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COASTAL VULNERABILITY: IMPACT OF PORT DISRUPTIONS
AND THE ECONOMIC IMPACTS OF TROPICAL CYCLONES

A DISSERTATION APPROVED FOR THE
SCHOOL OF INDUSTRIAL AND SYSTEMS ENGINEERING

BY THE COMMITTEE CONSISTING OF

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To

My mother, my safe harbor

My father, protecting me from above

And

My husband, the best partner and the love of my life

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Contents

List of Figures

List of Tables

Abstract

Coastal counties in the United States account for less than 10% of the nation's land mass. Yet, approximately 40% of the country's population, or over 127 million people, live in these areas. The population density of coastal counties is 461 people per square mile, much larger than the nation's average population density of 87 people per square mile. Coasts also present the logistic benefit of allowing the transportation of goods between countries and continents through maritime ports. However, the increase in coastal population and economic activity means an increased exposure and vulnerability to potential natural hazards, such as hurricanes and tropical storms. These weather events are powerful, with the capacity to devastate coastal regions. Therefore, understanding these potentially catastrophic events is critical to assess vulnerability and support informed decision-making at local, state, and federal levels. This research provides valuable insights related to the characteristics of tropical cyclones and to their potential impacts to the coastal United States.

First, an extensive review of the literature related to maritime supply chain resilience and the impacts of port disruptions to the maritime supply chain is performed. Ports are complex enterprises, comprised of a wide variety of stakeholders and subject to risks of many kinds, both man-made and natural hazards. This review allowed the identification of gaps of knowledge to be

explored on the topic of maritime supply chain resilience. One of the gaps is the lack of a clearly quantifiable metric for the impacts of one of the most common sources of weather disruptions: hurricane and tropical storms. Albeit the immediate impacts are limited to areas prone to these events, tropical cyclones have been known to impact extensive areas and cause long lasting negative effects.

Second, machine learning is used to rigorously explore and quantify the relationship of tropical cyclone characteristics and their destructive outcomes on the coast of the United States. Historical data on hurricanes and tropical storms is identified and curated to support supervised learning. A novel *Storm Damage Ratio* is introduced to address the inherent challenge of comparing damage to regions with distinct assets and population. Multiple mathematical models to predict economic impacts from tropical events are created using machine learning methods and the results are compared. Additionally, the storm features that most influence the accuracy of predictions are identified and ranked.

The third research component consists in analyzing coastal vulnerability to tropical cyclones at the state-level by providing mechanisms to account for uncertainty in studying the destructive potential of storms, supporting the decision-making process to improve community resilience. The previously developed concept of *Storm Damage Ratio* is extended, creating the *Local Storm Damage Ratio*, which assess the destructive potential of storms with respect to intrinsic characteristics, regardless of the local economic characteristics. Multiple machine learning models are developed to predict the value of *Local Storm Damage Ratio* at a state-level. The most promising machine learning model is used to study the relationship between state and damage, as well as evaluate state preparedness. Finally, this work makes the innovative approach of building state-level empirical fragility curves to tropical storms. The novelty curves are built for three damage levels: minor, moderate, and major damage.

Chapter 1

Introduction

1.1 Overview

Coastal zones have always been attractive locations to settle due to their rich resources and extensive supply of provisions. Coastal population growth and urbanization rates are exceeding the demographic development observed inland, driven by rapid economic growth and coast-ward migration [151, 210, 225]. Logistical reasons are a major motivation for coastal settlement, as these regions offer access points to marine trade and transport. In the United States alone, 90% of international trades involve at least one form of marine transportation, with the 25 largest maritime ports in the country handling over 1.88 billion tons in 2018 [161, 88]. Many of these ports are located in the Southeastern region of the United States, which is particularly vulnerable to severe weather events such as hurricanes and tropical storms, including the Ports of Houston, New Orleans, South Louisiana, Tampa, and Savannah.

Hurricanes and tropical storms are dangerous weather events and pose a considerable threat to the regions vulnerable to them. Between the years 2000 and 2019, the United States was affected by 273 events that resulted in costs of US $1 billion or more, recorded on the *billion-dollar events* list, which is updated annually by the National Oceanic and Atmospheric Administration (NOAA) [157]. Out of these 273 events, 45 were tropical cyclones, representing only 16.5% of the billion-dollar events occurrence. In terms of costs, however, tropical cyclones were responsible for 53.3% of the losses, or US $954.4 billion, out of the US $1,791.5 billion in total losses. Tropical cyclones also accounted for 6,507 deaths caused by billion-dollar events since 2000, a number that represents over 45% of the deaths from all types of disasters [157, 211]. Additionally, the intensity and destructive potential of these natural events are poorly understood. The strength of a hurricane is usually determined based solely on the maximum sustained wind speed observed, following the classification of the Saffir-Simpson Hurricane Wind Scale (SSHS). However, the SSHS does not consider other fundamental attributes of the storms' systems, resulting in discrepancies between expected and actual destruction caused by hurricane systems. This shortcoming has been observed, but has not yet been successfully addressed [186, 97, 98, 99, 96, 103, 191].

1.2 Problem Statement

As one of the main agents of the maritime supply chain, smooth port operations are critical for continuous and timely supply chain performance. Ports are complex entities, comprised of a wide variety of stakeholders and subject to significant uncertainties and risks from multiple sources. Identifying the sources of possible disruptions and exploring the impacts of these disruptions to the maritime supply chain allows for the identification of research gaps.

Among the identified gaps is the shortage of research focused on the risks and impacts that weather events, such as hurricanes and tropical storms, have on port operations and infrastructure.

The economic impacts caused by hurricanes and tropical storms to the United States are an understudied topic, with a vast opportunity for improvement and contributions. Existing methods are not able to adequately evaluate the destructive potential of a storm or to identify the intrinsic characteristics that are the most important when it comes to estimating the economic impacts of hurricanes and tropical storms. These methods are also unable to clearly determine and quantify the significance of inherent features of tropical cyclones.

The impacts that tropical cyclones have on regions vary significantly due, at least partially, to three elements: (i) the inherent variability of the economic, geographic, and human-related features of the impacted regions, (ii) the intricacy of critical storm features, and (iii) the complexity of the storm-region intersection. Addressing one or more of these elements will allow for a more definite understanding of the threat and, consequently, a more precise vulnerability assessment, which, in turn, will lead to more adequate resilience actions.

1.3 Research Objectives

The objectives of this research are: (i) identify sources of risk and uncertainty in port operations and their impact to maritime supply chain; (ii) explore, identify, and quantify the relationship of tropical cyclone characteristics and their destructive outcomes using supervised machine learning; (iii) assess coastal preparedness and vulnerability to tropical cyclones at a state level; and (iv) introduce a probabilistic methodology to quantify coastal vulnerability to tropical cyclones by adapting the concept of empirical fragility curves.

To achieve the stated goals, the specific research tasks are given as follows:

- Perform an extensive literature review in maritime supply chain resilience to port disruptions to identify gaps and future research potential.

- Perform a literature review on existing alternative metrics to the SSHS and on the utilization of machines learning methods on weather-related problems.

- Implement a weighted aggregation of storm features over time to obtain a single set of characteristics per storm.

- Develop a novel metric to account for the differences in assets among regions, allowing a clear distinction between region-specific and storm-specific factors.

- Perform an extensive exploration of storm's intrinsic characteristics and economic impacts using supervised machine learning.

- Explore historical storm characteristics and impacts and determine if there are significant distinctions between predictive models for different subsets of storms, namely all storms, including both hurricanes and tropical storms, only hurricanes, and only tropical storms.

- Obtain a machine learning model capable of obtaining a superior estimate of potential damage of tropical cyclones than existing methods.

- Determine the most important storm features and demonstrate their influence to the overall economic impact of the tropical cyclone.
- Use supervised machine learning to estimate the economic impacts of tropical cyclones at state-level.
- Explore and assess state-preparedness with respect to expected versus actual economic losses resulting from hurricanes and tropical storms.
- Develop a novel probabilistic methodology to quantify coastal vulnerability to tropical cyclones at a state-level using the concept of fragility curves.

1.4 Dissertation Organization

The remaining of this dissertation is organized as follows. Chapter 2 provides an extensive review of the literature on the impacts of port disruptions to the maritime supply chain. The sources of risk and uncertainties to port operations are identified, the impacts of port disruptions to the maritime supply chain are explored, and research gaps on the topic are discussed. Among the identified gaps is the shortage of research focused on the risks and impacts that weather events, such as hurricanes and tropical storms, have on port operations and infrastructure.

In Chapter 3, existing methods of assessing the strength of hurricanes and tropical storms are reviewed and tested with respect to their adequacy to measure the economical impacts of these storms. Subsequently, the concept of *Storm Damage Ratio* is presented as an alternative to address the obstacle of comparing damage between regions with different assets. Next, the methodology of the study is presented, including information on data selection and transformation, and details on the machine learning methods used to estimate the economic impacts of hurricanes and tropical storms based on the storm's characteristics. Finally, the most important storm characteristics to prediction accuracy are identified.

Chapter 4 presents an analysis of state-level vulnerability to tropical storms and hurricanes. The storm's intrinsic characteristics and the economic losses resulting from each storm are analyzed per state, allowing for an opportunity to explore the distinctions between states in terms of tropical cyclone vulnerability. The metric *Local Storm Damage Ratio*, based on the *Storm Damage Ratio* presented in Chapter 3, is developed to allow for a fair comparison between storm characteristics, irrespective of local assets. Multiple machine learning models are developed to predict the value of *Local Storm Damage Ratio* at a state-level using storm features. The most promising machine learning model is used to study the relationship between state and damage, as well as evaluate state preparedness. Finally, the concept of fragility curves is extended and historical information are used to empirically develop probabilistic functions associated with different impact states. The developed state-level empirical fragility curves to tropical storms are an innovative probabilistic methodology to quantify coastal vulnerability.

Finally, Chapter 5 contains the conclusion of this dissertation, summarizing the work completed and suggesting potential future work.

Chapter 2

Port Disruption Impact on the Maritime Supply Chain: A literature review

2.1 Introduction

Maritime transportation systems are as economically important as they are complex. Over 90 percent of the global trade is transported by sea and the world fleet is continuously growing, with over 93 thousand commercial vessels registered in 2017 [91]. This represents a capacity of more than 1.86 billion deadweight tons [7]. In the United States alone, the maritime transportation system is responsible for more than 23 million jobs, supports over 99% of the volume of oversea trades, and the total economic impact of ports (direct and indirect) exceeds US $4.5 trillion dollars annually [6, 226, 13].

Most ports are located in low-lying coastal areas or at mouths of rivers, exposing them to a variety of environmental hazards, such as tropical storms, which bring extreme winds, flooding, and storm surge. Climate change impacts in the form of sea-level rise, increased storm intensity, and increased flooding, aggravate these hazards and reveal ports' vulnerabilities [20, 226, 190].

Despite its undeniable importance to global trade and transportation, studies focused on port disruptions and on improving port resilience are still sparse, showing that the topics have not yet received substantial attention in the literature [77]. To the best of our knowledge, the most recent works reviewing maritime supply chain disruption and risk management were conducted by [132], [170], and [200].

[132] performed a thorough investigation of research on disaster resilience of transportation infrastructure and seaports. Their work covers papers published until 2011 in the areas of disaster in general, disaster resilience, transportation infrastructure resilience, and port resilience. They conclude that there is a significant amount of work on disaster resilience in terms of infrastructure disasters and community resilience. Work related to port resilience or disaster resilience of port linked intermodal transportation, on the other hand, is scarce. More recently, [170] reviewed applications of system dynamics in the maritime transportation system. According to the authors, system dynamic models are able to depict the complexity of the maritime transportation system and should be used to better understand and improve the maritime transportation system. Finally, [200] reviewed the literature related to supply chain risk management in the container liner shipping industry.

This literature review goes beyond that of the previous work in that it identifies and addresses the impacts of a disruption to multiple agents in the system and includes significant literature on the impacts of port disruption on maritime supply chains. Among the topics reviewed are the identification of the agents affected directly or indirectly by a port disruption and the impacts of a port shutdown to different stakeholders. This chapter also reviews port and maritime supply chain resilience, including both quantitative and qualitative methods. Finally, literature in maritime intermodal transportation is also reviewed.

2.2 Maritime Supply Chain and Port Disruption Impacts

Most literature available on maritime transportation systems and port disruptions apply analytical methods and simulation models to liner shipping network reliability and container terminals. Areas such as the integration between ports and other modes of transport, as well as the entire maritime supply chain are limited [3, 22]. The following sections present studies that (i) identify port stakeholders and (ii) address the sources of uncertainty in the maritime supply chain that may lead to port disruptions and identify the impacts of these disruptions to specific stakeholders.

2.2.1 Agents of a maritime supply chain: Port primary stakeholders

Ports are intricate operational systems and include multiple stakeholders. The vast network of stakeholders includes, but is not limited to, terminal operators, shippers, federal, state and local government representatives, environmental agencies and non-governmental organizations, academic researchers, as well as the surrounding communities [19, 207, 146]. These stakeholders commonly have different, if not competing, interests, such as higher revenue, increased customer satisfaction, or reduced environmental impacts [165, 172].

According to [77], protecting ports from adverse weather impacts while also considering all stakeholders and variables involved is a “wicked problem” – a problem characterized by being difficult or impossible to solve due to incomplete, contradictory, and changing requirements that are often difficult to recognize [77, 83].

It is possible to study a port through the lens of the stakeholder cluster [54, 19, 77, 245, 114]. Clusters are commonly used by strategic management scholars to analyze systems by identifying groups of stakeholders with common interests [71]. Based on the idea of clusters, some authors define the stakeholders of a port as any group or individual who can affect or is affected by the achievement of the port’s objectives [77]. Other authors [18, 19] include in the port stakeholder concept the key stakeholders that have an interest in the functioning of a port and can somehow contribute, either in planning or decision-making, to the port.

In general management, stakeholders may be clustered into three categories: internal, external, or interface. Internal stakeholders include employees and middle managers. External stakeholders include the local community, federal government, suppliers, competitors, and customers. Finally, interface stakeholders are represented by a corporation’s board of directors and its auditors [201]. An alternative stakeholder framework, proposed by [46] while evaluating corporate social performance and the relationship between corporations and society, consists of grouping stakeholders into primary and secondary classes. The former is comprised of stakeholders who have a formal relationship with and a direct economic impact upon the organization. The latter includes stakeholders that affect or are affected by the corporation's operations, but are not essential for the continuity of these operations.

In maritime transportation supply chain, stakeholders are commonly clustered into two primary categories: external and internal stakeholders [245, 55, 19, 58]. [19] define internal stakeholders as those who constitute parts of the port authority organization and are generally most concerned with return on investment, shareholder value and creation of wealth. The authors subcategorized the external stakeholders into four other groups: economic/contractual, public policy, community/environmental, and academic/research. Economic/ contractual stakeholders are involved in port operations and are represented by shippers, tenants, trucking companies, insurers, and others. Public policy stakeholders are further divided into local, state, and federal. They include government agencies that are responsible for transportation and economic affairs, environmental agencies, planning departments and emergency management agency. Community/environmental stakeholders consist of environmental groups, neighboring residents, community groups, and even the general public. Finally, academic/research stakeholders are an important group, since they often contribute with relevant information for the port planning process. This cluster includes organizations and non-governmental groups that either conduct their work independently or are contracted by another category of stakeholder [19].

[164] proposed a classification where stakeholders are divided into four groups: internal stakeholders, economic/contractual external stakeholders, public policy stakeholders, and community stakeholders. [58] argued that the last three stakeholder categories could be grouped together into a single category of external stakeholders, resulting in the aforementioned internal and external

stakeholder categorization. While studying the stakeholders' perspective for sustainable development of a port city, [115] divided port stakeholders similarly to [164]. The four groups identified by the authors are internal stakeholders, public sector, market players/corporate body, and community/interest groups. They determined the level of influence held by each group of stakeholders in making decisions and promoting reforms in favor of sustainable development.

In a somewhat similar approach to [46], [77] divided port stakeholders focusing on the activities performed by each group. The authors classified stakeholders in two groups: those who directly use, regulate, maintain, and police the port, and those who indirectly benefit or are otherwise affected by the port's activities.

While the majority of researchers cluster port stakeholders into internal and external groups, we observe that the choice of the paradigm should be driven by the research question of interest and the granularity of the problem. There is no single correct cluster method. Stakeholders' interest and alignments differ according to the problem being addressed and the diverse clustering approaches allow researchers to focus on the appropriate elements for any given scenario.

From the literature it is possible to determine the set of stakeholders that are commonly identified by most authors (see Table 2.1). Through time, since the early 2000's, one can observe a tendency of research to address a more holistic view, with a broader variety of stakeholders included in each study. Figure 2.1 is a simple representation of the maritime supply chain agents most commonly addressed in the literature: *vessels*, *ports*, *inland shippers*, and *manufacturers*.

Table 2.1: Stakeholders in the literature

Author	Port Authority and Terminal Operators	Vessels and shipping companies	Shippers (manufacturers)	Intermodal logistic providers	Government	Community	Researchers
[164]	✓	✓	✓	✓	✓	✓	
[165]	✓	✓	✓	✓			
[15]	✓	✓	✓	✓	✓		
[55]	✓	✓	✓		✓	✓	
[23]	✓	✓			✓		
[146]	✓				✓		
[60]	✓	✓			✓	✓	✓
[58]	✓	✓	✓	✓	✓	✓	
[114]	✓	✓	✓	✓	✓	✓	
[177]	✓	✓			✓	✓	
[44]	✓	✓	✓				
[18]	✓	✓	✓	✓	✓	✓	✓
[19]	✓	✓	✓	✓	✓	✓	✓
[113]	✓	✓	✓		✓		
[77]	✓	✓	✓	✓	✓	✓	✓
[231]	✓	✓		✓	✓		
[207]	✓	✓	✓	✓	✓	✓	✓
[115]	✓	✓	✓	✓	✓	✓	✓

[44] classifies *vessels* into three categories: tramp, liner, and industrial. Tramp ships operate as taxis, owned by the so called carriers and rented out by those to the shippers. It commonly operates from one port to others, with flexibility on its schedule, and following the demand of cargo owners. Liner ships, on the other hand, operate as buses: they have a fixed route and schedule. Liner ships usually carry cargo from many different shippers, meaning, each shipper uses only a portion of the liner ship capacity. Finally, industrial shipping is responsible solely for in-house traffic [227].

Ports are responsible for loading and unloading cargo from incoming and outgoing vessels, as well as for temporary storage of cargo. Ports are only a part of the operation of moving goods through a supply chain. Before being loaded (unloaded) to (from) the ship, the goods are transferred using inland transportation, that may be rail or road.

Inland shippers are the agents responsible for the movement of goods inland. Traditionally, inland shippers are third-party companies, hired by manufacturers to deliver finished goods or pick up raw material. However, it is not uncommon for large manufacturers to manage their own inland transportation.

Finally, the last represented stakeholders are *national manufacturers*. Manufacturers may import their supply chain's input through the port, may export their finished goods through the port, or both. In either one of these situations, the manufacturer will be impacted by a port disruption.

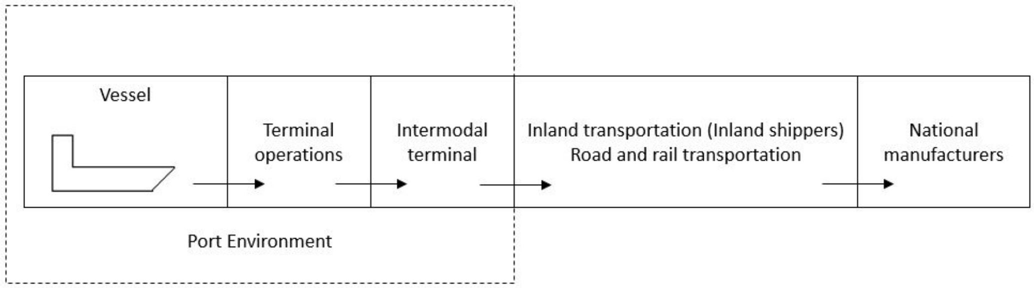

Figure 2.1: Port primary stakeholders

2.2.2 Sources of uncertainty and impacts to stakeholders

According to [102], the distinction between risk and uncertainty relies on the existence of probability. The term *risk* refers to situations in which probabilities associated to events are available. Meanwhile, *uncertainty* is used to describe situations in which information is too imprecise or unreliable to be represented by probabilities. Knight's definitions are commonly used in decision theory and economics [119, 228, 198, 199, 147].

In risk assessment and reliability engineering, however, these definitions should be used with caution since not all authors agree. Some authors argue that uncertainty is inherent to risk and thus safety should be addressed with the goal of both risk and uncertainty reduction [145]. Other researchers believe that a broader risk perspective is required and that uncertainty should replace the probability component in the concept of risk [9, 10, 11]. A more comprehensive definition of risk is presented in [74], where the authors define risk along three dimensions: probability of occurrence, the potential consequences of an occurrence, and the inherent source of the risk (e.g., negligence, natural hazard, etc.)

When considering specific areas of research, one can be more specific along defining the relevant components of risk. For example, in a global supply chain, [43] identified nine different categories of risk that need to be taken into account: disruptions, delays, systems risk, forecast risk, intellectual property risk, procurement risk, receivables risk, inventory risk, and capacity risk.

In maritime supply chains, commonly identified sources of uncertainty are weather, ground transportation, and information sharing. Some natural hazards, such as hurricanes and tropical storms, are continuously monitored. As time passes and they approach the coast, the uncertainty about the future evolution of the storm disappears but not about the consequences [124]. Even if it was possible to know for sure the category of a hurricane on the Saffir-Simpson Hurricane Wind Scale before it hit, the range of wind speed within a category is wide enough that the storm impacts vary. Ground transportation network also represents a significant source of uncertainty. Ground transportation network uncertainties include capacity, availability, and reliability. The final source of uncertainty that is frequently pointed out is related to information sharing throughout the network. The size, complexity, and number of stakeholders all contribute to make effective communication a challenge in the port environment [36, 207]. After a disaster, information sharing becomes both more crucial and more challenging. When an event takes place, it is likely that power will go out for extended periods of time, which interfere, if not completely disrupt, communication. This obstruction, combined with the fact that human behavior may become unpredictable after a disaster, might cause the flow of information to become compromised to the point of total lack of communication [213].

Risks and uncertainties can cause port delays and port inoperability, consequently leading to maritime supply chain disruptions. For example, if there is a possibility that a railroad leading to a port may be obstructed due to potential landslides caused by heavy rain, trains could not able to reach the port to be loaded with incoming cargo from ships. The port has a limited storage space for cargo and may become overcrowded if not managed properly. Therefore, faced with a potential railroad disruption, the port must make the decision to continue to unload cargo from vessels or not. If the port decides to suspend loading and unloading activities until further information on the railroad condition is gathered, docked vessels that are not unloaded will be delayed. Similarly, other intermodal transportation systems will also be impacted by port operations delay. This is just one example of the cascading effects that may impact port operations.

[196] divided the impacts of a port shutdown into three levels: *port level*, *macroeconomic level*, and *total impacts*. On the *port level*, common impacts are disruption of imports and exports as well as disruption of port activities. At the *macroeconomic level*, possible impacts are intermediate good shortfalls, final goods shortfalls, and reduction in final demand. Finally, the *total impacts* level consists in national impacts that expand from the port region as well as permanent loss of port business.

The following sections review literature on the impacts of port unreliability and disruptions to three stakeholders: ports, domestic manufacturers, and vessels. A list of the reviewed literature focused on the impacts of port disruptions to stakeholders is provided on Table 2.2.

Impacts to ports

Multiple authors [176, 95, 175, 130, 196, 222] used an input-output modeling approach to estimate the economic impacts of port disruptions. [175] quantify the impact of port disruptions across interdependent industries by combining the multi-regional inoperability input-output model to a simulation model of the operations of an inland port. Similarly, [222] measured the economic impacts of sudden disruptions to port operations by combining scenario analysis and interdependency modeling. [197] and [176] focused on man-made risks, evaluating the economic impact of a terrorist attack and shutdown of the port of Los Angeles/Long Beach. [196] estimated the total economic impact of a seaport disruption by combining demand-driven and supply driven input-output analysis, as well as including resilience through adjustments for each case studied.

