Finding and Identifying Objects Based on Noisy Subsurface Data: A Global Optimization Approach.

Part 1: Theoretical Approach and Applicability with Deployment Examples.

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Subsurface Object Identification

- Identification of Objects in the Subsurface has significant challenges:
  - Can't "see" below ground.
  - Data collection is expensive, often sparse.
  - Some objects are stationary, some mobile.
  - Some objects change in shape over time.

Objects can consist of groundwater plumes and DNAPL sources, UXO and landmines.

Subsurface Object Identification:

- It's a technique for modeling and identifying objects of interest in subsurface systems which consist of noisy, sparse data.
- Similar to photographic image analysis and the 3D reconstruction problem.
  - Pictures have many pixels per inch.
  - Much less information density in the subsurface (data points per square meter to square mile).

Technologies & Algorithms

- Information Theory
- Physics Based Modeling
- Signal Processing/Filtering
- Medical Imaging
- Machine Learning
- Cognitive Modeling
- Global Optimization

Challenge is to fuse the information content to extend the accuracy of predictive modeling.

Extension of Sensor Interpretation (SI)

- The tools developed and tested are a form of *situation assessment*, which is they provide a determination of explanation(s) of the sensor data and other information.
- In these examples, the *other* information is derived from the non-sensor data/evidence; the physics models and subject matter experts.

Tools developed are fused data, physics, and subject matter expert algorithms.

Demonstrations

- Cone Penetrometer Data to predict percent fines.
- Plume Finding, with uncertainty reduction.
- UXO finding and field clearing.

Cone Penetrometer

- Data collected from Cone Penetrometer.
- Tip and sleeve friction / pressure recorded.
- Predictive models:
  - Physics model => $R^2 = 0.26$ to 0.40.
  - Data mining => $R^2 = 0.60$
  - Fused model => $R^2 = 0.72$

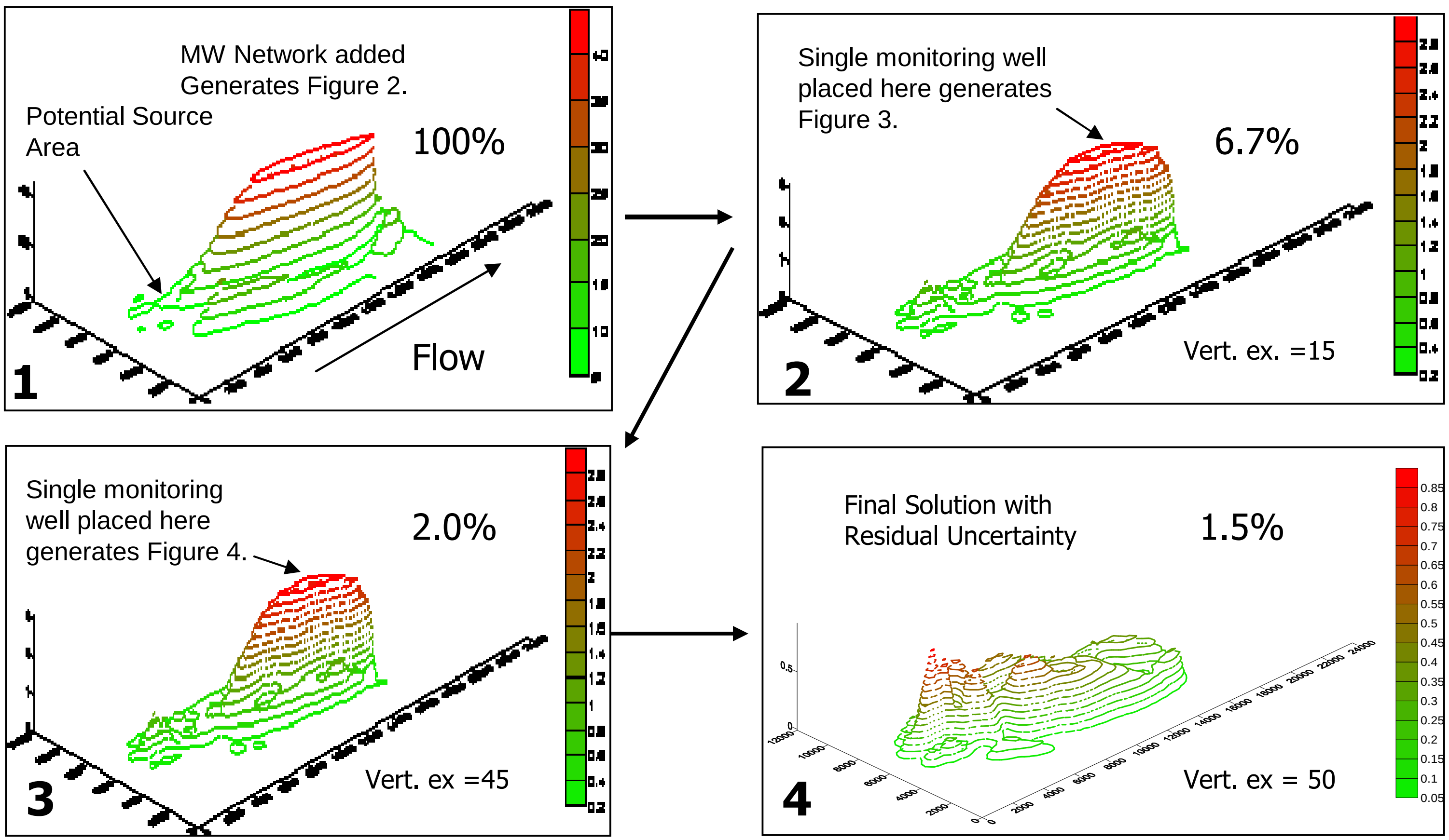
Only the fused model approach achieved the project objectives of $R^2 > 0.70$.

