A Spatial Decision Support System for Oil Spill Response and Recovery

by

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ABSTRACT

Coastal areas are susceptible to man-made disasters, such as oil spills, which not only have a dreadful impact on the lives of coastal communities and businesses but also have lasting and hazardous consequences. The United States coastal areas, especially the Gulf of Mexico, have witnessed devastating oil spills of varied sizes and durations that resulted in major economic and ecological losses. These disasters affected the oil, housing, forestry, tourism, and fishing industries with overall costs exceeding billions of dollars (Baade *et al.* (2007); Smith *et al.* (2011)). Extensive research has been done with respect to oil spill simulation techniques, spatial optimization models, and innovative strategies to deal with spill response and planning efforts. However, most of the research done in those areas is done independently of each other, leaving a conceptual void between them.

In the following work, this thesis presents a Spatial Decision Support System (SDSS), which efficiently integrates the independent facets of spill modeling techniques and spatial optimization to enable officials to investigate and explore the various options to clean up an offshore oil spill to make a more informed decision. This thesis utilizes Blowout and Spill Occurrence Model (BLOSOM) developed by Sim *et al.* (2015) to simulate hypothetical oil spill scenarios, followed by the Oil Spill Cleanup and Operational Model (OSCOM) developed by Grubesic *et al.* (2017) to spatially optimize the response efforts. The results of this combination are visualized in the SDSS, featuring geographical maps, so the boat ramps from which the response should be launched can be easily identified along with the amount of oil that hits the shore thereby visualizing the intensity of the impact of the spill in the coastal areas for various cleanup targets.

DEDICATION

To my family for all of their love and encouragement

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Chapter 1

INTRODUCTION

The concept of viewing computers as not just mere calculators but as tools to assist its users in making decisions began almost five decades ago when Gorry and Scott Morton (1971) discussed a framework on Management Information Systems which eventually drifted apart and evolved to be what we call today as the Decision Support Systems (DSS). Moore and Chang (1980) have put an end to the confusion and controversy on the term "DSS" by making its definition very clear. According to them, decision refers to " ...decision making in problem situations rather than simply information retrieval, processing, or reporting..."; support refers to "...the computer's role in aiding rather than replacing the decision maker..."; and system refers to "...the integrated nature of the overall approach, suggesting the wider context of man, machine, and decision environments...". DSS's find their applications in many fields for varying reasons and topics. However, the most common reason behind their development is to explore and analyze a multitude of possibilities and outcomes regarding a specific system. Once a user is aware of all the events that are likely to occur, it becomes easy to make a decision given his/her limitations and restrictions.

The spatial decision support system built for this thesis focuses on oil spills and the response strategies that can be applied to a spill scenario based on various factors. Oil spills have deeply impacted the communities, businesses and other life forms in the coastal areas of the United States of America over the past several decades. The Ixtoc I oil spill of 1980, the Exxon Valdez spill of 1989, Mega Borg oil spill of 1990, and the British Petroleum Deepwater Horizon spill of 2010 are some of the prominent spills. The Deepwater Horizon spill alone ejected over 200 million gallons of crude oil into Gulf of Mexico (Cruz and Krausmann (2008); Graham *et al.* (2011)). These disasters have affected several industries, including the oil and gas, housing, forestry, tourism, and fishing industry. The overall costs have been estimated to be in terms of billions of dollars (Baade *et al.* (2007); Smith *et al.* (2011)). Some spills may have dangerous repercussions even after a long time because some amount of oil may still remain unaffected, while others cause only short-term damages to the environment but can be recovered soon (Muller and Stone (2001); Boruff *et al.* (2005); Jepson (2007)). Most of the times, oil spills occur as a result of accidents due to high marine traffic, and sometimes due to bad weather such as hurricanes or storms, but sometimes they also occur as result of flawed designs and procedures employed in the oil rig, as was the case in the Deepwater Horizon Oil Spill incident (Graham *et al.* (2011)). According to Graham *et al.* (2011), 1) failing to plan effectively, (2) lack of coordination between the state and the local government officials to deliver an effective response, and (3) a lack of information and understanding concerning the efficacy of dispersants or booms, etc. were the main reasons behind a poor response.

The entire process of contingency planning for oil spills usually involves three core aspects: 1) strategic planning, and 2) tactical response, and 3) operational response (Psaraftis and Ziogas (1985)). While strategic planning is primarily concerned with where to locate the equipment and human resources for mounting a rapid and efficient response to a spill, tactical response deals with the scenario after a spill occurs and involves decisions concerned with the locations from where the equipment should be dispatched and how long should it stay on the scene. It also deals with the optimal set of equipment required for a spill (for example, skimmers, exclusion booms, etc.) (Psaraftis and Ziogas (1985)).

There has been quite some research in areas which provide a more comprehensive and multidimensional view of oil spill modeling and response efforts. For example, the

Natural Resource Damage Assessment Model for Coastal and Marine Resources (NRDAM/CMR) (Grigalunas *et al.* (1988)) is a comprehensive suite which demonstrates how oil disperses through the environment and damages the biological communities. In the past, a mixed-integer dynamic optimization model for oil-spill response and planning was developed by You and Leyffer (2011) to minimize the total response cost. A comprehensive spill modeling package that can be used to predict the trajectory of a pollutant in a body of water and how its physical and chemical properties change over time (also known as weathering) called General NOAA Operational Modeling Environment (GNOME) has been developed by the National Oceanic and Atmospheric Association (Zelenke *et al.* (2012)). There have been many prominent works such as MEDSLIK-II, a Lagrangian marine surface oil spill model for short-term forecasting (De Dominicis *et al.* (2013)), Oil Spill Contingency and Response (OSCAR) (Aamo *et al.* (1997)), MIKE from DHI Solutions (https://www.mikepoweredbydhi.com), SIMAP (http://asascience.com/software/simap), an integrated oil spill impact model system, etc.

On the other hand, there have been notable works which contributed significant research in the area of tactical response (Belardo *et al.* (1984); Psaraftis and Ziogas (1985); Iakovou *et al.* (1996)). However, the core weakness among the works is that the research done so far have only taken the side of either oil spill modeling or spatial optimization of the response efforts. There is very little work (Belardo and Harrald (1992); Keramitsoglou *et al.* (2003); Zahra Pourvakhshouri and Mansor (2003); Pourvakhshouri *et al.* (2006); Liu and Wirtz (2007)) that has tied both those ends together in the form a DSS. My contribution to this research would be implementing the facet of tactical response in the form of a Spatial Decision Support System (SDSS) which integrates spill modeling and spatial optimization that will aid the decision makers in making informed decisions when a spill occurs.

For this purpose, I make use of the oil spill modeling package Blowout and Spill Occurrence Model (BLOSOM) (Sim *et al.* (2015)) to run simulations of oil spills which generates data required for the spatial optimization model Oil Spill Cleanup and Operational Model (OSCOM) (Grubesic *et al.* (2017)) which again generates data required as an input to a mixed-integer programming solver, Gurobi (Gurobi Optimization (2016)) which finally creates a log file, and a solution file for each day of the spill. The required data is parsed and extracted from these files into several other files for various cleanup targets, and given as an input to the SDSS. Since all the shape files have geo-spatial data, the core visualization involves displaying geographical maps obtained from openstreetmap.org (OpenStreetMap contributors (2017)) displaying the oil spill with the help of a time slider, highlighting boat ramps from where the response crews and equipment is sent out, and visualizing how deeply different areas of the coastline have been affected with the help of an impact grid, based on the duration and intensity of the blowout for various cleanup targets such as 75%, 80%, 85%, 90%, and 95%. The cleanup targets here refer to the percentage of oil recovered from the ocean after it has been ejected because of the blowout.

The remainder of this thesis is organized in the following manner. Chapter 2 summarizes other works in the areas of modeling techniques for oil spills, hurricanes and other natural disasters; space time analysis of data; types of decision support systems; and vulnerability indexing. Chapter 3 gives an overview of the system, its architecture, data generation, description of the data, description of various components of the system, and the visual analytic techniques utilized. Chapter 4 covers five case studies exploring the use of the SDSS over a spill scenario occurring in the Gulf of Mexico and the corresponding response strategies that could be employed. Finally, in Chapter 5, the formal conclusion and future work are provided.

Chapter 2

RELATED WORK

2.1 Design of Decision Support Systems

As DSS's play an important role in managerial arenas and change the outcomes based on the decisions made by the end-users, it becomes imperative to focus on their design aspects. Though i) the human interaction with the DSS; and ii) the scope of the DSS being built are both pivotal, the ultimate goal in designing a DSS would be to build a system which incorporates both of these facets in the most appropriate way. Keen (1980) proposed a framework which stated that the design of an ideal DSS should be "adaptive" i.e. a DSS can be "effective" and "final", only when it undergoes a process of evolution as a result of the adaptive dynamics between i) the user - who propagates the requirements to the developer and learns from the system, ii) the builder - the actual developer who builds the DSS, and iii) the system - which is an integrated component that evolves from the user's new requirements and the developer-written code.

In a rationalized decision making environment, the data being aggregated for the development of a DSS has to be comprehensive. In fact, it should incorporate certain specific characteristics. Huber (1981) has elegantly organized information requirements for a DSS into three categories namely (1) Basic Data; (2) Elaborating Data; and (3) Performance Data.

" ...

Basic Data

1. What are the alternatives? (e.g., Who are the possible suppliers?)

2. What are the future conditions that might be encountered? (e.g., What are the possible interest rates?)

3. What are the criteria to be used in evaluating alternatives? (e.g., Is overhead a required component of the cost analysis? Is community reaction to be considered?)

Elaborating Data

4. What are the probabilities of the future conditions?

5. What are the relative importances of the various criteria?

Performance Data

6. What are the payoffs, or costs, associated with various outcomes?

7. What are the constraints on the payoffs or costs? (e.g., Is there a minimum rate of return? Is there a budget limit?)

...(p. 5) ".

In our system, the basic data is obtained from BLOSOM (Sim *et al.* (2015)), boat ramps, and the impact grid datasets whereas elaborating data is generated with the help of OSCOM (Grubesic *et al.* (2017)), and performance data is generated by performing spatial join on the elaborating data and impact grid.

When it comes to the aspect of human-computer interaction, the most important thing in building a DSS is its usability. In their paper on "Intelligent Decision Support Systems" (Angehrn and Lüthi (1990)) have mentioned that their "...first design principle is: Usability prior to functionality...p.19". According to Angehrn and Lüthi (1990), the development of a DSS has to be "user-centered", and not "method-and-data centered". This means that the development should not focus on the solving techniques first and then proceed to addition of user-friendly interfaces. Rather, it should focus on creating an interactive modeling environment first, and the integration of analytical methods should take place. In my work, the initial screen of the DSS was built first, made interactive, and then the integration of the supporting models, and methods took place. Also, it has to be noted that the decision support systems are not always accessed by just one individual. In fact, in scenarios where companies are huge, decisions are taken by not just one but by a group of individuals who are mostly the stakeholders of the company. Gray (1987) has come up with the idea of "Group Decision Support Systems" (GDSS) which were designed specifically to help groups of senior management or professionals to reach a general consensus. Our system, which when confronted with a group of individuals belonging to the United States naval or marine officers can be considered as a GDSS.

Now that we have a decision support system in hand, how do we know if it is effective ? In other words, how can someone surely say that the system impacts the decision maker in a positive way ? In order to answer these questions, Sharda *et al.* (1988), have conducted an empirical study on 96 senior undergraduate students who were studying a business policy course. They were split into teams of three. The results of the study showed that the teams who were allowed to use the DSS performed significantly well when compared to their non-DSS counterparts thus marking the importance of the decision support systems. From this evidence, we assumed that the SDSS built for this thesis helps influence the decision makers and enables them to take decisions wisely when compared to deciding making decisions manually without the help of my SDSS.

2.2 Decision Support Systems in Multi Criteria Decision Making

Consider three scenarios where: 1) a person wants to buy a car, 2) a person wants to book a hotel room, and 3) a person has to layout a schedule for a football league. In the first case, *price*, *mileage*, *used or new*, *miles driven* (if used), *color*, *make*, *year*, *number of doors*, *features*, *accessories*, play a major role in deciding which car to buy. In the second case, *price*, *size of the room*, *air conditioning*, *number of beds*, *size of* *bed*, *user ratings*, etc. play a key role. In the third case, a lot of factors come into play of which few crucial ones are *total number of weeks*, *specific days games can be held*, *teams cannot play against themselves*, *number of games a team plays home and on road*, *minimum number of games to be scheduled on a Friday*, *number of times a team plays in a week*, *maximum number of games that can take place in a day*, are important. These entities which influence the decision are called *decision variables* or *constraints* or *criteria*. As the number of these constraints or criteria increases, the complexity of the decision making task or the objective increases. The objectives in the above scenarios is 1) to buy a car, 2) to book a hotel room, and 3) to prepare a schedule when the corresponding constraints are specified. Decision making in such scenarios is usually termed as Multi Criteria Decision Making (MCDM).

Pajer *et al.* (2017); Dimara *et al.* (2018); Kostuk and Willoughby (2012) have developed decision support systems for dealing with the decision making tasks of buying a car, booking a hotel room, and designing a schedule for the Canadian Football League (CFL) respectively. These DSS's show how a multitude of alternatives can arise while trying to achieve an objective and how the various constraints play important roles in making a decision. Also, Kostuk and Willoughby (2012) incorporated mixed integer programming into their decision support system. In our system, the main goal to be achieved is - "minimize the total dispatching time and cost of the cleanup equipment" and the constraints are: 1) the cleanup capacity of the equipment, 2) the amount of oil that can be cleaned by using the equipment which should not exceed the total volume of the spill within the containment area of each site, 3) a site is cleaned up only if a vessel is dispatched to its containment area, 4) the total oil cleaned should match with the pre-specified cleanup target. This objective and the set of constraints are mathematically formulated as a mixed integer programming problem which forms the heart of OSCOM (Grubesic *et al.* (2017)).

2.3 Spatial Decision Support Systems

The problems discussed so far (buying a car, booking a hotel room, etc.) do not have a spatial dimension to them but when problems have a spatial dimension, they become not only complex, but also involve multiple criteria to be considered before making a decision. Per Densham (1991), a Spatial Decision Support Systems (SDSS) conceptually is an integrated system of database management systems, analytical models, graphical displays, and the expert knowledge of decision makers. An "easy-to-understand" interface doesn't necessarily be an "easy-to-use" and vice-versa. When a high priority is imposed on usability or ease-of-use of the system, there could be some compromises made on the functionality. Uran and Janssen (2003) suggests that a SDSS should have a user-friendly interface and simultaneously be comprehensive enough to cover a wide range of possible scenarios. In comparison to a conventional DSS, Densham (1991) goes on to explain the specific characteristics that a SDSS must provide which entail the following: 1) providing spatial input mechanisms, 2) represent complex spatial relations, 3) inclusion of analytical techniques unique to spatial analysis, and 4) provide output in spatial forms such as maps. Our system is definitely a combination of these characteristics, and hence can be addressed as a spatial decision support system. Densham (1991) suggests that, in assisting the decision makers with complex spatial problems, the spatial decision support systems must support a decision research process, and not merely a decision-making process. The former refers to an environment, where the system empowers and enables decision maker in not only refining the definition, but also helps in generating alternate solutions aiding the decision maker to investigate the trade offs between conflicting objectives. The system developed for this thesis makes sure that it provides the end-users with multiple clean up targets, where trade-offs among the number of boat ramps dispatched can be investigated visually, thereby making it easy to calculate the operational costs. Also, Li *et al.* (2001) have suggested that, quantitative information, when expressed visually in the form of maps, charts, and graphs exploits the natural human ability to understand and detect the visual patterns.

The two crucial concepts that contribute to a successful SDSS were communicated from the works of Halbich and Vostrovskỳ (2011); Uran and Janssen (2003); Wallace and De Balogh (1985). The first concept talks about the structure and attributes of the system while the second one talks about the user experience which eventually forms a base for a successful SDSS. The spatial data, spatio-temporal analysis, knowledge database, and the way in which these are combined together, form the components of the first concept. The second concept of user experience can be split into two components such as the user interface, and the perceived usefulness of the system as noted by Chang *et al.* (1997); Halbich and Vostrovskỳ (2011). It has to be noted that the two concepts are not exclusive but rather dependent on each other. For example, Uran and Janssen (2003) think that adding too much functionality to the system has been found to show negative impacts on the user experience . Also, uncertainty about the system renders the user experience negatively which adds to the lack of success of the SDSS. There has been a great emphasis on the user interface in the proposed architectures of the systems as it goes hand in hand with the ease of use, and there by the user experience (Rizzoli and Young (1997); Densham (1991); Wallace and De Balogh (1985)). The user interface should guide the user through the decision process. For example, whether the next step is self-explanatory or not (Uran and Janssen (2003)). Per Chang *et al.* (1997), the development phase of the user interface must be carefully outlined; especially if the SDSS involves a combination of multiple models and each of them requires input from the user. In our system, the design and development of the user interface has been given utmost care and importance as it involves a combination of multiple models and sufficient care has been taken such that it is easily understood to the targeted user.