[116] applied a stochastic timed Petri Net approach to model and analyze the impact of a port disruption on supply chains, while [252] evaluated the economic losses of port disruptions by taking into account both the daily cargo throughput of the port and the weather. The likelihood of a disruption was evaluated by [252] based on historic data of the ports, while the throughput estimation was given by a regression analysis. The total economic loss calculated was then split into loss to the shippers, loss to the carriers, and loss to the ports in terms of income and reputation.

Impacts to domestic manufacturers

Domestic manufacturers are also impacted by disruptions in ports and maritime transportations systems. [120] developed a model capable of quantifying the costs faced by a global supply chain firm that makes use of a seaport subject to unexpected closure. A Markov decision model with uncertain lead times was used to determine the cost-minimizing inventory management policy. [69] interviewed logistics and supply chain managers from a group of 30 companies based in Sydney, Australia. The researchers focused on supply chain disruptions caused by an international maritime transportation element. [69] gained a better understanding of the causes, implications, and costs of a supply chain disruption from a company's perspective. The disruption costs indicated by the interviewed managers were lost sales, expediting costs, loss of reputation, and impacts to the company's cash flow. More recently, [127] measured the impact of a port-related threat on supply chains faced by a manufacturer in Singapore by comparing the total costs, warehousing costs, and transportation costs for four different disruption scenarios.

Impacts to vessels

Although vessels can be classified in three different categories (tramp, industrial and liners), this review focus on liner shippers, as these are the most commonly studied types of vessels on the impact of port disruption to maritime shippers. As previously stated, liner shipping operations are different from other shipping operations, in the sense that they have a fixed itinerary and schedule. For that reason, ideal liner service networks have low operating costs, high frequencies, fast transit times, and both tight and reliable voyage schedules. Liner shipping most commonly transports containers. Container transport systems are characterized by tight time schedules. Therefore, when planning routes and schedules, liner services must maintain a high degree of schedule reliability [166, 195].

Port-related uncertainty is the primary source of volatility and unreliability on vessels schedules, leading to economic impacts to shippers. Moreover, global transport networks are growing in both size and complexity, making the design and operation of liner services a challenging task [187, 166]. While there is extensive research on route scheduling, port selection, and fleet size and scheduling regarding the liner shipping industry [236, 227], work focused on the impact of a disruption in liner shipping operations is still scarce.

[166] explored potential costs experienced by liner shippers and their clients, due to port unreliability. From the liner shippers perspective, the authors identified potential costs in the form of time loss, loss of customer, additional operating costs, additional port fees and tariffs, and increased fuel consumption. For the liner clients, delay may result in increased logistics cost, in the form of extra inventory and transportation costs, additional production costs, and potential product losses. The authors also explored the causes of schedule unreliability in the liner shipping industry and provided measures and planning tools available to shipping lines to address the issue. [166] classified the causes of delays into four categories: terminal operations, port access, maritime passages, and chance. The first and second groups are the ones of interest in this work. The first group, terminal operations, refers to port or terminal congestion before berthing or before starting the loading or unloading operations. Meanwhile, the second group, port access, refers to disruption in a port's access channel. This may happen for multiple reasons, such as irregularities in pilotage, low availability of pilots or tug boats, delays at sea locks, or access channel availability related to tidal windows.

Identifying potential risks and solutions are important steps to minimize the impacts suffered by the shippers due to port uncertainties and disruptions. [246] developed a risk assessment framework for container lines supply chains based on the Formal Safety Assessment methodology. The developed framework is summarized in five steps: vulnerability identification, quantified estimation of risks associated with the identified vulnerability, development of risk control options, cost and benefit analysis, and recommendation for decision making. [187] evaluated the impacts of port-related uncertainty on vessels schedules in liner shipping routes, focusing on minimizing fuel emissions. The authors formulated and solved the optimal vessel scheduling problem, in which both delay and fuel costs were considered, using simulation-based stochastic approximation methods. [38] assessed vulnerability of intercontinental ports and estimated the impact of port closures on the total supply chain cost from a liner shipping perspective through the formulation of different optimization models.

Finally, [28] proposed a formulation for dealing with disruptions in liner shipping named Vessel Schedule Recovery Problem based on the airline industry. The three recovery modes considered on their model are speed adjustment, port call omission, and port call swap. These actions can potentially lower costs by allowing the maintenance of slow-steaming policy, while also decreasing delay costs in a liner shipping network. The [28] formulation is particularly interesting given that there are many similarities between maritime and airway transportation. We speculate that there is more to be learned from the airline industry that could be applied to maritime transportation problems.

2.3 Port Resilience

[85] defines resilience "as the inherent capacity of a system to adjust its func-

Table 2.2: Impacts of port unreliability and disruptions to stakeholders

Author	Port	Manufacturers	Vessels
[197]	✓		
[176]	✓		
[95]	✓		
[175]	✓		
[130]	✓		
[116]	✓		
[196]	✓		
[252]	✓		
[222]	✓		
[120]		✓	
[69]		✓	
[127]		✓	
[246]			✓
[166]			✓
[187]			✓
[187]			✓
[38]			✓
[28]			✓
[195]			✓
[236]			✓
[227]			✓

tioning prior to or following changes and disturbances so that it can sustain operations even after a major mishap or in the face of continuous disruptions stress." [133] and [108] both define resilience in the context of a maritime supply chain as a function of system's vulnerability and its capacity to recover to a sufficient level of service within an acceptable time frame after a disruption takes place. Similarly, in [149], resilience accounts for both the innate reliability of a system and the ability of mitigating negative effects through quick recovery actions.

Supply chains involving port operations are particularly complex and vulnerable to both internal and external disruptions. Moreover, port-related disruption can trigger a cascade effect that can potentially affect the entire supply chain, as well as impacting economical and societal well-being of its surroundings [108]. Therefore, increasing global supply chain resilience is closely related to assessing port vulnerability [127, 15, 93].

Common resilience actions proposed by authors to minimize the impact of a port disruption from a manufacturer perspective are the use of inventories and input substitution [229, 196, 43]. Other authors suggest the promotion of structural integrity to increase resilience, through the development of physically stronger infrastructure systems during the design and construction phases [169, 53]. Creating modularity in systems, increasing staffing in safety-critical areas and promoting training to increase knowledge, flexibility, and redundancy in the system are also mentioned in the literature [94, 135, 169].

The actions mentioned above, even though useful when dealing with risks and uncertainty, may not be enough to address the magnitude of the impacts of a port disruption. In the following sections, resilience assessment approaches are analyzed following a classification scheme suggested by [86]. First, work on qualitative assessment of maritime supply chain resilience is presented, consisting of conceptual papers and frameworks. Next, literature regarding quantitative assessment methods is reviewed. This section includes probabilistic and deterministic approaches, risk assessment methods, optimization models, simulation models, and fuzzy logic models. Lastly, a brief review of port resilience in the light of climate change is presented.

2.3.1 Qualitative assessment of maritime supply chain resilience

Conceptual frameworks constitute the majority of qualitative approaches proposed to assess maritime supply chain resilience.

According to [15], the intricate interaction and complex interdependency between the elements of maritime supply chains result in an inherently vulnerable system. To examine maritime supply chain vulnerability, the authors defined two classifications of vulnerability. Type I refers to vulnerability emerging from operational complexity within a port, including both port infrastructure and operators. Type II refers to vulnerability of maritime movements, where the port is simply a node of the system. According to the authors, considering both types of vulnerability and their interdependencies can promote a better understanding of the system for future crises.

As explained previously, [77] classified the problem of port resilience as a "wicked problem". [77] work, above all, had the goal of changing the way that the port resilience problem is looked at. By presenting the port resilience in the wicked problem context, the authors aim to change the decision-making and policy-making approaches used by port managers. From the presented perspective, port managers should make decisions in terms of mitigation and minimization of the consequences of a disruption. The authors also emphasized that the problem cannot be solved overnight, rather, it should be mitigated overtime with the collaboration of stakeholders.

[134] developed a framework based on risk analysis and management methodologies that aids in the identification of elements of uncertainty in maritime infrastructure and transportation systems. Their framework consisted of three

phases: application of risk assessment methodology to identify, analyze and prioritize risks; utilization of a cause-and-effect diagram methodology to create a tree of events and effects; and at last, application of a decision tree analysis methodology to assess the strategies and their value for the system. [135] later applied a similar framework to port infrastructure systems.

[23] proposed a structured formal vulnerability assessment (FVA) methodology to evaluate the vulnerability of a maritime supply chain. According to the authors, the methodology allows a clear and systematic identification and mitigation of risks in the maritime transportation network.

[87] evaluated seven vulnerability factors derived from the literature and previous disasters applying geographic information systems. The produced model aimed to assist decision makers in obtaining a comprehensive understanding of port risk. Moreover, the risk analysis were to be used to help decision makers understand the vulnerable system they are dealing with and reduce disaster risks by choosing successful strategies of disaster prevention and preparedness.

[146] proposed the so-called Cognitive Process Architecture Framework (CPAF) to help seaport stakeholders sense changes, perceive operational scenarios, choose response alternatives based on trade-offs, and monitor the implementation of the responses. The authors believed that the great variety of stakeholders in seaports can easily produce fragmented information flows that undermine its ability of a systemic response to disruption events.

[77] developed a conceptual framework for developing resilience strategies for ports in the context of adverse weather events. The authors defend that, due to the dynamic nature and constant change of the problem, mitigation is the best way to approach the problem. The developed framework consists

of the following steps: data collection and analysis, stakeholder analysis, resilience strategies development, and strategies implementation.

Due to its complexity and high levels of uncertainty, [94] proposed that seaport operations should be broken down to facilitate the investigation of resilience strategies. The authors pointed out that different risk categories affect different stakeholders and developed a list of the most common risk events and the most significant causes of these events. They separated the risk events in five categories: operational risk factors, which included port equipment failure, vessel accident and cargo spillage; security risk factors, such as sabotage and terrorism attacks; technical risk factors, consisting of lack of equipment maintenance, lack of navigational aid maintenance, as well as lack of IT system and dredging maintenance; organizational risk factors, for example, labor unrest or congestion at the storage area, berth or gate; and, finally, natural risks factors, which include geologic, hydrologic and atmospheric events [94, 93].

Finally, [128] conducted interviews with professionals from the port management sector, as well as port users, to identify the most common port-related supply chain threats. Based on these interviews, the authors proposed a practical management model with the intent of increasing port resilience. [113] also conducted interviews in order to develop a quality function deployment approach to improve maritime supply chain resilience. They interviewed containers liners and cargo shippers in order to be able to take both customer requirements and maritime risks into account when prioritizing different resilience solutions.

Authors frequently classify ports as a system-of-system, due to their complexity, and suggest that they should be analyzed using System Dynamics or Systems Thinking methods. In terms of disruptions on the maritime transportation supply chain, multiple authors utilized system dynamics to model the uncertainties and complexities of those types of disruption [170, 247, 111].

[247] used system dynamics to evaluate the impact that security procedures have on the performance of seaports. More specifically, the authors analyze the relationship between seaport security levels and container throughput. Their results show that increasing port security has a ripple effect on the productivity level of the entire port. Similarly, [111] used System Dynamics modeling to analyze the impacts of policy interventions on the ability of different maritime agents to mitigate risks and recover from disruptions. Their model demonstrated that Disaster Preparedness levels are dependent, among other factors, on port activities and attitude towards risk prevention.

[136] also approached the maritime transportation system from a system of systems point of view. The authors applied systems thinking methodologies and its systemic tools to study critical properties of the system. According to the authors, applying a systems thinking approach can help stakeholders have a better understanding about the system and empower them to solve problems that may arise in a systemic way.

2.3.2 Quantitative assessment of maritime supply chain resilience

In this section, a review of quantitative assessment methods of port resilience is provided. These include quantitative risk assessment methods, simulation models, decision support, fuzzy assessments, among others.

In maritime transportation systems and maritime supply chain, risk assessment is frequently performed by researchers with a wide variety of goals

[78]. [75] utilized risk assessment to identify, manage, and reduce risks in the transport of petroleum products at sea, focusing on the environmental impacts of maritime transportation accidents. [251] constructed a Bayesian belief network model for risk assessment and prediction of the consequences of different types of accidents in the Tiajian port. [214] assessed the structural safety of ships at sea, while [122] reviewed quantitative risk assessment models for vessels sailing in maritime waterways.

The utilization of risk assessment methods to address and improve maritime supply chain and port resilience is less frequent. According to [12], resilience assessment and management can be performed without performing risk assessments, but both can be supported and even improved with risk assessment techniques. The author used redundancy as an example for their claims, arguing that adding redundancy to a system does not require assessing specific events and associated risk.

[25] identified event tree analysis, Markov process, failure mode and effects, and fault tree analysis as the major hazard analysis tools used in the literature of risk assessment in maritime transportation systems. [143] developed a risk assessment method consisting of a generic bow-tie based risk analysis combined with both Fault Tree Analysis and Event Tree Analysis to evaluate risk factors. Later, [144] proposed a new methodology for risk evaluation for seaport stakeholders based on fuzzy set theory and evidential reasoning.

In their work, [24] combined risk assessment methods and inventory routing simulation of a maritime supply chain. It aimed to systematically address vulnerability in a maritime transportation system using a formal vulnerability assessment approach. Simulations with heuristic-based tools allow the authors to quantify the impact of the disruption scenarios, as well as the mitigation measures.

[93] believed that the traditional risk modeling approaches cannot address uncertainty effectively and are, therefore, inappropriate to address the complexity of seaport operations risk assessment. To better address uncertainty in seaport operations, the authors proposed a methodology using fuzzy analytical hierarchy process and evidential reasoning. Later, [94] used Bayesian belief network (BBN) to assess the influencing factors leading to disruption of operations. According to the authors, differently than other approaches for risk analysis, BBN has the ability to address randomness and capture non-linear causal relationships in complex systems. The authors also used a Fuzzy Analytical Hierarchy Process to evaluate the relative influence of each influencing variable.

Ship rerouting is a mitigation strategy that is proposed by multiple authors. [229] proposed rerouting on their model through an online freight network assignment model. They proposed utilizing real time tracking technology to find the best recourse options for the users in order to minimize transportation costs while also avoiding costly delays and disruptions. The method could also be used to estimate network flows and predict the behavior of freight decision makers under a disruption. The authors addressed uncertainty by applying their model to different scenarios with different weather impacts and port operating conditions.

[137] developed a simulation model capable of making rerouting decisions with the goal of minimizing the impact of crisis conditions on a supply chain. They performed statistical analysis to illustrate how the simulation model can be used by port decision makers. The system performance was measured through the creation of five different scenarios, each with different percent-

ages of ships being rerouted to different ports when a port in Texas is under disruption. Each scenario was compared against a normal scenario (without disruption) and statistical tests were performed to determine the significance of the changes in terms of queue length and average time of a container in the system.

[117] used discrete-event simulation to explore the feasible paths before and during port disruptions on the West Coast of the United States. The model compared fully and partially disrupted scenarios to the port current operations.

[169] suggested a quantitative assessment of resilience for a maritime transportation system based on key performance measures of the system. Resilience is measured as the ratio between the original output of the system (prior to the disruption) to the output after the disruption. The three identified resilience metrics are tonnage resilience, time resilience and cost resilience. After the identification, the system is modeled using optimization techniques and a system dynamics model, where the objective function of the network optimization problem is to maximize the total flow on the network links.

[181] developed a decision support system that aims to optimize the movement of cargo through a port network during a disaster. The developed algorithm allocates ships to ports maximizing the use of network capacity, while considering inland transportation, port and inventory costs. Port capacities are updated dynamically, in order to reflect the congestion conditions during the disaster.

[14] used a dynamic decision model to minimize the loss of revenue a port may suffer during a hurricane by determining when a port shutdown should be ordered. A port is the agent that suffers the most with the disruption,

since it not only loses revenue, but also incurs cost of preparation. Due to the uncertainty of a hurricane path, finding the right moment to perform the port shutdown not only reduces the costs, but also avoids potential damage in case the preparation is not correctly made. [239] extended their work by adding the perspective of incoming cargo vessels to the problem. In the newly formulated problem, vessels seek to minimize the impact suffered from a hurricane landfall by making the choice between rerouting to a port outside the hurricane's path or waiting for the storm to pass and the port to reopen. The first option takes into account extra fuel and inland transportation costs incurred by the shipper, while the second option includes possible extra labor and delay costs. The authors formulated the problems as Markov decision processes and solved using a backward-induction dynamic programming.

Ship rerouting is an alternative to avoid delays due to port disruptions. However, it has multiple constraints associated with it, including: dock availability at the rerouted port, loading and unloading equipment availability at the port, cost of last minute docking and unloading, fuel availability onboard to complete the rerouting, cost of increased fuel consumption, and inland transportation network availability. Although the goal of rerouting is ultimately to minimize delay costs while the port returns to its normal operations, the aforementioned costs can easily outweigh rerouting benefits, especially if the rerouting is an unpremeditated decision. Existing papers account for many of these costs, but none takes all these aspects into consideration.

2.3.3 Port resilience to weather events

Located at the interface between land and large bodies of water, ports are particularly vulnerable to weather hazards such as floods and storms.

According to [141], vulnerability of ports to weather events is a function of three components: exposure, sensitivity, and adaptive capacity. Ports located in areas prone to hurricanes present a higher than average exposure to this type of extreme weather events. Other examples of exposure of ports to weather events are ports located in earthquake prone areas and areas presenting a higher than average rate of sea level change. Sensitivity is the degree to which the port is affected by climate-related stimuli. Poorly built or poorly maintained ports are notably more sensitive to extreme weather events than newer, well-maintained structures. Finally, adaptive capacity refers to the ability of port stakeholders to adjust to potential damage by investing in resilience actions, plans, and personnel. [140] studied seaport exposure and sensitivity to extreme weather by surveying port experts on their perceived correlation of previously determined indicators of port vulnerability and the three components of vulnerability.

Climate change is causing weather events to become more intense every year, and ports are specially vulnerable to its impacts, such as sea-level rise, stronger storm surges and increased coastal flood [18, 225]. Moreover, port cities are commonly important concentrations for population, with many of the most populated cities in the world being port cities. Therefore, dealing with extreme weather impacts in ports are not only an economical issue, but also a social issue [80].

Different reasons encouraged different ports to seek climate resilient structures. In the case of the Port of Rotterdam (Netherlands) the reason for addressing the vulnerability of the port structure to climate change was the need to deal with the city's extreme vulnerability. In order to do so, the port joined forces with other stakeholders with the ultimate goal of making the city one of the safest port cities in the world and fully resilient to climate impacts [184]. Meanwhile, in Australia, the reason behind resilience enhancement of the Sydney Port and Port Kembla was the fear that climate change might impact the successful operations of the port sector; and in the Port of New York and New Jersey the reason was actually a response to a poor ranking in an Organization for Economic Co-operation and Development (OECD) study [139, 168]. [212] compared the resilience actions taken by the ports of Rotterdam, San Diego, and the Naval Base Kitsap, and observed the most common adaptation choices made from a robustness perspective. However, most ports around the world are still unaware of the latent hazards of climate change or are slowly starting to acknowledge the necessity of investments in port resilience [18].

[168] conducted interviews with seventy senior managements of the maritime sector in Ireland, with the goal of understanding and identifying the preparedness of the sector to build adaptive capacity to adapt to climate change. The authors determined that, even though most interviewees were aware of the importance of environmental management of the port sector and most perceived the impact of climate changes on their lives, few actually comprehended the importance of mitigation and adaptation actions to climate change in the port sector. Similarly, [104] determined the perceptions of the various port stakeholders as to the responsibility of climate adaptation leadership at the Port of Providence. Through interviews, the authors concluded that while

stakeholders were aware of the importance of implementing resilience strategies, the groups diverged greatly on whose responsibility said implementation was.

There is a dearth of climate change related port resilience literature. The limited research that does exist primarily focuses on particular ports. While such work presents significant findings for the specific case studies involved, it is difficult or impossible to extend the work as a basis for general climate-change motivated operation policies, frameworks, or guidelines.

2.4 Ports as Part of an Intermodal Transportation Network

Intermodal transportation refers to the transportation of a person or a load from an origin to a destination, through a sequence of two or more transportation modes. The transfer between two modes is performed at an intermodal terminal. Similarly, when addressing freight rather than people, intermodal freight transportation refers to a multimodal chain of container-transportation services [41, 52, 73, 129]. In an intermodal transport chain, it is usual that the shortest possible length is traveled by road, due to its higher cost. Most of the route is traveled by rail, ocean-going vessel or inland waterway [129].

Globalization is transforming ports from simple bridges between land and sea to important providers, responsible for complex logistics networks through the usage of intermodal transportation networks [51, 173]. Intermodal transport operations in maritime ports are commonly located at container terminals, being divided into seaside operations, storage operations, and landside operations. On the landside, containers are loaded to or unloaded from trucks or trains. Similarly, on the seaside, containers are loaded to or unloaded from vessels. Storage operations refer to the transportation and storing of containers at the yard [108].

The tendency of increased integration between land and sea operations emerge from the understanding of the necessity of having a holistic container terminal operation [127]. This increasing importance has been attracting the attention of researches progressively, as studies related to containerization and intermodal transportation networks involving ports are beginning to emerge. However, there is still a massive gap between the amount of studies focused solely on rail and road intermodal transportation and the ones incorporating the maritime sector [217].

[36] performed a literature review where they identify intermodal research topics and determine gaps in the literature regarding decision support systems for intermodal transport. The authors were able to identify trends among the research papers. Three trends stood out: the development of models in a dynamic context, the introduction of environmental concerns, and the application of Operations Research techniques innovatively. The main difficulties regarding decision support models for intermodal transport identified by the authors in the literature refer to data availability and sharing, network size and computational time, and incorporation of all the agents in the decision support tools [36].

The following sections provide a literature review on containerization, resilience actions, and the utilization of quantitative methods to address intermodal transportation problems.

2.4.1 Containerization

Containerization is the name given to the transportation of cargo between different transportation modes through the use of standardized containers, eliminating the need for re-handling its contents [192]. A significant part of the international movement of goods is supported by containerized intermodal transportation and efficient container movement is fundamental for an overall efficient intermodal supply chain. Containerized transportation is also timely, reliable, and economical. Containers transportation equipment are standardized, meaning movements and handling can be performed efficiently. Containers are also considered a safe transportation method in terms of cargo loss and damage [52].

Transportation of cargo with containers is the foundation of globalization and international trade. Containerization is a key mechanism when providing a global transportation with high quality and low price [166]. The utilization of containers improve supply chain efficiency and reliability. Proof of these benefits is the growth rates of container transportation in the last century [3, 179]. Container transport is a highly synchronized process and, if a segment of the container transportation does not function accordingly, the entire chain will be affected [195].

To accommodate container ships and container handling, ports and container terminals have been renewed or built all over the world. Following the trend, containerization is increasingly receiving attention from the literature. Topics of interest include container vessels scheduling and operational planning and control in container terminals. The second category includes problems as berth scheduling, container crane scheduling, stowage planning and sequencing, storage activities in the yard, and allocation of yard cranes and transporters [52].

2.4.2 Resilience actions

Work in intermodal transportation network considering seaports as part of the network are still far behind when compared to intermodal networks consisting solely of railways and roads [217]. Similarly, research focused on intermodal transportation network resilience including maritime transportation are scarce. This section provides a review of the existing literature on the topic.

An action that is widely accepted among authors in terms of resilience in intermodal transportation networks refers to information sharing [207, 36, 108]. Due to the presence of multiple agents, an intermodal transport requires more data exchange than an unimodal transport system. Data exchange is a very sensitive feature in any network, and becomes especially problematic when multiple agents, with sometimes conflicting preferences, are involved [36, 207]. [108] used a simulation game to bring awareness to the fact that communication, information sharing, and plan alignment among main stakeholders within a container terminal is severely overlooked.

[149] proposed an intermodal resilience framework that can be applied for any intermodal component and has the ability to quantify the component's level of vulnerability, being a useful analysis tool for decision makers.

