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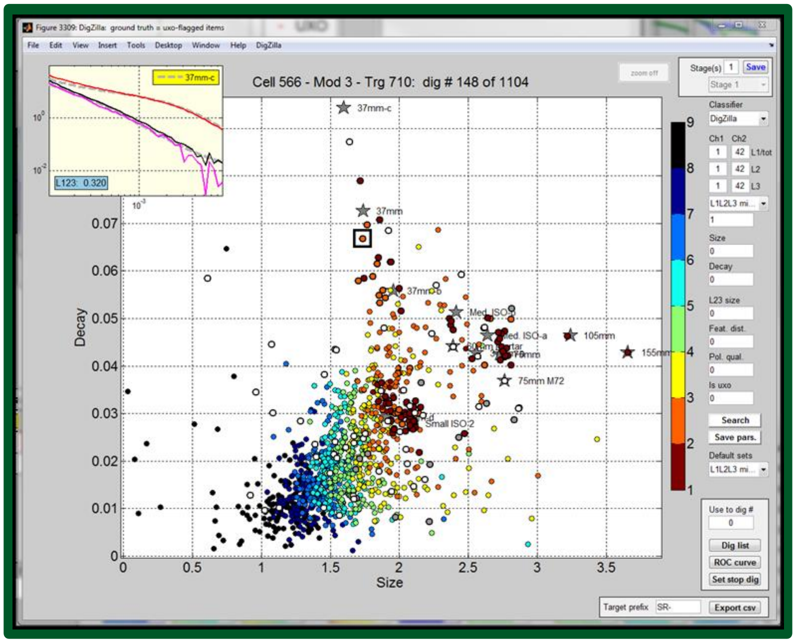

Dipole Models for UXO Discrimination at Live Sites

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14. ABSTRACT
This Cost and Performance report focuses on data collected as part of the ESTCP live site demonstration at Spencer Range. We present dipole based classification applied to dynamic and cued data from both the TEMTADS 2x2 dynamic and MetalMapper. All performance metrics except two were met: for the MetalMapper (URS) dynamic data, reliable target parameters were estimated for only 92.1% due to the lack of data coverage at the edges of the survey area. The data acquired in the treed area by the TEMTADS 2x2 had a depth estimate error standard deviation of 13 cm due to ground clearance height variations. A cost analysis of these methods was completed. We consider anomaly detection using advanced sensors, classifying many of the anomalies using the dynamic data, and only having to collect cued data over a subset of the anomalies. Given the reduced number of data collections, one might expect the savings from the advanced sensor only mode to be much greater than the hybrid approach. The current generation of advanced sensors are not configured to be deployed in arrays so the cost for the advanced sensor detection survey at this example site is much higher than for detection using an EM61-MK2 array. As the operation of advanced sensors in dynamic mode is explored further, it is possible that this cost disadvantage will lessen.

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ACRONYMS AND ABBREVIATIONS

2OI	Two Object Inversion
AGC	Advanced Geophysical Classification
API	Application Program Interface
BTG	Black Tusk Geophysics
BUD	Berkeley UXO Discriminator
CCR	Combined Classifier Ranking
cm	Centimeter(s)
EM	Electromagnetic
EMI	Electromagnetic Induction
ESTCP	Environmental Security Technology Certification Program
FAR	False Alarm Rate
HEAT	High-explosive, Anti-tank
IDA	Institute for Defense Analyses
IMU	Inertial Measurement Unit
in	Inch(es)
ISO	Industry Standard Object
IVS	Instrument Verification Strip
m	Meter(s)
mm	Millimeter(s)
MPV	Man Portable Vector
MSEMS	Man-portable Simultaneous EMI and Magnetometer System
MTADS	Multi-sensor Towed Array Detection System
NAEVA	Naeva Geophysics Inc.
QC	Quality Control
ROC	Receiver Operating Characteristic
RTS	Robotic Total Station
SERDP	Strategic Environmental Research and Development Program
SNR	Signal to Noise Ratio
SOI	Single Object Inversion
TEM	Time-domain Electromagnetic
TEMTADS	Time-domain Electromagnetic Towed Array Detection System

TOI	Target(s) of Interest
UBC-GIF	University of British Columbia – Geophysical Inversion Facility
UBC	University of British Columbia
URS	URS Corporation
UXO	Unexploded Ordnance

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EXECUTIVE SUMMARY

OBJECTIVES OF THE DEMONSTRATION

In 2003, the Defense Science Board observed: "The problem is that instruments that can detect the buried unexploded ordnance (UXO) also detect numerous scrap metal objects and other artifacts, which leads to an enormous amount of expensive digging. Typically 100 holes may be dug before a real UXO is unearthed! The Task Force assessment is that much of this wasteful digging can be eliminated by the use of more advanced technology instruments that exploit modern digital processing and advanced multi-mode sensors to achieve an improved level of discrimination of scrap from UXO." Since 2003, significant progress has been made in UXO classification technology. To date, testing of these approaches has been primarily limited to test sites with only limited application at live sites. Acceptance of classification technologies requires demonstration of system capabilities at real UXO sites under real world conditions. Any attempt to declare detected anomalies to be harmless and requiring no further investigation will require demonstration to regulators of not only individual technologies, but an entire decision making process.

At the Spencer Range Tennessee site covered by this report, the objective was to discriminate targets of interest (TOI) (including 37-millimeter [mm], 60-mm, 75-mm, 105-mm, 155-mm targets and small and medium industry standard objects [ISOs]) from non-hazardous shrapnel, range and cultural debris. We describe the performance of classification techniques that utilized: (1) full coverage, dynamically acquired survey data collected with both the Time Domain Electromagnetic Towed Array Detection System (TEMTADS) 2x2 and the MetalMapper advanced electromagnetic induction (EMI) sensors; and (2) static, cued interrogation style data acquired with MetalMapper and TEMTADS 2x2.

TECHNOLOGY DESCRIPTION

The Advanced Geophysical Classification (AGC) techniques applied to the Spencer Range data use dipole model-based features extracted from multi-static, multi-channel EMI data. Single source and multi-source dipole inversions were used to estimate target location, orientation, and principal polarizabilities. From the extracted feature vectors, prioritized dig-lists were created for: (1) the MetalMapper deployed in a dynamic, full coverage mode; (2) the MetalMapper deployed in a static, cued mode (for 2 unique datasets over identical targets collected by Naeva Geophysics Inc. [NAEVA] and URS Corporation [URS]); (3) the TEMTADS 2x2 deployed in a dynamic, full coverage mode; and (4) TEMTADS 2x2 deployed in a static, cued mode,

Anomalies were prioritized based on a match of estimated principal polarizabilities to a polarizability library of known TOIs, polarizability magnitude, and the rate of decay of polarizabilities. For each dataset, a reference library of polarizabilities was constructed from test pit measurements, site specific training data, and polarizabilities derived from data acquired at previous Environmental Security Technology Certification Program (ESTCP) demonstration sites. Since dynamic data have higher noise levels than cued data, a more conservative classification algorithm - the Combined Classifier Ranking (CCR) algorithm - was used. The MetalMapper (NAEVA) cued data were processed automated classification that combines multiple ranking rules (e.g. size, decay, etc.) and library matching. Classification parameters were determined by *DigZilla*, with the only input by the analyst being the reference library of ordnance polarizabilities.

All model fits and classification analysis were performed using a classification software suite (UXOLab) that was jointly developed by the University of British Columbia – Geophysical Inversion Facility and Black Tusk Geophysics (BTG).

DEMONSTRATION RESULTS

Performance metrics defined by the ESTCP program office were calculated for each data set. Application of dipole based classification was successful for all data sets, with 100% of TOI being identified and marked for excavation in each case. The reduction of clutter digs while retaining all TOI was greater than 80% in all cases. Not surprisingly, the data sets processed with the more conservative CCR algorithm had a higher percentage of false alarms than the data sets processed with a more aggressive approach. The number of "can't analyze" anomalies met the success criteria for all data sets except the MetalMapper (URS) dynamic data acquired in the Dynamic area. For the dynamically acquired data, reliable target parameters were estimated for only 92.1% due to the lack of data coverage at the edges of the survey area.

For the cued data sets with inertial measurement unit (IMU) information and the dynamically acquired data, the target location estimate error had a standard deviation of less than 10 centimeters (cm). Data acquired in the Open area and Dynamic area had depth estimate errors with a standard deviation of less than 10 cm. The data acquired in the Treed area by the TEMTADS 2x2 had a depth estimate error standard deviation of 13 cm, which did not meet the success criteria of having a depth estimate error with a standard deviation of less than 10 cm. The survey conditions in the Treed area may have resulted in variation of the ground clearance height of the instrument, whereas we assumed a fixed ground clearance height for all anomalies.

IMPLEMENTATION ISSUES

A major implementation issue with AGC technology is providing easy to use software tools so that non-expert staff can obtain good classification performance. This project included a technology transfer and training component. A member of Shaw Environmental’s production team attended a one week training session in Vancouver, British Columbia, Canada with BTG algorithm and software developers. The training session included an overview of UXO inversion and classification theory and software routines. The Shaw geophysicist was responsible for executing all parts of the classification workflow: from data and inversion quality control (QC), training data selection, to dig list creation and submittal. The dig list submitted by the Shaw geophysicist successfully identified all TOI and greatly reduced the number of non-TOI digs.

1.0 INTRODUCTION

1.1 BACKGROUND

In 2003, the Defense Science Board observed: "The problem is that instruments that can detect the buried unexploded ordnance (UXO) also detect numerous scrap metal objects and other artifacts, which leads to an enormous amount of expensive digging. Typically 100 holes may be dug before a real UXO is unearthed! The Task Force assessment is that much of this wasteful digging can be eliminated by the use of more advanced technology instruments that exploit modern digital processing and advanced multi-mode sensors to achieve an improved level of discrimination of scrap from UXO." Since 2003, significant progress has been made in UXO classification technology. To date, testing of these approaches has been primarily limited to test sites with only limited application at live sites. Acceptance of classification technologies requires demonstration of system capabilities at real UXO sites under real world conditions. Any attempt to declare detected anomalies to be harmless and requiring no further investigation will require demonstration to regulators of not only individual technologies, but an entire decision making process.

To demonstrate the viability of advanced detection and discrimination technologies, the Environmental Security Technology Certification Program (ESTCP) has now conducted multiple UXO classification studies. The results of the first demonstration, at the former Camp Sibert, Alabama were very encouraging. Although conditions were favorable at this site, including a single target-of-interest (4.2-inch [in] mortar) and benign topography and geology, all of the demonstrated classification approaches were able to correctly identify a sizable fraction of the anomalies as arising from non-hazardous items that could be safely left in the ground. Of particular note, the contractor EM-61-MK2 cart survey with analysis using commercially available methods correctly identified more than half the targets as non-hazardous.

To build upon the success of this first study, ESTCP expanded the program to include a second study at a site with more challenging topography and a wider mix of targets of interest (TOIs). A range at the former Camp San Luis Obispo, California, was selected for this demonstration. We again found that, with appropriate use of classification metrics applied to production quality EM-61 data, it was possible to significantly reduce the number of clutter items excavated without missing any TOI. Furthermore, the next generation of electromagnetic induction (EMI) sensors, when deployed in a cued-interrogation mode, produced significant additional reductions in the number of clutter items excavated. These sensors could also usually distinguish between different UXO types. A third ESTCP demonstration study was conducted in 2010 at Camp Butner, North Carolina. The site had very little topographic relief but required classification between small TOIs (37 millimeter [mm] projectiles and M48 fuzes) and metallic debris of similar size. Targets were also distributed with a higher density than previously encountered. In 2011, an ESTCP demonstration study was conducted at Camp Beale, California. The site had very little topographic relief but required classification between small TOIs (37-mm projectiles and M48 fuzes) and metallic debris of similar size. Targets were also distributed with a higher density than previously encountered. Also in 2011, a study was conducted at Pole Mountain, Wyoming. The smallest TOI at this site was a small industry standard object (ISO). Library based classification applied to features derived from cued MetalMapper data resulted in some of the best classification performances to date, with less than 5% of non-TOI requiring excavation before all TOI were recovered.

1.2 OBJECTIVES OF THE DEMONSTRATION

The objectives of this demonstration were to perform data modeling, classification, and classification using electromagnetic (EM) data collected by the various data collection demonstrators participating in the study. Specifically, we processed the following datasets collected at Spencer Range:

1) Time-domain Electromagnetic Towed Array Detection System (TEMTADS) 2x2 dynamic data;
2) TEMTADS 2x2 cued interrogation data;
3) MetalMapper dynamic data;
4) MetalMapper cued interrogation data acquired by URS Corporation (URS); and,
5) MetalMapper cued interrogation data acquired by Naeva Geophysics Inc. (NAEVA).

The Spencer Range demonstration site was divided up into three distinct areas differentiated by the sensors deployed: “Open” area; “Treed” area; and “Dynamic” area. The Open area was surveyed in a cued, static mode by the MetalMapper. Cued MetalMapper data were acquired by NAEVA and URS using the same anomaly list. A more challenging, treed survey area was surveyed by cued portable sensors including the HandHeld Berkeley UXO Discriminator (BUD), Man Portable Vector (MPV) and TEMTADS 2x2. There was also a relatively small dynamic area that was surveyed by the TEMTADS 2x2, MPV and MetalMapper in both cued and dynamic modes to provide cued versus dynamic deployment comparison for identical targets.

All performance metrics except two were met. For the MetalMapper (URS) dynamically acquired data, reliable target parameters were estimated for only 92.1% due to the lack of data coverage at the edges of the survey area. The data acquired in the treed area by the TEMTADS 2x2 had a depth estimate error standard deviation of 13 centimeters (cm) due to variations in the ground clearance height.

1.3 REGULATORY DRIVERS

The Defense Science Board Task Force on UXO noted in its 2003 report that 75% of the total cost of a current clearance is spent on digging scrap. A reduction in the number of scrap items dug per UXO item from 100 to 10 could reduce total clearance costs by as much as two-thirds. Thus, classification efforts focus on technologies that can reliably differentiate UXO from items that can be safely left undisturbed.

Classification only becomes a realistic option when the cost of identifying items that may be left in the ground is less than the cost of directly digging them. Because classification generally requires a detection survey as a precursor step, the investment in additional data collection and analysis must result in sufficient clutter rejection to recuperate the investment. Even with perfect detection performance and high signal-to-noise ratio (SNR) values, successfully sorting the detections into UXO and non-hazardous items is a difficult problem but, because of its potential payoff, one that is the focus of significant current research. This demonstration represents an effort to transition a promising classification technology into widespread use at UXO-contaminated sites across the country.