According to Uran and Janssen (2003), uncertainty of the model output, and the appropriateness of solving the decision question, are the major factors for DSS's not being widely accepted. For a given SDSS, the user might question the validity of the simulator or even the underlying data driving the models. To alleviate those uncertainties, it is always a wise choice to incorporate a tested and validated oil spill model into the SDSS and the same holds good for spatial optimization models. For example, Keramitsoglou *et al.* (2003) have used a third party oil spill model into their SDSS. This incorporation of the oil spill enabled the users to be more flexible in specifying accident scenarios for a specific type of spill. In our system, we make use of BLOSOM which is a well tested and validated model, in order to simulate spill scenarios. Hence the question of validity of the spill is nonexistent. In some cases, the SDSS may get technically very robust and surpass the general capabilities of the average user. Chang *et al.* (1997) have designed and developed a GIS based decision support for chemical emergency preparedness and response in urban environment. The final DSS was very comprehensive which integrated many specific models to simulate various chemical emergency spills. Every sub-model has its own input parameters and requires an extensive background in the areas related to the sub-models. This creates a requirement that the user who wants to use the system needs to have a very high level of understanding about all the models, and the system itself. As Uran and Janssen (2003) noted, the drawback of these systems happens to be that no matter how complex the system is, it is not optimal i.e., the ease-of-use of the system for a specific purpose becomes hard as the functionality and the complexity increases. Keramitsoglou *et al.* (2003) also mentions the SDSS's have been successful when they were designed and developed for the targeted user.

There has been a vast amount of research in spatial decision support systems and analytical DSS's in general. However, I could not find much literature which had a temporal aspect to it. Though Wang *et al.* (2017) has spoken about some methods and ways that can serve the purpose of visualizing spatio-temporal data, applying those concepts in a decision support system is hardly seen. In our system, we make use of the slider and represent the spatio-temporal data over a course of time, there by answering the question of when along with that of where.

Now that we added a spatial dimension to our decision making process, I searched for literature which involved testing the effectiveness of SDSS. Similar to the work of Sharda *et al.* (1988), I found out that there was a laboratory experiment conducted by Crossland *et al.* (1995) to investigate the effects on decision-maker's performance when a Geographical Information System (GIS) was used as a SDSS. According to Crossland *et al.* (1995), a SDSS is said to influence the decision maker positively if 1) the SDSS users reached a more accurate solution, or 2) attained a solution faster, or a combination of these when compared to their non-SDSS counterparts. From the results, it was clear that the subjects who used the SDSS were more efficient and faster in reaching an accurate solution, mostly because 1) the SDSS provided interactive, and colored graphical displays of information, than mere black and white text, and 2) the information presented by the SDSS made it more easy to grasp the problem to be solved. This evidence corroborates the effectiveness of our SDSS.

The process of effectively visualizing the geographical systems on maps commonly known as Geovisualization was elaborated by MacEachren *et al.* (2004) where they state that it is a process which helps to meet the scientific and the societal needs by leveraging the data resources. In the area of crisis management, Geovisualization plays an important role as it helps in assessing, integrating, and visualizing map-based displays which contains multi-source geospatial information. Our system makes use of complex geo-spatial data which is obtained from multiple sources. Also, similar to the architecture used by Kozal *et al.* (2004) in his DSS for drought assessment, our system has data, information, knowledge, and presentation layers. The data layer consists of all the shape files. The information layer, accesses this data and processes it in the optimization module and thereby converting it into meaningful information. Later, this information is used by the knowledge layer, which performs necessary actions such as applying power transformations, file optimization, etc. The presentation layer, makes use of the processed data and visualizes it to the end-user who will then learn from the system. Though their architecture is similar to our system, the naming of the layers however, varies in our case. Rao *et al.* (2007) have developed a web-based GIS DSS for managing and planning the United States Department of Agriculture (USDA)'s Conservation Reserve Program (CRP) which makes use of Java servlets for handling requests from the clients and retrieves the required information, and displays it to the user. The appreciable ideas of their system include the ability to host the DSS on a web server, and making use of the Geographical Information System (GIS). In our system, we went a bit further and incorporated javascript into our system which essentially removes the need for java servlets which can still make use of GIS, and makes it easy to be hosted on a web server.

2.4 DSS in Emergency Response

DSS have evolved and began to find their uses in the field of emergency response. There have been some works in the past with respect to the development of decision support systems exclusively in emergency management. However, it has to be noted that the core component of the systems discussed in the following section is the "simulation" modeling packages which predicts the course of the hazard.

2.4.1 *Efficient use of Simulation Modeling*

Vescoukis *et al.* (2012) have developed a DSS to tackle the problem of crisis management, esp. in regard to forest fires. The similarities of this work with my system include the use of geo-spatial datasets, and the use of simulation packages to predict the fate of the hazard. However, their system does not deal with the response and recovery of oil spills. Another research in this area was done by Wang *et al.* (2008) who addressed one of the widely seen problem of evacuation during a fire emergency in huge buildings. In their work, Wang *et al.* (2008) have developed a system which makes use of a graph layout which takes from with the help of decision nodes located at various points of interest in the building. This DSS however, makes use of the probabilistic hazard model by Elms *et al.* (1984) to predict how the hazard (fire) spreads.

Buildings are on land, but when it comes to oceanic environments, emergency events most commonly faced by the United States Coast Guard (USCG) are the Search and Rescue (SAR) operations. Once a person or a ship in the ocean goes missing, the response teams are dispatched to spot them and save them; but in the meanwhile, the location of the person or the ship would have changed drastically due to the currents in the ocean. Also, this difference in the distance increases during the times of hurricanes, or cyclones as the currents move more faster. Similar to Wang *et al.* (2008), a DSS was developed by Guoxiang and Maofeng (2010) to tackle the SAR operations effectively. Here, they make use of an Ocean Environment Database which helps the system to predict the drift behavior based on various oceanic factors. Another notable work in this area is by Zheng *et al.* (2010) where they developed a "Service Oriented Architecture" based DSS which can assess short-term risks from storms at the coastal area of Shanghai. For this system, they have used a "Hydrodynamic" model which is materialized by DHI Mike 21 software package developed by Warren and Bach (1992) which was also used by Lin *et al.* (2008).

In our system, the fashion in which the oil spill (hazard) spreads, and drifts over time in the ocean is modeled and visualized by the simulation package BLOSOM which takes into account, a lot of factors such as the temperature, pressure, salinity, winds, etc. at the spill site and then predicts the movement of the oil in the ocean. Since, this computation happens beforehand, the OSCOM model knows exactly where the oil is and hence makes it easy to find out the boat ramps from where response can be mounted and dispatched.

2.4.2 Oil spill response and cleanup

One of the best works on oil spill response was that of Ventikos *et al.* (2004) in which the authors talk about a decision-driven process by which one can effectively tackle the problem of oil spill response by choosing the right kind of equipment for a given spill. This way, dispatching unnecessary response equipment can be eliminated there by saving time as well as huge costs in an operational environment. Ventikos *et al.* (2004) go on to speak about oil spills as one of the facets of marine pollution. Per Ventikos (2002), the strategic or tactical planning to minimize oil spillage can be divided into two major parts: 1) preparedness; 2) control and recovery. Ventikos *et al.* (2004) also note that the clean up operations themselves should be well planned and done very cautiously as they can cause more damage than the spill itself because of the use of heavy machinery in sensitive spill sites. It is not a good practice to dispatch the same type of response for any type of a spill. Contingency planning is a crucial feature and the type and quantity of oil spill are the salient factors that should be considered when deciding what kind of equipment to be dispatched. As Ventikos *et al.* (2004) mention, the very first environment-friendly action when a spill occurs is to stop the pollution at the source or origin. The following actions include containment, and disposal. Tsocalis *et al.* (1994) have performed a survey on various response methods for marine oil spill clean up and divided the clean up processes into marine and shore operations. However, Ventikos *et al.* (2004) went a step further and divided the clean up methods into 1) conventional clean up methods, and 2) alternative/advanced cleanup methods. The conventional methods enlisted mechanical methods, chemical methods. Vergetis (2002) further illustrates the mechanical cleanup methods which consists of barriers/booms,skimmers, heavy oil skimmers, skimmer vessels, and sorbent materials. The chemical methods include dispersants, and other chemicals such as emulsion breakers, gelling agents, burning agents, neutralizing agent, sinking agents, etc. The alternate/advanced cleanup methods include bioremediation, in situ burning, and other advanced methods such as "*cleanmag*" which uses magnetic materials there by resulting in high clean up. Ventikos *et al.* (2004) state that since conventional methods are the most primarily used methods, the selection of appropriate equipment must be decided based on 1) wave height; 2) current velocity; and 3) viscosity of spilled oil.

In our system, the vessels dispatched from the boat ramps act as cleaners and recover oil from the ocean. In other words, we do not focus on the type of machinery used to recover the oil. Rather, we focus on the capacity of the vessel which specifies how much oil can the vessel hold and this is shown as "vessel capacity" for each boat ramp which is obtained from the boat ramps dataset. The idea here is that once the vessels fill up their containers with oil to their capacity, they go back to the boat ramp location (from where they were dispatched) by the end of the day and unload the recovered oil.

2.5 Vulnerability Indexing

Environmental Sensitivity Index (ESI), originally developed by Gundlach and O. Hayes (1978) tells us how sensitive a specific region of a coastal area is against an oil spill based on the value assigned to the region which is calculated based on many factors including the types of shores such as exposed rocky lands, mixed sand and gravel beaches, salt marshes and mangroves, etc. Getter *et al.* (1981) also made a study in this aspect considering the distribution of protected and valuable, oil-sensitive coastal fish and wildlife along the coastlines of Shelikof Strait (Alaska), Puget Sound (Washington), and southeastern Florida which include marine mammal haul-out, pupping areas, terrestrial mammal feeding areas, salmon and herring streams, nesting beaches, etc. This type of index helps the officials in making decisions as to predict the potential impact of oil along a shoreline and to allocate the resources accordingly. However the index values were given mostly based on the aerial surveys and hence introduced some error. Jensen *et al.* (1990) have eliminated this error, with the help of remote-sensing data obtained from SPOT satellite imagery and combined the ideas of Gundlach and O. Hayes (1978) and Getter *et al.* (1981) by employing planimetric basemaps using Geographical Information System (GIS).

Later, Boruff *et al.* (2005) has pointed out that the erosion hazards occurring at the coastal counties of the United States is not only due to the physical factors, but also includes social, and economic factors. According to Boruff *et al.* (2005), the Gulf Coast is a bit tricky as the erosion vulnerability here varies widely across counties. In some counties, the physical vulnerability is high whereas across some other counties, socioeconomic vulnerability is high. Adding to the thought of including social indicators in vulnerability indexing, Jepson (2007) has come up with the concept of measuring vulnerability for the fishing communities of the Gulf Coast. According to him, the social indicators and measurements that deeply impact the vulnerability of a fishing community include employment opportunities, and the community well-being.

Keeping in mind the socioeconomic and the natural/physical factors, de Andrade *et al.* (2010) studied the coastal zone of the Brazilian state of Maranhão, especially the Itaqui-Bacanga port Complex (IBC) as it is an area prone to oil spills and other forms or marine pollution resulting from storage, cleaning, etc. In their study, not only the geomorphological factors, but also income, education, and the dependence on fishing of the local population were considered. Also, Garcia *et al.* (2013) came up with an Oil Spill Hazard Index (OSHI) which is calculated based on the hydrocarbon emissions from the maritime traffic along the whole Italian coastline and waters. This index is an aggregation of 1) the hydrocarbons handled at ports, and 2) the hydrocarbons in transit. The entire Italian coastline (8660 km) was divided into 335 coastal stretches and an OSHI value was given to them.

Per Aps *et al.* (2016), mapping 4,000 km of the Estonian shoreline and classifying it according to the NOAAs ESI scheme would be time-consuming and expensive. Hence, the Aps *et al.* (2016) have adapted the ESI maps to Estonias existing shoreline and classified it geologically according to the new scheme (Orviku *et al.* (2010)) which they named as Regional Environmental Sensitivity Index (RESI). According to this new scheme, the Estonian shoreline divided the cliff into shores among sensitivity classes ranging from 1 to 5, with most of them falling under class 5 implying that they are the most difficult to clean up. Some examples of them being the mixed sediments on the beach, and those regions that have no access from the land.

However, since our area of study is the Gulf of Mexico, we stuck to the ESI scheme although the scheme itself does not play any role in the decision making process but merely acts as an additional layer for the user to know how sensitive the region is.

2.6 Effective Visualization

Now that we know how the oil moves when a spill occurs, the goal is to effectively visualize the spilled oil. When oil is floating on water, it actually spreads over a vast surface area and forms a layer which looks, darker if more oil parcels are concentrated, or lighter if fewer parcels are concentrated in that area. After going through the works of Malik *et al.* (2011), and Scheepens *et al.* (2011), we decided to use density estimated heat maps to visualize the oil. One of the notable works which combines the concepts of decision support and emergency response is the Run Watchers, developed by Konev *et al.* (2014) who make use of simulation-based approaches to design protection plans for effectively managing floods. However, in our system, we rely on the simulation by BLOSOM to find out the best possible trajectory of the oil movement over the course of the blowout for the given oceanic conditions. We do not interfere with the simulation process at any point whatsoever.

Wang *et al.* (2017) speak about how huge datasets having spatial, and temporal attributes can be visualized effectively. In their work, they talk about how interactive and dynamic maps can visualize spatial data, and line charts, and animation technology can visualize time-series data. Also, they go on to elaborate on how flow-map methodologies illustrated by Robinson (1967), and Tobler (1987) can visualize spatio-temporal data. In our system, the data generated is a combination of spatial and temporal attributes hence, we use maps obtained from openstreetmap.org (OpenStreetMap contributors (2017)) with the help of leaflet.js (`https://leafletjs.com/`) making them interactive. For representing the flow of time of the spatial data, we use a slider with which one can travel through the course of the blowout over time and see how the oil drifts in the ocean. However, it has to be remembered that this spatio-temporal data is obtained as a result of simulations run on BLOSOM.

2.7 Decision Support Systems in Oil Spill Response

The early works of the application of the DSS to the problem of planning for oil spills date back to 1992 when Belardo and Harrald (1992) have developed a GDSS for effective planning and managing of the response activities required when catastrophic natural disasters like earthquakes, and oil spills which pose a serious threat to the society occur. Their work was done subsequently after the EXXON VALDEZ oil spill in May 1989, hurricane Hugo in September 1989, and earthquake Loma Prieta in October 1989. Belardo and Harrald (1992) have stated that the lack of preparedness, and ineffective pre-crisis planning were the main factors that contributed to a failure in the response efforts. They proposed a system which contains six components such as 1) GDSS Interface, 2) Cue Evaluator, 3) Knowledge Base, 4) Scenario Manager, 5) Model Manager, and 6) Group Process Manager. This system was simultaneously accessed by a group of individuals, after which some discussions and debates took place, and they reached a general consensus thereby making sure that the decision is taken in a collaborative way. Our system is not a group DSS but can be accessed by a group of individuals (most likely the decision makers and other stakeholders) online through a URL.

Another notable work in this area was done by Keramitsoglou *et al.* (2003) in which the authors developed a DSS which focuses on the marine pollution caused by oil spills in the Mediterranean Sea, esp. in the Region of Crete which is susceptible to environmental damage from oil spills because of its ecological features , and economical activities that happen in that area. The DSS developed as a part of this work involves detecting an oil slick with the help of ERS-1 satellite's SAR imagery which is later sent to an assessment module where the extent of emergency of the spill is assessed and the resulting information forms the base for planning the response. The movement and evolution of the oil spill are calculated and simulated by the General NOAA Oil Modeling Environment (GNOME) developed by Beegle-Krause (2001) based on the type, size, location of the spill, wind and sea current characteristics of the spill location. In our system, we reduced the process of i) detecting the oil spill from the satellite imagery; and ii) using a simulation package (GNOME) to assess the extent of the spill into just one step by eliminating the need for a image processing engine with the help of BLOSOM.

