Alternative Financing for Harbor Infrastructure using Big Data Analytics in the Great Lakes Waterway

by

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PREFACE

By 1846 the importance of the Great Lakes waterway was growing and more federal investment to projects throughout the system yielded growth in sailing vessels and trade (Barton et al. 1846). Discovery of iron-rich rock formations in northern Michigan and Minnesota provided increased incentive to provide vessels access into Lake Superior and by 1855 the state of Michigan opened a navigation lock to traverse the rapids at Sault Ste. Marie. The iron ore trade blossomed to support steel production and derivative industries. Steel production requires both iron ore and coal which predetermined the location of mills in the region. As coking coal is more fragile in transport than iron ore, steel producers situated their mills to allow coal transport by rail and received iron ore by boat. The national importance of the Soo Locks was well established by 1881 when the federal government and U.S. Army Corps of Engineers assumed responsibility for the facility to secure and improve its operational efficiency. Steel production in the U.S. expanded and in 1901 US Steel (Pittsburgh, PA) under the leadership of Andrew Carnegie incorporated to become the world's first billion-dollar company. Since then, a series of federal projects have improved, expanded, and deepened the Great Lakes navigation system to its current form. Though technologies and production methods for both iron ore and steel have evolved, the importance of this waterway has endured and remains crucial to North American manufacturing. This study takes a multi-disciplinary approach to investigate the intersection of engineered systems, transportation performance, as well as market driven allocation of infrastructure funds that enable the efficacy of this waterway system.

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ABSTRACT

Decades of under-investment into aging infrastructure have resulted in uncertain reliability and systemic under-performance. The infrastructure spending gap in the U.S has grown to $2.6 trillion, and estimates suggest half of that is necessary within the next five years to avoid major impact to GDP. Yet spending levels remain below needs and policymakers seek more efficient allocation models for public funds and alternative financing mechanisms to accelerate the pace of investment to meet society's needs. There is substantial private capital ready to enter the infrastructure sector along with innovations in contractual public-private partnership models. Financing mechanisms, such as infrastructure banking, show promise in extending the value of federal spending. However, a gap exists in the modeling of revenue streams and risk exposures for private entities which are necessary for the integration of public and private capital. Big data analytics are applied in this research to reveal opportunity costs and risk exposures which we apply to model revenue streams and assess infrastructure funding decisions.

This dissertation investigated the waterway infrastructure of the Great Lakes, which comprises a network of deep-draft ports and connecting channels that serve a prominent role for commerce and manufacturing in North America. The waterway system requires annual funding to maintain navigable depths and functional port and lock infrastructure. An obstacle to funding decisions is the uncertainty surrounding financial returns on investment from improved maritime efficiency, in part because transportation and logistics metrics or benchmarks are lacking. Iron ore, the primary commodity in the Great Lakes, serves as the use case in this work to assess

performance metrics for the waterway infrastructure that enables efficient and sustainable transport from mines to steel mills.

This dissertation integrates new data analytics across traditional disciplinary silos to gain new insight into the risks, performance, and funding mechanisms for harbor infrastructure. Corporate financial metrics are used to map and quantify interdependencies within the value chain from iron ore production to finished goods. These interdependencies are further applied to assess financial risk exposures to infrastructure disruption using analytic tools such as input-output modeling. We applied big data analytic tools to assess the performance of maritime shipping with highly granular spatial and temporal datasets, including vessel draft, transit time and cargo. Vessel position information from historic Automatic Identification System (AIS) was used to develop a novel Maritime Transportation Efficiency (MTE) metric, defined as mass per time and directly applicable to bulk carriers. Regression analysis of vessel performance to hydrologic conditions in the waterway provided a means to predict changes in logistics performance resulting from infrastructure investment. We use Monte Carlo simulation to calculate expected MTE for vessels in the waterway under varying conditions which are correlated to transportation costs. Analytics techniques, like those applied in this dissertation, are useful to model revenue streams and reveal potential for new funding mechanisms and market-driven financing models.

We suggest a new funding model for harbor infrastructure based on user demand with a fee structure adaptive to actual vessel requirements, attainable through existing data sources and new analytical tools. Demand-driven funding decisions for harbor maintenance can maximize value returns for users. A fee structure, outside of the Congressional appropriations processes, is more responsive to user needs and provides a means to deploy alternative financing models such as infrastructure banking for waterway maintenance and port depth construction dredging.

CHAPTER 1

Background and Research Need

Funding requirements continue to outpace available public resources to improve and renew America's aging infrastructure, which threatens their service and reliability [2]. This is a challenge that governments and public infrastructure managers have contended with for decades. This issue first became popular in the academic literature in the 1990's following two decades of decline in public spending on infrastructure [3]. Aschauer [4], [5] established a connection between public investment to infrastructure, economic productivity, and private capital outlay, most evident in the Transportation and Water sectors. Those studies found that the lag in government investment in public facilities decreased economic productivity levels by up to 50 percent [5]. This was not uniformly accepted, and uncertainty over the apparent "spending gap" and the proper attribution for responsibility to resolve it remained in question [6]. Two areas of debate emerged; First, what is the causation and correlation between infrastructure investment and economic productivity? Second, what actions are appropriate, and by whom, to address lagging improvements [7]. Empirical evidence for the positive relationship between infrastructure and economic growth is offered by Sanchez-Robles [8], but considerable uncertainty remained in what alternatives are best to address the needs. Cain [9] investigated, but stopped short of resolving, the question of jurisdiction to reinvest in failing infrastructure. These questions persist and the infrastructure debate is far from resolved. What are the roles of public and private capital to address infrastructure needs? What is the jurisdiction between federal, state, and local governments for public goods? What assets are truly a "public good" and therefore expensed from the general treasury, versus separate funding mechanisms such as tolls or user fees?

We continue to contend with these questions and the "infrastructure gap" continues to grow. The estimated costs for addressing the infrastructure needs have escalated from $1.3 to $5.9 trillion in the U.S. since 2001 [10]. Calls for increased public spending continue, and political rhetoric favors massive infrastructure finance reform, but it is unlikely that spending at the federal or state levels alone will be sufficient to address the need. Alternative financing mechanisms such as those available through Public-Private Partnerships (PPPs) have garnered attention and are appealing to accelerate joint capital outlay for project delivery. There are clear advantages to the upfront provision of project funds which reduces construction costs and brings revenue sources online sooner. The added value from accelerated project delivery often exceeds the financing costs associated with borrowed money [11]. The concept of "Value for Money" has established itself in the PPP lexicon as are evaluation processes that intend to attribute value, costs, and risks to advance project considerations beyond the balance sheet [12]. A blend of public and private capital is necessary to address the infrastructure gap, but obstacles exist that have impeded private participation or failed to adequately mitigate financial risks. Studies that investigate critical drivers of success and failure for PPPs [13], [14] and our understanding of effective (and efficient) financing models continues to evolve. It is evident that successful financing arrangements are predicated upon a thorough understanding of system users, associated revenue streams, and risk exposure to variabilities in performance and structural health.

This dissertation is motivated by the investment gap in port and waterway infrastructure and the derivative impact that it has on waterway users. Ports and coastal infrastructure comprise one of seventeen sectors evaluated by ASCE's Infrastructure Report Card [10]. American ports annually carry more than $5 trillion dollars in goods accounting for 26% of the country's GDP [15]. Waterway infrastructure systems such as harbors, locks, canals, and breakwaters play an important role in industry supply chains and provide a competitive advantage to companies by reducing risks to transportation and logistics [16], [17]. Despite the importance of this sector to the economy, there is a spending gap of $32 billion for landside projects and a $28 billion dredging backlog which have resulted in inefficiencies, delays, and lost revenues for waterway users [15]. Maintenance shortfalls of harbors and waterways nationwide have prompted initiatives to explore alternative financing mechanisms and prioritization methods [18]. Concern over system performance has renewed examination into how America should fund the operation of its waterway infrastructure.

The U.S. Army Corps of Engineers (USACE) is responsible for managing the nation's navigation infrastructure under the agency's civil works mission and has engaged with industry in exploring alternative financing and revenue generating options [18], [19]. In its current state, existing revenue sources and funding from the general treasury have been unable to meet growing needs of existing assets. It is estimated that the value of USACE capital stock has declined from $250 billion in 1980 to $165 billion in 2011 [20]. The U.S. Congress included provisions for alternative financing options and directed pilot PPP projects that would address lagging project needs [21]. The Task Committee on Alternative Financing for Waterways Infrastructure identified several impediments including proper identification of revenue sources, and fiscal authority to manage those revenues separately from general treasury appropriations [18].

Existing funding mechanisms for waterway infrastructures are generally divided into two categories: Inland and Coastal Harbors. Inland waterways include the network of rivers and shallow draft ports (less than 20 feet) primarily accommodating barge traffic. This system of infrastructure combines funding from the general treasury and revenue from a Fuel Tax of $0.29 per gallon [22]. Coastal Harbors are funded through a Harbor Maintenance Tax (HMT) based on the value of cargo and taxed at a 0.125% rate, an *ad valorum* tax [23]. Whereas Inland Waterway funds support both maintenance and construction projects, Harbor funds are exclusively for operations and maintenance (O&M) activities. Funding for construction projects is shared between project sponsors (typically states or port authorities) and federal appropriations from the general treasury. The focus of this dissertation is on Coastal Harbor projects and Harbor Maintenance funding, specifically the Great Lakes system, as will be described in detail later in this chapter.

Despite the needs described here, the topic of financing and funding waterway infrastructure has received limited attention in the academic literature. A search within the Scopus database using keywords “Alternative Finance” + “Waterway Infrastructure” returned only three (3) results. keywords “Alternative Finance” + “Navigation” returned five (5), and keywords “Alternative Finance” + “Harbor Maintenance” returned a single result. A search on more common terms “Waterway Infrastructure” + “Funding” + “Navigation” returned twelve results, but only five since 2011 and two of those in academic journals. It is necessary to distinguish between funding and financing for infrastructure projects, though the two terms are frequently used interchangeably. Funding describes the payment for (the cost of) either maintenance or construction activities and is attributed to a revenue source, be it general treasury funds or harbor maintenance taxes. Financing involves leveraged funds, most commonly through bonds or loans, which are subject to interest and a cost of borrowed capital. Many of the financing mechanisms reside outside governmental or USACE authorities and require a private partner to become practicable, hence the motivation behind PPPs. Much of the discourse on the topic of alternative finance for waterways exists in government, or government-contracted, think tanks which would benefit from increased scholarly contribution. A fundamental challenge to addressing this in research is the complex, multi-disciplinary nature of the problem.

This dissertation applies new data analytics integrated across traditional disciplinary silos to gain new insight into the risks, performance, and funding mechanisms for harbor infrastructure in the Great Lakes. First, we seek to understand the network of corporate activities most closely connected to the waterway infrastructure through corporate supply chains. Risks associated with infrastructure disruption or under-performance most immediately affect direct users, but they also have a pronounced impact on derivative users that is not well-understood. Second, we investigate objective, data-driven measures for port and waterway performance. This is necessary to model commodity flows and associated financial transactions in the waterway. Third, this dissertation explores new management practices that connect maintenance funding to shipping logistics performance and demand which has potential to minimize overall costs and reduce unnecessary, or unwarranted, spending. Finally, we suggest a new approach to fund and finance harbor infrastructure based on user demand with a fee structure adaptive to actual vessel requirements, connected to revolving loans. We posit that such a fee structure, outside of the Congressional appropriations processes, would be more responsive to industry needs and accelerate capital outlay for improvements projects by making financing more available.

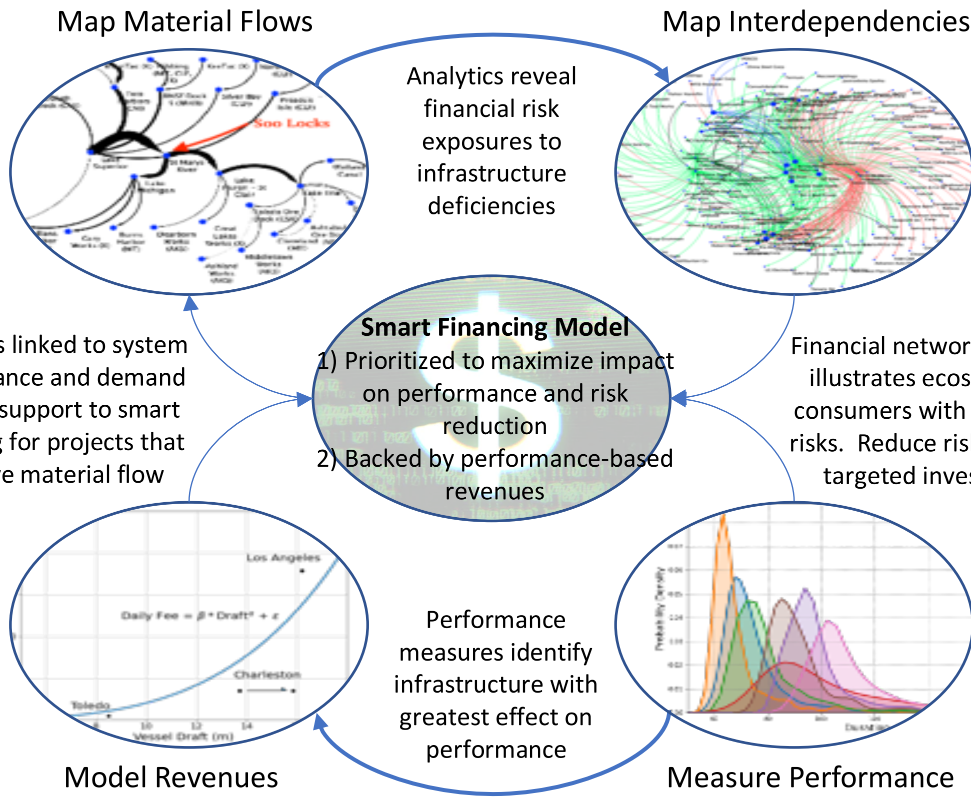

Figure 1.1: Dissertation approach

Ecosystem of Infrastructure Users and their Financial Risk Exposure

It is necessary to understand the network of interconnected users of an infrastructure system to assess the full value of the waterway. Simkins and Stewart argued that the full value of cargo, rather than tonnage, should inform port funding decisions and prioritization, but noted that economic relationships and financial data are often missing from decision models [24]. To address this need we have to understand how to value corporate risk exposures and target investments that yield the greatest capacity to mitigate opportunity costs and threats [25]. Network mapping is a tool that has been used in the financial industry to uncover non-systemic phenomena or vulnerabilities in financial transactions. These models have been adapted to understand financial interdependencies in industry supply chain networks [26]. Interpretations of these transactive maps using network theory have uncovered economic drivers in an industry ecosystem or the impacts of policies on capital flows [27], [28]. This approach could be adopted to map supply chain interdependencies for waterways and assist in valuing those infrastructures.

The disruption of port operations due to natural disaster, manmade-hazards, or functional degradation has a negative impact on economic activity [29]–[32]. A popular approach for estimating this impact is the application of Input-Output (IO) models to calculate propagated economic loss following a catastrophic event [29], [30]. Zhang and Lam estimate losses within the supply chain for adjacent industries using specified discrete scenarios [32]. MacKenzie et al. simulated the effects of shifts to alternate transportation modes under port closure scenarios on shipping costs increases [33]. Pant et al. assessed the multi-regional impacts of inland port disruption by applying dynamic inoperability input-output models [34]. Darayi et al. recommended investment strategies that mitigate risk of disruption by identifying critical node and component importance within an infrastructure system [35], [36]. We sought to integrate financial metrics and mapping techniques to quantitatively assess the full value of the waterway infrastructure and test sensitivity to disruption in various segments of the system.

Research Question1: What is the financial risk to supply chains from unplanned disruption to Great Lakes waterway infrastructure?

Measuring System Performance with Big Data

Funds for waterway infrastructure projects are primarily intended to reduce transportation costs by enhancing system performance, yet few objective performance metrics are in use. Mitchell and Scully identified this gap for improved management of USACE projects and identified vessel Automatic Identification System (AIS) data as a burgeoning asset for evaluation

[37]. These data are described in greater detail in Chapter 2. The application of AIS to the inland waterway system and for port fluidity characterization have expanded the availability of performance statistics and monitoring, but information gaps in the Great Lakes remain [38], [39]. Travel time and vessel turnaround time in port are important metrics for performance, but for the Great Lake system, variable water level and vessel payload are paramount.

Vessel payload is dependent on available draft and is determinant of shipping revenue and transportation costs to freight consumers. In the Great Lakes, available draft and resultant payload vary seasonally by up to two meters [40], which significantly affects performance and cashflows for shippers. Meyer et al. developed indexed-based insurance instruments to hedge against reduced revenue from restrictive vessel drafts [41], [42]. However, absent from the literature is any connection between actual vessel load and water surface levels. In the era of big data, we sought to apply analytics and machine learning tools to develop objective measures for waterway and port performance. These measures offer insight as a baseline, and a means to predict system response to investment activities.

Research Question2: How can big data analytics yield insight to port and waterway performance and operations?

Revenues for Harbor Maintenance

The allocation of funds for harbor maintenance follows federal budgeting procedures, which are based on estimated costs to achieve Congressionally authorized channel dimensions [43]. Appropriations from Congress determine the amount of available funds for individual projects in each fiscal year [23], but these are not necessarily reflective of vessel traffic and draft requirements. Appropriations are spent from the Harbor Maintenance Trust Fund (HMTF) which has been the subject of debate since it was first instituted in 1986. A value-based fee is unique to the United States. Other countries fund harbor maintenance from their General Treasury or directly through port user fees [44], [45]. As the HMT is value-based, the U.S. Supreme Court has ruled it a tax rather than a user fee and found it to be in violation of the Export Clause of the Constitution [46]. Since 1998 the tax is collected on imported goods and domestic shipments but excludes U.S. exports. The collection of taxes as applied only to imports remains contentious and is subject to consultation under the General Agreement on Tariffs and Trade (GATT) which today is governed by the World Trade Organization (WTO). There is a direct correlation between available draft and vessel payload, but only an abstract relationship between HMT collections and appropriation of maintenance funds. Freight consumers ultimately assume the cost of navigation channel maintenance activities either directly or indirectly (through the HMT), which should be considered in project decisions.

There have been several recommendations to amend, replace, or eliminate the HMT [45], [47], [48]. The Clinton administration pursued several alternatives, including replacement with a user fee and a return to expenditures from the General Treasury, but neither was taken up by the 106th Congress [47]. Kumar proposed a user fee structure based on tonnage, vessel draft, and time-in-harbor which would pass the constitutionality test and better adhere to principles set forth in the GATT [45]. McIntosh et al. investigated various plans including a fee based on tonnage alone, abolishment of expenses by General Treasury, and replacement with a fuel excise tax [48]. Each option necessarily shifts the burden of payment and would likely result in opposition and endorsement. Sentiment favors a user fee model based on objective data that reflect maintenance needs. Unfortunately, data availability to support such a model have been limited to date [49]. In recent years, big data and sensor technology have provided opportunities for improved insight in vessel and port usage that could result in the design of updated, equitable financing models for harbor infrastructure which this dissertation investigates for the Great Lakes.

Research Question3: Can alternate funding mechanisms for harbor maintenance reduce expenditures and operationalize market-based investment decisions?

The Great Lakes Waterway

The Great Lakes, on the border between the United States and Canada, comprise the largest freshwater system in the world and serve as a vital maritime highway for dry bulk commodities [50]–[52]. The system contains more than 100 U.S. and Canadian ports situated along 11,000 miles of coastline [53]. The Great Lakes are distinct from inland waterway systems in that they accommodate deep draft vessels (rather than barge traffic) to transport bulk commodities such as iron ore [51], [54]. The waterway connects to overseas markets through the St. Lawrence Seaway, but more than 90% of U.S. commodities remain within the system, being transported between domestic ports [54]. A series of improvements over the life of the system has deepened the most restrictive points (connecting channels between lakes) to a nominal depth of 8.2 meters, though functional depths change seasonally as lake levels fluctuate impacting vessel load [41], [55]. The network of interdependent ports, harbors, connecting channels, and locks annually carries more than 150 million tons of bulk commodities for U.S and Canadian manufacturing centers [53]. Gross revenue for transportation in the Great Lakes is approximately $1-2 billion annually [56]–[58]

The American States and Canadian Provinces that border the Great Lakes have an estimated GDP of $6 trillion, which, if combined, would represent the world's third largest economy, behind the U.S. and China [59]. Steel producers generate nearly half of the demand for freight movement, primarily iron ore from mining operations along Lake Superior to steel mills situated throughout the lower Great Lakes (Figure 1.2). These maritime shipping routes are at the core of the manufacturing supply chain in the U.S. and Canada. Iron ore vessels traverse the St Marys River and the navigation locks in Sault Ste Marie, MI (Soo Locks) which are owned and operated by USACE [55].

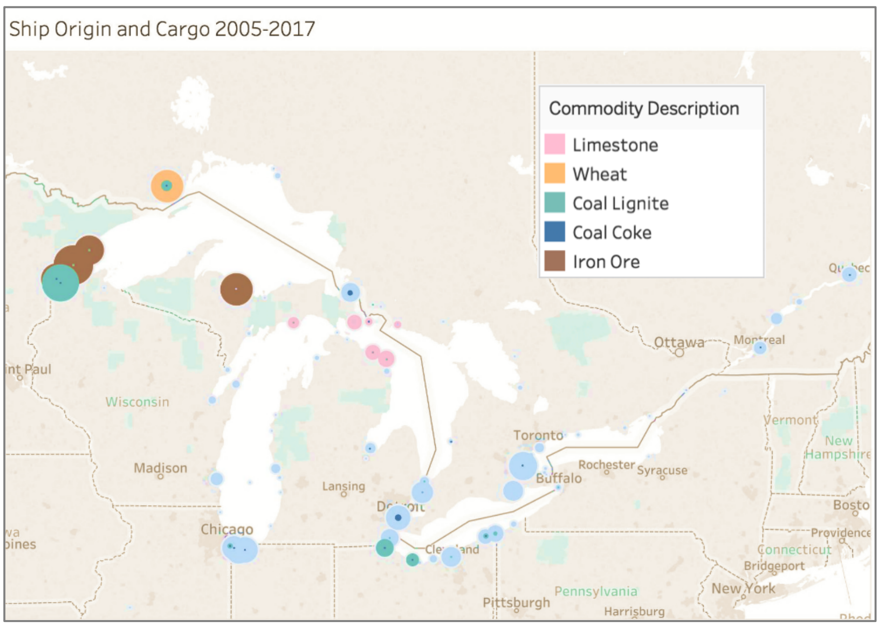

Figure 1.2: Primary cargos by origin in the Great Lakes

Periods of low water adversely impact cargo volumes which increase unit transportation costs and force higher transport pricing over long periods. Meyer et al. developed hydrology-based hedging instruments to insulate shippers from extreme conditions in the Great Lakes and evaluated tradeoffs between financial (insurance) and physical (dredging) risk mitigations [41], [42]. This issue was most pronounced from 2005-2013 when historic low water levels coincided with a dredging backlog [40]. The effect of reduced payload is most pronounced in iron ore vessels due to the density of that cargo. Increased transportation costs in this sector have derivative impacts on the price of steel production and manufacturing which is qualitatively understood, but not readily quantified.

Iron Ore and Steel in the Great Lakes Region

Steel production begins with molten pig iron or direct reduced iron and requires quality raw materials such as coal, limestone, and iron ore [60]. In the United States, iron ore is exclusively mined from the Mesabi and Marquette ranges located in northern Minnesota and Michigan, respectively [61]. Seven active mines with a combined production capacity of 53 million tons supply 15 steel mills in the U.S. and Canada which specialize in advanced steel making [62]–[65]. These "integrated" steel mills utilize blast furnaces for molten pig iron and basic oxygen furnaces for steelmaking to produce specialty grades of Advanced High Strength Steel (AHSS) used in manufacturing [66], [67]. See Appendix A for the full list of mines (Table A.1), transloading facilities (Table A.2), and integrated steel mills (Table A.3). The Great Lakes waterway serves as the critical transportation corridor to connect this network of mines and mills.

Virtually all iron ore produced in the United States is transported via the Great Lakes waterway and passes through the Soo Locks [52], [54], [68]. Ships on the Great Lakes transport processed iron pellets known as taconite, classified as iron ore in the North American Industry Classification System (NAICS code 1011). Taconite pellets are formed by pulverizing and separating raw ore and concentrating iron content with other flux material, especially crushed limestone which passes upbound through the waterway [69], [70]. There are two major producers of iron ore in the U.S.: Cleveland Cliffs (56%) and US Steel (44%) [64], [65]. These companies supply ore to more than 90% of all integrated steelmaking in the U.S. and more than 55% in Canada [61], [71]. Approximately 1.3–1.5 tons of taconite pellets are consumed to produce one ton of steel [72].

The demand for taconite in the Great Lakes is driven by integrated steelmakers who operate blast furnaces for production of molten iron. Integrated steel making is reliant on mined material (taconite pellets) which differs from electric arc furnace production, also known as mini-mills. Electric arc furnaces account for 60-70% percent of production in the United States and 45% of Canadian steel [72]. However, there is an important distinction between construction grade steel produced in mini-mills and higher strength products at the core of manufacturing, which places strict limits on substitution in the supply chain. Integrated steel makers have been responsible for advancing stronger and lighter steel grades collectively known as Advanced High Strength Steel (AHSS). The automotive industry is the primary consumer of these products and the streamlined delivery to manufacturing centers requires consistent production. In turn, these downstream supply chains require a continuous flow of raw materials on the Great Lakes [66], [67]. Annually 45-50 million tons of refined taconite pellets move through the Great Lakes Waterway to steel mills that specialize in production of AHSS.

The entire raw materials-to-finished goods value chain is connected to the Great Lakes waterway which needs to ensure efficient and resilient system performance. Taconite pellet and steel production, at mines and mills respectively, is relatively consistent throughout the year despite an annual disruption to navigation in the winter months. The navigation system, including the Soo Locks, experiences a scheduled 10-week closure from January 15 to March 25 when ice conditions are heaviest [55], severing iron mines from steel mills. During winter months, taconite producers stockpile material at iron ore docks on Lake Superior. Steel producers build stockpiles during the navigation season to sustain production throughout the winter. This stockpiling practice creates recurring cycles in both industries for inventory maintenance and operating costs of production.

Rail and transloading infrastructure facilitate the movement of taconite via dry bulk carriers to steel mills via the Great Lakes waterway. The network of railways, ore loading docks, and transloading facilities are owned and operated by a small group of firms. Mines operate year-round and move taconite by rail to one of five ore loading docks where material is stockpiled or loaded directly onto maritime vessels [64]. Most integrated mills are situated along the waterway and receives taconite directly from the vessels. Two mills in Middleton, OH and Pittsburgh, PA utilize transloading facilities along Lake Erie to complete the movement via rail [62], [65]. Only one integrated mill (Granite City, IL) primarily receives taconite via rail and is not directly dependent on the Great Lakes waterway. The value for chain for iron ore to steel manufactured products is highly dependent on maritime shipping in the Great Lakes.

Shipping in the Great Lakes

Most ships on the Great Lakes are from U.S. and Canadian flagged fleets travelling inter-lake routes. Canadian vessels are constructed to navigate the Welland Canal and St. Lawrence Seaway with lock dimensions restricting vessel size to 225.5 x 23.8 meters and are descriptively classified as “Seaway Max” [51]. Larger vessels, which comprise much of the U.S. fleet, remain above the Welland Canal and service ports on the upper four lakes [54]. Following construction of a new Poe Lock in Sault Ste Marie (1968), larger ships began to enter service to maximize dimensional use of the infrastructure. The Poe Lock is 365.9 x 33.5 meters (1,200 x 110 feet) while the MacArthur Lock (situated parallel to the Poe) is 243.9 x 24.4 meters (800 x 80 feet) wide. Over time the American fleet added larger vessels and decommissioned older, smaller vessels. Thirteen vessels of 1,000 feet or more in length, known as "Footers," are owned by the three largest U.S. shipping companies on the Great Lakes (Table 1.1). This finite subset of vessels accommodates a substantial portion of goods moving down from Lake Superior including more than 50% of iron ore [73]. Appendix B shows a complete list of U.S. flagged vessels operating in the Great Lakes. A vessel's Deadweight Tonnage (DWT) describes its maximum payload, but actual load varies with available depth and water surface elevations in the Great Lakes.

Table 1.1: List of 1,000-foot vessel "Footers" in operation on the Great Lakes

Vessel Name	Fleet	Length (feet)	Beam (feet)	Per-Trip Carrying Capacity (tons)	Capacity per foot of Draft (tons)
American Century	American Steamship Co.	1,000	105	68,880	3,192
Indiana Harbor	American Steamship Co.	1,000	105	68,757	3.192
Walter J McCarthy Jr.	American Steamship Co.	1,000	105	68,757	3,192
American Integrity	American Steamship Co.	1,000	105	68,320	3,168
Burns Harbor	American Steamship Co.	1,000	105	71,120	3,192
American Spirit	American Steamship Co.	1,000	105	66,080	3,180
Edwin H. Gott	Great Lakes Fleet	1,004	105	69,664	3,204
Edgar B Speer	Great Lakes Fleet	1,004	105	69,552	3,204
Presque Isle	Great Lakes Fleet	1,000	104	58,240	3,096
Paul R. Tregurtha	Interlake Steamship Co.	1,013	105	69,580	3,216
James R. Barker	Interlake Steamship Co.	1,000	105	67,475	3,168
Mesabi Miner	Interlake Steamship Co.	1,000	105	67,465	3,168
Stewart J. Cort	Interlake Steamship Co.	1,000	105	64,690	3,096

There is a clear connection between vessel and port performance, shipping costs, and funding for infrastructure which, to date, is inadequately quantified. A deeper understanding of these relationships is needed to reveal the full value of waterway infrastructure and unlock potential for private investment, improve allocation of public funds, and pursue alternative financing options.

Organization of Dissertation

We approached the primary research questions in three steps, as shown in Figure 1.3. The integration of diverse and granular data sets was fundamental to each of the research phases. A detailed description of data sources is provided in Chapter 2.

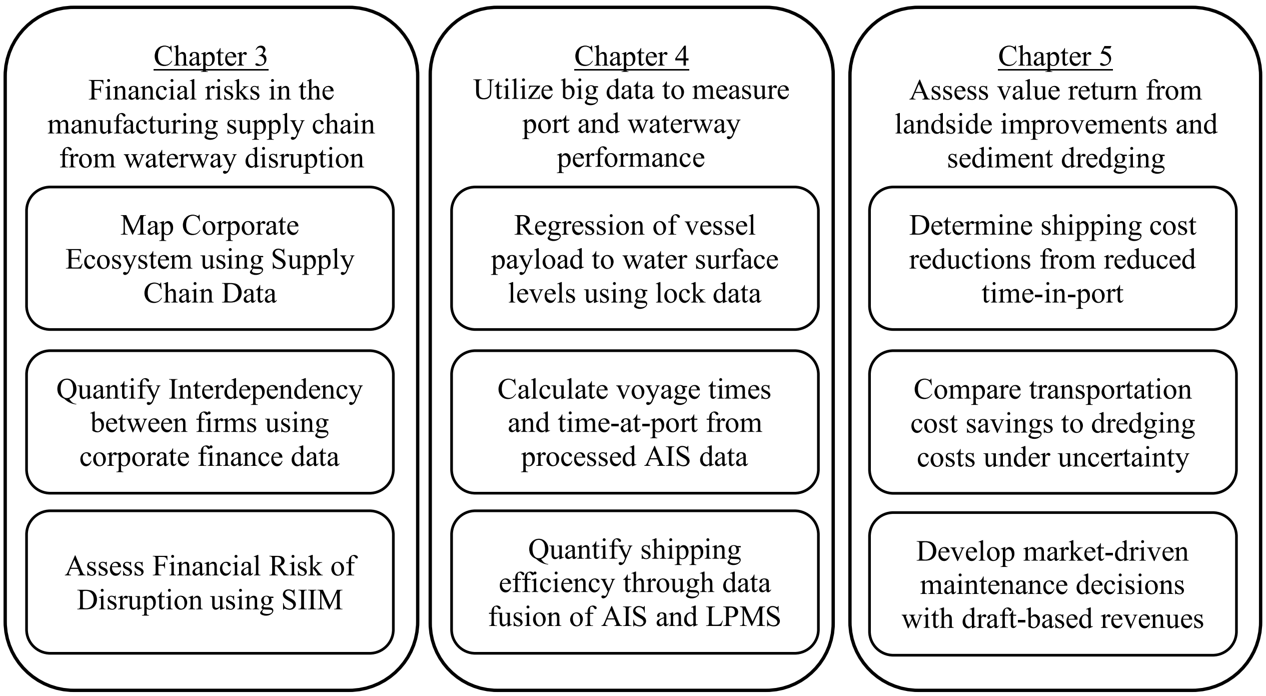

Figure 1.3: Dissertation organization

In Chapter 3 we create a digital twin for shipping in the Great Lakes and characterize the flow of commodities on the waterway with a focus on iron ore. Using corporate financial data, we map the value chain network for steel to finished goods. Quantified financial data are further applied to a supply-driven input output inoperability model (SIIM) to assess supply chain sensitivity and risk of disruption for specific infrastructure nodes within the waterway. This presents a robust valuation of waterway risks throughout the manufacturing supply chain.

