of these factors. Deboer et al. (2001) categorized these models into five types:

1- Linear weighting models;
2- Total cost of ownership models;
3- Mathematical programming models;
4- Statistical models; and
5- Artificial Intelligence (AI) models.

Linear weighting models: In these models, certain weights are assigned to different criteria. The weights are multiplied by the rates on the criteria and then summed up to create a single score for each supplier. The supplier with the highest score will then be chosen as the proper option to trade with (Zenz 1987; Timmerman 1987; De Boer et al. 1998; Grando and Sianesi 1996; Gregory 1986).

A common technique in linear weighting models is called Analytic Hierarchy Process (AHP). several researchers have proposed using AHP to manage imprecision in the supplier selection process (Nydick and Hill 1992; Barbarosoglu and Yazgac 1997; Narasimhan 1983; Masella and Rangone 2000). AHP avoids the difficulties on assigning exact numbers to weigh the criteria; instead, it uses verbal statements in comparison between different criteria (De Boer et al. 2001).

Total cost of ownership models: TCO models attempt to consider all life cycle costs of an item including: pre-transaction costs, transaction costs, and post-transaction costs (Ellram and Carr 1994). Cost-ratio is considered a TCO method (Timmerman 1987). In this method, all costs related to delivery, quality, and service are collected and then expressed as a penalty or benefit percentage on unit price. Several studies have been performed to increase the accuracy of cost indication for service and delivery criteria (Monczka and Trecha 1988; Smytka and Clemens 1993).

Mathematical programming (MP) models: In MP models, the decision problem is formulated in terms of an objective function that needs to be maximized or minimized. Weber et al. (Weber and Desai 1996; Weber et al. 1998) used Data Envelopment Analysis (DEA) and MP to create a tool for negotiations with suppliers. DEA is a linear programming (LP) technique for determining the relative performance of structural units (D. Wu 2009; D. Wu and Olson 2010). Saen (2010) proposed a DEA-based methodology in which both imprecise data and undesirable outputs were considered simultaneously .

In another study, Zeydan et al. (2011) considered both quantitative and qualitative variables in assessment of a supplier`s efficiency. In that study, qualitative variables were transformed to quantitative variables in order to be operational in the DEA method.

Statistical models: To solve problems regarding the stochastic uncertainty in supplier choices, statistical models have been proposed. Although most of purchasing situations have some sort of uncertainty, the studies that have considered this stochastic uncertainty are rare (De Boer et al. 2001; Soukup 1987; Ronen and Trietsch 1988; C. Wu and Barnes 2011).

Artificial Intelligence (AI) models: In these types of models incorporate historical data and computer-aided systems to train the models in such a way that in similar situations, a non-expert will be able to consult from the model (De Boer et al. 2001; C. Wu and Barnes 2011). Neural networks (NN), expert systems, and case-based-reasoning systems are the best examples of AI models (C. Wu and Barnes 2011; Golshani, Shabanpour, et al. 2017).

Comparing to traditional models, AI models can effectively manage the complexity and uncertainty. Because, they are designed to operate in an approach similar to human judgement. Researchers that have used AI models in their papers are numerous (Zhao and Yu 2011; Faez, Ghodsypour, and O'brien 2009; Humphreys, Wong, and Chan 2003; Choy et al. 2004; Yigin et al. 2007; Guo, Yuan, and Tian 2009; Lee and Ou-Yang 2009; Montazer, Saremi, and Ramezani 2009; Aksoy and Öztürk 2011; Miralinaghi et al. 2016).

Supplier evaluation and supplier selection are among the most important elements of FAME. The structure consists of two main steps (Pourabdollahi et al. 2014; Pourabdollahi et al. 2013; Samimi, Mohammadian, and Kawamura 2009; Mahmoudifard, Shabanpour, Golshani, Mohammadian, et al. 2017):

- A rank-ordered probit model is used to define the weight of each criterion.
- An optimization model is used to determine the supplier-buyer chain.

In FAME, the supplier-buyer chain formation confronts massive data loss which consequently results in inaccurate traffic assignment. To address these issues, we have proposed a procedure that reduces the computational restriction of the model.

Data mining techniques were employed to evaluate potential suppliers for a firm. A decision tree model and an ordered probit model were implemented on the data to analyze the behavior of the buyers and determine the distance-range in which the trade between supplier-buyer forms.

Our initial theory indicates that local businesses would perform their trade locally, meaning that small businesses would choose their suppliers in a limited range of distance. However, after performing the analysis, we found interesting facts about the distance range of supplier selection.

The rules that had been found in the decision tree were then implemented to the supplier selection structure in order to decrease the number of potential suppliers. It consequently addresses the computational issues of the FAME framework by improving the supplier evaluation part.

5.2.2. Methodology

5.2.2.1. Data Mining

Data Mining is defined as the procedure that uses mathematical, statistical, machine-learning, and artificial intelligence technics to identify and extract useful information out of large databases (Turban et al. 2007; Ngai, Xiu, and Chau 2009; Berson, Smith, and Thearling 2000;

Mahmoudifard, Kermanshah, Shabanpour, and Mohammadian 2017).

Decision tree (DT) is one of the most practical procedures in data mining. It divides the data into many segments in such a way to maximize the purity. Purity is defined as the degree to which the dependent variable fits into a certain class. The rules that are used for separating the data are called the inducted rules. DT is considered as a non-parametric procedure and it is suitable for finding the interaction effect or nonlinearity (Bae and Kim 2011).

In this section, we employed the decision tree procedure to analyze the results of the UIC freight establishment survey. The classification and regression tree (CRT) method was used to categorize the data sample into homogeneous categories. The categories have the same pattern, considering their supplier selection and transportation pattern (Breiman et al. 1984).

CRT results in a series of decision rules (Javanmardi, Langerudi, et al. 2016). The rules were used to determine the probability for choosing a supplier in a specific distance-range. A linear optimization is then conducted to complete the last step of suppler selection. The decision tree is presented in the results section.

5.2.2.2. Ordered Probit Model

As indicated in data section, six possible ranges of distance have been considered for a company's supplier selection. Since these categories can be considered in an ordinal scale, ordered probability models seem to be appropriate for solving the supplier evaluation problem. An Ordered probit model is estimated as follows (Washington et al. 2010):

$$z_i = \beta' X_i + \varepsilon_i\ ,\quad y_i = j\ if\ \mu_{j-1} < y_i < \mu_j\ , j = 0, \dots . J_{,} \tag{5.1}$$

where z_i is an unobserved variable that is used as the basis for modeling, X_i is the vector of independent variables that determines company supplier selection decision-making, β' is the vector of estimable parameters, μ_j is a threshold that defines y_i and it is estimated jointly with β', y_i corresponds to integer ordering, j is the integer ordered choice for the dependent variable, and ε_i is the random error term assumed to be normally distributed with mean zero and variance of one. Furthermore, the ordered selection probability of each choice can be written as (Greene and Hensher 2010):

$$P(y = j) = \Phi(\mu_j - \beta X) - \Phi(\mu_{j+1} - \beta X) \tag{5.2}$$

where, $P(y = j)$ is the probability of outcome j, and $\Phi(\,)$ is the cumulative normal distribution, and μ_j and μ_{j+1} are the lower and upper thresholds of outcome j, respectively. The likelihood function can then be written as (Greene and Hensher 2010):

$$L = \prod_{n=1}^{N} \prod_{j=1}^{J} \left(\Phi(\mu_j - \beta X_n) - \Phi(\mu_{j+1} - \beta X_n)\right)^{\delta_{jn}} \tag{5.3}$$

where, N is the total number of observations, J is the total number of choices, and δ_{in} is a binary variable indicating if observation n belongs to choice j.

5.2.3. Results

5.2.3.1. Ordered Probit Model

The dataset is divided into a training set for model estimation and a test set for model validation with 80% and 20% of the observations, respectively. Table 9 presents the ordered probit model estimation results for the supplier selection decision-making. For modeling all possible variable interactions are tested, and only the statistically significant variables at 90%, 95%, and 99% level of confidence are presented in the table.

For model interpretation, a positive value of a coefficient implies that increasing the explanatory parameter will increase the likelihood of the last response (i.e., 2000 miles and greater) and decrease the probability of the first response (i.e., less than or equal to 200 miles).

Table 9 Ordered Probit Model Estimation Results

Variable	Coefficient	*t*-stat	*P*-value
Model			
Constant	-0.13*	-1.65	0.10
Average weekly number of outbound shipping (in thousands)	0.01*	1.82	0.07
Number of employees	0.04*	1.95	0.05
Primary business indicator (1 if Agriculture, Forestry, Fishing and Hunting, 0 otherwise)	-0.95**	-2.35	0.02
Primary business indicator (1 if Transportation and Warehousing, 0 otherwise)	0.58***	4.62	0.00
Primary business indicator (1 if Wholesale Trade, 0 otherwise)	0.59***	4.42	0.00
Commodity indicator (1 if other, 0 otherwise)	0.21**	1.96	0.05
Commodity indicator (1 if Prepared foodstuffs, 0 otherwise)	-0.42**	-2.11	0.04
Model Summary			
μ_1	0.39***	11.36	0.00
μ_2	0.77***	17.01	0.00
μ_3	1.08***	20.17	0.00
μ_4	1.22***	21.09	0.00
Log-likelihood at convergence	-980.25		
Number of observations	661		

NOTE: *Significant at 90% , **significant at 95% , ***significant at 99%

To better interpret the results, mean partial derivatives (for continuous variables) and pseudo-elasticities (for dummy variables) are calculated for each exploratory variable and each category as follows (Washington et al. 2010):

$$\frac{\partial P(y=I)}{\partial X} = -\phi(\mu_{I-2} - \beta X)\beta' \tag{5.4}$$

$$E = \phi\left(\frac{\beta_j X_{j,1}}{\sigma}|X_i = 1\right) - \phi\left(\frac{\beta_j X_j}{\sigma}|X_i = 0\right) \tag{5.5}$$

where, $P(y = I)$ is the probability of outcome I, and $\emptyset(.)$ is the probability density function of the standard normal distribution. Table 10 presents the direct effects of the independent variables.

Table 10 Partial Derivatives and Pseudo-elasticities

Variable	Choices					
	0-200	200-500	500-1000	1000-1500	1500-2000	>2000
Average weekly number of outbound shipping (in thousands)	-0.009	0.001	0.006	0.011	0.015	0.001
Number of employees	-0.077	-0.005	0.048	0.092	0.123	0.208
Primary business indicator (1 if Agriculture, Forestry, Fishing and Hunting, 0 otherwise)	0.674	-0.395	-0.637	-0.820	-0.928	-1.133
Primary business indicator (1 if Transportation and Warehousing, 0 otherwise)	-0.415	-0.088	0.152	0.429	0.654	1.455
Primary business indicator (1 if Wholesale Trade, 0 otherwise)	-0.418	-0.095	0.146	0.428	0.657	1.486
Commodity indicator (1 if other, 0 otherwise)	-0.160	-0.003	0.089	0.185	0.256	0.467
Commodity indicator (1 if Prepared foodstuffs, 0 otherwise)	0.321	-0.098	-0.257	-0.396	-0.488	-0.699

A number of variables representing the characteristics of a company, affects the supplier selection. For example, both “Wholesale Trade”, and “transportation and warehousing” companies are less likely to acquire their required goods from 500 miles or less. They select suppliers located further than 500 miles away. On the other hand, “Agriculture, Forestry, Fishing and Hunting” businesses tend to provide their goods from local suppliers. These businesses increase the probability of selecting a supplier from 200 miles or closer by 0.674 (Table 12).

The results also indicate that an increase in number of employees of a company, increases the probability of selecting a supplier from “500-100 miles”, “1000-1500 miles”, “1500-2000 miles”, and “2000 miles and more” by 0.048, 0.092, 0.123, and 0.208, respectively. On a similar note, higher number of weekly outbound shipping of a company increases the chance of providing its goods from a further supplier. These variables may be capturing the effect of companies’ size on their supplier selection where larger companies can afford to pay higher transportation costs if the initial costs are lower.

5.2.3.2. Decision Tree model

CRT method was used to construct the decision tree. Figure 22 and 23 show the trees in which the depth of the trees was assumed to be 3 levels. The CRT basics for the development of the tree includes: A minimum number of 100 observations in parent nodes and 50 in child nodes. Gini procedure was used as the impurity measurement in which splits are found that maximize the homogeneity in the child nodes according to the value of target variable, and a cross-validation process performed on the results.

Table 11 illustrated the coding for development of the model and table 12 shows the specifications of the resulted tree. As it can be seen in the decision tree, firm`s Primary business, commodity type, average number of weekly outbound shipment, and number of orders from major supplier are the main variables found to be significant.

Initially, two variables including the size of a business and warehouse situation of that business considered to be important. The size of a business was represented by its floor area or number of employees. However, according to the results of the survey and the decision tree model, the distance to the supplier is not affected by these two variables.

Instead, commodity type showed a significant influence on the decision tree splits. Figure 22 indicates that chemical/pharmaceutical products, gravel/natural sands, mixed freight, and prepared foodstuffs showed the same pattern and other commodities behaved differently regarding their distance to the main supplier.

