

Accounting for geophysical information in geostatistical characterization of unexploded ordnance (UXO) sites

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Efficient and reliable unexploded ordnance (UXO) site characterization is needed for decisions regarding future land use. There are several types of data available at UXO sites and geophysical signal maps are one of the most valuable sources of information. Incorporation of such information into site characterization requires a flexible and reliable methodology. Geostatistics allows one to account for exhaustive secondary information (i.e., known at every location within the field) in many different ways. Kriging and logistic regression were combined to map the probability of occurrence of at least one geophysical anomaly of interest, such as UXO, from a limited number of indicator data. Logistic regression is used to derive the trend from a geophysical signal map, and kriged residuals are added to the trend to estimate the probabilities of the presence of UXO at unsampled locations (simple kriging with varying local means or SKlm). Each location is identified for further remedial action if the estimated probability is greater than a given threshold. The technique is illustrated using a hypothetical UXO site generated by a UXO simulator, and a corresponding geophysical signal map. Indicator data are collected along two transects located within the site. Classification performances are then assessed by computing proportions of correct classification, false positive, false negative, and Kappa statistics. Two common approaches, one of which does not take any secondary information into account (ordinary indicator kriging) and a variant of common cokriging (collocated cokriging), were used for comparison purposes. Results indicate that accounting for exhaustive secondary information improves the overall characterization of UXO sites if an appropriate methodology, SKlm in this case, is used.

Keywords: collocated cokriging, Kappa statistics, logistic regression, simple kriging with varying local means

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1. Introduction

Unexploded ordnance (UXO) is a problem all over the world, especially at former military test ranges as well as former battlefields (Young and Helms, 1999; Stohl, 2002), including undersea sediments (Darrach *et al.*, 1998). UXO is hazardous because it is explosive and it contains pollutants, such as 2,4,6-trinitrotoluene (TNT) or 2,4-dinitrotoluene (2,4-DNT) that may migrate after years under soil or water. Mapping the risk of occurrence of UXO at any site is important, especially as these sites are prepared for return to the public or private sector. Efficient and precise site characterization for UXO cleanup is necessary. Traditionally, site characterization has relied on the so-called 'mag and flag' approach, in which each location is investigated using hand-held detectors to find out whether there is UXO. Each suspected UXO location is then marked with a flag. The flagged locations are later excavated to remove objects or examined further to decide whether the locations need to be excavated. More recent developments have led to multi-sensor packages mounted on mobile platforms (towed by dune buggies or mounted on helicopters) that allow for fast, reliable, and efficient detection (e.g., Nelson and McDonald, 2001; Doll *et al.*, 2003). These sensors can detect magnetic and electromagnetic anomalies, but they cannot discriminate perfectly between UXO and other fragments, such as ordnance debris (i.e., false alarm) or even iron rich soils. As a result, additional cleanup costs are caused by unnecessary remedial action. To facilitate the accurate location of UXO and reduce the number of false alarms, a variety of geophysical sensors have been developed. Although a significant amount of work has been devoted to the development of sensors, they have never been able to distinguish UXO perfectly among all objects (Bell and Barrow, 2001).

Under constraints of time and cost, excavation of anomalies cannot be conducted over the entire site. One of the existing guidelines for UXO site characterization recommends the use of standard statistics to determine the number of samples that need to be collected (USAESCH, 1999). However, this approach ignores any information about the spatial correlation of detected objects. In the presence of limited sample information, geostatistical techniques are useful tools for mapping the risk of occurrence of UXO at unsurveyed locations. To date, only a few studies have used geostatistics to characterize UXO sites (McKenna, 2001; Singh and Singh, 2001). It is also well recognized that geostatistical site characterization improves when the primary variable is supplemented with abundant secondary information (Goovaerts, 2000). Especially when secondary information is available at all locations being estimated, it is referred to as 'exhaustive' secondary information. Such information can take the form of a numerical simulation generated based upon historical site-use information, or it can be in the form of information obtained in a relatively coarse resolution wide-area geophysical survey. The quality of secondary information will be critical to the final site characterization results because of its use for both the initial sampling design and probability mapping (McKenna *et al.*, 2001).

The main objective of this study is to present a methodology to incorporate an exhaustive geophysical signal map with primary transect data into geostatistical estimation of the risk of occurrence of UXO. The technique combines logistic regression, which is suited for the analysis of binary data, and standard geostatistics.

This technique allows for the flexible incorporation of exhaustive secondary information. The approach is illustrated using a hypothetical site contaminated with UXO. Classification performances for further investigation (e.g., excavation) are compared with ordinary indicator kriging, which does not account for secondary information, and collocated cokriging (CoCK), which is one of the most common approaches to incorporate exhaustive secondary information. Classification results are summarized in terms of correct- and mis-classification proportions, and the Kappa statistic.

2. Geostatistical theory

The risk of occurrence of UXO is mapped using geostatistical interpolation techniques. The basic approach is to estimate the probabilities of occurrence of UXO at unsampled locations using a limited amount of primary indicator data sampled from the UXO site and that can be supplemented with secondary information. This section summarizes geostatistical techniques used in this paper.

2.1 Univariate kriging

Consider first the problem of estimating the probability p of occurrence of an event (i.e., presence of UXO) at an unsampled location \mathbf{u} , where \mathbf{u} is a vector of spatial coordinates. The information available consists of binary data (i.e., indicators) at n locations \mathbf{u}_α , $i(\mathbf{u}_\alpha)$, $\alpha = 1, 2, \dots, n$. All univariate indicator kriging estimates are variants of the general regression estimate $p^*(\mathbf{u})$ defined as:

$$p^*(\mathbf{u}) - m(\mathbf{u}) = \sum_{\alpha=1}^{n(\mathbf{u})} \lambda_\alpha(\mathbf{u}) [i(\mathbf{u}_\alpha) - m(\mathbf{u}_\alpha)], \quad (1)$$

where $\lambda_\alpha(\mathbf{u})$ is the weight assigned to datum $i(\mathbf{u}_\alpha)$ and $m(\mathbf{u})$ is the trend component of the spatially varying attribute (Journel, 1983). In practice, only the observations closest to \mathbf{u} being estimated are retained, that is the $n(\mathbf{u})$ data within a given neighborhood or window $W(\mathbf{u})$ centered on \mathbf{u} (Saito and Goovaerts, 2000).

