Innovative Field Monitoring: Legacy Successes and the Future of Long-Term Monitoring - 14571

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ABSTRACT

Site closure is a milestone achieved when the remaining contamination in the soil, surface water, groundwater, or air meets a risk or cleanup threshold determined not to pose a significant threat to human health or the environment. Site closure requirements are myriad and they vary significantly among implementing agencies; thus, final closure actions must be documented and filed with the appropriate government agencies. Documentation typically includes narrative descriptions of the releases, a full summary of assessment and remedial/corrective actions, maps, closure transition plans, summaries of field and laboratory data with quality assessment, and a risk characterization. A final closure decision reflects acceptable confidence in the quality and quantity of the site characterization data available. Prescriptive methods such as those in U.S. EPA's SW-846 and other guidance documents traditionally dictated the laboratory analyses acceptable for contaminant analysis. Related guidance provides rigorous quality assurance and quality control protocols to be followed during the chemical analysis. With the development of field analytical techniques in the 1990s, regulatory agencies debated the tradeoff between sample size and data quality. During the implementation of the EPA's Triad Approach, which emphasized field analytical techniques, regulators determined that better coverage using reduced data quality reduced decision errors, especially in soils characterization. Today, miniaturized sensors and probes are being developed to analyze constituents in water at long-term monitoring sites and similar data quality issues have surfaced. Past experience demonstrates how the value of more complete data sets provided by field analytical devices outweighs the lower levels of data quality. A case study using field analytical data from a DOE NETL deployment illustrates the utility of increased data volumes.

INTRODUCTION

The U.S. Department of Energy's Office of Legacy Management (LM) was created in December 2003, with a primary mission to fulfill DOE's post-closure responsibilities and to ensure protection of human health and the environment. More than 75 sites that no longer have an ongoing mission have transitioned from the remedial activity stage into long-term, post-closure monitoring. Each of these sites has undergone extensive characterization, evaluation, remediation, and closure processes.

Applicable data quality issues center on items such as the recommended EPA analytical method for a given contaminant, observance of quality assurance/quality control (QA/QC) protocols, holding times, and detection limits at the fixed-base laboratory. These parameters are established during the Data Quality Objectives (DQOs) planning phase. The DQOs and other parameters are verified and validated in the post-analytical phase. Combined with the cost of field sampling planning and mobilization, sample acquisition, shipping, and other costs, quality data come with a high price tag.

Data quantity issues are also addressed in the DQO phase. This process determines how many samples are required in order to make decisions with tolerable levels of statistical confidence. After the field data have been collected and validated, the DQOs are verified for compliance through the Data Quality Assessment (DQA) process to ensure objectives and requirements were achieved. Despite meeting DQO and DQA requirements, data sets or sampling frequencies often seem minimalistic due to the inherent uncertainty in site characterization.

THE EMERGENCE OF FIELD ANALYTICAL CAPABILITIES

The availability of field analytical techniques and equipment starting in the 1990’s for soils analysis produced more data than were previously possible. This development also initiated the evaluation of the tradeoffs between data quality and data quantity. Whereas field analytical methods provided substantially more sample data, concerns arose regarding the lower quality associated with these data. Through implementation of the EPA’s Triad Approach, EPA concluded the increase in information derived from the field analytical approaches more than compensated for the diminished quality.

Today, miniaturized field analytical sensors and probes to measure physical and environmental parameters related to surface and groundwater parameters are available. Combined with mature wireless communication technologies, these systems provide opportunities to develop automated and real-time data acquisition and compliance reporting systems. These systems are capable of providing continuous data readings with benefits that include greatly increased data volumes, self-validating data, and early warnings for selected environmental releases. By increasing the temporal frequency of data collection, the chance of missing a release or other event of concern is greatly reduced. The systems also reduce the overall costs compared to physical sampling and manual analysis.

As with the field analytical methods for soils, data quality questions need to be addressed regarding the automated sampling systems. Many of the lessons learned in the development of the Triad Approach are applicable to real-time surface and groundwater monitoring at LM sites. DOE’s National Energy Technology Laboratory (NETL) has hosted a research application of automated remote environmental monitoring. The project monitored water quality parameters including pH, turbidity, specific conductance, temperature, dissolved oxygen, chlorophyll, and blue-green algae using field sensors and wireless communications. An NETL case study application of real-time environmental monitoring system to evaluate impacts of acid mine drainage demonstrates the value of abundant real-time data.

