RISK ANALYSIS OF THE EFFECTS OF EXTREME WEATHER CONDITIONS ON COMMERCIAL FISHING VESSEL INCIDENTS

by

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To My Loving Parents, Sisters, and Nephews. All This Would Have Been Impossible without Their Love from the Other Side of the World.

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Abstract

The fishing industry is one of the most dangerous occupations in the world. Extreme weather factors are an intrinsic part of the fishing operating environment and can present danger to fishers and fishing vessels. This thesis aims to investigate relationships between extreme environmental conditions and fishing incident activity levels, fishing incident rates and the severity level of fishing incidents in Canadian Atlantic Waters. The extreme environmental conditions in Atlantic Canada are most often associated with the passage of extratropical cyclones and icy water and can be characterized using wind speed, precipitation, air and sea surface temperature, Laplacian of pressure and ice coverage over the study area. Random Parameters Negative Binomial Regression showed that there was a strong relationship between the studied weather factors and fishing activity levels overall and, furthermore, different weather factors had different effects on various vessel sizes. There were correlations between harsh weather factors and fishing incidents. More specifically, incident rates increased in extreme weather conditions, but the effect of weather conditions were different in different seasons and some of factors were shown to be more significant than the others. Logistic Regression was used to examine how weather factors affect the severity level of fishing vessel incidents. The Laplacian of pressure, wind speed, sea surface temperature, and darkness were the most significant weather factors with respect to the severity level of fishing incidents associated with cyclones. Logistic Regression was also applied for individual fishery types, revealing that distinct fisheries can be effected by different weather factors.

The relationships between environmental conditions and fishing safety can change over time due to the effects of climate change on weather patterns. A general framework was proposed to quantify fishing incident risks in the future due to changes in weather conditions. We concluded that the risk from environmental conditions is projected to increase in Gulf of St. Laurence and South of Nova Scotia, decrease to the North of Newfoundland and Labrador, and remain similar in rest of the study area by the end of this century.

Finally this research suggests a knowledge mobilization structure to improve and update fishing policies with respect to the findings of this thesis in particular, as well as long and short term environmental considerations in general. The practical implications of this research include increasing the awareness of decision makers about fishers' vulnerability towards extreme environmental conditions, thus providing better response resources to lower the consequences of fishing incidents, and potentially devising better accident prevention strategies.

List of Abbreviations and Symbols Used

AIS	Automatic Identification System
AOGCM	Atmosphere-Ocean General Circulation Models
CART	Classification and Regression Trees
CCG	Canadian Coast Guard
CCGA	Canadian Coast Guard Auxiliary
CCPFH	Canadian Council of Professional Fish Harvesters
CMIP5	Coupled Model Intercomparison Project –Phase 5
DFO	Department of Fisheries and Oceans
EC	Environment Canada
ECMWF	European Centre for Medium-Range Weather Forecasts
FAO	Food and Agriculture Organization of the United Nations
IDW	Inverse Distance Weighting
JRCC	Joint Rescue Coordination Centre
LR	Logistic Regression
MERRA	Modern-ERA Retrospective Analysis for Research and Applications
NAFO	Northwest Atlantic Fishing Organization
NASA	National Aeronautics and Space Administration
NB	New Brunswick
NCEP-	National Centers for Environmental Prediction Climate Forecast
CFSR	System Reanalysis
NHC	National Hurricane Centre

NL	Newfoundland and Labrador
NOAA	National Ocean and Atmospheric Association
NS	Nova Scotia
ONF	Ontario Neurotrauma Foundation
PEI	Prince Edward Island
RCP	Representative Concentration Pathways
SAR	Search and Rescue
SART	Search and Rescue Transponder
SISAR	Search and Rescue Program Information Management System
SVM	Support Vector Machines
TC	Transport Canada
TSB	Transportation Safety Board of Canada
VMS	Vessel Monitoring System
WCB	Workers' Compensation Board
ZIF	Zonal Interchange Fishery

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Chapter 1 Introduction

1.1. Introduction to the Problem: Commercial Fishing Safety in Atlantic Canada

Commercial fishing in Canada can be traced back to the 15th century when Cod fishing drew Europeans' attention to Atlantic waters. Since then, the industry has survived two world wars, big business taking over many independent fisheries, and various economic pressures (CCPFH, n.d.). Today commercial fishing contributes $6.8 billion to annual Canadian economic activities and provides more than 80,000 direct jobs in four main regions of Canada: Pacific, Central and Arctic, Quebec, and Atlantic-based (Gulf of Saint Lawrence, Maritimes, and Newfoundland and Labrador) with the highest landed value and number of licensed fish harvesters in the Atlantic region (DFO, 2012). In many Atlantic areas, primary and secondary fisheries enterprises comprise the largest private sector employer and the whole region depends on fishing. But fishing is no easy job; hard labour, long work hours, hazardous working conditions, the competitive nature of the work, and harsh weather conditions are intrinsic parts of commercial fishing which puts thousands of fish harvesters at the mercy of the ocean every day. In fact, commercial fishing has the highest fatality rate among all industries in Canada. Workers Compensation Board (WCB) statistics show that 0.831 workers per 1000 died while on the job in the fishing industry. The average across all other industries is 0.044 worker fatalities per 1000 workers. This represents a 19 times higher risk of dying while at work in the fishing sector than in any other industry (WCBNS, 2012). (Twenty-two fish harvesters lost their lives and 1500 were seriously injured while fishing in the province of Nova Scotia in the past five years) (WCBNS, 2015).

Numerous research studies have been carried out to ascertain how to decrease the risk associated with the fishing industry from many different aspects such as vessel characteristics, operational regulations, human related errors, and environmental conditions. Weather factors are part of fishing environment that fish harvesters assume to be one of the leading factors in fishing incidents (Safecatch, 2006). It is not hard to imagine that any of strong winds, rough seas, ice, and freezing spray can prevent easy navigation and endanger the safety of the crew.

This thesis is mainly focused on the role of environmental factors, in particular extreme weather factors, on fishing vessel incidents in Atlantic Canada (the weather conditions in Atlantic Canada will be described in the following section 1.2). Although there is an extensive literature on different aspects of fishing safety, there are only a few studies that have tried to reveal the underlying patterns of weather factors and fishing incidents. Furthermore, up to the time of this research, nobody has quantified the risks associated with the characteristics of cyclones and fishing safety, nor forecast future risk variations due to changing conditions. Fishing safety is a complex system and its behaviour can change due to interactions between its various elements such as weather conditions and fishing traffic. The use of advanced statistical and mathematical methods make it possible for us to integrate fishing traffic, fishing incidents, and extreme weather data from different projects, disciplines, time spans, and geographic regions into a consistent framework. This step is essential to investigate relationships between cyclone weather factors and fishing safety in present and future time. Another aim of this research is to use effective visualization and knowledge mobilization methods to make a bridge from statistical findings to fishing safety practices.

1.2. Weather Conditions in Atlantic Canada

Atlantic Canada is said to have the most varied severe weather conditions in the country such as icebergs and extratropical cyclones due to climatic and geographic features of the region (Helicon Publishing, 2007). Ice-covered waters can affect the navigation of vessels, block their familiar paths, cause damage to a vessel's hull, and/or trap small vessels.

Extratropical cyclones are identified as any storm that occurs in the middle latitudes of the Earth and are characterized by strong winds, precipitation and temperature changes (Ulbrich et al., 2009). Extratropical cyclones get their energy from a temperature contrast of cold and warm air masses and can be at any intensity (i.e. from weak to very strong) (NHC, n.d.). The intensity of extratropical cyclones can be measured via different criteria such as central sea level pressure, wind speed, local Laplacian of pressure, and vorticity. The local Laplacian of pressure, or simply Laplacian of pressure, is the indicator of pressure difference between centre of a cyclone and its frontiers, while vorticity is a clockwise or counter-clockwise spin in the troposphere caused by a change in wind direction or wind speed with altitude (Serreze et al., 1997). Storms with high intensity (e.g. high Laplacian of pressure, high vorticity, strong winds, etc.) may have serious consequences such as fatal injuries in fishing incidents.

In this study, the percentage of area covered by ice (as an indicator of icy waters), wind speed, air and sea surface temperature, precipitation, and Laplacian of pressure (or vorticity) are chosen as characteristics of extratropical cyclones to represent extreme weather conditions in Atlantic Canada.

1.3. Fisheries in Atlantic Canada

Fisheries in Atlantic Canada are spatially distributed inshore, mid-shore, and offshore. Main target species are shrimp, groundfish, herring roe, seal, crab, lobster, tuna, salmon, scallop, and sea urchin. Many fishing vessels are used for multispecies fishing.

Table 1-1 presents the Department of Fisheries and Oceans (DFO, 2008) classification of vessel lengths with respect to fishery types. Lobster fishing vessels are mainly smaller than 45' and herring roe fishing vessels are larger than 65', but fishing vessels related to other species can be of any size.

Table 1-1. Classification of fishing vessel length and related fisheries (DFO, 2008)

Class	**Fishery**
1 - Less than 35'	Shrimp, Lobster, Crab, and Groundfish
2 - Between 35' and 45'	Shrimp, Lobster, Crab, and Groundfish
3 - Between 45' and 65'	Shrimp, Crab, and Groundfish
4 - Greater than 65'	Shrimp, Crab, and Herring Roe

Fisheries management in Atlantic Canada is based on three main systems: Individual Quota (allowable catch by weight for a given period of time per license), limited traps, and competitive (fishing for a given period of time) (DFO, 2008)

Weather conditions can have different effects on individual fishery types based on their location, vessel size, and management method. Larger vessels are typically more stable in strong winds and can carry more safety equipment. On the other hand, larger vessels can go further from shore, and therefore not be able to come back to harbour as readily in the case of an upcoming storm (cyclones can occur anywhere in the ocean; the spatial distribution of cyclones is illustrated in chapter 5). When fishing is especially competitive during a short fishing season, fish harvesters may go fishing or stay out in the ocean despite extreme weather condition in order to catch their quota.

1.4. Fishing Risk Management with Respect to Extreme Weather Conditions

Brooks and Pelot (2008) proposed a risk framework that illustrates the various phases of a risk event and strategy options to deal with it at each step (Figure 1-1).

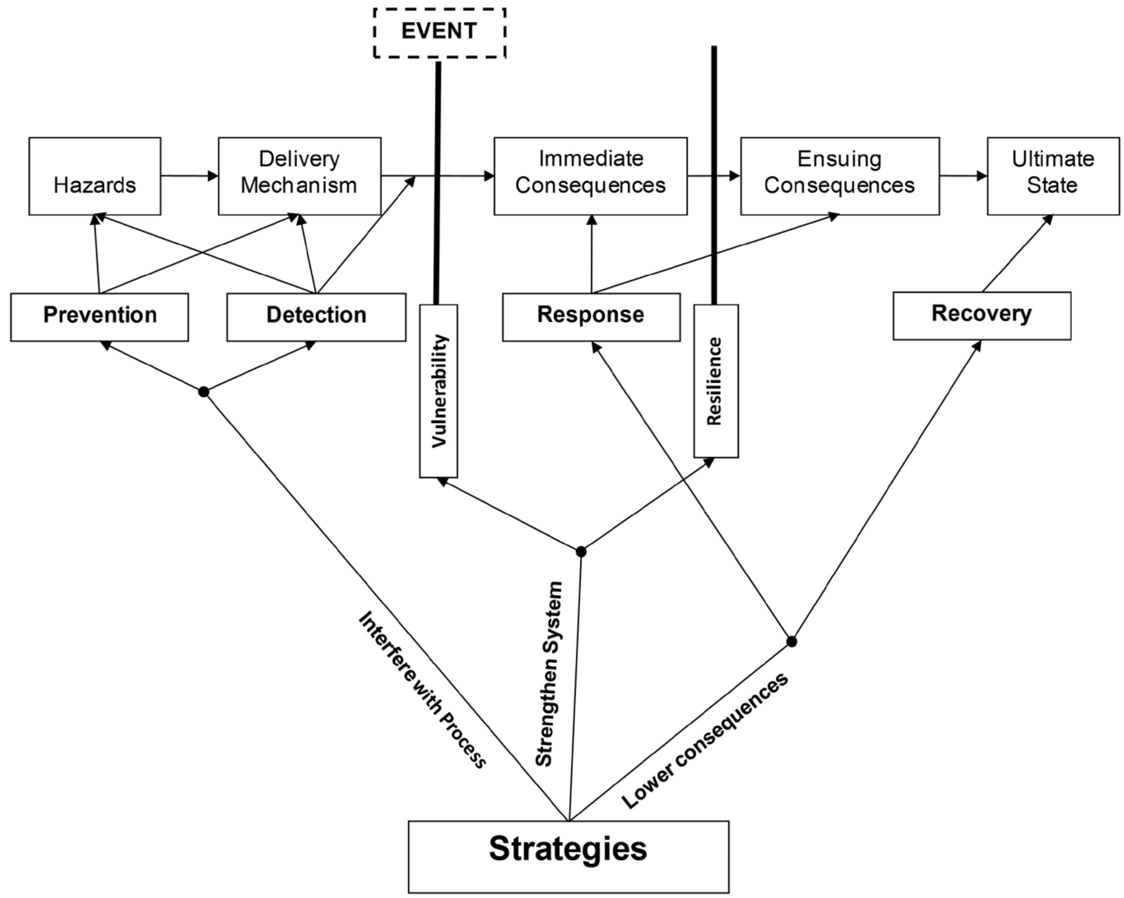

Figure 1-1. The risk management framework. Source: Brooks and Pelot, 2008.

In this study, *Event* is a fishing incident. It is defined as a discrete event in time that may last from a few minutes to a few days. *Hazards* includes a list of factors that may lead to a fishing incident such as weather conditions, engine failure, etc. This research focuses only on environmental conditions and doesn't investigate other *Hazards*. *Delivery Mechanism* indicates how a specific *Hazard* can affect an *Event*, for example whether a particular storm passing by a given region will affect a specific fishery type. *Immediate Consequences* refers to the consequences that happen during and just after an *Event* (e.g. damage to the fishing vessel, person in water, etc.). *Ensuing Consequences* is mainly about the consequences sometime after an *Event* (e.g. the time it takes for a vessel to be repaired or to clean up a spill from an accident). Ultimate states present the final stage at which fishing activities can be resumed (either similar, better, or worse state then the state before an *Event* occurrence).

There are different strategies to reduce the risk associated with each stage. The first group of strategies is entitled *"Interfere with the system"* and consists of *Prevention and Detection*. *Prevention* indicates actions undertaken to decrease the likelihood of an *Event* occurring with respect to determined *Hazards*. *Detection* presents the stage at which the imminent occurrence of an *Event* because of *Hazards* is detected by decision makers (i.e. Vessel Master, Fishing Company, etc.). *"Strengthen System"* is the second class of strategies that includes *Vulnerability* and *Resilience* assessments. *Vulnerability* is defined as susceptibility to negative impacts from a *Hazard* revealed only through the occurrence of that *Hazard*. In other words, it represents how likely a *Hazard* (extreme environment) can lead to an *Event* (fishing incident) in a particular set of conditions (e.g. fishery type, vessel size, etc.) and the magnitude of the consequences. *Resilience* refers to the capacity of a system (fish harvesters, fishing vessel, fishing company, etc.) to handle variations, adapt to potential damages, and cope with the *Consequences* of an *Event* (fishing incident).

The final class of strategies is entitled "*Lower Consequences*" which consists of *Response* and *Recovery*. *Response* actions can be applied at both stages *(Immediate and Ensuing Consequences*). For example, the Canadian Coast Guard can save a person in the water (*Response to Immediate Consequence*) and then this person may need medical help on land (*Response to Ensuing Consequence*). Finally *Recovery* shows the stage at which the system returns to an ultimate state (e.g. insurance pays the cost of medical treatment and the fish harvester can go back to work after a while).

We adopt this framework as a risk management structure for this study. Extreme environmental conditions are chosen as the *Hazards* and the three main phases of the study are defined based on the stages of the risk management structure of Figure 1-1, as follows.

Fishing Incident Occurrences

This phase aims to reveal the relationship between extreme weather factors and fishing incident occurrences. This section is mainly associated with *Prevention and Detection*. Weather factors are part of the fishing environment and severe environmental conditions can cause or contribute to incident occurrences in different ways (i.e. *Hazards*). Strong winds can affect the stability of vessels, ice can cause damage to the hull of a vessel, precipitation can decrease visibility and lead to a collision, a large difference between air and surface temperature can result in freezing spray and slippery decks, and low air temperature can also affect the proper functioning of crewmembers. Weather factors can also affect fishing traffic levels, and this effect is assumed to be dependent on vessel size. Small vessel sizes in general are more vulnerable to extreme weather conditions compared to medium and large size vessels. However, since larger vessels usually venture further offshore, they may not be able to take shelter or return to harbour in time when an intense storm arises.

This phase of the research applies various statistical methods to reveal the underlying patterns of harsh weather factors (i.e. low air and sea surface temperature, strong winds, high amount of precipitation, high ice concentration, and high Laplacian of pressure) associated with traffic levels of fishing vessels, fishing incident occurrences, and fishing incident rates (i.e. number of incidents over number of fishing trips). The statistical methods are chosen based on the characteristics of the problem and related literature, and statistical tests such as log-likelihood ratio test are carried out to choose the method with the best statistical fit for the data on hand.

To take seasonal weather trends into account, analyses have been carried out for each season individually. The analysis of the effect of weather factors on fishing traffic levels were also carried out for different vessel-length classes in Table 1-1.

Severity Levels of Fishing Incidents

This phase studies the relationship between the consequences of fishing incidents (e.g. life loss, vessel loss, minor injury, etc.) and extreme environmental factors. This section is mainly focused on *Strengthening the System* and *Lowering the Consequences*. It addresses *Vulnerability* and *Response*: *Immediate and Ensuing Consequences*, but doesn't extend to *Recovery* and getting to *Ultimate State*.

Weather factors can affect the severity of incidents in different ways; in the case of a person in the water, low sea surface temperature can be a critical factor; low visibility (i.e. high amount of precipitation or fog, or darkness) may lead to collisions with ice and the loss of the vessel; strong winds and consequently high waves can put distance between a person in the water and their vessel in a short time. Harsh weather conditions can also delay the arrival of help since Coast Guard vessels or helicopters have to follow safety regulations and may not be able to respond in very bad weather conditions.

In this phase, to measure the consequences of incidents, life loss or potential life loss is used to classify incidents into severe or non-severe groups. Statistical methods are then applied to fishing vessel incidents, air and sea surface temperature, wind speed, precipitation, Laplacian of pressure, ice coverage, and time of incident (day or night) to determine which environmental factors are significant in explaining severity levels of incidents.

Since different fishery types are generally associated with different vessel types, different fishing seasons, and different fishing locations, statistical models are also built for individual fishing types to determine the significant weather factors associated with impacts for each fishery type.

The Future of Fishing Safety

To conduct long term planning for commercial fishing safety, it is necessary to investigate climate change effects. This phase aims to suggest a general framework to quantify future fishing risks due to changes in weather patterns. This framework first builds relationships between fishing safety and environmental conditions based on historical data and then predicts future risks according to these model outputs. This part of the research mainly covers *Prevention*, *Detection*, *Vulnerability,* and *Response* stages with respect to long term changes in extreme weather conditions (i.e. changes in *Hazards*).

This framework is adopted to estimate the spatial distribution of fishing incident rates in Atlantic Canada towards the end of the century. Fishing vessel incident data and historical vorticity data (as an indicator of storms hitting Atlantic waters in the past) are used to determine relationships between frequency and intensity of storms and relative fishing incident rates. We use tree-based models to extract these relationships from historical data and present them as rules (e.g. storms with vorticity higher than 8.2 (10^{-5} s^{-1}) may lead to high fishing incident rates). These rules are then applied to projected storms in the period of 2081-2099 to estimate the spatial distribution of fishing incident rates in this period and compare it to the period 1980-2000. The results can provide information for strategic planning to ensure safe fishing practices despite changing weather patterns.

1.5. Knowledge mobilization

It is crucial that all people in, and involved with, the commercial fishing industry (e.g. fish harvesters, federal and provincial government, NGOs, etc.) attempt to ensure that fishing activities are practiced safely in harsh weather conditions. In other words, fish harvesters should be aware of the potential threats arising from extreme weather conditions; fishing policies and regulations should address short and long term weather considerations; and search and rescue planning should be carried out anticipating extreme weather events. All these considerations require that the findings from related research studies be presented in readily understandable language and through diverse means to decision makers. To achieve this goal, the final phase of this thesis adopts a knowledge mobilization structure (i.e. circulating the right information to the right people at the right time) to link the science to policy. First policies and regulations are reviewed to examine whether they are in alignment with findings of the proceeding phases of this research (i.e. Chapter 3 – Fishing Incident Occurrences, Chapter 4– Severity Levels of Fishing Incidents, and Chapter 5 – The Future of Fishing Safety) and recommendations are made to improve general fishing safety with respect to long and short term weather considerations.

1.6. Thesis Outline

This thesis is in manuscript-based format and each phase of the research is presented as a manuscript submitted to a journal. In all of the presented manuscripts, S. Rezaee made a substantial contribution to the conception and design of the model, and the analysis and interpretation of the data. All references cited in the chapters are included in a single complete reference list at the end of thesis.

To summarize, this thesis is focused on:

1. The existing relationships between extreme environment and fishing safety;
2. Changes in fishing safety over time due to climate change effects;
3. Recommendation on how fishing safety can be improved with respect to findings from 1 and 2.

In other words, this dissertation aims to the answer questions about how to develop, integrate, and present the relevant information to the decision makers. The questions that need to be answered are: what type of data and analysis results are needed and when, how, and to whom should they be presented? To answer these questions, this thesis is organized as follows:

- Literature Review: This section follows the examination of weather factors in fishing safety studies and establishes a list of significant weather factors based on the cited literature. The literate review that is related to more specific topics such as statistical methods, climate change, and knowledge mobilization are presented in the related chapters.
- Fishing Incident Occurrences: This chapter applies various statistical methods and compares them to determine the most appropriate method to reveal the relationship between extreme weather factors and fishing incident occurrences.
- Severity Levels of Fishing Incidents: This part of the dissertation investigates the consequences of fishing incidents and examines the relationship between extreme weather factors and severity levels of fishing incidents.
- The Future of Fishing Safety: To ensure fishing safety over long term, a framework is proposed in this chapter to estimate fishing incident risk with respect to potential climate change models towards the end of this century.
- Knowledge Mobilization: This section uses knowledge mobilization concepts to link the findings of Chapters 3, 4, and 5 to Canadian fishing related policies and recommends improvements with respect to short and long term weather considerations.
- Conclusion: The final part of these thesis summarizes the results from all the phases, points out the contributions, clarifies limitations of the results, and makes recommendation for pursuing future works in this area.

Figure 1-2 illustrates the thesis chapters and their interconnection:

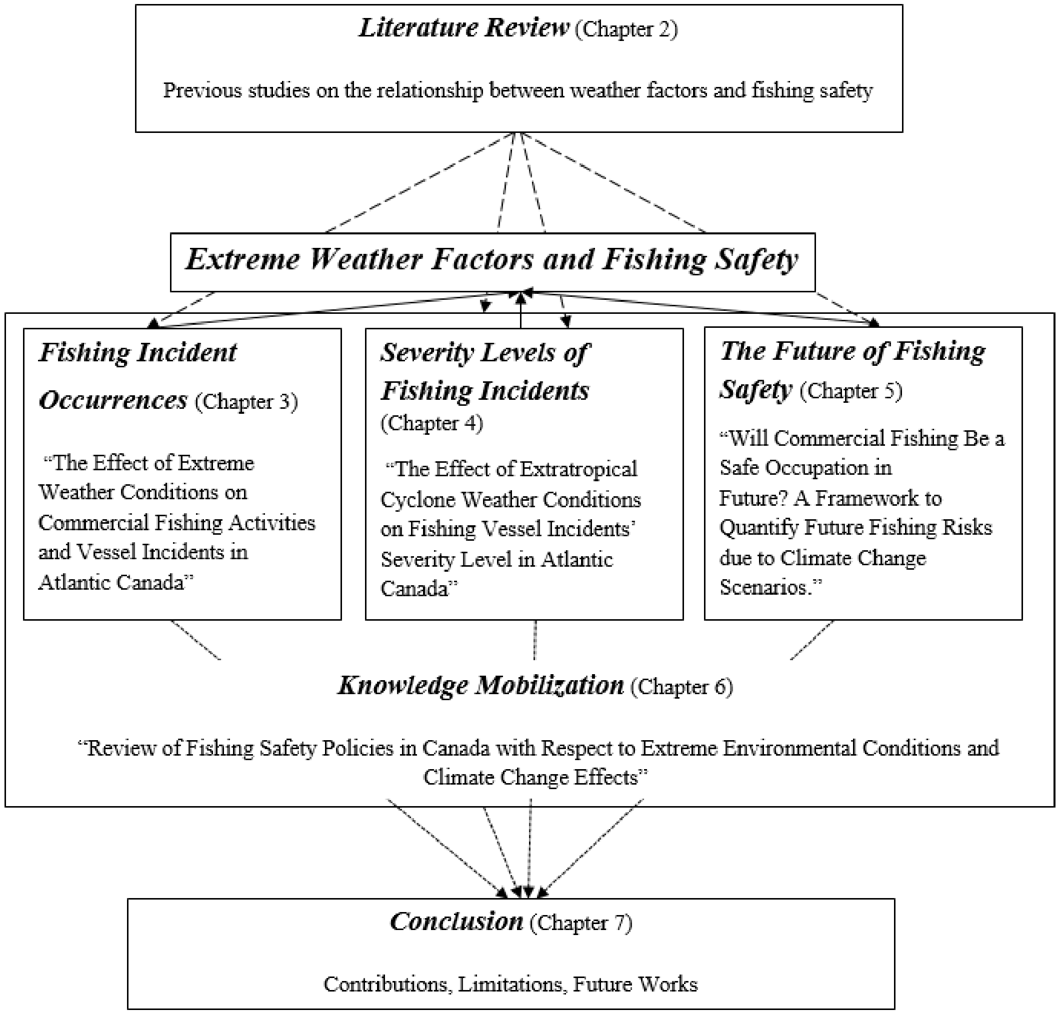

Figure 1-2. Thesis Outline

Chapter 2 Literature Review

There are many different interpretations of risk in the literature. To be consistent, in this research we adopted ISO 31000 (ISO, 2009) definition: “Risk is the effect of uncertainty on objectives and it is often expressed in terms of a combination of the consequences of an event (including changes in circumstances) and the associated likelihood of occurrence.” Based on this definition fishing risk can be characterized as the combination of various causes and consequences as shown in Figure 2-1. Generally speaking, environmental conditions (e.g. harsh weather), vessel-related problems (e.g. instability), human-related issues (e.g. fatigue) and/or the combination of these factors can cause different types of fishing incidents. These incidents can bring harm to individuals, damage to the vessel, cargo, or the environment, or negatively impact the reputation and/or financial situation of the fishers or their company when applicable. The objectives referred to in the definition are thus to avoid or mitigate any, or all, of these consequences.

Lloyd’s Register (2000) categorizes different maritime incident types as:

- Foundered: Sinking as a result of heavy weather, taking water in, breaking in two, etc.
- Missing: Not receiving any news after a reasonable period of time.
- Fire/Explosion: Vessel lost due to fire or explosion.
- Collision: Striking or being struck by another ship, regardless of whether underway, anchored, or moored.

- Contact: Striking an external item such as drilling rigs/ platforms (not another ship or sea bottom); in some texts this is referred to as “allision”.
- Wrecked/Stranded/Grounding: Touching sea bottom, sandbanks, seashore, or underwater wrecks.
- Other: war losses, hull/machinery damage or any other failure that cannot be categorized in the aforementioned groups.

However, when fishing incidents are studied, there is another category of incidents that should be added to the above list as well:

- Capsizing: Overturning due to instability of the boats (Wang et al, 2005).

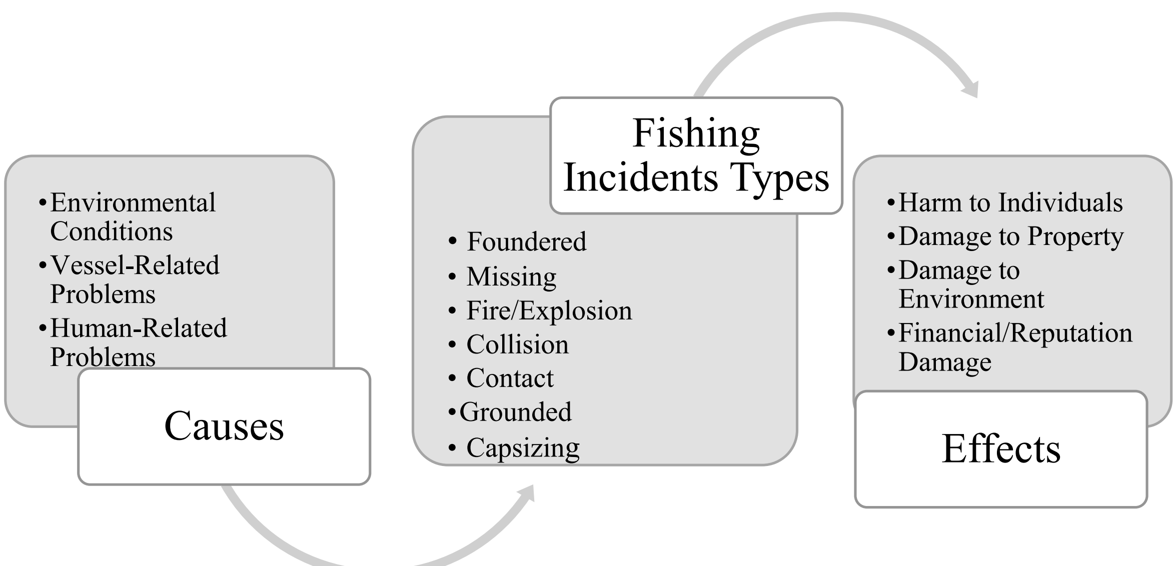

Figure 2-1. Fishing Incidents: Causes and Effects

This chapter mainly attempts to review the studies on the relationships between weather conditions and fishing safety in general, and more detailed and specific literature related to climate change, knowledge mobilization, and statistical methods will be presented in literature review section of each related manuscripts (i.e. Chapters 3 ,4 ,5 and 6). It must be noted here that despite the varying importance of the different fishing incident types or fishing incident consequences, this review is mainly focused on the causes of incidents and doesn’t discriminate between the different incident types and consequences.

Studies of fishing incidents causes are mainly focused on determining the most important factors. As mentioned before, these factors can be classified as environmental, vessel, and/or human related. Several representative studies, their critical factors, methods, and the relevant insights from the study are presented in Table 2-1. Each work is further explained in more detail in the following text.

Table 2-1. Summary of fishing incidents related studies

Article	**Factors**	**Methods**	**Insights**
Rothblum (2000)	• Environmental • Vessel-related • Human-Related	Literature Review	Getting an insight about the linkage between environmental, vessel, and human related causes in marine incidents
Jin et al (2001)	• Environmental • Vessel-related	Statistical Modelling	The application of statistical modelling in quantifying risk Understanding the importance of precipitation for fishing incidents

Article	Factors	Methods	Insights
Jin and Thunberg (2005)	• Environmental • Vessel-related	Statistical Modelling	The application of statistical modelling in quantifying risk Understanding the importance of wind speed in fishing incidents Understanding that different vessel sizes may encounter different risks
Wu et al. (2005, 2008, 2009)	• Environmental	Statistical Modelling	Better understanding of the relationship between weather factors and fishing incidents Understanding the importance of wave height, ice concentration, air and, sea surface temperature in fishing incidents. Understanding the importance of fishing activity levels on risk estimation
Brennan (2008)	• Environmental • Vessel-related • Human-Related	Survey	Better understanding of fish harvesters' decision making process Understanding that different vessel sizes may encounter different risks
Chatterton (2008)	• Environmental • Human-Related	Historical Data Exploration	Understanding the importance of sea surface temperature, icing, and wind in fishing incidents
Morel et al (2008)	• Environmental • Human-Related	Simulation/ Survey	Better understanding of fish harvesters' decision making process in harsh weather conditions
Niclasen(2010)	• Environmental • Vessel-related	Literature review	Better understanding of the relationship between waves (and winds) and vessels' stability

Rothblum (2000) suggested that fatigue, inadequate communication, inadequate general technical knowledge, inadequate knowledge of own ship systems, poor design of automation, decisions based on inadequate information, faulty standards, policies, and/or practices, poor maintenance, and hazardous natural environments can contribute to human error and incidents in the marine industry.