In simple indicator kriging (SIK) (Goovaerts *et al.*, 1997; Juang and Lee, 1998), the trend component $m(\mathbf{u})$ is modeled as a known constant mean m . SIK weights $\lambda_\alpha^{\text{SIK}}$ are obtained by solving the simple kriging system:

$$\sum_{\beta=1}^{n(\mathbf{u})} \lambda_\beta^{\text{SIK}}(\mathbf{u}) C_I(\mathbf{u}_\alpha - \mathbf{u}_\beta) = C_I(\mathbf{u}_\alpha - \mathbf{u}) \quad \alpha = 1, \dots, n(\mathbf{u}), \quad (2)$$

where $C_I(\mathbf{h})$ is the covariance function of indicator random function (RF) $I(\mathbf{u})$. The most common kriging estimate is ordinary indicator kriging (OIK), which estimates the probability $p(\mathbf{u})$ as a linear combination of neighboring indicators:

$$p^*(\mathbf{u}) = \sum_{\alpha=1}^{n(\mathbf{u})} \lambda_\alpha^{\text{OIK}}(\mathbf{u}) i(\mathbf{u}_\alpha).$$

In OIK, instead of using the constant mean, m , the mean at each estimation location (i.e., local mean, $m(\mathbf{u})$) is implicitly re-estimated. OIK weights $\lambda_{\alpha}^{\text{OIK}}$ are determined so as to minimize the error or estimation variance $\sigma^2(\mathbf{u}) = \text{Var}\{I^*(\mathbf{u}) - I(\mathbf{u})\}$ under the constraint of an unbiased estimate. These weights are obtained by solving system of linear equations known as the ordinary kriging system:

$$\begin{cases} \sum_{\beta=1}^{n(\mathbf{u})} \lambda_{\beta}^{\text{OIK}}(\mathbf{u}) C_I(\mathbf{u}_{\alpha} - \mathbf{u}_{\beta}) - \mu(\mathbf{u}) = C_I(\mathbf{u}_{\alpha} - \mathbf{u}) & \alpha = 1, \dots, n(\mathbf{u}) \\ \sum_{\beta=1}^{n(\mathbf{u})} \lambda_{\beta}^{\text{OIK}}(\mathbf{u}) = 1 \end{cases}$$

The unbiasedness of the OIK estimator is ensured by constraining the weights to sum to one, which requires the definition of the Lagrange parameter $\mu(\mathbf{u})$. The only information required by the system are the covariance values for different lags, and these are readily derived from the indicator covariance model $C_I(\mathbf{u})$ fit to experimental values.

2.2 Accounting for exhaustive secondary information

When the sparsely sampled primary attribute is supplemented by correlated secondary information, the estimation of the primary attribute can be improved. Consider the situation where the primary indicator data $\{i(\mathbf{u}_{\alpha}), \alpha = 1, \dots, n\}$ are supplemented by secondary data available at all estimation grid nodes (i.e., exhaustive information) and denoted $y(\mathbf{u})$. There are many techniques available to incorporate exhaustive secondary information into the estimation process, and they can be categorized mainly into three types. The first type is cokriging (CK) which accounts for correlation between the primary and secondary attributes, but if the secondary information is exhaustive and smoothly varying, numerical instability may arise in the solution of the CK equations (Goovaerts, 1997). The second type uses the exhaustive information to characterize the spatial trend of the primary attribute, and includes simple kriging with varying local means, e.g., Goovaerts (2000), and kriging with an external drift, e.g., Ahmed and De Marsily (1987), and Bárdossy and Lehmann (1998). The third type uses the exhaustive information to stratify the study area, then the primary attribute is estimated within each stratum using a univariate kriging algorithm (kriging with strata, Stein *et al.*, 1988; Stein, 1994). In this study, the first two types are considered.

CK allows one to account for the spatial cross correlation between primary and secondary variables. The CK estimate is written as:

$$p_{CK}^*(\mathbf{u}) - m_I = \sum_{\alpha_I=1}^{n_I(\mathbf{u})} \lambda_{\alpha_I}(\mathbf{u}) [i(\mathbf{u}_{\alpha_I}) - m_I(\mathbf{u}_{\alpha_I})] + \sum_{\alpha_Y=1}^{n_Y(\mathbf{u})} \lambda_{\alpha_Y}(\mathbf{u}) [y(\mathbf{u}_{\alpha_Y}) - m_Y(\mathbf{u}_{\alpha_Y})],$$

where $\lambda_{\alpha_I}(\mathbf{u})$ is the weight assigned to the primary datum $i(\mathbf{u}_{\alpha_I})$ and $\lambda_{\alpha_Y}(\mathbf{u})$ is the weight assigned to secondary datum $y(\mathbf{u}_{\alpha_Y})$. Collocated cokriging or CoCK (Goovaerts, 1997) is a variant of CK, which is preferred when the secondary data are available at every location being estimated because it reduces the size of the CK

system and leads to a numerically stable and simple system. The basic idea is to incorporate only the secondary datum co-located with the location \mathbf{u} being estimated. The CoCK estimate of attribute i is

$$p_{\text{CoCK}}^*(\mathbf{u}) = \sum_{\alpha_I=1}^{n_I(\mathbf{u})} \lambda_{\alpha_I}^{\text{CoCK}}(\mathbf{u}) i(\mathbf{u}_{\alpha_I}) + \lambda_Y^{\text{CoCK}}(\mathbf{u}) [y(\mathbf{u}) - m_Y + m_I] \quad (3)$$

