

Final Report

Real Time Quality Control Methods for Cued EMI Data Collection

ESTCP Project MR-201264

JANUARY 2016

Jonathan Miller
White River Technologies, Inc.

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FINAL REPORT

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**Jonathan Miller
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January 2016

TABLE OF CONTENTS

1.	INTRODUCTION	1
1.1	BACKGROUND	2
1.2	OBJECTIVE OF THE DEMONSTRATION	3
1.3	REGULATORY DRIVERS	4
2.	TECHNOLOGY	4
2.1	TECHNOLOGY DESCRIPTION	4
2.2	ADVANTAGES AND LIMITATIONS OF THE TECHNOLOGY	9
3.	PERFORMANCE OBJECTIVES	10
3.1	OBJECTIVE: IDENTIFICATION OF ALL RECOLLECT OPPORTUNITIES	12
3.1.1	Data Requirements	12
3.1.2	Metric	12
3.1.3	Success Criteria	13
3.2	OBJECTIVE: EFFECTIVE CORRECTIVE ACTION	13
3.2.1	Data Requirements	13
3.2.2	Metric	13
3.2.3	Success Criteria	13
3.3	OBJECTIVE: EFFECTIVE IN-FIELD CHARACTERIZATION	13
3.3.1	Data Requirements	13
3.3.2	Metric	13
3.3.3	Success Criteria	14
3.4	OBJECTIVE: EFFECTIVE QUALITY METRICS	14
3.4.1	Data Requirements	14
3.4.2	Metric	14
3.4.3	Success Criteria	14
3.5	OBJECTIVE: PRODUCTION RATE	14
3.5.1	Data Requirements	14
3.5.2	Metric	15
3.5.3	Success Criteria	15
3.6	Quantifying Improvements in Target Features	15
4.	SITE DESCRIPTION	23
5.	TEST DESIGN	25

6.	DATA ANALYSIS PLAN	25
6.1	PARAMETER ESTIMATION	25
6.2	PERFORMANCE ANALYSIS.....	26
6.2.1	Objective 3.1: Identification of All Recollect Opportunities	26
6.2.2	Objective 3.2: Effective Corrective Action.....	26
6.2.3	Objective 3.3: Effective In-Field Characterization	26
6.2.4	Objective 3.4: Effective Quality Metrics	27
6.2.5	Objective 3.5: Production Rate	27
7.	PERFORMANCE ASSESSMENT	27
7.1	Objective 3.1: Identification of All Recollect Opportunities	27
7.2	Objective 3.2: Effective Corrective Action.....	29
7.3	Objective 3.3: Effective In-Field Characterization	31
7.4	Objective 3.4: Effective Quality Metrics	32
7.5	Objective 3.5: Production Rate	36
7.6	Qualitative Objectives	37
8.	COST ASSESSMENT	37
8.1	Cost Drivers.....	37
9.	IMPLEMENTATION ISSUES	38
10.	REFERENCES	39
	Appendix A – Interim Proveout Report.....	40

ACRONYMS

AOI – Area of Interest
API – Application Programming Interface
DGM – Digital Geophysical Mapping
DQO – Data Quality Objective
EMI – Electromagnetic Induction
ESTCP – Environmental Security Technology Certification Program
GPS – Global Positioning System
IMU – Inertial Measurement Unit
ISO – Industry Standard Object
IVS – Instrument Verification Strip
MEC – Munitions and Explosives of Concern
MM – MetalMapper

MMRP – Military Munitions Response Program
MR – Munitions Response
MRS – Munitions Response Site
Preac – Percentage of reacquisitions
Prec(I) – Percentage of recollects resulting in improved classification
QC – Quality Control
Rx - Receiver
SNR – Signal to Noise Ratio
SOP – Standard Operating Procedure
TOI – Target of Interest
Tx – Transmitter
UTC – Coordinated Universal Time
UTM – Universal Transverse Mercator
UXO – Unexploded Ordnance
WMA – Waikoloa Maneuver Area

FIGURES

Figure 1. Typical operator display setup showing QC and acquisition interfaces. The QC Module provides the main navigation and analysis interfaces, while EM3D provides the acquisition capability with a simple acquire button..... 6

Figure 2. LEFT: The navigation interface displays the anomaly coordinates and the sensor location. RIGHT: As the operator moves the sensor closer to an anomaly, the display performs an auto-zoom to facilitate accurate positioning of the sensor head over the anomaly. After the data are acquired, the QC module updates the navigation display with the estimated target location (pink dot)..... 7

Figure 3. LEFT: Target libraries are built from data collected in controlled calibration areas within the site. This image shows a 37mm projectile placed in a test pit for library data collection. RIGHT: Library features are subsequently loaded into the QC module. The QC interface displays polarizabilities recovered from cued EMI data inversion and compares them to the best-match library features..... 7

Figure 4. LEFT: QC module performance tests were conducted by acquiring MetalMapper measurements over target items placed on a test grid. CENTER: Sensor positioning guided by the navigation interface was demonstrated to be within 2-3 cm of target pick location (red dot). RIGHT: Estimated target location determined by data inversion was within 5 cm of the true target location for target offsets extending to 70 cm from the center of the MetalMapper sensor head. 8

Figure 5. TOP LEFT: The red dot shows the location of the target pick. The pink dot shows the estimated target location. TOP CENTER: The sensor is repositioned over the estimated location, which is now represented by the red dot. TOP RIGHT: If the operator determines the quality of the recollected data is acceptable, the dot turns green indicating that the data corresponding to this anomaly have met the quality requirements. BOTTOM LEFT: QC interface for the

recollected data. BOTTOM RIGHT: The actual target (37 mm projectile) and target pick location (orange paint). 9

Figure 6. LEFT: Polarizabilities recovered from inversion of initial data acquired with 55cm offset from target. RIGHT: Polarizabilities recovered from inversion of recollect data acquired with MetalMapper centered over target. The blue, red, and green lines represent the primary, secondary, and tertiary principal polarizabilities, respectively (L1, L2, and L3, respectively). The grey lines represent the principal polarizabilities for the reference library match (60mm mortar)..... 16

Figure 7. Model noise values for L1 (top), L2 (middle), and L3 (bottom). Dashed lines represent noise values associated with the initial data file; solid lines represent noise values associated with the recollect data file. It is clear that only the L3 shows any significant improvements in noise associated with the recollect. 18

Figure 8. LEFT: Polarizabilities recovered from inversion of initial data acquired with >35cm offset from target. RIGHT: Polarizabilities recovered from inversion of recollect data acquired with MetalMapper centered over target. The blue, red, and green lines represent the primary, secondary, and tertiary principal polarizabilities, respectively (L1, L2, and L3, respectively). The grey lines represent the principal polarizabilities for the reference library match (small ISO40)..... 18

Figure 9. Test pit layout for multi-object scenario. The MetalMapper center was positioned over the frag item. 20

Figure 10. LEFT: Single-source results for the multi-object data collection. CENTER and RIGHT: Two-source results for multi-object data collection. Colored lines represent the recovered L1, L2, and L3 polarizabilities (blue, red, and green, respectively). Grey lines represent the 60mm library polarizabilities. Target 2 (right) shows a good match to the 60mm library. 20

Figure 11. Single-source model fit comparing concatenated data (blue) and model (red) outputs. 21

Figure 12. Two-source model fit comparing concatenated data (blue) and model (red) outputs. 21

Figure 13. LEFT: Polarizabilities recovered from inversion of initial data acquired with >35cm offset from target. RIGHT: Polarizabilities recovered from inversion of recollect data acquired with MetalMapper centered over target. The blue, red, and green lines represent the primary, secondary, and tertiary principal polarizabilities, respectively (L1, L2, and L3, respectively). The grey lines represent the principal polarizabilities for the reference library match (37mm projectile). 22

Figure 14. Initial acquisition model fit comparing concatenated data (blue) and model (red) outputs. The data produce a good model fit, but the solution is non-unique. 22

Figure 15. Recollect model fit comparing concatenated data (blue) and model (red) outputs. The data produce a good model fit and a unique solution. 23

Figure 16. Former Waikoloa Maneuver Area (from USACE Waikoloa map). 24

Figure 17. Former Waikoloa Maneuver Area site photos. 24

Figure 18. Independent scoring results for Dartmouth College WMA MetalMapper analysis indicate two difficult targets: WK-1027 and WK-1047.	28
Figure 19. Polarizabilities obtained from two different acquisitions over WK-724, a 37mm seed. For the initial acquisition, the sensor was offset 34 cm from the target. The recollect placed the sensor at an offset of 13 cm from the target. The polarizabilities (blue, red, and green lines) show a much better match to the library (dark grey lines) in the recollect.....	29
Figure 20. Polarizabilities obtained from two different acquisitions over WK-1053, a piece of munitions debris. The recollect provides better constraint on the third polarizability (green line).	30
Figure 21. Example of the recollect providing better resolution of target features. In this case the initial acquisition produced polarizabilities dominated by the ground response. The recollect provides features that more accurately represent the actual target (a piece of frag).....	31
Figure 22. Polarizabilities associated with anomaly WK-68, a piece of frag. Here the initial acquisition shows good resolution of target features; however, the recollect provides features dominated by the ground response.	32
Figure 23. Polarizabilities recovered from the initial acquisition data (left) and the recollect data (right). These polarizabilities correspond to anomaly WK-267, a medium ISO seed. Here the recollect was unnecessary.	33
Figure 24. Polarizabilities recovered from the initial acquisition data (left) and the recollect data (right). These polarizabilities correspond to anomaly WK-169, a piece of frag. Here the recollect was unnecessary.	33
Figure 25. Polarizabilities recovered from the initial acquisition data (left) and the recollect data (right). These polarizabilities correspond to anomaly WK-880, a fuze clip. The initial data do not fully constrain the third polarizability (green line) and indicate that the recollect was beneficial.	34
Figure 26. Possible decision flow for in-field QC. This decision flow incorporates the additional fit and model noise metrics along with the primary target location metric to support the decision to recollect or not. The objective of this type of decision flow would be to reduce unnecessary recollects that may occur within some margin of error of the 30 cm offset threshold (e.g., 25 – 40 cm). All metrics including the offset threshold could be adjusted for site specific requirements like smallest TOI, target density, etc. to reflect different tolerances for data recollects.	35

TABLES

Table 1. Performance Objectives	11
Table 2. Feature Quality Metrics for 60mm Mortar	16

Table 3. Feature Quality Metrics for Small ISO40.....	19
Table 5. Cost Model for In-Field Quality Control for Cued EMI Surveys.....	37

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Executive Summary

This project evaluated the effectiveness of in-field quality control (QC) procedures during cued EMI data collection. The in-field QC approach includes the use by cued sensor operators of a real-time inversion software module that provides immediate output of features associated with each anomaly investigated by cued EMI data collection. Among the relevant features provided by the software is an estimate of the location of the buried target. If the lateral offset of this estimated location is greater than 30 cm from the center of the cued sensor, the sensor operator can reposition the sensor over the estimated source location and recollect the cued data. Visual interpretation of the sensor location, the estimated target location, and other target features such as electromagnetic polarizabilities is enabled by the in-field QC software.

During the field demonstration component of this project, we supplied the Parsons field team with the in-field QC software during their cued MetalMapper survey at the Former Waikoloa Maneuver Area (WMA) on the island of Hawaii. During this survey, the field team encountered 1032 unique anomaly locations with the MetalMapper. Out of these 1032 encounters, 231 resulted in recollects based on the estimated target location feedback provided by the in-field QC software.

We performed a retrospective analysis of these MetalMapper data to determine:

- if there were any missed recollect opportunities, i.e., cases where a recollect was not performed, but should have been performed;
- the effectiveness of the in-field QC process by quantifying any improvements in target features obtained by recollecting the data;
- the efficiency of the in-field QC process by identifying the number of cases where the recollect was unnecessary, i.e., it did not produce better characterization of the target.

We used these recollect statistics to develop estimates of production rates for surveys conducted using the in-field QC approach and for surveys where no in-field recollect decision is made. A summary of the statistics and estimated production rates are as follows:

- out of 1032 anomalies investigated of which 231 resulted in a recollect, there was 1 potential missed recollect opportunity;
- out of 231 recollects, 153 recollects appeared to be a result of magnetic geology creating false source locations;
- out of the remaining 78 recollects that were due to legitimate sources (i.e., a metal object), 46 resulted in improvements in target characterization;
- of the remaining 32 recollects that did not significantly improve target characterization, we found 11 cases where the unnecessary recollect may have been avoided with the application of additional quality metrics (i.e., in addition to the estimated target location metric);
- Estimated production rates for surveying with and without the in-field QC process were 23 anomalies/hr (with in-field QC) and 26 anomalies/hr (without in-field QC).

The magnetic geology at the site presented the most significant challenge to the technology and contributed to the lower than expected production rate for the in-field QC approach. The 46 cases that resulted in quantifiable improvements in target features are an example of the potential benefits of applying in-field QC to cued EMI surveys. Possible ways to improve the efficiency of the technology at challenging sites, such as the WMA, could be to improve background selection and removal during in-field QC of the data or to implement multi-source solvers in the in-field inversion to account for magnetic soil effects and high target densities.

1. INTRODUCTION

This project was undertaken to evaluate and implement quality control processes for cued Electromagnetic Induction (EMI) data collection associated with munitions classification surveys. The primary objective of this effort was to establish an optimal set of metrics that will inform field teams of the classification quality of the data collected during a cued EMI survey. Incorporating these metrics in a software interface will enable field operators to determine immediately upon acquisition if cued data are of high enough quality to provide useful classification features. This ability to make an informed in-field decision regarding cued EMI data quality has the potential to greatly increase the efficiency of these surveys. Currently, most of the quality analysis for cued EMI surveys is performed off-site by trained analysts. While effective for identifying instances of poor data quality, this method can be costly as it often requires field teams to redeploy to certain areas to reacquire data. Enabling an in-field quality decision will produce immediate corrective actions that will obviate the need for subsequent redeployment and reacquisition by the field team.

During the first phase of this project, we evaluated an in-field Quality Control (QC) software module that incorporates a real-time inversion capability to provide field operators with a set of quality metrics that allows them to make high confidence quality decisions during cued surveys. If a low quality data collection event occurs, the software module also facilitates immediate corrective action by presenting the operators with a set of rectified sensor positioning coordinates. The QC module is currently designed to support MetalMapper operations; however, it can be modified to work with any advanced EMI sensor. As part of this initial phase we completed a series of proveout tests to verify the performance and functionality of the QC module applied to cued MetalMapper data collection. Results from these tests demonstrated that the software module performance met the objectives required for transition to field operations. These objectives included criteria for the reliability of inversion parameters as well as requirements for the sensor navigation and positioning accuracy.

The second phase of this project provided a field demonstration of the QC software module and associated quality control practices at the Former Waikoloa Maneuver Area (WMA). The field component of this demonstration involved the QC module and in-field quality control practices applied to a MetalMapper survey conducted by a field team at a live munitions site. This field demonstration helped to elucidate some of the practical and operational requirements for conducting efficient data quality control by the field team. It also provided a means for acquiring a substantial data set that can be used to quantify the overall effectiveness of the in-field quality control process. During our retrospective analysis of the WMA data set, we identified several instances where the in-field QC led to improvements in the data quality, as well as cases where it led to unnecessary recollection of cued data. These cases can be taken together to provide some insight into the benefits and limitations of the technology, as well as to reveal possible approaches for improving the effectiveness of the in-field QC approach. This document provides an overview of the technology and in-field QC approach, a summary of the performance results from our retrospective analysis of the WMA data, and suggestions for potential enhancements to the in-field QC approach.

1.1 BACKGROUND

The prevalence of innocuous clutter (e.g., scrap, fragmentation, etc.) at Munitions Response (MR) sites presents a challenge to remediation efforts that often devote substantial resources to the excavation and identification of these non-hazardous objects. Over the last 5-10 years, the development of advanced EMI sensor arrays that enable multi-axis or multi-angle illumination of cued anomalies has enabled the implementation of methodologies that effectively discriminate clutter from Unexploded Ordnance (UXO) or other Munitions and Explosives of Concern (MEC). These classification methodologies have the potential to significantly improve the efficiency of production cleanup efforts by reducing the time and costs associated with removal of benign objects; however, collection of high quality data with advanced sensors is critical to ensuring the effectiveness of these classification algorithms.

Currently, standard protocol for collecting advanced EMI sensor data includes static data acquisition over anomalies identified (cued) by prior dynamic or Digital Geophysical Mapping (DGM) surveys. These data are typically analyzed by off-site geophysicists upon completion of the cued survey. Often, this analysis results in a number of anomalies that are found to be insufficiently characterized by the initial cued data collection as a result of sub-optimal placement of the EMI sensor during the survey. Subsequently, reacquisition of data is necessary and additional surveying is required. Methods that significantly reduce reacquisitions and improve the overall quality of the data before completion of the initial cued survey will significantly improve the efficiency of production operations.

Because cued EMI sensors rely on multi-axis illumination to provide enough information to extract useful classification features from the data, the placement of the sensor relative to the object under interrogation is critical. In many instances when the cued data yield poor classification features, the reason is often an incorrectly positioned sensor. Positioning errors, misguided target picking, or multiple objects in the field of view are common causes of incorrect cued sensor placement. Most often, these errors are not discovered until the off-site geophysicist identifies them during analysis of the data. Once discovered, the analyst will determine a rectified set of coordinates to better represent the true location of the target. The field team will then reacquire the data by positioning the sensor over the new coordinates.

Providing the field team with the capability to assess data quality immediately following the initial data collection could significantly improve the cued survey process. By removing the off-site analyst from the initial quality decision making, the field team can take immediate action to reposition and recollect certain targets if deemed necessary. Immediate recollection based on in-field quality control can be much more efficient than subsequent reacquisition based on off-site decision making. Offsite analysis may still be important for identifying complicated target scenarios (e.g., multi-object, magnetic geology, etc.); however, many of the reacquires due to common errors such as inaccurate target picking could be replaced by in-field decision based recollects.

By incorporating the QC software module into the existing cued EMI survey process, we endeavored to establish a set of procedures that will bridge the current capability gaps associated with in-field quality control of munitions classification data. The QC module provides the field team with data inversion parameters such as target polarizabilities and estimated target location

while the EMI sensor is still in the vicinity of cued anomaly locations. These parameters may then be used to identify anomalies that are poorly characterized due to sub-optimal sensor positioning. Accordingly, the field team can take appropriate and immediate corrective action before leaving the survey area. This process can significantly improve the overall efficiency of production classification surveys by reducing the need for later redeployment and reacquisition.

1.2 OBJECTIVE OF THE DEMONSTRATION

During the initial phase of project MR-201264 we verified the basic performance capabilities of the QC module. This verification process included analysis of controlled test pit data to quantify the accuracy, speed, and reliability of the QC module output. We also conducted a preliminary evaluation of the process flows associated with the in-field QC protocol by performing cued surveys over surrogate test items. This evaluation yielded a qualitative assessment of the operational aspects of the QC process such as ease of use and level of operator interpretation required. The field demonstration phase of this project tested the performance, reliability, and operational feasibility of this QC process under more demanding field conditions.

The primary objective of the demonstration phase of this project was to gain further insight into the field practices that lead to the most effective and efficient cued EMI surveys. For this demonstration phase, we worked with a field team to apply the QC module during a cued survey of the Former WMA to identify anomalies that may have been insufficiently characterized by the initial data collection. After the survey and final ground truth stages were completed, we performed a retrospective analysis of the WMA data set to identify cases where recollects based on the in-field decision led to an improvement in data quality as well as cases where the recollect was unnecessary (i.e., it did not provide any improvements in classification features).

Other aspects of the demonstration that helped us gauge the overall utility of the QC module in supporting field operations included anecdotal evidence (based on the feedback supplied by several MetalMapper operators), which suggests that the QC module navigation interface offers a very intuitive approach to sensor positioning. In fact, user feedback indicates that the time spent performing an initial data collection as well as an immediate sensor reposition and recollection using the QC module is often less than the time required to perform only an initial collection without using the feedback provide by the QC module. This result has implications for survey production rates. It is possible that by reducing the level of operator interpretation required to position the sensor, the corresponding production rate will increase even when cases of recollection are accounted for (i.e., production rates are based on unique acquisitions per day as opposed to total acquisitions per day). While a number of factors influence production rate (e.g., anomaly density, terrain adversity, operator skill, etc.), a field demonstration of this technology nevertheless provides some indication of how the QC module might improve the efficiency of daily operations. By comparing the production rate associated with the in-field QC process to the production rates achieved during past demonstrations, we can get a sense of the overall utility of this approach regardless of the other influencing factors.

By testing the in-field QC process in a live site venue, this demonstration allowed us to quantify the benefits of the approach as well as identify practical strategies for improving the utility and effectiveness of the approach. The Former WMA site presented a unique set of challenges associated with magnetic soils; however, the suggested improvements to the in-field QC process can be applied generally to sites where background soil response may be variable.

1.3 REGULATORY DRIVERS

Military Munitions Response Program (MMRP) regulations require well defined Standard Operating Procedures (SOPs) for DGM surveys conducted throughout MR sites. These SOPs include guidelines for conducting daily verification of instrument functionality for both geophysical and positioning equipment used during the survey. Procedures are also defined for the processing and analysis of geophysical data to ensure that the survey produces high quality data that will indicate the location of any potential contaminants. While the SOPs associated with DGM operations have been refined through years of practice to produce effective survey results, the introduction of cued classification surveys to MMRP projects will require significant modifications to these procedures.

Classification surveys that rely on advanced EMI sensors require particularly strict guidelines for sensor positioning. This requirement is due to the fact that advanced sensors capture multi-axis data that are most useful if they contain information about the target's principal components. Placement of the sensor relative to the anomaly is critical for ensuring complete characterization of the target physical properties. Additionally, the data analysis associated with classification sensors is arguably more complex than DGM analysis. While DGM data processing includes such steps as filtering and gridding, there is no incorporation of physical models in the process. Classification analysis requires the inversion of data through comparison to physics-based models that represent the principal object properties. Accordingly, the data quality requirements for classification data are much different than the typical threshold quality objectives used for DGM data.

The in-field QC module provides the field team with an intuitive means for assessing not just basic instrument functionality, but also classification quality of the data. Without this immediate feedback, the field team must rely on off-site analysis before knowing if data quality objectives are achieved. Thus, providing the field team with relevant quality metrics is extremely important for ensuring that classification surveys are conducted in an efficient manner and meet the data quality objectives that are specific to these surveys.

2. TECHNOLOGY

The basis for the QC module technology is a C++ inversion and classification Application Programming Interface (API) that provides access to physical model (i.e., dipole) inversion algorithms, which can be used to rapidly estimate a variety of model parameters associated with each anomaly. The QC module allows the field team to obtain information about target physical properties immediately after acquiring a cued EMI data file. This information can then be used to assess the quality of the data based on the reliability of these target features.

The following subsection presents a concise overview of the QC module technology including the procedures associated with its use. A more detailed description of the technology is presented in the MR-201264 Interim Proveout Report submitted to the ESTCP Program Office (included in Appendix A).

2.1 TECHNOLOGY DESCRIPTION

The QC module functions as a parallel process to the cued EMI sensor data acquisition software. As such, the QC module does not provide any data acquisition functionality; it is used solely for

immediate in-field analysis of the cued sensor data. The QC module uses a file watch protocol, which means that it loads cued sensor data files immediately after they are created in a data acquisition file directory. In this sense, the QC software is truly modular in that it can be used in parallel with any data acquisition software, provided the associated data file formats are accepted.

The existing sensor data acquisition software (e.g., MetalMapper EM3DAcquire) provides the operator with the appropriate interfaces to set the acquisition parameters and trigger an acquisition event; however, all other processes associated with the survey including sensor navigation and data quality analysis are facilitated by the QC module. Because the ability to reposition the sensor head based on data inversion results is a key component of in-field QC, it was a logical step to include this capability as part of a QC navigation interface that functioned separately from the data acquisition software. Additionally, any cued sensor will require sensor head positioning information, typically in the form of GPS and Inertial Measurement Unit (IMU) data streams. It was a relatively straightforward process to split these incoming positioning data streams between the sensor data acquisition software and the QC module.

When the QC module executable performs a file watch on the cued data directory, any acquisition event triggered by the sensor acquisition software interface will create a new file in this directory. The QC module will immediately load this file and invert the data contained within it. The output of these inversions is subsequently transferred to the operator navigation and QC interfaces that display the various recovered dipole-model parameters (e.g., polarizabilities, location, depth, etc.) as well as the raw data channel output.

In practice, operating the sensor data acquisition software and the QC module in parallel is straightforward and does not require any shuffling of interfaces to acquire data. Our initial concern in having separate data acquisition and data QC processes was that it might be onerous for the operator to switch back and forth between the data acquisition interface for triggering an acquisition event and the QC interface for viewing results; however, in reality this process requires very few steps. We assessed these operational flows by integrating the software with a production MetalMapper system. Once the initial data acquisition parameters are set for the MetalMapper using the EM3D acquisition software, the QC module can be used to provide the primary navigation and quality analysis interfaces. Only a small trigger button from the EM3D interface must remain accessible for commencing a data acquisition event. Figure 1 shows a screenshot capturing a typical arrangement of these interfaces. It is possible to make both the data acquisition and QC functions available within the same display.

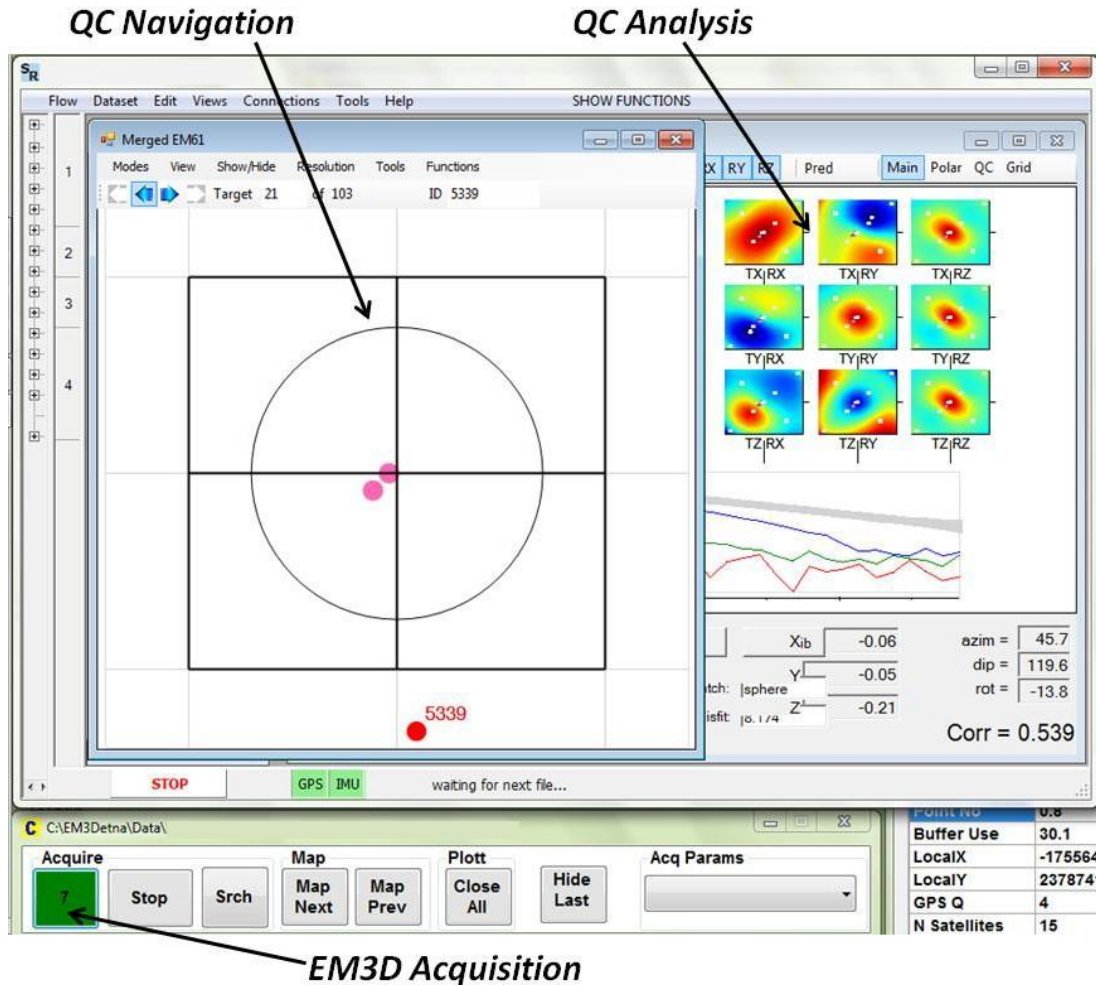


Figure 1. Typical operator display setup showing QC and acquisition interfaces. The QC Module provides the main navigation and analysis interfaces, while EM3D provides the acquisition capability with a simple acquire button.

The QC module navigation interface facilitates sensor positioning and data recollects by displaying target coordinates relative to the cued EMI sensor head location. Target picks identified from analysis of the DGM data can be loaded into the navigation interface to show the location of each anomaly that will be interrogated with the cued EMI sensor. Once the operator selects an anomaly for interrogation, the navigation interface will display both the anomaly location and the sensor head location (Figure 2). As the operator maneuvers the sensor head closer to the anomaly, the navigation display auto-zooms to enable accurate positioning of the sensor over the anomaly. The display provides a sensor frame-of-reference view such that the sensor heading is always directed toward the top of the operator display screen. Once the sensor head is positioned over the anomaly coordinates, the operator acquires a data file. Immediately, the data are inverted and the estimated coordinates of the target are displayed. If necessary the operator can then reposition the sensor using these new coordinates.

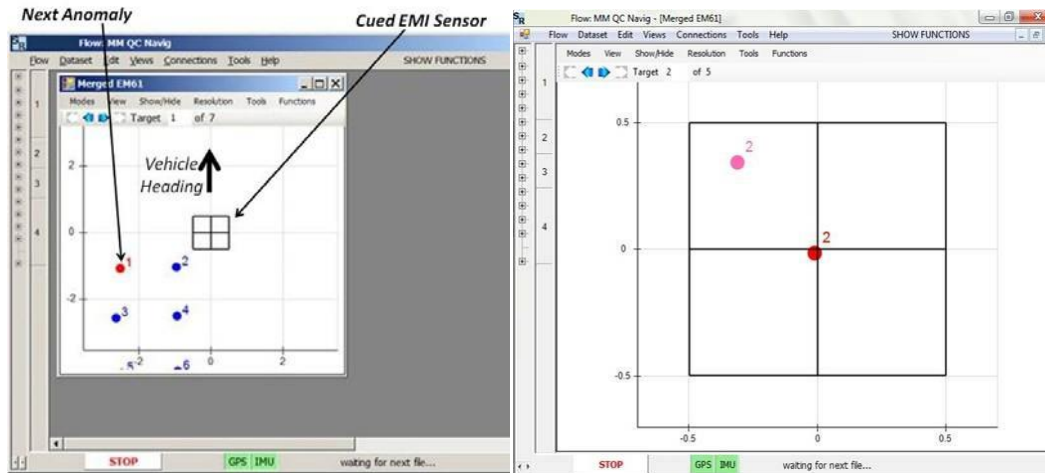


Figure 2. LEFT: The navigation interface displays the anomaly coordinates and the sensor location. **RIGHT:** As the operator moves the sensor closer to an anomaly, the display performs an auto-zoom to facilitate accurate positioning of the sensor head over the anomaly. After the data are acquired, the QC module updates the navigation display with the estimated target location (pink dot).

