# A Predictive Analytical Model for Predicting Munitions Surface Clearance Decontamination Activities

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## Dedication

The author wishes to dedicate this work to his entire family, beginning with my wife Lynne, my three children; Bianca, Christopher, Nicholas, and my two dogs Stormy and KoKo, who patiently waited by my side every minute while I worked, and especially to my parents, who are not physically here today but are here in spirit. My parents have blessed me with the perseverance to achieve my goals, no matter how long it takes. My entire family has given me support, understanding, and has been very patient with me seeking higher education goals while having to sacrifice their time and giving up the joy of many family events and vacations to support me in the pursuit of this terminal degree. Without their loving support, sacrifices, and devotion, it is very unlikely that this would have been possible to achieve.

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**Abstract of Praxis**

**A Predictive Analytical Model for Predicting Munitions Surface Clearance Decontamination Activities**

Unexploded ordnance contamination in the United States and its Territories has emerged as one of the nation's most significant environmental problems in 2001 and remains a serious environmental concern today. The locations, quantities, depths, and types of munitions remaining and areal extent of contamination at former live-fire training sites are currently unknown and unaccounted for. Site decontamination cleanup often takes longer to complete, necessitates more regulatory attention, and requires significantly more financial investment than anticipated.

The objective of this praxis was to develop a predictive analytics model using multiple regression techniques as a tool for project managers, program managers, field supervisors, and decision makers engaged in munitions response action planning, estimating, and field operations. The application to assist project and program managers in predicting munitions surface clearance rates for the clearance and decontamination of munitions items and munitions-related debris is aimed to support pre-bid decision making in acquisition opportunities, resource and operations planning, and management of ongoing field operations for surface decontamination activities. A forecasting tool will provide for additional risk management oversight to help minimize estimating and operational risks. The model examines the munitions response predictor variables that are significant or not significant in predicting the weekly number of surface acres decontaminated of munitions and munitions-related contamination. Model fitting

procedures converged upon a final model able to be used to predict surface acre clearance.

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## Glossary of Acronyms

| | |
|---|---|
| AAR | After Action Report |
| AIC | Akaike Information Criterion |
| AOC | Area of Concern |
| AR | Administrative Records |
| ARAR | Applicable or Relevant and Appropriate Requirement |
| AQ | Acquisition |
| ATG | Air-to-Ground |
| ASN I&E | Office of Assistant Secretary of the Navy (Installations and Environment) |
| AT&L | Office of the Under Secretary of Defense (Acquisition, Technology |
| ASR | Archive Search Reports |
| BIC | Bayes Information Criterion |
| BIP | Blow in Place |
| BRAC | Base Realignment and Closure |
| CAP | Corrective Action Plan |
| CERCLA | Comprehensive Environmental Response Compensation and Liability Act |
| CPEO | Center for Public Environmental Oversight |
| CTC | Cost to Complete |
| CTO | Contract Task Order |
| CQC | Contractor Quality Control |
| CWM | Chemical Warfare Material |
| DDESB | Department of Defense Explosives Safety Board |
| DEP | Department of Environmental Protection |

| | |
|---|---|
| DEQ | Department of Environmental Quality |
| DERP | Defense Environmental Restoration Program |
| DFAR | Defense Federal Acquisition Regulations |
| DGM | Digital Geophysical Mapping |
| DMM | Discarded Military Munitions |
| DoD | Department of Defense |
| DOI | Department of Interior |
| DON | Department of the Navy |
| DQO | Data Quality Objective |
| EBS | Environmental Baseline Survey |
| EE/CA | Engineering Evaluation/Cost Analysis |
| EHE | Explosive Hazard Evaluation |
| EM | Electromagnetic |
| EMM | Earth Moving Machinery |
| EOD | Explosive Ordnance Disposal |
| EPA | U.S. Environmental Protection Agency |
| EPCRA | Emergency Planning and Community Right-to-Know Act |
| ERA | Expanded Range Assessment |
| ERB | Environmental Restoration and BRAC |
| ER,N | Environmental Restoration, Navy |
| ESS | Explosives Safety Submission |
| ESTCP | Environmental Security Technology Certification Program |
| EZ | Exclusion Zone |

| | |
|---|---|
| FAR | Federal Acquisition Regulations |
| FFA | Federal Facility Agreement |
| FS | Feasibility Study |
| FUDS | Formerly Used Defense Site |
| FY | Fiscal Year |
| GAO | Governmental Accounting Office |
| GIS | Geographic Information System |
| HE | High Explosive |
| IR | Installation Restoration |
| IRA | Interim Remedial Action |
| IRP | Installation Restoration Program |
| ITRC | Interstate Technology Regulatory Cooperation |
| LTM | Long Term Monitoring |
| LTMgt | Long Term Management |
| LTO | Long Term Operation |
| LUC | Land Use Control |
| MEC | Munitions and Explosives of Concern |

# Chapter 1: Introduction

Unexploded Ordnance (UXO) contamination in the United States and its territories emerged as one of the nation's most significant environmental problems more than three decades ago. The number of former defense sites across the United States requiring the cleanup of UXO and the cost to complete the cleanup of these sites continues to grow. There has been almost a 300% increase in the number of sites added to the Military Munitions Site Inventory since 2002 (DoD, 2015). Although the Department of Defense (DoD) has made progress in cleaning up 61% of the UXO sites through various munitions response actions over the last 15 years, the cost of cleanup remains relatively the same as when the program started in 2002 (DoD, 2015).

The DoD's Annual Report to Congress states that changes in DoD scope, changes in cost estimating methodologies, the discovery of further contamination, changes in contract scope, and expansion of decontamination activities account for a 59% increase in cleanup costs for environmental and munitions response sites (MRSs) (DoD, 2015). The uncertainty of DoD changes in scope, land use, and areal extent of contamination not only increases the financial and operational risks to the contract service provider tasked with cleaning up the site, but it also continues to put human health and the environment at risk when site decontamination efforts are delayed or not achieved. As discussed in Chapter 5, these concerns drive the need for researching a solution that can assist munitions response project managers, program managers, and decision-makers in predicting munitions surface clearance rates of munitions items and munitions-related debris to help support pre-bid decision making for acquisition opportunities, resource and operational planning, and management of on-going field operations for surface decontamination activities.

### 1.1 Background

U.S. military downsizing and the closure and transfer of military facilities to non-DoD ownership over the last four decades has resulted in the closure of hundreds of defense sites, military bases, military training ranges, weapons research centers, and testing facilities (DSB, 2003). Thousands of sites located on these former military-owned facilities are known or suspected to contain UXO. UXO poses serious safety risks, and many sites are still unsafe and unsuitable for most kinds of public, commercial, agricultural, or private land use without significant DoD resources and capital investment in restoring these lands to within acceptable human health risk hazards (DoD, 2006; Siegel, 2004. The Defense Science Board reported that more than two million rounds of ordnance were typically fired annually as part of live-fire training exercises on active operational ranges located across the nation (DSB, 2003). Although UXO contamination emerged as one of the nation's most significant environmental concerns close to three decades ago, it continues today to be one of the nation’s leading environmental issues along with emerging contaminants (Siegel, 2004).

Unique and special risks associated with properties contaminated with munitions and explosives of concern (MEC), discarded military munitions (DMM), and munitions constituents (MC) present many complex challenges both to the DoD and participating stakeholders. Depending on the areal extent of contamination, the processes for restoring these former defense sites follows a lengthy and rigorous environmental restoration process that includes: (a) preliminary site assessments (PA), (b) site investigations (SI), (c) remedial investigations and feasibility studies (RI/FS), (d) remedial and/or removal actions (RA), (e) long-term operations and management (LTO/LTM), and (f) site closeout (SC). Unless there is an early decision on a site to recommend No Further Action (NFA), the performance of all these phases is necessary before the DoD can affirm that the site poses no unacceptable risk and can close it out of the inventory as Response Complete (RC) (DoN ERP, 2018). The process follows the requirements of the Comprehensive Environmental Regulations and Compensation Liability Act (CERCLA) and the Resource Conservation Recovery Act (RCRA).

Interim Removal Actions (IRA), such as surface clearance of UXO, can be implemented as an accelerated or emergency cleanup action as part of the restoration process. The IRA is a response action tool used during the investigation phases to mitigate risk and exposure to the public by removing and disposing of UXO items from the surface and or subsurface. Examples of UXO include an array of high explosive bombs, submunitions, grenades, projectiles, mortars, bomb fuses, and rockets. Figure 1.1 shows an example of inert Mk Series practice bombs cleared and collected from the surface area of an impact range within the boundaries of a munitions response site during a Time Critical Removal Action (TCRA).

*Figure 1.1* Inert MK Series Bombs collected from the surface area of an impact range; Source U.S. Navy

Figure 1.2 below provides an example of munitions-related debris cleared and collected from the surface of an impact range during a TCRA. The munitions-related debris removed within the munitions response site during the TCRA includes: range

*Figure 1.2.* Munitions related debris cleared and collected from the surface area of an impact range. Source: U.S. Navy

related debris, targets, scrap metal, and cultural debris. The material is cleared from the surface and stockpiled within the munitions response site for collection, demilitarization, and removal and disposal.

Restoring the land free of UXO is not only a costly and time-consuming process but also problematic due to the complexity of the UXO remediation process. Previous research indicates the process of cleaning up Munitions Response Sites may be quite antagonistic because of contrary opinions on cleanup standards between the regulatory community, the DoD, citizen groups, landowners, and land users (MacDonald, 2005). Stakeholder concerns and the uncertainty of quantifying the location and amount of UXO, makes it difficult to estimate the costs of clearing the surface and subsurface land area of UXO items (RAND, 2005). No accepted standard exists for the restoring lands free of UXO. The cleanup of UXO sites is unique and unlike the traditional cleanup of environmentally hazardous waste sites where standard acceptable limits for cleanup have already been established. Each site is unique and requires an agreed upon site-specific approach between the DoD and the stakeholders to reach an agreed-upon risk-based cleanup standard (e.g., surface clearance, subsurface clearance). For example, some stakeholders may want all the land cleared of UXO (e.g., surface, and subsurface clearance) to a depth of several feet below the surface, while other stakeholders may want to clear UXO from only the surface area to achieve immediate risk reduction until additional funding or risk scenarios change. The costs and time for clearing UXO from the surface only is the least costly alternative and could result in being 30 times less than the costliest alternative of clearing both the surface and subsurface of UXO to a depth of four feet below surface elevation.

The DoD sets an aggressive policy across each of the Military Service Components to implement Performance-Based Service Acquisitions for environmental and munitions response cleanups (PBSA) (OFPP, 2003). The Federal Procurement Policy challenges munitions response service firms to meet performance objectives or achieve results that may not be reasonably attainable for service-related contracts in the performance of decontamination efforts required for the cleanup of complex environmental and munitions response sites. Many of the munitions response sites have limited historical information on the amount and location of where UXO may be present and little or no information on the extent of surface and subsurface contamination. The DoD reported that the locations, quantities, depths, and types of munitions remaining and areal extent of contamination at these former military ranges are unknown and unaccounted for (DSB, 2003). Not knowing the areal extent of contamination becomes problematic and increases the financial risk when predicting the cost for site cleanup of large munitions response sites where thousands of acres contain Munitions and Explosives of Concern (MEC), Discarded Military Munitions (DMM) and Munitions Constituents (MC). PBSA-type contracts place the burden and financial risks on contractors to achieve a performance-based outcome that may be unrealistic to achieve within financial reason due to lack of pertinent historical site data, known levels of UXO contamination, and limited geophysical detection technologies. The uncertainty of DoD changes in scope, land use, and areal extent of contamination not only increases the financial and operational risks to the contract service provider but also continues to put human health and the environment at risk when the outcomes of site decontamination efforts are delayed or not achievable.

These uncertainties due to unforeseen levels of contamination further increase financial risks to firms performing decontamination activities under Firm Fixed Price Performance-Based Contracts being awarded based on lowest price. While one of the objectives of PBSA's is to save the DoD money, it may not be possible on service-type contracts where the government traditionally awarded and selected service-type contracting firms by "best value" technical approaches rather than "lowest price" (OFPP, 2003).

While the DoD continues to make progress in achieving Response Complete at UXO and hazardous waste sites, other factors continue to impact the progress in achieving Response Complete for the remaining sites on the Military Munitions Site Inventory. The DoD (2015) reported that 56% of the 5,230 Munitions Response Sites currently listed in the Military Munitions Site Inventory achieved Response Complete status in 2015. However, project scope changes and changes in cost estimates accounted for a 68% increase in environmental site decontamination cost estimates over prior year estimates (DoD, 2015). The DoD further reports that uncertainties in decontamination scope criteria accounted for changes in scope and accounted for 40% increase in site cleanup costs. Examples of changes in scope include adding cleanup phases, newly discovered contamination, increases in site dimensional area, changes in land re-use, additional risk pathways, additional site characterization, and additional remedial action operations (DoD, 2015). Changes in cost estimates unrelated to scope changes accounted for a 19% increase in clean-up costs compared to previous cost-estimating models. Whereas, changes in cost estimates unrelated to scope changes included changes in DoD cost estimating methodologies, changes in contract or contract methods, stakeholder delays, and estimates where actual contract costs for prior or ongoing work exceeded prior cost estimates and anticipated schedule durations (DoD, 2015).

### 1.2 Purpose and Incentive of Research

The DoD's remaining sites scheduled for decontamination present more complex challenges than in the past. The DoD anticipates the cleanup of remaining sites will take longer to complete and necessitate more regulatory attention resulting in increased financial investments (DoD, 2015). Scope growth and changes in cost estimates pose greater financial risks to both industry and government. These factors suggest that the DoD's aggressive policy on using PBSA-type service contracts may not be appropriate for performing munitions response decontamination activities at sites with limited historical information and site data. These concerns drive the interest and need for further research in exploring a practical solution that can assist project and program managers in promptly predicting preliminary baseline estimates of operational resources required for munitions surface clearance activities on a per acre basis during the bid/no bid process for munitions response type acquisition opportunities. The proposed forecasting methodology is a tool for decision makers that can assist them in predicting clearance activities to help support pre-bid detailed cost estimating, operational planning, and model on-going field surface decontamination operations to predict clearance rates ensure compliance with cost and schedule durations are achieved. A more detailed practical application is provided in Chapter 5.

The purpose of this research is to examine the relationship and influence of factors (independent and dependent variables) that predict the surface clearance acres cleared of munitions and non-munitions related debris at munitions response sites based on production data, labor resources, site physical properties, amount of munitions contamination, and vegetation removal. The application of multiple regression techniques is used to examine the relationship between the variables. Although treating munitions constituents and clearing subsurface land of munitions and munitions-related debris are typically part of the Comprehensive Environmental Response and Liability Act (CERCLA) process, they are not part of this exploratory research due to the additional complexity and need for additional variables unique to those activities. The development of a forecasting technique will have various practical applications in the Munitions Response Industry, such as assisting project and program managers in evaluating the field level operational performance capabilities for munitions clearance activities while performing their initial screening and risk decision-making process when deciding on pursuing or not pursuing certain risk-based acquisitions (e.g., lowest price PBSA-type munition response action contracts). Many of the acquisition opportunities have limited site characterization data, limited knowledge of contamination levels, and limited historical information on the past use of the site. Data from actual DoD munitions surface clearance activities were collected and used for building the multiple regression model. The following sections address the research problem beginning with the Problem Statement and ending with the proposed Research Methodology.

### 1.3 Problem Statement

Changes in DoD project scopes due to expansion of clean up area and discovery of additional contamination result in greater financial risks to firms performing Firm Fixed Price decontamination activities.

The Problem Statement focuses on Surface Clearance Decontamination Projects associated with Munitions Response Actions involving the Cleanup of Unexploded Ordnance, Discarded Military Munitions, and Non-Munitions Related Debris that follow the Environmental Clean Up requirements under the U.S. Environmental Protection Agency [EPA] Regulated CERCLA and RCRA Process. The uncertainties in the areal extent of surface site contamination, unknown quantities of contamination, the discovery of additional contamination, and unforeseen costs lead to the need of this study. Therefore, the proposed study is designed to develop a predictive analytical model to aide in predicting the surface clearance rate based on the level of labor resources, performance requirements, contamination levels, and physical site characteristics to minimize financial risks while minimizing risks to human health and the environment.

### 1.4 Thesis Statement

Because the areal extent of munitions contamination at munitions response sites is rarely known at the time of procurement actions or when changes in scope are issued, a predictive analytics model to forecast surface clearance rates will improve risk management decisions for firms making decisions on bid/no bid acquisition opportunities and decisions for cost/resource estimating when changes in scope occur during on-going surface clearance field operations.

### 1.5 Research Questions

**Research Question 1:** Will the implementation of a predictive analytics model assist in identifying the critical independent variables influencing the site munitions clearance and decontamination efforts?

**Sub-questions:**

- Which predictor (independent) variables are significant and insignificant in predicting the number of surface acres decontaminated of munitions and munitions related contamination?

**Research Question 2:** Will the use of predictive analytics model support the prediction of estimating the number of acres cleared of munitions and munitions related contamination based on the independent variables selected for the munitions response decontamination activity?

**Sub-questions:**

- Are the independent variables selected able to predict the surface clearance rate for decontamination activities?
- Which independent variables provide a better model in predicting the response variable (e.g., the number of weekly surface acres cleared)?

## 1.6 Hypotheses

### 1.6.1 Hypotheses for Research Question 1

**Ho:** Predictor (independent) variables $X_1$.... $X_{13}$, do not significantly predict the response (dependent) variable, *Y, (Total number of surface acres cleared per week)*.

**Ha:** At least one predictor (independent) variable, $X_1$.... $X_{13}$, significantly predicts the response (dependent) variable, *Y, (Total number of surface acres cleared per week)*

A summary of the predictor (independent) variables $X_1$ through $X_{13}$ are listed and defined in Table 1.1 below and Appendix D.

Table 1.1. *Predictor Variable Identification and Definition*

| ***Predictor Variable ID*** | **Definition of Predictor Variables** |
|---|---|
| $X_1$ | Total weekly number of days worked by UXO Field Technicians. |
| $X_2$ | Total number of weekly hours worked by UXO Field Technicians performing all related surface clearance activities |
| $X_3$ | Total number of actual weekly hours worked by UXO Field Technicians performing surface clearance activities within the grid ( does not include travel time and other non-grid work time). |
| $X_4$ | Total number of UXO Technicians performing all surface clearance activities. |
| $X_5$ | Total number of weekly work days worked by Vegetation Removal Technicians |
| $X_6$ | Total number of vegetation removal technicians performing vegetation removal activities ahead of surface clearance activities. |
| $X_7$ | Total number of weekly hours worked by vegetation removal technicians |
| $X_8$ | Total number of actual weekly hours of vegetation removal technicians performing vegetation removal activities within the grid (does not include travel time and other non-grid work time) |
| $X_9$ | Total weekly estimated number of individual UXO items, range related debris, material potentially presenting an explosive hazard, and munitions debris cleared from the surface. |
| $X_{10}$ | Total weight of non-munitions debris, metal scrap, targets, and cultural debris cleared from the surface. |
| $X_{11}$ | Average estimated slope of topography within sites completed on weekly basis. |
| $X_{12}$ | Average percentage of vegetation and tree canopy density within site area worked on weekly basis. |
| $X_{13}$ | Number of vegetation acres cleared per week within site area proceeding surface clearance activities. |

## 1.7 Research

The objective of this study is to develop a predictive analytics model as a tool for project managers, program managers, field supervisors, and decision-makers engaged in munitions response action planning, estimating, and field operations. The overall purpose of the model is to be able to assist munitions response in predicting munitions surface clearance rates to help support pre-bid decision making in acquisition opportunities, resource, and operational planning, and management of on-going field operations for surface decontamination activities to mitigate public health and environmental risks. The model examines the munitions response predictor variables that are significant or not significant in predicting the weekly number of surface acres decontaminated of munitions and munitions-related contamination based. The effectiveness of the model is based on the statistical relationship of predictor variables and response variable commonly used in the measurement of field operations for munitions response clearance activities. The variables are categorized by: (1) number and type of labor resources, (2) operational time in the field, (3) quantity of munitions and munitions-related contamination cleared, (4) physical site characteristics, and (5) density and amount of vegetation clearance. It is anticipated that the forecasting model will provide the foundation to explore further applications for subsequent phases of munitions decontamination activities, such as, digital geophysical detection operations, subsurface clearance operations, and underwater clearance activities. Additional discussions on the practical application is provided in Chapter 5.

## 1.8 Summary of Praxis Organization

This Praxis is divided into five chapters. Chapter One presents an overview of the research problem, the background of the research problem, purpose and incentive of the research, the problem statement, hypotheses, research questions, and the research objectives. A discussion of relevant literature is provided in Chapter Two. The overall research methodology is presented and discussed in Chapter Three. Analysis of the data and results are presented in Chapter Four. Chapter Five provides the discussions of the results, conclusion, and recommendations for further study. The appendices provide information related to the research and include a bibliography, data summary, results of the regression analysis, graphs and charts, and other pertinent information related to supporting the research, data analysis, and discussions presented in the research study.

## Chapter 2: Literature Review

### 2.1 Introduction

Chapter 2 provides a review of the literature search as it relates to the problem under study for this research. This chapter is divided into seven major sections and subsections that logically organize the literature research for review. The major sections include: (a) a historical overview of the munitions response program, (b) public health and environmental importance for the cleanup of UXO, (c) DoD's environmental liabilities, (d) acquisition issues in the munitions response program, (e) munitions response action process, (f) overview of multiple regression as a forecasting tool, and (g) knowledge gaps in literature review.

### 2.2 Historical Overview of Munitions Response Program

Former military ranges and Formerly Used Defense Sites (FUDS) contaminated with unexploded ordnance (UXO) pose a severe problem in both the United States and abroad. Today's munitions-related contamination concern in terms of impacted acreage, environmental liability, and the imminent danger to human health and environment emerged into one of the nation's leading environmental issues[1] (GAO, 2003). The cleanup of these former defense sites poses a multi-billion dollar environmental liability for the DoD and presents severe risks to the communities who live, work, and recreate on

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[1] For purposes of this paper the term munitions contamination or munitions-related contamination refers to either one or mix of any of the three categories of munitions-related contaminates: munitions and explosives of concern (MEC), discarded military munitions (DMM), and munitions constituents (MC). Munitions contamination refers to land or waterways containing a mix of UXO/MEC, DMM, and MC.

or near former defense sites that are no longer under the ownership or security of the military (GAO, 2003; Siegel, 2004). Over the last century, reports indicate that DoD utilized over 15 million acres of land and unaccountable millions more of waterways across the nation and its' territories for munitions-related activities for military training and testing of weapons in order train with live munitions and sustain the military's readiness[2]. Decades of military downsizing initiatives have led to the closure and transfer of over 3,600 former defense sites to other federal, state, local, and tribal governments, commercial, or private entities. These defense sites are known or suspected to contain unknown amounts of munitions and explosives of concern (MEC) discarded military munitions (DMM), and munitions constituents (MC) (GAO, 2003)[3.]

The cost to assess and remediate UXO is uncertain because of the lack of information on the number of sites and the many unknown factors associated with each site. Estimates in 2003 suggest that there were more than 2,300 UXO sites in the United States involving anywhere between 10 million and 15 million acres of land (DSB UXO, 2003). Recent estimates from DoD state that there are now over 5200 munitions response sites listed on the Munitions response Site Inventory (DoD, 2015). Preliminary

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[2] For purposes of this paper the term *munitions-related activities* refer to any DoD activities on former military ranges or former defense sites that involved the past use of munitions (e.g., military live fire training, testing, munitions storage, etc.), that resulted in the presence of unexploded ordnance (UXO), munitions and explosives of concern (MEC), discarded military munitions (DMM), and/or munitions constituents (MC) .

[3] For purposes of this paper the term UXO is used interchangeably with MEC. The terms UXO and MEC refer to armed military munitions that were fired and failed to detonate on impact with the surface land or targets; DMM refers to excess or expired military ordnance improperly disposed of on-site; MC refers to munitions chemicals released into the environment through either detonation, burning, or decaying munitions.

cost estimates suggest that the remedy cost is in the tens of billions of dollars and remains relatively the same two decades later.

In response to Public Law 107-107, the Department of Defense (DoD) established the Military Munitions Response Program (MMRP) in 2001 (DoD, 2002). The MMRP addresses the munitions-related contamination and cleanup at Formerly Used Defense Sites (FUDS), facilities closed and transferred under the Base Realignment and Closure (BRAC) Act, and closed ranges on active military facilities. As with DoD's environmental cleanup program, DoD complies with environmental cleanup laws, such as the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) and the Resource Conservation and Recovery Act (RCRA) for the investigation and cleanup of sites. DoD established and initiated the Munitions Response Site Inventory program, the development of a Site Prioritization Protocol, and advancement of UXO detection and remediation technologies. Since then, the range inventory program continues to identify munitions response sites (MRSs) for inclusion to the site inventory program for prioritization and funding for munitions response cleanup actions. MRSs are sites that are known or suspected to contain UXO, DMM, or MC. DoD's Munitions Response Site Prioritization Protocol was finalized in 2005 and is used to prioritize funding for sites where the scores warrant a munitions response action based on a hazardous ranking score. On the technology front, a significant amount of funding continues for investing in the development of advanced geophysical detection and discrimination technologies for both subsurface and underwater UXO through DoD's Strategic Environmental Research and Development Program (SERDP) and Environmental Security Technology Certification Program (ESTCP). The objective is to develop technologies that can detect and discriminate hazardous UXO or MEC items from non-hazardous scrap metal or cultural debris that will result in less intrusive subsurface excavation digs and reduce the costs of subsurface clearance by 40% to 50% (SERDP, 2014). SERDP and ESTCP respond directly to DoD's top environmental requirements generated by each military service component.

### 2.3 Public Health and Environmental Importance for Cleaning up UXO

Former defense sites are no longer in use for their intended purpose nor under the ownership and security of military enforcement. Because of their explosive and chemical hazards, former military properties containing munitions contamination remain a significant threat to communities and regions where it is suspected or known (Siegel, 2004). Serious injury or even death may occur to those who handle or encounter unexploded ordnance ( (Siegel, 2004). Increased public and political concern over the uncertainty of risk associated with the use of live munitions and the ordnance remaining on site is a primary environmental concern to the United States Environmental Protection Agency (U.S. EPA), Natural Resource managers, landowners, and other stakeholders as well. The release of munitions constituents into the environmental media is now suspected as a significant source for environmental contamination (i.e., soil, groundwater, and surface water) and natural resource damage (U.S. EPA, 2012). Human exposure to munitions constituents through contact with environmental media may potentially result in adverse human health effects. For example, manufactured forms of ammonium perchlorate have been released into the environment and found in soils, groundwater, and drinking water supplies near sites engaged in the use, testing, and disposal of ammunition, missile launches, manufacturing and use of rocket fuel. Perchlorate is a toxic contaminate regularly used in munitions, rocket propellants, signal flares and fireworks (US EPA, 2017). Perchlorate affects the thyroid glands and enters the bloodstream through food ingestion and intake of potable well water (ATSDR, 2008). The impacts of perchlorate to human health caused U.S. Environmental Protection Agency (U.S. EPA) to act by issuing Interim Drinking Water Health Advisories (US EPA, 2017). The release of perchlorate into the environment usually happens because of failed rocket launches, accidental releases, or mishandling and disposal of rockets and missiles (ATSDR, 2008). Excessive levels of perchlorate contamination in soil and groundwater were detected at numerous rocket manufacturing facilities and military training facilities in the past (ATSDR, 2008).

The extent of harm to the public as it relates to human contact and exposure to UXO is higher in areas where wars occurred or at former defense site where decades of live fire military training occurred. A study conducted by the EPA reported that human exposure to UXO resulted in 65 fatalities and 131 injuries in the U.S. between 1918 and 2001 (US EPA, 2001). Human contact with UXO accounts for 1.27 civilian fatalities per decade. The study also reported that a total of 126 civilian UXO incidents occurred and at least 83 of these incidents resulted in explosions (US EPA, 2001). Although the number of UXO related fatalities are extremely low in the U.S., any such event draws negative publicity to the party responsible for the cause of death, in this case, DoD.

The average number of civilian fatalities or injuries caused by contact with UXO within the U.S. is significantly low as compared to other sources for civilian deaths such as drownings and motor vehicle accidents. For example, The Washington Post reported that out of the 280 million people who visit U.S. National Parks each year, there are between 120 to 140 civilian fatalities that occur each year at U.S. National Parks. Table 2.1 provides the number of fatalities that have occurred at National Parks between the period of 2005 and 2014.  Excluding civilian suicides, approximately 1,271 civilian deaths occurred at national parks within the nine-year period (Ingraham, 2015). Drownings, vehicle accidents, and falls were the top three causes of death at national parks between 2003 and 2007 (Ingraham, 2015).

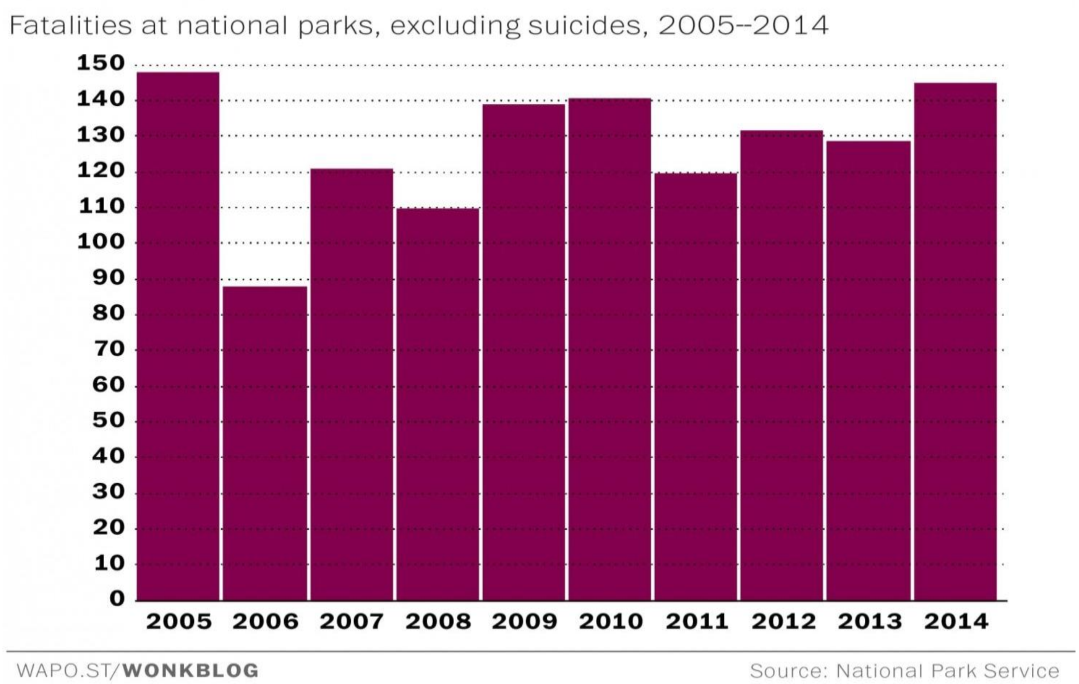


*Figure 2.1.* Fatalities at National Parks Between the Years 2005 and 2014
Note. Source: Wonkbog, Washington Post  (Ingraham, 2015)

UXO incidents among the civilian population abroad are significantly more frequent in war-torn countries than in the United States and are a significant public health concern (Morikawa, Taylor, & Persons, 1998).  Many of these foreign countries, such as Vietnam, Laos, Afghanistan, and Iraq, suffered through decades of air to ground bombings, ship to shore artillery, and ground to ground shelling. For example, reports indicate that Laos, per capita, is the most heavily bombed area in history (Vientiane Times Editor, 2016). A study performed by the Mines Advisory Group (MAG) in Laos twenty-two years after the Vietnam War ended reported that on average, there is one injury every other day and that half of the injuries and deaths related to UXO incidents involved children under the age of 15 years old (Morikawa et al., 1998). The photograph in Figure 2.2 shows two boys playing with and mishandling UXO projectiles in Afghanistan that could likely result in a detonation causing severe injury or death.

*Figure 2.2.* Children mishandling UXO. Source: UXOINFO.com.

The study also concluded that the fatality rate is high, and males were more likely to die of UXO injuries than females. In any case, almost all injuries were considered very serious requiring highly specialized medical and surgical services (Vientiane Times Editor, 2016). There were over 50,000 civilians killed or injured in Laos since 1964.

A photograph presented in Figure 2.3 below shows a family playing and walking around UXO littered and stockpiled on the land surface in Laos. Human Exposure to UXO is a common and daily event for many children and families living in Laos.

*Figure 2.3.* Children playing around UXO Bombs. Source: UXOINFO.com.

International organizations working closely with the NRA cleared over 1,782,682 cluster munitions, 7,529 large bombs, 7,154 land mines and over 900,000 other devices from 59,816 hectares of land between 1996 and 2015 (Vientiane Times Editor, 2016). The UXO problem in war torn countries is massive as compared to the United States. Nonetheless, UXO is a serious and deadly threat to civilians who come into contact or handle UXO that needs to be mitigated. Not only is there a concern for protecting public health and the environment, the presence of UXO also hinders the economic growth and development of lands for agriculture, forestry, hydro-electric power, transportation, residential development, and a host of other economic development initiatives (Vientiane Times Editor, 2016) . The clearing and decontamination of UXO from land continues to be of paramount importance for protecting the public, environment, and enhancing economic development of nearby communities within the United States and abroad.

### 2.4 DoD Environmental Liability

For the last 20 years, the federal government's environmental liability continues to grow as does DoD's environmental liability. Environmental liability is defined as an economic risk expressed in financial terms and exists if there are a likelihood and measurable outflow of future resources because of past practices or events (DoD, 2006). The cleanup costs at contaminated sites where federal activities contaminated the environment are the responsibility of the federal government and reported as a financial liability (GAO, 2017). The federal government’s liability has more than doubled over the last 20 years growing from $212 billion in 1997 to $447 billion in 2017 and will likely to continue to grow (GAO, 2017). DoD's total environmental and disposal liability for 2014 and 2015 was reported at $58.6 billion and $60 billion, respectively, while DoD's environmental restoration liability alone is $27.2 billion (U.S. Treasury, 2015).

Cost-effective solutions for reducing public health and safety risks is hampered because of the absence of complete information of the cleanup requirements and unreliable methods of making environmental cleanup decisions (GAO, 2017). When costs to contain the contamination is unknown or where there is no known technology available to clean up a site, then the federal agency accountable for the cleanup is responsible for estimating the costs to conduct actions (i.e., RI/FS’s, RA’s, etc.) under the

Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) as liabilities (GAO, 2017). Consequently, the estimated liabilities to clean up environmental and munitions sites remain uncertain and likely underestimated (GAO, 2003).