Zahra Pourvakhshouri and Mansor (2003) reviewed some of the decision support systems which are related to oil spills and listed out some of the important characteristics in them which include: 1) defining the present conditions of the environment, 2) identifying the conflicts or problems faced by the environment, and 3) introducing alternative solutions. Our system has gone some steps further and apart from just introducing the alternative solutions, it also showcases the intensity of the spill when it hits the coastal areas with the help of an impact grid.

Speaking of impact grid, Pourvakhshouri *et al.* (2006) have developed a DSS in which the main idea was to divide the 180 km coastline of the two states of Negeri Sembilan and Melaka, in West Malaysia, into blocks of 10 x 10 km^2 called "coastal cells". Each of those cells was ranked according to their corresponding human and environment sensitivity based on the points from experts for criteria such as 1) coastal, and physical characteristics; 2) biological, and ecological resources; 3) human health and use; and 4) significant sites. Later, an overall score for each cell was calculated which was termed as Coastal Prioritization Index. The underlying assumption of this prioritization was that not every part of the coastline may be of equal importance when it comes to emergency situations and hence when the oil hits the shore, only those cells which have a high priority index or ranking would be cleaned up primarily. However, in our system, we do not prioritize the coastline based on the risk resources and bias our cleanup. Rather, we focus more on the overall optimal cleanup of the oil spill. Also, our coastline of 2700 km was divided into cells of 2 x 2 km^2 that resulted in 18,478 grid cells which collectively formed our impact grid. However, we still employ the ESI in our SDSS to locate the regions with high and low ESI index, based on the sequential color scheme chosen.

Liu and Wirtz (2007) have rightly mentioned that "...a golden rule of oil spill contingency management is, therefore, to remove as much oil as possible from the sea surface in order to minimize the onshore impact...". In their work, they make use of a second order fuzzy comprehensive evaluation (FCE) logic which when confronted with a group of stakeholders via a group DSS would enable reaching a general consensus thereby making the process of decision making easy. However, it has to be noted that more emphasis in this work has been given to decision making at every step in the spill mitigation process including not only the stakeholders, but also the environmentalists, and the fishermen. This would delay the decision process, especially when a conflict of decision occurs, and may result in a biased decision which favors the economical growth ignoring the ecological degradation. In our system, this entire body of decision making has been assimilated into the the OSCOM package that decides which boat ramps should launch response and to which spill sites; to achieve maximum cleanup of the spill, which was the golden rule of oil spill contingency management that Liu and Wirtz (2007) were trying to achieve.

2.8 Design Requirements

After going through various works on DSS's and SDSS's discussed so far, and the approaches the authors used, several drawbacks were identified and the challenge was to design a SDSS which would not just show data on the screen but eliminate the drawbacks observed and assist the decision makers in making a wise and informed decision when a blowout occurs. Finally, the requirements listed below were considered pivotal during the entire development process of the SDSS.

Design Requirements:

1) BLOSOM shapefiles contain lots of rows each of which refers to an oil parcel. The primary requirement was to show each of these parcels as points on the screen. The same applies to the boat ramps data as well except that they were shown as stars because they play an important role of recovering oil. For this, we used the map obtained from openstreetmap.org with the help of leaflet.js and plotted the points on the map.

2) Since the data had a temporal aspect to it, a major requirement was to show how the data varied with time in both backward and forward directions. For this, a slider was chosen as the tool.

3) Once Gurobi listed the cleaned parcels for each day, the aim was to differentiate the cleaned parcels from the uncleaned ones. For this purpose, we used shades of purple for uncleaned parcels and green for cleaned parcels.

4) The oil parcels belonged to different categories based on their presence in the ocean (surfaced, sunk, beached, etc.). To filter only a desired category of oil parcels, a drop down menu was added to the map.

5) The decision-maker was interested to know the boat ramps which were activated. As boat ramps were already shown as stars, we had to differentiate the active ones from the inactive ones and therefore, we used hollow stars for inactive ones and filled stars for the active ones.

6) OSCOM performs spatial optimization on the boat ramps along with the oil parcels data for a specified cleanup target which usually was 95% but the decision-makers were curious to find out how does altering the cleanup target makes a difference in the number of boat ramps dispatched and the amount of oil cleaned up. Hence, we

ran OSCOM for clean up targets of 75%, 80%, 85%, 90%, and 95% and added a radio button menu on the map so the user can choose the desired level of cleanup. We also included an option of 0% cleanup in which no oil is cleaned to study the condition where no oil is recovered.

7) Now, the user was curious to compare how one cleanup target was different from the other. Since we had six cleanup targets, we replaced the one map we initially had with four maps which were all identical. Using six maps would take up too much space and does not preserve symmetry.

8) Another important requirement was to identify the coastal areas which were heavily impacted due to the spill. When a large number of oil parcels gather in a region, it is sometimes hard to differentiate the regions with heavy impact from that of low impact. To solve this, we employed the impact grid that showed us various levels of impact with the help of a sequential color scale.

9) After the impact grid was employed, the most important requirement was to compare the level of impact for different cleanup targets. Since the impact grid was initially given a sequential color scheme, the challenge was to visualize the difference of impact between the four maps. This problem was solved by allowing the decision-maker to choose one of the four maps as a baseline map with the help of a drop down menu while others showed the difference of impact with the baseline. Now, the issue here is that the difference with the baseline can be either positive or negative (for example, if lesser cleanup target was compared with a higher cleanup target). To solve this, a divergent color scheme with different colors was used for the other maps which showed the positive and negative differences while the baseline map retained its original sequential color scheme.

10) Once the oil is beached at one particular region, the decision-maker was interested in knowing how environmentally-sensitive is that region. To show this, a tile layer of ESI dataset was added to all the four maps which used a sequential color scheme to differentiate various sensitivity index values.

Finally, to make the system more user-friendly and free of clutter, options have been provided to the users to toggle various elements and layers (on each of the four maps) such as legends, impact grid, cleaned and uncleaned parcels, boat ramps, and the ESI layer.

Chapter 3

SYSTEM DESIGN

3.1 Overview

The goal of this Spatial Decision Support System is to assist the decision makers in exploring the various possibilities which can arise when an oil spill occurs so that they can make informed decisions on what kind of vessels, equipment and response crews should be dispatched, in what quantity, and from which boat ramps, to optimally reduce the operational costs while maintaining a high cleanup rate.

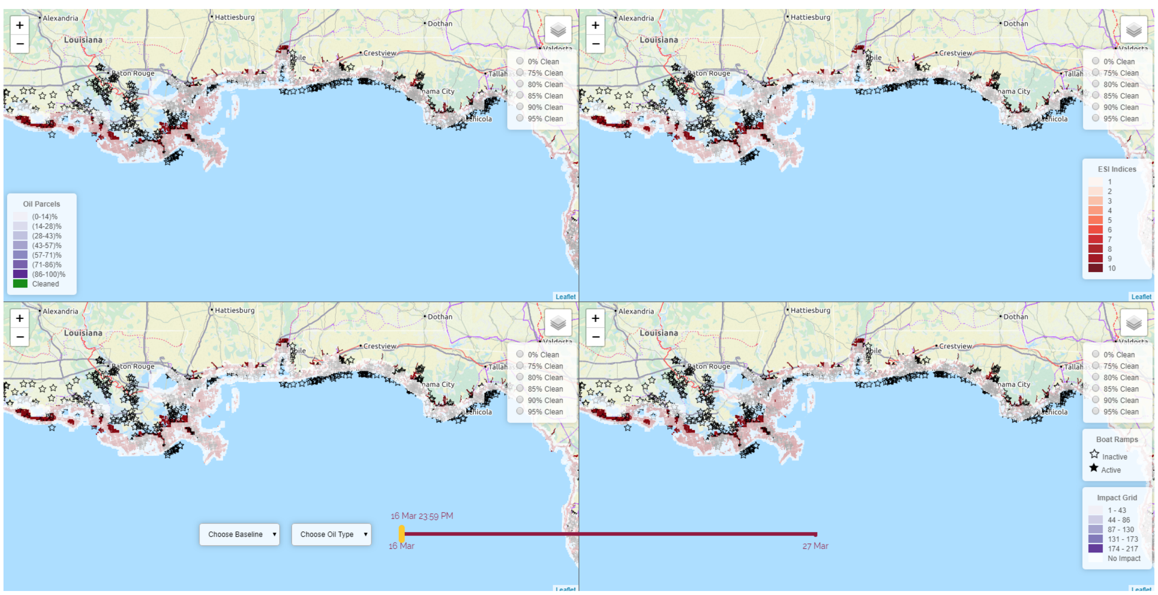


Figure 3.1: Overview of the proposed Spatial Decision Support System for Oil Spill Response and Recovery

As shown in the Figure 3.1, the initial screen of the visualization is composed of four different maps showing the coast of Gulf of Mexico which includes the coastline of Texas, Louisiana, Mississippi, and Florida. The main components of this decision support system are: 1) slider, 2) cleanup target selector, 3) boat ramps, 4) Oil type selector, 5) the oil parcels, 6) Baseline Map selector and 7) the impact grid.

3.2 Data Generation

At first, simulations are run on an integrated oil spill modeling package system called Blowout and Spill Occurrence Model (BLOSOM) (Sim *et al.* (2015)) which is designed to simulate offshore spills that occur in deep water and ultra-deep water blowouts. This model generates the simulation statistics, and simulation values upon adding a recorder to record the simulation at specified time intervals. This data is generated in various formats which include .txt, .csv for statistics, and .shp, .txt, .csv for values. For this system, we use the .shp (shape file) format.

For the simulations to run, important parameters like "Bathymety" and "Ambient" can be set by selecting the appropriate .tif bathymetry raster file, and .nc (NetCDF) ambience file for that particular day or period. The former indicates the depth of the water at a given point and the latter indicates the ambient conditions of the ocean at that point of time. The blowout parameters, such as the duration of the blowout, the location where it happens and the type of crude oil emitted and their corresponding physical properties can also be set in the "Blowout" tab. The values for diffusion, dispersion and weathering can be set in the "Advanced" tab. This simulation's name, the required fields to be recorded, the format of the output files to be generated, etc. can be specified in the "Model" section. Once all the required parameters are set, the simulator is run and the shape files are generated in the designated folder. Each shape file that is generated is actually a collection of files with the file name as a common prefix. These other files supporting the .shp files have the extensions .dbf, .prj, and .shx. Then, spatial optimization model "Oil

Spill Cleanup and Operational Model" (OSCOM) (Grubesic *et al.* (2017)) is used whose main objective is to minimize the total time and cost spent in dispatching the cleanup equipment. This objective is achieved against a set of constraints such as 1) the capacity limitation for cleanup equipment at each staging area, 2) limitations on the amount of oil that can be removed by using cleanup equipment, which should not exceed the total volume of the spill within the containment area of each site, 3) a spill site should be cleaned up only if a vessel is sent to its containment area, 4) the total amount of removed oil should achieve the pre-specified oil cleanup target, etc. A cleanup target is usually a value expressed in percentage that specifies the amount of oil recovered. For example, a 95% cleanup target indicates that 95% of the entire oil that has been ejected into the ocean would be recovered by this model. This model generates the model files (.lp format) considering the shape files generated by the simulator, and the boat ramp shape files provided as inputs. Later, these model files are sent to a mixed-integer programming solver Gurobi (Gurobi Optimization (2016)) which will optimize the model files and generates a solution file, and a log file in .txt format. The log file contains the entire log of the solving process, and the solution file contains information which specifies the boat ramps dispatched and the spill sites to which they have been dispatched. Also, the oil parcels which have been cleaned up are also listed down in the solution file.

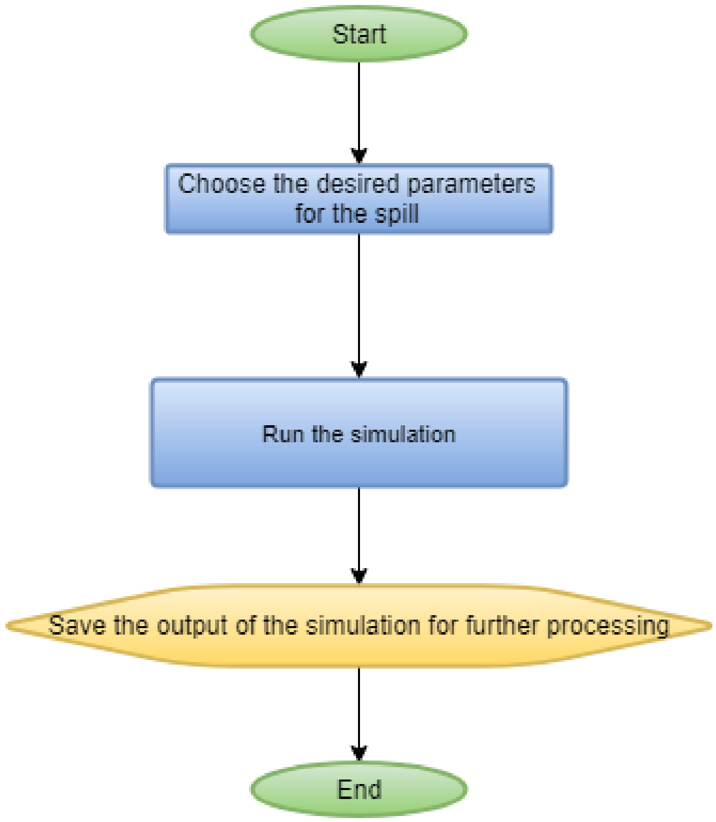


Figure 3.2: Blosom's simulation flow

3.3 Data Description

In the previous section 3.2 we spoke about how data is generated and what are some key aspects of it. Here, we go in detail and explain the different attributes of the main datasets used.

3.3.1 BLOSOM Data

BLOSOM usually generates data which has about 41 attributes. However, we are primarily concerned with only few key attributes that are mandatory for the SDSS. Those important attributes are listed down in the Table 3.1

In the above Table 3.1, ID of the parcel is always guaranteed to be unique for the duration of the simulation, and the "STAT_CODE" values 0, 1, 2, 3, and 4 indicate

Short Name	Long Name	Data Type	Units	Description
CURR_TIME	Current Time	string	UTC	The last time that the parcel had an active status.
PARCEL_NUM	Parcel Number	int	–	ID of parcel
STATUS	Status	string	–	water column or surfaced or
beached or sunk				
STAT_CODE	Status code	int	–	Value ranging from 0 - 4
LONGITUDE	Longitude	double	°E	Longitude of parcel.
LATITUDE	Latitude	double	°N	Latitude of parcel.

Table 3.1: Key attributes of shapefiles generated by BLOSOM

water column, surfaced, beached, sunk, and out of bounds respectively wherein water column refers to parcels active within the water column, surfaced refers to parcels active on the surface of the water, beached refers to inactive parcels that collided with dry land, sunk refers to inactive parcels that collided with the bathymetry layer, and finally, out of bounds refers to inactive parcels that have drifted out of the boundaries of the simulation.

3.3.2 Impact Grid Data

The impact grid dataset mainly comprises of 18478 polygons with each of them having a unique ID. Other important attribute of this dataset is Total_S which signifies the number of datasets that fall under each polygon.

3.3.3 Boat Ramps Data

Similar to BLOSOM, even boat ramps dataset contains many attributes. This is mainly because this dataset too has been aggregated by combining multiple datasets.