In addition to providing the operator with the estimated target location, the QC module also provides information about model parameters that correspond to target features. Classification features, such as target polarizabilities, are compared to those catalogued in a target library. This library corresponds to possible targets of interest (TOIs) that may be located at the site. The TOI library is built from data sets collected in controlled calibration areas within the site (Figure 3). Cued EMI data are collected in a calibration area (i.e., a test pit) over TOIs that are indigenous to the site. Features from these TOIs are then added to the library. During the subsequent cued survey, the QC interface will display the polarizabilities corresponding to each anomaly item and compare them to the library features. The QC interface also indicates the best match TOI. The library can be expanded with additional data sets collected throughout the survey if additional items of interest are found.

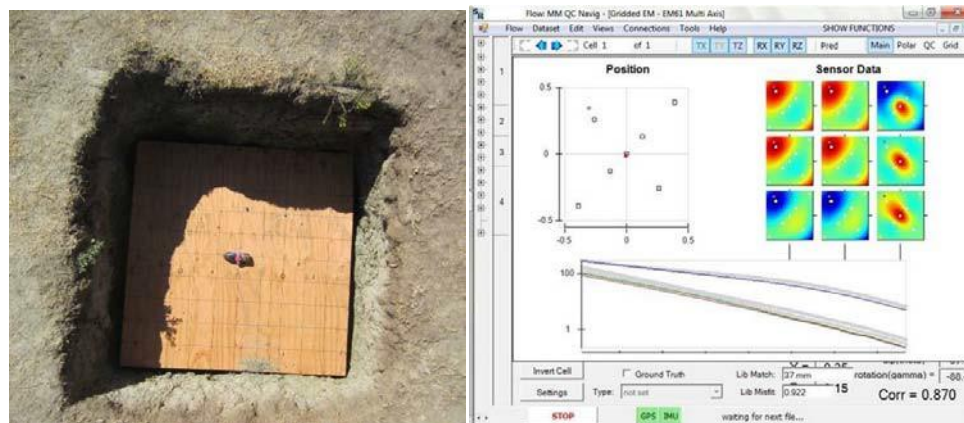


Figure 3. LEFT: Target libraries are built from data collected in controlled calibration areas within the site. This image shows a 37mm projectile placed in a test pit for library data collection. **RIGHT:** Library features are subsequently loaded into the QC module. The QC interface displays polarizabilities recovered from cued EMI data inversion and compares them to the best-match library features.

We performed extensive tests to quantify the performance of the QC module in terms of speed, accuracy, and reliability. One of the key requirements for production use is that the time required to invert the data and present results is negligible in comparison to the total time to acquire a data file (approximately 10-15 seconds for a cued MetalMapper file). We conducted several operational tests that demonstrated the inversion of data in each file typically requires 0.2 – 0.4 seconds to complete and produce results. We clocked the inversion time for many sample data files and found these results were highly repeatable. When incorporated as part of the data acquisition cycle, this inversion step has a minimal impact on the overall process flow.

We also verified the accuracy and reliability of the navigation functions. Through careful and controlled measurements, we found that the navigation interface provided enough positioning accuracy to guide the sensor head within 2-3 cm of the desired target pick location. Additionally, we found that once a data file was acquired, the inversion provided an estimated target location within 5 cm of the true location (verified by careful test grid measurements). The reliability of the estimated target location parameter was demonstrated for a range of lateral offsets between the target item and the center of the MetalMapper sensor head. We found that the accuracy of the target location parameter was maintained even for target offsets extending to 70 cm from the sensor center. Figure 4 shows an example of the results from these performance tests.

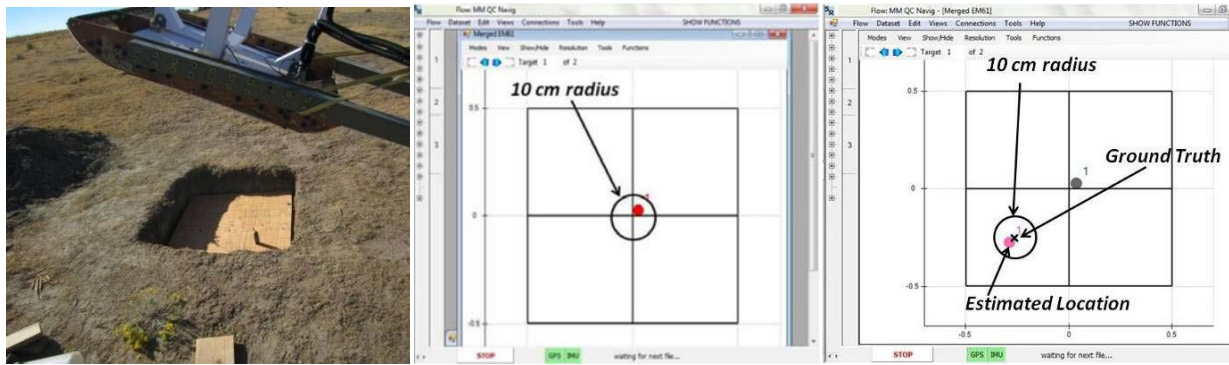


Figure 4. LEFT: QC module performance tests were conducted by acquiring MetalMapper measurements over target items placed on a test grid. CENTER: Sensor positioning guided by the navigation interface was demonstrated to be within 2-3 cm of target pick location (red dot). RIGHT: Estimated target location determined by data inversion was within 5 cm of the true target location for target offsets extending to 70 cm from the center of the MetalMapper sensor head.

After verifying the three operational requirements, we tested the QC module functionality during a mock cued survey using the MetalMapper system. We placed targets near several cued locations that we incorporated in a target pick file. Once these pick locations were loaded into the QC module, we performed a cued survey at each location. For each object, the initial sensor positioning and any subsequent repositioning were based entirely on the feedback from the QC module. Thus, the operator's quality decision was not based on any knowledge of the location or identity of the object under interrogation. An example of the resulting in-field QC analysis corresponding to one of these interrogations is shown in Figure 5.

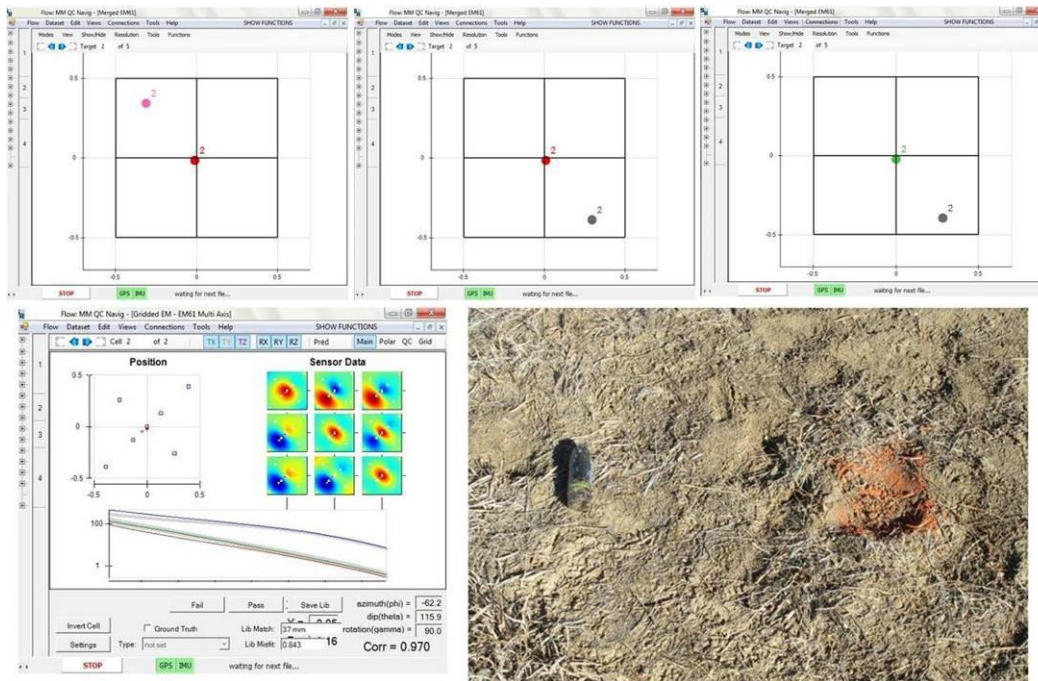


Figure 5. TOP LEFT: The red dot shows the location of the target pick. The pink dot shows the estimated target location. **TOP CENTER:** The sensor is repositioned over the estimated location, which is now represented by the red dot. **TOP RIGHT:** If the operator determines the quality of the recollected data is acceptable, the dot turns green indicating that the data corresponding to this anomaly have met the quality requirements. **BOTTOM LEFT:** QC interface for the recollected data. **BOTTOM RIGHT:** The actual target (37 mm projectile) and target pick location (orange paint).

2.2 ADVANTAGES AND LIMITATIONS OF THE TECHNOLOGY

The QC Module provides several advantages for field teams conducting cued EMI surveys. Currently, there are no commercially available software packages that directly link with advanced sensor output to provide data inversion results in real-time (i.e., immediately after the acquisition of a data file). The capability for sensor operators to obtain inversion parameters such as estimated target location and target polarizabilities while the sensor is still in proximity to the target pick location has significant implications for production rates. By providing the operator with the necessary information to assess data quality, the QC module facilitates immediate corrective action based on in-field decisions.

An alternative approach to in-field QC is to rely on direct sensor output (in lieu of inversion output) to determine data quality. This approach is currently a standard practice for MetalMapper surveys. The MetalMapper data acquisition software provides the operator with visual interpretation of the vector magnetic field measured in each sensor receiver. This information can be used to help guide the sensor to the target location. While this method can be effective, it does not provide the level of information that is contained in the inversion output. The raw sensor output makes it difficult to separate the target pick anomaly response from the influence of nearby objects. This influence can sometimes result in the misplacement of the sensor over smaller clutter objects. Also, as previously mentioned our conclusions based on feedback from several operators indicate that the interpretation of inversion results is more

intuitive and can produce a more efficient survey than the interpretation based on the raw sensor output.

The primary limitation of the technology is the current lack of a real-time multi-object inversion capability. During our preliminary tests, we found that for QC purposes the single-object inversion works fairly well for many cases involving multiple objects within the sensor's field of view; however, the effectiveness of the single-object approach depends largely on the size, proximity, and number of influencing objects. One of the objectives of the demonstration was to identify the limitations of our approach in regards to multi-object cases. Certain data or model parameters may be good indicators of whether multi-source solvers are necessary. Thus, it might be possible to flag data files that are likely to require multi-object analysis before the analyst receives them. Currently, our approach still relies on the off-site analyst to make decisions regarding more complex multi-object cases; however, we anticipate a future variant of the QC module could accommodate multi-source scenarios.

Another potential limitation that became apparent during demonstration of the technology at the Former Waikoloa Maneuver Area is the interference of magnetic soils with the real-time inversion output. Retrospective analysis of the Waikoloa data indicated that in many instances, the in-field inversion produced source locations that were due to geology. Mitigating the effects of magnetic soils poses a significant challenge not just for in-field analysis, but for off-site analysts as well. It may be difficult to remove these effects entirely during the in-field analysis; however, possible solutions could include more frequent background updates to the in-field software or the implementation of a decay fit to indicate to the field operator if the response is likely due to ground conditions.

3. PERFORMANCE OBJECTIVES

The basis for the field portion of the demonstration consisted of a cued (static) MetalMapper survey of anomalies identified from a prior EM-61 DGM survey. The MetalMapper field team conducted a survey of approximately 1000 anomalies while using the in-field QC module. The team conducted recollects for anomaly locations where the in-field software indicated the presence of a source that was more than 30cm from the center of the MetalMapper. These procedures led to 231 recollects over the course of the survey. These recollects formed the basis for our retrospective analysis of the QC performance. With the incorporation of the QC module into the survey protocol, there were five possible scenarios that can be used to establish the capabilities and limitations of the technology. These scenarios included:

1. Cases where no recollect was taken and no recollect was necessary. These cases accounted for about 80% of the total survey. While these instances did not contribute to any quantitative assessment of the technology performance, they can be used as a baseline to assess the qualitative aspects associated with ease of use and production efficiency.
2. Cases where no recollect was taken, but was necessary. Such instances are representative of the technology limitations (i.e., cases where the in-field QC process failed to correctly identify a recollect opportunity). Out of 1032 anomalies, we identified one case where repositioning and recollecting may have been useful. A possible missed recollect

opportunity occurred for seed item WK-1047, where the sole MetalMapper acquisition was collected at an offset of 43cm from the seed location. Seed WK-1047 was one of the two seeds missed in the classification stage by the project analysts. While it is unclear if repositioning and recollecting would have improved classification features, a 43cm offset would normally produce a recollect decision. Most likely this recollect opportunity was missed because of the very strong soil response in this area (post-survey analysis of this anomaly produced ground-like features), which may have produced inaccurate in-field source estimates.

3. Cases where a recollect was taken, was necessary, and improved the classification features. This scenario enables a quantitative assessment of the technology performance by providing clear examples of the advantages afforded by the in-field QC process. Our analysis indicated that there were 46 cases where the recollect improved classification features associated with the anomaly (in some cases this improvement was significant enough that without the recollect, correct classification may have been difficult).
4. Cases where the in-field model did not provide accurate characterization of the survey space. This scenario could include, for example, multi-object cases where the QC module correctly identifies a problematic target, but does not provide the in-field capability to characterize the situation correctly; however, for the WMA survey, the greatest challenge to the in-field QC models was presented by the magnetic geology. Out of the 231 recollects conducted in the WMA survey, 153 of these appeared to be caused by the in-field models indicating a ground source (114 of these occurred in areas where no target was present, 39 occurred in areas where small debris was found).
5. Cases where a recollect was taken, but was unnecessary. In other words, this scenario comprises cases where the initial acquisition provided sufficient classification features. During retrospective analysis, we found 32 cases where the initial acquisition produced accurate features for classification and the recollect did not offer any significant improvements. These were cases where the 30cm recollect rule was likely overly conservative.

Each of the aforementioned scenarios is associated with specific performance objectives. During our post-survey analysis, we applied a set of metrics that correspond to each of these objectives. Table 1 summarizes the performance objectives and corresponding metrics used during retrospective analysis.

Table 1. Performance Objectives

Performance Objective	Metric	Data Required	Success Criteria
Quantitative Performance Objectives			
Identification of all recollect opportunities	Percent of reacquires out of total recollect opportunities	<ul style="list-style-type: none"> Off-site QC analysis of all MM initial acquisition files 	Preac<0.1

Effective corrective action	Percent recollects out of total recollects resulting in improved target features	<ul style="list-style-type: none"> Off-site QC analysis of MM recollects and corresponding initial acq. files 	$Prec(I) > 0.9$
Effective in-field characterization	Number of ineffective recollects due to inadequate in-field models	<ul style="list-style-type: none"> MM recollect files that did not provide improved features 	Insufficient model characterization <5% of total recollect cases
Effective quality metrics	Number of ineffective recollects eliminated	<ul style="list-style-type: none"> MM recollect files that did not provide improved features 	Any reduction in ineffective recollects
Production rate	Number of unique anomalies surveyed per day (in terms of hourly quotas)	<ul style="list-style-type: none"> Field logs, data file time stamps 	Site dependent
Qualitative Performance Objectives			
Ease of use		<ul style="list-style-type: none"> Operator feedback regarding intuitiveness of display, QC results, and process flows 	

3.1 OBJECTIVE: IDENTIFICATION OF ALL RECOLLECT OPPORTUNITIES

Our goal was to use the QC module to identify any acquisition that could be improved by repositioning the sensor. This in-field QC decision was based on the estimated target location parameter. If the estimated target location was greater than 30 cm from the center of the sensor ($R > 0.30m$), the field team would reposition the sensor and conduct another cued sounding. This 30cm radius may have been somewhat conservative; however, it provided a baseline data set from which we can assess how well the estimated location works to predict classification quality in the live site environment.

3.1.1 Data Requirements

In order to assess the effectiveness of this approach we compared the in-field QC decision to the results obtained using the expertise of an off-site analyst. If the post-survey analysis identified any initial acquisition files that should have been reacquired, but were not identified as recollect opportunities during in-field QC, then these were deemed missed opportunities.

3.1.2 Metric

The actual reacquisition percentage ($Preac$ – total number of reacquires corresponding to missed recollect opportunities divided by total number of possible recollect opportunities) will serve as the appropriate metric. The number of missed recollect opportunities corresponds to any initial acquisition files that were identified as potential recollect opportunities during post-survey

analysis. The total number of possible recollect opportunities corresponds to the number of initial acquisitions where no subsequent recollect was taken.

3.1.3 Success Criteria

If successful, the technology should significantly reduce reacquisition rates. We will consider a reacquisition percentage $Preac < 0.1$ to be successful.

3.2 OBJECTIVE: EFFECTIVE CORRECTIVE ACTION

Out of the total number of recollects taken, we would expect that in most of these instances, the recollect provides better characterization of the target than the initial acquisition. Therefore, the percentage of recollects resulting in improved characterization provides a good measure of this objective.

3.2.1 Data Requirements

To determine if any recollect improves characterization, we performed both qualitative and quantitative analyses that included a visual QC of target features to look for improvements in resolution as well as an evaluation of model parameters (e.g., see section 3.6) to determine whether the recollect provided data that more accurately reflect unique target features.

3.2.2 Metric

$Prec(I)$, the number of recollects that provided improved characterization divided by the total number of recollects taken, serves as the metric.

3.2.3 Success Criteria

A $Prec(I)$ value greater than 0.9 indicates success.

3.3 OBJECTIVE: EFFECTIVE IN-FIELD CHARACTERIZATION

Some of the cases corresponding to ineffective recollects were likely a result of inadequate in-field model capabilities. For example, these limitations could be a result of applying a single source solver when multiple sources are present, or an inability to mask out ground effects from magnetic soil.

3.3.1 Data Requirements

For the purpose of future improvements to the in-field QC process, we wanted to identify cases where the in-field modeling capabilities may limit the technology performance. This analysis included a review of all data files associated with ineffective recollects (identified from metric 3.2.2). For these cases we determined the cause of the ineffective recollect, such as multiple sources or magnetic soil influence.

3.3.2 Metric

We identified the total number of cases where the in-field model produced inadequate characterization of the target space. This number divided by the total number of recollects serves as the metric to gauge performance.

3.3.3 Success Criteria

If the total number of cases corresponding to inadequate characterization is less than 5% of the total number of recollects, the performance objective will be met.

3.4 OBJECTIVE: EFFECTIVE QUALITY METRICS

Any additional ineffective recollects could correspond to cases where a recollect was unnecessary due to inherent sensor limitations (i.e., repositioning the sensor was ineffective because the target was beyond the classification capabilities of the sensor) or because the initial acquisition provided sufficient characterization of target features. These are cases where the recollect may have been unnecessary. Such cases are indicative of ineffective use of quality metrics.

3.4.1 Data Requirements

For this analysis, we applied data and model parameters (besides estimated target location) to these data to determine if these recollects could have been avoided by using additional quality metrics. We looked at several parameters including model fit, model noise, data noise, etc. that could be applied during the in-field process to potentially reduce unnecessary recollects (i.e., cases where the recollect cannot improve target characterization) without missing any necessary recollect opportunities.

3.4.2 Metric

The total number of unnecessary recollects that could be averted by using additional data or model parameters to serve as quality metrics is the metric for this objective.

3.4.3 Success Criteria

Any reduction in unnecessary recollects without an increase in missed recollect opportunities will identify effective quality metrics.

3.5 OBJECTIVE: PRODUCTION RATE

Production rate is a good indicator of the overall efficiency gains that are achieved by including the QC process in the survey protocol. While production rate is dependent on a number of factors including site conditions, we can make some assumptions that will enable a quantitative comparison of production rates achieved with and without the QC process.

3.5.1 Data Requirements

For each day of the survey, we analyzed production rates corresponding to a sample of consecutive data files. These samples were chosen to reflect ideal working conditions when production was uninterrupted by things like trips to the IVS, replacement of batteries, equipment down time, equipment transport across the site, etc. Therefore these samples tended to reflect the “optimal” production rate rather than the rate actually achieved over the course of each day. We estimated this optimal production rate as a way to understand how the QC module might affect production under ideal working conditions, and therefore, this production rate, to a large extent, did not reflect working conditions specific to the WMA site. Our optimal production rate was estimated by analyzing the time stamp information from a group of consecutive files collected over a period each day when production was uninterrupted (at least an hour or more for each

group of files). Each file is time-stamped with a Coordinated Universal Time (UTC) value. Based on the time-stamp information, we were able to establish production rate metrics corresponding to both the QC process and the standard protocol. These production rate metrics were averaged over several days to establish the representative ideal production rates.

3.5.2 Metric

For the production rate corresponding to the QC process, we obtained an average number of unique anomalies (i.e., recollects not included) interrogated per hour. While the recollects were not included in this number, we did include the time required to perform these recollects. Thus, for example, if it took the field team 2 hours to collect 100 files, but only 70 of these were initial acquisitions (i.e., 30 recollects) the baseline production rate would be 35/hr. For the production rate corresponding to the standard protocol (i.e., no QC process included), we subtracted the time required to perform the recollects from the calculation (based on UTC time stamp). Thus, out of the 100 original files acquired in 2 hours, if it took the field team 1 hour 40 minutes to perform the 70 initial acquisitions, this would result in a baseline production rate of 42/hr.

Finally, to establish a true production rate, we divided the baseline rate by a reacquisition factor. The reacquisition factor was determined based on an assessment of the survey totals. For example, this survey included 1032 unique anomalies with 46 necessary recollects and 1 possible reacquisition (based on objective 3.1 and 3.2 analyses). Thus, the reacquisition factors were $(1032+1)/1032=1.001$ and $(1032+46)/1032=1.045$ for the QC rate and the standard rate, respectively. Thus in our example, the true production rates would be $35/1.001=35.0$ and $42/1.045=40.2$ for the QC process and standard protocol, respectively.

3.5.3 Success Criteria

Any increase in the production rate corresponding to the incorporation of the QC process will be deemed a success.

3.6 Quantifying Improvements in Target Features

Several of the aforementioned objectives (specifically objectives 3.2, 3.3, and 3.4) require quantification of improvements (or lack thereof) in target classification features. The most straightforward method to quantify improvements in classification features is to apply a fit metric to known library features. While this method is applicable to targets of interest for which libraries exist, many of the recollects corresponded to non-TOIs and therefore required application of different metrics to quantify feature improvements.

For non-TOIs (or targets for which libraries do not exist) we applied two feature quality metrics:

1. Model Noise – a measurement of point-to-point jitter within the recovered principal polarizabilities; a value lower than 0.1 for the ratio between the recollect model noise standard deviation and the initial acquisition model noise standard deviation indicated an improvement in target features.
2. Model Consistency – a measurement of consistency between principal polarizabilities recovered from the initial acquisition and those recovered from the recollect; a deviation of greater than 10% in any polarizability match between the initial acquisition data and the recollect data indicated an improvement in target features.

The following examples demonstrate the application of these metrics. For each of these examples, we show the analysis results corresponding to data collected over targets for which libraries exist; thus, we have a well defined performance baseline reference to which we can compare the decisions based on the aforementioned feature quality metrics.

The first example shows inversion results for data collected over a 60mm mortar at 30cm burial depth (Figure 6). The initial data file was acquired with the MetalMapper center offset approximately 55cm from the target center; the recollect was acquired with the MetalMapper center approximately aligned with the target center. The recollect data clearly provide better target features as the polarizabilities generated from inversion of the recollect data show a much closer match to the library polarizabilities. Specifically, the L3 polarizability (green line) corresponding to the initial data shows a significant deviation from the library in late time. Additionally, the L2 polarizability (red line) corresponding to the recollect data shows a slightly better match to the library over the complete decay period.

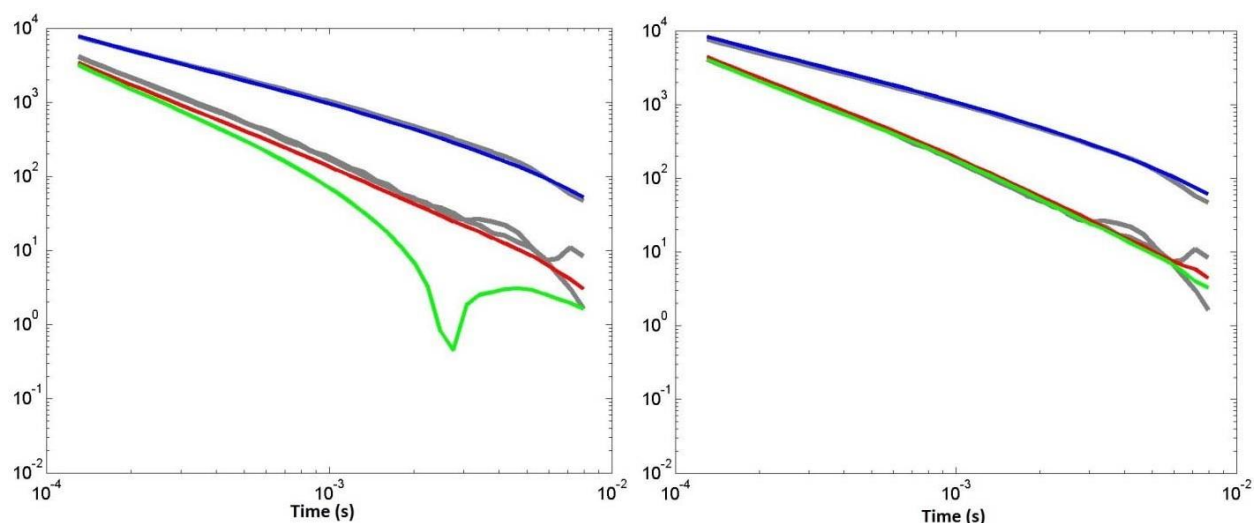


Figure 6. LEFT: Polarizabilities recovered from inversion of initial data acquired with 55cm offset from target. RIGHT: Polarizabilities recovered from inversion of recollect data acquired with MetalMapper centered over target. The blue, red, and green lines represent the primary, secondary, and tertiary principal polarizabilities, respectively (L1, L2, and L3, respectively). The grey lines represent the principal polarizabilities for the reference library match (60mm mortar).

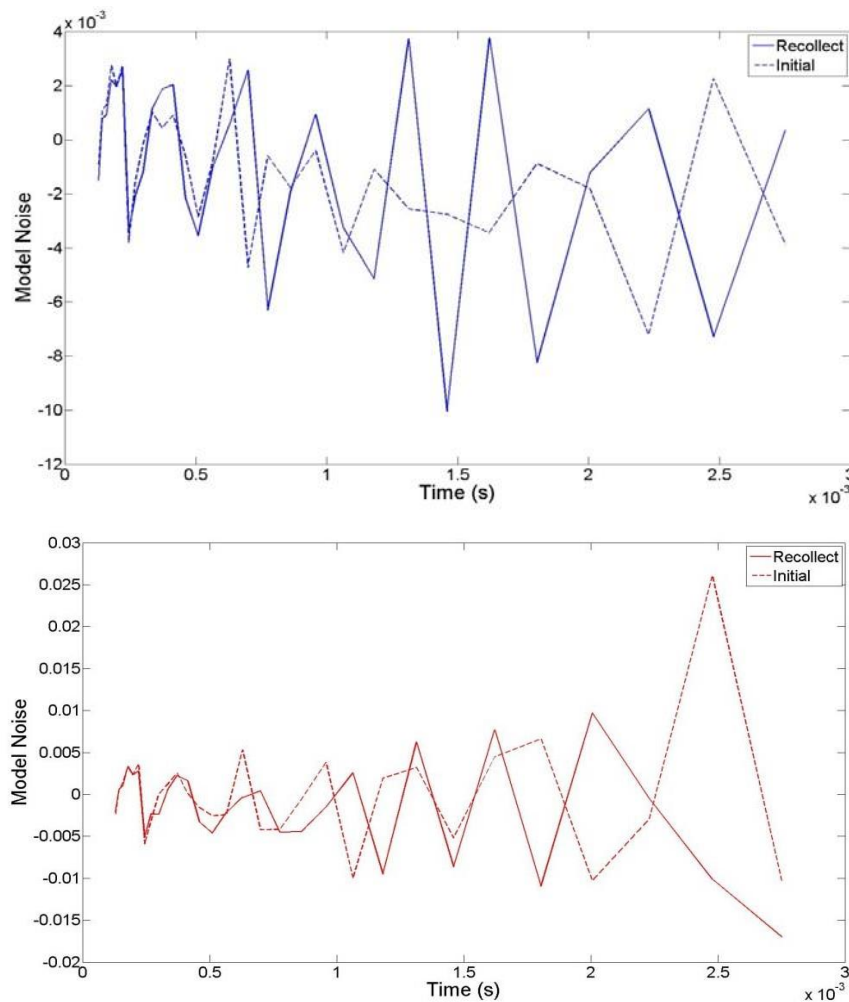
With reference libraries, it is relatively easy to identify improvements in the target features. To understand how the feature quality metrics perform in the absence of libraries, we can apply the aforementioned metrics to both data sets (Table 2).

Table 2. Feature Quality Metrics for 60mm Mortar

POLARIZABILITY	FEATURE QUALITY METRIC	
	Model Noise (<0.1)	Model Consistency % (>10%)
L1	1.44	1.46
L2	0.86	13.2
L3	0.01	1.96E4

Feature quality metric values in Table 2 that meet the objective thresholds (<0.1 and $>10\%$ for the model noise and model consistency metrics, respectively) are highlighted in red. These values indicate improvements in feature quality. The values in Table 2 can be related to the feature library matches shown in Figure 6. The feature quality metric values do not indicate any significant improvement in the L1 polarizability and this is confirmed by the library match. The model consistency metric indicates a slight improvement (13.2% compared to 10% threshold) in the L2 polarizability and this is supported by the marginally better library match for the recollect L2. Finally, both the model noise and model consistency metrics indicate significant improvements in the L3 polarizability. These improvements are evident in the L3 library match, which shows significant jitter in late time (i.e., model noise) as well as significant deviation from the library polarizability throughout the decay period (i.e., model consistency) for the initial acquisition.