Jin et al. (2001) investigated the significant factors in marine incidents by means of mathematical modelling. The variable in question was the number of vessel total losses and number of fatal or non-fatal crew injuries in the occurrence of commercial fishing vessel incidents. Unlike Rothblum (2000), their main focus was on vessel-related and environmental accidents which represent 57% of fishing incidents in the period of 1994-1999 based on a US Coast Guard report. They estimated the probability of a total loss or injury in this category of accidents as a function of:

- Event probability, and
- Severity of the event given that it has occurred.

They developed a Probit Regression model to predict the probability of total loss, and used a Negative Binomial Regression to predict the number of fatalities and non-fatal injuries. A Probit model is a type of regression model where the dependent variable is binary. The Probit model employs Probit link function which can be expressed as:

$$\Pr(Y=1|X) = \phi(X'\beta) \tag{1.1}$$

where Y is the binary response variable (i.e. fishing incident probability) , X is the matrix of predictors (which will be listed shortly), β is the coefficient matrix, and ϕ is the cumulative distribution function of the standard normal distribution (Hosmer et al., 2013).

The Negative Binomial Regression is a method that can accommodate count data, and the expected frequency for each possible value of the response variable (i.e. 1, 2, 3, ...) is assumed to be a function of explanatory variables as follows:

$$\mu_i = e^{\beta X_i + \varepsilon_i} \tag{1. 2}$$

where μ_i is the expected frequency of the response variable i (i.e. number of lives lost given that a fishing incident has happened), β is the matrix of coefficients, X_i is the matrix of predictors of the related response variable, and ε is the error term (Chang, 2005).

The predictors used in Jin's model are as follows:

- Type of the accident:
    - Collision,
    - Fire/explosion,
    - Material or equipment failure,
    - Sinking, and
    - Grounding.
- Cause of the accident (vessel based or environmental).
- Operational conditions:
    - Location (inland waterway or not), and
    - Weather conditions:

        - Presence of fog,
        - Presence of precipitation,
        - Wind speed.
- Waterway status (calm, choppy or very choppy).
- Time of accident (night or daytime).
- Vessel characteristics:
    - Size,
    - Age,
    - Hull type, and
    - Fuel type.
- Real price-fish

The results of Probit Model showed that capsizing, sinking, fire/explosion, and environmental causes (i.e. precipitation and night time) will increase the likelihood of total losses in fishing incidents on coastal and ocean waters.

The results of the Negative Binomial Regression indicated that fire/explosion, capsizing, and heavy precipitation are associated with high fatality rates. The fatality rate decreases when the price of fish catches increases: the higher the price of fish, the greater the incentive to reduce vessel damage to avoid interruptions; also, higher-priced catches are likely to result in greater funds available for repair and maintenance of fishing vessels. (Jin et al., 2001).

Later in 2005, Jin and Thunberg presented an assessment of key factors affecting incident occurrence in Northeastern United States through applying a Logistic Regression model. Logistic Regression estimates the probability of either level of the binary response variable occurring (i.e. incident occurrence that can be zero or one). The logit function maps the unit interval of probability [0, 1] onto the real domain (-∞, +∞) and the regression is carried out:

$$\Theta = \frac{1}{1+e^{-(\beta+\beta 1x)}} \tag{1.3}$$

where θ is the probability of the positive event occurring (i.e. fishing incident), X is the matrix of predictors (which will be listed shortly), β is the intercept, and β_1 is the matrix of coefficients of predictors (Hosmer et al., 2013)

Jin and Thunberg's database includes daily data of fishing vessel activities, fishing vessel incidents, wind speed, and spatial information on the incidents from 1981 up to 2000. The wind speed was recorded hourly from offshore buoys and nearshore weather stations. Each fishing area was assigned to the nearest weather recording station. The results revealed that accident probability is a function of wind speed, vessel location, time of the year and vessel characteristics. Higher winds speeds are associated with greater accident probability. Accidents were likely to happen near shore with the lowest possibility in the spring. Medium size vessels had the highest rate of incidents (number of incidents per unit of time) (Jin and Thunberg, 2005).

Wu (2005) examined the statistical relationship of weather patterns on fishing vessel incidents in Atlantic Canada. The main objective of the research was to develop a model, which can predict the probability of incidents or the level of severity based on weather conditions. In her research, she worked with three types of datasets:

1. Incident data.
2. Traffic data, and
3. Weather data.

Incident data (SISAR): When a Joint Rescue Coordination Centre (JRCC) of the Canadian Coast Guard receives a report of an incident, they dispatch the most available and suitable Search and Rescue (SAR) resource to provide assistance, and a record is created in the SISAR database. The SISAR (Search and Rescue Program Information Management System) database includes detailed information about the incidents such as time and location, type of vessel, type of incident, severity, etc.

Traffic data (ZIF): The Zonal Interchange Files database provides detailed information about commercial fishing trips in Northwest Atlantic Fishing Organization (NAFO) subdivisions. The database includes information about vessel identification number, gross tonnage, home port, etc.

Weather data:

- Wave and Wind: AES40 North Atlantic Wave hindcast model for 1958-2003 generated data at six-hour intervals.
- Fog: There were no systematic historical records for the presence of fog in Atlantic Canadian waters at the time of research. Nevertheless, fog was predicted based on

sun angle, inversion base height, sea surface temperature and the difference between dew point temperature and sea surface temperature, all factors that were available.

- The data about other weather factors and ice coverage were extracted from the National Ocean and Atmospheric Association (NOAA) database.

The weather factors included in Wu's (2005) analysis were as follows:

- Wave height,
- Air temperature,
- Sea surface temperature,
- Freezing spray,
- Ice concentration,
- Presence of fog, and
- Amount of precipitation.

Wu's study area was a specified region of the Atlantic Ocean on the East Coast of Canada, restricted to the most limited available gridded weather areas. Temporal coverage was 1997 to 1999, during which there were 2186 fishing incidents in the study area.

Classification tree-based modeling was used to reveal relationships between weather factors and incident features. The results showed that the most dominant factor is traffic count, and when the traffic variable was excluded from the model, wave height became the most significant factor. Presence of fog and precipitation were not significant factors based on statistical modelling of incident occurrence (Wu, 2008).

To determine the relationship between weather factors and the severity of incidents, the incident data were divided into two groups based on the Canadian Coast Guard classification: severe and non-severe incidents. A Logistic Regression model was used to estimate the severity levels of incidents. The results showed that wave height and ice concentration were the most important factors in the prediction of the severity level of an incident (Wu et al., 2005).

As mentioned before, the most significant factor in incident occurrence is the traffic. To circumvent the dominance of the traffic level, one approach is to find the relationship between weather factors and relative incident rate, which is defined as the number of incidents occurring for a given amount of traffic, on a given day within a certain grid cell given that there was at least one incident that took place within that grid-day. The term Relative Incident Rate (RIR) emphasizes relative comparisons and not absolute probabilities of incidents. Tree-based modelling was chosen as a data mining technique. The results revealed that fog and the amount of precipitation were not as critical as wave height, ice concentration, and air and sea surface temperature (Wu et al., 2009).

However, unlike road accidents analysis which has continued to develop toward more complicated and comprehensive mathematical modelling, fishing incident related studies that have applied advanced statistical methods are scarce and the main part of literature is built on interviews, surveys, and historical data exploration.

An interview with 46 fish harvesters in Newfoundland and Labrador revealed that 85% of them have experienced “being on board in extreme weather” (Brennan, 2008). When the fishing seasons are short and/or about to close, fishermen are more likely to go on fishing trips even when bad weather prevails. If a harvester had a particularly bad year, he/she will probably take greater risks to set out in bad weather or stay in a storm with inadequate safety equipment. The results also indicate that the crew on larger ships are less likely to consider weather as a safety problem and they are more tempted to go out fishing despite weather warnings. They may also go out to sea in good weather but after weather conditions deteriorate, they may be too far out to take shelter. Based on the results, Brennan (2008) listed biophysical elements in fishing safety as follows:

1. Gender of the harvester,
2. Species fished,
3. Fishing area,
4. Nature of the fishing grounds,
5. Weather conditions,
6. Water temperature, and
7. Vessel design.

Morel et al. (2008) argued that to improve safety in the fishing industry, it is necessary to reinject resilience into the fishing safety management system. Resilience here refers to the ability of the system to recognize the problem and make safe decisions. This kind of decision is called a sacrificial decision which means making a decision in a way that balances productivity and safety or security. They created a simulation of a 14-day fishing tour using written scenarios. Skippers volunteering as subjects could request information throughout the experimental situations. The available information is listed as follows:

- Information the skippers receive from the shore:

    - The weather forecast for the next 24 hours
    - The current price of fish/prawn
- Information exchanged between the skippers:
    - The geographical location of colleagues at sea,
    - The quantity of catch over the latest day of fishing,
- Information directly linked to the fishing activity
    - The quantity of catch since the beginning of the fishing tour,
    - Breakdowns or damage to the fishing gear,
- Permanent information throughout the fishing tour:
    - The price of diesel fuel,
    - Information related to the last fishing tour, and
    - Fixed expenses such as supplies, engine oil, etc.

The two contrasting scenarios are:

- SC1: very satisfying catch and steadily worsening weather conditions
- SC2: very poor catch and weather conditions are identical to SC1.

They asked skippers to make decisions in four stages: Day 0, Day 2, Day 6 and Day 10. Each stage was assigned a given safety level which is directly related to the weather conditions. These safety levels were determined based on experts' opinions. Weather conditions included wind force, visibility, condition of the sea, and height of swell. They could choose an action from the following list:

a) Continue operations in the same fishing zone,

b) Leave the fishing zone for another,

c) Temporarily suspend the fishing activity,

d) Return to harbour, or

e) Other.

Their reason for making each decision could be:

- They felt they could handle the situation,
- The situation was too dangerous for their crew,
- The situation was too dangerous for their fishing gear,
- They were satisfied with their catch, and
- Other.

The results showed that they never consider coming back to the harbour or stopping the fishing activity. If they feel the situation is too dangerous, they may go to another fishing zone where their colleagues are safely catching. In fact they rely on the information they can get from their colleagues and trust them or consult them more often than official weather reports (Morel et al., 2008).

Based on historical data, one of the major causes of incidents is icing. The accumulation of ice on a vessel's superstructure can cause instability, which in turn may lead to capsizing. In 1991, the United States Coast Guard established a series of icing and stability standards. Chatterton (2008) examined these standards to figure out if they are suitable for the vessels over 79 ft. long. Based on that research, seasonal darkness, cold water, high speed winds, icing, fatigue and short fishing seasons are the most important factors in icing-related accidents.

Niclasen et al. (2010) studied the important sea state parameters for small vessels' safety and warning indices, which have been adopted in related literature. A vessel is considered to be small if its length is shorter than average ocean wavelengths. Since the average wavelength is about 50-200 m, their study focused on vessels smaller than 45 m. Waves are assumed to create risk for vessels by affecting their stability and their study supported this assumption by showing that the incident rate rises with deteriorating weather and sea state conditions. One steep wave or synchronous rolling in a series of waves with a frequency close to the vessel's own rolling period can lead to capsizing. It has been concluded that small vessel safety is dependent on (Niclasen et al., 2010):

- Severity of the sea state:
    - Head sea: A sea in which waves or currents are running directly against the course of a ship. The danger here is slamming or shifting of cargo.
    - Following sea: A following sea refers to a wave direction that matches the heading of the boat. It is dangerous when waves are high.
    - Beam sea: A sea whose surface motion is approximately at a right angle to the course of a vessel. Sailing in beam seas can result in large roll angles and, in extreme conditions, the vessel can capsize.
    - Quartering sea: A sea striking a ship's quarter at an angle of about 45 degrees to its heading. Waves in this situation can affect the stability of the vessel significantly.

    - Crossing sea: A cross sea is a sea state with two wave systems traveling at oblique angles. It is particularly dangerous as the waves will approach a vessel from different directions.
- The occurrence of particularly dangerous waves. A vessel is particularly vulnerable to broadside breaking waves that are relatively large compared to the size of the vessel.
- Directionality of waves can affect the vessel's stability.
- Vessel's and operator's preparedness to deal with hazardous situations. There are some controllable factors, which can increase the danger in severe sea state conditions such as overloading, unsecured cargo, and unsecured openings.

Although determining the important factors in fishing incidents by using the firsthand experience of fish harvesters is of great value, there is a gap in the fishing safety literature about how to use these factors in predicting incidents and consequently preventing them. Applying advanced mathematical modeling, which is the main focus of this study (these mathematical methods will be explained in detail in relevant chapters), can help to evaluate potential critical factors in fishing incidents, use them to predict and reduce the future risks due to potential climate change effects, and provide means to put the scientific results into practice (i.e. knowledge mobilization).

Chapter 3 Fishing Incident Occurrences

Title: The Effect of Extreme Weather Conditions on Commercial Fishing Activities and Vessel Incidents in Atlantic Canada

Authors: Sara Rezaee, Dr. Ronald Pelot, Dr. Alireza Ghasemi

Abstract

Extreme weather factors as a part of the commercial fishing operating environment can present danger to fish harvesters and fishing vessels. In Atlantic Canada, these hazardous conditions are most often associated with the passage of extratropical cyclones. This research aims to identify extratropical cyclone weather conditions that are associated with the occurrence of maritime incidents, categorized both spatially and temporally. Quantifying the effects of cyclone weather factors on fishing traffic levels is a complementary objective. Negative Binomial Regression, Zero-Inflated Negative Binomial Regression, Fractional Logit Regression, and Random Parameters Negative Binomial Regression were applied to recognize patterns in historical fishing activity levels, incident data, and cyclone weather factors in Atlantic Canada. The results suggest that there is a strong relationship between the studied weather factors and fishing activity levels overall and, furthermore, different weather factors can have different effects on various vessel sizes. There are also correlations between harsh weather factors and fishing incidents with respect to activity levels. More specifically, incident rates increase in extreme weather conditions.

Key words: Fishing Vessel Incidents, Fishing Vessel Traffic, Extreme Weather Conditions, Random Parameters, Negative Binomial Regression, Zero-Inflated Negative Binomial Regression, Fractional Logit Regression.

3.1. Introduction

The fishing industry is one of the most hazardous occupations in the world. Fish harvesters are 52.4 times more likely to have a fatal incident at work compared to other occupations in Great Britain (Roberts, 2002). Fishing is also one of the most dangerous occupations in Canada with a fatality rate of 1.15 per 1000 persons, which is almost equivalent to the top-listed risk occupations of forestry workers. In addition to the high risk of fatality, fish harvesters are also at risk of a wide range of non-fatal injuries during their work at sea (Murray et al., 1997).

Mariners consider the most dangerous fishing situations to be associated with weather-related factors (bad weather/poor forecasts), vessel characteristics (such as size and stability), and lack of safety equipment (Safecatch report, 2006). There is an extensive literature investigating different risk factors in fishing incidents. In the majority of them, the weather conditions are part of the study. Results of a report prepared by the National Research Council of Canada and the Canadian Coast Guard in 2005 showed that there have been more than 1000 incidents in Canadian waters due to icing since 1970 (Kubat and Timco, 2005). Chatterton (2008) demonstrates that seasonal darkness, cold water, high speed winds, icing, fatigue and short fishing seasons are the most important factors in icing-related accidents for the vessels over 79 ft. long. Wu et al. (2005, 2008, and 2009) applied classification tree-based modelling to study the historical patterns of fishing vessel incidents and weather factors in Atlantic Canada. The results showed that the most dominant factor is the amount of exposure of vessels (i.e. fishing traffic levels or number of fishing trips in the study area), and when the traffic variable was excluded from the model, wave height became the most significant factor. Rezaee et al. (2015b) used Logistic Regression and Support Vector Machines to reveal the underlying relationships between extratropical cyclone weather factors and severity level of fishing incidents, showing that wind speed, ice concentration, sea surface temperature, and Laplacian of pressure are critical factors in the prediction of the severity levels of fishing incidents. The results of this study also suggested that incidents related to different fishery types might be affected by different weather conditions. Jin et al. (2001), Jin and Thunberg (2005), Wang et al. (2005), and Niclasen (2010) also investigated the key factors for fishing incidents and suggested that deteriorating weather is a significant environmental factor in their occurrences.

This research aims to investigate the relation between commercial fishing incidents, fishing activity levels, and extreme weather conditions, as well as other weather factors. Extreme weather conditions in this research refer to extratropical cyclones that occur in the middle latitudes of the Earth and are characterized by strong winds, precipitation and temperature changes. Extratropical cyclone can be at any intensity (i.e. from weak to very strong).

The analysis aims to determine if fishing activity levels and fishing incidents are significantly related to any or all of: wind speed, air and sea surface temperature, ice concentration, amount of precipitation, and/or Laplacian of pressure. Note that these hypotheses are not mutually exclusive.

The findings can help the Canadian Coast Guard or other decision makers in marine traffic to make more informed decisions about issuance of weather warnings such as Small Craft Advisories or to maintain a higher state of readiness of Search and Rescue resources under certain extreme weather conditions. Fish harvesters can also be provided with better information about the potential consequences of certain weather conditions so they can prepare better for, or even avoid, risky conditions.

This chapter is organized as follows: The next section on Data Sources describes the data preparation steps, Data Exploration looks at the different aspects of the datasets, the Model Development section elaborates on the modelling methods, Results presents the outcomes of the statistical analyses, and the Conclusion includes the discussion and concluding notes.

3.2. Data Sources

The study area for this research encompasses Atlantic Canadian Waters from 40° to 60° N latitude, and 73° 20' to 45° 50' W longitude over the years 2005-2010. Close examination of the data revealed that there were inconsistencies in the incident data collection process during year 2007; therefore, 2007 was excluded from the analysis.

3.2.1. Weather Data

Weather factors included in this study were chosen based on literature and personal communications with experts. Datasets with the finest available spatial and temporal resolutions were used to generate the subsets of weather data over Atlantic Canadian Waters during the study period. Since the chosen datasets have different characteristics, Table 3-1 presents the source, frequency of measurement, and grid size of each dataset.

Table 3-1. Weather Factors

Field (Unit)	Data Set	Frequency	Grid size
Wind Speed (miles per second)	NCEP /NCAR Reanalysis (Kalanya et al, 1996)	6 hour intervals	2.5 by 2.5 degrees
Air Temperature (degrees Kelvin)	NCEP/NCAR Reanalysis	6 hour intervals	2.5 by 2.5 degrees
Sea Surface Temperature (SST) (degrees Celsius)	NCEP OI SST V2 (NOAA, 2014)	Weekly mean	1 by 1 degree
Ice Concentration (percentage)	NCEP OI V2	Weekly mean	1 by 1 degree
Precipitation (mm)	ERA-Interim-ECMWF (Dee et al, 2011)	Daily total amount	0.75 by 0.75 degrees
Laplacian of pressure (mPa/km^{-2})	Cyclone Database (Serrze and Barret, 2008)	6 hour intervals	2.5 by 2.5 degrees

Weather factors can affect fishing vessels and fish harvesters in different ways. Wind speed is assumed to have a significant role in vessel stability. Air and sea surface temperature may affect the efficiency of crewmen and worsen the conditions after an incident happens. Ice concentration, which is presented as the weekly average of the percentage of each grid covered by ice, can cause navigation problems and may trap fishing vessels. Precipitation can reduce the visibility of fish harvesters and also affect their performance negatively. The Laplacian of pressure is an indicator of a passing extratropical cyclone's intensity and it has been calculated using the nine grid cells of sea level pressure around an identified cyclone center by a climatology expert (Personal Communication, 2013/09/01) following Serreze and Barrett's (2008) storm tracking algorithm. Although storms with higher Laplacians typically have stronger surface winds, this relationship is neither exact nor linear, as resulting winds can be affected by the storm size, rate of intensification, and the striking region (Mass and Dotson, 2010). For this reason, Laplacian of pressure and wind speed are both included in the current study, to better characterize individual cyclone events.

3.2.2. Incident Data

When a vessel encounters a problem in Canadian waters and calls the Search and Rescue (SAR) Joint Rescue Coordination Center (Canadian Coast Guard and Department of National Defence), a record is generated in the SISAR (Search and Rescue Program Information Management System) database and the most available and suitable SAR resources is sent to the location of reported call. The SISAR database includes detailed information about these reported incidents such as time and location, fishery type, type of vessel, type of incident, and severity level. In this study, the term 'incident' refers to a record in SISAR database. The total number of fishing incidents over the 5 years (i.e.2005, 2006, 2008, 2009, and 2010) within our area of interest is 3146.

3.2.3 Fishing Activity Data

Vessel Monitoring System (VMS) datasets were used as an indicator of fishing activities. VMS is a satellite-based, near real-time, positional tracking system, which allows the Department of Fisheries and Oceans (DFO) to monitor fisheries. The use of VMS allows fishing vessel positions to be transmitted to DFO at regular intervals. This information is relayed to a monitoring centre where data are analyzed and archived. This research uses a subset of VMS data within the study area, providing information for each unique (anonymized) vessel identifier its latitude and longitude, time, heading, speed, and vessel length.

3.2.4. Data Preparation

The entire study area is overlaid by a series of grid squares of size 2.5 degrees by 2.5 degrees (approximately 250 km by 250 km). This resolution is chosen to ensure the presence of at least one weather point in each grid. Consequently there are 88 grid squares that cover the study area of which thirteen are entirely on land, yielding 75 usable grids for the analysis. Over the five-year study period, the combination of grid cells and days thus yields 365*5*75=136,875 potential samples, referred to as grid-days. Figure 3-1 shows the gridded study area.

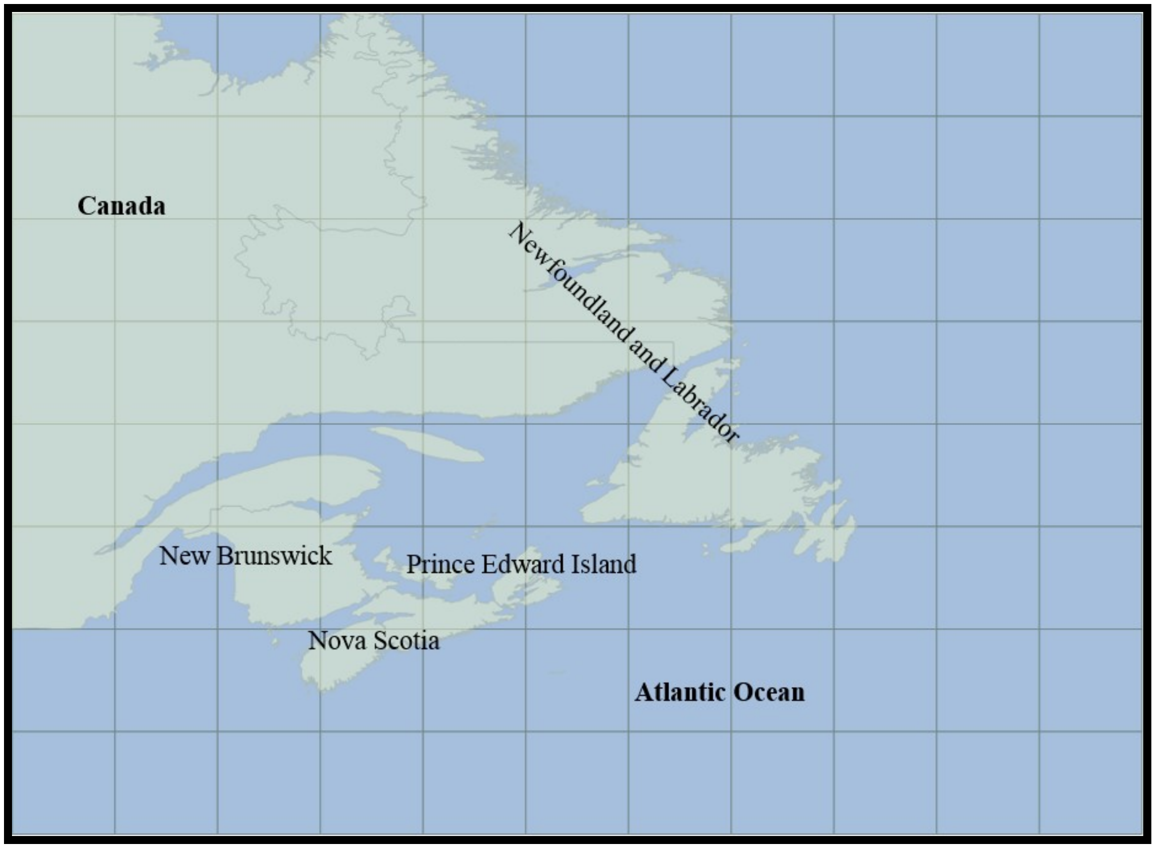

Figure 3-1. Gridded Study Area

To match incident data with grid-days, the number of incidents in each grid-day was counted and assigned to the related grid-day. However to match the weather data with grid-days, since all six weather factors are obtained in different frequencies and grid square sizes, decisions had to be made as to how to match weather factors with grid-days. Linear Interpolation was used to interpolate ice coverage and sea surface temperature (both measured weekly) to the related grid-day of the week. In the case of weather factors that were measured more than once in a day, thus with multiple values for a particular weather parameter at each grid point, two approaches were considered: 1. Assign the best, average or worst condition during the day to the grid (for example lowest air temperature); 2. Subjectively choose a combination of weather factors (e.g. air temperature measured at

6:00 am, wind speed measured at 12:00 pm., etc.) to be representative of weather conditions each day. The principal result of assigning the worst, best, or average weather condition to each grid for each day showed that using worst weather conditions results in better statistical fits. Therefore only the results for the worst weather conditions are reported in this research.

Matching fishing activity data with grid-days was carried out in two steps. First VMS data were processed to connect data points for each trip and calculate trip tracks (i.e. a track comprises a combination of line segments from starting point in grid A to ending point in grid C through the intervening grids). Then the number of line segments in each grid-day was counted and assigned to the related grid-day.

3.3. Data Exploration

3.3.1. Frequency of Incidents

The number of incidents by grid-day in the dataset varies from 0 to 7. Table 3-2 shows the frequency of each number of incidents in the dataset.

Table 3-2. Incident Frequencies

Number of Incidents	**Frequency**	**Percentage**
0	133,729	92.37%
1	2,639	1.93%
2	369	0.27%
3	96	0.07%
4	27	0.02%
5	10	0.01%
6	5	0.004%

Number of Incidents	Frequency	Percentage
7	2	0.001%
Total	**136,875**	**100%**

Since the number of incidents equal to or greater than one is notably fewer than the zeros, to accommodate this imbalance we grouped the nonzero incident grid-days by adding a binary variable named ‘Incident Occurrence’, which is set equal to 1 when at least one incident occurred in a grid-day and 0 otherwise. Figure 3-2 shows incident numbers and incident-occurrence numbers (number of grid-days with at least one incident) during the study period (excluding 2007). As Figure 3-2 shows the trend of temporal distribution of incident occurrences and incident numbers are similar; therefore, it was decided to use the binary variable incident occurrences instead of incident numbers in the analysis since the small number of samples with more than one incident may result in biased outcomes (i.e. there may not be sufficient patterns belonging to the minority classes (number of incidents greater than one) to adequately represent their distribution).

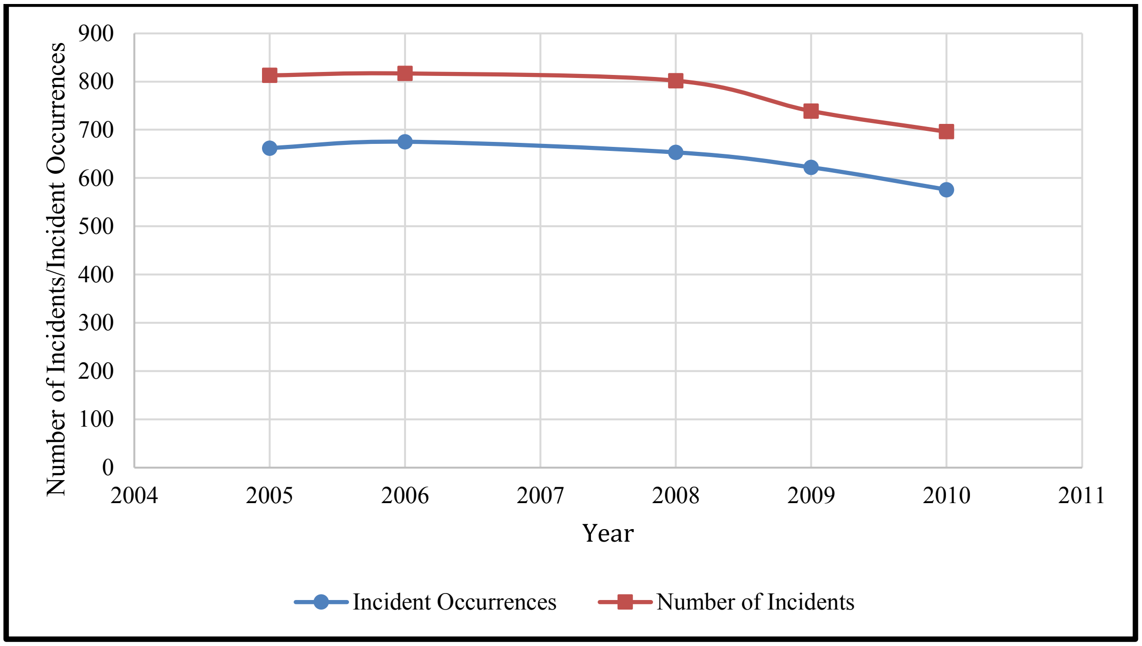

Figure 3-2.Temporal distribution of incident occurrences and incident numbers

3.3.2. Seasonal Effect

Different seasons are associated with different weather conditions and different traffic levels due to the opening and closing of fisheries. Table 3-3 presents the number of incident occurrences and total number of fishing trips in each grid-day for different seasons over the study period. One can conclude that despite the fact that fewer fishing trips took place in winter compared to the summer and spring seasons, the rate of incident occurrences per trip in winter is much higher than the other seasons which can be related to harsher weather conditions in wintertime compared to other seasons. Since the study period is restricted to 2005-2010 there are not enough data samples (i.e. five data samples for each season, e.g. winter incident rate for year 2005, 2006, 2008, 2009, 2010) to statistically test the differences between incident rates over different seasons (e.g. incident rates in spring versus incident rates in winter).

Table 3-3. Number of incidents, and total number of fishing trips in each grid-day for different seasons over the study period

Season	**Start**	**End**	**Number of Incident Occurrences**	**Number of Fishing Trips**	**Number of Occurrences per 1000 trips**
Winter	Dec 21	Mar 19	549	108,729	5
Spring	Mar 20	Jun 20	1359	424,632	3.2
Summer	Jun 21	Sep 21	1171	472,634	2.5
Fall	Sep 21	Dec 20	788	197,742	3.9

3.3.3. Vessel Length

Different vessel lengths can indicate different capabilities of vessels to handle harsh weather conditions. Larger vessels are typically more stable in strong winds and can carry more safety equipment. On the other hand, larger vessels can go further from shore, and therefore not be able to come back to the harbour as readily in case of an upcoming storm. Table 3-4 shows DFO's classification of fishing vessel length and related fisheries (DFO, 2008).

Table 3-4. Classification of fishing vessel length and related fisheries (DFO, 2008)

Class	**Fishery**
1 - Less than 35'	Shrimp, Lobster, Crab, and Groundfish
2 - Between 35' and 45'	Shrimp, Lobster, Crab, and Groundfish
3 - Between 45' and 65'	Shrimp, Crab, and Groundfish
4 - Greater than 65'	Shrimp, Crab, and Herring Roe

3.4. Model Development

Modeling approach for three main research question of this chapter listed as fishing activity levels, fishing incident occurrences, and fishing incident rates will be explained in section 3.4.1, 3.4.2., and 3.4.3, respectively.

3.4.1. Fishing Activity Levels

One of the goals of this research is to examine whether there is a relationship between fishing activity levels (i.e. number of fishing trips in each grid-day) and weather conditions for grid-days associated with a cyclone (i.e. those with the Laplacian of pressure greater than zero), with breakdowns by winter, spring, summer, fall, vessel length-class 1, vessel length-class 2, vessel length-class 3, and vessel length-class 4. To better understand the variations of environmental conditions and fishing activity levels throughout study period, Table 3-5 presents the descriptive statistics of variables for each model. As shown in Table 3-5, the number of trips in each grid-day is a non-negative integer value, which restricts our choices on statistical methods to count-data regression methods. It must be noted here, that this chapter only focuses on statistical methods, and doesn't include data mining methods such as neural networks. The main reason to focus on regression methods rather than data mining methods is that the majority of data mining methods are defined as black boxes which can predict future values based on historical relationships; however, these historical relationships would be unknown to the analyst. Regression methods, on the other hand, can provide information on analysis of the problem in terms of relationships between causal factors and response variables. These methods can determine which predictors are statistically significant and consequently how the risk associated with them can be reduced.