Short Name	Long Name	Data Type	Units	Description
RampID	Ramp ID	int	–	Unique ID of the Boat Ramp
VesCap	Vessel Capacity	double	bbl	Amount of oil the vessel can hold
EBcap	Exclusion Boom Capacity	double	bbl	Number of Exclusion Booms the vessel can deploy

Table 3.2: Key attributes of the boat ramps dataset

The crucial attributes of the boat ramps dataset are listed down in the Table 3.2

3.4 Spatial Optimization and Data Solving

Once the shape files are generated from the simulation, they are sent as inputs to the OSCOM model. This model generates the output in the form of a .lp model file for each day of the simulation for a given cleanup target. These .lp model files are again given as an input to a mixed-integer programming solver, Gurobi (Gurobi Optimization (2016)) in the same order in which they were generated, which creates a log file (.txt), and a solution file (.txt) for each day of the simulation. Now that we have the shape files, the .lp files, and the solution files available for each day, we have sufficient data to find out how the oil parcels have drifted, from where was the response launched, and what parcels have been cleaned by the equipment, for that particular day. The work flow of this implementation is shown in the Figure 3.3

The crucial aspect that has to be observed here is that some of the oil that has been spilled on Day 1 is cleaned by the dispatched response at the end of that day. Hence, the cleaned parcels on day 1 are not present on the following day (day 2). This implies that the shape files of the following day (day 2) should not contain the oil parcels that have been cleaned or skimmed the previous day (day 1). Therefore, with the help of the solution file generated by Gurobi, cleaned oil parcels are identified with their unique parcel numbers, and are removed from the shapefiles of the following day. For this, a copy of the following day shapefiles is created with the suffix _updated. Also, to easily identify which oil parcels have been cleaned, a new copy of the current day's shapefiles is generated with an additional field 'Cleaned' that is set to a value of 1 if the corresponding oil parcel is cleaned, or 0 otherwise. These shape files are renamed with the suffix '_cleaned'. The same procedure is followed for all the shapefiles that follow day 1. This process is depicted in the Figure 3.3

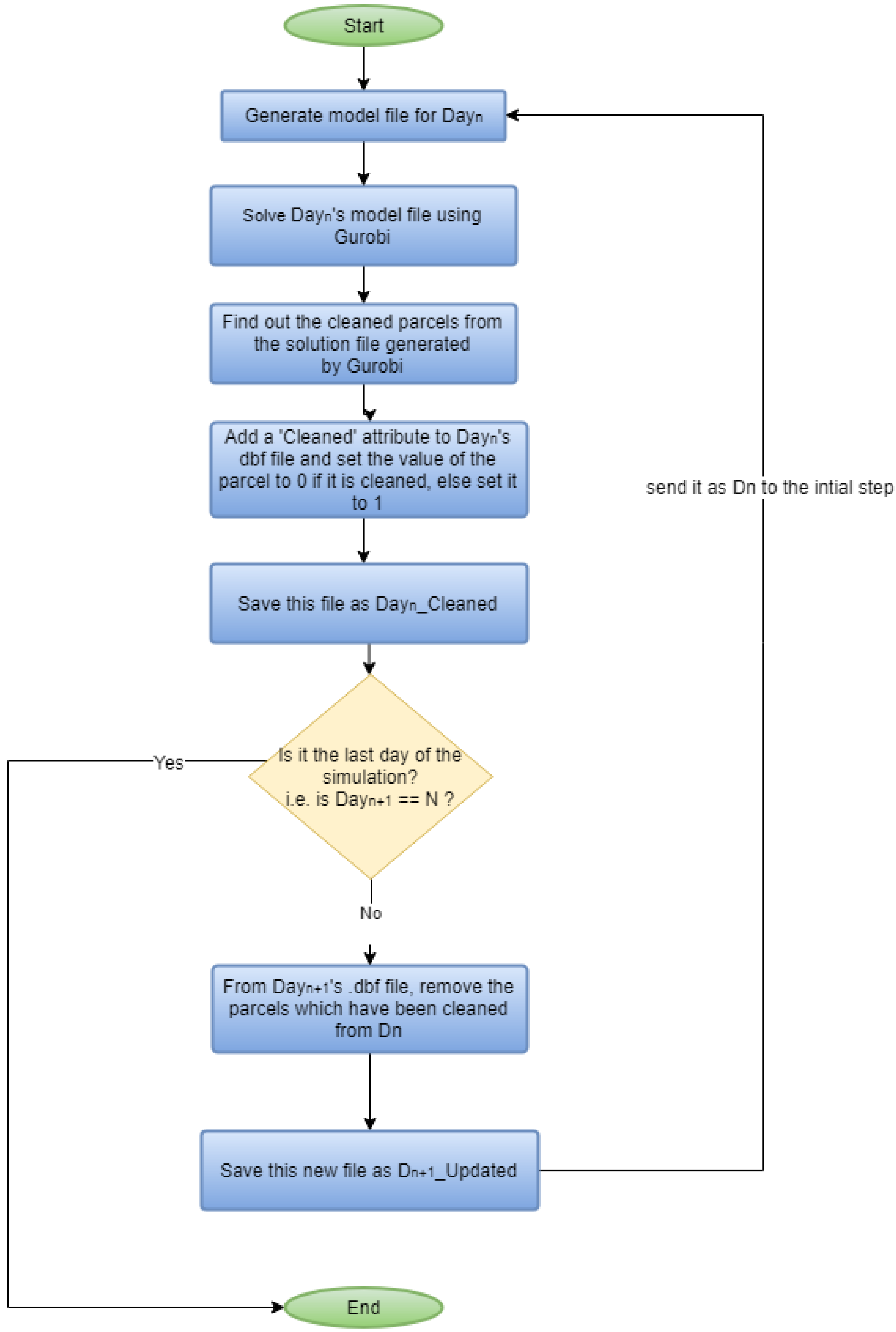


Figure 3.3: Cumulative removal of Oil Parcels

3.5 Data Processing

If the BLOSOM simulation is recorded at intervals less than 24 hours, say 4 hours, then we have 6 sets of shape files for each day. If the interval is set to 2 hours, then the simulation is recorded for every 2 hours and 12 sets of shape files are generated for each day of the simulation. However, this is done only to study the movement of oil parcels at every stage of the simulation and does not serve any purpose other than giving the user a continuous moving effect of oil along with time. Since, this intermediate oil is not cleaned until the slider reaches the 1st hour of the following day, a "Cleaned" attribute is added to these shape files separately and the value is set to 0 indicating that these parcels are not cleaned at that point of time and are saved as new shape files with the suffix _cleaned.

Once the data is solved and _cleaned, and _updated shape files are generated for each day of the blowout for every cleanup target, only the _cleaned shape files are put into a directory. If, the simulation recording interval is 24 hours, then there won't be any intermediate files. Otherwise, if the interval is anything that is less than 24 hours, all those shape files are merged, and converted into a .csv file which has only those attributes that are required by the web application. This additional step of removing unnecessary attributes makes the files less heavy and reduces the processing time required by the web application. Since, there are five clean up targets, five .csv files are generated, one for each of the clean up targets added as a suffix to those file names. This is pictorially represented in the Figure 3.4. The optimization module shown in the Figure 3.4 consists of all the processing that happens in the Figure 3.3.

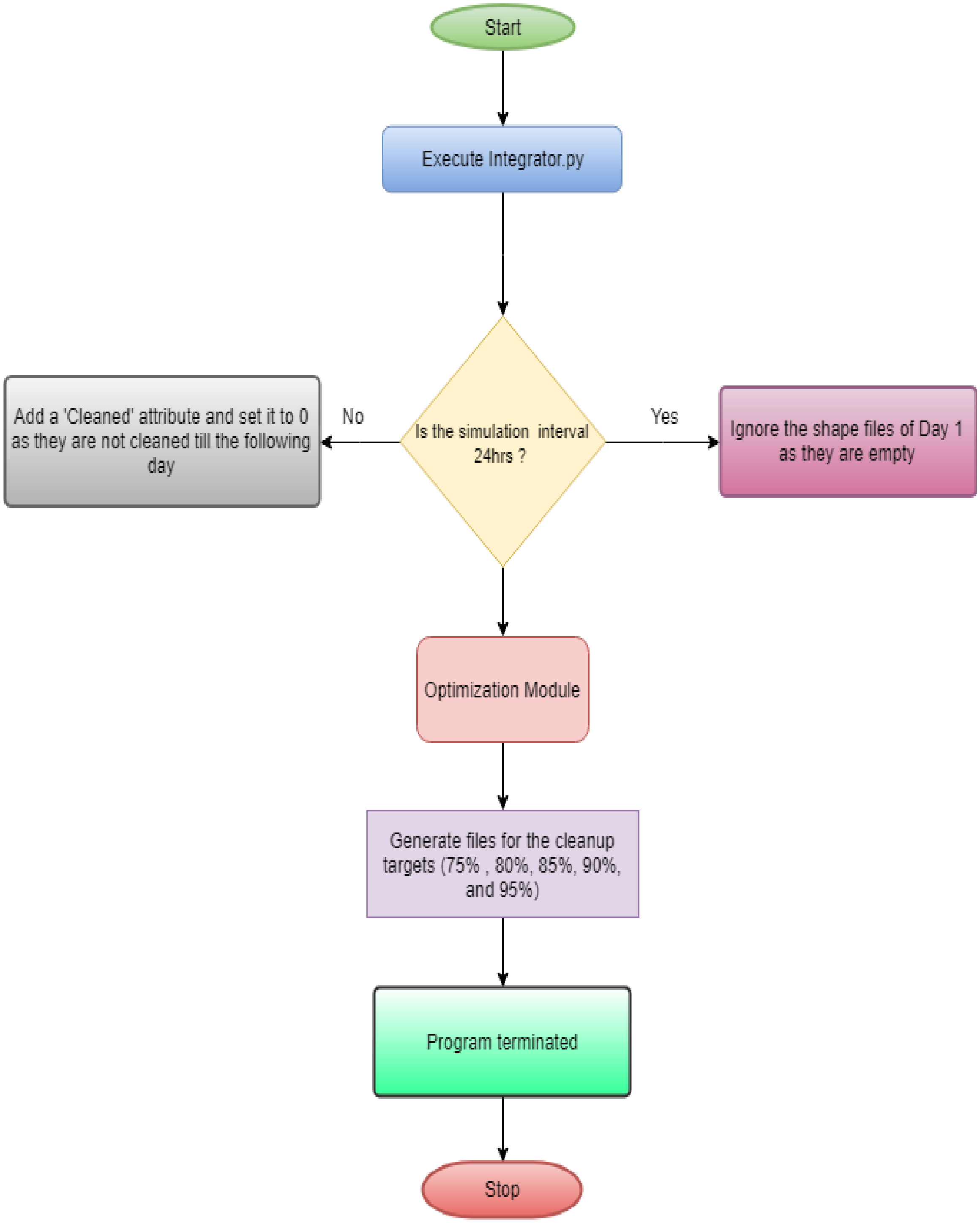


Figure 3.4: Work-flow of the final csv files generation

3.6 System Architecture

Since all the shape files have geo-spatial data, the core visualization involves displaying geographical maps (obtained from openstreetmap.org (OpenStreetMap contributors (2017))) visualizing the oil spill with the help of a time slider, highlighting boat ramps from where the response crews and equipment is sent out, and envisage how deeply different areas of the coastline have been impacted (with the help of an impact grid) based on the duration and intensity of the blowout.

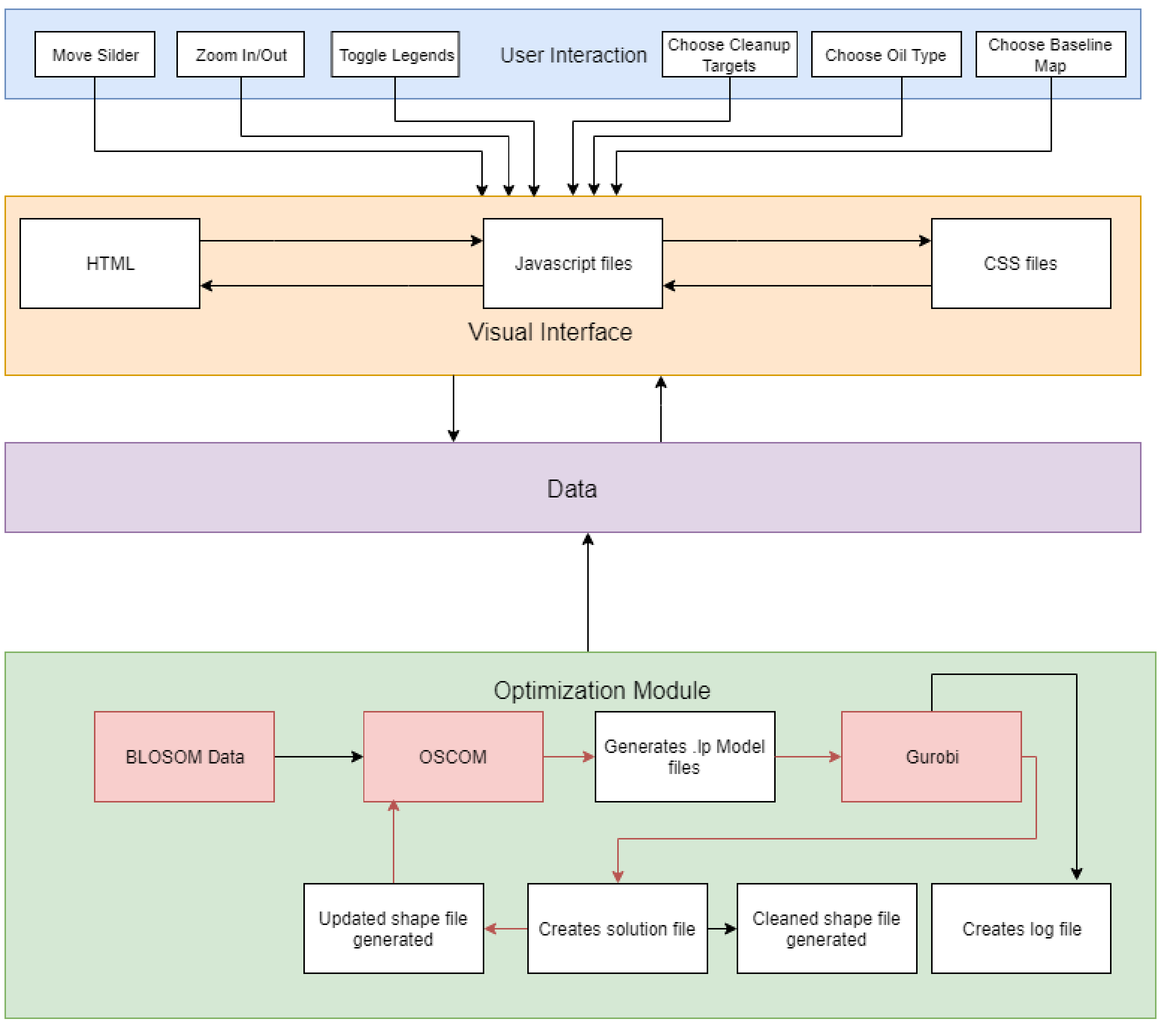


Figure 3.5: Architecture of the SDSS

The system designed and developed for this thesis is a combination of the user interaction with the visual interface which draws its data from the optimization module as shown in Figure 3.5. The user interaction comprises of all the actions performed by the user on the visual interface such as moving the slider, zooming in and out, choosing desired cleanup targets, choosing desired baseline map, choosing type of oil parcels to be displayed, toggling legends, etc. The visual interface on the other hand is a combination of several Javascript files coupled with HTML and CSS files with the given data. The optimization module consists of BLOSOM and OSCOM as key players which simulate the spills, and spatially optimize the response efforts respectively along with Gurobi which helps in solving the model files. All of the components and their functions are described in the following Section 3.6.1

3.6.1 Visual Interface and User Interactions

After the application is loaded in the browser, the initial screen showing the Gulf of Mexico on four dynamic maps obtained from Open Street Map (OSM) servers are loaded. The user can adjust the zoom level to watch the oil particles more clearly. It is possible to zoom in or zoom out based on the mouse rollover or with the help of "+" and "-" symbols present on the map.

Slider: A time slider which enables the user to traverse the timeline of the blowout is provided at the bottom of the screen in the center. When the user moves the slider to a desired point of time, the position of all the oil parcels at that particular time is visualized in the form of a density heat map. These oil parcels are visualized on a day-to-day basis. It has to be noted that the difference between one time step of the slider and the next symbolizes the duration of one day. Initially, the idea was to show ticks on the slider to symbolize the beginning of each day but this is not a good idea because as the number of days of the simulation increases, the number of ticks on the slider increase making it too cluttered thereby spoiling the visual appeal of the slider. However, the time of the day is shown adjacent to the slider to avoid confusion.

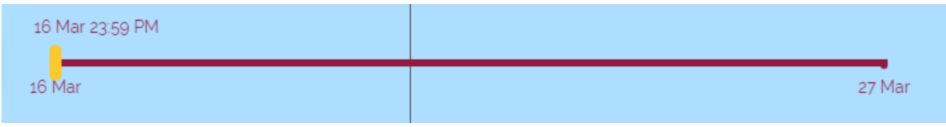


Figure 3.6: Time slider which helps the user to navigate from 15th April through 28th May

Oil Type Selector: The user can select the type of oil parcels to view on the screen with the help of the dropdown provided just beside the slider on the left side. The data has five types of oil parcels namely "Water Column", "Surfaced", "Sunk", "Beached", and "Out Of Bounds". For example, when the user chooses "Water Column", oil belonging to the other categories disappears leaving only the Water Column parcels on the screen.

