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ORDNANCE AND EXPLOSIVES SITE STATISTICAL SAMPLING BASED METHODOLOGY (SiteStats)

Final Report

For U.S. Army Engineer Division
Huntsville, Alabama

TECHNICAL REPORT 95-R-011

Contract: DACA87-94-C-0015

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EXECUTIVE SUMMARY

The OE Site Statistical Sampling Based Methodology (SiteStats) has been developed by QuantiTech, Inc., under contract DACA87-94-C-0015 to the U.S. Army Engineer Division, Huntsville (USAEDH), to address two specific purposes.

The first purpose is to provide guidance for sampling in areas potentially contaminated with ordnance and explosives (OE). Sequential sampling procedures are incorporated in SiteStats at two levels to determine sampling termination points. The sequential process performed at the sector level (where sectors are defined to be areas comprised of homogeneous features — terrain, vegetation, OE density, etc.) determines if an initially-defined sector truly is an area of homogeneous OE density. If an area is found to be non-homogeneous, then the homogeneous areas within the initially-defined sector are identified as unique sectors. This delineation of homogeneous areas is important in remediation planning, allowing for identification of the minimum area that may require remediation.

SiteStats sector level characterization provides random (by the software) or user selection of grids for intrusive investigations. Because this selection and the sequential test for homogeneity involves real-time decision-making based on the sequence of grid sampling results, it is not known prior to sampling exactly how many grids in a sector will require investigation. However, at the completion of each grid's sampling, the confidence in the conclusion drawn (concerning OE contamination homogeneity) is known.

An integral part of the intrusive investigation is the second level of sequential sampling tests. The sequential sampling occurs at this level within a particular grid selected for intrusive investigations. This second level is referred to as GridStats (Grid Statistical Sampling Tool).

The necessity for GridStats has been made clear by experiences at several FUDS. Many sampling grids have contained large number of anomalies, some on the order of 2,000 anomalies. Grids with these large numbers of anomalies could take weeks to investigate, at a substantial cost, if 100% investigated. After weeks of investigation, one would have a very good idea of what was located in that individual grid. Unfortunately, the rest of the FUDS would still be awaiting characterization. The idea behind SiteStats/GridStats is simple: accept a small amount of uncertainty in characterizing the individual grids in exchange for a much greater understanding of the contamination of the overall site using sequential sampling techniques to minimize costs.

To gain better overall site characterization, SiteStats efficient sampling methodology was developed so that a small uncertainty in grid characterization could lead to grid sample sizes that were a fraction of the total number of anomalies in the grid. This is accomplished using a sequential probability ratio test (SPRT) that incorporates the additional information gained by the known total number of anomalies within a grid. Because the SPRT involves real-time decision-making depending on the sequence of sampling results, it is not known prior to sampling exactly how many anomalies in a grid will be investigated. It is known that the average sample sizes are roughly 50% of the number of samples required using a fixed sample plan, where the number of anomaly samples required is known before actual sampling begins.

The second purpose of SiteStats is remediation planning after a density estimate has been acquired from SiteStats site characterization. The SiteStats Remediation Planning Tool (RPT) allows users to identify a criterion for planning: a given amount of work, a given cost, or a given residual risk. Once the analysis criterion has been specified, RPT determines the effect on the other two criteria and plots the results. RPT allows trade studies by FUDS project managers during the planning stage.

SiteStats is implemented in Visual Basic for field use on a personal laptop computer with 4MB of RAM. Microsoft Windows and a mouse are required.

ORDNANCE AND EXPLOSIVES SITE STATISTICAL SAMPLING BASED METHODOLOGY (SiteStats) FINAL REPORT

1.0 OVERVIEW

1.1 INTRODUCTION

To effectively and efficiently address site remediation, the U. S. Army Engineer Division, Huntsville, (USAEDH) Ordnance and Explosives (OE) Mandatory Center of Expertise (MCX) and Design Center requires a rational statistical methodology to assist decision makers in successfully characterizing OE contamination at various sites (e.g., FUD, BRAC, etc.). The methodology will be used to assist management in making level-of-remediation versus cost-of-remediation decisions. The tool is intended for "field use" and, as such, can be implemented on a laptop personal computer.

This Final Report (DI-A0005) contains documentation of the OE Site Statistical Sampling Based Methodology (SiteStats) developed by QuantiTech under contract DACA87-94-C-0015. All statistical and cost methodologies implemented and integrated into the tool are fully documented in the following sections. Section 2 contains a description of the use of SiteStats in sector characterization, i.e., estimating contamination density and homogeneity. Under this application, SiteStats addresses the question of: "What are the geographic boundaries of homogeneous UXO density?" Section 3 contains a description of the use of SiteStats at the grid level (i.e., GridStats). Under this application GridStats addresses the question of: "What is the expected UXO density (and total item density) of this grid?" Section 4 contains a description of the use of the Remediation Planning Tool, i.e., project manager choices between level of work, cost, and risk. Under this application, SiteStats addresses questions such as: "What is the cost and residual risk associated with clearance to 2 feet? What level of residual risk is achievable and what clearance depth is required if $2 M is spent on remediation? What is the cost and what clearance depth is required if risk (probability of exposure) is reduced to 1/100,000?"

1.2 HARDWARE REQUIREMENTS

The SiteStats methodology development contract specified that SiteStats must be designed for implementation on a laptop computer with 4 MB of RAM. SiteStats is implemented in Visual Basic which requires:

- any IBM-compatible machine with an 80286 processor or higher
- hard disk drive
- 5 1/4" or 3 1/2" floppy drive
- EGA, VGA, 8514, Hercules, or compatible display
- 1 MB of memory
- mouse
- Microsoft MS-DOS version 3.1 or later
- Windows version 3.0 or later in standard or enhanced mode.

1.3 USER INTERFACE

SiteStats is designed to provide complete, intuitive ease-of-use. The minimal number of inputs required for use of the tool are elicited from users through the use of input text boxes, check boxes, and selection buttons. Informational messages are provided to users to indicate their "location" in the processes. All user inputs are subject to an "error check" and "inappropriate" menu selections are disabled in SiteStats.

SiteStats SECTOR CHARACTERIZATION PROCESS SUMMARY

SiteStats may be used in sampling to characterize the OE contamination of a user-defined area. The SiteStats methodology guides sampling within a sector through use of a sequential process, ensuring that for given statistical errors, the minimum required grid sampling is accomplished. In addition to the statistical-based stopping rules, sampling can also be halted based on cost. If the original sampling budget is to be exceeded, then sampling can be halted, or, if the cost to sample the next grid is not worth the expected improvement in Type I errors and Type II errors, then sampling can also be halted. In the cases where sampling is halted based on cost, the achieved Type I and Type II errors are provided to the user.

The technical components of the SiteStats sector characterization process include: Type I error and Type II error thresholds, Hopkins Statistic, hypothesis tests, Sequential Probability Ratio Test, inverse distance interpolation, and clustering based on the Migrating Means method.

2.0 SiteStats SECTOR CHARACTERIZATION PROCESS

2.1 OVERVIEW

SiteStats may be used during sampling efforts at a site contaminated with OE, such as that occurring during the preparation of an Engineering Evaluation/Cost Analysis (EE/CA). SiteStats provides insight into establishing the boundaries of contaminated areas and estimating the density of contamination in an area. The tool factors are: the area to be investigated, the size of a sampling grid, the risk error and cost error levels, the sample data (item type and location), and the cost to sample.

SiteStats site characterization process can be considered at three levels of decomposition. (See Figure 2.1-1). The highest level, an overall site level, is focused on characterization of an entire site. Division of a site into a set of sectors, each with homogeneous ordnance density, is the desired result. The next lower level, a sector level, is concerned with characterization of a single sector. Establishing the sector boundaries of an area with homogeneous ordnance density and also estimating the sector density are the desired results. The methodology associated with the lowest level of decomposition, a single sampling grid, is referred to as GridStats. Estimation of the ordnance contamination density, within the grid, is the desired result. Sector level processing is described in this section and GridStats is discussed in Section 3.0.

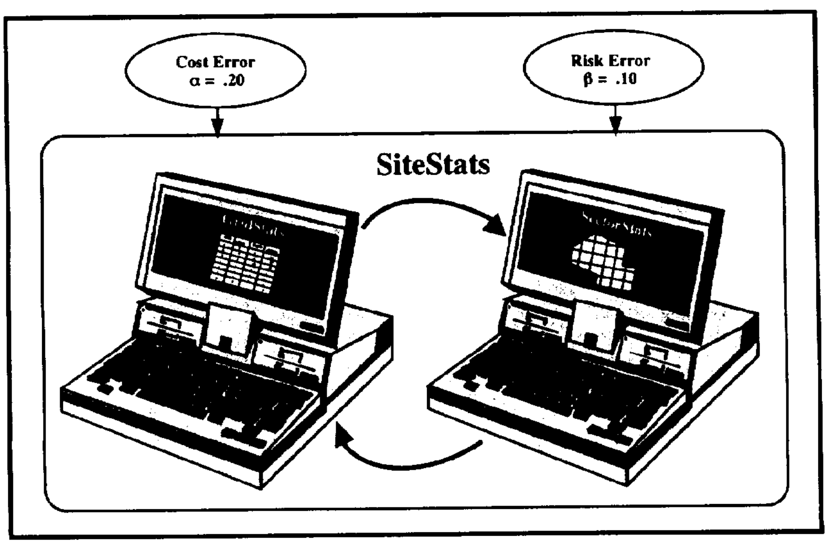


Figure 2.1-1. SiteStats Characterization Factors

2.2 SECTOR PROCESS DETAILS

The flow chart in Figure 2.2-1 shows a top-level view of the site characterization process using SiteStats.

2.3 SETUP

2.3.1 Sector Definition

The first step in the SiteStats sector characterization process is to establish the required parameters for the sampling activity. First the user must establish an initial sector decomposition of the site undergoing characterization. See Figure 2.3.1-1 for a notional representation. The user is required to input the maximum length and width dimensions of a rectangle that will encompass the entire sector. A rectangle of the specified area is then presented to the user for refinement. The user then must click "off" the area (represented as small squares within the encompassing rectangle) not included within the sector bounds.

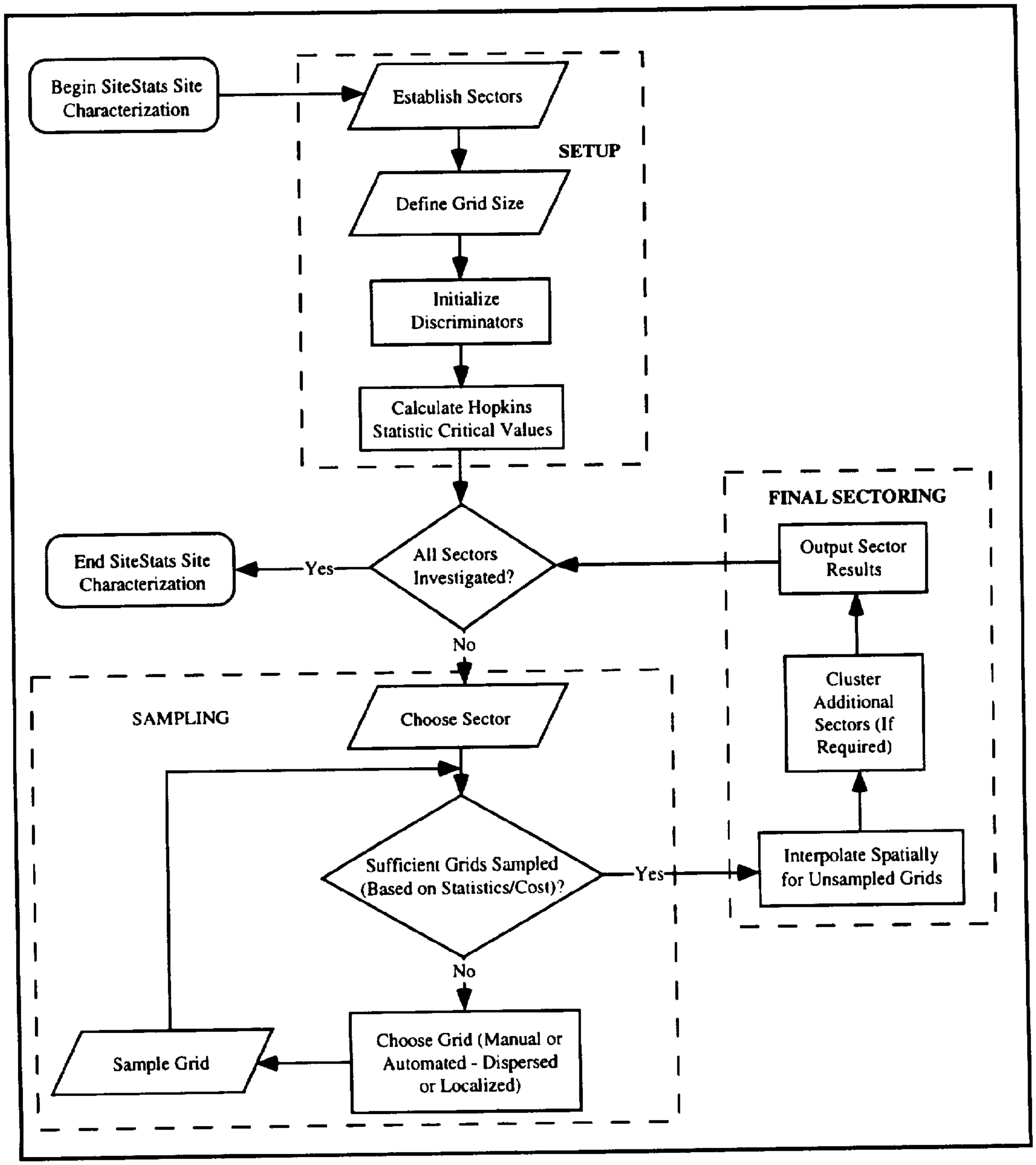
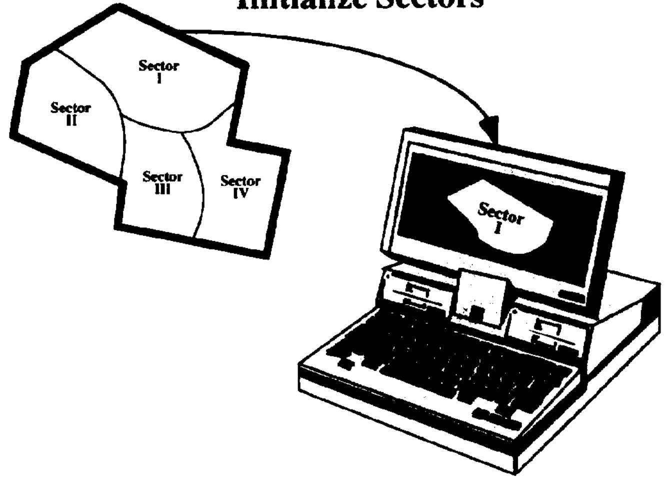


Figure 2.2-1. Site Characterization Process Using SiteStats

Initialize Sectors



- **Define Map Boundaries**
- **Portray Sector in Graphical User Interface Environment**
- **Boundary Basis**
  - **Archive Search Report**
  - **Site Assessment**
    - **Activities**
    - **Soil Type**
    - **Vegetation/Terrain**

Figure 2.3.1-1. Initial Sector Decomposition

The sectoring can initially be based on information gathered by observation and from the Archive Search Report. This information includes: vegetation, soil type, slope of the terrain, historical use, and current activities. The largest geographically continuous area with common (homogeneous) traits is defined as an initial sector.

2.3.2 Grid Size Definition

The next step in the SiteStats sector characterization process setup is to define the grid size to be used in sampling within the sector. From this length-by-width definition provided by the user, an internal grid system is stored in the computer as shown notionally in Figure 2.3.2-1. Although the sector will not be physically grided in this manner for the EE/CA sampling, this internal representation is used to record sampling performed in the "closest" physical grid to the internally-represented grid system.

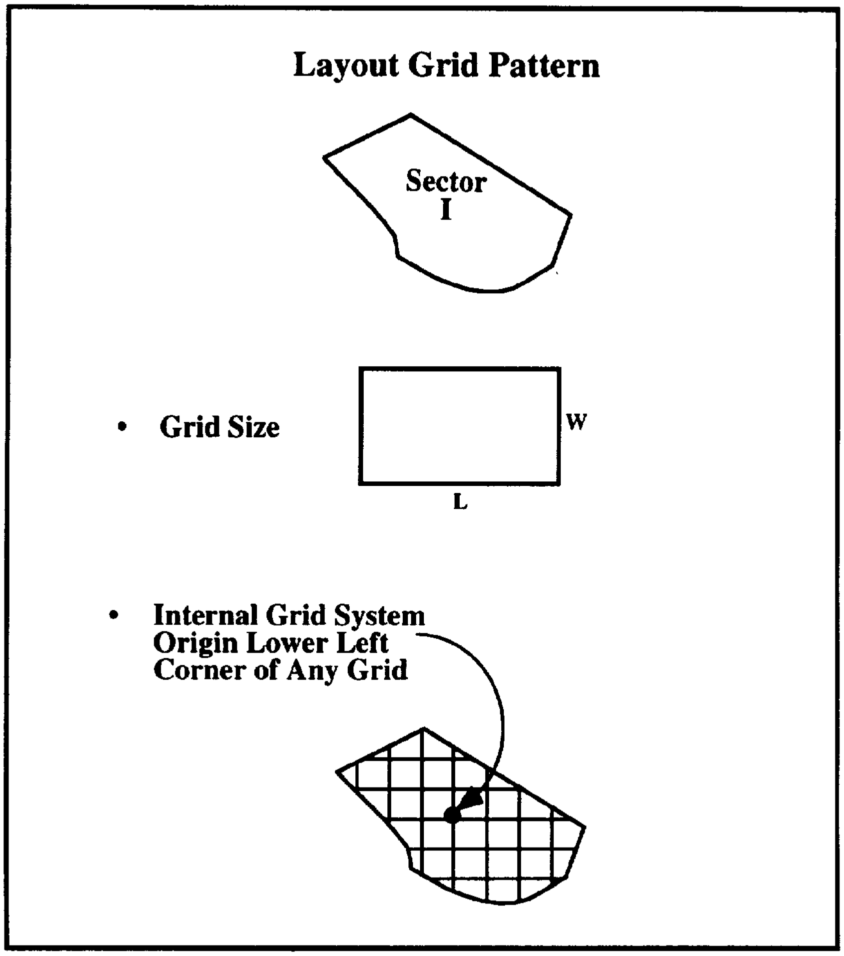


Figure 2.3.2-1. Grid Layout

Now a recommended number of grids to sample in each sector can be determined, using the following "rules of thumb." See Appendix A for a detailed discussion of their development.

$$\min \bar{n}_s = 3.28\ N_S^{0.217}$$

$$\text{average } \bar{n}_s = 6.55\ N_S^{0.217}$$

$$\max \bar{n}_s = 9.83\ N_S^{0.217}$$

where,

$\bar{n}_s$ = number of grids to sample

$$N_S = \frac{\text{Sector Area}}{\text{Grid Area}}$$

The minimum required number of grids to sample $(\min \bar{n}_s)$ is based on a regression of the data developed from "best case" SiteStats scenarios. This geometric regression was performed on the minimum sequential probability ratio test (SPRT) sampling requirements for drawing sector homogeneity conclusions using the Hopkins Statistic. The dependent variable for this regression is the number of grids in the sector, which is approximated by N_S.

The expected sector sampling requirements $(\text{average}\, \bar{n}_s)$ are based on a preliminary study of clustered and non-clustered areas within an original sector, using the SiteStats tool. A conservative estimate of the expected sample number is approximately two times the minimum requirements, although there is a large variance associated with this. This estimate is based on engineering judgment.

The maximum sector sampling requirements $(\max \bar{n}_s)$ are based on the fact that most sampling conducted using a SPRT terminates by an additional 50% of the expected sample requirements.

In the case of the SiteStats development efforts, grid size impacts upon sampling have been a point of concern. The following paragraphs address the issue of appropriate grid sizes. Currently, SiteStats evaluates sector level sampling using a measure of spatial UXO homogeneity, the Hopkins Statistic (discussed in a later section). This statistic is embedded in a sequential probability ratio test (SPRT) incorporating a hypothesis test (discussed in a later section) which attempts to answer the question: Is the sector of interest homogeneous with respect to the UXO spatial distribution, or does it appear that a significant spatial variation in UXO indicates more than one random process is appropriate for modeling the presence of UXO in this sector? The underlying distribution for this SPRT is hypergeometric, because the sampling grid area represents a proportion of the total (known and finite) sector area. Nevertheless, we can use the characteristics of the binomial SPRT to determine the worst case expected number of grids required for sector level sampling in SiteStats, when the area of the individual sampling grids is small (less than 1 %, as we will see) in comparison to the total sector area. When this binomial assumption is true, the sector area is statistically infinite relative to the sampling grid area. In other words, the sector area is so large in comparison to the grid area that from a **statistical** viewpoint, it is infinite in size. Alternatively, relative to the sector area, the sampling grids are sampling points regardless of their area, when this statistical situation occurs.

The worst case expected sample size for the binomial SPRT is given by:

$$E(n) = \frac{\ln(\frac{1-\alpha}{\beta})\ln(\frac{1-\beta}{\alpha})}{\ln(\frac{p_1}{p_0})\ln(\frac{1-p_0}{1-p_1})}$$

where

$\alpha =$ p(concluding the sector is not homogeneous when it is) = 0.2

$\beta =$ p(concluding the sector is homogeneous when it is not) = 0.1

$p_1 =$ Hopkins Statistic value above which sector is called non-homogeneous = 0.62

$p_0 =$ Hopkins Statistic value below which sector is called homogeneous = 0.50.

For the given SiteStats values of these statistical parameters, the worst case expected sampling requirement at the sector level, E(n), is found to be 63 grids. Using the standard rule that the binomial statistical requirement is met when a sample size is 10% or less of the total population results in 630 grids as the threshold requirement for the sampling grids to be sampling points, regardless of area. Thus, we may state that once the individual sampling grids are small enough that the total sector area is comprised of 630 sampling grids (or more), further reductions in sampling grid area have no statistical effect on sector level sampling. The threshold sector areas for common sampling grids are 145 acres (100' by 100'), 290 acres (200' by 100'), and 1158 acres (200' by 400'). Sector areas above these sizes are statistically infinite for these respective sampling grid sizes and smaller. A good rule of thumb for this threshold is 1.5 acres of sector area for every 100 square feet of sampling grid area.

In conclusion, when the area of the sector exceeds the threshold established above (relative to the sampling grid area), there are no additional sector level sampling requirements (i.e., no additional sampling grids to investigate) resulting from reductions in the sampling grid area, because the sampling grid is statistically a sampling point relative to a statistically infinite sector area. So grids on the order of 50' x 50' may be useful in the SiteStats implementation.

