Natechs and Climate Change: Wide-scale Spatial Modeling of the Occurrence Probability and Variability of Tropical Storm-Related Natech Events in the United States Under Various Climate Scenarios

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Natech 災害と気候変動：多様な気候シナリオの下での米国における熱帯低気圧を引き金とした Natech 事象の発生率と変動性に関する広範囲の空間モデリング

A dissertation submitted in partial fulfillment of the requirement for the degree of Doctor of Engineering

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Chapter 1 Natural Hazard-triggered Technological Accidents and Climate Change

1.1 Introduction

Technological accidents can affect human health, property, and the environment, and in some cases, can cause long-term and area-wide socioeconomic losses. The Chernobyl nuclear accident on April 26, 1986, demonstrated the powerful impact of technological disasters on local residents, as well as on neighboring countries and regions (International Atomic Energy Agency 2005). Even today, due to increasing wildfire risk in the Chernobyl Exclusion Zone, the contamination from the Chernobyl disaster could affect neighboring areas, through the release of radiation previously locked in the soil, leaves, and wood of local forests (Ludovici *et al*. 2020). Investigations have shown that Chernobyl was caused primarily by human factors (INSAG, 1992), although accidents like Chernobyl can also be caused by natural hazards. On March 11, 2011, a massive tsunami caused by the Great East Japan Earthquake engulfed the nuclear power plant in Fukushima. Subsequently, the three reactors experienced a total power shutdown, which meant that the reactor cooling systems were rendered inoperative, leading to meltdowns—which consequently led to seawater contaminated by radioactive materials being released into the Pacific Ocean (Hayashi and Hughes 2013). The wide-scale and long-term effects of the Fukushima nuclear accident remind risk managers, scientists, national and local governments, and broader populations that natural events can trigger technological accidents with serious consequences—even though such events are generally considered to be low-probability (Cozzani *et al*. 2014).

These natural hazard-triggered technological accidents are known as Natech accidents (Krausmann and Cruz 2013). This term was first used by Showalter and Myers (1992), when they were studying natural disasters as the cause of technological emergencies in the United States (US). The first research studies concerning Natechs were published in the 1990s, following earthquakes in California, in particular the Loma Prieta and Northridge earthquakes, in 1989 and 1994, respectively (Suarez-Paba *et al*. 2019). Currently, research interest has shifted toward hydrometeorological-related Natechs, because of their increasing prevalence. Among meteorological hazards, tropical storms (TSs) are increasingly prone to triggering Natech events. According to studies analyzing past Natech events using the National Response Center (NRC) database, more than 70% of such events up to the end of 2008 were attributed to meteorological hazards (Sengul 2005; Sengul *et al*. 2012). In the study by Sengul (2005), the author extracted Natech event-related reports by combining two accidental release databases—the Incident Reporting Information System (IRIS), and the Emergency Response Notification System (ERNS). From this, 9,257 chemical release incidents—constituting 1.5% of all chemical releases that occurred in the US over the period 1990–2003—were identified as Natech events. Later, in an extended study by Sengul *et al*. (2012), by the end of 2008, the percentage of

Natech events had doubled, to the point where they represented 3% of all chemical release incidents reported to the NRC up to 2008. Among these increased Natech events, hurricane-related Natech events increased 15-fold, compared to the number before 2005. In another study, Girgin and Krausmann (2014) examined Natech accidents involving pipelines, based on reports from the NRC database, and pointed out that the 2005 peak in the yearly reporting could be attributed to hurricanes Katrina and Rita (Girgin and Krausmann 2014).

Necci *et al*. (2018) reviewed Natech data recorded in multiple European databases used to collect chemical release incidents. They found that the number of storm-related Natech event reports was increasing, and that most of the storm hazards were referred to as cyclones or tropical cyclones (Necci *et al*. 2018). Thus, the question arises as to why the number of tropical storm-related Natechs are increasing.

Cruz and Krausmann (2013) proposed that climate change might be causing these observations. In their study, the authors noted that climate change may affect the incidence of Natech events by affecting the frequency and severity of the hydro-meteorological hazards that can trigger chemical releases. At present, it is often suggested that climate change[1] affects not only atmospheric and oceanic phenomena (Jevrejeva *et al*. 2003; Viles and Goudie 2003; Cohen and Barlow 2005), but is also influencing the formation, intensity, frequency, and associated characteristics of related natural phenomena (Elsner 2006; Mann and Emanuel 2006; Seidou *et al*. 2012; Mudd *et al*. 2014a; Ting *et al*. 2019; Marsooli *et al*. 2019; Pugatch 2019; Ebad Sichani *et al*. 2020). In the studies of Mudd *et al*. (2014a, b) and Ting *et al*. (2019), it was suggested that more intense and larger hurricanes might be formed in the future, due to climate change. It has also been suggested that climate change may lead to more and heavier rainfall during tropical storms (Pugatch 2019; Walsh *et al*. 2019), and that more frequent extreme events may occur (Dankers and Feyen 2008; Zscheischler *et al*. 2018; Olivera and Heard 2019). Other studies have found that the moving speed and paths of tropical storms could also be affected by climate change (Kossin *et al*., 2014; Chan, 2019; Collins *et al*. 2019; Hassanzadeh *et al*. 2020; Yamaguchi *et al*. 2020; Zhang *et al*. 2020). This means that the spatial and temporal distribution of tropical storm impacts may also change in a changing climate; hence, the exposure of installations and infrastructure which handle hazardous materials could also change.

While the vulnerability of exposed installations may change over time, due to aging installations, changes in construction codes, and safety regulations, it is worth exploring whether the incidence of tropical storm-related Natech events (TSNatech), may be affected indirectly by the influence of climate change on tropical storm activity (shown as Figure 1–1). If climate change does have an impact on the occurrence of TSNatech, it is necessary for risk managers, governments, facility owners, and other stakeholders to understand such connections, if they are to successfully develop and implement improved Natech risk reduction strategies.

Furthermore, being able to estimate the probability of TSNatech for the future, by considering the impacts of climate change, could be an important input for Natech risk managers, in their efforts to improve their Natech risk management planning over the longer term. These efforts need to be

[1] In this study, we followed the definition of climate change made by the Intergovernmental Panel on Climate Change (IPCC), which is: *"Any change in climate over time, whether due to natural variability or as a result of human activity."*(IPCC 2007).

made based on understanding the connection between TSNatech occurrence and climate change—however, there have not been any studies investigating this connection. Thus, in this research, we focused on determining the connection between climate change and TSNatech occurrence, and in analyzing variations in TSNatech probability under future climate scenarios. By analyzing the incidence of TSNatech, we expect that this work will contribute to quantifying the potential effects of climate change on the occurrence of—and variations to—Natech events.

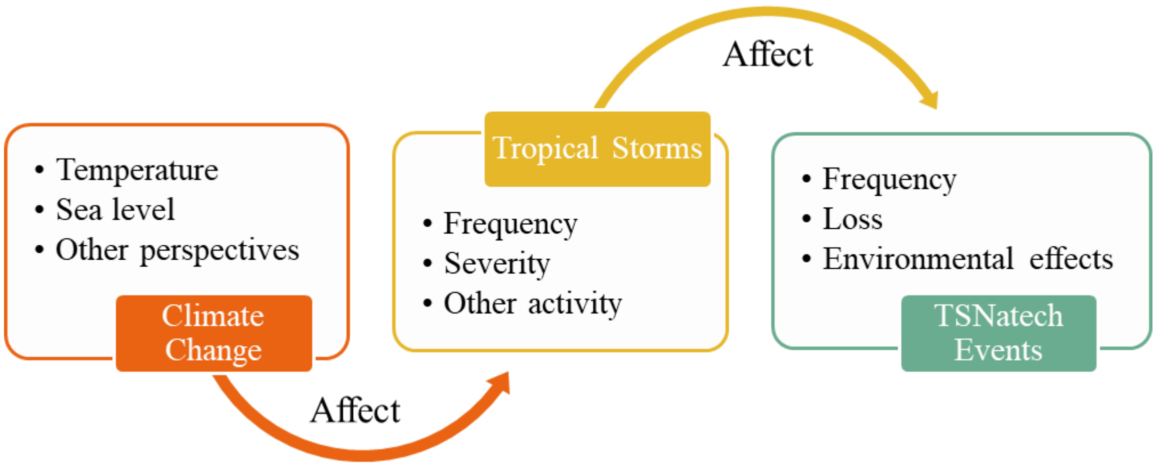

Figure 1–1 The potential connection between climate change, meteorological hazards, and Natech events

1.2 Research Aim and Objectives

The overall aim of the work described in this dissertation was to determine the impact of climate change, if any, on TSNatech occurrence, and to provide an outlook on how this may affect TSNatech in the future. The results of this study can help risk managers and stakeholders involved in Natech risk management to take the effects of climate change into consideration when developing and implementing risk reduction strategies. The objectives of our work were to:

1) Develop a method for efficiently retrieving Natech and TSNatech records from the NRC database;
2) Use spatial and statistical analyses to examine temporal–spatial variations in retrieved TSNatech events;
3) Analyze the data for potential links between climate change and temporal–spatial variations in TSNatech events;
4) Identify a suitable index and develop a method to quickly estimate TSNatech probability from a spatial perspective; and
5) Estimate the probability of TSNatech in the future, using scenario-based climate simulation data.

1.3 Research Methodology

To achieve the research objectives of this study, we decided that US provided the most suitable study area (Figure 1-2). Firstly, statistical analysis of the NRC database, which is managed by the US Coast Guard, and is the largest chemical release incident database, could provide a long-term record and large sample set of Natech records. Also, the National Oceanic and Atmospheric Administration (NOAA), the US Geological Survey (USGS), the Earth Science Data Systems (ESDS) program provided by the National Aeronautics and Space Administration (NASA), and other open source database could provide the climate metadata necessary to determine climate state, and to analyze relationships between climate change and TSNatech. In addition, many other publications about Natech events, tropical storms, and climate change—which could provide excellent gray literature support for this study—were available in the US.

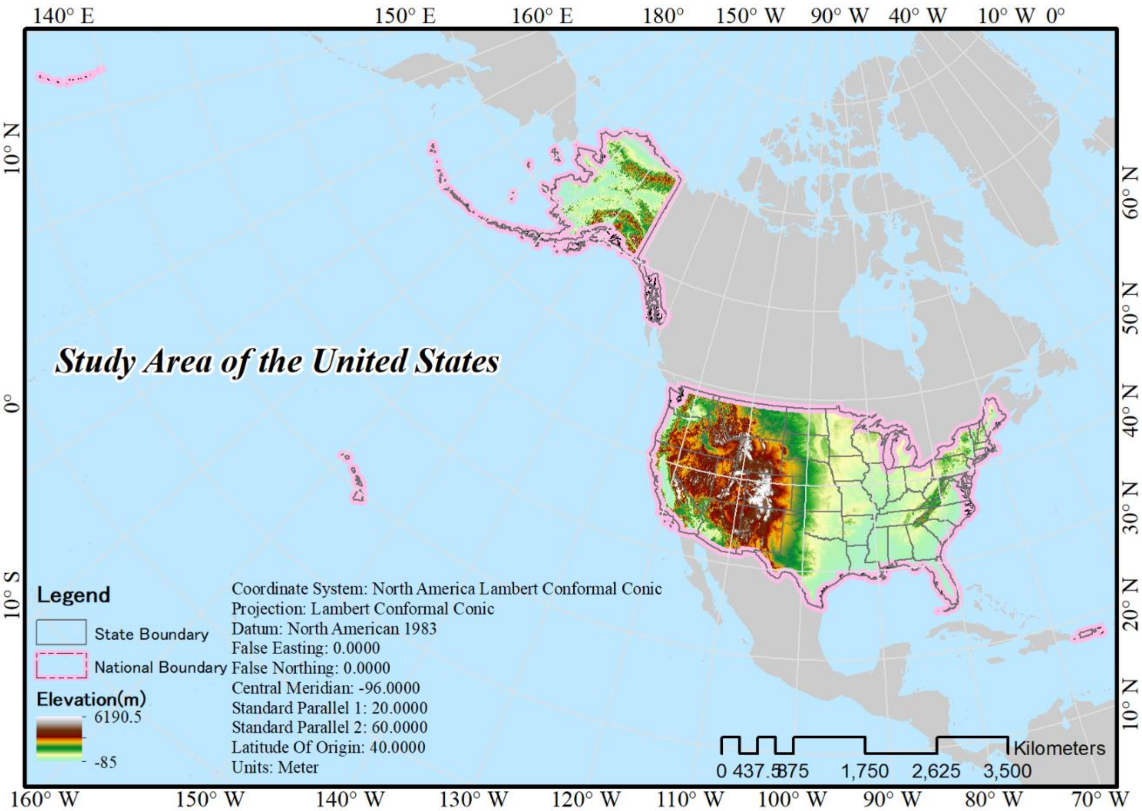

Figure 1–2 Study area

The first step in this study was data collection. Chemical release incident data for 1990–2017 were downloaded from the NRC database website, resulting in a data set of >800,000 records. Historical data on climate, tropical storm, industrial installations, and other basic geographic data covering the same period were collected from the websites of the above institutions, and climate simulation data based on different socioeconomic development scenarios were downloaded from the World Climate Research Programme (WCRP) website.

As the NRC database included information on chemical release incidents, as reported by any US citizen, and Natech events are only a small part of such a large database, our next step was to filter out Natech event data. Using the fields "incident description" and "incident cause," in which the incident cause and how it occurred are recorded in English, deep learning methods were introduced to analyze the dataset using these two fields—which resulted in potential Natech events being retrieved. By comparing the output to results achieved by a keyword extraction method, reducing duplicate records, and further cleaning, Natech-only event data were extracted from the NRC database, together with the data on the associated causal natural phenomena.

Subsequently, the retrieved Natech records were further cleaned by spatially analyzing the tropical storm data, to generate TSNatech data of interest. Then, Mann–Kendall trend analysis, wavelet analysis, and intensity analysis methods were employed, to determine temporal–spatial variations in TSNatech incidence (including numbers and probabilities). We also applied cross-wavelet analysis, to analyze relationships between climate indices and TSNatech frequency. Through systematic analysis of regulation changes, the temporal–spatial variation of industrial installations, and the cross-wavelet analysis results, we found that climate change might be the most important factor causing such variations.

In the next step, the annual probability and conditional probability of TSNatech were estimated spatially, to clarify the temporal characteristics related to these probabilities. After determining the increasing trends in event annual and conditional probabilities, we found that wind energy could be an important variable for estimating the probability / conditional probability of TSNatech, by building fragility curves. At this point, we also developed a fragility analysis method to estimate TSNatech occurrence probability for periods of interest.

Using the proposed estimation method and climate data provided by the WCRP, TSNatech probability was estimated for the periods 1990–2017 and 2021–2100. We found that any global warming would be likely to increase the number of TSNatech occurrences, while taking different socioeconomic development pathways could change TSNatech event probability outcomes. Finally, based on the main findings of this study, we have provided recommendations on how to take potential climate change effects into account, when trying to develop better TSNatech risk management.

1.4 Thesis Structure

In this section, the structure of this seven-chapter dissertation has been briefly presented, with the main content and tasks for each chapter (and their inter-connections) illustrated in Figure 1–3. A more detailed explanation of each chapter is provided below.

In Chapter 1, we have provided a brief introduction to Natech events and climate change. After posing our research questions, the main research objectives and overall goals of this study have been presented, with the methodology and dissertation structure discussed at the end of the chapter.

We have presented a literature review of previous studies related to TSNatech, climate change, and their relationships, in Chapter 2. Here, gaps in TSNatech research and its relationship with climate change have also been identified, and a pathway for developing new works to fill the gaps proposed.

The main outputs from Chapter 2 were the analysis and explanation of the connection between climate change and TSNatech, and development of new methods to analyze how TSNatech occurrence may change in a changing future climate.

In Chapter 3, we have described development of a deep learning method-based Natech extraction framework—the Semi-intelligent Natech Identification Framework (SINIF)—and the procedure for using this to retrieve Natech event data, together with their natural hazard causal factors. Approximately 32,841 Natech reports, covering events from 1990–2017, were extracted from the NRC database, and we found that the majority (97.85%) were related to meteorological phenomena, with hurricanes (24.41%), heavy rain (19.27%), and storms (18.29%) being reported as the main causes.

In Chapter 4, we have analyzed temporal–spatial TSNatech variation, using the Natech event data set identified in Chapter 3, based on analysis of past tropical storm data. A series of statistical and spatial analysis methods was applied, and spatial statistical analysis methods used, to analyze these temporal–spatial incidence variations. In order to explore causation for such changes, we investigated relationships between temporal and spatial variations in the incidence of tropical storm-related Natechs, as well as in accumulated cyclone energy, the North Atlantic Oscillation (NAO) index, the Oceanic Niño Index (ONI), and other variables. The results suggested links between climate change and temporal–spatial variations in the incidence of related Natechs, due to its effect on tropical storm activity.

In Chapter 5, we have presented a procedure for using spatial analysis to analyze probability / conditional probability trends related to TSNatech on a regional basis. Then, using these outcomes, fragility curves to describe the conditional probability of TSNatech, based on TS wind energy, have been developed. The results suggested that both the probability and conditional probability of tropical storm-related Natechs have been increasing, and that wind energy of tropical storms represented is found to be a good estimator of the conditional probability of tropical storm-related Natechs, from a regional perspective.

In Chapter 6, we have introduced a methodology for estimating TSNatech probability for 1990–2017 and 2021–2100, respectively, based on the estimation method presented in Chapter 5. By estimating TSNatech probability based on ScenarioMIP data, which were simulated using scenarios of shared socioeconomic pathways, we found that TSNatechs have much higher probabilities of occurrence in the future—with global warming one potential cause of such increases. We were also able to determine that TSNatech probability may change if different socioeconomic development pathways are pursued.

The main findings and limitations of this study have been summarized in Chapter 7, which also contains recommendations developed from reviewing our results, and for future work.

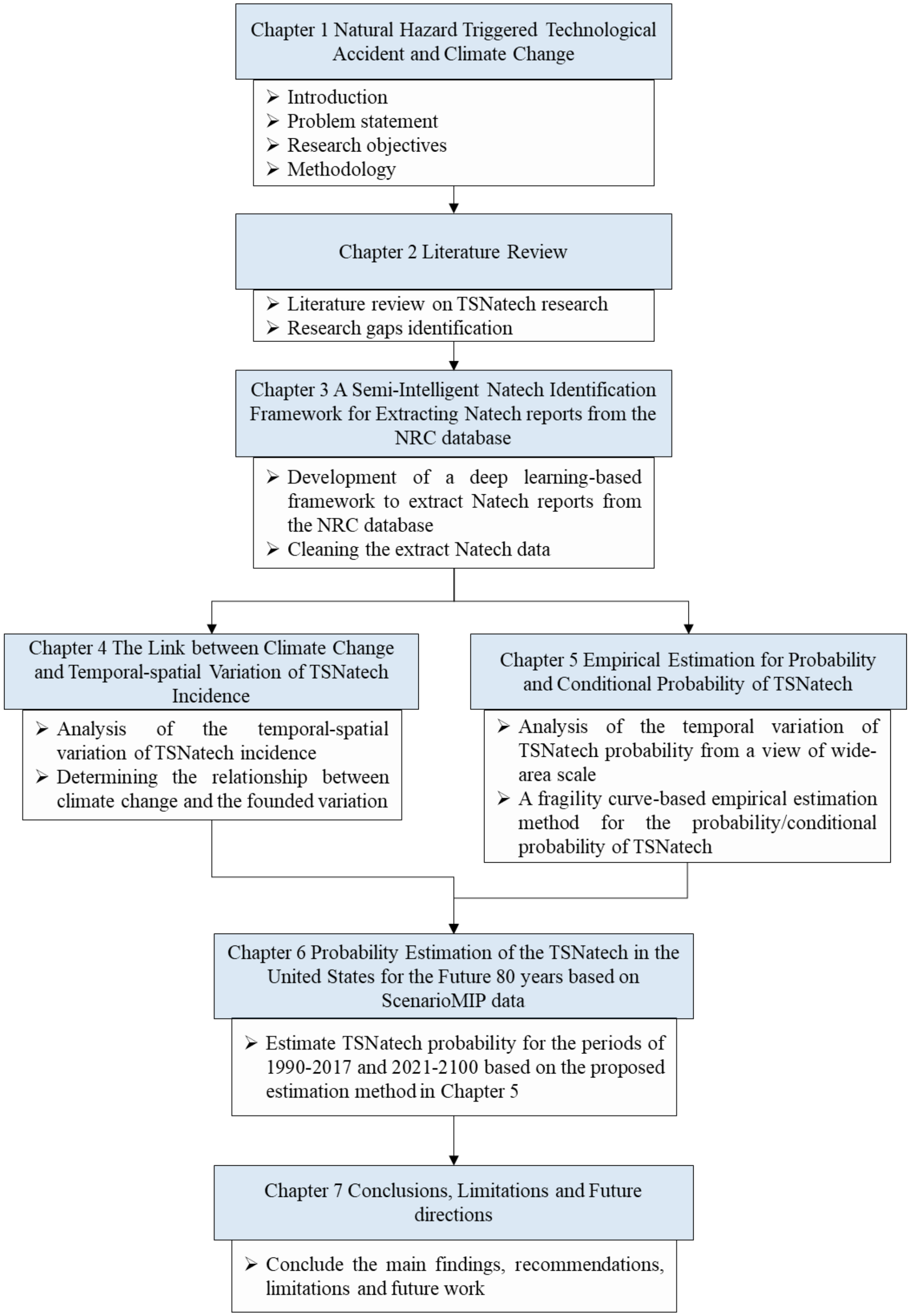

Figure 1–3 Dissertation structure

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Chapter 2 Literature Review

As discussed in the previous chapter, this dissertation involves TSNatechs and climate change, and its main objective was to determine the influence of climate change on the occurrence of TSNatech, and how it may affect TSNatech events in the future.

Thus, in this chapter, we have reviewed the findings and methodologies of research conducted on the occurrence and incidence of TSNatechs, and on the relationships between TSNatech and climate change. Research gaps regarding these relationships have been discussed in this section. More detailed literature reviews on the theoretical concepts and analytical methods used in each Chapter have been presented where most relevant, to help readers follow our research logic and understand out findings.

2.1 Studies Related to TSNatech Events

Contributions to the study of TSNatech have been developed from the collated TSNatech-related publications, using the perspectives of lessons learned from past events, and from TSNatech risk assessments, as discussed below. Studies related to Natech data extraction have also been presented in this section. Other studies related to TSNatech, but closer to the topics of risk awareness and communications, have also been described.

2.1.1 Lessons Learned Through Historical Data Analysis

Reviewing past Natechs has been the method often applied to understanding the most common damage to chemical-related equipment, which chemical types have been most commonly released during accidents, and the most vulnerable equipment types (Girgin 2011; Krausmann *et al*. 2011; Kumasaki and King 2020). Based on this knowledge, risk managers, local governments, facility owners, and other stakeholders have been able to develop reasonable and effective Natech event risk management plans (Krausmann *et al*. 2017).

Analysis has revealed that there are two main types of literature on this subject. The first has involved analyzing the incidence of Natechs or TSNatechs over the longer term, in order to characterize Natech occurrence. In the study by Sengul *et al*. (2012), which did not specifically focus on TSNatechs, 20% of the Natech recorded in the NRC database for the period 1990–2008 could be attributed to hurricanes, including many hurricane-related Natechs triggered by hurricanes Katrina and Rita. Necci *et al*. (2018) reviewed reports on storm-triggered Natechs in European industrial incident databases, including the major hazard incident data service (MHIDAS), and the Research and Information on Accidents (ARIA), Major Accidents Reporting Systems (eMARS), and TAD (the IChemE) databases. Their results showed that a high Natech percentage were reportedly triggered by storms, including 76.0% in the MHIDAS database, 73.6% in the ARIA database, 60.6% in the eMARS database, and 57.4% in the TAD database. These results showed that storms were important reported causes of Natechs, but just why this was the case has remained unclear.

The second literature grouping involved Natechs which occurred during the landfall of one or more serious hurricanes. Cruz and Krausmann (2008) reviewed the number of offshore drilling platforms damaged by hurricanes Katrina and Rita: they provided recommendations for platform design and pipeline management on platforms, and discussed the validity of the often-used 100-year event criterion. In another study by the same authors (Cruz and Krausmann 2009), they analyzed Natechs which occurred during the Katrina and Rita landfalls, from the perspective of hazardous material releases, based on more than 600 chemical release reports extracted from the NRC database. In Cozzani *et al*. (2010), the authors pointed out that floods caused by Hurricane Katrina was responsible for the release of > 30,000 m^3 of oil, which resulted in the soil of the affected area becoming polluted. Griggs *et al.* (2017) reported that > 4.6 million pounds of toxins and other chemicals were released, and that hundreds of oil spills occurred, during the 2017 Hurricane Harvey landfall. These studies served to convince risk managers that they should not ignore TSNatechs when preparing their risk management plans, even if the probability occurrence was low, as the consequences are so high. In particular, when considering the potential impact of climate change, it has been suggested that these low-probability levels will rise, as climate change may give rise to more intense tropical storms.

2.1.2 Studies Concerning TSNatech Data Extraction

To learn lessons from past TSNatech, and analyze their characteristics, related data first needed to be collected. Normally, historical Natech data could be retrieved from the chemical release accident databases, such as that of the NRC (USCG, 2017), the Failure and Accidents Technical Information System (FACTS) (2019), ARIA (2019), and eMARS (2019) databases, among others. The Joint Research Centre of the European Commission developed a sole indicated Natech database named eNatech (2019), although this has been difficult to use for Natech analysis over longer periods or wide areas, since only approximately 60 Natech events have been recorded, and accident data collection has not been systematic.

There are two main methods for retrieving relevant Natech events from existing databases. The first involves keyword extraction, which has been commonly used by others, including Santella *et al*. (2011); Sengul *et al*. (2012); Girgin and Krausmann (2014); and Girgin and Krausmann (2016). In the work by Sengul (2005), the basic keyword extraction method was described as checking the existence of selected keywords in the incident description and natural hazard type, to identify Natech incident reports from the NRC database. The main challenge of this method has always been that keyword selection relies heavily on the experience and specific knowledge of the searcher. In addition, regardless of which keywords are selected, if the data quality is low, there has always been the risk of either ignoring or incorrectly identifying relevant events.

The other main method has been to check descriptions of chemical release incidents among different databases manually, to ensure that each is a Natech-related record. For example, Krausmann *et al*. (2011) first extracted records regarding certain types of infrastructure, such as storage tanks or pipelines, and their accident cause, and then manually reviewed the description of the accident field for each record, to obtain more details on causation. In their analysis, the authors reviewed several databases, eventually identifying > 1000 relevant events, which surely took a long time to review by hand. This method was evidently quite useful for collating good quality extracted Natech event data, but it must be pointed out that it is an intensive resource-user.

2.1.3 Studies Concerning TSNatech Event Risk Assessments

We found that studies on risk assessment related to TSNatechs involved two main topics, with the first linked to risk assessment methodology development. Necci *et al*. (2014) developed a dedicated quantitative assessment methodology to quantify the risk of lightning-triggered Natech events, while Bernier *et al*. (2017) proposed the development and validation of a vulnerability evaluation model, to integrate storm surge exposure, structural vulnerability, and social vulnerability. Misuri *et al*. (2020) proposed another quantitative risk assessment method for lightning-triggered Natechs, in which the domino effects of cascading accidents were also considered. None of these risk assessment methodologies included potential or actual climate change impacts, however.

The other topic was related to TSNatech probability estimation using fragility analysis. Santella *et al*. (2011) presented an empirical estimation method for TSNatechs using the NRC database. The authors estimated TSNatech occurrence probability against wind speed and storm surge inundation from selected major hurricanes, using logistic regression methods. The work of the Santella team was valuable for estimating TSNatech probability from a spatial view, based on historical records. Moreover, some studies analyzed wind effects on storage tanks, by plotting fragility curves to describe equipment failure probabilities against wind speed (Olivar *et al*. 2018; Olivar *et al*. 2020). In fact, the fragility curves developed for flood-related Natechs could also be employed to analyze the risk of TSNatechs (Antonioni *et al*. 2015; Zuluaga Mayorga *et al*. 2019), since tropical storms could also trigger Natechs by causing floods. Again, none of the above studies considered the inclusion of climate change as a variable, when estimating Natech probability.

Among the collated TSNatech-related works, two studies described the mechanism of how storms / tropical storms trigger Natechs, which could contribute to assessing TSNatech risk, to understanding the uncertainty in TSNatech occurrence, and to improving the capacity of facilities to reduce TSNatech risk, by applying specific measures. Cruz *et al*. (2001) presented a comprehensive discussion on how hurricanes induced hazardous material releases in a refinery, including the concept of combining several individually dangerous phenomena—such as high speed wind, tornadoes, lightning, and flooding from heavy rainfall. In the study by Necci *et al*. (2018), storm surges were included among the phenomena which could cause chemicals releases, and this team mentioned that climate change could affect the occurrence of storm-related Natechs—although supporting data were not provided.

2.1.4 Other Topics Concerning TSNatechs

Some TSNatech studies—being those related to Natech risk communication and risk awareness—were harder to allocate, in terms of their approach. Bernier *et al*. (2019) presented a scenario-based framework for first responders and workers, to evaluate the accessibility of petrochemical facilities during storm surges. Motivated by the large number of chemical releases that occurred during hurricanes Katrina and Harvey, some researchers examined the perceived distinction between Natechs and natural hazards, and their relationships to lay persons' hazard perceptions—even speculating whether Katrina and Harvey should be considered as large Natech disasters (Picou 2009; Slack *et al.* 2020).

2.2 Studies Related to Climate Change and TSNatechs

As discussed in the first chapter, the authors hypothesized that TSNatech occurrence could be linked to climate change, due to its effects on the frequency, intensity, or other metrics of tropical storms. In other words, the effects of climate change on tropical storms might provide an important link between climate change and TSNatech occurrence, if climate change has an impact on the occurrence or variation of TSNatech. We have therefore presented a literature review of climate change, with respect to its impacts on tropical storms and TSNatechs, in this section.

2.2.1 Studies Related to the Effects of Climate Change on Tropical Storms

In order to check if the hypothesis presented at the beginning of Section 2.2 was realistic, we reviewed studies related to connections between climate change and tropical storms. The results showed that climate change could modify the intensity and duration of—and areas affected area of tropical storms. In the studies of Mudd *et al*. (2014a, b) and Ting *et al*. (2019), more intense and larger hurricanes might be formed in the future, due to climate change, with heavier rainfall also resulting (Pugatch 2019; Walsh *et al*. 2019). Moving speeds and pathways of tropical storms could also be affected by climate change, according to the work of Kossin *et al*. (2014), Chan (2019), Collins *et al*. (2019), Hassanzadeh *et al*. (2020), Yamaguchi *et al*. (2012), and Zhang *et al*. (2020). It seems that the connection between climate change and tropical storms might be a bridge linking the occurrence of TSNatechs to climate change, although our review of the studies related to the effects of climate change on the occurrence of TSNatech did not reveal any direct proof of this.

2.2.2 Studies Related to the Effects of Climate Change on TSNatechs

It has been suggested that Natechs will occur more frequently and be more serious, as a result of climate change (Krausmann *et al.* 2011; Cruz and Krausmann, 2013; Salzano *et al.* 2013; Tolo *et al.* 2017; Necci *et al.* 2018; Tsionis *et al.* 2019; Kumasaki and King 2020). However, this has simply been suggested on the basis of 'common knowledge,' highlighting the importance of conducting research on Natech, and none directly analyzed how climate change affected the occurrence of Natech events, let alone the incidence of TSNatechs.

Three papers were found that focused on Natechs in the climate change context. Cruz and Krausmann (2013) presented an overview of the vulnerability of oil and gas sector facilities to aspects of climate change, while Katopodis and Sfetsos (2019) put forward mechanisms for adapting the oil sector to climate change, based on their review of a climate change risk assessment framework and potential climate change effects on oil infrastructure. In contrast to these studies, Sichani *et al*. (2020) conducted a study to assess the risks and losses to refinery facilities using hurricanes simulated from sea-level rise and increased hurricanes moving speed characteristics postulated to be caused by a changing climate. It is worth highlighting that none of these reviewed papers investigated connections between Natech incidence and climate change.

2.3 Summary and Research Gaps

Based on the literature review, we concluded that tropical storms have become an important cause of Natechs since the number of TSNatechs increased, although no-one has suggested that the increased number of TSNatechs was attributable to climate change. There are many factors that can cause changes in TSNatech numbers, such as changes in regulations, changes in data collection measures, facility aging problems, performance improvement measures on chemicals-related infrastructure, and temporal–spatial variations in industrial facilities. Moreover, there has not been any studies which have used empirical analysis to explain the uncertain relationship between climate change and increasing TSNatech numbers.

As the aim of this study was to analyze climate change impacts on the occurrence of TSNatechs in future scenarios, estimating TSNatech probability under future climate scenarios was one potential approach. However, if we had attempted to analyze future TSNatech probability variation over time, it would have been necessary to identify each particular storm, using simulation data. This would have been necessary, as risk managers have to estimate the probability of TSNatechs according to natural phenomena induced by tropical storms (such as wind speed and storm surge inundation), regardless of the use of either empirical estimation or fragility analysis-based methods. However, we could not definitively identify tropical-storms dates or pathways over the long-term by using climate simulation data simulated by general circulation models (GCMs). Thus, a new method to evaluate the effects of climate change on TSNatech events was needed.

