A DECISION SUPPORT SYSTEM FOR ASSESSING OIL SPILL VULNERABILITY IN TEXAS COASTAL REGIONS.

A Thesis

by

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ABSTRACT

Oil spill disasters may have devastating impacts for coastal communities and the ecosystem (Baade et al., 2007). For instance, the coastal regions of the United States, especially the Gulf region, have been devastated by oil spill events of varying sizes, resulting in significant ecological and economic losses (Baade et al., 2007; Smith et al., 2010). In this study, a human-centered multi-criteria decision-making (MCDM) framework is proposed and then present an example assessment of oil spill vulnerability utilizing the framework to support oil spill risk-informed decision-making in Texas coastal areas and the Western Planning Area (WPA) in the Gulf of Mexico.

This work aims to assess oil spill vulnerability by defining three major conceptualizations of vulnerability: socioeconomic vulnerability, environment vulnerability, and vulnerability of spill impact risk through the Blowout and Spill Occurrence Model (BLOSOM) simulation. Furthermore, a decision support system is developed with an MCDM framework by combining spatiotemporal simulation results from BLOSOM and the vulnerability indexes. The proposed framework is applied to identify areas prone to oil spill disasters with the combination of spatial-temporal analysis and a customized multi-criteria evaluation. Areas with higher vulnerability scores in the case study are considered more vulnerable to oil spill impacts and should be considered with high priority in emergency response. Results indicated that communities in Galveston, Freeport, and Corpus Christi areas, are under great threat from oil spill disasters under conditions similar to those in the simulation. Moreover, the proposed framework emphasizes human-centered design and collaborative decision-making where different decision-makers can select the data that are important for their decision goals and assign weights for the evaluation criteria to generate an overall vulnerability score from vulnerability indexing to improve the performance of collaborative decision-making and eventually facilitate oil spill response and management.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a thesis committee consisting of Professors Zhe Zhang and Stacey Lyle of the Department of Geography and Professor Duane McVay of the Department of Petroleum Engineering.

The data analyzed for Section 4, the case study, was based on Ocean model data from HYCOM, Social Vulnerability Index data from Agency for Toxic Substances and Disease Registry, Environmental Sensitivity Index (ESI) Maps and Data from NOAA (National Oceanic and Atmospheric Administration), and the Blowout and Spill Occurrence Model developed by the Department of Energy National Energy Technology Laboratory. All the original data source and publications are listed in the reference.

All other work conducted for the thesis was completed by the student independently.

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1. INTRODUCTION

According to the Energy Information Administration, oil production in the federal offshore area of the Gulf of Mexico accounts for approximately 15% of total crude oil production in the United States (EIA, 2018). Offshore oil exploration and production have become a large and important component of the United States' energy sector, while marine oil exploration production technology has been advanced to improve offshore oil and gas production operations. While oil production and exploration activities in the GOM have been increasing, the coastal communities in the GOM region have suffered from various oil spill disasters, which motivates us to study how spill events can potentially impact the environment, the society and the ecosystem. Some chemical components from spilled oil which is poisonous can cause harm to living things, for example, causing eye irritation or skin illness (NOAA, 2017; Chiau et al, 2005). Therefore, developing methods and models for assessing vulnerability and oil spill implications is in great need for oil spill studies.

Oil spill vulnerability assessments as critical parts of oil spill disaster management and preparedness have attracted attention around the world. In general, there are two basic approaches for estimating and assessing oil spill risks and impacts (Nelson et al., 2018). According to work by Nelson et al. (2018), the first approach relies on historical datasets and in situ observations. Empirical observations of oiled locations are usually included in this procedure as well as subsequent analysis of the damages caused by spilled oil. The second approach is mainly based on simulations, which combines statistical analysis and numerical modeling methods to estimate the potential impacts of oil spills. The simulations are also applied to forecast the trajectory and the movement of spilled oil in many of these models. Recent scientific research has produced studies based on these approaches, especially the second one, by illustrating the efficiency of prediction models and approaches and their implications for oil spill disaster management and response. (Anselain et al., 2021; Aghajanloo et al., 2022). Although reasonable snapshots of predicted movements and impacts coming behind of oil spills have been proposed in many of these studies, few consider the spatiotemporal characteristic of oil spill impact distribution. Evaluating changes in spill impacts from both spatial and temporal perspectives remains a key gap, and it is a fundamental and critical aspect of response policy and contingency planning in oil spill disaster management (Nelson et al., 2021).

Additionally, in the case of an oil spill disaster, the first responders often have to make a rapid decision on evaluating the negative impacts of the event by combining all decision variables. Sometimes, the decision has several decision objectives which may conflict with each other. For example, it is challenging to distribute rescue resources to all the areas that are impacted by an oil spill disaster. Operations have to be prioritized based on the decision objectives associated with the level of degree of urgency. Different priorities on coastal resources and research purposes from different individuals usually lead to different decisions. Multi-criteria decision analysis has played an essential role in decision science for addressing the problems related to conflict decision objectives and priorities (Zhang et al., 2021). Multi-criteria decision-making analysis has shown its effectiveness in supporting decisions that have conflict decision objectives and it is also used for supporting decisions that often have a number of different criteria contained.

Those criteria are supposed to be all considered to meet decision objectives and help to improve collaborative decision-making (Zhang et al., 2018).

In this project, a collaborative decision support framework is developed by integrating the oil spill Blowout and Spill Occurrence simulation Model and various vulnerability assessment indicators derived from multi-source data. The results of this work can support oil spill environmental assessment and help the coastal communities to be better prepared for the oil spill hazard events. The proposed framework can be used to support oil spill disaster management in coastal areas from the following two perspectives: 1) supporting spatiotemporal decision making in oil-spill risk assessment by developing space-time oil spill simulations; 2) helping to improve situational awareness of oil spills by developing comprehensive oil spill vulnerability evaluation indices using social vulnerability and environmental vulnerability indicators; 3) advancing collaborative decision-making in oil spill assessment by developing an interactive user interface and multi-criteria decision analysis framework.

2. BACKGROUND

2.1 Oil Spill vulnerability and risk assessment

Assessments on vulnerability and impact of oil spill events are decisive sections of oil spill disaster preparedness. Considerable studies have been conducted focusing on advancing analytical techniques for highlighting community vulnerability, oil behavior, and spill outcomes in recent years. In order to provide supportive information to policymakers and first responders, oil spill vulnerability and impact analysis in coastal communities need to cover several fundamental components in general (Nelson et al., 2017).

First of all, the assessment of the sensitivity of the coastal environment that is potentially impacted by spilled oil must be determined by researchers. This often includes identifying metrics that describes the economic systems and environment of a region. Established metrics such as the environmental sensitivity index (ESI) and the social vulnerability index (SVI) are taken advantage of by Numerous researchers (Romero et al., 2013; Jensen et al., 1998) to assess the sensitivity of coastal ecosystem. ESI, originally produced by Gundlach and Hayes et al., (1978) revealed how sensitive a specific coastal region is against spilled oil according to the assigned ESI of the region. The ESI value is estimated based on plenty of indicators, including the types of shores such as mixed sand, salt marshes, exposed rocky lands and mangroves, etc. Environmental sensitivity risk (ESR) maps that are generated from ESI allow decision-makers, responders, and policymakers to make decisions about how to handle oil spill disasters. ESI has been utilized to a lot of recent studies. For instance, Andrade et al. (2010) conducted a study on the coastal region of the Brazilian state of Maranh˜ao because it is a region that is vulnerable to oil spill disasters and other pollution in the marine environment. In their research, not only the geomorphological variables but education, income, and the local population's dependence on tourism and fishing were considered. Going further on this viewpoint, it is necessary to prioritize the various kinds of resources at risk in an order of impact significance and adopt systematical approaches to disaster management and response. This may raise plenty of challenges because of the different priorities on resources and coastal assets decided by different individuals and groups. Additionally, the cooperation and interaction of these organizations and multiple stakeholders with diverse interests are required to combine resources and efforts to perform tasks beyond their individual capabilities in an oil spill response system to make decisions (Nelson et al., 2021). As result, customized indexing of coastal assets and resources that are likely to be affected by oil spills towards different interests of decision-makers is vital to perform more effective interactions with multiple user groups.

The second step is to quantitatively approximate the potential damage that an oil spill may bring forth for a specific coastal area to model vulnerability and risk. Knowing where the spilled oil is likely to go, the general susceptibility of communities to be impacted, the degree of damage, and the resources it may impact in a case of oil spill events can produce supportive information for oil spill disaster planning, response, and clean-up (Nelson et al., 2015). Within this circumstance, the broadest conceptualization of vulnerability is referred to as the susceptibility to oil spills (Cutter et al., 2006; Grubesic et al., 2013). Nevertheless, as detailed by Wu et al. (2002), vulnerability may be conceptualized differently depending on topics (e.g., risk assessment, infrastructure, climate etc.) and disciplines (e. g., coastal activity planning, geography, disaster management, etc.). Wu et al. (2002) also proposed that three main concepts of vulnerability in the literature are as follows: (a) physical vulnerability, (b) social vulnerability, and (c) spatial vulnerability. Physical vulnerability usually refers to potential oil spill hazards physically. Social vulnerability assumes some type of destructive event exposure but reveal and explain how social groups are affected differently (Cutter et al., 2006). Spatial vulnerability takes into account both the physical and social aspect to a particular coastal area (Cutter et al., 2008). According to Nelson et al. (2017), the three main concepts of oil spill vulnerability in recent research are (a) environmental vulnerability, (b) social and economic vulnerability, and (c) spatial vulnerability for spill assessment in coastal areas.

The ESI is used to estimate the environmental vulnerability of an oil spill. As mentioned above, the ESI's original development efforts centered on assessing the physical mechanisms driving oil-land interactions and transforming these interactions to an ESI value in a 1-10 scale. Hence, ESI values indicated the degree of oil deposition, the prevalence and persistence of spilled oil in the offshore environment, and the estimated magnitude of biological damage (Gundlach and Hayes et al., 1978). Exposed rock outcrops, for instance, are assigned a rating of 1 because the lack of permeability and wave action keep the majority of oil in the marine environment. Salt marshes and other densely vegetated areas score an ESI value of 10 not just because they represent the most productive aquatic ecosystems, but also because they are extremely prone to spilled oil. In these areas, oil can remain for years and is hard to eliminate (Gundlach and Hayes et al., 1978). Consequently, the ESI value became a crucial component in determining the environmental vulnerability of oil spills.

Social vulnerability indices are used to quantify the capacity of inhabitants, communities, and economic systems in coastal areas to recover from the oil spill impacts. This is especially important for communities with a quantifiable reliance on the offshore environment for their well-being. Several large-scale surveys were conducted for a more comprehensive evaluation of social and economic vulnerability during the past two decades, but many of them have only considered the population size (e.g., Sepp Neves et al., 2015). Other studies take into account metrics related to residential land use (Yang et al., 2015), and population marginalization (Mendoza-Cantú et al., 2011), as aspects of community residents' mental health after oil spill events (Allen et al., 2015; Grattan et al., 2011; Lazarus, 2016). According to Nelson et al. (2018), a more comprehensive assessment of social vulnerability should incorporate racial information, household income, ethnicity, age, and other critical variables that might represent the variety of a community and the diverse experiences of its citizens after a significant spill. Therefore, it is advised that the CDC/ATSDR social vulnerability index (SVI) be used to identify social and economic factors (Nelson et al., 2021). It defines the social vulnerability of each census tract using the Census data. Census tracts are spatial subdivisions for which the Census collects statistical information. The CDC/ATSDR SVI scores each tract based on 15 sociodemographic variables, such as poverty, lack of vehicle access, and overcrowding, and classifies them into four themes. Each tract is ranked and assigned scores separately for each of the four themes and an overall social vulnerability ranking.