Count methods are widely used in road safety literature. Despite some differences in marine and road safety such as frequency of incidents and trips and some environmental conditions (road characteristics versus ocean characteristics, visibility in roads versus oceans, traffic congestion in roads versus oceans), these topic have similarities such as the nature of the data (integer data), exposure variable (trips), some environmental conditions (wind speed, precipitation, etc.), human related problems (age, experience, etc.) and characteristics of vessel or car (age, maintenance, etc.). Therefore, it was decided to follow the road safety path for the analysis of traffic level data and benefit from the lessons learned in the rich road safety literature.

The most common method in modelling count data in road literature is Poisson regression (Mannering and Bhat, 2014). However since the average number of fishing trips per grid-day and the standard deviation of all the datasets are not equal, the datasets are likely to be overdispersed. In this case, the Negative Binomial Regression, which doesn't require the mean to equal the standard deviation, is the most suitable model (Hilbe, 2011). The expected traffic frequency for each grid-day in the Negative Binomial Regression is assumed to be a function of explanatory variables as follows:

$$y_i = e^{\beta X_i + \varepsilon_i} \tag{3-1}$$

where y_i is the expected traffic frequency for grid-day i, β is the matrix of coefficients, X_i is the matrix of predictors for the related grid-day, and ε is the error term. e^{ε_i} is a gamma distributed error term with mean of 1.0 and variance 'a', which is the measure of dispersion. If 'a' is not significantly different than zero, Poisson Regression should be chosen over Negative Binomial Regression. The conditional probability of having y fishing trips with randomly distributed error term ε in grid-day i is then defined by the following equation (Chang, 2005):

$$P(y_i|\epsilon_i) = \frac{\exp[-\mu_i\, exp(\varepsilon_i\,)][\,\mu_i\, exp(\varepsilon_i\,)]^{y_i}}{y_i\,!} \qquad y_i = 1,2,..,n \qquad (3\text{-}2)$$

Over time there has been a steady improvement in statistical methodologies in road safety literature to extract more information from available datasets, reveal underlying patterns, and determine significant factors in analyses of traffic levels and incidents (Mannering and Bhat, 2014). It has been shown that one of the fundamental issues that traditional statistical methods such as Negative Binomial Regression failed to address is the effect of unobserved factors on road (marine) traffic (safety in general). These factors that may not be observed (or included) in a dataset can have an important effect on results and overlooking these unobserved factors can lead to biased interpretation of the model outcomes. For example when fishing traffic levels (or fishing safety in general) are studied with respect to environmental conditions, factors such as the experience of fishers in handling extreme environmental conditions, economic and social pressure, and some other subtle factors which can be very important in risk-taking behaviour might not be addressed, thus substantially influencing findings and the inferences drawn from the analysis of data. Random Parameters methods can accommodate the unobserved heterogeneity by allowing regression coefficients to vary across the observations (i.e. traffic level increases for some observations and decreases for some other observations under the same circumstances due to the effect of unobserved factors). Therefore these methods are more informative in terms of the underlying relationships between predictors and response variable and shown to be a better statistical fit than traditional methods (Anastasopoulos and Mannering, 2009;

Christoforou et al, 2010; and Anastaspoulos et al[a]., 2012). The regression coefficients in Random Parameters Negative Binomial Regression are defined as:

$$\beta_i = \beta + \phi_i \tag{3-3}$$

where ϕ is a randomly distributed term (e.g. normally distributed term, lognormal, uniform, triangular, etc.) . In this case equation (3-1) changes to:

$$y_{i|\phi\, i} = e^{\beta X_i + \varepsilon_i} \tag{3-4}$$

The parameters can be estimated via maximum log likelihood. The log likelihood function is equal to:

$$LL = \sum_{i=1}^{n} g(\phi_i) P(y_{i|\phi_i} d\phi_i) \tag{3-5}$$

where g(.) represents the distribution of random parameters (Anastasopoulos et al[a], 2012).

The estimation of maximum likelihood is then carried out through a simulation-based method via the LIMDEP software (Greene, 2012).

Table 3-5. Descriptive Statistics for variables - Traffic Level Models

Variables	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Cyclone Grid-Days				
Number of Fishing Trips	18.43041799	28.77095805	1	214
Air Temperature(°K)	276.5552006	7.632909041	243.7	295
Sea Surface Temperature(°C)	5.580956694	5.095121252	-1.8	22.354
The Laplacian of Pressure(mPa/Km^2)	1.29506E-10	5.90127E-11	2.11E-11	3.86E-10
Ice Concentration (percentage)	7.134975177	17.4489402	0	100
Wind Speed(m/s)	10.67665412	4.726683725	0.8	33.4

Variables	Mean	Standard Deviation	Minimum	Maximum
Precipitation(mm)	0.001029259	0.002044957	0	0.035301
Winter				
Number of Fishing Trips	9.589258631	17.3466899	1	138
Air Temperature	267.295798	6.231758477	240.8	283
Sea Surface Temperature	0.94341058	1.628367531	-1.73	10.064
The Laplacian of Pressure	6.91278E-11	9.28243E-11	0	3.59E-10
Ice Concentration	19.01108804	24.92970705	1.22E-06	100
Wind Speed	11.27108573	4.824829448	0.9	33.4
Precipitation	0.000632131	0.001457932	0	0.019453
Spring				
Number of Fishing Trips	26.76439165	38.07032788	1	236
Air Temperature	275.8799082	4.745465712	250.8	293.1
Sea Surface Temperature	3.787238615	3.220877313	-1.8	16.607
The Laplacian of Pressure	3.99068E-11	6.0357E-11	0	2.61E-10
Ice Concentration	7.526351203	17.40519345	0	100
Wind Speed	8.283509301	3.722253037	0.8	24.4
Precipitation	0.000524638	0.001303572	0	0.025289
Summer				
Number of Fishing Trips	25.43641354	32.8283202	1	228
Air Temperature	285.2778166	4.162483813	265.8	296.5
Sea Surface Temperature	12.02146409	4.141602335	0.56	22.477
The Laplacian of Pressure	2.83711E-11	5.09263E-11	0	3.14E-10
Ice Concentration	0.242191598	3.196185124	0	71.143
Wind Speed	7.458640547	3.14501712	0.7	32.8
Precipitation	0.000600064	0.001584626	0	0.035301
Fall				
Number of Fishing Trips	13.26237425	20.1392323	1	147
Air Temperature	276.0189873	6.466018194	245.9	292.5
Sea Surface Temperature	6.300884842	4.001667773	-1.13	19.897
The Laplacian of Pressure	4.54713E-11	7.39636E-11	0	3.86E-10
Ice Concentration	2.574792733	10.17374775	0	71
Wind Speed	10.25293763	4.295348945	0.8	33.4
Precipitation	0.000697697	0.00170049	0	0.019891

Variables	Mean	Standard Deviation	Minimum	Maximum
Vessel Length-1				
Number of Fishing Trips	21.5122795	31.13216204	1	236
Air Temperature	277.9037069	8.202641128	240.8	296.5
Sea Surface Temperature	6.950800142	5.447837688	-1.8	22.477
The Laplacian of Pressure	4.11936E-11	6.76849E-11	0	3.86E-10
Ice Concentration	5.230101891	14.60019597	0	90
Wind Speed	8.756263306	4.009387914	0.7	33.4
Precipitation	0.000613618	0.001544025	0	0.035301
Vessel Length-2				
Number of Fishing Trips	3.093518744	2.696512927	1	16
Air Temperature	278.2533626	8.590137686	241	295.2
Sea Surface Temperature	7.757854863	5.214981431	-1.8	19.63
The Laplacian of Pressure	3.98426E-11	6.73E-11	0	3.86E-10
Ice Concentration	2.842669366	9.624942815	1.22E-06	85.857
Wind Speed	8.519516955	4.005761505	0.7	33.2
Precipitation	0.000666558	0.001741399	0	0.025289
Vessel Length-3				
Number of Fishing Trips	1.331559133	0.700924226	1	7
Air Temperature	276.319395	7.677286457	243.6	293.8
Sea Surface Temperature	5.366602212	5.176068711	-1.8	20.02
The Laplacian of Pressure	4.6992E-11	7.47186E-11	0	3.86E-10
Ice Concentration	7.215538318	17.4989849	1.22E-06	100
Wind Speed	9.893509022	4.512477353	0.7	33.4
Precipitation	0.000640737	0.001587215	0	0.035301
Vessel Length-4				
Number of Fishing Trips	1.317390959	0.626689556	1	7
Air Temperature	275.3401287	7.555422959	245.5	294.7
Sea Surface Temperature	4.49826669	4.885039221	-1.7414	19.891
The Laplacian of Pressure	5.07121E-11	7.6565E-11	0	3.86E-10
Ice Concentration	10.17541877	21.14480332	1.22E-06	100
Wind Speed	10.01423691	4.486524208	0.9	33.2
Precipitation	0.000601212	0.001441354	0	0.035301

3.4.2. Fishing Incident Occurrences

The grid-day database yields 136,875 data samples but only 3146 of these grid-days have had an accident during our study scope, which means that more than 92% of the data have zero values in their incident occurrence field. Traditionally the Poisson or Negative Binomial distribution is used to model accident counts in road or marine safety literature. However, analysis of such discrete events may result in biased outcomes due to infrequent occurrence over time-periods (i.e. the number of zeros compared to the number of incidents may dominate the patterns of non-zero data distribution). Zero-Inflated methods are widely applied in Road Incidents and occupational health literature (Kumara and Chin, 2003, Lee and Mannering, 2002, Lord et al., 2005, Chin and Quddus, 2003, Carrivick et al., 2003, and Lord et al. 2007) to address excess zero issues in datasets similar to the fishing safety data (sparse incident data over study period). These models assume that there are two types of zeroes: structural zero (there was no incident because there was no exposure in the grid-day and consequently the probability of fishing incident occurrences remains zero no matter how the environmental conditions change); and statistical zero (fishing vessels went through a grid on a particular day but no incident happened on that grid day; therefore, there is a probability [0 to 1] of incident occurrences on that grid-day based on environmental conditions even though none has occurred to date). Therefore, zero-inflated models have two components; the first component is a binary distribution that generates structural zeroes and the second one is Poisson or Negative Binomial Regression that generates counts, some of which may be zero. (Lord al., 2005):

$$P(y_i) = \pi + (1-\pi)\, f(y_i|X_i)\,; \quad y_i = 0 \tag{3-6}$$

$$P(y_i) = (1-\pi)\, f(y_i | X_i); \quad y_i = 1,2,3,..,n \tag{3-7}$$

where π is the probability of structural zeros, y is the response variable (i.e. number of incidents), n is the upper bound on y and X is the matrix of predictors. f(.) is a Negative Binomial probability distribution for y as given in equation (3-1).

The Maximum Likelihood method can be used to estimate the parameters.

3.4.3. Fishing Incident Rates

Wu et al. (2008, 2009) showed that the most dominant factor in fishing incident occurrences is traffic. One way to subsume the effect of traffic and understand the effect of weather factors on incidents is to study the incident rate associated with fishing traffic levels for grid-days associated with a cyclone, and for winter, spring, summer, and fall respectively. Incident rate, defined as the number of incidents over the number of fishing trips in each grid-day, can take any value between 0 and 1. However, since our goal is to determine the relationship between weather factors and relative incident rates (i.e. which weather factors may increase incident rates), only grid-days that contain at least one incident were kept for analysis. It must be noted that since grid-days with no incidents were excluded from the analysis, calculated incident rates cannot be used in an absolute sense to predict incident numbers from predicted traffic levels.

Table 3-6 presents the descriptive statistics of selected variables for each model.

Table 3-6. Descriptive Statistics for variables- Incident Rate Models

Variables	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Cyclone Grid-Days				
Incident Rates	0.11475983	0.212087279	0.004902	1
Air Temperature (°K)	278.1284434	7.340682873	250	292
Sea Surface Temperature (°C)	6.808535386	5.067773344	-1.3529	18.997
The Laplacian of Pressure (mPa/ $Km^{2)}$	1.14044E-10	5.03257E-11	2.33E-11	3.17E-10
Ice Concentration (percentage)	3.999678784	12.89275549	1.22E-06	92
Wind Speed(m/s)	9.357334826	4.071973615	1.9	26.4
Precipitation (mm)	3.50545E-05	0.000413418	0	0.025289
Winter				
Incident Rates	0.271565871	0.34163235	0.007246	1
Air Temperature	266.6556757	5.781437702	247.1	278.3
Sea Surface Temperature	1.304926424	1.984301911	-1.3843	7.5457
The Laplacian of Pressure	5.18324E-11	7.87551E-11	0	2.85E-10
Ice Concentration	18.61505734	24.68044468	1.22E-06	92
Wind Speed	0.000532961	0.001284963	0	0.008366
Precipitation				
Spring				
Incident Rates	0.07513741	0.174751502	0.00565	1
Air Temperature	276.7650651	4.501419368	259.3	288.9
Sea Surface Temperature	4.40744841	3.118319538	-0.88	12.623

Variables	Mean	Standard Deviation	Minimum	Maximum
The Laplacian of Pressure	3.76059E-11	5.69636E-11	0	2.55E-10
Ice Concentration	5.988135109	14.62558262	1.22E-06	79
Wind Speed	7.659459459	3.246062531	1.5	20.4
Precipitation	0.00048258	0.001449692	0	0.025289
Summer				
Incident Rates	0.06635692	0.149822288	0.004386	1
Air Temperature	286.4868098	3.221463943	272.9	293.8
Sea Surface Temperature	13.13513163	2.945925324	0.93143	19.29
The Laplacian of Pressure	2.25185E-11	4.28482E-11	0	2.22E-10
Ice Concentration	0.060767067	1.900329833	1.22E-06	59.429
Wind Speed	6.631288344	2.703836044	0.7	20.1
Precipitation	0.000517901	0.001443989	0	0.017109
Fall				
Incident Rates	0.158901334	0.232855946	0.007143	1
Air Temperature	275.9556291	6.746201051	253.9	291.9
Sea Surface Temperature	7.620266461	3.5436631	-0.24143	16.287
The Laplacian of Pressure	3.63725E-11	6.73507E-11	0	3.17E-10
Ice Concentration	0.667455819	4.498692265	0	52
Wind Speed	9.29089404	3.886260169	1.9	26.4
Precipitation	0.000499648	0.001285941	0	0.011044

Some researchers use Ordinary Least Squares Regression to model a fractional response variable, however this is conceptually flawed since the effect of predictors on the response variable tends to be non-linear and the variance of the response variable tends to decrease when the mean gets closer to 0 or 1. The most common way to handle this problem is to perform a logit transformation to map the original data to the real line (Baum, 2008):

$$\ln\frac{y}{1-y} = \beta X \quad (3\text{-}8)$$

where y is response variable, X is the matrix of predictors, and β is the matrix of coefficients. The problem with this approach is dealing with ones and zeros, since in the case of y=0, ln(0) is undefined and in the case of y=1, $ln\frac{1}{1-1}$ is undefined, therefore these values have to be removed from the dataset. Papke and Wooldridge (1993) proposed robust Logistic Regression to resolve this issue. Fractional Logistic Regression is a quasi-likelihood process that assumes that the extreme incident rates of zero and one (absolute certainty) are generated through the same process as the other (intermediate) incident rates. This method uses a logit function and binomial distribution to model the data. The variance of the binomial distribution must go to zero as the mean goes to either 0 or 1, as in each of these cases the variable is approaching a constant, and the variance will be maximized for a variable with mean of 0.5.

The conditional mean can be expressed through the logit function (Jonasson, 2011):

$$E(Y|X) = \frac{\exp(\beta X)}{1+\exp(\beta X)} \quad (3\text{-}9)$$

Equation (3-10) then can be estimated with the Bernoulli log-likelihood function:

$$LL_m(\beta) = Y.\ln(E(Y|X)+(1-Y)*\ln(1-E(Y|X)) \quad (3\text{-}10)$$

Since theoretically fishing incident rates can be any number between zero and one inclusively, Fractional Logistic Regression is preferred to truncating the data and dropping the observations with zero or unit values, or coding them with some arbitrary values such as 0.0000001 and 0.9999999. (Baum, 2008). The outcome of this method is expressed in the same way as Logistic Regression (i.e. the probability of having an incident with respect to traffic based on weather factors).

Applying Negative Binomial Regression is another way to investigate the relationship between incident rates and weather conditions. The incident rate is then defined as the number of incidents over fishing trips; therefore, multiplying both sides of equation (3-1) by the amount of exposure (i.e. number of fishing trips) moves the exposure to the right side of the equation (i.e. the log value of exposure is added to the regression coefficients in the final model). To account for unobserved heterogeneity in observations (as described in section 3.4.1), Random Parameters Negative Binomial Regression was applied on datasets in addition to traditional Negative Binomial Regression.

3.5. Results

3.5.1. The effect of extreme weather factors on fishing activity levels

Random Parameters Negative Binomial Regression is carried out for the effects of weather factors on fishing activity levels for grid-days associated with a cyclone (i.e. those with the Laplacian of pressure greater than zero), winter, spring, summer, fall, vessel length-class 1, vessel length-class 2, vessel length-class 3, and vessel length-class 4. For each model, grids with no traffic during the study period were excluded from the analysis (i.e. each model has different number of grids excluded). All predictors (i.e. wind speed, air and sea surface temperature, precipitation, ice coverage, and Laplacian of pressure) have been included in the models, however only factors that were significant at significance level of 0.05 have been reported in Table 3-7. Furthermore, since the correlation between air temperature and sea surface temperature is higher than 0.7, it was decided not to include both factors in the models simultaneously. Therefore two individual sets of predictors were tested for each model, whereby one includes sea surface temperature and one includes air temperature. The model with the highest log-likelihood ratio was chosen as the final model to be reported in Table 3-7.

Table 3-7 shows the coefficients (and standard errors) of significant weather factors for fishing activity levels for each model at a significance level of 0.05 for Fixed Negative Binomial Regression, and mean and standard deviation with their standard error of normally distributed coefficients of from the Random Parameters Negative Binomial Regression method. Since only variables with p-values less than 0.05 have been reported, it was decided to report standard errors instead of p-values to examine how precise an estimate of the population parameter (coefficients) is.

Table 3-7. Coefficient (standard error) of significant weather factors for fishing activity levels at significance level of 0.05 (Negative Binomial Regression)

Factors	**Negative Binomial Regression**	**Random parameters Negative Binomial Regression (Mean)**	**Random parameters Negative Binomial Regression (Standard Deviation)**
Incidents Associated with a Cyclone (#observations=43198)			
Sea Surface Temperature (°C)	0.21(0.011)	0.14(0.014)	0
The Laplacian of Pressure (mPa/Km^2)	-0. 21(0.013)	-0.36(0.08)	0
Ice Concentration (percentage)	-0.23(0.012)	0.01(0.009)	0.03(0.002)

Factors	Negative Binomial Regression	Random parameters Negative Binomial Regression (Mean)	Random parameters Negative Binomial Regression (Standard Deviation)
Wind Speed (m/s)	-0.23(0.009)	-0.29(0.007)	0
Precipitation (mm)	-0.11(0.009)	-0.14(0.01)	0. 12(0.005)
Log-likelihood (LL)	-518.097	-412.342	
Winter (#Observations)=31595			
Sea Surface Temperature	0.89(0.033)	0.16(0.0003)	0.016(7e-06)
The Laplacian of Pressure	-0.34(0.013)	-0.007(4e-06)	0
Ice Concentration	-0.25(0.015)	-0.04(0.0006)	0
Wind Speed	-0.27(0.016)	-0.009(2e-06)	0
Precipitation	-0.27(0.016)	-0.09(0.0002)	0.08(0.0001)
LL	*-352.0199*	*-276.5049*	
Spring(#observations=33015)			
Air Temperature(°K)	0.508(0.026)	0.07(3e-04)	0.01(0.0005)
The Laplacian of Pressure	-0.05(0.018)	-0.033(0.1e-06)	0
Ice Concentration	-0.03(0.014)	-0.008(9e-05)	0
Wind Speed	0.19(0.017)	0.4(0.0002)	0
LL	*-347.812*	*-276.0505*	
Summer(#observations=33015)			
Air Temperature	0.70(0.025)	-0.013(4e-06)	0.03(1e-6)
The Laplacian of Pressure	-0.08(0.018)		
Wind Speed	-0.10(0.018)	-0.18(0.0004)	0.06(0.0005)
LL	*-456.592*	*-314.174*	
Fall(#observations=31950)			
Air Temperature	0.39(0.018)	0.03(0.0001)	0.003(0.0007)
Ice Concentration	-0.36(0.027)	-0.081(0.0003)	0
Wind Speed	-0.16(0.014)	-0.09(0.0001)	0.05(7e-05)
LL	*-517.1309*	*-330.061*	
Vessel Length_1 (#observations=52609)			
Air Temperature	0.47(0.009)	0.095(0.0002)	0.09(8e-06)

Factors	Negative Binomial Regression	Random parameters Negative Binomial Regression (Mean)	Random parameters Negative Binomial Regression (Standard Deviation)
The Laplacian of Pressure		-0.008(1e-06)	0
Ice Concentration	-0.36(0.027)	-0.006(3e-5)	0
Wind Speed	-0.16(0.014)	-0.011(2e-04)	0
LL	*-245.3358*	*-233.147*	
Vessel Length_2 (#observations=12300)			
Sea Surface Temperature	0.32(0.014)	0.033(2e-03)	0.005(2e-04)
The Laplacian of Pressure	-0.03(0.015)	-0.016(3e-04)	0.007(1e-04)
Ice Concentration	-0.49(0.019)	-0.01(0.0027)	0
Wind Speed	-0.15(0.013)	0.049(0.0014)	0.04(0.007)
LL	-454.4014	-292.8335	
Vessel Length_3 (#observations=15408)			
Ice Concentration	-0.05(0.0009)	-0.005(1e-06)	0.003(7e-05)
LL	*-277.89079*	*-247.3920*	
Vessel Length_4 (#observations=12599)			
Ice Concentration	-0.17(0.009)	-0. 02(3e-04)	0.01(0.005)
LL	*-399.9107*	*-295.3218*	

The likelihood ratio test of Poisson and Negative Binomial Regression showed that Negative Binomial Regression is a better fit than Poisson Regression for all of the models. The Random Parameters method, for all the datasets, shows a higher log-likelihood (LL) ratio than Fixed Negative Binomial Regression. Since Fixed Negative Binomial Regression is nested in the Random Parameters Negative Binomial Regression (i.e. Fixed Negative Binomial Regression is a special case of the Random Parameters method with all the variances equal to zero), it is possible to statistically compare these models by conducting a likelihood ratio test. The test statistic is:

$$\chi h = -2[LL_1 - LL_2] \tag{3-11}$$

where LL_1 is the log likelihood at convergence of the fixed-parameters model, and LL_2 is the log likelihood at convergence of the random-parameters model (Washington et al., 2003). The tests for all the datasets resulted in statistical superiority of the Random Parameters model compared to the Fixed Parameters model.

The results of both methods show that activity levels decrease when weather conditions deteriorate in all of the models. When grid-days associated with a cyclone are studied, sea surface temperature, Laplacian of pressure, ice concentration, wind speed, and precipitation are chosen as the significant weather factors by both methods. To interpret the results of the Random Parameters method, the cumulative probability of $(X<0)$ can be calculated (X represents the normally distributed coefficients of the predictors). For example for ice concentration, $X_{\text{ice concentration}} \sim N\ (0.01,\ 0.03)$ and therefore $P(X_{\text{ice concentration}}<0) = 0.64$. This means that 64% of the observed traffic levels increase when ice coverage decreases. Similarly it can be shown that based on the results of the Random Parameters method for 90% of the observations, traffic levels decrease when the precipitation amount increases (i.e. $P\ (X_{\text{precipitation}}>=0)$). Since the Standard Deviation for the Laplacian of pressure, sea surface temperature, and wind speed are not significantly different than zero; these factors are fixed through observations.

Interpretations of odds ratios show that if wind speed increases by 1 mile per second, the relative incidence rate of traffic levels change by a factor of 0.74 (i.e. 26% decrease in traffic levels). Similarly one unit increase of Laplacian of pressure will result in 30% decrease in number of fishing trips in the related grid-day.

During the winter season, sea surface temperature, ice concentration, wind speed, and precipitation are the significant weather factors (sea surface temperature and precipitation as random parameters and others as fixed). 70% of the observations show a decrease in traffic levels when precipitation amount increases. In the spring, air temperature as a random variable, and Laplacian of pressure, ice concentration, and wind speed as fixed variables (i.e. Standard deviation of these factors is not significantly different than zero) become critical. Summer related weather factors are the same as the spring ones, except for ice concentration, which is not a factor in summer. Results of the Random Parameters method show that for 62% of observations traffic level decreases as wind speed becomes stronger. In the fall, air temperature, ice concentration, and wind speed are significant. For 85% of the observations, higher air temperature will result in higher traffic levels. The reason that precipitation is an important factor only in wintertime may be that during winter, precipitation can be in the form of icy rain and snow, which can decrease the visibility, ice up the superstructure thus affecting stability, and make the deck slippery. These conditions rarely occur in spring or summer, therefore precipitation is not a critical factor in these seasons.

When considering vessel length, air temperature, wind speed and ice concentration are the significant weather factors for small fishing vessels. For 84% of the observations, traffic levels increase when air temperature rise. Medium size vessels are mostly affected by sea surface temperature, Laplacian of pressure, wind speed, and ice concentration. Traffic levels of vessels with overall length greater than 45 feet were only affected by ice concentration (i.e. for 95% of vessels of length-class 3 and 97% of vessels of length-class

4, traffic levels decrease in higher ice concentration percentages). One explanation for this can be the capability of larger vessels to handle extreme weather conditions. In other words, despite weather factors being harsh, these vessels can still venture into the ocean.

3.5.2. The effect of extreme weather factors on fishing incidents

Zero-Inflated Negative Binomial Regression was applied for some models (Incidents associated with a cyclone, winter, spring, summer, fall) to study the effect of weather factors on fishing incidents. Because there were not enough data in the incident database to separate incident data based on vessel lengths, models related to the vessel lengths were not applicable for this part of the study.

To choose the best statistical combination of weather factors for each model, a code was developed to carry out Zero-Inflated Negative Binomial Regression on all possible combination of weather factors for each individual model and choose the combinations with the smallest Akaike Information Criterion (AIC). The AIC for any statistical model is equal to:

$$AIC=2k-2\ln(L) \tag{3-12}$$

where k is the number of parameters in the model and L is the maximized value of the likelihood function for the model. AIC aims to select the optimal model with the least mean squared error under the assumption that the true exact model is not among the candidates set (Akaike, 1974).

Tables 3-8 and 3-9 show the coefficients (and standard errors) of significant weather factors for the aforementioned models at significance level of 0.05 for count and zero-state model respectively. For each model, grids with no incidents during the study period were excluded from the analysis.

Table 3-8. Coefficient (standard error) of significant weather factors for fishing incidents at significance level of 0.05 (Count Model)

Models	**Observations**	**Sea Surface Temperature (°C)**	**Ice Concentration (percentage)**	**Wind Speed (m/s)**	**Precipitation (mm)**	**Traffic Data (# of fishing trips)**
Cyclone Grid-Days	20193	-	-	-0.13(0.043	-0.09(0.038)	0.50(0.014)
Winter	11322	-	0.12(0.057)	-	-	0.94(0.041)
Spring	15749	-	-	-0.15(0.044)	-	0.44(0.011)
Summer	18581	0.28(0.069)		-0.29(0.054)	-	0.44(0.014)
Fall	14911	0.38(0.093)	-0.38(0.187)	-0.15(0.051)	-	0.65(0.030)

Table 3-9. Coefficient (standard error) of significant weather factors for fishing incidents at significance level of 0.05 (Zero-State Model)

Models	**Observations**	**Air Temperature (°K)**
Cyclone Grid-Days	20193	-3.878(0.120)
Winter	11322	-3.53(0.843)
Spring	15749	-4.90(0.063)
Summer	18581	-4.42(0.148)
Fall	14911	-1.85(0.296)

The results indicate that traffic is the most significant factor in fishing incident occurrences in all of the count models. It was also shown that it is more likely for incidents to happen during calmer weather (i.e. higher air and sea surface temperature, lower wind speeds, lower amount of precipitation, and ice concentration) than extreme weather conditions. One potential explanation for this phenomenon is the strong correlation between traffic and incidents. Traffic levels increase in calm weather conditions and, as a consequence, the likelihood of having an incident increases as well. The results of zero-state models also show that when air temperature is low, it is likely that no incidents happen because of no exposure (i.e. no fishing activity). To subsume the dominant effect of fishing activity and understand the effects of weather conditions on fishing incidents, incident rates (number of incidents in each grid day per number of fishing trips in each grid-day) were studied as the next step.

3.5.3. The effect of weather factors on fishing Incident Rates

Fractional Logistic Regression, Negative Binomial Regression and Random Parameters Negative Binomial Regression models were applied to investigate the effect of weather factors on relative incident rates.

To choose the proper density distribution for Random Parameters, normal, lognormal, triangular and uniform distribution were tested whereby normal distribution was chosen as the best fit. Table 3-10 presents the results of four developed models for incidents associated with a cyclone, winter, spring, summer, and fall respectively. For each model, only parameters that are found to be significant at significance level of 0.05 are presented. The Random Parameters method, for all the datasets, shows a higher log-likelihood (LL) ratio than Fixed Negative Binomial Regression and Fractional Logistic Regression. Likelihood ratio tests to compare Fixed and Random Parameters method for all the datasets resulted in statistical superiority of the Random Parameters model. That is, Random

Parameters models are more explanatory in terms of the relationship between weather factors and incident rates.

Table 3-10. Coefficient (standard errors) of significant weather factors for fishing incident rates at significance level of 0.05

Factors	**Fractional Logistic Regression**	**Negative Binomial Regression**	**Random Parameters Negative Regression(Mean)**	**Random Parameters Negative Regression(Standard Deviation)**
Incidents Associated with a Cyclone (#observations=894)				
Air Temperature (°K)	-0.00334 (0.0011)	-0.00378 (0.0049)	-0.01510 (0.0056)	0.19440(0.009)
Ice Concentration (percentage)	0.00176 (0.0006)	0.00699 (0.0025)	0.00775 (0.0005)	0.02927(0.0053)
Wind Speed (m/s)	0.00195 (0.0002)	0.02744 (0.0088)	0.0320 (0.0019)	0.04287(0.002)
Laplacian of Pressure (mPa/Km^{2})	-	0.00039 (0.7e-04)	0.00037 (0.0001)	0
Log-Likelihood (LL)	-1769.93	-1769.72	-1434.01	
Winter(#observations=370)				
Sea Surface Temperature (°C)	-0.07302 (0.0102)	-0.32888 (0.0356)	-0.02886 (0.0008)	0.05562(0.007)
Wind Speed	-	0.04285 (0.0116)	0.03329 (0.0021)	0.04483(0.001)
LL	-781.47	-781.47	-520.98	
Spring(#observations=999)				
Sea Surface Temperature	-0.0062 (0.0021)	-0.02820 (0.0115)	-0.05519* (0.0224)	0
Ice Concentration	0.00104 (0.0004)	0.00551 (0.0021)	0.00806 (0.0043)	0.02465(0.004)
Precipitation (mm)	-	-	0.00018 (0.0001)	0.00288(0.005)
LL	-1789.76	-1789.76	-1394.79	
Summer(#observations=979)				
Air Temperature	-0.00599(0.0015)	-	-	0
Wind Speed	-	-	0.01297 (0.0021)	0.02605(0.0004)
LL	-1633.40	-1637.98	-1352.60	

Factors	Fractional Logistic Regression	Negative Binomial Regression	Random Parameters Negative Regression(Mean)	Random Parameters Negative Regression(Standard Deviation)
Fall(#observations=605)				
Sea Surface Temperature	-0.02081 (0.0027)	-0.11085 (0.0126)	-0.11262 (0.0164)	0
Wind Speed	-	0.03494 (0.0105)	0.00285 (0.0002)	0.02289(0.0021)
Laplacian of Pressure	-	-	0.00004 (1e-04)	0.00017(6e-06)
LL	-1188.49	-1185.49	-829.81	

Except for the summer case, the significant weather factors are almost the same in Fractional Logistic Regression and Negative Binomial Regression. The Random Parameters models usually have additional significant factors in addition to the ones in common with the other two. When studying incidents associated with a cyclone, air temperature, ice concentration, wind speed, and Laplacian of pressure (only in Fixed and Random Parameters Negative Binomial Regression) are significant. The signs of the coefficients in Fractional Logistic and Fixed Negative Binomial Regression indicate that lower air temperature, higher ice concentration, and intense storms (i.e. higher Laplacian of pressure) will result in higher incident rates. The Random Parameters model shows that 53% of the times lower air temperature, 60% of the times higher ice concentration, and 76% of the times stronger winds, will increases incident rates.