Plume Finding

- Potential plume area: ~ 9 square miles.
- Number of data points <50.
- Plumes are mobile:
  - Physics model (groundwater flow and transport).
  - Data model (from sampling).
  - Fusion technique (Kalman Filtering).

Objective is to quantify uncertainty of plume with existing monitoring wells, propose optimal location and quantify value for new ones.

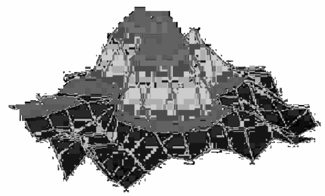
Plume Finding Analysis and Results: Effect of Monitoring Well Network Information on Plume Delineation and Uncertainty

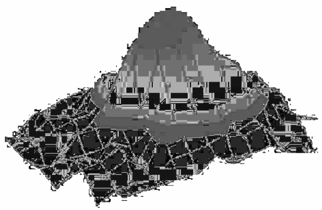


Initial normalized uncertainty reduces from 100% to 1.5% thru addition of monitoring wells.

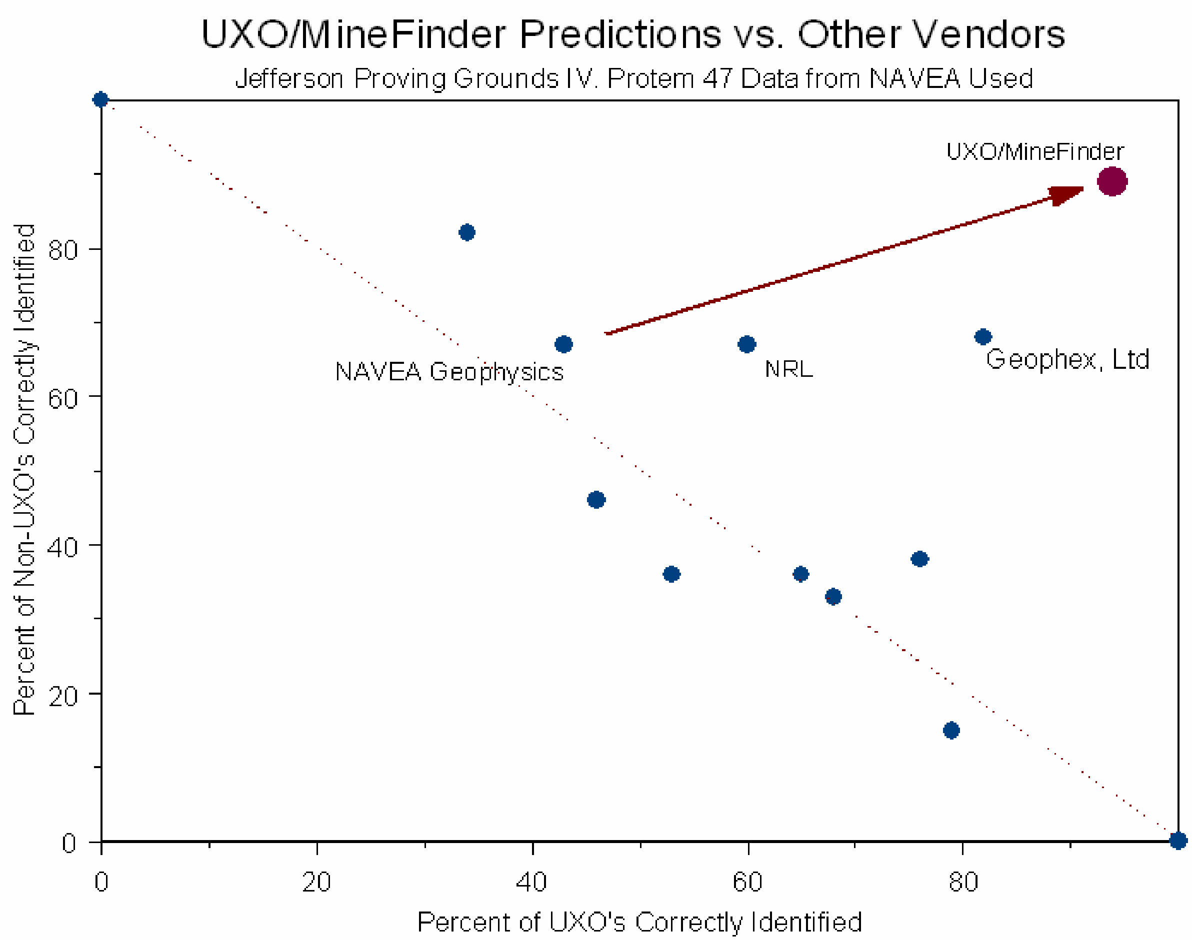
UXO Discrimination

- Unexploded Ordnance
- Manually Identified, labor intensive.
- Examples to right:
  - Clutter on top.
  - UXO on bottom.





UXO Discrimination
First Prove-Out:
Jefferson Proving Grounds IV



Peer reviewed approach *greatly* surpassed other published methods.
Better tools are predictions closest to the upper right corner.

Published Data Mining Results on JPG-IV

Well-Conducted data-mining only (Banks, 2005) approach less accurate than information-fused (Deschaine, 2002) approach.

