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A PROBABILISTIC COST ESTIMATION MODEL FOR UNEXPLODED ORDNANCE REMOVAL

by

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A PROBABILISTIC COST ESTIMATION MODEL FOR UNEXPLODED ORDNANCE REMOVAL

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ABSTRACT

The Department of Defense's proposed Range Rule greatly increases the number of unexploded ordnance (UXO) contaminated sites that the services must decontaminate. Existing models for estimating the cost of UXO removal often require a high level of expertise and provide only a point estimate for the costs; they do not provide a probability distribution of the potential costs. This thesis presents a probabilistic cost estimation model created as an "add-in" for *Microsoft Excel*. A test database consisting of descriptive and cost information on the historic cleanup of nineteen contaminated areas is created. To demonstrate the model, the thesis filters the database to find eight historic records characteristically similar to a fictitious cleanup scenario, and uses information from these historic records to build probability distributions for six cost elements. The model applies Monte Carlo simulation to these probability distributions to build a probability distribution for the total cleanup cost. The resulting distribution shows that for this cleanup scenario the most likely per acre cost is $8,400, but there is a 75% chance that costs fall between $8,500 and $26,000. Results for a scenario composed of three cleanups predicts a most likely total cost of $1.7 million with a 50% probability of costs falling between $1.7 million and $2.2 million.

DISCLAIMER

The reader is cautioned that computer programs developed in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs are free of computational and logic errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

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LIST OF SYMBOLS, ACRONYMS AND/OR ABBREVIATIONS

ASR	Archive Search Report
BRAC	Base Realignment and Closure
CTC	Cost to Complete
DERP-FUDS	Defense Environmental Restoration Program – Formerly Used Defense Sites
DOD	Department of Defense
EE/CA	Engineering Evaluation / Cost Analysis
EOD	Explosives Ordnance Disposal
EPA	Environmental Protection Agency
INPR	Initial Project Report
MCX	Mandatory Center of Excellence
OED	Ordnance and Explosives Database
OOU	Ordnance Operable Unit
ORCA	Ordnance Remediation Cost Analyzer
PDF	Probability Density Function
RA	Removal Action
RACER	Remedial Action Cost and Engineering Requirements
RIMS	Research and Development
R&D	Research and Development
USACE	United States Army Corps of Engineers
USAESCH	United States Army Engineering and Support Center, Huntsville
USD (A&T)	Under Secretary of Defense for Acquisition and Technology
UXO	Unexploded Ordnance
WBS	Work Breakdown Structure

EXECUTIVE SUMMARY

The Department of Defense's proposed Range Rule (CFR 32 Part 178) outlines the military's environmental response actions for non-active ranges contaminated with unexploded ordnance (UXO). The proposed rule greatly increases the number of UXO contaminated areas that the military services must decontaminate. The services need to plan the environmental remediation (cleanup) of their contaminated sites in response to the Range Rule, but most of the military services have limited experience in large-scale environmental restoration. The existing cost estimating models for ordnance removal are engineering cost models that are based on level-of-effort and material costs. These models often require an expert's judgement for the inputs and validation of the outputs. Furthermore, the current models provide only a point estimate for the costs; they do not provide a probability distribution of the potential costs. Headquarters Marine Corps (HQMC) desires a method to estimate cleanup costs for Marine Corps sites affected by the Range Rule, and an alternative to these existing models.

This thesis presents a probabilistic cost estimation model that allows for cost-risk analysis. It creates a test database from nineteen prior cleanups that are under United States Army Corps of Engineers' management. The database contains detailed physical descriptions of the contaminated areas and associated cost information. The database segregates cost information by labor costs, material costs, and travel/per Diem costs for the Removal Action (RA) and the Environmental Evaluation/Cost Analysis (EE/CA) phases of cleanup. This cost structure establishes six cost elements that account for all costs in these final two phases of a cleanup.

The model's design, as an "add-in" for *Microsoft Excel,* makes it accessible to most military users and provides a user-friendly means to filter records and find a pool of historic sites that are characteristically similar to a proposed cleanup. Prior research and analysis of the data shows that environmental characteristics of the contaminated area, characteristics of the UXO, proposed future use, and cleanup methodology, determine cleanup costs. Once the user finds an appropriate pool of data using these predictive factors, the model assists the user in analyzing the historic cost information and building probability distributions for the six cost elements. The model uses a weighted distribution for each cost element that is a linear combination of the empirical data and a user supplied triangular distribution. Monte Carlo simulation sums the weighted probability distributions of the six cost elements in order to build a total cost probability distribution for the RA phase and the EE/CA phase of a site restoration.

A fictitious cleanup scenario demonstrates the model's functionality. The resulting total cost probability distribution reveals that for this cleanup scenario the most likely cost is $8,400 per/acre, but the distribution also shows that there is roughly a 75% chance that costs actually fall between $8,500 and $26,000. The thesis further demonstrates how Monte Carlo Simulation can aggregate the total cost estimates for several related areas to produce a single multi-area estimate. Results for a scenario composed of three contaminated areas predict a most likely cost of $1.7 million with a 50% probability of costs falling between $1.7million and $2.2million.

This work recommends that future requirements standardize and automate the reporting of cost information by contractors. The limited amount of available cost data reduces confidence in the estimates that this model produces. More cost data can provide the user with a larger pool of similar cleanups and can reduce the assumptions that the user must make in performing an estimate. This thesis also recommends that the Department of Defense consider implementing cost-risk analysis in other models that it uses for estimating UXO cleanup costs.

Although HQMC is the impetus for the development of this model, the cost-risk model is suitable for all Department of Defense users interested in producing cost estimates for UXO cleanup. The thesis provides an easy-to-use model that allows the Marine Corps and other users to budget for the cleanup of UXO. Estimating the costs of environmental restoration of ordnance contaminated sites is a difficult process containing a substantial amount of unknowns. The cost-risk model provides the means to manage this uncertainty and risk.

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I. INTRODUCTION

The Department of Defense's proposed Range Rule (CFR 32 Part 178) outlines the military's environmental response actions for non-active ranges contaminated with unexploded ordnance (UXO). By publishing an acceptable rule that governs the handling of military munitions on closed, transferred and transferring ranges, the DOD hopes to avoid having to treat UXO as solid hazardous waste. The proposed rule, however, greatly increases the required number of UXO contaminated areas that the military services must clean. The services need to plan the environmental remediation (cleanup) of their contaminated sites in response to the draft rule, but with the exception of the Army the military services have limited experience in large-scale environmental restoration. The Army Corps of Engineers, through its involvement in the Defense Environmental Restoration Program - Formerly Used Defense Sites (DERP-FUDS) and Base Realignment and Closure (BRAC), has extensive experience in remediation of UXO sites. The existing cost estimating models for ordnance removal projects are engineering cost models that are based on level-of-effort and material costs. These models often require an expert's judgement for the inputs and validation of the outputs. Further, the current models provide only a point estimate for the costs; they do not provide a probability distribution of the possible costs.

This thesis presents a probabilistic cost estimation model that provides the military services the ability to perform cost-risk analysis. The user can develop a cost estimate using the cost data from historic sites that have characteristics similar to the proposed cleanup site. The model produces a probability distribution for the cost of a single cleanup or several combined cleanups. These distributions allow a user to budget for the cleanup of UXO on a specific site and to make decisions on how to approach the remediation of multiple sites.

Chapter II provides an overview of the UXO problem and current methods of estimating UXO cleanup costs. Included in Chapter II is related research in probabilistic cost estimating and general cost estimating of environmental projects. Chapter III outlines cost factors in the UXO remediation process. Chapter IV presents background information necessary for understanding the probabilistic cost model, and this chapter gives a detailed description of the data used in the model and discusses the general method of Monte Carlo Sampling used to produce total cost probability distributions. In Chapter V a "walkthrough" of the model is performed using a cleanup scenario to illustrate the model's functionality. Discussion of the simulation output and its interpretation is given in Chapter VI, and finally Chapter VII delivers recommendations and conclusions.

II. BACKGROUND

A. SCOPE OF THE UXO PROBLEM

UXO is a massive challenge; worldwide, nearly 500 people a week are killed or injured from a staggering 100 million landmines left over from prior conflicts [United States Department of Defense, Office of the Under Secretary of Defense for Acquisition and Technology (USD (A&T)) 1998]. Although in the United States death or injury is extremely rare, UXO has other substantial detriments. Estimates show that some level of UXO contaminates nearly 15 million acres in the United States. This contamination prevents civilian land use, threatens public safety, and causes environmental concern. Since many suspect sites have not been surveyed, the extent of this problem is uncertain. However, estimates show that if only five percent of these sites require remediation, cleanup costs could exceed 15 billion dollars [USD (A&T) 1998].

To address the UXO problems, the Environmental Protection Agency (EPA) published the Military Munitions Rule in February of 1997. The EPA, however, postponed a decision on whether to regulate UXO on closed, transferred, and transferring (CTT) ranges while the Defense Department develops its own Range Rule for these CTT ranges. If the DOD does not promulgate the Range Rule or if the Range Rule does not adequately protect the public and the environment, the EPA plans to force cleanup on these CTT ranges under United States environmental law [United States Department of Defense, Office of the Secretary 1997, sec. II.1.]. By drafting the Range Rule, the DOD hopes to uniquely define UXO from other hazardous wastes, and establish methods to handle UXO that is acceptable to the military, EPA, and other stakeholders. The different services understand that unless they voluntarily demonstrate responsible stewardship of these lands, as addressed in the Range Rule, restrictions could be imposed that would severely limit training and create insurmountable costs.

Due to the implications of the proposed Range Rule, the services are showing concern over the many issues surrounding UXO management and removal including the analysis of cleanup costs. One reason that the estimation of cleanup costs proves to be difficult is that there is tremendous variance found in the costs from one site to another. For example, the budget for the Navy's Kaho'olawe range in Hawaii is $400 million or approximately $14,000 per acre; the Army's Jefferson Proving Ground estimates are as high as $1.4 million dollars per acre; and parcels of Adak, Alaska have estimates up to a staggering $10 million per acre. [Rohrer 1997]

B. CURRENT STATUS OF UXO COST ESTIMATION

United States Army Engineering and Support Center Huntsville, Alabama USAESCH) manages and has managed the majority of UXO remediation projects in the United States. Throughout the 1970's and early 1980's the DERP-FUDS evolved. This program's goal is to remove any risk to human health, safety, and the environment caused by former DOD activities. The DOD delegates the execution of this program to the United States Army Corps of Engineers (USACE). As the chief executor of environmental activities at FUDS, the USACE is involved in a varying capacity of cleanup on approximately 1,500 FUDS. To create a focal point for all UXO activities the USACE created a Mandatory Center of Excellence (MCX) at Huntsville, Alabama in

1990. Along with the DERP-FUDS, the MCX is also responsible for managing UXO activities on BRAC sites, and Installation Restoration Program sites. In total the MCX has over 2,000 inventoried sites and usually administers from 60 to 80 restoration projects at any given time [Foley et al. 1996].

Huntsville Center produces cost estimates for UXO projects using either the Remedial Action Cost and Engineering Requirements System (RACER) [BTG Incorporated (Delta Research Division) 1998], or a proprietary spreadsheet model developed by Huntsville Center's cost engineers. Both RACER and the spreadsheet model base calculations on the number of teams that a project requires for UXO removal. The two models then determine total labor hours, equipment use, and material requirements based on these hypothetical teams. Finally, these two models use labor-rate costs and material unit costs to arrive at a single point estimate. Unfortunately, these models do not provide any information about cost uncertainty and also require expert knowledge of UXO remediation in order to verify inputs and results. The USACE uses experienced cost engineers to produce cost estimates. For other agencies these models would be difficult to use without background experience in UXO projects.

C. RELATED RESEARCH

Throughout the DOD cost analysts frequently use cost-risk analysis models, and the research in this field is abundant. Anderson and Cherwonik [1997] present an overview of cost-risk analysis in military acquisition programs. Their primer describes the current DOD shift away from point estimates to probabilistic estimates, and justifies the need for this shift. The paper focuses on providing the acquisition Program Manager and other integral DOD acquisition personnel with an appreciation of the benefits of cost-risk analysis.

More specifically related to this thesis, the DOD uses cost analysis directly in environmental programs. The MITRE Corporation, a subcontractor in the Army's chemical weapons demilitarization program, presents a methodology that compares two different processes used for demilitarizing chemical weapons [Hughitt, Wusterbath, and Zoepfl 1994]. The MITRE Corporation report uses Latin hypercube sampling of work breakdown structure cost-elements to create total cost probability distributions for the demilitarization process. The report then compares the life cycle costs of the current baseline process with the proposed cryofracture process. Since the two processes are in different stages of developmental maturity, MITRE develops input probability distributions with a combination of theoretical and empirical data. The results of the analysis provide a method to compare the economic merits of the two plant designs and their associated demilitarization processes.

In other research, Air Force Materiel Command contracted Aeronautical Systems Center to develop a funding estimator tool for pollution prevention in weapon system production [Aeronautical Systems Center 1994]. The EPA requirements to reduce the use of ozone depleting chemicals forces program managers to develop strategies and funding plans to meet the EPA goals. The Air Force Materiel Command model provides a means to produce rough order of magnitude funding estimates to support Program Objective Memorandum inputs. The model identifies a weapon system's logistic and manufacturing processes and the hazardous material associated with these processes.

Next, the model assigns each hazardous material involved in the production process an importance factor, difficulty factor, and substitute factor. Finally, the model uses regression analysis to provide pollution prevention funding estimates.

Hersey and Pederson's unpuplished report is one of the earliest works specifically addressing UXO removal costs [1981]. Their work outlines the factors that influence cleanup costs: characteristics of the contaminated area, characteristics of the ordnance, cleanup requirements, and the cleanup methodology. They present an engineering "bottom-up" model that provides a means to compare the cost of manual removal with removal assisted by a Sub-Surface Clearance Vehicle. The model compares the costs of the two removal methods under varying environmental conditions.

Delta Research, a division of BTG Incorporated, has done the greatest amount of research in estimating costs of UXO removal. Delta Research's team of environmental engineers, cost analysts, contractors, and economists developed the RACER System to provide the DOD and the private sector with a system to assist in estimating costs of hazardous waste cleanup. RACER consists of over 65 separate engineering cost and project management models, with a few dedicated solely to ordnance and explosive waste remediation. Delta Research consolidates the UXO models into a separate *Microsoft Excel* [Microsoft Corporation 1997] based package titled Ordnance Remediation Cost Analyzer (ORCA). These models are called RACER/ORCA in the remainder of this thesis. These models calculate quantities of equipment, labor, and materials needed for a job based on the underlying engineering processes [BTG Incorporated (Delta Research Division) 1999].

III. ORDNANCE REMOVAL PROCESSES AND COST DRIVERS

A. PHASES OF RESTORATION

UXO remediation usually follows three phases: "inventory," "study," and "removal." The total cost of site restoration from initial project identification through ordnance removal is known as the "cost to complete" (CTC). Estimating the CTC requires understanding the costs in each phase of a cleanup.

1. Inventory Phase

For a DERP-FUDS project, the inventory phase begins with the development of an Initial Project Report (INPR). The INPR determines whether a threat exists, whether the site is the responsibility of the DOD, and whether the site is eligible for cleanup under DERP-FUDS. The cost for an INPR is usually relatively small (less than $25,000) [Fanning 1999].

2. Study Phase

The study phase usually consists of two tasks: the Archive Search Report (ASR) and the Engineering Evaluation/Cost Analysis (EE/CA). The ASR is a detailed investigation of historic information related to the suspected contaminated areas. The agency conducting an ASR reviews any existing paperwork, conducts interviews, reviews maps, and visually examines the suspected and surrounding areas. Producing an ASR with reliable conclusions can be quite difficult because most military ranges have few if any records on their use. Range Boundaries shift over the years, ranges overlay onto other ranges, and ranges convert to alternate use. To compound this problem, ranges are often not segregated by use and are open to all types of ordnance and ordnance delivery

[Hersey and Pederson 1981]. The final ASR product includes maps of the suspected area, a detailed description of the physical composition of these areas, and a determination of the types and densities of the ordnance that may be encountered. The Saint Louis district or Rock Island district of the Corps of Engineers normally completes ASRs. Regardless of the project's size, an ASR usually has a fixed price of about $40,000 [Fanning 1999].

When the ASR identifies areas of contamination, then the study phase conducts an EE/CA. The EE/CA is a comparative study of removal options performed by the contractor. A large part of the EE/CA's cost is the initial sampling of the site. The sampling results subdivide the contaminated area into several sectors based on ordnance densities (number of ordnance per acre). Sampling usually involves choosing randomly located grids within a sector and surveying them with a magnetometer. All anomalies are then excavated to determine density. The contractor uses the sampling data to perform analysis on removal action alternatives and to develop plans for the Removal Action phase. EE/CA costs can be substantial. Current algorithms recommend sampling a minimum of two percent of a sector in order to determine ordnance density with a reasonable degree of confidence [Barrett 1999].

3. Removal Action Phase

Huntsville Center estimates that Removal Action (RA), an extremely labor–intensive operation, constitutes roughly 80% of the CTC [Young 1999]. Most RAs are "mag-and-flag" operations. Highly trained ordnance technicians divide the entire area of contamination into grids, and then subdivide the grids into approximately 20-foot wide lanes. The technicians sweep the lanes with handheld magnetometers and place flags wherever an anomaly in the earth's magnetic field is registered. Finally, the technicians use manual methods to dig up all anomalies. A newer method, called geophysical surveying, consists of sweeping the entire area with systems that automatically record anomaly locations and signatures. The data is then analyzed to filter out false readings from actual UXO. Unlike mag-and-flag, geophysical operations only remove those anomalies determined to be UXO. Geophysical methods can greatly reduce the cost of the RA by reducing the amount of "digs" to perform; however, geophysical surveying adds to costs in the EE/CA stage because of the additional resources and expertise required in the investigation phase.

All of the services have Explosive Ordnance Disposal (EOD) units; however, large-area environmental restoration differs in many ways from the typical missions performed by military EOD units. Due to this and the operational commitments on EOD units, civilian contractors perform nearly all Removal Actions on environmental restoration projects.

B. FACTORS AFFECTING COST

The factors that influence cost are well known throughout the UXO community, but the interrelationships of these factors are not fully understood. An economic model developed by members of the Naval Explosive Ordnance Disposal Technical Center in the early 1980s, shows the cost of range cleanup to be based on four factors: proposed future use, environmental characteristics of the site, expended ordnance characteristics, and method of removal [Hersey and Pederson 1981].

1. Proposed Future Use and Depth of Clearance

Proposed future use is one of the primary factors in the cleanup cost because it dictates the depth of removal. Table 1 shows clearance depths prescribed by the DOD for varying categories of future land use.

Projected Future Use	Depth of Clearance
Unrestricted	10 feet
Commercial / Residential / Utility /Subsurface Recreational	
Construction Activity	
Public Access	4 feet
Farming / Agriculture / Surface	
Recreation / Vehicle Parking / Surface	
Supply Storage	
Limited Public Access	1 foot
Livestock Grazing / Wildlife Preserve	
Not Yet Determined	Surface

Table 1: Projected Future Use and Required Depth of Cleanup. The depths listed in this table are default depths for ordnance removal. Actual depths may differ in accordance with contractor, DOD, and stakeholder negotiations. From [United States Department of Defense, Office of the Secretary 1995].

As the depth of clearance increases, the technology needed to locate UXO changes and the methods to excavate it become more complex. Although not necessarily indicative of all projects, the following table of projected costs to cleanup Naval Station Adak, Alaska shows exponential cost growth associated with increases in clearance depth.

Depth Of Clearance	Cost in Dollars/Acre
Surface	$2,260
1 Ft	$6,371
4 Ft	$24,715
10 Ft	$2,086,400

Table 2: Estimated Costs for Varying Depth of Clearance on Adak, Alaska. As depth of clearance increases, estimated costs per foot increase exponentially. Note that a four-foot clearance is approximately ten times the cost of a surface clearance while the ten-foot clearance is nearly one thousand times more expensive [Rohrer 1997].

2. Environmental Characteristics

The environmental characteristics of a contaminated area including topography, vegetation, and soil type also influence cost. The topography of the site may determine what methods of surveying and removal to use. Very hilly or mountainous terrain can limit both detection and removal to man-portable means only. Similarly, extremes such as frozen tundra or swamps limit certain technologies and removal methods. Vegetation of the range can also determine cost; often it must be removed prior to surveying and ordnance removal. For example, the dense jungle hampers the clearance of Panamanian ranges [Panama Canal Treaty Implementation Plan Agency 1997] while even the simple shrubs of the northern California coast make the clearance of the former Fort Ord costly and difficult [Meuser, and Szasz 1997]. Finally, soil type affects the maximum depth that ordnance penetrates, the ability of detectors to locate UXO, and the level of difficulty of removing ordnance. For example, ordnance penetrates far deeper into soft sand or silt then into hard clay or rock. Similarly, it is far more difficult to locate ordnance in clay and rocky soils because the heavy mineral content often produces false anomalies during magnetic surveys. Finally, it is physically more difficult to excavate ordnance in clay and rocky soils than in softer soils.

3. Ordnance Characteristics

Density (number of UXO per acre) and the types of ordnance present are also factors that influence cleanup costs. The density of the ordnance corresponds directly to the amount of excavation needed and the overall amount of work to be performed. More items in the ground means more holes need to be dug, and more items unearthed means more items to treat and dispose of. The poor status of current detection technology compounds the costs associated with higher density because the false alarm rate is often as high as six false alarms for every actual piece of ordnance [USD (A&T) 1998]. The type of ordnance and its delivery method also affects how deep the ordnance penetrates the earth. Finally, removing different types of ordnance clearly involves different means of removal. DOD ranges contain anything from small grenades a few inches long to 2,000 pound bombs several feet in length. In particular, chemical weapons require specialized removal methods. Figure 1 depicts the myriad of ordnance that ordnance technicians encounter in UXO removal.

