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Factors Affecting Oil Spill Quantity Released in Arctic Conditions: Alaska, U.S.A.

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Abstract: Environmental spill response of oil and hazardous substances has become more significant in recent years. Environmental spills cause negative ecological, economic, and socioeconomic impacts, especially in Arctic conditions. Numerous factors have the potential to contribute to an environmental spill or disaster, such as facility type, location, substance type, source type, and various others. The purpose of this study is to understand which factors affect the quantity of gallons of oil released during a spill incident; this is important to help reallocation of resources to mitigate impacts. For this research, a total of 6,313 records and thirty-one environmental related variables were analyzed from spill response logs collected by State of Alaska Environmental Protection Specialists and Technicians. The data were collected from a public database designed by the State of Alaska, Department of Environmental Conservation (ADEC). In this study, variables such as Pipe source, Drums/Containers (Other), Process Water and Hazardous Substance were found to be contributing factors to the number of gallons of a pollutant spilled. Overall. this paper provides support for local government agencies to prioritize causes, allocate resources, and enforce regulations specific to factors that increase the quantity released.

Keywords: Spill Response, Arctic, ADEC, SPAR, Regression Analysis

1. Introduction

There is a specific and significant need to quantify and interpret results from spill response in arctic environments (Wilson, et al. 2018, Bullock et al., 2019). Contingent upon the type of material and amount of material spilled, there can be millions of dollars spent in clean-up costs, impacts to various types of species, and an unquantifiable amount of ecological damage (Nixon and Michel, 2015). Alaska, United States of America, provides a unique and specific opportunity to investigate oil spill data, as there are environmental circumstances that make the location ecologically distinct from the rest of the world.

There is a high importance to continue to catalog spills that occur and to further understand the ways we can remediate areas based on a variety of substances (Sharma and Schiewer, 2016). Over the past century, more than seven million tons of oil has been spilled into the environment (Bullock, et al., 2019). Specifically, in Valdez, Alaska, an infamous oil spill, more commonly known as the 'Exxon Valdez oil spill' became one of the most highly publicized environmental accidents to date and has lasting effects on the environment (Nixon and Michel, 2015). If this oil spill had not been responded to and/or remediated, the environmental, economic, and socioeconomic losses would have been even more significant.

The State of Alaska utilizes their Department of Environmental Conservation (ADEC) to perform many duties and provide state wide assistance to protect and import the state's natural resources. Specific to active spill response, the Division of Spill Prevention and Response (SPAR) prevents spills of oil and hazardous substances, prepares for when a spill occurs, and responds rapidly to protect human health and the environment (Spill Prevention and Response, 2022). Within the Division of SPAR is the Prevention Preparedness and Response Program (PPR) which protects public health, safety and the environment by preventing and mitigating the effects of oil and hazardous substance release and ensuring their clean up (Alaska Department of Environmental Conservation, 2022). PPR is on the frontlines of spill response in the state of Alaska and their extensive data set was used for research in interpreting the results of this study.

PPR uses numerous variables when recording data for environmental spills in the state of Alaska. By prioritizing spill cleanup based on the most important variables, it will have the most significant positive impact to the environment, as well as economic and socioeconomic factors. To determine and establish which variables were most statistically significant, multiple linear regression model was used to find the correlation between many variables and the quantity of pollutant released. Pipe source, Drums/Containers (Other), Process Water and Hazardous Substance were found to be statistically significant and positive contributing factors to gallons released.

Communities respond to environmental spills and disasters differently and in a multitude of ways (Himes-Cornell, et al., 2018). This research paper is important because it can aid in narrowing the focus and prioritize variables related to spill response.

2. Background

There are many variables that need to be considered when interpreting environmental spills in the Arctic. Spills, including oil, could create extensive ecological change coupled with the vastness of hardships organisms already face in the wake of climate change (Wilson, et al. 2018). Even after twenty years, the Exxon Valdez oil spill demonstrated evidence of long-term impacts on certain species (Nixon and Michel, 2015). The Exxon Valdez oil spill leaked 40.8 million liters of oil which impacted various species, caused millions of dollars in cleanup costs, and an intangible amount of ecological damage (Nixon and Michel, 2015).