[5] sought to facilitate routing and rerouting options in the case of a network disruption. They did so by establishing models and solution approaches with the goal of determining the criticality of transportation infrastructures. The authors developed models for different disrupted transportation networks: two

for railroad networks and one for an intermodal system. The models built by the authors take into account the congestion effects that are likely to happen after a disaster takes place.

2.4.3 Quantitative methods in intermodal transportation

The use of Operations Research (OR) in intermodal transportation is still in its early stages [73, 52].

Large intermodal transportation network problems usually cannot be solved in a timely manner using traditional operations research techniques. The combinatorial explosion of these problems is one of its main difficulties when trying to obtain the optimal solution. [73] addressed this problem by decomposing the intermodal transportation problem into two subproblems and solving it with a new hybrid approach. The authors developed a combination of linear programming and automated planning. Linear programming is used to optimally solve the assignments subproblem, while automated planning solved the selection of the best transportation mode for the problem [73].

[101] developed a framework that combined the minimum cost flow problem on a intermodal freight network and three types of economies of scale: quantity, distance, and vehicle size. The authors solve the problem using a proposed genetic algorithm. [41] developed an optimal transport algorithm for intermodal transport using dynamic programming to solve a weighted constrained shortest path problem. Finally, [89] developed an optimization model to analyze the economics of container logistics systems beyond ports. The author focused on seaports at the Campania region, in Italy, and aimed to

evaluate possible economic advantages of utilizing regional intermodal facilities and intermodal solutions for inland distributions.

Simulation models were used by multiple authors to gain a better understanding of intermodal supply chains. [230] observed the Finnish intermodal maritime supply chain to identify and categorize the risks existent in the supply chain. The authors conducted interviews with members of different stages of the intermodal maritime supply chain and worked with them in identifying the risks and categorizing the risk effects. Once the risk probabilities and impacts were determined based on the interviews, the authors implemented a Monte Carlo simulation model to investigate the impacts that risk events had in terms of delay in the supply chain.

[1] developed three simulation models with the goal of understanding the movement of goods at a port. Similarly, [32] used an event-driven and agent-based traffic micro simulation model to analyze intermodal transport networks. The authors used real-life data to model a transport network, including the agents of the network and their decisions in the event of a disruption. The models aided planners and operators in the identification of critical portions of the network and make decisions to reduce network vulnerability.

2.5 Concluding Remarks

Ports are extremely important agents in a global supply chain, being responsible for transporting a large percentage of the world's freight. The large amount of cargo moved daily through ports, added to the presence of multiple stakeholders, make the job of securing port operations especially complex. Moreover, due to their location, ports are especially vulnerable to weather events, such as hurricanes, storm surges, and flooding.

The objective of this work is to review the existing literature on the impact of port disruptions in the maritime supply chain. This chapter reviews the existing agents on the maritime supply chain and the economic impacts they suffer in light of a port disruption. Literature on port resilience is also examined. Finally, intermodal transportation systems that account for maritime transportation nodes are reviewed.

It is clear that the number of studies available on port disruption is small when compared to the disruption of other agents in transportation systems. The lack of attention received is even more puzzling when considering the cargo volume traded daily at ports and the economic impact that port operations have to the global economy.

Several researchers have proposed qualitative frameworks and strategies to improve maritime supply chain resilience and address port vulnerabilities. Commonly, the motivation is to help port managers and stakeholders with the decision making process during disruptive events. Upon review, we find considerable overlap among the proposed frameworks along with significant repetition of ideas. Research to unify these frameworks into a general standard would help reduce redundancy and promote novel developments in the area.

This review also reveals that, even though there are quite a few quantitative port resilience methodologies, no author simultaneously considers more than a few possible resilience actions which are available in the literature. Ship rerouting, which is an alternative explored by various authors, has significant difficulties associated with it and is not always a viable option, especially in the case of short term disruptions. Moreover, we find that port sustainability and port resilience to climate change are important topics that are understudied.

While most of the existing quantitative work relating to climate change is characterized by case studies, with significant findings for the specific ports or port groups present in the study, the literature lacks guidelines that can be applied generally.

Finally, it is evident that maritime supply chain intermodal network resilience modeling is still in its early stages and has much room for improvement. This is especially clear when compared to railways and roads intermodal networks. Containerized intermodal transportation is the mode used to move a significant parcel of cargo, especially international cargo. Yet, studies including the maritime transportation portion of it are limited.

With respect to future research directions, we note that the existing literature on maritime supply chain resilience is dominated by qualitative concepts. We believe that more quantitative approaches would improve the rigor and clarity of the methodologies. There is a gap regarding the formulation of comprehensive ship rerouting problems, including all possible costs that may arise from the rerouting decision. Detailed analysis can improve decision-support and identify guidelines for determining when ship rerouting should be performed. Furthermore, there is deficiency of analytical frameworks addressing port resilience in context of climate change. An equally important research suggestion is in the maritime intermodal transportation area. As previously stated, port disruption's can cause cascading effects to the entire supply chain. There are insufficient studies to properly understand and address these effects. Helpful information and guidelines that could arise from resilience related research in this area include improved models for intermodal operations planning, optimal intermodal node allocations, and intermodal capacity planning.

In summary, ports are significant components of the U.S. economy accounting for trillions of dollars in economic activity each year. Given their location along coastlines they are susceptible to natural hazards such as hurricanes and storm surge, which are expected to intensify in the future due to climate change. Filling the research gaps identified in this chapter will help further the science relating to port and maritime supply chain resiliency.

Chapter 3

Modeling the economic impact of incoming tropical cyclones using machine learning

3.1 Introduction

Tropical cyclones are storm systems forming over tropical or subtropical waters that are characterized by a low pressure center and rapidly rotating strong winds. Depending on their maximum sustained wind speed, tropical cyclones can be classified as tropical depressions (winds below 33 knots), tropical storms (winds between 34 and 63 knots), or hurricanes (winds above 64 knots) [152, 84]. Tropical cyclones typically produce heavy rain and may cause storm surge [123]. Coastal regions are particularly vulnerable to the impact of these potentially destructive natural systems. Tropical cyclones account for a considerable fraction of economic losses due to natural hazards [182, 253]. Between 2000 and 2019, 26 tropical cyclones caused losses exceeding US $1 billion *each* across the United States [156]. During this period, nine out of the ten natural hazards that caused the most economic losses were tropical cyclones [156]. Not only expensive, tropical cyclones are also relatively frequent events. Between the same period, 306 named storms were recorded in the North Atlantic Ocean, 146 of which reached hurricane status. Figure 3.1 depicts the number of named storms per year, as well as the number of these storms that were classified as hurricanes. The observations of named storms from the National Hurricane Center (NHC) include tropical storms, hurricanes, and subtropical storms. Subtropical storms are subtropical cyclones with a maximum sustained wind speed of at least 34 knots [153] and are reclassified as fully tropical cyclones if they intensify enough to reach hurricane force winds.

Hurricanes are commonly classified using the Saffir-Simpson Hurricane Wind Scale (SSHS) which uses the maximum sustained wind speed when assessing its strength. The SSHS classifies hurricanes from categories 1 to 5, where 1 represents the least intense hurricanes and 5 represents catastrophic hurricanes with the highest maximum sustained wind speeds. The NHC has utilized the SSHS on its weather advisories and reports for over 40 years. Moreover, hurricane related communications, public warnings, evacuation orders, among other important mitigation actions are based on this scale. Port shutdown decisions, for example, are solely dependent upon wind speed [240, 241].

This scale, even though widely used, has the significant shortcoming of ignoring other important attributes of the storm system. As we demonstrate quantitatively in this research, wind speed characteristics alone are grossly inadequate to assess the damage potential of a tropical cyclone. It is not uncommon for hurricanes with low SSHS indices to be equally or more de-

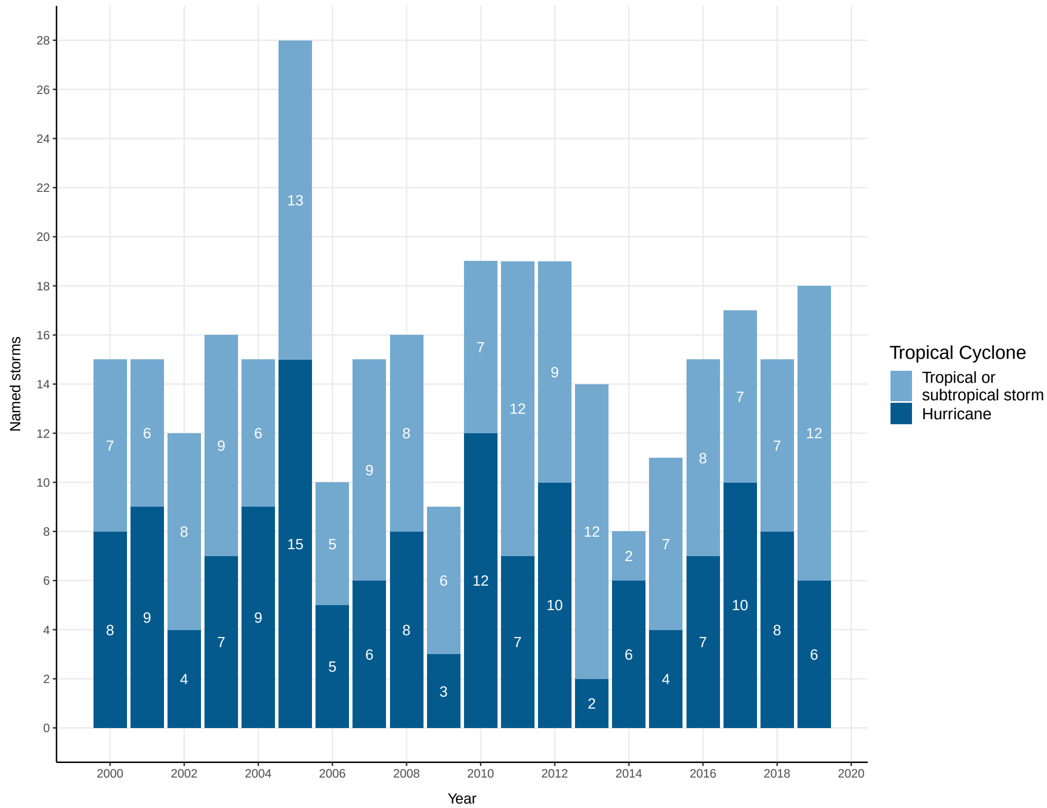

Figure 3.1: Named storms and hurricanes in the North Atlantic Ocean (2000 – 2019)

structive than hurricanes with higher SSHS indices. Furthermore, tropical storms, which are not even considered on the SSHS can also be destructive, as observed during tropical storm Alison in 2001.

Various researchers have observed the limitations of the SSHS and developed alternative methods to measure intensity and predict the impact of incoming hurricanes. However, these methods fail to accurately reflect the actual economic impact caused by a hurricane. To the best of our knowledge, no work to-date has successfully related the particular characteristics of tropical cyclones to the impacts and destruction caused by them. This is due, in part, to three elements: (i) the inherent variability of the economic qualities, geographic features, and built environment characteristics of the regions of impact, (ii) the complexity of understanding the critical storm characteristics, and (iii) the existing measures have been developed without direct consideration of the storm-region intersection. In this work, we address a component of the first element (namely, the economic variability), and we employ a data-driven and machine learning approach to address the second and third elements.

The remainder of this chapter is organized as follows: Section 3.2 presents literature associated with existing alternative metrics to the SSHS and a review of the utilization of machine learning methods on weather-related problems; Section 3.3 introduces the concept of *Storm Damage Ratio* and its calculation; Section 3.4 presents the methodology, including a discussion on weather data collection, selection, and transformation, as well as a description of the relevant machine learning methods; Section 3.5 presents the analysis results; and Section 3.6 concludes this dissertation chapter and describes appropriate extensions for future research.

3.2 Literature Review

Throughout this chapter, the following notation will be utilized: $v_{\max}$ is the maximum sustained wind speed of a tropical cyclone, tropical storm or hurricane; $p_{\min}$ represents the minimum central pressure of a storm; R_{34} is the radius of 34 knots wind speed, also referred to as the outermost wind radius; R_{50} is the radius of 50 knots wind speed; and R_{64} is the radius of 64 knots wind speed, also referred to as the radius of hurricane force winds.

3.2.1 Alternative Methods to SSHS

The accumulated cyclone energy (ACE) is the metric used by the NHC to evaluate the intensity of hurricane seasons [158]. The ACE, as the SSHS, depends exclusively on the maximum sustained wind speed and only considers events with maximum sustained wind speed above 64 knots. The ACE is defined as the sum of the squares of the maximum wind speed over the period containing hurricane-force winds [232, 235].

$$\mathrm{ACE} = \sum v_{\mathrm{max}}^2$$

The power dissipation index (PDI) is similar to ACE and, again, only takes wind speed into consideration. The PDI is the sum of the cubic of the maximum wind speed of a storm [232, 235].

$$\mathrm{PDI} = \sum v_{\mathrm{max}}^3$$

The integrated kinetic energy (IKE) metric was developed by [186] and is the foundation of multiple studies ever since it was published [142, 103, 17, 31]. It is more complete than ACE and PDI, given that it takes into account both wind speeds and storm radii. It is calculated by integrating over the storm domain volume (V), and accounting for different quadrants of the storm (since the storm may be asymmetric), for each wind speed threshold (34 to 50, 50 to 64, and 64 to v_{max}), where d is a constant value for air density and v is the surface wind speed within specific wind speed ranges [186].

$$\mathrm{IKE} = \int_V \frac{1}{2} d A v^2 dV$$

The hurricane classification index, proposed by [97] and further developed on [98] and [99], is a combination of three separate indices: hurricane intensity index (HII), hurricane hazard index (HHI), and hurricane surge index (HSI). HII is a function of the ratio of cyclone wind speed to a given reference wind speed, v_{ref}, equivalent to 64 knots.

$$\mathrm{HII} = \left(\frac{v_{\mathrm{max}}}{v_{\mathrm{ref}}}\right)^2$$

HHI includes both a maximum wind speed measure and a value for the storm size, in particular, the ratio of the size metric, R_{64}, to a specified reference value, R_{64}^{ref}, the radius corresponding to Hurricane Andrew [99],

$$\mathrm{HHI} = \left(\frac{v_{\mathrm{max}}}{v_{\mathrm{ref}}}\right)^3 \left(\frac{R_{64}}{R_{64}^{\mathrm{ref}}}\right)$$

HSI is intended to reflect the potential surge impact of a hurricane and is a function of the storm's size ratio and the *storm surge index* (SSI) defined in [92] and [99],

$$\mathrm{HSI} = 0.36 \left(\frac{R_{64}}{R_{64}^{\mathrm{ref}}}\right) \mathrm{SSI}$$

However, as demonstrated in [242] and expanded in this work to include named storms through 2018, none of the aforementioned measures (ACE, PDI, IKE, HII, HHI, or HSI) have a strong relationship to the immediate economic impacts of a hurricane after landfall on the US coast. Immediate damage data, obtained from the National Oceanic and Atmospheric Administration (NOAA), includes only direct losses associated with a storm's impact. Indirect damage or long-term macroeconomic effects are not considered [183]. The damage dataset used in this work contains over 1,200,000 entries on damage caused by multiple types of weather events between the years 2000 and 2018. The entries referring to tropical cyclones are selected and the name of the storm is obtained from the event description contained in the dataset. Table 3.1 shows the Pearson, Kendall, and Spearman correlation coefficients, r, τ, and ρ, respectively, for the alternative indices measured at time of landfall with the economic damages of hurricanes between 2000 and 2018. The Pearson coefficient is a measure of the strength of a linear correlation between two variables, whereas Kendall's τ and the Spearman coefficient are measures of rank correlation. The p-value of each measure is listed in parentheses below the coefficients. Empirically, HII has the largest *linear* correlation among the alternatives, yet $r = 0.280$ is not typically considered a strong correlation value. PDI has the strongest *rank* relationship with damage with both Kendall's τ and Spearman's ρ values of 0.318 and 0.446, respectively. The fact that PDI has a relatively weak linear relationship with damage, but a moderately strong rank relationship is indicative that non-linear relationships should be explored.

3.2.2 Machine Learning applied to weather-related events

Machine learning (ML) is a discipline that studies algorithms which, when applied to data, are able to extract information by identifying structures, patterns, and relationships among variables [223]. Machine learning algorithms are gaining popularity for a variety of natural hazard related problems, from weather prediction [39] to weather impacts in multiple areas (e.g., weather-related airline delays [42, 237, 238]; weather impacts to agriculture and food security [40, 107]; rainfall and water quality [110]; seismic impact prediction

Table 3.1: Index correlation to economic damages

Index	Pearson's r	Kendall's τ	Spearman's ρ
ACE	0.053 (0.633)	0.257 ($\leq$0.001)	0.365 ($\leq$0.001)
PDI	0.169 (0.035)	0.318 ($\leq$0.001)	0.446 ($\leq$0.001)
IKE	0.138 (0.521)	0.181 (0.223)	0.292 (0.166)
HII	0.280 (0.003)	0.222 ($\leq$0.001)	0.305 ($\leq$0.001)
HHI	-0.280 (0.003)	0.005 (0.940)	0.003 (0.973)
HSI	0.271 (0.329)	0.367 (0.059)	0.451 (0.091)

[194, 8]; landslide susceptibility [4]; and, predicting forest fires [218, 49]).

A variety of ML methods have been successful in weather-related problems. From relatively straightforward techniques such as *multiple linear regression* (MLR) to predict rainfall [64, 215, 209, 189], to more advanced and so-called 'black box' methods that produce highly non-linear models. For instance, [188] used *support vector machines* (SVM) to predict the maximum temperature of the following day and [90] applied SVM to the problem of short-term rain forecasting. Multiple authors used SVM to forecast solar power generation from weather forecast [206, 208, 250, 121]. [2] compared the performance of *multivariate adaptive regression splines* (MARS) to other methods for monthly rainfall forecast, while [59] utilized MARS to forecast drought in eastern Australia and [68] compared the performance of MARS to that of empirical equations to estimate the daily reference evapotranspiration with limited weather data.

The *k-nearest neighbors* (k-NN) algorithm, another non-linear ML supervised learning technique, has also been successfully applied to weather-related problems, albeit not as frequently as the methods already mentioned. For example, [126] created a forecast model based on k-NN to estimate the photovoltaic output based on weather and solar irradiance prediction data and [37] used k-NN, among other methods, to create short-term forecast of rainfalls.

Tree-based methods, such as *decision trees* (DT), *random forests* (RF) and *boosted trees* (BT), have also been applied to a wide variety of weather-related problems. [90] used DT, among other methods, for the problem of rain forecasting in Thailand. [244] and [50] used RF to help diagnose regions of atmospheric turbulence for aviation safety. [243] employed RF to identify the set of predictors that should be utilized in the forecasting of storms. [148] applied RF to improve monthly temperature forecasts, while [112] predicted wind power generation. [178] applied machine learning approaches – including RF and BT – to the problem of monitoring and assessing droughts in different regions. [248] used DT, RF, and BT to map landslide susceptibility in Saudi Arabia. Similarly, [100] used RF and BT models to map landslide susceptibility in Korea.

Although ML has been used to study and predict weather phenomena and their related impacts, it has yet to be employed to explore the complex relationship between tropical cyclones and their economic impacts at landfall. In this study, we address this gap in four steps, by (i) curating and transforming data for ML analysis, (ii) employing several ML strategies to construct economic impact models, (iii) evaluating the predictive performance of each model, and (iv) identifying and quantifying the important storm features associated with economic impact.

3.3 Storm Damage Ratio

The physical aftermath of hurricanes and tropical storms on land vary from flooding and minor structural damage, to complete destruction of roads and buildings. Similarly, the economic consequences can vary greatly, from thousands to billions of dollars per event. While this variance is explainable in part due to the strength of the incoming storm, it is also a function of the specific coastal and inland locations affected. Of particular importance are the socioeconomic characteristics of the impacted regions. Large population centers with significant civil infrastructure and commercial development have considerably more potential for damage than less populated, rural areas with few assets and little economic activity. Gross domestic product (GDP) is one well-established and comprehensive measure of a region's economic well-being. Among the coastal counties in the United States, the minimum GDP observed in 2018 was US \$28 million, in Yakutat County, Alaska. Meanwhile, the maximum was Los Angeles County, California, with a GDP of US \$710 billion – four orders of magnitude greater than the minimum. Figure 3.2 depicts the GDP variability between counties in 2018.

In order to evaluate the damage potential of a storm, irrespective of the economic particulars of the location of landfall and in terms purely related to the cyclone's endogenous characteristics, the geographic variability of GDP must be accounted for. To address this gap, we introduce the *Storm Damage Ratio* (SDR) to normalize the impact measure. The SDR is computed as the ratio of the immediate storm damages (in terms of dollars) to the annual GDP of the counties directly affected by the storm.

Table 3.2 lists the total damage caused by a storm, the GDP of the affected

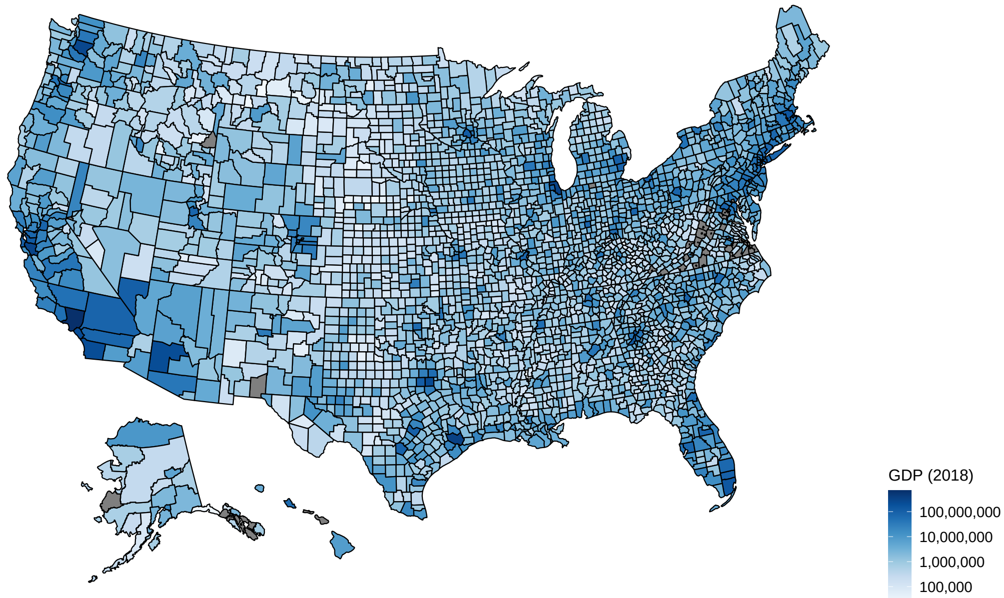

Figure 3.2: GDP by county (2018)

region, and the calculated SDR for the 15 storms with highest SDR. Hurricane Katrina, by far the most costly named storm in the history of the United States, has the highest SDR at 32 times the combined GDP of the 111 counties that were impacted. Hurricanes Sandy and Charley caused vastly different total damage in terms of dollars, yet the storms have relatively similar SDRs. The reason for this is the massive disparity between the GDPs of the counties affected by each storm. Hurricane Sandy impacted large metropolitan centers, including New York City, located in the New York County, which had GDP of US \$629.7 billion in 2015. In contrast, the highest GDP among the Hurricane Charley impacted counties was approximately one tenth of this at US \$72.3 billion. Another interesting comparison can be made between Hurricanes Wilma

Table 3.2: Hurricanes with the highest SDR values

Storm	Total damage (in millions of USD)	GDP of affected areas (in millions of USD)	SDR
Katrina	72,320	2,245	32.21
Harvey	13,844	879	15.75
Wilma	10,283	752	13.67
Charley	8,259	1,275	6.48
Sandy	22,964	4,585	5.01
Rita	6,028	1,525	3.95
Florence	2,062	534	3.86
Ike	12,675	4,174	3.04
Dolly	1,396	564	2.48
Ivan	6,872	2,920	2.35
Irma	3,732	1,882	1.98
Dennis	1,647	839	1.96
Allison	5,246	2,771	1.89
Frances	5,653	3,078	1.84
Matthew	3,957	2,421	1.63
Issac	982	601	1.63
Jeanne	1,724	1,953	0.88
Katia	1,151	1,625	0.71

and Ike, both having caused a similar amount of total damage, US \$10.3 and US \$12.7 billion, respectively. The SDR for these storms is notably different, with Wilma presenting an SDR more than four times that of Hurricane Ike. Hurricane Wilma impacted south Florida, where Florida's county with the highest GDP, the Miami-Dade County (GDP of US \$132 billion), is located. Hurricane Ike made landfall near Galveston and impacted multiple counties in Texas, including Harris county, which has a GDP of US \$418.4 billion. Figure 3.3 depicts the SDR versus the total immediate economic damage values for each of the 72 tropical cyclones considered in this study.