2.3.3 Discriminators

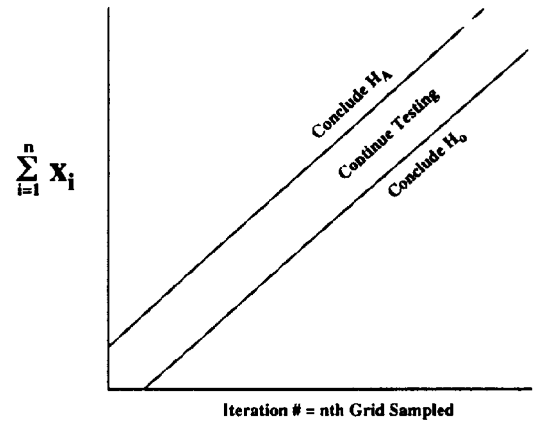
The next step in the SiteStats sector characterization process setup is to define the discriminators. These discriminators serve to identify the "stopping points" for the sequential grid sampling that occurs within a sector. Sampling within a sector is halted by a Type I error value, α, a type II error value, β, and Hopkins Statistic critical values. The Type I error, α, is defined as the probability of stating that a sector has non-homogeneous UXO density when actually the density is homogeneous. The Type II error, β, is defined as the probability of stating that a sector has homogeneous UXO density when actually the density is non-homogeneous across the sector. Appendix B contains a discussion of the sector characterization process discriminators--how they are established and how they are used within the methodology.

The Hopkins Statistic critical values are used to determine if clustering is required after the sampling is completed (is the sector homogeneous?). If the sector is non-homogeneous, the Hopkins Statistic will indicate how many clusters (i.e., new sectors) are required to encompass the non-homogeneous portions. Appendix C contains a technical discussion of the Hopkins Statistic in measuring the tendency of data to cluster and in identifying a preferred number of clusters.

2.4 GRID SAMPLING

The next step in the SiteStats sector characterization process is to identify a sector in which to begin sampling grids. The sampling procedure to be followed is sequential, so that after each grid is sampled, a decision (based on the cumulative results of the grids investigated) is made concerning whether or not sampling should continue. A grid is investigated using the procedure described in Section 3.0, and the expected UXO density of each grid is fed to this sector level process in SiteStats. Figure 2.4-1 shows a graphical representation of this sequential sampling process, referred to as the Sequential Probability Ratio Test (SPRT). Appendix D contains a technical discussion of the SPRT.

Sector Level Sequential Sampling



Sequential Probability Ratio Test:

- **Two parallel lines define the stopping rule**
- **Slope = f (Sampling Discriminator)**
- **Sampling Discriminator = f (Hopkins Statistic)**
- **Separation Distance = f (Type I Error, Type II Error)**
- **H_0: Sector is Poisson (has homogeneous UXO density)**
- **H_A: Sector is Not Poisson (does not have homogeneous UXO density)**

Figure 2.4-1. Sector Level Sequential Sampling

The two parallel lines shown in Figure 2.4-1 define the stopping rules. The slope of the lines is a function of the sampling discriminator and the sampling discriminator is a function of the Hopkins Statistic. The separation distance between the two parallel lines is a function of the cost error, α, and the risk error, β. The hypothesis test being evaluated is:

H_0: The sector exhibits characteristics of a homogeneous Poisson process.
H_a: The sector does not exhibit characteristics of a homogeneous Poisson process.

So, observing Figure 2.4-1, if the line plot of the results of the sequential sampling across the grids crosses outside the bottom line, then H_0 can be concluded. If H_0 is concluded then it can be stated with some certainty that the grids sampled within the sector appear to be homogeneous with respect to UXO count and spatial location. If plotting the results of the sequential sampling across the grids crosses outside the upper line, then H_a

can be concluded. If H_a is concluded, then it can be stated with some certainty that the initially-defined sector appears to be more than a single sector (with respect to UXO count and spatial location). If neither hypothesis can be concluded, sampling continues. Appendix D contains a discussion of hypothesis testing. The definition of a homogeneous sector is significant because removal actions should be applied only to the areas in which actions are necessary.

Grids to be sampled can be selected manually by the user or automatically by the SiteStats methodology. Random selection of grids by the computer is recommended to ensure the integrity of the methodology's statistical rigor. The SiteStats sector characterization process also provides for manual grid selection for those cases when users prefer a manual selection to investigate suspected hot spots, prefer to achieve some desired "full coverage," or prefer to sample in a particular area due to logistical considerations. Additionally, it is recommended that the center and "four corners" of a sector be selected manually to provide sampling coverage for those critical points.

The automated random selection is approached differently for two sector types within the SiteStats sector characterization process. The two sector types are dispersed and localized. Dispersed sectors have UXO randomly distributed over relatively large geographic areas. Examples of dispersed sectors are former bombing ranges and impact areas. Localized sectors have UXO confined to relatively small, well-defined areas. Examples of localized sectors are burial pits/trenches and OB/OD pits. The differentiation made between these two sectors types is necessary because the goal in sampling the area is different. For dispersed sectors, contamination is expected across the entire sector's area and the sampling occurs to determine the density of the residual contamination. For localized sectors, sampling occurs to determine the likelihood of encountering other, as yet undetected, localized contamination.

Random selection of grids within a dispersed sector is accomplished by generation of random numbers that correspond to the "row and column" locations of the grid within the SiteStats internal sector representation. Random selection of grids within a localized sector is accomplished by a more complex procedure. See Figure 2.4-2.

The approach for localized sectors is to quantify the likelihood of more contamination by calculating the probability that more localized contamination exists. The probability that more contamination exists around the localized sector is the complement of the probability that no more contamination exists. The probability that no further contamination exists increases with each negative sample, i.e., the anomalies sampled within grids are non-UXO. The localized sector grid selection process is implemented by generating two pseudo-random numbers. (Pseudo-random is used to represent the fact that since the values are generated using a known, set methodology, the values are not truly random.) The first random number is drawn from a uniform distribution and is used to identify the azimuth from the area identified by the user as the location of maximum ordnance density. The second random number is drawn from a triangular distribution and represents a distance along the identified azimuth chosen with the first pseudo-random number. This distance is weighted toward the identified concentration of contamination and away from the sector boundary. The grid at the intersection of this azimuth and range is designated for sampling.

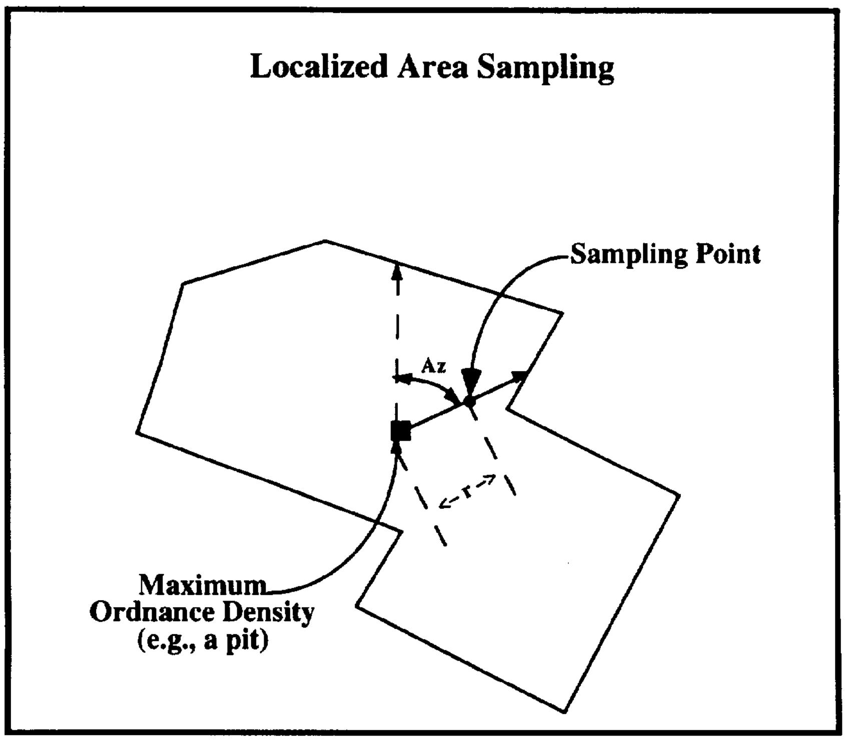


Figure 2.4-2. Grid Selection for Localized Area Sampling

2.5 FINAL SECTORING

The SiteStats sector characterization process can indicate that a sufficient number of grids have been sampled based on three different criteria. One criterion is the sector-level hypothesis test discussed in Section 2.4. The SPRT on-going in the process will indicate when the required sequential sample size has been achieved to conclude one of the alternative hypotheses.

For the cases when the sequential sampling encounters a "bad" random sequence, the sufficient number of grids sampled is based on a fixed sample size. Thus, the maximum number of grids to be sampled is the value of a fixed sample size given a population composed of the number of grids within the sector. Additionally, the SiteStats site characterization process provides other decision points at which decision-makers can decide to terminate sampling. The decision points are based on sampling cost issues. The sampling costs are determined through use of the Field Cost Model. Appendix F contains a technical discussion of the Field Cost Model.

The first of these alternative "stopping rules" is based on a comparison of the dollars spent on the sampling effort versus the planned budget for the sector. Before the "next grid" is identified for sampling within a sector, a check is made on the current cumulative cost of the sampling versus the budget identified by the user at the initiation of sampling. If the cumulative cost is larger than the budget, an appropriate message is presented to the user with the option to terminate sampling, even though the SPRT has not indicated termination based on statistical characterization of the sector.

The other alternative "stopping rule" is based on a decision maker's judgment. The expected improvement in the sector characterization Type I error and Type II error is evaluated against the cost of the next sample. Before the "next grid" is identified for sampling within a sector, the change in Type I error and Type II error resulting from the next sample is estimated, as is the cost to sample the next grid. A summary of this information is presented to the user, with the option to terminate sampling if the user determines that the improvement in error is not worth the cost to sample.

After one of the above three termination criteria is reached, the final decomposition of the initial sector can be determined if the Hopkins Statistic critical value indicates the grids sampled are non-homogeneous. If no further sector decomposition is required, then the sector characterization process is completed. Figure 2.5-1 shows the steps in the final sectoring process when further sector delineation is required. The first step of this final sectoring is to estimate a density for all the grids within the internal representation of the sector that were not sampled. A spatial interpolation routine based on inverse distance is invoked to provide the estimates for the non-sampled grids. The routine is intuitive, provides a smooth representation of density estimates across the sector and is minimally computationally complex. The routine provides no precision estimate, however. Appendix G contains a technical discussion of the routine.

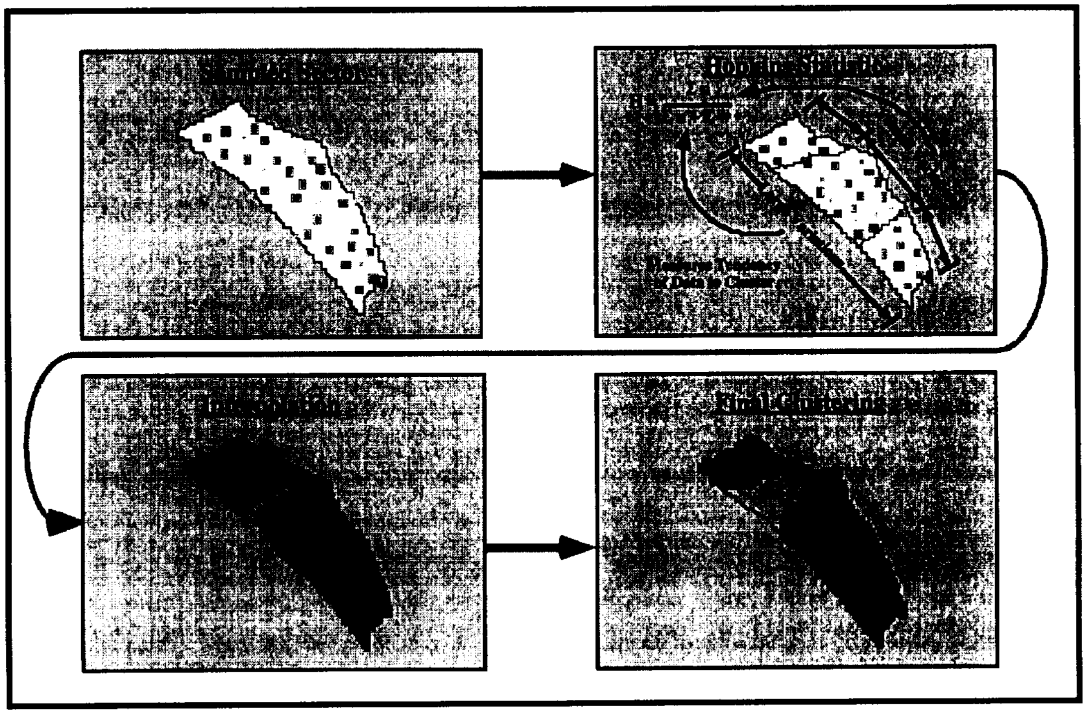


Figure 2.5-1. Final Sectoring Methodology

Once the unsampled grids have been assigned a density estimate through spatial interpolation, a clustering methodology is invoked to group the data into the number of clusters (i.e., sectors) provided by the Hopkins Statistic Critical Value. (See Section 2.3.3 and Appendix C for details on the Hopkins Statistic). If the Hopkins Statistic indicates that no further clustering is required, then the SiteStats process is completed upon performance of the interpolation. But, if the Hopkins Statistic indicates that the sector does not exhibit the characteristics of a homogeneous Poisson process (i.e., has grids with homogeneous UXO count and spatial location), then the initial sector being investigated must be decomposed into separate sectors that are homogeneous. The clustering routine used in the SiteStats site characterization process to create these homogeneous sectors implements the Migrating Means approach. Migrating Means is an approach that is widely used in the environmental/remote sensing disciplines. The method is low in computational complexity, is consistent with the Hopkins Statistics and implicitly places equal weights on all features of the grids. The details of the clustering approach are provided in Appendix H.

2.6 DATA REQUIREMENTS

The SiteStats sector characterization process requires several user inputs. Table 2.6-1 identifies the data item required, an explanation of each item and the use of each item.

Table 2.6-1. Sector Characterization Data Requirements

Data Item	Explanation	Use
Site Location	A meaningful name/number of the FUDS or other site at which the sampling will occur.	Identification in output reports
Sector ID	A meaningful designator for the area in which the sampling is to occur	Identification in output reports
Sector Type	Dispersed (e.g., firing range or impact area) or Localized (e.g., trench or burial pit)	Choice of appropriate grid selection scheme.
Sector Length	The maximum length of a rectangle which will encompass the sector	Notional representation of sector and establishment of contamination density and bounds
Sector Width	The maximum width of a rectangle which will encompass the sector	Notional representation of sector and establishment of contamination density and bounds
Grid Length	The length of the sampling grids which are to be used	Notional representation of grid and establishment of contamination density
Grid Width	The width of the sampling grids which are to be used	Notional representation of grid and establishment of contamination density
Slope	The predominant slope of the ground within the sector. Level (0^o - 10^o), Moderate (10^o - 30^o), or Steep (>30^o)	Estimate cost to sample the "next" grid. Cost increases with slope.
Vegetation Type	The predominant vegetation coverage within the sector--clear, brushy, trees, or marsh.	Estimate cost to sample the "next" grid. Cost increases with vegetation density.
Soil Density	The predominant soil density within the sector, either light (e.g., sand) or heavy (e.g., clay).	Estimate cost to sample the "next" grid. Cost increases with soil density.
Other Properties	The condition for footing within the sector, either slippery or not.	Estimate cost to sample the "next" grid. Cost increases with suspect footing.
Hours Breakdown	The percentage of the UXO removal team investigating a grid. Can be UXO specialists, geophysical instrument operators, or common laborers.	Estimate cost to sample the "next" grid. Cost increases with worker specialization.

GridStats GRID SAMPLING PROCESS SUMMARY

SiteStats may be used in sampling to characterize the OE contamination in a sampling grid. This is referred to as GridStats. The GridStats methodology guides anomaly investigations through use of a sequential process, ensuring that for given risk and cost errors, the minimum required anomaly sampling is accomplished.

The technical components of the GridStats process include: cost error, risk error, and discrimination thresholds. The cost error, $\alpha = 20\%$, is the probability of stating that a grid's contamination is above the discrimination threshold when it is not. The risk error, $\beta = 10\%$, is the probability of stating that a grid's contamination is below the discrimination threshold when it is not. The discrimination threshold is a contamination level at which removal actions may be necessary, 5 UXO in a grid or 0.0235 UXO to total anomalies in a grid.

3.0 GridStats GRID SAMPLING PROCESS

The flowchart in Figure 3.0-1 shows a top-level view of the anomaly sampling process within a grid using GridStats.

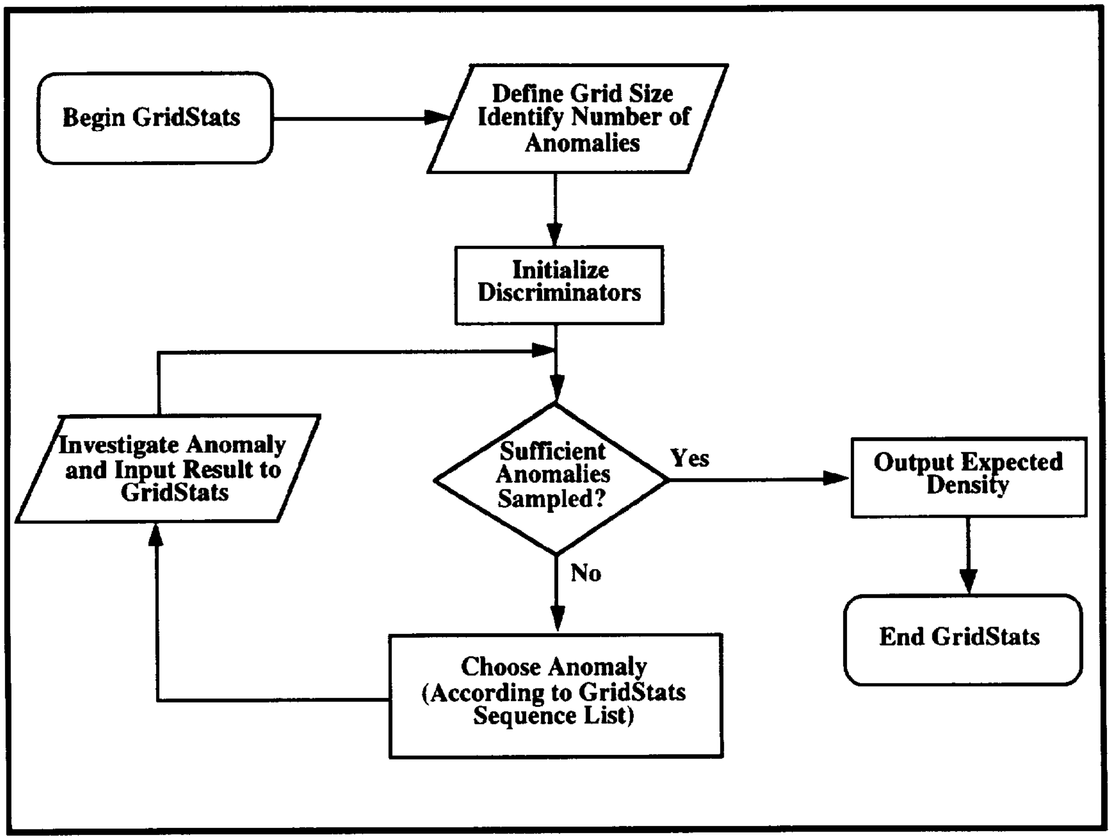


Figure 3.0-1. GridStats Logic

3.1 GRID SIZE DEFINITIONS

Users must identify the sampling grid size dimensions (length and width). The area measurement is used to predict UXO density and total item density.

Intuitively, an acceptable sampling grid size is one which allows for the sampling of a (statistically) sufficient number of anomalies for the determination of the presence of, and accurate estimation of, the quantity of UXO in that area. As an example, suppose the actual anomaly density in the sector is random and equal to 1 anomaly every 100 square feet. Suppose also that the actual UXO proportion in the sector is random and equal to 1 UXO for every 10 anomalies. Then, a sampling grid of area 1000 square feet has the potential of identifying 10 anomalies and 1 UXO item, on average. Provided enough sampling grids of this size are investigated, there is some opportunity that both the anomaly and UXO densities will be reasonably estimated. Estimates for the mean square error (ability to estimate) of the UXO density may be given by the variance of the hypergeometric distribution, since the hypergeometric SPRT used in GridStats is unbiased. The unbiased estimate of this variance is given by:

$$s^2 = n(\frac{D}{N})(1-\frac{D}{N})(\frac{N-n}{N-1})$$

where

n = the number of anomalies in the grid which are investigated,

D = the number of UXO items in the grid,

N = the total number of anomalies in the grid.

To determine the estimate of the variance, s^2, one needs the information to estimate n, D, and N. The number of anomalies investigated in the grid, n, may be estimated using the average sample sizes of GridStats. Unfortunately, the average within-grid sample sizes are usually a strong function of the (unknown) UXO proportion, D/N, and the (unknown) anomaly density, N/A, where A is the area of the sampling grid. The total number of anomalies in the grid, N, is generally known, provided the grid is completely magged and flagged, but is not known prior to investigation, when sampling grid size is determined. Thus, the best that can be done is to take a look at the empirical evidence that is available. The most statistically significant site at which GridStats has been used is Southwestern Proving Ground (SPG). The estimated average anomaly density at SPG is 213 anomalies/grid divided by 20,000 square foot grids, or 0.01065 anomalies/square foot. The estimated average UXO density at SPG is approximately 0.00122 UXO/square foot, or about 1 UXO for every 9 anomalies. The average sample size using GridStats at SPG was about 25 % of the (known) total number of anomalies. Given this (after-the-fact) information, the SPG UXO estimation variance can be rewritten in terms of the sampling grid area:

$$s^2 = \frac{0.00020255A}{0.01065A - 1}$$

As the sampling grid size becomes large, this variance approaches 0.019, or roughly 2 %. A plot of the estimated variance against sampling grid area is shown in Figure 3.1-1.