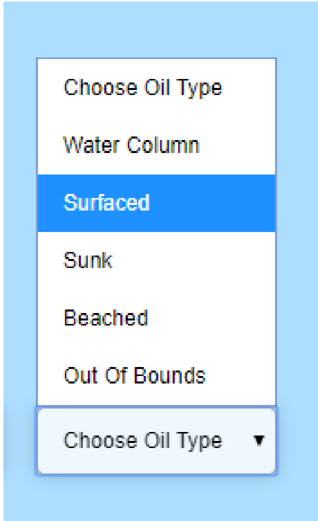


Figure 3.7: Helps to choose which type of spill parcels to display

Cleanup Target Selector: There is a radio button menu at the bottom right of each of the four maps which helps the user to compare and contrast how the spill proceeds and impacts the shore for different cleanup targets. As of now, we show 75-95% cleanup percentages along with 0% cleanup signifying no cleanup. For example, the user can choose a clean up of 75% on map 1, 85% on map 2, 90% on map 3, and 95% on map 4. This way, different spill scenarios can be observed closely. The key differences between each of those cleanup targets would be the number of boat ramps from where the response has been dispatched, the amount of oil parcels cleaned, and the impact of oil on the shore. The assumption here is that 95% cleanup cleans out more oil than 90% cleanup, and 90% more than 85%, and so on.

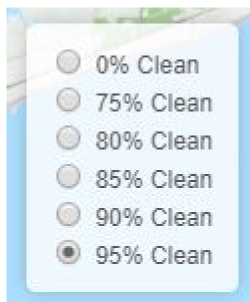


Figure 3.8: Helps to choose a specific type of clean up target in one map thereby enabling comparison with other maps

Oil Parcels Legend: To facilitate the user with the magnitude of density of the oil parcels, a legend is placed at the bottom right of the screen showing various colors and their corresponding percentage of proximity of the oil parcels. However, it has to be noted that this proximity varies with the zoom level. For e.g., the particles may look more cluttered when observed from a higher altitude, and hence a darker shade is observed; but if the same oil is observed from a lower altitude, they appear far apart in the ocean, and hence a lighter shade is given. To show oil that has been cleaned,“green” color is used. This legend can be seen in the figure 3.9

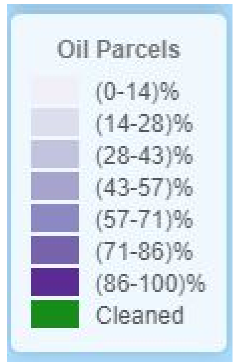


Figure 3.9: Shows how the color varies with the density of the oil parcels

Impact Grid Legend: To help users in understanding the magnitude of the number of oil parcels in each cell (polygon) of the impact grid (discussed later), a legend is placed at the bottom right of the screen. This scale consists of a sequential color scale with five classes which show five shades of Brown varying from a lighter shade to a darker shade. Each color represents a color bin in which the count for a given polygon falls when the dataset is divided at equal intervals. If there is no oil present underneath a given polygon, a white transparent color is given to the polygon. This legend can be seen in the figure 3.10

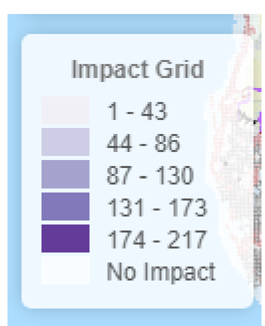


Figure 3.10: Shows how the color varies with the number of oil parcels under each polygon

Boat Ramp Legend: A legend is placed at the bottom right of the screen which shows two stars of black color, one filled and one empty signifying active and inactive boat ramps respectively. This can be seen in the figure 3.10

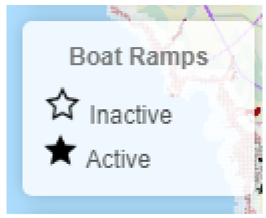


Figure 3.11: Filled black star represents an active boat ramp while the empty star represents an inactive one

ESI Tile Layer In the system we developed, the ESI data is visualized in the form of line segments along the shoreline of Gulf of Mexico and different sensitivity/index values are shown with the help of a sequential color scale with ten classes of color red. The higher the index value, the darker the shade. Similarly, the lower the value, the lighter the shade. This would help the decision maker in prioritizing the areas to which the response has to be dispatched and also helps in analyzing and determining the kind of response to be dispatched depending on the type of shore. This, however acts as an additional layer but not as a player in the decision making process. This layer can be seen in the Figure 3.12

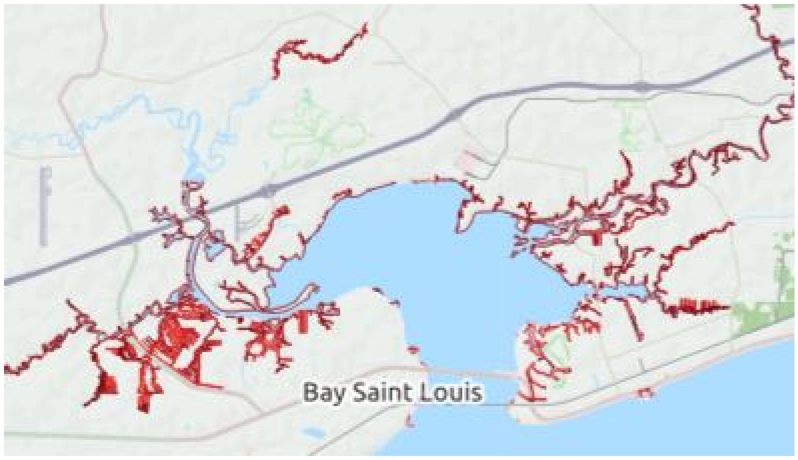


Figure 3.12: ESI layer around Bay Saint Louis area showing shades of light red for less sensitive areas and shades of dark red for more sensitive areas

Boat Ramps: Several boat ramps are located across the coastline of Gulf of Mexico to serve the purpose of oil recovery and emergency response whenever a blowout or an oil spill occurs. The rescue vessels sent out through these boat ramps help in skimming the oil and water mixture and extracting as much oil as possible that has been ejected during the course of the blowout. These boat ramps are visualized as black hollow stars (initially) on the maps. They may later turn into a filled black star indicating that the response has been dispatched from there. Also, when the mouse is hovered over a boat ramp, its corresponding details are displayed to the user as shown in the Figure 3.13

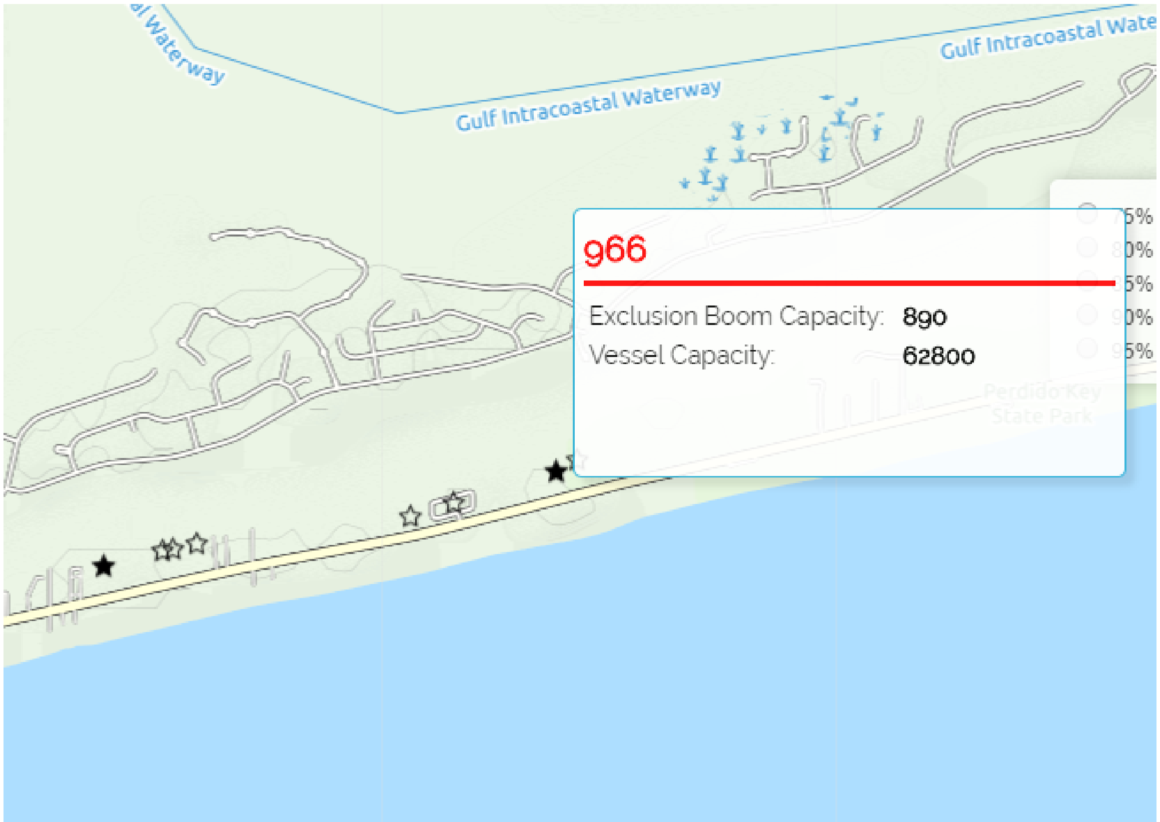


Figure 3.13: Active boat ramps are shown as filled black stars while the inactive ones are shown as hollow black stars. Details corresponding to those boat ramps are displayed with the help of a tooltip

3.6.2 Boat Ramps Highlighting

For every day of the blowout, response crews and equipment is dispatched from several boat ramps to clean the oil through various methods (Ventikos *et al.* (2004)) such as chemical methods like dispersants, and mechanical methods like skimmers, exclusion booms, etc. Out of 1143 boat ramps considered for this system, only a subset of boat ramps are participating in cleanup every day. The main aim here is to visualize the boat ramps that are dispatching response. As mentioned previously, a hollow black star represents a boat ramp which is inactive and a filled black star indicates that the boat ramp is actively participating in cleaning the oil (3.13).Now, the question is "How to find this list of boat ramps that are activated?" The answer to this lies in the solution file generated by Gurobi. Apart from the list of oil parcels that have been cleaned, the solution file also includes a list of boat ramps which have been activated on that day of the blowout. This file is parsed again, and a new file with the fields "BoatRampID", and "Date" is generated in a csv format. This file is used by the web application to fetch the list of boat ramps activated on the day the slider indicates and displays them in red color.

Impact Grid: The impact grid is an imaginary grid across the coast of the Gulf of Mexico which is a combination of 18,478 polygons, which are mostly squares. Any oil touching this grid is said to "impact" it i.e., oil has either hit the shore, or caused some serious damage because it traveled to that location. As the oil keeps floating and reaches the shore, some of the cells/polygons may contain more oil than the rest. To visualize this difference in the concentration of oil present in that cell, a sequential color scale with five classes (where each class denotes 20%) is chosen with the lightest shade indicating 1-20% damage, and the darkest indicating 81-100% damage. This impact grid is obtained from a set of shape files provided along with the BLOSOM. Later, these shape files are converted into geojson format and displayed on the maps.

It has to be remembered that the impact grid coloring is cumulative i.e. if the grid is impacted in a region say X, on Day 1 and never impacted at X again, the impact grid continues to show that the region X has been impacted even on Day 10. The purpose of this is to give the viewer an idea of all the regions that have been impacted by the spill by the time the spill ends. If only the present day impact was shown, previous days' impact would disappear which may leave the viewer with the assertion that the oil did not impact that region. Similarly, if a region X has been impacted with the oil concentration P on Day 1, and if the same region X has been impacted with a different concentration Q on some other day in the future, the region X is colored based on the latest value of the concentration, which in this case is Q.

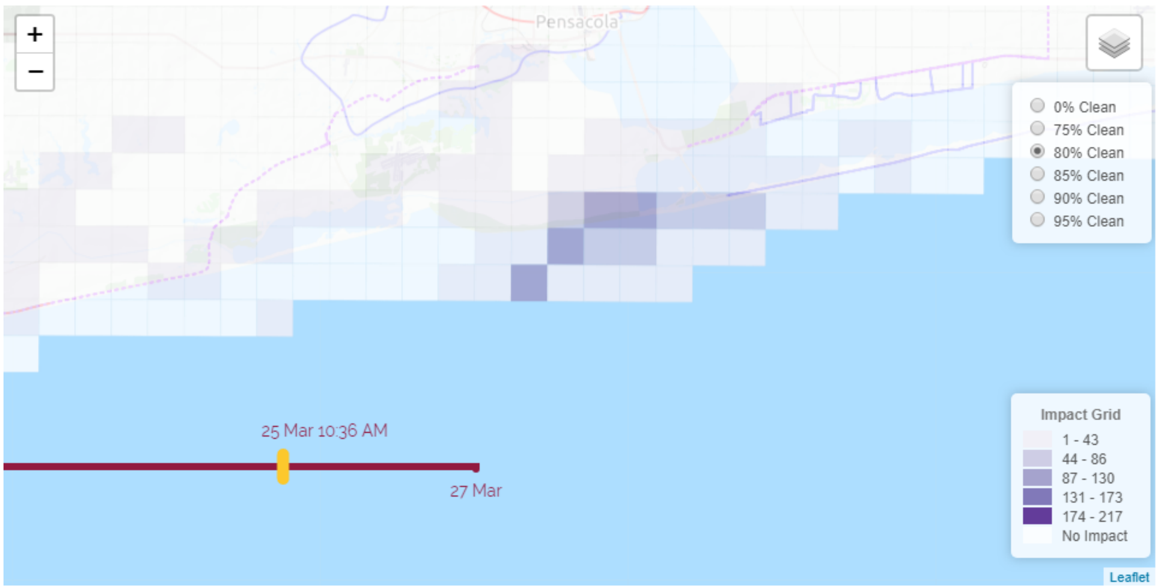


Figure 3.14: Different colors of the impact grid showing the different concentrations of the oil

3.6.3 Spatial Join for Impact Grid Analysis

Now that we have the impact grid, the goal is to find out which oil parcels fall under what cells of the grid, and if there are any such parcels, another goal is to calculate the number of such parcels under each of those cells. The impact grid is a set of shape files whose geojson geometry consists of Polygons, whereas that of oil parcels is Points. Essentially, the goal breaks down to the calculation of number of points in a single polygon. For this, a spatial join of the polygon layer with the point layer is performed in python using the python library "geopandas". The resulting join file is again a set of shape files which contains the polygons along with the points that lie under them as separate rows. For example, let us say there are 11 points under one polygon “A”. Then we have 11 rows of “A” with each row consisting of each of those 11 points respectively. Hence, it is required to simplify this set of shape files to a format more easily accessible with just the “Polygon ID”s, “Date”, and the “Count”. To achieve this objective, we parse the shape files, find out the number of points under each polygon for a specific time, sort the whole file in the ascending order of the polygon ids and write it to a new file after removing the duplicates. This file contains three fields “Polygon_ID”, “Date”, and “Count”. However, it has to be noted that, the join performed is an inner join and hence the polygons which do not contain any oil parcels at any point of time during the whole spill are not present in this file since their count would be zero on every day of the blowout. Sometimes, it so happens that on a given day, there could be more than one entry for a polygon during different times of the day. Contrary to the assumption that the count of the number of oil parcels increases before midnight, there would be situations where the count was high during the beginning of the day but reduced by the end of the day. This could happen due to a variety of factors including the water currents, oil being sunk, or oil being evaporated. In these cases, we consider only the count of oil parcels at the end of the day even if it is lesser than the count observed during earlier that day.

3.6.4 Computation of the Impact Intensity

To compute the intensity of the spill at various locations of the grid, we need to first calculate the highest impact occurring at any point of time during the entire course of the spill i.e., the maximum number of oil spill parcels in any cell during the entire blowout is taken from the file previously generated in Section 3.6.3 as *Maximum Impact*. Similarly, the lowest impact is taken from the same file as *Minimum Impact*.