For reference purposes, the model noise values corresponding to the initial and recollect files are shown in Figure 7. Typically, only noise values out to 2.8 ms are used in the standard deviation calculations since later time gates can have a spurious influence.



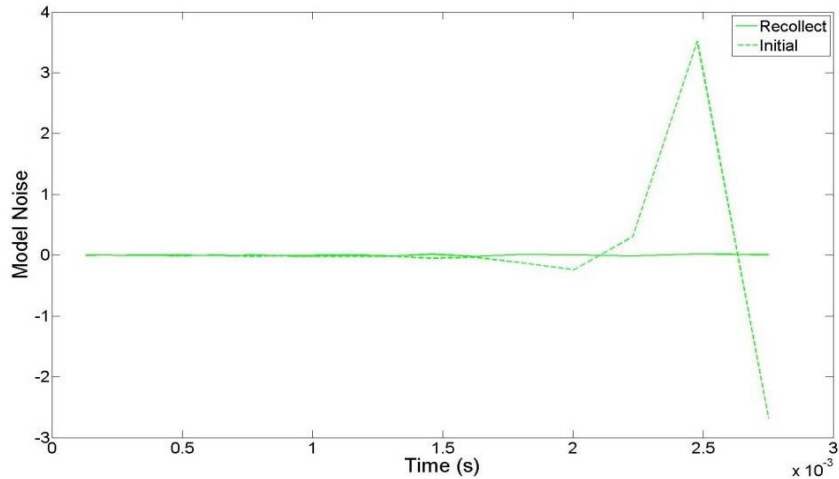


Figure 7. Model noise values for L1 (top), L2 (middle), and L3 (bottom). Dashed lines represent noise values associated with the initial data file; solid lines represent noise values associated with the recollect data file. It is clear that only the L3 shows any significant improvements in noise associated with the recollect.

The next example demonstrates how the feature quality metrics can be applied to identify a case where a recollect is unnecessary. Figure 8 shows the analysis results for data collected over a QC seed during a production MetalMapper survey. The seed object was a small ISO40. The figure shows the polarizabilities recovered from the data corresponding to both the initial acquisition and the recollect. During the initial acquisition, the MetalMapper center was offset more than 35 cm laterally from the ISO; during the recollect, the MetalMapper was approximately centered over the ISO.

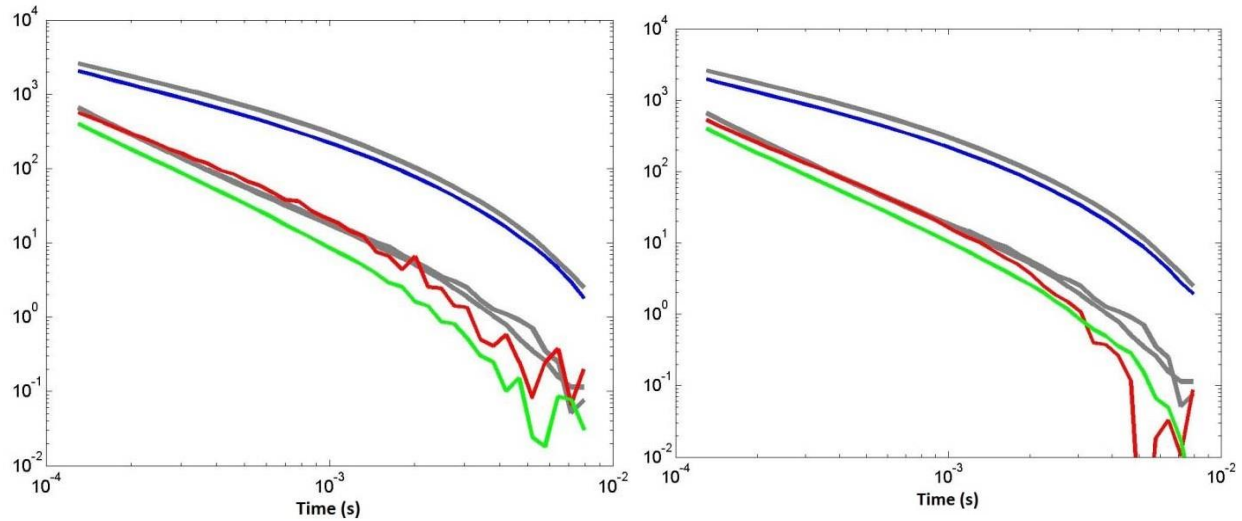


Figure 8. LEFT: Polarizabilities recovered from inversion of initial data acquired with >35cm offset from target. RIGHT: Polarizabilities recovered from inversion of recollect data acquired with MetalMapper centered over target. The blue, red, and green lines represent the primary, secondary, and tertiary principal polarizabilities, respectively (L1, L2, and L3, respectively). The grey lines represent the principal polarizabilities for the reference library match (small ISO40).

Visual inspection of the recovered polarizabilities does not indicate a clear improvement in the features recovered from the recollect. The L2 and L3 polarizabilities appear slightly noisier in the initial acquisition; however, in both cases a correct classification decision was made. A similar conclusion can be made by using the feature quality metrics instead of the target libraries. Feature quality metric values are shown in Table 3.

Table 3. Feature Quality Metrics for Small ISO40

POLARIZABILITY	FEATURE QUALITY METRIC	
	Model Noise (<0.1)	Model Consistency % (>10%)
L1	1.84	0.06
L2	0.22	3.22
L3	0.15	6.38

In this example, values for both the model noise and model consistency metrics are outside the objective thresholds, indicating no significant improvement in the classification features. In this case, the recollect was unnecessary. This conclusion is also supported by the visual inspection.

It should be noted that although the model consistency metric does not provide a direct measurement of the polarizability match to a library value it generally correlates strongly with library match quality. The reason for this correlation is because the recollect will reliably produce a very close library match assuming the sensor is properly centered over the object (also assuming no significant influence from other sources). The initial acquisition may or may not produce a close library match depending on the lateral offset and depth of the object. Thus, the model consistency metric applies the assumption that the recollect will provide good characterization of the object and therefore any significant deviations between initial acquisition results and the recollect results are indicative of improvements in target features. Again, this metric is only valid if we can ensure that the recollect provides good characterization of the object.

Consequently, we must also apply secondary metrics such as model fit to confirm the reliability of the recollect (such metrics play an important role in analysis related to objective 3.3: Effective In-Field Characterization). In scenarios where multiple objects are present, the model fit metric (particularly when used in conjunction with joint diagonalization analysis) is a reliable indicator of multiple sources. The following example demonstrates the effectiveness of applying model fit.

Figure 9 shows an example of a multi-target scenario. In this case, the MetalMapper was centered over a large piece of frag while a 60mm mortar was located at a large lateral offset from the center of the sensor. Applying a single-source solver does not produce a close match to the 60mm library; however, when a two-source solver is applied, a resulting set of polarizabilities is produced that shows a good match to the 60mm library (Figure 10).



Figure 9. Test pit layout for multi-object scenario. The MetalMapper center was positioned over the frag item.

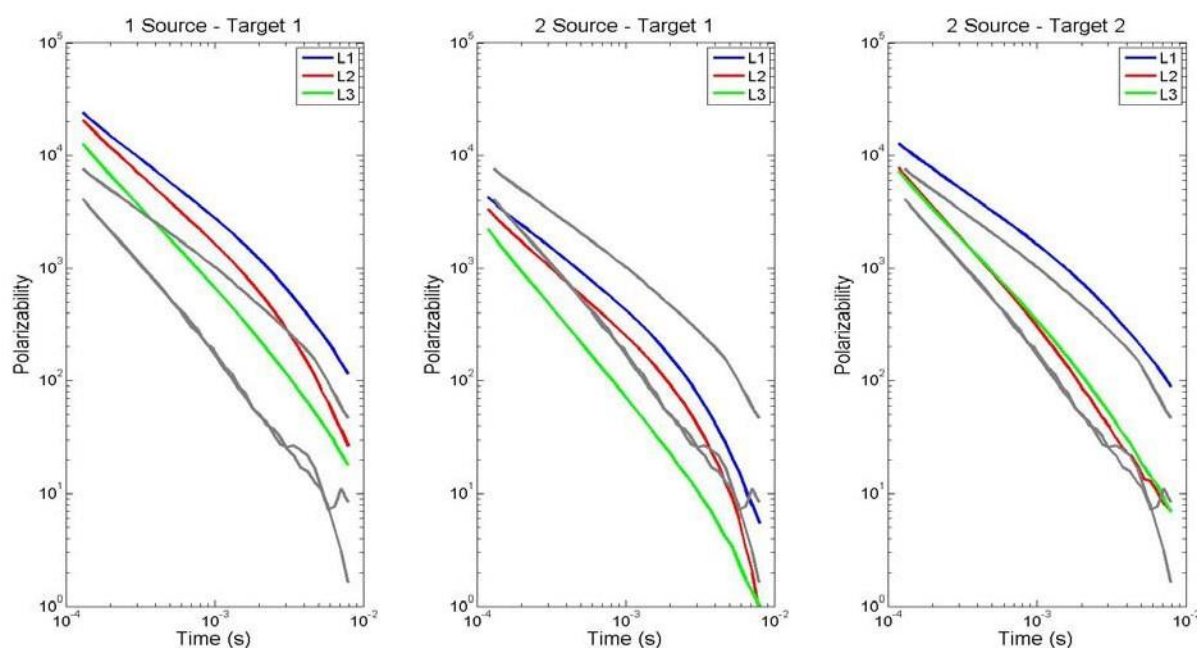


Figure 10. LEFT: Single-source results for the multi-object data collection. CENTER and RIGHT: Two-source results for multi-object data collection. Colored lines represent the recovered L1, L2, and L3 polarizabilities (blue, red, and green, respectively). Grey lines represent the 60mm library polarizabilities. Target 2 (right) shows a good match to the 60mm library.

The improved target space characterization provided by the two-source solver can be quantified by applying the model fit metric. The residual error between the data and the model output is significantly lower for the results of the two-source solution, indicating that the two-source model provides a better representation of the target space. Figure 11 and Figure 12 show

data/model comparisons for the single-source and two-source analyses, respectively. It is evident that the two-source solver results in a better model fit.

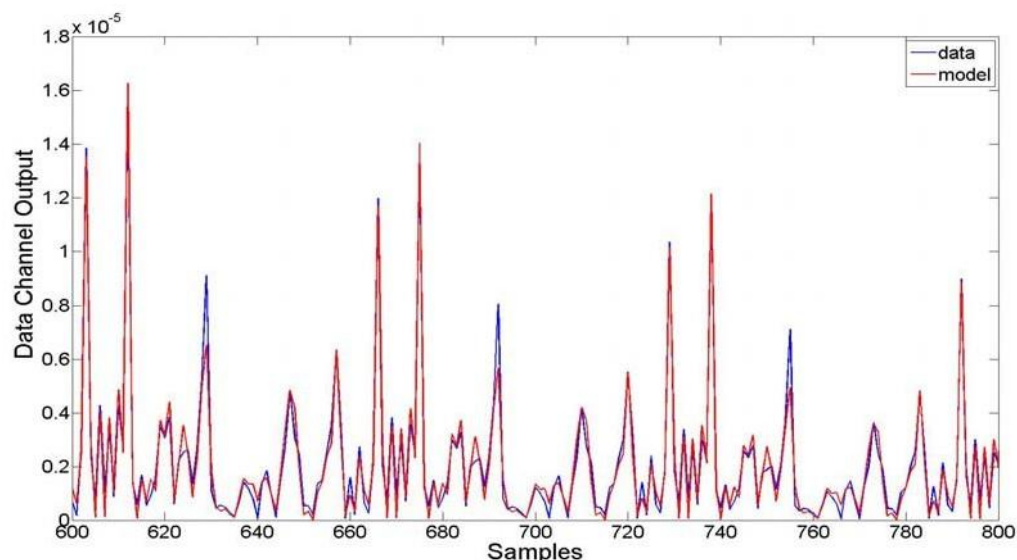


Figure 11. Single-source model fit comparing concatenated data (blue) and model (red) outputs.

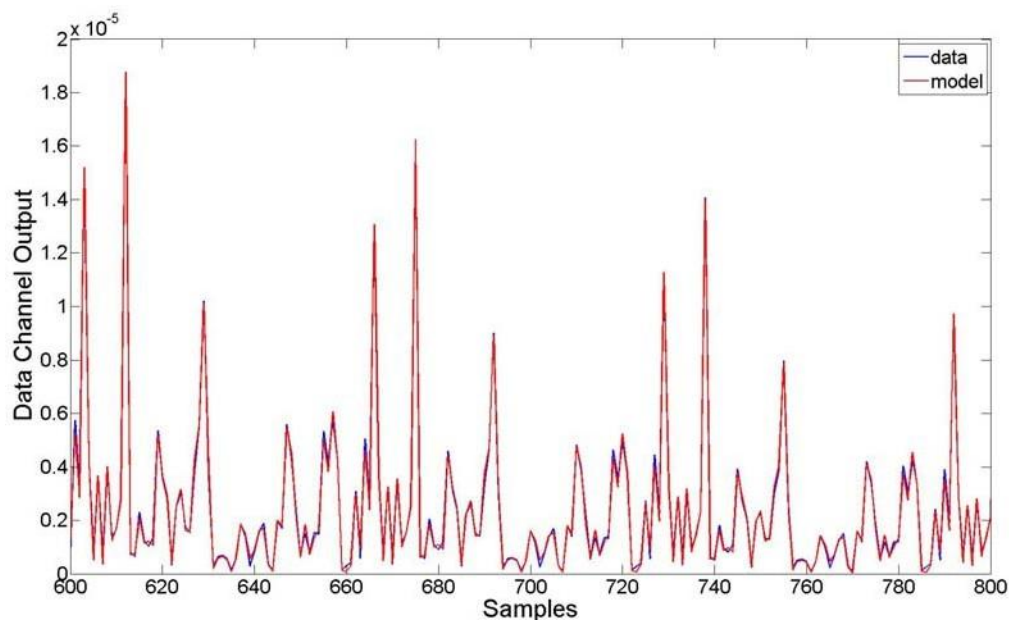


Figure 12. Two-source model fit comparing concatenated data (blue) and model (red) outputs.

While model fit is useful for identifying potential multi-object cases, it does not necessarily serve as a good metric for determining feature quality. In fact, in most cases model fit does not effectively identify improvements in target classification features. Consider the following example data set collected over a 37mm projectile (Figure 13).

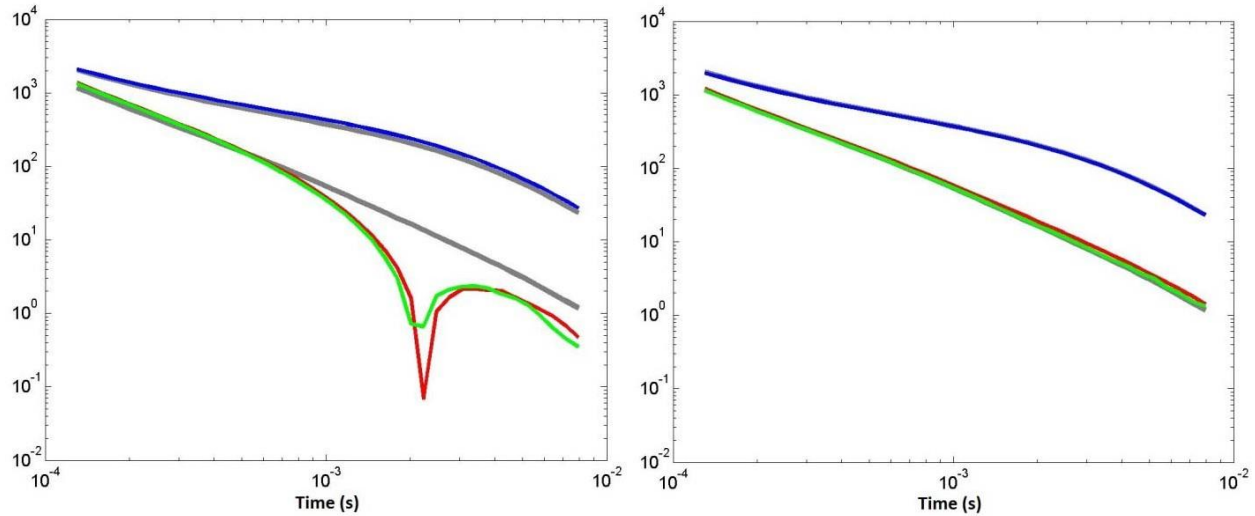


Figure 13. LEFT: Polarizabilities recovered from inversion of initial data acquired with >35cm offset from target. **RIGHT:** Polarizabilities recovered from inversion of recollect data acquired with MetalMapper centered over target. The blue, red, and green lines represent the primary, secondary, and tertiary principal polarizabilities, respectively (L1, L2, and L3, respectively). The grey lines represent the principal polarizabilities for the reference library match (37mm projectile).

The recollect clearly results in improved classification features; however, this result is not supported by the model fit metric (Figure 14 and Figure 15). Both the initial acquisition and the recollect result in good model fits (in fact, the residual error between the model and data is slightly lower for the initial acquisition). The initial acquisition provides a good model fit; however, the data do not sufficiently constrain the inversion to produce a unique solution that matches the true polarizabilities.

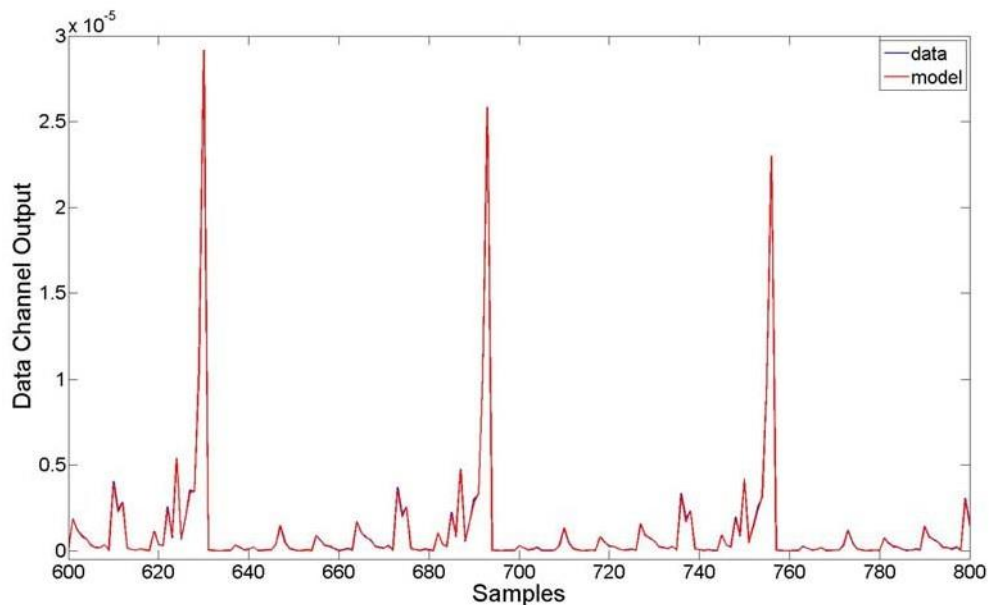


Figure 14. Initial acquisition model fit comparing concatenated data (blue) and model (red) outputs. The data produce a good model fit, but the solution is non-unique.

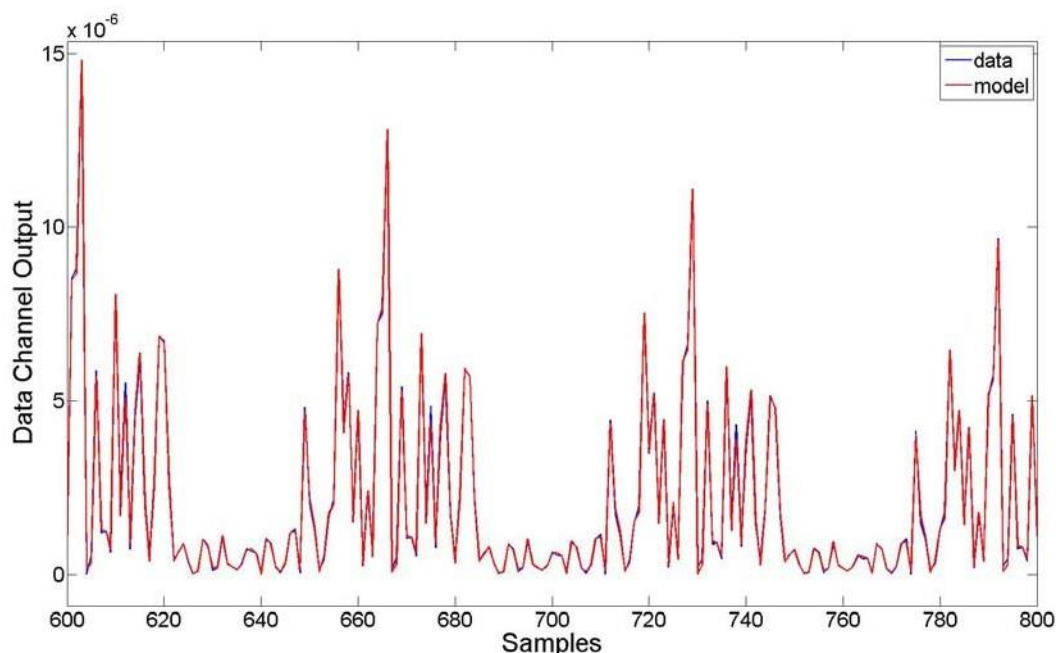


Figure 15. Recollect model fit comparing concatenated data (blue) and model (red) outputs. The data produce a good model fit and a unique solution.

Thus, the model fit should be used only to support decisions that are based primarily on the feature quality metrics. By applying these feature quality metrics retrospectively to the demonstration data set, we have a quantifiable way to identify instances where target features were improved as well as instances where recollects were unnecessary.

4. SITE DESCRIPTION

MetalMapper data collected at the Former Waikoloa Maneuver Area provide the basis for this technology demonstration. This area comprises approximately 100,000 acres on the northwest portion of the island of Hawaii and includes property that was used as a military training camp and artillery range (Figure 16). Over 100 munitions types including mortars, projectiles, hand grenades, and rockets are known to be present at the site. Details regarding site history and land usage can be found on the USACE Honolulu District web site:

<http://www.poh.usace.army.mil/Missions/Environmental/FUDS/Waikoloa.aspx>

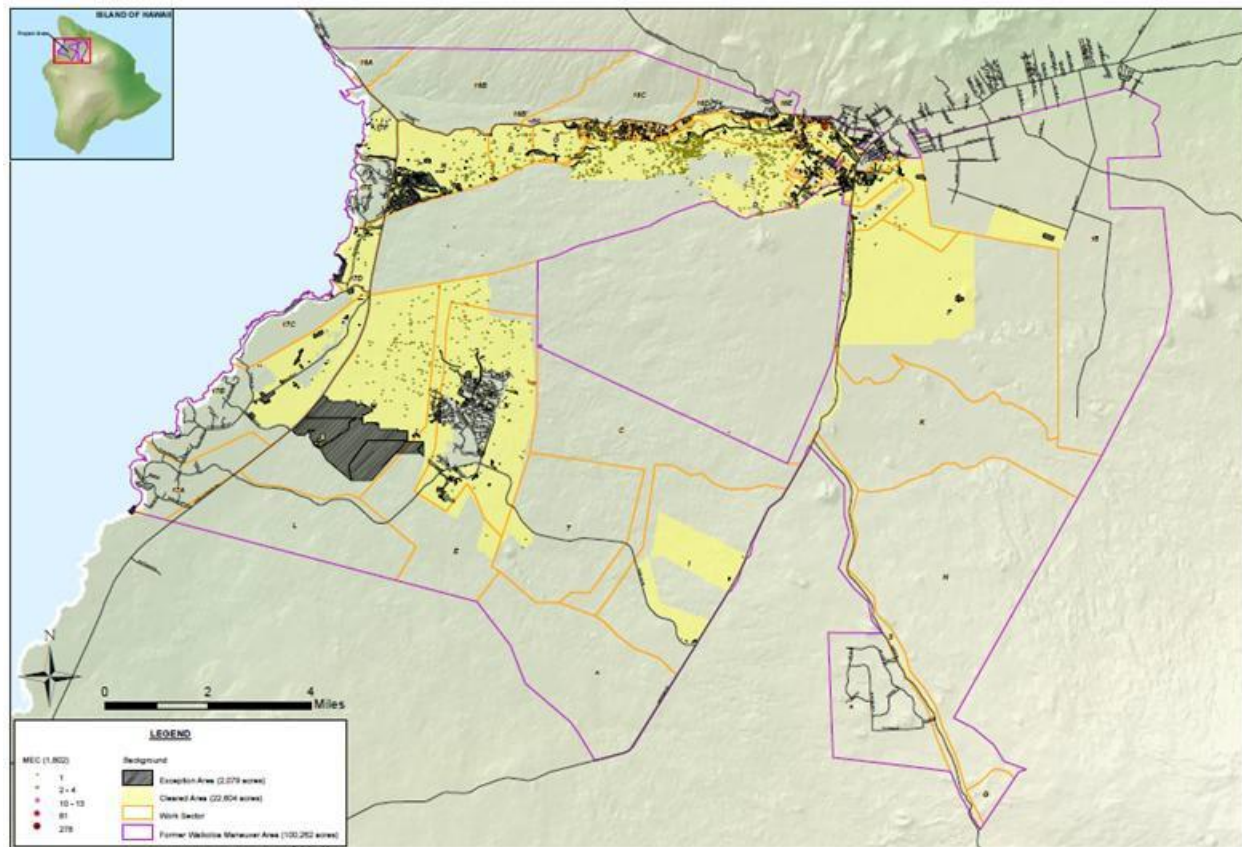


Figure 16. Former Waikoloa Maneuver Area (from USACE Waikoloa map).

The arid site contains sparse vegetation making it suitable for vehicle surveys (Figure 17). The main deployment challenge is the rocky soil, which can damage tires and make transport of equipment across the site difficult. The site is also known to contain significant magnetic geology, which can be problematic for electromagnetic background removal during data processing.



Figure 17. Former Waikoloa Maneuver Area site photos.

MetalMapper data were collected within three areas of interest (AOI), which included task order (TO)17 and TO20 areas A and B. Each of these areas provided unique magnetic geology that created variable levels of electromagnetic background across the data set. The magnetic soil influence proved to be one of the most significant challenges in the implementation of classification and in-field QC at this site.

5. TEST DESIGN

Demonstration of the in-field QC approach was included as a supplement to ongoing classification studies conducted at the WMA. The unique geology of the WMA offered significant challenges to classification and therefore, this site was selected for demonstration of several ESTCP technologies. We coordinated with Parsons, who were conducting one of the classification technology demonstrations at this site, to provide their field team a version of the in-field QC module to use during their cued MetalMapper survey of the aforementioned three AOI. Some of the Parsons field personnel were familiar with or had prior experience using the in-field QC software so transition of the technology was relatively straightforward.

Our objective for conducting this demonstration was to obtain data about the utility of the in-field QC process and at the same time to, hopefully, provide the Parsons team with a technology that would facilitate the demonstration of their technology as well. In order to minimize redundancy in the reporting of these related, but parallel efforts, we will not include details about the WMA MetalMapper demonstration field procedures in this document. A comprehensive summary of details related to the field activities (e.g., system calibration, data collection, ground truth validation, etc.) for this demonstration can be found in the Parsons MR-201104 demonstration report (see Van et al., 2015).

6. DATA ANALYSIS PLAN

Our analysis focused on retrospective interpretation of classification results to determine the effectiveness of the in-field QC process. To obtain relevant data and model parameters from each MetalMapper anomaly, we performed dipole inversions (single and multi-object) for each static MetalMapper file. These inversions provided parameters such as polarizabilities, estimated location, and fit that we subsequently used to obtain metrics for each anomaly. We also coordinated with analysts from Dartmouth College (MR-201227, PI: Shubitidze), who performed primary classification analysis for the WMA site, to identify any specific anomalies that might further elucidate the benefits or shortcomings of the in-field QC method.

6.1 PARAMETER ESTIMATION

To obtain the relevant parameters that would quantify any improvements in recollected data files, we performed dipole inversions for each MetalMapper file. One of the most important steps in this processing stage was the selection of background data that would be used for background removal in each cued data file. Because background response was so variable across the WMA, selection of different backgrounds could produce very different sets of model parameters obtained from each inversion. We initially used background files that had timestamps closest to those of the associated cued files. If background removal using these files still left a significant background response in the data, we would try other background files collected on the given day

to see if any improvements in background removal could be realized. In some cases, it was only possible to obtain parameters associated with a background response (this was the case, for example, with what turned out to be “no-contact” sources).

After background removal, we inverted each static file using both single and multi-object dipole models. In some cases, the multi-object could be used to constrain the ground response. The polarizabilities, estimated source location, and data/model fit for each inversion were saved for further review of performance metrics.

6.2 PERFORMANCE ANALYSIS

Performance analysis included a review of the aforementioned parameters associated with each recollect anomaly as well as identification of specific anomalies that proved challenging for the final classification stage (i.e., based on retrospective ROC curve analysis). We applied the objective metrics to each of these cases.

6.2.1 Objective 3.1: Identification of All Recollect Opportunities

Any cued sounding based on a DGM pick could be considered a recollect opportunity; however, one of the biggest issues with identifying these opportunities was whether to include the large number of no-contact encounters (i.e., no target found during excavation) as a potential recollect opportunity. There were a large number anomalies (about half of all the cued encounters) that could not be attributed to a legitimate source (other than the ground or “hot rocks”). Therefore, these encounters would have a significant impact on the overall recollect statistics. Because these encounters represented an opportunity to make a “no recollect” decision, we included them in the analysis; however, it should be noted that the in-field QC module did not have specific models to reject ground response, therefore, we would expect such cases to be challenging for the in-field decision.

6.2.2 Objective 3.2: Effective Corrective Action

To determine whether effective corrective action was taken, we compared the recovered model parameters from each recollect to those from the initial acquisition. For recollects associated with TOI, this analysis applied a library fit to the polarizabilities to determine any improvements in target features. For non-TOI encounters, we applied the model parameters described in section 3.6 to determine if the recollect provided improvements in features. Finally, for cases where we observed strong ground response, we assessed the polarizability decay to determine whether the features were associated with a metal object or the ground response.