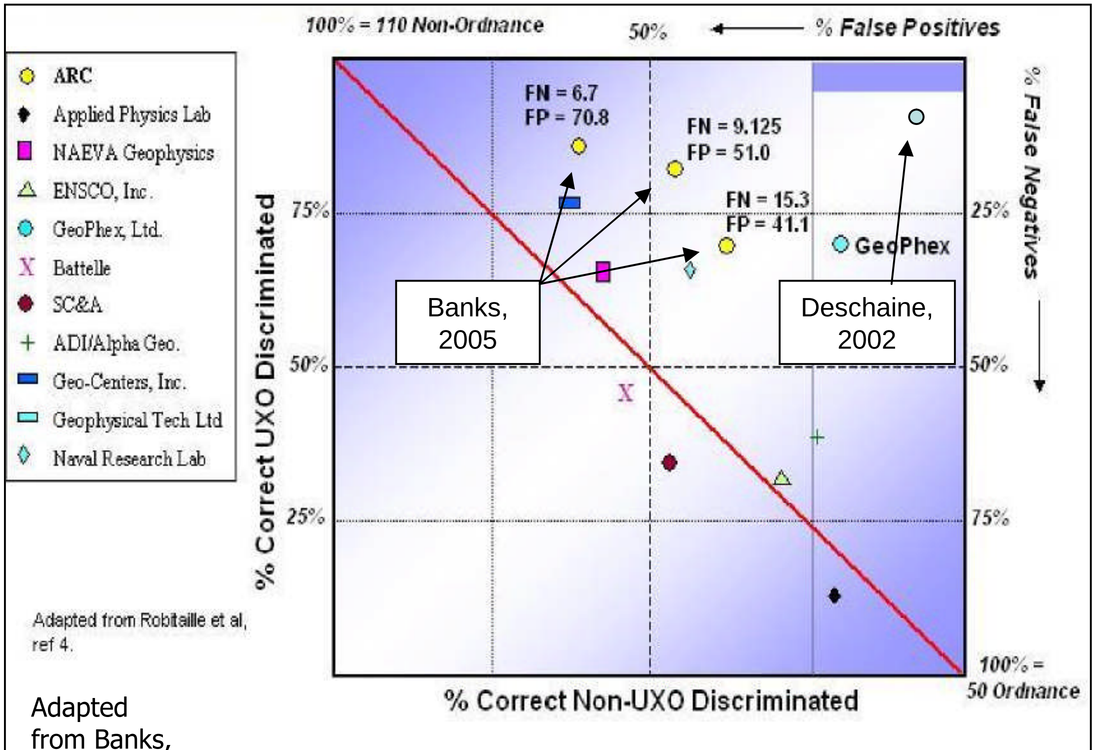
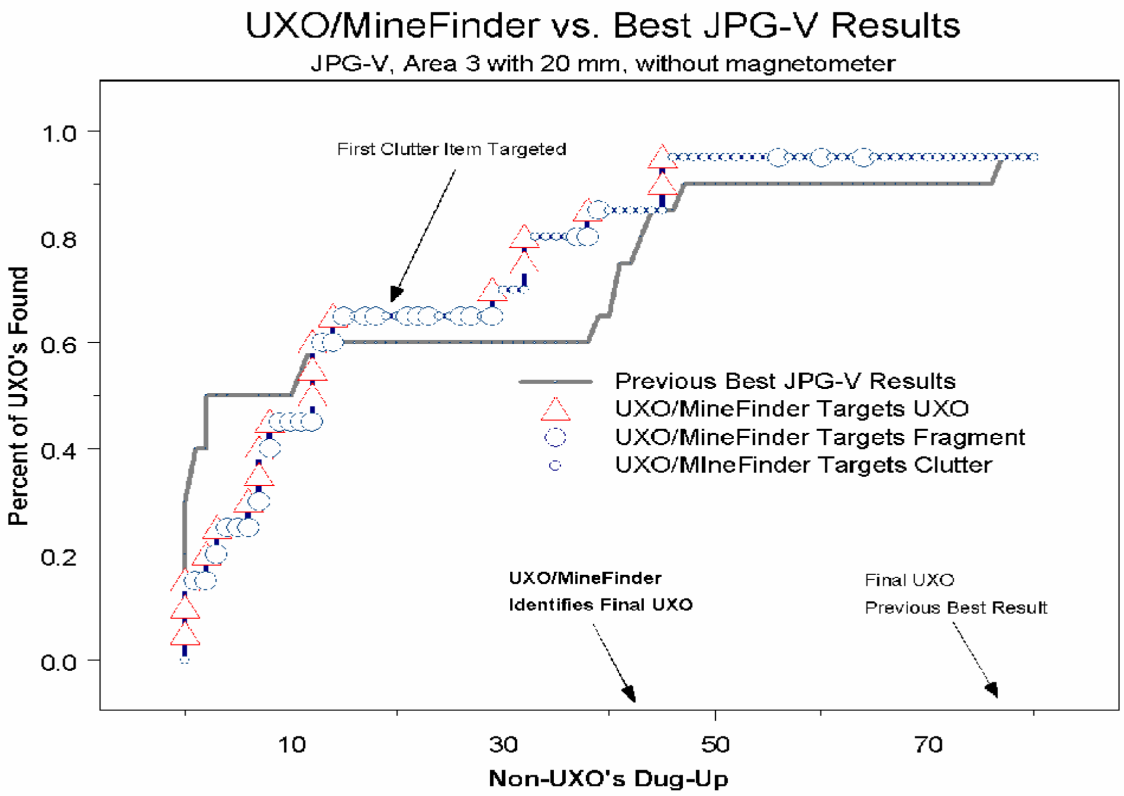


Figure 3. SMDC/ARC Results

(Banks, 2005) Provides independent validation of GP approach for UXO discrimination.