Chapter 4 quantifies port and waterway performance with transit and time-in-port statistics integrated with vessel load data. We assess machine learning models to regress variations in vessel payload to water surface elevations. This serves as a predictive tool to account for seasonal changes in performance. Using AIS data, we develop travel time statistics throughout the waterway, and present algorithms useful for the analysis of that data in a non-linear system. This is the first study to integrate vessel payload and travel time statistics to produce a Maritime Transportation Efficiency (MTE) metric for bulk carriers expressed as mass per time. The metric provides a meaningful proxy for transportation costs and serves as a predictable means to assess dredging project benefits.

We apply the proposed MTE metric in Chapter 5 to predict changes in performance using Monte Carlo simulation. We evaluate improvements to shipping efficiency and cost reductions for landside infrastructure investment at Burns Harbor. We assess the real value of maintenance dredging in Toledo Harbor under variable water levels and quantify diminishing returns that exist during periods of uncharacteristically high water or decreased demand for freight. Consideration of system performance and the return on value of dredging can improve capital outlay for waterway projects. We discuss a draft-based user fee model to replace HMT as the basis of revenue for harbor projects. This would enable market-driven decisions that link capital expenditure to system performance which is informed through real-time AIS data.

CHAPTER 2

Data Sources

This chapter is intended to provide an overview of the data types and sources used in this dissertation. Their specific applications, processing methods and integration in the analytical tools are described in the methods sections of the subsequent chapters. Datasets assembled and processed as part of this dissertation are available publicly through the University of Michigan Deep Blue data repository under creative commons Attribution-Noncommercial 4.0 International license (CC BY-NC 4.0).

Financial Data

Supply chain and corporate financial metrics are accessible through databases such as FactSet or the Bloomberg Terminal. Supplier-customer data available through the Supply Chain (SPLC) module within the Bloomberg terminal includes sales revenue dependence of suppliers on their customers as a percentage of a company's total sales. This module provides financial information on customers and suppliers estimated from a variety of sources including public (10-K) filings. All transactional relationship data in the supply chain are reported as percent revenue between suppliers and buyers. Data confidence is highest for relationships in which revenue streams account for 10 percent or more of a firm's total sales (percent of revenue). Reporting above that threshold is mandated by the SEC, but many other data are also available [74]. Few data were available on privately owned companies and those traded on the Canadian Stock

Exchange (e.g., Algoma and Stelco steel companies). Various corporate performance metrics are available for publicly traded firms, such as inventory turnover ratios. This study used inventory turnover to quantify supply-side dependency for manufacturing firms on intermediate goods. Five-year average inventory turnover ratios (2014-2018) were collected for all suppliers in the network using the FactSet financial database [58]. Financial and corporate data collected for the supply chain are available publicly through the University of Michigan Deep Blue data repository [75].

Lock Performance Monitoring System

The USACE collects data on all vessels transiting navigation locks which includes vessel name/number, origin/destination, cargo tonnage, and timestamp information which is stored in the Lock Performance Monitoring System (LPMS) [76]. Data available publicly on the USACE website is aggregated to protect proprietary information. This study utilized raw data from the facility in Sault Ste Marie, MI (Soo Locks) for the period from March 2005 to September 2018, includes the origin, destination, and individual vessel tonnage data necessary for this analysis (sample shown in Appendix D). The full LPMS dataset contains 55,342 records including 13,657 transits of iron ore. A modified version of the dataset with encrypted vessel names and removed vessel identifiers (to protect proprietary information) is available publicly through the University of Michigan Deep Blue data repository [73].

Great Lakes Water Levels

Water levels throughout the Great Lakes are monitored by the National Oceanic and Atmospheric Administration (NOAA) and USACE. Monthly average water levels for each of the waterbodies consider information from multiple stations coordinated between the agencies and publicly available on the USACE webpage [40]. Mean water surface elevation data is available for each of the waterbodies since 1918. Single station data containing instantaneous and mean daily levels are available from the NOAA Tides and Current website [77]. This study utilized single station data from the NOAA Tides and Current website for six gauges which are representative of system extremities (#9099064 Duluth, MN, #9076024 Rock Cut in St Marys River, #9087044 Calumet, IL, #9014070 Algonac, MI, #9063085 Toledo, OH, #9063063 Cleveland, OH).

Changes in water level are highly correlated in the Great Lakes system. We observed high correlation ($\rho_{x,y}$) between lakes and the connecting channels through Lake St. Clair and St Marys River. All the waterbodies are positively correlated and segments above Lake Erie exhibit correlation above 0.7 (see Appendix C for full correlation table).

Winter ice cover data is also available on a daily basis from NOAA [78]. These data records express percent of surface ice cover on each of the waterbodies in the system. Data are generally available from November through May, when ice is present in the waterway.

Automatic Identification System

Real time Automatic Identification System (AIS) data are collected and actively managed by the US Coast Guard with the primary purpose of improving safety. Transponders are mandated for all commercial vessels larger than 300 gross tons and on all passenger vessels [79]. The data include both static and dynamic features. Static features include vessel name, identification number, and dimensions which are specific to each vessel and do not change over time. Dynamic features include Position (Lat-Lon), Speed and Course over ground which are continuously updated and generally recorded in 1-minute increments. The historical AIS data is archived and publicly available through the Marine Cadastre website, managed jointly by the Bureau of Ocean Energy Management (BOEM) and NOAA [80].

This study expands the utilization of AIS in its application to the Great Lakes waterway. Historical data for Universal Transverse Mercator (UTM) Zones 15-18 is assembled over the period 2015-2017. Data for each UTM Zone is available in monthly files which required the collation of 132 data files for the Great Lakes. The AIS data is cumbersome in its raw form. The full dataset is comprised of several billion lines which is cropped to 41.3 - 49.0^{o} N Latitude and 72.3 - 92.2^{o} W Longitude, covering the Great Lakes. The data was further filtered by capturing entry and exit records for defined segments of the waterway. These "trimmed" datasets for each navigation season (2015-2017) contain 13 to 19 million lines each and are available publicly through the University of Michigan Deep Blue data repository [73].

Dredging Data

Historical dredging records are available through the USACE Navigation Data Center. The Institute for Water Resources (IWR) maintains contracted dredging data from 1990 which includes harbor/project name, expected and actual dredging volumes and costs [81]. The historical dataset includes 5,138 records from 1983-2018. The USACE reports consolidated contract data for fiscal years 2019 and 2020 separately.

CHAPTER 3

Applied Financial Metrics to Measure Interdependencies in a Waterway Infrastructure System

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Introduction

Waterway systems serve as critical logistics infrastructure for the movement of goods and are widely regarded as the most economical (and environmentally friendly) means of freight transportation [82], [83]. Impediments to waterway performance may restrict freight throughput and force the movement of goods via another mode at higher cost, or in severe cases, disrupt the supply chain [17], [84]. The estimation of regional and industry-wide losses due to waterway disruptions is fraught with uncertainty and requires the development of advanced methodologies to estimate the impact of supply shocks [17], [34].

Research has shown that the disruption of port operations due to natural disaster, manmade-hazards, or functional degradation impacts economic activity [29]–[31]. A popular approach to estimate this impact is the application of Input-Output (IO) models to calculate propagated economic loss following a catastrophic event [29], [30]. Zhang and Lam estimate losses within the supply chain for adjacent industries using specified discrete scenarios [32]. Research on coastal ports is dominant in the literature, but inland ports and waterways also exhibit significant cascading effects due to freight disruption [17], [33], [34]. MacKenzie et al.

simulated the effects of shifts to alternate transportation modes under port closure scenarios on shipping costs increases [33]. Pant et al. assessed the multi-regional impacts of inland port disruption by applying dynamic inoperability input-output models [34]. Darayi et al. recommended investment strategies that mitigate risk of disruption by identifying critical node and component importance within an infrastructure system [35], [36]. Others have recommended analytical approaches to allocate finite budgets for dredging of inland waterways to maximize total economic benefit, or minimize opportunity costs [85]. Common to these studies is the importance of accurately modeling the network of transportation systems and the interdependencies between waterway users.

This study applies corporate financial metrics to quantify the economic interdependencies between firms in the value chain of iron ore, steel, and manufactured goods in the Great Lakes Region. We apply network modeling to understand the flow of materials in the waterway and investigate the cascading effects of disruption on the value chain of manufactured goods. For publicly traded companies, robust data for corporate revenue and financial metrics provide a practical means to quantify interdependencies in production and test sensitivity to disruption.

Input-Output Model Background

The Leontief Input-Output (IO) model is widely used to investigate macro-economic perturbations across interconnected sectors of the economy [86], [87]. The balance equation for the IO model is shown as

$$x_i = \sum x_{ij} + c_i = \sum a_{ij} x_j + c_i \tag{3.1}$$

Where x_i is the total demand for product i, c_i is final demand for i, and x_{ij} is the demand for product i as input to produce j. The interdependency matrix (a_{ij}) describes the proportion of inputs (i) needed to produce a unit of j and is fundamental to the model. Equation 3.2 shows the model in its simplified matrix form.

$$\mathbf{x}=\mathbf{Ax}+\mathbf{c} \tag{3.2}$$

The IO model accounts for a series of linear relationships between sectors, and effectively models equilibrium changes given demand-driven shifts. For example, a decrease in demand for cars or industrial products would have a proportional reduced demand for steel and components as an intermediate good.

The IO model has been applied to investigate system-wide perturbations given disruption or inoperability of key sectors within a system. Haimes and Jiang developed the inoperability input-output model (IIM) for interdependent infrastructures and showed its usefulness in predicting shifts in demand for specified sectors given reduced operability of another [88]. Subsequent studies have investigated cascading effects in interdependent systems from inoperability to minimize total loss [89] which may result from natural disaster or manmade hazard [90], utility failure [91], or natural disaster [92]. The principal IIM is shown as

$$\boldsymbol{q} = \boldsymbol{A}^{*}\boldsymbol{q} + \boldsymbol{c}^{*} \tag{3.3}$$

Where $\boldsymbol{q}$ is the normalized inoperability vector, $\boldsymbol{A}^{*}$ represents the interdependency matrix of coupled industries, and $\boldsymbol{c}^{*}$ is the demand-side degree of inoperability. It is common to see this expressed in its Leontief inverse form using the identify matrix, $\boldsymbol{I}$.

$$\boldsymbol{q} = (\boldsymbol{I} - \boldsymbol{A}^{*})^{-1}\boldsymbol{c}^{*} \tag{3.4}$$

Interdependency between sectors of the U.S. economy is typically quantified using data from the Bureau of Economic Analysis (BEA) and researchers have mapped perturbations between sectors from major disruptions, terrorist attack for example [93], [94]. As with the

Leontief IO model, the usefulness of the IIM is highly dependent on quantifiable data to support relationships between industries conveyed by the interdependency matrix, $\boldsymbol{A}^*$.

Haimes et al. developed the Dynamic IIM (DIIM) which accounts for differing recovery times for industries after disaster [93], [95], [96]. Barker and Santos extended the use of the DIIM to evaluate how inventory levels within supply chain sectors affect recovery and total economic loss of disruption over time [97], [98]. Niknejad and Petrovic noted the difficulty assembling reliable data to describe interdependency across the global network and proposed a fuzzy multi-criteria method to quantify the relationship between entities [99]. Dass and Fox utilize metrics such as inventory turnover to model network interdependencies for complex supply chains [100]. We integrate such metrics to develop independency in the IO model.

A supply-driven approach to IO modeling was developed by Ghosh to provide a foundation for understanding the propagation of change through value added steps in the supply chain [101]. The supply-driven IIM (SIIM) has been further adapted to estimate disruptions passed forward in the supply chain from perturbations in the production of intermediate goods [102]. This is particularly applicable in systems where demand for goods is inelastic and substitution is limited, as in physical infrastructure supporting a network. The price impact of goods using the SIIM is calculated using Equation 3.5.

$$\Delta\boldsymbol{p} = \boldsymbol{A}^{(s)^*}\Delta\boldsymbol{p} + \boldsymbol{z}^* = \left(\boldsymbol{I} - \boldsymbol{A}^{(s)^*}\right)^{-1}\boldsymbol{z}^* \tag{3.5}$$

Where $\Delta\boldsymbol{p}$ is the price change for goods and $\mathbf{z}^*$ is exogenous change in value for value-added inputs. The usefulness of the SIIM in predicting forward impact of supply changes has been the subject of debate which requires consideration in its application [103]–[105]. For example, Oosterhaven notes that the SIIM may only be appropriate in modeling supply-driven changes where substitution and demand elasticities approach zero [106]. Researchers have revisited the efficacy of SIIM by applying it to manufacturing sectors with limited suppliers of unique production inputs [107]–[109]. As with other IIM approaches, the quantification of interdependencies is crucial. Wie et al. proposed an ordered weighted averaging technique to convey the relationship between nodes in manufacturing [110].

The application of SIIM in this paper is focused on supply chain disruption using detailed financial metrics to quantify supplier-customer relationships. Such metrics are publicly available through financial databases such as the Bloomberg Terminal and [58], [111]. Corporate revenue and inventory turnover ratios are used to map material flows in a steel value chain and to quantify interdependencies between firms. These metrics have significance in logistics and supply chain network analysis given their impact on supply availability and a firm's ability to meet customer demand in periods of disruption [100], [112], [113].

Case Study: Supply of Iron Ore to Steel Mills via the Great Lakes Waterway

Steel production begins with molten pig iron or direct reduced iron and depends on quality raw materials such as coal, limestone, and iron ore [60]. In the United States, iron ore is exclusively mined from the Mesabi and Marquette ranges located in northern Minnesota and Michigan, respectively [61]. Seven active mines with a combined production capacity of 53M tons per annum supply 15 steel mills in the U.S. and Canada which specialize in advanced steel making [62]–[65]. These "integrated" steel mills utilize blast furnaces for molten pig iron and basic oxygen furnaces for steelmaking to produce specialty grades of Advanced High Strength Steel (AHSS) used in manufacturing [66], [67]. See Appendix A for the full list of mines, integrated steel mills, and transloading facilities. The Great Lakes waterway serves as the critical transportation corridor to connect this network of mines and mills.

Ships on the Great Lakes transport processed iron pellets known as taconite, commonly classified as iron ore in the North American Industry Classification System (NAICS code 1011). More than 90% of iron ore produced in the United States is transported via the Great Lakes waterway and passes through the navigation locks in Sault Ste Marie, Michigan (Soo Locks) [52], [54], [68]. There are three producers of iron ore in the U.S.; Cleveland Cliffs (40%), US Steel (44%) and ArcelorMittal (16%) [64], [65] which supply ore to more than 90% of all integrated steelmaking in the U.S. and more than 55% in Canada [61], [71]. Approximately 1.3–1.5 tons of taconite pellets are consumed to produce one ton of steel [72].

Rail and transloading infrastructure facilitate the movement of taconite on dry bulk carriers to steel mills via the Great Lakes waterway. The network of railways, ore loading docks, and transloading facilities are owned and operated by a limited group of firms (see Appendix A). Mines operate year-round and move taconite by rail to one of five ore loading docks where material is stockpiled or loaded directly onto maritime vessels [64]. Most integrated mills are situated along the waterway and receive taconite directly from the vessels. Two mills in Middleton, OH and Pittsburgh, PA utilize transloading facilities along Lake Erie to complete the movement via rail [62], [65]. Only one integrated mill (Granite City, IL) primarily receives taconite via rail separate of the Great Lakes waterway. Transportation costs are typically $20-30 per ton of ore, roughly one third of raw material costs [114].

Turnover ratios are illustrative of financial performance and supply chain efficiency on the Great Lakes. For instance, the navigation system experiences a scheduled 10-week closure from January 15 to March 25 when ice conditions are heaviest [55], severing iron mines from steel mills. During winter months, taconite producers stockpile material at iron ore docks. Steel producers build stockpiles during the navigation season to sustain production throughout the winter. This stockpiling practice creates recurring cycles in both industries for inventory and operating costs of production. Seasonality is evident in Cleveland Cliffs' inventory turnover ratio that peaks in the fourth quarter and decreases sharply at the beginning of each year (Figure 3.1). In corporate accounting the inventory turnover ratio is a measure of the number of times inventory is sold or used in a reporting period [115]. Other studies have used these metrics as indicators of risk exposure in supply chains [116], [117].   We apply it along with attributional percentage or sales revenue to quantify customer-supplier relationships.

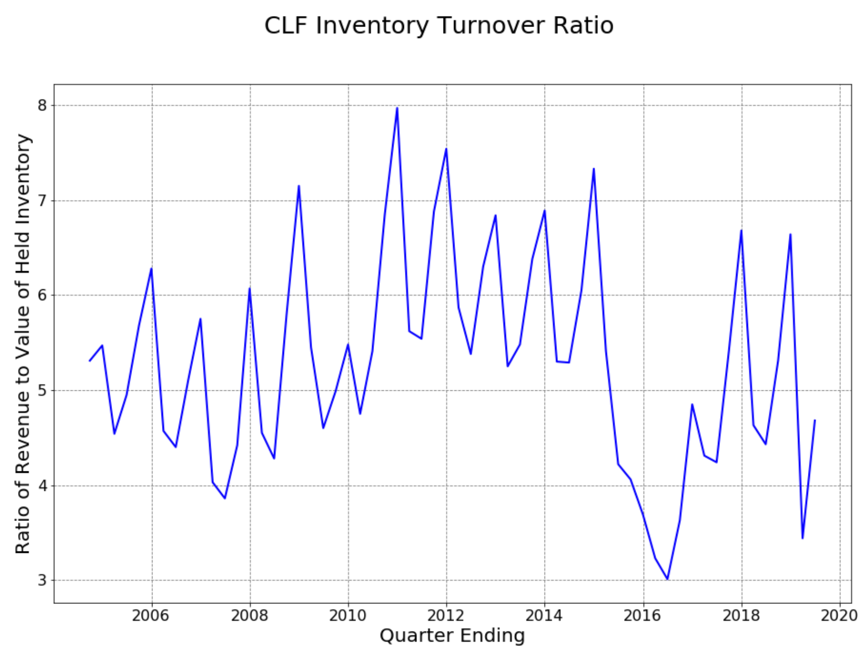

Figure 3.1: Inventory Turnover for Cleveland Cliffs (CLF). This demonstrates a seasonal cycle corresponding to navigation season. A pronounced demand-side market adjustment in 2016 resulted from subsidized foreign steel.

Methodology

This study assembled detailed data to quantify supplier-customer relationships for iron ore, steel, and manufactured goods with a shared dependence on transportation of raw materials on the Great Lakes waterway. Production, consumption, and transportation data for iron ore was assembled from corporate annual reports (Form 10-K) required by the U.S. Securities and

Exchange Commission (SEC) as well as navigation data available through the U.S. Army Corps of Engineers (USACE).

We developed two network models to illustrate the complexity and interdependencies between manufacturing supply chains and the Great Lakes and illustrate these relationships, using network theory. The first model incorporates information from annual corporate reports as well as shipping records available from the Lake Carriers' Association (LCA) and the USACE [54], [76] to quantify bulk commodity movement through the system. The second network represents consumer dependencies on steel using financial metrics to quantify supplier-customer relationships. The financial network map uses supply chain and financial performance metrics gathered from Bloomberg and FactSet financial databases [58], [111]. These tools compile available information on publicly traded companies from corporate disclosures, third party accounting validation, and proprietary Bloomberg algorithms used to compile missing data. We illustrate the directed flow network models using Cytoscape version 3.7 (San Francisco, CA).

Modeling the Transportation Network

This study modeled the supply-chain network for iron ore by representing facilities and transportation corridors as nodes and quantified flows (tonnage) between them as edges. The movement of goods between locations (edges) is based on 2017 vessel tonnage data available from the USACE Lock Performance Monitoring System (LPMS) [76]. We added tonnage to Algoma Steel from Cleveland Cliffs' Annual Report [64] to produce a complete record of freight transport on the waterway. Figure 3.2 illustrates the connection between iron mines and steel mills in the U.S. and Canada to include transloading facilities.

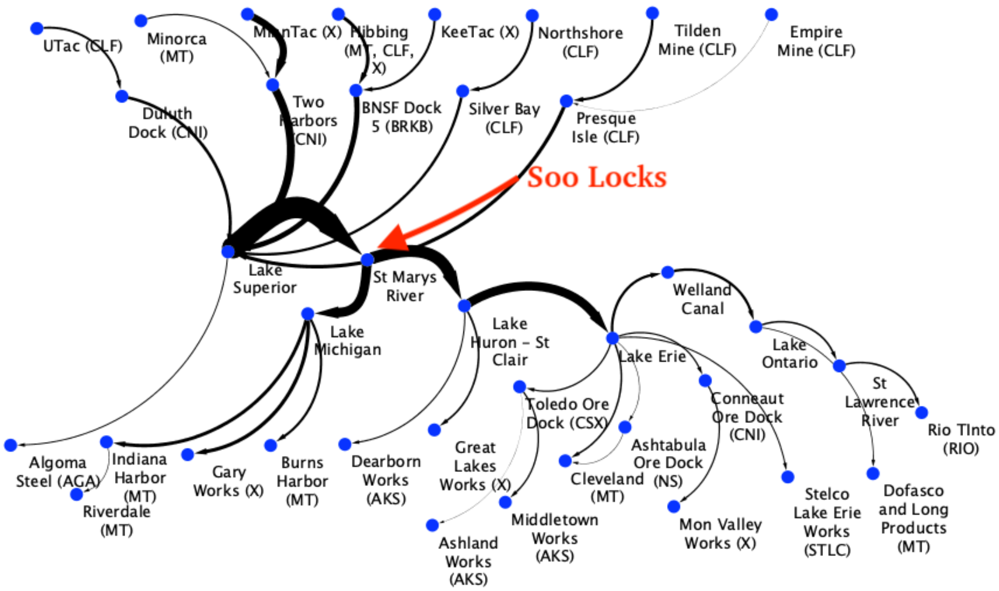

Figure 3.2: Transportation network for taconite (iron ore) on the Great Lakes

Modeling each of the lakes and connecting channels as separate nodes allows us to assess the importance of each segment to commodity flows between mines and steel mills, which in turn imparts a risk exposure should disruptions occur. Initial conditions in the model assume that flow of goods through each waterway segment (node) is unrestricted and balanced (inflow=outflow). The magnitude of commodity flows (edges) reflects the relative importance of each node to all commodity flow. Most pronounced is the 70-mile-long St. Marys River which connects Lake Superior to the northern portions of Lake Michigan and Lake Huron. Disruptions in this portion of the waterway would affect 90% of facilities and 70% of all iron ore delivered to U.S. and Canadian blast furnaces [118].

As shown by Haimes and Jiang, demand for goods (x_j) cannot exceed availability of resources (r_i) needed to produce them [88]. We assume freight transportation to be a limited resource where r_i represents the percent operability of node i in the network. Iron ore to individual mills (x_j) is then subject to Equation 3.6.

$$\sum b_{ij} x_j < r_i \tag{3.6}$$

Where b_{ij} characterizes material flows to mill j along path i. We use iron ore tonnage to quantify these relationships and assume that available supply (r_i) may be restricted by any node along path i. Disruptions in this infrastructure system may occur from failure at a dock or navigation lock, vessel accident or grounding in connecting channels, or other blockages such as bridge collapse or navigation restrictions imposed as part of emergency response [119]. We calculated the percent reduction in iron ore demand, and subsequent steel making, for each modeled steel mill (Figure 3.2) based on an assumed percent inoperability of specified nodes in the network over a navigation season. We make the following simplifying assumptions in this analysis:

- Disruptions affect all network flows through that node equally.
- No substitution to alternate pellet sources. Steel mills use taconite pellets tailored to specific operation of a blast furnace which strictly limits substitution [64].
- No change to alternate transportation mode. Mills situated along the shoreline have evolved operationally to receive material exclusively from port-side infrastructure. Ability to transport and receive taconite via rail or truck is severely restricted without significant infrastructure investment [62], [63], [65].

For example, a one-month outage of the Soo Locks during the 10-month navigation season would manifest as 90 percent operability for that node and impact all corresponding network flows equally. The cumulative impact on firms with multiple facilities was calculated using Equation 3.7.

$$z = \frac{\sum \hat{x}_j - \sum \tilde{x}_j}{\sum \hat{x}_j} \tag{3.7}$$

Where $\hat{x}_j$ is planned and $\tilde{x}_j$ is disrupted demand at mill j. The perturbation for steel companies was adjusted to reflect the percent of the company's operations in the Great Lakes region. For example, ArcelorMittal's NAFTA segment accounts for 26% of revenue (see Appendix B) and 78% of the company's NAFTA steelmaking capacity resides at mills included in our model [63]. It follows that a 10% reduction in Great Lakes facilities would yield a 7.8% reduction in NAFTA operations and a 2% impact to corporate financials. The adjusted perturbations for all firms ($\boldsymbol{z}^*$) serve as a subsequent input to the SIIM, Equation 3.5.

Modeling the Financial Network for steel consumers

Downstream consumers are indirectly exposed to these risks of supply chain disruption as steel serves as input to their products. To better assess the economic value of infrastructure to mitigate risk, it is necessary to consider both direct and indirect losses [120], [121]. We investigate economic losses due to disruption of Great Lakes infrastructure and indirect effects in the supply chain using a SIIM with interdependencies quantified using corporate financial data.

We developed the financial network using supplier-customer data available through the Supply Chain (SPLC) module available on the Bloomberg terminal. This module provides financial information on customers and suppliers estimated from a variety of sources including public (10-K) filings required by the Securities and Exchange Commission (SEC). All transactional relationship data in the supply chain are reported as percent revenue between suppliers and buyers. Data confidence is highest for relationships in which revenue streams account for 10 percent or more of a firm's total sales (percent of revenue). Reporting above that threshold is mandated by the SEC, but many other data are also available [74]. The Bloomberg terminal restricts automated download for supply chain data, and therefore information must be collected manually for individual firms. Supplier-customer relationship data along with percent-of-revenue for integrated steel producers were compiled for the 2017 calendar year. We expanded the network to include sales of intermediate goods such as refined metals and fabricated parts. We excluded relationships accounting for a negligible portion of revenue (reported as 0.00%) and those without quantified financial transactions. This typically was the case for sales to foreign entities such as those from the European segments of US Steel and ArcelorMittal. Few data were available on privately owned companies and those traded on the Canadian Stock Exchange (e.g., Algoma and Stelco steel companies). The collection of supply chain data yielded 278 business entities and 492 supplier-customer relationships [75].

In order to assess relative risk exposure for companies, we defined edge weights in the network using financial metrics. It was important to specify network direction to capture the different behaviors in supplier (out-degree connections) and customer (in-degree connections) relationships. To quantify a firm's closeness to others in the value chain, nodes (companies) and edges (financial relationships) in the network were weighted using inventory turnover ratios and percent revenue. Five-year average inventory turnover ratios (2014-2018) were collected for all suppliers in the network using the FactSet financial database [58]. Typical inventory turnovers for automotive parts and equipment firms are on the order of 15, while ratios for commodity producers like iron ore and steel, which require larger inventory, are on the order of 5 [75]. Higher ratios reflect shorter time periods to replenish inventory without impacting downstream consumers. For companies with risks assessed using Equation 3.7 we assigned a node weight of unity. The derivative risk exposure for firms downstream in the value chain were calculated using the inventory turnover ratio (I) and percent sales revenue (P) parameters. Consider a network with suppliers (i=1, 2..., m) and customers (j=1, 2…, n). Edge (financial relationship) weight describes the derivative risk via a single pathway between i and j and is calculated using Equation 3.8.

$$\omega_{ij} = n_i I_i P_{i,j} \tag{3.8}$$

Where:

ω_{ij} is the edge weight for firm i sales to firm j
I_i = Inventory Turnover ratio for firm i
P_{ij} = Percent of firm i's revenue from sales to firm j
n_i is the node weight of firm i; assigned as 1 for integrated steel companies and calculated for customer firms (n_j) using Equation 3.9 for as the sum of all incoming edges.

$$n_j = \sum_{i=1}^{m} \omega_{ij} \tag{3.9}$$

Figure 3.3 illustrates a conceptual example of downstream weight calculation. In this example, we assigned an inventory turnover ratio (I_i) of either 1 or 2 and percent revenue (P_{ij}) between 0.25-0.5 to demonstrate potential derivative impacts in the model. Notably, downstream firms can reflect a larger node size when many in-degree (supplier) relationships exist. Firms accounting for a small portion of sales would expectedly have a reduced weight within the network.

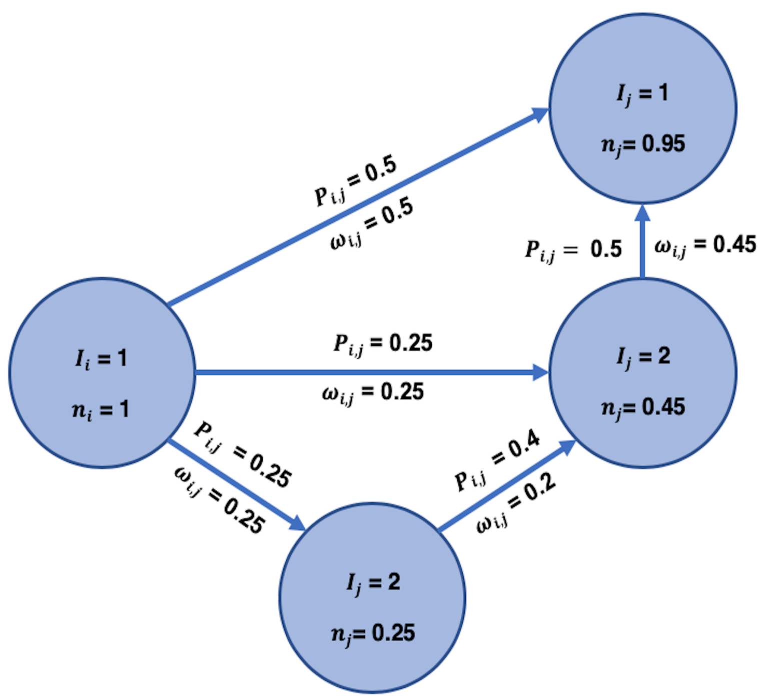

Figure 3.3: Conceptual edge and node weight calculations

By applying Equations 3.8 and 3.9, we computed edge weights for all 492 supply relationships in the model and calculated node size to represent the relative risk exposure to waterway disruptions for each downstream firm. We illustrate the network of interdependency using Cytoscape's Prefuse Force Directed Layout [122]. Major disruptions on the waterway that would impact supply chains can be queried for their derivative impact throughout the financial network.

Risk Propagation of Great Lakes dependency using SIIM

We further investigated loss perturbations (measured as percent inventory turnover) in the automotive sector using a SIIM [102]. This sector is prominent in the network given both quantity and magnitude of supplier-customer relationships. In our application, we use corporate entities (firms) as independent sectors in the SIIM. In this case, we do not explicitly know the production quantities for each firm but can model output using inventory turnover ratios. Recall that inventory turnover may be interpreted to be the number of times held inventory is replenished in a reporting period. As such, it serves as proxy for total output from each firm in the model and also reflects amplified risk-exposure that may result from Just-In-Time (JIT) logistics [123]. Let x_j be the output of finished automobiles, and x_i the steel-related inputs to production. If we consider a unit of production, then we can assume the consumption of all inputs to be proportional and quantify interdependencies using financial metrics described in Section 4.2. Interdependencies between firms are calculated using Equation 3.10.

$$a_{ij} = I_i P_{i,j} \tag{3.10}$$

Where a_{ij} is the unitless proportion of "inventory turnovers" required for the production of x_j. For example, Faurecia auto specializes in automotive parts and has an inventory turnover ratio of 13.58 with percent of sales to Ford and General Motors of 15% and 7%, respectively. Then a_{ij} = 2.04 and 0.95 for the two firms which we assume to be inputs to the production of x_j. We now apply Equation 3.5 to calculate the propagation of inoperability for steel companies due to waterway disruptions provided by Equation 3.7.

We selected ten automotive companies with the largest weighted nodes from the network model. Each supplier to the auto companies in the dataset was modeled in an NxN matrix, $\boldsymbol{A}$ (N = 21). The matrix includes the 10 auto firms and 11 suppliers of steel and intermediate goods derived from steel. By adapting the approach from Guerra and Sancho [107] we develop the $(\boldsymbol{I} - \boldsymbol{A}^{(s)*})$ matrix where $\boldsymbol{A}^{(s)} = \boldsymbol{A}', \boldsymbol{I}$ is the identity matrix, and $\hat{\boldsymbol{x}}$ is the vector of planned output, represented as inventory turnover in our model.

$$\boldsymbol{A}^{(s)*} = \boldsymbol{diag}(\hat{\boldsymbol{x}})^{-1}\boldsymbol{A}^{(s)}\boldsymbol{diag}(\hat{\boldsymbol{x}}) \tag{3.11}$$

The application of Equation 3.5 predicts the cost change in output ($\Delta\boldsymbol{p}$) for each firm based on the specified perturbation ($\boldsymbol{z}^*$) which we evaluate for three scenarios.

Results and Discussion

The results shown below indicate that, as expected, the manufacturing industry exhibits considerable risk exposures related to integrated steel producers in the region. This translates to billions of dollars in potential production loss or price adjustments that would result from supply chain disruption in the waterway system. The financial network model illustrates the corporate ecosystem and suggests that potential losses in the automotive sector are comparable to those for steelmakers. Significant economic risk exposure for automakers is revealed by the SIIM. Quantified interdependencies between firms using inventory turnover and percent revenue provide a meaningful and practical means to extend infrastructure value estimates beyond transportation costs.