In summary, we identified two important gaps in the research on relationships between TSNatechs and climate change. The first was the lack of analysis of the relationship between climate change and the occurrence of TSNatech, while secondly, there was no established methodology available to analyze how the occurrence of TSNatech may change in the future, in response to changing climate scenarios.

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Chapter 3 A Semi-Intelligent Natech Identification Framework for Extracting Natech reports from the NRC Database

3.1 Introduction

Natural hazard-triggered technological accidents are known as Natechs (Showalter *et al*. 1992; Cruz *et al*. 2006; Cruz and Okada 2008). In this study, we are interested in the Natechs that involve facility/equipment damage with the subsequent release of hazardous materials (hazmat). Natechs can cause huge economic losses (Girgin and Krausmann 2016; Krausmann and Salzano 2017) as well as long-term effects on human health and the environment (Krausmann and Cruz 2013). Natechs are generally considered as hazmat release accidents that occur from the impact of a natural hazard on vulnerable industrial infrastructures (for example, storage tanks, fixed facilities, oil drill platforms). As a result, Natechs are more complex, and can have more severe consequences than the triggering natural hazard alone. Therefore, Natechs bring a huge challenge to risk managers.

In this regard, learning from previous Natechs is crucial for risk analysis, assessment, and reduction. Over the past decades, researchers have studied Natech risk assessment methodologies and the vulnerability of storage tanks (Antonioni *et al*. 2007; Campedel *et al*. 2008; Antonioni *et al*. 2009; Antonioni *et al*. 2015; Khakzad and Van Gelder 2017, 2018; Khakzad *et al*. 2018). Meanwhile, many studies attempted to understand the incidence and characteristics of these events by historically analyzing Natechs (Krausmann and Mushtaq 2008; Cruz and Krausmann 2009; Cozzani *et al*. 2010; Krausmann and Cruz 2013; Girgin and Krausmann 2014, 2016; Kumasaki *et al*. 2017; Shah *et al*. 2018). Some of the above studies have used several databases that contain records of chemical release accidents (including Natechs) to support research concerning Natech-related issues, such as the National Response Center database of the United States (NRC 2017), the eNatech database of the Joint Research Centre of the European Commission (European Commission 2019a), the Failure and ACcidents Technical information System (FACTS) (2019), the Research and Information on Accidents database (ARIA) (2019), and the Major Accidents Reporting Systems (eMARS) database (European Commission 2019b), among others. Among these databases, the eNatech is the sole database specifically dedicated to Natechs. However, due to the fact that eNatech contains only few records (just over 60 records), and the collection of accidents is not systematic, this database is not very useful for analyzing Natech incidence over a territory and over time. Therefore, it is necessary to use other available and larger databases for this purpose. However, with larger databases come greater challenges.

Checking the description of chemical accidents to retrieve Natechs from the available databases has to be done in the previous studies. To do this, the researchers have to filter appropriate data according to the research purpose. For example, in a study by Krausmann *et al*. (2011), the authors first extracted records regarding certain types of equipment (for example, storage tanks, pipelines) and their hazmat release cause, and then reviewed the description of the incident field manually for each record to obtain more details regarding the incident causes. In their analysis the authors reviewed several databases. The total number of Natech events identified was just over 1,000, which must have taken some time to review by hand. The study of Krausmann *et al*. (2011) provided valuable insight concerning the extraction of Natech cases from databases, but also highlighted that this task is heavily time consuming, particularly if a larger set of incidents needs to be reviewed. This is the case when we attempt to retrieve a complete set of Natechs from a million-volume level database, such as the complete NRC database.

The NRC database is operated by the United States Coast Guard, receiving and cataloguing all citizens' reports for potential chemical release incidents. Since its establishment in 1974 (Clow 1980), the NRC database has evolved over the years, receiving approximately 25,000 to 35,000 hazmat release reports per year. The NRC database contains records from 1990 onwards, and it is open and available to the public. Furthermore, these reports, which can be downloaded from the NRC website, are released as separate files that contain all hazmat release reports recorded per year. During the period of 1990 to 2017, the total number of reports exceeded 820,000. According to Girgin and Krausmann (2014), there are over 110,000 records from 1983 to 1989. Compared with other available databases, the NRC database contains by far the largest number of reports about chemical release incidents. Due to the large amount of data, it is almost impossible to retrieve Natechs by checking the description one by one. Moreover, the NRC database is increasing by almost 29,000 records on average per year. This is near to the total size, for example, of the FACTS database, half of the total number of records in the ARIA database, and almost 29-fold the total number of records in the eMARS database. Also the number of potential chemical release incident and accident reports in all available databases per year is increasing. As these databases expand, it will be useful to find a fast and efficient method to retrieve Natechs from large databases for accident analysis.

Improving Natech identification in the NRC database is challenging also because the NRC database has many inherent problems (Girgin and Krausmann 2014). First, there are many different types of reports catalogued in the NRC database, such as: (1) reports of planned hazmat release incidents; (2) accident reports without hazmat release; (3) accident reports with hazmat release unrelated to natural phenomena; and (4) accident reports with hazmat release related to natural phenomena (Natech events). Moreover, there may be several reports on the same incident as well as incomplete or limited details about some incidents altogether. This is in part due to the fact that any citizen can report hazmat release cases to the NRC call center. This results in many records having incomplete information. Due to the lack of knowledge and information, these redundant, complex, and confusing reports bring a huge challenge on Natech identification. In addition, changes to reporting criteria and changes to the data collection and entry forms have resulted in differences in the database itself for different periods (Cruz and Okada 2008; Krausmann and Salzano 2017). For example, since 2003, the NRC database started to include "hurricane" as one of the incident causes in the field of "*Incident cause*."

Another problem concerns the uncertainty regarding the natural hazard cause, as the general option “natural phenomena” can also be indicated. Thus, we can deduct that one Natech was caused by a natural phenomenon, but not which particular type of natural hazard. In order to identify these accidents, we would need to review each and every accident description, which, if done manually, would be a monumental task.

One way to identify Natechs is keyword search. A keyword extraction method has been employed to extract Natechs from the NRC database in the study by Sengul *et al*. (2012). Nonetheless, due to the problems introduced by language expression, it is also a time-consuming work to extract Natechs from the NRC database by checking the description of each incident. For example, using “snow” as a keyword to extract snow-triggered accidents (or “incidents” as reported in the NRC database) from the NRC database, we will get some results as shown in Table 3.1. All the records in Table 3.1 were identified using this keyword. However, none of these records were actually caused by snow. One option to avoid having this type of problem is to check every record manually, although this method is practically infeasible for large databases. Consequently, an accurate and efficient automated method of retrieving Natechs from the NRC database is needed.

Table 3.1 Example records in the National Response Center (NRC) database

SEQNOS[2]	**Description of Incident**
199671	Unknown white substance on roadway / looks like snow / foul odor maybe ammonia smell.
293589	Caller states that there is a foamy substance like snowflakes in air / tan in color / caller has breathing concerns.
757912	Caller states there are two companies near her home one of which is somehow releasing materials that are falling from the sky that looks like glitter and is falling like snow.
807281	Caller stated that they spotted a sheen that looks like snow on the water.
1198261	Caller received a report of Styrofoam falling like snow from a high rise building onto a pier and into water from a unknown source.

For the purpose of extracting Natechs and identifying related natural phenomena from the NRC database, we introduce machine learning theory into this study. A new Natech retrieval framework, a Semi-Intelligent Natech Identification Framework (SINIF), is proposed based on a keyword extraction method and machine learning theory. A total number of 826,078 chemical release reports stored in the NRC database from 1990 to 2017 were analyzed using the proposed SINIF. In this particular study we focused on all the incidents reports involving chemical releases from fixed industrial facilities, storage tanks, processing equipment, on- and offshore platforms, and pipelines. Furthermore, we include in the analysis reports involving releases from mobile sources, such as tanker trucks, vessels, and trains.

In the following section we provide a brief introduction to machine learning, and why we selected it and how it is adapted for the purpose of this study. We then explain in detail the design and architecture of the SINIF. In section 3.4, we introduce the methodology including data collection,

[2] The NRC database creates a key field named “*SEQNOS*” as incident ID to distinguish the reports with each other.

processing, and analysis workflow. The results and discussion are elaborated in section 3.5, while the key conclusions of this study are presented in section 3.6.

3.2 What is Machine Learning?

Machine learning refers to a series of algorithms and statistical models that help researchers understand complex data, especially big data. They are typically developed and implemented on computer systems to perform specific tasks effectively based on pattern recognition and statistical inference (Bishop 2006). Notable applications of machine learning include image classification (Lu and Weng 2007; Sudharshan *et al*. 2019), regression (Huang *et al*. 2011; Bashar and Mahmud 2019), and face detection and recognition (Campadelli *et al*. 2004; Ranjan *et al*. 2019). Furthermore, another application area of machine learning is Natural Language Processing (NLP). Natural Language Processing attempts to make computers understand the natural language of human beings in order to tackle and complete useful tasks (Chowdhury 2003), such as document classification (Manevitz and Yousef 2001; Rubin *et al*. 2012), email spam filtering (Blanzieri and Bryl 2008; Diale *et al*. 2019), and so forth. Machine learning, in particular, has a remarkable performance record on solving problems of text multi-classification (Le and Mikolov 2014; Sboev *et al*. 2016; Sotthisopha and Vateekul 2018). In brief, text multi-classification methods attempt to classify series of long text or sentences into more than two categories depending on the specific purpose, such as content recognition and emotion recognition.

According to Murphy (2012), machine learning is generally divided into two principal types: supervised learning and unsupervised learning. Both approaches dictate that the models have to be initially trained in order to make the computer system “learn” or “understand” the characteristics of the input data so that these machine learning models can be used to evaluate the target dataset. However, the difference between supervised and unsupervised learning is that the former asks whether the training data contains any predetermined labels, while the latter has no such requirement. Therefore, supervised learning is better suited to perform tasks characterized by an expected and clearly defined output, such as classification or regression problems. On the other hand, unsupervised learning is more suitable for solving problems that do not have any a priori output, such as knowledge discovery. By conceptualizing our research aim in the context of machine learning, in essence we attempt to identify the NRC incident reports using certain labels that include either “NotNatech” or the type of the natural hazard that may have caused the chemical release. These labels are then used to evaluate whether the incident fits the description of a Natech or not and what is the associated triggering natural phenomenon. Considering the above characteristics of the two learning types, it would appear that we can employ a supervised deep learning method to achieve this and retrieve Natechs from the NRC database.

The incidents reports recorded in the NRC database do have a field named “*Description of incident*” to record the incident description from the reporter. The description is organized as a long text that includes information about the cause of the incident, the weather conditions when the incident happened, the affected equipment, whether this report was a duplicate report of the previous record or not, and when the incident happened and so forth. Based on this, it is logical to assume that the records, which can be potentially classified as Natech-related incidents, will probably have similar descriptions. For example, if there are several incident reports that can be potentially classified as hurricane-triggered Natech accidents, then certain defined keywords, such as “hurricane/typhoon,” “heavy rain,” “high speed,” “strong wind,” or the name of hurricane/typhoon, should appear in their respective descriptions. This concept explains the rationale why the keyword extraction method can be used to retrieve Natech-related records from the NRC database. However, such method requires the selected keywords to appear in the description of the analyzed incident report. If the description does not contain the selected keywords, then the analyzed incident report is omitted from being identified as a Natech, unless otherwise verified (such as in the studies of Sengul *et al*. (2012) or Girgin and Krausmann (2014), in which the authors confirmed whether the report was related to a Natech accident or not based on an analisys of multi-source incident databases). Conversely, when applying a deep learning method to analyze the description of the incidents, each incident description will be transformed into a word bag, which is a multi-set of containing words. These transformed word bags will be analyzed by the selected algorithms, and the content similarity will be determined. This analysis allows to identify whether the descriptions belong to one class or another, and consequently represents the final step in the Natech identification and classification stage.

Following this rationale, the process of extracting Natechs from the NRC database can be conceptualized in the following two steps. First, classifying the incident description into different categories depending on the triggering cause; secondly, filtering out and extracting the records of which the triggering accident cause is related to natural phenomena. Thus, the research purpose of this study, namely extracting Natechs from the NRC database, can be considered as a multi-classification problem. As mentioned above, machine learning algorithms based on supervised learning approaches are more suitable for solving this kind of problem. In order to decide on the appropriate machine learning algorithm for this case, we selected two commonly employed supervised learning algorithms, the Long Short-Term Memory (LSTM) and the Convolutional Neural Network (CNN), to develop the SINIF.

The LSTM was first proposed in 1997 (Hochreiter and Schmidhuber 1997), and is a kind of recurrent neural network (RNN). It was originally developed to address the challenges previous RNN faced with capturing long-term time correlations in the input data. By the time of this study, the LSTM has been widely employed in the areas of speech recognition (Fernández *et al*. 2007), handwriting recognition (Graves and Schmidhuber 2009), and text classification (Shih *et al*. 2018).

The CNN was first proposed by Fukujima (1980), who labeled it Neocognitron. A CNN network always has one or more convolutional layers. This method is commonly used in visual imagery. With the advancement of machine learning over the years, the application scope of the CNN has become much broader, coping competently with an array of complex tasks ranging from image recognition (Cireşan *et al*. 2012) to video analysis and human action recognition (Ji *et al*. 2013) and text classification (Shin *et al*. 2018).

3.3 Design of the Semi-Intelligent Natech Identification Framework (SINIF)

In order to extract Natechs by using machine learning, we designed the SINIF (see Figure 3-1). The main idea of the SINIF is that the input data (incident description) will be analyzed and classified by both the keyword extraction method and the network implemented by a machine learning algorithm, separately. In more detail, every record of input data will be classified into various categories according to the triggering cause determined by both the keyword extraction method and the network, separately. In the final step, the category classified by the keyword extraction method will be compared with the category classified by the network for each and every record. If the two automatically generated results do not match for any of the analyzed records, then the specific record will be manually checked and identified by the researchers. Following the above idea, five procedures are designed in the SINIF and described as follows:

(1) Keyword extraction analysis: The input data will be analyzed by the keyword extraction method in this step. According to the keyword identified by researchers, the input data will be classified into different categories.
(2) Network training: The network will be built based on the implementation of the machine learning algorithm selected by researchers in this step. The network will be trained by a set of sample data that was generated from the initial input dataset.
(3) Network analysis: The trained network will be used to analyze input data.
(4) Data comparison: A scan to check if the cause identified by the keyword extraction method matches the cause identified by the network will be conducted in this step. If the two automatically identified causes do not match with each other, researchers need to inspect the accident description and identify the triggering cause based on their own knowledge and understanding.
(5) Output results. The Natech reports will be separated from other hazmat release incidents reports on the basis of whether the triggering cause is related to a natural phenomenon, and if so, they will be further categorized according to the type of natural hazard.

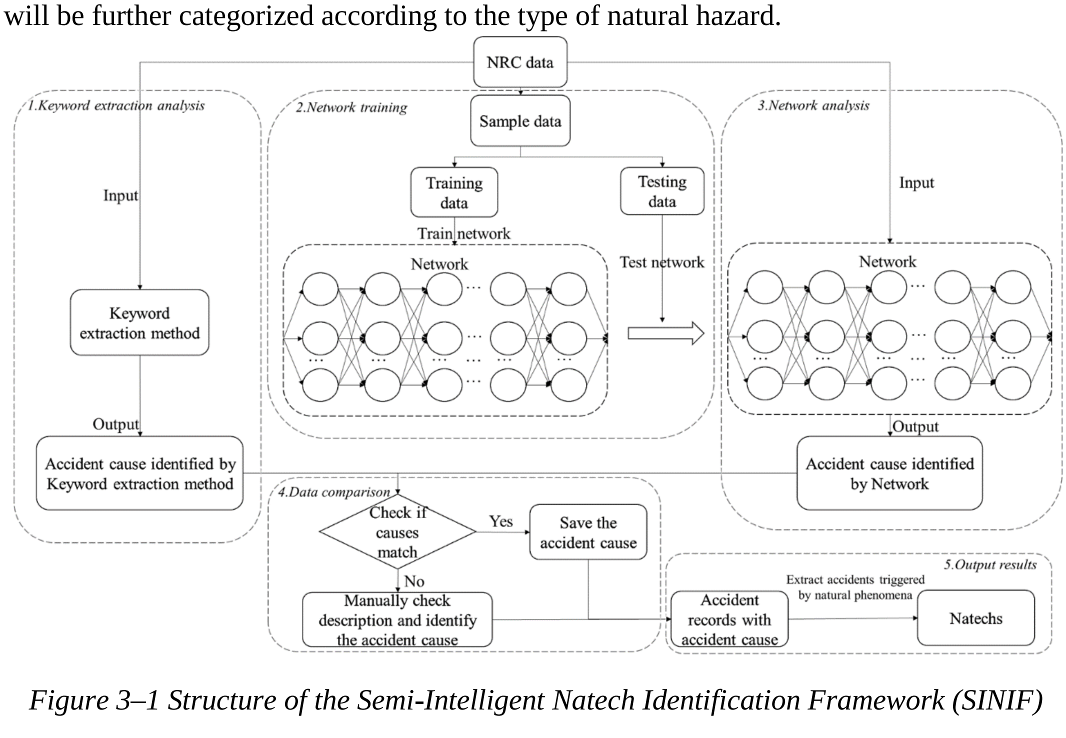

Figure 3–1 Structure of the Semi-Intelligent Natech Identification Framework (SINIF)

The network itself can be based on any of the machine learning algorithms available. As mentioned in section 3.2, we used the LSTM and CNN to develop the SINIF. Researchers can choose a suitable machine learning algorithm to build their own SINIF according to their research purpose. More details about the workflow of the SINIF are explained in section 3.4.1.

3.4 Methodology

The methodology for this study includes the review of the relevant literature and data collection from the NRC database. All NRC data during 1990 to 2017 were downloaded in the form of Excel files directly from the website of NRC (2017). Each file contains several sheets with the official information (such as report time, call type, responsible company, and so on), incident information (such as description, time, location, cause, if it was a planned event, and so on), hazmat information (whether there was hazmat release, type of hazmat, amount of release, equipment type, and so on), weather conditions, and other information.

In this section, we explain the data processing method, the workflow of the SINIF, and the indices that are used to measure the performance of machine learning algorithms.

3.4.1 Data Processing and Analysis

The NRC data were analyzed according to the following steps, the summary of which can be considered as the workflow of SINIF:

(1) The fields of "*SEQNOS*," "*Description of incident*," and "*Incident cause*" of all reports with a total number of 826,078 records between 1990 and 2017 in the NRC database were gathered into the total sample set named U.

(2) It should be noted that a preliminary inspection of the sample set U led to an important observation related to this next step. In more detail, it seems that when the NRC call center received reports related to a previously recorded incident, a copy of the original report's "*SEQNOS*" ID was also registered in the "*Description of incident*" field of the new report. Based on this finding, we eliminated 3,641 identified duplicate reports from the sample set U by examining the "*Description of incident*" and "*SEQNOS*" fields respectively for multiple listings of the same "*SEQNOS*" ID, merging any repeating or fragmented descriptions of identified duplicate reports into one per incident.

(3) Then the field "*Description of incident*" in U was analyzed through using the keyword extraction method with the aim of identifying and labeling the accident causes based on the same natural phenomenon classification used by Hatice Sengul *et al*. (2012) (that is, *Wind*, *Weather*, *Unknown*, *Tornado*, *Storm*, *Rain*, *Lightning*, *Hurricane*, *Flood*, *Earthquake*, *Cold*). Moreover, we decided to include an additional category named "NotNatech" so as to differentiate reports that are not Natech reports. After labeling all reports in set U using the selected keywords, we examined the content of the reports categorized as related to natural phenomena to assess if it was a planned event and whether there was hazmat release, in order to ensure those reports made reference to Natech reports. This process resulted in 32,348 records being identified as Natech reports and having the corresponding keyword label assigned to them, over 790,000 reports being labeled as "NotNatech."

(4) Based on the results of step 2, we manually checked the "*Description of incident*" of around 15,000 reports tagged with keywords related to natural phenomena and around 8,000 reports labeled as "NotNatech" to ensure they had been labeled correctly. Then these two groups of reports were merged as a new sample set named A with 24,060 records.
(5) The LSTM and CNN algorithms were employed as the kernel networks to analyze set A, separately.
(6) The sample set A was separated into a training set T_1 (80% of A) and a testing set T_2 (20% of A), so that the networks built in step 5 will be trained by T_1 and tested by T_2 accordingly. Afterwards, the text data in the T_1 dataset were transformed into sequences of word indices to match the requirements for the network training. A crucial point for the comparison of the two algorithms was to ensure that they were trained under the same conditions; therefore, we set the same values for the critical parameters for the two networks. For example, the learning rate was set at 0.01 and the epoch was set at 30.
(7) The accuracy of the trained networks was then assessed and verified, and the network with the highest accuracy was selected to analyze the original sample set U.
(8) Finally, a comparison of the results of steps 3 and 7 was carried out for each record to determine if the labels matched. If the results differed, the field "*Description of incident*" of each specific record was manually amended according to the researchers' interpretation.

3.4.2 Performance Measurement Indices

For the purpose of measuring the performance of selected machine learning algorithms, we present several indicative measurements to verify the networks (Özgür *et al*. 2005; Sokolova and Lapalme 2009; Sboev *et al*. 2016). First, we separated T_2 into four subgroups for each individual class X_i shown below, and then we calculated the performance indices according to the size of each group for each individual class X_i.

True Positive (TP): the item was labeled as class X_i in T_2, and was also labeled as X_i by the network. False Positive (FP): the item was not labeled as class X_i in T_2, but was labeled as X_i by the network. True Negative (TN): the item was not labeled as class X_i in T_2, and was not also labeled as X_i by the network. False Negative (FN): the item was labeled as class X_i in T_2, and was not labeled as X_i by the network.

According to the above identified subgroups, we introduced three main performance indices to evaluate the accuracy of selected deep learning algorithm. The Precision (P_i) calculated by Eq. 1 was used to evaluate the class agreement of data labels with the labels given by the network for each individual class X_i.

$$P_i = \frac{TP_i}{TP_i + FP_i} \tag{1}$$

The Recall (R_i) in Eq. 2 indicates the effectiveness of selected algorithm to identify given labels for each individual class X_i.

$$R_i = \frac{TP_i}{TP_i + FN_i} \tag{2}$$

A harmonic average value ($F^{i}_{\beta=1}$) of Precision and Recall was used to assess the efficiency of selected algorithm for class X_i.

$$F^{i}_{\beta=1} = \frac{(1+\beta^2)P_i R_i}{\beta^2 \cdot P_i + R_i}, \beta = 1 \tag{3}$$

The Macro-average value ($\bar{F}$), which is the average value of $F^{i}_{\beta=1}$, was calculated by Eq. 4 to indicate the overall effectiveness of selected algorithm; the Accuracy (*Acc*) based on Eq. 5 was used to evaluate the overall accuracy of the algorithm.

$$\bar{F} = \frac{\sum_{i=1}^{n} F^{i}_{1}}{n} \tag{4}$$

$$Acc = \frac{\sum_{i=1}^{n}(TP_i + TN_i)}{\sum_{i=1}^{n}(TP_i + FP_i + FN_i + TN_i)} \tag{5}$$

3.5 Results and Discussion

In this section, we first focus on the total number of Natechs and the associated natural hazard causes for each Natech report in the NRC database. The analysis was conducted based on data generated through the keyword extraction method. Then, we proceeded to assess which machine learning algorithm of the two—the LSTM and CNN—was more suitable to implement the SINIF in order to retrieve Natech information from the NRC database. Finally, we offer a discussion on the quality of the SINIF classifying results for retrieving Natech data from the NRC database.

3.5.1 Keyword Extraction Results

According to the results of the keyword extraction method, the total number of Natechs reported to the NRC from 1990 to 2017 is 32,348, which represents 3.93% of all incidents reported to the NRC during that period and corresponds to 2.22% to 7.39% of the total incidents in each year. As shown in Figure 3-2 (a), hurricanes produced the largest number of Natechs (22.73% in total), while storm triggered 20.60%, and an additional 38.71% were attributable to rain, wind, flood, and other undetermined weather hazards. Figure 3-2 (b) explains the frequency of Natechs caused by various natural phenomena in accordance with the results of the keyword extraction method. The total number of Natechs increased notably after 2005, due to the quantity change of hurricane-related Natechs. Meanwhile, another contributing factor is that hurricanes started to be registered as a separate triggering hazard from 2003 in the NRC database. Furthermore, it becomes apparent from Figure 3-2 (a) that using the keyword extraction method to identify the triggering natural hazard of Natechs has some issues, because there were 130 Natechs per year on average labeled as "*Unkown*."

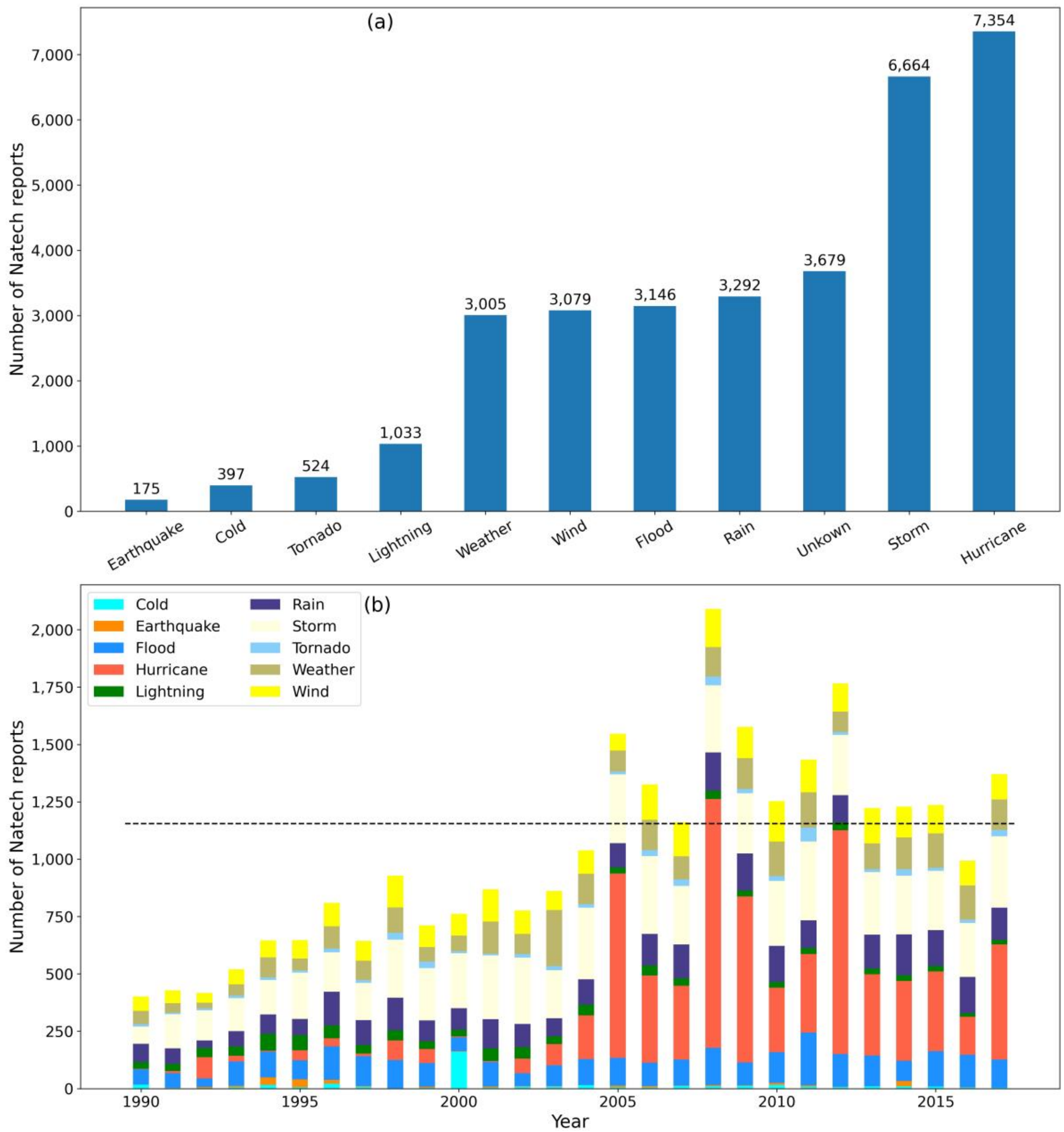

Figure 3–2 (a) Number of Natech reports with various natural phenomena; (b) Number of Natech reports associated with various natural phenomena according to the keyword extraction results (Note: the black line is the average number of Natech reports)

Although the results showed rates similar to those from the research of Sengul *et al*. (2012) considering the proportion of Natechs in all NRC incident reports for the study period, the triggering natural hazards demonstrate significant differences. The differences between these two results can probably be attributed to the following two aspects. First, the reports analyzed in this study cover a period from 1990 to 2017 instead of the period from 1990 to 2008, which was used in the original study of Sengul *et al*. (2012). Second, as mentioned in the introduction, due to the language expression, there will be a large bias if we only use the keyword retrieval method to analyze the NRC database without checking the description of an incident or checking other incident reports database. As a result, we can confirm that it is quite difficult to achieve the research target of this study through analyzing data by solely using the keyword extraction method.

3.5.2 Efficiency Analysis of Machine Learning Algorithms

In this study, we introduced machine learning to retrieve Natechs and identify their triggering natural hazard. We analyzed the training set and testing set by implementing two basic machine learning algorithms, the LSTM and the CNN, with the purpose of checking which algorithm is more suitable to achieve the research target. We then plotted the heat maps of the confusion matrix for each algorithm as shown in Figure 3-3.

Each cell in the confusion matrix represents the number of records the network misclassified into the classes of their respective columns, when they should have been placed into the classes indicated by their rows. Thus, the confusion matrix describes the distribution of the predicted classes in respect to the classes that have been identified by the keyword extraction method.

Through the analysis of the confusion matrices, it becomes apparent that it is not easy to extract Natechs and identify their natural hazard causes by using only the machine learning method. Figure 3-3 shows that both the LSTM and the CNN are capable of identifying the probable triggering natural hazards for most of the Natech records. However, due to the ambiguous descriptions of different natural hazards, there were certain biases in the Natechs triggered by hurricanes, storms, rain, or other weather-related causes. These findings are probably stemming from the fact that, for an untrained observer, the above natural hazards are induced by seemingly similar meteorological phenomena. Therefore, the vocabulary and expressions used to describe such accidents are often confusingly similar among Natechs. In addition, due to the same reason, some of the accidents, which were not triggered by natural hazards, were easily mistaken as Natechs by the networks. These ambiguities pose another set of challenges to this research endeavor, making it very difficult to accomplish through the use of machine learning or keyword extraction alone. In this context and following the discussion in the introduction, the development and implementation of the SINIF can be considered a potential method to retrieve Natechs and identify the natural hazard cause successfully.

As explained in section 3.3, we set out to find a suitable machine learning algorithm as the kernel network upon which the SINIF will be implemented. We calculated the indices explained in section 3.4.2 in order to assess which machine learning algorithm is more suitable to accomplish the main task of this study. Table 3.2 presents the results of these performance indices for each algorithm respectively. As the table shows, both the LSTM and the CNN scored differently depending on the index in each of the categories. In terms of precision indices for different categories, the LSTM could retrieve “NotNatech” and additionally identify the natural hazard cause more accurately than the CNN on Natechs triggered by flood, hurricane, lightning, rain, storm, tornado, weather, or wind. On the other hand, from the viewpoint of recall indices, the CNN could retrieve more “NotNatech” than the LSTM. As a comprehensive index of precision and recall, the harmonic average ($F_{\beta=1}^{i}$) index shows that the LSTM is superior to the CNN, a difference ranging from 0.03 up to 0.26 in favor of the LSTM was observed across all categories (Table 3.2). Furthermore, we calculated the macro-average value and accuracy for both algorithms under examination. The results show that the LSTM managed to retrieve 94.28% Natechs from the testing set, while the CNN only 85.64%. A larger macro-average value (0.8979) meant that the LSTM was more accurate than its competitor algorithm, which achieved a value of just 0.7497. The latter two indices emphatically show that the LSTM performed better in general and thus, is more suitable than the CNN in achieving the research target of this study. Moreover, the accuracy values of the LSTM and the CNN show that machine learning theory and the proposed SINIF in particular are more than capable in retrieving Natechs and identifying the associated natural hazards.