THE TRIAD APPROACH: LESSONS LEARNED

As hazardous waste site characterization processes matured in the 1990s, the U.S. Environmental Protection Agency (EPA) and other regulatory agencies realized more fully the multi-faceted nature of decision-making in the face of uncertainty and the associated risks. Whereas the initial emphasis had been focused almost exclusively on minimizing laboratory errors through mandating acceptable analytical protocols and procedures, retrospective reviews of sites closures revealed the largest source of uncertainty emanated from a lack of sampling, not analytical errors (Crumbling et al. 2001, 2003, 2004; Myers 1997). The development and availability of field analytical devices afforded the opportunity to revise both the science and the practical implementation.

The Triad Approach manages hazardous waste site decision-making uncertainty through a three-step process: (1) Systematic Planning; (2) Dynamic Work Strategies; and, (3) Real-time Measurement Technologies. The Triad Approach represented a new paradigm in environmental characterization because it allowed responsible parties to step outside the previous boundary, which allowed only fixed laboratory data analysis using EPA-prescribed methods to support site characterization and closure decisions. Under this new system, a “weight of evidence” approach using collaborative data sets could be applied that incorporated data with varying data quality pedigrees.

The systematic planning aspect built upon existing protocols such as DQOs and QA/QC procedures, but expanded the evaluation to include key decisions to be made, the development of a conceptual site model (CSM), and the evaluation and management of decision-making uncertainty within the context of the CSM. Dynamic work strategies allowed cleanup efforts to incorporate flexibility to change or adapt the CSM to new information, which is frequently obtained by the use of field analytical devices. Dynamic work strategies are documented as pre-approved decision logic in planning documents. Reduced-time measurement technologies include rapid turn-around from fixed laboratories, screening analytical methods, or field-based measurement technologies. Through field analytical technologies and the adaptive characterization structure afforded by the Triad Approach, site characterizations and closures produced more sample data and reduced decision-making risks

UNCERTAINTIES IN DECISION-MAKING

Sampling Uncertainties

Experience with sampling and analyzing heterogeneous soils, sediments, and other solid materials demonstrated how duplicate samples could produce order-of-magnitude (or more) variations from the same sample volume or location. Such results created a debate regarding the source of the error, which was typically attributed to the analytical laboratory. Sampling theory, developed in the mining industry and later transferred to the environmental arena (Gy 1979, Pitard 1993, Myers 1997), demonstrated the uncertainty associated with sampling and subsampling particulate materials along with solutions to minimize the sampling errors. This shifted much of the onus from the laboratory to field sampling.

Figures 1 and 2 show how an incorrect sample "size", i.e. physical volume/mass, known properly as *support*, can easily bias the sample result at either the field level or the laboratory level, even with relatively uniform distribution of the contaminant. When samples or subsamples have a small support, frequently the contamination is missed during the sampling or subsampling process and the analytical result is biased low, even with a zero laboratory error contribution. Conversely, occasional clusters are captured, which appear to be exceedances but simply represent the heterogeneous nature of the material. In either case, insufficient sample support introduces a bias and the analytical result fails to quantify the appropriate contaminant concentration. Larger sample supports are more likely to produce accurate characterization.