If a cell is not impacted at all, i.e., if no oil reaches to that point, then the cell is said to have "zero impact" and not considered. Then, the difference of *Maximum Impact* and *Minimum Impact* is calculated which gives us the *Overall Impact Range*.

$$\textit{Overall Impact Range} = \textit{Maximum Impact} - \textit{Minimum Impact} \tag{3.1}$$

Sometimes, it so happens that the data is not uniformly or not even close to uniformly distributed. In such cases, we see a lot of data falling in one particular interval, thus making the dataset highly skewed. In other words, it is sometimes possible that a large number of oil parcels fall under some polygons while the other polygons have only a very few of them. In such cases, we use the Box-Cox transformations explained in Maciejewski *et al.* (2013) to make sure that the data is close to normality. The choice of power in this case is usually $\frac{1}{2}$. However, depending on the dataset, it is left to the discretion of the user to choose the power required. This can be $\frac{1}{3}$, $\frac{1}{4}$, and so on if the data is positively skewed, and $\frac{-1}{2}$, $\frac{-1}{3}$, $\frac{-1}{4}$, etc. if the data is negatively skewed. If the data seems to be not so skewed, then the power would be simply 1. Hence, Equation 3.1 is modified as:

$$OverallImpactRange = MaximumImpact^{\lambda} - MinimumImpact^{\lambda} \tag{3.2}$$

where λ is the power chosen.

After the power is determined, the interval range is defined as:

$$ImpactRangeInterval = \frac{MaximumImpact^{\lambda} - MinimumImpact^{\lambda}}{Numberofclasses} \tag{3.3}$$

where the term "Number of classes" signifies the number of classes chosen for the sequential color scale. However, it has to be noted that the visualization consists of four maps and if every map has its own impact range interval, then it would not make up for an authentic inter-map comparison.

Hence, to avoid this problem, we have standardized the impact range interval among by computing it for all the maps. This is similar to Equation 3.1 except that the maximum impact, and the minimum impact values here are the highest and least values among all the four maps.

$$OverallImpactRange_{1-4} = MaximumImpact_{1-4} - MinimumImpact_{1-4} \quad (3.4)$$

where $OverallImpactRange_{1-4}$ is the overall impact range considering all the four maps and the $MaximumImpact_{1-4}$, and the $MinimumImpact_{1-4}$ are the maximum and minimum impact values among all the four maps respectively.

Baseline Map Selector: Sometimes there would be a requirement where one would like to see the contrast between one map and the other three maps. For instance, let us assume that Map 2 shows 95% cleanup whereas Maps 1,3, and 4 show 75%,80%, and 90% cleanups respectively. Now, how would one determine which map achieved more cleanup in a desired section (a group of polygons) of the Impact Grid? Though the underlying assumption is that the 95% cleanup yields maximum oil removal, it has to be remembered that this assumption holds true with respect to to the overall spill and does not pertain to a specific area in general. In other words, 95% cleanup would have removed less oil in one section of the impact grid compared to the 75% cleanup but cleaned up a lot more oil elsewhere in the Gulf of Mexico. To answer the question, we make use of the baseline map functionality, wherein one desired map is chosen as a "Baseline" and the others highlight whether the clean up is better or worse in a particular area by comparing the number of oil parcels in the respective polygons. The drop-down menu used to select the baseline map is shown in the Figure 3.15.

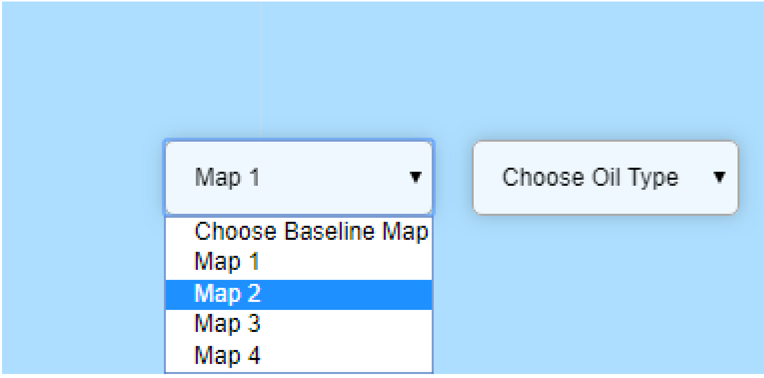


Figure 3.15: Drop-down menu to select the desired map as the baseline map

The formula used to find out the difference in cleanup between the polygons is as follows:

$$Cleanup\ Difference = B_{PC} - R_{PC} \tag{3.5}$$

where B_{PC} is the count of oil parcels in the polygon of the baseline map and R_{PC} stands for count of oil parcels in the polygon of the reference map.

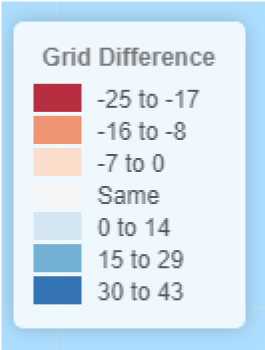


Figure 3.16: Legend showing various colors assigned to corresponding cleanup difference coefficient

This difference is visualized with the help of a divergent color scale with seven classes which ranges from a darker shade of blue to white and then to a darker shade of red which can be seen in the figure 3.16. Also, to make the comparison more effective to the user, it has been made sure that the views of the reference maps are changed per that of the baseline map. Also, if any of the other three maps is chosen as the baseline, the corresponding difference is computed and the legend is updated.

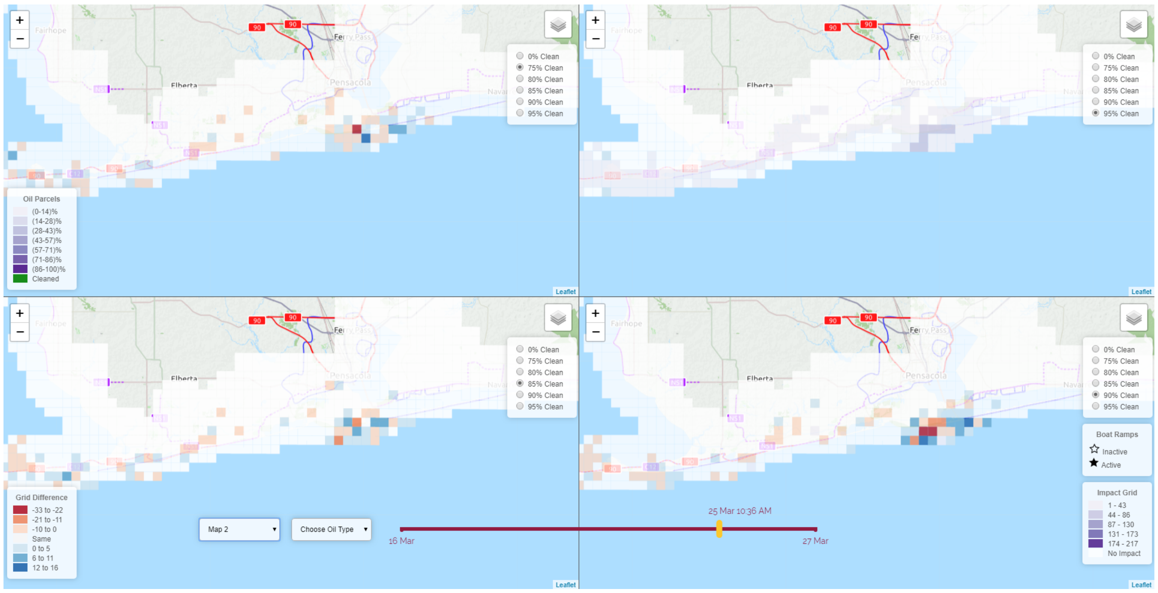


Figure 3.17: Map 2 is the baseline Map and acts as a reference while the other three maps highlight the cleanup differences based on a divergent color scale varying from red to blue

Let us consider a scenario where Maps 1, 2, 3, and 4 show cleanups 75%, 95%, 85%, and 90% cleanups respectively. Now using the drop-down menu at the bottom of the screen, Map 2 can be chosen as the baseline map and the other three maps show the differences in cleanup in their respective polygons as shown in the figure 3.17. For example, if one of the cells in the baseline map has a count of 20 oil parcels, and the same cell in any of the reference maps has only 5 oil parcels, it means that the cleanup target chosen in that particular map has saved the shoreline from an impact of 15 more oil parcels.

Now, we can observe in the above figure that even though all of the the reference maps have a cleanup target higher than the baseline map, there are some grid cells with the shades of red color. This is because though the higher cleanup targets failed to perform better than the low cleanup target chosen on the baseline map, they have succeeded in performing much better cleanup resulting in more amount of oil recovery in most of the other grid cells.

Chapter 4

CASE STUDY

Our Spatial Decision Support System has been built to help the decision makers in making informed decisions when an oil spill occurs. This system takes in the data generated by BLOSOM simulator and uses it against the Boat Ramps dataset in combination with the OSCOM model which would give the set of boat ramps that can actively dispatch response equipment and thereby participate in oil cleanup. These sets of activated boat ramps change with respect to the cleanup objective. Here, the underlying assumption is that the greater the cleanup objective, more is the number of active boat ramps. The spill continues to proceed with time, and the oil keeps floating in the ocean and eventually hits some parts of the shoreline of the Gulf of Mexico. To find out which parts of the shore have been "impacted" by the spill, we use the "impact grid". This not only gives the users a good idea of the impacted areas but also enables them to understand the difference of the oil concentration in each of those cells (or polygons) with respect to the other polygons. Finally, the user would also be able to compare the different cleanups of the same scenario in one map with the other maps on the screen.

In this section, I will be demonstrating how our SDSS helps the decision makers to explore and analyze the various possible outcomes that arise when a spill occurs by just adjusting the various parameters available on the screen. The collaborators were mainly interested in combining the BLOSOM simulator with the OSCOM model which not only brought together two separate entities, but also helped extensively in making logical and beneficial decisions. One of the main goals here is to be able to reduce the operational costs and other expenses while simultaneously maintaining a high cleanup rate. For the sake of convenience, this system considers only 75%, 80%, 85%, 90%, and 95% cleanup targets. However, other cleanup targets can also be studied.

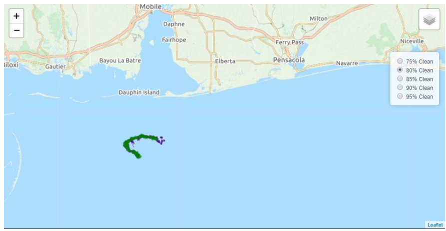
4.0.1 Spill Scenario Details

For this simulation, BLOSOM Version: 3.0.0 b37 was used. The simulation starts on 16th March 2017 at 00:00:00 (hh:mm:ss) UTC and runs for 11 days. The coordinates of the blowout are Lat/Long (WGS84): 30° N −88° E at a depth of -25 m. The blowout diameter is 0.25 m and the blowout angle is 0° altitude, 90° aszimuth. The total runtime of the blowout is 3 days. Here, it has to be noted that the "blowout runtime" is the duration of the blowout alone after which there won't be any blowout occurring i.e. no oil would be ejected anymore whereas the "model runtime" specifies how long the entire simulation lasts which includes how the ejected oil traveled in the ocean even after the blowout stopped. "Random Walk" horizontal diffusion scheme has been employed with a "Smagorinsky Coefficient" of 0.15. The entire simulation is recorded at intervals of 24 hours which would generate output in the form of shapefiles (.shp, .shx, .prj, .dbf).

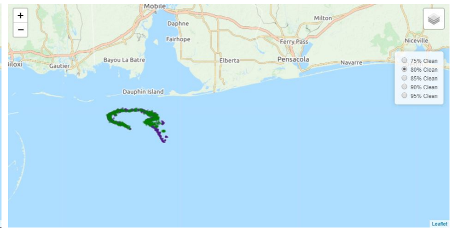
4.1 Exploring the fate of the Spill

Initially, when provided with the system, the first activity of the decision-maker is to explore is the trajectory of the oil spill and the fate of the oil from the day the blowout started till the spill eventually hit the shore (or) most of it has been recovered in such a way that the spill is of no serious threat to the environment and the coastal communities. To study this movement of the oil spill, the decision-maker starts moving the slider forward and backward. This gives the decision-maker a good idea of how the spill advanced over time which can be seen in the Figure 4.1. In this

Figure, 80% cleanup is shown but can be changed to the desired cleanup target by clicking on the corresponding radio button menu on the side. Also, on the overview screen in the beginning, the decision-maker is shown with a lot of entities such as boat ramps, impact grid, ESI tile layer, and the option to view only the cleaned or the uncleaned parcels which he/she can choose to toggle them on/off if need be. The purpose of this toggle feature would be to provide the user with much more clarity and a better view than compared to the one when all the elements are turned on. In the images shown in the later sections, elements that are not necessary to those scenarios have been toggled off for the reader's convenience.



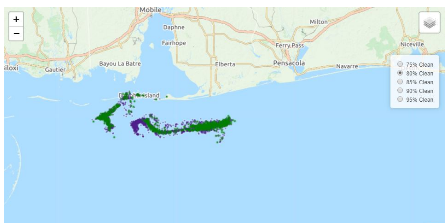
(a) Day 1



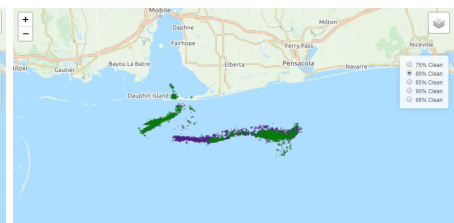
(b) Day 2

(c) Day 3

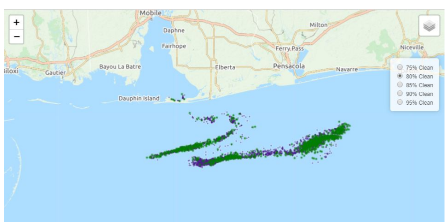
(d) Day 4



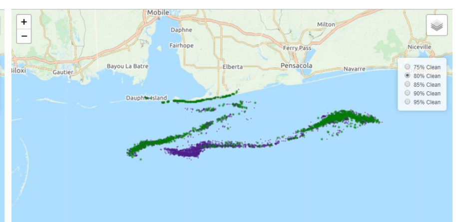
(e) Day 5



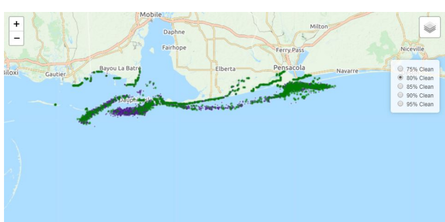
(f) Day 6



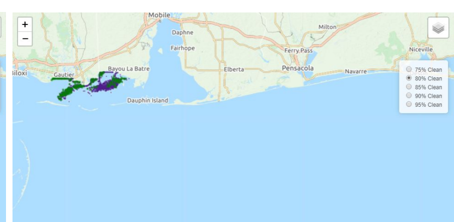
(g) Day 7



(h) Day 8



(i) Day 9



(j) Day 10

Figure 4.1: The above images show the trajectory of the oil spill over a period of 10 days

4.2 Exploring the Cleaned Parcels vs. Uncleaned Parcels for Different Cleanups

After looking at the "Oil Parcels" legend, the decision-maker will understand that the green colored particles are the cleaned oil parcels from the previous day and the purple shaded particles are the uncleaned parcels of the present day. To get a closer look at the oil parcels, the decision-maker starts to roll the mouse button or hits the "+" symbol on the map. After zooming in a few levels, the decision-maker observes that the darker shade of the uncleaned parcels has been replaced by lighter shades of purple as the zoom level increased, similar to a heat map, which in this case serves the purpose of depicting the oil concentration/density in a given region. Also, the decision-maker begins to realize that the entire slick of oil at a higher altitude is actually a collection of points at a deeper level.