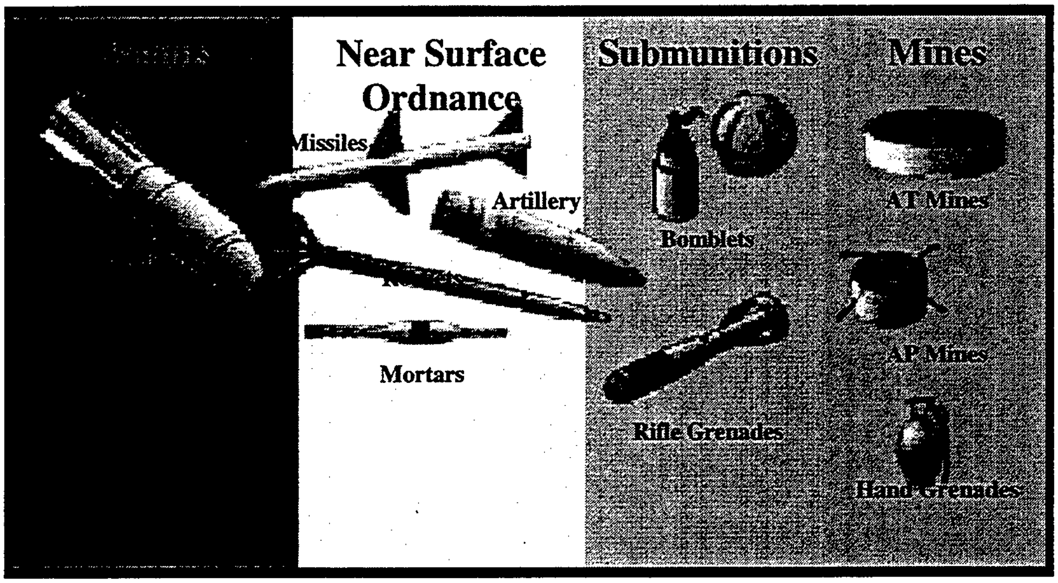


Figure 1: Common Types of UXO and UXO Categories. Different types of UXO impose a varying degree of difficulty for their removal. UXO type is thus an indicator of the cost of UXO removal. From [USD(A&T),1998].

4. Removal Methods

The cost factor generating the most interest and debate among experts is removal methods and removal technologies. As previously discussed, current methods for UXO removal are labor intensive manual operations. A Defense Science Board report [United States Department of Defense, Office of the Under Secretary of Defense for Acquisition and Technology (USD (A&T)) 1998] concludes that approximately $125 million is spent yearly by the DOD for UXO cleanup and that $70-$80 million of this cost is for labor. The report recommends a coordinated research and development (R&D) program and a doubling of the current amount spent on R&D. The Board believes that labor costs can be drastically reduced by the implementation of automating technologies. As the report states:

> Despite limitations of the current R&D program, there is enough scientific understanding and experimental data to convince the Task Force that an aggressive and well managed program could demonstrate dramatic improvements in cost effectiveness within the next few years. [USD (A&T) 1998]

The technologies being developed span the complete array of remediation requirements. Although the focus is on improving sensor capabilities used in detection, other technologies involve computer systems for automatic and digital mapping of a contaminated area, robots and advanced excavators for mechanized removal, and artificial intelligence knowledge-bases for discriminating UXO anomalies. Some of these emerging technologies are slowly being adopted; however, substantiated cost relationships based on these technologies do not exist.

IV. MODEL DEVELOPMENT

A. EXISTING ORDNANCE DATABASES AND MANAGEMENT SYSTEMS

Huntsville Center contracted Computer Systems Technologies to develop the Ordnance and Explosive Database (OED) [Computer Systems Technology 1996], but the contract was not fully completed. The database was intended to record historic information on all ordnance removal projects, provide a means to analyze information for use in future cost estimates, and provide a cornerstone for an overall project management system. Currently the database is sparsely populated and contains no cost information. The OED requires further development to become a mature system capable of fulfilling the needs of the USAESCH.

Besides the OED, two other DOD projects propose to develop an ordnance management system that contain information on all known and potential sites contaminated with UXO. A partnership between the Defense Environmental Security Corporate Information Management Program Office and the Department of Defense Explosive Safety Board is sponsoring the development of the Defense Explosive Management Suite which contains a module for ordnance management called Unexploded Ordnance Management [Hoehl 1997]. The other proposed system that incorporates overall program management is the Range Information Management System (RIMS) [Martino et al. 1998]. Although all three systems are in early stages of development, these projects suggest that some future system will exist that contains detailed ordnance cost information. This thesis designs a cost-risk model to interface with the OED, but the theory can be used to design a cost analysis module that can be incorporated into any future management system.

B. DATA DESCRIPTION

Since the OED is not populated with cost data, the author gathered cost information from USAESCH reports and created a test database that attempts to parallel the OED design. Final Removal Action Reports, EE/CA Reports, and project manager files are the sources for cost information. Currently collecting cost information from these sources is a slow manual process, and this limits the amount of cost records available for this thesis. Only recently has there been a requirement for the contractors to deliver information in a digital form. Most information exists only in paper reports stored in Huntsville Center's warehouse.

In relation to UXO program management, Huntsville Center defines a "site" as DOD property that contains UXO. A military base, proving ground, or test range is a site. A "project" is a subset of a site where some phase of remediation has occurred or is occurring. A site can have multiple projects each with a separate project manager. An "Ordnance Operable Unit (OOU)" is a subset of a project. An OOU is an ordnance-contaminated area that has homogenous physical characteristics and properties. Usually the removal action is similar throughout the OOU. Since a project can contain several very diverse OOUs, cost data must be captured at the OOU level in order to compare two cleanups. This thesis collects the costs for Removal Action of 19 OOUs. These 19 OOUs comprise 12 different projects from 11 separate sites. Table 3 shows the breakdown of the data set.

Site Location	Number of OOUs per Project
Plattsburgh AFB, NY	2
Miramar NAS, CA	2
Camp Croft, SC project 1	5
Camp Croft, SC project 2	1
Fort Sheridan, IL	1
Camp Maxey, TX	1
Fort Devan, MA	1
Savanna Army Dep, IL	1
Fort Wingate, NM	1
Erie Ord Depot, OH	1
Duck Target Facility, NC	1
Fort Ord, CA	1

Table 3: Breakdown of Data by Site. The thesis uses cost data for 19 OOUs to demonstrate the cost-risk model. The site location and the number of OOUs from each project are shown. Camp Croft is the only site used with data available for more than one project. The data for each site reflects information that was available during data collection, and may not encompass all projects for the site. The larger sites such as Fort Ord may contain more ongoing or completed projects, but the reports were not found.

The OED's design uses a 72-line work breakdown structure (WBS) for reporting costs in all phases of remediation. Although this type of detail is desired, there is no requirement for the contractors to report costs with this level of fidelity. Until requirements exist that force contractors to report costs in this format, the OED's cost input structure may be an unrealistic design. Cost data, however, is routinely reported in "labor," "material," and "travel/per Diem" costs. This thesis, therefore, collects cost data for each OOU using this breakdown. The thesis also assumes that these costs can be converted to costs per acre because they are generally variable costs dependent on the length of time to complete a project. Travel costs, however, are fixed costs that depend little on the size of the cleanup. The travel costs could not be separated from per Diem costs, but in general travel is a small fraction of the overall "Travel/per Diem" costs. This breakdown provides enough fidelity for estimates, but the cost-risk model can be adapted to handle higher fidelity WBSs.

C. COST-RISK ANALYSIS

The majority of the remainder of this chapter provides a general background of cost-risk analysis. Readers well versed in cost-risk analysis may skip to Subsection IV.C.4. *Weighted Estimate of a Distribution Function.* Much of the background discussion on cost-risk analysis in this chapter summarizes information contained in "The Probabilistic Approach to Cost Analysis" [Book 1999] and "Cost-risk and Cost Estimating Uncertainty Guidelines" [Anderson and Cherwonik 1997]. Additional sources of background information include many introductory operations analysis textbooks and the users' manuals of commercially available simulation software. Both the *@Risk* [Palisades Corporation, 1997] and *Crystal Ball* [Decisioneering Incorporated 1997] users' manuals, contain thorough discussion on performing cost-risk analysis.

1. Problems Associated With Point Estimation

The current engineering cost models estimate cleanup costs with a single point estimate. Due to uncertainty, it is highly unlikely that any point estimates are exactly correct, and a single point estimate gives the decision-maker no information on the probable range of cost values. Point estimates attempt to provide a single "best estimate," but these point estimates suffer from ambiguity in what the "best estimate" really means. Should this "best" estimate represent the "most likely" (mode) cost, the "average" (mean) cost or the 50th percentile (median) cost?

Often, cost analysts determine total program costs by summing up the "best estimate" for each cost element of a program. Cost analysts call the result the "roll-up" total cost, and often this "roll-up" is statistically incorrect because each cost element of the total cost has uncertainty, and therefore has an underlying probability distribution. Furthermore, cost analysts may report some of these "best estimates" as the mean of the underlying distribution, some as the mode, and some as the median. Even if the analyst reports each cost element in the same manner (e.g., all modes), summing these values may not give the intended results. When the analyst sums measures of central tendency of varying probability distributions, very rarely is the result the matching measure of the distribution of the total. The reason is because very few probability distributions having a mean, mode, and median located at the same value. The triangular distribution's probability density function (PDF) illustrates this point. The peak of a triangular distribution is the "most-likely" (mode) cost, and the end points are the extreme low and high costs. Figure 2 shows a triangular distribution of a cost element where the mode, mean, and median are not collocated.

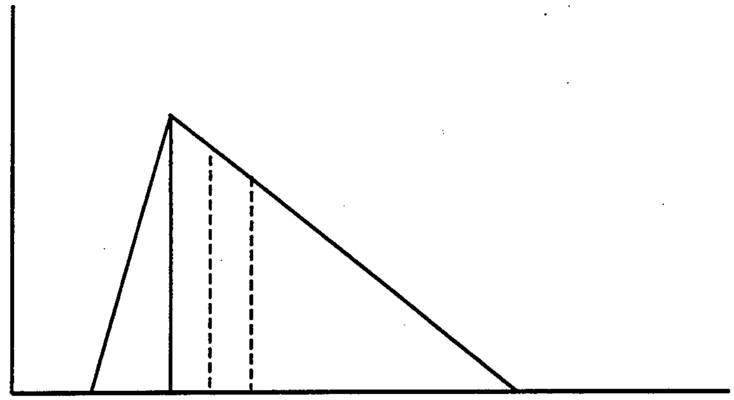


Figure 2: The Triangular PDF. The triangular PDF is an example of a distribution where the mode, mean and median are not collocated.

When many independent cost elements are summed to form a total cost, the central limit theorem states that the distribution of the sum should have an approximately normal distribution with a mean equal to the sum of the individual means. Since the mean, median, and mode of a normal distribution are all equal (located at the mid point of the distribution) it follows that:

1. Total cost mean = Sum of cost element means.
2. Total cost mode = Sum of cost element means.
3. Total cost median = Sum of cost element means.

And, therefore, it is most often the case that:

1. Total cost median ≠ Sum of cost element medians.
2. Total cost mode ≠ Sum of cost element modes.

Often in point-estimates the "best estimate" is the mode estimate, but Figure 3 shows a common example of when the sum of the modes of the cost element distributions does not equal the mode of the total cost. In this case the "roll-up" cost lies to the left of the total cost mode.

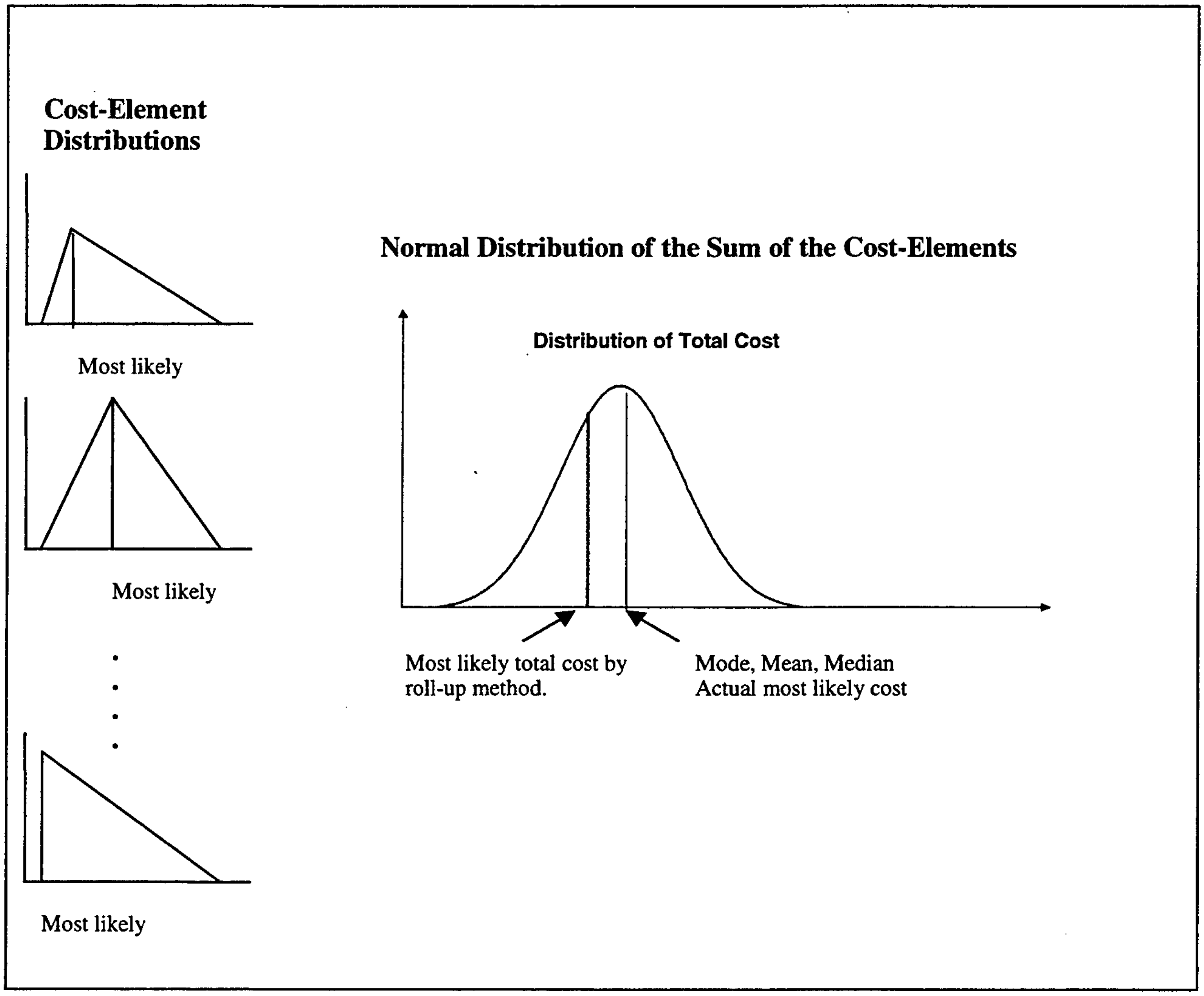


Figure 3: Roll-up Most Likely Cost vs Actual Most Likely Cost. The figure shows that the sum of the cost element modes is often not equal to the mode of the total cost distribution.

For most distributions the sum of cost elements' most likely costs does not equal the most likely total-cost. When the number of cost elements is small, there is no expectation that the total-cost distribution would be normally distributed. However, it is still unlikely that the sum of the most likely costs equals the most likely total cost.

2. Development of Total Cost Probability Distributions

In DOD acquisition programs, the roll-up method tends to underestimate costs by a wide margin [Book 1999]. The DOD is therefore shifting to a method known as "cost-risk analysis." The method involves developing a PDF for the overall cost. Two approaches exist for developing the total-cost PDF. The "top down" approach involves subjectively determining a PDF for the total cost while the "bottom-up" approach builds a PDF for each cost element. The "bottom-up" approach is usually preferred because it is often much easier to estimate the PDFs for the individual cost elements than for the total cost.

In the "bottom-up" approach the cost analyst estimates the PDF for each cost element. For example, it may be very hard for a cost analyst to subjectively determine the PDF for the total cost of developing a new fighter aircraft. Therefore, the analyst breaks down the aircraft into all of its constituent parts. In military acquisition, this is usually done in the work breakdown structure. The analyst may be able to make good estimates on the PDFs for the development costs of the engine, avionics, weapon system, radar, and other constituents. Next, a computer statistically sums the individual PDFs by Monte Carlo sampling to develop a PDF for the total cost. The final PDF provides the user with a probabilistic estimate, provides information on cost percentiles, and provides the means to produce confidence intervals for the estimated cost [Book 1999].

The first step in a "bottom-up" cost-risk analysis is to develop the PDFs for each cost element. Often in cost estimating very little information is known about the true distribution of cost; however, even limited information can aid the cost analyst in estimating a parametric distribution. The following discussion shows the most commonly used cost estimating distributions and how basic assumptions about costs can be used for choosing a PDF.

There are three qualities that make a probability distribution desirable for modeling cost: the distribution contains only positive, the distribution has a right skew, and the distribution has easily estimated parameters. Cost analysts usually desire distributions with non-negative ranges because they usually define costs as non-negative values. A right skew for cost distributions is a result of market place economics. Costs tend to be located around the mode, but very high costs occur with small probabilities. Unfortunately for the consumer very low costs do not usually happen with any probability. Two commonly used cost distributions that have these properties are the Weibull and lognormal distributions. These distributions are usually parameterized with two parameters, but an alternate three-parameter distribution can be used to shift the distributions away from the origin. These robust distributions can take many shapes and can usually be developed to fit right skewed cost data.

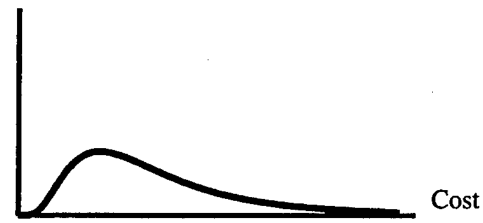


Figure 4: A Right Skewed lognormal Distribution. Both the lognormal distribution and certain Weibull distributions can take on the right skewed shape as seen in this figure. Both of these distributions are desirable for modeling cost data because their ranges are non-negative and the right skew is a typical phenomenon of costs.

Although the Weibull and the lognormal distributions tend to model true cost distributions well, their parameters are not easily defined. In contrast, cost analysts sometimes use the triangular distribution because it can be constructed easily. As previously introduced, this distribution requires three parameters: an absolute low cost, a most likely cost, and an absolute high cost. Even with limited prior data these parameters can be determined based on an expert's opinion. A triangular distribution appears in Figure 5.

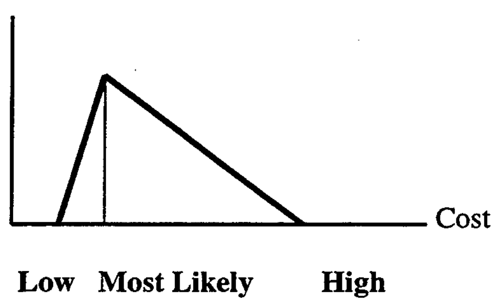


Figure 5: Triangular PDF Construction. Cost analysts often use the triangular PDF to depict the distribution of a cost-element because it can be easily created with only assumptions of the low, high, and most likely cost.

Cost analysts also commonly use the normal or Gaussian distribution. The normal distribution's familiar symmetric bell-shape supports the assumption that the cost is equally likely to be higher or lower than the most likely cost. The normal distribution is a two-parameter distribution that is completely defined by its mean μ and its standard deviation σ. The distribution benefits from the fact that its mean, mode, and median all occur at the same point centered in the middle of the distribution. This property simplifies many computations, and this point represents the "best estimate" of the cost under any definition (mean, mode, or median). To construct the distribution, the analyst often estimates the value that is greater than 95% off all possible costs. This value is roughly 1.96 standard deviations from the most likely cost, and the analyst uses this fact to determine the value of the standard deviation. With this value, the analyst has both parameters for defining the distribution. The normal PDF also gains favor from the fact that many naturally occurring numerical distributions are well estimated by this PDF. Figure 6 depicts the normal PDF.

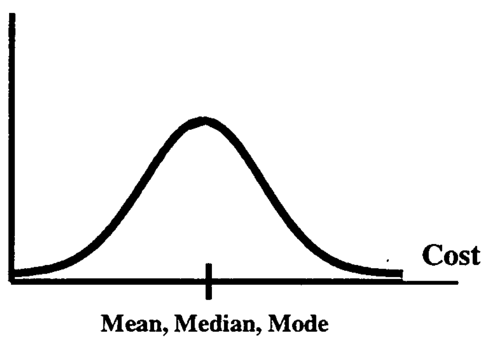


Figure 6: Normal PDF Construction. Cost analysts often use the normal PDF when there is an assumption that the cost is equally likely to be greater than or less than the most likely cost. The mean, median, and mode are all located at the same point, which simplifies many computations.

The third distribution that cost analysts sometimes use is the uniform distribution. This distribution does not have a single most likely value, and all outcomes are equally likely to occur between some high and low cost. It is unlikely that the uniform distribution models the true nature of a cost element, and is only used when there is no idea about the relative likelihood of possible outcomes. The uniform distribution can be modeled with two parameters: low cost, and high cost. Figure 6 depicts the uniform PDF.

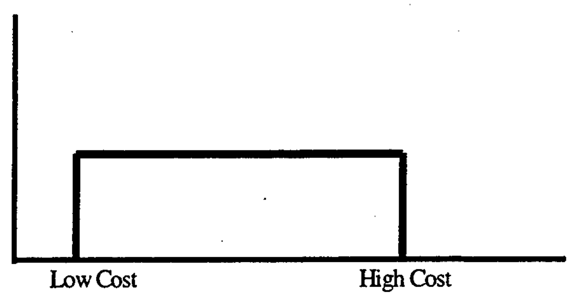


Figure 7: Uniform PDF Construction. Cost analyst use the uniform PDF when there is no knowledge of the most likely cost, but it is assumed that the costs fall within a range bounded by a high and low cost with equal probability.

In the second step of a "bottom-up" risk analysis, one random sample is taken from each of the cost elements and then summed together to form a single sample for the total cost distribution. The Monte Carlo simulation performs this sampling numerous times to form a frequency distribution of the total cost. Figure 8 graphically depicts this procedure.