Financial Network Model for Steel Consumers

The weighted network model (Figure 3.4) incorporates financial metrics and calculated weights using inventory turnover and revenue percentage, Equations 3.8 and 3.9. Parts manufacturers have relatively small node weights because they account for a marginal percentage of sales revenue for steel producers. On the other hand, they contribute considerable downstream edge thickness due to high inventory turnover.

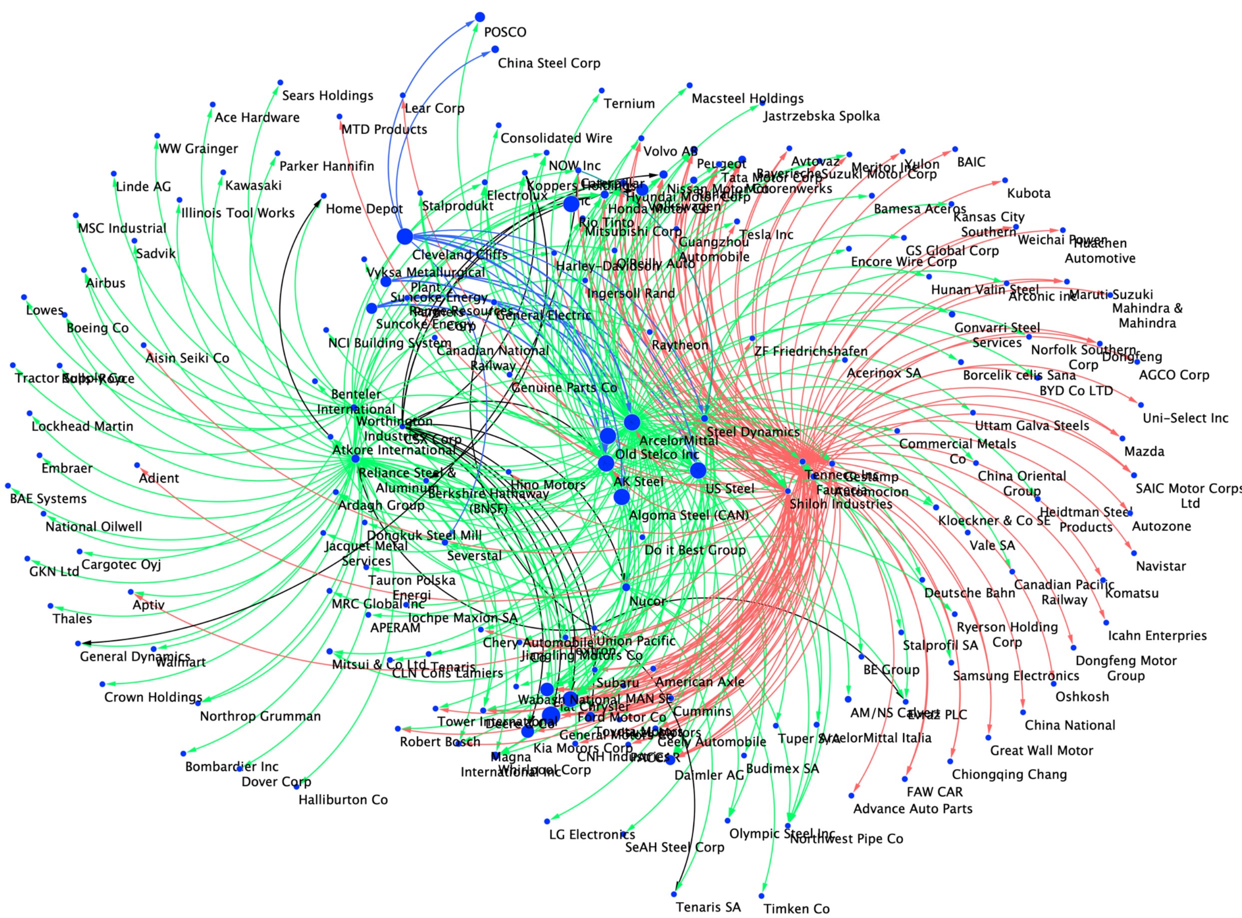

Figure 3.4: Financial network map depicting relative risk exposure to waterway disruption by node size

For example, the auto parts manufacturer Faurecia has a calculated node weight of 0.08 but larger downstream edges given the company's high inventory turnover (13.58) and large revenue percentage to automakers. The calculated edge weight between Faurecia and Ford Motor Co. (15% of Faurecia's revenue) is 0.16 which is twice the firm's calculated node weight. Inventory turnover ratios for steel producers range from 3.72-6.86 while those for parts manufacturers are 10.12-15.20. We interpret this feature to reflect supply chain dependencies and potential indirect risk exposures resulting from waterway disruptions.

The network model further shows that domestic automotive companies have a derivative risk comparable to that of integrated steel producers. Automakers exhibit a calculated node size in the range of 0.1-1.2 as shown in Table 3.1, which reflects their connection/dependency on the waterway. This metric does not value the magnitude of financial risks or opportunity costs directly, but it reflects supply chain dependency and relative risks of each node. This is especially important for supply chain components that have little resilience to disruptions, for example as the result of JIT inventory operations [123], [124]. The data indicate a higher exposure to waterway infrastructure for companies with primary manufacturing centers in North America, which source steel locally. The financial metrics used in creating the model reflect the demand of the auto manufacturers for raw steel as well as for value-added products such as refined metal and fabricated parts.

Table 3.1: Calculated node weights for auto manufacturers relative to unity for firms directly connected to the Great Lakes waterway

Company	Inventory Turnover Ratio	# Modeled Suppliers	Node Weight
General Motors	10.6	11	1.20
Ford	12.2	10	1.01
Fiat Chrysler	7.6	8	0.78
Volkswagen	4.5	10	0.65
Daimler	5.0	7	0.43
Toyota	10.0	8	0.40
Honda	8.1	9	0.24
BMW	6.0	7	0.20
Hyundai	7.9	8	0.14
Kia	5.6	5	0.08

Edge weights were interpreted as a proxy for supply-side risk. As calculated, the product of inventory turnover and percent revenue is the ratio of revenue from a single customer to total inventory held by the supplier. Larger edge weights suggest increased risk associated with disruptions on the supplier side. For example, Ford Motor Co., Fiat Chrysler, and General Motors respectively constitute 12%, 11% and 9.9% of AK Steel's revenue. Given AK Steel's inventory turnover of 5.26, we reason that the automakers respectively require 0.63, 0.58, and 0.52 "inventory equivalents" in the reporting period. A significant supply disruption for AK Steel would almost certainly affect operations for the automakers.

Downstream appliance and equipment manufacturers exhibit a connection to the waterway as well (Table 3.2). Whirlpool, headquartered in Michigan, has the largest risk exposure mainly derived from their financial connection to US Steel whereas other firms exhibit a more distant relationship reflected in their node weight. Further, steel companies using technologies which are less reliant on taconite pellets (e.g., electric arc furnace) appear in the model as consumers of raw or recycled materials. As steelmaking technologies evolve, it is expected that reliance on quality raw materials such as hot briquetted iron (HBI) from the Great Lakes Region will increase. For example, Cleveland Cliffs will open an HBI facility in Toledo, OH in 2020 to serve the demand for high quality iron feeding electric arc furnace (EAF) mills [64].

Table 3.2: Network parameters for select metals, intermediate parts, and appliance manufacturers

Company	Inventory Turnover Ratio	# Modeled Suppliers	Node Weight
Whirlpool	6.5	4	0.22
Deere & Co	5.3	5	0.040
General Electric	3.9	3	0.030
Electrolux	6.5	3	0.026
Nucor	6.1	2	0.19
Reliance Steel & Aluminum	4.57	6	0.16
Steel Dynamics	5.41	3	0.10
Worthington	7.18	5	0.10
Faurecia	13.58	3	0.080
Magna International	11.22	3	0.045
Tenneco	10.5	3	0.040
American Axle	14.34	2	0.021
Shiloh	14.53	3	0.011

Supply Perturbation in the Automotive Industry Value Chain

We considered three scenarios of waterway disruption to investigate perturbations of supply chain risk in the automotive sector. Scenario 1, closure of the Soo Locks, was selected to reflect an upper-bound perturbation resulting from a disruption affecting nearly all integrated steel mills. The other scenarios impact a subset of mills to compare perturbations originating from various steel suppliers. For each scenario, we specified a percent inoperability of one node within the transportation network and calculated percent availability (r_i) along each path, i. Using Equation 3.6 we found the corresponding disrupted tonnage ($\tilde{x}_j$) at each steel mill and the corresponding percent disruption (z) aggregated by firm using Equation 3.7. Finally, risk exposure in the automotive industry is assessed by applying Equation 3.5 using and interdependency matrix developed using Equation 3.10.

Scenario 1: One-month lock closure

The Soo Locks enable ships to navigate the 21-foot elevation difference at the head of the St Marys River and are necessary for all commercial vessels exiting Lake Superior [54]. An unscheduled closure of that infrastructure would affect all maritime traffic passing between Lake

Superior and the lower lakes. This scenario assumes a one-month closure of the Soo Locks at the beginning of the navigation season (when stockpiled taconite at steel mills is low) which could manifest through manmade hazard, or failure of the rail bridge spanning the approach channels, for example [55]. In the transportation model we asserted a 90% operability constraint to the St Marys River node, representing its unavailability one month of the navigation season.

Supply of iron ore to all integrated steel making is disrupted with exception of two facilities, Algoma Steel on Lake Superior, and Granite City Works which receives ore via rail. This requires a simplifying assumption that additional shipping capacity does not become available to reduce backlog during periods of operation. Note that Algoma and Stelco steel are excluded from the SIIM as no customer data was available from sources used in this study. As shown in Table 3.3, inoperability for integrated steel firms reflects the percent of all corporate revenue lost due to reduced operation at impacted facilities.

Modeled perturbations in SIIM ($\Delta \boldsymbol{p}$) traditionally reflect the change in price for goods where monetary value is used to quantify interdependencies [102], [103]. Perturbations in our model reflect changes in inventory turnover ratio and potential economic loss is calculated as the product of revenue and the change perturbation. Perturbations reflect the complex interaction of interdependencies (a_{ij}) captured in matrix $\boldsymbol{A}$ as well as each firm's output which is modeled as inventory turnover. For example, the Ford Motor Co. has modeled inputs including steel from AK Steel ($a_{ij} = 0.63$) and ArcelorMittal ($a_{ij} = 0.058$) as well as seven parts and steel refining companies who in-turn have inputs from integrated steel producers all having a derivative impact to Ford's production. Auto makers have common inputs with seemingly modest variation. Modeled inputs (a_{ij}) to Ford and GM are generally within 10% of each other with exception for Faurecia (2x higher for Ford), Shiloh (5x higher for GM) and an additional input to GM from US

Steel (a_{ij} = 0.34). Recall that the magnitude of these interdependencies is influenced by sales revenue as well as the size of held inventory. For a constant revenue, as inventory decreases the inventory turnover ratio would increase which will impart a greater perturbation on downstream consumers in the model.

The model indicates a 3 percent impact to GM and a 2 percent perturbation to Ford. For comparison, ArcelorMittal's inoperability is also 2 percent. Steel companies exhibit perturbations nearly equal to their specified inoperability ($|\Delta p - z| < 10^{-3}$) which reflect few modeled inputs to their production. ArcelorMittal has two inputs from Nucor and Shiloh industries with interdependencies of 0.05 and 0.04, respectively, conveying a minimal affect to its overall perturbation. Losses estimated by the model may manifest as the price change of intermediate and finished goods, loss of revenue due to production shortages, or more likely some combination.

Scaling the results by annual revenue for each firm shows that significant economic impacts extend to the indirect users of the waterway. Losses within the steel sector account for less than 10% of the total estimate and 83% is observed in six automakers with manufacturing centers in North America. This is explained by the network of supplier-customer relationships and illustrates the magnitude of supply chain dependency auto firms have to integrated steel production and taconite transportation on the waterway (Figure 3.3).

Table 3.3: Inoperability of integrated steel making and cost perturbation to industry given 1-month closure of Soo Locks

Company	# Facilities Impacted	Inoperability (z)	Perturbation (Δp)	2017 Revenue ($B)	Potential Loss ($B)
ArcelorMittal	6	0.020	0.020	68.7	1.4
US Steel	3	0.057	0.057	12.3	0.7
AK Steel	2	0.050	0.050	6.1	0.3
Ford Motors	--	0	0.020	156.8	3.1
General Motors	--	0	0.031	145.6	4.5
Fiat Chrysler	--	0	0.025	125.1	3.2
Volkswagen	--	0	0.030	260.2	7.9
Daimler AG	--	0	0.019	185.4	3.5
BMW	--	0	0.007	111.3	0.7
Toyota	--	0	0.010	265.1	2.6
Honda	--	0	0.007	138.6	1.0
Hyundai	--	0	0.005	85.3	0.4
Kia	--	0	0.004	47.4	0.2
Faurecia	--	0	0.001	22.8	0.03
Gestamp Automoc	--	0	0.001	9.3	0.01
Shiloh Industries	--	0	0.0002	1.0	0.0002
Tenneco Inc	--	0	0.001	9.3	0.01
Nucor	--	0	0.0	20.3	0.0
Reliance Steel& Al.	--	0	0.009	9.7	0.09
Steel Dynamics	--	0	0.0	9.5	0.0
Worthington Ind.	--	0	0.003	3.0	0.01

Scenario 2: Structural Failure of Bridge over Mackinac Straits

The Straits of Mackinac connect Lake Michigan and Lake Huron and are spanned by a suspension bridge overpassing the maritime corridor. Failure of the bridge would likely block vessel traffic, affecting all freight moving in and out of Lake Michigan. This hypothetical scenario assumes a two-month closure of this corridor which we modeled with an 80% operability constraint to the Lake Michigan node. This scenario would impact all mills situated along the Indiana shoreline, three of which are owned by ArcelorMittal and one by US Steel. These mills represent more than 50% of the integrated steelmaking capacity in the U.S. by tonnage [60] and taconite disrupted in this scenario would be approximately equal to that in Scenario 1. Inoperability estimates for ArcelorMittal and US Steel are nearly equal to those in Scenario 1 because roughly half of their capacity resides in their Indiana mills (see Appendix A). AK Steel experiences minimal disruption because their mills are situated in other segments of the waterway (Figure 3.2). Despite nearly equivalent losses in the steel sector, predicted indirect losses are much lower in this scenario which is explained by the interdependencies built into the model.

As previously described, automakers are more reliant on supplier-customer relationships with AK Steel than with other steelmakers. ArcelorMittal supplies all ten automakers with inputs to production in the range 0.01-0.15 whereas US Steel provides input of 0.05-0.35 to only four auto firms. As reflected in the resultant perturbation, GM, Daimler AG, and Volkswagen exhibit the largest steel purchases from ArcelorMittal and US Steel. Additional downstream losses from this scenario would surely occur but are outside the subset of 21 companies included in this model for the automotive sector.

Table 3.4: Inoperability of integrated steel making and cost perturbation to industry given 2-month restriction in Mackinac Straits

Company	# Facilities Impacted	Inoperability (z)	Perturbation (Δp)	2017 Revenue ($B)	Potential Loss ($B)
ArcelorMittal	3	0.026	0.026	68.7	1.8
US Steel	1	0.06	0.06	12.3	0.74
AK Steel	0	0.0	3e-5	6.1	0.0002
Ford Motors	--	0	0.002	156.8	0.3
General Motors	--	0	0.014	145.6	2.1
Fiat Chrysler	--	0	0.002	125.1	0.3
Volkswagen	--	0	0.001	260.2	2.9
Daimler AG	--	0	0.007	185.4	1.2
BMW	--	0	0.001	111.3	0.2
Toyota	--	0	0.0004	265.1	0.1
Honda	--	0	0.0005	138.6	0.07
Hyundai	--	0	0.001	85.3	0.1
Kia	--	0	0.0002	47.4	0.01
Faurecia	--	0	0.0003	22.8	0.006
Gestamp Automoc	--	0	3e-5	9.3	0.0002
Shiloh Industries	--	0	0.0001	1.0	0.0001
Tenneco Inc	--	0	2e-5	9.3	0.0002
Nucor	--	0	0.0	20.3	0.0
Reliance Steel& Al.	--	0	0.006	9.7	0.09
Steel Dynamics	--	0	0.0	9.5	0.0
Worthington Ind.	--	0	0.002	3.0	0.006

Scenario 3: Failure at ore loading docks in Lake Superior

The ore dock in Duluth, MN loaded more than 6.5 M tons of taconite onto vessels in 2017 representing 13.5% of all ore moved on the waterway that year [76]. As with other docks, the facility stockpiles material from mines, hoists taconite into an elevated dock and loads vessels with a series of conveyor belts that deliver ore into the ship's hold [57]. The complex system of infrastructure requires deliberate operation and investment to ensure sustained operations. This scenario assumes a reduction in Duluth Dock node performance to 60%. In this scenario, downstream impacts are less resultant from geographic factors and more from supplier-customer relationships to provide taconite for specified blast furnaces. This primarily affects mills owned by ArcelorMittal and AK Steel. While three of US Steel's facilities are impacted, the de minimis tonnage delivered to those facilities from Duluth limits the firm's inoperability.

Losses within the steel sector are roughly half that observed in the previous two scenarios, yet calculated perturbations are 70% higher than predicted for Scenario 2. As before, more than 85% of losses are attributed to six automakers as shown in Table 3.6. These firms exhibit high demand for specialty steel expressed in the model through interdependencies. For example, AK Steel's input to Ford, GM and Fiat Chrysler respectively is 0.63, 0.52, and 0.58 which is far greater than relationships modeled for other steelmakers. Losses for ArcelorMittal are five times that of AK Steel in this scenario, but downstream impacts to production are amplified by high inventory turnover and percent revenue parameters along supply-chain paths originating from AK Steel. Furthermore, as automakers require specialty grades of steel for production, steelmakers demand taconite pellets tailored to each blast furnace which places shared risk in the disruption of nodes along the commodity flow path. The modeled interdependencies between firms reveals a more complete estimate of losses originating from a single piece of waterway infrastructure. Comparing risk at harbors and channels throughout the waterway, which is beyond the scope of this study, would yield valuable insight to the derivative risk in this manufacturing sector.

Table 3.5: Inoperability of integrated steel making and cost perturbation to industry given 60% operation at Duluth Ore Dock

Company	# Facilities Impacted	Inoperability (z)	Perturbation (Δp)	2017 Revenue ($B)	Potential Loss ($B)
ArcelorMittal	3	0.015	0.015	68.7	1.0
US Steel	3	0.010	0.011	12.3	0.13
AK Steel	1	0.033	0.033	6.1	0.2
Ford Motors	--	0	0.013	156.8	2.0
General Motors	--	0	0.014	145.6	2.1
Fiat Chrysler	--	0	0.016	125.1	2.1
Volkswagen	--	0	0.017	260.2	4.5
Daimler AG	--	0	0.011	185.4	2.0
BMW	--	0	0.004	111.3	0.5
Toyota	--	0	0.007	265.1	1.8
Honda	--	0	0.005	138.6	0.7
Hyundai	--	0	0.003	85.3	0.2
Kia	--	0	0.003	47.4	0.1
Faurecia	--	0	0.0008	22.8	0.02
Gestamp Automoc	--	0	0.0006	9.3	0.006
Shiloh Industries	--	0	8e-5	1.0	8e-5
Tenneco Inc	--	0	0.007	9.3	0.006
Nucor	--	0	0.0	20.3	0.0
Reliance Steel& Al.	--	0	0.003	9.7	0.03
Steel Dynamics	--	0	0.0	9.5	0.0
Worthington Ind.	--	0	0.001	3.0	0.004

Model Application and Future Work

The Great Lakes waterway is crucial to manufacturing industries and the North American economy as demonstrated here with focus on the automotive industry [53]. Decision makers require an improved understanding of how operational efficiency and tail risk events impact the financial performance, opportunity cost and ultimately the economic competitiveness of the region [17], [85]. This analysis utilized data from the 2017 reporting period, but the methods we present are readily adaptable to any year or quarterly period for which data is compiled, making this approach flexible to changes as the corporate ecosystem and trade activities continue to evolve.

This work investigated these relationships using public data available through financial databases which accounted for 65% of revenue for AK Steel, 29% for ArcelorMittal, and 14% for US Steel. In the SIIM, unaccounted revenue is treated as exogenous demand which preserves the accuracy of the interdependency matrix. Future work may develop more complete supply chain data including attribution to specific facilities, including Canadian integrated steel mills, that more precisely predicts perturbations from specified waterway segments. Such trade relationships are highly complex but can be visualized and quantified using network models that serve as inputs to risk management decision tools, or for consideration in trade policy.

In this analysis we tested the hypothesis that disruptions in the delivery of iron ore would result in the loss of production capacity. Delays due to weather or vessel congestion in ports are not uncommon and stockpiled material is able to sustain consistent production under most conditions. In extreme cases, as those presented in the scenarios, persistent disruptions may cause steelmakers to exhaust operational stockpiles, cease production, and idle blast furnaces [62], [63], [65]. Idling blast furnaces results in months of operational downtime and tens of millions of dollars in repair and lost labor as experienced during extreme ice cover on the Great Lakes in 2014 [125], [126]. We provide a quantitative approach to estimate the indirect economic impacts of extreme waterway disruptions that more broadly accounts for value in the system.

Future work will investigate factors impacting transportation efficiency and the effect that waterway conditions have on financial risks to steel producers. For example, low water levels that reduce ship carrying capacity directly impacts shippers [41] and rationally affects freight pricing and transportation fuel costs for steel producers. Additionally, dredging and water quality concerns (e.g., algal blooms) have been problematic in some regions, impacting delivery times and cost. As further consideration is given to dredging budgets and project prioritization [85], decision makers may consider the full value of harbor maintenance to adjacent industries. This emphasizes those entities with close financial proximity in addition to geographic vicinity to harbors.

Investment for maintenance and upgrades of Great Lakes water infrastructure is predominantly funded from federal and state resources [127]. The current capital allocation practices take into account benefit-cost analysis of transportation cost savings to prioritize projects but could be amended to consider user opportunity costs or broader industry-related economic risk factors [24], [128]. Corporate finance indicators across the value chain enable the techniques presented herein and are useful to quantify potential losses that may influence public investment decisions or options to structure innovative alternative financing.

Conclusion

This study investigated the interdependencies for steel consumers as they relate to the Great Lakes waterway. We apply corporate financial metrics to measure interdependencies between firms and test their sensitivity to assumed disruptions in the waterway which impact delivery of iron ore to integrated steel mills. The cascading effects of waterway disruption are estimated through network mapping and the supply-driven inoperability input-output model (SIIM). The novel application of corporate financial metrics such as inventory turnover ratios to quantify interdependencies promotes extended application of the SIIM to manufacturing and production. Such metrics are publicly available through financial tools such as the Bloomberg terminal and FactSet, but future analyses may be enriched with more complete data that approaches 100% of total revenue. Robust data for corporate revenue and inventory turnover offer a practical means to quantify interdependencies and assess the fiscal perturbations from waterway disruption. These data also provide a meaningful way to map material flows and weight network relationships. Future work investigating transportation efficiency and waterway investment strategies may consider approaches that illustrate value and risk for both public and private entities.

CHAPTER 4

A Data Fusion Approach to Predict Shipping Efficiency for Bulk Carriers

This chapter is published in the International Journal *Transportation Research Part E*.

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Introduction

Maritime shipping is the largest contributor to freight movement around the world and plays a vital role in connecting economies. The maritime transportation system annually delivers more than 11 billion tons of materials and finished products worldwide with a projected annual growth of 4-6% [129]. Ports and harbors serve as critical infrastructure for efficient freight transportation within this system and are essential to economic trade. Concurrently, the industry is balancing multiple objectives to reduce the environmental impacts of maritime shipping [130]. In consideration of these objectives, emphasis has been placed on improving transport efficiency [131], [132]. Practitioners and researchers face the challenge of meeting demand while reducing the industry's environmental footprint which requires upgrades to improve efficiency [82].

Access to, and insights from, big data shows promise to enhance awareness of performance and produce objective measures of efficiency which are needed to inform decisions for capital outlay. Research into big data sources and advanced analytics provide novel insight to shipping and port performance [133]. The Automatic Identification System (AIS) is a source of big data that has garnered attention from researchers and practitioners. These data have the primary purpose to improve vessel safety but also have practical research applications, for example, investigation of port and waterway performance and measurement of voyage times [134]. The AIS data have been used to measure travel times to assess performance of inland waterways in the U.S. [37], [38]. Kruse et al. presented techniques to measure vessel time spent at anchorage and in berth for coastal ports using AIS to quantify "port fluidity", which they define as the reliability of port turnaround time [39]. Zhang et al. investigated ship traffic volumes in Singapore using AIS to identify operational bottlenecks and navigational safety concerns [135].

While AIS data provide meaningful insight to maritime performance, they have clear limitations with respect to cargo volumes and tonnage. Kruse et al. identify the need for expanded statistical metrics to quantify port and waterway performance to better reflect freight costs, which requires knowledge of vessel load [39]. Jia et al. presented a technique to estimate payload from AIS draught data, but note that actual payload information is virtually non-existent and AIS alone may be inadequate to comprehensively assess system performance [136]. As AIS records do not include vessel tonnage or volumes, it is necessary to pursue other data sources to discern efficiency of bulk or containerized goods movement. There is a knowledge gap to quantify efficiency in freight movements with integrated payload and time performance. This is particularly relevant for inland waterway systems or coastal ports with highly variable tides restricting available draft. For example, Ahadi et al. showed that decisions for dredging of inland waterways may be improved by giving consideration to commodity flows and reactive maintenance budgeting [85]. Objective, data-driven measures of efficiency and performance have the potential to inform operations and maintenance decisions as well as fleet deployment.

This study investigates transport efficiency of dry bulk carriers in the Great Lakes waterway and makes three fundamental contributions. We model vessel payload to water levels, which affords managers greater predictability over seasonal changes. Second, we present travel time statistics collected from AIS which provides time-based performance metrics in the Great Lakes. The techniques we present here effectively capture statistics in a non-linear system. Finally, we propose a data fusion approach that integrates payload and travel time information from disparate sources to express maritime transport efficiency.

The authors focus on iron ore carriers which are principally employed in short sea shipping in the Great Lakes [137], [138]. Cumulative impacts of inefficiency are more pronounced over short sea shipping routes where vessels make repeated calls to few ports [139]. The Great Lakes waterway is host to a network of inter-dependent deep sea ports that primarily transport dry bulk goods such as iron ore, coal, and aggregate [53], [54]. Given its characteristic vessel patterns, variable water depth, and prominent navigation lock infrastructure, this waterway serves as an exemplary application case to investigate data-driven efficiency measures.

The Great Lakes Waterway

The Great Lakes, on the border between the United States and Canada, comprise the largest freshwater system in the world and serve as a vital maritime highway for dry bulk commodities [50]–[52]. The system contains more than 100 U.S. and Canadian ports situated along 11,000 miles of coastline [53]. The Great Lakes waterway is distinct from other inland systems in that it accommodates deep draft vessels (rather than barge traffic) to transport bulk commodities such as iron ore [51], [54]. The waterway connects to overseas markets through the St. Lawrence Seaway, but the majority of goods remain within the system transported between domestic ports [54]. The network of interdependent ports, harbors, connecting channels, and locks annually carry more than 150 million tons of bulk commodities for U.S and Canadian manufacturing centers [53].

Steel producers generate nearly half of the demand for freight movement, primarily iron ore from mining operations along Lake Superior to steel mills situated throughout the lower Great Lakes. These maritime shipping routes are at the core of the manufacturing supply chain in the U.S. and Canada. Sugrue et al. demonstrated the waterway's importance to automotive and related manufacturing industries through financial network modelling, and quantified the economic impact of shipping disruptions on the supply chain [138]. Vessels annually move approximately 45 million tons of processed taconite pellets, commonly classified as iron ore in the North American Industry Classification System (NAICS code 1011) to Great Lakes steel producers [54]. All U.S. iron mines are situated in northern Minnesota and Michigan and transload ore through five iron docks situated on Lake Superior [68]. Iron ore vessels traverse the St Marys River and the navigation locks in Sault Ste Marie, MI, owned and operated by the U.S. Army Corps of Engineers (USACE) [55].

Management of the waterway, locks, harbors, and landside port infrastructure is shared between public and private owners. Private entities generally own and operate landside infrastructure such as cranes and transloading facilities [18]. Water-side channel and lock operation, as well as dredging and sediment management, is the responsibility of USACE. A series of improvements over the life of the system has deepened the most restrictive points (connecting channels between lakes) to a nominal depth of 8.2 meters, though functional depths change seasonally as lake levels fluctuate impacting vessel load [41], [55].

The majority of ships on the Great Lakes are from U.S. and Canadian flagged fleets travelling inter-lake routes. Canadian vessels are constructed to navigate the Welland Canal and

St. Lawrence Seaway with lock dimensions restricting vessels size to 225.5 x 23.8 meters and are descriptively classified as "Seaway Max" [51]. Larger vessels, which comprise much of the U.S. fleet, remain above the Welland Canal and service ports on the upper four lakes [54]. The cost of inefficiency in the transportation system is shared between transportation companies and consumers of bulk commodities [114].

The authors sought to quantify the average delivery efficiency of dry bulk carriers for iron ore along primary routes in the Great Lakes. We integrate vessel load and travel times from distinct data sources to quantify the transport efficiency of bulk iron ore.

Methodological Approach

Vessel capacity and travel times each reveal a component of system efficiency, but we propose that a more meaningful expression of bulk commodity movement is mass per unit time. This study defines maritime transport efficiency (MTE) as load (tonnage) per voyage time and characterized performance over a navigation season to understand changes and predictability. To do this, we assessed variability in vessel carrying capacity ('load') for distinct voyages due to fluctuations in water surface elevation throughout the Great Lakes. Next, we investigated AIS position data to characterize travel times for voyages across iron ore routes and within ports and harbors. Finally, a metric was developed to assess overall efficiency of transporting bulk iron ore in the Great Lakes by integrating data sources which contain vessel load and voyage time information (Figure 4.1).

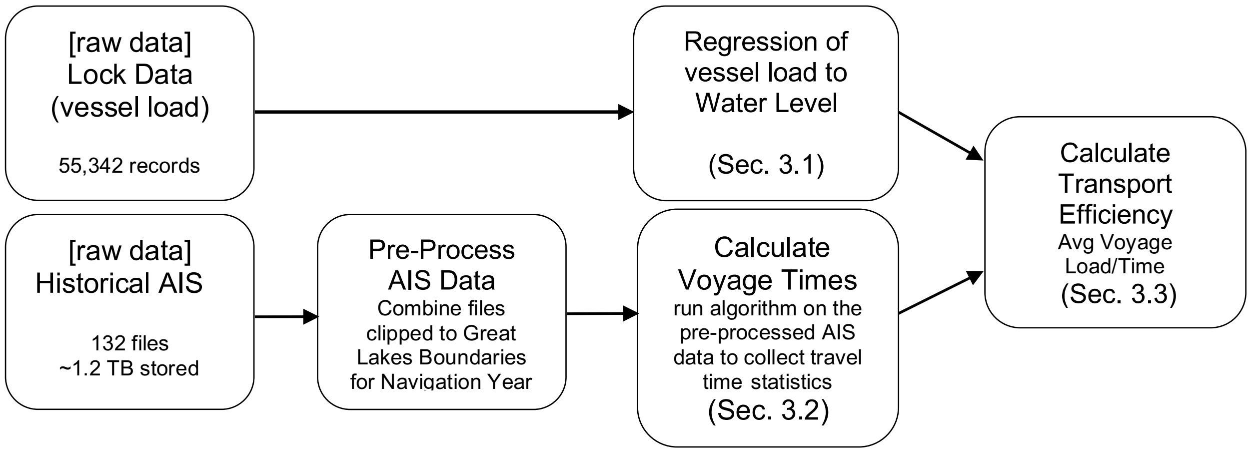

Figure 4.1: Study framework and approach

Regression of Vessel Load to Water Level

As vessel load is naturally dependent on draft, changes in carrying capacity are controlled by water level in the Great Lakes. Fleet capacity is higher in summer months and lower in the winter when seasonally low water levels negatively affect vessel tonnage [41]. As waterbodies of the Great Lakes hold large volumes of water, intra-annual autocorrelation is high and surface elevation changes occur gradually [140]. Although precise predictions of lake levels remain challenging, annual patterns yield observable trends in maritime performance that are useful for decision making [42], [141]. To account for seasonal changes in vessel capacity, we developed a predictive model to express expected vessel load for known water levels.

Vessel load data was assembled from the USACE Lock Performance Monitoring System (LPMS). The USACE collects data on all vessels utilizing navigation locks, including vessel name/number, origin/destination, cargo tonnage, and timestamp information which is stored in the LPMS [76]. Publicly available data on the USACE website is aggregated to protect proprietary information. We assembled raw data from the facility in Sault Ste Marie, MI (Soo

Locks) for the period March 2005 to September 2018 which includes the origin, destination, and vessel tonnage data necessary for this analysis (Appendix A). The LPMS data used in the study contained 55,342 records including 13,657 transits of iron ore.