The following stage is to estimate oil spill risk by analyzing the likelihood of an oil spill occurring at a specific location (Nelson et al., 2017; Al Shami et al., 2017; Sepp Neves et al., 2015). Risk is often described as the potential for vulnerability and the likelihood of oil approaching a certain place. Modeling oil spill risk may be achieved with a variety of methods, but the ultimate purpose is to assess the probability of spilled oil occurrence and the extent of oil spill that region may experience (Gasparotti et al., 2010). The basic method for risk modeling is using numerical spill simulation (Amstutz et al., 1984), which may be informed by historical oil spill data or simulations (Fernández-Macho et al., 2016). SIMAP (McCay et al., 2004), MEDSLICK (De Dominicis et al., 2013), and GNOME (Beegle Krause, 2001) are a few of the most often utilized simulation approaches to model oil spill risk (Aamo et al., 1997). In addition, several researchers have created transportation prediction models rather than using the more usual "pre-packaged" platforms for oil spill risk modeling as mentioned. For instance, by using a boundary-fitted grid approach, Naidu et al. (2013) created a model to predict the eventual landing locations of spills based on trajectory prediction, which is then be utilized to construct oil spill risk evaluation metrics. Mokhtari et al. (2015) assessed probability of oiling based on ship density along defined transportation routes, oil facilities, surrounding coasts, and oil well sites in the Persian Gulf using a generalized linear model. Beyond these measurements of susceptibility and risk of oil spill impact, French-McCay et al. (2004) emphasized the need of considering the possible spill repercussions. Following this viewpoint, it is proposed by Gasparotti er al., (2010) that the combination of vulnerability and risk assessment of oil spills and can eventually contributes to the generation of an effective assessment for simulated spill scenarios. However, it is critical to recognize that vulnerability analysis is not included in many oil spill impact assessments in their proposed assessment approaches. Those assessments frequently concentrate on a specific oil spill modeling approach or the development of an oil spill database for future academics to exploit (Boer et al., 2014; Amstutz et al., 1984). A deeper understanding of the likelihood and severity of a prospective occurrence of oil spills may be obtained by assessing risk independently of vulnerability as well as a combined assessment of the oil spill vulnerability and risk.

The outcome of an oil spill vulnerability assessment is usually an overall vulnerability score or index that integrates coastal assets prone to oil spills (e.g., socioeconomic, environmental, and cultural) with the likelihood and severity of oil spill events (Nelson et al., 2017). Numerous researchers utilized a weighted sum technique, in which indicators that occur within the pre-identified spatial units in the studied area are summed to determine an over vulnerability score for each sector or aspect (de Andrade et al., 2010; Kankara et al., 2007). Then, these weighted sums are allocated to specific categories and assessed to produce an overall index of vulnerability (Azevedo et al., 2017; Arockiaraj et al., 2016).

2.2 Multi-Criteria Decision Analysis

In recent years, the decision-making process has been continuously advanced and is recognized as the identification of alternatives to serve as potential solutions for an upcoming decision problem. Decision Support Systems (DSS) are defined as interactive computer-based systems that provide people with helpful solutions to deal with problems and make reasonable decisions (Power et al., 2002). DSSs can be clustered into five different categories: Data-driven DSSs, Communication-driven DSSs, Model-driven DSSs, Knowledge-driven DSSs, and Document-driven DSSs (Psarommatis et al., 2022; Felsberger et al., 2017). Data-driven DSSs explore external information and retrieve related data for decision-making procedures (Gandhi et al., 2018). Information technologies and communication is leveraged by Communication-driven DSSs to collect and share information (Al-Alawi et al., 2018). More efficient collaboration is enabled by this amongst the different user groups that are involved, both inside and outside the organization (Yazdani et al., 2017). Model-driven DSSs concentrate on a specific activity's simplification and assess possible alternative actions. Different possible actions and outcomes are compared, and an output performance score to estimate probability if assigned to each scenario (Psarommatis et al., 2022). Document-driven DSSs are capable of rapidly and efficiently retrieving information from valid documents such as images, sound recordings, text files, and videos. These documents are leveraged by them to support decision-based actions (Schuh et al., 2018). Data mining systems are used in Knowledge-driven DSSs to empower computer-based decisions. Advanced DSSs commonly apply the combination of two or more mentioned types of DSSs. Data-driven DSSs, knowledge-driven DSSs and model-driven DSSs are usually applied in recent studies (Psarommatis et al., 2022). According to research produced by Psarommatis et al., in 2022, two major sub-categories are identified for those hybrid DSSs.

The first type is formed of rule-based systems that are developed according to the knowledge of specialists replicating their decision processes (Prasad et al., 2018). These DSSs combine model-driven DSSs with some knowledge-driven DSSs aiming to provide solutions to real-world problems. For instance, Decision Tree models with Utility functions are usually applied in these DSSs (Pappalardo et al., 2021; Schwetschenau et al., 2022). Decision tree analysis is a graphical depiction of the expected outcomes of a series of actions and decisions. (Crundwell et al., 2008). The graphs in the decision tree model comprise events, terminal nodes, and decisions linked by using distinct branches. The graphs are used to represent an event node's predicted outcome and finally demonstrate a suggested decision. This structure allows decisions to be deconstructed so that their components can be easily viewed by analysts as well as the alternatives and the outcomes. With the predicted outcomes, probability analysis of each outcome is then integrated to assess the preferred decisions. Utility theory is a developed method to account for a decision maker's risk tolerance based on identified utility function (Crundwell et al., 2008). The utility function delineates the outcomes' utility which the decision-maker take into consideration to decide to take the risky options or certain options (Crundwell et al., 2008). Finally, predicted outcomes are transformed into a value to delineate the utility with the utility function. In this circumstance, the decision or preferred option is the one having maximum utility value. The outcomes in the decision tree model can be identified in terms of utility, which can increase the scope of the analysis and the model by explaining distinct preferences and risk tolerance in different research.

The second category follows through the combination of communication-driven DSSs and data-driven DSSs to explore the data's internal information with multi-criteria analysis, neural networks, artificial intelligence technologies, and machine learning algorithms (Mrzygłód et al., 2018) and share the information to support collaborative decision-making. These systems conduct presentation and analysis of the data and compare the outcomes that use assessment functions and indexes, thereby providing a more reasonable understanding of the problems to support decision making. Multi-Criteria DSSs are the well-recognized type in this category. Recent improvements in decision-making theories, enhanced design of the decision support framework, and capabilities to produce GIS analysis have provided Multi-Criteria Decision Support Systems' development with possibilities (Zhang et al., 2018). Multi-criteria decision-making (MCDM) model and analysis are usually formed by a mathematical framework that provides tools for the analysis of decision alternatives in the planning procedure. It is an approach to support decisions having different criteria that are supposed to be considered and integrated to meet one or several decision objectives and help produce a suggested decision as a solution. The Weighted sum model (WSM), which is mentioned above as a prevailing model to amalgamate the vulnerability score, is one of the commonly used multi-criteria decision analysis (MCDM) approaches (Shafiee et al., 2015). The key principle behind this approach is to ascertain the weighted sum of ratings for each decision alternative that is considered in decision analysis. In fact, a similar approach is used by most vulnerability assessments, including the work of Passos et al. (2014), who produced a multi-criteria decision-making approach to assess oil spill vulnerability, and the proposed approach is utilized in the Brazilian oil spill management and response. A fuzzy comprehensive evaluation-based decision-making approach was developed by Liu and Wirtz (2007) for oil spill management, and they used the prestige accident off the Spanish shore in 2002 as an instance to illustrate the proposed model's effectiveness. In other studies, normalized indices were developed to evaluate total vulnerability with the WSM to combined risk and vulnerability analysis (Olita et al., 2019; Sepp Neves et al., 2015).

To sum up, the first category of the advanced hybrid DSSs consists of model-driven and knowledge-driven decision-making to evaluate possibility, alternative actions, and utility coming behind and is aimed at providing specific decision suggestions. The second type concentrates more on the interpretation and sharing of the processed information based on data-driven and communication-driven approaches. The main purpose of this type of DSS is to help decision-makers explore detailed information contained in the various datasets and obtain a reasonable overall understanding of the data itself in order to support further decision-making, especially in the context of collaborative decision-making.

In general, research on oil spill vulnerability and risk assessment utilized a basic methodology consisting of developing metrics for evaluating coastal vulnerability or sensitivity, estimating the likelihood of oil spill occurrence for risk assessment, and integrating these metrics into an overall vulnerability score contained in a final vulnerability index (Nelson et al., 2017). The scores may be assigned to a large geographic region, a single spill scenario location, or smaller discrete units of assessment (Fattal et al., 2010; Nelson et al., 2015; Olita et al., 2019). However, several of these researches go beyond metrics of basic implications to address other features linked to spilled oil, such as the travel distance of a spilled oil from its original blowout location to the landing location to estimate its travel speed, or the magnitude of simulated spilled oil to determine the volume of its impact, or the prevailing wind direction and ocean currents movement to forecast the trajectory of spilled oil (Nelson et al, 2021).

Moreover, it is essential to highlight that, changes in the spatial and temporal dimensions of an oil spill might lead to considerable variations to the outcomes. However, many vulnerability evaluation frameworks in recent research are not designed to investigate the spatiotemporal variation of oil spills. Instead, many studies concentrated on proving the integrity of their proposed framework (Sepp Neves et al., 2015). These techniques proposed in their studies are undoubtedly possible for contributing to a better understanding of the relationship between spill behavior and impact in coastal regions (Azevedo et al., 2017). But these studies were mainly conducted to predict the trajectory of spilled oil rather than impacts and damages caused by oil spills in coastal communities (Brenner, 2015), and only a few oil spill risk and impact evaluations considered spatiotemporal variation of oil spill events. In addition, a small number of studies that evaluate the temporal aspect of oil spill risk and effect did not provide a mechanism for assessing the variations in outcomes across multiple oil spill scenarios. This is a critical gap, particularly in the Gulf area, where ocean circulation is very energetic and dynamically complicated. In light of the seasonal character of the Gulf of Mexico, it is necessary to take into account the temporal dynamics of oil spill occurrences in order to predict the potentially vulnerable regions impacted by oil spills, given their related trajectories and repercussions on coastal areas under various scenarios. For example, due to seasonal changes on wind force and ocean currents, the risk of a spill happening in January may differ from that of a spill occurring in July or August. Therefore, an analytical framework is crucial to minimize evaluation bias and promote a more scientific assessment for analyzing spill vulnerability. Specifically, a framework that takes into account the spatial and temporal variations of oil spills and the diverse interests of individuals and groups towards coastal resources is required to identify vulnerable areas.

To address the issues mentioned above, A multi-criteria decision support framework is proposed in this study to produce a vulnerability index with indicators based on users' preferences and to reveal the spatiotemporal variation of areas prone to spill impacts in simulated oil spill scenarios within coastal areas of Texas and the western planning area in Gulf of Mexico region.

3. METHODOLOGY

Figure 1 illustrates the general framework of the project, which includes five major modules: 1) Identifying specific decision goals based on collected and processed datasets and specifying socioeconomics and environmental vulnerability indicators; 2) Modeling oil spill risk at a spatiotemporal scale using the Blowout and Spill Occurrence Model (BLOSOM); 3) Developing socioeconomics and environmental vulnerability indices using indicators from collected and processed datasets; 4) Assessing and calculating overall vulnerability score using multi-criteria decision analysis; 5) Designing an interactive user interface to visualize the results for collaborative decision making. A detailed introduction of the methods used to fulfill the modules is as follows.

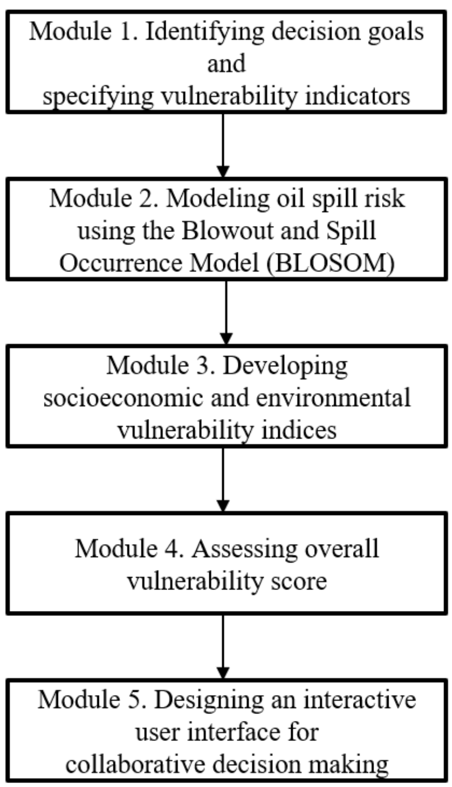

Figure 1. An overview of the workflow of this study.

3.1 Identifying decision goals and specifying vulnerability indicators (Module 1)

Two decision goals were introduced as examples to better explain the research purposes in this project and the case study:

Decision goal 1: How did the oil spill risks change across space and time in Texas coastal areas in 2016?