6.2.3 Objective 3.3: Effective In-Field Characterization

For each recollect case that did not lead to improved target features, we identified the reason that classification quality was not improved. Because we were interested particularly in cases where the in-field models did not accurately characterize the target space, we evaluated data/model fits and ground truth records to determine if, for example, multiple targets in the area may have led to misguided placement of the sensor. We also assessed the polarizability decay to determine if ground response likely had any significant influence on the in-field decision.

6.2.4 Objective 3.4: Effective Quality Metrics

For recollect cases where the initial acquisition provided sufficient characterization of the anomaly, we evaluated the application of alternative metrics to support a recollect decision. We also evaluated whether the positioning requirements (30 cm or closer) for the initial acquisition were overly stringent and resulted in too many recollects. Our goal was to determine if these unnecessary recollects could be avoided without risking any reduction in data quality.

6.2.5 Objective 3.5: Production Rate

To establish any efficiency gains resulting from the in-field QC process, we evaluated the production rates corresponding to the in-field QC protocol and the standard data collection protocol (no in-field QC) as described in section 3.5.2. We used the data time stamps in several groups of consecutively recorded MetalMapper files to establish the average, ideal production rates for both data collection methods.

7. PERFORMANCE ASSESSMENT

The following is a summary of the recollect statistics for the WMA MetalMapper survey:

- Out of 1032 total anomaly encounters, there were 231 unique recollects;
- Out of 104 TOI encounters, there were 18 unique recollects;
- Out of 393 non-TOI (debris) encounters, there were 99 unique recollects;
- Out of 535 no-contact (no target) encounters, there were 114 unique recollects.

These statistics provide the basis for our analysis of the performance objectives.

7.1 Objective 3.1: Identification of All Recollect Opportunities

To determine if there were any missed recollect opportunities during the WMA survey, we identified cases where the final MetalMapper location was more than 30 cm from an excavated source. We found three potential cases.

The first case involved anomaly WK-73, a 37mm seed buried at 11 cm depth. In this case, the initial (and only) MetalMapper file associated with this anomaly was acquired at an offset of 75 cm. This anomaly was problematic for analysts because the only features obtained were associated with a ground response due to the large offset. While repositioning over the seed location would undoubtedly have provided better data for characterizing the anomaly, we do not feel this was an instance where the in-field QC failed. A 75 cm offset placed the seed well outside the footprint of the sensor. Under ideal conditions (i.e., no significant soil response or presence of other nearby anomalies) it is possible that the in-field model could have located a source this far from the sensor and provided some guidance for better positioning; however, given the challenges posed by field conditions we would not typically expect accurate features would be obtained from a source located this far from the sensor. This case represented an error in the initial positioning of the sensor and was therefore removed from the list for classification analysis.

The other two cases involved anomalies WK-1027 and WK1047, which were a small ISO seed and a 60mm seed, respectively. These two seeds proved problematic for the classification analysts as evidenced by the ROC curve shown in Figure 18.

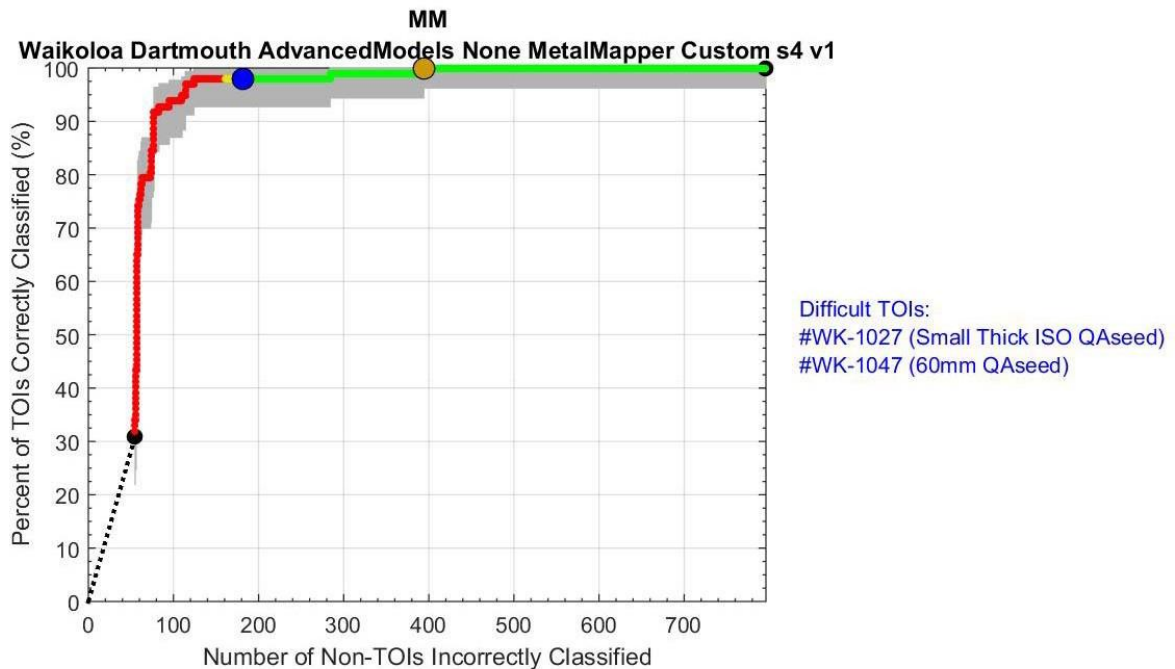


Figure 18. Independent scoring results for Dartmouth College WMA MetalMapper analysis indicate two difficult targets: WK-1027 and WK-1047.

In both of these cases, the features obtained during analysis appeared to be dominated or degraded by the ground response. Thus, insufficient background removal appeared to be the major cause of the classification failure; however, we wanted to determine if the sensor positioning could have been a factor as well. Since neither of these cases included a recollect, we assessed whether the initial sensor location may have contributed to the incorrect classification decision.

For seed WK-1027, the sensor was located 27 cm from the target. Since this offset is within the conservative 30 cm objective radius, we do not consider this case to be a failure of the in-field QC model. It is possible that given the small size of the object and the dominant ground response, that positioning the center of the sensor closer to the object could have provided better results in this case; however, we believe this case is more representative of the challenges posed by magnetic soils than of the limitations of the in-field QC approach.

For seed WK-1047, the sensor was located 43 cm from the target. This offset is significantly outside the 30 cm objective radius and, therefore, we consider this to be a missed recollect opportunity. While it is likely that under ideal conditions (i.e., no significant soil response or presence of other nearby anomalies) it would be possible to obtain accurate classification features at a 43 cm offset, the presence of a significant ground response makes it very difficult to obtain representative features with the sensor at this location. Most likely, if the in-field QC

model had access to a representative background at this location, a better QC decision could have been made at the time.

To obtain our metric for this objective, we identified the number of remaining recollect opportunities ($1032 - 231 = 801$). Out of 801 possible additional recollect opportunities, we believe there is only 1 case where repositioning the sensor may have led to a better classification result. Therefore the $\text{Preac} < 0.1$ was achieved.

7.2 Objective 3.2: Effective Corrective Action

To determine whether the recollects provided significant improvements in the classification quality of the data, we analyzed the features obtained from each recollect and compared them to those of the associated initial acquisition. For recollects over TOI, improvements were quantified by assessing the polarizability fit to the relevant TOI library. Figure 19 shows an example of an effective recollect over a 37mm seed.

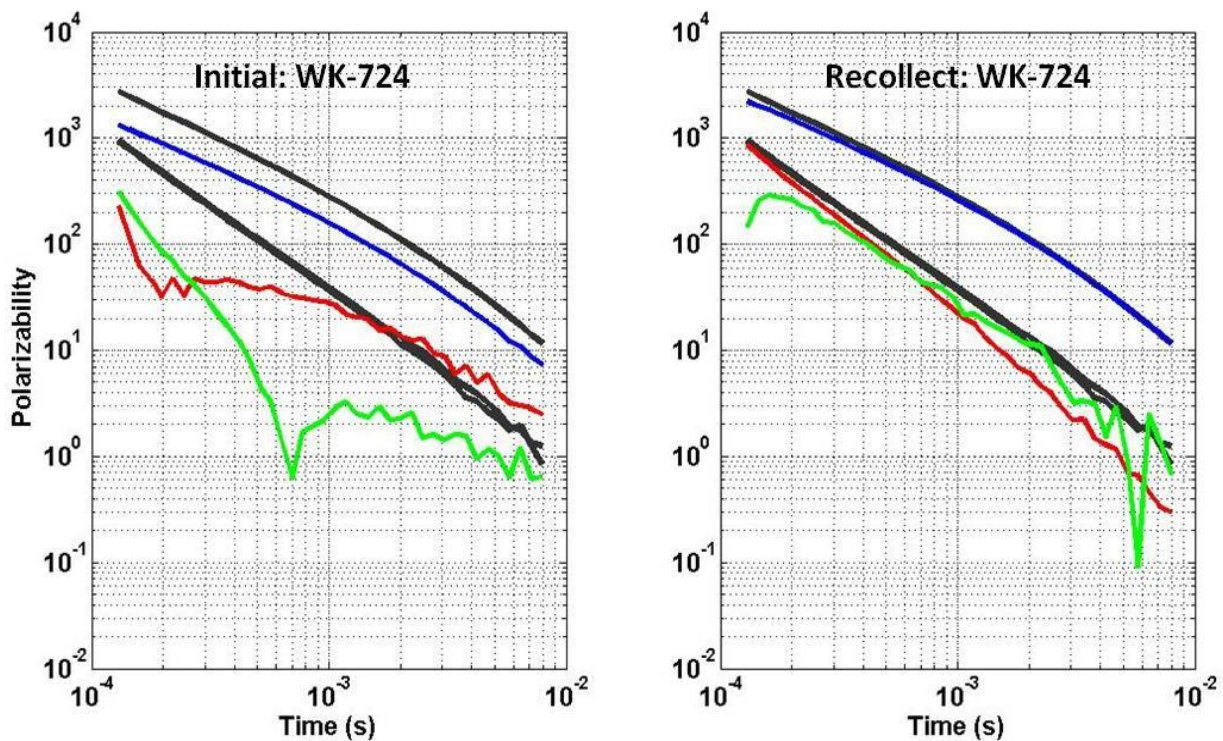


Figure 19. Polarizabilities obtained from two different acquisitions over WK-724, a 37mm seed. For the initial acquisition, the sensor was offset 34 cm from the target. The recollect placed the sensor at an offset of 13 cm from the target. The polarizabilities (blue, red, and green lines) show a much better match to the library (dark grey lines) in the recollect.

The results in Figure 19 are a good example of improvements achieved by recollecting with better sensor positioning (13 cm lateral offset in the recollect compared to 34 cm lateral offset in the initial acquisition). The initial acquisition did not enable accurate recovery of the polarizabilities; however, the recollect provided features that matched closely to the library. Review of the data showed that the initial acquisition may have been influenced by a small, nearby piece of clutter that was less evident in the recollect location.

For recollects over non-TOI (i.e., frag or other debris) we quantified any significant improvements using the model parameters described in section 3.6. For example, Figure 20 compares the polarizabilities obtained from initial and recollect acquisitions over munitions debris (WK-1053, fuze clip).

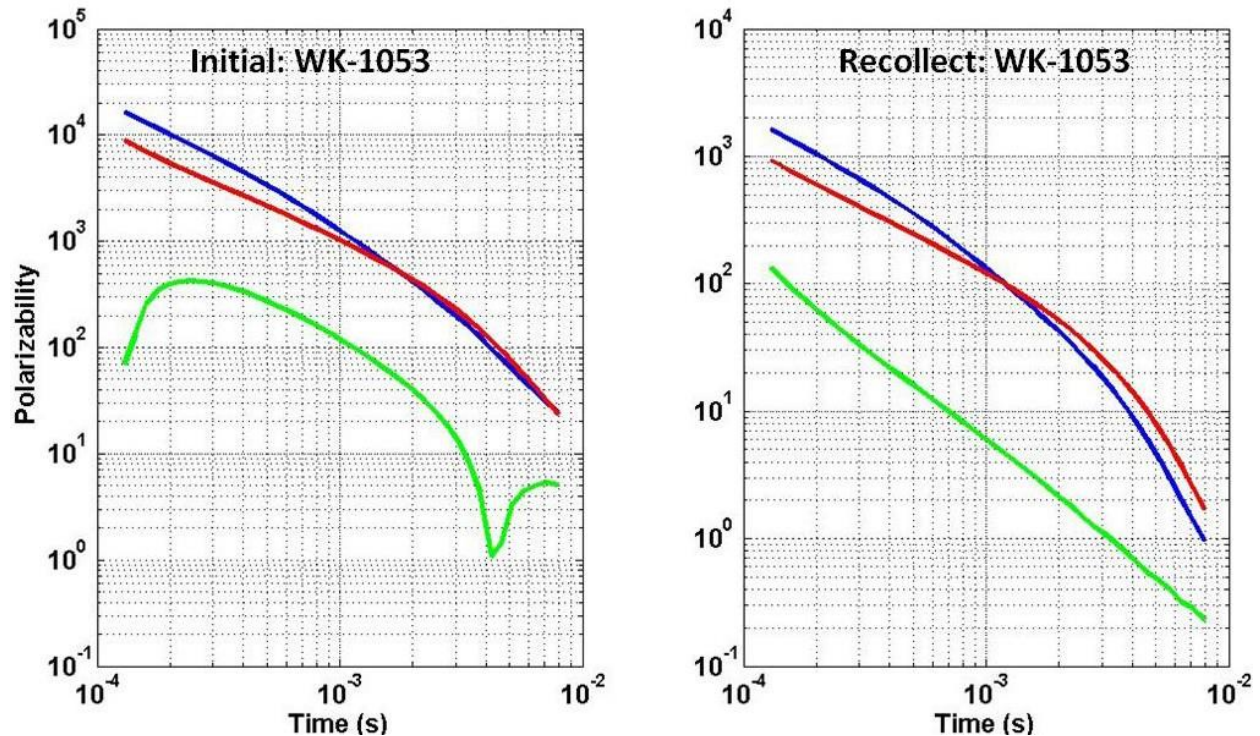


Figure 20. Polarizabilities obtained from two different acquisitions over WK-1053, a piece of munitions debris. The recollect provides better constraint on the third polarizability (green line).

The results shown in Figure 20 were quantified using the model noise and model consistency metrics described in section 3.6. Further validation was later provided by library matching to polarizabilities obtained from other fuze clips encountered throughout the site. The recollect shown in Figure 20 provided features that were much more consistent with those from other encounters with this target, which turned out to be a common debris item at the site.

Over the course of this analysis, we discovered several encounters where the recollect provided an entirely different set of features from those of the initial acquisition. These cases occurred when the initial acquisition was dominated by the ground response and the recollect was able to resolve the features associated with the actual target. A visual QC check of the polarizabilities could identify these cases as shown in Figure 21.

Overall, we found 46 cases where the recollect provided significant improvements in target features. While this number is a minority of the 231 total recollects, it should be noted that most of the recollects (153 cases) appeared to be due to inaccurate source locations created by the ground response. Counting these ground recollects we obtain a $\text{Prec(I)} = 0.19$ (i.e., 46 out of 231 recollects resulted in improved features), and disregarding the ground recollects we obtain a $\text{Prec(I)} = 0.59$ (i.e., 46 out of 78 recollects provided improvements). Both of these values fall short of the objective $\text{Prec(I)} = 0.9$ (i.e., 90% of recollects result in improved target features).

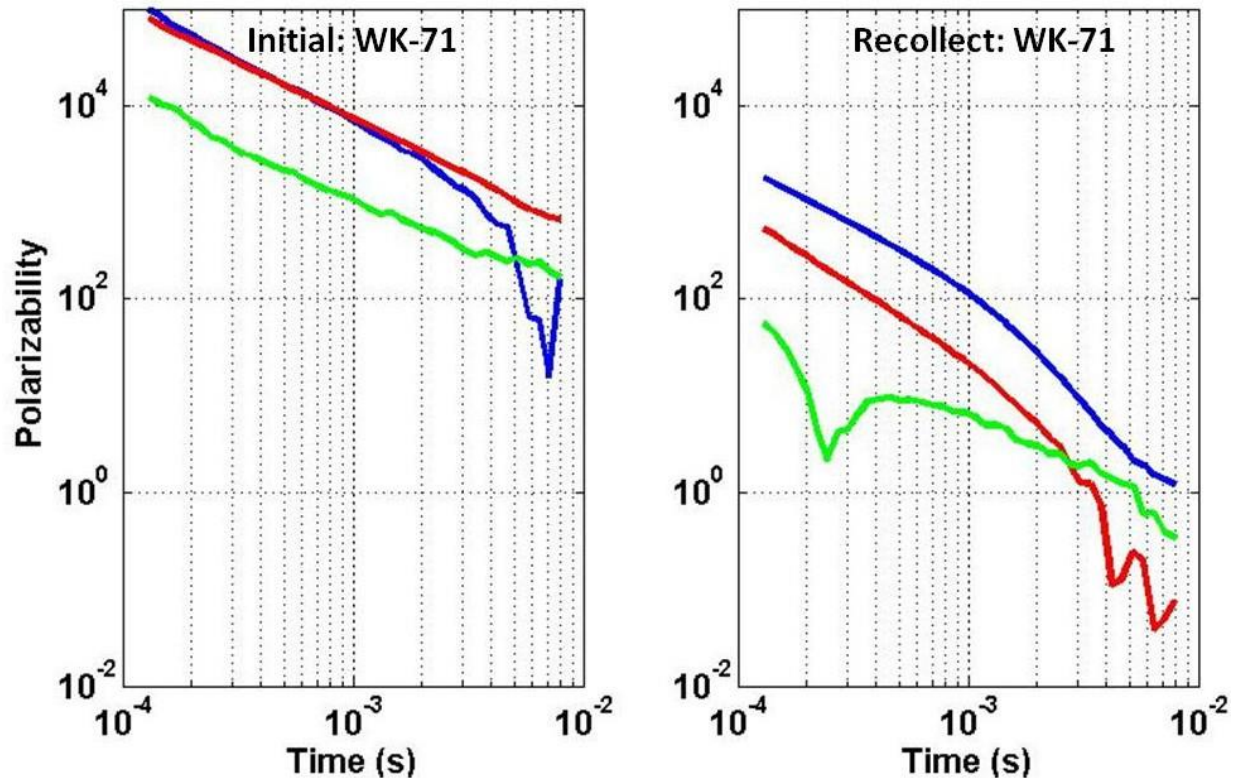


Figure 21. Example of the recollect providing better resolution of target features. In this case the initial acquisition produced polarizabilities dominated by the ground response. The recollect provides features that more accurately represent the actual target (a piece of frag).

7.3 Objective 3.3: Effective In-Field Characterization

The majority of cases where the recollect did not lead to improved target features appeared to be a result of insufficient background removal or inadequate ground models. An example of this is provided in Figure 22, which shows the initial acquisition and the recollect over anomaly WK-68, a piece of frag.

Multiple objects did not appear to present any significant problems for the in-field QC. We did not find any cases where an absence of multi-source solvers in the in-field models led to a poor classification of a target. While there were several instances where multiple sources were found within the search area, most of these cases included a number of small debris items. For TOI as small as 20mm, it is possible these cases could have been problematic; however, the smallest TOI encountered during the survey was a 37mm, which was not small enough to be masked by any of the nearby debris items.

Out of the 231 recollects, we found 153 cases where the soil response appeared to influence the in-field QC decision, resulting in insufficient characterization of the area. This number is significantly greater than the objective 5% of total recollects; however, given the known challenges associated with the site's geology, and the absence of any methods to mitigate these effects in the in-field software these results are reasonable.

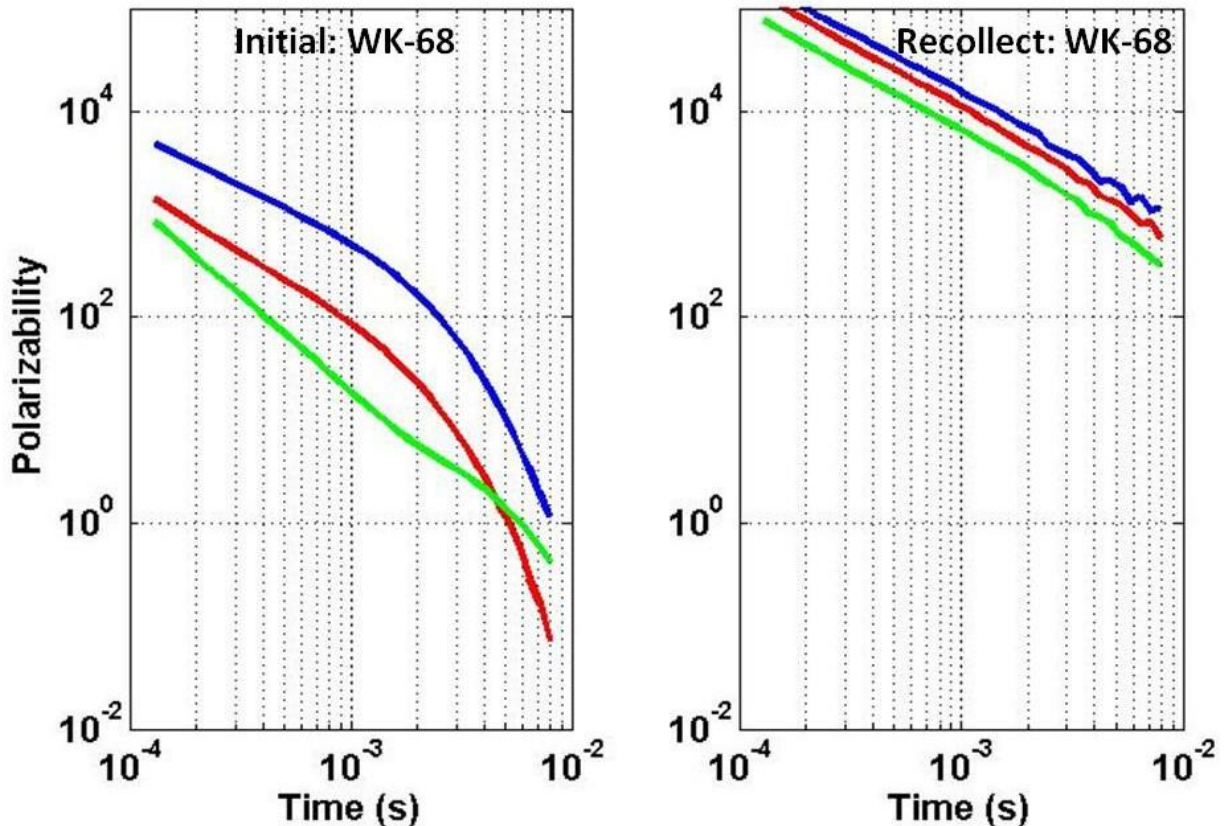


Figure 22. Polarizabilities associated with anomaly WK-68, a piece of frag. Here the initial acquisition shows good resolution of target features; however, the recollect provides features dominated by the ground response.

7.4 Objective 3.4: Effective Quality Metrics

The remainder of ineffective recollects (i.e., recollects that did not improve characterization and that were not a result of magnetic geology or multiple target influence) provided an opportunity to test quality metrics other than estimated location to see if these unnecessary recollects could have been avoided by using additional metrics. Overall, we found 32 cases where the initial acquisition provided sufficient characterization and the recollect did not offer any significant improvements. Figure 23 and Figure 24 show two examples (anomalies WK-267 and WK-169) of such cases.

For several of these cases, the initial acquisition was very close to the 30 cm offset threshold used to make a recollect decision (e.g., 32 cm for WK-267 and 26 cm for WK-169). For cases like these where the anomaly is close to the offset threshold, including a data/model fit metric into the decision could boost the operator's confidence. This information is currently provided to the operator and it could be factored into the decision. For example, in both the WK-267 and WK-169 initial encounters, the data/model fit was very high (>98%). If the initial acquisition is within, say, 25 – 40 cm of the anomaly, perhaps a fit of 98% or better could lead to a no recollect decision.

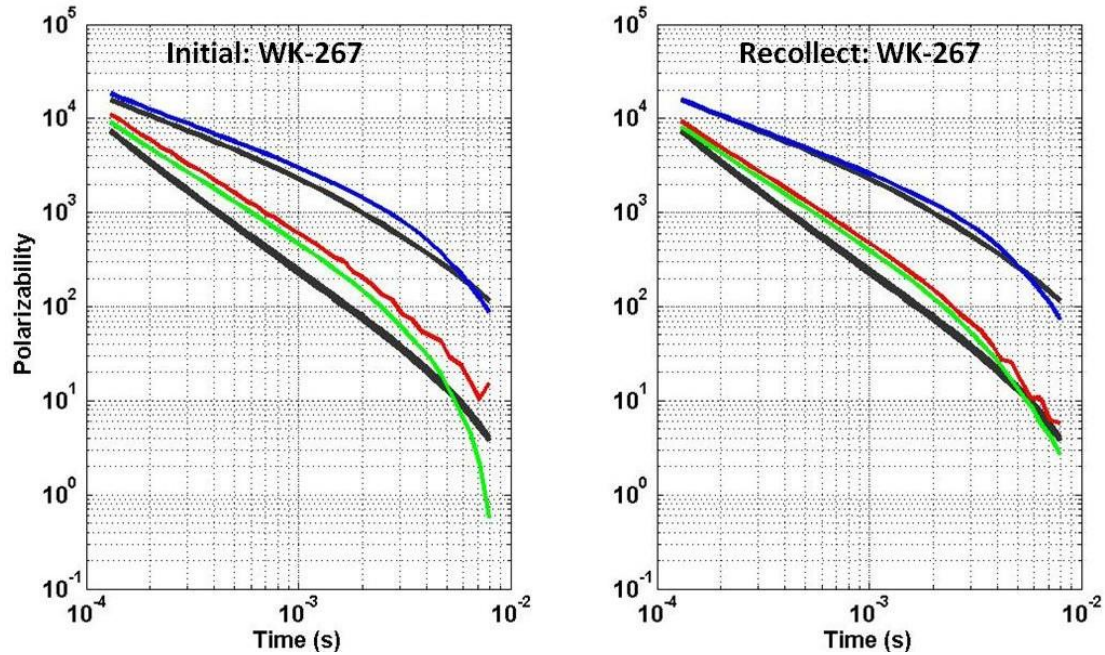


Figure 23. Polarizabilities recovered from the initial acquisition data (left) and the recollect data (right). These polarizabilities correspond to anomaly WK-267, a medium ISO seed. Here the recollect was unnecessary.

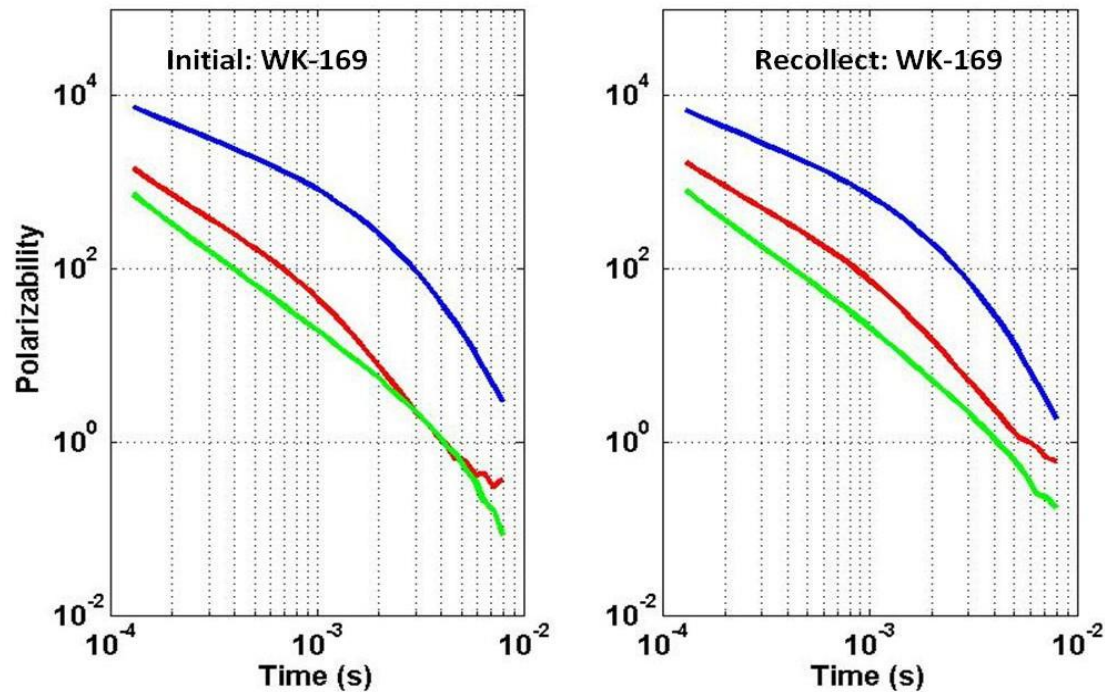


Figure 24. Polarizabilities recovered from the initial acquisition data (left) and the recollect data (right). These polarizabilities correspond to anomaly WK-169, a piece of frag. Here the recollect was unnecessary.

While the fit could be a good supportive metric in these cases, it is not always reliable. Consider, for example, anomaly WK-880, a fuze clip (Figure 25). Both the initial encounter (37

cm offset) and the recollect (9 cm offset) provided very good fits (>98% for both); however, it is clear that the third polarizability (green line in Figure 25) is not well constrained in the initial encounter data (although it could be argued that these initial encounter features are sufficient for making a classification decision). In this case, we could add a model noise metric (i.e., polarizability noise) to the decision flow to determine whether a recollect is necessary. In this case, the initial set of polarizabilities does not pass the model noise metric, leading to a recollect decision.