This analysis uses vessel tonnage from LPMS as the dependent variable. The authors considered using the load factor (load/DWT) but noted discrepancies between values reported for various fleets on the waterway. For example, M/V Stewart J Cort has a reported deadweight tonnage (DWT) of 58,000 [142]. Other fleets report two DWT ratings for expected changes in season load. For example, M/V Burn Harbor lists 62,100 DWT at 8.38 m. draft and 80,900 tons for “midsummer” draft [143]. Further, some records within the LPMS data are more than the reported DWT. For example, the maximum load recorded in our datasets for the Stewart J Cort is 66,055 tons. For consistency across our datasets and vessels, we elected to use actual vessel payload as the dependent variable. Standardized water levels $X_{std} = \frac{(X-\mu)}{\sigma} \sim N(0,1)$ served as input to the model. We used the monthly mean of standardized vessel tonnage as the response variable in the regression models.

We evaluated seven regression models and selected those with the lowest calculated error on predicted capacity. We considered common regression models including the Generalized Linear Model (GLM), Generalized Additive Model (GAM), Classification and Regression Tree (CART), Multivariate Adaptive Regression Splines (MARS), Random Forest, Bayesian Additive Regression Tree (BART), and a Neural Network [144]. We fit each of the models on two thirds of the data and predicted efficiency on the 33% random data holdout over 20 iterations. We calculated Mean Squared Error (MSE) as $\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$ between the predicted ($\hat{y}_i$) and actual (y_i) standardized vessel tonnage to compare models. We selected the GLM as the preferred regression model for this study because it exhibited slightly lower error than GAM and performed significantly better than other models. The GLM predicts the expected vessel load anomalies from the mean ($E[Y]$) using a linear predictor ($\boldsymbol{X}\beta$) and link function (g) for each of the input variables [145].

$$E[Y] = g^{-1}(X\beta) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \tag{4.1}$$

Since Great Lakes waterbodies are highly correlated (Appendix B), we sought to simplify the regression model to the fewest practical water level input features (x_i). Using Principal Component Analysis (PCA) for dimensionality reduction, the 5-feature inputs were mapped onto a 2-dimensional projection. We calculated dimensionally reduced inputs from the 5 x 2 matrix using Equation 4.2 and utilizing Python's scikit-learn module [146].

$$\boldsymbol{z} = \boldsymbol{W}\boldsymbol{x} \tag{4.2}$$

Note that $\boldsymbol{W}$ in this case represents the first two eigenvectors of the covariance matrix between the five water levels. Calculated eigenvalues for each vector showed that 97% of variance is explained by two principal components (84.5% and 12.5%, respectively). We compared predictive accuracy of the dimensionally reduced principal components (PC1 and PC2) as input features to the GLM versus the actual water surface level.

We preferentially selected input features to minimize MSE on predicted vessel load and considered interpretability of water level over principal component. We evaluated seven sets of input features including individual lakes, PC1 and PC2, and water levels for all five lakes which serve as independent variable inputs in the model. Lake Ontario was excluded from the set of input features as that waterbody only affects a small subset of vessels (those traversing the Welland Canal) and thus is not reasonably deterministic of capacity throughout the system. Each set of input variables (7 total) was used to predict vessel capacity over 100 iterations using two-thirds of available data selected at random to train the model and fit coefficients (33% held for testing).

Using AIS to Assess Voyage Times

This study determined voyage time and port fluidity metrics in the Great Lakes waterway by extracting vessel time and position information from historical AIS data. Historical data were assembled from the Marine Cadastre website [80] for Universal Transverse Mercator (UTM) Zones 15-18 over the period 2015-2017. Data for each UTM Zone is available in monthly files which required the collation of 132 data files. We cropped the raw data to 41.3° - 49.0° N Latitude and 72.3° - 92.2° W Longitude, inclusive of the Great Lakes. To assess continuous ship voyages, we assembled files into a single dataset for each navigation year, defined as 25 March to 15 January. This time period reflects the annually scheduled disruption when navigation locks and ice breaking operations cease during the winter [51], [55]. Pre-processing of AIS data was necessary to reduce the data to a manageable size (n = 48.8 million for years 2015-2017) [73].

The authors further analyzed AIS data to record entry and exit timestamps for vessels in defined features within the waterway. We defined 24 features (Appendix C) as geographic reference points, including iron loading docks, steel mills receiving harbors, and connecting channels between waterbodies. Voyage times are calculated based on vessel timestamp within these features. For example, voyage time from Superior, Wisconsin to Burns Harbor, Indiana may be calculated as the difference between entry to Burns Harbor and exit from Superior.

We selected vessels active in the iron ore trade by querying the LPMS data for all ships with more than 30 iron ore voyages over the three-year period. The Soo Locks (which populates LPMS data) is the single passage point for commercial vessels between Lake Superior and the lower lakes, providing a near complete record of ore movement. For each of the vessels (Appendix D), we assembled records for timestamps at each of the defined features. Let A be the original AIS data and let B be the subset of records for vessel i within geographic feature j. Let T be the set of contiguous timestamps representing each voyage of vessel i through feature j and let t be each unique timestamp within T. Equation 4.3 was used to create a subset of timestamps for each vessel within the defined features.

$$B_{ij} = \{(A \cap V_i) \cap G_j \qquad (4.3)$$

We reduced this to a single timestamp (the minimum) for each voyage through the defined features using Equation 4.4. Note that in the application to Great Lakes short sea shipping, it is common for vessels to make multiple calls to the same port, typically 6-9 days apart.

$$\underset{b \in B \subseteq A}{b_{ijt}} := \{(v, g, t_{min}) \mid (v \in V_i) \wedge (g \in G_j) \wedge (t_{min} \in T)\} \qquad (4.4)$$

It was necessary to identify contiguous timestamps which represent a single voyage. For ports and navigation locks, we also recorded exit timestamps (t_{max}) for voyages. We calculated voyage times and fluidity for ports and locks as the time delta between individual vessel timestamps (Equation 4.5) by adapting the approach developed by Kruse et al. which measured vessel time at port and anchorage as the difference between entry and exit timestamps in the AIS [39].

$$\Delta t = t_i - t_{i-1} \qquad (4.5)$$

The full algorithm for collection of voyage time statistics from the AIS is below.

1. Subset A for vessel i. Let $B_i \subseteq A$
2. Subset B_i in geographic feature, G_j. Let $B_{ij} \subseteq B_i$
3. Select t_{min} for each unique date or any consecutive dates, record as vessel i arrival to feature j, b_{ijt}
4. IF feature j is a harbor or lock, select t_{max} for each unique date or any consecutive dates, record as departure from feature j, b_{ijt}
5. Calculate time elapsed between features for each vessel

Maritime Transport Efficiency

The current study takes a data fusion approach which combines vessel load data from the LPMS and voyage times from AIS to assess operational efficiency in ports and transport efficiency along major ore routes. The selection of this dataset enabled a granular analysis which enhances insight to vessel and port efficiency. For example, Shetty and Dwarakish compared correlations between port productivity and indicators such as Turn Around Time and Average Output per Berth-day [147]. In the current study, we apply data fusion to integrate turnaround time and vessel payload to express a more comprehensive indication of performance which may be correlated to productivity. We integrate such metrics on a per vessel basis, as identified in Section 3.2., using vessel voyage information from AIS and payload data from LPMS using the algorithm below. The merged dataset contains timestamp information as well as position, origin, destination, cargo, and tonnage.

1. Subset A for vessel i. Let $B_i \subseteq A$
2. Subset B_i in geographic boundaries (46.5<Lat<46.6, -84.4<Lon<-84.3). Let $C_{i,lock} \subseteq B_i$
3. Select t_{min} for each unique date or any consecutive dates, record as arrival to Soo Locks
4. Select t_{max} for each unique date or any consecutive dates, record as departure to Soo Locks
5. For each arrival and departure date, record Origin, Destination, Cargo and Tonnage from LPMS

Notably, timestamp entries into the LPMS are recorded by human operators and may reflect the time a vessel makes radio contact or when the vessel arrives at the lock [55]. We observed time discrepancies up to 12 hours between LPMS and AIS timestamps. Records used in this study reflect the AIS timestamp which offers the best accuracy. The resultant dataset (b_{ijt}) contains 42,021 records for 30 vessels. It includes information on position, cargo, tonnage, origin-destination, and the time delta from each vessel's previous position in the dataset [73]. This allows the direct calculation of mass per time transport efficiency for bulk iron ore.

For each vessel i and voyage j along a specified route, let x be the vessel load and t be the voyage time. Then transport efficiency along the route η is calculated using Equation 4.6. We compare statistics for transport efficiency along major routes in the waterway for loaded voyages.

$$\eta = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{n}\sum_{j=1}^{n}\frac{x_{ij}}{t_{ij}} \tag{4.6}$$

We assessed the overall efficiency to include roundtrip voyage times which include time spent under ballast. Many iron ore voyages (approx. 85%) originate from a southern port, travel empty under ballast into Lake Superior and return full [138]. For example, the vessels Stewart J Cort and Burns Harbor are 305 m. x 32 m. freighters with predictable service primarily between Superior, Wisconsin and Burns Harbor, Indiana. We calculated average annual efficiency for the vessels which include upbound voyages under ballast using Equation 4.7. Let j represent laden voyage and $j-1$ be time under ballast

$$\eta_i = \frac{1}{n}\sum_{j=1}^{n}\frac{x_{i,j}}{t_{i,j}+t_{i,j-1}} \tag{4.7}$$

We extended this to assess transport efficiency to individual ports where annual average transport efficiency is calculated using Equation 4.8 for all vessel calls, k.

$$\eta_{port} = \frac{\sum x_k * \eta_k}{\sum x_k} \tag{4.8}$$

The average annual port efficiency serves as a useful baseline for performance and offers insight into the relative performances between similar infrastructures.

Results and Discussion

This study produced three types of results. First, we show that vessel capacity in the Great Lakes waterway can be modeled by using a linear relationship with water levels on Lake Michigan-Huron. This allows managers to better account for seasonal changes in water surface levels. Second, we present travel time statistics for bulk carriers on the waterway observed through historical AIS data which extends the body of knowledge from earlier works. Techniques presented here are effective in capturing travel time statistics in a non-linear interconnected system. Finally, we propose a maritime transport efficiency metric that integrates vessel load and time, attainable through data fusion of lock and AIS sources.

Vessel Capacity Modeled by Water Level

The regression of vessel capacity to water surface elevation showed that a simplified linear model serves as a useful proxy to predict vessel load in the waterway. Standardized water surface elevations for each lake serve as model inputs (Figure 4.2) along with the principal components calculated as described. Notably, the period of record used in this analysis is inclusive of record low water levels in 2013 and near-record high water levels in 2017 [40] which makes the model broadly applicable.

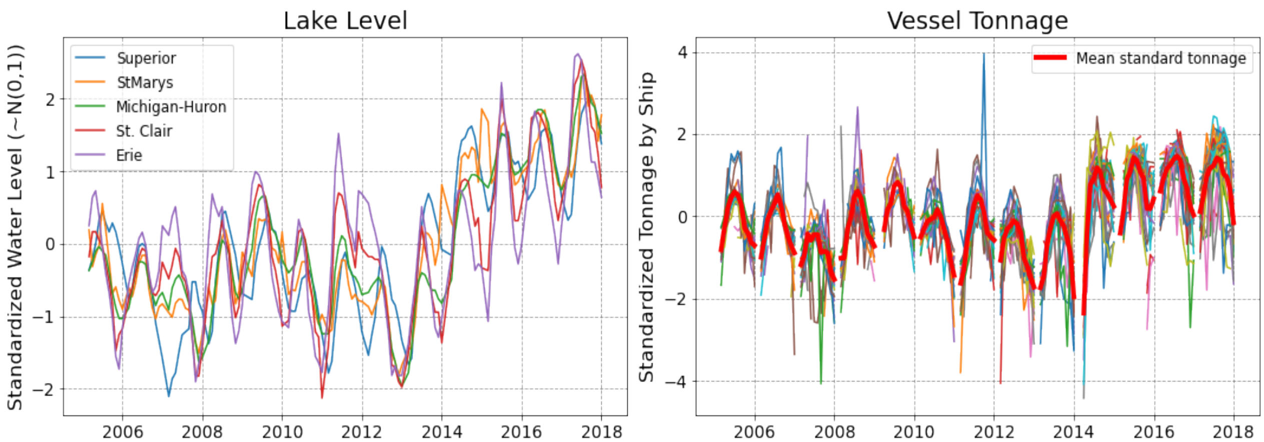

Figure 4.2: Water level anomalies from mean (left) and standardized vessel tonnage (right).

The results from multiple input regressions and PC analysis for water level prediction are shown in Figure 4.3. A GLM model with the single input of Lake Michigan-Huron water levels has similar predictive errors as the Principal Components (PC) analysis and marginally higher error than a robust model with five feature inputs. The various input features produced MSE estimates in the range 0.11-0.35 with the least error observed in the model with all five water

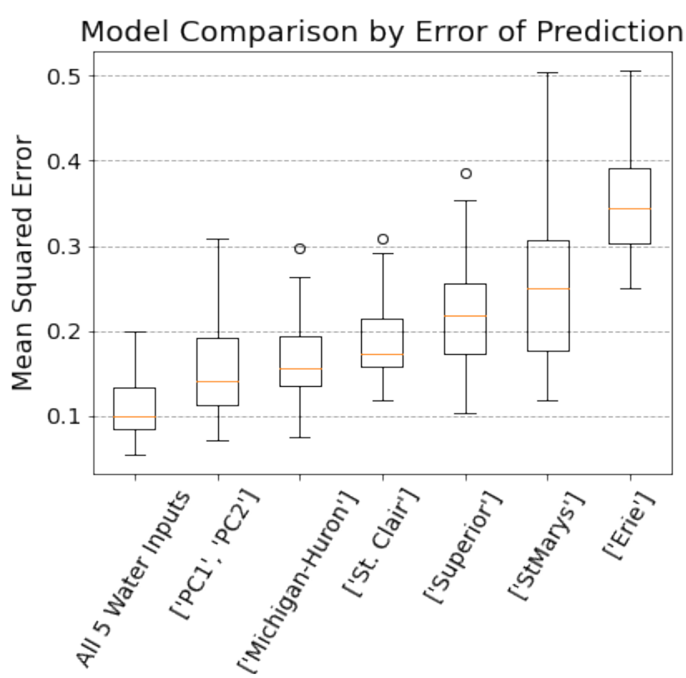

Figure 4.3: Compared predictive accuracy with varied input features. Calculated MSE over 100 iterations.

level inputs. The PC model, which is a mathematical projection accounting for 97% of variance in water levels, produced average error only 0.04 higher. Results from the PC model produced better average predictions than any single waterbody but had a marginally lower error than the regression on Lake Michigan-Huron and greater variance as illustrated in Figure 4.3. A paired t-test did not reject the hypothesis that those two means are equal (H$_o$: $\mu_1 = \mu_2$) when tested with a 95% confidence level. A significant drawback to the PC analysis is difficulty with interpreting the model for practitioners. As a result of this assessment, we elected to compare the 5-feature model to that using only Lake Michigan-Huron water level as input. A robust predictor of vessel capacity given water surface elevations for all 5-features is expressed below:

$$E[Y] = -572.5 + \begin{bmatrix} 1.98 \\ -1.50 \\ 1.15 \\ 2.40 \\ -0.86 \end{bmatrix} * \begin{bmatrix} x_{Superior} \\ x_{St\ Marys} \\ x_{Mich-Hur} \\ x_{St\ Clair} \\ x_{Erie} \end{bmatrix}$$

Predictions based on Lake Michigan-Huron levels offer comparable results.

$$E[Y] = -373.2 + 2.12x_{Mich-Hur}$$

We compared predictive skill for the two models evaluated as the area under the Receiver Operating Characteristic (ROC) curve [148]. The Area Under Curve (AUC) is calculated as

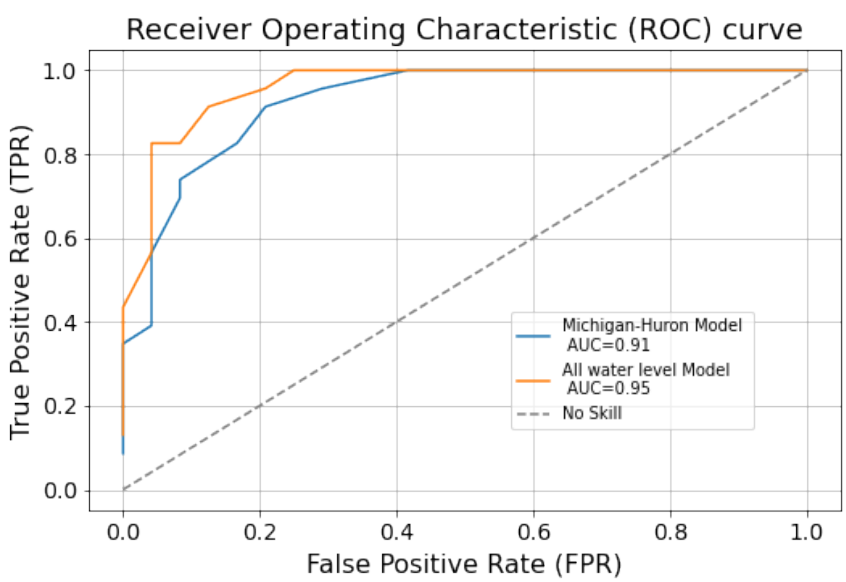

Figure 4.4: ROC comparing predictive skill of the 5-input GLM and linear regression on Lake Michigan-Huron

$\int_0^1 y(x)dx$, where True Positive Rate is $y(x)$ and False Positive Rate is x over all τ. As shown in Figure 4.4, we observed a marginally lower AUC for the Michigan-Huron model (0.91) compared to the more robust predictor (0.95).

Both the five-feature and single input model demonstrate reasonable prediction of vessel load as a function of water surface elevation. This is further illustrated in Figure 4.5 which depicts the actual vessel load compared to a linear prediction based on Lake Michigan-Huron and the 5-feature model. Computational approaches to predict vessel payload can be used to develop risk hedging strategies such as the financial instruments proposed by Meyer et al. [41], [42].

Vessel capacity for each port in the figure generally follows expected trends of increasing load with higher water level, but several ports diverge from expectations under high water scenarios. The model overpredicts expected tonnage (above 176.5 m) to Dearborn and Toledo Harbors as well as traffic to Quebec. Depth restrictions in the series of locks through the Welland Canal, connecting Lake Ontario, control vessel draft on those routes and limits the application of this model to ports on the upper four lakes. Hence, route-specific depth constraints along a ship's voyage are likely part of the explanation, in addition to the deployment of smaller vessel sizes providing service to specific ports. For example, four vessels in the study travel routes to Dearborn, MI and have maximum drafts between 8.2-8.5 meters, which limits additional load capacity when water levels are abnormally high.

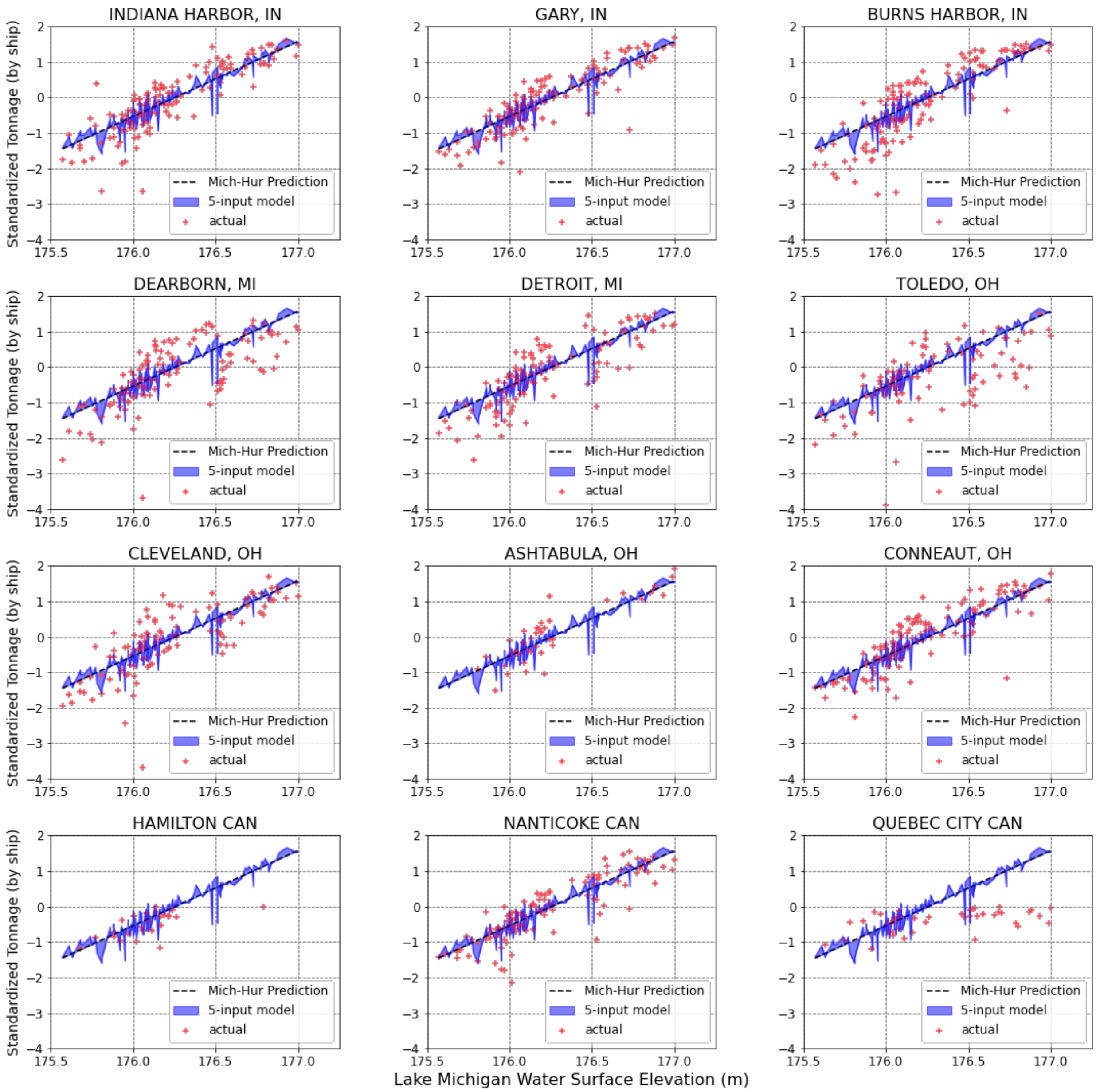

Figure 4.5: Model prediction of iron ore vessel capacity per destination port.

Statistics on Voyage Duration

By observing vessel patterns, we identified key features in the waterway including harbors, locks, and natural bottlenecks in the connecting channels. For example, Figure 4.6 depicts two weeks of traffic in the Duluth-Superior Harbor and clearly shows vessel paths. We defined outer boundaries of geographic features to separate the open water approach and anchorage areas as vessels await entry to harbors and locks as shown in the figure.

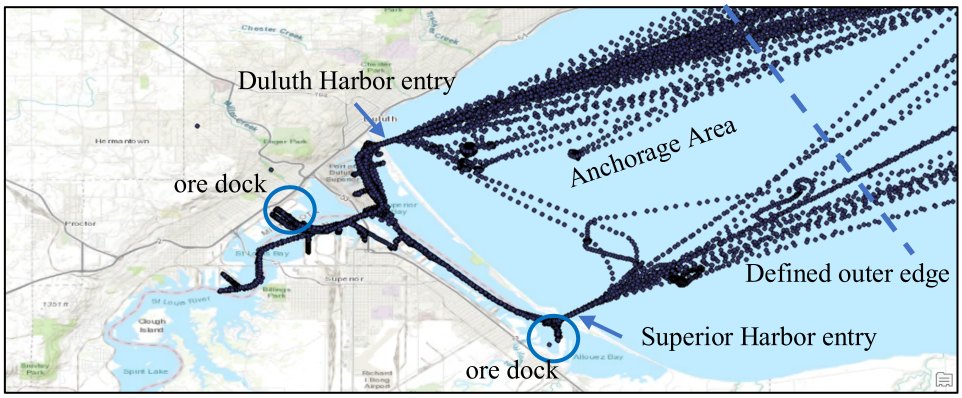

Figure 4.6: Sample AIS data viewed in ArcGIS for Duluth-Superior Harbor.

The defined 24 features ($\mathbf{G_j}$) and their geographic boundaries used to filter the AIS data are listed in Appendix C. The subset of data ($\mathbf{X} \cap \mathbf{G}$) for all features is depicted in Figure 4.7 which illustrates the geographic proximity of iron loading docks, navigation locks, and steel mills which are oriented along the southern coastline.

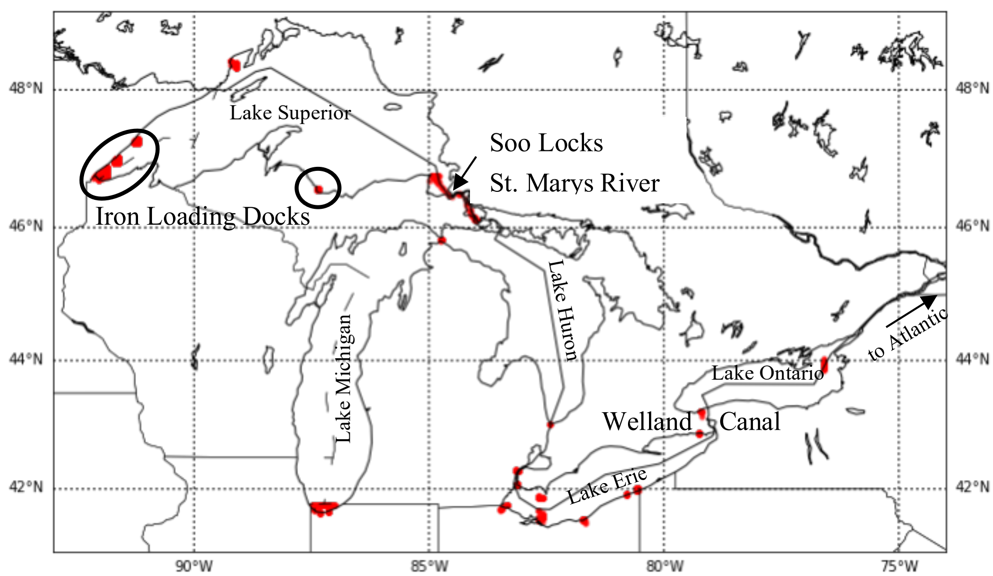

Figure 4.7: Filtered AIS data (red) over author-defined geographic features

Table 4.1 summarizes the 1,551 voyage times this study captured along iron ore routes for the three-year period. These results expand upon earlier work by Mitchell and Scully that reported 325 observations over five routes for a seven-year period (2007-2013) [37], and detailed fluidity metrics for the U.S. inland waterway system by DiJoseph et al. [38]. The data exhibit delays along certain routes, for example, voyages from Duluth to Indiana Harbor and from Presque Isle to Toledo are skewed toward longer times as evidenced by the 75th percentile. This may be caused by mechanical limitations with port-side infrastructure, high vessel traffic resulting in longer wait times, or it may reflect seasonal patterns for transport [149]. This warrants further investigation into harbor-specific operational bottlenecks and waiting times for ships in the harbor discussed later in this section.

Table 4.1: Travel times over major routes for iron ore in the Great Lakes (hours)

Route	Mean	Std	Min	25%	50%	75%	Max	n
Duluth, MN– Indiana Harbor, IN	114.9	102.5	58	64	70	91	495	118
Superior, WI – Burns Harbor, IN	70.9	20.0	57	63	66	70	247	224
Two Harbors, MN – Indiana Harbor	70.0	14.9	57	64	66	70	187	147
Two Harbors, MN – Gary, IN	68.9	28.2	57	61	63	68	474	310
Two Harbors, MN – Detroit, MI	64.0	29.0	38	57	59	63	337	119
Duluth, MN – Detroit, MI	81.7	66.1	56	58	60	62	334	27
Presque Isle, MI – Dearborn, MI	71.8	66.1	37	40	41	55	428	261
Presque Isle, MI – Toledo, OH	124.1	102.9	39	47	61	181	413	90
Silver Bay, MN – Cleveland, OH	87.2	79.2	45	61	65	72	477	131
Two Harbors, MN – Conneaut, OH	71.8	10.7	63	67	69	72	137	124

This analysis offers new insight into performance discrepancies within the waterway, as exemplified for the major routes to southern Lake Michigan. including Indiana Harbor, Burns Harbor, and Gary. The mean travel time for the 800 voyages observed is 76.4 hours, consistent with earlier results by Mitchell and Scully [37]. However, there is a noticeable discrepancy for voyages from Duluth to Indiana Harbor which likely reflects delays specific to vessel traffic at those ports. There is a clear disparity between the mean and median estimators of travel time. As voyages exhibit minimum necessary travel time and long tail delays, median values offer a more accurate estimator of expected duration. Tail events, represented by the 75th percentile in Table 4.1, are useful in identifying inefficiencies along specific routes (e.g., Duluth to Indiana

Harbor and Presque Isle to Toledo), which suggest more frequent delays.

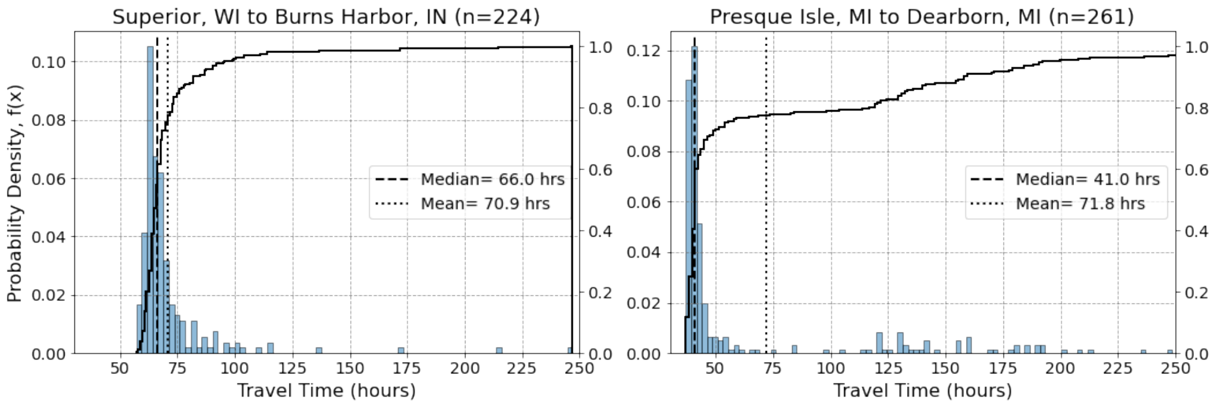

Figure 4.8: Travel time distributions to Burns Harbor (left) and Dearborn (right).

The profiles for voyage durations in Figure 4.8 illustrate the effect that prominent tail events have along some routes and the disparity between median and mean estimators. For the two routes shown, we analyzed eleven unique vessels carrying 14.9 million tons to Burns Harbor and four vessels carrying 7.6 million tons to Dearborn. Two vessels, M/V Stewart J Cort and M/V Burns Harbor (described in sections 3.1 and 3.3) accounted for 91% of voyages and 92% of tonnage delivered to Burns Harbor. Consistent and predictable patterns between the two vessels and servicing ports likely minimizes disruptions or delays. Tail events are more common for vessels accessing the port in Dearborn which requires navigation of 5 kilometers up a restrictive river, a possible cause for the delays. A comparison of transit times, performance, and predictability is useful to identify bottlenecks in the waterway or to inform fleet deployment strategies. These techniques are broadly applicable to waterways worldwide and offer insights to performance that informs operational management decisions.

Travel times on open water segments, defined between connecting channels, harbor, and lock infrastructure, vary with weather and traffic patterns and are relatively consistent with long tails reflecting adverse conditions such as heavy ice [150]. The current study applies detailed AIS processing to derive fluidity statistics throughout the Great Lakes waterway and expands on published statistics [37], [38]. Travel time statistics for open water travel are summarized in Table 4.2. This analysis captured more than 2,000 voyages in every part of the waterway over the three-year period.

Table 4.2: Vessel travel times (hours)

Segment	Mean	Std	Min	25%	50%	75%	Max	n
Duluth/Sup – Whitefish Bay	25.4	5.0	13.7	23.5	24.6	25.8	101.6	1,487
Two Harbors – Whitefish Bay	24.6	6.9	19.5	22.1	23.2	24.6	145.4	1,377
Silver Bay – Whitefish Bay	25.0	8.0	19.2	21.5	22.8	25.3	95.8	454
Thunder Bay – Whitefish Bay	17.7	3.5	14.8	16.3	16.9	17.5	35.8	60
Presque Isle – Whitefish Bay	9.8	4.1	7.6	8.2	8.6	10.0	55.8	207
Mackinaw Str. – S. Lk Michigan	26.3	7.1	19.8	24.1	25.2	26.6	172.8	989
St Marys R. – S. Lk. Huron	18.5	6.9	14.3	16.3	17.1	18.2	150.3	1,884
Lake Erie	15.3	6.0	12.3	13.4	14.1	14.9	78.7	221
Lake Ontario	18.4	22.2	9.5	10.6	11.4	13.4	159.9	164
Lake St Clair and Rivers	10.6	8.5	6.6	7.3	7.8	8.9	123.8	1,296
St Marys River incl Lock	10.7	7.7	4.2	8.1	8.9	10.4	161.5	3,892
Soo Locks	2.8	3.0	0.18	1.8	2.3	2.8	45.3	3,792

Open water travel on all waterbodies in the system have a similar distribution as shown in representative histograms (Figure 4.8). In consideration of long tails events, the median is more representative of the expectant travel time than the mean and has nominal improvement in some of the open water segments but represents a 20% difference in the estimator for connecting channels.