The SDR is fundamental for a proper evaluation of the storms' impact.

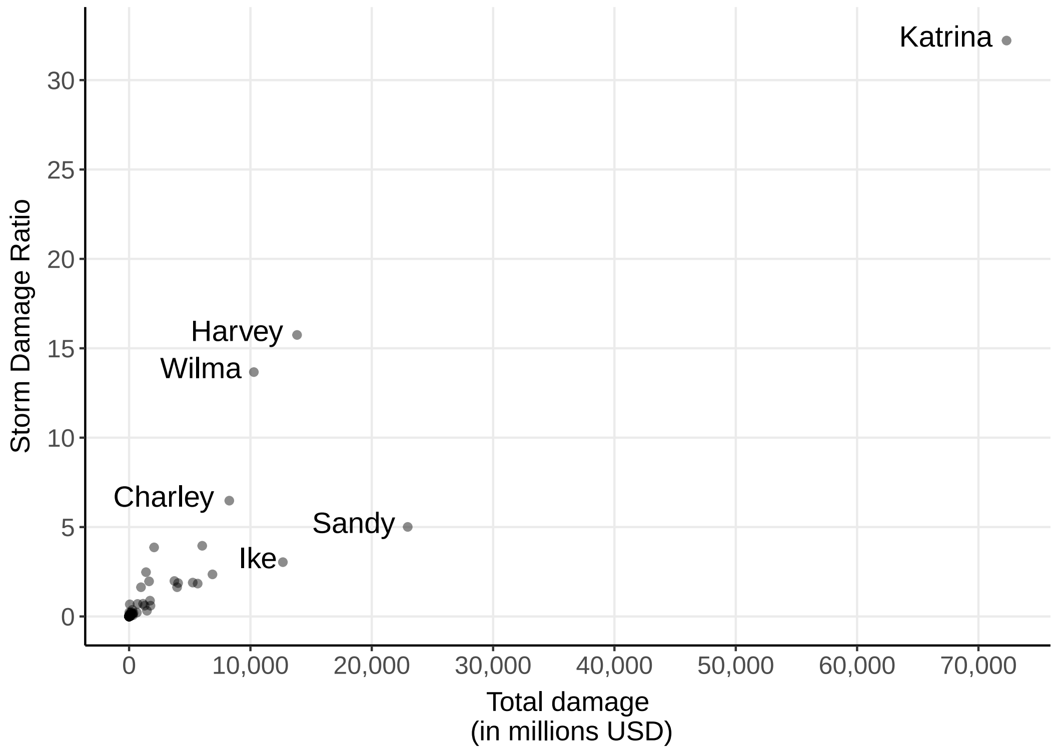

Figure 3.3: Total damage vs. Storm Damage Ratio

To support this, consider the simple linear regression results of the total damage as a function of GDP in Table 3.3. If the Katrina outlier is removed, the counties' GDP alone explains over 10% of the variance of storm damage. However, when evaluating SDR as a function of GDP, the explained variance drops to only 0.01% and GDP is no longer a significant predictor. This outcome also supports the hypothesis that storm damage is highly dependent on location of impact and thus cannot be accurately represented simply via storm characteristics. It also shows that SDR reduces this effect well.

Table 3.3: Economic damage and SDR as function of GDP

	Model	p-value	R^2
With Katrina	Damage $\sim$ GDP	0.0372	0.0389
	SDR $\sim$ GDP	0.4314	0.0056
Without Katrina	Damage $\sim$ GDP	0.0005	0.1044
	SDR $\sim$ GDP	0.6918	0.0014

3.4 Methodology

3.4.1 Data selection

Tropical cyclones are dynamic systems that evolve throughout their lifespan – increasing and decreasing in size, wind speed, pressure, among other features. Only cyclones that obtain wind speeds exceeding 34 knots at some point during their history, i.e., developed into either a tropical storm or hurricane, are considered in this study. Storm characteristics are collected by the NHC and stored in discrete time intervals, every six hours. Thus, the longer a storm is active, the greater the number of observations for that storm. The discrete nature of the collected data limits the granularity on analysis of the storm's evolution in time.

Tropical cyclones are directly dangerous to US counties only when they are close enough to the coast or after landfall. As such, we only consider the characteristics of a given storm if the radius of its outermost wind, R_{34}, plus a tolerance distance to allow for rainfall and storm asymmetries, intersects the United States coastline. For each storm, the entries are selected using the following criteria: if the great circle distance (GCD) of the center of the storm to the closest point in the United States is less than or equal to 1.1 R_{34}, the observation is used. Otherwise, the observation is discarded. Figures 3.4 and 3.5 show all tropical storm entries for the North Atlantic Ocean and the selected entries, respectively.

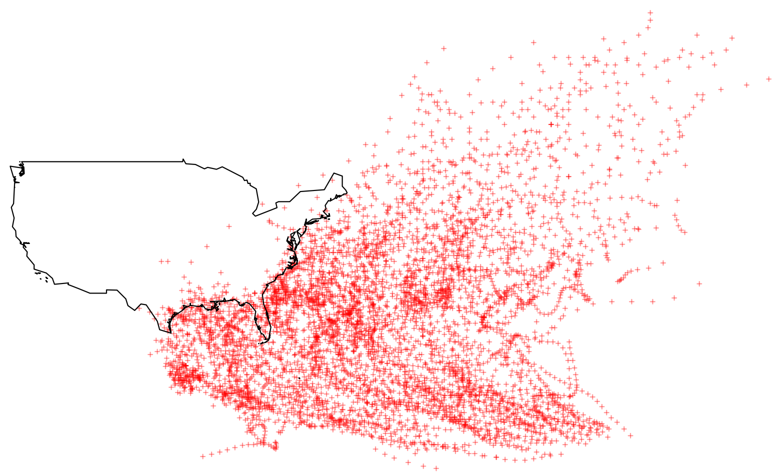

Figure 3.4: All tropical storm entries

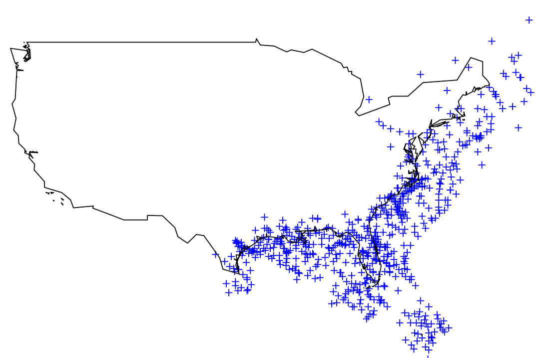

Figure 3.5: Selected tropical storm entries

3.4.2 Data aggregation

For the type of supervised machine learning modeling involved in this study, every data entry associated with storm characteristics must be associated with an economic impact value. Since, the economic measures available are single estimates in time (i.e., post-event immediate damage values), it is necessary to obtain a single set of measures to reflect the overall storm significance. This is addressed by creating a weighted aggregation of storm characteristics over time. More precisely, we assign weights to the observations according to the storm's distance from the US. If the eye of the tropical cyclone is over land or if the storm's center is less than one kilometer from land, that entry is assigned a weight value of 1. Otherwise, the weight of the observation is given by the inverse of the great circle distance of the center of the eye to the closest point on the United States' coast.

To demonstrate the data aggregation, consider Hurricane Sandy and it's path in 2012 (Figure 3.6) and an excerpt of related data including the date, time, observed $v_{\max}$, GCD of the eye of the storm to the US coast, and the resulting weighted $v_{\max}$ in Table 3.4. If the GCD value is greater than $1.1R_{34}$, the value is not used, e.g. the first two entries in Table 3.4. If the eye of the storm intersects the coastline or is within 1 km of the coastline, the values are given a weight of 1. All entries in Table 3.4 occurring after 10/29/2012 are associated with landfall, e.g., on midnight of 10/30/2012, the eye was 6.61 km inland. Otherwise, $v_{\max}$ is weighted by the inverse of the GCD value, e.g., the third and fourth entries in the table. The aggregation is made utilizing the weighted sum of the observed values. Thus, if a storm has many entries on land, it will be weighted heavier than a storm that spent a short time on land

Table 3.4: Hurricane Sandy

Date	Time	$v_{\max}$ (knots)	GCD (km)	Weighted $v_{\max}$
...				
10/29/2012	0:00	70	441.02	0
10/29/2012	6:00	80	456.01	0
10/29/2012	12:00	85	394.15	0.22
10/29/2012	18:00	80	157.55	0.51
10/30/2012	0:00	70	6.61	70
10/30/2012	06:00	55	46.48	55
10/30/2012	12:00	50	138.17	50
10/30/2012	18:00	40	229.01	40
10/31/2012	0:00	35	194.83	35
10/31/2012	06:00	35	137.80	35
...				
Weighted sum of maximum wind speed				285.73

or never made landfall.

Equation (3.1) defines the weight computation for each distinct date/time entry i in the storm's historical data. The binary variable P_i denotes the landfall status of the storm at period i. In particular, $P_i = 1$ if the eye of the storm is within at least 1 km of the coast or over land in that time period; and 0, otherwise. The values for GCD and R_{34} are also parameterized by i and thus associated with the storm's characteristics for the corresponding entry.

$$w_i = \begin{cases} 0, & \text{if } P_i = 0 \text{ and } \mathrm{GCD}_i > 1.1R_{34,i} \\ \frac{1}{\mathrm{GCD}_i}, & \text{if } P_i = 0 \text{ and } 1 \leq \mathrm{GCD}_i \leq 1.1R_{34,i} \\ 1, & \text{otherwise} \end{cases} \tag{3.1}$$

Weather entries are obtained from the data set HURDAT from the NHC and from the Extended Best Track data set [57]. Entries from the years 2000

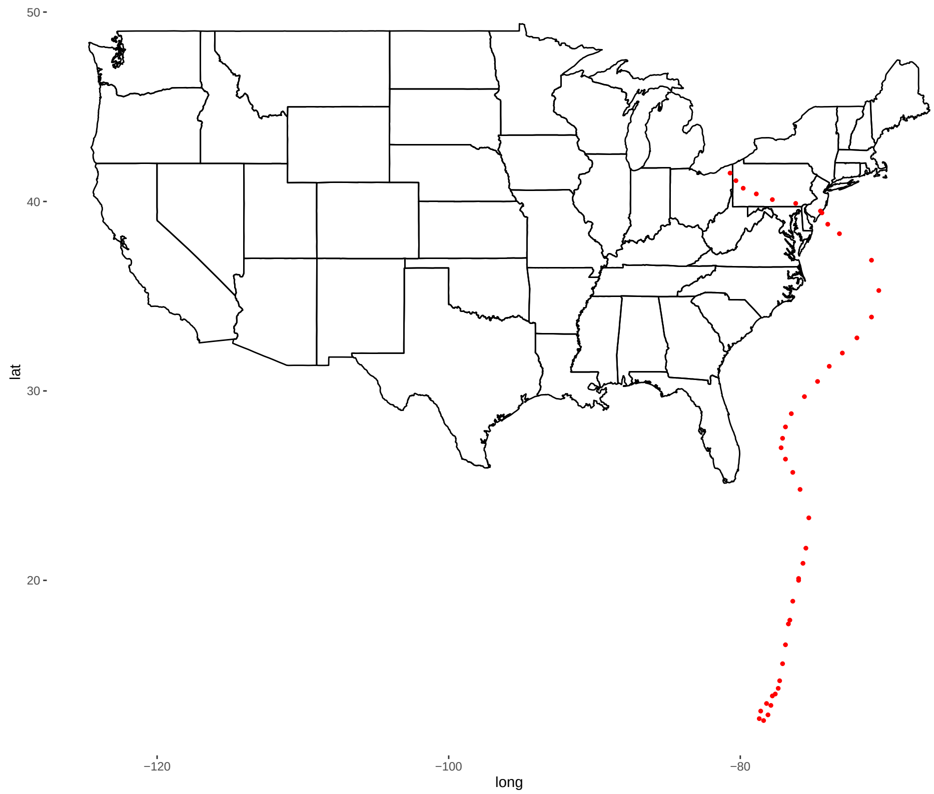

Figure 3.6: Complete Route of Hurricane Sandy

through 2018 on the North Atlantic Ocean were selected, resulting in a data set containing 6,091 observations. The final sample contains 72 observations of 9 attributes, the storm name and eight numeric attributes. The final list of attributes per storm and the attributes' type and unit is presented on Table 3.5. For convenience, the notation v_{max} refers to the weighted sum of maximum wind speed. The same is true for the other attributes.

3.4.3 Machine Learning methods

Machine learning algorithms can be divided into three categories: unsupervised learning, supervised learning, and reinforcement learning. In this work, we are evaluating supervised learning methods which learn to associate input

Table 3.5: List of attributes per storm

Notation	Attribute	Units
SDR	Damage Ratio	N/A
$v_{\max}$	Weighted sum of maximum wind speed	Knots
$p_{\min}$	Weighted sum of minimum central pressure	Hectopascals
R_{34}	Weighted sum of 34 knots wind speed	Nautical miles
R_{50}	Weighted sum of 50 knots wind speed	Nautical miles
R_{64}	Weighted sum of 64 knots wind speed	Nautical miles
Land	Periods that storm center is over land	N/A
Weighted *Dist*	Weighted distance traveled by storm center	Nautical miles

variables (a.k.a., features) with response variables (a.k.a., outcomes).

Many supervised ML models must be tuned to balance model bias with model variance thereby achieving sufficient predictive performance on new data. This is commonly achieved by iteratively adjusting model hyperparameters (parameters generally associated with the structural components of the models) to control model flexibility and evaluating the resulting predictive performance on several subsets of data using resampling methods such as k-fold cross-validation [106, 81]. Additionally, for the best hyperparameter values, the generalizable performance estimates (i.e., how well the model will perform on new data) are computed by aggregating performance measures from the k-folds. We consider the cross-validated (CV) estimates of R^2 and root mean squared error (RMSE).

Within supervised learning, there are two distinct types of modeling: classification and regression. The former is associated with predicted discrete outcomes, whereas the latter is associated with predicting continuous response values. In this work, eight distinct supervised machine learning methods for regression are employed to study the relationship between storm characteristics and immediate economic damages. These methods and their respective hyperparameters are briefly discussed in this section.

Tree-based methods: Boosted Tree and Random Forest

Boosted trees and random forests are both based on decision tree algorithms. Decision trees recursively split the data based on variable values to minimize the sum of squared error between the response and mean of the response of the respective subset [27]. The random forest is an ensemble method that combines the prediction of many trees, each built with additional randomness imposed during the tree construction: each tree is built from a random subset of the original data and only a random set of variables is considered during each split [26]. Due to the fact that they contain multiple decision trees, random forests have a lower risk of overfitting and tend to provide superior results than individual decision trees. An important RF hyperparameter to tune is the maximum number of variables considered during each recursive split, m_{try}. Boosted tree, another ensemble method, enhances predictive results by constructing a series of DTs, where each subsequent tree is created to address errors in previous trees [202, 248, 178]. Hyperparameters to tune are (i) the number of iterations (*n.trees*), (ii) maximum tree depth (*interaction.depth*), (iii) shrinkage or learning rate (*shrinkage*), and (iv) minimum size of the terminal node (*n.minobsinnode*).

Support Vector Machine

Support Vector Machine (SVM) is a supervised learning method that constructs hyperplanes in a multidimensional space. The data points in the input space are transformed, using a kernel function, to a higher dimensional feature space. The Radial Basis Function (RBF) kernel is often used with SVM to model complex nonlinear domains [21]. While commonly used for classification problems, SVM has been successfully extended for regression modeling. SVM models should be tuned by considering various model hyperparameters. In this work we consider the shape parameter (σ) of the RBF kernel and constant value (C) to penalize incorrect predictions.

k-Nearest Neighbors

The k-nearest neighbors method is based on determining distances between data points in the feature space (e.g., characteristics of different storms). For a given set of features, the predicted outcome value is computed by taking the mean of the response variables of the k-nearest points in the data. We tune the hyperparameter k which controls the model bias variance tradeoff.

Multiple Linear Regression

Multiple linear regression (MLR) is an extension of simple linear regression which fits a model to predict a dependent variable from two or more independent variables [64]. There are no tuning parameters for MLR.

LASSO

Least absolute shrinkage and selection operator (LASSO) is a regression method proposed by [224]. It estimates the regression coefficients through a penalized least-squares criterion, which imposes a penalty on the regression coefficients. The shrinkage coefficient ($lambda$) is the only hyperparemeter tuned for LASSO.

Elastic Net

Elastic Net is a regularization and variable selection method proposed by [254] and is considered a generalization of LASSO. Elastic net encourages a grouping effect in which predictors that are strongly correlated tend to be grouped in the model or removed from the model together. It is particularly useful in datasets where the number of predictors is larger than the number of observations. The hyperparemeters tuned for Elastic Net are the mixing percentage ($alpha$) and regularization parameter ($lambda$).

Multivariate Adaptive Regression Splines

Multivariate Adaptive Regression Splines (MARS) is a method for solving regression problems closely related to MLR. It was proposed by [72] and has since been successfully applied in several areas of knowledge [68]. MARS automatically transforms the input data to better model nonlinearities and interactions between variables. Hyperparameters to tune include (i) the maximum number of terms to be retained in the model ($n_{\max}$) and (ii) the degree of variable interaction to explore (mi).

3.5 Empirical analysis and results

Eight machine learning methods are used to create several new, competing mathematical models to estimate the economic impact of a storm, based on the storm's attributes. The eight approaches are BT, RF, SVM, k-NN, MLR, Elastic Net, LASSO, and MARS. The goal of this section is to perform an intensive exploration of the dataset's behavior, as well as to explore the potential of the ML methods with respect to the dataset.

Preliminary testing indicated that the radius of hurricane force winds, R_{64}, is critical for SDR prediction. This metric refers to the size of the storm, but is also directly related to the wind speed, since only storms that reached 64 knot wind speeds (hurricane classification) will have non-zero values for this feature. To further explore the data, we developed ML models for *all storms*, for a subset of the data consisting of *all hurricanes*, and for a subset of the dataset consisting of *all tropical storms.* Section 3.5.1 presents the results and variable importance of the aforementioned machine learning models for all 72 storms, encompassing both tropical storms and hurricanes. Sections 3.5.2 and 3.5.3 present the same information for hurricanes only or tropical storms only, respectively.

For a deeper understanding and an improved predictive performance, machine learning models are developed to predict two distinct outcomes: SDR and log SDR for each data group. Moreover, for each data group and for each desired outcome, four different sets of predictors are utilized. The dataset contains seven original predictors, as presented in Table 3.5. The number of original predictors is extended, via mathematical transformations on four of the original predictors, totaling 30 input variables. Two other scenarios are created using two-way interactions of predictors. The four sets of input variables for the models are: (1) ML models built using the seven original predictors (OP); (2) ML models built using the extended set of predictors (EP); (3) ML models built with OP two-way interactions (OP + interactions); and (4) ML models built with EP two-way interactions (EP + interactions). This results in two transformations of output and four transformations of input for each data group, or eight experiments in each data group. ML models are created for all eight combinations of input and output, with the exception of

MLR, which cannot be implemented when the number of input features is greater than the number of observations. The total number of models created is 182. The goal of performing such a vast exploration and developing multiple models is to obtain a ML model with the best prediction capability, as well as fundamental insights into storm characteristics.

3.5.1 All tropical storms and hurricanes

Results

For the entire dataset with all storms included, the results of the models to predict log SDR based on the different input sets are shown in Table 3.6. It is possible to observe that the best model is obtained with BT and the two-way interactions of the extended predictors (EP and interactions), with a RMSE of 2.899 and a R^2 of 0.564. RF is the second best model with very similar results, RMSE of 2.932 and associated R^2 of 0.558. These results can also be observed in Figures 3.7 and 3.8, that show the relationship of the predicted versus the actual SDR for BT and RF, respectively. The results are plotted utilizing a logarithmic scale. From the images it is possible to observe that both machine learning models provide satisfactory predictions for SDR values.

The direct SDR prediction results are shown in Table 3.7. When predicting the SDR outcome, SVM is the best method, with an RMSE of 2.888 and R^2 of 0.454, utilizing the extended predictors. BT is the second best model, presenting a RMSE of 2.967 and R^2 of 0.466. Even though the RMSE values are low, there are issues with the predictive performance for the storms that are not as economically impactful. This can easily be observed when plotting the relationship between predicted SDR versus the actual SDR of the storms,

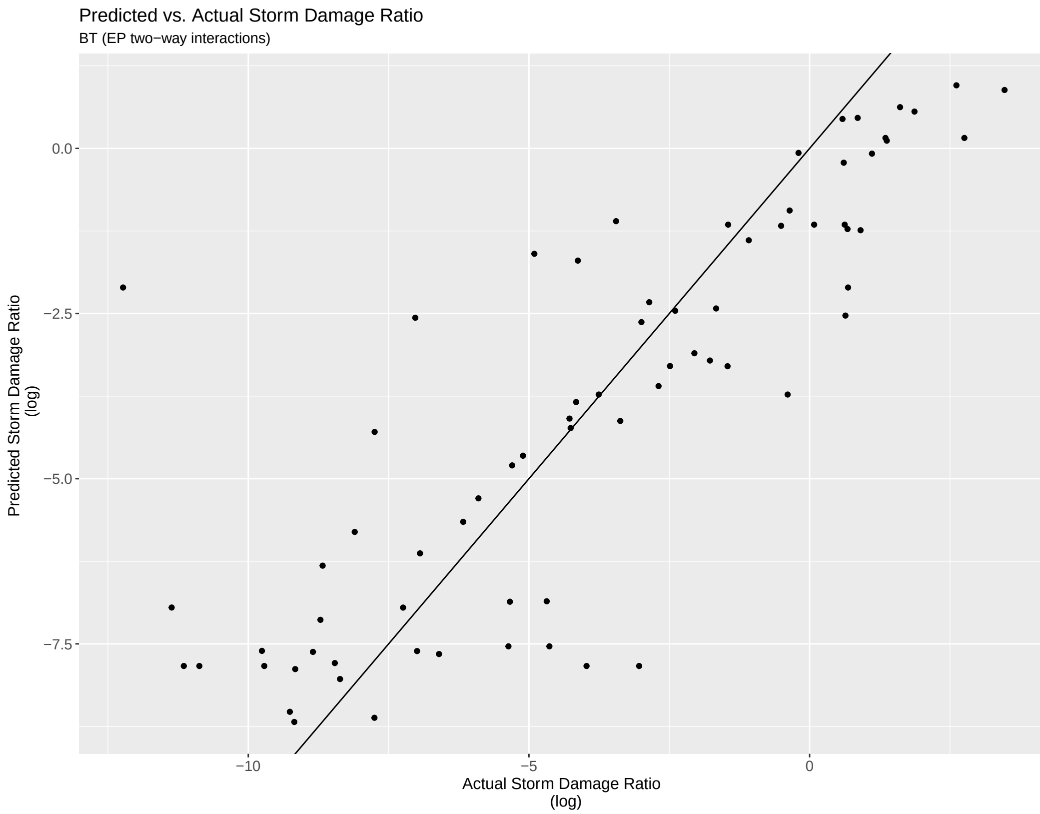

Figure 3.7: Predicted vs. Actual SDR for all storms with BT

where even the best method (SVM) creates a poorly fitting model (Figure 3.9).