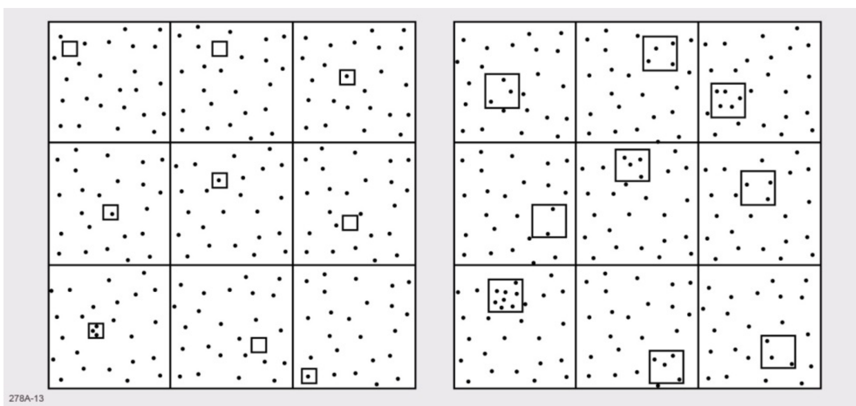

Fig. 1: Conceptual Model of Heterogeneity and Uncertainty – Small Particles

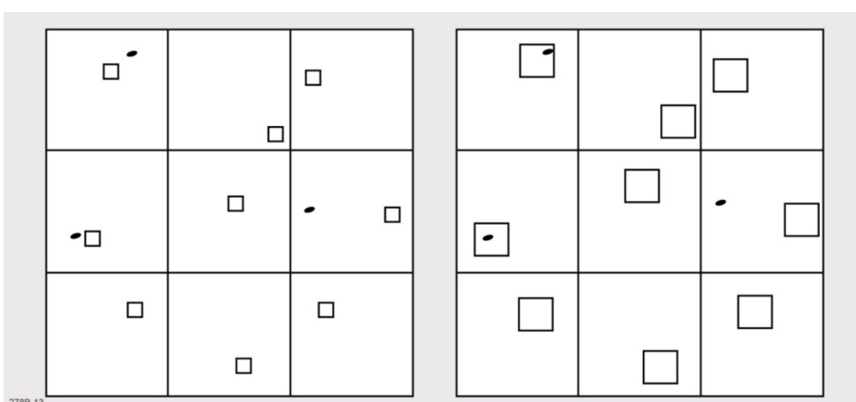

Fig. 2: Conceptual Model of Heterogeneity and Uncertainty – Large Particles

Figures 1 and 2 are fractal in nature, i.e., the patterns are self-similar and applicable at multiple scales. These figures illustrate how contamination can be missed at either the field level or subsampling level, a form of double jeopardy not associated with laboratory error. The fractal "particles" in the figures could be disseminated crystals of explosives in soils or PCB clusters on clay materials. Similarly, the "particles" could be unexploded ordnance over a large bombing range or multiple small disposal pits located on a large industrial site or military facility. Whether the fractal scale is site-wide, field sample, or laboratory subsample, two issues arise: (1) mischaracterization occurs if the particles are missed during sampling; and, (2) natural clusters of material can provide the illusion of a worse condition than actually exists. In either case, inappropriate characterization introduces a bias that can lead to decision-making errors.

Analytical Uncertainties

Laboratory analytical methods and associated QA/QC protocols produce data with a quantifiable range of uncertainty. Whereas sampling uncertainties and errors produce orders-of-magnitude issues, laboratory uncertainties are commonly in the 10 to 50 percent range. Thus, if field analytical techniques double or triple the uncertainty, analytical uncertainties still remain less than the field characterization uncertainties. Figure 3 shows a typical result of comparing fixed laboratory analysis to field analytical analysis (after Crumbling 2004).

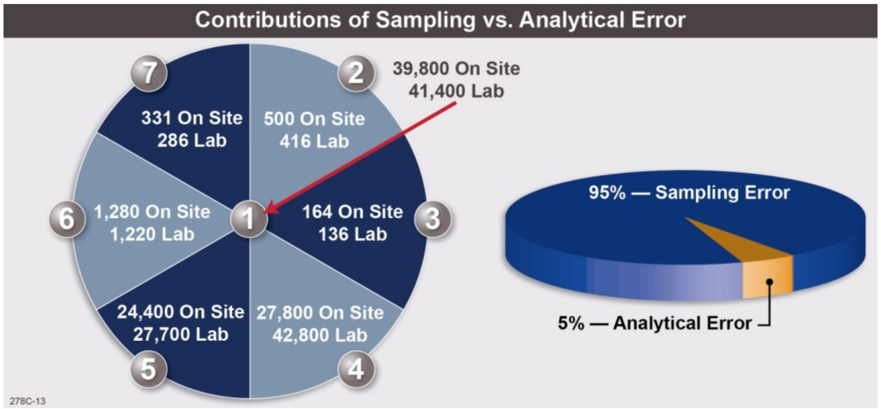

Fig. 3: Comparison of Field Sampling Error Magnitudes to Laboratory Error Magnitudes

By using both laboratory and field analytical data for material from the same sample location, EPA determined that sampling errors could easily contribute about 95 percent of the error while laboratory error contributed a mere five percent of the total. EPA further concluded that previous reliance on minimizing laboratory errors at the expense of ignoring field sampling errors had not yielded the intended result of minimizing decision risk.

Decision-making Uncertainties

Sampling and analytical issues converge during the decision-making process. Because these errors are cumulative, an increase in either one affects the overall probability of decision error. The key issue is the degree to which the disproportionately larger error from field analytical techniques impacts the final decision process. The appropriate question becomes, "To what degree does the dynamic affect total error and related decision error?"