In regards to the DoD liabilities specific to the Military Munitions Response Program (MMRP), the Government Accounting Office (GAO) reported that the magnitude of risks and the extent of liabilities associated with the UXO problem is uncertain and that DoD does not have a complete and viable plan for cleaning up sites contaminated with munitions (GAO, 2003). The DoD estimates that there are between ten and fifteen million acres of land potentially contaminated with Munitions and Explosives of Concern (MEC), discarded military munitions (DMM), and munitions constituents (MC). The costs and liabilities of cleanup as well as the potential harm to the public and the environment are still yet to be fully defined. The DoD reported its unexploded ordnance cleanup liability to be anywhere between $14 billion and $140 billion (GAO, 2003). The estimated costs to address risks from MEC, DMM, and MC at operational ranges were estimated to cost between $16 billion and $165 billion. Whereas the estimated costs to address risks at Munitions Response Sites (MRSs) (other than operational ranges) was estimated to cost anywhere between $8 billion and $35 billion (DoD, 2002). In 2009, the DoD reported the estimated Cost to Complete (CTC) for the MMRP at $12.2 billion (DoD, 2009). Table 2.2 summarizes the actual annual funding for the Military Munitions Response Program (MMRP) over a ten-year period between 2005 and 20015. The DoD has funded a total of $3.5 billion over the ten-year period, and the estimated cost to complete the UXO cleanup remains relatively the same today at

$11.2 billion as it did almost fifteen years ago (DoD, 2015). As presented in Table 2.1, the DoD's average funding for the MMRP cleanup program is approximately $340 million per year. Based on the annual average rate of funding for the MMRP, it is likely that it may take another 30 years or more to clean up former defense sites to achieve acceptable human health risk levels.

Table 1.1. *Overall Actual Fiscal Year MMRP Funding (Rounded in Millions of Dollars)*

| Summary of Actual Fiscal Year MMRP Funding for Active Installations, FUDS Properties, and BRAC Locations (Millions of Dollars) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| FY05 | FY06 | FY07 | FY08 | FY09 | FY10 | FY11 | FY12 | FY13 | FY14 | FY15 |
| $186 | $211 | $278 | $348 | $420 | $420 | $437 | $385 | $341 | $385 | $420 |

Source: Defense Environmental Funding FY 2009 and FY 2014 Annual Report to Congress.

Like the DoD's Environmental Restoration Clean Up Program (DERP), the DoD's MMRP was developed to address the contamination and remediation of MEC, DMM, and MC remaining on former DoD defense sites, FUDS, and BRAC Sites (DoD, 2002). The number of sites listed in the Military Munitions Site Inventory grew from 1754 sites in 2001 to 5230 sites in 2015 (DoD, 2015). As additional sites keep being added to the to the clean-up program, the cost to clean up these sites continues to increase and remains uncertain. The DoD reported that 61% of sites have been remediated to acceptable standards and classified as either Remedy in Place (RIP) or Response Complete (RC) (DoD, 2015). However, the inclusion of additional sites to the site inventory causes a cost growth to the program and continues to impact the time and cost to complete the cleanup of Munitions Response Sites (DoD, 2015).

### 2.5 Acquisition Issues in the Munitions Response Program

The DoD sets an aggressive policy across each of the Military Service Components to implement Performance-Based Service Acquisitions (PBSA) (OFPP, 2003). The Federal Procurement Policy challenges munitions response service firms to meet performance objectives or achieve results that may not be reasonably attainable for service-related contracts in the performance of decontamination efforts required for the cleanup of complex environmental and munitions response sites. Many of the munitions response sites have limited historical information on the amount and location of where UXO may be present and little or no information on the extent of surface and subsurface contamination. The DoD reported that the locations, quantities, depths, and types of munitions remaining and areal extent of contamination at former military ranges are unknown and not accounted for (DSB, 2003). Not knowing the areal extent of contamination becomes problematic and increases the financial risk when predicting the cost for site cleanup of large munitions response sites where thousands of acres are contaminated with MEC, DMM, and MC. PBSA-type contracts place the burden and financial risks on contractors to achieve a performance-based outcome that may be unrealistic to achieve within financial reason due to lack of pertinent historical site data, known levels of UXO contamination, and limited geophysical detection technologies. The uncertainty of DoD changes in scope, land use, and areal extent of contamination not only increases the financial and operational risks to the contract service provider but also continues to put human health and the environment at risk when the outcomes of site decontamination efforts are delayed or unachievable.

These uncertainties due to unforeseen levels of contamination further increase financial risks to firms performing decontamination activities under Firm Fixed Price Performance-Based Contracts awarded based on lowest price. While one of the objectives of PBSA's is to save the DoD money, it may not be possible on service-type contracts where the government traditionally awarded and selected service-type contracting firms by "best value" technical approaches rather than "lowest price" (OFPP, 2003).

While the DoD continues to make progress in achieving Response Complete at UXO and hazardous waste sites, other factors continue to impact the progress in achieving Response Complete for the remaining sites on the Military Munitions Site Inventory. The DoD reported that 56% of the 5,230 Munitions Response Sites currently listed in the Military Munitions Site Inventory achieved Response Complete status in 2015. However, project scope changes and changes in cost estimates accounted for a 68% increase in environmental site decontamination cost estimates over prior year estimates (DoD, DoD Environmental Restoration Program FY 2014 Annual Report to Congress, 2015). The DoD further reports that uncertainties in decontamination scope criteria accounted for changes in scope and accounts for 40% increase in site cleanup costs. Examples of changes in scope include adding cleanup phases, newly discovered contamination, increases in site dimensional area, changes in land re-use, additional risk pathways, additional site characterization, and additional remedial action operations (DoD, DoD Environmental Restoration Program FY 2014 Annual Report to Congress, 2015). Changes in cost estimates unrelated to scope changes accounted for a 19% increase in clean-up costs compared to previous cost-estimating models. Changes in cost estimates unrelated to scope changes included changes in DoD cost estimating methodologies, changes in contract or contract methods, stakeholder delays, and estimates where actual contract costs for prior or ongoing work exceeded prior cost estimates and anticipated schedule durations (DoD, 2015).

The DoD's remaining sites scheduled for decontamination present more complex challenges. The DoD anticipates the cleanup of remaining sites will take longer to complete and necessitate more regulatory attention resulting in increased financial investments (DoD, 2015). Scope growth and changes in cost estimates pose greater financial risks to both industry and government. These factors suggest that the DoD's aggressive policy on using PBSA-type service contracts may not be appropriate for performing munitions response decontamination activities at sites with limited historical information, site data, and unknown areal extent of contamination.

### 2.6 Munitions Response Action Process

DoD follows the CERCLA, Superfund Appropriations and Recovery Act (SARA), Resource Conservation and Recovery Act (RCRA), and Applicable Relevant and Appropriate Regulation (ARAR) process for cleaning up both environmental and munitions response sites. The cleanup process at large sites with thousands of acres like the cleanup at Ft. Ord California and the Former Atlantic Fleet Weapons Training Facility on Vieques Island, Puerto Rico can take decades to complete. Figure 2.3 presents a flow chart of the overall CERCLA process for cleaning up environmental and munitions response sites within the United States. Although the environmental and munitions response program follows the CERCLA process, there is a distinct difference. The environmental program is concerned with the protection of human health and the environment based on short and long-term exposures in the event of releases of hazardous wastes and substances whereas the munitions response program is concerned primarily with the acute risks of human exposure caused by explosive detonations. This section briefly discusses the phases and processes of the munitions response program as described in Figure 2.4 to provide the reader with an understanding of the Investigation and Remediation Cleanup phases of the CERCLA process and how certain munitions response actions, such as removal actions and remedial action, are initiated to protect the public and environment.

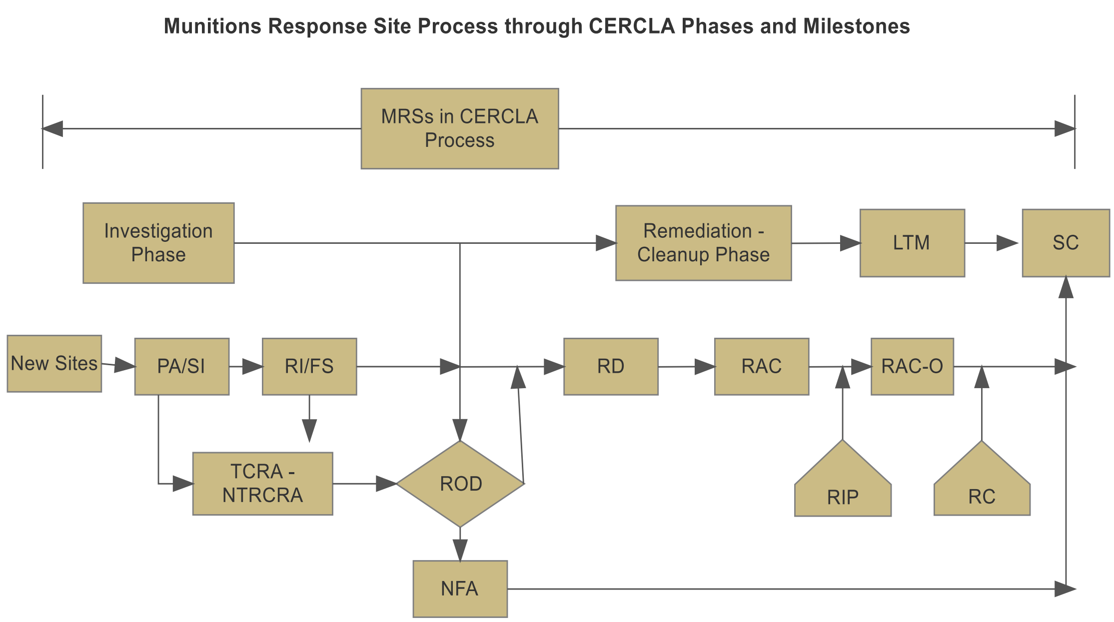


*Figure 2.4.* Munitions Response Site Process through CERCLA Phases and Milestones
Source: FY15 DoD's Annual Report to Congress.

## 2.7 Investigation Phase of the CERCLA Process[4]

### 2.7.1 Preliminary Assessment/Site Inspection Phase (PA/SI)

The first phase under the Investigation Phase of the CERLCA Process is the Preliminary Assessment/Site Inspection Phase (PA/SI) phase. The PA/SI under the Munition Response Program serves the same purpose as the SI for an environmental investigation in the CERCLA process (DoN ERP, 2018). After new sites have been identified in the Munitions Response Site Inventory list, a PA is initiated to identify potentially contaminated sites at a military installation or former defense site to determine if a hazardous waste or substance has been released into the environment or confirm the presence or non-presence of MEC, DMM, or MC. PA's typically include the reviewing all pertinent historical documents, collect and review data, conduct on-site reconnaissance if required, conduct interviews, and determine if a release or the potential presence of MEC, DMM, or MC requires further investigations in the SI phase. If the data screening results indicate that no unacceptable risk exists, then the site can be recommended for No Further Action (NFA), closed out, and removed from the site inventory. If the data screening results or site reconnaissance identified the presence of MEC, DMM, or MC, a Site Investigation is initiated to determine the initial extent of contamination and hazards associated with the munitions contamination.

[4] The description of the investigative and remediation cleanup phases follows the CERCLA process and are summarized based on the phases presented in the 2018 Department of Navy's Environmental Restoration Program Manual.

The purpose of an SI is to conduct a limited site investigation to gather additional sampling data and conduct a metal detector-aided survey to determine the presence of MEC, DMM, and MC on the site. SI's typically include information on the type of MEC found, quantities on the surface, vegetation density, topography, range scrap quantities, geology, and evidence of impact areas. The results of the SI assist the decision makers in determining if, (1) no further action is required, (2) a full scale Remedial Investigation is required to investigate the explosives hazards and extent of MEC, DMM, MC contamination, or (3) a Time Critical Removal Action (TCRA) or Non-Time Critical Removal Action (NTCRA) is needed to reduce the immediate threat to the public and the environment (DoN ERP, 2018). Vegetation clearance and limited surface and subsurface clearance of munitions items and munitions-related contamination are conducted during the SI phase to reduce the potential risk and hazards to the field crew performing the investigation during the site characterization efforts.

Remedial Investigation/Feasibility Study (RI/FS): As in the case of the PA/SI, the Remedial Investigation and Feasibility Study (RI/FS) for a munitions response action serve the same purpose as an RI/FS for an environmental investigation under the CERCLA process. The key difference between an environmental RI/FS and a munitions response RI/FS is that a detailed geophysical investigation is required for a munitions response RI to delineate the extent of munitions and munitions-related contamination both in the surface and subsurface land area. The objective of the RI/FS is to: (1) characterize the site and determine the nature and areal extent of munitions-related contamination, (2) assess the risks and explosive hazards to the public and environment, (3) assess the potential fate and transport of munitions-related contamination, (4) conduct pilot tests of viable munitions response technologies, and (5) perform an evaluation of remedial alternatives and cost estimates for the subsequent Remedial Design and Remedial Action phases (DoN ERP, 2018). Vegetation clearance and limited surface or subsurface clearance of munitions items and munitions-related contamination are conducted during the RI phase to reduce the risk and hazards to the field crew performing site characterization efforts.

### 2.7.2 Remediation and Cleanup Phase of the CERCLA Process

#### 2.7.2.1 Remedial Design (RD) and Remedial Action-Construction (RA-C)

The Remedial Design (RD) phase under the Remediation Cleanup Phase involves the development of the detailed cost estimates and the preparation of the detailed design of the Remedial Action-Construction (RA-C) remedy selected in the Record of Decision (ROD) for remediating the munitions and munitions-related contamination (DoN ERP, 2018). Depending on the remedial action objectives and future land use, the remedy may include vegetation removal, surface clearance of munitions and range related debris, digital geophysical mapping (DGM) of subsurface anomalies, subsurface clearance of anomalies identified in the DGM, demolition of munitions, and range scrap removal and disposal.

The RD phase is not widely implemented in the munitions response program, if at all. It is one of the most important phases for defining the scope of work required for the cleanup. The RD enables a more accurate prediction of the extent of contamination, delineation of vegetation removal, delineation of surface clearance and subsurface clearance, and the quantities of munitions and munitions-related debris to be encountered. A RD would provide for less uncertainty as it relates to the scope of work and to the amount of work expected during the performance of the clean-up contract resulting in a more accurate cost predictions and schedule duration for clean-up.

#### 2.7.2.2 Remedial Action Operation and Long-Term Management

This phase involves the operation, maintenance, and monitoring actions for the remedial action systems completed during the Remedial Action. Munitions response actions typically do not have any treatment systems constructed as in the case for remediating groundwater at environmental sites. The Remedial Action Operation and Long-Term Management (RA-O/LTM) for munitions response actions include the implementation, management, and maintenance of Land Use Controls after the completion of the remedial action (DoN ERP, 2018)

## 2.8 Removal Actions - The Munitions Response Action Phase

### 2.8.1 Removal Action (RA)

Removal Actions are conducted in either the investigation or remediation and cleanup phases under CERCLA. The National Oil and Hazardous Substances Pollution Contingency Plan (NCP) allows for the implementation of a munitions removal action to be conducted in an accelerated manner in circumstances where a rapid munitions removal action is required to minimize risk to the public and environment (DoN ERP, 2018). CERLCA Section 104 further warrants that whenever a threat of a release or actual release of a hazardous waste substance or contaminant, such as a munitions item, removal actions and succeeding remedial actions should be initiated to mitigate the substantial danger to the public health (DoN ERP, 2018). There are three types of removal actions and each have a distinct difference as described below (U.S. EPA, 1992):

a. **Emergency Removal Actions (ERA)**: An ERA is implemented when a release or contaminate needs to be addressed immediately (within hours or days) to be protective of the public health. Regarding the munitions program, a surface clearance or subsurface removal of individual munitions items may be needed to address the immediate risks posed by the munition items.

b. **Time Critical Removal Actions (TCRA)**: TCRAs are initiated when the threat is not immediate but considered imminent where the implementation of the action can begin within 6 months. TCRA's are typically considered an interim action until a final remedy can be selected through the CERCLA process. However, TCRA's can be final remedial actions if the threat is contained or removed. TCRA's are applied to small-scale or large-scale actions. TCRA's are implemented when the presence of MEC is known or suspected at a site. TCRA's are used at a large site when a large-scale surface clearance is needed as an interim or final action to reduce the immediate risk of MEC exposure to public health.

c. **Non-Time Critical Removal Action (NTCRA):** NTCRA serves the same purpose as a TCRA except for the planning period and initiation of implementation is 6 months or longer. NTCRA's are initiated when determined to be appropriate and can be applied to small scale and/ or large- scale actions. NTCRA's are implemented when the presence of MEC is known or suspected at a site. As in the case of TCRA's, NTCRA's are used at a large site when a large-scale surface or subsurface clearance is needed as an interim or final action to reduce the immediate risk of MEC exposure to public health.

As discussed above, removal actions can be initiated as either an interim action or final action. Removal actions are initiated based on the type of situation, urgency of the threat of release or exposure to contaminants, and subsequent period of the initiation of the removal action (U.S. EPA, 1992).

Depending on the objective of the munitions response action, actual field decontamination activities may vary for each type of munitions response action. It should be noted that most activities, at a minimum, involve some type of vegetation removal to gain access to assess surface contamination and surface clearance of contamination to minimize risk of exposure to munitions items laying on the surface. Besides reducing the immediate risk, vegetation removal and surface clearance activities are also conducted for preparation of the area for subsequent actions such as digital geophysical mapping and subsurface clearance activities.

Figure 2.5 below provides an example of where a large scale TCRA was initiated due to the presence of MEC and MPPEH. A large-scale surface clearance involves vegetation removal, if required, surface clearance of munitions and munitions related debris, demolition of live munitions, range clearance, processing and disposal of all range, related debris, munitions documented as safe for disposal, and scrap metal.

*Figure 2.5*. Example of site where a large scale TCRA munitions surface clearance was based initiated on the threat due to the presence of MEC and MPPEH on the land surface.

Figure 2.6 below provides an example of the amount of inert munitions and range related debris removed and collected from the surface within the munitions response site during the implementation of a TCRA. The inert munitions items will be demilitarized, and the remaining range related scrap is certified free of explosives and sent to a scrap metal facility for further processing and recycling. Surface and Subsurface Clearance of munitions and related munitions activities can be performed at any time during the investigation and remediation and clean up phases as described in CERCLA process shown in Figure 2.4. A munitions-related surface and subsurface clearance

*Figure 2.6.* Photograph of inert munitions items removed and collected from the surface during TCRA.
Source: US Navy

TCRA or NTCRA may involve vegetation removal, surface clearance of munitions and other related and non-related debris, demolition of munitions items, digital geophysical mapping, subsurface clearance of anomalies, collection, and disposal of munitions-related and non-related debris.

**2.9 Overview of Industry Tools for Current Estimating Techniques**

Since the mid-nineties, GAO has gone on record and developed at least 28 recommendations related to addressing the federal government's environmental liability. Thirteen of these recommendations remain unimplemented. GAO reports that if implemented, these recommendations would improve the inclusiveness and dependability of the estimated costs of future cleanup and lead to a more effective and efficient risk-based approach of the cleanup work (GAO, 2017).

Estimating the cost of UXO cleanups is a unique challenge due to the uncertainties and complexity of each site. Unlike typical construction and environmental restoration cost estimating tools, UXO cost estimating tools are insufficient. Since the inception of the military munitions program, the DoD has been utilizing Remedial Action Cost Engineering Requirements (RACER) as the model for estimating UXO cleanups. RACER, proprietary software was developed in 1996 by the US Air Force for estimating site remediation costs for DoD's hazardous and toxic and radiological waste sites (HTRW). Due to the lack of consistent and uniform UXO cost estimating tools within the industry, RACER was later modified to include UXO cost estimating modules. Researchers from the RAND Corporation explored the capabilities of RACER for a massive 7000-acre UXO site to do a cost analysis. Recommendations of the study indicated that the DoD's cost-estimation process for developing effective plans and cost estimates for UXO cleanup needs to improve by developing a uniform cost-estimating strategy, collaborating with industry to improve RACER's UXO cleanup estimating capabilities, along with calibrating and validating the RACER model (RAND, 2005). Besides RACER, there is no consistent and improved cost-estimating tool for UXO Cleanup. Most estimating tools are developed internally within the organization engaged in the munitions response program.

## 2.10 Overview of Multiple Regression Techniques for Predicting Munitions Response Actions

This section focuses on exploring the literature search for techniques for developing a forecasting tool to predict the surface clearance of munitions based on certain predictor variables that were found common in the data collection of surface clearance operations.

### 2.10.1 Statistical Learning Explained

Statistical Learning is focused on supervised and unsupervised modeling and prediction (Hastie, 2013). A set of input variables known as predictor variables are predetermined and have some impact on a set of output variables known as response variables. Modeling the underlying relationship between the predictor variables *X* and the response variable *Y* is known as *supervised learning,* a critical aspect of *Statistical Learning* (Hastie, 2013). Whereas *Supervised learning* models the relationship between the predictors and the response variable, another concept of *statistical learning theory* known as *unsupervised learning* is concerned with learning structure and finding patterns in data without using the response variable *Y*. In the statistical learning framework, a set of different approaches are used to estimate a function ***f*,** which represents the systematic information that the predictor variable inputs ***X*** provide about the response variable ***Y***. Since the true function ***f*** is unknown, it must be estimated, and the approximation is denoted as $\hat{\boldsymbol{f}}$ (Hastie, 2013)**.**

It is understood that there is some unknown relationship between a quantitative response variable **Y** and a set of predictors $\boldsymbol{X} = (\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{X_3}, \boldsymbol{X_4}, \ldots \boldsymbol{X_p})$. The goal of statistical learning is to model that relationship. The true relationship is defined by the unknown function $\boldsymbol{f}$. Since it is unknown, a function approximation $\hat{\boldsymbol{f}}$ is created to model the relationship between $\boldsymbol{X}$ and $\boldsymbol{Y}$.

In statistical learning literature, there are many different methods and models used to estimate $\boldsymbol{f}$. Models will range in complexity and require a thoughtful understanding to distinguish the best way to estimate the unknown population function $\boldsymbol{f}$. A discussion on some of the reasons as to why the population function $\boldsymbol{f}$ would want to be estimated are as follows ($\hat{f}$ is the estimation of $f$):

1. **Prediction**: In this setting, the goal is to predict future values of the response variable given an observation of predictor variable inputs. We are often not typically concerned with the exact form of $\hat{\boldsymbol{f}}$ if it yields accurate predictions for $\boldsymbol{Y}$. There are two errors to be concerned with for the prediction accuracy of $\hat{\boldsymbol{f}}$, *reducible* and *irreducible error* (James, Witten, Hastie, & Tibshirani, 2013). A reducible error is systematic variation in the response variable measured by our estimated function $\hat{\boldsymbol{f}}$. The *reducible error* represents a deterministic aspect of the modeling of the predictors (X) to the response variable (Y) and can be potentially improved when improving $\hat{\boldsymbol{f}}$. *The irreducible error* refers to the random variation in the response variable that we cannot model and therefore, cannot use them for its prediction capabilities (James et al., 2013).
2. **Inference:** In this setting, the true underlying function $\boldsymbol{f}$ is estimated. However, the primary goal is to understand the relationship and clarify the nature of this complex interaction. The model needs to be able to discriminate which predictor variables are significant with the response variable as well as

provide information on the relationship between the predictor variable and response variable by its magnitude and direction, and lastly, the model should be able to explain the relationship between the variables using a linear equation (James et al., 2013). A model with the least amount of predictor variables representing the most important part of the variation in the response variable is desired (Chatterjee & Hadi, 2012).

Residuals are the difference between the original and generated outputs, also known as *errors* (Hastie, 2013). The goal is that the artificial outputs produced by $\hat{f}$, our estimate of $f$, are close enough. When the residuals are small, our estimated model $\hat{f}$ is close to the underlying population function $f$, and thus our artificial outputs will be useful enough for all set of inputs likely to be encountered in real-world applications or practice (Hastie, 2013). For models such as linear regression, close is measured via Residual Sum of Squares (RSS), which is the sum of all the squared errors.

### 2.10.2 History of Linear Regression

For the past thirty or more years, linear models have been used extensively and have been the backbone of statistics (Hastie, 2013). Linear regression is a useful and widely used tool for predicting values of a quantitative response variable. Linear regression is an example of a parametric approach because it assumes a linear functional form for $f$ (Hastie, 2013). Simple Linear Regression (SLR) uses a single predictor variable, and Multiple Linear Regression (MLR) uses multiple predictor variables. The rest of the section focuses on multiple linear regression since explaining a complex process or predicting an output accurately involves utilizing more than one predictor variable. Given a vector of predictor variable inputs we can predict the response variable using a linear function of the parameters (Chatterjee & Hadi, 2012):

$$\widehat{Y_\iota} = \widehat{B_0} + \sum_{j=1}^{p} X_{ij}\widehat{B_J}$$

A model is fitted to the data using *the Least Squares* method. Model fitting is parameter estimation, and *least squares* are not the only method of estimation. Linear models such as linear regression offer interpretability advantages for inference modeling over other more flexible parametric and non-parametric models. Linear regression and other linear models also offer extremely competitive predictive performance for real-world problems when the underlying population relationship between the predictors and the response variable is linear, making them popular choices for many real-world applications (Chatterjee & Hadi, 2012). In summary, linear regression will outperform other models both in interpretability and most other models in predictive ability when the true form of ***f*** is linear, (i.e., when $f(X) \approx \hat{f}(X)$) (Chatterjee & Hadi, 2012).

### 2.10.3 Parametric vs. Non-Parametric Methods

Parametric methods assume about the functional form of the true underlying relationship ***f.*** A procedure is used to estimate the population parameters, ***B***. These estimates are the model coefficients $\boldsymbol{\widehat{B}}$. The *parametric* approach reduces the problem of estimating ***f*** down to that of specifying a functional form (i.e., class of functions) of the underlying relationship between ***X*** and ***Y,*** and then estimating the set "parameters" of that function. A *linear model* is a parametric model in which the assumed functional form that relates the predictors to the response variable is **LINEAR** (James et al., 2013)**.** The classic example is the linear regression:

$$f(X) = B_0 + B_1 X_1 + B_2 X_2 + \cdots. + B_p X_p$$

Most naturally occurring processes in social science and engineering are not entirely linear. If we specify a functional form that is far from the true underlying population function, ***f***, then our estimated model will perform poorly on new data, and any inferences drawn from the estimated parameters are likely to be inaccurate. However, if this is not the case, and the true underlying function that relates the predictor variables to the response variable is indeed linear or close to linear, then the estimated model will be well suited for both the tasks of prediction and inference (James et al., 2013).

The other class of methods is Non-Parametric. These methods do not make explicit assumptions about the functional form of the true underlying population model ***f.*** Instead they seek to estimate the population model which gets as close to the data points as possible. Non-parametric methods have a few significant advantages over parametric methods in that they avoid the assumption of a specified functional form of the population model that is being estimated, and they have the potential to fit a broader range of possible shapes and relationships**.** While the significant advantage of non-parametric methods is their lack of assumptions about the functional form of the population model and process under study, their main disadvantage lies in their increased complexity and scope and the large number of observations required to avoid overfitting and getting an accurate estimate for ***f***' (James et al., 2013).

### 2.10.4 Estimating Regression Coefficients

Linear Regression is a *parametric* method, so the process of function approximation has been reduced to specifying a functional form and then parameter estimation for that function. The true population regression coefficients are unknown and must be estimated. *Least Squares* is a method for estimating parameters which minimize the sum of squared residuals, also known as the residual sum of squared errors (RSS) (Chatterjee & Hadi, 2012)

$$RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$= \sum_{i=1}^{n}\left(y_i - \widehat{B_o} - \widehat{B_1}x_{i1} - \widehat{B_2}x_{i2} - \ldots - \widehat{B_P}x_{ip}\right)^2$$

As mentioned previously, the parameters $\hat{B}$, estimated from the *least squares* fitting of the data, are approximations of the true population coefficients β. These least squares estimated coefficients are the values that minimize the residual sum of squared errors (RSS). $\hat{B}_0$ represents the intercept, and $\hat{B}_j$ represents the estimated regression coefficient for predictor variable $X_j$.

A practical interpretation of a regression coefficient depends on whether the predictor variable is continuous or categorical. Accuracy and reliability of the coefficient interpretation depend on whether the regression model is valid based on its restrictive assumptions, whether collinearity exists between the predictor variables, whether we reject or fail to reject the null hypothesis of the model based on the F-Test, and whether the coefficient is significant or not based on the t-Test. Since Linear Regression is a parametric method, it makes certain assumptions, which are described below in the following section.

#### 2.10.4.1 Assumptions About the Functional Form of the Model

1. *Linearity assumption*: The underlying population model that relates the response ***Y*** to the predictor variables ***X*** is assumed to be linear in the regression parameters (Chatterjee & Hadi, 2012)

$$\mathrm{Y} = \mathrm{B}_0 + B_1X_1 + B_2X_2 + \ldots + B_pX_p + \varepsilon$$

2. *Additive assumption*: According to the functional form of the model, a one unit increase in $X_j$ results in an average of $\hat{B}_j$ unit increase in the response variable ***Y*** when all other predictor variables are held constant (Chatterjee & Hadi, 2012). If $\hat{B}_j$ is negative, then the one unit increase in $X_j$ corresponds to a $\hat{B}_j$ unit decrease in the response variable ***Y.***

#### 2.10.4.2 Assumptions About the Residuals

1. *Normally distributed*: The residuals are assumed to follow a normal distribution with a mean of zero, and an unknown variance parameter. The mathematical notation is below.

$$\epsilon \sim N(0\,, \sigma^2) \quad \text{,where } \epsilon \text{ represents the residuals (error terms)}$$

2. *Homoscedasticity*: The residuals are assumed to have constant variance. When the assumption is violated, the residuals are said to exhibit *heteroscedasticity*. Essentially when there is *heteroscedasticity* of the residuals instead of the variance being some unknown constant, $\sigma^2$, the variance of the residuals changes as a function of the inputs ***X.***

3. *Independent residuals:* The residuals are assumed to be independently and identically distributed (*i.i.d*). Residuals independent of each other have no correlation or covariances. *Autocorrelation* is the condition of correlated residuals (Chatterjee & Hadi, 2012).

#### 2.10.4.3 Assumptions About the Predictors

1. Nonrandom predictors: The predictor variables are assumed to be nonrandom, however in most real-world applications and scenarios, this assumption doesn't hold. The interpretation of a model's theoretical results can continue

to hold but altered to ensure all inferences are reserved conditional on the data observed. (Chatterjee & Hadi, 2012).

2. No measurement error: The input values of $x_{1j}, x_{2j}, x_{3j} \dots, x_{nj}; j = 1,2 \,..\, p$, are assumed to have been measured reliably without error. However, this assumption is usually not satisfied as measurement error and is a difficult problem to correct for. This is especially true in fields and domains where the variables of interest to a researcher are particularly difficult to measure and record. If measurement error does exist, then relationships between predictors and the response variable may be overestimated or underestimated (Chatterjee & Hadi, 2012).

3. The predictor variables are assumed to be independent of one another (Chatterjee & Hadi, 2012). Violation of this assumption, in which case the predictor variable is not independent and are instead associated with one another, is called "Collinearity". While this assumption in its most orthogonal sense is often violated, violations up to a certain extent do not pose any problems with the interpretation of the model. Weak correlations between predictor variables results in minimal interpretability issues. However, large correlations between predictors implies strong inter variable relationships, and this can pose an enormous risk in how the model is interpreted.

   The predictor variables are also assumed to be free of multicollinearity. Multicollinearity, an issue in model specification, occurs when two or more predictor variable are highly interrelated (James et al., 2013). Multicollinearity can be considered a redundancy of information in the model. Depending on the exact predictors under examination, multicollinearity is often an issue of an innate, existing relationship amongst the variables (Chatterjee & Hadi, 2012), such as between years of education and annual income. Multicollinearity may also occur because of insufficient data, incorrect use of dummy-coded variables, including a predictor that is calculated from two other predictors, or including very similar predictors (Chatterjee & Hadi, 2012). Often considered a source of error, the presence of multicollinearity can make interpretation of the model difficult and diminish the predictive utility of the model. Violations of this assumption often result in imprecise, fluctuating regression coefficient estimates.

#### 2.10.4.4 Assumptions About the Observations

1. Equal reliability: All observations are assumed to be reliable, and equally responsible in determining the regression results and influencing the conclusions (Chatterjee & Hadi, 2012). This is an assumption not often met as there are usually data points with unequal influence in most regression models.

## 2.11 Primer on Inference Modeling and Predictive Modeling

In general, there are a few broad reasons as to why someone may choose to build a regression model and how it fits the purpose of this study.

1. *Inference*: To put it simply, we use a regression equation to understand how the response variable $\boldsymbol{Y}$ is affected by changes in the predictor variables.
   a. Description: The regression equation is purely descriptive but provides the power and ability to model a complex system with interactions

(Chatterjee & Hadi, 2012). There are two goals of the model that are important: (1) account for as much systematic variation of the process as possible, (2) The other goal is to describe the process or complex system with a parsimonious model. The result provides a model that provides the least number of predictor variables to account for the largest part of the variation in the response variable (Chatterjee & Hadi, 2012).

b. Control: A regression equation may be used as a tool for control, in which the researcher seeks to determine the magnitude by which predictor variables must be manipulated (increased and/or decreased) to achieve a specific response variable value (Chatterjee & Hadi, 2012).

2. *Predictive Modeling*: The regression equation is constructed for the main goal of prediction, that is, predicting the response variable value of a future observation given their measured values for the set of predictor variables. In many scenarios, the set of predictor variable inputs are either easily obtained or readily available, but the response variable output is difficult to ascertain, extremely valuable, or extremely important, and hence we will attempt to predict it using the regression equation and model.

### 2.12 Tradeoff of Model Interpretability and Model Flexibility

There is a distinct tradeoff between flexible methods and inflexible methods and how they relate to model interpretability. In the setting where inference is the main goal, there is a greater emphasis and focus on estimations that are easy to interpret and very accurately interpreted. When the prime goal is inference, the estimated function $\hat{f}$, needs to be able to describe a given process or complex interacting system. Questions such as: (1) Which predictor variables are significantly associated with the response variable, and/or (2) What is the magnitude and direction of the relationship between the response variable and each predictor variable, are all questions better suited to be answered with a relatively inflexible parametric model such as linear models like linear regression. The linear model is chosen since the interpretation is easier to understand the predictor and response variable relationship but is conditional on a truly linear relationship between the predictors and response variables (James et al., 2013).

Inflexible methods generate a smaller hypothesis space of possible shapes to estimate $f$, while flexible methods generate a much wider range of possible shapes to estimate $f$. It is important to clarify that parametric methods are a broad class of methods that include both flexible and inflexible function estimations (James et al., 2013). Figure 2.6 provides an example of the tradeoff between flexibility and interpretability.