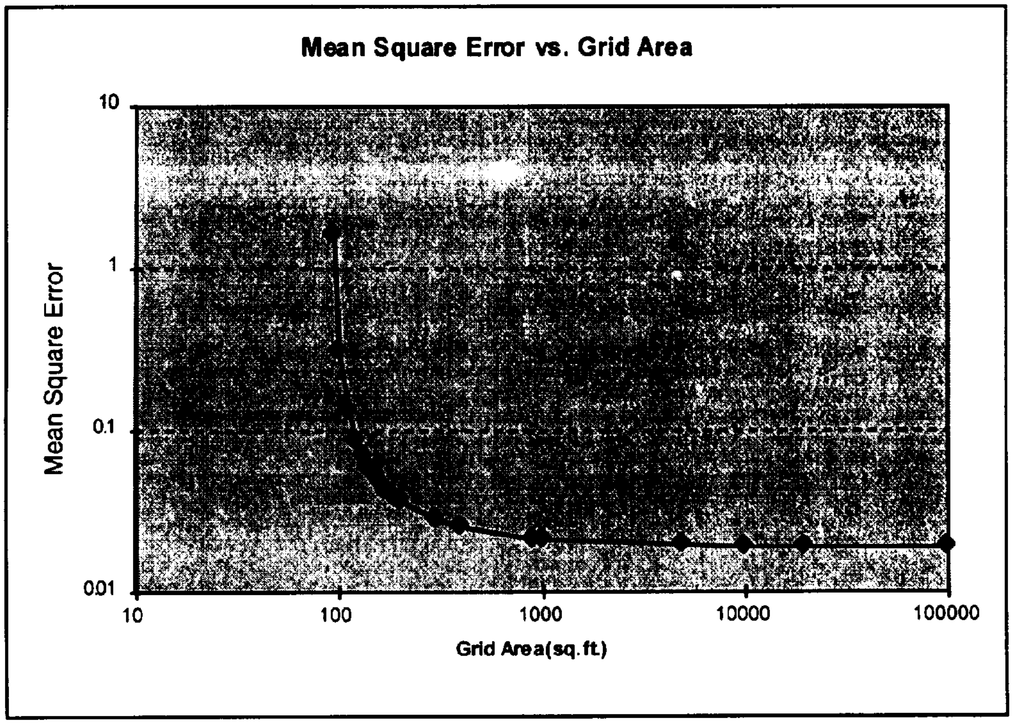


Figure 3.1-1. Variance versus Sampling Grid Area

The knee of the curve is somewhere near 400 square feet (20' by 20' sampling grid), where the variance is roughly 2.5 %. Given that there is not prior knowledge, it is best to err on the high side for sampling grid areas. However, it appears that once fairly high densities are established, smaller grid sizes could be used to ensure that higher UXO concentrations could be identified (see next section). A sequential process for grid size selection, within grids and across the sector, could be established based on this simple approach. In conclusion, 50' x 50' grids appear sufficient.

3.2 IDENTIFICATION OF NUMBER OF ANOMALIES

Three choices are available to users for identifying the number of anomalies.

1. The number of anomalies within a grid to be investigated is unknown, and not estimated (but possibly conjectured to be above a certain amount).

2. The number of anomalies within a grid to be investigated is known.

3. The number of anomalies within a grid to be investigated is unknown, but estimated through a partial assessment of the grid.

Under Scenario 1, a binomial module is implemented (see Section 3.2.1). Under Scenario 2, a hypergeometric module is implemented (see Section 3.2.2). Under Scenario 3, both the binomial and hypergeometric modules must be considered, and a decision made to use one based on anomaly count (see Section 3.2.3 for a discussion of the errors associated with the decision).

3.2.1 Grid Anomalies Unknown

Using this option, the number of anomalies within a grid is not determined prior to sampling. Thus, no estimate of the total number of anomalies within the grid is available for use during the sequential sampling process. The statistical ramification of this is that because no information (estimated or known) is provided on the total number of anomalies within the grid, the binomial distribution must be used as the basis for the sequential sampling process. The most efficient sequential sampling process for this application is a truncated binomial sequential probability ratio test (SPRT).

The binomial module includes a binomial SPRT with a number of stopping rules (truncation points), the most important of which is the fixed stopping rule when no UXO are found during sampling. Appendix I provides a technical discussion of the binomial module. To use the binomial SPRT, a target proportion discriminator (defined as UXO items to sampled anomalies within a grid) is used.

3.2.2 Grid Anomalies Known

Using this option, the total number of anomalies within the grid is determined prior to sampling. The statistical ramification of this is that because known information is provided on the total number of anomalies within the grid, the hypergeometric distribution may be used as the basis for the sequential sampling process, using the sequential probability ratio test (SPRT).

The hypergeometric module includes a hypergeometric SPRT with a number of stopping rules (truncation points), the most important of which is the fixed stopping rule when no UXO are found during sampling. Appendix I provides a technical discussion of the hypergeometric module. To use the hypergeometric SPRT, either a target proportion of UXO items to total anomalies within a grid or a fixed number of UXO items per grid is used as a discriminator.

3.2.3 Grid Anomalies Estimated

Using this option, the total number of anomalies within a grid is estimated prior to sampling. (This estimation could come from a partial investigation, such as would be the case if, due to heavy vegetation, a portion of the grid was cleared of vegetation and anomalies located in the cleared portions.) The statistical ramifications of this is that since the total number of anomalies within the grid are extrapolated from a smaller portion of the grid to the total grid area, two statistical errors (Type III and Type IV) associated with total anomaly count are introduced during sampling.

When the anomaly count in a grid is not known, but can be estimated based on a partial assessment of the grid, two new statistical errors are introduced relative to the estimation of the anomaly count. Note that these errors are not to be confused with the errors associated with UXO estimation that will be discussed later, Type I (α) and Type II (β) errors. The new statistical errors are called Type III (γ) and Type IV (δ) errors. These are associated with an important hypothesis test concerning the anomaly count a grid:

$$H_0 : N \leq N_{crit}$$
$$H_A : N > N_{crit}.$$

Here H_0 is the null hypothesis, which states that the actual number of anomalies in a grid (N) is less than or equal to some critical anomaly count (N_{crit}). H_A is the alternative hypothesis. The value of N_{crit} is an anomaly count of interest. In making a decision about using the binomial or hypergeometric module, N_{crit} is the minimum number of anomalies in a grid at which the binomial distribution approximates the hypergeometric distribution.

N_{crit} also is then the point at which the sampling requirements curves, associated with both types of discriminators (a fixed number of UXO or a fixed proportion of UXO), intersect. This intersection defines the discriminator decision point within the hypergeometric module. The Type III and Type IV errors are defined as:

Type III error = Probability that it is concluded that there are greater than N_{crit} anomalies in the grid when the opposite is actually true.

Type IV error = Probability that it is concluded that there are less than or equal to N_{crit} anomalies in the grid when the opposite is actually true.

In the case where a decision is being made between using the binomial and hypergeometric modules, a Type III error is costly in two ways:

1. Because a Type III error results in the use of the binomial module when the hypergeometric module should be used, more sampling will be performed in the grid than is necessary. This is due to the fact that a binomial module always requires more sampling than a hypergeometric module, and in the case of an overestimation of anomalies, the sampling requirements difference can be significant.

2. Because the total number of anomalies have been overestimated, the total number of UXO is likely to be overestimated, resulting in higher estimated remediation costs.

A Type IV error, however, is costly in one way and risky in another:

1. Because a Type IV error results in the use of a hypergeometric module when a binomial module should be used, additional flagging costs will be incurred to get an accurate anomaly count.

2. Because the total number of anomalies have been underestimated, the total number of UXO is likely to be underestimated, resulting in greater public risk.

Similar arguments may be made when the decision concerns the type of discriminator (fixed value or fixed proportion) to be used in the hypergeometric module. The technical details of the Type III and IV errors are presented in Appendix J.

3.2.4 GridStats Operational Logic

Figure 3.2.4-1 shows the decision logic for implementing the binomial and hypergeometric (using either a fixed value or proportion discriminator) modules.

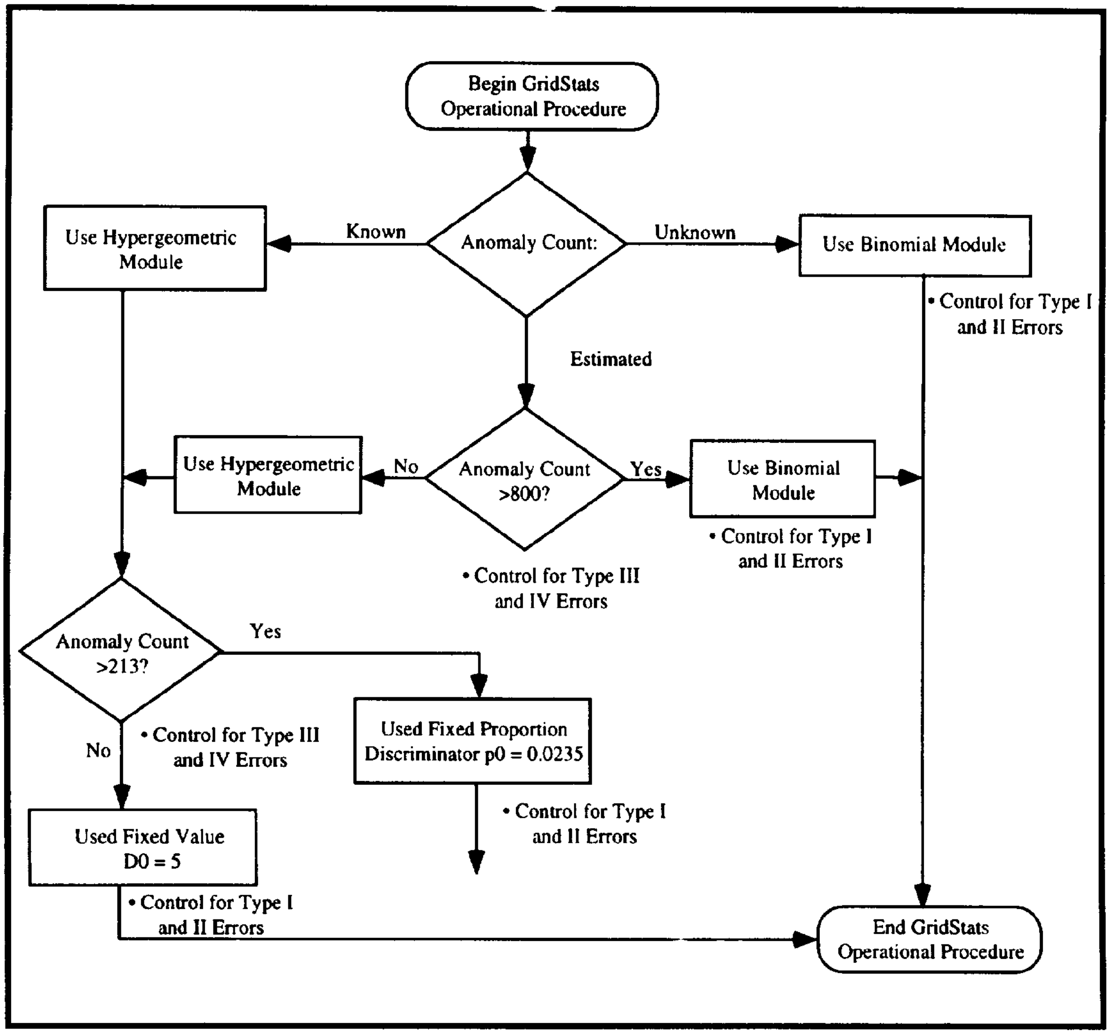


Figure 3.2.4-1. GridStats Logic Options Based on Anomaly Count Approach

3.3 INITIALIZING DISCRIMINATORS

The GridStats discriminators serve to identify the "stopping points" for the sequential anomaly sampling that occurs within a grid. A cost error value, α, risk error, β, and a UXO value, D, are all used in determining when to halt sampling within a grid.

The cost error, (α = 20%), is defined as the probability of stating that a grid's contamination is above the discriminator, D, when it is not. The cost error occurs when "unnecessary" removal actions are performed based on the incorrect conditions. The risk error, (β = 10%), is defined as the probability of stating that a grid's contamination is below the discriminator, D, when it is not. The risk error occurs when needed removal actions are not performed or are delayed based on the incorrect conclusion.

The discriminator value, D, is defined as the level at which removal actions may be necessary and is composed of two component pieces for use in the hypergeometric module. If a grid has not more than 213 anomalies, then a fixed value of 5 UXO/grid is used as the discriminator. If a grid has more than 213 anomalies, then a fixed proportion of 0.0235 UXO to total anomalies is used as the discriminator. Since the binomial module has no knowledge of anomaly count, the 0.0235 proportion is implemented as its discriminator. Appendix B provides a discussion of GridStats discriminators.

3.4 ANOMALY SAMPLING

A grid conforming to the user-specified grid dimensions is displayed to the GridStats user. The grid is decomposed into 32 smaller areas (each 25' x 25'). A random number selection is generated to provide users with a sampling sequence to follow for within-grid sampling. These sampling sequences (implemented in the tool's software) guide users to one of the 32 "squares" where the next anomaly should be sampled. When directed to a particular square, UXO clearance teams proceed to the indicated location and sample any anomaly in that area. Once the anomaly is identified, the results are entered into the GridStats methodology. Results are identified as: (1) UXO, (2) UXO-related scrap, and (3) other ferrous items. This anomaly-by-anomaly sampling process continues until the stopping rules established by the UXO discriminator used in the SPRT indicates that sampling can be discontinued. An estimate of the grid's UXO density (and total anomaly density) is provided to the SiteStats sector characterization process.

The stopping rules implemented in GridStats are shown in Figure 3.4-1.

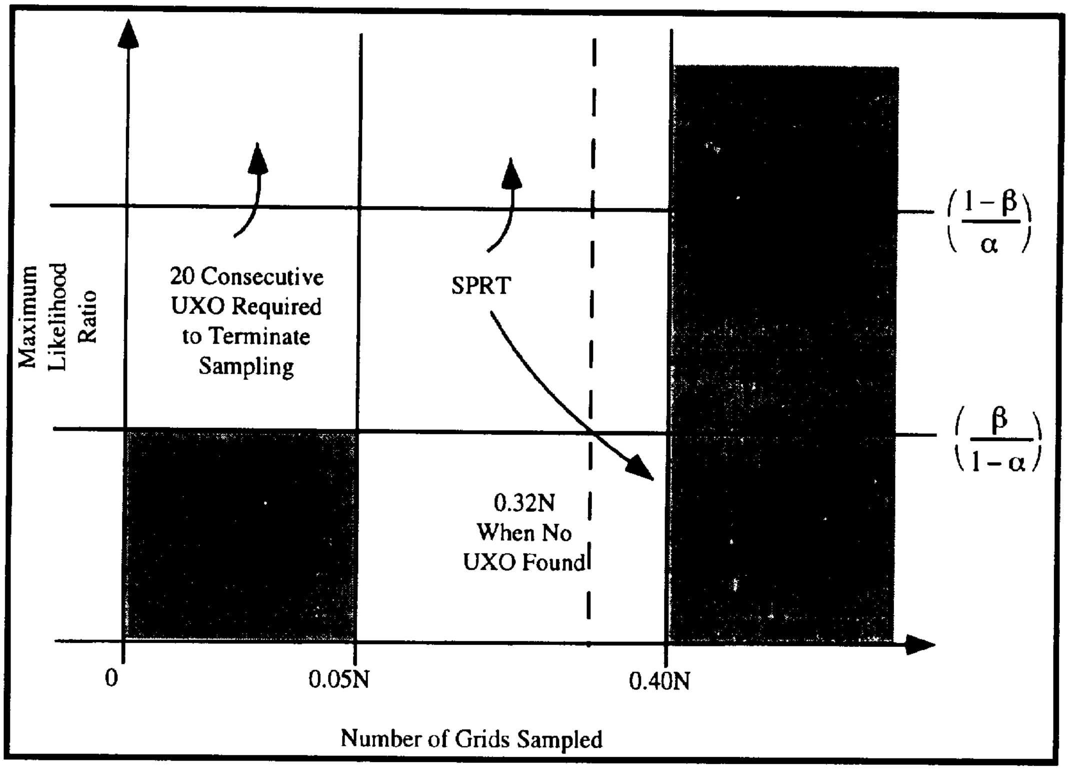


Figure 3.4-1. GridStats Stopping Rules

In Figure 3.4-1, the following definitions are applicable:

N = Total anomalies in the grid

β = risk error (0.20)

α = cost error (0.10).

Maximum Likelihood Ratio = $\dfrac{\text{Likelihood that grid has density that may require remediation}}{\text{Likelihood that grid has density that may not require remediation}}$

$$MLR = \frac{\binom{P_1 N}{X_n}\binom{N(1-P_1)}{n-X_n}}{\binom{P_0 N}{X_n}\binom{N(1-P_0)}{n-X_n}}, \text{ where}$$

P_0 = 5/N or 0.0235 = Proportional value that may not require remediation
P_1 = 1.2 * P_0 = Proportional value that may require remediation
N = Total anomalies in grid
n = Current anomaly sampled
X_n = Cumulative UXO found

Continue Sampling:

$$\frac{\beta}{1-\alpha} < MLR < \frac{1-\beta}{\alpha}$$

From Figure 3.4-1 it can be seen that the minimum anomalies investigated within a grid will be 5% of the total anomalies in the grid, unless 20 consecutive UXO are found before 5% of the anomalies have been investigated. The maximum anomalies investigated within a grid will be 40% of the total anomalies in the grid, unless the SPRT process concludes before 40% of the anomalies have been investigated. These minimum and maximum values are based on "best engineering judgment" and were developed in conjunction with USAEDH guidance.

3.4.1 Binomial SPRT

The binomial module requires a fixed proportion of UXO items to total anomalies as a discriminator, because the total anomaly count is unknown. Figure 3.4.1-1 depicts the binomial intermediate stopping rule sample sizes (assuming no UXO is found) using a fixed proportion of 0.0235 (UXO to total anomalies) as a grid discriminator. (Note: The intermediate stopping rule is a fixed sampling plan based on zero UXO found during sampling.) Since the binomial distribution presupposes no knowledge of anomaly count, the sample requirements of 80 (the requirement for p = .0235 as seen in Figure 3.4.1-1) anomalies are independent of anomaly count.

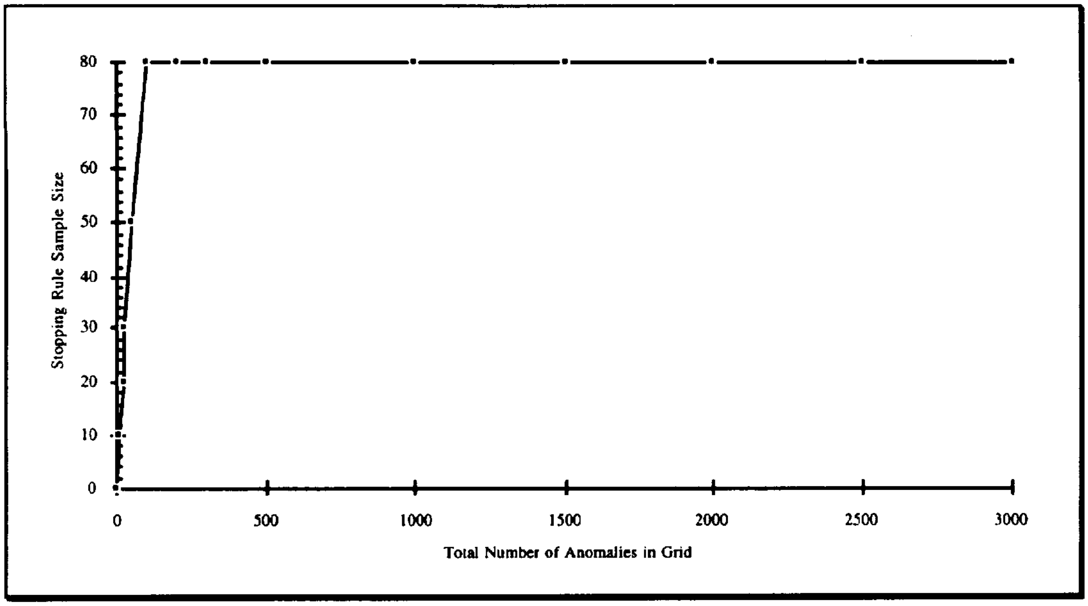


Figure 3.4.1-1. Binomial SPRT Intermediate Stopping Rules

Figure 3.4.1-1 shows that for a discriminator of 0.0235, 100% of the anomalies are investigated for all grids with less than 80 anomalies, and 80 anomalies are investigated for grids with greater than 80 anomalies. Table 3.4.1-1 summarizes this information.

Table 3.4.1-1. Data for Binomial SPRT Intermediate Stopping Rule

Number of Anomalies Within Grid	Anomalies to Sample ($p_0 = 0.0235$)
0	0
10	10
20	20
30	30
50	50
100	80
200	80
300	80
500	80
1000	80
1500	80
2000	80
2500	80
3000	80

Table 3.4.1-2 shows the sampling requirements for the binomial module when 0, 1, 2, 3, and 4 UXO are found.

Table 3.4.1-2. Data For Binomial SPRT Final Stopping Rule

Total Anomalies	0 UXO Found	1 UXO Found	2 UXO Found	3 UXO Found	4 UXO Found
0	0	0	0	0	0
10	10	10	10	10	10
20	20	20	20	20	20
30	30	30	30	30	30
50	50	50	50	50	50
100	80	100	100	100	100
200	80	147	188	200	200
300	80	147	188	236	282
500	80	147	188	236	282
1000	80	147	188	236	282
1500	80	147	188	236	282
2000	80	147	188	236	282
2500	80	147	188	236	282
3000	80	147	188	236	282

3.4.2 SPRT Hypergeometric

The hypergeometric module can operate with a either a fixed value of UXO items per grid as a discriminator or a fixed proportion of UXO items to total anomalies as a discriminator. This is because the hypergeometric module uses a known or estimated value for the total number of anomalies in a grid. Figure 3.4.2-1 depicts the hypergeometric intermediate stopping rule sample sizes using a fixed value discriminator of 5 UXO per grid and a fixed proportion discriminator of 0.0235 (UXO to total anomalies). (Note: The intermediate stopping rule is a fixed sampling plan based on zero UXO found during sampling.) As indicated in Figure 3.4.2-1, the sampling requirements vary with anomaly count since the hypergeometric distribution is dependent on full or partial knowledge of anomaly count.

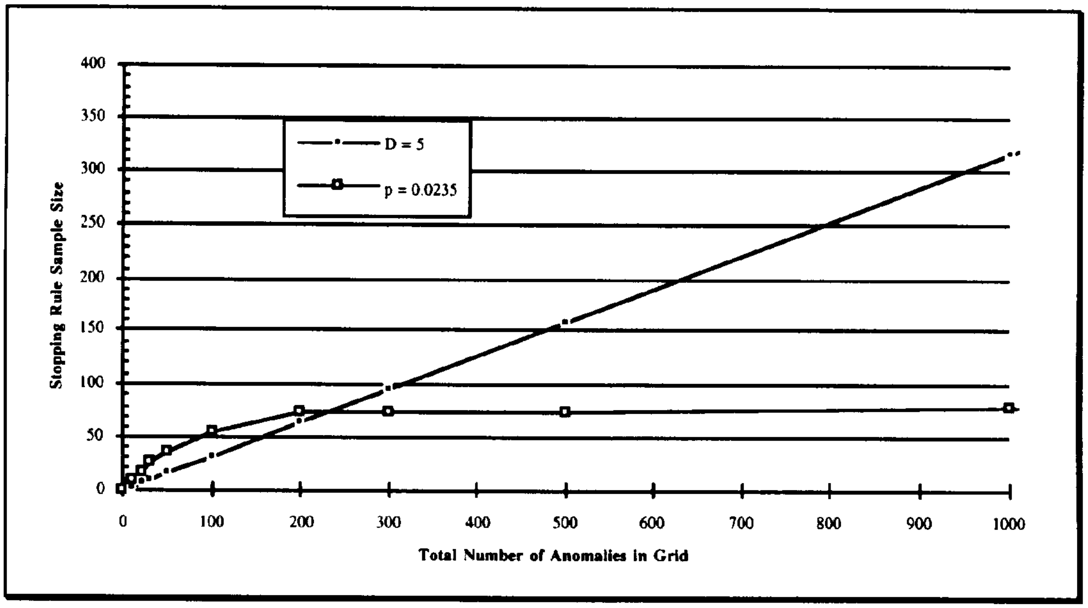


Figure 3.4.2-1. Hypergeometric SPRT Intermediate Stopping Rules

Because the sampling requirements for a fixed number of UXO items per grid is linear, while those for a fixed proportion of UXO items to total anomalies flattens out with increased anomaly counts, points of operational interest may be identified where these curves cross. The break point between using a fixed value discriminator and a fixed proportion discriminator for 5 UXO per grid is 213 anomalies. Above this anomaly count, the fixed proportion sampling plan is relatively insensitive to anomaly count, and below this anomaly count, the fixed value UXO per grid discriminator provides the lower sampling requirements. Table 3.4.2-1 summarizes this data.