with a single constraint that all weights must sum to one:

$$\sum_{\alpha_I=1}^{n_I(\mathbf{u})} \lambda_{\alpha_I}^{\text{CoCK}}(\mathbf{u}) + \lambda_Y^{\text{CoCK}}(\mathbf{u}) = 1,$$

where m_I and m_Y are the global mean of primary (indicator) and secondary variables, and the second term of equation (3) corresponds to a rescaling of the secondary variable to the mean of the primary variable to ensure unbiased estimation. The CoCK weights are obtained by solving the following system of $(n_I(\mathbf{u}) + 2)$ linear equations:

$$\begin{cases} \sum_{\beta_I=1}^{n_I(\mathbf{u})} \lambda_{\beta_I}^{\text{CoCK}}(\mathbf{u}) C_{II}(\mathbf{u}_{\alpha_I} - \mathbf{u}_{\beta_I}) + \lambda_Y^{\text{CoCK}}(\mathbf{u}) C_{IY}(\mathbf{u}_{\alpha_I} - \mathbf{u}), \\ \quad + \mu^{\text{CoCK}}(\mathbf{u}) = C_{II}(\mathbf{u}_{\alpha_I} - \mathbf{u}) \quad \alpha_I = 1, \dots, n_I(\mathbf{u}) \\ \sum_{\beta_I=1}^{n_I(\mathbf{u})} \lambda_{\beta_I}^{\text{CoCK}}(\mathbf{u}) C_{YI}(\mathbf{u} - \mathbf{u}_{\beta_I}) + \lambda_Y^{\text{CoCK}}(\mathbf{u}) C_{YY}(0) \\ \quad + \mu^{\text{CoCK}}(\mathbf{u}) = C_{YI}(0) \\ \sum_{\beta_I=1}^{n_I(\mathbf{u})} \lambda_{\beta_I}^{\text{CoCK}}(\mathbf{u}) + \lambda_Y^{\text{CoCK}}(\mathbf{u}) = 1 \end{cases},$$

where $C_{IY}(\mathbf{u}_{\alpha_I} - \mathbf{u})$ is the cross-covariance value between primary variable $i(\mathbf{u}_{\alpha_I})$ and secondary variable $y(\mathbf{u})$. This system does not require the covariance between secondary data $C_{YY}(\mathbf{h})$ for $|\mathbf{h}| > 0$ but still calls for inference and modeling of the primary covariance function $C_{II}(\mathbf{h})$ and the cross covariance between primary and secondary data $C_{IY}(\mathbf{h})$. The effort of the modeling can be reduced by applying the Markov model (MM1) which approximates the cross covariance by the following function of the primary covariance (Journal, 1999):

$$C_{IY}(\mathbf{h}) \simeq \frac{C_{IY}(0)}{C_{II}(0)} C_{II}(\mathbf{h}).$$

Journal (1999) claimed that this approximation may not be appropriate when a secondary variable is defined on a much larger support than the primary variable and proposed an alternative Markov approximation (MM2) as follows:

$$C_{IY}(\mathbf{h}) \simeq \frac{C_{IY}(0)}{C_{YY}(0)} C_{YY}(\mathbf{h})$$

In other words, the cross covariance function is inferred from the primary covariance in MM1, while it is approximated from the secondary covariance in MM2. In this study, the choice of the Markov model is determined through visual checking of the goodness of fit to the experimental semivariogram (i.e., appropriate linear models must be fit to the secondary covariances).

The simple kriging with varying local means (SKlm) estimate $p_{\text{SKlm}}^*(\mathbf{u})$ is given as the univariate kriging estimate (1), where the trend $m(\mathbf{u})$ is not the constant mean but a known varying mean derived from the secondary information $y(\mathbf{u})$ using linear regression (Goovaerts, 2000) or other techniques. This estimator thus can be thought of as kriging residuals between each datum and the local mean, $r(\mathbf{u}_\alpha) = i(\mathbf{u}_\alpha) - m(\mathbf{u}_\alpha)$, and then adding the local means back to the estimated residual. The SKlm estimate is rewritten as the sum of the regression estimate $m_{\text{SKlm}}^*(\mathbf{u}) = f(y(\mathbf{u}))$ and the simple kriging estimate of the residual value at \mathbf{u} :

$$\begin{aligned} p_{\text{SKlm}}^*(\mathbf{u}) &= m_{\text{SKlm}}^*(\mathbf{u}) + \sum_{\alpha=1}^{n(\mathbf{u})} \lambda_{\alpha}^{\text{SK}}(\mathbf{u}) [i(\mathbf{u}_\alpha) - m(\mathbf{u}_\alpha)] \\ &= f(y(\mathbf{u})) + \sum_{\alpha=1}^{n(\mathbf{u})} \lambda_{\alpha}^{\text{SK}}(\mathbf{u}) r(\mathbf{u}_\alpha), \end{aligned} \quad (4)$$

where the weights $\lambda_{\alpha}^{\text{SK}}(\mathbf{u})$ are obtained by solving the simple kriging system (2).

When binary data are used as the dependent variable, linear regression is not an appropriate model to derive local means because of several violations of underlying assumptions of the linear regression theory (Allison, 1999): 1. Prediction errors are not normally distributed because data can take only two values. 2. The errors are heteroscedastic, that is the variance of the dependent variable is a function of the value of the independent variable. 3. The predicted probabilities can be greater than 1 or less than 0 if the linear regression model, which is inherently unbounded, is used. Usually those values are arbitrarily set to either 1 or 0 which may lead to non-optimal estimate. There are many techniques available to analyze binary data, such as logistic, probit, and complementary log–log regressions. In this paper, logistic regression was used to derive the local means $m_{\text{SKlm}}^*(\mathbf{u})$ in SKlm (4), since it is one of the most common binary data analysis techniques.