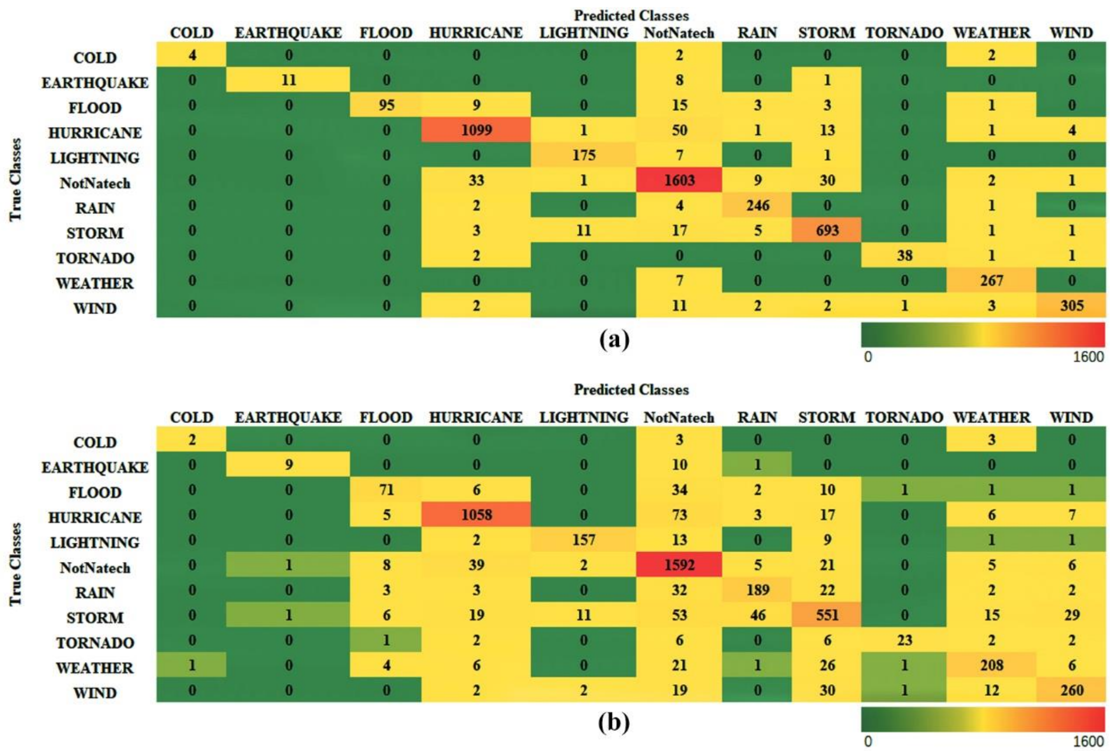

Figure 3–3 (a) Confusion matrix of classification results of the LSTM; (b) Confusion matrix of classification results of the CNN

There are two key reasons explaining the effectiveness of the LSTM over the CNN in extracting Natechs from the NRC database. First, the NRC data were organized as time series data in this study. This is supported by LeCun and Bengio (1995), who noted that CNN is not as competent as the recurrent neural networks (RNN) in analyzing time series data, while the LSTM is one advanced type of RNN. Second, the aim of this study has been framed as a kind of text multi-classification problem, and as LeCun and Bengio (2015) suggested, the LSTM algorithm is better suited to solve text-learning problems.

Table 3.2 Performance indices for each potential natural hazard cause determined by the machine learning algorithms

	LSTM			CNN		
	P_i	R_i	$F^i_{\beta=1}$	P_i	R_i	$F^i_{\beta=1}$
Cold	0.57	1.00	0.73	0.67	0.40	0.50
Earthquake	0.55	1.00	0.71	0.82	0.45	0.58
Flood	0.75	1.00	0.86	0.72	0.56	0.63
Hurricane	0.94	0.96	0.95	0.93	0.91	0.92
Lightning	0.96	0.93	0.94	0.91	0.90	0.91
NotNatech	0.95	0.93	0.94	0.86	0.95	0.90
Rain	0.97	0.93	0.95	0.77	0.75	0.76
Storm	0.95	0.93	0.94	0.80	0.75	0.77
Tornado	0.91	0.98	0.94	0.88	0.55	0.68
Weather	0.97	0.96	0.97	0.82	0.76	0.79
Wind	0.94	0.98	0.96	0.83	0.80	0.81

3.5.3 Semi-Intelligent Natech Identification Framework (SINIF) Results

The arguments supporting why LSTM is more suitable than CNN in designing the identification framework for the extraction of Natechs from the NRC database were presented above. After developing the SINIF and preparing the input dataset by removing any duplicates, the remaining NRC records between 1990 and 2017 (822,437 reports in total) were examined by the trained LSTM network. Then, they were classified either according to the triggering natural hazard, receiving a corresponding label, or as "NotNatech" if the hazmat release report was not caused by a natural hazard. The classification results of the LSTM network were then compared with the results of the keyword extraction method. There were 791,085 records successfully tagged either as "NotNatech" or with the corresponding label using the LSTM network; the keyword extraction method yielded the same record number. Of these, 25,467 records were classified as Natech reports. They were grouped as "certain Natech reports" set R_C. In contrast, the other 31,352 records did not obtain matching labels from the two methods, and thus formed the group "uncertain Natech reports" set R_U. After manually rechecking the field "*Description of incident*" and "*Incident cause*" for each record of R_U, an extra 7,444 accidents were identified and added to the final set of Natech reports R_N. Although we attempted to reduce duplicate data and succeeded to a certain extent on step 2, following the method described in section 3.4.1, there may still be other types of duplicate reports within R_N.

The NRC call center receives and catalogues hazmat-release reports made by any citizens in the United States. Due to the lack of information and multiple report sources, the NRC call center could not ascertain whether these reports were related to an already registered report or not. For the propose of reducing this kind of duplicate reports, we had to assume that all the information for the chemical release incidents recorded in the NRC database is correct, while the remaining doubt pertains to whether they were actually related to a single incident or not. Based on this, checking the location, address, incident date-time, and incident type presented a solution to sort and remove such duplicates in this study. The idea for this additional confirmatory step was to transform the address or location information to specific geographic coordinates, and then manually check the coordinate information, incident type, incident description, and other fields of reports that occurred at around the same time to ensure that they do not refer to the same Natech event.

Thus, in the first step we collected the location information of every accident mentioned in each report of the R_N set. For some reports in R_N (6,014 reports), the information of latitude and longitude had been registered already. However, the latitude and longitude information of the rest 26,897 reports in R_N was missing; only the address, street, county, and state information had been collected. With the aim of updating the missing location information of those reports, we re-organized the address, street, county, and state information of each report in a specific format according to the requirements of the Places API.[3] This service is provided by the Google Cloud Platform to help map developers obtain geographic coordinates by using address information. Through searching with the Places API service, the missing location information of the reports in R_N were updated.

Second, the reports in R_N were grouped based on the incident date-time. A total of 3,734 reports contained duplicate records, while there were 1,461 groups of date-time with multiple reports related to Natech events. As a result, the incident description, incident type, and release materials for each record of the 3,734 reports were manually checked to determine whether it was a duplicate report or not. The rest 29,177 reports of R_N were thus considered to refer to a single Natech event respectively due to the differences they exhibited in the date-time, even in cases where they may have been triggered by a single natural hazard phenomenon with a wide area of effect (such as a hurricane or a mudslide). An example to illustrate this follows: 20 incidents appear to have happened on 16 September 2004 at 12:00, and at the same location (38.19 N, 86.11 W). Moreover, all of these reports had quite similar description and the same type of fixed facility. Examining the above listed evidence, these 20 reports were considered duplicate records of a single incident and merged into one record. Following the above steps, 70 reports were identified as duplicate records, 84.29% of which were related to hurricanes and the rest to mudslide, cold, and storm. Remarkably, this additional confirmatory step to remove the duplicate records revealed that it is indeed quite probable for the NRC call center to receive multiple reports of a single incident in the case of natural hazards with a wide area of effect.

In summary, a total of 32,841 Natech reports was retrieved using the SINIF (examples are shown in Table 3.3). On average, there have been 1,173 Natech reports per year submitted to the NCR database during the period from 1990 to 2017. These Natech reports comprise 3.98% of all incident reports in the NRC database, and between 2.26% and 7.27% of the total reports each year. Figure 3-4 (a) shows that hurricanes were mentioned in the largest number of Natech reports (24.42%), while 19.27% and 18.29% of the Natech reports included references of “rain” and “storm” respectively. An additional 36.26% was attributable to wind, flood, cold, tornado, and other weather-related events. Figure 3-4 (b) shows that the number of Natech reports has an upward trend from 1990 to 2017. Apart from 2016, the number of Natech reports has exceeded the average value after 2005, 2008, and 2012 respectively, which coincides with a higher report count of hurricane-induced Natechs. The number of hurricane-triggered Natech reports increased sharply and fluctuated drastically after 2003, whereas

[3] https://developers.google.com/places/web-service/intro

the frequencies of rain, storm, flood, and wind caused Natech reports remained relatively stable for the same time frame.

Table 3.3 Examples of National Response Center (NRC) reports identified by the Semi-Intelligent Natech Identification Framework (SINIF)

Description of Incident [a]	Type of Incident [b]	Incident Cause in the NRC Database	SINIF Labels	CHRIS Code [c, d]	Released
BELOW GROUND AND WATER 4IN DOT REGULATED PIPELINE/WHILE FLUSHING LINE IN AN ATTEMPT TO REPAIR DAMAGES CAUSED BY HURRICANE GEORGE	PLATFORM	EQUIPMENT FAILURE	hurricane	OIL	Yes
A CORROSIVE LIQUID MATERIAL SPILLED ONTO THE DECK OF A CONTAINER VESSEL FROM A 55 GALLON DRUM. DUE TO HEAVY RAIN THE SOME MATERIAL HAS WASHED INTO THE ATLANTIC OCEAN. THE VESSEL IS BOUND FOR HAMPTON ROADS, VIRGINIA ON MORNING OF 10SEP2002.	VESSEL	EQUIPMENT FAILURE	rain	NCC	Yes
ATON BATTERY RELEASE REPORT RECEIVED VIA COAST GUARD MESSAGE TRAFFIC.	VESSEL	HURRICANE	NotNatech	MAR	Yes
CALLER STATED THAT AT 13:00 (E.D.T.) THE DIABLO CANYON POWER PLANT NOTIFIED THE U.S. NUCLEAR REGUALTORY COMMISSION OF AN UNUSUAL EVENT AT THEIR FACILITY. THE EVENT WAS BROUGHT ON BY AN EARTHQAUKE MEASURING BETWEEN 6.0-7.0 ON THE RICHTER SCALE AND GENERATING A VERTICAL DISPLACEMENT OF 0.012G.	FIXED	EARTHQUAKE	NotNatech	RAM	No
CALLER STATED A CRUSHED STEEL STORAGE TANK WAS BLOWN IN FROM HURRICANE IKE AND HAS THE PARTIAL NUMBER OF 326 ON THE TANK THE FORTH NUMBER CAN NOT BE SEEN. THE TANK HAS NOT BEEN INSPECTED OR TOUCHED BY ANYONE DUE TO THE CORROSIVE MATERIALS ON THE STORAGE TANK. CALLER ESTIMATED THE SIZE OF THE TANK CAPACITY AT 4000 GALLONS.	STORAGE TANK	HURRICANE	hurricane	UNK	Yes
CALLER REPORTED THAT DUE TO THE TROPICAL STORM THE WATER ROSE ABOVE THE SALT WATER BARGE WHICH IS FIXED AND RESIDUAL OIL FROM THE SUMP PUMP CAUSED A SHEEN ON THE WATER	FIXED	TORNADO	hurricane	OWA	Yes

a All the descriptions of Incident, type of incident, and incident cause in the NRC database listed here were copied from the NRC database directly, we did not do any modification on spelling or grammar.
b In the type of incident field, “FIXED” means that this incident happened in a fixed installation.
c Due to no cause-mentioned description or no chemical material released during the incident, labeled as “NotNatech” report.
d Chemical Hazard Response Information System (CHRIS) code is used in the NRC database to determine the type of released materials.

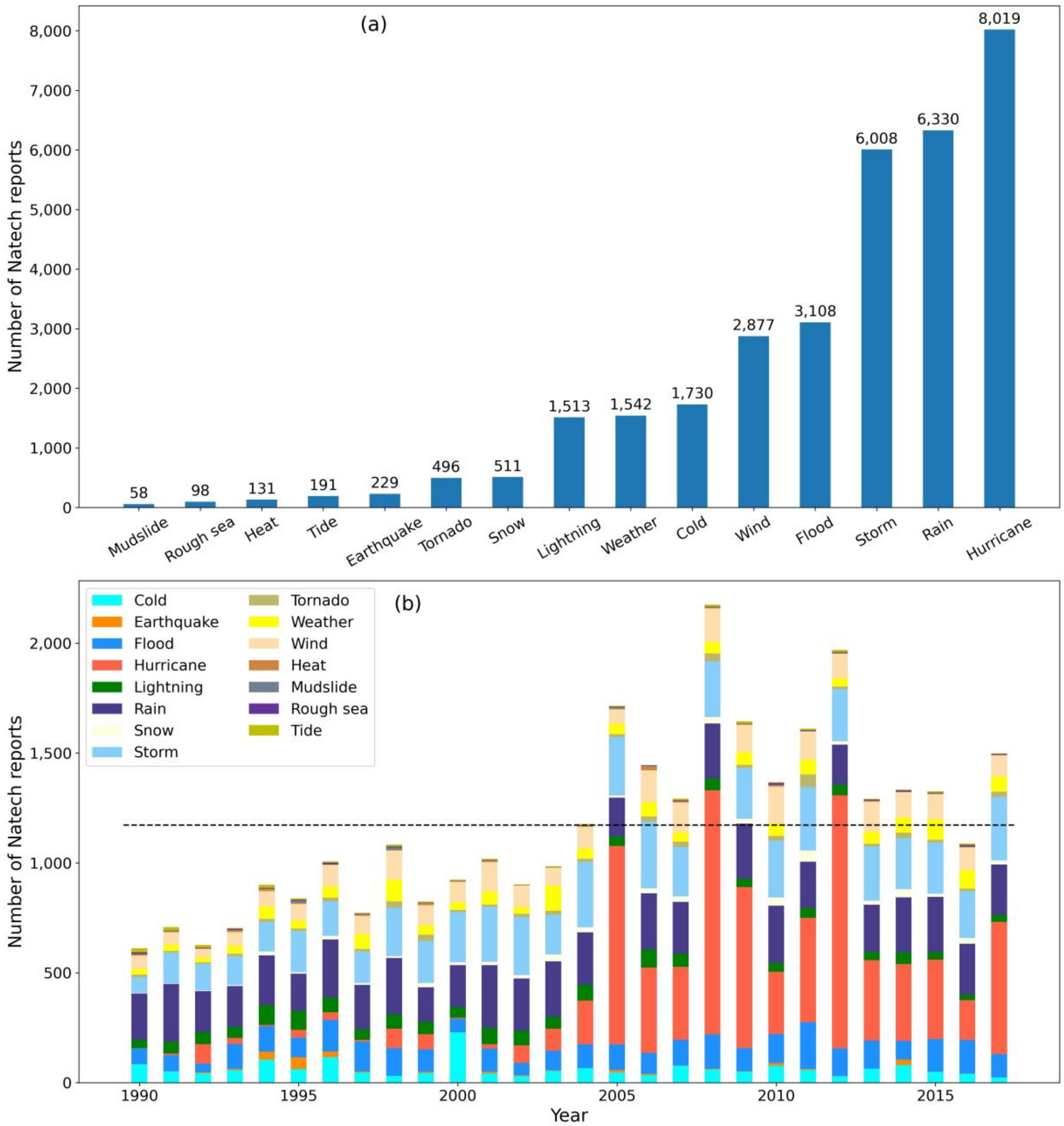

Figure 3–4 (a) Number of Natech reports with various natural phenomena; (b) Number of Natech reports associated with various natural phenomena according to SINIF results (Note: the black line is the average number of Natech reports)

During the process of comparing the results of the SINIF with those from the keyword extraction method alone, Natech reports involving snow, heat, tide, rough sea, and mudslides were also retrieved. Such records comprised 3.01% of the total number of the Natech reports in the NRC database during the study period. This finding shows that the accuracy of the keyword extraction method is directly affected by the selection of keywords. If the selected keywords do not explicitly include terms that describe the potential natural hazard types, the process is highly probable to miss reports of Natechs triggered by natural hazards not defined in advance. In other words, the system has no information about what to look for initially, and so fails to identify the triggering natural hazards. However, due to the comparison function embedded in SINIF's design, the framework is able to identify potential natural hazards, which might otherwise have been omitted by the keyword extraction method alone. The SINIF actually attempts to employ the networks based on deep learning method in its structure to identify the underlying patterns in the descriptions of the records in order to determine the triggering natural hazard, instead of seeking predefined terms in the text. Therefore, the SINIF seems to hold an advantage over the sole application of the keyword extraction method in this regard, as it offers an added identification and verification step.

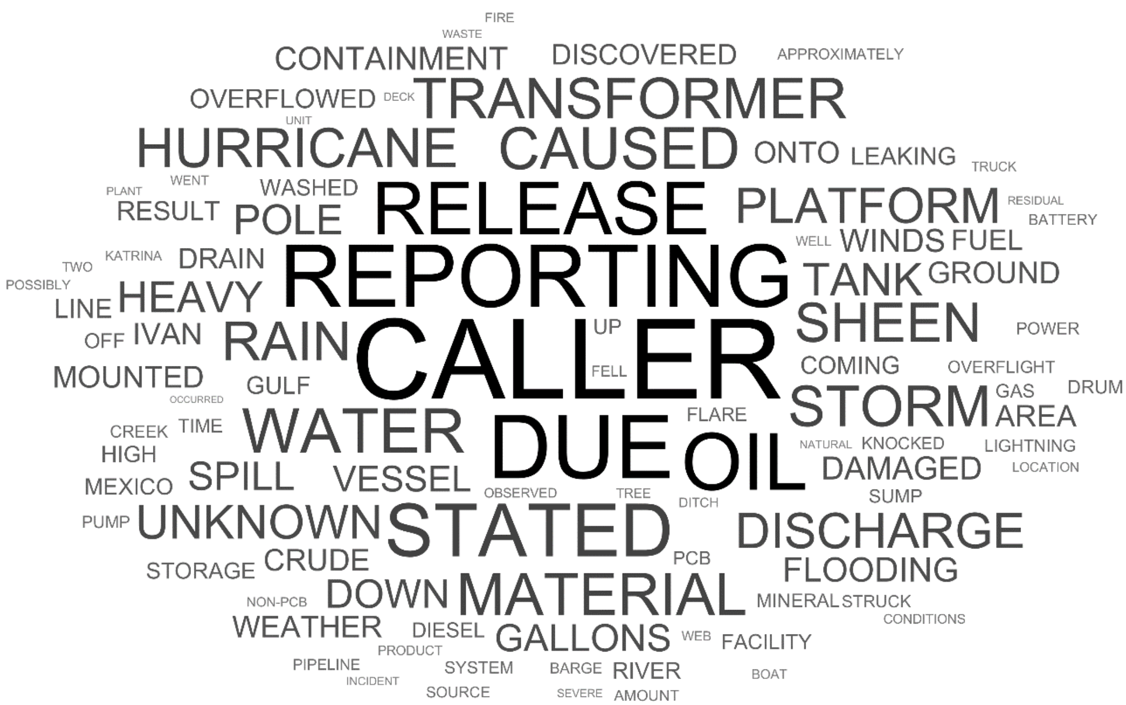

Figure 3–5 Word cloud map (Note: Among the terms, size increases proportionally to the frequency of usage.)

Another point to note is the distribution of Natech reports with regard to various climatic changes and natural phenomena. Generally, the distribution patterns generated by the SINIF seem more reasonable than the ones from the keyword extraction method in the sense that they align with certain observed environmental tendencies. Several researchers have noted a dramatic rise in terms of intensity, size, duration, and frequency of hurricanes around the Atlantic Ocean since the early 1980s, which could be attributed to climate change (Emanuel 2007; Knutson *et al*. 2010; Torn and Snyder 2012; Landsea and Franklin 2013). It is not unreasonable to assume, consequently, that hurricanes and hurricane-related natural hazards, such as storms, rains, and floods, are becoming increasingly likely to trigger Natechs, and that this tendency will continue in the future. Figure 3-4 (b) suggests that the number of Natech reports related to hurricanes grew remarkably since 2003, with notable spikes in 2005 when Rita, Wilma, and Katrina struck, 2008 with Ike, 2012 with Sandy, and 2017 when Harvey, Maria, and Irma occurred. Indeed, hurricane-related Natech reports increased 16-fold since the year 2003, thereby supporting this alarming trend. Apart from the above, the terms most commonly used in the incident descriptions were plotted in the form of a word cloud (Figure 3-5), in order to evaluate their frequency throughout the NRC records. As expected, hurricane, storm, and rain were almost always mentioned in the descriptions, they are indeed the most reported triggering cause as evidenced by Figure 3-5. This means that the majority of Natech reports throughout the period under investigation were probably induced by such weather-related causes. The fact that the SINIF demonstrated satisfactory competency in handling the practical issues and thus bringing into light these findings, serves as another example to support that it is a more suitable and accurate tool compared to the sole application of the keyword extraction method in retrieving Natech reports and identifying their associated natural hazards.

3.6 Conclusion

This study developed a Semi-Intelligent Natech Identification Framework (SINIF) to retrieve Natech related reports and identify the associated triggering natural hazards from the NRC database. The incident reports recorded in the NRC database between 1990 and 2017 were analyzed through the keyword extraction method and the SINIF, separately. The comparison of the results for the keyword extraction method alone and the SINIF indicates that the latter is a more suitable analytical technique to achieve accurately and efficiently the research purpose, namely the extraction of Natechs from a large database (the NRC database in this study). First, keyword selection has a reduced impact on the extraction results of the SINIF due to the implementation of a deep learning method-based network in its structure, which could identify potential Natech reports through identifying the underlying patterns in the descriptions but not rely on the presence of the selected keywords. Second, the SINIF's results are more reasonable compared to those from the keyword extraction method alone. Third, the SINIF is capable of analyzing large databases with comparatively higher accuracy than the alternative method of keyword extraction.

According to the results of the SINIF, 3.98% of hazmat release accidents were identified as Natech-related reports between 1990 and 2017. Furthermore, according to the retrieved NRC reports, the majority of Natech reports (98.24%) were mentioned as related to meteorological phenomena, while hurricanes (24.42%), heavy rains (19.27%), and storms (18.29%) were detected as the main causes of Natech reports. As evidenced by the findings of this study, the observed rising overall number of Natech reports since 2004 can be primarily attributed to the increased occurrence of hurricane-triggered Natechs. The frequency and severity of extreme weather-related events, such as hurricanes, might rise due to climate change. In turn, such an increase in these parameters would suggest that Natech reports could become more likely to happen in the future. However, due to the uncertainty of Natech events, we should be careful to conclude that the increasing trend on the number of Natech reports or events could be attributed to climate change. But the findings of this study points to an interesting research direction on whether climate change has an impact on the incidence of Natech event, and how it works.

As with any data extraction method, the human factor poses significant limitations to the SINIF. Arguably, its framework is very dependent on the keyword extraction method by design. The fact that this technique relies so heavily on the initial selection of searching terms, even the network analysis in steps 4 to 7 and the comparison in step 8 could reduce such effects. According to the workflow of the SINIF, in order to retrieve the target records from large databases, researchers must input "reasonable" search keywords—terms that they estimate adequately describe the target incidents—into the SINIF. However, no matter how the researchers selected keywords carefully, there still exist risks refer to that the selected keywords could not cover all the potential Natech reports unless they manually checked millions of chemical release records in the large database. Furthermore, if the researchers' selected keywords are not included in the actual incident descriptions within the dataset, such records may not be included by the training data in the following step, which may result in a part of Natech reports could not be identified because the SINIF has no way of assessing the keywords themselves. Another shortcoming of the SINIF is related to the selection of machine learning algorithm, which is implemented as the kernel network. As demonstrated by our analysis, various algorithms can produce starkly different results in classifying the descriptions of accidents. Therefore, we recommend researchers who want to apply the SINIF to assess the respective advantages and disadvantages of each kernel algorithm beforehand. In our case, the LSTM proved more suitable than the CNN to build the SINIF for retrieving Natech reports from the NRC database. The last weakness of the SINIF is the high requirements of technical expertise in computer science. The users should have a basic understanding of the machine learning algorithm they select in order to modify accordingly the parameters of the kernel network, and assure the accuracy of their results. In other words, the SINIF is not quite user-friendly yet.

Despite the aforementioned disadvantages of the SINIF, there are also significant benefits for researchers dealing with technological accidents. This endeavor set out to develop a machine learning algorithm for the extraction of Natech related reports from the NRC database and the identification of their triggering natural hazard causes. However, an important asset of this SINIF is its versatility. Naturally, this framework can be applied to analyze a wide array of databases, such as the FACTS or eMARS. Minor modifications may be necessary to take into account the different field names used in each database, though. But apart from employing the SINIF in order to accomplish the same task with different initial datasets, the algorithm can easily be used by researchers to focus on specific categories of Natechs, or even to examine other aspects of technological accidents depending on the information available in the dataset. In addition, because of its high compatibility, users can implement the SINIF based on any of the existing machine learning algorithms to improve the accuracy of the extraction results.

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Chapter 4 The Link between Climate Change and Temporal-spatial Variation of TSNatech Incidence

4.1 Introduction

When infrastructures related to chemical storage, processing or transportation are overloaded by the effects of natural hazards, accidents involving hazardous materials (hazmat) releases can happen. Such industrial accidents are called Natechs, an acronym which was first proposed by Showalter and Myers (1994). Typical examples were observed during hurricanes Karina and Rita in the United States (US) in 2005 which resulted in hundreds of oil spills triggered by the impact of the storm surge, flooding and high speed winds on storage tanks, pipelines, and offshore platforms (Ruckart *et al*. 2008; Cruz and Krausmann 2009; Steven Picou 2009; Miller 2016). The occurrence of Natechs can result in huge economic losses (Girgin and Krausmann 2016) and serious environmental and human health problems (Krausmann and Cruz 2013).

The effect of Natechs has increasingly attracted the attention of government, international organizations and scientists in the past several decades. At the European Union, the SEVESO III Directive specifically calls for the analysis of potential Natech hazards in its risk assessment rules, and some countries have adopted their own Natech specific regulations (e.g., France, Germany) (Krausmann *et al*. 2017). The Organization for Economic Cooperation and Development (OECD) has implemented specific Natech risk management programs (The Organisation for Economic Co-operation and Development 2020) including publishing Natech risk reduction guidelines, and the World Health Organization has included Natech in its list of definitions (World Health Organization 2018). The increasing interest has been accompanied by an increase in publications on the topic in recent years as reported by Suarez-Paba *et al.* (2019). According to a study by Cruz and Suarez-Paba (2019) , there is a growing research interest concerning weather-related Natechs could be explained by an increase number of weather-related Natechs, which might be attributed to the climate change.

In fact, several studies have shown an increasing trend in the frequency and severity of weather-related Natechs (Cruz 2004; Young *et al*. 2004; Sengul *et al*. 2012). Among the weather-related hazards, tropical storms (TSs) seem to be more likely to trigger Natechs. Based on the analysis of hazmat releases reported to the National Response Center (NRC) Database in the US, Sengul (2005) pointed out that hurricanes triggered around 6% of all Natechs in the US from 1990 to 2005. Yet, an extended analysis showed that this number increased to 20% by 2008 (Sengul *et al*. 2012). According to the results of SINIF, this percentage has again escalated to around 24% by the end of 2017. Coincidentally, Necci *et al.* (2018) reported a similar increasing trend on storms-related (including TSs) Natechs in Europe. These trends are likely to continue as climate change may result in a higher number of severe natural hazard events, such as stronger tropical cyclones affecting highly industrialized areas (Cruz and Krausmann 2013; Cruz and Suarez-Paba 2019).

Meanwhile, as many researchers have attested, climate change has a notable impact on TSs, particularly around the Atlantic Ocean area (Emanuel 2007; Toimil *et al*. 2017; Kossin *et al*. 2020). In this context, the causality between TSs and tropical storms-related Natechs (TSNatechs), directed research efforts towards investigating and understanding the underlying connection between climate change and TSNatechs. Still, only a few researchers have attempted to understand the potential impacts of climate change on the incidence of Natechs. For instance, Cruz and Krausmann (2013) discussed vulnerability changes in the oil and gas sector by considering the impacts of climate change and called for comprehensive Natech risk analysis and assessment methods or tools. Tolo *et al.* (2017) proposed a risk assessment model for nuclear fuel facilities by considering the impacts of climate change. Nonetheless, the above-mentioned studies only set climate change as a parameter or condition to demonstrate the potential effects on Natechs. Ebad Sichani *et al.* (2020) proposed a hurricane risk assessment framework to calculate the economic loss for refineries based on given changing climate conditions. Yet, the answer to whether climate change is affecting the incidence of TSNatechs as well as the interaction mechanism between the two have not been studied. However, it is quite important to understand whether climate change is affecting the incidence of TSNatechs, so that government, industry and communities can identify the spatial and temporal distribution of TSNatechs to be better prepared.

Aimed at finding that answer, this study investigates whether or not, how and to what degree climate change has affected the incidence of TSNatechs in the past decades, based on tracking the temporal-spatial variation of TSNatechs. Bearing in mind that climate change is a global phenomenon, only focusing on the occurrence of TSNatechs at a single industrial equipment/facility/park or at a small regional level would make it difficult —if not impossible— to investigate the wider impacts of the climate. Therefore, the US is considered as a basic study area based on the following reasons: 1) the NRC database, which includes more than 800,000 records related to hazmat-release incidents, could provide a satisfying dataset of historical TSNatechs; 2) The powerful earth monitoring system of the US provides high-quality historical climate data to track the changing climatic conditions; and 3) Important global oscillations, specifically the North Atlantic Oscillation and the El Niño-Southern Oscillation (ENSO), affect the tropical storms activity in the US. Considering the latter point, there is a large number of previous studies related to these two oscillations, which could provide a solid academic basis to understand and explain how climate change affects the variation of TSNatechs, if such kind of effect exists.

This Chapter is structured in the following way. In section 4.2, we introduce the data collection and, processing methods, elaborating on the methodology implemented for understanding the temporal–spatial variation of the incidence of TSNatechs. In section 4.3, we report in detail the characterizations of the temporal–spatial variation of TSNatechs, and in the following section, we discuss the reasons why such variation occurred. Finally, some conclusions are drawn in section 4.5.

4.2 Data and Methods

For the purpose of understanding the temporal-spatial variation of the incidence of TSNatechs in the US and clarifying the potential effects of climate change, the historical TSNatechs were retrieved from the National Response Center (NRC)[4] database, which is using to receive, manage and release the hazmat-release incidents reports from all stakeholders in the US. The TSNatechs could be identified and retrieved based on the fields of "*incident description*", "*incident type*", "*incident cause*", "*incident date*" and other location related fields. Due to the uncertain location of transportation related incidents, which would affect the analysis on the temporal-spatial variation of the incidence of TSNatechs, in this study we only consider the TSNatechs that occurred at fixed facilities, offshore platforms, and storage tanks. In addition, we consulted the Toxics Release Inventory (TRI) Program basic data[5] and the Oil and Natural Gas Platforms data[6] to support analyzing the effects of the temporal-spatial variation of facilities and offshore platforms on the temporal-spatial variation of TSNatechs. Furthermore, the *'Best Track Data'* (HURDAT2) (Landsea *et al*. 2015) dataset was used to track the TSs originating in the Atlantic Ocean. HURDAT2 records fundamental parameters for each tropical storm with 6-hour observation intervals, such as the position of the storm center, the maximum wind speed, the maximum radii of different wind speed levels, and so on. Moreover, it is worth noting that the North Atlantic Oscillation (NAO) (Osborn 2019) index and the Oceanic Niño Index (ONI)[7] were selected to analyze the effects of climate change on the incidence of TSNatechs. Aside from the above, some other supplementary basic geographic data[8] were used to identify the study area.

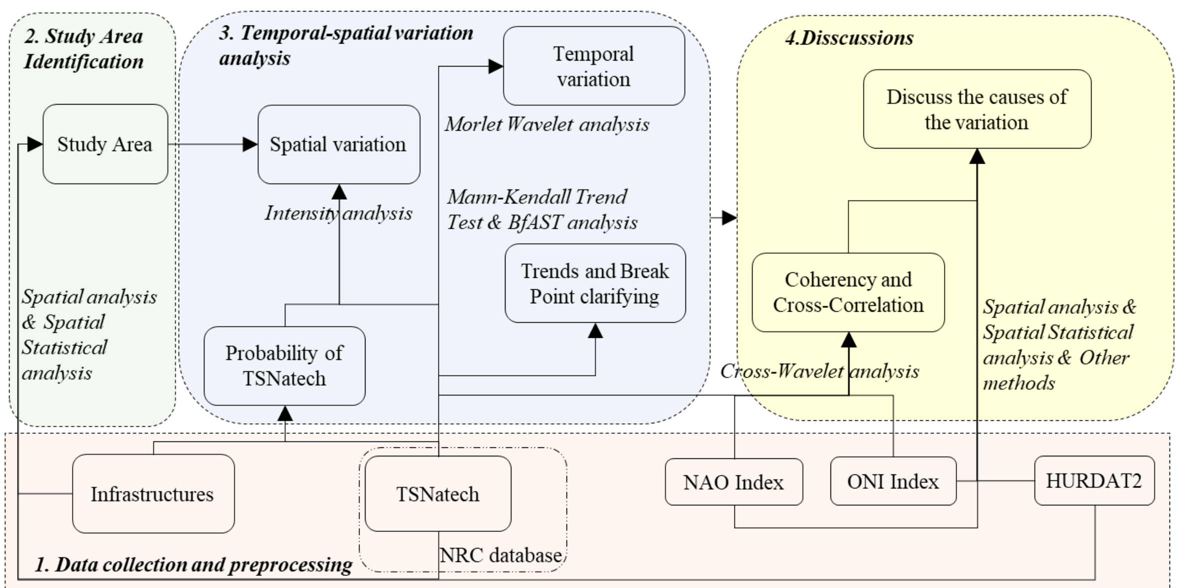

Figure 4–1 Workflow and methodology of this Chapter

Figure 4-1 shows the methodology of this study. After data collection, preprocessing, and the identification of the study area, the Mann-Kendall Trend Test and the Wavelet Analysis methods were employed to analyze the temporal variation of TSNatechs. The Intensity Analysis method was used to analyze the spatial variation of TSNatechs; and the Cross-wavelet Analysis method was used

[4] http://www.nrc.uscg.mil/
[5] https://www.epa.gov/toxics-release-inventory-tri-program/tri-data-and-tools
[6] https://gii.dhs.gov/hifld/
[7] https://www.cpc.ncep.noaa.gov/data/indices/
[8] https://www.usgs.gov/ and https://www.census.gov/geographies/mapping-files/2016/geo/carto-boundary-file.html

to analyze the correlation and coherence characteristics between climatic indices and the number of TSNatechs. Moreover, a combination of spatial analysis methods and the spatial statistical analysis methods were used to support data processing and calculating the probability of TSNatechs.