Finally, having the decision tree, the split rules can be extracted and then be used in the first step of supplier evaluation of the FAME framework. The FAME model then uses an optimization process to allocate the freight flows to the firm types in the U.S.

Table 11 Variable`s coding description

Primary Business	code
Agriculture, Forestry, Fishing and Hunting (NAICS code: 11)	1
Information (*NAICS code: 51*)	2
Manufacturing (NAICS 31-33)	3
Mining, Quarrying, and Oil and Gas Extraction (NAICS 21)	4
Other	5
Retail Trade (NAICS 44-45)	6
Transportation and Warehousing (NAICS 48-49)	7
Wholesale Trade (NAICS 42)	8
Commodity	
Agricultural products	1
Chemical / Pharmaceutical products	2
Coal / Mineral / Ores	3
Electronics	4
Gravel/ Natural sands/ Cement	5
Machinery / Metal products	6
Mixed freight/Miscellaneous	7
Motorized and other vehicles (incl. parts)	8
Other	9
Prepared foodstuffs	10
Wood / Paper / Textile / Leather products	11

Table 12 Decision tree model summary

Specifications	Growing Method	CRT
	Dependent Variable	DistancetoSupplier
	Independent Variables*	Floor area (FL_Ar), Average Number of weekly Internal shipping (Av_We_No_In_Shi), Average Number of weekly outbound shipping (Av_We_No_Ou_Shi), Internal Shipping Value (In_Value), Outbound shipping value (Ou_Value), Number of yearly orders from major supplier (Maj_Sup_NoOrd_1), value of yearly orders from major supplier (Maj_Sup_ValOrd_1), Employment, Primary Business (Pr_Business), Warehouse Situation (Ware_situation), Commodity
	Validation	Cross Validation
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	Primary Business (Pr_Business), Commodity, Average Number of weekly Internal shipping (Av_We_No_In_Shi), Number of weekly outbound shipping (Av_We_No_Ou_Shi), Outbound shipping value (Ou_Value), Internal Shipping Value (In_Value), Employment, value of yearly orders from major supplier (Maj_Sup_ValOrd_1), Floor area (FL_Ar), Number of yearly orders from major supplier (Maj_Sup_NoOrd_1)
	Number of Nodes	9
	Number of Terminal Nodes	5
	Depth	3

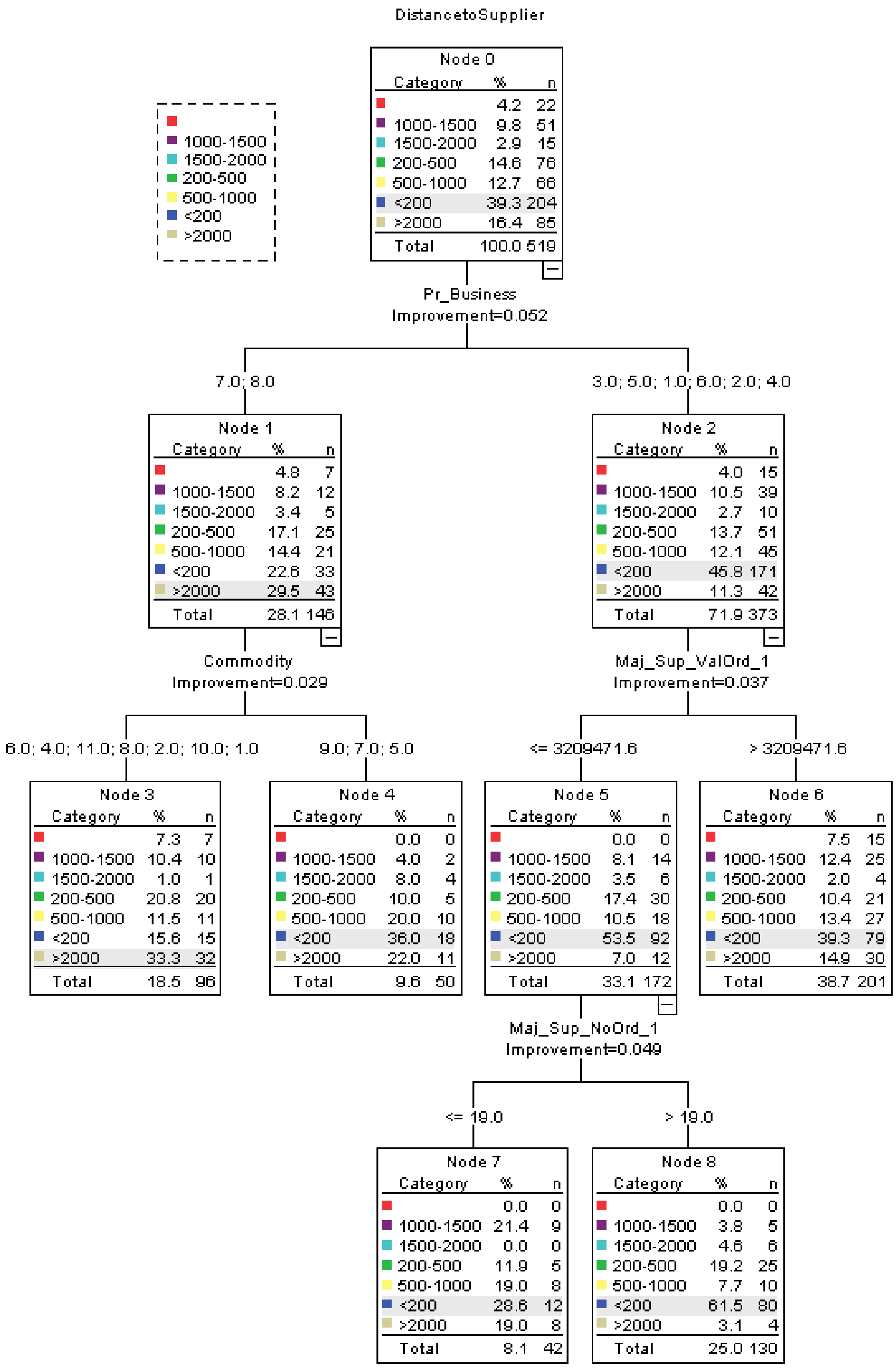


Figure 22 Decision tree cluster for distance to supplier category (training sample).

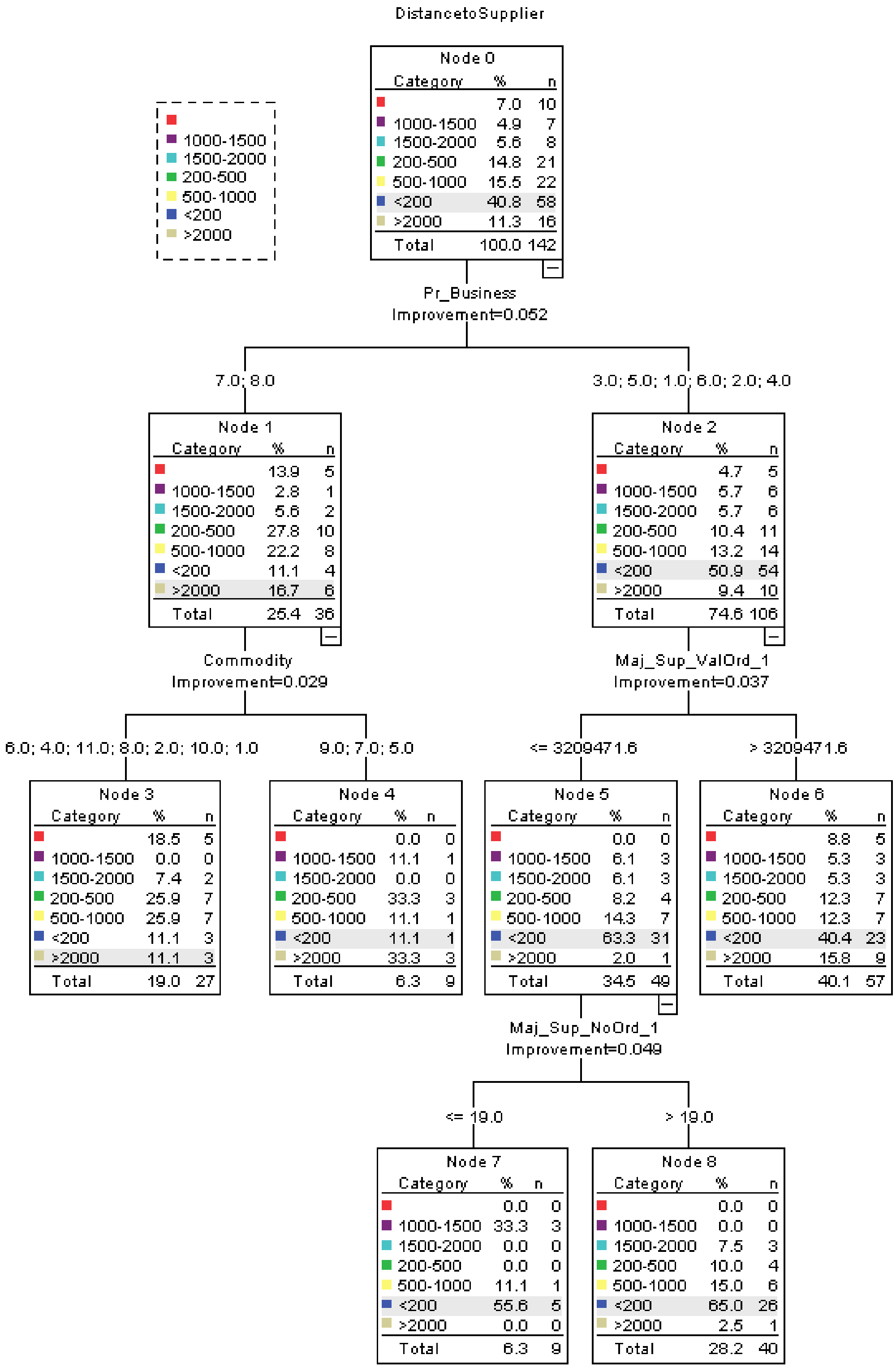


Figure 23 Decision tree cluster for distance to supplier category (test sample).

To visualize the differences between observed and prediction probabilities, a group of firms located in Illinois were selected. These firms have similar attributes, such as: “primary business” and similar range of “value of orders.” The distance range in which the trade had been formed and the corresponding probabilities for trade formation are plotted in Figure 24. Results are showing that decision trees are more successful in predicting the behavior of those specific companies. The outputs of the models for this group of firms are relatively similar, showing that in the distance range of 200 miles or less, the probability of trade formation is higher than other distance ranges.

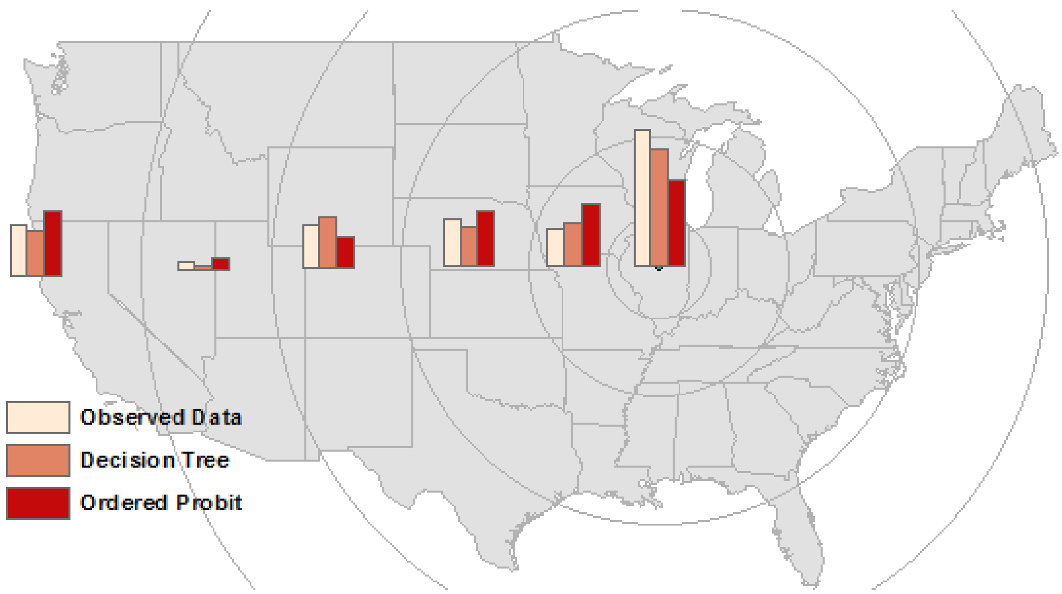


Figure 24 visualization of the probability distribution of firm`s supplier selection distance, located in Illinois

5.3. Seasonality analysis

5.3.1. Introduction

In the last layer of FAME commodity flows were converted to vehicle flows and then assigned to the transportation network (Pourabdollahi 2015; Mahmoudifard, Ko, and Mohammadian 2014b). The procedure is the same as FAF ton-to-truck conversion (Southworth et al. 2010). FAF and FAME both assume that the distribution of commodities is uniform during a year. This assumption seems to be a highly questionable one. One can argue that many commodities have seasonal patterns during a year. An obvious example is agricultural commodities.