Since the predictions are performed in two different scales, it is not possible to compare the results of RMSE for log SDR and SDR. However, by observing the R^2 obtained by the best method in each outcome, we verify that the R^2 obtained by BT when predicting log SDR is better than that obtained by SVM when predicting SDR. Additionally, this can be observed when comparing the plots of actual SDR versus the predicted SDR for both models. The predictions of BT, shown in Figure 3.7, follow a clear trend, unlike the predictions of SVM, shown in Figure 3.9. Therefore, when predicting SDR for all storms, BT is the most appropriate model.

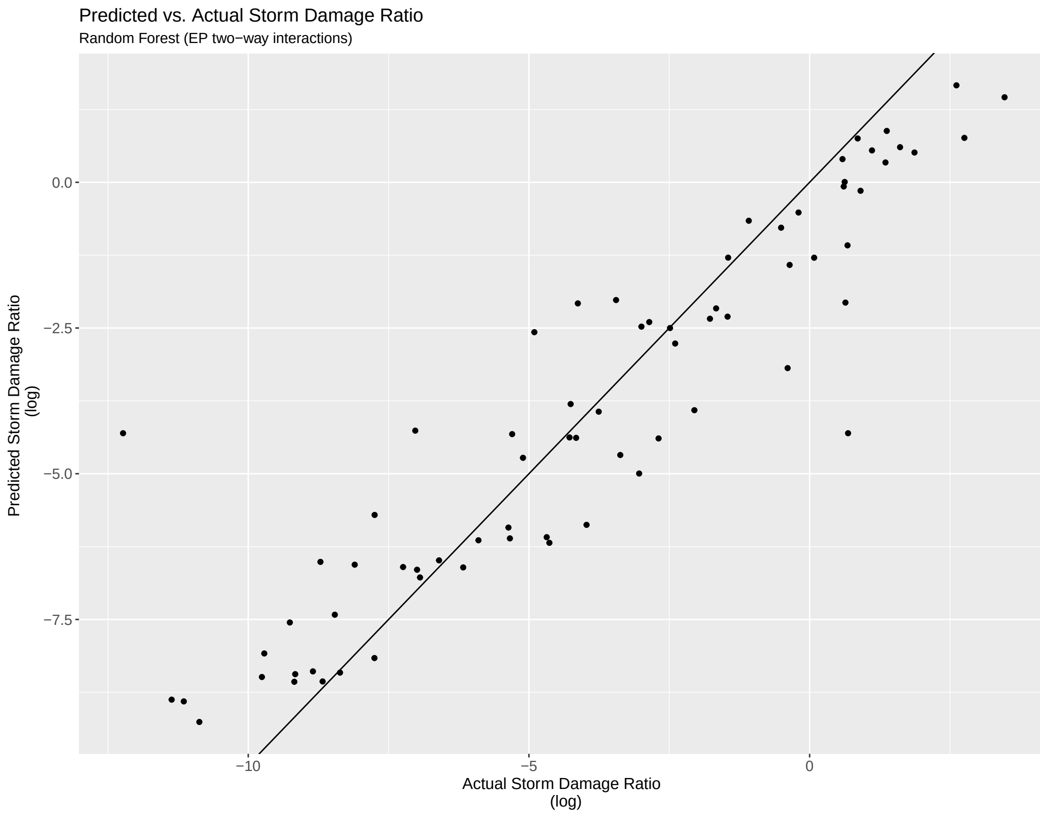

Figure 3.8: Predicted vs. Actual SDR for all storms with RF

3.5.2 Hurricane force wind speed radius

Results

Considering only the 35 named hurricanes in the dataset, the results for the prediction of log SDR are shown on Table 3.8. SVM presents the best results with an RMSE of 3.148 and R^2 of 0.46, followed by BT with an RMSE of 3.234 and R^2 of 0.438. Both methods provide adequate results and have similar distribution when plotted. Figures 3.10 and 3.11 depict the actual versus the predicted SDR on a logarithmic scale for SVM and BT, respectively.

Table 3.9 presents the results of the ML methods modeled for the SDR outcome. SVM remains the method with the best predictive performance,

Table 3.6: Results of log SDR predictions for all storms

Method	Metric	Outcome: log SDR			
		OP	EP	OP + interactions	EP + interactions
BT	RMSE	3.030	3.008	2.949	**2.899**
	R^2	0.517	0.505	0.522	**0.564**
RF	RMSE	3.079	3.062	3.010	2.932
	R^2	0.496	0.491	0.531	0.558
SVM	RMSE	3.251	3.23	3.521	3.264
	R^2	0.440	0.469	0.380	0.430
k-NN	RMSE	3.34	3.136	3.333	3.147
	R^2	0.439	0.486	0.418	0.499
MLR	RMSE	3.681	5.481	6.735	-
	R^2	0.343	0.305	0.252	-
LASSO	RMSE	3.568	3.066	3.27	3.179
	R^2	0.371	0.506	0.422	0.486
Elastic Net	RMSE	3.547	3.047	3.288	3.165
	R^2	0.404	0.525	0.425	0.510
MARS	RMSE	2.999	3.183	3.087	3.277
	R^2	0.518	0.465	0.516	0.459

with a minimum RMSE of 3.892 and R^2 of 0.53. k-NN presents the second best performance, with minimum RMSE of 4.182 and R^2 of 0.558. Figures 3.12 and 3.13 present the predicted versus actual SDR for SVM with and without a logarithmic scale, respectively. In Figure 3.13 it is possible to observe three hurricanes that are clear outliers. They are identified as hurricanes Katrina, Harvey and Wilma.

SVM is the method that presents the most promising results for hurricanes. The R^2 obtained while predicting SDR directly is slightly better than predicting log SDR.

Table 3.7: Results of SDR predictions for all storms

Method	Metric	Outcome: SDR			
		OP	EP	OP + interactions	EP + interactions
BT	RMSE	3.048	3.038	2.967	3.006
	R^2	0.475	0.446	0.466	0.469
RF	RMSE	3.248	3.233	3.159	3.235
	R^2	0.406	0.392	0.435	0.350
SVM	RMSE	2.948	**2.888**	2.972	2.949
	R^2	0.406	**0.454**	0.393	0.278
k-NN	RMSE	3.012	3.013	3.098	3.066
	R^2	0.416	0.402	0.319	0.305
MLR	RMSE	3.877	6.977	10.839	-
	R^2	0.386	0.314	0.31	-
LASSO	RMSE	3.154	3.23	3.603	3.141
	R^2	0.487	0.467	0.473	0.451
Elastic Net	RMSE	3.159	3.127	3.177	3.191
	R^2	0.507	0.476	0.433	0.414
MARS	RMSE	3.843	3.975	3.669	4.130
	R^2	0.341	0.334	0.394	0.322

3.5.3 Tropical storms

Results

The results for the prediction of log SDR for tropical storms can be observed on Table 3.10, with BT presenting the minimum RMSE, followed by RF. BT has a RMSE of 2.191and R^2 of 0.593, while RF has a RMSE of 2.233 and R^2 of 0.516. It is possible to see the good performance of these methods by plotting the predicted SDR versus the actual SDR. Figures 3.14 and 3.15 show the prediction results on a logarithmic scale for BT and RF, respectively.

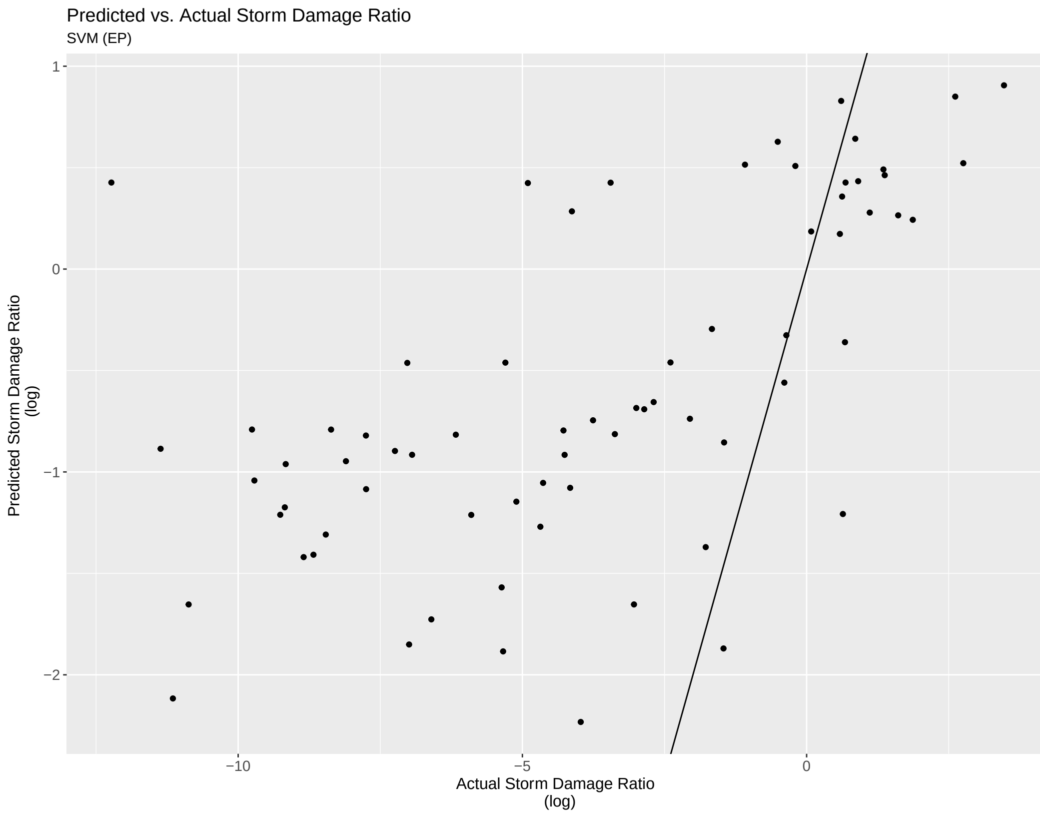

Figure 3.9: Predicted vs. Actual SDR for all storms with SVM

As it can be observed on Table 3.11, the ML model with the lowest RMSE is SVM with 0.128 and R^2 of 0.54. Figure 3.16 depicts the relationship between predicted and actual SDR on a logarithmic scale. Contrary of what one would expect by looking at Figure 3.16, SVM actually present a R^2 comparable to those of the methods BT and RF presented on Figures 3.14 and 3.15. When plotting SVM without the logarithmic scale (Figure 3.17), it is possible to clearly visualize tropical storm Allison as an outlier.

SVM, the best method for the SDR outcome, has a R^2 of 0.54, while BT, the best method for log SDR, has a R^2 of 0.593. Therefore, BT with EP two-way interactions and log SDR outcome is the ML model with the best performance when estimating the economic impacts of tropical storms.

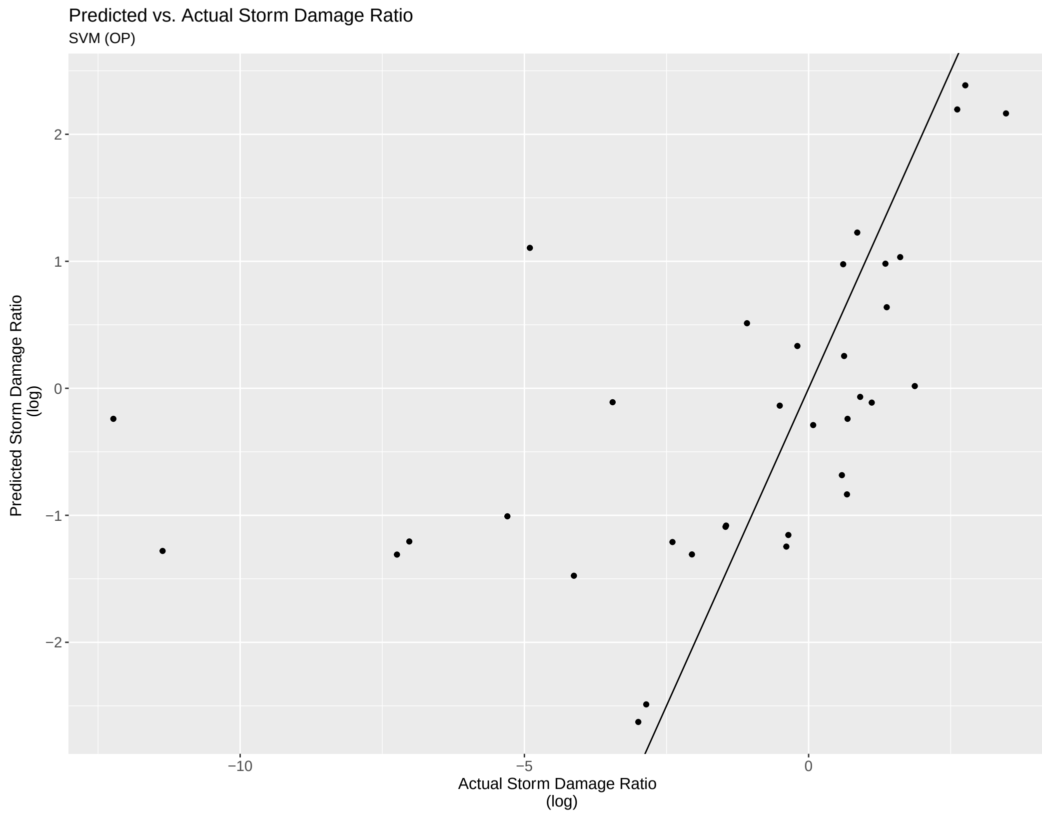

Figure 3.10: Predicted vs. Actual SDR for hurricanes with SVM

3.5.4 Variable Importance

Analyzing variable importance allows researchers to study the impact of different predictors and find the predictor combinations for specific problems [243]. For tree based methods the approximate relative influence of a variable is obtained as the sum of the empirical improvement when splitting said variable. For BT specifically, the calculated relative influence of a variable is averaged across all trees generated by the boosting algorithm [193]. For SVM, a local regression is fit between the outcome and the predictor. The relative measure of variable importance is given by the R^2 calculated for the model against the intercept only null model [105].

Tables 3.12, 3.13, and 3.14 present the most influential input features

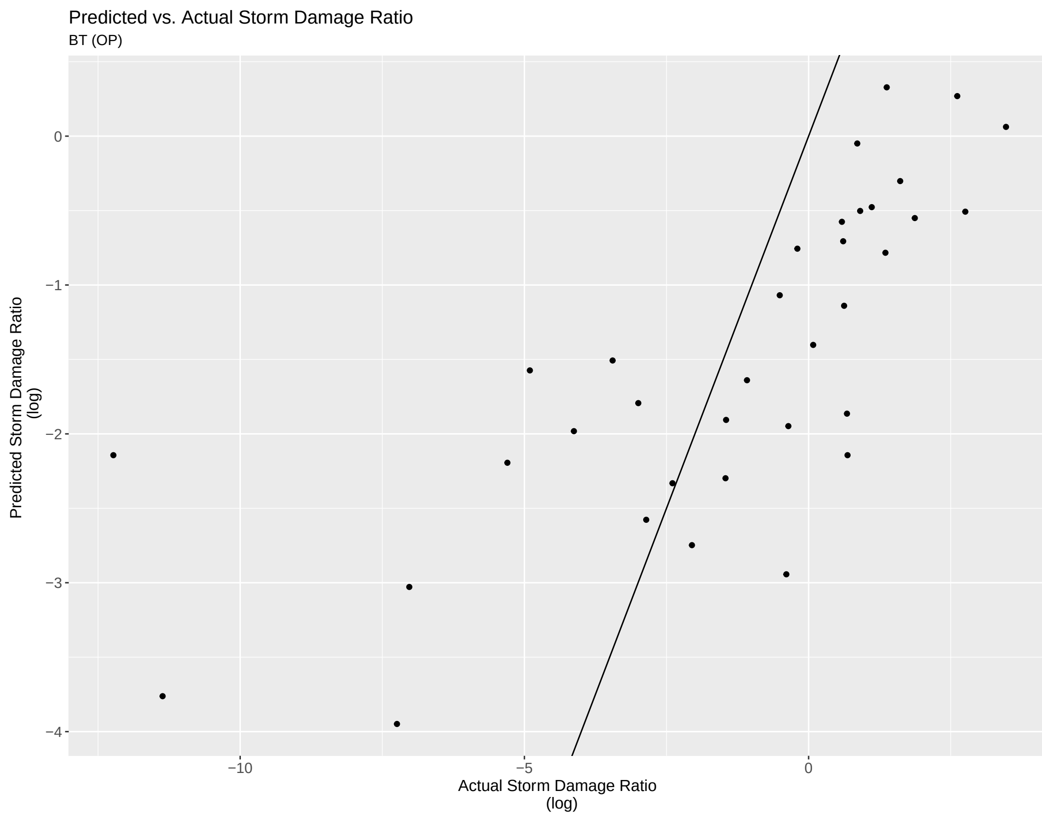

Figure 3.11: Predicted vs. Actual SDR for hurricanes with BT

ranked according to their importance scores of the best ML methods for *all storms*, *hurricanes*, and *tropical storms*, respectively. Variable importance is scaled between 0 and 1, with 0 representing low relative importance, and 1 representing a high relative importance.

BT is the best method when predicting SDR for all storms, with R_{64} as its most important variable, followed by the interaction between R_{50}^2 and $\log p_{\min}$. It is interesting to observe that the storm size, represented by R_{34}, R_{50}, and R_{64} is at least part of 8 out of 10 most important variables and variable interactions in Table 3.12. This indicates the important role that the size plays in the damage potential of a storm.

For hurricanes, the variable importance obtained with the SVM method is

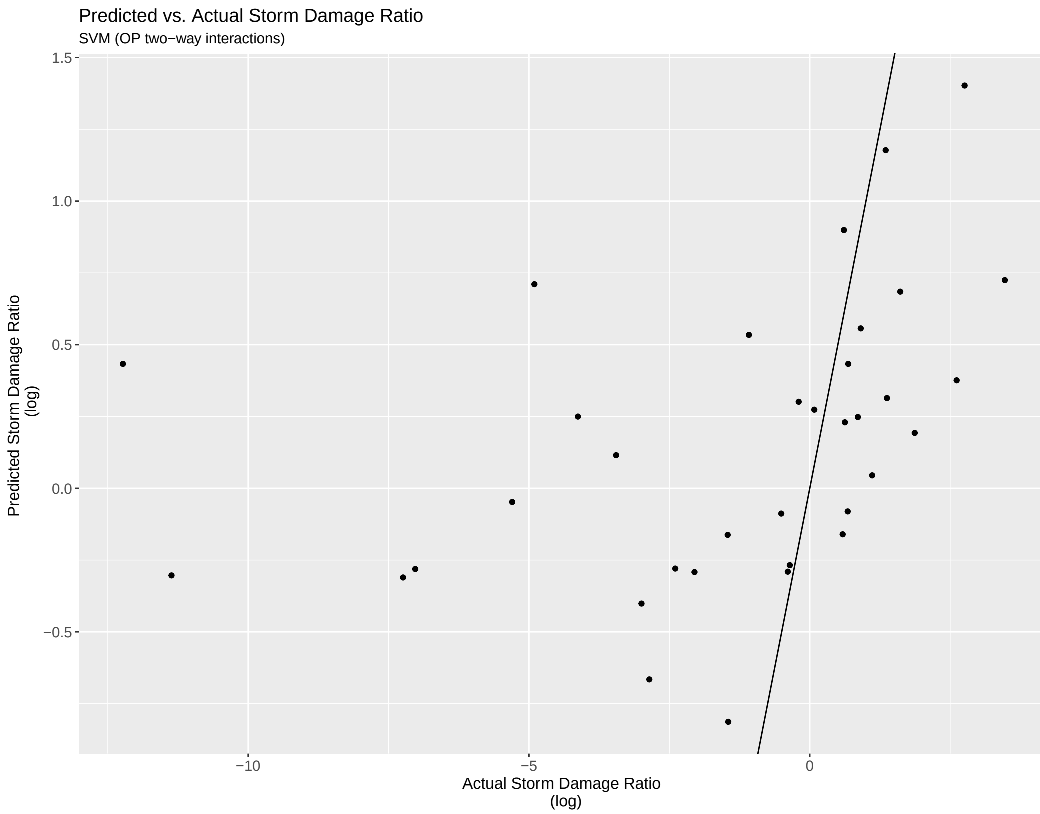

Figure 3.12: Predicted vs. Actual SDR for hurricanes with SVM on log scale

very different, as seen in Table 3.13. The first main distinction is that R_{64} is no longer the most important variable, being only the third most important feature. This happens because R_{64} no longer separates tropical storms from hurricanes. By removing the tropical storms, we are able to observe the other factors that influence the damage caused by hurricanes. *Land* becomes the most important variable, being twice as important than R_{64}. R_{50} is the second highest scaled feature, followed by *Dist*. Additionally, our model indicates that $v_{\max}$ is of no importance to estimate SDR for hurricanes. This directly contradicts the SSHS, in which hurricanes are classified solely based on their wind speed.

Finally, for tropical storms, the BT model produces interesting interactions

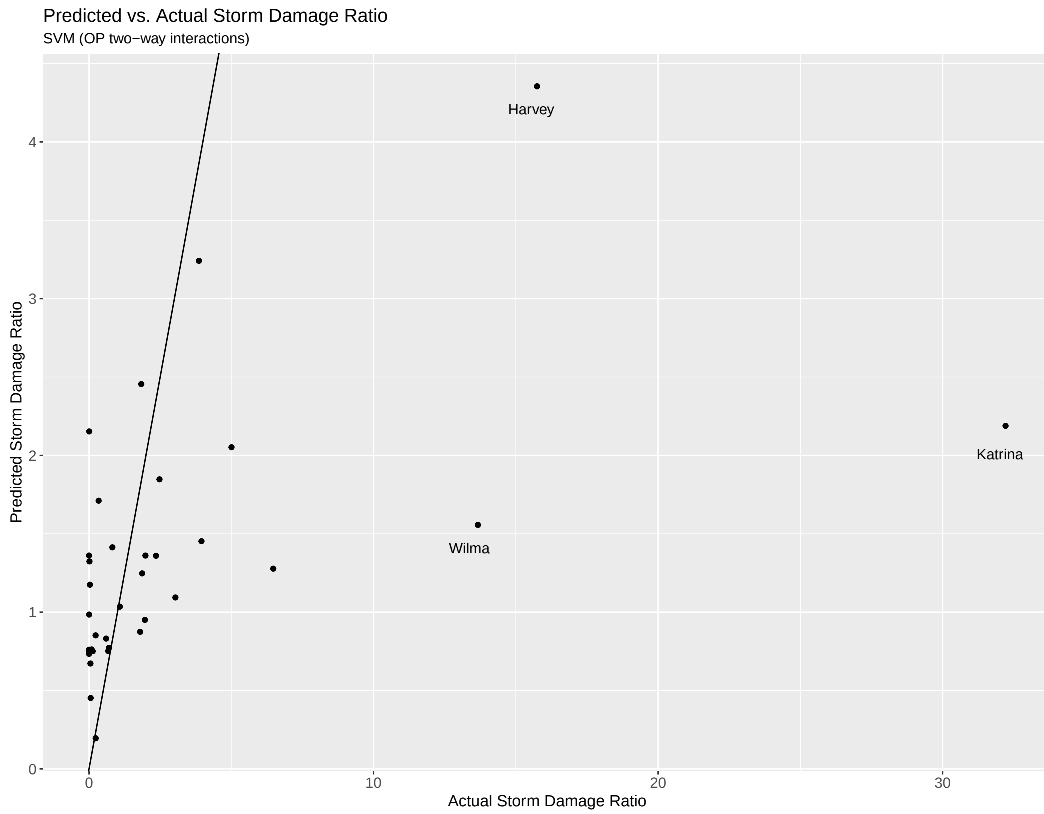

Figure 3.13: Predicted vs. Actual SDR for hurricanes with SVM

between the variables, as shown in Table 3.14. Here, $v_{\max}$ is the most important variable followed by R_{34}. The size of the tropical storm, represented by R_{34} and R_{50}, is part of six out of the ten most important variables and variable interactions. Notably, $v_{\max}$ is the most important variable to tropical storms, while it presented no importance on the model for hurricanes.