2.0 TECHNOLOGY

2.1 TECHNOLOGY DESCRIPTION

Magnetic and EM methods represent the main sensor types used for detection of UXO. Over the past 15 years, significant research effort has been focused on developing methods to discriminate between hazardous UXO and non-hazardous scrap metal, shrapnel and geology (e.g., Bell et al., 2001; Pasion et al., 2007; Tantum et al., 2008; Liao and Carin, 2009). The most promising classification methods typically proceed by first recovering a set of parameters that specify a physics-based model of the object being interrogated. For example, in time-domain electromagnetic (TEM) data, the parameters comprise the object location and the polarizability tensor which is generally decomposed into orientation and principal polarizabilities. Once the parameters are recovered by inversion, a subset of the parameters is used as feature vectors to guide either a statistical or rule-based classifier.

There are three key elements of the UXO classification process:

1. *Creation of a map of the geophysical sensor data*: This includes all actions required to form an estimate of the geophysical quantity in question (i.e., amplitude of EMI response at a given time-channel) at each of the visited locations. The estimated quantity is dependent on the following:
    a. Hardware, including the sensor type, deployment platform, position and orientation system and the data acquisition system used to record and time-stamp the different sensors;
    b. Survey parameters such as line spacing, sampling rate, calibration procedures etc.;
    c. Data processing such as merging of position/orientation information with sensor data, noise and background filtering applied;
    d. The background environment including geology, vegetation, topography, cultural features, etc.; and,
    e. Depth and distribution of ordnance and clutter.
2. *Anomaly selection and feature extraction*: This includes the detection of anomalous regions and the subsequent extraction of a polarization tensor model for each anomaly. The reliability of the recovered features is dependent on the quality of the survey data. If the data acquired for creation of the data map is not of sufficient quality to extract reliable parameters, cued data acquired in a static mode is required. Cued data has higher quality data due to having reduced sensor noise by being acquired in a static mode, and by having accurate sensor location information by being acquired with transmitters and receivers in a fixed geometry.
3. *Classification of anomalies*: The final objective of the demonstration is the production of a dig sheet with a ranked list of anomalies. This will be achieved via classification algorithms which will require training data to determine the attributes of the UXO and non-UXO classes.

The methodologies for data processing, feature extraction, and statistical classification described above have been implemented within the UXOLab software environment, which was used for this demonstration. UXOLab is a Matlab based software package developed jointly by Black Tusk Geophysics (BTG) and University of British Columbia – Geophysical Inversion Facility (UBC-GIF). Key modules include *QCZilla* for data and inversion review, *TrainZilla* for identifying training data, and *DigZilla* for applying statistical and library based classification techniques. The basic data processing workflow utilized is outlined in Figure 1.

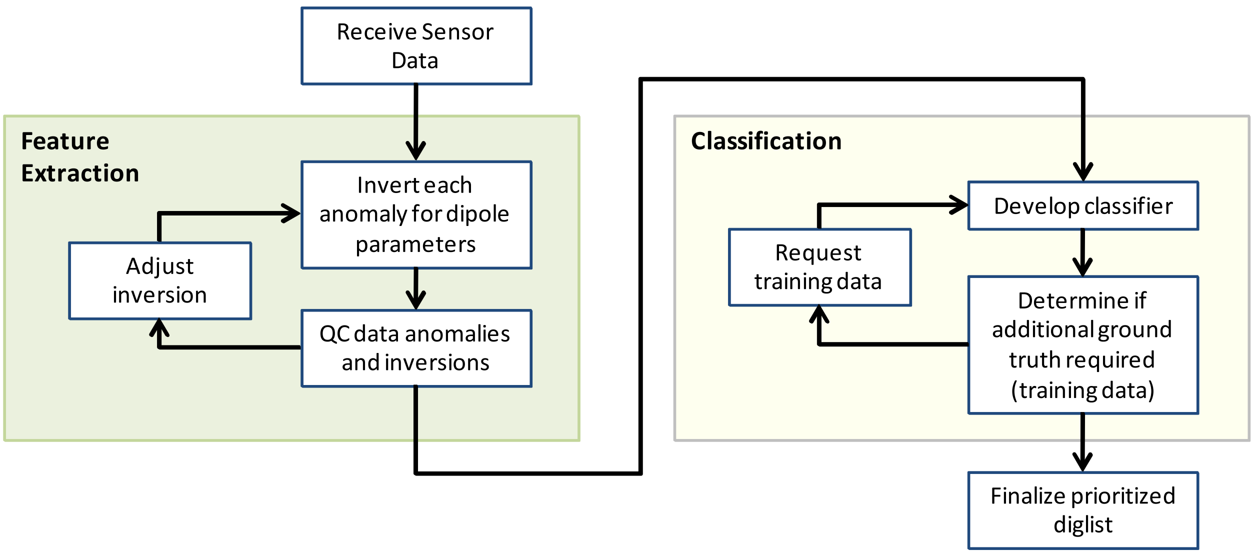

Figure 1. Overview of Workflow Applied to Each Dataset from Spencer Range

Table 1 provides a list of sites at which classification methods and software developed at the UBC-GIF and BTG were tested and demonstrated as part of the ESTCP program. The list summarizes ESTCP project work until May 2014. The blue text indicates projects that were ongoing at the time this report was being prepared. Green 'X's indicate data sets for which industry geophysicists submitted dig lists following a visit to BTG for training on classification theory and techniques. Table 2 provides additional detail for a selection of classification studies completed prior to the Spencer Range.

Table 1. A Summary of Sites at which Classification Has Been Implemented by BTG and UBC-GIF Personnel as Part of the ESTCP Munitions Program

		1st Generation			Vehicle Mounted			Man Portable			Dynamic		
SITE	PROJECT	MAG	Geonics EM61	Geonics EM63	BUD	MetalMapper	TEMTADS 5x5	BUD-HH	MPV	TEMTADS 2x2	MetalMapper	MPV	TEMTADS 2x2
Former Lowry Bombing and Gunnery Range, CO	MM-0504	X	X	X									
Former Camp Sibert, AL	MM-0504	X	X	X	X								
Former Fort McClellan, AL	MM-0504			X									
San Luis Obispo, CA	MM-0504	X	X		X	X	X						
Former Camp Butner, NC	MR-1004		X			X	X						
Camp Beale, CA	MR-1004		X			X		X	X	X			
Pole Mountain, WY	MR-1159		X			X							
Spencer Range, TN	MR-1158,59					X	X		X	X	X	X	X
Camp Edwards, MMR, MA	MR-1226					X				X			
Camp George West, CO	MR-1228								X			X	
Camp Ellis, IL	MR-1226					X				X			
Ft. Rucker, AL	MR-1226					X							
New Boston, NH	**MR-1158,59**								X	X		X	
Southwest Proving Grounds, AL	**MR-1226**					X				X	X		X
Waikaloa, HI	**MR-1226**					X						X	

Table 2. Examples of Inversion and Classification Testing Completed by UBC-GIF and BTG as Part of the ESTCP Program, prior to the Spencer Range Demonstration

Site	Camp Sibert
Sensors and survey mode	Geonics EM-61 cart, Multi-sensor Towed Array Detection System (MTADS) EM-61 array, MTADS mag array, and EM-63 single and cooperative inversions. EM-63 cued interrogations were positioned by a Leica TPS1206 Robotic Total Station (RTS) with orientation information provided by a Crossbow AHRS400 Inertial Measurement Unit (IMU). The objective of the surveys was the classification of a large target (4.2-in mortars). The site was unusual in that the primary munition known to have been used was the 4.2-in mortar, thus providing a site where the classification is a case of identifying a single large target amongst smaller pieces of mortar debris and clutter.
Description	For the EM-61, 3-dipole instantaneous amplitude models were fit to the available 3 time-channels, while for the EM-63, 3-dipole Pasion-Oldenburg models were recovered from the 26 time-channel data. MTADS and EM-63 data were also cooperatively inverted. Parameters of the dipole model were used to guide a statistical classification.
Results	The results for all sensor combinations were excellent, with just one false negative for the EM-63 when inverted without cooperative constraints. When inverted cooperatively, the EM-63 cued interrogation was the most effective discriminator. All 33 UXO were recovered with 25 false alarms (16 of these were in the "can't analyze" category). Not counting the "can't analyze" category, the first 33 recommended excavations were all UXO. The MTADS and MTADS cooperatively inverted were also very effective at discrimination, with all UXO recovered very early in the dig list. The MTADS data set suffered from a high number of false alarms due to anomalies with a geological origin. In addition, the operating point was very conservative and many non-UXO were excavated after recovery of the last UXO in the dig list. The results from the EM-61 cart were also very good, although 24 false-positives were required to excavate all 105 UXO. The lower data quality of the EM-61 cart resulted in a larger number of "can't analyze" anomalies over metallic sources than the MTADS.

Table 2. Examples of Inversion and Classification Testing Completed by UBC-GIF and BTG as Part of the ESTCP Program, prior to the Spencer Range Demonstration (Continued)

Site	**San Luis Obispo**
Sensors and survey mode	Detection mode surveys included: MTADS magnetometer and EM-61 arrays; Geonics EM-61 cart; and Man-portable Simultaneous EMI and Magnetometer System (MSEMS) cart. Cued interrogation mode TEMTADS, MetalMapper and BUD surveys were also conducted. At this site the objective was to identify TOI from a number of different target classes: primarily 60-mm, 81-mm, 4.2-in mortars, 2.36-in rockets, and one each of 37-mm, 3-in and 5-in projectiles. The site had significant topographic relief.
Description	For all TEM data sets, 3-dipole instantaneous amplitude models were fit to the available time-channels. Single dipoles were fit to targets in magnetics data sets, but cooperative inversion was not used at this site. For detection data sets, a threshold on the rate of decay of primary polarizabilities was used to rank targets. Dig sheets for cued interrogation data sets were generated using statistical classifiers trained on size/decay features, as well as with library methods and an "expert" method based on the judgment of an analyst.
Results	Magnetometer detection and classification performance at this site was quite poor. The EM-61 production datasets were much more effective than magnetics. Size estimated from the recovered polarizations was not an effective classification metric due to the small size of the 60-mm mortars and the inability to accurately constrain depth. However, the time-decay rate estimated from the recovered polarizabilities provided an effective ranking scheme. The EM-61 cart performance was marginally better than the MSEMS cart and MTADS EM-61 array. For the TEMTADS data the library method was the most effective with 204 of 206 TOI recovered along with 131 of 1076 non-TOI. The two false negatives were the rocket motor pieces declared non-TOI by all cued-interrogation methods and a 60-mm mortar with a target response that overlapped with some nearby clutter. The other classification methods were also effective, generating between 2 to 4 false-negatives. The library method was again most effective for the MetalMapper data with the excavation of 203 of 204 TOI and 175 of 1205 non-TOI. Correct classification of ordnance type was also achieved with up to 99% accuracy achieved with statistical classification.
Site	**Camp Butner**
Sensors and survey mode	Detection surveys with the EM-61 cart and MetalMapper dynamic sensors were conducted. Detected targets from the EM-61 data were revisited with MetalMapper static and TEMTADS cued interrogations. TOI at the site included 105mm high-explosive anti-tank (HEAT), 37mm, and M48 fuses. Topographic relief was benign, but there was a significant amount of clutter similar in size and shape to 37mm.
Description	For all TEM data sets, 3-dipole instantaneous amplitude models were fit to the available time-channels. For detection data sets, a threshold on the rate of decay of primary polarizabilities was used to rank targets. Dig sheets for cued interrogation data sets were generated using statistical classifiers trained on size/ decay features, as well as with library methods and an "expert" method based on the judgment of an analyst.
Results	Thresholding on time-decay rate of estimated polarizabilities estimated from EM-61 data performed quite poorly, with a 0.92 false alarm rate (FAR). This is likely attributable to poor depth estimation for small targets. The MetalMapper dynamic data produced reliable depth estimates, but did not measure sufficiently late in time to provide separation between TOI and non-TOI polarizabilities. FAR was approximately 0.7 for this sensor. Excellent classification performance was achieved with the TEMTADS data: all 171 TOI were found with a FAR of only 5%. MetalMapper static performance was similar to TEMTADS, but produced a much higher FAR (78%) owing to outlying TOI attributable to faulty data.

Table 2. Examples of Inversion and Classification Testing Completed by UBC-GIF and BTG as Part of the ESTCP Program, prior to the Spencer Range Demonstration (Continued)

Site	Pole Mountain WY.
Sensors and survey mode	Detection mode survey was EM-61. Cued interrogation mode MetalMapper survey was also conducted.
Description	Dipole models were fit to the available time-channels. Multi-object inversions were also carried out on the MetalMapper data set.
Results	Excellent quality MetalMapper data resulted in near perfect classification results with all TOI recovered with less than 5% non-TOI dug. Detection mode EM-61 data had limited detection ability.
Site	**Camp Beale**
Sensors and survey mode	Detection mode survey was EM-61. Cued interrogation mode MetalMapper surveys were conducted. Also, the first test of portable sensors including MPV, TEMTADS 2x2, Handheld BUD. The site had magnetic soil present which reduced the SNR of the data relative to previous sites.
Description	For all TEM data sets, dipole polarizabilities were fit to the available time-channels. Multi-object inversions were also carried out on all data sets. For EM-61 detection data, the polarizability rate of decay and size were used to rank targets. Anomalies collected by MetalMapper and portable sensors were ranked using statistical and library-based classification on polarizabilities.
Results	Similar classification performance was achieved for all portable sensors. For each portable sensor excellent classification performance was achieved with no false negatives. MetalMapper diglists also had excellent performance. A diglist featuring no false negatives was submitted for both sets of MetalMapper data.

2.2 ADVANTAGES AND LIMITATIONS OF THE TECHNOLOGY

The main advantage of the technology is a potential reduction in the number of non-hazardous items that need to be excavated, thus reducing the costs of UXO remediation. Advantages of UXOLab and the algorithms within the package include:

- All the functionality required to process raw geophysical data, detect anomalous regions, and perform geophysical inversion and classification.
- Algorithms for inverting magnetic and TEM data sets both separately and cooperatively using a number of different polarization tensor formulations.
- Extensive set of algorithms for rule-based and statistical classification algorithms.
- Configuration in a modular fashion, so that as new sensor technologies become available (e.g. new TEM systems with multi-component receivers etc), the inversion functionality will be immediately available to those new sensor systems.
- Intuitive design and user-friendly GUIs and workflows

The principal disadvantage is that UXOLab has not been configured for general use by contractors and non-specialists. However, as part of ESTCP MR-201004, we transitioned our inversion algorithms to an Application Program Interface (API) that enables access of the algorithms to other software.

3.0 PERFORMANCE OBJECTIVES

The performance objectives for this demonstration are summarized in Table 3. The first three analysis objectives refer to the classification part of the demonstration with the first two referring to the best results from each approach in a retrospective analysis and the third addressing how well each demonstrator is able to specify the correct threshold in advance. The final two objectives refer to the accuracy of target features extracted from the data.