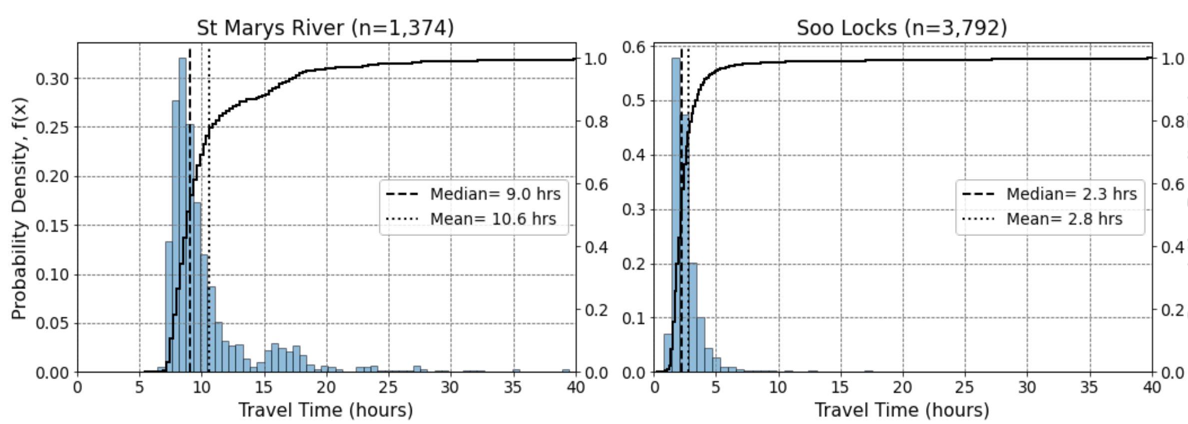

Figure 4.9: Travel time distribution for vessel voyages through the St Marys River (left) and the Soo Locks (right).

Further consideration is given to operation and efficiency transiting the Soo Locks. The right side of Figure 4.9 shows the time vessels physically spend occupying the navigation lock chamber or being tied-up along adjacent piers. Note that these records are inclusive of all vessels in the AIS data set, which contains tour boats, tugs, and other vessels not necessarily transiting the full waterway. Lock times of as little as 20 minutes are possible but seldom occur when ships enter directly into the chamber without delay. Extremely long lock times are often resultant of winter conditions when heavy ice floes accompany vessel traffic and must first be cleared from the lock [55]. Delays associated with the lock are observed when vessels are tied-off at the pier or delayed from reduced speed on approach. Vessels approaching upbound transit the 120 km St Marys River, and those in the down bound direction navigate 65 km through Whitefish Bay. It is common practice for vessels to adjust speed and coordinate arrival time to the navigation lock based on expected availability [149]. These speed adjustments are evident in the left side of Figure 4.9 which exhibits a bimodality and suggests delays of 7-10 hours. We interpret this to indicate that vessels expecting wait times of 5 hours or more will reduce speeds. This suggests that detailed evaluation of lock performance requires consideration of transit times through the entire connecting channel. This lock delay assessment is beyond the scope of this study.

Table 4.3: Vessel time spent in harbor and at the dock (hours)

Segment	Mean	Std	Min	25%	50%	75%	Max	n
Duluth-Superior Harbor	29.1	15.5	9.1	19.0	25.6	34.3	141.2	636
Duluth Ore Dock	16.9	8.2	5.8	11.5	14.8	20.7	52.0	307
Superior Ore Dock	16.9	8.4	5.8	11.5	14.8	20.2	80.4	421
Toledo Harbor	19.3	17.3	7.2	9.5	12.5	19.1	119.7	230
Toledo Ore Dock	7.7	2.0	5.1	6.3	7.1	8.6	14.8	170
Southern Lake Michigan	28.2	43.6	5.7	13.0	18.1	25.2	472.8	980
Indiana Harbor Dock	17.8	10.7	5.1	10.8	14.5	20.8	98.8	354
Gary Dock	13.4	4.4	5.0	10.9	12.9	14.8	49.4	359
Burns Harbor Dock	27.2	13.7	5.0	21.2	23.5	29.0	118.0	264

To investigate port performance, we separately assessed vessel time spent in harbor and that spent at berth to quantify delays attributable to the port. As shown in Table 4.3, ships spend nearly as much time waiting or approaching a dock as they do actively loading/unloading. Recall, that this study reports a higher incidence of tail events for voyages between Duluth – Indiana Harbor as compared to Superior – Burns Harbor despite virtually identical voyage routes, suggesting inefficiency at the ports. However, as shown in Table 4.3, Duluth exhibits nearly identical performance to Superior and vessel time in Indiana Harbor is 40% lower than for Burns Harbor. This suggests that delays for Duluth harbor are likely attributable to navigation into the harbor which traverses a vehicle draw bridge, rather than to delays resulting from port-side infrastructure. Toledo Harbor exhibits notably long times in the harbor without being active at the dock. This is likely due to the 20 km. approach channel which is dredged to maintain navigable depths in the shallow portion of the bay. Restricted navigability into the harbor manifests in vessel delays similar to those observed in Dearborn.

Excessive delays may result in increased costs, unnecessary fuel consumption and emissions, or restrictions to available freight supply. Assemblage of statistics like those reported here provide a reference for managers to assess performance in near real-time. This has applicability to port and harbor managers for track performance. To fully understand these impacts we need to consider vessel size and tonnage delivered.

Maritime Transport Efficiency

Integrated efficiency metrics provide a data-driven means by which operations managers can inform fleet deployment in near real-time. Transport efficiency for all routes in this study ranged from 200 to 1,000 tons per hour (Figure 4.10), heavily influenced by the size of vessels, and the route or port serviced. For example, ports such as Cleveland, Toledo, and Dearborn are primarily serviced by smaller vessels with a capacity of less than 35,000 tons. Others, such as Burns Harbor, are almost exclusively serviced by the largest freighters on the waterway with payloads in excess of 65,000 tons. While this offers some insight to efficiency, approximately 85% of vessels travel upbound under ballast without cargo. A more accurate reflection of efficiency in this short sea shipping context requires analysis roundtrip times. For example, this may drive different operations decisions to maximize freight volume, and therefore revenue, under spot rates or minimization of operating costs under time or bareboat charter [151].

We illustrate maritime transport efficiencies for two vessels with equivalent length and width dimensions travelling the same route. Despite the predictability in voyage route, transport efficiency is highly variable over time (Figure 4.11). The left side of the figure depicts each ship's tonnage and roundtrip time per voyage and illustrates different payloads due to maximum

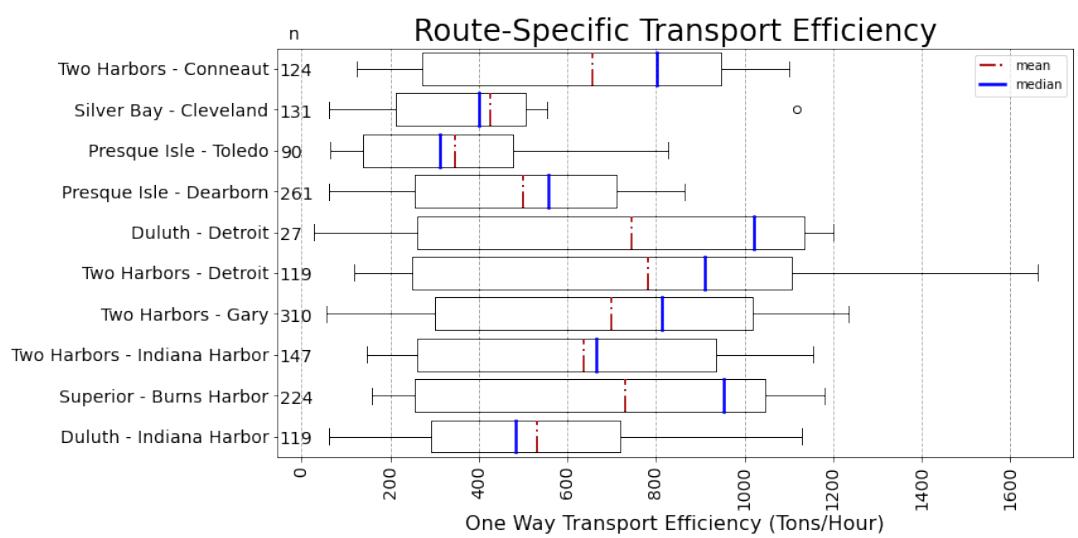

Figure 4.10: Route-specific transport efficiency of iron ore (tons/ship-hr.) for one-way travel

draft of the vessels (8.5m and 9.75m, respectively). Whereas water levels in the period evaluated were higher than normal, vessel draft and load were maximized by vessel 1 (8.5m draft) but remained seasonally variable for vessel 2. The calculated efficiency for each voyage is depicted on the right side of the figure, along with average annual rates for each vessel. Efficiency for vessel 1 decreased over time despite very consistent loads, being negatively impacted by longer voyage times. In contrast, vessel 2 demonstrates a consistent mean delivery rate despite variable loads. This is illustrative of the importance of vessel load and voyage time in assessing transport efficiency. Vessel-specific analyses are useful to establish an operational baseline to assist in monitoring vessel or fleet performance in near real-time.

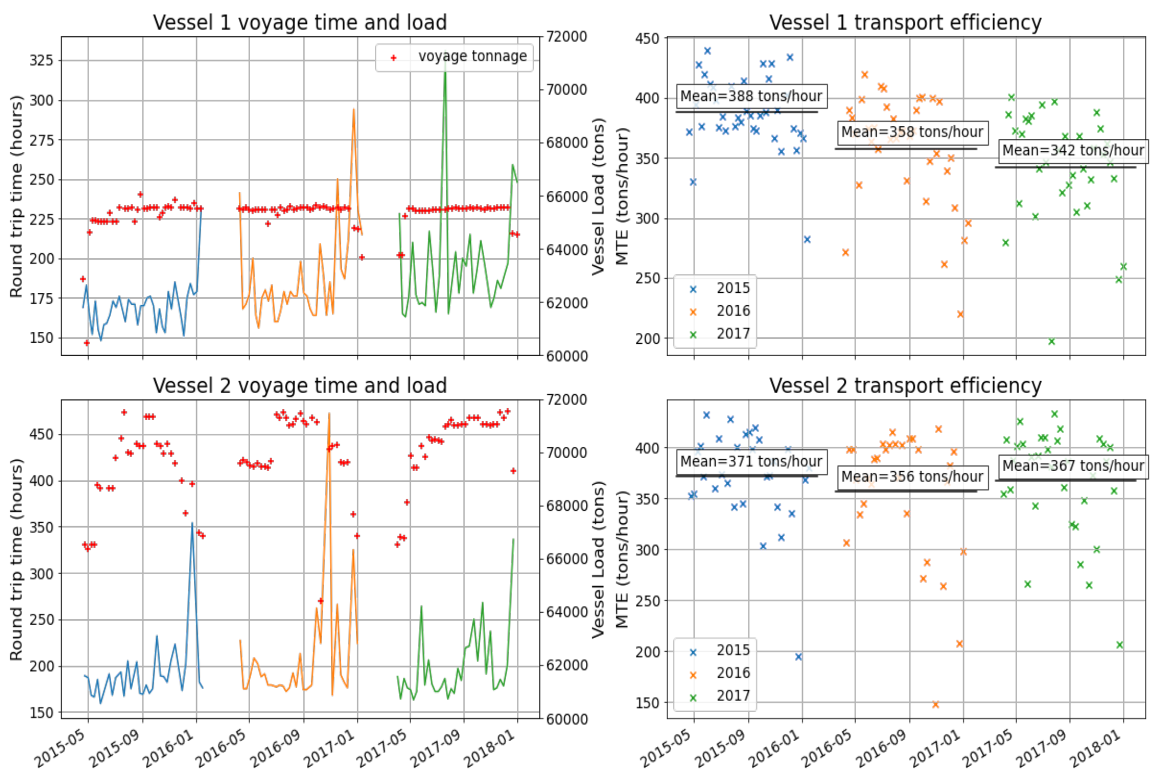

Figure 4.11: Payload and roundtrip travel time (left) and transport efficiency expressed as tons/hour (right). Calculated for two 305 m x 32 m vessels with 8.5m (28') and 9.75m (32') draft travelling the same voyage route.

The proposed efficiency metric can be applied collectively to a fleet of vessels or to individual harbors as shown in Figure 4.12. Data points in the figure represent efficiency for complete voyages with size reflecting tonnage carried. As calculated using Equation 4.8, the annual efficiency reflects the weighted average for each harbor. Naturally, smaller vessels have a lower efficiency on a per ton basis which is reflected in the performance metric.

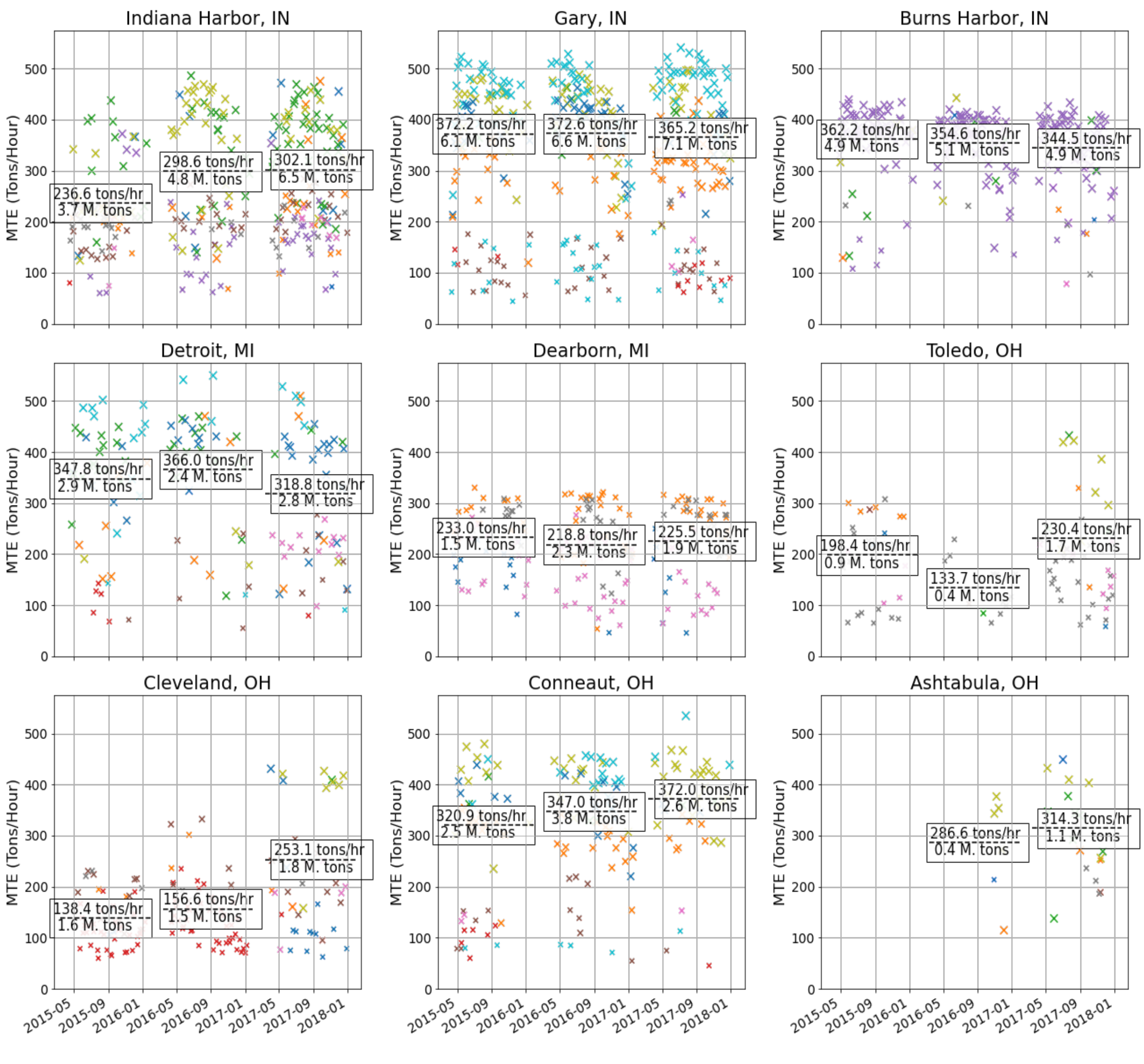

Figure 4.12: MTE of iron ore to Great Lakes harbors (2015-2017)

Transport efficiency reflects the aggregate performance of harbor infrastructure, vessel transit time, as well as the distribution of ship size and type providing service to each harbor. For example, the MTE to ports along Lake Erie were improved by increasing the fraction of larger vessels servicing them (in 2017), when others saw a reduced efficiency likely due to longer roundtrip durations (Figure 4.12). Resource managers require metrics to guide commitment of finite resources that leverage the most current and comprehensive information [152], [153]. This analysis of transport efficiency is useful to harbor managers as well as shipping companies and freight consumers to increase predictability of logistics time and costs. Particularly in the context of short sea shipping, this approach is useful to estimate delivery rates, which is deterministic of available supply and should inform freight pricing for both long-term contracts and on the spot market [154]. Future studies that incorporate freight costs, may be used to assess the impact of capital expenditure in harbors and port-side infrastructure.

Conclusions

This study presents a fusion technique for AIS and lock data that yields new insights into maritime transport efficiency metrics which are directly applicable to short sea shipping. This approach is readily adaptable to inland waterway or coastal harbors where vessel draft or load data is available. Where water levels are deterministic of vessel capacity, as in the Great Lakes, payloads are predictable given measured water level and historical ship performance. We present a linear model for vessel load based on water surface elevation for iron ore carriers in the Great Lakes. When integrated with travel times this model provides a means by which to estimate maritime transport efficiency. Deviations from expected transport efficiency are useful to operations managers and can inform decisions on fleet deployment or risk transfer mechanisms in near real-time. When applied to harbors, this metric can reveal limitations in the opportunity costs associated with port performance and infrastructure deficiencies. This offers operations managers better information to allocate funding for projects that yield the greatest improvement to system performance. This is particularly relevant to short sea shipping operations where improvements to efficiency have a concentrated benefit in the system. Future work will explore how financial value can be realized through improvements to efficiency that reduce freight costs or optimize return on operations and maintenance expenditures.

CHAPTER 5

Can a Port User Fee Financing Model for Harbor Maintenance Reduce Costs for Freight Consumers?

Introduction

Maritime transportation is the most cost effective and environmentally friendly means of moving freight, rendering ports and waterway infrastructure essential to trade. American ports annually carry more than $5 trillion in goods worth 26% of the country's GDP [10], [15]. Despite its importance, there is an investment gap of $32 billion for landside projects and a $28 billion dredging backlog which have resulted in inefficiency, delay, and lost revenues for waterway users [15]. This has prompted initiatives to improve allocation of public funds and explore alternative financing mechanisms that may accelerate and improve funding decisions [18].

Freight consumers assume the cost of harbor maintenance activities indirectly through HMT payments and receive a savings return on those payments resulting from decreased transportation costs and improved efficiency. The correlation between freight costs and efficiency of vessel operations is well documented [154], [155]. Wilmsmeier et al. noted freight rate reductions resulting from economies of scale from larger ship volumes, irrespective of other determinants of transportation costs, particularly for bulk commodities [156]. Efficient shipping via larger vessels requires deliberate maintenance of navigable depths in channels and harbors to maximize the utilization of cargo capacity. Reduced time in port also improves efficiency as well as freight supply over time which results from additional vessel loads over a navigation season [139].

However, there is an existing gap in quantifying the efficiency gained from specific investments and the expected reduction in transportation costs which could inform modern funding mechanism for this infrastructure. This study applied new data statistics and Monte Carlo simulation modeling to separately investigate landside infrastructure and maintenance dredging to quantify the impact of investment decisions.

Landside Infrastructure

Landside port infrastructure is generally funded through private owners or port authorities and decisions to upgrade require a business case. For example, decisions to upgrade cranes at a container terminal are based on projected increased revenue that would result from improved throughput [156]. For bulk commodity terminals, which are more common in the Great Lakes, landside infrastructure affects the rate that vessels may load or unload cargo. Bulk carriers in the Great Lakes are equipped with internal machinery and articulating booms that are self-unloading and can deliver cargo directly onto a dock or hopper [137]. For example, Burns Harbor is an integrated steel mill situated along the southern shoreline of Lake Michigan. That port receives iron ore via a stationary hopper from which commodities are belted to plant storage facilities at a maximum rate of 5,000 tons per hour (TPH) [157]. This places restrictive limits on most bulk carriers which can unload cargo at twice that rate (10,000 TPH).

Landside infrastructure restricting the rate of loading or unloading negatively impacts vessel turnaround time, and associated freight supply. This is amplified in the short sea shipping routes of the Great Lakes; however, the quantified effect is not well understood. We investigated the financial return that could be realized from reduced freight costs to Burns Harbor. This privately-owned facility has an annual production capacity of 5 million tons of steel product and receives 4.5 to 5.5 million tons of taconite each year [63]. Historically, 90 percent of this freight movement was handled by two vessels, the M/V Stewart J Cort and M/V Burns Harbor. The Cort operates on a "bareboat charter" lease agreement under which the vessel exclusively makes roundtrips between Superior, WI and Burns Harbor, IN to deliver as much taconite possible in a navigation season [142]. The M/V Burns Harbor, owned and operated by American Steamship, follows a similar pattern as observed through data analytics described in Chapter 4 [73]. Both vessels are 305 meters (1000 ft.) long and 32 meters (105 ft.) wide. However, the Cort has a maximum draft of 8.5 meters (27'11") and maximum capacity of 58,000 tons while the Burn Harbor has a listed capacity of 80,900 tons at its constructed draft of 10.4 meters (34'1") [157]. As observed in Chapter 4, these vessels typically make between 30 and 40 roundtrips in a navigation season dependent on weather conditions and service times at the port. Reduced time in port would maximize potential roundtrips and, therefore, the available freight supply for vessels delivering bulk commodities.

Research Question: What is the expected reduction of transportation costs resulting from unrestricted vessel unloading at Burns Harbor?

Maintenance Dredging

The cost of dredging in the United States has increased significantly in recent years which calls into question the long-term sustainability of existing funding mechanisms. The U.S. Army Corps of Engineers (USACE) is responsible for managing the nation's navigation infrastructure and receives annual appropriations of approximately $1 billion for maintenance dredging [127]. Since 1990, the average unit cost of dredging in the U.S. has increased approximately 250 percent (adjusted for inflation), which places additional strain on limited financial resources

[158], [159]. Several factors contribute to the increased costs, including dredging methods, distance to placement sites, restrictive time windows, and project size [159], [160]. Improvement of waterway infrastructure investment and maximization of benefits from public funding decisions is impeded by a knowledge gap on the correspondence between maintenance spending and maritime transportation costs.

Decisions to allocate funds for the improvement and maintenance of harbor infrastructure are based on estimates to achieve design dimensions and do not necessarily reflect variable demand or performance. Policymakers use benefit-to-cost ratios (BCR) to compare the expected benefits (transportation cost savings) to the cost of dredging when determining appropriate design dimensions for navigation channels [161]. Channel dimensions (including depth) are passed into law under a project authorization which becomes the basis for maintenance and funding needs. The allocation of O&M funds for channel maintenance requires Congressional appropriation from previous HMT collections and generally does not consider variations in project use (i.e. demand variability) which may impact the annual return-on-value for dredging [43]. In the current model, dredging is always desired by shippers irrespective of demand level because reduced depths negatively impact vessel payload and efficiency, but not HMT payments determined by the value of goods. Alternative funding mechanisms for harbors that maximize benefits from public funding decisions are impeded by a knowledge gap on the correspondence between maintenance dredging spending and maritime transportation costs.

We hypothesize that maintenance funding allocations in the Great Lakes waterway can be improved by applying expected Maritime Transport Efficiency (MTE) metrics for bulk commodities. This metric reflects the average rate [mass/time] of maritime transport and has been used to compare shipping routes and port activities in the Great Lakes [162]. The integration of MTE with shipping demand and fuel price provides a means by which to assess transportation cost savings in comparison with maintenance dredging expenditures. In the Great Lakes, the value gained from reduced transportation costs from harbor dredging varies with natural occurring water level and vessel traffic. Capital improvements over the life of the Great Lakes system have deepened the most restrictive segments to a nominal depth of 8.2 meters (27 feet), though functional depths change with seasonal variations in water surface levels [55]. Costs to transport goods on the Great Lakes waterway depend both on maintenance dredging as well as natural water surface levels that exhibit both annual and seasonal variations. Low water levels restrict vessel draft which results in light-loading, reduced revenue for shipping companies, and increased cost to move goods [41]. Conversely, water levels above normal may offer opportunities to amend dredging practices to reduce the total costs of using and maintaining the waterway. However, current allocation of funds to harbor maintenance projects assumes a depth of channel maintenance irrespective of variations in water levels. The integration of MTE with shipping demand and fuel price provides a means by which to assess transportation cost savings in comparison with maintenance dredging expenditures.

Meyer et al. developed hydrology-based hedging instruments to insulate shippers from extreme conditions in the Great Lakes and evaluated tradeoffs between financial (insurance) and physical (dredging) risk mitigations [41], [42]. This issue was most pronounced from 2005-2013 when historic low water levels coincided with a dredging backlog [40]. Legislation in consideration as of this writing would increase minimum spending to 12% of national allocations to Great Lakes projects [163]. This study considers the cost impact to freight consumers under abnormally high-water levels that naturally allow deeper drafts. Decisions to delay or forego dredging have potential to reduce total costs which we investigate for Toledo, OH.

Toledo Harbor, in northwest Ohio, is situated where the Maumee River empties into Lake Erie. Maumee Bay, in western Lake Erie, is naturally shallow and requires maintenance dredging to allow vessels access to the harbor. The federally authorized project includes seven miles of channel within the Maumee River and an 18-mile approach through Maumee Bay maintained at 8.2 and 8.5 meters depth, respectively [164]. Typical dredging requirements are 800,000 cubic yards per annum, the highest in the Great Lakes, and contracted separately for the inner and outer harbor areas which have distinct physical and chemical profiles [165]. Funding for harbor dredging has been between $4.7 and $7.6 million since 2009 [166]. Primary commodities moving through the port include iron ore, grain, and cement with tonnage ranging from 8.4 to 11.3 million tons since 2009 [167].

Research Question: *Can flexible dredging expenditure reduce the total cost of transportation and maintenance for Great Lakes harbors?*

Funding Harbor Maintenance

The maintenance of America's harbors is funded through a Harbor Maintenance Tax (HMT) which has been the subject of debate since its inception. In 1986 the U.S. Congress established the *ad valorem* fee which collected 0.04% of cargo value [47], [168]. Congress increased the tax to 0.125% in 1990 with intent to cover 100% of O&M costs and relieve the burden of maintenance costs from the General Treasury [47], [169]. A value-based fee is unique to the United States. Other countries fund harbor maintenance from the General Treasury or directly through port user fees [44], [45]. Since the HMT is value-based, the U.S. Supreme Court has ruled it a tax rather than a user fee and determined it in violation of the Export Clause of the Constitution [46]. As a result of this decision, since 1998 the tax is collected on imported goods and domestic shipments but excludes U.S. exports. The collection of taxes applied only to imports has been the subject of consultation under the General Agreement on Tariffs and Trade (GATT) which today is governed by the World Trade Organization (WTO) and remains a contentious issue for international trade [48], [170].

There have been several recommendations to amend, replace, or eliminate the HMT. The Clinton administration pursued several alternatives including replacement with a user fee and a return to expenditures from the General Treasury, but neither was taken up by the 106th Congress [47]. Kumar proposed a user fee structure based on tonnage, vessel draft, and time-in-harbor which would pass the constitutionality test and better adhere to principles set forth in the GATT [45]. Skalberg noted several persisting problems with the tax including its disproportionate collection on high-value goods and the inequity in regional maintenance requirements [171]. For example, naturally deep ports with high-value import cargo generate much of the HMT revenue but require little funding for maintenance [163]. Other systems, like the Great Lakes waterway, have higher maintenance needs but handle relatively low-value bulk commodities, such as iron ore and coal [137]. McIntosh and Skalberg expanded on the user fee model originally proposed by Kumar and developed weights for cost factors that would most equitably replace the tax [45], [49]. They later investigated various alternatives including a fee based on tonnage alone, abolishment with expense reverting back to the General Treasury, and replacement with a fuel excise tax [48]. Each option necessarily shifts the burden of payment and would likely have divided opposition and endorsement. Sentiment favors a user fee model based on objective data reflecting maintenance needs, but data availability to support such a model have been limited to date [49].

Today, big data and sensor technology provide improved insight to vessel and port usage that could drive a modern and equitable user fee for harbor infrastructure. The comprehensive use of AIS in commercial and passenger vessels provides a means by which fund managers can assess fees based on actual vessel draft and time in port. This would have the added benefit of informing harbor deepening decisions. In the current model, funds from the HMTF are limited to maintenance activities. Harbor improvement projects, such as channel deepening, are funded from the general treasury at a maximum federal share of 65 percent for harbors up to 15.25 meters (50 ft.) and 40 percent for deeper projects. The remainder of funds are provided by a project sponsor. A recent series of harbor deepening decisions faced the U.S. after the Panama Canal Expansion gave way to increased vessel sizes [172]. Charleston Harbor is the latest major deepening project, but access to the harbor has lagged Panamax completion by more than five years.

The Charleston Harbor is managed by the South Carolina port authority and is scheduled to complete a deepening project increasing the maximum depth from 13.7 to 15.9 meters (45 to 52 ft.) [173]. In 2012 the South Carolina General Assembly set aside $300 million for the non-federal project contribution [174]. The project was authorized by Congress in 2015 and first received federal funds in 2017. Federal allocations in successive years from 2017 to 2020 were $ 17.5M, $49M, $41.4M, and $138M [174]. Dredging began in 2018 and is scheduled to complete in 2021, nine years after state funds were available and five years following the opening of the third locks of the Panama Canal [172]. The prolonged appropriations process resulted in years of inaccessibility by post-Panamax vessels and millions of dollars in lost opportunity costs. We discuss the potential for a harbor user fee model to accelerate capital outlay for improvement projects using increased fees offsetting project finance offered through a Harbor Maintenance Bank.

Methods

This study applied a series of Monte Carlo simulations using detailed vessel statistics reported in Chapter 4 to determine changes in shipping efficiency. Expected Maritime Transportation Efficiency ($E[\psi]$) serves as a proxy to value transportation costs. In this section we first describe the Efficiency Simulation Model. Then we apply it to assumed conditions changes at Burns Harbor and Toledo Harbor, described separately in the following sections.

Efficiency Simulation Model

We determined expected Maritime Transportation Efficiency ($E[\psi]$) using Monte Carlo simulation integrating estimates for vessel load and voyage duration. In Chapter 4 we showed that vessel capacity in the Great Lakes waterway is effectively predicted from water surface elevations in Lake Michigan-Huron, central to the system. Historical monthly change in water level, available from 1918 to present, were used as inputs to the simulation model [40]. Monthly changes were calculated and were used to develop empirical cumulative distribution functions, F(x), for each month. The simulation begins with a specified March water level for Lake Michigan-Huron. Changes in water level for subsequent months were randomly generated by taking the inverse transform of that month's density function from a uniform variate (Equation 5.1) and monthly levels calculated using Equation 5.2.

$$\Delta H = F'(u_i) \quad where\ u_i \sim U(0,1) \tag{5.1}$$

$$H_t = H_{t-1} + \Delta H \tag{5.2}$$

We modeled normalized vessel capacity using the empirical regression (Equation 5.3) developed in the previous Chapter. Individual vessel load was calculated using Equation 5.4 and the mean and standard deviation of that vessel's performance over the period 2005-2018 was based on USACE data [73]. Then $V_{i,t}$ is the modeled payload for vessel i in month t. Appendix A includes a table of the vessels included in this simulation and their constructed dimensions.

$$Z_t = 2.12 * H_t - 373.2 \tag{5.3}$$

$$V_{i,t} = \begin{cases} Z_t * \sigma_i + \mu_i & where\ Max\ Draft \leq H_t \\ V_{i,max} & where\ Max\ Draft > H_t \end{cases} \tag{5.4}$$

Voyage times also affect vessel efficiency and available supply over time. Vessels in the Great Lakes often make round trips between a small set of ports. This is particularly true for iron ore carriers in the Great Lakes [138]. The impact of sailing time and time at port has a significant cumulative effect on vessel freight supply in short sea shipping [139]. The number of possible voyages within a shipping season, along with vessel payload, are deterministic of freight supply. We modeled the voyage times as the sum of random variates for distinct waterway segments as follows. A segment may be an open waterbody, port, or connecting channel between lakes. We developed cumulative density functions from travel time statistics in each waterway segment and generated random variates for each segment to model travel times of a vessel's route (Equation 5.5). Voyage times were then calculated as the sum of segments along a specified route with n segments (Equation 5.6). We assumed continuous operation throughout a navigation season, defined as 25th of March to 15th of January in the Great Lakes [55]. The number of voyages (m) within a navigation season, and each month therein, is finally determined by a vessel's cumulative voyage time.

$$t_{segment} = F^{-1}_{segment}(u) \quad where\ u \sim U(0,1) \tag{5.5}$$

$$t_{voyage} = \sum_{i=1}^{n} t_{i,segment} \tag{5.6}$$

The annual transport efficiency for individual bulk carriers (Equation 5.7) is calculated as the average of voyages payload per transit time and has units of mass per time.

$$\psi_i = \frac{1}{m}\sum_{j=1}^{m}\frac{V_j}{t_{j,voyage}} \tag{5.7}$$

Variance Reduction

For the largest vessels on the Great Lakes, the model produced estimates of annual efficiency in the range of 350±40 tons per hour for ore carriers. We specified an acceptable level of accuracy of +/- 1% and applied validation techniques first developed by Balci and Sargent to determine the minimum model replications (N) to achieve it [175]. Let $\bar{x}$ be the mean of N simulation results with variance S^2. For a 95% confidence level (a=0.05) the confidence interval (CI) is calculated as $CI = \bar{x} \pm t_{N-1,\,1-\frac{\alpha}{2}} * \sqrt{S^2/N}$. We found that a sample size of 400 replications achieved the specified level of accuracy for each set of inputs and reduced computational time from 26 hours (for 10,000 iterations) to 2 hours. We calculated the transport efficiency for each vessel (i) as the mean over 400 replications (Equation 5.8).

$$E[\psi_i] = \frac{1}{400}\sum_{j=1}^{400}\left(\frac{1}{m}\sum_{j=1}^{m}\frac{V_j}{t_{j,voyage}}\right) \tag{5.8}$$

Note that m varies for each replication based on the cumulative voyage time within the navigation season. A representative simulation for two vessels is shown in Appendix F (Figure F.4). The model calculates expected efficiency for individual vessels using March water depths and travel time statistics as described earlier.