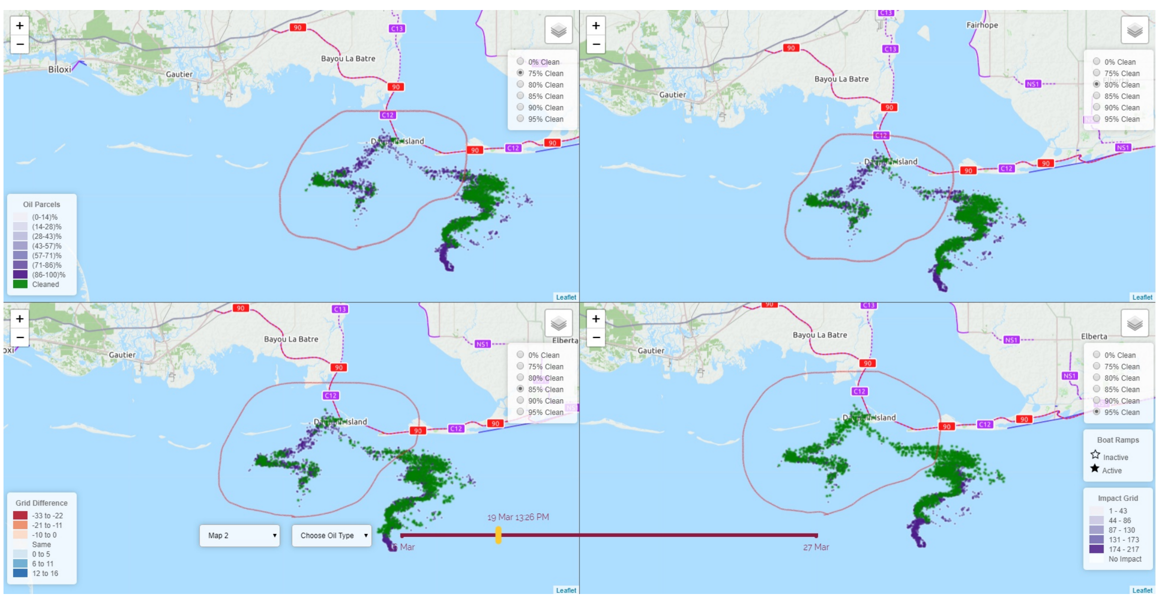


Figure 4.2: An image showing how the number of cleaned oil parcels increases as the cleanup target increases from Map 1 through Map 4 around the area surrounding Dauphin Island

Now, the decision-maker knows that the initial spill shown is the one with 95% cleanup and would be inquisitive to find out how the oil slick at 75% cleanup is different from that of the 95% one on day 9 of the spill. For this, the decision-maker looks at any other map on the screen (preferably the one on the adjacent side) for comparison and clicks on the radio-button menu on that particular map to choose the desired cleanup after moving the slider to day 9. As soon as the decision-maker chooses a cleanup target other than the one on the first map, a quick change in the oil parcels is observed. This is because the data shown on the initial overview screen is the one with 95% clean up target by default and when this changes to a different cleanup target (say 75%), the new data is loaded onto the screen. Let us assume that the decision-maker has a small area of interest in the ocean, or along the coastline of the entire Gulf of Mexico, and would like to explore how the different cleanup targets change. For demonstration purposes, let us consider the area surrounding the Dauphin Island as the decision-maker's area of interest. After comparing the cleaned parcels versus the uncleaned parcels in both 75% and 95% cleanups as shown in Figure 4.2, the decision-maker gets curious to know how the other cleanup targets are different from the ones already chosen. For this, the decision-maker picks two other maps and selects a cleanup target different than the ones already chosen. This way, the decision-maker can compare four out of six cleanup targets that the system offers simultaneously with the help of four different maps present on the screen.

Also, it has to be noted that sometimes, while comparing the cleaned oil in some regions, it may look as if the lower cleanup targets performed better than the higher ones. This is because OSCOM considers the entire oil as a whole and generates the model files which is not necessarily in a spatially uniform manner. That's why though the higher cleanup targets do poor in some regions compared to the lower cleanup targets, they do significantly better than them in most other regions.

4.3 Exploring the Activated Boat Ramps

Once an oil spill is reported to the marine officials, the main environmental-friendly goal and the very first action would be to stop the pollution at its source, Ventikos *et al.* (2004). Therefore, the decision-maker would want to know the set of boat ramps from where the response could be dispatched. It is not advisable to dispatch equipment from all the locations. Though this would ideally clean up almost all the oil, it falls heavy on the operational costs, and other expenses. Rather, it would be a wise decision to send response from only a selected set of locations which ensures that maximum oil is recovered (complete recovery is not practically possible). This not only saves a ton of expenditure, but also saves a lot of man power involved in the recovery process. Now, to visualize those boat ramp locations and the corresponding details of the equipment present at those sites, we made the boat ramp locations as "empty-black star"s and the activated boat ramp locations as "filled-black star"s on the geographical maps, which would change their states depending upon whether they have been activated or not for a particular day.

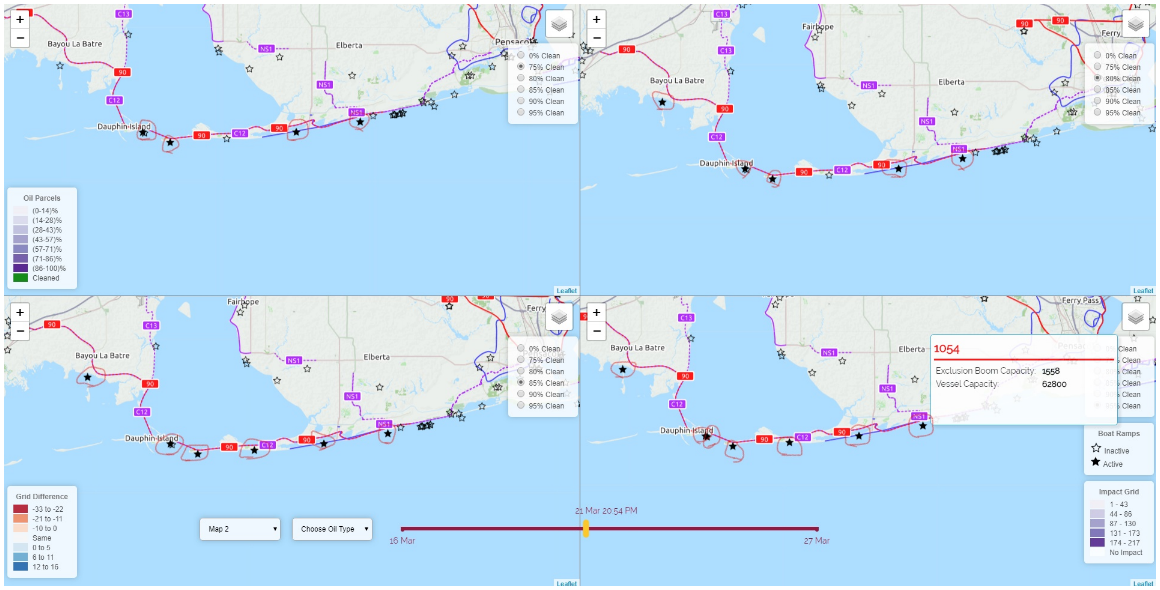


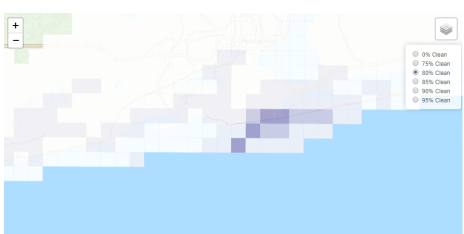
Figure 4.3: An image showing 4,5,6, and 7 boat ramps activated for 75%, 80%, 85%, and 95% cleanup targets respectively around the area surrounding Dauphin Island along with the tool-tip that shows facts about a boat ramp upon hovering over it

The decision-maker moves the slider to the fifth day of the spill and finds out that some of the stars have changed from their hollow state to a filled state and hovers over them. Upon hovering, the decision-maker finds that a tool-tip is shown which displays the information regarding the vessel capacity and the exclusion boom capacity of the boat ramp. This way, not only the location of the boat ramp is known, but also the facts about it are displayed. It is based upon these facts, one can estimate the amount of expenditure required to operate them.

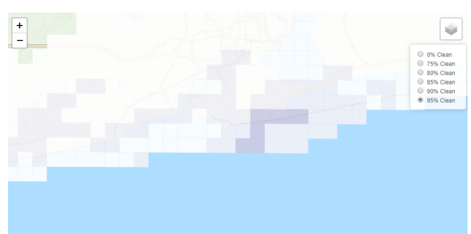
Now, the decision-maker would be interested to find out if there would be any difference in the number of boat ramps dispatched when a different cleanup target is considered on day 5. To know more about it, he chooses a different cleanup target in any of the maps which are neighbors to the one being focused, and tries to compare them side by side. This way, the decision-maker would weigh the trade-offs between the cleanup targets and the number of boat ramps dispatched. Here, the hypothesis is that, in most cases, the number of boat ramps dispatched for response would increase as the cleanup target increases. This is because more number of boat ramps are required to recover more oil thereby achieving a better cleanup target. Just to avoid cluttering, the decision-maker can turn on/off different elements such as the impact grid, the oil parcels, and the ESI layer but keeping only the boat ramps visible. In the above Figure 4.3, it can be clearly seen that when the decision-maker moves the slider to day 5 of the simulation, four boat ramps have been activated for 75% clean up, five for 80% cleanup, six for 85% cleanup, and seven for 95% cleanup targets. This is one example which emphasizes the fact that the number of boat ramps dispatched increases with increase in cleanup target. Other elements of the system have been toggled off for better clarity as shown in the Figure 4.3

4.4 Exploring the Impact of the spill on the shore

The decision-maker's next goal would be to find out where, and in what quantity did the uncleaned oil make it to the shore eventually and thereby "impacting" it. The entire coast of the Gulf of Mexico has been divided into 18478 polygons which formed an imaginary layer called the "Impact Grid" which would help the decision-maker in this process.



(a) Oil concentration on Day 9 of the spill for 80% cleanup



(b) Oil concentration on Day 9 of the spill for 95% cleanup

Figure 4.4: The combination of the above two images clearly shows us how higher cleanup target (b) achieved better cleanup compared to its lower counterpart (a) thereby reducing the oil concentration in the cells

It comes to the notice of the decision-maker that the color of the impact grid in certain regions changes upon dragging the slider to 9th day of the spill, as that is when most of the oil starts to beach. After referring to the legend, the decision maker would know what is the range of concentration of the oil in each of those cells/regions. Since the impact scale is a sequential one, it is easy to understand that the lighter shades of the color refers to lower concentration and the darker shades represent higher concentrations of the oil. When the decision-maker looks at the 80% cleanup, he/she sees a lot of cells in the darker shades in quite some polygons. Since we hypothesize that 95% cleanup provides maximum cleanup, it implies that there are lesser number of uncleaned oil parcels reaching the shore and hence the cells should contain lesser concentration of oil than compared to the lower cleanup targets. To verify this, the decision-maker changes the cleanup to 95% and finds out that the darker shade from the cells has disappeared leaving behind only the lighter shade and hence this hypothesis is proven correct with this evidence as shown in the Figure 4.4

4.5 Exploring the Difference in Impacts for Different Cleanups

The decision maker gets an idea of the region where the oil has impacted the shore and in what concentration from the previous section 4.4. We also saw how the decision maker compared the number of boat ramps activated for different cleanup targets in the section 4.3. Combining these two thoughts, the decision-maker would now be interested to compare how the oil concentration changes in the cells for different cleanup targets and would be interested in comparing them. For this purpose, the decision-maker makes use of the “Baseline Map” feature which would essentially let the decision maker choose one of the four maps on the screen to act as a reference map with which the other neighboring maps can be compared.

Let us suppose that the decision maker has chosen map 2 as the reference map. Now, the next step would be to choose the cleanup target for this map which he/she wants to act as the reference cleanup target. In other words, the decision-maker can compare 95% cleanup with the other maps or can change it to 75, 80, 85, or 90 as per his/her requirement. For example, consider a scenario where the decision maker wants to find out how better the cleanup targets 80%,85%, and 95% have performed over 75%. For this, the decision maker would choose any one map as a baseline map from the drop-down menu at the bottom of the screen and would select the cleanup target of 75%. All the neighboring maps would then be updated with different colors on their respective impact grids depicting how better or worse the cleanup has been, in those regions.

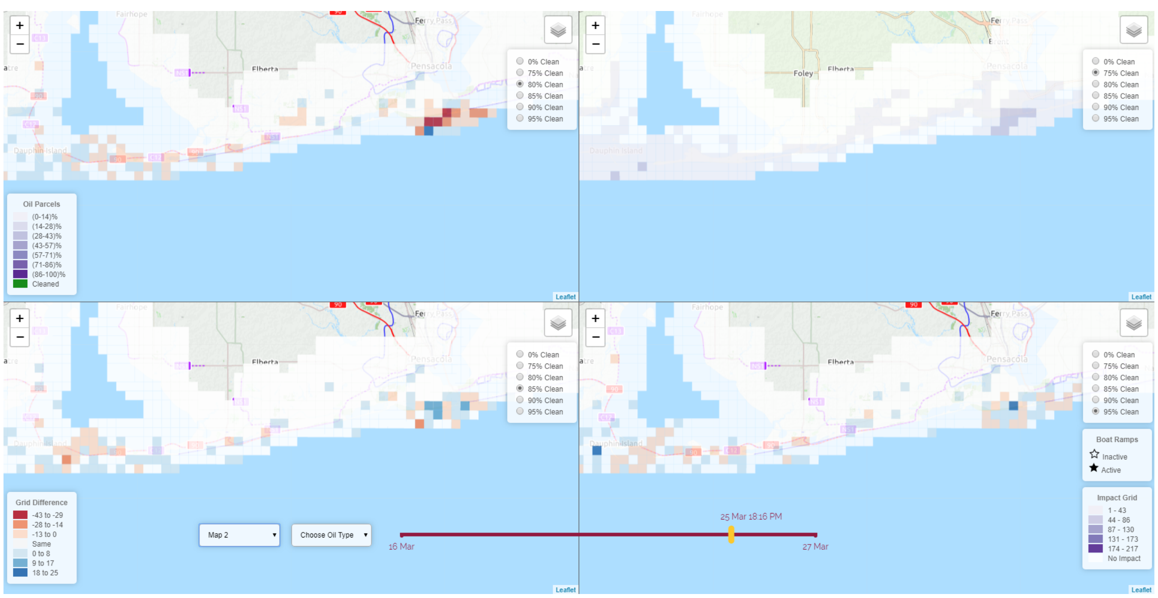


Figure 4.5: Scenario with Map 1, Map 2, Map 3, and Map 4 with 80%, 75%, 85%, and 95% cleanup targets respectively with Map 2 as the baseline selected from the drop-down below. The number of cells with light blue and dark blue shades in 95% is greater than that of 85% which is in turn greater than 80% cleanups

The decision-maker would then get an idea of the difference between cleanups upon referring to the colors listed in the “Grid Difference” legend. Here, the hypothesis is that higher cleanups would recover more oil from the ocean resulting in a better cleanup. Therefore, higher the number of cells with shades of blue, higher is the recovery in those regions and the lesser the number of cells with shades of red, lesser is the recovery when compared to the baseline map. The scenario discussed so far can be seen clearly in the Figure 4.5

Chapter 5

DISCUSSION AND LIMITATIONS

The system developed for this thesis benefits decision-makers in different ways. However, it has to be remembered that not every decision-maker thinks in a same way. For example, a decision-maker who is more interested in saving the environment or is concerned with the hazardous effects of the spill on the coastal communities would want to achieve maximum cleanup possible and would choose the scenario which offers the same. On the other hand, the decision-makers who are concerned with the budget of the oil recovery operations, are more likely to settle for a scenario which would be cost-effective while achieving a decent amount of cleanup and would mostly prioritize the operations based on the sensitivity of the concerned coastal regions. However, if a decision-maker is expecting the SDSS to show a cost estimate of the overall operations would not be interested in using the system because it does not support that requirement yet but it has to be noted that incorporating such models into the system would be beneficial especially if the cost-estimates are accurate and would save the decision-makers a lot of time in calculating the total expenses. This incorporation would also make the SDSS a comprehensive system which not only deals with the spill simulation, and recovery but also with the funds required thereby covering a wide range of decision-makers. Finally, we can say that this coupling of spill modeling (BLOSOM) with a spatial optimizer of tactical response efforts (OS-COM) would greatly enhance the ways in which a spill is handled and mitigate its hazardous effects to a great extent.

Although the SDSS being discussed proves useful in achieving its desired objectives, it still does come with some limitations. In a broad sense, we have seen that OSCOM model (Grubesic *et al.* (2017)) identifies the ideal subset of boat ramps which can dispatch response and achieve the desired cleanup. However, certain real-world conditions such as the waves produced when these vessels go into the ocean to recover the oil which can cause the oil to drift apart from its original location, the changes in temperature due to different times of the day, etc. are not completely considered. The drifting of oil results in a change of its locations ultimately leading us to compute its new locations based on this offset from their original locations and calculate the new set of boat ramps again. In most cases, this drifting is handled partially by BLOSOM (Sim *et al.* (2015)) as it predicts the movement of the oil in the ocean for the specified simulation parameters but does not handle this drift caused by vessels sent out by OSCOM. Though different ambient files (.ncdf) are loaded for every day of the simulation, the parameters specified in the blowout, model, and advanced tabs of the simulator are not changed for every day of the simulation and stay the same through out the blowout but this may not be the case in reality.