UXO/MineFinder—JPG-V Results.

ROC Curves: UXO/MineFinder vs. Previous Best



UXOMF™ second prove-out: Again best of all published results.

Part 2 – UXO Finding and Discrimination: Results from Field Production.

Translation of R&D work into
Field Production Tools
UXOMF^{TM}

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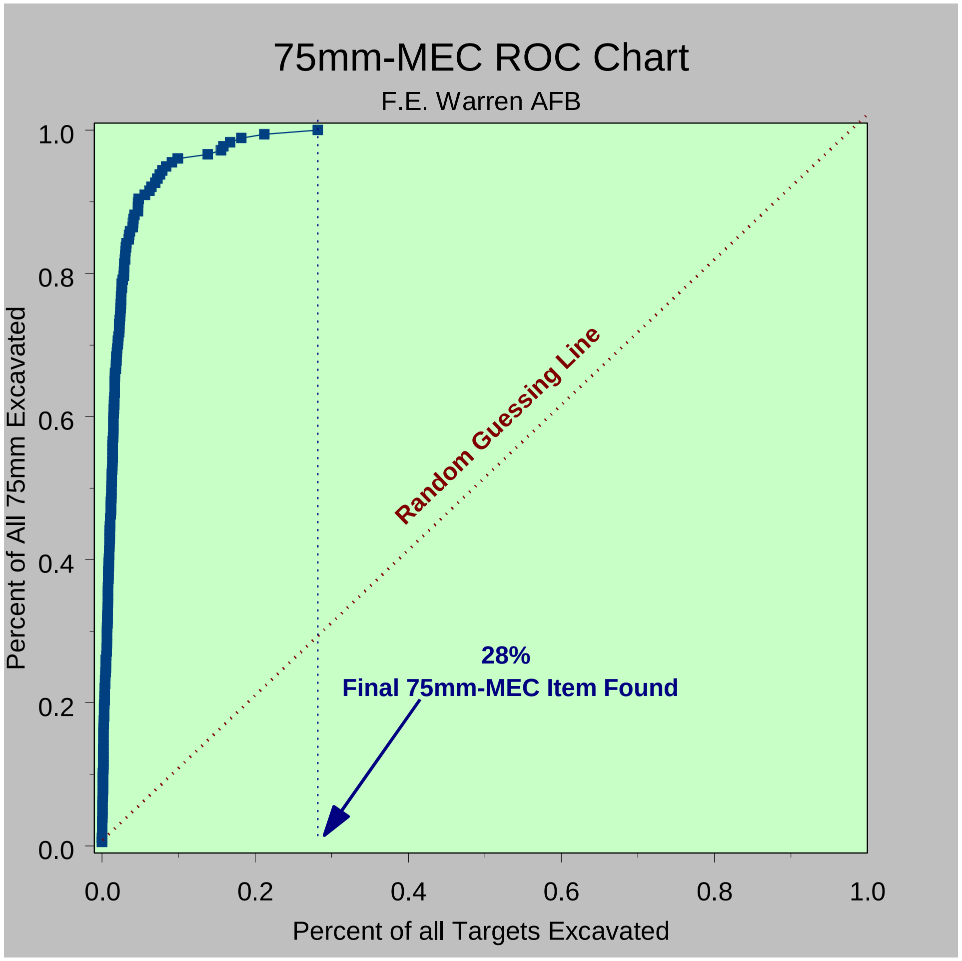
Research → Production Tool UXOMF™

- Further refine and extend algorithms.
- Production quality code.
- Production quality system.
- Deploy on data collected from UXO field survey.
- Previous excellent results repeated.

