Optimization of Large Scale Subsurface Environmental Impacts: Investigations and Long Term Monitoring.

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Why Optimize Investigations and Monitoring

- Efficient and effective use of information gathering resources.
- Subsurface aquifer protection
  - Improved response decisions.
  - Reduce risk of monitoring network failure.
- UXO:
  - 10 million acres, 1400 sites, DOD indicates that typically 100 holes dug before a single UXO is unearthed.

Corollary Between Military and Environmental Applications

- Military
  - Target identification
  - Target location
  - Target tracking
- Environmental
  - UXO/MineFinder
  - Plume finder
  - Long term monitoring

Solves the stationary or transitory boundary / topology challenge

Overview of Value

- Simulators provide a mathematical statement of subsurface current and expected future conditions.
- Optimization guides decisions that are defensible.
  - When is the sampling network good enough?
  - What is the best mix of low, medium and high quality data? Over time?
  - What data / parameter mix is best?

How Optimization Helps Aquifer Investigations

- Tells when to stop adding wells to delineate a plume.
- How to monitor it over time.
- When understanding of subsurface is supported by data.

See: Deschaine, L. M., Simulation and Optimization of Large Scale Subsurface Environmental Impacts; Investigations, Remedial Design and Long Term Monitoring. Journal of "Mathematical Machines and Systems", National Academy of Sciences of Ukraine, Kiev. No 3, 4. 2003. Pages 201-218.

How Optimization Helps UXO Discrimination and Remediation

- Identifies UXO in less attempts than other competing approaches:
- Initial prove-out at JPG-IV.
  - Same data used: transformed “guessing” to high accuracy.
- Extended prove-out at JPG-V.
  - Next best required 62% more holes than this approach.

Approach: Optimal Estimation

- Integrated algorithms consist of:
  - Simulation models based on physics.
  - Simulation models based on data.
  - Uncertainty handled through (geo)statistics.
- Information content fusion:
  - Signal processing (i.e. Kalman Filters, etc.)
  - Genetic Programming.

Optimal policy design uses a wide assortment of algorithms depending on problem formulation.

Fundamental Differences between Estimation

- Current methods typically gather data, calibrate model and use model for predictions.
  - Models break down as physics becomes complex, data sparse or input parameters not well known.
- This method fuses the information content via signal processing / machine learning algorithms:
  - Integrated data/physics model provide optimal estimates based on knowledge gain from both the physical simulator *and* the data.

Robust Environmental Simulators

- SA_MAPS
  - Stream - Aquifer Management and Planning Simulator
- BioFT3D/MINTEQ
  - Flow and Transport in the Saturated and Unsaturated Zones in 2 or 3 Dimensions
- BIOSLURP
  - Multiphase Hydrocarbon Vacuum Enhanced Recovery & Transport
- MOFAT & NAPL 2D/3D
  - Multiphase Flow and Transport of Multicomponent Organic Liquids

For additional information, see rasint.com & georgepinder.com

Developing Models from Data

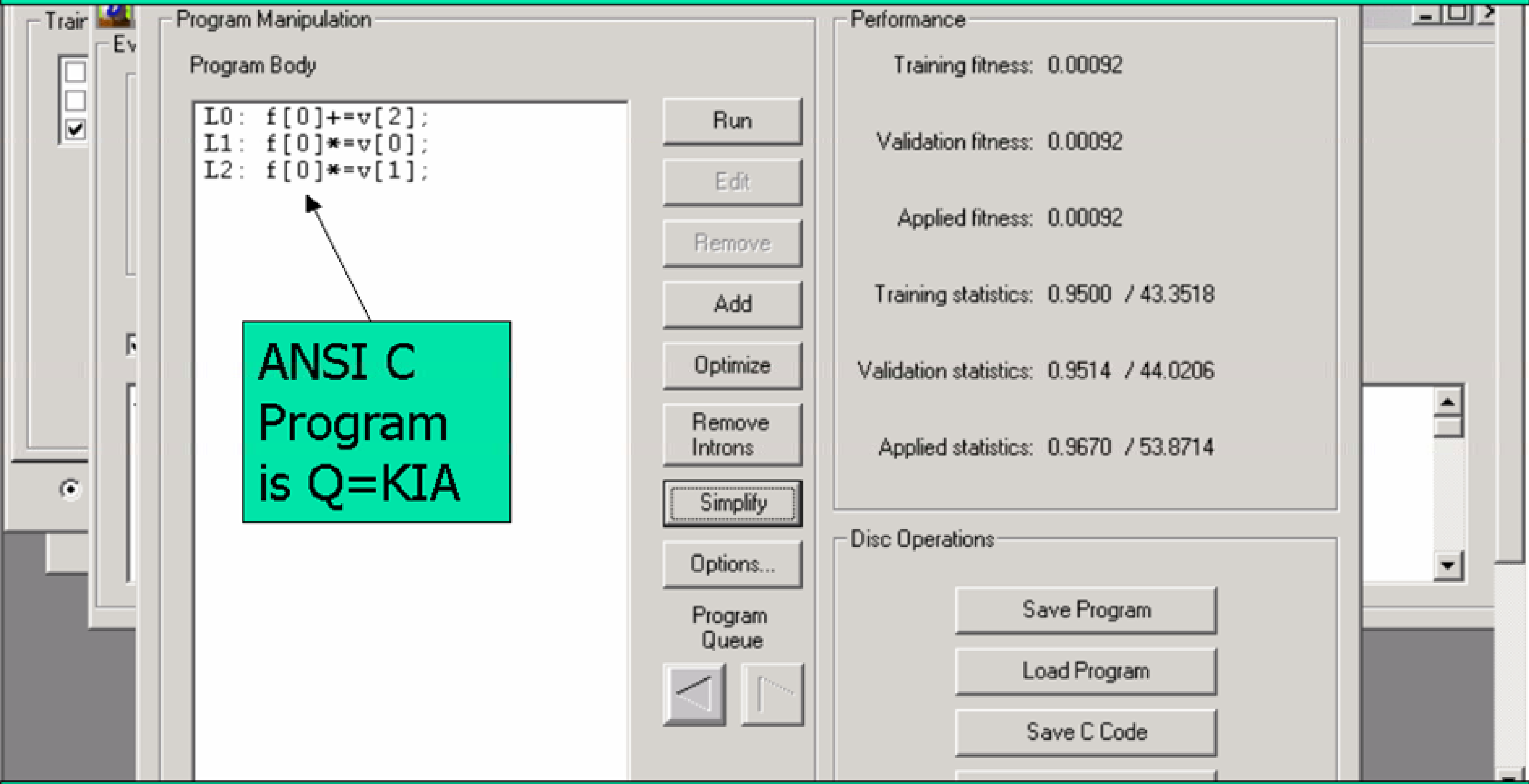
- Sometimes a simulator has not been written for a process, but data is available.
- Genetic programming is also used to develop a model or subroutine from the data.