Table 3. Description of Performance Objectives for the Spencer Range Demonstration

Performance Objective	Metric	Data Required	Success Criteria
Maximize correct classification of TOI	Number of TOI retained	• Prioritized anomaly lists • Scoring reports from Institute for Defense Analyses (IDA)	Approach correctly classifies all TOI
Maximize correct classification of non-TOI	Number of false alarms eliminated	• Ranked anomaly lists • Scoring reports from IDA	Reduction of clutter digs by > 75% while retaining all TOI
Specification of no-dig threshold	Probability of correct classification of TOI and number of false alarms at demonstrator operating point	• Demonstrator-specified threshold • Scoring reports from IDA	Threshold specified by the demonstrator to achieve criteria above
Minimize number of anomalies that cannot be analyzed	Number of anomalies that must be classified as "Unable to Analyze"	• Demonstrator target parameters	Reliable target parameters can be estimated for > 95% of anomalies on each sensor's detection list.
Correct estimation of target parameters	Accuracy of estimated target parameters for seed items	• Demonstrator target parameters • Results of intrusive investigation	Polarizabilities ±20% X, Y < 15 cm (1σ) Z < 10 cm (1σ)

Table 4 summarizes the performance of the different sensor modes in the Open and Treed areas while Table 5 covers summarizes the dynamic area. All performance metrics except two were met: for the MetalMapper (URS) dynamically acquired data, reliable target parameters were estimated for only 92.1%, due to the lack of data coverage at the edges of the survey area. The data acquired in the Treed area by the TEMTADS 2x2 had a depth estimate error standard deviation of 13 cm due to variations in the ground clearance height in that area.

Table 4. Summary of Performance Objectives for the Open and Treed Areas of the Spencer Range Demonstration.

Performance Objective	Metric	Success Criteria	Data Set		
			Open Area		Treed Area
			Metal-Mapper URS - Cued	Metal-Mapper Naeva - Cued	TEMTADS 2x2 - Cued
Maximize correct classification of TOI	Number of TOI retained	Approach correctly classifies all TOI	100%	100%	100%
Maximize correct classification of non-TOI	Number of false alarms eliminated	Reduction of clutter digs by > 75% while retaining all TOI	88.5%	84.8%	84.7%
Specification of no-dig threshold	Probability of correct classification of TOI and number of false alarms at demonstrator operating point	Threshold specified by the demonstrator to achieve criteria above	$P_{class} = 1$ $N_{fa} = 185$ (18.2%)	$P_{class} = 1$ $N_{fa} = 209$ (20.5%)	$P_{class} = 1$ $N_{fa} = 106$ (17.1%)
Minimize number of anomalies that cannot be analyzed	Number of anomalies that must be classified as "Unable to Analyze"	Reliable target parameters can be estimated for > 95% of anomalies on each sensor's detection list.	98.8%	99.7%	99.2%
Correct estimation of target parameters	Accuracy of estimated target parameters for seed items	Polarizabilities -/+20% X, Y < 15 cm (1σ) Z < 10 cm (1σ)	N(>20%)=4 N(<20%)=82 σ_x=0.08m σ_y=0.09m σ_z=0.05m	N(>20%)=6 N(<20%)=84 σ_x=0.09m σ_y=0.098m σ_z=0.05m	N(>20%)=4 N(<20%)=70 σ_x=NA σ_y=NA **σ_z=0.13m**

Table 5. Summary of Performance Objectives for the Dynamic Area of the Spencer Range Demonstration.

Performance Objective	Metric	Success Criteria	Data Set – Dynamic Area: Metal-Mapper URS - Dynamic	TEMTADS 2x2 - Cued	TEMTADS 2x2 - Dynamic	Metal-Mapper URS - Cued
Maximize correct classification of TOI	Number of TOI retained	Approach correctly classifies all TOI	100%	100%	100%	100%
Maximize correct classification of non-TOI	Number of false alarms eliminated	Reduction of clutter digs by > 75% while retaining all TOI	83.5%	91.5%	82.0%	95.3%
Specification of no-dig threshold	Probability of correct classification of TOI and number of false alarms at demonstrator operating point	Threshold specified by the demonstrator to achieve criteria above	$P_{class} = 1$ $N_{fa} = 67$ (21.2%)	$P_{class} = 1$ $N_{fa} = 44$ (13.9%)	$P_{class} = 1$ $N_{fa} = 75$ (23.7%)	$P_{class} = 1$ $N_{fa} = 35$ (11.1%)
Minimize number of anomalies that cannot be analyzed	Number of anomalies that must be classified as "Unable to Analyze"	Reliable target parameters can be estimated for > 95% of anomalies on each sensor's detection list.	**92.1%**	100%	100%	100%
Correct estimation of target parameters	Accuracy of estimated target parameters for seed items	Polarizabilities -/+20% X, Y < 15 cm (1σ) Z < 10 cm (1σ)	N(>20%)=3 N(<20%)=18 σ_x=0.09m σ_y=0.06m σ_z=0.03m	N(>20%)=4 N(<20%)=22 σ_x=NA σ_y=NA σ_z=0.08m	N(>20%)=7 N(<20%)=16 σ_x=0.07m σ_y=0.07m σ_z=0.07m	N(>20%)=3 N(<20%)=20 σ_x=0.07m σ_y=0.07m σ_z=0.05m

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4.0 SITE DESCRIPTION

4.1 SITE LOCATION AND HISTORY

Located in Spencer/Van Buren County, Tennessee, the 30,618 acre Spencer Artillery Range was established in 1941, and documentation identifies two impact areas: Jakes Mountain (5,060 acres) and Bald Knob (2,090 acres). Troop training took place until September 1944. Subsequent arrangements were made for Dyersburg Army Air Field to use the Spencer Artillery Range as an air-to-ground gunnery range. The site contains partially wooded and cleared areas. This demonstration will be conducted on three discrete areas within the former range: a 3.7-acre wooded area, a 4.4-acre open field area, and a 1.3-acre dynamic area.

4.2 SITE GEOLOGY

Details of site-geology can be found in the ESTCP (2014) summary report for this demonstration site.

4.3 MUNITIONS CONTAMINATION

Munitions expected at the site include 37mm, 75mm, 76mm, 105mm, and 155mm projectiles. Additional details regarding munitions contamination can be found in the ESTCP (2014) summary report for this demonstration site

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5.0 DATA ANALYSIS AND PRODUCTS

See the ESTCP (2014) summary report for a description of the test design for the overall project.

BTG/UBC-GIF processed data and delivered the following two prioritized dig lists for the Spencer Range Open Area:

1) Cued URS MetalMapper library match: A dig sheet was produced based on how well the recovered polarizabilities matched the polarizabilities in a library of ordnance items expected at the site; and
2) Cued NAEVA MetalMapper automated DigZilla ranking: A dig sheet was produced based on a weighted sum of fit to the library, polarizability size, polarizability decay, and a measure of how "rod-like" the target is based on secondary polarizabilities.

BTG/UBC-GIF processed data and delivered the following prioritized dig list for the Spencer Range Tree Area:

1) Cued TEMTADS 2x2 library match: A dig sheet was produced based on how well the recovered polarizabilities matched the polarizabilities in a library of ordnance items expected at the site.

BTG/UBC-GIF processed data and delivered the following four prioritized dig lists for the Spencer Range Dynamic Area:

1) Cued URS MetalMapper library match: Same method as Open Area;
2) Dynamic URS MetalMapper Combined Classifier Ranking (CCR) match: A dig sheet is submitted by combining separate ranked lists based on polarizability misfit, size, and decay;
3) Cued TEMTADS 2x2 library match: Same method as Tree Area; and
4) Dynamic TEMTADS 2x2 CCR: Same as in 3) but for the dynamic TEMTADS 2x2 data.

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6.0 DATA ANALYSIS AND PRODUCTS

The Spencer Range demonstration site was divided up into three distinct areas differentiated by the sensors deployed: “Open” area, “Treed” area, and “Dynamic” area. The Open area was surveyed in a cued, static mode by the MetalMapper. Cued MetalMapper data were acquired by NAEVA. and URS using the same anomaly list. A more challenging, treed survey area was surveyed by cued portable sensors including the HandHeld BUD, MPV, and TEMTADS 2x2. There was also a relatively small dynamic area that was surveyed by the TEMTADS 2x2, MPV and MetalMapper in both cued and dynamic modes to provide cued vs. dynamic deployment comparison for identical targets.

BTG processed multiple datasets in order to test practical UXO classification methods over a range of EMI instruments deployed. BTG processed all the Open area datasets, the TEMTADS 2x2 and MPV data-sets from the Treed area, and all the TEMTADS and MetalMapper URS data from the Dynamic area. All MPV processing was carried out under ESTCP MR-201158, and all MPV results are reported under that project.

The basic data processing workflow was the same for all datasets and is outlined in Figure 1. Classification was performed by BTG or University of British Columbia (UBC) analysts with a strict firewall maintained throughout the analyses. Due to this firewall, information that could aid classification for a particular dataset could NOT be transferred from another dataset (for example, classes of potential TOI).

In the interest of brevity, in this report we will only describe the data analysis procedures used for one of the datasets: MetalMapper cued data (URS) from the Open Area. The work-flows for the other datasets were very similar with additional details available in Pasion et al. (2013).

6.1 PREPROCESSING

MetalMapper cued data for all anomalies were received as a set of raw TEM files and two sets of CSV files (with and without background corrections). Our analyses used the background-corrected data.

6.2 TARGET SELECTION FOR DETECTION

Target detection lists were provided by the Program Office.

6.3 PARAMETER ESTIMATES

The data were inverted in UXOLab using a sequential inversion approach to estimate target location, depth and principal polarizabilities. Instrument height above the ground was assumed to be 10 cm. Noise standard deviation estimates were not available, so a constant noise value of 1 over all time channels was used. Target location was constrained to lie between ±0.5 meter (m) in both X and Y directions relative to the picked location. Target depth was constrained to lie between -1.2 and 0 m. The initial optimization for target location identified up to three starting models to input into the subsequent estimation of polarizabilities.

We performed two inversions per anomaly, solving for: (1) a single object (single object inversion [SOI]); and (2) two objects (two object inversion [2OI]).

Analysis of the data, including visual quality control (QC) of data and model parameters, selection of training data, and dig list creation, was performed using the UXOLab software suite. Visual QC of the data was performed using *QCZilla*, which provides a thorough overview of the observed and predicted data, predicted model parameters, and measures of data/model quality. Display of the gridded EM-61 data at each anomaly provides a useful indicator of the anomaly size and strength. Predicted polarizabilities were compared to reference polarizabilities for various ordnance items initially derived from instrument verification strip (IVS) measurements. The Spencer Artillery Range test pit contained four items: 75-mm projectiles, 37-mm projectiles, Small ISO, and Shot Put. The latter item was not used during the classification process. As the analysis proceeded, the library of reference items was augmented with additional items based on ground truth obtained through training data requests. Each item in the ordnance reference library was assigned a size (diameter) in mm. Each item classified as "likely TOI” in the submitted dig list was assigned a size based on the ordnance item in the reference library with the best matching primary polarizability (L_1).

During data/model QC the primary objectives were to (1) flag high-likelihood TOI; and (2) fail bad models and inversions. Anomalies flagged as high-likelihood TOI were monitored during the dig list creation phase to ensure they were being dug, ideally early in the dig list. Models and inversions were considered to be bad when the inversion failed (i.e., the data misfits are large), or when the recovered model location(s) were on, or near, an inversion boundary. With multi-object inversions, it is not uncommon that one of the models is unrealistic (e.g., deep, large in magnitude, sometimes located on or near a horizontal inversion boundary) yet provides the best fit to the reference polarizabilities (e.g., Figure 2). In all of these cases, the model was flagged as failed. Models flagged as failed were not used in the classification process. Anomalies with all models from all inversions failed were classified as "can't extract reliable parameters"; these anomalies will be dug. For a given anomaly, if more than one model was passed the classification procedure will consider all passed models and effectively use the one that is "best".

The Spencer Open Area MetalMapper Cued dataset comprised 1104 unique anomalies. Of the 3312 total models, 2623 were passed and used in the classification process; 689 were failed. Thirteen anomalies were classified as “cannot extract reliable parameters” due to poor inversion results. One of these (anomaly 308) corresponded to a TOI (37mm). 102 anomalies were classified as “high likelihood UXO" during QC; 83 of these (81%) correspond to actual TOI. The total number of unique TOI in the Spencer Open Area is 86.

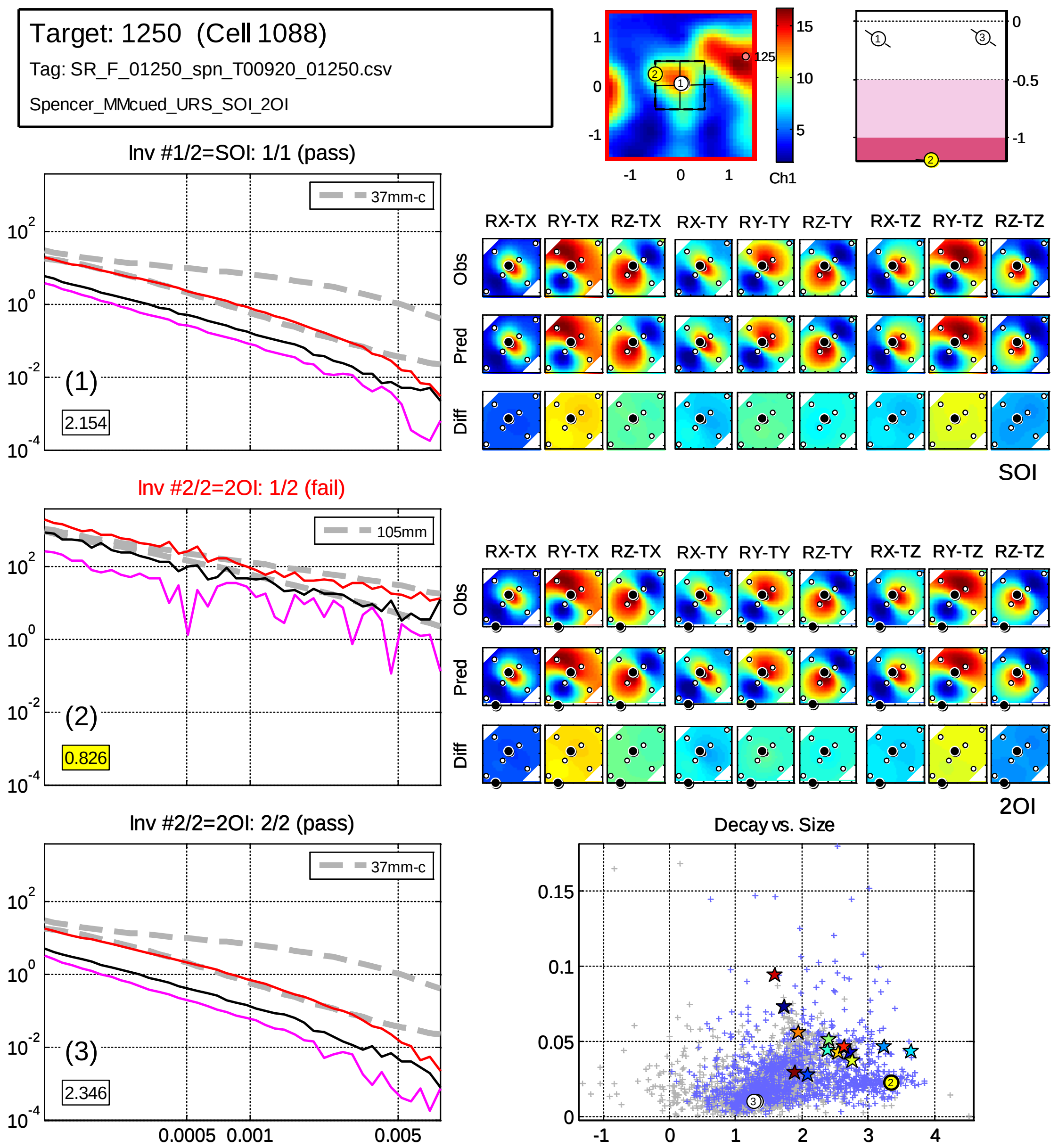

Figure 2. Example of an Unrealistic 2OI Model (anomaly 1250; frag)