3.6 Concluding Remarks

The 182 machine learning models developed in this study provide novel data-driven insights on the relationship between storm features and the potential for significant economic losses in a region. To create these empirical models,

Table 3.8: Results of log SDR predictions for hurricanes

Method	Metric	Outcome: log SDR			
		OP	EP	OP + interactions	EP + interactions
BT	RMSE	3.234	3.289	3.314	3.24
	R^2	0.438	0.419	0.413	0.499
RF	RMSE	3.485	3.416	3.543	3.499
	R^2	0.506	0.49	0.477	0.427
SVM	RMSE	**3.148**	3.227	3.195	3.340
	R^2	**0.460**	0.490	0.492	0.536
k-NN	RMSE	3.309	3.242	3.318	3.324
	R^2	0.452	0.488	0.500	0.419
MLR	RMSE	3.835	-	-	-
	R^2	0.451	-	-	-
LASSO	RMSE	3.29	3.308	3.348	3.358
	R^2	0.464	0.412	0.341	0.314
Elastic Net	RMSE	3.306	3.407	3.331	3.403
	R^2	0.468	0.508	0.486	0.389
MARS	RMSE	3.509	3.258	3.701	3.676
	R^2	0.304	0.440	0.221	0.474

we first introduce a new metric, SDR, that takes into account the GDP of the affected ares to distinguish storm-specific factors from region-specific factors. Through extensive exploration of historical storm characteristics and impacts, we discover notable differences between predictive models for *all storms*, *hurricanes*, and *tropical storms*.

The most accurate model for predicting impact for tropical storms and hurricanes is created using a boosted tree algorithm to predict log SDR. The most important variables are highly dependent on storm-size related features (i.e., R_{64}, $R_{50} \log p_{\min}$, and $R_{34} R_{50}$). For predicting SDR directly from hurri-

Table 3.9: Results of SDR predictions for hurricanes

Method	Metric	Outcome: SDR			
		OP	*EP*	*OP* + interactions	*EP* + interactions
BT	RMSE	4.429	4.549	4.453	4.474
	R^2	0.449	0.474	0.432	0.555
RF	RMSE	4.570	4.647	4.706	4.744
	R^2	0.436	0.412	0.438	0.432
SVM	RMSE	4.002	4.040	**3.892**	3.983
	R^2	0.482	0.510	**0.530**	0.482
k-NN	RMSE	4.182	4.385	4.263	4.552
	R^2	0.558	0.49	0.488	0.377
MLR	RMSE	6.118	-	-	-
	R^2	0.568	-	-	-
LASSO	RMSE	4.704	5.512	4.611	5.051
	R^2	0.451	0.504	0.436	0.437
Elastic Net	RMSE	4.600	4.765	4.474	4.554
	R^2	0.496	0.393	0.449	0.458
MARS	RMSE	5.532	6.072	6.002	7.684
	R^2	0.489	0.400	0.478	0.445

canes alone, the SVM method has the best performance. According to this model, the duration of a storm on land is the most important element, while surprisingly, the maximum sustained wind speed is of no importance. When considering only tropical storms which do not convert into hurricanes, the boosted tree approach generates the highest quality predictions, and here, the maximum sustained wind speed is the *most* important variable.

The best ML model performance is for the tropical storm data subset. This implies that it is easier to predict the damage associated with a tropical storm than from a hurricane. Nonetheless, it is still possible to obtain a better

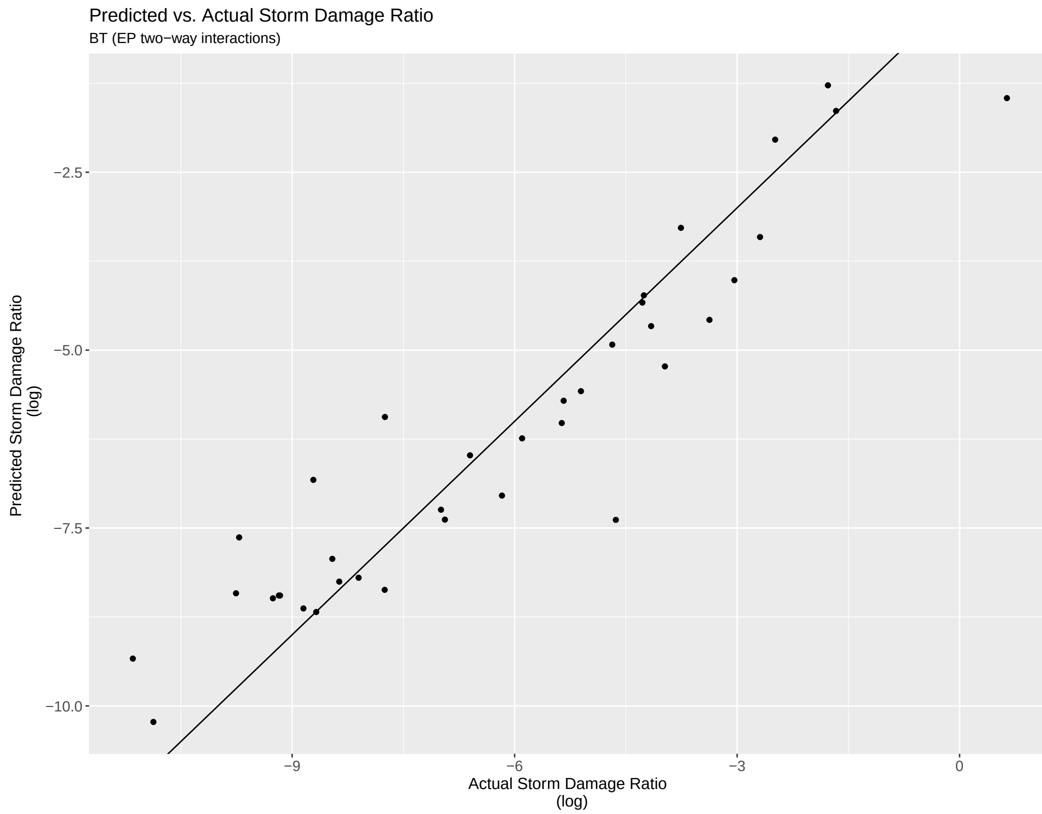

Figure 3.14: Predicted vs. Actual SDR for tropical storms with BT

estimation of hurricane potential damage than that provided by the SSHS or the alternative indices such as ACE or PDI. Indeed, we demonstrate that the heavy reliance on maximum sustained wind speed is unwarranted.

Tropical storms and hurricanes are natural and regularly occurring significant hazards which threaten coastal communities each year. The potential impact from these systems can be devastating to the local populations and to the economy at large. The results from this extensive analysis highlight some of the complexity involved in predicting and explaining this potential. The empirically derived mathematical models and variable importance measures provide one step towards enhancing our understanding.

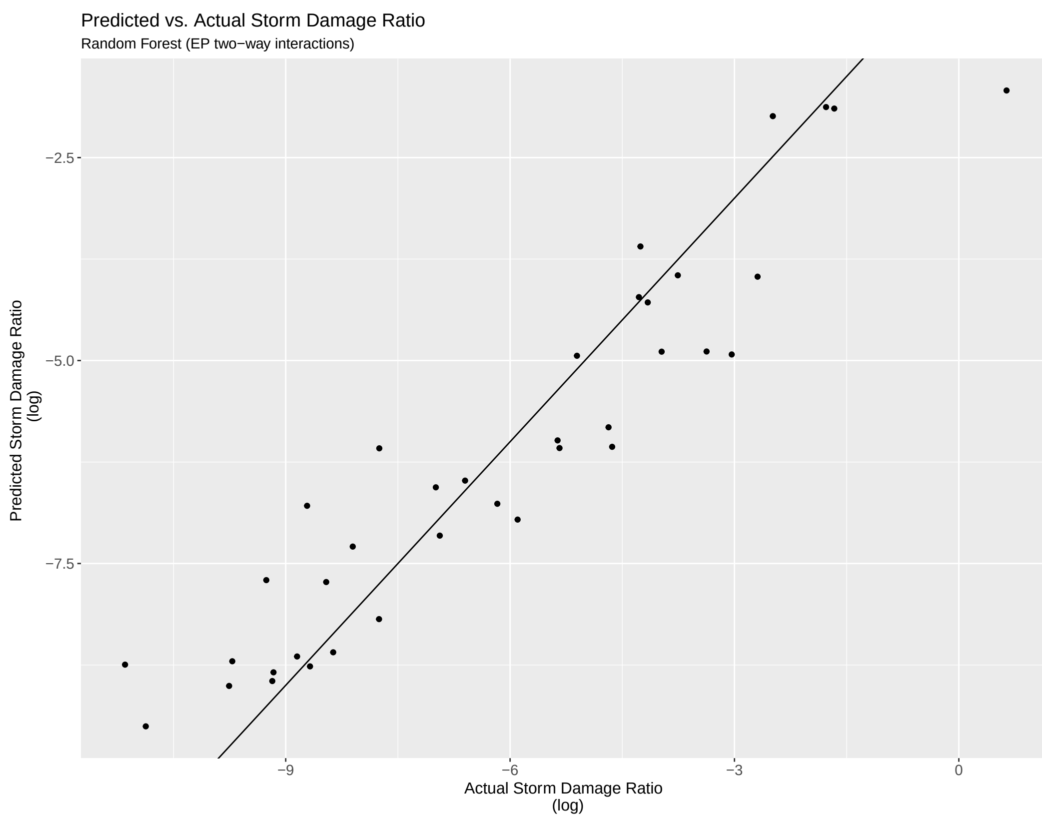

Figure 3.15: Predicted vs. Actual SDR for tropical storms with RF

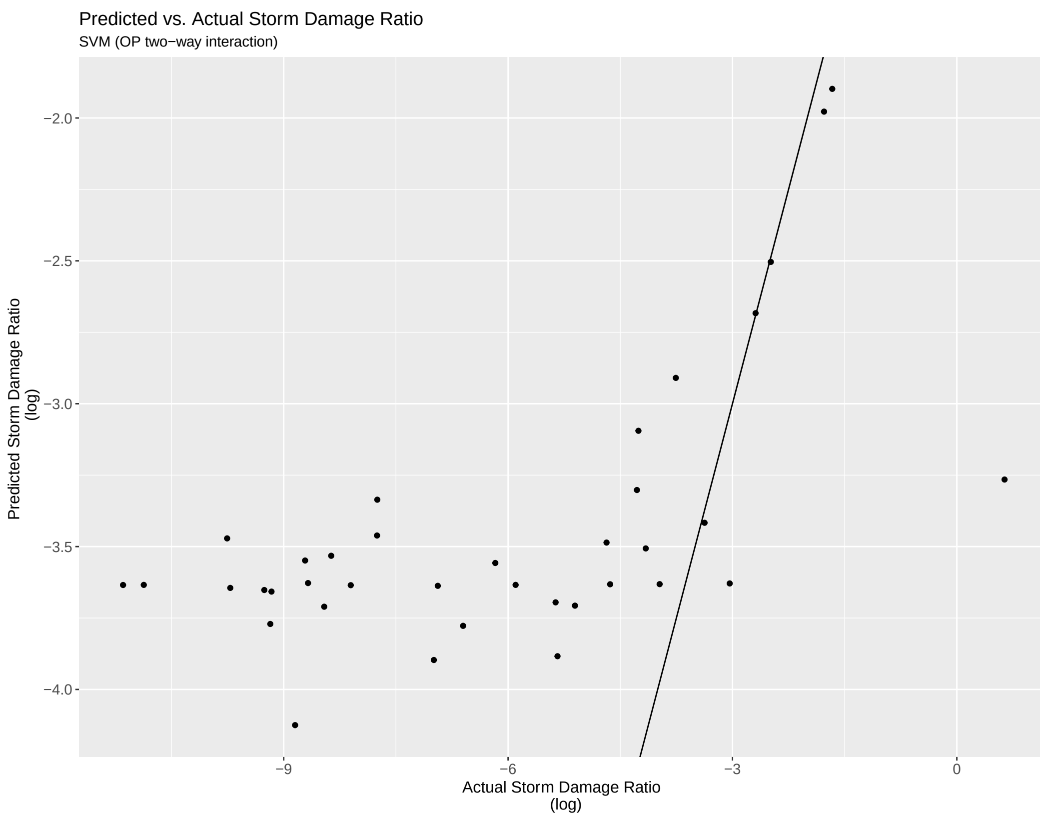

Figure 3.16: Predicted vs. Actual SDR for tropical storms with SVM on log scale

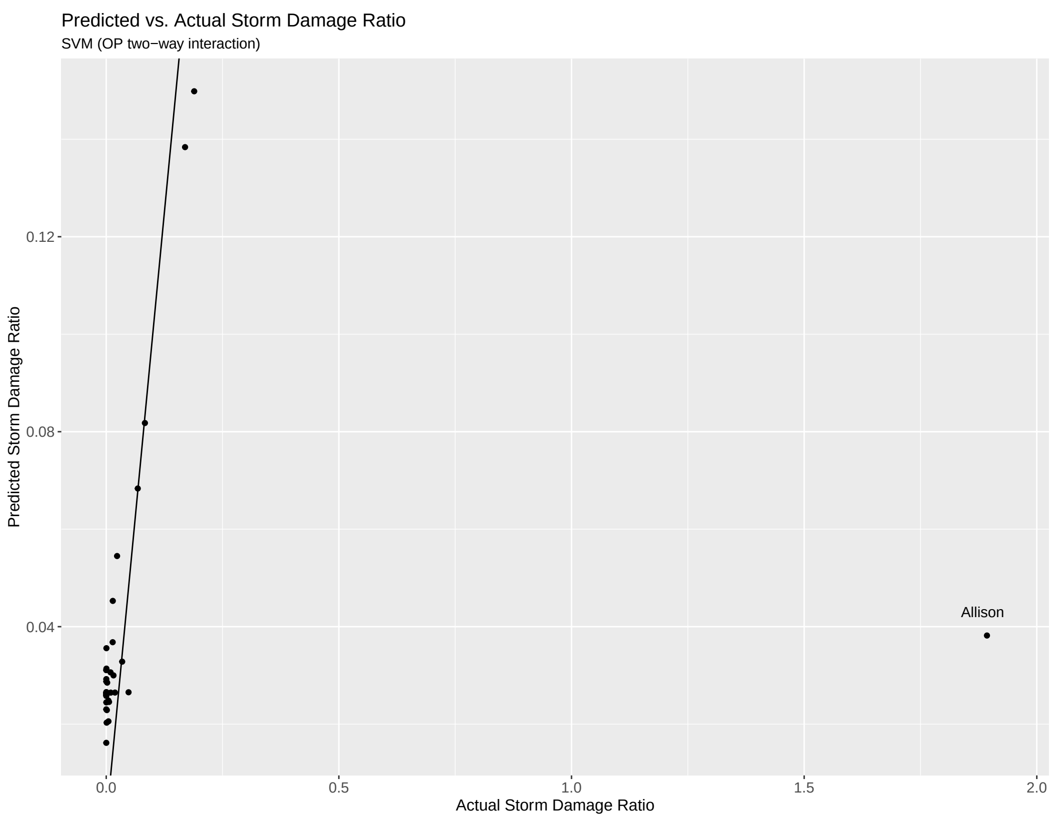

Figure 3.17: Predicted vs. Actual SDR for tropical storms with SVM

Table 3.10: Results of log SDR predictions for tropical storms

Method	Metric	Outcome: log SDR			
		OP	EP	OP + interactions	EP + interactions
BT	RMSE	2.397	2.27	2.381	**2.191**
	R^2	0.516	0.507	0.562	**0.593**
RF	RMSE	2.361	2.36	2.365	2.233
	R^2	0.523	0.558	0.488	0.516
SVM	RMSE	2.395	2.483	2.348	2.445
	R^2	0.532	0.569	0.521	0.466
k-NN	RMSE	2.373	2.418	2.408	2.34
	R^2	0.464	0.474	0.488	0.506
MLR	RMSE	2.631	54.560	42.338	-
	R^2	0.481	0.448	0.475	-
LASSO	RMSE	2.515	2.473	2.461	2.591
	R^2	0.563	0.456	0.488	0.454
Elastic Net	RMSE	2.443	2.51	2.379	2.625
	R^2	0.552	0.526	0.502	0.483
MARS	RMSE	2.597	2.642	2.938	3.176
	R^2	0.496	0.444	0.469	0.44

Table 3.11: Results of SDR predictions for tropical storms

Method	Metric	Outcome: log SDR			
		OP	EP	OP + interactions	EP + interactions
BT	RMSE	0.157	0.150	0.157	0.151
	R^2	0.596	0.532	0.566	0.428
RF	RMSE	0.185	0.194	0.188	0.191
	R^2	0.504	0.536	0.526	0.574
SVM	RMSE	0.131	0.136	**0.128**	0.133
	R^2	0.59	0.553	**0.540**	0.622
k-NN	RMSE	0.157	0.159	0.150	0.153
	R^2	0.491	0.446	0.415	0.422
MLR	RMSE	0.261	8.163	2.053	-
	R^2	0.508	0.562	0.499	-
LASSO	RMSE	0.157	0.156	0.166	0.187
	R^2	0.586	0.641	0.558	0.578
Elastic Net	RMSE	0.158	0.157	0.161	0.163
	R^2	0.560	0.546	0.554	0.501
MARS	RMSE	0.171	0.255	0.287	0.282
	R^2	0.412	0.700	0.578	0.722

Table 3.12: Variable Importance for all storms - BT

Variable	Scaled importance
R_{64}	0.144
$R_{50}^2 \log p_{\min}$	0.135
$R_{34}R_{50}$	0.105
$R_{64}^3 Dist$	0.092
$R_{34}^3 \sqrt[3]{R_{50}}$	0.079
$R_{34}\sqrt{R_{50}}$	0.071
$v_{\max} p_{\min}^3$	0.068
R_{50}	0.038
$\sqrt{p_{\min}} R_{50}^2$	0.033
$p_{\min}$	0.028

Table 3.13: Variable Importance for hurricanes - SVM

Variable	Scaled importance
$Land$	0.329
R_{50}	0.191
R_{64}	0.159
$Dist$	0.135
R_{34}	0.112
$p_{\min}$	0.075
$v_{\max}$	0

Table 3.14: Variable Importance for tropical storms - BT

Variable	Scaled importance
$v_{\max}$	0.239
R_{34}	0.199
$R_{34}\sqrt[3]{R_{50}}$	0.161
$v_{\max}R_{34}$	0.070
$Dist$	0.042
$\log v_{\max} \log R_{34}$	0.041
$v_{\max}^3 Land$	0.038
$p_{\min}$	0.027
$v_{\max}^2\sqrt[3]{R_{34}}$	0.024
$R_{34}^3\sqrt[3]{R_{50}}$	0.021

Chapter 4

State-level vulnerability to tropical cyclones: Empirical fragility curves and community preparedness assessment

4.1 Introduction

Tropical cyclones are among the most destructive weather phenomenons. These intense circular storms originate over warm tropical oceans and produce high wind speed and heavy rain. The population of coastlines in the United States is high, with approximately 40% of the nation's total population living in coastal counties [160]. Between the years 2000 and 2017, the population living in coastal areas vulnerable to hurricanes and tropical storms in the US increased 16%, with these areas reaching a total population of 60.2 million, according to [47]. Tropical storms and hurricanes pose a significant threat to these communities.

The surge in population of coastal areas, added to increasingly frequent and destructive tropical cyclones, confirm the importance of studying resilience of coastal areas. This work contributes to the understanding of the threat tropical storms and hurricanes pose to coastal communities, which is the first step to improve community resilience. Only after a clear understanding of the potential hazard, can a community prepare itself to withstand that impact. This work refines the Storm Damage Ratio (SDR) metric introduced in Chapter 3.3 to develop a localized ratio, *Local Storm Damage Ratio* (LSDR), which enhances the granularity of SDR and conveys the impact of a storm with respect to the storm's characteristics alone. Coastal preparedness and vulnerability are assessed at a state level by studying the relationships between state and destructive potential of tropical cyclones. Finally, using LSDR we extend the well known concept of fragility curves to introduce a probabilistic methodology to quantify tropical cyclone coastal vulnerability at a state-level.

The remainder of this chapter is organized as follows: Section 4.2 contains the background and motivation for this work. Section 4.3 explains the concept of LSDR and its importance. Section 4.4 contains a detailed explanation of the fundamental methodologies that are employed, including data selection, machine learning models, and fragility curves. Section 4.5 presents the results and discussion of this study. Finally, Section 4.6 summarizes and concludes this dissertation chapter.

4.2 Background and Motivation

Tropical storms and hurricanes pose a major threat to coastal areas susceptible to these events. Between the years 1998 and 2017, the proportion of the world's population living on coastlines vulnerable to cyclones increased 192%. During the same period of time, it is estimated that 726 million people worldwide were affected by storms, including tropical cyclones [233].

Between the years 2000 and 2019, a yearly average of 15.3 named storms, out of which an average 7.3 were hurricanes, were recorded in the Atlantic Ocean [156]. Named storms include tropical storms, subtropical storms, and hurricanes [152]. The number and cost of extreme weather events is increasing over time due to increased exposure, vulnerability, and climate change [211]. The intensity and frequency of tropical cyclones is also rising and improving the resilience of communities subject to these natural hazards is of utmost importance.

Resilience can be defined as "the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events" [35]. [29] defined resilience as the ability to adapt to changing conditions and withstand and rapidly recover from disruption due to emergencies. [159] defines community resilience as how well a community is prepared for and can respond to a natural disaster. According to the National Preparedness Goal, to increase community resilience is necessary to enable the recognition and understanding of risks, as well as empower the communities to make informed risk management decisions to adapt, withstand, and quickly recover from future incidents [204].

There is a substantial body of work in the development and improvement of specific metrics and measures of community resilience, but the development of assessment standards for measuring resilience remains a challenge. The ability to measure resilience is being identified as a key step toward disaster risk reduction. However, the literature lacks procedures to outline how to measure and compare resilience between communities [33]. According to [66], the resilience of a community is a combination of characteristics that reduce the vulnerability of said community. The authors add that knowledge and awareness of the possible hazardous events is also important to resilience improvement.

Coastal resilience is of particular interest in this dissertation. [159] developed a resilience cycle, in which the steps to improve community resilience are detailed. The first step of the cycle is to asses the risk and vulnerability of the community. Only after a community has an understanding of its vulnerabilities is that it is able to move to the next step of the resilience cycle, which is to plan and prioritize strategies and potential actions to address said vulnerabilities. Multiple authors studied the resilience of coastal communities to extreme events. [66] used knowledge acquired from past coastal disasters to develop a community resilience index to help communities identify their resilience strengths and weaknesses. [33] studied community resilience in the context of recovery from Hurricane Katrina at a subcounty level and determined a set of metrics for measuring and comparing disaster resilience among communities. [35] developed a quantitative method to assess community resilience to coastal hazards and to identify relationships between socio-environmental indicators and community resilience in the Lower Mississippi River Basin. [216] assessed community resilience to typhoons, which are rotating storm systems like hurricanes, but located on the Northwestern Pacific Basin. The authors performed the study in Guangzhou, China, and developed a composite resilience index to facilitate the identification of at-risk regions. [234] obtained performance objective of individual facilities and buildings exposed to extreme hazards by disaggregating broader community resilience goals. [62] performed a similar study and evaluated the resilience level of a residential community to hurricanes by disaggregating the community resilience goal to individual buildings resilience goals.

Fragility curves have been used to study resilience to multiple natural hazards. They provide the probability of reaching or exceeding a given damage state as a function of the intensity of the natural event. They can also be thought of as a conditional probability of exceedance, providing the probability that a certain level of damage will be met or exceeded at a certain condition [185]. Fragility curves are commonly used to evaluate the vulnerability of buildings and structures to a specific hazard of a given intensity (e.g. earthquakes, flooding, tsunamis, and hurricanes). Fragility functions are widely used in seismic risk and damage assessment, with its use to derive potential impacts of earthquakes to specific building types, based on its characteristics and structure, dating back to the 1980s [56, 185]. Accordingly, the literature on the topic is extremely vast, including the study of bridge fragility [150, 180, 63, 205, 70, 155, 131, 171, 109, 154, 45, 221, 249], residential and housing structures [79, 65, 174], among others. Fragility functions are increasingly being developed for other hazards, such as fires [76], flooding [82, 162, 163], and tornadoes [138].