Francone, F. D., and Deschaine, L.M., Extending the Boundaries of Design Optimization by Integrating Fast Optimization Techniques with Machine-Code-Based Linear Genetic Programming, Information Sciences Journal, Elsevier Press, Vol. 161/3-4 pp 99-120: 2004. Amsterdam, the Netherlands.

Examples: Developing Models from Data

- Hydraulic conductivity
- Unconfined compressive strength
- Leachability Index
- Vapor emissions from the ground
- Percent fines from CPT data
- Emissions from waste incineration
- Soil classification from LandSAT
- Power plant, etc.

Deriving subroutines and physical models from data using linear genetic programming and evolution strategies – Darcy Law Derivation



Darcy's Law [Q=KIA] was derived by Linear Genetic Programming on March 11, 2001

Plume Finding

- Finding a plume is like finding a target’s boundaries:
  - Extended approaches of Wiener, Kolmogoroff, Kalman, Lindgren and Nordin.
  - Goal is to reduce the uncertainty in the estimation of target’s boundary location, it’s fringe.

Plume Finding Technology

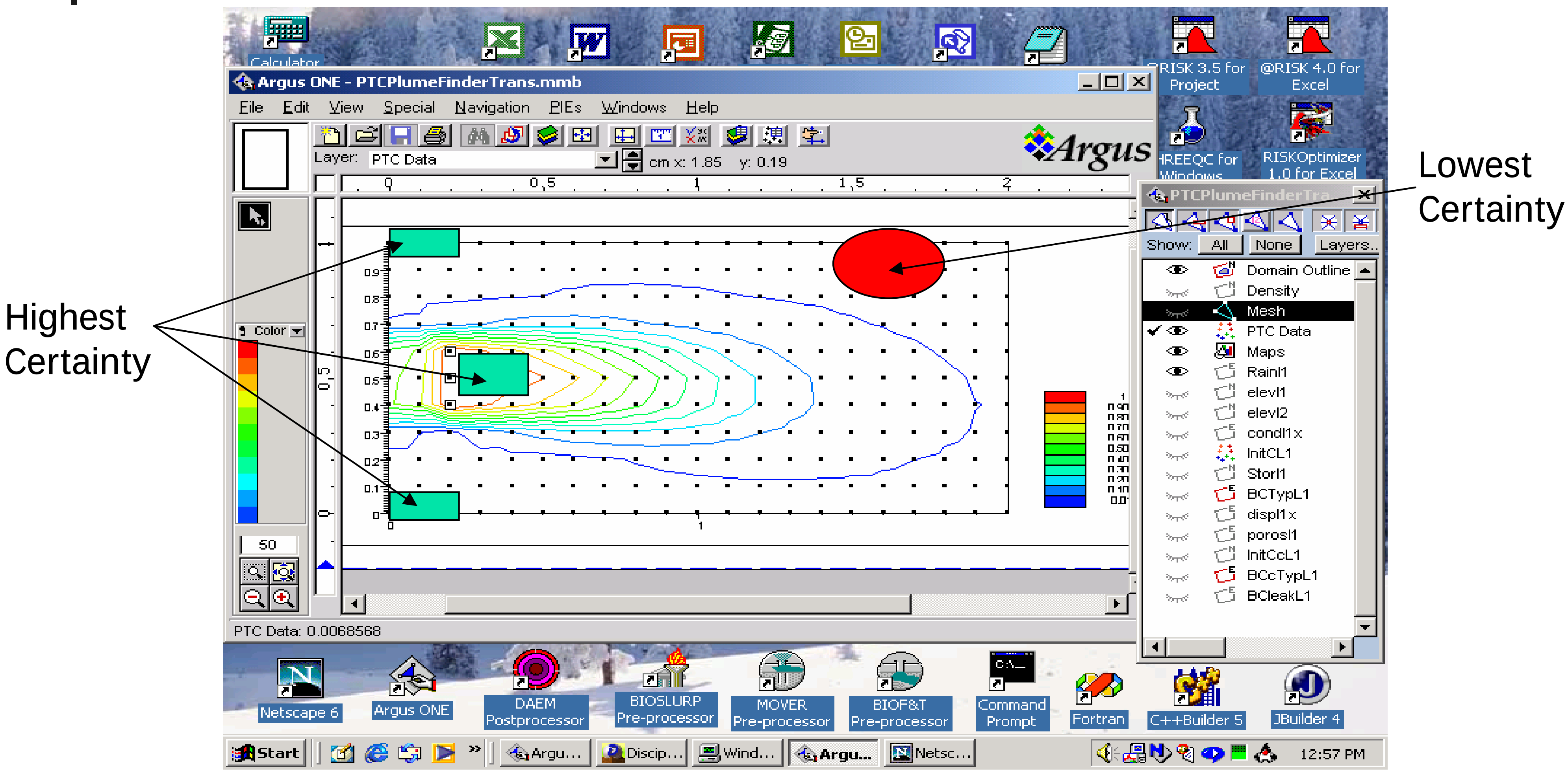
- USEPA requires certainty in plume location in order to evaluate remedial options, including.
  - Monitored natural attenuation.
  - Active remediation.
  - Technical impracticability.
- USEPA recognizes that the plume fringe location is a “zone”, not a line.