The first model of the 2OI (model 2) provides the best fit (i.e., minimum misfit) to the reference polarizabilities (misfit = 0.826), but the predicted depth of 1.2 m, the location at the edge of the instrument (i.e., at the vertical and horizontal inversion boundaries), and the high amplitude and jittery appearance of the polarizabilities, are classic signs that this model is an artifact of the multi-object inversion process. Accordingly, this model was failed during QC. Polarizabilities for SOI and 2OI are shown at left. Modeled target locations (X-Y and Z) are shown at the top right (gridded EM-61 data is displayed behind the X-Y plot). Gridded observed, predicted and residual data for SOI and 2OI are shown below location maps. Decay versus size feature plot is shown in bottom right. Dots are test data; stars are reference items. Numbered circles are models for this anomaly.

6.4 CLASSIFIER AND TRAINING

Figure 3 shows the distribution of passed models in decay versus size feature space.

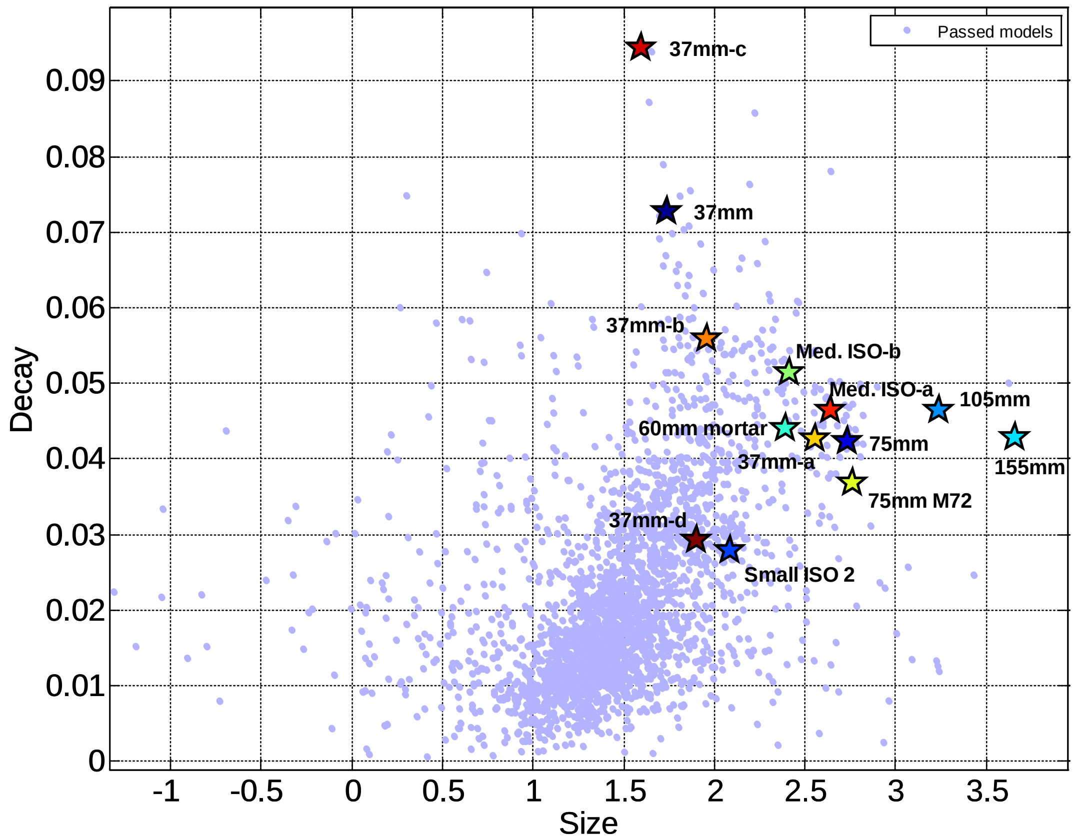

Figure 3. Distribution of Passed Models in Decay(t1,t29) versus Size(t1) Feature Space

where size(t1) is the total polarizability measured at the first time channel (t1=0.106 milliseconds), and decay(t1,t29) is size(t1)/size(t29) where t29=2.006 ms. Some outliers are not shown. Labeled stars represent ordnance library reference items.

Our analysis method is based primarily on polarizability matching with respect to ordnance items in a reference library. For this approach to be successful, it is important to determine the types of ordnance present at the site. During visual QC the analyst keeps track of suspicious, UXO-like items (i.e., items with modeled polarizabilities possessing UXO-like properties). Training data for some of these, particularly those with polarizabilities different from the items in the reference library, would be requested. In addition, we used our custom training data selection tool, *TrainZilla*, to explore feature space and automatically search for clusters of items with self-similar polarizabilities. In *TrainZilla*, the user selects a region in feature space by drawing a polygon, and the program automatically identify clusters of self-similar feature vectors by computing a misfit matrix **M** with elements

$$M_{jk} = \sum_{i=1}^{N} (L^{j}{}_{total}(t_i) - L^{k}{}_{total}(t_i))^2$$

where L_{total}^{j} is the log-transformed total polarizability for the j^{th} feature vector. Feature vectors with mutual misfit less than a user-specified threshold define a cluster in polarizability space. This analysis helps to identify clusters that may not be readily evident in decay-size feature space: e.g., targets with consistent polarizabilities that may be hidden in the "cloud" of non-TOI features. A basic example of the use of *TrainZilla* is shown in Figure 4 and Figure 5.

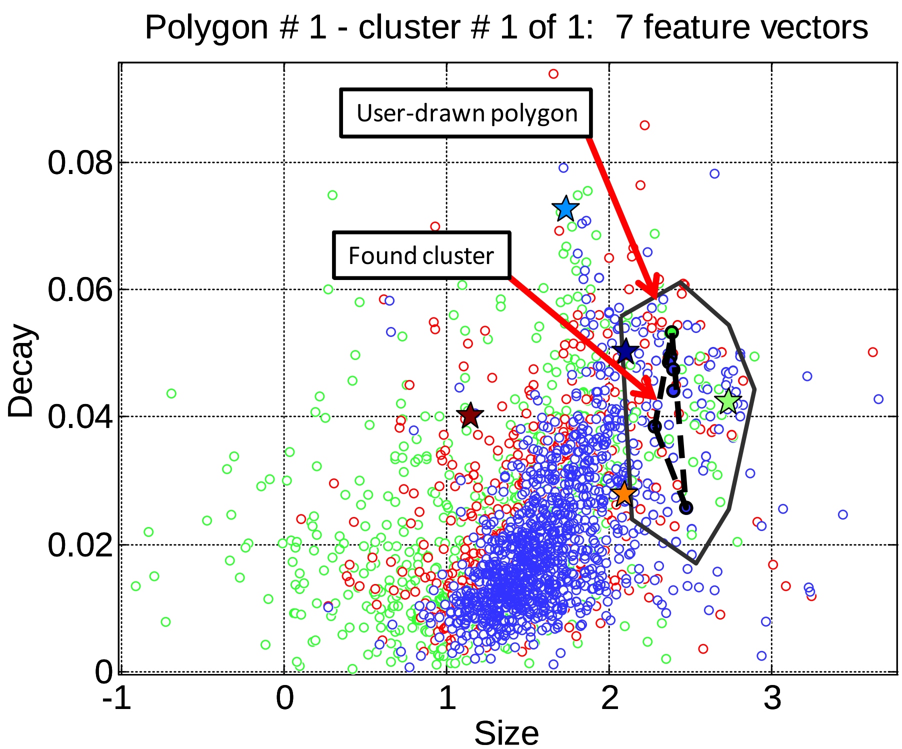

Figure 4. Example of Use of the Training Data Selection Tool (*TrainZilla*)

A polygon (solid black line) is drawn in feature space. Clusters of items with self-similar polarizabilities are automatically found based on the specified cluster search parameters. In this case a cluster comprising 7 features is visible (solid feature symbols encompassed by broken line). Polarizabilities for this cluster are shown in Figure 5.

Our training data requests typically focused on: (1) items whose polarizabilities exhibited UXO-like properties distinct from those of items in our reference library; (2) items with polarizabilities similar to items in our reference library, but with degraded quality; and (3) one-off items. Figure 6 shows the location in decay-size feature space of all training requests. We paid particular attention to items with polarizabilities suggestive of small objects such as fuses and small caliber projectiles. All of these turned out to be non-TOI.

In our initial training request for 49 items, twelve of these were TOI, two of which were previously unknown ordnance items: 60mm mortar and medium ISO. We subsequently requested training on two more items, both of which proved to be non-TOI.

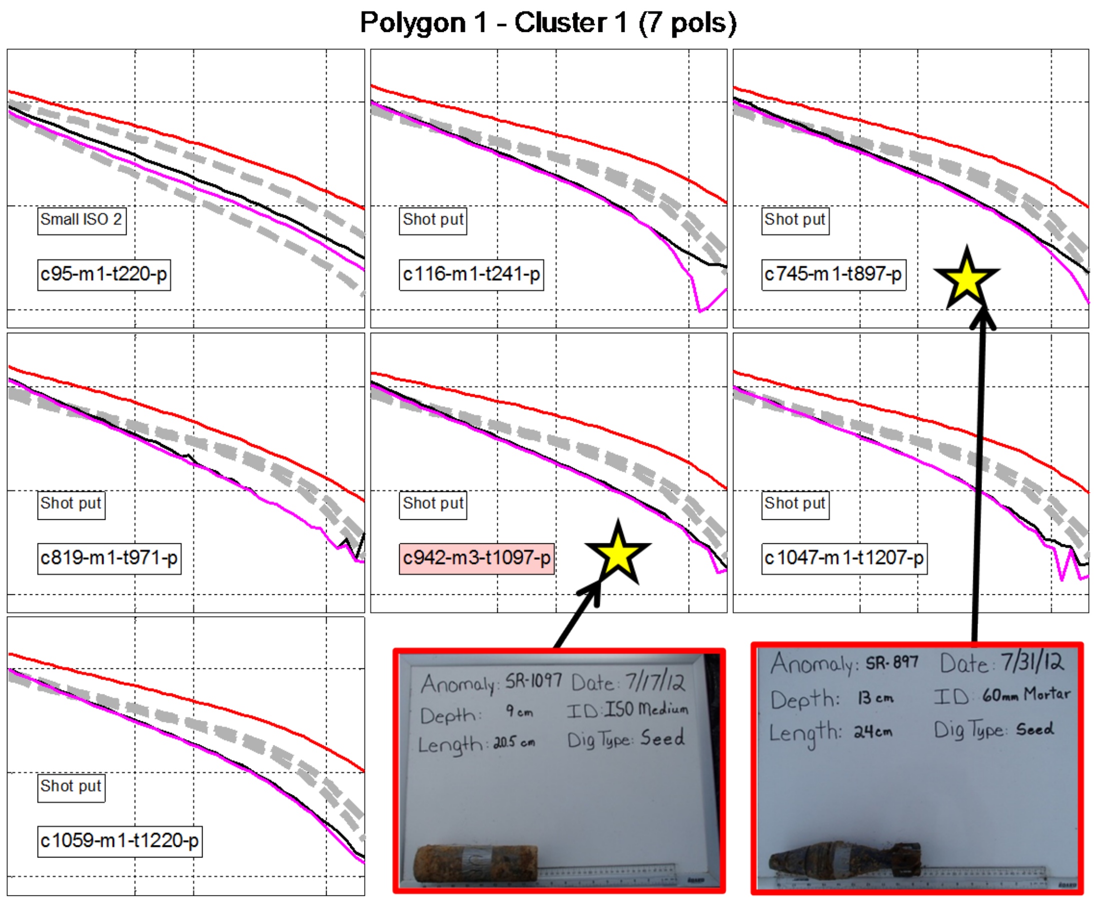

Figure 5. Polarizabilities for the Cluster Shown in Figure 4

Colored lines are predicted polarizabilities. Broken grey lines are best fitting reference polarizabilities. Training data were requested for Anomalies 897 and 1097 (stars); ground truth (photos) revealed that both of these anomalies are new TOI (relative to our starting ordnance reference library which comprised the four items from the test pit). Anomaly 897 is 60mm mortar; Anomaly 1097 is a medium ISO. These items were added to the reference library.

6.4.1 Classification Method

Our dig lists were developed using the *DigZilla* module of UXOLab (Figure 7). *DigZilla* allows for the creation of multi-stage dig lists with minimal effort, and supports a number of classifiers.

Our initial dig list comprised two stages. For the early digs (1-201) the order was based on polarizability misfit using all three polarizabilities. The second stage (digs 202-1104) was based on polarizability misfit using only the primary polarizability. Figure 8 contains the polarizabilities used for classification.