OSCOM currently supports interaction only with BLOSOM which restricts the spatial optimization of oil recovery with other modeling tools such as GNOME (Beegle-Krause (2001)) for instance. Also, the results of this model tend to vary significantly if employed at different times of the year given the stochastic nature of Gulf of Mexico. Spill response efforts which often include shoreline protection strategies to ensure the safety of delicate ecosystems currently do not go in to the list of objectives considered by OSCOM.

When it comes to the SDSS, one of the compelling ideas was to develop the system in 3D. The main drawback of this idea is that the coastal impacts of the spill may not be properly visualized. For example, consider a scenario where the impacts of the spill on the coastal areas are implemented as bars (instead of a 2D grid) whose height increases with the increase in oil concentrations. While looking at an oblique angle, the grid cell with highest amount of oil concentrations would have a tall bar thereby overshadowing the grid cell behind it which has a low concentration. Also, in scenarios where there is a data skew, very few bars would be tall leaving most of the other bars short which would not form a proper visualization especially if there are considerable differences between those shorer bars.

Another limitation was the addition of shapefiles into the SDSS. It is easy to represent a shapefile as a tile layer if it is not required to be interactive to the user but the Impact Grid layer for instance, has its grid cells to be colored based on the baseline map selection, the cleanup target specified, and the day of the spill and this is computed for four maps on the screen and hence cannot be represented as a tile layer which limits the speed of the system when the impact grid is turned on. However, the system runs smooth when the impact grid is turned off on all the maps as the need of extra rendering by the browser is eliminated.

Chapter 6

CONCLUSIONS AND FUTURE WORK

In this thesis, a spatial decision support system for oil spill response and recovery for the spills has been presented. This SDSS allows the decision makers to explore a wide variety of possible outcomes that can arise when an oil spill occurs in the Gulf Of Mexico. This system helps in exploring and visualizing the movement of the oil spill with the help of geographical maps with respect to change in space and time. The system also enables the user to identify the set of boat ramps from which response has to be dispatched. The system essentially gets its necessary data regarding the oil spill from BLOSOM and becomes more powerful upon combining it with OSCOM. There has been some notable research in the past in the area of spill modeling and response modeling. However their support has been limited to their domain of either spill modeling or response modeling. There is only a little literature which combines both these facets together in a systematic approach. Our SDSS goes beyond the limitations of the past works by integrating BLOSOM, which forms the heart of our SDSS by providing the necessary shapefiles required to visualize the oil spill, and OSCOM, that adds the cleanup capability to it. Given the expected percentage of oil to be recovered as an input parameter, different scenarios with given cleanup targets can be explored. Additionally, the SDSS helps the user to explore how the shoreline is impacted with the help of an imaginary impact grid along the coast of Gulf of Mexico.

In the case studies, the capabilities of our SDSS to to compare and analyze the cleaned and uncleaned oil parcels, activated boat ramps, and different impacts on the shoreline for different cleanup targets has been demonstrated. In our first case study, we presented how the entire oil spill trajectory and the movement of oil over time and space can be explored. In the second case study, we combined the cleanup capability to the first one and explained how the number of cleaned parcels increase with the increase in the cleanup target. In our third case study, we elaborated on how the number of boat ramps selected for response dispatch increases with the increase in the cleanup target. In our fourth case study, we went on to explain the importance of impact grid by showcasing its power in detecting not only the areas with oil presence but also its concentration by using a sequential color scale. Finally, we demonstrated how the addition of cleanup target parameter can be applied to the impact grid by keeping one map as a baseline map for reference and comparing the others with it for different levels of cleanup. All these cases can be studied for every day of the simulation thereby assisting the decision makers to make decisions at any point of the time during the blowout.

Even though the spill data, boat ramps data, and impact grid datasets have been put together and made into an interactive SDSS, it still has its own limitations. The first limitation is the hypothetical nature of the oil spills. BLOSOM takes many factors such as wind velocity, ocean currents, temperature, salinity, pressure, depth, etc. into consideration to predict the further movement of the oil in the ocean. This data is not real time. However, the argument here is that the spill movement produced in the simulation is almost similar to the real world movement. The authenticity of BLOSOM in this aspect can be confirmed by taking real world oil spill datasets and comparing them with the results produced by BLOSOM for the same oceanic conditions. Since oil spills of large magnitude are rare phenomena, it is difficult to acquire datasets and do this comparison but for sure feasible. The second limitation is the complexity of the shapefiles produced in the later versions of BLOSOM. As complexity and the size of the shapefiles increases, the time taken by OSCOM to generate model files increases drastically which again leads to very high solving times by the commercial solver. Sometimes, the model files ended up in sizes ranging in tens of gigabytes which often resulted in lack of memory even on machines with 64 gigabytes of RAM. If not a memory crash, those model files took more than weeks to be solved which is a very large wait time especially in the real world scenario because the list of boat ramps from where response could be launched would be based on the solution file generated by the solver and it is not a wise thing to wait for weeks to dispatch response when a vast majority of resources are at risk. Third limitation is the infeasibility of some spill simulations. This situation arises when a huge amount of oil than usual is ejected into the ocean from the blowout well and spreads over vast areas quickly due to various oceanic conditions. In such cases, it is almost impossible to recover 95% of the oil that has been spilled which results in infeasible solutions by the solver. However, in real-world scenarios, the recovery and response processes have to be carried no matter the solution is infeasible or not. One workaround for this would be to compromise with lesser clean up targets, say 90% or less whichever proves feasible. Fourth limitation is a follow up of the third one where the oil that has escaped or traveled too far from the clean up sites can be contained or deflected using exclusion booms. For the same purpose, a model named "Exclusion Boom Allocation Model" has been developed. A tight integration of this model with the OSCOM model would most probably reduce the number of infeasible solutions or can at least contain the oil before impacting the shoreline. Fifth limitation lies with the implementation part of the SDSS. Most of the visualization, interaction, and computations happen in the front-end i.e. in the browser. Though, lot of pre-processing of shapefiles, spatial join files, boat ramp files, and impact grid files happens before the data is given to the SDSS, still the Javascript engine of some browsers can handle only so much that they can get slow or lag if the size of the datasets increases drastically. For instance, the impact grid dataset has around 18478 polygons in it which forms a huge part of the browser's memory heap. Upon removing the impacting grid from all the maps using the check boxes, one can feel the difference in the smoothness of the SDSS. Also, for every day of the simulation oil particles emitted would be in thousands, and if this increases to tens of thousands or even worse hundreds of thousands, the system would be really slow as most of the time would be spent in populating the oil parcels on the screen. From these limitations, we can begin to identify the areas of future work.

Future work for this thesis can be categorized into: 1) improvements to the models, and 2) enhancements to the environment that combines and integrates them. Reduced complexity in BLOSOM shapefiles would lead to relatively smaller model files and ultimately shorter periods of time to solve. Also, by coming up with a heuristic in the OSCOM model to generate model files which can aggregate the points in the ocean could improve the solving times of the model files significantly. Also, this would solve the problem of infeasible solutions and would not result in many memory crash scenarios. It is always advisable to employ as many response equipment as possible to mitigate the spread of oil and exclusion booms are one such type of equipment. We strongly believe that the integration of EBAM model to the current system would reduce the number of oil parcels eventually hitting the shore. Coming to the enhancements to the SDSS, we can make sure that the user experience is never compromised by achieving a smooth flow of the interface which could be a result of smaller sized shapefiles, lesser number of oil parcels to be displayed per day that is possible by proper aggregation of points, etc. Also, adding new features to the interface such as having multiple tabs to view different scenarios of spills, and the ability to do a comparison between two different spills,would allow the users to get a better idea of the system.

It has to be noted that BLOSOM is actually a probabilistic model which means that multiple spills simulated with the same parameters are not always the same. To study these differences, it would be a good practice to create an ensemble of spills for the same set of parameters and represent it in the SDSS which helps us to identify the upper and the lower bounds of the spread of the spill for the given parameters. Finally, the system developed and presented in this thesis represents a crucial combination of spill modeling and spatial optimization of response efforts as it gives the users a holistic approach to tackle the problem of planning for oil recovery and response efforts.

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APPENDIX A

IMPACT GRID DATA COMPUTATION

The equation used to calculate the difference between the oil concentration of one grid cell with its corresponding grid cell of the baseline map is:

$$\text{Cleanup Difference} = B_{PC} - R_{PC} \tag{A.1}$$

Consider the following examples where $Cell_A$ is the grid cell of the non-baseline map, and $Cell_{AB}$ is the same grid cell but of the baseline map. Having said that, consider the following examples:

Negative Difference Group:
Say $Cell_A = 20$
$Cell_{AB} = 11$
Therefore the difference = 11-20 = -9

Say $Cell_A = 12$
$Cell_{AB} = 5$
Therefore the difference = 5-12 = -7

Say $Cell_A = 24$
$Cell_{AB} = 6$
Therefore the difference = 6-24 = -18

Say $Cell_A = 32$
$Cell_{AB} = 2$
Therefore the difference = 2-32 = -30

Positive Difference Group:
Say $Cell_A = 3$
$Cell_{AB} = 5$
Therefore the difference = 5-3 = 2

Say $Cell_A = 3$
$Cell_{AB} = 12$
Therefore the difference = 12-3 = 9

Say $Cell_A = 3$
$Cell_{AB} = 24$
Therefore the difference = 24-3 = 21

Say $Cell_A = 1$
$Cell_{AB} = 20$
Therefore the difference = 20-1 = 19

So if the difference is positive, it means that the baseline map has done worse or the reference map has done better. On the other hand, if the difference is negative, it means that the reference map has done worse than the baseline map or the baseline map has done better than the reference map. As we are using a divergent color scheme with three classes representing a positive difference, and three of them representing negative difference, while the remaining one class represents no difference, we decided to split the entire positive difference range into three equal intervals where each of them shows the specific ranges where a given difference may lie. Similarly, for the negative difference, we divided the entire negative difference range into three equal intervals. However, since this difference changes with respect to the change in the baseline map, we re-compute this difference and re-calibrate the legend based on the new difference obtained.

On the third day of the simulation, these are the values for the polygon ID 8516, 14658, and 16815.

Polygon_ID	CURR_TIME	Count	Cleanup
8516	2017-Mar-19 00:10:00	8	75%
8516	2017-Mar-19 00:10:00	3	85%
8516	2017-Mar-19 00:10:00	2	95%

Table A.1: Polygon 8516 on Mar 19

Polygon_ID	CURR_TIME	Count	Cleanup
14658	2017-Mar-19 00:10:00	27	75%
14658	2017-Mar-19 00:10:00	15	85%
14658	2017-Mar-19 00:10:00	7	95%

Table A.2: Polygon 14658 on Mar 19

Polygon_ID	CURR_TIME	Count	Cleanup
16815	2017-Mar-19 00:10:00	24	75%
16815	2017-Mar-19 00:10:00	20	85%
16815	2017-Mar-19 00:10:00	3	95%

Table A.3: Polygon 16815 on Mar 19

From the above Tables A.1, A.2, and A.3 can see how the count of number of oil parcels decreased as the cleanup target increases on March 19th.

On the sixth day of the simulation, these are the values for the polygon ID 11748, 14937, and 17558.

Polygon_ID	CURR_TIME	Count	Cleanup
11748	2017-Mar-22 00:10:00	16	75%
11748	2017-Mar-22 00:10:00	13	85%
11748	2017-Mar-22 00:10:00	11	95%

Table A.4: Polygon 11748 on Mar 22

Polygon_ID	CURR_TIME	Count	Cleanup
14937	2017-Mar-22 00:10:00	22	75%
14937	2017-Mar-22 00:10:00	15	85%
14937	2017-Mar-22 00:10:00	10	95%

Table A.5: Polygon 14937 on Mar 22

Polygon_ID	CURR_TIME	Count	Cleanup
17558	2017-Mar-22 00:10:00	4	75%
17558	2017-Mar-22 00:10:00	4	85%
17558	2017-Mar-22 00:10:00	3	95%

Table A.6: Polygon 17558 on Mar 22

From the above Tables A.4, and A.5, we can see how the count of number of oil parcels decreased as the cleanup target increases on March 22nd. However, in Table A.6, there is no change in cleanup from 75% to 85%. This is probably because the cleanup is significant in other polygons.

On the ninth day of the simulation, these are the values for the polygon ID 9960, 12883, 13808, 10487, 14494, 15679, 9716, 16605 and 17136.

Polygon_ID	CURR_TIME	Count	Cleanup
9960	2017-Mar-25 00:10:00	82	75%
9960	2017-Mar-25 00:10:00	74	85%
9960	2017-Mar-25 00:10:00	58	95%

Table A.7: Polygon 9960 on Mar 25

Polygon_ID	CURR_TIME	Count	Cleanup
12883	2017-Mar-25 00:10:00	23	75%
12883	2017-Mar-25 00:10:00	19	85%
12883	2017-Mar-25 00:10:00	14	95%

Table A.8: Polygon 12883 on Mar 25

Polygon_ID	CURR_TIME	Count	Cleanup
13808	2017-Mar-25 00:10:00	37	75%
13808	2017-Mar-25 00:10:00	28	85%
13808	2017-Mar-25 00:10:00	17	95%

Table A.9: Polygon 13808 on Mar 25

From the above Tables A.7, A.8, and A.9 we can observe that 95% target performs much better than its 75%, and 85% competitors.

Polygon_ID	CURR_TIME	Count	Cleanup
10487	2017-Mar-25 00:10:00	21	75%
10487	2017-Mar-25 00:10:00	21	85%
10487	2017-Mar-25 00:10:00	20	95%

Table A.10: Polygon 10487 on Mar 25

In the Table A.10, we can see that 75%, and 85% have performed similarly but 95% has still outdone both of the other targets.

Polygon_ID	CURR_TIME	Count	Cleanup
14494	2017-Mar-25 00:10:00	30	75%
14494	2017-Mar-25 00:10:00	40	85%
14494	2017-Mar-25 00:10:00	43	95%

Table A.11: Polygon 14494 on Mar 25

In the Table A.11, we can see that 75% has performed much better than 85%, and 95%.

Polygon_ID	CURR_TIME	Count	Cleanup
15679	2017-Mar-25 00:10:00	24	75%
15679	2017-Mar-25 00:10:00	32	85%
15679	2017-Mar-25 00:10:00	29	95%

Table A.12: Polygon 15679 on Mar 25

In the Table A.12, we can see that 75% has performed better than 85%, and 95% but 95% has done better than 85%.

Polygon_ID	CURR_TIME	Count	Cleanup
9716	2017-Mar-25 00:10:00	23	75%
9716	2017-Mar-25 00:10:00	16	85%
9716	2017-Mar-25 00:10:00	17	95%

Table A.13: Polygon 9716 on Mar 25

In the Table A.13, we can see that 85% has done better than 75%, and 95%.

Polygon_ID	CURR_TIME	Count	Cleanup
16605	2017-Mar-25 00:10:00	49	75%
16605	2017-Mar-25 00:10:00	42	85%
16605	2017-Mar-25 00:10:00	49	95%

Table A.14: Polygon 16605 on Mar 25

In the Table A.14, we can see that 85% has done better than 75%, and 95% but it has to be observed that 75%, and 95% have achieved the same amount of cleanup in those cells.

Polygon_ID	CURR_TIME	Count	Cleanup
17136	2017-Mar-25 00:10:00	4	75%
17136	2017-Mar-25 00:10:00	4	85%
17136	2017-Mar-25 00:10:00	4	95%

Table A.15: Polygon 17136 on Mar 25

In the Table A.15, we can see that all of 75%, 85%, and 95% have achieved same amount of cleanup.

The discrepancies in the cleanup performance on March 25th arose because of the non-uniformity in the spatial optimization of response efforts. In other words, we can say that oil recovery need not be the uniform across all the cells of the grid. This means that the usual assumption of 95% recovering more oil than 85%, and 85% recovering more oil than 75% may not be always true. This is because even though 95% may not recover more oil than its counterparts in the Tables A.11, A.12, A.13, A.14, and A.15 it has recovered way more oil in the Tables A.7, A.8, and A.9. From this we can say that it is the overall amount of oil recovered by each cleanup target on the whole that matters but not whether if the recovery is spatially uniform where higher cleanup targets perform better than its lower counterparts in every cell of the grid.