Table 3.4.2-1. Data for Hypergeometric SPRT Intermediate Stopping Rules

Number of Anomalies	Anomalies to Sample (D=5)	Anomalies to Sample (p_0=.0235)
0	0	0
10	3	9
20	6	18
30	9	27
50	16	34
100	32	54
200	63	63
300	95	67
500	159	75
1000	318	78
1500	477	79
2000	636	79
2500	795	80
3000	954	80

Fundamentally, the purpose of using statistics during grid investigation is the inherent nonlinearity of statistical sampling. While sampling more than is necessary can provide better information within a grid, it is not necessary from a statistical standpoint and can be very costly. Switching from a fixed value discriminator to a fixed proportion discriminator at the appropriate critical anomaly count provides minimum sampling requirements (in the region to the left of the critical anomaly count, where the nonlinearity works against us and the region to the right, where the nonlinearity works for us) while maintaining control of Type I and II errors.

Table 3.4.2-2 provides the final stopping rule sampling requirements for the hypergeometric module when 0, 1, 2, 3, and 4 UXO are found.

Table 3.4.2-2. Data For Hypergeometric SPRT Final Stopping Rules

Total Anomalies	0 UXO Found	1 UXO Found	2 UXO Found	3 UXO Found	4 UXO Found
10	3				
20	6	10	13		
30	9	15	20	24	
50	16	25	33	40	45
100	32	51	66	80	91
200	63	107	126	148	167
300	67	115	140	170	196
500	71	126	154	189	221
1000	76	130	170	211	250
1500	78	132	176	219	260
2000	79	133	179	223	265
2500	80	134	182	228	270
3000	80	134	185	233	275

3.4.3 Comparison of Approaches

Table 3.4.3-1 provides a rough cost comparison of the percentage of anomalies investigated using three potential options in GridStats:

1. The hypergeometric module with a fixed value discriminator of 5 UXO/grid.

2. The hypergeometric module with a fixed value discriminator (5 UXO/grid) for grids with fewer than 213 anomalies, switching to the fixed proportion discriminator of 0.0235 UXO/anomaly for grids with at least 213 anomalies.

3. The binomial module with a fixed proportion discriminator of 0.0235 UXO/anomaly.

These results are valid for the data derived from Southwestern Proving Ground where the anomaly density is estimated to be 0.01065 anomalies/square foot and the proportion of UXO is estimated to be 0.11455 UXO/anomaly. Sites with density characteristics other than these would experience different relative efficiencies.

SiteStats REMEDIATION PLANNING TOOL SUMMARY

SiteStats may be used for remediation planning after a density estimate has been acquired from SiteStats sector characterization. The SiteStats Remediation Planning Tool (RPT) allows users to identify a criterion for planning: a given amount of work, a given cost, or a given residual risk. Once the analysis criterion has been specified, RPT determines the effect on the other two criteria and plots the results. RPT allows trade studies by FUDS project managers during the planning stage.

4.0 SiteStats REMEDIATION PLANNING TOOL

4.1 OVERVIEW

The SiteStats Remediation Planning Tool (RPT) is provided so that FUDS project managers (PMs) may assess site remediation plan alternatives based on: (1) a specified level of work performed, (2) a specified cost of remediation, or (3) a specified residual risk. The tool is intended to assist PMs in making level of remediation versus cost of remediation decisions. Each of these three options is discussed in the paragraphs below. The flow chart in Figure 4.1-1 shows a top-level view of the RPT process using SiteStats. Appendix K provides details of the risk estimating and cost estimating methodologies that form the basis of RPT.

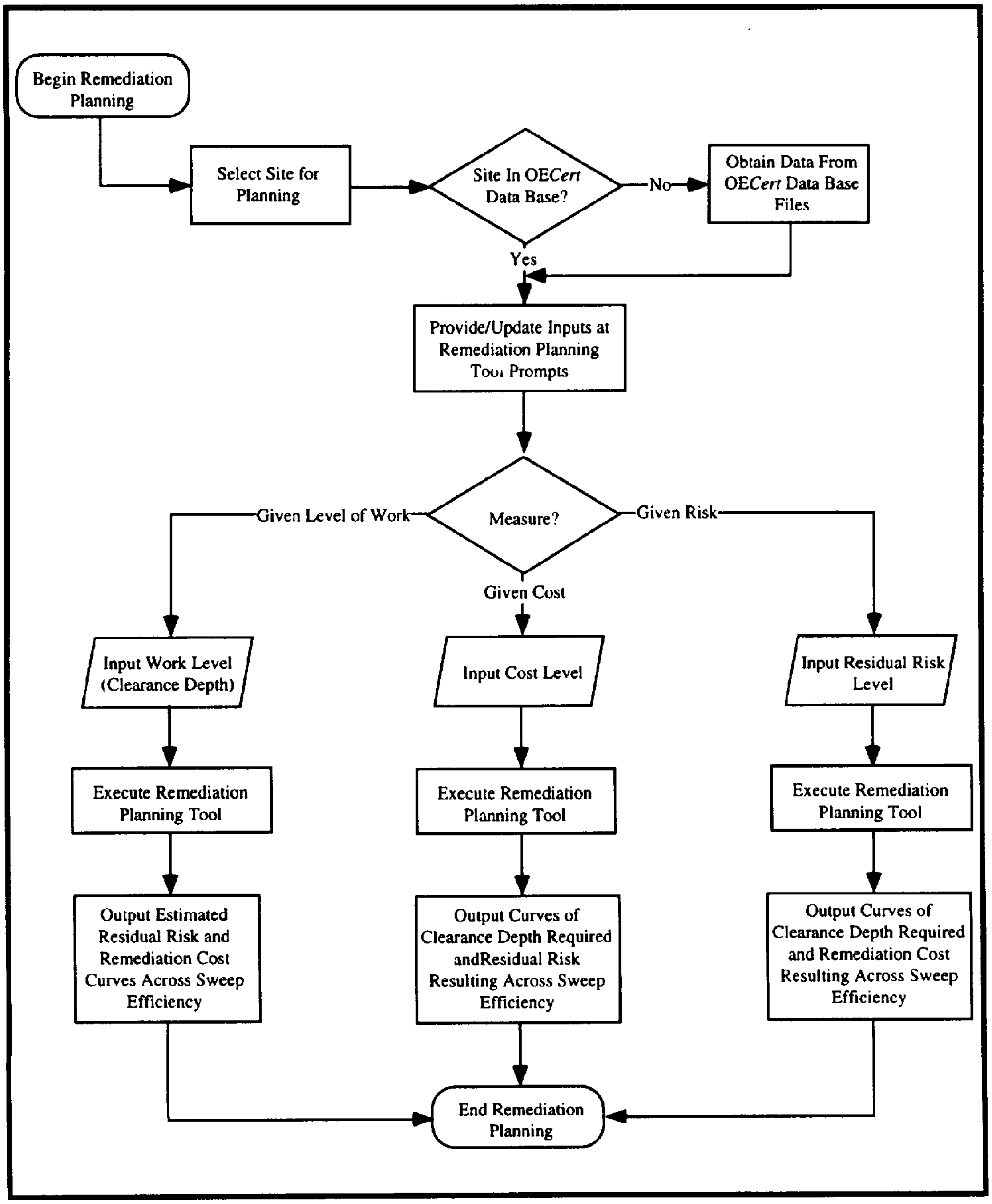


Figure 4.1-1. SiteStats Remediation Planning Tool Logic

4.2 SPECIFIED LEVEL OF WORK

A specified level of work is defined to be clearance of UXO to a specified depth, assuming some achieved sweep efficiency, where efficiency is the portion of anomalies detected and removed in the clearance action. To use this option of the SiteStats RPT, users must specify the depth (in feet) to which ordnance will be removed in the effort. The SiteStats RPT will determine the residual risk (in terms of probability of exposure) and removal cost (in dollars) associated with the user-specified clearance depth. The available data plots are curves showing the residual probability of exposure and remediation cost versus the clearance depths as shown in Figures 4.2-1 and 4.2-2. The output table shown in Table 4.2-1 is presented to users, highlighting the p(exposure) and cost achieved with the specified clearance depth (in this table, 5 feet).

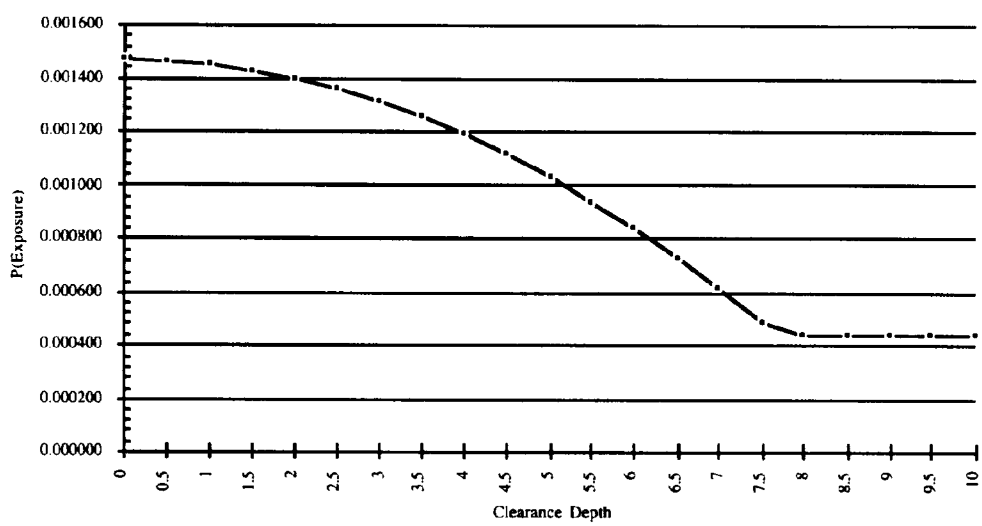


Figure 4.2-1. Risk Plot from RPT With Specified Level of Work

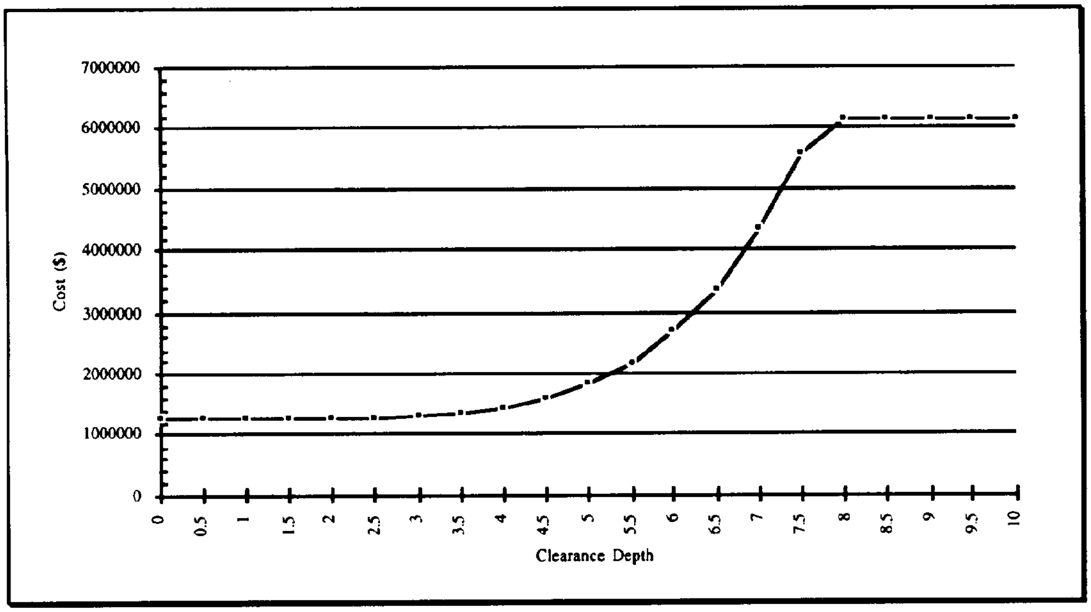


Figure 4.2-2. Cost Plot from RPT With Specified Level of Work

Table 4.2-1. Output Values from RPT With Specified Level of Work

Clearance Depth	P(Exposure) (0-1)	Cost ($)
0	0.001466	1258899
0.5	0.001461	1258905
1	0.001448	1259081
1.5	0.001426	1260283
2	0.001396	1264733
2.5	0.001357	1276702
3	0.001309	1303199
3.5	0.001253	1354649
4	0.001188	1445580
4.5	0.001114	1595304
5	**0.001031**	**1828604**
5.5	0.000940	2176414
6	0.000840	2676506
6.5	0.000732	3374173
7	0.000614	4322907
7.5	0.000488	5585094
8	0.000439	6146767
8.5	0.000439	6146767
9	0.000439	6146767
9.5	0.000439	6146767
10	0.000439	6146767

4.3 SPECIFIED COST

A specified cost is defined to be the cost associated with clearance of UXO to the clearance depth which will result in the specified dollars. To use this option of the SiteStats RPT, users must specify the dollars available for the removal effort. The SiteStats RPT will determine the clearance depth and concomitant risk reduction that can be achieved within the specified dollar constraints. The available data plots are curves showing the residual p(exposure) versus clearance depth and cost versus clearance depth as shown in Figures 4.3-1 and 4.3-2. The output table shown in Table 4.3-1 is presented to users, highlighting the clearance depth and p(exposure) achieved with the specified cost (in this example, $2M).

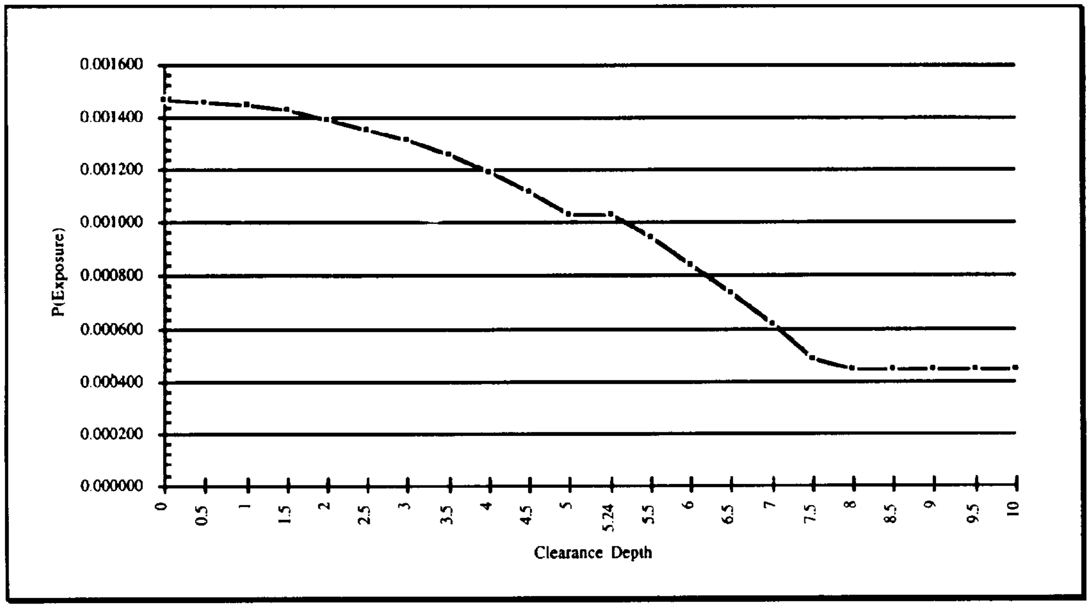


Figure 4.3-1. Risk Plot from RPT With Specified Cost

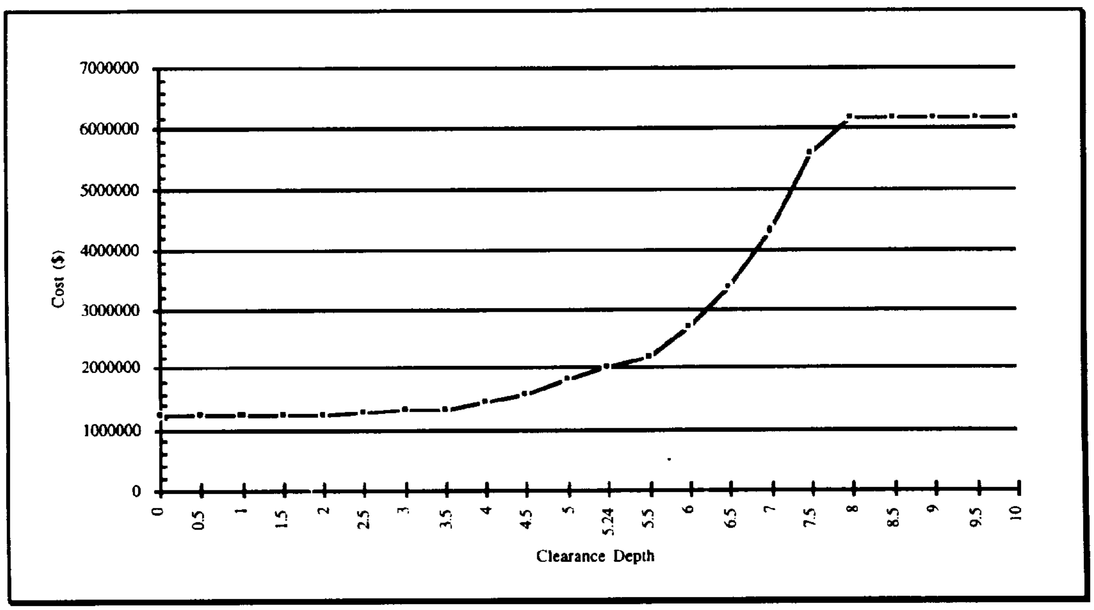


Figure 4.3-2. Cost Plot from RPT With Specified Cost

Table 4.3-1. Output Values from RPT With Specified Cost

Clearance Depth	P(Exposure) (J-1)	Cost ($)
0	0.001466	1258899
0.5	0.001461	1258905
1	0.001448	1259081
1.5	0.001426	1260283
2	0.001396	1264733
2.5	0.001357	1276702
3	0.001309	1303199
3.5	0.001253	1354649
4	0.001188	1445580
4.5	0.001114	1595304
5	0.001031	1828604
5.24	**0.001031**	**2000000**
5.5	0.000940	2176414
6	0.000840	2676506
6.5	0.000732	3374173
7	0.000614	4322907
7.5	0.000488	5585094
8	0.000439	6146767
8.5	0.000439	6146767
9	0.000439	6146767
9.5	0.000439	6146767
10	0.000439	6146767

4.4 SPECIFIED RISK

A specified risk is defined to be the probability of exposure for a single individual over all activities occurring at the site associated with clearance of UXO to some clearance depth which will result in the specified residual risk. To use this option of the SiteStats RPT, users must specify the probability of exposure to be achieved after remediation. The SiteStats RPT will determine the clearance depth that will result in this risk level. Additionally, the removal cost associated with the clearance actions that will yield the risk level is estimated. The available data plots are curves showing the remediation cost versus clearance depth and residual p(exposure) versus clearance depth as shown in Figures 4.4-1 and 4.4-2. The output table shown in Table 4.4-1 is presented to users, highlighting the clearance depth and resulting cost required to achieve the specified p(exposure) (in this example, 0.001).

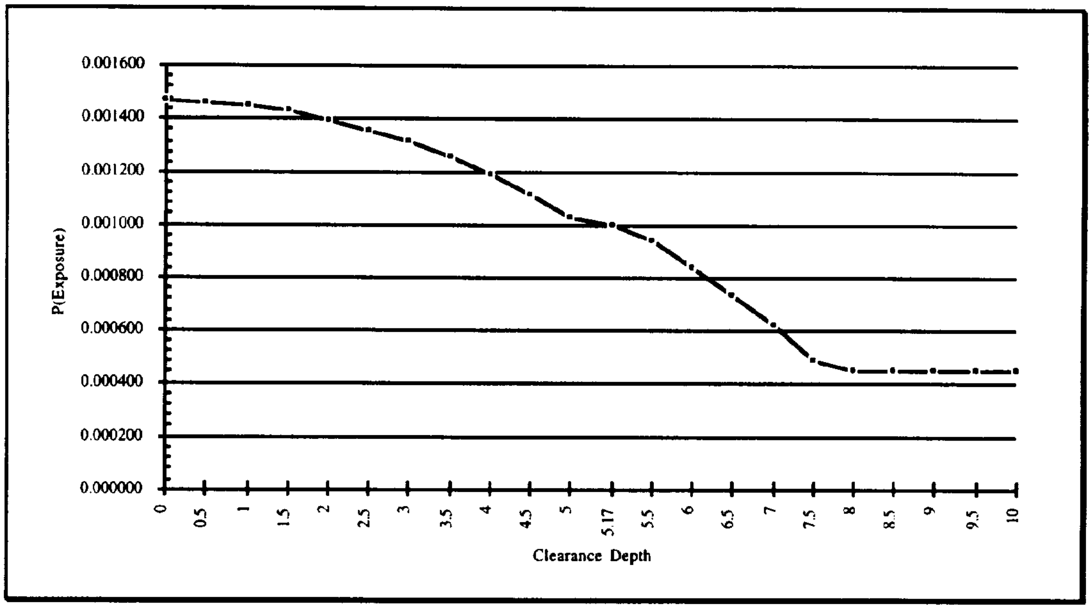


Figure 4.4-1. Risk Plot From RPT With Specified Risk

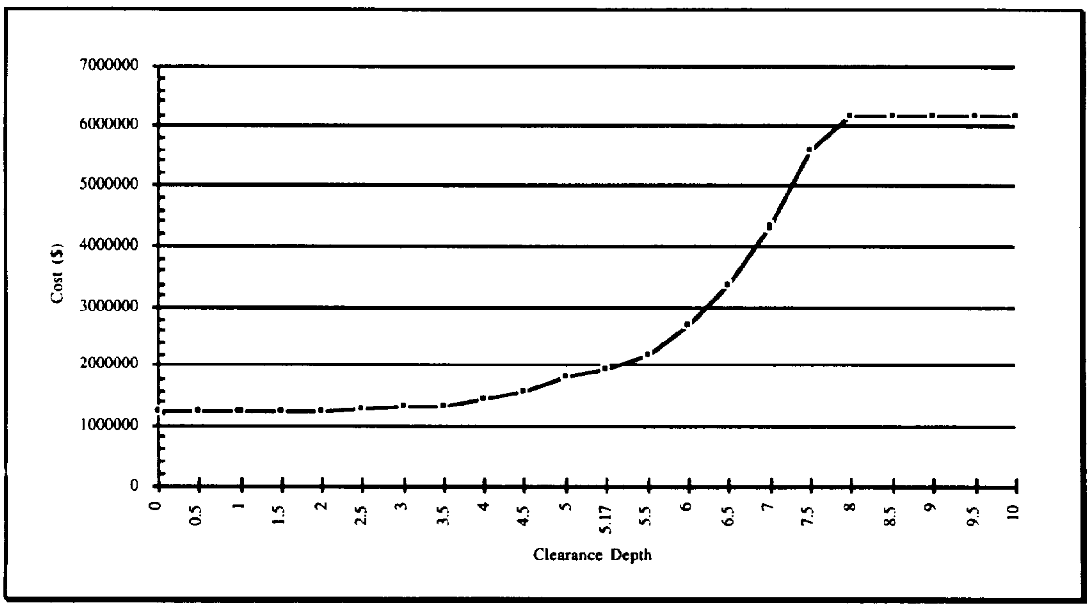


Figure 4.4-2. Cost Plot From RPT With Specified Risk

Table 4.4-1. Output Values From RPT With Specified Risk

Clearance Depth	P(Exposure) (0-1)	Cost ($)
0	0.001466	1258899
0.5	0.001461	1258905
1	0.001448	1259081
1.5	0.001426	1260283
2	0.001396	1264733
2.5	0.001357	1276702
3	0.001309	1303199
3.5	0.001253	1354649
4	0.001188	1445580
4.5	0.001114	1595304
5	0.001031	1828604
5.17	0.001000	1947950
5.5	0.000940	2176414
6	0.000840	2676506
6.5	0.000732	3374173
7	0.000614	4322907
7.5	0.000488	5585094
8	0.000439	6146767
8.5	0.000439	6146767
9	0.000439	6146767
9.5	0.000439	6146767
10	0.000439	6146767

4.5 DATA REQUIREMENTS

The SiteStats RPT requires many user inputs. If the site to be considered is resident in the OE*Cert* data base, the data can be extracted and moved to RPT. Otherwise, the data items shown in Table 4.5-1 (along with an explanation and statement of use) are required inputs by the user.