4.2.1 TSNatechs Retrieval and Study Area

In this study, a framework based on deep learning, developed exactly for such purposes, namely the Semi-Intelligent Natech Identification Framework (SINIF), was employed to retrieve TSNatechs from the NRC database. The workflow of the SINIF consisted of the following steps. Firstly, the NRC data (826,078 records) were analyzed using the keyword retrieval method (Necci *et al*. 2018). When certain keywords (e.g. hurricane, tropical storms) appeared in the incident description and/or incident cause fields, then this entry was identified as a potential TSNatech record. Next, several reports describing typical cases of TSNatechs were manually verified and selected from the aforementioned queried data as a new dataset to train and test a network. After successfully training it and confirming its satisfactory accuracy, the network was used to analyze the whole NRC dataset with the aim of identifying whether each record was a TSNatech-related report or not. Then, the records classified by the keyword retrieval method (7,354 reports) and those categorized by the network (17,575 records) were manually checked, to confirm whether they correspond to TSNatechs or not. Finally, the manually checked dataset was further analyzed to remove any duplicate records.

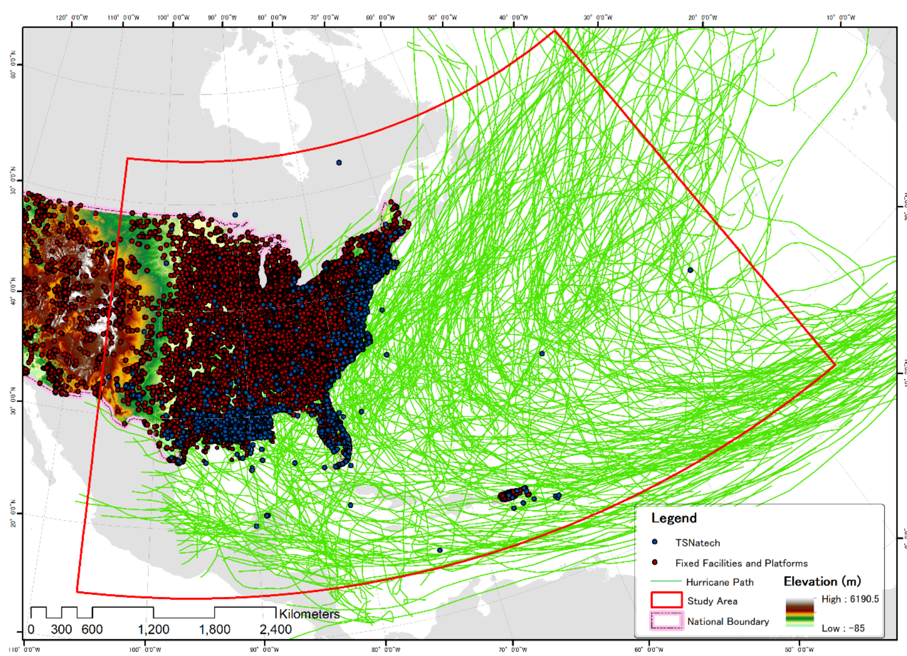

Figure 4–2 Study area (the red line frames the study area, the red spots are the locations of retrieved TSNatechs, and the blue spots are the locations of TRI facilities and offshore platforms)

As a result, 8,078 TSNatechs were retrieved from the NRC database. Moreover, 19 events were excluded as their locations did not fall within the study area limits. Finally, 7,552 reports (93.49% of all retrieved TSNatechs) comprised the final dataset for this study, including only records related to fixed facilities, storage tanks and offshore platforms, and excluding the remaining 507 related to pipelines or transportation incidents.

In order to explore the temporal–spatial variations of the retrieved TSNatechs, we mapped the spatial distribution of the records in conjunction with facilities and offshore platforms based on their position information. Furthermore, by transforming the HURDAT2 data into spatial track data, the study area was determined as shown in Figure 4-2. It, also, maps the retrieved TSNatechs and the recorded tracks of TSs on the eastern coast of the US.

4.2.2 Methods

4.2.2.1 Mann-Kendall Trend Test

The Mann-Kendall Trend Test (MK-test) method was used in this study to investigate the trend of monthly TSNatechs. The MK-test method is a widely-applied non-parametric test to analyze and identify the trend of time series data in meteorological and hydrological sciences (Gerstengarbe and Werner 1999; Shen *et al*. 2018). The procedure can be described by the following steps:

For a time series dataset $\{x_i\}(i = 1,2,\dots,\mathrm{n})$, according to the relationship between the finite difference of two consecutive variables and 0, a new set can be constructed:

$$\{S_k | S_k = \sum_{i=1}^{k} V_i\} \tag{1}$$

Where

$$V_i = \begin{cases} 1, x_i - x_j < 0 \\ 0, x_i - x_j = 0 \\ -1, x_i - x_j > 0 \end{cases} \quad 1 \le j \le i \tag{2}$$

When $n > 10$, the variance *Var(*S_k*)* can be calculated by equation (3)

$$Var(S_k) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{e} t_i(t_i-1)(2t_i+5)}{18} \tag{3}$$

Where e is the number of tied groups and t_i is the number value in each i group (Ahmed *et al*. 2017; Araghi *et al*. 2017).

Thus, the normal Z-test can be calculated based on S_k and $Var(S_k)$ by (4)

$$\mathrm{Z} = \begin{cases} \frac{S_k - 1}{\sqrt{Var(S_k)}}, S_k > 0 \\ 0, \quad S_k = 0 \\ \frac{S_k + 1}{\sqrt{Var(S_k)}}, S_k < 0 \end{cases} \tag{4}$$

When the absolute value of Z is larger than 1.96 and 2.58, the input data can be considered as having a significant trend at a 0.95 and 0.99 confidence level, respectively.

4.2.2.2 Wavelet Analysis

Since the 1990s, the wavelet analysis has become a widely-used method for examining time series data in geophysics (Torrence and Compo 1998). Nowadays, it is considered an efficient tool for analyzing observed time series data from the time and frequency domains by many researchers (Li *et al*. 2013; Araghi *et al*. 2017). According to the selected basis function for the wavelet transform, the input signal is transformed into a continuous bivariate pattern within the wavelet spectrum. The wavelet spectrum allows researchers to analyze the periodical characteristic and temporal variation of the input variable. In this study, The wavelet function is defined following the study of Torrence *et al.* (1998):

$$\psi_0(\eta) = \pi^{-\frac{1}{4}} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2},\ i^2 = -1 \tag{5}$$

Where ω_0 is the frequency scale, η is dimensionless time. The wavelet spectrum is defined based on equation (5) as:

$$W_n(s) = \sum_{n'=0}^{N-1} x_{n'}\, \psi_0(\eta) * \left[\frac{(n'-n)\delta t}{s}\right] \tag{6}$$

Where the $(*)$ indicates the complex conjugate, s is the scale of wavelet, and the $x_{n'}$ is the input time series data. The real part of $W_n(s)$ can be used to explain the return period of the input time series data on different frequencies. The module square of $W_n(s)$ is the wavelet power spectrum, the value of which shows whether the periodicity of the input data is significant or not at the given position.

4.2.2.3 Intensity Analysis

The intensity analysis was originally proposed by Aldwaik *et al.*(2012),and has been used to quantitatively measure the size and stationarity of land use changes in terms of interval, category, and transition. The transition intensity from one land-use category to another among different periods can be evaluated through monitoring and calculating the area transitions of different land-use categories in the region of interest. Moreover, the intensity analysis method has been introduced in analyzing the spatial variation of drought events (Tong *et al*. 2018; Wang *et al*. 2019), which suggests it can also be adapted to assess the spatial variation of natural hazards or related events. Valorizing this idea, this method was used to analyze the spatial variation of TSNatechs. As shown in Table 4.1, we initially divided the whole research period into four, approximately equal sub-periods. Also, using a square grid (mesh) with a resolution of 0.625×0.625 degrees as basis, we counted for each spatial unit the number of TSNatechs (NTSN) and the number of facilities[9] and offshore platforms (NFOP). Finally, following the procedure described by Santella *et al.* (2011) for the calculation of the conditional probability of Natech, we calculated the probability of TSNatech (PTSN) at location (i, j) for each sub-period as follows:

[9] We assume that all the storage tanks are located in facilities. Thus, we will use facilities to group fixed facilities and storage tanks henceforth.

$$P_{ij} = \frac{n_{TSNatech}}{n_{Infrastructures}} \tag{7}$$

Where $n_{TSNatech}$ is the number of TSNatechs in the period, and $n_{infrastructures}$ is the number of related infrastructures in the same period.

Table 4.1 Sub-time period and NTSN/PISN categories

Sub-period	Time interval	Categories	NTSN	PTSN
I	1990-1996	NoTSNatech	0	0
II	1997-2003	Low	[1,151)	[1.07x10^{-6}, 0.92x10^{-3})
III	2004-2010	Intermediate	[151,686)	[0.92x10^{-3}, 3.81 x10^{-3})
IV	2011-2017	High	[686,+∞)	[3.81 x10^{-3},1]

According to the respective histograms of NTSN and PTSN and by employing the Jenks Natural Breaks method, the results were divided into four categories: *NoTSNatech*, *Low*, *Intermediate*, and *High* (Table 4.1). The now classified NTSN and PTSN data were used as the input data for the intensity analysis.

4.2.2.4 Cross-wavelet Analysis

Endeavoring to explain the relationship between climate change and the temporal–spatial variation of the TSNatechs, we used the cross-wavelet analysis method to investigate the relationship between the climate indices (i.e. NAO and ONI in this study) and the NTSN. Cross-wavelet analysis is a statistical method to evaluate the relation between two signals through analyzing the covariance and coherent in time-frequency space based on the cross-wavelet transformation (CWT). The cross-wavelet spectrum was identified as $W^{X_1X_2} = W^{X_1}W^{X_2*}$, where W^{X_1}, W^{X_2} are the wavelet spectrums of X_1 and X_2 based on equation (6), and the $(*)$ indicates the complex conjugate, while the cross-wavelet spectrum can be considered as the covariance of input signals in time-frequency space.

Furthermore, another useful method to analyze the relationship of the two signals is squared wavelet coherence (SWC), which measures the coherency between two signals. The coherency was calculated by:

$$C_{(X_1X_2)} = \frac{\left|S\left(s^{-1}W^{X_1X_2}(s)\right)\right|^2}{S\left(s^{-1}\left|W^{X_1}(s)\right|^2\right)\cdot S\left(s^{-1}\left|W^{X_2}(s)\right|^2\right)} \tag{8}$$

Where S is a smoothing operator, the cross-wavelet spectrum. The above cross-wavelet-related equations were defined following the studies of Grinsted *et al.* (2004) and Jevrejeva *et al.* (2003).

4.3 Results

4.3.1 Temporal Variation of TSNatechs in the US

4.3.1.1 Trend Analysis and Breakpoints Determined for TSNatechs

The trend of the monthly number of TSNatechs was analyzed by using the MK-test method. The result of the MK-test shows the statistic Z is equal to $13.08 > 2.58$ ($p < 0.01$), which suggests that the monthly number of TSNatechs has a statistically significant, increasing trend between 1990 to 2017. Aimed at determining whether any break points exist, the Breaks for Additive Season and Trend (BfAST) test method (Wang *et al*. 2019) was employed. The results of the BfAST test demonstrate one breakpoint in June 2005, before which an increasing trend is observed, but a decreasing trend afterwards. However, the magnitude of the decreasing trend is smaller than the magnitude of the preceding increasing trend. In summary, the monthly number of TSNatechs has a significant increasing trend with only one breakpoint between 1990 to 2017 in the US. It is worth noting that this break point might have occurred due to the dramatic large number of TSNatechs in August 2005 due to hurricane Katrina and Rita.

4.3.1.2 Periodical Characteristics of TSNatechs

In this study, the Morlet-based wavelet transform was implemented to analyze the periodicities of TSNatechs. Figure 4-3 (a) depicts the monthly number of TSNatechs from 1990 to 2017 in the US. Six high peaks can be observed across the dataset, matching the incidence of serious hurricanes in 2004, 2005, 2008, 2011, 2012 and 2017. Moreover, the wavelet coefficient and the wavelet variance spectrum are illustrated in Figures 4-3 (b) and (e), respectively. Whilst there are four distinct peaks in the curve of the wavelet variance spectrum, only three dominant periodicity scales are not affected by the cone of influence (COI): 0.3–0.7 years, 1–2 years, and 3–4 years. All three periodicity scales passed the significance test at the 0.75 confidence level, while the former two proved significant also at the 0.9 level. However, none of the above periodicity scales is stable throughout the whole study period. More specifically, the first one continued in three short-term intervals: August 2004–June 2006, January 2008–April 2009, and May 2011–August 2013. The second periodicity scale covers two intervals: February 2004–August 2009 and January 2011–March 2014, while the last one stretches over the longest time interval, October 2002–June 2016. As far as the oscillation energy in the periodicities of TSNatechs is concerned, Figure 4-3 (c) demonstrates that all observed periodicity scales are located in the strong energy area enclosed by the black line of the 5% significance level, which represents the monthly number of TSNatechs has an intense periodicity during these time-scale intervals. Meanwhile, the scale-average variance curve in Figure 4-3 (d) shows that the highest peak appears in August 2008. This means that the periodicity of TSNatechs becomes the most evident around this point.

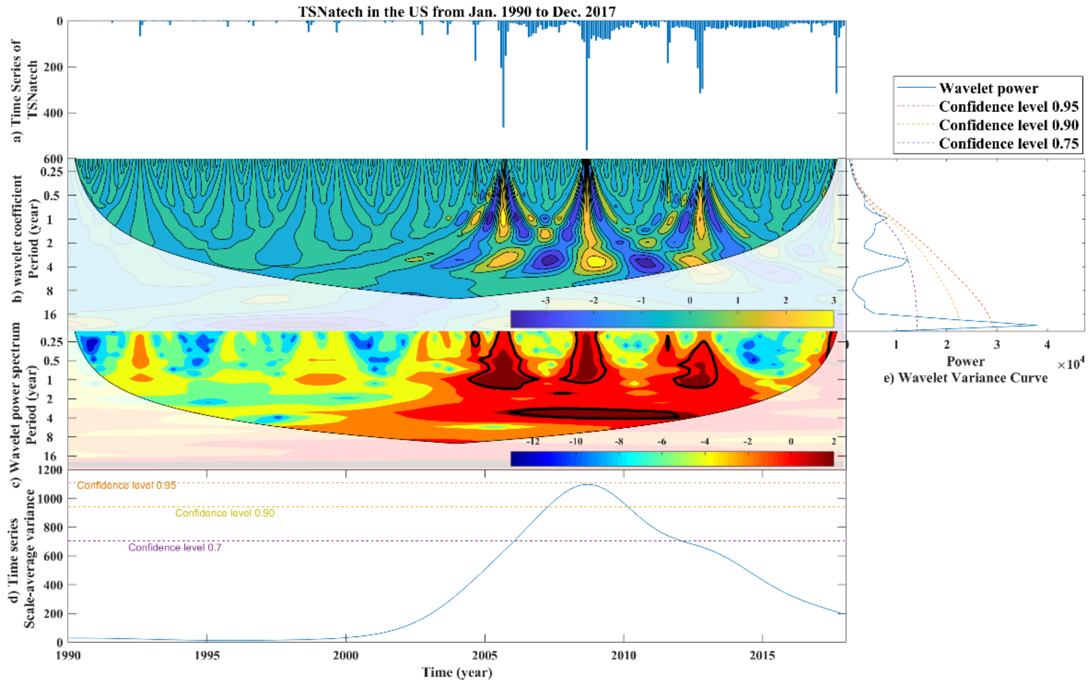

Figure 4–3 (a) Time series of the monthly number of TSNatechs. (b) Wavelet coefficient. (c) Wavelet power spectrum. (d) Scale-average time series. (e) Wavelet variance curve. In Figures (b) and (c), the thick black lines represent the 5% significance level based on a red-noise model, while the translucent white areas mark the zones of the cone of influence (COI).

4.3.2 Spatial Variation of TSNatechs in the US

In this study, the whole period was divided into four, approximately equal sub-periods, whilst the probability of TSNatechs (PTSN) and the number of TSNatechs (NTSN) were separated into four categories (NoTSNatech, Low, Intermediate and High). Based on the data pre-processing, the intensity analysis method was used to evaluate the intensity of area transition, the amount and speed of change between different categories across the various sub-periods. Figure 4-4 (a) and (b) indicate these transition intensities from a macro-perspective. The spatial distribution of NTSN and PTSN was relatively stable during the periods I and II, but became gradually more unstable since 2005, which is the boundary year for both period II and III, and destabilized even further during the progression from period III to IV. Detailed analysis revealed that the rate of transition between categories was not very intense from the period I to II (both of the annual changes on PTSN and NTSN are smaller than the uniform annual change), but the rate of area transition started to accelerate from period II to III with the annual change on both of PTSN and NTSN becoming larger than the uniform annual change rate. Additionally, from period III to IV, the transition intensity became the highest across the whole research timescale.

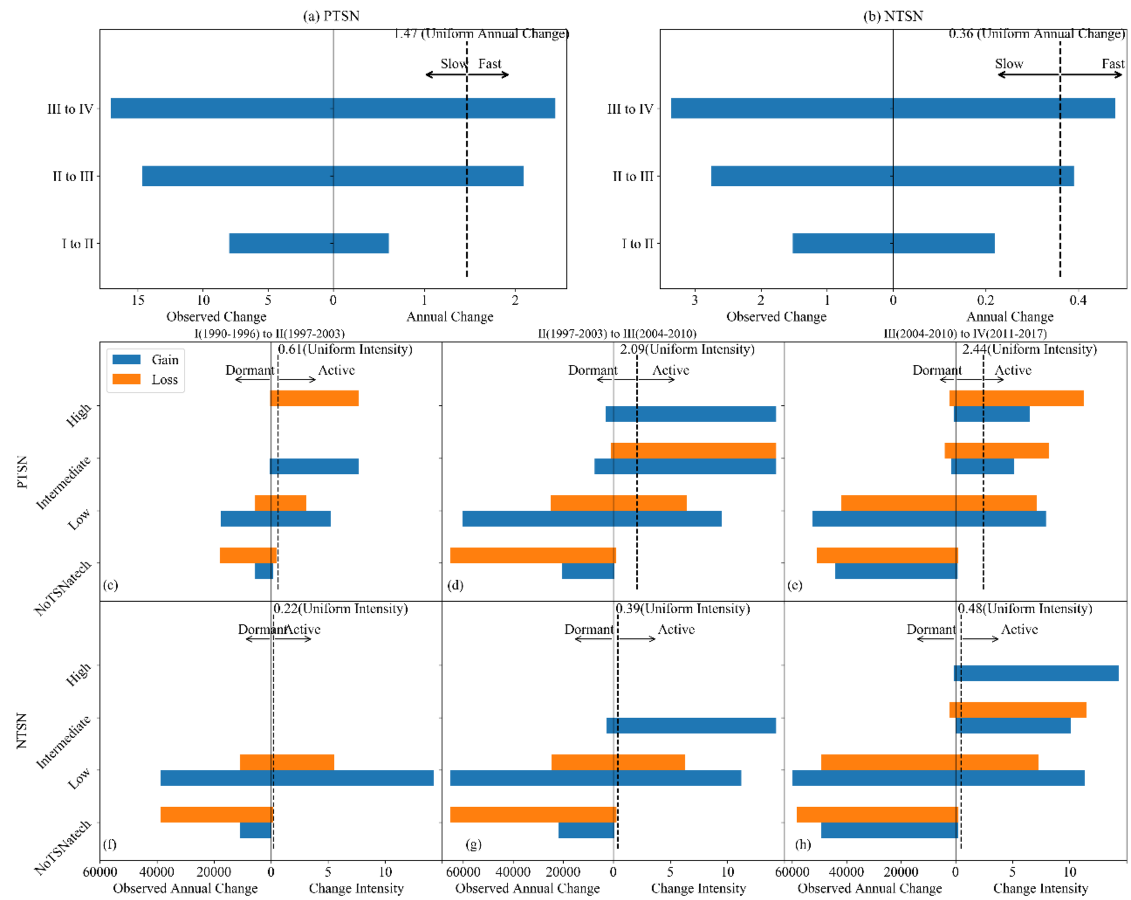

Figure 4–4 (a)-(b) indicates the macro-perspective on the spatial variation of the indices of the probability of TSNatechs (PTSN) and the number of TSNatechs (NTSN); (c)-(h) explain the intensity analysis of change among different categories of NTSN and PTSN. In each Figure of (c)-(h), the left side indicates the observed annual area changes, and the right side indicates the changing intensity among categories. The black dotted line shows the value of Uniform Intensity (UI) for each sub-period. If the value of changing intensity is larger than the UI, the category's area gains or losses on this category are active, otherwise are dormant.

4.3.2.1 Spatial Variation of the PTSN

During the implementation processing of the intensity analysis method, the transition matrix was calculated also to explain —from a quantitative perspective— the mutual transitions and the intensity among the different categories and during the various sub-periods. As demonstrated by the transition matrix of the PTSN, the categories of *NoTSNatech*, *Low* and *High* were identified in the study area during period I. However, in period II, the *High* category areas (4,120.38 km^2) was transformed into *Low* areas, meanwhile, the *Intermediate* (6,475.07 km^2) area was gained from the *NoTSNatech* areas. From period II to III, certain areas identified as *High* (18,398.45 km^2) reappeared, and were partially redistributed in the IV period. The upper row in Figure 4-4 (c)-(e) summarize the area gains and losses for each category level of PTSN. As evidenced, transitions of *High, Intermediate* and *Low* areas were particularly active throughout the whole research period. Especially, from period II to III, a large portion of *NoTSNatech* areas was transformed into these other categories, whereas, from period III to IV, transitions mainly happened among *Low*, *Intermediate* and *High* areas. Consequently, a gradually increasing number of places became prone to the occurrence of TSNatechs over the course of the research period. Besides, from a macro-perspective, the total number of areas transitioned into categories with TSNatechs occurrence (i.e. *Low*, *Intermediate* and *High* area) was greater than the number of areas lost from the above categories. Thus, the areas with a higher TSNatechs probability have been actually increasing, which suggests that the probability of TSNatechs also increased from 1990 to 2017 in the US.

4.3.2.2 Spatial Variation of the NTSN

According to the transition matrix of the NTSN, there were no areas identified in the *High* and *Intermediate* categories during periods I and II across the study region. However, a few areas (19,323.85 km^2) transformed into the *Intermediate* category during the interval from II to III. It is only in period IV, that areas in the *High* category (3,911.81 km^2) appear within the study region. The lower row in Figure 4-4 (f)-(h) offer the overview of the area gains and losses for each category level of NTSN., Similar to the results of PTSN, transitions of *High*, *Intermediate* and *Low* areas were also quite active across the research period. Furthermore, there were numerous areas in the category *NoTSNatech* that transformed into other categories in every period, which in turn means that more places became prone to the occurrence of TSNatechs. Over the course of the research period, the *Intermediate* and *High* categories started gradually appearing, and the corresponding areas increased smoothly. Overall, a high number of TSNatechs appeared and persisted afterward through the rest of the research period. Consequently, TSNatechs spread over the study area and with an increasing density over time.

4.3.3 Cross-wavelet Correlation between TSNatechs and Climatic Indices

In order to understand the relationship between climate change and the temporal–spatial variation of the incidence of TSNatechs, this study employed the Cross-wavelet analysis method to analyze the monthly number of TSNatechs and monthly climatic indices (the NAO index and the ONI). Figure 4-5 (a) presents the two running correlation coefficient curves of NAO–TSNatech and ONI–TSNatech. It is noteworthy that the numerical correlation between the NAO index and the TSNatechs is characterized by opposite correlations in different periods. More precisely, before 1997, NAO index and TSNatechs had a very weak numerical correlation, but this turned into a negative numerical correlation by 2004 (peak at -0.43, $p<0.01$). In the period 2004–2010, the correlation turned to positive (peak at 0.24, $p<0.05$), but changed to negative (peak at -0.37, $p<0.01$) again afterward, and continued so until 2017. In the meantime, the running correlation between the ONI and the TSNatechs also showed an unstable function over time. Before 2000, ONI and TSNatechs were negatively correlated (peak at -0.37, $p<0.01$). After 2000, the correlation took a weak positive value, but turned into a negative value again in 2004 (peak at -0.31, $p<0.05$) and continued so until 2006. After 2006, the correlation fluctuated frequently between positive and negative values ranging from -0.20 to 0.12. The above results suggest that the number of TSNatechs is numerically correlated with the NAO and ONI indices, but with varying intensities and direction over time.

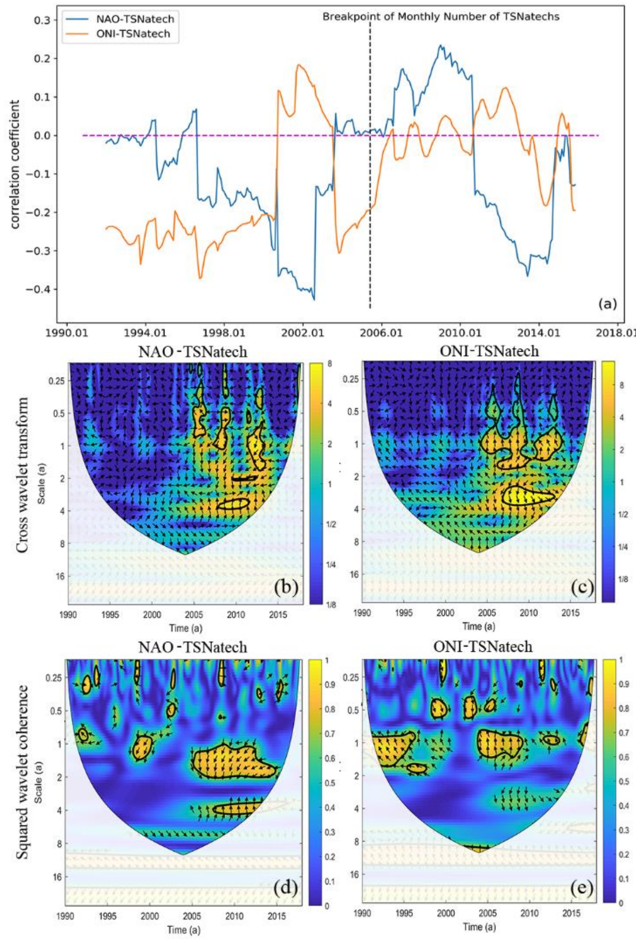

Figure 4–5 (a) Running correlation coefficient of NAO–TSNatech and ONI–TSNatech on monthly time series data (4 years/48 month window); (b) the CWT of standardized number of TSNatechs and NAO monthly time series; (c) the CWT of standardized number of TSNatechs and ONI monthly time series; (d) the SWC of standardized number of TSNatechs and NAO monthly time series; (e) the SWC of standardized number of TSNatechs and ONI monthly time series. In Figures (b), (c), (d) and (e), the thick black lines represent the 5% significance level based on a red-noise model, while the translucent white areas mark the zones of the cone of influence (COI). The relative phase relationship is shown as arrows: with in-phase pointing right, anti-phase pointing left, and ONI or NAO leading TSNatechs by 90° pointing straight up.

NAO index and TSNatechs exhibited high cross-wavelet spectrum power between 2004–2006 in the 0.25–0.9-year scale, between 2007–2009 in the 0.5–1.1-year scale, between 2011–2013 in the 0.63–1.7-year scale, and between 2006–2012 in the 3–4-year scale (in Figure 4-5 (b)). In the first and third areas, the phase angle is randomly distributed. In the second area, the NAO index and TSNatechs were in-phase in the 0.5–0.73-year scale, but with randomly phase angles in the 0.73–1.1-year scale. In the fourth area, the NAO index led TSNatechs. There are three main areas with significant coherence between the NAO index and the TSNatechs, as indicated in Figure 4-5 (d). These are between 1998–2000 in the 0.86–1.44-year scale, between 2005–2014 in the 1.11–2.1year scale, and between 2007–2012 in the 3.83–4.25-year scale. Only the third area has a NAO index-leading phase angle, while the other two areas show an alternating phase angle that changed over time.

ONI and TSNatechs exhibited trends similar to the relationship between NAO index and TSNatechs (Figure 4-5 (c)). The high cross-wavelet spectrum power was distributed in the range between 2004–2009-in the 0.25–1.88-year scale, between 2009–2013 in the 0.74–1.44-year scale, and between 2006–2012 in the 2.52–3.74-year scale. In the first area, the ONI led TSNatechs around the 1-year scale, but the phase angle was randomly distributed in the other places. Meanwhile, the other two areas also exhibited a random phase angle. Significant coherence appeared mainly in two areas; one is between 1991–1996 in the 0.92–1.81-year scale, and the other one is between 2004–2008 in the 0.87–1.49-year scale. The phase angle is around 135˚in the first area, but the ONI led TSNatechs in the second area.

All the above results suggest that the NAO index and the ONI have an unstable relationship with the number of TSNatechs during 1990–2017, which means that the NAO and ENSO may affect the incidence of TSNatechs. Nonetheless, whether this connection could be explained as causality needs to be further explored.

4.4 Discussion

This study analyzed the temporal–spatial variation of tropical storm-related Natechs (TSNatechs) between 1990 and 2017, which were reported to the NRC database. The result suggests there are following temporal-spatial variation in the incidence of TSNatechs: 1) the monthly number of TSNatechs has a significant increasing trend a breakpoint in June 2005, after which the periodicity became more evident; 2) TSNatechs were reported across a wider area than before, while their density has also been increasing over time; and 3) the probability of TSNatechs displayed an uncertain, increasing trend in the US from 1990 to 2017.

First of all, the quality of the retrieved TSNatechs is considered as a critical factor affecting directly the results. In this study, the TSNatechs were retrieved from the NRC database by using the SINIF. Aiming at testing such quality, we counted the number of retrieved TSNatechs from 1990 to 2008 to do a comparison with the study of Sengul *et al.* (2012), which was focusing on understanding Natechs in the US in such period. There were 19,767 entries identified as Natech by the SINIF, with 3,557 of those being related to TSs in the period 1990–2008. Sengul's research showed similar results: 16,600 Natech events with 3,320 Natech being related to hurricanes. The difference between the two datasets can be attributed to the fact that hurricanes are a sub-category of TSs, and in this study Natech reports related to other TSs were also considered. Hence, we advocate that the validity of our results is acceptable.

In this context, the discussion on the temporal–spatial variation of TSNatechs is presented here. As we only focus on the TSNatechs concerning facilities and offshore platforms, the following factors were considered when investigating the temporal–spatial variation results of the TSNatechs: 1) changes on the number and spatial distribution of infrastructures; 2) changes on regulations and reporting formats; and 3) changes on the number, intensity and spatial distribution of TSs. Of course, there might be other factors, such as the aging of infrastructures, that will affect the occurrence of TSNatechs. But since it is quite difficult to track the state of thousands of infrastructures simultaneously, we have to hypothesize that all the infrastructures have been in the best possible condition and have been undergoing regular maintenance in the whole research period.

Figure 4-6 (a) shows the annual number of TRI facilities, offshore platforms, and TSNatechs. There are observable decreasing trends on both facilities and offshore platforms, although the annual number of TSNatechs has an upward trend. This suggests the changes in the number of facilities and offshore platforms are not sufficient to explain the temporal variation of TSNatechs.