Decision goal 2: Where are the most vulnerable areas in a case of oil spill when considering socioeconomic and environmental aspects, and oil spill risks?

The first decision goal focused on observing the oil spill's spatiotemporal pattern to support risk-informed decisions. The second decision goal took into consideration of socioeconomic and environmental indicators and the oil spill risks derived using the Blowout and Spill Occurrence model (BLOSOM). Here, the scenario was focused on all those three components (socioeconomics, environment, and spill risks) with equal weights to observe the overall vulnerability score across the Texas coastal areas. Specifically, the SVI and ESI data was collected and processed as socioeconomic and environmental indicators to model vulnerability. Detailed information about the collected and processed datasets is included in the case study section (section 4.3)

3.2 Modeling oil spill risk using the Blowout and Spill Occurrence Model (BLOSOM) (Module 2)

BLOSOM is a Java-based simulation software tool (Sim, 2013). It was developed to model offshore oil spills scenarios caused by deep-water and ultra-deep-water well blowouts. BLOSOM contains many sub-models, such as Jet/Plume model, crude oil simulation model, transportation prediction model, gas/hydrates simulation model, weathering model, and a hydrodynamic handler. The hydrodynamic handler is applier to model the tides, currents, and wind direction with the input of multiple datasets (Nelson et al., 2015). BLOSOM is also flexible to permit the modification of any or all input parameters. Rose et al. (2014) provides an overview of the model, while Sim et al. (2013) provides a more in-depth introduction and validation analysis.

In this project, BLOSOM was used to simulate the hydrocarbon release effects caused by the spill event. BLOSOM is a four-dimensional that can simulate the oil spill event at a spatiotemporal scale. Detailed information about how the BLOSOM was applied is included in the case study section.

3.3 Developing socioeconomic and environmental vulnerability indices (Module 3)

Social Vulnerability Index (SVI)

Social vulnerability is recognized as the possible negative impacts in disaster scenarios in social communities, especially on human health, caused by external stresses. Reducing social vulnerability can decrease both human suffering and economic loss (Agency for Toxic Substances and Disease Registry). The CDC/ATSDR SVI ranks each tract based on 15 factors (as detailed in Table 1) considering social aspects, including poverty, transportation status, and crowded housing, etc. Then the factors are grouped into four major related themes. Every census tract will receive separate ranking scores for each of the four themes, as well as an overall ranking score. An example SVI map of the study area in the case study is as figure 2 shows.

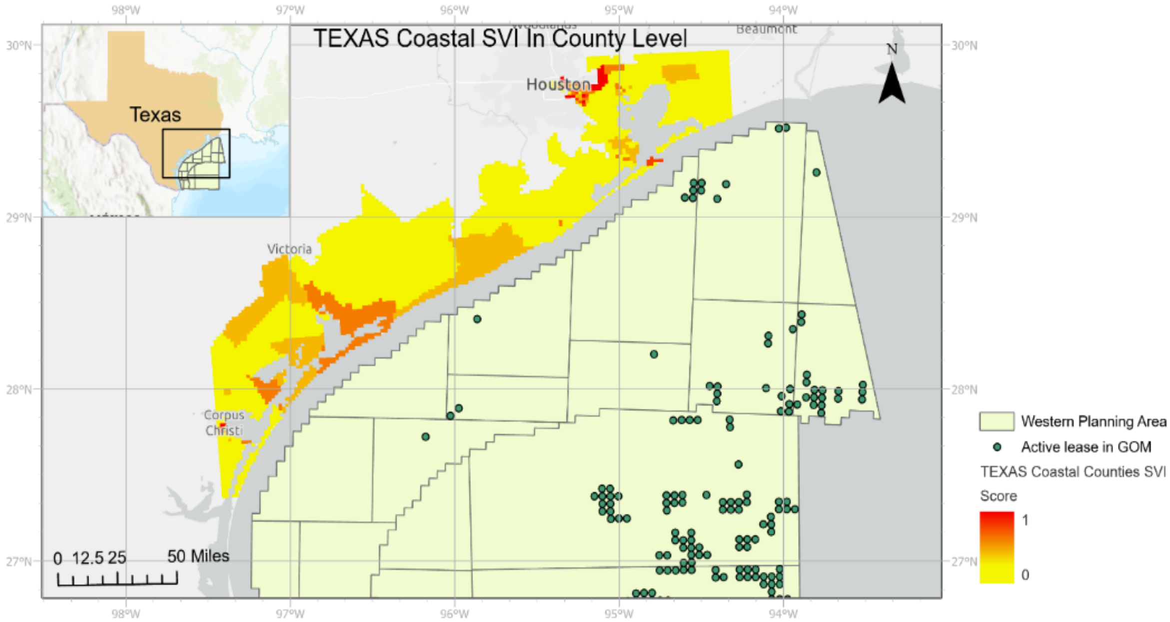

Figure 2 SVI of Texas coastal areas

. Table 1. An illustration of social vulnerability indices and variables.

CDC SVI Themed indices	Variables
Socioeconomic status	Income, unemployed, education attainment, poverty
Household composition and disability	Age 65 or older, age 17 or younger, older than age 5 with a disability, single-parent households
Minority status and Language	Minority, non-English speaking

Housing type and Transportation	Multi-Unit Structures, mobile homes, crowding, no vehicle, group quarters

Table 1. An illustration of social vulnerability indices and variables.

Environmental sensitivity Index (SVI) map

Gundlach and Hayes (1978) developed an environmental sensitivity index map to illustrate the environmental sensitivity of the region towards the oil spill events. The environmental sensitivity index includes the factors telling how sensitive a specific region of a coastal area is against an oil spill based on the value assigned to the region with the ESI values. The ESI values are calculated based on the factors including the types of shores such as exposed rocky lands, mixed sand, gravel beaches, salt marshes, and mangroves, etc. The greater the value is, the more sensitive the region is against oil spills. An example ESI map of the study area in the case study is as figure 3 shows.

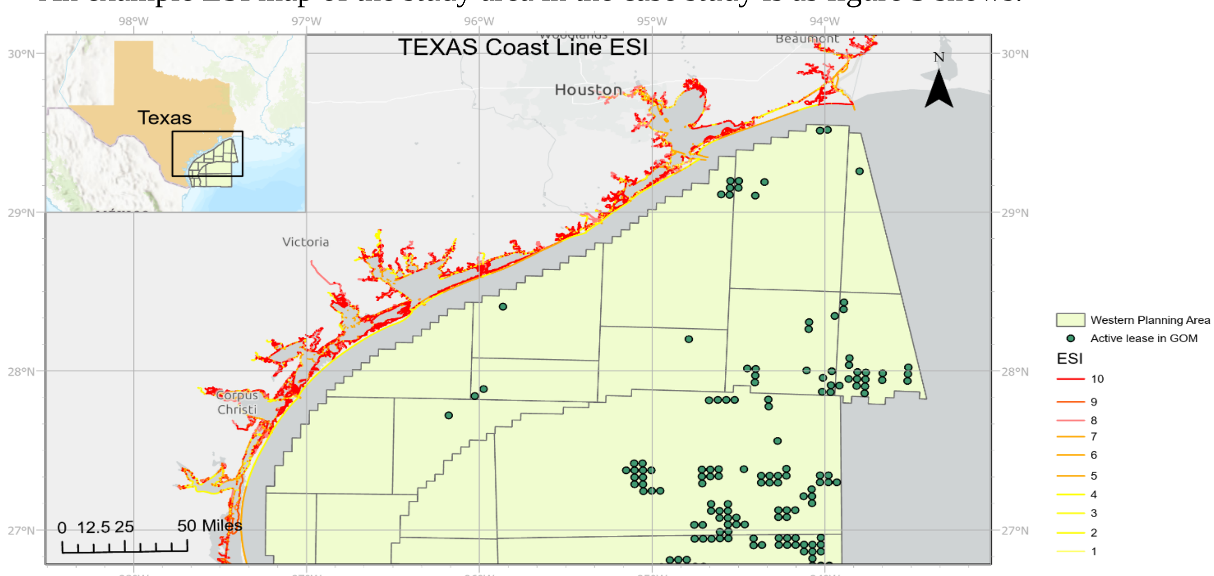

Figure 3 Texas coastline ESI map

3.4 Assessing overall vulnerability score (Module 4)

The decision-making for oil spill assessment is a typical multiple criteria decision-making (MCDM) problem where first responders need to make the decisions under conflict decision objectives (Wu et al., 2021). Specifically, first responders can make timely decisions based on the evaluation criteria that are most relevant to his/her decision goals. The areas that have the highest overall vulnerability score refers to the area that needs the most attention for the decision makers.

The Multi-Criteria Decision-Making (MCDM) model and analysis provide tools for the evaluation of potential decision alternatives. As indicated in earlier sections, it is an approach used to assist decision-making in which a variety of diverse criteria are evaluated and integrated to fulfill one or more objectives. The MCDM's decision process integrates criteria that often represent conflicting and complementary decision objectives into a single composite assessment index. The index and its associated values are then utilized to output a suggested decision (Zhang et al., 2018). According to Fishburn et al., (1967), specifically in a weighted sum model (WSM), if there are *m* alternatives and *n* criteria, the decision-maker is expected to assign a performance value a_{ij} (for i = 1, 2, 3, … , m and j = 1, 2, 3, … , n) of each alternative in terms of each criterion and the weight of the relative performance of the decision criteria W_j. Then a matrix *A* that is formed by a_{ij} values multiple the assigned weight W_j is derived. Usually, these weights are normalized to add up to one. Finally, the alternatives are ranked. The suggested alternative is output based on the following expression (Fishburn et al., 1967):

$$A = \sum_{j=1}^{n} w_j a_{ij}, \text{ for } i = = 1, \dots, m \text{ and } j = 1, \dots, n \qquad (1)$$

Where a_{ij} is the assigned value of i^{th} alternative in terms of the j^{th} criterion, n is the number of decision criteria, and w_j is the assigned weight of the j^{th} criterion.

Therefore, the study area in the case study section is gridded into sub-spatial cells with a cell size of 2 km x 2 km. Each of the cells is a potential alternative for decision-makers to evaluate. The aij values are scores from each of the aspects detailed in previous sections, including environmental, social, and modeled spill risk. Wj are weights that decision-makers give to the scores from each aspect based on their evaluation. All scores and assigned weights are combined with the WSM to calculate the final score that will be included in the matrix A. The final score is the vulnerability score representing the degree of vulnerability that the cell is considered to spill impacts.

4. CASE STUDY AND RESULTS

The Gulf of Mexico is an area of high hydrocarbon exploration and production activity. According to the NOAA (2017), it is the largest producing reservoir in the United States. The Gulf of Mexico also hosts to a wide variety of marine biota and constitutes a variety of marine ecosystems. Furthermore, the GOM is host to a wide range of economic activity that generates billions in annual revenue for the surrounding communities. Texas coastal communities, based on previous studies, are especially prone to oil spill disasters (Nelson et al., 2015) because the seasonal characteristic of the GOM region. In this project, a case study is presented with the proposed framework to study the spatiotemporal variation of vulnerable areas in oil spill scenarios in Texas coastal areas and the western planning area (WPA) in the GOM to support decision-making process in oil spill response and management.

4.1 Study area

This study mainly focuses on coastal areas in Texas and the western planning area (WPA) in the GOM region, as shown in Figure 4. The WPA has 5,240 blocks, 213 active leases and takes up around 28,576,812 acres. The WPA, together with the Central Planning Area (CPA) of the GOM, are major parts of the world's major areas of oil and gas production in the gulf areas. Oil production serves as the feedstock for the majority of the liquid hydrocarbon products on the markets, including aviation and diesel fuel, natural gas, gasoline, and various petrochemicals. Oil from the WPA can help to reduce the Nation's dependence on foreign oil imports (Bureau of Ocean Energy Management, 2022).