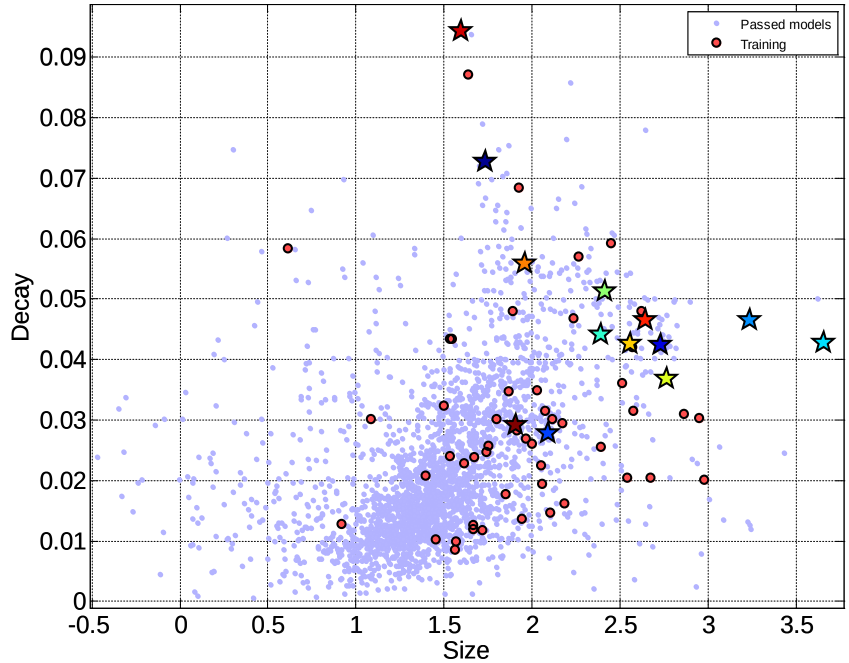

Figure 6. Decay versus Size Feature Space Plot Showing Passed Models (blue dots) and the Location of Training Data Requests (red dots)

Stars are library reference items.

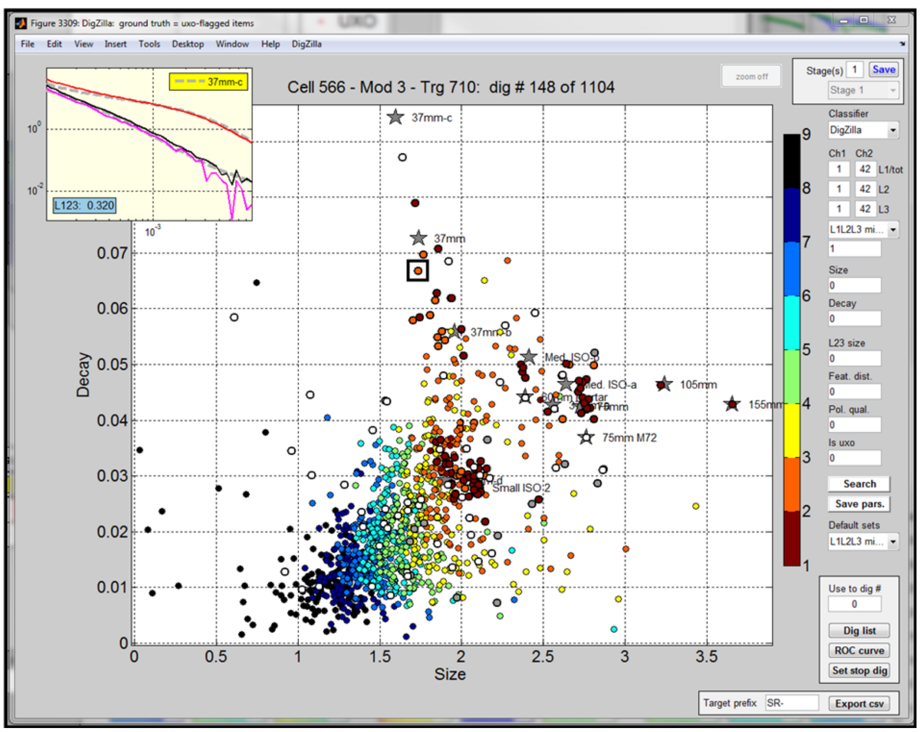

Figure 7. Screen Shot of the *DigZilla* Graphical User Interface

Features in the decay versus size feature plot are color coded according to dig list order.

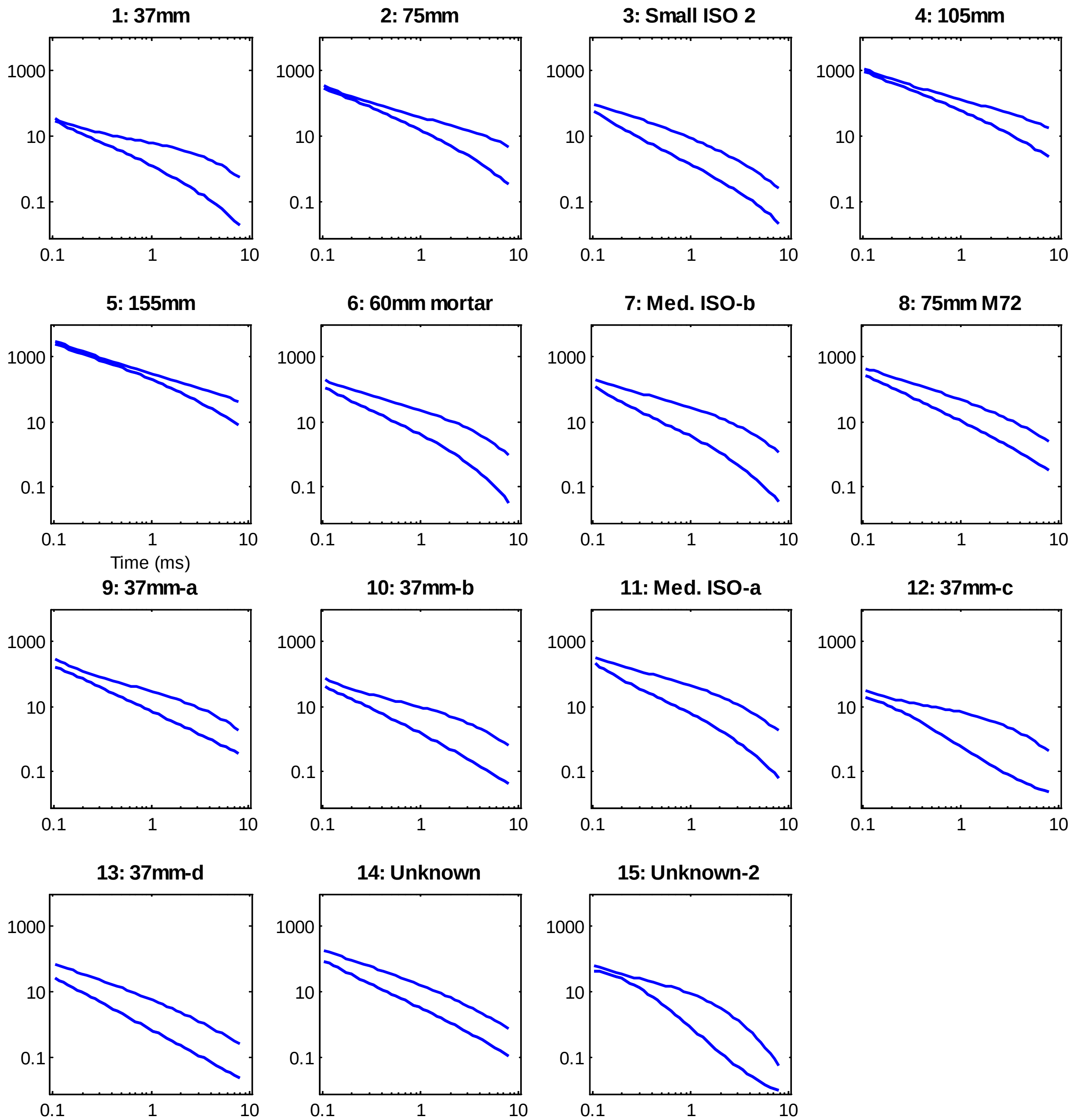

Figure 8. Ordnance library for the MetalMapper URS Cued Data

Polarizabilities 1 to 13 were used for the Open area. Polarizabilities 14 and 15 were added processing cued data acquired in the Dynamic area.

7.0 PERFORMANCE ASSESSMENT

Table 6 and Table 7 summarize the classification performance for all of the data sets. The classification metrics were calculated using the ground truth file delivered by the ESTCP program office and the final submitted dig list for each dataset. The model fit statistics (i.e., polarizability percent error, estimated location error, and depth error) were calculated using all anomalies collected. Therefore, if multiple data soundings were acquired over the same target, the resulting best-fit model from each sounding was included in the calculations. For the TEMTADS 2x2, the location errors were not recorded due to the absence of IMU information. The IMU information is required for estimating the dipole source location (and therefore target location) in geographic coordinates.

Table 6. Classification Results from Open and Tree areas of Spencer Range

		Open Area		**Trees**
	Instrument	**Metal Mapper URS**	**Metal Mapper NAEVA**	**TEMTADS 2x2**
	Site	Open	Open	Trees
	Survey Type	Cued	Cued	Cued
	Analyst	Zelt	Kingdon	Song
Anomaly Statistics	Total Anomalies	1104	1104	690
	Num TOI	86	86	71
	Num Non-TOI	1018	1018	619
FAR	Percent of Non-TOI	0.115	0.152	0.153
	Num Non-TOI Dug	117	155	95
Stop Dig Point	Digs	271 (24.5%)	295 (26.7%)	177 (25.7%)
	TOI Digs	86 (100.0 %)	86 (100.0 %)	71 (100.0 %)
	Non-TOI Digs	185 (18.2 %)	209 (20.5 %)	106 (17.1 %)
Training Data	Digs	51	43	63
	TOI	12	8	4
	Non-TOI	39	35	59
"Cant Analyze" anomalies	Digs	13	3	5
	TOI	1	0	0
	Non-TOI	12	3	5
Polarizability Percent Error	>20%	4	6	4
	<20%	82	84	70
Position Error	□(Easting)	0.08	0.09	NA
	□(Northing)	0.09	0.098	NA
	□(depth)	0.05	0.05	0.13

Table 7. Classification Results from Dynamic area of Spencer Range

Due to an absence of IMU information for the cued TEMTADS metrics related to target location estimate accuracy were not calculated.

		Dynamic Area			
	Instrument	**Metal Mapper URS**	**TEMTADS 2x2**	**TEMTADS 2x2**	**Metal Mapper**
	Site	Dynamic	Dynamic	Dynamic	Dynamic
	Survey Type	Dynamic	Cued	Dynamic	Cued
	Analyst	Pasion	Song	Billings	Zelt
Anomaly Statistics	Total Anomalies	339	339	339	339
	Num TOI	23	23	23	23
	Num Non-TOI	316	316	316	316
FAR	Percent of Non-TOI	0.165	0.085	0.18	0.047
	Num Non-Toi Dug	52	27	57	15
Stop Dig Point	Digs	90 (26.5%)	67 (19.8%)	98 (28.9%)	58 (17.1%)
	TOI Digs	23 (100.0 %)	23 (100.0 %)	23 (100.0 %)	23 (100.0 %)
	Non-TOI Digs	67 (21.2 %)	44 (13.9 %)	75 (23.7 %)	35 (11.1 %)
Training Data	Digs	17	20	22	0
	TOI	9	1	5	0
	Non-TOI	8	19	17	0
"Cant Analyze" anomalies	Digs	27	0	0	0
	TOI	3	0	0	0
	Non-TOI	24	0	0	0
Polarizability Percent Error	>20%	3	4	7	3
	<20%	18	22	16	20
Position Error	□(Easting)	0.09	NA	0.07	0.07
	□(Northing)	0.06	NA	0.07	0.07
	□(depth)	0.03	0.08	0.07	0.05

7.1 PROCESSING OPEN AREA DATASETS

Cued MetalMapper data were acquired by URS and NAEVA over an identical set of targets using the same instrument. Three different analysts created ordered dig lists for each MetalMapper dataset to ensure a firewall was maintained for training data requests and groundtruth. The performance of the various sensors are summarized in Table 4.

7.1.1 URS Cued MetalMapper Results

The methodolody for the URS Cued MetalMapper was described in detail in section 6.

The dig list comprised two stages. For the early digs (1-201) the order was based on polarizability misfit using all three polarizabilities. The second stage (digs 202-1104) was based on polarizability misfit using only the primary polarizability. Additional details on the classification approach were provided in our demonstration report (Pasion et al., 2013).

The final receiver operating characteristic (ROC) curve for the URS MetalMapper data is shown in Figure 9. At the stop dig point, all TOI were found and greater than 80% of non-TOI were left in the ground.

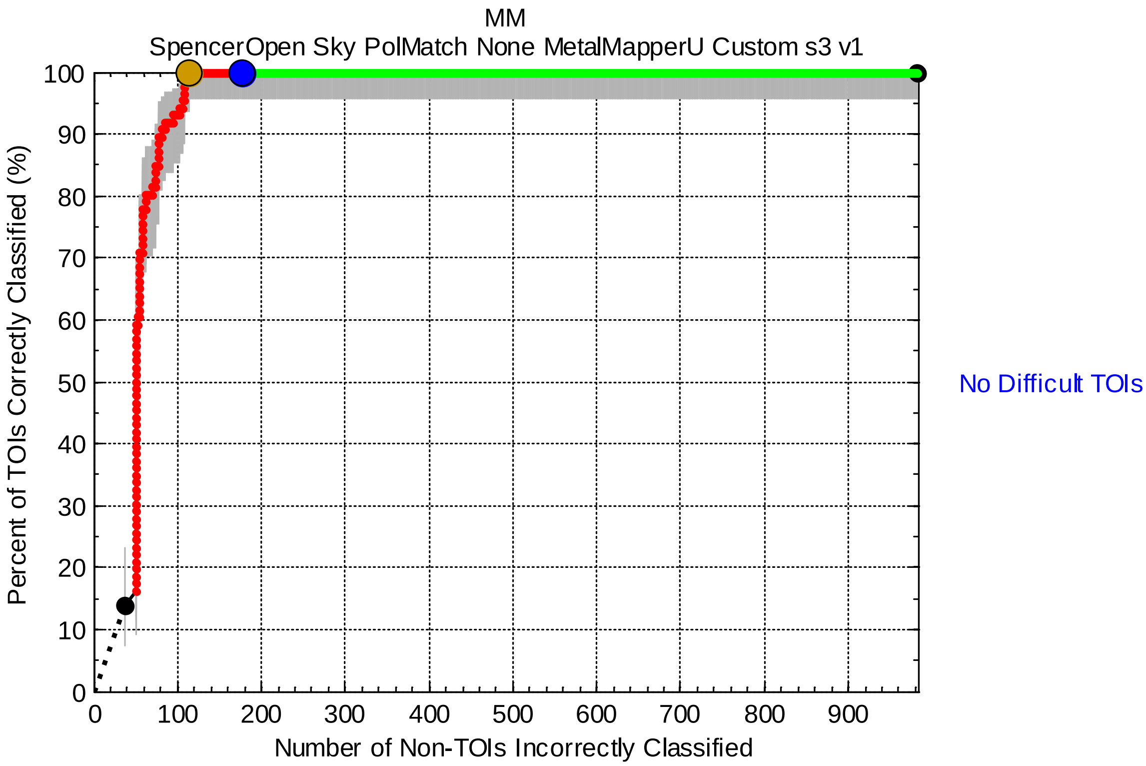

Figure 9. Final ROC Curve for Cued MetalMapper (URS) for the Open Area

7.1.2 NAEVA MetalMapper Results

NAEVA MetalMapper data was imported, inverted and QC'd in a similar manner as described in the previous section for the URS MetalMapper data. Training data selection involved looking for: (1) self–similar polarizabilities; (2) polarizabilities exhibiting UXO-like properties distinct from those of items in our reference library; and (3) polarizabilities that were similar to reference library items but of degraded quality. Figure 10 illustrates a cluster of self-similar polarizabilities that not only revealed a new TOI to add to the reference library (60-mm mortar) but also alerted the analyst to the potential of seeded multi object scenarios at the site.