3. Materials and methods

3.1 Data sets

The primary data for geostatistical probability mapping are indicators of the presence of at least one UXO, or, more generally, one geophysical anomaly of interest, at any location. Primary indicators are either 1 or 0 depending upon whether at least one UXO exists or not (i.e., 1 = at least one UXO, 0 = no UXO) within a sampling cell of a given size. These primary data are available at locations where actual sampling (e.g., excavation) is conducted. Because of time and cost constraints, sampling is rarely done exhaustively but only for limited number of locations. UXO site surveys can be conducted using geophysical sensors, which can be attached to a helicopter (Doll *et al.*, 2003), and it is reasonable to collect samples along selected transects. Optimization of sampling transect locations has been discussed in McKenna *et al.* (2001) and Bilisoly and McKenna (2003). In this paper, since high signal values usually correspond to UXO, the primary indicator data are collected

along two transects that have the highest mean signal values, as determined from the secondary data, and are selected under the constraint of the minimum inter-angle between transects of 30° .

The UXO site investigated in this paper is a hypothetical site created with a Poisson simulator. The benefit of using the hypothetical site is that the true spatial distribution of objects is known so that any type of investigation is possible and the accuracy and precision of the results can be fully evaluated. In the simulator, the spatial distribution of UXO is viewed as a point process since the location of the individual UXO is the variable of interest, and the stochastic simulation of a Poisson process is used to model the spatial distribution of UXO. The Poisson processes provide a common class of models for objects distributed in space according to a uniform intensity (homogeneous Poisson process). In reality, however, the spatial distribution of UXO is not uniform since its intensity changes spatially because of the existence of specific targets. In such a case, one of its variants (the doubly stochastic Poisson process (DSPP), McKenna *et al.*, 2001) is used to model the spatial distribution of UXO. McKenna (2001) showed that the DSPP can provide accurate and precise distributions of UXO by analyzing the Pueblo of Laguna data collected at the N-10 Target Area on the Pueblo of Laguna in New Mexico, USA by the Naval Research Laboratory (McDonald and Robertson, 2000).

This simulator has been developed to generate non-conditional UXO realizations as a Poisson process (McKenna *et al.*, 2001). In the simulator, two types of ordnance can be considered: airborne and mortar ordnance. For both types of ordnance and fragments, the simulator can also associate analytic signal values of a geophysical sensor (e.g., magnetometer). The input to the simulator for analytic signal simulation is the probability distribution of signal values for UXO and fragments. In this simulator, lognormal distributions are considered for analytic signal values of both UXO and fragments. To obtain an idea of the distribution of real signal values, the histogram of signal values collected at the Ileta S3 site by Oak Ridge National Laboratory (Doll, et al., 2003; Doll, W.E., Written Communication) using the airborne system is first examined (Fig. 1). The distribution is positively skewed (mean = 1.22 [nT/m], while median = 0.65 [nT/m]) and the tail to the right is extremely long (the maximum signal value is 192.90 [nT/m]). Thus, even though the data include signals for both UXO and fragments, it is reasonable to assume that separate log-normal distributions describe the analytic values for each type of object for simulation of the positively skewed distribution. The user needs to specify the ranges of the logarithm of signal values for UXO and fragments, respectively, and 95.45% of the logarithms of the simulated values will lie within these ranges (i.e., the maximum and minimum values of the range correspond to $\pm 2\sigma$ from the mean).

In this paper, the simplest case (i.e., one airborne target) is considered for further investigation. The size of the hypothetical site is 5000×5000 m and the single target is located in the center of the site: target coordinates are (2500, 2500). Figure 2 (top) shows the spatial distribution of UXO generated by the simulator and this is used as the true distribution of UXO. In this study a 50×50 m cell is used as the spatial support over which any characterization decision is made. There are a number of simulated objects in each cell but only the largest signal value within the unit is retained as a representative value of the cell for further investigation (Fig. 2, middle). Their distribution is positively skewed as expected (Fig. 2, bottom). Signal ranges in

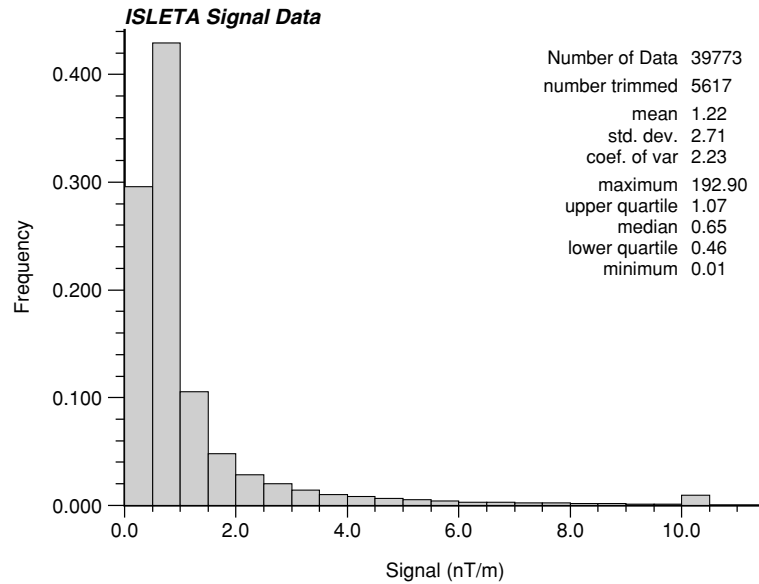


Figure 1. Histogram of analytic signals [nT/m] at the Pueblo of the Isleta site (S3) in New Mexico.

the actual signal unit [nT/m] used in this simulation are listed in Table 1. The map of simulated analytic signals is used as exhaustive secondary information to locate sampling transects and to map risks (see Section 2.2).