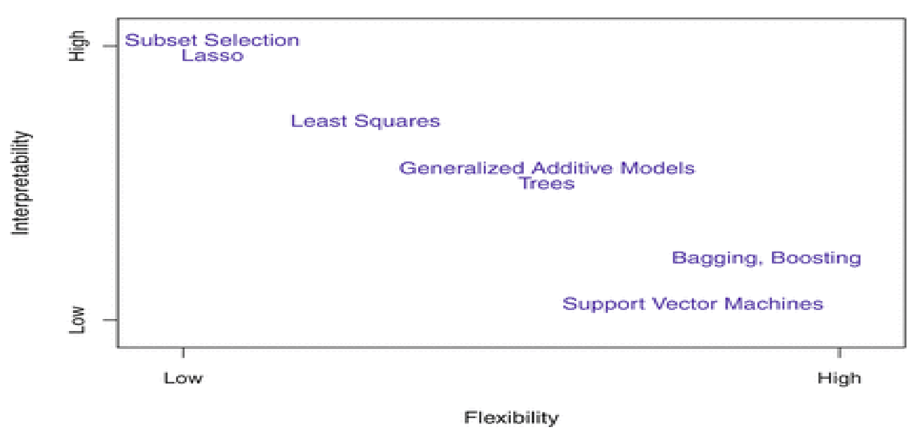


*Figure 2.6.* Flexibility vs interpretability tradeoff. Source: Introduction to Statistical Learning.

## 2.13 Framework for Measuring Error

There is a range of different criterion to be used to judge the accuracy of various fitted equations. The most important criterion used in comparing sets of candidate models ultimately depends on the prime goal of the analysis, whether it is prediction or inference. The regression model with the greatest $R^2$ is the full fitted model accounting for all the predictors. However, models with the lowest test set error should be chosen (James et al., 2013). The reason full fitted models always will have the highest $R^2$ and lowest RSS is explained later in this chapter. Selecting the best model by test set error is dichotomized to two common approaches (James et al., 2013):

1. Directly estimating the Test Error via resampling methods or hold out sets of unseen observations.
2. Introducing an adjustment to the training error to explain the bias for overfitting is made by indirect estimating (James et al., 2013).

### 2.13.1 Indirect Estimate of Test Error

In this case we are not creating a validation set or test set to measure error on and use as generalization error. Instead we are approximating it using the error from the data we trained and built the model on, (e.g., the *Training* Error). Adjusted $R^2$, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) are all ways to indirectly estimate the generalization error of a model. These techniques penalize *overfitting* by adjusting the RSS (residual sum of squares) based on the size of the data in which the model was built on, and the number of parameters in the model. In cases where there are many samples the model was trained on relative to the number of parameters in the model, the imposed penalization or adjustment of the RSS is small. However, in the opposite case, in which there is a small number of samples in the data relative to the number of parameters in the model, then the penalization is much larger. This is because models trained on large sets of data relative to a moderate number of parameters in the model often do not *overfit* the data, whereas in the inverse scenario, the model is *overfitting* the data (James et al., 2013).

Models will be selected based on the attempt to balance conflicting demands of fitting accuracy and simplicity (Chatterjee & Hadi, 2012). When parameters are added to the model in which case they do not result in a large enough decrease in training error, a penalty is applied in the form of a larger AIC and BIC value for that model. When comparing various candidate models, smaller values of BIC and AIC are preferred since they suggest a lower test error and thus better generalization performance. BIC is preferred over AIC due to its larger penalization of overfitting when irrelevant predictor variables are included in the model (Chatterjee & Hadi, 2012).

$AIC = \frac{1}{n\hat{\sigma}^2}(RSS + 2d\hat{\sigma}^2)$ where *d* equals the number of parameters in the model

$BIC = \frac{1}{n\hat{\sigma}^2}(RSS + \log(n)d\hat{\sigma}^2)$ where *d* equals the number of parameters in the model

Adjusted $R^2$ is a goodness of fit measure like $R^2$. It is used for selecting among models containing different numbers of parameters (e.g., selecting among a set of models which contain different numbers of predictor variables). Adjusted $R^2$ is a popular and well-motivated alternative to $R^2$ and should be used in place of $R^2$ (Chatterjee & Hadi, 2012). Whereas $R^2$ represents the total proportion of variance in the response variable explained by the model, Adjusted $R^2$ provides a neutral estimate of the portion of variance explained. Adjusted $R^2$ also takes the sample size and number or predictor variables into account as well (Duke University, 2015) . $R^2$ is a measure of goodness of fit that increases as more predictors are added to the model. Adjusted $R^2$ attempts to account for overfitting, by adjusting the value of $R^2$. Adding additional noise variables to the model increases the size of the model and will lead to an increase in $R^2$ quantity and decrease in Adjusted $R^2$ quantity (James et al., 2013). The formula for Adjusted $R^2$ is stated below:

$R_a^2 = 1 - \frac{\left(\frac{RSS}{n-d-1}\right)}{\left(\frac{TSS}{n-1}\right)}$ where *d* represents the number of variables in the model, *n* is the number of observations, RSS is the residual sum of squares, and TSS is the total sum of squares.

For the above equation TSS, *total sum of squares*, is defined as TSS $=\sum_{i=1}^{n} y_i - \bar{y}$. It is the sum of the squared differences between a sample observation response variable value and the overall mean. The above-adjusted $R^2$ equation shows that if predictor variables are added to the model, and there is not a corresponding sufficiently large enough decrease in RSS, then adjusted $R^2$, which is an unbiased measure for *goodness of fit*, is decreased. Large discrepancies between $R^2$ and adjusted $R^2$ suggest overfitting and thus high generalization error or high-test set error. As in the case for $R^2$, larger values of adjusted $R^2$ are desired when selecting between similar models containing different numbers of parameters.

Adjusted $R^2$, AIC, and BIC were all used during the model selection process to choose a final model amongst a set of different candidate models. This is further expounded upon in later chapters, specifically Chapters 3 and 4.

### 2.13.2 Direct Estimate of Test Error

The alternative approach is to directly estimate the generalization error (test set error) using cross validation or other resampling techniques which has an advantage over the indirect estimates of generalization error. The advantage is that there are less assumptions being made about the true underlying model (James et al., 2013) . The advancements in computers and computational power has decreased the challenges in the past regarding the performance capability in cross validation for very large numbers of either ***n*** samples, and/or ***p*** predictor variables in the model. Resampling methods are an indispensable tool in modern statistics and facilitate refitting the model by repeatedly selecting and drawing samples for a training set and then refitting the model to gain a better understanding of the model (James et al., 2013). Cross-validation is one of the most popular methods and has various types. Three of the main types of cross-validation are:

1. Validation Set Approach
2. Leave One Out Cross-Validation
3. K-Fold Cross-Validation

The *validation set approach* involves dividing the available data into two parts, *training set* data and *validation set* data. The validation set is also called a *hold-out set.* The parameters of the model are estimated using the training set data. The fitted model is used to make predictions on the hold-out set. Performance on the holdout set is measured and then used to compare different candidate models. The model which performs best on the hold-out set is the preferred (James et al., 2013).

*Leave-One-Out Cross-Validation* (LOOCV) is an approach that splits the observed data into two parts much like the *Validation Set* approach. However, LOOCV differs is in the size of the validation sets. For LOOCV, the validation set for a single observation is sample size 1 and the training set is the remaining *n*-1 observations. The model is then fit on *n*-1 observations and is tested on a single observation. The real magic of LOOCV is that the above procedure is repeated "*n"* times. For each of the ***n*** number of repeats, the data is split into two partitions, the *n*-1 sized training set and a single observation validation set. No single observation is used as the validation set more than once. Therefore, repeating the process *n* times produces *n* predictions and thus *n* residual errors (James et al., 2013).

*K-Fold Cross-Validation* is another approach to cross-validation. The process involves a random division of the observation set into some set of groups of equal size. The validation set is the first fold (k) which is typically set to 5. The remaining k-1 folds are the basis for fitting the model. Errors are calculated based on the observations placed in the hold out fold of the model (James et al., 2013). As shown in Figure 2.7, this is repeated *k* times, thus each of the *k* folds gets to act as the hold-out set *k* times and as a part of the training set *k-1* times. The result is *k* estimates of error, which are averaged together to form the *k-fold Cross-Validation* estimate. This estimate is used when comparing different models as a part of the model selection process (James et al., 2013). Below are two examples of k-fold cross validation in which the *mean squared error (MSE)* and *mean absolute error* (MAE) were used to calculate prediction error (James et al., 2013).

$CV_k = \frac{1}{k}\sum_{i=1}^{k} MSE_i$ , i.e. the average of the *k* estimates of mean squared error for all the *k-folds* ( $MSE_1, MSE_2, MSE_3, \ldots., MSE_k$)

$CV_k = \frac{1}{k}\sum_{i=1}^{k} MAE_i$ ; i.e. the average of the *k* estimates of mean absolute error for all the *k-folds* ( $MAE_1, MAE_2, MAE_3, \ldots., MAE_k$)

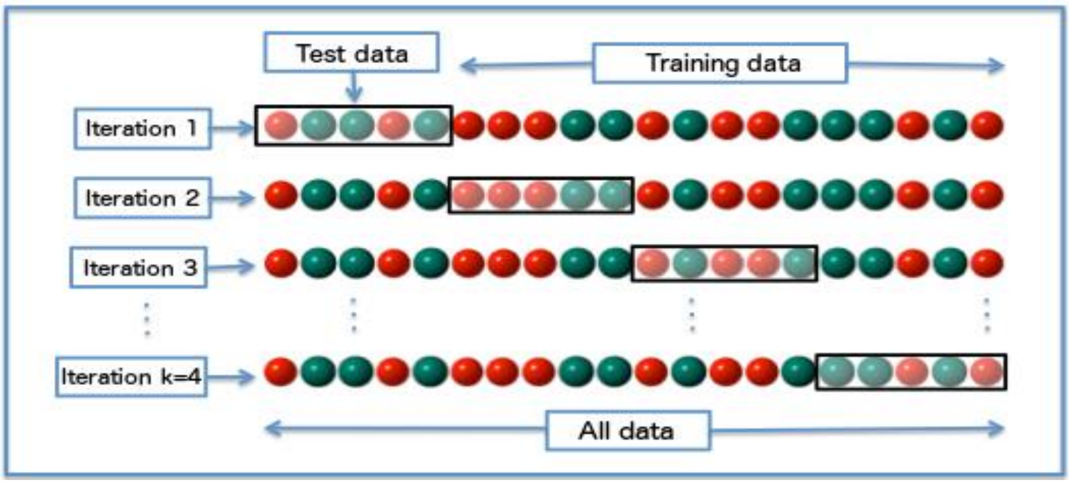


*Figure 2.7.* Example of k-fold cross validation iterations. Source: Introduction to Statistical Learning.

There are advantages and disadvantages to each of the above-mentioned methods of cross-validation. The first approach, *Validation Set* method, has the advantage of being easy to understand and fast to compute. However, its major disadvantages are that the resultant cross validation estimate of test error can be high for the variable. The test error depends on which observations were included in both the training set and validation set (James et al., 2013). Most statistical models tend to perform worse when trained on fewer observations. In contrast, the other disadvantage with the *validation set* approach is that the validation set error may be an overestimate of the generalization error (James et al., 2013). *Leave-Out-One Cross-Validation* or *K-Fold Cross-Validation*, have the major advantage of using a procedure which requires the training of the model multiple times on different subsets of the data. For that reason, these approaches tend to not over estimate generalization error for a model as much as the *validation set* approach (James et al., 2013). When Leave-*One-Out cross-validation* is not computationally feasible due to dealing with an extremely large data set, *K-Fold cross-validation* is an efficient alternative (James et al., 2013). Typically, the number of folds is usually between 5 and 10.

Neither Leave One Out Cross Validation (LOOCV) or K-Folds Cross Validation was used as a part of the model selection procedure detailed in Chapters 3 and 4 of the praxis. However, it is presented here within the literature review since it is relevant to the research.

### 2.13.3 Choosing the Right Error Metric to Assess Predictive Power

*Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE)* are popular measures for quantifying the extent to which a predicted output matches the observed output (James et al., 2013). MSE is the average of the Residual Sum of Squares (RSS), while RMSE is the square root of that quantity. As mentioned earlier, RSS is the sum of the squared differences between the estimated functions output and the true observed output, $RSS(\beta) = \sum_i^n (y_i - \hat{f}\,(x_i))^2$ . The formulas for MSE and RMSE are presented below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{f}\,(x_i))^2$$

$$\text{RMSE} = \sqrt{MSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{f}(x_i))^2}{n}}$$

MAE on the other hand is the average of the absolute differences between predicted outputs and observed outputs. Mean Absolute Error, much like Root Mean

Squared Error, has the advantage of expressing error in the units of the response variable of interest. Since the absolute error, $| \, y_i - \hat{f}(x_i) \, |$ is used and instead of the squared error formula, $\left( y_i - \hat{f}(x_i) \right)^2$, when using MAE, all errors are relatively weighted the same. MAE places a linear penalty on the error, whereas MSE and RMSE place a quadratic (squared) penalty on the errors (James et al., 2013).

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} | \, y_i - \hat{f}(x_i) |$$

Thoughtful and careful consideration should be employed when selecting between different error measures. RMSE has the benefit of penalizing large errors more than smaller errors since it applies a quadratic (squared) weight, while MAE penalizes all errors equally since it uses a linear weight. An appropriate example if one might use MAE as the primary criterion is when forecasting prices and for the organization employing the model, a forecast error of 8 units only costs TWICE as much as an error of 4 units. In this scenario the true cost of an error is proportional to the size of the error.

Within Chapter 4, all three above mentioned statistics, Root Mean Squared Error, Mean Squared Error, and Mean Absolute Error (MAE) are reported for various candidate models and the selected final model.

### 2.14 Linear Regression Variable Selection Procedures

There are many methods and techniques for variable selection, both classic and modern. These techniques that are chosen are in part due to scenarios of either (1) Subsets of the predictor variables are correlated with one another to a problematic degree, (2) Subsets of the predictor variables are "noise", which is irrelevant and unrelated to the response variable (Chatterjee & Hadi, 2012). Retention of these variables can lead to unnecessary complexity, inflated variance, loss of precision, overfitting, and other problems in the model, affecting interpretability and predictive ability. There are three important classes of variable selection methods, (1) Subsets Selection, (2) Regularization, and (3) Dimension Reduction Techniques (James et al., 2013). This praxis utilizes a type of Subsets Selection technique called *Best Subsets Selection*. Further details and information regarding how *Best Subsets Selection* were utilized in choosing which predictor variables to include in the final model can be found in Chapters 3 and 4. Other subset techniques for variable selection are Forward Selection, Backward Elimination, Stepwise Method, and Best Subsets Selection.

The application and use of the variable selection procedures Forward Selection, Backward Elimination, Stepwise method, and Best Subsets Selection all produce several regression equations containing different numbers of predictor variables (Chatterjee & Hadi, 2012). These various equations can be evaluated using advanced statistics such as AIC, BIC, or Adjusted $R^2$, since they provide a suitable way to compare models of different numbers of predictor variables.

### 2.15 Knowledge Gaps in Literature Review

Extensive literature research for the use of predictive analytics and multiple regression in forecasting the rates of surface clearance based on the various predictor variables associated with surface and subsurface clearance operations were conducted. The use of predictive analytics for forecasting munitions clearance rates or levels of resources required for munitions response action is not widely used, if at all. The literature research resulted in no literature related to predicting munitions-related resources or predicting the number of acres that could be surface or subsurface cleared based on certain predictor variables. The munitions response industry is rather unique due to the acute risks related to munitions and relatively a new industry as compared to more established industries such as the construction and environmental remediation. Most forecasting for munitions clearance durations, level of resources needed, the number of acres cleared per day or week is based on the expert judgment within an organization. Historical cost and operational performance data are not readily available to the public due to the sensitivity of cost data and competitive nature of the acquisition tools used to acquire the services of munitions response contractors.

As presented earlier, most of the munitions response related literature were related to DoD policies, processes, GAO reports, EPA guidance, stakeholder guidance, magnetic sensor development for UXO detection, hazardous risk assessments, and explosive safety. A host of literature were also found in research and testing munition response technologies related to intrusive subsurface work, geophysical mapping, detection, and discrimination of munitions items from non-munitions items located beneath the land surface. DoD's Strategic Environmental Research and Development Program (SERDP) has been the leader in funding research in geophysics based terrestrial detection systems for subsurface munitions and underwater munitions.

In recent years, government agencies and companies have been generating massive amounts of data associated with business processes, finances, and operations. Big data analytics involves using data mining techniques to mine data from various sources and merge it which historical data to make predictions and informed decisions about the performance of a business market or other industry. The amount of data collected and stored by firms in the munitions response industry is massive, especially digital geophysical data. However, operational and performance data within the munitions response industry appears to remain hidden within each firm and may be dormant and unused for any data analytics. The use of predictive analytics within the munitions response industry is not widespread publicly. There was very little to no predictive analytics information available about the performance of surface and subsurface clearance operations in the literature search. The potential benefits of analyzing munitions clearance and cost information could be significant. Appropriate data analytics techniques could help firms identify key factors or variables that contribute to munitions clearance operational performance and the risks associated with those operations.

These concerns and gap in the literature search drive the interest and need for research in examining a solution that can assist firms in predicting preliminary baseline estimates of operational resources required on a per acre basis to perform specific response actions. The purpose of this research is to examine the relationship and influence of factors (independent and dependent variables) that predict the surface clearance acres cleared of munitions and non-munitions related debris at munitions response sites based on production data, labor resources, site physical properties, amount of munitions contamination, and vegetation removal. The application of multiple regression techniques is used to examine the relationship between the variables. It is anticipated that a forecasting technique will have a practical application in the Munitions Response Industry by assisting firms in their initial screening and risk decision-making process when deciding on pursuing or not pursuing various acquisition opportunities associated with munitions response action contracts.

## Chapter 3: Methods

Unexploded ordnance (UXO) poses serious safety risks to the public. Many sites are still unsafe and unsuitable for most kinds of public, commercial, agricultural, or private land use without significant Department of Defense (DoD) resources and capital investment in restoring these lands to within acceptable human health risk hazards (DoD, 2006). No accepted standard exists for the restoring lands free of UXO. The cleanup of UXO sites is unique and unlike the traditional cleanup of hazardous waste sites where standard acceptable limits for cleanup have already been established. Each site is unique and requires an agreed upon site-specific approach between the DoD and the stakeholders to reach an agreed-upon risk-based cleanup standard (i.e., surface clearance, subsurface clearance, etc.). For example, some stakeholders may want all the land cleared of UXO (i.e., surface, and subsurface clearance) to a depth of several feet below the surface, while other stakeholders may want to clear UXO from only the surface area to achieve immediate risk reduction until additional funding is obtained or risk scenarios change. Surface clearance is the least costly alternative, with up to 30 times less expensive than subsurface clearance (RAND, 2005).

Estimating the cost of UXO cleanups is a unique challenge due to the uncertainties and complexity of site factors, such as: vegetation density; the amount of UXO and non-UXO related contamination; amount, and depth of subsurface UXO and subsurface metal debris; limitations of UXO detection technologies; available resources; site coordination; stakeholder and regulatory engagement; current and future land use; and budgetary constraints. The cost of cleanup is further compounded by changes in

DoD project scopes and expansion of cleanup areas due to the discovery of additional contamination as presented in the Problem Statement.

These issues of concern drive the interest and need for further research in exploring a practical solution to aid in predicting munitions surface clearance rates. The overall purpose of the model is to be able to assist munitions response project managers, program managers, and decision makers in predicting munitions surface clearance rates to help support pre-bid decision making in acquisition opportunities, resource, and operational planning, and management of on-going field operations for surface decontamination activities to mitigate public health and environmental risks. The application of multiple regression techniques is used to examine the statistical relationship and significance of the variables. The model examines the munitions response predictor variables that are significant or not significant in predicting the weekly number of surface acres decontaminated of munitions and munitions-related contamination based. The effectiveness of the model is based on the statistical relationship of predictor variables and response variable commonly used in the measurement of field operations for munitions response clearance activities. The variables are categorized by (1) number and type of labor resources, (2) operational time in the field, (3) quantity of munitions and munitions-related contamination cleared, (4) physical site characteristics, and (5) density and amount of vegetation clearance. It is further anticipated that the forecasting model will provide the foundation to explore subsequent applications for munitions decontamination activities, such as digital geophysical detection operations, subsurface clearance operations, and underwater clearance activities. Data from actual DoD surface clearance site decontamination activities were collected and used for building the multiple regression model.

Chapter 3 provides a comprehensive summary of the research methodology performed to address the Research Questions and Hypothesis presented in Chapter 1. Chapter 3 is divided into the following main sections: data collection, research design and methodology, appropriateness of research, data identification and collection, data analysis process, and a chapter summary.

Figure 3.1 below provides a graphical representation of the methodology followed in the study and begins with defining the initial problem through data analysis, model building, and the final model evaluation for the intended purpose of the study. The data analysis plan in Chapter 3 and results provided in Chapter 4 follows the methodology closely as presented in Figure 3.1.

**3.1 Data Identification and Collection**

The removal and clearance of munitions from the land surface add immediate value to the land by reducing the immediate risk and human exposure to UXO. The likelihood of a severe accident or potential death resulting from an unintentional detonation is reduced significantly. By clearing the surface area, access to the site can occur with certain restrictions and facilitate subsequent munitions response action activities. The ability to forecast the number of surface acres cleared on a weekly rate

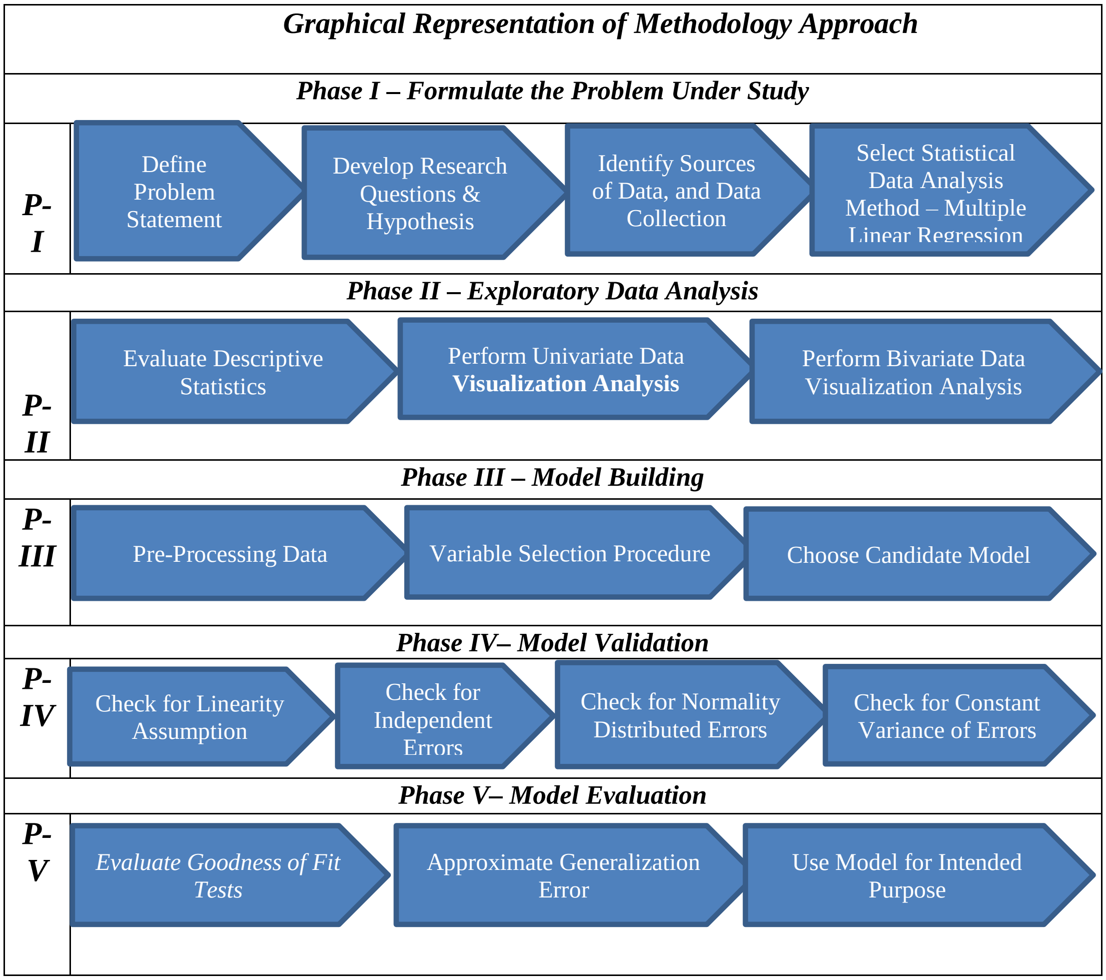


*Figure 3.1*. Graphical Representation of Methodology Approach

based on the quantity of contamination, available labor resources, quantity of vegetation removal, and certain physical site properties would provide munitions response firms the practical ability to predict surface clearance production for decision making criteria needed for initial bid or no bid decisions, support for estimating, and performance of on-going munitions response field operations. Assessing only the surface clearance response action activity provides a clear separation of other activities (i.e., digital geophysical mapping and subsurface excavation of anomalies), which are usually combined and integrated with a different set of variables, different level of contamination, and level of resources. Focusing on activities associated with only surface clearance decontamination will assist in determining the value of the proposed methodology for further use in predicting other subsequent munitions response activities, such as digital geophysical mapping, subsurface clearance, demilitarization and range scrap processing and disposal.

To help support and provide value in forecasting the number of surface acres that can be decontaminated and cleared of munitions items, data were collected from five different contractors working at various sites within one munitions response area. This approach consisted of using actual field data collected from various sources specific to surface clearance operations conducted at a large and heavily contaminated military range impact area. Sources of data consisted of: (1) field operational performance charts, (2) surface clearance production tables, (3) monthly and quarterly field operational summary reports, (4) After Action Reports, (5) weekly field summary reports, and (6) production maps. The data was used to construct the linear regression model which estimates the quantity and rate of surface acres cleared of munitions items and munitions-related contamination. The surface area cleared of munitions items and munitions-related contamination were representative samples of munitions response sites located within a 3500-acre former military live impact area used in the past for air to ground, ship to shore, and ground to ground-live fire training. The large impact training area was used for over 60 years with live fire training. The area is grossly contaminated with tens of thousands of live and inert munitions items, hundreds of destroyed targets, and tens of millions of pounds of munitions-related debris and cultural debris.

A map of the Munitions Response Area (MRA) is provided below in Figure 3.2. The MRA is divided into individual munitions response sites (MRS's) and numbered accordingly. MRS's vary in size and can range from one acre to thousands of acres. The MRS's are further divided into grids that are approximately one-quarter (1/4) acre in size. UXO Teams work are assigned to various grids to perform surface clearance activities. Progress of work is tracked and annotated on the map when completing various phases of surface clearance activities within each grid of a MRS. The tracking process of the surface clearance activities includes: (1) initial sweep of non-UXO material, (2) vegetation removal, (3) surface clearance of munitions debris and UXO deemed safe to move, (4) collection of munitions debris for further processing and disposal, (5) consolidation and preparation of UXO items for explosive demolition activities as shown in Figure 3.3 below, and (7) final clearance and contractor quality control/quality assurance activities.

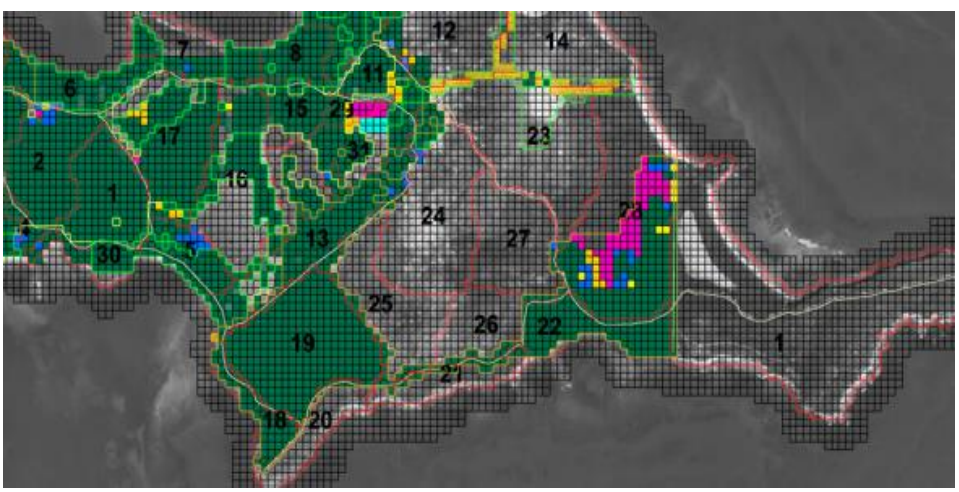


*Figure 3.2. Sample Map of a Munitions Response Area divided into Munitions Response Sites*

Figure 3.3. Consolidation of UXO items and preparation of explosive demolition

Sampling data was collected to represent the predictor, or independent variables of (1) the number of workdays worked per week for UXO Techs, (2) total number of UXO Tech hours worked per week, (3) number of true hours worked in the field per week, (4) number of UXO Technicians working in the field per week, (5) number of workdays worked per week for vegetation removal technicians, (6) number of Vegetation Removal Technicians, (7) total hours worked by vegetation removal technicians, (8) true number of hours worked in the field performing vegetation clearance, (9) quantity of munitions and explosives of concern (MEC), material potentially presenting an explosive hazard (MPPEH), range-related debris (RRD) and munitions debris items cleared per week, (10) weight of metallic scrap items removed and cleared per week, (11) slope condition of munitions response site, (12) vegetation density, and (13) number of vegetation acres cleared. Data were also collected to represent the response variable Y, the quantity of the number of acres cleared of munitions and munitions-related debris. The abbreviated version of independent and dependent variables are listed in Table 3.1.

Appendix 4 lists the independent and dependent variables and provides a definition for each variable. Table 3.1 presents the independent and dependent variables along with the description of each of the variables under evaluation in the development of the model.

Data collection consisted of extracting data from actual field operations. Sources of data consisted of: (1) field operational performance charts, (2) surface clearance production tables, (3) monthly and quarterly field operational summary reports, (4) After Action Reports, (5) weekly field summary reports, and (6) production maps. An Excel spreadsheet was used to compile the raw data into weekly summaries of the independent variables selected for study to predict the response variable (i.e., the number of surface acres cleared) and is included in Appendix E.

Consideration was given to add additional sites with similar characteristics from other munitions response areas at other locations. However, the differences in the raw data collected and reported, the differences in clearance objectives (i.e., surface, DGM, and subsurface combined), and inconsistencies in data collection and recording would have required significant transformation, additional assumptions, and labor details that were not readily available nor obtainable due to sensitive and contractor privileged information. It was determined that multiple sites within a large munitions response area with similar physical characteristics, level of contamination, and similar processes would be more consistent for developing for analysis purposes. It is anticipated that the modeling of the one munitions response area was applied to the modeling approach of other munitions response areas with similar variables, similar site characteristics, and similar surface contamination levels.

The data represent vegetation removal and surface clearance activities over a five-year period. There were 149 observations recorded, which represents vegetation and surface clearance activities performed over a total of 149 weeks. The weekly data represent surface clearance activities that occurred between a five-year period from 2006 through 2011. The operation and process of manual vegetation removal and manual surface clearance remained similar over the time. Except for the use of standard chainsaws to cut vegetation, no mechanized equipment was utilized for actual vegetation cutting or actual surface clearance activities for the sites under study. Mechanized equipment and other labor resources from separate and independent contractors were used to move large masses of cut vegetation material, and stockpiles of range scrap and munitions debris from each of the acres surface cleared to other locations for further demilitarization and processing of recycled materials, which were not evaluated for this study. Data were initially reviewed and collected through online research of DoD sites containing Administrative Records on file for the environmental and munitions response program. Research for performance related data was performed and collected for sites with the desired data variables, specifically for sites that had Remedial Actions or Removal Actions completed in the past. Four sources of data were used for this research as described below:

- **After Action Reports (AAR):** The purpose of the AAR is to document that all explosives safety aspects of the selected response have been completed per the approved Explosive Safety Submission (ESS) required by the Naval Ordnance Safety and Security Activity (NOSSA; 2011). AARs provide a brief description of the MRA or MRS; summary of the MEC or MPPEH found, description of the relative effectiveness and any limitations of the technologies used, a summary of the Quality Control (QC) and Quality Assurance (QA) reports for the response, anticipated end use of each area, a summary of land use controls implemented and summary of provisions of long-term management.

- **TCRA Contractor Monthly and Quarterly Progress Reports:** The purpose of the progress reports is to report an overall summary of the MEC Removal Action that was performed at a specific MRS under contract during the reporting period. The progress report contains a technical summary, non-field operations, weather data, weekly field production reports (field labor, MEC/MPPEH removed per grid or acre, Vegetation cut and removed per acre or grid, removal of non-MEC related debris), production charts, contract task orders issued, variance reports, corrective actions taken, difficulties encountered, maps of progress, and other contract administrative issues specific to the performance of the munitions response action.
- **TCRA Field Production Data:** The purpose of the production data is to record and track contractor daily or weekly field activities to monitor field labor utilization, production, schedule, and other performance criteria. Field data were recorded in Daily Field Production Reports or Personal Digital Assistant devices and transferred to Access or Excel Data Files. The information collected consisted of:
    - identification of locations and amount of munitions items and non-MEC related debris removed per grid or acre,
    - number of field labor personnel and hours worked for MEC activities,

- number of vegetation field labor personnel and hours worked,
- weekly hours of field labor,
- number of vegetation grids or acres cleared of vegetation,
- number of subsurface anomalies identified and removed,
- identification of anomalies and depth of anomalies,
- Quality Control, disposal, and demolition of live MEC items.

- Remedial Investigation/Feasibility Studies (RI/FS): The RI/FS serves as the CERCLA investigative phase for collecting environmental or munitions related data to characterize site conditions, determine the areal extent of contamination, nature of the waste, and assesses the risk hazards to human health and the environment. The RI/FS is an investigative process and not a production type process such as a Remedial or Removal Acton that is directed towards remediating the site of all contaminants. A review of the RI/FS data showed very little production type data on surface clearance and was not considered any further for this study.

A summary of the sources and screening for appropriate data collection for the study is provided in Table 3.1. Monthly, Quarterly Progress Reports, and Field Production Reports were selected based on the most detailed data available for predictor variables and considered important for selection of variables.