When the price or supply/demand of a commodity is measured more than once during a year, there might be seasonal patterns in the nature of the commodity. The reason could be due to the fluctuations in the weather or the behavior of decision makers. Seasonal effects could take three different forms (Hylleberg et al. 1990);

- stochastic,
- deterministic or
- a combination of the two.

Stochastic seasonality does not follow a distinctive seasonal pattern. Its behavior varies over time (e.g., winter becomes summer). They also retain the shocks for a longer period. On the other hand, deterministic seasonality has the same seasonal pattern every year and unlike stochastic series, shocks diminish comparatively quicker (Kavussanos and Alizadeh 2001).

Seasonality is one of the main features of commodities such as cereal grain and petroleum products. These commodities share a large amount of the tonnage moved on the U.S. freight network ("FAF" 2016).

5.3.2. Commodities Description

5.3.2.1. Coal

Coal is an essential element for generating electricity and also for steel production. The U.S. produces 44% of its electrical energy by using coal. As previously mentioned in Table 5, coal has the highest mode shares of tonnages transported by rail. Figure 25 underscores the U.S. monthly coal demand for 3 years (Sanikidze 2013). As it can be seen, during February to May usage of coal is at its minimum and the maximum demand is during July and August.

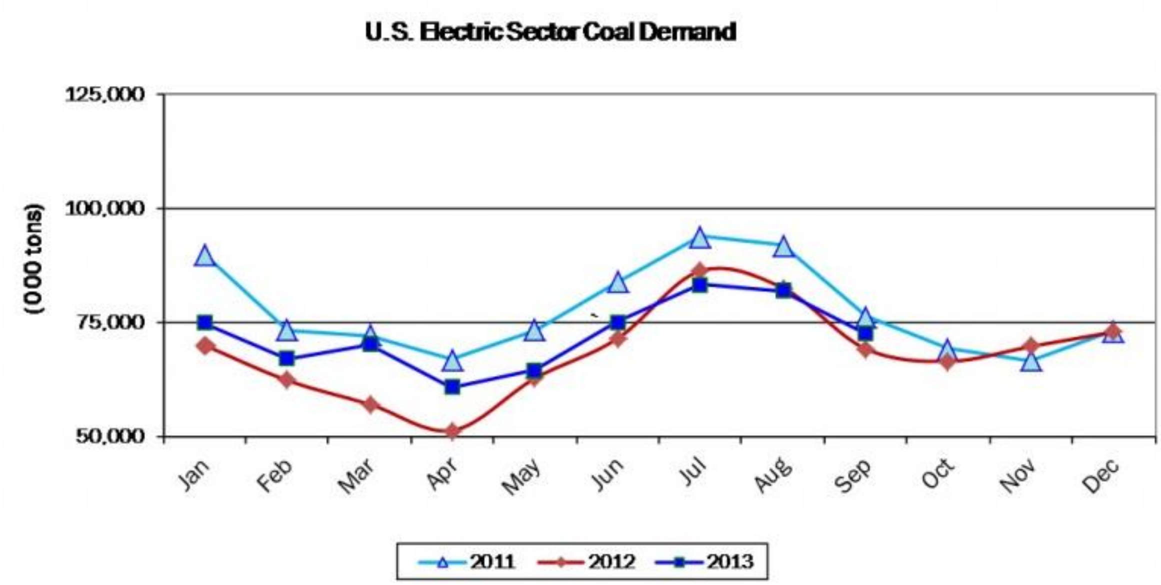


Figure 25 U.S. monthly Coal demand for 3 years (Sanikidze 2013)

5.3.2.2. Gravel and Non-metal Mineral Products

According to the CFS 2012, SCTG 12 includes limestone flux, agricultural limestone, other gravel and crushed, powdered, or broken limestone and chalk, and other gravel and crushed stone (U.S. DOT and U.S. DOC 2015). Figure 26 shows the demand for sand and gravel in years 2012 and 2013. The maximum demand for "construction sand" and "gravel" occurs during the summer (U.S. Geological Survey 2013). This is an important fact because most commodities have their peak distribution time, during the summer.

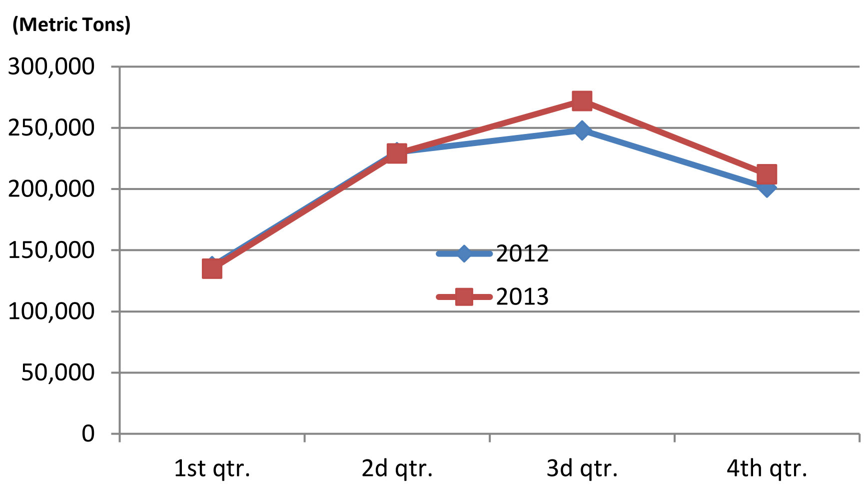


Figure 26 Construction sand and gravel sold or used by producers in the U.S. (metric tons)

5.3.2.3. Cereal Grains

Seasonality is one of the most common features of agricultural commodities. Several research papers studied seasonality patterns in agricultural products. Robert (2001) indicates that production of agricultural products has a typical behavior in commodity price, because of its seasonality pattern. Malick and Ward (1987) analyzed price volatility in frozen concentrated orange juice and Netz (1996) studied the seasonal effect in corn.

Most agricultural commodities are harvested during summer. However, it is hard to determine the exact harvesting time because each year has its own harvesting time. After harvesting season, agricultural products are available in large quantities and consequently at lower prices. According to product storage conditions, they gradually become more expensive and up at an ultimate price.

For example, Figure 27 shows the seasonality for corn over 37 years (Seasonal harts 2015). The peak time for corn availability occurs during September and November and the lowest availability occurs between May and July. Similarly, Figure 28 shows a different trend for Wheat (Seasonal harts 2015). Considering that wheat is mainly harvested during mid-June and late August, the lowest price is during these periods. The price increases during December.

Figure 27 corn seasonality over 37 years (Seasonal harts 2015)

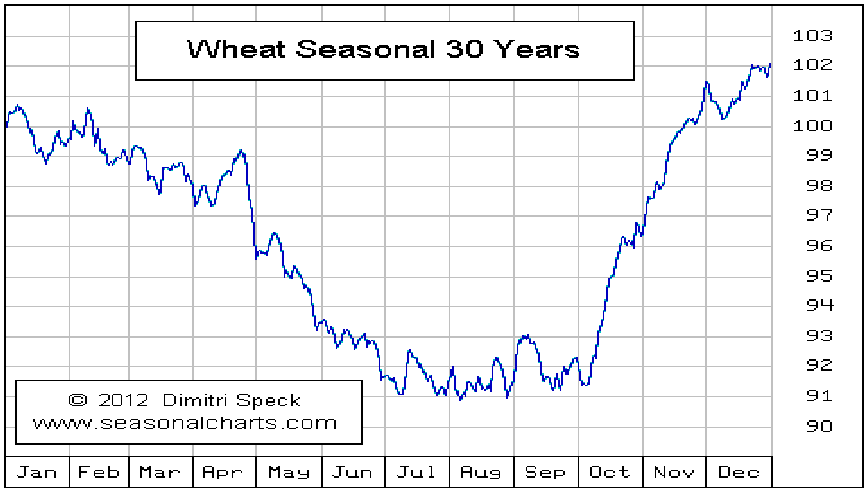


Figure 28 Wheat seasonality over 30 years (Seasonal harts 2015)

5.3.2.4. Gasoline and Crude Petroleum

Gasoline and Crude Petroleum encompass a total of 9.76% of total tonnage flows in the U.S. One of the important features of these commodities is their seasonality pattern. Figure 30 illustrates the U.S. monthly Product Supplied of Crude Oil and Petroleum between 2004 and 2013 (U.S. Energy Information Administration EIA 2015). According to this Figure, the maximum demand occurs during August.

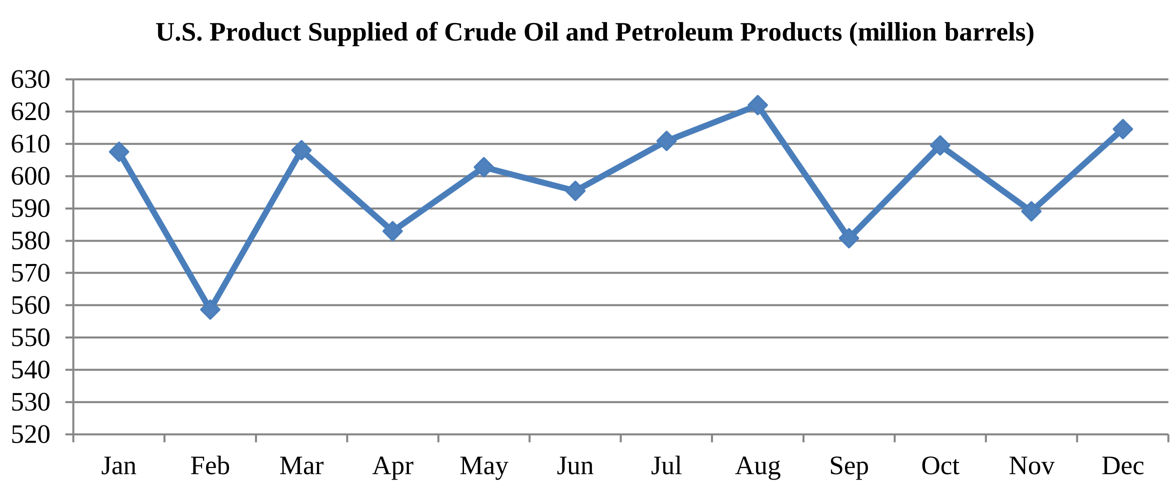


Figure 29 U.S. 10 years average monthly Product Supplied of Crude Oil and Petroleum (Million Barrels) for years 2004-2013 (Seasonal harts 2015)

5.3.3.Methodology

Implementing seasonality analysis in the freight transportation framework requires massive data mining efforts. Possible variables that can affect the seasonality implementation are listed in Figure 30 including: commodity type, weight, transportation mode, etc. For further analysis, several variables were chosen (subject to data availability) including type of commodity, commodity weight, and monthly production share of the commodity.

To implement seasonality, monthly distribution of each commodity was first obtained. Using Equation (5.4) will result in the maximum time distribution with respect to tonnage and mode.

$$Max\left[\sum_{i=1}^{i=43} T_{ij} * f_{mi}\right] for\ m \in [1, 2, \dots, 12] \qquad \text{Equation (5.4)}$$

in which

i denotes the commodity;
j denotes the Mode;
f is the fraction of monthly production of commodity i in month m;
m denotes the month; and
T_{ij} denotes the tonnages of commodity *i* which transported by mode *j*.

Equation (5.4) does not capture the effect of the subcategories in each commodity type. While these sub-categories are homogeneous in many attributes, many of them are not similar in terms of time distribution.