Interpretations of odds ratios show that increase in wind speed by 1 mile per second will lead to a 3.25% increase in relative incident rates. Similarly one unit increase of Laplacian of pressure and one unit increase in ice concentration will result in 0.3% and 0.8% respective increase in relative fishing incident rates in the related grid-day. Based on these results one can conclude that wind speed is very important in increasing the risk of incidents in case of stormy weather. The standard deviation of the Laplacian of pressure is found not to be statistically different than zero which indicates that it doesn't vary much across observations. In winter time, Fractional Logistic Regression only resulted in significance for the sea surface temperature. However wind speed is also shown to be important in the Random Parameters model. For 70% and 78% of observations, incident rates increase with lower air temperature and stronger winds respectively. In the spring, sea surface temperature, ice concentration, and precipitation are chosen by Random Parameters model as significant weather factors. Sea surface temperature is found to be constant and not varying throughout the observations. The results indicate that incident rates increase for 63% of the observations when ice concentration is increasing. One potential explanation of why ice concentration is found to be significant in spring and not winter could be the preparedness of fish harvesters to navigate through ice. The results also show that 53% of the time precipitation may lead to an increase in incident rates. The results from the summer time are complicated. The Fractional Logistic Regression results show that incident rates increase when air temperature decreases. The results of the Random Parameter model indicate that for 85% of observations, stronger wind speed will result in higher incident rates. However, Fixed Negative Binomial Regression resulted in no statistical relationship between incident rates and weather factors. One can explain these results based on the opening of the majority of fishery seasons and the presence of recreational boating traffic in the ocean. Opening of the fisheries means long work hours, hard labour in a very competitive and stressful job situation. All of these factors may lead to increased incident rates regardless of weather factors. During this season, there may also be collisions between inexperienced boats and fishing vessels, which is also not particularly tied to weather conditions. Finally in the fall, sea surface temperature, wind speed, and Laplacian of pressure are shown to be significant in the Random Parameters model. Sea surface temperature is found not to vary across the observations. For approximately 55% of the observations, stronger winds and higher Laplacian of pressure results in an increase of incident rates. Despite the fact that different weather factors are important in different seasons, one can conclude that extreme weather conditions (i.e. lower air and sea surface temperature, stronger winds, higher ice concentration, and intense storms) can increase incident rates for the majority of the observations. However the effect of these factors are different for each season. Precipitation is also found to not be significant most of the time.

3.6. Discussion and Conclusion

This research aims to investigate the relationships between weather factors and commercial fishing activity levels and incidents. Negative Binomial Regression and Random Parameters Negative Binomial Regression were applied to the grid-days associated with cyclones, four seasons, and four vessel length classes, to examine the relationship between weather factors and fishing activity levels. The quality of incident data doesn't allow us to classify incident data based on vessel length, therefore Zero-Inflated Negative Binomial Regression was carried out only on the grid-days associated with cyclones and four seasons to show how the probability of having incidents can change in different weather conditions. Random Parameters Zero-Inflated Negative Binomial Regression is a useful extension of this work to take unobserved heterogeneity of data into consideration. Fractional Logistic Regression, Negative Binomial Regression, and Random Parameters Negative Binomial

Regression were also applied to the same models as Zero Inflated Negative Binomial Regression to study the effect of weather factors on fishing incident rates (number of fishing incidents/ number of fishing trips in each grid day).

The results of the Random Parameters Negative Binomial Regression show that in each of the individual models fishing activity levels decrease when weather factors deteriorate. One can also conclude from the results that vessels with different lengths can be affected differently by weather conditions. For example, wind speed is a significant factor for small size vessels, however it is not critical for larger vessels. The outcomes of Zero-Inflated Negative Binomial Regression suggest that the pure probability of having an incident grows with an increase in traffic intensity, which in turn increases in the absence of extreme weather conditions. The results of the incident rate analysis showed that Random Parameters models are a statistically better fit than the traditional fixed models and they can also better explain the underlying relationships between weather factors and incident rates. The results of the Random Parameters model showed that for the majority of the observations, harsh weather factors can increase incident rates. Analyzing the distribution of coefficients will provide information on how each factor can affect the incident rates.

Tobit modeling, another way to analyze incident related data has been widely used in road incident literature. However, it is mainly used when the average of weather factors over a period of time is studied (e.g. Anastasopoulos et al. 2012b). Therefore, if the goal of a study is to look at the effects of general weather factors (not particularly extreme weather factors) on incidents, Tobit modeling can be an alternative way to Zero-Inflated Negative Binomial Regression and Fractional Logistic Regression.

These results can be instructive for preventive measures, such as changing the regulations for commercial fishing season openings if certain weather conditions are deemed unacceptable or for better education of mariners leading to improved decision-making with respect to weather conditions. This information can also be useful inputs for boat design or for the issuance of specific warnings for different vessel sizes. Search and Rescue planning can also be reviewed in better anticipation of incident occurrences as a function of the weather forecasts generally and storm warnings in particular. (The practical implications of this research will be explained in detail in Chapter 6).

Chapter 4 Severity Levels of Fishing Incidents

Title: The Effect of Extratropical Cyclone Weather Conditions on Fishing Vessel Incidents' Severity Level in Atlantic Canada

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Abstract

Fishing is one of the most dangerous occupations in the world. In addition to the high risk of fatality, fish harvesters are also at risk of a wide range of non-fatal injuries during their work at sea. Weather factors are an intrinsic part of fish harvesters' operating environment and they consider the most dangerous situations at sea to be associated with weather-related factors. This research aims to answer questions regarding the effects of extratropical cyclone weather conditions on the severity level of maritime incidents to provide more insight for fish harvesters and/or marine traffic decision makers such as Canadian Coast Guard. To achieve these goals, weather and incident data in Atlantic Canadian Waters were matched spatially and temporally then analyzed to explore their relationships. Logistic Regression was used to examine how weather factors affect the severity level of fishing vessel incidents. Ice concentration, wind speed, sea surface temperature, and darkness were the most significant weather factors with respect to severity level of fishing incidents. When only incidents associated with cyclones were taken into consideration, Laplacian of pressure as an indicator of cyclone's intensity replaces ice concentration as a significant factor. Logistic Regression was also applied for individual fishery types, revealing that distinct fisheries can be effected by different weather factors. Improving our understanding of extreme events and revising safety related policies in commercial fishing is particularly important under climate change scenarios as fish harvesters' reliance on traditional weather patterns becomes increasingly questionable.

Key Words: Fishing Vessel Incidents, Cyclone Weather Conditions, Logistic Regression

4.1. Introduction

Commercial fishing is one of the most dangerous occupations. In a United States Coast Guard report (US Coast Guard, 1999), it was noted that the commercial fishing fatality rate was 16 times higher than that for fire and police protective service occupations in 1996. Extreme weather conditions are one of the risk factors of fishing incidents. In particular, short fishing seasons may compel fish harvesters to achieve their quota as soon as possible and take serious risks to make trips regardless of weather conditions and stay at sea for long periods of time (Chatterton, 2008). An interview with 46 fish harvesters in Newfoundland and Labrador revealed that 85% of them have experienced being on board in extreme weather and harsh environmental conditions. If a harvester is having a particularly bad year, he/she may take greater risks setting out in bad weather or staying in a storm with inadequate safety equipment (Brennan, 2008). When skippers were asked to make decisions during a study and presented with a desired safety level directly related to the weather conditions, they never chose to come back to the harbour or stop the fishing activity no matter how severe the weather conditions were in the simulated exercise. If the situation was considered too dangerous, they sometimes opted to go to another fishing zone where their colleagues were safely operating (Morel et al, 2008). Harsh weather conditions can also combine with other risk factors such as machinery damage or engine failure thus leading to a disaster (Wang et al, 2005).

There is an extensive literature investigating different risk factors in fishing incidents and, in the majority of them, the weather conditions are part the study. Jin et al. (2001) focused on significant factors related to vessel total losses and the number of fatal or non-fatal crew injuries arising from commercial fishing vessel incidents. Type of incidents, operational conditions (e.g. weather conditions), cause of incidents, vessel characteristics, waterway status, and time of incident were the model elements. The results showed that if an accident is due to environmental factors, it is the precipitation, which is the most significant factor. Jin and Thunberg (2005) presented an assessment of key factors affecting incident occurrences in Northeastern United States, applying a Logit Regression model to examine daily data on fishing vessel activities, fishing vessel incidents, wind speed, vessel characteristics, and spatial information on the incidents from 1981 up to 2000. The results showed that accident probability is a function of wind speed, vessel location, time of year and vessel characteristics. Wu et al. (2005, 2008, and 2009) examined the relationship between statistical weather patterns and fishing vessel incidents in Atlantic Canada. Weather factors included in Wu's analyses were wave height, air temperature, sea surface temperature, freezing spray, ice concentration, presence of fog, and amount of precipitation. Wave height appeared as the most significant factor in incident occurrence and wave height and ice concentration were shown to be statistically significant factors for severity levels of incidents. Chatterton, 2008 looked at ice-related incidents for vessels over 79 ft. long and, based on his research, seasonal darkness, cold water, high speed winds, icing, fatigue and short fishing seasons are the most important risk factors. Niclasen et al. (2010) studied the important sea-state parameters for small vessels' safety and warning indices, extracting their information from relevant literature. Their study showed that the incident rate rises with deteriorating weather and sea state conditions.

Adverse environmental conditions are often associated with strong low pressure weather systems, or cyclones. These include both hurricanes (i.e. tropical cyclones), as well as more common mid-latitude cyclones (i.e. extratropical cyclones). Extratropical cyclones are typically less powerful than their tropical counterparts, however strong extratropical cyclones can produce winds similar to weak hurricanes, cover larger areas, and intensify rapidly. These characteristics make these cyclones a significant forecasting challenge and marine safety hazard. Unlike hurricanes, extratropical cyclones can also occur during cold conditions, contributing to icing events, producing blizzard conditions, and compounding the impacts of winds and waves with cold weather phenomena. The current study focuses exclusively on extratropical cyclones exclusively, as they are a much more common marine hazard than hurricanes; hereafter, the terms 'extratropical cyclone' and simply 'cyclone' will be used interchangeably. To illustrate, Figure 4-1 shows the tracks of the 50 most intense extratropical cyclones that passed through Atlantic Canada during 2000-2006.

Figure 4-1. Tracks of the 50 most intense extratropical cyclones that passed through Atlantic Canada during 2000-2006. (Source: STORMS Extratropical Cyclone Atlas, 2011)

This research aims to investigate the relationship between severity of commercial fishing incidents and extratropical cyclone weather factors, determine which weather factors are more significant, and compare incident severity levels in cyclone weather and non-cyclone weather conditions. The criterion to distinguish between cyclone and non-cyclone weather conditions is the presence of an identified cyclone centre within 750km of a given incident.

The hypotheses to be tested are to determine whether severe incidents are significantly related to any or all of: wind speed, air and sea surface temperature, ice concentration, amounts of precipitation, Laplacian of pressure, and/or darkness.

This article is organized as follows: Section 4-2 describes data sources and the data preparation step, Section 4-3 elaborates on the modelling method, Section 4-4 describes the results, and Section 4-5 includes the discussion and concluding notes.

4.2. Data Sources

4.2.1. Study Scope

The study area for this research encompasses Atlantic Canadian Waters from 40° to 60° N latitude, and 73° 20' to 45° 50' W longitude over the years 2000-2010. Close examination of the data revealed that there were inconsistencies in the incident data collection process during year 2007; therefore, 2007 was excluded from the analysis.

4.2.2. Weather Data

Several weather factors were chosen to be included in the analysis based on the literature and personal communication with experts. These factors were extracted from datasets with the highest available spatial and temporal resolutions to achieve the greatest possible accuracy. These datasets cover the study area with different resolutions of frequency and spatial grid sizes. The details of each chosen weather factor are presented in Table 4-1.

Table 4-1. Weather Factors

Field	**Data set**	**Frequency**	**Grid size**
Wind Speed (miles per second)	NCEP /NCAR Reanalysis (Kalnay et al., 1996)	6 hour intervals	2.5 by 2.5 degrees
Air Temperature (in degrees Kelvin)	NCEP/NCAR Reanalysis	6 hour intervals	2.5 by 2.5 degrees
Sea Surface Temperature (SST) (in degrees Celsius)	NCEP OI SST V2	Weekly mean	1 by 1 degree
Ice Concentration (percentage)	NCEP OI V2	Weekly mean	1 by 1 degree

Field	Data set	Frequency	Grid size
Precipitation (mm)	ERA-Interim-ECMWF (Dee et al., 2011)	Daily total amount	0.75 by 0.75 degrees
Laplacian of pressure (mPa/km^{-2})	Cyclone Database	6 hour intervals	2.5 by 2.5 degrees

Wind speed is one of the most important factors in fishing vessel stability. Although air and sea surface temperature are likely contributing factors to the conditions after an incident happens, they can also adversely affect the normal functioning of crewmen. The ice data field represents the weekly median ice concentration values stored as the percentage of area covered, which can cause navigation problems and/or displace and trap fishing vessels. Precipitation gives an indication of visibility and can also affect the proper performance of fish harvesters. Identification of extratropical cyclones follows Serreze and Barrett (2008), and is based on the identification of local minima in 6-hourly sea level pressure fields. The Laplacian of pressure is used here as a measure of cyclone intensity; it is calculated using the nine grid cells of sea level pressure around an identified cyclone center. Although storms with higher Laplacians typically have stronger surface winds, this relationship is neither exact nor linear, as resulting winds can be affected by the storm size, rate of intensification, and the striking region (Mass and Dotson, 2014) For this reason, Laplacian of pressure and wind speed have both been included in the current study, to better characterize individual cyclone events.

4.2.3. Incident Severity Data

When a Search And Rescue (SAR) Coordination Center of the Canadian Coast Guard receives a report of an incident, they dispatch the most available and suitable SAR resource to provide assistance and a record in the SISAR database is created. The SISAR (Search and Rescue Program Information Management System) database includes detailed information about the incidents such as time and location, fishery type, type of vessel, type of incident, and severity.

Maritime incidents are sub-classified according to the level of their severity as follows (Canadian Coast Guard 2000, 2001):

- M4- False alarms and hoaxes
- M3- Incidents resolved in the uncertainty phase (Non-Distress)
- M2- Potential Distress incidents
- M1-Distress incidents

For the purposes of this research, only incidents classified as M1, M2, and M3 were studied, and M4 incidents weren't included since such incidents do not create any real demand on SAR vessels.

Table 4-2 shows the distribution of fishing incidents during the study period based on their severity level:

Table 4-2. Distribution of Marine Incidents in Atlantic Canada Based on Severity Level (2000-2010)

Incident Type	**Number Of Incidents**	**Percentage**
M1	540	6%
M2	746	9%
M3	7364	85%
Total	8650	100%

Since the small numbers of M1 and M2 incidents, compared to M3 incidents, can reduce the robustness of statistical analysis, M1 and M2 distress incidents are grouped into one category as serious consequence events (Severity=1) and Severity=0 is assigned to the remaining cases (i.e. M3). The total number of incidents in the test dataset is thus 8650.

Since different fishery types can exhibit differences in vessel characteristics, seasonality of fishing, approximate geographic location, and distance from shore, it was decided to study the effect of cyclones on individual fishing types. Unfortunately not all of the SISAR incidents possess fishing type data, thus eliminating those, which are incomplete leaves us with 5393 records.

Table 4-3 shows the distribution of fishery types in the incident database.

Table 4-3. Distribution of Severe Incidents in Different Fisheries

Fishing type	Number of Incidents	Percentage of Total Incidents	Number of Severe Incidents	Percentage of Severe Incidents
Shrimp Fishing	448	8.31%	115	15.52%
Groundfish Fishing	594	11.01%	103	13.90%
Crab Fishing	1317	24.42%	152	20.51%
Herring Roe	294	5.45%	28	3.78%
Lobster Fishing	2065	38.29%	173	23.35%
Tuna Fishing	56	1.04%	4	0.54%
Salmon Fishing	7	0.13%	1	0.13%
Scallop Fishing	193	3.58%	31	4.18%
Seal Fishing	402	7.45%	131	17.68%
Sea Urchin Fishing	17	0.32%	3	0.40%
Total	53393	100%	741	100%

4.2.4. Data Preparation

To match incident data with weather data, Inverse Distance Weighting (IDW) interpolation has been applied. IDW methods are based on the assumption that the interpolating surface should be influenced most by the nearby points and less by more distant points. The interpolating surface is a weighted average of the sample points and the weight assigned to each sample point decreases as the distance from the interpolation point to the sample point increases. Shepard (1968) first introduced the IDW weight function as:

$$w_i = \frac{h_i^{-p}}{\sum_{j=1}^{n} h_j^{-p}} \qquad (4\text{-}1)$$

where h_i is the distance between the interpolated point and the sample point (i), p is the power and it controls the influence of nearby points, n is the number of sample points which will be used to estimate the value of the interpolated point, and w_i is the weight assigned to each sample point i. Franke and Nielson (Franke and Nielson, 1980) modified this formula in the following way:

$$w_i = \frac{[R\text{-}h_i/R\cdot h_i]2}{\sum_{j=1}^{n}[R\text{-}h_j/R\cdot h_j]2} \tag{4-2}$$

where h_i is the distance from the interpolation point to sample point j, R is the distance from the interpolated point to the most distant sample point, and n is the total number of sample points.

IDW and Modified IDW were tested on 100 samples of each weather factor with known values to see which method provides better estimation. IDW was chosen to interpolate the air temperature and precipitation values to the incident locations. Sea surface temperature and ice concentration were interpolated by the IDW method taking land presence into consideration (i.e. only points for which the path between an incident and an adjacent concurrent weather point does not cross land were used). Modified IDW worked slightly better for wind speed. The number of sample points was at most 4 points for any of the weather factors. The Laplacian of pressure was not interpolated by this method; instead, considering the large size of extratropical cyclones (i.e. 500 to 1000 km) the highest Laplacian of pressure in a 750 km search radius from an incident at the time of its occurrence was assigned to it. Effectively, this means that the most intense, nearby extratropical cyclone is used as a decision criterion.

To determine whether an incident happened during darkness, first, sunset and sunrise time were calculated for each incident date. To do so, NOAA Sunrise/Sunset and Solar Position Calculators (2014) were applied. To determine how long after sunset it is considered to be dark, the concept of civil dawn and civil twilight was employed. Tables 4-4 and 4-5 show the number of incidents that happened during darkness in each year and for each fishery type over the study period, respectively:

Table 4-4. Number of incidents happened during darkness for each year

Years	**Incident Numbers**	**Incidents That Happened During Darkness**	**Ratio**
2000	1013	196	19%
2001	1019	190	19%
2002	1011	212	21%
2003	928	186	17%
2004	827	154	28%
2005	824	230	28%
2006	828	227	22%
2008	802	181	23%
2009	750	182	24%
2010	707	178	25%
Total	8709	1936	22%

Table 4-5. Number of incidents that happened during darkness for each fishery type over the study period

Fishery Type	**Incident Numbers**	**Incidents Happened During Darkness**	**Ratio**
Shrimp Fishing	506	143	28%
Groundfish Fishing	630	166	26%
Crab Fishing	1421	297	21%
Herring roe Fishing	303	128	42%
Lobster Fishing	2097	275	13%
Tuna Fishing	59	21	36%

Fishery Type	Incident Numbers	Incidents Happened During Darkness	Ratio
Salmon Fishing	7	2	29%
Scallop fishing	207	58	28%
Seal Fishing	509	150	29%
Sea Urchin Fishing	17	4	24%

4.3. Model Building

4.3.1. Data Exploration

Table 4-6 shows the correlation coefficients between weather factors. The only high correlation is between air and sea surface temperature, which may be caused by the annual cycle of temperature. Therefore, it was decided not to use both of these variables in the same model.

Table 4-6. Correlation Coefficients between Weather Factors

Weather Factors	Air Temperature	Laplacian of Pressure	Ice Concentration	Precipitation	Sea Surface Temperature	Wind Speed
Air Temperature (°K)	1	-	-	-	-	-
Laplacian of Pressure (mPa/Km^2)	-0.09	1	-	-	-	-
Ice Concentration (percentage)	-0.34	0.02	1	-	-	-
Precipitation (mm)	0.02	-0.02	-0.04	1	-	-
Sea Surface Temperature (°C)	0.82	-0.12	-0.35	0.05	1	-
Wind Speed (m/s)	-0.16	0.19	0.07	0.01	-0.13	1

Figure 4-2 illustrates the cumulative percentage of severe and non-severe incidents in different weather conditions. Based on the results, severe incidents occur relatively more frequently in stronger winds, more intense cyclones, lower sea surface temperature, and more ice concentration than non-severe incidents. Conversely, with respect to precipitation, there was no visible difference between severe and non-severe incidents.

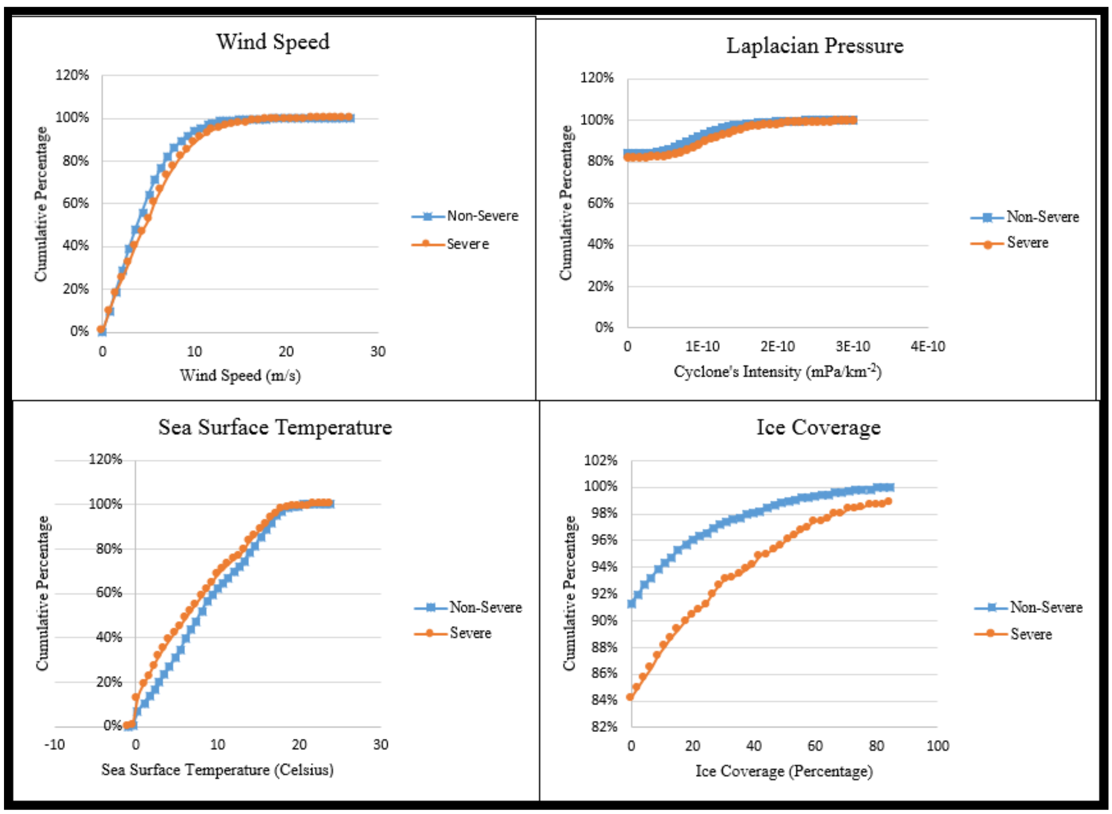

Figure 4-2. Cumulative Percentage of Severe and Non-Severe Incidents in Different Weather Conditions. Upper Left: Wind Speed. Upper Right: Laplacian of Pressure. Lower Left: Sea Surface Temperature. Lower Right: Ice Concentration.

4.3.2. Methods

At first, Logistic Regression (LR) and Support Vector Machines (SVM) were used to examine how weather factors affect the severity of fishing vessel incident. However, the comparison of these initial results showed that LR is more suitable for this data set, therefore, only LR and its results will be explained in this paper (For details on SVM method and results please see Appendix A). LR is an appropriate method for the fishing incident data in several respects: in LR the dependent variable is categorical; LR does not require the predictors to be normally distributed; and, unlike Linear Regression, LR can accommodate metric and non-metric independent variables.

The probability of each level of the categorical response variable is the outcome of the LR. The logit function maps the unit interval of probability [0, 1] onto the real domain ($-\infty$, $+\infty$) and the regression is carried out:

$$g(\theta)= \ln \frac{\theta}{1-\theta} \tag{4-3}$$

where θ is the probability of the positive event occurring (i.e. incident is severe).

$$\theta= \frac{1}{1+e^{-(\beta+\beta 1x)}} \tag{4-4}$$

where x is the matrix of predictors, β is the intercept, and β_1 is the matrix of coefficients of predictors(Hosmer and Lemeshow, 2004).

To highlight the effects of cyclone weather conditions on incident severity level, two different models were tested: one including all incidents regardless of whether they coincided with a cyclone or not (Model 1), and one with only incidents which were associated with a cyclone (Model 2).

After generating primary results for the effect of weather factors on the severity level of incidents, the fishery type was also included in the study as a dummy variable. In addition to a joint estimation including all fishery types, individual models were also built for different fishery types. Since the number of data points for Tuna, Salmon, and Sea Urchin fishing were quite few and LR is sensitive to sample size, it was decided not to study these three fishery types.

4.4. Results

Table 4-7 represents the results of LR applied to Model 1 (entire database) and Model 2 (incidents associated with cyclones, i.e. Laplacian of pressure>0) at a significance level of 0.05. To test statistical significance of the models, a Chi-Square test was carried out. The null hypothesis was stated as "All regression coefficients are equal to zero". Calculated p-values were equal to 4.44e-25 and 3.48e-09 for Model 1 and 2, respectively. Based on these p-values, the null hypothesis can be rejected at any confidence level.

Table 4-7. LR Results from Model 1 and Model 2

Model	**Number of Incidents**	**Significant Factors**	**Coefficients**	**P-value**	**Cross-Validation**
Model 1	8650	Ice Concentration	0.008	7.2e-3	0.12
		Sea Surface Temperature	-0.02	3e-4	
		Wind speed	0.06	1.04e-13	
		Darkness	0.32	4.84e-06	
Model 2	1413	Laplacian of Pressure	3.33e+09	0.04	0.13
		Sea Surface Temperature	-4.11e-02	8e-3	
		Wind speed	6.13e-02	1e-3	
		Darkness	0.43	0.01	

The results show that when the entire database, regardless of a cyclone happening or not, is examined, ice concentration becomes a significant factor along with wind speed, sea surface temperature, and darkness. However, when only incidents associated with a cyclone are taken into account, ice concentration as a significant predictor is replaced by cyclone intensity (i.e. Laplacian of pressure) and actually ice is not even an important factor anymore.

One potential explanation can be the fishery types. The seal fishery is one of the most dangerous fishery types, and ice plays an important role in that activity. Table 4-8 shows the number of severe incidents that happened in the presence of ice or cyclones for each fishery type.

Table 4-8. Number of Severe Incidents Happened In Presence of Ice or Cyclones for Each Fishery Type

Fishery Type	**Number of Severe incidents-Ice**	**Number of Severe Incidents-Cyclone**
Shrimp Fishing	18	33
Groundfish Fishing	4	24
Crab Fishing	5	33
Herring Roe	1	0
Lobster Fishing	10	30
Scallop Fishing	1	5
Seal fishing	144	28
Total (% of all incidents)	183 (25%)	153 (21%)

Figure 4-3 shows the spatial distribution of incidents, which are associated with ice presence and those associated with cyclone presence over the study period. It appears that incidents associated with ice happen mostly around the north of Newfoundland and the Gulf of St. Laurence, which could be related to seal fishing, while most of the incidents associated with cyclones are happening further from shore or south of Nova Scotia which could be related to lobster and shrimp fishing incidents. These results suggest studying individual fishing types to see how they are affected by different weather factors.

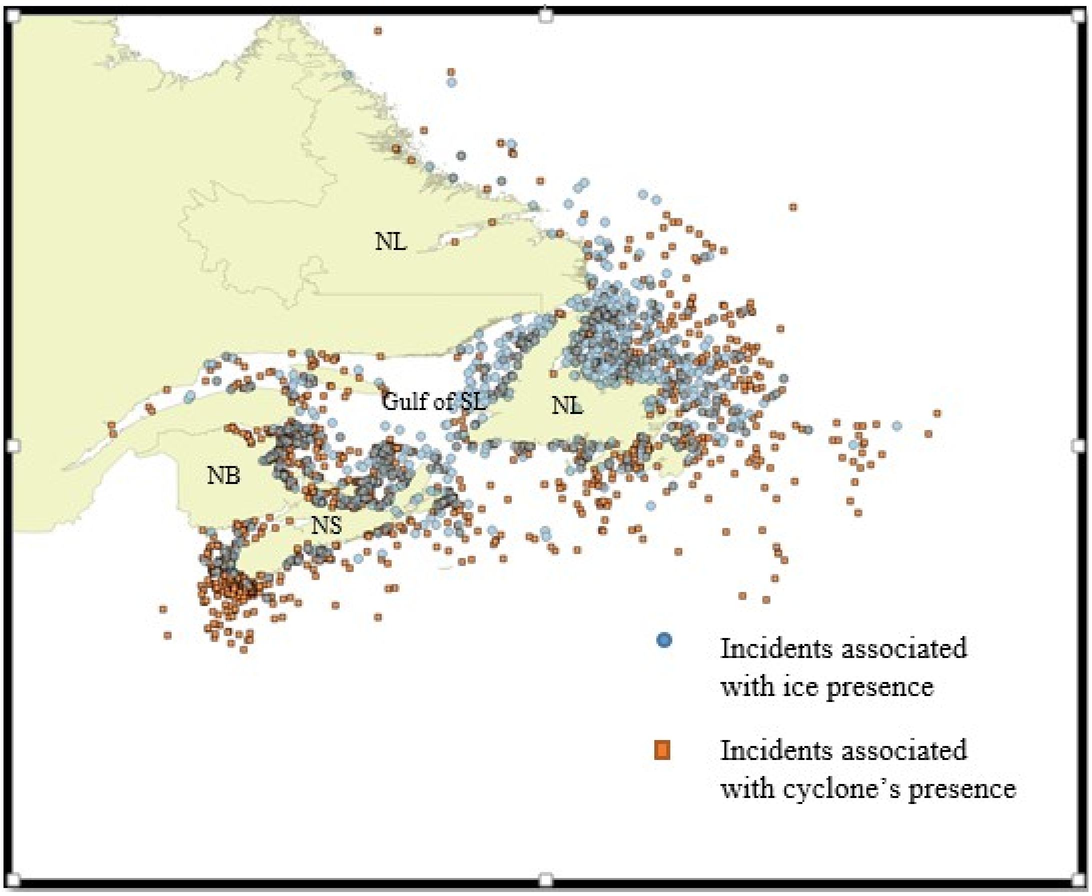

Figure 4-3. The Spatial Distribution of Incidents Which Are Associated with Ice Presence and Incidents Associated with Cyclone Presence Over the Study Period.

A sensitivity chart for the likelihood of high severity incidents by sea surface temperature (Celsius) and wind speed (m/s) from Model 1 is shown in Figure 4-4. This chart shows how the risk of severe fishing incident changes as wind speed and sea surface temperature change. For this illustration, it was assumed that incidents are happening during the day and ice concentration is constant and equal to 13%, which is the most frequent value other than zero that was observed in database. It shows that likelihood increases with wind speed and decrease with sea surface temperature. This chart also indicates interactions between wind speed and sea surface temperature, since the slopes of likelihood lines for sea surface temperature range (given wind speed range) are not constant for different wind speeds, nor vice versa. In other words, likelihood lines are not parallel.