Need to perform site investigations in a cost effective manner while maintaining accuracy.

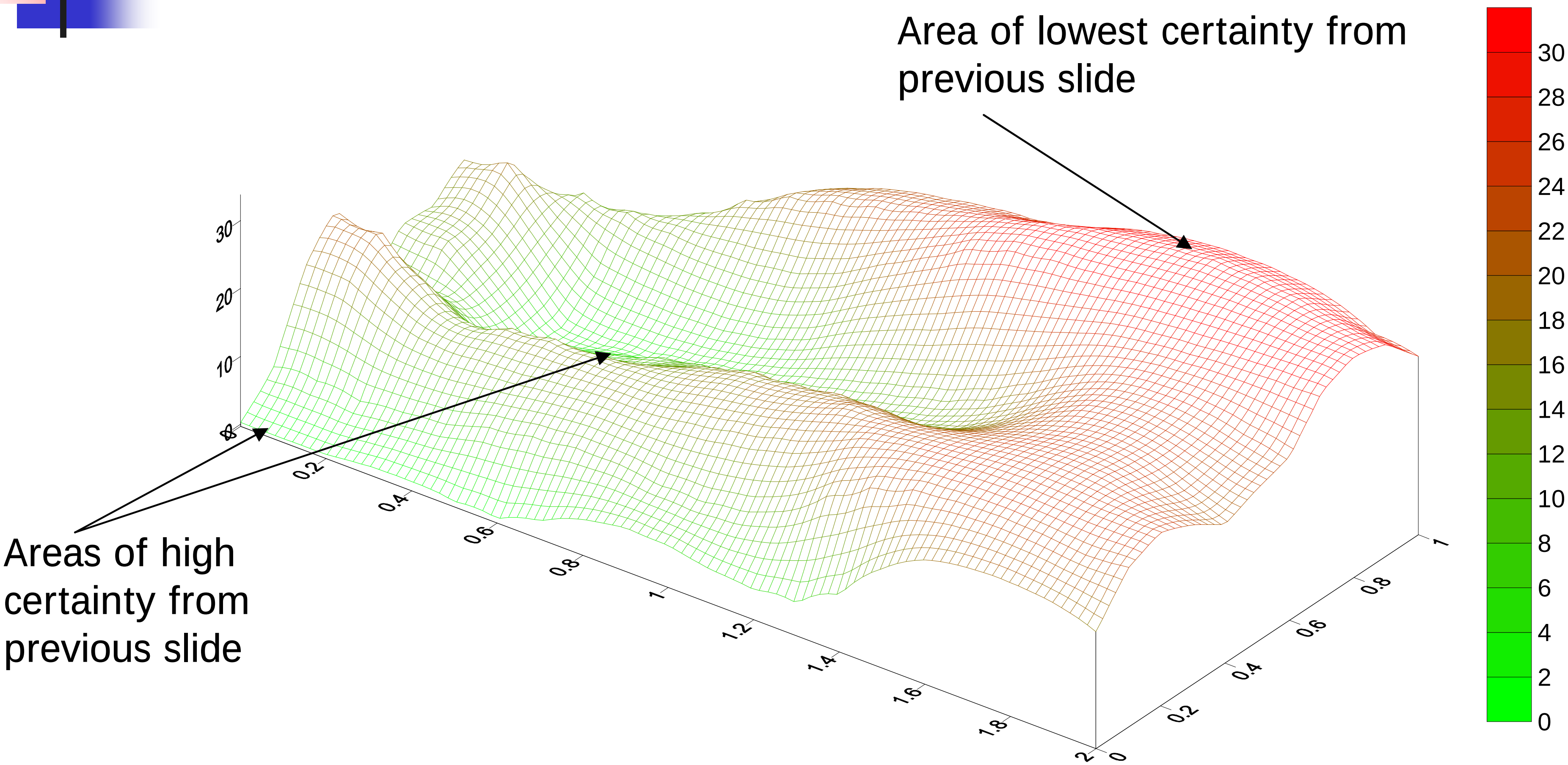
Example Solution

Red: Least Plume Fringe Certainty [Best area to install new well(s)]

Green: Best Plume Certainty [New well provides almost no value.]



Output: 3D Rendering of Uncertainty



The higher the output value, the more uncertain we are about where the plume is, and the more valuable a well is in this location.

Red is uncertain, green is higher confidence.

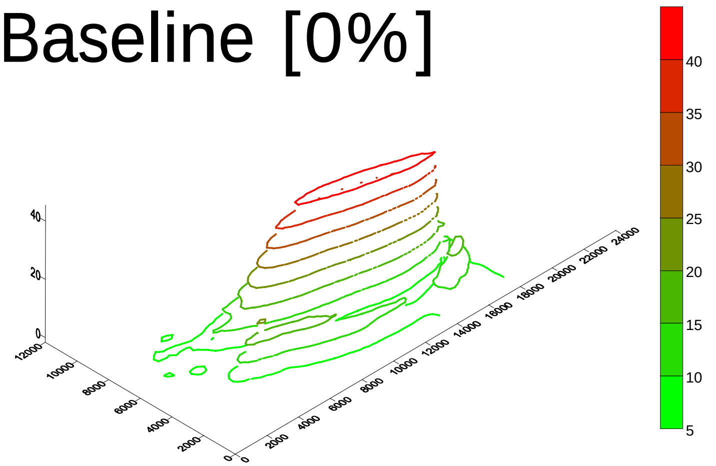
Complex Application

- Site investigation area about 9 square miles.
- Between 6 & 12 wells deep wells (100's of feet) were considered for installation.
- The plume finding technology assessed that the existing MW network was already very good, and that perhaps 1-2 more wells (if any) would satisfy the project's objectives.
- Results presented to DOE, EPA and state regulators. Both analysis and conclusions were accepted.

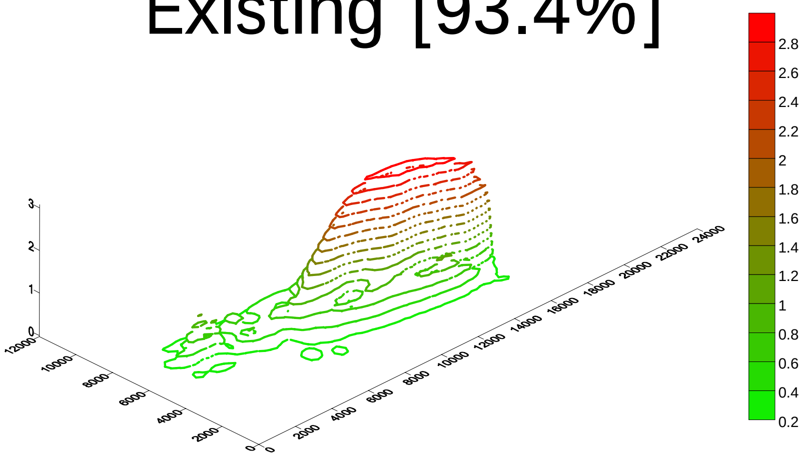
Summary of PlumeFinder Analysis

Value of Additional Wells, Scale Exaggerated To See Results
[Results of 4000 flow and transport simulations]

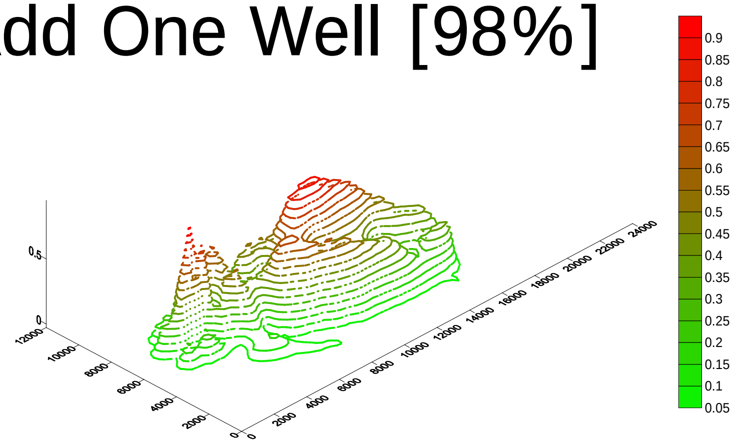
Baseline [0%]