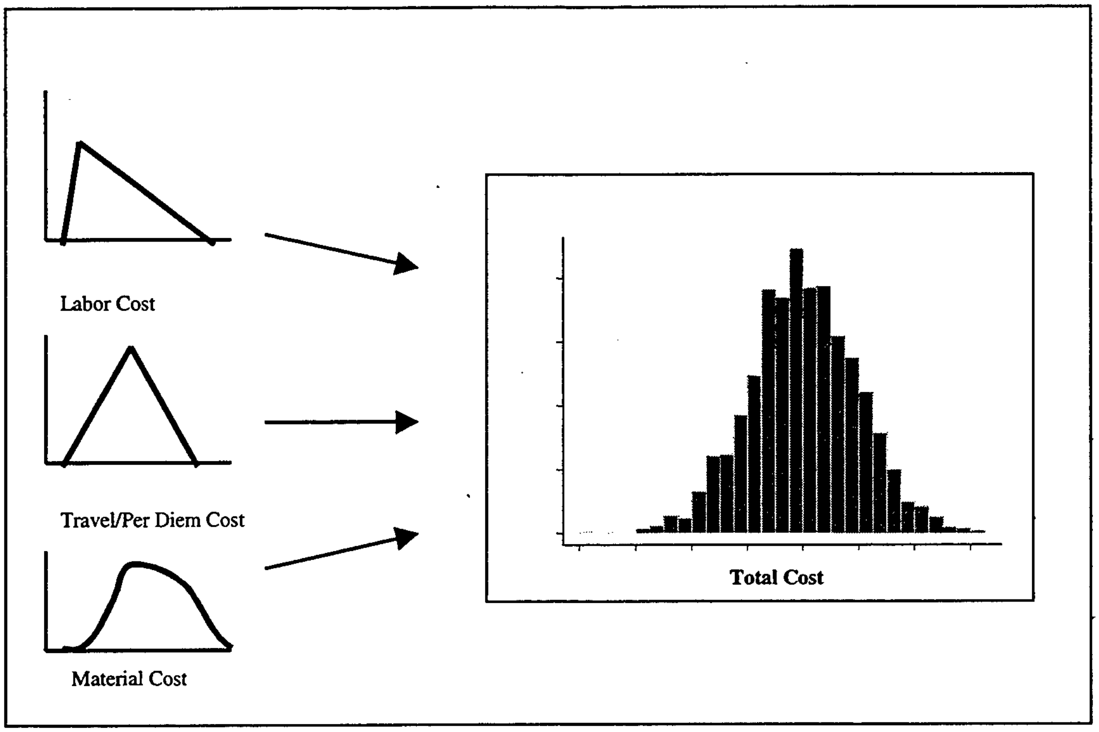


Figure 8: Monte Carlo Simulation to Form the Total Cost PDF. Monte Carlo simulation produces a total cost probability distribution from individual cost element distributions.

3. Sampling From Historic Data

When an abundance of historic cost data exists, parameterized PDFs do not have to be hypothesized. Instead of sampling from the hypothesized PDFs of each cost element, samples from the empirical data set can be taken. To demonstrate how this method works, assume that a cost analyst uses cost data from the cleanup of 15 OOUs to estimate the cost of a proposed cleanup. Figure 9 presents the histogram of the labor costs for the 15 selected OOUs.

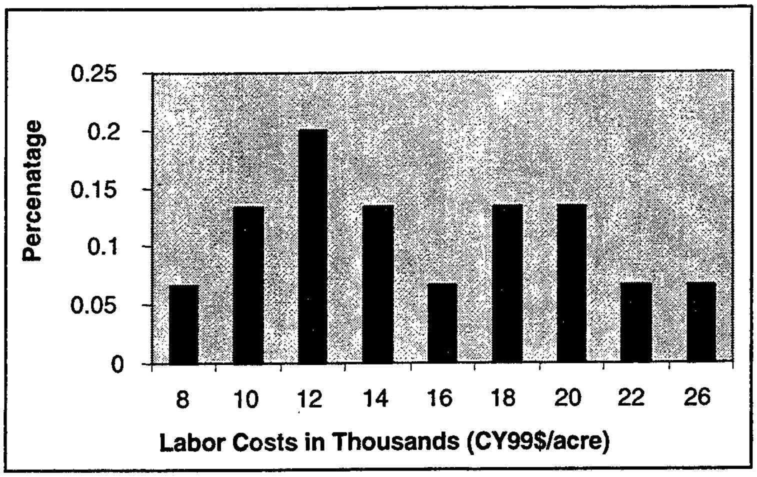


Figure 9: Histogram of Labor Costs for 15 OOUs. Monte Carlo simulation can use empirical cost distributions from the cost element instead of hypothesized PDFs.

The method of sampling from historic data is analogous to creating a spinner that has slices proportional to the frequency of each value. For the above histogram the spinner looks like Figure 10.

Sampling Labor Costs

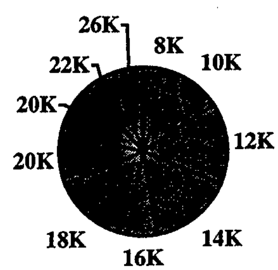


Figure 10: An Analogy for Sampling From Empirical Data. A spinner models sampling from empirical data by creating slices proportional in size to the relative frequency of each cost.

By this analogy a person draws a random sample by spinning the spinner and recording the value under the spinner's pointer. A cost structure composed of N cost elements requires N separate spinners. For each sample the person spins the N spinners, records all

N values, and sums the values to form one sample for the total cost. The person performs this procedure many times to form a histogram of the total cost.

4. Weighted Estimate of a Distribution Function

Both methods of sampling, from historic data and from hypothesized PDFs, have advantages and disadvantages. It may be difficult to fit cost probabilities with a common parameterized distribution, while sampling from historic information does not require fitting a distribution. Sampling from historic data provides some actual information about the true cost distribution. However, sampling from the historic data suffers when only a few data points exist because sampling purely from these points is equivalent to assuming that the costs can only take on one of these few values. Most likely the data set does not contain the values near the extreme high or extreme low of the true cost distribution. Thus, when sampling purely from the historic data, a lot of information in the tails of the distribution may be. The ideal probability distribution for a cost element benefits from the properties of both a hypothesized parametric probability distribution and an empirical data set.

The benefits of both methods of sampling can be obtained by using a method similar to the Bayesian estimate of the distribution function [Ferguson 1973, p.272]. Ferguson shows that the Bayesian estimate of a probability function can be expressed as the weighted average of the hypothesized prior distribution and the empirical distribution of the data. For a data set of $\boldsymbol{n}$ observations the Bayesian estimate is

$$\hat{f}_n(t \mid X_1,\ldots,X_n) = \rho_n f_0(t) + (1-\rho_n) f_n(t \mid X_1,\ldots,X_n) \qquad (4.1)$$

Where:

$$\rho_n = \alpha / \alpha + n \qquad (4.2)$$

$f_0(t)$ - The prior hypothesized PDF

$f_n(t \mid X_1,...,X_n)$ - The empirical PDF given the data set $X_1,\ldots,X_n$

α - Weighting factor

Equation (4.1) weights the prior distribution by ρ_n and the empirical distribution by $(1-\rho_n)$. It can be seen that as n increase ρ_n decreases; hence, the equation weights the prior distribution less and weights the empirical distribution more. The constant α is a weighting factor that can be interpreted as the faith in the prior distribution measured in n units. This thesis uses this weighted distribution to estimate cost element probability distributions.

5. Handling Correlation

The traditional Monte Carlo sampling theory of summing cost elements to produce a total cost probability distribution is valid only when the cost elements are independent. It is often the case that cost elements are not independent but correlated. Two random variables X and Y are correlated when the value of X has some predictive power on the value of Y. For example labor costs and material costs in UXO cleanups have an intuitive relationship that leads to correlation. A difficult cleanup that uses a lot of materials requires a lot of labor hours to employ the materials; hence, a strong positive correlation exists. Traditional Monte Carlo sampling provides the correct value for the total cost mean regardless of whether the cost elements are independent or correlated; however, the variance of the total cost probability distribution depends strongly on the correlation of the individual cost elements [Book 1999]. Let $X_1, X_2, \ldots X_n$ be n random variables representing n cost elements, μ_i the mean of cost element X_i, σ_i the standard deviation of cost element X_i, and TC be the total cost. It follows that:

$$\text{Total Cost: } TC = \sum_{i=1}^{n} X_i \tag{4.3}$$

$$\text{Mean of Total Cost} = \mathrm{E}\left(\sum_{i=1}^{n} \mathrm{X}_i \right) = \sum_{i=1}^{n} \mu_i \tag{4.4}$$

$$\text{Variance of Total Cost} = \mathrm{var}\left(\sum_{i=1}^{n} X_i \right) \tag{4.5}$$

$$= \sum_{i=1}^{n} \sigma_i^2 + 2\sum_{j=2}^{n} \sum_{i=1}^{j-1} \rho_{ij}\sigma_i\sigma_j \tag{4.6}$$

As seen in equation (4.4) no cost element correlation term appears in the calculation of the total cost mean; however, the correlation coefficient, ρ_{ij}, appears in equation (4.6), the calculation of the total cost variance. Not accounting for correlation is equivalent to setting ρ_{ij} equal to zero, and equation (4.6) then simplifies to:

$$\text{Var of Total Cost} = \sum_{i=1}^{n} \sigma_i^2 \tag{4.7}$$

The differences in equation (4.7) and (4.6) shows that strong positive correlation can greatly increase the total cost variance while strong negative correlation can greatly reduce the total cost variance. Thus not accounting for correlation gives the incorrect total cost probability distribution. Accounting for correlation is not a simple proposition:

> The ideal way to simulate total cost would be to specify inter-cost-element correlations, generate correlated random numbers, and sum them. Probability theory allows this to be done exactly only for multivariate normal cost distributions, not in general [Book 1999]

Book further points out that Lurie and Goldberg [1998] have been working for several years on the correct method to generate correlated random numbers that correctly model cost-element cost distributions.

An accepted approximate solution to the above problem is to use rank-order correlation, a distribution free measure of correlation. Several rank-order measures of correlation exist including Kendall's tau and Spearman's rho. The two most popular software packages that perform cost-risk analysis: *Crystal Ball* [Decisioneering Incorporated,1998] and @ *Risk* [Palisades Corporation 1997], use rank-order correlation. Rank-order correlation between a pair of data sets involves ranking the corresponding sets from lowest to highest value. To illustrate the calculation of Spearman's rho, Table 4 shows the labor cost per acre and the corresponding material cost per acre for 10 OOUs. Next to each cost is the rank of the cost within its column.

OOU	Labor/Acre Cost	Labor Rank $R(X_i)$	Material/Acre	Material Rank $R(Y_i)$
1	$360.20	1	$30.05	1
2	$532.24	2	$2,254.77	10
3	$705.21	3	$153.52	3
4	$809.14	4	$243.56	6
5	$1,071.02	5	$113.93	2
6	$1,196.95	6	$175.19	4
7	$1,402.56	7	$208.83	5
8	$2,445.69	8	$312.65	8
9	$3,068.89	9	$744.64	9
10	$4,225.71	10	$284.73	7

Table 4: Determining Spearman's Rho by Rank Ordering Cost Elements. This example shows how to determine rank-order correlation between variable *X* (Labor cost) and variable *Y* (Material Cost).

If the cost elements have perfect positive rank-correlation ($\rho = +1$) then the corresponding rank value for each pair would be equal. If the cost elements have perfect negative correlation ($\rho = -1$), then the lowest labor costs would be paired with the highest material costs, and the highest labor costs would be paired with the lowest material costs. Equation (4.8) calculates ρ [Conover 1999, p. 315]:

$$\rho = \frac{\sum_{i}^{n} R(X_i) R(Y_i) - n\left(\frac{n+1}{2}\right)^2}{\left(\sum_{i=1}^{n} R(X_i)^2 - n\left(\frac{n+1}{2}\right)^2\right)^{\frac{1}{2}} \left(\sum_{i=1}^{n} R(Y_i)^2 - n\left(\frac{n+1}{2}\right)^2\right)^{\frac{1}{2}}} \tag{4.8}$$

Where:

$R(X_i)$ – Rank of the ith X variable
$R(Y_i)$ – Rank of the ith Y variable

For the above example (***X*** = labor cost, ***Y*** = material cost, ***n*** = 10), ***ρ*** is calculated as follows:

$$\rho = \frac{338 - 302.5}{(385 - 302.5)^{\frac{1}{2}}(385 - 302.5)^{\frac{1}{2}}} = .430 \tag{4.9}$$

The process of generating rank-correlated pairs of sampled values is a two step process that requires the user to supply correlation coefficients for each pair of data. In the first step, the simulation software generates randomly distributed rank scores for each random variable. The software generates one score for each iteration of the simulation. Sampling 10,000 times would require 10,000 random rank scores for each random variable. These rank scores are then rearranged to give pairs of scores that match the desired rank correlation coefficient. In the second step, the software generates another set of random numbers for each random variable, and again generates one number for each iteration of the simulation. For each variable the procedure assigns the smallest random number to the smallest rank score, the second smallest random number to the second smallest rank score, and so on. The final result is a set of pairs of random numbers that can be used in sampling values from correlated distributions [@*Risk* User's Manual, p.179]. The software creates correlated pairs for every random variable with every other random variable and finally arranges the pairs to fit a matrix of specified correlation coefficients.

V. MODEL APPLICATION

This thesis creates a probability distribution of the CTC of a proposed contaminated area by analyzing cost data from previous cleanups. Location characteristics, ordnance characteristics, and cleanup requirements can be vastly different for two separate projects. In order to account for variance in costs caused by these differences, the cost-risk model uses only data from areas "similar" to the proposed area of cleanup. Once similar records are found the cost-risk model uses the historic cost data to generate cost per acre estimates that incorporate cost-risk analysis.

As previously mentioned, USAESC, Huntsville maintains the Ordnance and Explosives Database of completed and ongoing UXO removal projects. Although this database is sparsely populated with cost information, there is interest within the DOD to produce and maintain a DOD-wide ordnance and explosive management system. The assumption of this thesis is that either the OED will be populated in the future or another repository of information will be created. This thesis presents a model with designs to incorporate the OED data fields, but the model can be easily modified to accept historic information from any repository of UXO data. Appendix A outlines the information fields needed by the cost-risk model but that currently do not exist in the OED. The same appendix also makes recommendations to modify some fields so that the cost-risk model can incorporate them.

A. DATA FIELDS

The following discussion outlines the necessary fields that the cost-risk model must obtain from a database. Although these recommendations have designs to specifically incorporate the OED, the same recommendations hold for any other UXO data repository if developed. The cost-risk model uses database fields segregated into three groups: record identification, OOU descriptive characteristics, and cost information. The record identification fields provide a means to identify each OOU as unique. The fields include site, project, and OOU identifiers. Table 5 shows the required record identification fields.

Field Name	Description
SITE_NAME	Name of site (e.g., Fort Ord, Aberdeen Proving Grounds).
PROJECT_NO	Unique Identifier throughout the database. Identifies the project that an OOU falls under.
OOU_ NO	Unique identifier within each project. Identifies a specific OOU within a project.

Table 5: Record Identification Fields. The cost-risk model needs record identification fields to uniquely identify OOUs. All fields exist in the OED.

The second group of fields is the OOU descriptive characteristics. These fields include environmental characteristics, ordnance characteristics, and cleanup characteristics. These are the fields that the user queries to find records similar to the proposed cleanup. Table 6 summarizes the OOU descriptive characteristic fields required by the cost-risk model.

Field Name	Description
TYPE[a]	Type of cleanup (chemical weapons or conventional)
ACRES[a]	Total OOU acres
SOIL[a]	Difficulty factor based on the type of soil in the OOU
TERRAIN[a]	Difficulty factor based on the dominant terrain in the OOU
VEGETATION[b]	Difficulty factor based on the dominant vegetation in OOU
DENSITY[b]	Density of ordnance within the OOU
DEPTH_CLEAR[b]	Depth of clearance in feet
TYPE_ORDNANCE[b]	A weighted difficulty factor based on the types of ordnance contained in the OOU
SURVEY_TYPE[c]	Method of surveying (mag and flag operation, geophysical)

Table 6: Ordnance Operable Unit (OOU) Descriptive Characteristics. The cost-risk model requires these fields to identify an OOUs environmental characteristics, its unexploded ordnance characteristics, and its cleanup characteristics.
[a]Field currently exists in OED
[b]Recommend modification of existing field in OED (see Appendix A)
[c]Recommend addition of field in the OED (see Appendix A)

The final required fields from the database are the cost information fields. The cost fields in the database summarize information on six cost elements that make up total cost. These elements are:

1. EECA Labor Cost per acre.
2. EECA Material Cost per acre.
3. EECA Travel/Per Diem Cost per acre.
4. Removal Action Labor Costs per acre.
5. Removal Action Material Cost per acre.
6. Removal Action Travel/Per Diem per acre.

The model converts all costs to FY99 costs. The cost-risk model produces estimates following a completed ASR; therefore, it does not include cost information on the first two phases of the remediation process (Preliminary Assessment and Investigation (ASR) phases). The cost fields that the cost-risk model obtain from the database differ from the fields in the current OED structure. The recommended fields, however, reflect data that is realistically accessible. Ideally cost data would exist for all phases of a project (Preliminary Assessment, Investigation, and Removal Action); unfortunately this thesis is only able to acquire Removal Action cost data. Huntsville Center cost engineers estimate Removal Action costs account for 80% of the total cost to complete [Young 1999]. For the purpose of demonstrating this model, the thesis assumes the costs for the three EECA cost elements to be equal to two percent of its corresponding RA cost element. The basis of this rough figure is the current procedure of sampling approximately two percent of an OOU during the EECA phase in order to determine ordnance density. Table 7 outlines the cost fields that the cost-risk model uses.

Field Name	Description
EECA_YEAR[c]	Year EE/CA completed.
RA_YEAR[c]	Year RA completed
EECA_LABOR_COST[b]	EE/CA Labor Cost
EECA_MAT_COST[b]	EE/CA Material Costs
EECA_TRAVPDIEM_COST[b]	EE/CA Travel Per Diem Costs
RA_LABOR_COST[b]	RA Labor Cost for the OOU
RA_MAT_COST[b]	RA Material Cost for the OOU
RA_TRAVPDIEM_COST[b]	RA Travel and Per Diem cost for OOU

Table 7: Ordnance Operable Unit (OOU) Cost Information. These fields are needed to report cost information.
[a]Field currently exists in OED
[b]Recommend modification of existing field in OED (see Appendix A)
[c]Recommend addition of field to OED (see Appendix A)

B. FINDING SIMILAR CLEANUPS

The user imports the current ordnance data file into the cost-risk model, and then begins developing a cost-risk estimate. If the ASR is complete for a site, the user has approximate information on the areas to be cleaned up. The user's first step is to find records similar to a proposed area of cleanup by filtering the data based on the OOU descriptive characteristics. An important trade-off exists when filtering; as the user specifies more criteria the amount of available records decreases. Conversely, the more detailed the search criteria the more similar the selected OOUs are to the proposed cleanup area. Unfortunately a detailed search may leave few records for sampling. Since the current data set is small the user is only able to filter the data using a few different criteria. As the database grows in number of cleanups, the user can increase the search criteria.

C. FILTERING PRECEDENCE

The user filters the records beginning with the OOU descriptive field that is most indicative of cost. If after a query enough records remain, the user refines the search by querying on the next most influential field and so on. The user stops filtering when he determines that further filtering could reduce the data set below a useable size. The OOU descriptive fields can be subdivided into three groups based on how strongly they influence cost. These groups consist of "type of cleanup," "primary indicators," and "secondary indicators."

1. Type of Cleanup

The TYPE field determines if the cleanup is a chemical weapons cleanup or a conventional weapons cleanup. Users should always filter this field first since chemical weapon cleanups are far more difficult than conventional weapons, and costs of chemical weapons cleanups are not indicative of the costs of conventional cleanups.

2. Primary Indicators

Plotting each OOUs descriptive characteristic versus the total cost for RA determines the remaining filtering precedence. Primary fields are those fields that indicate a strong relationship between them and costs. The first plot shows density of each OOU plotted against RA total cost. Although there are several possible measures to describe the density of ordnance within an OOU, the cost-risk model uses total scrap (UXO scrap and non-UXO scrap) as the measure of density. Density usually refers to the amount of UXO per acre, but this definition may not be a good indicator of costs. Ordnance technicians must remove UXO scrap as well as non-UXO scrap from a contaminated area, and they still must excavate false anomalies caused by non-UXO along with actual UXO. The relationship between actual UXO density and non-UXO scrap density and its effect on costs is extremely difficult to define. This thesis defines density as the total scrap metal removed from an area. A more detailed analysis of the relationship of UXO scrap and non-UXO scrap and its effects on cost is beyond the scope of this thesis and should be the subject of further research (see Appendix A for further discussion). Figure 11 shows the relationship of density to cost. This plot shows a strong relationship of increasing costs with increasing density.

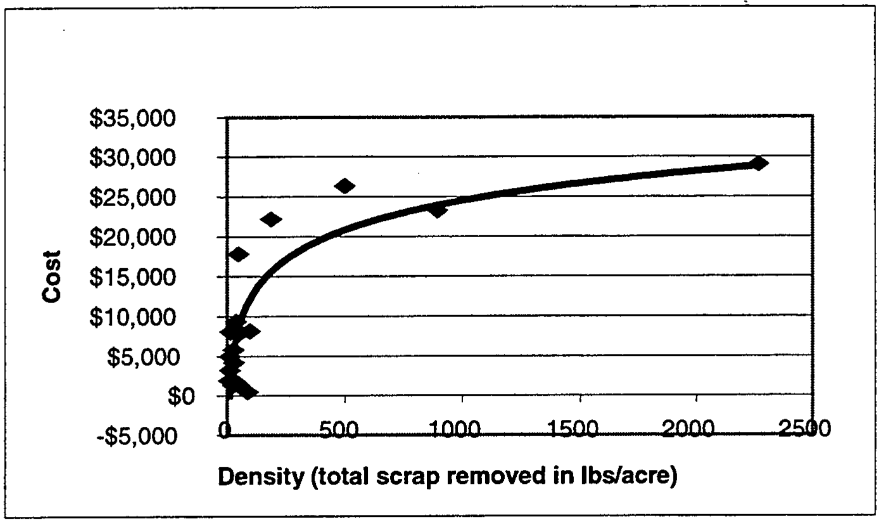


Figure 11: Scatter Plot of OOU Ordnance Density vs Total Cost. The scatterplot shows a strong relationship of increasing RA costs with increasing density. The log trend line suggests that costs increase proportionally to the log of density.

Figure 12 shows that the increase in cost is roughly linear with the log of density.

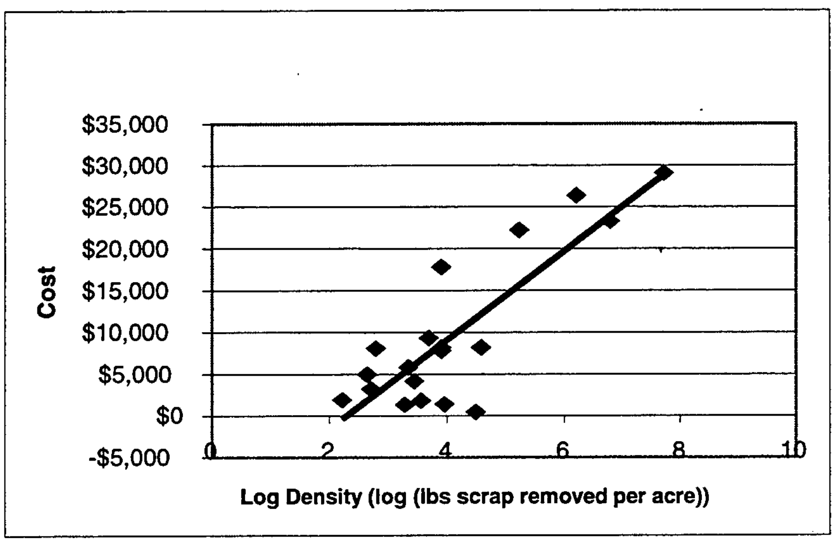


Figure 12: Scatter Plot of OOU Ordnance Log-density vs Total Cost. The figure shows a strong relationship of increasing RA costs with increasing log-density. The trend line shows that the relationship is approximately linear.