Table 4.5-1. Remediation Planning Tool Data Requirements

Data Item	Explanation	Use
Parameter to Fix	Either Clearance Depth, Fixed Dollars, Fixed Level of Risk	To guide the RPT iteration and provide outputs
Site Inputs	Define parameters associated with Site	Drives cost/risk calculation and method of process
Subset Type	Indicate type for sector: Dispersed, Localized (surface, buried, building), or Water (dispersed or localized)	Determine method of processing
Sector Inputs	Define physical parameters of each sector	Drives risk and cost calculations
Activities	Identify activities (both recreational and occupational) which occur in sector	Drives risk calculations
Direct Cost Factors	Identify remediation actions and rates for direct cost	Drives cost calculations
Indirect Cost Factors	Identify remediation personnel and rates for indirect costs	Drives cost calculations

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APPENDIX A

DEVELOPMENT OF EXPECTED SAMPLE SIZE "RULES OF THUMB"

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DEVELOPMENT OF EXPECTED SAMPLE SIZE "RULES OF THUMB"

The number of grids per sector that must be sampled to reach a sampling determination decision is dependent upon the sampling sequence of results. To estimate an expected minimum number of grids to be sampled in a sector, the following regression was performed:

$$n_s = k(N_s)^a,$$

where:

n_s = Number of Grids Sampled,

k = constant,

N_s = Number of Grids in Sector, and

a = exponent.

The data for the regression was obtained from a plot of the number of samples required to terminate sector sampling due to meeting the minimum sequential probability ratio test requirements for drawing sector homogeneity conclusions using the Hopkins Statistic. These requirements were:

Number of Grids in Sector	Required Sample Size (Best Case)
25	7
100	8
500	13
1000	15

The $n_s = k(N_s)^{an}$ regression was then performed to determine values for k and a_n. The solution proceeded as:

$$\ln(n_s) = \ln(k) + a_n \ln(N_s)$$

$$X = \begin{pmatrix} 1 & 3.22 \\ 1 & 4.61 \\ 1 & 6.21 \\ 1 & 6.91 \end{pmatrix}, X^T = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 3.22 & 4.61 & 6.21 & 6.91 \end{pmatrix}$$

$$Y = \begin{pmatrix} 1.95 \\ 2.08 \\ 2.56 \\ 2.71 \end{pmatrix}$$

$$X^T X = \begin{pmatrix} 4 & 20.95 \\ 20.95 & 117.93 \end{pmatrix}$$

$$\left(X^T X\right)^{-1} = \frac{1}{32.83}\begin{pmatrix} 117.93 & -20.95 \\ -20.95 & 4 \end{pmatrix}$$

$$X^T Y = \begin{pmatrix} 9.30 \\ 50.49 \end{pmatrix}$$

$$b = \left(X^T X\right)^{-1}\left(X^T Y\right) = \begin{pmatrix} 1.1865 \\ 0.2170 \end{pmatrix}$$

$$k = 3.2756, a = 0.2170$$

The predictor equation then for the expected minimum number of grid samples within a sector is $n_s(\min) = 3.28(N_s)^{0.217}$. From engineering judgment and empirical observation, the expected number of grids to sample within a sector is twice the minimum expected sample size, or $n_s(\text{avg}) = 6.55(N_s)^{0.217}$. Again, from engineering judgment and empirical observation, the maximum expected number of grids to sample within a sector was set as 50% greater than the expected sample size or $n_s(\max) = 9.83(N_s)^{0.217}$.

APPENDIX B

SiteStats/GridStats

PROCESS DISCRIMINATORS

APPENDIX B

SiteStats/GridStats PROCESS DISCRIMINATORS

B.1 INTRODUCTION

Estimation of sector contamination homogeneity and ordnance density is an important aspect of the site characterization process. Density estimates can be evaluated by use of a preset value referred to as the sampling discriminator. Accuracy of density or homogenity estimates is measured against preset acceptable error parameters. The sampling discriminator and error parameter values are both important in the determination of sampling requirements (i.e., the number of samples required to achieve a desired outcome).

This appendix defines the error parameters and the sampling discriminator required for the SiteStats and GridStats characterization processes. The values currently implemented in SiteStats and GridStats are provided along with the sources and rationales used to derive the values.

B.2 SiteStats ERROR PARAMETERS

Two different types of sector contamination homogeneity determination errors may occur during the sector characterization process. These errors may take the form of either Type I error or Type II error. Type I error (α) is the probability of stating that a sector has non-homogeneous UXO density when actually the sector is homogeneous. Type II error (β) is the probability of stating that a sector has homogeneous UXO density when the sector actually has non-homogeneous density across it.

The error parameter values currently utilized by the SiteStats sector characterization process are a Type I error limit of .20 and a Type II error limit of .10. These values are based on the EPA standards for environmental restoration, as provided in "Guidance for

Data Usability in Risk Assessment (Part A)" dated April 1992. The implications of these error values are that there is a 10% probability that when a sector is said to be "homogeneous," it will actually be non-homogeneous and there is a 20% probability that when a sector is said to be "non-homogeneous," it will actually be homogeneous.

B.3 GridStats ERROR PARAMETERS

Two different types of ordnance density estimation errors may occur during the site characterization process. These errors may take the form of either risk error or cost error. Risk error (β) is the probability of stating that a grid may not require remediation when it does. This erroneous conclusion results in risk error since "unidentified" UXO may be left at the site, or at least its removal delayed. Either of these scenarios could increase the public's exposure to UXO.

Cost error (α) is the probability of stating that a grid may require remediation when it does not. This erroneous conclusion results in cost error because remediation actions are based on the expected UXO density at a site. Over-estimated ordnance density could lead to unnecessary remediation actions.

The error parameter values currently utilized by GridStats are a cost error limit of .20 and a risk error limit of .10. These values are based on the EPA standards for environmental restoration, as provided in "Guidance for Data Usability in Risk Assessment (Part A)" dated April 1992. The implications of these error values are that there is a 10% probability that when an area is said to be "uncontaminated," it will actually be contaminated and there is a 20% probability that when an area is said to be "contaminated," it will actually be uncontaminated.

B.4 GridStats SAMPLING DISCRIMINATOR

The site characterization sampling discriminator (D) is a threshold value against which each grid within a sector sample is tested. Sufficient sampling is accomplished for each grid within a sector to state, within the preset error bounds (α and β), that the ordnance contamination of that grid is above or below the discriminator value (D). Grids estimated to have UXO density values greater than the discriminator are considered contaminated relative to grids with density estimates below the discriminator value. Such a "sufficiently" contaminated grid is expected to require some remediation action. Two discriminators are available for use in GridStats. A fixed value discriminator is used when fewer than 213 anomalies are present in the grid. A fixed proportion discriminator is used when more than 213 anomalies are present in the grid.

The fixed value discriminator value used by GridStats is 5 UXO per grid. This value has been successfully employed in analyses using the GridStats methodologies at Southwestern Proving Grounds and at the Former Pantex Ordnance Plant. The sampling discriminator value of 5 was initially employed in the GridStats application at Southwestern Proving Grounds. This value was based on the residual UXO density estimated for the Tierrasanta project in San Diego, CA. Analysis of the items removed from the Tierrasanta site revealed that an average of 1.02 UXO per 100′ x 200′ grid remained after remediation was completed. This number was determined by totaling the UXO removed during remediation efforts recently completed at the site. Using this total value, the "beginning" number of UXO was estimated by dividing by $(0.75)^2$ to represent the sweep efficiency experienced during remediation (two sweeps to include QA/QC). Next, the residual number of UXO items could be determined from the difference in the beginning number of UXO and the number of UXO removed. This total residual UXO was then determined for a 100′ x 200′ grid basis. The resulting grid density was then increased by a factor of 4 to account for the population differences between Hope, AR (≈9,000) and Tierrasanta, CA (≈36,000). The value was rounded to 5 items per grid for use as an expression for "equivalent density," and has been empirically validated at both Southwestern Proving Grounds and Pantex.

The fixed proportion discriminator value used by GridStats is a proportion of 0.0235 UXO to total anomalies. The proportion is calculated as:

$$p_0 = \frac{5\text{ UXO}}{213\text{ Anomalies}} \cong 0.0235.$$

In the equations for determining p_0, 5 UXO items per grid is the fixed value discriminator found to be a useful discriminator (through ground testing) in GridStats at Southwestern Proving Ground. The 213 anomalies is the mean anomalies per sampling grid at Southwestern Proving Ground. Other measures of central tendency (e.g., median) could also be used.

B.5 APPLICATION

Type I (α) and Type II (β) error parameters are implemented in the sector level Sequential Probability Ratio Test (SPRT). Grids are sampled within a sector while:

$$\frac{\beta}{1-\alpha} < MLR < \frac{1-\beta}{\alpha}$$

The sector level MLR is calculated as:

$$\text{Maximum Likelihood Ratio} = \frac{\text{Likelihood Sector has "Clustered" Grids (Not Poisson)}}{\text{Likelihood Sector has Homogeneous Grids (Poisson)}}$$

$$MLR = \frac{\binom{P_1 N}{Xn}\binom{N(1-P_1)}{n-Xn}}{\binom{P_0 N}{Xn}\binom{N(1-P_0)}{n-Xn}} \quad \text{where}$$

P_0 = 0.5 = Hopkins value indicating data does not tend to clustering
P_1 = 0.62 = Hopkins value indicating data tends to clustering
N = Total number of grids in Sector
n = Current sampled grid
X_n = Cumulative number of times Hopkins > 0.62 (indicating non-homogeneity)

Note: See Appendix C for a discussion of the Hopkins Statistic.

Cost error (α), Risk error (β) and discriminator parameters are implemented in the grid level (GridStats) SPRT. Anomalies are sampled within a grid while:

$$\frac{\beta}{1-\alpha} < MLR < \frac{1-\beta}{\alpha}$$

The GridStats MLR is calculated as:

$$\text{Maximum Likelihood Ratio} = \frac{\text{Likelihood that grid has density that may require remediation}}{\text{Likelihood that grid has density that may not require remediation}}$$

$$MLR = \frac{\binom{P_1 N}{X_n}\binom{N(1 - P_1)}{n - X_n}}{\binom{P_0 N}{X_n}\binom{N(1 - P_0)}{n - X_n}}$$ where

P_0	=	5/N or 0.0235 = Density value that may not require remediation
P_1	=	1.2 * P_0 = Density value that may require remediation
N	=	Total anomalies in grid
n	=	Current anomaly sampled
X_n	=	Cumulative UXO found

APPENDIX C

HOPKINS STATISTIC

APPENDIX C

HOPKINS STATISTIC

C.1 DISCUSSION

The Hopkins Statistic is a spatial statistic which is used to test for the spatial randomness of UXO as it distributed throughout a sector. This test of randomness is important because the underlying assumption in risk assessment is that a sector is homogenous with respect to UXO densities. This test allows SiteStats to determine if a sector is homogeneous or, if not, the number of homogeneous subsectors that would be appropriate. The Hopkins Statistic also provides a basis for:

1. the selection of a sector level sampling discriminator,
2. establishing the need or lack of need for clustering, and
3. establishing the appropriate number of clusters.

Advantages of use of the Hopkins Statistic include its ability to act as an indicator for homogeneous Poisson processes and clustering tendency, the fact that it is beta-distributed, which relates to the hypergeometric distribution used in sampling, and the fact that it does not require Monte Carlo simulation to develop appropriate clustering thresholds. One disadvantage is that the Hopkins Statistic is purely statistical, and does not relate to logistical, cost, or risk information directly.

The methodology for establishing the threshold values for the Hopkins Statistic is shown in Figure C-1. The appropriate beta distribution is first integrated from 0 to p_0, where p_0 is the desired clustering threshold value. This result is then numerically iterated to solve for the p_0 which satisfies the integrated Hopkins Statistic required confidence level. Hopkins Statistics are then calculated as the sampling progresses. These statistics are tested to see if a conclusion can be reached concerning the homogeneity of the sector of interest. Figure C-2 shows the interface between sampling and clustering using the Hopkins Statistic. The sector level sequential probability ratio test is checked for possible termination. If neither the null (homogeneous) nor alternative (non-homogeneous) hypotheses may be rejected, sampling continues. If the alternative hypothesis may be rejected, sampling is discontinued, and no clustering takes place. If the null hypothesis is rejected, the Hopkins Statistic is used to indicate the appropriate number of clusters, and clustering takes place.

$$\int_0^{p_o} \frac{z^{m-1}\,(1-z)^{m-1}}{B\,(m,m)}\,dz \geq 1-\alpha$$

$\alpha = .2$

m	p_o (m)
2	0.8
3	0.72
4	0.68
5	0.65
6	0.64
•	
•	0.62
•	

- D = Threshold value above which a grid is considereded relatively highly contaminated
- $H = \dfrac{\sum_{j=1}^{m} U_j}{\sum_{j=1}^{m} U_j + \sum_{j=1}^{m} W_j}$

  $\sum U_j$ => Density variation between randomly chosen grids and their nearest sampled neighbor

  $\sum W_j$ => Density variation between randomly chosen sampled grids and their nearest sampled neighbor

H_o : Sector is Poisson — H_A : Sector is Not Poisson

=

$H_o: p \leq p_o = 0.5$ — $H_A: p > p_o = 0.5$

Figure C-1. Hopkins Statistic Methodology

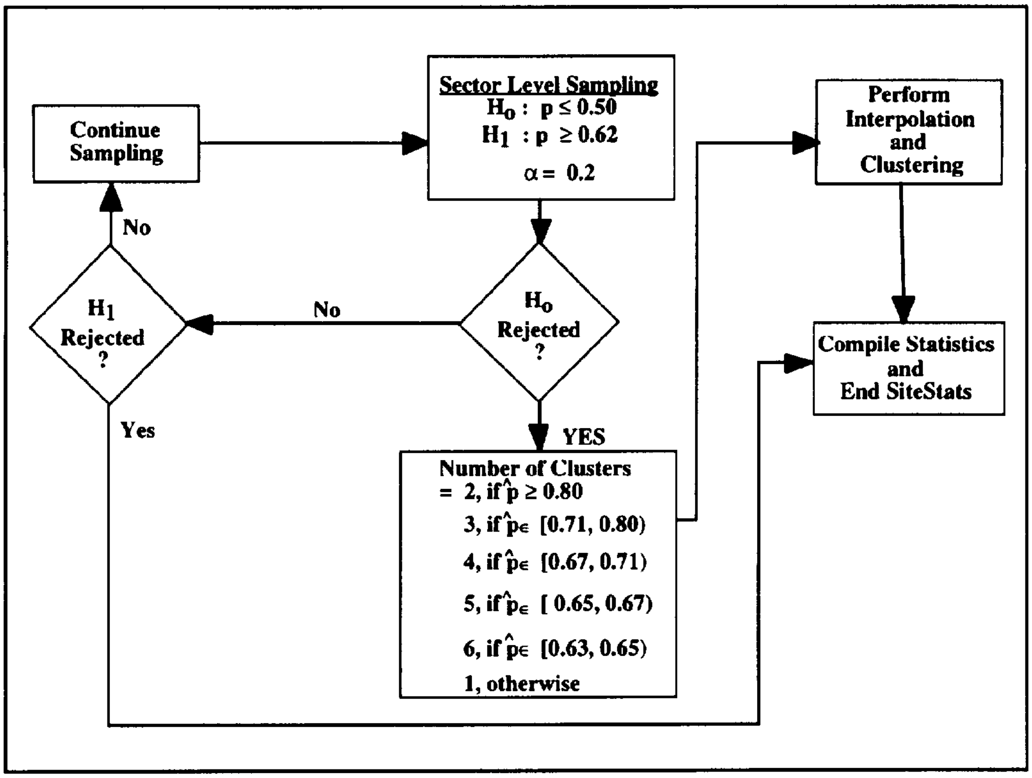


Figure C-2. Example of SiteStats/Cluster Interface Using Hopkins Statistic

C.2 INTEGRATION

An example integration required to establish the Hopkins critical values is given below. In the example m = 3, number of clusters = 4, and $\alpha = 0.2$. First:

$$\beta(m, m) = \frac{[(m-1)!]^2}{(2m-1)!}$$

$$\beta(3, 3) = \frac{[(3-1)!]^2}{(2(3)-1)!}$$

$$= \frac{4}{5!}$$

$$= \frac{4}{120}$$

$$= \frac{1}{30}$$

Then:

$$\int_0^{P_{o\alpha}} \frac{Z^{m-1}(1-Z)^{m-1}}{\beta(m, m)} \, dz \geq 1 - \alpha$$

$$\int_0^{P_{o\alpha}} \frac{Z^2 (1-Z)^2}{\beta(3, 3)} \, dz \geq 0.8$$

$$30\int_0^{P_{o\alpha}} Z^2 (1-Z)^2 \, dz \geq 0.8$$

$$30\int_0^{P_{o\alpha}} Z^2 (1 - 2Z + Z^2) \, dz \geq 0.8$$

$$30\int_0^{P_{o\alpha}} (Z^2 - 2Z^3 + Z^4) \, dz \geq 0.8$$

$$30 \left[\frac{P_{o\alpha}^3}{3} - \frac{P_{o\alpha}^4}{2} + \frac{P_{o\alpha}^5}{5}\right] = 0.8$$

$$10 P_{o\alpha} - 15 P_{o\alpha} + 6 P_{o\alpha} = 0.8$$

$$P_{o\alpha} = 0.67 \quad \Rightarrow \; 0.795 \; \cong \; 0.8$$

Thus, 0.67 is the threshold value for clustering the initially-defined section into three new sectors with an error of 20% that the initially-defined sector actually needs no clustering and is homogeneous with respect to UXO.

C.3 EXAMPLE

The following example shows how the Hopkins value is calculated at the end of each grid's investigation. Again the Hopkins measure is defined as:

$$H = \frac{U}{U + W} \quad \text{where}$$

U = Difference in the "just sampled" grid and the nearest sampled grid (nearest neighbor). Difference metric is Manhattan distance and absolute difference in expected UXO.

W = Average difference from all other sampled grids to their nearest neighbors.

Figure C.3-1 shows a very simplistic sector with 25 grids. Four grids have been sampled (indicated by the small number in the grid's upper left hand corner). The expected UXO found in the grids are indicated in the larger font and are listed in Table C.3-1.

4 0				
			1 10	
	2 3			
				3 4

Figure C.3-1. Example Sector

Table C.3-1. Sampling Results

Sample Number	UXO Found
1	10
2	3
3	4
4	0

To calculate the "U" value for sample number 4, first it's "nearest neighbor" is located. This is found by the Manhattan (or city block) distance. Each row and column separating two grids are counted and the sum is the Manhattan distance between the two. Table C.3-2 summarizes the distance measures for sample 4.

Table C.3-2. Distance Measures

Path	Distance
4 to 1	1 Row 3 Columns = 4
4 to 2	3 Rows 1 Column = 4
4 to 3	4 Rows 4 Columns = 8

So sampled grid 1 and sampled grid 2 are the same distance from sampled grid 4. The second part of the "U" metric to determine the Hopkins value is the absolute difference in UXO counts in the grid. Table C-3.3 summarizes these measures for sampled grid 4.

Table C.3-3. UXO Distance Measures

Path	Distance
4 to 1	$\lvert 0 - 10 \rvert = 10$
4 to 2	$\lvert 0 - 3 \rvert = 3$
4 to 3	$\lvert 0 - 4 \rvert = 4$

Now the "U" measure can be calculated. Table C.3-4 summarizes the measures for sampled grid 4.

Table C.3-4. "U" Measures

Path	U
4 to 1	4 + 10 = 14
4 to 2	4 + 3 = 7
4 to 3	8 + 4 = 12

Since U is at it's minimum (7) between sampled grid 4 and sampled grid 2, the value of U is set to 7. (Sampled grid 2 is the nearest neighbor to sampled grid 4.) Next, the measure W is calculated. The procedure outlined above for sampled grid 4 is repeated for sampled grids 1, 2, and 3. The average of these values is then calculated.

Observing Figure C.3-1, the "nearest neighbor" to sampled grid 1 (where nearest neighbor is the sum of the Manhattan distance and the absolute difference in UXO count), is grid 4 and the distance measure is 10. For sampled grid 2, the distance measure is 5 to sampled grid 3. Likewise, for sampled grid 3, the nearest neighbor is sampled grid 2 and the distance measure is 5. Now W is calculated as an average of the distance measures:

$$W = \frac{10+5+5}{3} = 6.67$$

Finally, the Hopkins value for sampled grid 4 can be calculated as:

$$H = \frac{U}{W+U} = \frac{7}{6.67+7} = 0.51.$$

APPENDIX D

SEQUENTIAL PROBABILITY RATIO TEST (SPRT)

APPENDIX D
SEQUENTIAL PROBABILITY RATIO TEST (SPRT)

The purpose of this appendix is to provide an introduction to sequential probability ratio test (SPRT) methodologies, their foundations, applications in GridStats and SiteStats, and examples using simulated and actual site data. It is important to understand the details and motivation for the use of SPRT techniques, because they form the statistical decision-making engines of the SiteStats sampling methodologies.