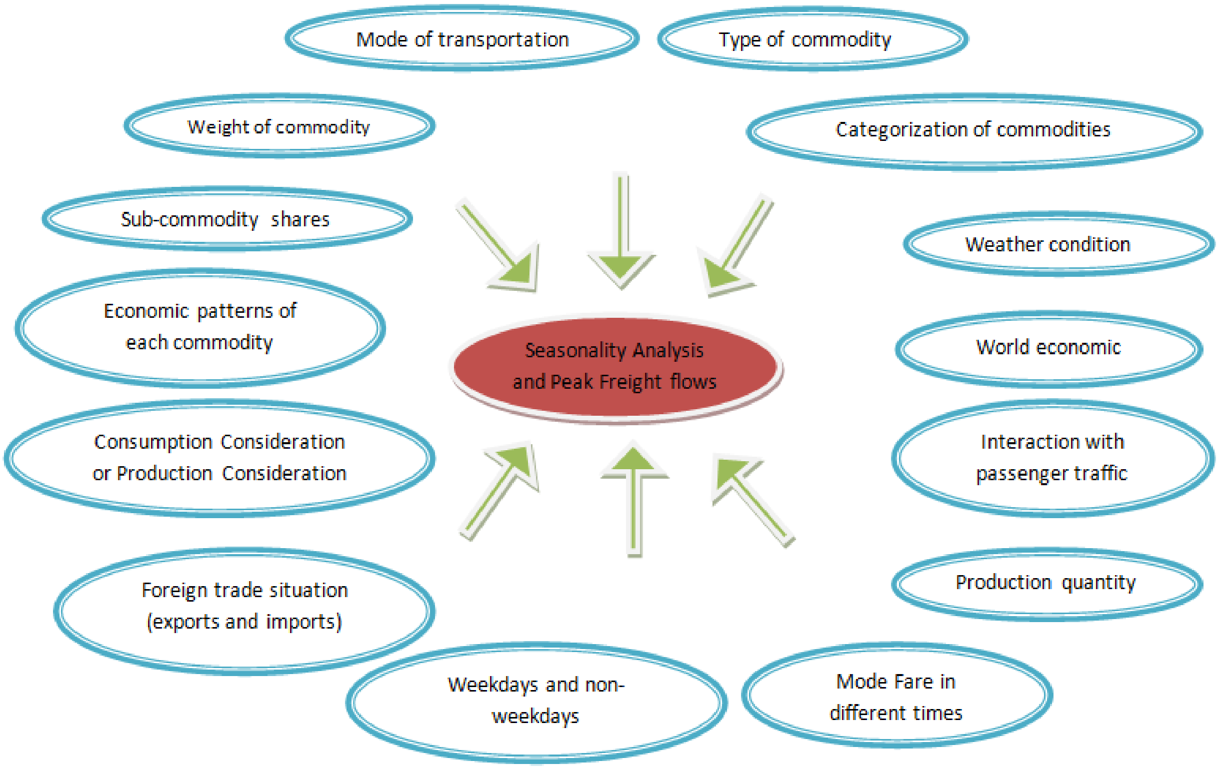


Figure 30 Factors that can affect freight seasonality analysis and traffic assignment

5.3.4. Case Study

FAME model generates Annual Truck Traffic (ATT) per commodity. Then, instead of previous method in which the annual flows were divided by 365, the proposed methodology was implemented for each commodity. Figure 31 represents the time-of-year distribution of freight over a year long period. As shown in this figure, September is in the peak period by almost 10.8% of total freight flows and February is at the bottom with 6.1% of freight flows.

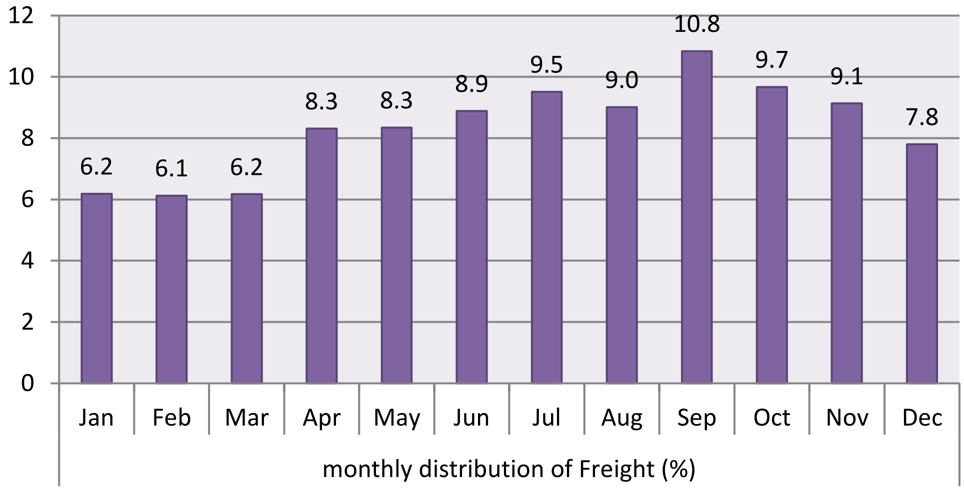


Figure 31 Truck freight distribution over a year

6. Simulation Results

In this section, a comprehensive comparison between FAF commodity distribution and the outputs of FAME, GAME, and FAME2 were performed. First, we explain why we did this comparison and then the process of comparison will be elaborated. Then, the results will be presented.

Supplier evaluation and supplier selection models are among the most important layers of FAME. In previous version of FAME, these models were not evaluated with FAF data. The authors proceeded to other layers such as mode choice and then traffic assignment which did not show satisfactory results. The model`s malfunctions could be the result of:

- tonnage to truck conversion,
- traffic assignment,
- firm reduction procedure, or
- supplier selection model.

Therefore, one cannot indicate why the traffic assignment was not accurate. That is why we performed this comparison to validate the commodity distribution prior to the other steps.

To compare the results in a same level, FAF data and FAME outputs needed to be aggregated to state level. We used the traffic assignment module in TransCAD environment. It should be noted that, this procedure is not a real traffic assignment because we did not convert the tonnages into units of trucks or railcars (A Kermanshah and Derrible 2016; Amirhassan Kermanshah and Derrible 2016). Instead we visualized the commodity flows in a network to show their distribution. The major settings in TransCAD for performing “traffic assignment” includes:

- U.S. major highways line layer were selected to create the network.
- All-or-Nothing method were used to prevent the confusion on V/C ratio
- The capacity for each link considered to be unlimited.
- Speed in each link were considered constant.

Figure 32-45 shows the commodity distribution comparison between FAF, FAME, and FAME2. In general, FAME and FAF show a good match in some commodities such as chemical products, electronic equipment, furniture products, and plastic products. But in other commodities, FAME cannot capture the same pattern with FAF commodity distribution.

Commodity class 14 or “Waste and scrap”, did not show good results in FAME. The reason could be due to unknown supply chain of this category. Clearly, no industry specifically produce scrap as one of its major outputs. Meaning that supplier selection for this commodity could lead into many uncertainties.

A major conclusion could be induced by comparing the results in this section and Table 3 in section 3. The more we reduced the number of firms, our distribution results become more inaccurate.

Figure 32 and 33, specifically compares agricultural commodities. The results of GAME show a closed match with FAF distribution. In general, GAME captures the commodity distribution more effectively comparing to FAME.

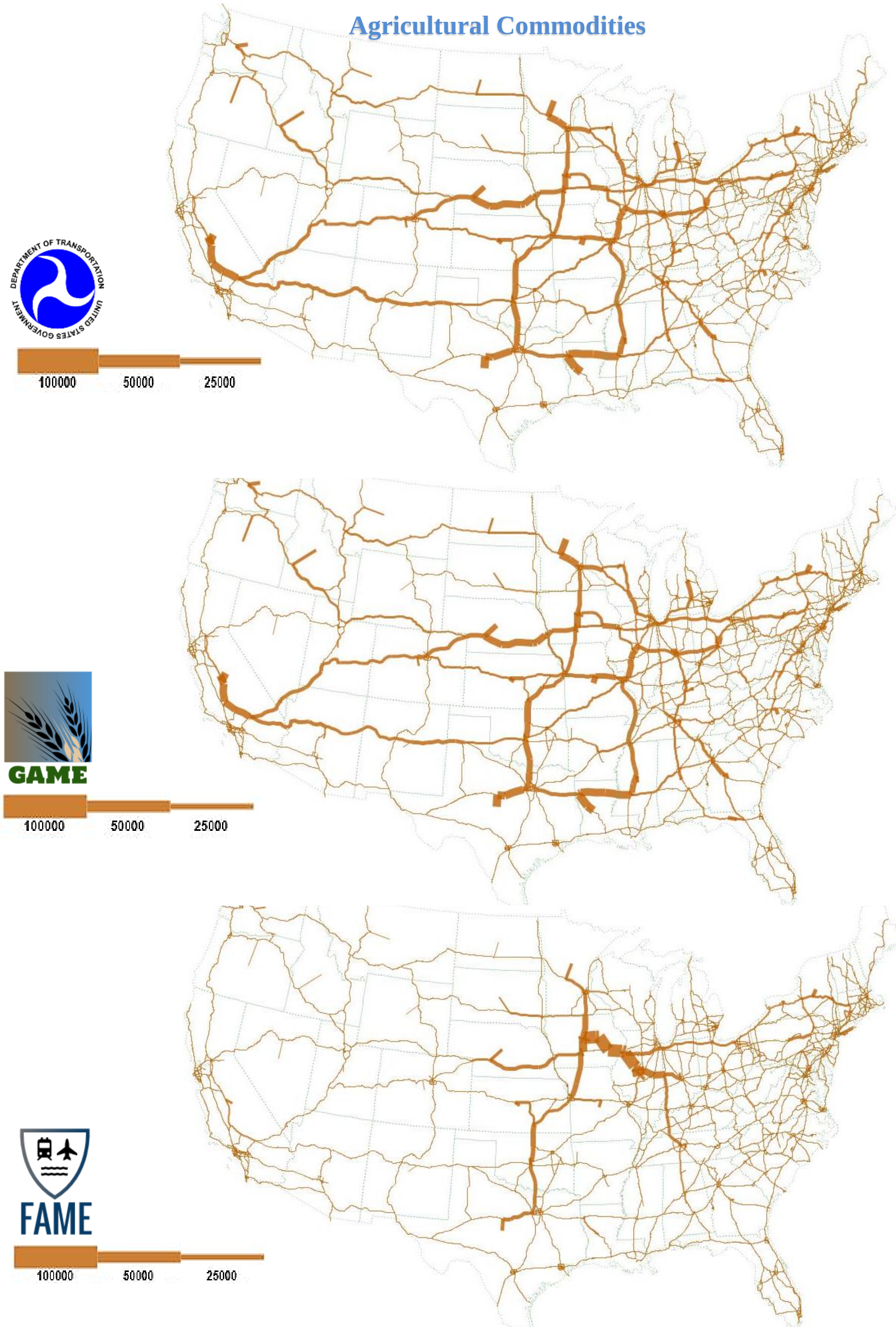


Figure 32 Comparison between FAF, GAME, and FAME for Agricultural Commodity distribution