3.2 Geostatistical UXO site characterization

The simulated hypothetical UXO site has been used to investigate the impact of accounting for exhaustive secondary information in geostatistical UXO site characterization. The basic approach is, first to map the risk (i.e., probability) of occurrence of at least one UXO at any location, and then to classify each location using a given probability threshold for further investigation. In this paper, two approaches were considered for geostatistical probability mapping: (1) no secondary information was considered, (2) primary indicator data were supplemented with exhaustive secondary information (i.e., geophysical map). The following are details of each technique:

1. Univariate approach

- (a) Two 50-m wide sampling transects are positioned based on the simulated analytic signal data (secondary information), which are available exhaustively.
- (b) Each transect is subdivided into 50×50 m cells. At each sampling cell, indicator data (1 = at least one UXO, 0 = no UXO) are collected by sampling the cell.

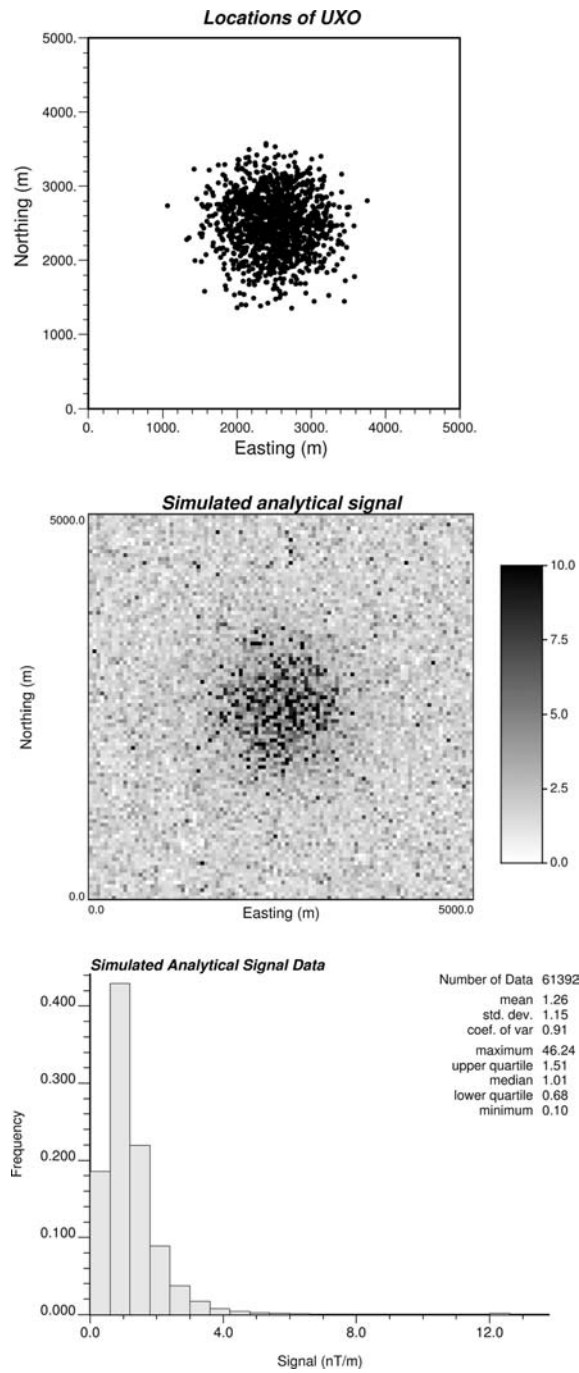


Figure 2. Locations of UXO simulated around the target in the center of the hypothetical study site. The maximum signal value in each 50×50 m cell is retained to create an exhaustive map of simulated analytic signals [nT/m] at the site and their histogram.

Table 1. Ranges of analytic signal values [nT/m] for UXO and fragments. The values correspond to $\pm 2\sigma$ from the mean of the normal distribution of the log-transformed signal values.

Object	UXO	Fragments
Analytic signal	0.1–100.0	0.1–10.0

- (c) The probability of occurrence of at least one UXO is computed at each unsampled cell (i.e., 50×50 m cell) of the hypothetical site using ordinary indicator kriging.
- (d) Each cell is classified as hazardous or not using a series of probability thresholds. Cells are flagged for further action if the estimated probabilities exceed a given threshold. If the probability is below the threshold, then the cell is left for no action. In the rest of this paper, the term ‘design reliability’ R_D (McKenna, 2001) is used and it is defined as $1-p_t$ where p_t corresponds to any selected probability threshold.
- (e) Classification achieved at the previous step is compared with the true UXO distribution of the hypothetical site to compute the proportion of correct decisions, false positive, and false negative. The correct classification applies when the location is correctly excavated (at least one UXO exists) or is left untouched (no UXO). When the location is wrongly excavated, it is a false positive result, while the false negative occurs at any location wrongly declared clean. This is done for the following 10 design reliabilities: 0.05, 0.15, \dots , 0.95.

2. Multivariate approach

- (a) Indicator data used in this approach are prepared by the same procedure as used for the univariate approach (see 1(a) and 1(b)).
- (b) The probability of occurrence of at least one UXO at any unsampled location is estimated using CoCK and simple kriging with varying local means derived from logistic regression (SKlm). The exhaustive map of simulated analytic signal data (Fig. 2) is used as secondary information.
- (c) The classification of each cell and the comparison to the true data are performed using the procedure described in 1(d) and 1(e).