Due to lower temperatures, harsher environments, low salinity, remote locations, and frozen soils, bioremediation is not always possible in the state of Alaska (Sharma and Schiewer, 2016). Seasonality also plays a role in the ecological change that a spill could potentially disrupt. If an oil spill occurred in warmer months, the spill material could be refrozen and stored in ice during the winter, only to create different ecological issues and remedial barriers at a later date (Wilson, et al. 2018). Additionally, due to lower temperatures in Alaska, hydrocarbon products volatilize at a lower-than-average rate, which increases the persistence of the pollutant in the environment. Therefore, biodegradation would take longer in arctic conditions (Sharma and Schiewer, 2016). As shown in Afenyo, Veitch, & Khan's (2016) study, illustrated response and contingency planning of an oil spill in ice-covered waters is significantly different than an area in warmer climates. The transport of oil through frozen or colder waters is much slower and requires a unique approach (Afenyo, Veith & Khan, 2016).

It is increasingly important that release of fuel in the Arctic tundra does not occur for many reasons, but a significant reason is the permafrost. A permafrost zone has different characteristics than soil because of the properties contained in the substrate. Additionally, when permafrost and/or soil is removed in a remedial action, due to contamination, the permafrost will affect the surrounding ecosystem, which is not easily corrected. Due to permafrost's fragile nature, it does not regenerate and will thaw when exposed. This high level of thermokarsting and erosion makes establishment of vegetation nearly impossible. This ultimately limits the amount of food sources for a variety of organisms, causing shifts in the environment (Barnes, 2016).

On top of environmental effects, there is also a need to understand spill response from a socioeconomic perspective. In the state of Alaska, the fishing industry and vessel transport bring significant economic value (more than $4 billion USD in sales annually) (Beaudreau, et al. 2019). A large oil spill can cripple the main income source for most of Alaskans and disrupt a vital cultural and subsistence source of Native communities in the area. Beaudreau, et al. (2019) explain that fisheries in Alaska are dynamic and research shows the Exxon Valdez oil spill caused fisheries to create more diverse species portfolios and substantial losses to commercial fishers in 1989. There is a positive correlation to overlap needs for environmental, socioeconomic, and regulatory pressures that shape fishery participation and diversification (Beaudreau, et al. 2019).

There are numerous previous studies that research oil spills and Arctic environments after the spill has occurred. However, there is a limited amount of research performed specifically to the state of Alaska spill response and even less with a proactive response. Many studies use linear regression for modeling variables not examined within this study, such as the following relationships: carbon system variability in the Northern Gulf of Alaska (Evans, et al., 2013), red tides, and oil spills (Liu, et al, 2021), Arctic freshwater content and atmospheric circulation (Johnson, et al. 2018) and polycyclic aromatic hydrocarbons and the volume of oil spills (Hong, et al. 2020).

These studies show the environmental applications of multiple linear regression. For instance, Nixon and Michel (2015) identified the predictor variables that significantly contributed to a study using predictive modeling. The predictor variables, boosted regression trees, tree-based models and nonlinearities were used to study each variable in the shoreline oil presence models. Another study performed by Wenning, et al. (2018) explains that planning strategies are developed through exposure, vulnerability, and recovery of Arctic ecosystems, and methods for spill impact mitigation assessments in the Arctic support analysis of potential consequences of oil spills. Mohammadiun, et al. (2021) created a fuzzy decision tree and regression based on oil spill response in the Arctic. This research used linear regression and applied frameworks to make decision trees possible to ensure proficient performance. Numerous variables were used to see the influences they had on the environment, such as type of spilled oil and remoteness of location. Regression modelling was used by Muhammad and Frost (2020) to determine oil spill cleanup cost estimation. This filled the gap in economic value or clean-up. The majority of this data is useful in knowing what to do reactively. However, there is still a significant gap in the literature that does not show the proactive use

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of multiple linear regression on environmental spills. This study can help fill gaps in the research pertaining to proactive actions in reducing oil spills and utilizing this data by focusing efforts on the statistically significant positive variables.