The relationship of depth of clearance to cost appears weaker than that between density and cost, but the plot shows that as depth of clearance increases total cost tends to increase. Unfortunately the data set does not contain any clearances in excess of four feet. Figure 13 plots of depth of clearance versus cost and adds a linear trend line to show the increasing relationship.

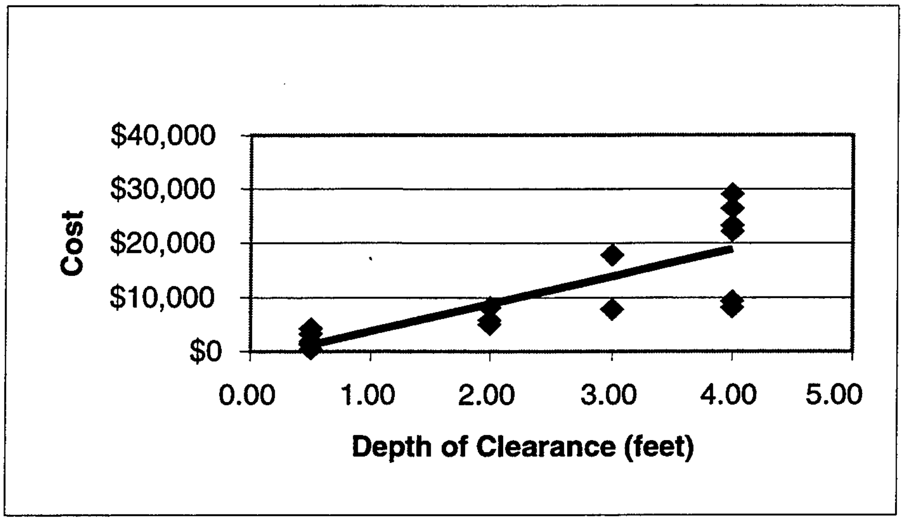


Figure 13: Scatter Plot of OOU Depth of Clearance vs Total Cost. The figure shows a relationship of increasing RA costs with increasing depth of clearance.

A similar relationship appears in the plot of vegetation difficulty factor versus total cost (see Appendix A for discussion of difficulty factors). In Figure 14 the reader sees positive correlation between total cost and the vegetation factor of an OOU. As the difficulty factor increases the cost of ordnance removal tends to increase.

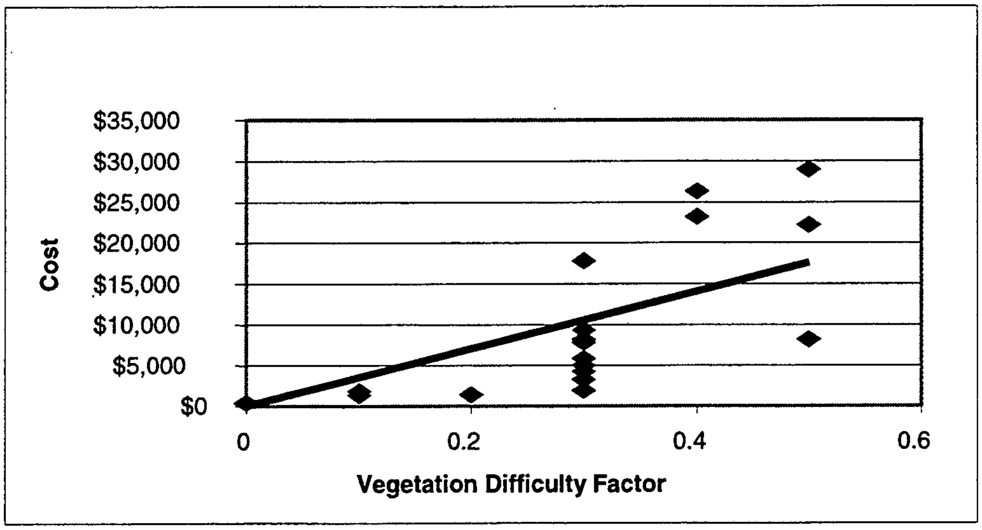


Figure 14: Scatter Plot of OOU Vegetation Difficulty Factor vs Total Cost. The figure shows a relationship of increasing RA costs with increasing vegetation difficulty factor.

2. Secondary Indicators

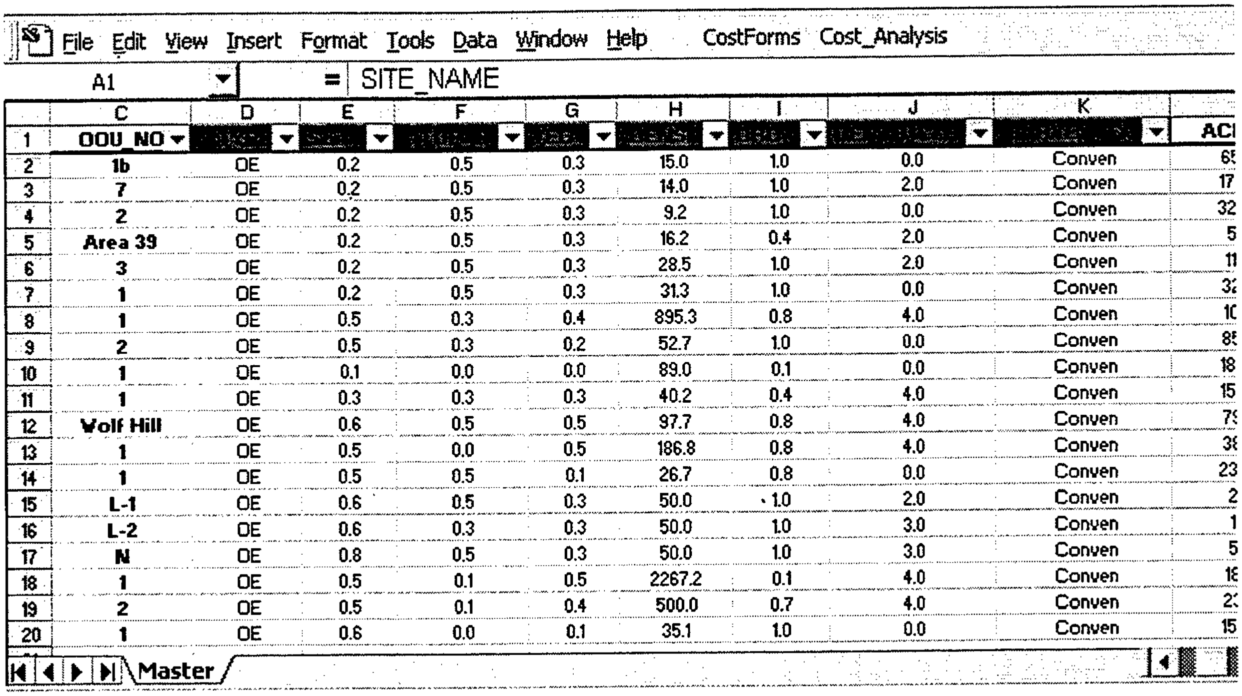
Appendix B contains the scatter plots of the remaining OOU characteristics: topography, soil type, and ordnance type. These plots do not indicate the expected cost relationships. The author hypothesizes that these secondary fields do not provide the expected cost relationships because the primary indicators overshadow the effects of the secondary indicators. For example, clay soil is difficult because clay contains a lot of minerals that make detection of UXO difficult using conventional magnetometers. Most research assumes that if two cleanups are identical except for soil type, the area with the higher soil type difficulty factor will be more expensive. Unfortunately, the only data points with clay soils also have low densities and low vegetation factors, and thus have low costs. The second explanation for why secondary indicator cost relationships do not reflect expected results is interactions with the primary fields. For example, one can hypothesize that heavily used firing areas tend to be located in flatter terrain, or that certain soil types indicate the amount of sustainable overgrowth. Analysis with additional data should better reveal the true cost relationships of these factors.

D. MODEL INTRODUCTION

1. Initial Worksheets

Visual Basic for Applications creates the cost-risk model as an add-in for *Microsoft Excel.* When the user loads the add-in into *Excel,* one worksheet is visible and two worksheets are hidden. The hidden worksheet "InflationIndices" contains the inflation indices needed to normalize all costs to base year 1999. The other hidden worksheet is "Tables" which provides non-changing descriptive information about the OOU characteristics. The user should not need to alter or access either of these worksheets.

When the model user opens the add-in the "Master" worksheet is the only visible worksheet. This worksheet contains all of the Record Identification, OOU Descriptive Characteristics, and OOU Cost Information fields, as discussed in subsection V.A.2. The add-in can update these fields from a text file of current data and automatically convert costs to fiscal year 1997 costs. Figure 15 shows the cost-risk model when initially opened.



File Edit View Insert Format Tools Data Window Help CostForms Cost_Analysis

A1 = SITE_NAME

	C	D	E	F	G	H	I	J	K	
1	OOU_NO									ACI
2	1b	OE	0.2	0.5	0.3	15.0	1.0	0.0	Conven	65
3	7	OE	0.2	0.5	0.3	14.0	1.0	2.0	Conven	17
4	2	OE	0.2	0.5	0.3	9.2	1.0	0.0	Conven	32
5	Area 39	OE	0.2	0.5	0.3	16.2	0.4	2.0	Conven	5
6	3	OE	0.2	0.5	0.3	28.5	1.0	2.0	Conven	11
7	1	OE	0.2	0.5	0.3	31.3	1.0	0.0	Conven	3[illegible]
8	1	OE	0.5	0.3	0.4	895.3	0.8	4.0	Conven	1[illegible]
9	2	OE	0.5	0.3	0.2	52.7	1.0	0.0	Conven	8[illegible]
10	1	OE	0.1	0.0	0.0	89.0	0.1	0.0	Conven	18
11	1	OE	0.3	0.3	0.3	40.2	0.4	4.0	Conven	15
12	Volf Hill	OE	0.6	0.5	0.5	97.7	0.8	4.0	Conven	7[illegible]
13	1	OE	0.5	0.0	0.5	186.8	0.8	4.0	Conven	3[illegible]
14	1	OE	0.5	0.5	0.1	26.7	0.8	0.0	Conven	23
15	L-1	OE	0.6	0.5	0.3	50.0	1.0	2.0	Conven	2
16	L-2	OE	0.6	0.3	0.3	50.0	1.0	3.0	Conven	1
17	N	OE	0.8	0.5	0.3	50.0	1.0	3.0	Conven	5
18	1	OE	0.5	0.1	0.5	2267.2	0.1	4.0	Conven	1[illegible]
19	2	OE	0.5	0.1	0.4	500.0	0.7	4.0	Conven	2[illegible]
20	1	OE	0.6	0.0	0.1	35.1	1.0	0.0	Conven	15

Master

Figure 15: View of Cost-Risk Model on Opening. This figure shows the only visible worksheet when the *Excel* add-in is loaded. Visible in the figure is the OOU number and associated OOU characteristics. The model updates this worksheet from a text file of current data.

2. Forms

Additionally, the add-in contains several forms that the user can use to input filtering criteria. The scenario discussion, later in this thesis, presents each of these forms in detail. These forms provide a Graphical User Interface and simplify navigation through the model. Figure 16 shows one of the forms that assists the user in filtering records. This form is the Depth of Removal Form used to filter the records based on a minimum and maximum depth of clearance.

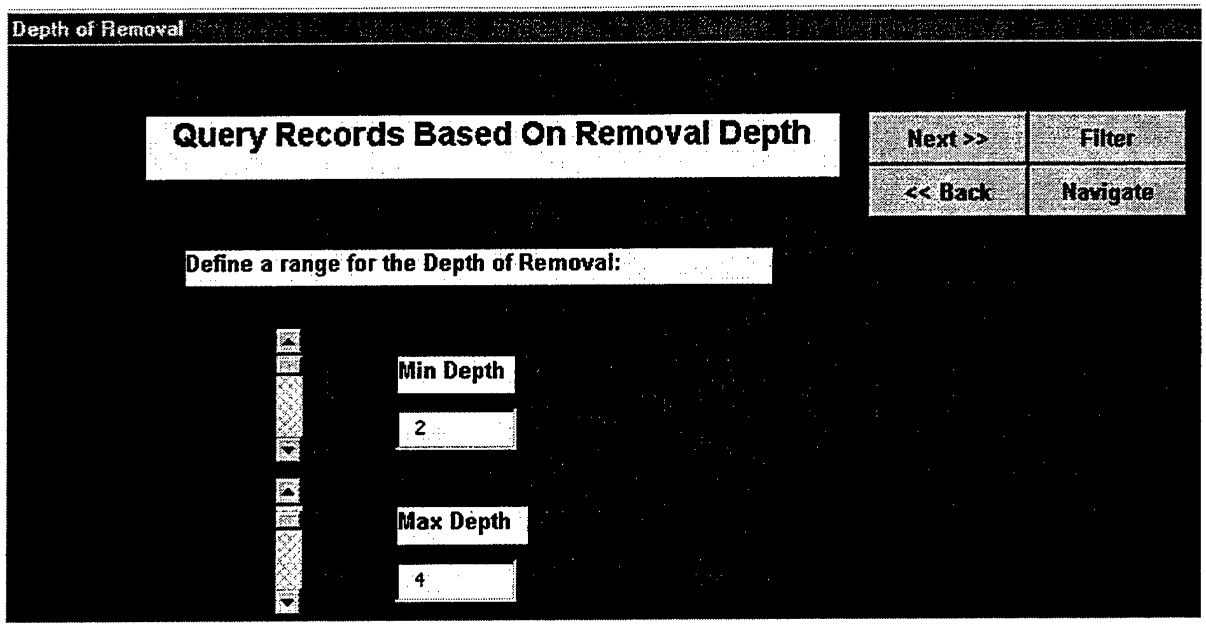


Figure 16: Example of a Form. The Depth of Removal Form is an example of the many forms available to assist the user in entering data. The user can use the scroll bars at the bottom to set the minimum and maximum depth of clearance. The buttons in the upper right help to navigate through the model.

3. Menus

The add-in creates two additional menus in *Excel*: "Cost Forms" and "Cost_Analysis." These two additional menus appear on the right of the toolbar.

Figure 17: Added Excel Menus. The cost analysis add-in creates two additional menus in excel. These menus are "CostForms" and "Cost_Analysis," and are visible on the far right of the menu bar.

The Cost Forms menu provides additional means to navigate through the different forms; this menu lists all available forms. Figure 18 shows this pull down menu.

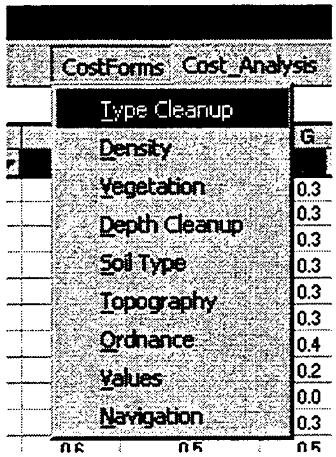


Figure 18: The CostForms Menu. The CostForms menu assists the user in navigating through the available forms.

The "Cost_Analysis" pull down menu contains submenus that allows the user to access the model's important functions. These three functions are: 1) Filter the records to find similar cleanups, 2) Perform an analysis on the filtered historic data, and 3) Build probability density functions for input into the simulation software. The scenario presentation discusses each function in detail, and Figure 19 shows the "Cost_Analysis" menu.

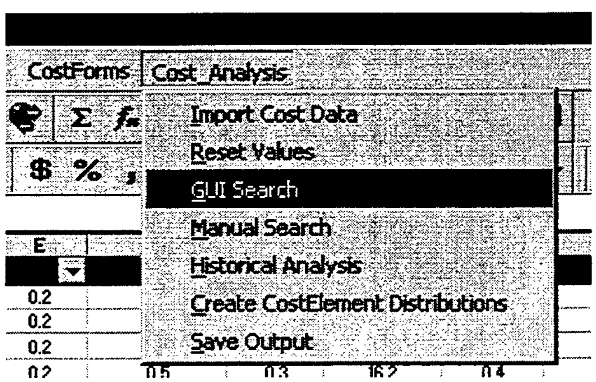


Figure 19: The "Cost_Analysis" Menu. The "Cost_Analysis" menu provides access to the model's important functionality including filtering records, analyzing historic costs, and building probability density functions.

E. SCENARIO DEVELOPMENT AND MODEL DEMONSTRATION

This thesis uses the following scenario to demonstrate how to interface with the cost-risk model and to aid the user in the understanding of the internal workings of the model.

> Scenario: The Marine Corps conducts an Archive Search Report on Marine Corps Base Camp Lejeune, North Carolina. The ASR shows a suspected Ordnance Operable Unit of 45 acres contaminated with a mixture of high explosive ordnance including 155mm Artillery rounds, 81mm and 60mm mortar rounds, 40mm grenades, and hand grenades. The ASR does not suspect any small arms ammunition. The area has not been used for several years and the vegetation is overgrown with shrubs and small trees. The contaminated site is in the western part of the base with predominately flat terrain. The soil type is a mixture of silt and sand. EOD units conduct semiannual range sweeps of this area, and only a small amount of surface scrap is found during the ASR. Further, range control records show that range usage for this area is low because of its proximity to the edge of the base property. The Marine Corps plans to convert this area back to a maneuver area.

1. Step One: Find Similar Cleanups by Filtering Database

Using the "Cost_Analysis" menu the user selects the sub menu "GUI Search" (Graphical User Interface Search) or "Manual Search." The GUI Search submenu starts a sequence of user forms that help refine the search criteria. The Manual Search submenu sends the user to the Master worksheet where the user can search the records using *Excel's* AutoFilter function.

a. Filter by Type of Cleanup

If the user selects "GUI Search" the model first presents the Type of Cleanup Form where the user checks what type of cleanup concerns them: conventional ordnance and explosives or chemical weapons. The ASR for the scenario shows it is a conventional cleanup, and therefore the user selects "Ordnance and Explosives" as Figure 20 shows.

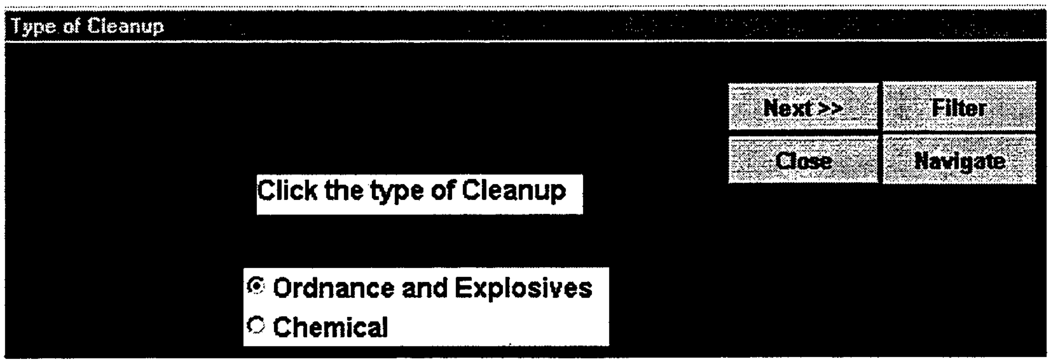


Figure 20: The Type of Cleanup Form. This form helps to filter the database based on the type of cleanup. When the user selects the Ordnance and Explosives Button the model filters out all of the chemical weapons cleanups.

By selecting the "Next>>" Button the model presents the user with the next filtering form; the Close and Navigate buttons close out the form and allow the user to go to different forms or worksheets. Finally, the Filter Button shows the user how many records are remaining in the filtered set. By selecting "Ordnance and Explosives" and clicking the Filter Button, the user reduces the data set to nineteen records (i.e., the current data base does not contain any chemical weapons cleanups). Figure 21 shows the Found Records Form that displays the number of remaining records.

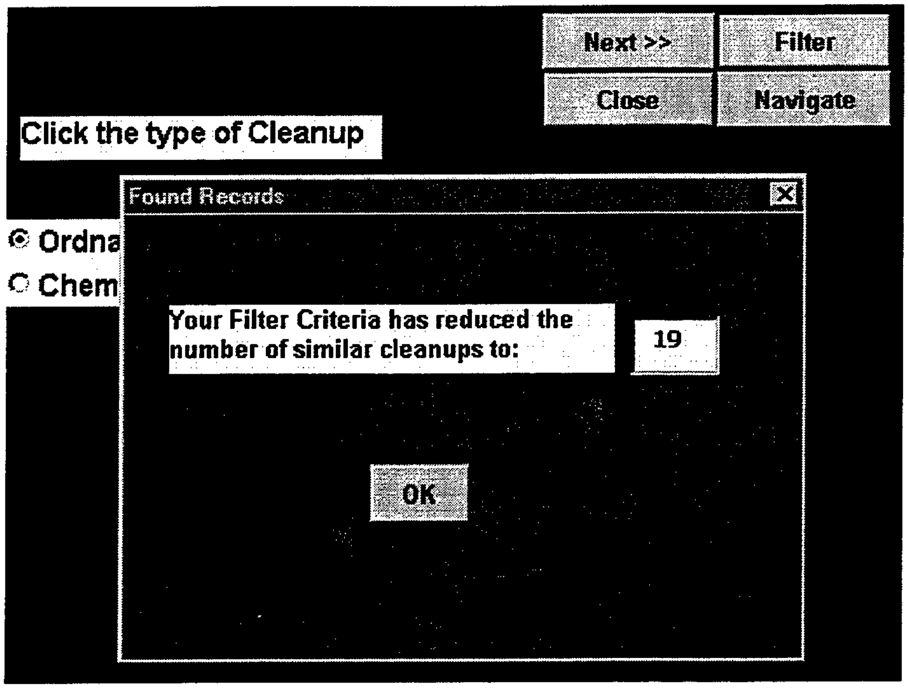


Figure 21: The Found Records Form. The user can use the Found Records Form from any location in the model to show how many records remain in the selected data set.

b. Filter by Density

The "Next>>" Button sends the user to the Density Form. Density tends to be a strong predictor of cost, unfortunately prior to surveying the user may only be able to make a rough guess on the expected density. The user should use a broad range if there is uncertainty concerning the density. The form provides four preset ranges: "Sparse," "Low," "Medium," and "High." Dividing the current data set into approximately equal quartiles, determines these preset ranges. For the given scenario, the ASR shows that the Marine Corps did conduct periodic range sweeps and that investigators found only a small amount of surface scrap during the site investigation. For these reasons the user is somewhat confident that the range is sparsely populated and selects a liberal density (total scrap per acre) range of 0-100 pounds per acre. This selection reduces the data set to 14 records. The Density Form appears below in Figure 22.