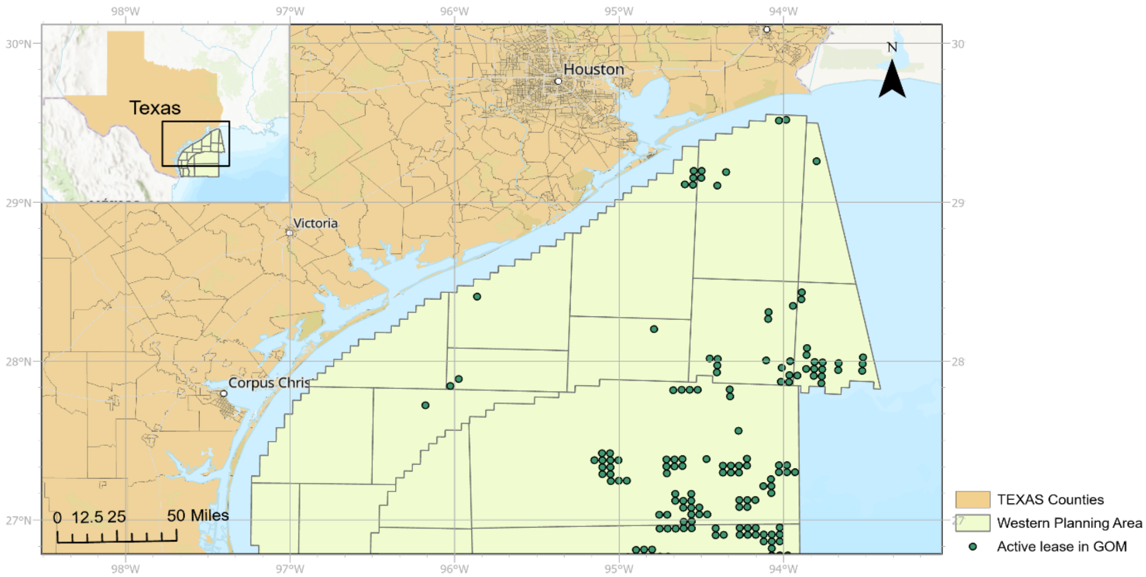

Figure 4 Illustration of the study area

In this context, the two decision goals that are introduced as examples this case study are:

Decision goal 1: How the oil spill risk changes across space and time in Texas coastal areas in 2016?

Decision goal 2: Where are the most vulnerable regions for oil spills when considering all socioeconomic and environmental variables?

The structure of the proposed framework is presented in Figure 5. In this framework, information for making decisions is collected with the user interface. The collected datasets were processed and stored in a database. The model management system consists of a decision-making model that is applied to combine multiple evaluation criteria (e.g., socioeconomic and environmental vulnerability indicators) for producing an overall vulnerability score to support decision-making procedures.

The designed framework enables the users to select indicators and their associated weights to produce customized overall vulnerability assessment scores. The indicators that users selected from the collected and processed datasets based on their interest along with the weights of those indicators will then be applied to the weighted sum model as a multi-criteria decision analysis model to determine vulnerable areas in the studied region with the combination of vulnerability index from socioeconomic(SVI) and environmental aspects(ESI) updated by users' preference as well as an additional index generated from the spatial-temporal analysis results of oil spill scenarios.

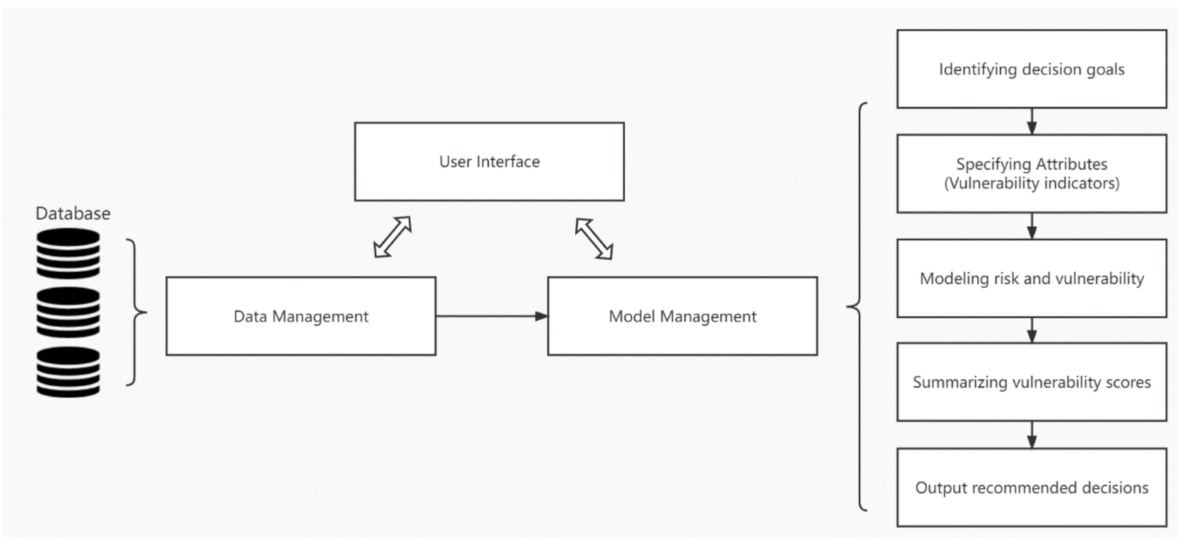

Figure 5 Overview of the MCDM framework

4.2 Spatiotemporal Oil Spill Risk Assessment (Decision Goal 1)

This section introduced the details of using BLOSOM model to estimate oil spill risks across space and time. The results of this task can be used to answer the questions related to the first decision goal: *How did the oil spill risks change across space and time in Texas coastal areas in 2016?*

The risk level of oil spill is defined as the frequency that modeled oil spill parcels occur in Texas coastal areas in the simulated scenarios. The oil spill scenarios were simulated for all active leases in the western planning area every month from in 2016, based on the availability of the SVI and ESI data. The Blowout Spill and Occurrence Model (BLOSOM) is used to conduct the simulation, which is developed by the Department of Energy National Energy Technology Laboratory. Every scenario was simulated to release 500 barrels of oil per day for a five-day time period at all 213 active leases' locations within the WPA shown in Figure 4. All scenarios was simulated to begin on the first day of every month in 2016 and is tracked for thirty days. The simulated oil spill parcel that reached Texas coastal areas was output at the end of the thirty-day simulation, and then transferred to raster files to be counted in predefined grids with a cell size of 2 km X 2 km.

$$Risk(r) = \frac{\mathrm{n}(A)}{\mathrm{N}} \tag{2}$$

The modeled risk score r is then calculated based on the function above. *A* is the simulated scenarios that spills reach the specific cell and n(*A*) is the counted number of scenarios that spills reach the specific cell in the simulation. N is how many simulations has been run in total.

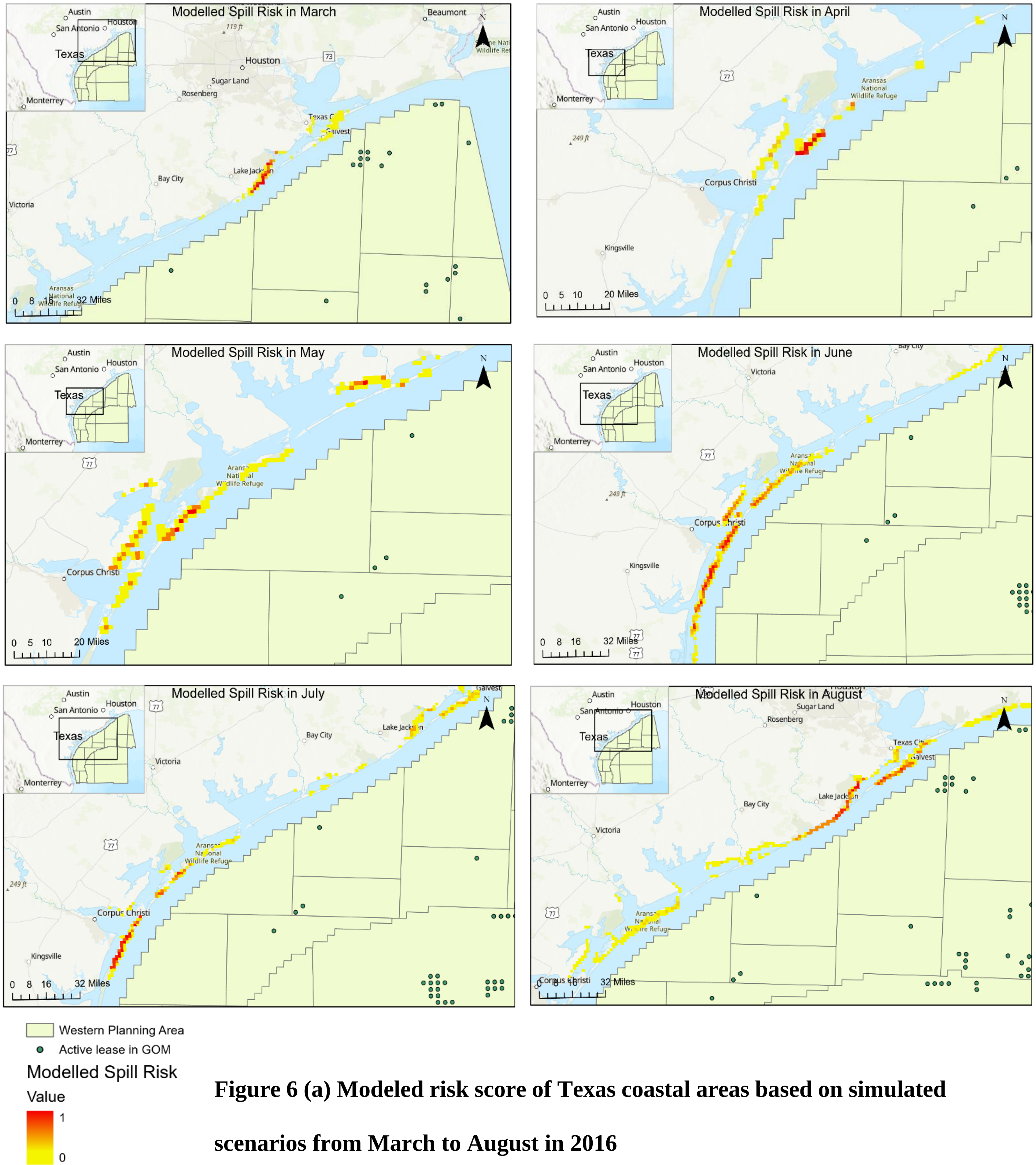

Figure 6 (a) Modeled risk score of Texas coastal areas based on simulated scenarios from March to August in 2016

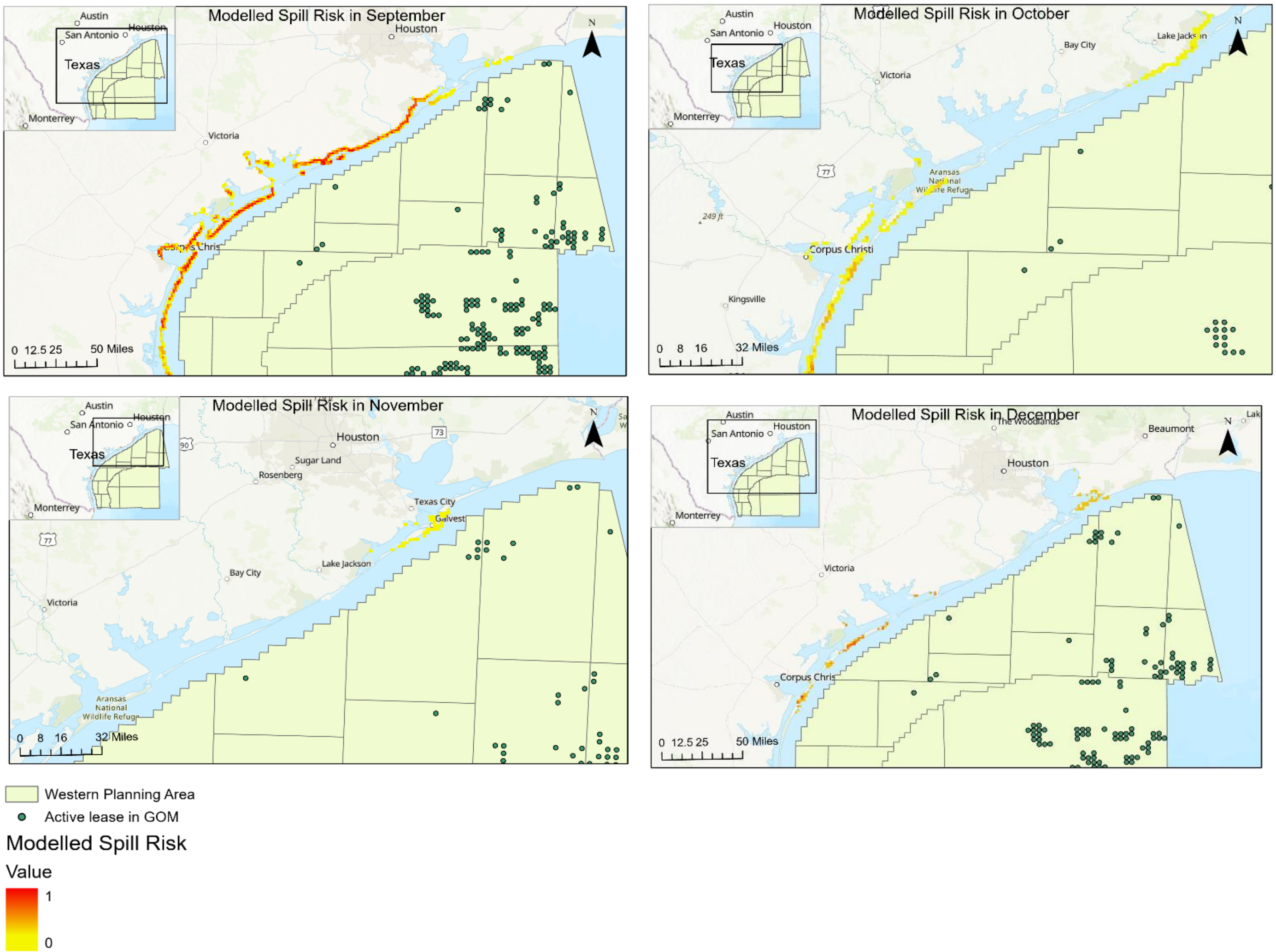

Figure 6 (b) Modeled risk score of Texas coastal areas based on simulated scenarios from September to December in 2016