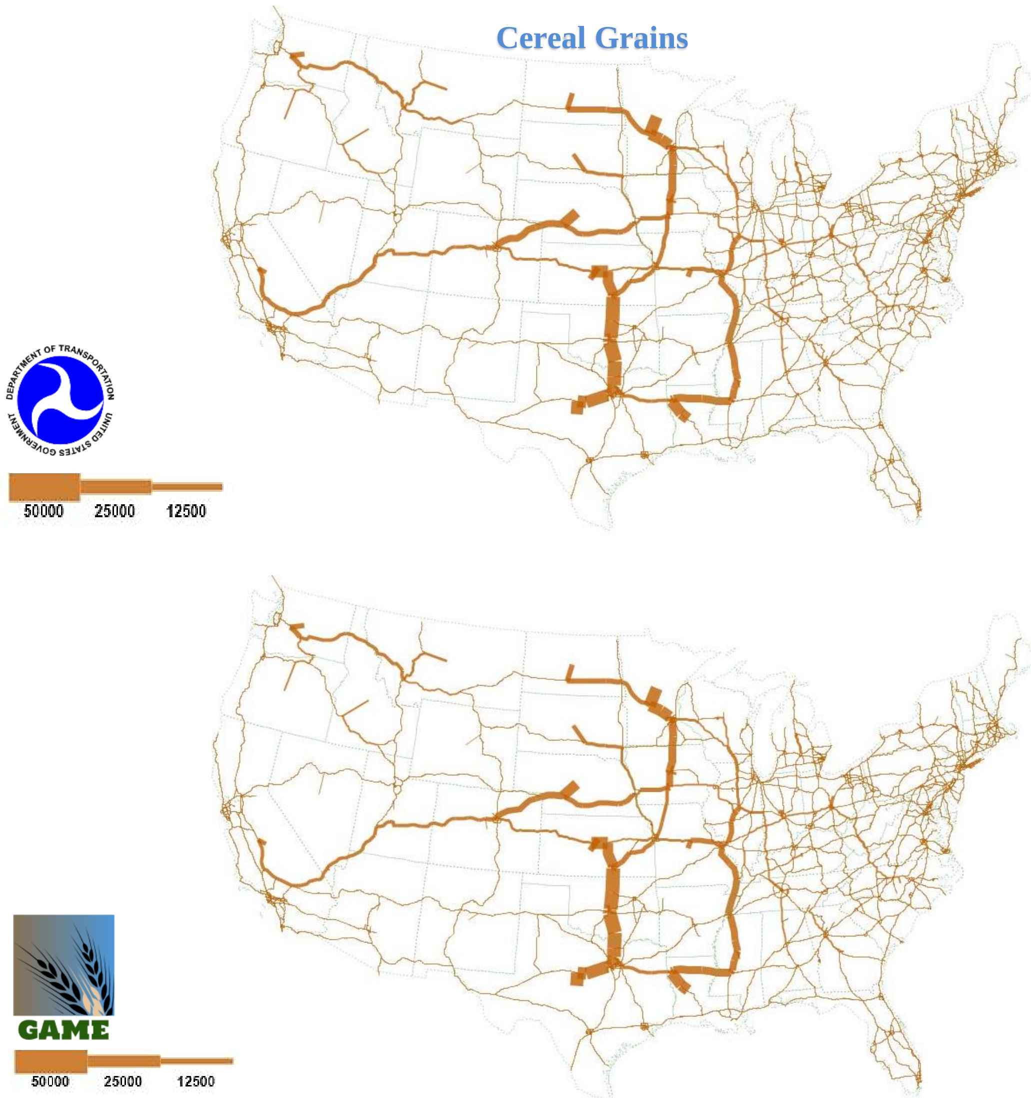


Figure 33 Comparison between FAF and GAME for Cereal Grains distribution

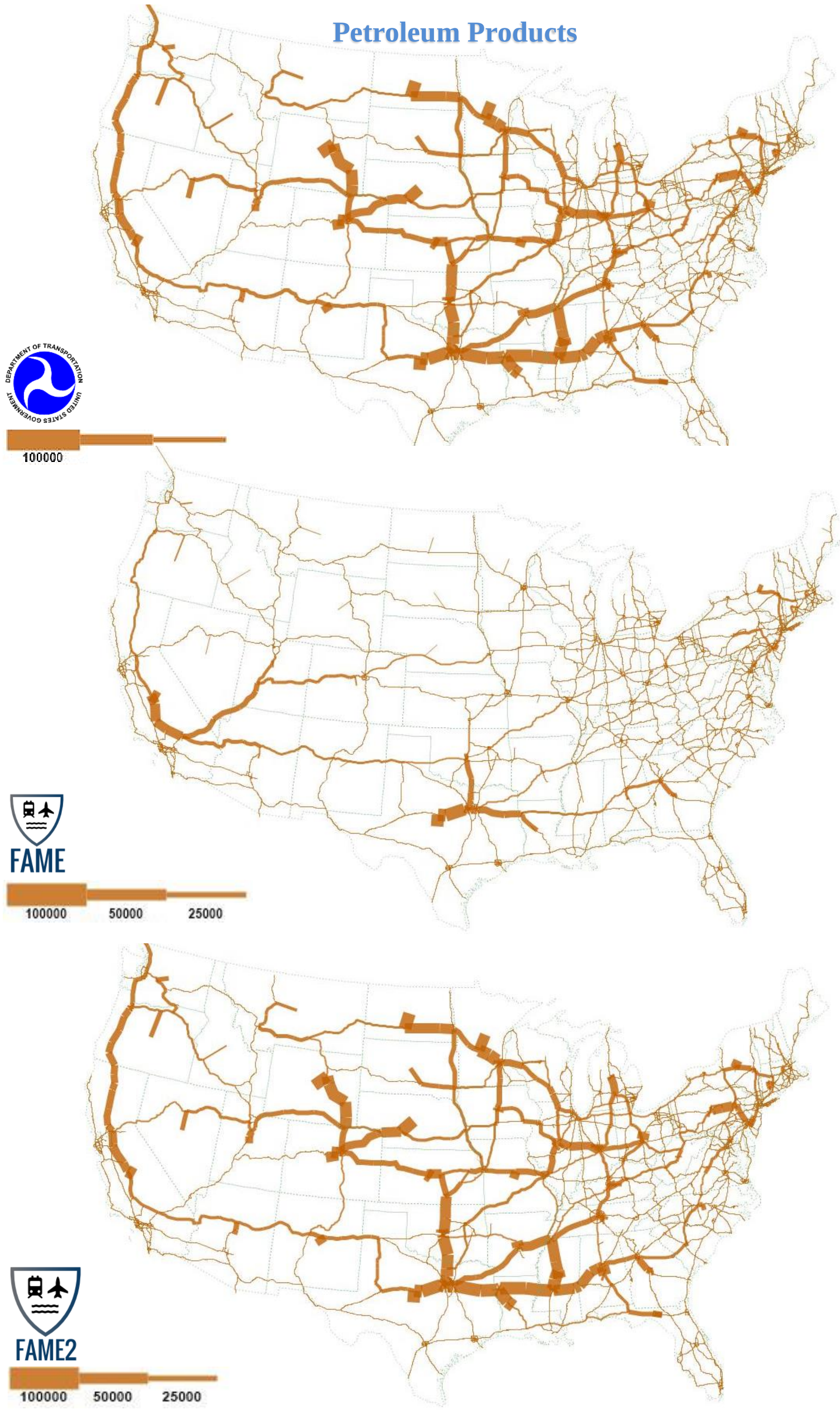


Figure 34 Comparison between FAF, FAME, and FAME2 for Petroleum Products distribution

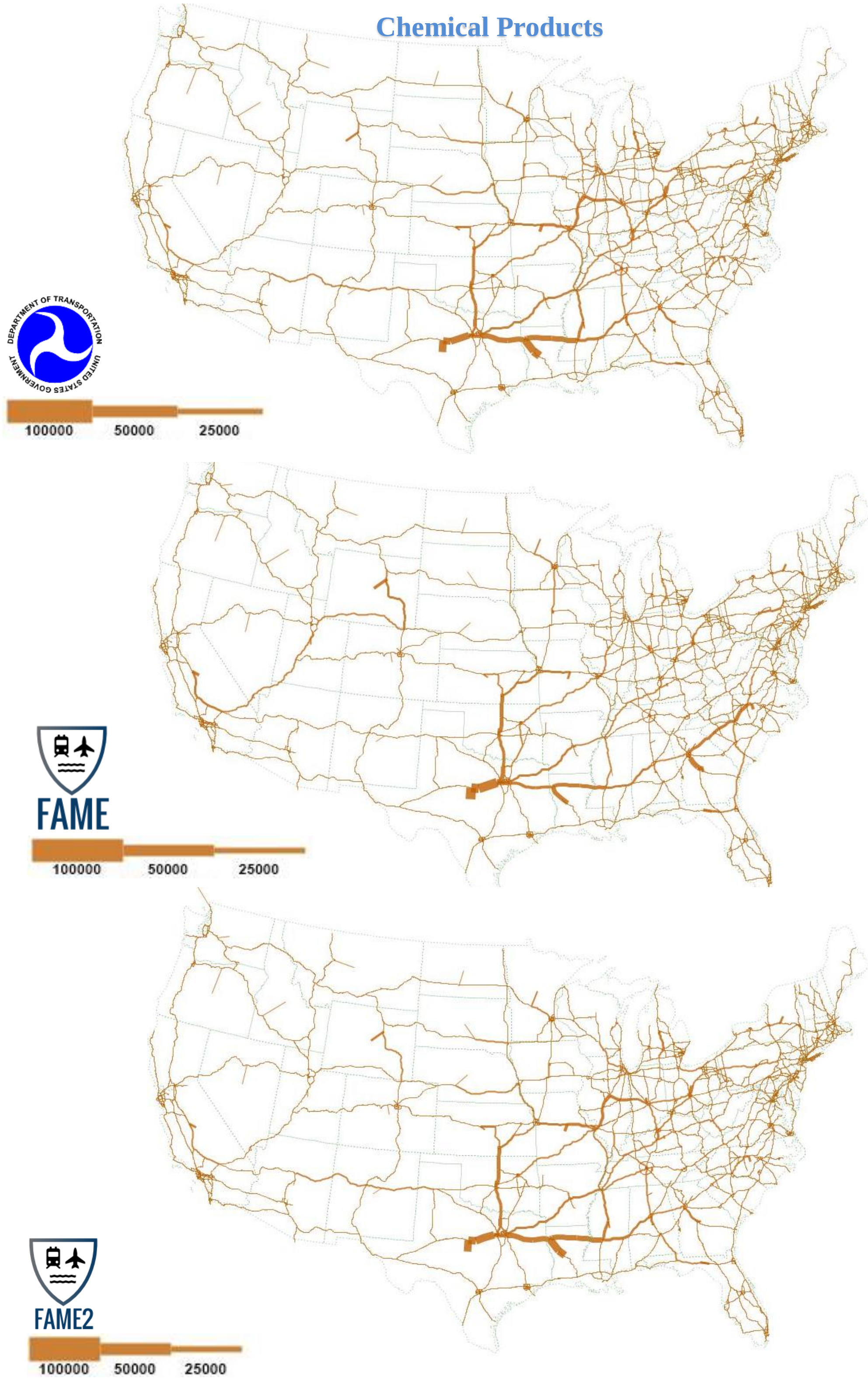


Figure 35 Comparison between FAF, FAME, and FAME2 for Chemical Products distribution