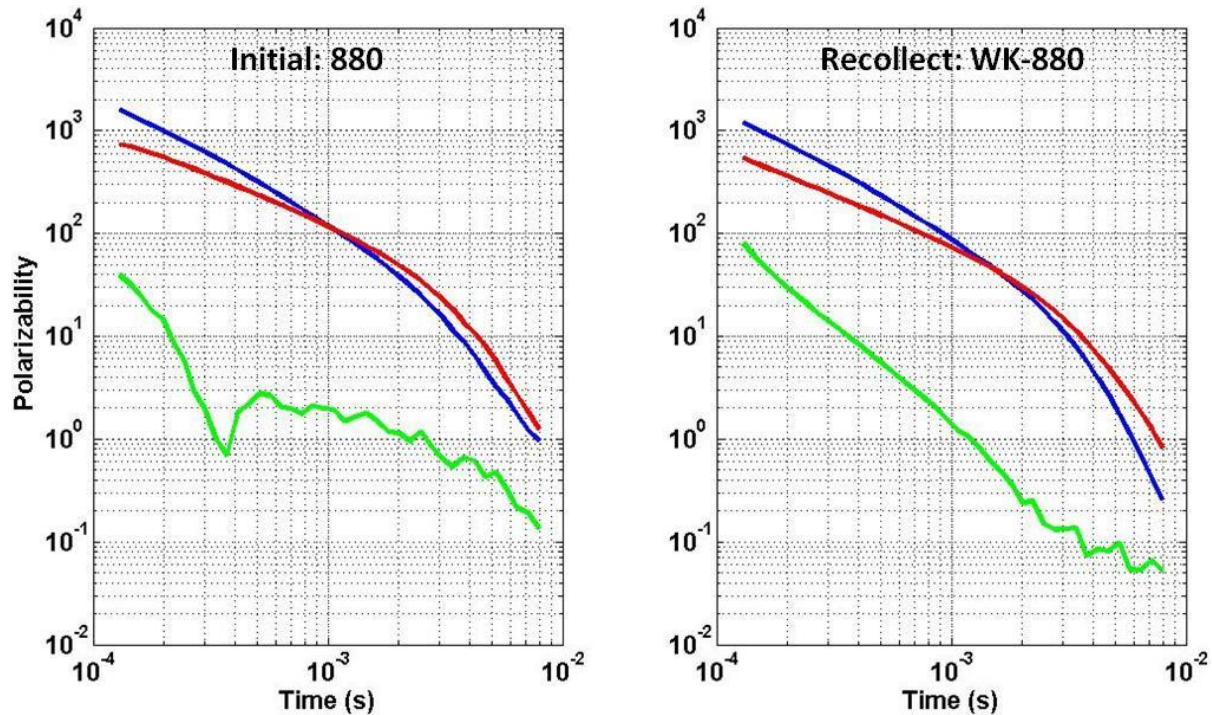


Figure 25. Polarizabilities recovered from the initial acquisition data (left) and the recollect data (right). These polarizabilities correspond to anomaly WK-880, a fuze clip. The initial data do not fully constrain the third polarizability (green line) and indicate that the recollect was beneficial.

Model fit provides a good indication that the target is well represented by the model parameters. For example cases where there are interfering sources, such as ground response or other nearby targets, will produce a reduced fit value. Obtaining a high model fit (i.e., >98%), however, does not necessarily indicate that the model parameters are well constrained. The model noise metric is a measure of the polarizability stability and is an indication of whether or not the data provide good constraint on the model parameters. For example, the initial features shown in Figure 20 and Figure 25 indicate that the third polarizability (green line) is unstable and is, therefore, not well constrained. Taken together, these two metrics could be a robust way to assess whether the initial acquisition data provide accurate classification features.

One possible solution for reducing unnecessary recollects is to include these additional metrics into the decision flow. This information is currently available to the operator; however, it could be possible to make this flow automated to provide a recollect/no recollect decision for the operator. Figure 26 presents a possible flow for including additional metrics. While reducing

unnecessary recollects is not critical to improving the outcome of the in-field QC process, it could improve the efficiency of the process.

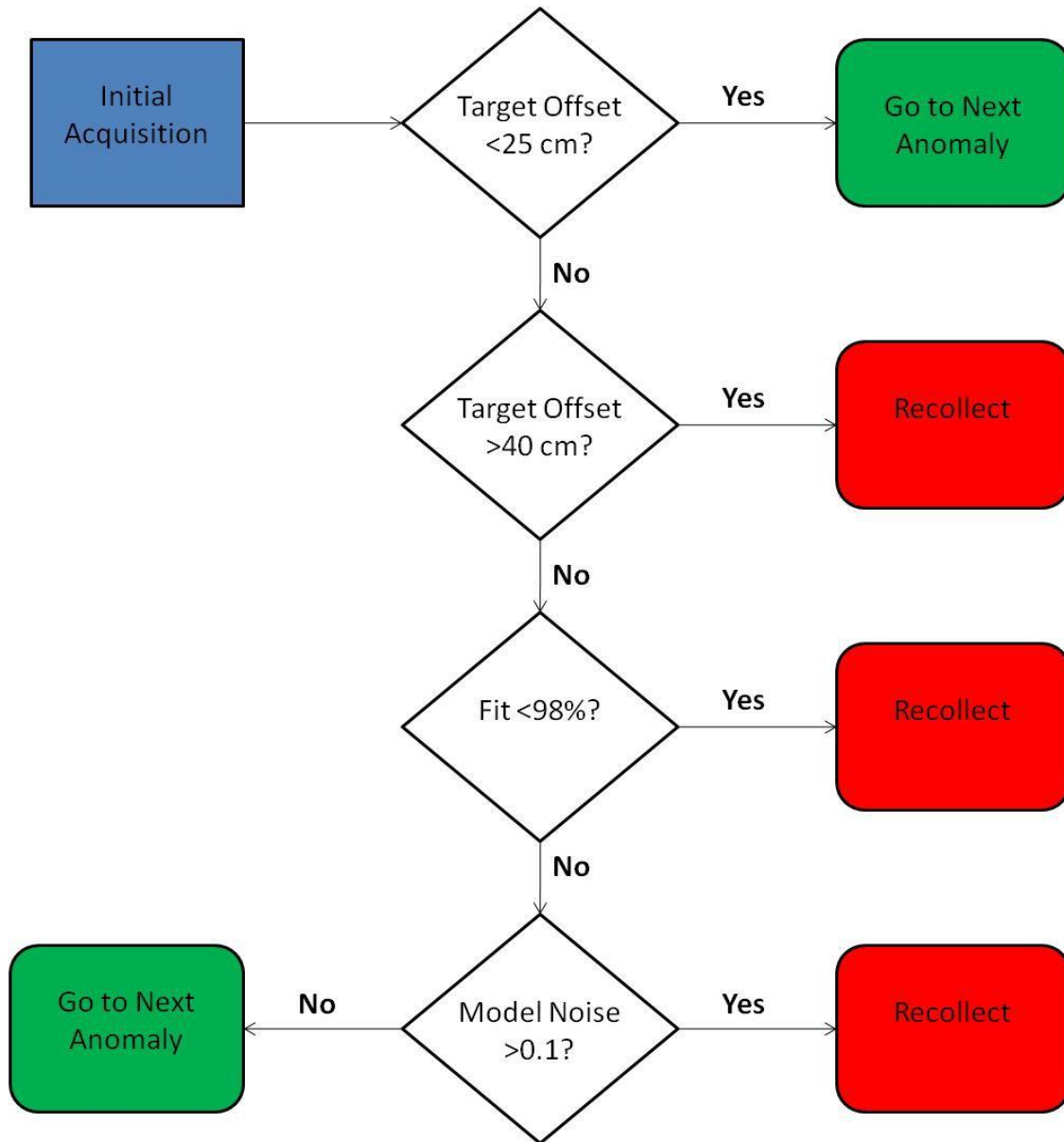


Figure 26. Possible decision flow for in-field QC. This decision flow incorporates the additional fit and model noise metrics along with the primary target location metric to support the decision to recollect or not. The objective of this type of decision flow would be to reduce unnecessary recollects that may occur within some margin of error of the 30 cm offset threshold (e.g., 25 – 40 cm). All metrics including the offset threshold could be adjusted for site specific requirements like smallest TOI, target density, etc. to reflect different tolerances for data recollects.

Out of the 32 cases where the recollect did not improve target features, we found 11 cases that could have potentially been avoided by incorporating the basic fit and model noise metrics into the decision flow. In our retrospective analysis we set the fit metric threshold to a conservative

value ($\geq 98\%$) such that these additional metrics could be implemented without creating missed recollect opportunities. Setting a high value for the fit metric was an effective way to avoid missed recollect opportunities as most of the “necessary” recollect cases that we analyzed failed the initial fit metric $\geq 98\%$.

7.5 Objective 3.5: Production Rate

For the production rate analysis, we wanted to establish representative production rates for surveys performed with and without the in-field QC. As described in section 3.5, we did not want factors specific to the WMA survey, such as equipment down time, equipment transport time, etc. to influence these rates. Therefore, we relied on the time stamp information from groups of consecutively recorded data files that were created during periods of uninterrupted survey time. Our time stamp analysis indicated that with the in-field QC process, the field team could achieve an ideal baseline production rate of 23 unique anomalies per hour. Without the in-field QC process in place, the field team could achieve an ideal baseline production rate of 27 unique anomalies per hour.

When these production rates were adjusted based on the number of necessary recollects for the survey (see section 3.5.2 for description of baseline and true production rate calculations), the true production rate for the in-field QC approach remained at 23 anomalies/hr while the standard approach true production rate dropped to 26 anomalies/hr.

Using this analysis, it appears that performing a survey without in-field decision-based recollects may have been slightly more efficient than applying the in-field QC approach; however, a number of additional factors should be considered. First, a large number of recollects (about 66%) appeared to be a result of ground response (i.e., no contacts), for which there is currently no in-field mitigation process. This large number of unnecessary recollects lowered the average baseline production rate for the in-field QC survey. Second, the number of necessary recollects (those that led to improved target features) was relatively small at 46. This number did not significantly lower the adjusted rate for the standard approach (it dropped from 27/hr to 26/hr). Therefore, we might expect that sites without difficult geology or sites that contain higher anomaly densities could potentially alter these production rates significantly.

Another way to assess the impact of the in-field QC method on production rate is to view it specifically in the context of the WMA survey. The actual production rates achieved during the survey were lower than the 23/hr rate would indicate. This lower rate was due primarily to the difficult terrain, which slowed transport of the sensor across larger areas of the site (see Van et al., 2015). Actual production rates achieved were in the range of 65 – 75 anomalies per day. Based on the data time stamp information, we estimated that the average time required to perform a recollect was about 105 seconds. Viewed in this context, the 231 recollects probably added about 6-7 hours of additional survey time. Going back and reacquiring 46 anomalies (the necessary recollects) would have probably taken 1 – 2 days of additional survey time given that these anomalies were spread across different AOI's within the site. Thus, it is likely that even with the recollects associated with ground response; the in-field QC enabled a slightly more efficient survey for this particular site.

7.6 Qualitative Objectives

We have discussed ease-of-use with a number of MetalMapper system operators who have performed surveys with the in-field QC software. Overall, feedback has been positive. One of the most common reports is that having an inversion-based location that can be used to position the sensor provides the operator with additional confidence in the quality of the data. Another positive response has been utility of the software for performing IVS activities. Having the in-field output for the polarizabilities and estimated location of each IVS item provides immediate and quantitative feedback about the functionality of the system hardware.

8. COST ASSESSMENT

The MetalMapper survey costs can be referenced in the MR-201104 final report (Van et al., 2015). Total costs applying the in-field QC approach during the survey were \$76,100 for cued acquisition of 1032 unique anomalies. This figure produces an average rate of \$74/anomaly. This rate can be adjusted for the standard method (i.e., no in-field recollects) using the aforementioned true production rates for both methods. An additional cost component is the time required for set up and installation of the in-field QC software.

Table 4. Cost Model for In-Field Quality Control for Cued EMI Surveys

	Data to be Tracked
Survey costs (in-field QC)	\$74/anomaly <ul style="list-style-type: none"> Assumes 1032 unique anomalies surveyed at a rate of 23 unique anomalies per hour Includes 153 recollects associated with ground response
Survey costs (standard)	\$65/anomaly <ul style="list-style-type: none"> Assumes 1032 unique anomalies surveyed at a rate of 26 unique anomalies per hour Includes 46 reacquisitions
Training/installation	\$2400 <ul style="list-style-type: none"> Approximately ½ day of survey time

8.1 Cost Drivers

Production rate analysis indicates that the cost per anomaly may have been lower if the survey had been applied without recollects. This is due to the fact that a large number of recollects (153) were associated with ground response, which produced inaccurate source locations. Additionally, there were relatively few recollects (46 out of 231 total) that provided significant improvements in target features. These cost drivers reflect the challenges that were specific to the WMA site.

The true cost comparison of the two methods for the WMA site may be somewhat different than what is reflected by the cost per anomaly in Table 5 if the specific conditions of the site are considered. For example, it is unlikely that reacquisition of 46 targets could actually be accomplished in ~2 hours. In reality, this would likely have required 1 – 2 additional survey days given that these anomalies covered 3 different AOI's and transport between these areas was

time consuming. We expect that the true costs for each method at this particular site were comparable, if not slightly lower for the in-field QC method.

9. IMPLEMENTATION ISSUES

The greatest challenge to effective implementation of the in-field QC process at the WMA site was the presence of significant magnetic geology throughout the AOI's. Our retrospective analysis of the survey data indicated that a significant portion of recollects based on the in-field decision were a result of the soil response (153 out of 231). After analyzing the recollect data, we have developed a few recommendations that could improve the effectiveness and efficiency of the in-field QC process at other challenging sites:

- One approach to enable in-field mitigation of magnetic geology could be to enhance the background selection and removal process of the in-field software. For example, multiple background locations based on DGM analysis of magnetic geology in the survey area could be included in the background selection process for the in-field software. Background files collected at these locations could be loaded into the module and automatically selected based on location of the sensor. Proximity to different background locations in the site would drive the selection of the optimal background file to apply before inverting each subsequent data file.
- In many cases, however, there will not be an ideal background file. This was evident in the post-survey processing when it became apparent that none of the background files collected on a given day was adequate for removing the ground response for a number of anomaly encounters. In cases such as these, more sophisticated inversion strategies are required. For example, replicating the ground response by constraining the location of a deep dipole source during inversion has been effective for isolating the response from targets buried in magnetic soil (see e.g., Pasion et al., 2012). It could be an effective approach to include a 2-source solver in the in-field model that would allow one source to be constrained to represent the ground response. Decay fit metrics could be applied to determine if the constrained source does indeed produce ground-like features that indicate the presence of significant magnetic geology.
- While the WMA survey did not appear to produce many cases where multiple objects influenced the in-field QC decision, there are sites where this could be an issue. In some cases, implementing a multi-source solver could be effective for isolating the ground response (see above) as well as for isolating responses from multiple, closely spaced targets.
- Finally, using quality metrics in addition to the estimated source location could prove useful for eliminating unnecessary recollects. In cases where the target is isolated from any interfering sources (e.g., ground response, other nearby targets, low SNR, etc.), the 30 cm offset threshold may be overly stringent. While eliminating unnecessary recollects may not be critical to improving the effectiveness of the process, it could improve the efficiency of the process, leading to better overall cost performance. Incorporating other metrics into the decision flow (see Figure 26 in section 7.4 for example) could eliminate

recollects in some of these cases where the initial acquisition provides adequate characterization of the target.

While the WMA survey elucidated several challenges for the in-field QC process, we believe that overall the process proved beneficial for the survey. There were 46 cases where the recollect provided significant improvements in the characterization of the target and most likely improved the final classification result. Given the challenges of transporting and moving equipment around the different AOI's, these 46 anomalies would likely have added an additional 1-2 days of surveying if they had not be recollected based on the in-field decision (for comparison, we estimate the 231 total recollects for the survey added 6-7 hours of actual survey time over the course of field activities). Additionally, there are other benefits to providing the field team with immediate inversion-based metrics including the immediate feedback about instrument functionality during IVS activities.

It should also be noted that during most of the survey, one of the corner receivers on the MetalMapper was malfunctioning. It is unclear to what extent this faulty receiver influenced the in-field decisions; however, it is possible that it had some effect on the accuracy of in-field target location estimates.

It is likely that a large number of sites could benefit from implementing an in-field QC process for cued surveys. Applying some of the aforementioned improvements could make the process more effective for particularly challenging sites, such as those containing magnetic geology or high anomaly densities.

10. REFERENCES

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Appendix A – Interim Proveout Report

The following pages include an interim report submitted after the initial proveout phase of the project. This report provides a detailed description of the in-field QC hardware and procedures and demonstrates the feasibility of including this process during a cued survey.

1. In-Field Quality Control

Currently, standard protocol for collecting advanced EMI sensor data includes static data acquisition over anomalies identified (cued) by prior dynamic or Digital Geophysical Mapping (DGM) surveys. These data are typically analyzed by off-site geophysicists upon completion of the cued survey. Often, this analysis results in a number of anomalies that are found to be insufficiently characterized by the initial cued data collection as a result of sub-optimal placement of the EMI sensor during the survey. Subsequently, reacquisition of data is necessary and additional surveying is required. Methods that significantly reduce reacquisitions and improve the overall quality of the data before completion of the initial cued survey will significantly improve the efficiency of production operations.

Because cued EMI sensors rely on multi-axis illumination to provide enough information to extract useful classification features from the data, the placement of the sensor relative to the object under interrogation is critical. In many instances when the cued data yield poor classification features, the reason is often an incorrectly positioned sensor. Positioning errors, misguided target picking, or multiple objects in the field of view are common causes of incorrect cued sensor placement. Most often, these errors are not discovered until the off-site geophysicist identifies them during analysis of the data. Once discovered, the analyst will determine a rectified set of coordinates to better represent the true location of the target. The field team will then reacquire the data by positioning the sensor over the new coordinates.

Providing the field team with the capability to assess data quality immediately following the initial data collection will significantly improve the cued survey process. By removing the off-site analyst from the initial quality decision making, the field team can take immediate action to reposition and recollect certain targets if deemed necessary. Immediate recollection based on in-field quality control will be much more efficient than subsequent reacquisition based on off-site decision making. Offsite analysis will still be important for identifying complicated target scenarios (e.g., multi-object, magnetic geology, etc.); however, many of the reacquires due to common errors such as inaccurate target picking could be replaced by in-field decision based recollects.

1.1. Quality Control Technology Proveout

During the initial phase of this project, we evaluated an in-field quality control software module to provide real-time analysis of cued EMI data. For demonstration purposes, we have specifically designed the QC module to analyze MetalMapper data. Because the MetalMapper is a commercially available sensor that has been selected for a number of live site demonstrations, we believe that applying real-time quality control to the MetalMapper data acquisition process is highly relevant to ESTCP's need for production technologies that have the ability to collect classification-quality survey data. It should be noted, however, that while the QC module is currently optimized for MetalMapper surveys, it can easily be modified to analyze any cued EMI sensor data.

The QC module provides three principal capabilities:

1. Real-time inversion of cued MetalMapper data to identify quality metrics while the MetalMapper is still within the vicinity of the cued anomaly (on the order of 1 second);
2. Analysis of quality metrics to enable the user to make an informed decision as to whether the data are of sufficient quality to advance to the next anomaly or whether recollection is required;
3. Guidance for optimal placement of the sensor in the event that data recollection is required.

This project comprises two phases: (1) a technology proveout phase, and (2) a technology demonstration phase. We verified the aforementioned capabilities during the initial proveout phase of this project through a series of tests conducted at the Former Lowry Bombing and Gunnery Range (FLBGR) in Aurora, Colorado. These tests included simulated cued surveys as well as controlled test pit data collections over standard test objects.

In order for the project to proceed to a live site demonstration of the in-field QC technology, the QC module must meet the following requirements to verify its principal capabilities:

1. Inversion of static MetalMapper data and display of dipole-fit parameters within 1 second (nominal) of acquisition completion;
2. Display of sensor position within 10 cm of true GPS coordinates;
3. Display of estimated dipole/target location within 10 cm of true anomaly location.

This report summarizes the results of the proveout tests and provides confirmation that the QC module meets the performance requirements for advancing the project to a live site demonstration phase.

2. In-Field QC Module

The QC module functions as a parallel process to the cued EMI sensor data acquisition software. As such, the QC module does not provide any data acquisition functionality; it is used solely for immediate in-field analysis of the cued sensor data. The QC module uses a file watch protocol, which means that it loads cued sensor data files immediately after they are created in the data acquisition file directory. In this sense, the QC software is truly modular in that it can be used in parallel with any data acquisition software, provided the associated data file formats are accepted.

Initially, we considered a design that would more closely integrate the QC software with the data acquisition software. This design would have combined the inversion and classification Application Programming Interface (API), which provides the backbone for the QC module, with the acquisition software to form a single process. To implement this process for the MetalMapper, several methods, events, and properties found in the MetalMapper data acquisition software, known as EM3D, would need to be declared “public” in the C# code. This would allow the API to gain direct access to the acquired data rather than rely on the file watch protocol.

The intent with this approach was that it would create a seamless process where the EM3D software would provide both the data acquisition and sensor navigation interfaces, the latter of which would receive updates from the classification API. This approach would essentially

maintain the existing functionalities of the EM3D software and give it an added feature of providing real-time data inversion capabilities. While providing EM3D with this feature would build an in-field QC capability into the MetalMapper sensor package, we determined that this approach would limit options for adapting the QC capability to other sensor forms. Additionally, because EM3D is currently being transitioned to commercial use, we felt that modifying any of its features might impede this commercialization process.

Instead, we focused on developing a software executable that was completely modular and could be adapted to any cued sensor data format. Our initial concerns about the file watch approach not being robust enough for production operations proved to be unfounded. We performed extensive tests with our field teams using the QC module in a production environment over a period of several weeks. Not only was the file watch process 100% reliable during these operations, but it was completely transparent to the MetalMapper operators, i.e., the results obtained using the file watch protocol were effectively instantaneous. There is no noticeable lag that occurs between the data acquisition process and the QC module data inversion. Observing the reliability of the file watch process convinced us that this approach was optimal for enabling future transition of the module to cued sensor applications that extended beyond just MetalMapper surveys.

With our initial development concept shifted towards a more modular design, we required that the QC module take on some of the tasks normally assigned to EM3D. Specifically, the QC module needed to provide some navigation functionality. We determined that this capability would be relatively easy to develop and, more importantly, that it would be a critical component of a modular QC interface. Because the ability to reposition the sensor head based on data inversion results is a key component of in-field QC, it was a logical step to include this capability as part of a QC navigation interface that functioned separately from the data acquisition software. Additionally, any cued sensor will require sensor head positioning information, typically in the form of GPS and Inertial Measurement Unit (IMU) data streams. Thus, it would be relatively straightforward to split these incoming positioning data streams between the data acquisition software and the QC module.

The result of our modified design concept is a QC module that provides both navigation and quality analysis interfaces. We currently maintain use of EM3D solely for

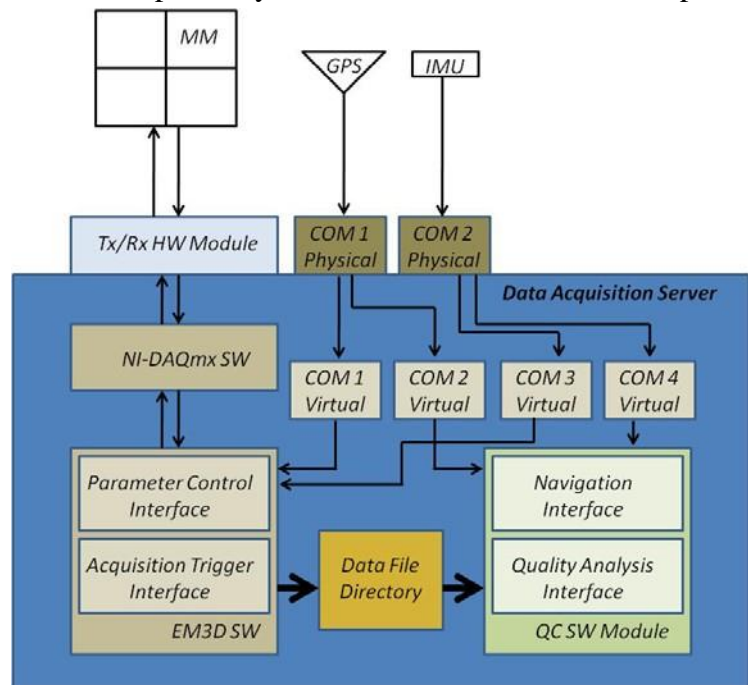


Figure 1. Block diagram representing data flow patterns between various hardware (HW) and software (SW) components.

data acquisition capabilities that enable selection of MetalMapper data acquisition parameters as well as triggering of data acquisition events. A block diagram that shows the separate functionalities of the acquisition and QC software components is presented in Figure 1.

In practice, operating the EM3D acquisition software and the QC module in parallel is straightforward and does not require any shuffling of interfaces to acquire data. Our initial concern in having separate data acquisition and data QC processes was that it might be onerous for the operator to switch back and forth between the data acquisition interface for triggering an acquisition event and the QC interface for viewing results; however, in reality this process requires very few steps. Once the initial data acquisition parameters are set for the MetalMapper using EM3D, the QC module can be used to provide the primary navigation and quality analysis interfaces. Only a small trigger button from the EM3D interface must remain accessible for commencing a data acquisition event. Figure 2 shows an operator display that demonstrates the typical setup for enabling both QC and data triggering functions.

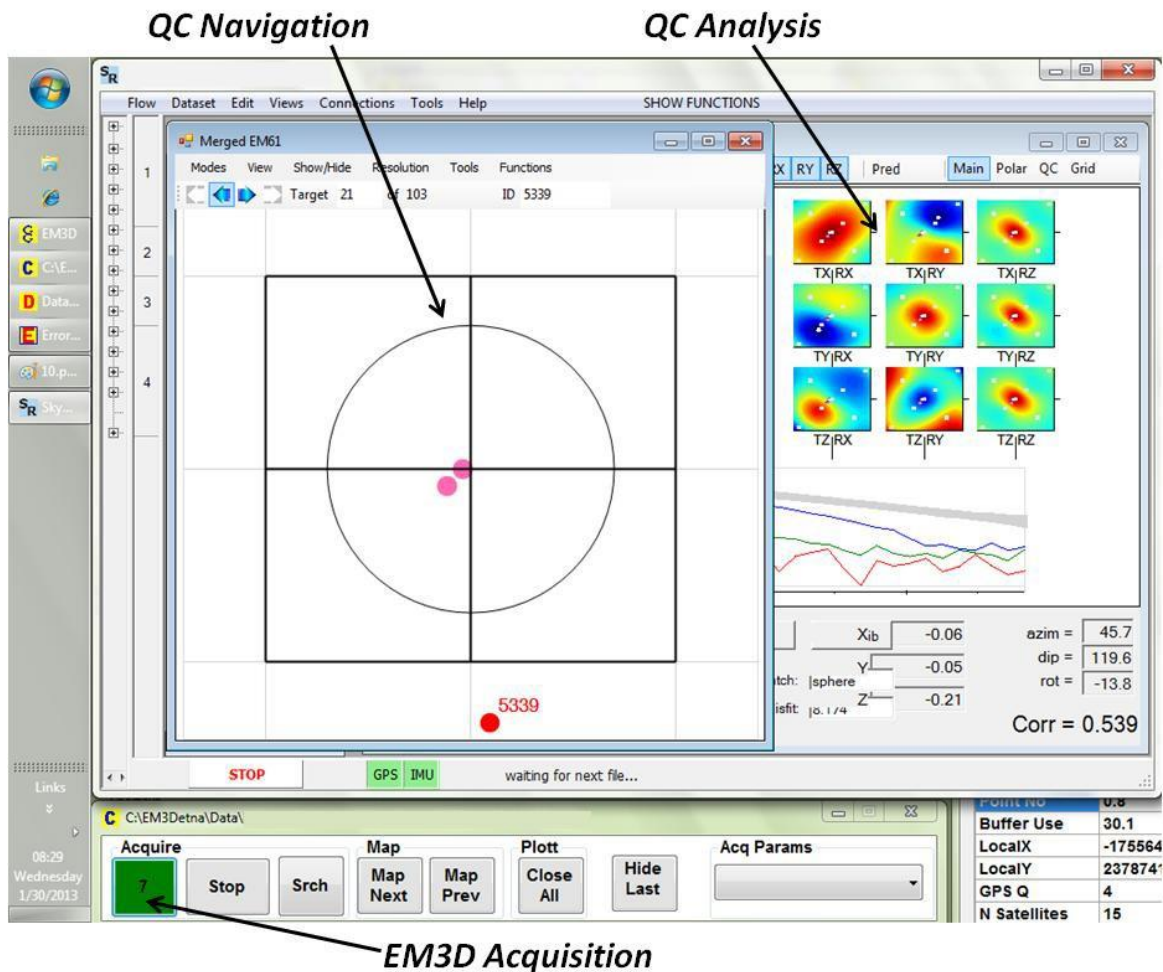


Figure 2. Typical operator display setup showing QC and acquisition interfaces. The QC Module provides the main navigation and analysis interfaces, while EM3D provides the acquisition capability with a simple acquire button.

As mentioned previously, the QC module is built around our C++ inversion and classification API that provides access to the inversion algorithms, which can be used to rapidly estimate a variety of model parameters associated with each anomaly. These parameters include principal target polarizabilities and estimated target location. When the QC module executable performs a file watch on the cued data directory, any acquisition event triggered by the EM3D interface will create a new file in this directory. The QC module will immediately load this file and invert the data contained within it. The output of these inversions is subsequently transferred to the operator navigation and QC interfaces that display the various recovered dipole-model parameters (e.g., polarizabilities, location, depth, etc.) as well as the raw data channel output.

The versatility of the API highlights the modularity of the QC executable. The API can be adapted to a variety of sensors. Before the API can work with new sensor data, information about the sensor configuration is required. The sensor configuration tells the API how the data are collected; it consists of specifications such as the geometry of the sensors with respect to the GPS sensor location, the types of sensors used, the geometry of transmitter and receiver coils, the number of time gates used, etc. This information enables an initialization of the API once for any given cued survey sensor. After the operator sets the sensor configuration, the calling application will initialize the inversion configuration, which determines the inversion method (a specific forward model), the parameter scaling, parameter bounds, solver stopping criteria, and additional options that control the inversion.

2.1. QC Module Setup and Features

Step 1. Building a Reference Library: The first step in implementing the in-field QC process is to establish a target library. The QC module facilitates this by allowing the operator to create reference polarizability libraries for standard objects as well as for objects that may be indigenous to the site. The operator starts by opening the QC module flow that enables the creation of a library file. Within the flow, the operator can select a background data file to use for processing of subsequent acquisition files. The operator also indicates the location of the data file directory where EM3D deposits the acquisition files (Figure 3).