4. Results and discussions

In this study, two sample transects are first selected according to information available, such as the simulated analytic signal map. Along the selected transects, every 50×50 m cell is sampled to collect primary data indicating whether or not there is at least one UXO. Figure 3 shows locations where primary data are collected (actually sampled). Filled cells indicate there is at least one UXO found, while open

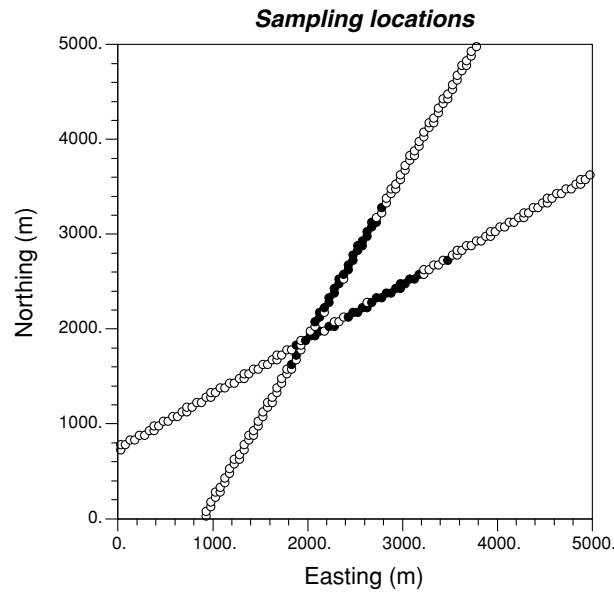


Figure 3. Location maps of indicator data obtained along two sampling transects. Filled circles indicate at least one UXO found and open circles imply no UXO found. Transects are selected using the exhaustive map of analytic signals.

cells depict locations where there is no UXO found. The indicator semivariogram is first computed and modeled (Fig. 4, left) to use in OIK and CoCK. The cross semivariogram between indicators and secondary information (i.e., exhaustive geophysical map) is modeled using the MM1 and MM2 models (Fig. 4, right). The MM1 model fits well to the cross semivariogram, while the MM2 model basically overstates the cross semivariances and is inappropriate here. To perform simple

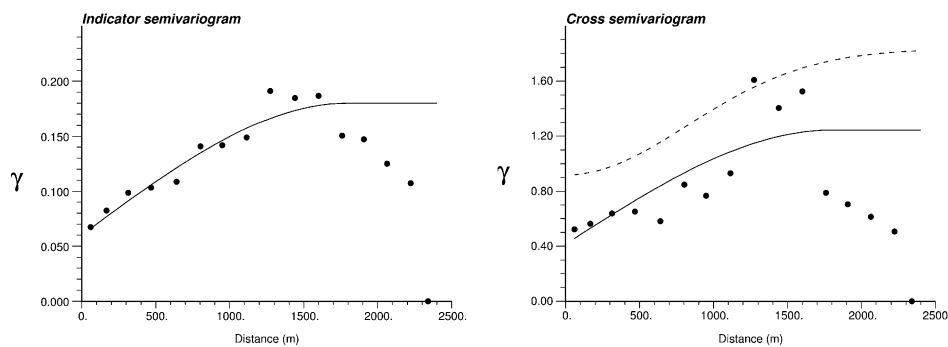


Figure 4. Experimental indicator semivariogram and the linear model fit. The MM1 (solid) and MM2 (dashed) models are used to model the cross semivariogram between the primary indicator variable and secondary variable (analytic signals).

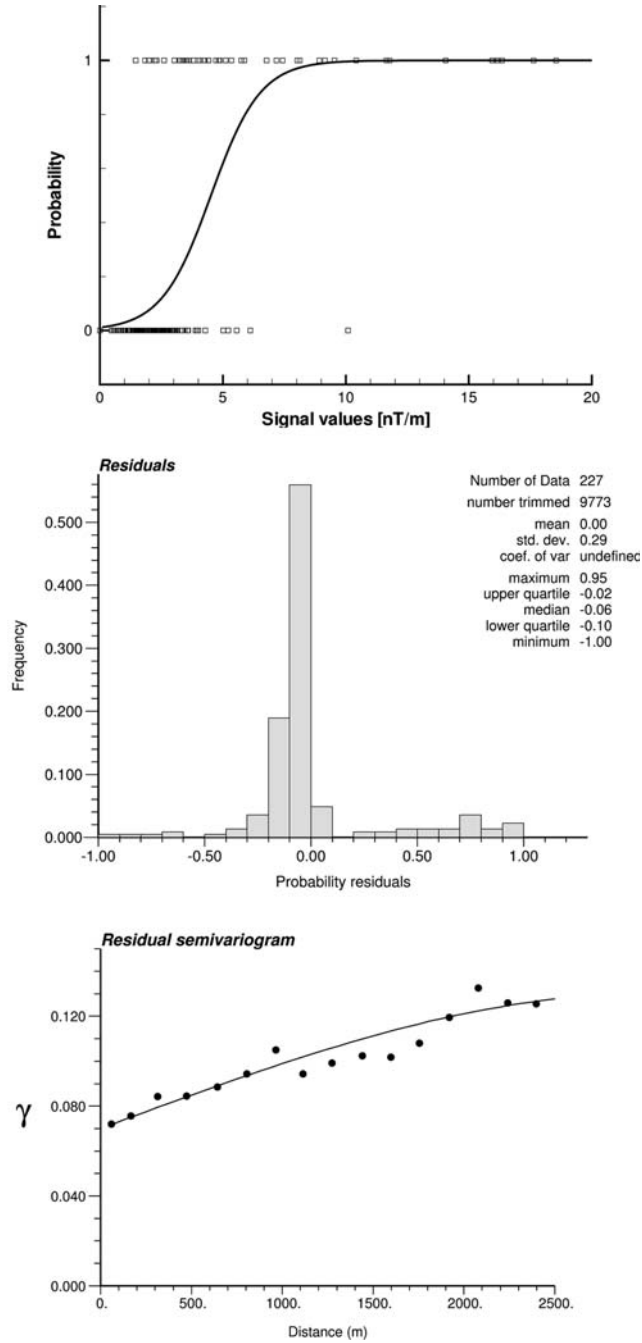


Figure 5. Indicator data obtained from two sampling transects and the logistic model fit. Histogram and experimental semivariogram with a spherical model fitted of probability residuals.

kriging with varying local means derived from logistic regression (SKlm), a logistic model is first fit to the indicator data (Fig 5, top), and residuals are computed. In general, the model fits well to the indicator data for high signal values. The residuals have a zero mean and a unimodal distribution (Fig. 5, middle). Positive errors are associated with 1s, while negative errors are associated with 0s, because the logit model always returns values greater than 0 and less than 1. The semivariogram of residuals with a spherical model fit is also depicted in Fig. 5 (bottom), and the residuals are used in simple kriging. Kriged residuals are, then, added to trend components to estimate probabilities. Figure 6 shows three probability maps obtained using OIK, CoCK, and SKlm from the transect data. All approaches well reproduced the target zone, while OIK and CoCK yield higher probabilities in top left and bottom right corners of the site. Probabilities are overestimated in those areas because there are not enough sampling locations to have unbiased estimates in those regions.