D.1 FOUNDATIONS

Prior to 1929, statistical sampling methodologies were based on predefined or fixed sample size approaches. The number of test samples required were defined before the test began, samples were taken, and the conclusions of the test were made after all of the samples had been taken. In 1929, Dodge and Romig realized that tendencies in the data could be determined after only a portion of data had been collected, and that a second phase of the test could then be planned based on the results of the first phase. This double-sampling plan methodology was found to result in reduced sample sizes, compared to a single, fixed sample plan. In the double sample plans, a fixed sample for the first phase was drawn, the results were analyzed, and a results-dependent second phase fixed sample plan, if necessary, was established. In 1943, Bartky extended this double sample concept to multiple sample plans with multiple phases. Finally, in 1947, Wald pioneered the development of SPRT's, when he recognized that continuation and termination decisions could be made after each sample, with potentially drastic reductions in sample sizes. The trick was to define the statistical criteria for making such decisions. The Wald Approximations were the output of this development. Around 1952, Cox extended the Wald SPRT for single parameter probability distributions to multiparameter families. Perhaps the best compilation of SPRT theory, applications, approximations, and exact solutions was provided in 1970 by Ghosh.

D.2 FUNDAMENTALS

The easiest way to understand SPRT applications is graphically. Figure D-1 depicts the standard representation of an SPRT. The x-axis is the sample number during the test. The y-axis is the maximum likelihood ratio (MLR), which is the ratio of the

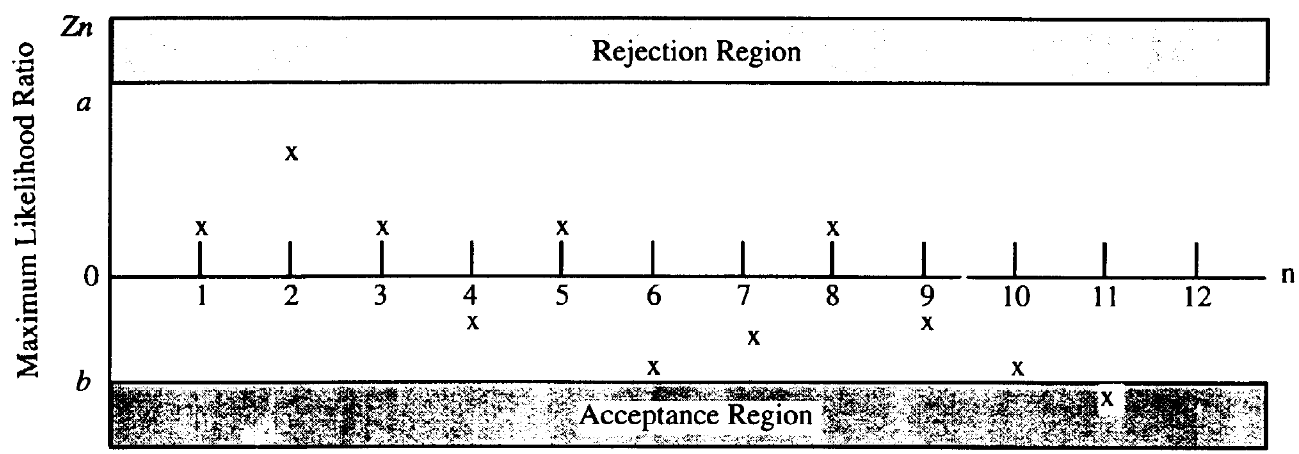


Figure D-1. Graphical Representation of a SPRT

likelihood of the alternative hypothesis to the null hypothesis, discussed below and in Appendix E. The X's are the MLR's for their respective sample values. The rejection region is that area for which the null hypothesis may be rejected. Similarly, the acceptance region is that area for which the null hypothesis is not rejected. Any single hypothesis SPRT associated with any probability distribution may be graphically represented as in Figure D-1.

SPRT's were first developed for the binomial distribution, because of its easy MLR representation and its widespread use in QA/QC sampling. The binomial distribution also results in binary data form for an infinite population, and it may be easily represented graphically by plotting the number of "hits" (cumulative 1-data) versus the sample size. In this alternative graphical representation (shown later), the acceptance and rejection regions are characterized by two parallel lines with (generally) nonzero slope. The alternative graphical representation was developed for ease of plotting by manufacturing engineers and technicians. The binomial SPRT results in average sample size reductions of 50% over comparable fixed sample plans.

The primary SPRT used in GridStats and SiteStats is the hypergeometric SPRT, although the binomial SPRT is an option in GridStats. This SPRT is also based on discrete sample data, but incorporates the additional information provided by the known population of the test. The sector level population in SiteStats is the number of grids contained within a sector. At the grid level, it is the number of anomalies detected through the geophysical survey of a grid. This SPRT always results in sample sizes that are less than or equal to the binomial SPRT. Greatest relative sample size reductions are achieved for mid-range populations, on the order of 50-1000. One drawback of the hypergeometric SPRT is the difficulty of producing the alternative graphical representation. Because of the iterative nature of this alternative representation for the hypergeometric SPRT, the hypergeometric SPRT will generally be represented in the classical MLR form.

SPRT's have been developed for other probability distributions. These include the SPRT's associated with the Poisson mean, normal mean (known variance), normal variance (known mean), exponential mean, uniform mean, and certain multinomial distributions. Other SPRT uses include the sequential sign test, the sequential test for the size of a random sample, multiple hypothesis discrimination, sequential analysis of variance, and sequential regression.

D.3 SiteStats APPLICATIONS

The fundamental motivation for using SPRT's in SiteStats is the reduction in intrusive sampling costs while providing good site characterization with acceptable confidence in determining the ordnance density and power in protecting the public from unknown risks. These sample size reductions must be appropriately balanced within and across the site sampling grids. The fundamental application of the hypergeometric SPRT at the grid and site levels is the same. However, the meaning of the parameters of interest changes between these two levels.

The application of the hypergeometric SPRT at the grid level (GridStats) is shown in Figure D-2. The notation and hypothesis tests are discussed in detail in Appendix E. The critical inequality for the continuation of sampling is provided in this figure. The MLR is calculated as the product of J(Xn) and Kn(Xn). The acceptance and rejection regions are determined using the Wald approximations shown.

Figure D-3 provides the setup conditions for a comparison of the binomial and hypergeometric SPRT's as applied to actual grid data at Southwestern Proving Grounds, near Hope, Arkansas. The actual grid density is unknown. The discrimination chosen is 5 UXO per grid. The risk and cost errors (see Appendix B) were established based on acceptable EPA requirements. There were 278 anomalies in this grid. Specific SPRT variables are shown. The sampling results are shown in Figure D-4, where the binomial SPRT y-axis is on the left, and the hypergeometric SPRT y-axis is on the right The hypergeometric SPRT terminates with a rejection of the null hypothesis after 22 samples. The binomial SPRT would require at least 4 more samples prior to termination.

Notation

p_0 = Discrimination for Proportion of Anomalies with UXO

p_1 = Discrimination Probability Above p_0

α = Cost Error Probability

β = Risk Error Probability

n = Sample Number

Xn = Cumulative Number of UXO Found

N = Total Number of Anomalies in Grid

Hypotheses

$$H_0 : p \leq p_0$$

$$H_a : p > p_1$$

Applicability Requirement

$$0 \leq p_0 \ N < p_1 N \leq N$$

Critical Inequality

$$b^* < J(X_n) K_n(X_n) < a^*$$

$$J(X_n) = \left[\binom{p_1 N}{X_n} \Big/ \binom{p_0 N}{X_n} \right]$$

$$K_n(X_n) = \left[\binom{N(1-p_1)}{n-X_n} \Big/ \binom{N(1-p_0)}{n-X_n} \right]$$

Wald Approximation for Fixed (Static) SPRT

$$b^* \equiv \left(\frac{\beta}{1-\alpha} \right), \quad a^* \equiv \left(\frac{1-\beta}{\alpha} \right)$$

Figure D-2. GridStats Hypergeometric SPRT

Conditions:

Grid	16
Sequence	7

Actual Grid Density = Unknown

p_o = 4 / N

p_1 = 5 / N

Number of Anomalies (N) = 278

α = 0.2

β = 0.1

100' x 200' *Grids*

Binomial

$$S = \frac{\ln\left(\frac{1-p_o}{1-p_1}\right)}{\ln\left(\frac{p_1}{p_o}\right)+\ln\left(\frac{1-p_o}{1-p_1}\right)} = 0.0161$$

$$h_1 = \frac{\ln\left(\frac{1-\beta}{\alpha}\right)}{\ln\left(\frac{p_1}{p_o}\right)+\ln\left(\frac{1-p_o}{1-p_1}\right)} = 6.6317$$

$$h_2 = \frac{\ln\left(\frac{\beta}{1-\alpha}\right)}{\ln\left(\frac{p_1}{p_o}\right)+\ln\left(\frac{1-p_o}{1-p_1}\right)} = -9.1686$$

$$h_2 + Sn < \sum \chi_i < h_1 + Sn$$

Hypergeometric

$$b^* = \frac{\beta}{1-\alpha} = 0.125$$

$$a^* = \frac{1-\beta}{\alpha} = 4.500$$

$$MLR = \frac{\binom{p_1 N}{X_n}\binom{N(1-p_1)}{n-X_n}}{\binom{p_o N}{X_n}\binom{N(1-p_o)}{n-X_n}} = \frac{\binom{5}{X_n}\binom{273}{n-X_n}}{\binom{4}{X_n}\binom{274}{n-X_n}}$$

$$b^* < MLR < a^*$$

Figure D-3. Binomial and Hypergeometric SPRT Example - GridStats
Former Southwestern Proving Ground

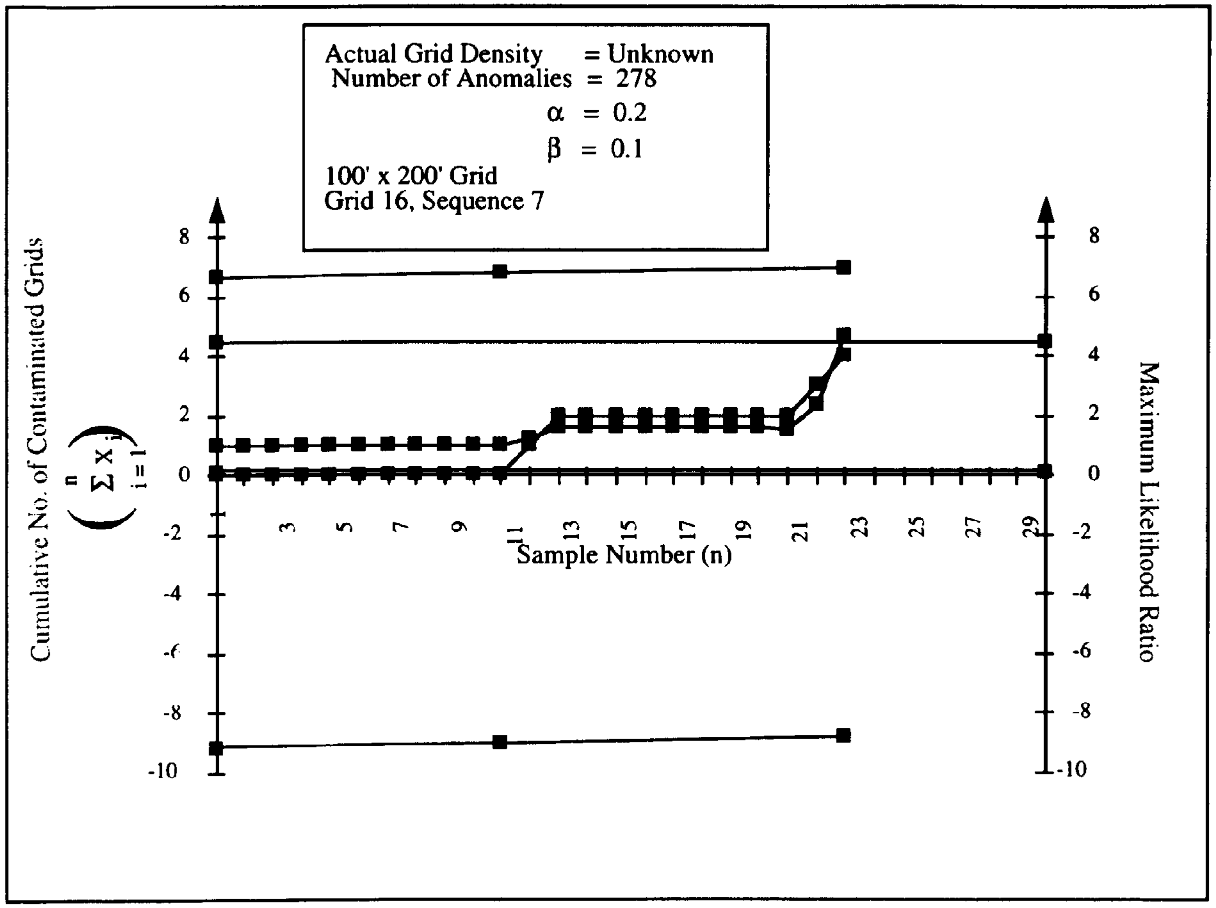


Figure D-4. Binomial vs. Hypergeometric SPRT
Former Southwestern Proving Ground

APPENDIX E

HYPOTHESIS TESTS

APPENDIX E

HYPOTHESIS TESTS

Hypothesis tests are used to make a decision about or test the validity of a statement or claim about a population. For SiteStats, hypothesis testing is used in the sector characterization process and in the grid sampling process. Table E-1 shows the hypothesis tests for each process.

Table E-1. SiteStats/GridStats Hypothesis Tests

Sector	H_o : $p \le p_0 = 0.5$ H_a : $p > p_0 = 0.5$ or H_o : The Sector is Homogeneous Poisson H_a : The Sector is Not Homogeneous Poisson where p = proportion of sampled grids with Hopkins Statistic greater than 0.62 (Hopkins Statistic = 0.5 implies randomness)
Grid	H_o : UXO Density ≤ Discriminator (D) H_a : UXO Density > Discriminator (D) or H_o : The grid UXO is less than or equal to a threshold value at which the grid may require remediation H_a : The grid UXO density is greater than a threshold value at which the grid may require remediation

For each hypothesis test, two erroneous conclusions can be reached: either H_0 is true but is rejected, or H_0 is false but is not rejected, traditionally known as Type I and Type II errors, respectively. Acceptable probabilities of committing Type I and Type II errors must be established. These error probabilities are traditionally designated α (confidence) and β (power).

The null and alternative hypotheses were chosen in this manner because rejection of the null hypothesis H_0: $p \leq p_0$ results in concluding the grid may require remediation. This hypothesis criteria is equivalent to the EPA procedures in environmental remediation.

APPENDIX F

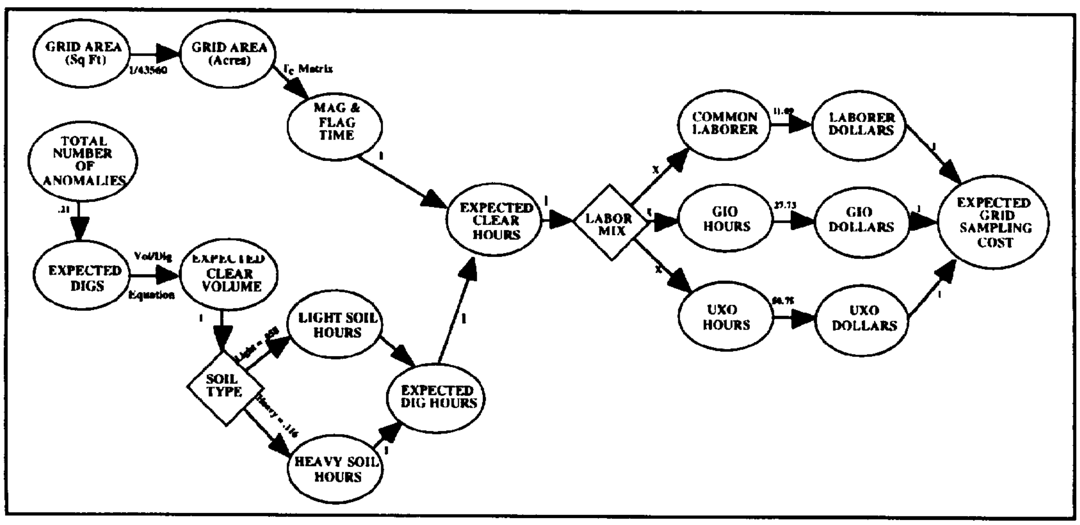
FIELD COST MODEL

APPENDIX F

FIELD COST MODEL

The Field Cost Model was developed to calculate the expected cost associated with the sampling of a grid. The model calculates expected sampling costs based on the area of the grid and the total number of anomalies located in the grid. The actual costs resulting from the sampling of a grid are also collected and the differences between expected and actual costs are calculated.

The Field Cost Model is based on the direct remediation cost methodology from the Ordnance and Explosives Cost-Effectiveness Risk Tool (OE*Cert*). The cost calculation logic for the Field Cost Model is represented in the flowgraph shown in Figure F-1.



UT-1451a-022795

Figure F-1. Field Cost Model

Tracking the logic presented in Figure F-1, the first input required is the grid area in units of square feet. Square feet are then converted to acreage by dividing by 43,560 (the number of square feet per acre). The "clearance time" matrix of values is then applied to the grid acreage to determine the number of hours required to mag and flag the grid. The "clearance time" matrix is based on time estimates provided by Tierrasanta project remediation personnel.

After the grid has been completely magged and flagged, the number of anomalies that were discovered during that process is input to the model. The number of anomalies entered is multiplied by .21 to calculate the expected number of anomalies that will have to be investigated to satisfy the statistical requirements of the GridStats sampling methodology. Empirical data from GridStats applications at Southwestern Proving Grounds and the Former Pantex Ordnance Plant indicate that on average 21% of the anomalies within a grid will require investigation before density estimation can be made.

The calculated expected number of intrusive investigations is multiplied by the appropriate equation for determining the volume per dig. A series of equations have been developed to take into account different combinations of clear depth, ordnance penetration depth, and water table depth in the calculation of volume per dig. The result of this multiplication is the expected volume of soil, measured in cubic feet, that will be removed during sampling. Different time factors are then applied to the expected volume depending upon whether the soil type is classified as light or heavy. Application of the appropriate soil type factor will yield the expected number of hours required to investigate the anomalies.

The expected investigation time is added to the calculated mag and flag time to yield the expected number of hours required to sample the grid. The time to sample the grid is then allocated to the appropriate labor categories. Currently it is assumed that sampling will be performed solely by UXO qualified personnel, but inclusion of this decision logic allows for mixes of personnel to be used if the need arises. The number of hours allocated to each labor category is then multiplied by the labor rate for that category. The resultant dollar figures are summed to yield the expected cost to sample the grid chosen for sampling.

APPENDIX G

SPATIAL INTERPOLATION

APPENDIX G

SPATIAL INTERPOLATION

Once the SiteStats site characterization sector-level sampling has concluded, but prior to any required clustering, interpolation of the density values for the unsampled grids is performed to ensure the smoothest possible clustering. A number of spatial interpolation methods may be found in the literature. A fast form, called inverse distance and described here, is implemented in SiteStats. Figure G-1 shows the calculations necessary for the inverse distance interpolation method. The ordnance density values for the sampled grids are weighted by the inverse of the distance of each grid from the unsampled grid. The values are then summed over all sampled grids. This sum is then normalized by the sum of the inverse distances to arrive at the ordnance density estimate for the unsampled grid. The distance measurement used is the Manhattan (or city block) metric. The distance between points i and j [d(i,j)] is calculated as:

$$d(i,j) = \sum_{k=1}^{j}\left[w_k\left|x_{i,k} - x_{i+1,k}\right| + u_k\left|y_{i,k} - y_{i+1,k}\right|\right]$$

where w_k and u_k are weights (in this case1).

Spatial Interpolation for Non-Sampled Grids

Inverse Distance

$$O(j) = \frac{\sum_{i=1}^{n} \frac{O(i)}{d(i,j)}}{\sum_{i=1}^{n} [d(i,j)]^{-1}}$$

- **Intuitive**
- **Smooth Representation**
- **Minimal Computational Complexity**
- **No Precision Estimate**

Figure G-1. Inverse Distance Interpolation Method

Figure G-2 provides a very intuitive example of this process. In this case, the distances of the sampled grids from the unsampled grid are equal. This results in an ordnance weighted value for the unsampled grid of 17.5.

20		10
	j	
30		10

$$O\,(j) = \frac{\left(\frac{20}{2} + \frac{10}{2} + \frac{10}{2} + \frac{30}{2}\right)}{\left(\frac{1}{2} + \frac{1}{2} + \frac{1}{2} + \frac{1}{2}\right)} = 17.5$$

Figure G-2. Sector-Level Grid Interpolation Example

APPENDIX H

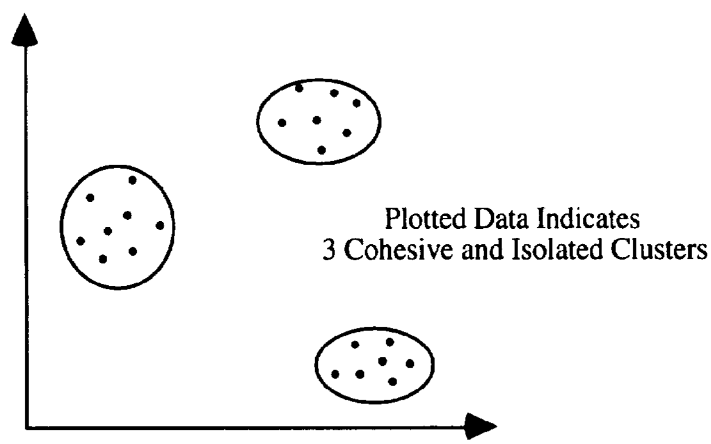
CLUSTER ANALYSIS

APPENDIX H

CLUSTER ANALYSIS

H.1 DISCUSSION

Cluster analysis is a generic name for a variety of mathematical models that can be used to find out which objects in a set are similar. The objective of cluster analysis is to separate a set of objects into constituent groups (classes, clumps, clusters, sectors, etc.) so that the members of any one group differ from one another as little as possible, according to a chosen criterion. Some visual examples are provided in Figure H-1. For the purposes of SiteStats, a cluster is synonymous with a homogeneous UXO sector. The basic data for cluster analysis is a set of some number of entities (for example sector grids) on which some number of measurements are recorded.