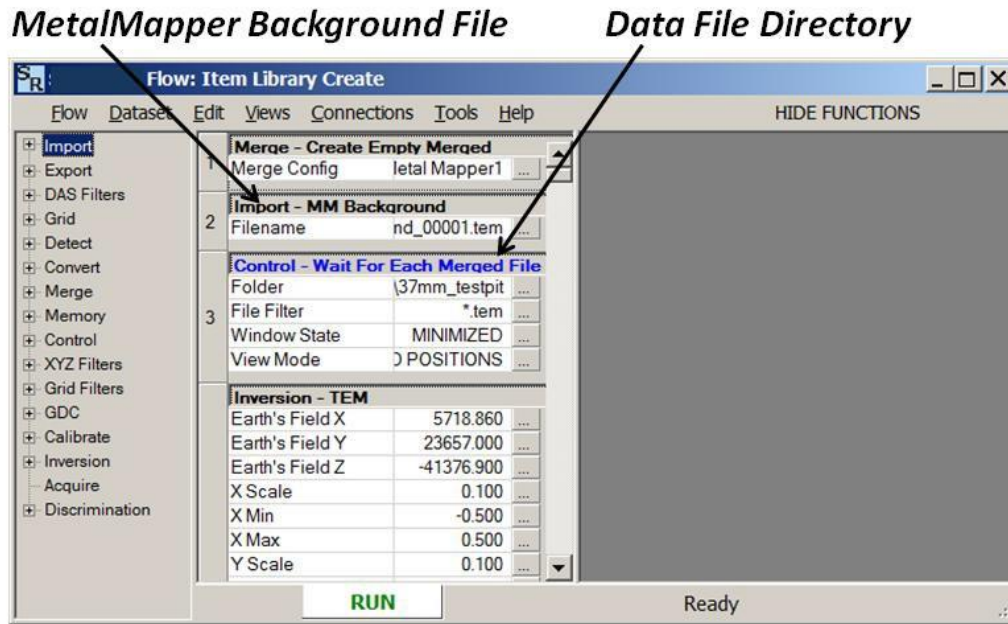


Figure 3. Library Create Flow. The operator selects a background data file as well as the location of the incoming data file directory.

Once the flow functions are established, the operator selects the “RUN” button to start the flow. This will activate the file watch mode and the QC module will wait for EM3D to generate a MetalMapper data file in the directory. The operator will then place a library object under the MetalMapper sensor head and select the “Acquire” button in the EM3D acquisition interface. Once the MetalMapper data file is created, the QC module will invert the data and display the quality analysis interface for the library object (Figure 4). If the recovered polarizabilities are acceptable for library cataloguing, the operator will check the ground truth box and select a target type corresponding to the library object. This process can then be repeated for a number of library objects. Once the library is fully populated with the desired object polarizabilities, the operator can save the library file for future reference.

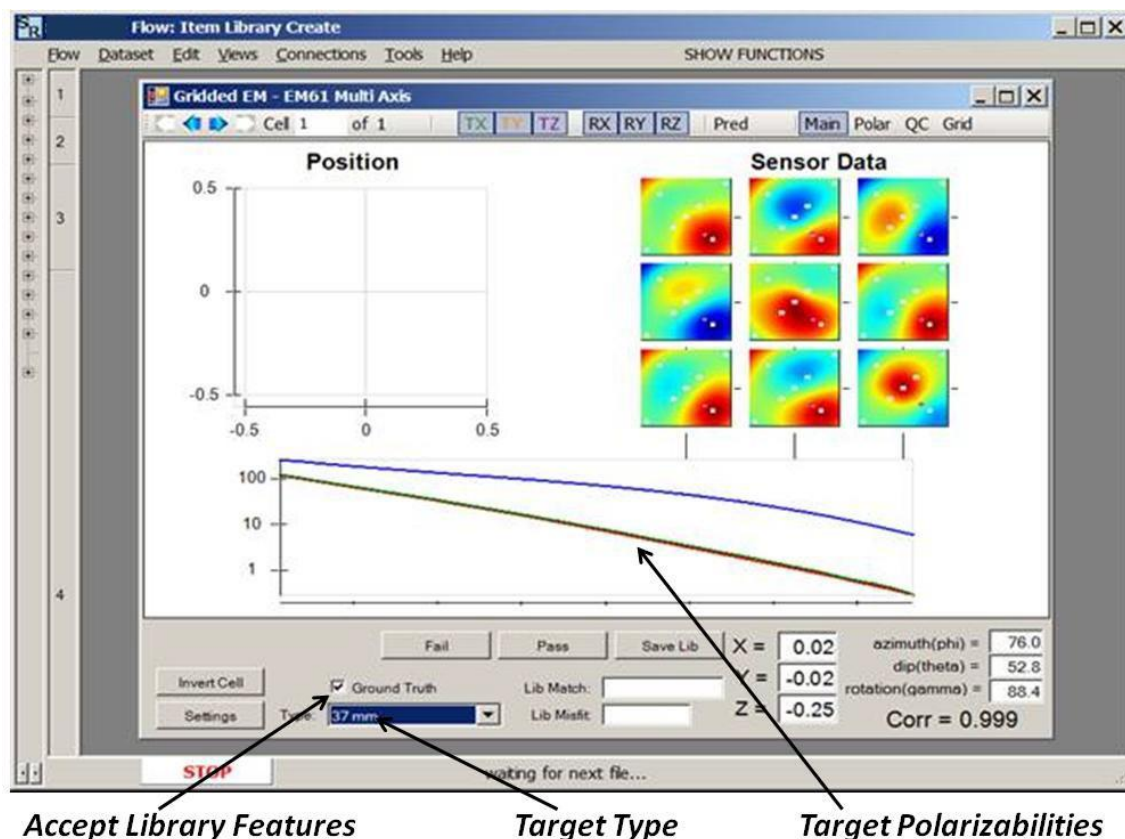


Figure 4. Quality analysis interface showing library object features. If the target polarizabilities are acceptable, the operator can add them to the library by checking the ground truth box and selecting the target type.

For best library results, the library data should be collected in a clean area such as a test pit or calibration zone so that the data will reflect only the target response. Additionally each library object should be placed directly under the center of the sensor head to ensure full characterization of the target features (Figure 5). Background files should also be collected in the same area without any target present to provide sufficient background response characterization.

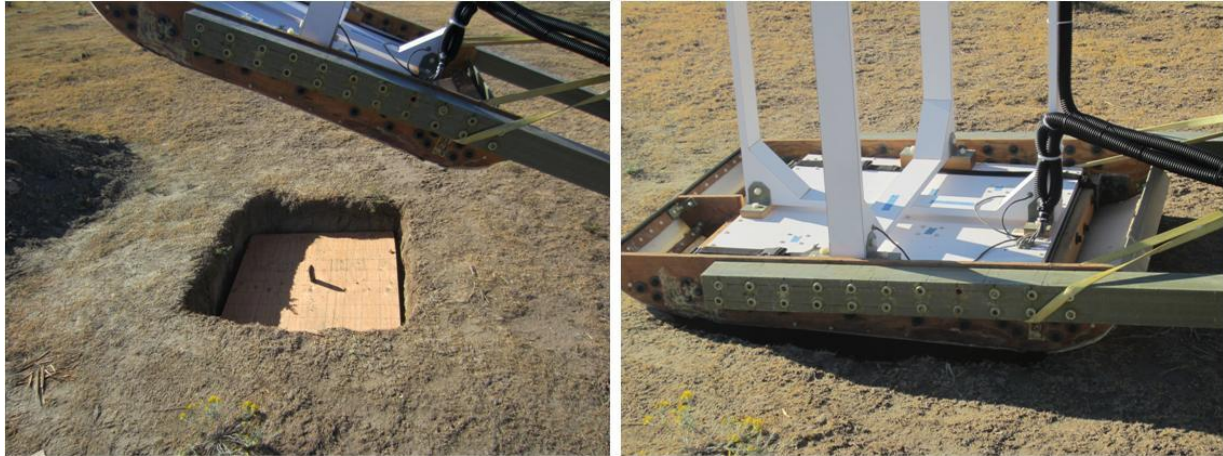


Figure 5. Library data collection. Library objects are placed in a clean area such as test pit (left). Once centered, the sensor head is lowered over the object for data collection (right).

Step 2. Loading Target Picks: Once the library file is created, the operator must load a target pick file into the QC module before commencing cued survey operations. This step provides the QC module with the location of each target so that the coordinates of these picks can be displayed in the navigation interface. The target file features a basic .xyz file format that assigns an easting, northing, and target ID number to each pick. The operator can load the target file by opening the QC module flow that creates an SRD file (Figure 6). This flow enables selection of a specific target file that corresponds to the anticipated working area of the site. Once the correct target file is selected, the operator can select the “RUN” button to load the target pick coordinates into the QC module. Running this flow will create an SRD file that corresponds to the target picks in the selected target file. The SRD file will be used in subsequent cued survey operations to record model information (such as recovered polarizabilities and estimated location) for the data files corresponding to each target pick.

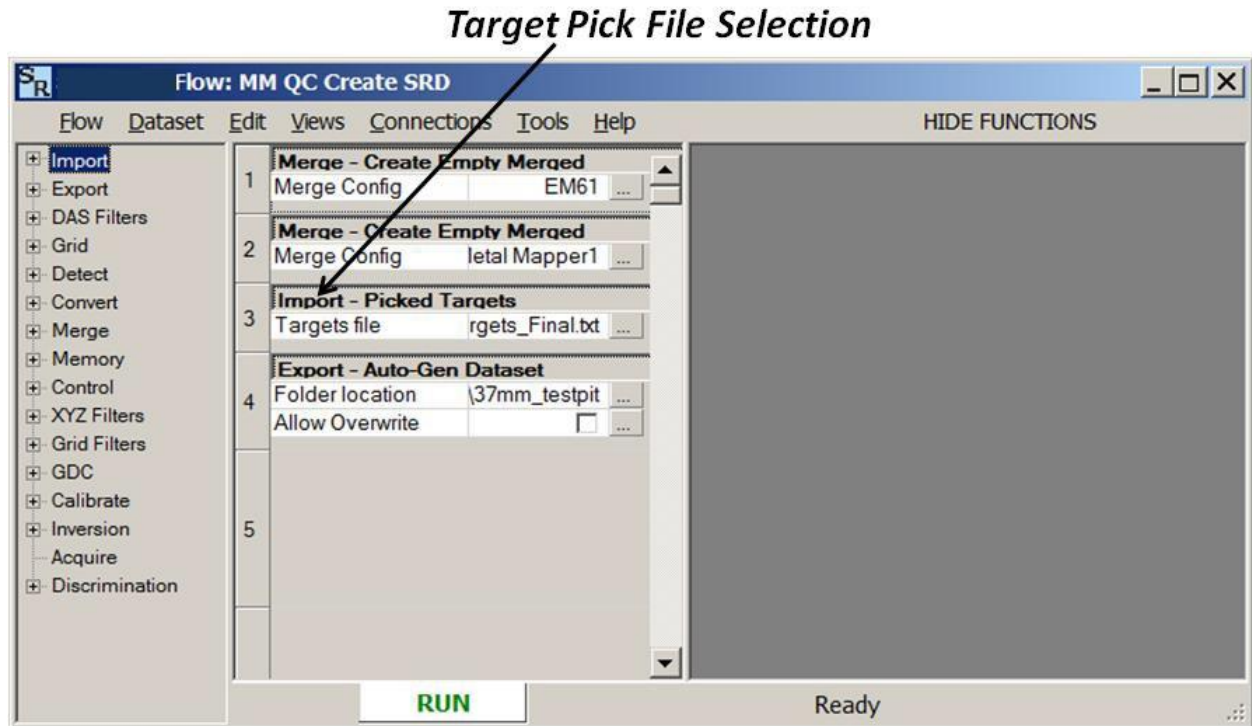


Figure 6. Create SRD Flow. This flow allows the operator to load target files into the QC module. The target pick coordinates will then be displayed in the navigation display during subsequent cued survey operations.

Step 3. Opening the Navigation and QC Interfaces: After loading the target pick coordinates, the operator can view the navigation and QC interfaces by opening the Navigation and QC Flow (Figure 7). This flow enables selection of the SRD file (created in Step 2) that corresponds to the target picks located in the anticipated working area. Within this flow, the operator can also select a reference library file (created in Step 1), a MetalMapper background file, and the location of the data directory where EM3D will create new data files during the cued survey. Once these flow functions are correctly assigned, the operator can select the “RUN” button to open the navigation and QC interfaces.

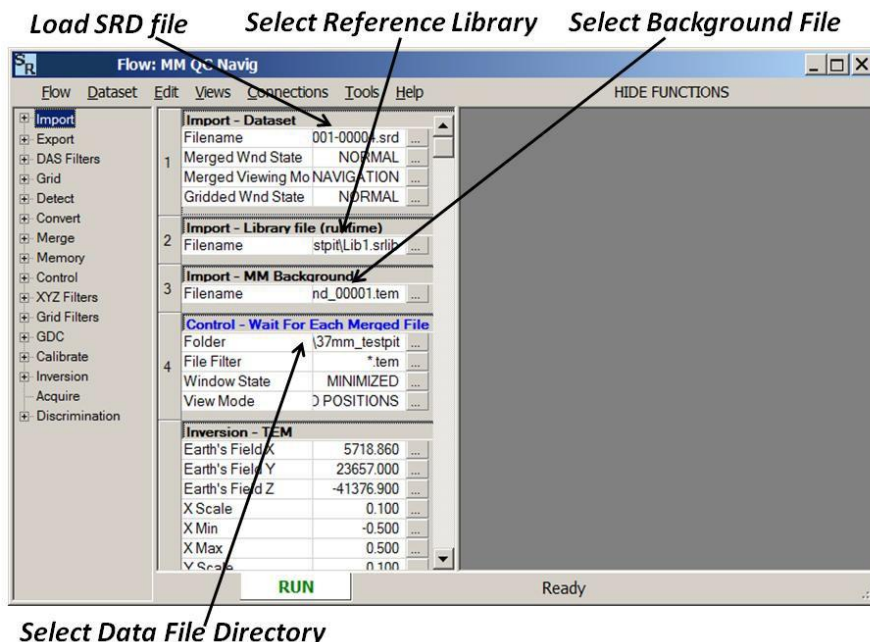


Figure 7. Navigation and QC Flow. The operator assigns an SRD file, a library file, a background file, and the data directory in these flow functions. Running the flow opens the navigation and QC interfaces.

Running the Navigation and QC Flow automatically opens the navigation interface, which displays the coordinates of each pick in the target file as well as the location of the MetalMapper sensor head (Figure 8). The target picks are displayed using a vehicle-referenced coordinate system. Thus, the MetalMapper location is always fixed in the center of the display with the vehicle heading fixed towards the top of the screen. The targets are queued such that the next target for surveying is shown in red and the remaining picks are shown in blue.

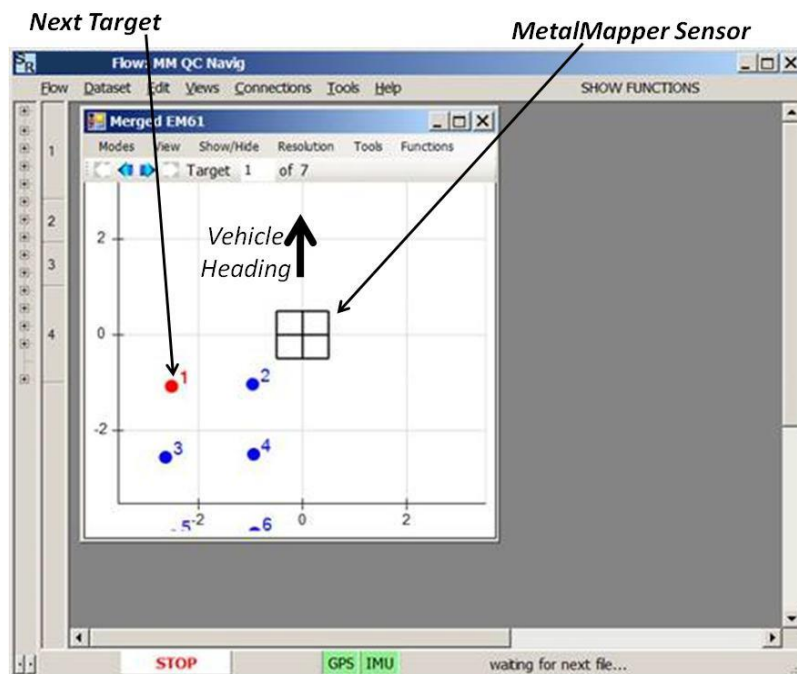


Figure 8. Navigation interface. Target pick (red and blue dots) locations are shown relative to the MetalMapper sensor head.

Step 4. Starting a Cued Survey: With the available target picks displayed in the navigation interface, the operator may use the interface to select the next target for surveying. As the operator drives towards the next target, the display screen will rotate to reflect the changing heading. As the sensor head approaches the target, the display auto-zooms to facilitate positioning of the sensor head directly over the target. Once the sensor is centered over the target, the operator will select the EM3D acquisition button to acquire a data file. When the acquisition is complete, EM3D will generate a .tem data file in the directory. The QC module then uses the API to invert the data stored in this file. The QC interface will automatically open to display the results when the inversion is complete. These results include the recovered polarizabilities, the estimated target location, and a correlation coefficient that indicates how well the model results match the data (Figure 9). The polarizabilities are plotted against the best library match to indicate the likelihood that the target is one of the items catalogued in the library. The estimated target location will also be displayed in the navigation interface.

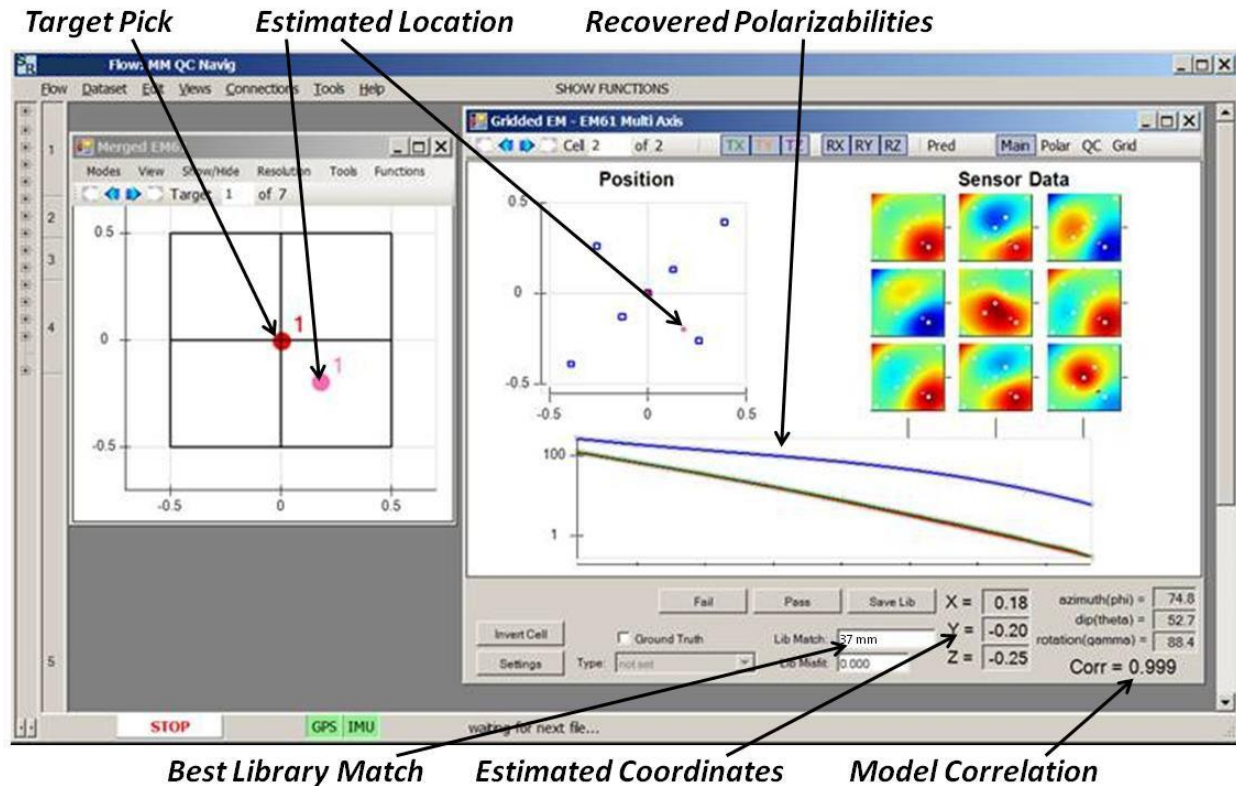


Figure 9. Navigation interface (left) and QC interface (right) displaying the data inversion results corresponding to the current target pick (number 1). The original pick coordinates are represented by the red dot and the estimated target coordinates are represented by the pink dot. The recovered polarizabilities (colored lines) are plotted in the QC interface along with the best library match (grey lines). In this case, the recovered polarizabilities show an exact match with the library polarizabilities for this item so it is difficult to see the library features in the plot.

Based on the inversion results, the operator can assess the quality of the data and decide whether the data are of sufficient quality or whether a recollection is necessary. If a recollection is required, the operator selects the “Fail” button on the QC interface. This action will update the current target pick coordinates based on the estimated target location (the original coordinates are still stored in the SRD file). The operator can then navigate using this new set of coordinates and position the sensor head over the estimated target location to recollect the data. Once the data are determined to be of sufficient quality, the operator can advance to the next target in the queue and repeat the cued acquisition sequence.

Step 5. Analyzing the SRD Data: After the cued survey is completed for all targets in the pick file, the survey quality statistics (e.g., percentage of targets requiring recollects, model correlation distribution, etc.) may be compiled by analyzing the data stored in the SRD file. This analysis is typically performed offsite since it does not affect any of the in-field QC processes. The SRD file contains all of the metadata for the survey as well as the data inversion results corresponding to each data file collected during the survey.

The SRD file can be opened at any point after the survey is completed using the QC module. The results for each acquisition can be viewed using a post-survey analysis interface.

Additionally, the QC module provides a function to export the data and results to MATLAB for more detailed analysis (Figure 10).

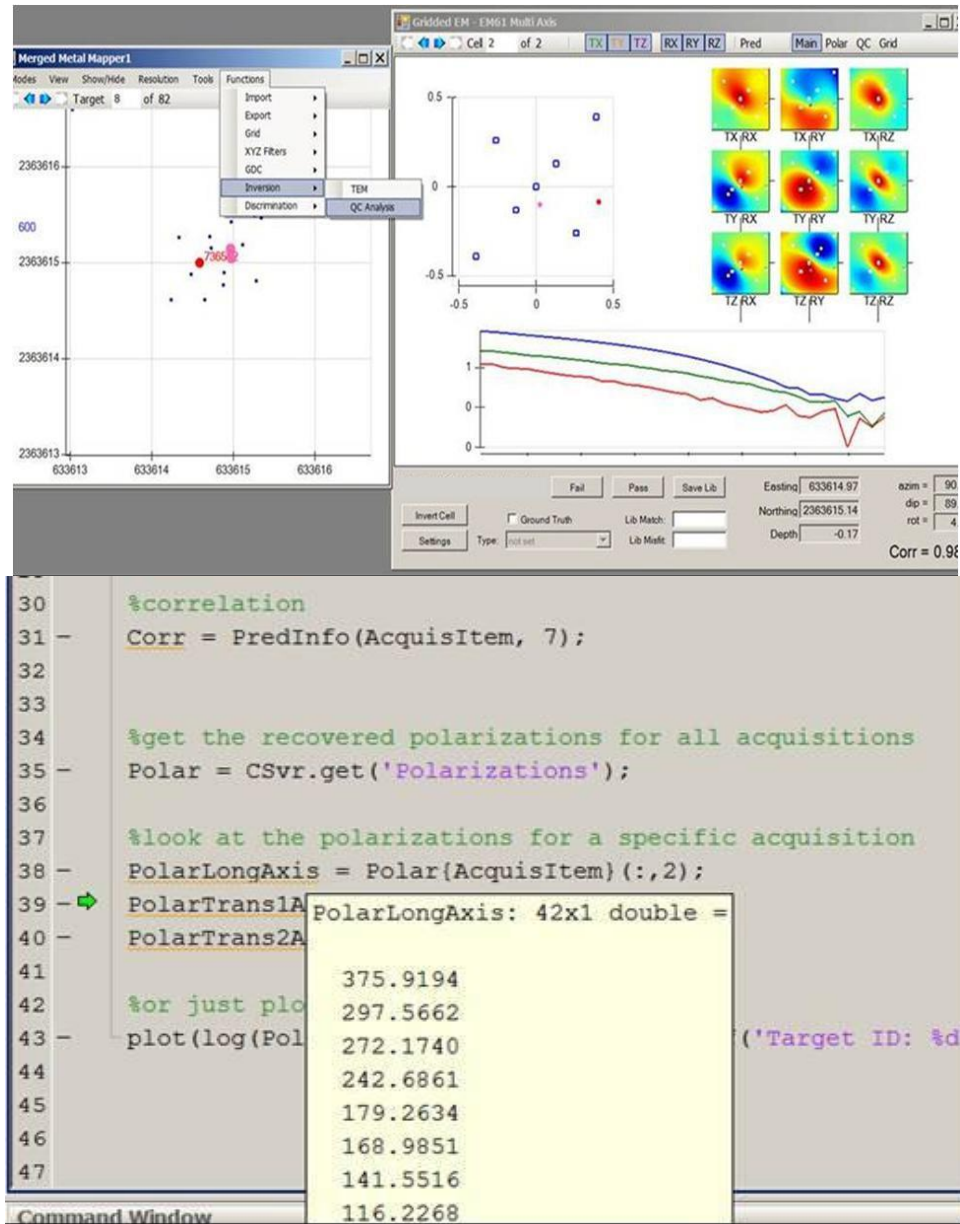


Figure 10. SRD data analysis. The QC module provides a post-survey analysis interface (top) for opening SRD files, as well as a function that exports the SRD data to MATLAB (bottom).

3. Data Quality Metrics

Effective data quality metrics are critical to ensuring successful in-field quality decisions. As part of the initial proveout phase of this project, we undertook an extensive data analysis study to identify the most practical and effective set of quality metrics to apply to our in-field QC software module.

Over the course of numerous live site demonstrations of cued EMI sensors, it has been well established that sensor position relative to the target is important for ensuring the data contain good classification information. Because most cued sensors rely on multi-axis magnetic field illumination of the target to enable effective characterization, these sensors must be positioned such that they achieve excitation of all three principal axes of the target. For the MetalMapper, optimal sensor positioning requires that the MetalMapper sensor head is centered directly above the target. Poor sensor positioning can often result in poor classification results (Figure 11).

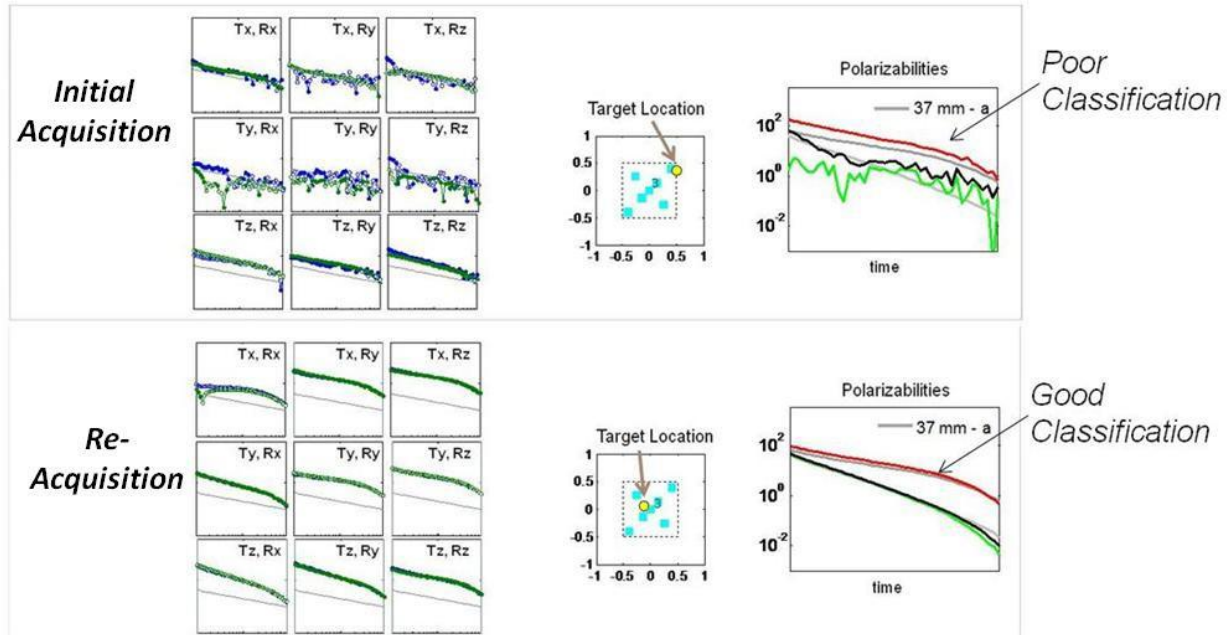


Figure 11. MetalMapper data collected during the Pole Mountain, WY live site demonstration. The initial acquisition was conducted with poor sensor placement relative to the target (top). Consequently, the data produced poor classification features. Data were subsequently reacquired using better sensor placement (bottom), which yielded good classification features for the target.

Because classification quality correlates strongly to sensor positioning quality, the estimated target location is a fairly robust quality metric; however, there are instances where somewhat misguided sensor placement can still produce data that yield good classification features. The key objective of our data analysis study was to identify additional quality metrics that could further guide quality decisions that were initially based on sensor positioning alone. These metrics could be used to identify cases where relatively large offsets between the target and the sensor still resulted in good classification. In these instances, recollection would be unnecessary. Thus, these additional metrics could further improve survey efficiency by reducing the number of data recollects.

3.1. Test Pit Data Compilation

To assess the merits of potential quality metrics, we compiled a set of controlled data. We collected over 600 unique MetalMapper measurements at our test pit at the FLBGR site. This data set provided a statistically large sample of test cases for identifying data quality metrics. For each test case, we placed a standard UXO test object (e.g., 37mm projectile, 60 mm mortar, small ISO40, etc.) on a grid surface within the test pit (Figure 12).