The BLOSOM model presents the trajectory of the simulated oil spill, and only the oil that had beached was considered. It is worthy to note that no oil slicks in this simulation were simulated to reach the Texas coast in January and February in the 30-day time period. Some of the oil slicks in the January and February eventually reached Mexican coasts, and some could reach Texas coasts but with longer travel time than the predefined 30-day time period. Here those were not considered valid information to model the risk of oil spill impacts in Texas coastal areas. Consequently, January and February were not included in the result both in this risk modeling section and the following vulnerability modeling sections. As results, an index with scores that describes modeled risk caused by simulated oil spills was generated by the number counted in each cell. The larger score is within the cell, the greater risk the cell has from simulated oil spills.

The results of modeled oil spill risk in the simulations are visualized in Figure 6. According to Figure 6, areas around Freeport are considered as high-risk areas in March, July, August, and October. Areas around Corpus Christi have high risk scores in April, May, June, July, September, and December. Areas around Galveston show high risk scores in March, July, August, and November.

4.3 Use of Multi-criteria Decision Analysis to Assess the Overall Vulnerability Score (Decision Goal 2)

This section introduces the process of using MCDM to assess the overall vulnerability score of the oil spill cases using socioeconomic, environmental, and oil spill risks (results from 4.2) indicators. The results of this task can be used to answer the questions related to the second decision goal: *where are the most vulnerable areas in a case of oil spill when considering socioeconomic and environmental aspects, and oil spill risks?*

Table 2 Collected and processed datasets

Data Variable Name	Descriptions	Source
Census data	Official count or survey of detailed information of individuals in 2016.	U.S. Census Bureau

Ocean model data	Information about oceanic boundary conditions from a global coupled ocean-atmosphere prediction model	HYCOM
Social Vulnerability Index	Potential negative effects on communities, Texas in 2016	Agency for Toxic Substances and Disease Registry
Environmental Sensitivity Index	Sensitivity of specific regions of Texas coastal area is against an oil spill in 2016	Gundlach and Hayes (1978)
Oil spill simulation results	Simulated beached oil spill distribution	BLOSM model

Table 2 Collected and processed datasets

Here, each raster cell represents a decision alternative (*A* in equation 1) and is evaluated using three different types of criteria (socioeconomic, environmental, and oil spill risk levels). The raster cell is considered as a vulnerable area if the cell receives a high overall vulnerability score based on those three evaluation criteria. Each evaluation criteria is specified into several evaluation indicators listed in Table 2. Here, an equal weight was assigned to each evaluation indicator to generate the overall weight matrix. Based on collected datasets, the SVI and ESI information was processed to fit our research purposes and then be visualized as shown in Figure 2 and Figure 3 in the methodology section. Similar to the procedure in that the risk is modeled mentioned above, the modeled vulnerability scores were also counted and calculated in predefined grids with a cell size of 2 km X 2 km.

The first step was to count SVI information in each of the grid cells. The original SVI contains information, such as age information, race information, income information, etc., that can be input to form different vulnerability indexes based on different purposes. Here users can select input datasets and parameters, defining indicators, and assigning weights to the indicators to calculate the overall vulnerability score based on their preference using the proposed framework.

The total SVI scores from the SVI datasets, the ESI scores which is the ESI values normalized to a 0-1 scale, and equally assigned weights to the SVI, ESI, and risk scores are used to index the overall vulnerabilities in Texas coastal areas. The total SVI scores is developed to estimate all important factors that can describe the social vulnerability of a community. The counted information in each grid cell was then normalized to a 0-1 scale as scores to illustrate the vulnerability in the social-economic sector, as shown in Figure 2.

Next, the same procedure was applied to the ESI information and modeled risk scores from the simulated oil spill scenarios to calculate scores to illustrate the vulnerability in the environmental sectors and oil spill risk possibility.

4.4 Results and vulnerability mapping

Finally, the SVI, ESI, and risk scores were used as input to the MCDM model with the assigned weights to index the spatial vulnerability in Texas coastal areas and therefore identify the most vulnerable areas. Figure 7 visualizes the identified vulnerable areas with vulnerability maps. The vulnerability maps are visualized with an appropriate scale to present the entire coastline that may be impacted by the simulated oil spills and other necessary geographical information and the results of modeling.

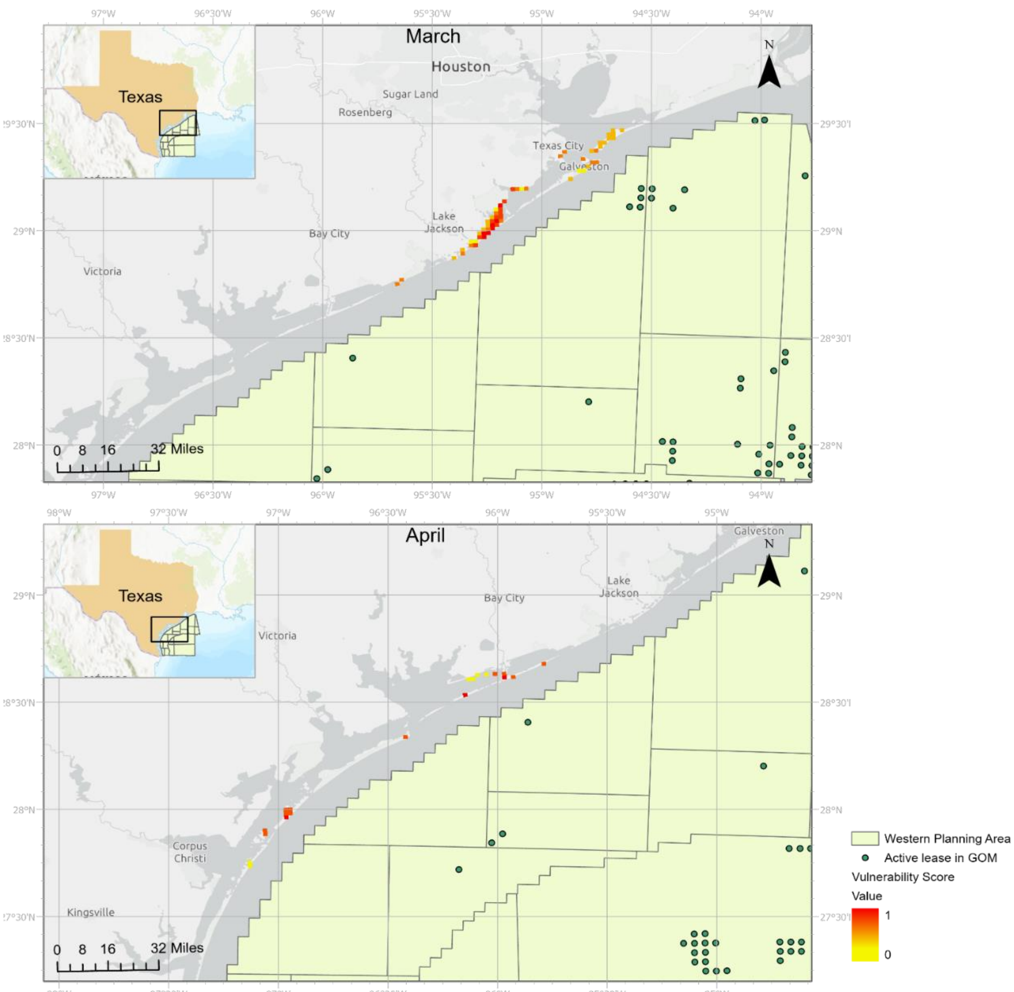

Figure 7 (a) Results of the spatial distribution of the vulnerable areas in March and April in 2016

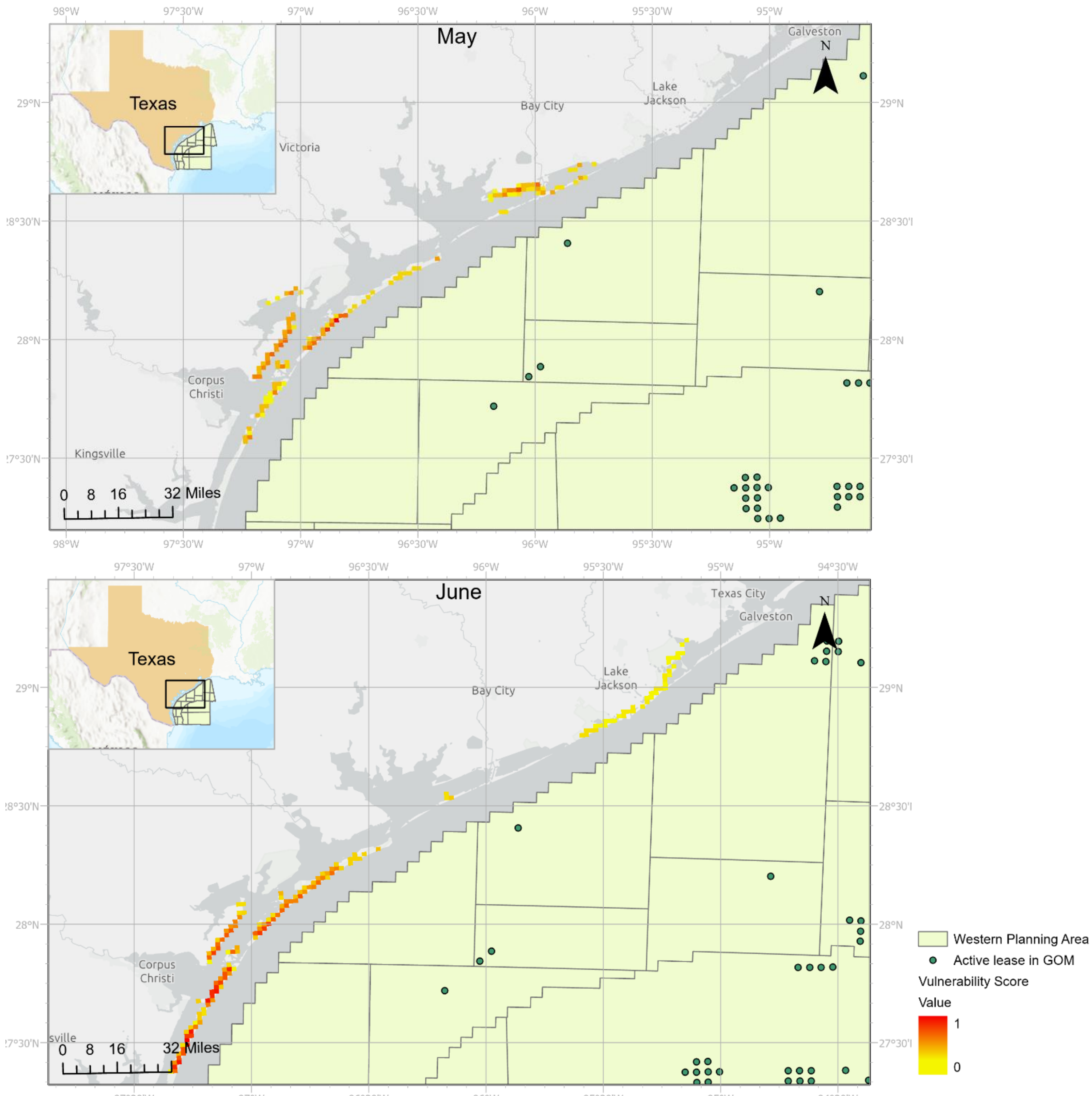

Figure 7 (b) Results of the spatial distribution of the vulnerable areas in May and June in 2016