Figure 11 shows the location in decay-size feature space of all training requests. A single stage dig list was generated where targets were ranked based on a combination of misfit using all three polarizabilities (with a weighting of 1) and decay rate (with a weighting of 0.5). The choice of polarizabilities and decay rate and the respective weightings was determined automatically by allowing the *DigZilla* software to search throughout parameter space using a set of starting weights and a bisection approach. The algorithm searches for the set of weights that results in all anomalies that have been flagged as potential/probable TOI being dug as early as possible. A stop dig point was determined by visual inspection of the predicted polarizabilities (in relation to the best fitting reference polarizabilities) of each anomaly plotted in dig list order.

The stop dig point was conservatively set to the latest anomaly in the dig list with polarizabilities judged to have a realistic possibility of corresponding to a TOI. The final ROC curve for the NAEVA MetalMapper data is shown in Figure 12. Although the performance of the non-automated classification was slightly better (Figure 9), all TOI were found and approximately nearly 80% of non-TOI were left in the ground at the stop dig point.

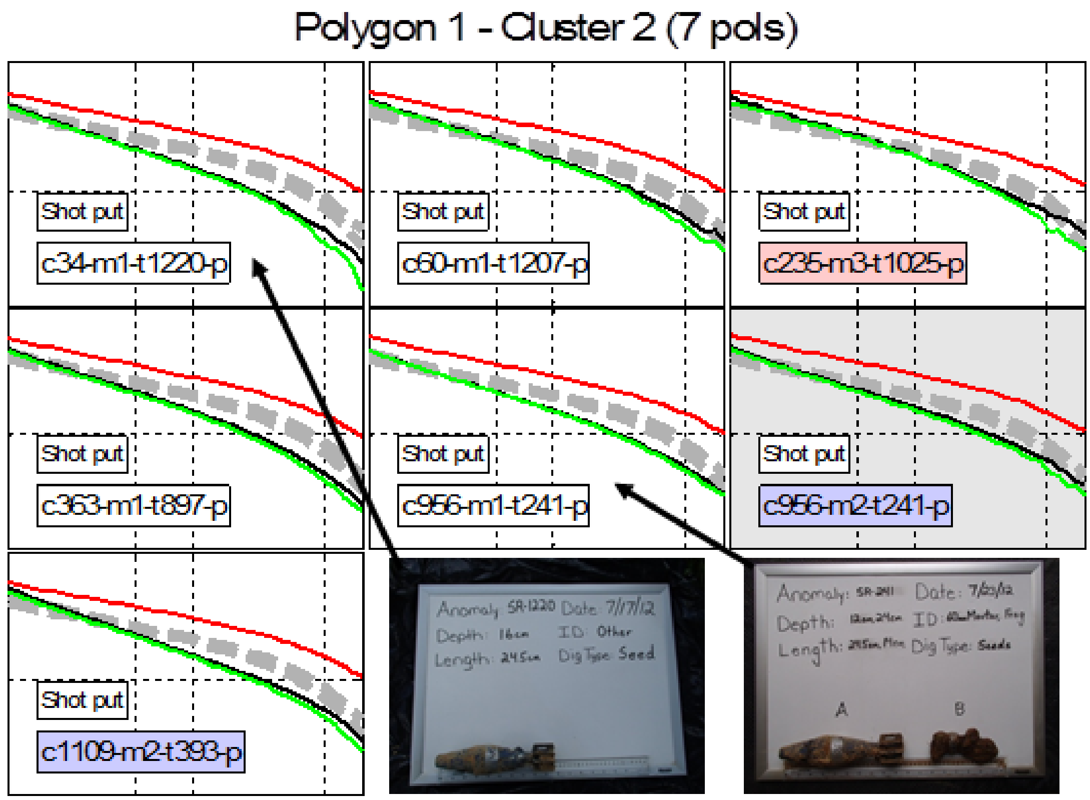

Figure 10. Polarizabilities for a Cluster Identified via Self-similar Polarizabilities

Colored lines are predicted polarizabilities. Broken grey lines are best fitting reference polarizabilities. Training data were requested for Anomalies 1220 and 241; ground truth (photos) revealed that both of these anomalies were 60mm mortars, a new TOI. These items were added to the reference library.

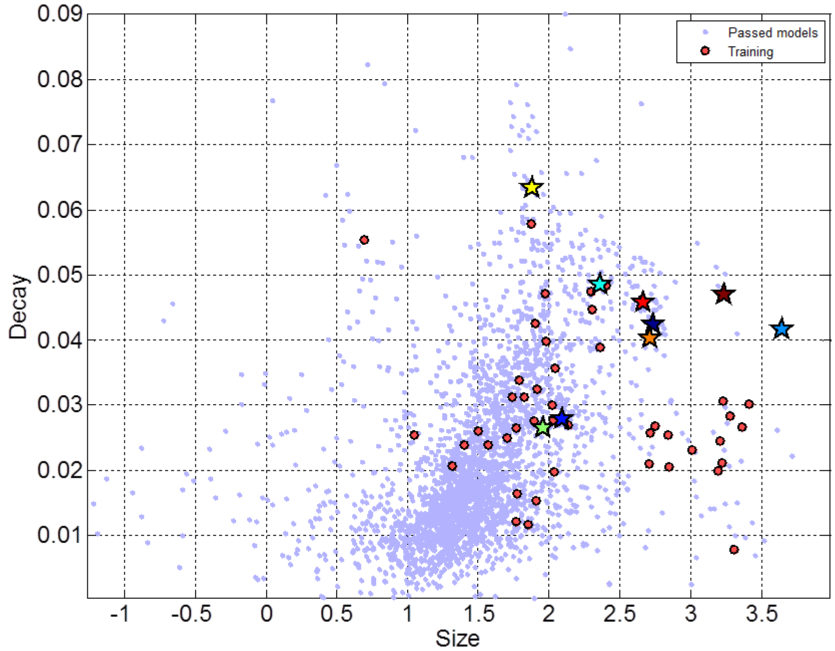

Figure 11. Decay versus Size Feature Space Plot Showing Passed Models (blue dots) and the Location of Training Data Requests (red dots)

Stars are library reference items.

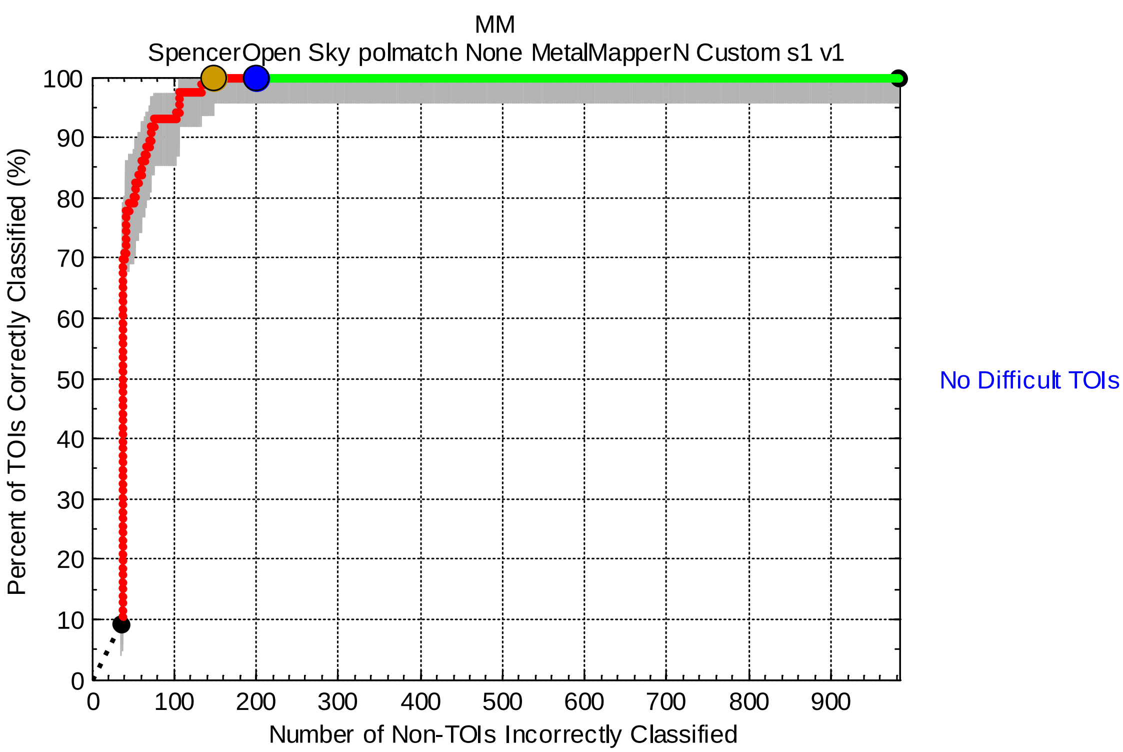

Figure 12. Final ROC Curve for Cued MetalMapper (NAEVA) for the Open Area

7.2 PROCESSING TREED AREA DATASETS

For this project, BTG generated a dig list for the cued TEMTADS 2x2 in the Portable area at Spencer Range.

7.2.1 TEMTADS 2x2 Cued Data Results

Training data over 69 items were requested and four TOI were recovered. There were then two stages with two submitted dig lists in the classification process. In stage one, 106 anomalies were dug. Of these 106 anomalies, 67 were TOIs. No QC seeds were missed. Based on the ground truth information for stage one, three additional anomalies were dug in stage two. These three anomalies were all non-TOI. A total of 178 items were dug. Five items were assigned to the "Can't extract reliable parameters" class. As a result, all 71 TOI were recovered. 514 anomalies were left in the ground and not dug, i.e., 82.8% of the non-TOI items were correctly labeled as non-TOI; all of the TOI were correctly identified.

Due to an absence of IMU information, metrics related to target location estimate accuracy were not calculated. The depth estimate errors have a standard deviation of 13 cm, which exceeds the success criteria of less than 10 cm. The survey conditions in the Treed area may have resulted in variation of the ground clearance height of the instrument, whereas we assumed a fixed ground clearance height for all anomalies. It is possible that having a more accurate measure of the ground clearance height for each anomaly would reduce the amount of error in the depth estimates.

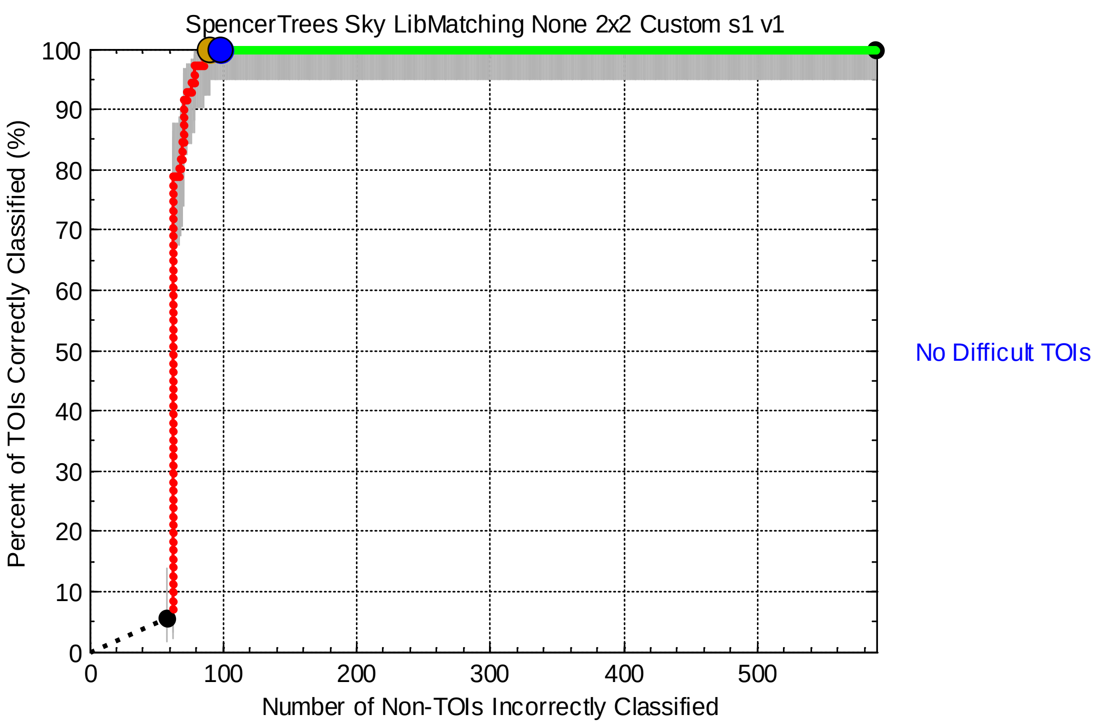

Figure 13. ROC Curve for the TEMTADS 2x2 Cued Data Analysis in the Treed Area

7.3 PROCESSING DATA COLLECTED IN THE DYNAMIC AREA

In the Dynamic area at Spencer Range, BTG generated dig lists for the cued TEMTADS 2x2, dynamic TEMTADS 2x2, cued URS MetalMapper and dynamic URS MetalMapper data. We note that BTG also produced a dig list for the cued and dynamically acquired MPV data as part of ESTCP MR-201158. We refer the reader to the ESTCP MR-201158 Spencer Demonstration report for MPV processing details and results.

7.3.1 URS Cued MetalMapper Results

Cued URS MetalMapper data in the Dynamic area were analyzed by the same BTG analyst who previously generated a cued dig list for the URS open area MetalMapper data. A similar approach to the one used for the open area was applied to the dynamic area data. No training data were requested for the dynamic area as it was assumed that the ground truth information that had been received (up to the stop dig point) for the open area was sufficient training data. During visual QC of the data, a new class of suspicious, but unknown, TOI was added to the ordnance library based on the polarizabilities for Anomalies SR-1729 and SR-1550. Both of these turned out to be 37-mm TOI. One of these (SR-1729) was a multi-object scenario (i.e., 37-mm with four medium to large pieces of frag). The training data tool was used to look for other "hidden" clusters, but none were found.