Success Repeated Using UXO Production Data – 75mm

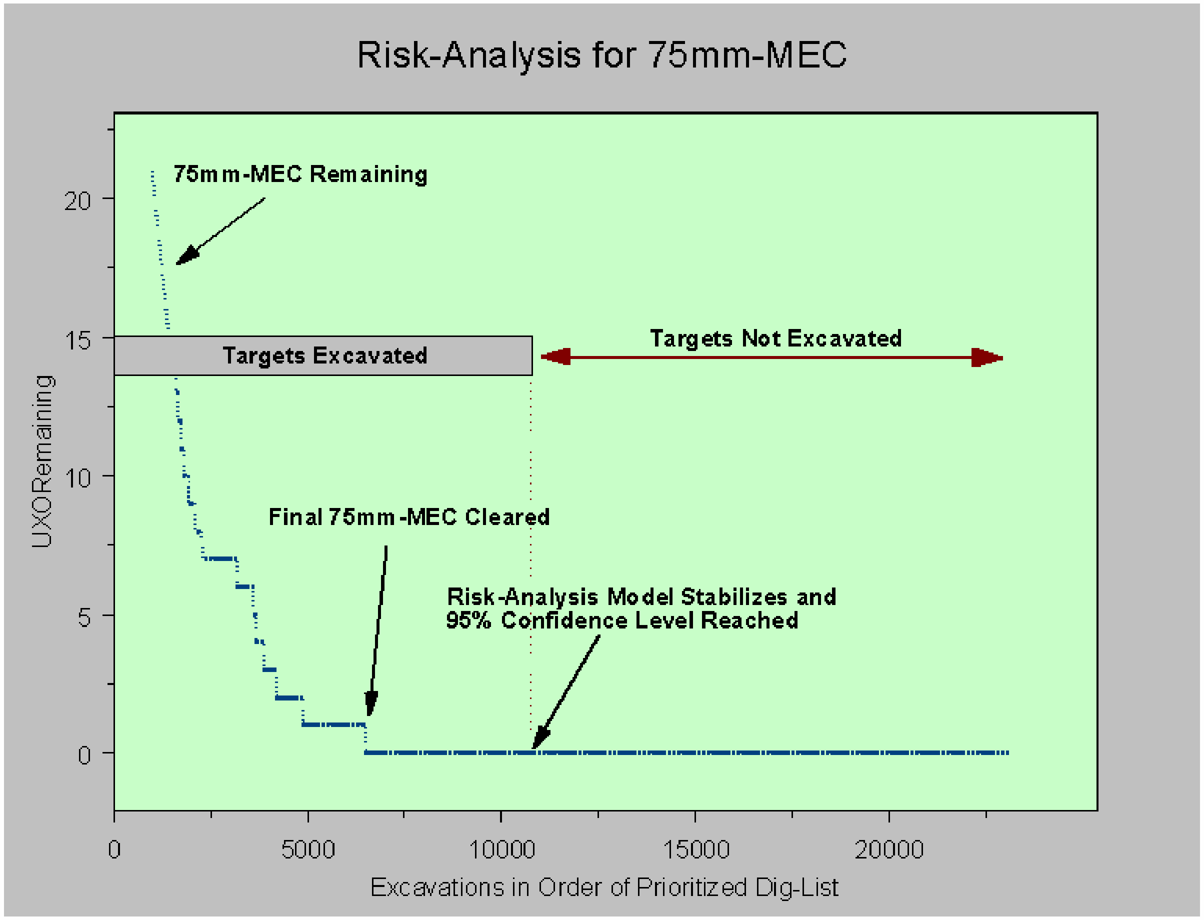


Final MEC is found after digging only 28% of the Targets.

Donated by:Wayne Schoer
Australian Army EOD Tech

Example of a 75mm Projectile.