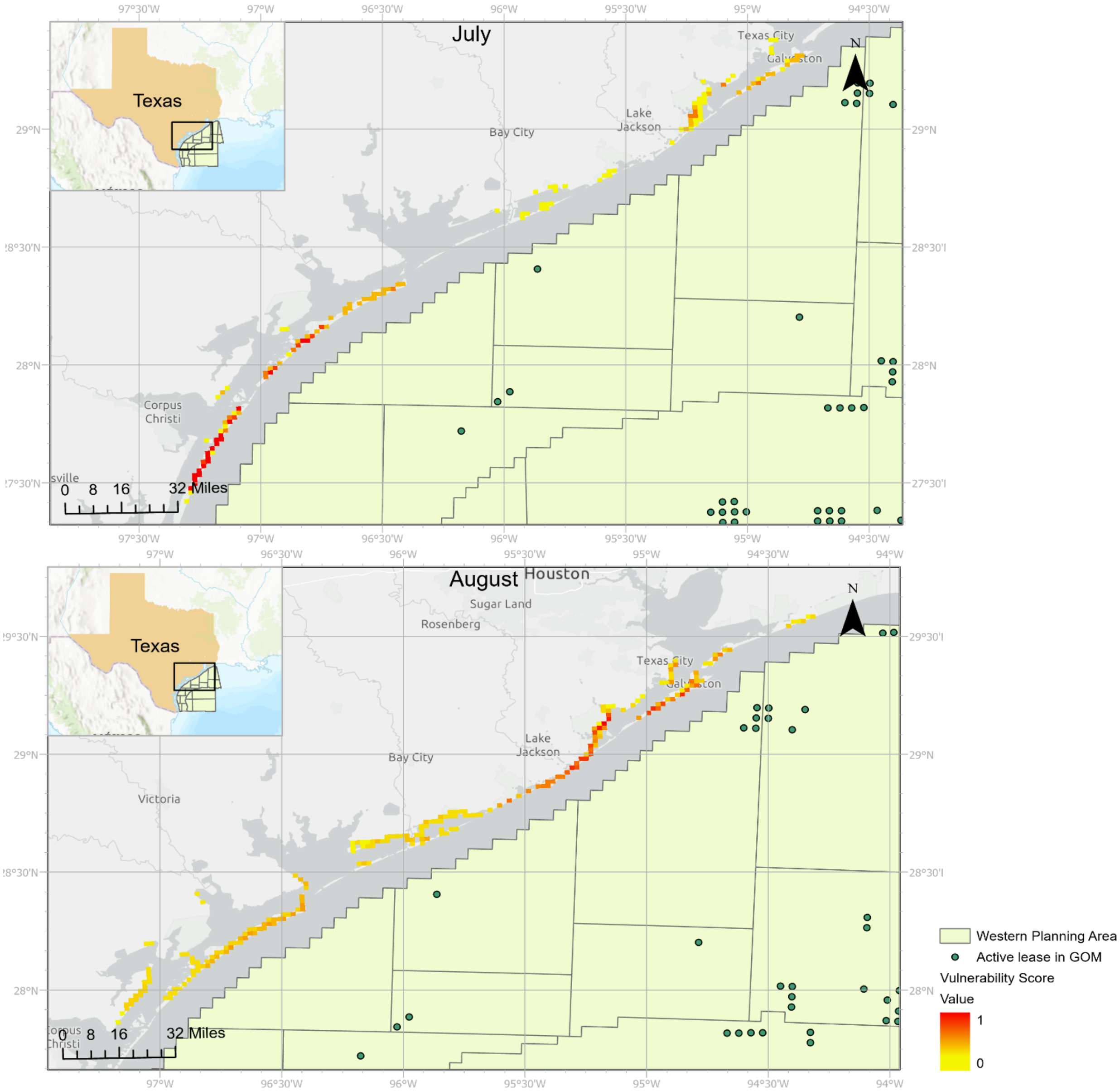

Figure 7 (c) Results of the spatial distribution of the vulnerable areas in July and August in 2016

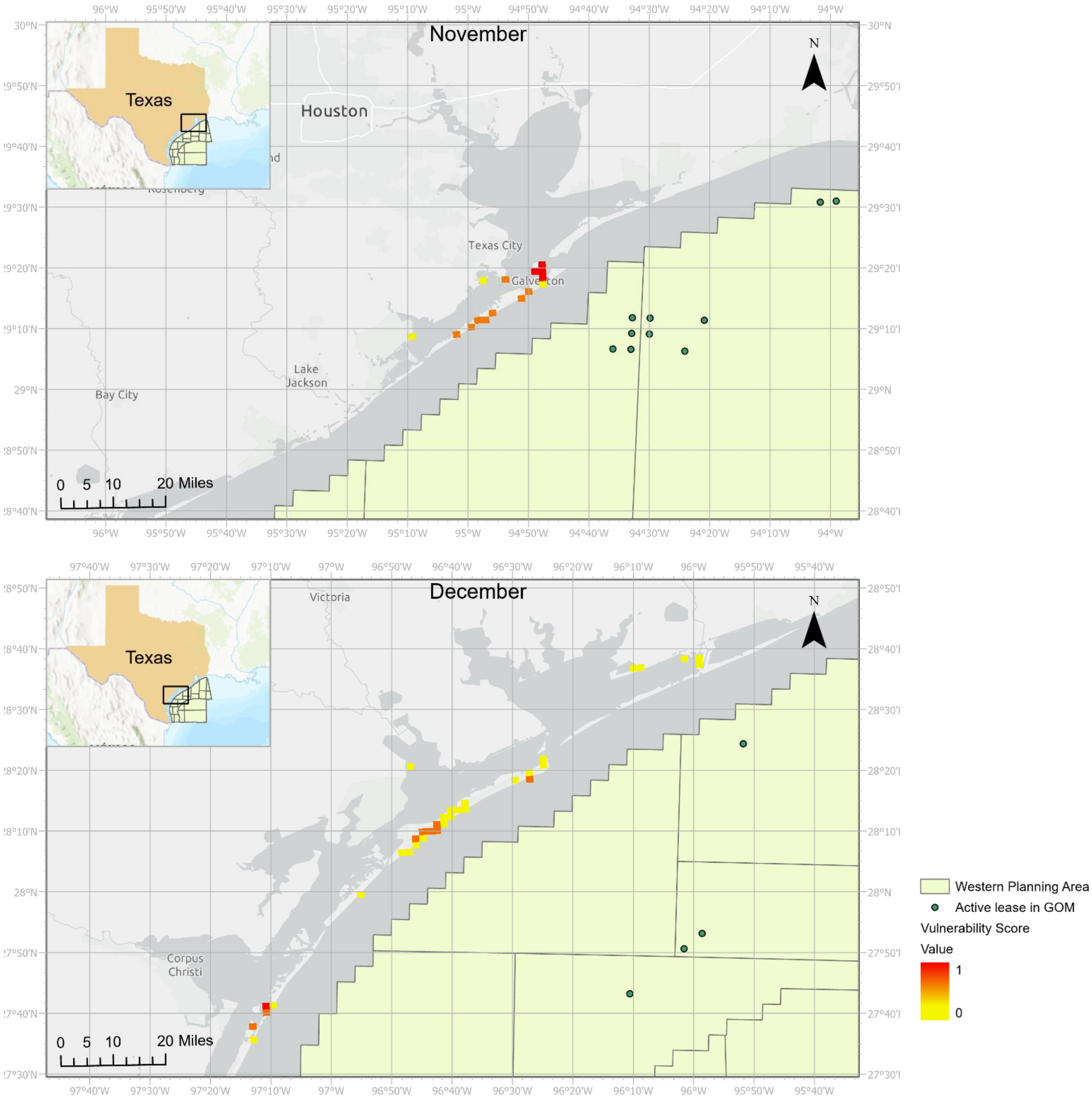

Figure 7 (d) Results of the spatial distribution of the vulnerable areas September and October of 2016

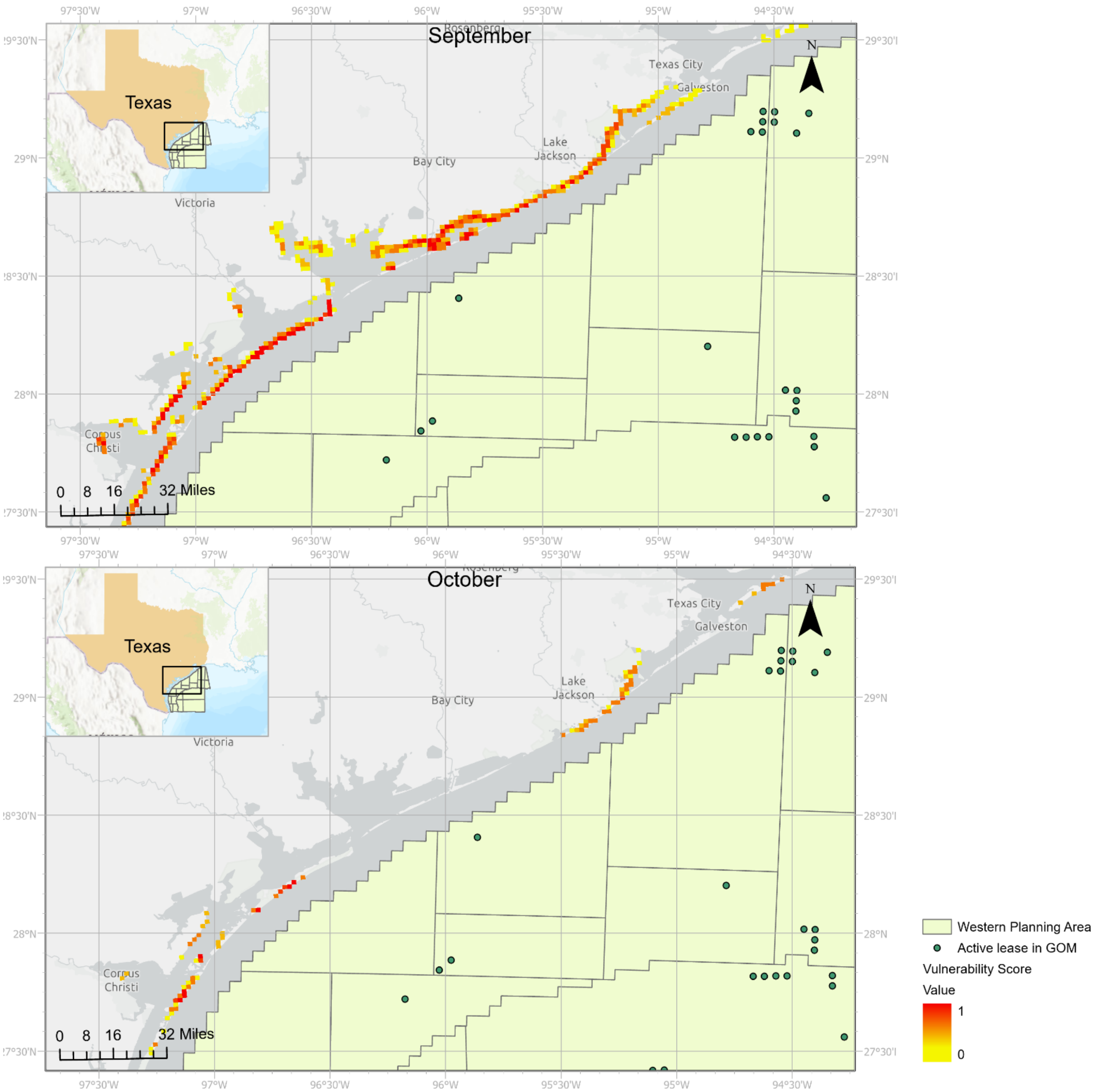

Figure 7 (e) Results of the spatial distribution of the vulnerable areas in November and December of 2016

The degree of oil spill vulnerability is color-coded. Yellow cells correspond to regions with smaller vulnerability scores to oil spill scenarios, while red cells correspond to regions with higher vulnerability scores. The grid cells in darker red color have larger vulnerability scores, and the grid cells in lighter yellow color have smaller vulnerability scores. In other words, areas in red color are more vulnerable to oil spill disasters than areas in yellow areas. Areas with no color (remaining grey on the maps) are safe from oil spills in the simulated scenarios. As mentioned in the previous section, January and February are not included in the result maps both in this risk modeling and the vulnerability modeling sections because no valid information could be observed in the simulated oil spill scenarios. Based on the vulnerability maps, summarized areas around major cities along the Texas coastline showing high vulnerability to oil spill impacts and their temporal distribution in each month of 2016 are shown in Table 3 and Figure 8.