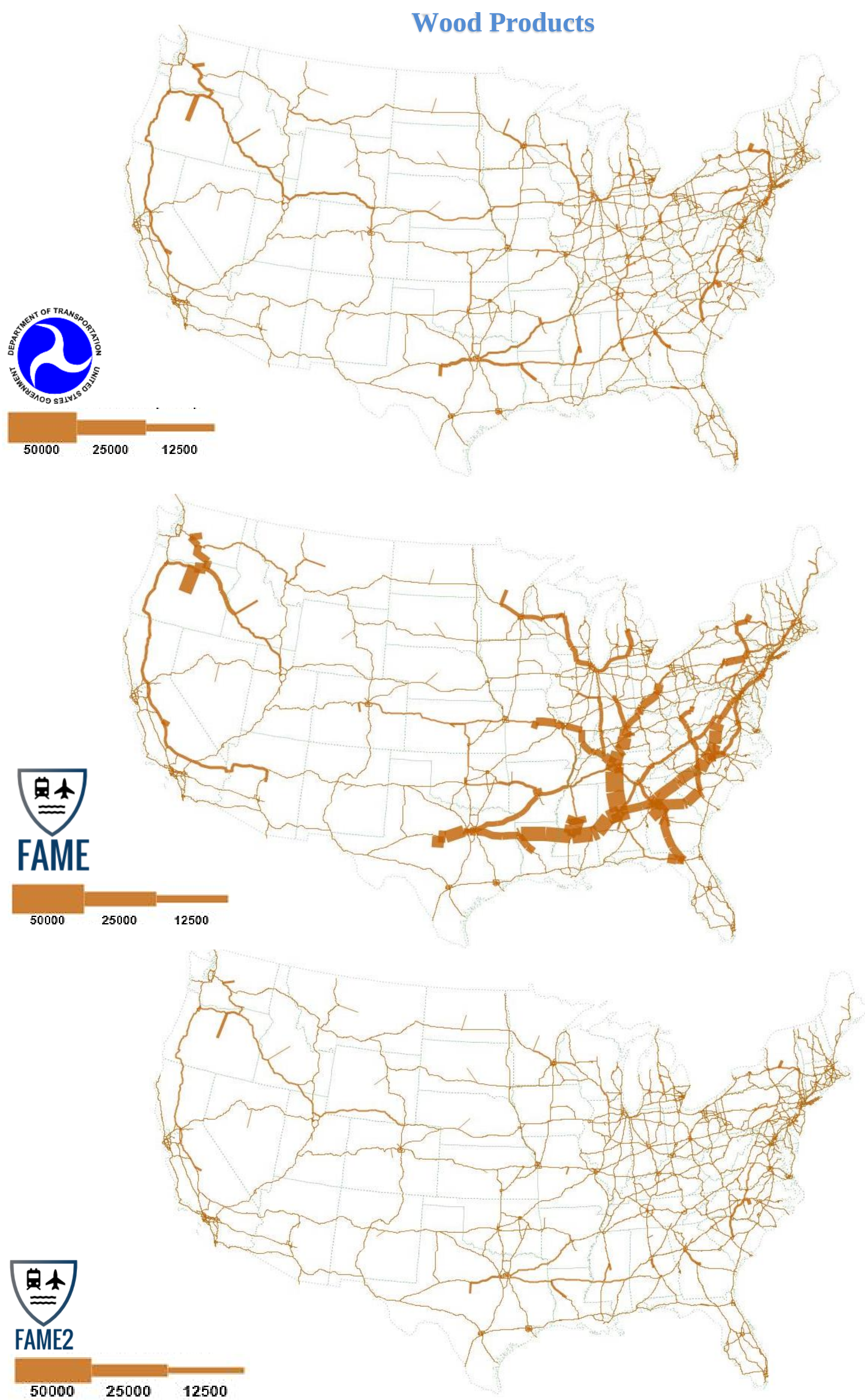


Figure 36 Comparison between FAF, FAME, and FAME2 for Wood Products distribution

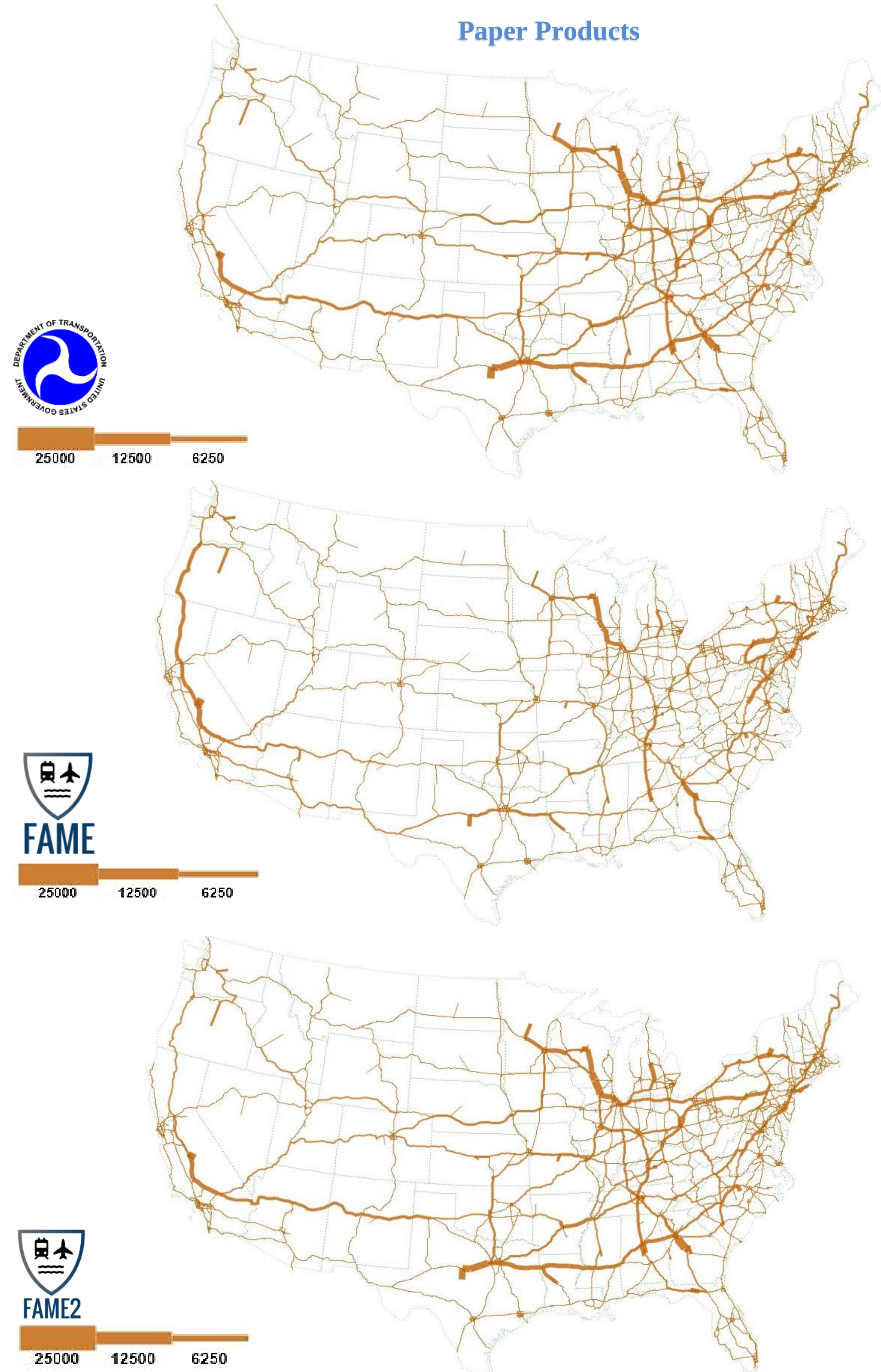


Figure 37 Comparison between FAF, FAME, and FAME2 for Paper Products distribution

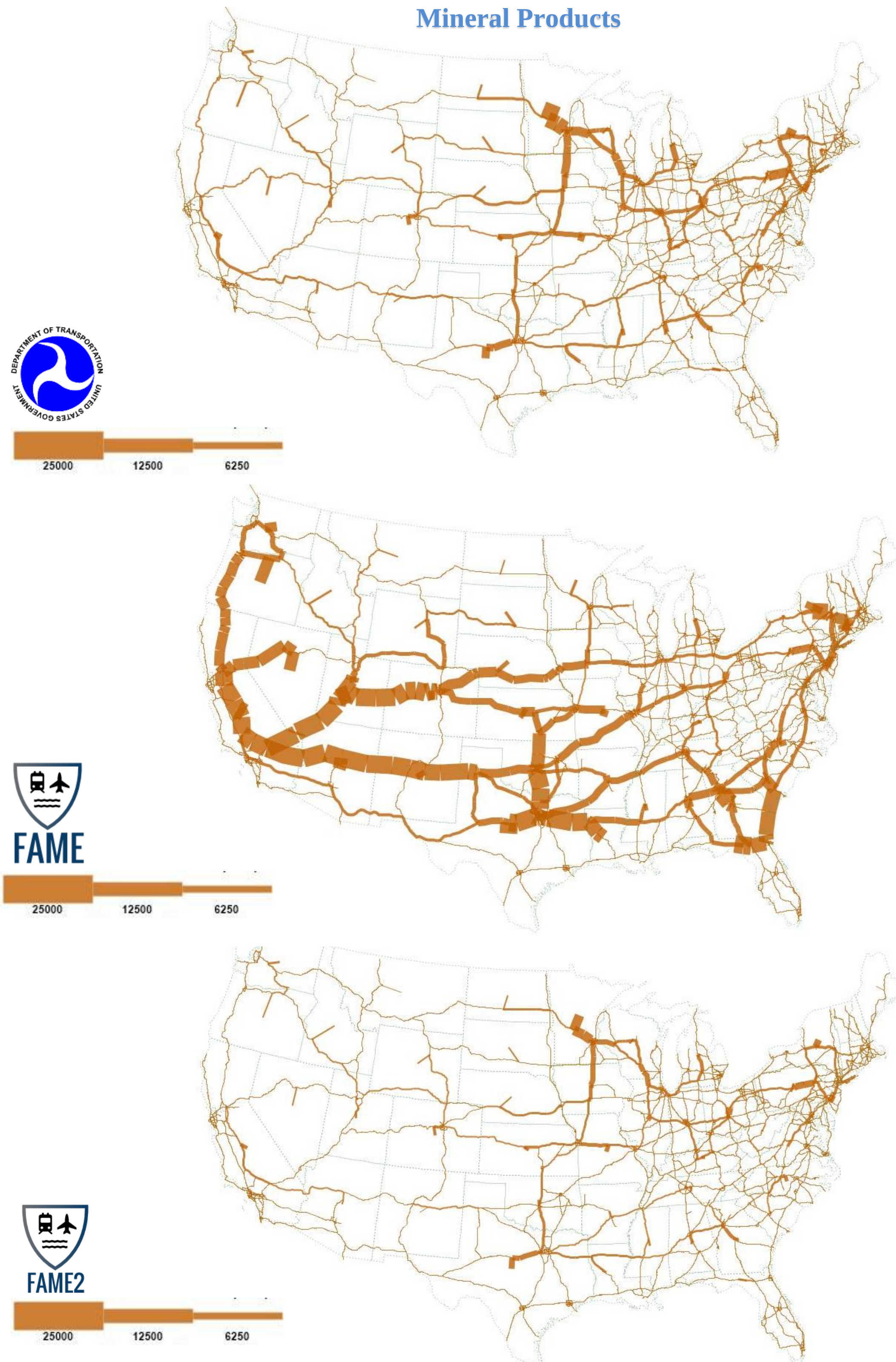


Figure 38 Comparison between FAF, FAME, and FAME2 for Mineral Products distribution

Machinery Products

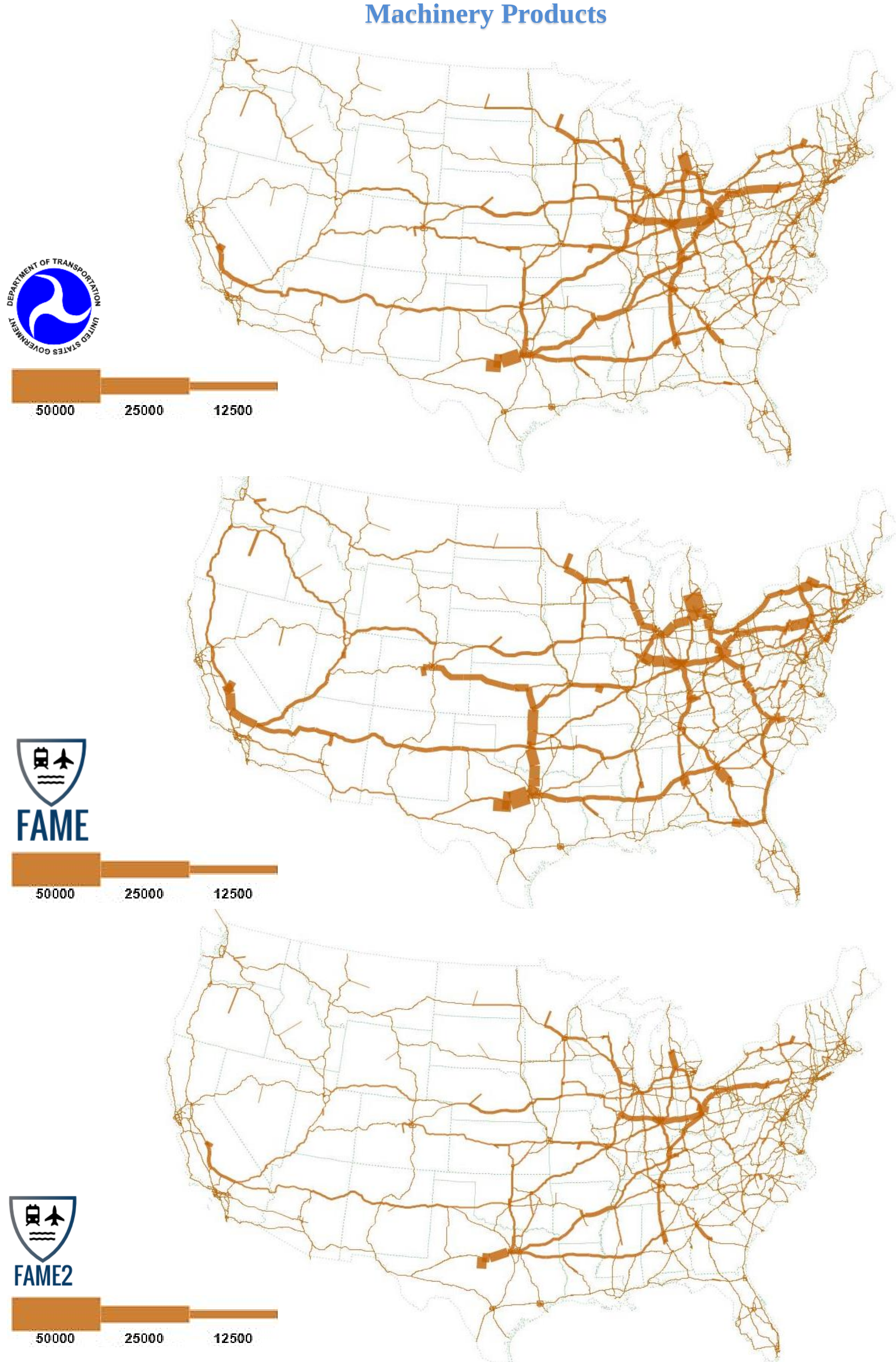


Figure 39 Comparison between FAF, FAME, and FAME2 for Machinery Products distribution

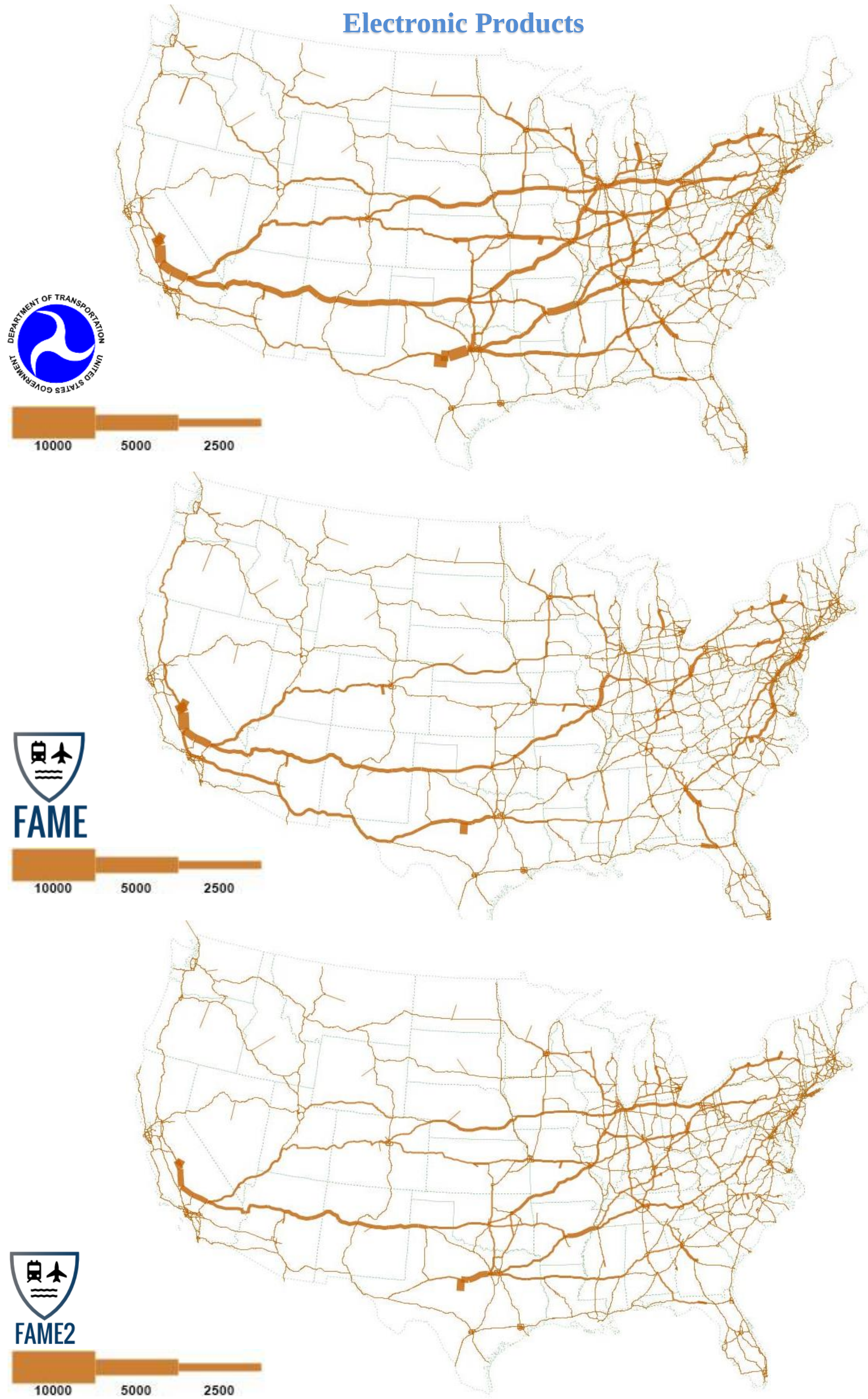


Figure 40 Comparison between FAF, FAME, and FAME2 for Electronic Products distribution