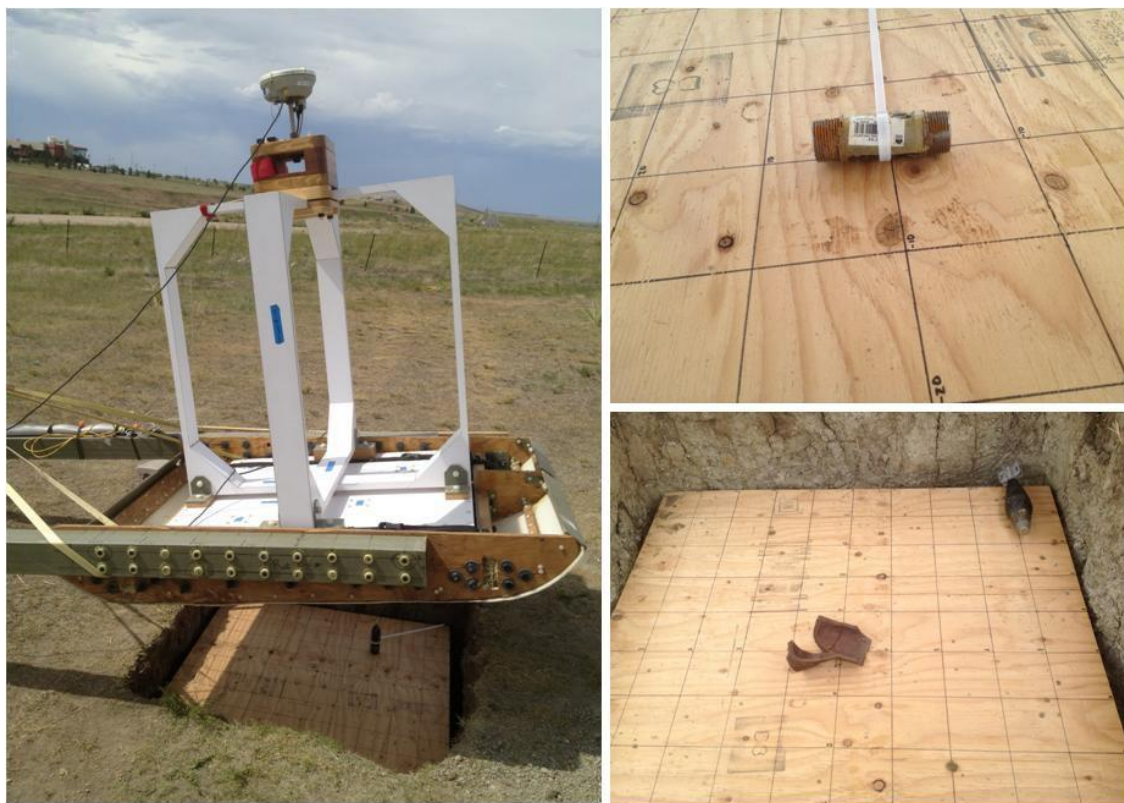


Figure 12. Test pit data collection. Objects were placed on a test grid beneath the MetalMapper sensor head (left). Test cases comprised mostly single standard test objects placed at various offsets from the grid center (top right); however, some cases included clutter samples to increase noise (bottom right).

Because we were interested in identifying data or model parameters that would indicate the classification quality of the data, we needed to ensure that our data set comprised samples that produced both high quality and low quality classification features. To ensure a diverse set of samples, we varied a number of test parameters including target depth, orientation, and lateral offset. Over the course of the data collection, we moved each test object to a number of positions on the grid, ranging from centered directly beneath the MetalMapper (i.e., grid center) to lateral offsets of up to 70 cm from the center of the MetalMapper. We varied the depth and orientation for each test case, and we also included clutter items in some measurements to increase noise levels. These variations provided a diverse data set that included both low and high Signal-to-Noise Ratio (SNR) samples.

It should be noted that while we did conduct test cases that included multiple objects, the focus of our testing was acquiring data on which we would apply single object inversions. Because the QC module currently implements a single object inversion, we wanted to establish the limits of this method even in cases where multiple objects were within the sensor field of view. We are currently compiling a more extensive set of multiple object cases. We will eventually use these data to establish metrics that will indicate the reliability of single object inversions and identify the necessity for multiple object inversions within the QC module.

3.2. Quality Metrics Analysis

After compiling an extensive set of test pit data, we performed an in-depth analysis to identify data and model parameters that could be used to indicate the classification quality of the data. To begin this process, one of our classification analysts conducted a visual QC analysis of the inversion results from each test case. He evaluated the recovered polarizabilities from each sample and determined whether these produced good or insufficient classification features. Specifically, each case was selected for one of three categories: 1) cases that yielded good classification features; 2) those that yielded a good primary polarizability, but poor secondary or tertiary polarizabilities; and 3) those that did not produce any good classification features. Examples from these categories are shown in Figure 13.

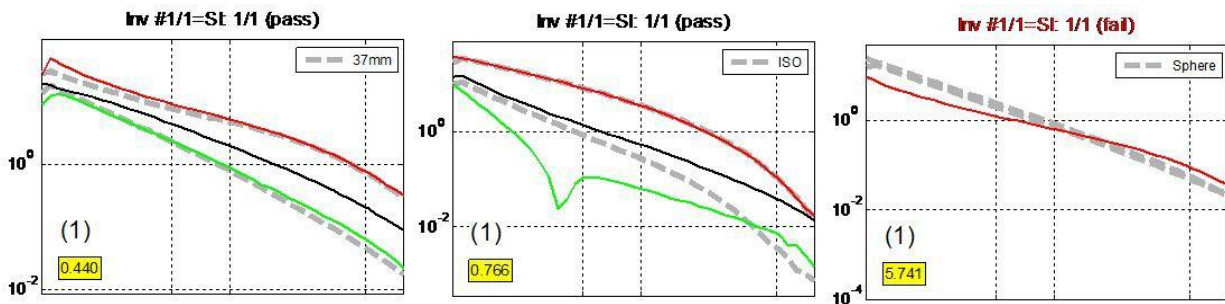


Figure 13. Examples of test pit data that produced poor classification features: (left) one bad polarizability; (center) two bad polarizabilities; (right) no good polarizabilities.

We were particularly interested in identifying cases where the data produced good classification features, but the target offset was large. A typical rule of thumb for quantifying large offsets is to select cases where the target lateral offset is greater than 30 cm from the center of the sensor head. While 30 cm is fairly conservative (i.e., it is possible to achieve good classification for targets well outside this range), it provides a practical threshold since most production surveys will likely require the target to be within a 30 – 40 cm lateral offset (somewhat site dependent). Accordingly, we identified all cases where the target lateral offset was greater than 30 cm, but the corresponding data still enabled good classification of the target (Figure 14).

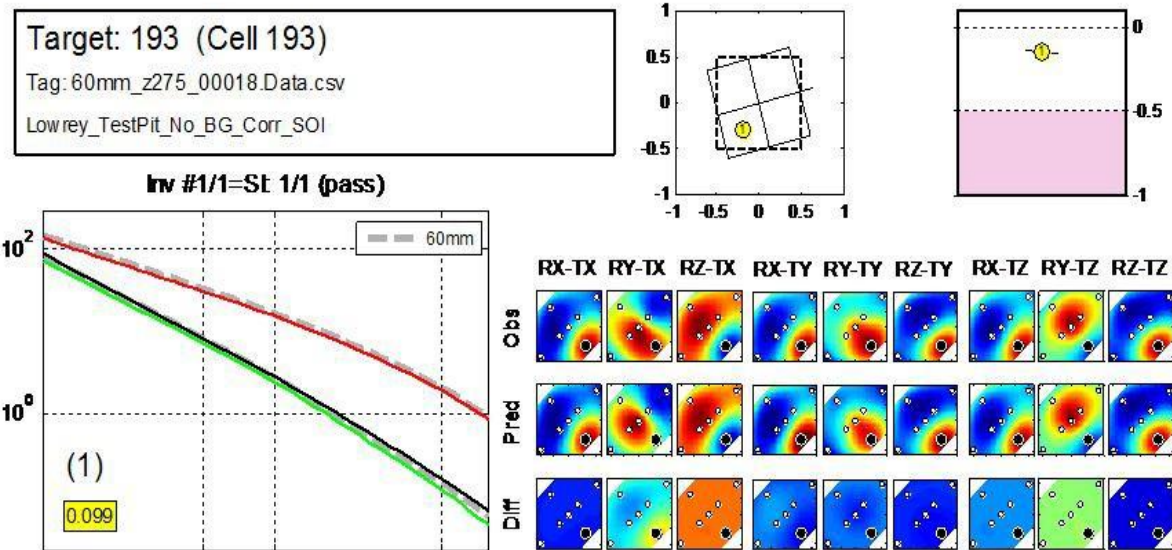


Figure 14. Example of good classification features obtained when target lateral offset is greater than 30 cm.

After completing the initial analysis and subsequent categorization of each test case, we evaluated the effectiveness of different data and model parameters in separating the good classification data from the poor classification data. Specifically, we searched for metrics that would produce a threshold such that all of the “poor quality” cases could be placed on one side the threshold while as many “good quality” cases as possible remained on the other side. Figures 15 and 16 show examples of data and model parameters, respectively, that are applied as quality metrics.

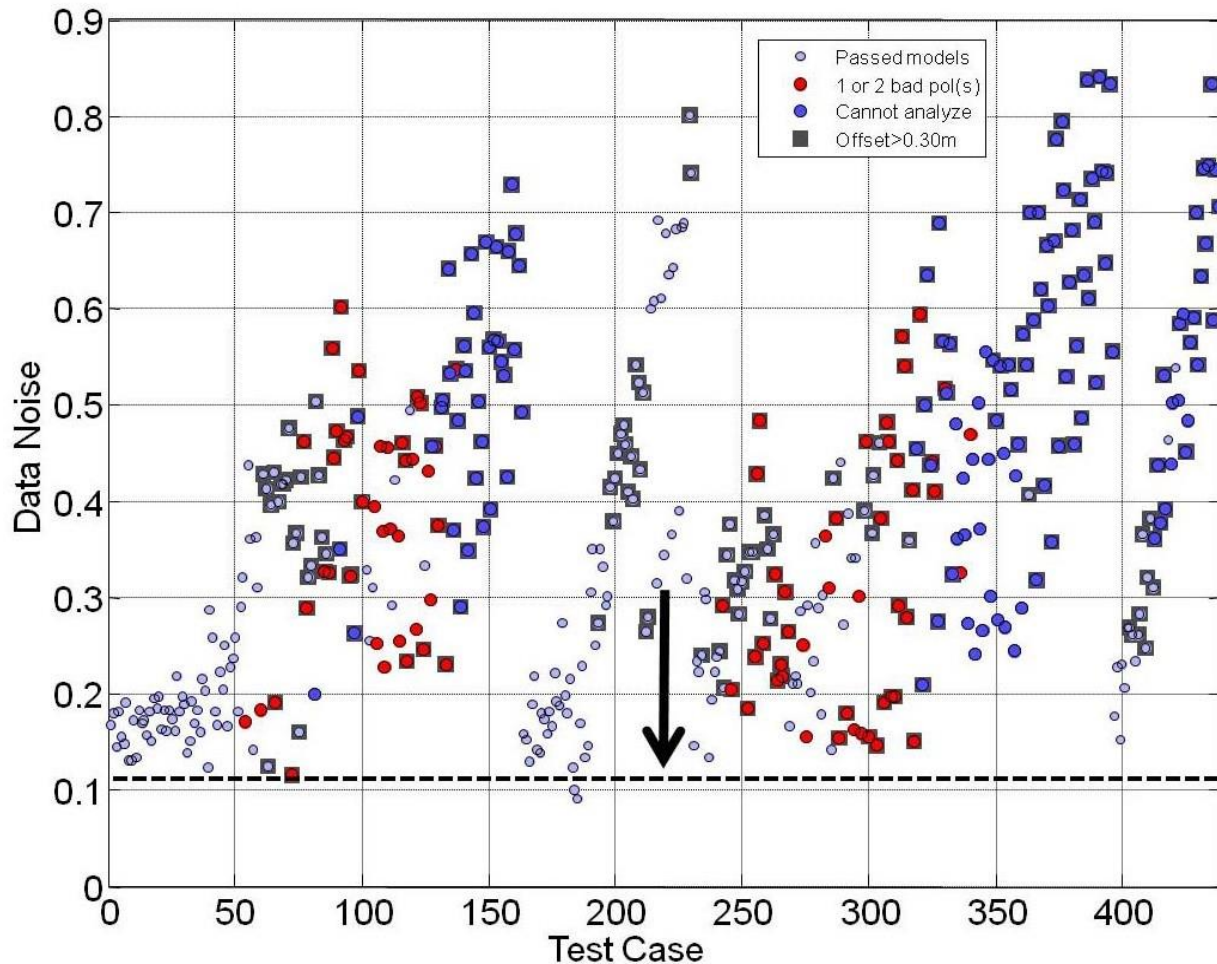


Figure 15. Example of a data parameter (in this case data noise) used as a quality metric. Each dot in the plot corresponds to a specific test case. Grey dots correspond to test cases that produced good classification features; red dots correspond to test cases that produced 1 or 2 bad polarizabilities (poor classification); and blue dots correspond to test cases that did not produce any good classification features. The threshold (dashed line) is placed so that all poorly classified test cases (red and blue dots) are on one side. The black arrow indicates the direction of increasing quality (according to the specific metric used). Test cases in which the target lateral offset exceeded 30 cm are also marked in the plot with squares.

Figure 15 is an example of a data parameter that does not work effectively as a quality metric. In this case we would anticipate that decreasing data noise might correspond to increasing classification quality; however, this relationship does not correlate strongly. Both “good quality” and “poor quality” cases are distributed fairly evenly across this parameter space and when the threshold is set to contain all “poor quality” cases, almost no “good quality” cases pass the threshold.

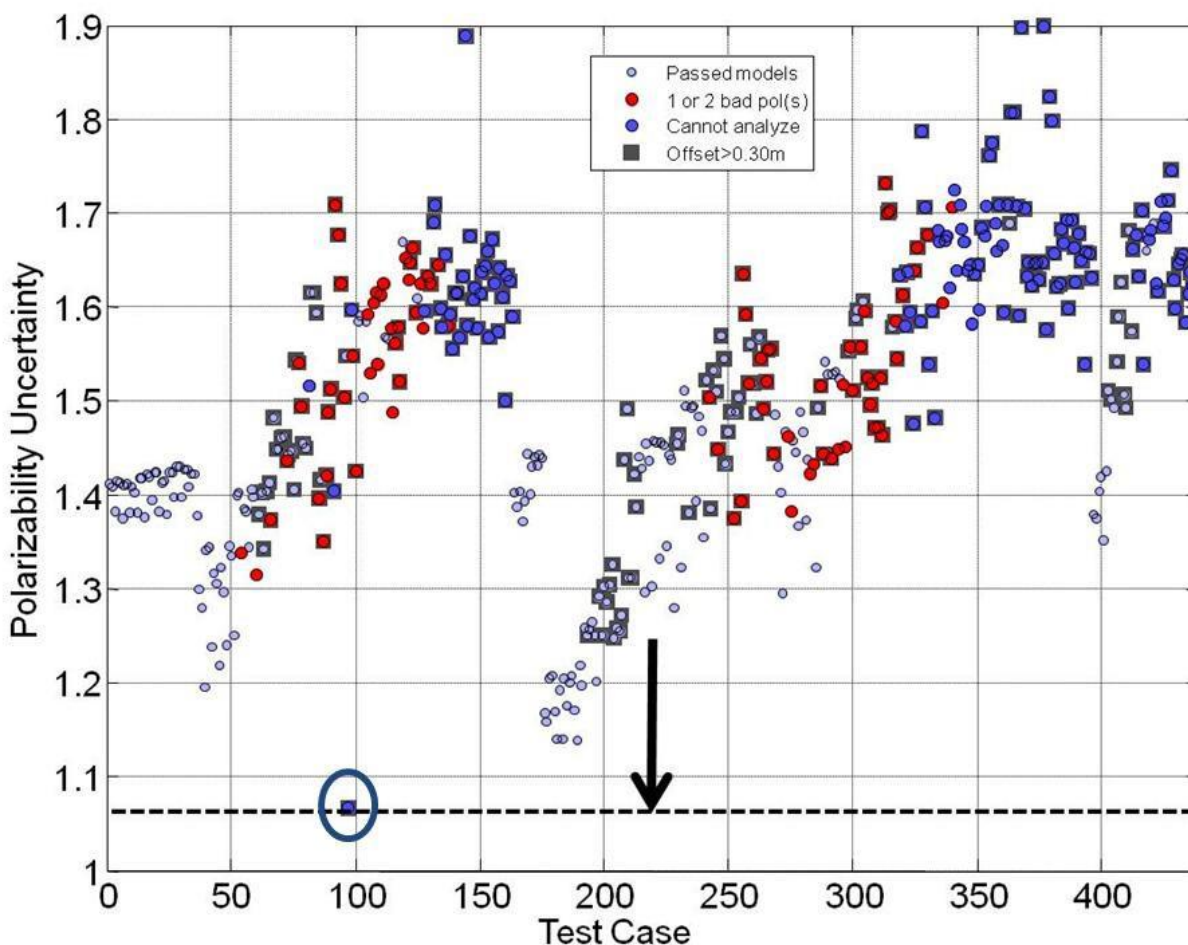


Figure 16. Example of a model parameter (polarizability uncertainty) used a quality metric. Threshold setting is determined by “poor quality” outlier (circled in blue).

Figure 16 provides an example of a model parameter applied as a quality metric. In this case, polarizability uncertainty works somewhat effectively as a quality metric. Most of the “poor quality” cases (blue and red dots in the figure) correspond to higher uncertainty values while most of the “good quality” cases (grey dots) correspond to lower uncertainty values. In this analysis, however, a threshold setting based on this metric does not work very well because of a “poor quality” outlier. Thus, in evaluating quality metrics it is important to consider not only correlation to data quality, but also the robustness of these metrics. Outliers may indicate that a particular metric may not be robust enough to use for in-field quality decisions.

During our analysis of various model and data parameters, we found several that showed promise as effective quality metrics; however, many of these metrics produced some degree of outliers in the parameter space. In order to improve upon the robustness offered by individual quality metrics, we started creating quality indicators that were based on several different metrics. These indicators, known as figures of merit, provide an output that is an aggregation of several quality metric values. Consequently, a figure of merit can be much more robust than an

individual parameter that is used as a quality metric. Figure 17 shows an example of an effective figure of merit.

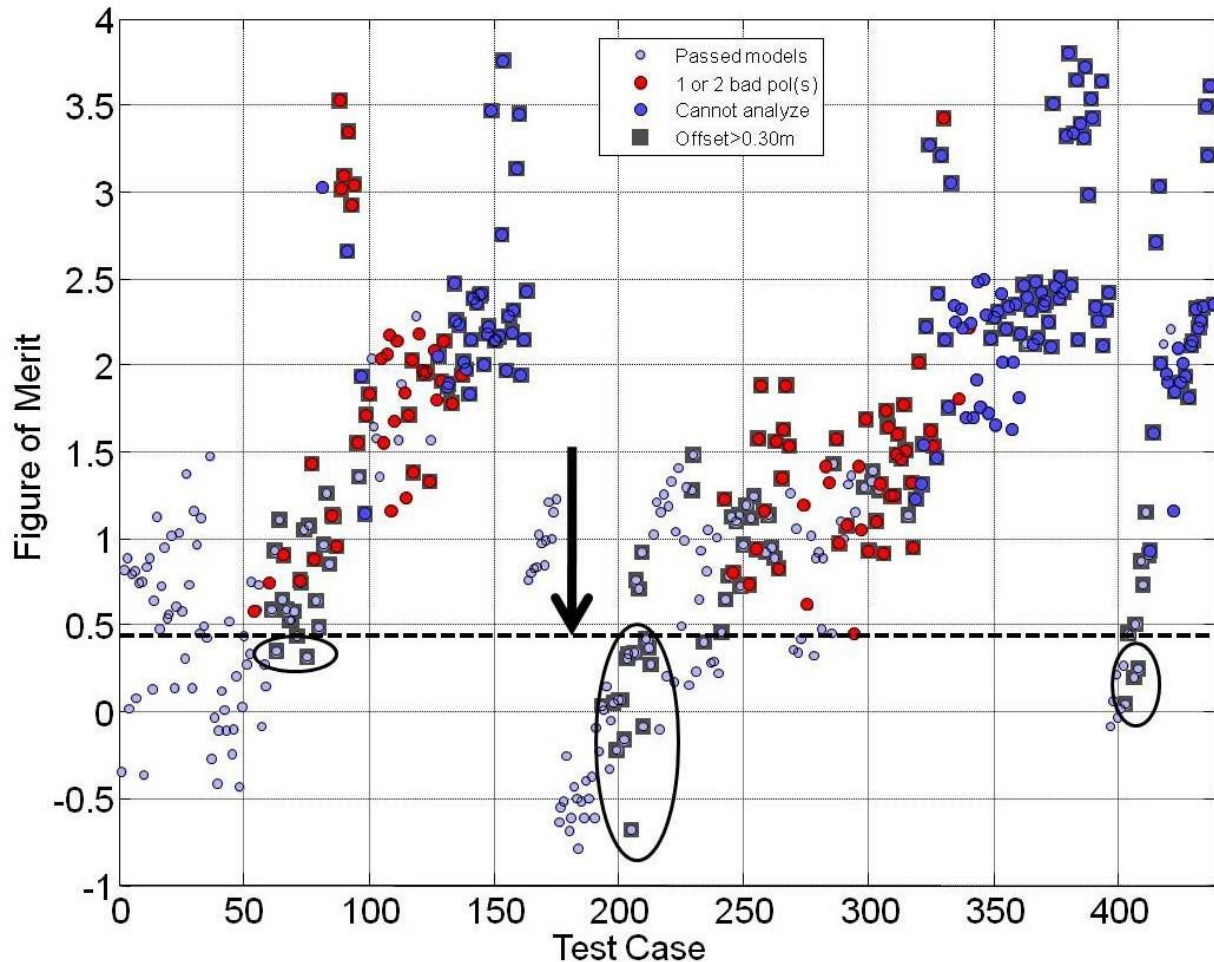


Figure 17. Example of a figure of merit that applies several quality metrics. This figure of merit shows good correlation to data quality and is fairly robust in that it does not produce significant outliers in the feature space. In this example, the figure of merit could effectively improve the in-field quality decision process since there are several cases that yield good classification features, but correspond to large lateral offsets (circled in black). These are instances where the figure of merit could be used to avert recollects.

The figure of merit presented in Figure 17 could be effective for improving the in-field quality decision process. It is calculated as the log of the product of five measures: (1) data misfit (cumulative point-to-point absolute difference between the observed and predicted data scaled by the absolute value of the observed data amplitude); (2) correlation between observed and predicted data (linear relationship between the predicted and observed data; does not account for constant offsets); (3) jitter (time series point-to-point difference) in the observed data; (4) fraction of data above the standard deviation; and (5) size of the difference between L2 and L3 (secondary and tertiary polarizabilities). (1) through (3) are calculated using only data above the standard deviation. (1) through (4) are data-based measures; (5) is a model-based measure. Once the threshold is set to contain all “poor quality” cases, there are many “good quality” cases that

pass the threshold. Many of these “good quality” cases correspond to targets with a lateral offset exceeding 30 cm. Applying the figure of merit to the quality decision process would avert recollection of these data sets, thus improving the overall efficiency of the survey.

Table 1 shows the results of the quality metrics analysis and compares the effectiveness of individual quality metrics to the aggregate figure of merit. The threshold value in Table 1 corresponds to the threshold setting that provides containment of all “poor quality” cases (i.e., the operating threshold). The percent effective value is the percentage of “good quality” cases (out of the total) that exceed this threshold. This percentage is an indicator of how well the quality metric separates good data from bad data. It is evident that the figure of merit outperforms the individual metrics significantly.

Table 1

Metric	Threshold	%Effective
Model SNR	157.499	9.8
Data Noise	0.115	1.1
Figure of Failure	0.264	10.3
Polarizability Uncertainty	1.067	0.0
Log10(Polarizability Jitter)	0.288	14.4
Log10(L23 Separation)	-4	0.0
Correlation Coefficient	0.999	1.1
Figure of Merit	0.456	46.6

Table 1 demonstrates the utility of applying additional metrics to support data quality decisions that would otherwise be based on estimated target location alone. Applied on an individual basis, these metrics would not be particularly effective for separating good data from bad data; however, when used in a supporting role, they could significantly reduce the necessity for recollects. This additional insight would be particularly important during projects when relying on the estimated target location alone would lead to an unnecessarily high percentage of recollects.

As an example, consider the data analysis shown in Figure 17. In this instance, the figure of merit effectively identifies 46.6 percent of the “good quality” cases. Out of these correctly identified data, approximately 23 percent (19 data files) correspond to cases where the target offset exceeded a distance of 30 cm from the center of the sensor. Thus, 19 out of the 66 total “good quality” data files that corresponded to offsets exceeding 30 cm were correctly identified using the figure of merit. This analysis demonstrates that if we applied the figure of merit to support the data quality decision, we would achieve an almost 30 percent (19/66) reduction in the number of recollects that would otherwise have been required if we had relied on the estimated target location metric alone.

3.3. Implementing Quality Metrics

Quality metrics provide several possibilities for enabling sensor operators to make better in-field quality decisions. Estimated target location should be used as the primary metric during in-field QC. Because misguided sensor placement (whether a result of operator error or inaccurate target

picking) can be easily rectified, metrics that identify sensor positioning errors are most relevant to in-field QC. Operators can use the estimated target location to identify cases where sensor positioning errors are likely to degrade data quality. If the estimated target location exceeds an established data quality threshold, the operator may immediately reposition the sensor and recollect based on this information.

As we saw from our previous analysis of quality metrics, however, relying on estimated target location alone can potentially lead to unnecessary recollects (i.e., high quality data files corresponding to target offsets that exceed the pre-defined data quality threshold). Consequently, a secondary subset of data and model parameters recovered from in-field analysis of the data may be used to further support quality decisions. These parameters can be combined to produce a figure of merit that provides additional insight into the data quality. This information should be used to identify cases where the estimated location exceeds the established threshold, but data quality remains high.

While it is possible to apply these primary and secondary quality metrics as standard practice, the actual thresholds selected for these metrics will most often depend on the specific site where they will be used. The estimated location threshold should be determined based on the complexity of the site. While the 30 cm threshold provides a good rule of thumb, sites that contain a low density distribution of anomalies may allow for larger offset thresholds. Conversely, high density sites or areas that contain magnetic geology are more complex and may require more conservative thresholds. A careful site assessment should be conducted before determining the appropriate offset threshold.

The decision to use other supporting quality metrics, or a figure of merit, should also be influenced by the site complexity. While it may be possible to reduce the number of recollects by using metrics other than estimated location, the reliability of these supporting metrics may depend on the site's target density and geology. The best practice for implementing an additional figure of merit may be to establish its reliability using an Instrument Verification Strip (IVS) and calibration procedure prior to incorporating it during a production survey.

This approach is similar to the process used to establish Data Quality Objectives (DQOs) for detection sensors. As an example, we might use a calibration pit to establish the effectiveness of a figure of merit for specific target types. Typically, classification library data files corresponding to seeded targets or potential targets of interest would be acquired in a calibration area prior to the start of cued survey operations. Because these library items are selected based on their relevance to the site, they would provide good test cases for establishing figure of merit reliability. Once the initial reliability of supporting metrics is established for the relevant target subset, verification could be conducted in the IVS by acquiring data files at various offsets from each IVS item. This process would ensure the supporting metrics are incorporated in the classification DQOs.

4. System Proveout

After completing the initial development of the real-time QC software, we performed a series of tests to ensure the QC module has obtained the planned objectives:

1. Inversion of static MetalMapper data and display of dipole-fit parameters within 1 second (nominal) of acquisition completion;
2. Display of sensor position within 10 cm of true GPS coordinates;
3. Display of estimated dipole/target location within 10 cm of true anomaly location.

These basic capabilities are required for the project to proceed to a live site demonstration. The following subsections present the results of our testing and demonstrate that the QC module has achieved these objectives.

4.1. Real-Time Inversion

The file watch inversion process adds minimal time to the existing data acquisition cycle. We performed several operational tests that have demonstrated the inversion of data in each file typically requires 0.2 – 0.4 seconds to complete and produce results. We clocked the inversion time for many sample data files and found these results were highly repeatable. Occasionally the inversion will require more than 1 second; however, this only occurs if the file contains data that are poorly represented by the model. For example, when we perform a sensor calibration with an object placed on top of the sensor, the inversion time is slightly longer. Because the inversion constrains the target space to a region below the sensor, placing an object above the sensor will produce poor inversion results. It is very rare for this type of scenario to occur during an actual cued survey.

The additional time required for the file watch inversion is negligible when compared to the typical static data acquisition period of approximately 20-30 seconds. The immediate return of dipole-fit parameters provides the operator with data quality metrics while the MetalMapper is still in proximity to the target. Once the proper QC module flows are started (steps 1 – 4 in subsection 2.1), the quality metrics (e.g., estimated location, model-fit parameters, etc.) are automatically displayed in the navigation and QC interfaces once the acquisition file is generated. Figure 18 shows an example of the dipole-fit results displayed in these interfaces.

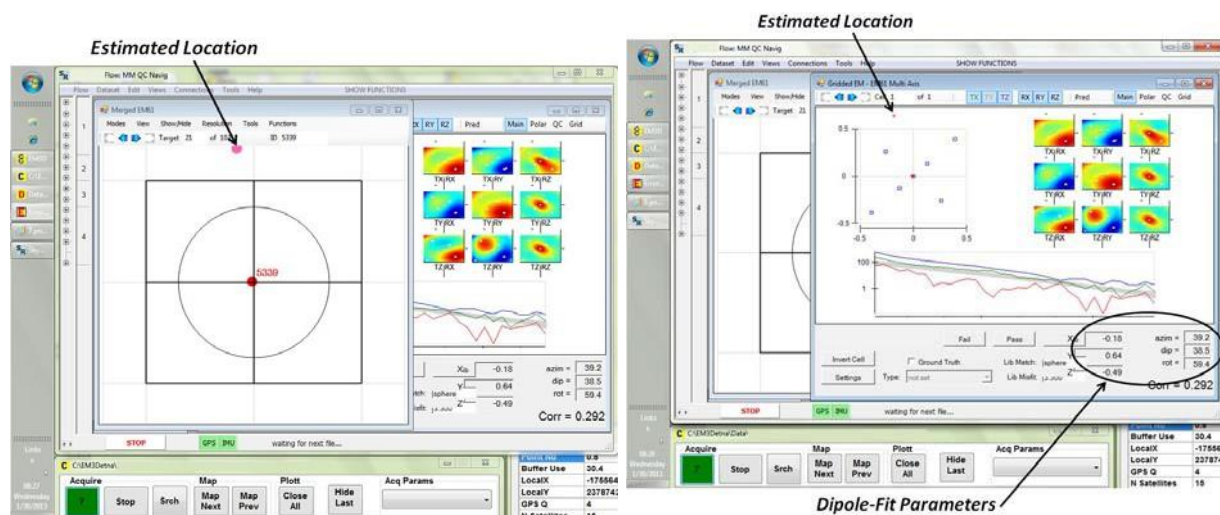


Figure 18. The QC module updates the navigation interface (left) and QC interface (right) with estimated location and dipole-fit parameters immediately after a MetalMapper data file is acquired using the EM3D acquire button (green button on bottom interface display).