Figure 4 presents a graphical representation of the effects of reduced QA/QC associated with field analytical methods. As shown in Figure 4, sampling uncertainty represents the largest error component, which is shown as the horizontal legs of the triangles in Figure 4. Conversely, analytical error is the much smaller error component, as shown by the vertical lines of the triangles. The total error (field + laboratory) is shown by the hypotenuses (A, B, and C), and can also be calculated by the standard sum of variances approach (Pitard 1993).

By applying proper methods to minimize sampling error (Pitard 1993, Myers 1997), the length of the horizontal axis can be reduced. Even if the field analytical error is increased substantially, the total error is greatly reduced, as shown by hypotenuse B. If a fixed laboratory is used along with sufficient field sampling, the hypotenuse (total error) shrinks further (hypotenuse C).

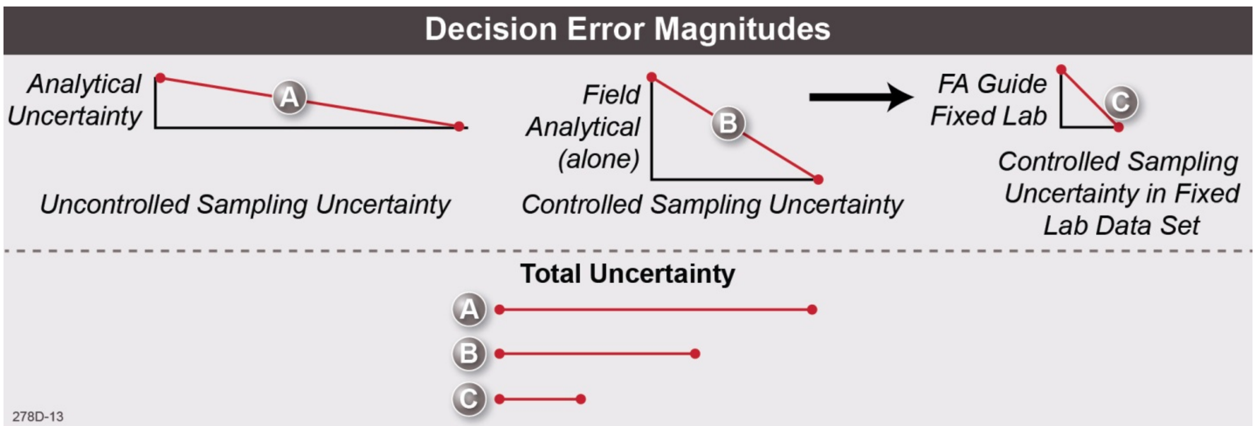

Fig. 4: Additivity of Uncertainties and Errors for Decision-making

Figures 1 and 2 show how “coverage” associated with sample support benefits characterization and decision accuracy. This same principle applies to spatial and temporal coverage for environmental characterization. Figure 5 shows a spatial example of how greater coverage, even with poorer quality data, enhances the confidence in decision-making. If contamination exists in a spatial context, more data points provide a greater chance of locating and bounding the contamination. Conversely, even with the best available laboratory QA/QC, minimal sample coverage carries the risk of missing undiscovered contamination.