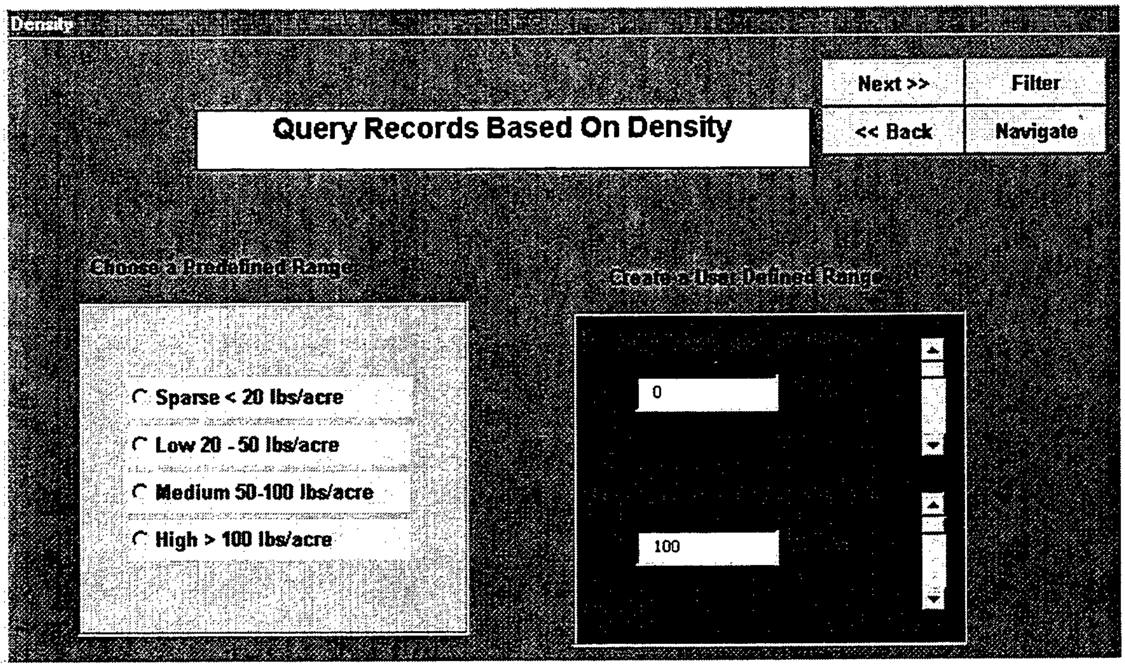


Figure 22: The Density Form. The Density Form allows the user to filter the data set based on the total scrap. Prior to performing an EECA the user may only have a rough estimate on the amount of scrap per acre. The user should enter a liberal density range unless surveying data gives a good estimate on the scrap density.

c. Filter by Vegetation

The next form in the filtering precedence is the Vegetation Form. An ASR categorizes an OOUs vegetation factor based on the primary vegetation throughout the OOU. The data set contains a ranking for each OOU based on vegetation difficulty factors. The cost-risk model adapts the RACER/ORCA difficulty factors, and these factors appear in Table 8. For simplicity, the cost-risk model refers to these rankings as V1 through V5.

VEGETATION	Difficulty Factor
V1: Flat barren or low grass	0
V2: Low grass and few shrubs	0.1
V3: Heavy grass with numerous shrubs	0.2
V4: Shrubs with some trees	0.3
V5: Heavy shrubs and trees or forest	0.5

Table 8: Vegetation Characteristics and Associated Difficulty Factors. In accordance with the RACER/ORCA model, the cost-risk model ranks vegetation by difficulty factors. Unlike density, the user has certainty of the type of vegetation contained in a contaminated area.

The contaminated area in the scenario contains heavy vegetation; therefore, the user may choose to select categories V4 and V5. This selection narrows the data set down to 11 records. Figure 23 is a depiction of the Vegetation Form.

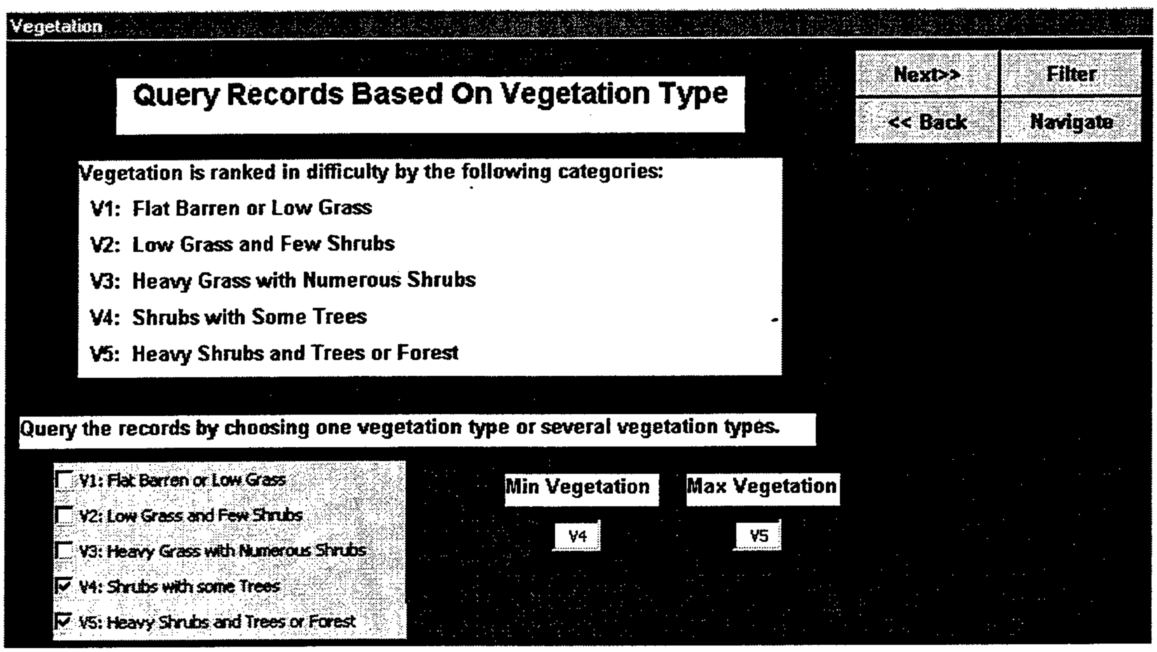


Figure 23: The Vegetation Form. The model user can use this form to set the minimum and maximum vegetation type for the contaminated area. For the current scenario a range from V4 to V5 best depicts the area.

d. Filter by Depth of Clearance

Following the Vegetation Form is the Depth of Removal Form. The final depth of clearance requires deliberation among all concerned parties prior to RA, but the intended future use of the land suggests about a four-foot clearance. Setting the minimum depth to two feet and the maximum depth to six feet reduces the number of available records to nine. The Depth of Removal Form appears in the Figure 24.

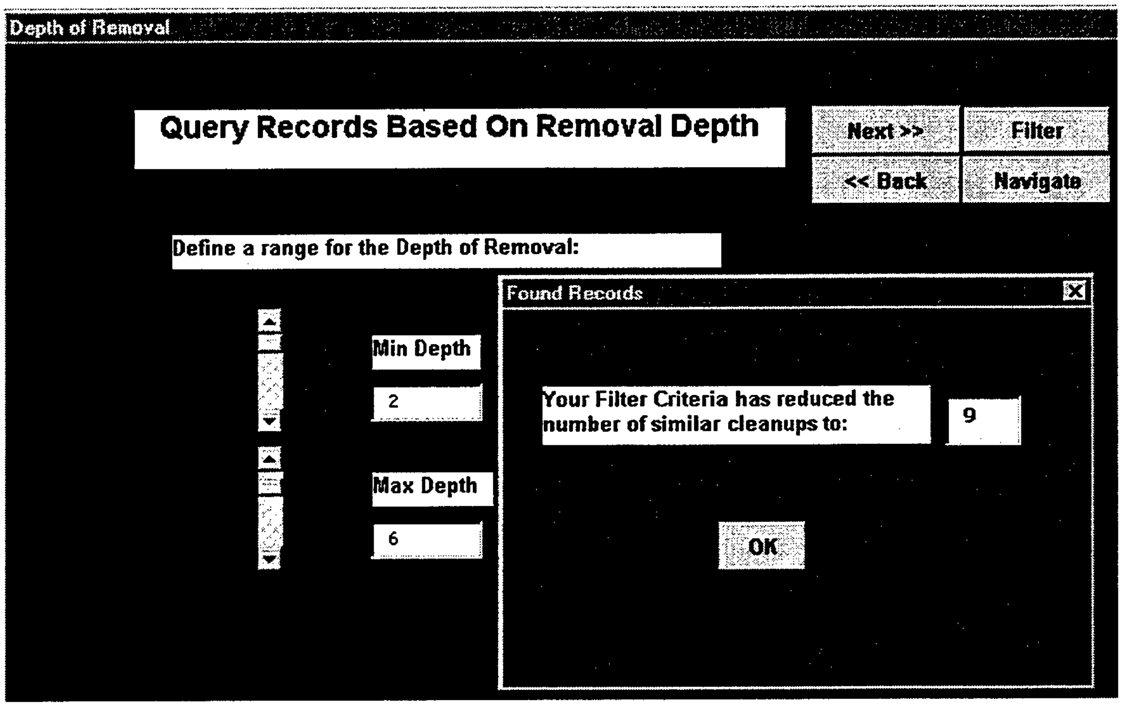


Figure 24: The Depth of Removal Form. The Depth of Removal form allows the user to find historic cleanups with similar clearance depths. For the current scenario, filtering by depth reduces the amount of available records to nine.

e. Filter by Topography

Once the user completes filtering on the primary cost indicators he begins filtering with the secondary cost indicators. Due to small number of records in the filtered data set (9 records), the user would likely quit at this point. When more records are added to the database, the user would likely have enough remaining records to continue refining the search. However, in this case the user should concentrate on removing the extremes of the secondary indicators so as not to significantly reduce the number of records any further. Like vegetation the model ranks topography using the RACER/ORCA difficulty factors. Table 9 lists the topography categories and the associated difficulty factors. The cost-risk model labels these categories as T1 through T5.

Topography	Difficulty Factor
T1: Flat	0
T2: Gently Rolling	0.1
T3: Heavy Rolling	0.3
T3: Flat with Gorges	0.3
T4: Rolling With Gorges	0.5
T5: Mountainous	0.7

Table 9: Topography Categories and Associated Difficulty Factors. In Accordance with the RACER/ORCA model, the cost-risk model ranks topography by difficulty factors.

The contaminated area in the scenario falls in the T1 and T2 categories, by selecting a minimum of T1 and a maximum of T4 the user eliminates one record in the mountainous category (T5) leaving eight records in the data set. Figure 25 shows the selection of topography categories.

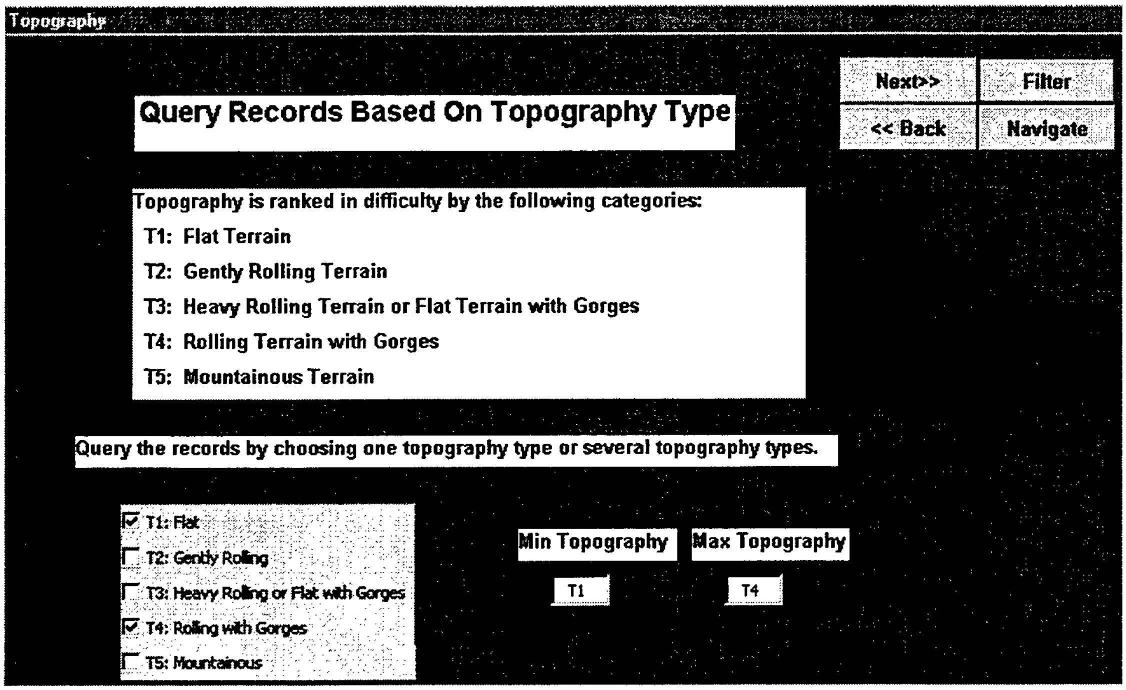


Figure 25: The Topography Form. The Topography Form allows the user to filter the data set based on the predominant topography of the OOU. This figure shows a minimum topography of T1 and a maximum topography of T4 selected.

f. Filter by Soil Type

The next form is the Soil Type Form (Figure 26). Soil categories have ORCA/RACER difficulty factors (Table 10) and the cost-risk models labels these categories as S1 through S6.

Soil Type	Difficulty Factor
S1: Sand	0
S2: Gravel Sand mixture	0.2
S3: Silt or Sand-Silt	0.3
S4: Clay/Sand or Clay Silt	0.5
S5: Clay/Sand with stone	0.6
S6: Clay	0.7
S7: Rock	0.8

Table 10: Soil Categories and Associated Difficulty Factors. In accordance with the RACER/ORCA model, the cost-risk model ranks soil types by difficulty factors.

The scenario site is in the S2 to S3 categories, and since the user does not want to eliminate too many records he selects S1 through S5 to eliminate the very difficult cleanups in the clay and rock categories. Using these criteria the filtering removes no further records.

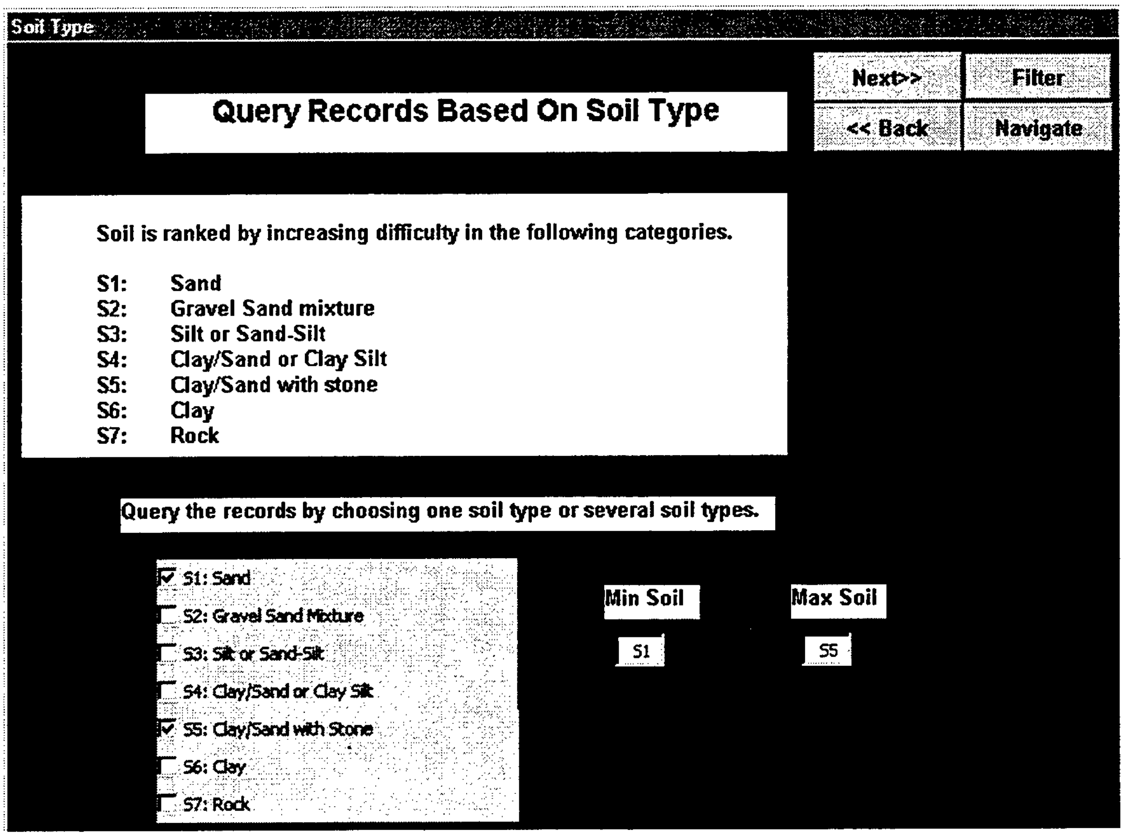


Figure 26: The Soil Type Form. The Soil Type Form allows the user to filter the data set based on the OOU's predominate soil type. This figure shows a minimum soil type of S1 and a maximum soil type of S4.

g. Filter by Ordnance Type

The final filtering category is ordnance. Here again, difficulty factors for ordnance types exist as specified in RACER/ORCA. Table 11 lists ordnance types ranked by difficulty factor.

Ordnance Category	Difficulty Factor
O1: Bombs (Practice)	0.1
O1: Grenades (Practice)	0.1
O1: Landmines (Practice)	0.1
O2: Detonators, Blasting Caps, Fuzes, Boosters, Bursters	0.3
O3: Grenades, Hand and Rifle (Explosive)	0.4
O4: Small Arms	0.5
O5: Landmines (Explosive)	0.7
O6: Rockets, Guided Missiles (Explosive)	0.8
O7: Medium/Large Caliber Rounds (Explosive)	1.0
O7: Bombs (Explosive)	1.0

Table 11: Ordnance Categories and Associated Difficulty Factors. The cost-risk model ranks ordnance RACER/ORCA difficulty factors.

Often there is uncertainty in the amount and type of ordnance that is present in an OOU. In some cases a range contains only one specific type of ordnance, at other times the contaminated area has everything from practice rounds to high explosive submunitions to 2000-pound air delivered bombs. In order to filter OOUs by ordnance type, each OOU in the database has a mean ordnance difficulty factor. Equation 5.1 calculates the ordnance difficulty factor by a weighted average of the proportion of an ordnance type and its difficulty factor:

$$\sum_{OT} \text{Expected Proportion}_{OT} * \text{Difficulty Factor}_{OT} \qquad (5.1)$$

where OT is the ordnance type

In many cases it is difficult for the user to estimate the type of ordnance and proportions of each type of ordnance; however, there is usually enough information to rule out extreme records. In the scenario the ordnance difficulty factor has a value equal to a minimum of (0.4). Ruling out records below (0.3) is a viable solution. Figure 27 shows the Ordnance Form.

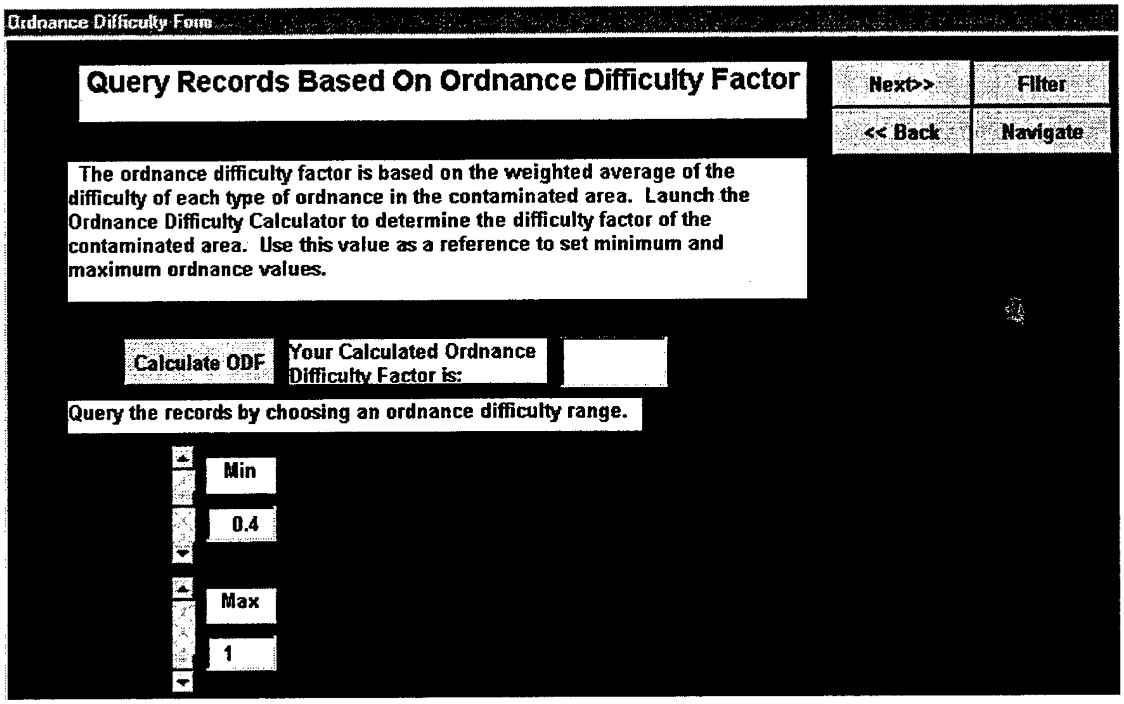


Figure 27: The Ordnance Form. The Ordnance Form allows the user to filter a range of ordnance types based on their difficulty factor. The figure shows the minimum factor set at 0.4 and the maximum factor set at 1.

To help decide the ordnance difficulty factor for the contaminated area, the user can click the Calculate ODF Button in the center of the form. This button launches the "Ordnance Difficulty Calculator" to determine the mean difficulty factor using the inputs and equation 5.1. Figure 28 is the Ordnance Difficulty Calculator.