Table 3.1. *Preliminary Research Screening Matrix for Dependent and Independent Variables*

| Data Screening Matrix | | | | | |
|---|---|---|---|---|---|
| Research Resource | Project Data Summary | Weekly Field Production Performance Data | Field Labor Resources | Physical Site Characteristics | Weekly Count of MEC and Non-MEC Related Debris |
| AAR | X | | | X | |
| Monthly Reports | X | X | X | X | X |
| Field Production Data | | X | X | X | X |
| RI/FS | X | | | X | X |

## 3.2 Data Analysis Procedures

To examine the research questions, a multiple linear regression was conducted to assess if predictor variables, $X_1$ through $X_{13}$ predict the response variable, $Y_1$. Multiple linear regression is used to assess the relationship among a set of categorical or continuous predictor variables and a single continuous response variable (Pallant, 2016). The following regression equation (main effects model) was used, where $Y$ is the response variable, $B$ is the unstandardized beta coefficients (slope), $a$ is the intercept, and $X$ is the predictor:

$$Y_1 = a + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 + B_6X_6 + B_7X_7 + B_8X_8 + B_9X_9 + B_{10}X_{10} + B_{11}X_{11} + B_{12}X_{12} + B_{13}X_{13} \quad (3.1)$$

Since serious distortions and misrepresentations of model coefficients, t-Tests, and p-values could occur, digital environments were used to perform the statistical analysis. Each digital environment is essentially a different suite of tools or statistical software package. The initial analysis was performed in Microsoft Excel with the aid of the Statistical Analysis Software (SAS) plug in. SAS provides a software suite for advanced multivariate analytics, predictive modeling, business intelligence, and data mining. Both SAS and Intellectus Statistical Software was used for the analysis.

The initial examination of data begins with an Exploratory Data Analysis (EDA). EDA is a critical early step in data analysis that employs a variety of graphical and numerical techniques to summarize datasets, determine relationships between variables, and uncover underlying structure (Cox, 2017). The goal of EDA is to maximize insight into the data through both graphical visualization and numerical analysis to detect patterns and anomalies in the data (Cox, 2017).

### 3.2.1 Variable Identification

The first step in the Exploratory Data Analysis is Variable Identification. The type of variable, whether predictor or response, is first determined. The variables examined were selected from the munitions response performance charts and field data reports as it related to labor resources, physical site characteristics, and amount of contamination that were decontaminated from the surface land area. Other variables, such as type of ordnance and depth of find were also available in the data search. However, there was inconsistency in the data collected between the various contractors and sites under analysis. Because these variables that were not reported consistently in each of the data collection reports, they were not included as candidates for variable identification. A summary of the identified variables selected for the regression model and their levels of measurement are provided in Table 3.2 and Appendix D. Appendix D provides a more detailed description of the definitions for each predictor and response variable.

Table 3.2. *Identification of Dependent and Independent Variables for Surface Clearance Activities*

| Variable ID | Variable Name | Variable Type | Definition |
|---|---|---|---|
| **Response (dependent) variable:** | | | |
| Y1 | Weekly Number of Surface Acres | Continuous | Number of acres surface cleared per week of MEC, MPPEH, RRD, MD, metal scrap, targets, and debris |
| **Predictor (Independent) Variables:** | | | |
| Variable ID | **Predictor Variable Name** | | **Definitions** |
| $X_o$ | Site ID | Scale | Identification of Munitions Response Site |
| $X_1$ | MEC_WRKDAYS/WK | Scale | Weekly number of Field UXO Tech Days worked |
| $X_2$ | Total MEC-SITE-HRS/WK | Scale | Total number of weekly hours for UXO technicians performing all related surface clearance activities ( |
| $X_3$ | True MECHRS/WK | Scale | Weekly number of True hours for UXO Technicians working in the grid |
| $X_4$ | Num of UXOTECH/WK | Scale | Weekly number of UXO Technicians performing surface clearance activities |
| $X_5$ | VEG_WRKDAYS/WK | Scale | Total number of workdays per week for Vegetation Removal Technicians performing vegetation clearance ( |
| $X_6$ | Num of VEGTEC/WK | Scale | Weekly number of Vegetation Removal Technicians performing vegetation clearance |
| $X_7$ | TOTAL_VEG SITE HRS/WK | Scale | Total number of weekly hours for Vegetation Removal Technicians performing vegetation clearance |
| $X_8$ | True VEGHRS/Wk | Scale | Weekly number of true hours for Vegetation Removal Technicians working in the grid |
| $X_9$ | NumOFMEC/MPPEH/RRD/ MD _ITEMS | Scale | Weekly estimated number of individual MEC, MPPEH, RRD, and MD cleared from the surface area |
| $X_{10}$ | SCRAPLBS | Scale | Weekly estimated weight of metal scrap, targets, and cultural debris removed from surface |
| $X_{11}$ | SLOPE | Scale | Average estimated slope of topography within sites completed on weekly basis |
| $X_{12}$ | VEGDEN | Scale | Average percentage of vegetation and tree canopy density within site area worked. |
| $X_{13}$ | Num of VEGACRE Cleared/Wk | Scale | Number of vegetation acres cleared per week within site area proceeding surface clearance activities. |

### 3.2.2 Descriptive Statistics

This stage of the Exploratory Data Analysis included the application of graphical methods to explore the distributions of the variables. The graphical techniques for the data analysis of the univariate variable will include histograms, box plots, frequency charts, and bar charts. The choice of graphs will depend on the type of variable.

For continuous variables, the plots are meant to provide information about the central tendency of the distribution, spread of the distribution, and the shape of the distribution. For example, predictors with bell shaped normal distributions are easy to interpret and have desirable properties for many ensuing statistical tests in the data analysis. For variables that do not have symmetric or close to symmetric distributions, robust numerical estimates were used to measure central tendency and spread, or a data transformation can be used on the data to achieve normality. For categorical variables, frequency tables were used to study the distribution of each category, nominal or ordinal, of the variable. Specifically, the analysis is concerned with how categorically balanced or imbalanced the observations are.

### 3.2.3 Bivariate Analysis

This phase of the Exploratory Data Analysis involves the use of graphical and numerical methods to visualize the relationship between variables. Scatterplots and correlation coefficients were used to visualize and quantify the bivariate relationships between variables (Pallant, 2016).

A key assumption of linear regression is the linearity of the relationship between the predictors and the response variables. The functional form of the linear regression equation is assumed to be linear of the parameters, $\boldsymbol{B_0}$ ..... $\boldsymbol{B_p}$, where $p$ equals the number of predictor variables. For predictor variables that are determined to be continuous, scatter plots between the response variable $Y$ and the individual predictor variable $X_j$ can reveal important information about the strength and type of relationship. Strong relationships, as evidenced by the scatter plot and further justified via a large correlation coefficient, are further potential indications that the predictor variable could be useful in modeling and predicting the response variable. The spearman correlation coefficient was used to assess the nonlinear relationship between variables. "*While the presence of a linear pattern is reassuring, the absence of such as pattern does not imply that the linear model is incorrect*" (Chatterjee & Hadi, 2012, p. 102)

Another fundamental and crucial assumption of the linear regression model is that the predictor variables are independent, therefore they are not correlated with one another. For continuous predictor variables, scatter plots and correlation coefficients were used again as tools to reveal if there are strong interrelationships in the data. Large (in absolute value) Pearson correlation coefficients indicate collinearity between two predictor variables. A key assumption for the Pearson correlation requires that the relationship between each pair of variables is linear (Conover, 1981). A violation of this assumption was detected if there is curvature among the points on the scatterplot between any pair of variables.

The purpose of Exploratory Data Analysis is to investigate the data, and thus if there are strong collinear inter-relationships between the predictor variables, this will not be explicitly corrected for at this stage of the analysis. It will however be noted, as these non-orthogonal relationships can create problems in future analysis and model interpretation.

### 3.2.4 Potential Outlier Detection and Exploration

Exploratory Data Analysis is also used to help identify univariate or multivariate outliers (Cox, 2017). Univariate plots such as the histogram or box plot can be used to identify potential univariate outliers, while scatterplots can help detect bivariate outliers, which are points that may exist very far away from the higher density areas of data points in the plot (Pallant, 2016). At this point of the exploratory and investigative stage, outliers will only be identified and flagged as possible high leverage points; "*In any analysis, points with high leverage should be flagged and examined later in the modeling process to see if they are influential*" (Chatterjee & Hadi, 2012, p. 108).

### 3.2.5 Missing Values and Data

Exploratory Data Analysis was used to identify observations with missing predictor variable values, and to quantify the magnitude of missing values for each individual predictor variable. Since this is an exploratory phase, the actual decision on how to handle the missing values are addressed in the pre-processing stage of the actual data analysis and presented in Chapter 4.

### 3.2.6 Pre-Processing

The pre-processing phase includes centering and scaling the data. The specific strategy that was used is *standardization.* Centering and scaling of the input data has the effect of making the regression coefficient estimates unitless. With standardization, these estimates are interpreted as marginal effects of the predictor variables in standard deviation units. For example, a one standard deviation unit of $X_j$ results in a $\widehat{B_j}$ change in the standardized units of $Y$. Centering and scaling are also a preferred method of preprocessing the input data, it is especially when the data exhibits collinearity (Chatterjee & Hadi, 2012).

Management of missing data and values is also included in the pre-processing phase. There a few strategies to deal with missing data. One such strategy is to omit records with missing data from the analysis. Depending on the number of records with missing data, this can either lead to small or large losses of data. Obviously, a large loss of data which would reduce the size of the data set can be harmful for the analysis. Such harmful effects include increased risk of overfitting, collinearity, and total model variance. "*An alternative to omitting records with missing values is to replace the missing value with an imputed value, based on the other values for that variable across all records"* (Calit Shmueli, 2010, p. 23). Another viable alternative to handling missing data is to examine the importance of the predictor variables whom have the most missing values and then decide whether to drop or retain that predictor. "*If the variable is not very important than it can be dropped. If it is important perhaps a proxy variable with fewer missing values can be used instead"* (Calit Shmueli, 2010, p. 24). These approaches were considered during the model building phase and further elaborated on during the data analysis phase and discussed in the findings presented in Chapter 4.

### 3.3 Model Building

The aim of the research is to create a model that is both descriptive and has predictive ability. The linear regression model is chosen because of its advantages with interpretability, lending practical value to the results. Coefficients are interpreted as the change in $Y$ corresponding to a one-unit change in $X_j$ when all other predictor variables are held constant (Chatterjee & Hadi, 2012). Finally, the linear model is preferred due to the principle of *Occam's Razor*, which suggests simpler explanations over unnecessarily complex ones (Kneale, 1962).

### 3.3.1 Modeling Procedure

At a basic level, the model building process will follow the flow chart process developed by Chatterjee and Hadi as presented in Figure 3.2 (Chatterjee & Hadi, 2012). The process consists of: (1) Model Formulation, (2) Model Estimation, and (3) Model Evaluation. This is an iterative procedure, as it is unlikely that the first attempt will produce the best model. During the modeling process, there were several reoccurring questions to consider and address during the modeling process (James et al., 2013) and they are as follows:

1. Is there a relationship between the predictor variables and the response variable?
2. How well does the model fit the data, and how strong is the relationship between the predictor variables and the response variable as determined by the model.
3. Which predictors contribute to the response variable?
4. How accurately can we estimate the effect of each predictor variable on the response variable?
5. Is the relationship linear?
6. How accurate are our predictions?

Figure 3.2 below provides a flowchart showing the iterative process for multiple regression that was used to support the analysis of the multiple regression techniques used for the study. This was used as the baseline model to improve upon.

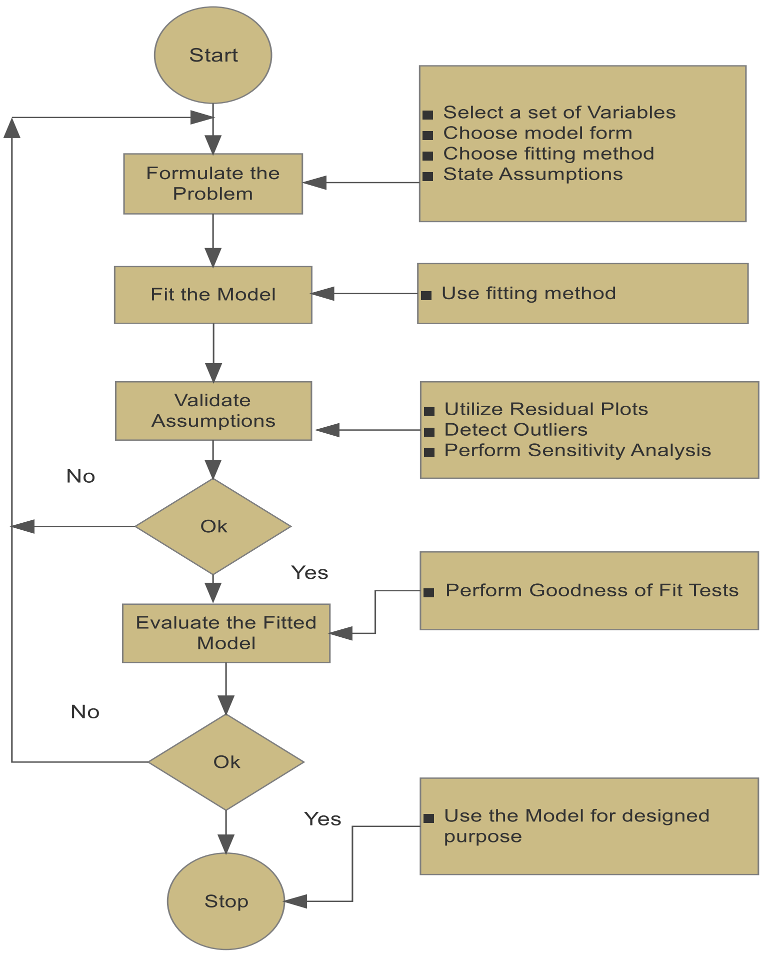


*Figure 3.4*. Flowchart showing iterative regression analysis process
Adapted from Chatterjee and Hadi, 2012.

First, a full model was fitted to the data. The full model contained the full set of predictor variables as presented in Table 3.2. Candidate models was chosen using a *Best Subsets Selection* procedure. Best Subsets selection procedure involves fitting a separate least squares regression equation for each possible combination of the set of $p$ predictor variables. In total, the procedure fits $2^p$ separate regression equations on different subset combinations (James et. al, 2013). Of all the possible subset combinations of the predictor variables, a final model was chosen which maximizes the Adjusted $R^2$ values. The authors of Introduction to Statistical Learning suggest that since training error (i.e., the error on the dataset to fit the model) is a much smaller estimate of test error, that when choosing amongst candidate models, a different criterion should be utilized. Recommended criterion includes either cross validated prediction error, which is a direct estimate of test set error, or other metrics that provide indirect approximations of test set error such as Adjusted $R^2$ and Bayesian Information Criterion (BIC) (James et. al, 2013).

The reason *Best Subsets Selection* is used as the method for choosing which predictor variables to include in the final model is because this procedure can be used in both scenarios of when the predictor variables are collinear, and when the predictor variables do not exhibit strong collinearity (Chatterjee & Hadi, 2012). When the data does exhibit collinearity, neither *Forward Selection, Backward Elimination, or Stepwise* methods are recommended. Best Subsets Selection procedure is considered as one of many preferred alternatives (Chatterjee & Hadi, 2012). The most efficient way to use the results of *Best Subsets Selection* procedure is to choose the top performing candidate models based on a few chosen statistics such as Adjusted $R^2$, Bayesian Information Criterion (BIC), or cross validated prediction error. For the top performing candidates, additional analysis is required such as assessing the residuals to ensure the strict assumption of linear regression are met (Chatterjee & Hadi, 2012).

### 3.3.2 Model Validation

Validating a model consisted of checking and validating the assumptions of the linear model: linearity of the relationship between predictors and response variable, normality of the error distribution, homoscedasticity (i.e., constant variance) of the errors, independence of errors, and absence of multicollinearity. If the model failed to validate the residual assumptions, these failures were detailed and discussed extensively.

Inclusion of new predictors into the model and transformations of the predictors or the response variable to remedy these above-mentioned failures were either performed or strongly considered.

### 3.3.3 Checking the Linearity and Homoscedasticity Assumption

Linear regression models operate on the assumption that there is a linear relationship between the predictor and response variables (James et. al, 2013). If the true underlying relationship between the predictors and the response variable is linear or close to linear, then a linear model should have the capacity to accurately describe this underlying linear relationship (James et al., 2013). The assumptions were examined via scatterplots. The points should be randomly scattered around a horizontal line. The first is the scatterplot of the standardized residuals versus the predicted values. Any type of discernible and systematic pattern such as a nonlinear *bow* is an indication of non-linearity in the relationship between the predictors and the response variable (Stevens, 2016). From this same scatterplot, homoscedasticity can be assumed if there are no *fan* or *funnel* like patterns when moving horizontally from left to right (Tabachnick & Fidell, 2014). The second scatter plot is of the observed versus predicted values. The points should be randomly scattered around the diagonal line for linearity (James et. al, 2013).

### 3.3.4 Checking Independence of the Error Terms

In linear regression, the error terms are assumed to be independent (i.e., not correlated (James et. al, 2013). Violation of this assumption, (i.e., error terms that are correlated), is defined as autocorrelation (James et al., 2013). The Durbin-Watson statistic was used to check for autocorrelation (Tabachnick & Fidell, 2014). To indicate absence of autocorrelation, the Durbin-Watson statistic should be near 2.00 (Field, 2013)

### 3.3.5 Checking for Normality Distributed Error Terms

For best model fit, error terms should be approximately normally distributed (Tabachnick & Fidell, 2014). To check and validate this assumption, a distribution analysis was conducted on the residuals. The graphical tools employed to assess normality of the residuals were the histogram and normal probability plot. Histograms should show data that follow a normal bell curve, while the normal probability plot should show data that conform to the diagonal normality line (Field, 2013).

### 3.3.6 Multicollinearity Analysis

Multicollinearity occurs when two or more predictor variables are highly related (James et al., 2013). The presence of multicollinearity presents a significant problem when one of the goals of the research is inference modeling or process control, as it causes difficulty separating the variability in the response variable associated with each predictor and may be considered a source of error (James et al., 2013). Therefore, the problem of multicollinearity can not only make interpretation and inference of the regression coefficients difficult, it can also diminish predictive ability of the model. Multicollinearity may be present due to a deficiency in the sample data, and therefore can be potentially remediated through the collection of more data (Chatterjee & Hadi, 2012). This is a common strategy to address overfitting. Another possible reason for multicollinearity may be because the interrelationships among the predictor variables are inherently a characteristic of the system or process under investigation (Chatterjee & Hadi, 2012). To examine the possibility of multicollinearity, the variance inflation factor (VIF) was calculated for the estimated regression coefficients. "The VIF is the ratio of the variance of $\widehat{B}_j$ when fitting the full model divided by the variance of $\widehat{B}_j$ if fit on its own" (James et al., 2013, p. 101). VIF scores over 10 are an indication of extreme collinearity, while VIF scores of 1 indicates the complete absence of any interrelationships (Menard, 2009).

### 3.3.7 Outliers, Influential Points, and High Leverage Points

The next aspect of model building is examining the effects outliers, leverage, and influential points can have on a model's fit. Outliers were detected with a scatter plot of the studentized residuals vs fitted values. An outlier was considered any observation that has a studentized residual larger than ±3.00. Treatment of the outlier will happen upon further examination on a case by case basis. Outliers should not necessarily be removed if they convey interesting information about the research or process under study (James et al., 2013).

### 3.3.8 Hypothesis Testing of the Candidate Models

An *F* test was used as an omnibus test to assess whether the set of predictor variables collectively predicts the response variable (Field, 2013). The null hypothesis is that all the predictors have no explanatory power. The alternative hypothesis is that at least one of the predictors in the model has explanatory power.

$$H_0: \beta = 0 \text{ ; i.e. all the parameters equal } 0$$

$$H_A: \beta \neq 0 \text{ ; i.e at least one of the parameters is non} - \text{zero}$$

If the p-value associated with the test is less than the chosen significance level of, α = .05, then the null hypothesis is rejected, and the alternative hypothesis is accepted. However, if the p-value from the F-test is greater than the significance level, then there is a failure to reject the null hypothesis.

## 3.4 Model Evaluation and Model Selection

### 3.4.1 Evaluating the Candidate Models

For candidate models whose null hypothesis has been rejected, and make it past the residual analysis, various statistics can be used to assess performance. As previously mentioned, *Best Subset selection* results in the creation of a set of candidate models, each of which contains a subset of the predictor variables. To determine which of the candidate models is best, specific criterion are used to compare models. Since the model containing all the predictors will always have the smallest Residual Sum of Squares (RSS) and the largest $R^2$, these quantities are not used as they are poor estimates of test set error and generalizability (James, et. al, 2013). Instead, a criterion that penalizes model complexity was used as the final criteria for selecting between different candidate models. Statistics such as Adjusted $R^2$, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) all penalize the model for added complexity that does not result in a large enough decrease in error. It is important to note that sometimes individually, these three statistics can all point to the same conclusion and model, however in other scenarios, these different individual statistics may point to different suggested models. This is due to different imposed penalties for model complexity and overfitting. "BIC statistic places a heavier penalty on models with many variables, and hence results in the selection of smaller models" (James et al., 2013, p. 212).

Generally, if there are two extremely similar models in terms of their diagnostics and error statistics, then the model that is more parsimonious was preferred. To adhere the principle of parsimony suggests that for ease of interpretation and understanding, to describe the relationship between the predictors and the response variable in as few variables as reasonably possible. The term, reasonably, in this context translates to candidate models with high performance and low error statistics.

### 3.4.2 Final Words on Model Selection

Considering there is no single best subset of predictor variables, and multiple subsets of the predictor variables could be equally satisfactory and adequate, the model selection procedure will consider several candidate models for estimating the true underlying unknown population relationships between the response variable and a subset of the predictor variables. "*The various sets of the adequate variables provide insight on the structure of the data and help us in understanding the underlying process. In fact, the process of model selection should be viewed as intensive analysis of the correlational structure of the predictor variables and how they individually and jointly affect the response variable under study*" (Chatterjee & Hadi, 2012, p. 303). The model selection procedure allows the researcher to consider several candidate models for estimating the true underlying population relationship between the response variable and subset of predictor variables.

## 3.5 Summary

Data involving site contamination levels, physical site characteristics, and site clearance performance data were collected for multiple sites heavily contaminated with munitions within a munitions response area. An iterative model building process was used to determine the best multiple linear regression model to assess the research questions. The results and findings of the data analysis methodology are presented in Chapter 4.

# Chapter 4: Results

Chapter 4 provides the results of the data analyses presented in Chapter 3 and the findings of the research study. Chapter 5 will include the interpretation and discussion of the findings, along with the conclusion of the research study results. Chapter 4 focuses on presenting the results of the data analyses and findings and is divided into four parts. Part 1 presents the findings and results of the Exploratory Analysis. Part 1 includes the Missing Values, Descriptive Statistics, Univariate Plots and Distributions, Bivariate Plots and Distributions, and Preprocessing of Data. Part 2 presents model selection and validation process. Part 3 includes an analysis of the final model. Part 4 is a summary of the results and findings.

## 4.1 Part 1: Exploratory Data Analysis

### 4.1.1 Missing Values

None of the seven original sites for data collection (A1, A2, B, D, E, F, or G-West V) had any missing values, whether a predictor variable or the response variable. For this reason, no imputation of missing values or dropping of cases with missing values was warranted.

### 4.1.2 Descriptive Statistics

Frequencies and percentages were calculated for categorical variables and means, and standard deviations were calculated for continuous variables. Sites A1 and A2 were grouped together due to their similarity and small counts for site A1. This grouping of sites A1 and A2 was only for the purposes of Exploratory Data Analysis. No sites were grouped during the regression analysis.

Figure 4.1 shows the frequency distribution for the Site IDs. Most cases came from sites F and G are where the most samples are drawn from.

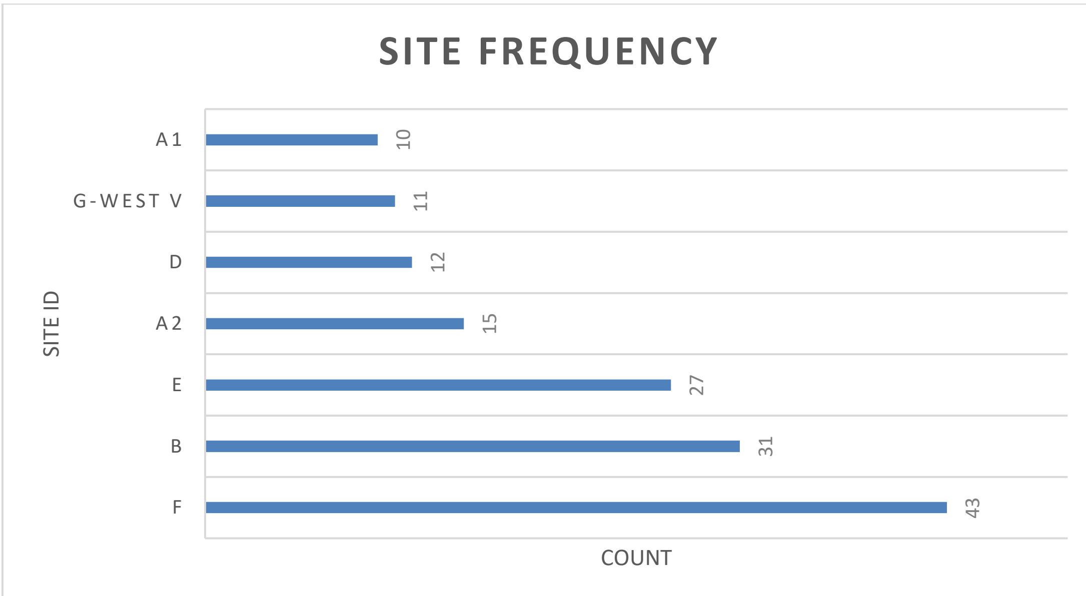


*Figure 4.1.* Frequency of records belonging to site.

Table 4.1 below presents all the descriptive statistics segmented by Site ID. The results show differences in central tendency (mean and median) and spread (variance and standard deviation) for a variable depending on the site.

### 4.1.3 Univariate Plots and Distributions

To facilitate ease in the ability to recognize differences and similarities in patterns of a single variable, $X_j$, graphs and plots are presented. Figure 4.2 below provides the separate univariate distributions of the continuous variables in the model using a boxplot. Generally, boxplots are used to examine the distribution of the variables based on quantiles. It can also be used to identify univariate outliers as is the case with variable x9.

Table 4.1. *Descriptive Statistics for the Continuous Predictors Segmented by Site ID*

| Descriptive Statistics for Continous Variables | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 25% | 50% | 75% | max |
| X1: MEC WRKDAYS | 149 | 4.6 | 0.73 | 1 | 4 | 5 | 5 | 5 |
| X2: Total MEC SITE Hrs | 149 | 1323.19 | 833.81 | 0 | 400 | 1350 | 2000 | 2700 |
| X3: TRUE MECHRS | 149 | 864.06 | 534.25 | 0 | 272 | 870 | 1326 | 1666 |
| X4: Quantity of UXOTECH | 149 | 26.34 | 15.1 | 0 | 10 | 28 | 39 | 49 |
| X5: VEG WRKDAYS | 149 | 3.86 | 1.45 | 0 | 4 | 4.5 | 4.5 | 5 |
| X6: Quantity of VEGTECH | 149 | 23.89 | 14.78 | 0 | 10 | 32 | 36 | 42 |
| X7: TOTAL VEG SITE HRS | 149 | 1054.66 | 677.63 | 0 | 400 | 1440 | 1600 | 2100 |
| X8: TRUE VEGHRS | 149 | 717.12 | 460.78 | 0 | 272 | 979 | 1088 | 1428 |
| X9: Quantity OFMEC/MPPEH/RRD/MD/ ITEMS | 149 | 13926.99 | 19300.06 | 0 | 2000 | 5000 | 20661 | 129100 |
| X10: SCRAPLBS | 149 | 22633.63 | 23889.64 | 0 | 4500 | 12000 | 39965 | 94296 |
| X13: Quantity of VEGACRE Cleared | 149 | 5.32 | 3.69 | 0 | 2.35 | 5.13 | 8.1 | 15.75 |
| Y: Quantity of SURFACRE Cleared | 149 | 5.38 | 3.82 | 0 | 2.44 | 4.7 | 8 | 14.5 |

Figure 4.2 below shows the distributions of these same variables within the context of the different Site ID's. Predictors X2, X3, X5, and X13 appear to share a trend of increasing quantities when segmented by Site ID. Variations between the segmented distributions of an individual predictor variable is useful in identifying potential importance of that predictor. For example, for the predictors X4, X6, and X10, the boxplots reveal considerable variation in the distribution depending on Site ID.

The response variable is plotted as a boxplot both in its aggregate form (i.e. not segmented by Site ID), and when segmented by Site ID**.**

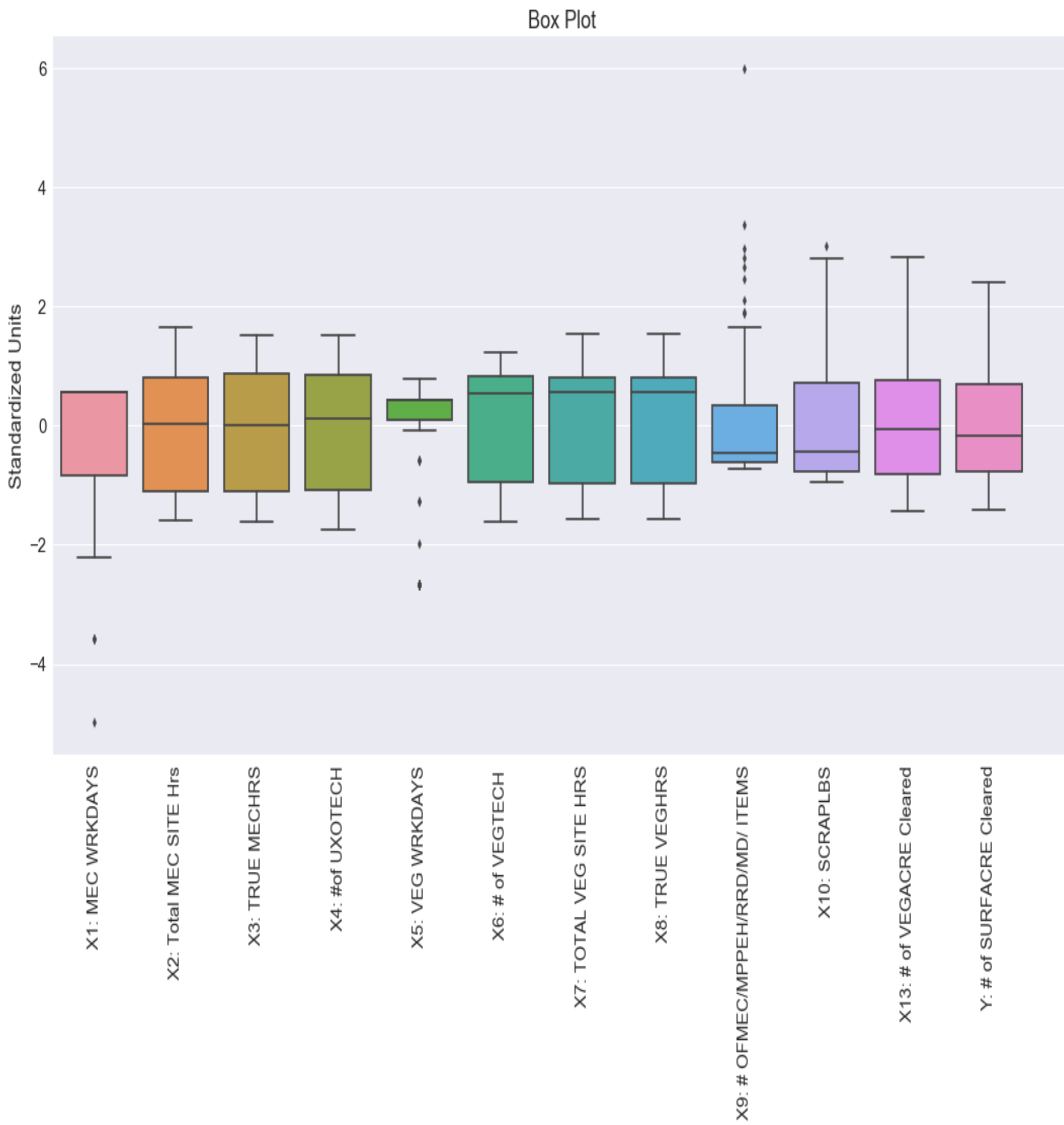


*Figure 4.2*. Boxplots of all rescaled (standardized) continuous predictors.

The boxplots and visualization for all the continuous predictor variables in the original units segmented by Site ID is presented in Figure 4.3 below.

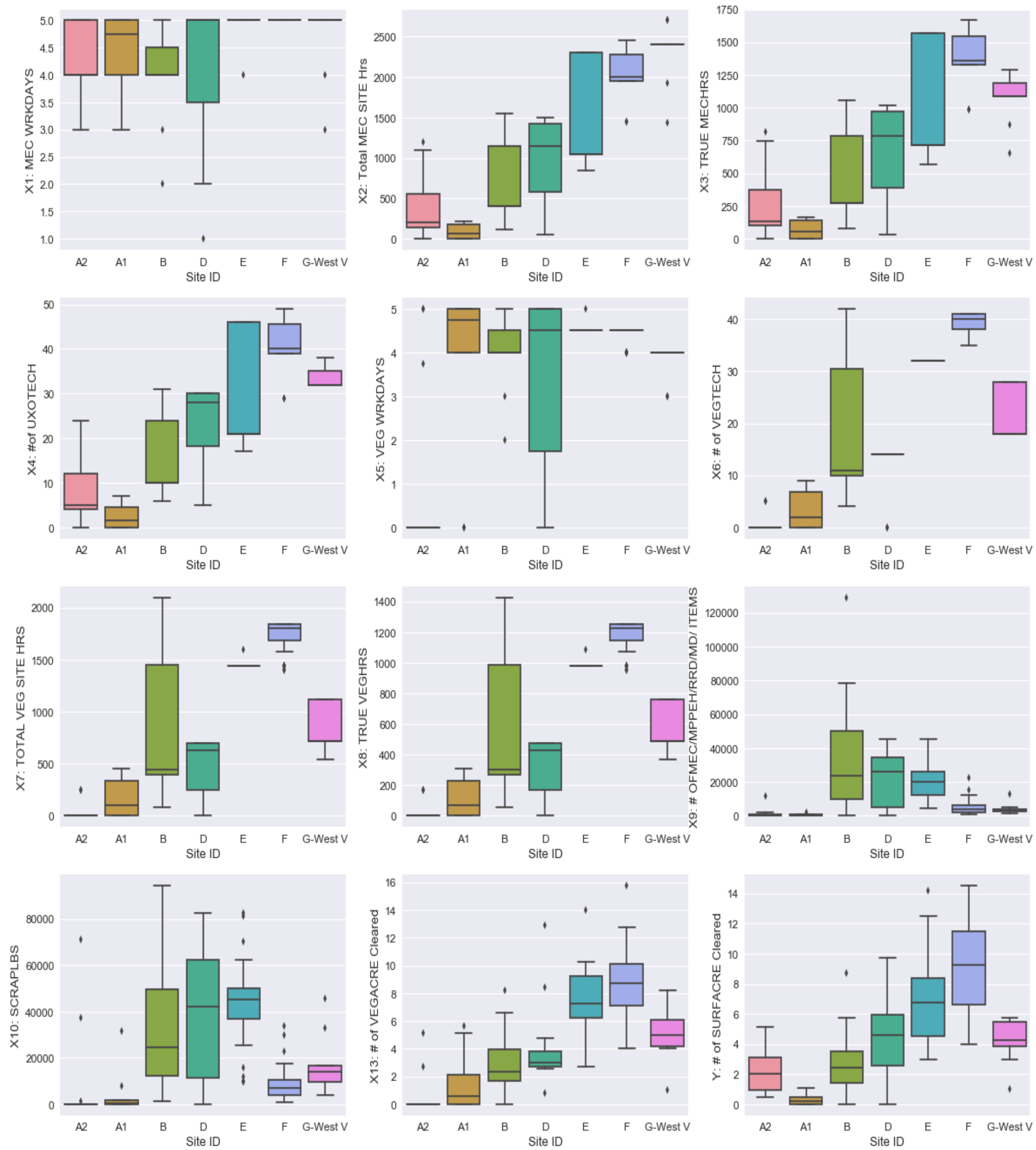


*Figure 4.3.* Boxplots of all the continuous variables in original units segmented by Site ID.