Each of the three probability maps constructed using different approaches are then classified using a series of probability thresholds (i.e., design reliabilities). The proportions of correct, false positive, and false negative classification as a function of the design reliability are plotted in Fig. 7. The rates of correct classification and false positive obtained for OIK and CoCK are similar over the different design reliabilities. SKlm yields systematically higher correct classification rates and lower false positive rates, thus is better, than other two approaches as long as the design reliability is less than 0.95. Higher false positive rates for OIK and CoCK lead to lower false negative rates, while SKlm results in slightly higher false negative rates although they are less than 5% at any R_D . For all three approaches, the percent of false negatives is less than 2% for any R_D greater than 0.8. Results indicate that accounting for exhaustive geophysical information improves overall classification results if an appropriate approach, SKlm in this case, is used. One advantage of SKlm is that this technique can be easily expanded to incorporate more than one secondary exhaustive map compared to CoCK. At UXO sites, there may be many different types of ancillary information available, such as Archival Search Reports (ASR), aerial photos, or remote sensing images. As long as they can be mapped, they can be used in the logistic model and accounting for such information is expected to improve the overall classification.

The classification results can be summarized using the Kappa statistic (κ) originally formulated by Cohen (1960). It was developed to assess agreement between two observers classifying subjects into two possible categories. The simplest assessment is to measure the proportion of agreement between two observers p_0 , however, it includes the proportion of agreement caused by chance p_e . In order to remove the effect of chance agreement, Cohen (1960) defined the Kappa statistics as:

$$\kappa = \frac{p_0 - p_e}{1 - p_e},$$

where $p_0 - p_e$ is the difference between the proportion of observed agreement and that of chance agreement, while $1 - p_e$ is interpreted as *the maximum possible correct classification beyond that expected by chance* (Cook, 1998). The Kappa statistic can be used to summarize overall classification performances by accounting for all three rates (i.e., correct classification, false positive and false negative), and has been used

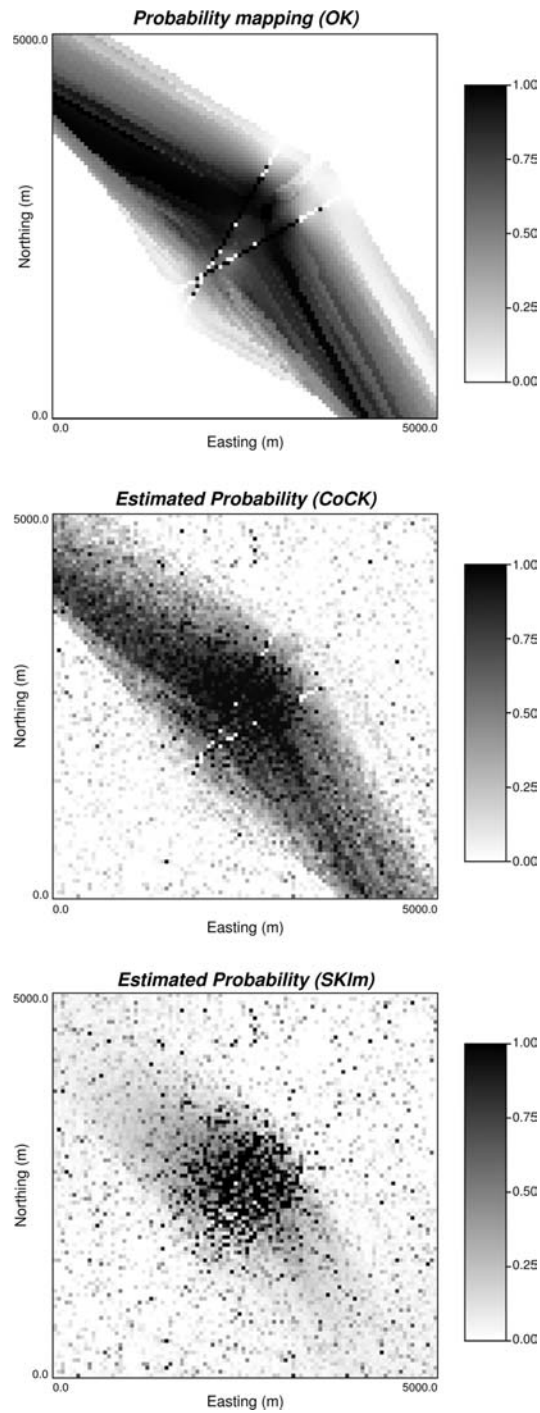


Figure 6. The probabilities of occurrence of at least one UXO at any location are estimated using OIK, CoCK, and SKIm derived from logistic regression (top to bottom).