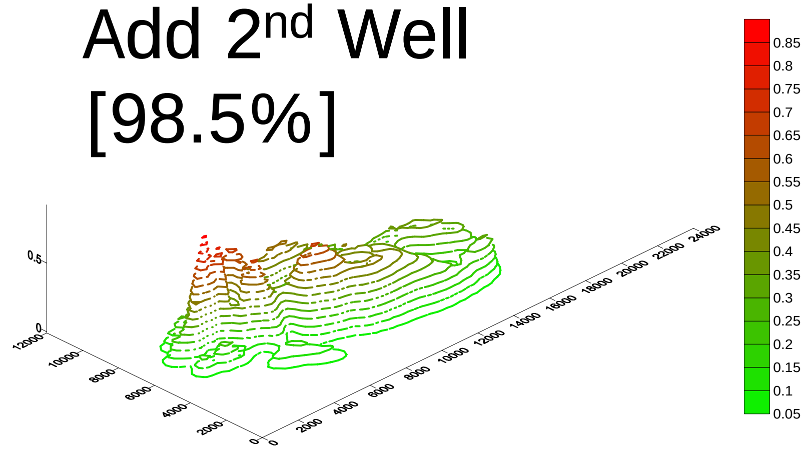
Existing [93.4%]



Add One Well [98%]



Add 2nd Well
[98.5%]



UXO Finding

- Initial test conducted on information from JPG-IV & extended on JPG-V.
- Algorithm tested on blind data significantly outperformed other methods:
  - Same data used (no additional data collected).
  - Only change was information / signal processing approach.