To assess the overall transport efficiency to the various ports, we apply a weighting to each of the vessels based on percentage of total tonnage delivered to these ports over a three-year period (2015-2017). The expected maritime transport efficiency for ports ($E[\psi]$) is calculated using Equation 5.9, where $E[\psi_i]$ is the simulated expected efficiency for vessel i and $V_{i,j}$ is the observed payload for vessel i on voyage j.

$$E[\psi] = \sum_{i=1}^{n} \frac{\sum_{j=1}^{m} V_{i,j}}{\sum_{i=1}^{n} \sum_{j=1}^{m} V_{i,j}} E[\psi_i] \tag{5.9}$$

Expected efficiency under varied simulated conditions are used to assess changes in Burns Harbor and Toledo Harbor and associated changes to freight costs as described below.

Landside Investment at Burns Harbor

To investigate transportation cost savings from landside port investment at Burns Harbor we applied the weighted port efficiency metric calculated using Equation 5.9 to estimate the change in transportation costs. We assess efficiency for two initial conditions (H_0) of 176.0m and 176.6m which represent the 25th and 75th percentile for Lake Michigan-Huron, respectively [176]. The simulation for Burns Harbor includes 16 unique vessels (n=16). Voyage times were calculated for each vessel using empirical cumulative distributions for waterway segments along the route between Superior, WI and Burn Harbor, IN. We compared time-in-port for two adjacent harbors owned by a single firm. Burns Harbor exhibited a median time-in -port of 23.5 hours whereas Indiana Harbor was 14.5 hours as described in Chapter 4. Indiana Harbor is able to receive material directly onto its dock which allows vessels to unload at an unrestricted rate [157]. We assume that replacement of the existing conveyor belt at Burns Harbor would remove rate restrictions, and vessels servicing that port would exhibit a time distribution like that of Indiana Harbor. Other time segments in the route remain unchanged between simulation runs.

We validated model consistency over 20 iterations, each calculated as the mean of 400 repetitions as described for Equation 5.8. We tested the difference between means using a paired t-test [177]. Under a null hypothesis that the true mean difference is zero, we calculated a two sided p-value using Python's Scipy Stats module [178]. Statistical significance was assessed at the 90% level and we used a Bonferroni corrected significance level of 0.005 for m=20 pairs ($\alpha_{pw} = {}^{\alpha}/_{m}$) [179].

We calculated relative transportation costs from the change in ship-hours necessary to meet a specified demand. Let T be required ship hours to deliver demand D, calculated as $T = D / E[\psi]$. Freight pricing is negotiated for long-term contracts and fuel costs are reimbursed by the consumer [149]. That is, a change in expected ship-hours will not directly affect freight price but will impact fuel consumption and liability to the freight consumer. Fuel costs are calculated as $C = p_f kT$ where p_f is fuel price (US $ / ton) and k is the fuel consumption rate for vessels. The rate of fuel consumption (k) is dependent on traveling speed and engine rating, which varies significantly from ship to ship. We estimate fuel consumption rates to be 62 and 48 tons per day which corresponds to estimates for laden and ballast bulk carriers, respectively, with a cruising speed of 13 knots [180]. We assume fuel price to be $300 +/- 100 per ton which is reflective of normal market volatility [181].

Flexible Dredging Practices in Toledo Harbor

The methodology to investigate potential cost savings from flexible dredging practices in the Great Lakes followed a three-step process (Figure 5.1). First, we evaluated dredging costs nationwide to assess trends and quantify cost savings realized through economies of scale. We express transportation costs as a function of Maritime Transport Efficiency [162] which we predict over a navigation season for changing water surface levels using the Efficiency Simulation Model. Finally, we estimate transportation costs using the Expected Transport

Efficiencies and compare the total spending under current practices with more flexible management practices that could defer dredging decisions.

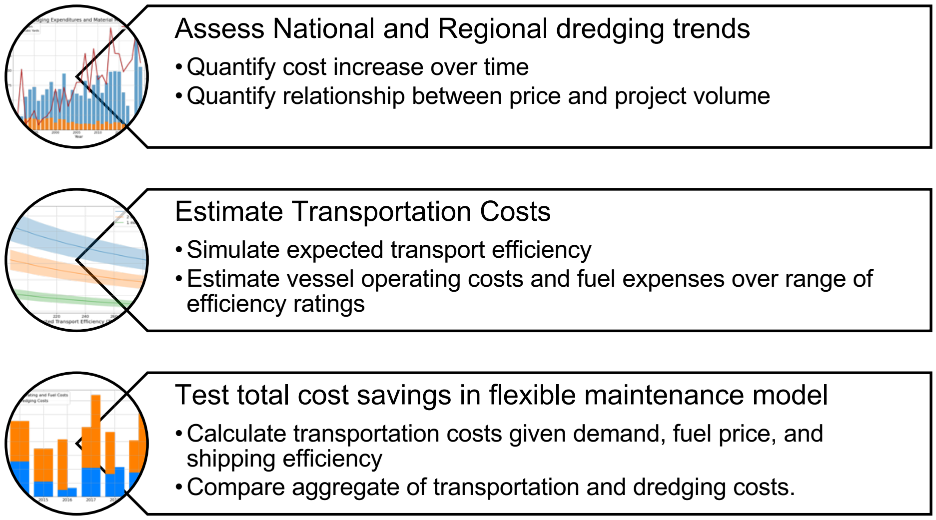

Figure 5.1 Methodology to assess impact of flexible dredging practices

Contracted Dredging Trends

Trends in commercial dredging from 1990 to 2020 show that funding for dredging projects has been robust over the past two decades, but the amount of material moved has decreased over time. Hence, unit costs have risen more than 250% (Figure 5.2), which places additional strain on limited financial resources [158], [159]. Data available from the USACE Navigation Data Center contains 5,138 records from 1990 to 2018 and offers the most complete information on dredging in the U.S. [81]. Within the dataset, 3,895 entries contain information on cost and volume of dredged material with partial reporting available for 2018. Dredging data for fiscal years 2019 and 2020 are published separately and contain 240 records [182], [183]. We calculated the unit cost of dredging as the contract price divided by volume of material moved. All monetary values are adjusted to 2020 equivalents using a constant inflation rate of 2%. We removed one data point thought to be in error where, reportedly, 156 million cubic yards of material was dredged in a single contract in the Ohio River. This is an order of magnitude higher than the next largest dredging requirements which are present along the Gulf Coast.

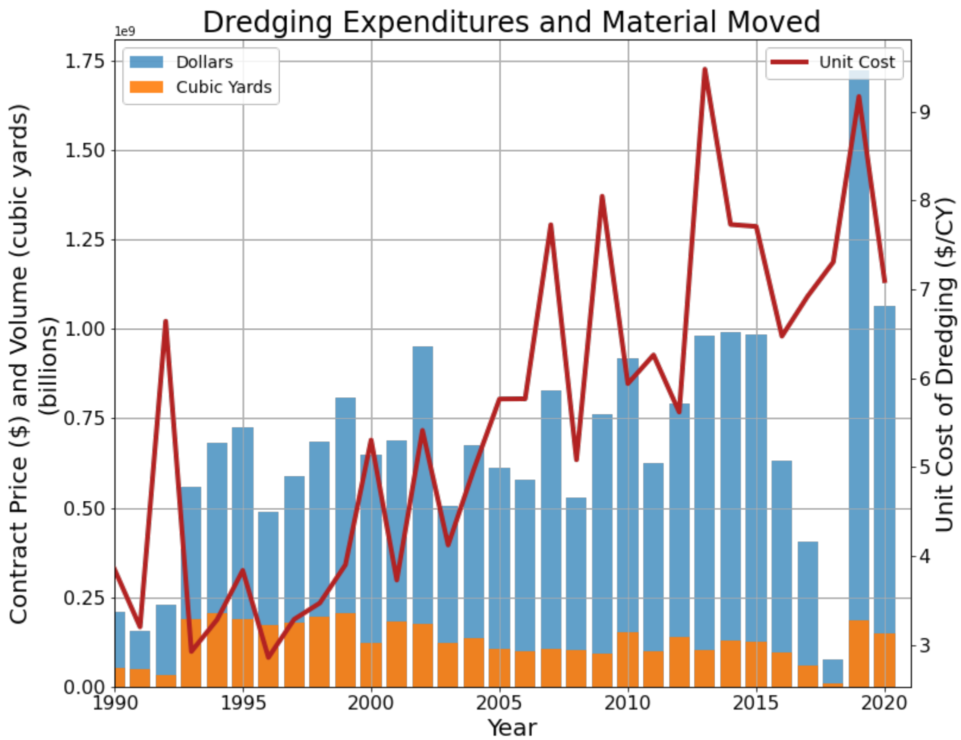

Figure 5.2: Dredging statistics and trends in the U.S. (Data Source: USACE Institute for Water Resources)

Increased costs may be attributed to material handling requirements, limited contract competition or restrictive time windows [159], [160]. Unit costs are correlated to volume of dredged material for contracted projects. This is to be expected as mobilization and administrative costs account for a greater portion of total expense on smaller projects. For example, nine contracts removed less than 1,000 cubic yards of material and exhibited unit costs more than twice the average. We compared unit cost to the volume of material dredged and modeled the relationship using a least squares regression. Using Equation 5.10 where P is contract price (2020 equivalent) and V is volume of dredge material (cubic yards), we fit parameters to estimate the contract costs from dredged volume.

$$\ln\left(\frac{P}{V}\right) = \beta * \ln(V) + \varepsilon \tag{5.10}$$

While dredged volume is not singularly deterministic of cost, a portion of cost variability may be explained by this factor which we assess at national and regional levels. The linear model provides an estimation of explained variance in unit costs which this study assesses using the coefficient of determination ($r^2 = 1 - \frac{RSS}{TSS}$). This cost model is used to estimate changes in contract price given project volume.

Transportation Saving Resulting from Dredging

Transportation savings from harbor dredging are often assumed to be linear for individual vessels, but the benefits depend on the constructed dimensions of the ship. Vessels in the Great Lakes report a "Tons Per Inch" (TPI) characteristic which reflects the incremental payload for each inch of draft [157]. Vessel dimensions determine variable payload with depth, which is maximized at a ship's constructed draft, generally ranging from 8.2 to 10.4 meters (27 to 34 feet) in the Great Lakes. A ship with maximum draft less than available water depth will reach its maximum (Deadweight) capacity, as illustrated in Figure 5.3.

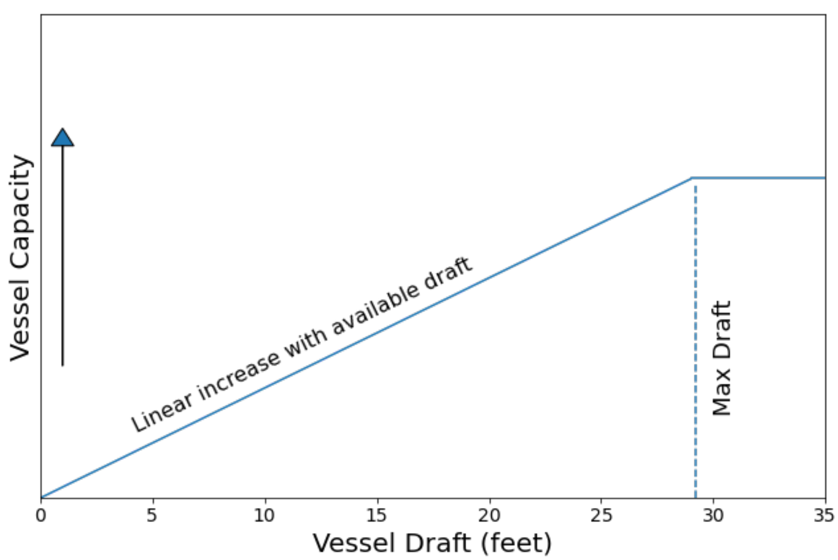

Figure 5.3: Vessel payload relative to available water depth

In the Great Lakes, available vessel draft is determined by dredging as well as naturally available water level. Authorized project dimensions are based on the low water datum (LWD) in accordance with the International Great Lakes Datum (IGLD-85). The LWD for Lake Michigan-Huron is 176.0m and 173.5m for Lake Erie [176]. We assume that water levels above the LWD add available draft. Increasing water depth above a vessel's maximum draft has diminished returns which can be assessed for a fleet of vessels with varied dimensions. For bulk commodities, such as iron ore, the variable payload (a function of draft) directly correlates to revenue per voyage. Freight consumers in the Great Lakes commonly pay a per-ton price for bulk commodities along with reimbursable fuel expenses [149].

From a freight consumer's perspective, the total cost of shipping includes the per-ton rate, reimbursable fuel expenses, as well as dredging costs which are paid indirectly through the HMT ($Cost = Per\ ton\ contracted\ price + Fuel + Dredging$). By considering these costs together, it is possible to optimize fund allocations to minimize total costs. Freight pricing for bulk commodities in the Great Lakes is negotiated using long term contracts [56]. Prices reflect expected operating costs of shipping companies which vary with waterway conditions (i.e., low water levels). Financial risks associated with variations in performance over a navigation season reside with shipping companies, but can be mitigated through insurance instruments and included in freight pricing [41]. For this study, contracted freight pricing was assumed to be consistent over a navigation season, even though they are subject to increases as shipping companies shift risks associated with increased operating costs. The increases are assumed to be proportionate to the average time to deliver bulk commodity orders.

Aggregated fuel costs vary with vessel payload which, in turn, determines the number of ship voyages necessary to meet contracted demand. The number of voyages is primarily determined by water depth and available draft. Psaraftis and Kontovas showed fuel consumption as a function of vessel speed and payload $f(v_{ij}, w_{ij})$ where v is velocity and w is payload between ports i and j [180]. Fuel costs are approximated as $pf(v_{ij}, w_{ij})t_{ij}$, where p is the price of fuel and t is sailing time between ports. We model total voyage time as the ratio of demand to transport efficiency (D / ($E[\psi]$). In this study, the average vessel payload is reflected in the efficiency term, and velocity is assumed to be 13 knots, representing typical cruising speed observed by way of the Automatic Identification System (AIS) data [162]. At 13 knots, we estimate fuel consumption to be 62 and 48 metric tons (m.tons) per day for loaded and ballast (empty) bulk carriers [180]. We averaged the fuel consumption (55 m.tons/day) by assuming that bulk iron ore carriers travel down-bound loaded and return under ballast in typical patterns [138]. Fuel consumption is weighted by the percentage of time vessels spend at sea and in port, which we estimate using AIS data. For example, the AIS data for vessel traffic from 2015-2017 indicate a median one-way travel time between Presque Isle and Toledo Harbors of 61 hours. In addition, respectively 24 and 12 hours are spent at each port during offloading processes [73]. We determined that 77 percent of the total voyage time is at sea and 23 percent at port for this common iron ore route, expressed as P_{sea} and P_{port}, respectively. Fuel costs are calculated using Equation 5.11, where D is the specified annual demand for bulk iron ore, $E[\psi]$ is the expected transport efficiency, and p_f is the price of fuel [US $/m.ton].

$$Fuel\ Costs = \frac{D}{E[\psi]} * \left(55\ P_{sea} + 3\ P_{port}\right) * p_f \tag{5.11}$$

The efficiency of moving bulk goods can be determined from vessel payload and voyage time and is expressed as mass per time. The actual performance is vessel-specific and challenging to predict discretely for fleets of vessels and various shippers providing service to bulk customers. For example, in the 2017 navigation season, 14 distinct vessels delivered 3.3

million tons of iron ore to Toledo Harbor, combined over 103 voyages [76]. The costs associated with individual voyages is knowable post-delivery but challenging to predict *ex ante* when it would be most useful to inform dredging decisions.

Deepening activities of navigable waterways are considered to be economically beneficial when the savings of reduced transportation costs and fuel consumption exceed the costs of dredging. Many vessels realize diminished returns from increased available draft if it exceeds constructed ships dimensions. This is illustrated in Figure 5.4 for two vessels delivering iron ore to Toledo Harbor between 2012 and 2018. The M/V Victory has a maximum draft of 6.8 meters (22.3 feet) and exhibits seasonal fluctuations in load but does not realize gains from increasing water levels since 2013. On the other hand, the M/V H. Lee White (max draft 9.1 m) exhibits increased payloads commensurate with rising water levels.

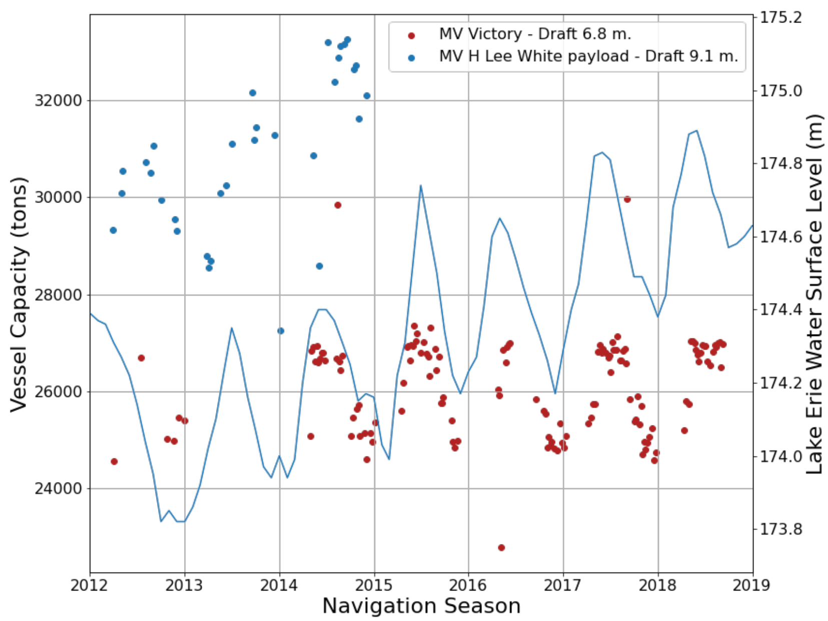

Figure 5.4: Seasonal fluctuations in water level and their impact on vessel load

This study produced *ex ante* estimates of transportation efficiency using water surface elevations at the beginning of the navigation season (March). We use $E[\psi]$ to calculate expected ship-hours necessary to deliver a specified demand for bulk iron ore and estimate its costs by combining Equations (5.9) and (5.12) inclusive of operating costs other than fuel (OC). These costs include crew salaries, stores, and insurance, for example. Total transportation costs are calculated using Equation 5.12 with assumptions listed below.

$$Transportation\ Costs = \frac{D}{E[\psi]} * [\left(F_{sea}P_{sea} + F_{port}P_{port}\right)\left(\frac{1\ day}{24\ hour}\right) * p_f + OC] \quad (5.12)$$

D = bulk commodity demand [tons]
$E[\psi]$ = Expected maritime transport efficiency to port [tons/hr]
F = Fuel consumption rate at sea / in port, assumed to be 55 and 3 [tons/day]
P = Percent of voyage time spent at sea / in port, calculated to be 77% and 23%
p_f = fuel price, assumed to be 300 +/- 100 [$/m.ton]
OC = Vessel Operating Costs other than fuel, assumed to be 250 [US $/hour]

Actual fuel and operating expenses vary by vessel type and size. For example, crew size and company overhead expenses determine actual operating costs. Fuel price and market fluctuations are different for diesel and low-sulfur bunker fuel. We make simplifying assumptions for pricing in accordance with average industry estimates [161], [184].

Cost Comparison for a Dredging Decision Model

We compare current dredging practices to a hypothetical model that allows contract deferral when predicted cost savings are below a threshold level. We apply this to Toledo Harbor using historical appropriations, water surface levels, and demand.

Toledo Harbor, in northwest Ohio, is situated where the Maumee River empties into Lake Erie. Maumee Bay, in western Lake Erie, is naturally shallow and requires maintenance dredging to allow vessels access to the harbor. The federally authorized project includes seven miles of channel within the Maumee River and an 18-mile approach through Maumee Bay that are maintained at 8.2 and 8.5 meters depth, respectively [164]. Typical dredging requirements are 800,000 cubic yards per annum, the highest in the Great Lakes, and are contracted separately for the inner and outer harbor areas which have distinct physical and chemical profiles [165].

Funding for harbor dredging has ranged from $4.7 to $7.6 million since 2009 [166]. Primary commodities moving through the port include iron ore, grain, and cement with load delivery ranging from 8.4 to 11.3 million tons since 2009 [167].

We simulated the shipping efficiency between Presque Isle, MI and Toledo, OH which is the most common route for iron ore to the harbor. In a typical year, 1 to 3 million tons of ore delivered by 50 to 100 vessels move along this route. The Toledo ore dock is situated on the outer edge of the harbor which requires vessels to navigate the deepened approach channel in the Maumee Bay, but not the inner harbor area. We utilized historical dredging, shipping, and water level data from 2008-2020, available from USACE data centers, to investigate the potential for cost savings between transportation and harbor maintenance requirements [40], [76].

We assessed increased transportation costs from deferred dredging using Equation 5.12 and by adjusting the estimated transport efficiency commensurate with decreased draft. The available draft is not perfectly correlated with water surface level since sedimentation occurs in the channel over time. We make a simplifying assumption that the channel is maintained to authorized dimensions given annual appropriations but would accumulate one meter of sediment in a non-maintained navigation season, reducing draft by the same amount. This is consistent with bathymetric surveys within the most restrictive portions of the navigation channel [185]. We assume that any deferred dredging is resumed the following year at the combined volume. However, we discount dredging costs based on the unit cost relationship to volume (Equation 5.11). For example, assume $5 million is appropriated in two consecutive years and deferred in the first year. In this case, we assess zero dredging costs in the first year and $10 million, discounted using regression parameters, in the second year. This is described in greater detail in the Results and Discussion section. Total costs in each year are calculated as the sum of transportation and dredging.

Results and Discussion

Landside improvements for Burns Harbor

Unrestricted cargo unloading at Burns Harbor would result in an Expected Transport Efficiency increase of approximately 5 percent. For lower water levels (H_0=176.0m) the modeled estimated efficiency improvement from 340 to 357 tons per hour following landside improvements. Higher water levels (H_0=176.6m) resulted in efficiency improvement from 363 to 382 tons per hour. The calculated mean for model iterations varied slightly. However, we did not reject that null hypothesis (H_0: $\mu_1 = \mu_1$) as the paired t-test over 20 iterations produced p-values in the range of 0.012-0.99. None of the tests met the Bonferroni corrected threshold for statistical significance at the 90% confidence level ($p < 0.005$). The corresponding change in total ship hours for given demand and efficiency is summarized in Table 5.1.

Table 5.1: Transport efficiency improvement and total transit time change

	H_0=176.0m (25th Percentile)		H_0=176.6m (75th Percentile)	
Demand	$\Delta E[\psi]$ (tons/hr.)	ΔT (ship-hrs.)	$\Delta E[\psi]$ (tons/hr.)	ΔT (ship-hrs.)
4.5	17	630	19	616
5.0	17	700	19	685
5.5	17	770	19	754

It is interesting to note that higher efficiency gain is apparent for higher water levels, however, total travel time exhibits lower returns. This is attributable to vessel loads that are increased during high water periods and require fewer roundtrips to meet demand. Put differently, decreased vessel capacity increases the number of shiploads necessary to meet demand and the value return from reduced time-in-port. Figure 5.5 illustrates the impact of time savings over the range of uncertainty in fuel price and consumptions rates. Each line in the figure represents an assumed fuel price and depicts uncertainty over the range of fuel consumption.

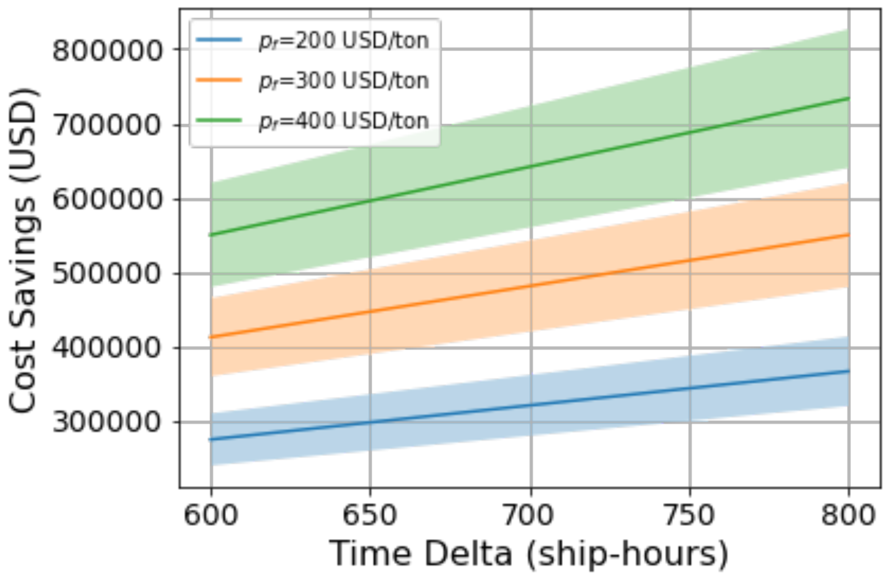

Figure 5.5: Cost impact of time savings

Cost savings vary substantially over typical uncertainty ranges for model inputs which is illustrative of the complexity in valuing landside port improvements. The low estimate of time saving (ΔT= 613 hours) would yield cost savings in the range of \$252,000 to 651,000 per annum. The upper estimate (ΔT= 770 hours) produced savings of \$308,000 to 795,700. Results are most sensitive to fuel price, which is an external variable not controlled for in this study. Still, these results illustrate the enhanced insight gained from highly granular data applied through simulation modelling. This further supports the value of a Maritime Transport Efficiency metric in the Great Lakes as a proxy measure for freight costs and value return on project investments. The cost estimates developed here for Burns Harbor reflect fuel costs only, which account for approximately 60 percent of vessel costs [154]. These costs are directly attributed to freight consumers and most directly affect decisions for landside port improvements. Decisions for publicly funded projects should also consider daily fixed costs for vessels, which is discussed further for Toledo Harbor.

Flexible Dredging in Toledo Harbor

Unit costs are correlated to volume of dredged material for contracted projects. This is to be expected as mobilization and administrative costs account for a greater portion of total expense on smaller projects. As shown in Figure 5.6, considering nationwide data, the single independent variable (volume) explains 44 percent of variance in unit costs (as expressed by the coefficient of determination). Hence, maximizing the volume of material dredged on a single contract can reduce the overall costs of dredging. This could be achieved by reducing dredging frequency by combining contracts.

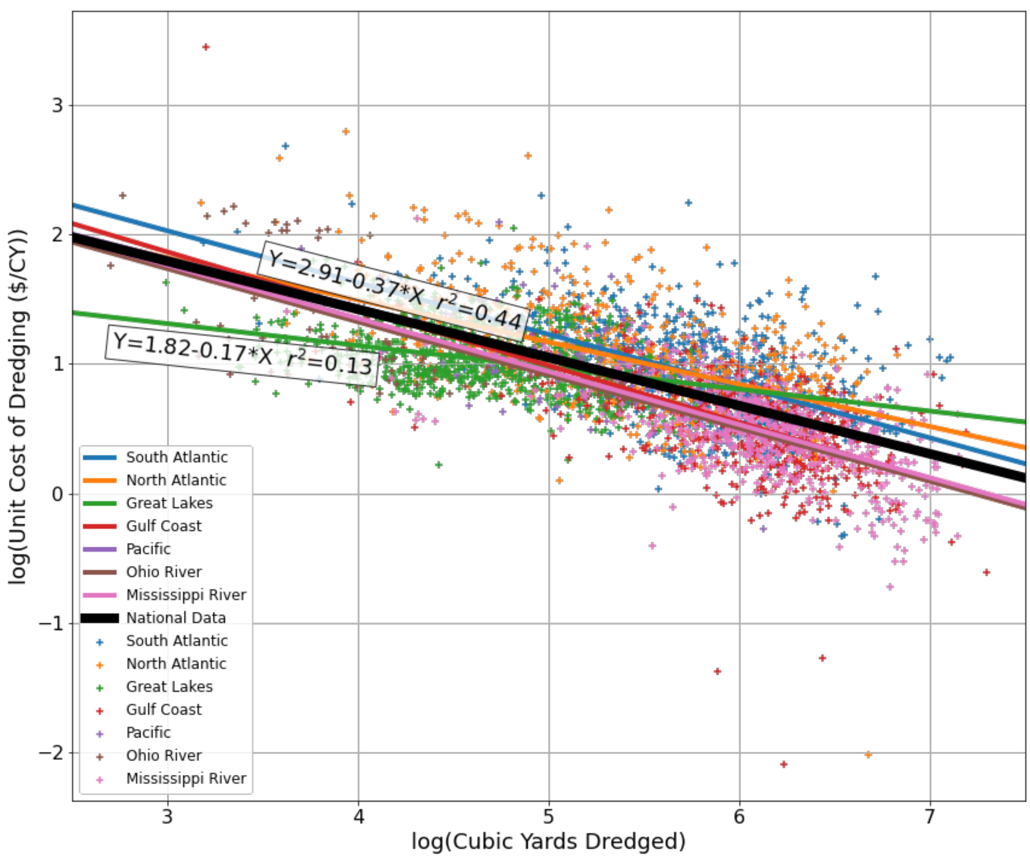

Figure 5.6: Unit cost of dredging as a function of dredged volume (1990-2020)

For example, assuming an average annual requirement of 500,000 cubic yards, contracted costs could be reduced if managed in 2-year intervals versus annually, even if material requirements remain unchanged. We solve the regression equation to calculate an expected contract price (CP) as a function of volume (V), $CP = 10^{2.91} * V^{(1-0.37)}$. Two contracts to remove 500,000 cubic yards would have a total cost of $6.33 million whereas the expected price for a single contract to remove 1 million cubic yards would be $4.90 million, a 23% decrease. Such a change in practice could alleviate spending, or make funds available for enhanced sediment management practices, such as habitat enhancement and coastal resiliency [186].

The quantified relationship between unit price and project volume is consistent for most regions, with exception of the Great Lakes. Competition for dredging contracts is geographically constrained for normal maintenance dredging as mobilization costs between coasts are prohibitively expensive. Using the same assumptions from the example above where $CP = 10^{1.82} * V^{(1-0.17)}$, the total cost of two contracts would be $7.10 million and $6.31 million on a single contract, an 11% decrease. The coefficient of determination is much lower for Great Lakes contracts (r^2=0.13). This suggest that changes in dredging costs in this region may be less dependent on project volume and driven more by other factors as described above. Analysis of Toledo Harbor exhibits a stronger correlation where $CP = 10^{1.98} * V^{(1-0.23)}$ (r^2=0.25) for dredging contracts since 2005. We use this relationship to investigate potential savings within the harbor from reduced dredging frequency.

Decisions to forego dredging would likely meet resistance within the shipping community and, indeed, may be more costly unless conditions exist that limit increased transportation costs. Opportunities to limit dredging activity are apparent in periods of abnormally high-water levels, or during weakened demand for freight. Reduced fuel consumption and emissions are correlated to increased shipping efficiency which reduces costs. However, as discussed for the Great Lakes, variable water levels present an opportunity to amend dredging and budgeting practices to be responsive to changing lake levels.

A series of simulations on shipping efficiency for the Port of Toledo show diminishing returns on dredging where available draft exceeds 9 meters (29.5 feet) with de minimis returns beyond 9.3 meters (30.5 feet) as illustrated in Figure 5.7. This corresponds to the dimensions of vessels accessing the port. Expected efficiency levels in this simulation are specific to iron ore delivery, but proportionately apply to other commodities as well assuming comparable vessel dimensions. That is, increasing the available draft from 8.5 to 9.0 meters yields an expected efficiency increase of 12% whereas depth increases from 9.0 to 9.5 meters only produce a 5% improvement. We simplify the relationship between available draft and lake levels which varies seasonally and as sedimentation occurs in the channel. Scaling used in Figure 5.7 reflects authorized project dimensions and normal water level difference of 2.3 meters between Lakes Erie and Huron.