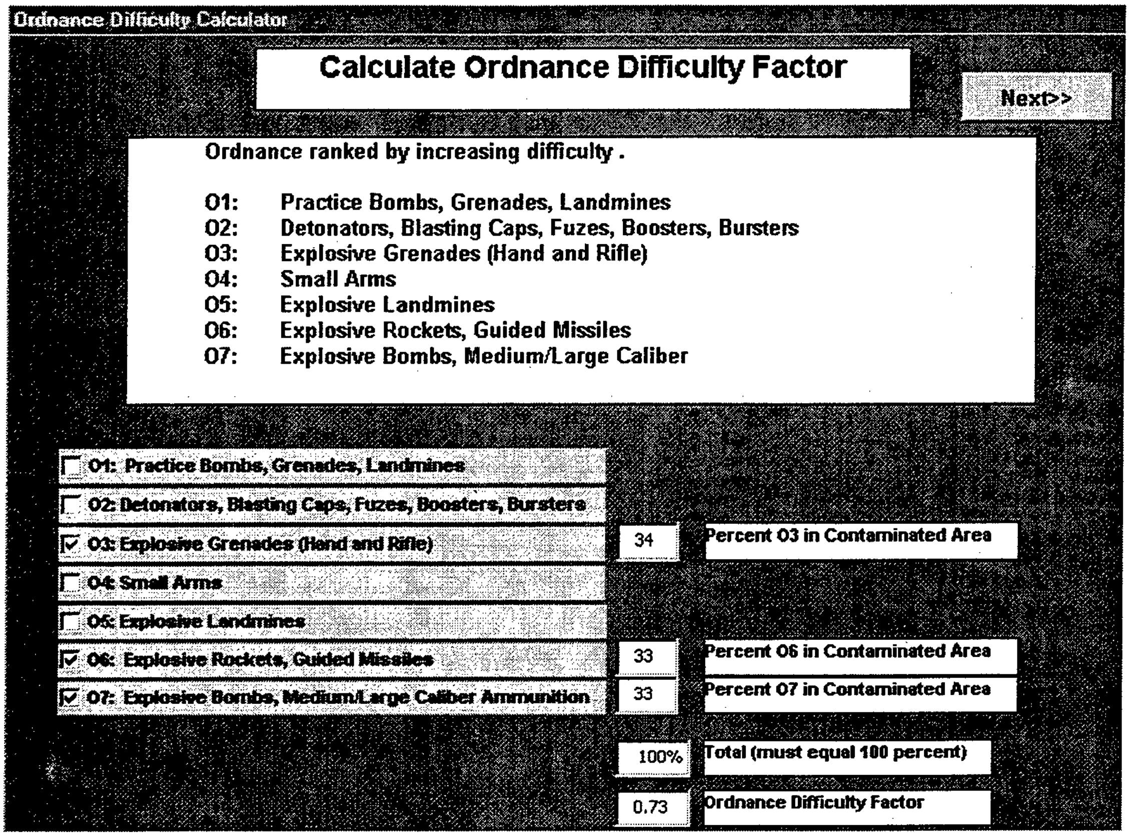


Figure 28: The Ordnance Difficulty Calculator Form. To help the user determine the average ordnance difficulty factor, the user checks the types of ordnance and fills in the percentages of that type. The user assumes that the area contains 34% O3, 33% O6, and 33% O7. The bottom value (0.73) is the mean difficulty factor.

Once the user is satisfied with the filter criteria the values can be reviewed by selecting the Values Form.

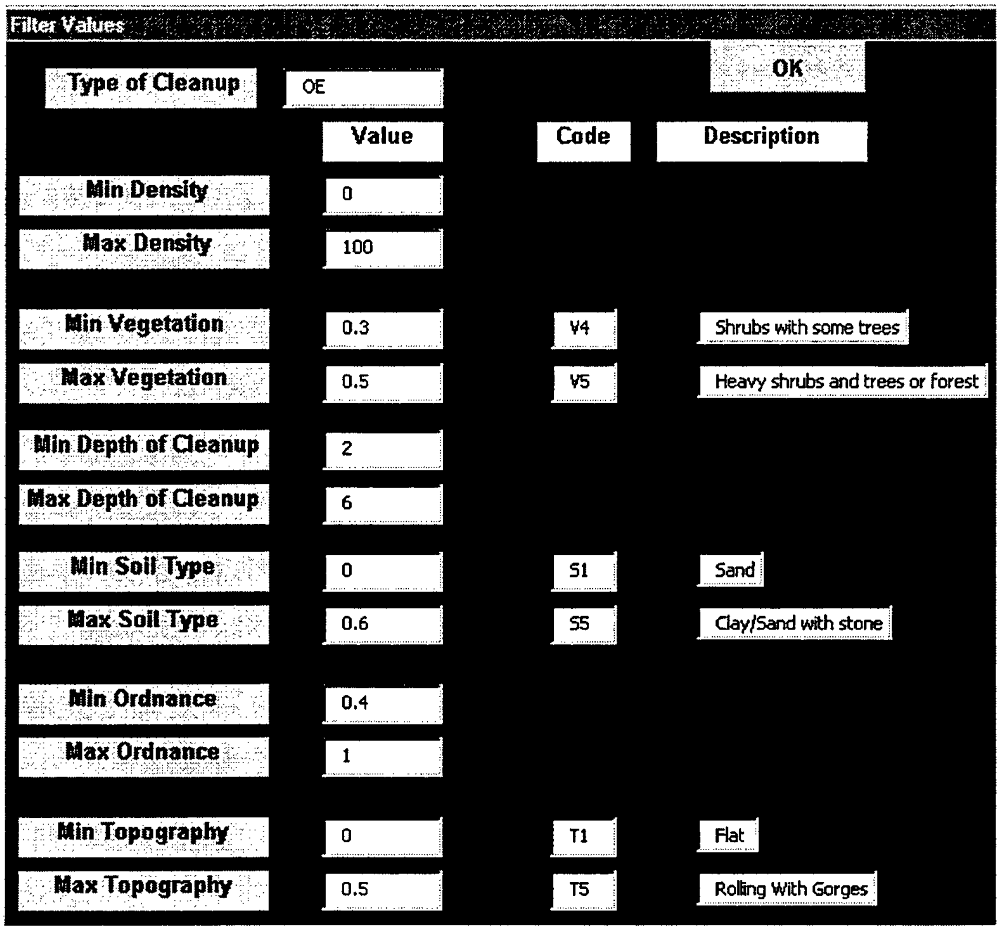


Figure 29: The Values Form. The user can view the Values Form at anytime to see the filtering criteria.

2. Step Two: Historical Analysis

With the data set reduced down to a satisfactory group of similar cleanups, the user selects "Historical Analysis" from the "Cost_Analysis" pull-down menu. This selection generates three additional sheets in the workbook. These sheets are "DescStats," "Histograms," and "Correlation."

a. Descriptive Statistics of Similar Cleanups

The "DescStats" sheet is the descriptive statistics on each cost element of the filtered set. The cost-risk model presents the minimum, median, average, maximum, and standard deviation of the data set in a matrix. Table 12 is the output of "DescStats" for the scenario cleanup.

Per Acre Costs	Minimum	Median	Mean	Max	Stan Dev
EECA Labor Cost	$650	$900	$999	$1,340	$237
EECA Material Cost	$60	$200	$354	$1,070	$348
EECA Travel/Per Diem Cost	$250	$380	$526	$1,530	$450
RA Labor Cost	$3,170	$4,440	$4,907	$6,700	$1,202
RA Material Cost	$300	$1,000	$1,720	$5,240	$1,700
RA Travel/Per Diem Cost	$1,210	$1,840	$2,571	$7,520	$2,218

Table 12: Output of Historical Analysis "DescStats" Worksheet. This table appears in the worksheet "DescStats" after running a historical analysis on the filtered set of similar cleanups. The worksheet contains descriptive statistics of the individual cost elements.

b. Histograms

The second sheet contains the Histograms for each of the six cost elements. The histograms give a graphical representation of what has been spent in a specific area for similar cleanups. Figure 30 is a view of this worksheet.

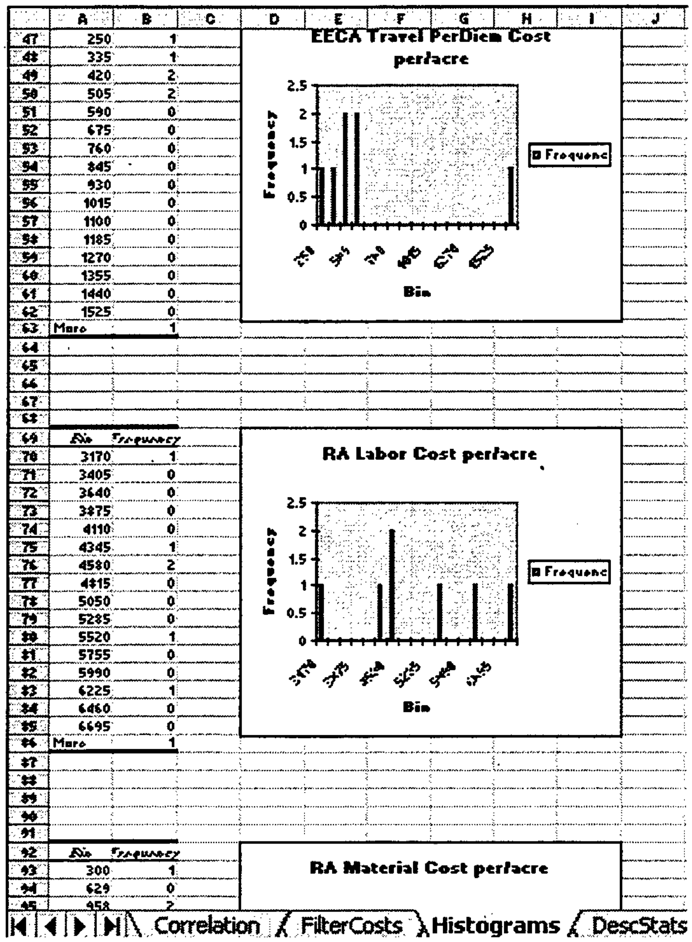


Figure 30: Output of Historical Analysis Histograms. This figure shows the second sheet that the model generates when performing a historical analysis. Visible in the figure are two out of the six cost element histograms. The user can use this visual information to get a feel for the empirical distribution and make inferences on the true distribution

c. *Correlation Matrix*

The final sheet produced during the historic data analysis is "Correlations." This sheet contains the correlation matrix from the filtered data set. The matrix shows how each cost element correlates with every other cost element. The correlation matrix for the unfiltered data set and the scenario data set appear in Table 13.

All Records	EECA Labor	EECA Material	EECA Travel PerDiem	RA Labor	RA Material	RA Travel PerDiem
EECA Labor	1.000					
EECA Material	0.710	1.000				
EECA Travel PerDiem	0.798	0.907	1.000			
RA Labor	1.000	0.710	0.799	1.000		
RA Material	0.714	1.000	0.908	0.714	1.000	
RA Travel PerDiem	0.799	0.906	1.000	0.800	0.907	1.000

Filtered Set	EECA Labor	EECA Material	EECA Travel PerDiem	RA Labor	RA Material	RA Travel PerDiem
EECA Labor	1.000					
EECA Material	0.077	1.000				
EECA Travel PerDiem	0.253	0.933	1.000			
RA Labor	0.999	0.075	0.258	1.000		
RA Material	0.082	[illegible]	0.938	0.080	1.000	
RA Travel PerDiem	0.257	0.932	[illegible]	0.263	0.937	1.000

Table 13: Correlation Matrices for all Records and the Scenario Records. The upper matrix is the correlation matrix that the model generates when performing an historical analysis on all the records in the database. The Lower matrix is the correlation matrix for the scenario data set. The off diagonal correlation coefficients that equal 1.0 (highlighted values) result from how the EECA data was generated.

The values highlighted in the table have a correlation value of 1.0 because taking 2% of the corresponding RA values generates the unavailable EECA data. One should note the high correlation in the unfiltered set for RA data. Material and Labor have a value of 0.71, Labor and Travel/per Diem have a value of 0.8, and Material and Travel/per Diem have a value of 0.90. For the filtered set these values were, 0.08, 0.263, and .937 respectively. The coefficients in the filtered set tend to be much smaller except for

Material-Travel/per Diem. The small correlation in the filtered set is likely a result of a few outliers in the small set. This thesis recommends that the user input correlation coefficients closer to the unfiltered set. As data sets of similar cleanups become larger the user can choose the correlation coefficients from the filtered data set.

3. Step Three: Create Cost Element Probability Distributions

a. Choosing Alpha

The next step prior to simulation is to create weighted probability density functions for each cost element (the cost-risk model uses a linear combination of the empirical distribution and the user's supplied triangular distribution to form a weighted-distribution). The user must determine the weighting factor α for each cost element distribution (see Equation 4.1). The weighting factor α expresses the user's faith in the triangular distribution. For example when α is equal to n (the number of records) the empirical distribution is equal in weight to the triangular distribution. When α equals zero the formula gives no weight to the triangular distribution and when α is very large the weight shifts to the triangular distribution. Figure 31 visually shows the effects of varying α. The first graph Figure 31 is the histogram of the weighted PDF with alpha equal to zero. The second histogram is with an alpha equal to the number of records (19). The final histogram uses an alpha of 100.

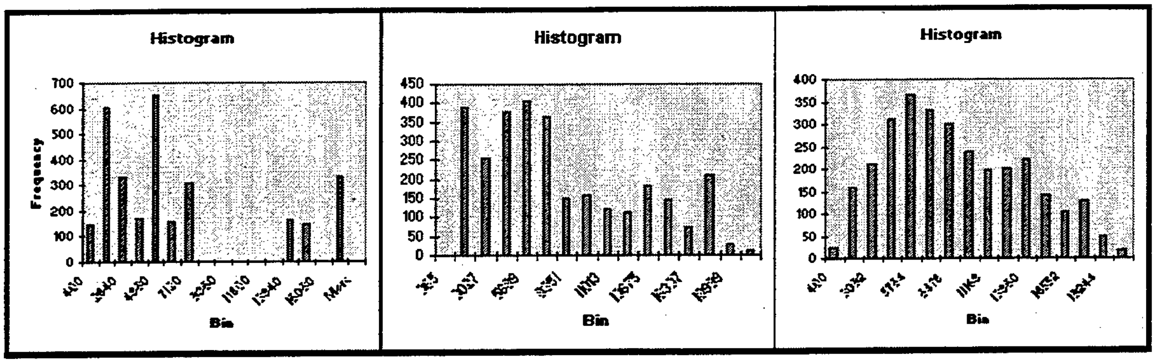


Figure 31: Increasing Alpha and the Shape of the Weighted PDF. This example uses the same empirical distribution and triangular distribution but varies the alpha. With $\alpha = 0$ the first histogram mirrors the empirical PDF. With an $\alpha = n$ the middle PDF is slightly triangular with spikes at the discrete values. At $\alpha = 100$ the last PDF is nearly triangular with some slight spikes.

b. Inputting Triangle Parameters

By selecting "Create Cost Distributions" from the "Cost_Analysis" menu, the cost-risk model presents the user with the "Set Triangular PDFs" form. Visible on this form are the statistics for the cost element (minimum, mean, average, maximum), and input boxes to set alpha and the triangular distribution's parameters (minimum value, most-likely value, and maximum values). The model sets the default value for α equal to the number of records, it sets the triangle's minimum and maximum to 80% of the empirical distribution's minimum and 120% of the empirical distribution's maximum, and sets the triangle's most-likely value equal to the empirical distribution's mean value. The default values are only starting points and may not be realistic or desirable. The user should carefully consider each cost element when setting α and the triangular distribution's parameters.

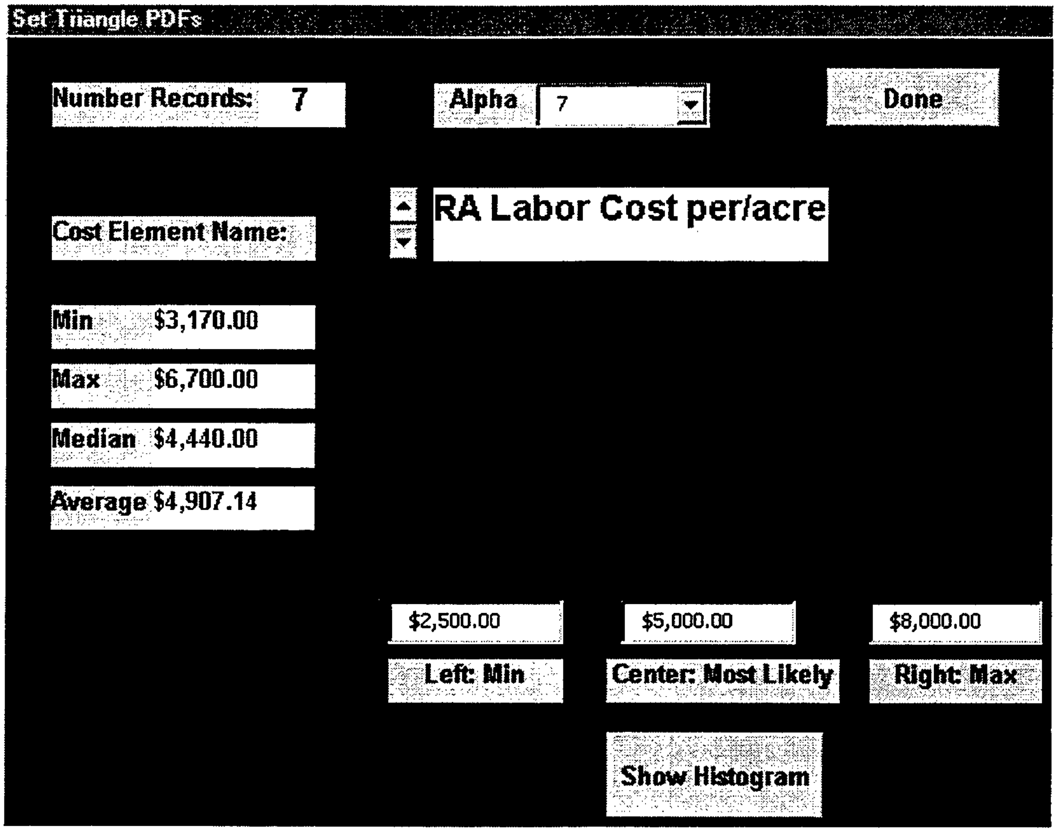


Figure 32: The Set Triangle PDFs Form. The user uses this form to set α, and set the triangular distribution's parameters (minimum value, most-likely value, and maximum value). The form shows the statistics for each cost element and the user can click on the Show Histogram Button to view the histogram of the filtered data.

The form displays the name of the cost element in the center, and the user uses the scroll bar next to the cost element's name to cycle through all of the cost elements. For the scenario, the form shows that seven similar cleanup records are found. For the Removal Action labor costs the user may feel that the hypothesized triangular distribution is as valuable as the empirical distribution, and sets alpha equal to seven (the number of records). An alpha equal to the number of records gives equal weighting to the empirical distribution and the traingular distribution. The user looks at the statistics along the left side of the form and then reviews the histogram for the cost element (Figure 33).

Bin	Frequency
3170	1
3405	0
3640	0
3875	0
4110	0
4345	1
4580	2
4815	0
5050	0
5285	0
5520	1
5755	0
5990	0
6225	1
6460	0
6695	0
More	1

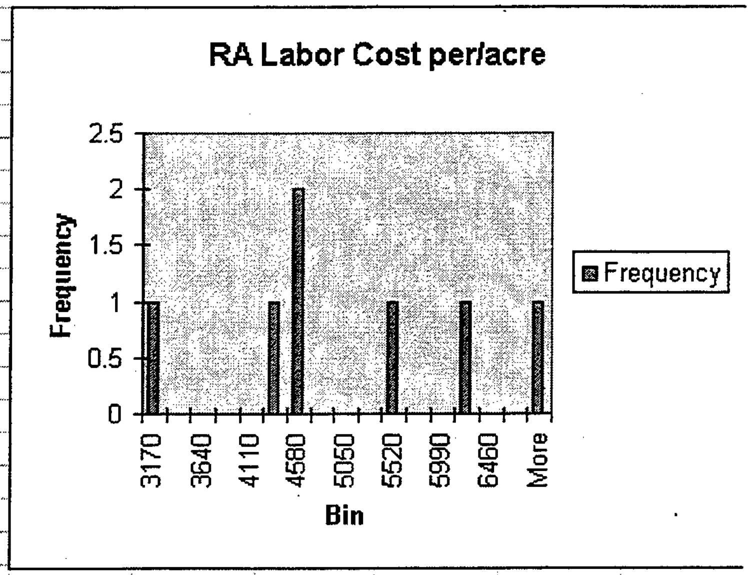


Figure 33: The Histogram for Removal Action Labor Costs in Dollars/Acre. The histogram for RA labor costs does not reveal much of a trend in the data, but provides a visual depiction of costs of similar cleanups.

Assume that a cost analyst believes that contractors never charge less than $2,500/acre and that the government never enters into contracts for this type of cleanup for more than $8,000/acre. To provide more insight the user runs the RACER/ORCA model and gets a point estimate of $6,200/acre for the labor costs . The analyst builds a triangular distribution based on the RACER/ORCA estimate and the historic data. The user sets the minimum of the triangular distribution at $2,500/acre, the center at $5,000/acre, and the maximum at $8,000/acre. The user then enters these values at the bottom of the form. The same methodology applies for all cost elements. When the user gets to EE/CA material costs he feels that the data accurately reflects the true distribution (unlikely with only seven records) and decides to put all of the weight onto the empirical data by setting α for this cost element to zero. Conversely, policy changes have altered how per Diem is paid and the user determines that the empirical data is too high and not reflective of current costs. The analyst thus sets α for "RA Travel/Per Diem" cost to 100, heavily weighting the user supplied triangular distribution.

When the user clicks the Done button the model creates the weighted PDFs for each cost element composed of 10,000 random points from the empirical and triangular distribution. The cost element's α determines how many points come from each distribution. If the weighting is 4/5 for the empirical and 1/5 for the triangular distribution then the model generates 8,000 random points from the empirical distribution and 2,000 points from the triangular distribution. Code is written in visual basic using the inverse transform method to create these distributions. Any simulation package can then draw with equal probability from these 10,000 numbers to form the weighted-distribution.

4. Step Four: Run Simulation

a. "OutPutReport"

The cost-risk model creates two additional sheets at this time: "OutPutReport" and "SimInputs." The "OutPutReport" sheet summarizes the statistical data for each cost element, the triangular distributions for each cost element, the filtering criteria, and the correlation matrix. Figure 34 shows the information that the "OutPutReport" sheet contains.