The classification approach was similar to that used for the open area data. The dig list comprised two stages. For the early digs (1-39), the order was based on polarizability misfit using all three polarizabilities. The second stage (digs 40-339) was based on polarizability misfit using only the primary polarizability. The stop dig point was set at dig number 55.

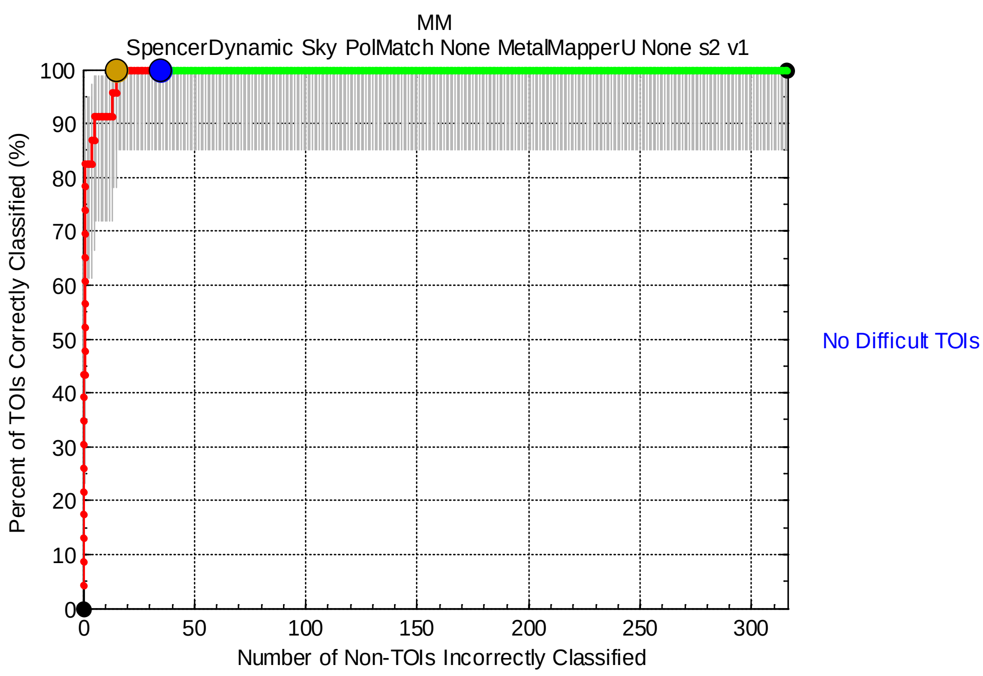

Figure 14. Final ROC Curve for Cued MetalMapper (URS) for the Dynamic Area

7.3.2 URS Dynamic MetalMapper Results

MetalMapper data acquired in a dynamic, full coverage mode were processed using UXOLab. The data were background corrected by identifying regions in the data that did not contain data anomalies, and then using these anomaly-free regions to estimate background levels which would subsequently be removed from the data.

BTG/UBC-GIF did not carry out any target picking or anomaly selection. An anomaly list was provided by the ESTCP program office. Data within a 1.5 m^2 region surrounding each anomaly flag was extracted from the background corrected dataset, and a one and two dipole source inversion was used to provide location, orientation and dipole polarizability estimates.

We performed a semi-automated cluster analysis to search for clusters of items with self-similar polarizabilities. Clusters were formed in three ways: (1) total polarizability; (2) primary polarizability; and (3) 1st and 2nd largest polarizabilities. Clusters that were judged to be UXO-like or vaguely-UXO like were selected as clusters of interest. From these clusters of interest, we typically selected a couple of example items for training data. In addition, anomalies lying on the edge of clusters of very likely UXO-like items would be selected for training data as a means of gauging both the potential variability of a cluster class, and the quality of the data. A single training data request of 17 anomalies was submitted to the program office.

The CCR algorithm was used for creating a prioritized dig list. Dig list order is based on four metrics: (1) best polarizability misfit relative to a library of reference ordnance items calculated using all three polarizabilities (L_1, L_2 and L_3); (2) same as (1) but calculated using only the primary (L_1) polarizability; (3) polarizability size; and (4) polarizability decay. The anomalies are sorted according to each metric, creating four lists of ordinals for each anomaly. The final "score" for each anomaly is a weighted sum of the ordinals.

The ROC curve for the submitted list is shown in Figure 15. At the stop-dig point – excluding training data digs and "can't analyze" digs – there were 90 total digs, of which 23 were TOI and 67 were non-TOI. At this operating point, 100% of the TOI were identified for excavation and 21.2% of the non-TOI anomalies were marked for excavation. The FAR was 0.165, with 52 of the 316 non-TOI excavated.

All performance metrics related to the accuracy of estimated target location were successfully met (Table 5). A percent error was calculated to quantify the misfit between estimated polarizabilities and the library polarizability corresponding to the ground truth. The percent error is calculated using all three principal polarizabilities. Only three TOI exceeded the 20% threshold for the polarizability percent error metric. Of these three TOI, SR-1502 was identified in the training data stage of the classification, and the other two TOI (SR-1506 and SR-1729) had a low enough primary polarizability misfit to be selected for excavation.

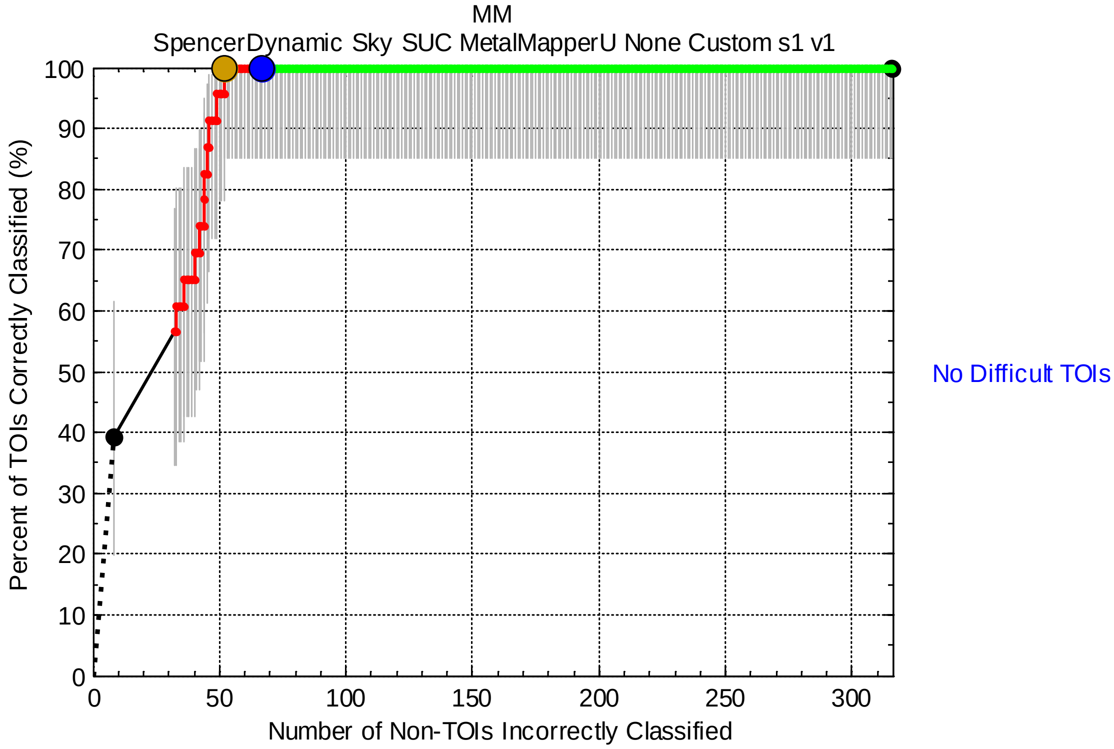

Figure 15. Final ROC Curve for MetalMapper (URS) Data Acquired in Dynamic Mode

7.3.3 Cued TEMTADS 2x2 Results

The analyst that processed TEMTADS 2x2 cued data in the Treed area also processed TEMTADS 2x2 data in the Dynamic area. The polarizability library used in the Treed area was used for the dynamic area. The process for requesting training data was similar to that used in the Treed area, and resulted in a total of 20 training anomalies.

A single classification dig list was submitted. No QC seeds were missed in this initial dig list. After reviewing the ground truth information for these anomalies, it was determined that it was unlikely that there would be additional TOI in the remaining anomalies. All 23 TOI were correctly marked for excavation. 86.9% of the non-TOI items were correctly labeled as non-TOI while retaining all of the TOI on the dig list. Figure 16 shows the final ROC curve provided by IDA.

All performance metrics related to classification of TOI and non-TOI satisfied the success criteria. Location estimates were not calculated, due to the absence of IMU information available for the survey. The standard deviation of the depth estimate error is 0.08 m. A percent error was calculated to quantify the misfit between estimated polarizabilities and the library polarizability corresponding to the ground truth. The percent error is calculated using all three principal polarizabilities. Only 4 TOI exceeded the 20% threshold for the polarizability percent error metric. Of these 4 TOI, SR-1502 was identified in the training data stage of the classification. Two of the 4 TOI (SR-1564 and SR-1576) had data recollected, for which the polarizability fit of the recollected data had a percent error that met the success criteria. Although anomaly SR-1609 had a poor fit to the library item, it was still dug just before the stop-dig point.

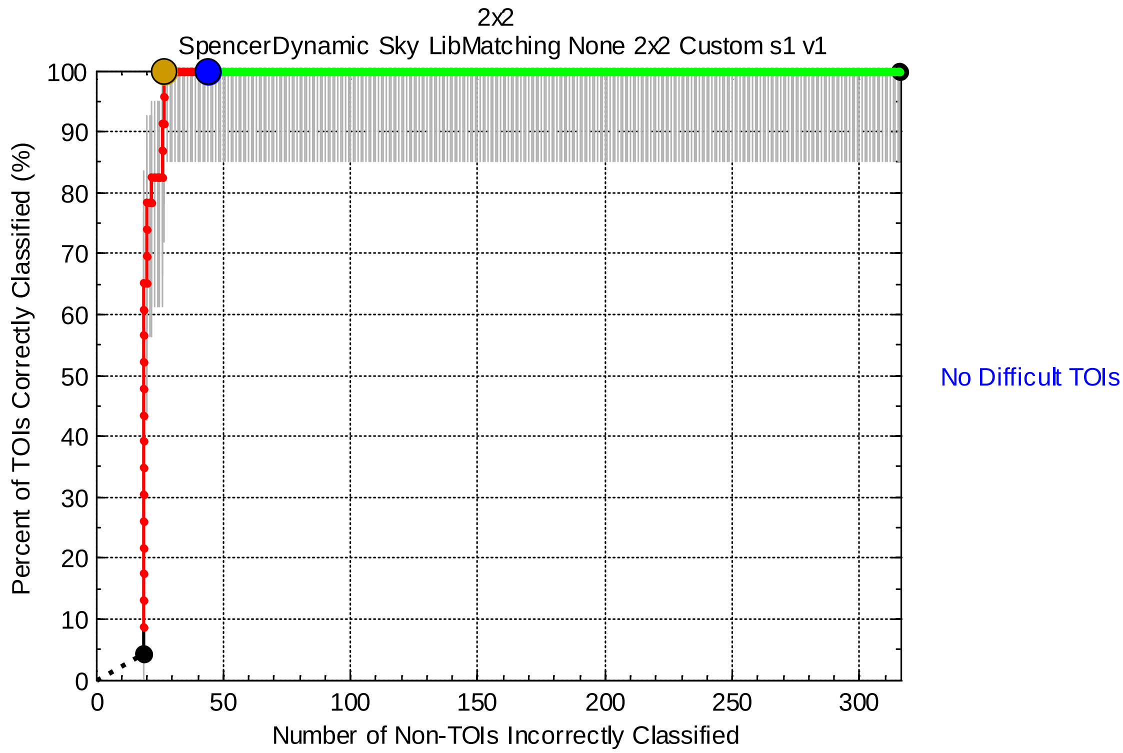

Figure 16. Final ROC Curve for TEMTADS 2x2 Cued Data Acquired in the Dynamic Area

7.3.4 Dynamic TEMTADS 2x2 Results

The background corrected TEMTADS 2x2 dynamic data collected at Spencer Range were inverted using a sequential inversion approach to estimate target location, depth and principal polarizabilities. Two SOIs were performed per anomaly: (1) using all data within 75 cm of the picked target location; and (2) by inverting only the data along the transect that passed closest to the picked target location. Where necessary, the analyst adjusted masks and/or fit a 2OI model to the data. The best fitting model for any of the inversions performed for a particular anomaly was used to make classification decisions.

Analysis of the data, including visual QC of data and model parameters, selection of training data, and dig list creation, was performed using the UXOLab software suite. Visual QC of the data was performed using *QCZilla*, which allowed us to compare the observed and predicted data, review predicted model parameters, and examine measures of data/model quality. Predicted polarizabilities were compared to reference polarizabilities for various ordnance items initially derived from IVS and test pit measurements. As the analysis proceeded, the library of reference items was augmented with additional items based on ground truth obtained through training data requests.

Training data information was requested for twenty-one items spread across two requests. The training data requests focused on items with similar size and time-decay parameters to the known ordnance items and items that appeared to exhibit axial symmetry. Figure 17 shows the location in decay-size feature space of all training requests.

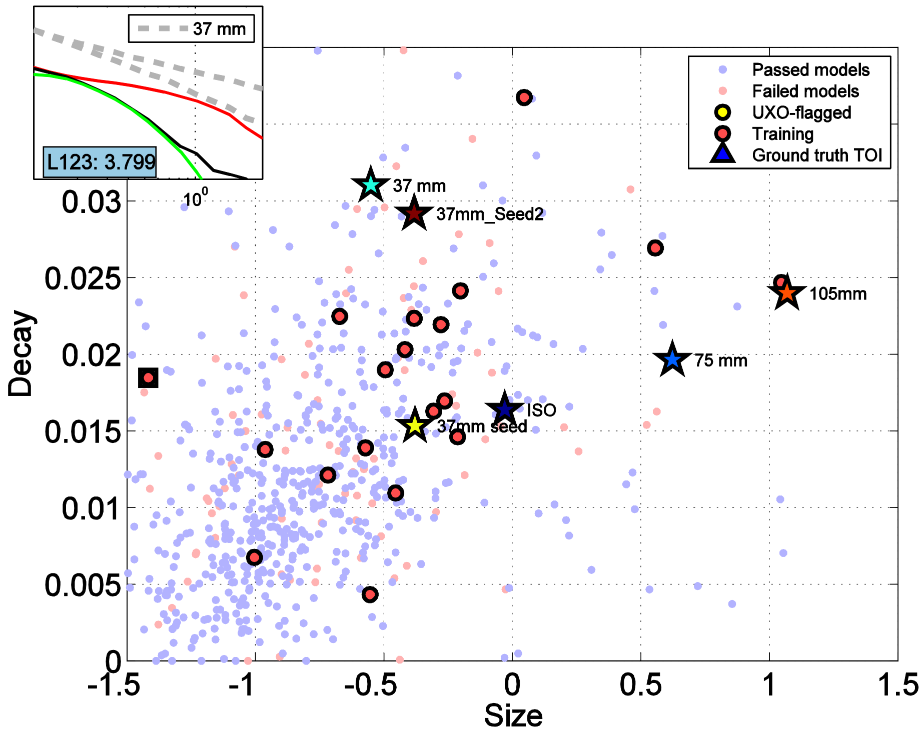

Figure 17. Decay Versus Size Feature Space Plot Showing Passed Models (blue dots) and the Location of Training Data Requests (red dots)

Stars are library reference items.