UXO/MineFinder – JPG IV Prove-out

Bookmarks
UXO Technology Demons
Report Documentation Pa
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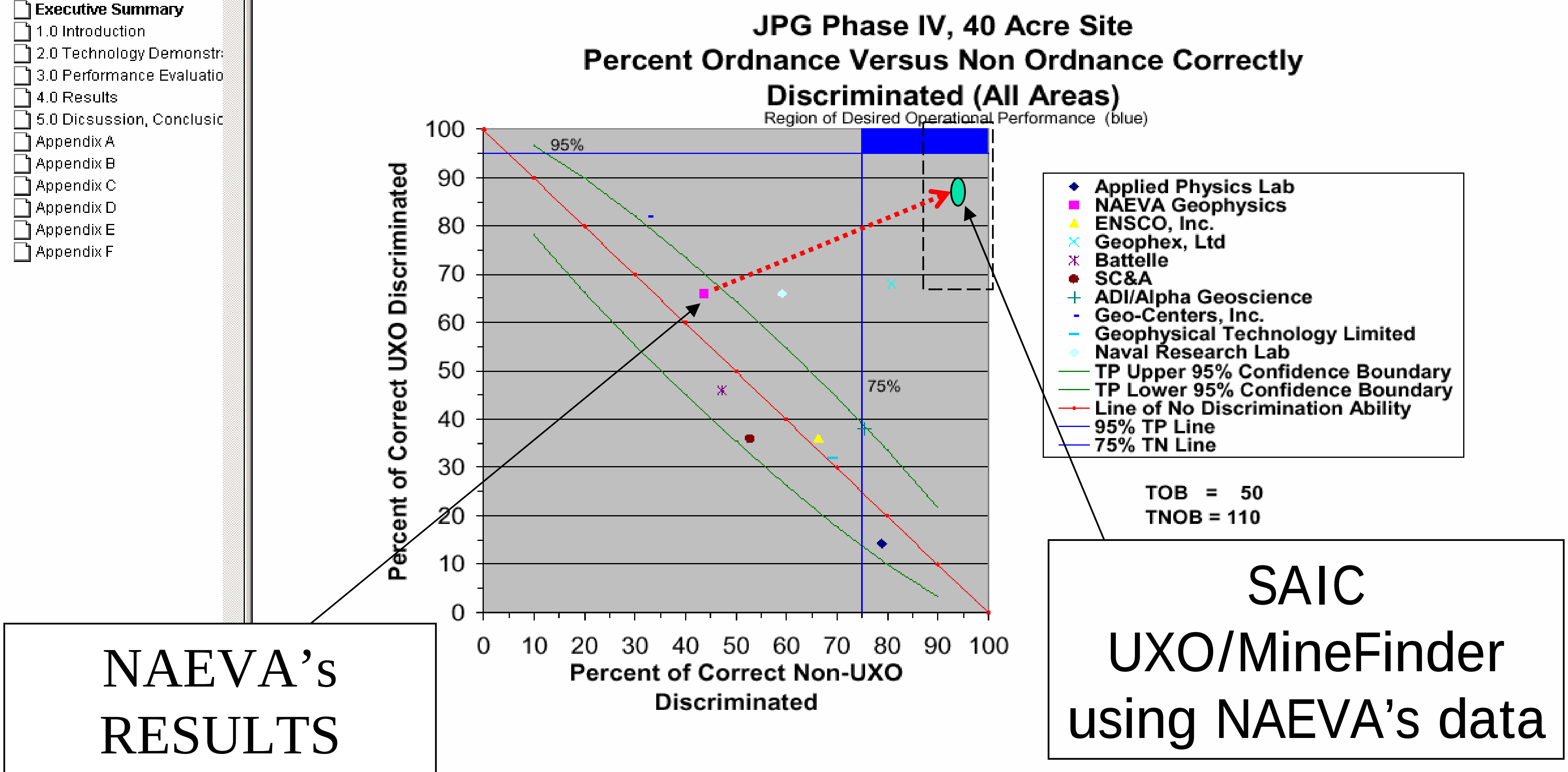
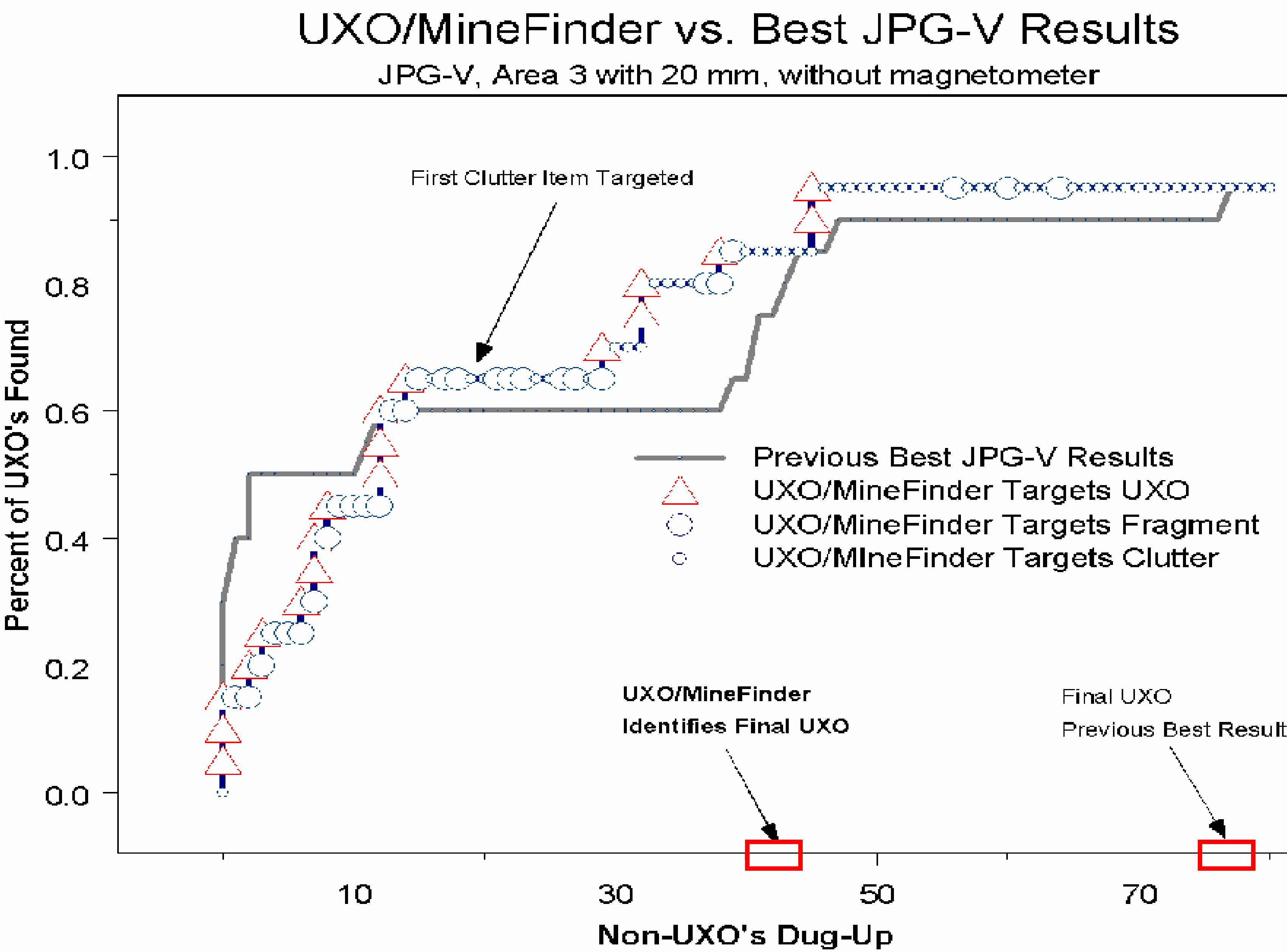
discriminate non-ordnance from ordnance while maintaining a relatively high TP rate. Though this is an important first step, no demonstrator was able to meet the desired performance level, 95% TP and 75% TN, established before the demonstrations began.

Graph ES-1. Discrimination Effectiveness



Deschaine, L. M., Hoover, R. A., Skibinski, J. N., Patel, J. J., Francone, F. D., Nordin, P. and Ades, M. J., Using Machine Learning to Compliment and Extend the Accuracy of UXO Discrimination Beyond the Best Reported Results of the Jefferson Proving Ground Technology Demonstration. Society for Modeling and Simulation International's Advanced Technology Simulation Conference, San Diego, CA April 2002.