3. Methodology and Results

3.1 Data Collection and Transformation

In this study, data was collected from SPAR/PPR's public database. The query application searches the statewide oil and hazardous substance spills database. This data is collected and entered by SPAR employees who are alerted to spills across the state of Alaska. All data was collected from July 1, 1995 (the start of the database) until March 1, 2022.

56,080 records were collected from individual spill response records within the state of Alaska. Data cleaning and transformation of these records occurred to remove highly correlated variables (such as Area and SubArea). Several fields were eliminated due to specific site information utilized by SPAR employees. More frequently occurring factors were included to help understand the correlation with the quantity of spills released. The categories shown in Table 1 illustrate the variables used in this analysis and contributed to the linear regression. The final data set included 6,313 individual spill response records.

Table 1. Spill Response Data Variables.

Attribute	Description	Value	Field Summary
Quantity Released (Y)	Result of the number of gallons of a pollutant spilled	Continuous	Minimum: 0.001 Maximum: 135,000 Mean: 209.13 Standard Deviation: 3526.67
Facility Type (X1)	Type of facility the spill occurred at	Categorical	Air Transportation, Gas Station/Highway Maintenance Station, Harbor/Port/Marina, Mining Operation, Oil Production, School/Residence, Vehicle, Vessel
Source Type (X2)	What was the source of the spill	Categorical	Drum(s)/Containers, Other
Location (X3)	Type of location spill occurred at	Categorical	Facility or Site
SubArea (X4)	Where the spill occurred	Categorical	Aleutian, Bristol Bay, Cook Inlet, Interior Alaska, Kodiak Island, North Slope, Northwest Arctic, Prince William Sound, Southeast Alaska, Western Alaska
Substance Type (X5)	What substance was spilled	Categorical	Crude Oil, Extremely Hazardous Substance, Hazardous Substance, Non-Crude Oil, Process Water, Unknown
Cause Subtype (X6)	Why did the spill occur	Categorical	Equipment Failure, Human Error, Leak, Line Failure, Overfill, Seal Failure, Valve Failure

3.2 Linear Regression

Alteryx, and end to end data analytics program was used to conduct regression analysis for the collected spill response data. Initially, categorical data was converted into numerical data using one hot encoding method. Then, an Ordinary Least Squares Regression Model was built to understand the relationship between spill response data variables and the quantity release (gallon of oil spilled).

The linear regression model can be shown as the following equation, where βs are regression coefficients and the Xs are predictors. The importance of this equation is to include all necessary variables to determine what influences the quantity of spills released.

$$lm = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots \beta_k X_k + \epsilon \tag{1}$$

where, lm is the linear regression of the dependent variable, $X_i \dots k$, are the variables being analyzed and ϵ is the Error of the variance that cannot be explained by the model.

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4. Results

When including all the variables listed in Table 1., the results from the regression analysis showed the model is statistically significant with a p value of less than 0.05. Table 2. Shows the regression summary from the linear regression model. The R squared value explains how much variance in Quantity Released can be explained by the combination of all these variables in the model. 2.58% (R^2) of the model can be explained when including all variables in the equation. It is expected that the R squared value is lower due to the number of variables that correlate to oil spills. There are many variables that affect the released quantity which can work together and/or separately. Chen, et al. (2020) demonstrated that human errors, equipment failures, accident processes, and lack of preparedness can affect the affected the Sanchi oil spill in 2018. Even though their study focused on one specific spill, they still examined twenty variables that could have affected why the spill occurred and how much oil was released (Chen, et al., 2020). The adjusted R squared (R^2) shows a decreased R squared value based on any additional variables that might be added. The F value demonstrates where there is a relationship between our predictors and the response variable, F(6280)=5.36, $p < 2.2e^{-16}$.

Table 2. Regression Summary.

R^2	Adjusted R^2	F	Pr (>|t|)
0.02578	0.02097	5.36	< 2.2e-16

To test for multicollinearity, which looks at strong intercorrelated variables, the variance inflation factor (VIF) test was performed. If two or more variables are strongly correlated it may cause serious difficulty with the model parameters. If the VIF test demonstrates a smaller the VIF value, the less multicollinearity in the variables (Aylin, 2010). For this research, all VIF values were considered acceptable (minimum: 1.0140, maximum: 7.6502, mean: 1.9907).