	$ Assessment Total	Archive Search Report Total Cost	Labor Cost per/acre	Material Cost per/acre	Travel PerDiem Cost	Labor Cost per/acre	Material Cost per/acre	PerDiem Cost per/acre
Min	$25,760	$41,890	$650	$60	$250	$3,170	$300	$1,210
Median	$26,190	$42,700	$900	$200	$380	$4,440	$1,000	$1,840
Average	$26,414	$42,581	$999	$354	$526	$4,907	$1,720	$2,571
Max	$27,190	$43,500	$1,340	$1,070	$1,530	$6,700	$5,240	$7,520
Standard Deviation	$471	$725	$237	$348	$450	$1,202	$1,700	$2,218
Alpha	7	7	7	0	100	7	3	25
Triangle Left Side	$23,184	$37,701	$500	$60	$250	$2,500	$200	$1,000
Triangle Center	$26,190	$42,700	$800	$200	$500	$5,000	$1,000	$1,500
Triangle Right	$32,628	$52,200	$1,500	$1,070	$1,000	$8,000	$6,500	$6,000
Values:	**Min**	**Max**						
Density	0	100						
Vegetation	Shrubs with some trees	Heavy shrubs and trees or forest						
Depth	2	6						
Soil Type	Sand	Clay/Sand with stone						
Topography	Flat	Rolling With Gorges						
Ordnance	0.4	1						
Type	OE							

Figure 34: The "OutPutReport" Worksheet. The "OutPutReport" worksheet shows the statistics for each cost element, the triangular distribution parameters, α for each cost element, the filter criteria, and the correlation matrix for the found set. The correlation matrix is not visible in the figure.

b. "SimInputs"

The worksheet "SimInputs" (See Figure 35) contains formulas composed of the random variables, and the simulation software uses this sheet to run the simulation. The worksheet's formulation works with *@Risk* but can be easily modified to interface with other simulation packages.

	C	D
2		
3	EECA Labor Cost per/acre	RISKDUNIFORM(PDFthree)
4	EECA Material Cost per/acre	RISKDUNIFORM(PDFfour)
5	EECA Travel PerDiem Cost per/acre	RISKDUNIFORM(PDFfive)
6	RA Labor Cost per/acre	RISKDUNIFORM(PDFsix)
7	RA Material Cost per/acre	RISKDUNIFORM(PDFseven)
8	RA Travel PerDiem Cost per/acre	RISKDUNIFORM(PDFeight)
9		
10		
11	Removal Action Only Total Cost	[redacted]
12	Removal Action/EECA Total Cost	
13		

Figure 35: The "SimInputs" Worksheet. The "SimInputs" worksheet sets up the simulation. Cells D3 to D8 draw random samples from the weighted PDFs of the corresponding cost elements. Cell D11 is the sum of all RA only cost elements, and D12 is the sum of all cost elements.

Although different simulation packages require slightly different formulation, in general the inputs are the cost element PDFs and the outputs are functions of these inputs. A great advantage of simulation is that multiple functions of the inputs can be created. The "SimInput" sheet provides an example of this with one output being the sum of all cost elements and one being the sum of only the RA inputs. In this way one derives an RA total cost per acre PDF and a combined RA/EECA total cost per acre PDF (both PDFs are in dollars/acre). Further the user could write another function that sums up the inputs and then multiplies them by the acreage of the contaminated area. This final formulation becomes the total cost PDF in dollars. After the user writes any additional output formulas he desires, he enter the inputs and outputs into *@Risk* along with the correlation matrix and then runs the simulation.

F. JUSTIFICATION OF FILTERING

To demonstrate that the filtering can accurately locate cleanups with similar costs, the thesis runs two additional scenarios. The thesis considers the original scenario as a medium difficulty cleanup because it contains a mixture of difficult and easy OOU characteristics. The density is low to medium; the vegetation is high in difficulty; the depth of clearance and ordnance type is medium in difficulty; and the terrain and soil types are easy. The "hard" and "easy" scenarios contain the same amount of records (7) as the original, "medium," scenario. The "hard" scenario filters the records by setting all the OOU characteristics in the difficult ranges (i.e., high density, high vegetation difficulty factor, deep depth of clearance, etc.). The "easy" scenario does the converse, setting the OOU characteristics to the lower degrees of difficulty. For all cost elements and for all summary statistics, the "easy" cleanup has lower values than the "medium" cleanup and the "medium" cleanup has lower values than the "difficult" cleanup. Figure 36 shows the minimum, maximum, average, and median value for each cost element of each scenario.

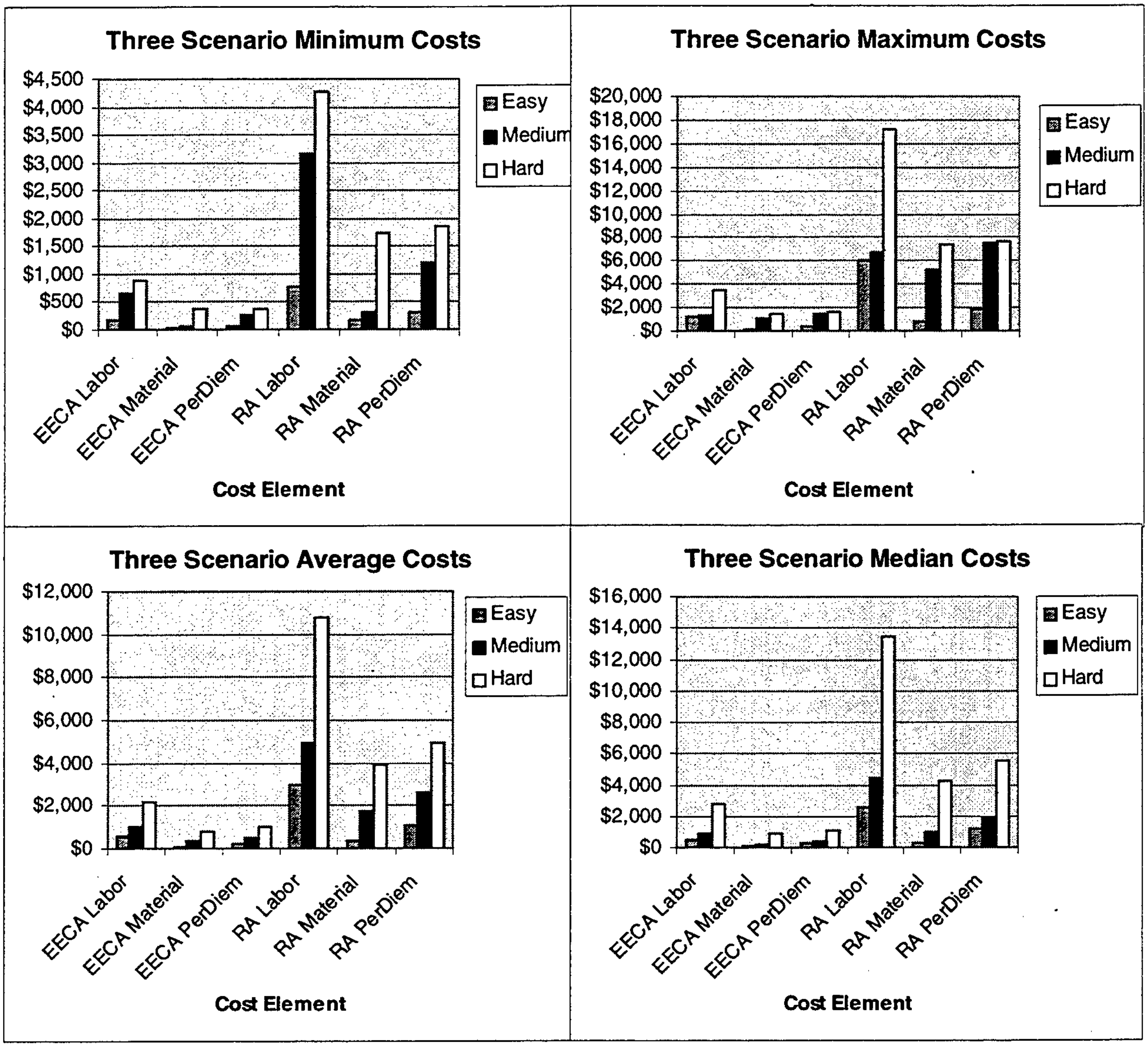


Figure 36: Summary Statistics for "Easy," "Medium," and "Hard," Scenario. The model develops three scenarios: "Easy" cleanup, "Medium" cleanup and "Hard" cleanup. The filtering process finds similar cleanups as can be seen in the summary statistics. For each cost element the minimum cost, the maximum cost, the median cost, and average cost increase as difficulty increases.

VI. SIMULATION OUTPUT AND INTERPRETATION

A. SINGLE CLEANUP RESULTS

The Monte Carlo simulation is run for the Chapter V scenario cleanup using the "all records" correlation matrix at the top of Table 18, and by setting *@Risk* for 10,000 iterations. To emphasize the necessity of considering correlation effects, the thesis shows the results for an identical simulation that assumes zero correlation among cost elements. Appendix C contains the output report from the scenario. Figure 37 shows how Monte Carlo sampling forms a total cost PDF from the cost element PDFs.

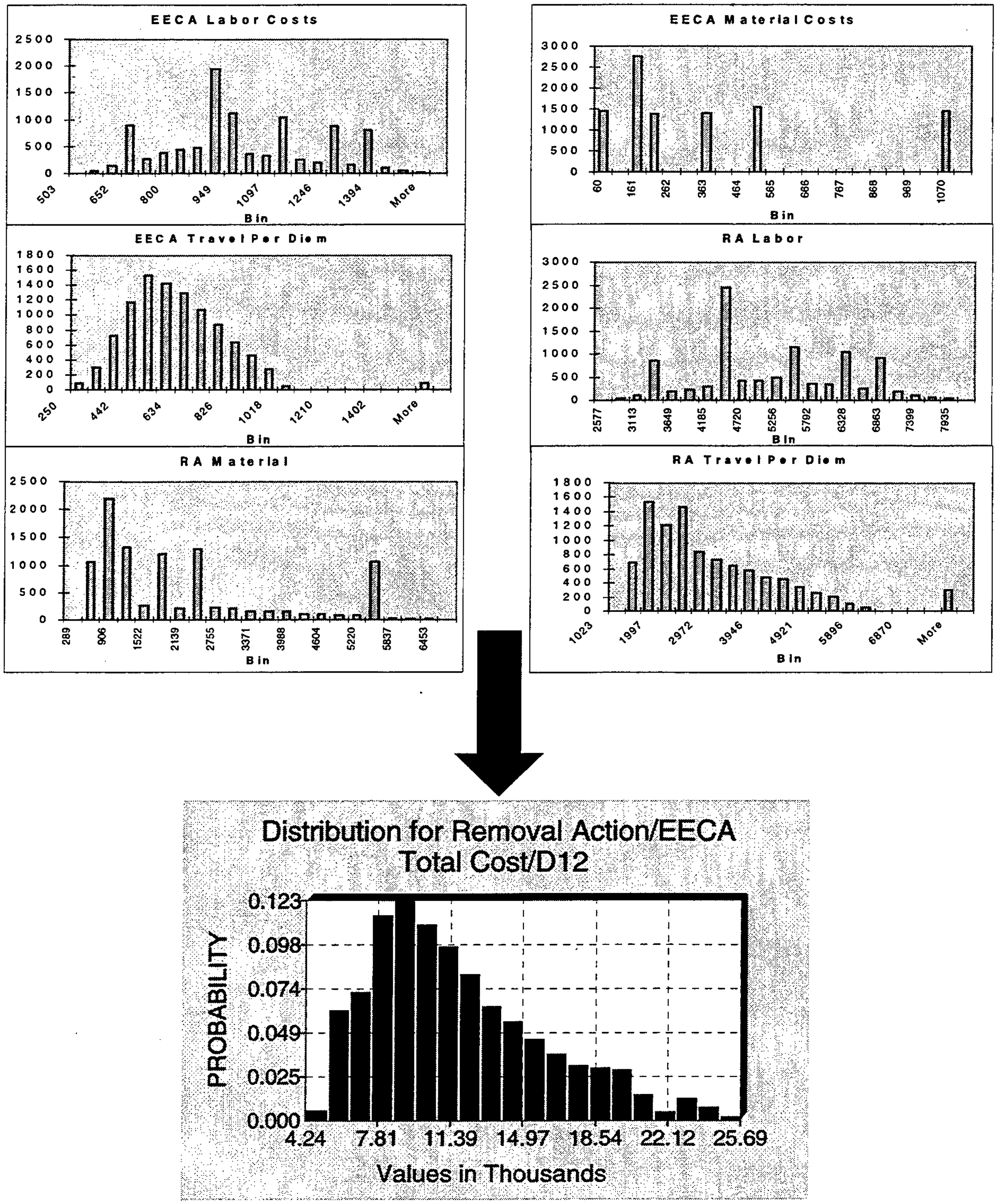


Figure 37: The Total Cost PDF for the Scenario. Monte Carlo Simulation samples from the individual cost element PDFs to produce the total cost PDF for the "medium" scenario presented in Chapter V. The simulation is run with 10,000 iterations and the "all records" correlation matrix. All values are in dollars/acre.

The *@Risk* software package generates the total cost PDF shown at the bottom of the previous figure. Since only a few cost elements exist in the simulation, the total cost PDF does not approach the normal distribution shape, but the distribution does begin to smooth out.

To portray the importance of considering correlation, Figure 38 compares the uncorrelated (left side) and correlated (right side) total cost probability density functions. As is expected, the PDF for the uncorrelated case is more symmetrical and less spread out (less variance).

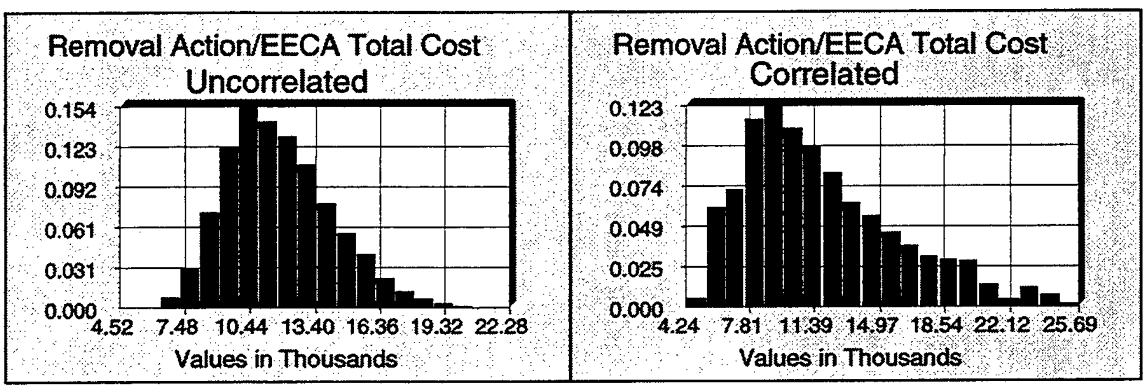


Figure 38: Comparison of Uncorrelated and Correlated Total Cost Per Acre PDFs. The comparison of the uncorrelated (left side) and correlated (right side) simulation outputs shows that uncorrelated random variables produce a tighter distribution. Costs are in dollars/acre.

The comparison shows that by ignoring correlation, the analyst assumes an artificial "reduction in risk." Reduction in risk refers to the fact that there is a reduced chance of getting values in the tail

In addition to the PDF, the simulation software generates the summary statistics for the total cost distribution. Table 14 lists the summary statistics for the correlated and uncorrelated scenario cleanup.

Statistic	Correlated Value	Uncorrelated Value
Minimum	$4,239	$4,518
Maximum	$25,694	$22,284
Mean	$11,715	$11,711
Std Deviation	$4,260	$2,415
Mode	$8,400	$9,600

Table 14: Correlated and Uncorrelated Summary Statistics for the Scenario Cleanup. The simulation software produces summary statistics for all input and output cells. This table lists the summary statistics for the total cost per acre of performing an EECA and RA on the contaminated area.

The summary statistics for the correlated inputs show that for the scenario cleanup the simulation estimates total cost per acre to fall between $4,239/acre and $25,694/acre. The results estimate the most-likely value to be around $8,400/acre (mode), but shows in the long run an average around $11,715/acre (mean). As is expected, both the correlated and uncorrelated scenarios have the same mean but the standard deviation is much greater for the correlated case.

Before the cost analyst can make informed decisions about costs, he needs the cumulative probability distribution for the total cost. The cumulative probability distribution is also an output of the simulation software, and Table 15 shows tabulated values of the cumulative probability distribution.

X (Correlated)	*X* (Uncorrelated)	Probability that True Total Cost is Less than *X*
$6,141	$8,272	0.05
$6,881	$8,853	0.10
$7,575	$9,256	0.15
$8,061	$9,623	0.20
$8,505	$9,959	0.25
$8,910	$10,250	0.30
$9,343	$10,544	0.35
$9,803	$10,804	0.40
$10,327	$11,114	0.45
$10,794	$11,433	0.50
$11,340	$11,745	0.55
$11,924	$12,067	0.60
$12,586	$12,432	0.65
$13,355	$12,789	0.70
$14,221	$13,219	0.75
$15,219	$13,692	0.80
$16,527	$14,284	0.85
$18,172	$15,008	0.90
$20,005	$16,077	0.95
$25,694	$22,284	1.00

Table 15: The Total Cost Per Acre Cumulative Distribution for the Chapter V Scenario. The simulation software generates the table of the cumulative distribution. The value in the far right column gives the probability that the total cost per acre is less than the corresponding value in the left column. To emphasize the effects of correlated random variables, the table gives values for both the correlated simulation and the uncorrelated simulation.

The cumulative distribution shows the probability that the cost of cleanup will fall below a given value. As mentioned previously, there is an artificial reduction in the risk when not considering correlation. For example the cost analyst may be asked, "what is the probability of costs exceeding $15,000 per acre ($675,000 total for 45 acres)?" Using the false assumption of no correlation of cost elements, the analyst's answer is about 10%. The proper correlated result shows an answer closer to 20%.

With the above information the cost analyst can make informed decisions about the estimated cost and the risks associated with it. For example, the analyst may feel that that \$8,600/acre (mode) is the most likely cost for the EE/CA and RA, but he is also aware that the probability of exceeding this cost is roughly 75%. For budgeting purposes the analyst may choose a value closer to \$11,000/acre (median), because the probability is equally likely that the cost is greater than or less than this value.

B. MULTIPLE CLEANUPS

Although users of the cost-risk model need estimates for individual OOUs, they more often desire project level estimates. Since projects consist of one or more OOUs, the user can use the individual OOU estimates to produce project estimates. In an individual OOU estimate each iteration of the Monte Carlo simulation forms an input for the OOUs total cost probability distribution, and the model maintains these values after the simulation. For example, setting the simulation to 10,000 iterations forms 10,000 random observations from the OOUs total cost distribution. The simulation software can sum the individual total cost probability distributions for several OOUs to form a single estimate for the combined cleanup. To demonstrate this capability, consider a cleanup project consisting of three OOUs: the "hard," "medium," and "easy" scenario cleanups presented in Section V. The "hard" cleanup is 10 acres in size, the "medium" is 45 acres, and the "easy" cleanup is 60 acres. To estimate the entire project cost, the analyst first produces estimates for each individual OOU. Next, Monte Carlo simulation sums the three OOU total cost distributions. Each iteration of the simulation consists of randomly drawing a value from each of the three total cost distributions and summing them together. The analyst converts the units of each input distribution from "dollars per acre" to "dollars" so that the resulting distribution of the simulation is the total "dollar cost" of cleaning the three OOUs. Figure 39 visually depicts the simulation.

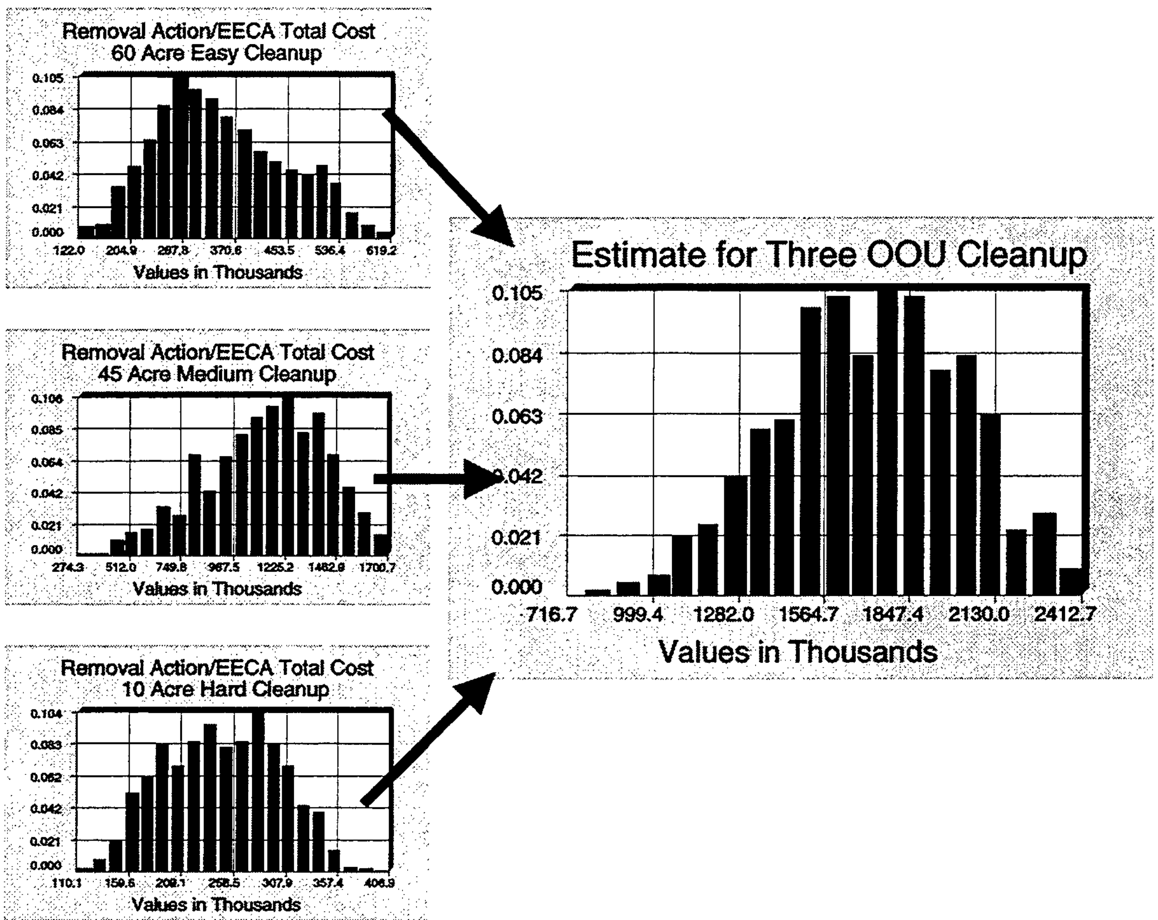


Figure 39: A "Multi-OOU" Estimate. Users most often desire a combined estimate for several cleanups. The user initially produces individual OOU distributions and then uses the OOU distributions as the inputs for the "multi-OOU" estimate. This figure shows a project that consists of three OOUs: 60-acre "easy" cleanup, 45-acre "medium" cleanup, and 10-acre "hard" cleanup.