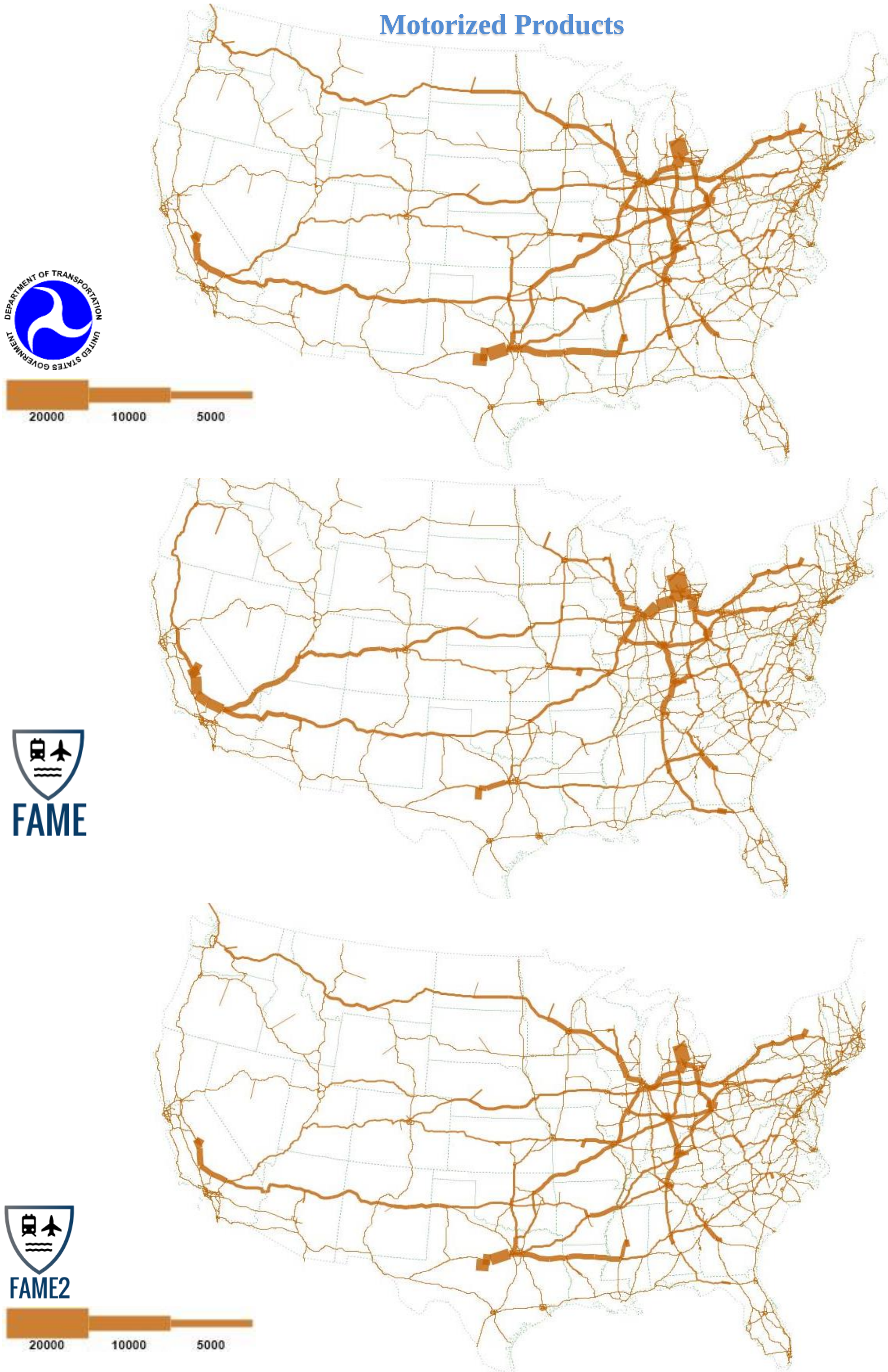


Figure 41 Comparison between FAF, FAME, and FAME2 for Motorized Products distribution

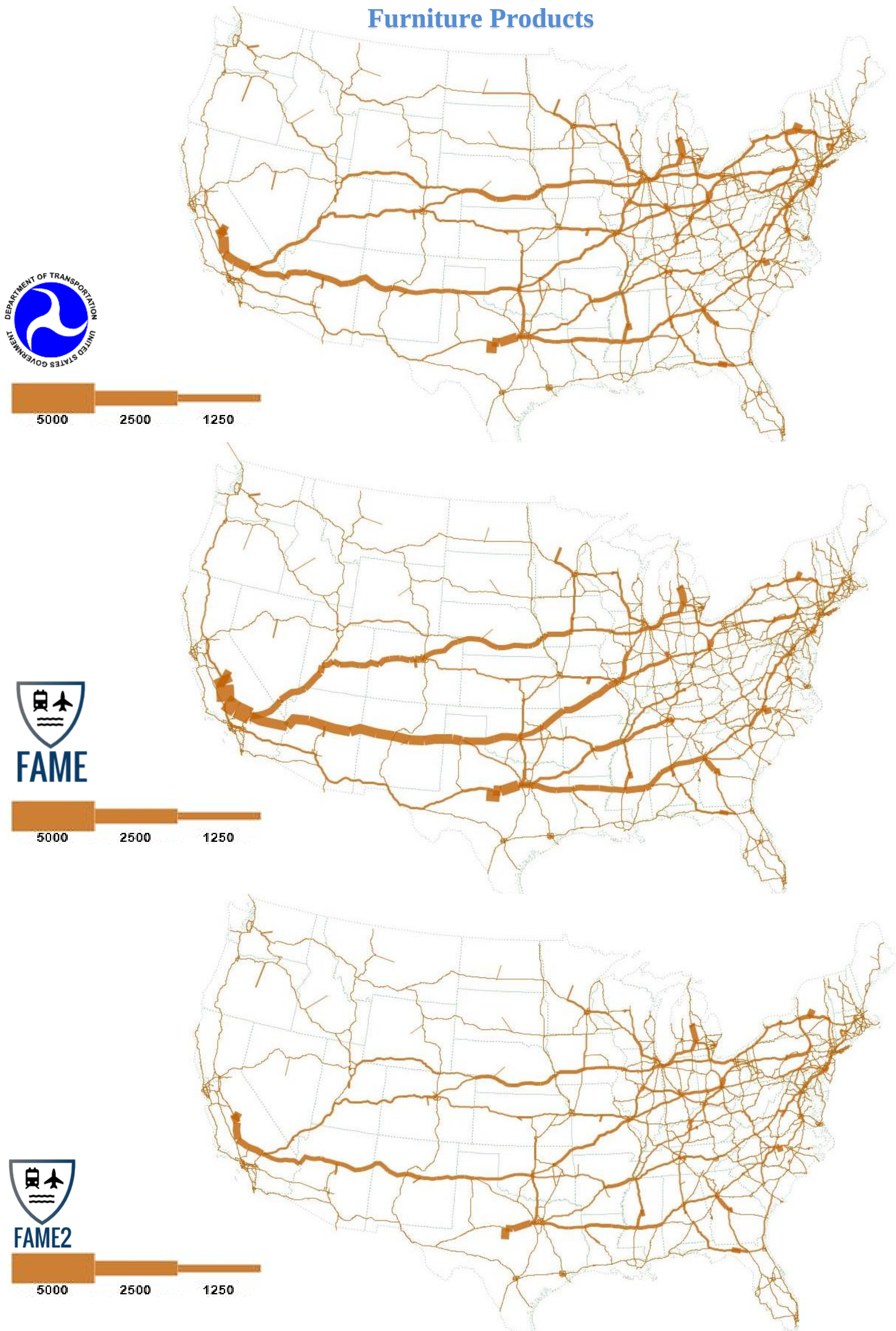


Figure 42 Comparison between FAF, FAME, and FAME2 for Furniture Products distribution

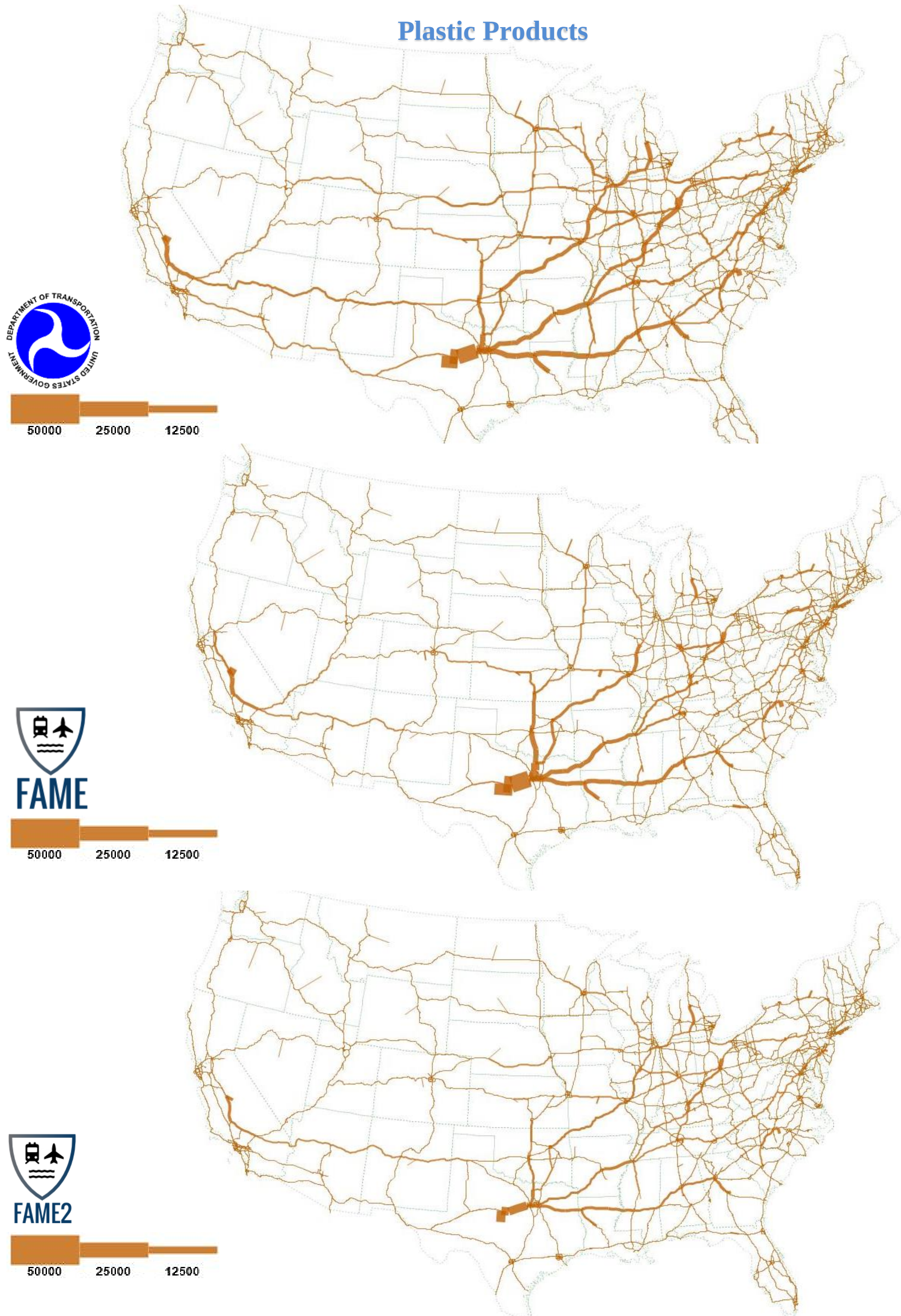


Figure 43 Comparison between FAF, FAME, and FAME2 for Plastic Products distribution