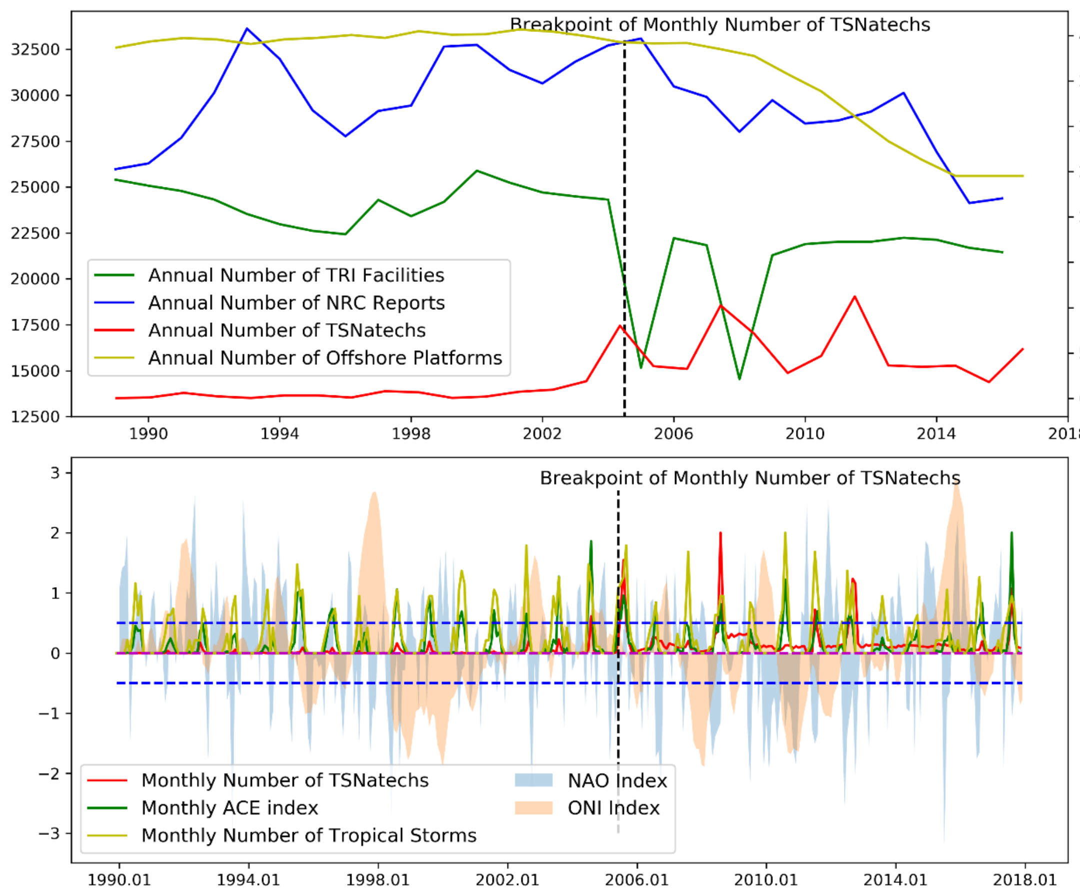

Figure 4–6 (a) Annual number of TRI facilities, the NRC Reports related to hazmat release incidents, offshore platforms, and TSNatechs. The value range of the former two variables was indicated on the left side, and the value range of the latter two variables on the right side. (b). The time-series data of monthly number of TSNatechs and tropical storms, and the monthly data of Accumulated Cyclone Energy (ACE), NAO, and ONI indices. Meanwhile, the former three variables were normalized into the range of [0,2] to compared with the NAO and ONI indices. The blue dotted line depicts the weakest line of the El Niño and La Niña events.

Aimed at confirming whether the spatial variation of the instalations will affact the spatial variation of TSNatechs, the mean moving center pathes and the spatial distribution of facilities, offshore platforms, and TSNatechs were analyzed. The results show that the spatial distribution of facilities did not change remarkably from 1990 to 2017, as there are four hotspots for facilities in the study area and the total mean center did not change much either. In addition, the offshore platforms correspondingly distributed in the Gulf of Mexico without any significant changes. However, the spatial distribution of TSNatechs has been continuously changing over time. There were three main hotspots of TSNatechs, and the total mean center of TSNatechs has been constantly switching between the above three areas. Considering that we are interested in the occurrence of TSNatechs in facilities and offshore platforms, the above evidence suggests that a large number of facilities distributed in a certain area does not necessarily translate to a large number of TSNatechs, even if those areas are affected by TSs. Thus, we can conclude that the changes in the number and spatial distribution of facilities and offshore platforms are likely not important factors in explaining the temporal–spatial variation of TSNatechs in the US from 1990 to 2017.

Another potential factor for causing the temporal–spatial variation of TSNatechs is the changes in regulations or reporting formats used by the NRC in registering hazmat releases. We checked the website of the US Environmental Protection Agency (EPA) that is managing the NRC database and collecting the hazmat release reports. There are two main regulations or rules, the Clean Water Act and the Risk Management Plan (RMP) Rule, which address how the facility owner or operator should report hazmat release incidents. According to these, the EPA required facility owners/operators to have a risk management plan to reduce the effects of hazmat release risk and to report any hazmat release incidents, past or recent. Apart from this, the EPA has modified the hazmat list and readjusted the Reportable Quantity (RQ) Level for released chemicals, in order to relieve the government from the burden of responding to small quantities of hazmat release reports. EPA's abovementioned activities can actually indirectly affect the trend and number of hazmat release reports, influencing in turn the TSNatechs under study. In Figure 4-6 (a), the annual number of hazmat release reports in the NRC database is depicted by the blue curve. The changes of the curve match quite well the regulatory changes. For example, there are two increases on the blue curve in 1993 and 1997, when the EPA was readjusting the RQ levels and modifying the hazmat list. Meanwhile, the RMP rules announced in 1996, made the EPA start gathering 5-year historical accident reports and risk management plans from facilities. Furthermore, the RMP rules were amended last time in 2004, reiterating the necessity for facilities to draft risk management plans. As a result, we can observe a gradual decrease in the number of all hazmat release reports due to the implementation of more effective risk management plans since 2004. However, the red curve in Figure 4-6 (a), which indicates the annual number of TSNatechs, does not reflect the above changes very well. Therefore, we can deduce that the regulatory changes are probably a significant variable in the trend of all hazmat release reports in the NRC database, but may not be an important factor influencing the temporal–spatial variation of TSNatechs. From the perspective of changes in the reporting formats, it is worth noting that in the NRC data files, '*Hurricane*' appeared as a cause of incidents only since 2003, but there is no evidence that the EPA made any changes to the collection formats prior to that year. Nonetheless, no evidence supports that EPA made any changes in the formats when dramatic peaks on the number of TSNatechs occurred in 2005, 2008, 2012. Therefore, we are considering that the changes in regulations or reporting formats used by the NRC might not be such an important factor to help explain the resulting temporal-spatial variation, especially the temporal variation of TSNatechs.

According to the above discussion, it seems like the changes in the number, intensity and spatial distribution of TSs, might be the main reason why the TSNatechs present the temporal–spatial variation exhibited in section 4.3. Figure 4-6 (b) presents the curves of the monthly TSNatechs, the monthly Accumulated Cyclone Energy (ACE) index and the monthly number of TSs in the study area. It should be noted that the ACE index is considered an important measure to express the activities of TSs by many institutes, and it is used here to evaluate the intensity of TSs (Camargo and Sobel 2005; Yu *et al*. 2009; Murakami *et al*. 2014). Examining Figure 4-6 (b) suggests that the monthly number of TSNatechs are probably affected by the other two factors, as most peaks in the monthly reported TSNatechs matched either the monthly ACE index or the number of TSs. Meanwhile, the rising trend in the monthly number of TSs and the monthly ACE index indicates that the intensity and frequency of TSs in the study area are increasing. These results align with findings from previous studies (James B Elsner *et al*. 2008; James B. Elsner *et al*. 2011; Aslak Grinsted *et al*. 2012). Besides, several researchers have already pointed out that changes in tropical storm patterns could be attributed to the Climate Change (Lindell and Perry 1997; A. Grinsted *et al*. 2004; Menoni *et al*. 2012). As shown in Figure 4-6 (b), when a strong ENSO phenomenon occurs (displayed as large absolute value of ONI), there is a large value of the normalized monthly number of TSs located at the same time, which suggests that the ENSO could affect the number and frequency of TSs around the Atlantic Ocean. Actually, the studies of Elsner *et al.* (1999) and Iizuka *et al.*(2009) arrived to similar conclusions. Examining the NAO index, when its absolute value is high, the ACE index also exhibits a large value. This implies that the NAO could affect the intensity of TSs. Similar results have been presented by Fraza *et al.* (2016). Likewise, some researchers have pointed out that the NAO index additionally captures the influence on the trajectories of TSs because it is an evaluation index of the different atmospheric pressures between the Icelandic Low and the Azores High. With positive NAO index values, TSs have been observed to make landfall on the eastern US coast more easily, but in negative values, TSs tend to move rather towards the Gulf of Mexico (J. B. Elsner *et al*. 2000; Kossin *et al*. 2010).

Before the breakpoint of monthly TSNatechs (Figure 4-6 (b)), the ENSO phenomenon was strong and the number of TSs was relatively larger, but the ACE index was not nearly as strong at the same location with a small NAO value. This could explain why the number of TSNatechs was not as high in this period. After the breakpoint, large values of both the NAO index and the ONI appeared at the same positions for longer, which shows an overlap of the large values of the intensity and the tropical storm number. Especially in the years 2005 and 2008, negative, large NAO index values dominated the study area for longer periods than in other years. Correspondingly, during these seasons Hurricanes Katrina and Rita (2005) and Ike (2008) made landfall at the Gulf of Mexico bringing a large number of TSNatechs. Another example is in 2012, when hurricane Sandy occurred during a transition period, in which the NAO index changed from a negative value (in October) to a positive one (in November). This might have led to Hurricane Sandy making landfall on the eastern coast, also resulted in numerous TSNatechs. Other points, such as in April 2004, show that a large number of TSs occurred with notable intensity, but brought only a small number of TSNatechs. This could be explained by the inherent uncertainty in the occurrence of TSNatechs. According to the study of Santella *et al.* (2011), the conditional probability of Natechs can be described as a fragility curve against the wind speed, which means that the growing intensity of TSs will in turn increase the conditional probability of TSNatechs, even though it may never reach 1.

To further analyze the relationship between climatic indices and TS activity, the Cross-wavelet Analysis method is also used to analyze the indices of monthly NAO index, ONI index, ACE index, and TS count, whose results are shown in Figure 4-7. The CWT and SWC in Figure 4-7 show that both of the NAO and ENSO phenomena have unstable effects on the TS activity with respect to intensity and number of TSs on the 2-4-year scale (Figure 4-7 (e)-(h)). However, the relationships among the monthly NAO index, ONI index, ACE index, and TS count are more stable on the 1-year-scale than on the 2-4-year scale, as shown in Figure 4-7 (a)-(d). Meanwhile, it becomes evident that the ENSO phenomena has more stable and longer time-scale effects on the intensity and number of TSs around the Atlantic Ocean, since the significant area in Figure 4-7 (g) and (h) are much larger than those indicated in Figure 4-7 (e) and (f). These results show that the NAO and ENSO phenomena affect TS activity on different time-scales.

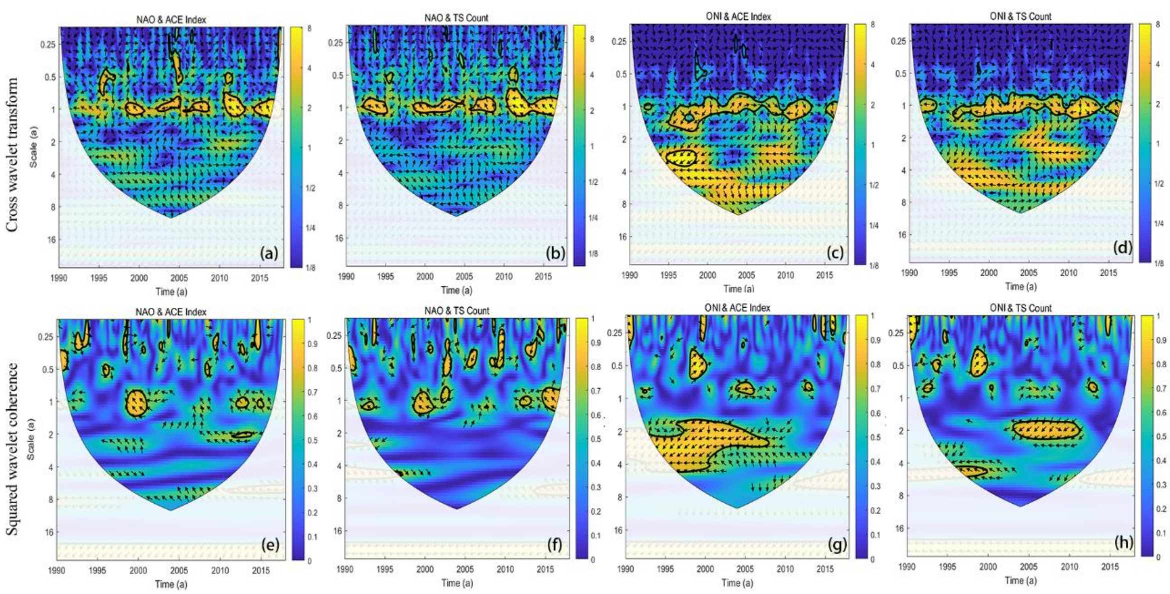

Figure 4–7 (a) the CWT of standardized ACE index and NAO monthly time series; (b) the CWT of standardized number of TS and NAO monthly time series; (c) the CWT of standardized ACE index and ONI monthly time series; (d) the CWT of standardized number of TS and ONI monthly time series; (e) the SWC of standardized ACE index and NAO monthly time series; (f) the SWC of standardized number of TS and NAO monthly time series; (g) the SWC of standardized ACE index and ONI monthly time series; (h) the SWC of standardized number of TS and ONI monthly time series. In the above Figures, the thick black lines represent the 5% significance level based on a red-noise model, while the translucent white areas mark the zones of the cone of influence (COI). The relative phase relationship is shown as arrows: with in-phase pointing right, anti-phase pointing left, and ONI or NAO leading ACE index or TS count by 90° pointing straight up.

Finally, the results of the cross-wavelet analysis in section 4.3.3 also showed that the number of TSNatechs correlated to the NAO and ONI index in the temporal–frequency space. Therefore, we can conclude that the NAO and ENSO phenomena could be key factors in monitoring the variation of TSNatechs. Meanwhile, many researchers have suggested that NAO and ENSO could be affected by the increasing temperature caused by global warming (Cohen and Barlow 2005; Yeh *et al*. 2009;

Hafez 2016). Hence, academicians and practitioners ought to be aware that the climate change could cause more TSNatechs in the future.

4.5 Conclusions

This study investigated the temporal–spatial variation of tropical storm-related Natechs in the NRC database from 1990 to 2017, using trend, intensity, and wavelet analysis methods. Based on the findings and subsequent discussion, the following conclusions were drawn. First, the number of TSNatechs has an increasing trend with a rising spatial density, while TSNatechs have been gradually expanding in area through the course of time. Second, the periodicity of the monthly number of TSNatechs intensified notably after June 2005. Third, the above temporal–spatial variation of TSNatechs seems to be related to the variation of the number, intensity and spatial distribution of tropical storms. Fourth, the variation of tropical storms could be explained by two, widely-used climatic indices, the NAO and ONI indices; Fifth, the NAO and ONI indices are numerically correlated with the number of TSNatechs in the temporal–frequency space. Sixth, due to the connection between NAO, ENSO and climate change, climate change might indirectly affect the incidence of TSNatechs by means of affecting the variation of tropical storms through NAO and ENSO. Finally, the overall study findings indicate that the increased number of TSNatechs might be related to climate change in the US from 1990 to 2017. Yet, given the uncertainty of both the climate system and the occurrence of TSNatech, and their complexity, it is rather early to come to this conclusion. However, the results suggest climate change has in fact brought more tropical storm-related Natechs to the US, and in a wider area in the period studied. In addition, the presented evidence suggests that, when developing Natech risk management plans, the effects of climate change should not be ignored. Not only facilities' owners/operators, but the governments should consider climate change effects and implement more effective regulations to respond to TSNatech risk in wider areas.

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Chapter 5 Empirical Estimation for Probability and Conditional Probability of TSNatech

5.1 Introduction

Chemical-release accidents may potentially occur due to the interaction of natural hazards and industrial installations when the relevant infrastructure are overloaded by the effects of natural hazards. Such cascading accidents are known as Natech events (Showalter and Myers 1994; Cruz and Krausmann 2013). The Fukushima nuclear accident (Krausmann and Cruz 2013; Yu *et al*. 2017), oil-release accidents occurred during Hurricane Katrina and Rita (Cruz and Krausmann 2008; Cruz and Krausmann 2009), and the chemical-release accidents due to the Kocaeli earthquake (Steinberg and Cruz 2004) are typical examples of Natech events that caused severe consequences on the environment (Krausmann and Cruz 2013), human health (WHO 2018), and regional economies (Girgin and Krausmann 2016).

Among the natural hazards capable of triggering Natech events, weather-related hazards seem to increasingly draw the academic interest, a trend which might be reinforced within the framing of climate change (Cruz and Suarez-Paba 2019; Suarez-Paba *et al*. 2019). Especially so for tropical storms, a typical weather phenomenon, with the potential to cause severe Natech events considering the tremendous amount of energy and vapor they carry (Necci *et al*. 2018). Sengul (2005) and Sengul *et al*. (2012) have determined that the percentage of hurricane-triggered Natech events among all types of recorded Natech events increased from around 10% to 20% during the period from 1990 to 2008 in the US. Based on the Natech incidents reported to the National Response Center (NRC)(National Response Center 2017) database, the percentage of hurricane-related Natech records has increased to almost a quarter of all Natech records by 2017 according to the results of SINIF. Furthermore, research studies revealed that the damages to hundreds of offshore oil platforms causing a significant peak of the annual pipeline-Natech reports in 2005 could be attributed to Hurricanes Katrina and Rita (Cruz and Krausmann 2008; Girgin and Krausmann 2014). Moreover, Necci *et al*. (2018) reported similar results in the increasing trend of storms-related Natech events in Europe. Therefore, hurricanes, as a characteristic type of tropical storm, could be considered as the hazard most likely to trigger Natech events in recent years.

Several studies have noted that Natech events may be occurring more frequently and seriously due to climate change (Cruz and Krausmann 2013; Salzano *et al*. 2013; Tolo *et al*. 2017; Necci *et al*. 2018; Tsionis *et al*. 2019; Kumasaki and King 2020). The increasing number of tropical storm-related Natech events (TSNatech) could also be, somehow, attributed to climate change. Cruz and Krausmann (2013) discussed the vulnerability of the oil and gas industrial sector to tropical storms under climate change. Katopodis and Sfetsos (2019) made recommendations for adapting the oil sector to risk of tropical storms concerning the effects of climate change. Although, those two studies are quite valuable, they only provided an overview discussion about the potential link between climate change and Natech events, but they did not determine the actual relationship between climate change and Natech events directly. Understanding the effects of climate change on the occurrence of Natech events may provide valuable inputs in coordinating the efforts to improve the capacity of local governments and industry owners/operators to cope with TSNatech risk. However, the increasing trend in the number of TSNatech events cannot be directly used to determine whether climate change affects the incidence of TSNatech, since the number and distribution of installations could also work on the number of TSNatech events. Analyzing the changes in TSNatech probability could be a more confident measure to investigate the effects of climate change on the incidence of TSNatech events.

Some researchers provided methods to estimate the probability of TSNatech indirectly through analyzing the failure probability of equipment based on fragility analysis. Olivar *et al*. (2019) estimated the fragility curves of storage tanks affected by strong winds, while Olivar *et al*. (2020) analyzed the effects of extreme winds on storage tanks. Kameshwar and Padgett (2018) proposed a method to estimate the failure probability of storage tanks against storm surge. These fragility analysis-based probability estimation methods hold significant value for industrial facility owners and risk managers in terms of refining risk assessment methods and creating a basis for effective management strategies against Natech risk brought by serious tropical storm systems like hurricanes. However, these studies have only focused on single installations/equipment affected by a single type of natural phenomenon (e.g. wind effect, flooding, storm surge inundation, and so forth), an approach that makes it inefficient to employ when estimating the probability of Natech events over a wide area and for long periods of time considering the potentially large numbers of individual installations to be included.

There are limited studies however that have tried to estimate the probability of Natechs based on past accident data. Santella *et al*. (2011) proposed a method for estimating the conditional probability of Natech events related to severe hurricanes, floods, and earthquakes in the US by counting the number of Natech events and related facilities in a hazard impact zone for each selected natural hazard event. Based on the calculated conditional probability of Natech events, Santella *et al*. developed fragility curves to describe the conditional probability of Natech events against each natural phenomenon. In the case of hurricane-triggered Natech events, their analysis considers wind speed and storm surge effects separately. Their work is very valuable in understanding the occurrence of historical Natech events and providing inputs for the standard development of equipment design, however, it may increase the time cost and the uncertainty of results by combining the simulation models of storm surge and wind effects to assess Natech risk for future. If we can estimate Natech probability based on the concurrent consideration of multiple effects due to tropical storms, the risk managers, facility owners, governments, and other stakeholders could quickly receive more integrated risk information for Natech events to make plans to reduce the risk and potential losses.

However, there have been so far, no attempts to estimate TSNatech probability by concurrently considering the multiple natural phenomena that accompany tropical storms. According to a study by Cruz *et al*. (2001), the multiple natural phenomena that accompany tropical storms such as high wind speeds, flooding, heavy rain, lightning, and storm surge, can affect infrastructure in facilities or industrial parks, particularly if they are located near areas where tropical storms make landfall. Thus, from the perspective of engineering, the occurrence probability of TSNatech could be estimated by considering the mechanisms by which different natural phenomena affect or even damage equipment, very often occurring simultaneously during a tropical storm. Notwithstanding, this is a challenging, resource-intensive, and complicated task to estimate the probability of TSNatech regarding multiple natural phenomena occurring concurrently; and would require having a vast amount of detailed data about the natural phenomena, the equipment, and impacts loads.

Another way to estimate TSNatech probability, is to identify a variable that can capture the loading effects on installations of the various natural phenomena that accompany tropical storms. Wind energy, which is considered as the kinetic energy of a tropical storm, could serve as a single variable, since all the above mentioned natural hazards induced by tropical storms can be regarded as consequences of the energy dissipation mechanism of a tropical storm. Powell and Reinhold (2007) pointed out that the wind energy not only scales with the surface stress which causes storm surge but also scales with wind pressure on a structure. In addition, the precipitation brought by the tropical storm system, which may cause heavy rain and flooding, is also related to its energy (Makarieva *et al*. 2017). Thus, the wind energy carried by tropical storms in a period (e.g. one year) is considered as an important variable to estimate the probability of TSNatech.

Aimed at developing and implementing an approach for assessing the probability of TSNatech in a wide area, this study provides a grids analysis-based methodology to spatially estimate the probability and the conditional probability of TSNatech in the US from 1990 to 2017, and further analyze the changes of the probability and conditional probability of TSNatech in the same period. Moreover, the wind energy is introduced for the first time in the field of Natech risk assessment to estimate the conditional probability of Natech events considering the occurrence of tropical storms.

The structure of this paper is organized as follows. Section 5.2 presents the methodology including data collection and processing, the study area identification, and the methods used to calculate the TSNatech probability and annual wind energy brought by tropical storms. In Section 5.3, we present the results and analyze the annual variation of the conditional probability of TSNatech and the probability of TSNatech occurrence. Furthermore, section 5.3 also presents the estimation of the conditional probability of TSNatech based on wind energy. In the final section, we present conclusions and recommendations for future research.

5.2 Methodology

In this research study, we used data from the National Response Center (NRC) database (National Response Center 2017) to identify and retrieve TSNatech events within the target area, because the NRC database contains the largest number of chemical release incidents in the world (more than 800,000 from 1990 to 2017). Moreover, the NRC database records the description and cause of the reported incident, which makes it possible to extract TSNatech events data through data mining approaches. In addition, the Toxics Release Inventory (TRI) Program basic data (EPA 2017) and the Oil and Natural Gas Platforms data (USGS 2018) were consulted to count the installations that were affected by tropical storms. The former one is released by the United States Environmental Protection Agency (EPA), and it is a database for collecting the annual reports related to the toxic chemicals from the US facilities in different industry sectors and sharing such information to the public. The latter one contains all the offshore platforms information by year in the US. These two databases could provide the information of facilities and offshore platforms by year to support this study to calculate TSNatech probability in the following section. Furthermore, the 'Best Track Data' (HURDAT2) (Landsea *et al*. 2015) ,which contains the fundamental parameters for each tropical storm with 6-hour observation intervals (such as the maximum wind speed, the maximum radii of different wind speed levels, etc.), were used to identify the historical tropical storms around the eastern side of the US which is the core study area of this project. Moreover, the Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) (GMAO 2015), which is a re-analysis data for supporting meteorological-related studies based on historical atmospheric data (such as observed station data, remote sensing data, simulation data, etc.), were used to spatially verify the retrieved TSNatech cases, and calculate the wind energy carried by tropical storms in the period of study.

5.2.1 Calculation of the TSNatech Probability

Aimed at calculating the TSNatech probability from a regional perspective, the study area is converted into a square grid with a spatial resolution of 0.625×0.625 degrees. Following the estimation method for the conditional probability of TSNatech proposed in the study of Santella *et al.* (2011), the probability of TSNatech for each grid cell is calculated according to equation (1):

$$P_{(i,j)} = \frac{n}{N} \tag{1}$$

where (i, j) is the location index of each grid cell, n is the number of Natechs that occurred within one certain period (it depends on the time scale of interest), N is the number of target installations. In this study we consider TSNatech events that occurred at fixed facilities, storage tanks, and offshore platforms. It should be noted that Natech events that occurred in transportation systems or transmission pipelines are not considered in this study due to the difficulty of monitoring such systems. In terms of equation (1), if N is considered as the number of target installations in the period of tropical storm occurrence, then $P_{(i,j)}$ will be the conditional probability of TSNatech for the considered tropical storm, otherwise, it will be the probability of TSNatech for the interest period (e.g. one month, one year, or any certain time period).

5.2.2 Retrieving of TSNatech

As we explained in section 5.2.1, we are interested in TSNatech events that occurred at fixed installations and offshore platforms. Since the study area is located in the US, the NRC database was used to identify the TSNatech by following the process as depicted in Figure 5-1. In brief, all reported chemical release incidents for the target timeframe registered in the NRC database were analyzed to identify hazmat release incident reports caused by natural hazards through employing the Semi-Intelligent Natech Identification Framework (SINIF). Out of over 820,000 chemical releases incidents from 1990 to 2017, a total of 32,841 Natech reports have been identified with their natural hazard cause, including Wind, Weather, Tornado, Storm, Rain, Lightning, Hurricane, Flood, Earthquake and Cold, etc. Among these data, more than 14,000 Natech reports were related to hurricanes and storms. In addition, over 13,000 Natech reports were related to Rain, Wind, Lightning, and Flood. However, due to the inherent limitations of the NRC data (Girgin and Krausmann 2014) that include 1) the lack of details for each incident report, 2) an unclear classification standard for the incident cause, and 3) multi-hazard Natech incidents that could be induced by tropical storm but through different triggering natural phenomena, the retrieved Natech data need to be further analyzed and cleaned.

In order to overcome the issue of misidentified TSNatech cases from the dataset, a spatial analysis method was used to verify the NRC records classified as TSNatech, and examining their spatial intersection with available atmospheric data. In detail, the location information of retrieved TSNatech events were updated by using the Places API provided by Google Cloud Platform[10] according to their address information, because not all the incident reports included longitude and latitude coordinates. Afterward, the hourly perceptible vapor data from the MERRA-2 dataset were analyzed to identify the affected areas on the eastern side of the US from each tropical storm in the period of 1990 to 2017. It should be noted that the wind speed data—which are also included in the MERRA-2 dataset—were not employed to identify the affected areas by the tropical storm, because by using only wind speed data, we would have omitted Natech events that occurred due to rain, flood, and lighting, which may have also been triggered by the tropical storm (Cruz *et al*. 2001). Next, the perceptible vapor data were classified into 5 levels according to the distribution value by using an unsupervised classification method, namely the Iterative Self-Organizing Data Analysis Technique (ISODATA), in the environment of ESRI ArcGIS Desktop 10.5.1. By using the highest level of the classified perceptible vapor data, we delineated the potentially affected areas for each tropical storm. We then updated the associated locations of the retrieved TSNatech records according to their registered coordinates and address fields. Afterwards, a spatial intersection analysis technique was applied between the tropical storm-affected area and the retrieved Natech data. Finally, only those Natech that occurred at fixed facilities, storage tanks, and offshore platforms and for the matching period of each tropical storm were selected. This process yielded 9,295 Natech events which were subsequently designated as the target of this study. It is noteworthy that around half of the selected Natech events occurred at offshore platforms.

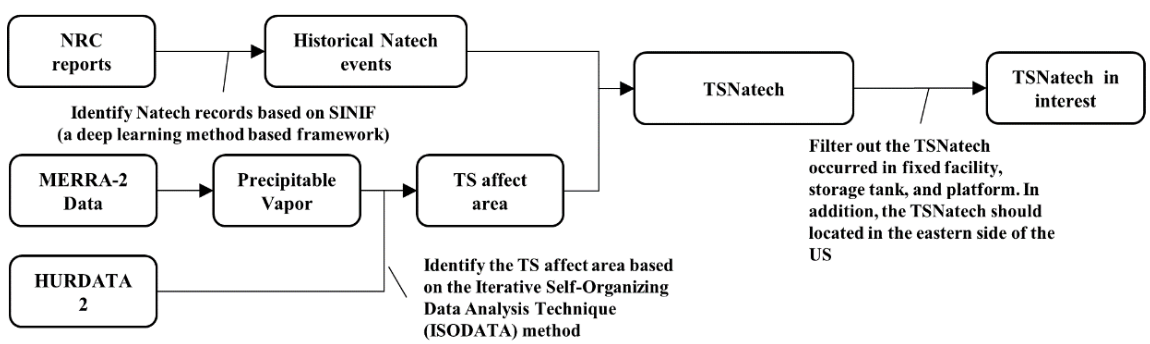

Figure 5–1 The workflow of TSNatech extraction

5.2.3 Study Area Identification

Figure 5-2 visualizes the retrieved TSNatech cases as blue spots, the TRI facilities and platforms as red spots, and the historical tropical storm paths, which were extracted and transformed from the

[10] https://developers.google.com/places/web-service/intro.

HURDAT2 dataset, as green lines. For the purposes of analyzing the spatial distribution of the retrieved TSNatech data, a Kernel Density Estimation (KDE) was performed with the results being illustrated in the form of a heat map as shown in the at the upper-right corner of Figure 5-2.

According to the Kernel Density analysis, there were two main central regions in the related heat map basically representing two major spatial conglomerations of TSNatech occurrence in the US from 1990 to 2017. Accordingly, these two central regions were designated as study areas A and B for this study. As a remark, study area A consists of 68.75% of the total retrieved TSNatech cases, while study area B includes 12.06% of them. In addition, based on the spatial distribution of the tropical storm-tracks, area C is generated as an additional study area to determine whether the selection of the study areas has actually an impact on the estimation of TSNatech probability or not.

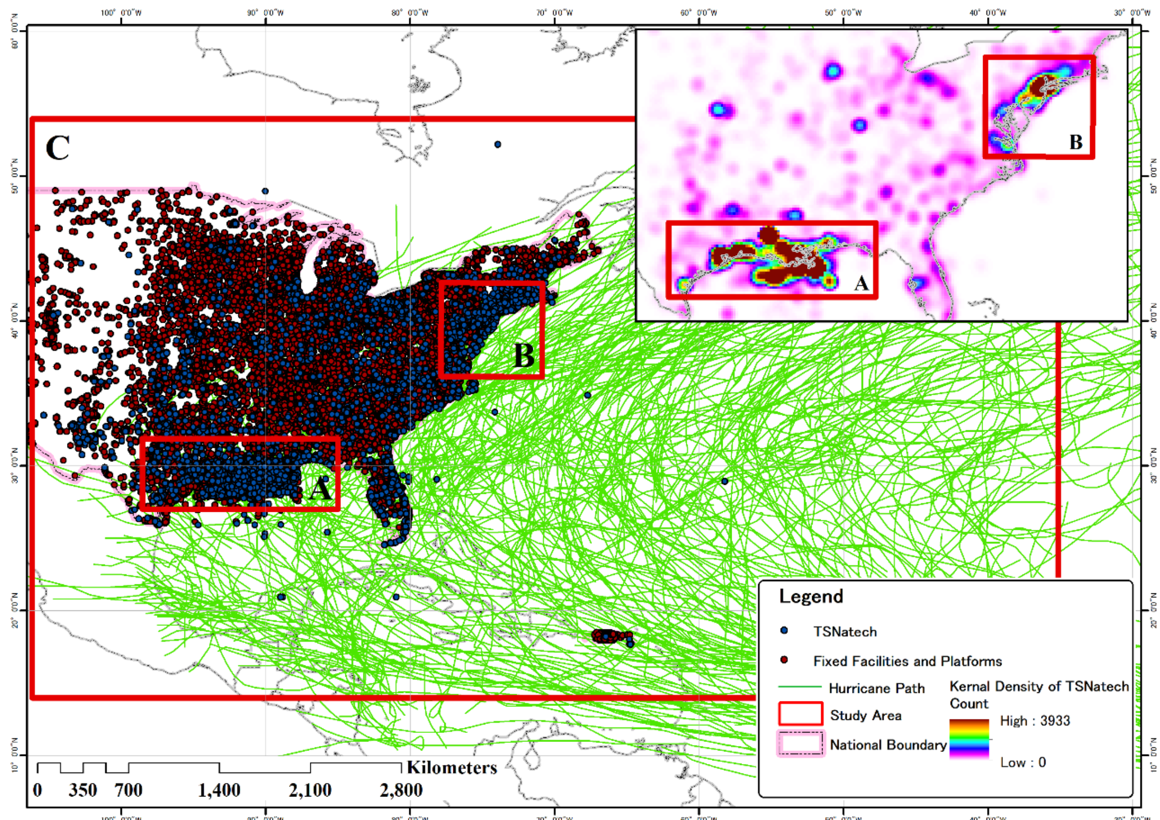

Figure 5–2 Study area, the heat map on the up-right corner is the Kernel Density analysis result of retrieved TSNatechs, which is used to identify the sub-study-areas A and B

5.2.4 Calculation of the Wind Energy

In the research field of atmospheric science, wind energy (WE) is considered as the kinetic energy of a mass of air during its motion (Şahin *et al*. 2006). Given that wind constitutes an important energy resource for human beings to harness and use, scientists have invested a great efforts in developing technologies to effectively measure and monitor this type of renewable and clean energy (Pimenta *et al*. 2008). However, as discussed earlier, WE can also become dangerous for people and their built environment when it is out of control, for example, when hurricanes occur (Scheitlin *et al*. 2011). In this study, we followed the equations of Archer C.L. (2013) to calculate the WE carried by each tropical storm for each individual grid cell within the three study areas described in the previous section. The basic equation is shown as follows:

$$E = \frac{1}{2}\rho A_{air}\Delta t {v_w}^3 \quad (2)$$

where ρ is the air density; A_{air} is the cross-sectional area of the airflow; Δt is the duration; and v_w is the wind speed. In this study, the air density and wind speed can be exported from MERRA-2 data directly, while Δt is set as 1 hour to match the temporal resolution of MERRA-2 data. Considering that all grid cells in the three study areas have the same size and assuming that wind speed is measured at the same height, A_{air} should be the same everywhere and for any given time. Thus, A_{air} is considered a constant for our purposes. As a result, the WE of each tropical storm and the annual WE brought by tropical storms from 1990 to 2017 are calculated utilizing equation (3) and equation (4), respectively:

$$E_{TS} = \sum E_t \quad (3)$$

where E_t is the WE of the given tropical storm in duration t; and:

$$E_{annual} = \sum_{i=1}^{N_{TS}} E_{TS_i} \quad (4)$$

where *i* is the index of the tropical storm and E_{TS_i} is the WE of the related tropical storm, and N_{TS} is the total number of tropical storms in that year.