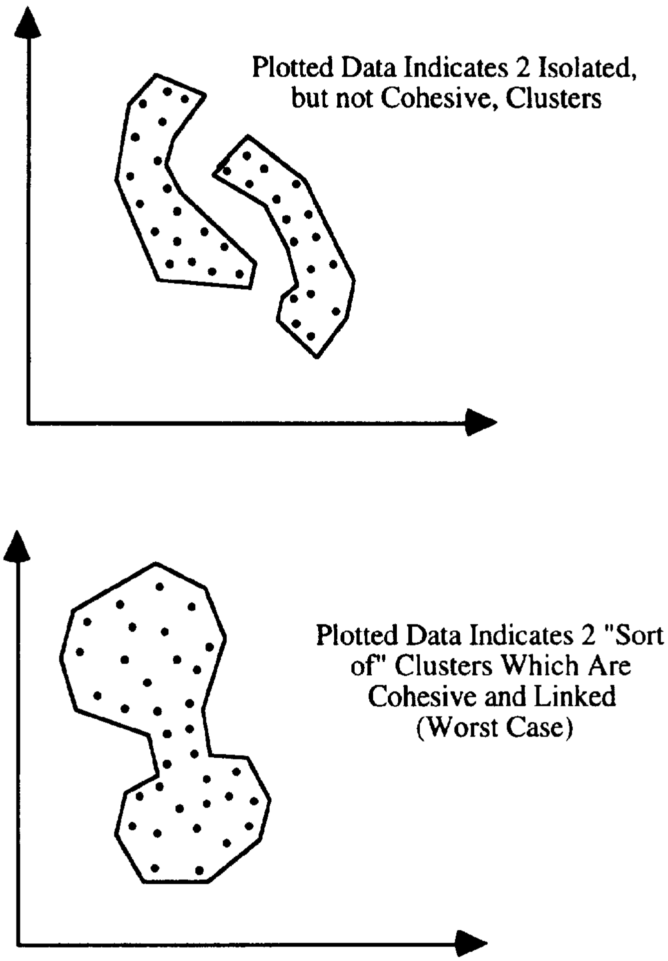


Figure H-1. Example Clusters

A migrating means algorithm is used in the SiteStats clustering methodology. This iterative algorithm is classified as a partitioning technique. The basic idea of the algorithm is to start with an initial partition and assign entities (sector grids) to clusters in such a way as to reduce square error. An initial partition is formed by selecting seed points or cluster centroids. Partitions are updated by reassigning grids to clusters in order to reduce the square error. Each update is referred to as a "pass" or a "cycle." Partitional algorithms terminate when the criterion function cannot be improved. In SiteStats, the criterion function is based on cluster stabilization – when sector grids no longer "switch" from one cluster to another. The steps of the algorithm are as follows:

Step 1: Locate data centroid (1st centroid)
Step 2: Locate greatest outlier (2nd centroid)
Step 3: Assign grids to nearest centroid
Step 4: Find new centroids
Step 5: Return to step 3 until there are no changes in grid membership
Step 6: Increase the number of cluster centroids by locating the greatest outlier
Step 7: Return to step 3 until the specified number of clusters (Hopkins statistic) has been reached

In assigning entities to clusters, similarities or dissimilarities between entities must be determined. In SiteStats, entities (sector grids) are measured based on expected UXO density and geographic location. Grids are classified or clustered based on these similarities or dissimilarities. Figure H-2 diagrams these measures.

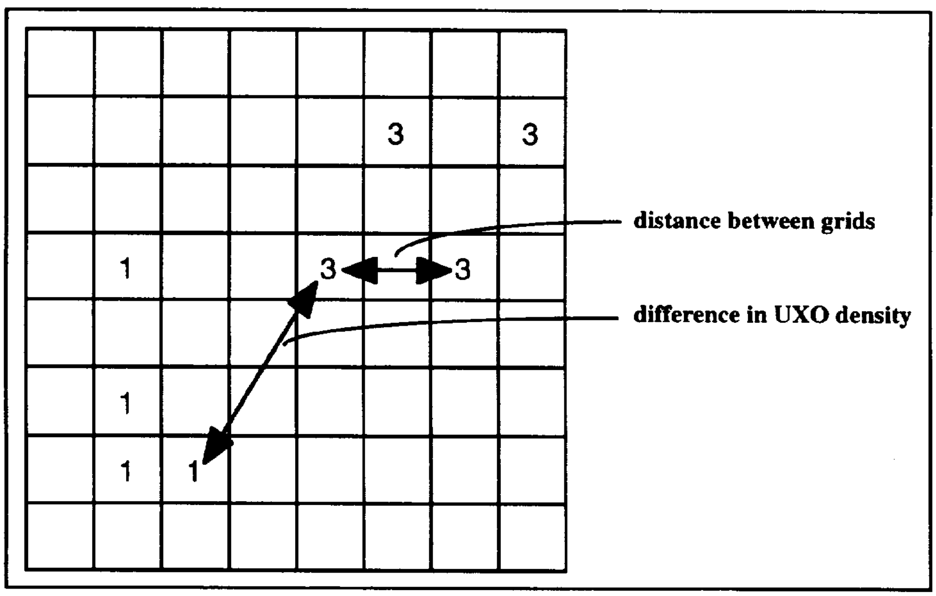


Figure H-2. Measures of Similarity/Dissimilarity

These similarity/dissimilarity distances are measured by the following equation.

$$\text{distance}(C,G) = \left[| X_C - X_G | + | Y_C - Y_G | + | \overline{UXO}_C - UXO_G | \right]$$

where X_G = Row location of the grid

Y_G = Column location of the grid

UXO_G = Expected number of UXO in the grid

X_C = Row location of the centroid

Y_C= Column location of the centroid

$\overline{UXO}_C$ = Average of the expected number of UXO in all sampled grids

The distances are computed iteratively until the square error has been minimized and the grids have stabilized among the clusters.

H.2 EXAMPLE

A simplistic sector representation with 25 grids is shown in Figure H.2-1. In this example, 10 grids (indicated by the shading) were sampled and the expected UXO items are indicated by the values shown in each grid. The value shown in each unsampled grid is the interpolated (see Appendix G) expected UXO.

1	9	**3**	16	**20**
9	**2**	13	20	21
13	13	**5**	26	**30**
12	**4**	21	**40**	27
3	15	25	**50**	29

*Note: Shading indicates sampled grid.

Figure H.2-1. Example Sector

The first step in clustering is to locate the centroid of all the grids within the sector. The centroid is expressed as a row location, grid location, and average UXO count. For this example, the centroid's row location is $\frac{\text{75 row indices}}{\text{25 grids}} = 3$. Similarly, the column location is $\frac{\text{75 column indices}}{\text{25 grids}} = 3$. The average UXO count is $\frac{1+9+...+50+29}{25} = 17$.

From this centroid the greatest outlier (in terms of row/column location and absolute difference in UXO count is determined). Table H.2-1 summarizes this data for each row/column location.

Table H.2-1. Data to Determine Greatest Outlier

Position	Row Distance	Column Distance	UXO Distance	Total Distance
(1, 1)	$\lvert 1 - 3 \rvert = 2$	$\lvert 1 - 3 \rvert = 2$	$\lvert 1 - 17 \rvert = 16$	2 + 2 + 16 = 20
(1, 2)	$\lvert 1 - 3 \rvert = 2$	$\lvert 2 - 3 \rvert = 1$	$\lvert 9 - 17 \rvert = 8$	2 + 1 + 8 = 11
(1, 3)	$\lvert 1 - 3 \rvert = 2$	$\lvert 3 - 3 \rvert = 0$	$\lvert 3 - 17 \rvert = 14$	2 + 0 + 14 = 16
(1, 4)	$\lvert 1 - 3 \rvert = 2$	$\lvert 4 - 3 \rvert = 1$	$\lvert 16 - 17 \rvert = 1$	2 + 1 + 1 = 4
(1, 5)	$\lvert 1 - 3 \rvert = 2$	$\lvert 5 - 3 \rvert = 2$	$\lvert 20 - 17 \rvert = 3$	2 + 2 + 3 = 7
(2, 1)	$\lvert 2 - 3 \rvert = 1$	$\lvert 1 - 3 \rvert = 2$	$\lvert 9 - 17 \rvert = 8$	1 + 2 + 8 = 11
(2, 2)	$\lvert 2 - 3 \rvert = 1$	$\lvert 2 - 3 \rvert = 1$	$\lvert 2 - 17 \rvert = 15$	1 + 1 + 15 = 17
(2, 3)	$\lvert 2 - 3 \rvert = 1$	$\lvert 3 - 3 \rvert = 0$	$\lvert 13 - 17 \rvert = 4$	1 + 0 + 4 = 5
(2, 4)	$\lvert 2 - 3 \rvert = 1$	$\lvert 4 - 3 \rvert = 1$	$\lvert 20 - 17 \rvert = 3$	1 + 1 + 3 = 5
(2, 5)	$\lvert 2 - 3 \rvert = 1$	$\lvert 5 - 3 \rvert = 2$	$\lvert 21 - 17 \rvert = 4$	1 + 2 + 4 = 7
(3, 1)	$\lvert 3 - 3 \rvert = 0$	$\lvert 1 - 3 \rvert = 2$	$\lvert 13 - 17 \rvert = 4$	0 + 2 + 4 = 6
(3, 2)	$\lvert 3 - 3 \rvert = 0$	$\lvert 2 - 3 \rvert = 1$	$\lvert 13 - 17 \rvert = 4$	0 + 1 + 4 = 5
(3, 3)	$\lvert 3 - 3 \rvert = 0$	$\lvert 3 - 3 \rvert = 0$	$\lvert 5 - 17 \rvert = 12$	0 + 0 + 12 = 12
(3, 4)	$\lvert 3 - 3 \rvert = 0$	$\lvert 4 - 3 \rvert = 1$	$\lvert 26 - 17 \rvert = 9$	0 + 1 + 9 = 10
(3, 5)	$\lvert 3 - 3 \rvert = 0$	$\lvert 5 - 3 \rvert = 2$	$\lvert 30 - 17 \rvert = 13$	0 + 2 + 13 = 15
(4, 1)	$\lvert 4 - 3 \rvert = 1$	$\lvert 1 - 3 \rvert = 2$	$\lvert 12 - 17 \rvert = 5$	1 + 2 + 5 = 8
(4, 2)	$\lvert 4 - 3 \rvert = 1$	$\lvert 2 - 3 \rvert = 1$	$\lvert 4 - 17 \rvert = 13$	1 + 1 + 13 = 15
(4, 3)	$\lvert 4 - 3 \rvert = 1$	$\lvert 3 - 3 \rvert = 0$	$\lvert 21 - 17 \rvert = 4$	1 + 0 + 4 = 5
(4, 4)	$\lvert 4 - 3 \rvert = 1$	$\lvert 4 - 3 \rvert = 1$	$\lvert 40 - 17 \rvert = 23$	1 + 1 + 23 = 25
(4, 5)	$\lvert 4 - 3 \rvert = 1$	$\lvert 5 - 3 \rvert = 2$	$\lvert 27 - 17 \rvert = 10$	1 + 2 + 10 = 13
(5, 1)	$\lvert 5 - 3 \rvert = 2$	$\lvert 1 - 3 \rvert = 2$	$\lvert 3 - 17 \rvert = 14$	2 + 2 + 4 = 8
(5, 2)	$\lvert 5 - 3 \rvert = 2$	$\lvert 2 - 3 \rvert = 1$	$\lvert 15 - 17 \rvert = 2$	2 + 1 + 2 = 5
(5, 3)	$\lvert 5 - 3 \rvert = 2$	$\lvert 3 - 3 \rvert = 0$	$\lvert 25 - 17 \rvert = 8$	2 + 0 + 8 = 10
(5, 4)	**$\lvert 5 - 3 \rvert = 2$**	**$\lvert 4 - 3 \rvert = 1$**	**$\lvert 50 - 17 \rvert = 33$**	**2 + 1 + 33 = 36**
(5, 5)	$\lvert 5 - 3 \rvert = 2$	$\lvert 5 - 3 \rvert = 2$	$\lvert 29 - 17 \rvert = 12$	2 + 2 + 12 = 16

Note: Shading indicates greatest outlier.

The greatest total distance (thus, greatest outlier) from the table is 36, at position (5, 4). This location with a UXO count of 50 becomes the initial centroid for the second cluster.

Now each grid is assigned to the cluster centroid nearest the grid (Centroid 1 is position (3, 3) with a UXO count of 17 and Centroid 2 is position (5, 4) with a UXO count of 50). The distance from each grid to both the centroids are shown in Table H.2-2. Calculations are performed as was demonstrated in Table H.2-1.

Table H.2-2. Distances to Original Centroids

Position	Total Distance to Centroid 1	Total Distance to Centroid 2	Nearest Centroid
(1, 1)	20	56	1
(1, 2)	11	47	1
(1, 3)	16	52	1
(1, 4)	4	38	1
(1, 5)	7	35	1
(2, 1)	11	47	1
(2, 2)	17	53	1
(2, 3)	5	41	1
(2, 4)	5	33	1
(2, 5)	7	33	1
(3, 1)	6	42	1
(3, 2)	5	41	1
(3, 3)	12	48	1
(3, 4)	10	26	1
(3, 5)	15	23	1
(4, 1)	8	42	1
(4, 2)	15	49	1
(4, 3)	5	31	1
(4, 4)	25	11	2
(4, 5)	13	25	1
(5, 1)	18	50	1
(5, 2)	5	37	1
(5, 3)	10	26	1
(5, 4)	36	0	2
(5, 5)	16	22	1

As indicated by the last column of Table H.2-2, 23 of the grids are now in Cluster 1 and 2 grids are in Cluster 2. Figure H.2-2 graphically shows the clusters.

1	9	3	16	20
9	2	13	20	21
13	13	5	26	30
12	4	21	40	27
3	15	25	50	29

*Note: Shading indicates Cluster 2 Membership.

Figure H.2-2. Clusters After 1 "Pass"

Now the centroids of the two clusters "migrate" as a result of the change in membership. The row location of Centroid 1 is located at $\frac{66 \text{ row indices}}{23 \text{ grids}} = 2.9 = 3$. The column centroid moves to $\frac{67 \text{ column indices}}{23 \text{ grids}} = 2.9 = 3$. The average UXO count is $\frac{1+9+...+25+29}{23} = 14.7 = 15$.

The row location of Centroid 2 is located at $\frac{9}{2} = 4.5 = 5$ (or position 5,4) while the column location is at $\frac{8}{2} = 4$. The average UXO count is $\frac{40+50}{2} = 45$.

With the new centroids, grids are again assigned to the "nearest" centroid using the same calculations as presented previously. Table H.2-3 presents the results.

Table H.2-3. Distances to Second Set of Centroids

Position	Total Distance to Centroid 1	Total Distance to Centroid 2	Nearest Centroid
(1, 1)	16	51	1
(1, 2)	7	42	1
(1, 3)	14	47	1
(1, 4)	4	33	1
(1, 5)	9	30	1
(2, 1)	7	42	1
(2, 2)	13	48	1
(2, 3)	3	36	1
(2, 4)	7	28	1
(2, 5)	9	28	1
(3, 1)	4	37	1
(3, 2)	3	36	1
(3, 3)	12	43	1
(3, 4)	14	21	1
(3, 5)	19	18	2
(4, 1)	6	37	1
(4, 2)	13	44	1
(4, 3)	9	26	1
(4, 4)	29	6	2
(4, 5)	17	20	1
(5, 1)	16	45	1
(5, 2)	3	32	1
(5, 3)	14	21	1
(5, 4)	40	5	2
(5, 5)	20	17	2

As indicated in the last column of Table H.2-3, 21 of the grids now are in Cluster 1 and 4 grids are in Cluster 2. Figure H.2-3 graphically shows the clusters.

1	9	3	16	20
9	2	13	20	21
13	13	5	26	30
12	4	21	40	27
3	15	25	50	29

*Note: Shading indicates Cluster 2 Membership.

Figure H.2-3. Clusters After 2 "Passes"

The methodology then proceeds the same until no grids change cluster membership. If the Hopkins Statistic has indicated more than two clusters are required, then the number of centroids is increased by one (again, the greatest outlier is used for the next centroid) and grids are assigned to the nearest cluster until the indicated number of clusters has been established.

APPENDIX I

TECHNICAL DISCUSSION OF GridStats BINOMIAL AND HYPERGEOMETRIC MODULES

APPENDIX I

TECHNICAL DISCUSSION OF GridStats BINOMIAL AND HYPERGEOMETRIC MODULES

I.1 BINOMIAL MODULE TECHNICAL DISCUSSION

This appendix contains a discussion of the binomial SPRT and fixed stopping rule. The binomial distribution is useful when the sampling of grid anomalies is discrete in terms of the ability to identify and count anomalies as the sampling process is being conducted, and when the sampled anomalies may be identified as hits (UXO) or misses (non-UXO). The binomial distribution assumes no prior knowledge of the total number of anomalies present in the grid. Statistically, this is equivalent to the assumption of an infinite population of anomalies. (Note, that one purpose of this study is to determine at what population of anomalies, the population is statistically infinite and has little effect on the sampling requirements.)

The equations for the binomial SPRT are given by:

$$s = \frac{\ln\left(\frac{1-p_0}{1-p_1}\right)}{\ln\left(\frac{p_1}{p_0}\right) + \ln\left(\frac{1-p_0}{1-p_1}\right)}$$

$$h_1 = \frac{\ln\left(\frac{1-\beta}{\alpha}\right)}{\ln\left(\frac{p_1}{p_0}\right) + \ln\left(\frac{1-p_0}{1-p_1}\right)}$$

$$h_2 = \frac{\ln\left(\frac{\beta}{1-\alpha}\right)}{\ln\left(\frac{p_1}{p_0}\right) + \ln\left(\frac{1-p_0}{1-p_1}\right)}$$

$$h_2 + sn < \sum x_i < h_1 + sn$$

where:

p_0 = Discrimination for Proportion of Anomalies with UXO
p_1 = Discrimination Probability Above p_0 $(1.2 * p_0)$
α = Cost Error Probability
β = Risk Error Probability
n = Sample Number
X_n = Cumulative Number of UXO Found.

The sample size requirements for the binomial fixed stopping rule, when no UXO has been found, is given by:

$$n = \frac{\ln(\beta)}{\ln(1-p_1)}$$

I.2 HYPERGEOMETRIC MODULE TECHNICAL DISCUSSION

This section contains a discussion of the hypergeometric SPRT and fixed stopping rule. Like the binomial distribution, the hypergeometric distribution is useful when the sampling of grid anomalies is discrete in terms of the ability to identify and count anomalies as the sampling process is being conducted, and when the sampled anomalies may be identified as hits (UXO) or misses (non-UXO). Unlike the binomial distribution, the hypergeometric distribution assumes prior knowledge of the total number of anomalies present in the grid. Statistically, this additional information reduces (often significantly) the sampling requirements. In situations where the cost to obtain this additional information is small compared to the cost to sample, the hypergeometric distribution is most useful.

The equations for the hypergeometric SPRT are given by:

$$b^* = \frac{\beta}{1-\alpha}$$

$$a^* = \frac{1-\beta}{\alpha}$$

$$MLR = \frac{\binom{p_1 N}{X_n}\binom{N(1-p_1)}{n-X_n}}{\binom{p_0 N}{X_n}\binom{N(1-p_0)}{n-X_n}}$$

$$b^* < MLR < a^*$$

where:

p_0 = Discrimination for Proportion of Anomalies with UXO

p_1 = Discrimination Probability Above p_0 $(1.2 * p_0)$

α = Cost Error Probability

β = Risk Error Probability

n = Sample Number

X_n = Cumulative Number of UXO Found

N = Total Number of Anomalies in Grid.

The sample size requirement for the hypergeometric fixed stopping rule when no UXO has been found is determined by iterating over n until the following equation is satisfied:

$$\beta = \frac{\binom{N(1-p_1)}{n}}{\binom{N}{n}}.$$

Figure I-1 provides the hypergeometric intermediate stopping rule sampling requirements for fixed value discriminators in terms of number of UXO items per grid as a function of grid anomaly count. These values are linear, with sizable reductions in sample size from 100%. Sample requirements reduce significantly as discriminator values increase, up to a value of roughly 12 UXO items per grid.

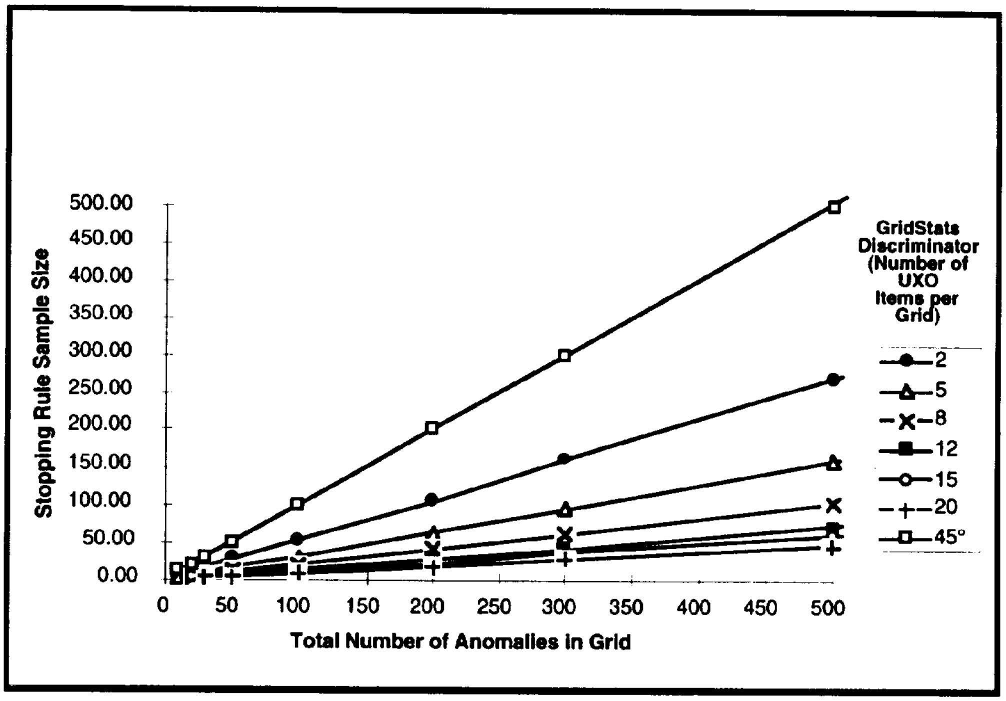


Figure I.2-1. Hypergeometric Intermediate Stopping Rule Sample Sizes - Fixed Number of UXO Items Per Grid

APPENDIX J

STATISTICAL ERRORS ASSOCIATED WITH ANOMALY ESTIMATES

APPENDIX J

STATISTICAL ERRORS ASSOCIATED WITH ANOMALY ESTIMATES

Figures J-1 and J-2 show the distribution of anomaly counts for sampled grids at Southwestern Proving Ground (SPG) and Fort Devens. The mean and standard deviation of anomaly counts, respectively, are 83 and 70 for Fort Devens and 213 and 317 for SPG. This supports a Poisson distribution conclusion, because the means and standard deviations are statistically equal.