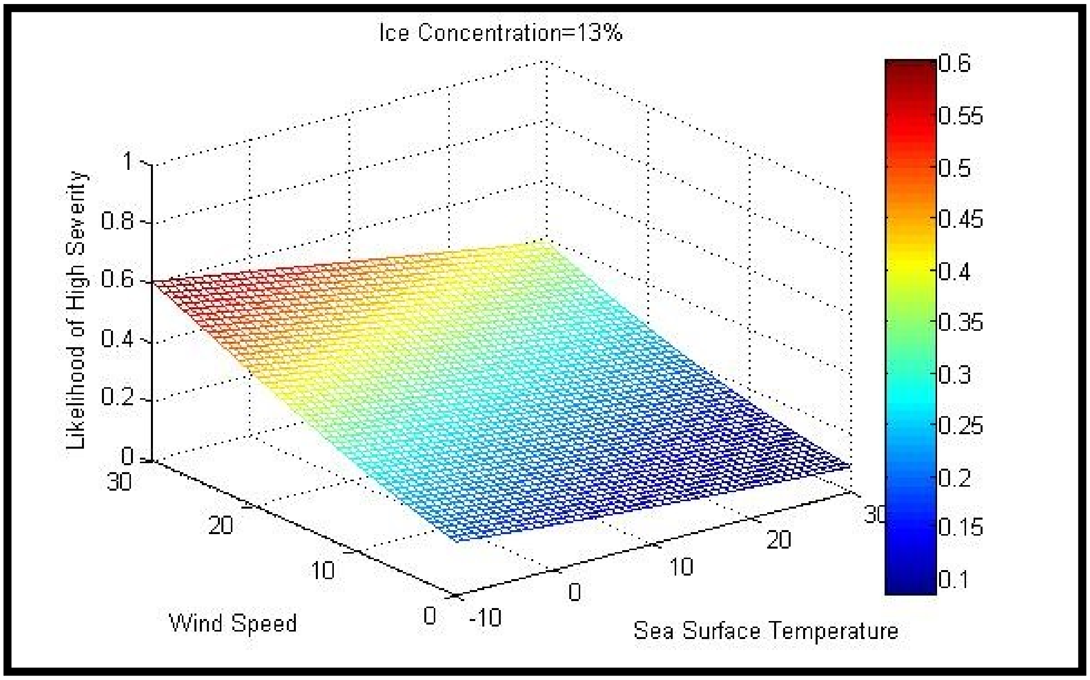

Figure 4-4. Sensitivity Chart for Likelihood of High Severity Incidents from Model 1 (Ice Concentration=13%)

To determine significant weather factors for different fishery types a dummy variable (as an indicator of fishery type) was generated to build a new LR model (Model 3). The results of this model could provide general insight to compare the risk of severe incidents among different fisheries, however, to determine which weather factors that can affect each distinct fishery type, individual models were also studied. Tables 4-9, 4-10, and 4-11 summarize the results for Model 3 and individual models, respectively.

Table 4-9. LR Results from Model 3 (Fishery type as a dummy variable)

Significant Factors	**Coefficient**	**P-Value**	**Cross-Validation**
Sea Surface Temperature (°C)	-0.02	8e-03	0.11

Significant Factors	Coefficient	P-Value	Cross-Validation
Wind Speed (m/s)	0.06	7.5e-07	
Groundfish Fishing	-0.04	7e-03	
Crab Fishing	-0.09	4.29e-11	
Herring Roe	-1.05	6.8e-06	
Lobster Fishing	-1.28	2e-16	
Scallop Fishing	-0.50	0.03	
Seal fishing	0.21	1.8e-04	

Table 4-10. Significant Coefficients (p-values) from Individual Fishery Types

Fishery Types	Sea Surface Temperature (°C)	Wind Speed (m/s)	Ice Concentration (percentage)	Laplacian of Pressure (mPa/Km^2)	Darkness
Shrimp Fishing	-	-	-	4.17e+09(0.02)	-
Groundfish Fishing	-0.04(0.04)	0.09(1e-03)	-	-	-
Crab Fishing	-	-	-	-	-
Herring Roe	-	-	-	3.22e+11(4e-03)	-
Lobster Fishing	-	0.06(6e-03)	-	-	0.59(0.01)
Scallop Fishing	-	0. 14(0.01)	-	-	-
Seal fishing	-	-	0.03(0.02)	-	-

Table 4-11. LR Results from Individual Fishery Types (Chi-Square Test and Cross-validation)

Fishery Type	**Chi-Square Test**	**Cross-Validation**
Shrimp Fishing	0.005	0.15
Groundfish Fishing	0.0003	0.14
Crab Fishing	Insignificant for all weather factors	
Herring Roe	0.004	0.08
Lobster Fishing	0.001	0.08
Scallop Fishing	0.004	0.13
Seal fishing	0.008	0.14

Sea surface temperature and wind speed were shown to be significant weather factors in the joint Model 3, which uses shrimp fishing as the reference fishery type. Therefore, the indicator variables for fishery type show the changes in the risk of having a severe incident compared to the shrimp fishery. For example, comparing seal fishing versus shrimp fishing, the log odds of severity increases by 0.21, whereas for lobster fishing, it decreases by 1.28. These results and the outcomes from the individual models show that weather factors can have different effects on different fishery types, which is likely related to the environment they work in, their distance from shore and the characteristics of their vessels. For example the severity level of crab fishing incidents is not dependent on weather factors; one potential explanation for this can be the locations of this fishery type, which is very close to shore so in case of emergency fish harvesters are better able to reach a harbour. It was also shown that darkness is only important for the severity level of the lobster fishing but does not affect other fishing types.

4.5. Discussion and Conclusion

This analysis aims to examine whether certain weather factors can discriminate between high distress and less severe marine fishing incidents. Logistic Regression was used to reveal these patterns. It was shown that ice concentration, sea surface temperature, wind speed, and darkness are significant weather factors for the occurrence of severe incidents but when there is a cyclone present, the cyclone's intensity, sea surface temperature, wind speed, and darkness become the critical weather factors. It is also demonstrated that different fishing types may be predominantly affected by different weather factors.

These results can be instructive for preventive measures, such as changing the regulations for commercial fishing season openings if certain weather conditions are deemed unacceptable or better education of mariners leading to improved decision-making with respect to weather conditions. Since different weather factors can affect different fishery types, this information can be useful inputs for boat design or for the issuance of specific warnings for individual fishery types. For example Scallop Fishing is more sensitive to wind speed that should be taken into account when making decisions. Another example is Lobster Fishing that is affected by wind speed and darkness, so providing fish harvesters with this kind of information may help them to be better equipped for high risk situations. Search and Rescue planning can also be reviewed in better anticipation of severe incident occurrences as a function of the weather forecasts generally and storm warnings in particular.

Chapter 5 The Future of Fishing Safety

Title: Will Commercial Fishing Be a Safe Occupation in Future? A Framework to Quantify Future Fishing Risks under Climate Change Scenarios.

Authors: Sara Rezaee, Dr. Christian Seiler, Dr. Ronald Pelot, Dr. Alireza Ghasemi

Abstract

Weather factors are an intrinsic part of the fishing environment. Changes in weather patterns due to climate change may affect the fishing environment and fishing safety. This article proposes a general framework to quantify fishing incident risks in the future due to changes in weather conditions. This framework first builds relationships between fishing safety and weather conditions based on historical data and then predict future risks according to these relationships with respect to changes in weather patterns. This paper applies the suggested framework using fishing incident data, fishing activity levels, and extreme weather conditions in Atlantic Canada to estimate the spatial distribution of fishing incident rates in the future. To do so, a classification tree is applied to historical storm tracks based on several climate models and then generated rules are applied to future storm tracks projected by selected climate change models towards the end of this century to predict fishing risks associated with changes in weather factors. We conclude that the environmental conditions that drive fishing incidents are projected to remain very similar by the end of this century.

Keywords: Climate Change, Extreme Weather Events, Fishing Safety, Fishing Incidents, Classification and Regression Trees

5.1. Introduction

The fishing industry is one of the most hazardous occupations in the world. In addition to the high risk of life loss, fish harvesters are exposed to the risk of different non-fatal injuries during their work at sea (Murray et al., 1997). Fatigue, inadequate communication, decisions based on incomplete information, and the hazardous natural environment can contribute to incidents in the marine industry (Rothblum, 2000). Fish harvesters' appreciation of risk and safety are dynamic. This dynamism is caused by uncertain circumstances associated with changing regulations, technology development, industrial conditions and environmental circumstances (Power, 2008). Recently, fish harvesters' reliance on traditional weather patterns and familiar environmental conditions has become increasingly questionable due to climate change effects which can contribute to high risks associated with fishing industry. Although different fishing safety studies have shown that there is a correlation between fishing incidents and weather factors (Jin et al, 2001; Jin and Thunberg, 2005, Chatterton, 2008; Wu et al, 2008, 2009; Niclasen, 2010, Rezaee et al. 2015a, Rezaee et al 2015b), there is nevertheless a gap in understanding about how changes in weather patterns in the future may affect fishing safety. Studies such as Berkes and Dolly (2002), and Furgal and Seguin (2006) have investigated the effects of climate change on fishing traditions of Canadian communities, and Schulte and Chun (2009) have looked at different aspects of climate change on fish harvesters' occupational safety. However, up to the time of this research, we did not encounter research papers that apply mathematical models to estimate the risk to commercial fishing based on different climate change scenarios.

This research suggests a framework to estimate future risks to the fishing industry arising from changes in weather patterns. Figure 5-1 visualizes this framework and presents some examples of its key elements. The inputs include fishing incident data, fishing activity levels (the amount of exposure), and extreme weather characteristics such as the frequency and intensity of storms. Based on the question at hand, some other key factors such as fishery type and vessel characteristics may be added to the list. Different mathematical models can be applied to the available data to reveal underlying relationships (i.e. fishing incidents as the dependent variable and weather conditions and/or other variables such as fishery type as predictors). After building historical relationships, mathematical models can be used to predict fishing incident probabilities for the period of interest based on weather factor predictions or new fishing locations. The results of this prediction can then be reported as vulnerability maps, statistical reports, or in some of other format stipulated by the user.

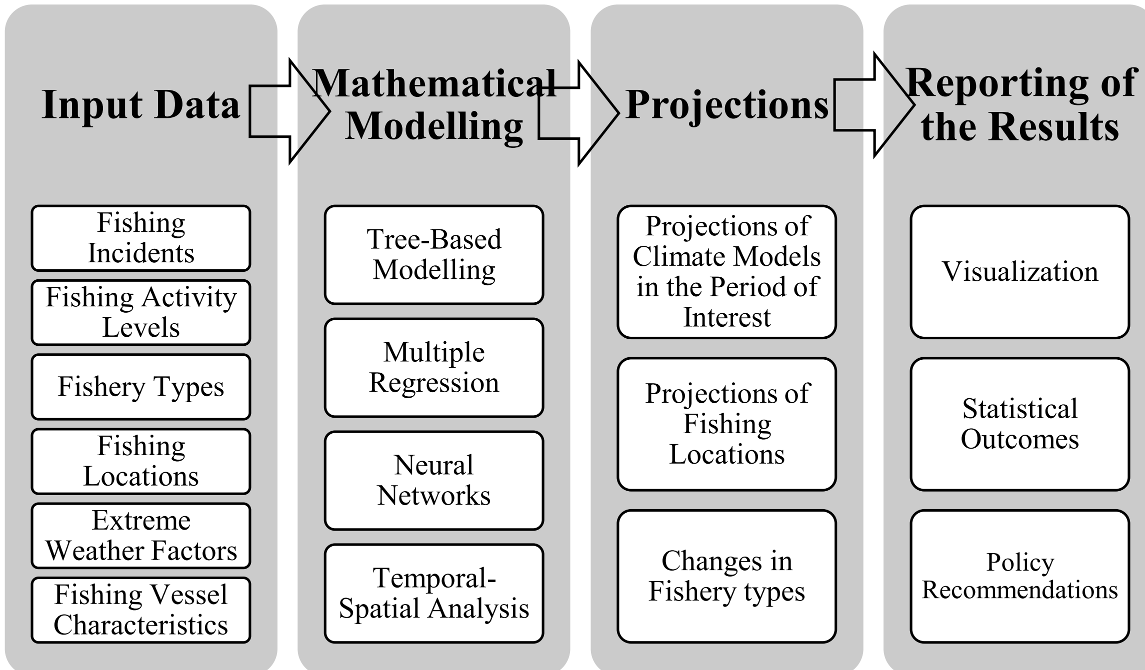

Figure 5-1. Framework to estimate future risks in the fishing industry under climate change scenarios

This paper explores the application of this framework to predict fishing incident rates (number of fishing incidents over the number of fishing trips) in the period 2081-2099 based on the historical relationships between fishing incidents, fishing trips, and the frequency and intensity of storms over the years 2000-2004 in Atlantic Canada. Figure 5-2 illustrates the tracks of the 50 most intense extratropical cyclones (i.e. highest vorticity) in the area of interest during 2000-2005.

In this study it is assumed fishing locations, technology, and fishing methods wouldn't change dramatically in the future. If any of this information is available, it should be added to the framework and considered in fishing incident rate estimations.

This article is organized as follows: Materials and Methods section provides information on input datasets and the Classification Tree method; the Results section interprets the outcomes of the trees, Discussion and Conclusion follows Results and includes the concluding notes.

Figure 5-2. Tracks of the 50 most intense extratropical cyclones that passed through Atlantic Canada (area limited to the red rectangle) during 2000-2005 (Source: STORMS Extratropical Cyclone Atlas, 2011)

5.2. Materials and Methods

The study area for this research encompasses Atlantic Canadian Waters from 40° to 60° N latitude, and 73° 20' to 45° 50' W longitude (see Figure 5-4). The historical fishing and incident data span the years 2000-2004, and the incident rate is forecasted for the period 2081-2099 (since the climate projections in the area are available for that period), and the incident rate predictions are compared to the patterns from the years 1980-2000 to identify changes.

5.2.1. Incident Data

The Search and Rescue (SAR) Joint Rescue Coordination Center (staffed by the Canadian Coast Guard and Department of National Defence) is responsible to provide help in the case of reported maritime incidents. The SISAR database (Search and Rescue Program Information Management System) records detailed information about these incidents and the actions that SAR resources have taken to provide help. This information includes time and location of the incident, type of vessel, type of incident, severity level of the incident, characteristics of the assigned SAR resources, etc. The total number of fishing incidents within our area of interest in the SISAR dataset over 2000-2004 is 4782. Spatial distribution and some other characteristics of the incident data are shown in the data exploration section.

5.2.2. Traffic Data

The traffic data comprises a post-processed version of a subset of the Department of Fisheries and Oceans (DFO) Zonal Interchange Fishery (ZIF) files for the years 2000-2004, within the specified study area of this research. The ZIF data include information on commercial fishing vessel trips such as date landed (of the catch), homeport, port landed, and NAFO (Northwest Atlantic Fishery Organization) subdivisions where the fishing effort(s) took place. A "Path Generation Algorithm" developed by Pelot et al. (2002) and Shields (2003) which includes an essential land-avoidance algorithm (Hilliard and Pelot, 2002) was applied to the ZIF files to generate feasible catch-effort positions within the NAFO unit areas reported by a fishing vessel for each day, and then the points are connected in chronological order to simulate the travel history of the vessel for each trip.

Figure 5-3 shows the spatial distribution of fishing trips in Atlantic Canada over 2000-2004.

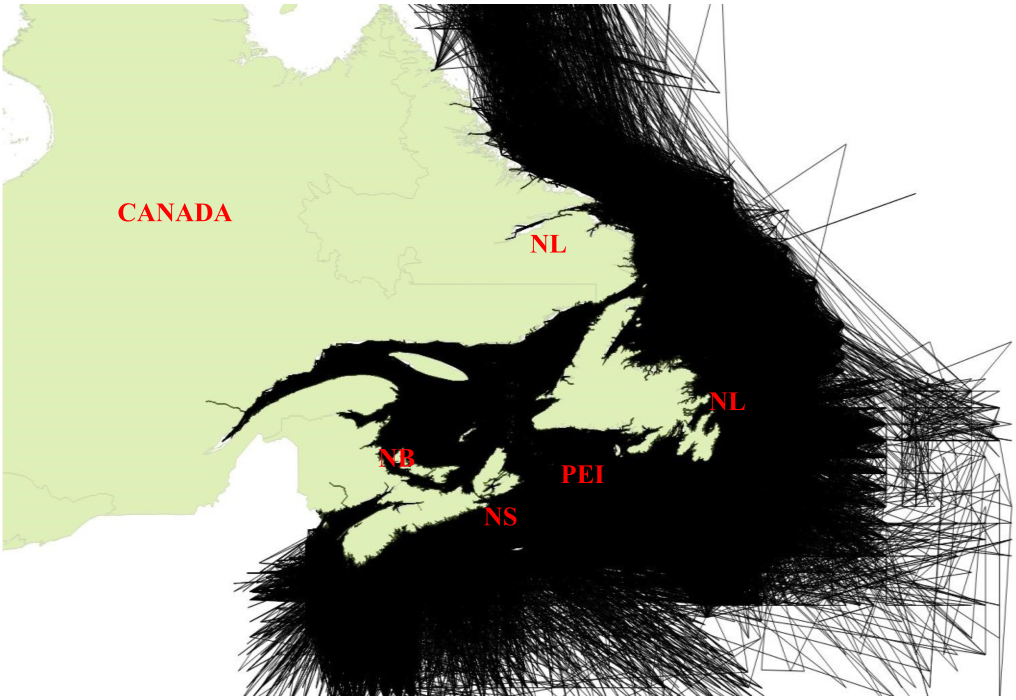

Figure 5-3. Spatial Distribution of Fishing Trips in Atlantic Canada over 2000-2004 (NB: New Brunswick, NL: Newfoundland and Labrador, NS: Nova Scotia, PEI: Prince Edward Island)

5.2.3. Historical Storm Data

Storm tracks were obtained from the Seiler and Zwiers (2015a) analysis. This historical database includes information about the computed storms paths and their relative intensity. To plot a cyclone track, the position of the centre of a cyclone should be identified and tracked throughout the cyclone's life cycle and then be connected in chronological order. To identify the position of a cyclone's centre, different algorithms have been introduced in the related literature (Hodges, 199; Serreze and Barrett, 2008). These algorithms identify and track extratropical cyclones in observational reanalysis data and climate model simulations based on different criteria such as vorticity and minimum sea level pressure, using threshold values to differentiate actual cyclones from noise (Seiler and Zwiers, 2015). However, it has been shown that results are consistent for strong cyclones when applying different algorithms to the same reanalysis data (Neu et al, 2012).

In this research extratropical cyclones were identified using the objective-feature tracking algorithm TRACK (Hodges, 1999) which was run on three reanalysis products: NCEP-CFSR (Saha et al, 2010), ERA-Interim (Dee et al., 2011), and NASA -MERRA (Rienecker, 2011).

Climate reanalysis products generally combine climate models with observations and generate numerical descriptions of the current climate. The National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) includes estimates of several atmosphere-ocean-land surface-sea ice variables such as wind fields, air temperature, ocean currents, etc. from 1979 to 2011. ERA-Interim is a global atmospheric reanalysis product from 1979 to present, provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) organization and it also includes same variables as NCEP_CFSR. Modern-ERA Retrospective Analysis for Research and Applications (MERRA) is a National Aeronautics and Space Administration (NASA) reanalysis product that covers 1979 to present and has similar output variables to the other reanalysis products.

TRACK (objective feature tracking algorithm) works in a way that first computes relative vorticity from the 6-hourly zonal and meridional wind components at 850 hPa. The next step is to remap vorticity to a common T42 grid (128 x 64 regular longitude/latitude global horizontal grid cells mainly used in atmosphere, ocean, and land modelling, with a resolution of approximately 2.8125 degrees), and to identify cyclone centers from the maximum of T42 vorticities. The path of these centers are then tracked if the cyclone exceeds: (i) a vorticity of 10^{-5} s^{-1}, (ii) a lifetime of 2 days, and (iii) a propagation of 1000 km.

In this chapter, the terms storm and extratropical cyclones are used interchangeably.

5.2.4. Climate Change Models

Projections from 20 climate change models referred to as the Coupled Model Intercomparison Project –Phase 5: CMIP5 (Taylor et al., 2012) were simulated over the study area for the period 2081-2099 (Seiler and Zwiers, 2015b). The CMIP5 project is a standard experimental protocol for studying the output of coupled Atmosphere-Ocean General Circulation Models (AOGCM). AOCGMs allow the simulated climate adjust to changes in climate forcing such as increasing atmospheric carbon dioxide. The objective of CMIP5 models is to better understand future climate changes arising from either natural, unforced variability or in response to changes in radiative forcing in a multi-model context. There are mechanisms associated with the carbon cycles and clouds which lead to model differences and the CMIP5 project aims to assess these mechanism and determine why similarly forced models may produce a range of responses. The uncertainty and differences in models are due to differences in model components, parameterizations schemes, and resolutions. The resolutions of the climate models used in this study are listed in Table 5-1.

The emission scenario for these climate models is RCP8.5. The Representative Concentration Pathways (RCP) address the changes in the balance between incoming and outgoing radiation to the atmosphere caused by changes in atmospheric composition and provide inputs for climate modeling. RCP8.5 represents a rising radiative forcing pathway leading to 8.5 W/m^2 in 2100.

Table 5-1. CMIP5 Models, references, and their corresponding resolutions (number of grid squares in the zonal (x), meridional (y) and vertical (z) direction of the atmospheric model component, e.g. 128x64 L 26 means 128 grids in zonal direction , 64 grids in meridonal direction and 26 vertical layers)

Climate Model	Reference	Resolution (x,y,z)
BCC_CSM1.1	Xin et al., 2013	128x64 L 26
BCC-CSM1.1(m)	Xin et al., 2013	320x160 L 26
CanESM2	Arora et al., 2011	128x64 L 26
CCSM4	Gent et al, 2011	288x192 L 26
CNRM-CM5	Voldoire et al, 2013	256x128 L31
FGOALS-g2	Li et al, 2013	128x60 L 26
GFDL-CM3	Donner et al, 2011	144x90 L 49
GFDL-ESM2G	Dunne et al, 2013	144x90 L 24
GFDL-ESM2M	Dunne et al, 2013	144x90 L 24
HadGEM2-ES	Martin et al, 2011	192x144 L 38
INM-CM4	Volodin et al, 2010	180x120 L 21
IPSL-CM5A-LR	Dufresene et al, 2013	96x96 L 39
IPSL-CM5A-MR	Dufresene et al, 2013	144x143 L 39
IPSL-CM5B-LR	Dufresene et al, 2013	96x96 L 39
MICRO-ESM	Watanabe et al, 2011	128x64 L 80
MICRO-ESM-CHEM	Watanabe et al, 2011	128x64 L 80
MPI-ESM-LR	Giorgetta et al, 2013	192x96 L 47
MPI-ESM-MR	Giorgetta et al, 2013	192x96 L 95
MRI-CGCM3	Yukimoto et al, 2012	320x160 L 48
MRI-ESM1	Yukimoto et al, 2011	320x160 L 48

5.2.5. Data Matching

To determine the relationship between storm characteristics and fishing safety, it is necessary to integrate fishing incident data, fishing traffic data, and historical cyclone data into a consistent structure. To do so, the study area is overlaid by a series of grid squares of size 2.5 degrees by 2.5 degrees, then fishing incidents, fishing traffic levels, and cyclone databases are matched with these grid cells. There are 88 grid squares that cover the study area, however thirteen of them are completely on land and therefore removed from study area. Figure 5-4 shows the gridded study area.

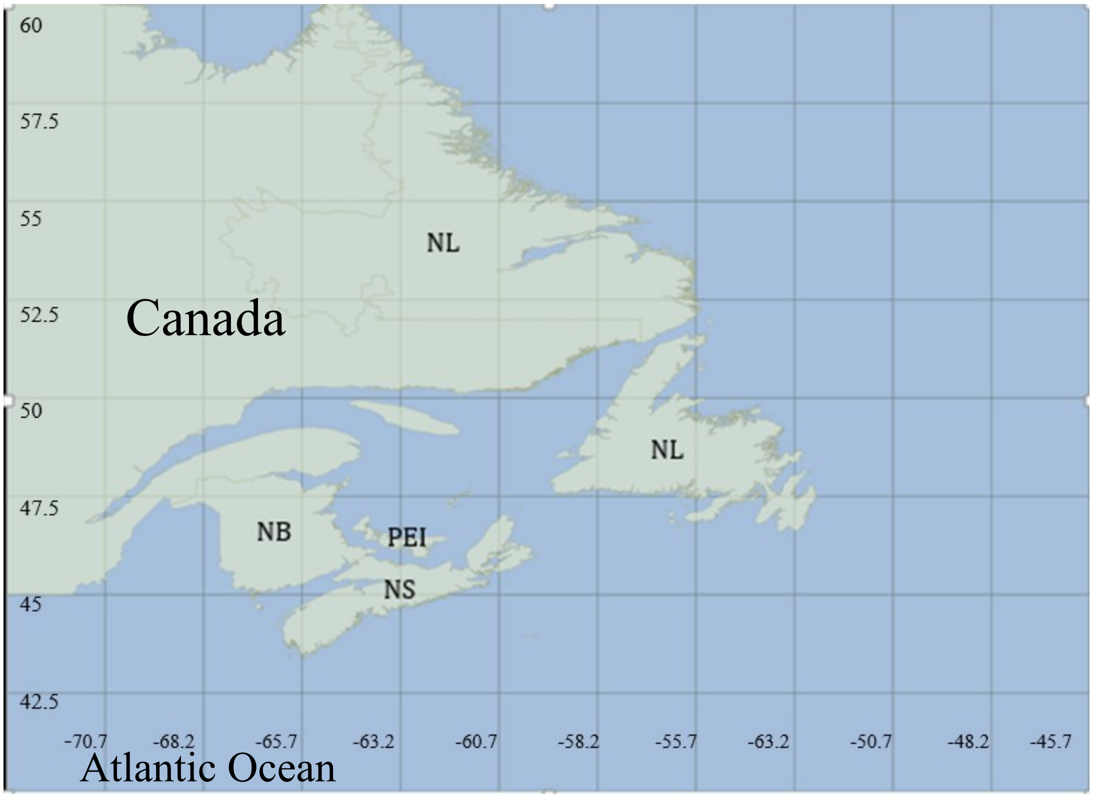

Figure 5-4. Gridded Study Area (NB: New Brunswick, NL: Newfoundland and Labrador, NS: Nova Scotia, PEI: Prince Edward Island)

To match incident data with grids, the number of incidents were counted in each grid cell over the study period (2000-2004). The study period was restricted based on data availability). For the corresponding traffic levels, the number of line segments for fishing vessel trajectories (see Figure 5-3) in each grid was assigned to that grid.

Frequency and intensity of cyclones were chosen to represent cyclone weather conditions and these variables were matched with fishing incident and fishing traffic data. The frequency of storms in this study was defined as the number of storms passing a specify grid square and it was calculated for the grids via the same process as the incident data with an assumption that a storm can affect an area 750 km around its centre (i.e. approximately eight surrounding grids about the centre of the storm). The intensity of a storm can be measured by its vorticity. To match intensity of storms with other datasets, the highest vorticity of all the storms passing through a grid in each year over the study period (2000-2004) was assigned to that grid, where the spatial and temporal resolution is a grid-year for this part of the study.

5.2.6. Data Exploration

To get a better understanding of the relationships among fishing incidents, fishing traffic levels, and cyclone characteristics in Atlantic Canada, the hot spots of storms (in terms of frequency and intensity), fishing incidents, and fishing traffic levels were examined.

Table 5-2 shows the number of grid-days that were associated with storms as simulated by NCEP-CFSR, ERA-Interim and NASA-MERRA respectively over the study period. Grid-days are defined as a combination of grids and days represented by grid-day$_{ijk}$ where i is the grid ID, j is the ordinal day in each year, and k is the index for each year. NASA-MERRA has apparently simulated fewer storms over this period compared to NCEP-CFSR and ERA-Interim over the study area, which may lead to different outcomes in the model development phase.

Table 5-2. Number of grid-days that were associated with a storm tracked via NCEP-CFSR, ERA-Interim and NASA-MERRA projects respectively in 2000-2004

Year	NCEP-CFSR	ERA-Interim	NASA-MERRA
2000	393	401	356
2001	392	369	334
2002	373	380	319
2003	419	411	363
2004	415	438	393
Total	1992	1999	1765

Figure 5-5 presents the spatial distribution of storms simulated by NCEP-CFSR, ERA-Interim and NASA-MERRA. To colour-code the maps, the Natural Break method (Jenks, 1967) was used. In this method, data are divided into an arbitrary number of classes (in our case 5 classes) and then the data are repeatedly broken into sets to obtain the sets with the smallest in-class variance. The darkest red represents the highest frequency while yellow stands for the lowest number of stormy days. Even though these Figures are not exactly the same, they all suggest that grid cells in the eastern part of Newfoundland and Labrador have the greatest number of stormy days, while areas in South of Nova Scotia and New Brunswick have the least during 2000-2004.

Figure 5-5. Spatial distribution of storms frequency simulated by (a) NCEP-CFSR. (b) ERA-Interim. (c) NASA-MERRA during 2000-2004

Figure 5-6 shows the spatial distribution of severe storms (i.e. grids with highest vorticity) over the study area for NCEP-CFSR, ERA-Interim, and NASA-MERRA. Again to colour code the maps, the Natural Breaks method was applied. Dark red shows the highest vorticity and yellow represents the lowest vorticity in the dataset. Despite some differences in the maps of Figure 6, all of them suggest that the most severe storms (i.e. storms with high vorticities) happen in Southeast part of the study area.

Orange and dark yellow grids in the North part of Newfoundland and Labrador in the ERA-Interim and NASA-MERRA maps compared to the corresponding yellow grids in the NCEP-CFSR map indicate that ERA-Interim and MERRA simulated more intense storms in this area than did NCEP-CFSR which again may lead to different results in the model development phase.

Comparison of Figures 5-5 and 5-6 indicates that grid squares in the far East of the study area and North of Newfoundland and Labrador experience more frequent and intense storms than other areas.

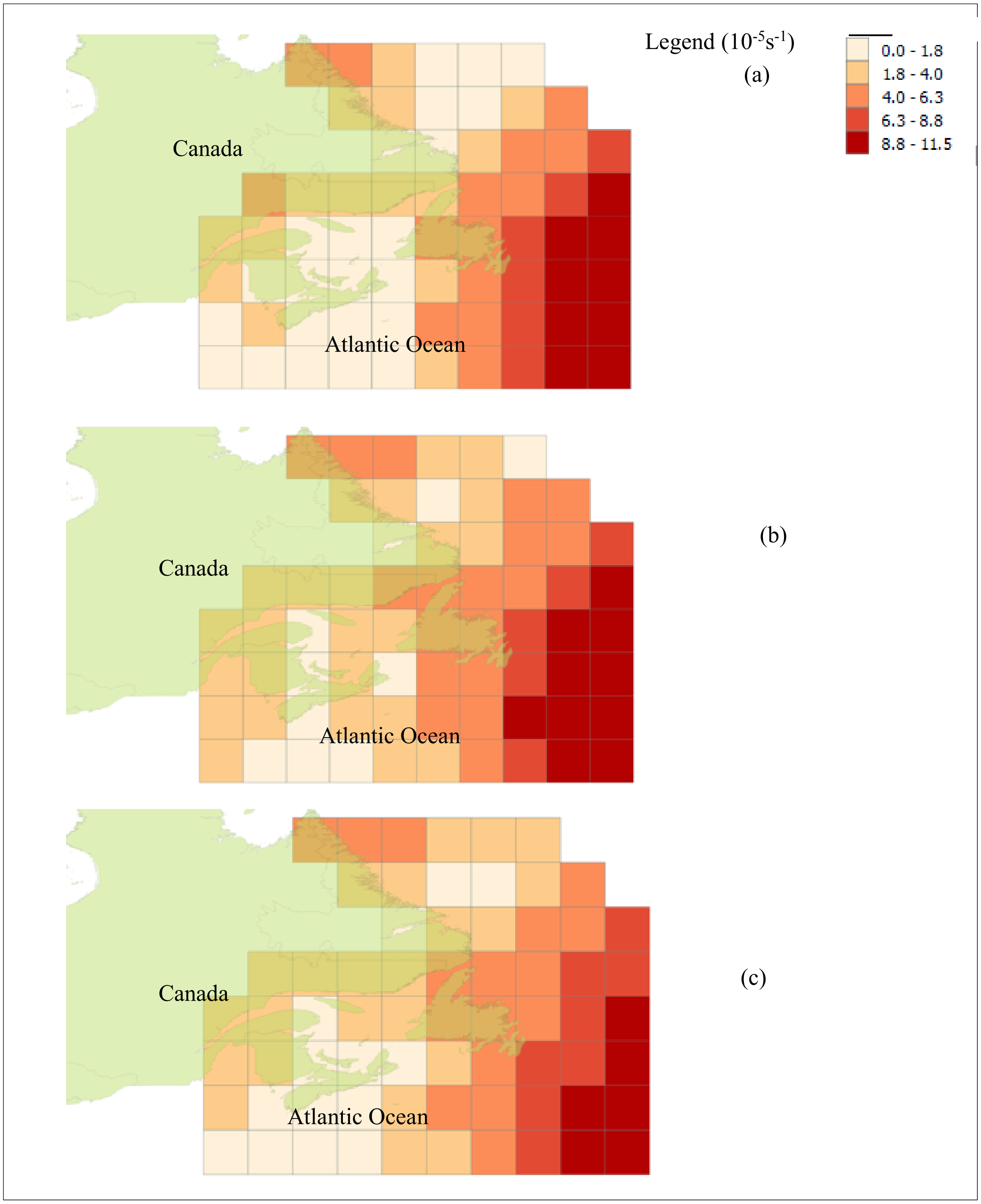

Figure 5-6.Spatial distribution of severe storms simulated by (a) NCEP-CFSR (b) ERA-Interim (c) NASA-MERRA during 2000-2004

Figure 5-7(a) shows the spatial distribution of grids with incidents during 2000-2004. Natural Breaks were used to colour code the map. Dark red shows the grids with the highest concentration of incidents. Grids around Nova Scotia and Prince Edward Island (PEI) are areas with the most frequent incident occurrences. Figure 5-7(b) shows the distribution of fishing activity in the study area during 2000-2004. Again Natural Breaks were used to colour code the map with dark red associated with the highest number of fishing trips. Fishing trips mostly occur near shore around Nova Scotia and South and East of Newfoundland and Labrador. To adjust for the dominant effect of traffic on incidents, Figure 5-7(c) shows the spatial distribution of incident rates (number of incidents per number of fishing trips) in each grid over 2000-2004. Grids with no traffic during the study period were removed from the database. The results show that although most of the incidents happened near the shore of Nova Scotia, grids to the north of Newfoundland and Labrador, grids in the eastern part of the map, and far south have higher incident rates. As mentioned earlier, these grids have also high number of storms and/or severe storms, which suggests the existence of some relationships between storms and fishing incidents.