5.2.5 Empirical Estimation of the Conditional Probability of TSNatech

Typically, in the risk and vulnerability assessment literature, the relationship between the conditional probability of equipment failure and the related natural phenomenon (such as wind speed, flood inundation, and peak ground acceleration, and so forth) is described by an S-curve (e.g. logistic function (Khakzad and Van Gelder 2017) or lognormal function (Shinozuka *et al*. 2000; Yang *et al*. 2016). Thus, we introduced in this vein a generalized logistic function, namely equation (5), to estimate the annual conditional probability of TSNatech (Annual TSNatech Conditional Probability – ATSCP) based on the calculated wind energy:

$$P = \frac{1}{1 + Ae^{-Bx^C}} \quad (5)$$

where P is the calculated ATSCP; x is the variable used to estimate the ATSCP; and A, B, and C are estimated through the Least-Squares Method (LSM) which is implemented in the environment of Python 3.0.

This study proposes two indices based on the calculated wind energy for each grid cell in each study area in order to estimate the annual conditional probability of TSNatech at different spatial scales. The first one is the annual wind energy for each grid cell, assuming that the relationship between the conditional probability of TSNatech and wind energy remains the same across the respective study area. The second one is the annual average wind energy for the entirety of each study area. The details of the estimation procedure can be divided into the five steps illustrated in Figure 5-3.

As a first step in the process of calculating the index of annual WE for each grid cell, a scatterplot considering the conditional probability of TSNatech and the annual WE was drawn for each grid cell. All values were then divided into multiple groups according to the distribution of annual WE based on the Natural Breaks (Jenks)(Jenks 1967) method. In step 2, the histogram of the conditional probability of TSNatech for each group was created. Next, the Kernel Density Estimation (KDE) method was employed to find the distribution of the conditional probability of TSNatech in step 3. Using the estimation result of the KDE method as a foundation, the abscissa value of the highest density point was established as the conditional probability of TSNatech for each group respectively. At the same time, the average value of the wind energy was set as the representative WE value of that group. Based on the above steps, a new scatterplot could be generated in step 4 to indicate the relationship between the annual WE and the conditional probability of TSNatech. In the final step, the Least-Squares Method was used to determine the parameters in equation (5). Interestingly, the fitted function/curve can be conceptualized as a kind of fragility curve that could be used to evaluate the conditional probability of TSNatech based on the annual wind energy at the scale of the grid cell.

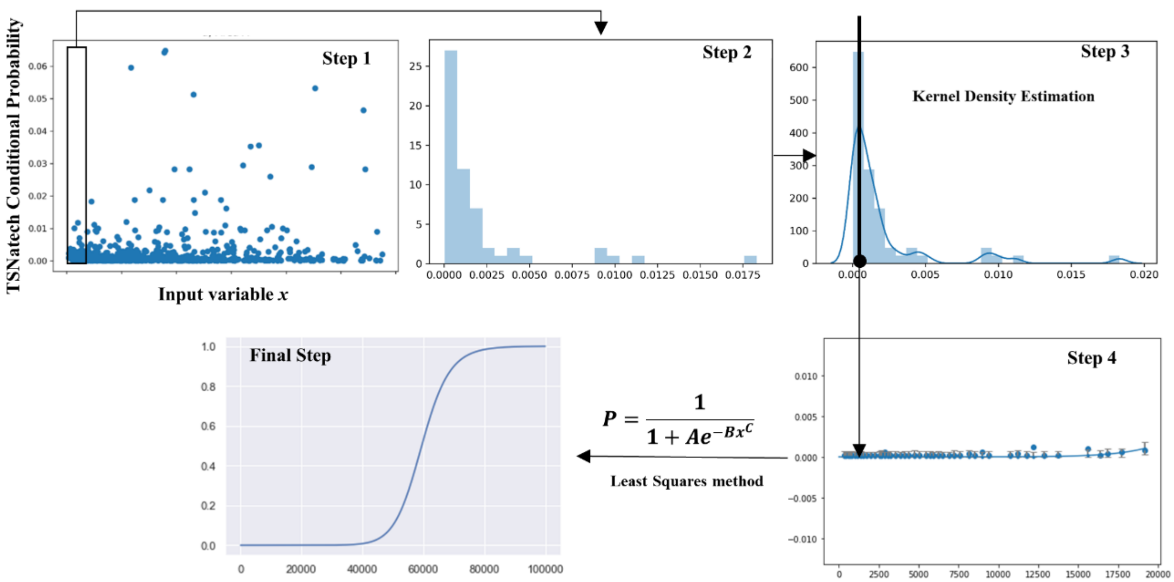

Figure 5–3 The general process of TSNatech conditional probability estimation

The estimation procedure of the second index, the annual average WE for each study area, is quite similar to the first index (see Figure 5-3). The difference lies in step 1, where in this case the values were divided into different groups based on the year and not on the distribution of wind energy. The average value used in step three is the average WE value for each year. In the final step, another fitted function/curve was produced to describe the relationship between the conditional probability of TSNatech and the annual WE at the scale of the entire study area.

5.3 Results and Discussion

According to the equations explained in the previous section, the annual wind energy brought by tropical storms, the annual probability of TSNatech (ATSP), and the annual conditional probability of TSNatech (ATSCP) were calculated for each grid cell in each of the three study areas. This section first analyzes the characterizations of the conditional probability and the probability of TSNatech over the whole research period from 1990 to 2017 to understand the occurrence of TSNatech. After that, the variations of the ATSP and the ATSCP are examined to reveal any underlying patterns. Finally, the results from the empirical estimation of the conditional probability of TSNatech based on the WE of tropical storms are discussed.

5.3.1 Characterization of the ATSP and the ATSCP in the Whole Research Period

To understand the general characterization of the ATSP and the ATSCP in each study area, we estimated their respective distributions. On account of the values of both the ATSP and the ATSCP for each study area falling at the far left side of the value range, a logarithmic transformation was carried out for each study area, correspondingly. After that, the Kernel Density Estimation method was used to analyze the distributions of the $\ln(\text{ATSP})$ and the $\ln(\text{ATSCP})$ for each study area, as shown in Figure 5-4. For study area A, the average value of $\ln(\text{ATSP})$ is -8.62 ± 1.56, and the mean value of $\ln(\text{ATSCP})$ is -7.37 ± 1.57. In study area B, the mean value of $\ln(\text{ATSP})$ is -8.80 ± 1.37, while the mean value of $\ln(\text{ATSCP})$ is -6.80 ± 1.35. For study area C, which includes the other two study areas, the mean value of $\ln(\text{ATSP})$ is close to the value of study area A, that is -8.63 ± 1.44, but the mean value of $\ln(\text{ATSCP})$ is -6.95 ± 1.47, which is close to the value of study area B. This finding basically means that the ATSP and the ATSCP values in study area C have integrated the characterizations of the values of the other two study areas. It is noteworthy that the value of ATSP estimated through our approach is similar to the probability of a Natech accident happening as calculated by other researchers from the perspective of engineering (Krausmann *et al*. 2017).

Furthermore, the value of ATSCP is larger than the ATSP across all study areas. This can be explained by the mathematical definition of the conditional probability: $P(A|B) = \frac{P(A \cap B)}{P(B)}$. From here, it is not difficult to deduce the following equation based on $P(TSNatech \cap TS) = P(TSNatech)$:

$$P(TSNatech) = P(TSNatech|TS) \times P(TS) \qquad (6)$$

where $P(TSNatech|TS)$ is the conditional probability of TSNatech given a tropical storm; $P(TSNatech)$ is the probability of TSNatech; and $P(TS)$ is the probability of a tropical storm. Consequently, due to $P(TS) \in [0,1]$, $P(TSNatech|TS) \geq P(TSNatech)$.

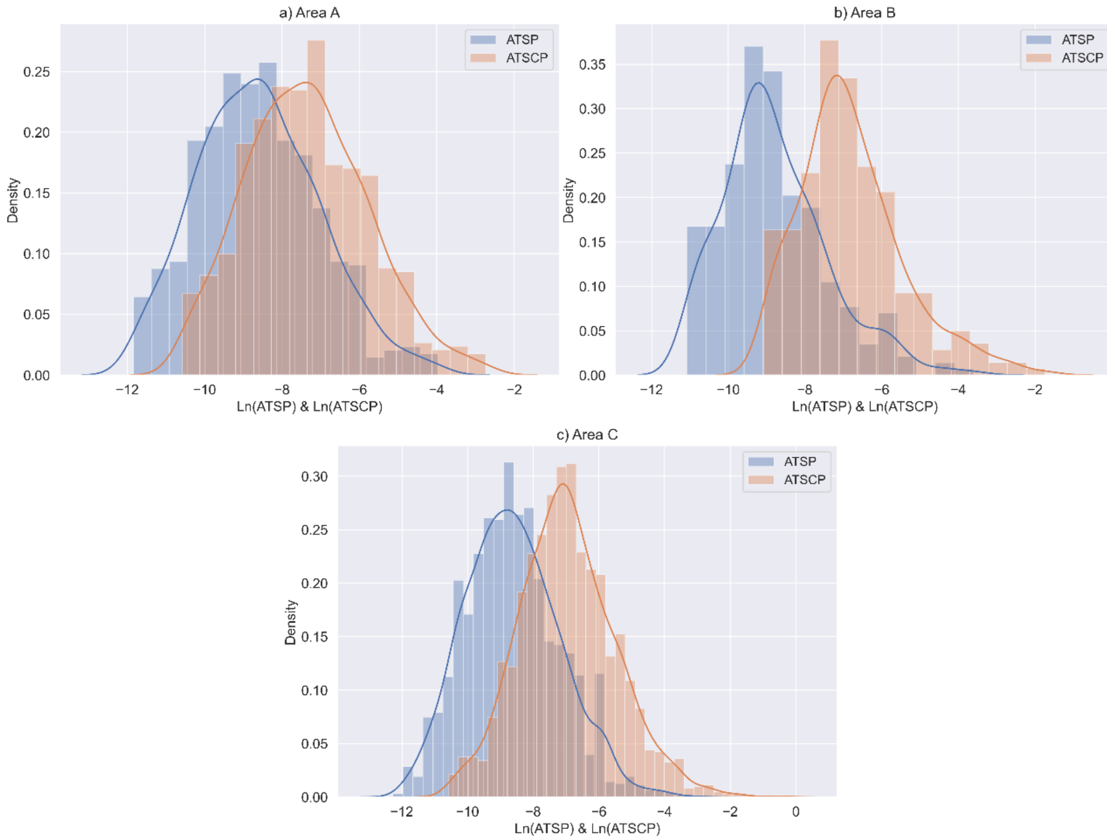

Figure 5–4 Kernel Density Estimation on the annual probability and the annual conditional probability of TSNatech for the whole study period

5.3.2 Temporal Variation in the ATSCP and the ATSP

Several studies have already pointed out that the number of TSNatech per year is seems to be gradually increasing (Sengul 2005; Sengul *et al*. 2012). However, it still remains unclear how the probability and the conditional probability of TSNatech change over time. In an attempt to explore their temporal variation, we assessed the ATSCP and ATSP by using the Kernel Density Estimation method, and then visualized the results in the form of heat maps in Figure 5-5 and Figure 5-6. In both Figures, the color indicates the probability density of the ATSCP and ATSP, while the size of the colored region designates the uncertainty of the distribution for each year. Moreover, linear regression was employed so as to analyze the time-series data for the mean value of the ATSCP and ATSP, and finally determine the trends of the ATSCP and ATSP respectively.

Figure 5-5 presents the heat maps of the ATSCP for each study area. By comparing the three sub-Figures, we can see that the heat map of area A is quite similar to that of area C—especially the black line, which represents the mean value of each year. This suggests that the distribution of the ATSCP in area A has a greater effect on the wider area C, compared to that of the distribution of ATSCP in area B. In other words, the distribution of ATSCP in area A plays a major role in defining the ATSCP of the wider area. In section 5.2.3, we counted the number of TSNatech records within each area, and discovered that area A includes over one third of the records found in the whole area C, yet area B only accounts for around 10%. Hence, the reason why the distribution of ATSCP in area C bears closer resemblance to the result of area A becomes apparent. Furthermore, all the regression results for the three study areas reveal a clear upward direction, suggesting that ATSCP has an increasing trend on the eastern side of the US during the research period.

Going beyond the initial comparison between the two sub-study areas and the greater study area C, we also examined study areas A and B together more in-depth. In Figure 5-5 (a), there appear to be three main peaks on the mean value line going over the regression line. The one in 2005 might be related to Hurricanes Katrina and Rita; the one in 2008 might be caused by Hurricane Ike; and the one in 2012 could be attributed to Hurricane Sandy. In contrast, in Figure 5-5 (b)—except for the year 2012—the ATSCP in area B for the years of 2005 and 2008 was not similar to that of area A, which means that Hurricane Katrina, Hurricane Rita, and Hurricane Ike had greater effects in area A than in area B. This finding could also be supported by looking at the recorded tracks of these three hurricanes which all converged over the Gulf of Mexico (located in the southern part of study area A). Likewise, Hurricane Sandy in 2012 made landfall very close to where study area B is, which may have caused a higher peak on the mean value line in that year in area B compared to area A. Finally, there is another peak on the mean value line in Figure 5-5 (b) in 1998 which might be related to Hurricane Mitch.

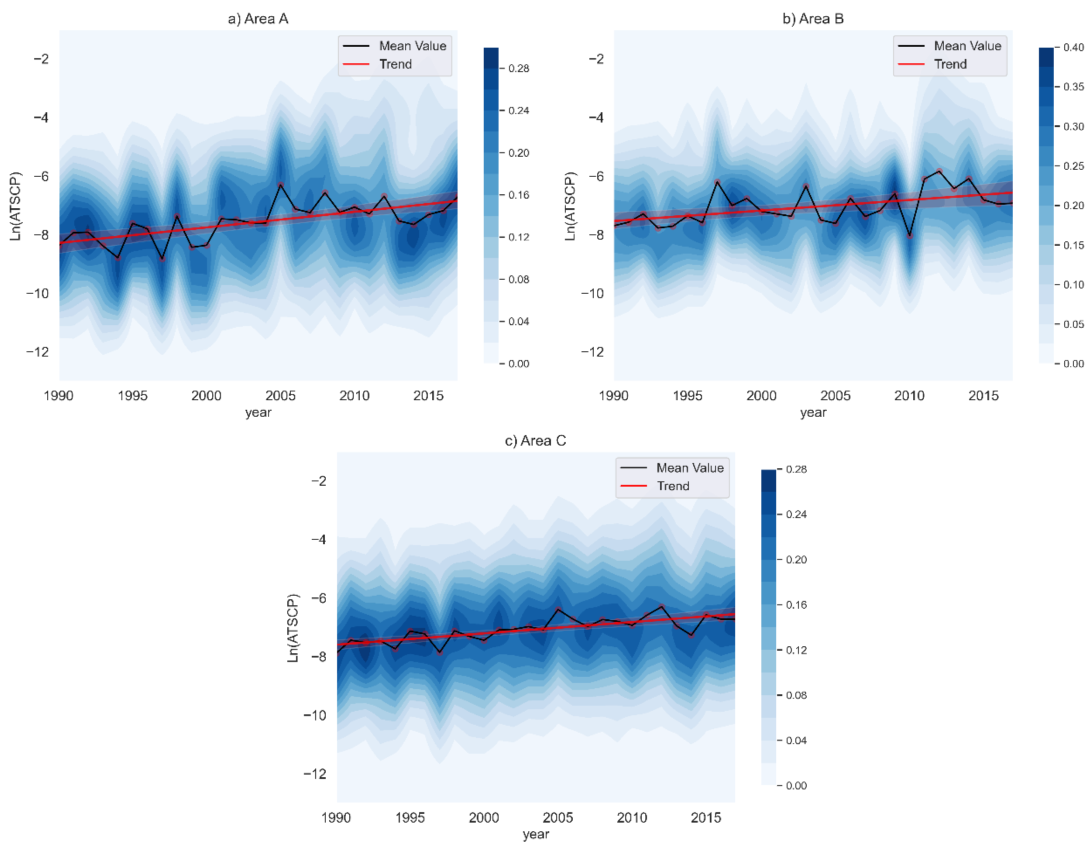

Figure 5–5 Heat map of the conditional probability of TSNatech from 1990 to 2017

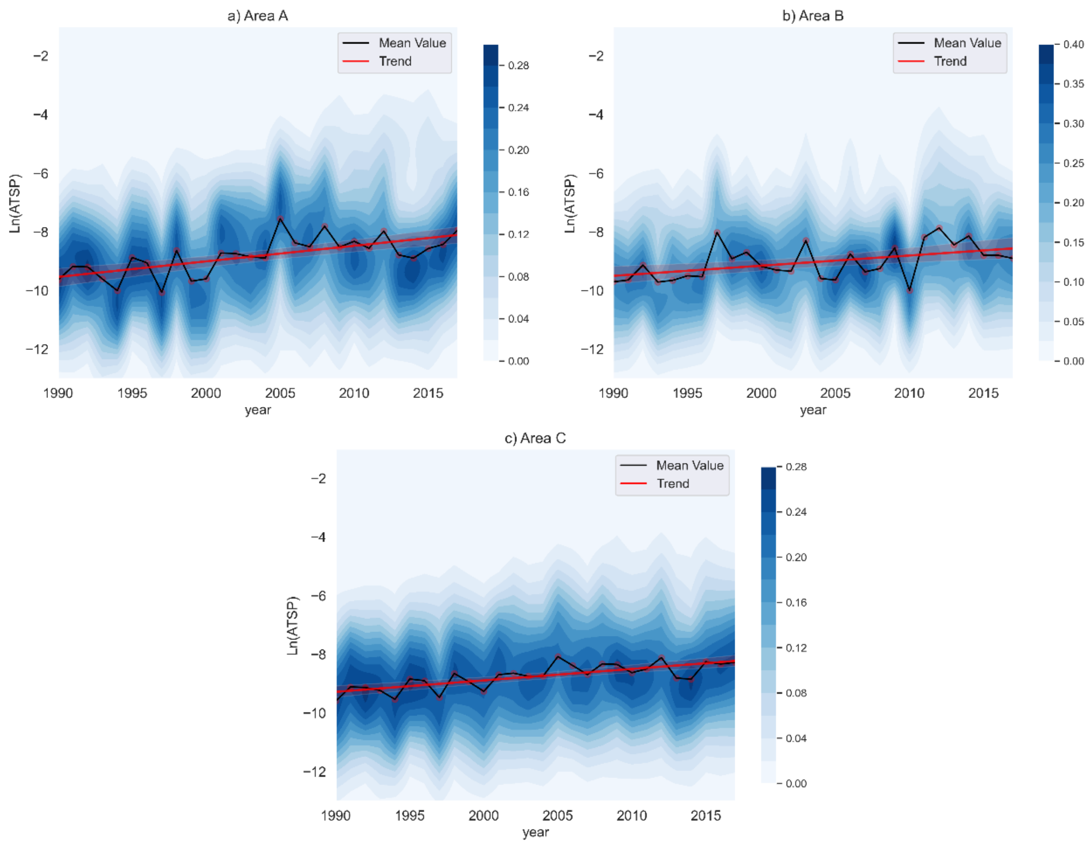

Figure 5–6 Heat map of the probability of TSNatech from 1990 to 2017

Additionally, special attention should be given to the blue zone delineated in the graphs. Particularly, while the color may gradually fade out analogous to the distance from the black line, indeed the total size of the colored area is becoming wider and wider over time. This suggests that there seem to be some underlying factors that increased the uncertainty of ATSCP. However, apart from speculation about the cause, we can derive no evidence to determine whether these unclear factors area actually related to climate change or something entirely different, but it may point to an interesting direction for future academic work.

On the other hand, Figure 5-6 shows the heat maps of the ATSP for each area from 1990 to 2017. Compared with Figure 5-5, all the sub-Figures show similar trends and characterization, apart from the value ranges that are slightly different. Nonetheless, there are some minor differences in area B on the mean value line in Figure 5-5 (b) and Figure 5-6 (b), for instance in 1991, 1995, and 2016, which are much larger than the differences between Figure 5-5 (a) and Figure 5-6 (a). In other words, the mean value curves of ATSCP and ATSP are more similar in the study area A than those in the study area B. When we calculate the ATSP, the denominator of equation (1) will be the annual number of all installations, N_1, of each grid, but when we calculate the ATSCP, the denominator will be the annual number of the installations affected by tropical storms, N_2, of each grid. According to the MERRA-2 and the HURDAT2 data, the duration of tropical storms in area A was much longer than in area B, which may cause N_2 to be closer to N_1 in study area A than the values of N_1 and N_2 in study area B. This might be a reason why there is a small difference on the mean value line in area B. This in turn could also be used to explain the small differences in terms of trends and characterizations observed in the different years between Figure 5-5 (b) and Figure 5-6 (b).

5.3.3 Empirical Estimation of the ATSCP Based on the Wind Energy

In this section, we discuss how the ATSCP changed in conjunction with the changes in annual wind energy brought by tropical storms. Figure 5-7 presents the fitting result between conditional probability of TSNatech and the annual WE for each grid cell. It should be initially noted that, due to the differences in wind energy distribution within each study area, the curves for study areas A and C are drawn over a significantly wider value range for the annual wind energy, compared to study area B, in order to adequately display the relationship between the conditional probability of TSNatech and the annual WE. In addition, the fitted curves for the study areas A and C exhibit similar trends as regards to the conditional probability of TSNatech by changing over annual WE: an almost straight line with a subtle slope and a short inflection in the beginning. In contrast, the curve for study area B shows a steadily rising curve with a slowly increasing slope. Also, Table 5-1 presents the estimated parameter values for each study area, as well as the performance of the fitted curves based on the Root-Mean-Square Error (RMSE) and the coefficient of determination (R-Squared). As demonstrated by the R-Squared values in Table 5-1, equation (6) could not be confidently used to explain the relationship between the annual conditional probability of TSNatech and the annual WE for the study areas A and C due to the rather poor values, but it has an acceptable performance on explaining this relationship in the study area B. Perhaps unsurprisingly, the differences in wind energy distribution could justify this finding.

Table 5.1 Estimated parameters value and the performance of the derived function based on TSNatech conditional probability and annual wind energy for each grid cell

	A	B	C	RMSE	R Square
Study Area A	532.308	0.044	0.231	1.87×10^{-3}	0.023
Study Area B	1624.14	0.011	0.590	3.95×10^{-3}	0.634
Study Area C	345.96	0.043	0.212	2.60×10^{-3}	0.018

Figure 5-8 depicts the annual wind energy distribution at the places where TSNatech have occurred, within study areas A and B, and for the whole study period (1990-2017), as assessed using the Kernel Density Estimation method. The annual wind energy distribution of study area C has not been drawn in Figure 5-8 due to the fact that it has a similar characterization with study area A, as explained earlier (see section 5.3.1 for more details). As shown in Figure 5-8, the value range of the annual WE for the places where TSNatech have occurred in study area B is shorter than the one for study area A. Moreover, places with high annual wind energy (i.e. $> 30{,}000$) within study area A did not necessarily correspond to a high number of locations with TSNatech observations; therefore, this results in a not large enough sample size in the value range of $(30{,}000, +\infty)$ to estimate a more detailed distribution of the conditional probability of TSNatech in that value range. Similar observations could also be noted for Figure 5-7. More precisely, below the 30,000 mark in Figure7 (a) and (c), the values displayed an inconsistent increasing trend, but after that point, both the conditional probability of TSNatech and its standard deviation became smaller and smaller. Of course, these issues detrimentally affect the fitting results. However, we could not simply remove these values to improve the goodness-of-fit, because then important issues of reliability would emerge when attempting to use the estimated fragility curve to predict the conditional probability of TSNatech.

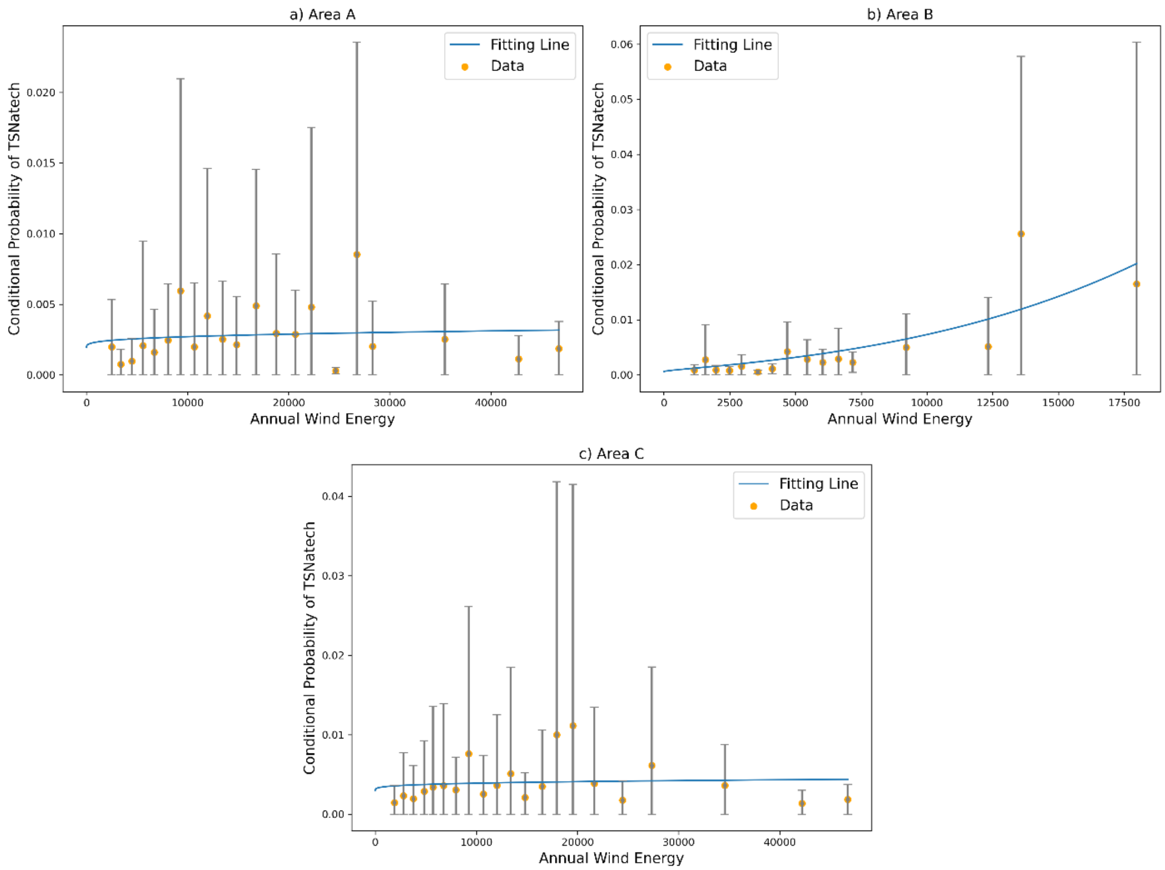

Figure 5–7 Fragility curves describing the annual conditional probability of TSNatech against the annual wind energy due to tropical storms for each grid cell (the error bars were indicated by Standard Deviation)

The fitting results of the annual conditional probability of TSNatech considering the mean value of annual wind energy in each study area are illustrated in Figure 5-9, while Table 5-2 presents the estimated parameters and the goodness-of-fit of each curve for study areas A, B, and C correspondingly. This time, equation (6) was characterized by diametrically different performance compared to what was observed from the index of annual WE for each grid cell. The curves in study areas A and C exhibited an increasing trend of the annual conditional probability affected by the changes in the mean value of the annual wind energy, whilst the curve in study area B displayed a rather straight curve without many deviations. When inspecting the fitting results shown in Table 5-2, the calculated R-Square value for study area B immediately stands out. This negative value essentially means that the relationship between the annual conditional probability of TSNatech and the mean value of the annual WE cannot be explained at all using equation (6). However, the R-Square values in study areas A and C show that equation (6) performs satisfactorily in fitting the data.

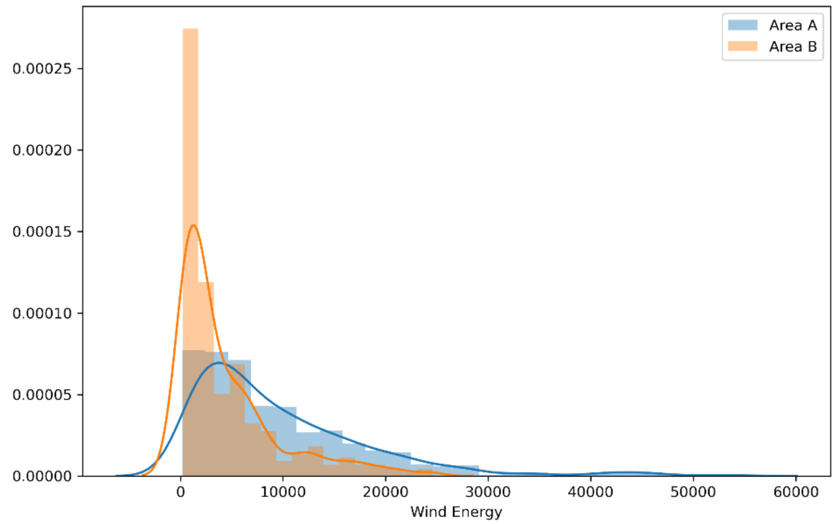

Figure 5–8 Distribution of annual wind ennegy in the study period of 1990-2017 in study area A and study area B where TSNatech have occurred based on the Kernal Density Estimation method

A large variation becomes evident from the corresponding error bars when reviewing all the fitting results indicated in this section. The fact that such variations are present in our results invites an interesting discussion around two main factors. The first one is related to the fact that TSNatch could not only be triggered by direct damage to the installations from the tropical storm system, but also via indirect damage associated for example with loss of power or other factors. In the study by Necci *et al*.(2018) power loss is the only one damage mode that could be linked to all the listed effects of storms (storm surge, lighting, strong wind, and heavy rainfall and flash flood) for Natech events. In addition, Necci *et al*. pointed out that power loss could cause the unavailability of safety systems and barriers which are implemented to prevent accident occurrence. Similar examples could also be found from the study by Santella *et al*. (2011) The other factor is related to the estimated variable itself. In this study we attempted to estimate the conditional probability of TSNatech using only wind energy as an input variable, instead of considering the various individual phenomena caused by the tropical storm system (Santella *et al*. 2011; Bernier *et al*. 2019; Olivar *et al*. 2019). This may have resulted in an accumulation and combination of multiple uncertainties inherent to the different phenomena and their physical impact on infrastructure, which in turn caused such incremental deviations in our findings. Moreover, the performance of the methodology for the empirical estimation of the ATSCP based on wind energy is affected by the selection of the study areas, as evidenced by our analysis. Furthermore, the selection of the estimation variable may also have affected the goodness-of-fit.