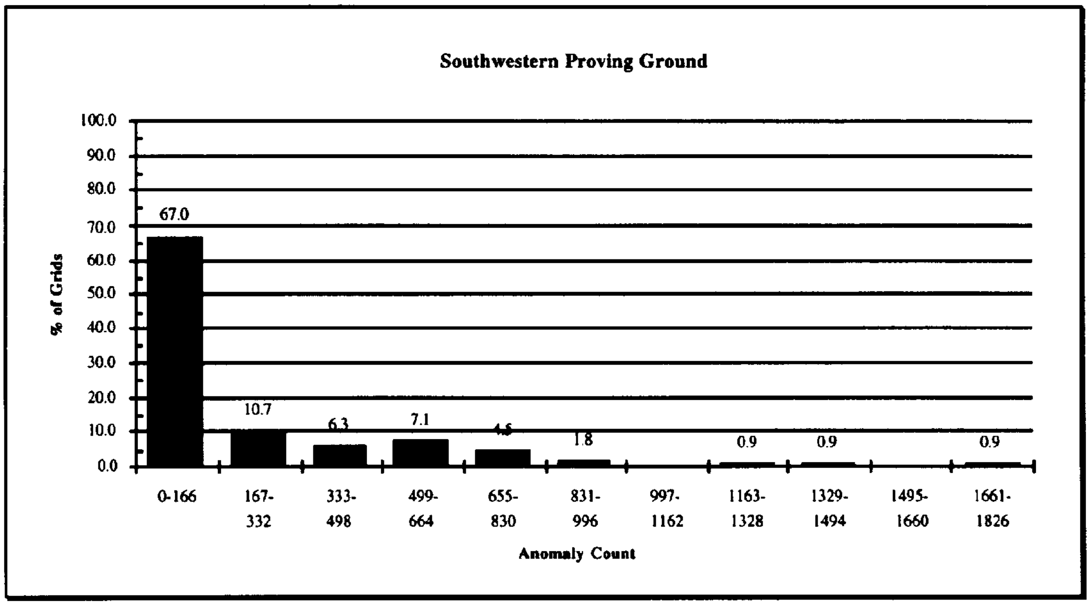


Figure J-1. Southwestern Proving Ground Grid Anomaly Frequency

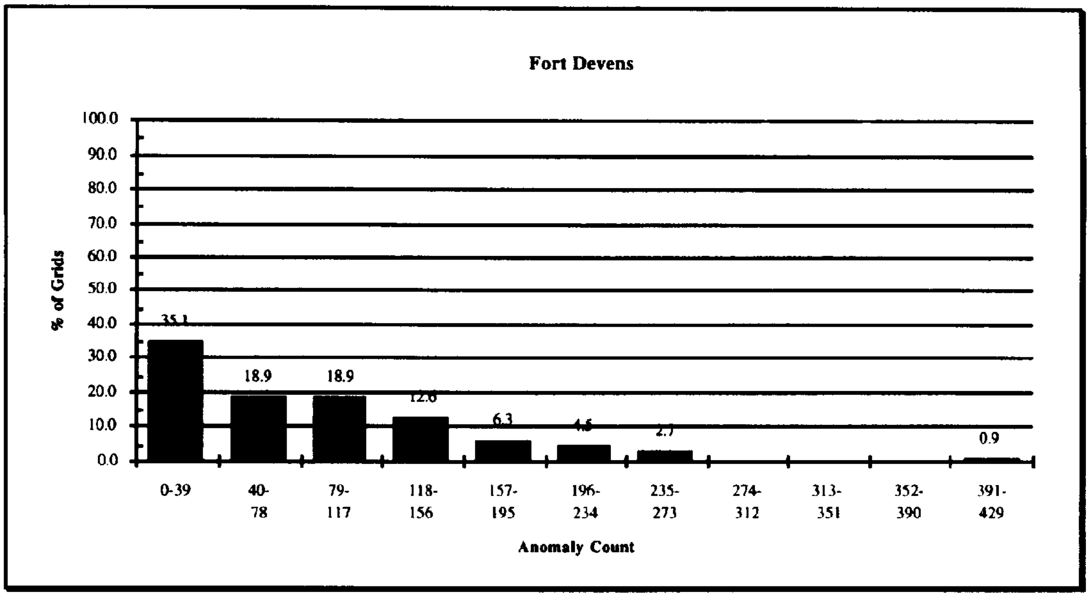


Figure J-2. Fort Devens Grid Anomaly Frequency

To control for Type III and IV errors, a sequential probability ratio test for the Poisson distribution was developed. The mathematical details of the errors estimated with this SPRT are presented below.

Type III errors are given by:

$$\gamma = \exp\left[(\lambda_1 - \lambda_0)n - X_n \ln\left(\frac{\lambda_1}{\lambda_0}\right)\right]$$

Type IV errors are given by:

$$\delta = \exp\left[X_n \ln\left(\frac{\lambda_1}{\lambda_0}\right) - (\lambda_1 - \lambda_0)n\right]$$

where:

γ = Type III error

δ = Type IV error

λ_0 = grid anomaly count discriminator

$\lambda_1 = 1.2 * \lambda_0$

n = proportion of grid area assessed for anomalies

X_n = anomaly count for assessed portion.

In controlling for Type III and IV errors in making the decision between the binomial and hypergeometric modules, an appropriate choice for λ_0 is 800. In controlling for Type III and IV errors in making the decision with the hypergeometric module about the type of discriminator, an appropriate choice for λ_0 is 213.

APPENDIX K

REMEDIATION PLANNING TOOL RISK AND COST ESTIMATING METHODOLOGIES

APPENDIX K

REMEDIATION PLANNING TOOL RISK AND COST METHODOLOGIES

K.1 INTRODUCTION

The US Army Corps of Engineers, Huntsville Division, (CEHND) has been designated as the Mandatory Center of Expertise (MCX) for the remediation of ordnance and explosives (OE). In support of this mission, QuantiTech, Inc., developed a methodology to aid in the estimation of public risk and life cycle cost at Formerly Used Defense Sites (FUDS). The methodology is the Ordnance and Explosives Cost-Effectiveness Risk Tool (OE*Cert*).

OE*Cert* is comprised of two modules, the cost module and the risk module. These modules are further broken down into sub-modules based on the type of site that is being analyzed; a dispersed site, a localized site, or a water site. The risk module outputs an overall risk value of the site before and after remediation has occurred. Supplementary outputs of the risk module include the expected number of exposures to UXO, both to the public as a whole and to a single individual, before and after remediation. From these outputs, the probability of exposure to one person on one site visit, performing a particular activity, can be calculated. The output of the cost module is the life cycle cost to the Government of a FUDS. Life cycle cost is calculated both inclusive of remediation and without remediation of the site. The following sections describe the risk module and cost module in more detail.

K.2 RISK MODULE

The OE*Cert* risk estimating methodology is based on the following definition of risk:

Risk = (# Expected Public Exposures to OE) * (OE Hazard Factor).

An exposure is defined as a member of the public being present at a place where UXO is located. An exposure could occur either with or without an individual's knowledge. Public exposure to both surface and subsurface UXO items is characterized by a Poisson process. The public exposures result from individuals performing specific activities (both recreational and occupational) within UXO-contaminated areas. The expected number of surface UXO exposures per participant in an area is dependent on UXO density, the proportion of UXO on the surface of the ground, and the activity participant's exposure area (the area traversed by an individual while performing an activity). The expected number of subsurface UXO exposures per participant in an area is dependent on the UXO density, the proportion of UXO beneath the surface of the ground, the density distribution of the subsurface UXO, and the area associated with an intrusive activity performed in the area. For both surface and subsurface UXO items, the expected number of exposures to UXO items for a single individual while performing a specific activity is determined. Next, the total number of expected participants entering an area is determined based on the demographics of the area in which the UXO-contaminated site is located and upon activity participation data. The total expected number of exposures, based on this total number of participants in the activity, is calculated by the following relationship:

E[Activity Exposures] = E[Exposures for single participant] * [# participants].

For each activity performed in a UXO-contaminated area, the expected number of exposures are summed for a total exposure value shown in the following relationship:

$$E[\text{Total Exposures}] = \sum_{\text{All Activities}} E[\text{Activity Exposures}].$$

For the Remediation Planning Tool, the applicable risk value is the probability of exposure for one person, one site visit. This value is calculated at the activity level as follows:

$$p(\text{exposure}) = 1 - e^{-\mu}$$

where μ = E[exposures, one person].

K.3 COST MODULE

The OE*Cert* cost estimating methodology separates costs into three time periods: pre-remediation, remediation, and post-remediation. Pre-remediation cost consists of site assessment (investigation, planning, and design), site security (fencing, guards, facilities, utilities, and communication), and other costs (evaluation). Remediation direct cost consists of surveying, surface clearance, brush removal, subsurface clearance, UXO disposal, and site restoration. Remediation indirect cost consists of site logistics (mobilization, monitoring, and environmental costs) and indirect support labor and materials costs. Post-remediation cost includes security and communications cost.

Cost estimates are projected from regression curves, bottoms-up detail, or elapsed time analysis. Pre-remediation site assessment costs are projected from regression curves. Pre-remediation site security cost, other cost, and remediation direct costs are built from bottoms-up detail. Remediation indirect costs are derived from elapsed time analysis. Post-remediation costs are seldom considered since any remediation activity is expected to reduce UXO exposure potential to an "acceptable" level.

The cost portion of the remediation planning tool is based on remediation direct and indirect costs. Pre- and post-remediation are not part of the remediation planning operations. To aid in the understanding of the cost estimating methodology, Computer-Aided Flow Economics (CAFE) flowgraphs have been developed. These flowgraphs provide details of the methodology in a flowgraph form. The remediation direct and indirect flowgraphs are shown in figures K.3-1 and K.3-2 respectively.

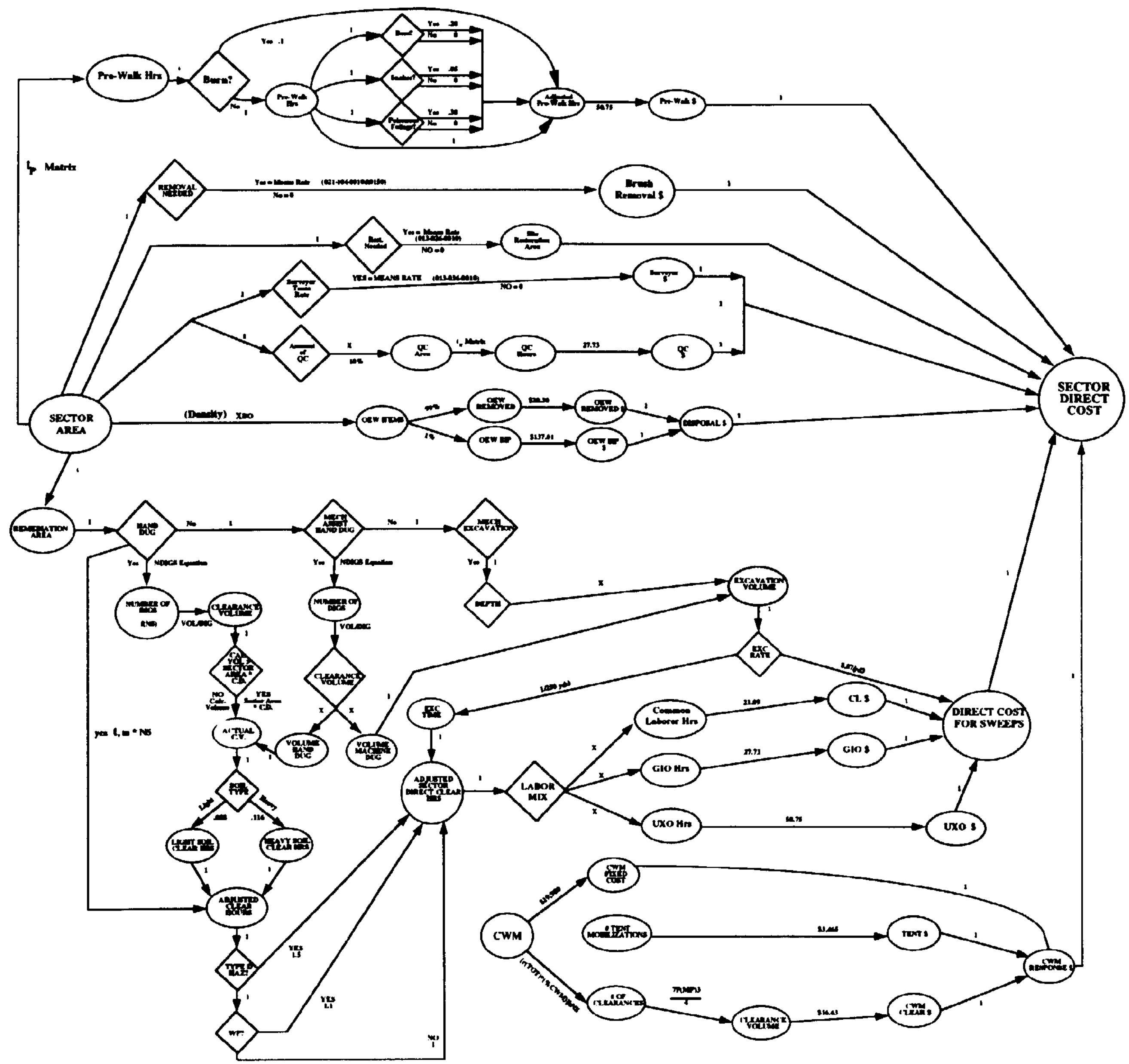


Figure K.3-1. Remediation Direct Cost Flowgraph
(Remediation Planning Tool)

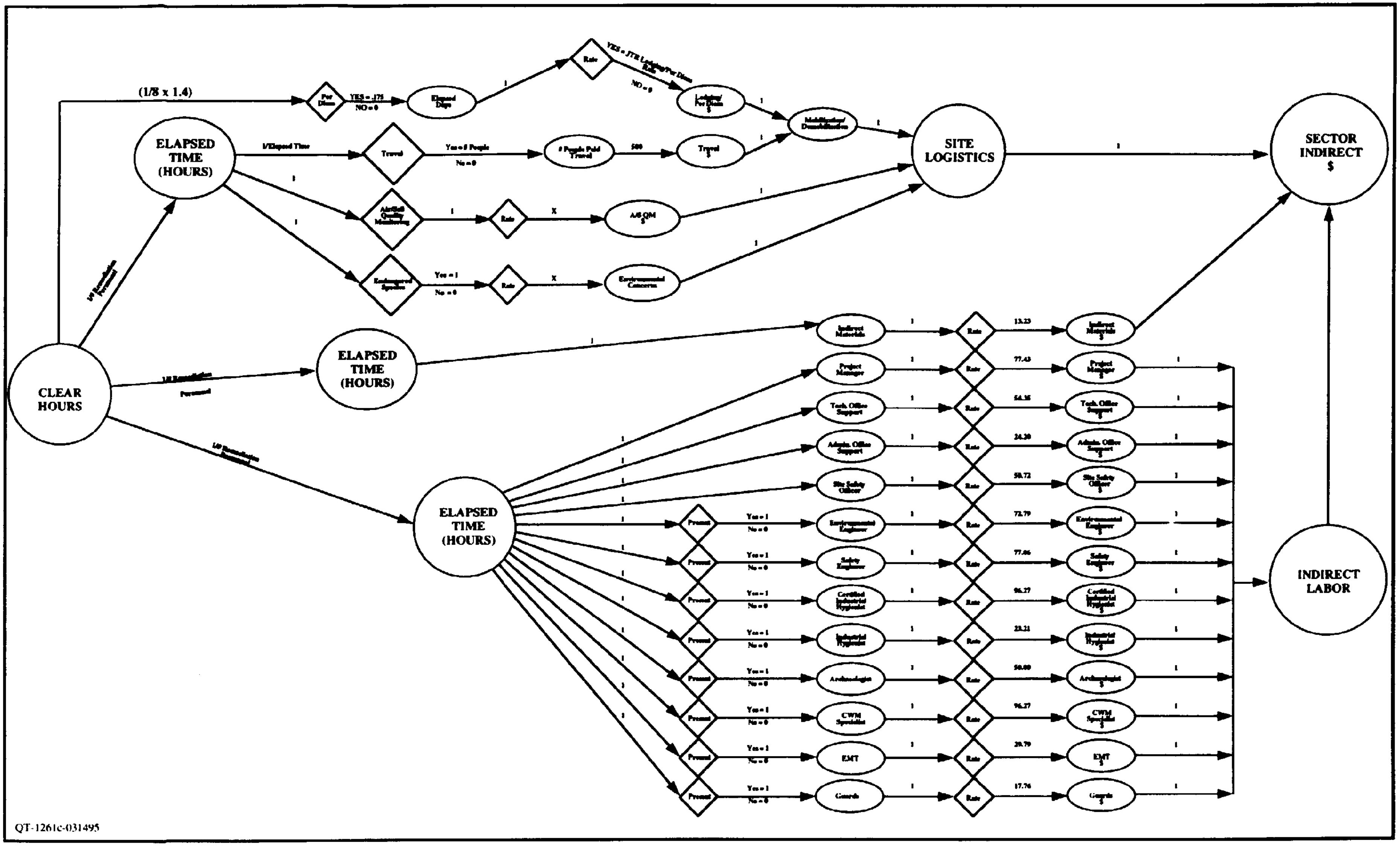


Figure K.3-2. Remediation Indirect Cost Flowgraph (Remediation Planning Tool)

APPENDIX L

RESPONSES TO TECHNICAL COMMENTS

APPENDIX L

RESPONSES TO TECHNICAL COMMENTS

Comments by Heaton

1. Throughout the Document, it refers to it's applicability to FUDS Sites. Will this software also work on active, BRAC or work for other sites? If so, recommend deleting the references to use only at FUDS. If not, the MCX needs to take action to insure the rest of the OEW world is covered by tools such as this.

Response: The software is applicable for sampling at any site. The references to FUDS have been deleted from the Final Report.

2. Para 1.2 states that the hardware requirements are 4mb of RAM but the bullets state a requirement for 1mb RAM. Clarify.

Response: SiteStats requires 4 mb RAM. The bullet in the draft report referred to the software's functional validation version that was delivered with the draft report.

3. From a user perspective, the most important part of the manual is Appendix K. Recommend this portion of the manual with the executive summary and a summary of each subroutine be published as a separate additional manual for distribution to users.

Response: The SiteStats Software User's Manual was published separately and delivered to USAEDH under a separate purchase order. QuantiTech has not been funded for the delivery of any separate documents.

4. Several times throughout the manual, references are made to "currently this is the way it works" or "currently this is the color standard." If a change is planned the manual should reflect the way the final product will be, not the current developmental standard. If no change is planned, then all references to "currently" should be deleted as they lead to reader confusion.

Response: Agree. All such references have been deleted.

5. Unsure if its a contract requirement for this contract, but for most AE contracts, the contractor name is not supposed to dominate over the cover, and the HSV division, contract numbers, etc., are supposed to be on the cover. If appropriate to this contract, correct, otherwise disregard.

Response: This contract has no such requirement.

Comments by A. Fanning

1. The executive summary should be expanded. Please state the significance of SiteStats to the users and please emphasize the reduction in data collection, reduction in cost and statistical objectivity that will be introduced into the EE/CA effort by use of SiteStats. The average reviewer and most of the managers will just read the executive summary here. Get them here or you may lose them forever.

Response: Executive summary has been expanded in Final Report.

2. Please give a generic discussion of what it means to the PM if H_a or H_0 lines are crossed.

Response: Discussion has been included in Final Report.

3. Please define what is meant by a pseudo-random number.

Response: Definition has been included in Final Report.

4. Please do not specify a magnetometer. Please state that all anomalies in a grid must be determined and numbered but do not specify a technology that has to be used to do this.

Response: Correction has been included in Final Report.

5. GridStats must be able to accept more than just one type of Grid. Please discuss how varying grid sizes will be accommodated.

Response: GridStats now accepts any size grids and this has been reflected in the Final Report.

6. The report has too much statistical/ops research jargon and phraseology. Remember that target audience at CEHND is not a statistician but a Civil or Mechanical engineer. Be descriptive please, but do not use words such as algorithms, heuristics, nearest neighbor statistics, etc. Very few of the reviewers will know what those phrases mean.

Response: An attempt has been made to delete or further explain/define the terms used to describe the methodology.

7. The proposed QA/QC process does not require sweeping in every grid/sector. This could be a public relations problem.

Response: As a result of a VE Study performed earlier in 1995, the QA/QC portion of SiteStats has been deleted by direction of the USAEDH Contracting Officer.

8. The proposed QA/QC process assumes that all sectors have been remediated uniformly (i.e., only chance variation exists in the remediated grids). This will seldom be the case. The success of remediation in a grid is highly dependent upon the technology used and the characteristics of the grid. The same UXO worker using the same method will not necessarily have the same success from one grid to the next.

Response: As a result of a VE Study performed earlier in 1995, the QA/QC portion of SiteStats has been deleted by direction of the USAEDH Contracting Officer.

9. "Exonomics" should be "Economics."

Response: This change has been incorporated into the Final Report.

10. Please work an example showing how all parameters work. Show the alpha, beta, D, assumptions, and stopping rules. Work an example where the stopping rules tell you to sample more. Work another showing where the sampling rules tell you to stop. The original SOW asked for examples for all of your mathematical/statistical techniques.

Response: This change has been incorporated into the Final Report.

11. Please define all parameters. Please work an example. Show how to perform the integration required.

Response: This change has been incorporated into the Final Report.

12. Excellent spatial interpolation write-up.

Response: Noted.

13. Please work an example.

Response: This change has been incorporated into the Final Report.

14. Would it be possible to "bail" or compile the RPT files so that they could be used on any DOS computer and not have to have Excel.

Response: RPT is now implemented in Visual Basic which is compiled and executable on any Windows computer.

15. Suggest changing "area" to another word such as "initiatives" when referring to tasks addressed by SiteStats because areas has a specific technical connotation and leads to confusion when used in the nontechnical sense.

Response: This change has been incorporated into the Final Report.

16. Page K-12, Figure K.5.1-12. Predicted Cost Error and Risk Error Changes. Suggest using "Cost Error" and "Risk Error" on the screen rather than "Alpha Value" and "Beta Value." This change in terminology will be more useful to the users.

Response: This change has been incorporated into the final software.

Comments by W. Watanabe

1. Page 1, last sentence. Revise 4M to 4MB.

Response: This change has been incorporated into the Final Report.

2. SiteStats Remediation Planning Tool Logic. Interchange Yes and No after "Site in OEW Cert Data Base?"

Response: This change has been incorporated into the Final Report.

Comments by Sally Parsons

1. Clear, thorough, well laid out.

Response: Noted.

2. The difficulty in reviewing this draft final report lies in the fact that operational comments were addressed in the proposals from the Value Engineering (VE) study. Rather than repeat the VE proposals in this report review, the contractor is to incorporate those changes which arise as the VE proposals are incorporated.

Response: These changes have been incorporated into the Final Report.

Comments by Mr. Sang

1. Since sampling grids are dispersed throughout the site, using SiteStats to make a decision whether or not the sampling should continue may not be feasible. Using SiteStats to make a decision within the sector is more appropriate.

Response: GridStats can be using independently in the grids that may be dispersed throughout a sector, then those results all rolled-in to SiteStats for the sector decision.

Comments by McCowan, Young

1. GridStats uses 100' x 200' grids. The U.S. Army Corps of Engineers currently has projects that use various size grids, i.e., 100' x 100' and 200' x 200'; therefore, the program needs to be flexible in this area.

Response: SiteStats/GridStats can now accommodate any size grid. This has been indicated in the Final Report.

2. Remediation direct costs are listed twice in the first paragraph with different cost items in each list. Remediation indirect costs should include field and home office overheads, handling costs, etc., from detailed cost estimates.

Response: These typographical errors have been corrected in the Final Report.