When examining the linear regression model, several categorical variables did not demonstrate statistical significance. Table 3. shows the output values for each categorical variable. The estimate, or coefficient, illustrates the direct numerical value of influence given to the linear regression model. Equipment Failure, Human Error, Leaks, Valve Failure, Drums/Containers (Other), Pipe or Line, Hazardous Substance, and Process Water demonstrated a statistically significant correlation with quantity released.

Table 3. Linear Regression Anova Table.

Variable	Sum Sq	F value	Pr (>|t|)
(Intercept)			0.26492
Cause_SubType_Equipment_Failure	55380837.82	4.55	0.03299
Cause_SubType_Human_Error	162456805.41	13.34	0.00026
Cause_SubType_Leak	95459198.13	7.84	0.00513
Cause_SubType_Overfill	28804804.59	2.37	0.12409
Cause_SubType_Seal_Failure	8074539.31	0.66	0.41549
Cause_SubType_Valve_Failure	66487171.47	5.46	0.01949
Facility_Type_Air_Transportation	379586.55	0.03	0.85986
Facility_Type_Gas_Station_Highway_Maintenance_Station	1508392.51	0.12	0.72488
Facility_Type_Harbor_Port_Marina	145452.45	0.01	0.91297
Facility_Type_Oil_Production	25366029.69	2.08	0.14898
Facility_Type_School_Residence	1767854.02	0.15	0.70319
Facility_Type_Vehicle	6347525.66	0.52	0.47032
Facility_Type_Vessel	3256107.66	0.27	0.60509
LocationData_Site	925626.07	0.08	0.78278
Source_Type_Drums_Containers__Other	73443626.59	6.03	0.01408
Source_Type_Hydraulic_HVAC_System	9486516.59	0.78	0.37746
Source_Type_Pipe_or_Line	192672476.83	15.82	7e-05
SubArea_Aleutian	10014988.45	0.82	0.36449

Variable	Sum Sq	F value	Pr (>|t|)
SubArea_Bristol_Bay	4895058.37	0.4	0.52608
SubArea_Cook_Inlet	25150436.7	2.07	0.15072
SubArea_Interior_Alaska	25.3	0	0.99885
SubArea_Kodiak_Island	6544363.54	0.54	0.46352
SubArea_Northwest_Arctic	5239409.35	0.43	0.51187
SubArea_Prince_William_Sound	2706873.17	0.22	0.63731
SubArea_Southeast_Alaska	8731724.18	0.72	0.39713
SubArea_Western_Alaska	2173665.92	0.18	0.67267
Substance_Type_Crude_Oil	20486271.28	1.68	0.19465
Substance_Type_Extremely_Hazardous_Substance	43335.14	0	0.95243
Substance_Type_Hazardous_Substance	88454238.58	7.26	0.00705
Substance_Type_Process_Water	854389779.66	70.17	< 2.2e-16
Substance_Type_Unknown	292100.58	0.02	0.87692

5. Discussion

The linear regression model demonstrated there is a minimal correlation to all the variables and the quantity of pollutants released but is still statistically significant. However, some variables showed a stronger correlation than others. A total of thirty-one categorical variables were considered in the model. In this model, eight out of thirty-one showed to be statistically significant, both negatively and positively.

When compared to the respective dummy variables, the following variables were considered statistically significant: Substance Type Process Water, Substance Type Hazardous Substances, Source Type Pipe or Line, Source Type Drum(s)/Containers, Other, Cause Subtype Valve Failure, and Cause Subtype Leak, Cause Subtype Human Error, Cause Subtype Equipment Failure.