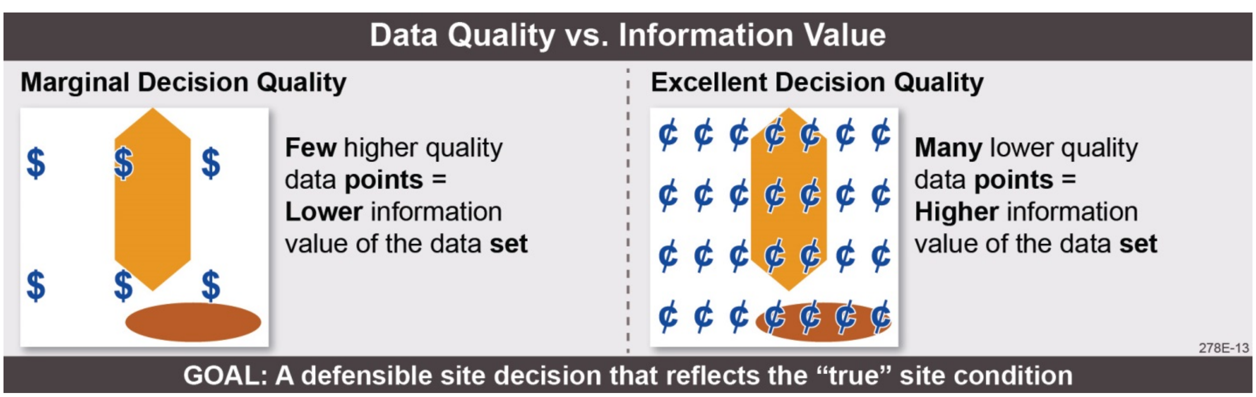

Fig. 5: The Value of More Field Analytical Data vs. Fewer Fixed Laboratory Data

Temporally, the situation is highly analogous, and is especially important for mobile fluid media. Quarterly groundwater sampling can miss or understate peaks due to the timing of the sampling event. Moreover, sparse temporal sampling could miss releases altogether. By deploying field analytical devices for groundwater monitoring, much greater temporal coverage is achieved, which can detect previously unseen releases and quantify the length and severity of upticks in the contaminant concentrations being monitored by long-term management (LTM) programs.

This enhanced temporal coverage contrasts to situations where a contaminant increase is observed during quarterly sampling, and resampling is subsequently initiated. If the increase is confirmed in a *one of n* approach, the next available data will come after the next quarterly sample is taken and analyzed, leaving interim uncertainty regarding concentrations between sampling events. If the resample discredits the uptick, uncertainty remains as to whether the first or subsequent sample most adequately characterizes the status of contamination in the aquifer. With field analytical methods, continuous repeat samples (isolated or in situ) are measured automatically to confirm or refute the aberration. Despite lower data quality, the volume of resample data provides a more definitive assessment.

NETL CASE STUDY

The U.S. Department of Energy's National Energy Technology Laboratory has deployed field sensors to locations where acid mine drainage and/or hydraulic fracturing operations may be impacting negatively surface waters. To monitor acid mine drainage impacts, NETL deployed a YSI 6600 sonde to West Run Creek in Morgantown, West Virginia (Figure 6). The sonde contains seven sensors which monitor water quality parameters: pH, temperature, specific conductance, turbidity, dissolved oxygen, chlorophyll, and blue-green algae. Hourly readings are provided by the sensor and are delivered via wireless communications to a user interface program for examination and interpretation.

Fig. 6: YSI Sensor Deployment in West Run Creek

Figure 7 is a time series plot of 24-hour averages for each water quality parameter being monitored, resulting in a single point value for each parameter for each day. In sampling terms, the temporal sampling support presented on this graph is one day. A one-week snapshot of water quality daily averages is shown on the graph in Figure 7. Considerable variation between daily results can be seen in the plot. None of the parameters is of concern except temperature, which is highlighted by red triangles indicating threshold exceedances. These exceedances indicate the temperature fell below 33 degrees Fahrenheit. Whereas low temperatures are not an environmental issue, ice buildup on the sonde may cause damage. The wireless communications platform sends an instant alert whenever a pre-set threshold is breached.