Figure 4.4 below provides the visualization as presented in the boxplots of the response variable in aggregate and segmented by Site ID. In the corner of the chart is the Coefficient of Variation, a widely used statistic in engineering for measuring the variability and dispersion of a distribution. The coefficient of variation compares the ratio of the standard deviation to the mean, large values indicating that samples are far away from the mean(average), and smaller values indicating the opposite. The coefficient of variation is .71, since it is less than 1, the distribution is considered low variance. Figure 4.4 also shows on average, site F has the largest response variable value, and site A has the smallest. An interesting question derived from this plot is, *"what characteristics of site F provide the reasoning for this"?* The Figure 4.4 plots also reveals generally an increasing pattern in the values of the response variable across sites from A to F, the trend abruptly stopping thereafter.

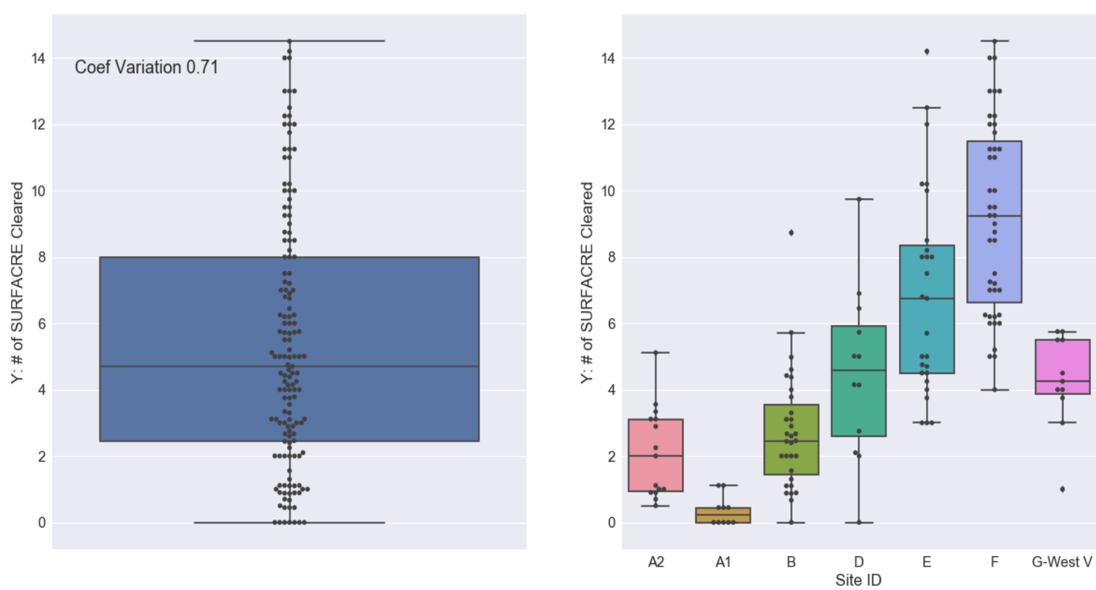


*Figure 4.4.* Boxplots of the response variable in aggregate and segmented by Site ID.

Another interesting breakdown of the response variable is within the context of the variables slope (*X11*) and vegetation density (*X12*). Both are plotted at Figure 4.5 below. As slope (*X11*) increases, the response variable, surface acres cleared, on generally becomes less. For vegetation density(*X12*), the trend is different, more surface acres are cleared when the vegetation density is moderate. An interesting question derived from the plot would be "*are different tools and resources used for moderate vegetation density that are not utilized when there is low or high vegetation density? Or is there a hidden variable to account for this variation, such as different contracting companies of different efficacies and skills being employed in the cases of low, moderate, and high vegetation densities?*"

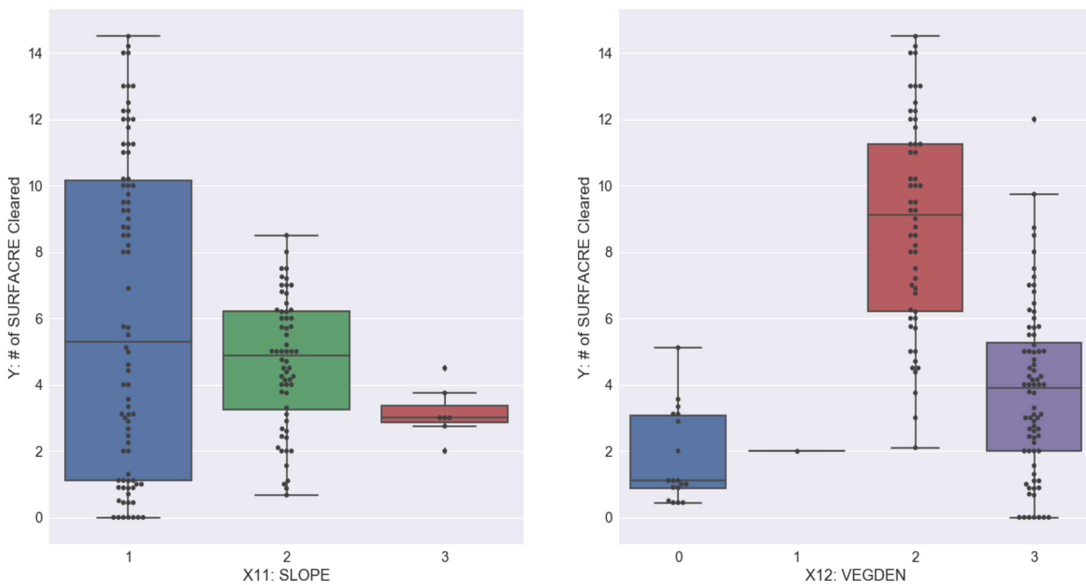


*Figure 4.5.* Boxplots of response variable by slope and vegetation density.

### 4.1.4 Bivariate Plots and Distributions

The bivariate associations between all the predictor variables were analyzed using Pearson correlations. The *Pearson correlation* is used to measure the linear association between two variables (Pallant, 2016). As seen in Figure 4.6**,** the bivariate relationships of $(X_2, X_4)$ , $(X_2, X_3)$, $(X_6, X_8)$, $and$ $(X_7, X_8)$ are all extremely high, implying strong liner associations.  A scatter plot matrix of all the relationships can be found in Appendix B.

Pearson and Spearman correlations were used to evaluate the bivariate relationship between each predictor variable and the response variable. Spearman correlation is used to measure monotonic relationships (Pallant, 2016). Both correlations can vary between -1.00 and +1.00, with 0.00 implying no correlation (Pallant, 2016). The Pearson correlations are summarized using a correlation table and heatmap in Figure 4.6**.**

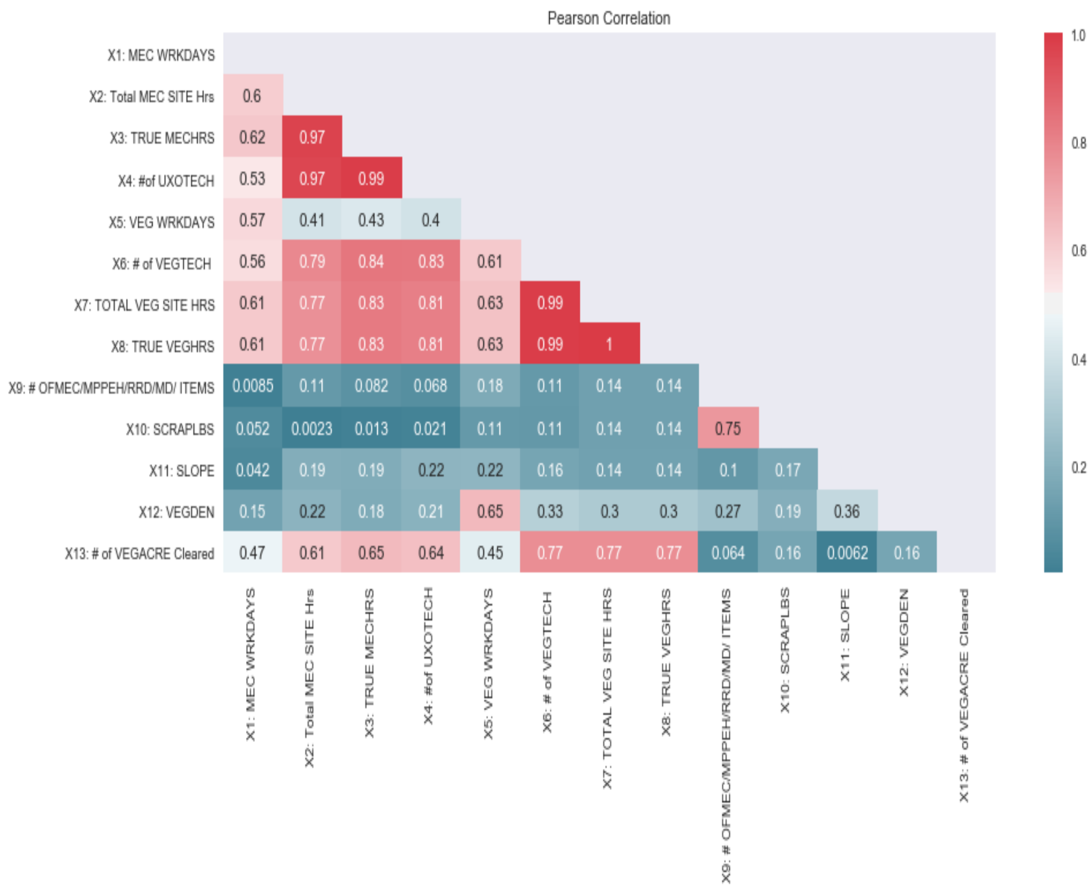


*Figure 4.6.* Pearson correlations of the predictor variables with heatmap.

The bivariate associations of predictor variable to response variable relationships are provided in Appendix H,  for both Pearson and Spearman correlations. The heatmaps, in which color intensities denote the strength of the association, provide a quick way to find and locate the strongest bivariate associations. To constrain the total range of possible color intensities, the absolute values of the correlations were used. Therefore, all associations now fall within the interval [0,1], as opposed to the original interval [-1,1]. Most of the predictor variables have strong associations with the response variable. As expected, the highly collinear variables $(X_6, X_7, X_8)$ $and$ $(X_2, X_3, X_4)$ all have similar strength in their associations with the response variable.

Scatter plots for each predictor–response combination can be found in Appendix C**.** These scatter plots also show density estimation; thus, each scatter plot can also be regarded as a two-dimensional density plot. The x-axis is the predictor variable, and the y-axis is the response variable. The contours represent the probability density. Each contour is a probability density value and any point on the contour is inferred to have that same probability density. Any point inside the contoured region is inferred to have a smaller probability density than that which the contour line represents; whereas, any point out of the contoured region is inferred to have a greater probability density than that of the contour lines. These plots therefore provide a sense of density in a two-dimensional space.

Lastly, as one final step in the preprocessing process, all the simple linear regressions between each predictor variable and the response variable were calculated. The results of these simple linear regressions can be found in Figure 4.7a. through Figure 4.7c., and Appendix F**.**

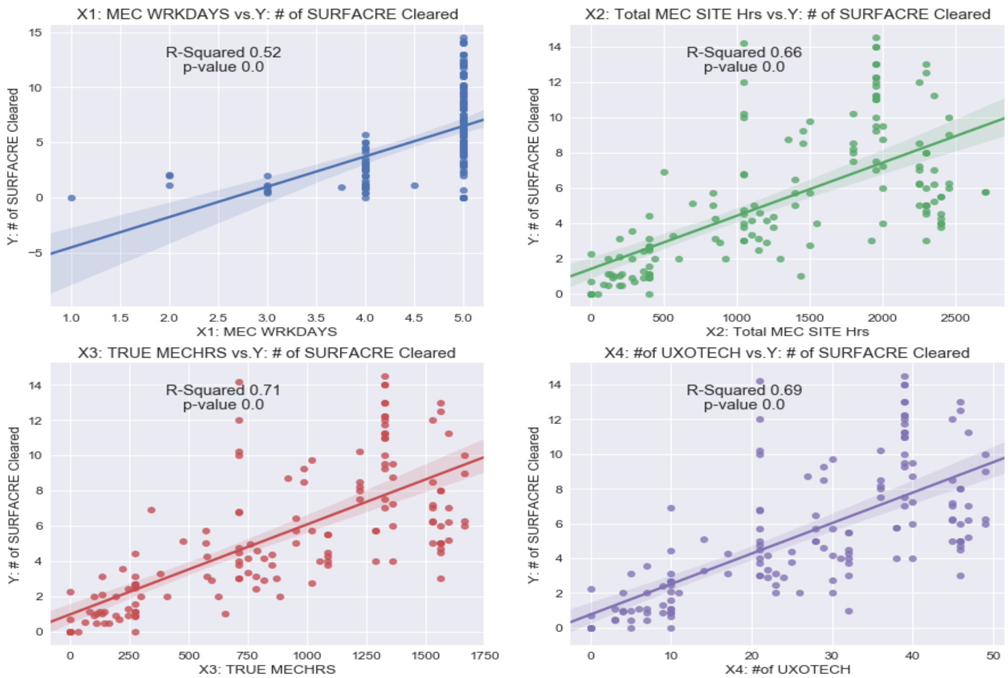


*Figure 4.7a*. Simple linear regression for predictor X1, X2, X3, and X4 with response variable.

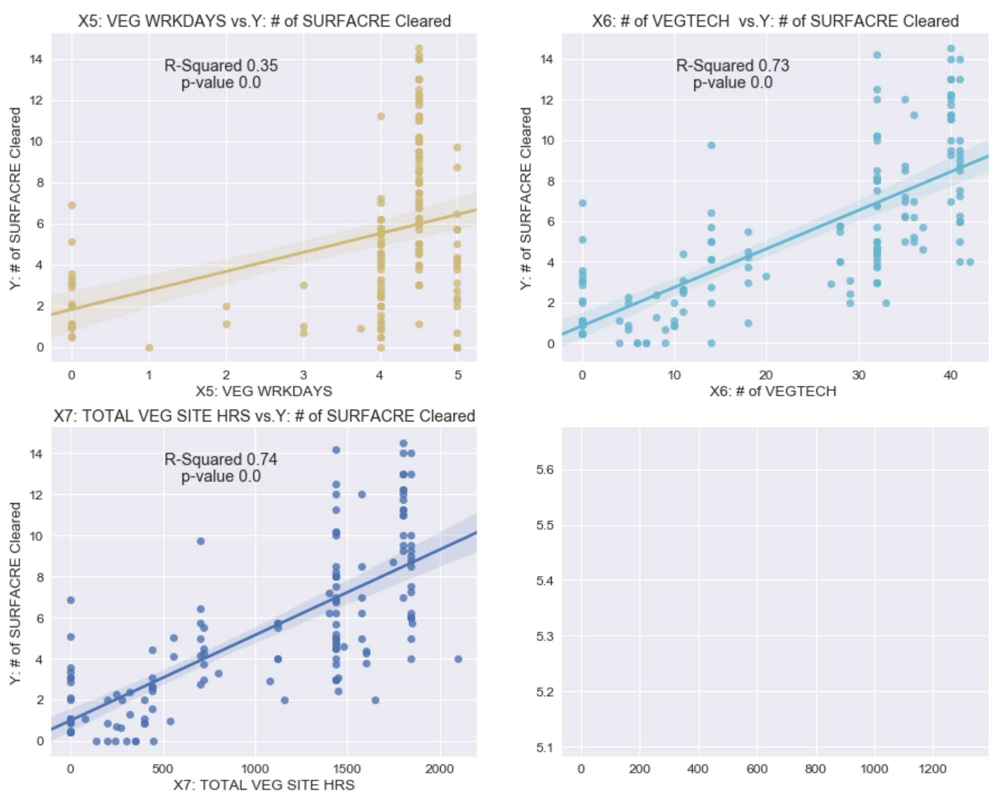


*Figure 4.7b*. Simple linear regression for predictor X5, X6, and X7 with response variable.

This was a useful exercise in graphically examining the individual bivariate relationships between each of the predictor variables and the response variable. Additionally, it was useful in locating and identifying potential bivariate outliers. For example, in the simple linear regression plot where Y: Surface Acres Cleared is regressed on x9: Quantity of MEC items, there is a case with an extreme value of MEC

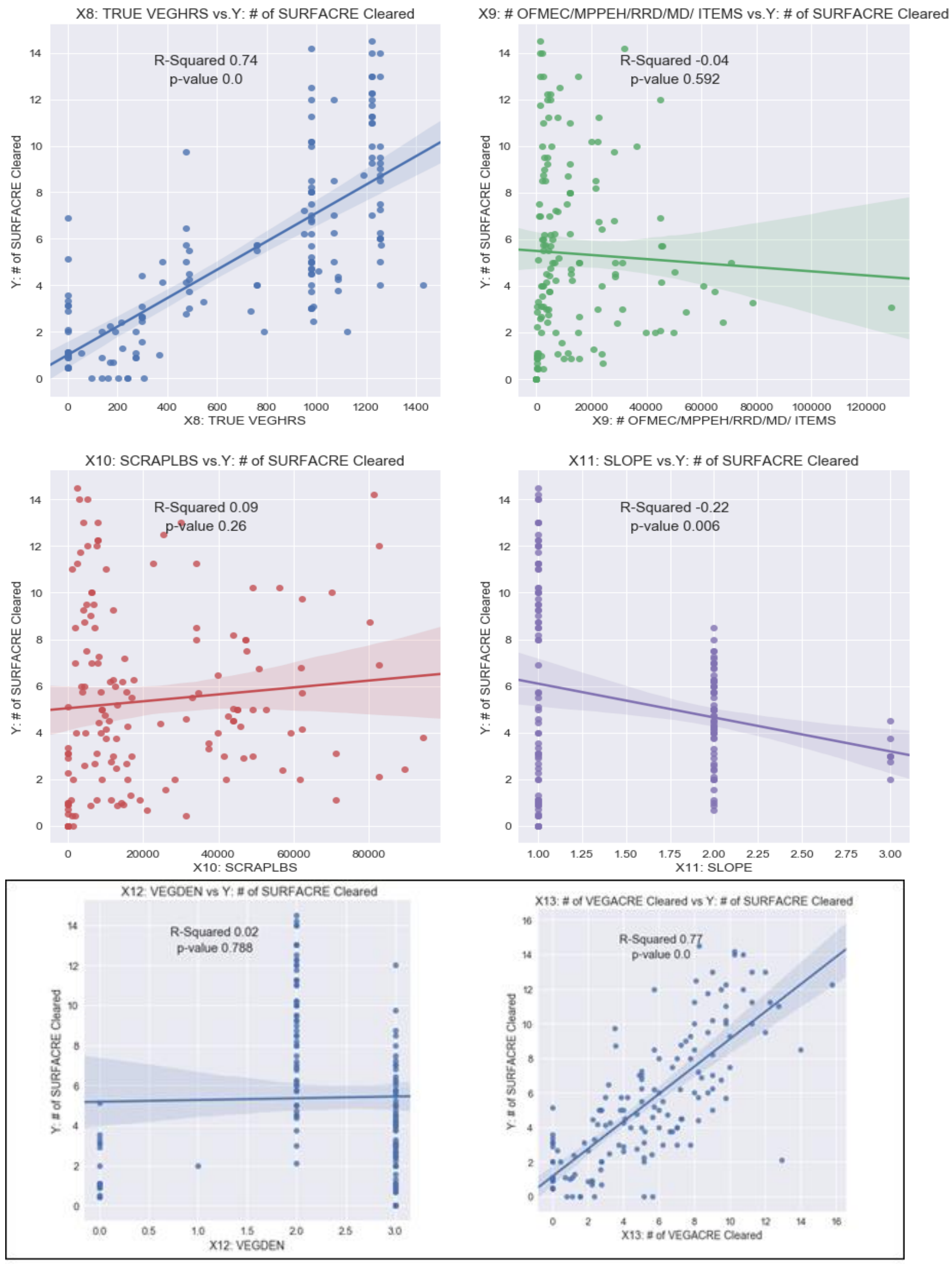


*Figure 4.7c. Simple linear regression for predictor X8, X9, X10, X11, X12, and X13 with response variable.*

### 4.1.5 Preprocessing - Binning of Predictors x10 and x9

The predictor variables $X_9$ and $X_{10}$ have large spread and variance as determined by the graphs in Figure 4.8 and 4.9**.** Both variables have *Coefficients of Variation* greater than 1, suggesting high variance. The univariate distributions which lacked symmetry were highly skewed. During the preprocessing state right before model building, both these predictor variables underwent a binning procedure. Each predictor was binned one of five discrete bins. The discretization into five bins was chosen based off quantile ranges. Table 4.2 shows the range of values that characterize each bin and the frequencies of records in each of the bins. Based on the frequency percentages in Table 4.2, the data is approximately evenly dispersed. Table 4.2 shows the original distribution of the continuous variable, and then the distribution after binning into discrete values. The coefficient of variation, which is the ratio of standard deviation to the average, is also plotted. The difference between pre-binning and post-binning coefficients of variation indicate stabilization of variance.

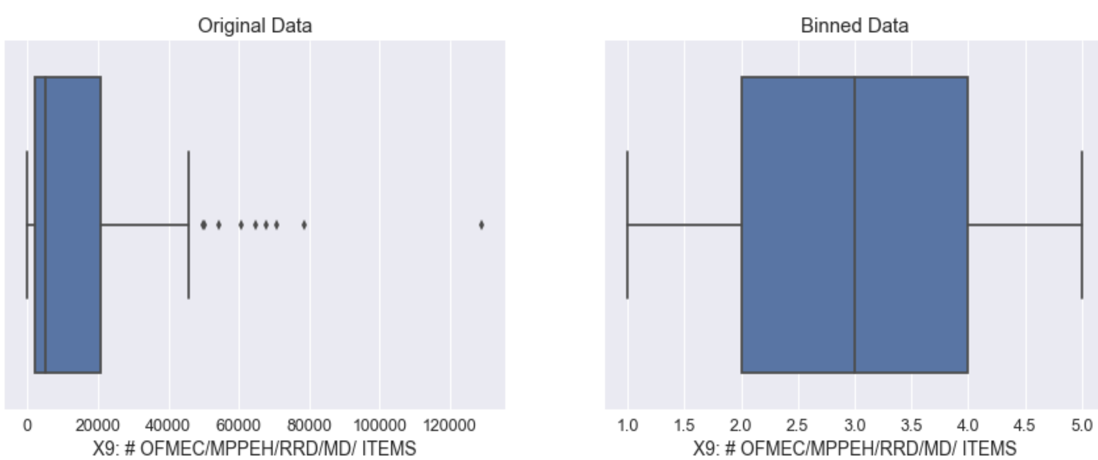


*Figure 4.8.* Original distribution (left) and distribution after Binning (right).

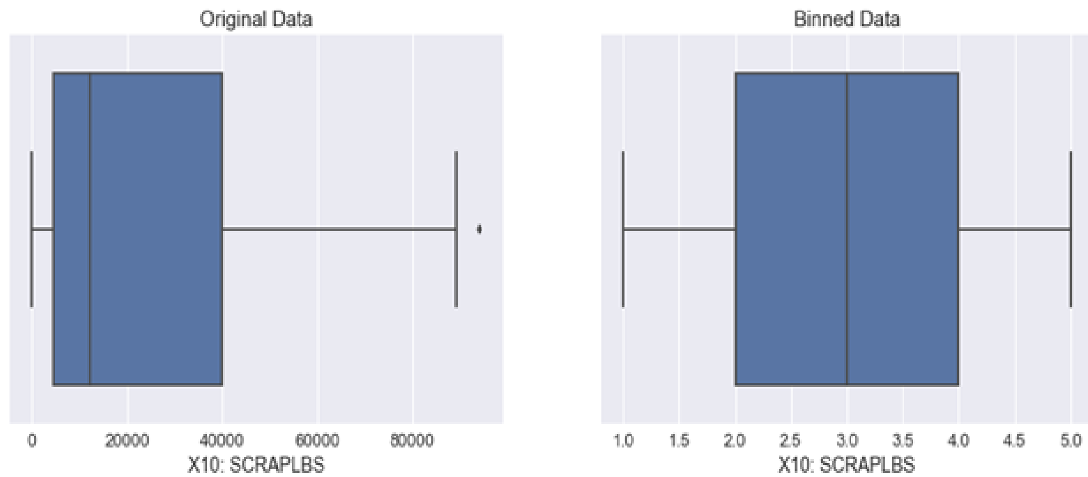


*Figure 4.9.* Original distribution (left) and distribution after Binning (right).

Table 4.2. *Frequency Table After Binning*

| X9: # OFMEC/MPPEH/RRD/MD/ ITEMS | | |
|---|---|---|
| Bins | Frequency | % Frequency |
| (0 , 1548.6] 1 | 30 | 20.13% |
| (1548.6, 4000.0] 2 | 32 | 21.48% |
| (4000.0 , 9090.0] 3 | 27 | 18.12% |
| (9090.0, 23768.0] 4 | 31 | 20.81% |
| (23768.0, 129100.0] 5 | 29 | 19.46% |
| Grand Total | 149 | 100.00% |

| X10: SCRAPLBS | | |
|---|---|---|
| Bins | Frequency | % Frequency |
| (0,3180] 1 | 30 | 20.13% |
| (3180, 8377.4] 2 | 30 | 20.13% |
| (8377.4, 16612.4] 3 | 29 | 19.46% |
| (16612.4, 44433.4] 4 | 30 | 20.13% |
| (44433.4, 94296.0] 5 | 30 | 20.13% |
| Grand Total | 149 | 100.00% |

## 4.2 Part 2: Model Selection and Validation

The final model was chosen based on the results from the variable selection procedure *Best Subsets Selection*, plus some additional improvements**.** Best Subsets selection applies equally well to scenarios of both collinear and noncollinear data (Chatterjee & Hadi, 2012). The variable selection procedure Best Subsets Selection, which evaluates all the possible equations evaluated on different subsets of the predictor variables, was optimized for $Adjusted\ R^2$ values, meaning that the procedure sought to maximize $Adjusted\ R^2$ values. The SAS output of that procedure can be found in Appendix J**.** An efficient way of using the results from the SAS Best Subsets procedure that evaluates all possible variable combinations is to choose the best three based on specific criteria. These top three choices represent initial candidate models which should further be examined by checking to see if they do not violate the key assumptions of the linear model (Chatterjee & Hadi, 2012). Among the three top performing candidate models in Table 4.3, all of which have extremely similar $Adjusted\ R^2$ values, we will choose the top model, since not only does it have the largest $Adjusted\ R^2$ value, but it also has the lowest Bayesian Information Criterion (BIC) score, and is more parsimonious than the other two candidates. *"The BIC will tend to take on a small value for a model with a low-test error"* (James et al., 2013, p. 212).

Table 4.3. Top 3 Candidate Models Chosen by Best Subsets Selection

| Model Index | Number in Model | Adjusted R-Square | R-Square | BIC | MSE | Root MSE | Variables in Model |
|---|---|---|---|---|---|---|---|
| 1 | 8 | 0.7667 | 0.7793 | 194.5203 | 3.399339 | 1.84373 | x1 x2 x4 x6 x10 x11 x12 x13 |
| 2 | 9 | 0.7665 | 0.7807 | 195.8791 | 3.402179 | 1.8445 | x1 x2 x3 x6 x8 x10 x11 x12 x13 |
| 3 | 9 | 0.7665 | 0.7807 | 195.8828 | 3.40228 | 1.844527 | x1 x2 x3 x6 x7 x10 x11 x12 x13 |

The top model utilizes 8 predictor variables while the other two models were fitted on data consisting of nine predictor variables. Since inference and using the regression equation as a tool for modeling a complex process is an important goal of the praxis, we will adhere to the principle of parsimony. To adhere to the principle of parsimony, it is suggested that the process be described in as few variables as possible since it provided easier interpretation (Chatterjee & Hadi, 2012).

The initial chosen subset of predictor variables was: $X_1$ – *Quantity of MEC WRKDAYS*, $X_2$ - *Total MEC SITE Hrs*, $X_4$ - *Quantity of UXOTECH*, $X_6$ - *Quantity of VEGTECH*, $X_{10}$ - *SCRAPLBS*, $X_{11}$ - *SLOPE*, $X_{12}$ - *VEGDEN, and* $X_{13}$ - *Quantity of VEGACRE Cleared*. This was used as the initial model, which we improved on significantly after a few adjustments were made. The specific steps undertaken to derive the final model include:

1. The variance inflation factor (VIF) scores of the predictor variables determined multicollinearity from the original best subsets selection routine model. Since serious distortions and misrepresentations of model coefficients, t-Tests, and p-values can be introduced into the analysis when collinear or multi-collinear data is present, one of two recommended approaches is to break down the collinearity of the data by deleting offending variables (Chatterjee & Hadi, 2012). This issue was handled and resolved by removing the predictor, $X_4$ - *Quantity of UXOTECH*, whose specific VIF score was 23.35. The entire table of VIF scores can be found in Appendix L**.**
2. A new regression equation was fitted omitting, $X_4$ - *Quantity of UXOTECH***.** Therefore, new, and final model is characterized as the subset of predictors, $X_1 -$ *MEC Workdays* , $X_2 -$ *Total MEC Site Hrs* , $X_6 -$ *Quantity of VEGTECH*, $X_{10} -$ *Quantity of Scrap Lbs* , $X_{11}$ - *Slope* , $X_{12} -$ *Vegetation Density*, $X_{13} -$ *Quantity*

*of VEGACRE Cleared*, predicting the response variable *Y, number of surface acres cleared.*

The results of the overall regression model were significant using a rejection cutoff of p = .05, $F(7,141) = 63.55$, $p < .001$, $R^2 = 0.76$. The null hypothesis that all coefficients are zero, and hence the model has no explanatory power in modeling the variation of the response variable, is rejected due to a p-value less than the significance level, .05. The alternative hypothesis is accepted. The full results of the regression model are further expounded upon in the Hypothesis Resolution section.

### 4.2.1 Assumption Testing and Residual Analysis

The set of predictor variables for the final model include $X_4$ - *Quantity of UXOTECH. Therefore, new, and final model is characterized as the subset of predictors,* $X_1 -$ *MEC Workdays*, $X_2 -$ *Total MEC Site Hrs*, $X_6 -$ *Quantity of VEGTECH*, $X_{10} -$ *Quantity of Scrap Lbs*, $X_{11}$ - *Slope*, $X_{12} -$ *Vegetation Density*, $X_{13} -$ *Quantity of VEGACRE*. Model validation was performed by testing the key assumptions of the linear regression. These include linearity in the relationship between the predictors and response variable, normally distributed errors, independence of errors. Additionally, multicollinearity between the predictor variables was examined, and measure of influence were calculated on the errors.

The assumption of normality was assessed using a histogram and normal probability plot of the residuals, as shown in Figure 4.10. The histogram presents data generally following the normal bell curve, and data points closely followed the theoretical normality (diagonal) line in the probability plot, indicating that the assumption of normality was met.

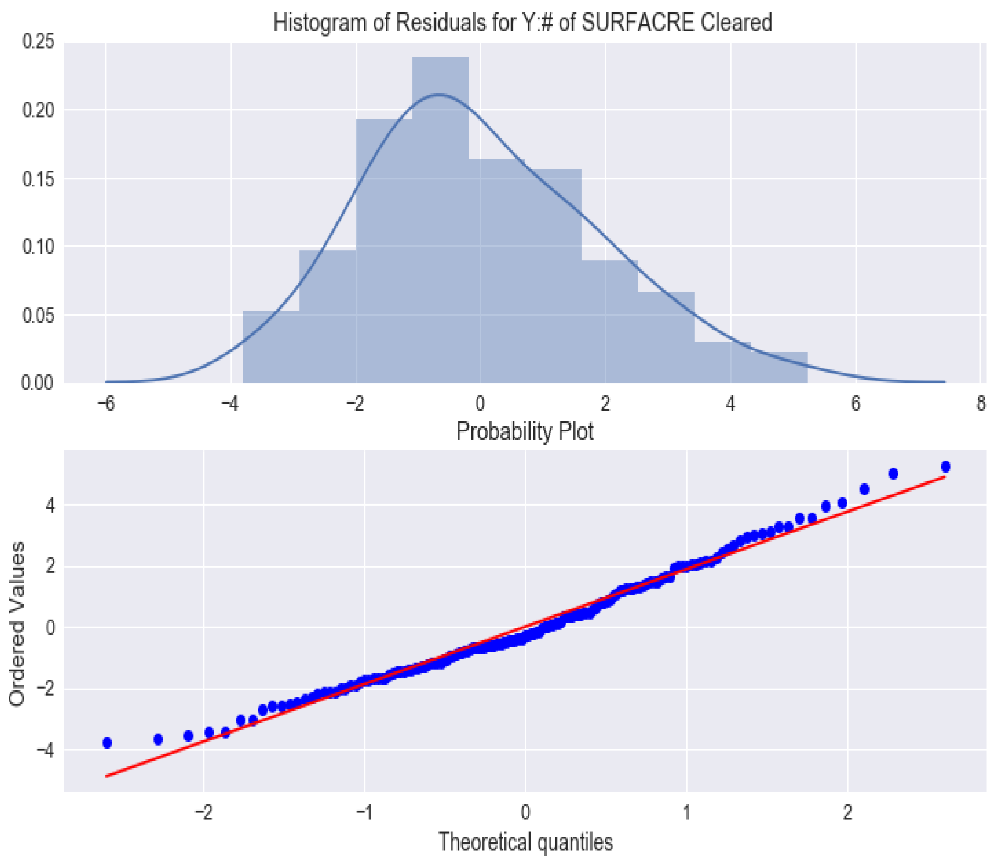


*Figure 4.10.* Histogram and normal probability plot of the residuals.