UXO / MineFinder – JPG V Prove-out



Francone, F. D., Deschaine, L. M., Battenhouse, T., Warren, J. J., Discrimination of Unexploded Ordnance from Clutter Using Linear Genetic Programming. In Press: The Genetic and Evolutionary Computation Conference (GECCO-2004), June 26th – 30th, 2004, Seattle, WA, USA.

Long Term Monitoring

- Depending on the remedial alternative chosen:
  - Monitored natural attenuation.
  - Active remediation.
  - Source control.
  - Technical impracticable.
- Long term monitoring is required to evaluate the effectiveness of the decision.

The value of long term monitoring is to provide relevant information to the stakeholders to monitor the solution.

Long Term Monitoring

- Like the Plume finding, Long Term Monitoring can be optimized:
  - Location of where to sample.
  - Frequency of sampling
  - What to sample.
- Like Plume finding, but with time added.
  - Correlated time and space information.

Long Term Monitoring

- Each sampling event provides information content:
  - Sample events that are to close together (in space & time) provide redundant [unnecessary] information.
  - Sampling events spaced to far (in space & time) apart leave to much uncertainty to what is happening.
- Optimal LTM design provides the best balance of cost and knowledge.

LTM Case Study

- Industrial site.
  - Huge costs.
  - Desire to do the right thing, and to be efficient and effective at the same time.
- Solution is that the sampling needs are front-end loaded:
  - Most sites have more than ample existing data to apply this technique.
  - Much information collected expected redundant.