Fragility curves have also been built to estimate potential damage of hurricanes and tropical storms [219]. The *Hazus-MH Hurricane Model*, developed by the Department of Homeland Security and the Federal Emergency Management Agency (FEMA), is a tool for estimating potential losses to buildings from hurricane winds [67]. The losses calculated with the program can be used on a local and state level to improve mitigation actions and reduce damage caused by hurricane winds. It is worth noting that the losses identified by the Hazus software tool only account for the physical damage to buildings and facilities. Also, it only refers to direct economic losses to the structure, contents, and loss of use of buildings and for the loss of shelter. [219] evaluated the prediction capability of the Hazus-MH Hurricane Model using machine learning to explore sources of errors. The authors also improved the Hazus Hurricane Model by developing a more refined fragility-curve-based model of wind damage risk at 1 km^2 blocks. [61] evaluated the forces on buildings structures caused by hurricane's surge and waves, while [220] identified critical facilities in the Cayman Islands and determined their level of exposure to hurricanes and related natural hazards by using existing fragility functions for different hazardous events and building types. [48] developed a simulation model able to provide the probability of structural damage for multiple types of residential structures based on hurricane's wind speeds. The study was performed in Florida and focused on typical residential structures of the state. [62] performed a risk assessment of wood residential constructions subjected to hurricanes. The authors used a hurricane simulation model to predict future wind speed and performed a fragility analysis of the constructions utilizing four structural damage modes.

Once obtained for a single building, fragility functions can be expanded to determine how many buildings of similar type in an area will experience at least a certain level of damage [48]. [163] developed flood fragility curves to predict flood damage and losses at a community level in North Carolina, while [138] developed fragility curves to evaluate the performance of community components under tornado loading. [34] incorporated probabilistic building performance and recovery curves to the existing performance-based engineering frameworks related to seismic events and [30] developed a framework for defining community resilience and specifying quantitative measures of resilience to seismic events. [125] studied the performance of individual buildings exposed to natural hazards compared to the overall performance of a building portfolio. The authors introduced the concept of building portfolio fragility function (BPFF), defined as the probability that a building portfolio fails to achieve the expected performance under hazardous conditions. According to the authors, the ability to characterize the vulnerability of a building portfolio, rather than individual buildings, can support resilience-driven decisions at the community level.

In the present work, we extend the concept of fragility curves, which are typically used for individual structures or sets of structures, as a mechanism for quantifying regional vulnerability to hurricanes. Instead of fragilities associated with physical structures, we use historical information on hurricane paths, storm characteristics, and regional damage measured as LSDR to empirically develop the probabilistic functions associated with different impact states.

4.3 Local Storm Damage Ratio

The concept of *Storm Damage Ratio* (SDR), presented on Chapter 3, allows for an evaluation of the potential damage of a storm, irrespective of the economic characteristics of the location of landfall. In order to do so, the geographic variability of assets of a given region must be accounted for. Large population centers with significant civil infrastructure and commercial development have considerably more potential for damage than less populated, rural areas with few assets and little economic activity. Gross domestic product (GDP) is one well-established and comprehensive measure of a region's economic well-being.

The SDR allows an evaluation of storm's strength solely based on the cyclone's endogenous characteristics. It is computed as the ratio of the immediate storm damages (in terms of dollars) to the annual GDP of the counties directly affected by the storm. In this work, the concept of SDR is adapted to consider the impacts to the region of interest through the development of the *Local Storm Damage Ratio*. This study is performed at a state-level, for the states more commonly impacted by hurricanes and tropical storms in the East Coast and Gulf of Mexico. The states included in this study are colored on Figure 4.1. Therefore, throughout this study, LSDR refers to the storm's strength observed at the state-level, irrespective to the economic characteristics of the location. The concept can be easily adapted to county or even city level, if desired.

The values of LSDR can vary greatly for the same storm, ranging from close to 0 to double digits values. This variation is explained by the difference in characteristics of the storm when reaching each state, such as storm wind speed, average radius of 34, 50, and 64 knots wind speeds, time periods over the state, and forward speed. Table 4.1 shows the LSDR for storms Harvey, Irma, and Matthew, all of which affected multiple states in recent years. Hurricane Harvey, for example, affected both Texas and Louisiana. The damage to those states, however, were widely different. The state of Texas suffered major losses, with a calculated LSDR of 23.81. Meanwhile, Louisiana was affected much more lightly, with a LSDR of 0.0003.

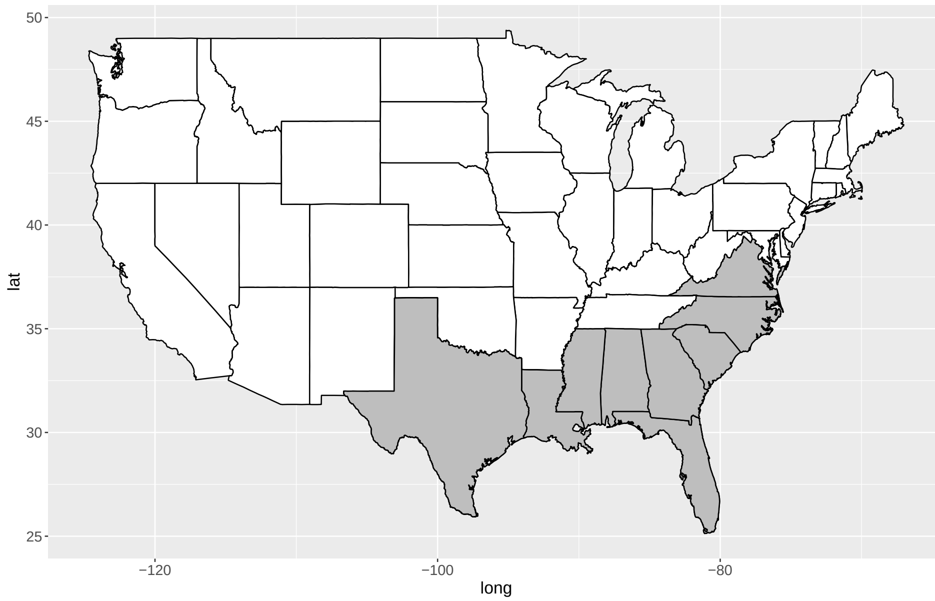

Figure 4.1: States included on the analysis

4.4 Methodology

4.4.1 Data selection

Tropical cyclones are dynamic systems with intrinsic characteristics that vary throughout their lifespan, such as size, wind speed, pressure, among other features. Only cyclones that obtain wind speeds exceeding 34 knots at some point during their history, i.e., developed into either a tropical storm or hurricane, are considered in this study. Storm characteristics are collected by the NHC and stored in discrete time intervals, every six hours. Thus, the longer a storm is active, the greater the number of observations for that storm. The discrete nature of the collected data limits the granularity on analysis of the storm's evolution in time.

Figure 4.2 shows how Hurricane Harvey (non-filled circle) and Hurricane Irma (filled circle) moved through time. Note that all these entries were ob-

Table 4.1: LSDR of storms in different states

Storm	Year	State	LSDR
Matthew	2016	FL	3.35
		GA	0.0022
		NC	11.23
		SC	3.14
Harvey	2017	LA	0.0003
		TX	23.81
Irma	2017	AL	0.0018
		FL	4.44
		GA	2.44
		NC	0.0019
		SC	0.0020

served under a six-hour interval, Thus, the distance between subsequent points are an indicator of the speed with which the storm moves, also referred to as the storm's forward speed. Points close together mean that the storm has a low forward speed and is, therefore, impacting the same area. Hurricane Harvey, for example, was over the coast of Texas for multiple six-hour intervals, which led to flooding being one of the primary causes of economical impact.

Tropical cyclones are directly dangerous to the states only when they are close enough to the state's border or over the state. As such, we only consider that a given storm has affected a state if the radius of its outermost wind, R_{34}, plus a tolerance distance to allow for rainfall and storm asymmetries, intersects the state's borders. For each storm, the entries are selected using the following criteria: if the great circle distance (GCD) of the center of the storm to the closest point of the state border is less than or equal to 1.25 R_{34}, the observation is used. Otherwise, the observation is discarded. Figures 4.3 and 4.4 illustrate entry selection for Hurricane Harvey on Texas and Irma on

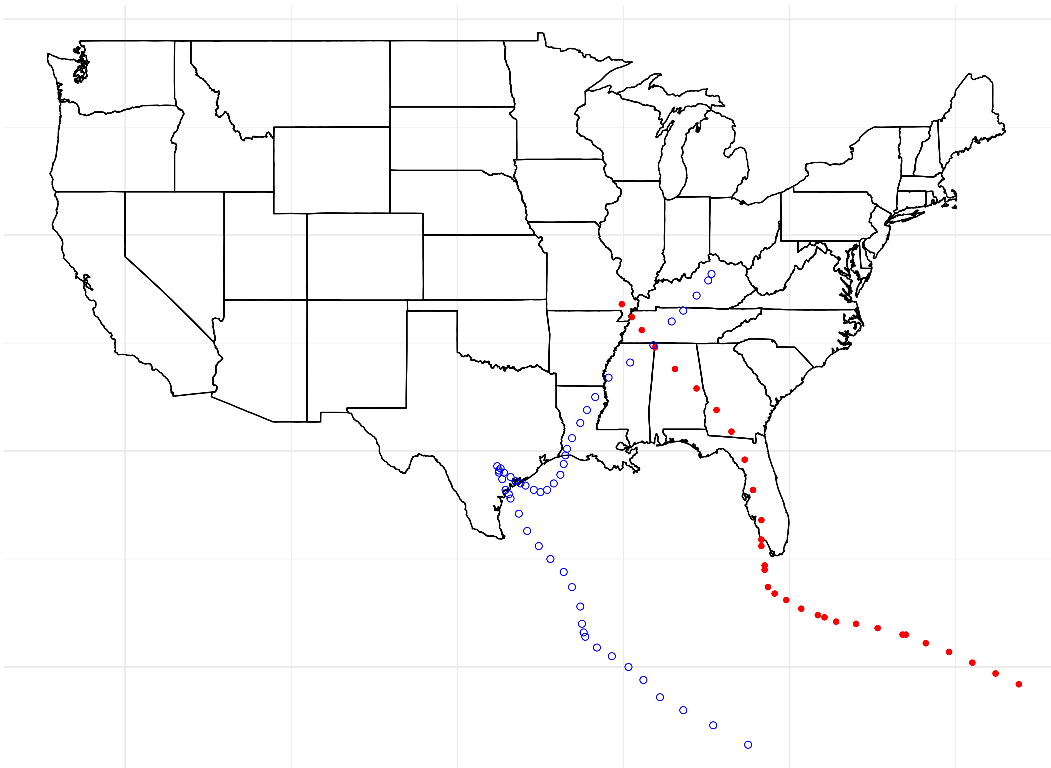

Figure 4.2: Paths of Hurricanes Harvey and Irma

Florida, respectively. The filled circles in each image represent the entries that were used to calculate the impact of the hurricanes in each of the states.

4.4.2 Machine Learning methods

After the entries of the storms are selected, machine learning is used to predict the LSDR based on the storm's characteristics. The methods used are Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net, k-Nearest Neighbors (k-NN), Support Vector Machine (SVM), Random Forest (RF), Boosted Trees (BT), and Multivariate Adaptive Regression Splines (MARS). More information on the methods is provided in Section 3.4.3.

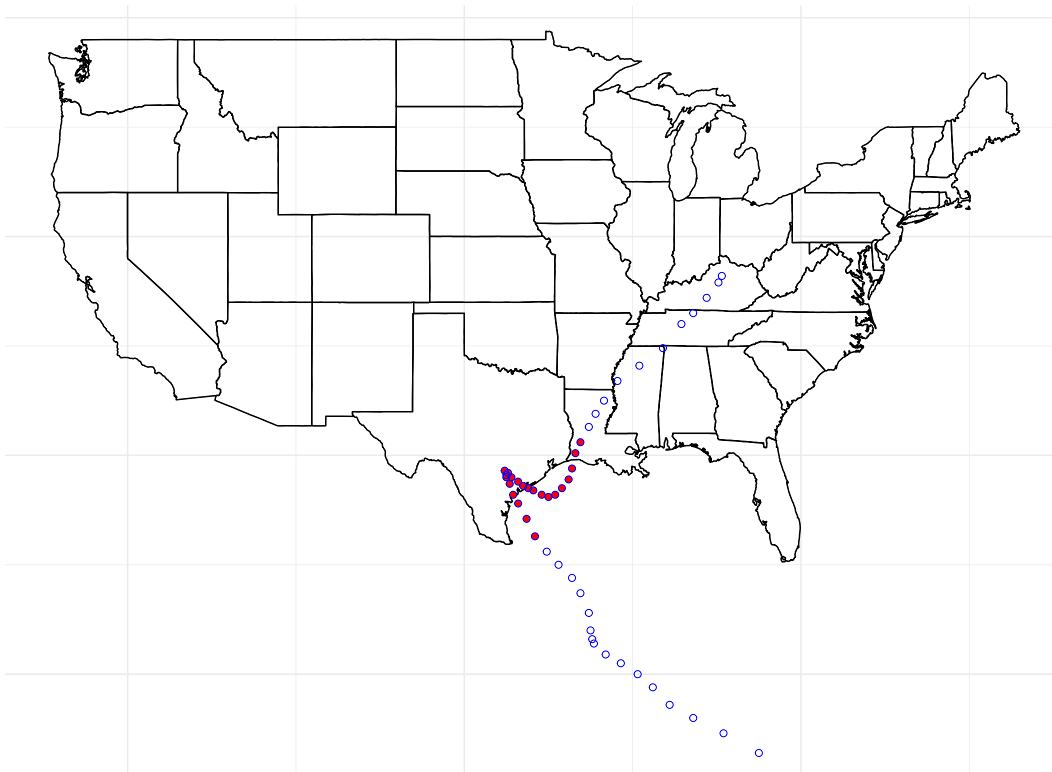

Figure 4.3: Selected entries of Hurricane Harvey affecting Texas

4.4.3 Fragility Curves

Fragility curves can be a powerful way to assess vulnerability, as they convey the probability of a structure reaching or exceeding a damage state due to a natural hazard. There are four approaches to developing fragility curves: judgmental, empirical, analytical, and hybrid [185]. This work uses the empirical approach, which consists in the utilization of logistic regression to generate fragility curves. This approach has been widely used in the literature [16, 118, 205, 203].

The value of LSDR varies greatly, ranging from 0 to 281. The vast majority of storms cause low to moderate damage, while few storms cause significant or major damage. Of the 178 storms in this study, 145 have a LSDR between 0

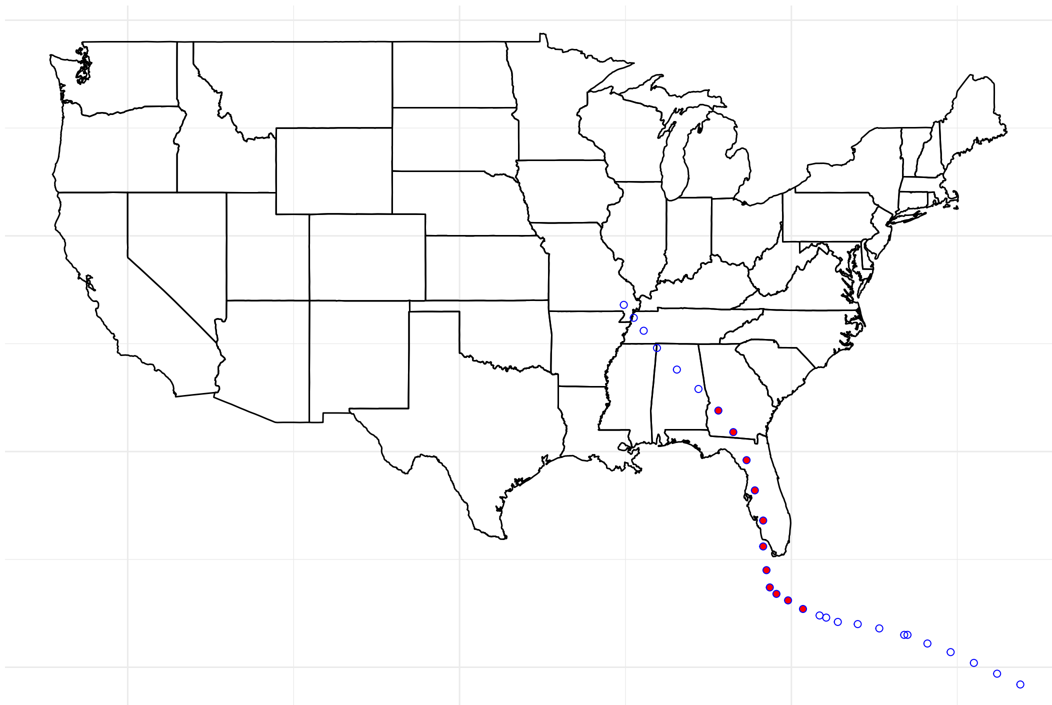

Figure 4.4: Selected entries of Hurricane Irma affecting Florida

and 1, meaning that their economic impact to the state was less than the value of the GDP of the region. For this reason, when building the fragility curves to estimate the probability of exceedance of each damage level, the natural logarithm of the LSDR was used. The logarithmic value of the LSDR for the storms varied from -12.62 to 5.64. Utilizing the logarithmic function allowed us to obtain a less skewed distribution, as seen on Figure 4.5.

The impact of tropical cyclones are divided into damage levels to the community, hereby called *Storm Damage Levels*, or SDL. The SDL categories are determined empirically by analyzing the description of the damage caused by the storms on the immediate damage data, obtained from the National Oceanic and Atmospheric Administration (NOAA). Reports available on hurricane and tropical storms are analyzed to add expert perspective to the classification process. Unfortunately, said reports are vastly available for large and catastrophic

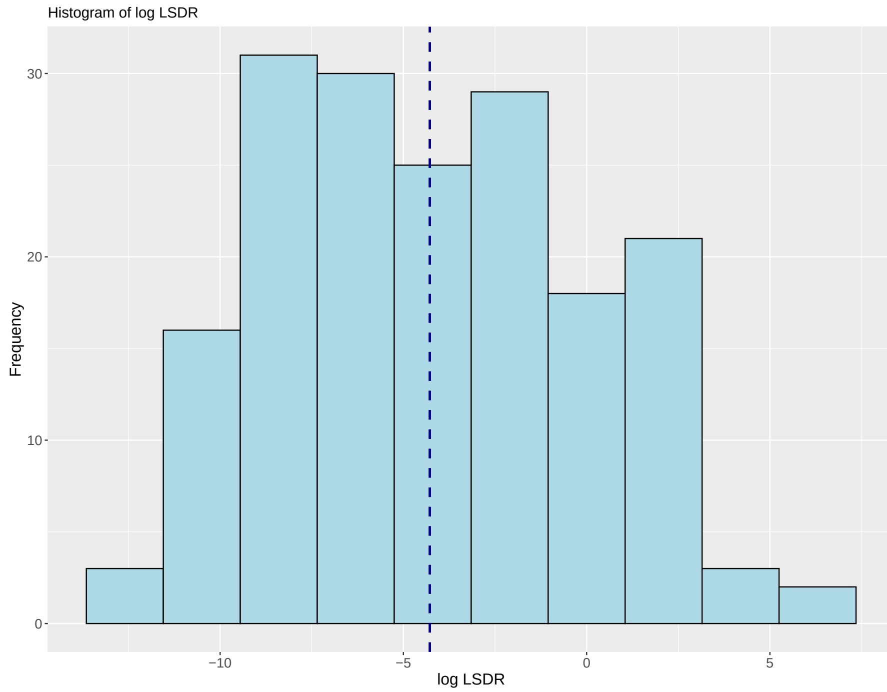

Figure 4.5: Observations of log LSDR

storms, less so for smaller and less damaging events. Additionally, definitions and details of technical terms are obtained from the National Weather Service [167]. Relatively common forms of damage, that do not represent significant threat to human life are considered low damage. Examples of low damage are: roof damage to some properties; non-life-threatening damage to mobile homes; slight tree damage; minor flooding (roads may be covered in water, but few, if any, building structures are inundated); few power outages (short duration and not affecting multiple communities). Examples of moderate damage are: widespread roof damage; lengthy tree damage to properties; moderate flooding (many roads are covered, building inundation is possible, but limited to vulnerable locations, not considered a significant threat to human life); localized power outages. Storms are classified as causing significant damage if one or more of the following were observed on reports or description: extensive dam-

Table 4.2: Storm Damage Levels and respective log LSDR

Storm Damage Level	Degree of damage	Value of log LSDR
Storm Damage Level 1 (SDL 1)	Low damage	log LSDR > -6
Storm Damage Level 2 (SDL 2)	Moderate damage	log LSDR > -2
Storm Damage Level 3 (SDL 3)	Significant damage	log LSDR > 0

age to houses and buildings structures (including, but not limited to roofing); extensive flooding in multiple areas (including life-threatening levels in some locations); lengthy and widespread power outages; water supply interruption; casualties due to the storm.

After storms are classified in each of the categories described, the value of log LSDR the storms are observed and the maximum value is rounded to the next integer. The final Storm Damage Levels, degree of damage, and value of logarithmic LSDR can be observed on Table 4.2.

4.5 Results

4.5.1 Results of Machine Learning Methods

Machine learning models are developed for the data set with two possible outcomes: log LSDR and LSDR. Similarly, two set of inputs are used to build the machine learning models, an extended set of predictors (EP) and the original predictors (OP). Additionally, the interactions between the two sets of predictors is also used. The results of the machine learning models can be observed on Table 4.4. Two methods present the lowest RMSE for the log LSDR outcome, Elastic Net and LASSO. When comparing their R^2 value, Elastic Net presents a slightly better value of 0.413 versus 0.410 for LASSO.

Table 4.3: Results of machine learning models for log LSDR predictions

Method	Metric	Outcome: log SDR			
		OP	EP	OP + interactions	EP + interactions
Elastic Net	RMSE	**3.228**	3.647	3.251	3.515
	R^2	**0.413**	0.285	0.404	0.310
LASSO	RMSE	3.228	3.687	3.245	3.532
	R^2	0.410	0.311	0.409	0.307
BT	RMSE	3.285	3.268	3.331	3.340
	R^2	0.390	0.405	0.385	0.375
RF	RMSE	3.427	3.391	3.415	3.367
	R^2	0.346	0.361	0.347	0.366
SVM	RMSE	3.272	3.602	3.348	3.564
	R^2	0.406	0.297	0.374	0.298
k-NN	RMSE	3.396	3.656	3.376	3.658
	R^2	0.359	0.258	0.359	0.252
MARS	RMSE	3.387	3.433	3.458	3.584
	R^2	0.360	0.351	0.343	0.306

For the LSDR outcome, k-NN presents the lowest RMSE, with a value of 16.746 and a respective R^2 of 0.403. Given the fact that the Elastic Net model presented a better R^2, it is a better model for this empirical work. Therefore, the remainder of this work uses the results of the Elastic Net machine learning model when it predicts the values of log LSDR.

Model Validation

The Elastic Net model using the entire set of predictors (EP) for the log LSDR outcome produces the best results, with an RMSE of 3.228 and a R^2 of 0.413. Figure 4.6 shows the actual LSDR versus the predicted LSDR for the Elastic

Table 4.4: Results of machine learning models for LSDR predictions

Method	Metric	Outcome: SDR			
		OP	EP	OP + interactions	EP + interactions
Elastic Net	RMSE	20.845	19.907	24.180	20.487
	R^2	0.376	0.359	0.404	0.435
LASSO	RMSE	22.122	19.882	31.895	20.047
	R^2	0.390	0.363	0.377	0.392
BT	RMSE	18.292	17.484	17.580	16.945
	R^2	0.414	0.446	0.454	0.399
RF	RMSE	20.310	21.299	19.627	20.502
	R^2	0.440	0.465	0.413	0.343
SVM	RMSE	16.923	16.766	17.179	16.980
	R^2	0.375	0.376	0.448	0.383
k-NN	RMSE	17.211	17.019	17.179	**16.746**
	R^2	0.408	0.440	0.395	**0.403**
MARS	RMSE	20.889	20.176	21.045	21.905
	R^2	0.360	0.407	0.420	0.339

Net model. Each point in the graph refers to the impact of one storm in a single state. The different states are identified in different colors. Florida is the state with more occurrences in the graph, with a total of 47 storms. North Carolina and Georgia are the states that have the second highest number of entries, with 19 each.