Table 5.2 Estimated parameters value and the performance of the derived function based on TSNatech conditional probability and annual average wind energy for each study area

	A	B	C	RMSE	R Square
Study Area A	4946.67	8.56×10^{-5}	0.999	2.02×10^{-4}	0.568
Study Area B	1002.00	2.51×10^{-4}	2.49×10^{-4}	5.32×10^{-4}	-0.326
Study Area C	1.42×10^{6}	8.05×10^{-4}	0.999	7.24×10^{-4}	0.899

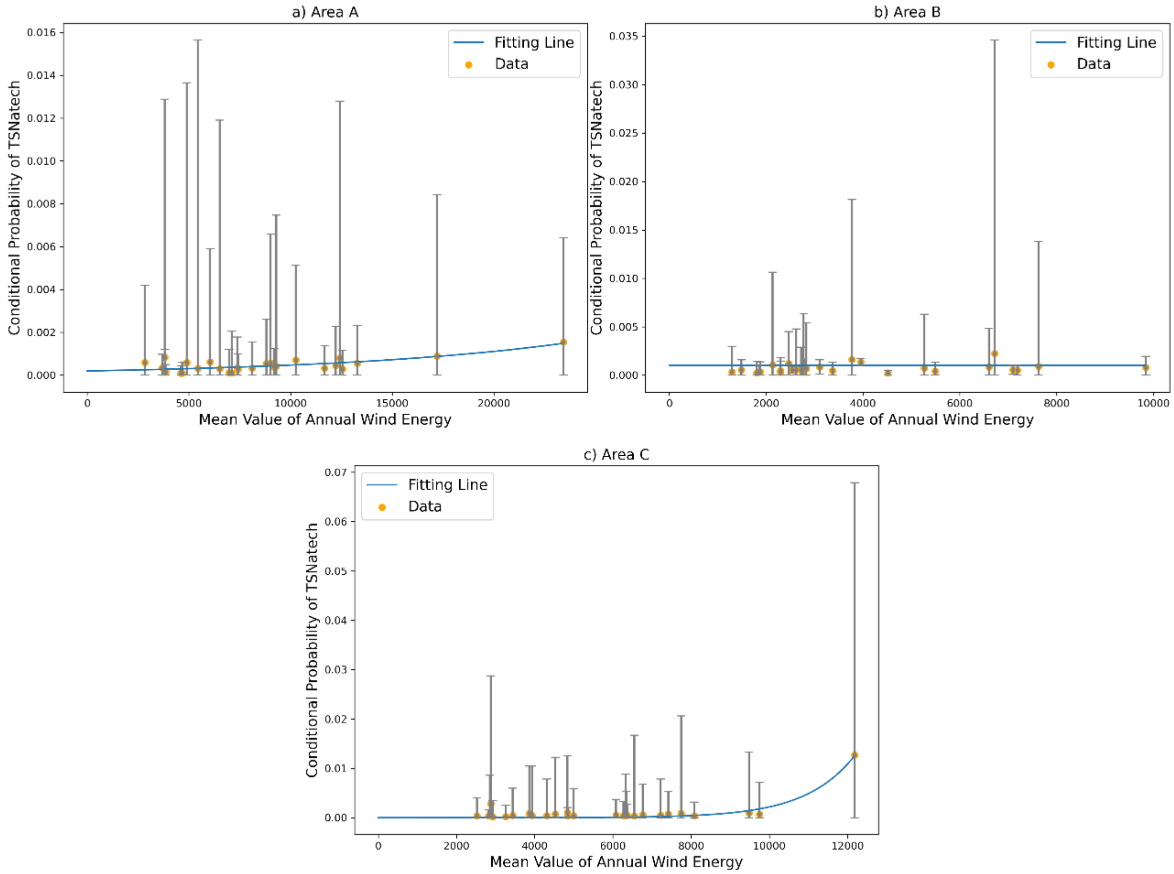

Figure 5–9 Fragility curves describing the annual conditional probability of TSNatech against the mean value of annual wind energy due to tropical storms (the error bars were indicated by Standard Deviation)

5.4 Conclusions

In this study, we propose a methodology to estimate the annual conditional probability of tropical storm-related Natechs (ATSCP) and the annual probability of tropical storm-related Natechs (ATSP) based on tropical storm-related Natech (TSNatech) incidents reported to the NRC database. Furthermore, we evaluated how the wind energy brought by tropical storms affected the ATSCP. According to the results from our analysis, there seems to be an increasing trend of the ATSP and the ATSCP across all three study areas from 1990 to 2017, thus providing important evidence in supporting the conclusion that the probability of TSNatech—for the geographical region and time period examined—is indeed increasing. In addition, the results of the relationship between the ATSCP and the annual wind energy brought by tropical storms suggest that the performance of this grid-based Natech probability estimation method is affected by the selection of the study area and the estimation variable. Researchers attempting to apply this method to evaluate the probability and the conditional probability of Natechs in a given study area, should pay due attention in defining their study area(s) to select regions with similar natural conditions among one another, so as to minimize any large spatial discrepancies. In this sense, study area C presents a typical case of choosing an unsuitable study area, because the respective Kernel Density for the TSNatech number there displayed notable spatial variation.

Since our approach focused on the estimation of the conditional probability and the probability of TSNatech from a perspective of the temporal-spatial domain, a noteworthy limitation of this study is ignoring either the effects of industrial installations' aging or any actions that risk managers could take to reduce Natech risk, because it is a big challenge to monitor the aging effects and collect the changes in risk management plans on thousands of installations over such a long period of research (28 years in this study). Apart from that, another point for further improvement of this study is that we did not consider the conditional probability and the probability of TSNatech in conjunction with the amounts of chemicals released, because many of the TSNatech records retrieved from the NRC database lacked such information.

Despite the above disadvantages, there are also significant contributions for researchers and practitioners who are interested in Natech risk assessment at the regional level and base their exploration on historical records. First of all, this study provides valuable insight concerning the requirements of such spatial analysis approaches. Although 28 years' worth of historical Natech data were used in this study, the sample size still proved insufficient for the estimation of the conditional probability of TSNatech. The findings of this study could be considered as important evidence in highlighting the need for more and accessible data on Natech incidents and other chemical release accidents in order to promote and expand empirical estimation work in the risk management field, as well as for lessons learning. This makes for a compelling argument to motivate and actively engage governments and other stakeholders to continue cooperating on building and improving data collecting and management systems. On the other hand, the proposed spatial analysis method could be practically implemented by risk managers in government or community organizations for their respective regions of interest to estimate in the conditional probability and the probability of TSNatech and monitor their changes over time. Moreover, after certain necessary adaptations, the main framework of this estimation method could also be applied to calculate the probability for other types of Natechs considering different triggering natural hazards. Furthermore, this method makes it possible to estimate the probability and the conditional probability of Natechs based on the simulated meteorological data for future scenarios, which will be a crucial step in understanding how Natech risk is influenced by climate change at a large scale.

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Chapter 6 Probability Estimation of Tropical Storm-related Natech Events in the US, Using ScenarioMIP Data

6.1 Introduction

Natural hazard-triggered technological accidents, Natechs (Cruz and Okada 2008), are a typical type of cascading disaster, which always involve chemical releases, resulting in economic loss, and environmental and human health problems (Krausmann and Cruz 2013; Krausmann *et al.* 2017). tropical storms can trigger Natechs (TSNatechs) during landfall, by causing multiple natural phenomena (Cruz *et al*. 2001; Necci *et al*. 2018) as a function of their energy dissipation. According to 1990–2017 SINIF results, 8,019 Natech events could be attributed to hurricanes, based on the NRC database. After checking the amounts of chemicals released, we found that (even allowing for the consideration that there might be some bias involved, due to volumes needing to be transformed between different units and standards) these releases included 228,998 tons of oil petroleum, 1,557,780 tons of other chemical substances, and 978 million m^3 of natural gas.

These were significant amounts, even though only approximately one-third of the records in the NRC database for these Natechs quantified materials losses. Girgin and Krausmann (2014) reported the damage to hundreds of platforms, and that the significant peak in the 2005 pipeline-related Natech reports could be attributed to hurricanes Katrina and Rita. During Hurricane Katrina, 25,110 barrels of crude oil spilled from an oil refinery in Meraux, Louisiana, USA (NOAA 2020), while many other studies have reported damage and loss due to hurricane-related Natechs (Picou 2009; Santella *et al.* 2011; Griggs *et al.* 2017; Necci *et al.* 2018). The increasing number of TSNatech / hurricane-related Natechs (Sengul 2005; Sengul *et al*. 2012) eventually led to an increasing number of studies on risk management with reference to Natechs (Suarez-Paba *et al*. 2019).

Climate change represents a major challenge in TSNatech risk management, as it could influence tropical-storm intensity and duration, and the areas they affect. The studies of Mudd *et al*. (2014a, b) have suggested that climate change could cause more intense (maximum wind speed) and larger hurricanes (radius to maximum wind speed) in the future. Ting *et al*. (2019) reported a similar result, showing that more intense hurricanes could be formed, due to the impacts of climate change on vertical wind shear along the US coast. In other studies, it has been suggested that climate change could result in more heavy rainfall caused by future tropical storms (Yamada *et al*. 2017; Pugatch 2019; Walsh *et al*. 2019). Meanwhile, the moving speed of hurricanes could also be affected by climate change (Chan 2019; Hassanzadeh *et al*. 2020; Yamaguchi *et al*. 2020; Zhang *et al*. 2020), while other researchers have suggested that tropical-storm pathways could influence larger latitudinal (Kossin *et al*. 2014) and longitudinal swathes (Collins *et al*. 2019).

Taken together, these findings could be used to speculate that in the future, facilities and industrial installations across a wider area will be affected by more intense or prolonged tropical storms, due to climate change. In fact, we have considered temporal–spatial TSNatech variations in Chapter 4, and found that they might be linked to climate change. Cruz and Suarez-Paba (2019) concluded that the increasing research by scientists on metrological hazard-related Natechs may also be associated with climate change. Although many researchers have expressed concerns that climate change may cause more TSNatechs (Cruz and Krausmann 2013), and economic losses (Ebad Sichani *et al*. 2020), a research gap on the connection between climate change and TSNatech probability has remained.

TSNatech event probability is a crucial element in Natech risk assessment, and its resolution could lead to improved Natech event risk management, which would help reduce Natech event risks and potential losses. To address this gap, we have developed a methodology to estimate TSNatech probability, using the Scenario Model Intercomparison Project (ScenarioMIP) data, based on the empirical estimation of TSNatech probability against wind energy. ScenarioMIP data were simulated under different Shared Social-economic Pathways (SSP) scenarios, developed in the latest (6^{th}) version of the Coupled Model Intercomparison Project (CMIP 6) at a regional scale—that is, at a scale more or less equated to the size of a US state. The methodology could be applied by experts in Natech risk management to understand better how TSNatech probability will change in future, SSP-based scenarios.

In the following sections, a brief introduction to ScenarioMIP data has been provided first, in Section 6.2, with materials and methods then described in Section 6.3. In Section 6.4, we have presented the results of TSNatech probability estimations against historical and future, simulated wind energies, while the reasoning behind the future TSNatech probability estimates, in Section 6.4 have been discussed in Section 6.5, together with a review of result uncertainty. Finally, the key findings of this study have been presented in Section 6.6, together with discussion covering its limitations, and recommendations for future work.

6.2 Scenario Model Intercomparison Project (ScenarioMIP) Data

The Scenario Model Intercomparison Project (ScenarioMIP) was a primary CMIP 6 activity, in which 21 Model Intercomparison Projects (MIPs) were initially endorsed (Eyring *et al*. 2016), followed by two others proposed by Keller *et al*. (2018) and Smith *et al*. (2019), giving a total of 23 MIPs, which were then made available on the WCRP website[11]. Among these MIPs, ScenarioMIP could provide multi-model climate projections, based on new scenarios (SSPs)–to help researchers understand societal climate impacts better—rather than simply understanding physical climate system consequences in isolation (O'Neill *et al*. 2016).

SSPs are a series of basic scenarios developed by the climate change research community to further support establishment of new scenario frameworks (Riahi *et al*. 2017). Combining SSPs with representative concentration pathways (RCPs) in a scenario matrix architecture, the WCRP has been able to provide a new version of simulated climate data for the long-term future, based on considering the interaction of climate and socioeconomic systems (Absar and Preston 2015; O'Neill *et al*. 2016; Riahi *et al*. 2017). This new, scenario framework-based climate data have been simulated according to a commonly designed storyline for socioeconomic development, and have supported academic communities or groups in promoting studies regarding impacts, their mitigation, and adaptation, with respect to climate change (Moss *et al*. 2008; IPCC 2010).

[11] https://www.wcrp-climate.org/modelling-wgcm-mip-catalogue/modelling-wgcm-cmip6-endorsed-mips. Last accessed on Nov. 6, 2020

To create the base-storylines for ScenarioMIP, five SSP narratives were qualitatively described (O'Neill *et al*. 2017; Riahi *et al*. 2017), and were identified as SSP1, sustainability; SSP2, middle of the road; SSP3, regional rivalry; SSP4, inequality; and SSP5, fossil-fueled development. Detailed narratives for these five SSP scenarios can be found in the works of O'Neill *et al*. (2014, 2017). Some key features were quantified, including population growth (KC and Lutz 2017), urbanization level (Jiang and O'Neill 2017), and economic development (Dellink *et al*. 2017). By assessing the impacts of these qualitative and quantitative narratives on energy systems and land-use change, multiple integrated assessment models (IAMs) were developed. In these IAMs, greenhouse gas emissions and atmospheric concentrations under different SSP scenarios were also determined (Absar and Preston 2015; O'Neill *et al*. 2017; Riahi *et al*. 2017), together with different climate change mitigation policy options.

Through the complex scenario framework development procedure, ScenarioMIP data were simulated, using the latest CMIP 6 climate model versions, which were driven by the newly proposed SSP-forcing combination scenarios (refer to the scenario matrix architecture). The ScenarioMIP data have been loaded onto a CMIP 6 website subpage[12], and named as SSPx-y, where x indicates the specific SSP, and y refers to the forcing pathway. For example, one climate simulation data used in this study was named SSP5-8.5 (Yukimoto et al. 2019a), in which the first "5" indicates that this data was simulated using the SSP5 scenario, with the following "8.5" referring to the 8.5 W/m^2 forcing pathway.

To analyze how TSNatech probability would change under the same socioeconomic development scenario while using different forcing pathways, over the period of 2020–2100, SSP4-3.4 (Yukimoto *et al*. 2019c), and SSP4-6.0 (Yukimoto et al. 2019c) were used. There was actually another option to achieve this objective, which was selection of SSP1-1.9 and SSP1-2.6, however, according to Fig. 1 in the work of O'Neill *et al*. (2014), SSP1 was the best scenario to use when everything changed in response to optimum conditions. In contemplating this scenario, we did not assume that the SSP1 scenario was impossible, but because we needed some scenarios that were much closer to what we had during our study period, the data under scenarios SSP4-3.4 and SSP4-6.0 were selected instead.

We could also see that, based on the narratives for the five SSPs, SSP4 and SSP5 displayed opposite directions on mitigation and adaptation challenges for climate change. SSP4 presented a world which had large climate change adaptation challenges, but small challenges on mitigation, while SSP5 represented the opposite. Thus, to understand how TSNatech probability would change under different socioeconomic development scenarios, data for SSP5-8.5 were also included in this project.

6.3 Materials and Methods

As shown in Figure 6-1, the workflow of this study was mainly divided into data collection, TSNatech retrieval, TSNatech probability calculation, wind energy calculation, TSNatech probability estimation against wind energy, and estimating TSNatech event probability using simulated future climate data from the SSP scenarios. The basic process for estimating TSNatech probability against wind energy came from implementing the final two steps. These steps therefore constituted the core of this study. Step 5 provided the relationship and function between TSNatech probability and wind

[12] https://esgf-node.llnl.gov/search/cmip6/. Last accessed on Nov. 9th, 2020

energy (which could be considered as a type of fragility curve), based on the assumption that equipment performance would not change in the future. After this, the last step produced the final outputs of this study—that is, how TSNatech probability would change in the future, in response to different climate change scenarios. Furthermore, TSNatech retrieval was another challenge for this study, due to the inherent problems of the NRC database (Girgin and Krausmann 2014).

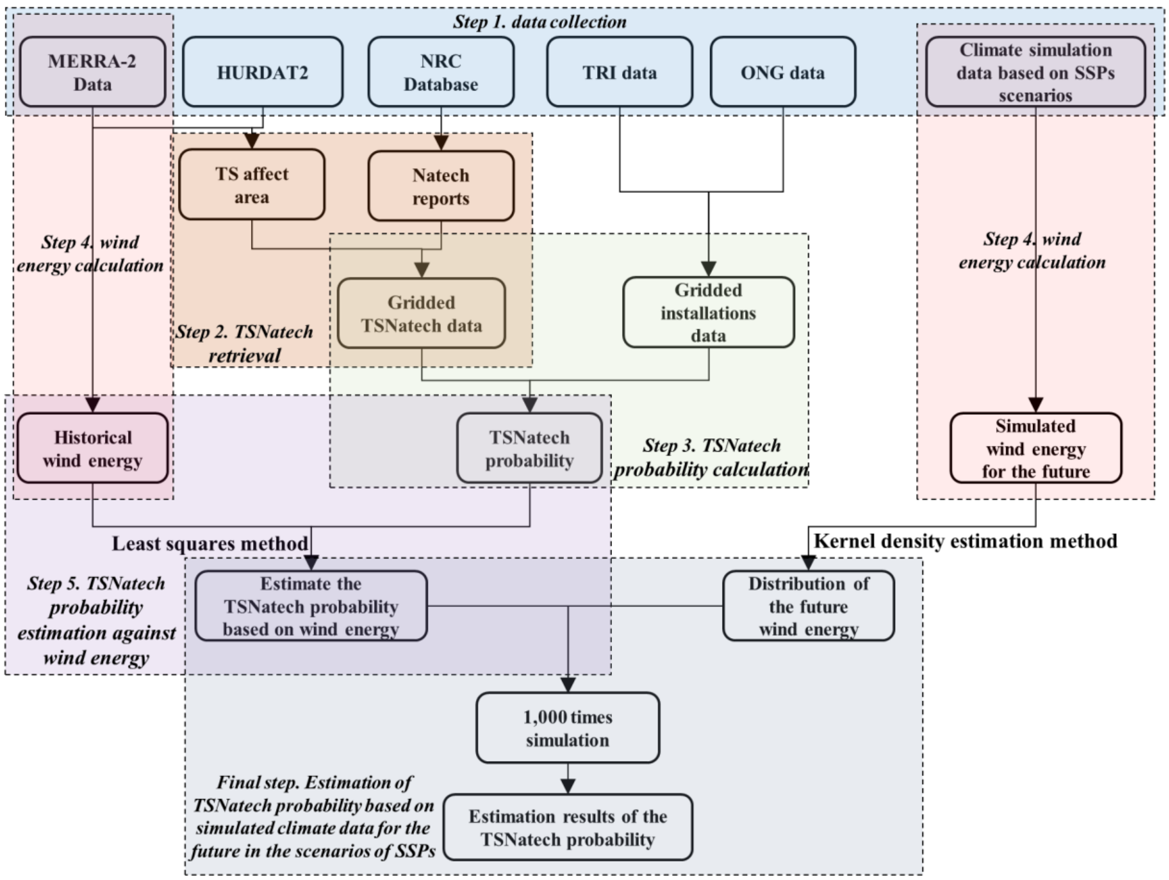

Figure 6–1 Methodology for this Chapter

6.3.1 Data Collection and TSNatech Retrieval

As the main aim of this study was to focus on TSNatech probability, we were interested in such events occurring in fixed installations and offshore platforms. This allowed us to calculate TSNatech probability without the uncertainty caused by unstable or incorrect location information regarding pipeline systems or mobile equipment. As the main Natech data source, the US NRC database (United States Coast Guard 2017) was used to identify TSNatech occurrences. The NRC database is an open public database for collecting and cataloging reports related to any type of potential chemical release from any citizen in the US, and it currently holds data from 1990 up to the present day. We analyzed all NRC database chemical release incident reports for the period 1990–2017, using the SINIF. These records were systemically labeled, using their natural hazard cause, as Wind, Weather, Tornado, Storm, Rain, Lightning, Hurricane, Flood, Earthquake, and Cold, with the label NotNatech used to designate events which were not Natechs.

Among > 820,000 chemical release incident-related reports for 1990–2017, 32,841 Natechs were identified. Among these, hurricanes and storms contributed 42.7% of the identified causal mechanisms, while approximately 42.1% of retrieved Natechs were attributed to rain, wind, lightning, or flood. The lack of a detailed reporting protocol for incidents had resulted in some being assigned to confusing natural hazard causes, which has been identified before as an inherent limitation of the NRC database (Girgin and Krausmann 2014), and meant we were unable to use such reports in our analyses. Furthermore, according to a study by Cruz *et al*. (2001), hurricanes or tropical storms could trigger Natechs by driving multiple natural phenomena, such as heavy rainfall, lightning, and storm surge-related floods, which was another reason why we decided to use the SINIF results directly.

To clean the SINIF results further and consequently retrieve target TSNatech event data, one solution was to analyze the location and time of each Natech event, to check if it was tropical storm-related. Thus, the MERRA-2 (GMAO 2015) dataset was employed to determine the affected area of historical tropical storms on the Atlantic Ocean side of the US, from 1990–2017. Based on historic tropical storm duration and pathway information recorded in the HURDAT2 (Landsea and Franklin 2013), hourly MERRA-2 perceptible vapor data were classified into five levels, by applying the iterative self-organizing data analysis technique (ISODATA), which is an unsupervised classification method found in ESRI ArcGIS Desktop 10.5.1. By applying an integrated analysis, based on the highest level of classified perceptible vapor data, tropical storm duration, and pathway, areas potentially affected by each tropical storms were identified.

Using coordinates and address information for each retrieved Natech, their location information was updated using the Places API[13], as provided by Google Cloud Platform. Through a spatial intersection analysis, Natech data related to hurricanes, storms, lightning, flooding, rain, and wind were spatially retrieved as TSNatechs, using the processed tropical storm duration data and Natech accident time. Finally, only those TSNatechs occurring in fixed facilities, storage tanks, or offshore oil drill platforms were selected as target data (approximately 9,295 events) for this study.

In a further step, as part of calculating TSNatech probability, the Toxics Release Inventory (TRI) Program Basic Data (US Environmental Protection Agency 2017), and the Oil and Natural Gas (ONG) Platform data (Homeland Infrastructure Foundation-Level Data (HIFLD) 2018) were consulted, to retrieve their data on which installations had been affected in the past by tropical storms.

6.3.2 Wind Energy Calculation

According to a study by Cruz *et al.* (2001), infrastructure in facilities can be affected by multiple natural phenomena—such as high wind speed, flooding, heavy rain, lightning, and storm surge—during the landfall of a TS system. These effects can be considered as the tropical storm energy dissipation process. In other words, the cumulative effects of wind on industrial installations are an external manifestation of the energy carried by the tropical storm system, and the associated precipitation has also been related to the storm's energy (Makarieva *et al*. 2017). Thus, the wind energy carried by tropical storms has been considered an important variable for estimating TSNatech probability, based on both MERRA-2 data, and the climate simulation data under the SSP scenarios used in this study.

Because the main objective of this study was to estimate how TSNatech probability could change in the future, under different SSP scenarios, we needed a solution for determining the wind energy

[13] https://developers.google.com/places/web-service/intro.

related to tropical storms, based on future data, or had to find other measurements for assessing wind energy.

Climate simulation data provided by the WCRP had been simulated from climate models, but not weather prediction models, however, and so we could not definitively forecast tropical storms dates or pathways—for example, we could not say whether there would be a hurricane around the Gulf of Mexico on September 26, 2050. Thus, we did not calculate the wind energy for every single tropical storm, but calculated the wind energy for the months occurring in tropical storm seasons, and assumed that most TSNatech events occurred in those months. Consequently, two wind energy datasets had to be calculated, one for the period 1990–2017, and the other covering 2021–2100.

Thus, we followed the equations of Archer (2013) to calculate wind energy for the selected months over the period 1990–2017, with an explanation how the months of interest were identified provided in 6.3.4. The basic equation can be seen in Eq. (1):

$$E_H = \frac{1}{2}\rho A_{air}\Delta t {v_w}^3 \tag{1}$$

where ρ indicates air density, A_{air} represents the airflow cross-sectional area, v_w denotes wind speed, and Δt stands for the duration, which was the same as the time resolution of the MERRA-2 data for 1 hour. Thus, E_H indicates hourly wind energy. The air density and wind speed could be directly imported from the MERRA-2 data. As the wind energy in this study was calculated at the same height above sea level, A_{air} was considered as a constant for every grid—and was set to 1 m to simplify the calculation process. Then, based on the selected months of interest, the target wind energies for each year were calculated using Eq. (2):

$$E_T = \sum_{i=1}^{n}\sum_{j=1}^{d\times 24} E_H \tag{2}$$

where E_T indicates the target WE, *i* represents the index of selected months, *n* denotes the number of selected months, *j* shows the index of hours for month *i*, and *d* represents the number of days in month *i*.

Eq. (1) was also used to calculate the wind energy in the future. However, as SSP4-3.4, SSP4-6.0, and SSP5-8.5 data did not include air density information, Eq. (3) was used in tandem with Eqs (1) and (2) to calculate the wind energy:

$$\rho = \frac{P}{R_d T} \tag{3}$$

where ρ indicates air density, P represents absolute pressure (Pa), T denotes absolute temperature (K), and R_d represents the specific gas constant, which is 287.058 J/kg·K (Floors and Nielsen 2019).

6.3.3 Study Area Identification

As typical meteorological systems, tropical storms play an essential role in the occurrence of TSNatechs, and the fact that the spatial distribution of TSNatechs has been strongly affected by tropical storms is a typical character trait of these events. Based on the updated TSNatech location information, we created a map to illustrate the spatial distribution of the retrieved TSNatech data (Figure 6-2 (a)), by implementing the spatial kernel density analysis method. In Figure 6-2, two TSNatech foci can be seen, one around the Gulf of Mexico, and the other near New York, and our two study areas were generated using these foci (A and B in Figure 6-2 (a)). More than 6,300 retrieved

TSNatech events were located in area A, and approximately 1120 were distributed in area B. Since > 80% of TSNatechs were contained in these two areas, this was considered to represent strong spatial clustering characterization.

Such uneven distribution characterization could also be described as a type of spatial heterogeneity, which could cause TSNatech data to follow different relationships in response to the same natural phenomena occurring in different areas. Thus, to reduce the impacts of such spatial heterogeneity when estimating TSNatech probability, areas A and B were designated as the main study areas for this study, and were selected for estimating TSNatech occurrence probability.

As explained in Section 6.3.2, we identified the months of interest with most TSNatech occurrences and locations in the hurricane seasons. Monthly TSNatech and tropical storm event numbers for the period 1990–2017 were counted, and have been plotted in Figure 6-2(b), where it can be seen quite clearly that the numbers were above average for July–October. Thus, July, August, September, and October were selected as the months of interest for this study.

Subsequently, the TSNatech event data, TRI facilities data, and ONG platform data were allocated into square grids having the same resolution as the MERRA-2 data, 0.625 × 0.625°. These gridded data were then used to calculate TSNatech occurrence probabilities, and to extract related wind energy data.

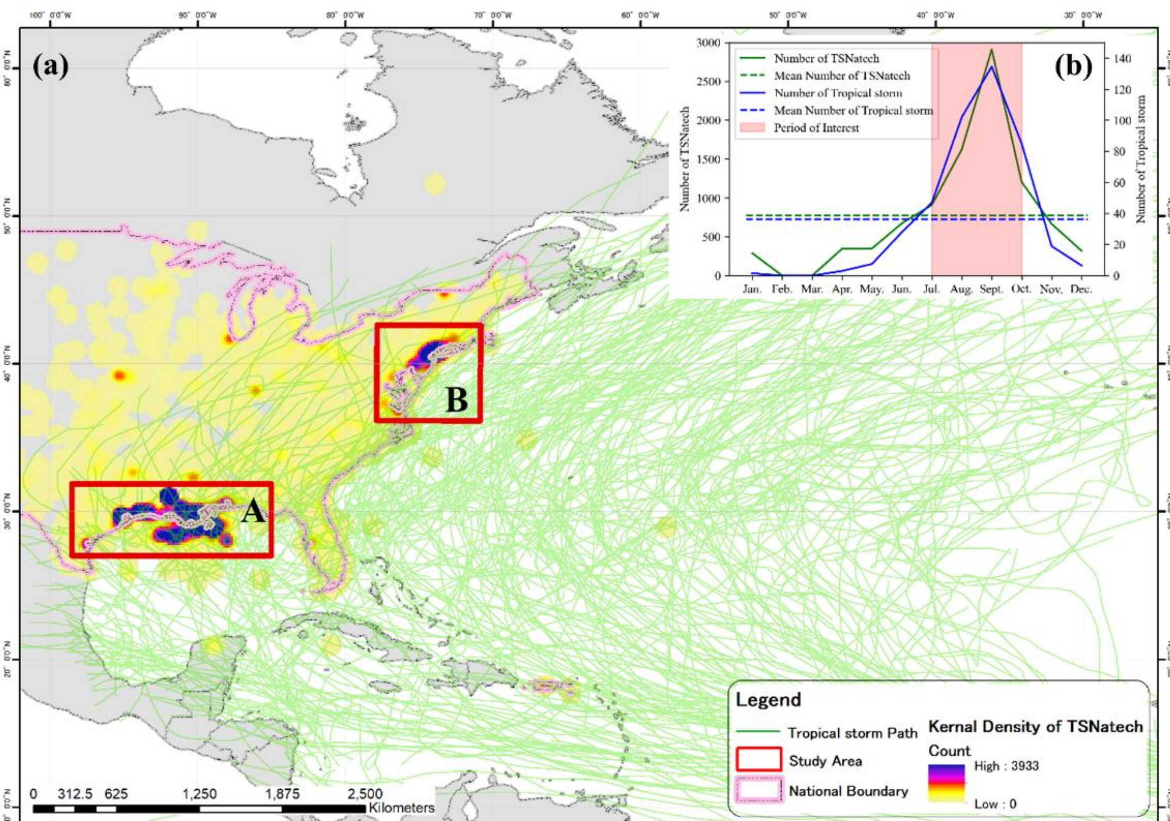

Figure 6–2 (a) Study area; (b) TSNatech and tropical storm numbers per month

6.3.4 Using Wind Energy to Estimate TSNatech Event Probability

The term 'TSNatech probability' has been used in this study to refer to the probable number TSNatechs occurring in a given period (four months), after a similar definition in the work of Santella *et al*. (2011), in which they calculated Natech probabilities for specific hazard zones. Our work related to each grid within the target areas, so that, if TSNatechs were clustered more, our probability results could be higher, by virtue of using deliberately selected higher probability grids in this study.

Reviewing Figure 6–1 suggested that the relationship between TSNatech probability and wind energy should be determined first. Through a literature review, the relationship between Natech probability and related natural phenomena—wind speed, flood inundation, and peak ground acceleration—could be indicated as an s-curve (e.g., as either a logistic function (Khakzad and Van Gelder 2017), or a lognormal function (Yang *et al*. 2016)). Even though the wind energy in this study was calculated for four months (July, August, September, and October), rather than for a single tropical storms, the selected months contained > 84% of the tropical storms recorded for the study period. The relationship between TSNatech probability and calculated wind energy should also follow an s-curve, and so a generalized logistic function (Eq. (4)) was introduced to estimate the TSNatech event probability, based on calculated wind energy:

$$P = \frac{1}{1+Ae^{-Bx^C}} \tag{4}$$

where P indicates the TSNatech probability, x represents the calculated wind energy, and A, B, and C could be estimated using the least-squares method, in the Python 3.0 environment.

By calculating TSNatech event probabilities and extracting related wind energies for each grid, for each year from 1990–2017, a TSNatech event probability and wind energy scatter map was established. Using these wind energy distributions, locations were divided into several groups, based on the natural breaks (Jenks) method (Jenks 1967). Mean values for TSNatech probabilities and wind energies were then calculated for each group, which gave rise to a new scatter map, which showed the relationship between event probability and wind energy. The least-squares method was then used to solve the parameters in Eq. (4), to fit the plotted scatter map, before the fitted function / curve ($F_{P\&WE}$)—which could be considered as a type of fragility curve—was used to evaluate TSNatech probability, based on wind energy, at the grid scale.

The procedure for estimating TSNatech probability based on SSP4-3.4, SSP4-6.0, and SSP5-8.5 has been explained in the following portion. The distribution of gridded wind energy (f_{WE}) for the future climate was estimated annually, for the months of July, August, September, and October over the period 2021–2100, using the kernel density estimation method. At the same time, because TSNatechs did not occur at every location, the distributions for the counts (f_{GN}) of the girds where TSNatechs occurred in the selected months for each year were also found, again using the kernel density estimation method. A simulation algorithm was then built to simulate TSNatech probability in the selected months, for each year from 2021–2100.

In this algorithm, f_{GN} was used initially, to generate a number, (N_G), which represented those girds where TSNatechs may occur for one target year (Y_T). The function, f_{WE}, was then used to simulate a sample (S_{WE}), of size N_G, which was taken as the wind energy value for those TSNatech-occur-grids. The function S_{WE} was then used as the input of fitted function $F_{P\&WE}$, to calculate TSNatech probability in those grids, before the mean value of those probabilities was used as the probability from July to October for the year Y_T.

The entire simulation algorithm was run 1,000 times for each year, and each simulation represented a probable case. In other words, within the period 2021–2100, the algorithm was run 80,000 times for this study, resulting in 1,000 potential 80-year time-series of data for TSNatech probability.

During the TSNatech probability estimation process, for both 1990–2017 and 2021–2100, the effect of installation aging was ignored in this study, as accounting for this variable across thousands of industrial installations would be highly resource intensive and very challenging. Furthermore, to reduce the level of impact uncertainty on estimations, we assumed that TRI facility and ONG platform locations would not change significantly over the next 80 years.

6.4 Results

6.4.1 Probability Estimations for 1990–2017

By following the procedure discussed in Section 6.3.4, probability estimations vs wind energy for the selected months in 1990–2017 (July–October) were calculated, and have been plotted in Figure 6-3. The fitted s-curves for each study area can be seen in Figure 6-3 (a) and (b), respectively, and these represent a form of fragility curve, describing the relationship between TSNatech probability and wind energy for the selected months, in each grid, for each year. The function parameters for the fitted s-curves for each study area can be seen in Table 6.1, together with the performances of the fitted curves as represented by the root-mean-square error (RMSE) and the coefficient of determination (R^2). High R^2 and low RMSE values showed that the s-curves were acceptable for estimating TSNatech probability against wind energy data, as calculated using the climate data from the SSP scenarios applicable to each study area.