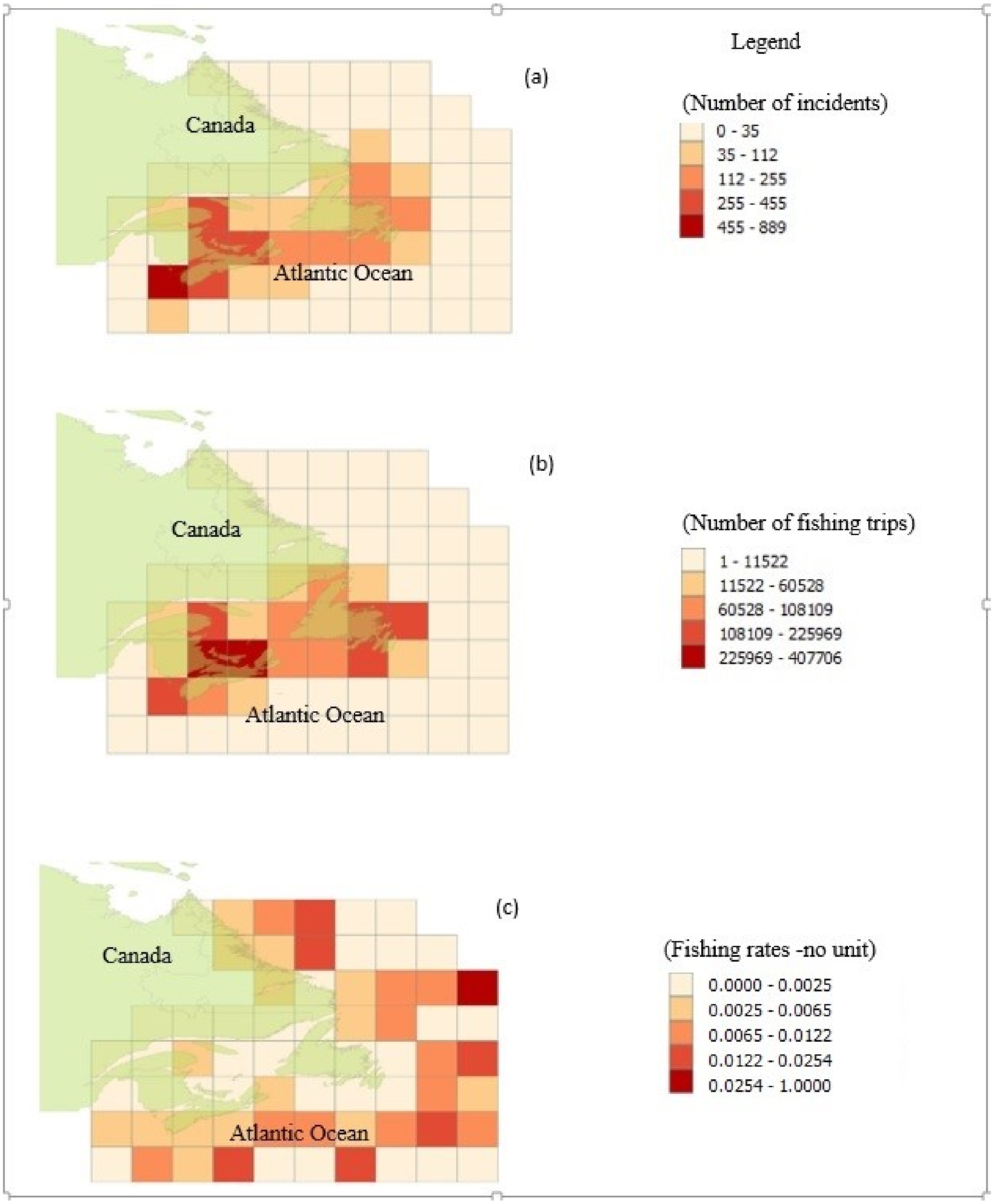

Figure 5-7. Spatial distribution of (a) fishing incidents (b) fishing trips (c) fishing incident rates during 2000-2004

In addition to studying the spatial distribution of storms and fishing incident hotspots, some characteristics of those fishing incidents associated with a storm were studied to better understand the conditions at the time of the storm. Unfortunately not all of the records in the SISAR database were filled out completely, which left us with very few incidents to do this analysis (157, 169, and 142 records for incidents associated with storms simulated by NCEP-CFSR, ERA-Interim, and NASA-MERRA, respectively). Tables 5-3, 5-4, and 5-5 show different fishery types, incident types, and actions taken by Canadian Coast Guard in cases of incidents associated with storms simulated by NCEP-CFSR, ERA-Interim, and NASA-MERRA, respectively:

Table 5-3. Number of incidents by fishery type that are associated with a storm tracked by NCEP-CFSR, ERA-Interim and NASA-MERRA respectively

Fishing type	**NCEP-CFSR**	**ERA-Interim**	**NASA-MERRA**
Shrimp fishing	20	20	18
Groundfish fishing	14	21	18
Crab fishing	38	42	32
Herring roe fishing	3	1	1
Lobster fishing	42	25	28
Tuna fishing	1	1	3
Scallop fishing	2	0	0
Seal fishing	37	59	42
Total	157	169	142

Due to differences in the spatial distribution of the frequency and intensity of storms related to each reanalysis product, different fishery types were matched with each model. Based on the results in Table 5-3, Lobster Fishing is the most frequent fishing type concurrent with storms simulated by NCEP-CFSR. ERA-Interim and NASA-MERRA related storms, on the other hand, are mostly matched with seal fishing. This could be explained by the spatial distribution of severe storms, since Figure 4(b) and 4(c) demonstrated that some severe storms reflected in these models occurred in to the north of Newfoundland and Labrador which is the location of seal fisheries.

Table 5-4. Types of fishing incidents associated with a storm tracked by NCEP-CFSR, ERA-Interim and NASA-MERRA respectively

Type of Incident	**NCEP-CFSR**	**ERA-Interim**	**NASA-MERRA**
Capsized	0	0	1
Disabled	114	131	103
Disoriented	1	1	1
Grounded	6	0	3
On fire	1	4	4
Medical	9	8	8
Foundered	0	1	0
Taking on Water	15	12	13
Missing Person(s)	2	1	1
Stranded	0	1	0
Other	9	10	8
Total	157	169	142

The results suggest that disabled vessels and taking on water are the most common types of incidents during a storm.

Table 5-5. Canadian Coast Guard action in case of Incidents associated with a storm tracked by NCEP-CFSR, ERA-Interim and NASA-MERRA respectively

Action	**NCEP-CFSR**	**ERA-Interim**	**NASA-MERRA**
Assist another unit	0	2	0
Assistance in ice	2	6	2
Communication	1	0	1
Escort	21	21	21
Evacuation	10	9	8
Fire Fighting	0	0	1
Investigation	2	1	1
Monitoring	18	15	14
None	0	1	1
Other	9	7	7
Rescue	2	2	2
Search	3	6	3
Technical assistance	2	1	2
Towed	87	97	79
Transport of person(s)	0	1	0
Total	157	169	142

Although different incidents have required different response actions, the numbers in Table 5-5 suggest that incidents that happened during a storm mostly needed to be towed, escorted, monitored, or evacuated.

5.2.7. Data preparation

To make the interpretation of incident rates easier, it was decided to categorize rates into three main groups: Low, Medium and High. Theoretically, incident rate in each grid square can adopt any value between 0 and 1. However as the histogram of incident rates over the study period shows (Figure 5-8), most of the rates except a couple of outliers are less than 0.03. To ensure sufficient data in each of the three classes, tertiles were used with the first 33% of sorted incident rate values categorized as Low, the next third as Medium and the rest as High. The upper bound for the first group was 0.001, for the second group it was 0.006, and for the third group was 1.

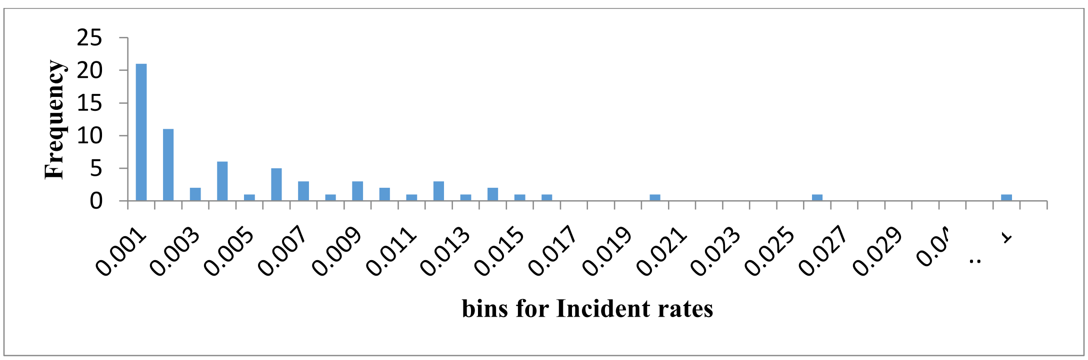

Figure 5-8. Histogram of incident rates (incidents per unit traffic in a grid square) over 2000-2004

5.2.8. Model Development

The objective of this step is to develop a model that can predict fishing incident rate classes in each grid square based on frequency and intensity of storms passing through that grid. Table 5-6 summarizes the descriptive statistics of predictors from NCEP-CFSR, ERA-

Interim, and NASA-MERRA storm databases. Minimum frequency and/or intensity of zero shows that there were grids with no storms associated with them over the study period.

Table 5-6. Descriptive statistics of predictors from NCEP-CFSR, ERA-Interim, and NASA-MERRA storm databases

Dataset	**Frequency of Storms**			**Intensity of Storms**		
	Min	**Average**	**Max**	**Min**	**Average**	**Max**
NCEP-CFSR	1	26.30	86	1.27	4.92	12.09
ERA-Interim	0	26.49	93	0	4.76	11.52
NASA-MERRA	0	23.67	93	0	4.36	12.97

Figure 5-9 shows the scatter plot matrix of incident rate class, and frequency and intensity of storms simulated by NCEP-CFSR. As shown, no linear, monotonic or even functional correlation between the dependent variable (i.e. Incident Rate Class) and independent variables (i.e. storm Frequency and Intensity) can be recognized. Therefore, standard multiple regression methods are not appropriate here. Tree-based modelling can be used as an alternative exploratory technique for uncovering structures in the data pool when the relationships between dependent and independent variables are hard to find. Breiman et al. (1984) suggested an algorithm that is commonly referred to as Classification and Regression Trees (CART) to handle these situations. CART has the advantage of being able to analyze complex data and provide an informative way of showing results in the form of decision trees. It can accommodate any type of predictor variable and can handle missing values in both the response variable and predictors (Speybroeck, 2012).

CART aims to partition the space X (predictor variables X_1, X_2…) into disjoint sets A_1, $A_{2,..}$, each one as homogenous as possible. Belonging to a given set indicates the predicted class of the observations, for example, if observation i belongs to set A_k it means that the value of response variable for this observation is k. The pseudocode for binary recursive partitioning is as follows (Loh, 2011):

1. Start at the root node;
2. Choose the split point that minimizes the sum of the node impurities (e.g. number of misclassifications) in the two child nodes;
3. If a stopping criterion is reached then stop, otherwise apply step 2 to each child node in turn.

The node impurity is called the deviance, and a deviance of zero corresponds to a perfectly homogenous node. The deviance decreases as the tree size increases. The deviance of a node is defined as the sum of the deviances of all observations in the node:

$$D(\mu;y)=\sum D(\mu,y_j) \tag{5. 1}$$

where y is the predicted value at the particular node and μ is estimated by the node average (i.e. the mean of the values of the cases from sample space X assigned to that node), y_j is the predicted value for each observation that gets classified under this particular node. Splitting proceeds by choosing the candidate children, which minimize the deviances (Breiman et al., 1984).

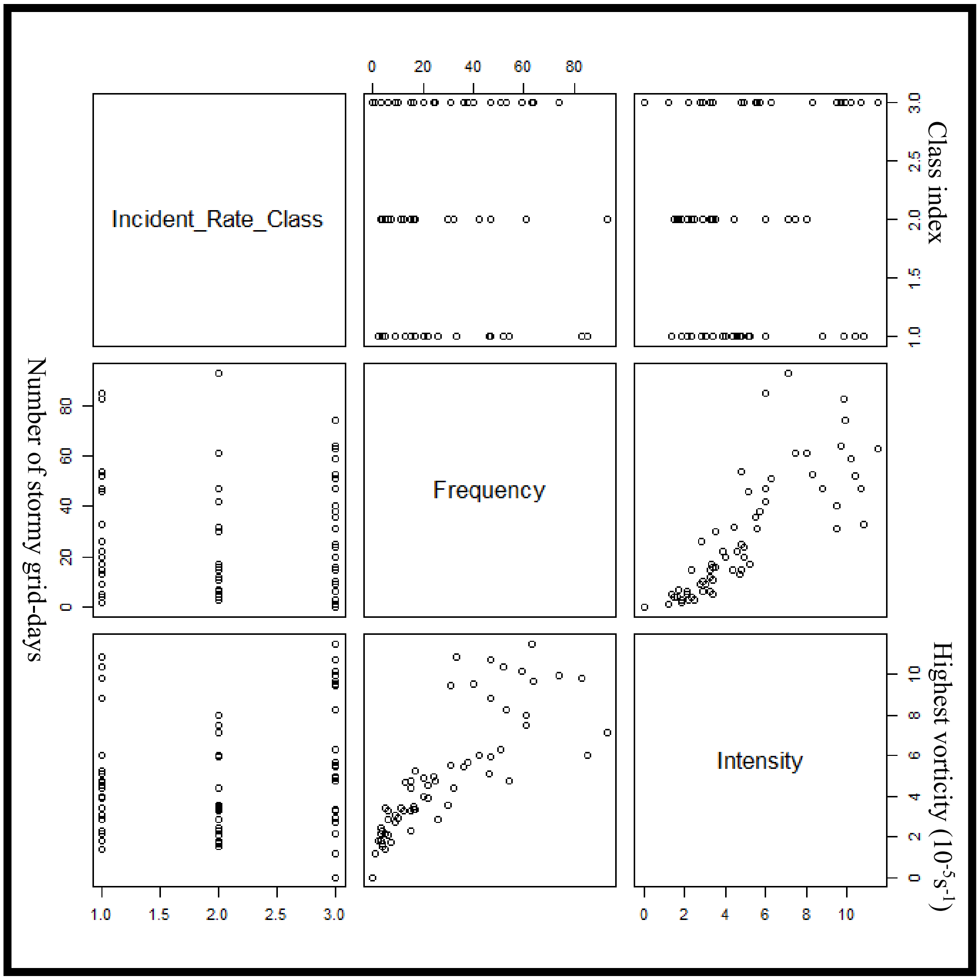

Figure 5-9. Scatter Plot Matrix of Incident Rate Class, and Frequency and Intensity of Storms

5.3. Results

5.3.1. Historical Relationships

Table 5-7 shows the summary of the full classification trees based on the NCEP-CFSR, ERA-Interim, and NASA-MERRA models respectively.

Table 5-7. Results of full classification trees for NCEP-CFSR, ERA-Interim, and NASA-MERRA datasets

Dataset	**Number of End Nodes**	**Residual Mean Deviance**	**Misclassification Rate**	**Best Number of Nodes**
NCEP-CFSR	9	0.43	0.32	7
ERA-Interim	11	0.38	0.28	10
NASA-MERRA	10	0.44	0.34	5

Both predictors (frequency and intensity) are included in the full trees. The size of tree is based on the number of end nodes. The residuals were obtained by subtracting the fitted values from the response variable. The mean was calculated based on the sum of the deviance over all of the leaves, divided by the number of total cases in the dataset minus the number of end nodes in the final tree. Generally speaking, the full tree is a fairly accurate partition of the datasets, however due to the small ratio of the number of observations to the number of potential predictors (67/2= 33.5), the likelihood of overfitting data is high (Hansen et al., 1996). To avoid overfitting, filter out noise, and reduce the complexity of the final model, classification trees should be pruned. The basic idea of pruning is to define the "cost" of adding another variable (split) to the model with respect to the information it adds to the final model (similar to the stepwise approach in regression, when no additional variables are added to the model when the F-Test for the remaining variables fails to achieve the significance level (e.g. 0.05)) (Therneau, 1997). Cross validation is a common method to prune classification trees, which divides the dataset into "k" mutually exclusive subsets. For each subset, a tree is fitted to the remaining (k-1) subsets and the k^{th} subset is used to evaluate the results. This procedure is repeated k times. Deviances are summed up over all the subsets for different tree sizes and the size of the next best tree is chosen based on the cross-validation results (miss-classification rate). The best numbers of nodes based on cross-validation results are reported in the last column of Table 5-7 for each tree. Based on these results, the trees have been pruned to their best size. Table 5-8 summarizes the results of the pruned trees for the NCEP-CFSR, ERA-Interim, and NASA-MERRA datasets.

Table 5-8. Results of pruned trees for NCEP-CFSR, ERA-Interim, and NASA-MERRA datasets

Dataset	Number of End Nodes	Residual Mean Deviance	Misclassification Rate
NCEP-CFSR	7	0.53	0.37
ERA-Interim	10	0.47	0.29
NASA-MERRA	5	0.56	0.41

Figure 5-10, 5-11, and 5-12 show the pruned trees for NCEP-CFSR, ERA-Interim, and NASA-MERRA respectively.

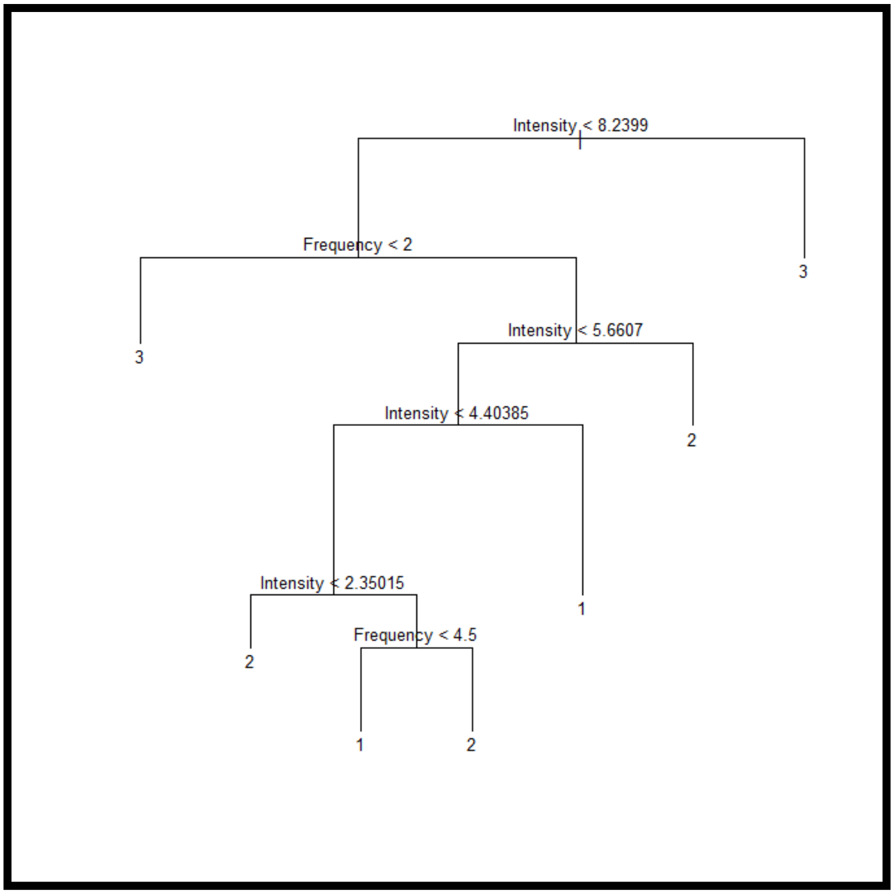

Figure 5-10. Classification Tree for NCEP-CFSR where the labels at the end of the nodes represent the incident rate class (1 means low, 2 means medium, and 3 means high)

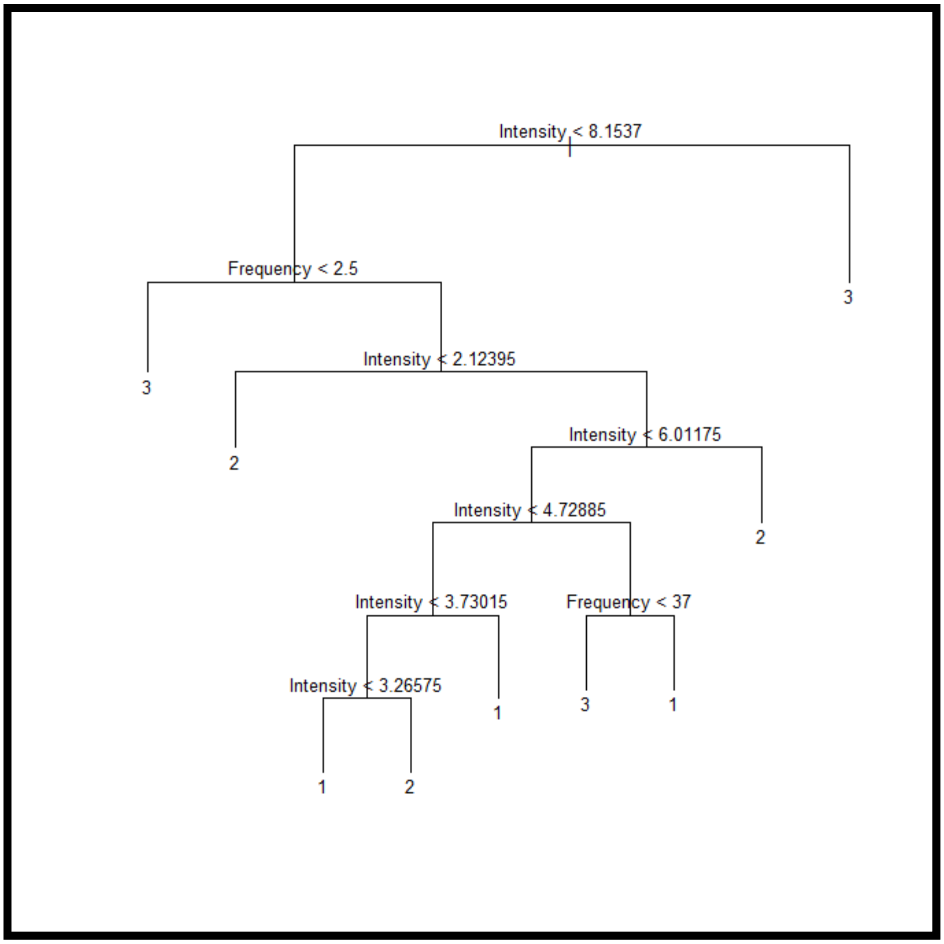

Figure 5-11. Classification Tree for ERA-Interim where the labels at the end of the nodes represent the incident rate class (1 means low, 2 means medium, and 3 means high)

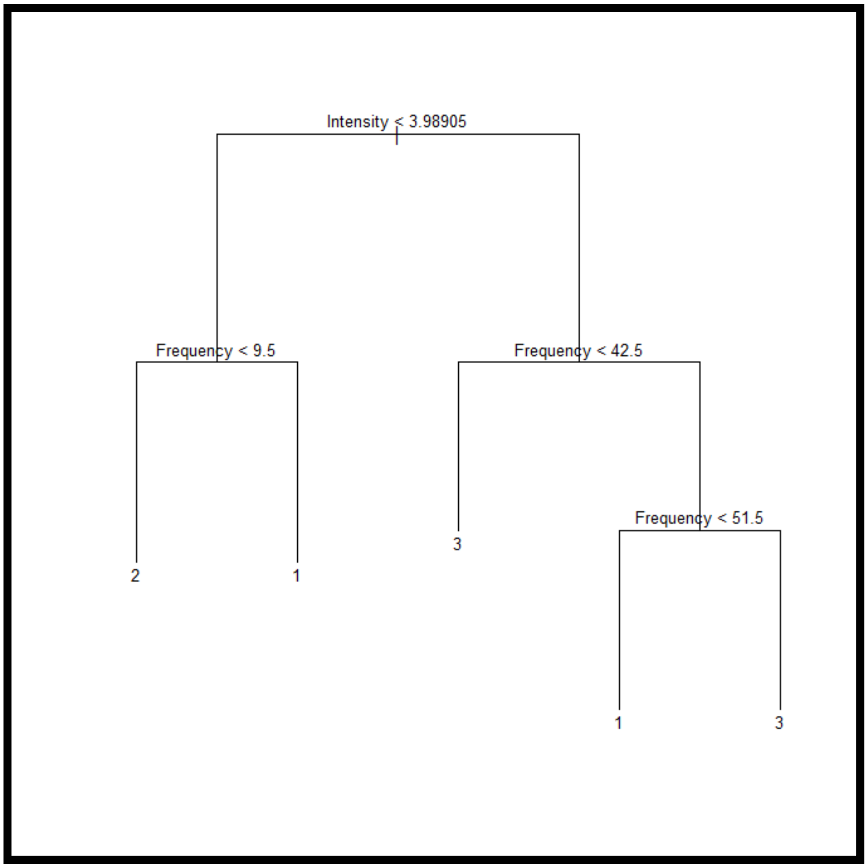

Figure 5-12. Classification Tree for NASA-MERRA where the labels at the end of the nodes represent the incident rate class (1 means low, 2 means medium, and 3 means high)

Generally all these trees indicate that high storm intensity will lead to high incident rates. The only exception is in the NASA-MERRA tree (Figure 5-12) when high intensity and medium frequency has led to low risk class (second final node from right). One potential explanation can be the combination of frequency and intensity in this tree. Unlike the other two trees (i.e. NCEP-CFSR and ERA-Interim related trees), the NASA-MERRA tree doesn't divide data at a high intensity threshold but uses a fairly medium value (the average intensity for the dataset is 4.36 which is greater than 3.98), so a combination of average (or even low) intensity and average frequency led to the low risk class node in this tree.

It was also shown that a combination of low frequency and average intensity storms can produce high incident rates. One explanation for this outcome could be the fact that when storms are rare in some areas, fish harvesters may not be well prepared for stormy conditions and even a storm with average intensity could lead to incident occurrences. Average intensity and average frequencies of storms generally lead to medium or low incident rates but the thresholds are different in each model (for example high intensity means more than 8.23 for the NCEP-CFSR-Tree and more than 8.15 for the ERA-Interim-Tree).

Misclassification rates residuals have been calculated using cross validation (K=10). Note that none of the models have a classification rate greater than 70 % (4th column of Table 5-8). The potential explanation for this is that there are many other factors (human related, environmental factors other than storms), which were not included in these models. However, considering that only storm frequency and storm intensity are introduced as the predictors of incident rates, the performance of this model seems fair.

5.3.2. Predictions

To study changes in fishing risks due to climate change, fishing incidents rates estimated based on frequency and intensity of storms in two periods (1980-2000) and (2081-2099) were compared. To do so, storms simulated by CMIP5 models for the period 2081-2099 were spatially matched with the grids over the study area and the number of storms and the highest vorticity estimated in each model was assigned to the corresponding grid. Trees built on historical data from NCEP-CFSR, ERA-Interim and NASA-MERRA were applied to each of the 21 CMIP5 models individually, therefore, each grid was classified as low, medium, or high risk based on the predicted weather factors in each climate model (e.g. grid i may be classified as low risk based on CCSM4 projection, medium risk based on FGOALS-g2 projection, and high risk based on MRI_ESM1 projection). Figure 5-13 shows the grids with pie charts indicating what percentage of models classified the related grid as having low (white), medium (yellow), or high (red) incident rates based on the tree built on NCEP-CFSR as an example. One can conclude that hot spots of incident rates in the period of 2081-2099 will be located to the south of Nova Scotia, the south of New Brunswick, and Eastern parts of the study area. Figure 5-13 demonstrates a fair amount of consistency around the risk level in each grid associated with all of the 21 models, although north of Newfoundland shows more variability in this regard. Since there may be more than one risk class estimated for a grid by the 21 CMIP5 models, the class which is predicted by the majority of CMIP5 models (i.e. largest sections in pie charts of Figure 5-13) was chosen as the representative risk class in 2081-2099 and then it was compared to the risk classification for the period 1980-2000. To get the risk estimates for the period 1980-2000, storms simulated for this period by NCEP-CFSR, ERA-Interim, and NASA-MERRA were spatially matched with grids over the study area and fishing incident rates were calculated based on built trees.

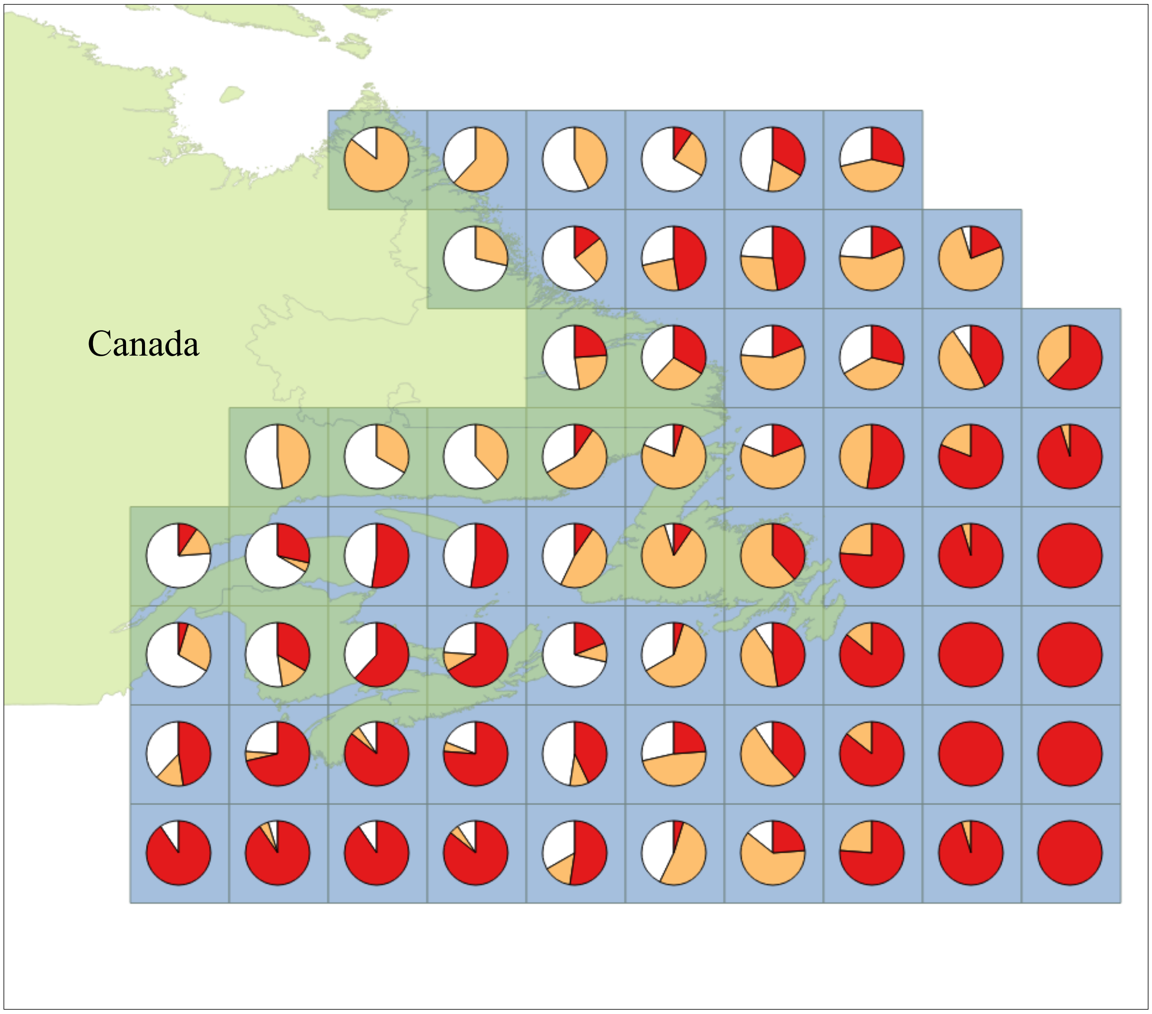

Figure 5-13. Estimated incident risks for the period 2081-2099 based on NCEP-CFSR-Tree. Pie charts illustrate the percentage of projections that classify the grid as high risk (red), medium risk (orange), and low risk (white).