A single stage dig list was generated in which targets were ranked using the CCR algorithm using feature vectors comprising: (1) all polarizabilities; (2) primary polarizability; (3) size; and (4) decay. Rankings for each of the four sets of feature vectors are obtained by comparison to the equivalent features in the reference library. The CCR is obtained by the weighted sum of the rankings in the four separate ranking schemes. Thus, a feature vector that ranks high in more than one scheme will rank high in the CCR. The stop dig-point was determined subjectively by the analyst; digging ceased after all items deemed to be high-priority TOI and/or low-confidence non-TOI items were dug. In the original dig-list submission, one seed item (SR-1676) occurred past the stop-digging point. This item had a lower than expected time-decay parameter that placed it just past the stop-dig point. The CCR weights were adjusted so that items in the region of feature space below the ISO and 37-mm feature vectors were ranked higher. The final ROC curve for the dynamically acquired TEMTADS 2x2 data in the dynamic area is shown in Figure 18. All TOI were identified for excavation and greater than 80% of non-TOI were left in the ground at the stop-dig point.

7.4 TECHNOLOGY TRAINING AND TRANSFER

A member of the Shaw Environmental production team attended a one week training session in Vancouver, B.C., Canada with BTG algorithm and software developers. The training session included an overview of UXO inversion and classification theory and software routines. The Shaw geophysicist was responsible for executing all parts of the classification workflow: from data and inversion QC, training data selection, to diglist creation and submittal. The final ROC curve is shown in Figure 19.

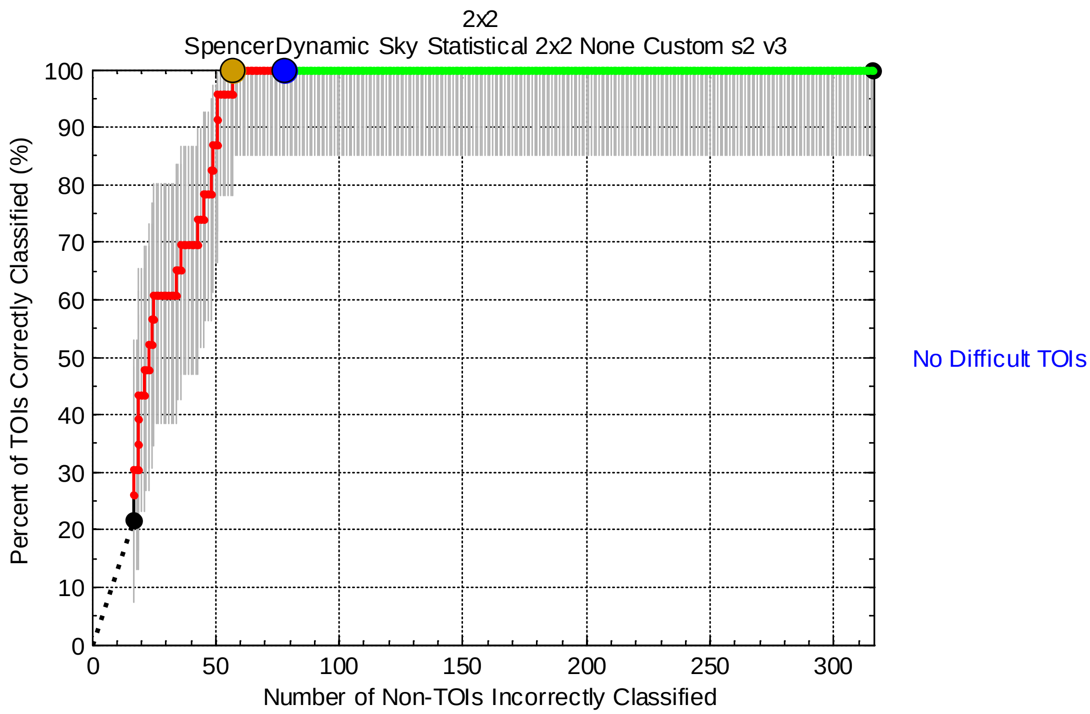

Figure 18. Final ROC Curve for the Dynamic TEMTADS 2x2 Data from the Dynamic Survey

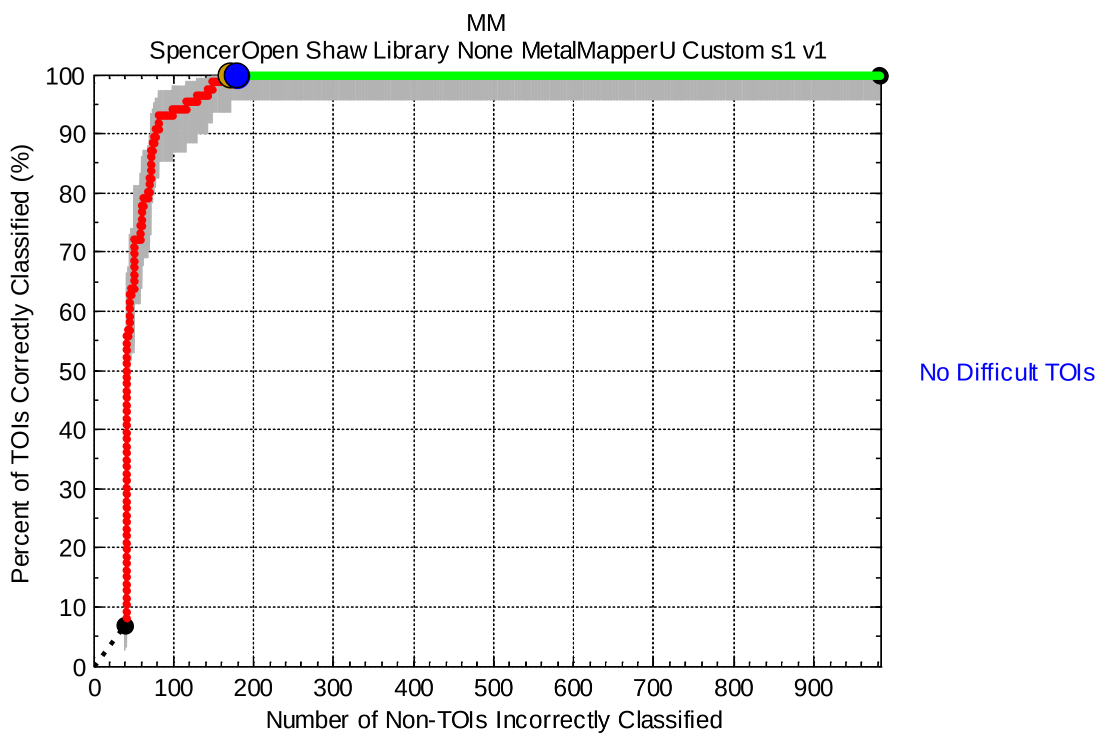

Figure 19. ROC Curve for the Library Based Classification of MetalMapper (URS) Data Carried Out by a Shaw Environmental Geophysicist

8.0 COST ASSESSMENT

The majority of the work reported here was performed while the data analysts were employed by Sky Research. When the project team moved to BTG, they lost access to the labor information required to meaningfully compare the costs of the different technologies. Here, we reproduce the cost analysis provided by the Program Office in the ESTCP (2014) report on the Spencer demonstration, which was specifically for the MetalMapper deployed in dynamic mode.

8.1 COST MODEL

The demonstration took place on a small part of the former Spencer Artillery Range and incurred costs for many items specific to a demonstration that would not be needed in an application of classification to a real site. Nevertheless, we can extract meaningful projected performance for the technology and apply reasonable industry unit costs for various elements to arrive at a total cost comparison for clearing an example 100-acre site with and without the use of classification.

We made the following assumptions:

- The example takes place in an area with similar munitions types and the same density of anomalies as seen in this demonstration. There were approximately 250 anomalies per acre at the demonstration site. Extrapolating, we would expect about 25,000 anomalies in a similar 100-acre area, with 24,925 clutter.
- Mob/demob and a surface sweep would be required for either scenario.
- Three TOI were found during the intrusive investigation of the ~4-acre area. We predict about 75 native TOI in a 100-acre site.
- The baseline is an EM-61 survey with 0.5 m line spacing. This would be used to select anomalies for digging without classification and for cueing with the advanced sensor in hybrid mode.
- Survey data will be collected using MetalMapper in dynamic mode for the advanced sensor only mode.
- The site is seeded at a rate so on average one seed will be encountered each day of MetalMapper data collection. With an estimate of 25,000 total anomalies and a production rate of 200 anomalies per day, we seed 125 inert items. These QC seeds would be used whether classification was used on the site or not.
- The classification performance is as achieved by the production firms with ~80% of the clutter correctly identified and remaining undug.
- The unit costs are as shown in Table 8.

With these assumptions, the costs were calculated using the elements shown in Table 9. A 49% savings on project field work can be realized using a hybrid approach, in which anomalies are identified from an EM-61-MK2 survey and cued data is collected with the MetalMapper (the method used in this demonstration).

Table 8. Unit Cost Assumptions

Item	Units	Cost
Mob/Demob	1	$7,000
Surface Sweep	acre	$2,500
IVS and Seed Emplacement	125 seeds	$22,650
EM-61 Survey Data Collection and Analysis	acre	$1,000
Dynamic MetalMapper Data Collection and Analysis	acre	$5,000
Cued MetalMapper Data Collection and Analysis	per anomaly	$30
Digs	per dig	$125

Table 9. Cost Comparison for 100 Acres of Comparable Spencer Range Site

	No Classification		Hybrid Approach[1]		Advanced Sensor Only[2]	
Work Item	**Quantity**	**Cost/$**	**Quantity**	**Cost/$**	**Quantity**	**Cost/$**
Mob/demob	1	7,000	1	7,000	1	7,000
Surface Sweep	100 acres	250,000	100 acres	250,000	100 acres	250,000
Seeds	125 items	22,650	125 items	22,650	125 items	22,650
EM-61 Survey	100 acres	100,000	100 acres	100,000	n/a	
MetalMapper Survey	n/a		n/a		100 acres	500,000
Cued MetalMapper	n/a		25,000 anomalies	750,000	8,333 anomalies	249,990
Seeds Dug	125	15,625	125	15,625	125	15,625
Native UXO Dug	75	9,375	75	9,375	75	9,375
Clutter Dug	24,925	3,115,625	4,985	623,125	4,985	623,125
TOTAL		3,520,275		1,777,775		1,677,765
Percent Savings				**49%**		**52%**

1 Hybrid approach denotes the method used in this demonstration, anomaly detection from an EM-61-MK2 survey with cued data collection using advanced sensors.

2 Advanced sensor only approach refers to anomaly detection and classification of 2/3 of the anomalies using MetalMapper in dynamic mode and cued data collection on the remaining 1/3 of the anomalies.

8.2 COST BENEFIT

As the Classification demonstration program has progressed, it has become apparent that a significant number of anomalies can be classified using data collected dynamically using advanced EMI sensors. This raises the possibility of performing the anomaly detection step using advanced sensors, classifying many of the anomalies using the same data set (2/3 of the anomalies in a recent test), and only having to collect cued data over a subset of the anomalies. The cost estimate for this "Advanced Sensor Only" mode is given in the rightmost two columns in Table 9.

Given the reduced number of data collections, one might expect the savings from the advanced sensor only mode to be much greater than the hybrid approach. The current generation of advanced sensors are not configured to be deployed in arrays, so the cost for the advanced sensor detection survey for this example site is much higher than for detection using an EM-61-MK2 array. As the operation of these advanced sensors in dynamic mode is explored further, it is possible that this cost disadvantage will lessen.

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9.0 IMPLEMENTATION ISSUES

Specific implementation issues related to the technologies demonstrated here are:

- Access to good, high-quality, reliable hardware for collection of data suitable for Advanced Geophysical Classification (AGC) continues to be a problem for the industry.
- UXOLab software was used for all the processing and interpretation activities described in the report. While UXOLab is available under license from UBC, it is not suitable for general distribution to government contractors. Firstly, using the software successfully requires advanced knowledge of geophysical inversion and statistical classification. Secondly, while the software doesn't require the user to have a Matlab license, it was built entirely within the Matlab software environment to support the needs of UXO researchers. Thirdly, UBC is not set up to provide maintenance and support for the software. As part of Strategic Environmental Research and Development Program (SERDP) MR-2318, BTG are in the process of porting the Matlab code to C++ so that the software will be accessible with Geosoft Oasis Montaj (the industry standard processing software).
- Access to the appropriate software and hardware is the first critical step in successful implementation of the technology. Ensuring that operators have the appropriate level of training and experience is the second. This requirement for training and experience applies to both the feature vector extraction and classification steps. While the process of feature extraction is straightforward and reliable for a large number of anomalies, there is always a certain percentage of anomalies where the default parameters don't produce a sensible or reliable result. Recognizing those situations is critical to minimize the probability of a false negative, while being able to appropriately adjust the strategy is important for reducing the FP count. For classification, each site has unique challenges and the most appropriate classification strategy changes. Thus, each analyst must be capable of exploring (and understanding the potential pitfalls of) different feature spaces that could be used for discrimination. In summary, we believe that a very solid understanding of both feature extraction and classification are required for the discrimination technology to be reliably applied to different DoD sites.

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APPENDIX A POINTS OF CONTACT

Points of contact (POCs) involved in the demonstration and their contact information are presented below.

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Kevin Kingdon	Black Tusk Geophysics, Inc. Same address	Tel: 604 428 3382 kevin.kingdon@btgeophysics.com	Project management and personnel coordination
Dr. Barry Zelt	Black Tusk Geophysics, Inc. Same address	Tel: 604 428 3382 barry.zelt@btgeophysics.com	Data analyst and UXOLab programming
Dr. Stephen Billings	Black Tusk Geophysics, Inc. Same address	Tel: +1 720 306 1165 stephen.billings@btgeophysics.com	Data analyst
Dr. Laurens Beran	Black Tusk Geophysics, Inc. Same address	604 428 3382 laurens.beran@btgeophysics.com	Data analyst, classification theory
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