VII. The "three-OOU" distribution shows that the most likely cost for cleanup of the three OOUs is roughly $1.7 million. Appendix D contains the simulation summary for the "three-OOU" estimate. The summary includes the cumulative distribtuion and the summary statistics.

RECOMMENDATIONS AND CONCLUSIONS

This thesis demonstrates a model for conducting cost-risk analysis of UXO cleanups. This research shows that UXO contaminated areas with similar characteristics have similar costs. Given appropriate data the model is capable of finding historic cleanups that have characteristics similar to a proposed cleanup. With the historic records, the cost analyst has descriptive information to assist him in building cost element PDFs. Using the output of Monte Carlo simulation of cost element PDFs, the cost analyst has the tools to make a cost estimate that incorporates cost-risk analysis.

A. RECOMMENDATIONS

1. Model Advantages and Disadvantages

The reader should consider the cost-risk model as a prototype. The main shortfall of the model is the limited amount of historic data records it contains. This lack of records reduces the users ability to find a satisfactory pool of similar cleanups. The USAESCH is implementing procedures that will make historic cost data more available and thus allow for the population of a cost database. The cost-risk model requires some modification to the OED in order to obtain the information in the proper format. Appendix A outlines required OED modifications.

The second shortfall of the cost-risk model is in the cost elements that the model uses. These cost elements reflect the cost information format that is available, and they do not represent an ideal breakdown of costs. The cost elements have high correlation, and because of their broad nature may be difficult for an analyst to estimate. The advantage of a large numbe of cost elements is that smaller "pieces" are usually more intuitive for an analyst to estimate. For example "Labor" costs may be more difficult to estimate than the components: "Supervisor Labor," "Ordnance Technician Labor," "Engineering Labor," and "Quality Control Technician Labor" costs. Appendix E. contains the 72-line work breakdown structure (WBS) that is the basis for reporting costs in the OED. This thesis recommends that future cost models or modifications to this model attempt to use cost elements that are a compromise between the cost-risk model cost elements and the WBS costs. Regardless of the cost reporting fidelity, the USAESCH should establish a consistent digital cost reporting format that can be entered into a database. Currently, contractors submit most cost information in "hard-copy" reports. Cost analysts must enter this information manually into the OED. The cost-risk model design allows for easy modification to accept additional cost elements.

One advantage of the model is that it refines itself as more data becomes available. Experts in this field believe that as detection technology improves, ordnance removal costs will drastically decrease. Future records added to the database would reflect these lower costs. Conversely, a parametric cost relationship built today may become obsolete due to these cost changes. More records also mean that the set of similar cleanups will be larger.

Another advantage of the model is that its design allows for records to be updated from a text file. Maintainers of ordnance information could download the text file from the OED or another ordnance management system and then disseminate it to users around the country. The Defense Environmental Network and Information Exchange (DENIX) is the ideal means for disseminating this data. This internet service provides DoD personnel access to environmental legislative, compliance, restoration, cleanup, and DoD guidance information. It serves as a central electronic "meeting place" where information can be exchanged among environmental professionals worldwide. Users of the cost-risk model could easily retrieve updated data from this exchange while the DOD could still control who is permitted access to the data.

Finally, the model's "Historical Analysis" function provides the USAESCH a means to analyze what was done in the past. Even if the user is not performing a cost estimate, this feature can be used to answer many questions. For example the user could manually select records from a specific contractor to analyze whether or not their "Labor" costs differ significantly from other contractors.

2. Further Research

This thesis gives insight to many other possible areas of research. Primarily, information management research needs to be done to determine how cost information can be easily acquired and managed. The OED is intended to gather cost information, but it appears that little structure was developed to make this possible. Further, raw cost information provides little information without a means to analyze it. The cost-risk model's "Historical Analysis" function provides some analysis, but these features can be greatly increased.

Validation of this model is also needed. USAESCH is currently trying to validate the RACER/ORCA models so that USAECH can delegate RACER/ORCA's use down to the individual Regions of the Army Corps of Engineers. This task proves difficult because little information has been kept on initial government estimates and actual costs [Young 1999].

Finally, the RACER/ORCA models could be easily modified to perform cost-risk analysis. According to an USAESCH cost analyst, "These models give accurate results as long as the correct assumptions are made [Young 1999]." Unfortunately the models have no means for a user to express uncertainty in their assumptions. The RACER/ORCA models could be modified so that all inputs containing uncertainty have a probability distribution. For example, a user must specify the density of the ordnance, but this is often uncertain even after sampling. Instead of entering the ordnance density as a single value, the user could enter a probability distribution of the ordnance density. The final result would be a "bottom-up" engineering model that benefits from cost-risk analysis. These changes are feasible since the RACER/ORCA models and computer code are property of the DOD. Modifying RACER/ORCA may prove easier to implement than the cost-risk model presented in this thesis. These models already contain extensive features for project management and are already familiar to many users who deal with environmental restoration.

B. CONCLUSIONS

The Range Rule requires the services to dedicate a significant amount of additional resources to an already monumental problem. Only a few agencies such as USAESCH have experience in this area, but the cost-risk model gives many possible users the ability to use USAESCH historic data to budget and estimate the cost of ordnance remediations. Estimating the costs of environmental restoration of ordnance contaminated sites is a difficult process containing many unknowns. The probabilistic cost model of this thesis provides the means to manage this uncertainty and risk.

APPENDIX A. ADDITIONS AND MODIFICATIONS TO THE ORDNANCE AND EXPLOSIVES DATABASE

This appendix makes recommendations for additions and modifications to the data fields contained in the Ordnance and Explosives Database (OED). These recommendations allow for the cost-risk model proposed in this thesis to use the OED structure. The OED is an attempt by the United States Army Engineering and Support Center, Huntsville (USAESCH) to create a repository of information on unexploded ordnance cleanups. The database is not complete and is not sufficiently populated with existing information. The database may likely be the framework for a future unexploded ordnance management system, and therefore the thesis attempts to use the current structure as much as possible. Further OED developments can incorporate these changes. This appendix breaks down the data fields into two groups: OOU descriptive characteristics, and cost information.

A. OOU DESCRIPTIVE CHARACTERISTICS

1. Soil

The OED only allows for three descriptive characteristics of soil type. The OED should expand the allowable inputs in order to reflect the structure of the ORCA/RACER cost model. The ORCA/RACER model assigns difficulty factors to each soil type, and the cost-risk model adopts theses rankings. Table 16 recommends the allowable soil inputs and associated difficulty factors.

Soil	Difficulty Factor
Sand	0
Gravel Sand mixture	0.2
Silt or Sand-Silt	0.3
Clay/Sand or Clay Silt	0.5
Clay/Sand with stone	0.6
Clay	0.7
Rock	0.8

Table 16: Recommended Soil Categories and Associated Difficulty Factors. This thesis recommends that the OED incorporate the above soil categroies and the associated difficulty factors. This cost-risk model uses the above structure. From [BTG Incorporated (Delta Research Division). Remedial Action Cost Engineering and Requirements (RACER) System 3.2.a. Computer Software 1998]

2. Vegetation

The OED does not allow enough descriptive categories for the vegetation of an OOU. Similar to soil type, the current OED fields do not provide the ability to capture the difficulty in remediation associated with differing soil types. Again, this thesis recommends the adoption of the RACER/ORCA difficulty factors. Table 17 lists the vegetation categories and the difficulty factors.

VEGETATION	Difficulty Factor
Flat barren or low grass	0
Low grass and few shrubs	0.1
Heavy grass with numerous shrubs	0.3
Shrubs with some trees	0.3
Heavy shrubs and trees or forest	0.5

Table 17: Recommended Vegetation Categories and Associated Difficulty Factors. The thesis recommends that the OED incorporate the above vegetation categories and associated difficulty factors. This cost-risk model uses the above structure. From [BTG Incorporated (Delta Research Division). Remedial Action Cost Engineering and Requirements (RACER) System 3.2.a. Computer Software 1998]

3. Topography

The OED only allows three inputs for terrain: "flat," "rolling," and "rugged." In order to capture the difficulty in cleanup due to topography this field should use the six topography categories used in RACER/ORCA. Table 18 lists these categories and their associated difficulty factors.

TOPOGRAPHY	Difficulty Factor
Flat	0
Gently Rolling	0.1
Heavy Rolling	0.3
Flat with Gorges	0.3
Rolling With Gorges	0.5
Mountainous	0.7

Table 18: Recommended Topography Categories and Associated Difficulty Factors. This thesis recommends that the OED incorporate the topography categories and associated difficulty factors. From [BTG Incorporated (Delta Research Division). Remedial Action Cost Engineering and Requirements (RACER) System 3.2.a. Computer Software 1998]

4. Density

Density usually refers to the amount of UXO per acre, but this definition may not be a good indicator of costs. Technicians must remove both UXO scrap and non-UXO scrap from a contaminated area, and false anomalies must be excavated along with actual UXO. The relationship between UXO density and non-UXO scrap density and its effect on costs is extremely difficult to define. The cost-risk model records density in total scrap per acre. A more detailed analysis of the relationship of UXO scrap and non-UXO scrap and its effects on cost is beyond the scope of this thesis and should be the subject of further research.

5. Depth of Clearance

The OED records depth at which individual UXO is located. There, however, is not a field in the OED that captures the contracted depth of clearance. The OED should incorporate a depth of clearance field.

6. Type of Ordnance

The OED and RACER/ORCA use the same inputs for the type of ordnance found in the OOU, and these inputs should remain unchanged. The cost-risk model uses the RACER/ORCA ordnance difficulty factors. However, since many ranges are multi-use, a large variety of ordnance may exist. The OED should represent the ordnance difficulty by a weighted average of each type of ordnance and its difficulty factor. Table 19 shows the allowable ordnance inputs and their difficulty factors.

TYPE_ORDNANCE	Difficulty Factor
Bombs, Practice	0.1
Grenades, Practice	0.1
Landmines, Practice	0.1
Detonators, Blasting Caps, Fuzes, Boosters, Bursters	0.3
Grenades, Hand and Rifle, Explosive	0.4
Small Arms	0.5
Landmines, Explosive	0.7
Rockets, Guided Missiles, Explosive	0.8
Medium/Large Caliber (20mm and target)	1.0
Bombs	1.0

Table 19: Recommended Ordnance Categories and Associated Difficulty Factors. The OED already incorporates the above ordnance types but not the RACER/ORCA difficulty factors. From [BTG Incorporated (Delta Research Division). <u>Remedial Action Cost Engineering and Requirements (RACER) System 3.2.a.</u> Computer Software 1998]

7. Type of Operation

The "type of operation" refers to the survey and removal methods used at the site. Traditional removals use mag-and-flag techniques. More modern methods use global positioning surveying and automated recording and mapping. The OED needs to track the type of removal as a predictor of costs. Although beyond the scope of this thesis, this data will also be important in the future for justifying investment strategies. The OED should use the RACER/ORCA categories; Table 20 shows these fields. The OED may need to increase the categories if some of the proposed technologies prove useable (ground penetrating radar, synthetic dog noses, acoustic, etc.).

TYPE_OPERATION	MEANING
Conventional	Mag-and-flag
HH GPS	Hand held GPS used. Manual Recording
GPS Auto	GPS surveying with automated removal and mapping

Table 20: Recommended Type of Operation Categories and Their Meanings. The OED should track the type of cleanup operation performed on an OOU. The table lists the recommended inputs for this field. From [BTG Incorporated (Delta Research Division). <u>Remedial Action Cost Engineering and Requirements (RACER) System 3.2.a.</u> Computer Software 1998]

B. COST INFORMATION

Huntsville Center requested that the OED have a 72-item work breakdown structure for reporting cost information. The contractor responsible for populating the OED stated that finding cost information in this detail was unrealistic since no requirement exists for contractors to report cost information in this detail [Chandler 1999]. A more detailed cost structure is desirable, but this thesis requires the following fields at a minimum.

1. Date Fields for Cleanup Phases

The database needs to add date fields so that cost information can be normalized for inflation. The database needs to use year that the phase (Preliminary Assessment, Archive Search Report, Engineering Evaluation/Cost Analysis, and Removal Action) was completed.

2. Preliminary Assessment and Archive Search Report Total Cost

Preliminary Assessments and Archive Search Reports usually have fixed prices. These costs usually represent less than 20% of the cost to complete and therefore require a single total cost entry.

3. Labor, Material, and Travel/per Diem Costs for EE/CA and RA

The majority of the cost to complete occurs in the EE/CA and RA phases. The OED, at a minimum, needs to report costs for these two phases by "labor," "material," and "travel/per Diem" costs.

APPENDIX B. SCATTER PLOTS OF SECONDARY INDICATORS OF COST

This appendix contains the scatter plots of the OOU characteristics that the thesis considers as secondary indicators of cost. These plots do not show any discernable relationship between the OOU descriptive characteristics and cost of ordnance removal. The "secondary indicators" are topography, ordnance type, and soil type. Figure 40 shows the plots of the "secondary indicators."

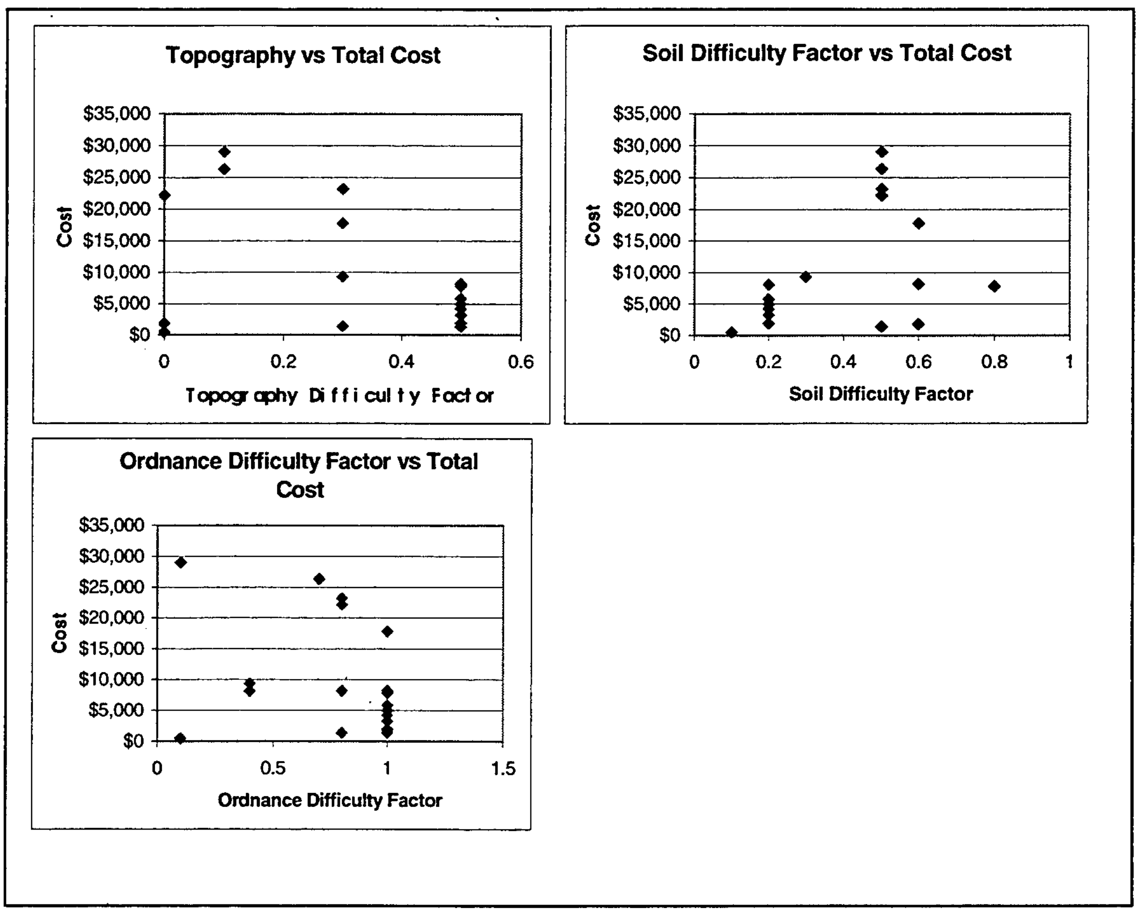


Figure 40: Scatter Plots of Secondary Cost Indicators. The secondary cost indicators include soil, topography, and ordnance difficulty factors. These cost indicators do not show expected cost correlations. The causes of these unexpected results may be due to interactions with and overshadowing by the primary indicators.

APPENDIX C. SCENARIO OUTPUT REPORT

STATS	Preliminary Assessment Total Cost	Archive Search Report Total Cost	EECA Labor Cost per/acre	EECA Travel PerDiem Cost per/acre	EECA Material Cost per/acre	RA Labor Cost per/acre	RA Material Cost per/acre	RA Travel PerDiem Cost per/acre
Min	$25,760	$41,890	$650	$250	$60	$3,170	$300	$1,210
Median	$26,190	$42,700	$900	$380	$200	$4,440	$1,000	$1,840
Average	$26,414	$42,581	$999	$526	$354	$4,907	$1,720	$2,571
Max	$27,190	$43,500	$1,340	$1,530	$1,070	$6,700	$5,240	$7,520
Standard Deviation	$471	$725	$237	$450	$348	$1,202	$1,700	$2,218
TRIANGLES								
Alpha	7	7	7	100	0	7	3	25
Triangle Left	$23,184	$37,701	$500	$250	$60	$2,500	$200	$1,000
Triangle Center	$26,190	$42,700	$800	$500	$200	$5,000	$1,000	$1,500
Triangle Right	$32,628	$52,200	$1,500	$1,000	$1,070	$8,000	$6,500	$6,000

SELECTION CRITERIA	Min	Max
Density	0	100
Vegetation	Shrubs with some trees	Heavy shrubs and trees or forest
Depth	2	6
Soil Type	Sand	Clay/Sand with stone
Topography	Flat	Rolling With Gorges
Ordnance	0.4	1
Type	OE	

Table 21: Output Report For the Scenario Cleanup. The report shows the summary statistics and selection criteria for the scenario cleanup.

APPENDIX D. SIMULATION SUMMARY FOR THE THREE-OOU CLEANUP

Statistic	Value
Minimum =	$716,691
Maximum =	$2,412,688
Mean =	$1,712,636
Std Deviation =	$304,859
Mode =	$1,776,624
Percentile	**Value**
5% Perc =	$1,192,057
10% Perc =	$1,303,245
15% Perc =	$1,384,165
20% Perc =	$1,452,002
25% Perc =	$1,507,119
30% Perc =	$1,550,193
35% Perc =	$1,587,742
40% Perc =	$1,630,812
45% Perc =	$1,671,128
50% Perc =	$1,727,992
55% Perc =	$1,775,038
60% Perc =	$1,803,516
65% Perc =	$1,841,867
70% Perc =	$1,886,668
75% Perc =	$1,942,782
80% Perc =	$1,997,554
85% Perc =	$2,048,605
90% Perc =	$2,102,828
95% Perc =	$2,187,061

Table 22: Simulation Summary for the Three-OOU Cleanup. This table shows the summary statistics and the cumulative density function for the cost of the three-OOU cleanup. The distribution is nearly symmetrical with the mean, median, and mode all roughly $1.7 million.

APPENDIX E. 72-ITEM WORK BREAKDOWN STRUCTURE

Work Breakdown Structure ID	Description
1	Document
32	Program Management
321	Project Management
322	EE/CA
3221	In-House Work-Agreements
322102	Project Support Product Services
322103	Work Plans
322105	Field Investigations
322111	Formulation and Evaluation of RA Alternatives
322112	Draft Investigation Report
322113	Final Investigation Report
322114	Value Engineering Studies
322115	Decision Documents and Related Products
322116	Other
3222	AE and Professional Services Procurement
3223	AE and Professional Services Contracts
322302	Project Support Products/Services
322303	Work Plans
322304	Records Research
322305	Field Investigations
322311	Formulation and Evaluation of RA Alternatives
322312	Draft Investigation Report
322313	Final Investigation Report
322314	Value Engineering Studies
322315	Decision Documents and Related Products
322316	Other
3224	AE Supervision and Review
322403	Project Support Products
322404	Work Plans
322406	Field Investigations
322411	Final Risk Assessment Report
322412	Formulation and Evaluation of RA Alternatives
322413	Draft Investigation Report
322414	Final Investigation Report
322415	Value Engineering Studies
322416	Decision Documents and Related Products
322417	Other
3225	Customer Technical Assistance
322502	Project Support Products/Services
322503	Work Plans
322504	Records Research
322505	Field Investigations
322511	Formulation and Evaluation of RA Alternatives
322512	Draft Investigation Report
322513	Final Investigation Report
322514	Value Engineering Studies
322515	Decision Documents and Related Products

322516	Other
33	Remediation Action
3301	Mobilization and Preparatory Work
3302	Monitoring, Sampling, Testing, and Analysis
3303	Site Work
3304	OE Removal and Destruction
330401	Community Relations Meetings
330402	Location Surveys and Mapping
330403	Ordnance Removal and Destruction
3318	OE Disposal
3320	Site Restoration
3321	Demobilization
3322	General Requirements
332201	Supervision and Management
332202	Administrative Job Office
332203	Warehouse, Materials Handling, and Purchasing
332204	Engineering, Surveying, and Quality Control
332205	Equipment Maintenance and Motor Pool
332206	First Aid, Fire Protection, Traffic Control, and Security
332207	Health and Safety
332208	Temporary Construction Facilities – Ownership
332209	Temporary Construction Facilities – Operation
332210	Project Utilities
332211	Misc. Project Expenses
332212	Insurance, Interest, and Fees

Table 23: The 72-Item Work Breakdown Structure. The OED cost reporting structure incorporates this work breakdown structure. The structure is hierarchical and indents subtasks of primary tasks. Populating the OED with cost data proves difficult because contractors rarely report data with this fidelity. This thesis uses a more aggregated cost breakdown based on available cost data.

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