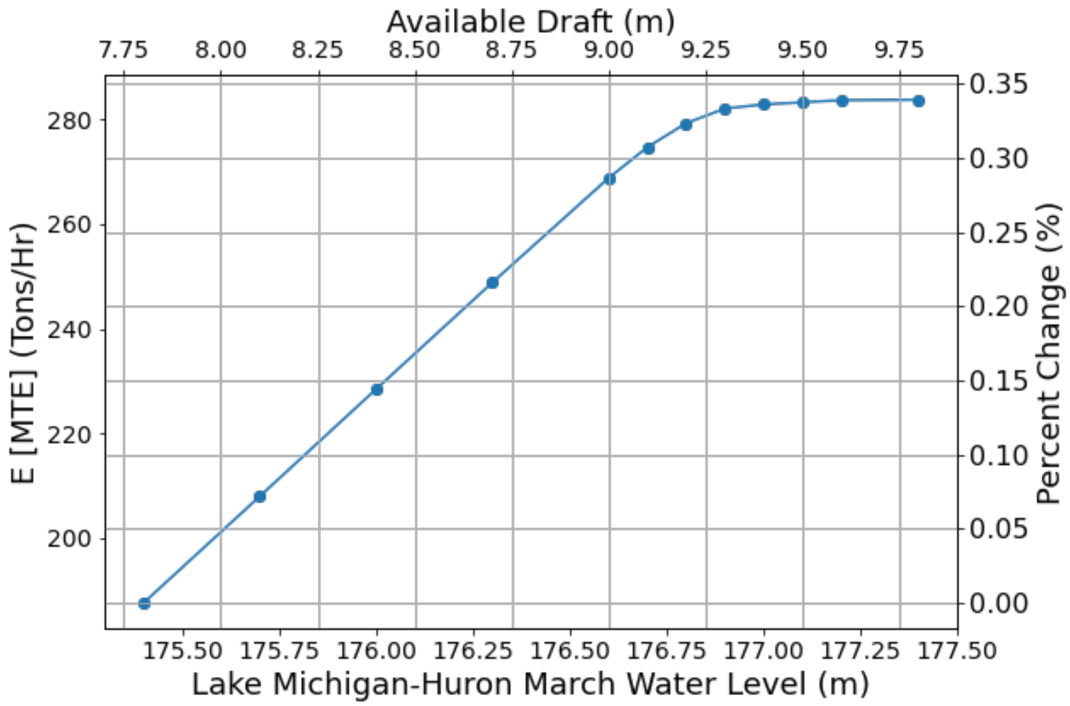

Figure 5.7: Simulated MTE as a function of available water depth.

The expected MTE is used to estimate vessel operating costs which are determined by their time in operation. Figure 5.8 illustrates changes in operating costs for three assumed levels of demand. These estimates use a fixed operating cost of $250 per hour and per-ton fuel prices of $300 +/- 100 which reflect recent market volatility for marine fuels [184], [187]. As discussed in the previous section, fuel expenses comprise a significant share of total costs. Actual fuel prices vary by type, geographic market, and normal volatility, which is substantial for marine grades. Uncertainty in fuel prices is represented by shaded regions. As expected, transportation costs scale linearly with demand and cost savings are realized as efficiency increases. A 34% cost savings is observed over the full range but diminishes in the upper range. As previously discussed, this is due to the increasing number of vessels that realize their maximum draft with increasing water depth, because of their constructed dimensions.

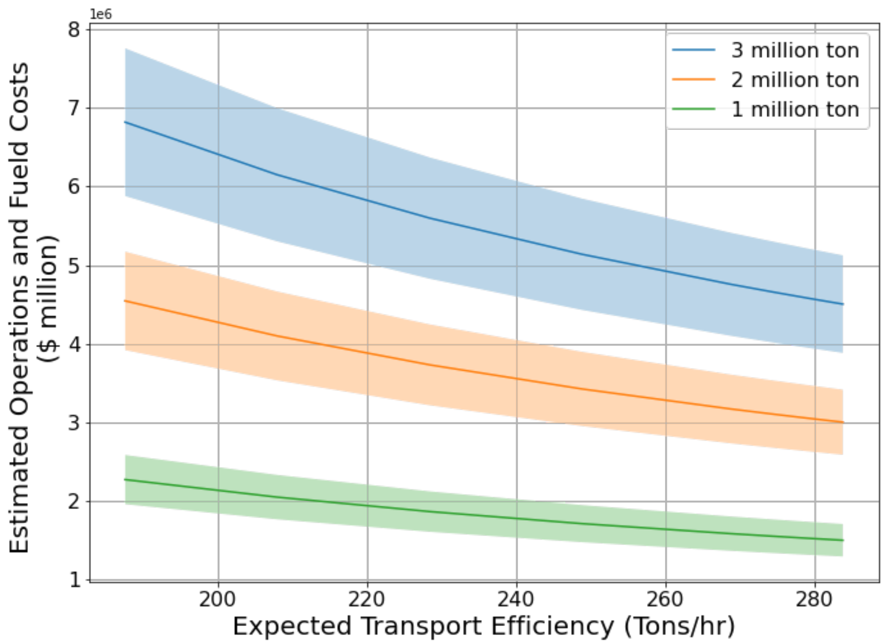

Figure 5.8: Estimated vessel operating costs with assumed fuel price of $300 +/- 100 per ton

Decisions to defer dredging would result in decreased transport efficiency and higher shipping costs. The magnitude of the cost impact varies with the level of demand and fuel prices as illustrated in the figure. Table 5.1 shows historical water levels and iron ore demand with MTE and transportation costs calculated using Equations 5.11 and 5.12, respectively. The dredging costs listed reflect actual contracted amounts in those years. Total cost is the sum of transportation and dredging costs but recall that these are separate in the existing system. Transportation costs are paid by shippers and dredging expenditures are maintained by the government, having already been paid through the HMT.

Table 5.2: Assessed costs under existing practices

Year	March Water Level (m)	Demand (M Tons)	Fuel Price ($/m.ton)	MTE (Tons/Hr.)	Transportation Cost ($M)	Dredging Cost ($M)
2016	176.61	0.70	200	269	1.59	7.37
2017	176.53	3.29	150	265	6.45	5.91
2018	176.76	2.5*	200	279	5.45	6.12
2019	176.86	2.5*	250	282	6.19	4.68
2020	177.20	2.5*	300	284	4.16	6.55

* Tonnage estimates in these years was incomplete or unavailable. We assumed average demand levels of 2.5 million tons.

We assessed the change in total costs for deferred dredging in years 2016 and 2018 when demand was atypically low (2016), and water levels were high, above the 75th percentile. Under the assumption that deferred dredging in a season would result in a reduced depth of one meter within the channel due to sedimentation, we assessed an efficiency loss for those years and recalculated transportation costs as shown in Table 5.2. Transportation costs increased by 30 percent in those years with a calculated increased cost of US $2.12 million to shipping customers. This is outweighed by potential cost savings resulting from combined dredging contracts in 2017 and 2019. Combined appropriations with applied discount from economies of scale reveals potential savings of 1.94 and US $1.57 million in those years, respectively.

Under existing management practices this hypothetical change would be opposed by shippers who would incur increased transportation costs but would pay the same level of HMT, as shown in Figure 5.4. However, adoption of a port user fee based on vessel requirements, to replace the HMT, would operationalize decisions to optimize dredging based on vessel demand [48]. In consideration of national and regional regressions (Figure 5.5) for the port of Toledo, the range of plausible savings in maintenance dredging costs in the two periods are US $1.46 - 2.97 and $1.18 - 2.40 respectively. Flexible management practices could reduce total costs of transportation and dredging over the four-year period. This is illustrated in Figure 5.9 where spending under traditional practices is depicted on the left for each year and flexible dredging expenditures are shown on the right.

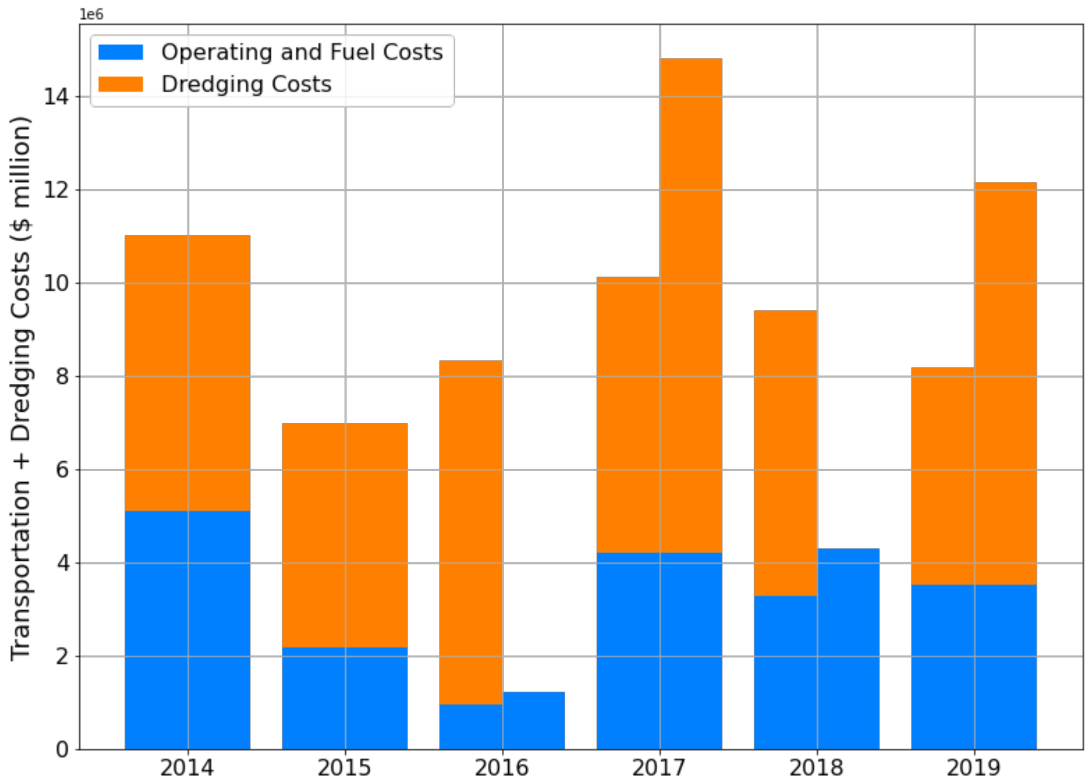

Figure 5.9: Combined transportation and dredging costs comparison for current and flexible decision models

These savings could be leveraged to dredge additional material in the channel, or to offset costs for enhanced management practices, such as placement for coastal resiliency or shallow wetland creation. By extension, typical appropriations of $50 to 70 million for dredging in the Great Lakes region could yield $3 to 4 million (6%) in savings annually. These results point to greater efficiencies that are possible through harbor funding mechanisms that are performance driven (i.e., determined by vessel draft).

Potential for Demand Driven Harbor Maintenance

This study applied predictions of Maritime Transport Efficiency (MTE) to estimate changes in transportation costs resulting from maintenance dredging and natural variations in water level throughout the Great Lakes navigation system. As navigation dredging is intended to increase available vessel draft and shipping efficiency, this study quantified the tradeoffs in spending for dredging and associated freight costs. We demonstrate that transportation cost savings from dredging are diminished where available depth exceeds fleet dimensions, observed when water levels exceed the 75th percentile. Funding allocations for maintenance dredging should consider the array of vessels (and draft requirements) as well as reduced ship traffic during periods of low freight demand. Transportation cost estimates are improved by application of MTE predictions which this study achieved using Monte Carlo simulation.

Changes to status quo maintenance and funding procedures are necessary to address industry requirements under fiduciary constraints. Fundamental to this problem is the disunion between funding for dredging through a value-based tax and federal appropriations to meet authorized depths without regard to changing conditions. A funding mechanism based on vessel draft and time-in-port would operationalize maintenance dredging decisions and as is a direction of future research. Further development of a user fee model is needed before policymakers can replace the harbor maintenance tax with an improved demand-driven fee structure.

The disconnect between HMT payments and maintenance requirements needs remedied before the adoption of alternative practices becomes practical. Consider two vessels, one drafting 6.5 meters carrying automotive parts from Ontario, and the other drafting 8.8 meters loaded with iron ore from Presque Isle. Both vessels arrive at Toledo and are subject to the HMT, but higher payments apply to the auto parts given the value of that cargo, despite the lower maintenance needs of that vessel to access the harbor. A more egalitarian model would levy user fees based on vessel requirements, depth and time spent in port. A user fee model has previously been proposed, but data availability and sensor technology at the time limited its feasibility [48], [49].

The wealth of sensor technology and data analytics in today's environment provides opportunity to renew financing models for harbor infrastructure. Geolocation data via AIS is ubiquitous on commercial vessels as it is required on all vessels larger than 300 gross tons and real-time monitoring is in place [188]. Data from the AIS are readily adaptable to provide information on actual draft and time in port which could drive a user fee model. Consider three ports as a basis for such a fee structure, Toledo, Los Angeles, and Charleston. A vessel carrying 40,000 tons of iron ore to Toledo Harbor (depth 8.5m) with taconite price of $100 per ton will pay $5,000 in Harbor Maintenance Tax. In 2019, the Port of Los Angeles (depth 16.2 m) received 1,867 vessels and handled $267 billion in cargo [189]. Those cargos vary greatly but allow that on average each vessel exchanges $143 million in cargo and pays $178,750 in Harbor Maintenance Tax. Finally, the Port of Charleston reported $75 billion in cargo (47.7 billion imports) carried on 1,700 vessels [190]. Based on imported cargo only, we estimated $35,000 in HMT per vessel accessing that harbor. Charleston Harbor has had maximum depths of 13.7 meters (45 ft) until its deepening to 15.9 meters (52 ft) scheduled to complete in 2021.

Figure 5.10 depicts these payments against a hypothetical draft-based user fee model in which vessels would pay proportionately to their required draft. Within the same harbor, a vessel requiring 8 m. draft would pay a higher fee than one requiring 6 m. regardless the value of its cargo. It logically follows that shippers would make operational decisions to minimize total costs, weighing the tradeoffs between increased cargo and higher fees. Calibration of this user fee model to match maintenance requirements and generally mirror the current geographic distribution of payments is necessary, but outside the scope of this study. Adoption of the fee model would bring U.S. harbor funding practices in line with international standards as it would apply equally to imports and exports and it would meet the constitutionality test [45].

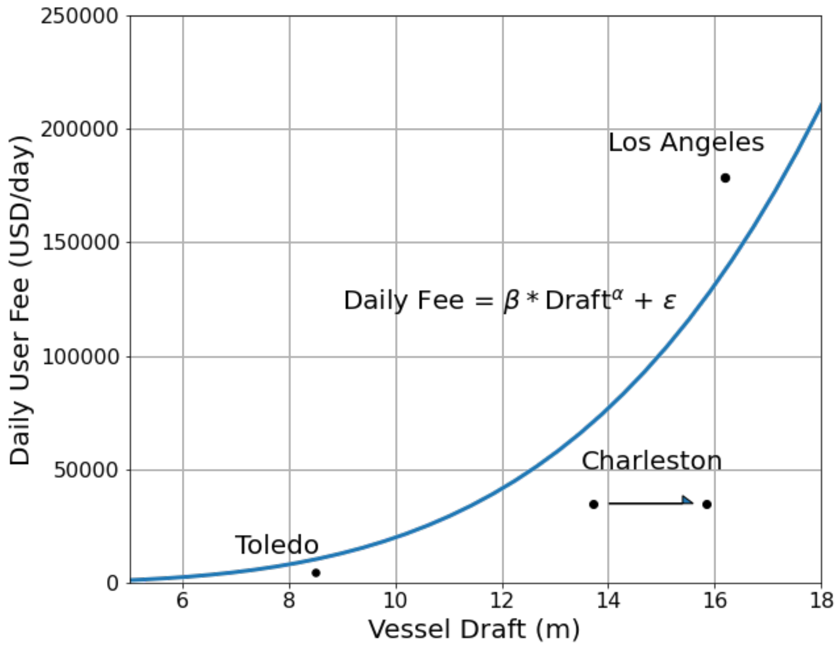

Figure 5.10: Hypothetical Harbor User Fee Model (α=4, β=2, ε=0)

Such a fee structure could also inform harbor deepening decisions given market pressures. Post Panamax vessel dimensions have prompted deepening of U.S. harbors to accommodate increasing vessel size, particularly on the Atlantic Coast [172]. Economic impetus to deepen harbors under the proposed model would be driven by vessel traffic and willingness to incur higher port user fees.

We apply this hypothetical fee structure to Charleston Harbor. Using AIS data collected for UTM Zone 17 for all of calendar year 2017 (N=9,042,612) and processing algorithms described in Chapter 4. We removed non-cargo vessel codes from the dataset such as tugs, pleasure craft, and research vessels to limit the dataset to cargo, tanker, and cruise ships (N=2,950,756). We further subset the data around the six port terminal boundaries (listed in Appendix E) as illustrated in Figure 5.11. The right side of that figure depicts the first subset of AIS data in blue and the subset for vessels at port in orange (N=2,373,988).

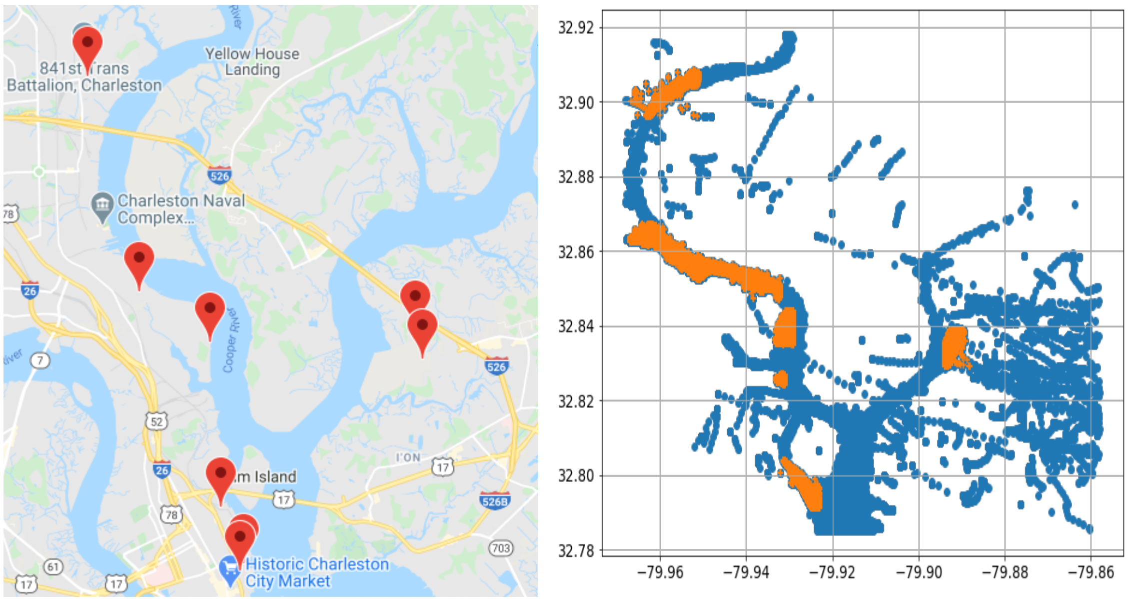

Figure 5.11: Charleston Harbor terminal map (left) AIS data for terminal (right) (Map Source: SCPA [190])

From the AIS data, we identified vessel calls in the six terminal boundaries based on the duration of contiguous timestamps each vessel exhibited. The time-in-port was calculated for each vessel as the difference between timestamps entering and exiting the features. We established a minimum threshold of 3 hours to remove vessels transiting through features without accessing the port which resulted in 1,789 port calls made by 699 unique vessels. The distribution of vessel time-in-port is depicted in Figure 5.12 for Charleston Harbor port calls in 2017.

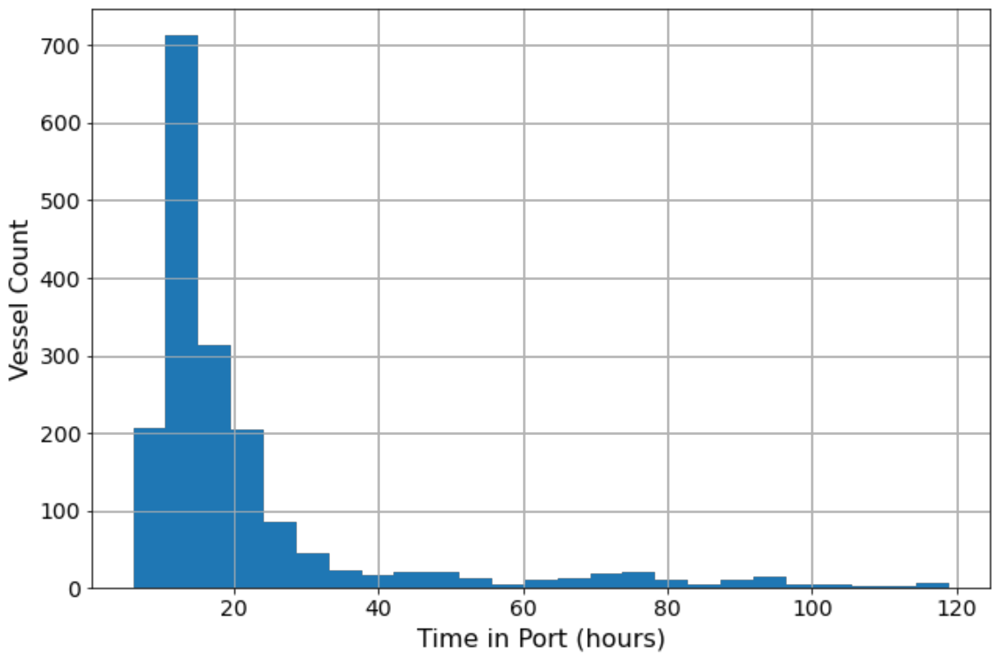

Figure 5.12: Distribution of vessel time in port for Charleston Harbor

Of the 1,789 identified vessel calls, 1,202 (67%) had draft registered in the AIS data. This feature in the AIS data typically reflects the maximum draft of the vessel and is entered manually by the operator and not necessarily updated in real time [136]. However, it could easily be adapted for this purpose, and likely would, if it were determinate of user fee. In this study we make a simplifying assumption that vessels would access the harbor at their constructed draft when available. The distribution shown in Figure 5.13 indicate that 675 (47%) of vessels have a constructed draft in excess of available depths in the harbor. The vertical dashed line indicates the existing navigation channel depth of 13.7 meters (45 ft) before deepening. It may be assumed that those vessels were light-loaded in order to access the harbor.

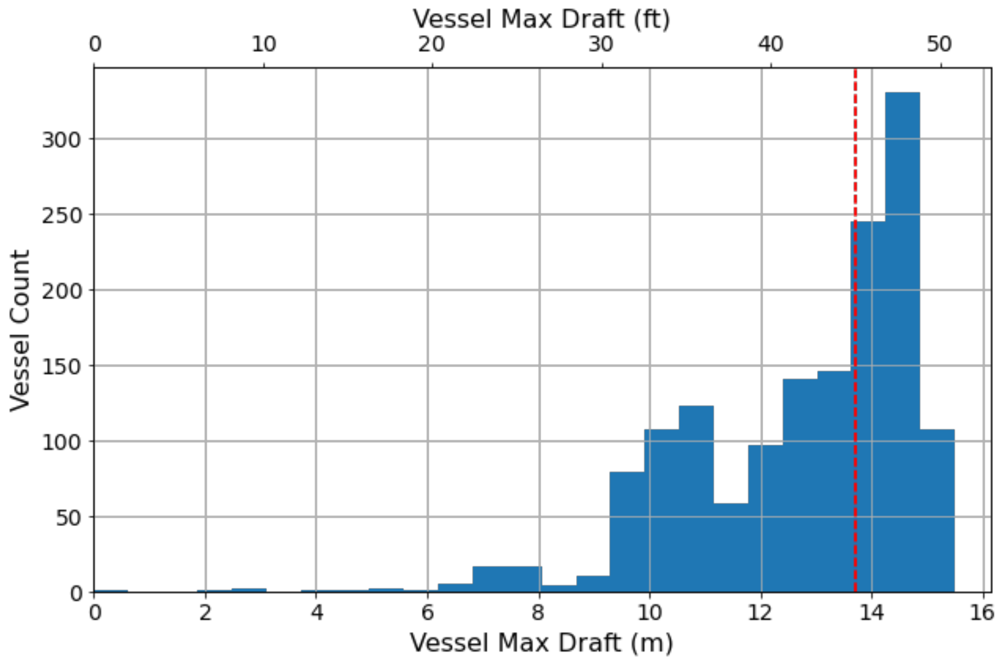

Figure 5.13: Vessel draft according to AIS data for Charleston Harbor

The sum of user fees $\sum(2 * Time * Draft^4)$ over the set of vessels with listed draft (n=1,202) was calculated as \$45.5 million before deepening (max draft 13.7 meters) and \$51.8 million after. If we assume the distribution of vessel draft to apply to the full set of vessel calls (n=1,795) those estimates increase to \$66.9 and 76.2 million, respectively. For comparison, we estimated \$59.6 million HMT exacted on the \$47.7 billion imported to Charleston in 2019. This is not intended as a true calibration of the user fee model. However, it illustrates how such a model could drive decisions to deepen a harbor based explicitly on willingness to pay. As discussed for Toledo Harbor, it would also inform maintenance decisions in periods of low demand, such as the economic recession in 2008 and COVID pandemic in 2020.

We compare the proposed user fee to previous models considered for harbor maintenance using five key performance indicators. Models are evaluated on (1) their conformance to international standards, (2) Constitutionality in accordance with the Export Clause, (3) Relief of burden on the General Treasury, (4) Basis of fee connected to maintenance requirements (e.g., depth), (5) Readily attained from existing data streams. We compare the existing HMT model to that proposed under the Clinton administration calling for a Harbor Service Fund (HSF) with fees based on cargo type and number of port calls [47]. Models advanced by Kumar, McIntosh and Skalberg weight a user fee based on Tonnage, Berth-Days, and Draft [45], [49]. The two studies proposed different weighting to the inputs and noted the correlation between tonnage and draft, which may render either unnecessary. We identify the use of tonnage as problematic to a user fee. While it is useful to compare vessels with uniform commodity types, it would inconsistently apply to various finished goods, dry bulk, bulk liquid, and passenger vessels. Further, it is likely unnecessary given granular data on vessel draft and time in port, available via AIS. A likely criticism of the proposed fee based on draft (and not cargo type) is the effect it would have making bulk cargo more expensive to transport and finished goods generally less expensive. This could be addressed with a fee structure calibrated for each cargo type, as intended under the HSF.

Table 5.3: Comparison of Harbor Fee models

	Conforms to International Standards (GATT/WTO)	*Passes Constitutionality Test (Export Clause)*	*Relieves Taxpayer Burden (General Treasury)*	*Performance-Based Fee*	*Attained from existing data stream*
Harbor Maintenance Tax		✓	✓		✓
Harbor Services Fund	✓	✓	✓		✓
Revert to General Treasury Expense	✓	✓			
User fees based on Tonnage, Berth-Days, Vessel Draft	✓	✓	✓	✓	
User fee based on Draft and Time in Port	✓	✓	✓	✓	✓

Conclusions

This study demonstrates that granular performance data provide valuable insight to investment decisions for landside and in-harbor improvements. As exemplified for Burns Harbor, projected return on investment is possible through simulation modeling using Maritime Transport Efficiency (MTE) to assess changes in transportation costs in the Great Lakes. While these estimates exhibit large uncertainty due to fuel prices, they produce a compelling business case for investment to privately-owned port infrastructure which impacts vessel performance. As discussed, freight consumers ultimately bear the cost of inefficiencies in the system, either directly or indirectly. The tradeoffs in spending for dredging and transportation cost savings are quantified and assessed to diminish where water surface levels exceed the 75th percentile. Funding allocations for maintenance dredging should consider the array of vessels (and draft requirements) as well as reduced ship traffic during periods of low freight demand. Transportation cost estimates are improved by application of MTE predictions which this study achieved using Monte Carlo simulation.

Changes to status quo maintenance and funding procedures are necessary to address industry requirements under fiduciary constraints. This study demonstrates that transportation cost savings from dredging are limited where available depth exceeds vessel draft. This is evident for changing water levels in the Great Lakes but applies to coastal harbors as well which receive vessels of diverse dimensions. Fundamental to this problem is the disconnect between funding for dredging through a value-based tax and federal appropriations to meet authorized depths. A funding mechanism based on vessel draft and time-in-port would create market forces that balance transportation and infrastructure spending. A user fee model offers additional benefits in consideration of harbor deepening projects, as demonstrated for Charleston Harbor.

Fundamental to these outcomes is a system of payment and maintenance expenditure that is responsive to user demand for infrastructure, principally draft in this study. Further calibration of a user fee model is needed before policymakers can replace the harbor maintenance tax with an improved demand-driven fee structure.

CHAPTER 6

Conclusions and Future Recommendations: Big Data and the Next Generation of Harbor Infrastructure Financing

Data analytics applied in this dissertation yielded novel insight to the value (opportunity cost) of waterways infrastructure, its associated risks, and performance that reveals opportunities for improved revenue streams to update and maintain waterway infrastructure. These insights inform the development of innovative financing models that connect public and private capital which is necessary to address growing infrastructure needs.

Government spending alone will not close the infrastructure spending gap. Over the course of this dissertation, the U.S. federal deficit grew by 37 percent to $27.8 trillion (from $20.2 trillion in 2017) [191]. Unfortunately, the portion of the federal budget directed to non-defense discretionary accounts (e.g. transportation) is decreasing and trends indicate that investment as a percentage of GDP has actually declined and is well below historically sustained levels [192]. Experts estimate that $2 trillion is needed by 2025 to avoid major shortfalls in system performance [193]. In its latest infrastructure report card, ASCE estimates a $15.5 billion funding gap in America's ports which threatens the efficient movement of goods comprising 26% of the nation's GDP [10]. The integration of public and private capital is necessary to address the need.

The imperative to deploy more private capital to infrastructure is reflected in the distribution of available capital, which currently favors the private sector. Tens of trillions of dollars in assets reside in pension and insurance funds with risk-and-return expectations that are well matched to the long-duration and relatively low volatility of infrastructure investments [194]. In fact, estimates as of 2017 indicate that more than $137 billion in private capital sits undeployed in infrastructure-focused private equity funds [195]. These "dry powder" accounts could initiate an upsurge in new investment, particularly if leveraged at as equity against borrowed funds wherein project revenues meet debt service obligations. This is common practice in the private sector but not feasible for governments without a private partner. Private capital has been slow to enter the realm of public infrastructure in part due to uncertainty surrounding revenue streams and asset performance, and internal rates of return (IRR) that do not meet investor expectations. It is vital to balance the necessary revenues and risks for parties involved in PPP agreements [14]. Ports and waterways have an oversized impact and value to the economy, but revenue streams can be volatile.

Revenues for ports and harbor maintenance come from freight consumers and shipping companies, either in the form of user fees or harbor maintenance tax. Operating income for port authorities is generated from tariffs or user fees which support cargo handling, berth operation, security, and other operating costs. These fees vary substantially based on the individual port's cost of delivering services and other market forces. The cost to maintain navigable depths also varies between ports and can be improved by connecting it to market demand as discussed in Chapter 5. This was impractical when the HMT was first established because of limited access to data and the perceived burden of administering user fees. Today, data accessibility and the digital economy have reduced barriers to a user fee model and offer increased opportunity for alternative financing.

Big Data to the Rescue?

This dissertation demonstrates the application of data to reveal a more comprehensive valuation strategy for waterway infrastructure and illustrates a set of use cases for better allocation of risks from degraded performance and corporate opportunity cost. We developed and applied techniques to convey quantifiable, objective, and therefore more meaningful performance measures used to model and predict the value returns of system improvements. These measures are applied to evaluate the expected return on investment decisions for ports in the Great Lakes from the resultant savings in transportation costs, which would provide real returns to freight consumers.

Risks associated with failing or underinvested infrastructure in the Great Lakes are better understood because of the systemic insights developed in this work. The propagated effects of waterway disruption are estimated through financial network mapping and the supply-driven input-output inoperability model (SIIM) as described in Chapter 3. The application of corporate financial metrics (e.g., inventory turnover ratios) to quantify and propagate interdependencies in the SIIM allowed me to tie infrastructure performance to manufacturing and production segments in the supply chain. This technique improves upon earlier studies of insulated supply chain disruption stemming from held inventory [98]. The availability of corporate revenue and inventory turnover data offers a practical means to quantify interdependencies and assess perturbated risks from disruption of individual nodes or pathways in a network. These data also deliver a meaningful way to map material flows and weigh network relationships.

Objective and precise measures of port and waterway performance are shown to be possible through data analysis techniques developed in this dissertation. A major contribution of this work was the design of a big data informed Maritime Transport Efficiency (MTE) metric, which is useful to assess, at a highly granular level, the effective rate of s shipping from harbor to harbor over time. This approach is readily adaptable to inland waterways or coastal harbors where vessel draft or load data is available. We achieve precise measurement of MTE through fusion of granular datasets (e.g., AIS and LPMS) that integrate vessel payload and timestamp information. When applied to harbors, this metric can reveal limitations and opportunity costs associated with port performance and infrastructure deficiencies. This offers operations managers improved and near real time information to allocate funding for projects that yield the greatest improvement to system performance. Historical AIS and LPMS data enabled robust statistics and baseline performance metrics for infrastructure in the Great Lakes waterway. Applications of AIS data in waterways logistics continue to expand into research areas that evaluate infrastructure performance [196]. The potential for these data in real-time monitoring to inform real-time monitoring of vessel traffic that allows us to transform revenue streams for harbor maintenance through user fee structures informed by port and vessel needs. This is a future research direction arising from this work.