Success Repeated Using UXO Production Data – 75mm

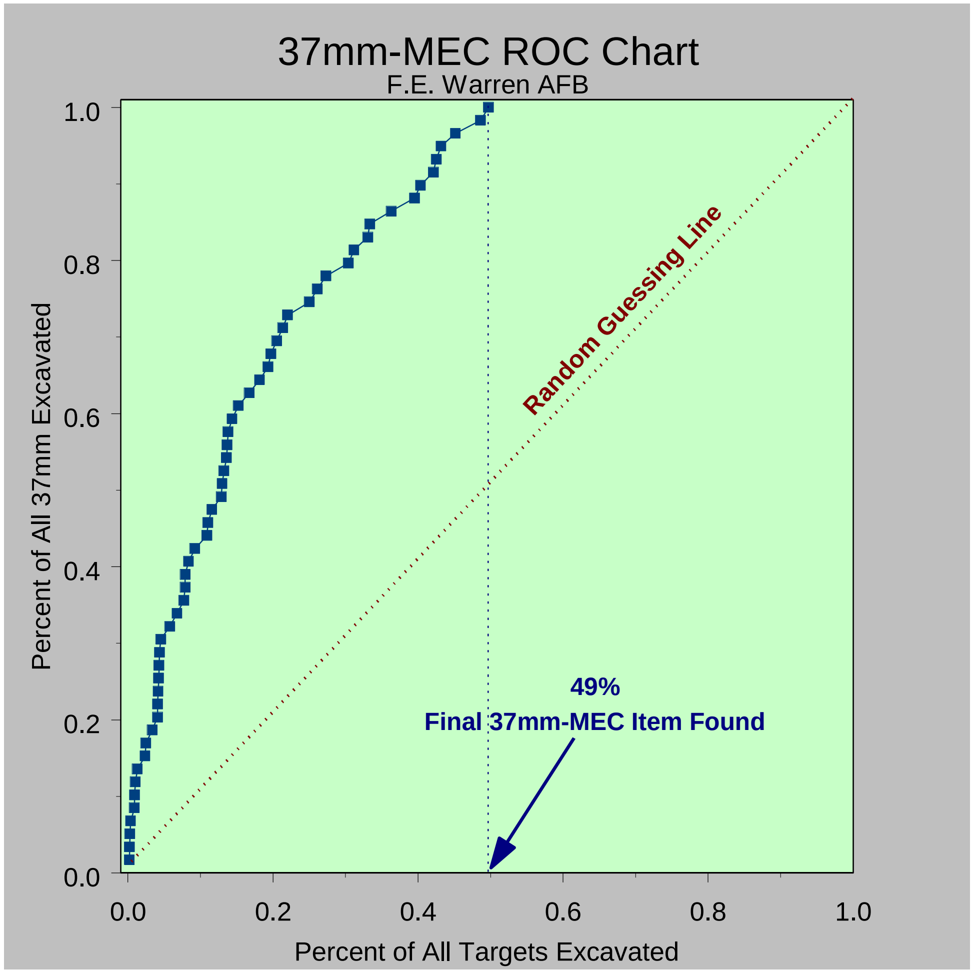


Note: Excavation continues even after the final 75mm in cleared until the predetermined confidence (stopping) criteria is reached.

This is because we do not know apriori when to stop.

Tool supports that decision.