Table 4.5 presents the results of the Pearson correlation coefficients tests for the predicted log LSDR per state and actual log LSDR. Pearson was chosen due to its appropriateness to evaluate two linearly related variables. Georgia and South Carolina are the only two states to present a p-value greater than 0.05. Additionally, Georgia is the only state to present a Pearson correlation

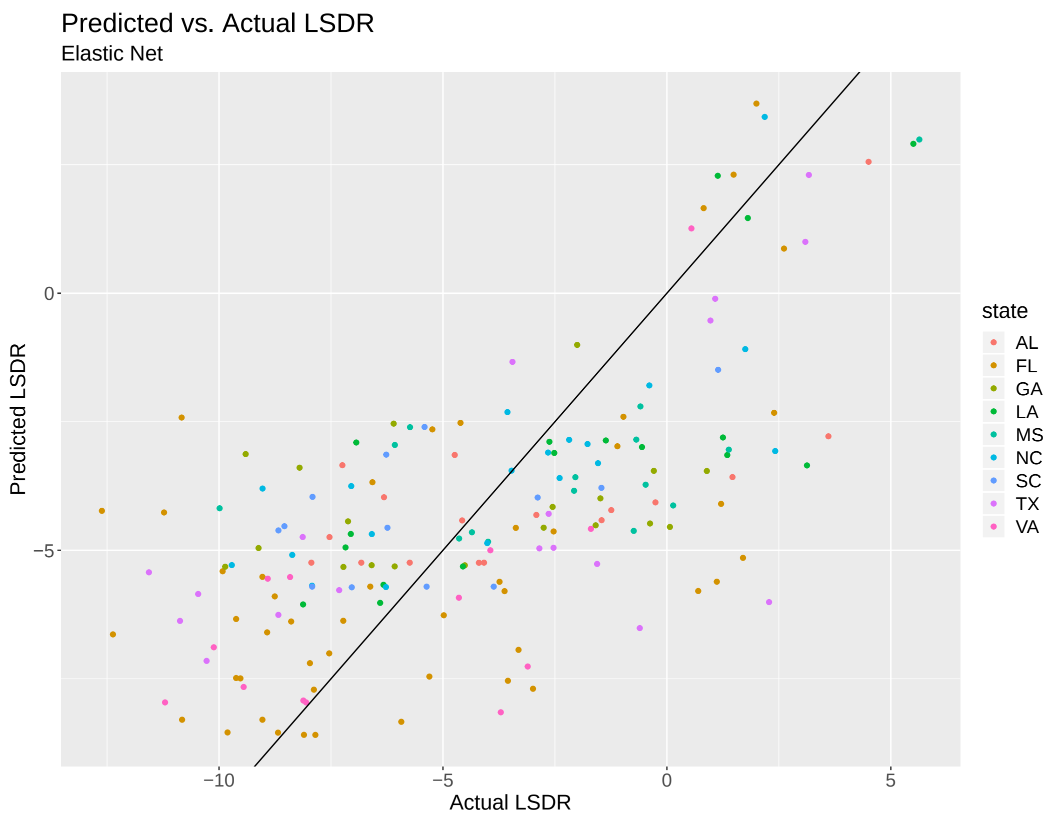

Figure 4.6: Predicted vs Actual LSDR - Elastic Net

coefficient below 0.5 for the two variables. Louisiana and North Carolina are the states with the highest correlation coefficients, 0.7708 and 0.7443, respectively. This means that, except for the states of Georgia and South Carolina, the two variables are correlated. Therefore, we can conclude that the developed machine learning model is able to adequately predict LSDR.

4.5.2 State Preparedness

Based on their location, states are more or less prone to be impacted by storms of higher intensity, i.e. higher LSDR. The LSDR model obtained using machine learning is able to explain over 40% of the variation. There are factors that the model is not able to predict, as a result of noise and state's preparedness.

Table 4.5: Pearson correlation coefficients between predicted and actual log LSDR per state

State	Correlation	p-value
AL	0.6622	0.0038
FL	0.5844	< 0.0001
GA	0.2506	0.3008
LA	0.7708	0.0003
MS	0.6493	0.0088
NC	0.7443	0.0003
SC	0.5256	0.0651
TX	0.6756	0.0021
VA	0.6532	0.0155

Table 4.6: Analysis of Variance (ANOVA) and Kruskal-Wallis test results for actual LSDR

ANOVA	$Pr(> F) = 0.0350$
Kruskal-Wallis	p-value $= 0.0389$

An analysis of variance (ANOVA) is performed to evaluate whether the state has an influence in the value of LSDR, or if the two variables are independent. The result of the ANOVA test, shown on Table 4.6, is that there is a statistically significant relationship between states and the value of LSDR. In other words, the state that the storm impacts makes a difference on its destructive potential, represented by LSDR. Additionally, the Kruskal-Wallis test, which does not make the assumption that the data is normally distributed, is performed and the result obtained supports the ANOVA results that there is a statistically significant difference between the values of LSDR and the state, as seen on Table 4.6.

Figure 4.7 shows the boxplot of the LSDR values per state for the states included in this study. It is possible to observe the difference between the mean LSDR for each state, as well as the variability of the distributions. South Carolina, Georgia, and Virginia, for example, present a much smaller range of LSDR values than other states, such as Texas and Louisiana.

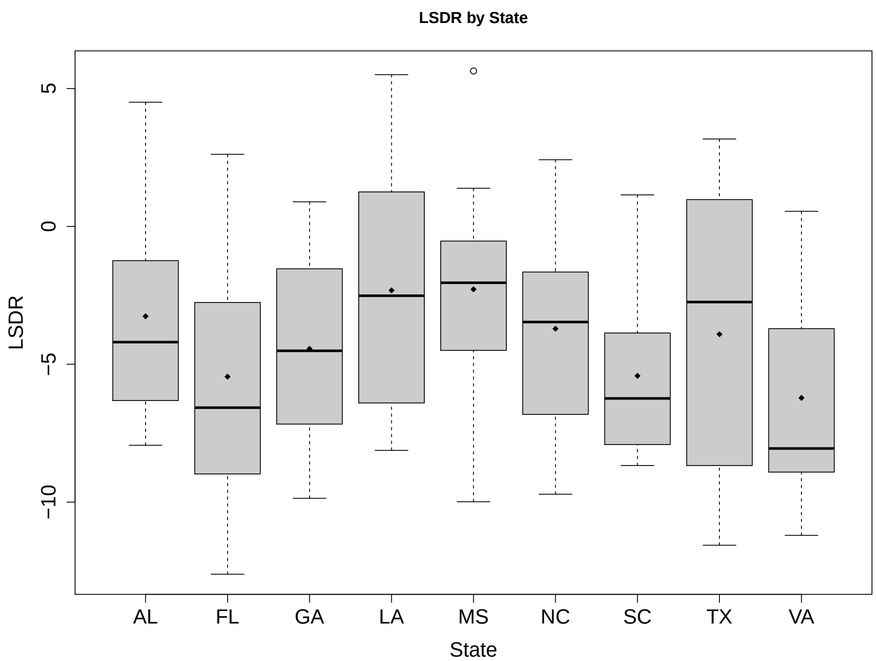

Figure 4.7: Boxplots of LSDR values by state

Similarly, ANOVA and Kruskal-Wallis tests are used to evaluate whether the state has an influence in the predicted value of LSDR using the selected elastic net machine learning model. The results of the ANOVA test and the Kruskal-Wallis test, shown on Table 4.7, are that there is a statistically significant relationship between states and the predicted value of LSDR. This means that the machine learning model was able to assimilate these differences in LSDR intensities among the states.

The fact that there is a statistically significant difference between both actual and predicted LSDRs between the states corroborates that each state

Table 4.7: Analysis of Variance (ANOVA) and Kruskal-Wallis test results for predicted LSDR

ANOVA	$Pr(> F) = 0.0126$
Kruskal-Wallis	p-value = 0.0003275

is affected by storms with intrinsically different characteristics and strengths. In other words, there is an inherent difference between the storms that reach each state.

After demonstrating the substantial difference between the storms that affect each location, state preparedness is evaluated. Evaluating preparedness of multiple locations to natural hazards is a challenge due to the fundamental differences between places.The metric *Binary State Preparedness* (BSP) is created to assess state preparedness by analyzing the difference between the actual and the expected (or predicted) LSDR. The BSP calculation and results are detailed in Section 4.5.2.

Binary State Preparedness

The first metric, called *Binary State Preparedness* (BSP), is a binary variable that conveys the information if the actual state damage, measured in terms of LSDR, is above or below what was predicted with the machine learning model developed. If the state suffered a damage above the predicted, the state is said to be poorly prepared and the binary variable received the value of 1. On the other hand, if the state suffered damage below the predicted, the state is said to be well prepared and the binary variable receives the value of 0. Equation 4.1 shows how the BSP variable is calculated for each state.

$$BSP = \begin{cases} 0, & \text{if Actual LSDR} \leq \text{Predicted LSDR} \\ 1, & \text{if Actual LSDR} > \text{Predicted LSDR} \end{cases} \tag{4.1}$$

Table 4.8 shows the count of each type of preparedness ($BSP = 0$ and $BSP = 1$) for each state, as well as the total number of storms and the percentage of times the state is deemed poorly and well prepared. It is possible to see that Florida is by far the state with the most occurrences, with 47 observed storms. Out of these 47, Florida presented damage below the expected, i.e. was well prepared, for 27 of these, or 57.45% of the occurrences. Among the states, Virginia is the best prepared, with 76.92% of its storms (or 10 out of 13) causing lower damage to the state than what was predicted. Mississippi, on the other hand, is the state that is the least prepared, with 80% of the storms causing damage above what was predicted.

A Chi-square test is performed to evaluate if the BSP and state variables are independent. The result of the Chi-square test is p-value = 0.1387, meaning we fail to reject the null hypothesis that there is no relationship between the two variables, i.e. there is not sufficient evidence to determine that the variables are dependent. Variable independence is also checked using Cramer's V, in which values vary from 0 to 1, with 1 indicating a perfect association between the two variables. A Cramer's V value of 0.1549 is obtained, supporting the Chi-square result of independence between the two variables. These results lead to the conclusion that all states are similarly prepared for incoming storms.

The analyses in this chapter suggest that while states are important (statistically significant) to the strength and destructive potential of the storms,

Table 4.8: Count of Binary State Preparedness (BSP) per state

State	BSP	Count	Total storms	% Preparedness
AL	$BSP = 0$	7	17	41.18
	$BSP = 1$	10		58.82
FL	$BSP = 0$	27	47	57.45
	$BSP = 1$	20		42.55
GA	$BSP = 0$	10	19	52.63
	$BSP = 1$	9		47.37
LA	$BSP = 0$	7	17	41.18
	$BSP = 1$	10		58.82
MS	$BSP = 0$	3	15	20.00
	$BSP = 1$	12		80.00
NC	$BSP = 0$	9	19	47.37
	$BSP = 1$	10		52.63
SC	$BSP = 0$	8	13	61.54
	$BSP = 1$	5		38.46
TX	$BSP = 0$	8	18	44.44
	$BSP = 1$	10		55.56
VA	$BSP = 0$	10	13	76.92
	$BSP = 1$	3		23.08

measured in terms of LSDR, they are not significant in terms preparedness. In other words, the lack of significant difference on the averages of BSPs among states lead to the conclusion that all states are similarly prepared for incoming storms. However, the characteristics of the storms are not the same among states.

4.5.3 Fragility Curves

Fragility curves represent the probability of a community reaching or exceeding a damage level as a function of the intensity of a tropical cyclone, numerically represented as the log LSDR. This means that the intensity of a given event, in this case tropical cyclones, is measured on the x-axis, while the probability of exceedance of a damage level is shown on the y-axis. Utilizing fragility curves provides a way of incorporating uncertainty in damage estimates and risk assessment, thus supporting risk-informed and resilience-driven decisions at a higher level.

As mentioned in Section 4.4.3, the empirical fragility curves are generated using logistic regression analysis. The *Storm Damage Levels*, or SDLs, are determined based on the log LSDR values of observed storms and the damage reported. Figure 4.8 shows the fragility curves for SDLs 1, 2, and 3. The fragility curve for SDL 1, with non-filled circles, is the the first curve to show points with probability of occurrence above zero. That happens because, as the values of log LSDR become slightly larger, the probability of minor damages raises. As the value of log LSDR rises, the probability of moderate damage, represented by SDL 2 (middle curve, "x"), occurring also rises. Finally, major damage, represented by SDL 3 (filled circles), occurs in few storms that present log LSDR of greater values. The majority of storms presents log LSDR on the lower end and, consequently, only cause minor to moderate damage to communities. However, as log LSDR increases, the probability of major damage occurring also increases, as can be observed in Figure 4.8. To the best of our knowledge, this is the first time empirical fragility curves have been built for tropical cyclones at a state-level.

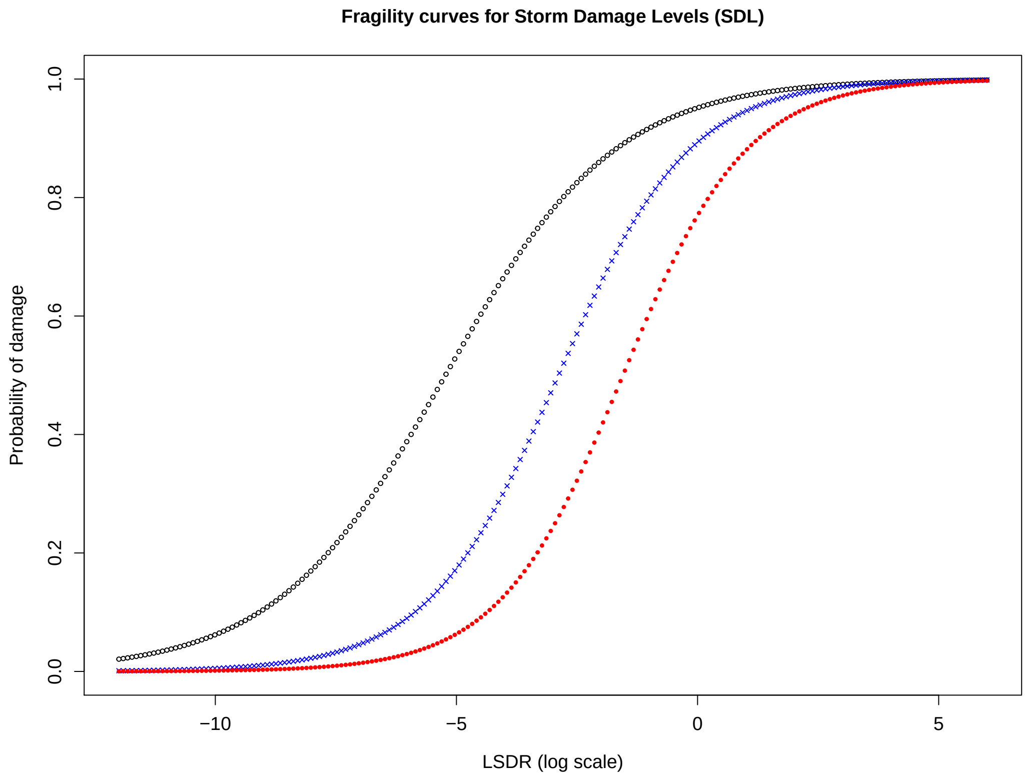

Figure 4.8: Logistic Regression for Storm Damage Levels

4.6 Concluding Remarks

This work contributes to the understanding of the threat tropical storms and hurricanes pose to coastal communities, which is the first step to improve community resilience. The first contribution of this paper is the development of the concept of LSDR, which allows for an assessment of storm's strength based solely on the storm's intrinsic characteristics, without influence from economic particulars of the affected location. Multiple machine learning models are built to predict the values of LSDR based on the storm's characteristics. Eight different models are built for each method, using two different outcomes and four different sets of input variables. Elastic Net provides the best result and is, therefore, used for the state preparedness study and empirical fragility curve generation.

The study indicates that there is a statistically significant relationship between states and the values of both actual and predicted LSDR, i.e. these variables are not independent. It can be concluded that both the actual and predicted strength of the storms, measured through LSDR, are dependent on the state where the storm makes landfall. State preparedness is evaluated with the BSP metric and statistical tests performed lead to the conclusion that state preparedness is independent of the state. This means that, while there is a significant difference between the strength of the storm in each of the studied states, they are all equally prepared for the storms.

Finally, this work also contributes to the study of community resilience by innovatively building state-level fragility curves with respect to hurricanes and tropical storms. The empirical fragility curves are built using logistic regression analysis and are a function of the intensity of the storms, in terms of log LSDR. The curves represent the probability of a community reaching or exceeding a given damage level, i.e. the probability of a certain level of damage occurring. Fragility curves were developed for three storms damage levels: minor, moderate, and major damage. As the strength of the storm increases, so does the probability of exceeding the damage threshold for each of the damage levels. This fragility-based approach allows for uncertainty to be added into the analysis of resilience and preparedness to hurricanes and tropical storms, supporting resilience-driven decisions at the state-level.

The results from this study could be utilized by decision makers at the community, city, or state-level to support resilience decision. The method LSDR created in this work can potentially be expanded to other types of natural hazards. Additionally, the original approach of fragility curves for state-level damage assessment can also be implemented for other events.

Chapter 5

Conclusion

5.1 Summary

The extensive literature review presented in Chapter 2 reveals critical elements and research gaps in the field of maritime resilience. The review identifies key port operations, stakeholders, and the related intermodal networks. Ports are fundamental agents of global supply chains, being responsible for moving a large percentage of the country's cargo. Although there are studies available on the impacts of port disruption, the extent to which the topic is covered is limited, especially when compared to the disruption of other agents in transportation systems. Ports are frequently located along coastlines, in areas particularly vulnerable to natural hazards such as hurricanes and tropical storms, which are expected to intensify due to climate change.

While the threat hurricanes and tropical storms pose to coastal areas is significant, the understanding of these natural hazards in terms of their intensity and potential impacts is limited. Various researchers have observed and attempted to address the deficiency of the SSHS in evaluating a hurricane's destructive potential by developing alternative methods to measure intensity. However, these methods failed to provide an acceptable prediction of potential losses resulting from incoming hurricanes. Chapter 3 successfully addresses this limitation, obtaining a machine learning model that better predicts the economic impacts of an incoming storm than existing metrics. A vast number of empirical models are developed, using multiple machine learning methods, and, through this extensive exploration, important differences between the predictive models for all storms (i.e. hurricanes and tropical storms), only hurricanes, and only tropical storms are discovered. Furthermore, the generated models are used to explore and obtain crucial insights in the relationship between storm features and the potential economic impact of said storm. Chapter 3 also explains the importance of the novel *Storm Damage Ratio*, a metric that addresses the challenge of evaluating the damage of different regions that possess different assets and population. This metric allows the evaluation and comparison of tropical cyclones based on their intrinsic characteristics alone, irrespective of the particularities of the affected areas.

In Chapter 4 the economic impacts of hurricanes and tropical storms are further investigated at a state-level. The previously developed SDR metric is refined to enhance its granularity, obtaining the LSDR metric, which is used to convey the impact of the storm characteristics alone. Supervised machine learning is used to estimate potential losses due to tropical cyclones at a state-level. The relationships between destructive potential of tropical cyclones and actual state losses are analyzed to assess vulnerability and coastal preparedness of states. The concept of fragility curves is then extended and used to quantify regional vulnerability to hurricanes and tropical storms. Historical data related to storm paths, characteristics, and regional damage measured as LSDR are utilized to empirically develop probabilistic functions for three damage levels.

5.2 Contributions

This dissertation makes multiple contributions, as listed below:

- Identifies risks and uncertainty in port operations and examines the impacts of port disruption to maritime supply chains, thus providing valuable insights and allowing for the identification of research gaps and areas where further investigation is necessary. Among these areas is the limited understanding of the impacts of hurricanes and tropical storms to ports and the overall coastal areas.

- Compares and contrasts existing metrics alternative to the SSHS, proving that while some may consider additional features other than solely sustained wind speed, no existing metric is able to provide adequate estimations of potential economic losses caused by hurricanes.

- Uncovers novel data-driven insights on the relationship between storm features and the potential for significant economic losses in a region through the innovative use of supervised machine learning and the development of 182 models.

- Introduces the new SDR, a metric that takes into consideration the GDP of the affected areas to distinguish region-specific factors from intrinsic storm characteristics.

- Explores, quantifies, and ranks the intrinsic characteristics of tropical cyclones and their effect in a cyclone's destructive potential, providing further awareness of other storm features that are relevant to the potential of a tropical cyclone's to cause economic losses.

- Demonstrates that, contrary to the suggested by the widely accepted SSHS, wind speed is not of the utmost importance in the context of potential economic losses of hurricanes. Shows that damage potential is actually highly dependent on other characteristics, particularly storm-size related features.

- Demonstrates that there are significant distinctions between predictive models for *all storms*, *hurricanes*, and *tropical storms*. Shows that the economic impacts of tropical storms alone are relatively easier to estimate than that of hurricanes, reinforcing the importance of continuing to research the behavior, characteristics, and overall interactions of hurricanes.

- Extends the previously created SDR metric to increase its granularity, thus allowing for a similar approach of distinguishing intrinsic storm-specific from region-specific factors at a local level, resulting in the novel LSDR metric.

- Assesses state-level coastal preparedness and vulnerability by examining the relationships between state and destructive potential of tropical cyclones. Demonstrates that there is a statistically significant difference between the intrinsic characteristics of the storms affecting each state. Meanwhile, there is no evidence suggesting that there is a difference in state preparedness, measured in terms of the novel BSP metric.

- Creates the novel SDL to determine the damage levels resulting from tropical cyclones at a state level. Performs an extensive review to establish the degree of damage observed per storm and the appropriate thresholds for the damage levels obtained.

- Develops a probabilistic approach that further assist in measuring coastal vulnerability to tropical cyclones at a state level based on the concept of fragility curves.

5.3 Future Work

The literature review in Chapter 2 reveals multiple research gaps. There is a lack of quantitative methods to assess maritime supply chain resilience, an area that is dominated by qualitative concepts and methodologies. Likewise, there is significant lack of broad and robust solutions to vessel rerouting problems. Additional focus should be given to maritime intermodal transportation, as there is a lack of body of knowledge in the topic to understand and address cascading effects throughout the supply chain resulting from disruptions to intermodal operations. Finally, more attention should be directed to port resilience to natural hazards. This dissertation partially addressed this gap by focusing on developing a clearer understanding of one of these hazards, namely hurricanes and tropical storms. However, given the fact that ports are specially vulnerable to the effects of the stronger and more frequently weather events resulting from climate change, due to their location, research efforts in the topic are of utmost importance.

A valuable future work would be to perform similar studies utilizing machine learning to estimate the economic impact of hurricanes and tropical storms at county and city levels. This would allow for a valuable comparison of vulnerability and preparedness to these events at national, state, county, and regional level. Similar to the approach of this dissertation, empirical fragility curves can be derived for county and city levels, potentially creating insightful tools to assess and improve both county and city resilience to tropical cyclones.

The metrics SDR and LSDR created in this dissertation can be utilized in the studying of other weather events that affect extensive and potentially diverse geographical areas. Additionally, other natural hazards can be studied utilizing the same innovative concept of empirical state-level fragility curves.

Finally, the results of the studies performed in this dissertation can be adapted and utilized by decision makers at the community, city, or state-level to support decision making process involving resilience to tropical cyclones.

Future research focused on assessing vulnerability and improving resilience in coastal areas have the potential of reducing both financial and human losses caused by hurricanes and tropical storms. Every year, the lives of millions of people are put at risk during these events, due to limited understanding and insufficient studies of these natural hazards. Tropical cyclones have caused over US $954.4 billion in losses in the United States from the year 2000 to 2019. These destructive weather phenomenons also result in the disruption of critical infrastructure systems and of important components in local and global supply chains. Promoting resilience to hurricanes and tropical storms is essential at national, state, and regional levels, and should be a priority of leaders at all levels.

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