As water levels in the Great Lakes are deterministic of vessel capacity, payloads are predictable given measured water surface level and historical ship performance. We evaluated an array of machine learning tools to model maximum vessel payload based on water levels and determined that a Generalized Linear Model (GLM) is most accurate as a predictive tool. When integrated with travel times, this model provides a means by which to estimate the MTE. Through Monte Carlo simulations, we assessed the expected MTE over a navigation season (March-January) which can be applied to individual ports or along key shipping lanes. The model uses March water levels and historical travel time statistics (developed in Chapter 4) to determine expected MTE over a navigation season. Deviations from expected transport efficiency are useful to operations managers and can inform decisions on fleet deployment or risk transfer mechanisms in near real-time.

We simulated the return on investment from improvements to landside infrastructure at Burns Harbor. Predictions of return on investment are possible through the application of statistics and simulation modeling. These estimates produce a business case for investment into privately-owned port infrastructure. As discussed in Chapter 5, the aggregated impact of landside investment to vessel performance results in transportation cost savings. As previously discussed, freight consumers ultimately bear the cost of inefficiencies in the system, either directly through freight or fuel pricing or indirectly through opportunity cost. Investments that improve system performance and efficiency yield returns in reduced transportation costs as well as social benefit from emissions associated with transportation.

The simulation model was further applied to evaluate flexible dredging and spending practices in the Great Lakes. We demonstrated that transportation cost savings from dredging are limited where available depth exceeds vessel draft which manifests when Great Lakes water levels exceed the 75^{th} percentile. Innovative maintenance and funding practices that tailor spending decisions to market conditions are necessary to prioritize port requirements under fiscal constraints. Amended dredging practices become practical under an infrastructure banking model, as described in greater detail below. We note the mismatch between harbor maintenance collections (based on cargo value) and allocation of funds to meet authorized depths irrespective of variable demand or vessel traffic. We posit that a more sustainable and egalitarian model would match harbor fees to maintenance requirements for the types of vessels it accommodates. It follows that user fees based on required depth, as others have proposed [45], [48], would best match revenues to maintenance needs.

A user fee model based on vessel draft and time in port to fund harbor maintenance would operationalize decisions that minimize the total transportation costs. Such a fee is presented conceptually. Future research is needed to calibrate this fee structure to nationwide vessel traffic obtainable from historical AIS data. This funding mechanism would benefit project managers by optimizing allocations for dredging based on demand. This could be achieved through a Harbor Infrastructure Banking (HIB) structure that lends funds for harbor maintenance which are paid through higher, draft-based, fee collections.

Harbor Infrastructure Banking

We introduce the idea of HIB as a more efficient financing mechanisms for the maintenance and improvement of ports. A model for such a system exists in State Infrastructure Banks (SIBs) which operate as revolving funds with matching government contributions. States have successfully administered these revolving funds since the 1990s and have demonstrated enhanced investment levels up to $7 for every dollar of federal commitment [197], [198]. One of the conditions necessary for such a fund is seed money which already exists for harbor projects in the unspent balance of the HMTF, $9.5 billion as of this writing [163]. Rather than depleting the balance through increased status quo spending, bank managers would use the balance to make low-interest loans for port and harbor improvements and recover funds from the increased user fees or directly from borrowers resulting from savings realized in lowered transportation costs, like those demonstrated for Burns Harbors. The availability of funds would accelerate investments in port infrastructure and naturally prioritize projects with the greatest return on value under market-driven conditions.

Government appropriations can be minimized through contributions to the HIB similar to existing programs such as the Transportation Infrastructure Finance and Innovation Act (TIFIA). The TIFIA program was established in 1998 to accelerate investment in surface transportation projects and is administered by the Department of Transportation. Loans made through the TIFIA program encourage capital outlay by lowering financing risk for private partners through low borrowing rates, term length, and repayment flexibility [199]. If adapted for harbor improvements, government contributions to HIB would replace commitments from the general treasury for port deepening or construction. In the current model, expenditures from the general treasury are made in increments on the federal cost share of projects, as described for Charleston Harbor in Chapter 5. In 2012 the South Carolina General Assembly set aside $300 million for the non-federal project contribution [174]. The project was authorized by Congress in 2015 and first received federal funds in 2017. Federal allocations in successive years from 2017 to 2020 were $ 17.5, $49, $41.4, and $138 million [174]. Under the HIB, funds would have been available immediately following project authorization in 2015. Upfront availability of funds would concurrently reduce construction costs and provide benefits years earlier than the current model. Increased user fees (resulting from deeper depths) would be directed to service the debt on the loan paid back into the HIB and made available to other projects. Detailed development of an HIB structure is a third future research direction identified in this dissertation.

The insight to infrastructure valuation, risk analysis, and project performance developed through data analytics in this dissertation uncover opportunities for innovative project financing. New financing models, such as infrastructure banking, are possible under renewed demand-driven funding mechanisms based on draft and time in port. Implementation of a new harbor user fee model and HIB would require legislation that replaces the HMT with draft-based user fees and authorizes the use of those funds for both maintenance and construction projects. Public funds from the general treasury would be committed into the HIB for disbursement through loans rather than annual appropriations for specific projects. This seems bold and aggressive, but far-reaching initiatives are needed to transform existing mechanisms into more sustainable infrastructure financing models.

APPENDICES

APPENDIX A

Iron Ore Mines, Steel Mills and Transloading Facilities in the Great Lakes

Table A.1: Iron ore mines in the United States

Mine Name	Mining Range	Owning Company	Common Name	Production Capacity (M Tons)
Tilden Mine	Marquette	Cleveland Cliffs	Tilden	8.0
Empire Mine[1]	Marquette	Cleveland Cliffs	Empire	inactive
Northshore Mining	Mesabi	Cleveland Cliffs	Northshore	6.0
Mt. Iron	Mesabi	US Steel	MinnTac	16.0
Minorca	Mesabi	ArcelorMittal	Minorca	2.8
United Mine	Mesabi	Cleveland Cliffs	UTac	5.4
Keewatin	Mesabi	US Steel	KeeTac	6.0
Hibbing[2]	Mesabi	62% ArcelorMittal 23% Cleveland Cliffs 15% US Steel	HibTac	9.1

[1] Empire Mine has been idled since 2016. CLF maintains operational control and mineral rights; [2] Hibbing operates under a cooperative agreement, with co-owners guaranteed a percentage of production

Table A.2: Transloading facilities for iron ore

Facility Name	Location	Owning Company
Silver Bay	Silver Bay, MN	Cleveland Cliffs
CN Two Harbors	Two Harbors, MN	CNI
CN Duluth Dock	Duluth, MN	CNI
BNSF Railway Dock 5	Superior, WI	BNSF
Toledo Ore Dock	Toledo, OH	CSX
Pinney Dock, Ashtabula	Ashtabula, OH	Norfolk Southern
Pittsburgh & Conneaut Dock	Conneaut, OH	CNI

Table A.3: U.S. and Canadian integrated steel mills

Facility Name	Location	Owning Company	Production Capacity (M Tons)
Indiana Harbor	Indiana Harbor, IN	ArcelorMittal[3]	6.4
Riverside Works	Riverside, IL	ArcelorMittal[3]	1
Gary Works	Gary, IN	US Steel	7.5
Burns Harbor	Burns Harbor, IN	ArcelorMittal[3]	5
Granite City Works	Granite City, IL	US Steel	2.8
Dearborn Works	Dearborn, MI	AK Steel[2]	3
Great Lakes Works	Ecorse, MI	US Steel	3.8
Middletown Works	Middletown, OH	AK Steel[2]	3
Ashland Works	Ashland, KY	AK Steel[2]	--[1]
Cleveland Works	Cleveland, OH	ArcelorMittal[3]	3.8
Mon Valley Works	Braddock, PA	US Steel	2.9
Algoma Steel	Sault Ste. Marie, ON	Algoma Steel	4
Lake Erie Works	Nanticoke, ON	Stelco	2.5
Dofasco	Hamilton, ON	ArcelorMittal[3]	5
Long Products	Montreal, QC	ArcelorMittal[3]	2

[1] AK Steel indefinitely idled production at their Ashland Works facility in 2018 [62].
[2] Cleveland Cliffs (CLF) acquired AK Steel in March 2020, thereafter consolidating reports under CLF [200].
[3] Cleveland Cliffs (CLF) acquired the North American operations of ArcelorMittal in December 2020.

APPENDIX B

US Flagged Vessels in the Great Lakes

Table B.1: U.S. flagged vessels in the Great Lakes

Vessel Name	Fleet	Length (feet)	Beam (feet)	Per-Trip Carrying Capacity (tons)	Capacity per foot of Draft (tons)
American Century	American Steamship Co.	1,000	105	68,880	3,192
Indiana Harbor	American Steamship Co.	1,000	105	68,757	3,192
Walter J McCarthy Jr.	American Steamship Co.	1,000	105	68,757	3,192
American Integrity	American Steamship Co.	1,000	105	68,320	3,168
Burns Harbor	American Steamship Co.	1,000	105	71,120	3,192
American Spirit	American Steamship Co.	1,000	105	66,080	3,180
St. Clair	American Steamship Co.	770	92	44,308	2,136
American Mariner	American Steamship Co.	730	78	35,583	1,704
H. Lee White	American Steamship Co.	704	78	34,247	1,644
John J. Boland	American Steamship Co.	680	78	32,772	1,584
American Courage	American Steamship Co.	635	68	26,992	1,284
Sam Laud	American Steamship Co.	635	68	26,216	1,284
Samuel De Champlain / Innovation	Andrie Inc.	536	70	17,600	888
Gary . Ostrander/Integrity	Andrie Inc.	530	70	17,600	888
Joseph L. Block	Central Marine Logistics	728	78	41,664	1,704
Edward L. Ryerson	Central Marine Logistics	730	75	30,800	1,524
Wilfred Sykes	Central Marine Logistics	678	70	24,080	1,320
Edwin H. Gott	Great Lakes Fleet	1,004	105	69,664	3,204
Edgar B Speer	Great Lakes Fleet	1,004	105	69,552	3,204
Presque Isle	Great Lakes Fleet	1,000	104	58,240	3,096
Roger Blough	Great Lakes Fleet	858	105	50,305	2,616
John G. Munson	Great Lakes Fleet	768	72	28,616	1,560
Arthur M. Anderson	Great Lakes Fleet	767	70	28,336	1,524
Philip R. Clarke	Great Lakes Fleet	767	70	28,336	1,524
Cason J. Callaway	Great Lakes Fleet	767	70	28,336	1,524
Great Republic	Great Lakes Fleet	635	68	27,183	1,296
Alpena	Inland Lakes Management	520	67	17,097	1,044
Paul R. Tregurtha	Interlake Steamship Co.	1,013	105	69,580	3,216
James R. Barker	Interlake Steamship Co.	1,000	105	67,475	3,168
Mesabi Miner	Interlake Steamship Co.	1,000	105	67,465	3,168
Stewart J. Cort	Interlake Steamship Co.	1,000	105	64,690	3,096
Hon. James L. Oberstar	Interlake Steamship Co.	806	75	35,280	1,752
John Sherwin	Interlake Steamship Co.	806	75	35,280	1,752
Lee A. Tregurtha	Interlake Steamship Co.	826	75	32,884	1,644
Herbert C. Jackson	Interlake Steamship Co.	690	75	27,776	1,416
Kaye E. Barker	Interlake Steamship Co.	767	70	29,008	1,548
Dorothy Ann / Pathfinder	Interlake Steamship Co.	699	70	23,800	1,344
Undaunted/Pere Marquette 41	Pere Marquette Shipping	494	58	5,750	636
St. Marys Conquest	Port City Marine Services	437	52	9,529	638
St. Marys Challenger	Port City Marine Services	538	56	12,656	972
Commander	Port City Marine Services	495	71	14,453	971
Joyce VanEnkevort / GL Trader	VanEnkevort Tug & Barge	845	78	39,766	1,812
Joseph Thompson Jr.	VanEnkevort Tug & Barge	707	71	23,744	1,344
Clyde S. VanEnkevort / Erie Trader	VanEnkevort Tug & Barge	8/45	78	39,766	1,812

Table B. 2: Prominent iron ore carrier dimensions. (Data source: Greenwood [157])

i	Vessel	Gross Tonnage	Length (feet)	Width (feet)	Draft (feet)	TPI (ton / inch)
1	American Century	33,535	1,000	105	34	266
2	American Integrity	35,652	1,000	105	34	264
3	American Spirit	34,569	1,004	105	28	265
4	Buffalo	11,619	635	68	26’6”	107
5	Burns Harbor	35,652	1,000	105	34	266
6	Cason J Callaway	12,309	767	70	26’4”	127
7	CSL Assiniboine	19,205	740	78	30’4”	n/a
8	CSL Laurentien	19,865	740	78	31’4”	n/a
9	CSL Niagara	19,824	740	78	30’7”	n/a
10	Edgar B Speer	34,620	1,004	105	32’1”	267
11	Edwin H Gott	35,592	1,004	105	32’1”	267
12	Herbert C Jackson	12,292	690	75	27’	118
13	Hon James L Oberstar	16,285	806	75	27’10”	146
14	James R Barker	34,729	1,004	105	29’1”	264
15	John G Munson	15,179	768	72	26’8”	130
16	Joseph L Block	14,956	728	78	30’11”	142
17	Joyce L Vanenkevort*	16,522	740	78	30’	151
18	Kaye E Barker	11,949	767	70	27	129
19	Lee A Tregurtha	14,672	826	75	28’1”	137
20	Mesabi Miner	34,729	1,004	105	29’1”	264
21	Philip R Clarke	12,341	767	70	27	127
22	Presque Isle	22,621	1,000	105	28’7”	258
23	Roger Blough	22,041	858	105	27’11”	218
24	RT Hon Paul J Martin	19,830	740	78	31’4”	n/a
25	Sam Laud	11,619	635	68	28	107
26	Stewart J Cort	32,930	1,000	105	27’11”	258
27	Thunder Bay	24,430	740	78	29’6”	n/a
28	Clyde S Vanenkevort**	15,823	740	78	30’10”	151
29	Victory	505	140	43’1”	n/a	n/a
30	Walter J McCarthy Jr	35,923	1,000	105	34’1”	266

* Tug is paired with barge Erie Trader. Cargo dimensions reported here are for the barge.

** Tug is paired with barge Great Lakes Trader. Cargo dimensions reported here are for the barge.

APPENDIX C

Correlation Between Lake Water Levels

Water surface elevations are highly correlated, especially for waterbodies above the Detroit River, which includes Lake Superior, the St. Marys River, Lake Michigan-Huron, and Lake St. Clair. These tables were developed using Panda's correlation matrix in Python and the Pearson correlation method [178].

$$\rho_{x,y} = corr(x,y) = \frac{E[(x-\mu_x)(y-\mu_y)]}{S_x S_y}$$

	Superior	Michigan-Huron	St. Clair	Erie	Ontario	StMarys
Superior	1	0.866071	0.739428	0.528243	0.215174	0.927913
Michigan-Huron	0.866071	1	0.932263	0.784899	0.45368	0.9511
St. Clair	0.739428	0.932263	1	0.939312	0.681195	0.845543
Erie	0.528243	0.784899	0.939312	1	0.831653	0.680194
Ontario	0.215174	0.45368	0.681195	0.831653	1	0.359608
StMarys	0.927913	0.9511	0.845543	0.680194	0.359608	1

Figure C.1: Correlation matrix for Great Lakes water levels

Monthly changes in water level result from the difference in basin precipitation and continuous outflow from the system, known as net basin supply [201]. Changes from one month to the next have a low correlation and are treated as independent variables in this research.

	1	2	3	4	5	6	7	8	9	10	11	12
1	1.00	0.42	0.19	0.32	0.25	0.15	0.06	0.14	0.12	-0.03	0.09	0.08
2	0.42	1.00	0.28	0.19	0.30	0.36	0.36	0.21	0.13	0.14	0.11	0.06
3	0.19	0.28	1.00	0.40	0.15	0.06	-0.02	-0.07	0.01	-0.03	0.02	-0.04
4	0.32	0.19	0.40	1.00	0.38	0.19	0.09	0.12	0.02	0.07	0.13	0.07
5	0.25	0.30	0.15	0.38	1.00	0.58	0.37	0.40	0.20	0.19	0.23	0.03
6	0.15	0.36	0.06	0.19	0.58	1.00	0.55	0.32	0.12	0.08	0.07	-0.05
7	0.06	0.36	-0.02	0.09	0.37	0.55	1.00	0.55	0.24	0.14	0.04	-0.09
8	0.14	0.21	-0.07	0.12	0.40	0.32	0.55	1.00	0.53	0.29	0.16	0.16
9	0.12	0.13	0.01	0.02	0.20	0.12	0.24	0.53	1.00	0.54	0.30	0.24
10	-0.03	0.14	-0.03	0.07	0.19	0.08	0.14	0.29	0.54	1.00	0.49	0.32
11	0.09	0.11	0.02	0.13	0.23	0.07	0.04	0.16	0.30	0.49	1.00	0.61
12	0.08	0.06	-0.04	0.07	0.03	-0.05	-0.09	0.16	0.24	0.32	0.61	1.00

Figure C.2. Correlations between monthly change in water level

APPENDIX D

Sample Data from Lock Performance Monitoring System (LPMS) and Automatic Identification System (AIS)

LPMS data (N=55,342) 2005-2017

	VesselName	Country	Origin	Destination	Code	Tons	Cargo
BaseDateTime							
2005-03-25 00:01:00	INDIANA HARBOR	840	STURGEON BAY, WI	TWO HARBORS, MN	1	0	Empty Barges
2005-03-25 02:56:00	AMERICAN SPIRIT	840	SUPERIOR, WI	GARY, IN	4410	53952	Iron Ore
2005-03-25 11:25:00	PRESQUE ISLE	840	TWO HARBORS, MN	GARY, IN	4410	55608	Iron Ore
2005-03-25 13:14:00	CHARLES M BEEGHLY	840	CALUMET HARBOR, IL	PRESQUE ISLE, MI	1100	22287	Coal Lignite
2005-03-25 14:33:00	LEE A TREGURTHA	840	PORT LAMBTON CAN	DULUTH, MN	1	0	Empty Barges

Figure D.1: Sample Lock Performance Monitoring (LPMS) data

AIS data (N=48,828,206) 2015-2017 filtered for 24 geographic features

	MMSI	LAT	LON	SOG	VesselName	Status	Draft	Cargo
BaseDateTime								
2017-12-31 23:59:52	316023341	46.75485	-91.97143	0.2	WHITEFISH BAY	under way using engine	NaN	NaN
2017-12-31 23:59:53	366904880	46.73642	-91.97368	0.1	MESABI MINER	under way using engine	NaN	NaN
2017-12-31 23:59:53	366938750	46.78724	-92.02204	0.1	ST CLAIR	under way using engine	NaN	NaN
2017-12-31 23:59:56	316001877	43.12395	-79.19358	0.5	VAC	under way using engine	NaN	31.0
2017-12-31 23:59:59	366980890	46.75361	-92.09417	0.0	ARKANSAS	undefined	NaN	NaN

Figure D.2: Sample historical Automatic Identification System (AIS) data

Merged dataset (N=42,021)

Datetime	VesselName	LAT	LON	Origin	Position	Duration	Destination	Cargo	Tons	From
2015-03-01 03:14:00	PHILIP R CLARKE	41.69872	-83.45046	TOLEDO, OH	Depart Toledo	0.0	TWO HARBORS, MN	Empty Barges	0.0	Arrive Toledo
2015-03-01 03:14:00	PHILIP R CLARKE	41.69872	-83.45046	TOLEDO, OH	Arrive Toledo	0.0	TWO HARBORS, MN	Empty Barges	0.0	Arrive Toledo
2015-03-02 16:50:01	RT HON PAUL J MARTIN	42.88318	-79.24848	TOLEDO, OH	Arrive Welland Canal	156.0	DULUTH, MN	Empty Barges	0.0	Arrive Welland Canal
2015-03-02 19:26:23	RT HON PAUL J MARTIN	42.88314	-79.24848	TOLEDO, OH	Depart Welland Canal	156.0	DULUTH, MN	Empty Barges	0.0	Arrive Welland Canal
2015-03-03 11:28:41	PHILIP R CLARKE	41.69873	-83.45055	TOLEDO, OH	Arrive Toledo	3374.0	TWO HARBORS, MN	Empty Barges	0.0	Depart Toledo

Figure D.3: Sample merged dataset from fusion of LPMS and AIS data

APPENDIX E

Geographic Features (G_j) Used to Subset AIS Data

Table E.1: Geographic boundaries for Great Lakes waterway features

j	Feature	West	East	North	South
1	St Marys R. and Whitefish Bay	-84.996	-83.955	46.770	46.107
2	N. Boundary St Clair River	-82.466	-82.375	43.015	43.009
3	S. Detroit River	-83.219	-83.062	42.075	42.064
4	W. Lake Erie nav lane	-82.671	-82.572	42.057	41.406
5	Welland Canal	-79.261	-79.182	43.220	42.868
6	Mackinaw Straits	-84.753	-84.725	45.857	45.766
7	S. Lake Michigan	-87.548	-86.847	41.750	41.743
8	E. Lake Ontario	-76.599	-76.592	44.274	43.421
9	Thunder Bay, ON	-89.267	-89.092	48.476	48.311
10	Silver Bay, MN	-91.277	-91.199	47.292	47.239
11	Two Harbors, MN	-91.713	-91.601	47.064	46.958
12	Duluth-Superior Harbor	-92.160	-91.852	46.926	46.633
13	Presque Isle, MI	-87.395	-87.357	46.582	46.561
14	Indiana Harbor, IN	-87.496	-87.429	41.682	41.641
15	Gary, IN	-87.329	-87.319	41.628	41.609
16	Burns Harbor, IN	-87.153	-87.144	41.647	41.634
17	Zug Island (Detroit, MI)	-83.110	-83.106	42.281	42.278
18	Dearborn, MI	-83.161	-83.153	42.307	42.297
19	Toledo, OH	-83.543	-83.333	41.769	41.460
20	Cleveland, OH	-81.725	-81.663	41.514	41.460
21	Ashtabula, OH	-80.804	-80.781	41.919	41.878
22	Conneaut, OH	-80.598	-80.540	42.008	41.951
23	Nanticoke, ON	-80.054	-80.029	42.802	42.766
24	Hamilton, ON	-79.780	-79.802	43.262	43.303

Table E.2: Geographic boundaries for Charleston Harbor terminals

j	Feature	West	East	North	South
1	Tanker Terminal	-79.935	-79.931	32.827	32.824
2	Wando Welch Terminal	-79.894	-79.888	32.839	32.829
3	Veterans Terminal	-79.894	-79.932	32.867	32.847
4	Hugh K Leatherman Terminal	-79.934	-79.929	32.844	32.835
5	Union & Columbus Terminals	-79.934	-79.923	32.804	32.791
6	North Charleston Terminal	-79.967	-79.951	32.910	32.896

APPENDIX F

Preliminary Results from Monte Carlo Simulation for Efficiency

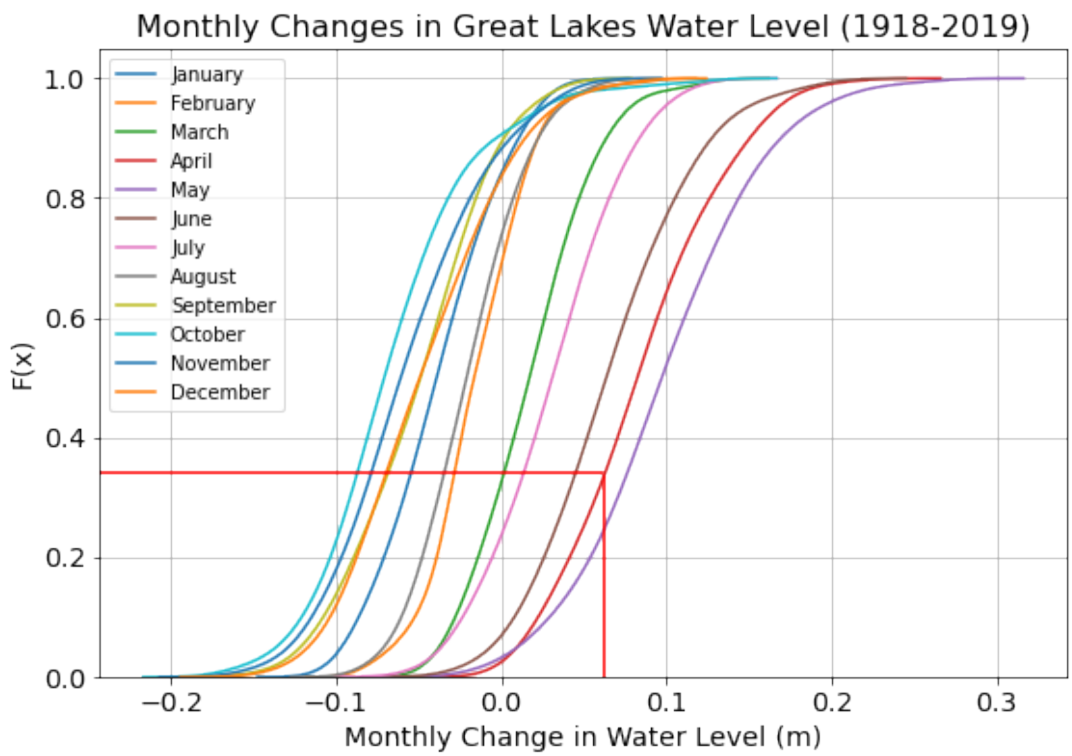

Figure F.1: Cumulative Distribution Functions for monthly water level change on Lake Michigan-Huron

Water surface elevations over a navigation season are simulated from initial conditions, defined as water surface elevations on Lake Michigan-Huron in March (beginning of the navigation season). Figure F.2 illustrates 50 simulation iterations for a navigation season.

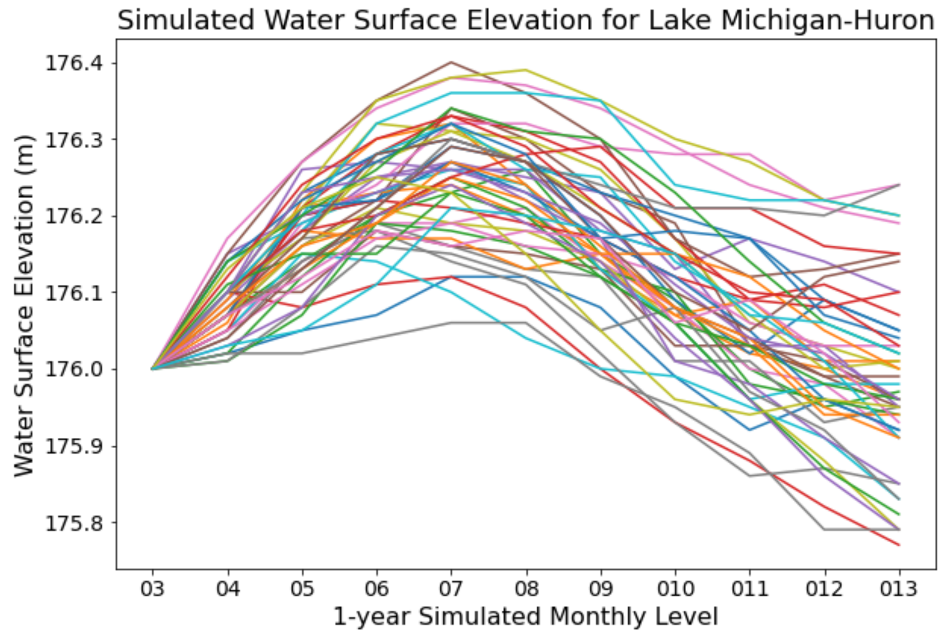

Figure F.2: Simulated water surface elevations (n=50) over a navigation season

Vessel payload is calculated for each month within a navigation season based on historical payload data using Equations 5.5 and 5.6. This is illustrated for two vessels in Figure F.3.

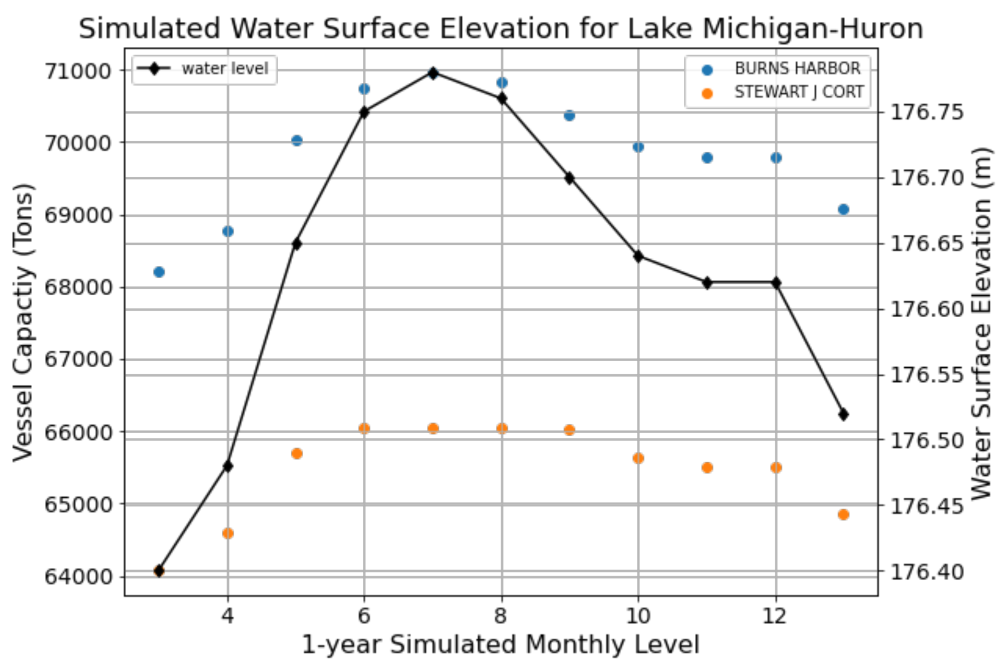

Figure F.3: Modeled vessel payload based on simulated water surface elevation

Travel time for each ship voyage is randomly generated using Equations 5.7 and 5.8 and average annual efficiency for each vessel is calculated using Equation 5.9. This is illustrated for two vessels over a single iteration in Figure F.4.

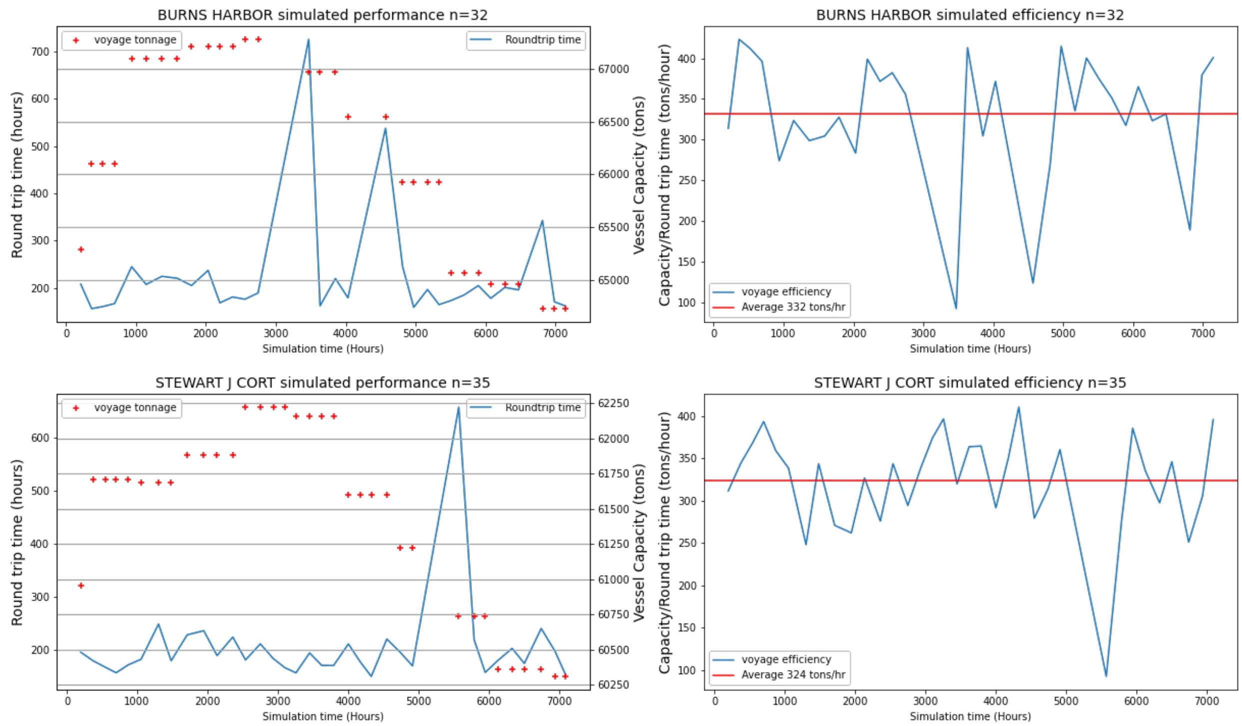

Figure F.4: Simulated vessel payload and voyage time (left) trip and annual efficiency (right)

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