Table 3 Summarized areas around major cities along the Texas coastline showing high vulnerability to oil spill impacts in each month of 2016

Areas Around Major Cities along Texas Coastline	Months showing high vulnerability to oil spill impacts
Galveston	March, July, August, September, November
Freeport	March, June, August, September
Corpus Christi	April, May, June, July, September, October, December

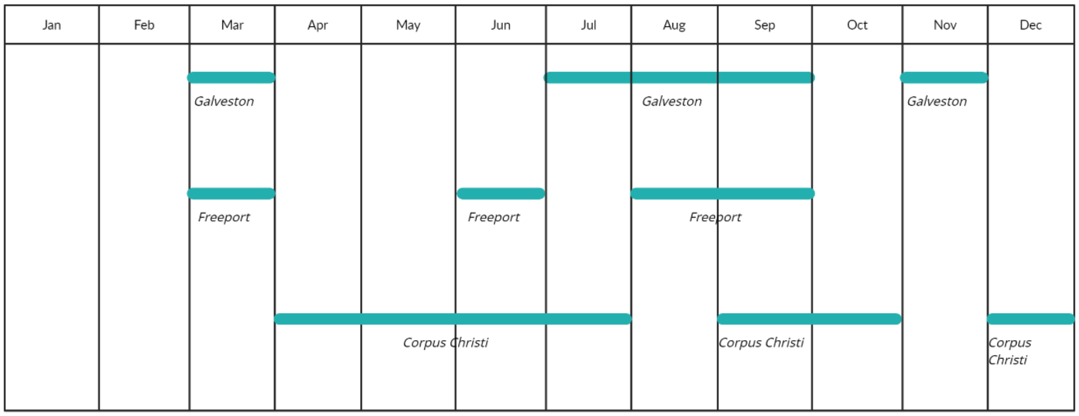

Figure 8 Temporal distribution of areas around the three major cities along the Texas coastline showing high vulnerability to oil spill impacts

According to the vulnerability maps, Table 3, and Figure 8, an obvious finding is that although the spatial distribution of the vulnerable areas in each month from March to December shows great discrepancy, more areas are under threat of oil spill impacts in the summertime than other time period considering temperature difference and seasonal characteristic of the GOM (temperature and weather are similar from May to September). This completes our second decision goal. Among these, coastal communities and coastlines from Galveston to Corpus Christi are nearly all vulnerable to oil spill impacts and should be cautious and get well-prepared strategies for oil spill disasters in September and August. Fewer areas are in great vulnerability in August compared to September, only areas around Galveston and Freeport are extremely vulnerable to oil spills, but other areas still need to be paid more attention than other times to prevent damage from oil spill disasters. Similarly, in the time of March and November, some areas around Freeport and Galveston are vulnerable to oil spills, but the spread of these areas is much smaller compared with that in the summertime. Communities and coastline in South Texas around

Corpus Christi have the largest potential vulnerability to the oil spill in May, June, and July. The difference in the spatial distribution of the vulnerable areas in these three months is that areas around Corpus Christi and Port Aransas are the major areas suffer from potential impacts of oil spills in June and July, but areas in the north of Corpus Christi, such as Port O'Connor are in great danger together with Corpus Christi areas in May. Only a few areas in the north of Corpus Christi and Port O'Connor are vulnerable to spill impacts in April and December. In addition, communities around Corpus Christi, Freeport, and Galveston may be impacted by oil spills in October. These findings answered the second decision goal with identified vulnerable areas to oil spills in both spatial and temporal perspectives.

After examining published and original datasets of sea current and winds from the Gulf of Mexico, these trajectories of simulated oil spill slicks and the spatial distribution of the vulnerable areas showed similar patterns to other oil spill simulation models in published works of literature. For example, Nelson et al., (2015) simulated vulnerable areas from oil spills in March 2013. Areas around Freeport are also showing vulnerability, according to his results. Additionally, results from another vulnerability model based on a simulation in the Oil Spill Risk Analysis model (OSRAM) model (Guillen et al., 2004) found that launch points of oil spill trajectories tend to focus on the lower Texas coast, which is areas around Corpus Christi.

4.5 An interactive web-based multi-criteria decision-making analysis (Module 5)

The proposed decision support system with an MCDM framework (as presented in Figure 5) is integrated into a web-based application developed with the ArcGIS app builder. The designed framework enables the users to decide indicators and their weights to produce customized vulnerability indexing. The indicators that users selected from the collected and processed datasets based on their interest along with the weights of those indicators will then be applied to the weighted sum model as a multi-criteria decision analysis model to determine vulnerable areas in the studied region with the combination of vulnerability index from socioeconomic(SVI), environmental aspects(ESI) updated by users' preference as well as an additional index generated from the spatial-temporal analysis results of oil spill scenarios. The decision-makers using our app are able to select different datasets stored in our database as input layers to identify the vulnerability indicators according to their specific decision goals. By following procedures similar to the case study presented in the above sections, they can assign their preferred weights to the vulnerability indicators and produce vulnerability indexing to locate vulnerable areas in different oil spill scenarios. Selecting input datasets and assigning weights can be directly achieved through the user interface, as shown in Figure 9.

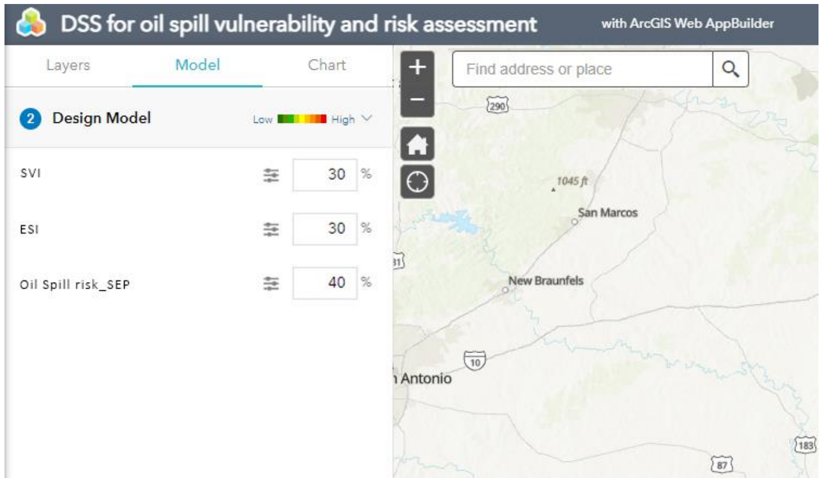

Figure 9 Selecting input layers and assigning weights panel on the user-interface.

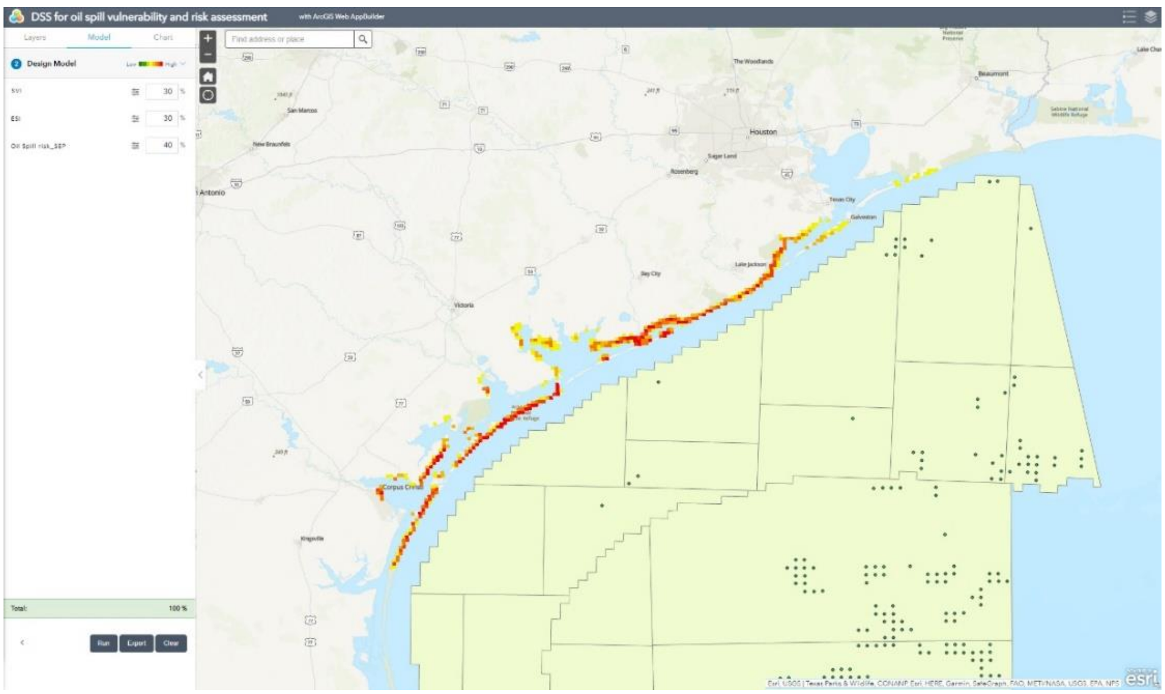

Figure 10 Corresponding vulnerability map of the example inputs.

Figure 9 shows the example of selecting SVI, ESI, and modeled spill risk results in September from the BLOSOM model with weights of 30%, 30%, and 40%. The corresponding results are mapped in the vulnerability map as presented in Figure 10. Since the input datasets, vulnerability indicators, and assigned weights are similar to the case study, the results and vulnerability map have little difference compared to the result map of September in the case study as presented in Figure 7.

5. DISCUSSION

Several facets of this study are worth discussing in detail. Firstly, for each of the simulated scenarios in the western planning area of the GOM, regardless of the original locations of the simulated spills, the trajectories of the spills had a very obvious westward movement, mainly because of the prevailing winds, ocean currents, and tides in the simulation. Although the movement of the oil would be different in different time periods, some of the simulated oil slicks would eventually reach the coast of Texas. This finding revealed the high level of exposure that the Texas coast was for all the scenarios simulated in this study. This has important implications for the Texas coastal communities in terms of oil spill preparedness and response.

Second, for the simulated scenarios focusing on spatial vulnerability, areas that are closer to major cities and bays along the Texas coastline with the densest coastal assets presented high vulnerability scores. This can be attributed to the relatively strong socioeconomic and environmental dependence of communities in Texas coastal regions. For example, according to the vulnerability maps and Table 3, there is a significant frequency of showing high vulnerability scores around Galveston Bay because the density of coastal assets in this area contributed to high social-economic vulnerability. As results, a high SVI score can be observed in the area of Galveston.

Additionally, it is important to note that temporal differences in the vulnerable areas are extremely critical in oil spill vulnerability assessment, especially in the GOM region. This is due to the transportation of spilled oil being dominated by ocean currents and wind forces. Whether the spilled oil can reach the coast and where it may reach is determined by the movement of sea currents and wind, which is dynamic in different time periods of a year. Since the evaluation of studies on spill behavior has significance for a range of decision-makers, including stakeholders, regulators, and other specialists, to assist decision-making and support oil spill preparedness, consideration of temporal difference of the movement of spills and consequently, the distribution of vulnerable areas along the coast, are sectors that cannot be ignored to support oil spill disaster response and management.