Figure 5-14 maps the differences between risk classification of the grids in 1980-2000 and 2081-2099 according to each of the three tree-based models NCEP-CFSR, ERA-Interim, and NASA-MERRA. The maps are colour coded in such a way that dark blue shows reduction in risk by two classes (from high to low), blue shows reduction in risk by one class (from high to medium, medium to low), white means no change, orange means increase in risk by one class (low to medium, medium to high), and red means increase in risk by two classes (low to high). It is assumed that changes from high to medium and medium to low (or vice versa) are equivalent (i.e. it can be presented by the same colour).

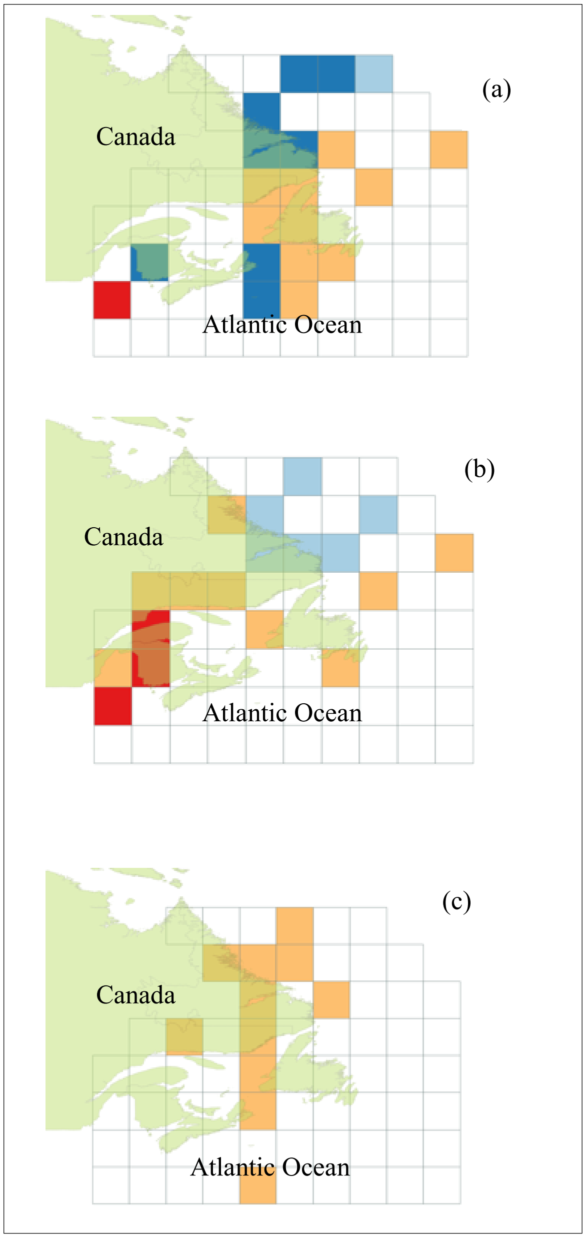

Figure 5-14. Differences between incident rate classes in 1980-2000 and 2081-2099 based on (a) NCEP-CFSR (b) ERA-Interim (c) NASA-MERRA. Dark blue: Reduction in risk by two classes (from high to low), Blue: Reduction in risk by one class (from high to medium, medium to low), White: No change, Orange: Increase in risk by one class (low to medium, medium to high), and Red: Increase in risk by two classes (low to high).

As Figure 5-14 suggests, NCEP-CFSR-Tree and ERA-Interim-Tree both predict risk reduction in the area North of Newfoundland and Labrador. The results of all three models indicate that there is an increase in the risk rate in the Gulf of St. Laurence and southern parts of Labrador. Despite the differences in the three maps, one can conclude that there wouldn't be many changes in fishing risk due to climate change in the future and decreases and increases in risk may occur only in a few grids. To study these differences mathematically two methods are carried out:

1. Raster Analysis, which generates a cross-tabular listing of map intersections and counts the number of cells within each class to represent the coincidence percentage. This method gives a general idea of how well the maps match (Berry, 2007).
2. Percent Difference, which simply investigates the change of category for each grid. It is an alternative approach for statistical tests such as the t-test. Statistical tests require some conditions such as normal distribution or independence of the data, which is rarely the case in mapped data. To interpret the results of Percent Difference, the Thirds rule can be adopted. "Thirds rule of thumb" for comparing map surfaces indicates "if two-thirds of the map area is within one-third (one unit class change) difference, the surfaces are fairly similar; if less than one-third of the area is within one-third difference, the surfaces are fairly different" (Berry, 2007).

Raster analysis results yielded 70%, 73%, and 83% similarity among estimated fishing risks for 1980-2000, and 2081-2099 periods based on NCEP-CFSR, ERA-Interim, and NASA-MERRA trees, respectively. Percentage Difference results indicated that 74%, 77%, and 100% of grids are in the 33% difference area when comparing 1980-2000 and 2081-2099 periods based on NCEP-CFSR, ERA-Interim, and NASA-MERRA tress, respectively. All these results imply that these periods are fairly similar in terms of fishing incident rates; however these results are based on intensity and frequency of storms and if more variables are included in the study or if historical relationships are built based on a larger time span, these findings may change.

5.4. Discussion and Conclusion

This research aims to reveal the underlying relationships between extreme weather events and fishing safety and to investigate how the spatial distribution of fishing incidents may change due to climate change effects. This paper proposes a general framework:

1. Build a mathematical model based on historical relationships between fishing incidents, fishing activity levels, and extreme weather events.
2. Run the model developed in step one using storm projections for the period of interest.

In our case, extreme weather conditions relate to storm frequency and storm highest intensity in each grid of 2.5 degrees by 2.5 degrees over Atlantic Canadian waters during 2000 to 2004. To track storms, three reanalysis products, namely NCEP-CFSR, ERA-Interim, and NASA-MERRA were used. Classification tree analysis was then applied to the incident rates (number of incidents over number of fishing trips in each grid) and storm frequency and intensity data. Both frequency and intensity of storms appeared to be important for the prediction of incident rates for all of three datasets (NCEP-CFSR, ERA-Interim, and NASA-MERRA). Projections of 21 CMIP5 climate models were used as potential climate change scenarios for the period 2081-2099 in Atlantic Canada. Despite some disparities in results across the scenarios, we conclude that the environmental conditions that drive fishing incidents are projected to remain very similar by the end of this century. However, including other extreme weather factors, such as surface wind speed, precipitation, and temperature in the analysis could lead to more precise results since fishing safety can be affected by many environmental and non-environmental factors, whereas assuming that it can be explained through few factors is somewhat simplistic.

The dynamic characteristic of storms is another factor that could be taken into account when interactions between fishing safety and changing climate are studied. Frequency and intensity of storms are different each year and some individual years may be particularly harsh. Figure 5-15 populates the grids with pie charts indicating what percentage of the models classified the related grid as having low (white), medium (yellow), or high (red) incident rates based on the tree built on NCEP-CFSR for individual year 2081 as an example. Comparing Figure 5-15 to Figure 5-13 shows that although the bottom left corner of the map shows low fishing risk averaged over the whole period, it is risky in that specific year.

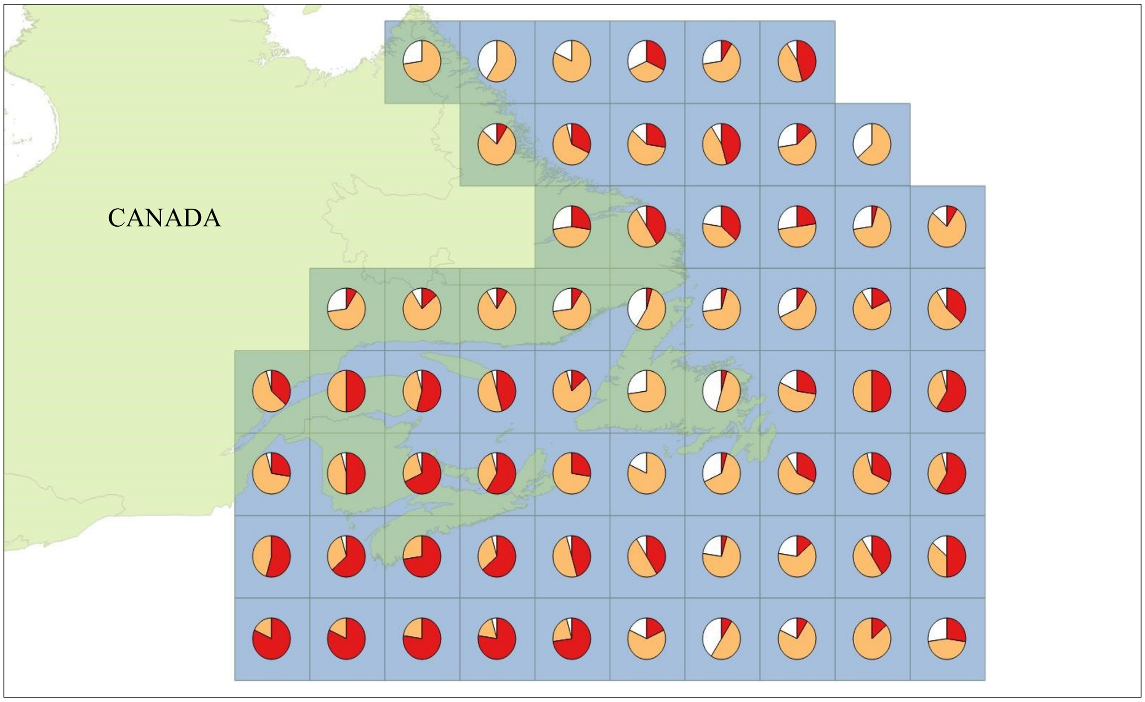

Figure 5-15. Estimated incident risks for year 2081 based on NCEP-CFSR-Tree. Pie charts illustrate the percentage of projections that classify the grid as high risk (red), medium risk (orange), and low risk (white).

This makes the point that inter-annual variability of the risk level can be significant, even though multi-year averages a fairly stable. The variability of risk for each year is especially important in short term and tactical planning such as search and rescue resource allocation. Even though search and rescue stations are located and built based on long term considerations, information on the hot spots of incidents with respect to possible weather patterns in particular years may enhance their preparedness and the accessibility of search and rescue resources to these hotspots, which consequently can improve safety and lower the cost of search and rescue.

Chapter 6 Knowledge Mobilization

Title: Review of Fishing Safety Policies in Canada with Respect to Extreme Environmental Conditions and Climate Change Effects

Authors: Sara Rezaee, Dr. Mary R.Brooks, Dr. Ronald Pelot

Abstract

Fishing is one of the most dangerous occupations in the world. Numerous research studies have been carried out to ascertain how to improve fishing safety from many different perspectives. Several of these studies focused on the relationship between environmental factors, climate change effects, and fishing safety. This paper aims to suggest a knowledge mobilization structure to improve and update fishing policies with respect to fishing safety and environmental conditions. Significant safety factors extracted from related literature are stability of vessels, fisheries management, safety equipment, communication, insurance, training, safety information and culture, weather forecasts, fatigue, and search and rescue planning. The paper then reviews policies related to these factors to examine if they address extreme environmental conditions and climate change. The paper presents recommendations to improve general fishing safety with respect to short and long term environmental considerations.

Key words: Fishing Safety, Fishing Policies and Regulations, Extreme Environmental Factors, Climate Change

6.1. Introduction

Fishing is identified as the deadliest occupation in Canada. The fatality rate for fish harvesters is 0.831 per 1000 persons per year, which is 19 times higher than any other industry in the country. In addition to the risk of life loss, fish harvesters are at danger of serious or minor injuries during their work at sea. In the province of Nova Scotia, approximately 4% of fish harvesters have experienced at least one serious injury while fishing. It is important to note that these numbers only represent incidents reported to Workers Compensation Boards (WCBs) in Canada as not all injuries or fatalities of small fishing operations may appear in these statistics (WCBNS, 2012).

An overview of incidents reported to the Canadian Coast Guard (CCG) in Atlantic Canada showed that 8,650 incidents occurred in this area during the period 2000-2010, and that 15% of these were classified as severe incidents (i.e. life loss or total vessel loss) (Rezaee et al., 2015a). Hard labour, long working hours, hazardous working conditions, and the competitive nature of the work are the elements of commercial fishing that contribute to the risks associated with the industry. Harsh environmental conditions combined with any of these factors could lead to a disaster. Several studies show that there is a correlation between various weather factors and fishing incidents (Jin et al, 2001; Jin and Thunberg, 2005, Chatterton, 2008; Wu et al, 2008, 2009; and Niclasen, 2010). Rezaee (2015a, 2015b) studied the relationship between extreme environmental factors (i.e. air temperature, sea surface temperature, wind speed, ice concentration, precipitation, and Laplacian of pressure as the indicator of cyclones' intensity), fishing incident rates, and severity levels of fishing incidents, respectively. The results of these studies showed that there is a statistically significant relationship between these factors and fishing incidents and that these relationships and the degree of correlation between predictor factors and incidents are different for specific fishery types. Another important issue that should be taken into account when studying the effects of environmental conditions on fishing safety is climate change. Global warming may cause short and long term changes in weather patterns and this may also affect fishing safety. Rezaee (2015c) proposed a framework to estimate fishing risk with respect to potential climate change scenarios. The results of these studies will be explained in detail in section 6.2.2.

It is concluded from cited literature that generally harsh environmental factors can increase the risk of fishing incidents and worsen the situation during the period of recovery after an incident happens. Findings from the literature indicate that environmental factors and climate change are important elements to consider in formulating policies to improve fishing safety. This paper uses a knowledge mobilization structure to link the outcomes of different research efforts to safety policies and regulations. Knowledge mobilization is commonly defined as "getting the right information to the right people in the right format at the right time, so as to influence decision making" (ONF, n.d.). Knowledge mobilization can be challenging for many reasons including differences in priorities of researchers and end-users, a lack of a common language between them, uncertainty around use of research, lack of mutual trust, different understandings of policy and practices, time related challenges, and so on (Shantz, 2012). Therefore, it is very important to find a proper way to present knowledge in a readily understandable language for all the users and strengthen the connection between research, policy, and practice as much as possible. Knowledge mobilization models are mainly presented as a product model with three main elements: input (evidence and research), outcome (practice and decisions), and process that links input to output (Levin, 2008). The knowledge mobilization structure proposed in this paper has the following elements:

1. Input: Input to the framework comprises significant fishing safety factors in Canada extracted from related literature (along with a review current Canadian policies related to these factors) and findings of the studies related to the effects of extreme environmental conditions on fishing safety (section 6.2);
2. Process: To build a bridge between the input items, relationships between research findings and safety factors are determined (section 6.3);
3. Outcome: Recommendations to modify regulations and policies in an attempt to make commercial fishing a safer occupation with respect to weather considerations are presented as the output of this framework (section 6.4).

Before the knowledge mobilization structure approach can be used, the bodies within Canada responsible for fishing safety policies and regulation are introduced.

Many federal and provincial organizations are involved in fishing safety in Canada. Federally, Transport Canada (TC) and the Department of Fisheries and Oceans (DFO) are responsible for setting regulations and policies. Generally speaking, TC establishes policies on construction and stability of vessels, navigation and fishing equipment, lifesaving appliances, licensing, and the vessel-related training of fish harvesters. DFO is responsible for fisheries management, such as the setting of fishing seasons, fishery location, species that may be caught and the catch limits (i.e. size and/or legal number of fish that can be caught). The Canadian Coast Guard (CCG), located within DFO, provides safety services for mariners and also regulates radio communication and ice navigation in Canadian waters. After a fishing incident, search and rescue in Canada is a shared responsibility across government departments and several agencies; for Atlantic Canadian waters, that responsibility is housed within the Joint Rescue Coordination Centre (JRCC) located in Halifax, one of three Canadian JRCCs. Other governmental or non-governmental organizations such as the Nova Scotia Fisheries Safety Council, the National Research Council and various fishers' associations mainly work on research, training, and increasing safety awareness among fish harvesters. All of these departments and policies can directly or indirectly affect fishing safety in Atlantic Canada, the geographic location for this research.

6.2. Input

Input items of the knowledge mobilization framework are classified into two categories: fishing safety factors and the effects of extreme environmental conditions on fishing incidents. Fishing safety factors involves a review of fishing safety literature to provide a list of safety factors that may need improvement in Canada and examines current Canadian policies related to each factor.

The second part of the input summarizes findings of several research studies on the effect of extreme environmental factors on fishing incidents and determines which environmental factors are significant in fishing safety in Atlantic Canada.

6.2.1. Fishing Safety Factors

Kaplan and Kite-Powell (2000) indicated that fish harvesters find policies on reduced crewmembers, short fishing seasons, and restricted areas to be the main safety-related policies implicated in fishing incident levels. Loughran et al. (2002) concluded from a study on fishing vessel safety that safety culture is not very strong in fishing industries. Piniella (2007) focused on the use of safety equipment in a Spanish fishing fleet and showed that there is a need for training on the proper use of this equipment; he also highlighted the lack of safety culture among fishing communities. Windle et al. (2008) compared regulatory regimes and fishing safety outcomes in six countries (including Canada) and recommended improvements in policies with respect to safety training, safety equipment, inspection and enforcement, communication, search and rescue, weather forecasting resources, and fisheries infrastructure. Håvold (2010) showed that fish harvesters' safety attitude, safety training, and management's safety attitudes have significant influence on fishing safety policies and practices. An investigation of small fishing vessel incidents that occurred in Canadian waters during 1999-2010 showed that the main safety issues in Canada are as follows: vessel stability, fisheries resource management, lifesaving appliances, regulatory approach to safety, training, safety information, cost of safety, fatigue, fishing industry statistics, and safe work practices (TSB, n.d.). From the above it is clear that literature on fishing safety policies, mostly are focused on identifying factors of relevance.

Adopting the findings of the preceding studies, a list of factors that policies and regulations related to them may need improvement is created. The list comprises:

Factors related to incidents occurrences:

- Stability: The stability of a vessel is defined as its ability to deal with strong winds, high waves, loading, and other forces resulting from the vessel's operations. Loss of stability is one of the main factors leading to fishing incidents. TC requires every new fishing vessel to go through a stability inspection on, or near, the completion of construction. The inspection should include loading conditions (half load and full load), departure and arrival situations, worst case operating conditions, and accumulated ice on topside and rigging. If a vessel is larger than 150 gross tons, it needs to have a stability booklet on board that specifies the limits of that particular vessel's stability (Minister of Justice, 2007a, 2007b).
- Fisheries Management Strategies: DFO's vision is declared as follows (DFO, 2004):

  "Safe, healthy, productive waters and aquatic ecosystems, for the benefit of present and future generations by maintaining the highest possible standards of: service to Canadians, marine safety and environmental production, scientific excellence, and conservation and sustainable resource use."

  Although safety is stated as one of its main objectives, DFO's policies over time show that fishing safety has not been a main priority in the fisheries management decision-making process. DFO's policies mainly focused on sustainable and responsible fishing over economic, social and safety considerations (FAO, 2000). In other words, DFO mainly regulates the time of opening and closing of the fisheries, effort intensity, and vessel size in a way that fish stocks are protected as much as possible, with little explicit consideration of fishing safety.

- Weather Forecasts: Environment Canada (EC) provides marine weather forecasts for shippers, boaters and fish harvesters through their website and radio stations. There are no stated policies or regulations on how fish harvesters get the weather forecast and no specified safety practices in cases where weather warnings are issued.
- Fatigue: Hours of work is not included in policies or regulations but fatigue has been determined to be one of the main causes of fishing incidents. Harsh weather conditions can have a significant effect on levels of fatigue. It is not hard to imagine that working in strong winds, heavy rain, and low temperatures can be exhausting and mentally frustrating.

Factors related to incident consequences

- Safety equipment: Fishing vessels are required by TC to carry lifesaving appliances, vessel safety equipment, visual signals, navigation equipment, and firefighting equipment (TC, n.d.).
- Communication: The CCG is responsible for fishing vessel radio communication regulations. Radio communication service is mainly used to exchange messages for safety and navigation. Fishing vessels that are 20 meters or more are required to have a SART (Search And Rescue Transponder) in their vessels under lifesaving regulations (Minister of Justice, 2014). DFO also requires certain fisheries to carry vessel monitoring system (VMS) devices on their vessels for fisheries management

purposes (DFO, n.d.). Automatic Identification System (AIS) is another transponder, which is mandatory for every ship operating in Canadian waters, which is 500 tons or more, other than a fishing vessel (TC, 2007).

- Search and Rescue: Search and rescue can be conducted via air and ocean. The JRCC Halifax coordinates maritime search and rescue operations in emergencies carried out by the CCG and Canadian Coast Guard Auxiliary (CCGA) and the Canadian armed forces assist with airside support. CCG and CCGA have their own limitations in harsh weather conditions as well. A search and rescue resource cannot venture out to sea if there is a big storm occurring or imminent, thus their response may be delayed.
- Insurance and Workers Compensation Boards: Insurance is not mandatory for fishing vessels; however some provincial governments require proof of insurance coverage before issuing permits for some fisheries. Workers Compensation Board coverage is only mandatory for certain size vessels, and the premium is relatively high (WCBNS, 2012).

<u>Factors related to fishing safety in general</u>

- Safety Information and Culture: There is no policy on fishing safety culture; however TC, DFO, Transportation Safety Board of Canada (TSB), etc. can effectively increase awareness among fish harvesters which may potentially foster a culture of safer practices among fishing communities.
- Training: Training can have a considerable effect on fishing safety. Currently, training is only compulsory for Masters and watchkeeping officers (TC, 2011). The

> Master of the fishing vessel should also make sure that all the crewmembers know how to use safety equipment. Several federal and provincial organizations such as the Canadian Council of Professional Fish Harvesters, Professional Fish Harvesters Certification Board, Nova Scotia Fisheries Sector Council, and Prince Edward Island Fishermen's Association attempt to increase awareness among fish harvesters and provide training courses for them.

Fishing safety is a complex system and there is a dynamic relationship between its elements. In other words, safety related factors are not independent of each other and any change in one factor can affect others. For example, fishing management strategies may lead to competitive fishing during a short season that can add considerably to the fatigue factor. Proper training on use of safety equipment may decrease the severity level of fishing incidents considerably and a decreased number of severe fishing incidents may eventually decrease insurance rates.

To study the relationship between safety factors and environmental conditions, the results from Rezaee et al. (2015a, 2015b, and 2015c) will be described in the following section.

6.2.2. The Effects of Extreme Environmental Conditions on Fishing Safety

Rezaee et al. (2015a) focused on the relationships between fishing incident rates (i.e. number of fishing incidents over related fishing traffic) and extreme environmental factors in Atlantic Canada. The environmental factors were chosen based on the related literature and experts' opinions, and comprise wind speed, air and sea surface temperature, precipitation, ice coverage and Laplacian of pressure. Several statistical methods were applied to the data sets and the following results were obtained:

- On stormy days, lower air temperature, higher ice coverage, and strong winds will increase fishing incident rates.
- Low sea surface temperature, and high wind speed are critical weather factors in winter.
- Low sea surface temperature, high ice coverage, and heavy rain are significant weather conditions for fishing incident rates in spring.
- Wind speed is the main weather factor that affects safety in summer and wind speed and high Laplacian of pressure may lead to risky situations for fishing incidents in the fall.

Rezaee et al. (2015b) investigated the effects of environmental conditions after an incident happens (i.e. incident consequences which can be severe or non-severe). The results are summarized as follows:

- High Laplacian of pressure, low sea surface temperature, and strong wind speeds are significant weather factors in severe incident occurrences (i.e. life loss and/or total damage to the vessel)
- Shrimp and herring roe fisheries are more vulnerable to intense storms (i.e. high Laplacian of pressure).
- Strong wind speeds and low sea surface temperature can cause severe incidents for Groundfish fishers.

- Ice coverage is the critical environmental factor in the severity level of seal fishing.
- Scallop fishing and lobster fishing are at danger of severe incidents when the Laplacian of pressure is high (i.e. intense storms). (Rezaee et al, 2015b).

Rezaee et al. (2015c) proposed a general framework to study the effects of climate change on fishing safety. Intensity and frequency of storms hitting Atlantic Canada were chosen as predictors of fishing incident rates. Comparing the estimated fishing incident rates in 2081-2099 to the historical records from the years 1980-2005 in the area of interest showed a great of deal of similarity between the spatial distributions of incident rates in these two periods. Figure 6-1 compares these two periods: White shows no change, blue indicates risk reduction by one class (i.e. medium to low or high to medium), orange implies risk increase by one class, and red shows risk increase by two classes (i.e. low to high) in 2081-2099 compared to 1980-2005. Based on this figure, one can conclude that generally the shorelines around New Brunswick and Gulf of St. Lawrence could experience an increase in fishing risk due to climate change effects. However, it must be noted that this study only adopts frequency and intensity of storms as fishing safety predictors, whereas including more determinants, such as air and sea surface temperature, vessel characteristics, fisheries location, etc., could result in more accurate estimations of impacts.

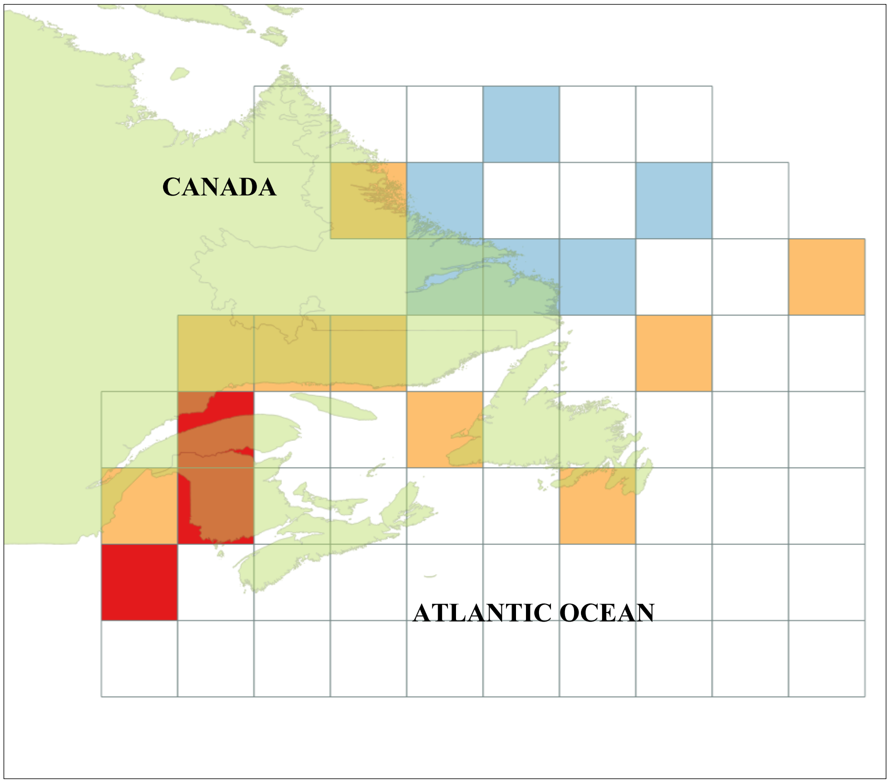

Figure 6-1.Differences between incident rates classes in 1980-2000 and 2081-2099 based on ERA-Interim Reanalysis product storm simulation. White: no difference, blue: risk reduction by one class (i.e. medium to low or high to medium), orange risk increase by one class, and red risk increase by two classes (i.e. low to high) in 2081-2099 compared to 1980-2000.

When climate change is studied, it is also necessary to consider annual variations in the frequency and intensity of storms. These factors differ for each individual year in that period and some years may be particularly harsh. This dynamic characteristic of storms can lead to high fishing incident risks in some years despite the average over longer periods remaining steady.

6.3. Process of Linking Research Findings to Safety Factors

This step attempts to reveal relationships between safety factors and significant environmental conditions in fishing safety. These relationships will be employed to recommend improvements in fishing policies and regulations.

Each of the significant environmental factors in fishing incidents (listed in section 6.2.2) might affect safety factors (listed in section 6.2.1) directly or indirectly. For example, strong wind speed can affect stability, complicate search and impede timely rescue. Working in strong winds can be stressful and add to fatigue. Low temperature can worsen the situation of a person in the water and lead to serious injuries; this brings attention to the importance of proper insurance for risky fisheries (smoothing the recovery phase if an incident happens). Low sea surface temperature causes cold shock and drowning would be inevitable for a person in water without a personal floating device even in calm seas. Ice coverage can trap vessels and cause damage to the hull, which signifies the importance of communication, search and rescue and insurance. Precipitation lowers visibility, may affect communicating devices and add to the fatigue of crewmembers. The Laplacian of pressure is an indicator of intense storms which implies strong winds, heavy rains, and changes in temperature, therefore vulnerability towards strong storms can affect vessel stability, search and rescue planning, communication, and usage of insurance and personal safety equipment.

Table 6-1 summarizes the results from Rezaee (2015a) and (2015b) and shows the relationships between environmental and safety factors.

Table 6-1. The relationship between environmental and safety factors.

Environmental Factor	**Season**	**Fishery Type**	**Safety Issue (Direct effect)**	**Safety Issue (Indirect effect)**
Wind Speed	• Winter • Summer	• Groundfish • Scallop • Lobster	• Stability • Search and Rescue	• Fisheries Management • Safety Information and Culture • Weather Forecast • Fatigue • Training
Air and Sea Surface Temperature	• Winter • Spring	• Groundfish	• Insurance • Safety Equipment	• Fisheries Management • Safety Information and Culture • Weather Forecast • Fatigue • Training
Ice coverage	• Spring	• Seal	• Stability • Search and Rescue • Communication • Insurance	• Safety Information and Culture • Weather Forecast • Fatigue • Training
Precipitation	• Spring	--	• Communication • Fatigue	• Safety Information and Culture • Weather Forecast • Training
Laplacian of Pressure	• Fall	• Shrimp • Herring Roe	• Stability • Safety Equipment • Search and Rescue • Communication • Insurance	• Safety Information and Culture • Weather Forecast • Training

Weather patterns may alter due to climate change. All the relationships listed in Table 6-1 should be reviewed periodically due to short term and long term climate change considerations and revised if necessary.

In the following section, recommendations are presented with respect to results from Rezaee (2015a, 2015b, and 2015c) and similar studies (Jin et al., 2001; Jin and Thunberg, 2005; Chatterton, 2008; Wu et al, 2008, 2009; and Niclasen, 2010), to modify Canadian policies in a way that general fishing safety is improved.

6.4. Output (Fishing Safety Policies)

Stability: Extreme environmental conditions, and the resulting poorer operating conditions are different in each part of the country and each fishery type (see Table 6-1); therefore, inspections should be customized based on the particular environmental characteristics of each location/fishery. However, these considerations should be periodically updated due to short and long term climate change effects. It is also important to increase awareness among fish harvesters about the role of stability in fishing vessel incidents and inform them about factors that can affect stability. Currently there are training courses on stability like the Fish SAFE Stability Education Program (Fish SAFE, n.d.) and Fishing Vessel Stability Simulator (CCPFH, n.d.). However, providing a more comprehensive and consistent training on stability all over the country, offered by TC and/or Fishers Associations, particularly for fishery types that are more vulnerable to strong winds (e.g. Lobster fishing), may decrease fishing incidents risks. Spot checks of fishing vessels' stability by TC can also improve safety, particularly if a vessel is modified or the location/target species of fishing has changed significantly since the previous inspection.

Fisheries Management: Including safety of fish harvesters in general, and extreme environmental conditions in particular, in fisheries management infrastructure can significantly reduce fishing risk. DFO's regulations can indirectly affect many safety related issues. Short fishing seasons can increase fatigue, lead to overloaded vessels (thus decreasing stability) and/or cause fish harvesters to stay out in harsh weather conditions. Adopting quota-based fishing programs instead of tightly specified fishing seasons gives more flexibility to fish harvesters and may improve safety especially as Table 6-1 shows that each fishery can be affected by different weather conditions. Involving fish harvesters in decision-making processes from the beginning, and considering the specific environmental conditions for each location in decision making, as well as updating this information periodically based on climate change effects, can also help manage fishing risk.

Weather Forecasts: Governmental agencies' (e.g. TC, EC, DFO, and CCG) support of research on more accurate weather forecasts, and research on the most effective ways to share forecasts with fish harvesters, could improve fishing safety. Additional regulations towards better adherence to good safety practices in case of storm warnings could improve fishing safety.