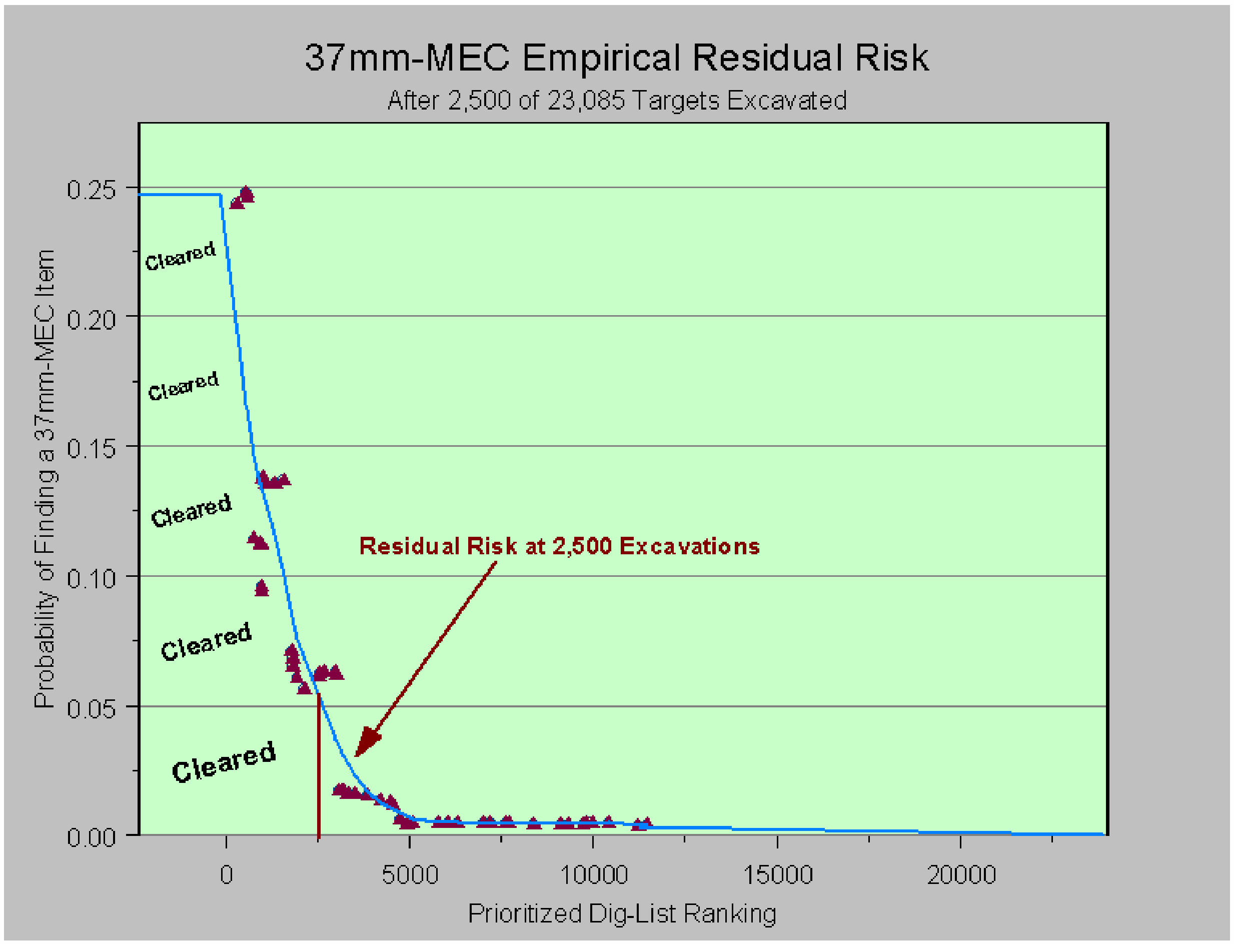
Success Repeated Using UXO Production Data – 37mm



Final MEC is found after digging only 45% of the Targets.

Example of 37mm Projectiles.

Success Repeated Using UXO Production Data – 37mm



Here we show how the residual risk declines with additional excavations.

Summary of Production Run: UXOMF™

- Actual production data on major UXO cleanup
  - Ordnance specific discrimination
  - Physics based feature extraction
  - Over 900 features extracted and analyzed
- LGP results reduce excavation costs by 30-50%

Information-fused Approach

- Uses Linear Genetic Programming as the Integrator.
  - Determines which inputs / models are of value, which are not.
  - Helps focus information needs.
  - All solutions inspectable, not a black box.
  - As the data, physics or subject matter expert sub-models improve, so do these tools.

Journal Publication in Progress.

Complementary advance copy available upon request.

Summary

- Subsurface Object Identification is a complex challenge involving sparse data in noisy environments.
  - By fusing the information content of data, physics and subject matter expert models, extensions to accuracy are made.
- Work accomplished using published, publicly available algorithms / software.
  - Extended and refined by authors for specific task.
- Best of any published results for UXO.

Thank you for your attention!

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