The linearity and homoscedasticity assumptions of a linear regression model were assessed using a scatterplot of model residuals and predicted values, as seen in Figure 4.11. The data generally appears randomly and equally distributed, but with some slight *fanning* and *bowed* pattern. However, the data does not show an extreme curvilinear trend, so linearity in the relationship between the predictor variables and the response variable is assumed. Validating the assumption of constant variance of the errors (homoscedasticity) based on Figure 4.11, is more ambiguous**.** Therefore, as a follow up, Bartlett's Test was run in SAS to assess the homoscedasticity assumption**.** The justification for the use of Bartlett's Test was because the errors are normally distributed. Using the standard cutoff of p=.05, the Bartlett's test result was not significant, p = .069, indicating that homoscedasticity can be assumed. The residuals are approximately constant, not significantly growing larger as a function of the predicted values.


*Figure 4.11*. Residuals vs Predicted (Fitted) Values Plot & 4-18-2 Observed vs Fitted Values.

Table 4.4. *SAS Output Bartlett's Test on Model Residuals*

| Bartlett's Test for Homogeneity of loss Variance | | | |
|---|---|---|---|
| Source | DF | Chi-Square | Pr > ChiSq |
| Groups_Median_Split | 1 | 3.289536461 | 0.0697 |

The assumption of statistical independence of the errors (i.e. no correlation between consecutive residuals) was assessed using an Index Plot of the residuals and the Durbin-Watson statistic. The Durbin-Watson statistic for this data, which should be near 2.00 to indicate absence of autocorrelation (Pallant, 2016). Both the Durbin-Watson statistic and the Index Plot of the residuals in Figure 4.12 suggests that some degree of autocorrelation is present. The index plot shows residuals that are not randomly and symmetrically distributed around zero. *"Large positive errors are followed by other positive errors, and large negative errors are followed by other negative errors"* (Chatterjee & Hadi, 2012, p. 209). This is not a major case of autocorrelation, *as* Durbin Watson statistics well below 1.0 usually indicate a fundamental structural problem to the model (Regression diagnostics:  testing the assumptions of linear regression and the Durbin-Watson statistic of the model is only 1.043 (Duke University, 2015) .

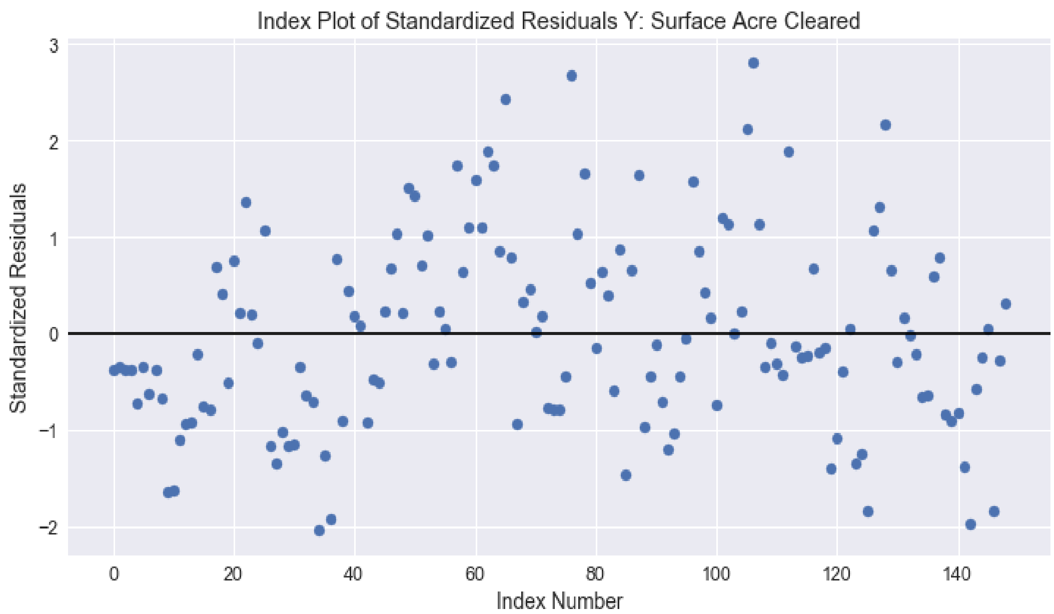


*Figure 4.12*.  Index plot of standardized residuals.

Multicollinearity was assessed by examining the Variance Inflation Factors (VIFs) of the final model. A VIF score more than 10 is an indication that collinearity is present and may be causing issues with the accuracy of estimated regression coefficients (Chatterjee & Hadi, 2012). No VIF values exceed 10, therefore absence of multicollinearity was confirmed using VIF values, as seen in Table 4.5 below**.**

There is an ongoing debate in literature as to under what circumstances should outliers be dropped from the model. Some say only if it’s obvious there were data entry errors. Some say any time it appears they are an extreme case and might be influencing your regression line as a source of bias (Field, 2013).

Table 4.5. *Final Model VIF Scores*

Variance Inflation Factors for X1_MEC_WRKDAYS, X2_Total_MEC_SITE_Hrs, X6_of_VEGTECH, X10_SCRAPLBS, X11_SLOPE, X12_VEGDEN, and X13_of_VEGACRE_Cleared

| Variable | VIF |
|---|---|
| X1_MEC_WRKDAYS | 1.64 |
| X2_Total_MEC_SITE_Hrs | 3.00 |
| X6_of_VEGTECH | 4.52 |
| X10_SCRAPLBS | 1.20 |
| X11_SLOPE | 1.27 |
| X12_VEGDEN | 1.36 |
| X13_of_VEGACRE_Cleared | 2.64 |

Influential points, of which if deleted will cause substantial changes in the fitted model. It is very important to identify influential observations if they exist in the data (Chatterjee & Hadi, 2012, p. 109). The measure of influence is *Cook's Distance,* and each observation of Cook's Distance can be found in Figure 4.14, the index plot**.** None of the specific cases have cook's distance values that exceed *1*, however case number 67 and 56 are distanced from the others, having cook's distance value around .08**.** Figure 4.13 shows the outlier and leverage diagnostics for the response variable, *number and rate of surface acres cleared of munitions and munitions related debris*. It shows scatter plot of the studentized residuals (y-axis) and leverage scores (x-axis) for each case. "*In general, studentized residuals are preferable to standardized residuals for purposes of outlier identification"* (Williams, 2016, p. 5). Influential observations are cases with both high leverage and high studentized residuals of the response variable. Figure 4.14 shows no cases which warrant the status of *influential observation*, however case number 57 is close.

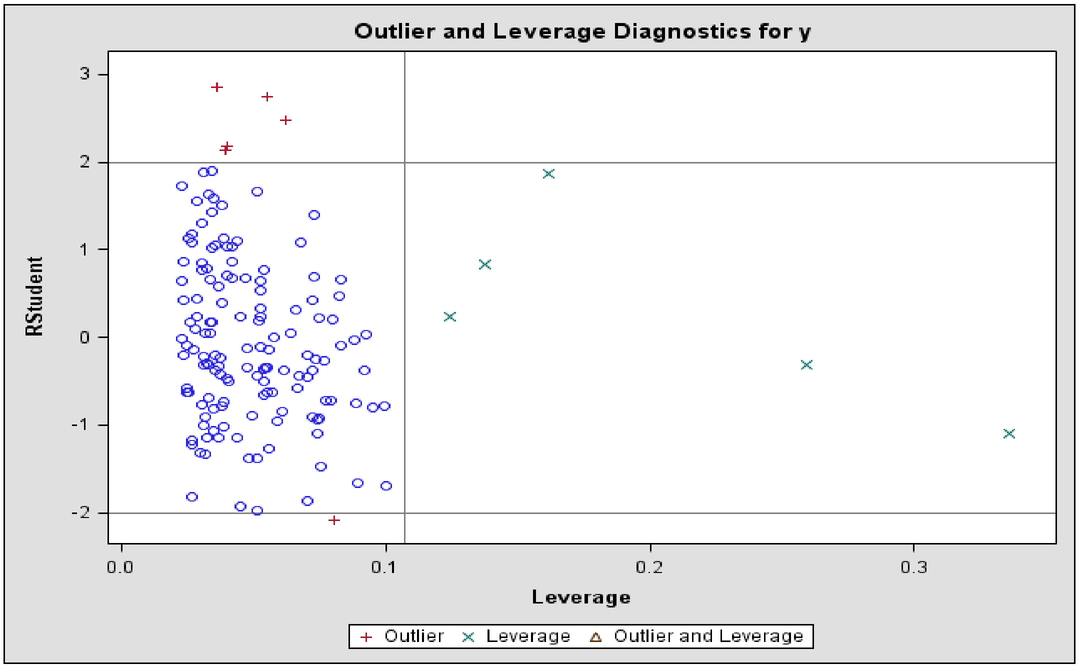


*Figure 4.13*. Outlier and leverage diagnostics for response Variable Y.

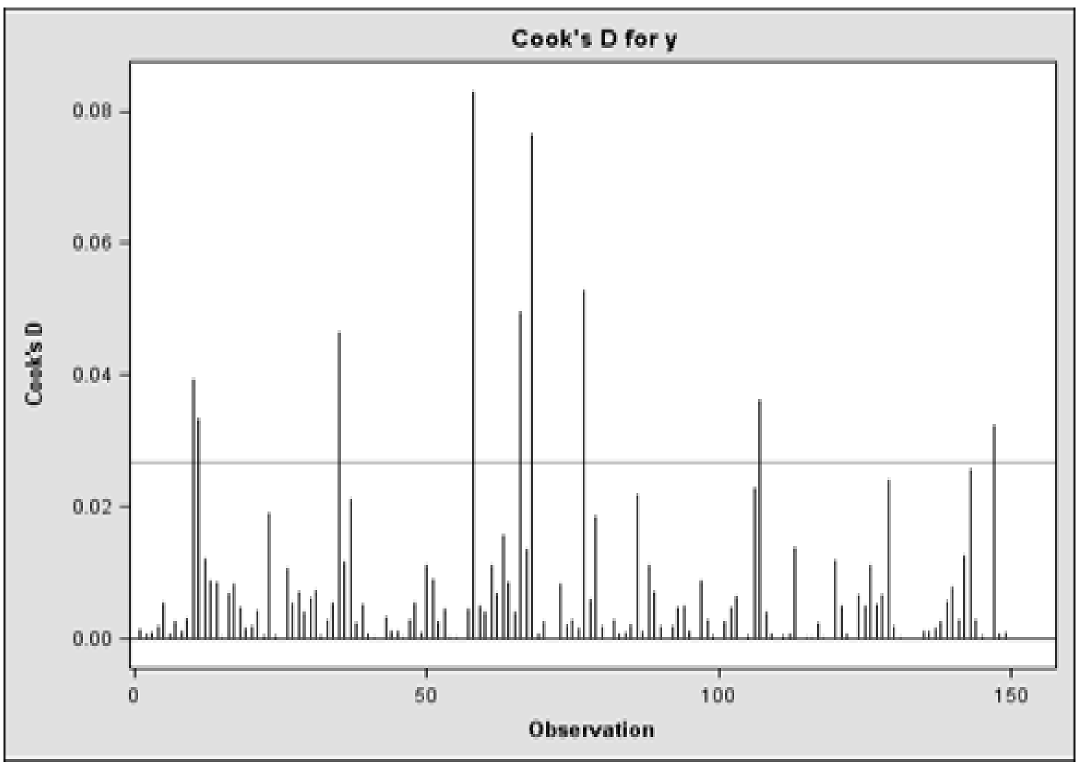


*Figure 4.14*. Cook's distance for response Variable Y, number, and rate of surface acres cleared.

### 4.2.2 Model Fit

The error framework is provided in Table 4.6. This includes (1) measures of total variation of the response variable explained by model (i.e. $R^2$), (2) error estimates on the data used to fit the model, and (3) estimates of generalization by indirectly estimating test error but penalizing the model for overfitting and size.

The regression results from fitting the model to the data are given in Table 4.6 and Table 4.7. $R^2$, the proportion of variation in the response variable, *number of surface acres cleared*, explained by the variability in the predictor is 75%**.** Since the results of $R^2$ can be misleading, used instead is the more useful metric $Adjusted\ R^2$, which is the amount of variation in the response variable explained by the predictor variables when

Table 4.6. *Performance Metrics for Final Model*

| Performance Metrics | |
|---|---|
| **Final Model Predictors** | **x1,x2,x6,x10,x11,x12,x13** |
| **R-Squared** | 0.759 |
| **Adjusted R-Squared** | 0.747 |
| **Mean Squared Error** | 3.681 |
| **Root Mean Squared Error** | 1.919 |
| **Mean Absolute Deviation** | 1.504 |
| **Predicted Residuals Error Sum of Squares (PRESS)** | 580.1020 |
| **Mean of PRESS** | 3.8933 |
| **Bayesian Information Criterion** | 225.98 |

Adjusting or penalizing for inclusion of variables that either do not or only trivially improve the existing model (James et al., 2013). When adjusted for the number of predictor variables in the model to prevent overfitting, the total variation of the response variable explained by the model is 74%**.**

Based on the Root Mean Squared Error (RMSE), the error on average was 1.91 units from the response variable. The Mean Absolute Deviation, which is another popular statistic used in forecasting and prediction is 1.5, suggesting that the forecasting error is on average 1.5 units from the response variable**.**

It is important to note, that the Root Mean Squared Error (RMSE) and Mean Absolute Deviation statistics in Table 4.6 were calculated for the original data the model was constructed on. Since the $Adjusted\ R^2$, which looks at variance explained, and the RMSE were calculated from the data used to construct the model, both run the risk of being overly specific to the exact dataset being used, the Bayesian Information Criterion (BIC) score is also reported. BIC, which uses the model size to adjust the training error, provides an indirect estimate of generalizability (James et al., 2013) for the final model is 225.98**.**

The Predicted Residual Error Sum of Squares (PRESS) statistic of the final model, which is a model validation statistic that provides a summary of predictive ability, is 580.101. The average of the PRESS statistic for the final model is 3.893. Both the PRESS statistic and the average of the PRESS statistic metrics are reported by the SAS statistical software package and can be seen in Table 4.6**.**

## 4.3 Part 3: Analysis of The Final Model

The results of the overall regression model were significant using a rejection cutoff of p = .05, $F(7,141) = 63.55$, p < .001, R2 = 0.76. The null hypotheses may be rejected. The model does have explanatory power in modeling and describing the response variable. The alternative hypothesis that at least one of the predictor variables has a non-zero coefficient value is accepted.

Since the magnitudes of the regression coefficients depend on each variables unit of measurement (Chatterjee & Hadi, 2012), both the original regression coefficient and the standardized regression coefficients are reported. Table 4.7 reports both the coefficients in their original units, and also reports the standardized coefficients in their unitless form. Table 4.8 provides an additional upper and lower bound confidence interval for each of the parameter estimates. The following coefficient analysis is based on the standardized coefficients. Using standardized coefficients represents the marginal effects of a predictor variable in standard deviation units (Chatterjee & Hadi, 2012).

The variables $X_1 - MEC\ Workdays\ and\ X_{10} - Quantity\ of\ Scrap\ Lbs$ were not statistically significant predictors of the response variable, *number of surface acres cleared.* For the predictor $X_2 - Total\ MEC\ Site\ Hrs$, which is statistically significant, for everyone standard deviation increases in *Total MEC Site Hrs* Worked, the model predicts a 0.217 increase in standardized units of surface acres cleared, the model predicts a 0.217 increase in standardized units of surface acres cleared.

The variable, $X_6 - \ Quantity\ of\ VEGTECH$ is a significant predictor: for everyone standard deviation unit increase in *Number of VEGTECH,* the model predicts a 0.303 increase in standardized units of surface acres cleared as shown in Table 4.7.

The variable $X_{11}$ - *Slope* is a significant predictor: for every one standard deviation unit increase in slope, the model predicts a 0.29 decrease in standardized units of surface acres cleared as shown in Table 4.7.

The variable $X_{12} - \textit{Vegetation Density}$ is a significant predictor: for every 1 standard deviation unit increase in vegetation density, the model predicts a 0.107 decrease in standardized units of surface acres cleared as shown in Table 4.7.

Table 4.7. *Standardized Coefficient Estimates*

| Variable | Parameter Estimate | Standardized Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|---|
| Intercept | 1.6999 | 0.0000 | 1.2341 | 1.3774 | 0.1706 |
| X1_MEC_WRKDAYS | 0.3770 | 0.0716 | 0.2784 | 1.3543 | 0.1778 |
| X2_Total_MEC_SITE_Hrs | 0.0010 | 0.2174 | 0.0003 | 3.0370 | 0.0028 |
| X6_of_VEGTECH | 0.0785 | 0.3038 | 0.0227 | 3.4570 | 0.0007 |
| X10_SCRAPLBS | 0.1725 | 0.0644 | 0.1213 | 1.4228 | 0.1570 |
| X11_SLOPE | -1.9023 | -0.2933 | 0.3021 | -6.2958 | 0.0000 |
| X12_VEGDEN | -0.4256 | -0.1080 | 0.1897 | -2.2429 | 0.0265 |
| X13_of_VEGACRE_Cleared | 0.3846 | 0.3722 | 0.0694 | 5.5412 | 0.0000 |

Table 4.8. *Results of Final Model*

*Results for Linear Regression with X1_MEC_WRKDAYS, X2_Total_MEC_SITE_Hrs, X6_of_VEGTECH, X10_SCRAPLBS, X11_SLOPE, X12_VEGDEN, and X13_of_VEGACRE_Cleared predicting Y_of_SURFACRE_Cleared*

| Variable | *B* | *SE* | 95% CI | *β* | *t* | *p* |
|---|---|---|---|---|---|---|
| (Intercept) | 1.70 | 1.23 | [-0.74, 4.14] | 0.00 | 1.38 | .171 |
| X1_MEC_WRKDAYS | 0.38 | 0.28 | [-0.17, 0.93] | 0.07 | 1.35 | .178 |
| X2_Total_MEC_SITE_Hrs | 0.00 | 0.00 | [0.00, 0.00] | 0.22 | 3.04 | .003 |
| X6_of_VEGTECH | 0.08 | 0.02 | [0.03, 0.12] | 0.30 | 3.46 | < .001 |
| X10_SCRAPLBS | 0.17 | 0.12 | [-0.07, 0.41] | 0.06 | 1.42 | .157 |
| X11_SLOPE | -1.90 | 0.30 | [-2.50, -1.30] | -0.29 | -6.30 | < .001 |
| X12_VEGDEN | -0.43 | 0.19 | [-0.80, -0.05] | -0.11 | -2.24 | .026 |
| X13_of_VEGACRE_Cleared | 0.38 | 0.07 | [0.25, 0.52] | 0.37 | 5.54 | < .001 |

Finally, the variable $X_{13} - Quantity\ of\ VEGACRE$ cleared is a significant predictor: for every 1 standard deviation unit increase in the amount of vegetation acres cleared, the model predicts a 0.372 decrease in standardized units of surface acres cleared as shown in Table 4.7.

### 4.4 Part 4: Results Summary

This chapter detailed the results of the methodology analyses presented in Chapter 3. Exploratory data analysis was performed. Model fitting procedures converged upon a final model, which consisted of , $X_1 - MEC\ Workdays$ , $X_2 - Total\ MEC\ Site\ Hrs$ , $X_6 - Quantity\ of\ VEGTECH$, $X_{10} - Quantity\ of\ Scrap\ Lbs$ , $X_{11}$ - *Slope* , $X_{12} - Vegetation\ Density$, $X_{13} - Quantity\ of\ VEGACRE$ predicting the Y: *Number of surface acres cleared*. Results indicated that the overall model was significant, and that all the above predictors were statistically significant except for $X_1 - MEC\ Workdays$ and $X_{10} - Quantity\ of\ Scrap\ Lbs$. The final unstandardized regression equation is:

*Y = 1.70 + 0.3770*X1 + 0.0010*X2 + 0. 0785*X6 + 0. 1725*X10 - 1. 9023*X11- 0. 4256*X12 + 0. 3846*X13.*

The results and discussion are discussed in more detail in Chapter 5 along with the Practical Application of the model and conclusion of the study.

## Chapter 5: Discussion and Conclusions

### 5.1 Introduction

The research presented in this praxis study addresses two important research questions, (1) Will implementation of a predictive analytics model assist in identifying the critical risk factors influencing the level of effort in the decontaminating efforts and (2) Will use of the predictive analytics model better predict the levels of effort required for each decontamination activity? This research approaches the unique complexity of munitions response actions by presenting a multivariate model which uses a wide range of inputs to model the variation in the response variable, *Number of surface acres cleared.* This approach consisted of using actual field data collected from various sources specific to surface clearance operations conducted at a large and heavily contaminated military range impact area. Sources of data consisted of: (1) field operational performance charts, (2) surface clearance production tables, (3) monthly and quarterly field operational summary reports, (4) After Action Reports, (5) weekly field summary reports, and (6) production maps. The data was used to construct the linear regression model which estimates the quantity and rate of surface acres cleared of munitions items and munitions-related contamination. The surface area cleared of munitions items and munitions-related contamination were representative samples of munitions response sites located within a 3500-acre former military live impact area used in the past for air to ground, ship to shore, and ground to ground live fire training. The large impact training area was used for 60 years of live fire training and severely and grossly contaminated with tens of thousands of live and inert munitions items, hundreds of targets, and tens of millions of pounds of munitions related debris and cultural debris.

The null hypothesis, which states there is no significant relationship between the predictors and the response variables, suggests that the constructed model is no better than the aggregated average of the response variable $Y$, *number of surface acres cleared*, was tested, and rejected. The alternative hypothesis that states that at least one of the predictors has a significant relationship with the response variable was accepted, suggesting the model does have an explanatory and predictive ability.

While these results are clarifying, it is essential that the reader understand that there is no quantifiably unique *best* set of variables, since there are multiple purposes and applications in which a regression equation can be utilized. The model presented from the research utilizes the following predictor variables described in Appendix D and Table 3.2, *[* $X_1$*: MEC Workdays,* $X_2$*: Total MEC Site Hrs,* $X_6$: *Quantity of VEGTECH,* $X_{10}$*: Quantity of Scrap Lbs,* $X_{11}$*: Slope,* $X_{12}$*: Vegetation Density,* $X_{13}$*: Quantity of VEGACRE Cleared], to predict the response variable Y, the number of surface acres cleared***.** However, this by no means states that other predictors cannot be used to model the variation in the response variable, *number of surface acres cleared.* "*A regression equation can be used for several purposes. The set of variables that may be best for one purpose may not be the best for another. Since there is no best subset of variables, there may be several subsets that are adequate and could be used in forming an equation"* (Chatterjee & Hadi, 2012, p. 303). The subset of predictor variables used in the final model presented forth by the research was chosen based on:

1. The *Best Subsets* variable selection procedure which generated a list of candidate models based on the maximization of the criterion $Adjusted\ R^2$.
2. Adhering to the principle of parsimony, therefore attempting to describe the process under study in as few variables as possible while simultaneously ensuring a high amount of variation as possible in the response variable, *the number of surface acres cleared*, is accounted for.
3. For candidate models with similar $Adjusted\ R^2$ values, utilizing information criterion such as the Bayesian Information Criterion (BIC) scores can be interpreted as a metric which tries to balance the demand for model accuracy and parsimony (Chatterjee & Hadi, 2012). The BIC score will usually take on smaller values for models with better generalization performance (Hastie, 2013).

The initial results of the *Best Subsets Selection* procedure run in SAS were surprising. At least the top 10 chosen models were similar in their performance metrics and even more apparent for the top 3 candidate models. This suggests that numerous regression equations could have been used for the task of modeling and predicting the response variable *Y*, *number of acres surface cleared***.** This makes sense considering the strong bivariate *Pearson* correlations between predictor variables as seen in the correlation matrix. The argument of redundancy in the collected data is further supported by the extremely high variance inflation factor (VIF) scores for the estimated coefficients in the fully fitted model which includes ALL the predictor variables. The table containing the SAS output of the *Best Subsets Selection* procedure is in Appendix J**,** the figure containing all pairwise correlations is in Appendix G, and finally, the table containing the results of the linear regression model containing the full set of predictor variables can be found at Appendix O and Appendix P.

As stated above, the top ten choices for the Best Subsets variable selection procedure can be found in Appendix J. As previously discussed, the entries are ordered in descending order based on the objective of maximizing $Adjusted\ R^2$. Amongst the list of candidate models, Model 1 was chosen as the base subset of predictor variables to improve upon. Model 1 is the model which had the highest $Adjusted\ R^2$ of all the candidate models and is the most parsimonious of the top five candidate models. The chosen subset of predictors was later further augmented with the removal of predictor variable $X_4$: Number of UXO Techs/wk. As previously mentioned, this exclusion was intended to remove the remaining multicollinearity that existed between predictors $X_2$ and $X_4$ *(i.e., Total MEC Site Hrs. and Number of UXO Techs/wk).* Although predictor variable $X_4$ was eliminated, one can still calculate the number of UXO Techs required per week by calculating the number of Total MEC Site Hrs. per week required to achieve the number of surface acres cleared.

It is important to clarify why Model 9 was not selected amongst the top ten candidate models since the subset of predictors is more parsimonious and produced a model with slightly lower BIC values than the chosen candidate, Model 1. The performance metrics of all models were quite similar. When looking at all models that have similar but slightly different performance values, it is important to also look at the difference in BIC Values as part of the decision process in selecting the candidate model. It may not be worth more than a bare mention when two candidate models have a difference in BIC values between 0-2 (Kass & Raffery, 1995). Whereas, when the difference in BIC values between two models is in the range of 2-6 and 6-10, this is strong evidence for not selecting the model with the higher BIC value, even though it had a higher $Adjusted\ R^2$ value (Kass & Raffery, 1995). The difference in BIC scores between Model 1 and Model 9 is less than 2. Additionally, candidate Model 1 includes the predictor variable *$X_{12}$: Vegetation Density,* which is the average percentage of vegetation and tree canopy density covering the site area where vegetation and surface clearance activities are performed. Within regression analysis, there are specific cases where it is advantageous to include certain predictors, even if they are determined to be insignificant or excluded from a variable selection procedure. For example, age in medical studies, race and socioeconomic status in income and education studies are all such examples. Vegetation density is an important predictor variable due to the additional resources and time expended in clearing moderate to high density areas as compared to low or non- vegetated areas. It is likely that low vegetated areas may not even be a concern where no time or resources would even be expended on vegetation clearance. Therefore, caution should be applied when determining if the vegetation density predictor variable should be excluded from the regression analysis model unless the vegetation density is of little concern regarding the impact on surface clearance activities.

Therefore, after balancing fit statistics such as $Adjusted\ R^2$, the concept of model parsimony, and relative importance of some of the predictor variables included in *Model 1* that were not included in the subset of predictors for candidate *Model 9*, the author arrived at the conclusion that candidate *Model 1* is slightly superior to *Model 9* and the other candidate models. However, for future research it would be interesting and prudent to explore how Model 9 and the other models may perform in a production environment with slight variations in the variable units.

### 5.2 Research Question 1

The first research question is concerned with using the regression equation and results to describe the complex process for modeling the initial operational phase of a munitions response removal action, a Surface Clearance Removal Action. In this instance, the research results and regression model can be used both as:

1. A tool for inference and control. The regression equation is used to describe the interaction between the predictor variables described in Appendix D and Table 3.2: $X_1$: *MEC Workdays,* $X_2$: *Total MEC Site Hrs,* $X_6$: *Quantity of VEGTECH,* $X_{10}$: *Quantity of Scrap Lbs,* $X_{11}$: *Slope,* $X_{12}$: *Vegetation Density,* $X_{13}$: *Quantity of VEGACRE Cleared*, and the response variable *Y*, *number of surface acres cleared.*
2. A tool to determine the magnitude by which to increase a single predictor variable or set of predictor variables to arrive at a specific value of the response variable.

Both cases mentioned above rely on a model which accounts and explains for as much variation as possible in the response variable while also simultaneously being parsimonious and having small standard errors for the coefficient estimates. The key finding is that caution should be used if using the model suggested by the research study as a tool for inference and control. The final model posited by the study does not contain any multicollinearity and has validated two key assumptions of normally distributed errors, constant variance (i.e., homoscedasticity) of the errors, and linear relationship between the predictors and response variable. However, the model does violate the assumption of uncorrelated errors. The study results show mildly correlated errors (autocorrelation).

Adjacent errors that are correlated with each other can occur for several reasons. The most plausible is that *"observations sampled from adjacent experimental plots or areas tend to have residuals that are correlated since they are affected by similar external conditions"* (Chatterjee & Hadi, 2012, p. 209). The second most plausible explanation for the autocorrelation is that there is some predictive information present that the current model is unable to capture. This generally results in biased regression coefficients due to omitted variable bias, and potential spurious correlations. The exclusion of relevant variables, whether intentional or unintentional can bias the estimated regression coefficients for the variables included in the model (Northwestern, 2015).

Autocorrelation can appear because of key predictor variables having been omitted form the right-hand side of the regression equation (Chatterjee & Hadi, 2012). Therefore, it is not the autocorrelation alone that is biasing (i.e., overestimating or underestimating) the regression coefficients themselves. The autocorrelation does however affect the regression coefficients in the sense that they no longer have minimum variance, so they may be further from the *true value* (Chatterjee & Hadi, 2012)

Obviously, this poses interpretability and inferential concerns since the effects of a predictor variable can now be overestimated or underestimated. A sub research question was concerned with discerning which predictor variables are critical factors influencing the level of effort needed for decontamination**.** As with the conclusion above, caution should be exercised when using the model to determine which variables are the critical factors influencing the level of effort needed for decontamination. This is because the estimated regression coefficients for the final model proposed by the research study are no longer the best linear unbiased estimates.

Some of my theoretical assumptions are not accurately reflected in the research results. For example, predictor variable, $X_9$: (*number of MEC/MPPEH/RRD/MD ITEMS*) should have been significant since this variable, in a true practical sense, represents a significant portion of the predictor variables $X_3$: *the number of True MECHRS/Wk,* and $X_4$: *the number of UXO TECH/Wk* in actual surface clearance operations. One would assume that the predictor variable, $X_9$: *the number of MEC/MPPEH/RRD/MD/ITEMS,* which represents the number of munitions and munitions related items cleared from the surface would have the same or more theoretical significance as predictor $X_{10}$: *SCRAPLBS*, which represents the weight of all metallic debris cleared and collected from the site. Since both predictor variables represented large quantities in the surface clearance operations requiring considerable amount of labor resources, one would postulate that predictor variables, $X_9$: *the number of MEC/MPPEH/RRD/MD/ITEMS, and* $X10$: *SCRAPLBS,* should relatively have the same significance in comparison. Considering that there are various reasons for which why the statistics may not be cohesive with theory, this provides an excellent opportunity for refining the data variables and data collection approach for further research. A variable may not be significant for various reasons such as small sample size, collinearity, and lack of overall variation in the univariate distribution of the predictor variable. Data is usually collected with the hope that there is enough variation and interesting information to determine how changes in $X$ affect $Y$. However, when there is lack of variation or action from one case to the next, then it can be argued that it will be difficult for any model to determine precisely how changes in $X$ affect $Y$ (Northwestern, 2015). The result is that in the model summary, some of the predictor variables, which may have theoretical importance and significance will not have any practical or statistical significance and may not be included in the final model. This is especially true when using a variable selection procedure such as *Best Subsets, Stepwise, or Backward Elimination*.

### 5.3 Research Question 2

The second research question is concerned with use of the regression equation as a tool for estimation and prediction of the response variable $Y$, *number of surface acres cleared.* $Adjusted\ R^2$ and Bayesian Information Criterion (BIC) were used as proxies to estimate generalizability among a set of candidate models. The first major advantage of $Adjusted\ R^2$and BIC is that both statistics account for *overfitting*, which is when the model too closely models the random error component of the dataset that it was trained on (James et al., 2013). The second advantage of $Adjusted\ R^2$ and BIC is that both statistics can be used to compare nested and non-nested models of different numbers of variables.

The final model posited by the research study is significant, offering significant improvements over a naïve average only model. For a more detailed comparison of the final model suggested by the research study which consist of the predictor variables, $X_1$: *MEC Workdays,* $X_2$: *Total MEC Site Hrs,* $X_6$: *Quantity of VEGTECH,* $X_{10}$: *Quantity of Scrap Lbs,* $X_{11}$: *Slope,* $X_{12}$: *Vegetation Density,* $X_{13}$: *Quantity of VEGACRE Cleared*, and the naive model which uses the average of the response variable $Y$ (i.e., average of the *number of surface acres cleared)* to make predictions, readers can refer to Appendix M and Appendix N

## 5.4 Hypothesis

The Hypothesis was presented in Chapter One and presented below.

- $\boldsymbol{H_0}$: Predictor (independent) variables (IV), $X_1 \dots . \dots X_{13}$, do not significantly predict the response (dependent) variable (DV) Y1.
- $\boldsymbol{H_a}$: At least one predictor (independent) variable (IV), $X_1 \dots . X_{13}$, significantly predicts the response (dependent) variable (DV) Y1.

The null hypothesis, which states there is no significant relationship between the predictors and the response variables, suggests that the constructed model is no better than the aggregated average of the response variable *Y*, *number of surface acres cleared*, was tested, and rejected. The alternative hypothesis, which states that at least one of the predictors has a significant relationship with the response variable, was accepted, suggesting the model does have an explanatory and predictive ability.

While these results are clarifying, it is essential that the reader understand that there is no quantifiably unique *best set* of variables, since there are multiple purposes and applications in which a regression equation can be utilized.

## 5.5. Implications

Due to the final model violating certain fundamental assumptions of linear regression such as independent and uncorrelated errors, caution should be exercised by project managers, program managers, field supervisors, and decision makers attempting to use this model as a tool in predicting munitions surface clearance rates to help support pre-bid decision making in acquisition opportunities, resource and operational planning, management of on-going field operations for surface decontamination activities. The autocorrelation was not extreme enough to suggest an extreme misspecification of the model, however there is still enough autocorrelation to conclude that the estimated regression coefficients are no longer the best linear unbiased estimates. It was initially the goal of the praxis that project managers could use this research during munitions cleanup to adjust schedules. For whatever reason, the project managers would be able to use the model, adjusting its inputs to see how it would affect the project timeline. With this information project managers would have the ability to create a strategy more accurately for the task of either moving the managed project ahead of schedule, behind schedule, or right on schedule.