Fatigue: Increasing awareness about fatigue through public engagement programs and training courses provided by TC and Fishers Associations could better prepare fish harvesters for critical environmental conditions.

Safety Equipment: Several studies show that life-saving appliances may not be very easy for fish harvesters to use (Piniella, 2007; TSB, n.d.) so training courses offered by CCG, TC, and Fishers Associations on how to use this equipment in case of storms and improvements in life-saving appliance designs to increase the efficiency and ease of use would improve safety. More frequent and extensive inspections of this equipment by TC or provincial Fishers' associations is another action that can increase safety; however, there should be a cost-benefit analysis to find a balance between the cost of these inspections and the value they may add to safety. Furthermore, the issue of who would bear the cost is also another challenge for such policy changes. Improving awareness by fish harvesters about the critical role of the safety equipment in case of incidents particularly in stormy and cold weather can also save lives.

Communication: Encouraging all fishing vessels to carry radio-communication devices (SART, VMS, or AIS), even when it is not required by law, and training all crewmember on how to use these devices in case of an emergency (offered by CCG and Fishers' Associations) can improve fishing safety. TC's periodic inspection of equipment to make sure that it works efficiently in extreme weather conditions (heavy rain and storms) is also of high importance and can save lives.

Search and Rescue: CCG's support of research to determine hotspots of incidents based on short and long term weather patterns (research similar to that presented in Figure 1), and planning and allocating search and rescue resources based on the findings of related fishing safety research studies can save life, time, and money.

Insurance and Workers Compensation Boards: Despite the fact that insurance and Workers Compensation Board coverage is not directly related to safety, encouraging all fish harvesters (particularly the ones with more vulnerability to extreme weather such as shrimp and herring roe fishing) to have proper insurance would alleviate the potentially harsh consequences of incidents. The need for insurance is also an important consideration in case of climate change, since factors such as weather conditions and locations of fisheries may change and fish harvesters may encounter unfamiliar situations, which may contribute to the risks associated with the industry.

Safety Information and Culture: Knowledge mobilization, involving fish harvesters in decision-making processes from early stages of developing new policies and practices, and encouraging research programs on safety culture in all governmental and provincial fishing related organizations may improve overall fishing safety.

Training: Training courses on the stability of the vessels, the use of safety equipment in case of extreme environmental conditions, and technical topics can improve fishing safety effectively. TC, DFO, and provincial Fishers' associations could offer these training courses. To encourage all the fish harvesters to attend, the fee of these courses should be kept as low as possible.

Table 6-2 summarizes key safety related policies and recommendations (responsible agencies).

Table 6-2. Summary of key safety related policies and recommendations (responsible agencies)

Safety Issue	Current Policy	Recommendations
Stability	• Inspection at the time of (or close to) completion of a new vessel • Safety Booklet for large vessels	• Inspection based on updated extreme environment conditions and climate change effects (TC) • Training courses on stability (TC and Fishers' associations) • Spot checks (TC)
Fisheries Management	• Time, location, and effort intensity regulations in alignment with protection of fish stocks • Limitation on vessel sizes for some fisheries	• Quota-based fishing programs (DFO) • Involvement of fish harvesters in decision making process from the early stages (DFO) • Extreme weather consideration for individual fisheries, temporally and spatially (DFO)
Weather Forecasting	• --	• Support research on weather forecast improvements (TC, DFO, CCG, and EC) • Support research on sharing forecast information among fish harvesters (TC, DFO, CCG, and Fisheries' associations) • Increasing reliability and effective use of weather forecasts and warnings (EC)
Fatigue	• --	• Increase awareness (Fisheries' associations) • Training courses (Fishers' associations)
Safety Equipment	• Mandatory for all fishing vessels to carry safety equipment with respect to number of crewmembers	• Training courses on how to use the equipment in case of extreme weather (TC, CCG, and Fisheries associations) • Improvements in design of the equipment (TC) • Periodic inspection of the equipment (TC) • Increasing awareness among fishing communities (TC and Fishers' associations)
Communication	• Mandatory for large vessels	• Periodic inspections (TC) • Training for all crewmembers (CCG and Fisheries' associations) • Encourage use of radio-communication (SART, VMS, and AIS) for all vessels (Fishers' association and DFO)
Search and Rescue	• Responsibility of Canadian Coast Guard and Canadian Coast Guard Auxiliary	• Support research on operational and tactical resource planning with respect to extreme environmental conditions and climate change (CCG)

Safety Issue	Current Policy	Recommendations
Insurance and Workers Compensations Boards	• Mandatory for certain fisheries	• Encourage to have proper insurance coverage for all vessels (Fishers' associations and TC)
Safety Information and Culture	• --	• Knowledge mobilization (TC, DFO, and Fishers' associations) • Support research on safe work practices (TC, DFO, and Fisheries' associations) • Involvement of fish harvesters in decision making processes from the early stages (TC, DFO, and Fishers' associations)
• Training	• Mandatory for Masters and watchkeeping officers	• Consistent training courses on stability of the vessels; use of safety equipment in case of extreme environmental conditions, and technical topics for all crewmembers (Fishers' associations, TC, and DFO)

6.5. Moving Forward

6.5.1. Implications for Managerial Practice

Fishing safety literature demonstrates that there is a correlation between environmental factors and fishing incidents. To improve fishing safety and lower the consequences of incidents, it is of great importance to consider environmental factors and potential climate change scenarios in the context of fishing safety related policies and regulations. This study identifies different fishing vessel safety issues in Canada and discusses relationships between these safety factors and environmental conditions (see Table 6-2). However, this research examines the policies from a general point of view as it does not investigate all the details, exemptions, vessel characteristics, fishery types, regional infrastructures, and cost and benefit considerations. In this section we show how decision makers can utilize these recommendations to address safety issues, customized as needed for different fishing fleets, vessel types, and so on.

The following list presents some of the key questions that should be answered through ongoing research about each safety factor with consideration of weather conditions:

Vessel Stability: Wind speed and wave heights directly affect vessel stability and may lead to an incident. Hence, consideration of weather factors in stability inspections is a must, however it should be clarified whether:

- Is it necessary to update stability inspection procedures with respect to changing weather patterns in the particular area of interest? If yes, how often?
- Is there already sufficient training for fish harvesters to periodically inspect the stability of their own vessels? If not, is it economically and technically possible to train them to do periodic inspections of their vessels with respect to weather considerations? Is there any local organization other than TC (e.g. Fishers' association) that can help them on this subject?

Fisheries Management: Individual quota based management system allows fish harvesters to catch a specific amount of fish (measured by weight) in a given period of time. This management strategy would give flexibility to fish harvesters in choosing a good time for fishing (avoiding trips in harsh weather conditions). However, it is necessary to conduct a multi-stakeholder study that compares the advantages and disadvantages of quota based management from both ecological and safety perspectives for each fishery type. It is also important to create a comprehensive stakeholder engagement plan to involve fish harvesters in an evidence-based decision making process about fishing safety related strategies for each aspect of interest.

Weather forecast: New research studies show that people prefer probabilistic forecasts to deterministic forecasts in extreme weather conditions (LeClerc and Joslyn (2012); (2015)). There should be specific survey based studies to investigate what the best ways are to circulate weather forecast information to fish harvesters to support their decision making process for different fishery types, length of fishing trips, and fishing communities.

Fatigue: Extreme weather factors can add to fatigue; it is not hard imagine that it is harder to work in strong winds than calm weather, but it is necessary to measure these effects scientifically. Experimental studies can quantify the effects of weather factors in each region on fatigue, and subsequently crew work plans might be revised accordingly. Here are some sample questions:

- Does precipitation increase fatigue? Would it be safer to get to shelter as quickly as possible or would it be better to take more frequent breaks, depending on fishing location and distance to shore?

Safety equipment: There are numerous studies on how safety equipment can affect fishing safety. However there are still issues to be investigated regarding training fish harvesters on safety equipment such as: Is it beneficial (economically and practically) to train fish harvesters to inspect their equipment periodically? Is there any local organization other than TC or CCG (e.g. Fishers' association) that can help them on this subject?

Communication: There is a gap in the policy literature on how communication can affect fishing safety. There are some key questions to be answered in this respect:

- Is there any statistical change in fishing incident rates (and/or consequences) before and after usage of a communication device on specific vessel types or sizes or by fishery locations? The same questions can be posed particularly for incidents related to weather conditions?
- Will training crewmembers about communication devices improve safety considerably? What are the cost-benefit results in this regard?

Search and Rescue: Search and Rescue stations are mainly built to maximize the availability of various response resources and accessibility to incident hot spots. Search and Rescue stations are responsible to address all type of incidents (i.e. fishing, shipping, recreational boating, ferries, etc.) (Pelot et al, 2015). However, a comprehensive spatiotemporal study that tries to answer following questions would particularly benefit fishing safety:

- Where are new locations of fish stocks for different fisheries, and does this affect Canadian Coast Guard resource allocation?
- What are the potential weather patterns in different areas due to climate change? What are the effects of changing weather patterns on fishing safety?

Insurance: An empirical study should be conducted to examine the effects of insurance on fishing safety in an attempt to answer the following questions:

- How fishing vessel's insurance premium is calculated? What are the important factors affecting insurance market? How do fish harvesters evaluate the insurance rates?

- Does having insurance encourage fish harvesters to take more risk in extreme weather conditions? (What are their risk perceptions?)
- What are the different types of insurance? What is the best insurance plan for each type of vessel or fishery? Should insurance be obtained through large companies or small community based groups?

In conclusion, it is important to recognize the research gaps in different aspects of fishing safety related policies and ascertain these policies are in alignment with fishing safety research findings. Different entities (e.g. TC, CCG, DFO, NGOs, fishing communities, etc.) could be involved in addressing these research gaps to mitigate fishing risk. The methodology proposed in this paper can be customized and applied by these entities as needed.

6.5.2. Contributions to scholarly knowledge

In this research, current Canadian policies related to fishing safety factors are reviewed to examine whether they adequately address extreme environmental factors and climate change. The results showed that there is a gap between current practices and research findings. Therefore recommendations are made to highlight these gaps and improve fishing safety based on these findings. However, fishing related policies were reviewed from a general point of view and did not investigate all the regulatory details and exemptions. Addressing individual fishery types, vessel sizes, fishing communities, etc. would provide better links between understanding fishing policies and the implications of extreme environmental conditions. Future research studies that examine the relationship between weather factors and safety factors more deeply with respect to specific characteristics of a fishing safety system for a particular fishery type would be of high importance in improving fishing safety.

Chapter 7 Conclusion

7.1. Findings

This thesis has shown that there are statistically significant relationships between extreme weather factors and fishing incidents in Canadian Atlantic Waters. To explain these relationships, this dissertation structure is formed on a risk framework suggested by Brooks and Pelot (2008). Based on this framework, a fishing incident is defined as a discrete event in time that is proceeded by hazards (environmental conditions) which has immediate and ensuing consequences (life loss, total damage to the vessel, minor injuries, etc.).

This study is focused on providing information that could help decision makers to interfere with the system (prevent and detect fishing incidents when extreme weather conditions are anticipated), strengthen the system (decrease vulnerability of fishing industry towards extreme weather conditions) and lower the severity of immediate and ensuing consequences of fishing incidents (provide timely and proper response in case of extreme events). The objectives of this thesis can be summarized as follows:

1. To reveal the existing relationships between extreme environmental conditions and fishing safety;
2. To show changes in fishing safety over time due climate change effects;
3. To present recommendations on how fishing safety can be improved with respect to findings from points 1 and 2.

To achieve these objectives the following questions have been asked and several statistical methods were applied to provide answers to these questions. It must be noted here that this research was conducted for an area of interest on the east coast of Canada (Canadian Atlantic Waters), and the specific results may not apply elsewhere, but the approach could be replicated in other regions.

Do the environmental factors have any effect on the level of fishing activities (i.e. traffic amount)? Yes they do. Negative Binomial Regression and Random Parameters Negative Binomial Regression methods were used to determine if there is a relationship between fishing activity levels and any or all of air temperature, sea surface temperature, wind speed, precipitation, ice coverage, and Laplacian of pressure. Individual models were developed for specific situations including for cyclone weather conditions exclusively (i.e. Laplacian of pressure is greater than 0), for the four seasons (winter, spring, summer, fall), and for different size vessels notably vessel length-class 1 (i.e. less than 35'), vessel length-class 2 (i.e. between 35' and 45'), vessel length-class 3 (i.e. between 45' and 65'), and vessel length-class 4 (i.e. greater than 65'). The study period included years 2005 to 2010.

The results showed that fishing activity levels decrease when weather conditions deteriorate in all the models that were developed. When cyclone weather conditions are studied specifically, sea surface temperature, Laplacian of pressure, ice concentration, wind speed, and precipitation are the statistically significant environmental factors. During the winter season, sea surface temperature, ice concentration, wind speed, and precipitation are the significant environmental factors. In the spring, air temperature, Laplacian of pressure, ice concentration, and wind speed become critical. Summer related weather factors are the same as the spring ones, except for ice concentration which is not a factor in summer. In the fall, air temperature, ice concentration, and wind speed are significant.

When considering vessel length, air temperature, wind speed and ice concentration are the significant environmental factors for small fishing vessels. Medium size vessels are mostly affected by sea surface temperature, Laplacian of pressure, wind speed, and ice concentration. Traffic levels of vessels with overall length greater than 45 feet are only affected by ice concentration.

Do the environmental factors have any effect on the occurrence of commercial fishing incidents? Yes they do; however, the traffic level is a more significant factor in fishing incident occurrences than environmental factors. Zero-Inflated Negative Binomial Regression was used to determine the relationship between fishing incidents, environmental factors (similar to the preceding question), and fishing traffic levels (as a predictor of fishing incidents) for cyclone weather conditions specifically, and for the winter, spring, summer, and fall. The study period included years 2005 to 2010.

The results indicate that traffic is the most significant factor in fishing incident occurrences in all of the count models. It was also shown that it is more likely for incidents to happen during calmer weather (i.e. higher air and sea surface temperature, lower wind speeds, lower amount of precipitation, and ice concentration) than extreme weather conditions. One potential explanation for this phenomenon is the strong correlation between traffic and incidents. Traffic levels increase in calm weather conditions and, as a consequence, the likelihood of having an incident increases as well. The results of zero-state models also show that when air temperature is low, it is likely that no incidents happen because of little exposure (i.e. almost no fishing activity). To isolate the effects of environmental conditions, fishing incident rates (number of incidents per number of fishing trips) were studied as the next step.

Do the environmental factors have any effect on the fishing incident rates (incident frequencies relative to the traffic amount)? Yes they do. Fractional Logistic Regression, Negative Binomial Regression, and Random Parameters Negative Binomial Regression were applied for various situations including cyclone weather conditions, winter, spring, summer, and fall. The resulting significant environmental factors are the same as in the previous question. The study period included years 2005 to 2010.

When studying incidents associated with a cyclone, it was shown that lower air temperature, higher ice concentration, stronger wind, and higher Laplacian of pressure will result in higher incident rates. In wintertime, incident rates increase with lower air temperature and stronger winds. In the spring, sea surface temperature, ice concentration, and precipitation are chosen by the Random Parameters model as significant weather factors. The results from the summertime are complicated. The Fractional Logistic Regression results show that incident rates increase when air temperature decreases. The results of the Random Parameters model indicate that stronger wind speed will result in higher incident rates. However, Fixed Negative Binomial Regression resulted in no statistical relationship between incident rates and weather factors during the summer. One can explain these results based on the opening of fishery seasons and the presence of recreational boating traffic in the ocean. Opening of the fisheries means long work hours and hard labour in a very competitive and stressful job situation. All of these factors may lead to increased incident rates regardless of weather factors. During this season, there may also be collisions between inexperienced boats and fishing vessels which is also not particularly tied to weather conditions. Finally in the fall, sea surface temperature, wind speed, and Laplacian of pressure are shown to be significant. The general conclusion is that extreme environmental conditions (i.e. lower air and sea surface temperature, stronger winds, higher ice concentration, and intense storms) can increase incident rates. However different weather factors are shown to be statistically significant at different times of the year. Precipitation is also found to not be significant most of the time.

Do the environmental factors have any effect on the severity level of commercial fishing incidents? Yes they do. Logistic Regression was used to determine the relationship between extreme environmental factors and the severity of fishing incidents for several models: Entire database (regardless of weather conditions and fishery type), cyclone weather conditions, joint model that uses fishery type as a dummy variable, and finally individual fishery types (i.e. shrimp, herring roe, groundfish, seal, lobster, scallop, and crab fisheries). The study period included years 2000 to 2010.

The results show that when the entire database, regardless of a cyclone happening or not, is examined, ice concentration becomes a significant factor along with wind speed, sea surface temperature, and darkness. However, when only incidents associated with a cyclone are taken into account, ice concentration as a significant predictor is replaced by cyclone intensity and actually ice is not even a statistically relevant factor anymore. Sea surface temperature and wind speed are shown to be significant weather factors in the model, with fishery type as a dummy variable (whereby shrimp fishing is used as the reference fishery type). Results show that seal fishing is the only fishery more risky than shrimp fishing. The outcomes from the individual fishery type models show that weather factors can have different effects on severity for different fishery types, which is likely related to the environment they work in, their distance from shore and the characteristics of their vessels. Shrimp and herring roe fisheries are vulnerable to intense storms (i.e. high Laplacian of pressure), groundfish fishing is affected by strong wind speeds and sea surface temperature, seal fishing is only affected by ice coverage, and scallop and lobster fishing are risky in high winds. Severity levels of crab fishing incidents are not significantly related to environmental conditions.

Does climate change have any effect on commercial fishing safety? Yes, it does in some locations. A framework was proposed to quantify fishing incident risks with respect to climate change effects. The framework was then applied using fishing incident data (2000-2005), historical vorticity data (1980-2000), and potential climate change scenarios (2081-2099) in Atlantic Canada. Intensity (i.e. vorticity) and frequency of storms hitting the study area were chosen as predictors of fishing incident rates.

Comparing the estimated fishing incident rates in 2081-2099 to 1980-2000 in the area of interest showed a great of deal of similarity between the spatial distributions of incident rates in these two periods. Based on the results, generally the shorelines around New Brunswick and the Gulf of St. Laurence would experience increase in fishing risk due to climate change effects.

When climate change is studied, it is also necessary to consider annual variations in frequency and intensity of storms. In other words, the overall trends over a period can be different for each individual year in that period, with some years being particularly harsh.

This inter-annual variability in the characteristics of storms may lead to high fishing incident risk in some specific years.

How can these results be put into practice? A knowledge mobilization structure was suggested to improve and update fishing policies with respect to fishing safety and environmental conditions. Significant risk factors that may need improvements in Canada were extracted from the relevant literature. The list comprised stability of vessels, fisheries management practices, safety equipment, communication, insurance, training, safety information and safety culture, weather forecasts, crew fatigue, and search and rescue planning. Policies related to these issues were reviewed to examine whether they address extreme environmental conditions and climate change. Finally recommendations were presented to improve general fishing safety with respect to short and long term environmental considerations.

7.2. Contributions

The contributions of this study involve three facets: the research aspect, the modelling developments, and the practical applications.

7.2.1. Research aspect

Numerous studies have been carried out on fishing safety, however, nobody up to the time of this research has studied the statistical relationships between cyclone characteristics and commercial fishing safety. This research provides answers to the questions of whether cyclones can affect fishing traffic levels, fishing incident occurrence, and fishing severity level, by means of advanced statistical models. In addition to that, this research proposes a general framework to estimate fishing incident rates and highlight variations in risk towards the end of century based on potential climate change scenarios. No one up to the time of this study has addressed fishing incident risk estimations due to climate change effects.

7.2.2. Model development

Databases used in this study were gathered from different sectors and projects, covering various time spans, geographic locations, resolutions, and time frequencies. This research transforms all these data to a consistent framework to perform the analysis and ensure that they are accurate and compatible with each other in terms of the requirements of the statistical analyses. It also adopts advanced statistical analysis methods such as the Random Parameters Models to reveal the underlying relationships between environmental factors and fishing incident rates and activities. These methods, unlike traditional ones that treat parameters as constant across observations, considers the unobserved heterogeneity among observations. Hence the models are more complicated than traditional ones, but they are statistically better fit for the data and are more explanatory in terms of relationships between predictors and dependent variables.

7.2.3. Practical application

These findings of the research provide a better understanding of impacts of the environmental on fishing activity level, incident rates and severity of fishing incidents and also highlights risk variations due to climate change.

These results can be instructive for preventive measures, such as changing the regulations for commercial fishing season openings if certain weather conditions are deemed unacceptable, or better education of mariners leading to improved decision-making with respect to weather conditions. Since different weather factors can affect different fishery types, this information can provide useful inputs for boat design or for the issuance of specific warnings for individual fishery types. Providing fish harvesters with this kind of information may help them be better equipped for high risk situations. Search and Rescue planning can also be reviewed, with better anticipation of severe incident occurrences as a function of the weather forecasts generally and storm warnings in particular.

To present findings from this research to decision makers, in addition to using effective visualization tools and statistical reports, this research proposes a general knowledge mobilization framework to improve fishing safety policies with respect to weather considerations. The outcomes of this research are also inputs to ongoing work on fishermen's perception towards weather factors, which can help to increase awareness among fish harvesters and foster a safe work practice culture among them.

7.3. Limitations

Due to the nature of this study, that is a data-driven statistical analysis based on historical data, the quality of data obtained and the methods to process the data impose limitations on the results from the study.

7.3.1. Data Accuracy Limitations

The biggest challenge of this research is not having access to the real-time data. The incident records in the SISAR database do not have accurate weather conditions at the time of incident, and all the weather data is modelled and assumed to be a good representation of the conditions at the time of the incident, which may not be true in some cases.

The traffic data is also not real-time data but is generated by connecting reported latitudes and longitudes of a fishing vessel's locations via straight lines in chronological order. However vessels may not move in straight lines all the time. Not knowing the actual path of a fishing trip also restricts our capability to calculate length of fishing trips in each grid. In addition to that, the traffic data is a subset of the VMS dataset and not all the fishing vessels are required by law to carry a VMS device on board. Therefore, this dataset may not represent comprehensive traffic data of small fishing vessels.

The SISAR database does not include enough data on vessel sizes and the provided VMS dataset does not have information on fishery types. Hence it wasn't possible to develop fishing incident rate models for various vessel sizes or individual fisheries.

Since some minor fishing incidents can be managed with the help of other nearby fishing vessels, there is a probability that these incidents may not be reported to CCG. Therefore the SISAR database may not represent all fishing incidents in the study area.

Fog (indicator of visibility) is considered as an important safety factors by fish harvesters in literature, however up to the time of this study, fog data is generated based on the modelled weather data, so due to dubious quality of the data it was decided not to use these kind of factors.

7.3.2. Data Availability Limitations

Although the SISAR dataset includes a field named "Primary cause of the incident", the completion rate of this field is very low. Therefore it is not possible to separate incidents which occurred due to environmental conditions from non-environmental conditions. Furthermore, in some cases even if environmental conditions may not be the "primary" cause of an incident, they may have a role in incident occurrence or consequences. For example the primary cause of an incident can be indicated as fatigue; however, fatigue might be intensified by harsh weather condition. Therefore, the quality of the current datasets doesn't allow is to isolate fishing incidents, which are associated with environmental conditions from other factors (i.e. considered as noise in our model).

When the effect of climate change on fishing safety is studied, it is assumed that nothing will change except weather patterns. However this may not be true and fish stock locations, vessel characteristics, fishing methodologies, and fishermen's risk perception may change accordingly. These factors and other significant environmental factors such as air temperature, ice coverage, etc. in the late-century period of interest were not available at the time of this study.

In general, data limitations on variables arise due to several reasons:

- The variable is not measured or no data are collected (or estimated) on the variable. Some examples are estimated precipitation, temperature, and new location of fisheries in the future in related literature, fishers' ages or experience levels in the SISAR database, and lobster fishing activity levels in the VMS dataset.

- Data collected on a variable doesn't possess the essential quality for statistical analysis. Some examples are weather conditions at the time of fishing incidents and vessel characteristics such as vessel length and vessel age in the SISAR database.
- Data are collected on the variable but the data availability is restricted due to legal and policy considerations. Some examples are fishery types in the VMS dataset which are not available for safety related studies, or the vessel licencing database which can be used to extract information on vessel characteristics through cross-referencing with the SISAR database and/or the VMS database. This database is not available for safety related studies.

Some of these limitations can be overcome by changing regulation and policies. For example the CCG can make filling out vessel characteristics related fields mandatory in the SISAR database, and databases such as the Licensing database can be shared with researchers to extract useful information on vessel characteristics.

7.4. Future Work

Possible extensions of this work are listed as follows:

- Collecting more detailed and accurate real time data would be very helpful to pursue more work in this regard. Adding other environmental factors such as fog, wave heights, etc. may also help to obtain a better understanding of fishing safety with respect to environmental conditions.

- The length of fishing trips can indicate the exposure of fishers to environmental conditions. Including these factors as one of the predictors of fishing incidents with respect to environmental conditions can lead to more realistic results and provide more insight into relative differences of risk of inshore, mid-shore, and offshore fisheries.
- In all the phases of this study, other contributing risk factors such as vessel characteristics and human error were deemed to be constant. Considering fishing safety as a system and studying the interaction between all the elements such as environmental factors, human factors, vessel related factors, etc. would provide more insight into fishing safety.
- This study did not distinguish among different locations of fishing due to data limitations. However doing spatial analysis combined with weather and traffic conditions would be a potential extension to this work.
- Adding more weather factors such as air and sea surface temperature, ice coverage, etc. to the climate change model output variables may help to achieve more accurate estimations of fishing incident rates in the desired period. Future work could also be dedicated to using climate projections for the near future (forecast for 5 to 10 years ahead) and study the dynamic behavior of fishing safety over time (i.e. comparison among past, current, near future, and longer time horizons)
- Fishing related policies were reviewed from a general point of view and did not investigate all the regulatory details and exemptions. Addressing individual fishery types and vessel sizes would provide better links between understanding of fishing policies and extreme environmental conditions.

- The relationship between fishers' perception and reality needs to be addressed in future work. Studies have shown that fishers perceive factors such as fog or precipitation as risky factors (Findlay, 1997); however, statistical methods have shown that these factors may not be statistically significant in fishing incidents (Wu et al., 2005; 2008, 2009; Rezaee et al, 2015a, 2015b). Revealing the reasons behind these differences can provide better insight into the driving factors of fishing incidents.

Appendix A- Supplementary Material

A.1. Support Vector Machines Method

Logistic Regression (LR) and Support Vector Machines (SVM) were used to examine how weather factors affect the severity of fishing vessel incident. However, the initial results showed that LR is a more appropriate method than SVM for the problem in hand. In this section, the SVM method, the outcomes of applying this method on the severity of incidents data, and the results of comparison between LR and SVM are explained.

Support Vector Machines (SVMs) are a set of supervised learning methods that can be used for classification and regression analysis. The main idea is to separate data with a hyperplane that has the largest minimum distance from all training data (i.e. largest margin).

In other words, the algorithm is looking for a linear classifier which is as far as possible from the closest members of both classes and separates the two classes. Points which are located outside of the hyperplane are called non-support vectors and data points which are located on the hyperplane are named support vectors.

Figure A-1 shows the principles of SVM. The objective here is to separate squares and circles. D(x) is the decision function for classifying data. Margins are represented by dotted lines.

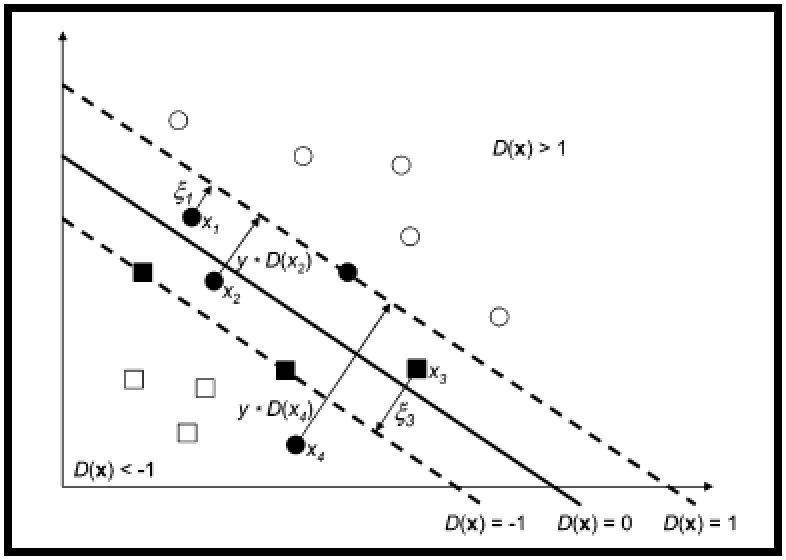

Figure A-71. Principles of SVM classification. Source (He and Ghodsi, 2010)

If the data are not linearly separable, a trade-off parameter is added to the model which minimizes the distance of misclassified points to the correct margin (i.e. ε in Figure A-1). The search for the optimal hyperplane is carried out through the following optimization problem (Hearst et al., 1998):

$$\text{Min } \frac{1}{2}\beta^T\beta + C\sum_i \varepsilon \qquad \text{(A-1)}$$

s.t.

$$y_i(\beta^T x_i + \beta_o) \geq 1 - \varepsilon_i \quad \forall \text{ for } i=1..n \qquad \text{(A-2)}$$

$$\varepsilon_i \geq 0 \qquad \text{(A-3)}$$

where β_o and β are hyperplane parameters, called weight and bias respectively, C is the trade-off parameter, and ε is the distance of each error point from its correct place. x_i is the training matrix, y_i is the label of the training data (i.e. severe or non-severe), and n is the number of training data points.

The above problem is a Lagrangian problem. The solution of this problem can be expressed as a linear combination of the training vectors:

$$\beta = \sum_{i=1}^{n} \alpha_i \; y_i x_i \tag{A-4}$$

$$\alpha_i \geq 0 \quad i=1..n \tag{A-5}$$

where α is the Lagrange multiplier.

Replacing β with the above equation, the dual form of the model will be the following:

$$\min \; \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i \, y_j \, K(x_i, x_j) - \sum_i \alpha_i \tag{A-6}$$

$$\text{s.t.} \;\; \sum_i \alpha_i y_i = 0 \tag{A-7}$$

$$0 \leq \alpha_i \leq C \tag{A-8}$$

where K represents the Kernel function which maps the not linearly separable data into another space where the data are linearly separable.

Since the distribution of severe incidents is skewed (the non-severe class has more records than the severe class) then the decision boundary is driven towards the rare class (i.e. it is biased to predict 0 rather than 1). To address this problem, the cost sensitive version of SVM was applied since it has a greater penalty for misclassifying the rare class than the zero class (Osuna et al., 1997).

A.2. Results

The hyper parameters for the SVM model are determined via tuning before running the model, using a grid search over given parameter ranges; for example if the Class Weight range is (0,5), provided by the analyst, the algorithm looks for the optimal weight in this range . Table A-1 shows the tuning of SVM.

Table - 7-1. SVM Parameter Tuning

SVM-Kernel (K)	$\exp(-\gamma * \lvert x_i - x_j \rvert^2)$
γ	0.0001
Cost of Constraints Violation (C)	1000
Class Weight-Severe	2
Class Weight-Non_ Severe	0.5

The Kernel function was chosen to be the Gaussian radial basis function. The value of this function is always between 0 and 1 and decreases with distance between x_i and x_j. γ is a free parameter of this function.

Table A-2 represents the results of LR and SVM applied to Model 1 (entire database) and Model 2 (incidents associated with cyclones, i.e. Laplacian of pressure>0).

Table 7-2. SVM and LR Results of Model 1 and Model 2

Model	**Chi-Square Test for LR**	**LR-Cross Validation error**	**LR-F1 Score**	**SVM-Cross Validation error**	**SVM-F1 Score**
Model 1	4.44e-25	0.12	0.58	0.15	0.6
Model 2	3.48e-09	0.13	0.58	0.15	0.62

The comparison between the SVM and LR results was carried out using two criteria: Cross-Validation and F1-Score. As shown in Table A-2 the cross-validation results of LR are better than SVM. This may be caused by assigning more weight to the severe class than the non-severe class in the SVM method which increases the number of false positives (i.e. non-Severe incidents which are classified as severe).

The F1-score is measured as follows:

$$F1 = \frac{2*\text{True Positives}}{2*\text{True Positives}+\text{False Positives}+\text{False Negatives}} \tag{A-9}$$

Since the greater weight given to the severe class incidents in SVM increases the number of true positives and decreases false negatives, the F1-score for SVM is better than that for LR. But because the number of false positives are also increasing proportionally, this improvement is not considerable. Since LR is easier to interpret and it is more explanatory in terms of relationship between weather factors and fishing incidents, it was decided to only conduct LR for the rest of analysis.

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