Some shortcomings of the proposed methods are also worth discussing. Firstly, it is essential to admit that spatial errors may exist when combining processed information and datasets into an overall index included in the 2 km x 2 km cells. This is because numerous datasets may be integrated as input layers for the modeling and mapping process, and the scales of the datasets from different sources are likely to be different from each other. Therefore, maintaining accuracy and consistency across multiple datasets from different data sources requires users to more carefully understand each selected input dataset and the occurrence of the potential errors when working with multiple data. For example, the input datasets, SVI and ESI datasets, in the case study have different spatial scales. The SVI data are originally at census tract level as polygon features, and the ESI data are linear features that contain the ESI score information. In this case study, every cell in the same census tract is assumed to have the same SVI value. The ESI value in every cell is based on the ESI line and its ESI score information contained in the cell. If multiple lines are contained in one cell, only the maximum value as the ESI value of this cell can be accepted at the current stage. It is also important to recognize that associating different features from differing datasets may lead to vagueness based on the characteristics of the input geographical features and the interpretation by the user in different degrees. Similarly, the accuracy and consistency of the features and datasets are also affected not only by original sources but also by the user's interpretation of the appropriate representative position of the features. Further evaluation of the accuracy, consistency and spatial errors that may occur when combining these different types of data could be critical support to obtaining a better understanding and interpretation of both the input datasets and the reported results. These errors and issues could be optimized with the application of more advanced gridding methods and spatial analysis models to have a more reasonable understanding of the spatial subunits, features, and datasets for different research and decision purposes. For example, methods of quantifying spatial accuracy using statistical methods such as the Root Mean Square Error (RMSE) could be integrated to evaluate and describe the spatial error of the spatial features. Geographically weighted regression (GWR) methods are other options to obtain further analysis on not only the vagueness but also the correlation between various data and variables. With the application of these methods, further understanding of the reliability and variability of the data itself, as well as the reported results, can be provided for our users to optimize the overall performance of the proposed framework. Furthermore, it is not possible to expect all decision makers with a background of geography to have a reasonable understanding of the data accuracy and consistency in collaborative decision-making. Consequently, the application of the methods to enhance the understanding of the accuracy and consistency is also important for collaborative decision-making to keep all members and decision makers in the same stage to complete decision goals. Since the main purpose of this study is to construct the decision-making framework, the need to study how advanced approaches and robust analysis can be integrated for optimization remains for further studies.

Another shortcoming is the cost comes behind the results of this study to suggest the decision is not considered. As mentioned, the proposed framework is more data-based and communication-driven. The main purpose is to explore the processed information contained in the input datasets with our framework and models so that decision-makers could have a better understanding of the data and further support decision-making aims. The cost comes behind, and the payoff with risk is not considered in this context because those could be the targets for the next decision-making stages after the provided analysis of the input datasets from our framework and models. The decision-makers may make further decisions with results from our analysis to decide response strategies and whether to take action with more data and information needed to achieve cost and payoff analysis and further decisions. For example, when an oil spill occurs in September, and according to our results, areas around the three major cities are more vulnerable. Decision-makers could therefore make further decisions, such as distributing more rescue resources to these areas. But the cost of distributing rescue resources to different areas can vary differently. Since resources in disaster scenarios are usually limited and invaluable, analysis of the cost coming behind is especially critical in real-world decision-making. The application of a more advanced model-based decision support analysis could help to improve the performance of the DSS framework in terms of cost analysis to solve these problems. For example, the Decision Tree model and the Utility Function, as mentioned in previous sections, could be more suitable to support decisions related to cost and payoff analysis. This could be another point that future research can explore to improve the performance of similar frameworks.

Furthermore, it is also vital to note that the empirical findings according to this study suggest that the application of both oil spill simulations and geographical data could enhances the effectiveness of oil spill vulnerability assessments. It is crucial to notice that areas receiving a high modeled risk score suggesting high potential occurrence of oil spills, but lacking valuable economic and ecological assets, may not need to be considered as high priority in disaster management as an area that may be impacted by fewer oil spills but has more coastal assets that are vulnerable to oil spills. Since equal weights were assigned in the case study to the three aspects (social-economic, environment, and risk scores) to calculate the final vulnerability scores in the MCDM model, the results showing vulnerability is influenced by whether an area is located around the major cities along the Texas coastline because major cities usually have higher SVI scores. Thus, different research purposes and preferences from different individuals can have great influences on the results of modeled vulnerability. For example, results can be different if only average income, poverty level, and employment status information are considered as socioeconomic aspect while environmental aspect is ignored. Figure 10 shows the results in this context in September since Texas coastal areas have shown the widest spread and significant vulnerability in September according to results in the case study (Figure 9). By comparing the vulnerable areas in these two maps, it is obvious that fewer areas are

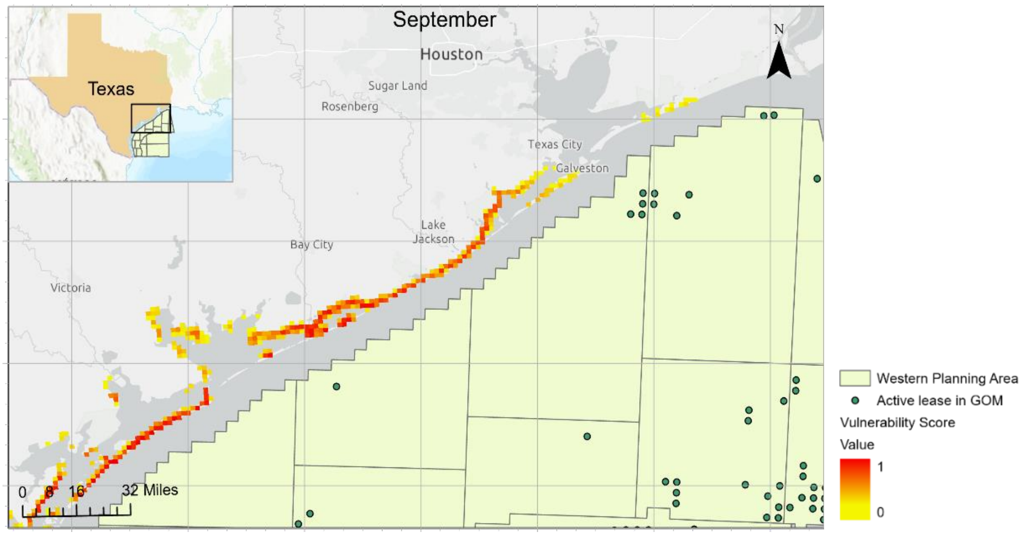

Figure 11 Results of vulnerable areas in September in the case study considering all indicators from socioeconomic and environmental aspects

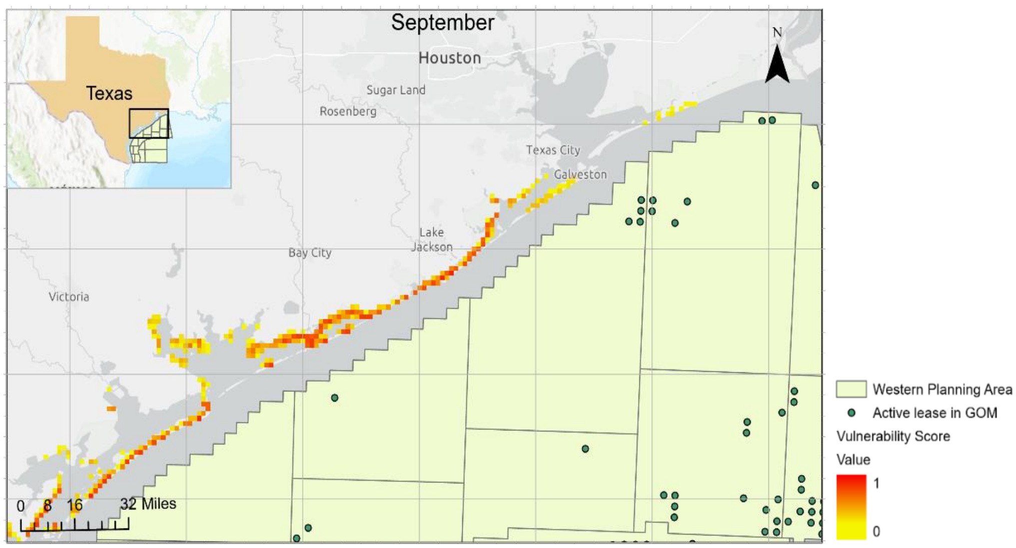

Figure 12 Results of vulnerable areas in September when only poverty information is considered in socioeconomic aspect

reported vulnerable to spills when only average income, poverty level, and employment status information are considered as socioeconomic aspect, especially in areas located in the north of Port Aransas and areas near Matagorda. The reasons that caused this decrease in vulnerable areas include: 1) Areas in the north of Port Aransas and areas near Matagorda are less vulnerable to oil spills in socioeconomic aspect if only poverty-related information is considered. 2) Environmental vulnerability is not considered in this context. These findings can lead to difference in suggested decisions.

For instance, decision-makers may decide to distribute emergency aid and rescue sources to areas that show significant vulnerability when only poverty information is considered (e.g., areas near Freeport and Matagorda Bay) in rapid response to an oil spill event in September. Changing the input datasets for specific purposes can help improve the efficiency of short-time response and management of oil spill disasters compared to the suggested decision based on the information in the results from the case study suggesting that near all areas along the Texas coast are vulnerable to oil spills.

In other context, one from an environment department may assign different weights since the main consideration of his research is to support environmental management. By considering the environment vulnerability sector with greater weights, the results would be very different from our examples. This is the reason the interaction between users is emphasized here in this framework, different priorities on indicators to vulnerability indexing from individuals are important in decision-making. And in order to decide whether an area is vulnerable, it often requires the collaboration of decision-makers with different backgrounds and interests. Also, developing a valid oil spill response system and other similar assessment approaches typically require the interaction and cooperation of multiple stakeholders and organizations with diverse interests. The capability of changing and updating different research orientations is crucial in the context of human-centered cooperation. Considering this, a human-centered decision support system with an MCDM framework that allows users to customize different input datasets as indicators to assess vulnerability and risk can therefore make a contribution to the decision-making procedure from an empirical perspective by enhancing the ability to identify spill prevention efficiencies and strategies in terms of decision-making because, in most disaster response scenarios, the time to respond and the resources to support emergency response are very limited.

6. CONCLUSION

This study proposed a human-centered decision support system with an MCDM framework to produce vulnerability analysis with indicators based on users' preferences and to study the spatial-temporal variation of areas prone to spill impacts in simulated oil spill scenarios within coastal areas of Texas and the western planning area in the Gulf of Mexico region. The framework is flexible in that it can evaluate indicators based on users' preferences to assess vulnerability to oil spills in coastal areas.

By completing pre-identified decision goals, the results of this work can highlight the temporal variation in beached spill scenarios in various coastal areas. This may be used to provide recommendations for when to restrict or potentially terminate offshore oil production activities in order to minimize the probability of catastrophic oil spill disasters in coastal regions.

Moreover, this work suggests that the use of a more human-centered evaluation framework integrated with an MCDM model can be crucial for oil spill risk and vulnerability assessment. Only few existing assessment frameworks consider taking measures from temporal aspects together into a cohesive framework. Especially, few approaches take the difference between different individuals and groups' research interests into consideration. Oil spill response systems and other similar assessment approach typically require the interaction and cooperation of multiple stakeholders and organizations with diverse interests. The capability of changing and updating different research orientations is crucial in the context of human-centered cooperation. Taken together, the framework proposed in this study made it a step further by combining spatial-temporal analysis and a customized multi-criteria decision-making framework to identify areas prone to oil spills within the studied area. The vulnerability of coastal areas impacted by oil spills was determined through simulated oil spill scenarios according to several critical impact aspects, for example, socioeconomic assets, coastal and marine resources, and the total amount of beached oil in simulations. Indicators in each of these categories were weighted and compared using a weighted sum as a multi-criteria decision analysis model based on users' preferences to evaluate indicators and produce vulnerability scores.

Finally, this work is meant to highlight ways of vulnerability assessment for oil spill scenarios so that policymakers, communities, response teams and organizations can better support oil spill disaster management and preparedness by considering spatiotemporal variation and the interests of different individuals. More importantly, the application of this framework need not be limited to the studied area. One could incorporate many other sites not only in the Gulf of Mexico region but also in the context of oil and gas production areas all over the world. Thus, this work can be further supportive of oil spill disaster response and management in this way.

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