4.2. Sensor Positioning Accuracy

To verify the positioning accuracy of the QC module navigation component, we conducted a series of measurements at the FLBGR compound test pit. We started this process by surveying the center of the test grid with an RTK differential GPS receiver to obtain accurate coordinates for the test pit. We then guided the MetalMapper over the center of the test pit using a set of crosshairs placed directly above the test pit center (Figure 19). We estimated that this method enabled us to center the MetalMapper over the test pit center with a total accuracy of approximately 2-3 cm (combined GPS and manual positioning errors).



Figure 19. We carefully aligned a set of crosshairs with the center of the test grid (left) and then manually guided the MetalMapper sensor head (center, right).

Using the surveyed coordinates for the test grid center, we created a target file to load into the QC module navigation interface. By displaying these coordinates in the navigation interface, we were able to verify that the module provide the desired accuracy of within 10 cm of the ground truth (Figure 20). This test ensured that the MetalMapper GPS and IMU were properly calibrated and that the QC module interpreted the navigation data streams correctly.

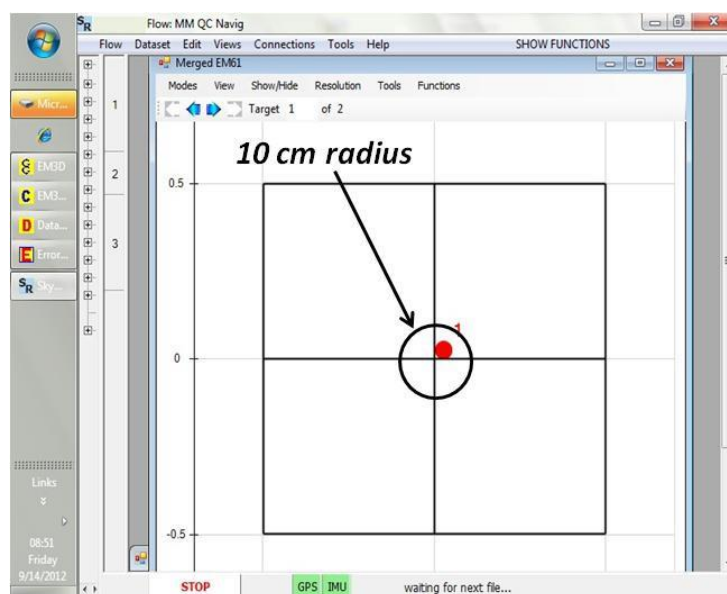


Figure 20. Navigation display showing the location of the test pit center (red dot). Positioning of the sensor was achieved by manually guiding the MetalMapper sensor head over the test pit center. The total positioning error for this process was estimated to be 2 – 3 cm. It is evident that the QC module provides a positioning accuracy that is well within the desired 10 cm threshold.

4.3. Estimated Location Reliability

To verify the reliability of the estimated location metric, we collected several MetalMapper data files over targets placed on the test grid. We varied the lateral offset from the center of the grid for each test case to provide a range of locations. We then compared the estimated target location to the actual ground truth location (based on the grid coordinates) to determine the accuracy of this metric. We found that the estimated location was well within the desired 10 cm threshold. In fact, this accuracy was maintained even at large lateral offsets where the targets were placed near the corners of the grid (~70 cm offset). Figure 21 shows an example of the estimated location accuracy.

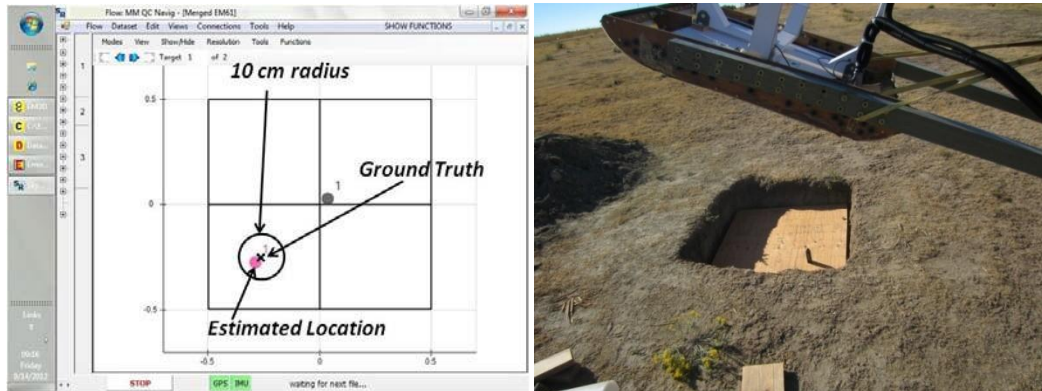


Figure 21. Estimated location verification tests. Targets were placed at several locations on the test grid (right) and the QC module was used to estimate the target coordinates (left). Tests verified the 10 cm accuracy was achieved.

4.4. Software Functionality

We tested the overall functionality of the QC module by performing a mock cued survey. We acquired GPS coordinates for several locations within the FLBGR compound area and placed target objects within a 50 cm radius of each location (the offset was varied to establish realistic target pick errors). We loaded these target pick coordinates into the QC module (step 2, section 2.1) and conducted a cued survey at each location. We tested the software functionality by going through the process of failing an initial acquisition, repositioning the sensor using the navigation interface and the estimated target location, and recollecting in the new location. An example of this sequence follows (Figures 22 – 32):



Figure 22. Mock cued survey performed at FLBGR compound. Target objects were placed near surveyed locations around the site.

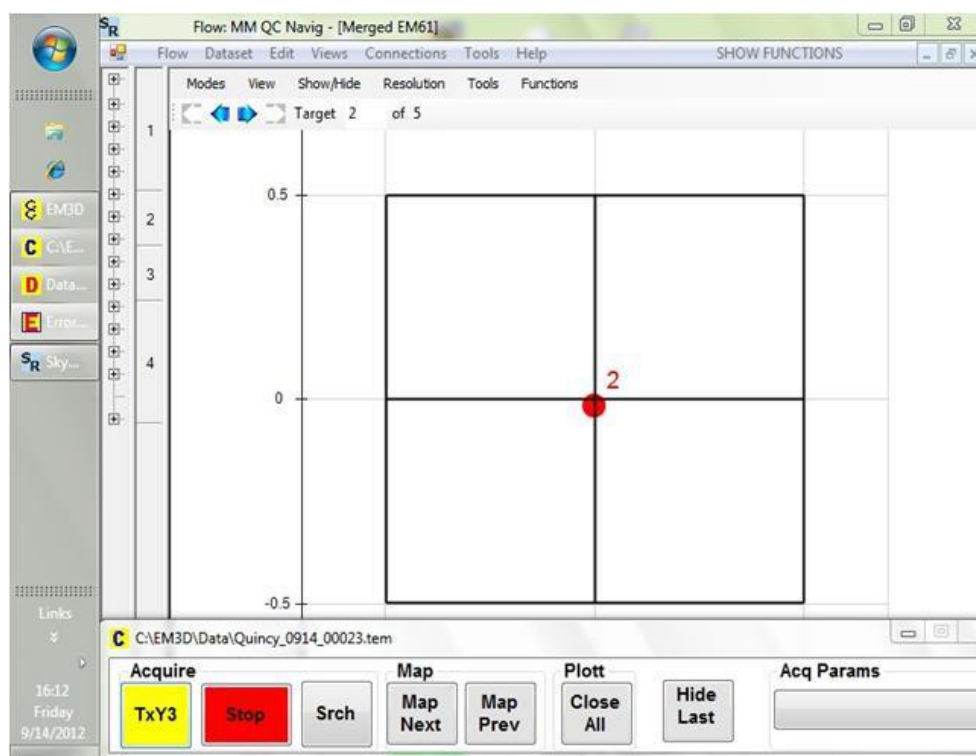


Figure 23. Navigation interface showing sensor position over one of the target pick coordinates (red dot). The EM3D software is in the process of acquiring a static data measurement.

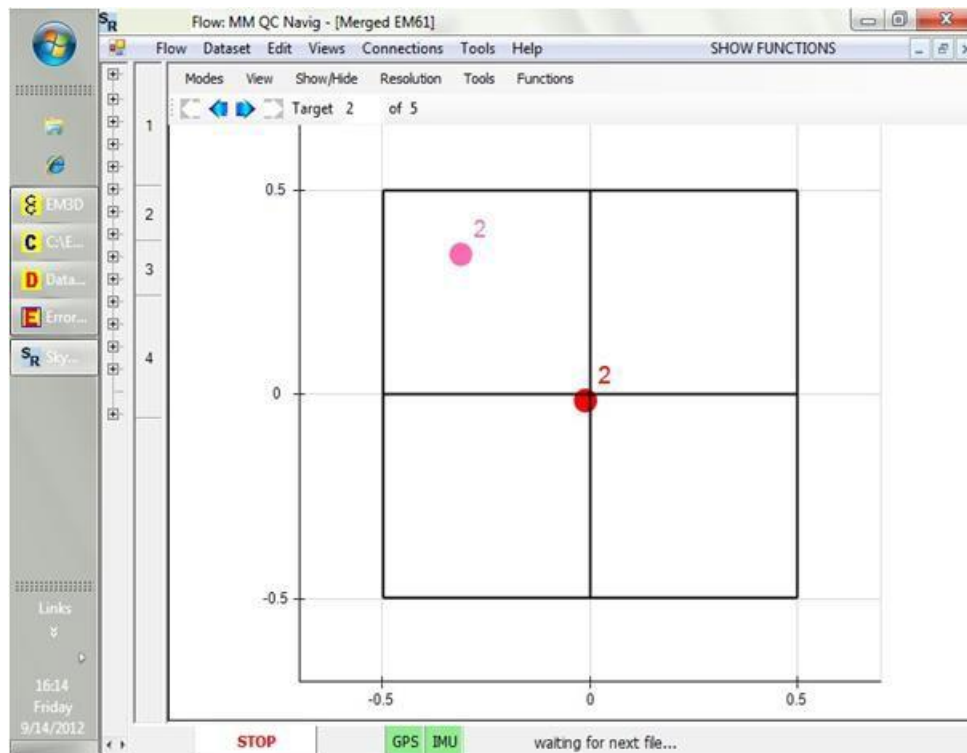


Figure 24. Once the acquisition is complete and the data file is created, the QC module updates the navigation interface with the estimated target location (pink dot).

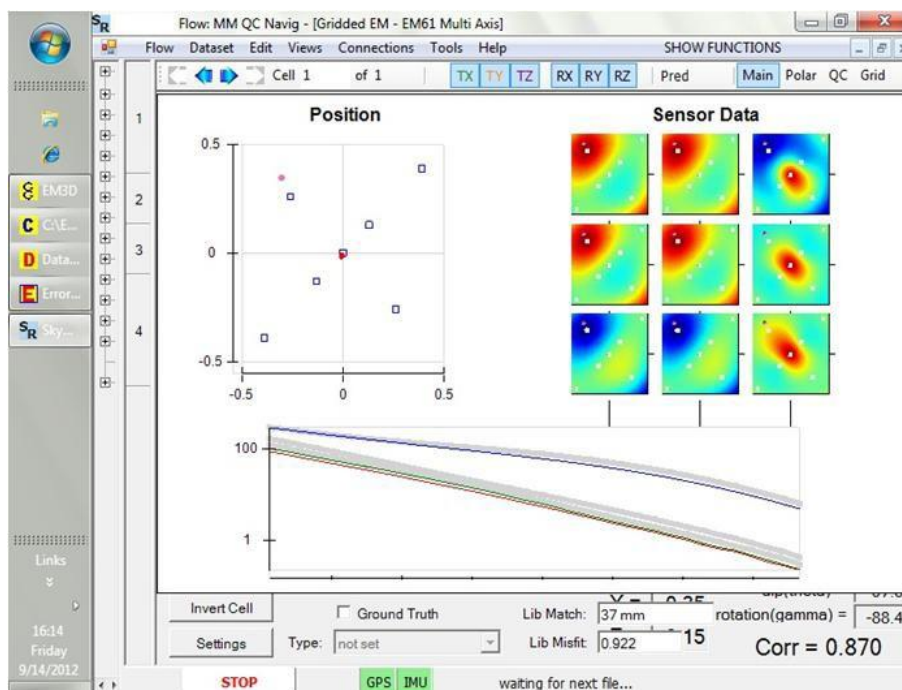


Figure 25. The QC interface is also updated to display the recovered location, model parameters, and best library match (note: some of these parameters do not display properly here due to the resolution of the monitor on which this image was captured).

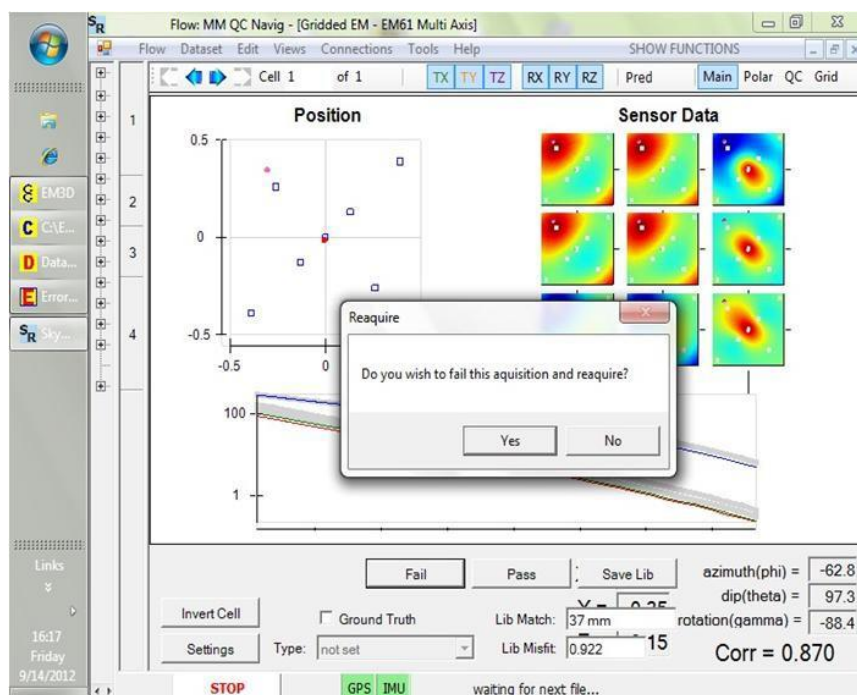


Figure 26. The QC interface prompts the operator to assess the quality of the acquisition based on the estimated location and model parameters. This particular case will be selected as a “fail” due to the large target offset indicated by the estimated target location.

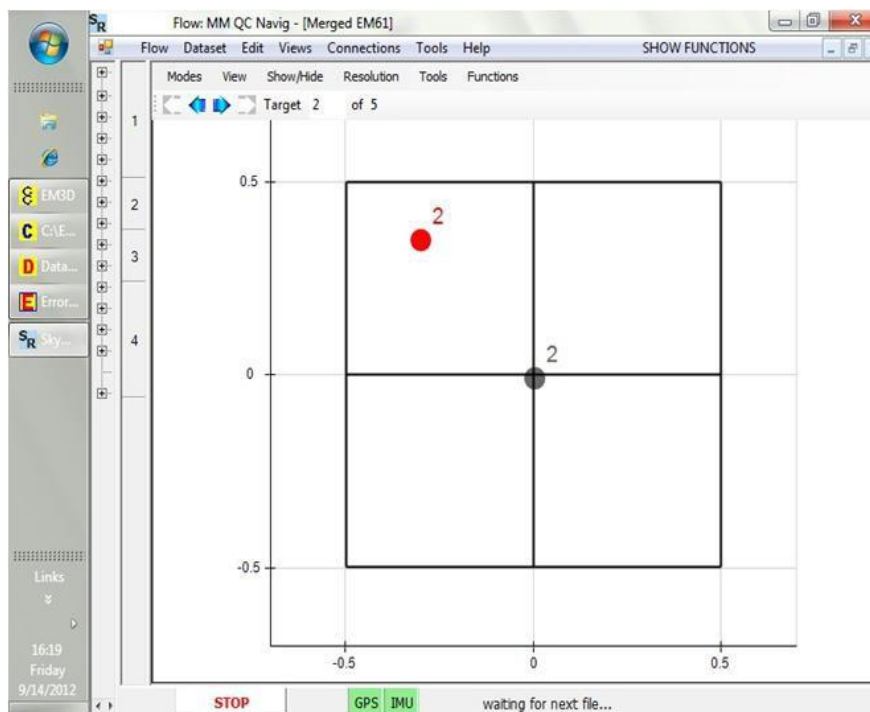


Figure 27. Once the initial acquisition is selected as a “fail”, the navigation interface is updated to reflect this decision. The initial pick coordinates are changed to grey and the estimated location coordinates are changed to red. The operator now repositions the sensor based on these new coordinates (red dot).

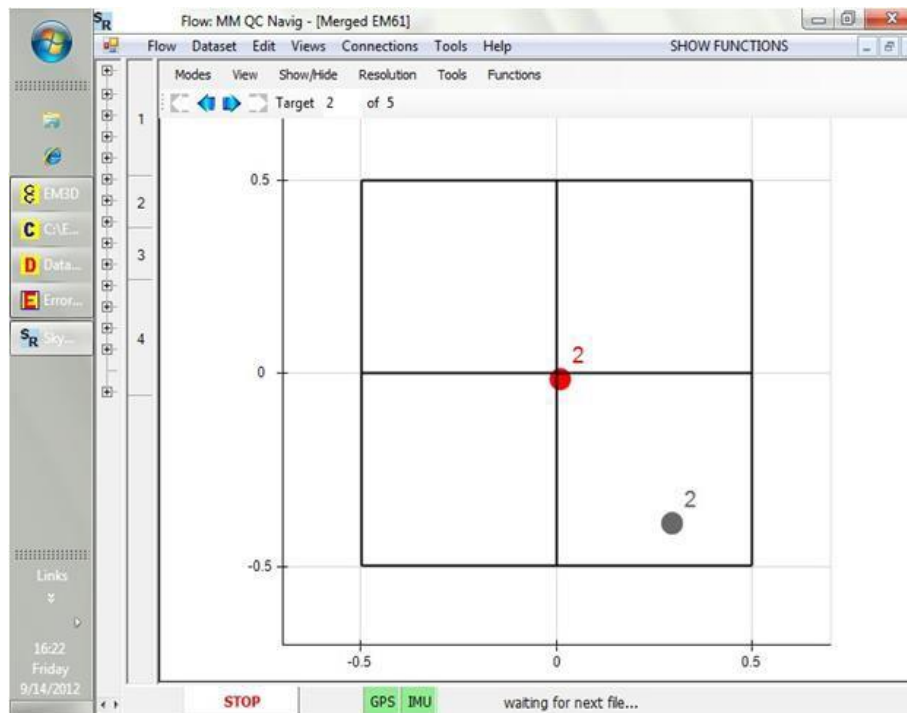


Figure 28. Once the operator repositions the sensor over the estimated target location coordinates (red dot), the operator can recollect the data.

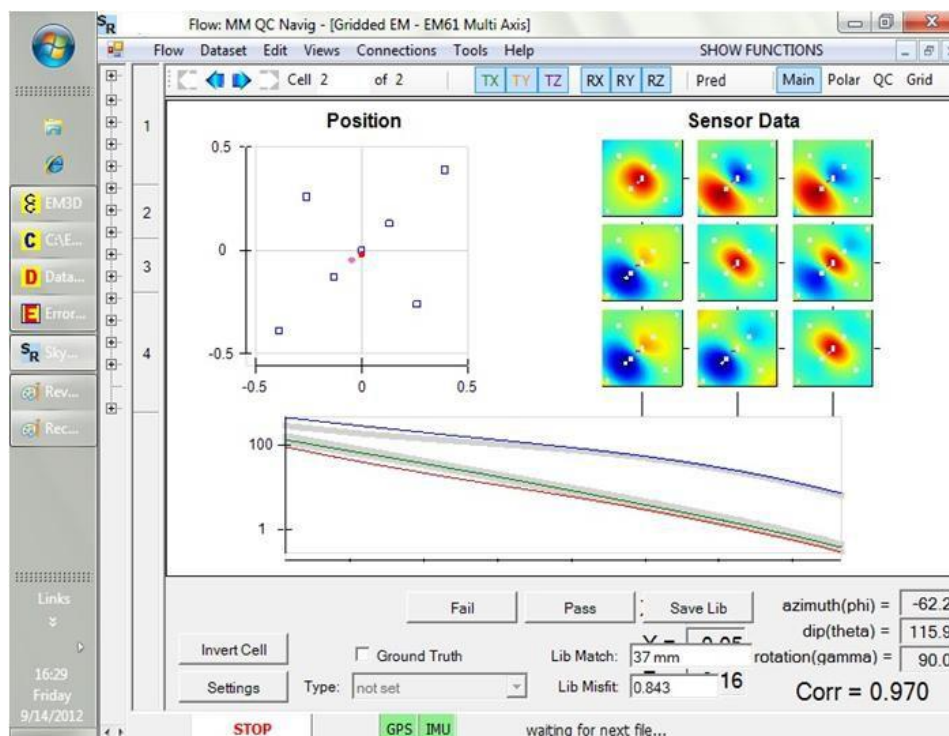


Figure 29. After the recollect is complete, the QC interface is updated with the recollect inversion results. In this example, the estimated target location (pink dot in the position plot) is now very close to the center of the sensor.

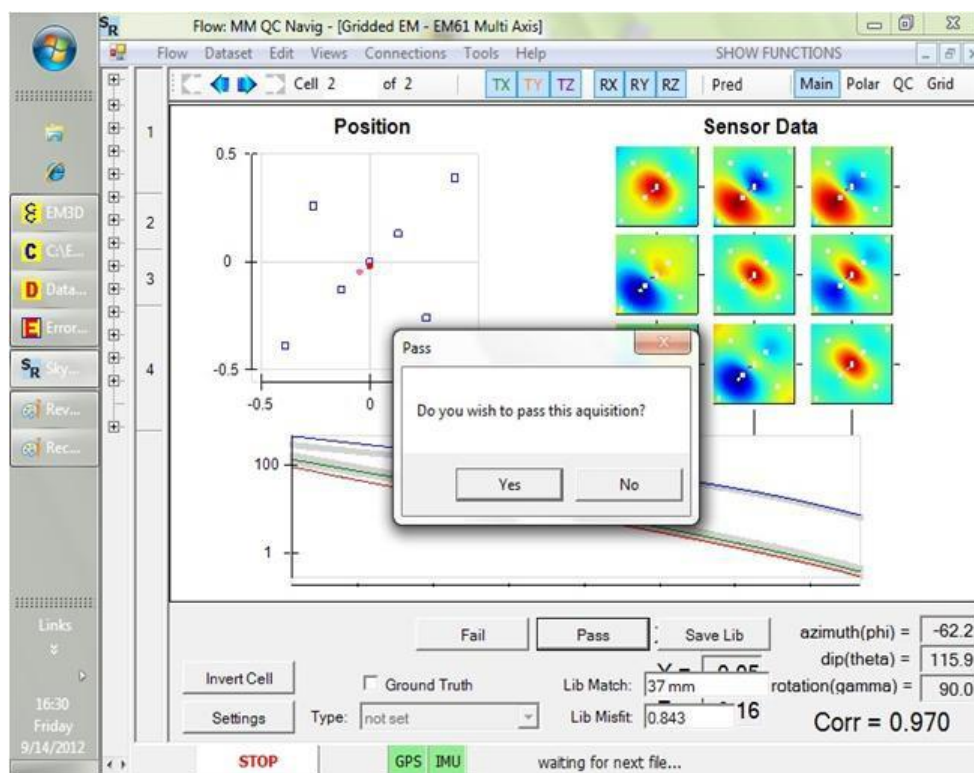


Figure 30. The QC interface once again prompts the operator to make a quality decision based on the new inversion results. This case will now be selected as a “pass” due to the consistent estimated target location.

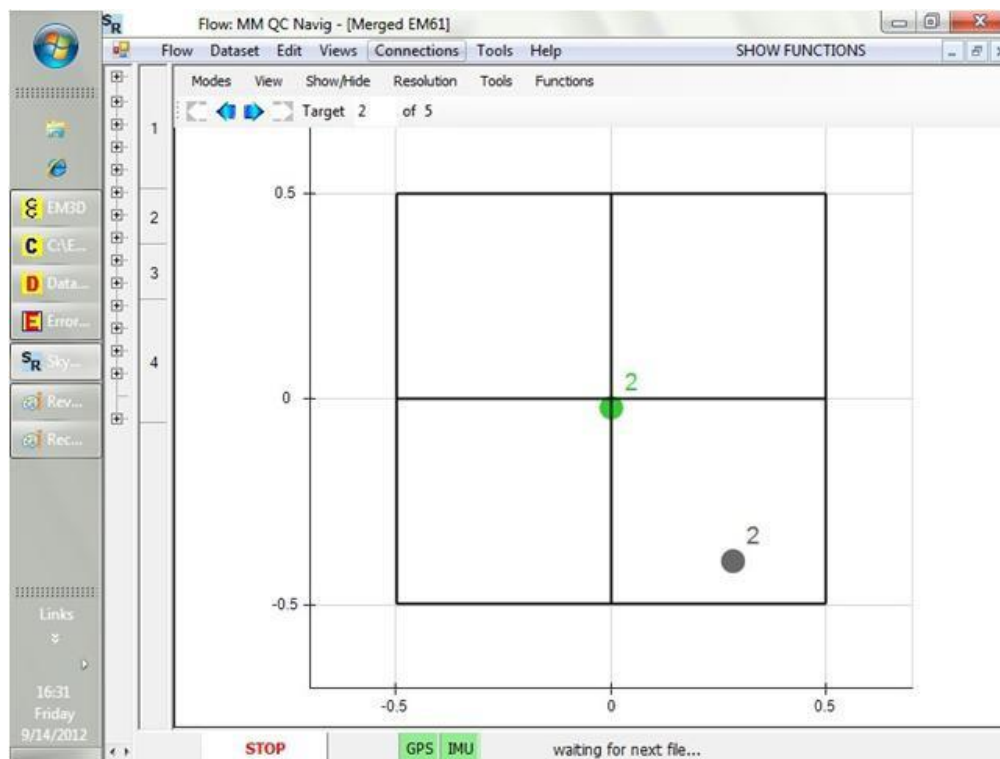


Figure 31. When the recollect is accepted, the estimated target location coordinates are changed to green. The original target pick coordinates remain grey. The operator can now proceed to the next target pick.



Figure 32. The actual target (37 mm) and the initial target pick coordinates (orange mark) corresponding to the survey described in the last several figures.

By verifying the functionality of the QC module during a mock survey, we were able to assess how well these additional in-field QC steps can be incorporated in a cued survey, and whether they would add any complexity to the overall survey process. We repeated the mock survey for numerous target picks and allowed several different operators to try the QC routine. Our initial assessment based on these tests is that the QC module adds a very intuitive sequence to the cued survey procedure. Once the QC and navigation flows are initialized, and the EM3D parameters are selected, very few additional steps are required during the actual survey. The general consensus, based on feedback from several operators, was that the QC module provides sufficient information for enabling quality decisions and corrective action, but not so much information that interpretation of the results becomes onerous.

5. Demonstration Phase

Following the proveout phase of this project, we will further evaluate our in-field QC process through a live site demonstration. While the proveout phase allowed us to assess the basic functionality of the software module and verify that it provides the desired capabilities, a live site demonstration will provide more insight into the operational aspects of implementing an in-field QC component to cued surveys.

As our overarching objective is to improve the efficiency of production surveys by ensuring in-field that cued data are acquired at a quality sufficient for classification, we will evaluate the effectiveness of our approach using two principal performance metrics: (1) total anomaly acquisition rate; and (2) total percentage of recollects.

To implement these metrics, we will demonstrate the in-field QC process at a production-level site and compare the performance of our approach against that of the current practice (i.e., off-site quality analysis only). We will perform a static MetalMapper survey of a statistically relevant number of samples (~1000-1500) while incorporating our in-field QC module. The number of acquisitions requiring corrective action (i.e., a recollect) will indicate the number of anomalies that would require a resurvey (i.e., a reacquire) if the in-field quality process were not in place. As part of this demonstration, we will implement the quality metrics analysis conducted as part of the initial proveout phase to determine the necessity for data recollects during the survey. Based on the specific site characteristics (e.g., anomaly density, geology, etc.), we will define the quality objectives for each metric. For example, the estimated location offset threshold will be chosen to reflect the targets of interest, the depth of detection, and the local anomaly density. Additionally, the site characteristics will also determine how we apply additional metrics in the form of a figure of merit. It may be beneficial, for this demonstration, to apply a figure of merit during post analysis to determine how many recollects could have been averted.

To assess the overall efficiency gains, the acquisition rate for anomalies that do not require recollects will indicate the baseline acquisition rate for the current practice (the real-time inversion adds a negligible amount of time to each acquisition). For acquisitions requiring recollects, we will compare the timestamp of the initial data acquisition to that of the corrective data acquisition. This difference will indicate the additional time required to perform a recollect. To determine the overall reduction in survey time afforded by the real-time quality control process, we will compare the total time spent on recollects to the total time that would be

required to redeploy and reacquire those anomalies at the baseline acquisition rate. Thus, the outcome of this demonstration will be a quantifiable assessment of any productivity gains resulting from the in-field quality analysis.

6. Future Development

Based on our testing to date, the QC module shows significant promise for improving the efficiency and overall quality of production cued EMI surveys. The ability to perform real-time inversions of the cued sensor data and present the corresponding quality metrics to sensor operators will enable in-field quality decisions that will likely produce better classification results.

Incorporating the QC module into live site demonstrations and production MMRP surveys will help to establish the best practices for implementing these quality metrics. For example, production surveys will require DQO's to establish the reliability of these metrics at each site. The more opportunities that we have to practice in-field quality decisions, the more information we will acquire to guide the development of these DQO's and quality metric thresholds.

As we look beyond the current scope of this project, there are several opportunities to further extend in-field QC capabilities based on the initial development conducted during the proveout phase. Specifically, these opportunities include:

1. Incorporation of multi-object inversion capabilities into the in-field software module. This would enable better quality decisions in high density areas. Ideally, adding the multi-object capability would be transparent to the operator; the decision to use a multi-object inversion versus a single object inversion would be automated and dependent on the value of certain model parameters.
2. Extension of the in-field QC module to additional cued EMI sensors such as the TEMTADS and MPV instruments. The MetalMapper shows significant promise for gaining MMRP acceptance; however, other sensors are likely to follow. By applying the QC module to other sensors that implement different operational modes (e.g., handheld, towed, etc.), we can ensure that the quality practices are developed for these instruments before they are incorporated in MMRP projects.

We are confident that the QC module provides capabilities that are highly relevant to current MMRP practices. Further demonstration of these capabilities will enable us to refine in-field QC practices to ensure the future success of classification surveys performed in production environments.