Concept for Optimal LTM:
For Point of Compliance Configuration

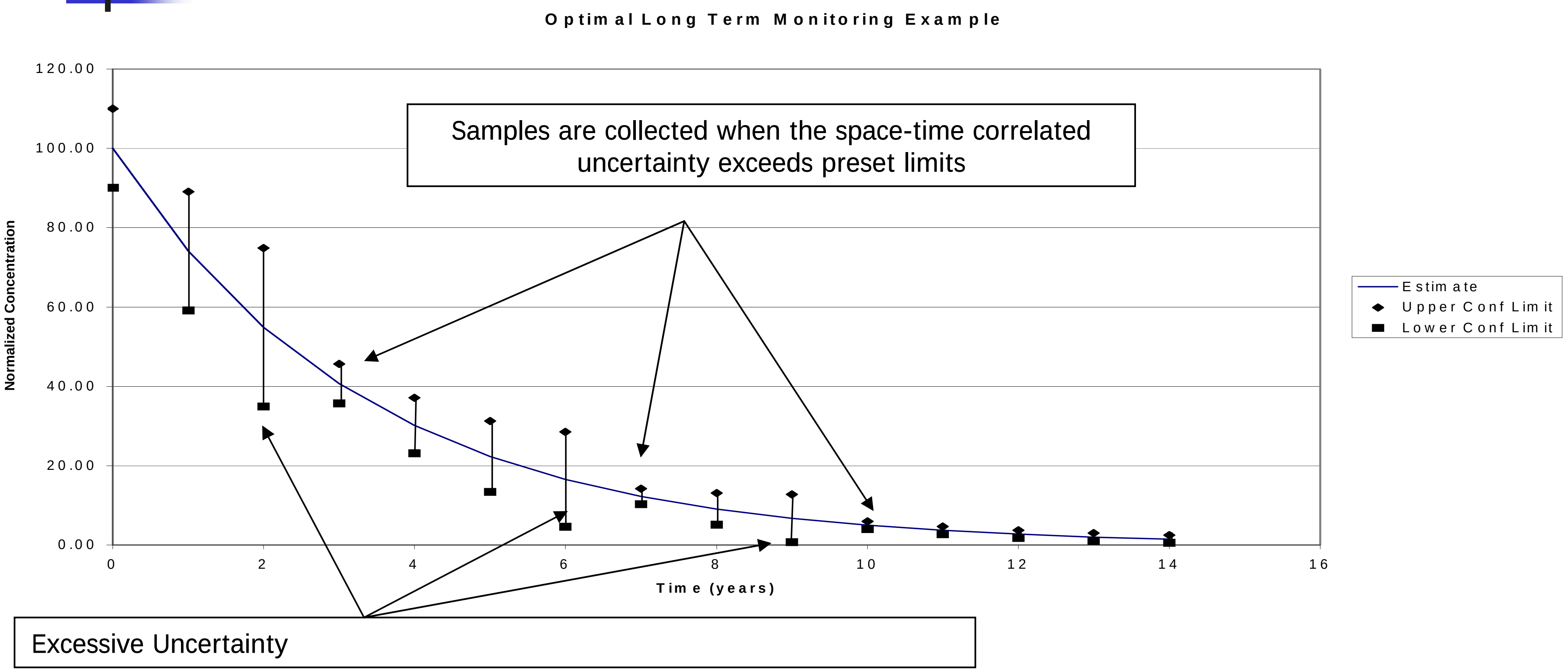
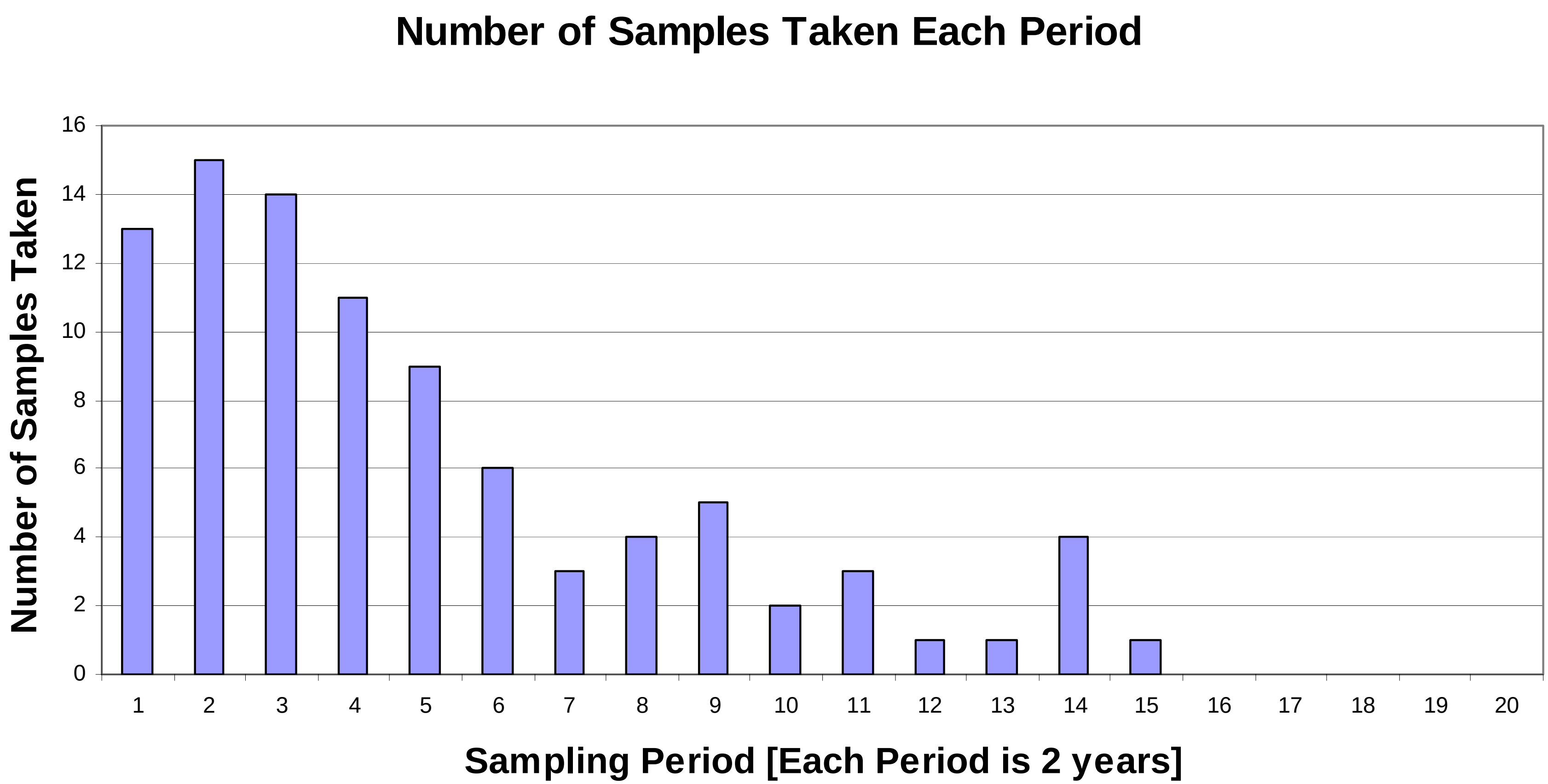


Figure 7. Long-term Monitoring Optimization Algorithm Concept.

Note: The uncertainty is a function of both space and time information.

Results of Long Term Optimization Analysis



Note: Number of samples increase and decrease with time, and generally decrease (Article in Draft form).

Discussion of Results

- Note that at the start of the monitoring, many samples are taken.
  - This is similar to how many monitoring programs are started.
  - Notice also that at the start, to few were taken.
- The number and location of samples points gets increased and decreased over the sampling periods to maintaining optimal confidence of plume knowledge with time.

The sampling frequency test period is adjustable.

Summary

- Optimization of feature location (plume configuration / UXO) is proven effective.
- Long-term monitoring policies optimally estimate plume topology (concentration maps in space & time).
- Long-term monitoring policies optimally estimate confidence at point(s) of compliance is achieved.

Reference Material to Get Started

- Kailath, T., Sayed, A. H., Hassibi, B., Linear Estimation, Prentice Hall, 854 pp., 2000.
- Huyakorn & Pinder, Computational Methods in Subsurface Flow, Academic Press, 473 pp. 1983.

Acknowledgements

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Thank You...

...for your attention