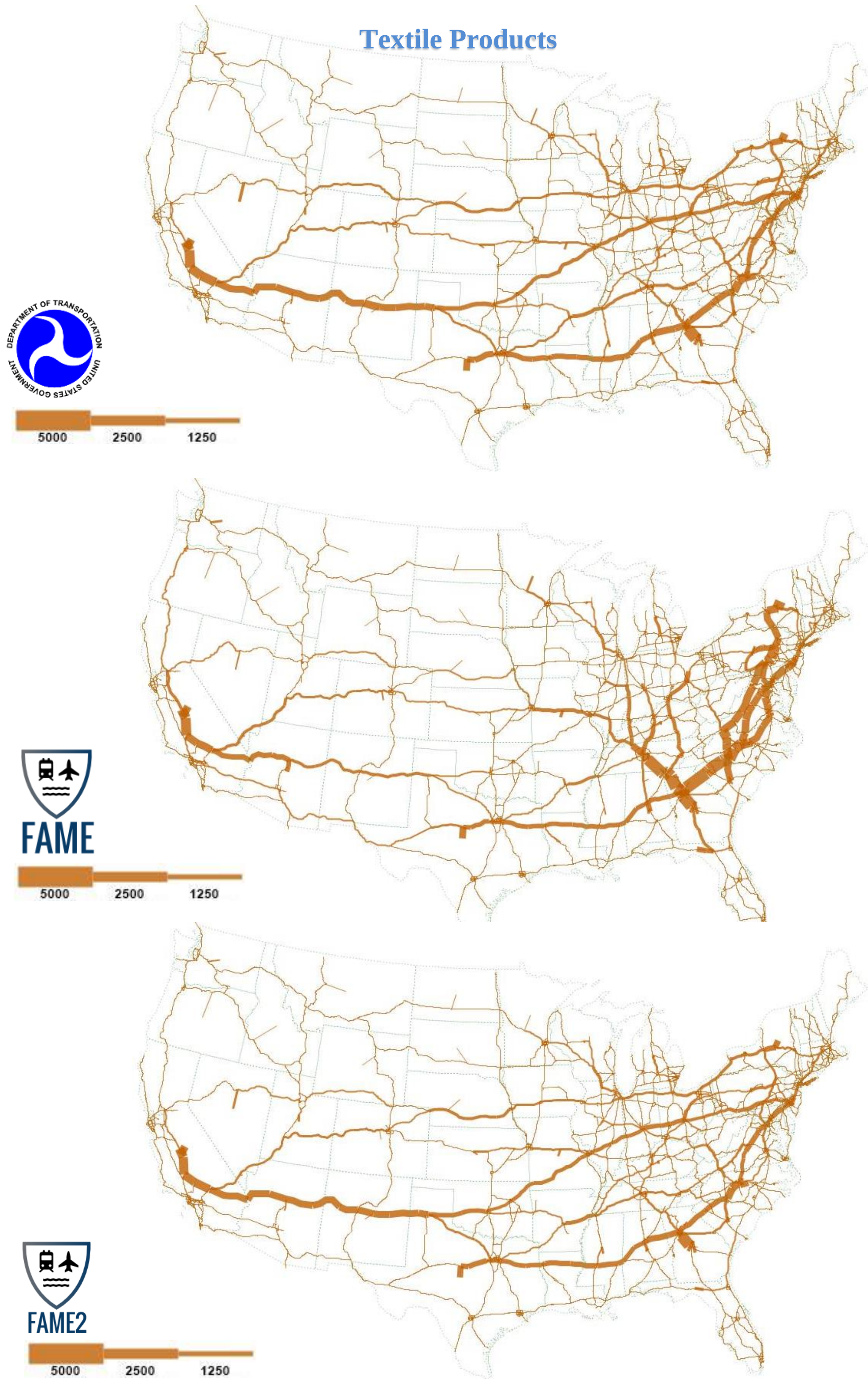


Figure 44 Comparison between FAF, FAME, and FAME2 for Textile Products distribution

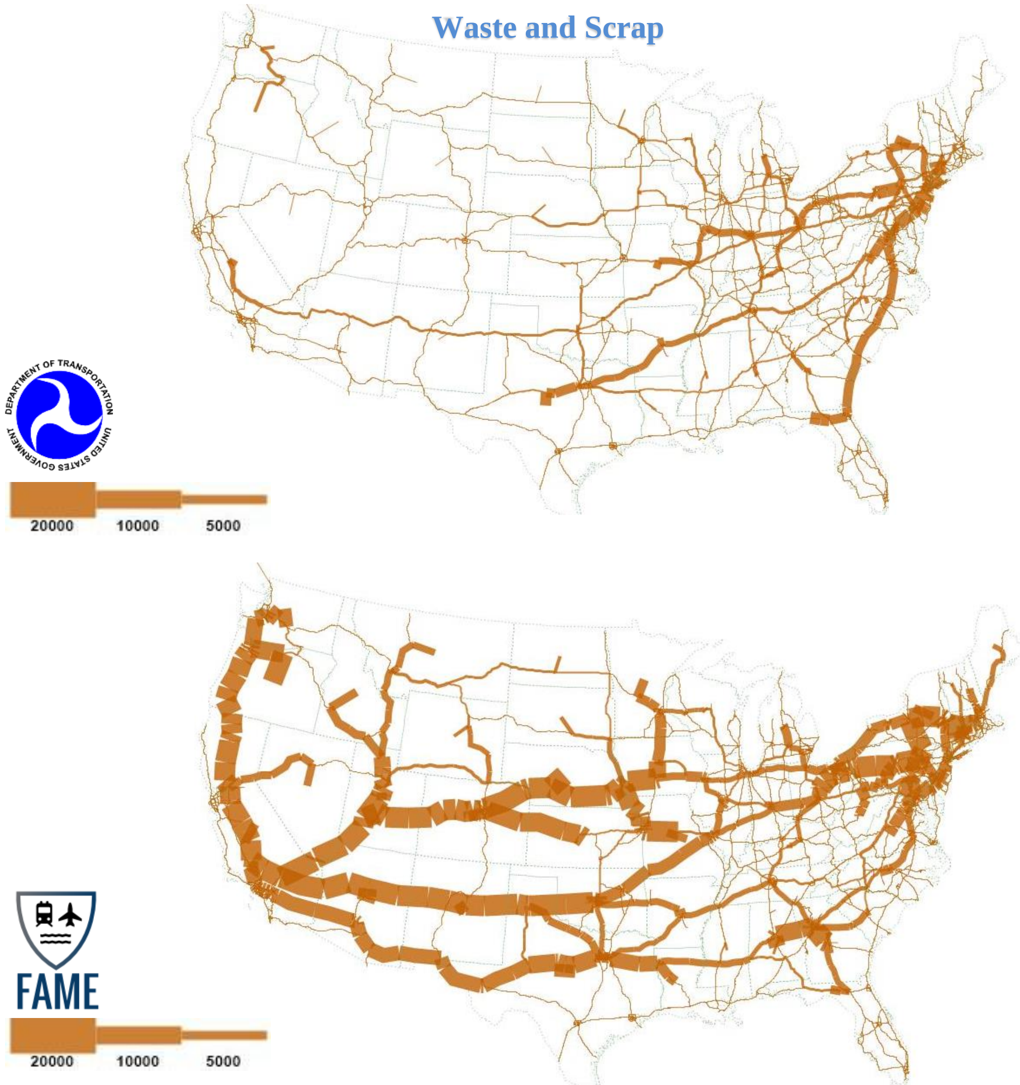


Figure 45 Comparison between FAF and FAME for Waste and Scrap distribution

7. Conclusion

7.1. Summary

Effective transportation systems are vital elements of the economy and in order to have an operational one, special tools and models need to be provided. There are several problems with current freight models.

- They are too aggregate and as a result, new strategies and policy-changes cannot be tested on them.
- Because of freight complexity, there is a big gap in modeling logistic elements such as determining the exact structure of supply chain.
- Despite the fact that agricultural commodities are a major component of freight movements, only few studies have mentioned them specifically.

The focus of this research, was on expanding FAME as one of the best freight frameworks. FAME while contains very innovative, interesting and sophisticated models, suffers from commodity aggregation issues and computational problems.

In his study, the accuracy of the models improved by; presenting another supplier evaluation model and adding more data sources to make the models more realistic. The computational problems of the previous model were solved. And finally, a specific framework was introduced to capture the effect of cereal grain movements in the U.S. transportation network.

7.2. Contributions

The main contributions of this study could be categorized into 6 sub-sections:

- Solving FAME computational problem by introducing a new supplier evaluation model;

Using the result of UIC establishment survey, the supplier selection model was revised. A decision tree model and an order probit model were developed to capture the buyer's behavior on the distance-range in which the trades are forming. This approach reduces the number of firms entering the simulation and consequently, the computational burden of the model reduces and the framework becomes more functional.

- Validating the distribution results with FAF data

As a part of this study, commodity distributions were analyzed in TransCAD software. The results compared supplier selection approach in previous version of FAME and the model presented in this study. For each commodity, a distribution map created and compared to FAF commodity distribution. The outputs showed that in several cases the FAME could not forecast the supply chain very well. However, the new model can handle the distribution more effectively.

- Specific Firm Synthetization Model for Grains

To perform this task, original agricultural commodities in FAME, disaggregated into 2 groups: cereal grains and other agricultural commodities. Many datasets and factors have been considered in this study that are the key elements in determining the transportation and supply chain of grains. Specific firms dealing with grains were determined and their grain demand were calculated and entered into the simulation process.

- Introducing a specific microsimulation model for cereal grain commodities

GAME possess unique features that distinguish it from other similar studies. It develops an optimization supplier evaluation and selection model with a decision tree analysis which constitute supply chains between grain suppliers and consumers. It micro-simulates grain supplier selection in the U.S. and presents the annual grain flow between regions. And as a result, a huge improvement was observed on modeling the distribution of cereal grains.

- Seasonality analysis

Seasonality analysis was added to the last module of the framework to enhance the accuracy of network assignment. Seasonality analysis was not dedicated only on grain commodities but it was implemented for any other commodity in which the seasonal data were available.

- Importing new dataset to the framework

Agricultural specific data such as CropScape data, USDA data, grain consumer's data such as biofuel production demand, and ports of entry data are the most important data sets that were entered to the framework for a more accurate analysis.

7.3. Future Direction

FAME is a step toward improving the existing transportation modeling for freight. However, some aspects of it requires further exploration and improvement. Possible expansions of the framework are listed below:

- Network assignment: One of the main modules of FAME that need to be developed and improved is the last layer of the framework. This module however, is one of the most important part of the FAME, was not completed yet (Amirgholy et al. 2017; Karduni, Kermanshah, and Derrible 2016).
- Policy analysis: As a result of this study, effect of major national or international changes such as fluctuations in world grain demand could be captured and observed. One may implement the results of other models and incorporate it in the simulation process to see

the final results on the network (Amirhassan Kermanshah et al. 2014; Peiravian, Kermanshah, and Derrible 2014).

- Integration of FAME and GAME with international freight transportation model. The major focus of the framework was on the domestic part of commodity flows. However, incorporation of global changes could be an interesting and challenging topic. This topic also can improve the supply chain formation models and also analyze its consequent effects on commodity flows inside the U.S.
- Considering other modes of transportation. FAME considers truck, rail, air and courier as transportation mode. Other modes such as water, intermodal, etc. can be included in FAME to improve the model power.
- Considering role of third party logistics (3PL). FAME Assumes that the decision makers are producer and receiver firms. However, other freight agents such as 3PLs play a significant role in making logistics decisions. Considering and modeling the behavior of these agents also can be a very interesting and challenging topic.

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VITA

NAME: Seyed Mehdi Mahmoudifard

EDUCATION:

B.S., Hormozgan University, 2006

M.S., Sharif University of Technology, 2008

Ph.D., Transportation Engineering, University of Illinois at Chicago

TEACHING:

Department of Civil Engineering, University of Illinois at Chicago; Highway Design, 2013 and 2016

Department of Civil Engineering, University of Illinois at Chicago; Traffic Engineering, 2014

Department of Civil Engineering, University of Illinois at Chicago; Strength of Materials, 2015

PROFESSIONAL MEMBERSHIP:

Institute of Transportation Engineers (ITE)

American Society of Civil Engineers

PUBLICATIONS:

· Mahmoudifard, S. M., A. Kermanshah, R. Shabanpour, and A. K. Mohammadian. Assessing public opinions on Uber as a ridesharing transportation system: explanatory analysis and results of a survey in Chicago area. In Proceedings of the 96th Annual Meeting of the Transportation Research Board (TRB), Washington, D.C., 2017.

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