For instance, the coefficients for Cause SubType Equipment Failure, Cause SubType Human Error, Cause SubType Leak, Cause SubType Valve Failure showed a negative correlation to quantity released when compared to Line Failure. While Source Type Drum(s)/Containers, Other, Source Type Pipe or Line showed a positive correlation to quantity released when compared to Heavy Equipment. Substance Type Hazardous Substance and Substance Type Process Water showed a positive correlation to quantity released when compared to non-crude oil. When reviewing the data from an environmental science field, the positive correlation data makes sense in a logical manner. When a spill occurs from the Source Type: Pipe or Line, there is often a large volume of pollutants released due to continuous flow. This would support the idea that more gallons of pollutant occur when there is a spill from a pipe or a line; therefore, making the coefficient larger. A similar idea can be seen in hazardous substances (which are conventionally transported in large drums for disposal) and process water (disposed of in large amounts.) Simply put, the addition of process water and pollutants from line or pipe showed the most significant positive correlation to quantity released (holding all other variables constant), adding 2011.97 and 539.56 gallons, respectively, as opposed to non-crude oil and heavy equipment. Chen et al., (2020) demonstrated that human error was a statistically significant and positively increasing variable when evaluating a specific oil spill from a tanker collision. However, in this study, human error is statistically significant but shows a negative impact on quantity released. It is important to illustrate that the database chosen utilizes spill response for the entire State of Alaska and includes many variables which contribute more heavily than human error.

Interestingly, all statistically significant Cause SubTypes showed negative correlation to the quantity released as opposed to line failure. Additionally, analysis of Cause SubTypes is specifically needed to ensure a full understanding of how this affects the quantity of pollutants released. None of the Facility Types or SubArea variables were considered statistically significant when compared to Mining Operations and North Slope, respectively, which can demonstrate that the type of facility and location of the spill contributes minimally to the quantity of pollutant released. This is an interesting finding, as facility type differs greatly in the state of Alaska. Facility type and location would both make a difference in the quantity of spill released into the environment. Spill response studies for facilities in Newfoundland showed that location is an important factor in oil spill emergencies (Verma, Gendreau & Laporte, 2013). However, the linear regression model did not support this idea. More research is needed to verify this finding and conclude that facility type and location do not have a relationship with the quantity released.

Spill response is needed for both proactive and reactive protection of the environment. Due to the seemingly infinite variables affecting spill response, multiple linear regression is needed to determine statistically significant categorical variables. The research demonstrates that the main contribution to the quantity of pollutants released is the release of process water and

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hazardous substances and pollutants coming from end of pipe or a line. Logically, these results make sense in an environmental setting due to the volume used in each application.

By looking at the variables that cause spills in the State of Alaska, more resources can be allocated appropriately. For example, in this study it was demonstrated that pollutants coming from a pipe or line contributed heavily to the quantity released when compared to heavy equipment. This means more resources and/or regulations could be placed to help pipe or line areas where spill response may occur. When looking at the negatively correlated variables, such as equipment failure, there should be more resources given to the reference point, line failure. Previously, most spill response data can be viewed as reactive in evaluating spills that have already occurred and how they affected the environment (Afenyo, et al., 2016; Barnes, 2016; Beaudreau, et al., 2019). The research performed in this paper is reactive with the application to be proactive. Spill response studies are significantly important across the world, but specifically remote locations like the Arctic. This study showed that location is not a statistically contributing factor to quantity released when comparing it to the reference point. However, Nixon and Michel (2015) observed that proximity to previous oil spills (such as Exxon Valdez) may still contain residues and persist longer in the environment.

6. Conclusion

This study's research can be useful to allocate resources to efforts, laws and/or regulations that incorporate the statistically significant variables into policies, regulations, or even environmental focuses. It is likely that this dataset could be further studied by just using a portion of the data, focusing on a fewer number of variables, or using different reference points. Additionally, future research is needed to see if other variables exist outside of the ones monitored by ADEC. This could allow both independent and government agencies to proactively be involved in variables that are statistically significant.

Limited studies on spill response data in the Arctic conditions have been performed. By looking at ADEC/SPAR spill response data, spills may be minimized and the impact to the environment, economy and socioeconomic factors lessened. Many of the relevant previous studies look at reactions to oil spills but do not consider proactive approaches. There are gaps in knowledge of which variables have a significant correlation to spills. This research paper aims to close that gap and provide variables that are statistically significant. However, this research is based upon ADEC/SPAR's dataset. For some recent spills, data may not have been entered yet or may not be complete. The data presented is provisional and subject to ongoing quality assurance/quality control for accuracy of the data.

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