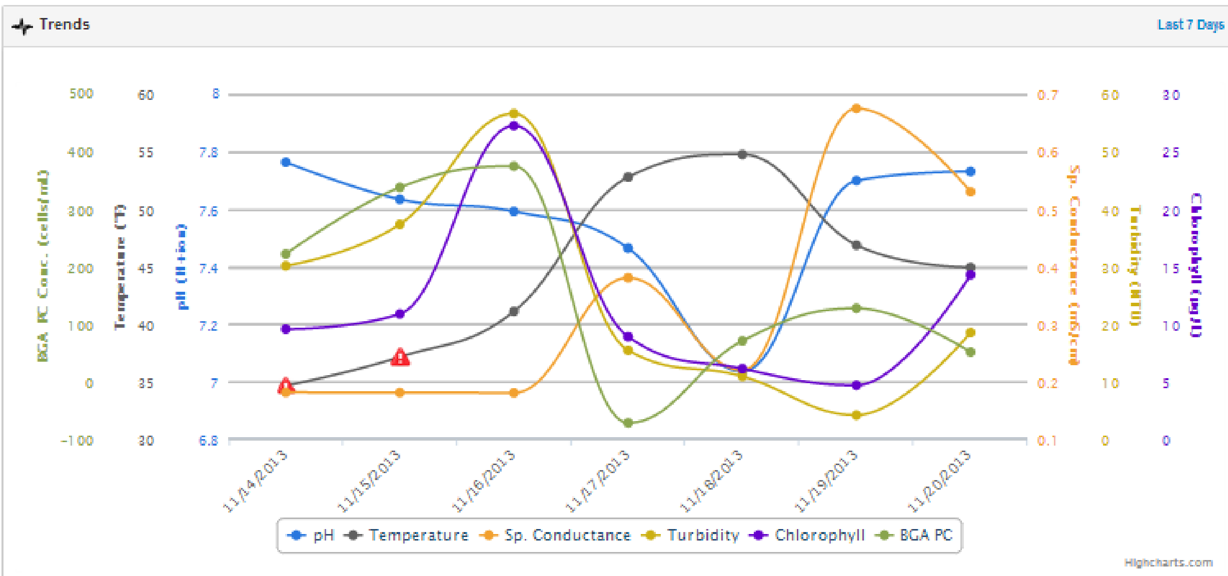

Fig. 7: Daily Averages of Water Quality Data over a Seven-Day Period

Figure 8 displays the data at a smaller level of support, an hourly time series over the course of a single day. Again, the variation in parameter values is noticeable over the course of the day as the temporal support has been reduced. Note how the temperature readings reflect the daily warming and cooling cycle. Note also the general correlation between pH and temperature. Correlation between parameters offers the opportunity to use more easily obtained parameter data to predict concentrations of parameters for which sensors are expensive, or for which technology is currently unavailable.

NETL published a study of available sensors for air and water, with emphasis on sensors capable of detecting impacts to water quality from hydraulic fracturing operations (MRIGlobal 2013). Whereas the study noted a need for more types of sensors, especially those for environmental contaminants, it also noted the accelerating pace of commercial sensor development due to the increased interest in continuous environmental monitoring data.

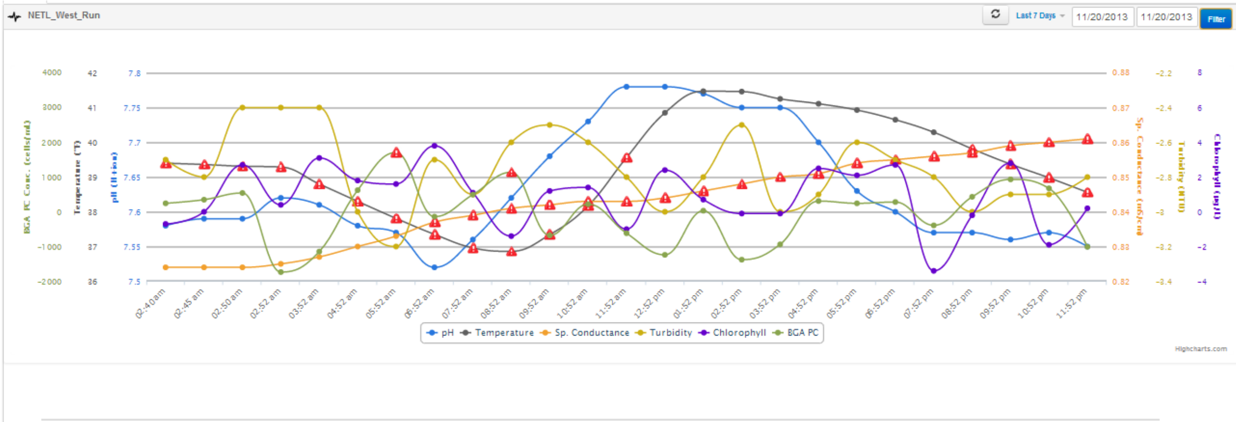

Fig. 8: Hourly Sensor Readings for Water Quality Parameters

CONCLUSIONS

Sparse yet compliant data sets were tolerated for years in environmental remediation due to cost constraints. With the advent of field analytical technologies and regulatory innovations such as the Triad Approach, amplified data sets provide better coverage and reduce the chances of missing contamination. The examination of error contributions from field sampling vs. laboratory sampling supports the adoption of field analytical methods because decision errors are minimized and better coverage is achieved.

LTM sites offer similar opportunities to use field analytical approaches to reduce the long-term expenditures associated with monitoring. Whereas contaminant concentrations at sites undergoing characterization and closure are presumed to be non-compliant until demonstrated otherwise, closed sites in LTM programs are presumed to be compliant unless evidence indicates upward changes in concentrations. Thus, the burden of proof is reversed and mitigated at LTM sites. Using field analytical and correlation techniques to track contaminant concentrations through either direct measurements or surrogate parameters offers a cost-effective path to enhancing the quality of long-term monitoring at DOE legacy sites. This approach is based on experience obtained during site characterizations and closures, and is applicable to the expanding network of LTM sites in the DOE complex.

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