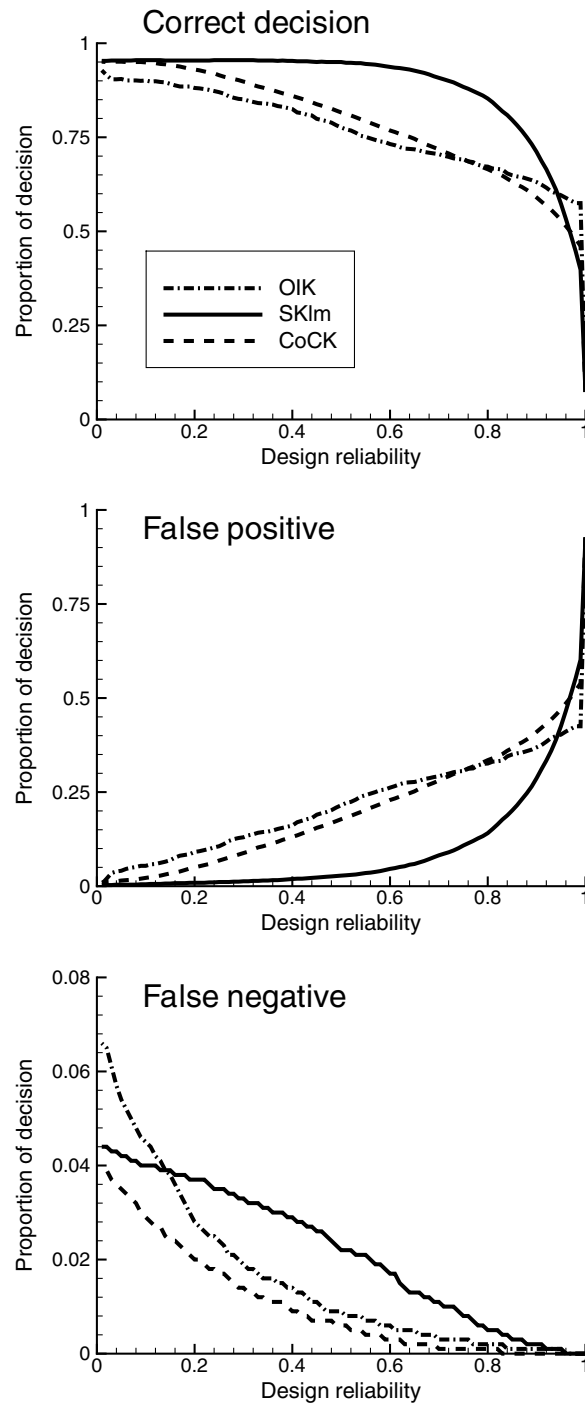


Figure 7. The impact of design reliability over proportions of correct, false positive, and false negative classification produced by three techniques (OIK, CoCK, and SKIm) for the hypothetical UXO site. Note the expanded vertical scale in the false negative plot.

to assess the performance of image classification (Martin *et al.*, 1998; Goovaerts, 2002). In this paper, the classification results are summarized using the Kappa statistic as a function of design reliability (Fig. 8). SKlm outperforms other two approaches in terms of Kappa statistics over most design reliabilities, which is consistent with what has been observed in Fig. 7.

This study shows the benefit of incorporating exhaustive secondary information into geostatistical characterization of UXO sites if an appropriate methodology is used. The other factor that one needs to examine is the quality of secondary information. McKenna *et al.* (2001) investigated the impact of accounting for spatially biased secondary information on the final classification decisions. It was found that, as long as secondary information is unbiased, it can improve the estimation when combined with primary indicator data. Although it is obvious that the quality of secondary information has a crucial impact on the final decisions, it is still not well quantified and needs to be investigated more carefully in the future.

The last issue discussed in this paper concerns false negatives associated with the site characterization. When sites contaminated with chemicals, such as heavy metals or organics, are being characterized for remediation, regulators usually allow false negative to a certain extent. For example, the U.S. EPA set the 5% false negative rate as a goal for remediation of dioxin contaminated sites (Ryti, 1993). However, this should not be applied to UXO sites, since leaving only a single UXO could have a serious consequences. A zero false negative rate should be the ultimate goal, but it is never achieved unless the entire site is excavated. In the future, to minimize the rate of false negatives, probability maps need to be

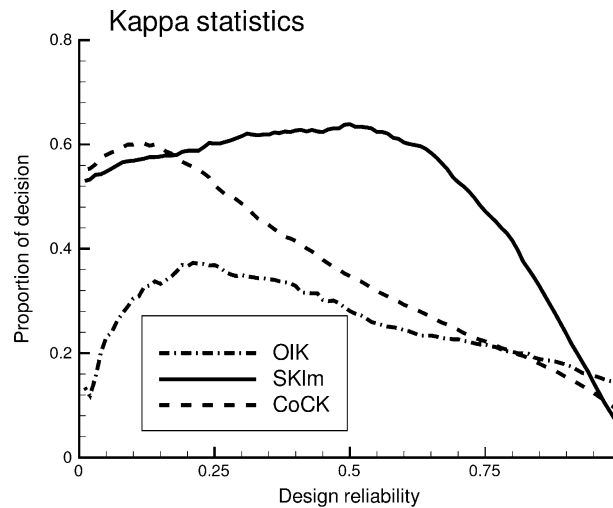


Figure 8. Kappa statistics as a function of design reliability for three different geostatistical methodologies (OIK, CoCK, and SKlm). The higher the Kappa statistics, the better the classification.

updated by collecting additional observations based upon the results from the initial sample data (i.e., Bayesian updating).

5. Conclusions

Geophysical signal maps are one of the most valuable sources of information available at UXO sites. Incorporation of such information with more local sample data into site characterization requires a flexible and reliable methodology. Geostatistics allows one to account for exhaustive secondary information in many different ways. In this study, the probability of occurrence of at least one UXO location was estimated at any unsampled location using simple kriging with varying local means (SKlm), which is one of the most straightforward and versatile geostatistical techniques to account for such secondary information. SKlm consists of deriving the trend component directly from a geophysical map through regression and interpolating residuals through kriging. The trend component and the kriged residual are then added to estimate the probability at each location. In this paper, logistic regression is used to determine the trend component, since the observations are binary (i.e., indicator). The technique is compared to collocated cokriging (CoCK) which is one of the most common approaches when secondary information is spatially exhaustive. The classification results show the superiority of SKlm derived using logistic regression over CoCK in terms of proportions of correct and incorrect decisions. Results also show that SKlm outperforms ordinary indicator kriging which ignores secondary information.

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