### 5.6 Limitations of the Research

The research praxis was limited by the modest sample size of data. The researcher recommends not to only expand the data collection process in amount of data collected, but also providing more consistency and altering the way the data is reported on summary files for the number of MEC/MPPEH/RRD/MD items and quantity of Scrap collected. Although there are unique and significant differences between other site locations, data collected from a host of other project sites may add more variation and presents the opportunity to improve the deterministic aspect of the model.

The research also suggests for the collection and measurement of more variables. The study was limited in part due to the scope of the variables available for analysis. As mentioned previously, some autocorrelation was present in the model. The measurement of more variables would provide more information to the researcher in better understanding and perhaps circumventing a major reason for autocorrelation, *omitted* *variable bias.* It is simple to speculate about other variables that may further explain the response variable, *number of surface acres cleared***,** and if included in the model may remove the autocorrelation**.** The addition of a consistent approach regarding the quantification of MEC and Scrap Metal would be helpful. MEC/MPPEH/MD is quantified by the number of items whereas Scrap and munitions related debris cleared is estimated by weight. Both the number of items and weight of the items should be included for both categories to help support the consistency and measurement of manhours and labor required for clearing each item and weight. To measure more data, a more modern suite of data collection and measurement tools will be needed to help support the prediction of clearance activities. SERDP and ESTCP are actively engaged in developing and testing new detection and discrimination technology for subsurface and underwater clearance. The use of other surface detection and removal technology would be as useful and helpful as the subsurface technology in improving efficiency and reducing worker safety risks.

Finally, perhaps the most limiting aspect of the praxis study is the niche application of the research. The data was collected from numerous sites but within one large munitions response area with similar physical characteristics and high quantities of contamination which resulted in larger labor forces and total man hours worked. The large quantities of contamination and larger work force used in this model may not be representative of other sites with less contamination levels and less vegetation removal. This poses some generalization problems for project managers and program managers working at other locations around the country or abroad.

## 5.7 Practical Application of the Predictive Model

The practical application for this study and model is founded as an operational and financial risk management assessment tool to predict the number of acres cleared of munitions and munitions debris based on a level of resource effort, level of contamination, and physical site characteristics required to complete a Munitions Response Surface Clearance. Munitions Surface Clearance presently is regulated following the EPA CERCLA process with requires a Remedial Investigation (RI) to determine extent of contamination, munitions risks, and hazard in the process. Typically, 3% to 10% of the area of a munitions response site is investigated during the CERCLA RI process. The area percentages of the investigation depend on the size of the munitions response site, cost of the investigation, and historical information related to potential target impact areas, range fans, and firing positions. The sampling percentage of larger areas are typically less because of the increased cost for sampling larger areas. Although these percentages fall within acceptable limits for collecting representative samples of a CERCLA investigation, they typically result in significant data gaps for estimating the quantities of munitions contamination and areal extent of contamination across the site. Data gaps increase as the size of the site increases, especially for larger sites of a thousand or more acres. The uncertainties of contamination levels increase the financial and operational risks for firms pursuing munitions response acquisition opportunities and for those already in the field implementing clearance operations at sites where the firm's estimates were based on limited investigative data collected and provided in acquisition Request for Proposals (RFP's). Normal practice by munitions response firms offset the financial risk by applying contingency pricing for "known, unknowns" and management reserves for "known, unknowns" thereby reducing the true competitiveness of a procurement where lowest price is an evaluation factor.

A predictive model for munitions surface clearances based on historical information will benefit project managers and cost estimators by providing an initial basis of estimate adjusted by near or like site conditions. A predictive model would aid in identifying various risk profiles moving forward through the cost estimating process thereby either increasing financial risk or reducing financial risk, which translates in contingency risk pricing which leads to increasing the costs and reducing competitiveness of the bidding firm. Various risk profiles for the estimating process include variations of the predictor variables estimated to achieve completion of the surface clearance activities. Examples of predictor variables for munitions surface clearance include: (1) quantities of munitions and munitions-related contamination, (2) amount of vegetation removal, (3) number and availability of labor resources, (4) specific site conditions and, (5) estimated time to perform and complete surface clearance operations. Additional predictor variables unique to the project site should also be assessed for future analysis.

A predictive model is a dynamic tool that provides the parameters of a munitions site to be updated as the data is collected through the field execution of munitions response actions. Data elements such as production data, and site conditions (munitions density, environmental consideration) would be used to further define the parameters moving forward in initial cost estimating, but also moving forward to assist in predicting the time and cost to complete during the execution of the munitions clearance operations so that operational and financial risks are effectively managed. The use and application of the predictive model can aide both the client and munitions response firms when preparing estimates for modifications due to scope changes and scope growth during while in the field implementing the clearance operations. In addition, project managers and field supervisors may use the model to aide in risk management decisions when forecasting the clearance rates based on labor resource changes between the time lapse of when the initial proposal was completed and the time of field implementation, thereby reducing schedule and financial risks.

Additionally, a predictive model will assist project and program managers in managing risk. The predictive model will provide the necessary data to perform a qualitative risk analysis of numerous sites (identifying individual project risks and numerically categorizing the risk) based on both the site density of contamination anticipated and typical historical site conditions. It is anticipated that the predictive model will support quantitative risk analyses to assist in identifying production and resource concerns that impact the ability to predict project budget and overall cost to complete of a munitions clearance.

### 5.8 Recommendations for Future Research

As discussed in this chapter, it is recommended that further research be initiated to refine and include other variables related to surface clearance activities and explore other response variables that may be more significant in supporting the estimating forecasting of response actions, such as *manhours per acre cleared*. Further research should include extensive examination of all possible models to ensure the selection of the best and final model that meet the performance metrics is achieved. In addition, further research in the application of a predictive model should focus on predicting the labor hours required to support and implement subsequent munitions response activities, such as, subsurface clearance and digital geophysical mapping of subsurface anomalies and munitions items. Designing an experiment to define and collect the necessary variables during current and future operations may contribute in supporting further research in forecasting other munitions response activities to help mitigate financial and operational risks.

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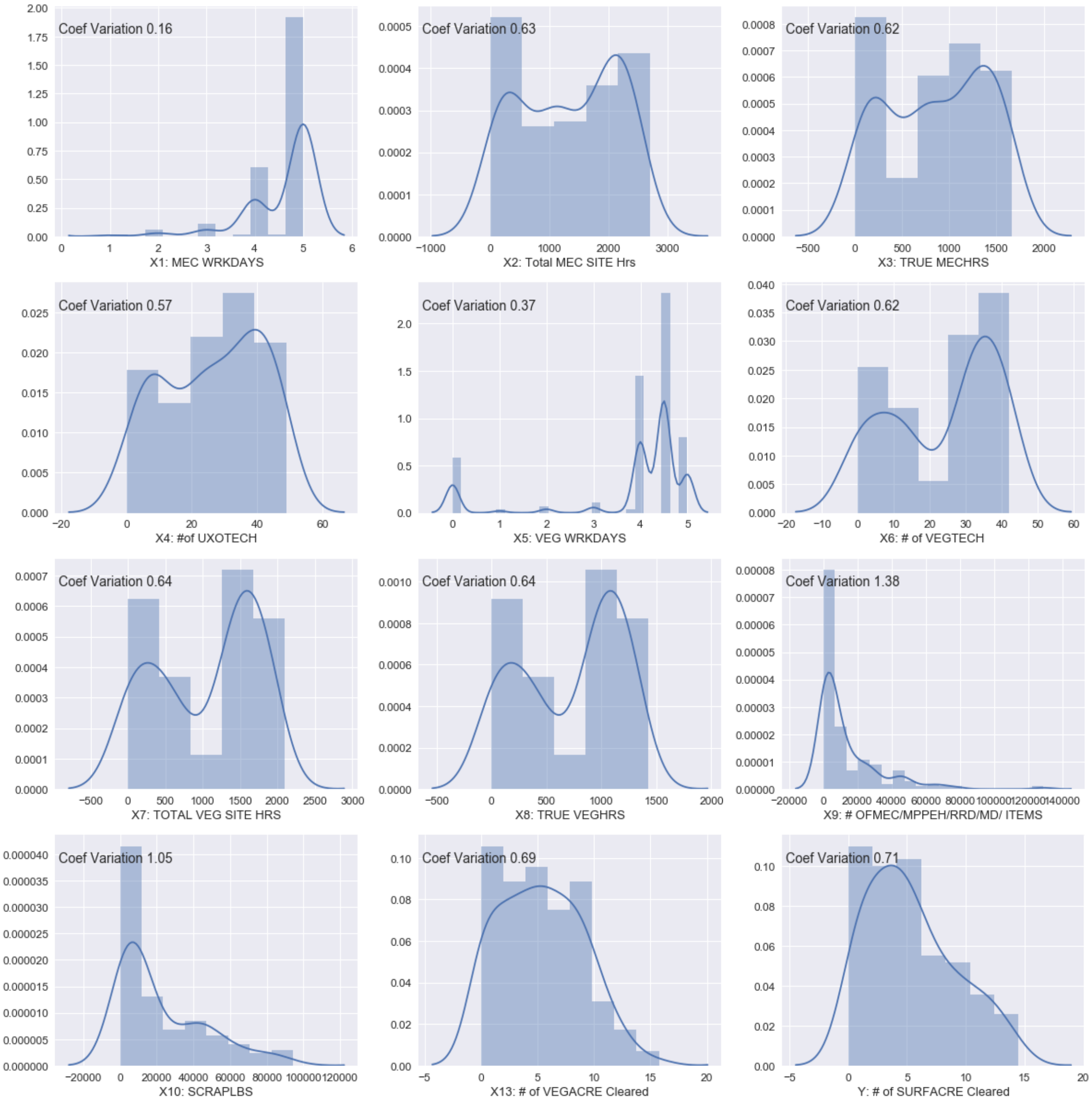
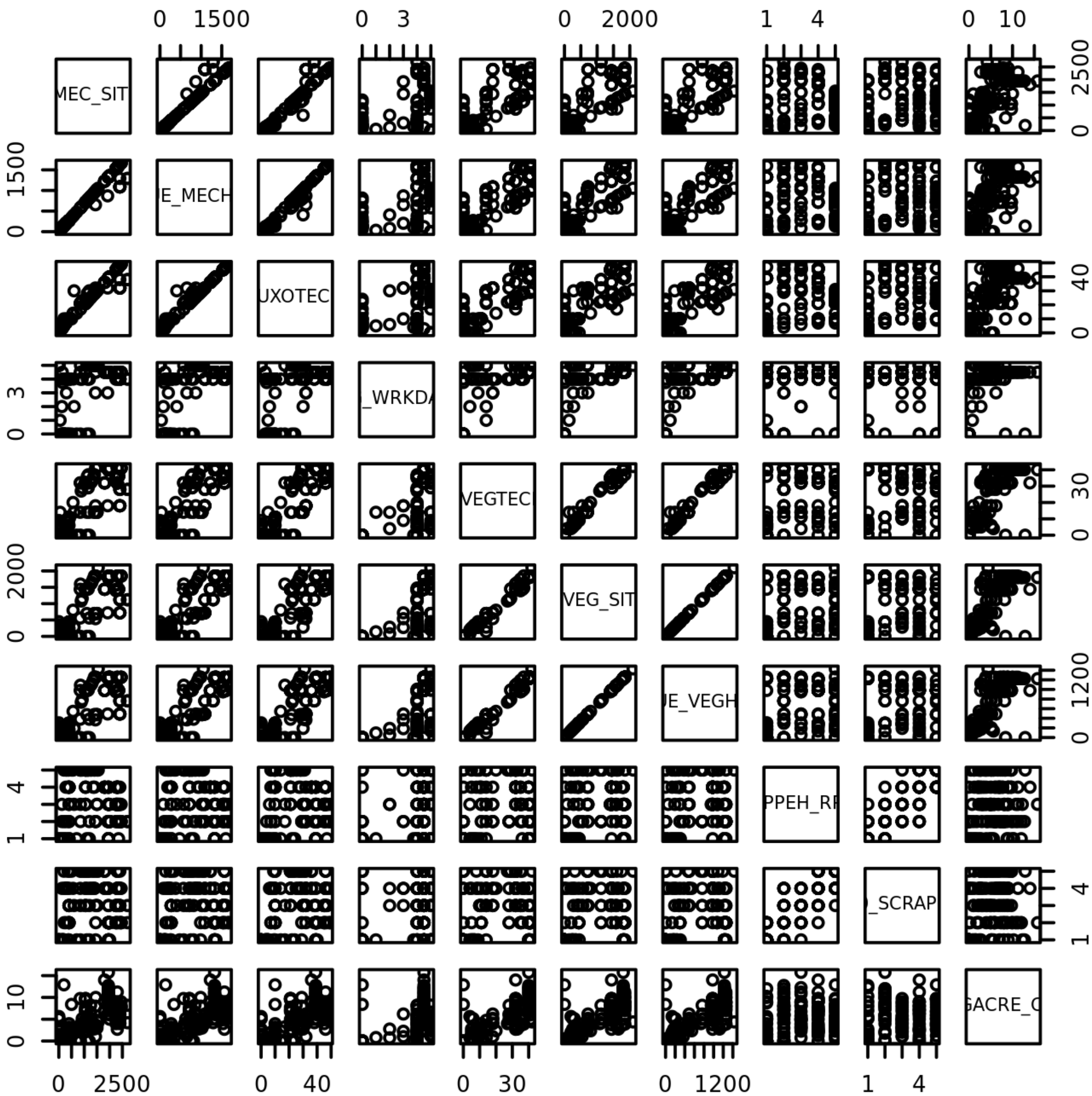
**Appendix A –**

**Histograms of All the Univariate Distributions for Continuous Variables**



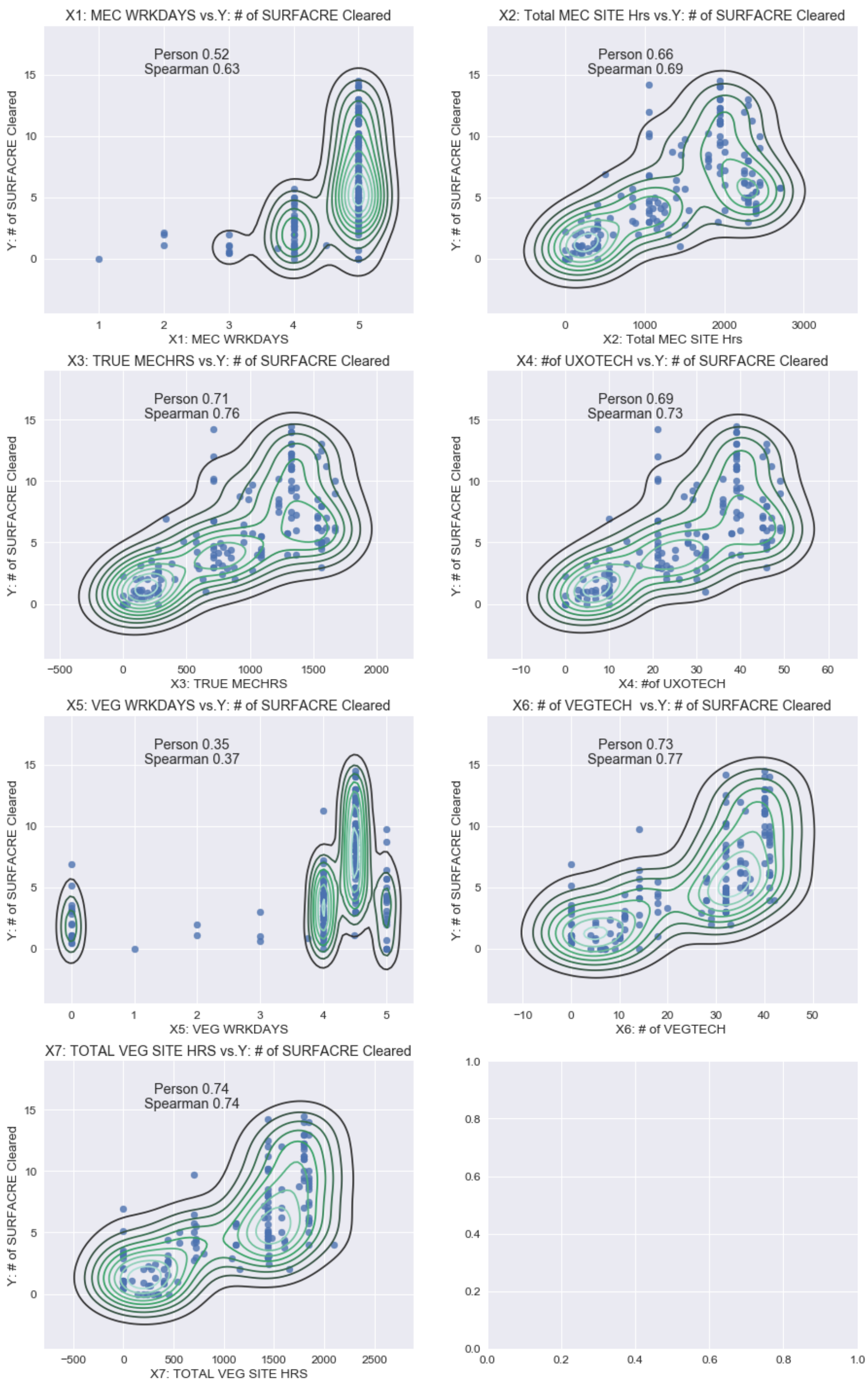
**Appendix B –**

**Scatterplot Matrix of all Predictor Variables**

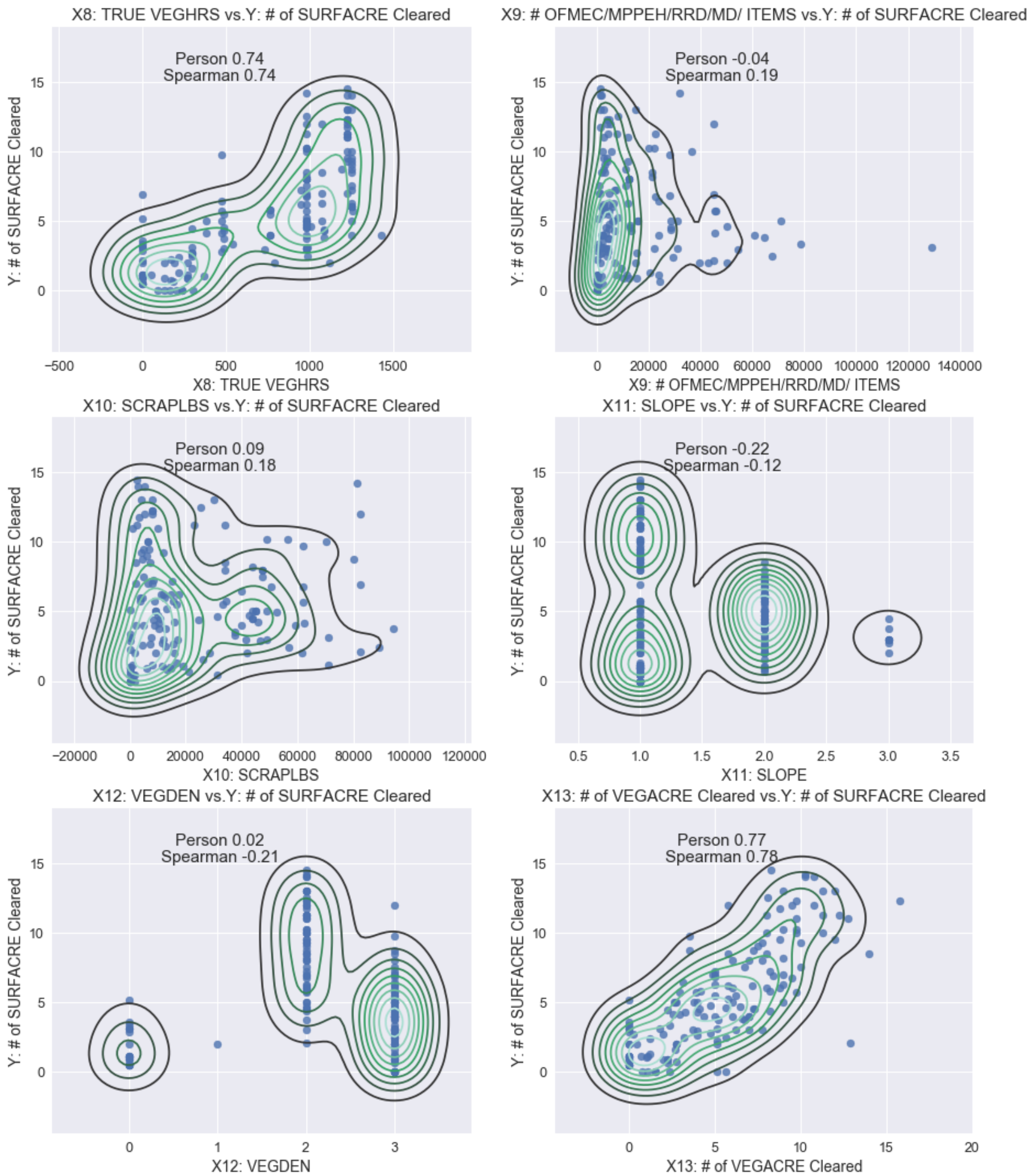


# Appendix C –

## Scatter Plots for All Predictor Response Variable Pairs



## Scatter Plots for All Predictor Response Variable Pairs



# Appendix D –

## List of Independent and Dependent Variables

| Variable ID | Variable Name | Variable Type | Definition |
|---|---|---|---|
| **Response (dependent variable**: | | | |
| Y1 | Weekly Number of Surface Acres | Continuous | Number of acres surface cleared per week of munitions related contamination (MEC, MPPEH, RRD, MD, metal scrap, targets, and cultural debris) |
| **Predictor (Independent) Variables:** | | | **Definitions** |
| **Variable ID** | **Predictor Variable Name** | | |
| $X_o$ | Site ID | Scale | Identification of Munitions Response Site |
| $X_1$ | MEC_WRKDAYS/WK | Scale | Weekly number of Field UXO Tech Days worked performing or supporting (QC, Demo, Safety, Supervision) surface clearance activities |
| $X_2$ | Total MEC-SITE-HRS/WK | Scale | Total number of weekly hours for UXO technicians performing all related surface clearance activities (supervision, quality control, safety, demolition, and final clearance) |
| $X_3$ | True MECHRS/WK | Scale | Weekly number of hours for UXO Technicians performing surface clearance activities within the grids and does not include average daily hours associated with travel time to site, daily safety briefings, daily site set up/close out, breaks, and lunch |
| $X_4$ | Num of UXOTECH/WK | Scale | Weekly number of UXO Technicians performing surface clearance activities (includes supervision, quality control, safety, all field technicians) |
| $X_5$ | VEG_WRKDAYS/WK | Scale | Total number of workdays per week for Vegetation Removal Technicians performing vegetation clearance (includes supervision and UXO Technician oversight) |
| $X_6$ | Num of VEGTEC/WK | Scale | Weekly number of Vegetation Removal Technicians performing vegetation clearance |
| $X_7$ | TOTAL_VEG SITE HRS/WK | Scale | Total number of weekly hours for Vegetation Removal Technicians performing vegetation clearance |
| $X_8$ | True VEGHRS/Wk | Scale | Weekly number of hours for Vegetation Removal Technicians performing vegetation clearance activities within the grids and does not include average daily hours associated non-grid work as indicated above in X5. |
| $X_9$ | Num OF MEC/MPPEH/RRD/MD _ITEMS | Scale | Weekly estimated number of individual MEC, MPPEH, RRD, and MD discovered and cleared from the surface area |
| $X_{10}$ | SCRAPLBS | Scale | Weekly Estimated weight of metal scrap, targets, and cultural debris removed from surface for each acre on weekly basis. |
| $X_{11}$ | SLOPE | Scale | Average estimated slope of topography within sites completed on weekly basis (0=flat; 1=low slope; 2=moderate slope; 3=steep slope) |
| $X_{12}$ | VEGDEN | Scale | Average percentage of vegetation and tree canopy density within site area worked ( 1= low density; 2= moderate density; 3 = heavy density). |
| $X_{13}$ | Num of VEGACRE Cleared/Wk | Scale | Number of vegetation acres cleared per week within site area proceeding surface clearance activities. |

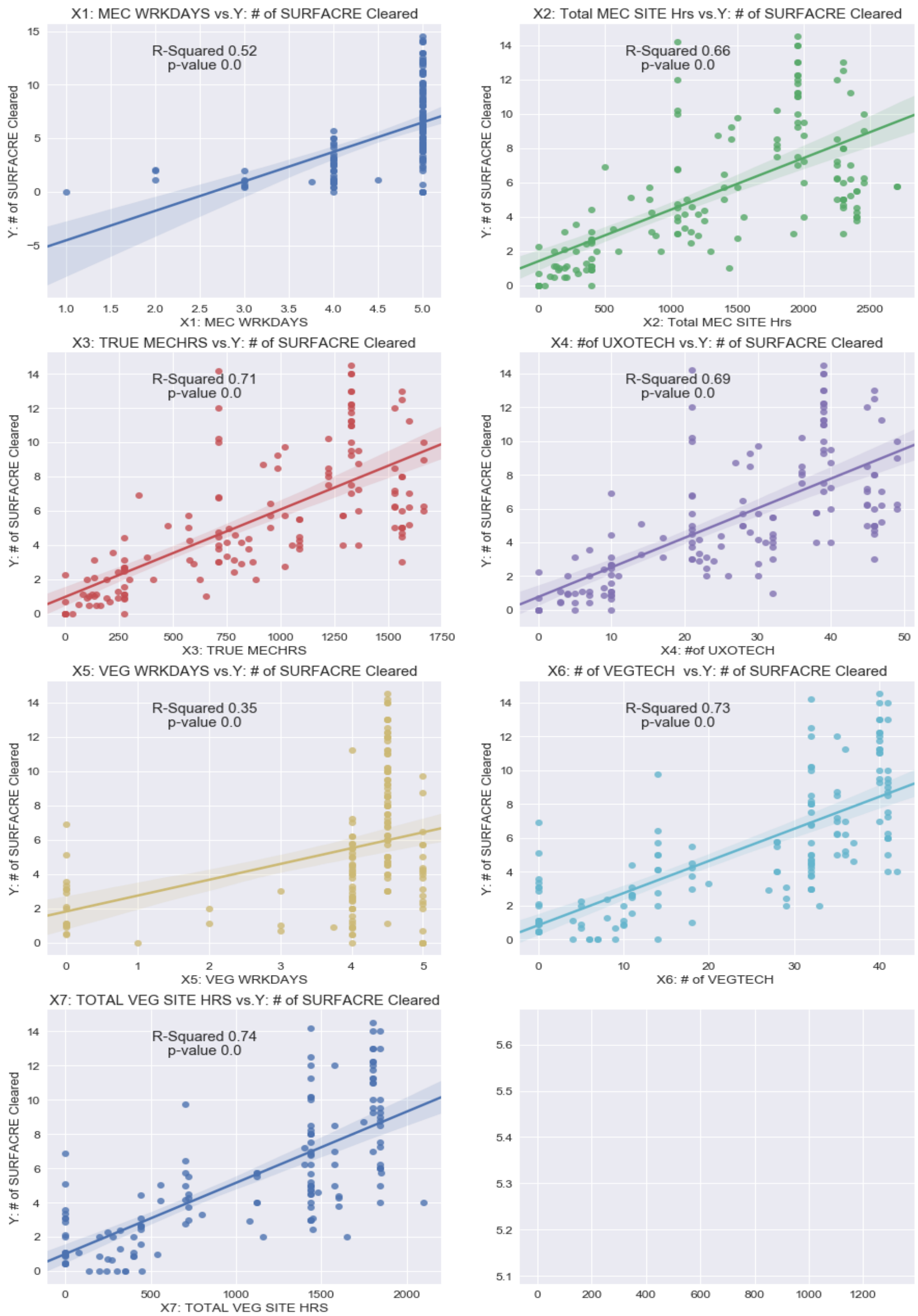
## Appendix E –

## Example of Compilation of Data Variables

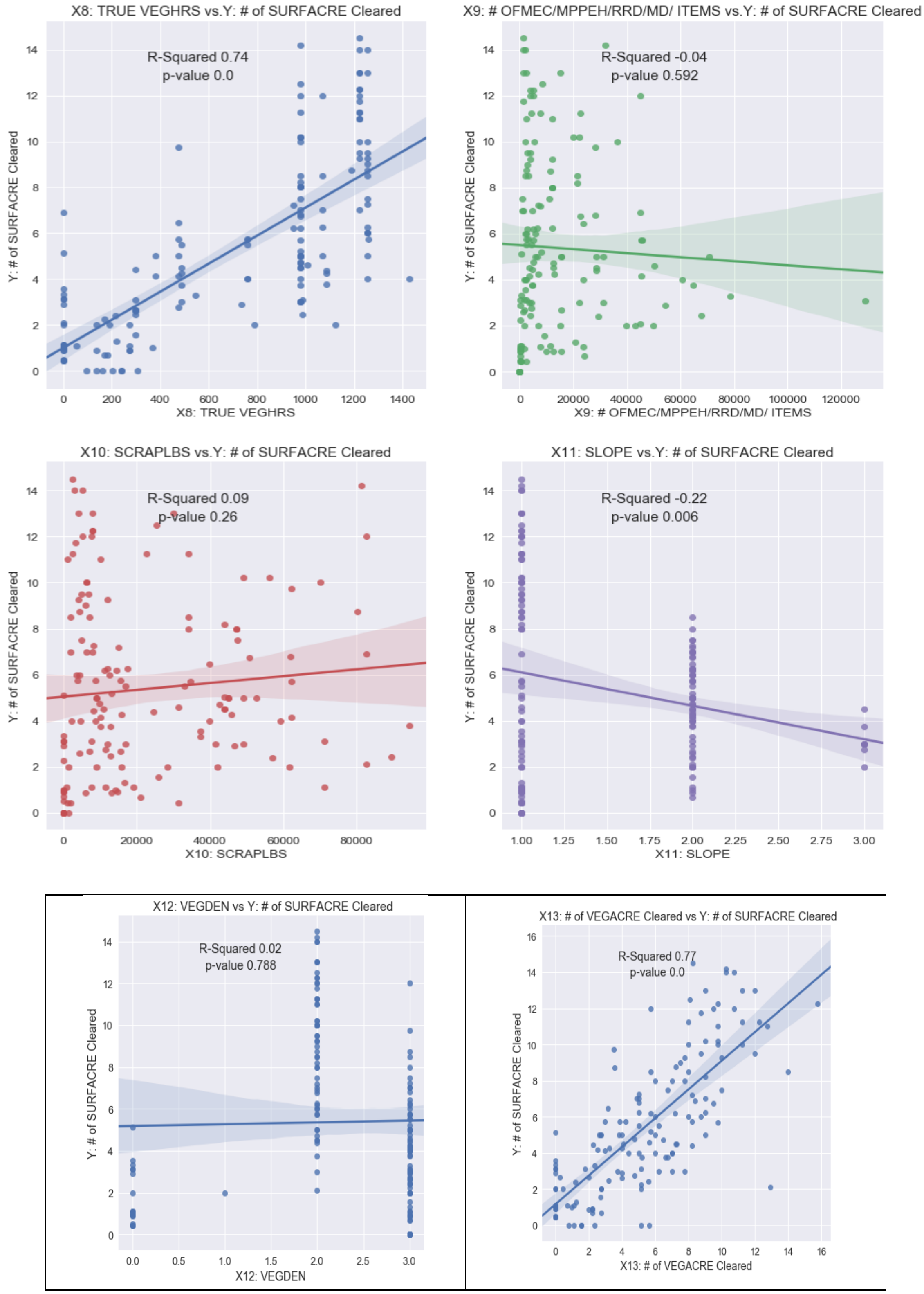
| SITEID | Week # | X1 MEC WRKDYS/WK | X2 TOTMECHRS/WK | X3 TRUEMECHRS/WK | X4 NUMUXOTECH_WK | X5 VEGWRKDYS_WK | X6 NUMVEGTECH_WK | X7 TOTVEGHRS_WK | X8 TRUEVEGHRS/WK | X9 NUMMEC/MPPEH/RRD/MD/ITEMS | X10 SCRAPMETWT | X11 SLOPE | X12 VEGDEN | X13 NUMVEGAC_CLR/WK | Y1 NUM SURF AC CLR_WK |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VAL-MK | 1 | 3 | 96.19 | 78.19 | 3 | 1 | 4 | 20.17 | 12.17 | 81 | 1062 | 2 | 1 | 0.25 | 2.15 |
| VAL-MK | 2 | 3 | 120.52 | 66.03 | 6 | 1 | 6 | 60.2 | 48.2 | 46 | 2889 | 2 | 1 | 1.25 | 2.25 |
| VAL-MK | 3 | 1 | 30.7 | 31.01 | 5 | 3 | 5 | 56.79 | 26.79 | 15 | 1238 | 2 | 2 | 0.75 | 0.75 |
| VAL-MK | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| VAL-MK | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| VAL-MK | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| VAL-MK | 7 | 3 | 128 | 89 | 7 | 2 | 5 | 74.5 | 54.5 | 56 | 1534 | 2 | 2 | 1.275 | 1 |
| VAL-MK | 8 | 4 | 170 | 138 | 4 | 3 | 6 | 170.3 | 146.3 | 35 | 2070 | 2 | 3 | 0.9 | 1.05 |
| VAL-MK | 9 | 4 | 177 | 129 | 6 | 4 | 4 | 112.8 | 80.8 | 67 | 3445 | 2 | 2 | 1.3 | 2.25 |
| VAL-MK | 10 | 4 | 203 | 155 | 6 | 4 | 5 | 157.5 | 117.5 | 125 | 4557 | 2 | 2 | 2.5 | 2.35 |
| VAL-MK | 11 | 3 | 116 | 86 | 5 | 3 | 5 | 131.3 | 101.3 | 47 | 928 | 2 | 2 | 2.5 | 2.275 |
| VAL-MK | 12 | 4 | 224 | 176 | 6 | 1 | 3 | 45.3 | 39.3 | 156 | 2982 | 1 | 3 | 0.4 | 3.275 |
| VAL-MK | 13 | 3 | 185 | 155 | 5 | 0 | 0 | 0.0 | 0.0 | 202 | 2295 | 2 | 0 | 0 | 0.975 |
| VAL-MK | 14 | 2 | 130 | 102 | 7 | 0 | 0 | 0.0 | 0.0 | 105 | 9019 | 2 | 0 | 0 | 0.925 |
| VAL-MK | 15 | 4 | 288 | 232 | 7 | 0 | 0 | 0.0 | 0.0 | 238 | 16041 | 2 | 0 | 0 | 0.787 |
| VAL-MK | 16 | 4 | 226 | 178 | 6 | 2 | 6 | 63.3 | 39.3 | 59 | 18910 | 2 | 2 | 0.75 | 1.725 |
| VAL-MK | 17 | 3 | 308 | 278 | 10 | 1 | 5 | 51.0 | 41.0 | 109 | 15110 | 2 | 3 | 0.25 | 1.875 |
| VAL-MK | 18 | 4 | 297 | 265 | 4 | 3 | 5 | 42.4 | 12.4 | 128 | 12602 | 2 | 2 | 1 | 2.57 |
| VAL-MK | 19 | 4 | 342 | 286 | 9 | 4 | 4 | 101.6 | 69.6 | 302 | 21006 | 1 | 2 | 1.5 | 3.05 |
| VAL-MK | 20 | 3 | 302 | 278 | 10 | 2 | 5 | 73.1 | 53.1 | 239 | 20610 | 2 | 3 | 0.75 | 2.08 |
| VAL-MK | 21 | 3 | 280 | 244 | 9 | 2 | 6 | 58.5 | 34.5 | 191 | 19813 | 2 | 2 | 1.5 | 2.24 |
| VAL-MK | 22 | 4 | 359 | 309 | 9 | 3 | 6 | 118.4 | 82.4 | 162 | 14763 | 2 | 3 | 0.75 | 2.6 |
| VAL-MK | 23 | 4 | 376 | 336 | 9 | 3 | 5 | 146.0 | 116.0 | 344 | 18567 | 2 | 3 | 3 | 3 |
| VAL-MK | 24 | 4 | 423 | 393 | 10 | 2 | 6 | 132.9 | 116.9 | 203 | 26349 | 2 | 3 | 0.5 | 3.11 |
| VAL-MK | 25 | 4 | 322 | 282 | 8 | 0 | 0 | 0.0 | 0.0 | 82 | 17775 | 2 | 1 | 0 | 1.67 |
| VAL-MK | 26 | 4 | 412 | 371 | 10 | 1 | 5 | 45.0 | 35.0 | 86 | 23000 | 2 | 1 | 0.25 | 1.96 |
| VAL-MK | 27 | 4 | 425 | 377 | 10 | 3 | 4 | 103.5 | 67.5 | 108 | 26486 | 2 | 2 | 1.4 | 2.09 |
| VAL-MK | 28 | 4 | 187 | 155 | 4 | 3 | 4 | 90.72 | 66.72 | 37 | 11266 | 2 | 2 | 2.25 | 1.01 |
| VAL-MK | 29 | 5 | 462 | 422 | 9 | 1 | 5 | 49.87 | 39.87 | 108 | 24305 | 1 | 2 | 0.75 | 3.11 |
| VAL-MK | 30 | 4 | 220 | 180 | 6 | 0 | 0 | 0 | 0 | 33 | 5191 | 2 | 2 | 0 | 1.36 |
| VAL-MK | 31 | 2 | 151 | 127 | 7 | 5 | 5 | 205.83 | 155.83 | 57 | 15750 | 2 | 2 | 0.75 | 0.75 |
| VAL-MK | 32 | 2 | 40 | 24 | 2 | 3 | 4 | 82.2 | 58.2 | 0 | 8 | 2 | 2 | 2.7 | 0.5 |