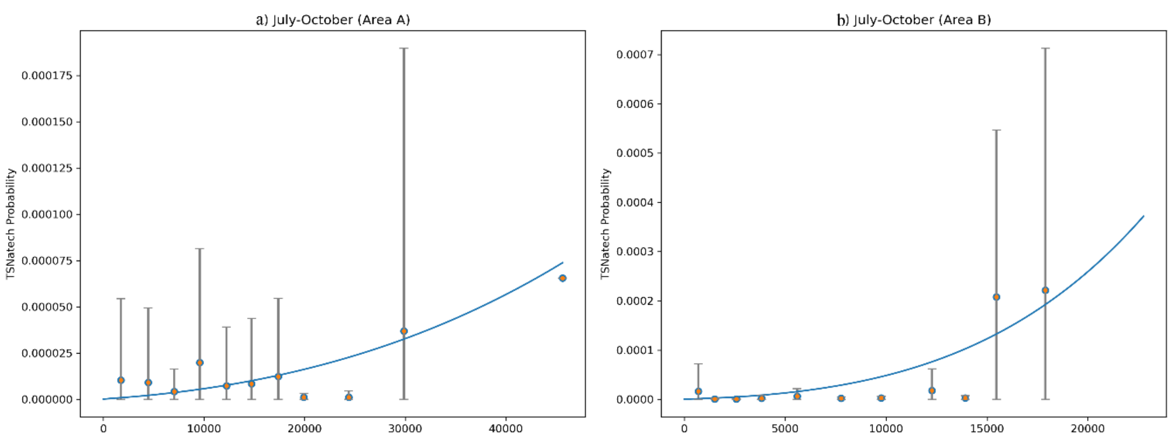

Figure 6–3 Fragility curves describing TSNatech probability against wind energy; the error bars are one standard deviation

In Figure 6-3, it can be seen that the TSNatech event probabilities increased smoothly in each study area, using the gridded wind energy for July–October, 1990–2017. It can also be clearly seen that the wind energy was distributed through quite different ranges, with the range for area A much larger than that for area B. Moreover, the fragility curve for study area B increased much faster than it did for study area A, as when the gridded wind energy increased to 20,000, the TSNatech probability increased to 2.61×10^{-4} in study area B, while showing probability estimates approximately one-twentieth (1.64×10^{-5}) of that value, in study area A.

The results showed that, from 1990–2017, tropical storms were more likely to have triggered Natechs in study area B, even though they were weaker than those in study area A. Furthermore, the fitted curves for both study areas showed that the uncertainty in estimating TSNatech probability increased with increased gridded wind energy, which might have been a result of the indirect impacts—such as power loss—which stem from tropical storms, (Santella *et al*. 2011; Necci *et al*. 2018).

Table 6.1 Estimated parameter values and s-curve function performance, based on TSNatech probability and monthly wind energy for each grid, from July–October

	A	B	C	RMSE	R^2
Study Area A	29,596,959.70	0.444	0.266	1.01×10^{-5}	0.70
Study Area B	9,445,590.95	0.244	0.350	4.55×10^{-5}	0.68

6.4.2 Probability Estimation Based on ScenarioMIP Data for the Period of 2021–2100

Based on the s-curve functions in Section 6.4.1, and the procedure discussed in the last part of Section 6.3.4, TSNatech probabilities for the selected months from 2021–2100, in study areas A and B, were estimated against gridded wind energy. The estimated probabilities for study area A, under scenarios SSP4-3.4, SSP4-6.0, and SSP5-8.5 can be seen in Figure 6-4 (a)–(c), respectively, while those for study area B under the same scenarios can be seen in Figure 6-4 (d)–(f). In the figure, 1,000 simulations have been plotted as gray lines, with the means indicated by blue lines. The LOWESS method (Cleveland 1979) was used (red lines) to track the blue lines and the historical TSNatech probability trends (the orange line; *observed probability*, in Figure 6-4). The peak study area B values in 2011 and 2012, as well as the many extreme values appearing in the 1,000 simulations from 2021–2100, made it quite difficult to observe the changes in the blue curves in study area B (Figs 6-4(d), (e), and (f)), and so a small inset has been included in the upper left of each figure, to clarify these.

In study area A, TSNatech probabilities showed an increasing trend from 1990–2017, with several peaks. In contrast, the mean probability estimates for 2021–2100 showed decreasing trends in the SSP4-3.4 and SSP5-8.5 scenarios, while in the SSP4-6.0 scenario, TSNatech probability had an initially decreasing trend, followed by an increasing trend. According to the smoothed lines for these periods, the TSNatech probability increased by more than 68% from 2021–2100, in comparison to that from 1990–2017, in study area A, under all three scenarios.

In study area B, TSNatech probability also followed an increasing trend from 1990–2017. The mean simulated TSNatech probabilities for the future scenarios followed decreasing trends in SSP4-6.0 and SSP5-8.5, while an increase–decrease–increase trend was observed for scenario SSP4-3.4. Based on the LOWESS smoothed study area B results, the TSNatech probability increased more than was seen for study area A under all three scenarios, showing a rise of up to 93%.

Our estimates have suggested that TSNatech event probability might be much higher over the next 80 years than it has been for 1990–2017, in both study areas A or B, with the increases calculated to be as follows: SSP 4-3.4: (A) 107.19% ± 4.65%, (B) 149.96% ± 26.20%; SSP 4-6.0: (A) 109.65% ± 4.78%, (B) 144.73% ±25.61%; SSP 5-8.5: (A) 101.67 ± 4.48%, (B) 136.32 ± 23.73%. Based on these increasing rates, we concluded that climate change might affect TSNatech occurrence in study area B more seriously than in study area A.

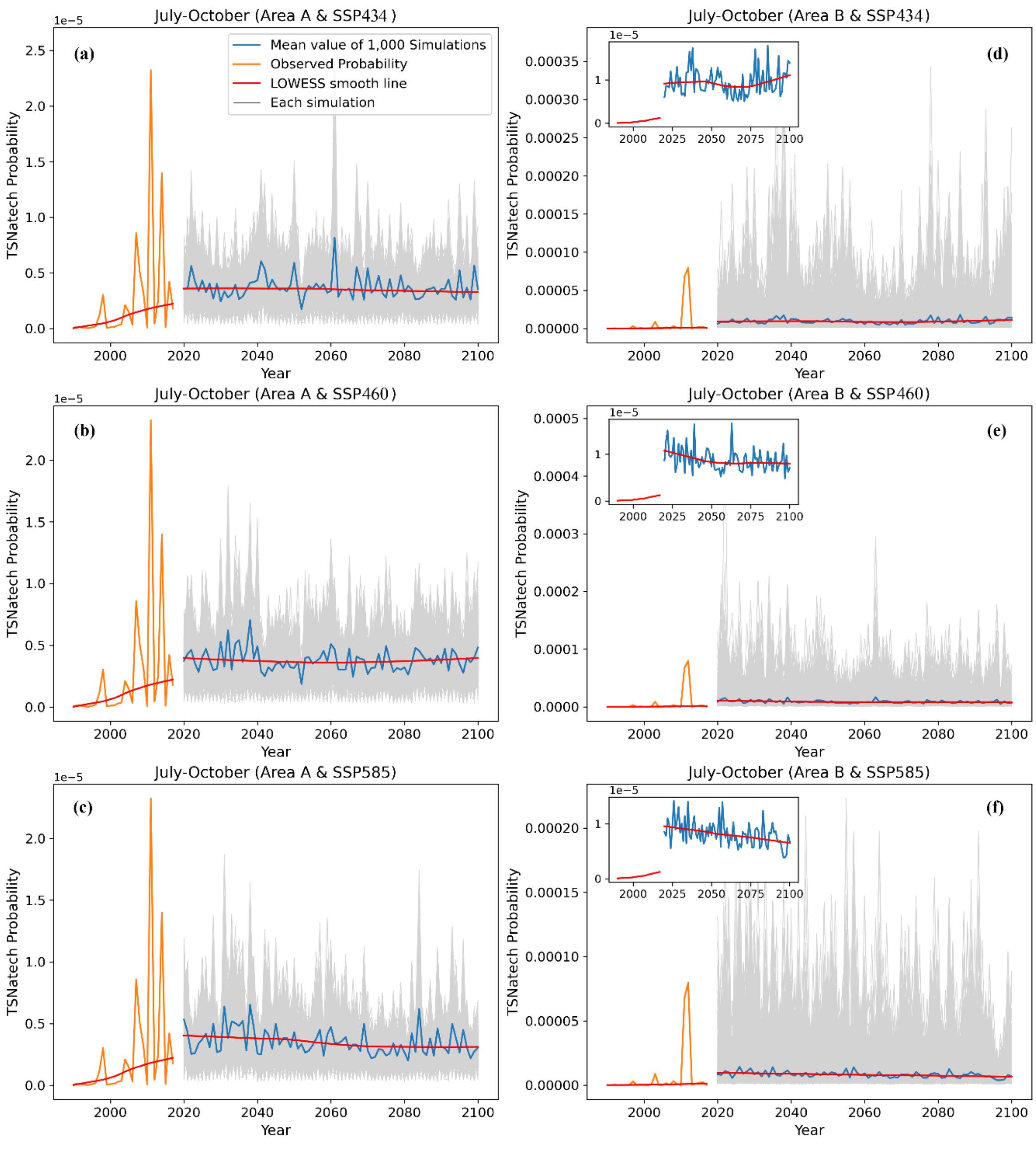

Figure 6–4 Simulation results for estimating TSNatech probabilities, based on simulated climate data under different SSPs scenarios. Blue lines in each panel show the means for 1,000 simulated TSNatech probabilities; orange lines show estimated TSNatech event probabilities based on past

TSNatech records; gray lines show each simulation result; red lines are smoothed lines, based on using the LOWESS method to track long-term trends in the simulated TSNatech probabilities

6.5 Discussion

Tropical storms can cause Natechs in different ways (Cruz *et al*. 2001; Necci *et al*. 2018). Since previous studies reported that climate change could affect tropical storm intensity (Knutson *et al*. 2019), frequency (Walsh *et al*. 2019), and affected area (Kossin *et al*. 2014), it is suggested that the occurrence of TSNatech might also be affected by climate change. In contrast to previous studies on climate change and TSNatech (Cruz and Krausmann 2013; Ebad Sichani *et al.* 2020), TSNatech event probabilities for past and future climate scenarios, based on wind energy, event reports for past TSNatechs, and ScenarioMIP data, have been estimated in this study.

According to the s-curves fitted in Section 6.4.1, gridded wind energy could be used successfully to estimate TSNatech probability. In previous studies, hurricane-related wind speed was used to estimate Natech (Santella *et al*. 2011), and storage tank failure (Zuluaga Mayorga *et al*. 2019; Olivar *et al*. 2020) probabilities, which could also be considered as evidence to support the concept represented by Eq. (1). Furthermore, we have seen that tropical storms have been more prone to triggering Natechs in study area B, from 1990–2017. According to the applicable US regulations—the Clean Water Act and the Risk Management Plan (RMP) Rule—the United States Environmental Protection Agency (USEPA) requires industrial facilities to prepare and submit risk management plans covering accidental chemical releases at least every five years (EPA, 2015). These regulations do not, however, require facility owners to provide risk management plans covering Natechs specifically (Krausmann et al. 2017).

In other words, the probability of TSNatechs in the study areas is highly related to the performance of the infrastructure against natural phenomena related to tropical storms. Moreover, according to the records in HURDAT2 relating to the 435 tropical storms which formed on the Atlantic Ocean side of North America and the Gulf of Mexico, the pathways of 82 of these crossed study area A only, 45 crossed study area B only, and another 46 intersected both. Thus, the lower TSNatech probability in study area A might be due to this area being more likely to be affected by tropical storms than area B, which has probably resulted in either infrastructure being located / built / managed to higher standards, or the stakeholders analyzed and prepared for tropical storm effects better thus reducing their impact. It would be of interest in future studies to check whether the higher probabilities in Area B were related to other factors.

From the perspective of TSNatech probabilities, which were estimated by using SSP-based simulation climate data, the results have shown that changes can be expected, as probability trends may follow different pathways from 2021–2100. This could be explained by the changes in the wind energies calculated from the climate simulation data (SSP4-3.4, SSP4-6.0, and SSP5-8.5). Plots for the annual sequences of calculated wind energies—for July–October in the different study areas, and under different SSP scenarios—can be seen in Figure 6–5. According to the blue lines in this figure, wind energies showed a weakly decreasing trend in scenario SSP4-3.4, a robust decreasing trend in SSP5-8.5, and a stable decrease–increase trend under scenario SSP4-6.0, in study area A.

In study area B, wind energy estimates presented weak and robust decreasing trends in scenarios SSP4-6.0 and SSP5-8.5, respectively, and a stable increase–decrease–increase trend under scenario SSP4-3.4.

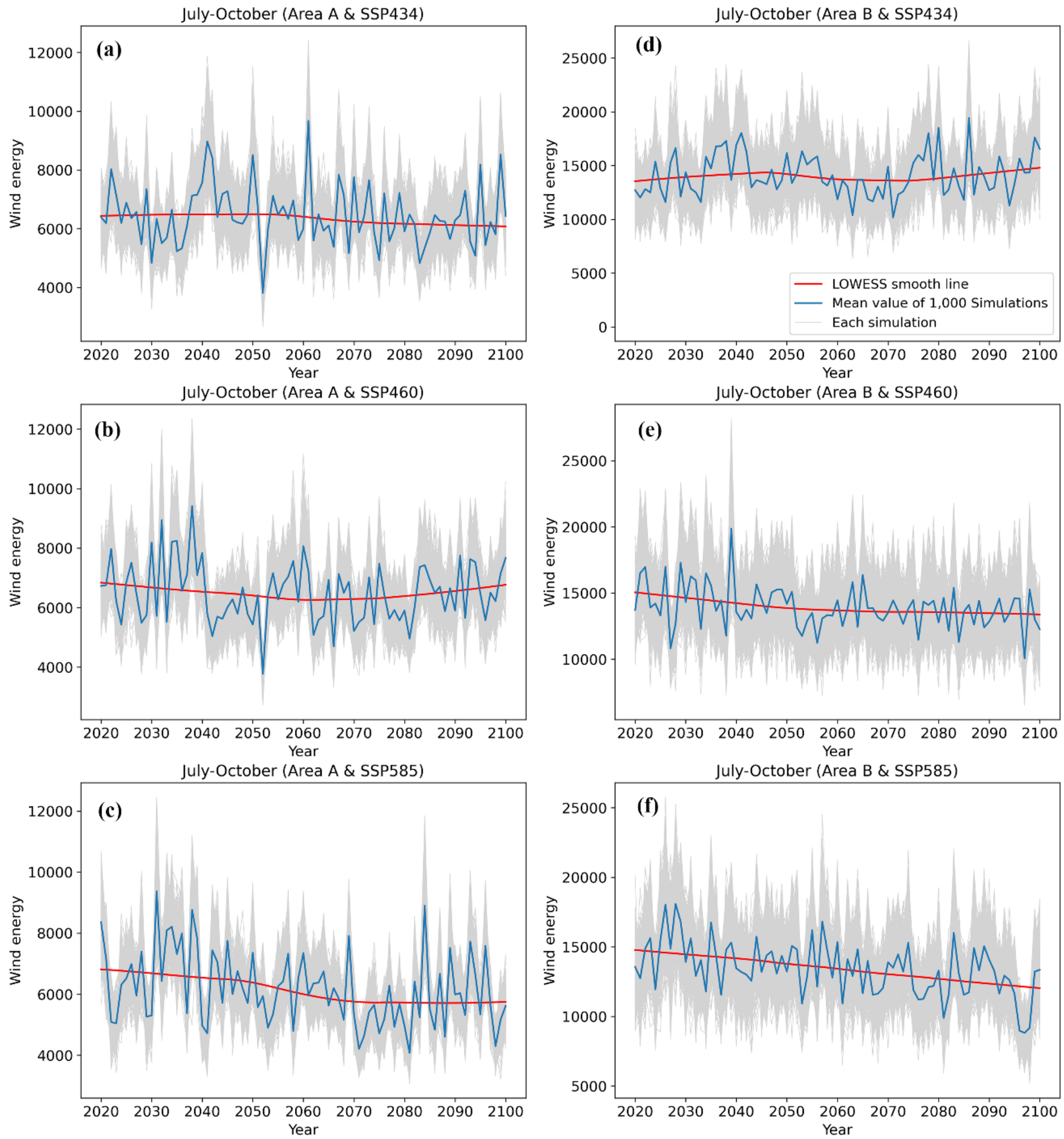

Figure 6–5 Wind energies for TSNatech locations, based on simulated climate data under different SSP scenarios, and for the two study areas

When the overall TSNatech probability estimation methodology in this study was considered, these wind energy trends explained the estimated probability trends plotted in Figure 6-4. In fact, similar decreasing trends in wind energy in the same study area for the future were also found in the study by Chen (2020), who analyzed the impacts of climate change on wind energy in North America. In particular, the decreasing wind energy trend in study area B was also generated in the studies by Tobin et al. (2015) and Carvalho et al. (2017), however, since most of their work was based on RCP scenarios, the future wind energy differences may have been caused by introducing SSP scenarios in this study. Even though TSNatech probabilities seemed to decrease from 2021–2100, it is important to point out that if Earth's temperature continues to rise, tropical storms will become more prone to triggering Natechs in coastal industrial areas—and this will occur regardless of whether the facility is located in a low (study area A) or middle (study area B) latitude. Climate change resulting in increased temperatures will, however, bring more challenges for Natech risk managers in study area B, due to the greater increase in TSNatech probabilities for this region.

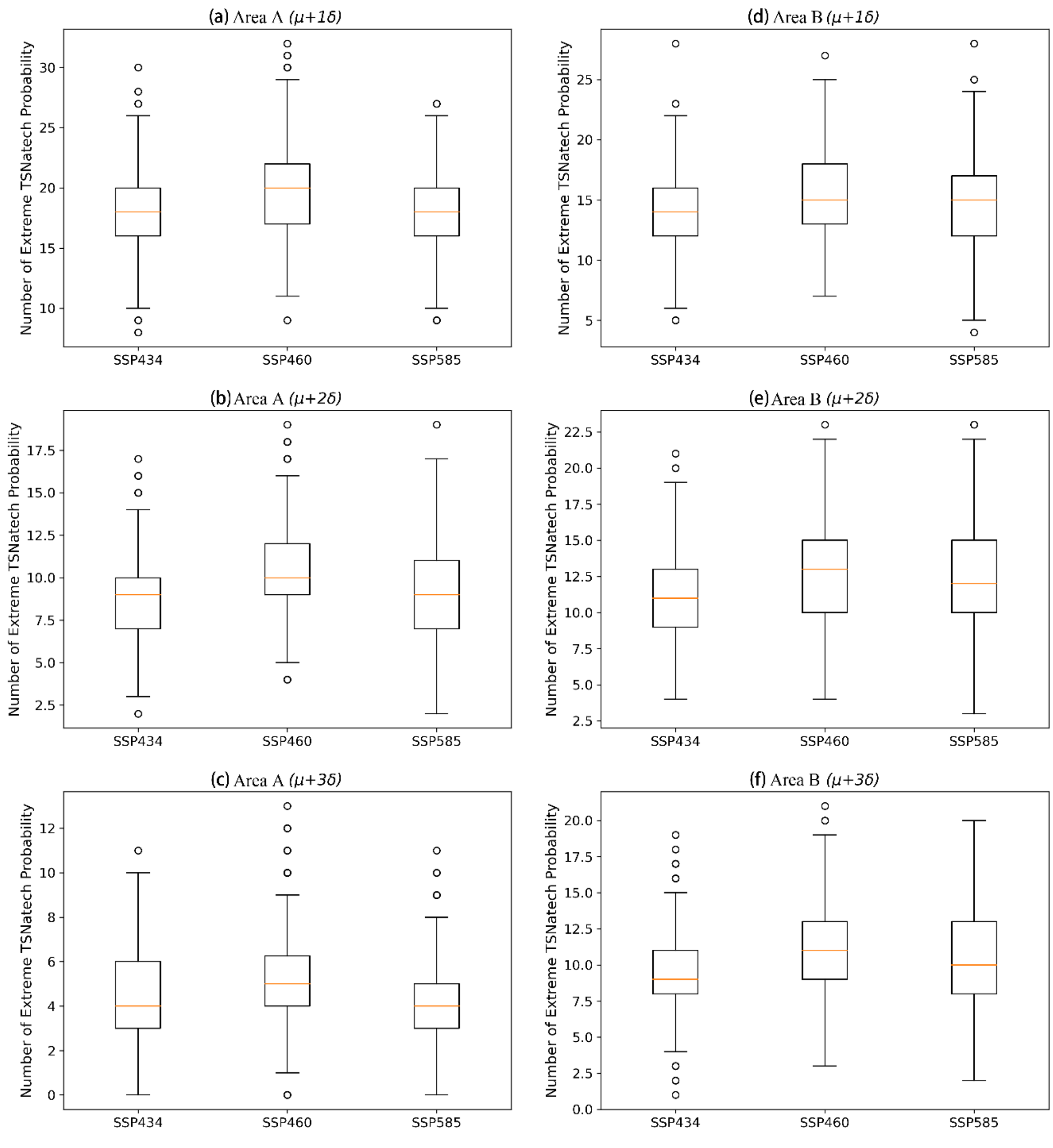

Figure 6–6 Boxplots for the estimated numbers of extreme TSNatech probabilities, for each simulation; μ *indicates the average mean value from 1,000 TSNatech probability simulations, and* σ *represents one standard deviation from* μ

Analyzing the modeled changes in TSNatech probability in the future helps experts in Natech event risk management understand how climate change could potentially affect TSNatech occurrence of better, but it is difficult to determine the effects of socioeconomic changes under the SSP scenarios. To analyze these impacts, extreme TSNatech probabilities were used in this section.

Averages (μ) and mean value standard deviations (σ) for the 1,000 simulations were used to determine the extremes of the simulated TSNatech occurrence probabilities, and the resulting counts for each of the 1,000 simulations have been plotted as boxplots in Figure 6–6. In this study, three types of extreme TSNatech probabilities were counted for each simulation, by checking whether the values were larger than either $\mu + \sigma$, $\mu + 2\sigma$, or $\mu + 3\sigma$.

In Figure 6-6, the counts of extreme TSNatech probabilities due to increased radiative forcing (from 3.4 to 6.0 W/m^2) did not increase at either study area A or B, when considering the same SSP scenario (SSP4). In contrast, the probability counts did not change significantly (the value was larger than $\mu + \sigma$ only), or even decreased, from SSP4 to SSP5 (the values were larger than $\mu + 2\sigma$, or $\mu + 3\sigma$), even though the radiative forcing level increased from 6.0 to 8.5 W/m^2. These results reconfirmed that if the climate continued warming, tropical storms would be increasingly likely to trigger Natechs, and that the occurrence of TSNatechs would be more clustered.

Taking different socioeconomic development pathways, and operating different climate change mitigation policies, could, however, result in TSNatech occurrences having different characteristics. Despite our findings, among all the elements considered in the SSPs—such as population growth, urbanization, international cooperation, energy politics, and even climate change mitigation methods—the particular factor(s) most responsible for the TSNatech probability results needs further analysis.

Based on our simulation results, we have been able to analyze how TSNatech probability from July–October, will change over the next 80 years in the two US study areas, based on multiple SSP scenarios. It should be highlighted however, that the simulation results may include some uncertainty—with most of this caused by the inherent problems of the NRC database, and by the TSNatech extraction method. The NRC center allows any US citizen to report a potential chemical release incident directly, with no standard format used in the reports. Thus, the descriptions had been categorized using a variety of terms and expressions, and many incident records were incomplete. These factors may have led to some Natech events being under-reported.

It should also be noted that using SINIF in this study also contributed some uncertainty. The SINIF is a semi-intelligent method for identifying Natech-related reports in the NRC database, replacing the need to check all the records manually, and may have led to some Natechs being either under-reported, or misidentified. In addition, the fragility curves built in this study were simplified statistical models, based on retrieved TSNatech records, and so there would have been some bias from the actual relationships between wind energy and TSNatech event probability. This may also have contributed some uncertainty to the results.

Additional uncertainty might be attributable to the climate simulation data. The data used in this study were simulated by other academic groups, using GCMs under scenarios involving different radiative forcing levels and economic development conditions. These GCMs have their own problems, in terms of their simulated climate data uncertainty, which may have been transferred into the uncertainty patterns of our results.

6.6 Conclusions

In this study, we have presented a methodology to establish empirical estimations for TSNatech probability. This was done for the months with most TSNatech occurrences and tropical storms, over the period 1990–2017. Based on this methodology, TSNatech probabilities were also forecast for 2021–2100, using ScenarioMIP data. In the proposed methodology, wind energy was used as the variable to estimate TSNatech probability, since wind energy could be taken as an evaluation metric for the potential energy which could be released during the dissipation of tropical storm energy. Analyzing the resulting estimations showed weak changes in TSNatech probabilities for 2021–2100, although, compared to TSNatech probabilities for 1990–2017, TSNatech event occurrence probabilities might have increased significantly around the Gulf of Mexico, and along the US east coast. Moreover, in a warming climate, the counts of extreme TSNatech probability may increase, and the clustered TSNatech event occurrences may also become more serious. Although we were able to conclude that the TSNatech occurrence probabilities may change in reaction to different trends / pathways under different SSPx-y scenarios, the mechanism of how the elements in the SSP scenario affect the changes in TSNatech probability have remained unclear—making this a very important forward research direction.

The methodology presented here involved applying a statistical model to estimate TSNatech occurrence probabilities—and could be improved by enlarging the population of past TSNatechs. There have been limitations that need to be addressed in future studies. Aspects such as equipment aging, land-use changes, changing or improving building standards, and whether facility managers / owners improve their approaches to risk management, were not addressed in this study, it being too resource intensive to collate these at the regional scale—and we concede that these elements are very important in estimating the probability of equipment failure. Furthermore, grid location information was not included as a variable when estimating TSNatech probability, which meant that the proposed methodology could not be used to predict and visualize TSNatech probability spatially. Finally, it should be pointed out that the findings presented in this study included the uncertainty caused by the inherent problems of the NRC database, the incomplete retrieval of TSNatech events, and the unclear relationship between wind energy and tropical storm system energy.

In summary, this has been a basic study, and represents an initial step in assessing TSNatech risk with potential climate change effects included. As it stands, it nonetheless provides support to decision-makers, local governments, and other stakeholders who live around the Gulf of Mexico and along the eastern US coast, by building their understanding of likely TSNatech occurrence in the context of climate change. The methodology presented here could also be transformed to quantify the risks presented by other meteorological hazard-triggered Natechs, such as floods or heavy rain.

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Chapter 7 Conclusions, Limitations and Future Directions

7.1 Main Findings

Tropical storms can affect chemical production, processing, and transport systems / equipment, causing chemical releases and oil spills (Cruz and Krausmann 2009; Santella *et al*. 2010; Necci *et al*. 2018). Such technological accidents are known as Natech, and tropical storm-related Natech events have been referred to as TSNatechs in this study. In the future, tropical storms could deliver more heavy rainfall and larger storm surges due to climate change (Knutson *et al*. 2019; Walsh *et al*. 2019; Zhang *et al*. 2020), which may also lead to tropical storms affecting wider areas (Kossin *et al*. 2014). Based on the effects of climate change on tropical storms, and the serious consequences of TSNatechs, experts in risk management have asked stakeholders to improve the risk management framework for TSNatech risk, including climate change, as an important risk factor (Cruz and Krausmann 2013).

By bearing that in mind, the aims of this study were on determining the effects of climate change on TSNatech occurrence, by using data from past TSNatech events, and on providing an outlook on how climate change could affect TSNatechs in the future. We first developed a deep learning-based framework (SINIF) to retrieve 1990–2017 Natech reports from the NRC database. By employing multiple statistical and spatial analysis methods, we found a potential link between temporal–spatial variation in TSNatechs and climate change. By reorganizing the retrieved TSNatech data, we then developed a method to generate a fragility curve for estimating the probability and conditional probability of TSNatechs, using wind energy. Based on this proposed estimation method, and on climate data provided by the WCRP, TSNatech probabilities were estimated for the periods 1990–2017 and 2021–2100. We were then able to show that global warming is likely to cause more TSNatechs to occur, although the event probabilities may be represented by different characteristics under different socioeconomic development pathways.

Based on the SINIF, 32,841 Natech reports were retrieved from the NRC database, comprising 3.98% of all incident reports. Among these, 24.42% were related to hurricanes, while 19.27% and 18.29% respectively were related to rain and storms. An additional 36.26% were attributable to wind, flood, cold, tornado, or other weather-related events. In summary, meteorology-related natural hazards caused the most (98.24%) Natechs over the period 1990–2017 in the US. In further use of SINIF, it was determined that the Long Short-Term Memory algorithm was more suitable for building SINIF (to retrieve Natech reports from the NRC database) than the CNN algorithm.

By analyzing temporal–spatial variations in TSNatech counts, we found that the number of TSNatechs increased over the period 1990–2017, and that changing occurrence trends showed that they had been occurring closer together over time. Similar increasing trends were found in the probability and conditional probability for TSNatechs, by estimating them spatially, using GIS methods. Changes to regulations and formats used by the NRC center to collect chemical release reports, as well as temporal–spatial variations to industrial installations (fixed facilities, storage tanks, and offshore oil drill platforms), and cross-wavelet analysis results between climate indices and TSNatech numbers were also reviewed in this study. We concluded that there might be a link between climate change and the incidence of TSNatechs, as climate change could affect the occurrence of TSNatech indirectly, by influencing tropical storm activity.

When analyzing temporal variations in TSNatech probability, we found that wind energy could be used to estimate their occurrence probability, through use of a generalized logistic function, which could be considered as a type of fragility curve. According to the resulting fragility curves, regional TSs were more prone to triggering TSNatechs along the eastern coastal area of the US, rather than the Gulf of Mexico.

By reorganizing the retrieved TSNatech data and calculating wind energies using climate simulation data, TSNatech probabilities were forecast for the period 2021–2100. We found that the TSNatech probability might be much higher than now in the future, on the Atlantic side of the US. Furthermore, the probability values suggested that, by adopting the SSP4 scenario for socioeconomic development, the number of extreme TSNatechs could increase, in response to increased radiative forcing (from 3.4 to 6.0 W/m^2). However, the number decreased between scenarios SSP4-6.0 and SSP5-8.5, even when the radiative forcing level increased from 6.0 to 8.5 W/m^2. The results showed that if global warming continued, TSs may become more prone to triggering Natechs, and that TSNatech occurrence levels could be more densely populated.

7.2 Limitations

The results achieved in this study could perhaps be used as evidence to support the hypothesis that climate change could affect the occurrence of TSNatechs, and that such events may become more frequent. However, due to the limitations of this study, we should be careful in reaching such conclusions. Firstly, the inherent problems of the NRC database, which have been discussed in earlier chapters, could have affected the sample size, accuracy, and quality of the retrieved TSNatech data. It will always be difficult to retrieve all potential TSNatechs from the NRC database, unless all chemical release reports are manually checked. In addition, the aging effects of industrial installations, and the outcomes achieved by improving risk reduction actions were ignored in this study—as accounting for these variables would have been too resource intensive.

The limited TSNatech sample size brings uncertainty when estimating TSNatech probability using wind energy. Furthermore, with respect to the SSP scenarios, the elements that are the key factors causing changes to TSNatech probability in the future were not discussed in this study, as we used the climate simulation data for each SSP scenario provided by WCRP directly. Finally, uncertainties in the climate simulation data could also have affected the credibility of the conclusions of this study.

7.3 Recommendations and Future Directions

Based on the main findings and limitations of this study, we present the following recommendations for Natech risk management:

1. Upgrading industrial installations might be an efficient way to improve their performance when faced with tropical storms that have become more intense due to the effects of climate change. However, as suggested by Cruz and Krausmann (2013), decision-makers, risk managers, and facility owners would need to maintain the balance between investment costs and the requirements necessary for facility and worker protection.
2. More effort needs to be applied to improving the reporting system. As shown in this study, and others (Campedel 2008; Cozzani *et al*. 2010; Girgin and Krausmann 2014; Girgin and Krausmann 2016; Krausmann *et al*. 2017), almost all chemical release accident databases have their own inherent problems, capable of affecting the quality of Natech extraction. Even though the eNatech database was developed as a specific database for Natechs, the low number of Natech records there to date makes it unsuitable to use for historical event analyses, from long-term or wide-scale perspectives.
3. Increasing international cooperation is another recommendation from this study. Because climate change, tropical storm formation, and Natech occurrence are quite complex academic problems, cooperation by scientists from varied disciplines would help determine the effects of climate change on the incidence of Natechs. Moreover, encouraging data sharing among different academic groups may also uncover broader Natech distributions, which could help quantify the effects of climate change on the occurrence of Natechs on a wider scale.
4. Finally, local-level governments should take more responsibility for organizing facility owners, and for building broader cooperation with other stakeholders, to improve their state of preparedness for managing Natech risk better, by considering climate change. Moreover, state- or national-level governments should take more actions on Natech risk assessment from a spatial perspective, to support better urban planning and industrial facility dispersal and avoid concentrated numbers of facilities in high-hazard areas.

Although this study has limitations, the methodology proposed herein will support researchers, local governments, and risk managers when analyzing potential effects of climate change on Natech occurrence. We have reconfirmed, through this study, that climate change effects should not be ignored in Natech risk management, and that it is urgent for action to be taken to respond to the likelihood of increased Natech occurrence risk, in the context of climate change.

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