## Appendix F –

## Simple Linear Regressions for All Predictor Response Variable Pairs

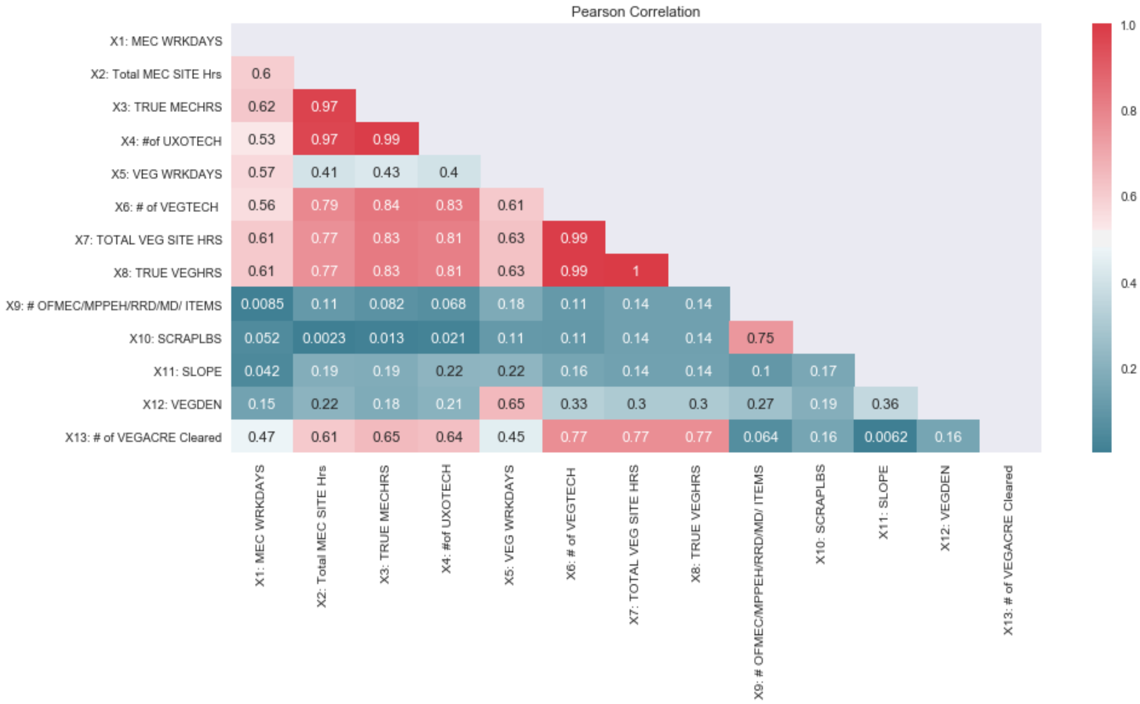


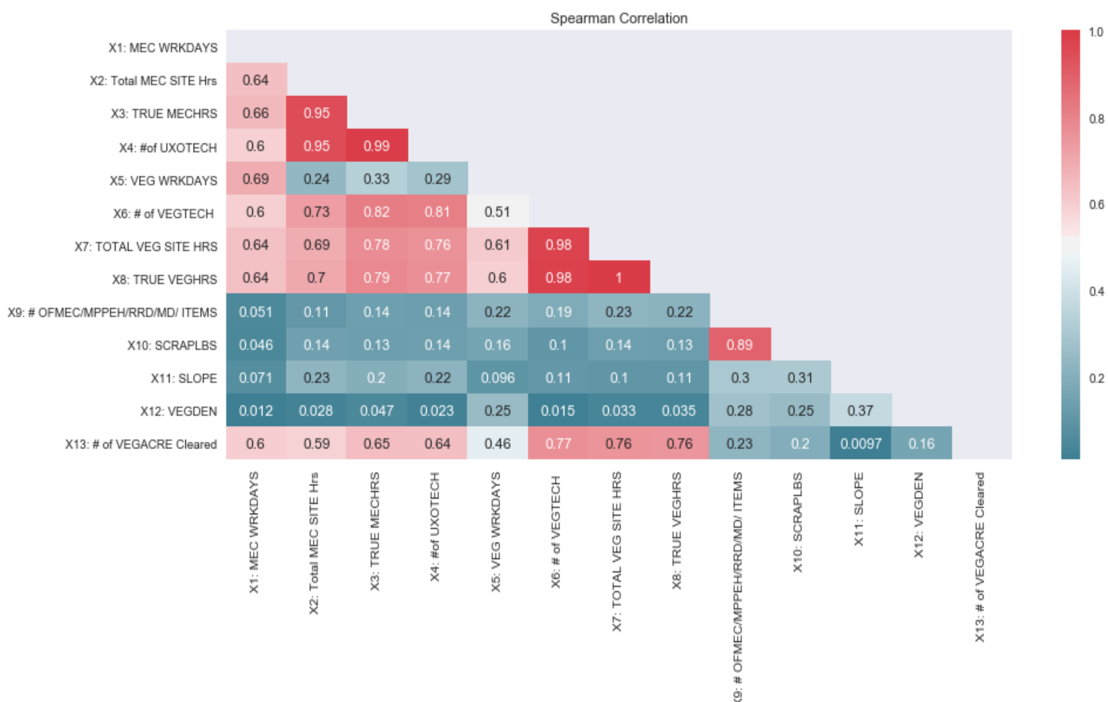
Simple Linear Regressions for All Predictor Response Variable Pairs



## Appendix G –

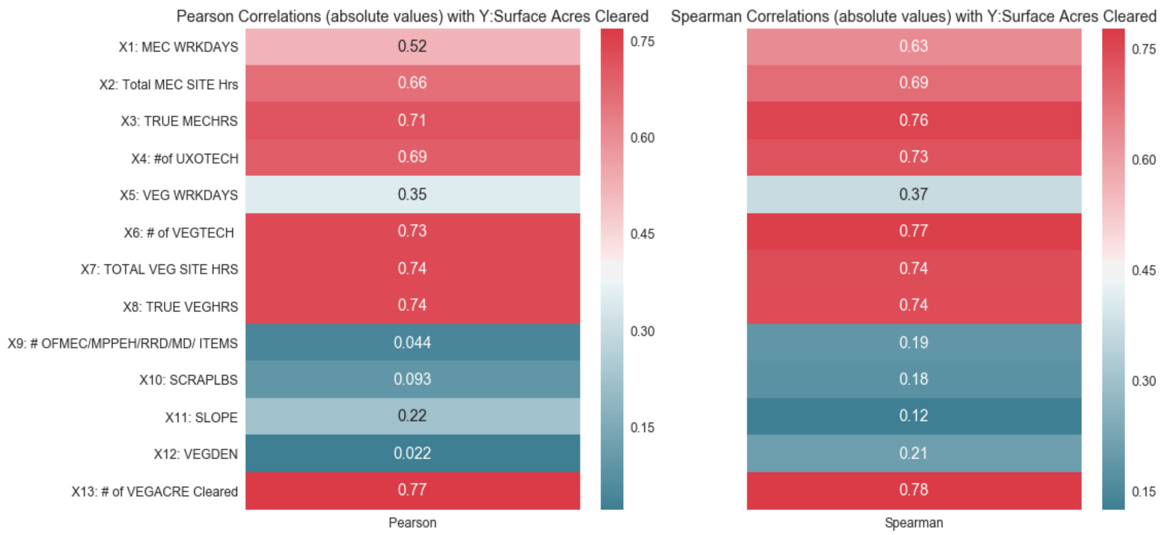
## Pearson and Spearman Pairwise Correlations for All Predictor Variables



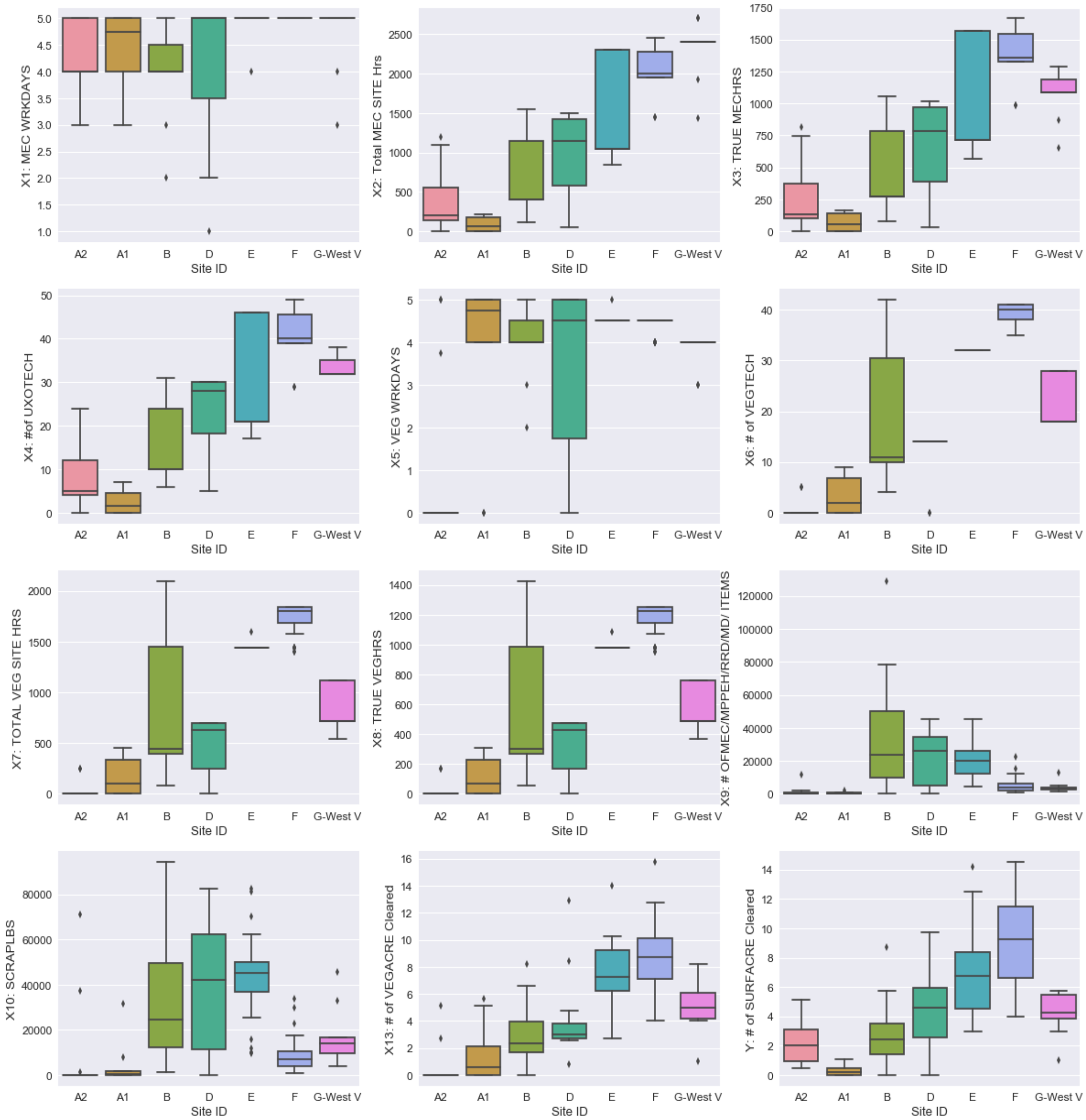
## Appendix H –

## Pearson and Spearman Correlations for All Predictor Response Variable Pairs



# Appendix I –

## Boxplots of All Continuous Variables Segmented by Site ID



## Appendix J –

## SAS Subsets Selection Top 10 Optimized for Adjusted R-Squared

| Model Index | Number in Model | Adjusted R-Square | R-Square | BIC | MSE | Root MSE | Variables in Model |
|---|---|---|---|---|---|---|---|
| 1 | 8 | 0.7667 | 0.7793 | 194.5203 | 3.399339 | 1.84373 | x1 x2 x4 x6 x10 x11 x12 x13 |
| 2 | 9 | 0.7665 | 0.7807 | 195.8791 | 3.402179 | 1.8445 | x1 x2 x3 x6 x8 x10 x11 x12 x13 |
| 3 | 9 | 0.7665 | 0.7807 | 195.8828 | 3.40228 | 1.844527 | x1 x2 x3 x6 x7 x10 x11 x12 x13 |
| 4 | 9 | 0.7660 | 0.7802 | 196.1549 | 3.409542 | 1.846494 | x1 x2 x4 x6 x8 x10 x11 x12 x13 |
| 5 | 9 | 0.7660 | 0.7802 | 196.1574 | 3.409609 | 1.846513 | x1 x2 x4 x6 x7 x10 x11 x12 x13 |
| 6 | 10 | 0.7658 | 0.7816 | 197.5366 | 3.412557 | 1.847311 | x1 x2 x3 x4 x6 x8 x10 x11 x12 x13 |
| 7 | 10 | 0.7658 | 0.7816 | 197.5398 | 3.412645 | 1.847335 | x1 x2 x3 x4 x6 x7 x10 x11 x12 x13 |
| 8 | 8 | 0.7658 | 0.7784 | 195.0350 | 3.412836 | 1.847386 | x1 x2 x4 x7 x10 x11 x12 x13 |
| 9 | 6 | 0.7658 | 0.7753 | 192.6241 | 3.412864 | 1.847394 | x2 x3 x6 x10 x11 x13 |
| 10 | 8 | 0.7658 | 0.7784 | 195.0363 | 3.412869 | 1.847395 | x1 x2 x4 x8 x10 x11 x12 x13 |

# Appendix K –

## SAS Model Summary for Top Model in Best Subsets Selection Output

Model: Linear_Regression_Model

Dependent Variable: y

| | |
|---|---|
| Number of Obse | 149 |
| Number of Obse | 149 |

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 8 | 1680.50997 | 210.0637463 | 61.80 | 0.0000 |
| Error | 140 | 475.9074329 | 3.399338807 | | |
| Corrected Total | 148 | 2156.417403 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 1.84373 | R-Square | 0.7793 |
| Dependent Mean | 5.37875 | Adj R-Sq | 0.7667 |
| Coeff Var | 34.27806 | | |

Parameter Estimates

| Variable | DF | Parameter Estimate | Standard Error | t Value | Pr > \|t\| | Standardized Estimate | Tolerance | Variance Inflation | 95% Confidence Limits | |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 1 | -0.028913 | 1.281478984 | -0.02 | 0.9820 | 0 | . | 0 | -2.5624657 | 2.504639844 |
| x1 | 1 | 0.7295787 | 0.28522575 | 2.56 | 0.0116 | 0.138625357 | 0.53671421 | 1.863189 | 0.16567206 | 1.293485322 |
| x2 | 1 | -0.001643 | 0.000804974 | -2.04 | 0.0431 | -0.35893115 | 0.05098386 | 19.61405 | -0.0032346 | -5.1678E-05 |
| x4 | 1 | 0.1727556 | 0.048509558 | 3.56 | 0.0005 | 0.683276918 | 0.04282307 | 23.3519 | 0.07684962 | 0.268661621 |
| x6 | 1 | 0.0356313 | 0.024913505 | 1.43 | 0.1549 | 0.137944051 | 0.16945315 | 5.901336 | -0.013624 | 0.084886651 |
| x10 | 1 | 0.1632373 | 0.116560034 | 1.40 | 0.1636 | 0.06088545 | 0.834015 | 1.199019 | -0.0672082 | 0.393682713 |
| x11 | 1 | -2.090807 | 0.295144807 | -7.08 | 0.0000 | -0.32232005 | 0.76145546 | 1.313274 | -2.674324 | -1.50728972 |
| x12 | 1 | -0.273788 | 0.187251121 | -1.46 | 0.1459 | -0.06945937 | 0.698524 | 1.43159 | -0.643994 | 0.096417083 |
| x13 | 1 | 0.3917387 | 0.066730133 | 5.87 | 0.0000 | 0.379143129 | 0.37792385 | 2.646036 | 0.25980968 | 0.523667789 |

| | |
|---|---|
| Durbin-Watson D | 1.106 |

**Appendix L –**

**Intellectus Model Summary Top Model in Best Subsets Selection Output**

*Variance Inflation Factors for X1_MEC_WRKDAYS, X2_Total_MEC_SITE_Hrs, X4_of_UXOTECH, X6_of_VEGTECH, X10_SCRAPLBS, X11_SLOPE, X12_VEGDEN, and X13_of_VEGACRE_Cleared*

| Variable | VIF |
|---|---|
| X1_MEC_WRKDAYS | 1.86 |
| X2_Total_MEC_SITE_Hrs | 19.61 |
| X4_of_UXOTECH | 23.35 |
| X6_of_VEGTECH | 5.90 |
| X10_SCRAPLBS | 1.20 |
| X11_SLOPE | 1.31 |
| X12_VEGDEN | 1.43 |
| X13_of_VEGACRE_Cleared | 2.65 |

*Results for Linear Regression with X1_MEC_WRKDAYS, X2_Total_MEC_SITE_Hrs, X4_of_UXOTECH, X6_of_VEGTECH, X10_SCRAPLBS, X11_SLOPE, X12_VEGDEN, and X13_of_VEGACRE_Cleared predicting Y_of_SURFACRE_Cleared*

| Variable | *B* | *SE* | 95% CI | β | *t* | *p* |
|---|---|---|---|---|---|---|
| (Intercept) | -0.03 | 1.28 | [-2.56, 2.50] | 0.00 | -0.02 | .982 |
| X1_MEC_WRKDAYS | 0.73 | 0.29 | [0.17, 1.29] | 0.14 | 2.56 | .012 |
| X2_Total_MEC_SITE_Hrs | -0.00 | 0.00 | [-0.00, -0.00] | -0.36 | -2.04 | .043 |
| X4_of_UXOTECH | 0.17 | 0.05 | [0.08, 0.27] | 0.68 | 3.56 | < .001 |
| X6_of_VEGTECH | 0.04 | 0.02 | [-0.01, 0.08] | 0.14 | 1.43 | .155 |
| X10_SCRAPLBS | 0.16 | 0.12 | [-0.07, 0.39] | 0.06 | 1.40 | .164 |
| X11_SLOPE | -2.09 | 0.30 | [-2.67, -1.51] | -0.32 | -7.08 | < .001 |
| X12_VEGDEN | -0.27 | 0.19 | [-0.64, 0.10] | -0.07 | -1.46 | .146 |
| X13_of_VEGACRE_Cleared | 0.39 | 0.07 | [0.26, 0.52] | 0.38 | 5.87 | < .001 |

*Note*. Results: $F(8,140) = 61.80$, $p < .001$, $R^2 = 0.78$
Unstandardized Regression Equation: Y_of_SURFACRE_Cleared = -0.03 + 0.73*X1_MEC_WRKDAYS - 0.00*X2_Total_MEC_SITE_Hrs + 0.17*X4_of_UXOTECH + 0.04*X6_of_VEGTECH + 0.16*X10_SCRAPLBS - 2.09*X11_SLOPE - 0.27*X12_VEGDEN + 0.39*X13_of_VEGACRE_Cleared

# Appendix M –

## SAS Model Summary for Final Model

Model: Linear_Regression_Model

Dependent Variable: y

| | |
|---|---|
| Number of Observations Read | 149 |
| Number of Observations Used | 149 |

| Dimensions | |
|---|---|
| Number of Effects | 8 |
| Number of Parameters | 8 |

Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 7 | 1637.397374 | 233.9139106 | 63.55 | 0.0000 |
| Error | 141 | 519.0200291 | 3.680993114 | | |
| Corrected Total | 148 | 2156.417403 | | | |

| | |
|---|---|
| Root MSE | 1.91859144 |
| R-Square | 0.759313745 |
| Adj R-Sq | 0.747364782 |
| AIC | 352.951429 |
| AICC | 354.2463931 |
| SBC | 225.9829995 |
| ASE | 3.4833559 |

Parameter Estimates

| Parameter | DF | Estimate | Standardized Estimate | Standard Error | t Value | Pr > \|t\| | Tolerance | Variance Inflation | 95% Confidence Limits | |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 1 | 1.699921016 | 0 | 1.234123459 | 1.38 | 0.1706 | . | 0 | -0.7398565 | 4.139699 |
| x1 | 1 | 0.376983385 | 0.071629636 | 0.278351381 | 1.35 | 0.1778 | 0.6102452 | 1.638686 | -0.1732982 | 0.927265 |
| x2 | 1 | 0.000995143 | 0.217379234 | 0.000327671 | 3.04 | 0.0028 | 0.3331889 | 3.001301 | 0.00034736 | 0.001643 |
| x6 | 1 | 0.078478962 | 0.303825629 | 0.022701479 | 3.46 | 0.0007 | 0.2209945 | 4.524999 | 0.03359969 | 0.123358 |
| x10 | 1 | 0.172528675 | 0.06435103 | 0.121262389 | 1.42 | 0.1570 | 0.8344331 | 1.198418 | -0.0671988 | 0.412256 |
| x11 | 1 | -1.902272454 | -0.293255476 | 0.302147587 | -6.30 | 0.0000 | 0.7867687 | 1.271022 | -2.4995975 | -1.30495 |
| x12 | 1 | -0.425569353 | -0.107965764 | 0.189739793 | -2.24 | 0.0265 | 0.7366885 | 1.357426 | -0.8006719 | -0.05047 |
| x13 | 1 | 0.384604576 | 0.372238358 | 0.069408311 | 5.54 | 0.0000 | 0.3782647 | 2.643651 | 0.2473891 | 0.52182 |

| | |
|---|---|
| Durbin-Watson D | 1.043 |

## Appendix N –

## Intellectus Model Summary for Final Model

*Variance Inflation Factors for X1_MEC_WRKDAYS, X2_Total_MEC_SITE_Hrs, X6_of_VEGTECH, X10_SCRAPLBS, X11_SLOPE, X12_VEGDEN, and X13_of_VEGACRE_Cleared*

| Variable | VIF |
|---|---|
| X1_MEC_WRKDAYS | 1.64 |
| X2_Total_MEC_SITE_Hrs | 3.00 |
| X6_of_VEGTECH | 4.52 |
| X10_SCRAPLBS | 1.20 |
| X11_SLOPE | 1.27 |
| X12_VEGDEN | 1.36 |
| X13_of_VEGACRE_Cleared | 2.64 |

*Results for Linear Regression with X1_MEC_WRKDAYS, X2_Total_MEC_SITE_Hrs, X6_of_VEGTECH, X10_SCRAPLBS, X11_SLOPE, X12_VEGDEN, and X13_of_VEGACRE_Cleared predicting Y_of_SURFACRE_Cleared*

| Variable | *B* | *SE* | 95% CI | β | *t* | *p* |
|---|---|---|---|---|---|---|
| (Intercept) | 1.70 | 1.23 | [-0.74, 4.14] | 0.00 | 1.38 | .171 |
| X1_MEC_WRKDAYS | 0.38 | 0.28 | [-0.17, 0.93] | 0.07 | 1.35 | .178 |
| X2_Total_MEC_SITE_Hrs | 0.00 | 0.00 | [0.00, 0.00] | 0.22 | 3.04 | .003 |
| X6_of_VEGTECH | 0.08 | 0.02 | [0.03, 0.12] | 0.30 | 3.46 | < .001 |
| X10_SCRAPLBS | 0.17 | 0.12 | [-0.07, 0.41] | 0.06 | 1.42 | .157 |
| X11_SLOPE | -1.90 | 0.30 | [-2.50, -1.30] | -0.29 | -6.30 | < .001 |
| X12_VEGDEN | -0.43 | 0.19 | [-0.80, -0.05] | -0.11 | -2.24 | .026 |
| X13_of_VEGACRE_Cleared | 0.38 | 0.07 | [0.25, 0.52] | 0.37 | 5.54 | < .001 |

*Note*. Results: $F(7,141) = 63.55$, $p < .001$, $R^2 = 0.76$
Unstandardized Regression Equation: Y_of_SURFACRE_Cleared = 1.70 + 0.38*X1_MEC_WRKDAYS + 0.00*X2_Total_MEC_SITE_Hrs + 0.08*X6_of_VEGTECH + 0.17*X10_SCRAPLBS - 1.90*X11_SLOPE - 0.43*X12_VEGDEN + 0.38*X13_of_VEGACRE_Cleared

# Appendix O –

## SAS Model Summary for Model with Full Set Predictor Variables

Model: Linear_Regression_Model

Dependent Variable: y

| | |
|---|---|
| Number of Obs | 149 |
| Number of Obs | 149 |

| Analysis of Variance | | | | | |
|---|---|---|---|---|---|
| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
| Model | 13 | 1687.127915 | 129.77907 | 37.33 | 0 |
| Error | 135 | 469.2894878 | 3.4762184 | | |
| Corrected Tot | 148 | 2156.417403 | | | |

| | | | |
|---|---|---|---|
| Root MSE | 1.86446 | R-Square | 0.7824 |
| Dependent Me | 5.37875 | Adj R-Sq | 0.7614 |
| Coeff Var | 34.66351 | | |

| Parameter Estimates | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | DF | Parameter Estimate | Standard Error | t Value | Pr > \|t\| | Standardized Estimate | Tolerance | Variance Inflation | 95% Confidence Limits | |
| Intercept | 1 | -0.01853178 | 1.827361549 | -0.01 | 0.9919 | 0 | . | 0 | -3.63249 | 3.595427 |
| x1 | 1 | 0.752955761 | 0.447055923 | 1.68 | 0.0944 | 0.143067173 | 0.223414 | 4.476005 | -0.13118 | 1.637095 |
| x2 | 1 | -0.00209103 | 0.000973061 | -2.15 | 0.0334 | -0.45676492 | 0.03568 | 28.02664 | -0.00402 | -0.00017 |
| x3 | 1 | 0.003266334 | 0.00360494 | 0.91 | 0.3665 | 0.457164653 | 0.006332 | 157.9232 | -0.00386 | 0.010396 |
| x4 | 1 | 0.083759416 | 0.111576718 | 0.75 | 0.4541 | 0.331282283 | 0.008277 | 120.8098 | -0.1369 | 0.304424 |
| x5 | 1 | -0.05580262 | 0.205563775 | -0.27 | 0.7865 | -0.02120231 | 0.264255 | 3.784219 | -0.46234 | 0.350739 |
| x6 | 1 | 0.125572724 | 0.11872953 | 1.06 | 0.2921 | 0.486145724 | 0.00763 | 131.0647 | -0.10924 | 0.360383 |
| x7 | 1 | 0.573769771 | 0.907013867 | 0.63 | 0.5281 | 101.8578924 | 6.22E-08 | 16083022 | -1.22002 | 2.367564 |
| x8 | 1 | -0.84678532 | 1.333049431 | -0.64 | 0.5264 | -102.219254 | 6.23E-08 | 16063384 | -3.48315 | 1.789576 |
| x9 | 1 | -0.00597268 | 0.239032919 | -0.02 | 0.9801 | -0.00222379 | 0.203521 | 4.91351 | -0.47871 | 0.466761 |
| x10 | 1 | 0.177832355 | 0.235966286 | 0.75 | 0.4524 | 0.066329236 | 0.208107 | 4.805229 | -0.28884 | 0.644501 |
| x11 | 1 | -2.09551886 | 0.30240868 | -6.93 | 0 | -0.32304646 | 0.741718 | 1.348221 | -2.69359 | -1.49745 |
| x12 | 1 | -0.20770919 | 0.263930199 | -0.79 | 0.4327 | -0.052695245 | 0.359554 | 2.78122 | -0.72968 | 0.314264 |
| x13 | 1 | 0.392794492 | 0.067672268 | 5.80 | 0.0000 | 0.380164943 | 0.375785 | 2.661096 | 0.25896 | 0.526629 |

| | |
|---|---|
| Durbin-Watson D | 1.111 |

**Appendix P –**

**Intellectus Model Summary for Model with All Predictor Variables**

*Variance Inflation Factors for X1_MEC_WRKDAYS, X2_Total_MEC_SITE_Hrs, X3_TRUE_MECHRS, X4_of_UXOTECH, X5_VEG_WRKDAYS, X6_of_VEGTECH, X7_TOTAL_VEG_SITE_HRS, X8_TRUE_VEGHRS, X9_OFMEC_MPPEH_RRD_MD_ITEMS, X10_SCRAPLBS, X11_SLOPE, X12_VEGDEN, and X13_of_VEGACRE_Cleared*

| Variable | VIF |
|---|---|
| X1_MEC_WRKDAYS | 4.48 |
| X2_Total_MEC_SITE_Hrs | 28.03 |
| X3_TRUE_MECHRS | 157.92 |
| X4_of_UXOTECH | 120.81 |
| X5_VEG_WRKDAYS | 3.78 |
| X6_of_VEGTECH | 131.06 |
| X7_TOTAL_VEG_SITE_HRS | $2 \times 10^7$ |
| X8_TRUE_VEGHRS | $2 \times 10^7$ |
| X9_OFMEC_MPPEH_RRD_MD_ITEMS | 4.91 |
| X10_SCRAPLBS | 4.81 |
| X11_SLOPE | 1.35 |
| X12_VEGDEN | 2.78 |
| X13_of_VEGACRE_Cleared | 2.66 |

*Results for Linear Regression with s*

| Variable | *B* | *SE* | 95% CI | β | *t* | *p* |
|---|---|---|---|---|---|---|
| (Intercept) | -0.02 | 1.83 | [-3.63, 3.60] | 0.00 | -0.01 | .992 |
| X1_MEC_WRKDAYS | 0.75 | 0.45 | [-0.13, 1.64] | 0.14 | 1.68 | .094 |
| X2_Total_MEC_SITE_Hrs | -0.00 | 0.00 | [-0.00, -0.00] | -0.46 | -2.15 | .033 |
| X3_TRUE_MECHRS | 0.00 | 0.00 | [-0.00, 0.01] | 0.46 | 0.91 | .367 |
| X4_of_UXOTECH | 0.08 | 0.11 | [-0.14, 0.30] | 0.33 | 0.75 | .454 |
| X5_VEG_WRKDAYS | -0.06 | 0.21 | [-0.46, 0.35] | -0.02 | -0.27 | .786 |
| X6_of_VEGTECH | 0.13 | 0.12 | [-0.11, 0.36] | 0.49 | 1.06 | .292 |
| X7_TOTAL_VEG_SITE_HRS | 0.57 | 0.91 | [-1.22, 2.37] | 101.86 | 0.63 | .528 |

| Variable | *B* | *SE* | 95% CI | β | *t* | *p* |
|---|---|---|---|---|---|---|
| X8_TRUE_VEGHRS | -0.85 | 1.33 | [-3.48, 1.79] | -102.22 | -0.64 | .526 |
| X9_OFMEC_MPPEH_RRD_MD_ITEMS | -0.01 | 0.24 | [-0.48, 0.47] | -0.00 | -0.02 | .980 |
| X10_SCRAPLBS | 0.18 | 0.24 | [-0.29, 0.64] | 0.07 | 0.75 | .452 |
| X11_SLOPE | -2.10 | 0.30 | [-2.69, -1.50] | -0.32 | -6.93 | < .001 |
| X12_VEGDEN | -0.21 | 0.26 | [-0.73, 0.31] | -0.05 | -0.79 | .433 |
| X13_of_VEGACRE_Cleared | 0.39 | 0.07 | [0.26, 0.53] | 0.38 | 5.80 | < .001 |

*Note*. Results: $F(13,135) = 37.33$, $p < .001$, $R^2 = 0.78$
Unstandardized Regression Equation: Y_of_SURFACRE_Cleared = -0.02 + 0.75*X1_MEC_WRKDAYS - 0.00*X2_Total_MEC_SITE_Hrs + 0.00*X3_TRUE_MECHRS + 0.08*X4_of_UXOTECH - 0.06*X5_VEG_WRKDAYS + 0.13*X6_of_VEGTECH + 0.57*X7_TOTAL_VEG_SITE_HRS - 0.85*X8_TRUE_VEGHRS - 0.01*X9_OFMEC_MPPEH_RRD_MD_ITEMS + 0.18*X10_SCRAPLBS - 2.10*X11_SLOPE - 0.21*X12_VEGDEN + 0.39*X13_of_VEGACRE_Cleared